Statistical Downscaling

Outline

- Introduction: statistical downscaling vs. dynamical downscaling
- Statistical downscaling: assumptions
- Statistical downscaling: methods
- Statistical downscaling: limitations

What is downscaling?

- Downscaling refers to the statistical or dynamical approaches to obtain regional or local scale climate information from the coarse-resolution GCM output or reanalysis data (von Storch et al., 1993, Liu et al., 2012).
- Coarse-resolution global climate models can not well represent/predict regional climate conditions, especially in regions that are characterized by strong spatial variability of meteorological variables due to complex terrain or mesoscale processes.

Three Types of Downscaling

- Three types of downscaling:
  - Statistical downscaling: a statistical model is developed based on the statistical relationship between the large-scale conditions that are resolved by a global climate model (predictors) and the regional climate conditions of interest (predictand)
  - Dynamical downscaling: a high-resolution limited-area (i.e., regional) model is driven by a global model that has relatively coarse resolution
  - Hybrid downscaling: the combination of dynamical and statistical downscaling. Example: Walton et al. (2015) applied dynamical downscaling to five GCM outputs and derived a statistical model for the relationship between the GCM and regional climate model (RCM) outputs. The statistical model was then applied to more GCM outputs to generate downscaling results.

Statistical Downscaling vs. Dynamical Downscaling

- Dynamical downscaling
  - advantage: formulated on the basis of physical principles and can resolve various processes
  - disadvantage: computationally expensive; subject to the biases of the driving model
- Statistical downscaling :
  - Simple and computationally economical
  - A long observation record is needed to establish a robust statistical model
  - The statistical relationship between the predictors and predictand may change in the future climate
  - The downscaled variables may not follow physical principles of meteorology

Statistical Downscaling: Assumptions

1. A strong relationship exists between the predictor variable(s) and the predictand (i.e., the variable being predicted).
2. The predictor variable(s) can be skillfully predicted/projected by a global climate model.
3. The relationship between the predictor(s) and predictand is stationary (e.g., the same relationship holds for different time periods).

See Giorgi et al. 2001 and Schoof 2013

Predictor Selection

- Predictor selection is critical for statistical downscaling and affects the performance of the downscaling.
- Only physically reasonable or meaningful potential predictors should be chosen.
- Predictors with strong mutual correlation should be avoided.
- Screening regression (such as forward selection) can be used to select a good set of predictors.
- It is often necessary, especially for climate change problems, to include both dynamical (e.g., wind, SLP) and thermodynamical (e.g., temperature, humidity) variables.

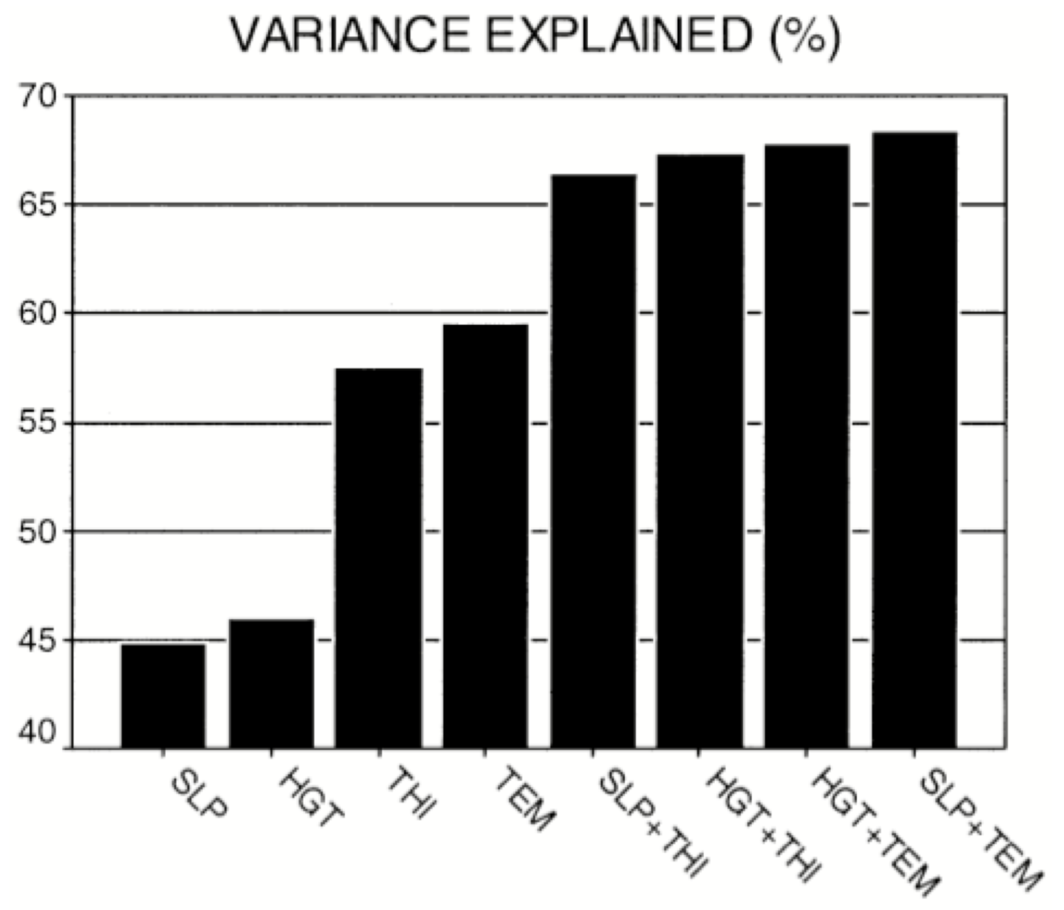
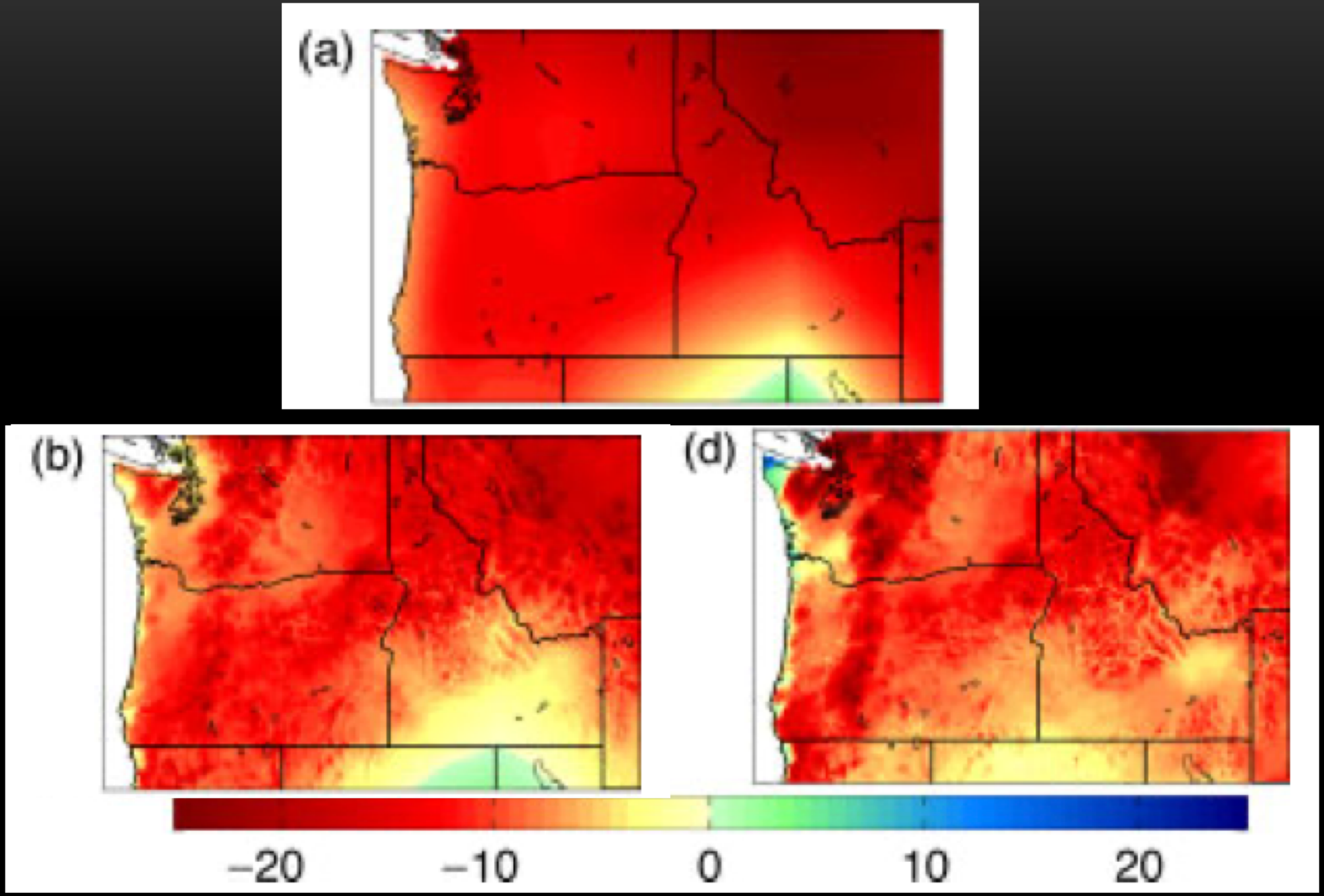


FIG. 2. Percentage of variance explained, averaged over 39 stations, for different predictors and their combinations. All for pointwise MLR.

In a study on statistical downscaling of daily temperature over Central Europe, Huth (2002) showed that a pair of thermodynamical&dynamical predictors performs the best (Figure from Huth 2002 © American Meteorological Society. Used with permission).

Methods

- Some commonly used statistical downscaling methods (Wilby and Wigley 1997; Schoof 2013)
  1) scaling method
  2) regression-based approach
  3) weather pattern-based approach
  4) analogue forecasts
  5) weather generators



(top) Interpolated, (left) daily BCSD downscaled and (right) observed minimum relative humidity anomalies for 4 Sep 2006. From Abatzogloua and Brown (2012).

1) Scaling Methods

- Scaling methods employ spatial interpolation or disaggregation, which can be followed by bias correction or an adjustment for elevation (Wang et al. 2011; Wood et al. 2004).
- Bias correction and spatial downscaling (BCSD):
  - First, GCM output is spatially interpolated to the downscaled grid.
  - Second, these fields are then bias corrected, such as using quantile mapping that is constructed from the model climatology and the observed climatology.

Simple Mean and Variance Bias Correction

- Simple bias correction: The prediction is bias-corrected using the differences in the mean and variability between observations and predictions in a reference period. Let's use temperature prediction as an example.
  - If the observations and predictions have the same variance, the predicted value is simply shifted by the mean bias in the reference period

$$T_{BC}(t) = T_{Raw}(t) - (\bar{T}_{ref} - \bar{O}_{ref})$$

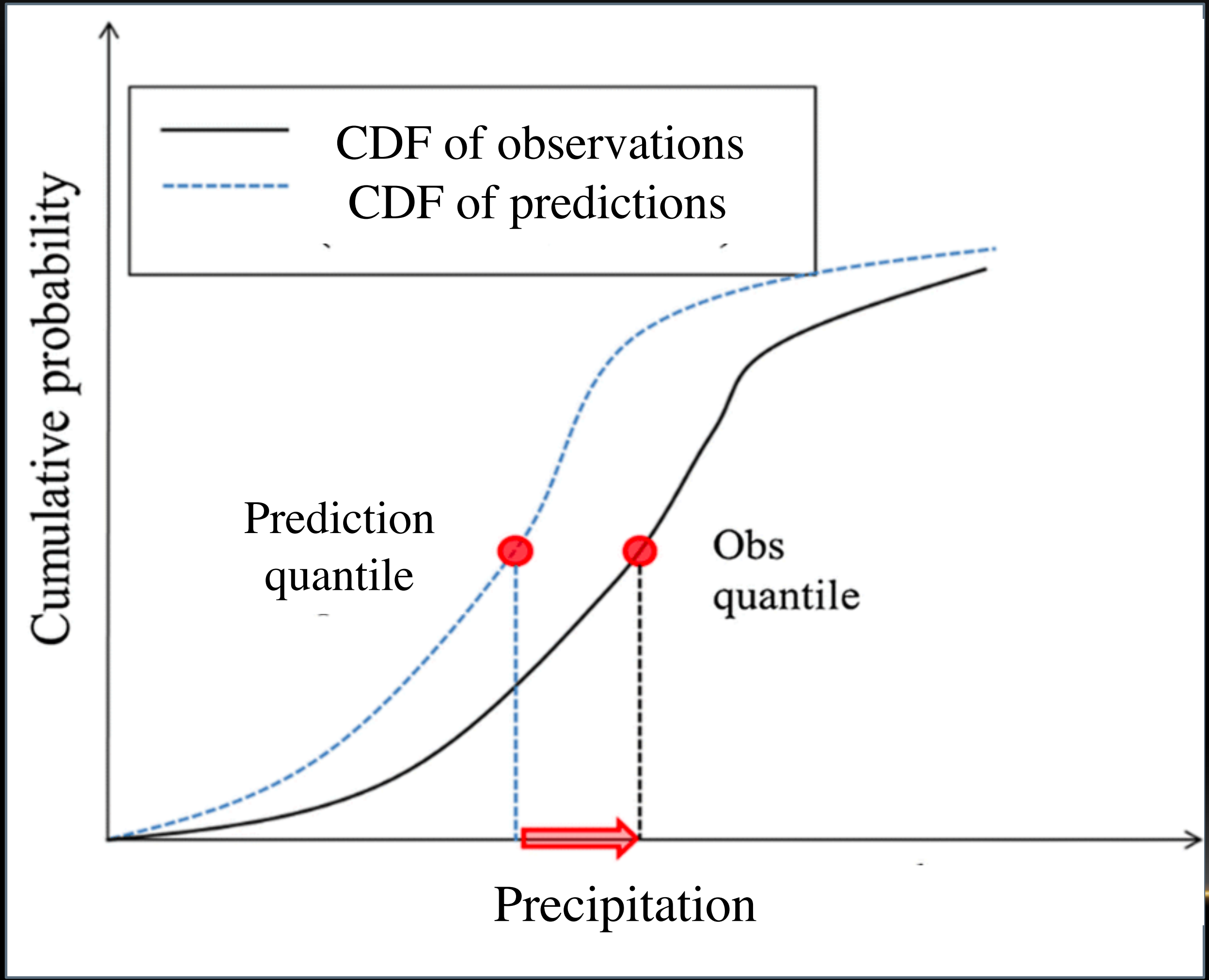
  - The variances can also be corrected (or inflated):

$$T_{BC}(t) = \bar{O}_{ref} + \frac{\sigma_{O,ref}}{\sigma_{T,ref}}\left(T_{Raw}(t) - \bar{T}_{ref}\right)$$

T_{BC} bias-corrected prediction
T_{Raw} : raw prediction
$\bar{T}_{ref}$: mean prediction during the reference period
$\bar{O}_{ref}$: mean observations during the reference period
$\sigma_{O,ref}$: standard deviation of observations
$\sigma_{T,ref}$: standard deviation of prediction

Kawkins et al. 2013 https://doi.org/10.1016/j.agrformet.2012.04.007

Quantile Mapping Bias Correction



- Quantile mapping is one of the commonly used method to correct biases of regional climate model simulations compared to observational data.
- Quantile mapping can be applied to variables that do not follow the Gaussian distribution. It not only removes the mean biases but also removes quantile-dependent biases.

Adapted figure from https://www.sciencedirect.com/science/article/pii/S0168192312001372

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