Quantifying sources of uncertainty in projections of future climate

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Human-induced climate change

Greenhouse gases (warming)
CO_2 (fossil fuels, deforestation)
methane (livestock), N_2O (fertilizers)
Industrial air pollution (cooling)
sulphates, soot

↓

Increase in global temperature
Arctic shrinkage, sea level rise
change in disease patterns, species extinctions

↓

Changes in climate (long-term weather)
change in rainfall patterns, extreme weather?
floods? drought?

Sources of climate uncertainty

Question: Is variability in projected climate variables due mainly to choice of

- General Circulaton Model **GCM** (climate simulator),
- future greenhouse gas emissions **scenario,** or
- GCM **run** (simulation number)?

…or a mixture of these?
…does it matter how far into the future we want to look?
…does the climate variable matter?
…does the region of the world matter?

Simple measures of climate change, e.g. global temperature

1. average change in **2020–2049** (relative to 1980–1999)
2. average change in **2069–2098** (relative to 1980–1999)

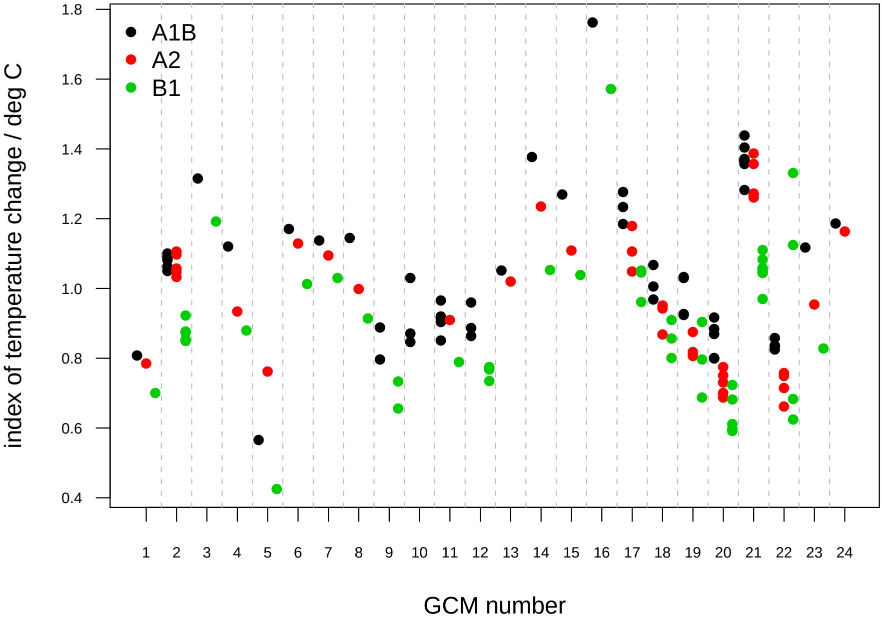
IPCC 4th Assessment Report 2007 data

		scenario		
GCM number	GCM name	A1B	A2	B1
1	bccr:bcm2:0	1	1	1
2	cccma:cgcm3:1	5	5	5
3	cccma:cgcm3:1:t63	1	0	1
4	cnrm:cm3	1	1	1
5	csiro:mk3:0	1	1	1
6	csiro:mk3:5	1	1	1
7	gfdl:cm2:0	1	1	1
8	gfdl:cm2:1	1	1	1
9	giss:aom	2	0	2
10	giss:model:e:h	3	0	0
11	giss:model:e:r	5	1	1
12	iap:fgoals1:0:g	3	0	3
13	ingv:echam4	1	1	0
14	inmcm3:0	1	1	1
15	ipsl:cm4	1	1	1
16	miroc3:2:hires	1	0	1
17	miroc3:2:medres	3	3	3
18	miub:echo:g	3	3	3
19	mpi:echam5	4	3	3
20	mri:cgcm2:3:2a	5	5	5
21	ncar:ccsm3:0	7	5	8
22	ncar:pcm1	4	4	4
23	ukmo:hadcm3	1	1	1
24	ukmo:hadgem1	1	1	0
total		57	40	48

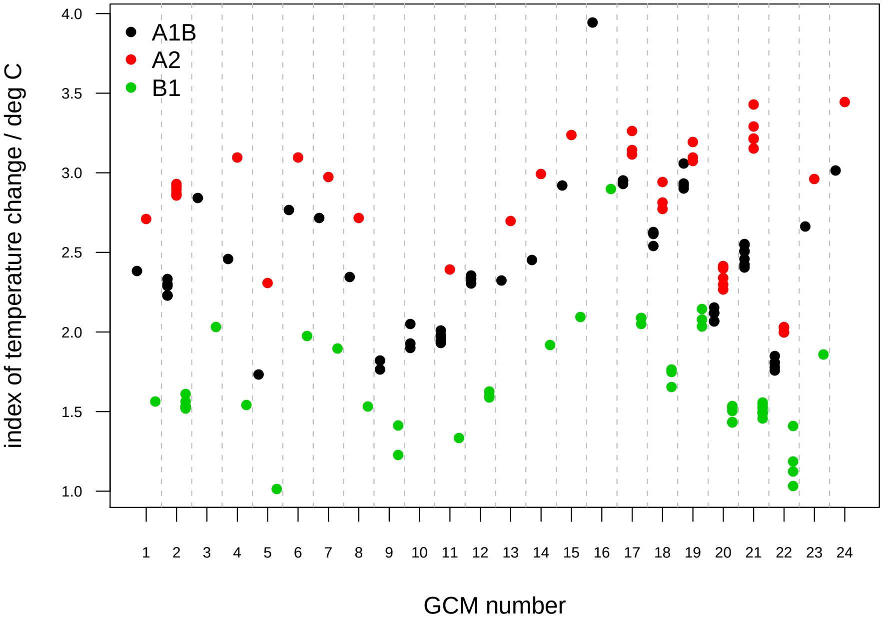
No design. Lack of balance. Zero cells.

Complicates analysis. Each run takes approx. 1 month.

Global temperature change 2020–2049



Global temperature change 2069–2098



A 2-way random effects ANOVA

Y_{ijk} = measure of change for **GCM *i***, **scenario *j*** and **run *k***.

$$Y_{ijk} \quad = \quad \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk},$$

μ	overall mean change	
α_i	adjustment for GCM *i*	$\alpha_i \overset{iid}{\sim} N\left(0, \sigma_G\right)$
β_j	adjustment for scenario *j*	$\beta_j \overset{iid}{\sim} N\left(0, \sigma_S\right)$
γ_{ij}	scenario-specific adjustment for GCM *i*	$\gamma_{ij} \overset{iid}{\sim} N\left(0, \sigma_{GS}\right)$
ϵ_{ijk}	residual effect of variability over runs	$\epsilon_{ijk} \overset{iid}{\sim} N\left(0, \sigma_R\right)$

- $\alpha_i \overset{iid}{\sim} N(0, \sigma_G)$ means $\alpha_1, \alpha_2, \ldots$ are independent and normally distributed with mean 0 and st. dev. σ_G.
- Imagine a population of GCMs, each producing a separate effect on Y_{ijk}.
- We assume that all random variables are independent.

Interpretation of parameters

μ	overall temperature change (headline value)
σ_G	variability over GCMs
σ_S	variability over scenarios
σ_{GS}	variability of scenario-specific adjustment for GCM
σ_R	variability over runs

- Large value of $\sigma \Rightarrow$ variable makes a big difference to predictions of global temperature:
  e.g. if σ_G is large then the choice of GCM really matters.
- Large variability $\Rightarrow$ large uncertainty.

Statistical inference

Issues

1. Lack of balance.
2. No runs for some GCM-scenario combinations.
3. Scenario has only 3 levels. Little information in data about variability over scenarios σ_S.

- Benefit from incorporating information about σ_S.
- Bayesian inference
  - (independent) prior distributions for $\theta = (\mu, \sigma_G, \sigma_S, \sigma_{GS}, \sigma_R)$: distribution of θ in absence of data $\boldsymbol{y}$
  - posterior distribution $\pi(\theta \mid \boldsymbol{y}) \propto L(\boldsymbol{y}; \theta)\, \pi(\theta)$ = likelihood $\times$ prior.
  - sample from $\pi(\theta \mid \boldsymbol{y})$ using Markov Chain Monte Carlo (MCMC).

Weakly-informative priors

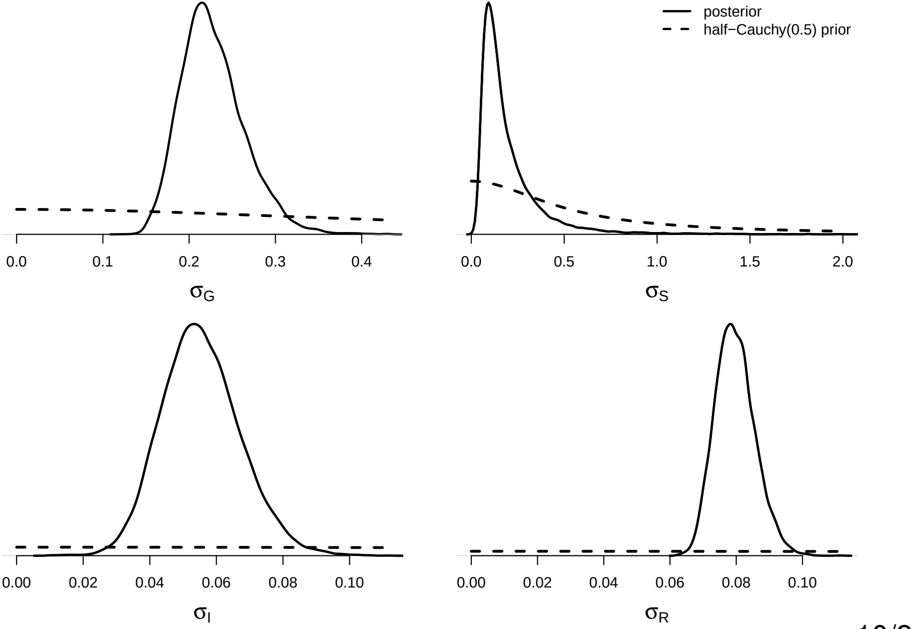
Use a prior distribution that is

- weakly-informative for σ_S, and
- (effectively) uninformative for $\sigma_G, \sigma_{GS}, \sigma_R$ (and μ).

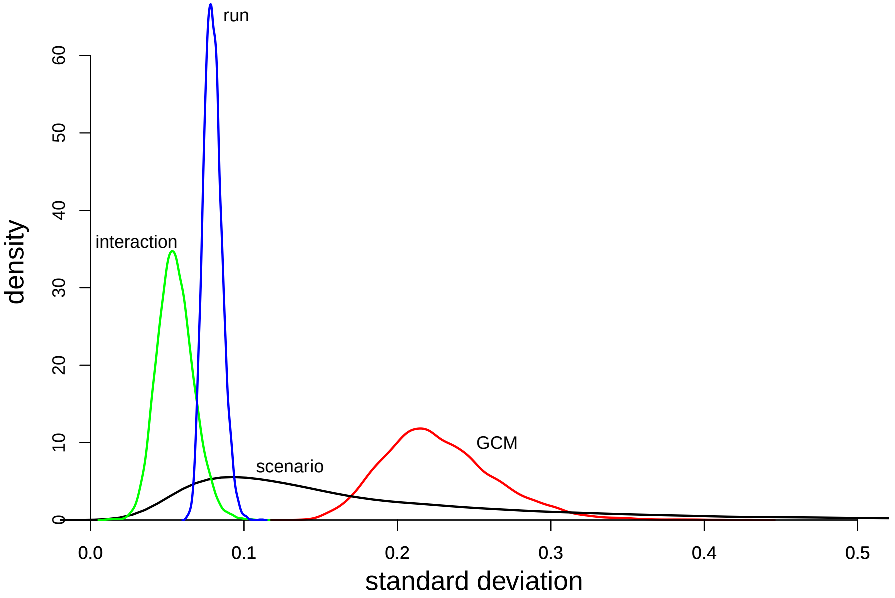
Idea

- downweight unrealistic values of σ_S - because the data aren't informative enough to discount these values;
- ... e.g. unlikely that end of 21st century projections from two different scenarios differ by as much as 20°C;
- otherwise let the data speak for themselves;
- use half-Cauchy priors for the σs (Gelman, 2006);

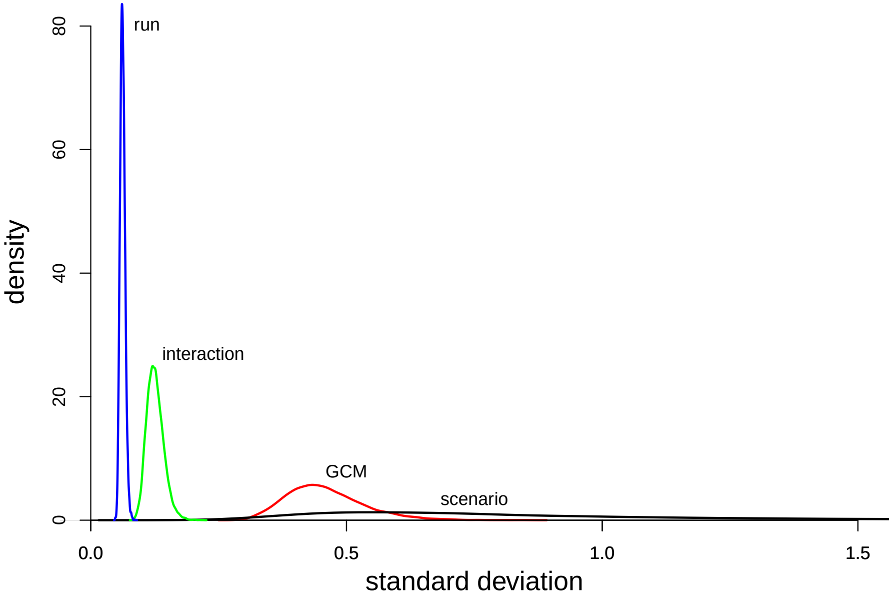
Global temperature 2020–2049



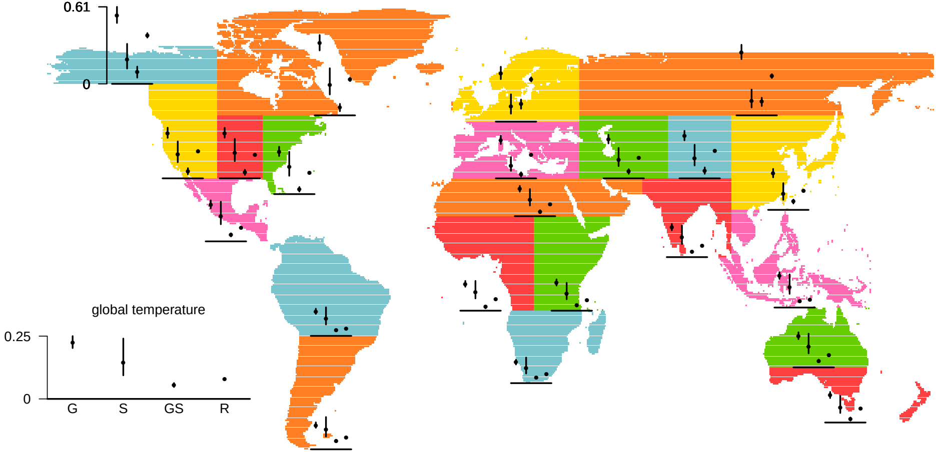
Global temp. 2020–2049: posterior distns



Global temp. 2069–2098: posterior distns

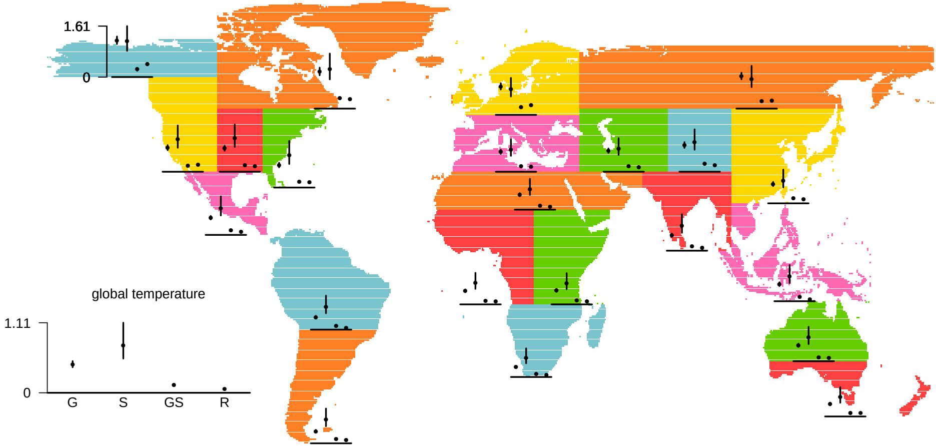


Regional temperature: 2020–2049



median (•) and line between quartiles

Regional temperature: 2069–2098



median (•) and line between quartiles

Summary for temperature

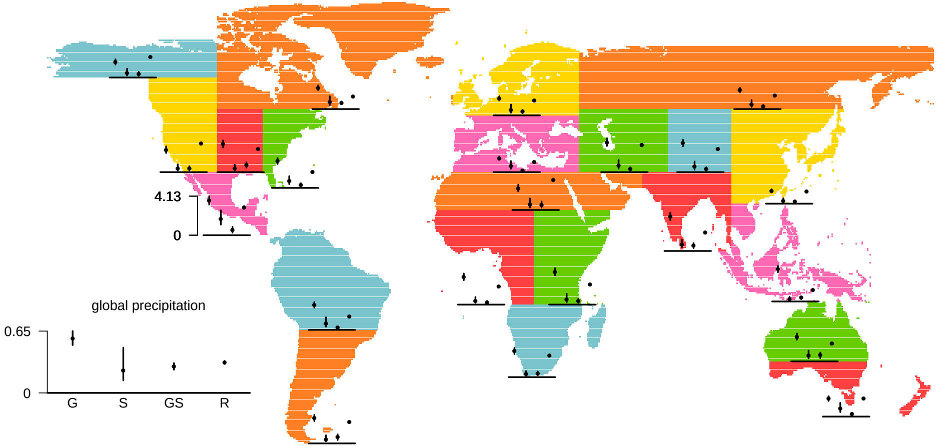
2020–2049

- Global : variability over GCMs $>$ scenario $>$ runs
- Regional: runs matters more than scenario in some areas, e.g. In the north

2069–2098

- Scenario matters more as we move through the 21st century (obviously!)
- Scenario is at least as important as GCM in most regions

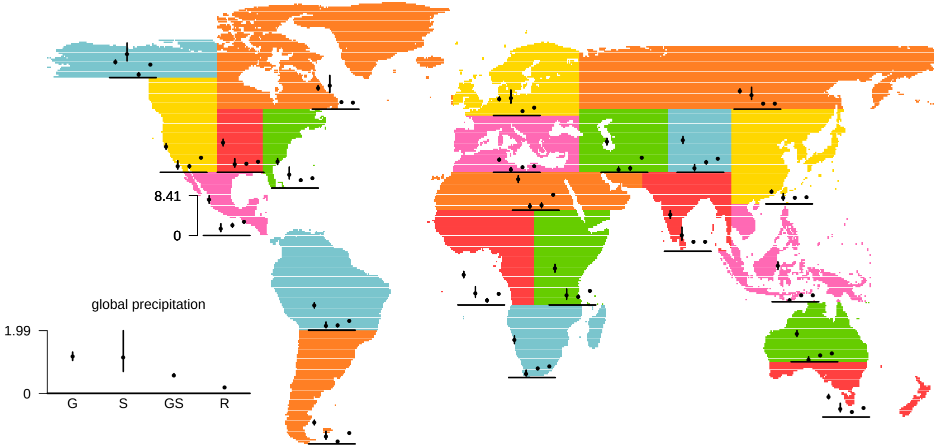
Percentage change in mean from 1980–1999



median (•) and line between quartiles

Regional rainfall: 2069–2098

Percentage change in mean from 1980–1999



median (•) and line between quartiles

Summary for rainfall

2020-2049

- Global : variability over GCMs largest, but relatively high variability over different runs from the same GCM
- Regional : a similar picture. In some areas (e.g. Alaska) var. over runs $>$ var. over GCMs

2069-2098

- Global : choice of scenario becoming more important as century progresses
- In many regions scenario is relatively unimportant

Concluding remarks

1. Climate uncertainty depends on
   - the **variable** of interest;
   - the **region** of the world;
   - the **time horizon**.
2. Simple statistical models are useful.
3. Scope to improve design of climate experiments.
4. How best to combine projections from multiple climate simulators? See Marianna Demetriou's poster.

References

- Gelman, A. (2006) Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis*, **1**(3), 515–533
- Chandler, R. E., Rougier, J. and Collins, M. (2010) Climate change: making certain what the uncertainties are *Significance*, **7**(1), 9-12
- WCRP CMIP3 Multi-Model Dataset Archive at PCMDI `https://esgcet.llnl.gov:8443/home/publicHomePage.do`
- Northrop, P. J. and Chandler, R. E. Quantifying sources of uncertainty in projections of future climate. *Available very soon*

Thank you for your attention

Socio-economic scenarios

(Educated) guesses at what the world will be like over the next 100 years.

B1: low emissions, clean and efficient technologies, global sustainability, population peaks in 2050.

A2: medium-high emissions, economic growth on regional scales, increasing population.

A1B: high emissions (a balance across all fuel sources), very rapid economic growth, market forces dominate, population peaks in 2050.

…and many others.

Experimental design (2-way RE ANOVA)

- Review of design for variance components estimation: Khuri, A.I. (2000) Inst. Statist. Rev., 68(3),311–322
- Optimal design depends on $\sigma_G, \sigma_S, \sigma_R$ (prior information; adaptive designs?)

1. Fixed number of GCMs and scenarios
   - Balanced design is optimal
2. Can choose numbers of GCMs and scenarios
   - If σ_R is dominant, balanced design is optimal
   - If not, there are more efficient unbalanced designs
   - If $\sigma_S >> \sigma_R$ we need large number of scenarios and small number of runs per scenario.