Impacts and adaptation assessments: Downscaling, uncertainty quantification and stakeholder-driven approaches

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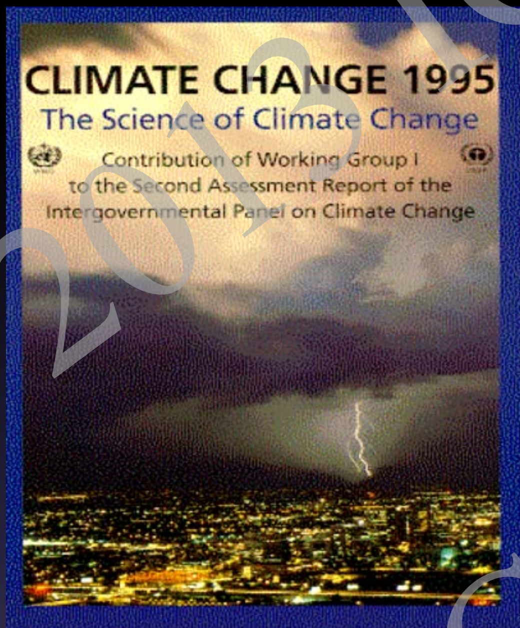
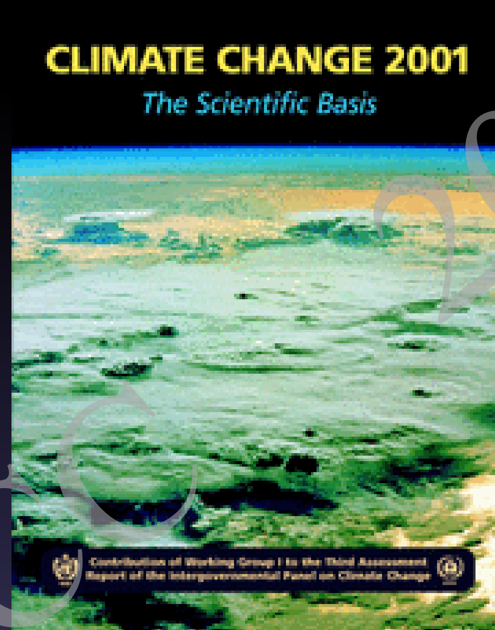
Outline

- Introduction
- Downscaling
- Uncertainty quantification (UQ)
- Stakeholder-driven ("bottom-up") approaches to adaptation

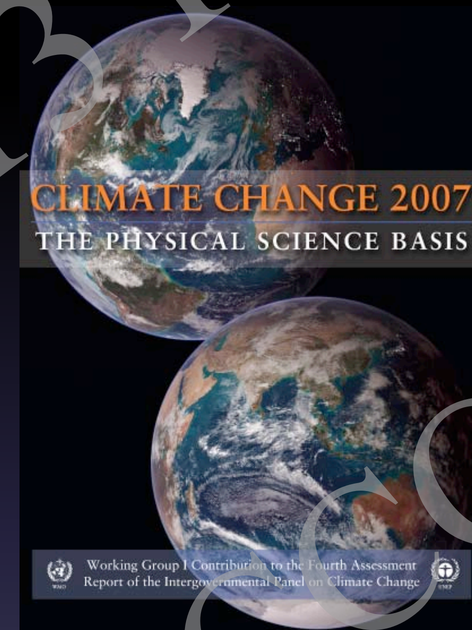
~~Is climate change real?~~
What do we do about it?



"The balance of evidence suggests a discernible human influence on global climate"



"There is new and stronger evidence that most of the warming observed over the last 50 years is attributable to human activities"



"Most of the observed increase in globally averaged temperatures since 1950 is very likely [>90%] due to the observed increase in anthropogenic greenhouse gas concentrations"

Motivations for climate modeling have changed

Historically, climate models were research tools.

Now, we need to use them to inform real-world adaptation decisions.

The need to inform decisions introduces important modeling challenges

- Representation of fine spatial-scale results
- Representation of extremes
- Deterministic forecasts of natural variability ("decadal prediction")
- Uncertainty quantification (UQ)

All of these are model weaknesses.

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Downscaling methods

Nested dynamical: A limited-domain model driven by boundary information from a global-domain model

Global dynamical: A fine resolution atmospheric model driven by prescribed SSTs from a coupled OAGCM.

Empirical/statistical: Fine-scale information form observations is combined with large-scale projected changes from GCMs.

Fine-resolution global model

The Good news ☺

Provides a globally consistent solution.

Is not subject to errors introduced by poor-quality boundary data

Can work beautifully to drive a nested model.

Since results are global, a good area for international collaboration

The Bad news ☹

The most computationally demanding of any option.

Produces a lot of output

Presently limited to about 20 km

Difficult to downscale a large number of GCMs.

~300 km
grid spacing

("T42")

Cloud fraction

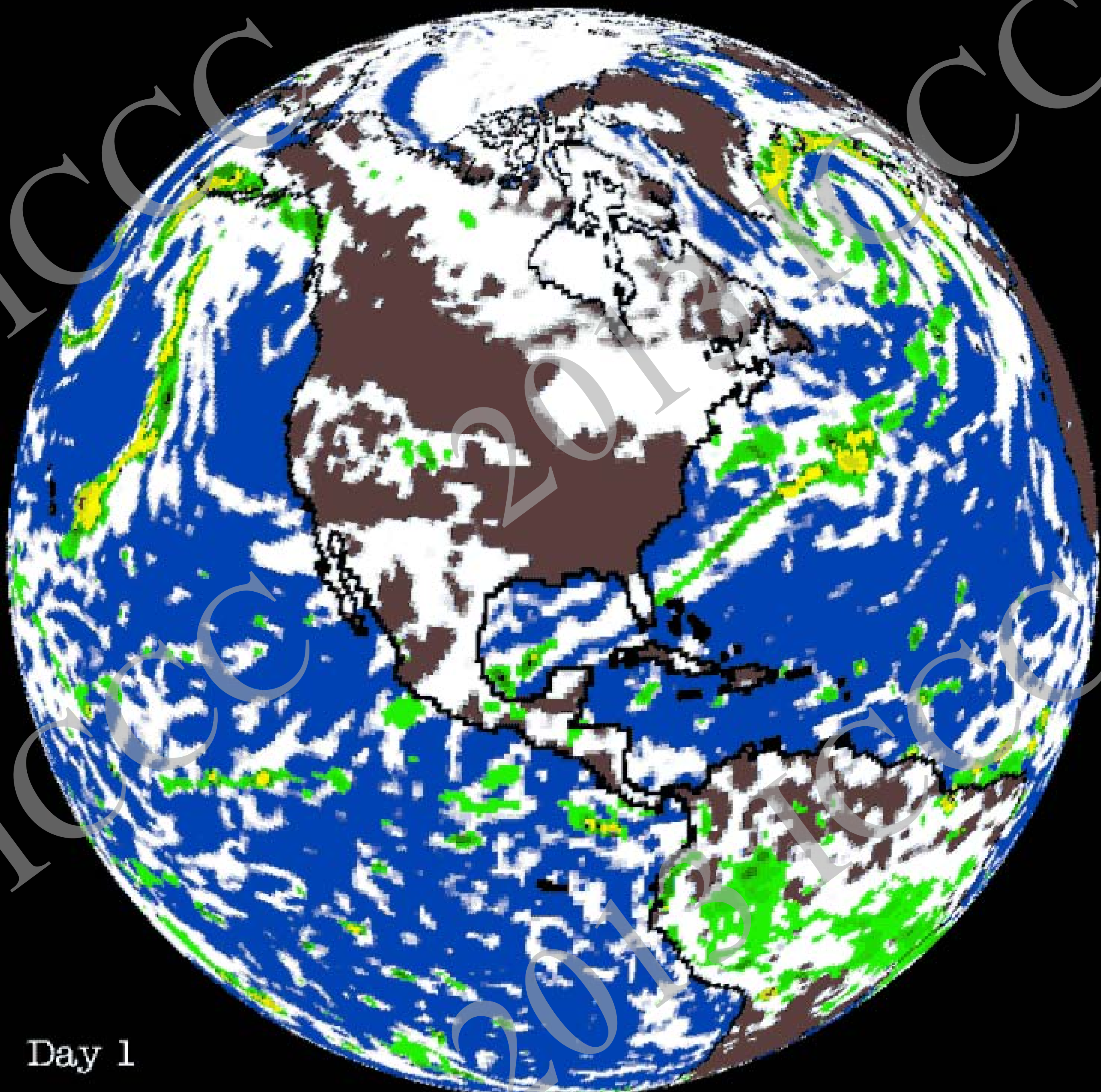
Precipitation rate

~50 km
grid spacing

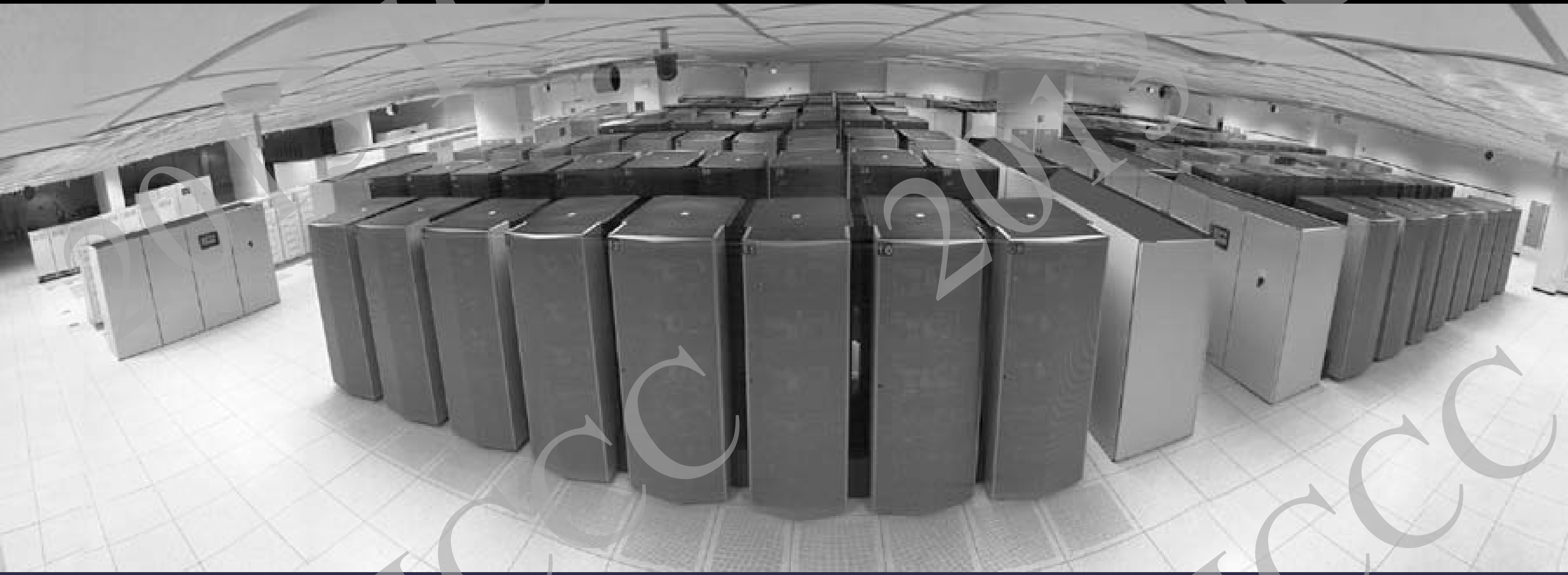
("T239")

Cloud fraction

Precipitation rate



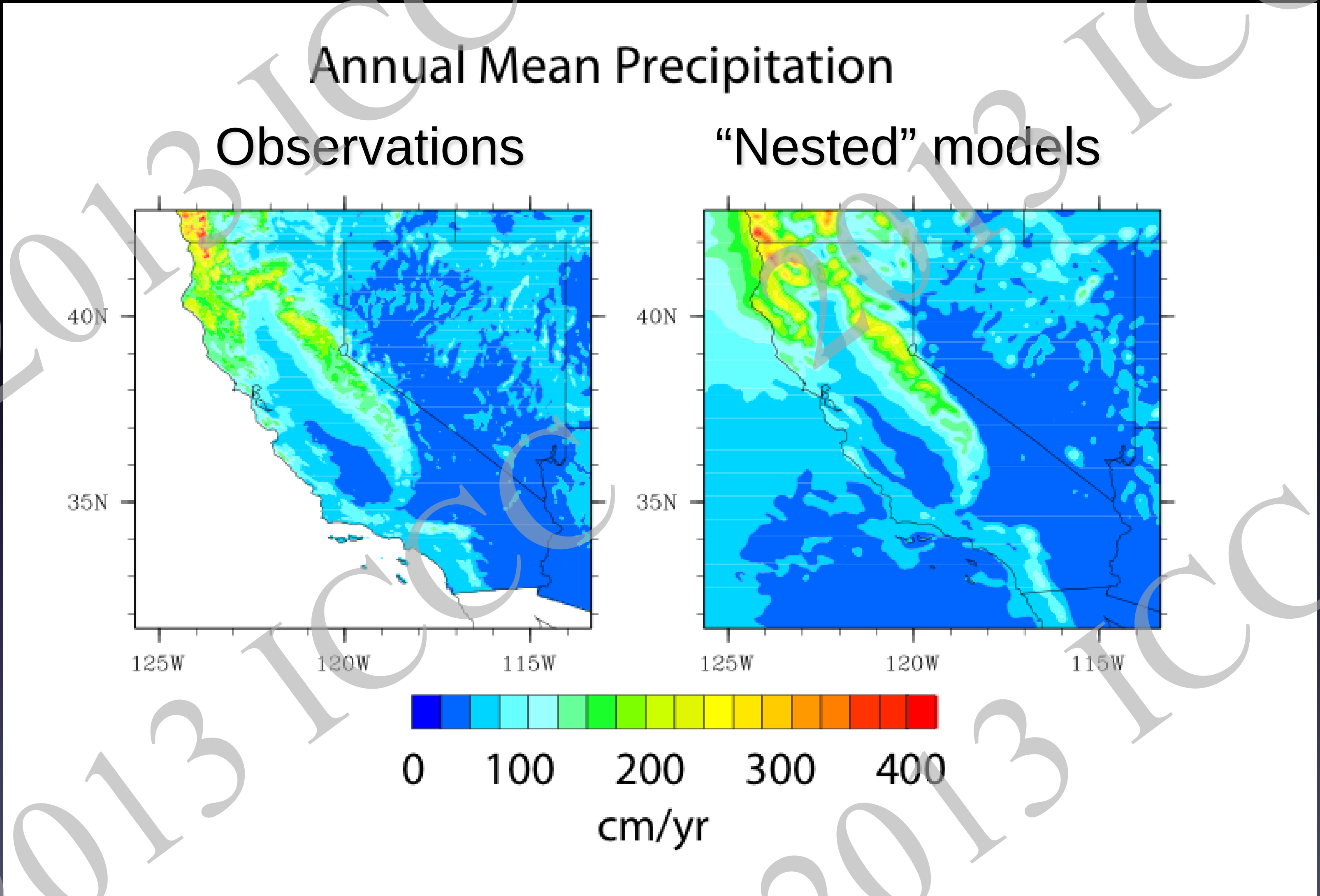
LLNL” ASCI White:” August, 2001



ASCI @

“Accelerated Strategic Computing Initiative”

Limited domain model nested within a fine-resolution global model

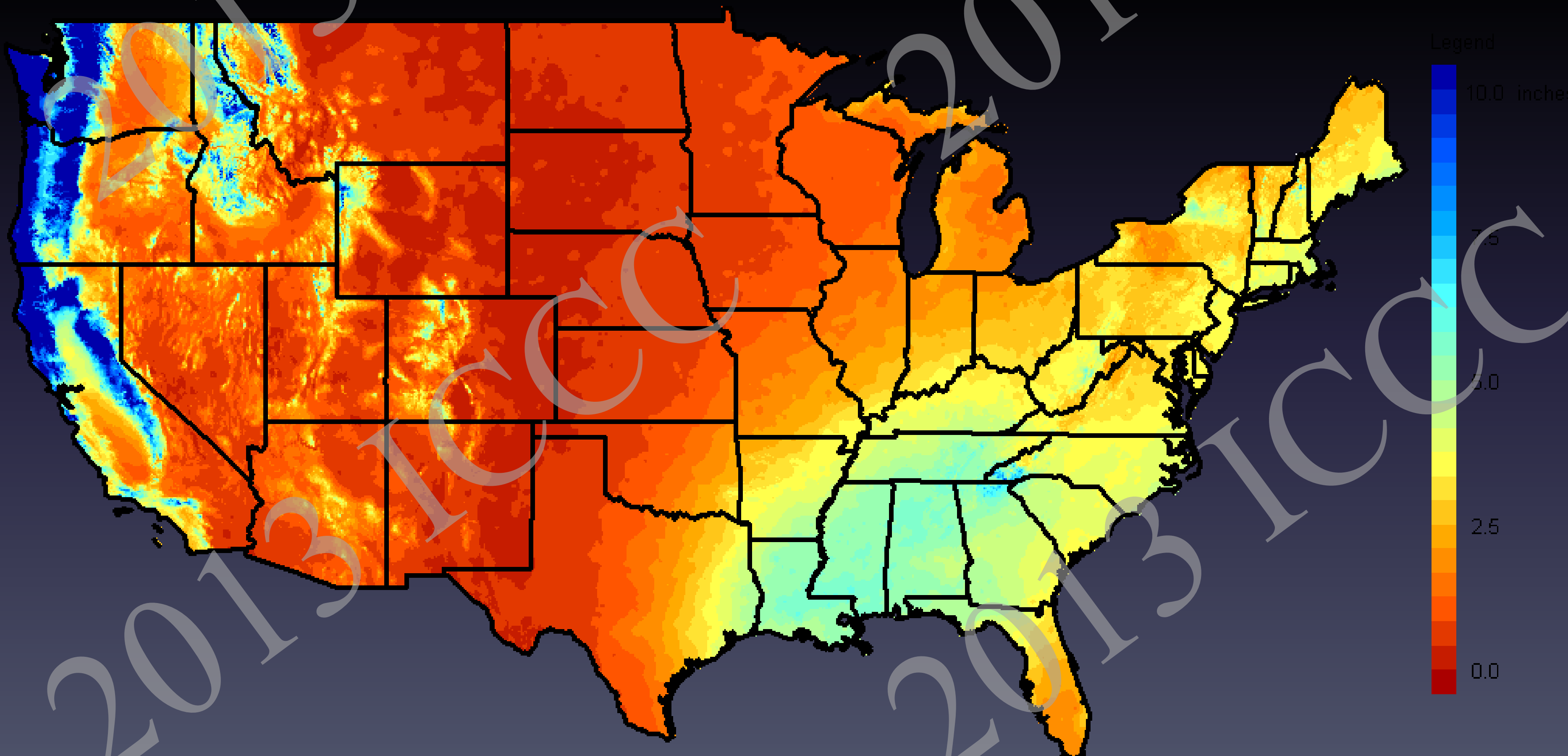


Statistical/Empirical downscaling

Adds detail based on observations

Uses climate model prediction of changes on large scale

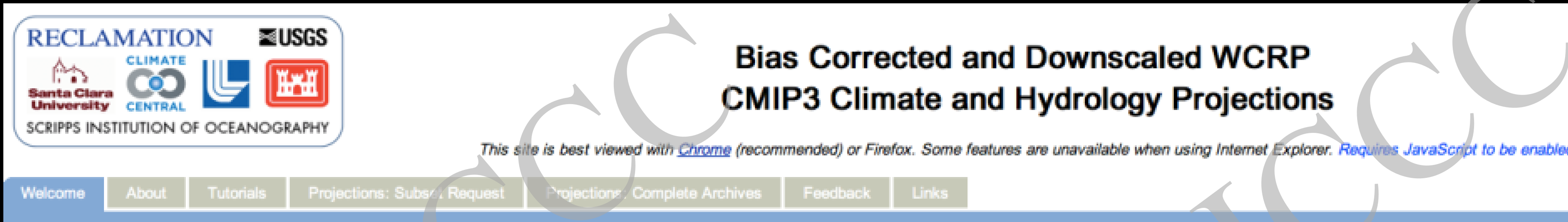
Easy to downscale multiple GCM simulations



Archive of downscaled climate projections

http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html

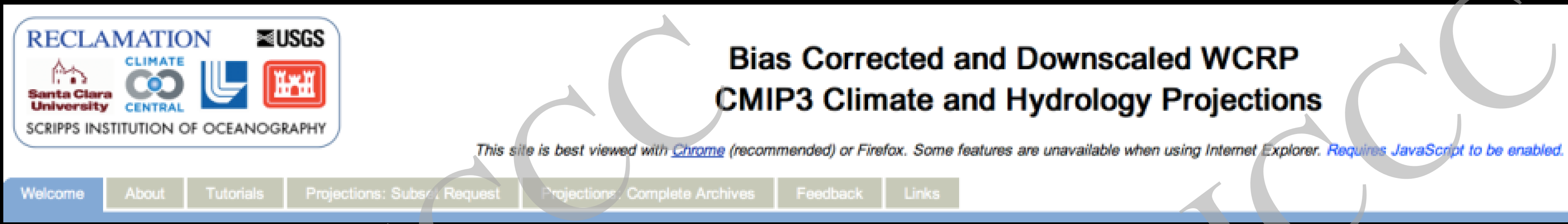
- A cooperative effort of multiple institutions
- Thousands of users since 2007
- Results for United States only



Available now:

- Bias-Corrected, Statistically Downscaled (BCSD) monthly T and P from 16 CMIP3 GCMs, 3 scenarios
- Bias-Corrected Constructed Analog (BCCA) daily T_{max}, T_{min}, and P from 7 CMIP3 models, one scenario
- Daily simulations of surface hydrology from 16 CMIP3 models, 3 scenarios
- All downscaled results at 0.125° grid scale

http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html

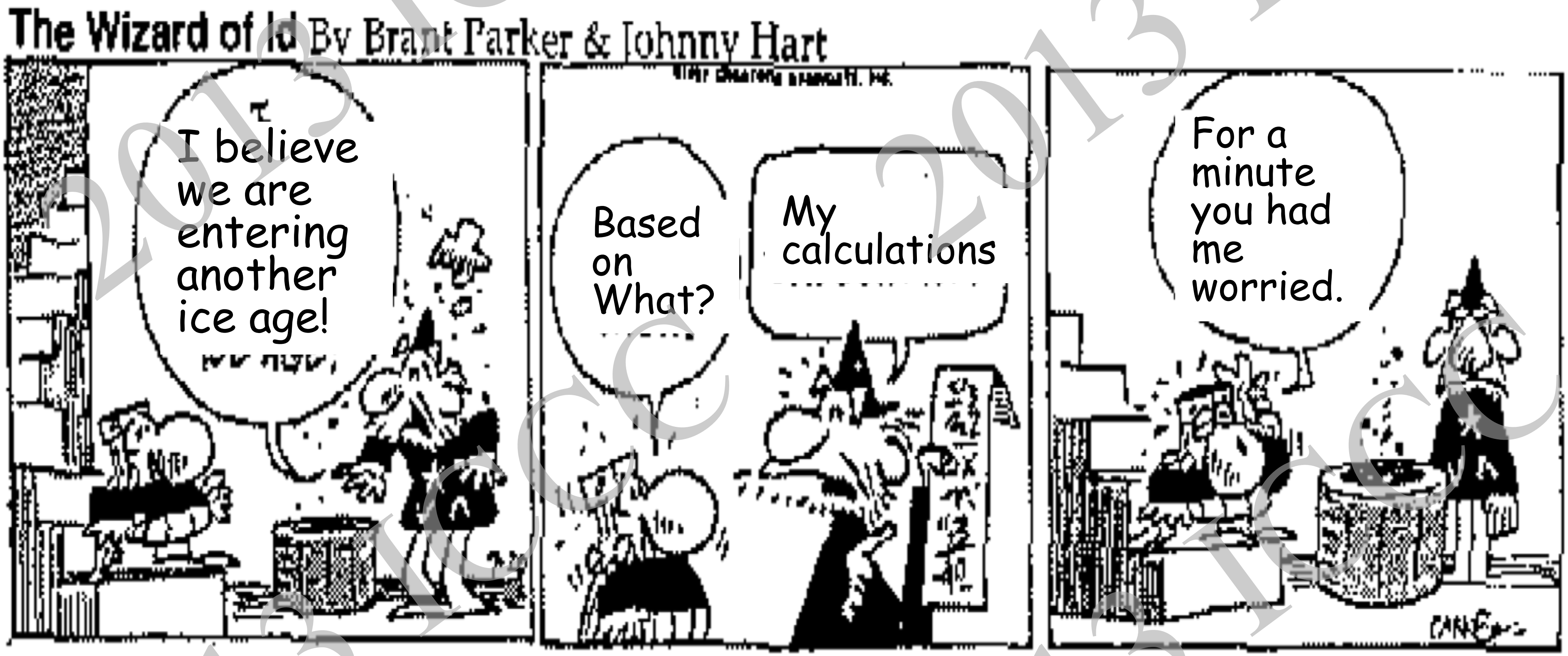


Available soon: CMIP5 results:

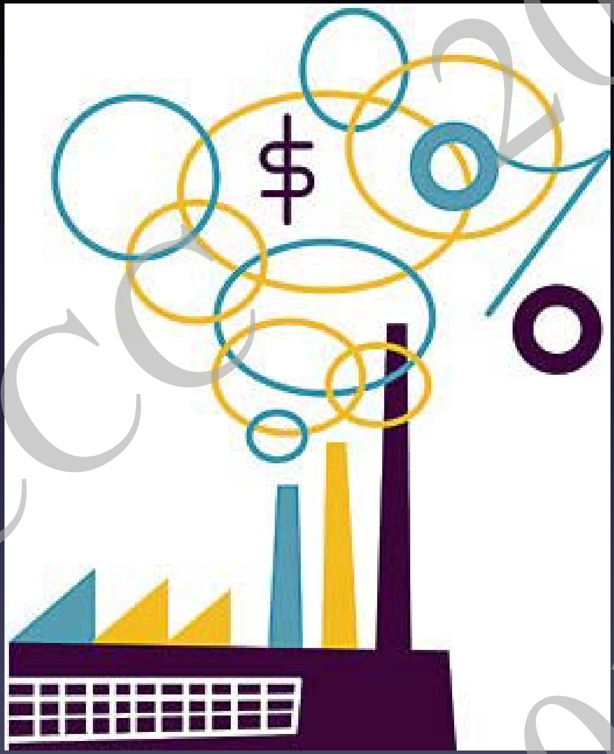
- Bias-Corrected, Statistically Downscaled (BCSD) monthly T and P from 237 projections, 4 RCPs
- Bias-Corrected Constructed Analog (BCCA) daily T_{max}, T_{min}, and P from 147 simulations, 4 RCPs
- Daily simulations of surface hydrology from 100 simulations
- All downscaled results at 0.125° grid scale
- Results for United States only

http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html

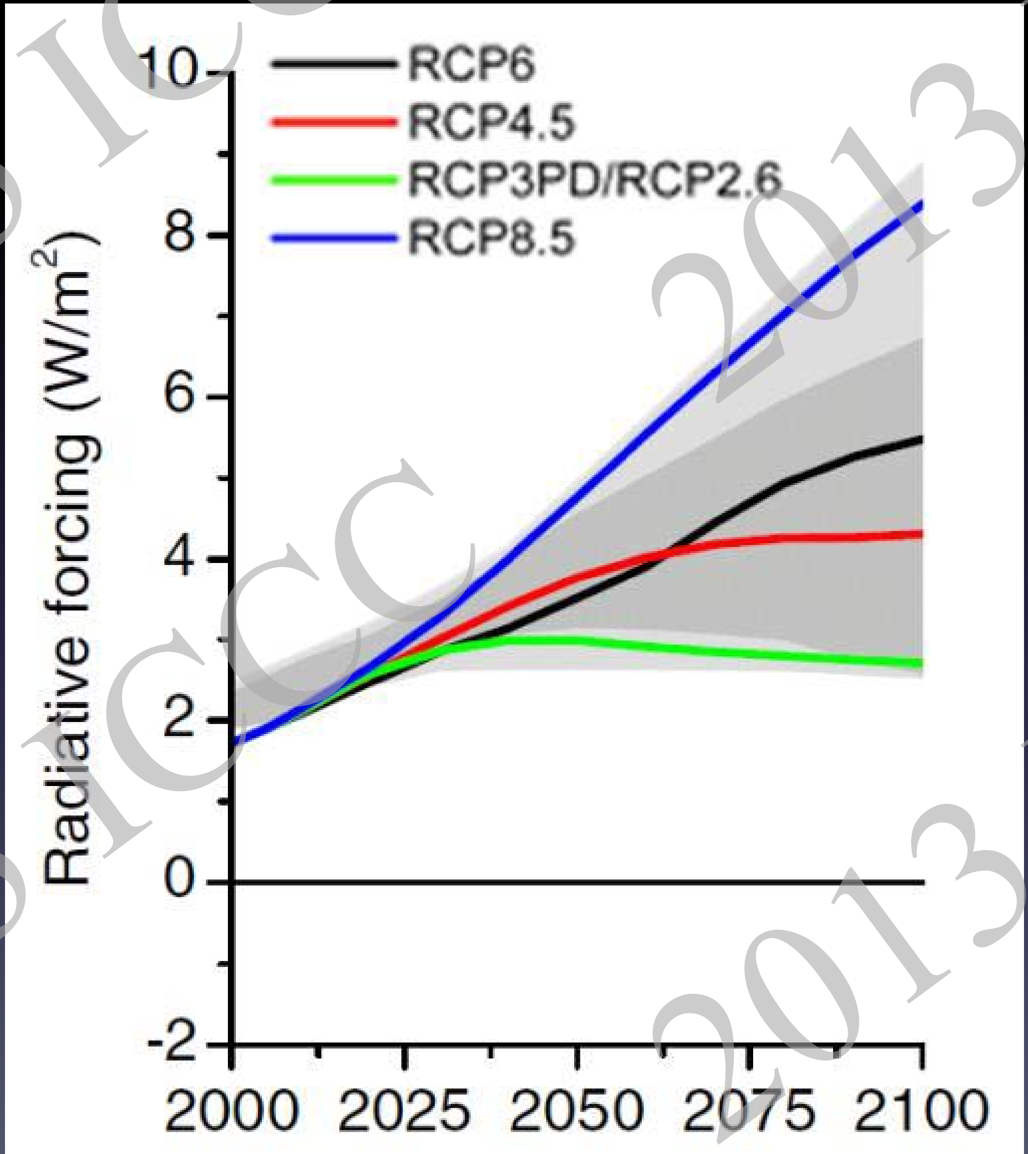
Uncertainty: How reliable are climate projections?



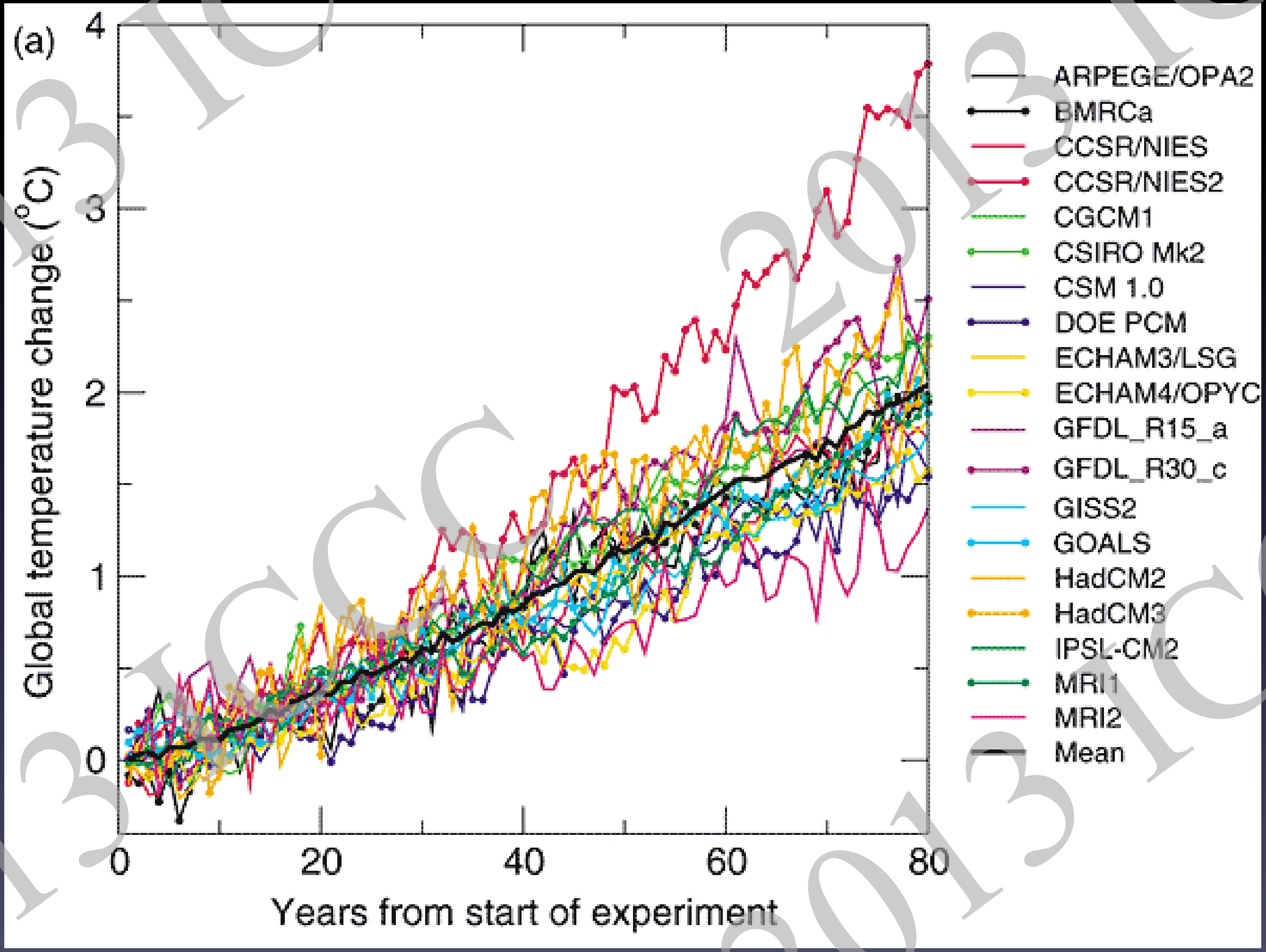
Why is future climate uncertain?



“Scenario uncertainty:” Future forcings are *unknowable*;

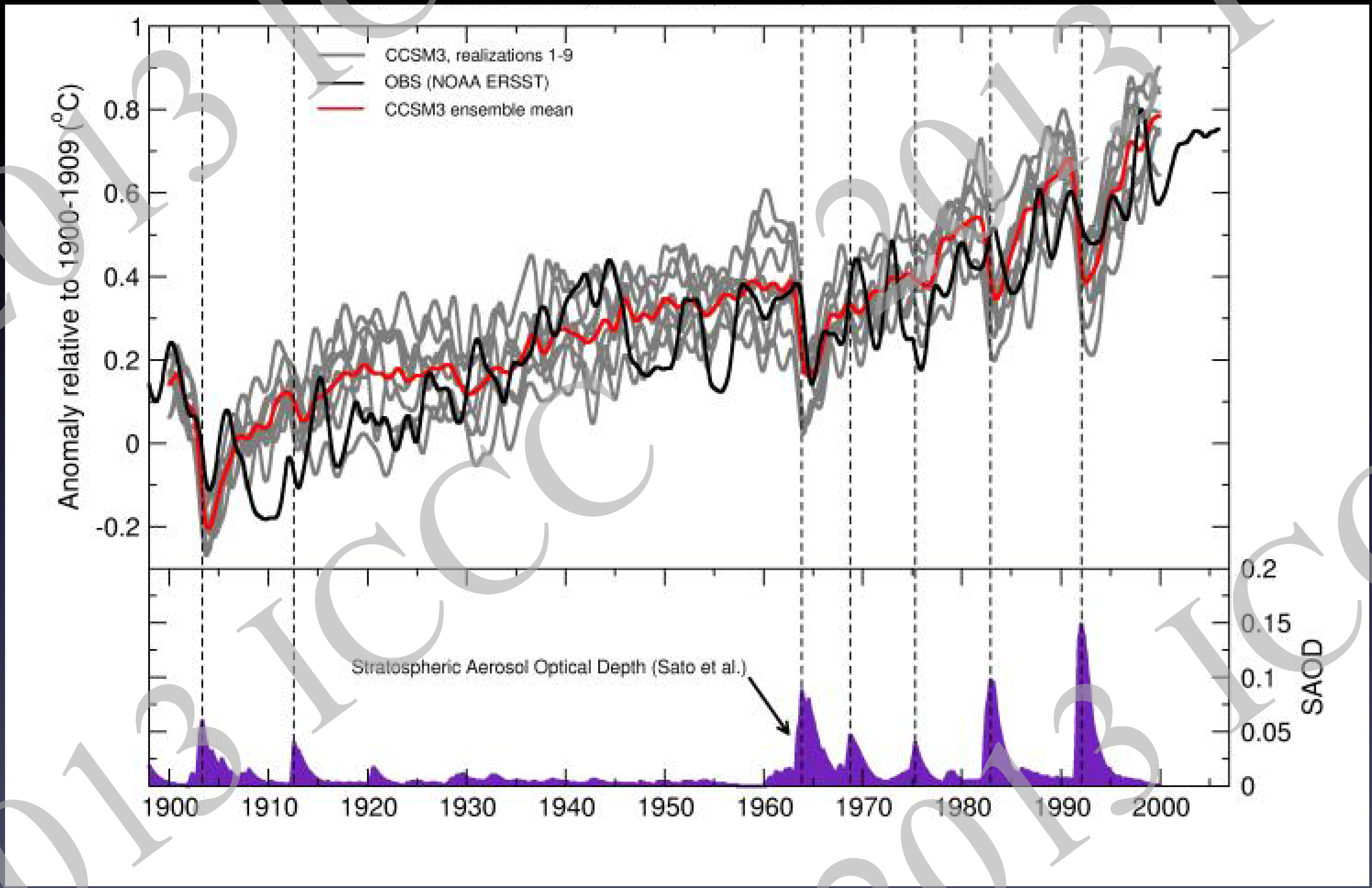


"Response uncertainty:" Different models respond differently to same forcings



Simulated responses to 1%/year CO_2 increase

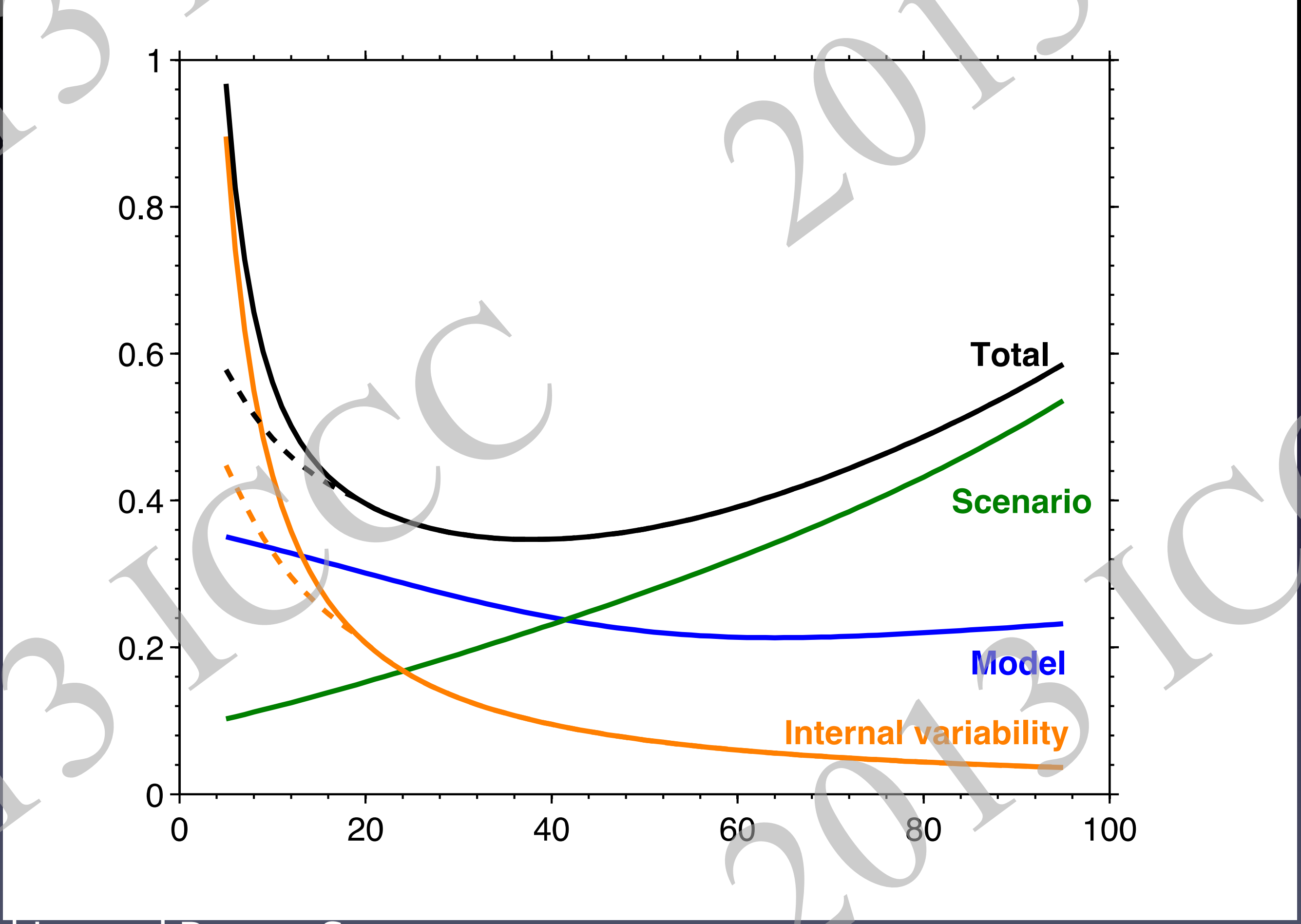
Inability to predict internal variability introduces uncertainty



Regional SSTs simulated from different initial conditions

Relative importance of different sources of uncertainty varies with time horizon

90% uncertainty range divided by predicted change in global T



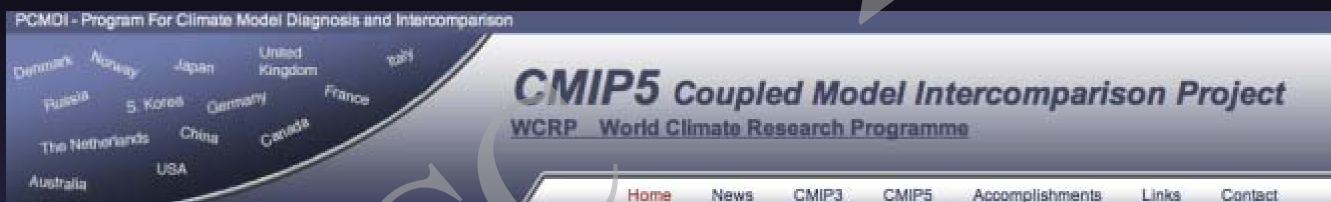
Source: Ed Hawkins and Rowan Sutton, 2009

UQ for adaptation decisions

- Typically involves:
  - Local spatial scale
  - time horizons as short as 20-30 years
- Natural variability may be the dominant source of uncertainty
  - Response uncertainty less important
  - Scenario uncertainty may be negligible
- Systems often sensitive to extremes

UQ usually based on ensembles of simulations

"Ensemble of opportunity" e.g. CMIP3, CMIP5: Simulations from different quasi-independent models. Forcings very similar.



"Perturbed physics ensemble (PPE):" e.g. CPDN,: Multiple simulations resulting from systematic variation of parameter values within one model

climateprediction.net

"Ensembles of opportunity: " Not a good basis for UQ

(e.g. CMIP3, CMIP5)

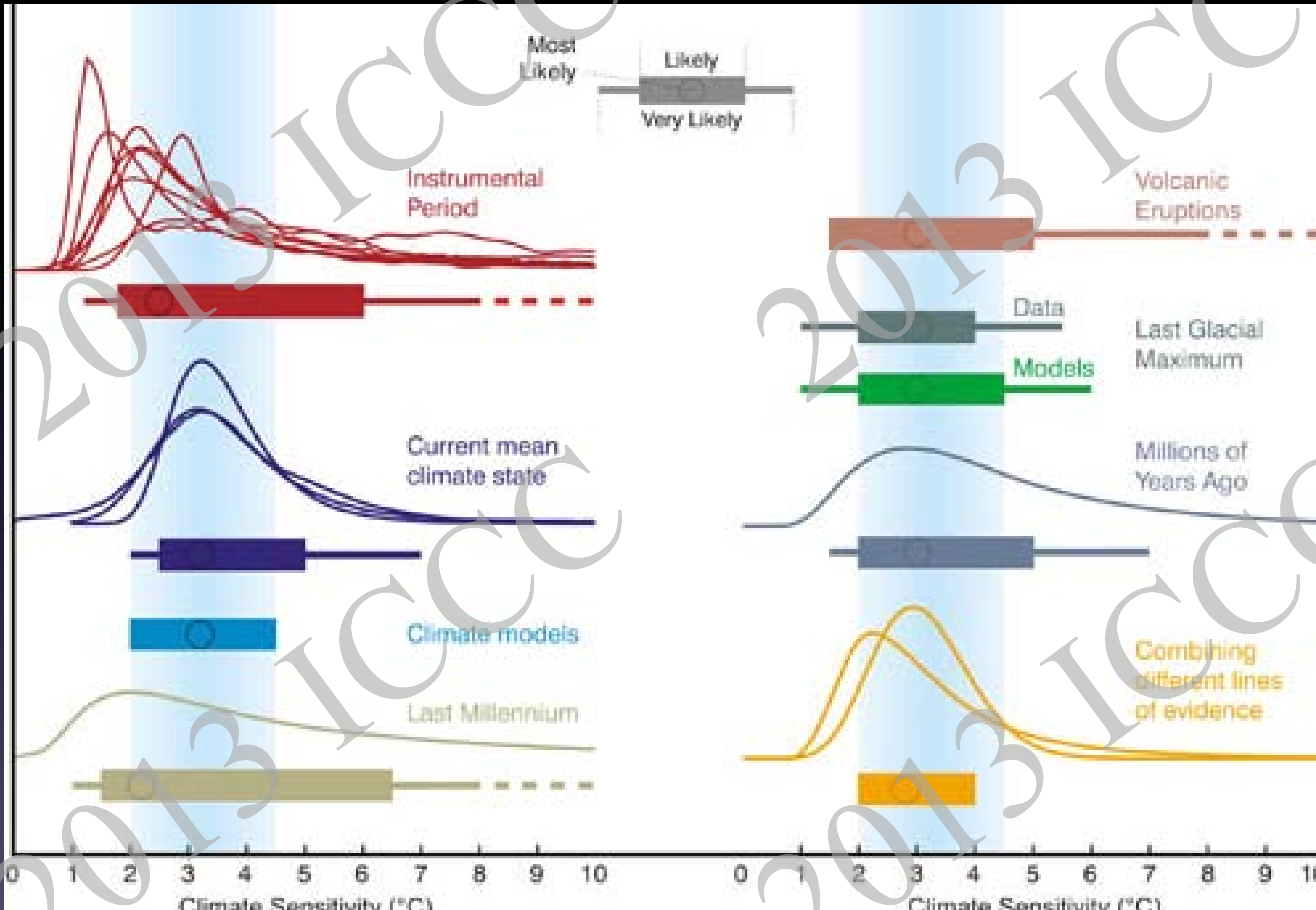
- Are affected by errors common to multiple models (i.e. lack of model independence);
  - They have errors in common; we don't know how important!
- *By design* do not sample the full range of possible outcomes;
- These shortcomings discussed by e.g. Knutti and Tebaldi.

Perturbed Physics Ensembles (PPEs)

- Can better sample the full range of outcomes
- But are subject to systematic model errors
- Example: UQ project at LLNL exploring sensitivity to 28 parameters

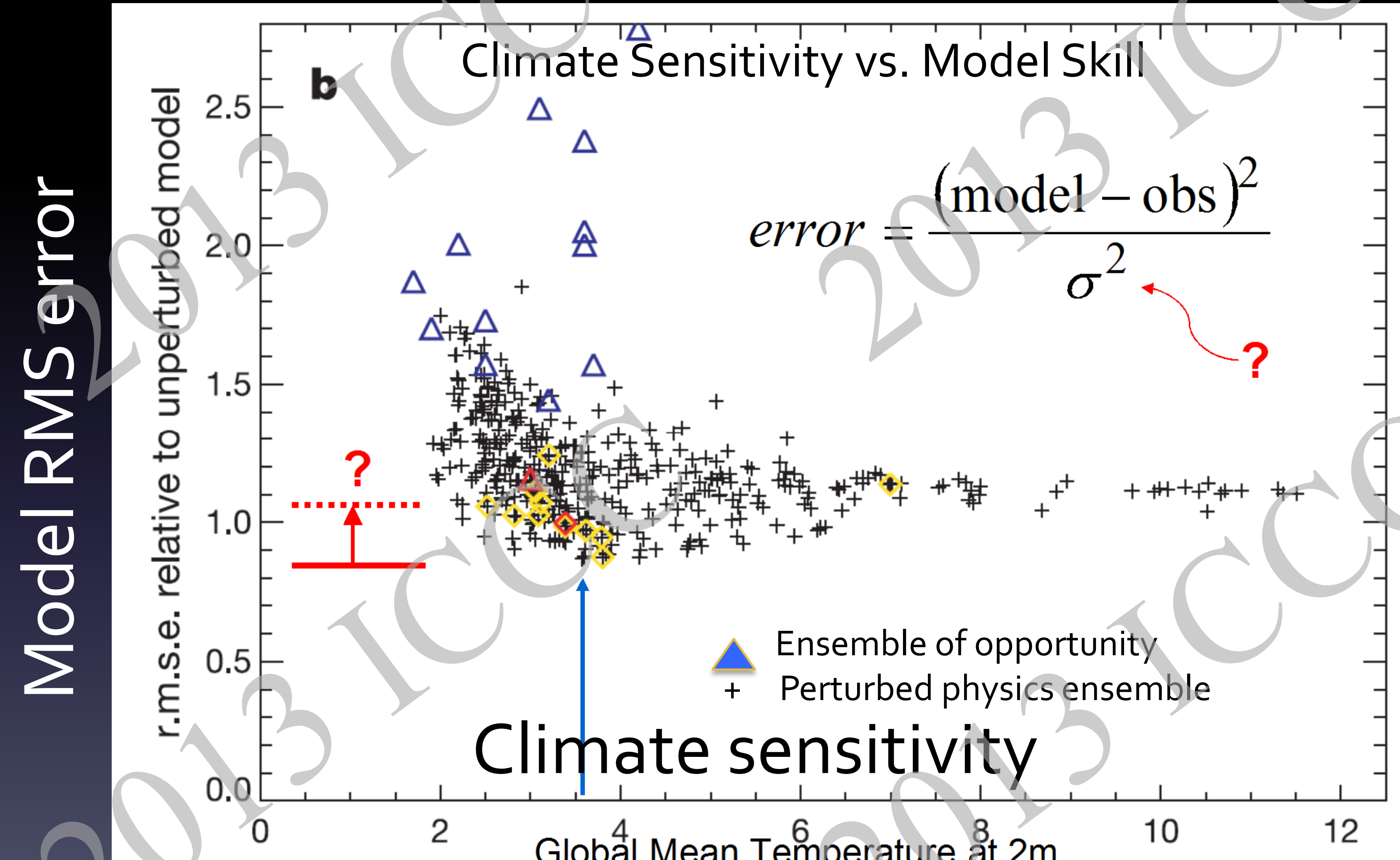
20-petaflop peak IBM BlueGene/Q system at LLNL

Estimates of climate sensitivity are skewed.



Source: Knutti and Hegerl, *Nature Geoscience*, 2008

Ensembles of opportunity do not capture skewness of climate sensitivity.



Source: Stainforth et *al*. Nature, 2005

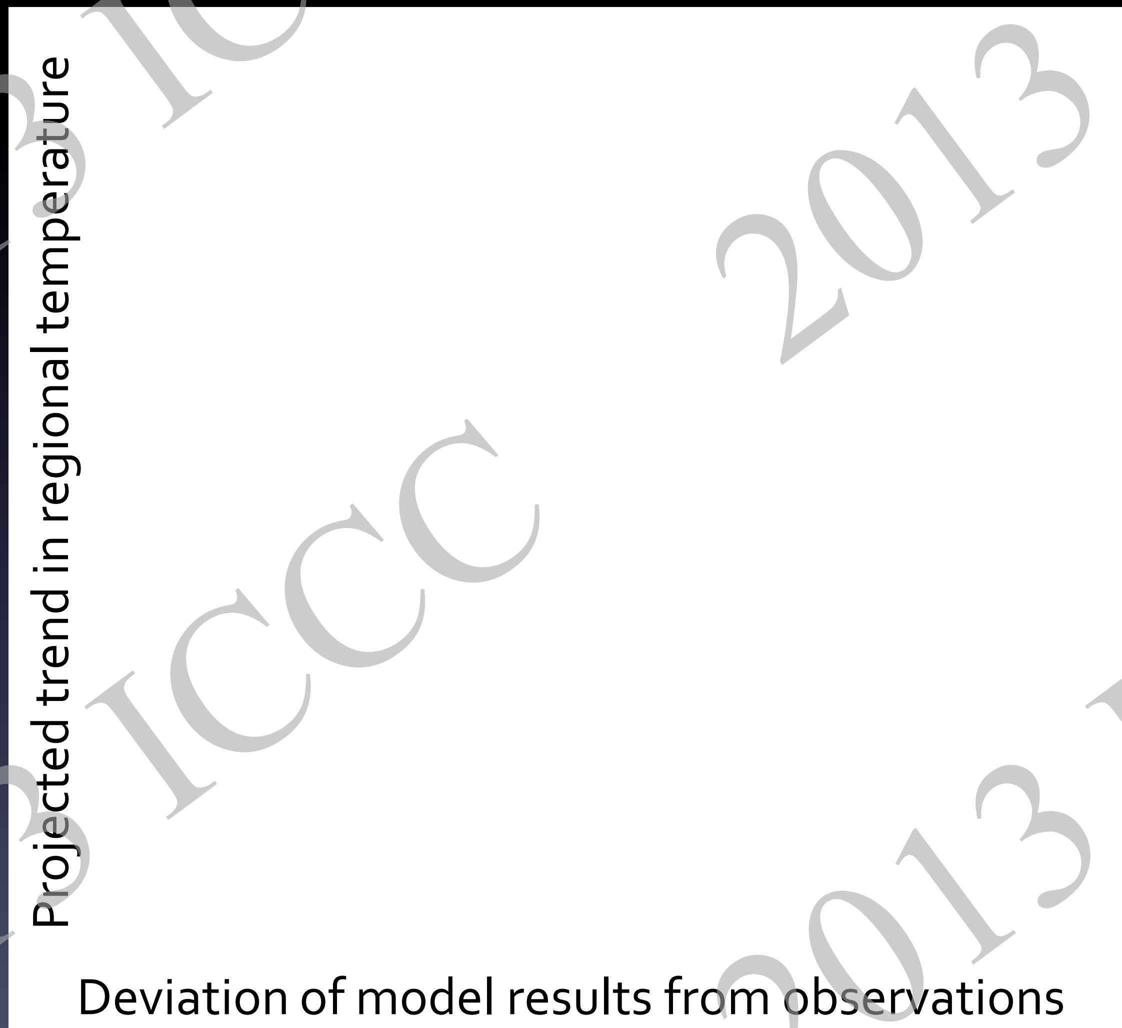
"An inconvenient truth:"

Climate model evaluation *assumes* that better ability to reproduce observations implies better predictions of the future.

This is not always true:

Predictions of "better" models are often indistinguishable from projections of "worse" models.

No correlation between model quality an projected trends in future seasonal temperature



Source: David Pierce, UC San Diego

Summary of UQ challenges

- Ensembles of opportunity are are not a good basis for UQ.
- Tests of model quality are of limited help in reducing and estimating uncertainty.
- Perturbed physics ensembles are subject to systematic errors.

Reality:

- We can't reliably estimate PDFs of future climate.
- Many decision-makers wouldn't know how to use them if we did.
- "Bottom-up" adaptation methods allow more reliable estimation of uncertainty by asking narrower questions.

“Bottom up” approaches ask narrower questions

- “Bottom-up:” Analyze stakeholder vulnerabilities and decisions.
  - Ask specific questions; example on next slide
- “Top-down:” construct PDFs of future climate variables and impacts-related variables.
  - Ask broad questions: e.g. How does climate change affect water supply reliability?

Why are "bottom up" approaches better?

- *Because much of the uncertainty in future climate doesn't affect decisions.*
- Example: water supply reliability in California.
- Not clear if mean precipitation will increase or decrease (about 50% of GCMs predict increase; 50% predict decrease).
- But water supply reliability does not depend strongly on mean precipitation. It does depend on
  - Amount of snow and timing of snowmelt
  - Duration and severity of droughts

Research needs for adaptation

- Improve “decadal” climate prediction.
- Identify more tests of model quality that narrow ranges of future projections.
- Cooperate on global dynamical downscaling.
- Increase sharing of data and experiences.
- Improve methodologies by learning from other fields, e.g. disaster preparedness.

Let's have lunch!