Regional climate model assessment via spatio-temporal modeling

Peter F. Craigmile

The Ohio State University
department of STATISTICS

http://www.stat.osu.edu/~pfc/

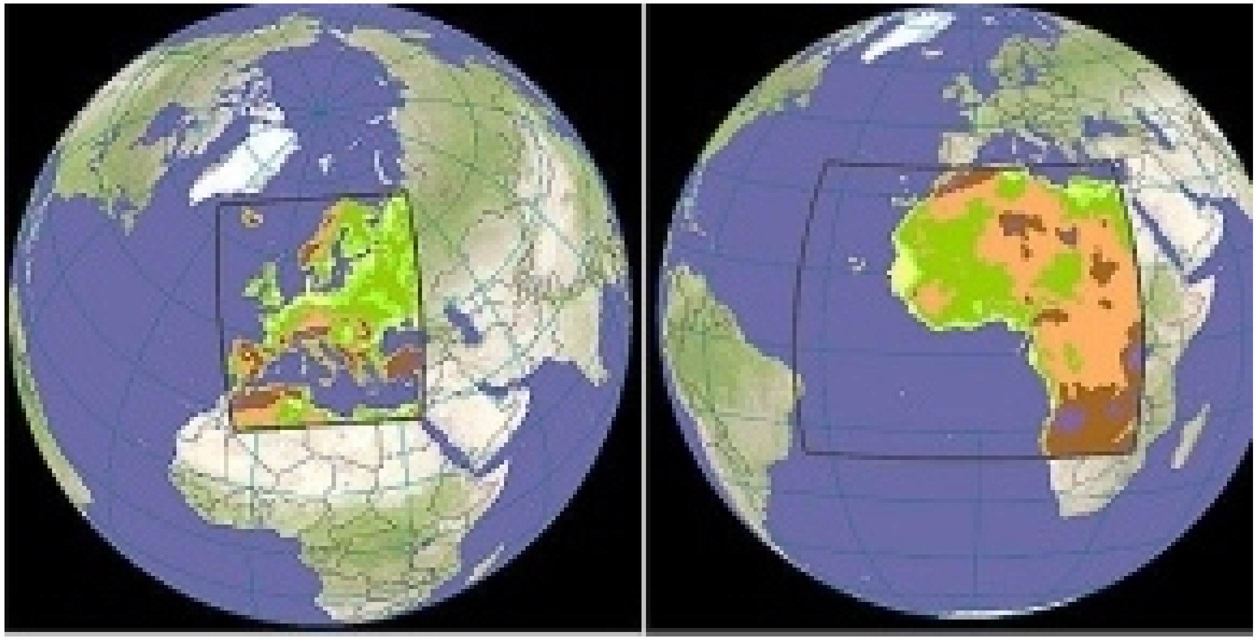
Symposium on Data Science and Statistics, Reston, VA

May 16-19, 2018.

Adapted from research carried out with Peter Guttorp (U. Washington and Norwegian Computing Center) and Veronica Berrocal (U. Michigan)

Supported by the US National Science Foundation.

Regional climate models (RCMs)



Source: http://www.smhi.se/en/research/research-news/combined-science-on-climate-models-1.14533

RCMs are a downscaled global circulation/climate models (GCMs).

Mathematical model that describes, using partial differential equations, the temporal evolution of climate, oceans, atmosphere, ice, and land-use processes over a gridded spatial domain of interest.

Regional climate models

- RCMs typically operate on relatively **small areas**.
  - Within these small areas, there are more spatial locations than from a GCM (more data! more information?)
- RCMs need to use **boundary values** for the global distribution of the atmosphere, oceans, etc. (typically drawn from a GCM).
- Thus, there are **two** sources of variation to consider:
  1. Inadequacies in the RCM;
  2. Inadequacies in the boundary values (can be reduced using a **re-analysis**) [Samuelsson et al., 2011].

Regional climate model assessment

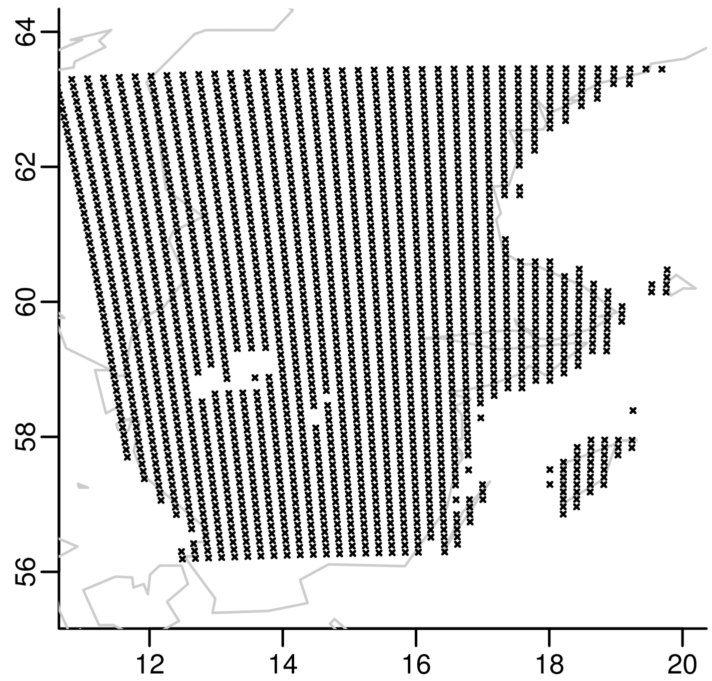
The assessment of RCMs **using observations** is a non-trivial task.

Climate, being the distribution of weather and other climatic factors over long time periods [Rossow et al., 2005, Guttorp and Xu, 2011], cannot be measured directly.

Rather, a variety of quantities (including weather) are measured, and usually their **long-term averages** are compared to the model output.

- More accurately, we argue one should compare the **distribution** of observations and model output, on **comparable spatial** and **temporal** scales.

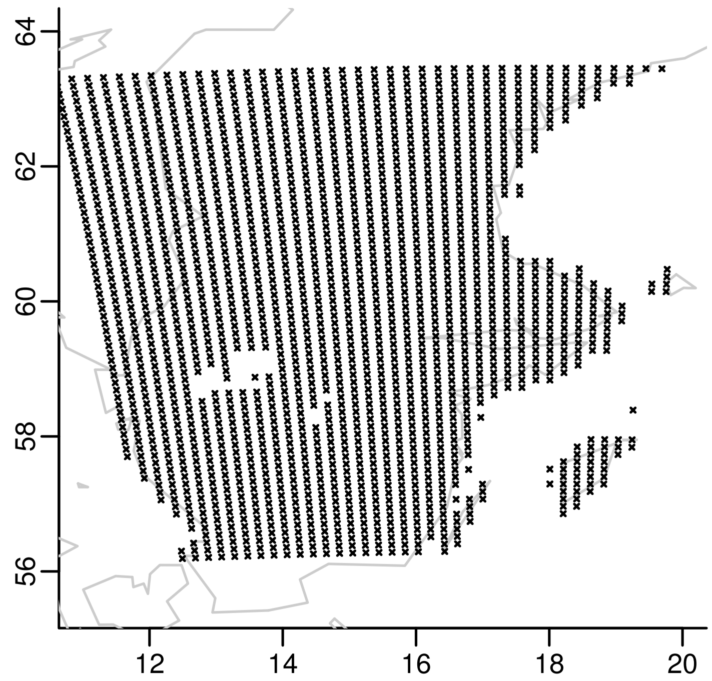
Example: SMHI RCM output



A **control run** of the Swedish Meteorological and Hydrological Institute (SMHI) regional climate model RCA version 3 [Samuelsson et al., 2011].

Run using boundary conditions given by the two re-analyses [Uppala et al., 2005, 2008].

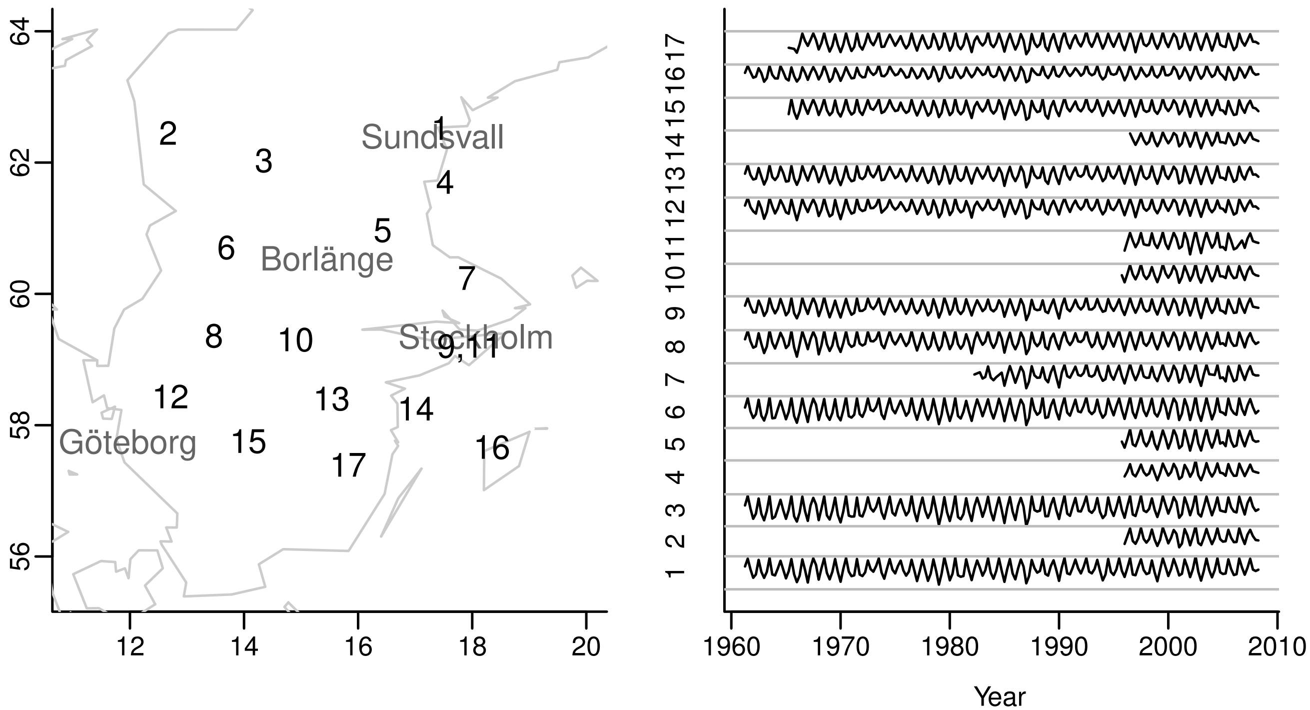
SMHI RCM output, cont.



Fractioned to different land types – we restrict our analysis to the 2 meter temperature given for the **open land** and **snow land covers**.

Available from Dec 1, 1962 to Nov 30, 2007 with a **temporal resolution** of 7.5 minutes. 12.5 km × 12.5 km **spatial resolution**.

Observational data



- Daily synoptic observations from 17 sites in an area of south central Sweden (Also from Swedish Meteorological and Hydrological Institute, SMHI).

Two analyses

1. A comparison of **seasonal averages** (DJF, MAM, JAJ, SON) of **daily mean temperature** [Berrocal et al., 2012].

2. A comparison of **seasonal minima** (DJF, MAM, JAJ, SON) of **daily mean temperature** [Craigmile and Guttorp, 2013].

In each case we fit (Bayesian hierarchical) **statistical models** to the

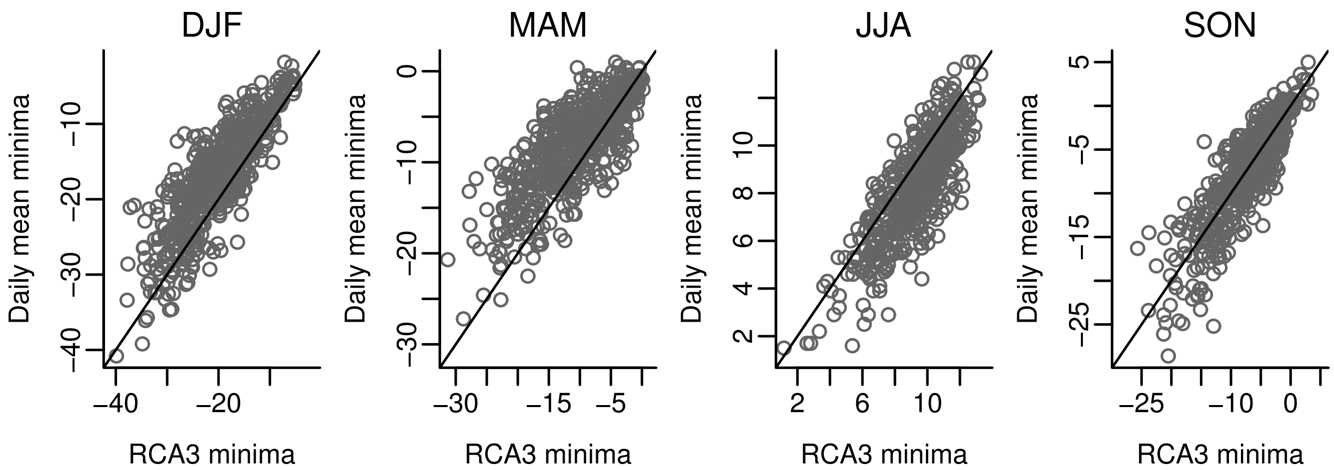
Observational data from reserved stations (point referenced), and

RCM output, observed on grids.

We **infer** upon the parameters in these models to learn about climate.

We focus on the second analysis here.

Non spatio-temporal comparisons



Seasonal minima for the station data and RCM agree best in the autumn (SON).

In the winter (DJF) and spring (MAM), the observed minima tend to be slightly higher than is observed for the RCM; we observe the opposite for summer (JJA).

Comparing distributions using **Doksum's shift function** [Doksum, 1974], we find anomalous behavior of the RCM around 0°C.

Extreme value theory-based comparisons

Use **extreme value theory** to analyze and model the seasonal minima for both the

station data

and the

RCM output.

[See Wang et al., 2016, for another example of this.]

Example: modeling the station data

At location $\boldsymbol{s} \in D$ and time index $t = 1, \ldots, N(\boldsymbol{s})$:

let $Z_t(\boldsymbol{s})$ denote the **block minima** in year $y_t(\boldsymbol{s})$ and

season $d_t(\boldsymbol{s})$ (taking on values 1: DJF; 2: MAM; 3: JJA; 4: SON).

Modeling the **negative of the minima** we suppose

$$[-Z_t(\boldsymbol{s})] \sim \text{GEV}(\widetilde{\mu}_t(\boldsymbol{s}), \sigma_t(\boldsymbol{s}), \xi_t(\boldsymbol{s})),$$

conditionally independent over $\boldsymbol{s}$ and t.

The GEV parameters

$\widetilde{\mu}_t(\boldsymbol{s}) \in \mathbb{R}$: **location parameter** indicating values which the distribution of the negative minima are concentrated around.

$\sigma_t(\boldsymbol{s}) > 0$: **scale parameter** defining the spread of the distribution.

$\xi_t(\boldsymbol{s})$: **shape parameter**. The tails of the GEV distributions are heavier for higher values of the shape parameter (A negative shape parameter leads to bounded tails; otherwise the tails of the distribution are unbounded.)

Interpreting the GEV parameters

We think GEV parameters as **describing climate**, with the changes in the parameters indicating seasonal differences and possible trends.

Given the climate, the model technically assumes that weather at different stations is **conditionally independent**.

- A **oversimplification**, since typically events of extremely cold air arise from arctic air moving south during a high pressure situation.

  Given that one station is extremely cold, it is more likely that another is.

  (**Multivariate** extreme-value modeling is left as a future exercise!)

Modeling the location parameter

Spatio-temporal model for $\{\mu_t(\boldsymbol{s}) = -\widetilde{\mu}_t(\boldsymbol{s})\}$:

$$\mu_t(\boldsymbol{s}) \;=\; \beta_0(\boldsymbol{s}) + \beta_1(\boldsymbol{s})(y_t(\boldsymbol{s}) - 1960) + \sum_{d=2}^{4} \beta_d(\boldsymbol{s}) I(d_t(\boldsymbol{s}) = d).$$

where $I(\cdot)$ is the indicator function.

We assume each $\{\beta_j(\boldsymbol{s})\}$ are independent **Gaussian processes** each with mean λ_j and isotropic covariance, $\mathrm{cov}(\beta_j(\boldsymbol{s}), \beta_j(\boldsymbol{s}+\boldsymbol{h})) = \tau_j \exp(-||\boldsymbol{h}||/\phi_j)$.

Here $\tau_j > 0$ is the (partial) sill parameter, $\phi_j > 0$ is the range parameter, and $||\cdot||$ denotes the Euclidean norm.

Modeling the scale and shape parameters

Assume that the **scale parameters** vary over space, but are constant in time:

$\sigma_t(\boldsymbol{s}) = \sigma(\boldsymbol{s})$ for all t and $\boldsymbol{s}$.

We suppose $\{\log \sigma(\boldsymbol{s})\}$ is a **Gaussian process** with mean λ_σ and isotropic covariance $\mathrm{cov}(\log \sigma(\boldsymbol{s}), \log \sigma(\boldsymbol{s} + \boldsymbol{h})) = \tau_\sigma \exp(-||\boldsymbol{h}||/\phi_\sigma)$.

Our assumption of a **constant shape parameter**, ξ, is an oversimplification, but is reasonable [e.g. Cooley et al., 2007, Sang and Gelfand, 2010].

Bayesian inference

Our **parameters** of interest are

$$\begin{aligned}\boldsymbol{\theta} \;=\; \Big(&\{\beta_j(\boldsymbol{s}) : \boldsymbol{s} \in D, j = 0, \ldots, 4\}, \{\log \sigma(\boldsymbol{s}) : \boldsymbol{s} \in D\}, \xi, \\ &\{\lambda_j : j = 0, \ldots, 4\}, \{\tau_j\}, \{\phi_j\}, \lambda_\sigma, \tau_\sigma, \phi_\sigma\Big)^T.\end{aligned}$$

With the exception of the hyperparameters for the **shape** parameter ξ and the **spatial range** parameters, we assume **vague priors**.

For the **range** parameters we use the gamma prior choice of Craigmile and Guttorp [2011], who modeled daily mean temperature from the same synoptic stations.

The posterior

The **posterior distribution** of $\boldsymbol{\theta}$ given the data is not available in closed form.

We use a Markov chain Monte Carlo (MCMC) algorithm to sample from the posterior distribution.

The algorithm used is adapted from Mannshardt et al. [2013].

Fit one model to the observational data; another model to the RCM output.

The results are **robust** to **minor changes** in this choice of prior distribution.

Approximations required to fit the RCM model

Because we have 1989 spatial locations, we made two approximations:

1. In updating the spatially varying GEV parameters, we calculated the acceptance ratios for Metropolis updates at each spatial location using the 15 **nearest neighbors**, rather than all the spatial locations.

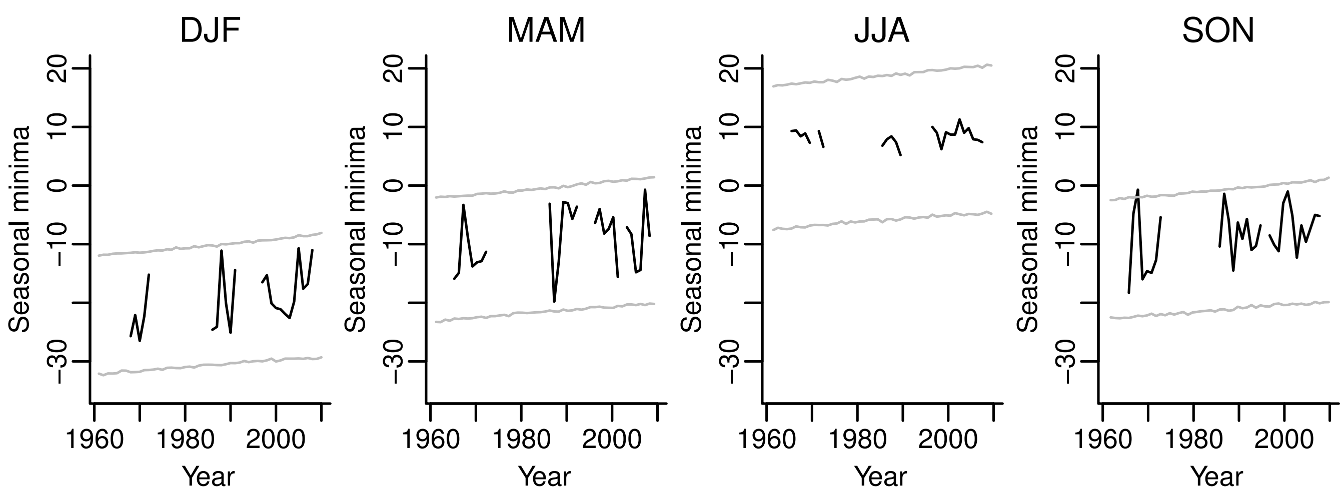
2. In updating the hyperparameters in the spatial models, we broke the spatial field up into 4 **sub-regions** (NW, NE, SW and SE). This sped up matrix inversions.

Experiments demonstrated our results were robust to these approximations.

Model verification

Quantile plots [e.g., Coles, 2001, Section 6.2.3] indicate excellent goodness of fit, especially compared to a model in which the scale parameter is held constant over locations.

But, using un-modeled data from Borlänge, we learn GEV model is **underestimating** the **variation** of seasonal minima in the summer (JJA).



GEV model results: the shape parameters

We fit our spatio-temporal GEV model to both the observational data and the RCM output.

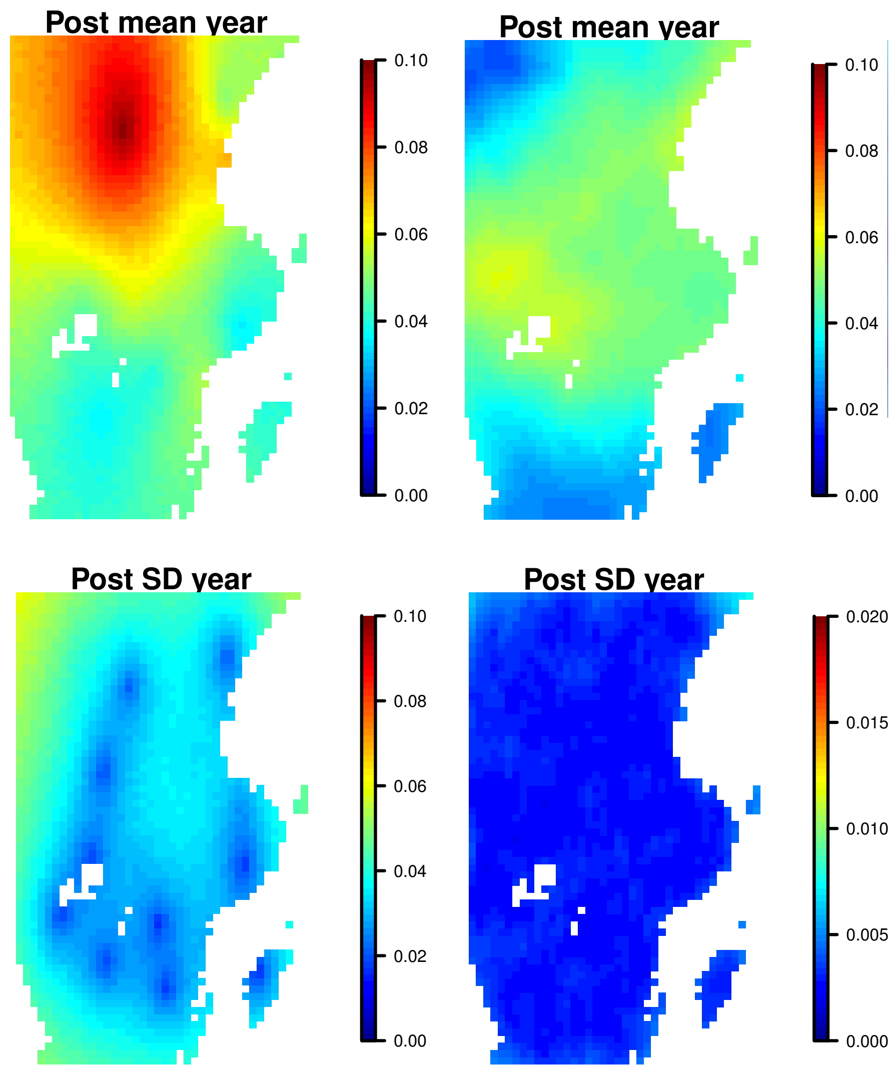
	Observed stations		RCM	
Parameter	Post. mean	95% CI	Post. mean	95% CI
ξ	-0.18	(-0.21, -0.15)	-0.14	(-0.15, -0.14)

Shape parameters, ζ, are similar in both models.

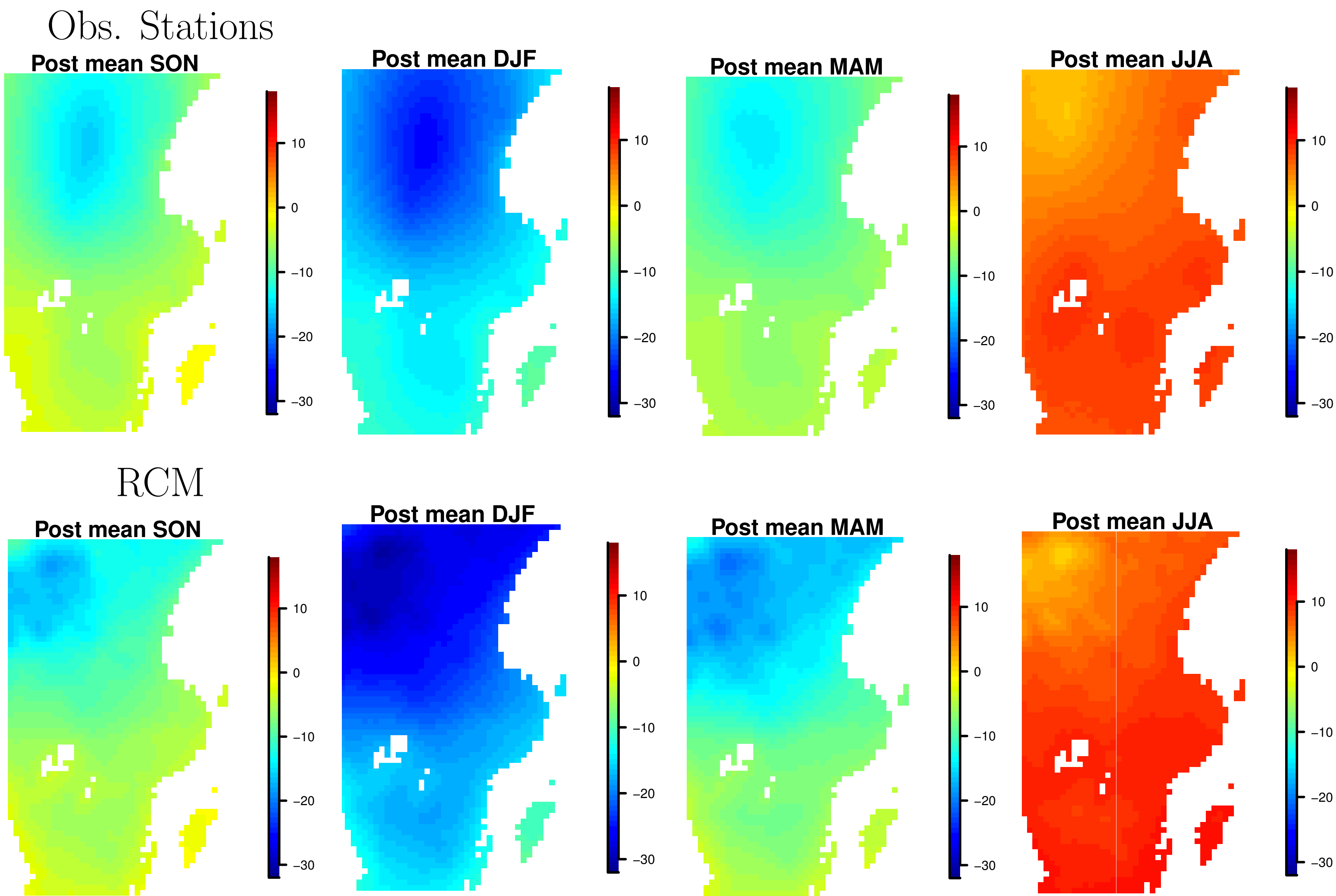
Both parameters negative: hence distribution of seasonal minima is bounded.

GEV model results: temporal trends

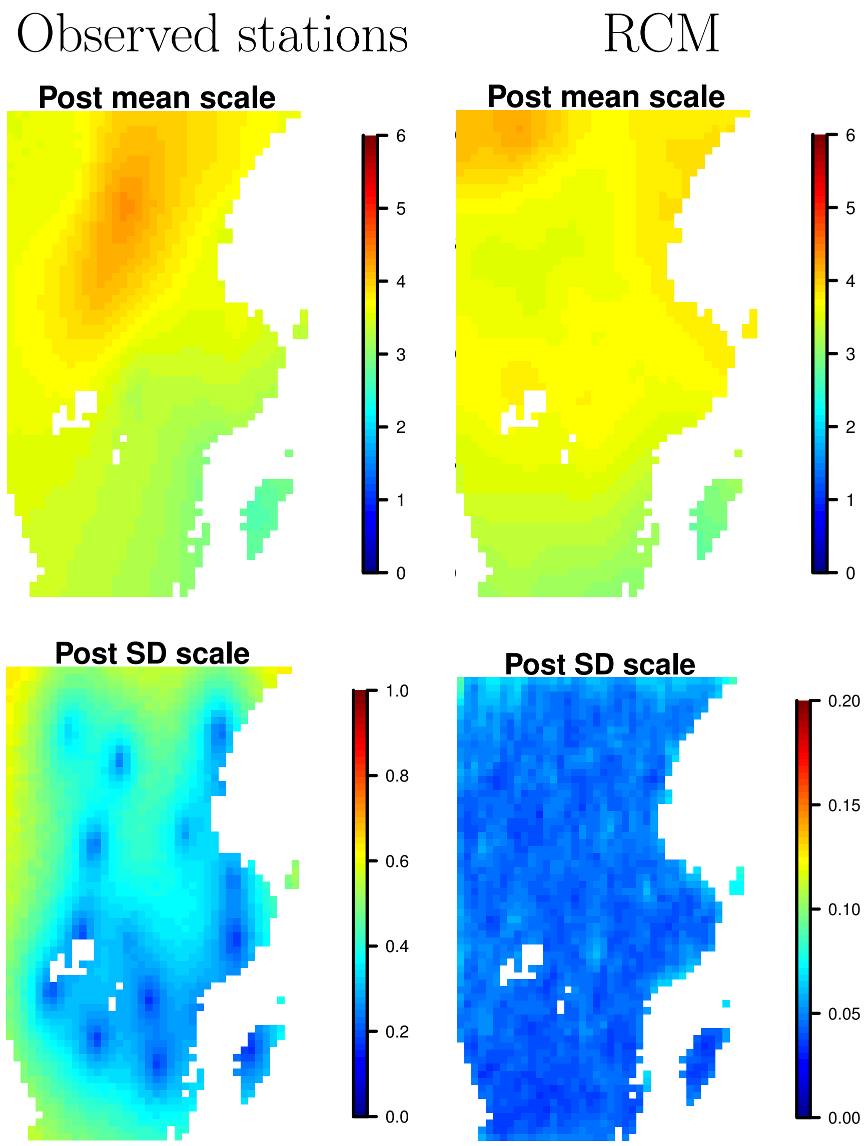
Observed stations RCM



GEV model results: seasonal effects



GEV model results: scale parameters



Summary of GEV modeling results

1. Increasing trend in seasonal minima – warming underestimated in the RCM.

   For observations, change per year ranges from 0.04–0.10 ^{o}C.

2. Seasonal patterns in observations and RCM output are similar in direction.

   RCM too cold in DJF.

3. Differences in the spatial distribution of the scale parameter.

Challenges moving forward

- Building statistical models that capture the important features of climate.
- Handling massive datasets: model complexity versus computation
- Change of support
- How do we diagnose and compare statistical models used for assessing RCMs?
- Uncertainty quantification (e.g., understanding the uncertainty of spatial features – for example, the peaks and troughs over space of temperature minima).

Discussion: Why are we assessing RCMs?

Do we believe that observations are the best information about the truth?

- Are we using these observations (in some sense) to grade how well RCMs perform?

  See Heaton et al. [2014] for a non-trivial example of how one might grade a computer model.

What are the RCMs being used for?

[e.g. Jun, 2017]

- To learn about the spatio-temporal dynamics of the climate system
- To compare different climate models [e.g. Smith et al., 2009, Sain et al., 2010]
- To distinguish between different forcing scenarios [e.g. Tingley et al., 2015]
- To blend model outputs [e.g. Kang et al., 2012]
- For projections [e.g. Poppick et al., 2016]
- For detection and attribution [e.g. Hegerl et al., 2000]

How are we assessing regional climate model assessment

- Do we just compare the observations and RCMs directly? [e.g. Craigmile and Li., 2017]
- Do we build models independently on observations and RCMs and compare the parameters from each model?
- Do we regress one on the other, trying to learn about possible associations? [e.g. Sain et al., 2010, Braverman et al., 2016].
- What about joint modeling, rather than conditional modeling? [e.g. Philbin and Jun, 2015]

(The statistical modeling gets more complex as we move down the page.)

References

V. Berrocal, P. Craigmile, and P. Guttorp. Regional climate model assessment using statistical upscaling and downscaling techniques. *Environmetrics*, 23:482–492, 2012.

A. Braverman, S. Chatterjee, M. Heyman, and N. Cressie. Probabilistic evaluation of competing climate models. Technical report, National Institute for Applied Statistics Research, University of Wollongong, Australia, 2016. URL http://ro.uow.edu.au/niasrawp/42/.

S. Coles. *An Introduction to Statistical Modeling of Extreme Values*. Springer-Verlag, 2001.

D. Cooley, D. Nychka, and P. Naveau. Bayesian spatial modeling of extreme precipitation return levels. *Journal of the American Statistical Association*, 102: 824–840, 2007.

P. F. Craigmile and P. Guttorp. Space-time modelling of trends in temperature series. *Journal of Time Series Analysis*, 32:378–395, Apr. 2011.

P. F. Craigmile and P. Guttorp. Can a regional climate model reproduce observed extreme temperatures? *Statistica*, 73:103–122, 2013.

P. F. Craigmile and B. Li. Instruments, proxies, and simulations: exploring imperfect measures of climate. *CHANCE*, 2017. To appear.

K. A. Doksum. Empirical probability plots and statistical inference for nonlinear models in the two sample case. *Ann. Statist.*, 2:267–277, 1974.

P. Guttorp and J. Xu. Climate change, trends in extremes, and model assessment for a long temperature time series from Sweden. *Environmetrics*, 22:456–463, 2011.

M. J. Heaton, W. Kleiber, S. R. Sain, and M. Wiltberger. Emulating and calibrating the multiple-fidelity Lyon-Fedder-Mobarry magnetosphere-ionosphere coupled computer model. *Journal of the Royal Statistical Society, Series C (Applied Statistics)*, 64:93–113, 2014.

G. C. Hegerl, P. A. Stott, M. R. Allen, J. Mitchell, S. Tett, and U. Cubasch. Optimal detection and attribution of climate change: Sensitivity of results to climate model differences. *Climate Dynamics*, 16:737–754, 2000.

M. Jun. Climate model intercomparison. *CHANCE*, 2017. To appear.

E. L. Kang, N. Cressie, and S. R. Sain. Combining outputs from the North American Regional Climate Change Assessment Program by using a Bayesian hierarchical model. *Journal of the Royal Statistical Society, Series C (Applied Statistics)*, 61:291–313, 2012.

E. Mannshardt, P. F. Craigmile, and M. P. Tingley. Statistical modeling of extreme value behavior in North American tree-ring density series. *Climatic Change*, 117:843–858, 2013.

R. Philbin and M. Jun. Bivariate spatial analysis of temperature and precipitation from general circulation models and observation proxies. *Advances in Statistical Climatology, Meteorology and Oceanography*, 1:29, 2015.

A. Poppick, D. J. McInerney, E. J. Moyer, and M. L. Stein. Temperatures in transient climates: Improved methods for simulations with evolving temporal covariances. *The Annals of Applied Statistics*, 10:477–505, 2016.

W. B. Rossow, G. Tselioudis, A. Polak, and C. Jakob. Tropical climate described as a distribution of weather states indicated by distinct mesoscale cloud property mixtures. *Geophysical Research Letters*, 32, 2005. doi: 10.1029/2005GL024584.

S. R. Sain, D. Nychka, and L. Mearns. Functional anova and regional climate experiments: a statistical analysis of dynamic downscaling. *Environmetrics*, 22: 700–711, 2010.

P. Samuelsson, C. G. Jones, U. Willén, A. Ullerstig, S. Gollvik, U. Hansson, C. Jansson, E. Kjellström, G. Nikulin, and K. Wyser. The Rossby Centre regional climate model RCA3: model description and performance. *Tellus A*, 63:4–23, 2011.

H. Sang and A. E. Gelfand. Continuous Spatial Process Models for Spatial Extreme Values. *Journal of Agricultural, Biological and Environmental Statistics*, 15: 49–65, 2010.

R. L. Smith, C. Tebaldi, D. Nychka, and L. O. Mearns. Bayesian modeling of uncertainty in ensembles of climate models. *Journal of the American Statistical Association*, 104:97–116, 2009.

M. Tingley, P. F. Craigmile, M. Haran, B. Li, E. Mannshardt, and B. Rajaratnam. On discriminating between gcm forcing configurations using Bayesian reconstructions of late-holocene temperatures. *Journal of Climate*, 28:8264–8281, 2015.

S. Uppala, P. Kölberg, A. Simmons, U. Andrae, V. da Costa Bechtold, M. Fiorino, J. Gibson, J. Haseler, A. Hernandez, G. Kelly, X. Li, K. Onogi, S. Saarinen, N. Sokka, R. Allan, E. Andersson, K. Arpe, M. Balmaseda, A. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, S. Caires, F. Chevallier, A. Dethof, M. Dragosavac, M. Fisher, M. Fuentes, S. Hagemann, E. Hólm, B. Hoskins, L. Isaksen, P. Janssen, R. Jenne, A. McNally, J.-F. Mahfouf, J.-J. Morcrette, N. Rayner, R. Saunders, P. Simon, A. Sterl, K. Trenberth, A. Untch, D. Vasiljevic, P. Viterbo, and J. Woollen. The ERA-40 re-analysis. *Quarterly Journal of the Royal Meteorological Society*, 131:2961–3012, 2005.

S. Uppala, D. Dee, S. Kobayashi, P. Berrisford, and A. Simmons. Towards a climate data assimilation system: status update of ERA-Interim. *ECMWF Newsletter*, pages 12–18, 2008.

J. Wang, Y. Han, M. L. Stein, V. R. Kotamarthi, and W. K. Huang. Evaluation of dynamically downscaled extreme temperature using a spatially-aggregated generalized extreme value (GEV) model. *Climate Dynamics*, pages 1–17, 2016.