Raising the Bar: Climate Projections for Decision Support

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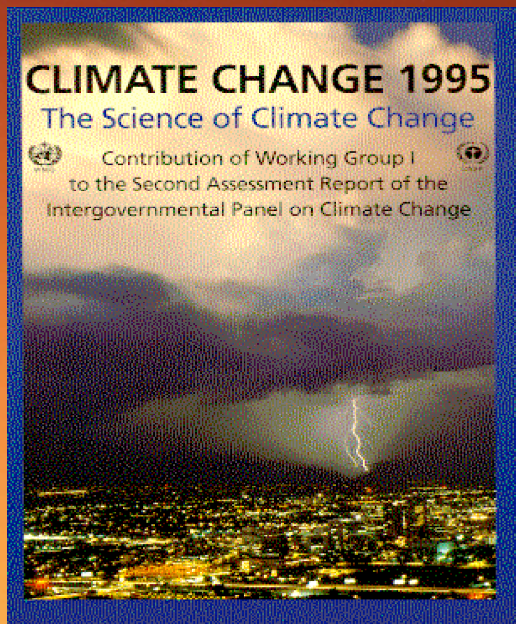
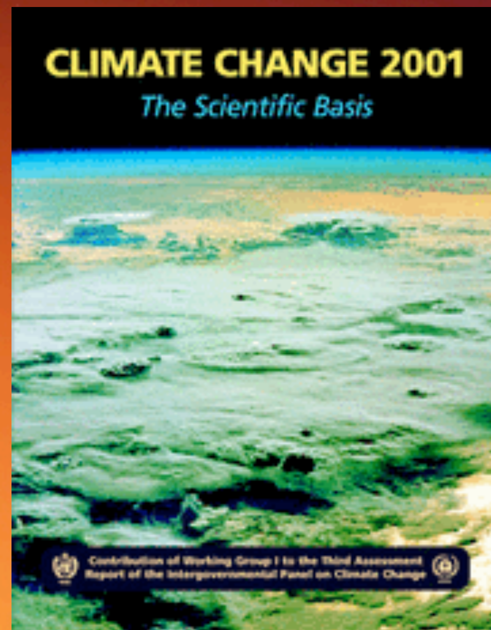
Climate Central, Inc.

“Drink Responsibly”

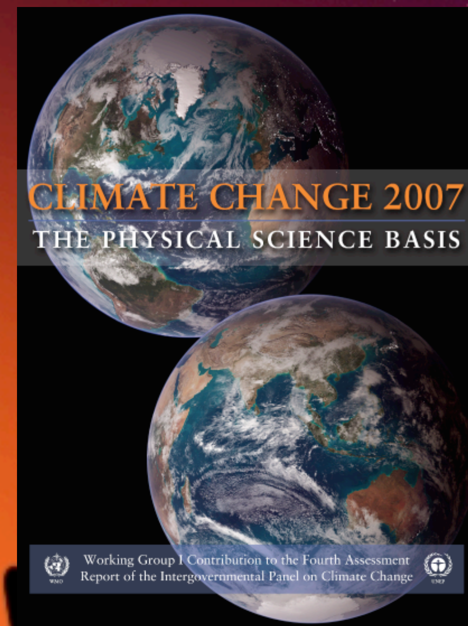
We have increasing confidence that humans are changing Earth's climate



"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"

The Challenges:

- Refine spatial resolution
- Refine temporal resolution (really, save high-frequency output
    - Eats up disk space
- Reliably simulate extremes
    - Because these have disproportionate societal impacts
- Quantify uncertainties
    - Usually by analyzing an ensemble of simulations
- Work with users to
    - Better understand their needs
    - Ensure appropriate use of our results

Fine spatial resolution

- Not the solution to every problem,
- But it helps!
- How can we refine spatial resolution?

How can we refine spatial resolution?

Dynamical downscaling

The Good news ☺

Based on physical laws, so should correctly represent changes mesoscale circulation and local feedbacks in response to increasing GHG.

Produces a full suite of output variables.

The Bad news ☹

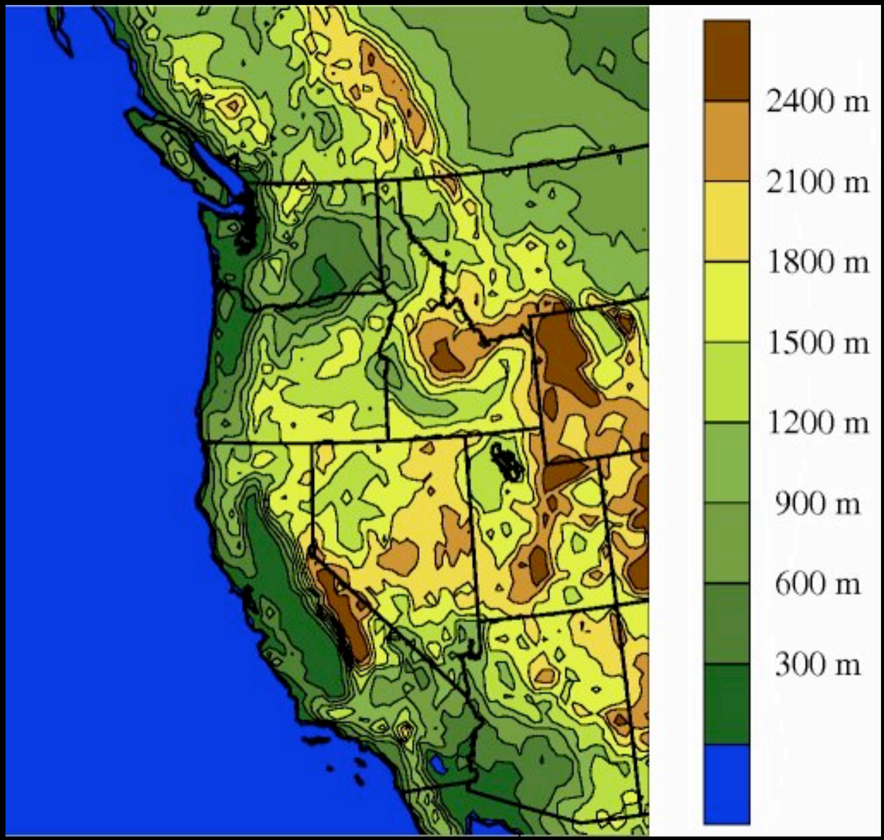
Computationally very demanding.

Generally preserves biases (errors) in the results of the driving GCM. ("GIGO")

Most GCM simulations don't save output needed for dynamical downscaling.

Something new: a perturbed physics nested model ensemble

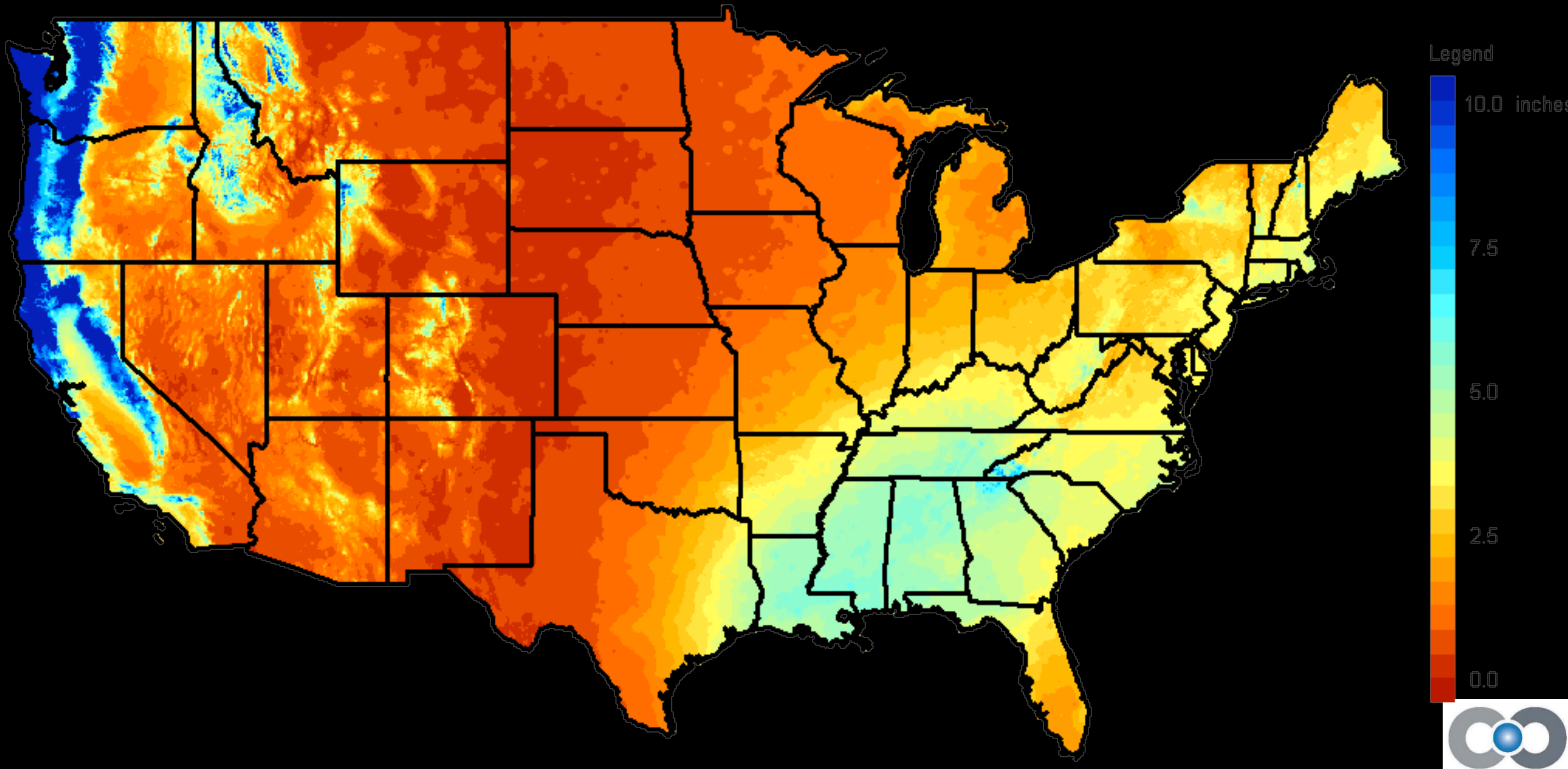
- Richard Jones, Phil Mote, et al.
- Vary parameters in both nested and driving models.
- Hope to perform thousands of simulations



See: Climateprediction.net/content/regional-model

Statistical downscaling

- Most methods designed to work at only one location.
- Several methods produce spatially gridded output.
- These add detail obtained empirically from observations



Statistical downscaling…

The Good news ☺

Computationally *not* very demanding

Does not require special output from the GCM

Can be applied to large ensembles of GCM simulations

Can include correction of GCM biases

The Bad news ☹

Produces results for only a few variables

Resolution and domain limited by availability of gridded observations (a version of GIGO)

Depends on dubious critical assumptions:

1. relationships derived from observations will apply in the future – *not* true where local feedbacks or circulation changes important
2. bias correction derived in historical period will apply in the future.

Large library of statistically downscaled projections

- Multiple institutions involved: Climate Central, Santa Clara U., USBR, Army Corps, U. of Washington, The Nature Conservancy, ESRI, IPCC WGII, GFDL, maybe Scripps
- Successor to: http://gdo-dcp.unllnlorg/downscaled_cmip3_projections/dcpInterface.html#Welcome
- Will downscale CMIP5 simulations to 50 km grid globally, finer grids in US
- Will include derived indices of societal-impacts (e.g. drought)
- Results will be distributed through IPCC Data Distribution Centers

Shameless self-promotion slide

(I'm allowed one, right?)

Fine-resolution global model

The Good news ☺

Compared to coarse-resolution GCMs, can have

- better simulation of large- scale climate
- improved representation of extremes

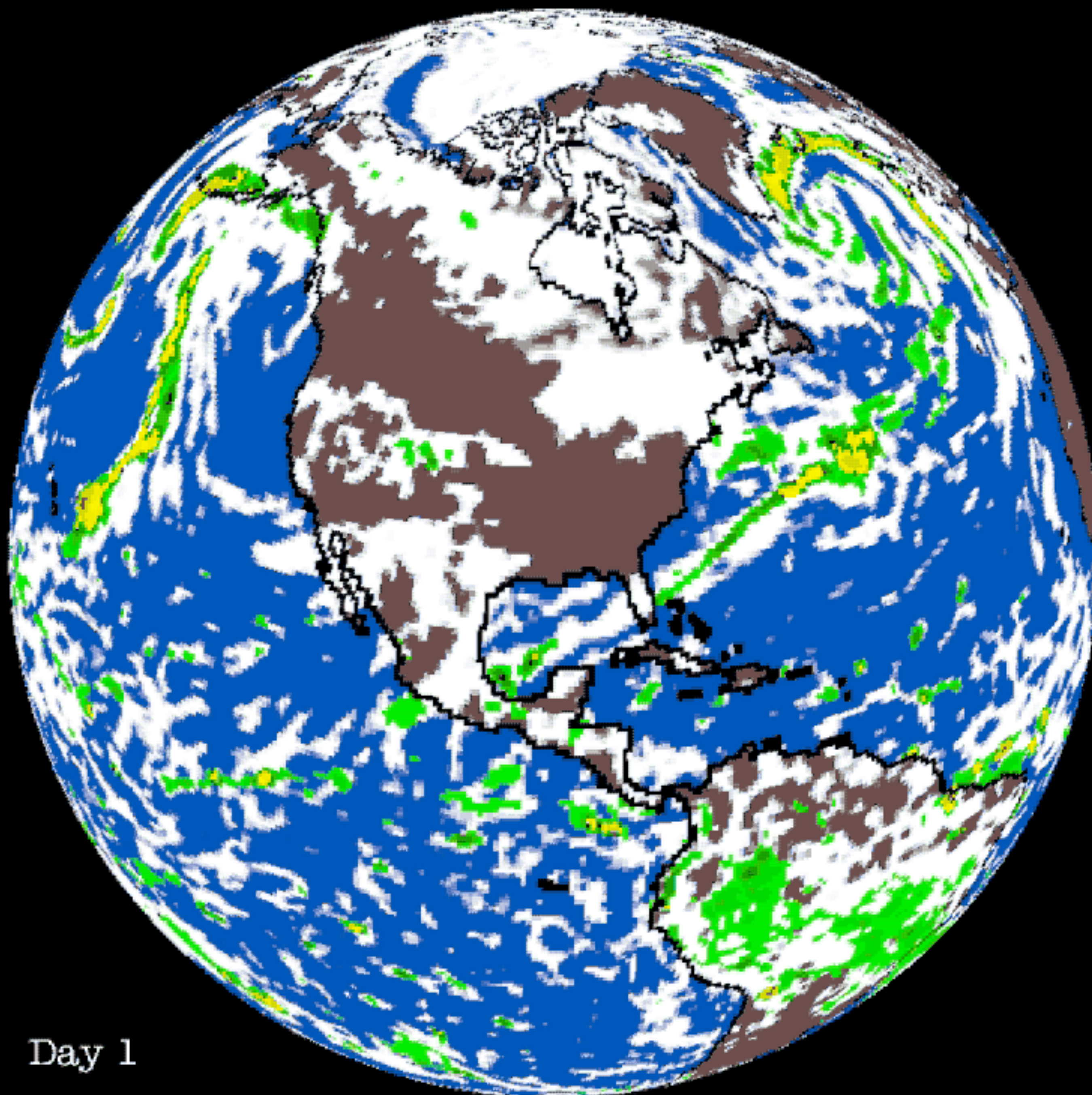
Provides a globally consistent solution.

The Bad news ☹

The most computationally demanding of any option.

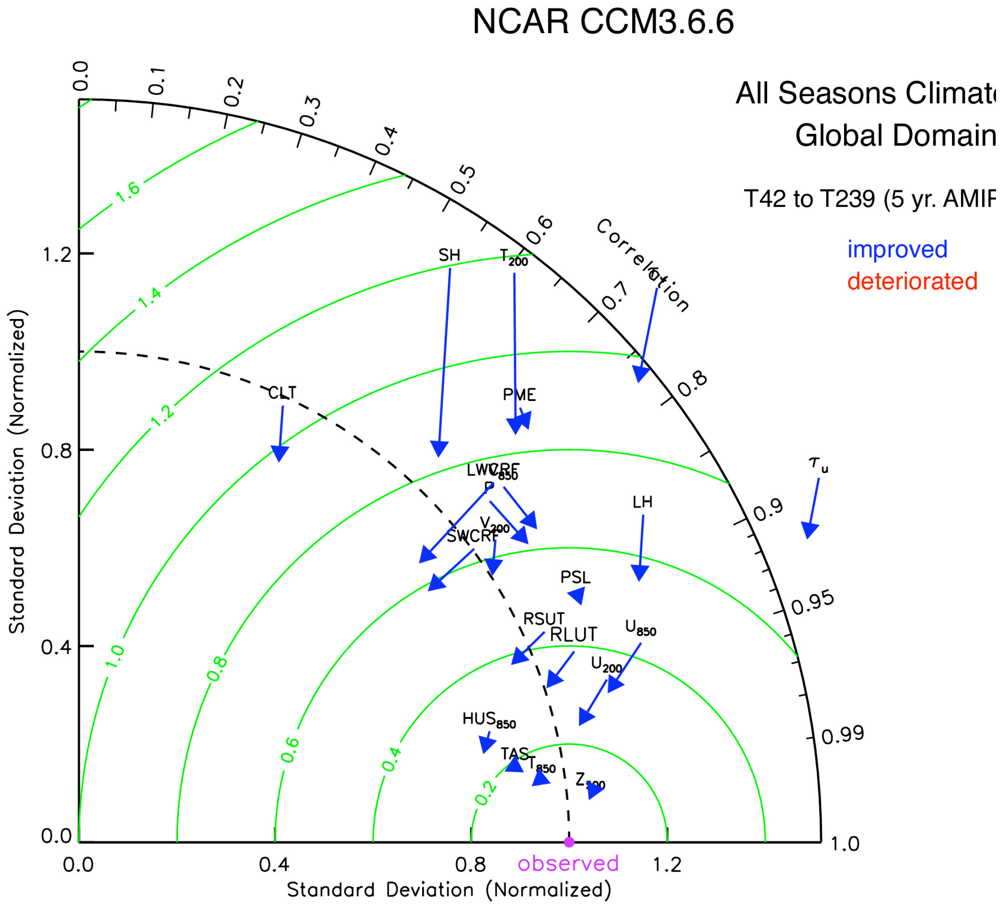
Need fundamental changes to the model if resolution too fine.

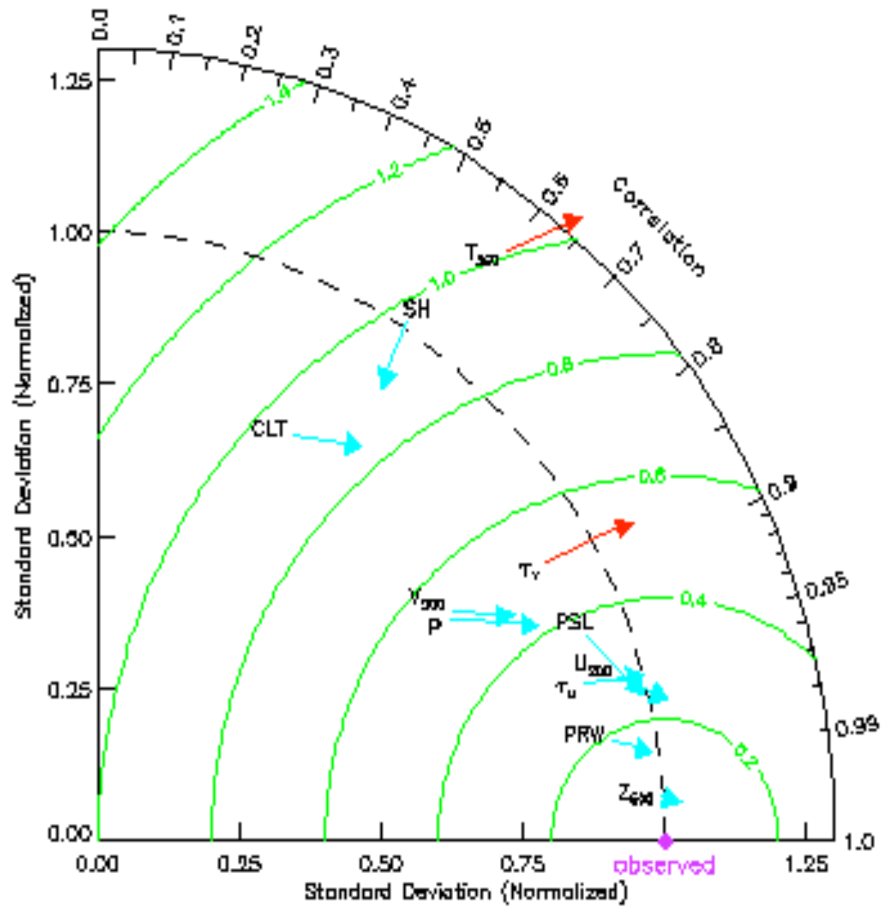
T239
50 km
grid spacing



Refining resolution improves results more than thinking does (in this case)

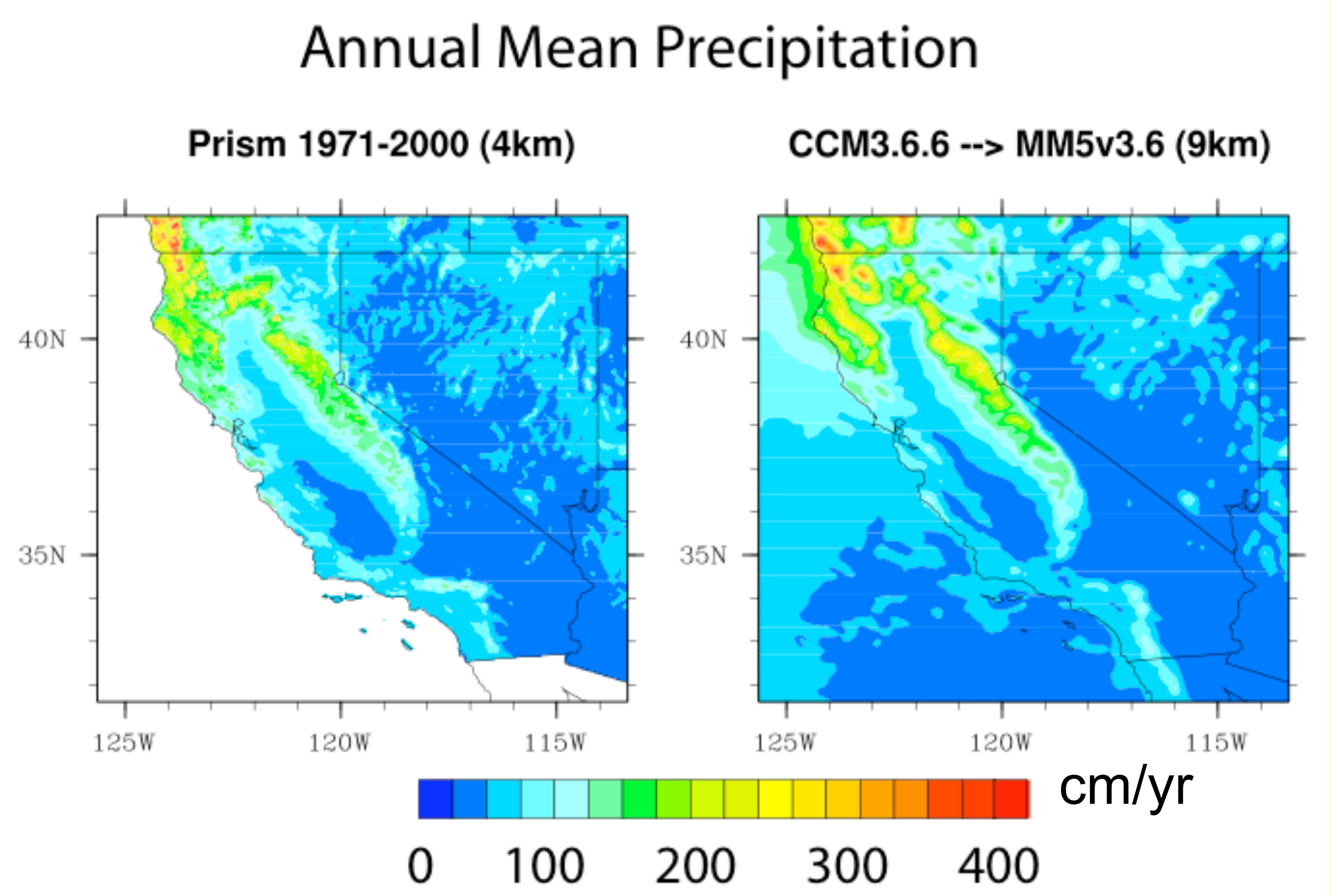
T42 -> T239 | AMIP 1 -> AMIP 2





Comparisons performed on T42 grid

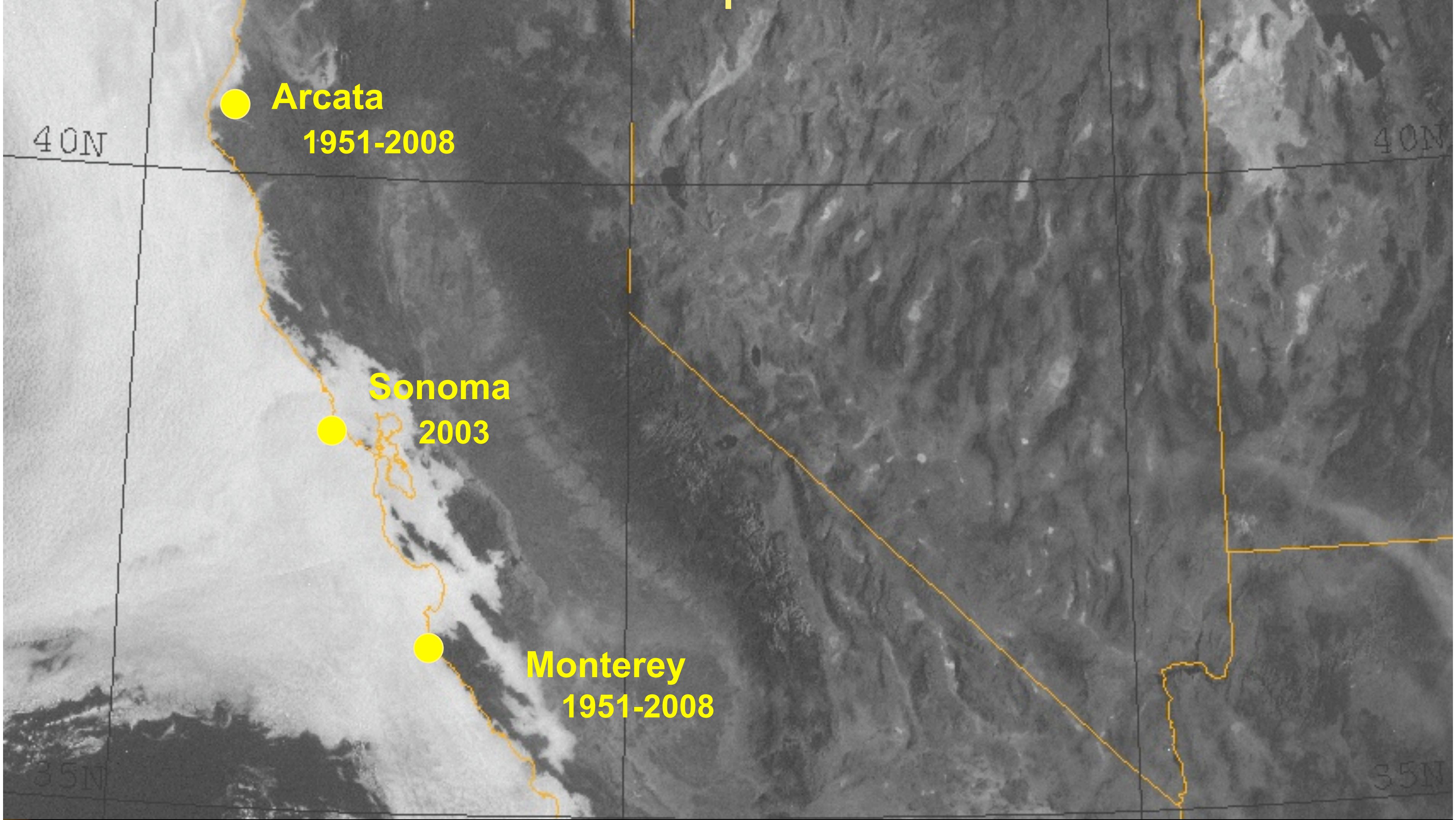
A thing of beauty: high-resolution regional model driven by high-resolution global model



PRISM

Nested model at 9 km driven by global model at T170

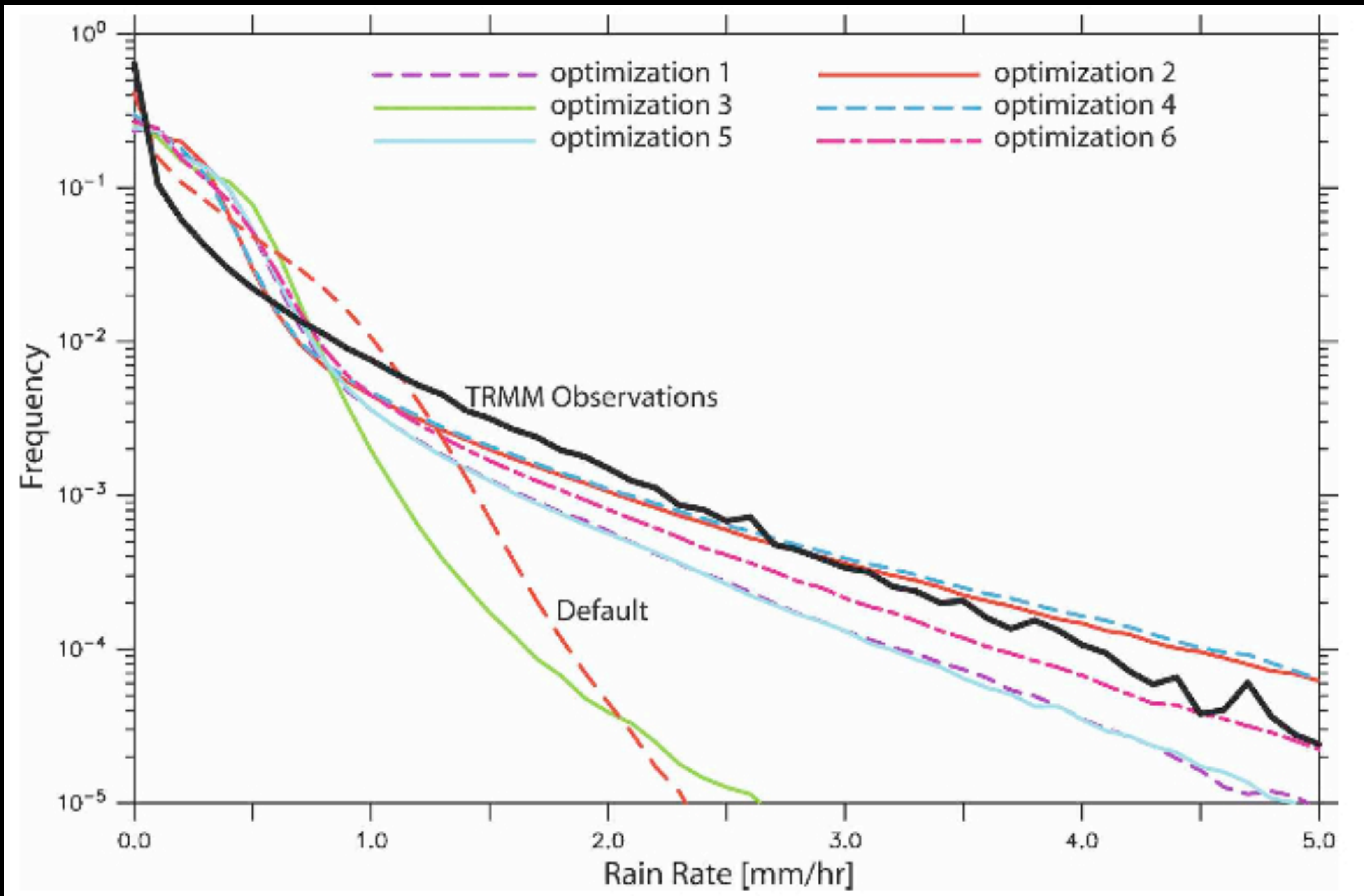
Some regional phenomena depend on ocean-atmosphere interactions



Source: Jim Johnstone, UC Berkeley

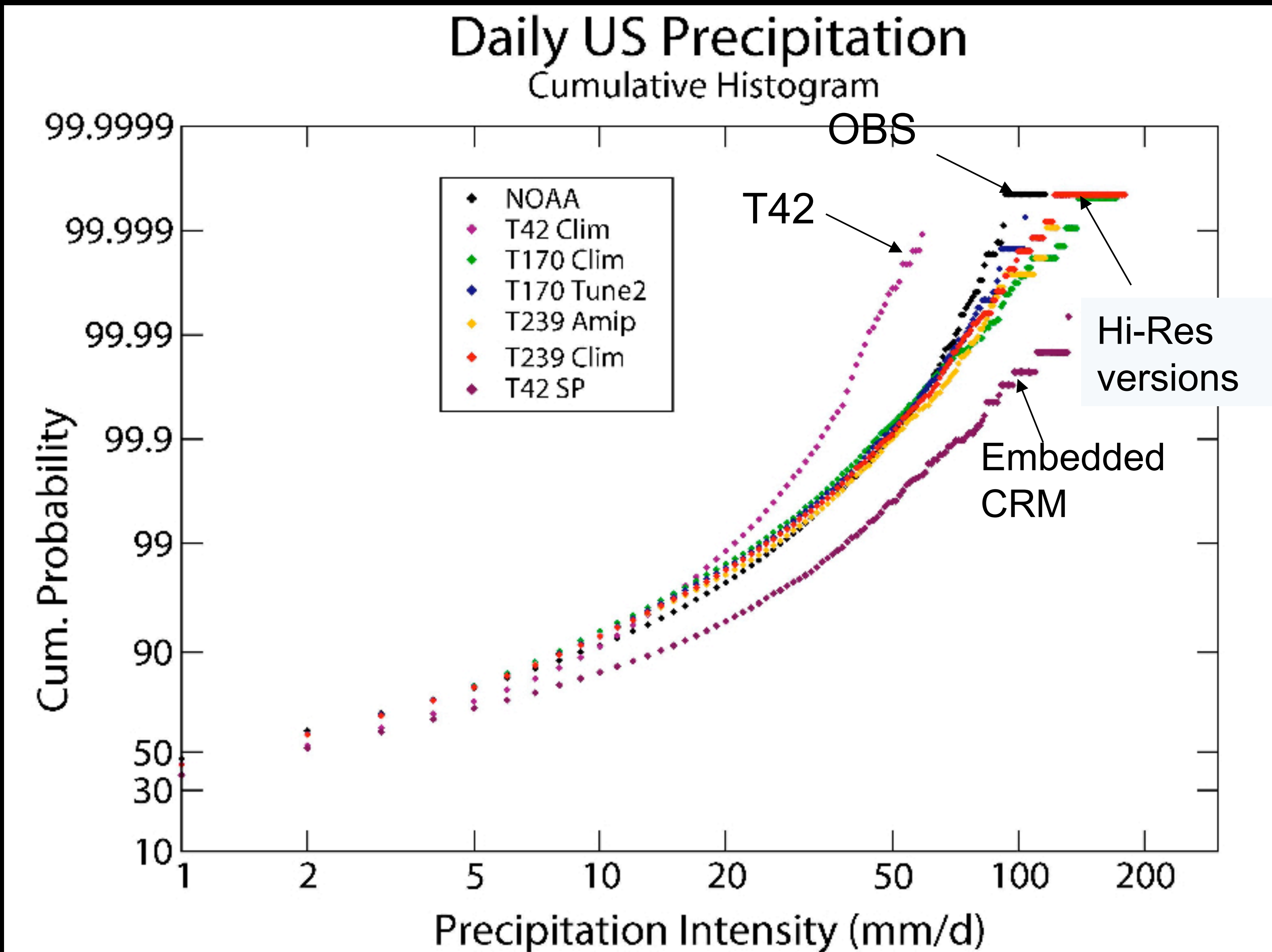
How well do we simulate extremes?

Tuning can improve GCM simulation of extremes

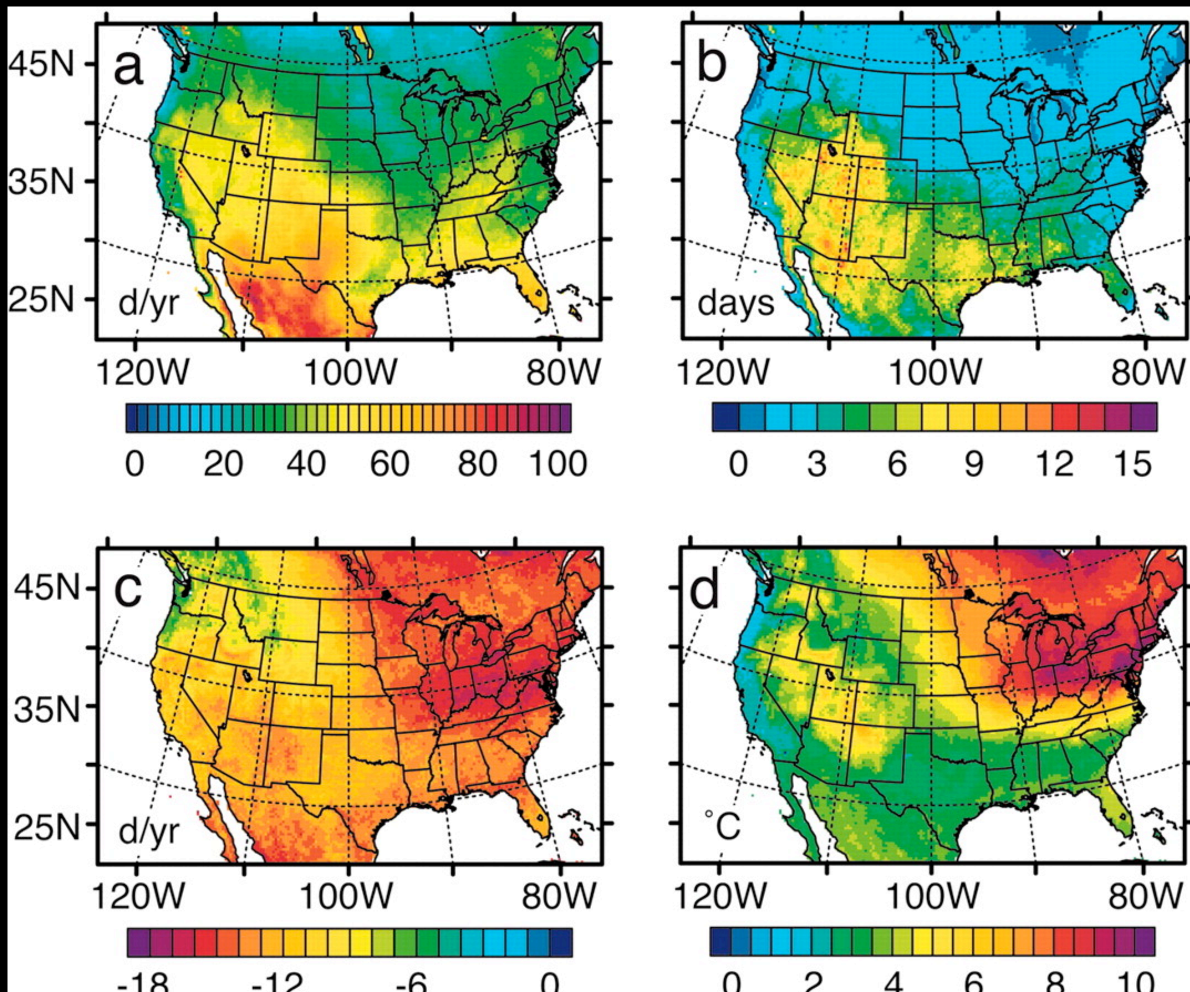


Source: Chas. Jackson *et al. J. Climate* 2008

Refining resolution can improve simulation of extremes



Anomalies (A2 - RF) in T95 event frequency (days/year) (a), T95 mean heat-wave length (days/event) (b), T05 event frequency (days/year) (c), and 95th-percentile cold-event value (°C) (d)



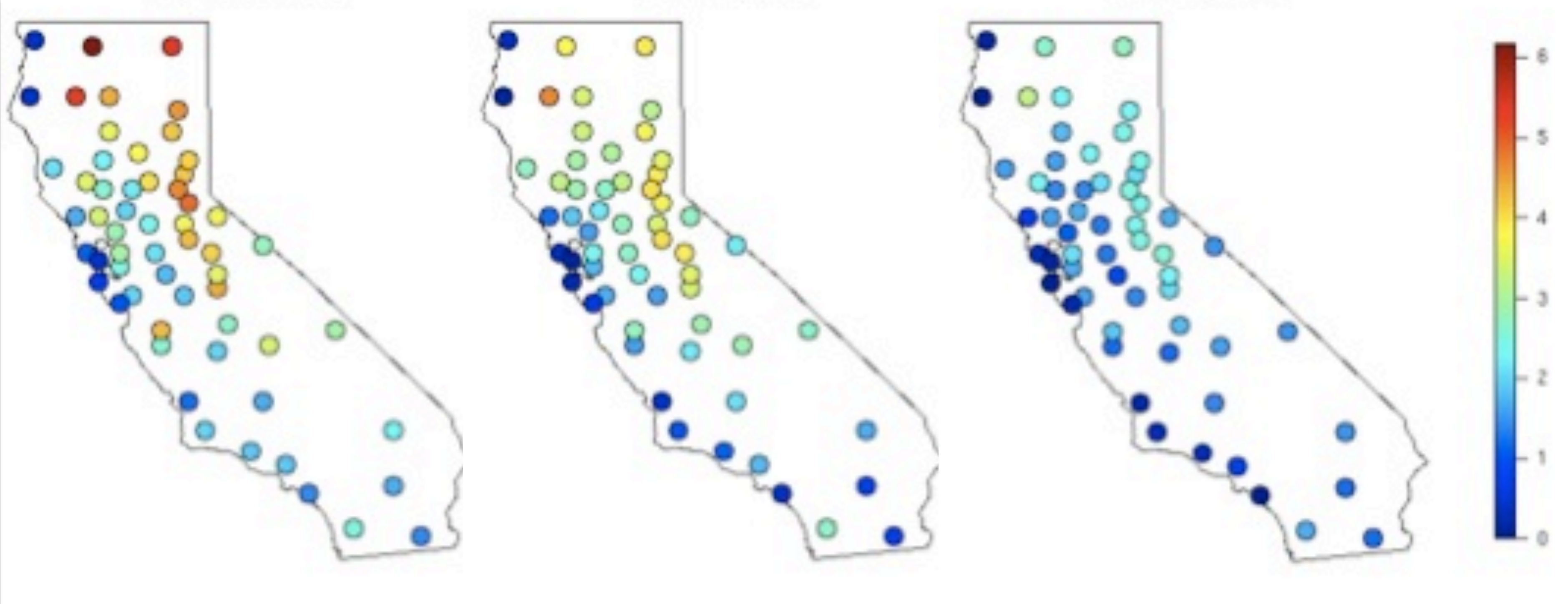
Diffenbaugh N. S. et.al. PNAS;2005;102:15774-15778

Messages:

- Increasing GHG substantially alters statistics of extreme daily T and P.
- These changes are strongly influenced by mesoscale circulation changes, and local-scale feedbacks.
- *The above phenomena cannot be represented using statistical downscaling.*

Heat Wave Duration

Observations BCSD C Analogs



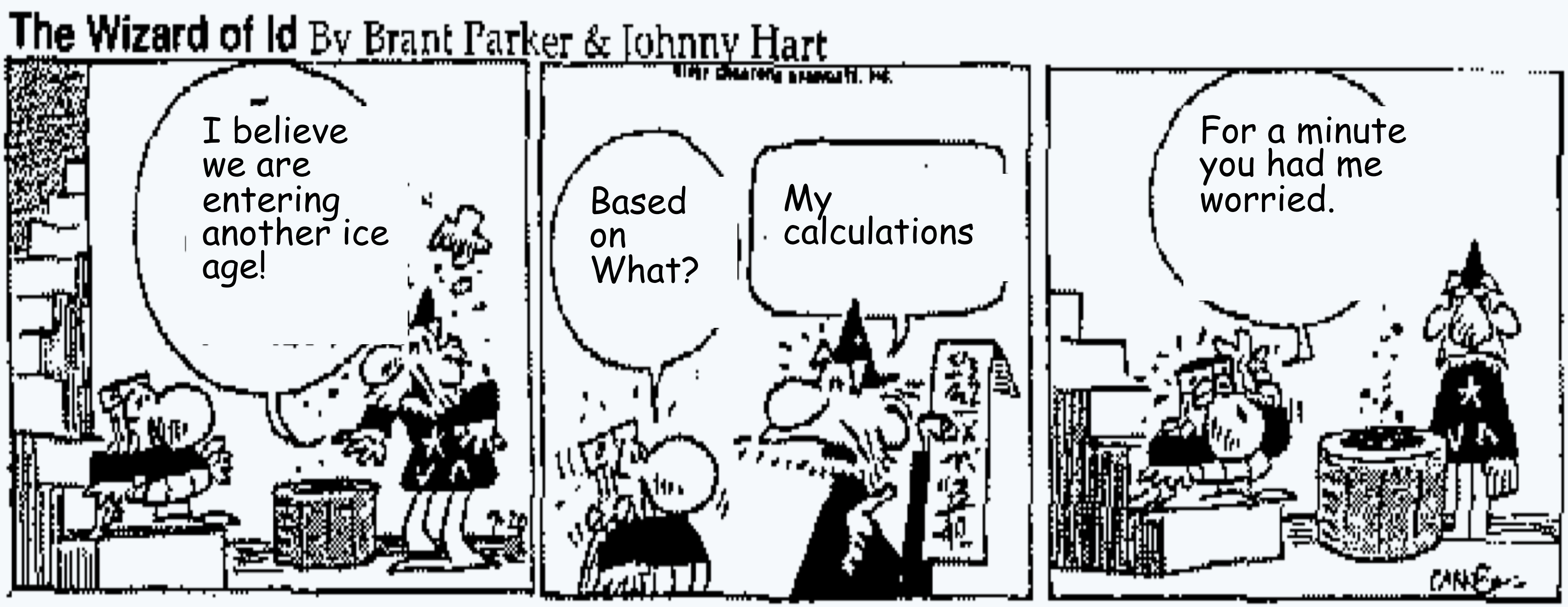
Length of the maximum period of at least five consecutive days with a maximum temperature higher by at least 5^o than the climatological norm for that calendar day. Computed only over May through September)

Source: Mike Mastrandrea, et al.

Caveats:

1. Results for BCSD use a temporal disaggregation scheme that we know will not represent extremes correctly
2. “Constructed analogs” (CA) has been superseded by “Bias Corrected Constructed Analogs” (BCCA)

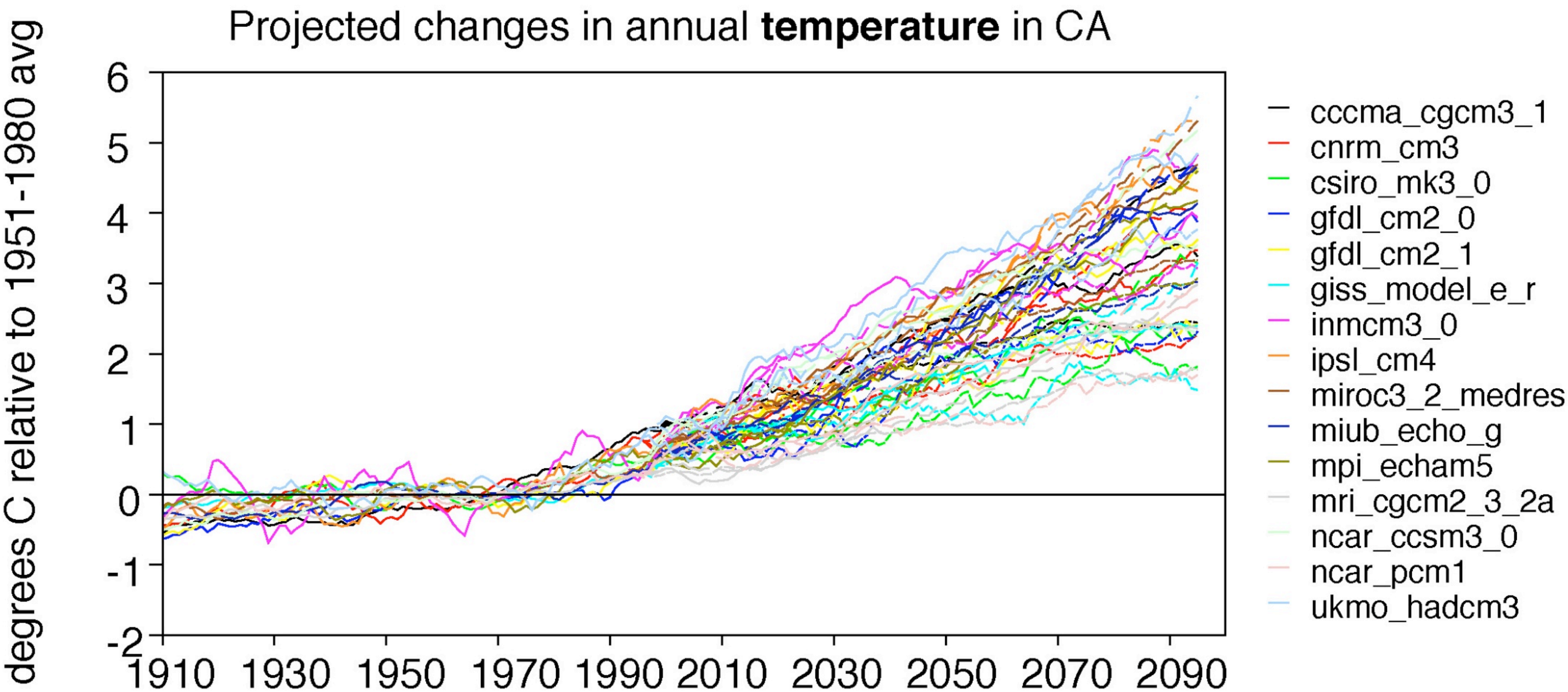
How do we quantify uncertainty?



What are sources of uncertainty?

- Initial conditions
  - Important but straightforward to quantify
- Boundary conditions
  - both human and natural forcings are unpredictable
- Response to forcings
  - relatively less important on longer time horizons, unless a “surprise” occurs

Typical uncertainty quantification: an "ensemble of opportunity"



What's **good** about quantifying uncertainty in this way?

1. It's a start

What's **good** about quantifying uncertainty in this way?

1. It's a start
2. The mean or median of large multi-model ensembles robustly performs better than any single model
    - This is true in climate simulation and in seasonal NWP

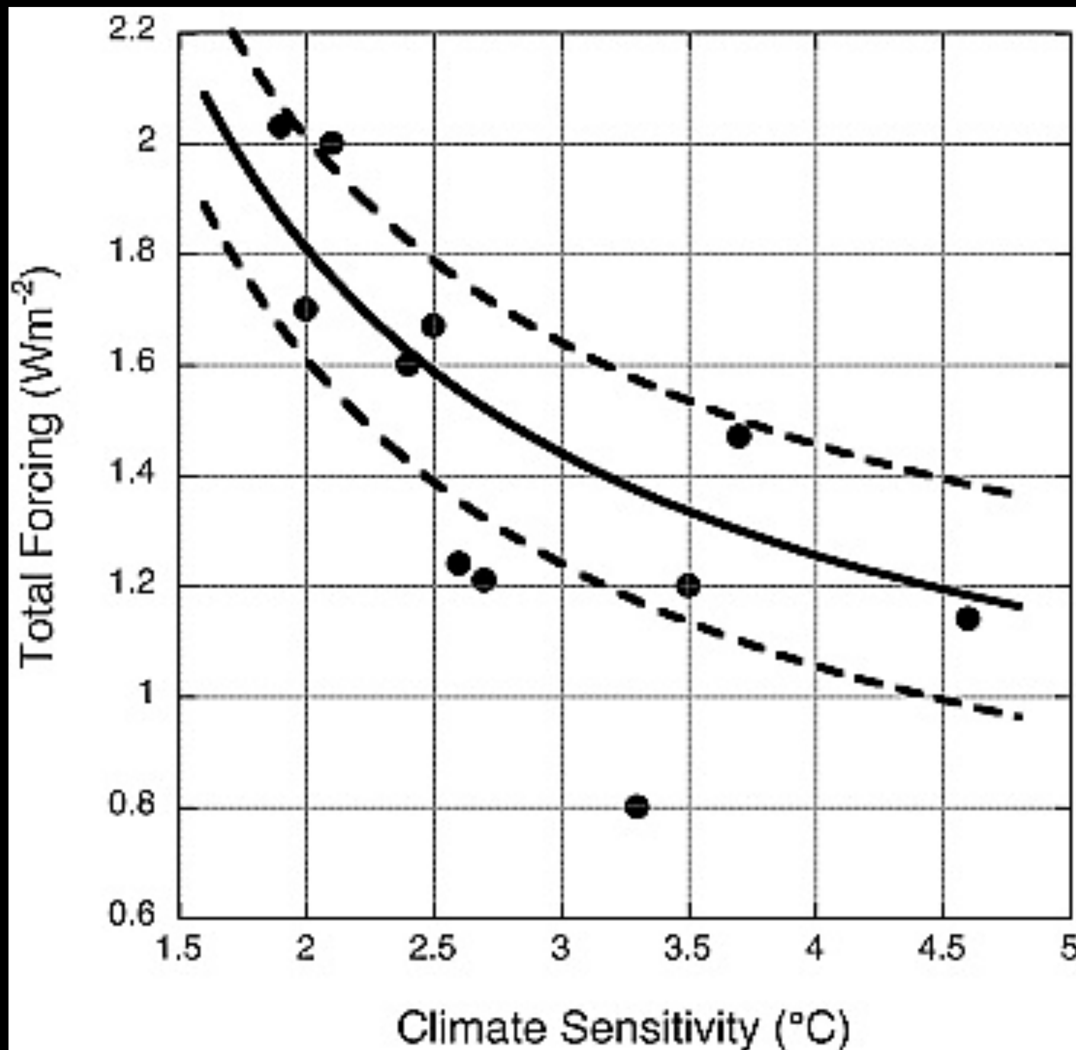
What's **bad** about quantifying uncertainty in this way?

1. Results can be influenced by selection of models, which is haphazard
2. Can be misleading because errors common to multiple models may be important. I.e., even if models agree with each other, they could all be wrong
   - Superiority of mean model *suggests* that this is not important

What’s **bad** …

3. Some evidence that GCMs have been unconsciously “tuned”

Were CMIP3 models unconsciously “tuned” to reproduce 20th century warming?

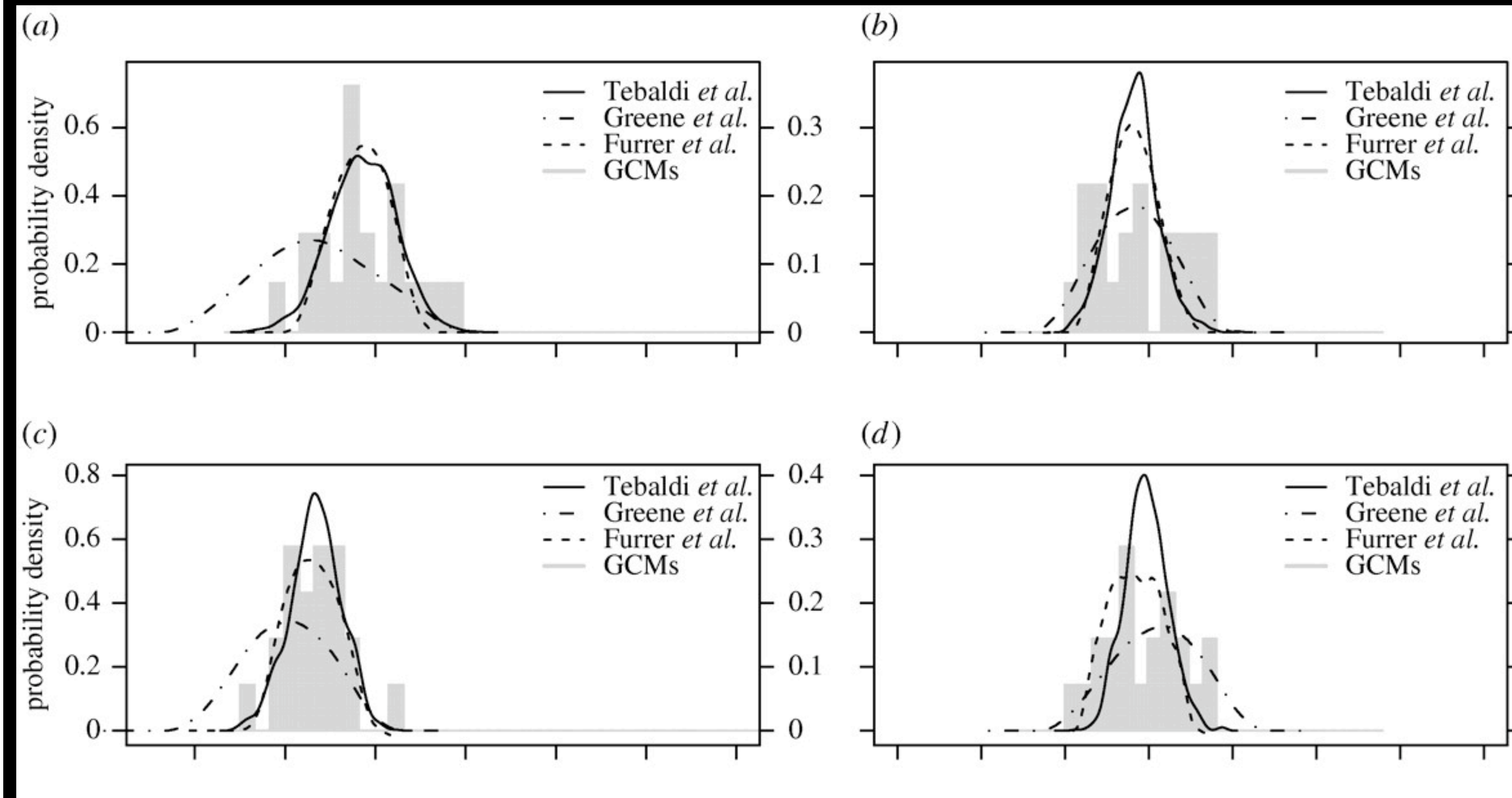


Source: Kiehl, GRL (2007)

What’s **bad** …

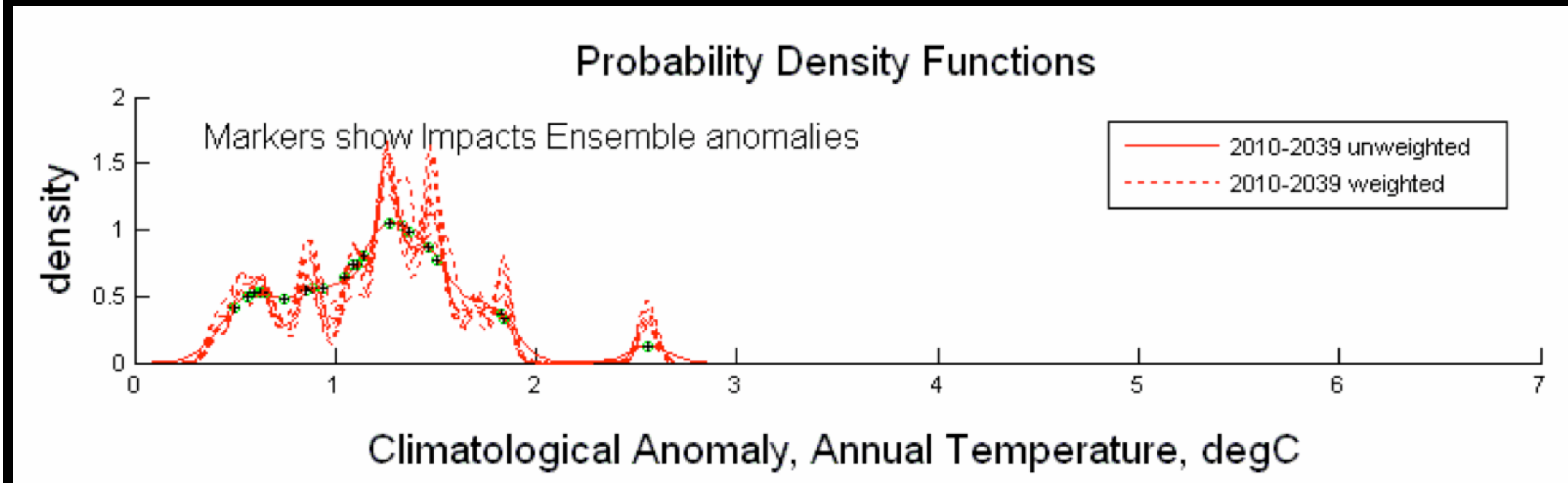
3. Some evidence that GCMs have been unconsciously “tuned”
4. Values all models equally, which can’t be optimal
   - but of course we can’t agree on best way to combine models

Different methods for combining multiple models can yield very different PDFs



Tebaldi C., Knutti R. Phil. Trans. R. Soc. A;2007;365:2053-2075

Model weighting does not affect PDFs of future temperature



Source: Levi Brekke (USBR)

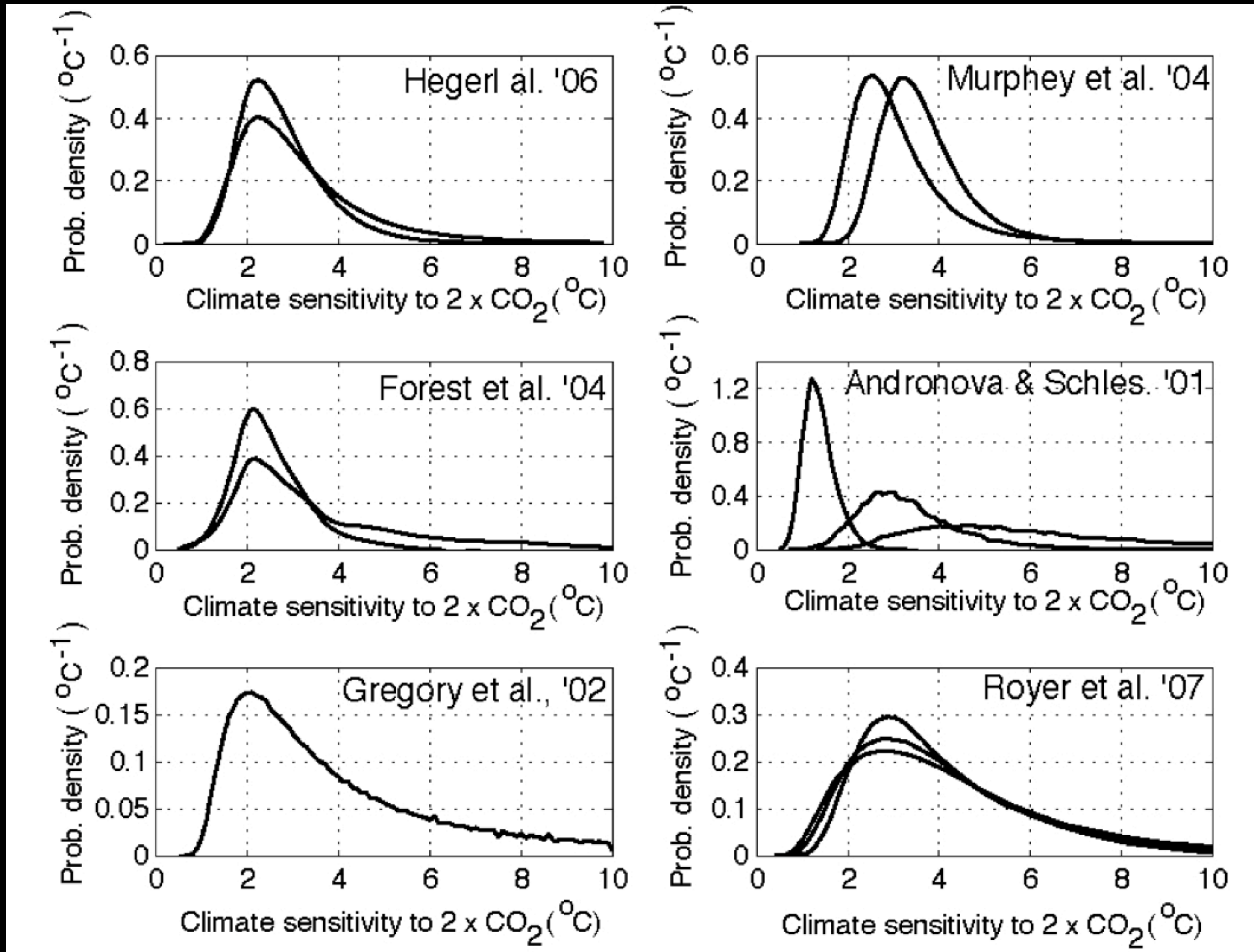
Let me get this straight:

1. Climate model evaluation is based on the assumption that better ability to reproduce observations implies better predictions of the future.
2. Available evidence does not support this assumption:
   - Predictions of "better" models are indistinguishable from projections of "worse" models.
3. Therefore, point (1) is a religious belief.

What’s **bad** …

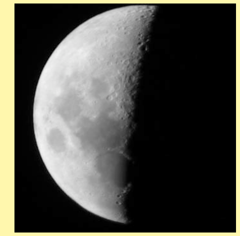
3. Some evidence that GCMs have been unconsciously “tuned”
4. Values all models equally, which can’t be optimal
    - but of course no one can agree on best way to combine models
6. Does not show outcomes that all agree have low (but non-zero) likelihood.

High climate sensitivity is unlikely, but can't be ruled out



Source: Roe and Baker, UW

More problems with uncertainty quantification:



- Uncertainty in future forcings is difficult to quantify
- For time horizons of ~20 years or less, natural variability may produce larger changes than forced response, and this is hard to predict.

This seems mighty difficult!
How about a different approach?

"Work backwards" from decision to climate, rather than vice versa.

- So, e.g. instead of asking for a PDF of ΔT, ask for probability that ΔT will exceed a critical value.

Parting Thoughts (1):

Outstanding technical problems

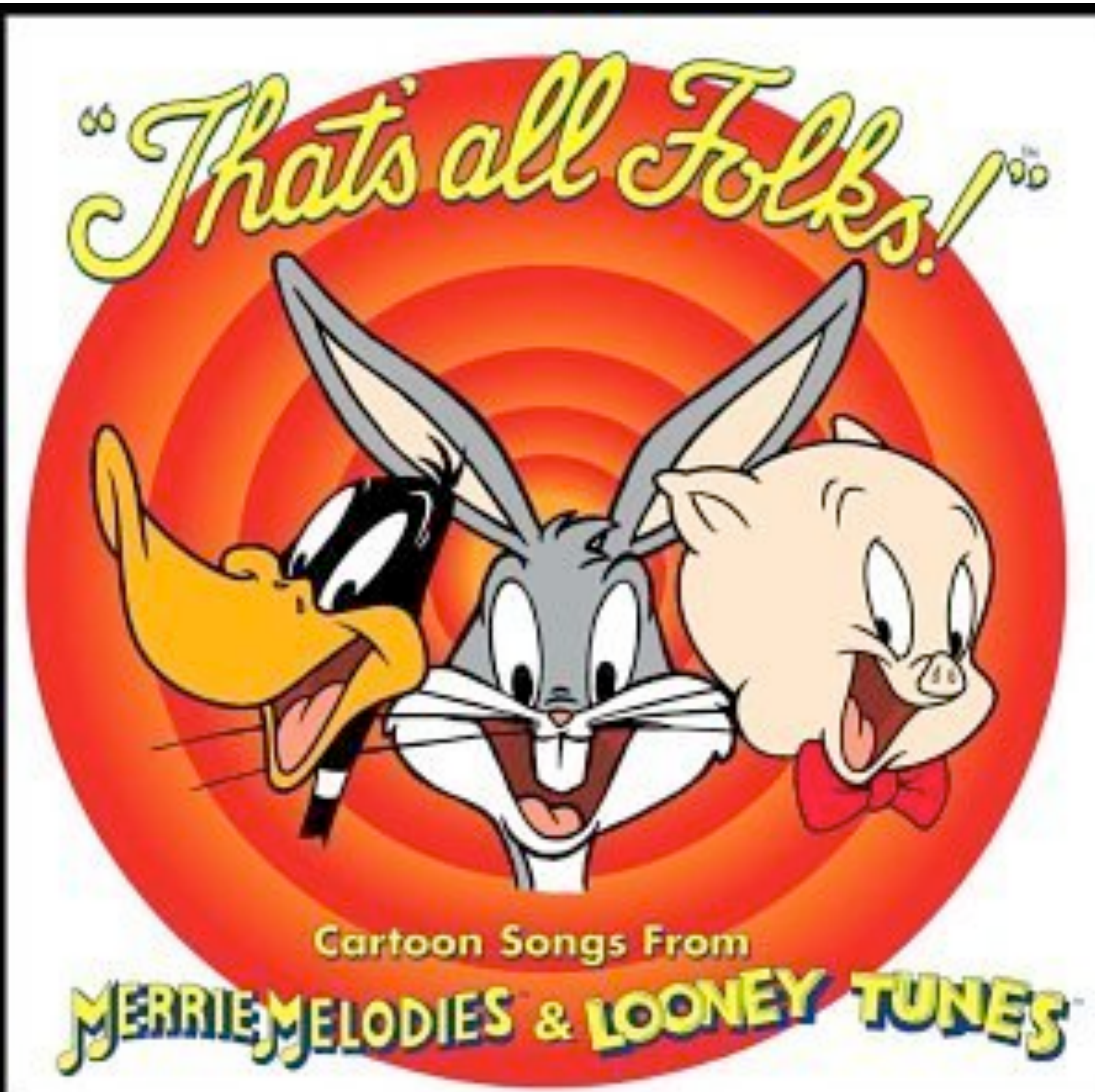
1. Uncertainty quantification presents inherent and practical difficulties
2. We need quantitative methods for incorporating probabilitstic climate projections into decision processes
3. Dynamical downscaling is arguably superior, but producing comprehensive libraries of dynamically downscaled results takes a lot of work!
4. Statistical methods allow “easy” downscaling of ensembles of GCM simulations.
5. Simulation and downscaling of extremes, especially of precipitation, are challenges.
6. In coastal regions a fine-resolution ocean-atmosphere model is probably needed to represent “coupled” phenomena like fog, upwelling, etc.

Parting Thoughts (2):

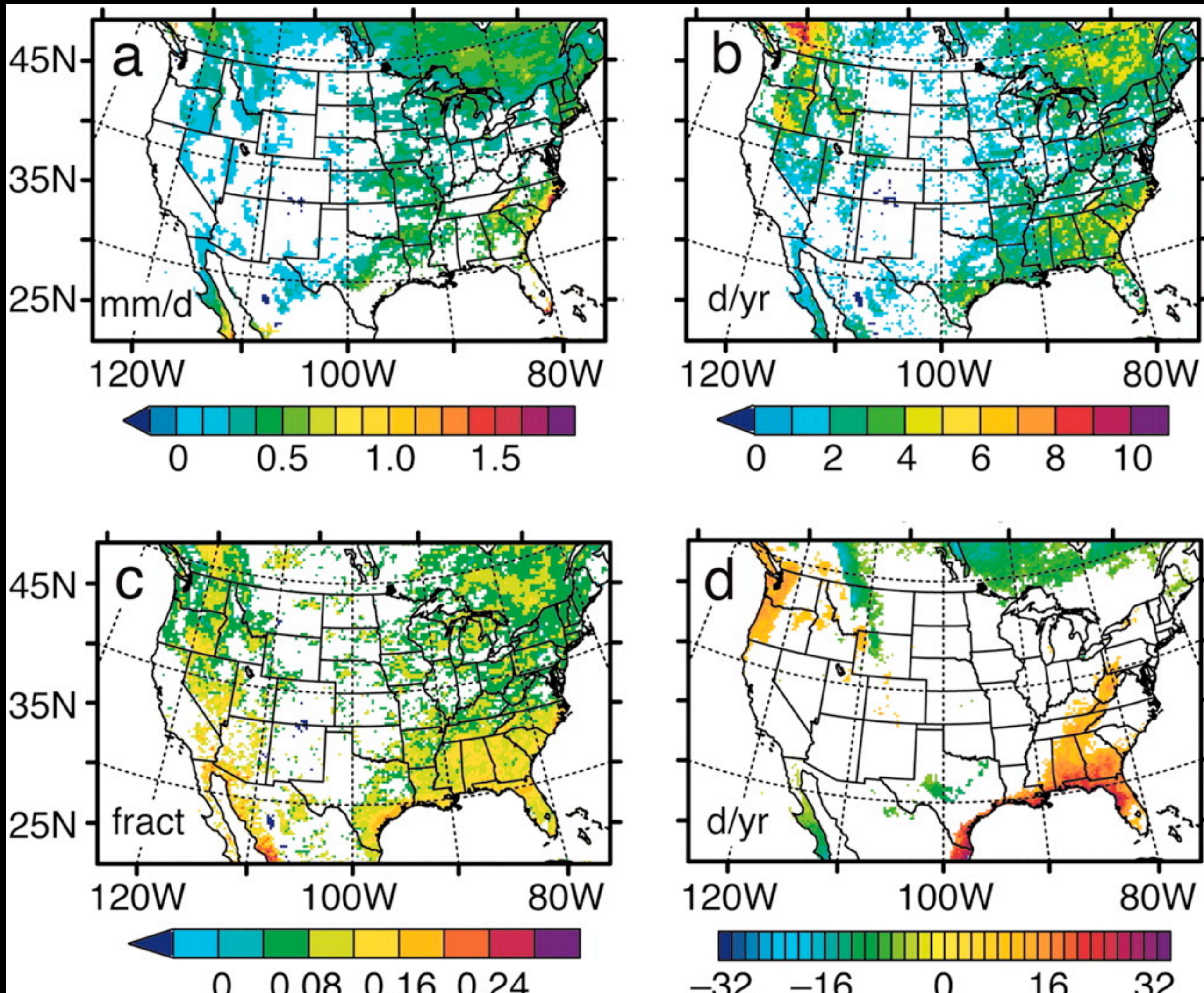
Given all the limitations, what can we learn using today's climate projections?

We can:

1. develop methodologies for doing multidisciplinary impacts/ adaptation assessments;
2. assess what aspects of climate impacts results are sensitive to;
3. determine if future climate is too uncertain to allow us to draw reliable conclusions;
4. improve our understanding of how natural and human systems respond to climate change.


"That's all Folks!"
Cartoon Songs From
MERRIE MELODIES & LOONEY TUNES

Anomalies (A2 - RF) in mean annual precipitation (mm/day) (a), P95 event frequency (days/year) (b), extreme-precipitation fraction (fraction) (c), and dry-day frequency (days/year) (d)



Diffenbaugh N. S. et.al. PNAS;2005;102:15774-15778

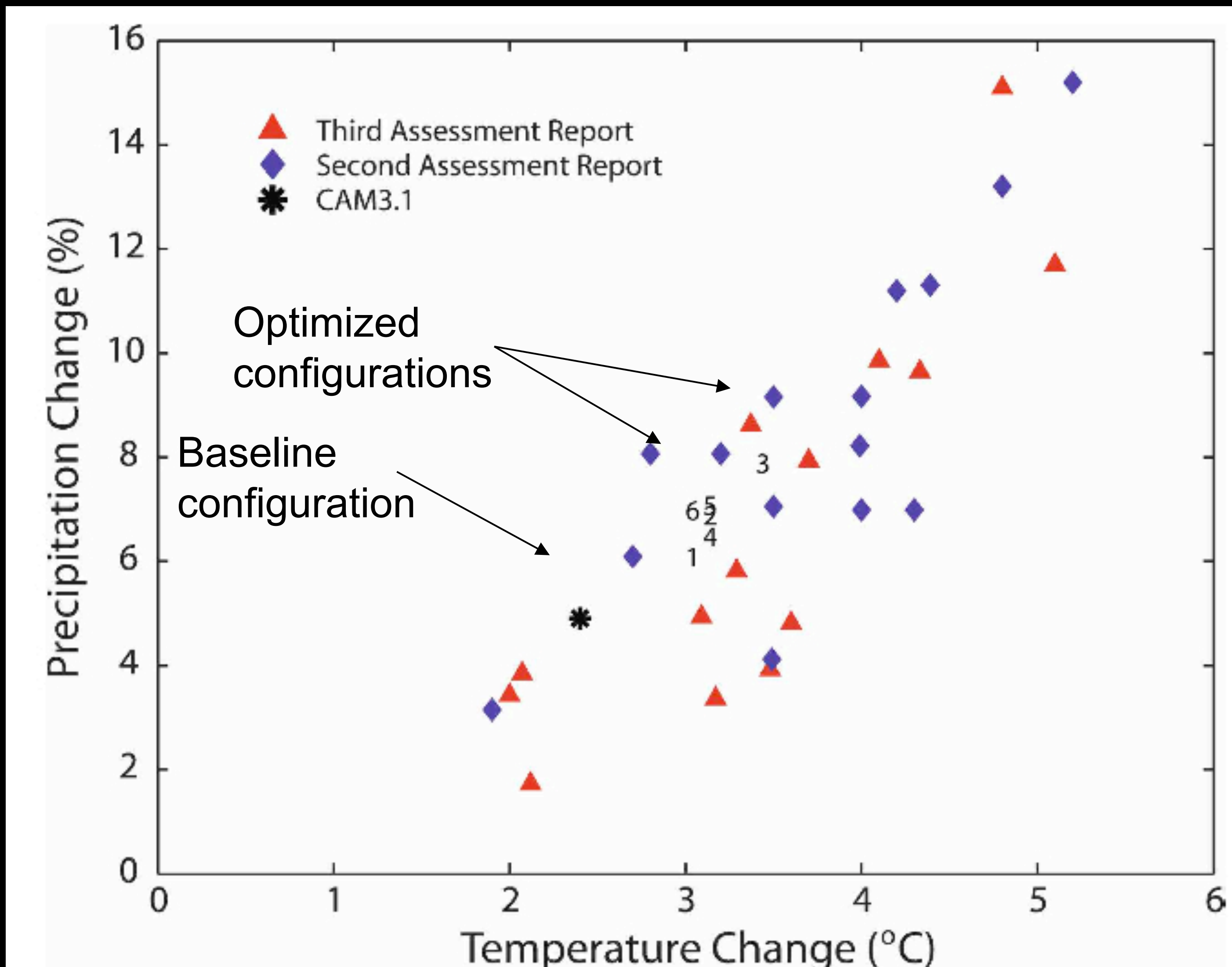
Percent Total Precipitation in Very Wet Days

Observations BCSD C Analogs

[redacted]

Source: Mike Mastrandrea, et al.

PPE suggests that range of climate sensitivities may be small than we think



Source: Chas. Jackson *et al. J. Climate* 2008

On the other hand….

- … other factors, e.g. the possibility of important common errors and omission suggests that this range may be *larger* than commonly assumed.

Examining a is a poor way to characterize uncertainty