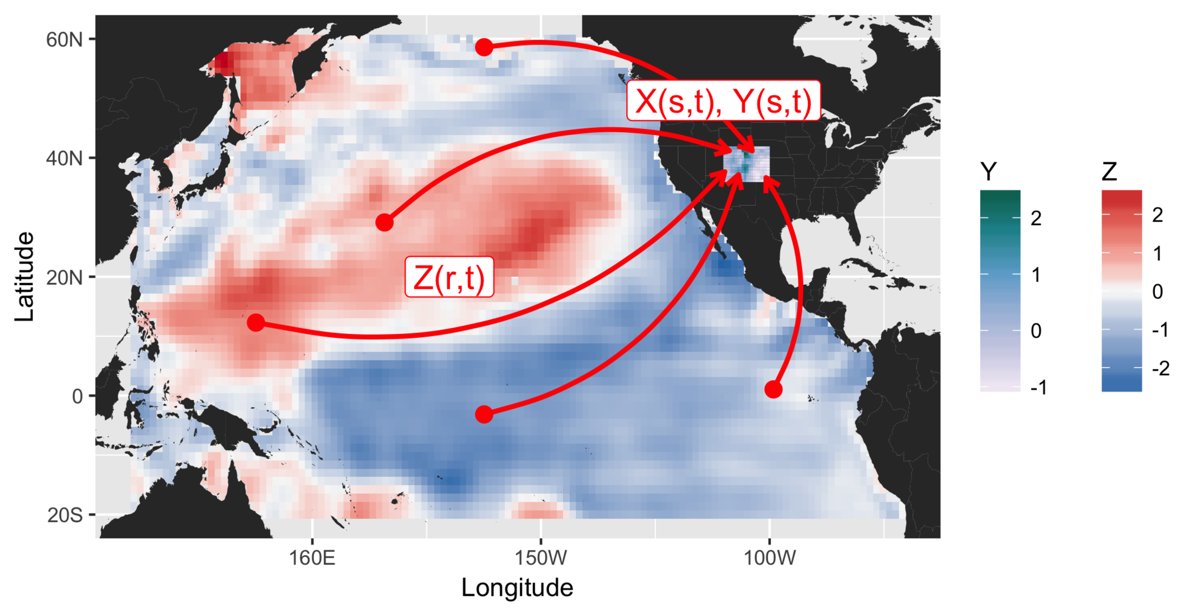
Remote effects spatial process models for modeling teleconnections

Joshua Hewitt[1], Jennifer A. Hoeting[1], James Done[2], and Erin Towler[2]

[1]Department of Statistics, Colorado State University; [2]National Center for Atmospheric Research

Overview

We develop a new geostatistical model to study how teleconnections and local factors impact regional climate. Teleconnections are a climate phenomenon in which geographically distant areas influence regional climate patterns. Our model advances existing spatial models, which do not account for effects of both local and remote covariates on a spatial process.



Teleconnections occur when remote covariates, like Pacific Ocean sea surface temperatures (SSTs), influence regional climate variables, like average winter precipitation in Colorado.

Remote effects spatial process model

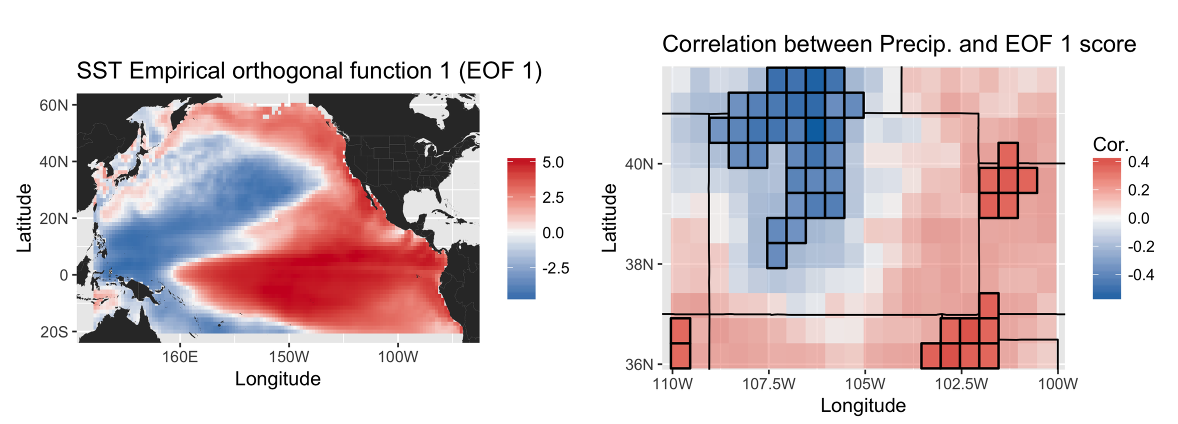
We introduce the remote effects spatial process model (RESP) to study the impact of local and remote/teleconnection effects at each mainland location $\boldsymbol{s}$ and time t with a simple, flexible form (below).

$$\underbrace{Y(\boldsymbol{s},t)}_{\text{Precip. anomaly}} = \underbrace{\boldsymbol{x}(\boldsymbol{s},t)^T\boldsymbol{\beta}}_{\text{Local effects}} + \underbrace{\boldsymbol{\alpha}(\boldsymbol{s})^T\boldsymbol{z}_t}_{\text{Teleconnection effects}} + \underbrace{\varepsilon(\boldsymbol{s},t)}_{\text{Spatially correlated error}}$$

- $\boldsymbol{x}(\boldsymbol{s},t)$: Local covariates (Water vapor, temp., elevation, 700hPa pressure level height)
- $\boldsymbol{z}_t$: Vector of sea surface temperature (SST) anomalies in year t
- $\boldsymbol{\alpha}(\boldsymbol{s})$: Spatially varying teleconnection effects vector for location $\boldsymbol{s}$

Regional teleconnections

Data: (1981-2013) Average winter (DJF) land and sea surface temperature anomalies from ERA-Interim Reanalysis data; PRISM precipitation anomalies (total rain and melted snow).



Exploratory correlation maps show teleconnection effects vary spatially. Our model includes this property. The correlation map (above right) suggests Precip. tends to increase in Eastern Colorado and decrease in Western Colorado during El Niño events, which occur when the PC 1 pattern (above left) of Sea surface temperatures (SSTs) is strongly expressed.

Model refinements

Transformation of teleconnection effects

We use the principal component transformation to estimate more scientifically meaningful teleconnection effects. Principal component basis expansions are known as Empirical Orthogonal Functions in climate science.

- Basis function expansions of the remote covariates $\boldsymbol{z}_t = W\boldsymbol{T}_t$ allow the original teleconnection effects to be reparameterized as $\boldsymbol{\alpha}'(\boldsymbol{s}) = W^T\boldsymbol{\alpha}(\boldsymbol{s})$ since

$$\underbrace{\boldsymbol{\alpha}(\boldsymbol{s})^T\boldsymbol{z}_t}_{\text{Teleconnection effects}} = \boldsymbol{\alpha}(\boldsymbol{s})^T W\boldsymbol{T}_t = \underbrace{\boldsymbol{\alpha}'(\boldsymbol{s})^T\boldsymbol{T}_t}_{\text{Reparameterized effects}}.$$

Reduced rank approximation

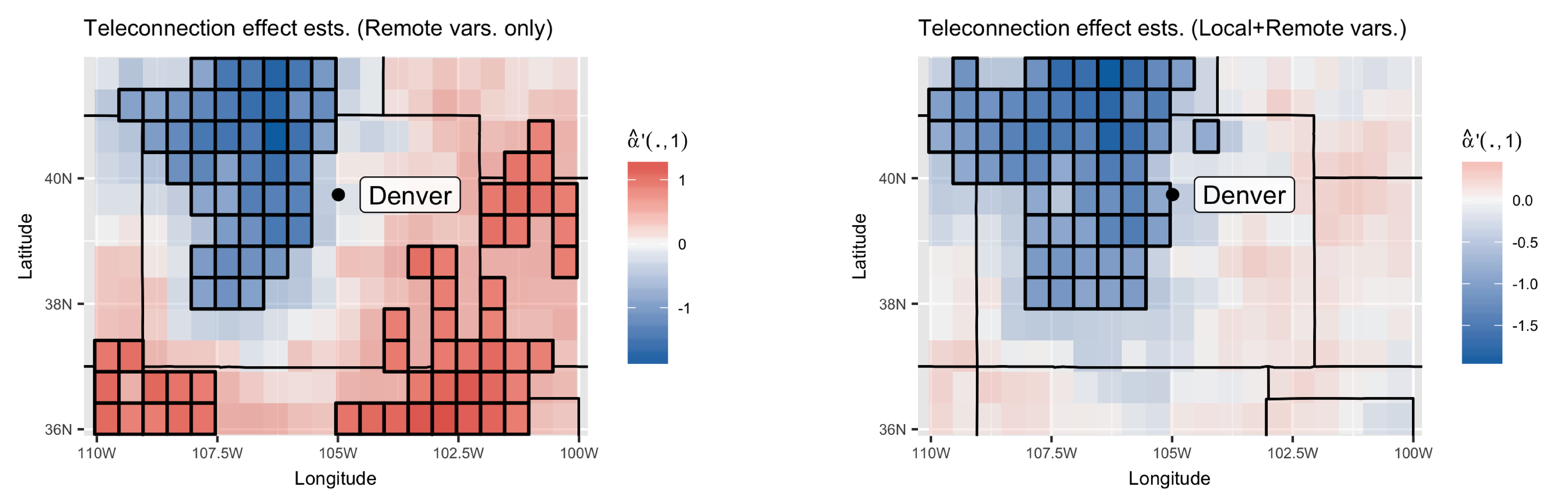
We use a reduced rank approximation to mitigate potential multicollinearity issues and reduce computational complexity.

$$\boldsymbol{\alpha}(\boldsymbol{s}) \approx \boldsymbol{c}^* R^{*-1}\boldsymbol{\alpha}^*(\boldsymbol{s})$$

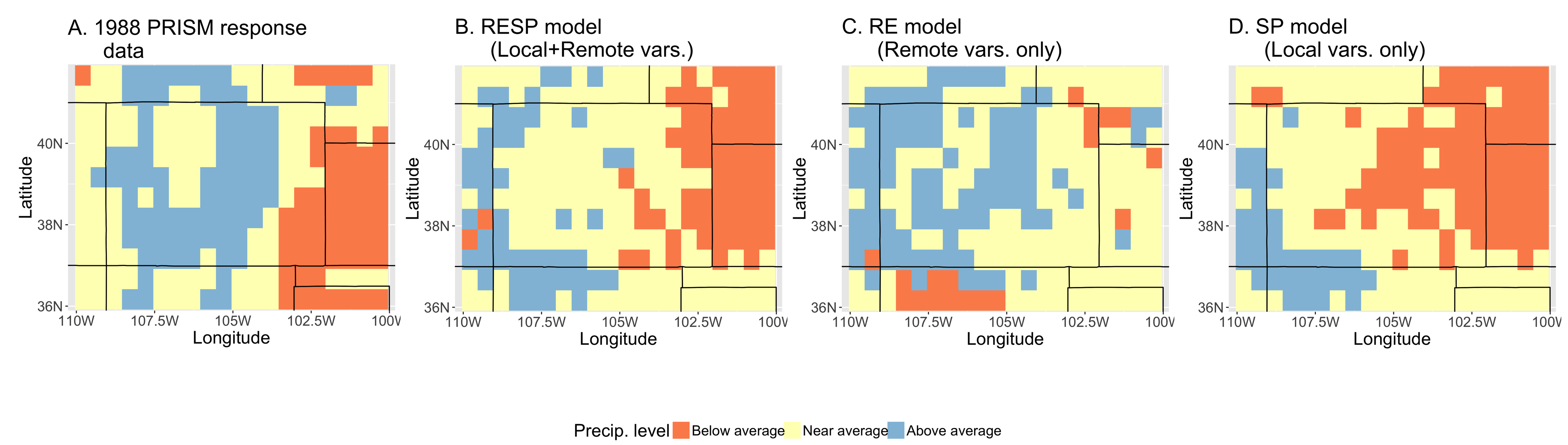
- We assume the teleconnection coefficients $\boldsymbol{\alpha}(\boldsymbol{s})$ can be approximated with a weighted average of teleconnection coefficients $\boldsymbol{\alpha}^*(\boldsymbol{s})$ at knot locations
- Use of the weighting matrix $\boldsymbol{c}^* R^{*-1}$ is similar to predictive processes (Banerjee et al., 2008) as the most natural approximation uses kriging weights estimated during model fitting.

Results

- 95% Bayesian highest posterior density (HPD) intervals suggest significant teleconnection effects (highlighted boxes below) depend on local conditioning variables, implying teleconnection effects may act as a proxy for missing local variables or interactions.



- Including both local and remote covariates (B) improves fit in teleconnected regions as compared to models that only account for remote (C) or local (D) covariates. While seasonal precipitation is generally hard for all models to predict, these results show that accounting for physical processes is beneficial.



Computational approach

- Hierarchical Bayesian framework to estimate model parameters via marginalized Gibbs algorithm.
- Exploit hierarchical model structure to estimate teleconnection effects in parallel using composition sampling.
- Use streaming algorithms to reduce memory required to compute parameter means and covariances.

Key contributions

- Developing methods for geostatistical regression with near and distant spatial fields.
- Geostatistical model that incorporates both local and spatially remote covariates modeled via different spatial processes.
- The geostatistical model provides a more formal framework for studying and testing teleconnection patterns while accounting for local covariates than previously available.

Future work

- Extend model to allow temporal variation to account for changing teleconnection effects.
- Study model's ability to bias-correct and downscale climate model output.

References

Banerjee, S., Gelfand, A.E., Finley, A.O., and Sang, H. (2008). Gaussian predictive process models for large spatial data sets. *JRSSB* **70** 825–848.

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