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Understanding and Managing Uncertainties

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ADB-APAN Workshop on climate change and disaster risk management in planning and investment projects

June 27-29, 2016

Taj Palace, New Delhi, India

Aims of the talk

1. Describe main sources of uncertainty in future climate projections

2. Explain how ensembles of climate model simulations are used to explore and quantify different types of uncertainty

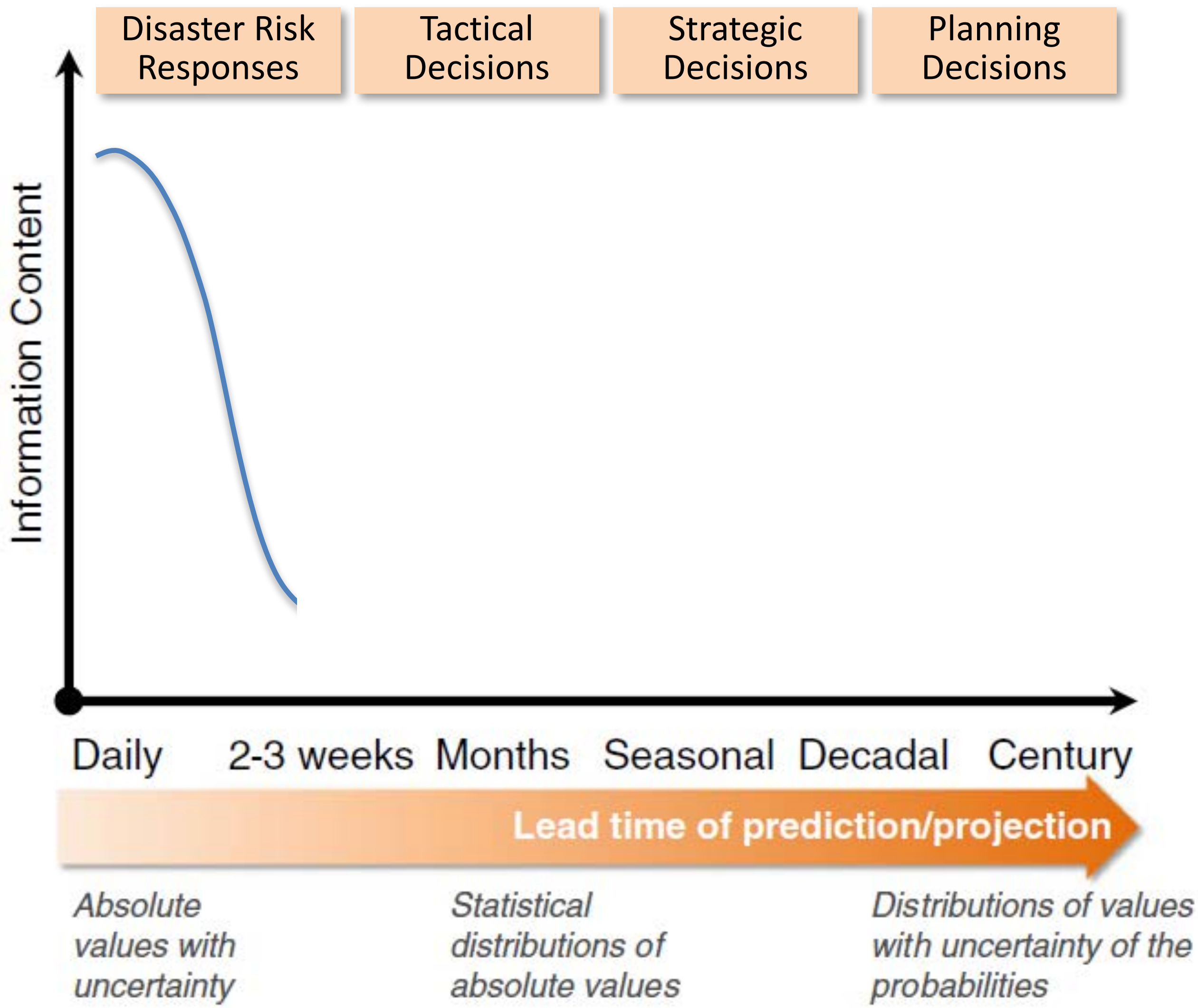
3. Outline some practical approaches for integrating and managing climate uncertainties in adaptation decisions and planning processes

Why consider uncertainty?

Uncertainty = lack of certainty

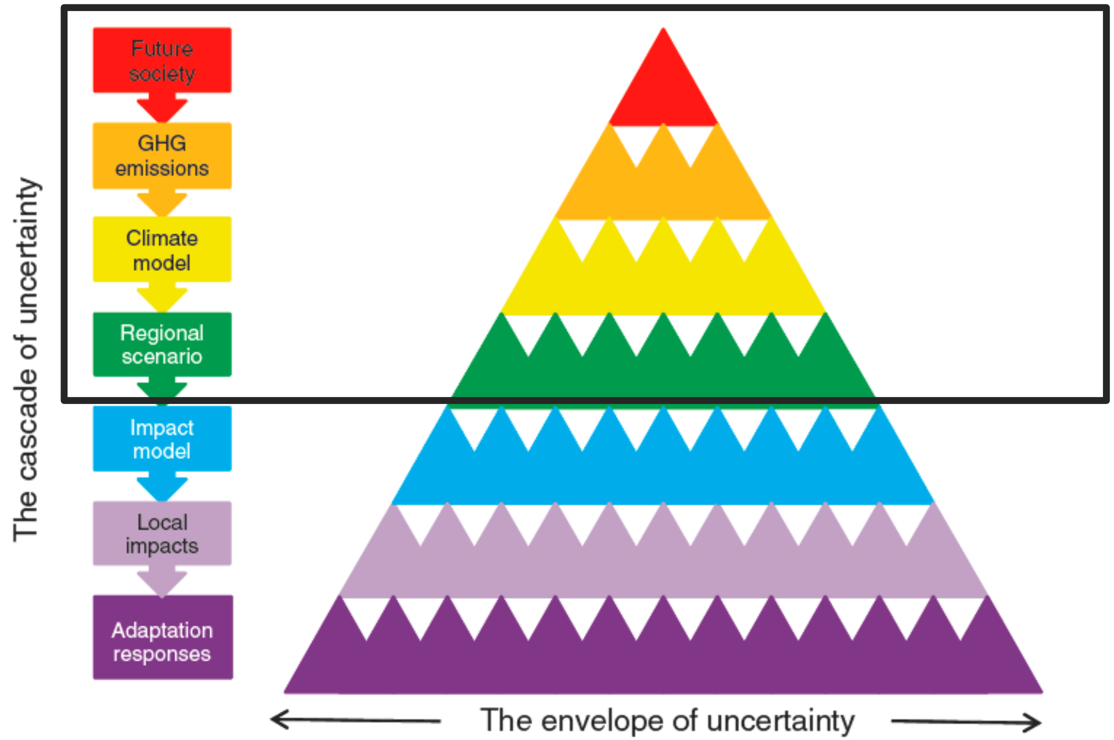
MR. EVANS REALIZES THAT HE IS LIVING IN UNCERTAIN TIMES.

Weather and climate prediction information content for different decision time horizons



Adapted from Hewitson et al (2013) Climatic Change

Uncertainties relevant to climate change adaptation

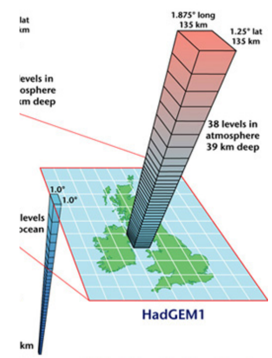


Wilby and Dessai, 2010
Robust Adaptation to Climate Change

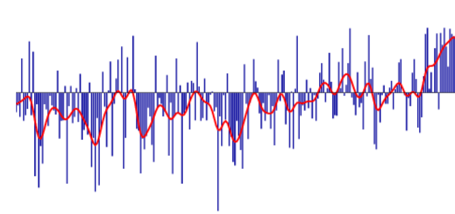
Sources of climate projection uncertainty

1. **Scenario** uncertainty
   – Arises from uncertainty in future human and natural emissions of greenhouse gases

2. **Model** uncertainty
   – Arises from difficulties in modelling the climate system and limited understanding of some processes



3. **Initial Condition** (IC) uncertainty
   – Arises from inherent chaos and natural variability in the climate system



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1. Emission Scenario Uncertainty

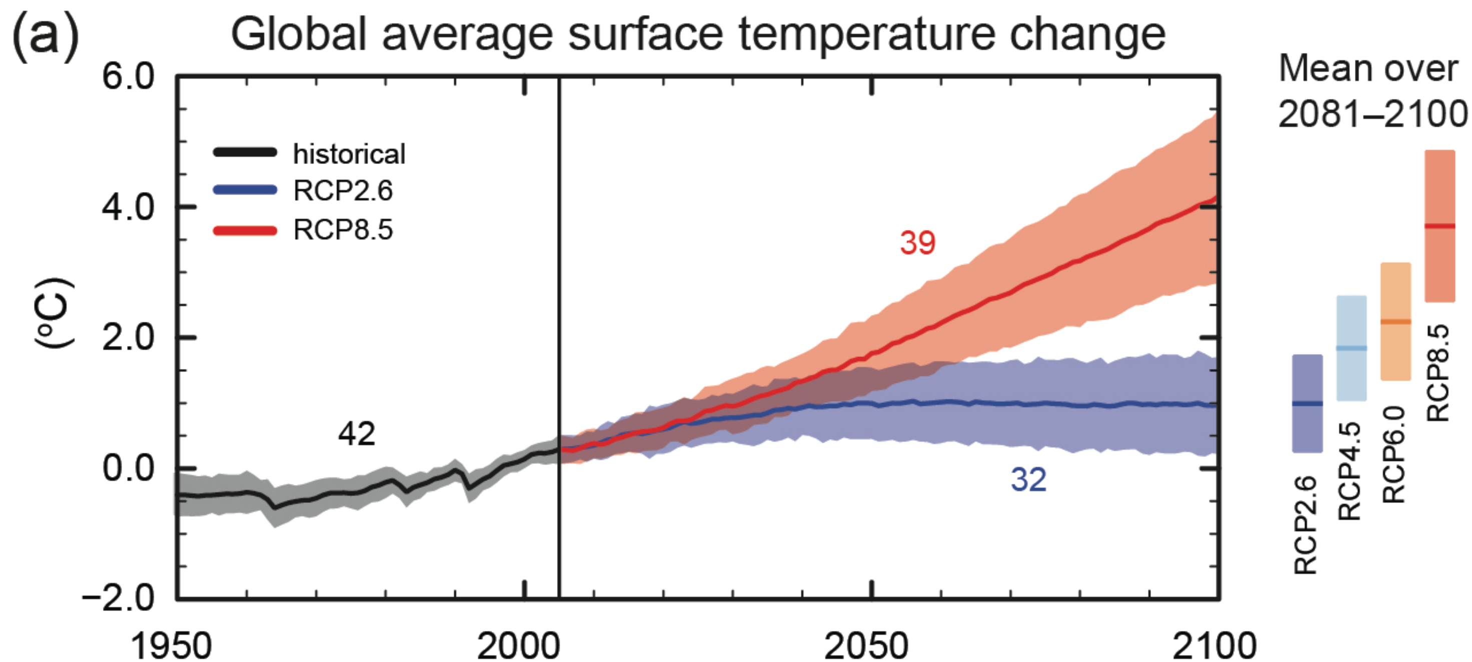
Uncertainties in the key assumptions and relationship about future population, socio-economic development and technical changes.

We are currently working with 2 sets of scenarios:

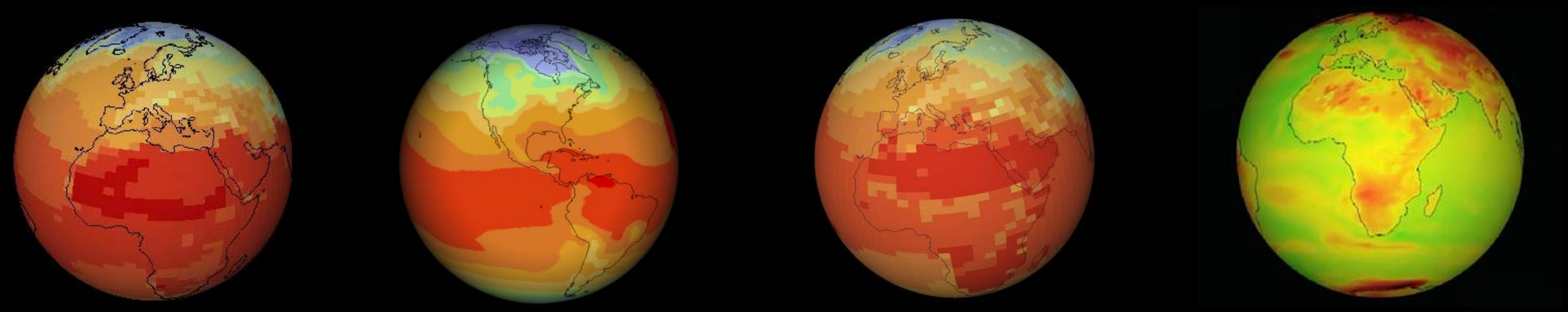
- Special Report on Emissions Scenarios (SRES) used for IPCC AR4
- Representative Concentration Pathways (RCPs) used for IPCC AR5

The IPCC does not assign probabilities to these scenarios.

1. Emission Scenario Uncertainty

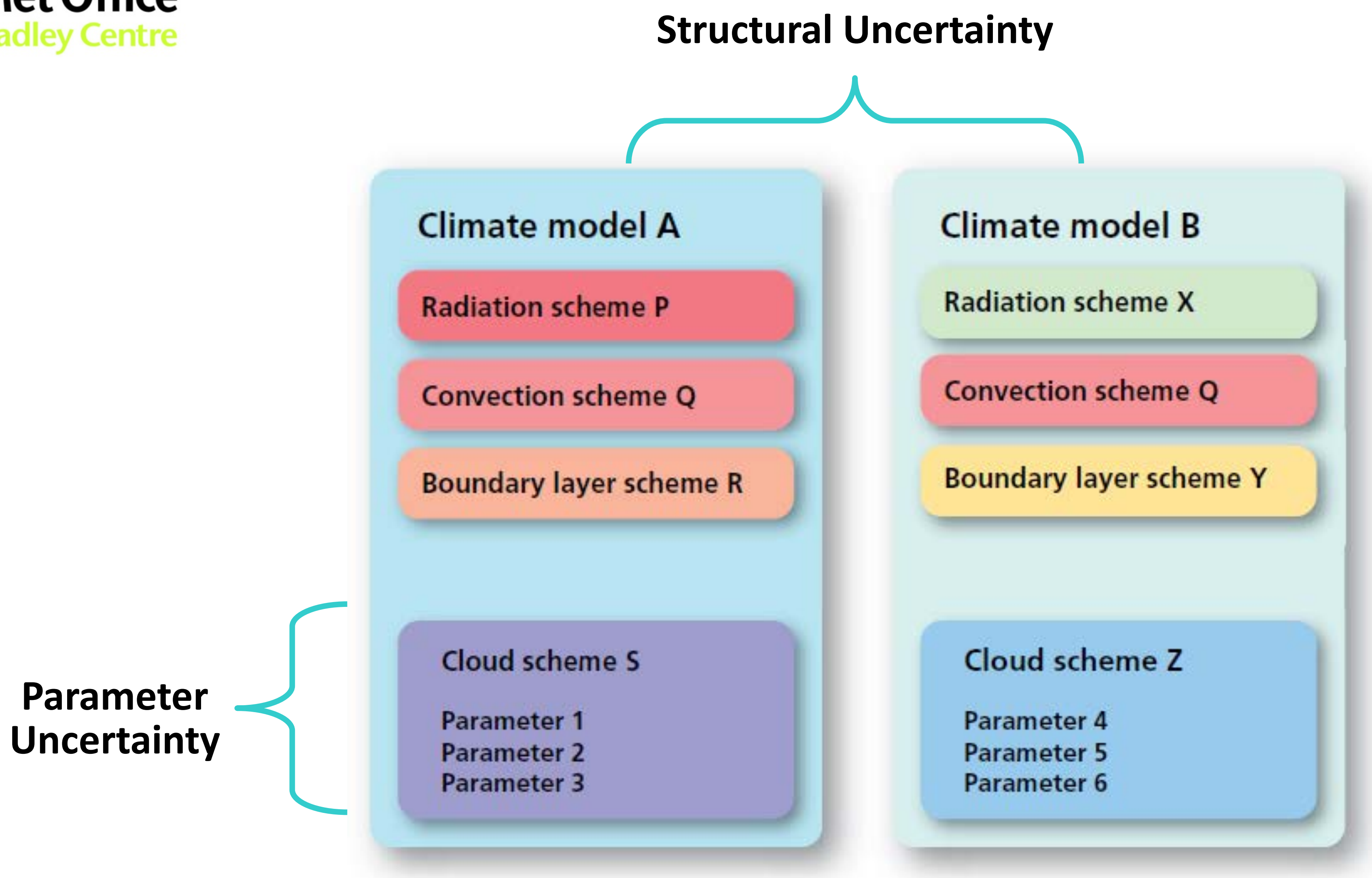


2. Model Uncertainty

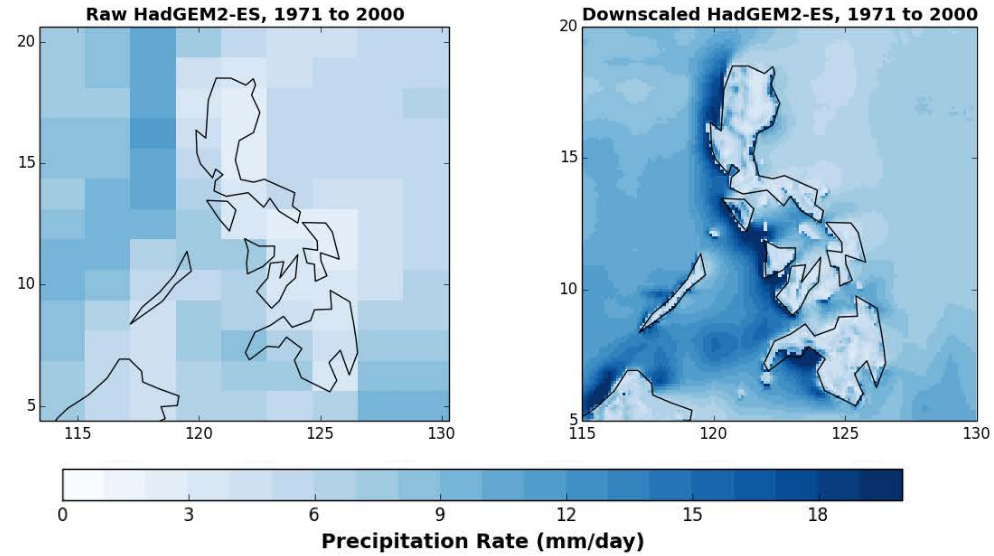


Only one planet Earth

How do models differ?



Downscaled model projections

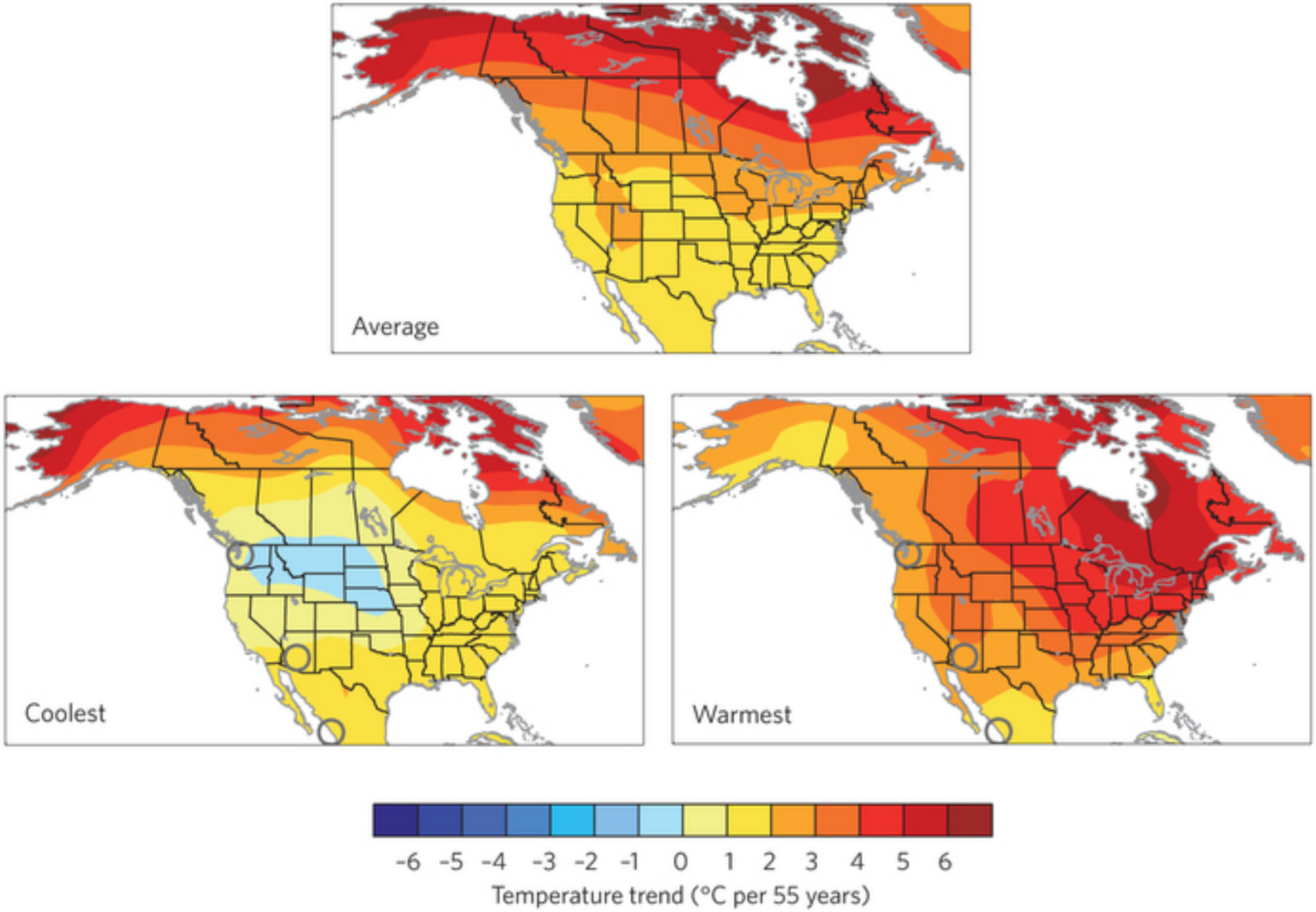


Uncertainty in large-scale climate (GCM ensemble) + Multiple downscaling models / methods → Large resource implications!

Recommended approach to model selection (McSweeney et al 2015):

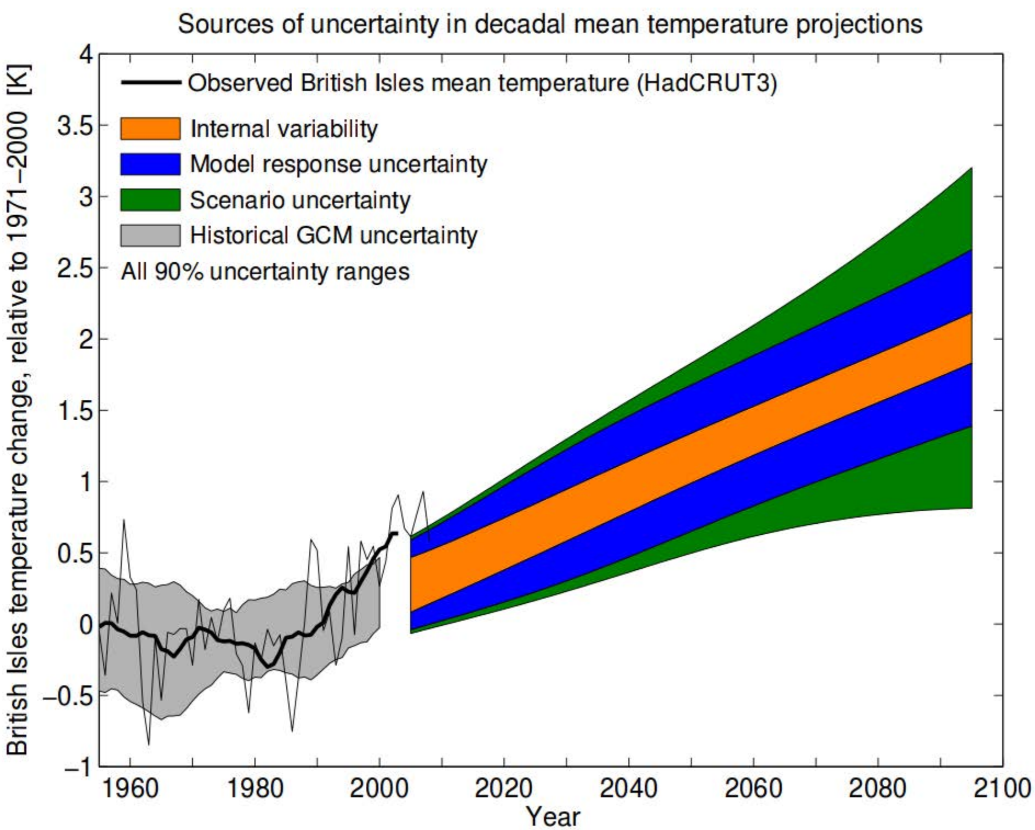
1. **Evaluate performance:** Eliminate models which are poor at capturing key processes and past climate
2. **Sample Uncertainty:** Select models that span the range of projected future climates

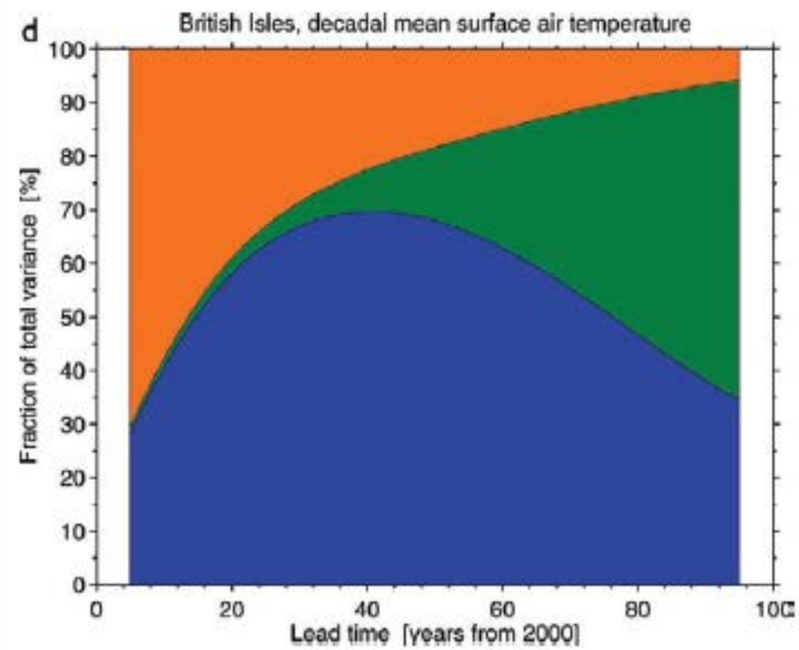
3. Initial Condition Uncertainty



Deser et al (2012) Nature Climate Change

Contributions to total future climatic uncertainties





Hawkins and Sutton, 2009

http://climate.ncas.ac.uk/research/uncertainty/plots.html

Managing climate uncertainties

(aka “managing climate risk”)

Robust Decision Making

Alternative to a science-prescriptive approach:

Projections → Impacts → Policy Responses

Policy Responses → Sensitivities/vulnerabilities → Uncertainties

Robust Decision Making

Daron, J. (2015) Challenges in using a Robust Decision Making approach to guide climate change adaptation in South Africa, *Climatic Change* **132**,459–473

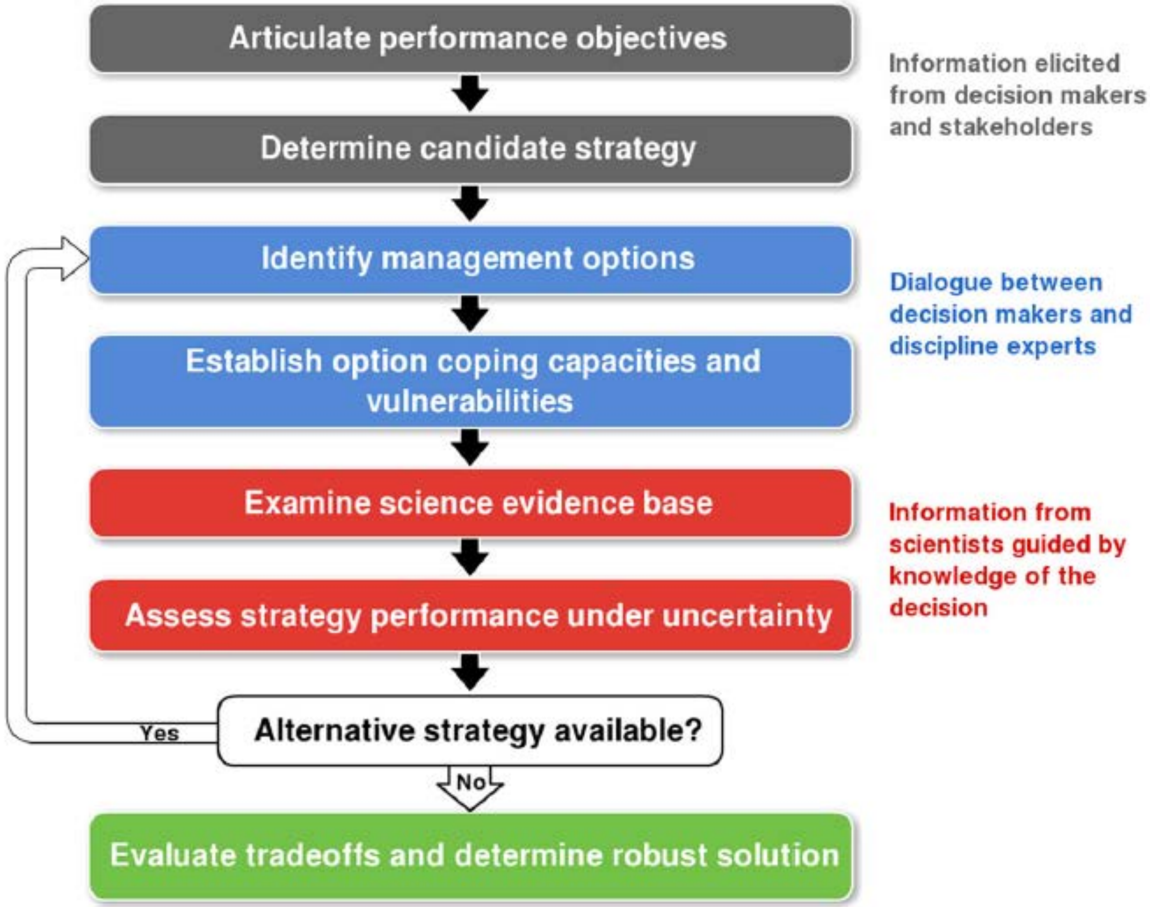
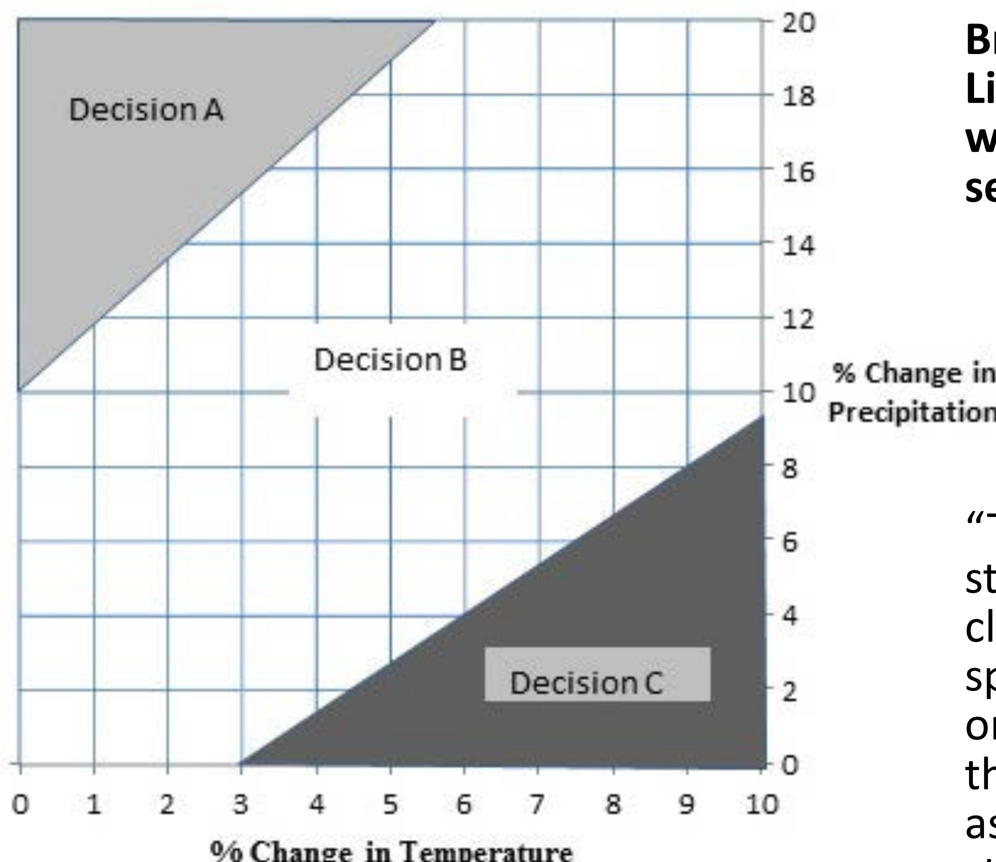


Fig. 1 The sequence of analytical steps in the heuristic robust decision making approach

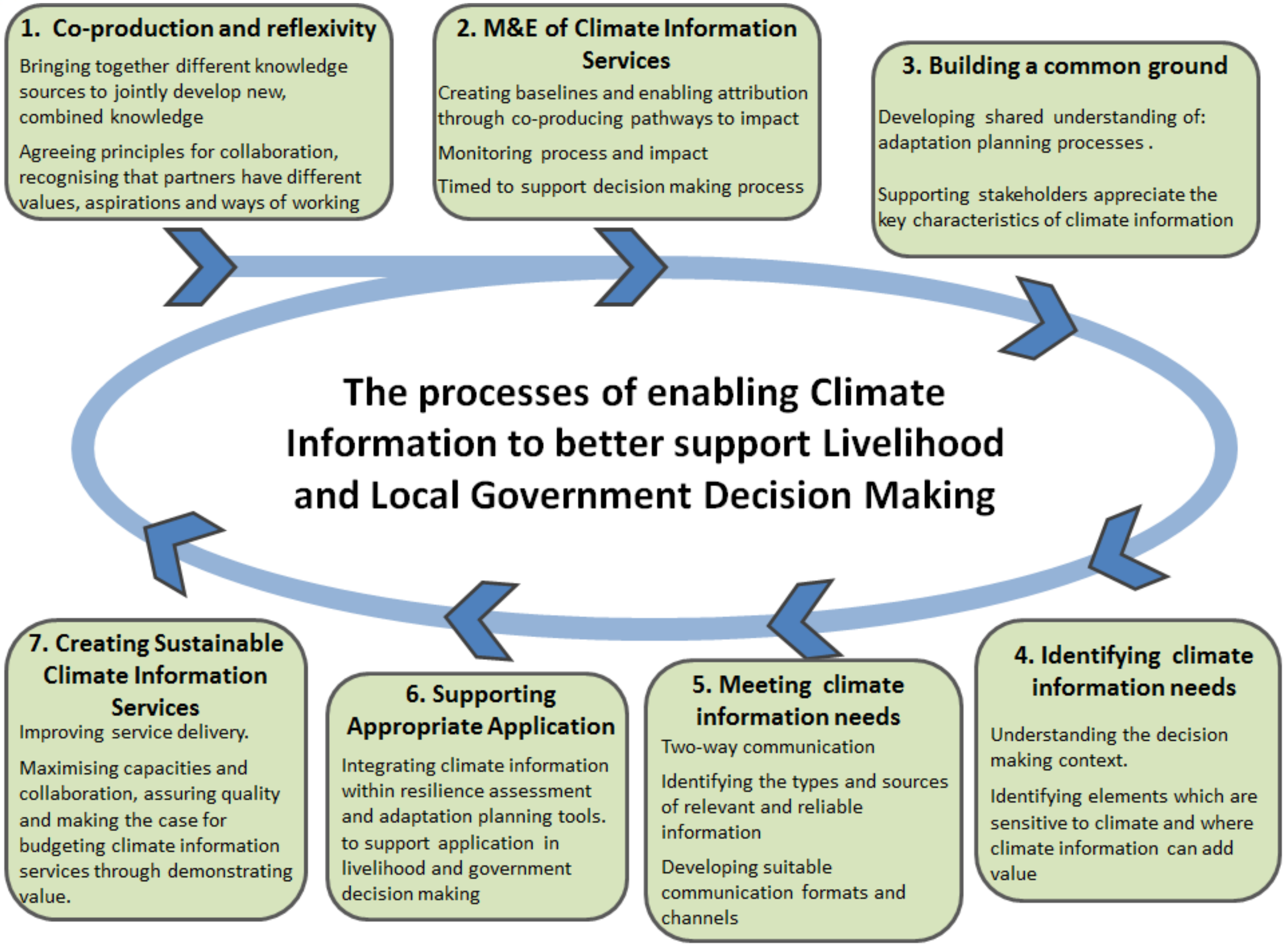
Decision Scaling



Brown et al (2012) Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector

"The parsing of the climate space into states has several advantages. It makes clear to stakeholders and analysts the specific climate conditions that pose risk or favor a particular decision. When those climate conditions are presented as changes in climate from the present, stakeholders gain an intuitive sense of what potential climate changes represent to them. "

Integrating climate information into decision making



From: A practical guide on how weather and climate information can support livelihood and local government decision making. Ada Consortium, February 2016

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Summary

- There is a range of possible future climates due to: 1) uncertain future GHG emissions, 2) imperfect climate models, and 3) inherent natural variability and chaos in the climate system.

- Climate model ensembles sample different uncertainties. While downscaling can add further value, relating large-scale changes to more relevant spatial scales, it also increases resource requirements .

- Decisions can be made in the face of climatic uncertainties. Policy-first risk management frameworks, that incorporate climate with non-climatic factors, can help support long-term adaptation and planning decisions.

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Thanks for listening

Designing ensembles: What is a good strategy?

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Selecting CMIP5 GCMs for downscaling over multiple regions

C. F. McSweeney · R. G. Jones · R. W. Lee · D. P. Rowell

Clim Dyn (2015) 44:3237–3260
DOI 10.1007/s00382-014-2418-8

Recommended approach:

1. **Evaluate performance:** Eliminate models which are poor at capturing key processes and past climate

2. **Sample Uncertainty:** Select models that span the range of projected future climates

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Designing ensembles: What is a good strategy?

I might choose 4 GCMs that span the widest possible range of future rainfall changes.

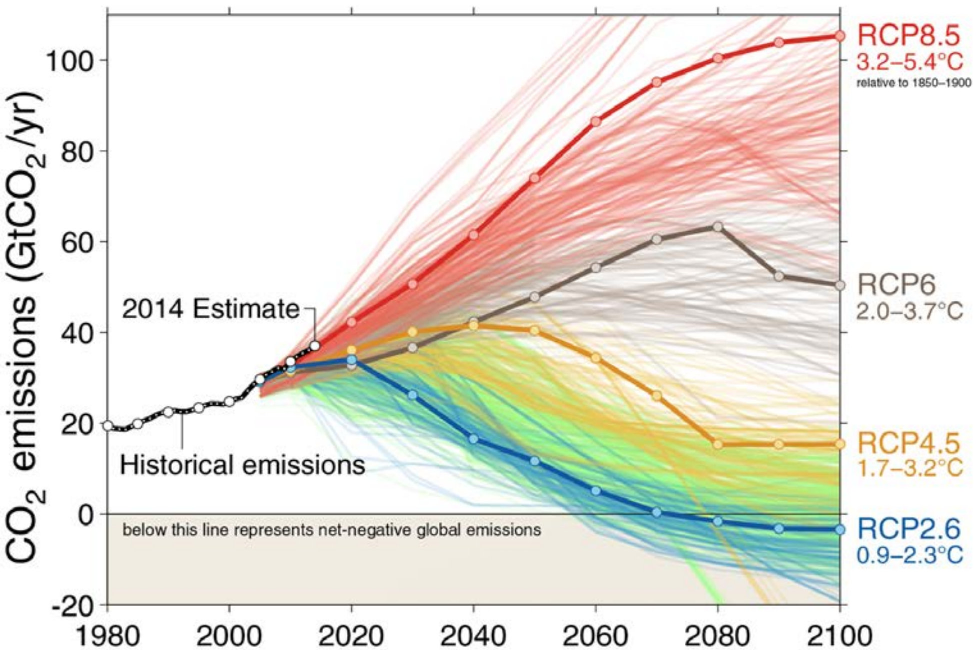
I can only downscale one GCM. Shall I choose the one that best simulates the observed climate?

I could use a higher resolution RCM, but do I have enough computing resource?

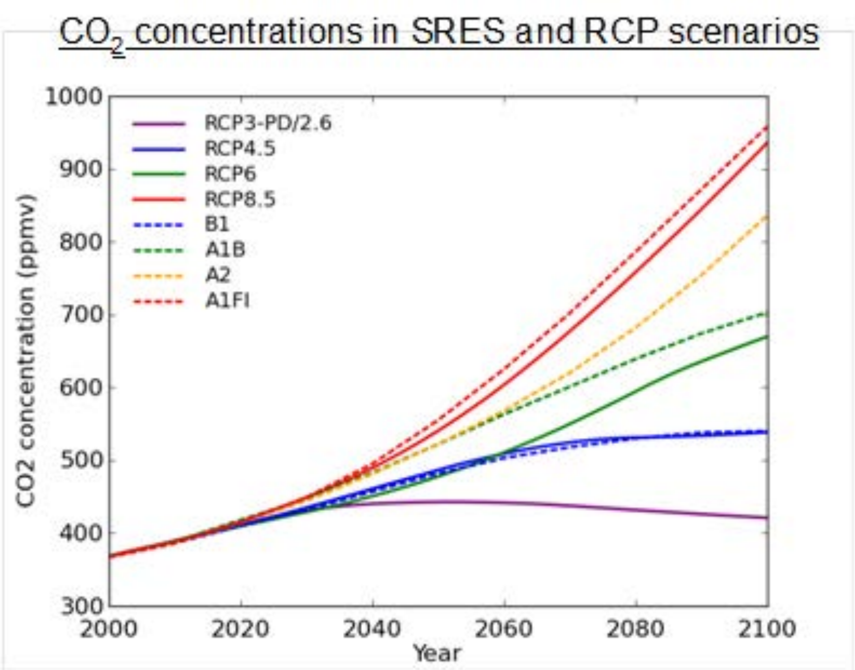
I see a lot of variability in the historical climate. Perhaps I need to use simulations with different initial conditions.

1. Emission Scenario Uncertainty

Representative Concentration Pathways (RCPs)



Fuss et al. 2014



Source: Climate Futures

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Perturbed parameter ensembles (PPEs)

- **Systematic** sampling can be done by perturbing parameter values in a single GCM (but structural uncertainty is not sampled)
- Each ensemble member has different sets of parameter values chosen from likely ranges

Parameter	Range of values
Ice fall speed	
Degree of cloud overlap	
Roughness of sea surface	
Roughness of forests	
Depth of plant roots	
:	:

List of Current Global Climate Models used in IPCC AR5

http://cmip-pcmdi.llnl.gov/cmip5/availability.html

Center	Models	Institution	Country
BCC	BCC-CSM1.1, BCC-CSM1.1(m)	Beijing Climate Center, China Meteorological Administration	China
CCCma	CanAM4, CanCM4, CanESM2	Canadian Centre for Climate Modelling and Analysis	Canada
CMCC	CMCC-CM, CMCC-CMS, CMCC-CESM	Centro Euro-Mediterraneo per I Cambiamenti Climatici	Italy
CNRM-CERFACS	CNRM-CM5, CNRM-CM5-2	Centre National de Recherches Meteorologiques	France
COLA and NCEP	CFSv2-2011	Center for Ocean-Land-Atmosphere Studies and National Center for Environmental Prediction	USA
CSIRO-BOM	ACCESS1.0, ACCESS1.3	CSIRO (Commonwealth Scientific and Industrial Research Organisation) and BOM (Bureau of Meteorology)	Australia
CSIRO-QCCCE	CSIRO-Mk3.6.0	CSIRO (Commonwealth Scientific and Industrial Research Organisation) and the Queensland Climate Change Centre of Excellence	Australia
EC-EARTH	EC-EARTH	EC-EARTH consortium	International consortium
FIO	FIO-ESM	The First Institute of Oceanography, SOA	China
GCESS	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University	China
INM	INM-CM4	Institute for Numerical Mathematics	Russia
IPSL	IPSL-CM5A-LR, IPSL-CM5A-MR, IPSL-CM5B-LR	Institut Pierre-Simon Laplace	France
LASG-CESS	FGOALS-g2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University	China
LASG-IAP	FGOALS-gl, FGOALS-s2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences	China
MIROC	MIROC4h, MIROC5, MIROC-ESM, MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	Japan
MOHC	HadCM3, HadCM3Q, HadGEM2-A, HadGEM2-CC, HadGEM2-ES	Met Office Hadley Centre	UK
MPI-M	MPI-ESM-LR, MPI-ESM-LR, MPI-ESM-P	Max Planck Institute for Meteorology (MPI-M)	Germany
MRI	MRI-AGCM3.2H, MRI-AGCM3.2S, MRI-CGCM3, MRI-ESM1	Meteorological Research Institute	Japan
NASA GISS	GISS-E2-H, GISS-E2-H-CC, GISS-E2-R, GISS-E2-R-CC	NASA Goddard Institute for Space Studies	USA
NASA GMAO	GEOS-5	NASA Global Modeling and Assimilation Office	USA
NCAR	CCSM4	National Center for Atmospheric Research (NCAR)	USA
NCC	NorESM1-M, NorESM1-ME	Norwegian Climate Centre	Norway
NICAM	NICAM.09	Nonhydrostatic Icosahedral Atmospheric Model Group	Japan
NIMR/KMA	HadGEM2-AO	National Institute of Meteorological Research/Korea Meteorological Administration	South Korea
NOAA GFDL	GFDL-CM2.1, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GFDL-HIRAM-C180, GFDL-HIRAM-C360	Geophysical Fluid Dynamics Laboratory	USA
NSF-DOE-NCAR	CESM1	National Science Foundation, Department of Energy, National Center for Atmospheric Research	USA

Parameters perturbed in the Met Office QUMP PPE

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Large Scale Cloud

Ice fall speed

Critical relative humidity for formation

Cloud droplet to rain: conversion rate and threshold

Cloud fraction calculation

Convection

Entrainment rate

Intensity of mass flux

Shape of cloud (anvils) (*)

Cloud water seen by radiation (*)

Radiation

Ice particle size/shape

Cloud overlap assumptions

Water vapour continuum absorption (*)

Boundary layer

Turbulent mixing coefficients: stability-dependence, neutral mixing length

Roughness length over sea: Charnock constant, free convective value

Dynamics

Diffusion: order and e-folding time

Gravity wave drag: surface and trapped lee wave constants

Gravity wave drag start level

Land surface processes

Root depths

Forest roughness lengths

Surface-canopy coupling

CO_2 dependence of stomatal conductance (*)

Sea ice

Albedo dependence on temperature

Ocean-ice heat transfer