

Estimation of multiscale fields representing anthropogenic CO₂ emissions from sparse observations

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Problem statement

- **Aim:** Develop a technique to estimate anthropogenic CO₂ emissions from sparse observations
- **Motivations:**
 - An alternative to estimating CO₂ emission using bottom-up (economic model) techniques
 - Can provide independent verification in case of CO₂ abatement treaties
- **How is it done?**
 - Measure CO₂ concentrations in flasks at measurement sites; also column-averaged satellite measurements
 - Use an atmospheric transport model to invert for source locations

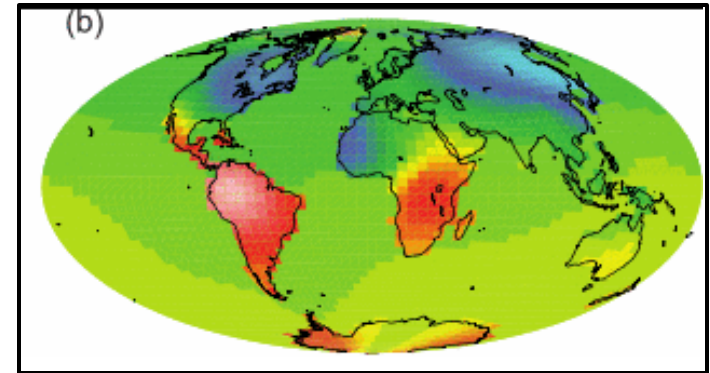


Technical challenges

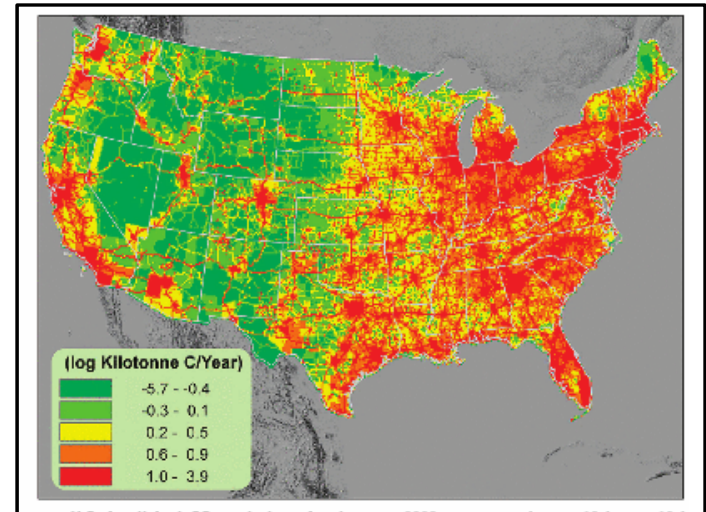
- **Atmospheric transport model** - largest source of uncertainty
- **Limited measurements** - second-largest contribution to uncertainty
- **Spatial models for anthropogenic CO₂**
 - Non-stationary distribution in space
 - No spatial models exist to date – but need one is emissions are to be estimated from sparse observations
 - Impact of choice of spatial model on emission estimates?
- **Discriminating between anthropogenic and biogenic CO₂**
(biogenic is 10x larger)
 - But anthropogenic and biogenic CO₂ are different (and known) proportions of ¹²CO₂ and ¹⁴CO₂

Differences in spatial characteristics

- **Biogenic CO₂ fluxes:**
 - Smoothly variable in space
 - Modeled using multivariate Gaussian
 - Separate correlation lengths over land and oceans
- **Anthropogenic (fossil fuel) emissions**
 - Currently, only bottom-up estimates exist
 - A few databases – Vulcan (US-only, 2002); EDGAR (world)
 - Gaussian process will probably not work
 - What non-stationary covariance model to use?



Biogenic emissions: Mueller et al, *JGR*, 2008



Anthropogenic emissions: Gurney et al, *EST*, 2009



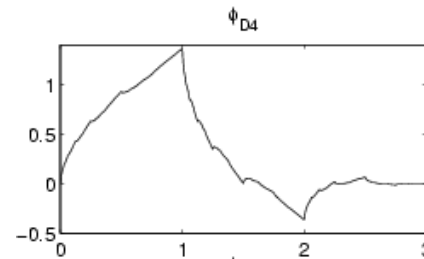
Outline of the talk

- Choosing a spatial model
 - Our hypothesis: *wavelets*
 - Study spatial and temporal characteristic of CO₂ emissions
 - Use Vulcan as source of emissions
 - Search for a good wavelet model - and what makes it good
- Demonstrate the spatial model in an OSS (observing system simulation)
 - Estimate CO₂ emissions from synthetic CO₂ observations
 - Using Ensemble Kalman Filters
 - Can handle large number of unknowns; estimates uncertainty in them
 - Using sparsity-enforcing methods used in compressive-sensing
 - If a parameter makes no difference to outputs, identifies and zeros it out

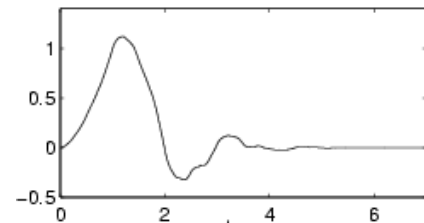
How does one represent emissions with wavelets?

- Propose $E(x) = \sum_{s,l} w_{s,l} \phi_{s,l}(x)$
 - $\phi_{s,l}(x)$ is a wavelet basis; s , l are its *scale* and *location* indices
 - $w_{s,l}$ are weights
- So what are wavelets?
 - Basis set with compact support
 - Belong to different families
 - Within a family, can have different orders (high order ~ smoother)
 - One chooses a family and an order, to expand $E(x)$
 - The expansion consists of varying
 - s , to get different frequency content
 - l , to shift in space (location)

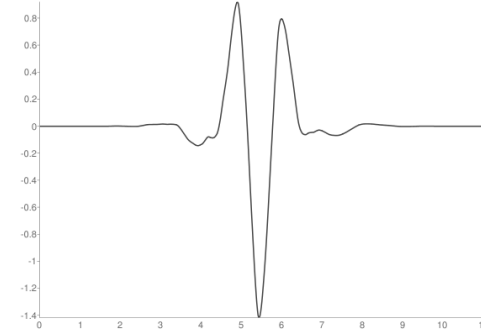
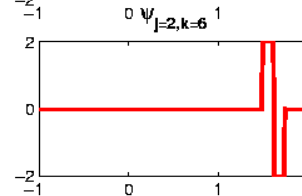
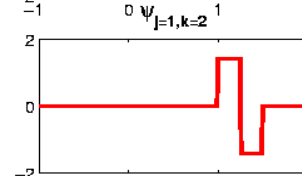
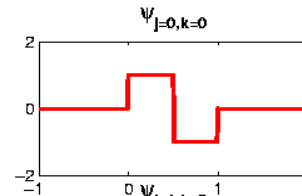
Haars at different scales and locations



Daubechies, order 4



Daubechies, order 6



Symlet, order 6



Posing the problem

- An emission field on $2^N \times 2^N$ pixels
 - Can be decomposed on a wavelet basis, N deep
 - Each level s has $2^s \times 2^s - (2^{s-1} \times 2^{s-1})$ weights

- Emissions

$$E(\mathbf{x}) = \sum_{s=1}^N \sum_{i=1}^{2^s} \sum_{j=1}^{2^s} w_{s,i,j} \phi_{s,i,j}(\mathbf{x})$$

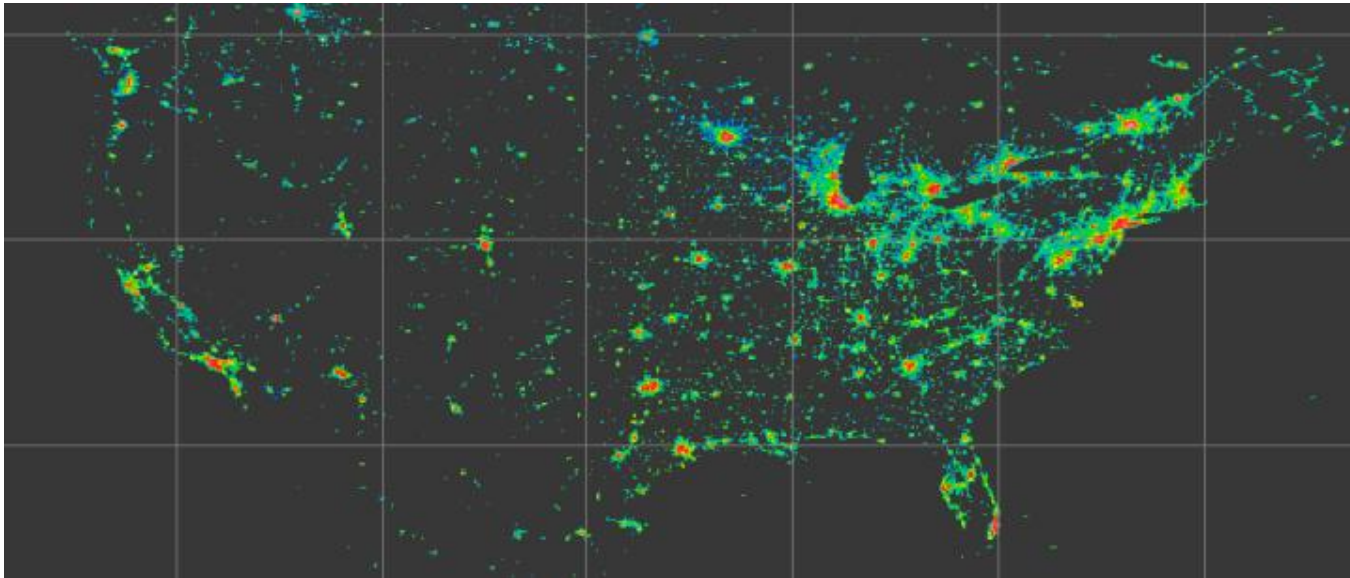
- Conjecture

- $w_{s,i,j}$ are mostly zero (i.e., is sparse)
- $w_{s,i,j}$ and $w_{s+1,i,j}$ are correlated – parent-child relationship

- Conjecture checked

- Using CO₂ emissions from Vulcan (SIAM GeoSc, 2011)
- Checked Haars, Daubechies of different orders
- Found that Haar wavelets provided the sparsest representation
- Reconstruction error was also small

Dimensionality reduction



- Nightlights are a good proxy for FF emissions
 - Except emissions from electricity generation and cement production
 - Nightlights easily observed – DoD's DMSP-OLS
- Use thresholded radiance-calibrated nightlights from 1997-98 to mask out unpopulated regions

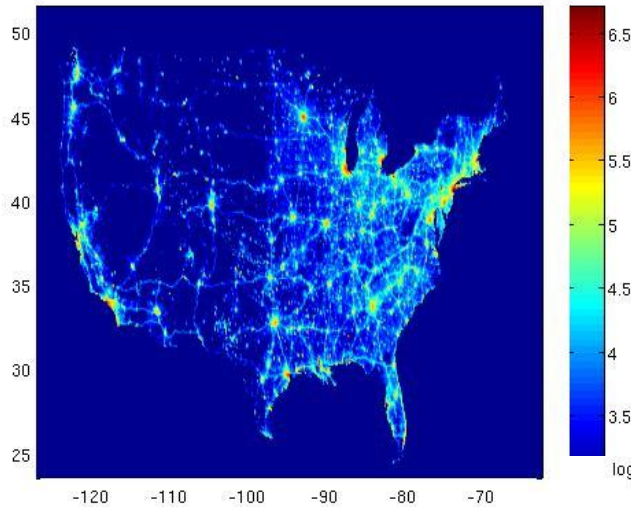


Random field model using nightlights

- Threshold nightlights at radiance R_{\min}
 - Removes low-population regions of the US
 - Make a nightlight “mask”
- Mask EDGAR fluxes (1° resolution; annual average for 2002)
 - Project to a Haar wavelet basis set & retain non-zero wavelet coefficients
- Wavelet-based Random Field model
 - With 635 coefficients (“mid-complexity”)
 - Remove wavelet coefficients at finest level too – 253 parameter model (“low” complexity)
- Errors introduced by this approximation
 - We lost some emissions due to nightlight masking
 - We lost spatial fidelity due to coarsening

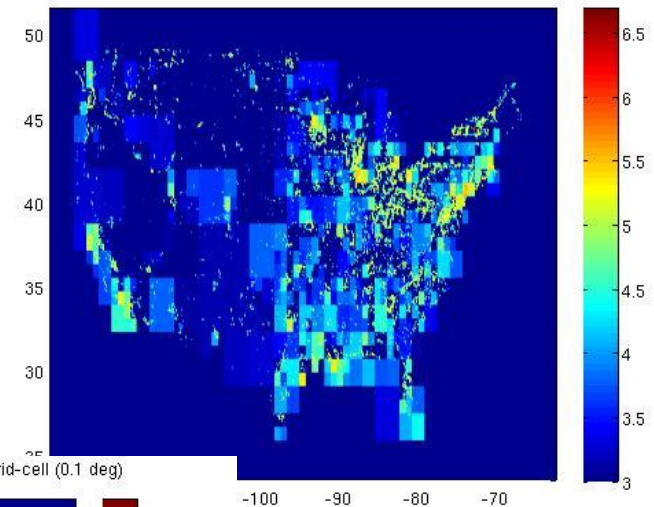
Emission reconstruction comparison

$\log_{10}(\text{emissions})$ in tonnes/hr/grid-cell (0.1 deg), (-127.5W, 51.5N) (-62.5W, 23.5N)

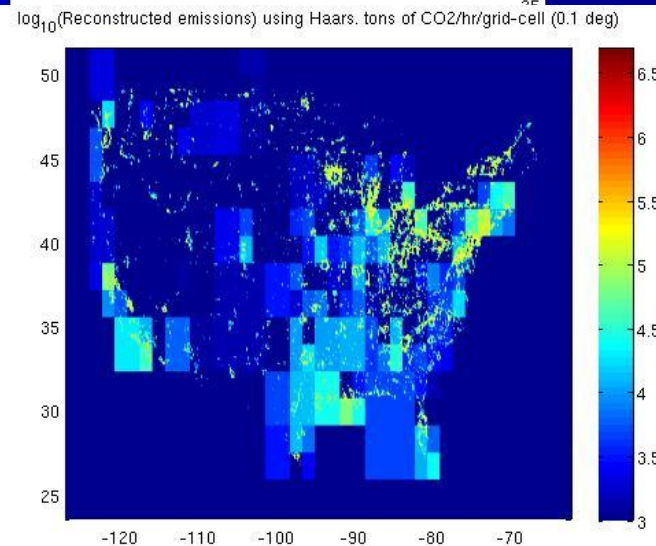


Original from Vulcan database

$\log_{10}(\text{Reconstructed emissions})$ using Haars. tons of CO2/hr/grid-cell (0.1 deg)



635 parameter model



253 parameter model

- Lost 10% of total emissions due to masking
- 253 or 635 parameters may be still too many to estimate



Emission estimation problem

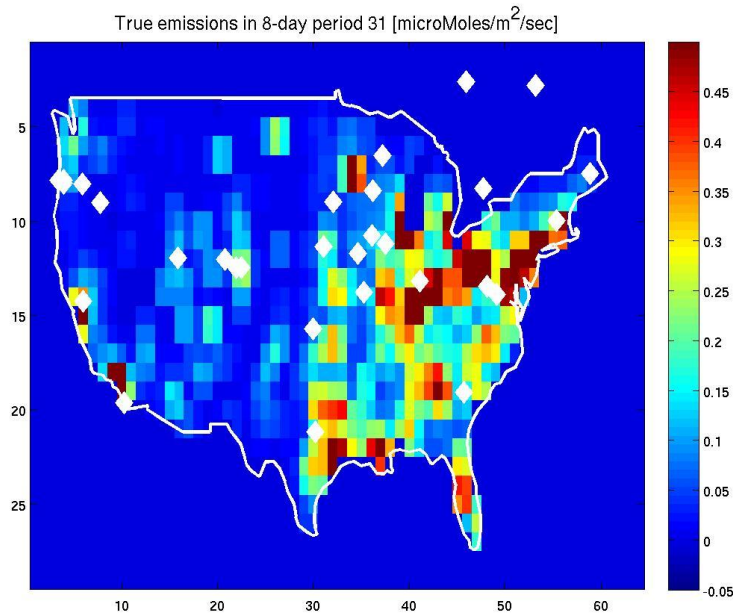
- Use the 2 wavelet RF models to fit to synthetic CO₂ concentration data
 - Is the dimensionality of the model high enough?
- Synthetic data generation
 - Choose location of 35 towers (NOAA's network)
 - Use Vulcan emissions, coarsened to 1° resolution, to generate time-dependent CO₂ concentration “observations”
 - Concentration measurements at every 3 hours
 - Atmospheric transport simulated using WRF
- Inverse problem is linear
 - $y = H x$, where y = CO₂ concentrations; x = emissions over ~ 1 year
 - We estimate emissions averaged over 8-day periods (“Period”)
 - $x = \Phi w$, where F = wavelet bases, w = basis weights
 - H constructed using WRF and 2008 wind fields



Sparsity-enforced estimation

- The observations may not be sufficient to estimate 253 (or 635) parameters per “Period”
 - Atmospheric transport is diffusive – destroys information
 - If RF model parameters w cannot be estimated, set to zero
- Fitting procedure
 - Minimize $\|y - H \Phi w\|_2 + \|w\|_1$
 - Uses a greedy, orthogonal matching pursuit algorithm called StOMP (Donoho & Tsaig, 2006)
- The basic idea is borrowed from compressive sensing
 - H is the “sampling” matrix, but is neither random, nor maximally incoherent with Φ , nor does it satisfy Restricted Isometry
 - But will prevent overfitting

Estimated emissions

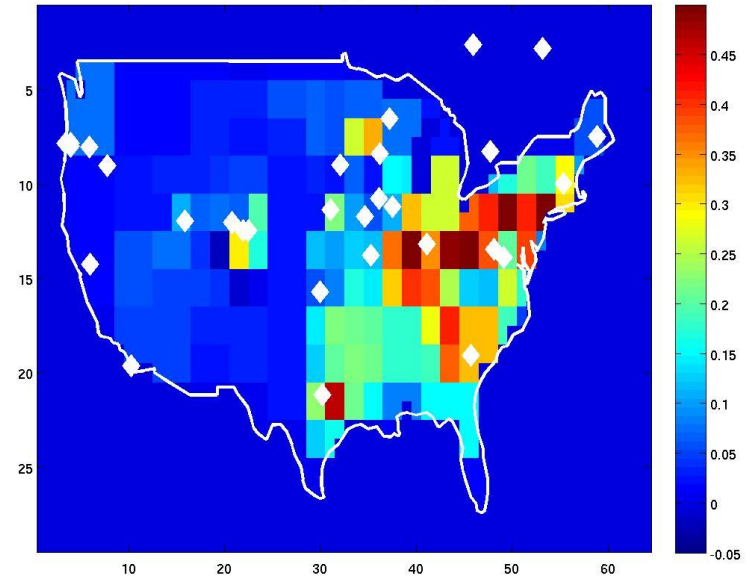


Vulcan emissions; coarsened to 1°

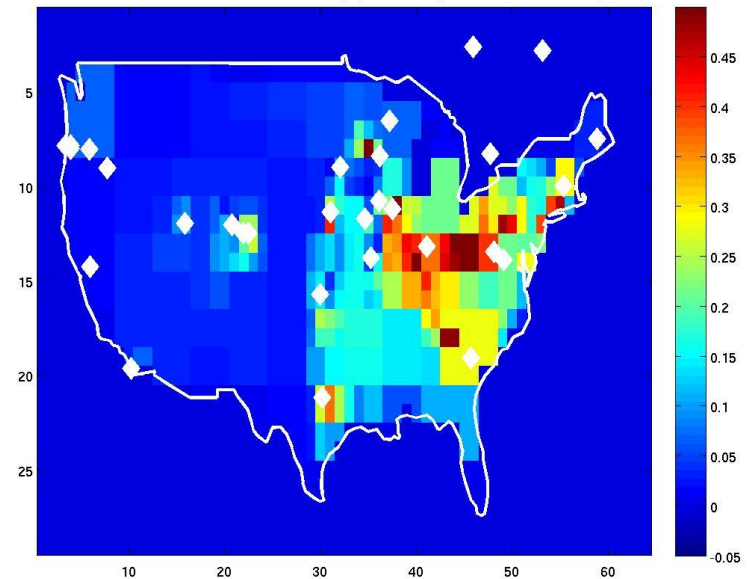
- Reconstructions look similar for Period # 31 (~August 2008)
- Mid-complexity model (635 parameters) has more spatial fidelity
 - Significant, or just artifact?

Reconstruction; mid-complexity RF model

Reconstructed emissions in 8-day period 31 [microMoles/m²/sec]

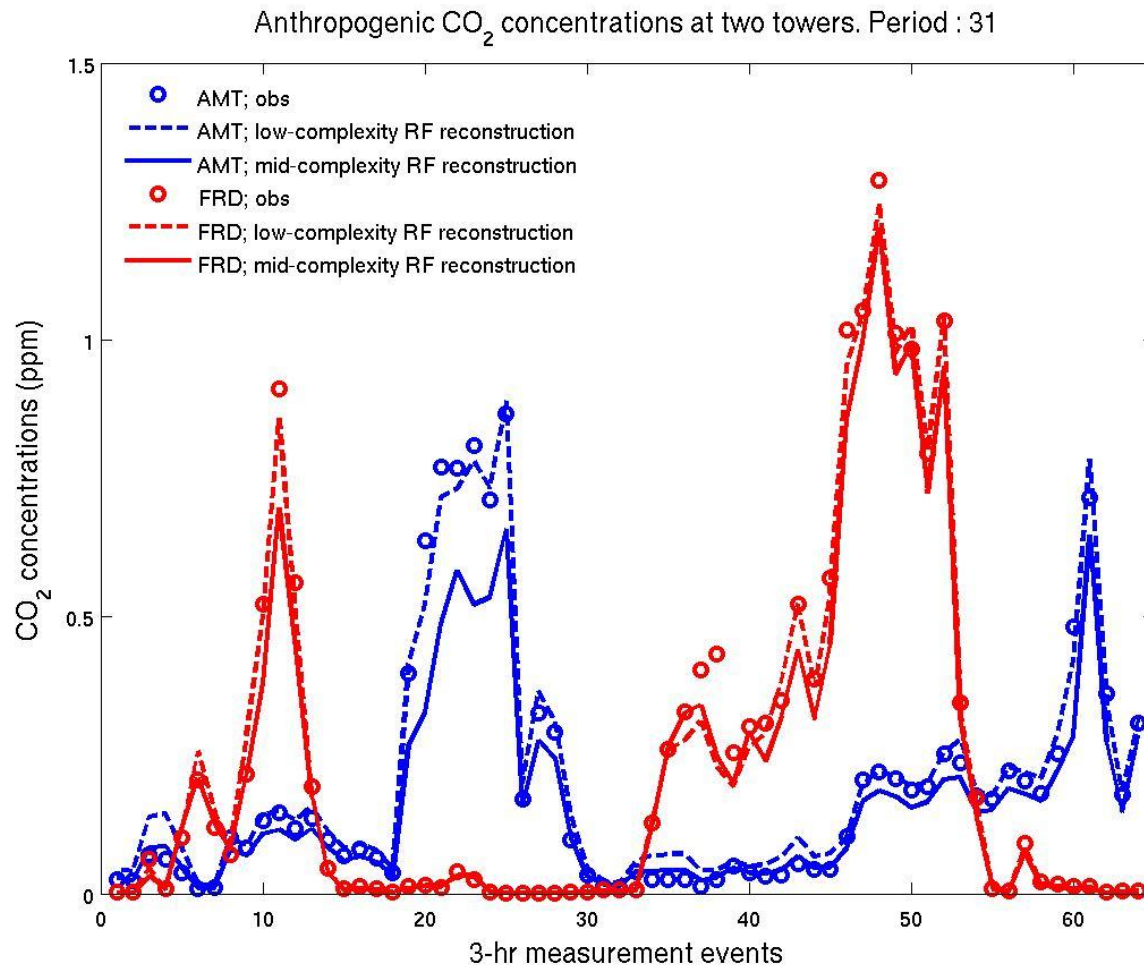


Reconstructed emissions in 8-day period 31 [microMoles/m²/sec]



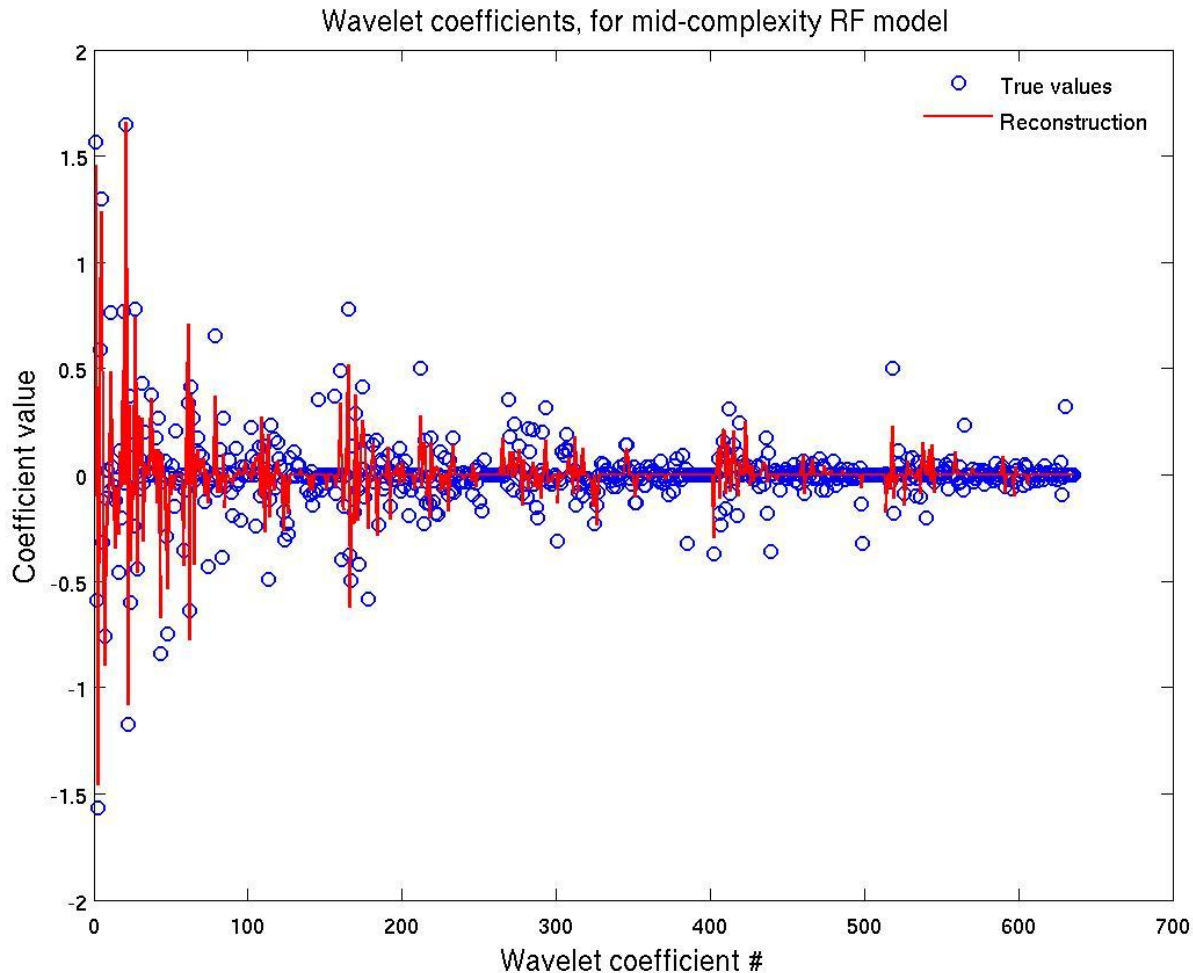
Reconstruction; low-complexity RF model

Predictive capacity



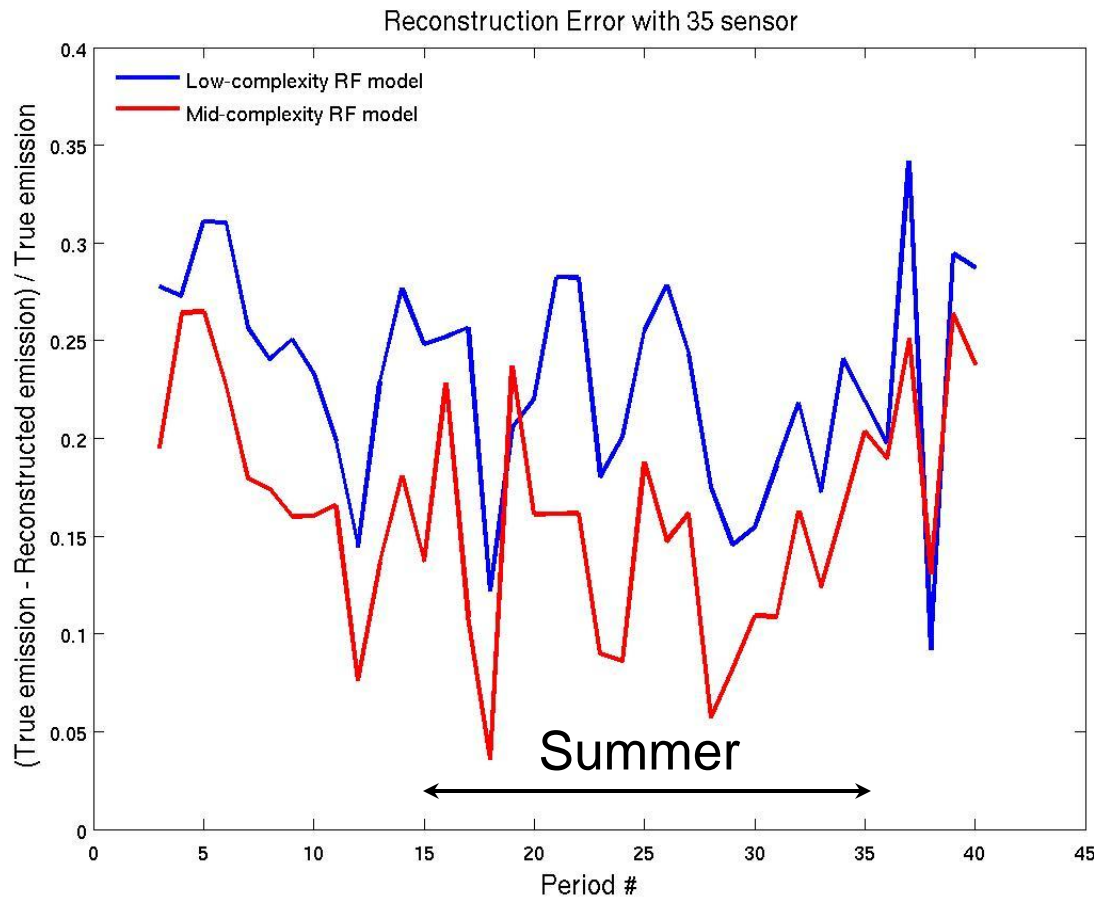
- Predicted CO₂ concentrations at 2 towers
 - Basically, not much difference between 2 RF models
- Results shown for Period 31

Did sparsification work?



- In the mid-complexity model (635 parameters), about 57% of the parameters are set to zero
- In the low-complexity, about 30%
- **Lesson learnt:** Our RF models are still too high-dimensional
 - But perhaps we're not over-fitting

Accuracy of reconstruction



- The mid-complexity RF model has lower errors
 - But the errors are uncomfortably high
- Requirements
 - Need UQ of parameters
 - Need finer spatial resolution, but
 - With sparsity enforcement
- More sensors would be nice



Estimating emission

- **Aim:** Estimate emissions, given time-variant CO₂ concentrations
 - Use a wavelet-based RF model
 - Quantify uncertainty in estimates
 - Use EnKF (scalable; also captures uncertainty in estimates)
- **Basically:**
 - Can wavelet-based RF models be used in estimation with UQ?
 - How large are the uncertainties if no model-reduction is done (CS or a priori)
- **Data** – CO₂ concentrations at sensor locations
 - Generated synthetically, using a transport model
 - Domain: Lower 48 states of USA (51.5N, -127.5W) to (23.5N, 62.5W)



Modeling and numerical details

- **Transport model:** Simple advection-diffusion

$$\frac{\partial c}{\partial t} - D\Delta c + v\nabla = f \quad \in \omega \times (0, T)$$
$$\nabla c = 0 \quad \in \Gamma \times (0, T)$$

- c = concentration
- v = velocity,
- f = CO₂ source
- D = diffusion coefficient.

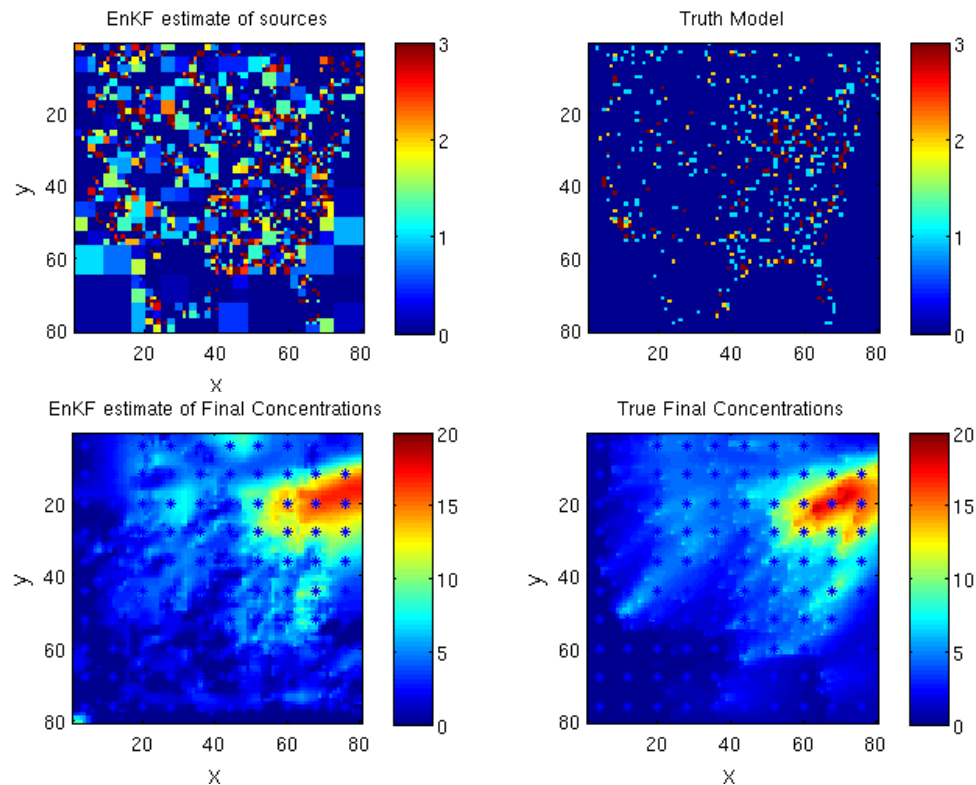
- **Ensemble Kalman filters**

$$u_k = u_{k-1} + K(z_k - Hu_k)$$
$$K = P_k H^T (H P_k H^T + R)^{-1}$$
$$P_k = A P_{k-1} A^T + Q$$

- **Spatial models**

- Used Haars and Debauchies (order = 8)

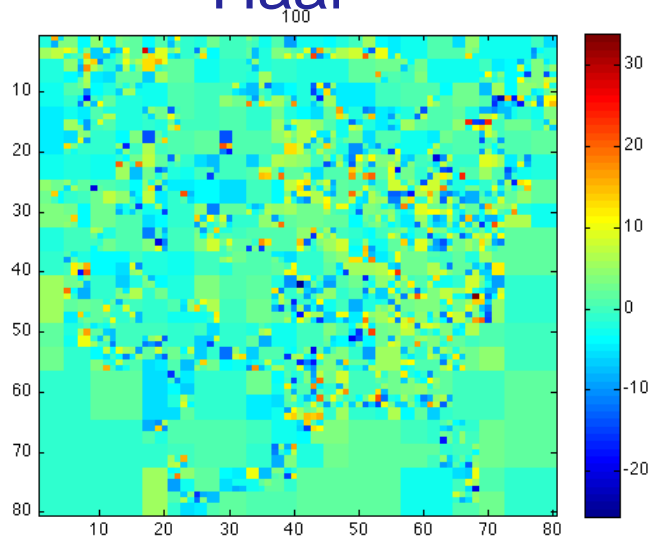
Emission estimation (MAP estimates)



- Emissions with Haars (wavelets on all levels)
- 80x80 grid resolution; sensor grid = 10 x 10

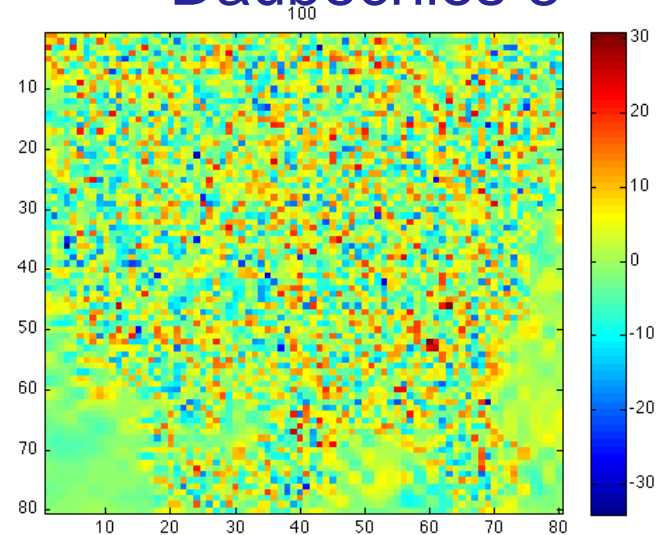
Emission reconstruction – impact of wavelet model

Haar



RMSE = 1.44

Daubechies 8



RMSE = 1.61



Conclusions

- We have created a multiresolution random field (RF) model for CO₂ emissions
- RF model can be fitted to data by enforcing sparsity
 - No uncertainty quantified, by > 50% of the coefficients were identified and inactivated
 - The 35 sensors that we have can estimate anthropogenic emissions if it were an inert tracer
 - 20-30% errors are observed
 - But the sensors were placed for biospheric, not anthropogenic fluxes
 - Unknown when joint anthropogenic and biospheric inversion can be done
- RF model also tested with EnKF, but with simplified transport
 - Both CO₂ concentrations and sources can be estimated

Questions?

