Dynamical Downscaling

Common Approaches of Dynamical Downscaling

There are four commonly used approaches of dynamical downscaling (Xu et al. 2019)

1. Traditional dynamical downscaling
2. Pseudo-global warming downscaling
3. Dynamical downscaling with GCM bias correction
    - mean bias correction, mean and variance bias correction, quantile-quantile correction, bias correction with physical consistency constraint, bias correction of low frequency variability, bias correction of multi-model ensemble
4. Dynamical downscaling with spectral nudging

2). Mean and variance bias correction

- Assuming that the GCM mean and variance remain stationary, biases can be corrected for the mean and variance of the GCM projection.

$$BC_F = \overline{GCM}_F - \left(\overline{GCM}_H - \overline{RA}_H\right) + GCM'_F \frac{S_{RA|H}}{S_{GCM|H}},$$

Where the last rhs term represents the projected anomalies rescaled by the standard deviation ratio of a reanalysis dataset (RA) to the GCM.

- Strengths: This method can better represent the temporal variability in the future climate, and the variance correction helps improve the projection of extremes (see the figure on the right).
- Limitations: Bias correction of variance by rescaling may adversely affect the GCM trend. Hoffmann et al. (2016) removed the GCM trend before the variance bias correction and added it back afterwards.

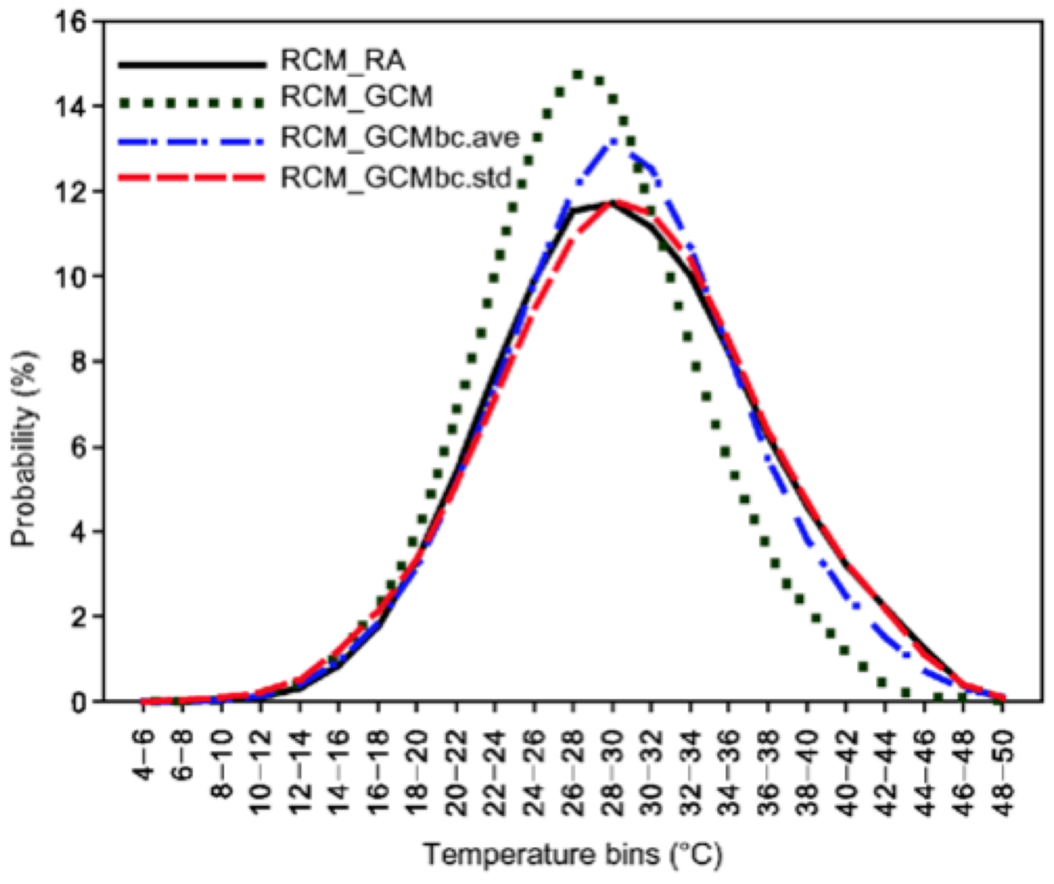

Figure 2 Frequency of daily maximum temperature in summer over the central United States and Canada (40°–50°N, 100°–85°W) generated by various dynamical downscaling methods. RCM_RA: reanalysis-driven RCM simulation (reference experiment); RCM_GCM: TDD method; RCM_GCMbc.ave: RCM simulation with GCM mean bias correction; RCM_GCMbc.std: RCM simulation with both GCM mean and variance bias corrections. Modified based on Xu and Yang (2012).

From Xu et al. 2019

3). Quantile-quantile correction

- Assuming the cumulative distribution function (CDF) of the GCM is stationary, one can correct the CDF of the GCM using the quantile-quantile correction method before deriving the boundary conditions for the RCM.
- Strengths: the whole PDF of a GCM variable is bias-corrected instead of just the mean and variance.
- Weaknesses: The correction is not constrained by physical principles and the inter-variable dependence may be lost, which may result in spurious precipitation variability.

4). Bias correction with physical consistency constraint

- Physical constraints are explicitly considered in this method.
- An example (Meyer and Jin 2016)
  - Step 1: air temperature, relative humidity, surface temperature and surface pressure are bias-corrected using a simple linear regression method.
  - Step 2: The bias-corrected variables from Step 1 are used to derive other variables. For example, geopotential height is derived using the hydrostatic balance, and geostrophic wind is then derived from geopotential height.
  - Step 3: Ageostrophic wind is bias-corrected using the simple linear regression method, and the total wind is obtained by adding the bias-corrected ageostrophic wind to the geostrophic wind.
  - Step 4: The corrected GCM fields are then used to drive the Weather Research and Forecasting (WRF) model to simulate the North American monsoon.
  - Bias-correction led to improved simulation of the North American monsoon.

5). Bias correction of low frequency variability

- Rocheta et al. (2017) corrected the GCM low-frequency biases by replacing the lag-1 autocorrelations in the GCM with the observed lag-1 autocorrelations. The corrected GCM data were then used to drive a RCM.
- The method significantly improves the climatological mean, variance, and low-frequency variability in GCM data.
- Weaknesses:
  - Rocheta et al. (2017) found that correcting the monthly and annual lag-1 autocorrelations did not significantly improve the low-frequency precipitation variability in RCMs over a simpler GCM bias correction.
  - In addition, it is not clear how well the inter-variable dependencies are retained.

From Xu et al. 2019

6). Bias correction of multi-model ensemble

- The difference between GCM climatology and reanalysis climatology may result from both model biases and internal variability. Multi-model ensemble mean can smooth out internal variability and better reveal systematic model biases.
- *Should we use the multi-model ensemble mean to drive a RCM?*
    - Multi-model ensemble averaging would lead to underestimated variability in the RCM if it is used to derive the boundary conditions, which would affect the simulations of extreme events.
- To retain the anomaly magnitude, the anomaly field is derived from a single model (GCM'_F) while the model biases and the future GCM mean are both derived from multi-model ensemble mean:

$$BC_F = \overline{GCM}_{EF} + GCM'_F - (\overline{GCM}_{EH} - \overline{RA}_H),$$

where the subscript E denotes the multi-model ensemble mean, H denotes historical records and RA denotes reanalysis.

From Xu et al. 2019

5. Dynamical downscaling with GCM bias corrections and spectral nudging

- In addition to GCM biases, biases also exist in RCMs, which need to be constrained.
- Spectral nudging forces the large-scale fields of the RCM toward the corresponding bias-corrected GCM fields but retains small-scale features generated by the RCM.
- Weaknesses: Xu and Yang (2015) showed that the ageostrophic wind component was increased in RCM when spectral nudging was applied, and suggested that reducing the nudging strength helps mitigate this effect.

References

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