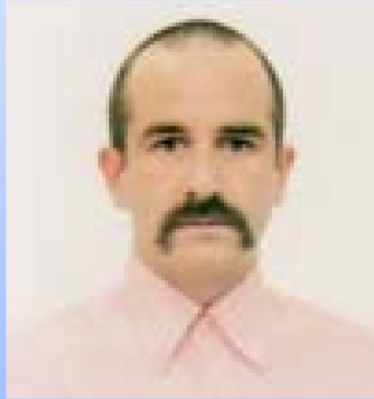
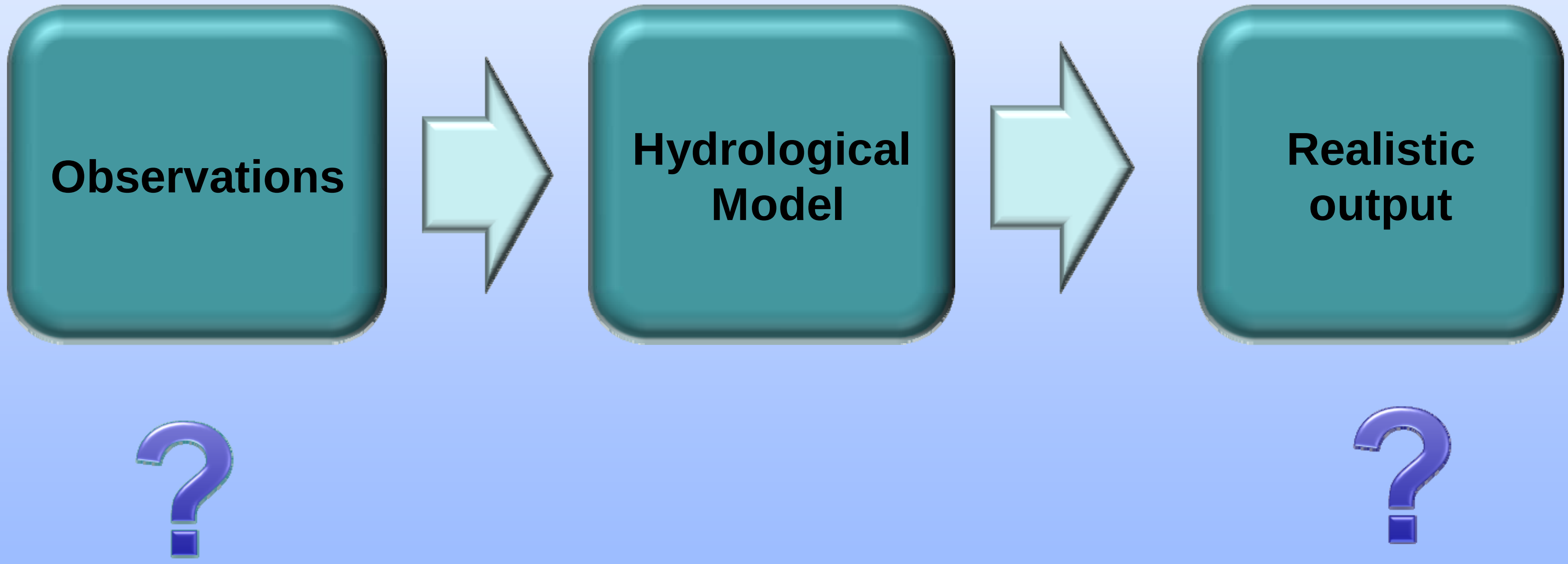
The problem of bias correcting climate model output for hydrological modeling purposes.

C. Piani, J. O. Haerter, E. Coppola



What is the problem?

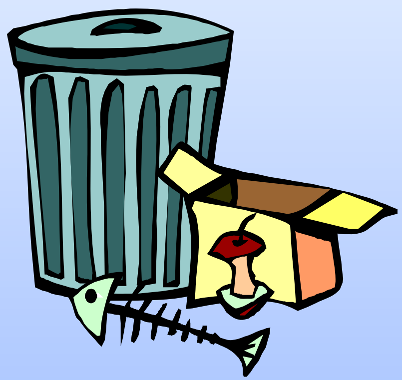
Hydrological models are developed, by sensible people, to give sensible results when forced with observed forcing fields.



What is the problem?

Forcing the same hydrological model with unprocessed GCM output and you don’t get an acceptable result…

Global climate model → **Hydrological Model** →



WHY ?

What is the problem?

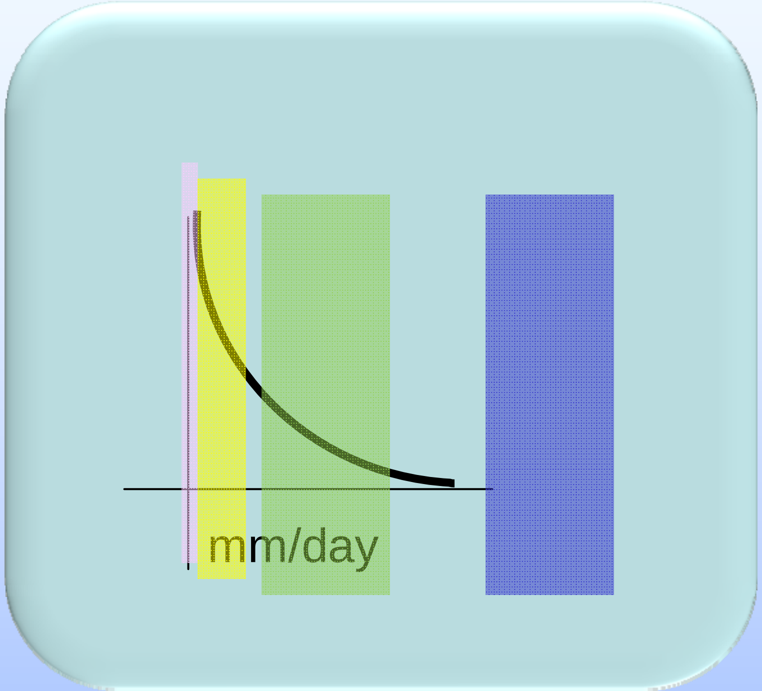
GCM output fields generally are not the same physical quantity as the observed counterparts (temporal and spatial averages, under-catch corrections, etc..).

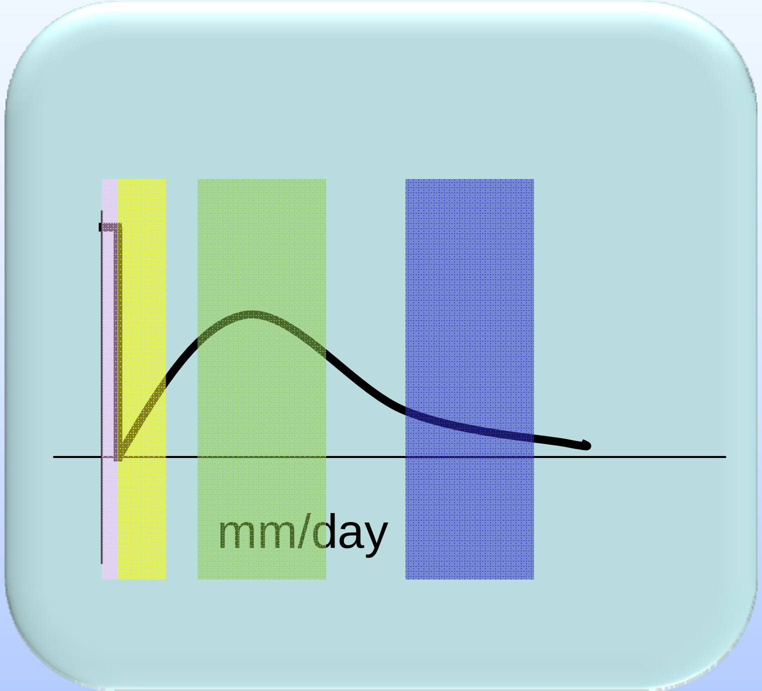
Many statistical properties of the fields are affected by bias: mean (climatology), variance (variability), skewness (for precipitation: dry days, drizzle, extreme events etc)

Bias is not the same as error or uncertainty!

Case of precipitation.

Synthetic example of differences between the intensity spectra of GCM and observed daily precipitation.

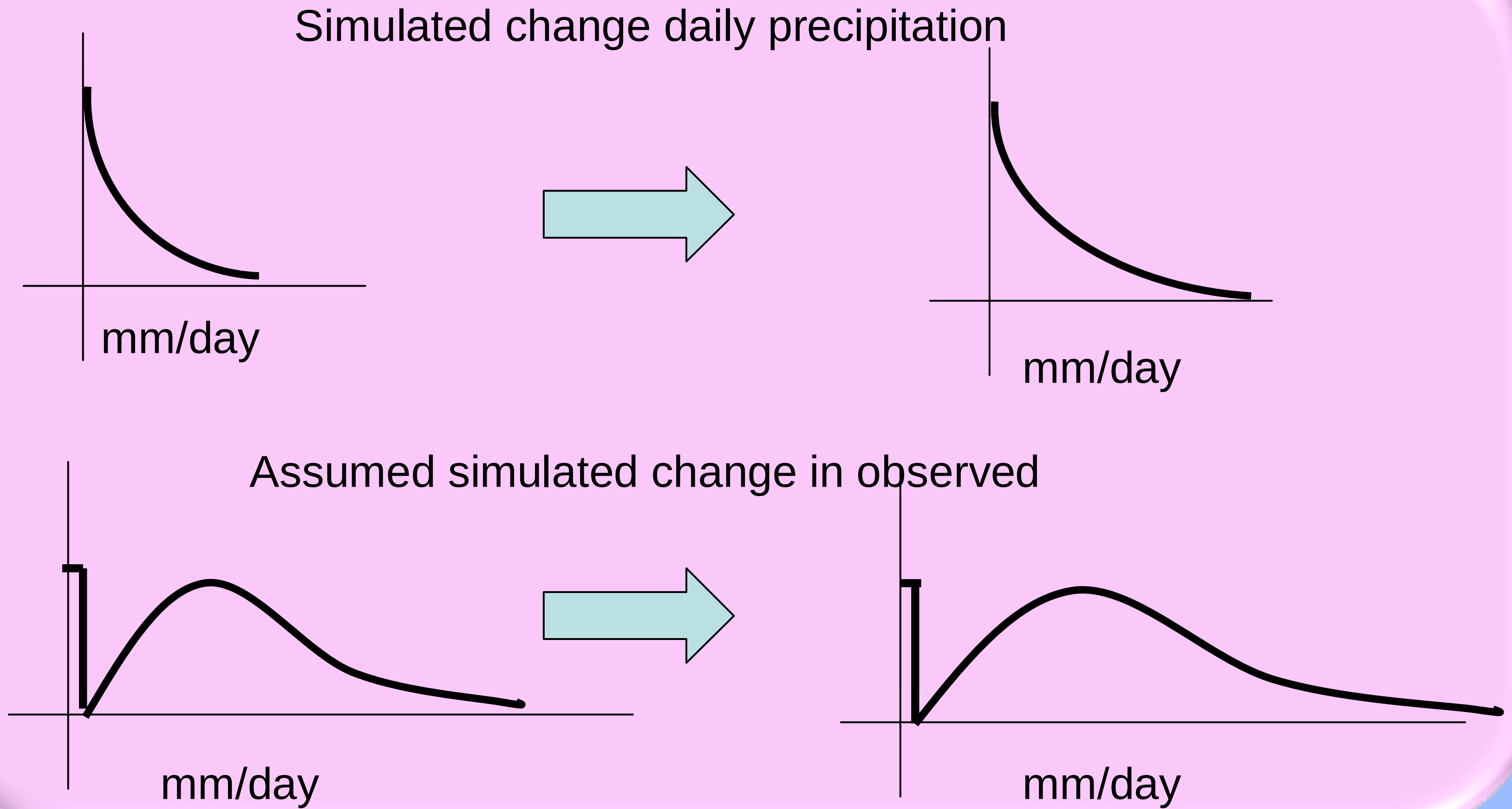




- Dry days.
- Drizzle
- Moderate precipitation
- Extreme precipitation

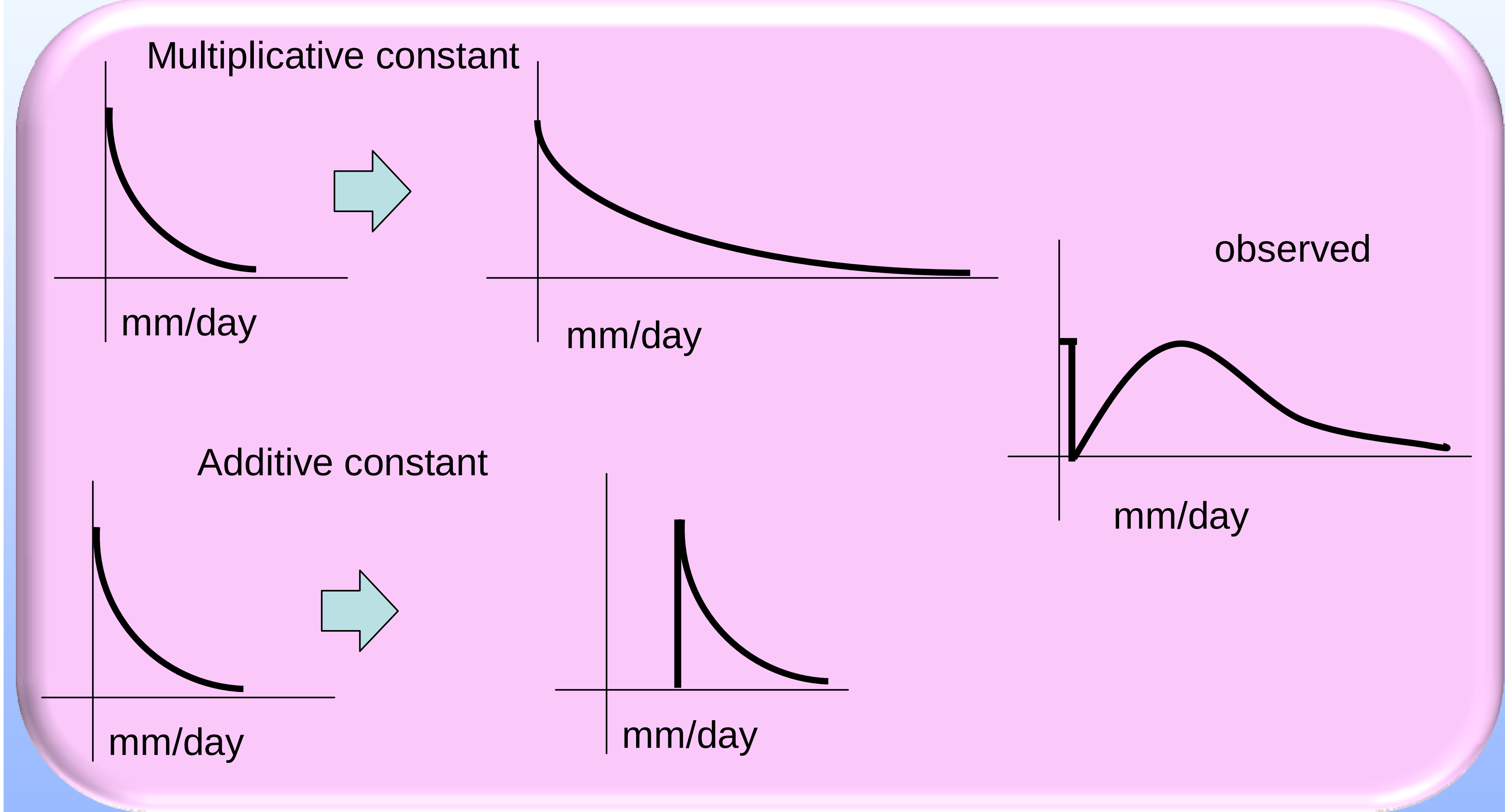
What is usually done?

Take statistical changes from climate change experiments and superimpose them on observations:

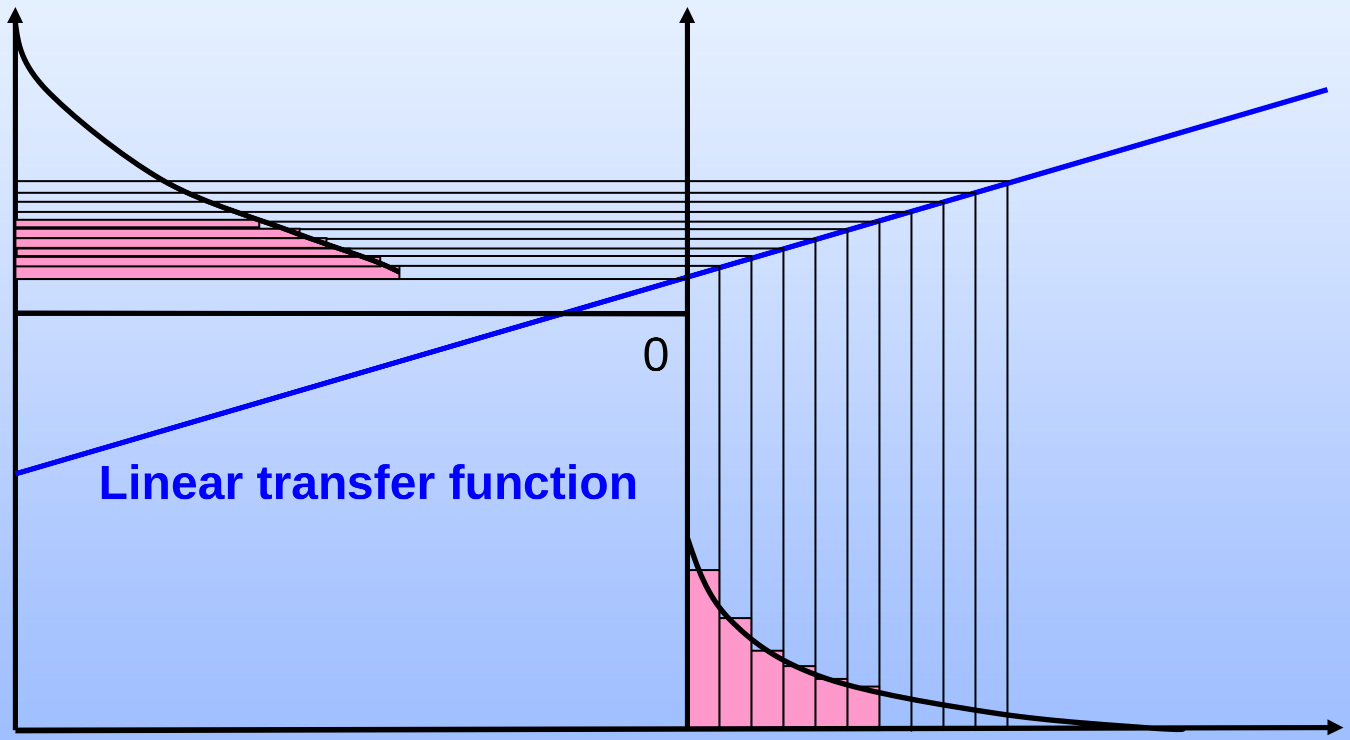


What is usually done?

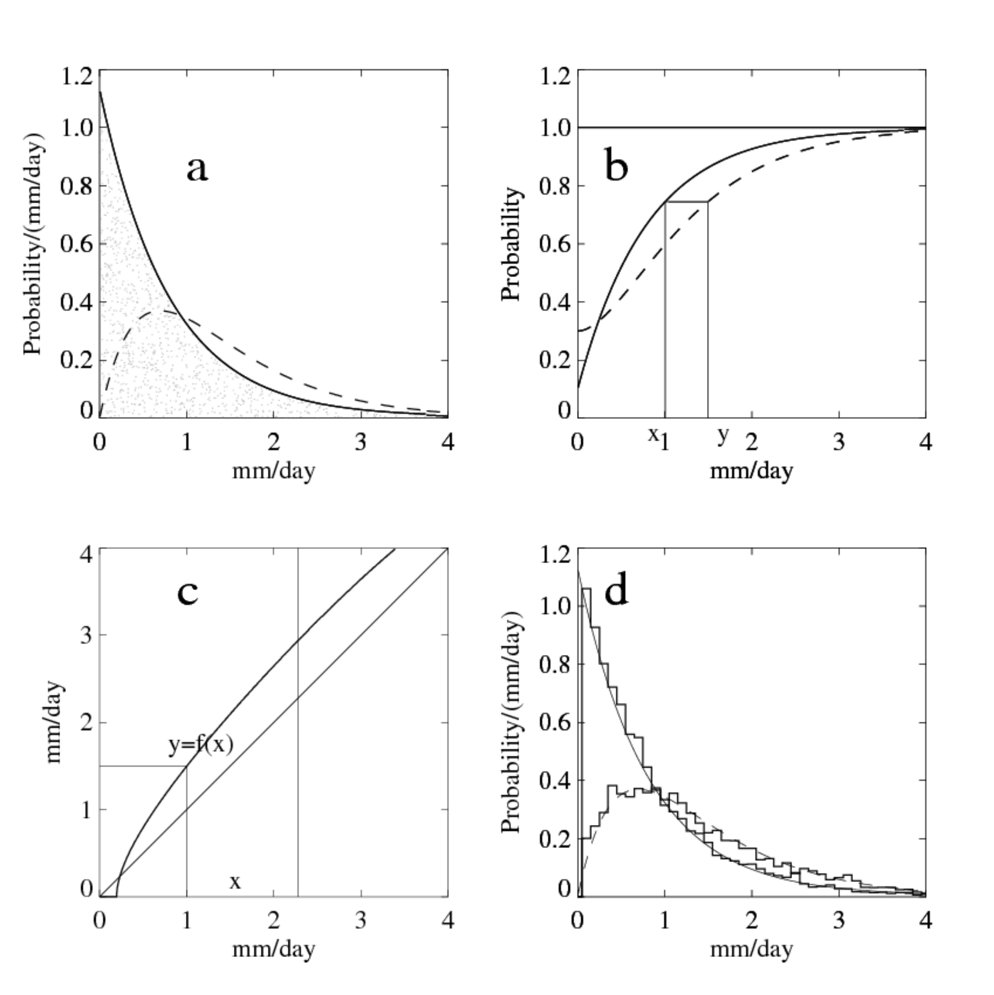
Even worse: take a bias correction in the form of a multiplicative or additive constant to match the observed mean …



We propose a histogram equalizing methodology



We propose a histogram equalizing methodology



Yes it does work:

a) Idealized histograms of simulated (solid line) and observed (dashed line) daily precip.

b) Cumulative distributions.

c) Transform function. Is determined by few (< 3) parameters.

d) Synthetic dataset transformed. Original dataset looks like simulated, transformed looks like observed.

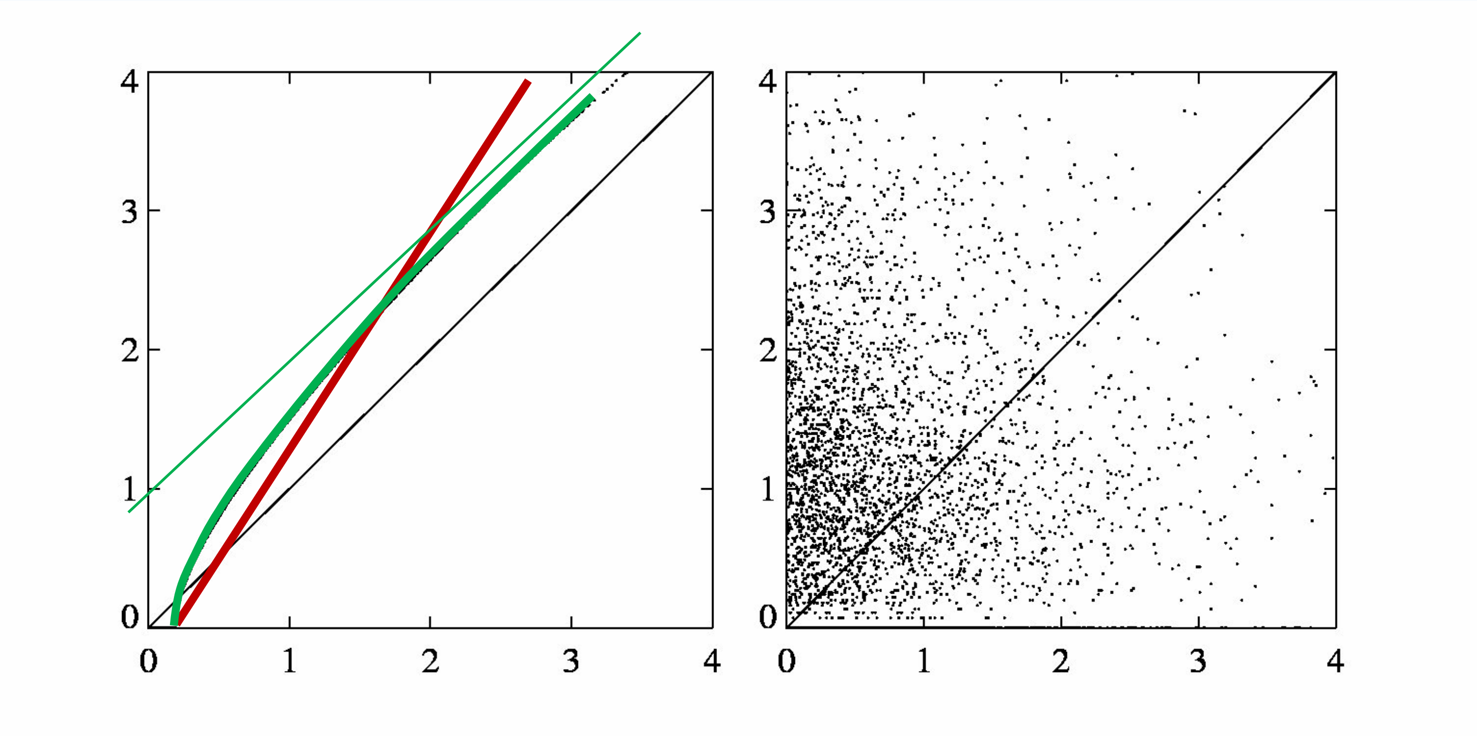
Requirements for the transform function

All aspects of the field statistics need to be corrected (true by construction).

Must be constant, or almost constant, in time to be applicable to climate change related hydrological studies.

Must be well constrained, that is have few parameters. The more parameters a transform function has the more susceptible it is to decadal and multi-decadal variability.

Candidates for the transform function



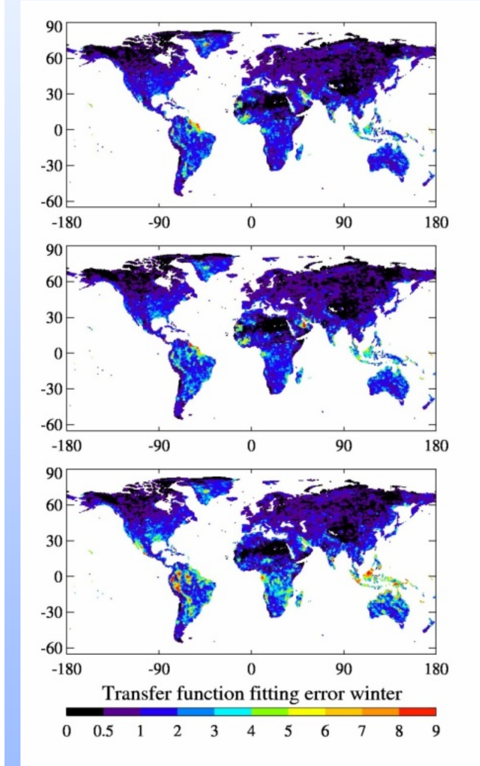
1) $y = (a + bx)(1 - e^{-(x-x_0)/\xi})$

2) $\ln y = a + b\ln(x - x_0)$

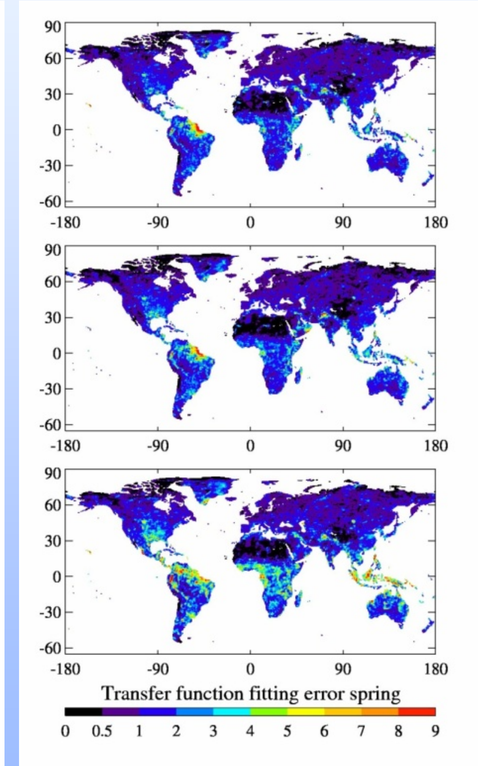
3) $y = a + bx$

Transform function fitting error for all three curves for all seasons separately.

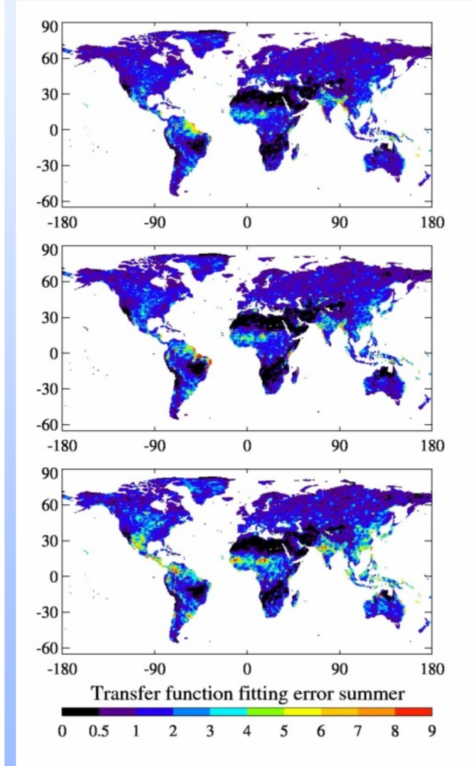
- Curves with higher number of parameters work better.
- This does not necessarily mean they are more robust in time.



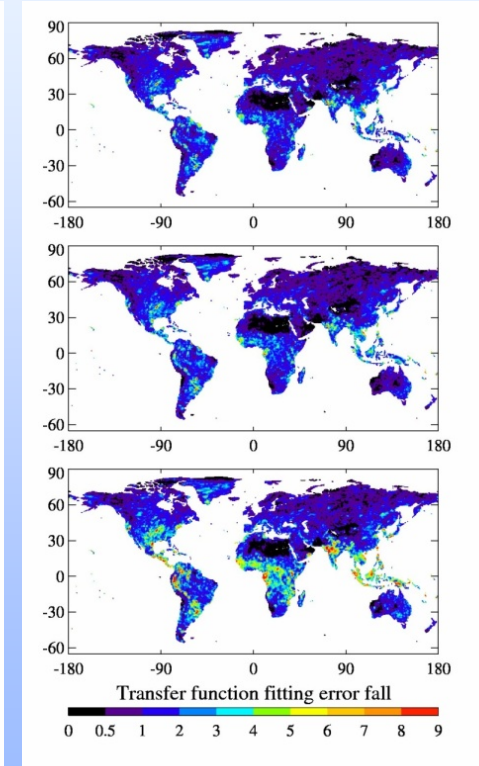
Transfer function fitting error winter



Transfer function fitting error spring



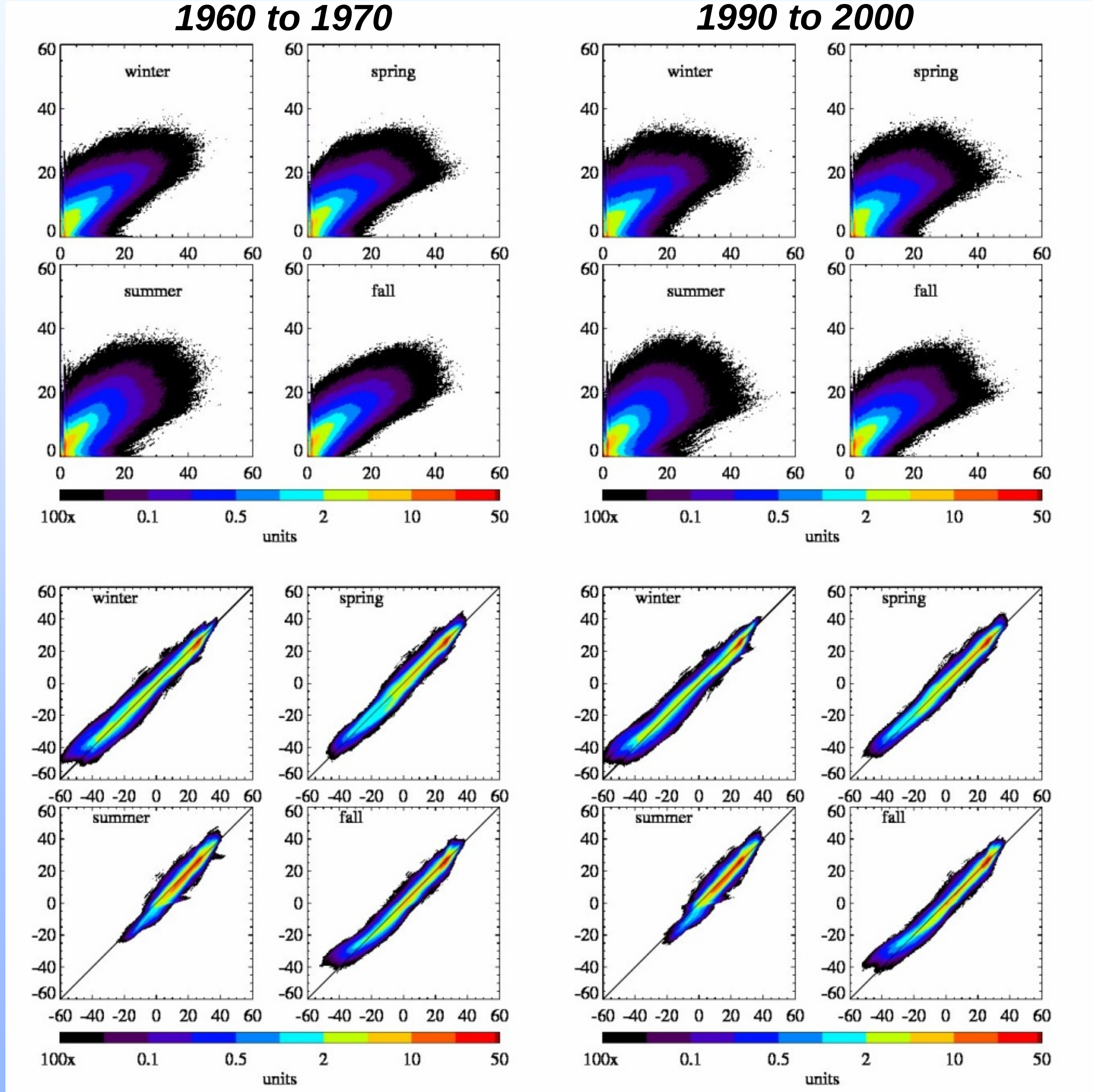
Transfer function fitting error summer



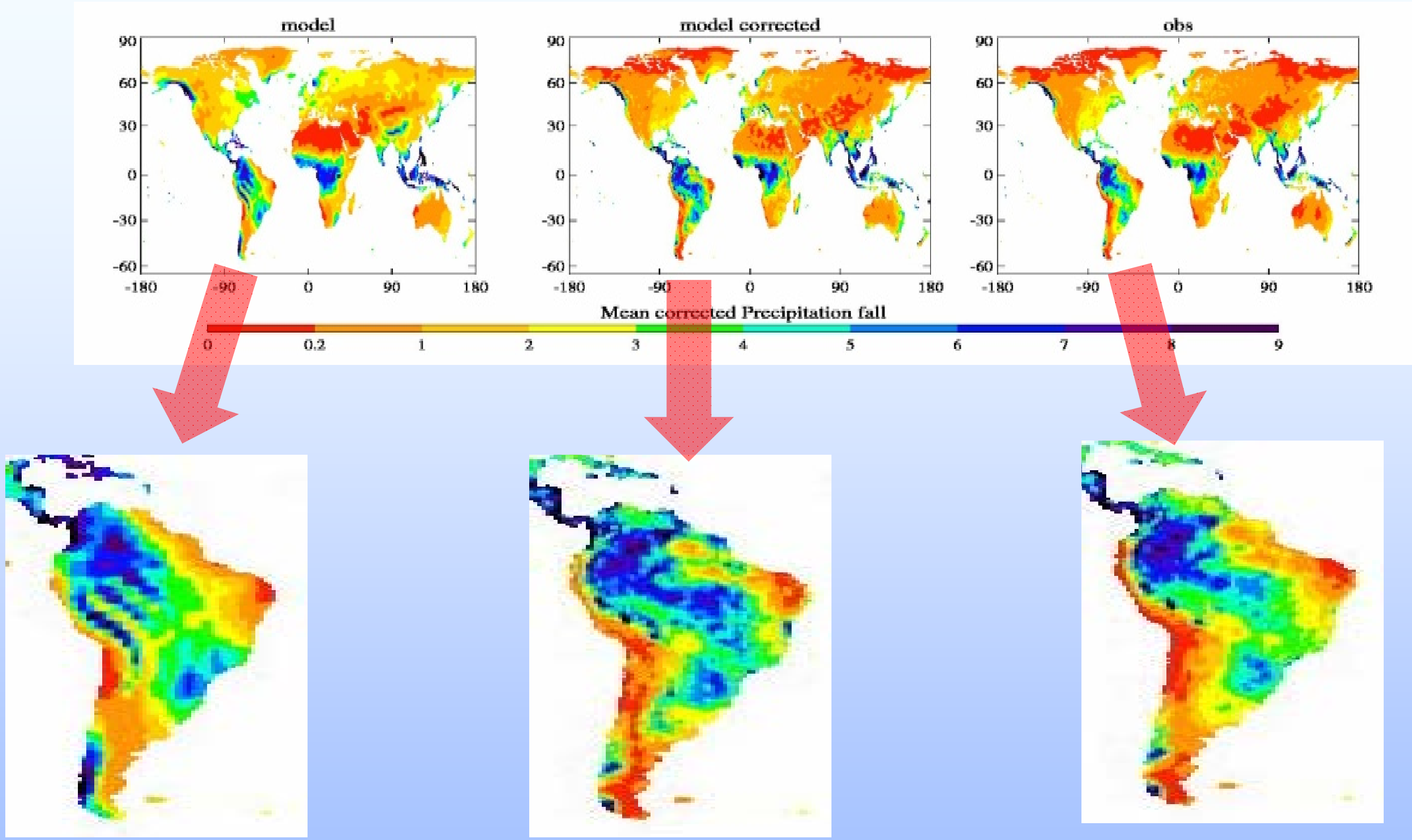
Transfer function fitting error fall

ECHAM5 vs WFD 1960 to 1970

How robust are the emerging transform functions relative to decadal variability?.



Down-scalling effects



This is the final product not the calibration…

Tests with observations on same grid

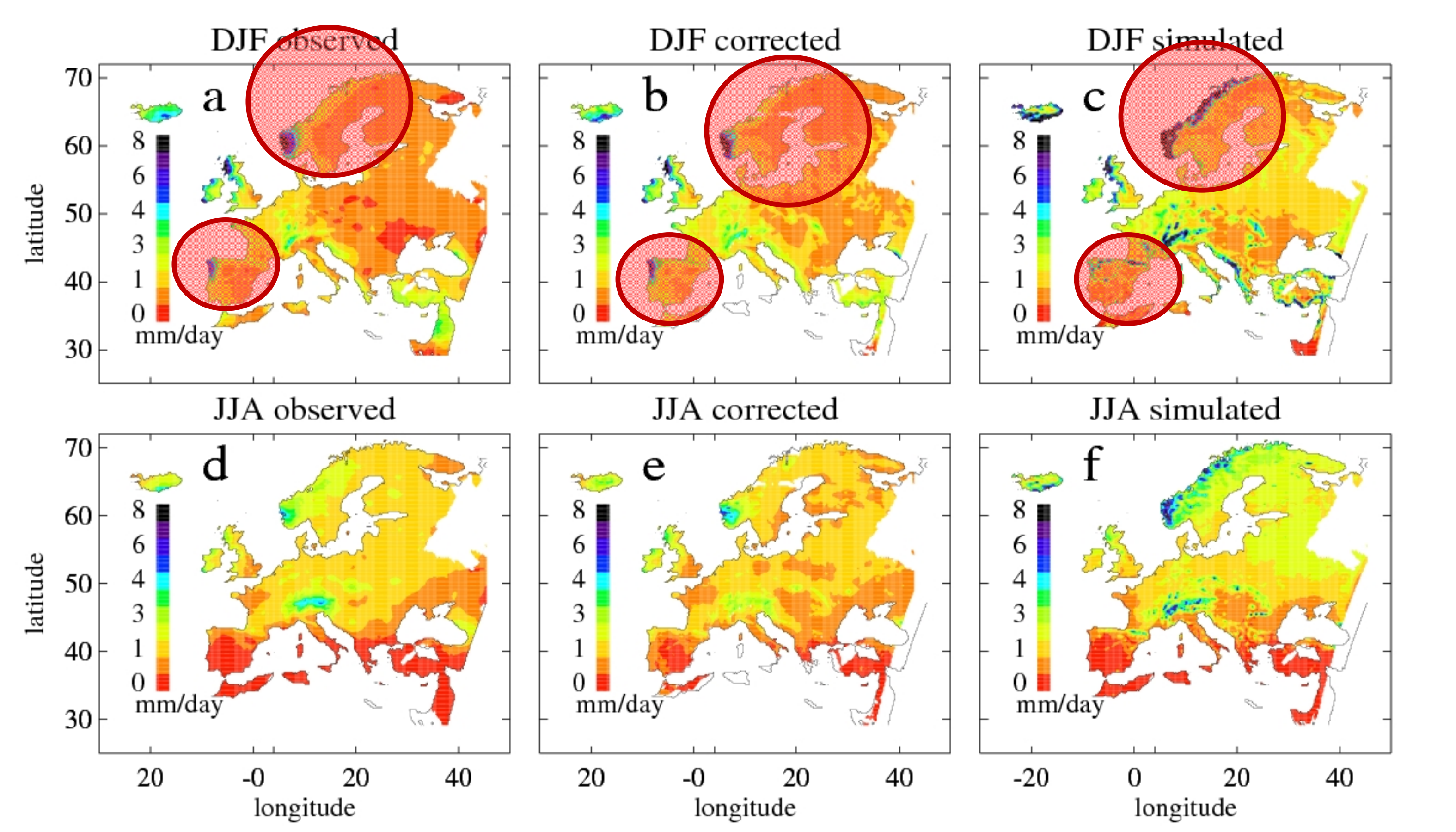
•Bias correction was applied to the simulated daily precipitation data from the DMI regional model over Europe interpolated onto the CRU 25km x 25km grid for 1961 to 2000 (ensembles project output).

•Transform functions, with 4 parameters, were calculated for the whole year, without subdividing into seasons, using the1961 to 1970 decade.

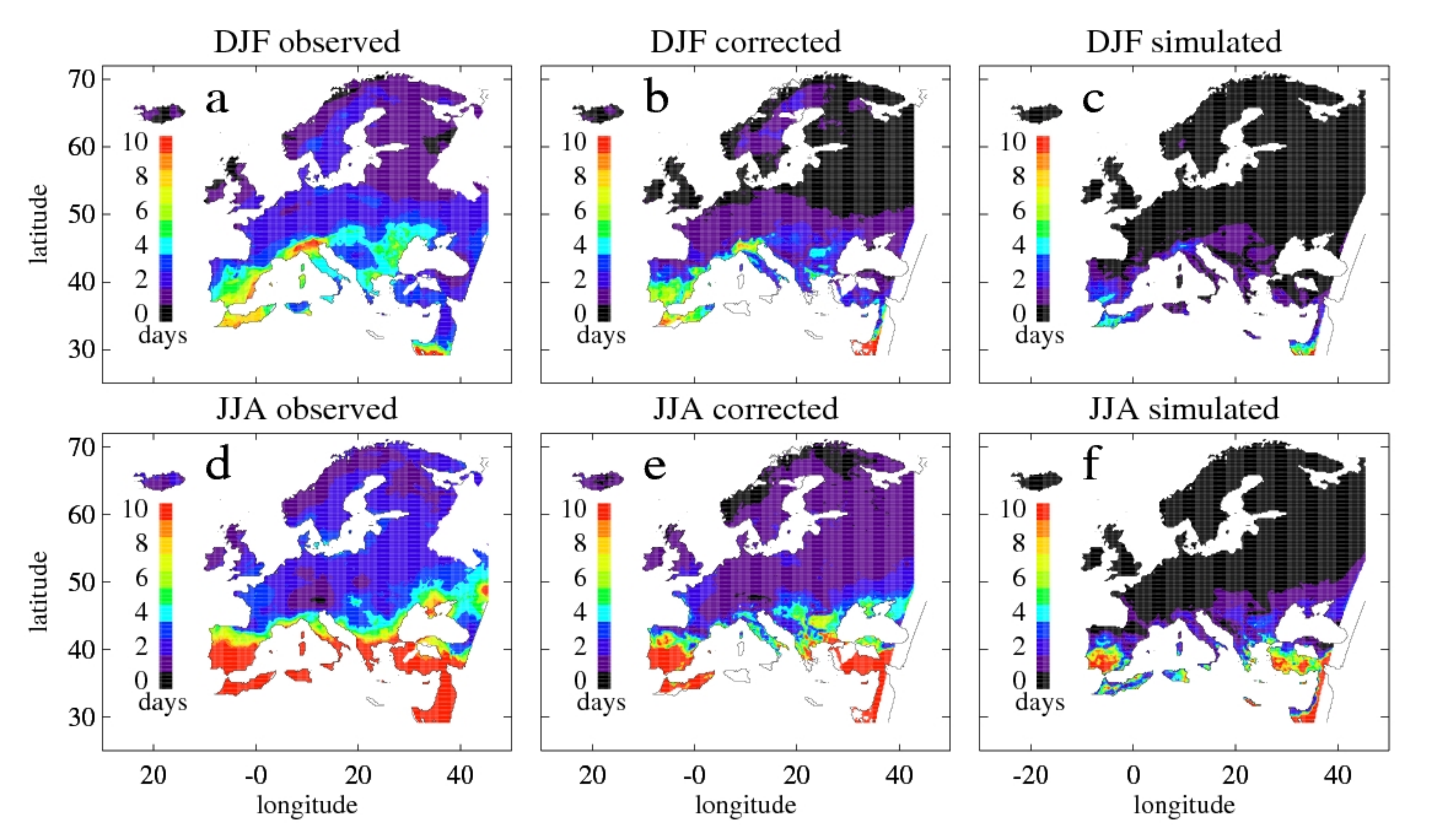
• Results are tested for winter and summer separately for the 1991 to 2000 to maximize temporal independence of data.

•Tests are not performed on intensity distribution parameters alone (mean variance, frequency). But, crucially, on variables that depend on the temporal spectra as well (consecutive dry days and heavy precipitation events).

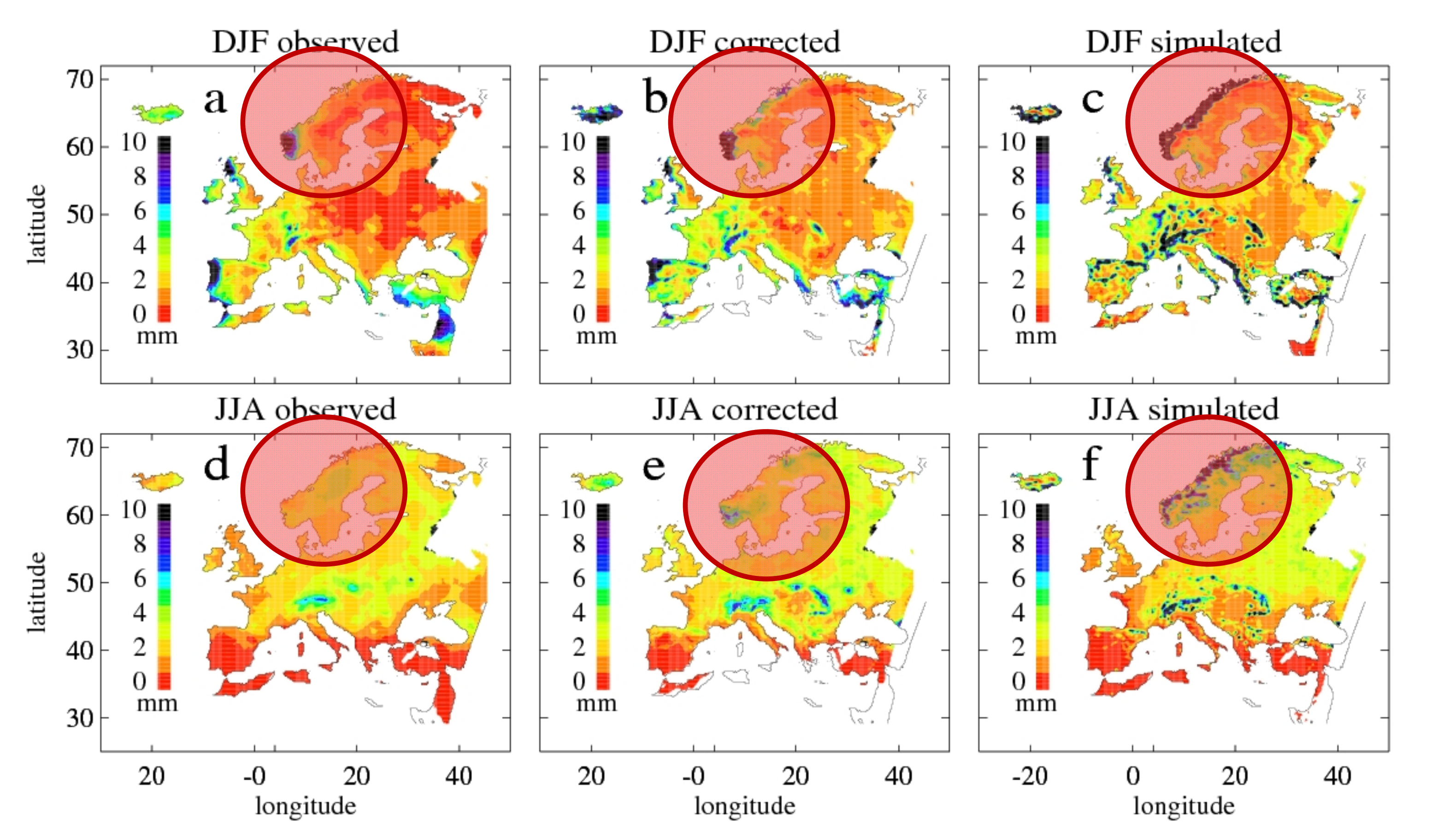
Seasonal mean



Seasonal consecutive dry days



Seasonal heavy precipitation events



Partial Conclusions

- Methodology proves to be robust relative to
  - Decadal variability.
  - Seasonal variability.
- Methodology greatly improves not only variables that depend on the intensity histogram (i.e. mean and individual daily extremes).
- but also variables which depend on the temporal spectrum (i.e. consecutive dry days and multi-day heavy precipitation events.)

Application of bias correction to high resolution simulations from PRUDENCE.

Application of bias correction to high resolution simulations from PRUDENCE.

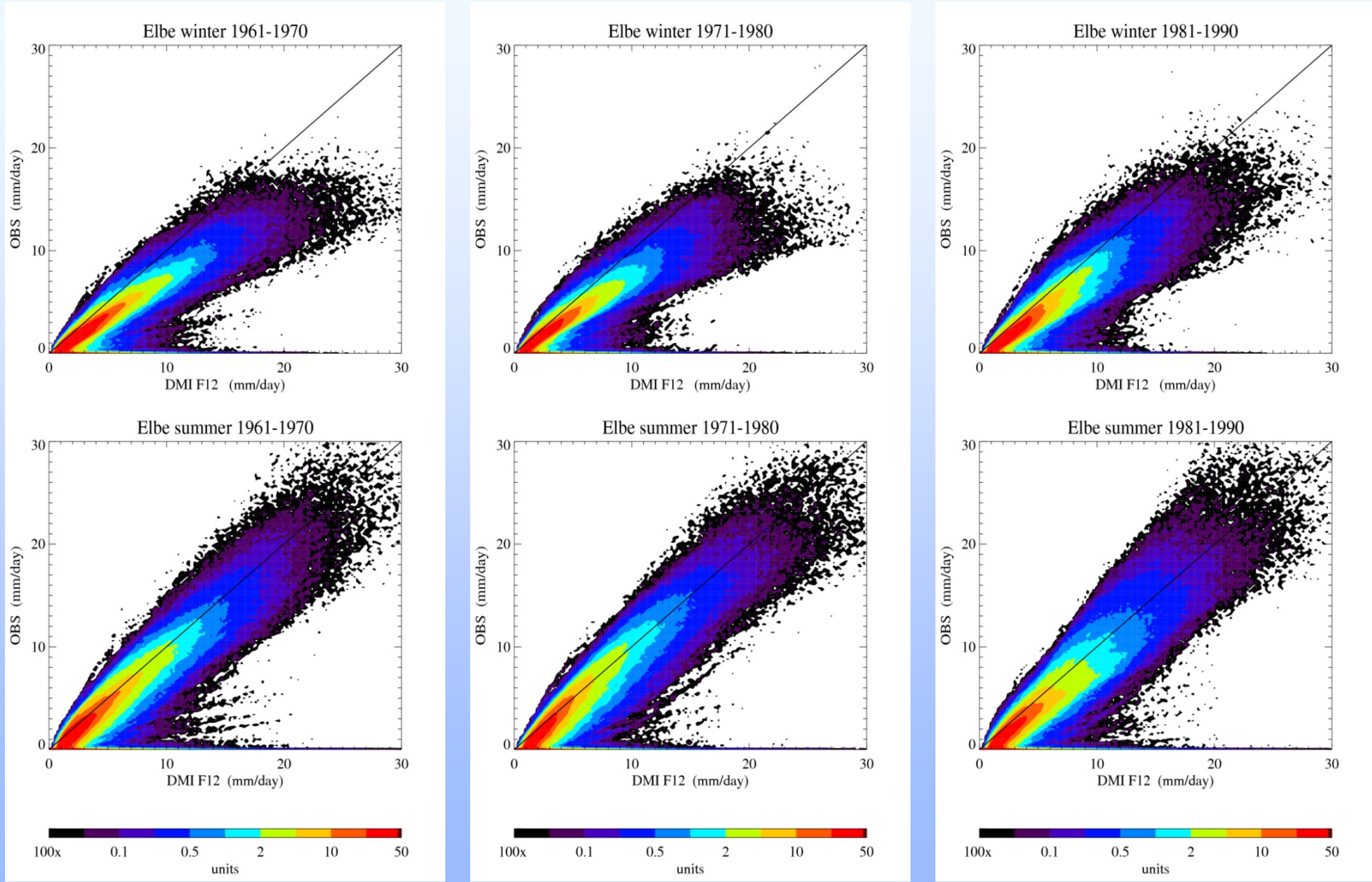
•Bias correction was applied to the simulated daily precipitation data from the DMI regional model F12 simulation from the PRUDENCE project.

•Transform functions were calculated for summer an winter separately and for each of the three decades 1961 to 1970; 1971 to 1980; 1981 to 1990.

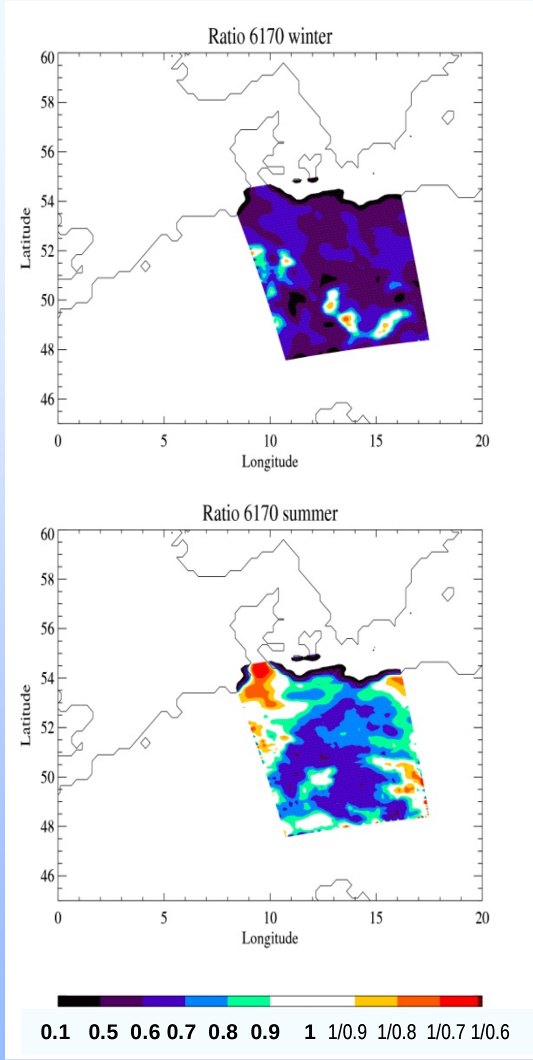
•Observations from the ENSEMBLES project were interpolated onto the hi-res. 12km grid.

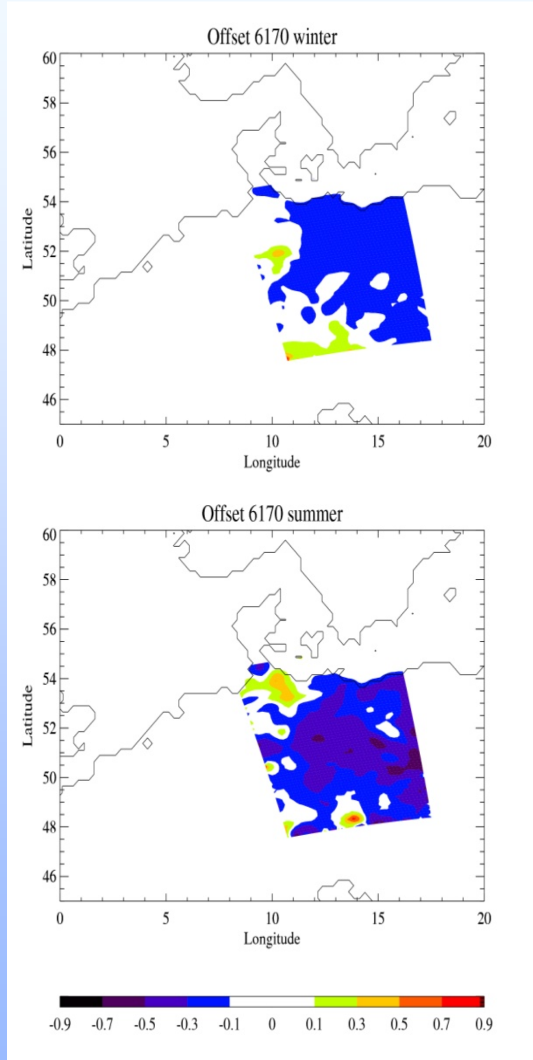
•We then apply the averaged bias corrections to A2 scenario simulations for 2070 to 2100 and analyze results and the uncertainty associated to the bias correction.

2D-histogram for transform functions.

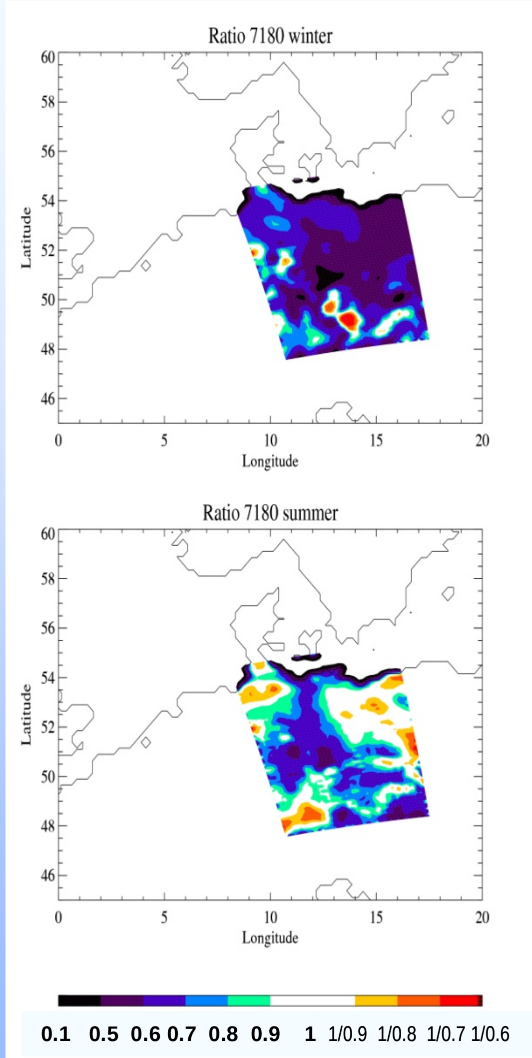


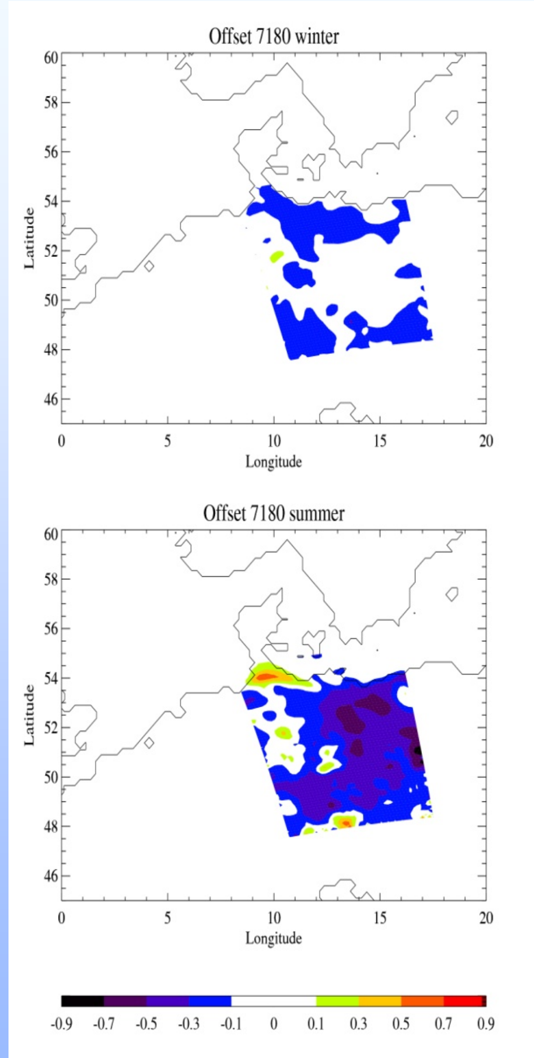
Linear fit to transform 1961 to 1970.



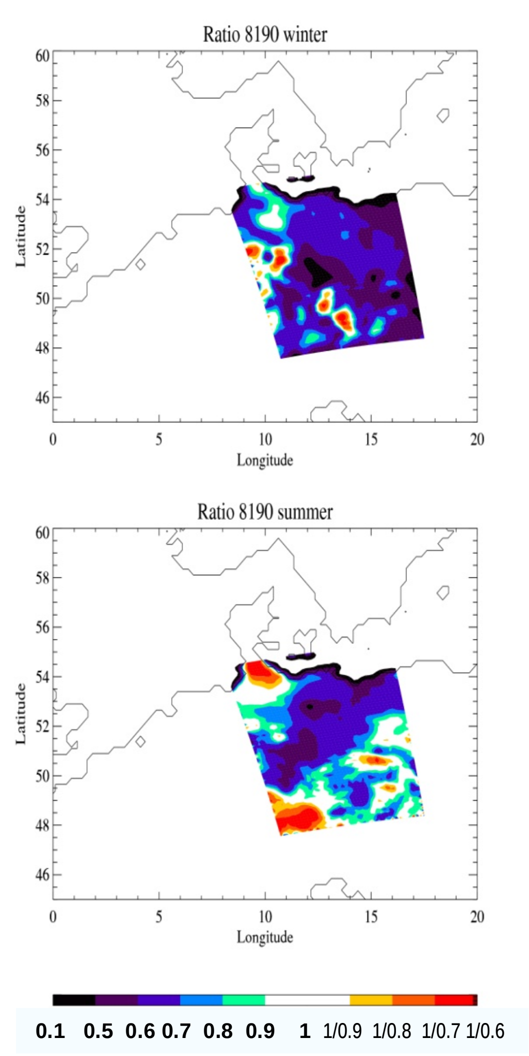


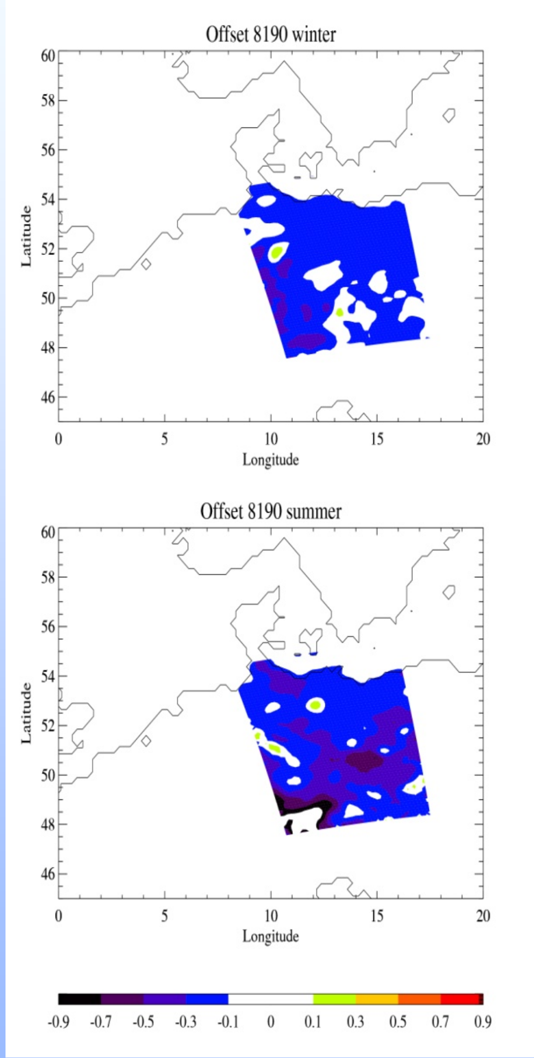
1971 to 1980


Ratio 7180 winter
Latitude
Longitude
Ratio 7180 summer
Latitude
Longitude
0.1 0.5 0.6 0.7 0.8 0.9 1 1/0.9 1/0.8 1/0.7 1/0.6

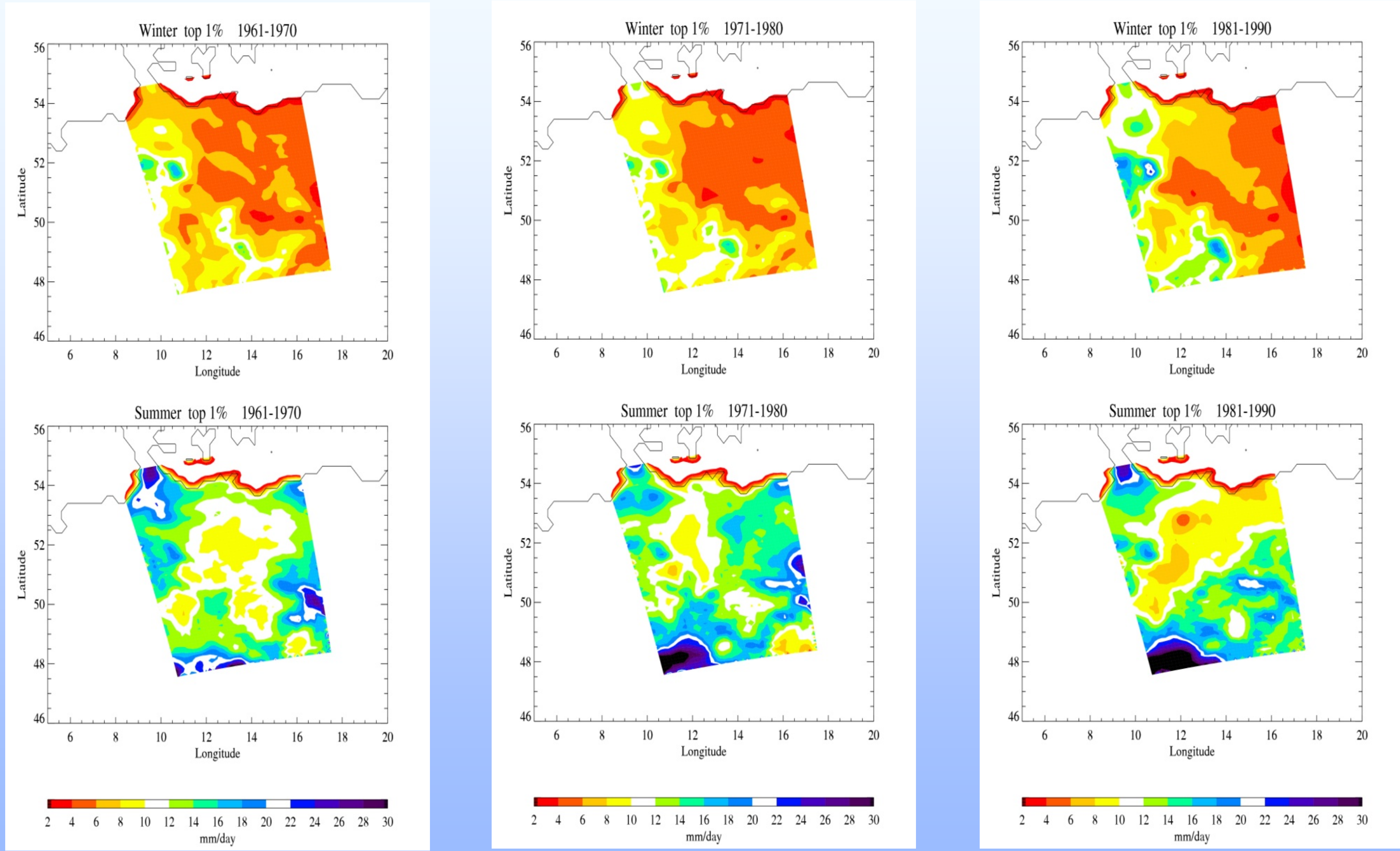

Offset 7180 winter
Latitude
Longitude
Offset 7180 summer
Latitude
Longitude
-0.9 -0.7 -0.5 -0.3 -0.1 0 0.1 0.3 0.5 0.7 0.9

1981 to 1990

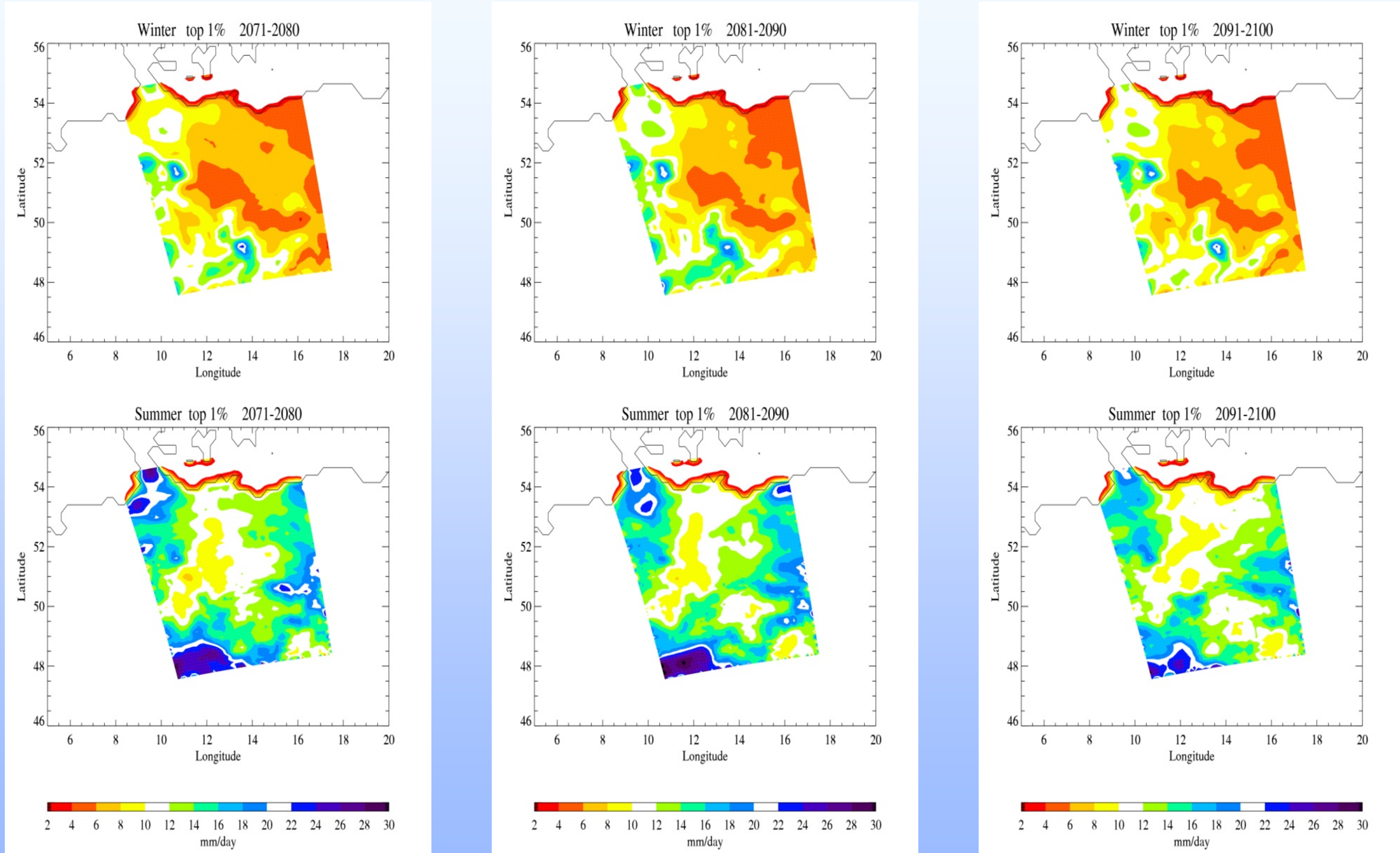

Ratio 8190 winter
Ratio 8190 summer
Latitude
Longitude
0.1 0.5 0.6 0.7 0.8 0.9 1 1/0.9 1/0.8 1/0.7 1/0.6


Offset 8190 winter
Offset 8190 summer
Latitude
Longitude
-0.9 -0.7 -0.5 -0.3 -0.1 0 0.1 0.3 0.5 0.7 0.9

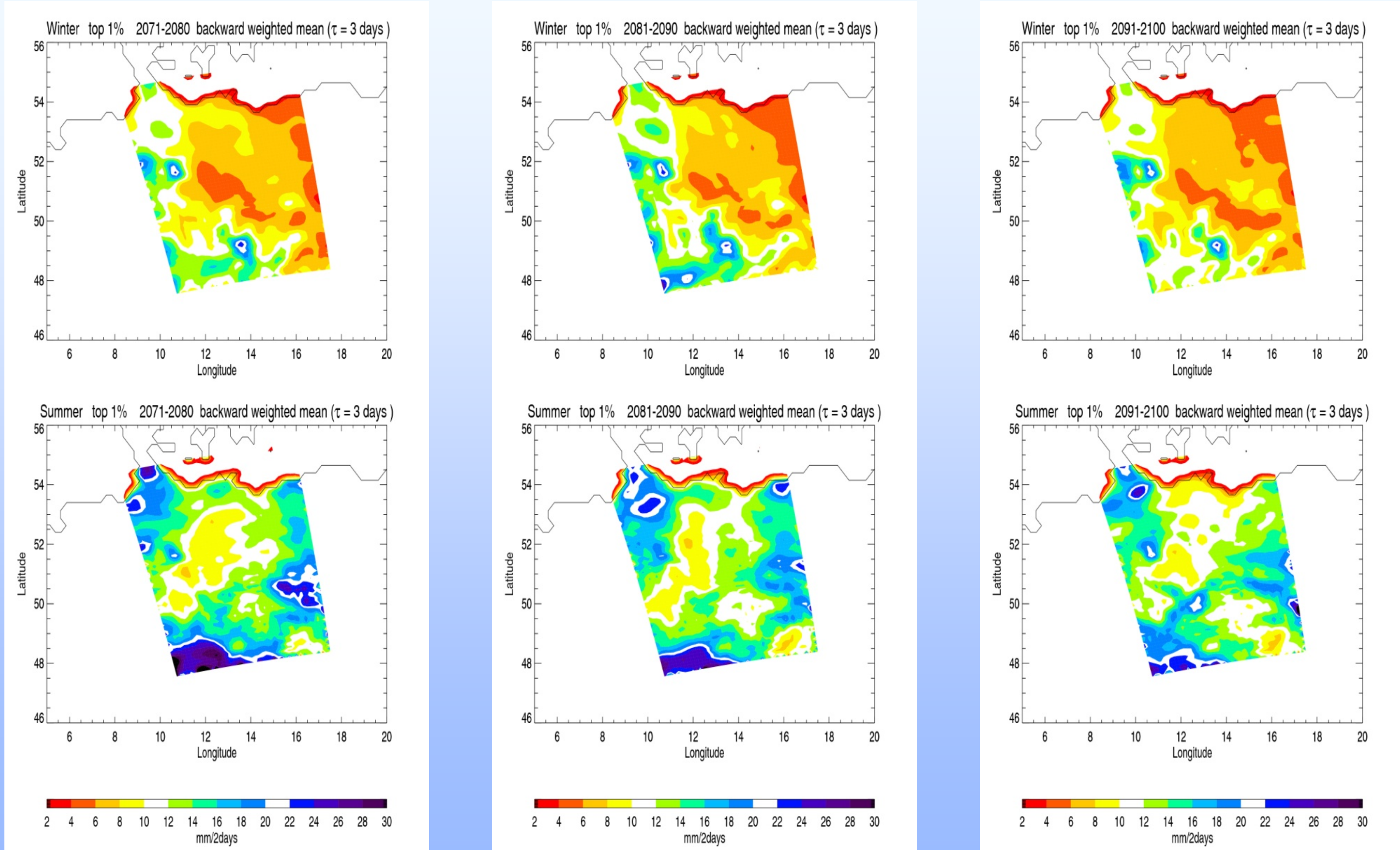
top 1% of intensity distribution hindcast



top 1% of intensity distribution projection A2



top 1% of backward running mean τ = 3days



Preliminary conclusions

•Analysis of the distribution of the cdf to cdf transform function is a powerful tool to analyze:

- the temporal and spatial structure of the bias.
- the ensuing uncertainty.

Uncertainty in the bias correction

•Linear fits to the transform function are associated with uncertainty from different sources:

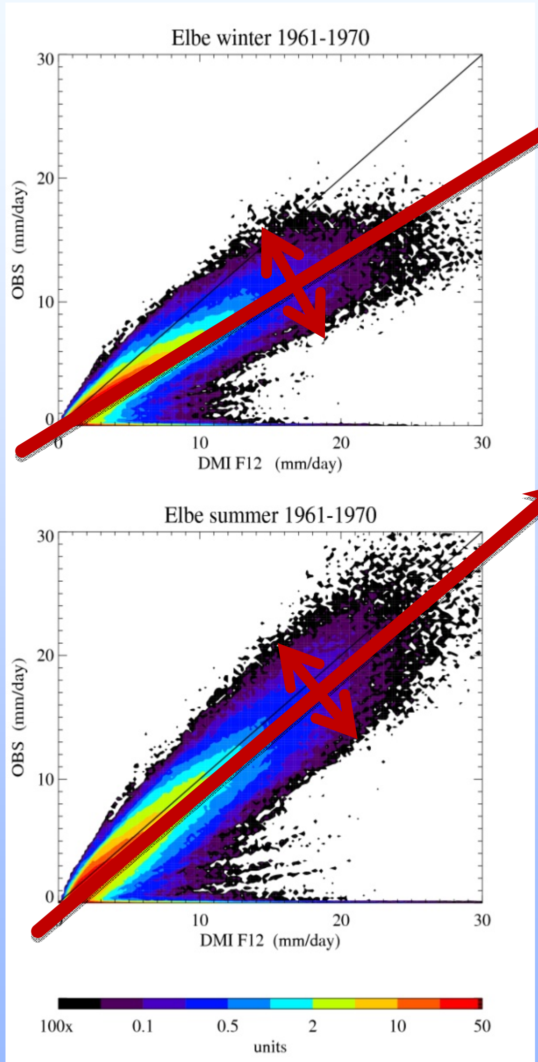
o Standard error associated with fit (negligible).

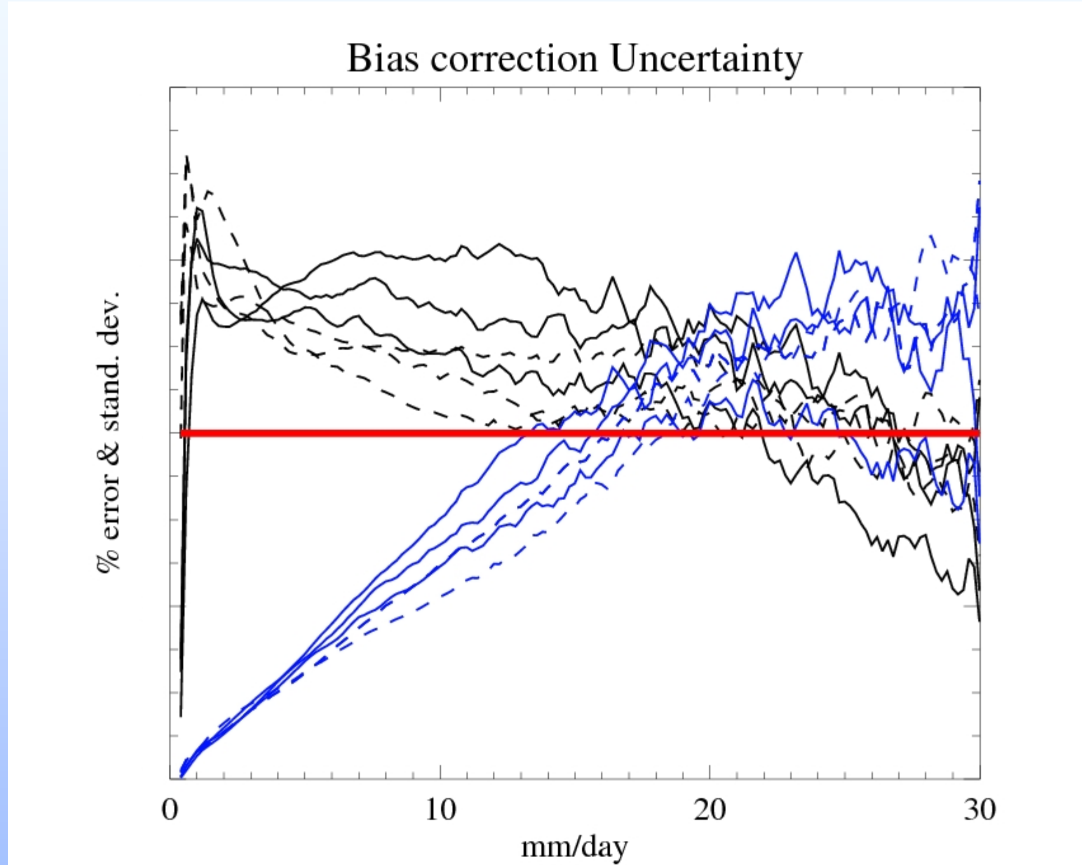
oDecadal variability of fit parameters.

oSpatial variability of fit parameters. (can be made to include the former)

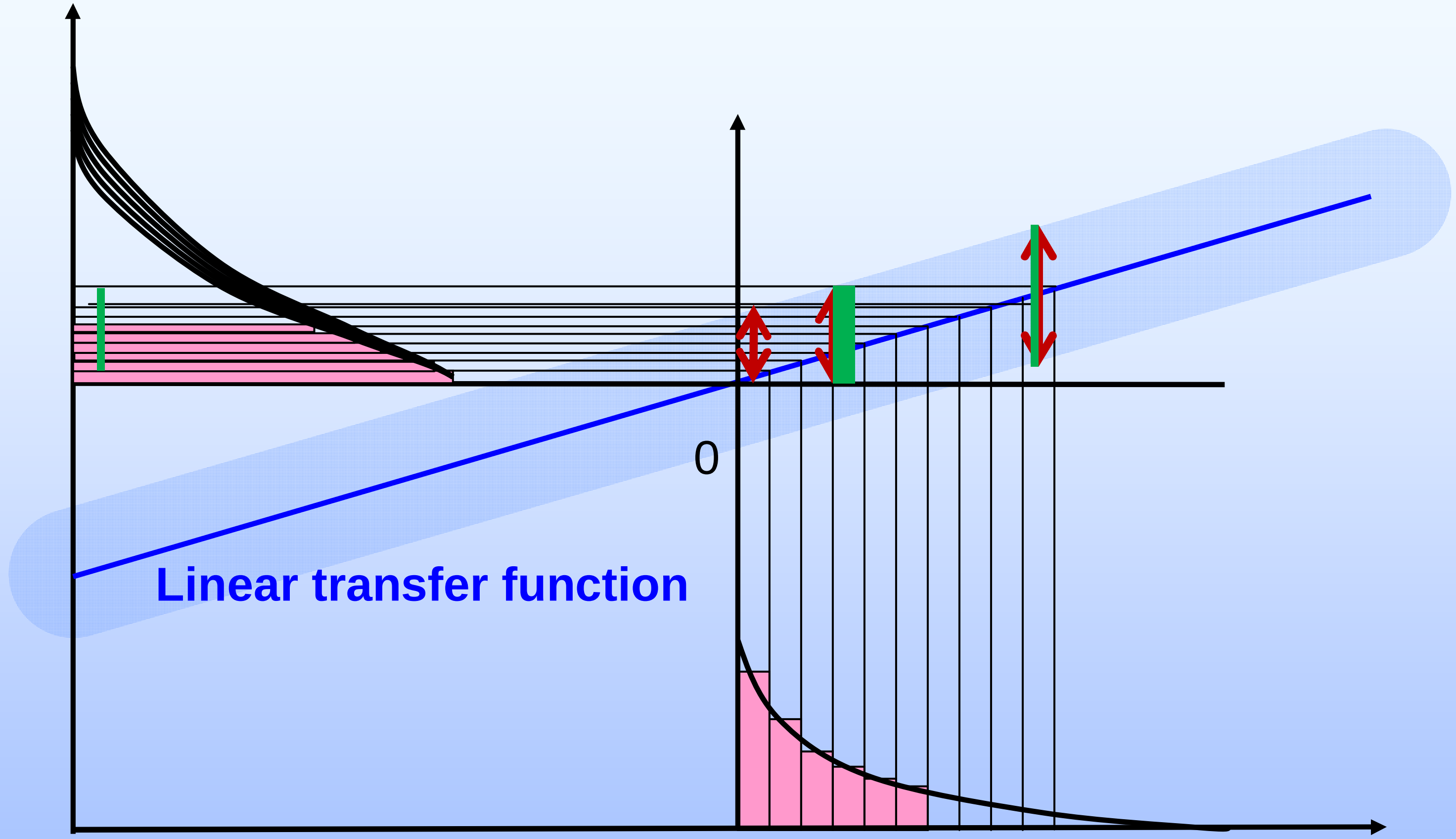
oChoice of fitting function. (can be made negligible, trade-off with robustness)

Uncertianty in the bias correction

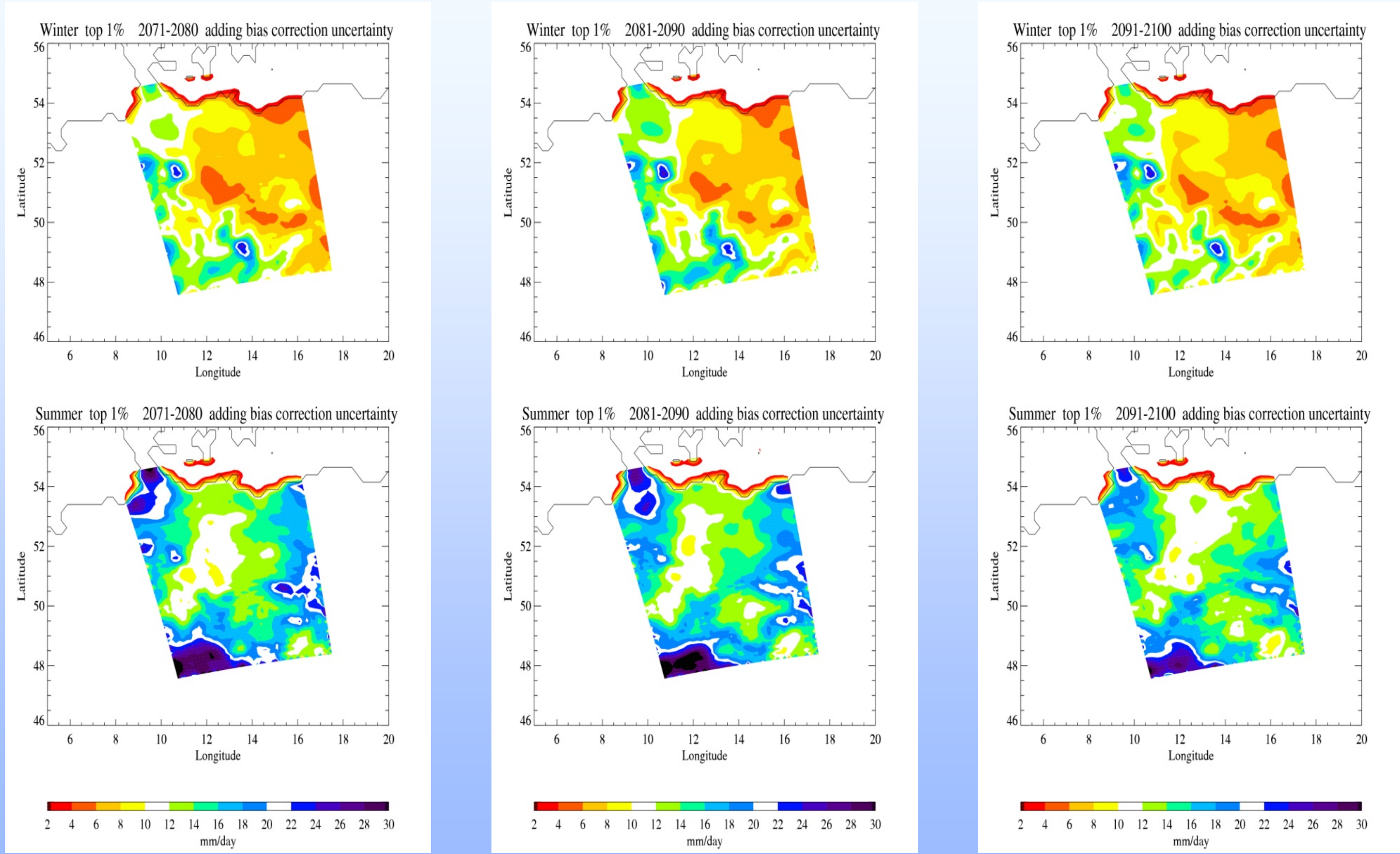




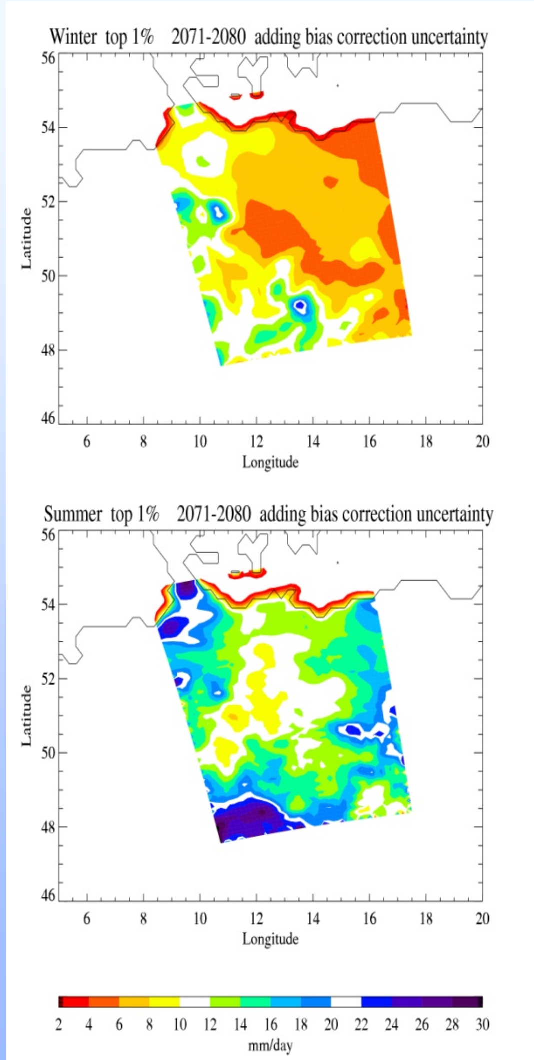
How does uncertainty affect the extremes?

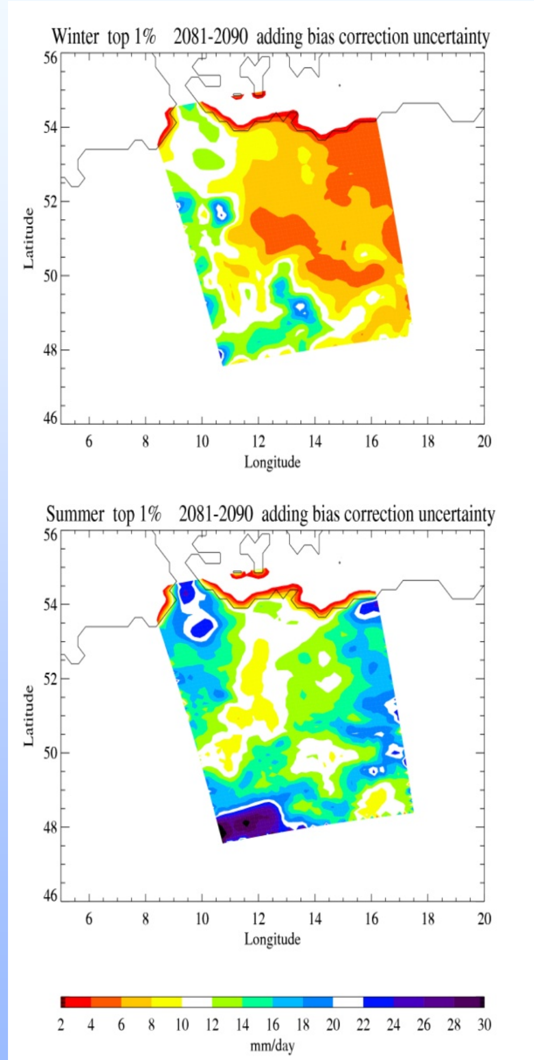


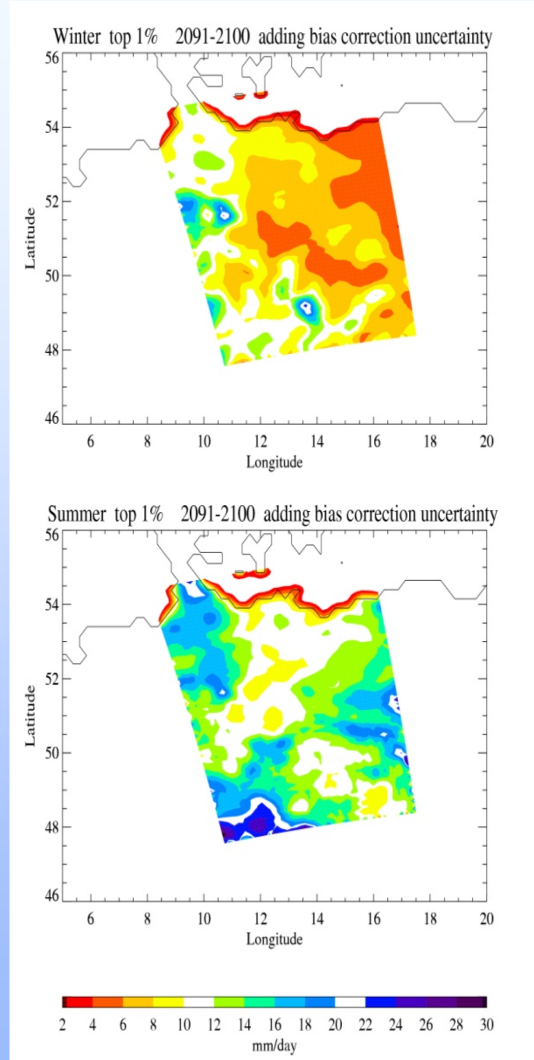
Effect on the extremes of %BCU = 0.1



Effect on the extremes of BCU = 0.1







Conclusions

•Once the details of the cdf bias correction method are established, it is fairly straight forward to account for the associated uncertainty.

•In talking to policymakers, or other end users, we should distinguish between:

- •increased probabilities due to a projected change in the climate and
- • increased probabilities due to our decrease in knowledge!

In an uncertain climate anything is possible!