

4D-Var and hybrid inversion of NO_x emissions & the impact of satellite retrievals on emission estimates

Zhen Qu

Harvard University

Nov 19, 2020

4D-Var method

Description	Variable	
Model simulation	c	
Observation operator	\mathcal{H}	Maps c to obs space
Satellite observation	SCD_{obs}	vector
Prior emission scaling factor	σ_a	= 1
Emission scaling factor	σ	= Emis / Emis_prior
Observational error covariance matrix	S_{obs}	diagonal
Prior error covariance matrix	S_a	

$$J(\boldsymbol{\sigma}) = \frac{1}{2} \sum_{\mathbf{c} \in \Omega} (\mathcal{H}\mathbf{c} - \text{SCD}_{\text{obs}})^T \mathbf{S}_{\text{obs}}^{-1} (\mathcal{H}\mathbf{c} - \text{SCD}_{\text{obs}}) + \frac{1}{2} \gamma_r (\boldsymbol{\sigma} - \boldsymbol{\sigma}_a)^T \mathbf{S}_a^{-1} (\boldsymbol{\sigma} - \boldsymbol{\sigma}_a)$$

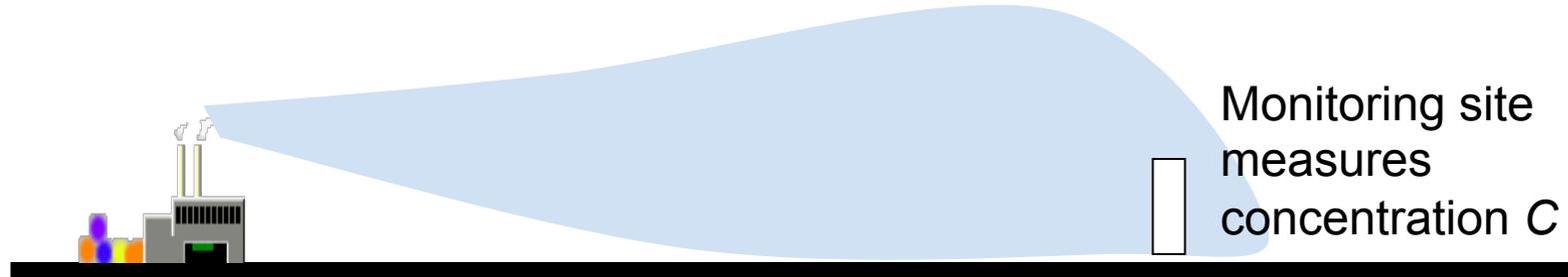
- 4D-Var:

- Summed over time (4D)
- Seeks σ iteratively (Var)
- Requires adjoint model calculates the sensitivity of cost function w.r.t. scaling factor σ

(Sandu et al., 2005)

Inverse Modeling

Atmospheric “forward” model gives $C = kE$



(fuel burned) \times (emission factor)
 \Rightarrow *a priori* “bottom-up” estimate

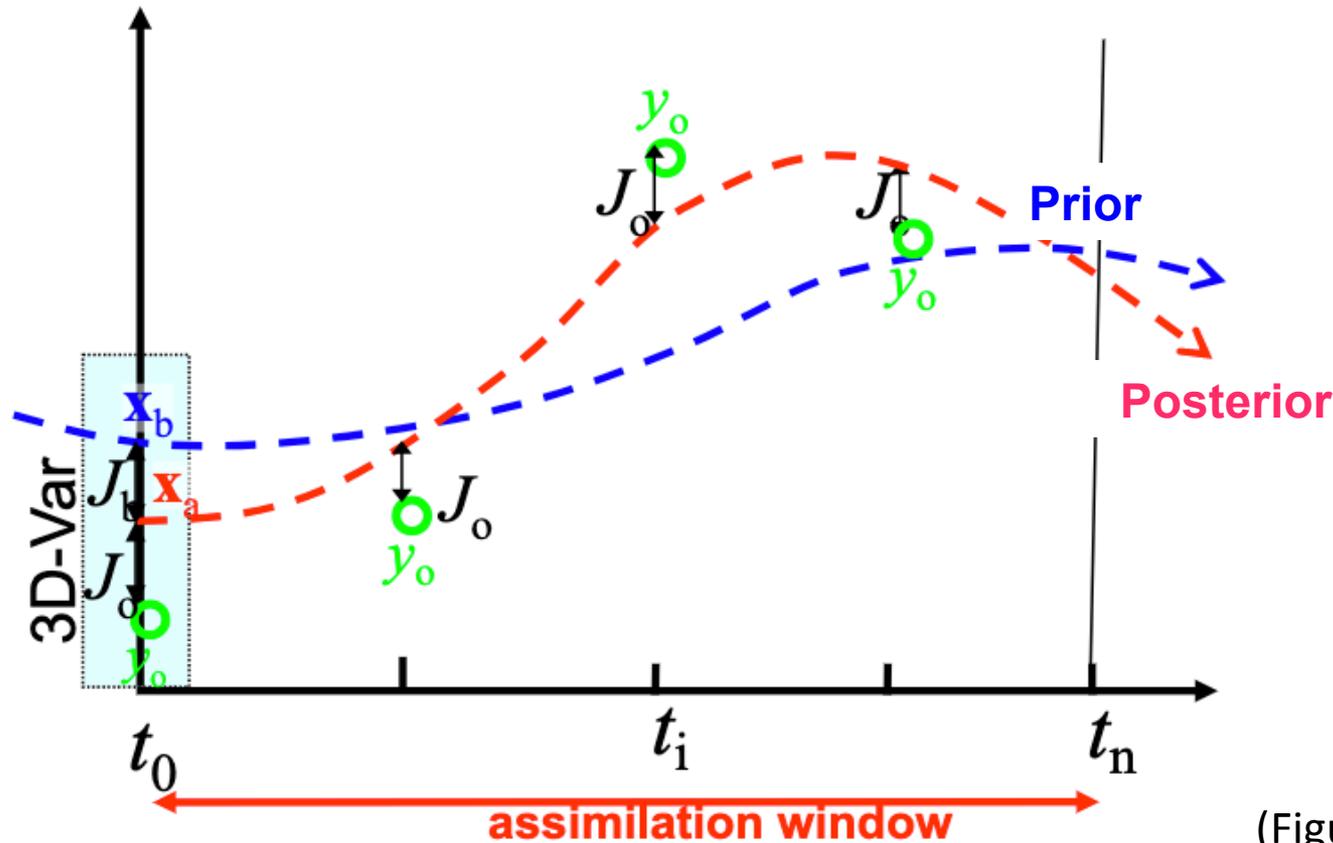
$$E_a \pm \sigma_a$$

Inverse model $E = k^{-1}C$
 \Rightarrow “top-down” estimate

$$E_\varepsilon \pm \sigma_\varepsilon$$

- Forward model: CMAQ, WRF-Chem, GEOS-Chem
- Adjoint code is required for each process in the forward model

4D-Var v.s. 3D-Var



(Figure from ECMWF)

- 3D-Var finds the best estimate using an observation and a state at **one specific time point**.
- 4D-Var adjusts the initial state (NO_x emissions) to optimize the model trajectory to better match the observations distributed **over the assimilation window**, needs adjoint.

Shortcoming of 4D-Var:

- Time consuming (search minimum iteratively)
- 17 hours/ iteration, more than 20 iterations
- ~ 2 - 3 weeks to finish monthly inversion (1 node, 24 threads)

Mass balance:

- Scale prior emission E_a by the ratio of observed and simulated column density

$$E_t(i, j) = E_a(i, j) \frac{SCD_{obs}(i, j)}{SCD_{GC}(i, j)}.$$

(Martin et. al, 2003)

- Computational cost: ~ 8 hours for monthly regional estimates.

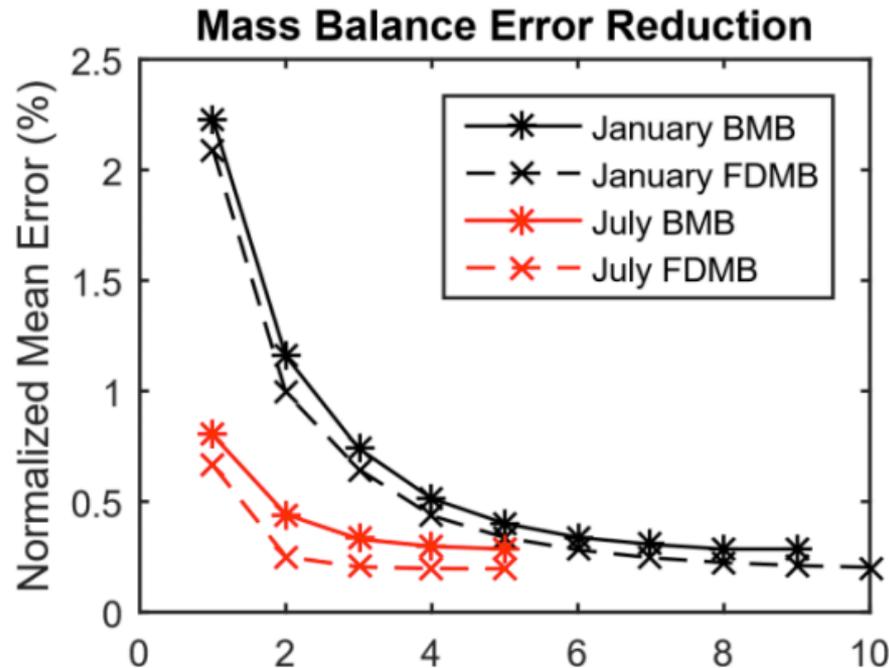
Hybrid 4D-Var / Mass balance

Computational cost of 4D-Var is especially challenging when applying to TROPOMI and geostationary satellite data

- 4D-Var (base year) + mass balance (trend)

(*Qu et. al, 2017*)

- Iterative mass balance



(*Cooper et. al, 2017; Li et al., 2019*)

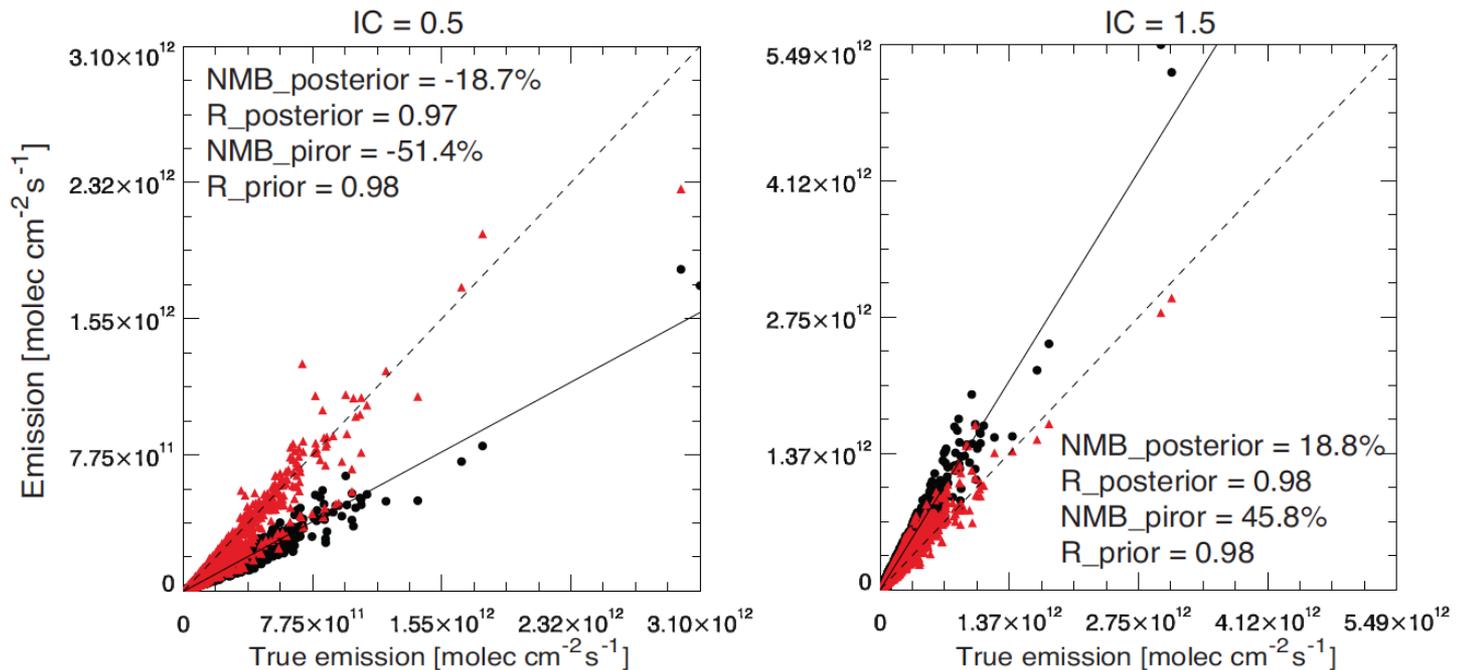
- Iterative mass balance (global) + 4D-Var (regional) (*Choi et. al, in prep*)

Evaluation: pseudo observation tests (simplified OSSE)

- Design inverse problem with known solution (true emission) to evaluate the performance of the new inversion framework
- Pseudo observations: NO₂ column densities from model simulation at satellite overpass time and locations using “true emissions” (random noise applied to observations)

Pseudo observation tests: 4D-Var

- 135915 pseudo observations generated for Jan, 2010 (random noises applied in observations)
- Initial guesses : 0.5 x true emission for IC = 0.5; 1.5 x for IC = 1.5; normally distributed random noises applied in emissions



- Smaller NMSE (by 61%, IC=0.5 and 41%, IC=1.5) in posterior emissions

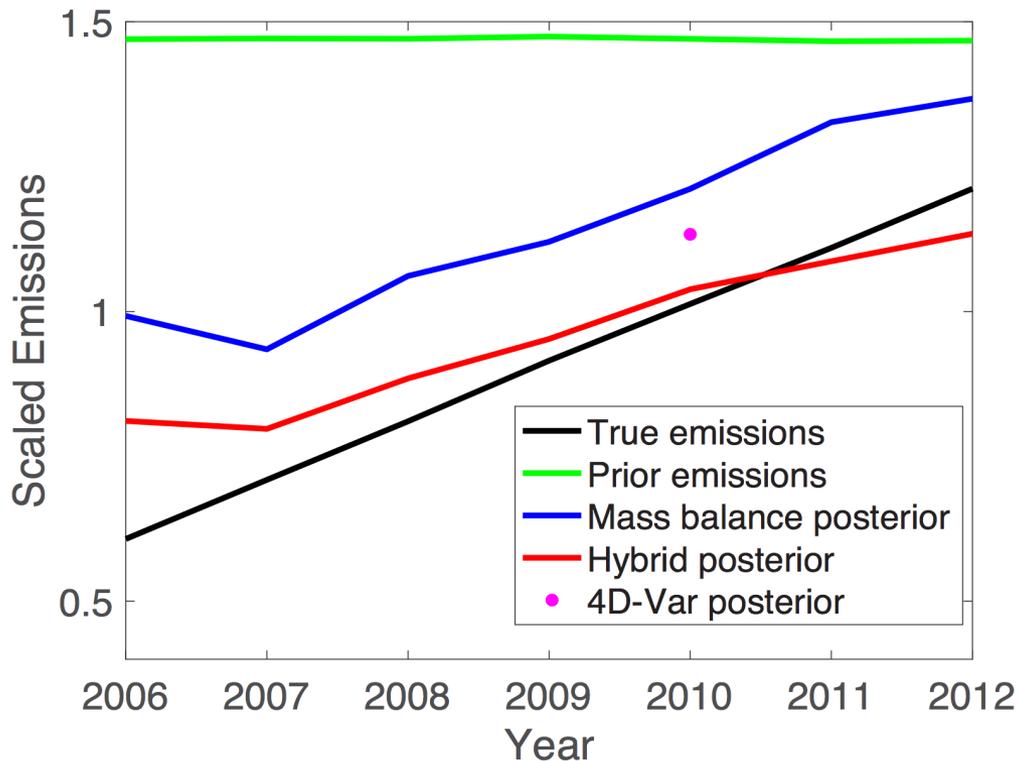
(Qu et al., 2017)

Pseudo observation tests: Hybrid 4D-Var + mass balance

Base year (2010): 4D-Var

Other years (2005-2012): use 2010 4D-Var posterior for mass balance

Scaled emissions in pseudo observation test

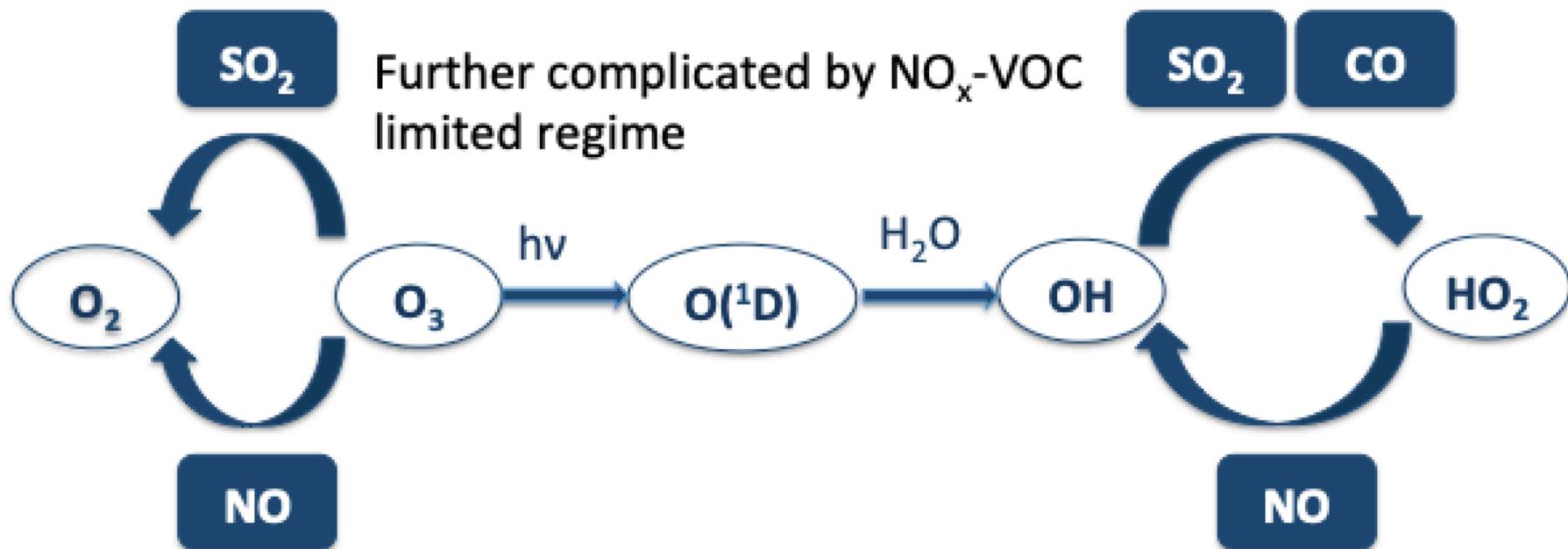


- Hybrid posterior has smaller NMSE (by 59% to 78%) and better correlation compared to mass balance.

Top-down emission estimates

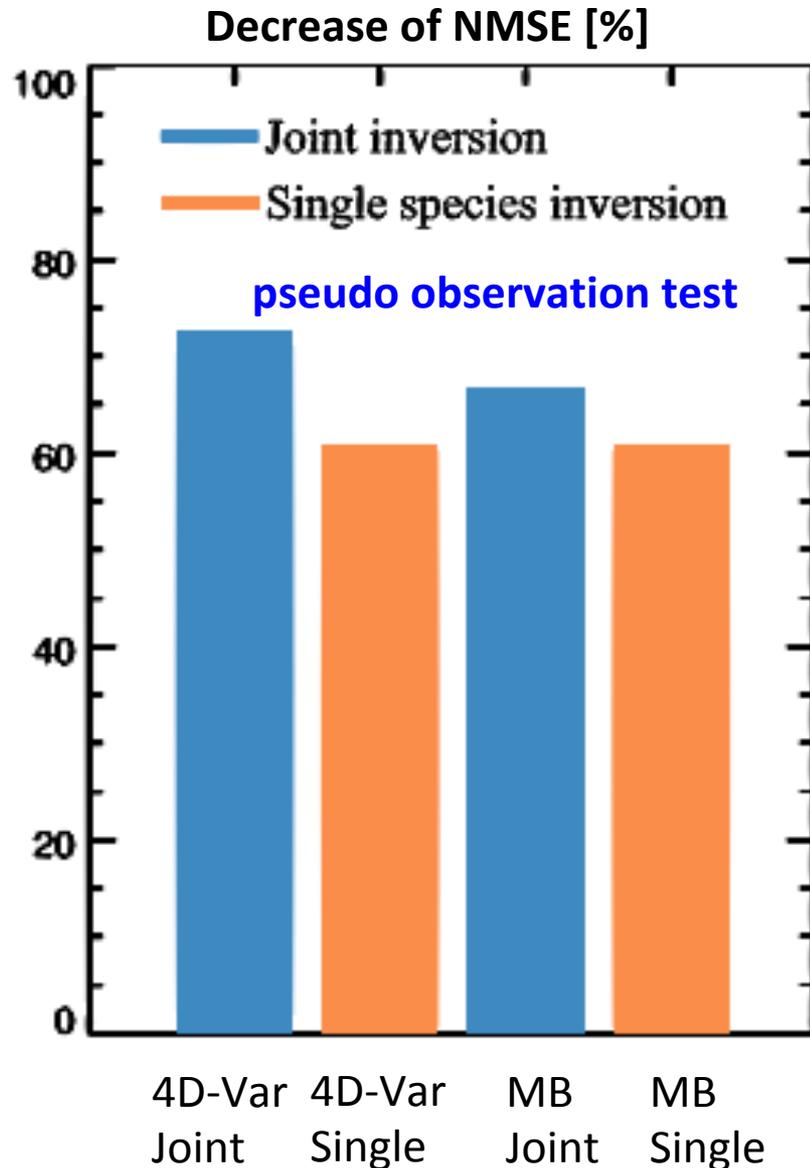
Still ...

- The impacts of adjusting emission of one species on changes in concentrations of other species are not being considered so far
- Errors in other species emissions are likely biasing the top-down emission of the constrained species



Joint NO_x & SO₂ inversion

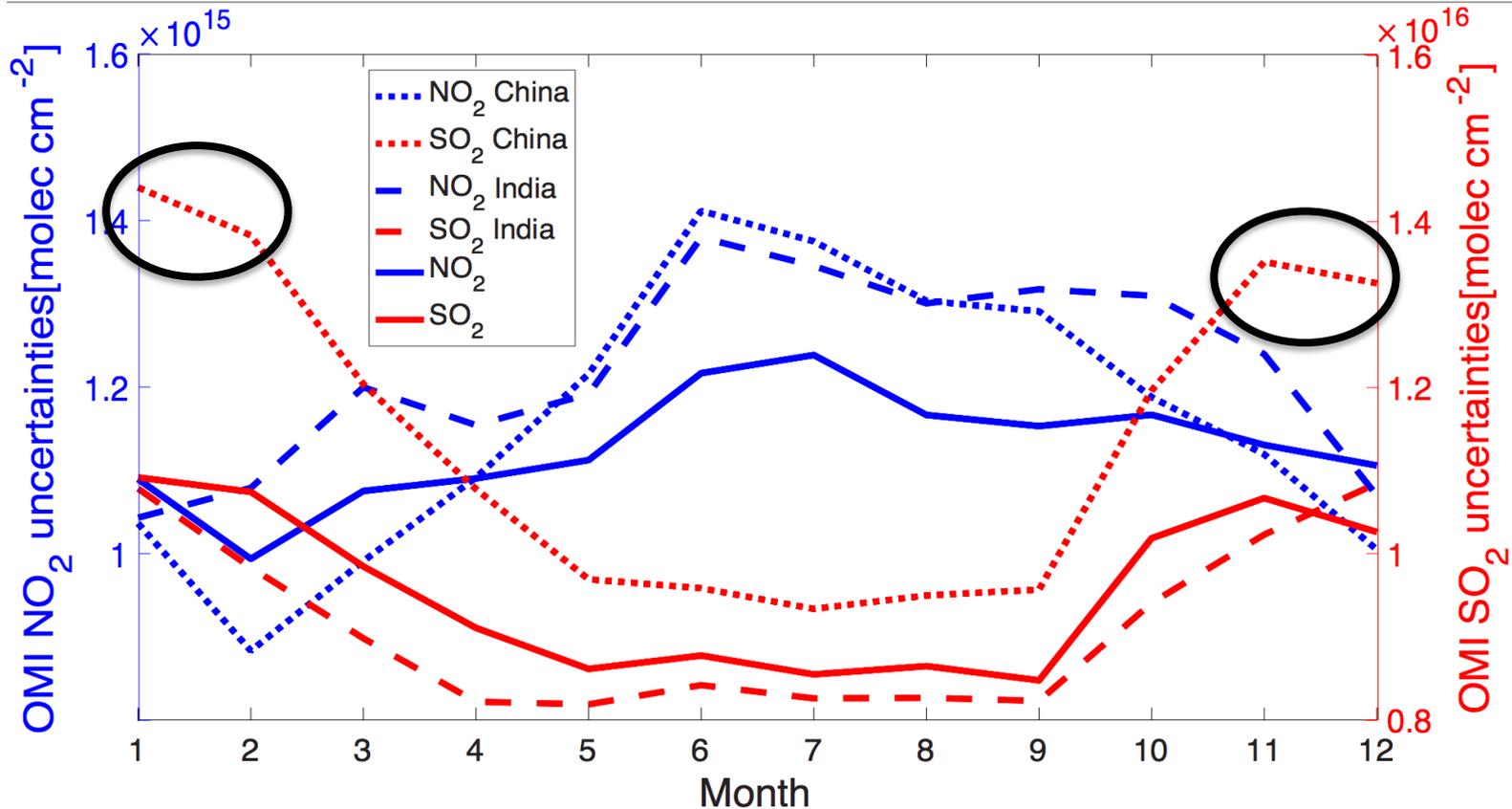
- Use both NO₂ & SO₂ observations to optimize NO_x and SO₂ emissions



- Joint inversion decreases NMSE in pseudo observation test

Impact of observation uncertainties

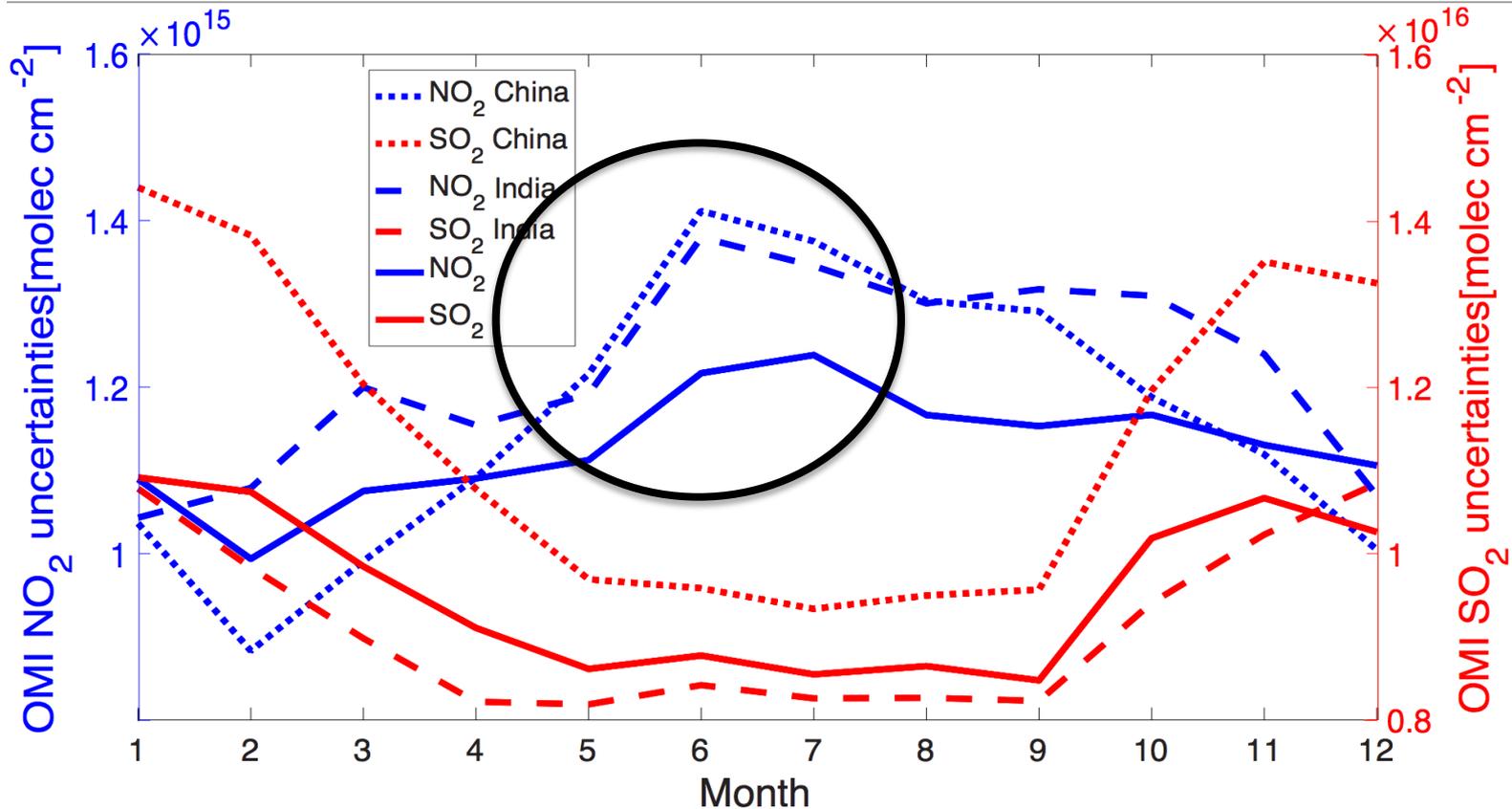
Monthly mean uncertainties in OMI observations (2010)



- In China, NMB and NMSE of SO₂ joint posterior reduce by up to 26% and 18% compared to single species posterior in most months between November and February;

Impact of observation uncertainties

Monthly mean uncertainties in OMI observations (2010)



- In China, NMB and NMSE of SO₂ joint posterior reduce by up to 26% and 18% compared to single species posterior in most months between November and February;
- For NO_x, joint posterior has reduced NMSE from May to October and reduced absolute value of NMB from May to July

Sector-based inversion

Bottom-up emission inventory:

$E = \text{species emission factor} \times \text{activity}$



New sector-based inversion:

$$E_{\text{NO}_x_{\text{pos}}} = SF_{\text{industry}} \times E_{\text{NO}_x_{\text{industry}}} + SF_{\text{energy}} \times E_{\text{NO}_x_{\text{energy}}} + \dots$$

$$E_{\text{SO}_2_{\text{pos}}} = SF_{\text{industry}} \times E_{\text{SO}_2_{\text{industry}}} + SF_{\text{energy}} \times E_{\text{SO}_2_{\text{energy}}} + \dots$$

$$E_{\text{CO}_{\text{pos}}} = SF_{\text{industry}} \times E_{\text{CO}_{\text{industry}}} + SF_{\text{energy}} \times E_{\text{CO}_{\text{energy}}} + \dots$$

Sector-based inversion

Bottom-up emission inventory:

$E = \text{species emission factor} \times \text{activity}$



New sector-based inversion:

$$E_{\text{NO}_x\text{pos}} = \text{SF}_{\text{industry}} \times E_{\text{NO}_x\text{industry}} + \text{SF}_{\text{energy}} \times E_{\text{NO}_x\text{energy}} + \dots$$

$$E_{\text{SO}_2\text{pos}} = \text{SF}_{\text{industry}} \times E_{\text{SO}_2\text{industry}} + \text{SF}_{\text{energy}} \times E_{\text{SO}_2\text{energy}} + \dots$$

$$E_{\text{COpos}} = \text{SF}_{\text{industry}} \times E_{\text{COindustry}} + \text{SF}_{\text{energy}} \times E_{\text{COenergy}} + \dots$$

Adjust sector and species emissions simultaneously

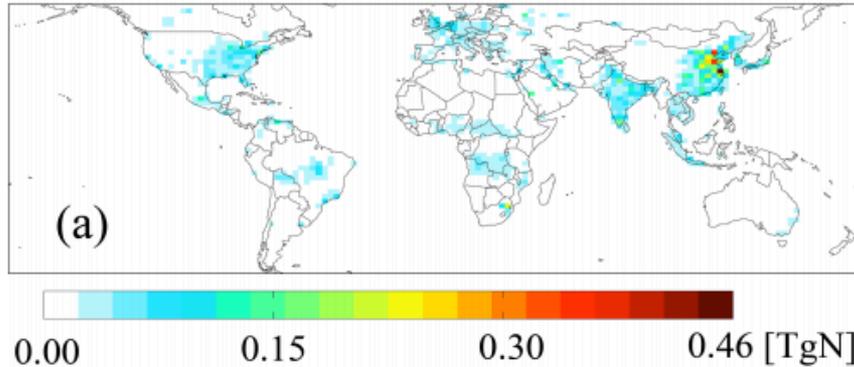
$$E_{\text{NO}_x\text{pos}} = \text{SF}_{\text{industry}} \times E_{\text{NO}_x\text{industry}} \times \left[\text{SF}_{\text{NO}_x\text{industry}} \right]$$

$$E_{\text{SO}_2\text{pos}} = \text{SF}_{\text{industry}} \times E_{\text{SO}_2\text{industry}} \times \left[\text{SF}_{\text{SO}_2\text{industry}} \right]$$

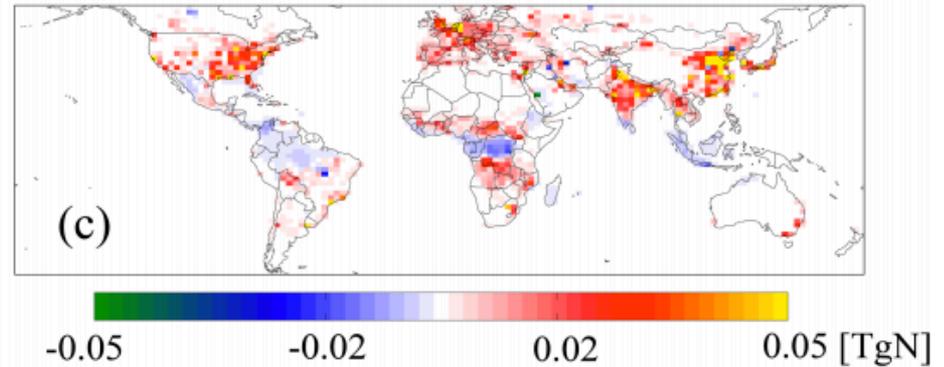
$$E_{\text{COpos}} = \text{SF}_{\text{industry}} \times E_{\text{COindustry}} \times \left[\text{SF}_{\text{COindustry}} \right]$$

Impact of NO₂ retrievals on top-down NO_x emissions

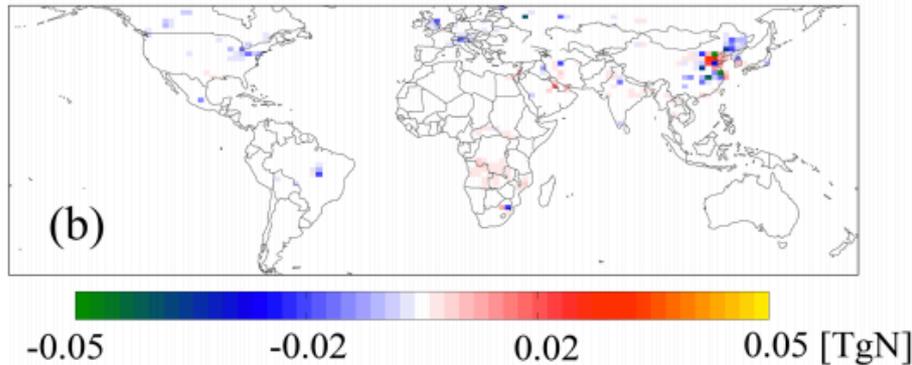
Total bottom-up NO_x emissions in 2010



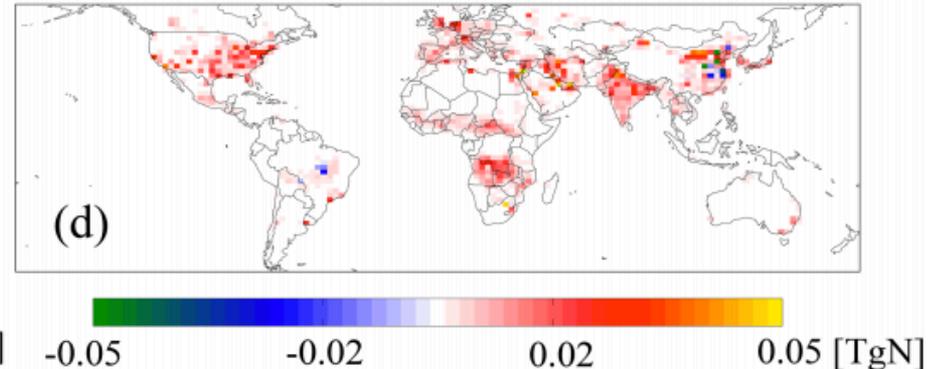
DOMINO posterior - prior



NASA posterior - prior



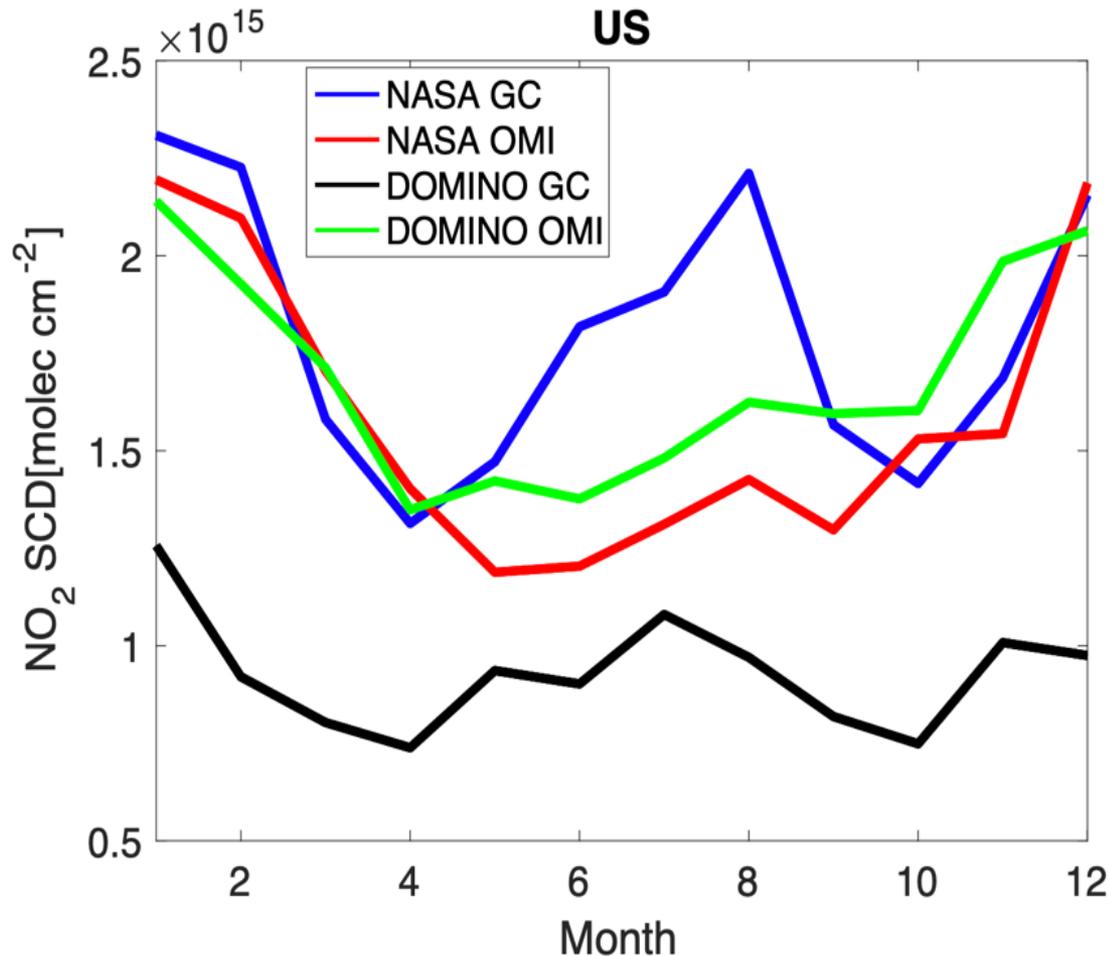
QA4ECV posterior - prior



(*Qu et al., 2020*)

- NASA SP version 4 is up to 50% higher in urban regions
- Expect more similar results between newest NASA and KNMI retrievals

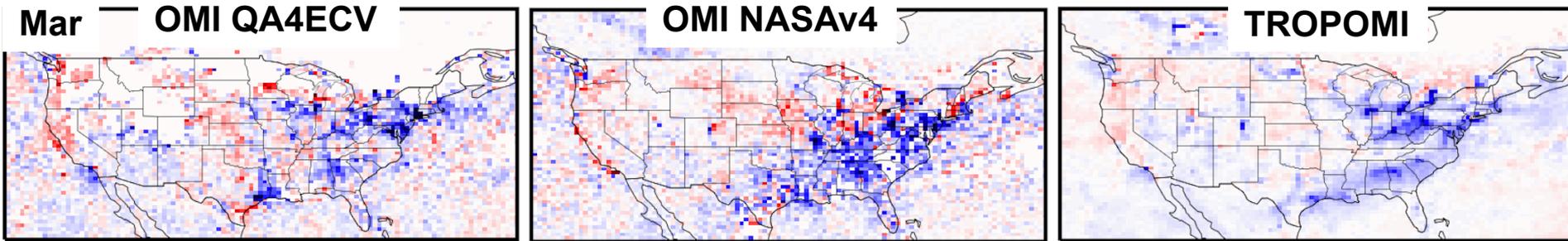
Impact of NO₂ retrievals on top-down NO_x emissions



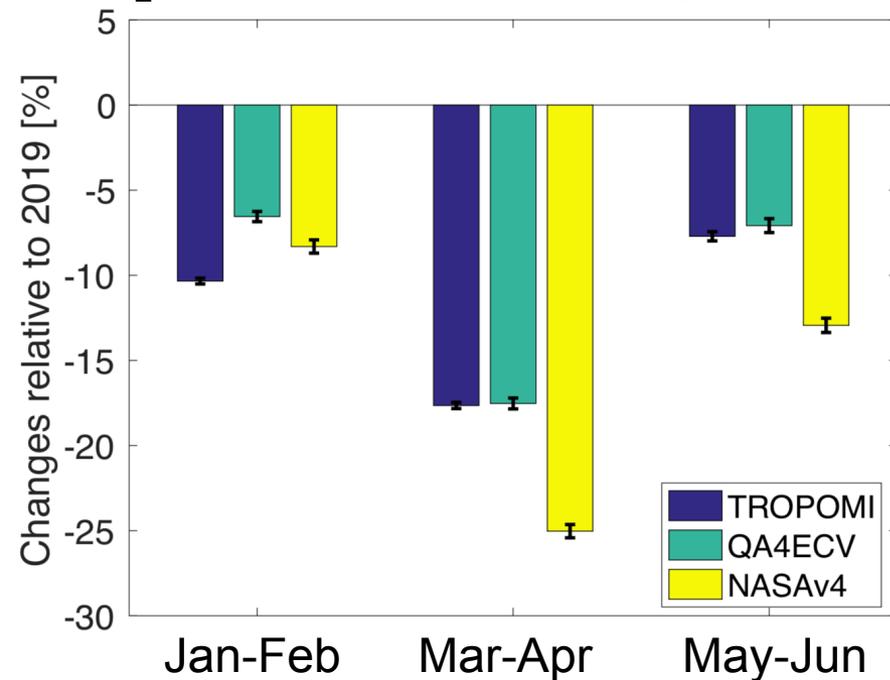
- The different magnitude and seasonality of top-down NO_x emissions reflect the AMF structural uncertainties when retrieving NO₂ columns using different ancillary data

Impact of NO₂ retrievals on top-down NO_x emissions

Changes in NO₂ column densities (2020-2019) [$\times 10^{15}$ molec cm⁻²]



NO₂ reductions in CONUS (2020-2019)



- TROPOMI NO₂ is less noisier than OMI NO₂
- More consistent reductions between TROPOMI and QA4ECV



Summary

- 4D-Var is relatively accurate in emission estimates but is time-consuming and requires adjoint model.
- 4D-Var can be combined with other methods (mass balance) to reduce computational costs – important for TROPOMI and geostationary satellite data.
- Addressing chemical interactions and co-emissions can reduce errors in top-down emission estimates.
- Uncertainties from satellite retrievals also impact top-down emission estimates.



Thanks!