Challenges in Downscaling Research

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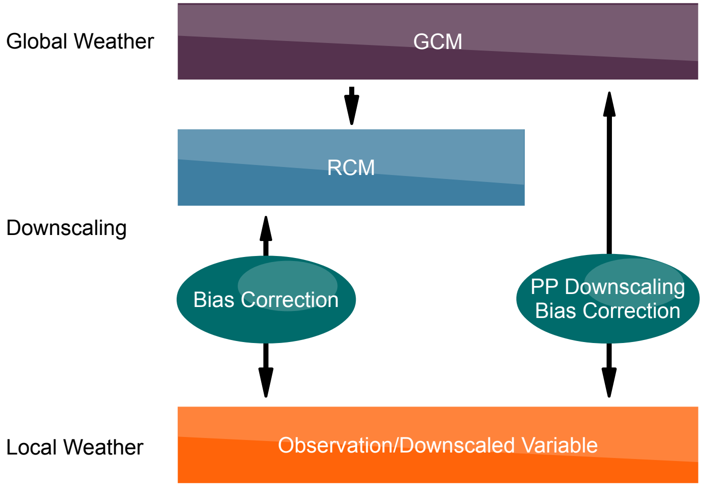
- “Researchers are still struggling to develop tools to accurately forecast climate changes for the twenty-first century at the local and regional level.” *Nature Editorial, 2010*

- “Time to Adapt to a Warming World - But Where’s the Science?” *Kerr, Science, 2011*

Regional Modelling Chain



Outline

Dynamical Modelling Issues

VALUE Evaluation Results

Bias Correction Limitations

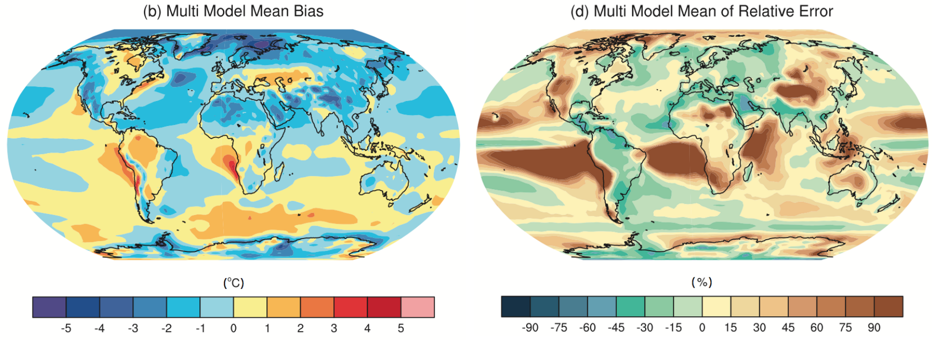
Dynamical Modelling Issues

VALUE Evaluation Results

Bias Correction Limitations

Temperature and precipitation biases

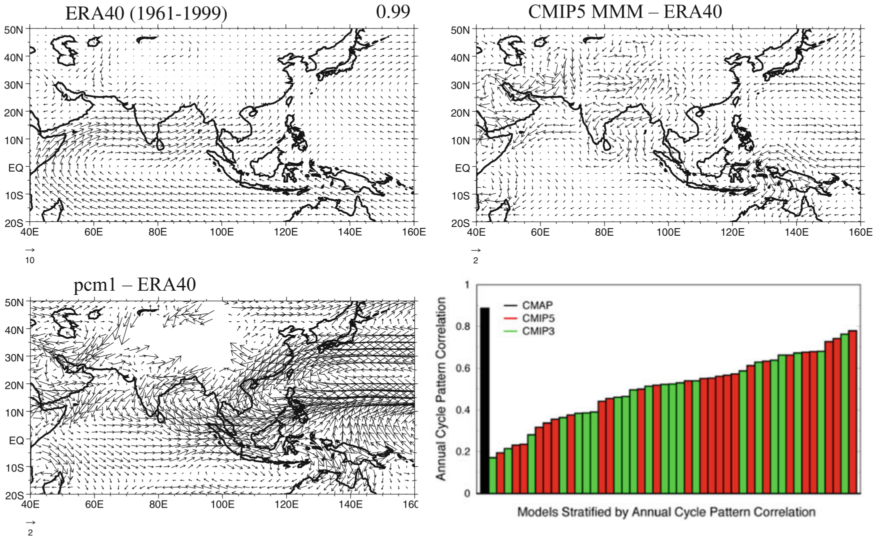
CMIP5, multi-model mean



Biases are (not just wrong numbers, but) surface climate expressions of climate model errors!

Flato et al., IPCC AR5, 2013

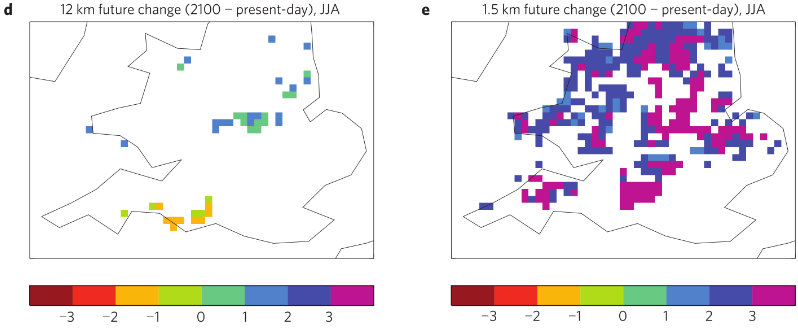
Circulation Bias Example: Monsoon



Sperber et al., Clim. Dynam., 2013

Small-Scale Bias Example: Extreme Rainfall

Projected change of summer subdaily precipitation extremes

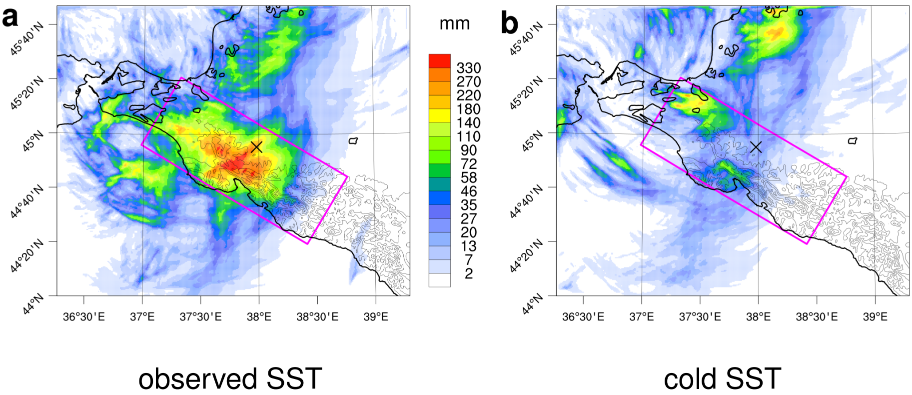


left: RCM at 12km resolution; right: RCM at 1.5km simulation

Kendon et al., Nat. Clim. Change, 2014

Case Study: Krymsk Event, Jul 2012

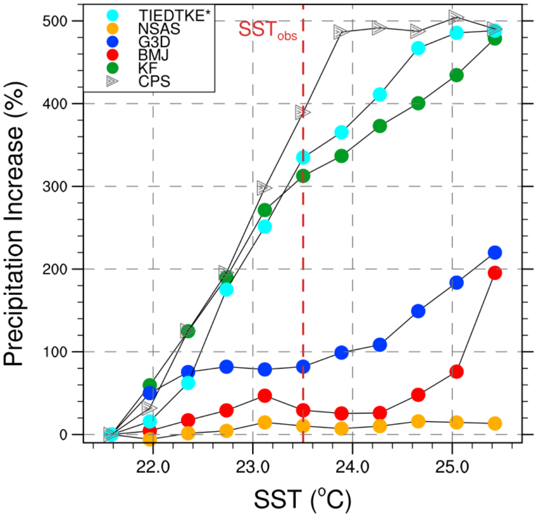
Precipitation response to SST trend, ensemble mean daily precipitation total



Meredith et al., Nat. Geosci., 2015

Resolved vs. parameterised deep convection

High uncertainty due to representation of vertical velocities in conv. parameterisations



Meredith et al., J. Geophys. Res., 2015

Summary Dynamical Modelling Issues

- The resolution of current generation GCMs is too low to realistically simulate the large-scale atmospheric circulation.
- Climate models with parameterised convection struggle simulating a plausible response of extreme precipitation to external forcing.

For a successful downscaling, driving dynamical models are required that realistically simulate present climate conditions and credibly simulate the response to global warming at all relevant scales.

Dynamical Modelling Issues

VALUE Evaluation Results

Bias Correction Limitations

Framework paper

AGU PUBLICATIONS

Earth's Future

RESEARCH ARTICLE
10.1002/2014EF000259

VALUE: A framework to validate downscaling approaches for climate change studies

Douglas Maraun[1], Martin Widmann[2], José M. Gutiérrez[3], Sven Kotlarski[4], Richard E. Chandler[5], Elke Hertig[6], Joanna Wibig[7], Radan Huth[8], and Renate A.I. Wilcke[9]

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Key Points:

- VALUE has developed a framework to validate and compare downscaling methods
- The experiments comprise different observed and pseudo-reality reference data
- The framework is the basis for a comprehensive downscaling comparison study

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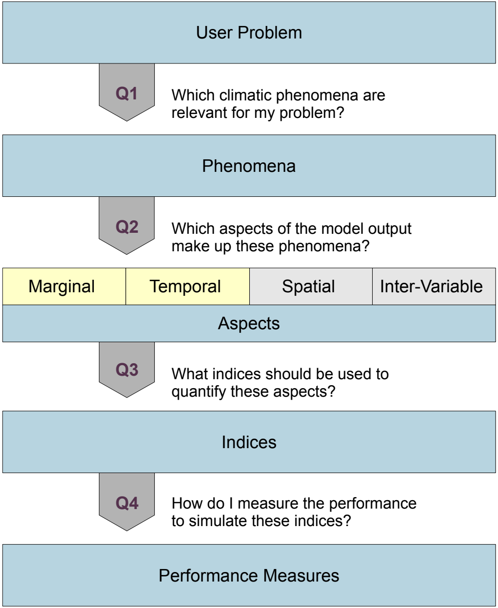
Validation tree



Examples of Indices and Performance Measures

www.value-cost.eu/reports

Marginal Distributions

Index	Performance Measure
Mean, Variance, 98% Percentile	(relative) bias

Temporal Dependence

Index	Performance Measure
Spell statistics	Bias

Spatial Dependence

Index	Performance Measure
Decay lengths of correlation/tail dependence	(relative) bias

Multivariate Dependence

Index	Performance Measure
Joint threshold exceedances	(relative) bias
Variable conditioned on large-scale circulation	(relative) bias

Validation experiments

www.value-cost.eu/validation

- **Perfect Predictor**
  Predictors/boundary conditions from ERA-Interim Reanalysis

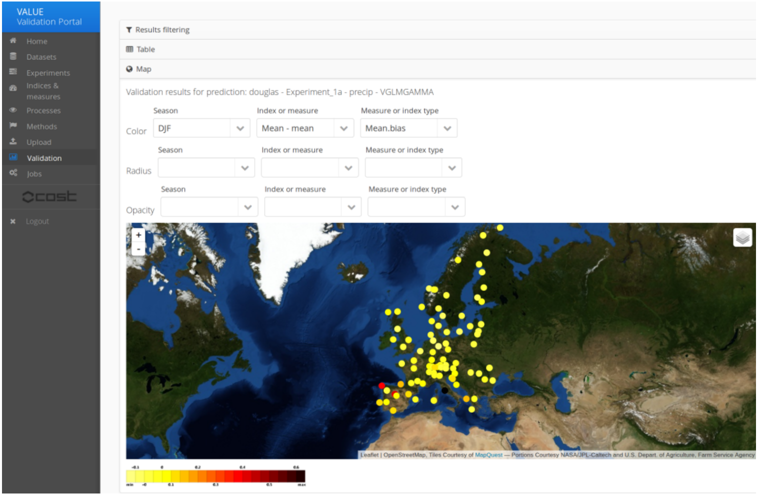
- **Pseudo Reality**
  Predictands from regional climate models (Present and future)

- **GCM-Predictors**
  Predictors/boundary conditions from global climate models

Maraun et al., Earth's Future, 2015

VALUE Portal (open upload!)

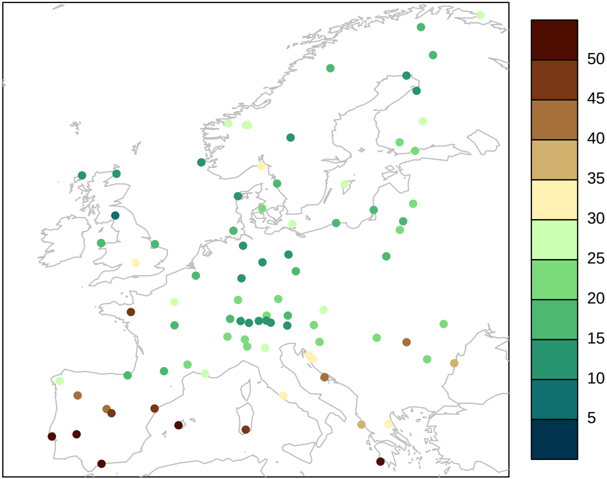
www.value-cost.eu/validationportal



Many thanks to José Gutierrez, Sixto Herrera, Daniel San Martín, Joaquín Bedia

Precipitation - mean annual maximum dry spell

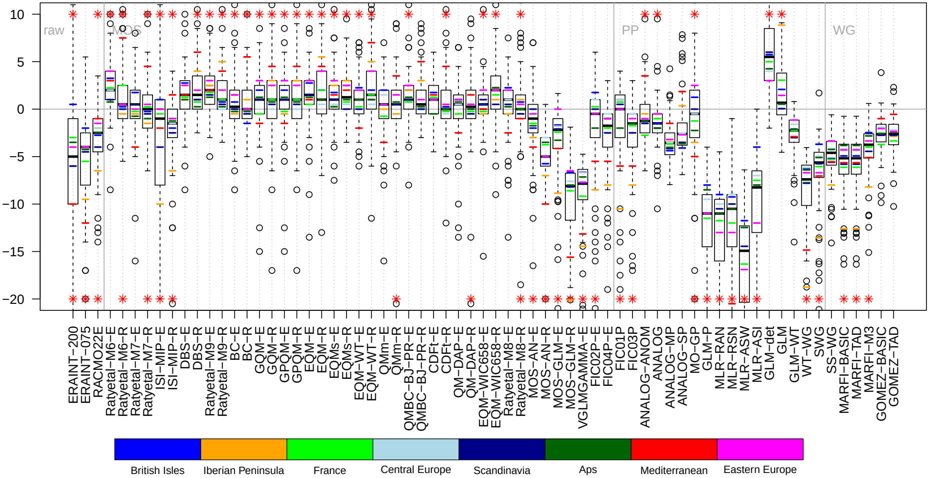
Observed climate [days]



Maraun et al., Int. J. Climatol., 2017

Precipitation - mean annual maximum dry spell

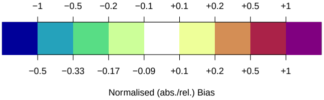
Biases across all stations [days]



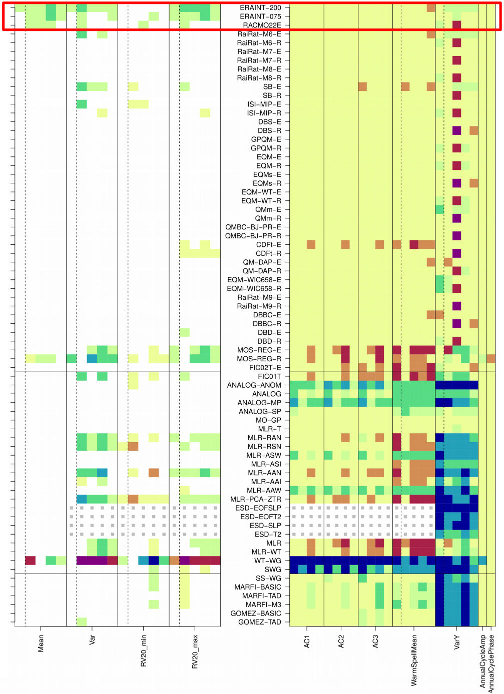
* values outside plotted range

Maraun et al., Int. J. Climatol., 2017

T_{max} | Raw Model Data

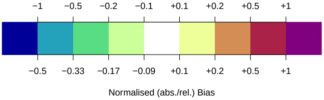


- Reanalyses slightly underestimate marginal properties;
- Reanalyses slightly too smooth in time;
- RCM adds value, but overestimates MAM interannual variability.

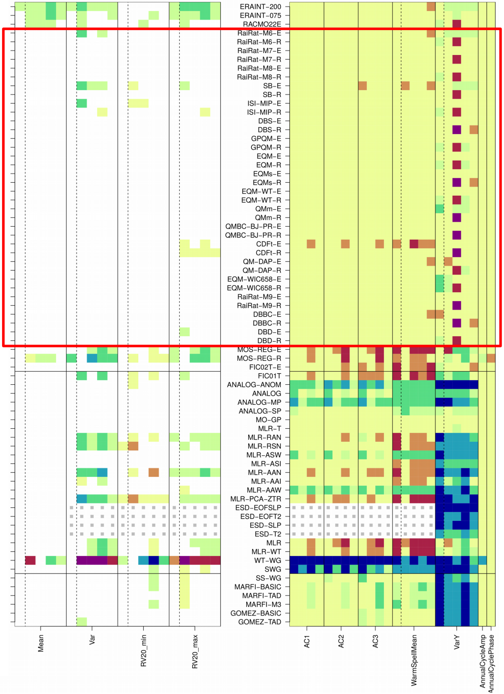


Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

T_{max} | MOS

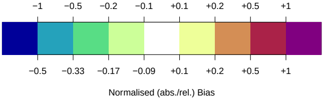


- any bias correction essentially removes all marginal biases;
- temporal structure more or less inherited from driving data;



Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

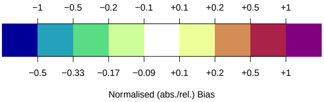
T_{max} | Analog



- performs well for marginal properties;
- too little temporal structure;

Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

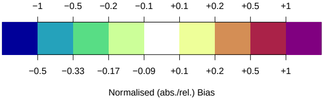
T_{max} | MLR



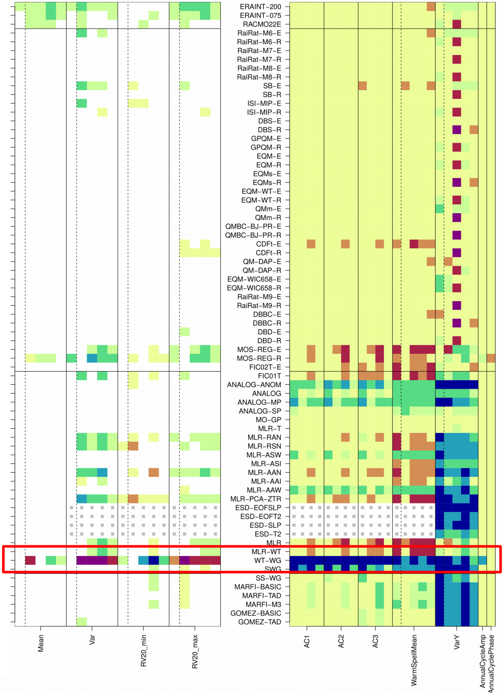
- means okay, other marginal properties else underestimated;
- temporal structure too smooth, for white noise randomisation too noisy;
- interannual variability underestimated;

Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

T_{max} | Weather Typing

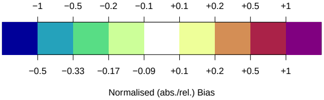


- depends very much on the predictors and implementation;
- typically rather badly;

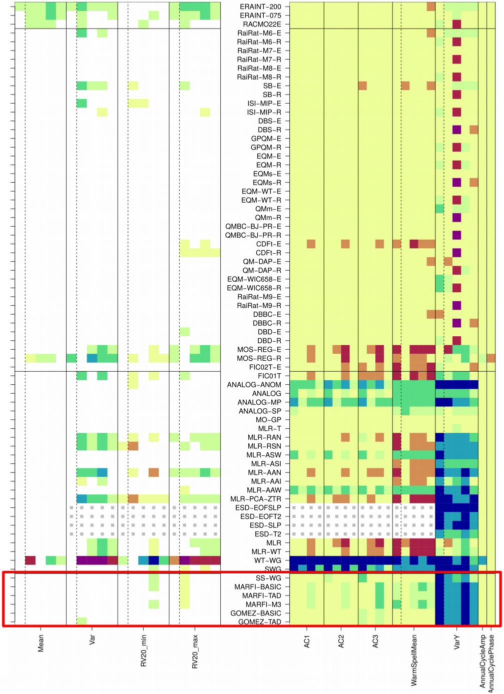


Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

T_{max} | Weather Generators

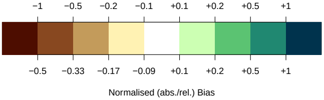


- good for marginal aspects
- temporal aspects okay but interannual variability



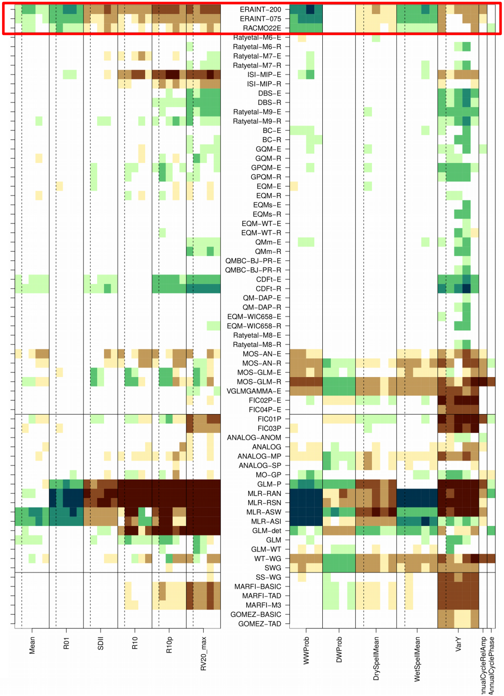
Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

Precip | Raw Model Data

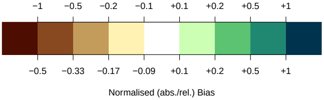


- Reanalyses slightly overestimate means and wet day frequency, all other marginal aspects underestimated;
- wet spells too long, dry spells too short; interannual variability too weak;
- RCM adds value for many aspects;

Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

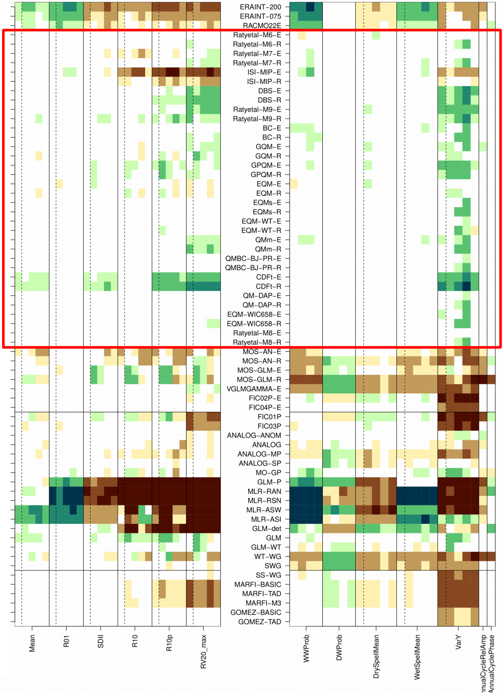


Precip | MOS

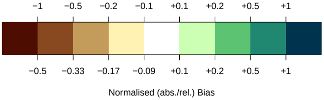


- okay for means; for extremes strong dependence on implementation;
- temporal aspects much improved by wet day correction;
- interannual variability too large;

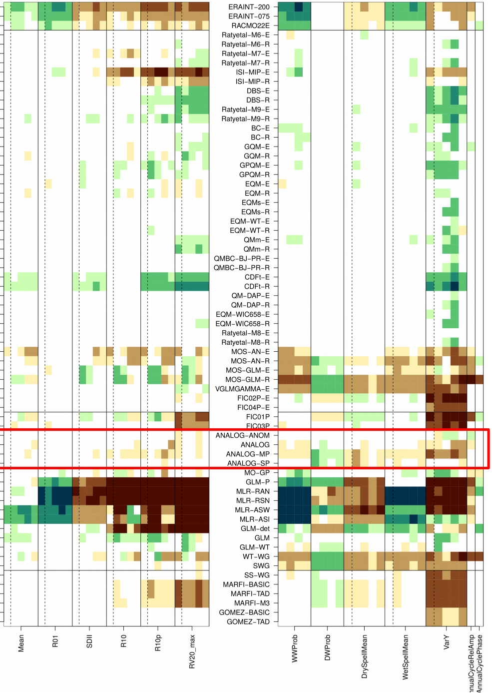
Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017



Precip | Analog

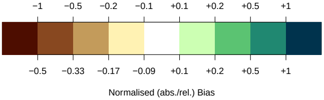


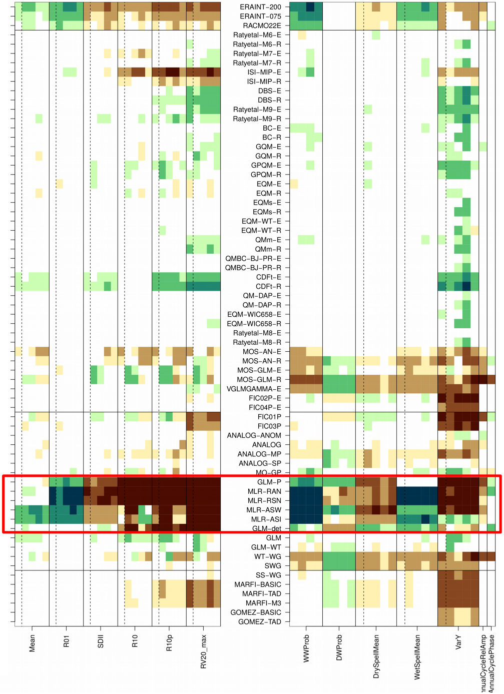
- well performing for most marginal aspects;
- okay for temporal aspects;
- interannual variability depends strongly on implementation;



Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

Precip | MLR

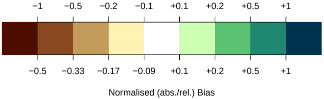




- MLR is not suitable for downscaling daily precipitation.

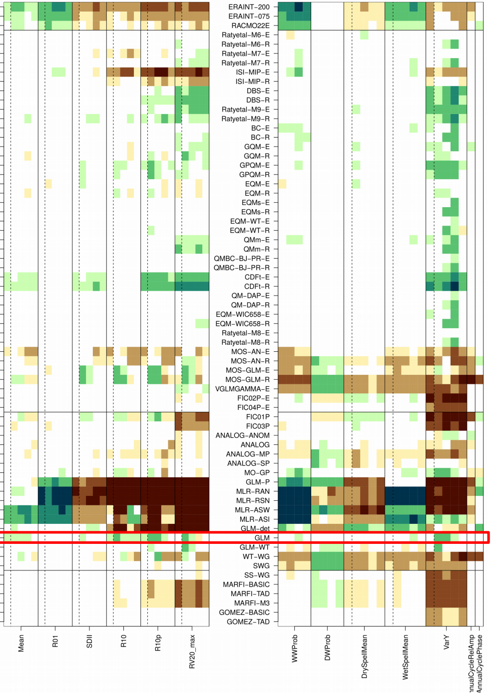
Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

Precip | stochastic GLM

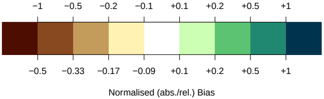


- performs well for most aspects;
- underestimates extremes (gamma distribution) and interannual variability;

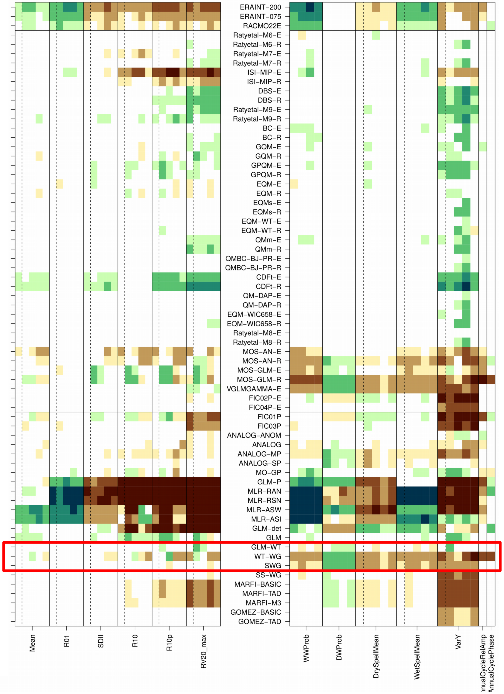
Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017



Precip | Weather Typing

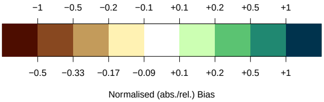


- mostly rather bad, depends on predictors;

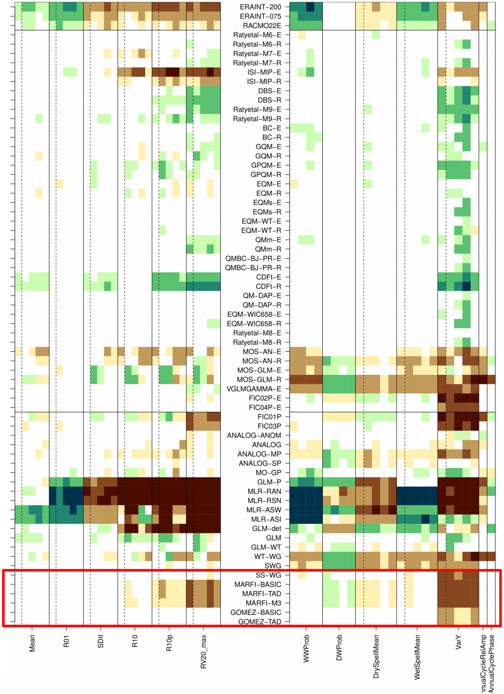


Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

Precip | Weather Gen.



- good for calibrated aspects;
- underestimates extremes and interannual variability.



Gutierrez et al., 2017; Maraun et al., 2017; Hertig et al., 2017

Summary VALUE Evaluation

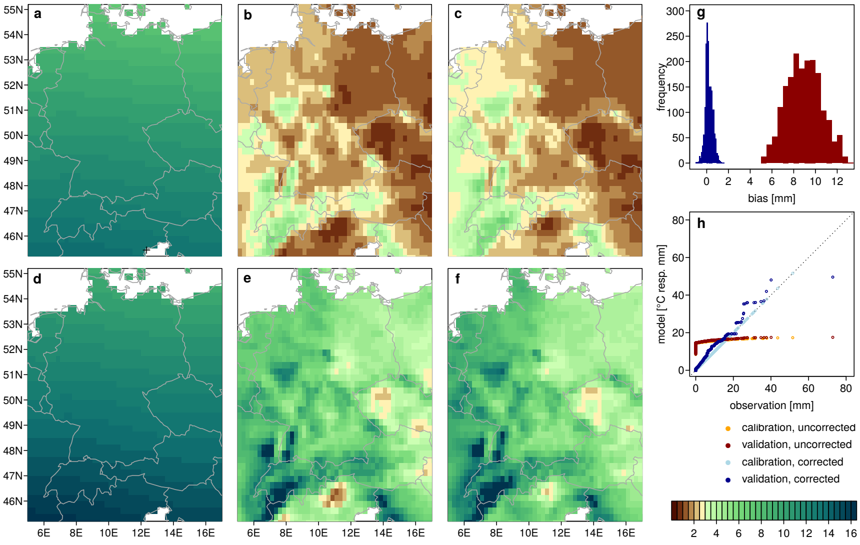
- MOS/Bias correction removes marginal biases, temporal structure is inherited by driving models;
- most PP/ESD methods have difficulties simulating anything beyond the mean; for precipitation stochastic GLMs are required.
- weather generators get everything right they are calibrated for, everything else wrong.
- Special Issue in Int. J. Climatol. (forthcoming)

Dynamical Modelling Issues

VALUE Evaluation Results

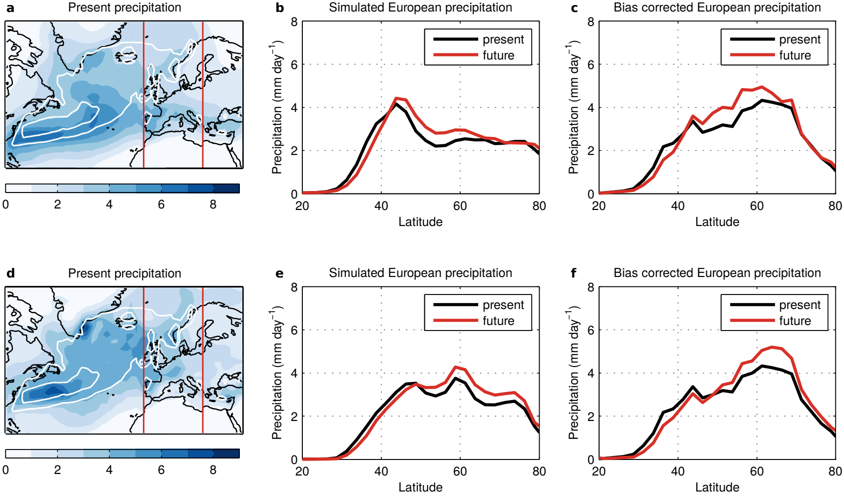
Bias Correction Limitations

Validation Problem



Maraun et al., Nat. Clim. Change, 2017

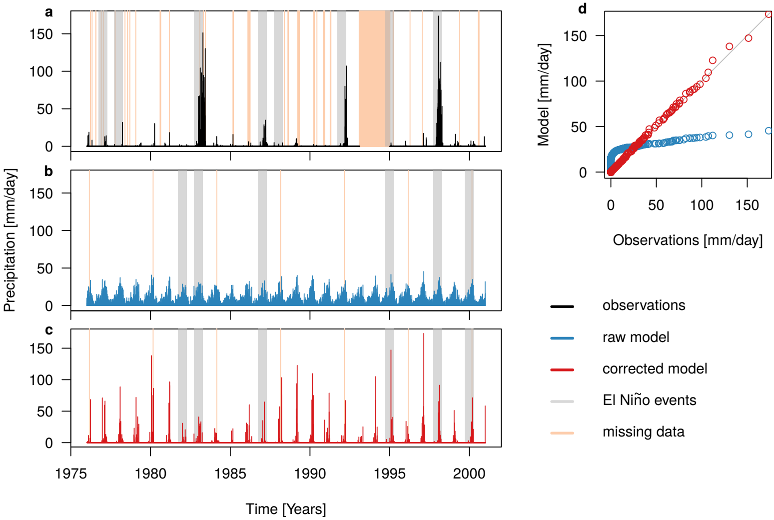
Storm Track Bias



Maraun et al., Nat. Clim. Change, 2017

Representativeness

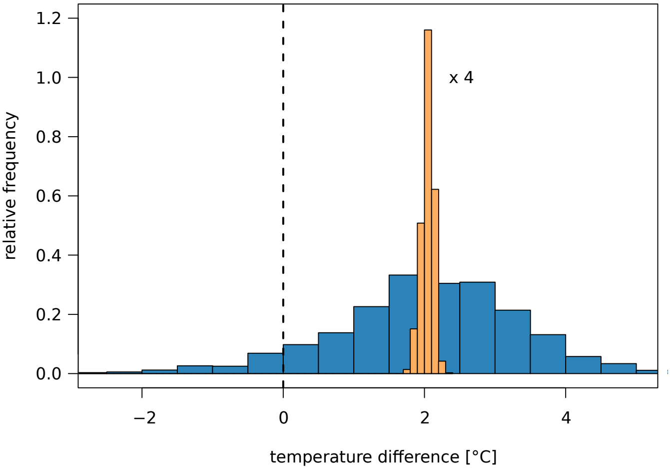
ENSO Variability



Maraun et al., Nat. Clim. Change, 2017

BC & Downscaling: Temperature Inversion

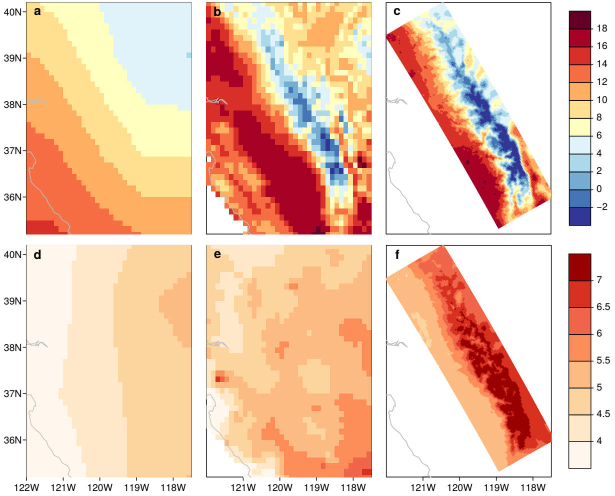
Temperature difference between two sites in Central Valley & Sierra Nevada, California; blue: observated temperature difference; orange: bias corrected GCM difference



Maraun, J. Climate, 2013; Maraun et al., Nat. Clim. Change, 2017

BC & Downscaling: Elevation Depend. Warming

MAM; top: present, bottom: climate change signal.
Left: raw GCM; center: QM corrected; right: 3km RCM



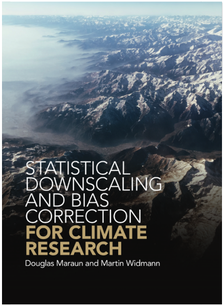
Maraun, J. Climate, 2013; Maraun et al., Nat. Clim. Change, 2017

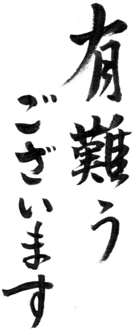
Summary Bias Correction Limitations

- Bias correction requires realistic, credible and representative input.
- Applying bias correction requires physcial understanding, otherwise artefacts are likely to occur.

Summary

- For successful downscaling, the driving dynamical models need to realistically simulate present climate conditions and credibly simulate the response to global warming at relevant scales.
  $\rightarrow$ **Process-based dynamical model selection.**
- **Statistical downscaling/bias correction needs to be selected for each individual application.**
- Bias correction needs to be process-informed.
- **Thinking out of the box!**





Forthcoming perspective in Nat. Clim. Change
Special Issue in Int. J. Climatol. (publ./subm.)
Forthcoming book, Cambridge Univ. Press