NASA Earth Exchange (NEX) Workshop

The NEX-GDDP Dataset

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Downscaled Climate Datasets on NEX

DCP30 (Downscaled Climate Projections at 30 arcsec)
Domain/Resolution: CONUS, ~800m
Frequency: Monthly
Variables: Tmax, Tmin, and Precip
No of CMIP5 models: 34
Baseline Data: Daly et al., 2002

GDDP (Global Daily Downscaled Climate Projections)
Domain/Resolution: Global, ~25km
Frequency: Daily
Variables: Tmax, Tmin, and Precip
No of CMIP5 models: 21
Baseline Data: Sheffield et al. 2006

LOCA (Localized constructed analogs)
Domain/Resolution: CONUS, ~6km
Frequency: Daily
Variables: Tmax, Tmin, Precip; Humidity, Windspeed (in progress)
No of CMIP5 models: 32
Baseline Data: Livneh et al. 2013

GCM Simulations and Projections

Coupled Model Intercomparison Project Phase 5 (CMIP5)

- 21 models
- Historical experiment (1950-2005)
- Representative Concentration Pathway (RCP) experiments
  - *RCP 4.5 & RCP 8.5*
  - *2006-2099*
- Daily output
- Precipitation, maximum temperature, minimum temperature

Observational Fields

Global Meteorological Forcing Dataset (obs)
http://hydrology.princeton.edu/data.pgf.php

- Terrestrial Hydrology Research Group at Princeton University
- Near-surface meteorological data
- Blends reanalysis data with observations
- Disaggregates in time and space
- Currently available at 1.0 degree (plus 0.5 and 0.25 degree), 3-hourly (plus daily and monthly) resolution globally for 1948-2008

BCSD Downscaling Method

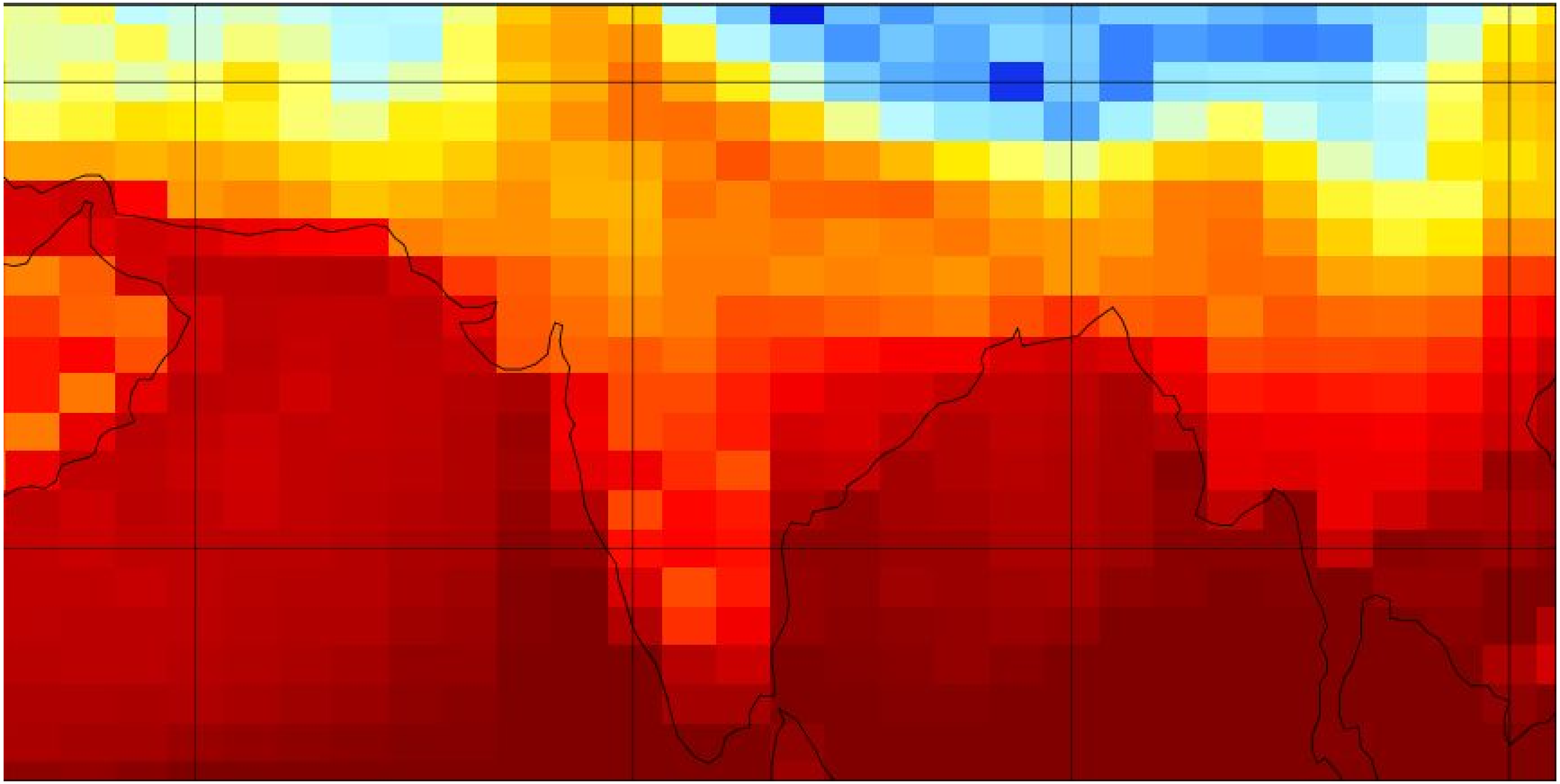
Bias Correction

- Performed at GCM grid scale
- Aggregate obs fields to lower resolution

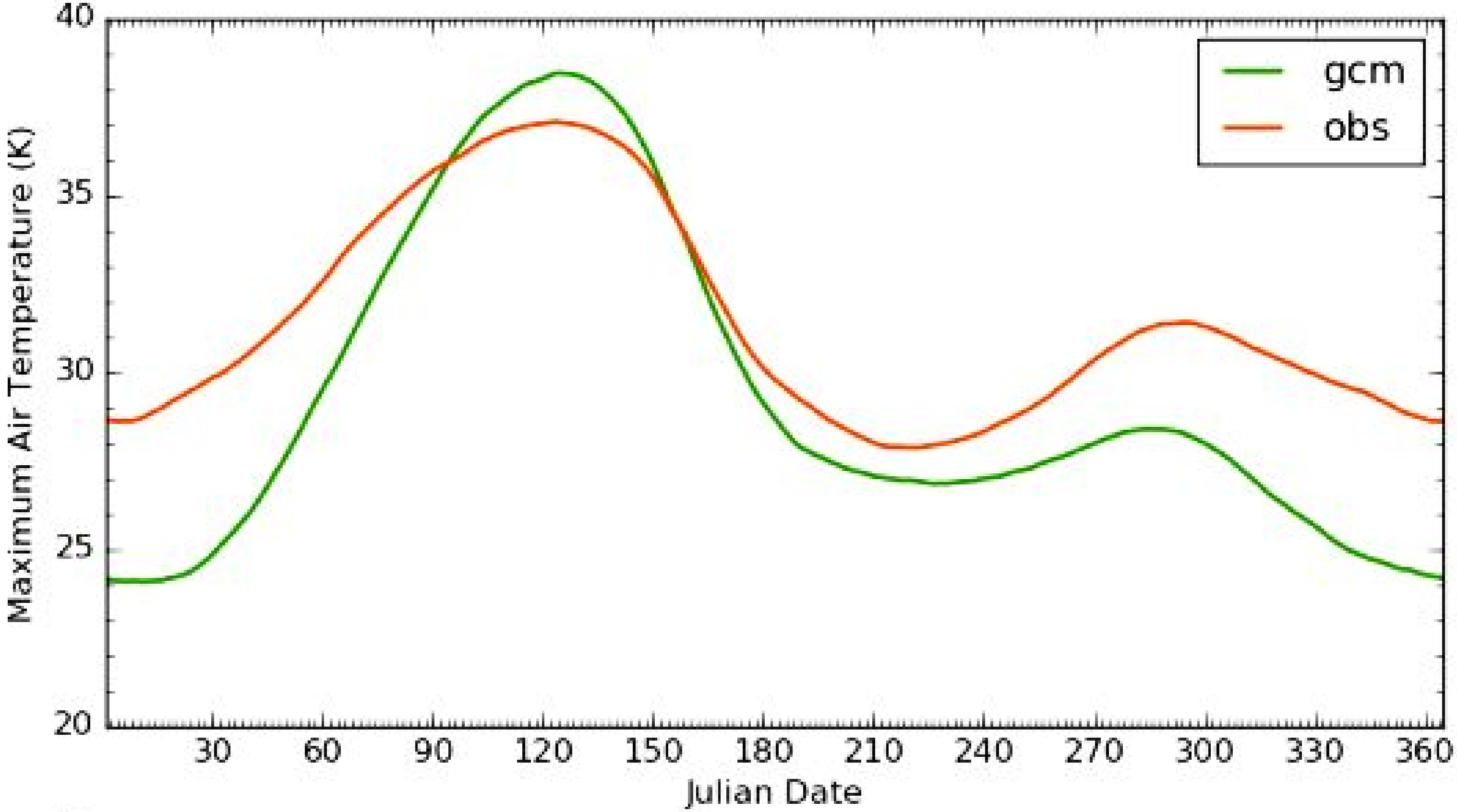
Spatial Disaggregation

- Disaggregate to target grid

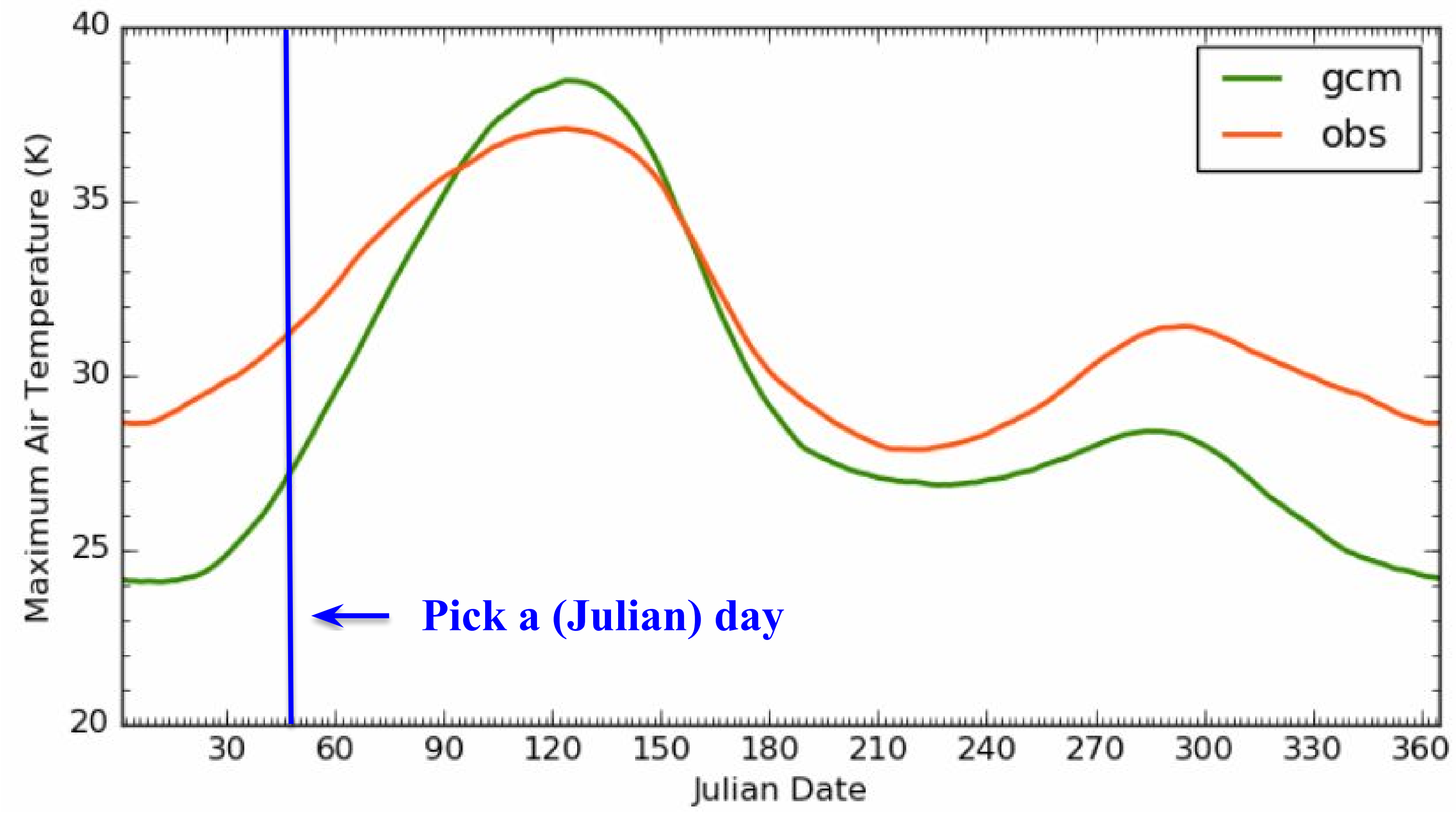
Raw GCM Output



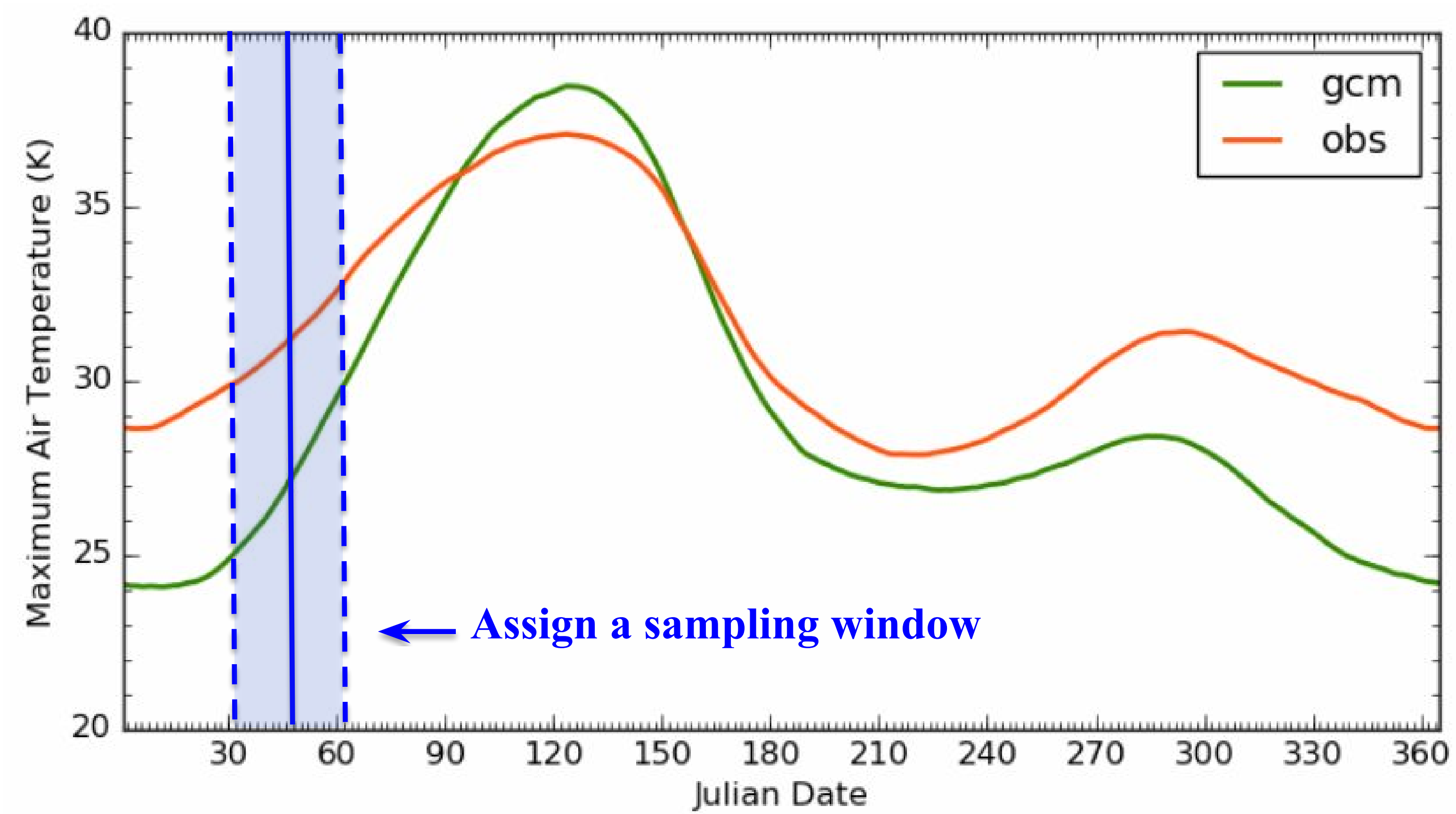
Observation vs. Simulation: Climatology



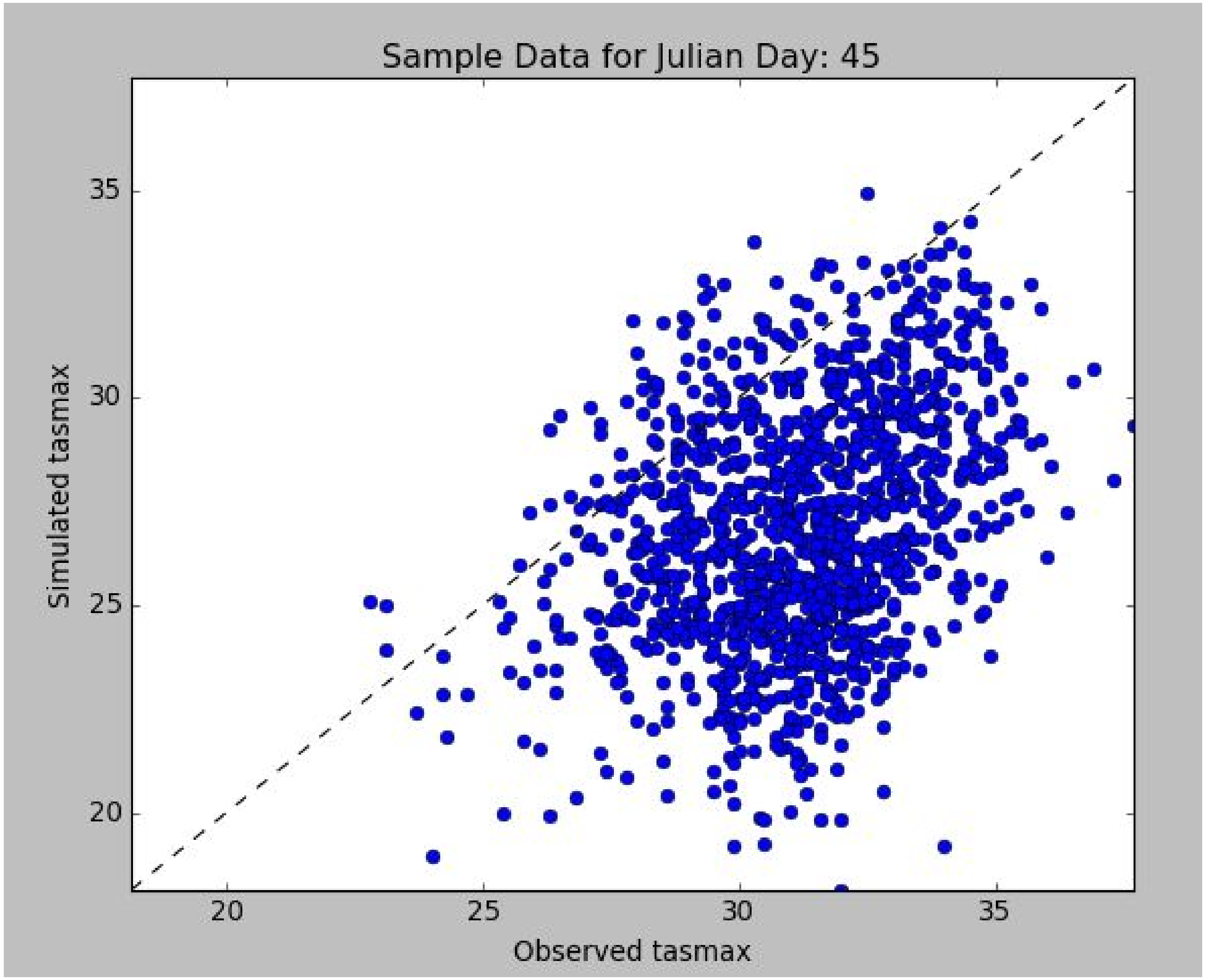
Bias-Correction Step by Step



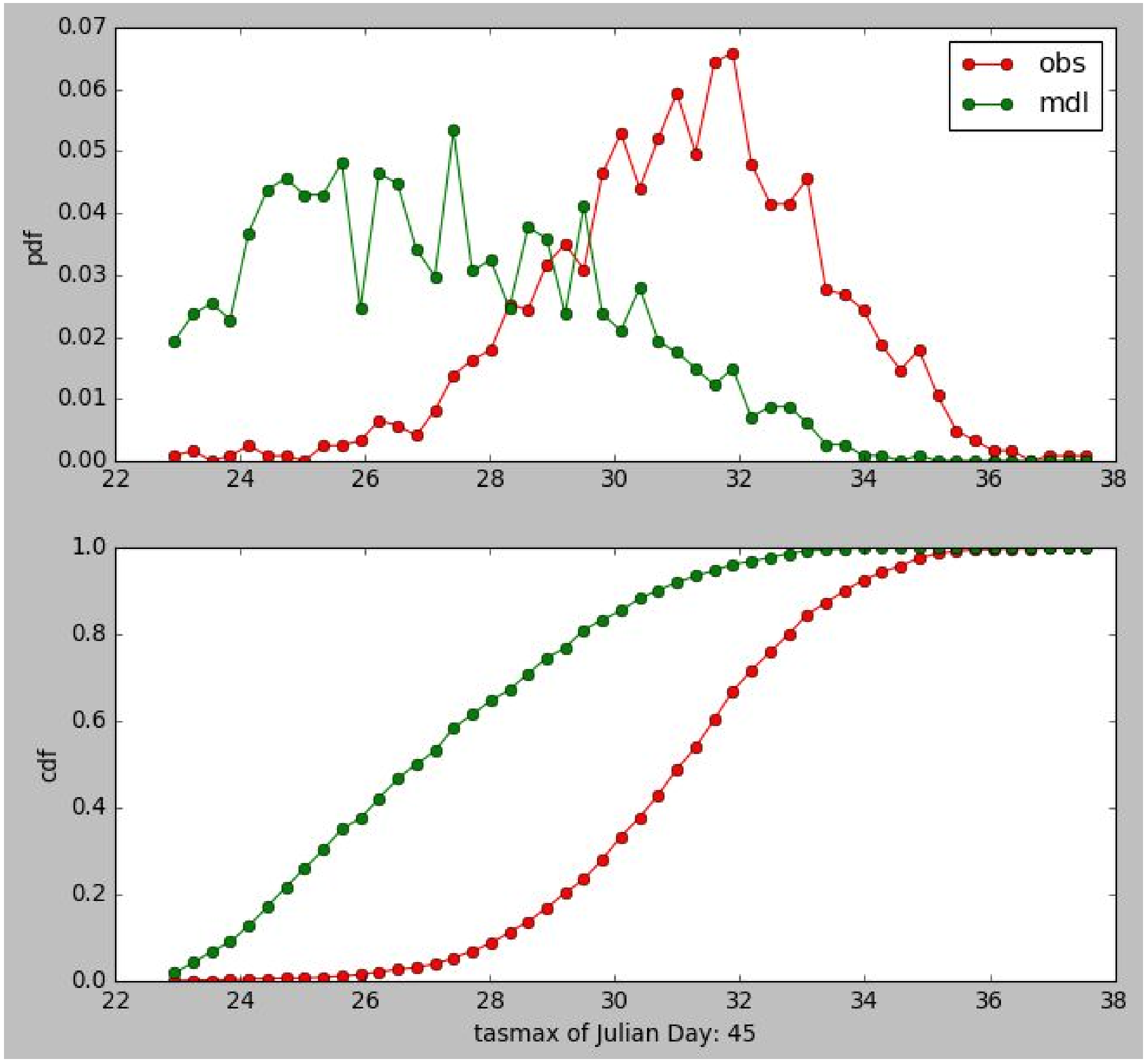
Bias-Correction Step by Step (continued)



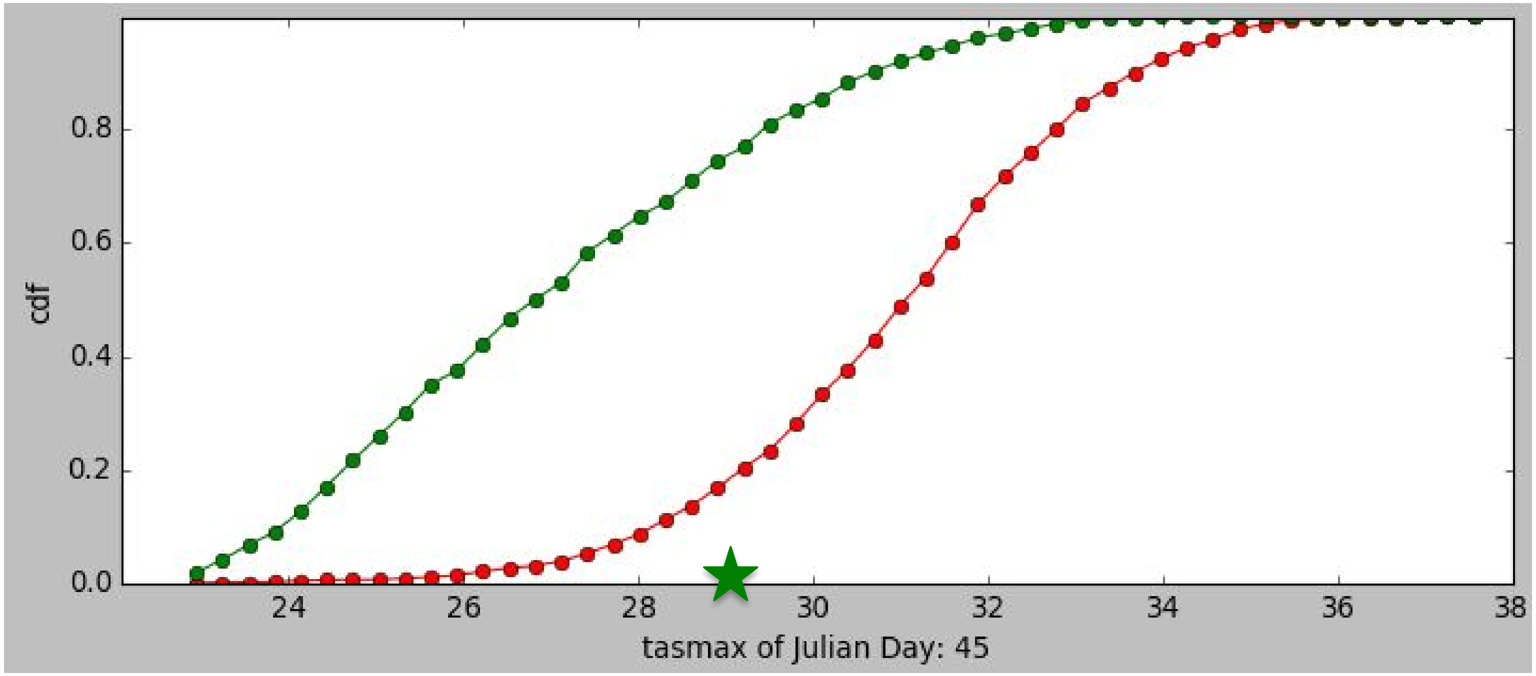
First Look of the Data



Generating PDF and CDF

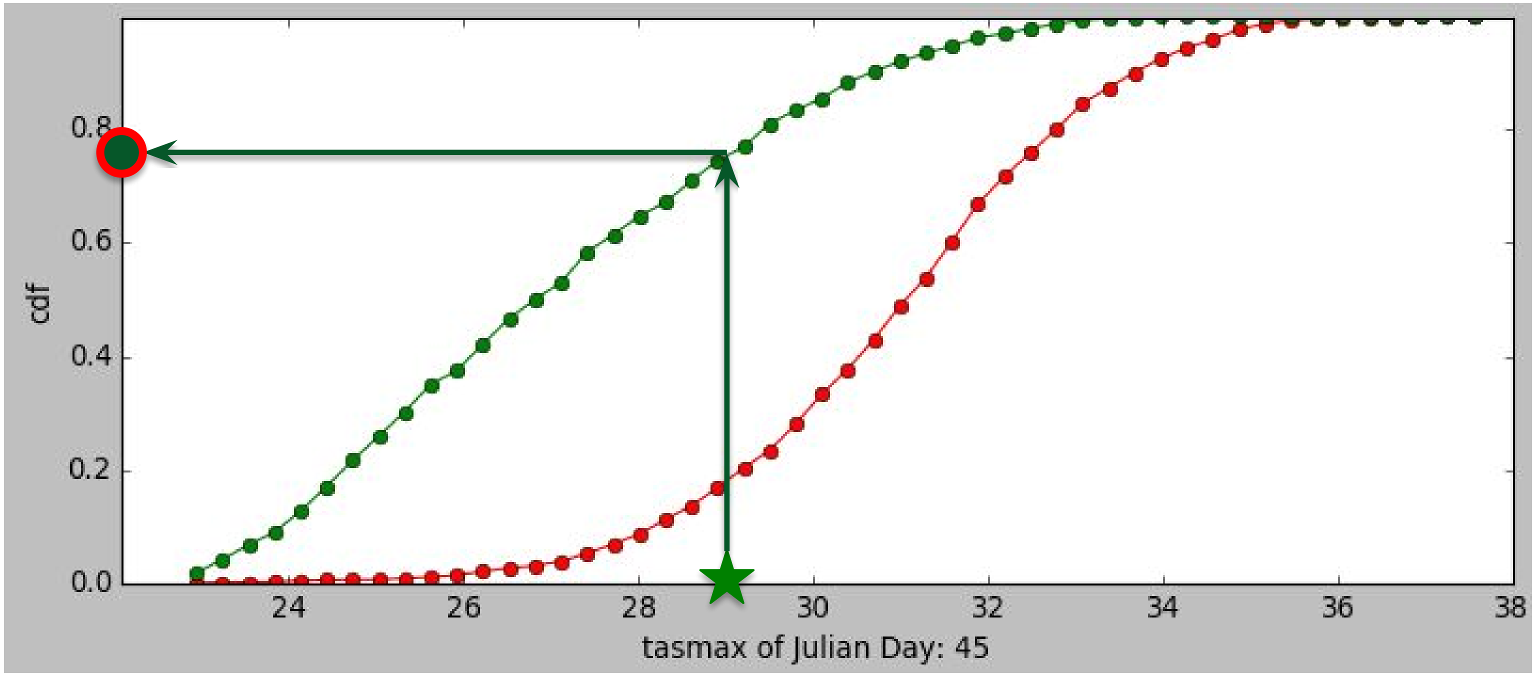


Quantile Mapping with CDF



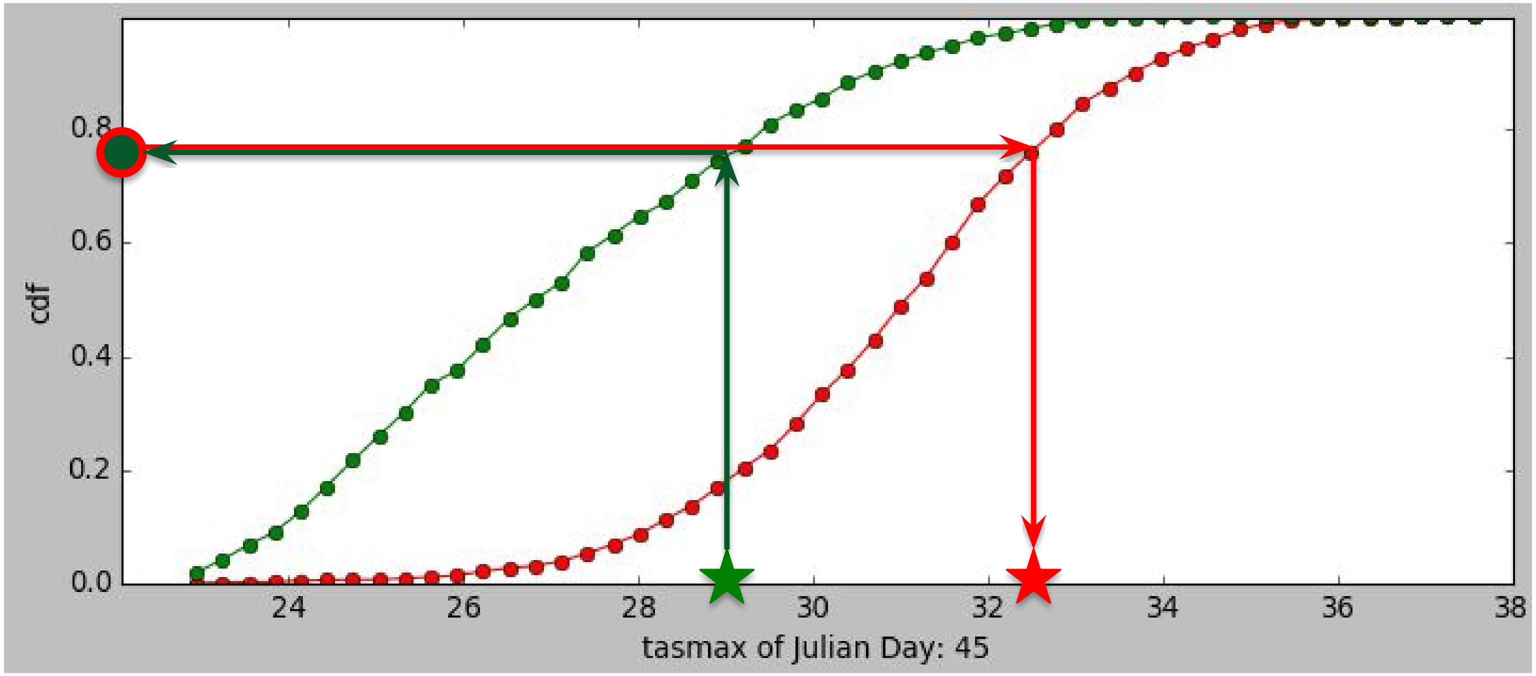
1. For a (raw) simulated T_raw of 29°C

Quantile Mapping with CDF



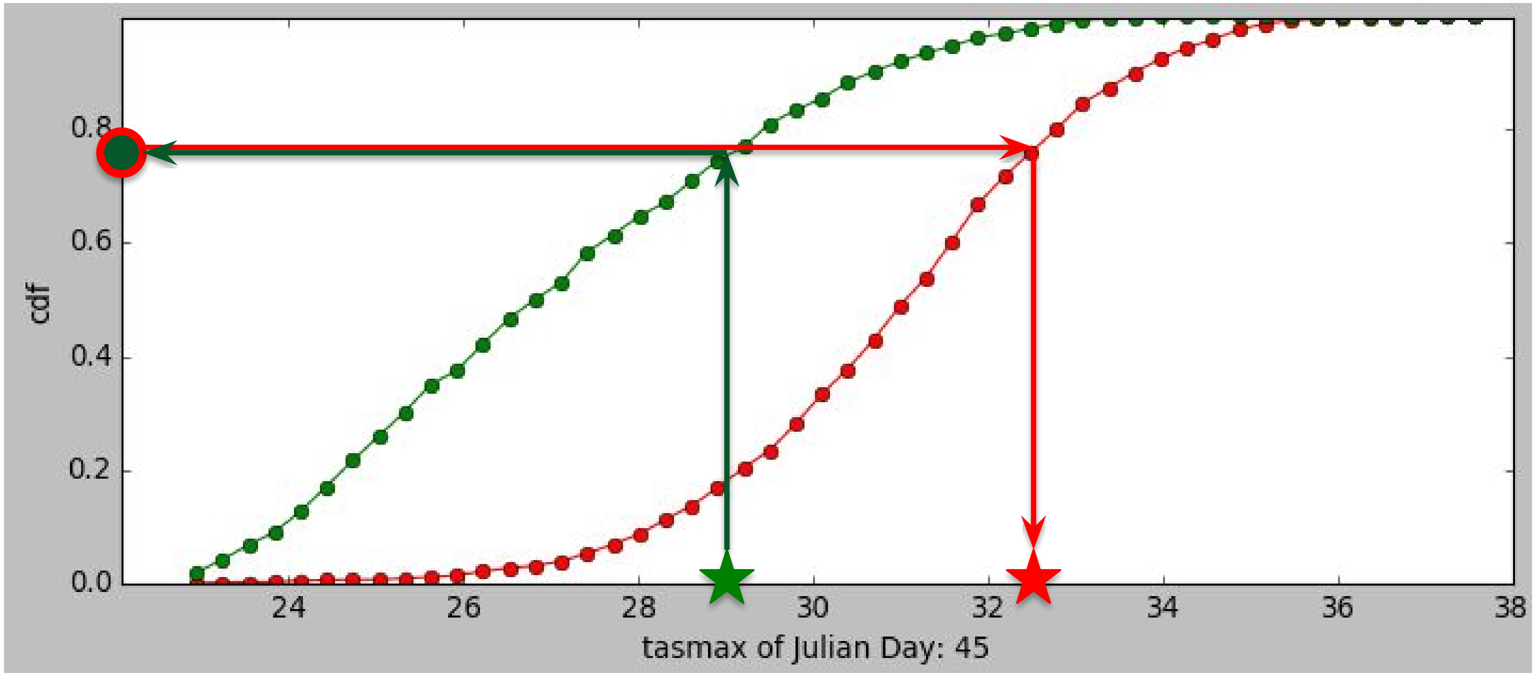
1. For a (raw) simulated T_raw of 29°C
2. Find the probability *p*(T<T_raw) = 0.78 based on CDF_gcm

Quantile Mapping with CDF



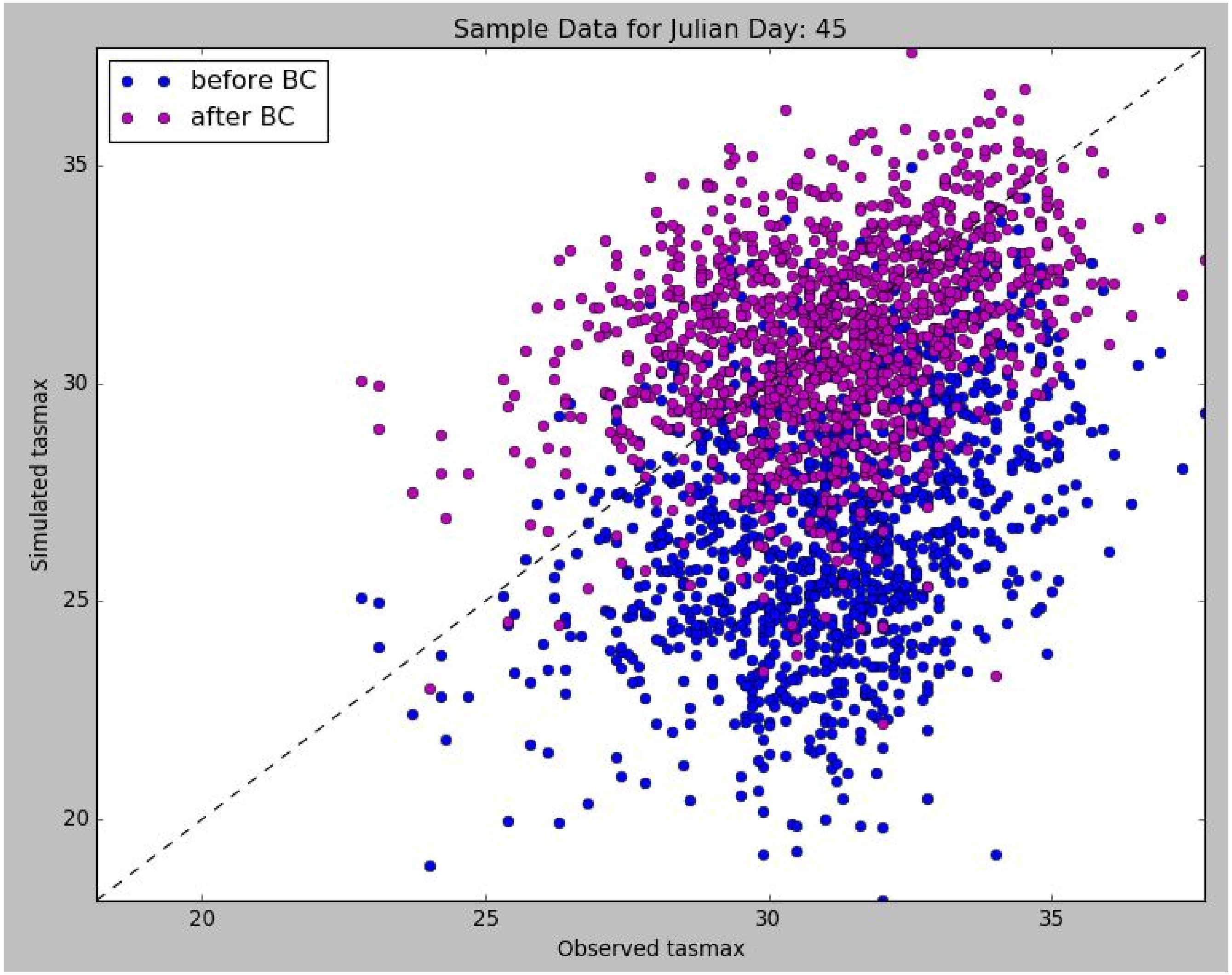
1. For a (raw) simulated T_raw = 29°C
2. Find the probability *p*(T<T_raw) = 0.78 based on CDF_gcm
3. On CDF_obs, find T_obs = 32.5°C, such that *p*(T<T_obs) = 0.78

Quantile Mapping with CDF

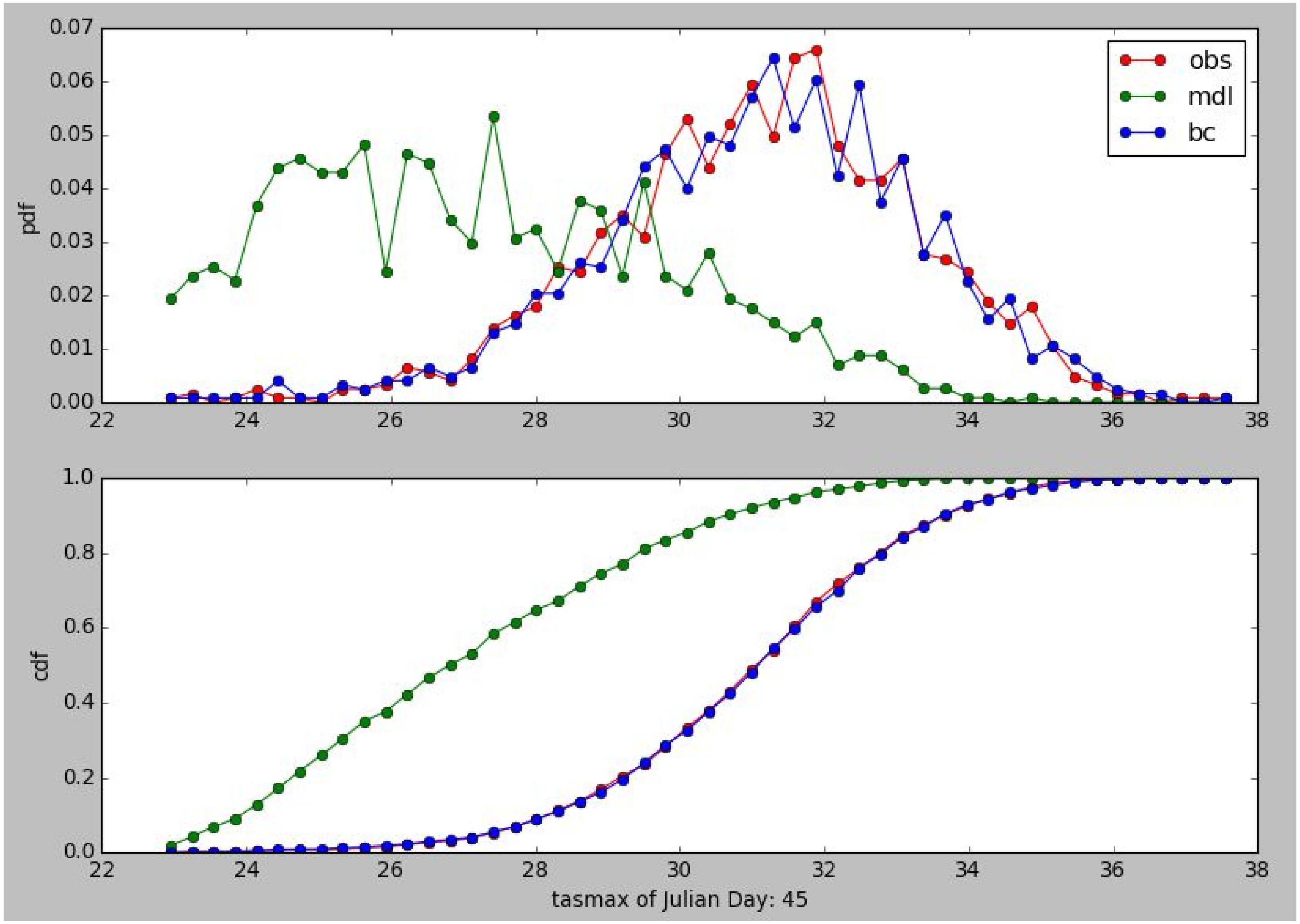


1. For a (raw) simulated T_raw = 29°C
2. Find the probability p(T<T_raw) = 0.78 based on CDF_gcm
3. On CDF_obs, find T_obs = 32.5°C, such that p(T<T_obs) = 0.78
4. Assign the bias-corrected simulation T_bc to 32.5°C

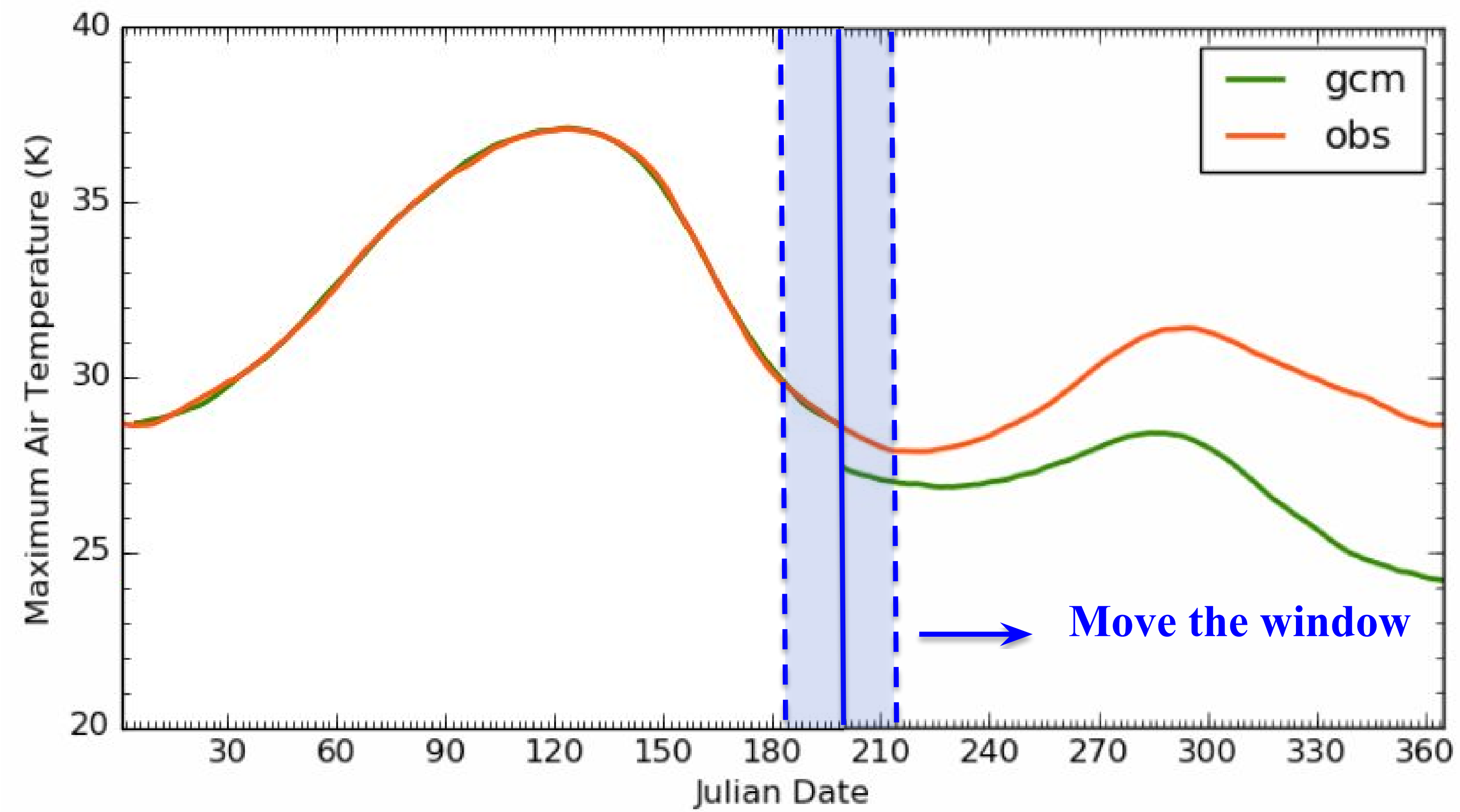
The Results: Scatter-Plot



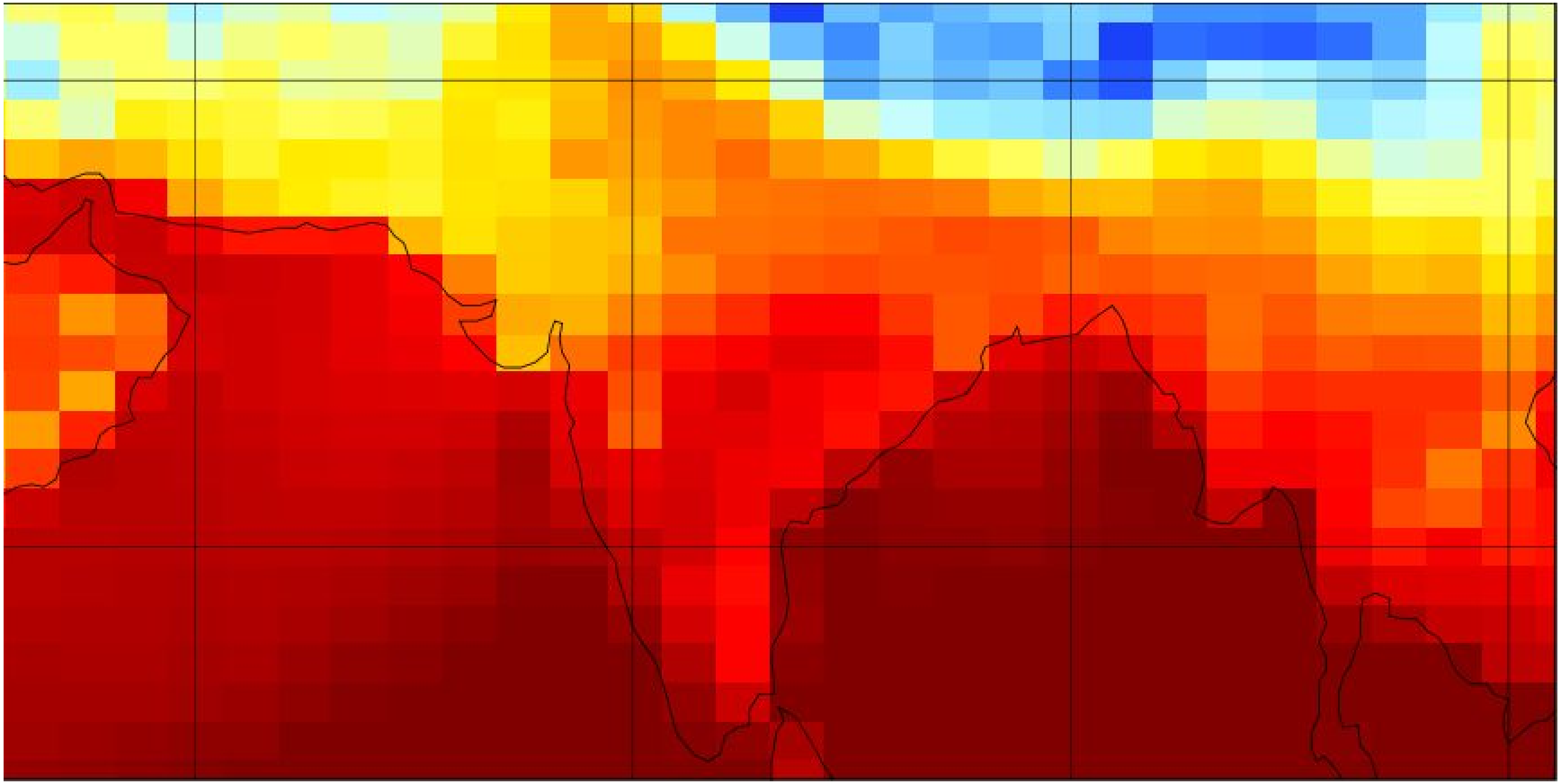
The Results: PDF and CDF



Bias-Correction for All Days



Post-Bias Correction

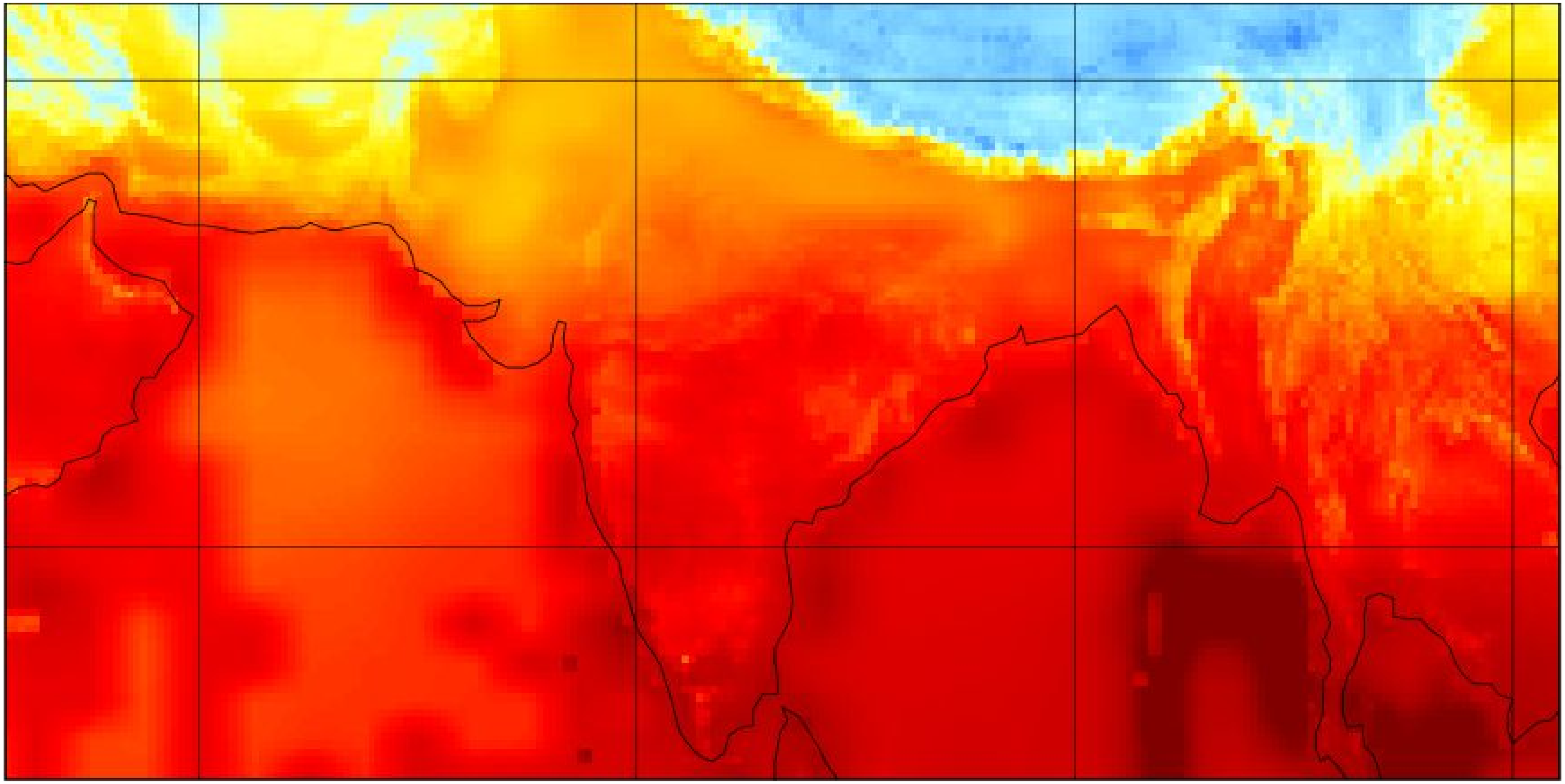


Spatial Disaggregation

Three-step process

1. Remove low-resolution obs climatology
2. Bilinearly interpolate to target (obs) grid
3. Replace high-resolution obs climatology

Post-Spatial Disaggregation



Thank You!

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Discussion Questions

1. **Temporal stationary assumption:** In correcting future climate projections, the bias-correction methodology assumes that the PDFs/CDFs of the climate variables are largely stationary in time. But ***climate is changing***! How should we address this issue? Discuss possible solutions in terms of their pros and cons.

2. **Spatial scale differences between observations and simulations:** In-situ climate observations are influenced by localized meteorological conditions and often have large variability. In comparison, climate variables from GCM simulations represent the "mean" state over large (~100km) grid cells. With such spatial scale differences considered, should we directly compare GCM projections with observations from individual stations? Or what do you think may be a better approach?