Flux inversion modeling across scales: The Carbon Monitoring System Multiresolution Flux (CMS-MFlux)



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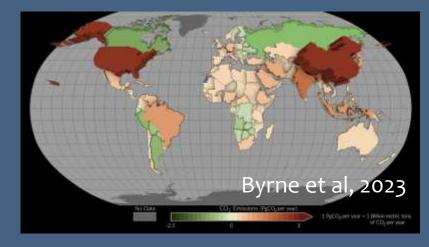
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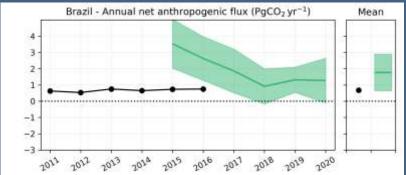
Characterization of inversions: the problem of scale



The OCO-2 MIP and the CEOS Global Stocktake is a bellwether contribution to country-scale net emissions.

- What is the flux resolution of an inverse model estimate?
 - When and where do we have information?





What is resolution?

How do we quantify the ability to "resolve" one grid box relative to another?

A robust concept of resolution is well-developed in the remote sensing literature (Rodgers, 2000; Jones et al, 2003; Bowman et al, 2006, etc.)

$$\hat{\mathbf{x}} = \mathbf{x}_a + \mathbf{A}(\mathbf{x} - \mathbf{x}_a) + \epsilon$$

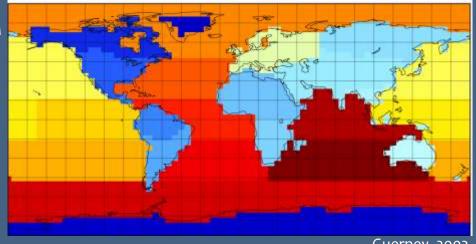
$$\frac{\partial \hat{\mathbf{x}}}{\partial \mathbf{x}} = \mathbf{A}$$

$$\text{dofs} = \text{Tr}(\mathbf{A})$$

4D-var and EnKF systems implicitly have an averaging kernel. **The problem is how to compute it.**

The old standard TRANSCOM

- Inverse models minimize the Bayesian cost function.
- Analytic systems are explicit, but with a reduced control vector, z.
 - Complete characterization, e.g., averaging kernels and diagnostics
- 4D-var systems are implicit, but with a full control vector, x.
 - Approximate error characterization.



Guerney, 2002

$$J(\mathbf{x}) \equiv \frac{1}{2} (H\mathbf{x} - \mathbf{y})^T \mathbf{R}^{-1} (H\mathbf{x} - \mathbf{y}) + \frac{1}{2} (\mathbf{x} - \mathbf{x}^b)^T \mathbf{B}^{-1} (\mathbf{x} - \mathbf{x}^b)$$
forward model data error covariance prior error covariance

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{B}^{1/2} (\mathbf{I} + \mathbf{B}^{1/2} \mathbf{H}^{\mathsf{T}} \mathbf{R}^{-1} \mathbf{H} \mathbf{B}^{1/2})^{-1} \mathbf{B}^{-1/2} \mathbf{H}^{\mathsf{T}} \mathbf{R}^{-1} (\mathbf{y} - \mathbf{H}(\mathbf{x}))$$

Bridging the scales: a multiresolution approach

Start with a coarse basis set (e.g., TRANSCOM) and then build a set of orthogonal anomalies

$$f(x,y) = \sum_{i} \alpha_{i} \Phi_{i}(x,y) + \sum_{j} \gamma_{j} \Psi(x,y)$$

TRANSCOM

<<Ondelletes>>

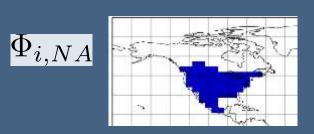
We can write this in vector-matrix format as

This decomposition is orthogonal

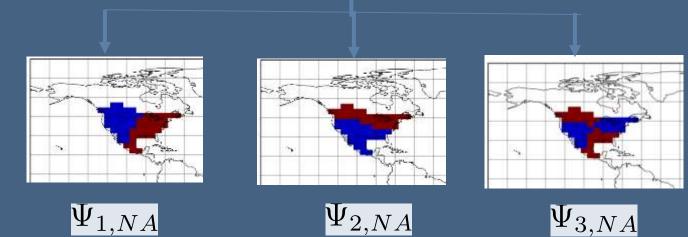
$$\mathbf{x} = \mathbf{W}\mathbf{z}$$

$$\mathbf{W}^{\top}\mathbf{W} = \mathbf{I}$$

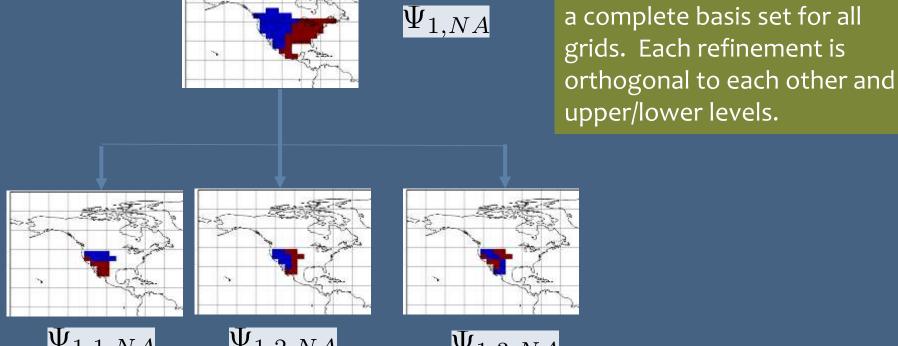
First Multiresolution Refinement



US is decomposed into a North-South, East-West, and Diagonal anomaly. These anomalies are orthogonal to each other and the North American mean flux



Second multiresolution refinement



Successive refinements lead to

Emulation of CMS-Flux with CMS-MFlux

- An analytic solution requires a limited basis set--M<<N wavelets.
- Here, we choose the wavelets that best represent the "support" of CMS-Flux

Choose
$$oldsymbol{\phi_i}$$
 for $\mathbf{x}_M = \sum_{i=1}^M < \mathbf{x}_{CMS}, \phi_i > \phi_i$

For this case, M ~4000, where N ~ 40000 for one year. So, about 10% of all available grid boxes.

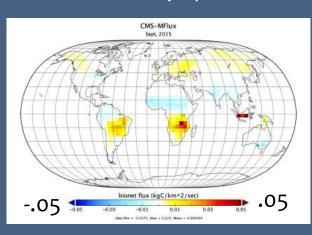
Adding the scales

Adding more wavelets enables finer spatial resolution estimates. Example of fluxes for Sept 2015

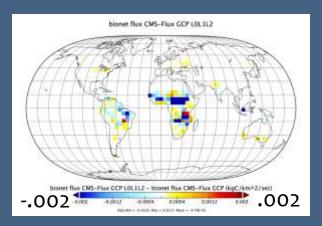
CMS-MFlux (all)

all- Lo 🗕 L2

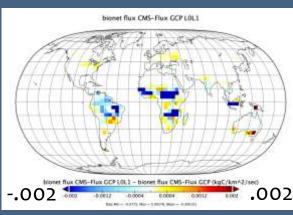
all- Lo→L1



CMS-MFlux (all the scales) (~325 wavelets)

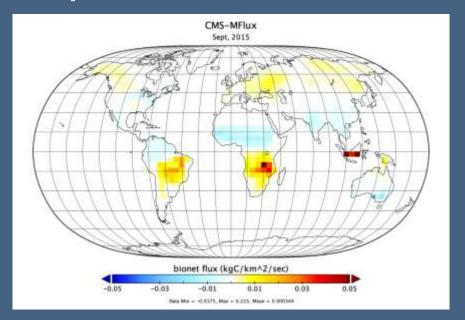


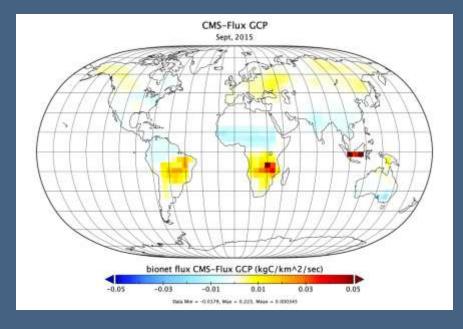
CMS-MFlux - Lo+L1+L2 (~135 wavelets)



CMS-MFlux - Lo+L1 (~53 wavelets)

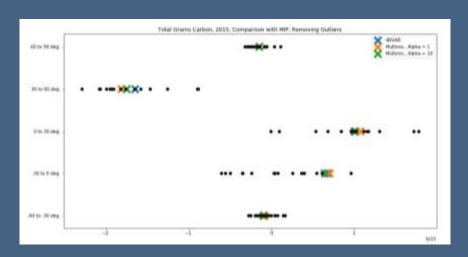
Comparison between CMS-Flux 4D-var and CMS-MFlux

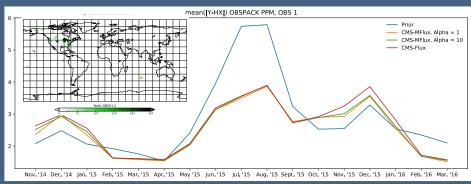




- CMS-Flux and CMS-Mflux use the same assimilation window and priors.
- CMS-MFlux basis and covariance are constructed to mimic the 4D-var solution.
 - Virtually the same flux pattern.

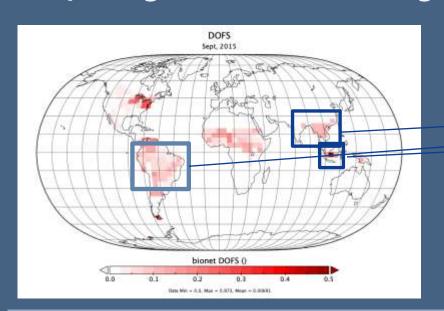
Comparison of CMS-MFlux to OBSPACK and OCO2-MIP

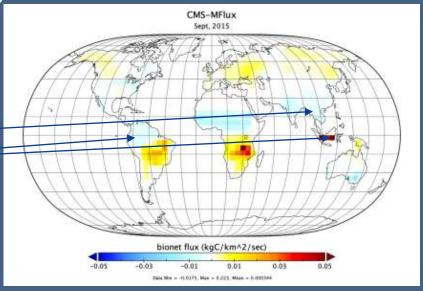




- CMS-MFlux is well within the range of the OCO2-MIP ensemble
- CMS-MFlux and CMS-Flux are in close agreement
- CMS-MFlux is in substantially better agreement to independent observations (OBSPACK) relative to the prior
- Overall good agreement in errors
 between CMS-Flux and CMS-MFluxpl.nasa.gov

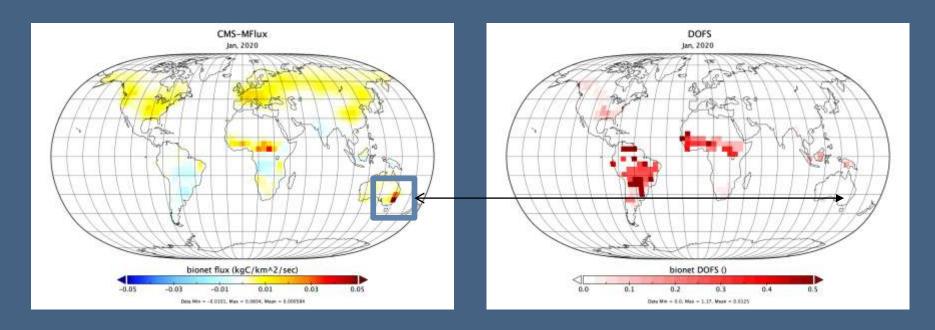
Interpreting the inversion: Averaging Kernel





- Information content from OCO-2 for 2015
 - DOFS Lo = 33, L1 = 69, L2 = 134, total DOFS = 675
- Remarkably, Indonesia (Kalamantin) is resolvable in Sept. 2015.
- The dofs indicates that there is information in South America, Northern Africa, and Southeast Asia
- However, there is not information in Southern Africa

The inferno of 2020



- Australia suffered one of its worse biomass burning episodes in recent history.
- However, OCO-2 does not provide a strong constraint in Southeast Australia.

Some subtilities with DOFS calculation—the prior projection

- By approximating the solution x_a of any χ^2 -minimizing inversion (e.g. 4D-var) in our wavelet basis, we can
 - 1. simulate the inversion in the reduced-dimensional basis,
 - 2. bound the associated DOFS with high probability.

$$\operatorname{Tr}\left(\left(\mathbf{C} + \mathbf{\Pi}_{\mathbf{M}^{T}\tilde{\mathbf{x}}}^{\perp}\mathbf{M}^{T}\mathbf{B}^{-1}\mathbf{M}\mathbf{\Pi}_{\mathbf{M}^{T}\tilde{\mathbf{x}}}^{\perp} + \mathbf{Y}\right)^{-1}\mathbf{Y}\right) \lesssim \operatorname{Tr}\left(\lambda \cdot \mathbf{M}^{T}\tilde{\mathbf{y}}\tilde{\mathbf{y}}^{T}\mathbf{M} + \mathbf{Y}\right)^{-1}\mathbf{Y}\right)$$

- If we use this as the prior covariance in the reduced-dimensional space, the corresponding low-dimensional inversion retrieves the 4D-var solution with negligible error.
- The posterior covariance and averaging kernel can then be computed analytically, and yield provable bounds on the corresponding quantities for the full-dimensional 4D-var system.

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\begin{split} \mathbf{A} &:= (\mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H}, \text{ (the 4D-var averaging kernel)} \\ \mathbf{M} &:= \text{ Matrix of columnized basis elements for reduced-dimensional space} \\ \tilde{\mathbf{x}} &:= \mathbf{x}_a - \mathbf{x}_b \\ \tilde{\mathbf{y}} &:= \mathbf{H}^T \mathbf{R}^{-1} \left( \mathbf{y} - H(\mathbf{x}_b) - \mathbf{H} \mathbf{M} \mathbf{M}^T \tilde{\mathbf{x}} \right) \\ \lambda &:= \frac{1}{\tilde{\mathbf{y}}^T \mathbf{M} \mathbf{M}^T (\tilde{\mathbf{x}})} \\ \mathbf{Y} &:= \mathbf{M}^T \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H} \mathbf{M} \\ \mathbf{\Pi}_{\mathbf{M}^T \tilde{\mathbf{x}}} &:= \text{Projection onto } \mathbf{M}^T \tilde{\mathbf{x}} \\ \mathbf{\Pi}_{\mathbf{M}^T \tilde{\mathbf{x}}}^{\perp} &:= \text{Projection onto the orthogonal complement of } \mathbf{M}^T \tilde{\mathbf{x}} \\ \mathbf{C} &:= \lambda \cdot \left[ \mathbf{\Pi}_{\mathbf{M}^T \tilde{\mathbf{x}}} \mathbf{M}^T \tilde{\mathbf{y}} \tilde{\mathbf{y}}^T \mathbf{M} \mathbf{\Pi}_{\mathbf{M}^T \tilde{\mathbf{x}}} + \mathbf{\Pi}_{\mathbf{M}^T \tilde{\mathbf{x}}}^{\perp} \mathbf{M}^T \tilde{\mathbf{y}} \tilde{\mathbf{y}}^T \mathbf{M} \mathbf{\Pi}_{\mathbf{M}^T \tilde{\mathbf{x}}}^{\perp} + \mathbf{\Pi}_{\mathbf{M}^T \tilde{\mathbf{x}}}^{\perp} \mathbf{M}^T \tilde{\mathbf{y}} \tilde{\mathbf{y}}^T \mathbf{M} \mathbf{\Pi}_{\mathbf{M}^T \tilde{\mathbf{x}}}^{\perp} \right] \end{split}
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DOFS of 4D-var

Conclusions

- Resolution and information content are critical metrics for inverse models and their use, e.g., Global Stocktake.
 - OCO-2 MIP ensembles are crude proxies for resolution
- CMS-MFlux shows that flux resolution—as defined by dofs-enabled by OCO-2 varies substantially in space and time in 4Dvar systems.
 - Kalamantin was resolved in Sept, 2015, but not SE Australia in Jan 2020
 - Amazon and north-equatorial Africa can be inferred.
- For 2015, the dofs ~ 675, (~1.5% of all flux grids)
- CMS-MFlux can help interpret the OCO-2 MIP ensemble
 - Currently calculated for 2015-2020 in LNLGOIS