The influence of bias correction on modeled hazards: The case of heat stress and fire risk

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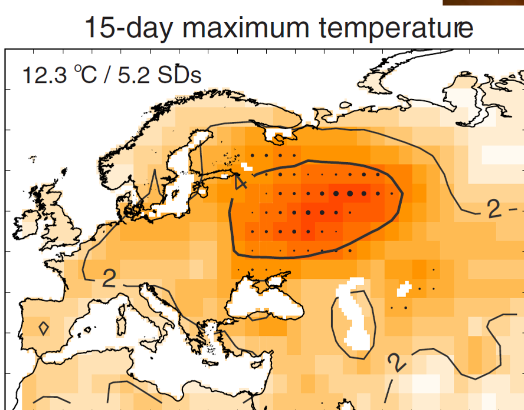
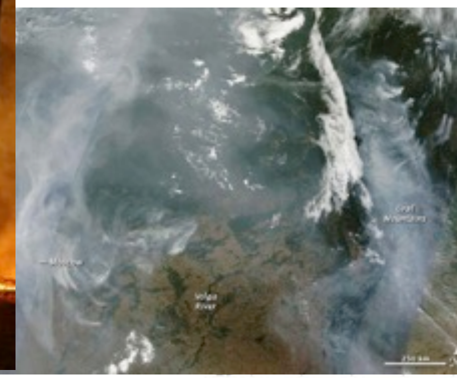
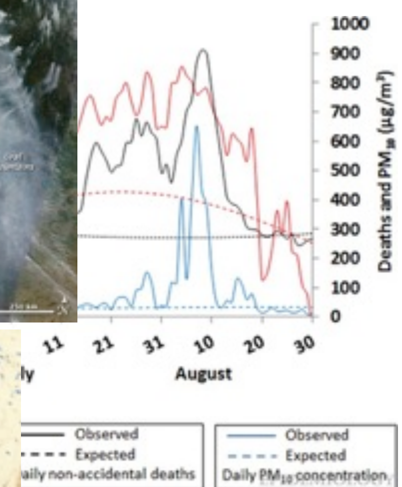
8th GEWEX Open Science Conference, Canmore, 2018

2010 — Precipitation deficit, Atmospheric blocking, High temperatures, Drought, Wildfires, Crop failure, Vegetation mortality, Air pollution, Human mortality → time

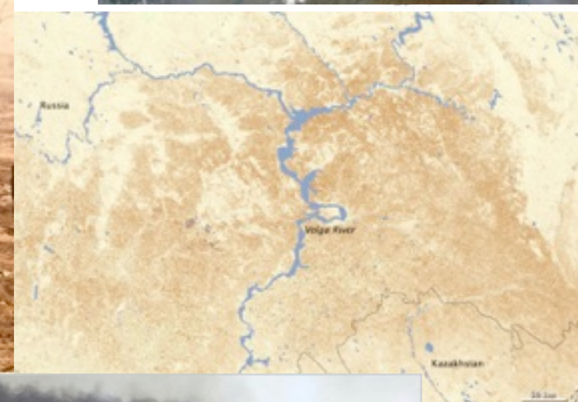


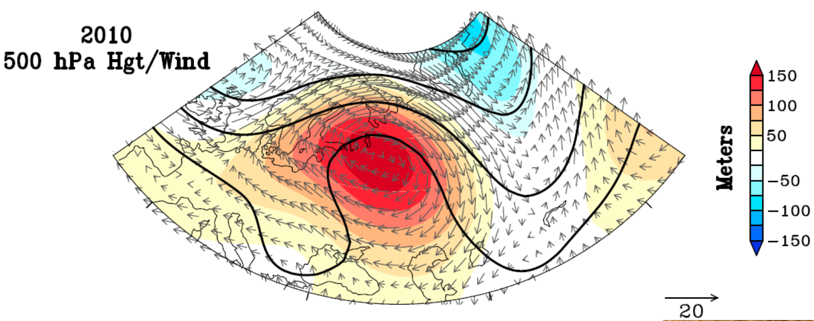
Barriopedro et al., 2011, Science



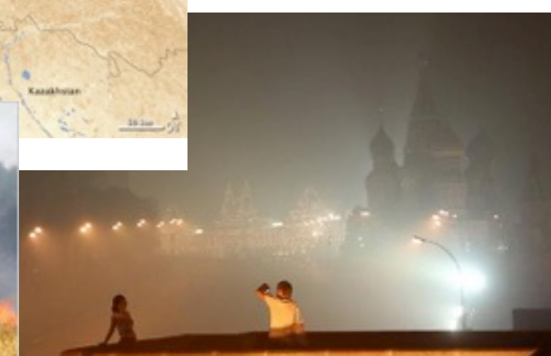


...ov et al., 2014, Epidem.

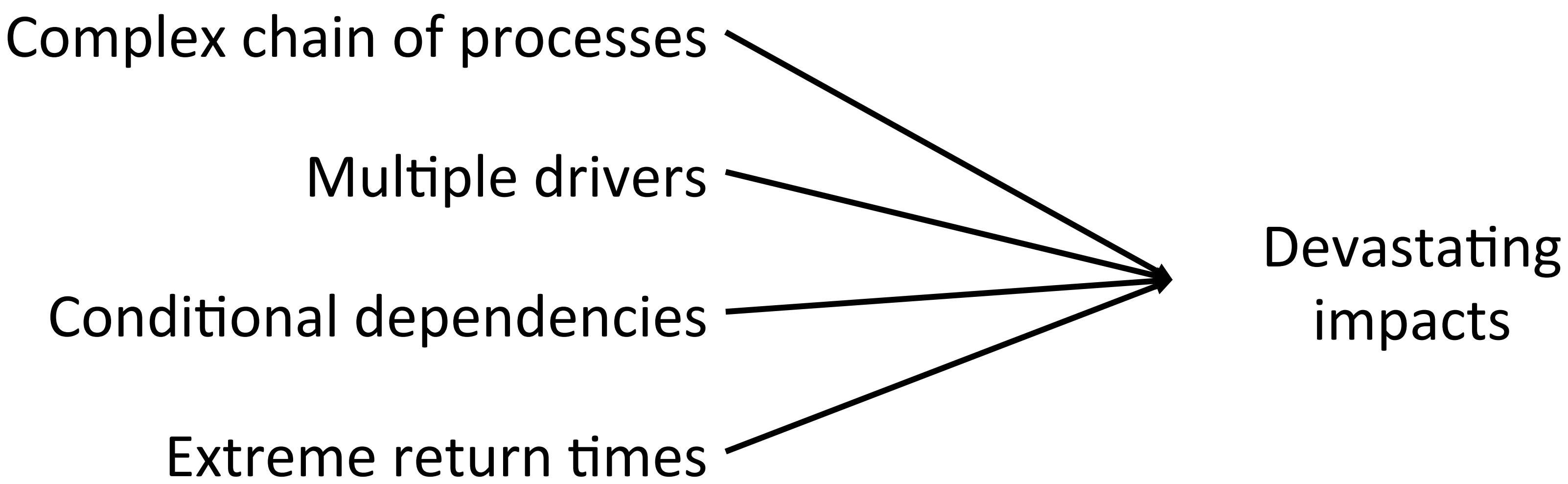




Dole et al., 2011., Geophys. Res. Let.

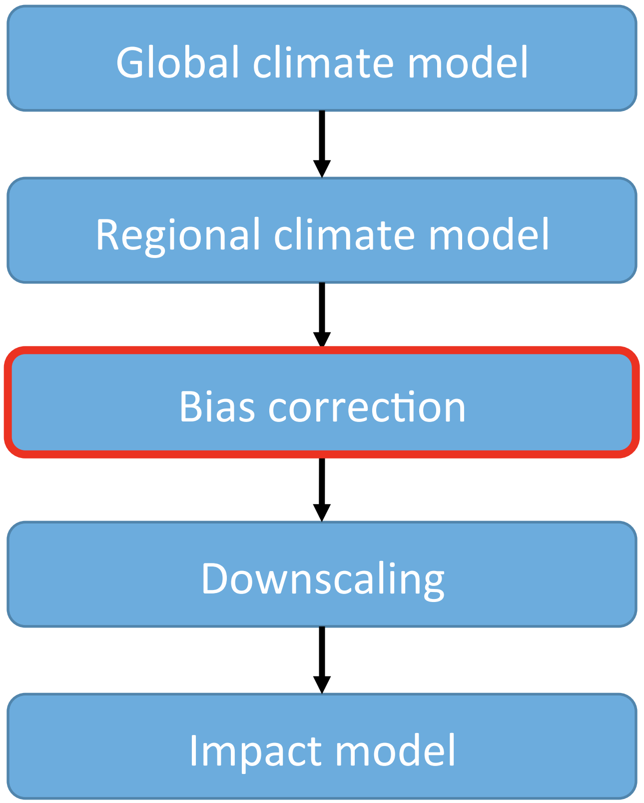


Compound weather/climate events



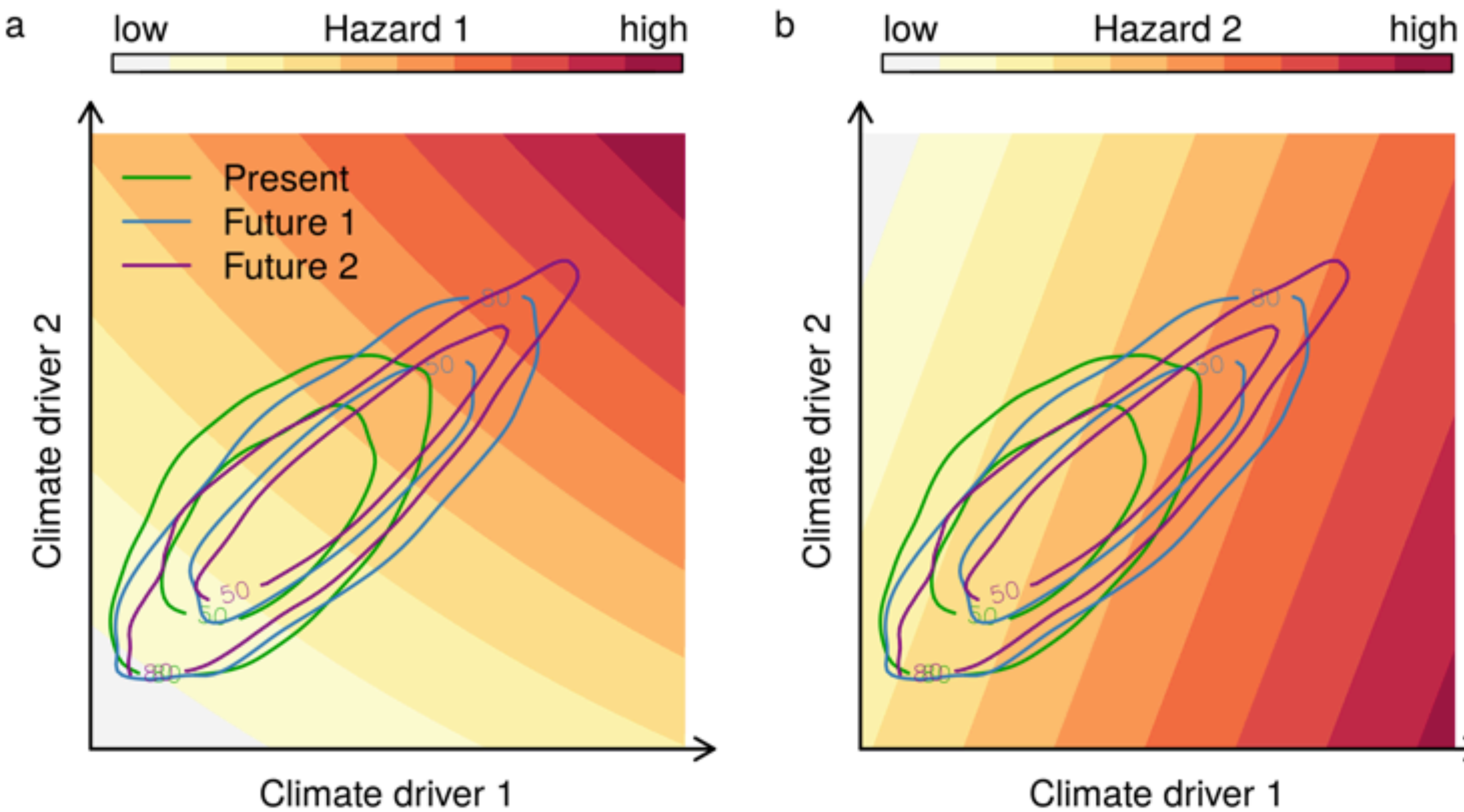
Zscheischler et al., *Nature Climate Change, in press*

Current paradigm: Top-down approach



Prudhomme et al., 2010; Hazeleger et al., 2015

Hazards/impacts and hazard drivers



- Small changes in the driver distribution can lead to large changes in hazards/impacts → influence of bias correction?

Zscheischler et al., *Nature Climate Change, in press*

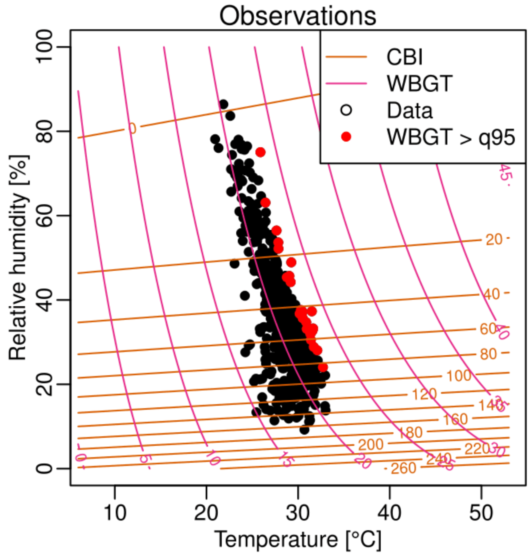
How does bias correction affect impacts?

- Use hazard indicators as a proxy for modeled impacts
- Hazards: heat stress (WBGT[1]), fire risk (CBI[2])
- Hazard drivers: temperature, relative humidity
- Daily data from the warmest month of the year (1951-1980)

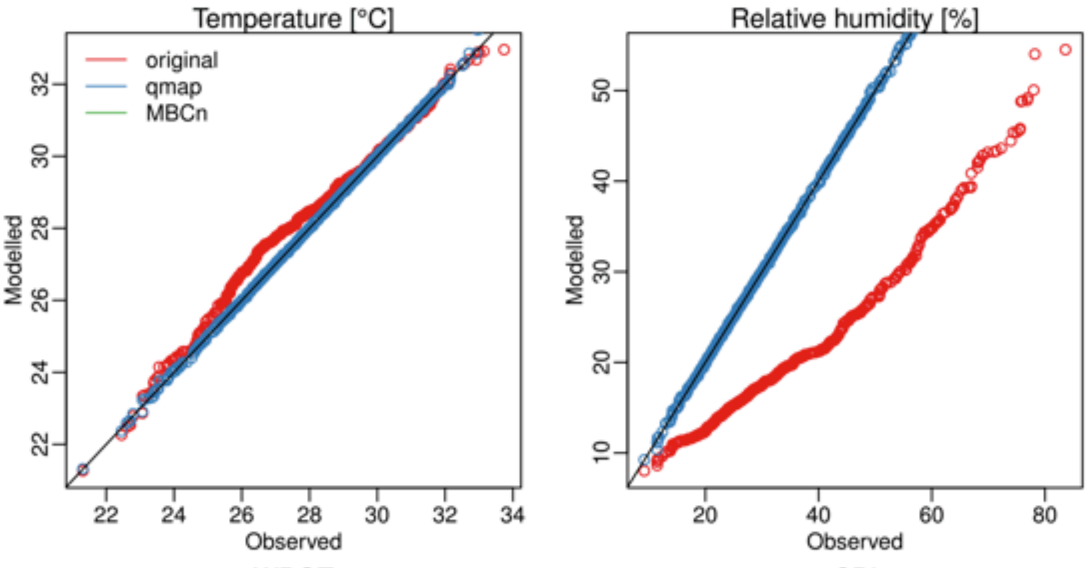
Observations	Model	Bias correction method
ERA Interim	CMIP5	Quantile mapping, MBCn
EWEMBI	Selected GCMs (ISI-MIP2b)	ISI-MIP2b approach

[1] Dunne et al., 2013; [2] Chandler et al., 1983

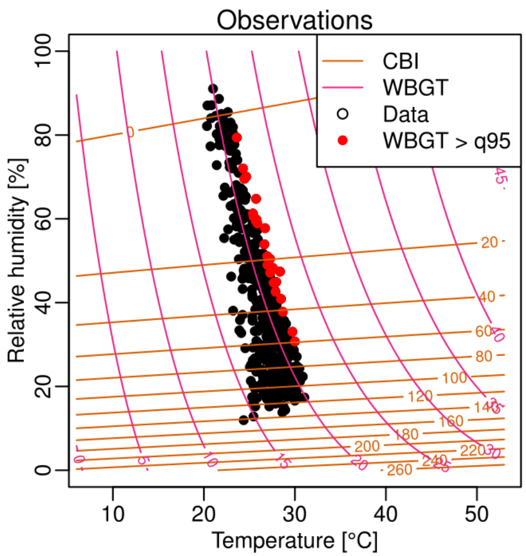
ACCESS, Western North America



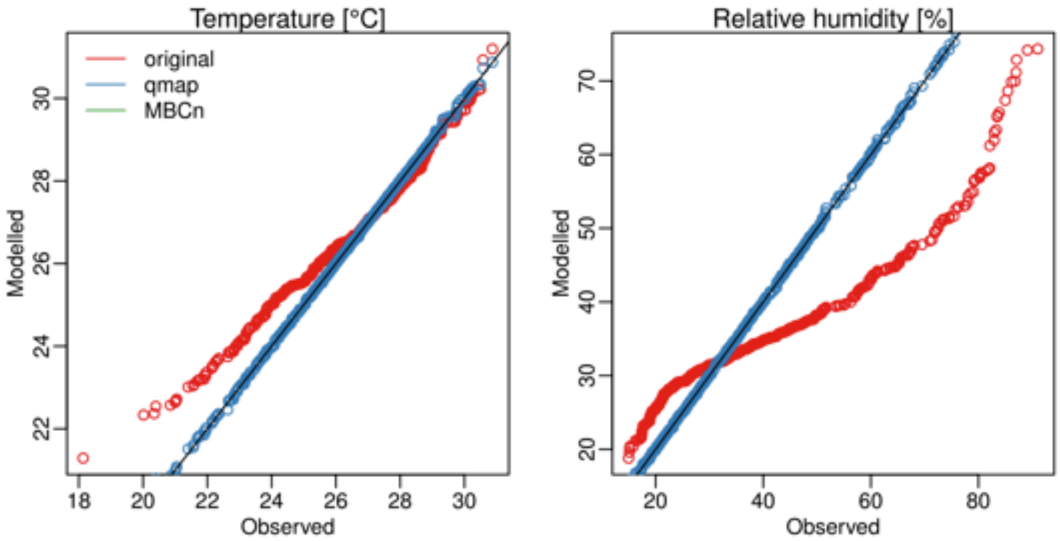
QQ-plot, ACCESS, Western North America



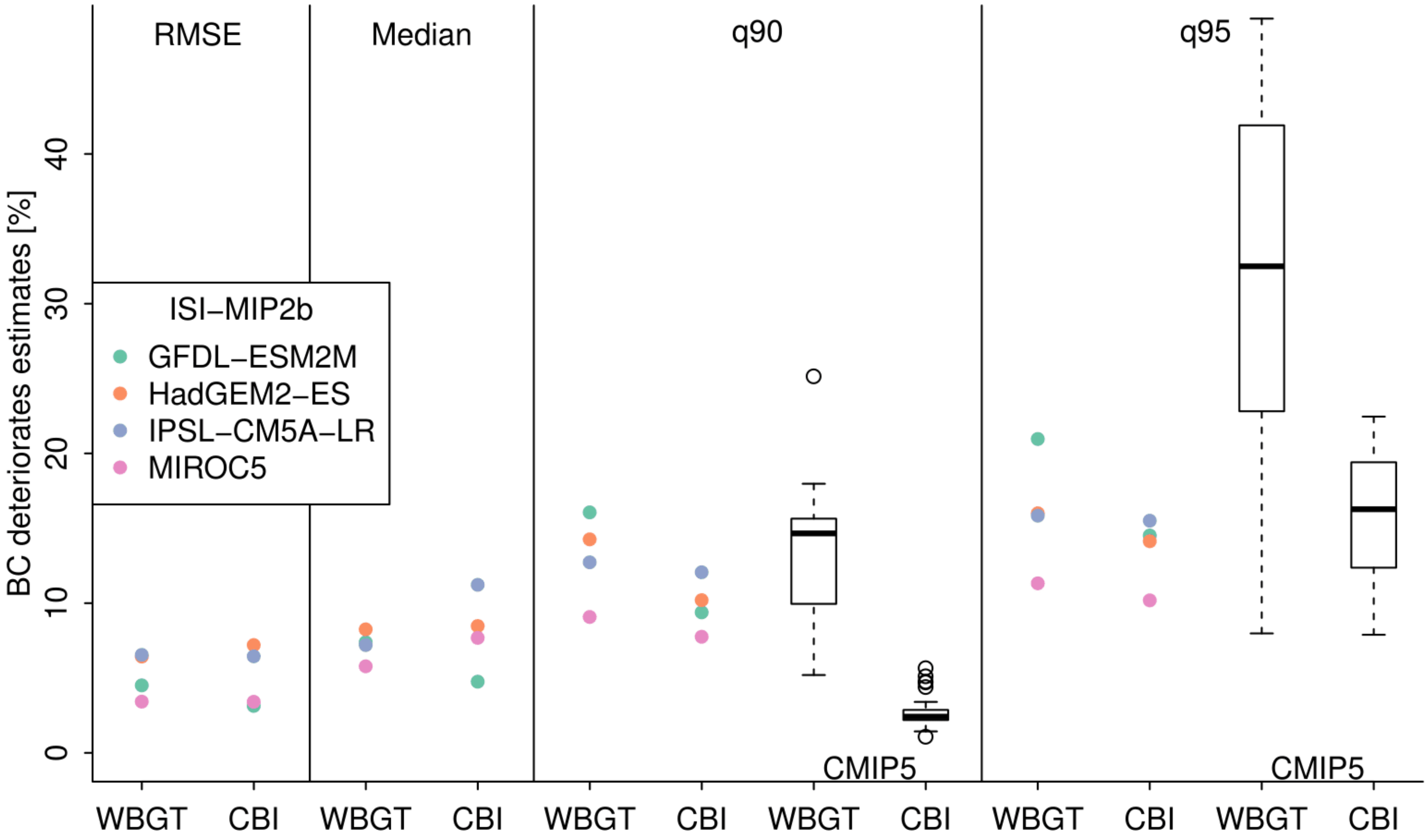
IPSL-CM5A-MR, Central Africa



QQ-plot, IPSL-CM5A-MR, Central Africa



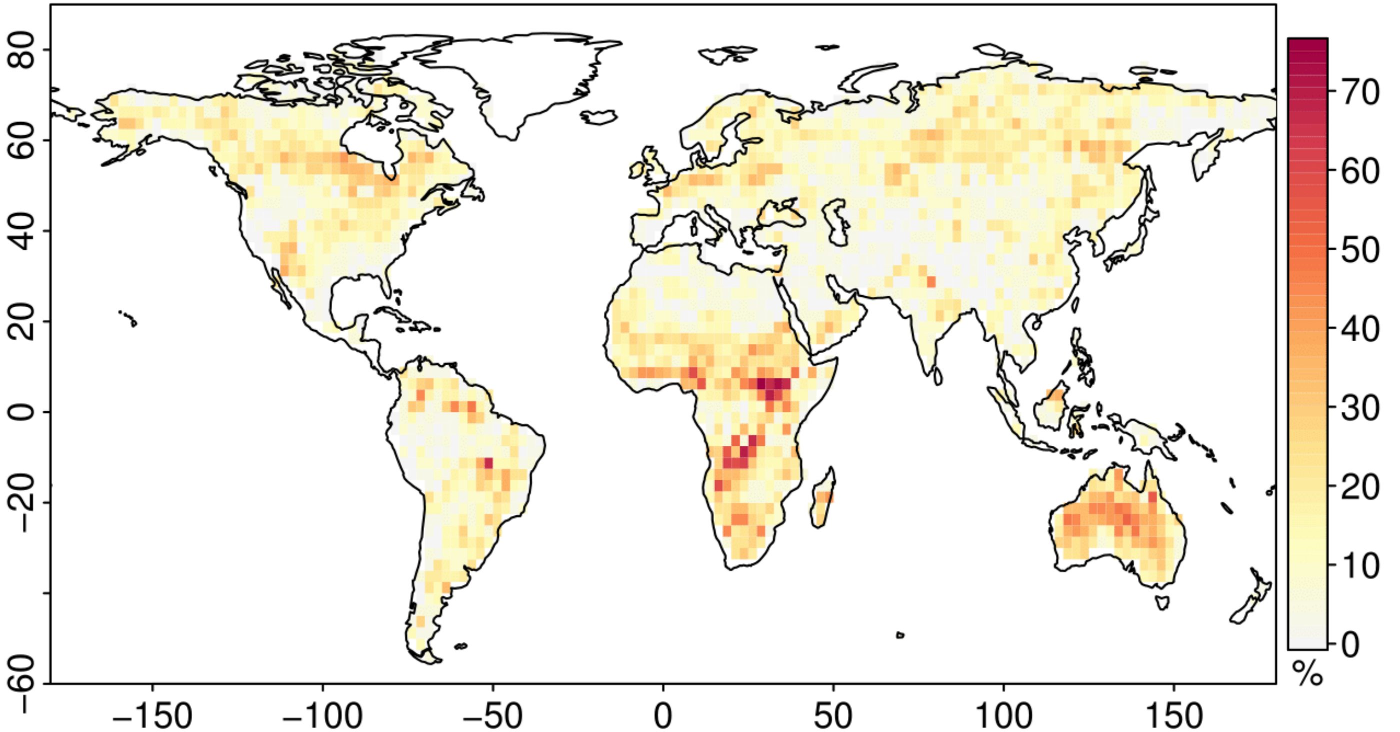
Summary of worst cases



Which regions are affected?

Fraction of models where quantile mapping deteriorates estimate

Hazard: WBGT
Data: CMIP5
90th percentile



Multivariate Bias Correction

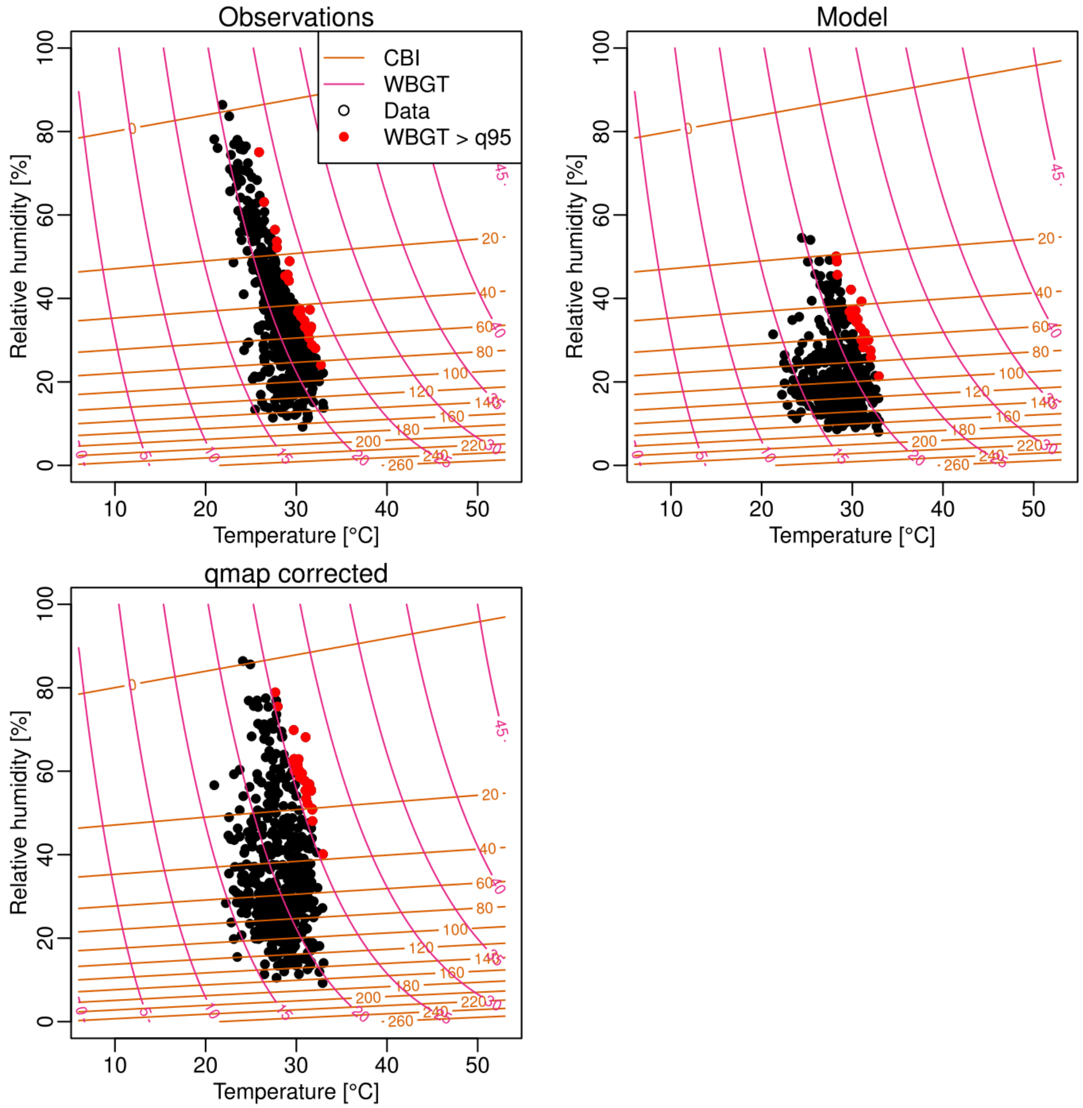
MBCn

a) Apply random rotation to multivariate distribution
b) Apply quantile delta mapping (QDM)
c) Rotate back

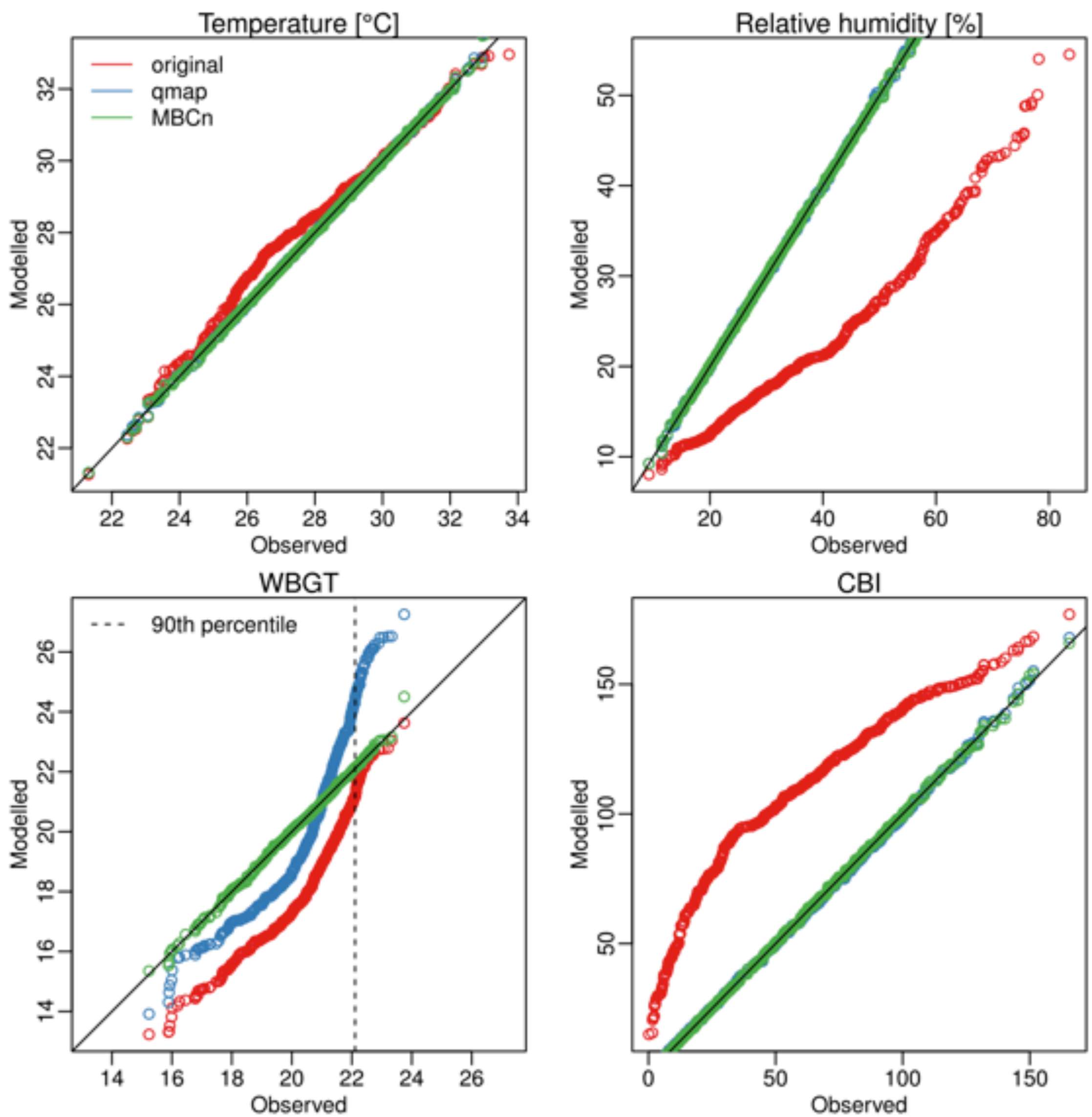
Repeat a)-c) until multivariate modeled distribution matches multivariate observed distribution.

Cannon, 2017

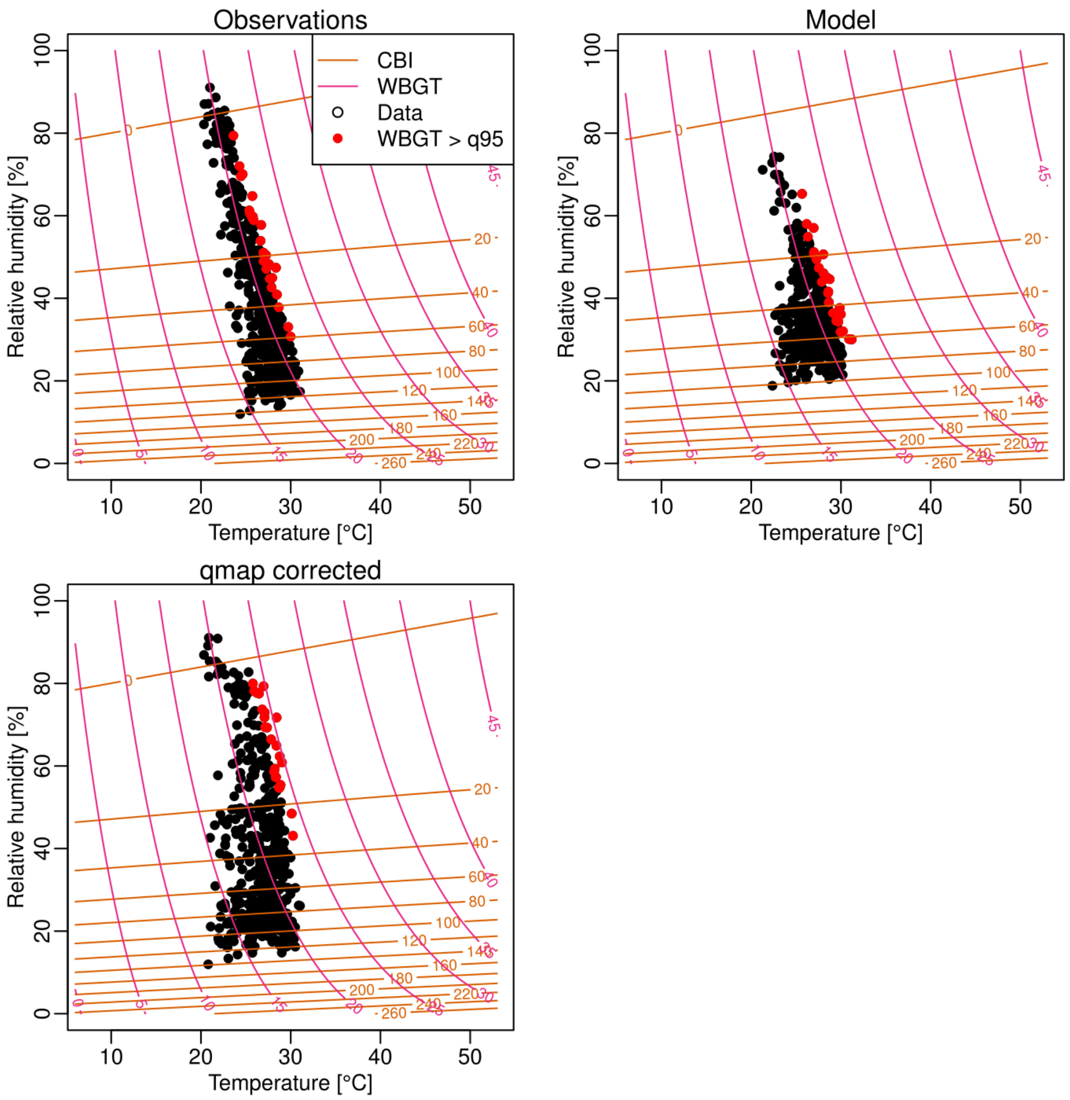
ACCESS, Western North America



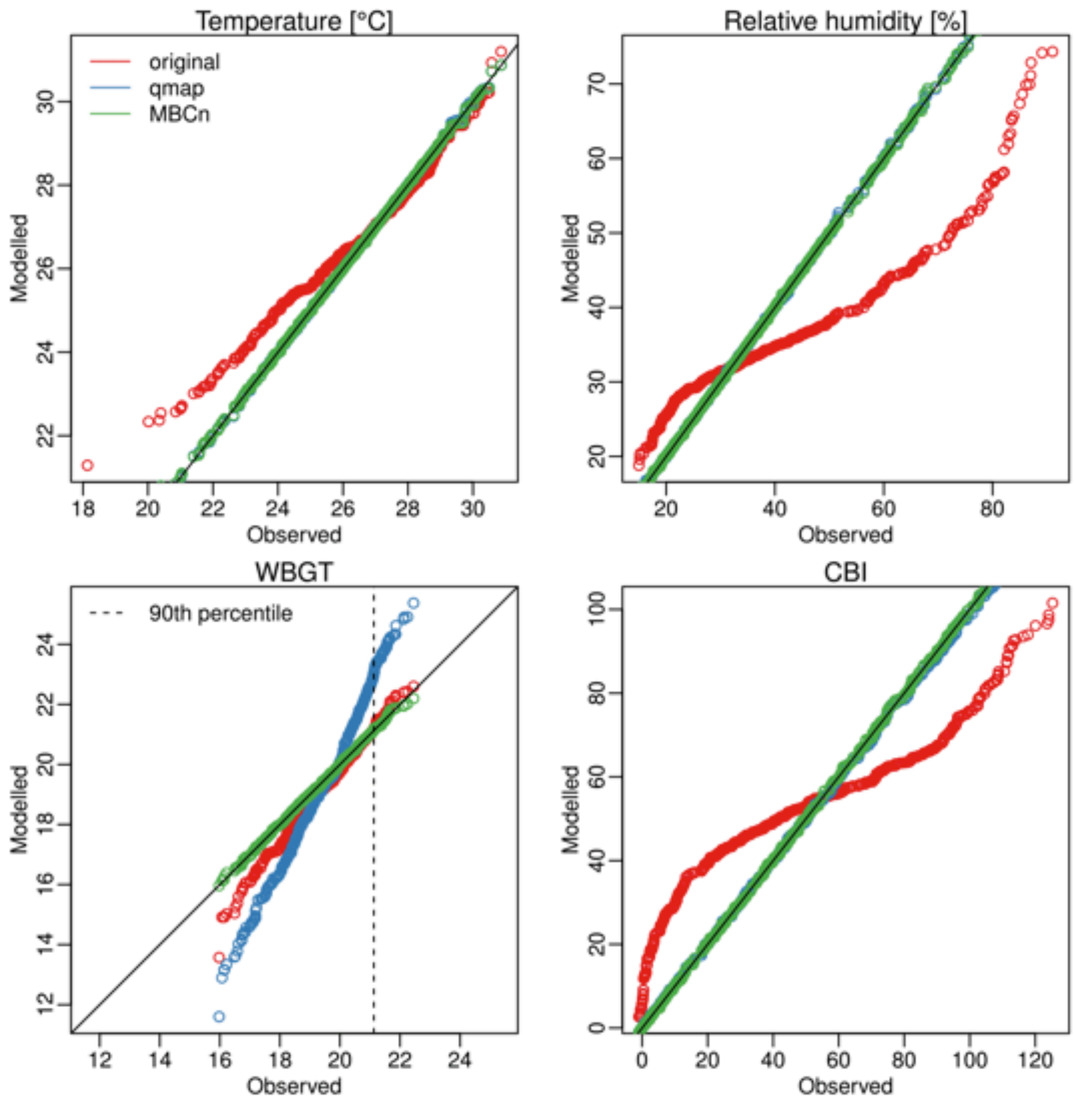
QQ-plot, ACCESS, Western North America



IPSL-CM5A-MR, Central Africa



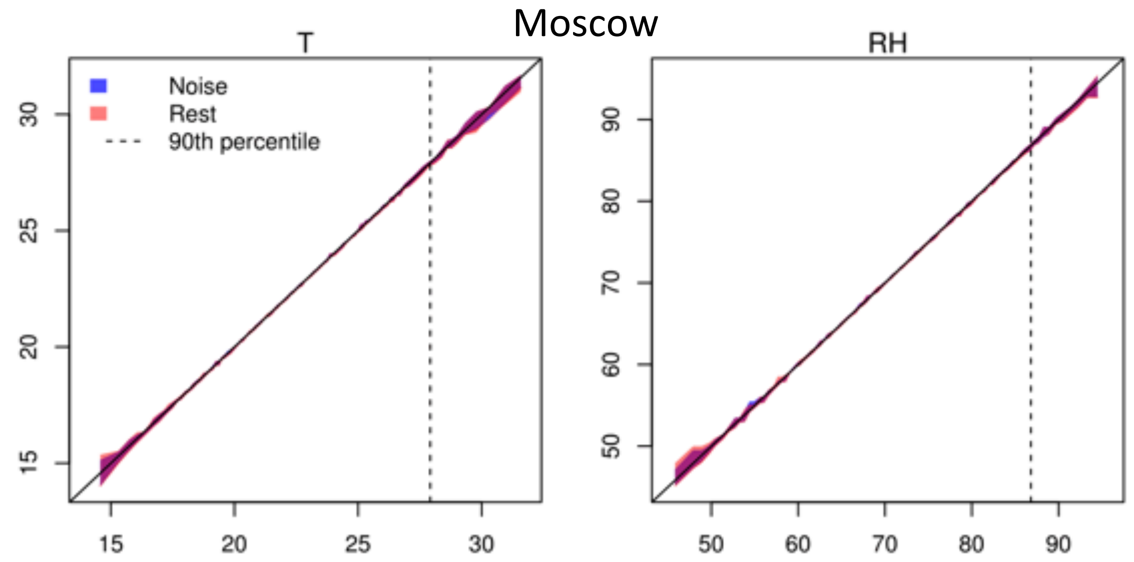
QQ-plot, IPSL-CM5A-MR, Central Africa



Perfect model approach

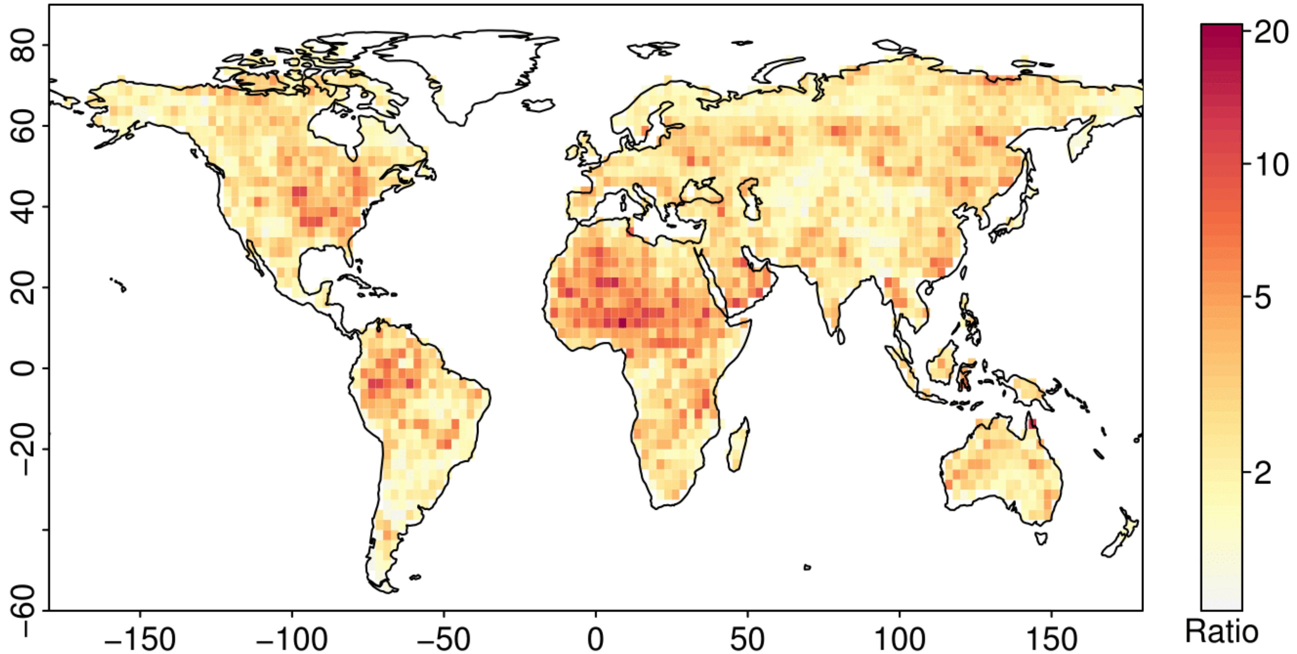
- Goal: study how uncertainty in observations propagates to hazard estimates
- How?
  - Choose a model with multiple runs to illustrate multiple “observations”
  - Bias correct “observations” against “observations” → noise
  - Bias correct other model runs against “observations” → full uncertainty range

Illustration of perfect model approach



Ratio full range/noise

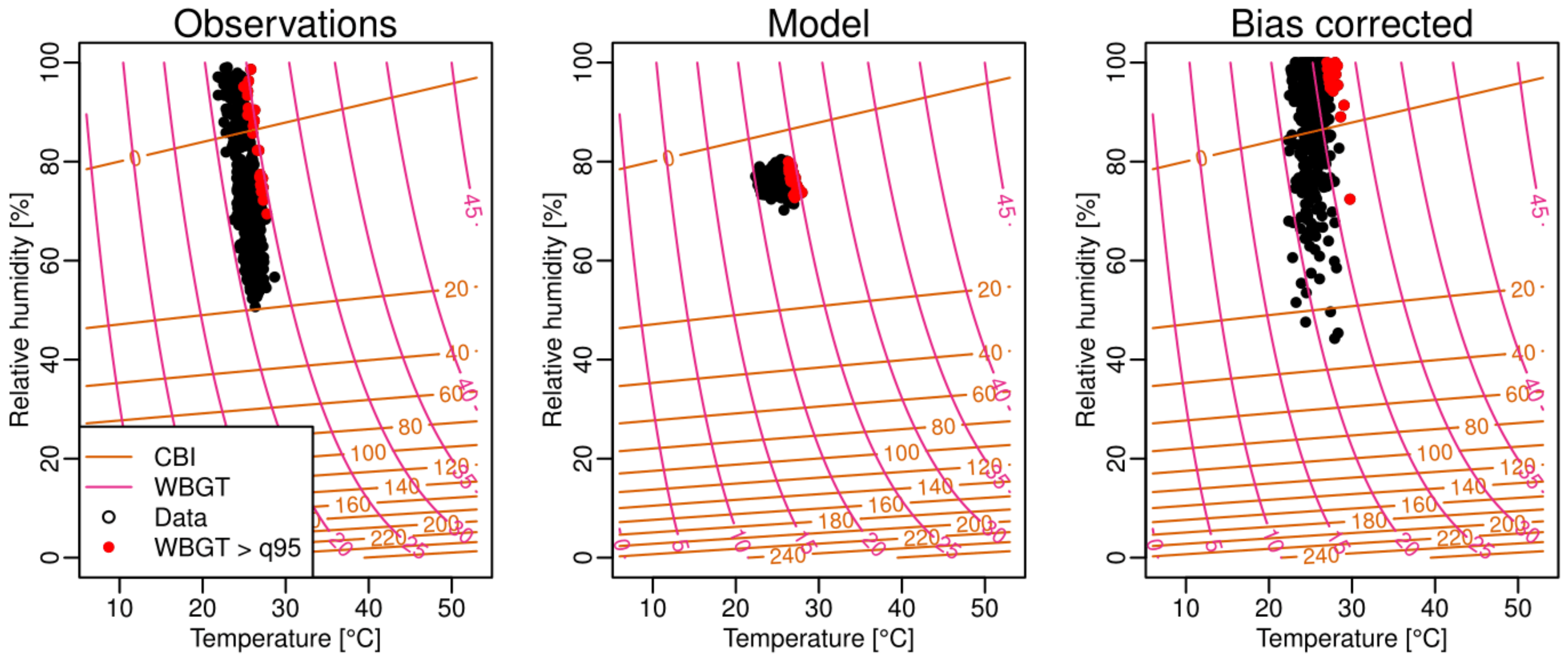
Heat stress, 90th percentile



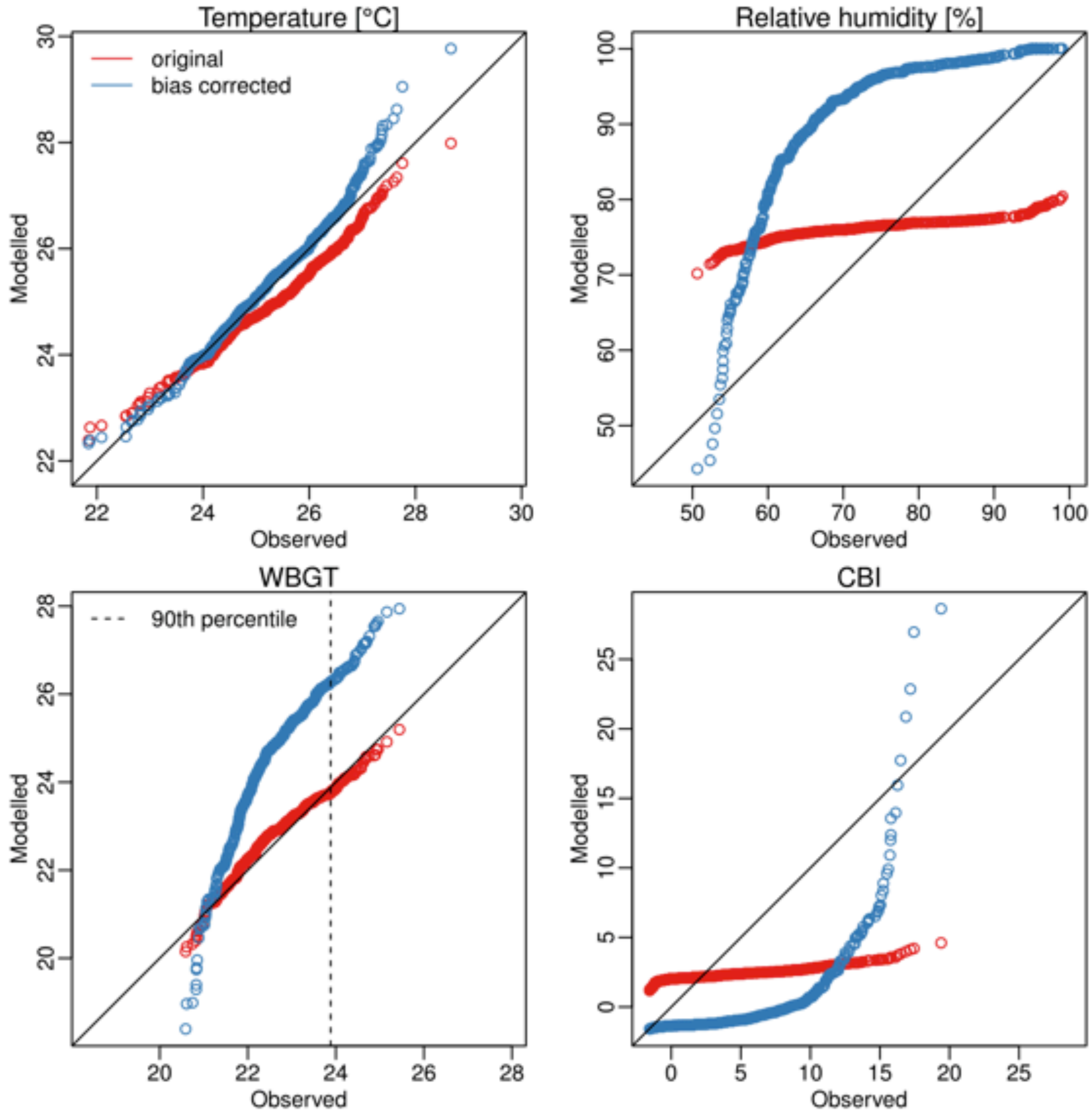
Conclusions

- The effect of widely used bias correction approaches on modelled climate impacts is unclear
- Bias correction methods may in some cases deteriorate hazard estimates
- If impacts depend on multiple variables, bias correction methods that account for multivariate dependencies should be used

ISI-MIP2b, IPSL-CM5A-LR, Central America



QQ-plot

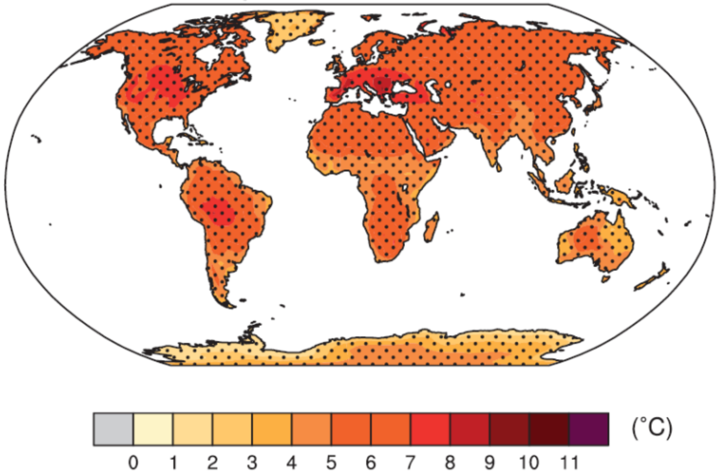


Temperature [°C]
original
bias corrected
Modelled
Observed
Relative humidity [%]
WBGT
90th percentile
CBI

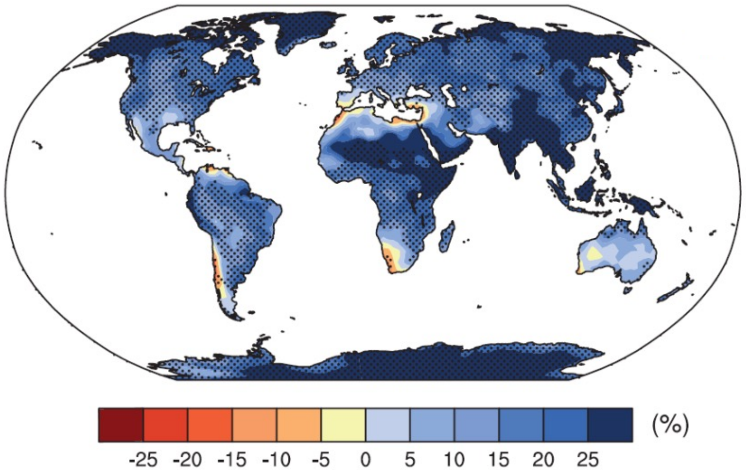
How do we assess climate risks?

- Analyze indicators in climate change projections
- Indicators are derived from expert judgement/ experience

Warming of the hottest day of the year

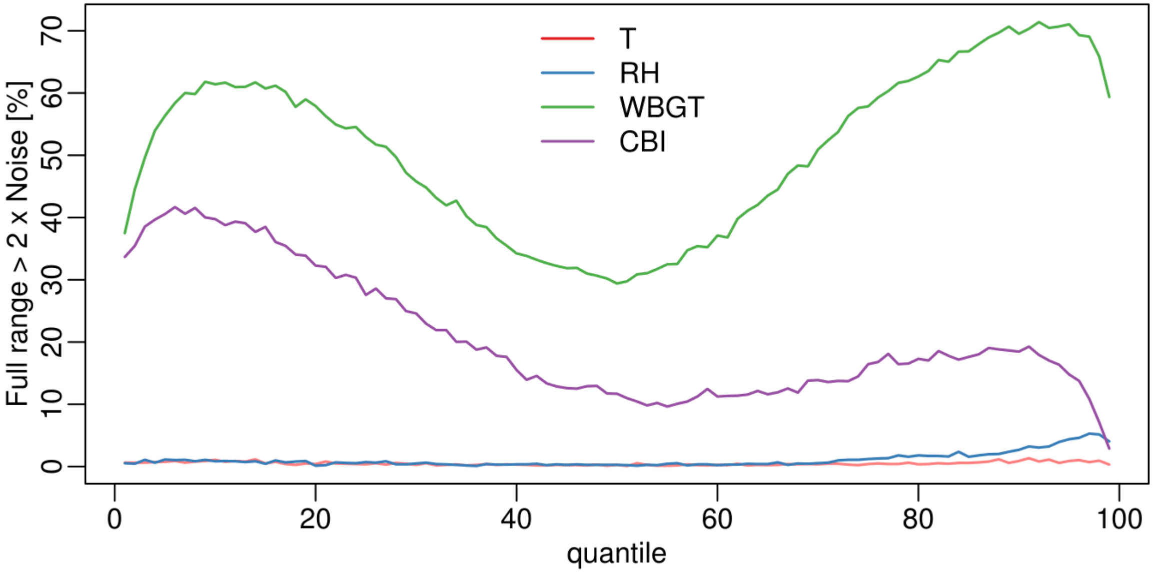


Change in maximum 5-day precipitation



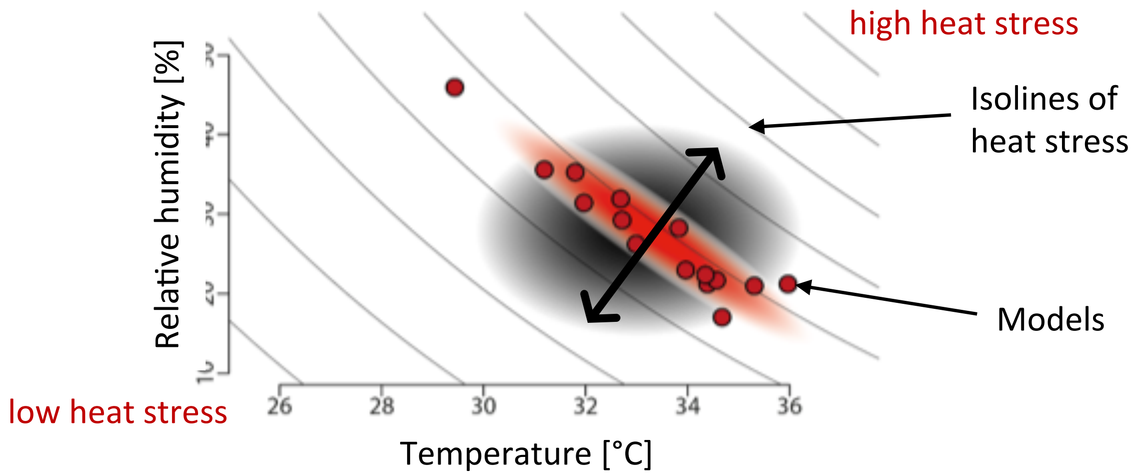
Intergovernmental Panel on Climate Change, 2013

Percentage of pixels: full range > 2 × noise



Dependence can reduce uncertainty

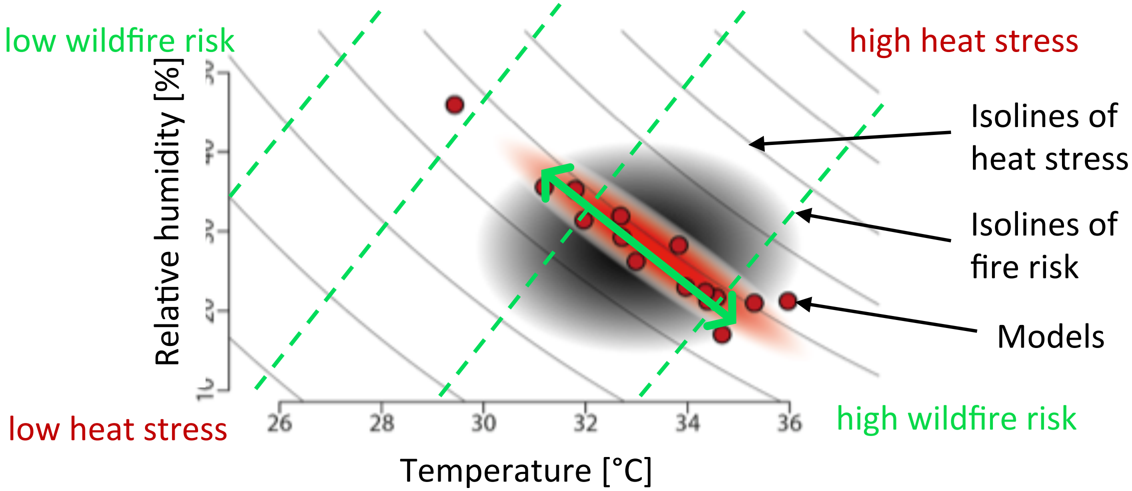
- Heat stress (temperature, relative humidity)



Fischer & Knutti, 2013

This may increase uncertainty for others

- Heat stress (temperature, relative humidity)
- Fire risk (temperature, relative humidity)



Fischer & Knutti, 2013

Dependence affects uncertainty of hazards