



Evaluation of Regional Climate Projections

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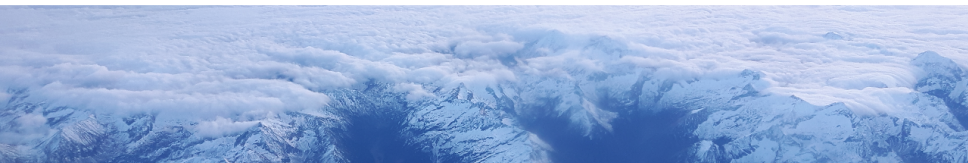
Uncertainties

Evaluation Framework

Dynamical Model Performance

Statistical Downscaling Performance

Practical Guidelines



Uncertainties

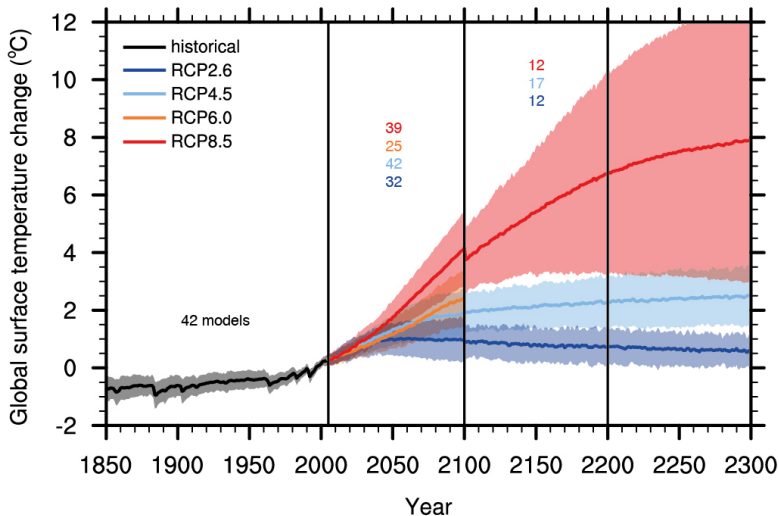
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Projected global mean temperature



Collins et al., IPCC, 2013

Sources of Uncertainty

Forcing Uncertainty

- ▶ greenhouse gas emissions
- ▶ other anthropogenic forcings
- ▶ natural forcings

Model Imperfections

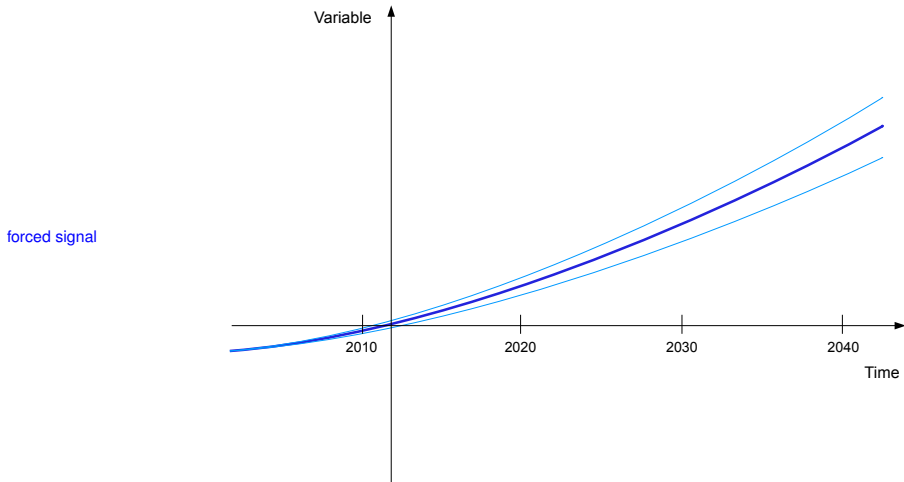
- ▶ model inadequacies (processes misrepresented or missing)
- ▶ model uncertainty (choice of parameters, parameterisations)

Internal Climate Variability

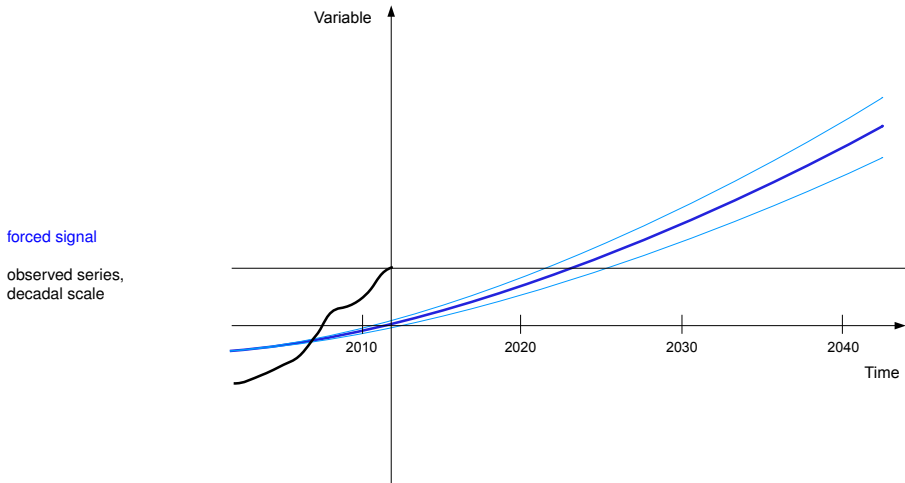
- ▶ Random fluctuations on scales from days to centuries

Model ensembles are required to sample uncertainties!

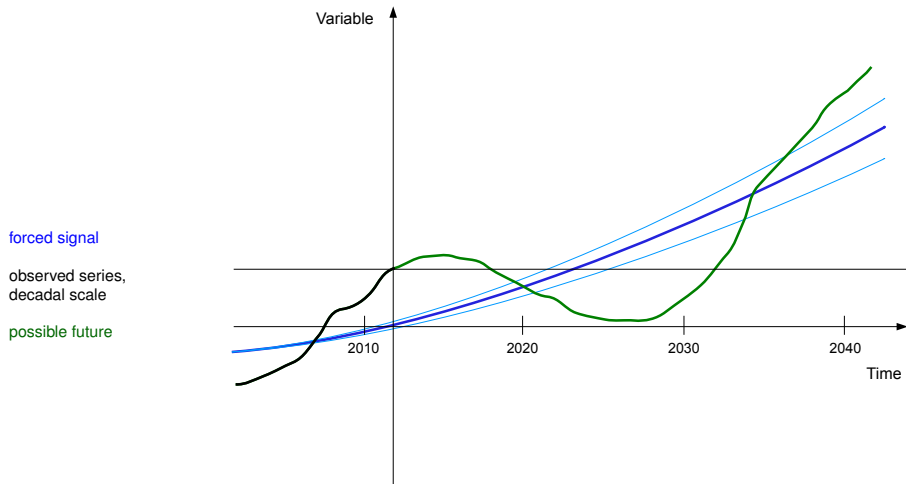
The Role of Internal Climate Variability



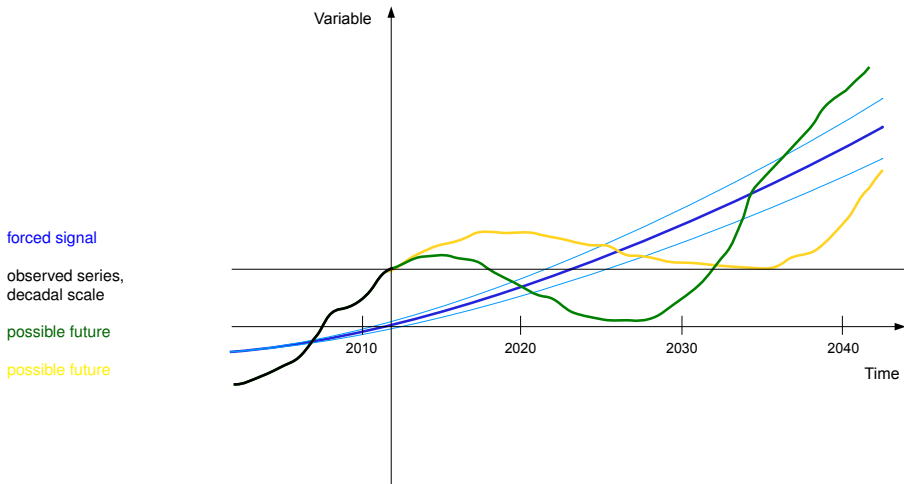
The Role of Internal Climate Variability



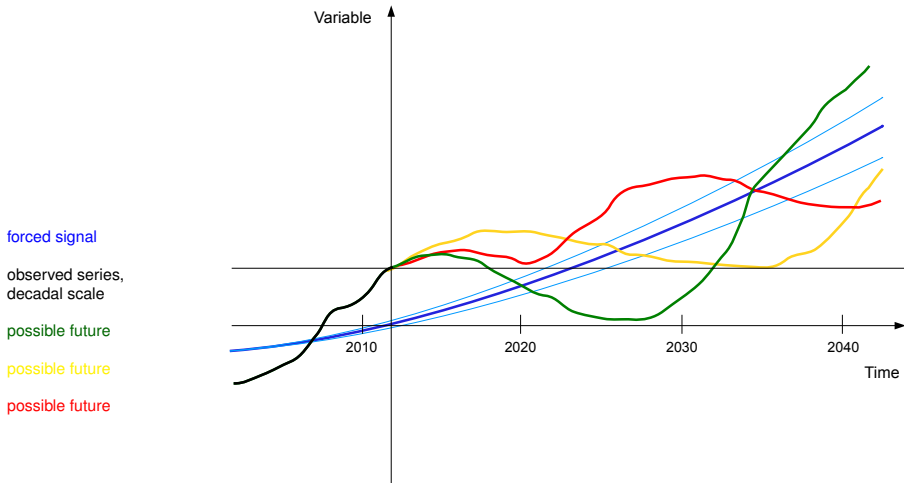
The Role of Internal Climate Variability



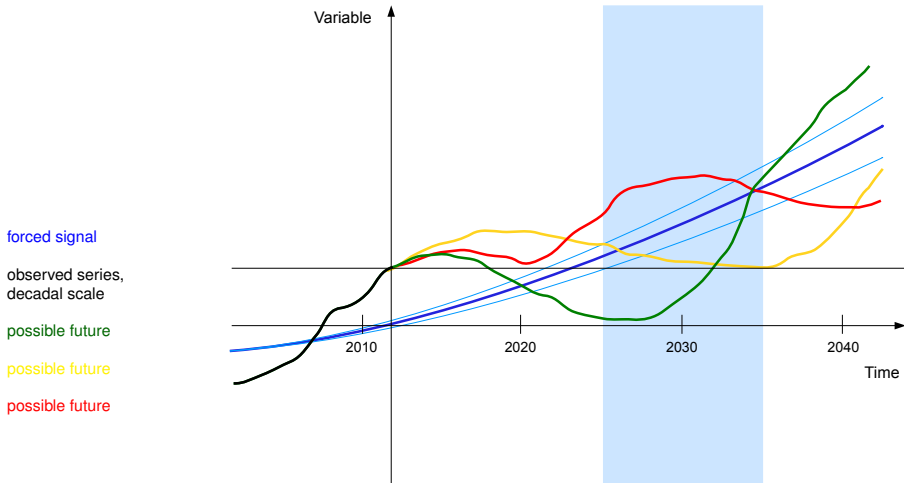
The Role of Internal Climate Variability



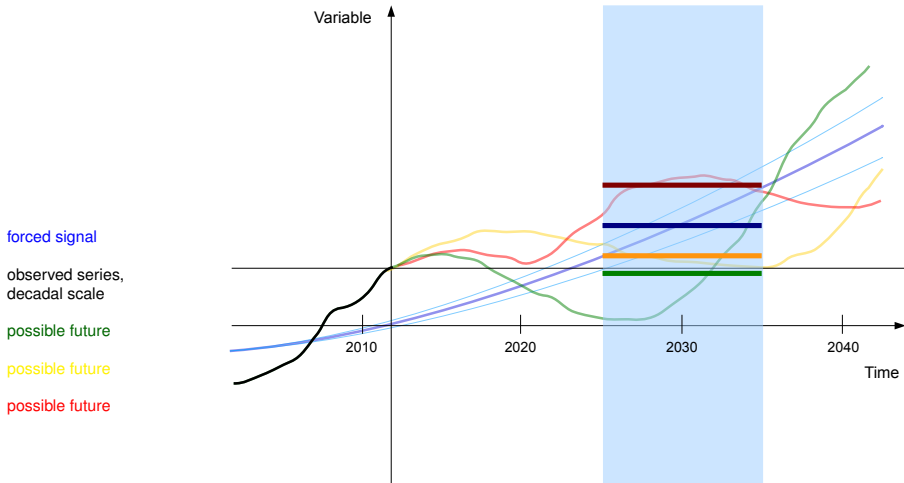
The Role of Internal Climate Variability



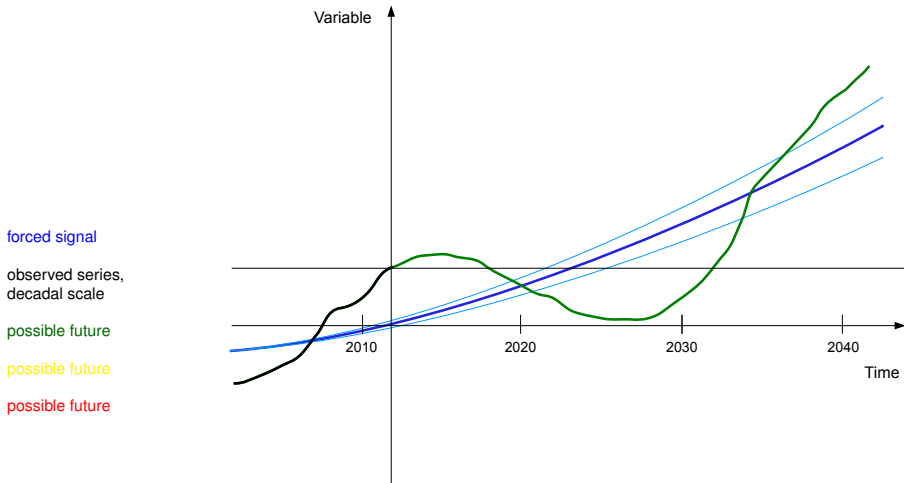
The Role of Internal Climate Variability



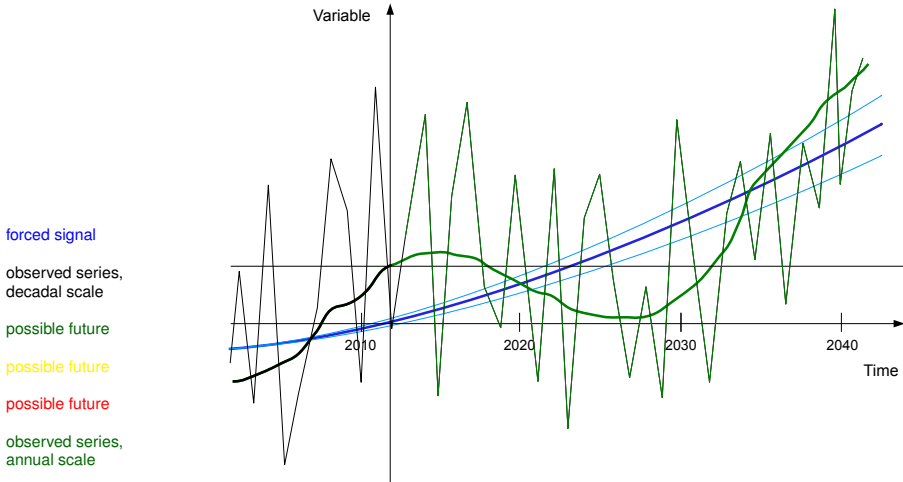
The Role of Internal Climate Variability



The Role of Internal Climate Variability



The Role of Internal Climate Variability



Representativeness and Deep Uncertainty

Does the climate model represent the processes of interest?

- ▶ A GCM does not simulate local precipitation extremes
- ▶ A GCM does not simulate local elevation dependent warming
- ▶ Many GCMs do not realistically simulate monsoonal precipitation

Here, the **simulated uncertainties** (from an ensemble) do not represent **real uncertainties**. The missing uncertainties are **deep uncertainties**.

Climate projections should not be interpreted as reliable probabilistic projections! They at best represent **credible** simulations of future climate



Uncertainties

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Framework paper

www.value-cost.eu



Earth's Future

RESEARCH ARTICLE

10.1002/2014EF000259

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

Douglas Maraun¹, Martin Widmann², José M. Gutiérrez³, Sven Kotlarski⁴, Richard E. Chandler⁵, Elke Hertig⁶, Joanna Wibig⁷, Radan Huth⁸, and Renate A.J. Wilcke⁹

¹GEOMAR Helmholtz Centre for Ocean Research Kiel, Kiel, Germany, ²School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, UK, ³Institute of Physics of Cantabria, IFCA, Santander, Spain, ⁴Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland, ⁵Department of Statistical Science, University College London, London, UK, ⁶Institute of Geography, University of Augsburg, Augsburg, Germany, ⁷Department of Meteorology and Climatology, University of Lodz, Lodz, Poland, ⁸Department of Physical Geography and Geoecology, Faculty of Science, Charles University and Institute of Atmospheric Physics, Academy of Sciences of the Czech Republic, Prague, Czech Republic, ⁹Rosby Centre, Swedish Meteorological and Hydrological Institute, Norrköping, Sweden

Key questions

for regional climate change research

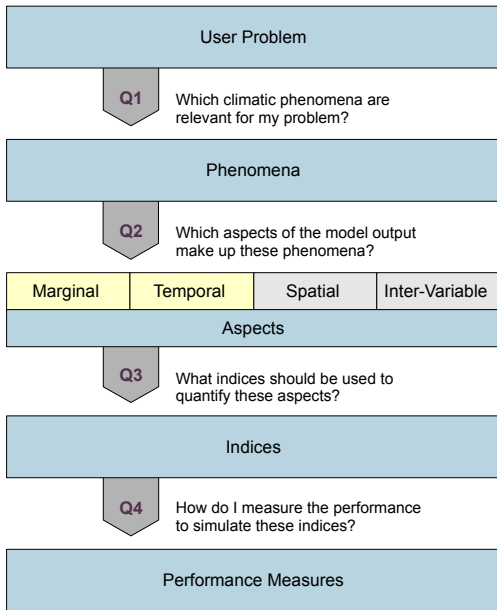
- ▶ How well do GCMs simulate the input for regional climate change projections?
- ▶ How well do downscaling methods work, in particular under climate change?
- ▶ How strong is the signal-to-noise ratio between climate change trends and internal climate variability at regional scales?



Evaluation Framework

Evaluation Diagnostics

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



Evaluation Framework

Standard Evaluation Experiments

Standard Evaluation Experiments

► **Perfect Predictor**

Predictors/boundary conditions from ERA-Interim Reanalysis
What is the downscaling skill?

► **GCM-Predictors**

Predictors/boundary conditions from global climate models
What is the overall skill of the regional simulation?



Evaluation Framework

Trend Evaluation Experiments

Trend Evaluation

► **Perfect Predictor**

Predictors/boundary conditions from reanalysis

What is the skill of the downscaling approach to capture observed trends?

► **GCM-Predictors**

Predictors/boundary conditions from global climate models

What is the overall skill to capture observed trends?

► **Pseudo-Reality**

Predictors/boundary conditions from global climate models

What is the downscaling skill to capture simulated future trends?

► **Credibility of GCM and RCM Projections**

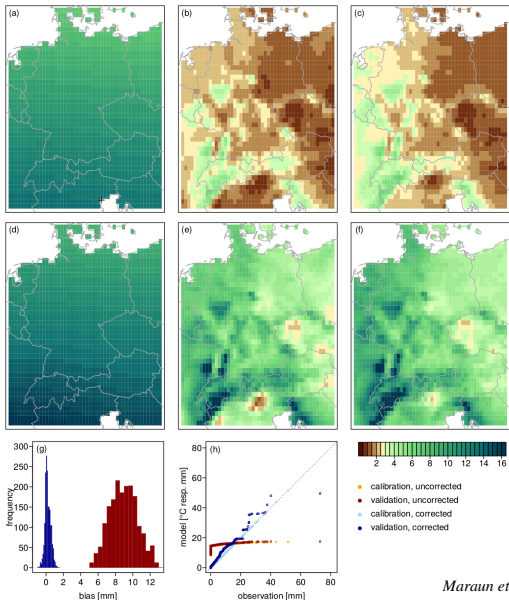
How realistic are large- and local-scale processes controlling climate change, how credible are thus the predictors?



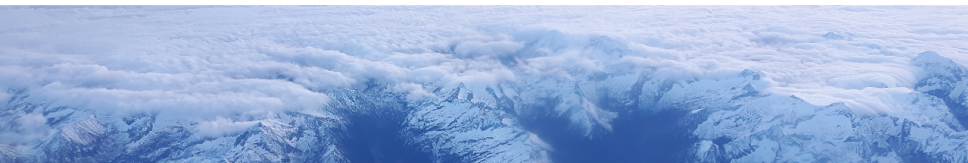
Evaluation Framework

Evaluation of Bias Correction Methods

Validation Problem



Maraun et al., in revision



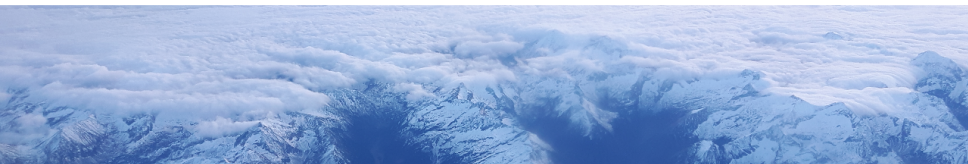
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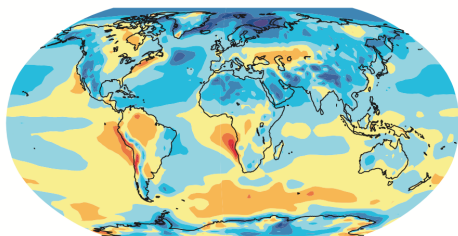
Dynamical Model Performance

Large-Scale Errors

Temperature and precipitation biases

CMIP5, multi-model mean

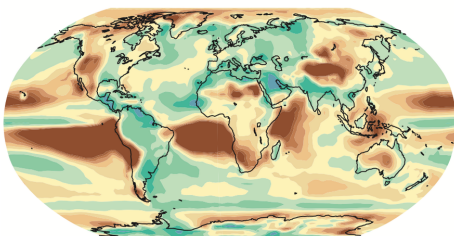
(b) Multi Model Mean Bias



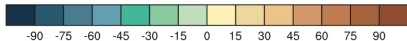
(°C)



(d) Multi Model Mean of Relative Error



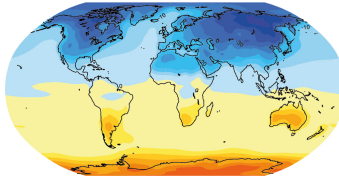
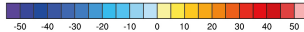
(%)



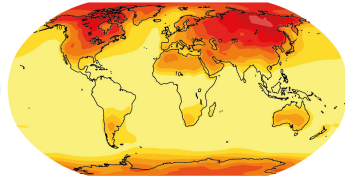
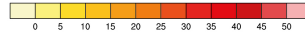
Flato et al., IPCC AR5, 2013

Temperature seasonality

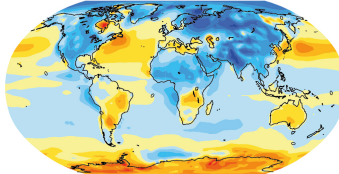
(a) Multi Model Mean Surface Temperature Seasonality

($^{\circ}\text{C}$)

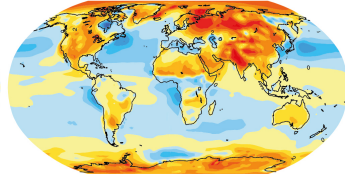
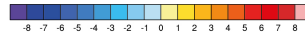
(b) Multi Model Mean of Absolute Seasonality

($^{\circ}\text{C}$)

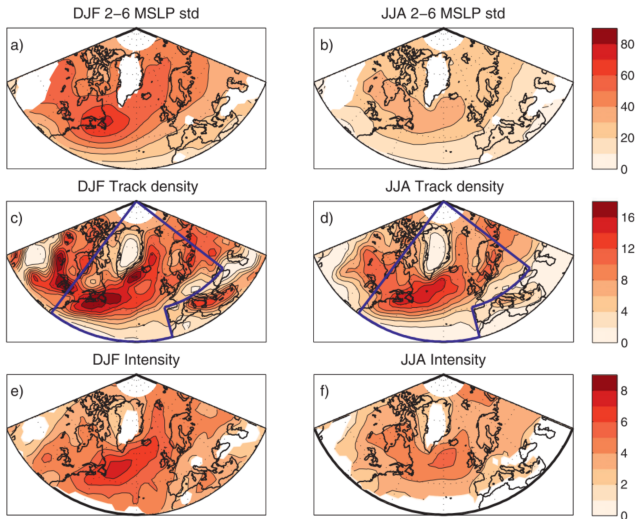
(c) Multi Model Mean Bias in Seasonality

($^{\circ}\text{C}$)

(d) Multi Model Mean Bias in Absolute Seasonality

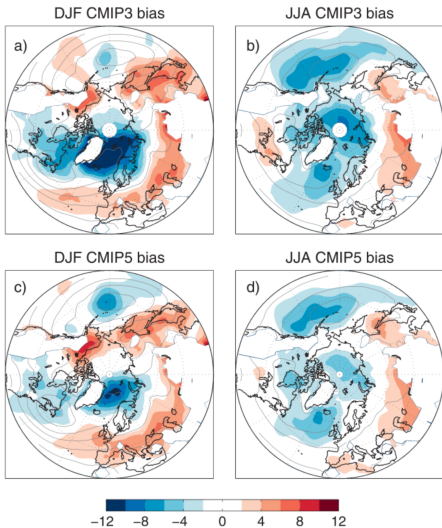
($^{\circ}\text{C}$)*Flato et al., IPCC, 2013*

Observed storm track (ERA-Interim)



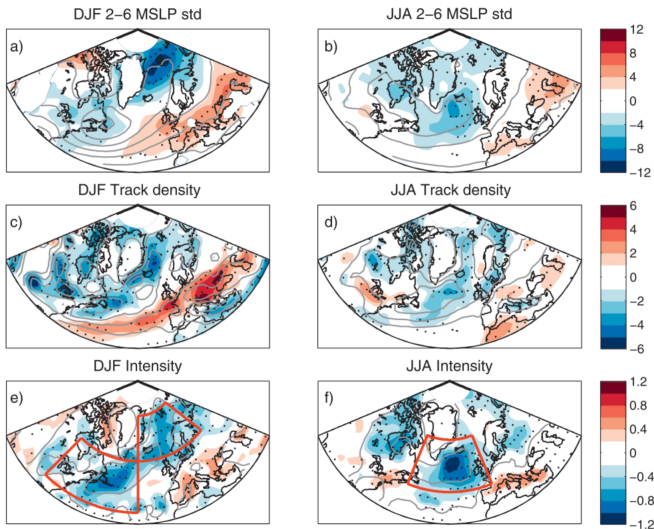
Zappa et al., J. Climate, 2013

Mean bias (2-6 day MSLP sdt dv)



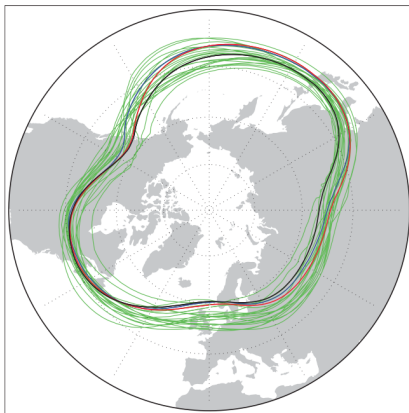
Zappa et al., *J. Climate*, 2013

Mean bias (CMIP5)



Zappa et al., J. Climate, 2013

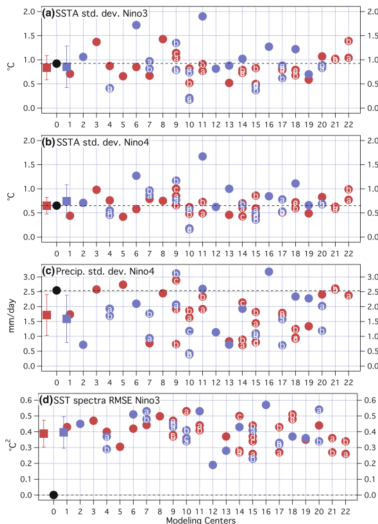
Displaced storm tracks



black: ERA40; green: CMIP3 models; red, blue: two high resolution models

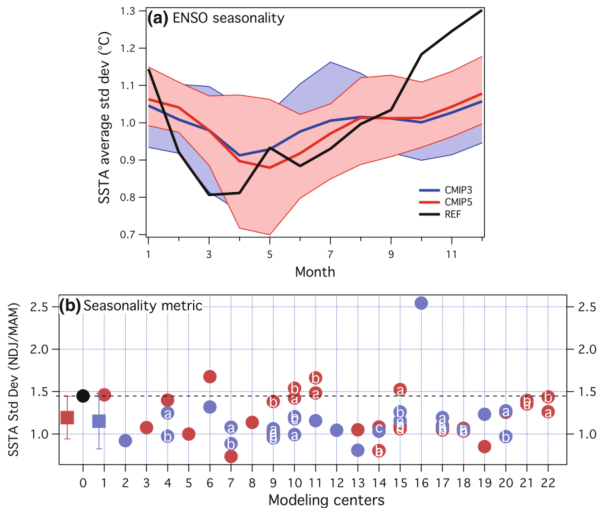
Woollings, Phil Trans R. Soc, 2010

ENSO SST variability



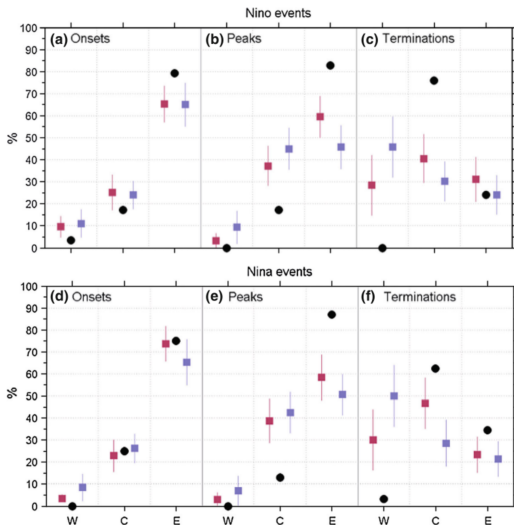
Bellenger et al., *Clim. Dynam.*, 2014

ENSO seasonality



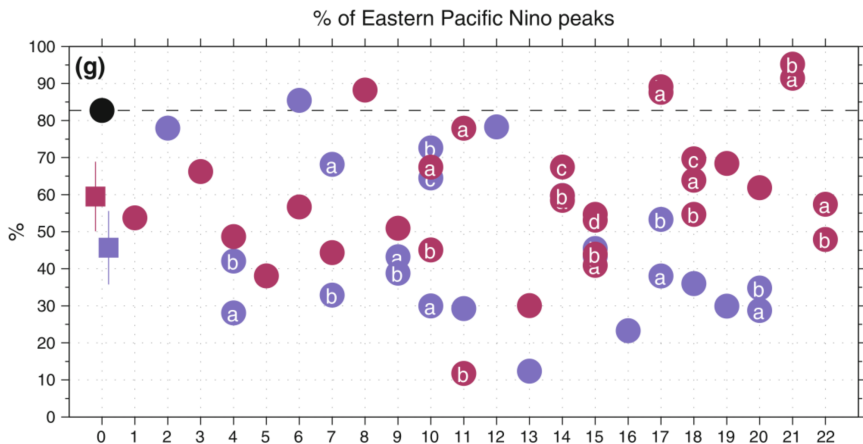
Bellenger et al., Clim. Dynam., 2014

ENSO timing



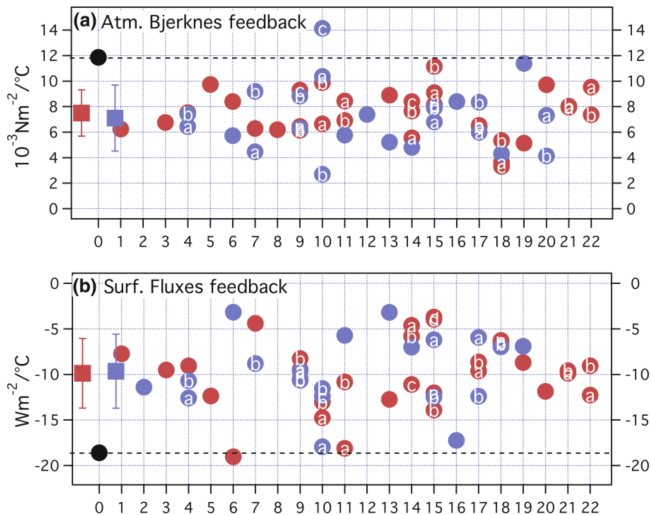
Bellenger et al., Clim. Dynam., 2014

Eastern Pacific ENSOs



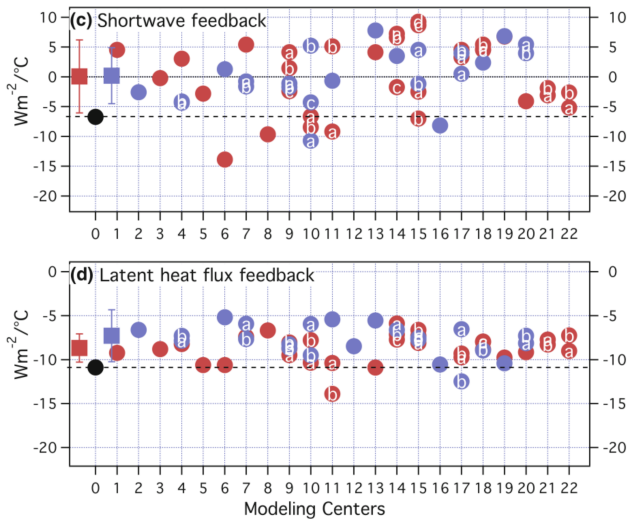
Bellenger et al., Clim. Dynam., 2014

ENSO feedbacks



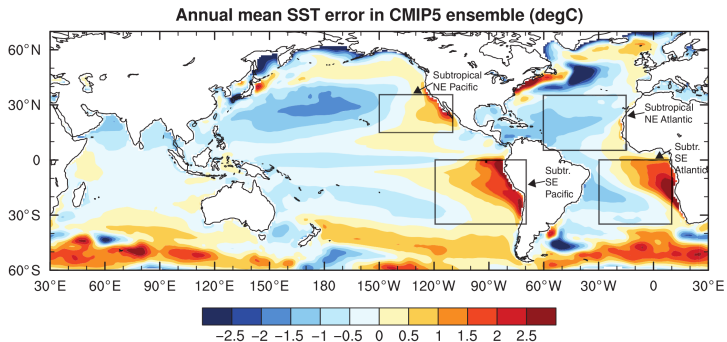
Bellenger et al., Clim. Dynam., 2014

ENSO feedbacks



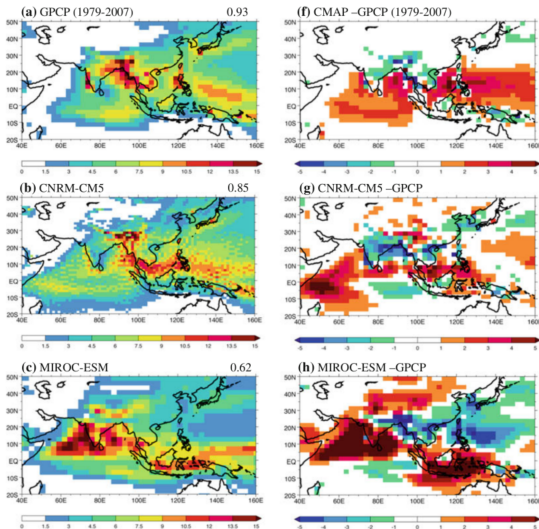
Bellenger et al., *Clim. Dynam.*, 2014

Eastern Tropical Oceans



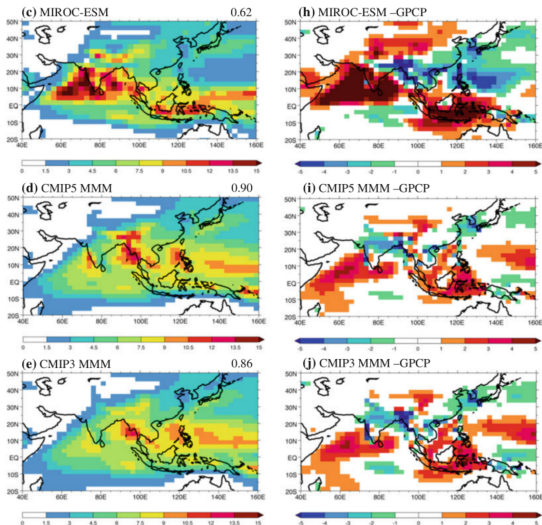
Richter, WIREs, 2015

South Asian Monsoon intensity



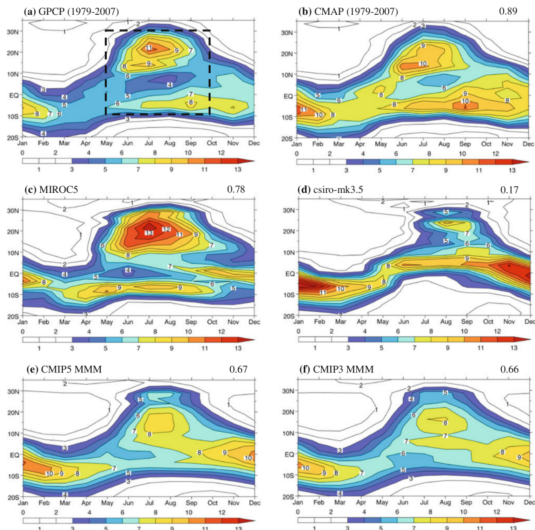
Sperber et al., *Clim. Dynam.*, 2013

South Asian Monsoon intensity



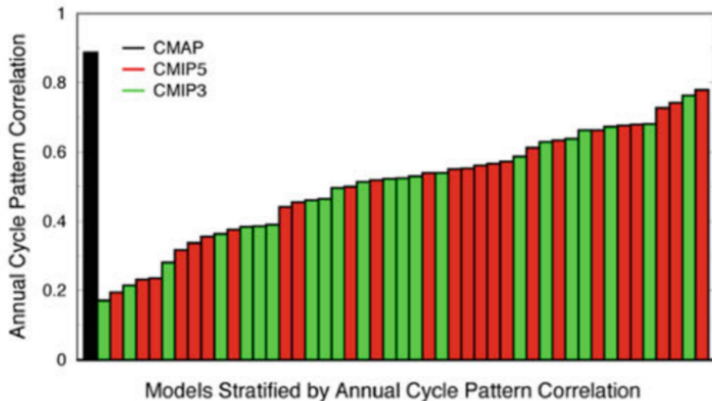
Sperber et al., *Clim. Dynam.*, 2013

Monsoon seasonality



Sperber et al., *Clim. Dynam.*, 2013

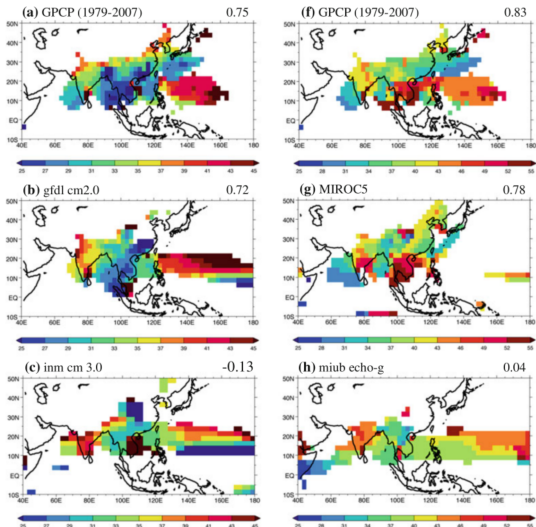
Monsoon pattern agreement



Sperber et al., *Clim. Dynam.*, 2013

Monsoon Onset and Peak

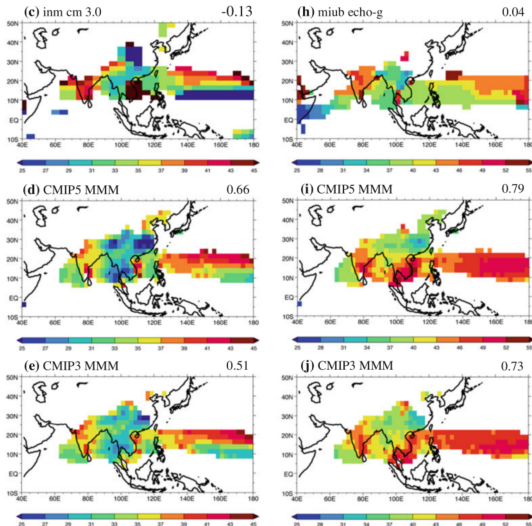
Number of 5-day period for onset (left) and peak (right)



Sperber et al., *Clim. Dynam.*, 2013

Monsoon Onset and Peak

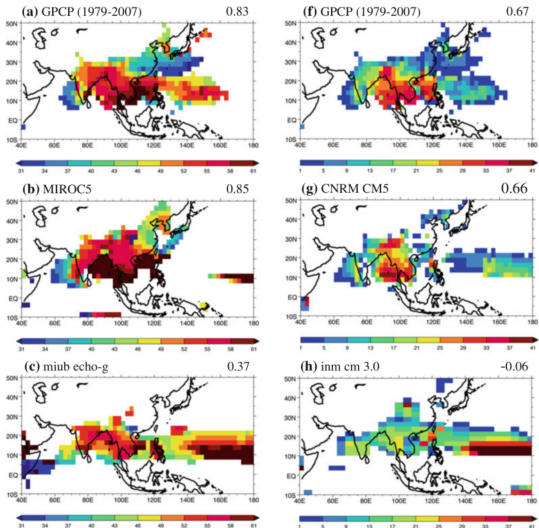
Number of 5-day period for onset (left) and peak (right)



Sperber et al., *Clim. Dynam.*, 2013

Monsoon Withdrawal and Duration

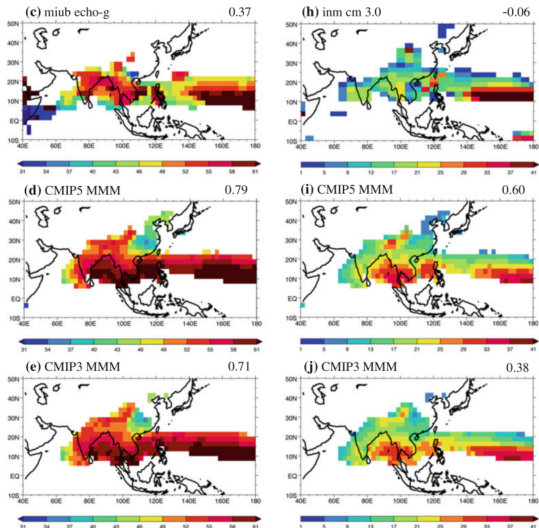
Number of 5-day period for withdrawal (left) and length in 5-day periods (right)



Sperber et al., Clim. Dynam., 2013

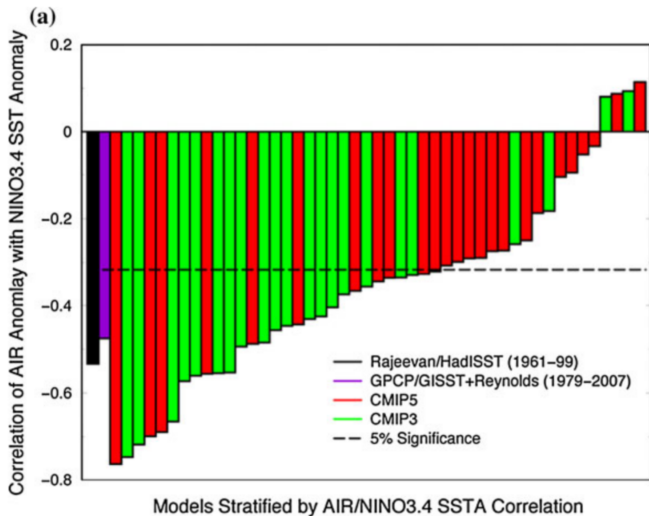
Monsoon Withdrawal and Duration

Number of 5-day period for withdrawal (left) and length in 5-day periods (right)

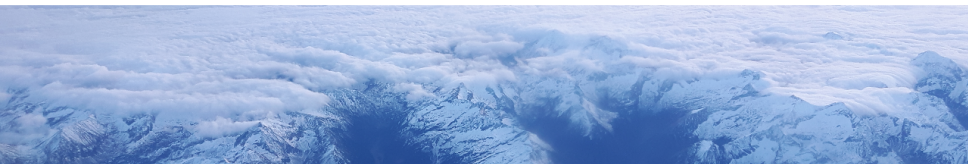


Sperber et al., *Clim. Dynam.*, 2013

ENSO-Monsoon teleconnection



Sperber et al., *Clim. Dynam.*, 2013

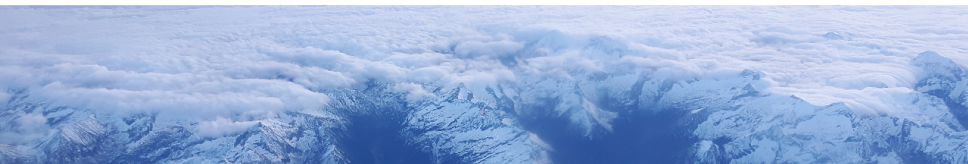


Dynamical Model Performance

Regional- and Local-Scale Errors

Regional Errors and Uncertainties

- ▶ Mesoscale circulation in mountain regions
- ▶ Soil moisture temperature and precipitation feedbacks
- ▶ Snow albedo feedbacks
- ▶ Extreme convective precipitation



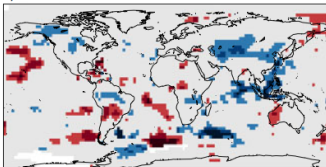
Dynamical Model Performance

Representation of Observed Trends

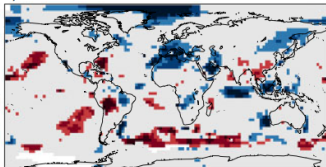
GCM vs. Observed Trends

Inconsistencies between model and observed trends, mean temperature;
top: CMIP5, bottom: CMPI3; left: DJF, right: JJA.

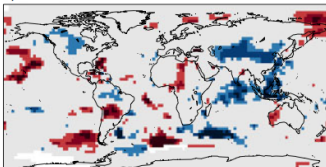
c) Fraction of 24 CMIP3 models with inconsistencies



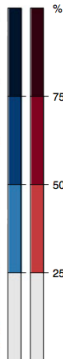
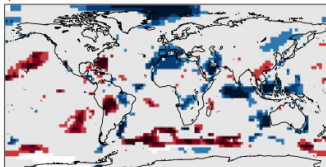
d) Fraction of 24 CMIP3 models with inconsistencies



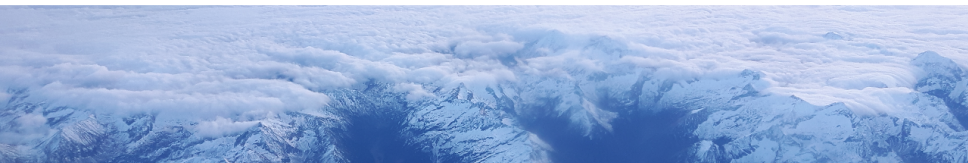
e) Fraction of 26 CMIP5 models with inconsistencies in DJF



f) Fraction of 26 CMIP5 models with inconsistencies in JJA



Bhend & Whetton, Clim. Change, 2013



Uncertainties

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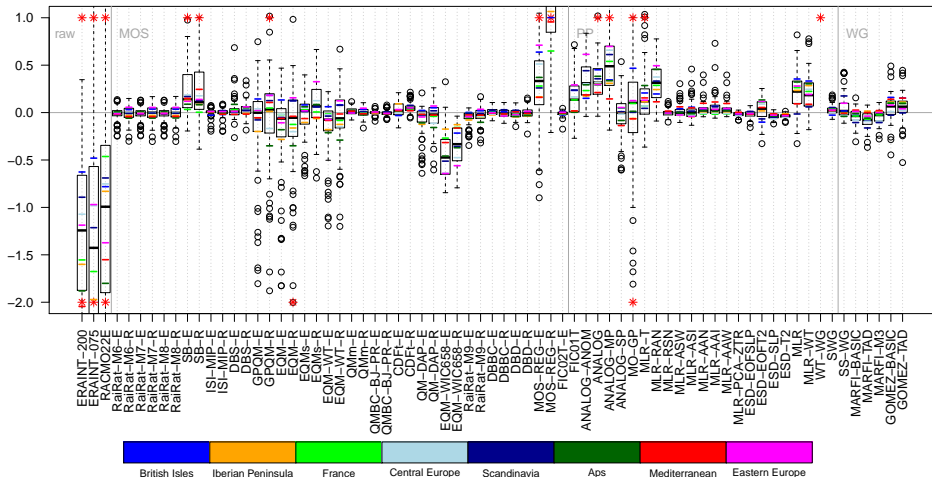


Statistical Downscaling Performance

Temperature

Tmax - mean, winter (DJF)

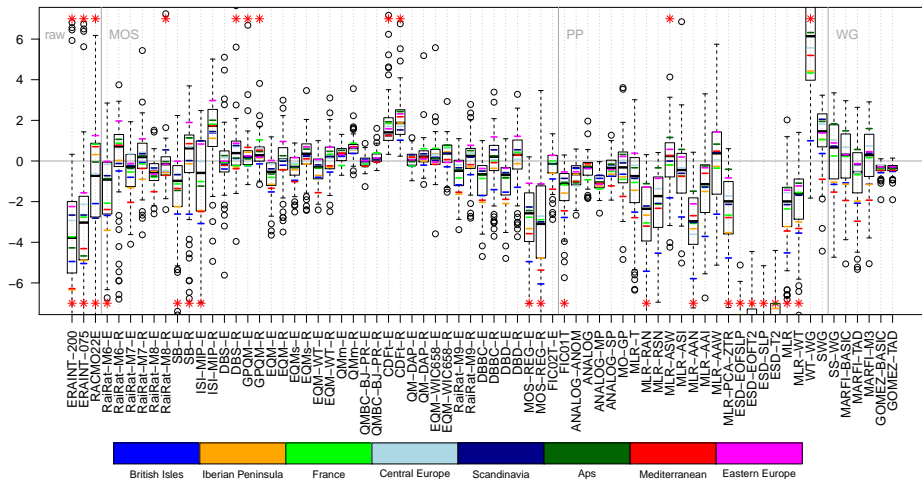
Biases across all stations [°C]



* values outside plotted range

Tmax - 20 season return level, summer (JJA)

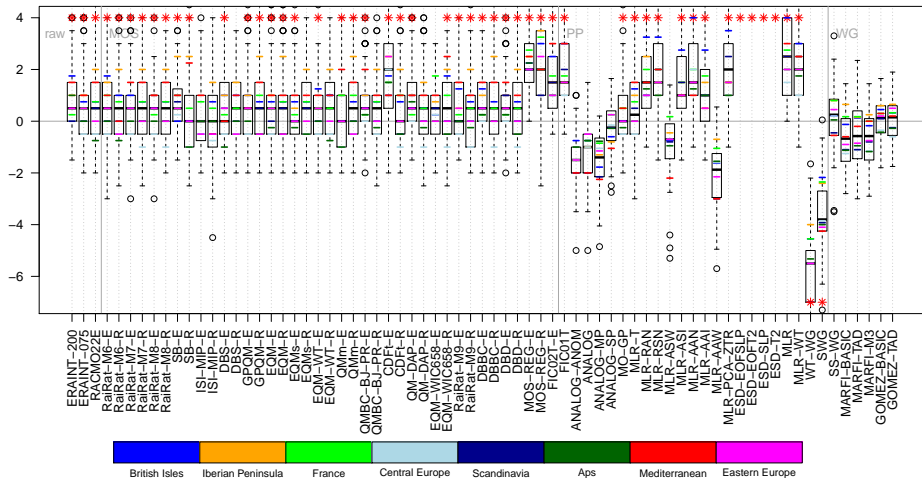
Biases across all stations [°C]



* values outside plotted range

Tmax - mean annual maximum warm spell

Biases across all stations [days]

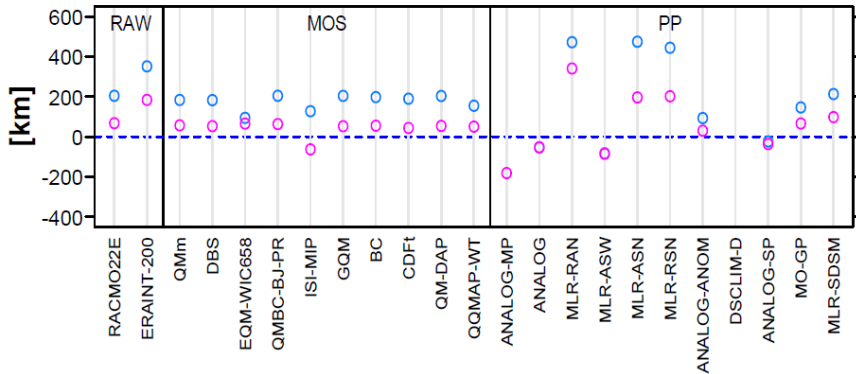


* values outside plotted range

Temperature - de-correlation length

Biases across all stations

Tmax - Correlation length bias



Correlation length in OBS

DJF: 1359 km

JJA: 1013 km

DS methods

○ Winter (DJF)

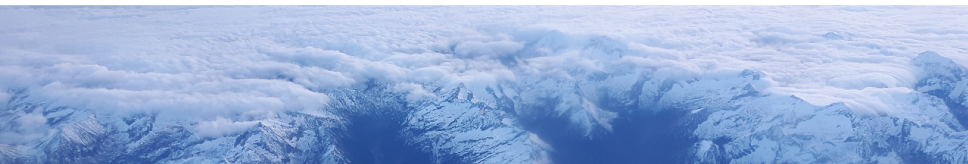
○ Summer (JJA)

Temperature Summary

Aspect	MOS				PP				WG ¹				
	BC	QM emp.	QM para.	QM extreme	REG det.	REG infl.	REG stoch.	ANA SS/MS	RI U SS/MS	RI C SS/MS	POI SS/MS	HM U/C	
Temperature, marginal													
mean	+	+	+	+	+	+	+	o	+	+	+	+	
variance	o	+	+	+	-	o	+	o	+	+	+	+	
extremes ²	o	+	+	+	-	o	+	+	+	+	+	+	
Temperature, temporal variability													
autocorrelation	+	+	+	+	+	+	-	-	+	+	+	+	
mean spells	+	+	+	+	o	o	-	-	+	+	+	+	
extreme spells	+	+	+	+	+	+	-	o	+	+	+	+	
interannual variance	+	o	o	o	-	o	-	-	-	o	-	-/o	
climate change	+	o	o	o	+	-	+	-	+	+	+	+	
Temperature, spatial variability													
means	+	+	+	+	o	o	-	-/+	-/?	-/?	-/?	?	
extremes	+	+	+	+	-	-	-	-/+	-/?	-/?	-/?	?	

¹We consider standard WGs with Gaussian distribution for temperature.

²We consider extreme events within the range of observed values. No extrapolation is assessed.

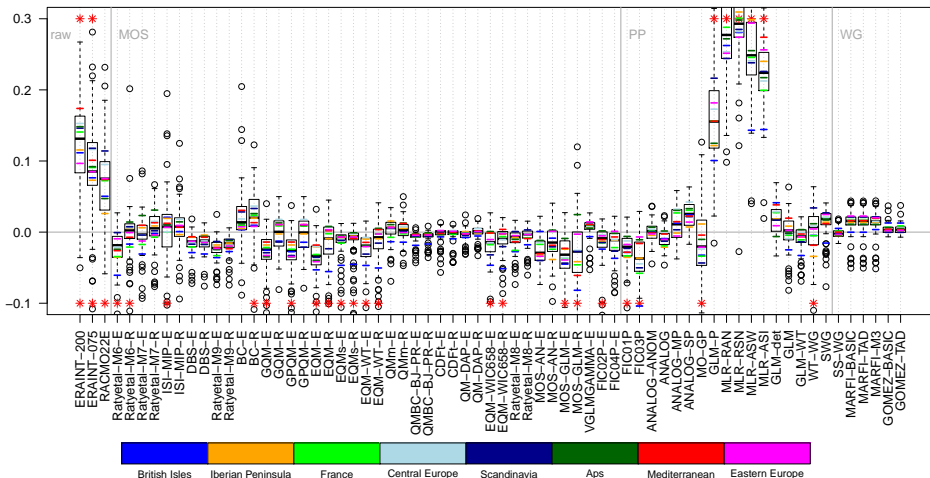


Statistical Downscaling Performance

Precipitation

Precipitation - wet day probability, winter (DJF)

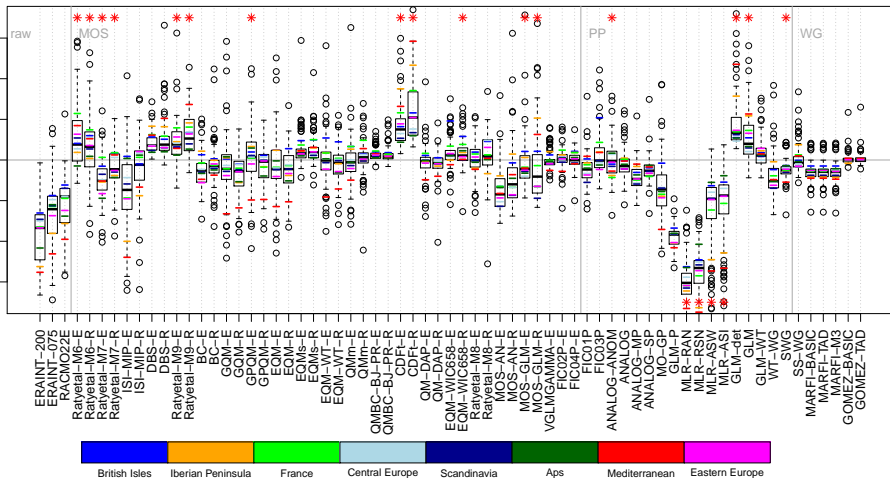
Biases across all stations



* values outside plotted range

Precipitation - intensity, summer (JJA)

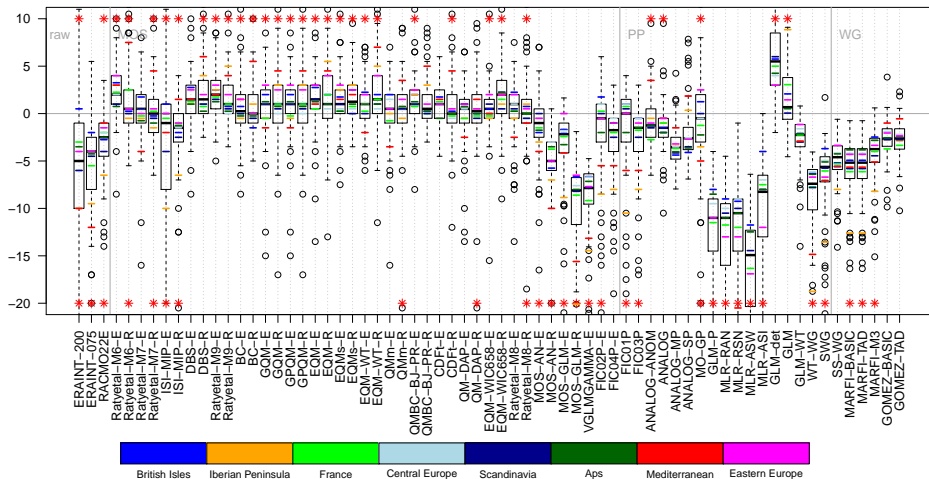
Relative errors across all stations [mm/wet day]



* values outside plotted range

Precipitation - mean annual maximum dry spell

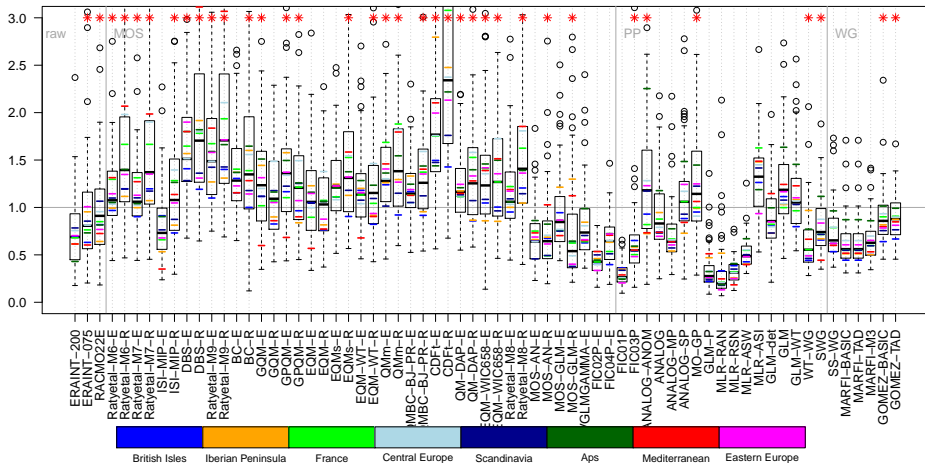
Biases across all stations [days]



* values outside plotted range

Precipitation - interannual variability, summer

Relative errors across all stations

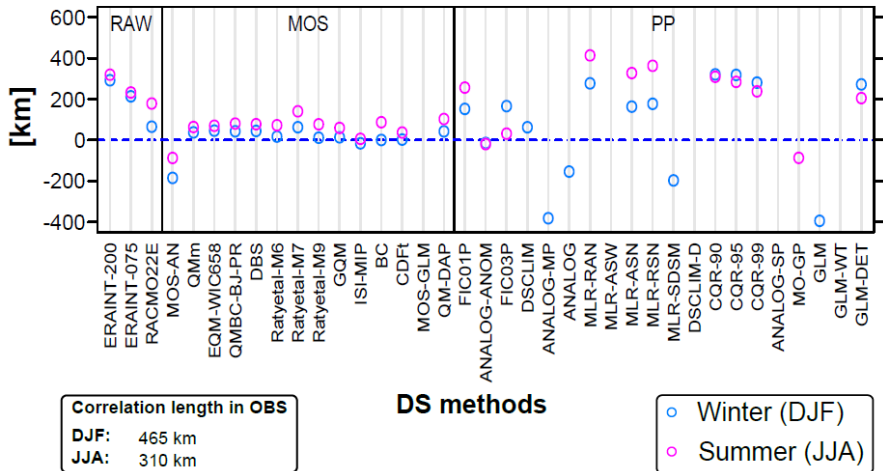


* values outside plotted range

Precipitation - de-correlation length

Biases across all stations

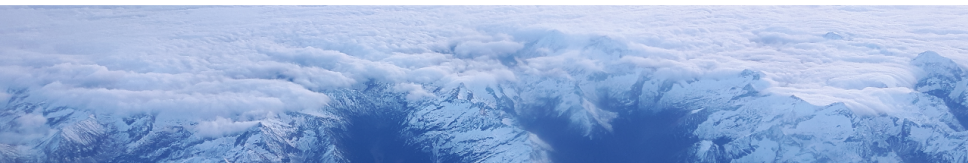
P - Correlation length bias



Precipitation Summary

Aspect	MOS				PP				WG ³			
	BC	QM emp.	QM para.	QM extreme	REG det.	REG infl.	REG stoch.	ANA SS/MS	RI U SS/MS	RI C SS/MS	POI SS/MS	HM U/C
Precipitation, marginal												
wet-day probabilities	+	+	+	+	-	-	+	+	+	+	+	+
mean intensity	+	+	+	+	-	-	+	+	+	+	+	+
extremes ^b	o	+	o	+	-	-	+	+	o	o	o	o
Precipitation, temporal variability												
transition probabilities	o	+	+	+	-	-	+	+	+	+	+	+
mean spells	o	+	+	+	-	-	+	+	o	+	o	o/+
extreme spells	+	+	+	+	-	-	+	+	-	o	-	-/o
interannual variance	+	o	o	o	-	o	o	o	-	o	-	-/o
climate change	+	o	o	o	+	-	+	o	+	+	+	+
Precipitation, spatial variability												
means	o	+	+	+	-	-	-	-/+	-/o	-/o	-/o	o
extremes	o	o	o	o	-	-	-	-/+	-/?	-/?	-/?	?
Multivariable												
bulk	+	+	+	+	-	-	-	+	+	+	+	+

³We consider standard WGs with gamma distribution for precipitation.



Uncertainties

Evaluation Framework

Dynamical Model Performance

Statistical Downscaling Performance

Practical Guidelines

Assessing the Relevance of Climate Change

- ▶ **Is climate change a relevant factor?**
Socio-economic or environmental factors might dominate over the influence of climate change in a given context.

- ▶ **Is climate information relevant?**
Decision makers may be able to sufficiently reduce vulnerability to climate change by implementing low regret measures. In some cases, adaptation measures can be designed to be easily extendable.

Assessing the Climate Information Requirements

- ▶ **Understanding the Spatial-Temporal Scales of the Impact:**
what are the relevant impact processes and their characteristic time and space-scales (might be different from the input resolution of the chosen impact model).

- ▶ **Understanding the Relevant Climatic Phenomena:**
different meteorological and climatic phenomena, spanning a wide range of scales, might control the considered impact.

Choosing the Driving GCMs

Select GCMs that

- ▶ well represent the relevant large-scale processes and their response to climate change
- ▶ have no major location biases of the large-scale circulation
- ▶ span the range of uncertainty in global climate sensitivity

Choosing the Downscaling and Bias Correction Options

► **Is Downscaling Required?**

Do the driving GCMs represent the relevant climate phenomena at the scale of interest?

► **Is Dynamical Downscaling Required?**

Is bias correction sufficient? Can PP statistical downscaling be used instead of dynamical downscaling?

Dynamical downscaling may be required if local feedbacks or small-scale processes are important.

► **Choosing the Statistical Downscaling Method**

Determined by the desired statistical climate aspects (see summary tables in previous section). Select methods that provide **salient information**.

Resources:

- ▶ www.value-cost.eu
- ▶ Maraun et al. (2015): VALUE: A framework to validate downscaling approaches for climate change studies, *Earth's Future* 3, 1–14, doi:10.1002/2014EF000259.
- ▶ Maraun (2016): Bias Correcting Climate Change Simulations - A Critical Review, *Curr. Clim. Change. Rep.* 2, 211-220, DOI 10.1007/s40641-016-0050-x.
- ▶ IPCC (2015): IPCC Workshop on Regional Climate Projections and their Use in Impacts and Risk Analysis Studies, Sao Jose dos Campos, Workshop Report.
- ▶ Maraun and Widmann (2017): *Statistical Downscaling and Bias Correction for Climate Research*, Cambridge University Press.

Thank you for your attention!