

A geostatistical model for teleconnections

Josh Hewitt

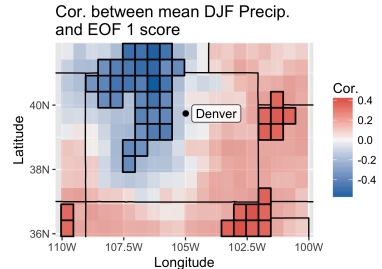
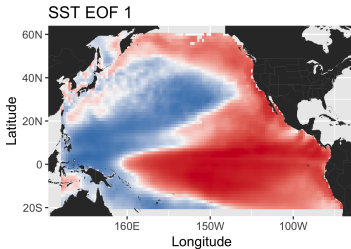
12 May 2017

Joint work with

- Jennifer A. Hoeting
- James Done
- Erin Towler

Motivation

- Estimate teleconnections and test for significance while
 - accounting for spatial dependence
 - accounting for impact of local factors



Contributions

Climate science

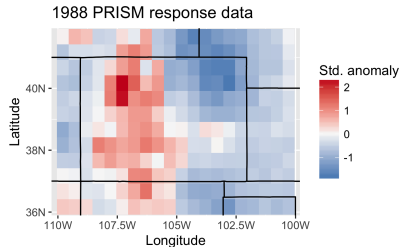
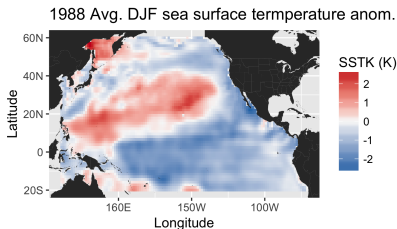
- Alternative to compositing by directly controlling for local covariates
- Alternative to post-hoc multiple testing corrections by directly accounting for spatial dependence

Spatial statistics

- Methodology for spatial modeling with remote effects

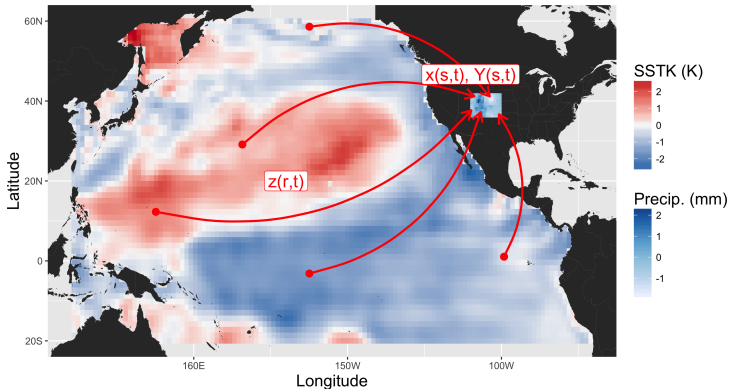
Case study: Colorado precipitation

- (Reanalysis) Data (33 winters: 1981–2013)
 - $Y(\mathbf{s}, t)$: PRISM precipitation
 - $\mathbf{x}(\mathbf{s}, t)$: ERA-Interim covariates
- Local covariates: $TCWV$, T , Z_{700} , $Elevation$
- Local domain: 240 42km-resolution grid cells
- Remote domain: 5,252 78km-resolution grid cells



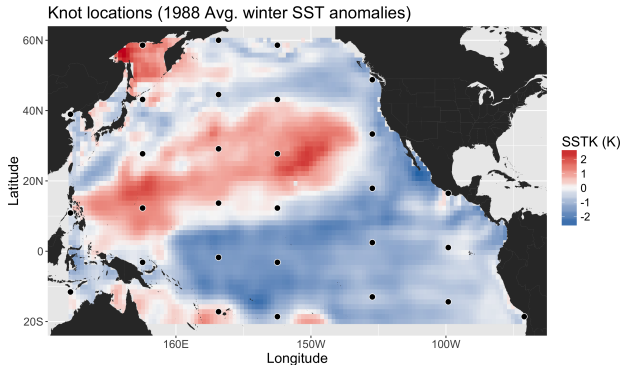
Remote effects spatial process (RESP) model

$$\underbrace{Y(s, t)}_{\text{Std. Precip. anomaly}} = \underbrace{x(s, t)^T \beta}_{\text{Local effects}} + \underbrace{w(s, t) + \varepsilon(s, t)}_{\text{Spatial + Independent error}} + \underbrace{\int_{\mathcal{D}_Z} z(r, t) \alpha(s, r) dr}_{\text{Teleconnection effects}}$$



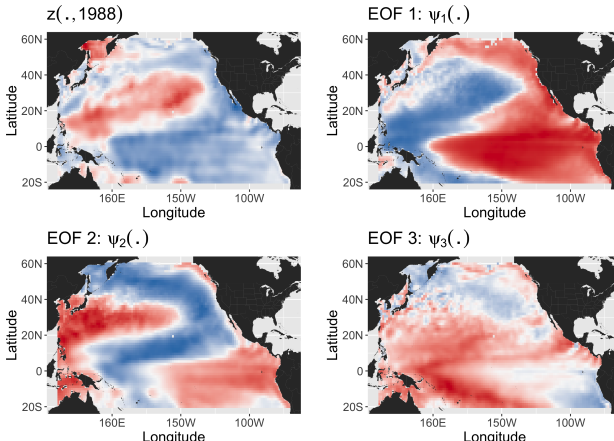
Remote effects spatial process (RESP) model

- Reduced rank approximation
 - Aggregate ocean data for more stable results
 - Aggregation parameters statistically optimized/estimated
 - $\alpha(\mathbf{s}, \mathbf{r}) = \sum_{j=1}^k h(\mathbf{r}, \mathbf{r}_j^*) \alpha(\mathbf{s}, \mathbf{r}_j^*)$



Remote effects spatial process (RESP) model

- Remote effects parameterization: Spatial basis fns.
 - Estimate teleconnections for EOFs or other patterns
 - $z(\mathbf{r}, t) = \sum_{k=1}^K a_k(t) \psi_k(\mathbf{r})$



Bayesian hierarchical implementation

$$\mathbf{Y}_t = \begin{bmatrix} \mathbf{Y}(\mathbf{s}_1, t) \\ \vdots \\ \mathbf{Y}(\mathbf{s}_{n_s}, t) \end{bmatrix} \sim \mathcal{N}(\mathbf{X}_t \boldsymbol{\beta} + (\mathbf{I}_{n_s} \otimes \mathbf{z}_t^T) \tilde{\boldsymbol{\alpha}}, \boldsymbol{\Sigma})$$

$$\tilde{\boldsymbol{\alpha}} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma} \otimes \mathbf{R})$$

$$\boldsymbol{\beta} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Lambda})$$

$$\sigma^2 \sim \text{Inv-Gamma}(k, \theta)$$

$$\rho \sim \text{Uniform}(a, b)$$

$\mathbf{X}_t$: Matrix of all local covariates for time t

$\tilde{\boldsymbol{\alpha}}$: Vector of teleconnection effects for all locations

$\boldsymbol{\Sigma}$: Covariance matrix for Colorado locations

$\mathbf{R}$: Covariance matrix for teleconnection effects $\boldsymbol{\alpha}(\cdot)$

$\boldsymbol{\theta} = (\sigma^2, \rho)$: Covariance matrix scale and range parameters

$(\boldsymbol{\Lambda}, k, \theta, a, b)$: Hyperparameters

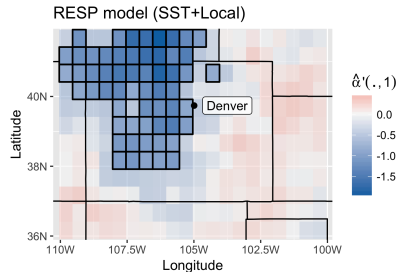
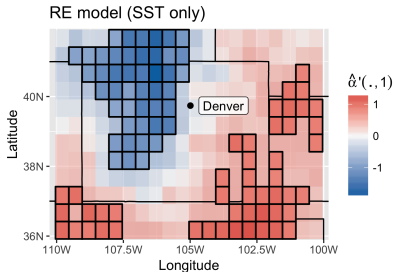
Case study: Parameter estimates

- Estimates account for remote covariates

	Posterior mean	95% HPD	VIF
β_0	0	(-0.058, 0.059)	1
β_{TCWV}	0.491	(0.424, 0.554)	1.2
β_T	-0.302	(-0.362, -0.241)	1.1
$\beta_{Z_{700}}$	-0.149	(-0.224, -0.078)	1.2
β_{ELEV}	0	(-0.049, 0.046)	1
σ_w^2	0.322	(0.303, 0.341)	
σ_α^2	0.004	(0.003, 0.005)	
$\tilde{\sigma}_\varepsilon^2$	0.093	(0.086, 0.099)	
ρ_w	37.11	(35.766, 38.332)	
ρ_α	6.657	(1.306, 11.166)	

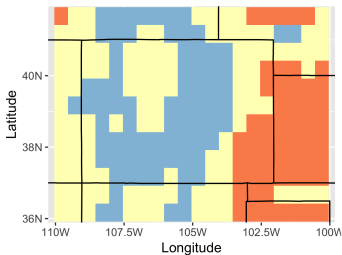
Case study: Teleconnection estimates

- RE model uses spatial dependence to “interpolate” significance in correlation maps
- RESP model suggests positive (red) teleconnection effects are fully expressed through local covariates

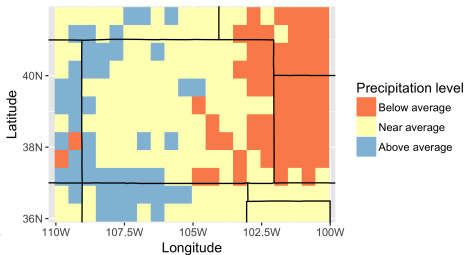


Case study: Data fit

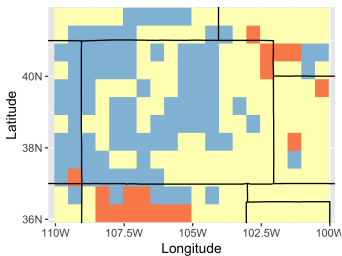
1988 PRISM response data



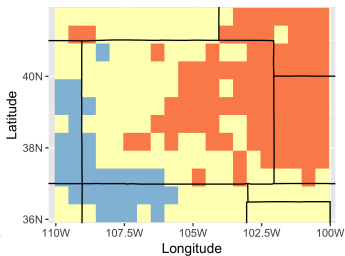
RESP model (SST+Local)



RE model (SST only)

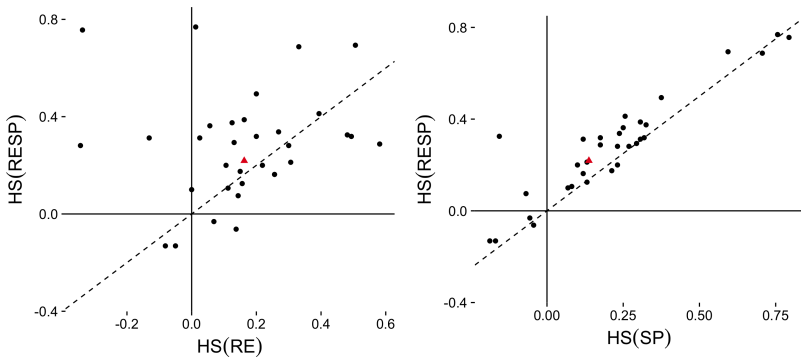


SP model (Local only)



Case study: Model comparison

- Fit measured with Heidke skill: $HS \propto P(\hat{Y}(s, t) = Y(s, t))$



Conclusions and future work

- Conclusions
 - A new class of spatial statistics problems in which distant locations are correlated.
 - Geostatistical model that incorporates both local and spatially remote covariates modeled via different spatial processes.
 - A more formal framework than previously available for studying teleconnection patterns while accounting for local covariates and spatial dependence.
- Possible future work
 - GLM version of model to study teleconnection impacts on annual number of rain events.
 - Extension to allow temporal variation to account for changing teleconnections.

Acknowledgements

- Conference and workshop travel under NSF research network on STATMOS through grant DMS-1106862.
- This material is based upon work supported by the National Science Foundation under Grant Number (NSF AGS - 1419558). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.