Inter-comparison of multi-regional results of five approaches for forming probabilistic climate change projections

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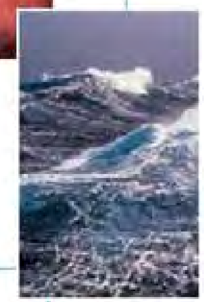

A. Moise, P. Whetton, J. Bathols, L. Hanson
CAWCR,

Greenhouse2011, 7 April 2011

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Overview

CCiA Report (2007) provided probabilistic climate change projections.
CCiA (2013-4) will very likely go down the same path.

This study contributes to the overall process of determining how these probabilistic projections will be achieved by inter-comparing a variety of methods.

Focus of this talk:
(1) Description of the methods
(2) Show some resulting PDFs of (mainly) temperature change
(3) Assess the sensitivity of the resulting probability density functions (PDFs) of projected climate change to choice of method.

AF Moise, P Whetton, J Bathols, L Hanson (2011) *Intercomparison of the multi-regional results of five approaches for forming probabilistic Climate Change Projections* (in preparation)

Methods – quick overview

1. **REA method** (REA): model evaluation, probability density and model weighting based on the original REA (Reliability Ensemble Average) method first introduced by Giorgi and Mearns (2002)
2. **Modified REA method** (mREA): model evaluation and weighting based on an updated version of the REA method which significantly changed the methodology and therefore is expected to show different results. (Xu et al., 2010).
3. **Watterson method** (WAT): model evaluation and weighting based on the M statistic introduced by Watterson (1996). This method was used in the Australian Climate Change Projections Technical Report in 2007
4. **Tebaldi univariate method** (TEB-UV): model evaluation and weighting based on the univariate method using Bayesian techniques first introduced by Tebaldi et al. (2004)
5. **Tebaldi multivariate method** (TEB-MV): As an expansion of method 4, this method is the multivariate version where the different regions are not dealt with independently but simultaneously (Tebaldi and Knutti, 2008).

REA – weighted ensemble mean

REA-mean

$$\boxed{\Delta\tilde{T}} = \frac{\sum_i R_i \boxed{\Delta T_i}}{\sum_i R_i}$$

REA-rmsd

$$\tilde{\delta}_{\Delta T} = \sqrt{\frac{\sum_i R_i (\Delta T_i - \Delta\tilde{T})^2}{\sum_i R_i}}$$

Model reliability is a function of model bias (B) AND the distance (D) from the REA average

R_i

Performance criterion **Convergence criterion**

$$R_i = R_{B,i} * R_{D,i} = \left[\frac{\varepsilon}{abs(B_i)}\right] * \left[\frac{\varepsilon}{abs(D_i)}\right]$$

ε = Natural variability

$\boldsymbol{\varepsilon_T}$ = Max{30yr-runMean[detrended(20th century observed T time series)]} – Min{[(…..)]}

$$\text{IF } |B_{T,i}| < \varepsilon_T \text{ THEN } R_{B,i} = 1$$

$$\text{IF } |D_{T,i}| < \varepsilon_T \text{ THEN } R_{D,i} = 1$$

Model is “reliable” ($\boldsymbol{R}_i$=1) when its bias and distance from the REA mean are within natural variability.

REA – empirical distributions

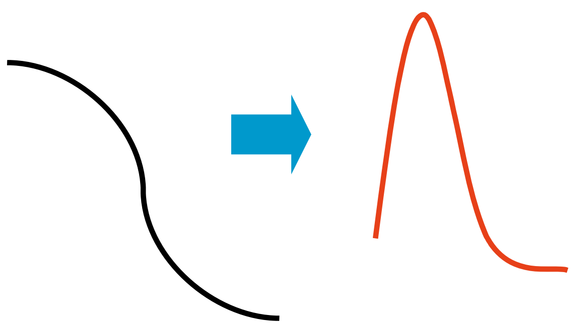
Probabilities of regional climate change: $$P(m_i) = \frac{R_i}{\sum_{j=1}^{N} R_j}$$

Threshold probability = summing over all $P(m_i)$ exceeding a given threshold of climate change.

$$P^{\Delta T_i > \Delta T_{th}}(m_i) = \sum_i P(m_i) \quad \text{where} \quad \Delta T_i > \Delta T_{th}$$

= probability of a temperature change exceeding ΔT_{th}

PDFs = derivative of $P(m_i)$ $$\frac{\partial P(m_i)}{\partial(\Delta T)}$$



REA – modified version

1. Abolish CONVERGENCE criteria for future simulations
2. Add test of variability and spatial correlation
3. Add more fields (now three)
4. Use EFFECTIVE model number

$$N_{\mathrm{eff}} = 1 \Big/ \sum_{i=1}^{N} P_i^2$$

$$\bar{\delta}_{\Delta T} = \sqrt{\frac{N_{\mathrm{eff}}}{N_{\mathrm{eff}} - 1}} \times \tilde{\delta}_{\Delta T}$$

$$R_i = \left[f_1(\overline{T})\right]^{m1} \times \left[f_2(T_{\mathrm{var}})\right]^{m2} \times \left[f_3(\overline{P})\right]^{m3} \times \left[f_4(P_{\mathrm{var}})\right]^{m4} \times \left[f_5(SLP_{\mathrm{corr}})\right]^{m5} \quad (9)$$

where

$$f_1(\overline{T}) = \frac{\varepsilon_T}{abs(Bias)};\ f_2(T_{\mathrm{var}}) = \frac{\varepsilon_{\mathrm{STD}}}{abs(\mathrm{STD}_{\mathrm{model}} - \mathrm{STD}_{\mathrm{obs}})}$$

$$f_3(\overline{P}) = \frac{\varepsilon_P}{abs(Bias)};\ f_4(P_{\mathrm{var}}) = \frac{\varepsilon_{\mathrm{CV}}}{abs(\mathrm{CV}_{\mathrm{model}} - \mathrm{CV}_{\mathrm{obs}})}$$

$$f_5(\mathrm{SLP}_{\mathrm{corr}}) = corr(\mathrm{SLP}_{\mathrm{model}},\ \mathrm{SLP}_{\mathrm{obs}})$$

REA – modified version

1. Abolish CONVERGENCE criteria for future simulations
2. Add test of variability and spatial correlation
3. Add more fields (now three)
4. Use EFFECTIVE model number

$$N_{\text{eff}} = 1 \Big/ \sum_{i=1}^{N} P_i^2$$

$$\bar{\delta}_{\Delta T} = \sqrt{\frac{N_{\text{eff}}}{N_{\text{eff}} - 1}} \times \bar{\delta}_{\Delta T}$$

$$R_i = [f_1(\bar{T})]^{m1} \times [f_2(T_{\text{var}})]^{m2} \times [f_3(\bar{P})]^{m3} \times [f_4(P_{\text{var}})]^{m4} \times [f_5(SLP_{\text{corr}})]^{m5} \quad (9)$$

where

T - Bias

T - Variability

PR - Bias

PR - Variability

MSLP – spat. Corr.

Watterson: global PDFs and weights

Fitting a **theoretical distribution** to the model ensemble of changes of global means.

Assumes that this captures uncertainty in real world global warming.

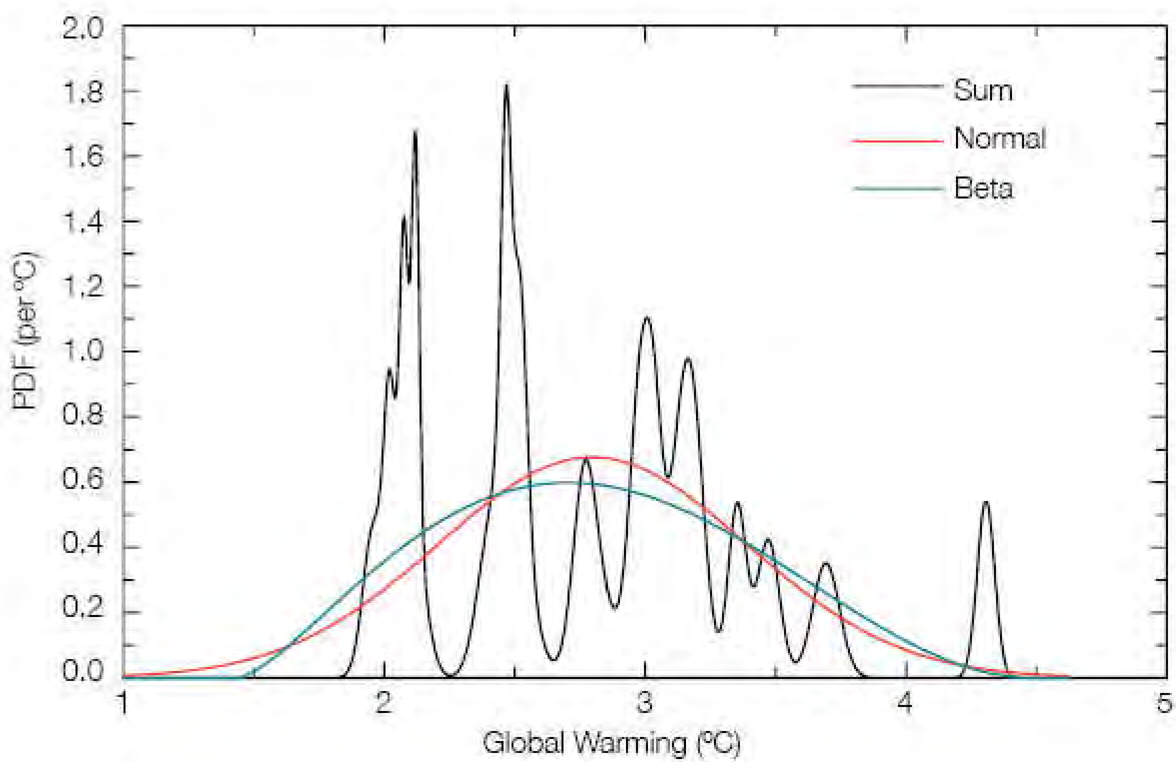


Figure 4.6: Probability distribution functions for the global mean warming for A1B over the 21st century, calculated from 22 models.

M-Statistics for weighting:
This uses the non-dimensional measure of similarity 'M' (Watterson 1996) determined from the maps of simulated and observed seasonal mean temperature, precipitation and sea level pressure.

from: CCiA Report, 2007

Watterson: local response

(1) For each model, variable and grid point, the local change per degree of global warming is obtained using a linear regression between the variable and global warming for the period 2001-2100 from the simulation for scenarios.

(2) The PDF of local climate response can be derived from the standard regression error for an individual model result.

(3) One representation of the ensemble of model results is the weighted sum of these curves (using the M weighting), labelled 'Sum'. This is comparable to the Reliability representation in the Reliability Ensemble Averaging (REA).

(4) Several ways of constructing a smooth PDF based on the model results, as represented by the Sum curve, have been considered.

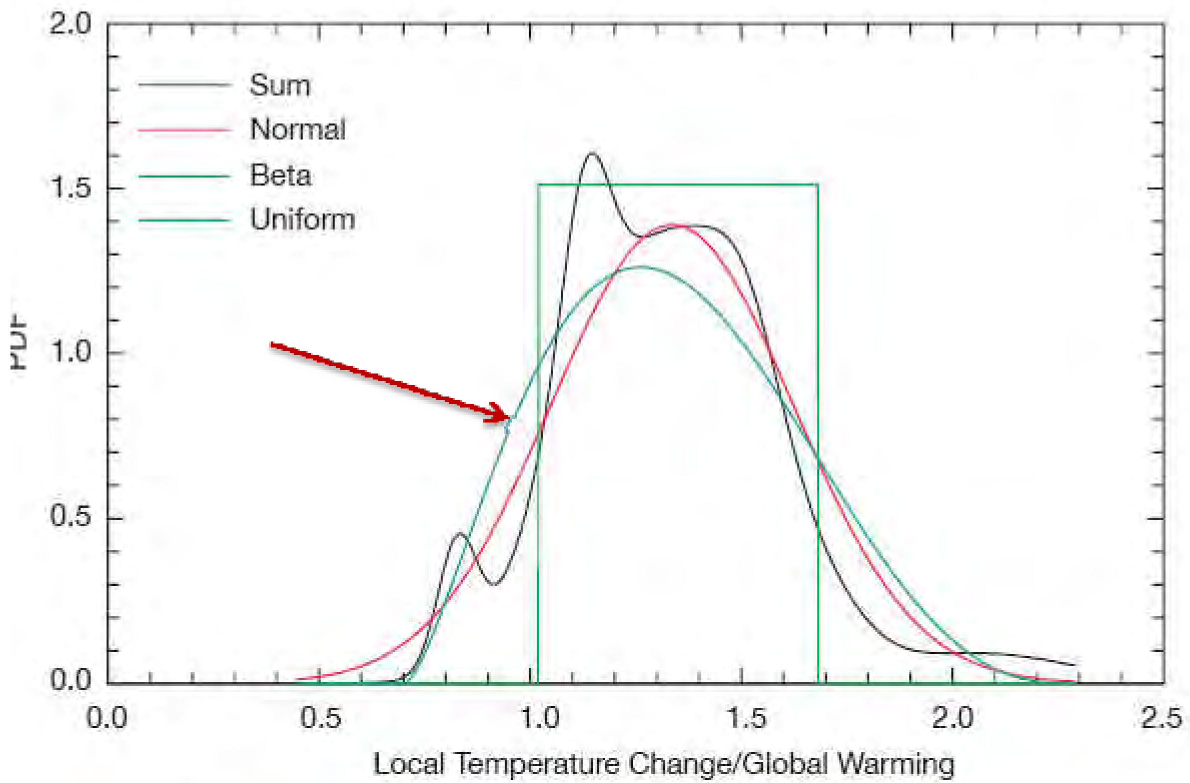
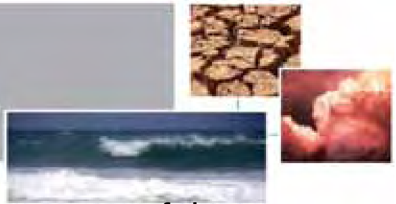


Figure 5.1: Probability distribution functions for the local temperature change per degree of global warming (non-dimensional) for December-February at Alice Springs (the point 134°E, 24°S) calculated from the 23 models. This shows variation in the distribution obtained using four different curve fitting methods – Normal, Sum, Beta and Uniform.

from: CCiA Report, 2007

Tebaldi – Bayesian approach



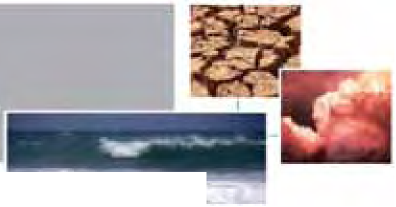
- Adopting the Bayesian viewpoint the uncertain quantities of interest become the parameters of the statistical model and are treated as random variables.
- A *prior probability distribution* for them is specified independently of the data at hand.
- The *likelihood* component of the statistical model specifies the conditional distribution of the data, given the model parameters.
- Through Bayes's theorem prior and likelihood are combined into the new *posterior distribution* of the parameters, given the data. These are PDFs describing the uncertainty of the parameter (ie. Mean temperature change).

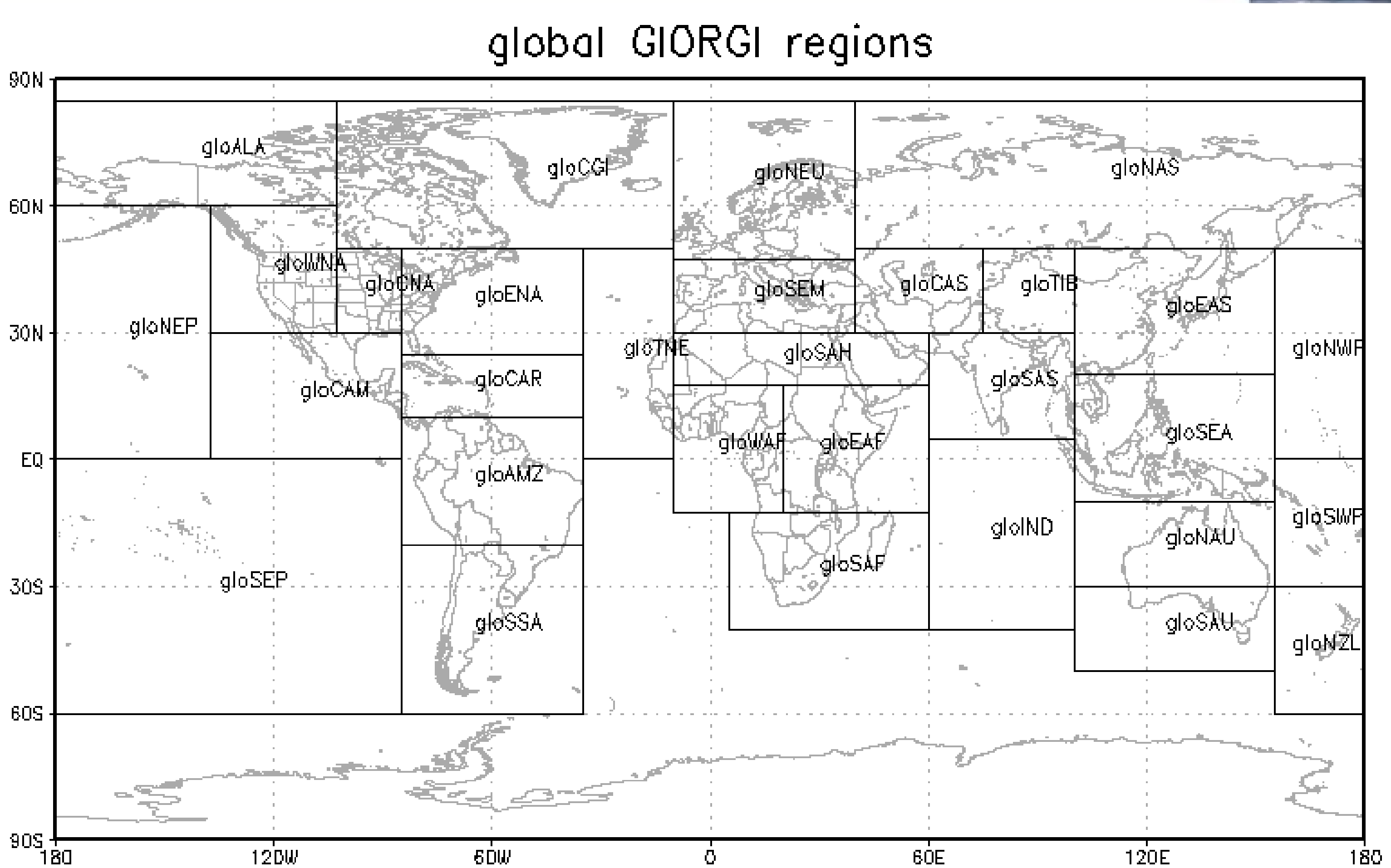
An empirical estimate of the posterior distribution can be obtained through MCMC simulation.

Likelihoods: Gaussian distribution for X(20c3m), Y(A2) and X_o (OBS)
Priors: model parameters have Gamma priors
climate mean have uniform priors
Posteriors: calculated using MCMC

Data = area averages from Giorgi regions
Uni-variate model → each region treated separately
Multi-variate model → regions are treated simultaneously

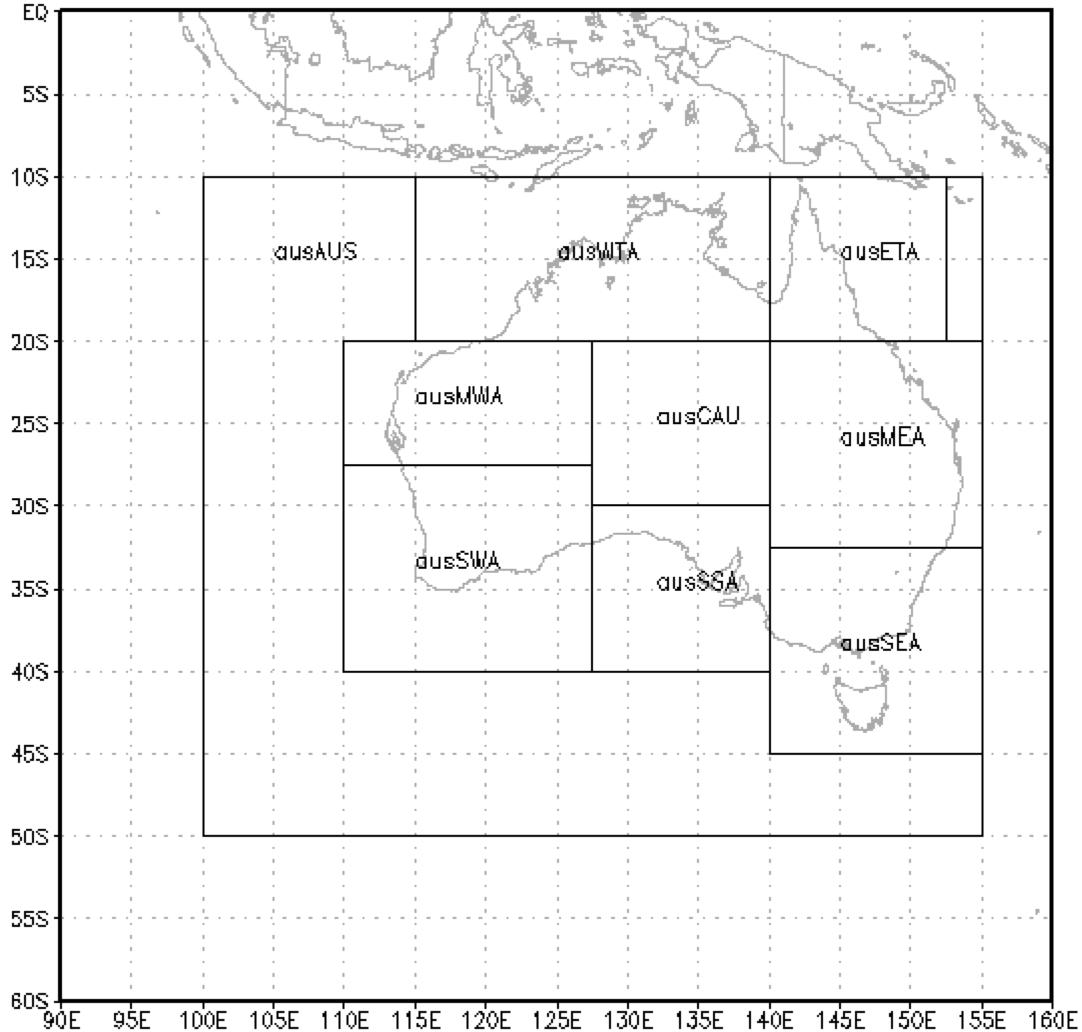
Domains used - global





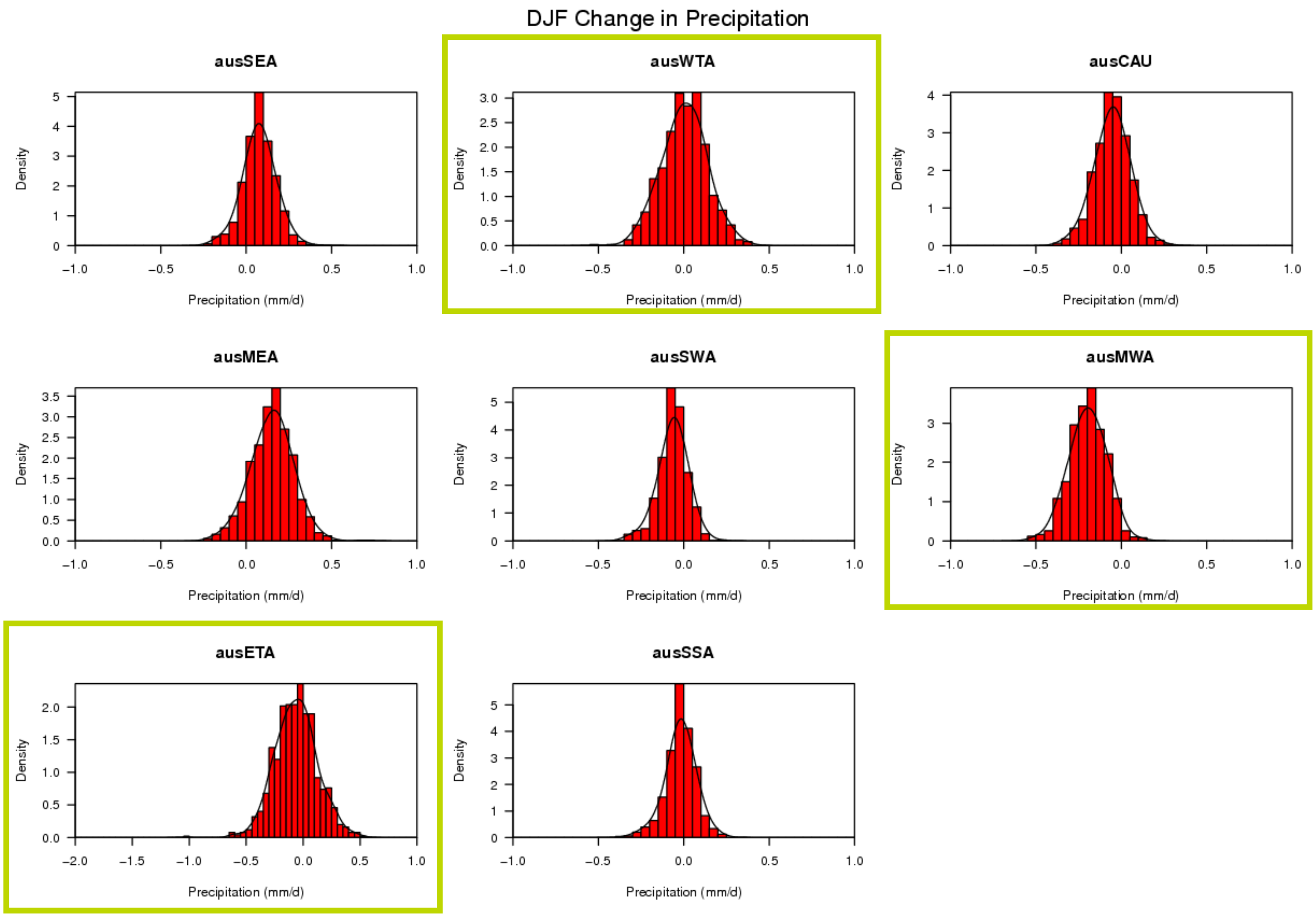
The analysis was undertaken using climate model results from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset and PDFs were prepared for the set of ‘Giorgi’ regions, globally.

Additional Domains used - Australia



Selected results

Example: Tebaldi-MV dfj precipitation change



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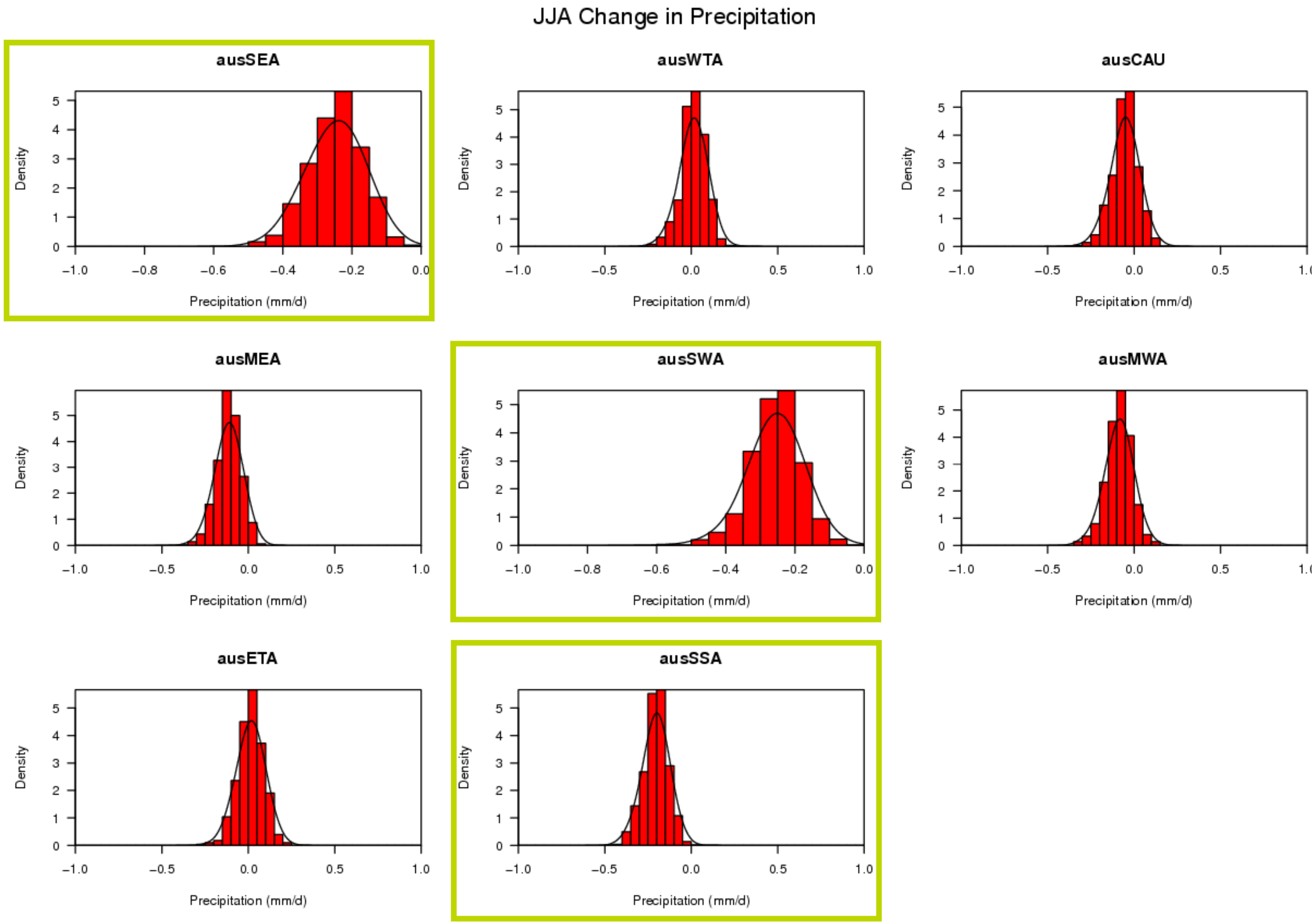
Example: Tebaldi-MV jja precipitation change



Summary statistics example

Change in annual **temperature** across 5 methods for one region

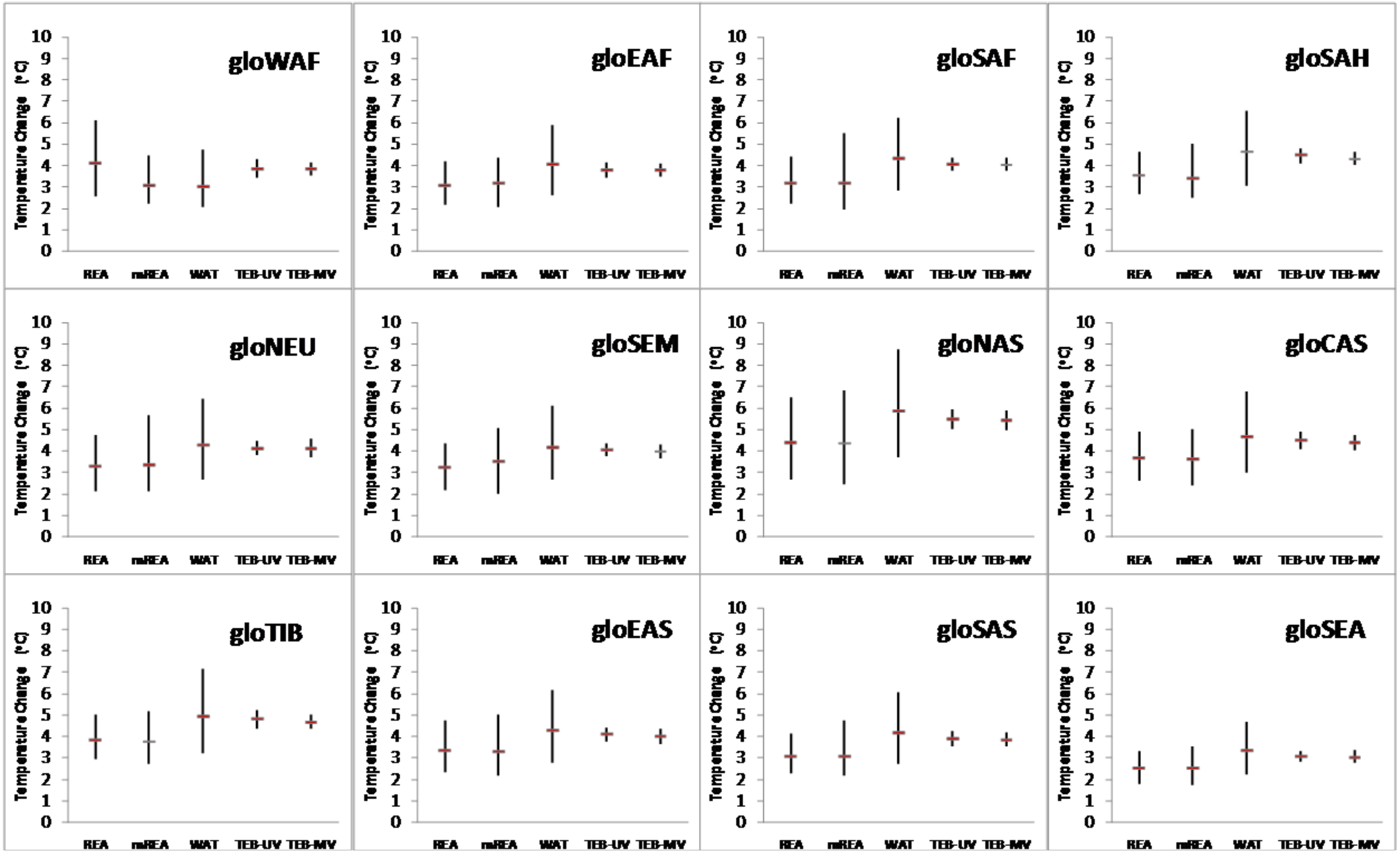
	WAT	REA	mREA	TEB-UV	TEB-MV
Ave Median	4.39	3.29	3.33	4.17	4.11
Ave Range (P95-P05)	3.66	2.44	3.04	0.74	0.72
Ave Skew factor (P95-P50)/(P50-P05)	1.30	1.39	1.49	0.97	1.05

Change in annual **precipitation** across 5 methods for one region

	WAT	REA	mREA	TEB-UV	TEB-MV
Ave Median	2.1	0.9	0.9	2.4	3.1
Ave Range (P95-P05)	47.5	41.0	47.4	**9.1**	**11.3**
Ave Skew factor (P95-P50)/(P50-P05)	1.21	1.02	0.98	1.00	0.98

Annual temperature change

Median, 5th and 95th percentile



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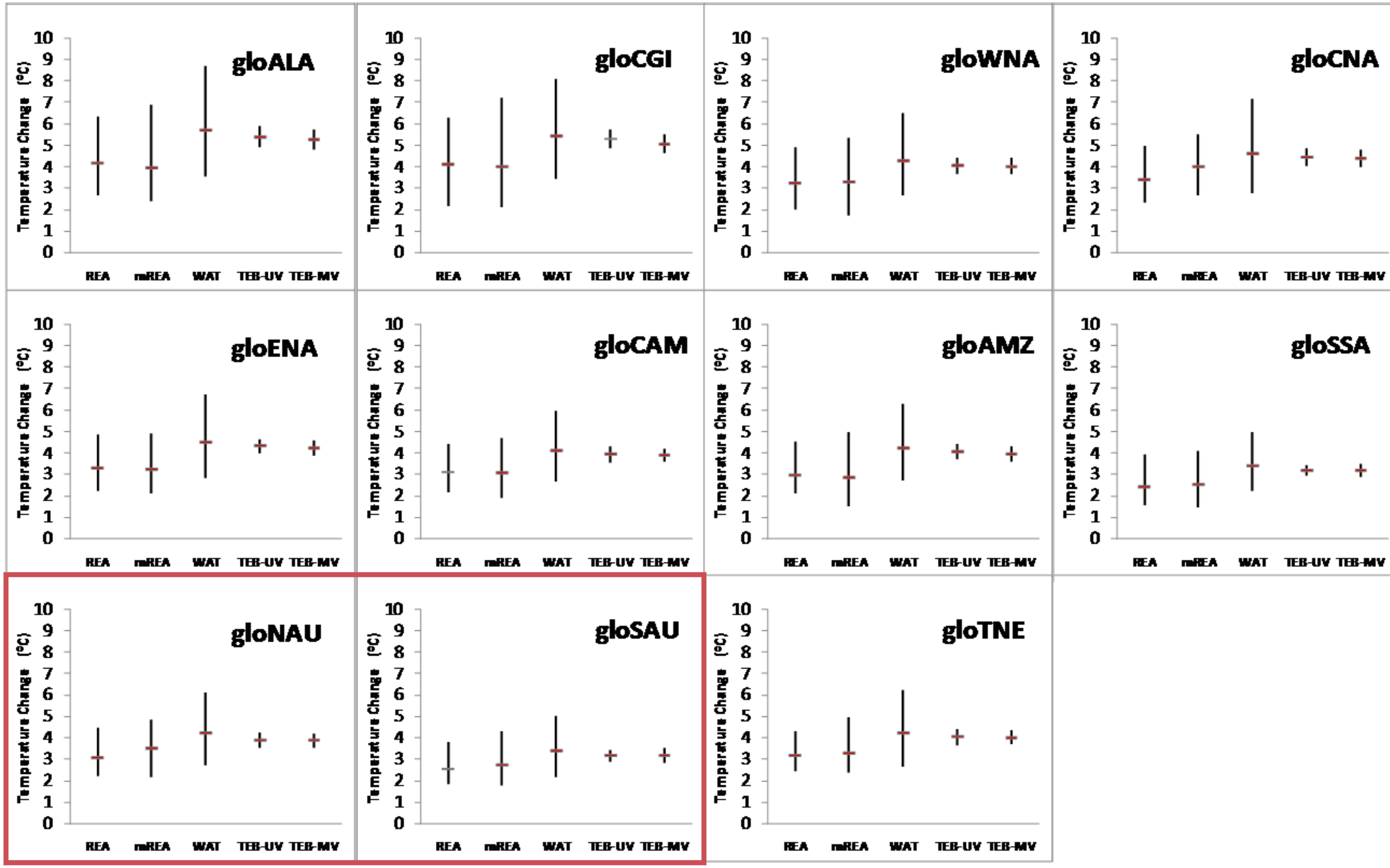
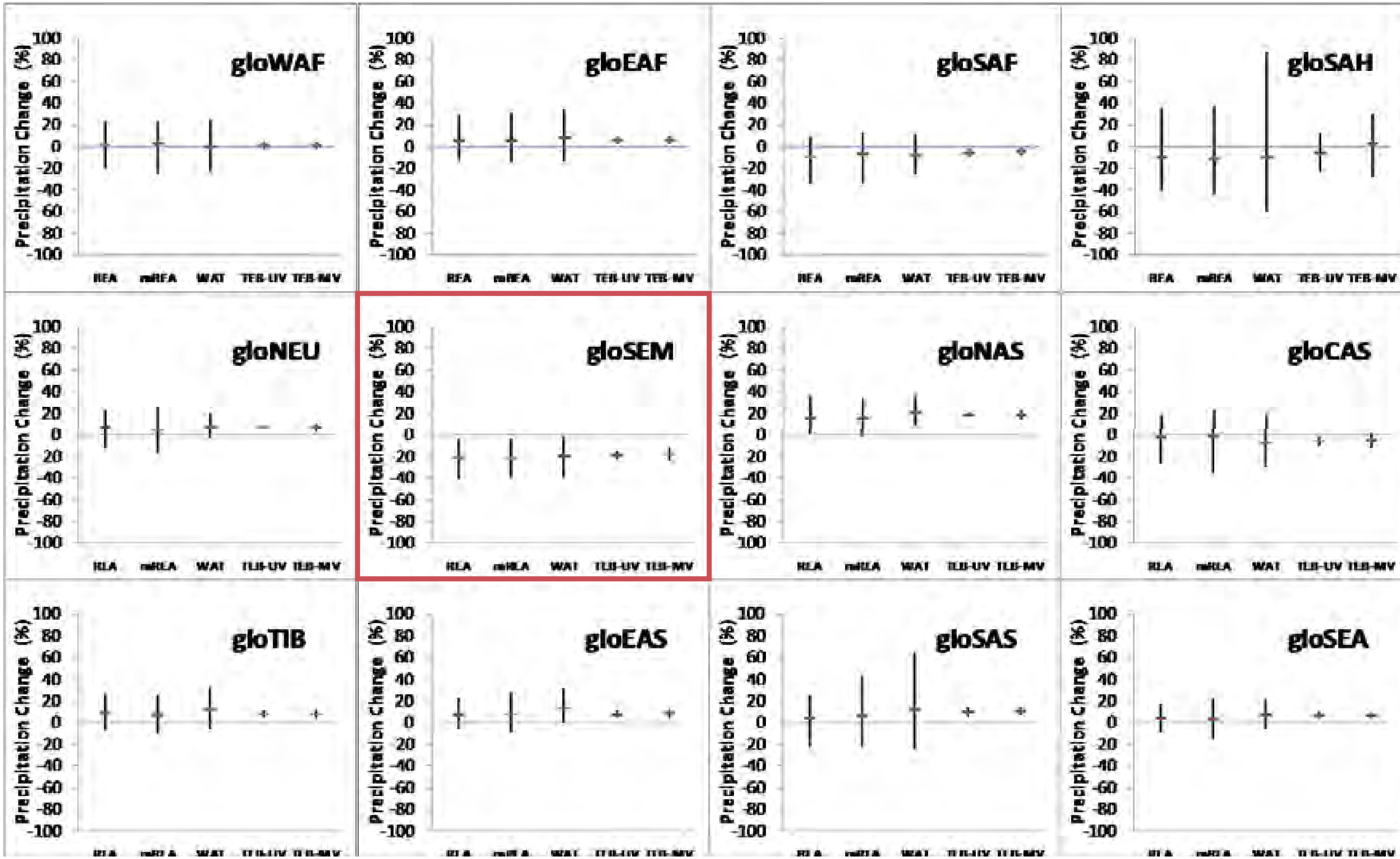

gloALA
gloCGI
gloWNA
gloCNA
gloENA
gloCAM
gloAMZ
gloSSA
gloNAU
gloSAU
gloTNE
Temperature Change (ºC)
0 1 2 3 4 5 6 7 8 9 10
REA
mREA
WAT
TEB-UV
TEB-MV

Annual precipitation change



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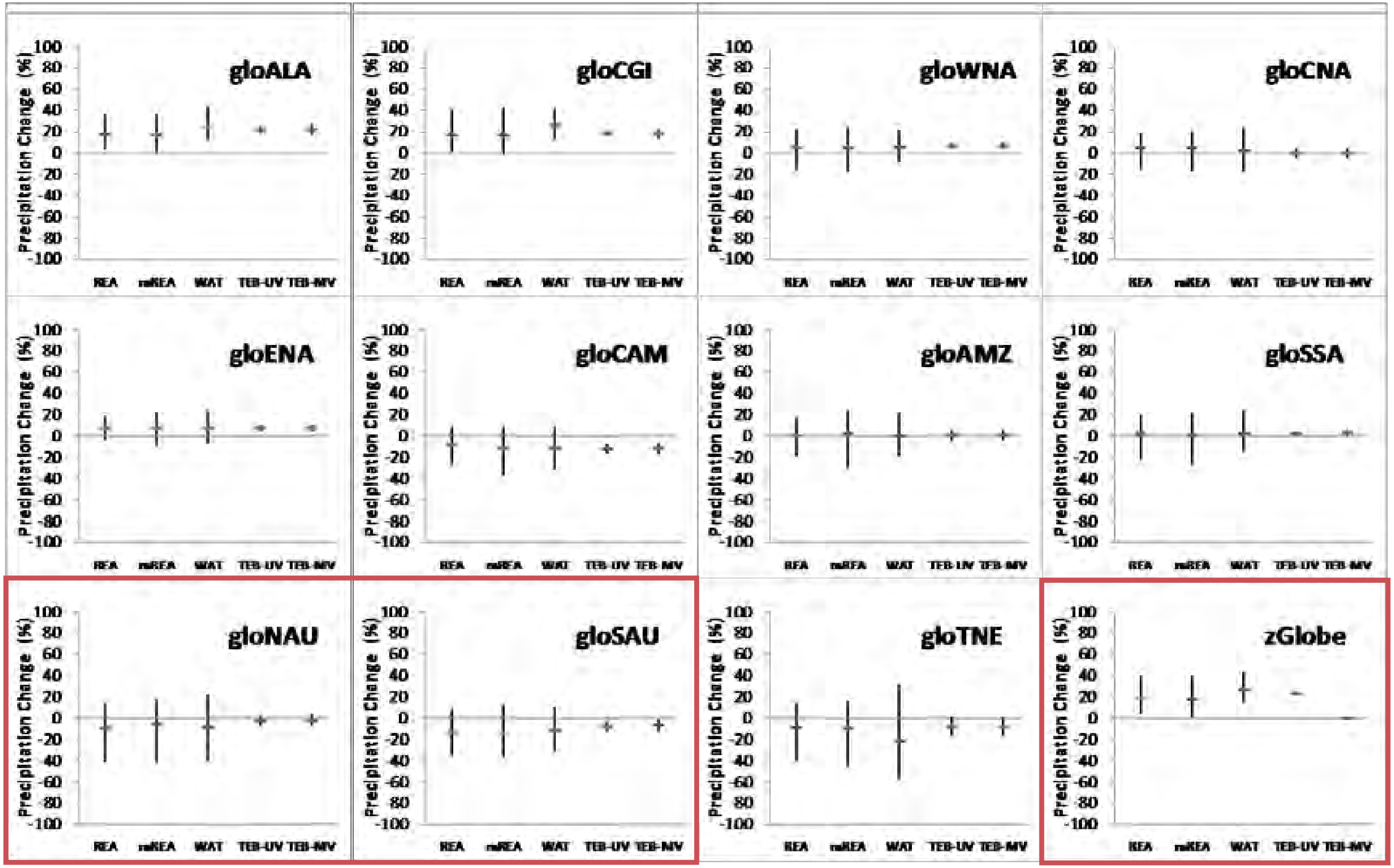


gloALA
gloCGI
gloWNA
gloCNA
gloENA
gloCAM
gloAMZ
gloSSA
gloNAU
gloSAU
gloTNE
zGlobe
Precipitation Change (%)
REA
mREA
WAT
TEB-UV
TEB-MV

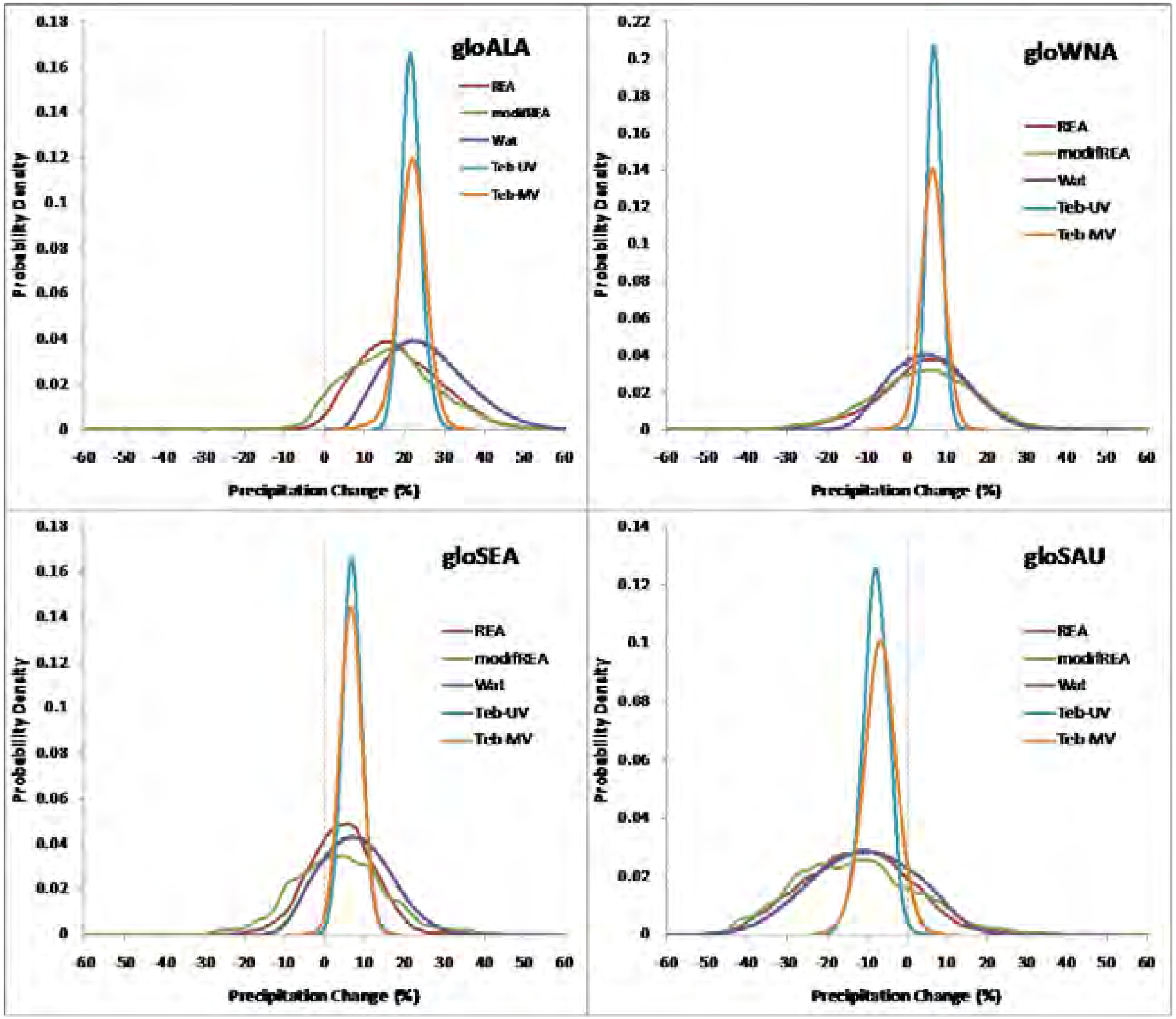
PDF of annual rainfall changes

Alaska

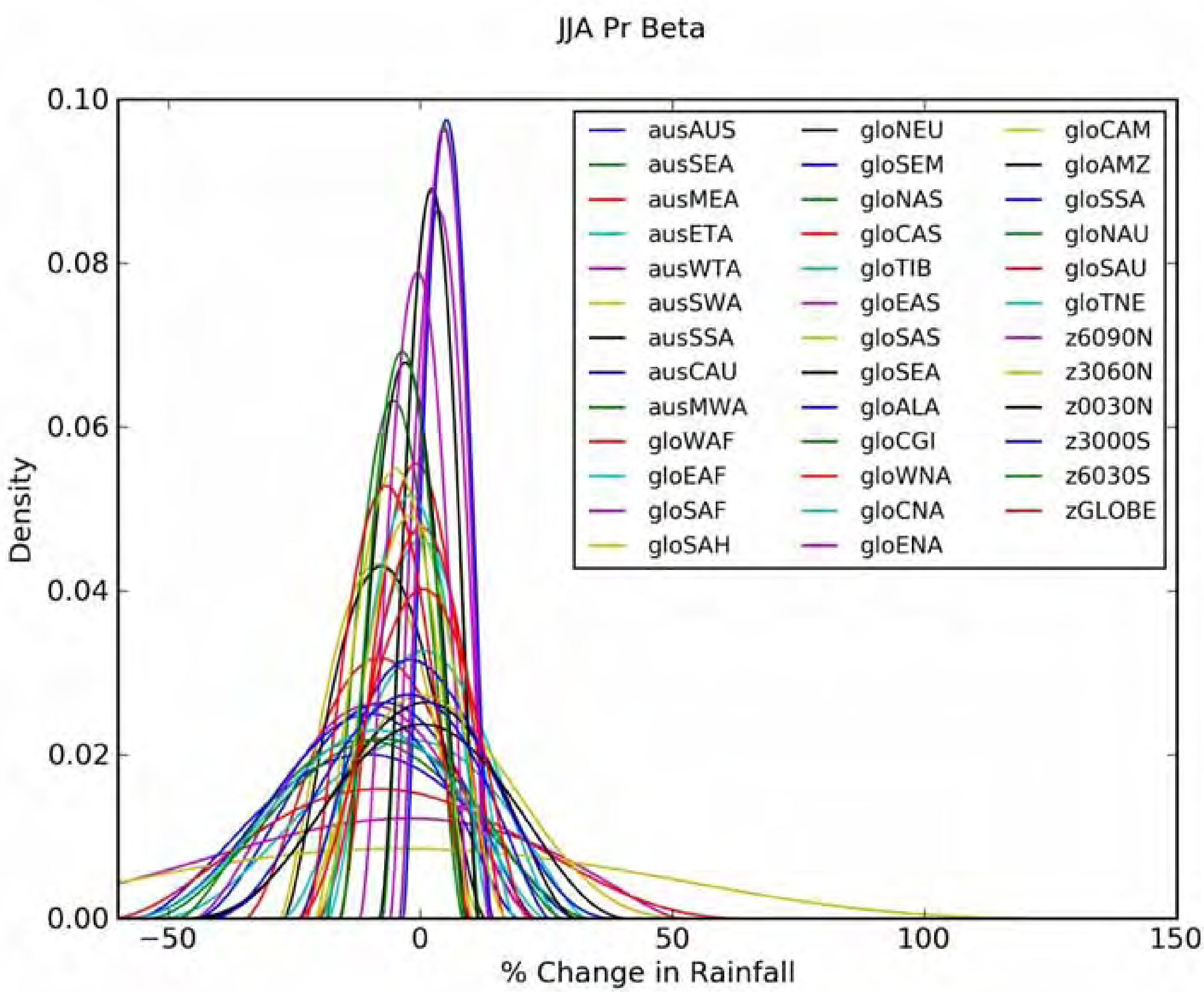
Western North America

South East Asia

Southern Australia



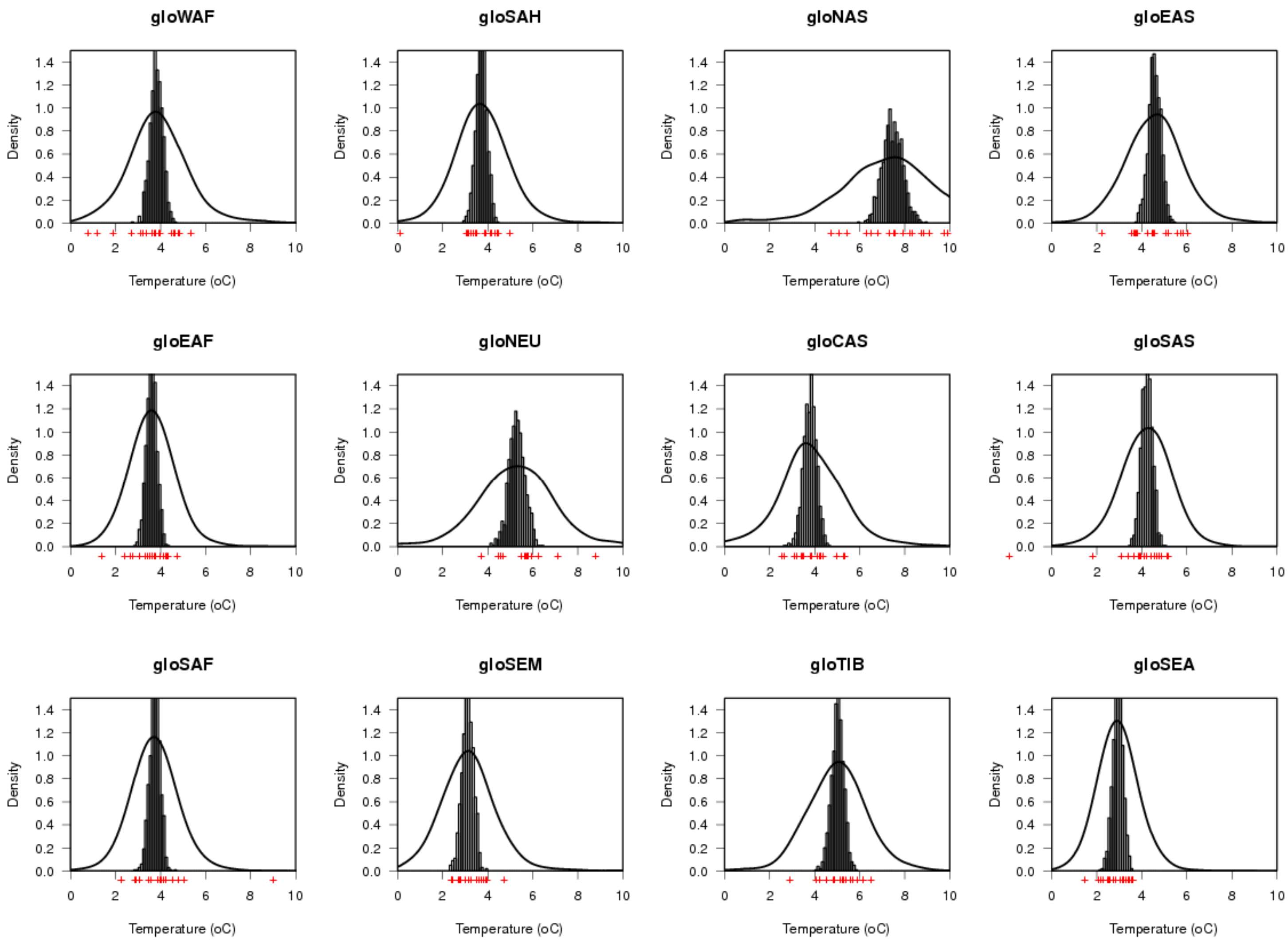
Watterson: BETA distribution jja rainfall change



Tebaldi extension

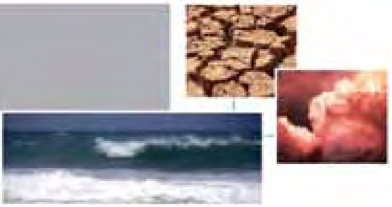
- We know that the Bayesian model gives only the most likely mean changes + some uncertainty around that BUT NOT capturing the entire uncertainty of future possible climates.
- We can use the POSTERIOR PREDICTIVE DISTRIBUTION to sample a ‘new’ possible future climate distribution (based on the data and parameters we have) which then has the uncertainty built in.
- This is usually a ‘less precise’ estimate, i.e. we expect wider distributions, but ones that should capture a much wider uncertainty with respect to future climates.

Posterior predictive distributions - Temp



Summary

Summary – we used 5 methods



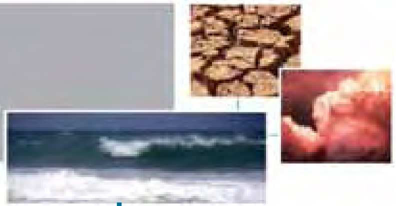
Methods	Assessment criteria	PDF forming technique
Old REA	Bias in current climate, convergence in future.	Empirical
New REA	Bias, variability and corr in current climate.	Empirical
Watterson	M-statistic	5 Fitted theoretical (beta)
Univariate Tebaldi	Bias	Bayes - univariate
Multivariate Tebaldi	Bias	Bayes - multivariate

The methods compared range from simple approaches based on forming PDFs directly from cumulative density distribution of the model results, a method based on curve fitting to such distributions, and two versions of a Bayesian approach. The approaches also differ in how model results were evaluated against observations and given a relative weighting.

Summary

- PDFs were prepared for the set of 'Giorgi' regions, globally.
- The results showed significant differences in the location and shape of the PDFs. These differences appeared to be primarily driven by the method used for forming the PDF, rather than differences in how the models were weighted.
- TEMPERATURE: All of the PDF approaches show a very similar pattern of regional variation, so the choice of PDF approach does not affect this basic result.
- There is a tendency for the range of warming to be greater in the Arctic (CGI, ALA) areas, irrespective of the methods applied
- **PRECIP**: The regional variations in the results are much stronger than for temperature and include some regions where rainfall decreases predominate (e.g. SEM, SAU).
- As for temperature, the five approaches show a very similar pattern of regional variation, so the choice of PDF approach does not significantly affect this result. This includes variation in range, which is largest in some drier subtropical regions (e.g SAH and SAS).

Summary



- Differences in PDFs such as illustrated in this study can have quite significant impact on policy relevant application of climate projection information.
- Much climate change application work takes a risk perspective: the most likely future is of interest, but low probability ‘worst case’ future climates are a necessary consideration to allow planning adaptations to make our climate sensitive systems robust to climate change.
- The extent to which PDF methods can affect extremes of the range is directly evident in comparing the 95th and 5th percentile results in this study. This underlines the importance of developing consensus on the most appropriate probabilistic methods, but as may be concluded from this study but much further work is required to achieve that.
- In the absence of this consensus, methods that produce broader PDFs may be viewed as the more appropriate, conservative, approach.

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Thank you

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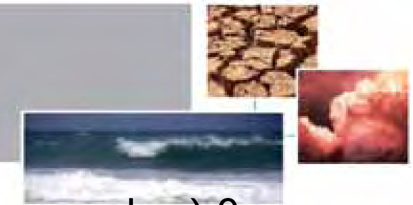
Bayesian inference



Non-Bayes: Model fitting given data X to gain info on model parameters (mean, sd,…) θ
→ fitting a theoretical distribution for example.

Bayes:

(1) Collect information about processes that are influenced by the parameters
(2) Use this data and the models to infer possible values of the parameters
(3) Summarise our beliefs about the possible values as probability distributions
(4) Adding data changes these distributions (inference is a learning process)

Bayes' Theorem: allows to invert conditional probabilities

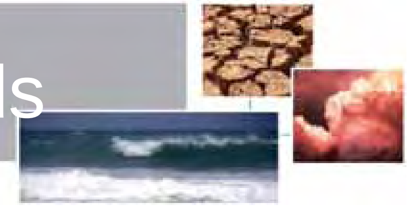
$$P(\theta \mid X) \propto P(X \mid \theta) * P(\theta)$$

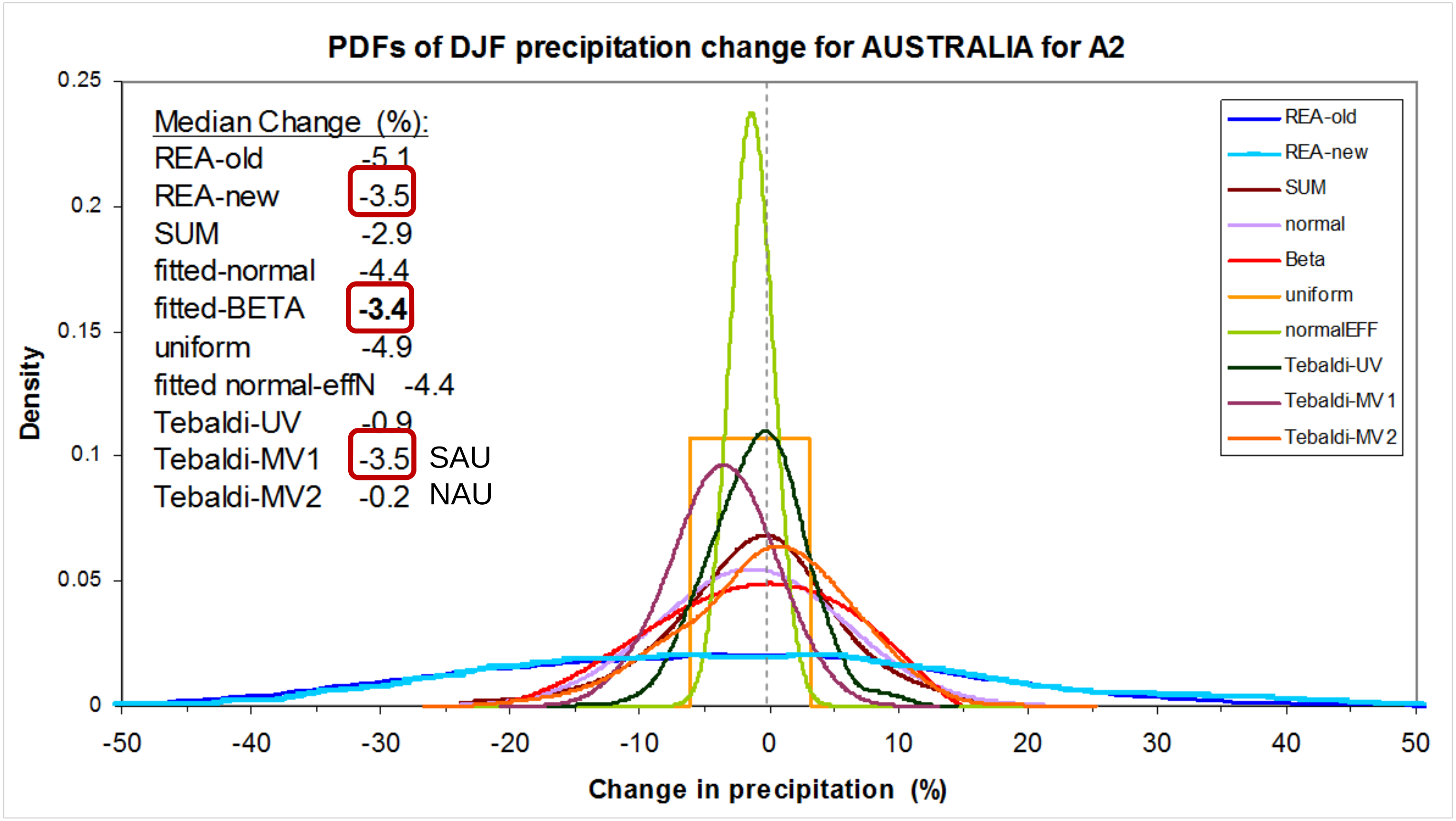
Posterior Distr. Likelihood x Prior Distr.

$P(\theta|X)$ is new Distribution of parameters (mean, sd, …) AFTER we have the data.
$P(\theta)$ is the distribution for the parameters, independent of the data = our subjective uncertainty about the parameters before we see the data (could be "somewhere between minus or plus infinity" or more narrow, or uniform distr., or beta distr.)
$P(X|\theta)$ is Likelihood function (likelihood of the data given the parameters).
→ Posterior Predictive Distribution $P(X_{new}|X)$ is a predictive new 'observed' data set that includes the uncertainty in the parameters.

$$P(X_{new} \mid X) = \int P(X_{new} \mid \theta) P(\theta \mid X) d\theta$$

Australia DJF rainfall changes – all methods





Empirical distributions showing large spread