Regional climate model assessment using upscaling and downscaling techniques

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Introduction

- **Regional climate models** (*dynamic downscaling*) operate at regional scale and use boundary values (typically from a general circulation model)

- Assessing a regional climate model using data is a non-trivial task
  - climate, being the distribution of weather and other climatic factors over long time period, cannot be measured directly
  - usually long term averages are compared to the model output.
    More accurately, one should compare the distribution of observations and model output on *comparable spatial* and *temporal scale*.
Introduction

- Regional climate models (RCM) use boundary values for the global distribution of the atmosphere, oceans, etc.
- Hence, when assessing an RCM, there are two sources of discrepancies
  - inadequacies in the RCM
  - inadequacies in the boundary values
- One way to control for the second source of variation is to use observed weather or re-analysis.
Our goal

• To assess a regional climate model using two Bayesian hierarchical models:
  1. a downscaling model that combines observational data and RCM output and downscales it to point level
  2. an upscaling model that uses only observational data and provides predictions at RCM grid boxes

• Assessment will be carried out at:
  • point level: comparing observational data with predictions at reserved stations
  • grid level: comparing RCM output with predictions at the RCM grid boxes
- **Output of the Swedish Meteorological Hydrological Institute (SMHI) Rossby Centre Atmospheric (RCA) RCM model**

- **Daily output for 2-m temperature from December 1, 1962 to November 30, 2007, then aggregated to quarterly averages (DJF, MAM, JJA, SON)**

- **Output at 12.5 km × 12.5 km grid boxes**
RCM data

- Output of the *Swedish Meteorological Hydrological Institute (SMHI) Rossby Centre Atmospheric (RCA)* RCM model

- Daily output for 2-m temperature from December 1, 1962 to November 30, 2007, then aggregated to *quarterly averages* (DJF, MAM, JJA, SON)

- Output at *12.5 km × 12.5 km grid boxes*
Observational data

- **Observed daily average temperature** from 17 stations in the SMHI network of synoptic stations
- **Period:** December 1, 1962 to November 30, 2007
- Daily data aggregated to quarterly scale
- Three stations, Göteborg, Stockholm and Borlänge held out for validation
A first exploratory comparison might look at the station data and the RCM output at grid boxes that contain the stations.

- Observational data is point-referenced; RCM output is at the grid box level ($g=2640$ grid boxes).
A first comparison
Downscaling model
Downscaling model

• Goals are:
  • to combine the two sources of information (→ data assimilation)
  • to address the difference in spatial scale between the RCM output and the observational data
  • to derive improved predictions at point level
Downscaling problem

• Suppose we are in 1-D and we have a spatial process $Y(s), s \in [0, 1]$. 

![Spatial process $Y(s)$](image.png)
Downscaling problem

- We observe the process $Y(s)$ only at a finite number of points
Downscaling problem

- We also have information on the average of the process $Y(s)$ (or a surrogate of $Y(s)$) over regular subsets of $[0,1]$.

- We want to infer upon $Y(s)$ for $s \in [0,1]$.
- The extension to the 2-D case is straightforward.
Downscaling model

• Some notation:

  • $B_1, \ldots, B_g$: RCM model grid boxes with centroids $r_1, \ldots, r_g$
  
  • $x(B_1, t), x(B_2, t), \ldots, x(B_g, t)$: RCM output of quarterly average temperature for quarter $t = 1, \ldots, T$ at grid box $B_1, B_2, \ldots, B_g$
  
  • $Y(s, t)$: observed quarterly average temperature at station $s$ for quarter $t = 1, \ldots, T$

• A first model for downscaling could be: for $s$ in $B$ and $t = 1, \ldots, T$

\[
Y(s, t) = \beta_{0,t} + \beta_{1,t} x(B, t) + \varepsilon(s, t) \quad \varepsilon(s, t) \overset{iid}{\sim} N(0, \tau^2)
\]

• But for $t = 1, \ldots, T$ and all $s$ in $B$, $\hat{\beta}_{0,t} + \hat{\beta}_{1,t} x(B, t)$ would yield the same value!
Downscaling model

• A better model would be: for \( s \) in \( B \) and \( t = 1, \ldots, T \)

\[
Y(s, t) = \tilde{\beta}_0(s, t) + \tilde{\beta}_1(s, t)x(B, t) + \varepsilon(s, t) \quad \varepsilon(s, t) \sim N(0, \tau^2)
\]

• For \( i = 0, 1 \), we assume \( \tilde{\beta}_i(s, t) = \beta_{i,t} + \beta_i(s, t) \) with \( \beta_{i,t} \) overall mean and \( \beta_i(s, t) \) local adjustment with mean zero.

• \( \beta_{0,t}, \beta_{1,t}, \) and \( \beta_0(s, t), \beta_1(s, t) \) can be considered as calibration terms for the RCM output.

• \( \beta_0(s, t) \) and \( \beta_1(s, t) \) are mean-zero stationary Gaussian spatial processes with exponential covariance functions and range parameter that vary in time.
Downscaling model

We consider RCM output and observational data:
We consider RCM output and observational data:

We establish the spatial linear model: for \( s \in B \) and \( t = 1, \ldots, T \)

\[
Y(s, t) = \tilde{\beta}_0(s, t) + \tilde{\beta}_1(s, t) \times (B, t) + \epsilon(s, t) \quad \epsilon(s, t) \sim N(0, \tau^2)
\]
Downscaling model

- An even better model would be: for \( t = 1, \ldots, T \)

\[
Y(s, t) = \tilde{\beta}_0(s, t) + \beta_1 \tilde{x}(s, t) + \varepsilon(s, t) \quad \varepsilon(s, t) \sim N(0, \tau^2)
\]

with

- \( \tilde{x}(s, t) \): spatio-temporal weighted average of the RCM output:

\[
\tilde{x}(s, t) = \sum_{k=1}^{g} w_k(s, t) x(B_k, t)
\]

- \( \tilde{\beta}_1(s, t) \) replaced by \( \beta_1 \) for identifiability reasons

- The weights \( w_k(s, t) \) should be:

  - positive and sum up to 1
  - spatially correlated within sites and across sites
Downscaling model

- If \( r_1, \ldots, r_g \) are the centroids of the RCM grid boxes, we can take the weights \( w_k(s, t) \) to be

\[
w_k(s, t) = \frac{\mathcal{K}(|s - r_k|; \lambda)}{\sum_{l=1}^{g} \mathcal{K}(|s - r_l|; \lambda)}
\]

- \( \mathcal{K}(\cdot; \lambda) \) kernel function with bandwidth \( \lambda \).
  For example: \( \mathcal{K}(|s - r_k|; \lambda) = \exp(-\frac{|s-r_k|}{\lambda}) \).
We consider RCM output and observational data:
Downscaling model

We consider RCM output and observational data:

We establish the spatial linear model: for $s \in B$ and $t = 1, \ldots, T$

$$Y(s, t) = \tilde{\beta}_0(s, t) + \beta_1 \tilde{x}(s, t) + \varepsilon(s, t) \quad \varepsilon(s, t) \sim N(0, \tau^2)$$
Downscaling model

For $t = 1, \ldots, T$, the weight $w_k(s, t)$ is:
Downscaling model

- To allow for the weights $w_k(s, t)$ to be directional, we modify the expression

$$w_k(s, t) = \frac{\mathcal{K}(|s - r_k|; \lambda)}{\sum_{l=1}^{g} \mathcal{K}(|s - r_l|; \lambda)}$$

to

$$w_k(s, t) = \frac{\mathcal{K}(|s - r_k|; \lambda) \cdot \exp(Q(r_k, t))}{\sum_{l=1}^{g} \mathcal{K}(|s - r_l|; \lambda) \cdot \exp(Q(r_l, t))}$$

where for $t = 1, \ldots, T$, $Q(r, t)$ is a latent stationary mean-zero spatial Gaussian process with variance 1 and exponential correlation function.

- For $t = 1, \ldots, T$, the range $\phi$ of the latent spatial process $Q(r, t)$ influences the directionality of the weights.
Downscaling model

• Finally, the downscaling model is: for \( s \) and \( t = 1, \ldots, T \):

\[
Y(s, t) = \tilde{\beta}_0(s, t) + \beta_1 \tilde{x}(s, t) + \varepsilon(s, t) \quad \varepsilon(s, t) \sim N(0, \tau^2)
\]

• \( \tilde{\beta}_{0,t}(s) = \beta_{0,t} + \beta_0(s, t) \) with \( \beta_0(s, t) \) stationary mean-zero Gaussian spatial process with time-varying range parameter.

• \( \tilde{x}(s, t) = \sum_{k=1}^{g} w_k(s, t) x(B_k, t) \)

• \( w_k(s, t) = \frac{\mathcal{K}(|s-r_k|;\lambda) \cdot \exp(Q(r_k, t))}{\sum_{l=1}^{g} \mathcal{K}(|s-r_l|;\lambda) \cdot \exp(Q(r_l, t))} \)

• \( Q(r, t) \) is a latent stationary mean-zero spatial Gaussian process with variance 1 and exponential correlation function with range parameter \( \phi \).

• For \( t = 1, \ldots, T \), the calibration parameters, \( \beta_{0,t}, \beta_0(s, t) \) are assumed to be independent in time, and so is the latent process \( Q(r, t) \).
Downscaling model

- We fit the model within a Bayesian framework using an MCMC algorithm.

- The bandwidth parameter $\lambda$ and the range parameter $\phi$ that influence the weights are fixed a priori.

- Dimensionality problem when fitting the model because of the large number of RCM grid boxes $\rightarrow$ dimensionality reduction approach

- Predictions of quarterly average temperature from the model are generated at:
  - the three reserved stations of Göteborg, Stockholm and Borlänge
  - over the RCM grid boxes (via numerical integration)
Upscaling model
Goals are:

- to provide a spatio-temporal model that uses only the station data
- to capture the seasonality and both the spatial short and long-range dependence in the station data
- to provide predictions at point-level and over RCM grid boxes
Suppose we are in 1-D and we have a spatial process $Y(s), s \in [0,1]$
Upscaling problem

- We observe the process $Y(s)$ only at a finite number of points.
We want to infer upon the averages of the process $Y(s)$ over regular subsets of $[0,1]$ using only $Y(s_1), \ldots, Y(s_N)$. 

Spatial process $Y(s)$

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Upscaling model

• For our application, we want to predict quarterly average temperatures $Y(B_k, t)$ for $k = 1, \ldots, g$ and $t = 1, \ldots, T$ using only observed daily average temperature at the 17 stations.

• We will develop a model at point level for the quarterly average temperature exploiting the correlation:

  • in time between daily average temperatures observed at a station

  • in space between daily average temperatures observed at different stations

• We will upscale predictions at the quarterly time scale and to RCM grid boxes.
Upscaling model

- Let $D(s, t)$ denote the daily mean temperature at site $s$ and year $t$ (with $t = \text{year} + \text{day in the year}/365.25$):

$$D(s, t) | Z(s, t), \sigma^2 \sim N(Z(s, t), \sigma^2).$$

- The model for the latent daily mean temperature is

$$Z(s, t) = \mu(s, t) + \psi(s, t) + \exp(\alpha(s, t))\eta(s, t)$$

- $\mu(s, t)$: space-time trend term
- $\psi(s, t)$: seasonal term with spatially-varying amplitude and phase terms
- $\alpha(s, t)$: volatility term
- $\eta(s, t)$: irregular noise process that captures spatially-varying short and long range dependence.
Thus, at each spatial location, we model $Z(s, t)$ as the sum of trend plus seasonality plus irregular noise.
Upscaling model

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Thus, at each spatial location, we model $Z(s, t)$ as the sum of trend plus seasonality plus irregular noise.
• The space-time trend term $\mu(s, t)$

is defined via a wavelet transform of the data, using Daubechies “least asymmetric” wavelet filter of width 8.

• We assume smooth averages of the time series over 512 days at each spatial location is a separable space-time process with an AR(1) dependence in time, and exponential dependence over space.
Upscaling model

- The seasonal term $\psi(s, t)$

and volatility term $\alpha(s, t)$

are modeled to:
  - allow for yearly and half-yearly periods
  - have parameters that vary spatially.
Upscaling model

• The noise process $\eta(s, t)$ is a stationary Gaussian mean-zero space-time process with spatially-varying spectral density function at frequency $f$ and location $s$ given by

$$S(f; s) = \Delta |2 \sin(\pi f \Delta)|^{-2\delta(s)} \exp\left( \sum_{j=1}^{p} \theta_j(s) \cos(2\pi f \Delta j) \right).$$

Thus $\eta(s, t)$ is a spatially-varying fractional exponential process of order $p$.

• We fit the model within a Bayesian framework.

• We predict at the daily level and upscale predictions to a seasonal time scale and to grid box scale.
Results
• We fit both models to the quarterly average temperature data (observations and RCM output) for the period Winter 1962-Autumn 2007.

• **Downscaling model:**
  \[ Y(s, t) = \beta_{0,t} + \beta_0(s, t) + \beta_1 \tilde{x}(s, t) + \varepsilon(s, t) \]

  • **Multiplicative calibration term** \( \beta_1 \) estimated to be slightly below 1.

  • **Additive calibration term** \( \beta_{0,t} \) mostly negative in the Autumn quarters.
Results

• We fit both models to the quarterly average temperature data (observations and RCM output) for the period Winter 1962-Autumn 2007.

• **Upscaling model:**
  \[ D(s, t) = \mu(s, t) + \psi(s, t) + \exp(\alpha(s, t)) \eta(s, t) + \varepsilon(s, t) \]

  • Strong temporal and seasonal patterns in daily temperature over South Central Sweden.
  
  • Evidence of oscillatory but slightly warming time trends.
  
  • Greater amplitude of seasonality in the north part of the domain.
  
  • Non-trivial spatially varying seasonal volatility.
Predictions at point level

- We predicted quarterly average temperature at three reserved stations and compared them with:
  1. observed data
  2. the quarterly average temperature, output of the RCM at the grid box containing the station.
Predictions at Borlänge

**Black line:** observed data  
**Blue line:** downscaling model prediction  
**Red line:** RCM output  
**Magenta line:** upscaling model prediction

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Predictions at Borlänge

- Borlänge station has long stretches of missing data.
- RCM predicts temperature at Borlänge rather well.
- Downscaling model is strongly driven by the RCM (and has better RMSE).
- Upscaling model yields predictions that are quite different from the RCM (and agree less well with the observed data).
- Downscaling model has narrower predictive intervals.
Predictions at Stockholm

**Black line:** observed data

**Blue line:** downscaling model prediction

**Red line:** RCM output

**Magenta line:** upscaling model prediction

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Upscaling and downscaling
Predictions at Stockholm

• Downscaling and upscaling model yield good predictions, particularly in Winter and Summer.

• RCM tends to predict temperatures that are too cold (worse RMSEs).

• Upscaling predictions tend to be too smooth.
Predictions at Göteborg

**Black line:** observed data

**Blue line:** downscaling model prediction

**Red line:** RCM output

**Magenta line:** upscaling model prediction
Predictions at Göteborg

- Göteborg is close to the edge of the domain and lacks stations nearby.

- The upscaling and downscaling model predict quarterly average temperature that are colder than observed.

- RCM predicts colder than observed, especially in Winter and Spring.

- A possible explanation is the fact that the data from Göteborg have not been homogeneized for urbanization effects.
Predictions of spatial fields

- We predicted quarterly average temperature over the 12.5 km × 12.5 km RCM grid boxes using the two statistical models.

- We compared the predictions to the RCM output only over mainland Sweden.

- We looked at the difference between the predictions from the two statistical models and the RCM output.
Spatial differences

Downscaling — Climate: Winter 2002

Upscaling — Climate: Winter 2002

Downscaling — Climate: Spring 2002

Upscaling — Climate: Spring 2002

Downscaling — Climate: Summer 2002

Upscaling — Climate: Summer 2002

Downscaling — Climate: Autumn 2002

Upscaling — Climate: Autumn 2002

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Upscaling and downscaling
Spatial differences

- Predictions from the downscaling model tend to match closely the RCM output and present also similar spatial patterns.

- The difference between upscaling predictions and RCM output are more extreme, with clear seasonal and spatial patterns.

- Upscaling predictions are typically warmer than RCM output in the north and, in general, they tend to be colder than the RCM output in the south.

- In the extreme quarters, both the downscaling model and the upscaling model predict warmer temperature than the RCM.
There is no gold standard: assessing the performance of a climate model is, in some respects, an impossible task.

In the future:
1. Improve the statistical models.
2. Understand the effect of boundary conditions.
3. Work on more involved distributional comparisons.
4. Investigate finer temporal scales.

For the movie of spatial differences see:
http://www.stat.osu.edu/~pfc/research/documents/animated_spatial_differences.mov