

Credits

- Steve Sain, Nathan Lenssen, Tamra Greasby, NCAR
- Dorit Hammerling, SAMSI/STATMOS/NCAR
- Soutir Bandyopadhyay, Lehigh
- Finn Lindgren, Bath, Norway

Outline

A flexible spatial estimate for large problems.

- Regional Climate simulation and NARCCAP
- Compact basis functions (b),

 Markov Random fields (H)
- Changes in the seasonality for future climate

Key idea: Introduce sparse basis and precision matrices without compromising the spatial model.

Does not require tapering covariance functions — supports dependence over large distances.

A climate model grid box (?)

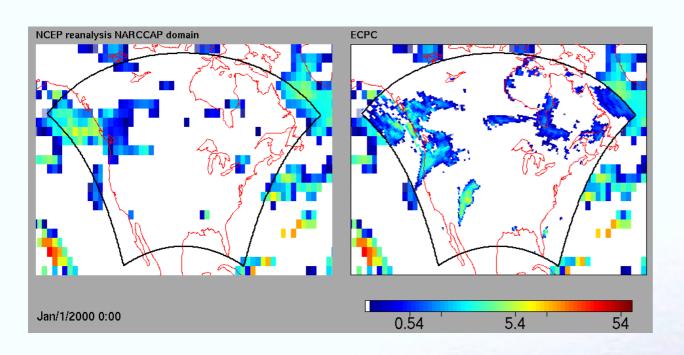


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An approach to Regional Climate

 Nest a fine-scale weather model in part of a global model's domain.

Regional model simulates higher resolution weather based on the global model for boundary values and fluxes.



A snapshot from the 3-dimensional RSM3 model (right) forced by global observations (left)

Consider different combinations of global and regional models to characterize model uncertainty.

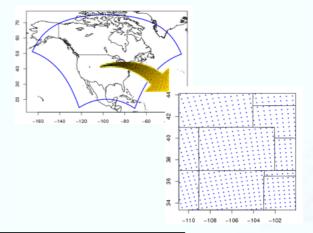
NARCCAP — the design

4GCMS × 6RCMs:

12 runs — balanced half fraction design

Global observations × 6RCMs

X High resolution global atmosphere



GLOBAL MODEL	REGIONAL MODELS					
	MM5I	WRF	HADRM	REGCM	RSM	CRCM
GFDL			•	•	O	
HADCM3	0		•		•	
CCSM	•					
CGCM3				•		
Reanalysis	•	•	•	•	•	

A designed experiment is amenable to a statistical analysis and can contain more information.

But just 2-d temperatures fields are 72Gb of data.

Climate change

How will the seasonal cycle for temperature change in the future?

Estimating a curve or surface.

An additive statistical model:

Given n pairs of observations (x_i, y_i) , i = 1, ..., n

$$y_i = g(x_i) + \epsilon_i$$

 ϵ_i 's are random errors and g is an unknown, smooth realization of a Gaussian process.

Random Effects/Linear model for g

 $\{b_j\}$: m basis functions

$$g(x) = \sum_{j} b_{j}(x)\beta_{j}$$

A linear model:

$$y = X\beta + \epsilon$$

Random effects:

$$m{eta} \sim MN(\mathbf{0}, m{
ho} m{Q}^{-1})$$
 and $m{\epsilon} \sim MN(\mathbf{0}, m{\sigma^2} m{I})$

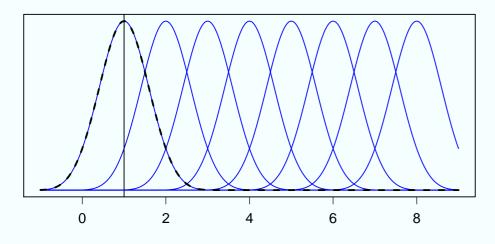
Implied Covariance:

$$E[g(\boldsymbol{x})g(\boldsymbol{x}')] = \sum_{j,k} b_j(\boldsymbol{x}) \rho \boldsymbol{Q}_{j,k}^{-1} b_k(\boldsymbol{x}')$$

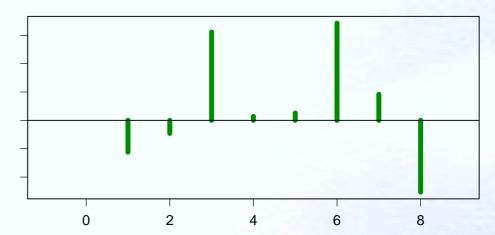
 $\lambda = \sigma^2/\rho$ plays an important role as a parameter.

An example of a 1-d basis ...

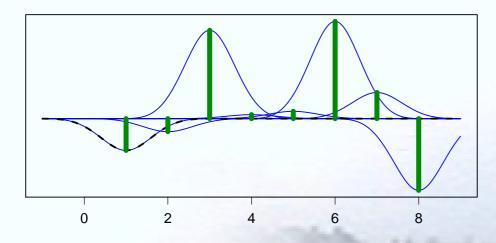
8 basis functions



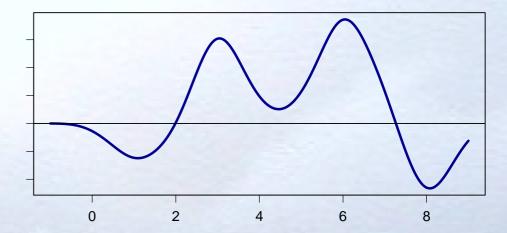
8 (random) weights



weighted basis

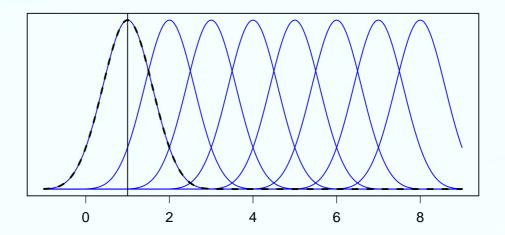


Random curve

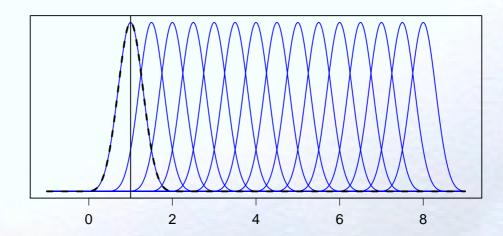


A Multiresolution

8 basis functions

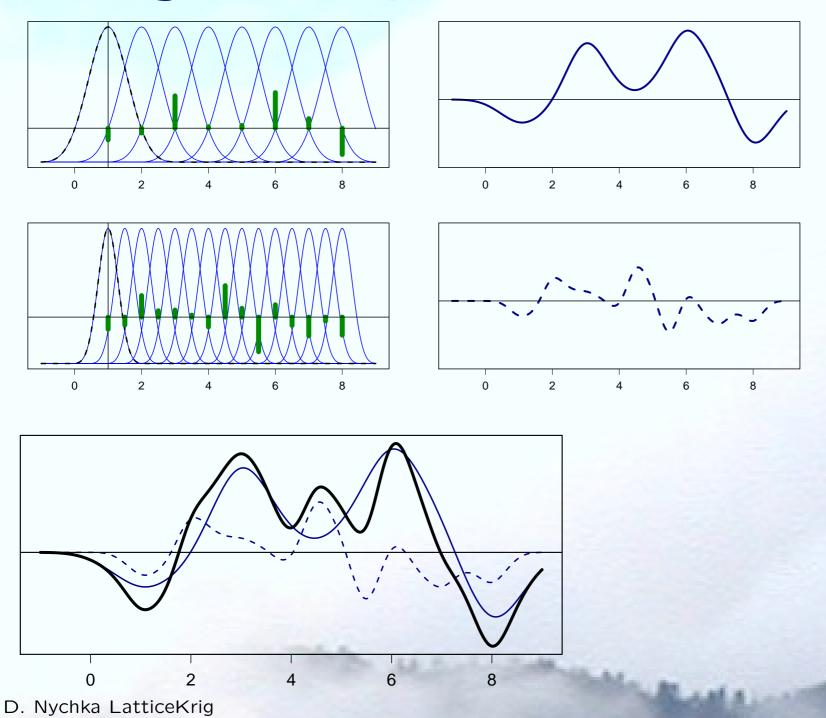


16 basis functions



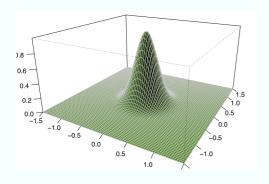
:

Adding them up



A recipe for 2-d RBFs

Basis function
$$_j(x) = \varphi(||x - u_j||/\theta)$$



2-d Wendland

- φ is a positive definite, compactly supported function a nice bump.
- ullet $\{u_j\}$ basis centers on a regular grid
- \bullet θ scale set to provide some overlap

Four level multi-resolution starting with 11×11 grid has 8804 basis functions.

A recipe for Q

Recall:
$$g(x) = \sum_{j} b_{j}(x)\beta_{j}$$

eta at each resolution level is a Markov random field:

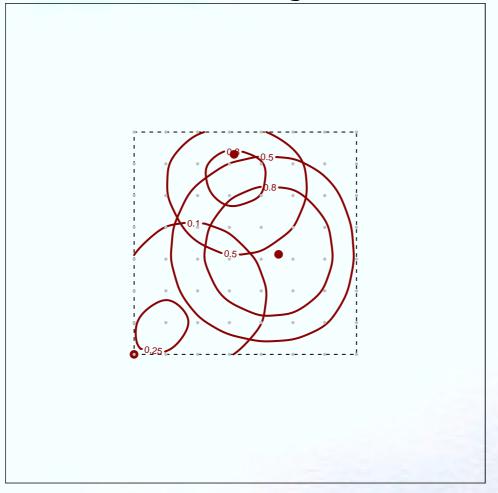
$$\alpha \beta_j - \sum\limits_{\mbox{neighbors}} \beta_l = e_j \quad \mbox{i.e. } H\beta = e$$

- $\{e_j\}$ are uncorrelated N(0,1)
- H has only 5 nonzero elements in each row.

Precision matrix for β is sparse: $Q = (H^T H)$

Assumed covariance model

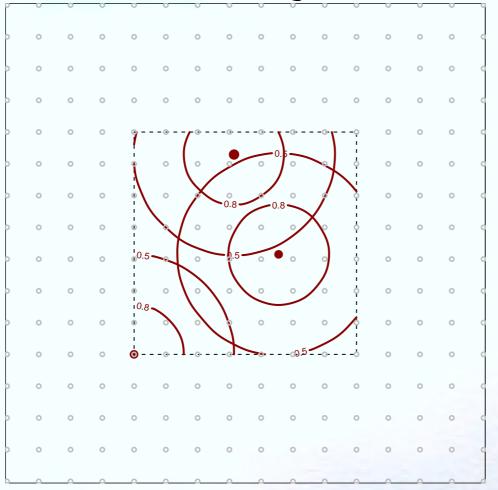
 8×8 grid with no grid points of buffer Covariance function for a single level $\alpha = 4.2$



Stationary? This is really poor!

Fixing this problem

 8×8 grid with 5 grid points of buffer Correlation function for a single level $\alpha = 4.2$

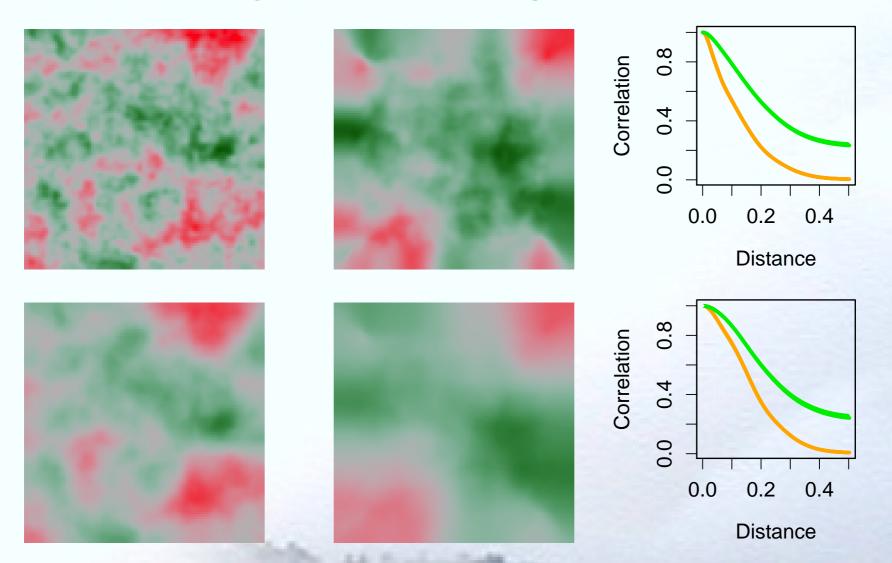


Close to being stationary!

What does the model do?

Combination of 4 levels starting with an 8×8 grid

Uncorrelated weights Correlated weights Correlation functions



Computation

Ridge regression/ conditional expectation/ BLUE/

Posterior conditioned on covariance.

$$\hat{g}(x) = E[g(x)|y, P] = \sum_{k=1,n} \hat{\beta}_k b_k(x)$$

$$\widehat{\beta} = \left(X^TX + \lambda Q\right)^{-1} X^T y, \quad \lambda = \sigma^2/\rho$$
 X^T , X^TX , Q are sparse.

Computation continued

Likelihood:

Dominated by finding $log(det(X^TX + \lambda Q))$ take advantage of sparsity.

Conditional simulation for standard errors:

Simulation of fields and the spatial prediction also take advantage of sparsity.

At 20,000 observations:

- Ordinary Kriging about 21 minutes
- LatticeKrig models 5 20 seconds.

Climate change

How will the seasonal cycle for temperature change in the future?

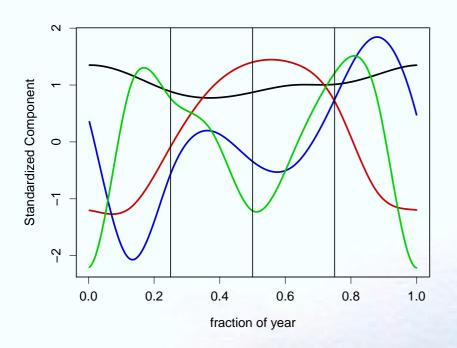
Back to NARCCAP



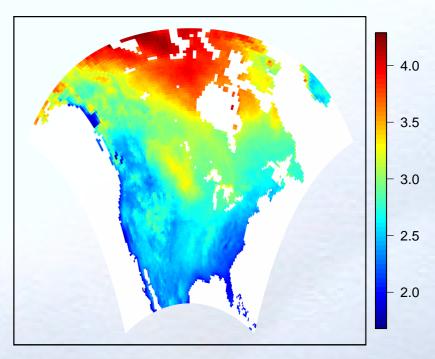
Back to NARCCAP

- A 2 × 2 subset of NARCCAP (4 global/regional combinations)
- (Future Present) seasonal cycle expand in 4 principle components ... gives 4 coefficient spatial fields for each model.
- Approximately 8000 spatial locations

Seasonal PCs (future - present)



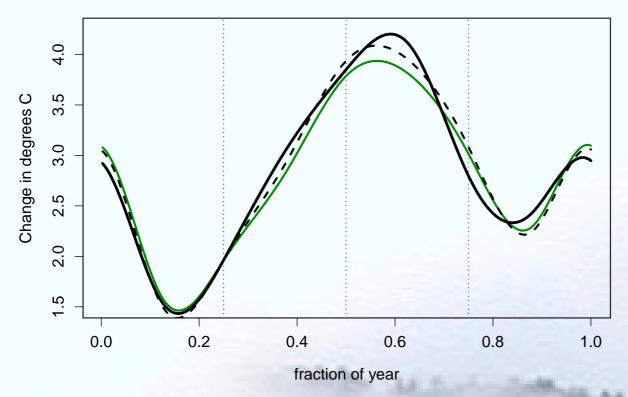
First coefficient CRCM ccsm



Spatial model

- Four coefficients of seasonal profile for the four model combinations and at each grid box ($16 = 4 \times 4$ fields each with 9K locations.)
- "measurement error": the interannual variation of models

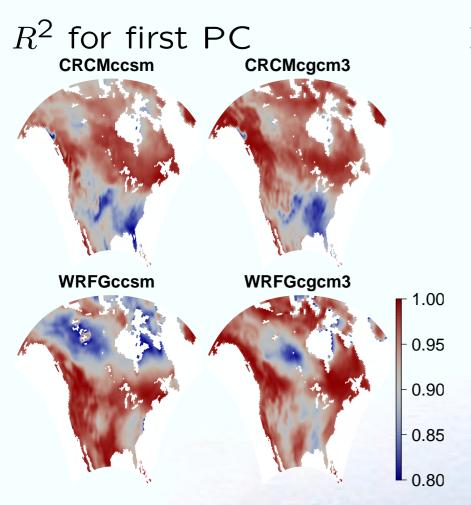
Boulder grid box, CRCM/ccsm



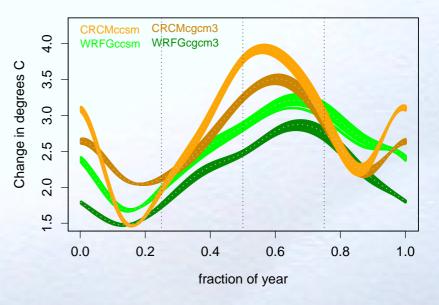
Solid - 8 Bsplines,
Dashed - projection
from 4 EOFS/PCs,
Difference with spatial smoothing

Results

- Thin plate spline-like model (1 level $120 \times 55 \approx 6000$ basis functions)
- λ found by MLE (equivalent to sill and nugget)
- Conditional simulation of fields (facilitates nonlinear statistics)



Inference for Boulder grid box



Summary

- Computational efficiency gained by compact basis functions and sparse precision matrix.
- Can reproduce usual spatial analysis: flexible covariances, parameter estimation, spatial prediction, inference.

See LatticeKrig package in R

Thank you!

