

Multi-resolution (wavelet) Based Nonstationary Covariance Modeling

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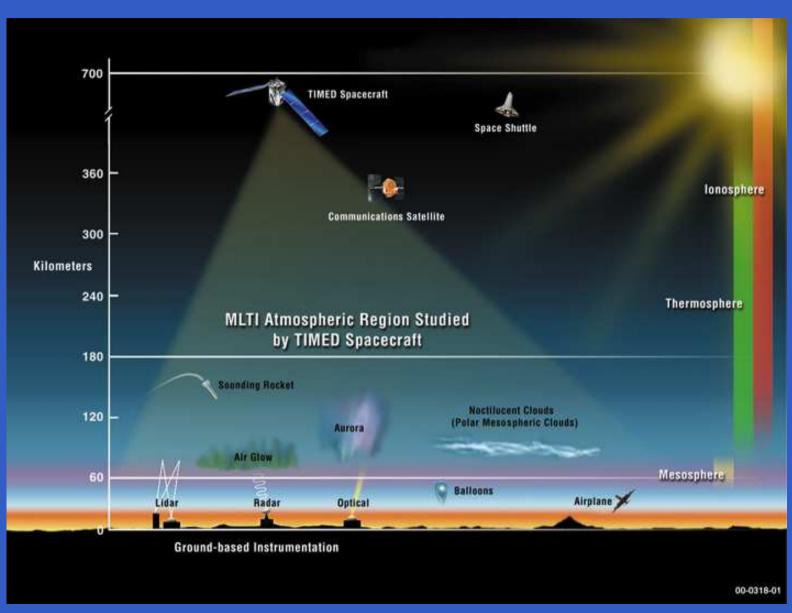
in collaboration with

Doug Nychka & Debashis Paul (Stanford Univ)

NSF visit, Dec 2, 2004

INTRODUCTION





OUTLINE



Background:

- Challenges of covariance modeling in data assimilation application
- Observations

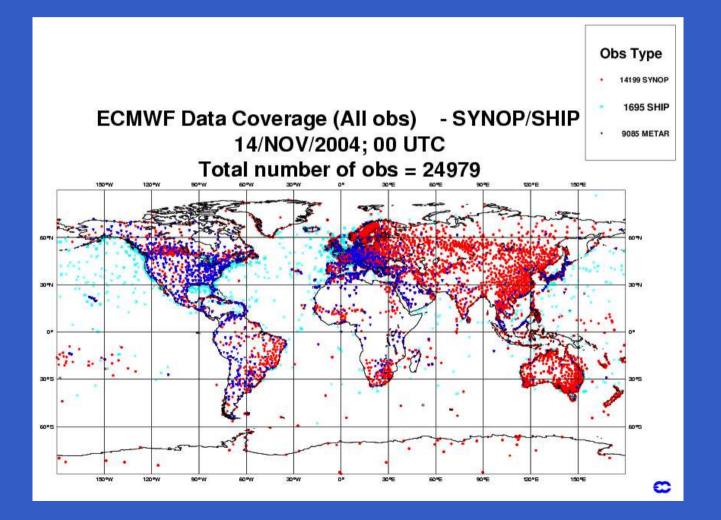
Multi-resolution (wavelet) based covariance

- Heuristic EM-type approach
- Examples (ground-level ozone data)
- Summary and Future Work





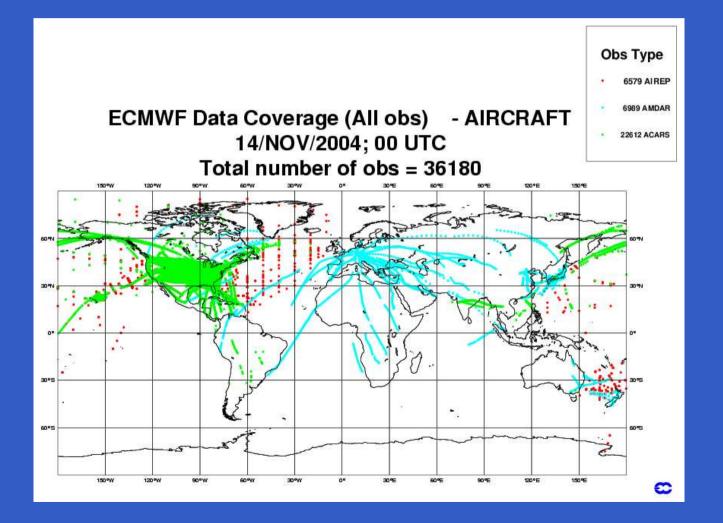
Numerous, Incomplete, Irregularly distributed







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MOTIVATION and **GOAL**



Spatial analysis of large nonstationary processes poses challenges in both modeling and computation.

- Need the flow-dependent nonstationary covariance
- Incomplete, irregularly distributed observational data
- Require computational efficiency



 $\Sigma = \mathcal{W} \hat{H}^2 \mathcal{W}^T$

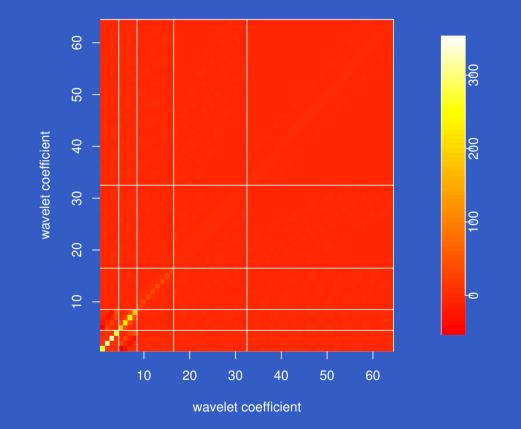
- DWT: $h_{\mathcal{W}} = \mathcal{W}^{-1}\mathbf{x}$
- $\hat{H}^2 = \operatorname{cov}(h_{\mathcal{W}})$
- **Determine** \hat{H}
- Enforce sparsity on \hat{H}



Multi-resolution based covariance

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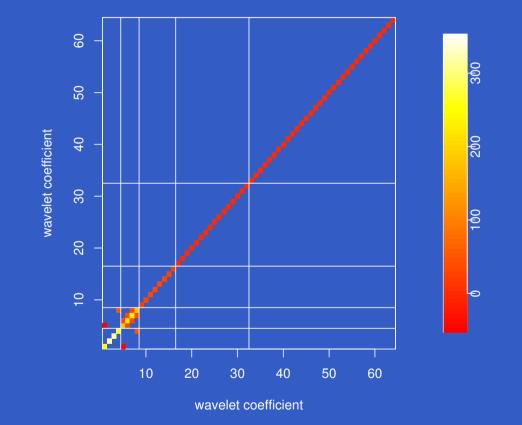




Multi-resolution based covariance

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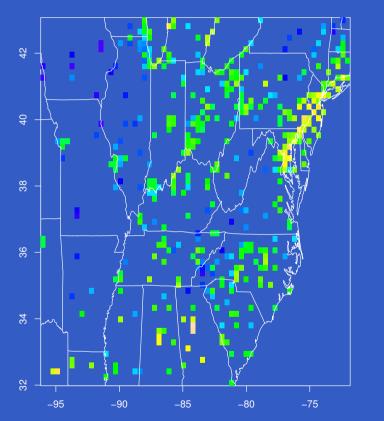
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standard deviation

513 stations930 realizations

- over 5 years
- 10% on 64-by-64 grid

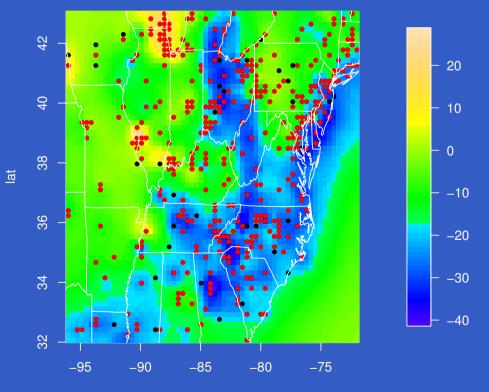
EM-type approach



$$\mathbf{x} = \begin{pmatrix} \mathbf{x}_{obs} \\ \mathbf{x}_{mis} \end{pmatrix} \sim \mathcal{N}(0, \Sigma), \quad \Sigma = \mathcal{W} \hat{H}^2 \mathcal{W}^T$$

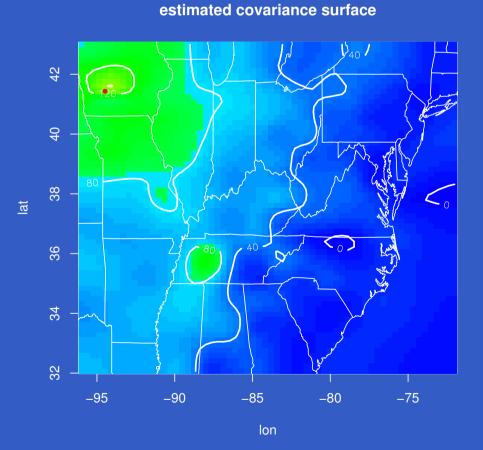
• Predict \mathbf{x}_{mis} [$\mathbf{x}^{(k-1)} | \mathbf{x}_{obs}, \hat{H}^{(k-1)}$]

• $h_{\mathcal{W}} = \mathcal{W}^{-1}\mathbf{x}$ • \cdots • $\hat{H}^{(k)}$

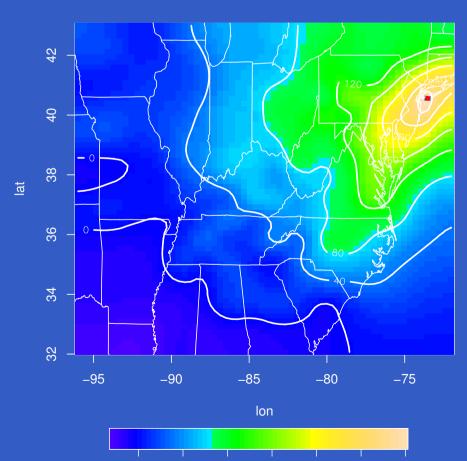


Results: Covariance Surface





estimated covariance surface





Summary and Future Work



It is possible to model nonstationary covariance using wavelet basis with computational efficiency

Summary and Future Work



- It is possible to model nonstationary covariance using wavelet basis with computational efficiency
- Use of EM algorithm to handle irregularly distributed incomplete data
 - Proof of concept: Heuristic approach
 - Parameterization: $\Sigma(\theta) = W H^2(\theta) W^T$

Summary and Future Work



- It is possible to model nonstationary covariance using wavelet basis with computational efficiency
- Use of EM algorithm to handle irregularly distributed incomplete data
 - Proof of concept: Heuristic approach
 - Parameterization: $\Sigma(\theta) = \mathcal{W}H^2(\theta)\mathcal{W}^T$
- Application to a large data set:
 - Aurora Image data (\sim 2K)
 - NCEP data (\sim 100K)