Approaches for deriving future climate information

Andrew W. Robertson
International Research Institute for Climate and Society (IRI)
The Earth Institute, Columbia University, NY

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Preface: Climate Risk Management

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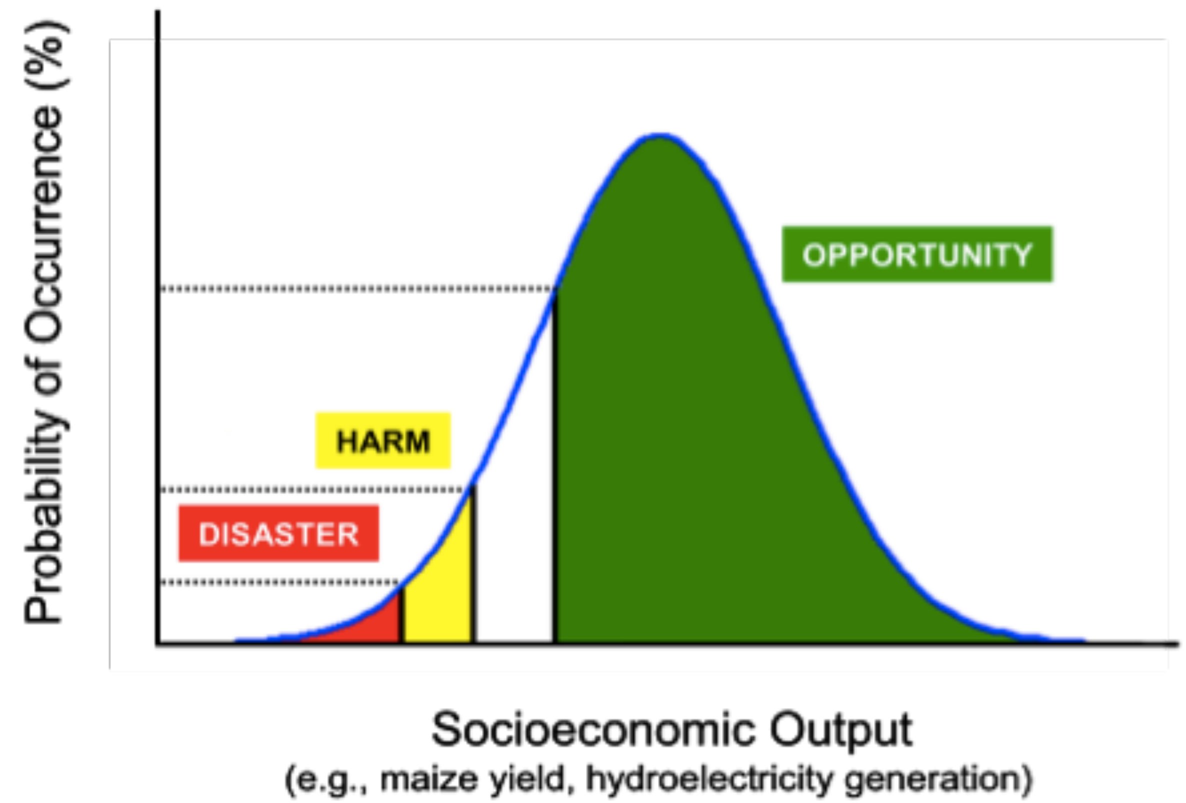
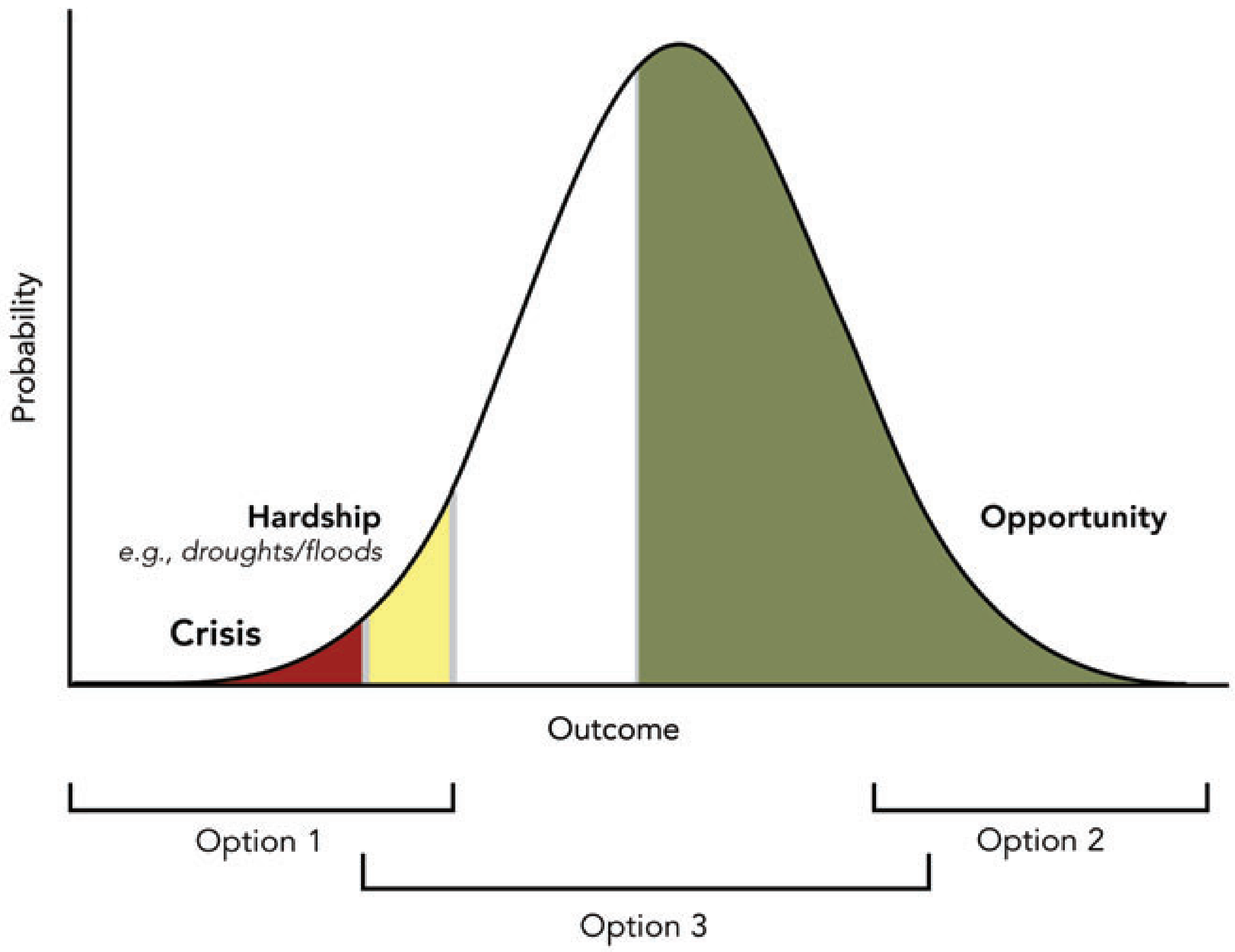
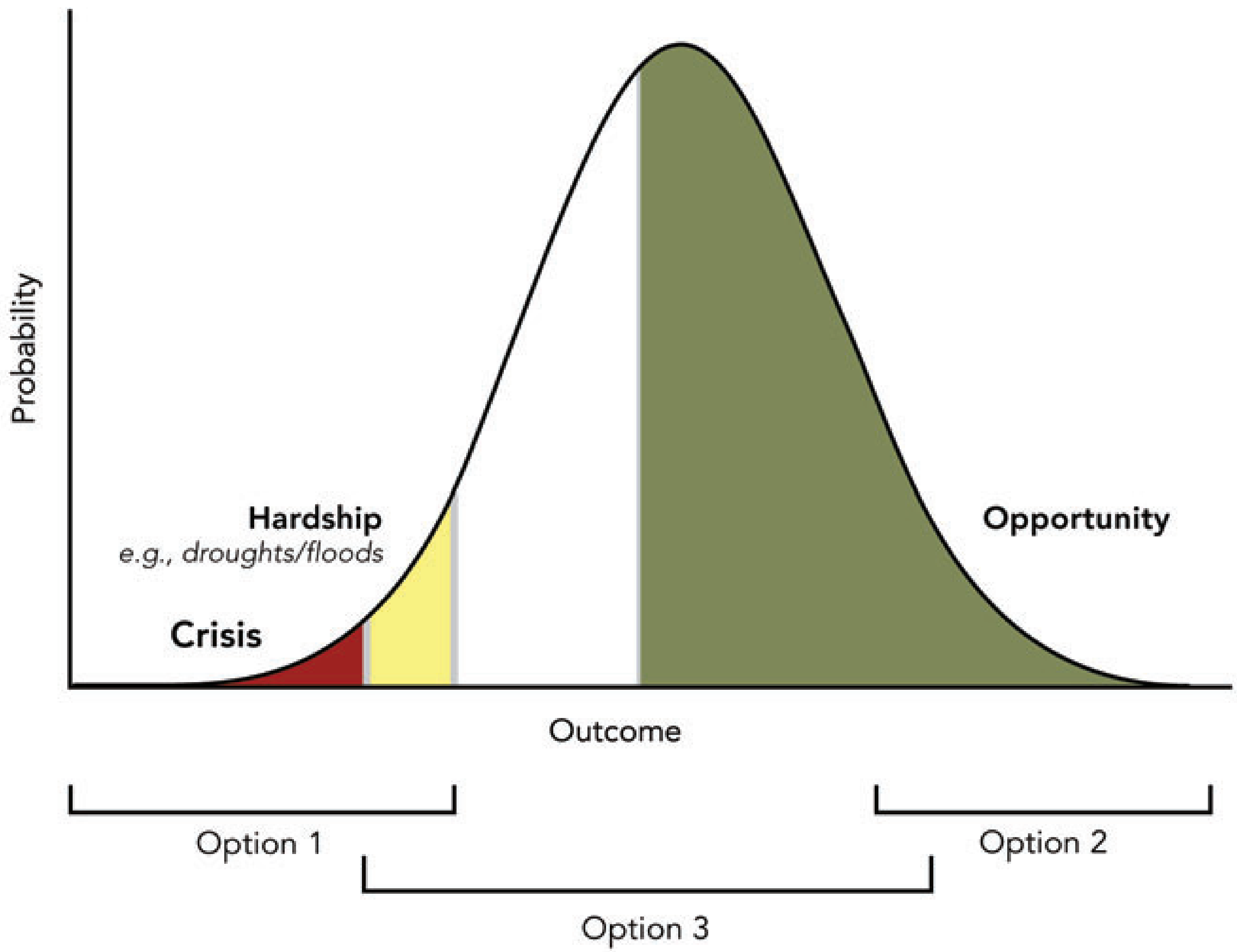


Options


Probability
Hardship
e.g., droughts/floods
Crisis
Opportunity
Outcome
Option 1
Option 2
Option 3

Options



for example, a drought-tolerant seed variety may not be as high-yielding as a normal one, given sufficient rainfall

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3. What are the sources of uncertainty?
4. What are the options for using the information for adaptive management of water resources? – Managing climate risks across timescales

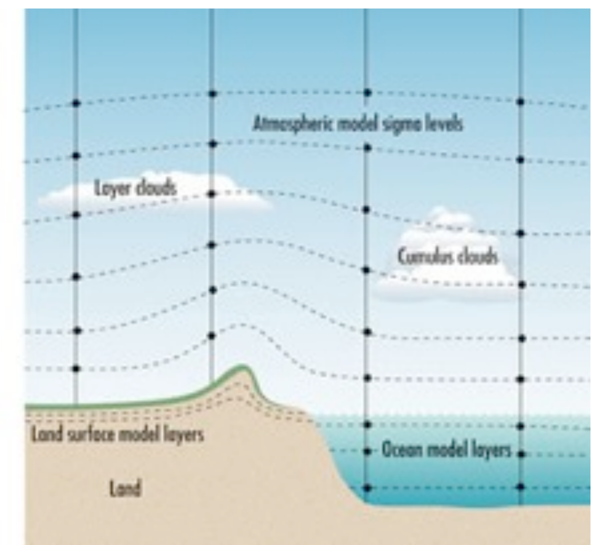
1. Climate Models and Climate Change Projections

3-D Dynamical Models (General Circulation Models)

Atmosphere (including land surface) (AGCM)

Ocean (sometimes including sea ice) (OGCM)

Coupled Atmosphere-Ocean (CGCM, AOGCM)

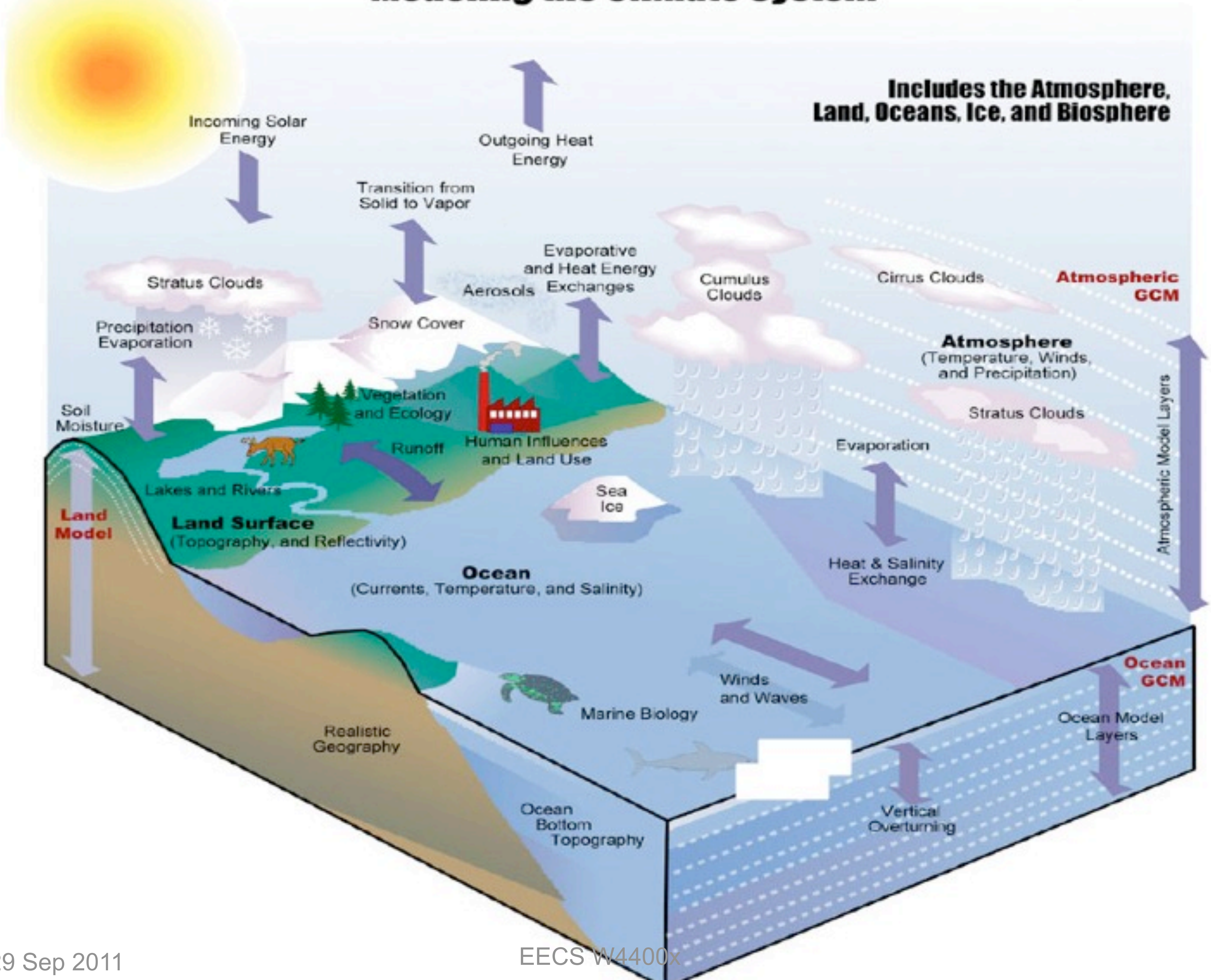


<u>Uses</u>:

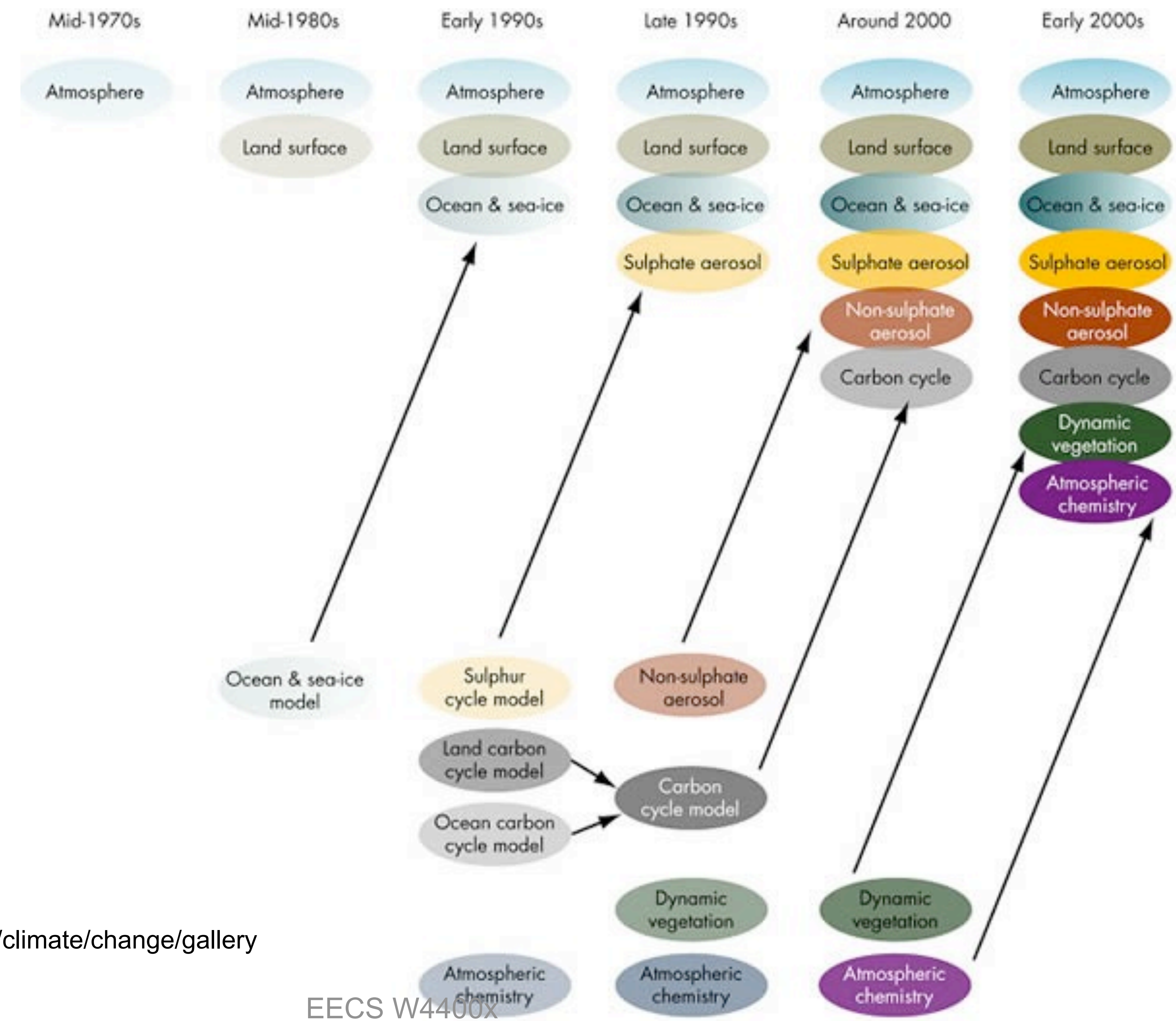
- **Simulations:** 3-dimensional circulation of the atmosphere and/or ocean
- **Experiments:** Can modify any aspect of the Earth or climate system or its forcing and examine the response
- **Forecasting**
  - * Weather forecasts
  - *** Seasonal-to-interannual forecasts**
  - *** Climate change projections**

…

Modeling the Climate System



GCM Evolution



Development of climate models over the last 25 years, showing how the different components are first developed separately and later coupled into comprehensive climate models

Source: http://www.bom.gov.au/info/climate/change/gallery

2. What do the models say for South America?

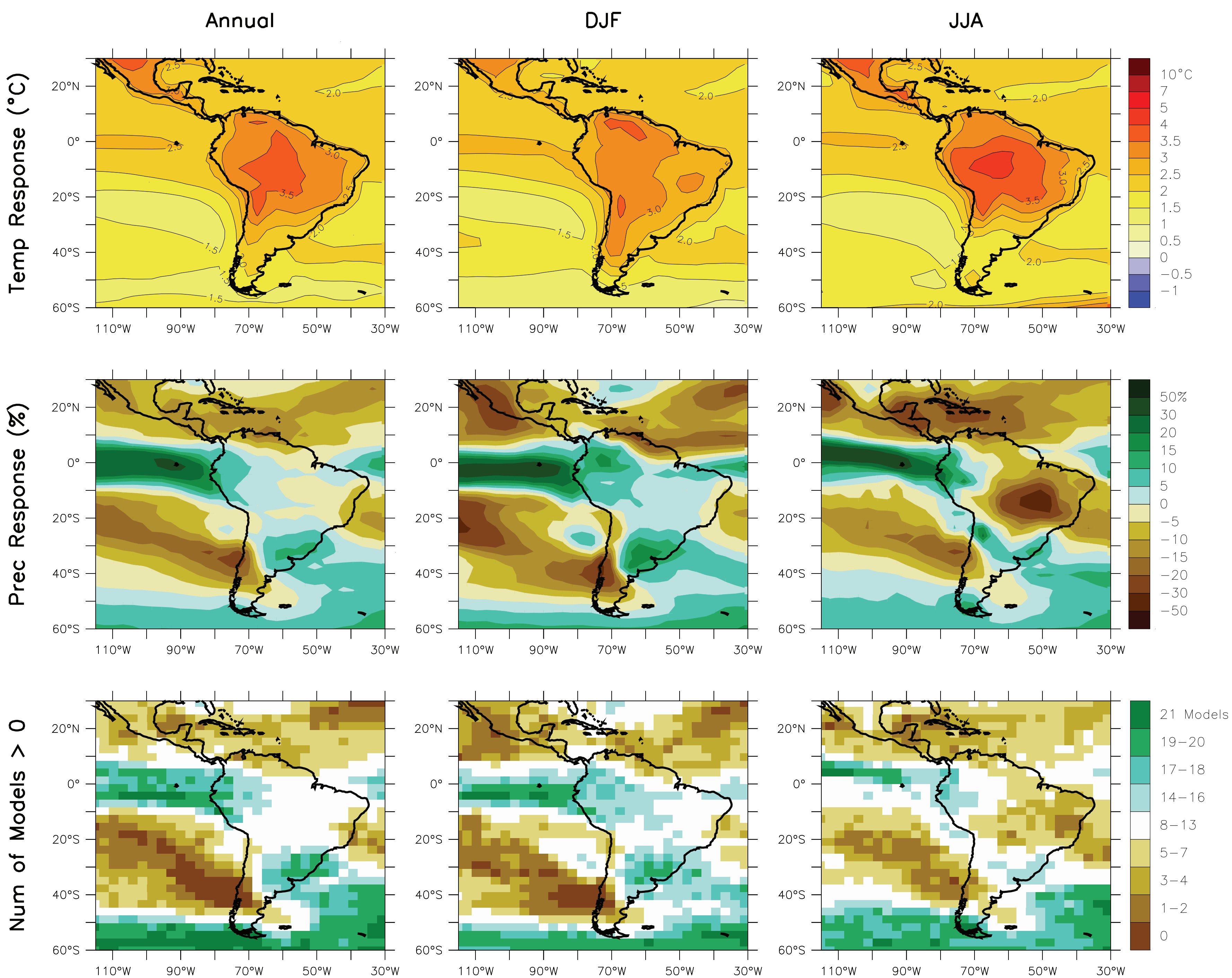


Figure 11.15. *Temperature and precipitation changes over Central and South America from the MMD-A1B simulations. Top row: Annual mean, DJF and JJA temperature change between 1980 to 1999 and 2080 to 2099, averaged over 21 models. Middle row: same as top, but for fractional change in precipitation. Bottom row: number of models out of 21 that project increases in precipitation.*

IPCC, AR4, WG1

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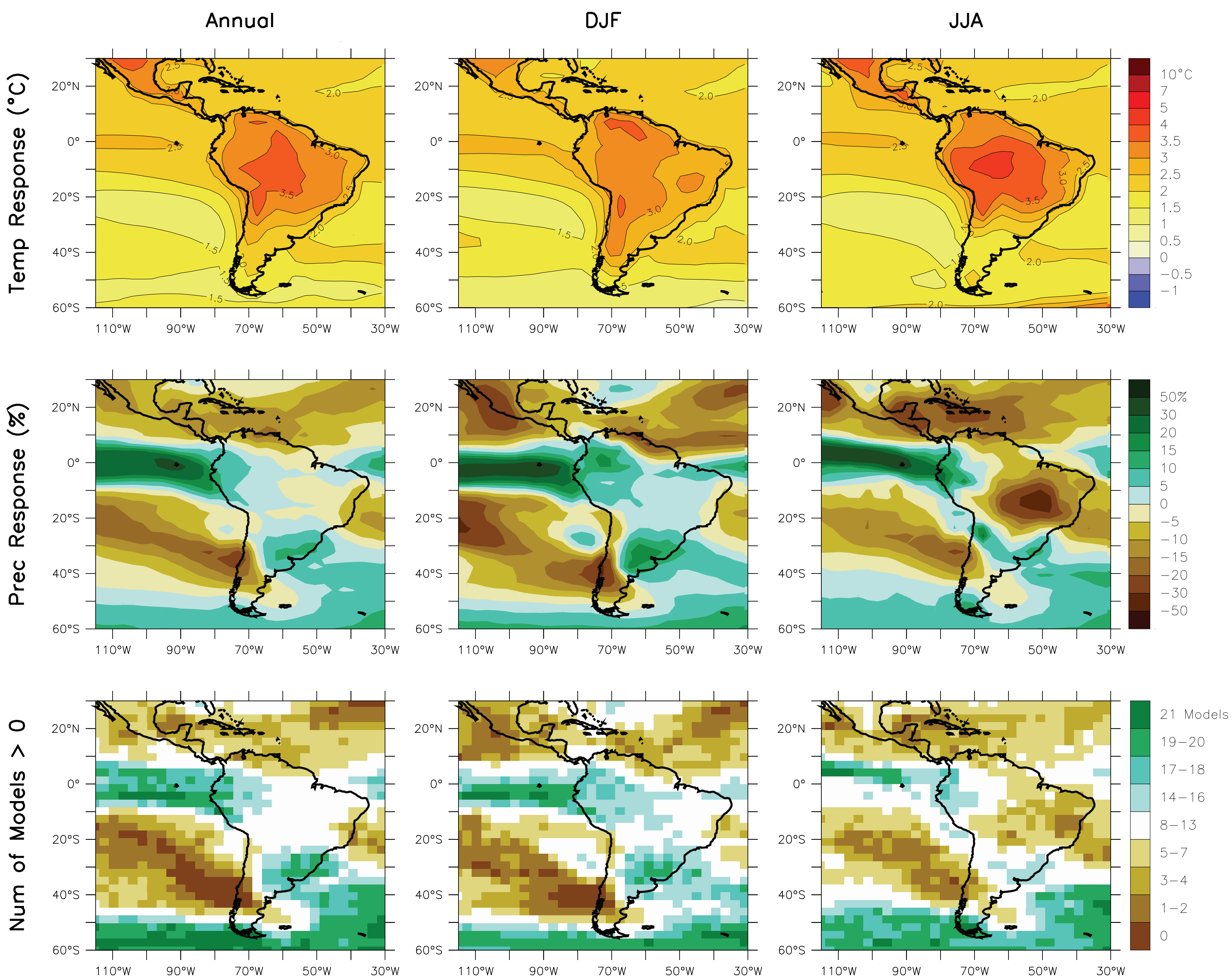

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How best to present projections of future climate?

Ensemble mean? What about uncertainty? Are all the models equally good?

 # models with a given answer? Do models span range of possibilities?

IPCC, AR4, WG1

... important to interpret regional changes in the context of global picture

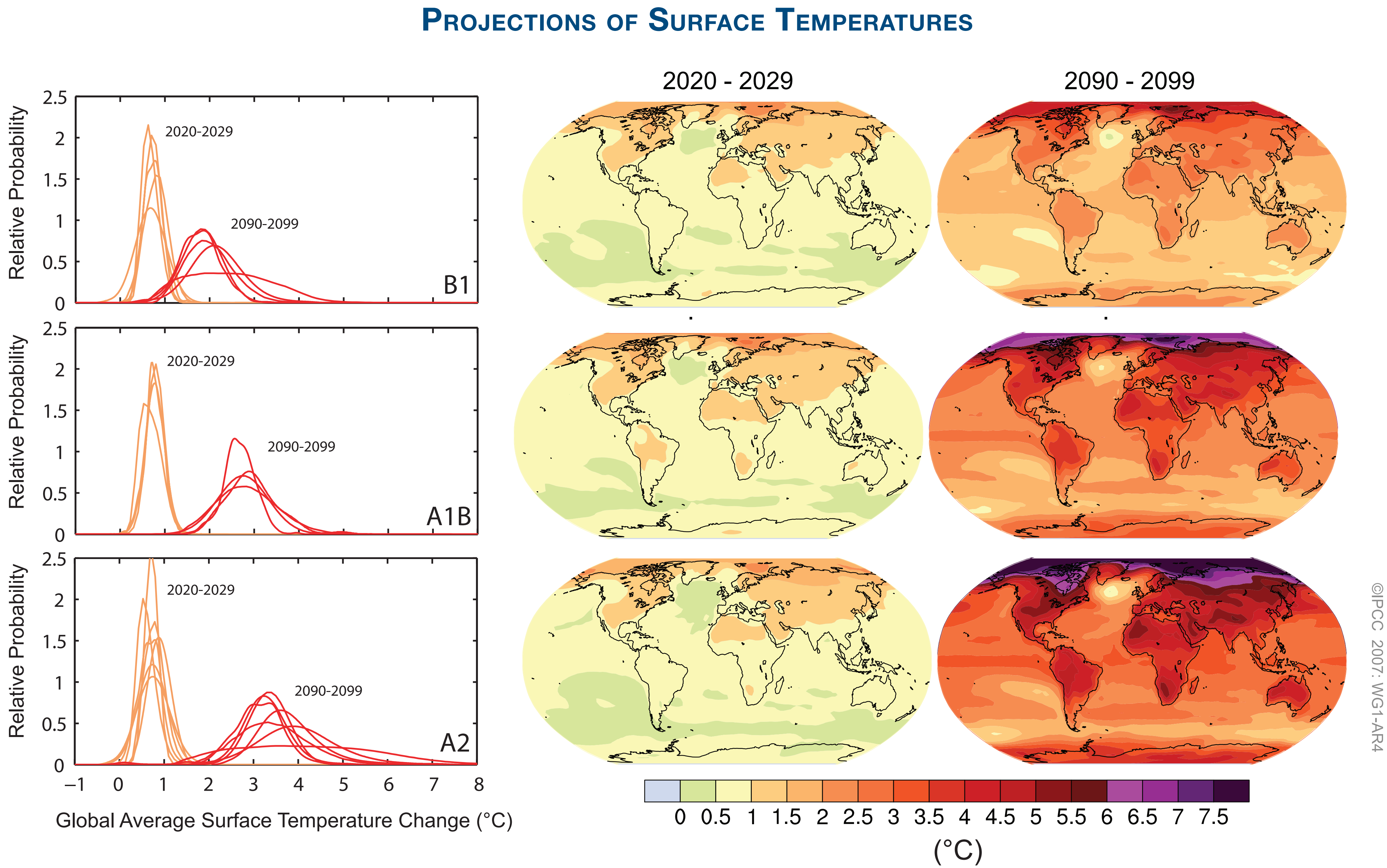


Figure SPM.6. *Projected surface temperature changes for the early and late 21st century relative to the period 1980–1999. The central and right panels show the AOGCM multi-model average projections for the B1 (top), A1B (middle) and A2 (bottom) SRES scenarios averaged over the decades 2020– 2029 (centre) and 2090–2099 (right). The left panels show corresponding uncertainties as the relative probabilities of estimated global average warming from several different AOGCM and Earth System Model of Intermediate Complexity studies for the same periods. Some studies present results only for a subset of the SRES scenarios, or for various model versions. Therefore the difference in the number of curves shown in the left-hand panels is due only to differences in the availability of results. {Figures 10.8 and 10.28}*

IPCC, AR4, WG1

Projected Patterns of Precipitation Changes

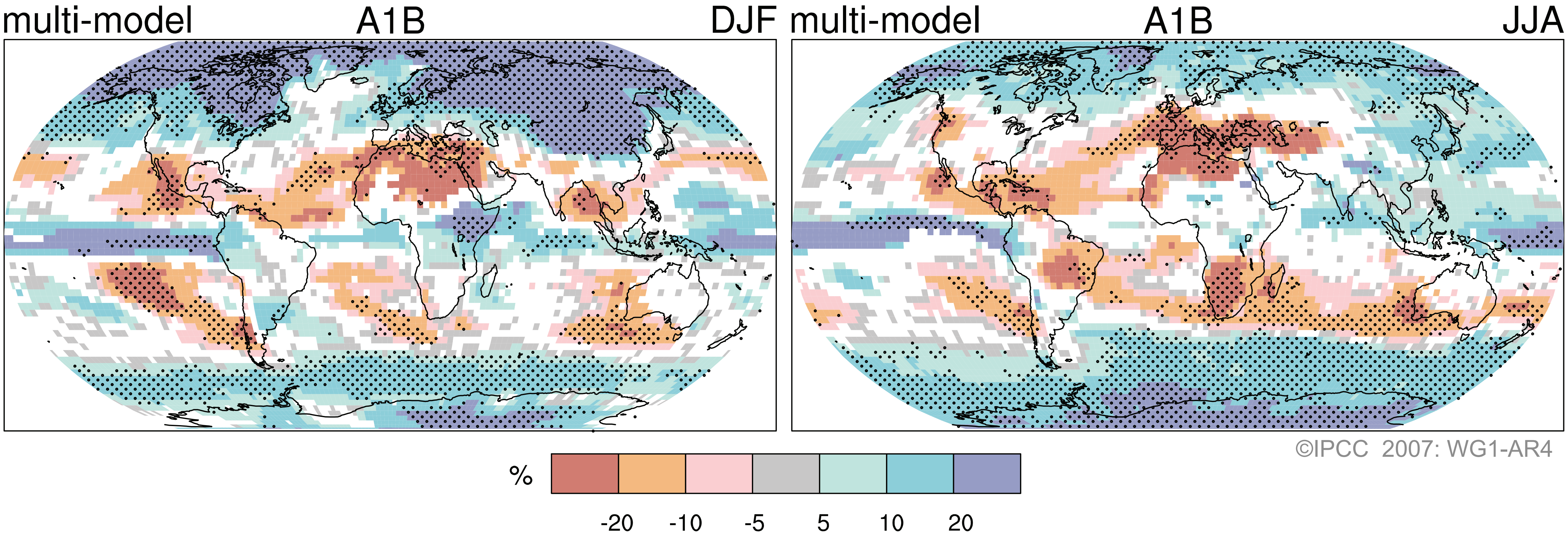


Figure SPM.7. *Relative changes in precipitation (in percent) for the period 2090–2099, relative to 1980–1999. Values are multi-model averages based on the SRES A1B scenario for December to February (left) and June to August (right). White areas are where less than 66% of the models agree in the sign of the change and stippled areas are where more than 90% of the models agree in the sign of the change. {Figure 10.9}*

IPCC, AR4, WG1

3. Sources of uncertainty

There is uncertainty in IPCC model projections.

- *Emission scenarios*
- *Model formulation*
- *Internal variability*

are all sources of uncertainty.

Uncertainty can vary in character depending on variable considered, and on spatial/temporal scales considered.

Trust in Models (Outline & Main Points

1) Models are based on physical laws (conservation of momentum, energy, etc.)

2) Models can simulate the current climate (mostly)
   - Temperatures, precipitation patterns, heat transports

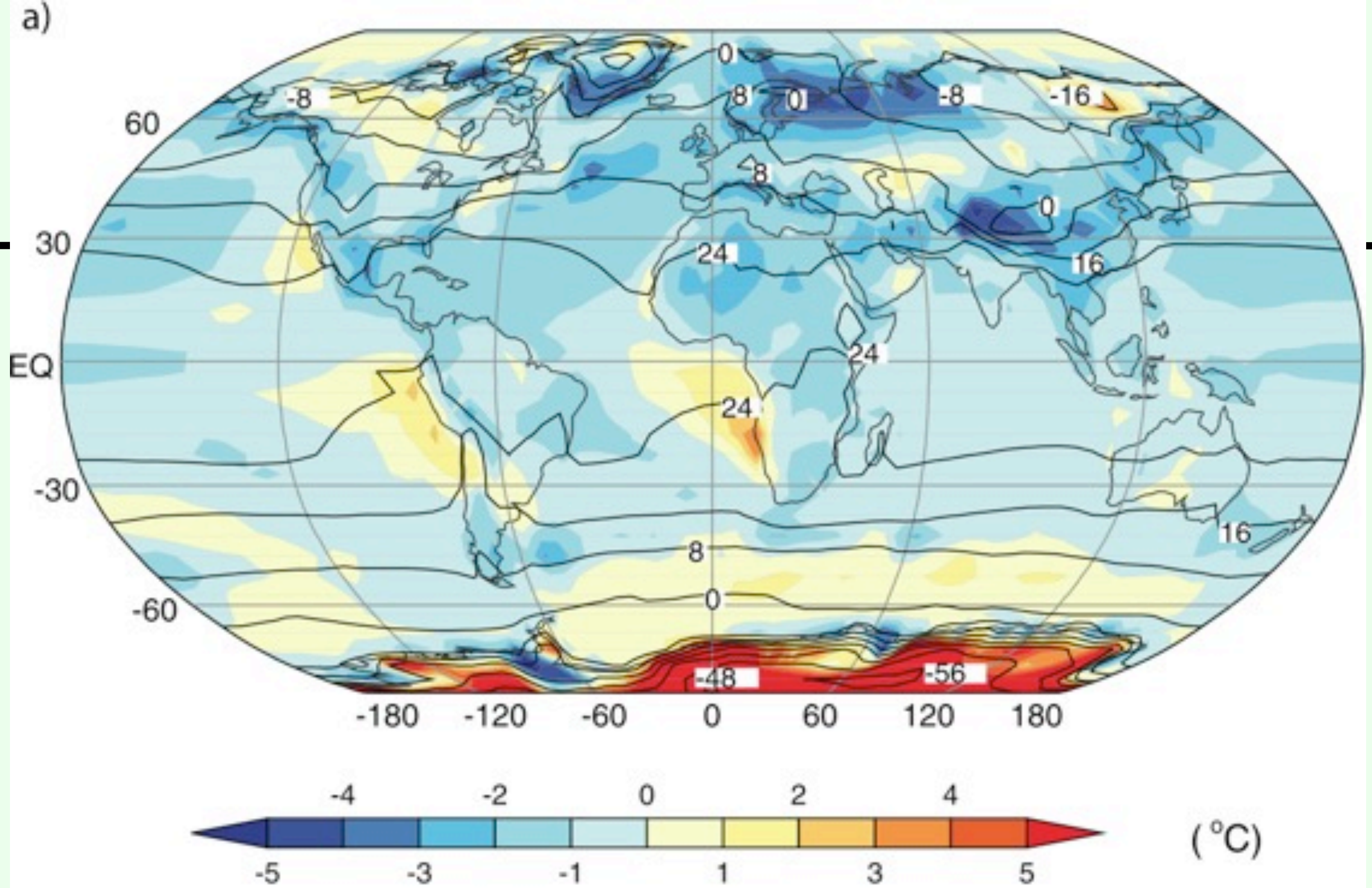
3) Models can produce features of past climates & climate changes (mostly)
   - faster increases in night T than day T
   - accelerated Arctic warming
   - Post-volcano cooling

➔ Assuming we *do* trust the models (kinda) how best to use the information? What specificity of information can we expect on seasonal to centennial timescales?

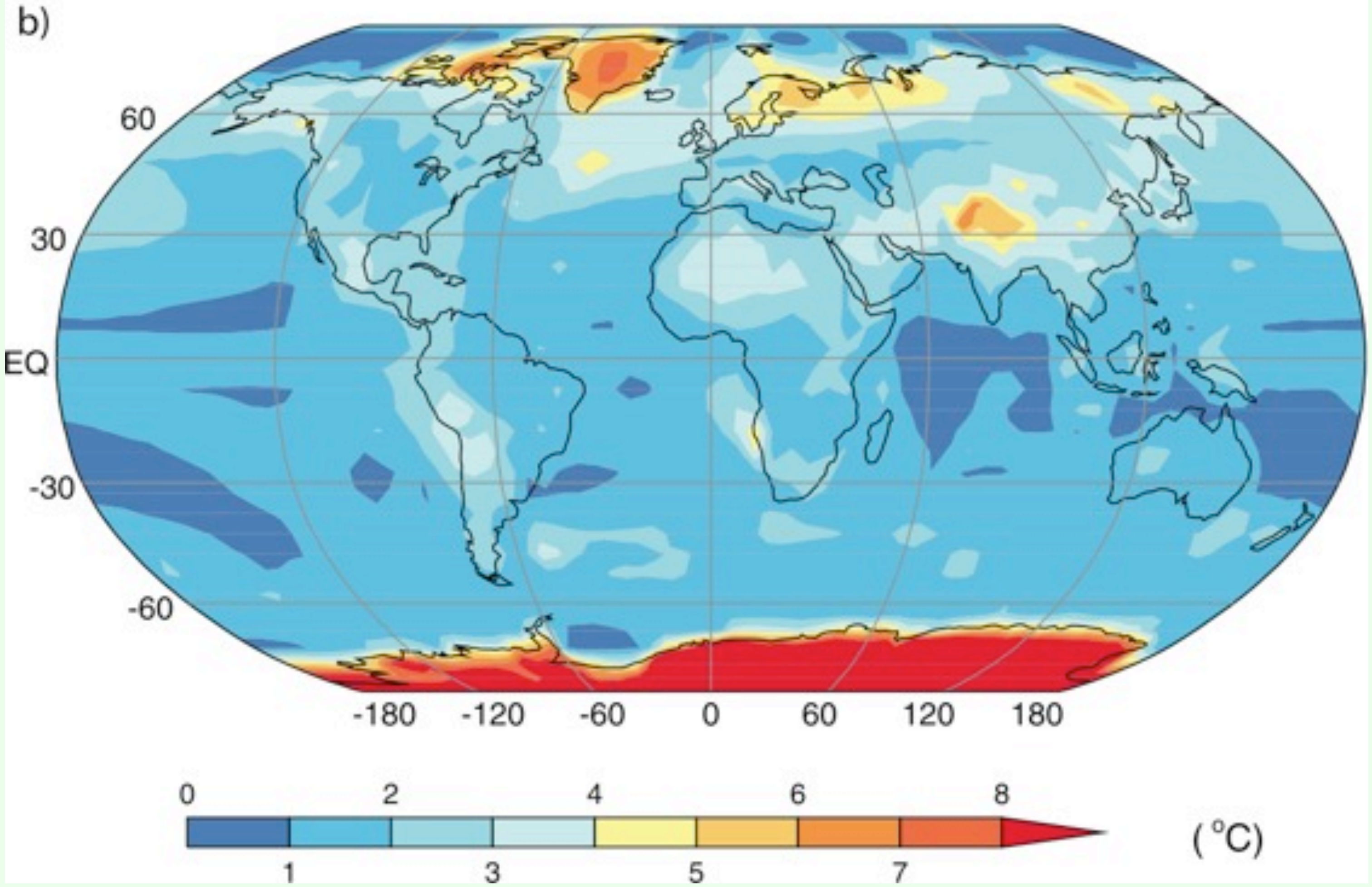
Current Climate

Surface temperature (contours)

Error in multi-model mean temperature (shading)



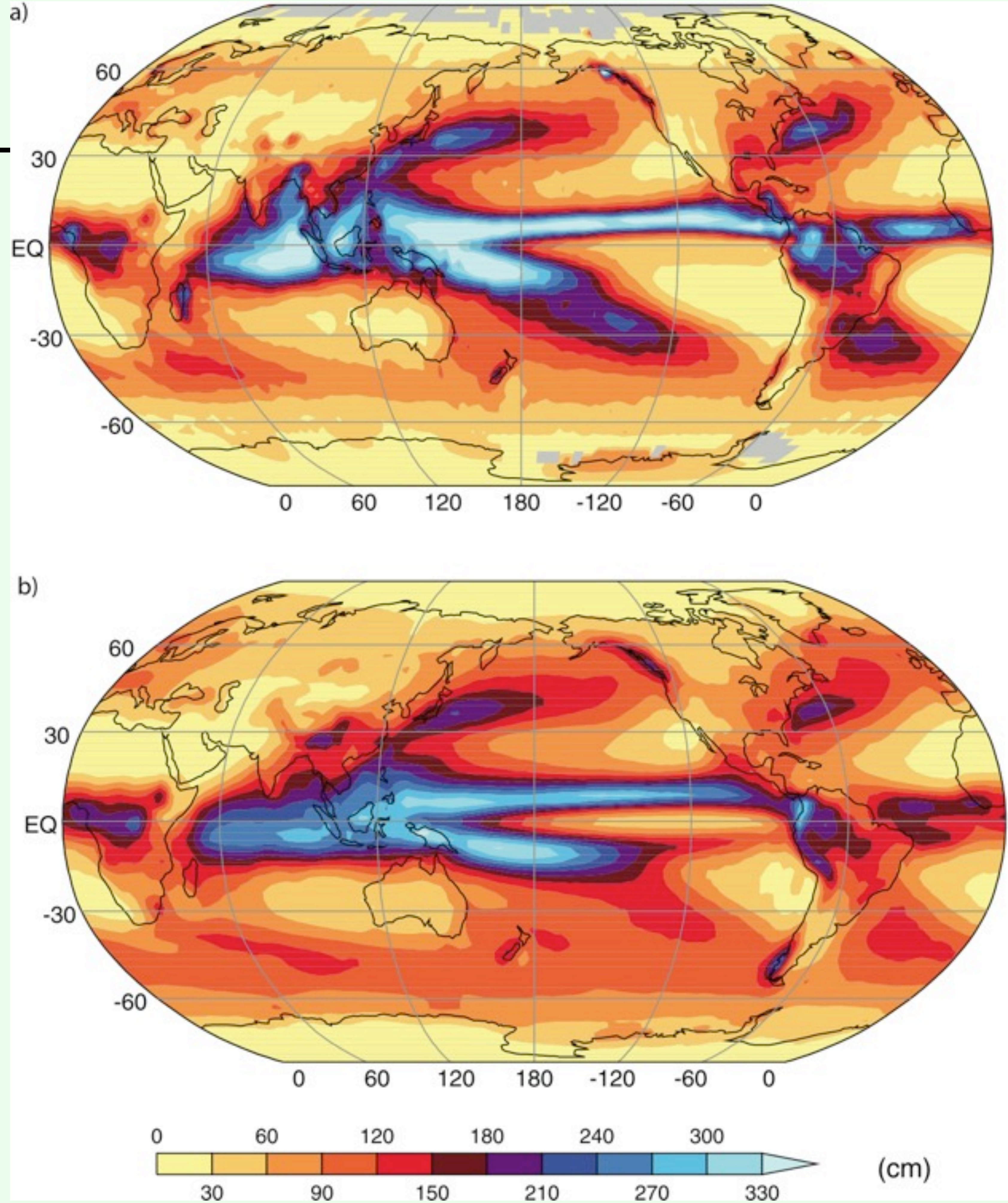
Typical magnitude of error in individual model
(i.e. RMSE across models)



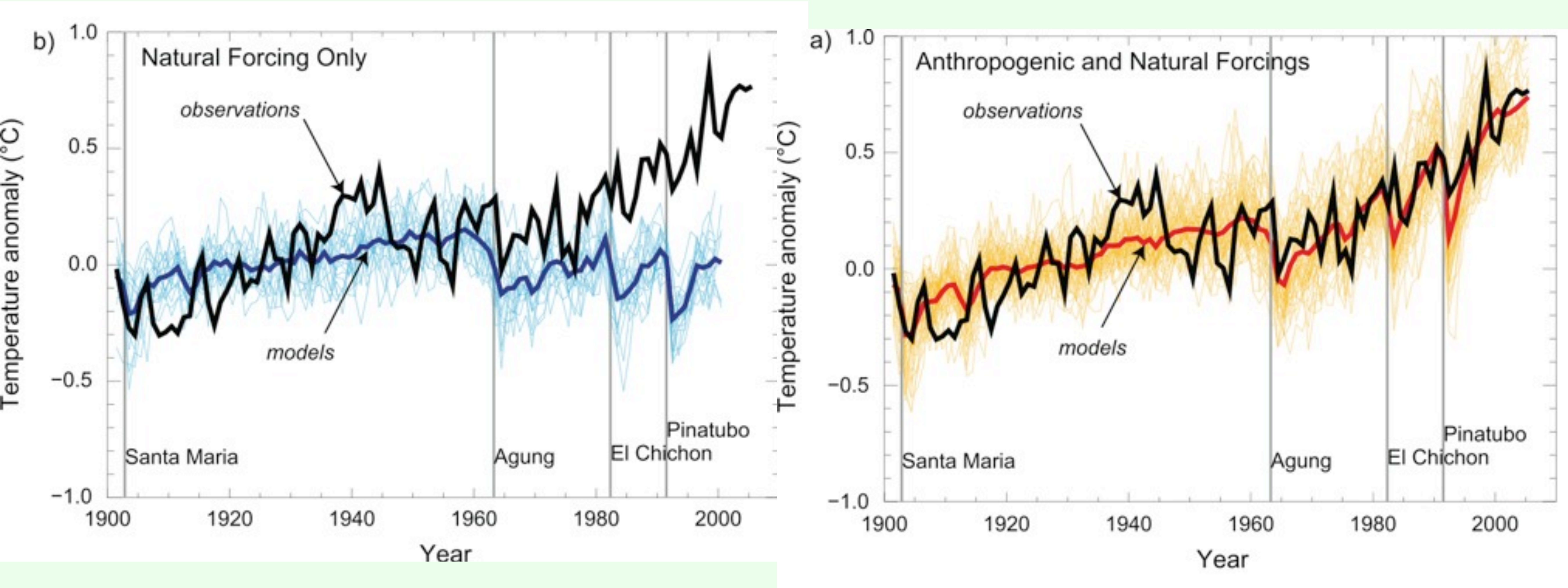
Current Climate

Observed Precipitation

Multi-Model Average Precipitation



Reproducing the Past

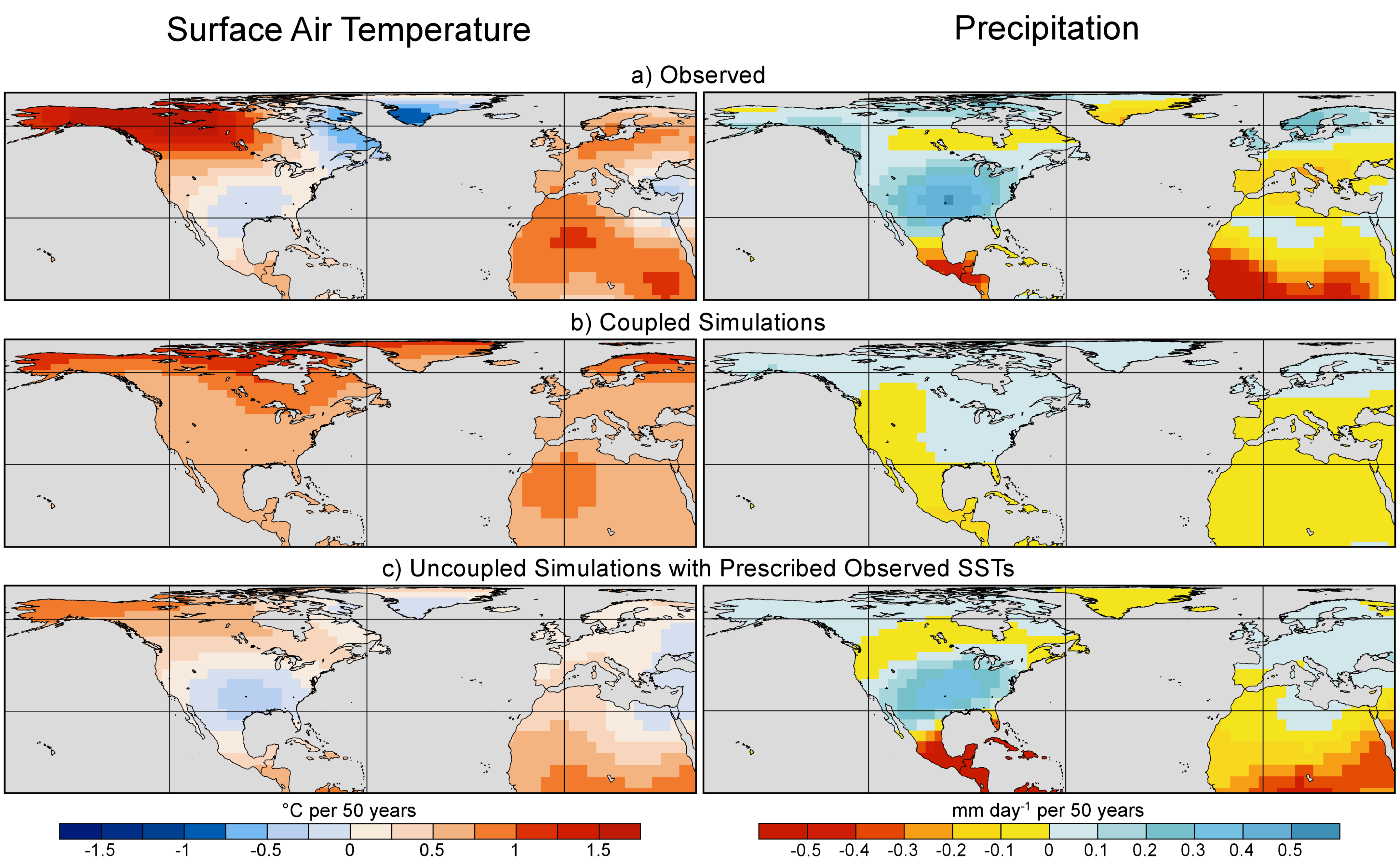


Correlation-type measure perhaps less informative here than the result that global temperature increases (particularly in the past few decades) if anthropogenic forcings are included. Notice also the clear episodic cooling response due to large volcanic eruptions.

On average, the global models can capture the main features of climatological patterns of temperature and precipitation

but ...

Trends in annual means over 1951–1999



Shin & Sardeshmukh (2010, Climate Dynamics)

Why the disagreement?

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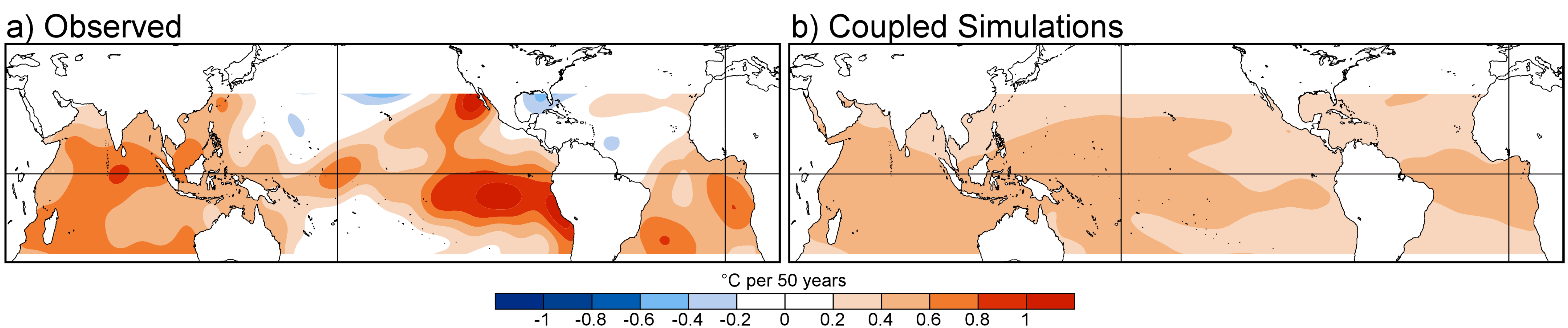
Trends in tropical sea surface temperatures



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These mis-represented interdecadal trends are particularly an issue for “near term” climate change until 2050. They are less problematic as the signal of the forcing comes to dominate at end-of-century.

Decadal forecasts – Can we predict this low-frequency ocean evolution?

Decadal prediction skill over land: Yet to be demonstrated

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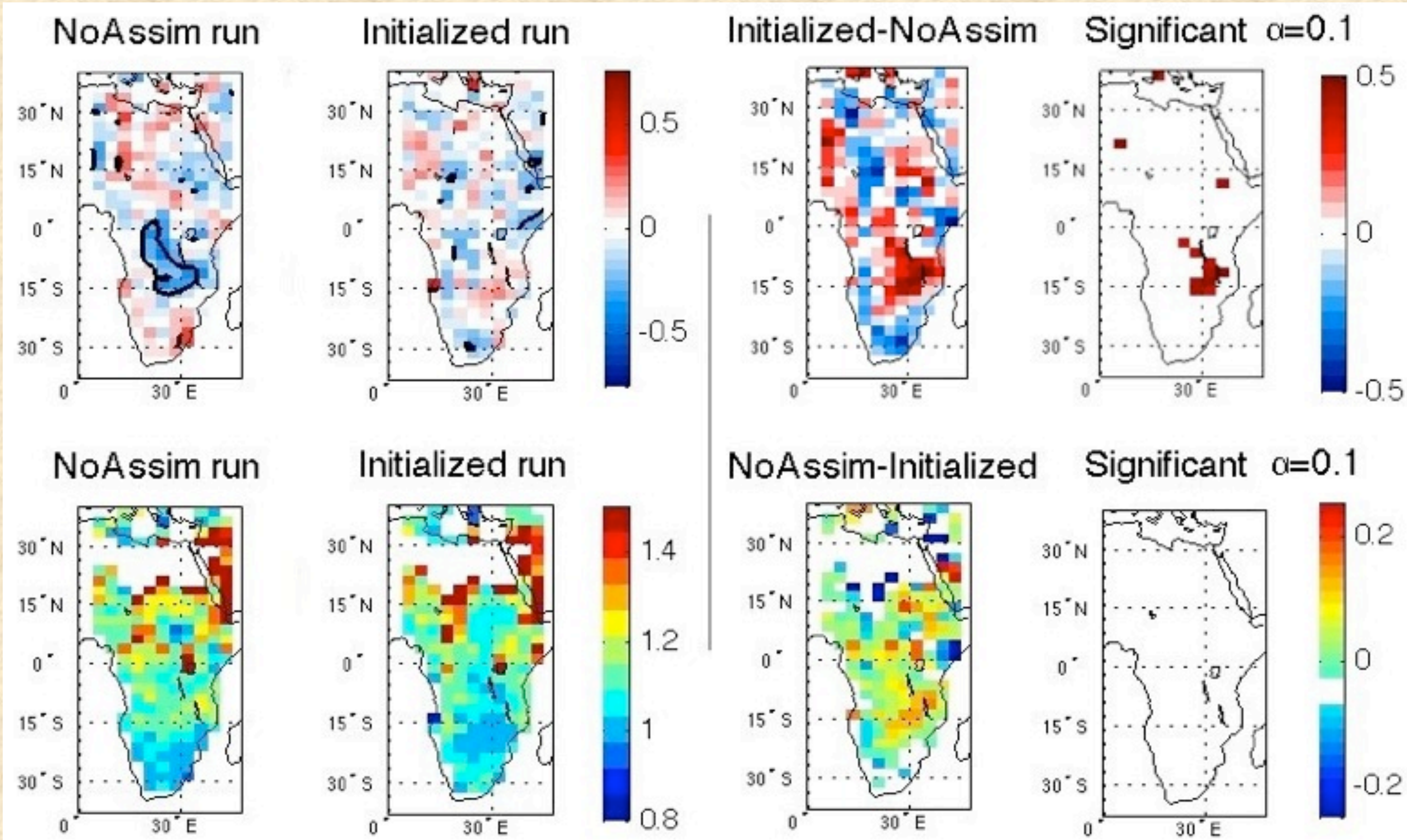
RMSE



- The forecast “target” here is precipitation averaged over the period 2-5 years ahead. Statistics are computed over 40 forecasts that were produced using a sophisticated modeling and prediction scheme that targets the decadal scale.
- Two metrics for forecast skill are shown (top and bottom rows). Third and fourth columns show skill improvement (if any) resulting from ocean initialization.
- Conclusion: Little if any skill evident in terrestrial Africa, including the Western Cape.

4. What are the options for using the information for adaptive management of water resources?

Managing climate risks across timescales

Timescales of Variability in Observations

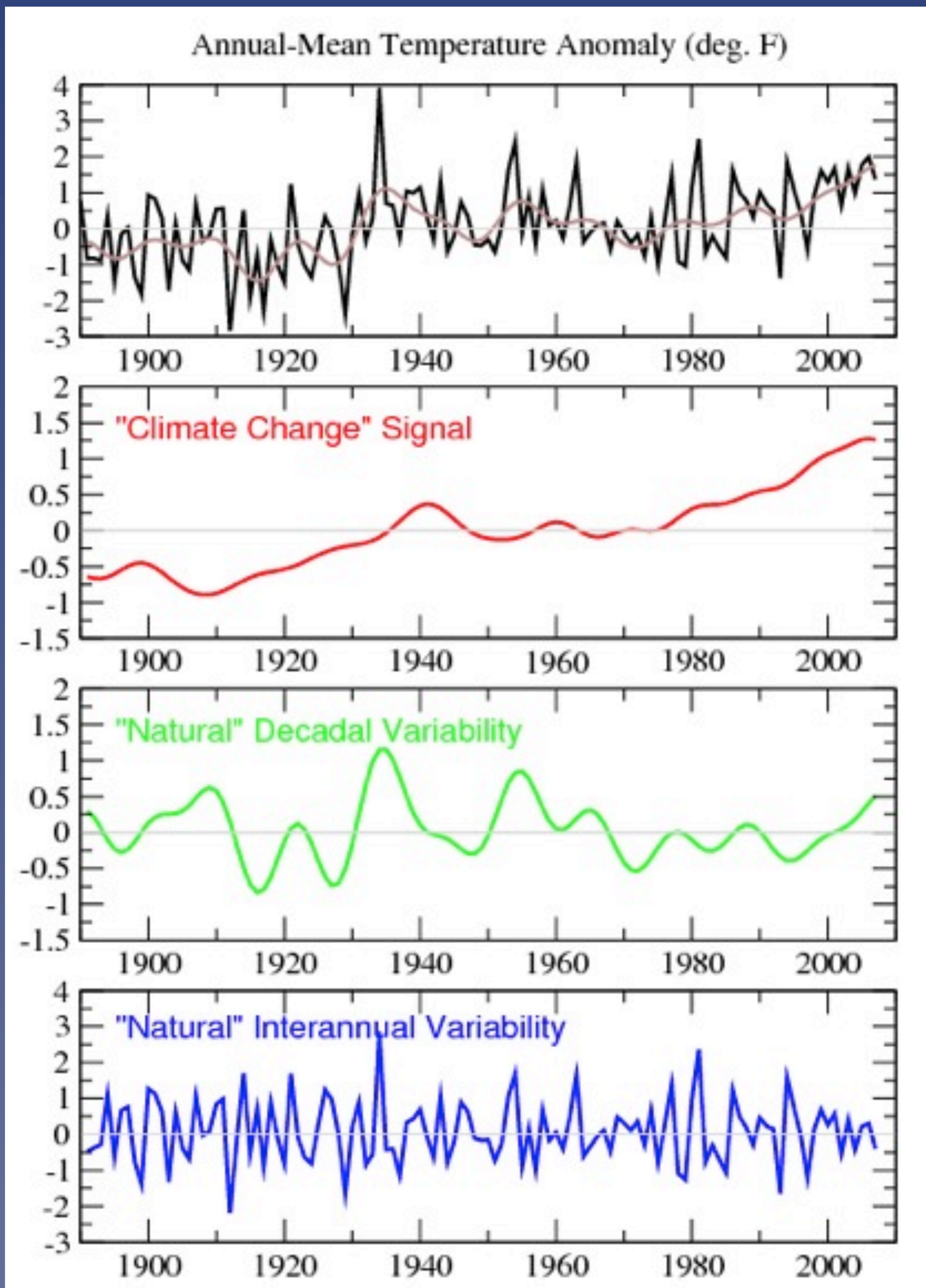
e.g. Climate Variability & Change in CO

Temperature

25%

13%

62%

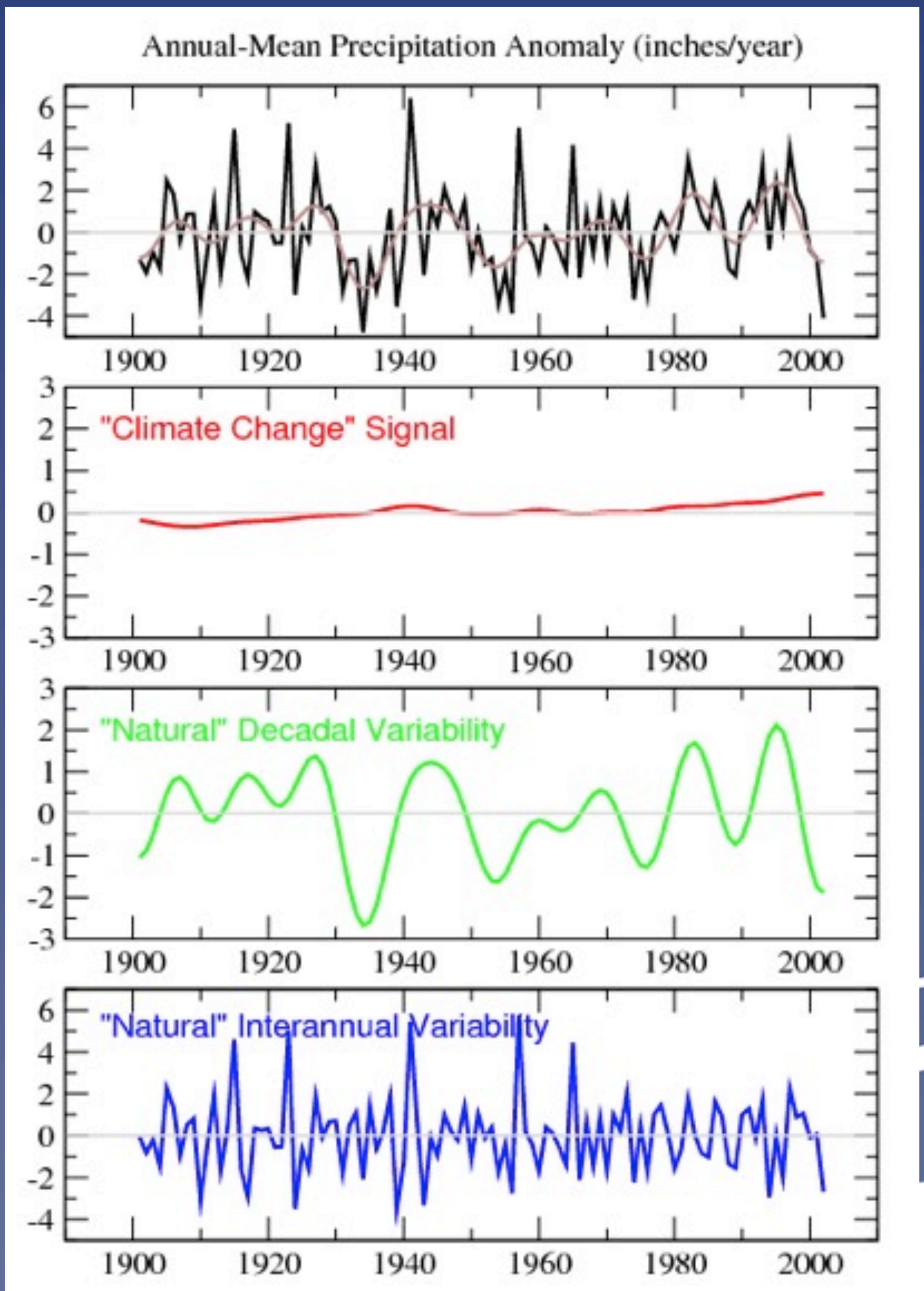


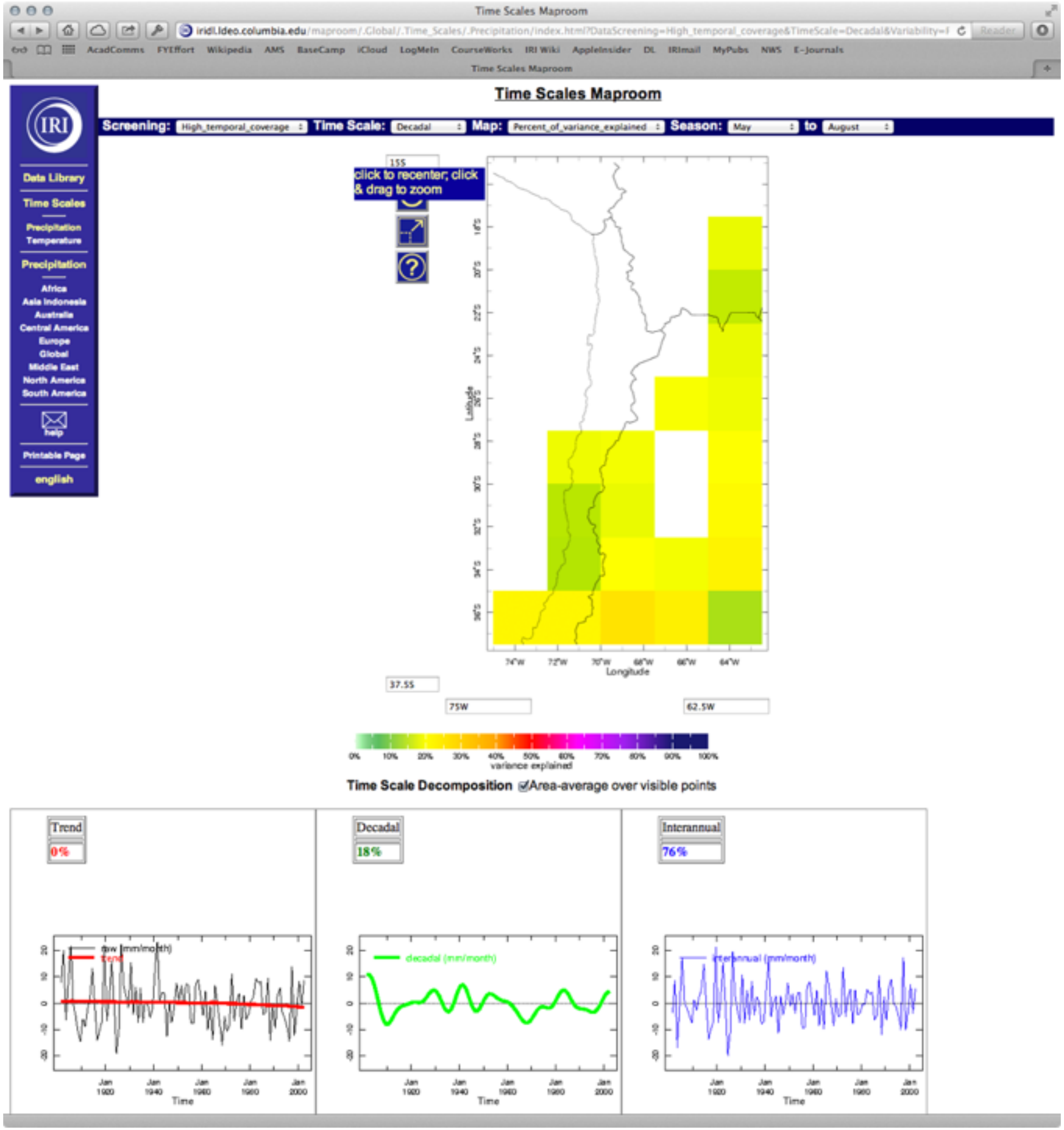
Precipitation

1%

25%

74%





http://iridl.ldeo.columbia.edu/maproom/.Global/.Time_Scales/

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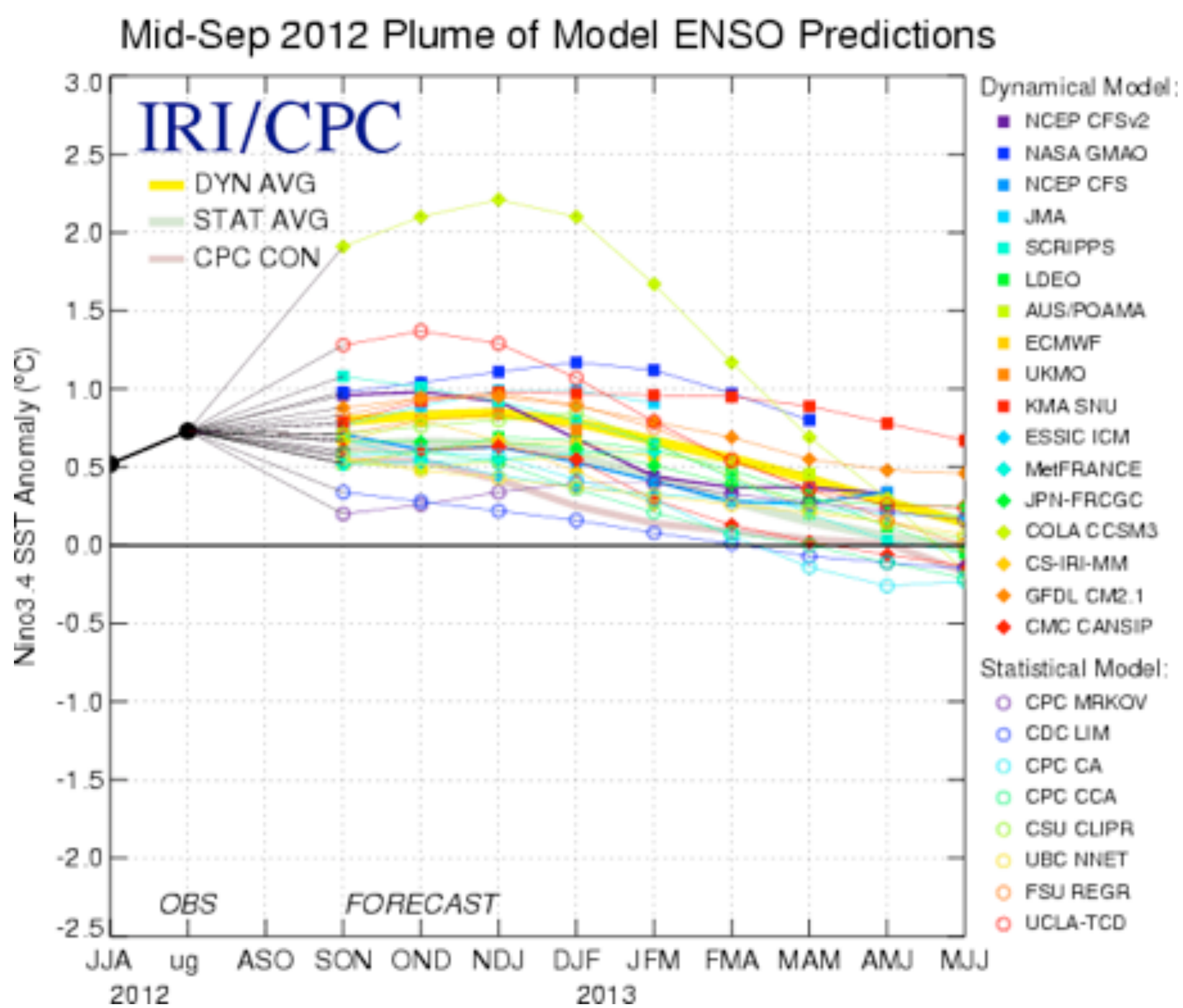
- much is understood about interannual variability driven by ENSO
- interdecadal variability is much more poorly understood

Seasonal probabilistic forecasts



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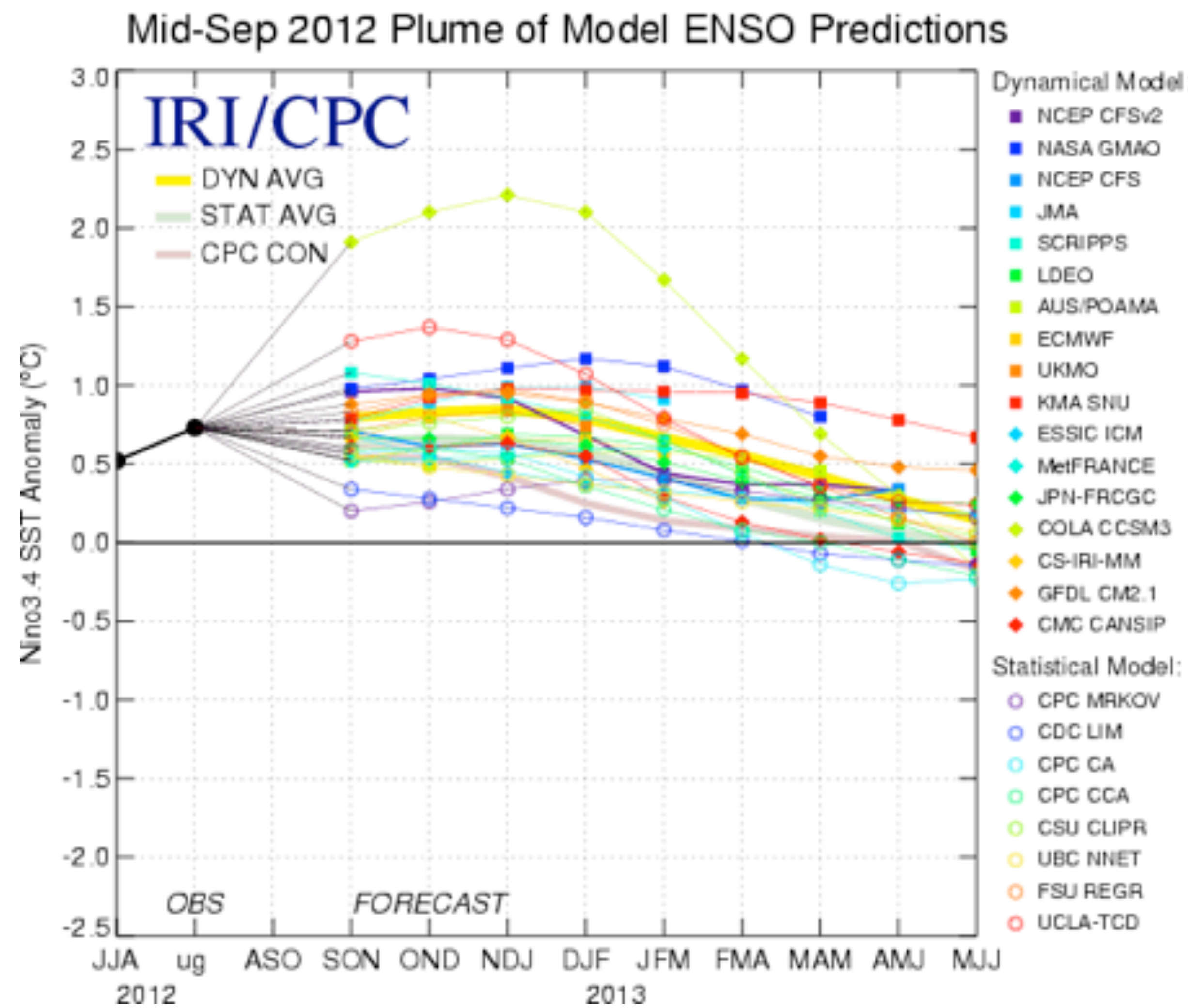
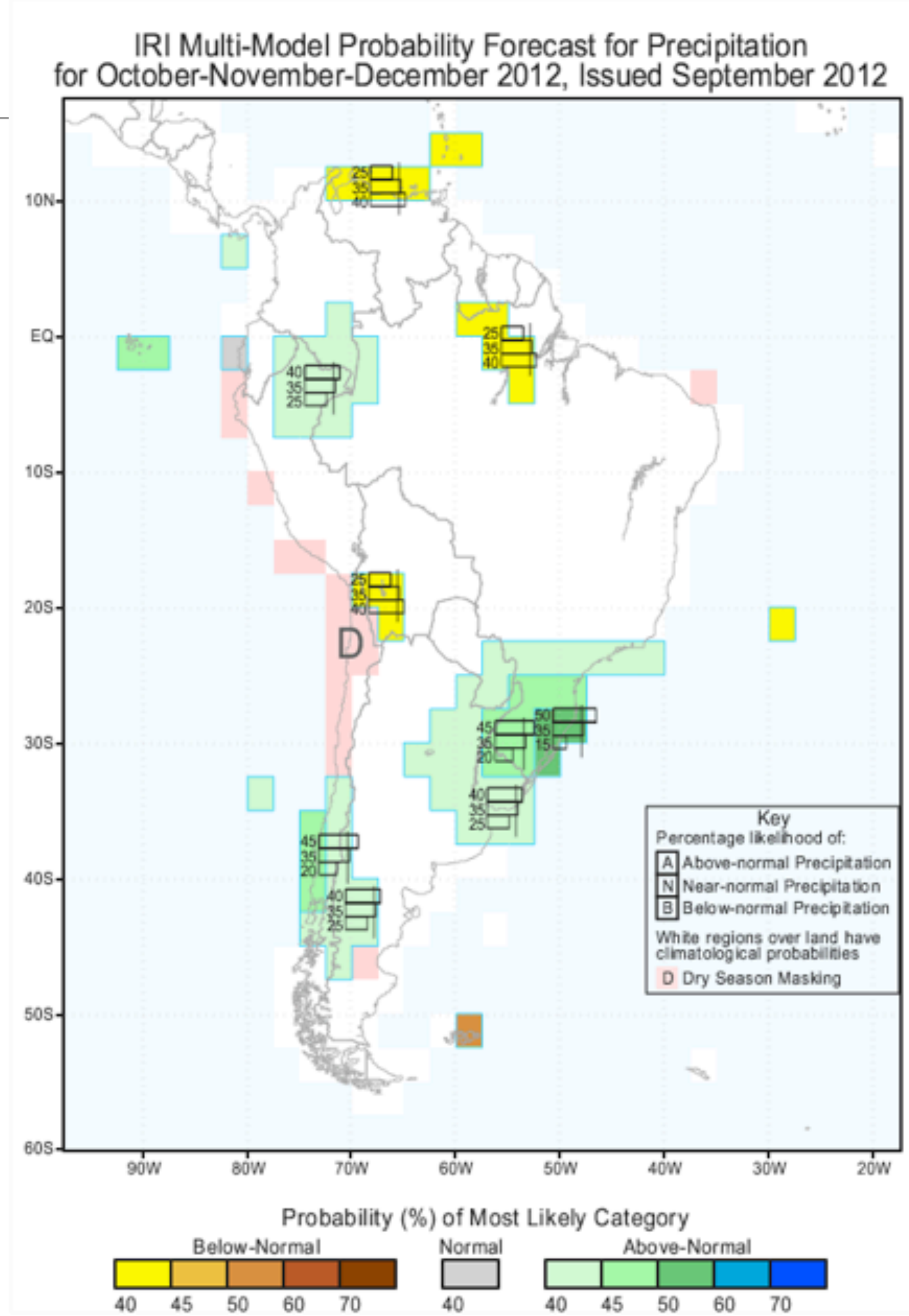
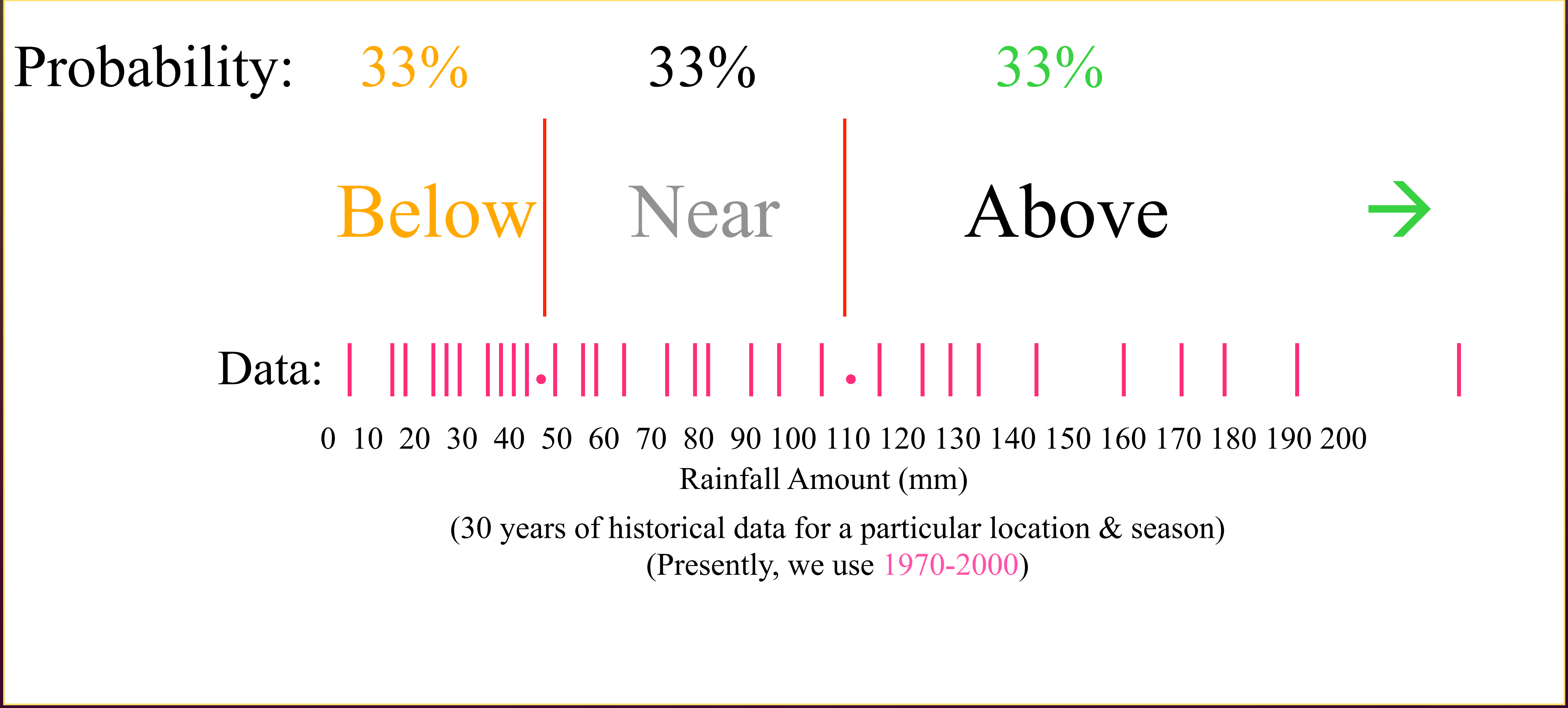
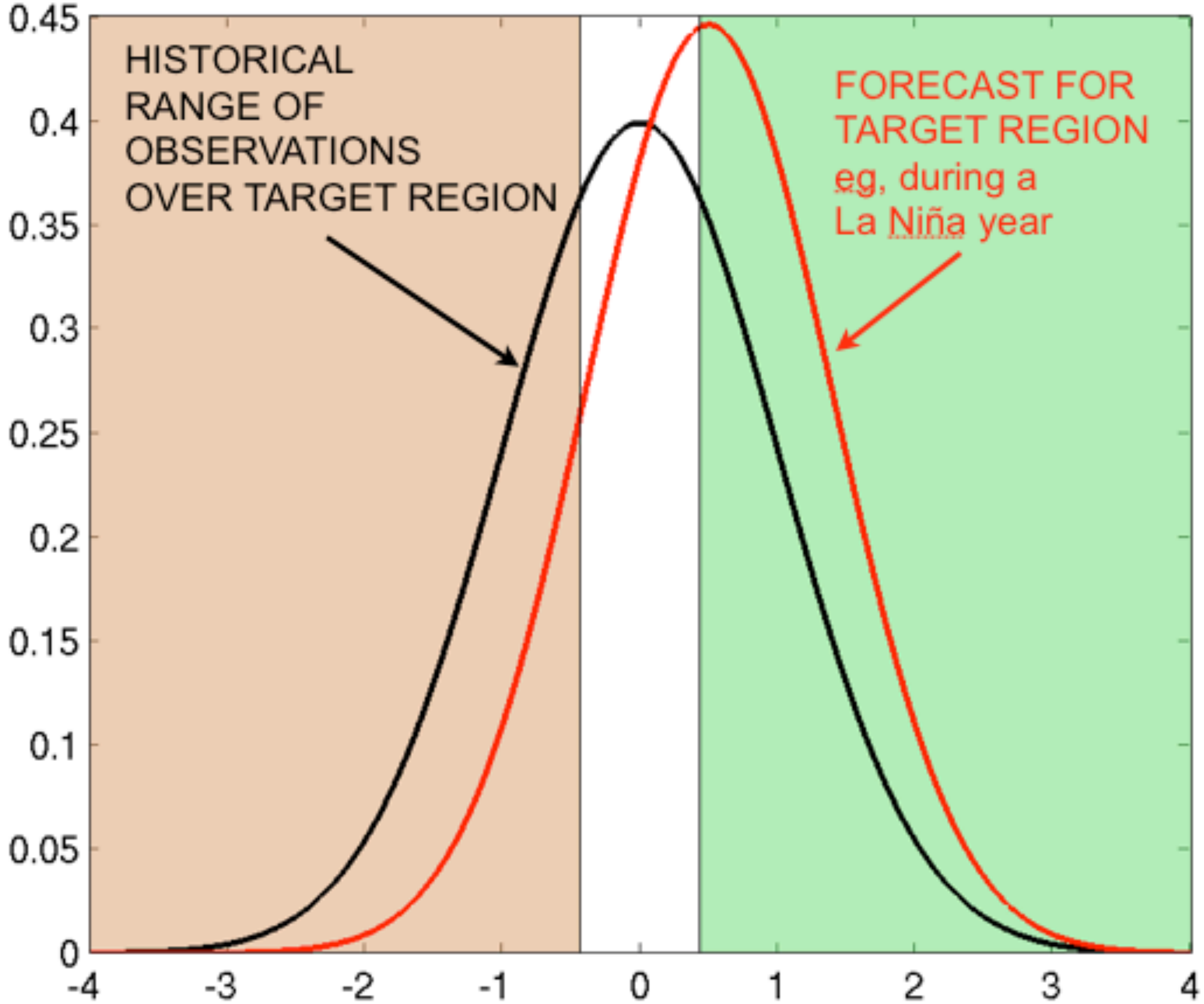




Tercile categories



What Seasonal Forecasts Represent

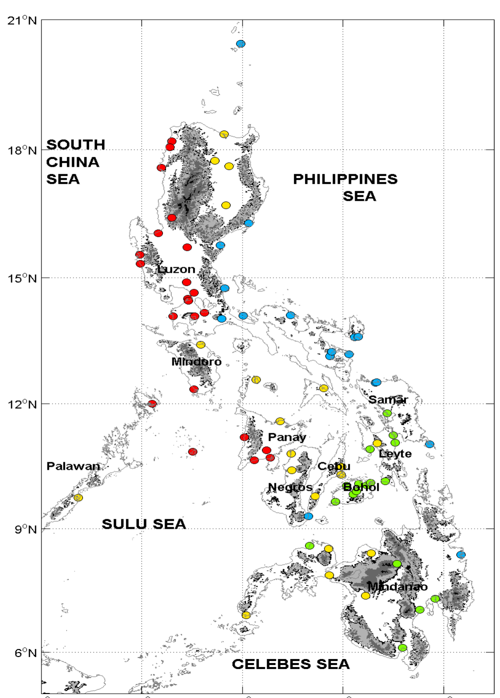


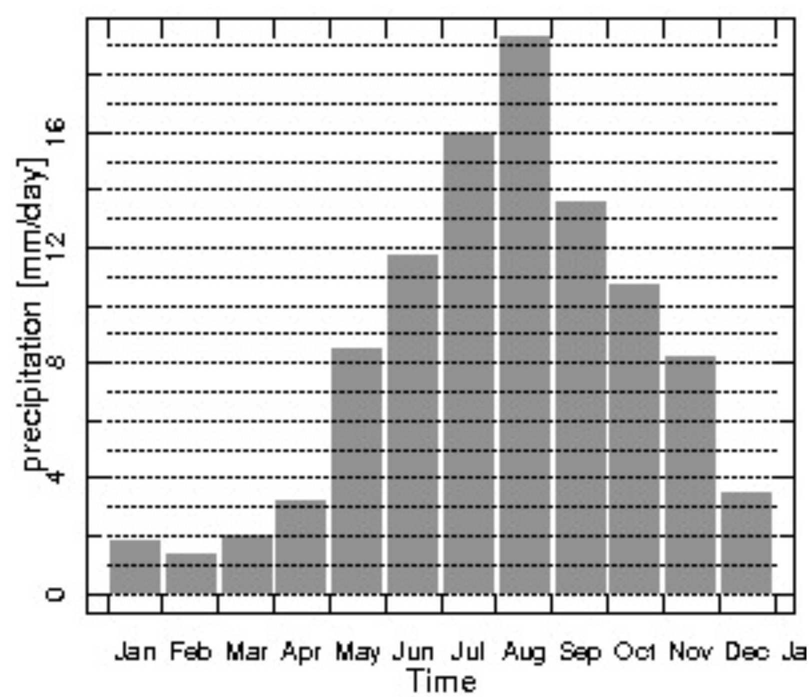
Shifts in the odds

Philippines example of using seasonal climate forecasts in reservoir management

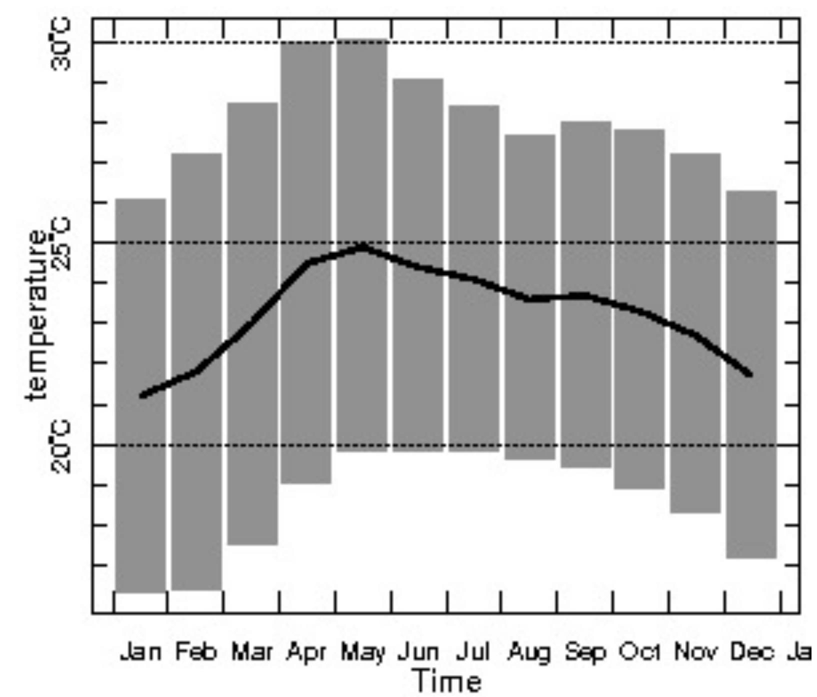
How can climate science knowledge and models help inform adaptation planning?

Example:
the Angat reservoir in the Philippines





Longitude 121.25E Latitude 16.75N



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Integrating Forecasts for Reservoir Management: Angat, Philippines

Angat Reservoir, Bulacan Province. ***Photo:*** PAGASA.

Project objectives:

- Understand Angat reservoir decision process and appropriate entry points for improved climate information
- Work with PAGASA to develop downscaled forecasts of inflow
- Integrate inflow forecasts into existing reservoir model to manage competing water use

Angat Reservoir: Key Collaborators

Project Partners

•National Water Resources Board

•PAGASA

•University of the Philippines Los Banos

Extensive consultation with water users, including:

•National Irrigation Administration (national and provincial levels)

•Metropolitan Waterworks and Sewerage System (+2 concessionaires)

•National Power Corporation

Support from:

USAID, NOAA, Columbia University

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- A target reliability might be 90%

Reservoir management in Philippines

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Anticipating drought of record in every year

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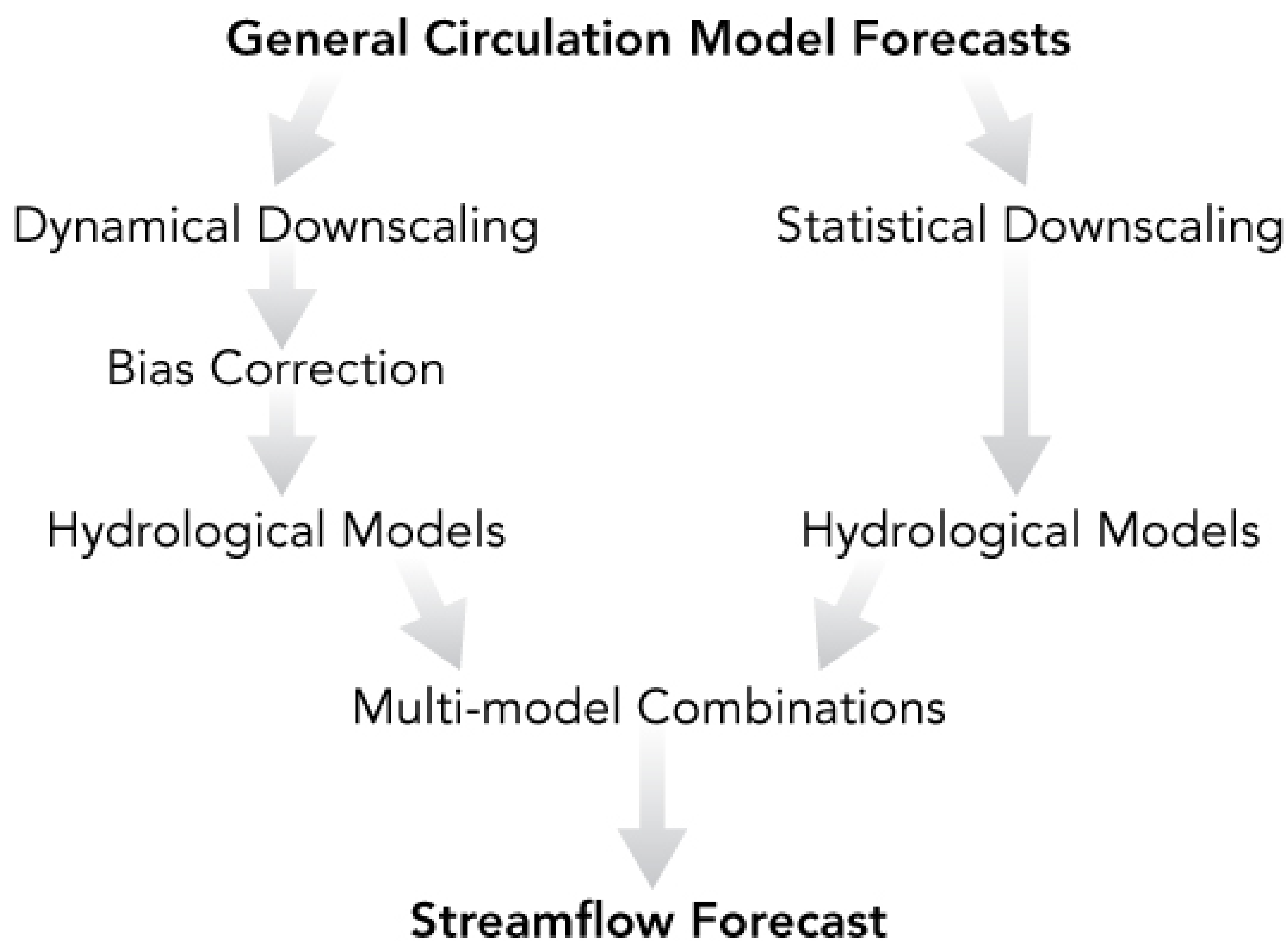
3. Decision Support System communicates forecast in relevant terms

   Reservoir levels, reliability, water deliveries

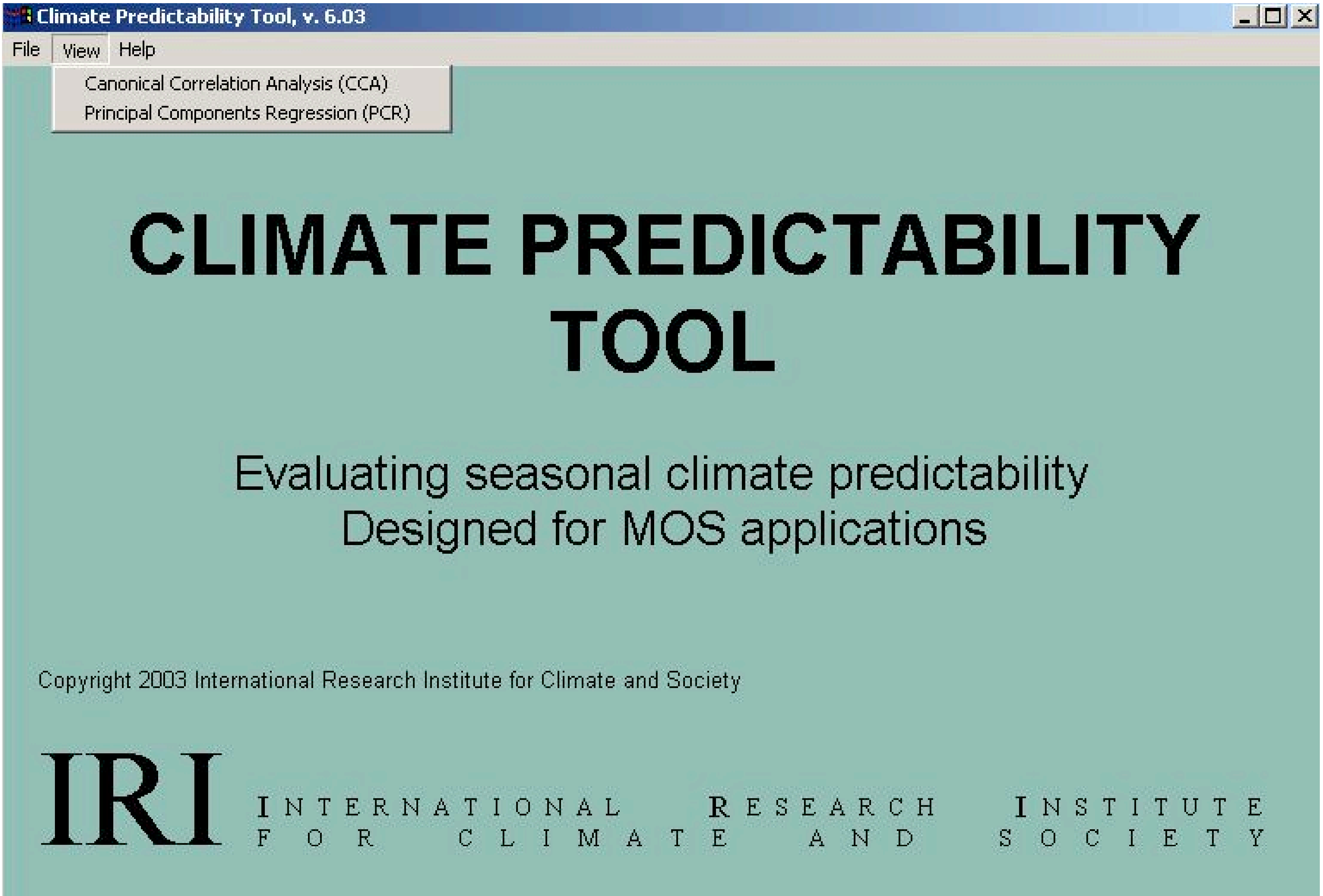
4. Risks of forecast use must also be managed

How to translate (or "tailor") climate forecasts to the needs of reservoir managers?



motivated by experience at Climate Outlook Fora (COFs) in Africa

Tool for tailoring seasonal forecasts



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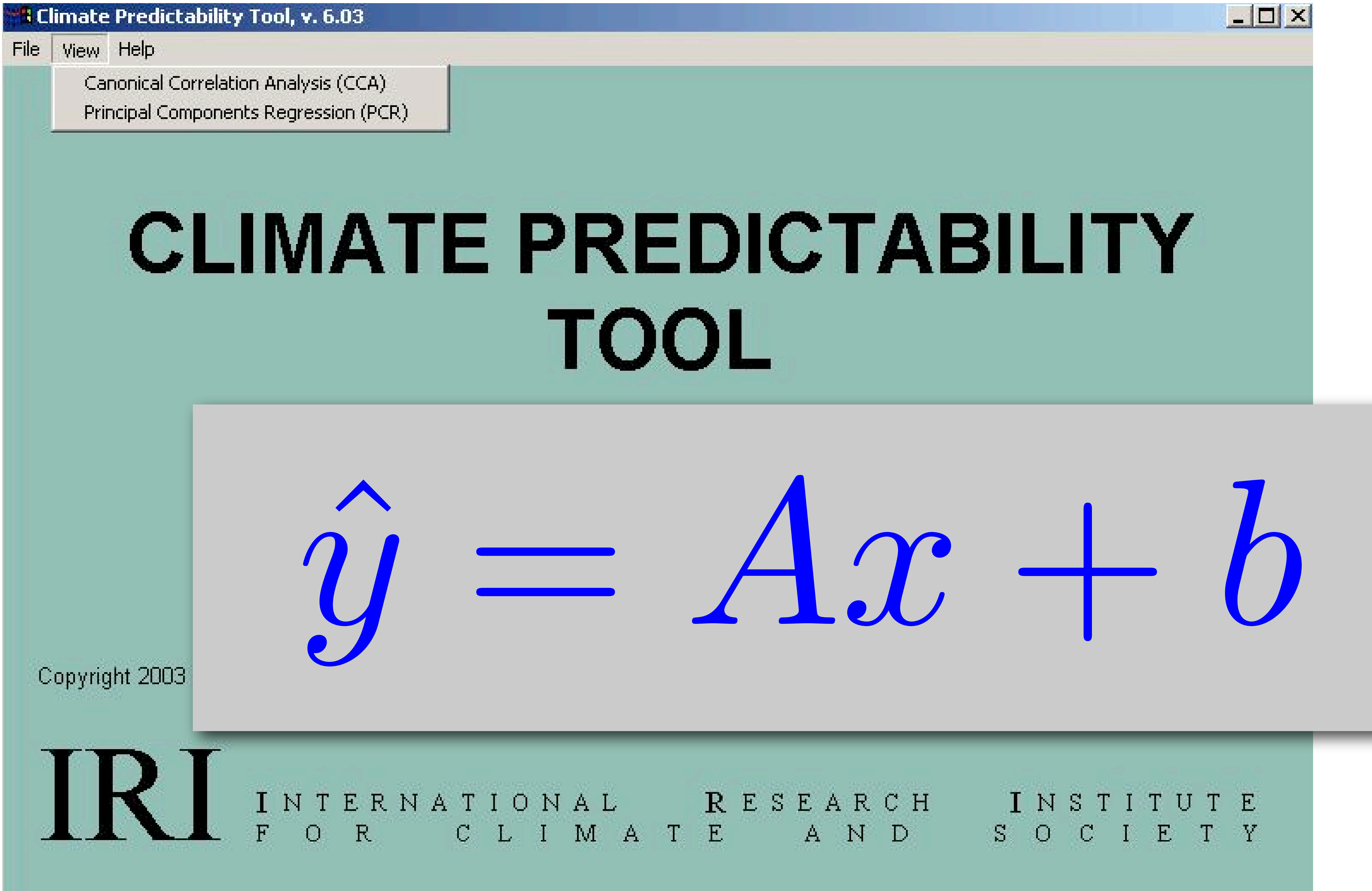


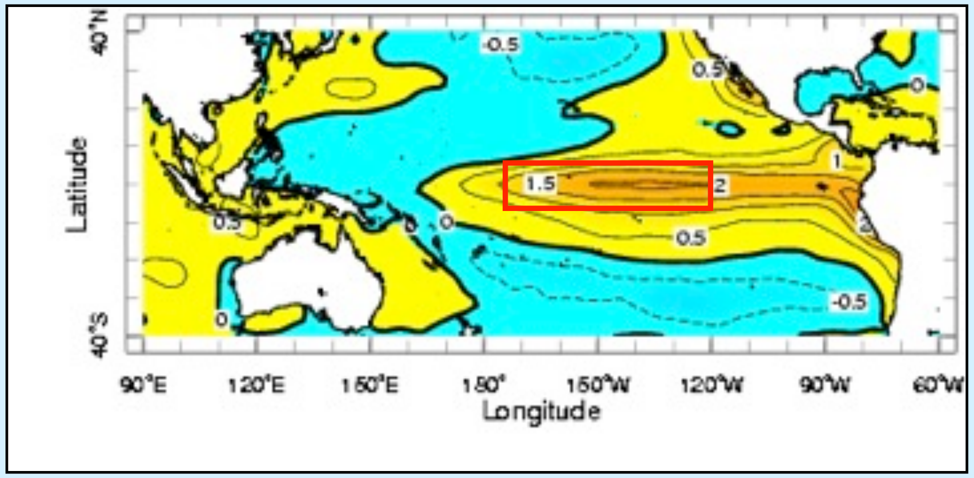
$$\hat{y} = Ax + b$$

Tailoring seasonal forecasts for reservoir inflow

B. Lyon (IRI)
A. Lucero (PAGASA)

Historical Angat Inflow Observations (1968–2000)

Sea Surface Temperatures (1968–2000)



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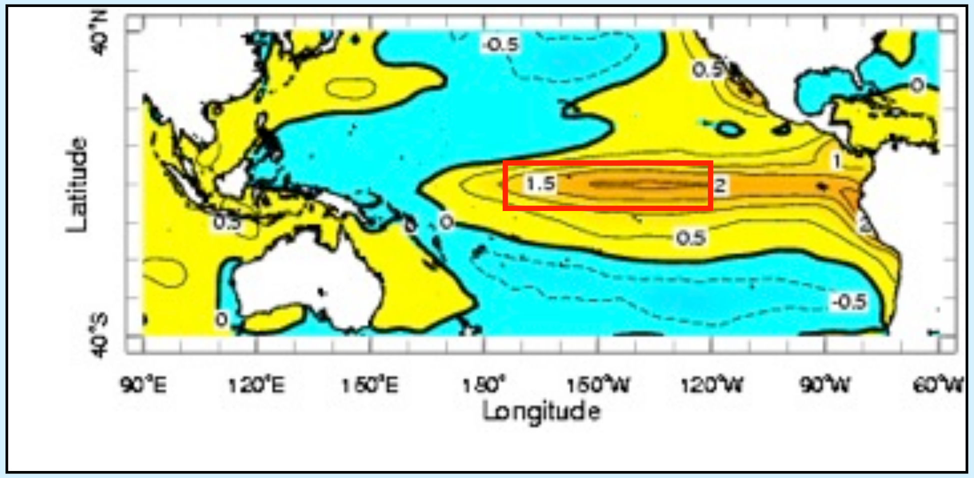

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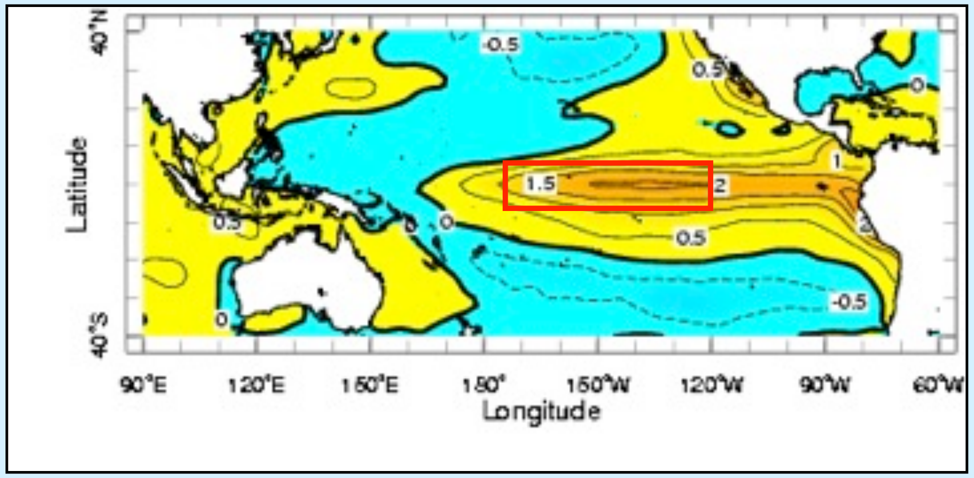

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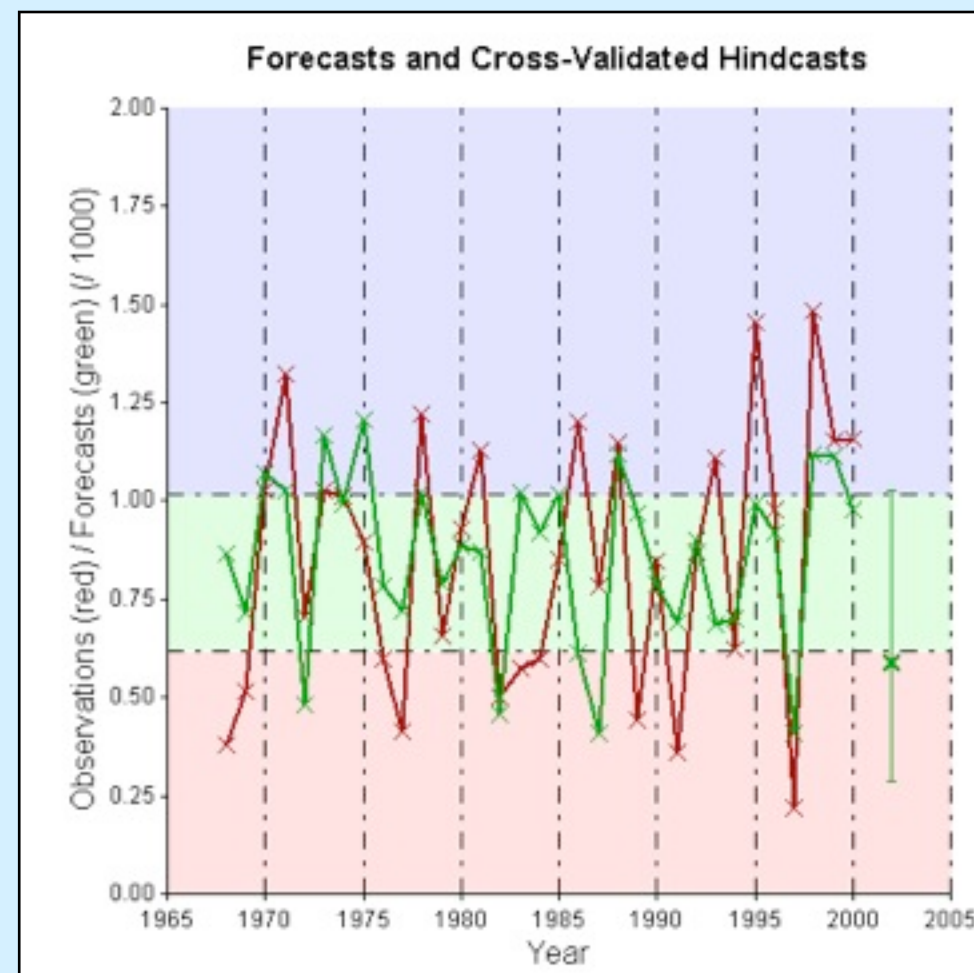

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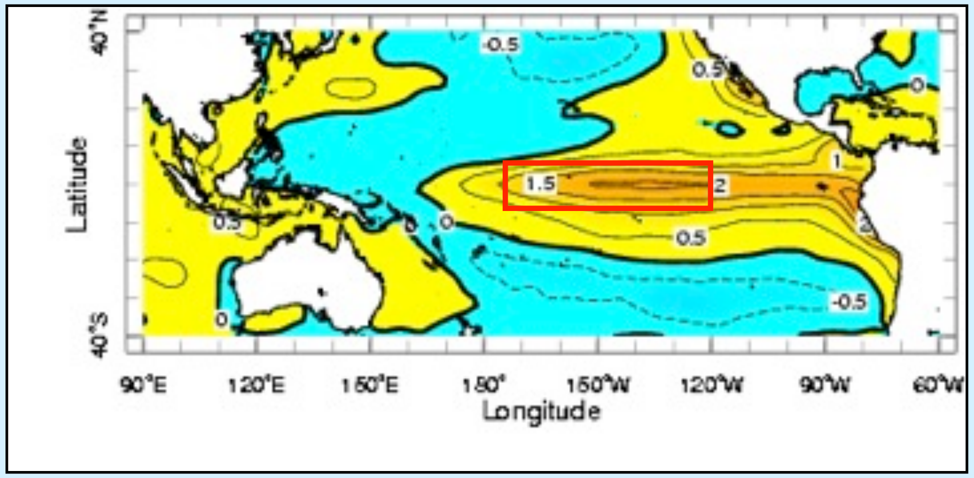

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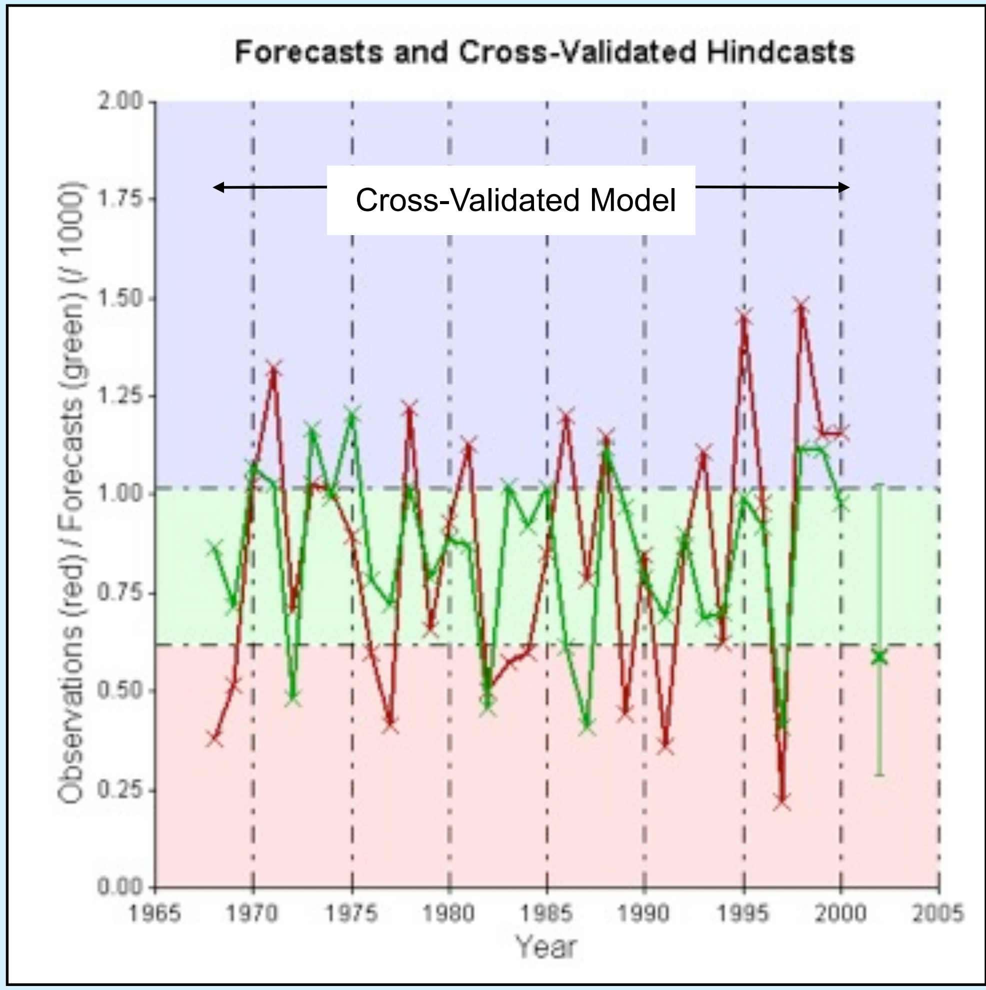

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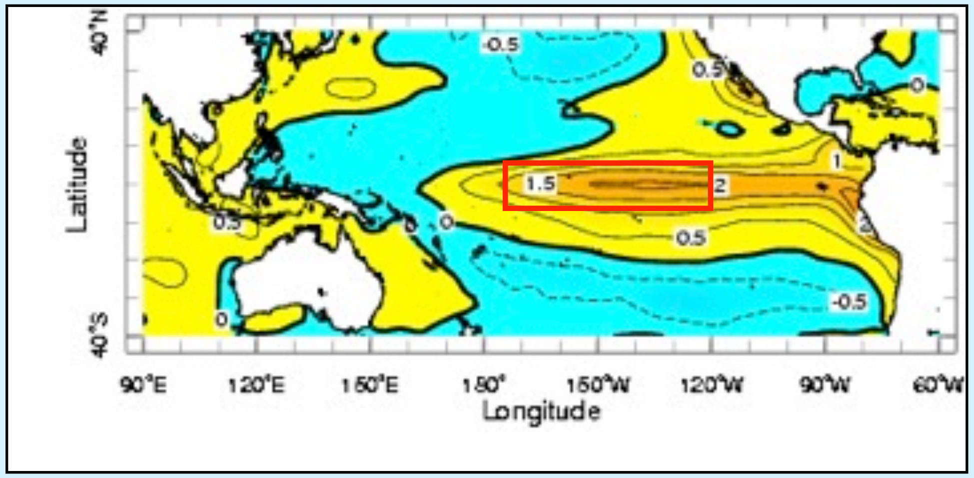

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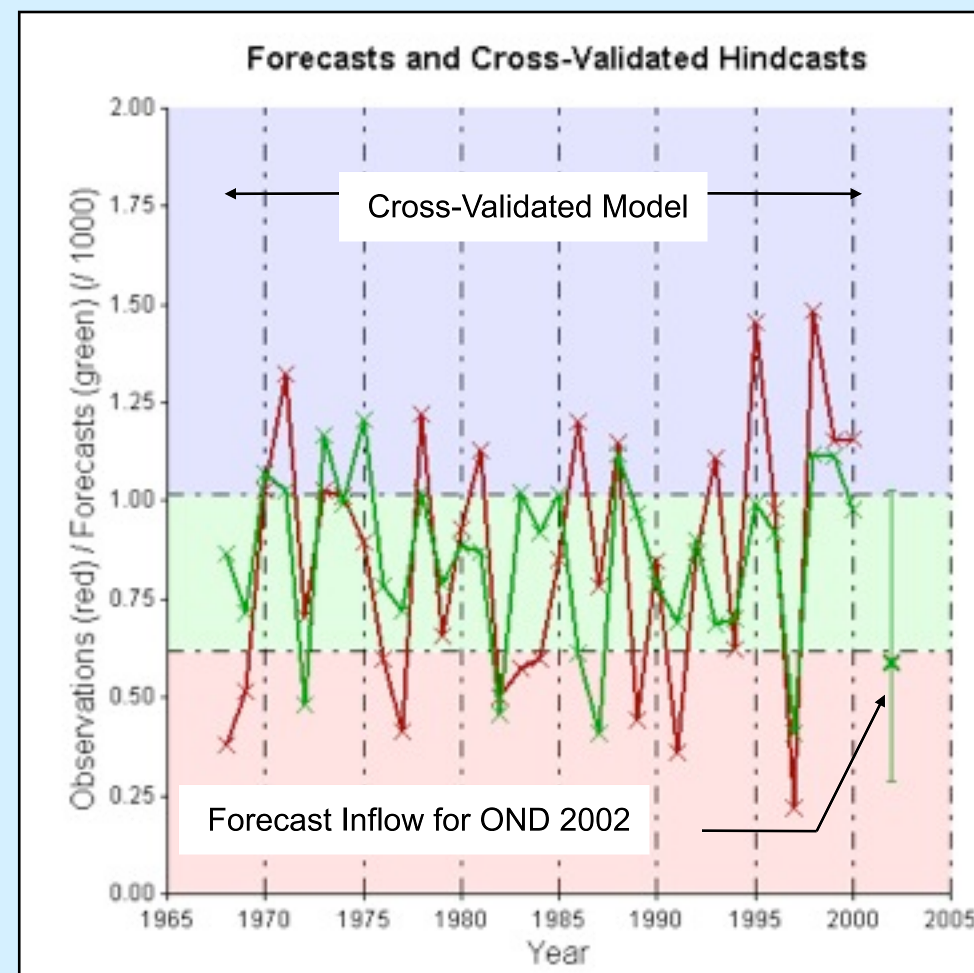

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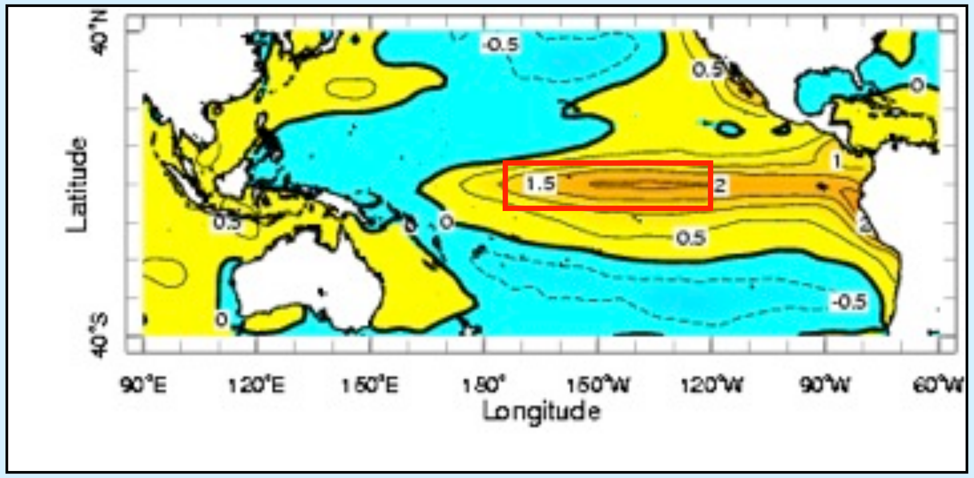

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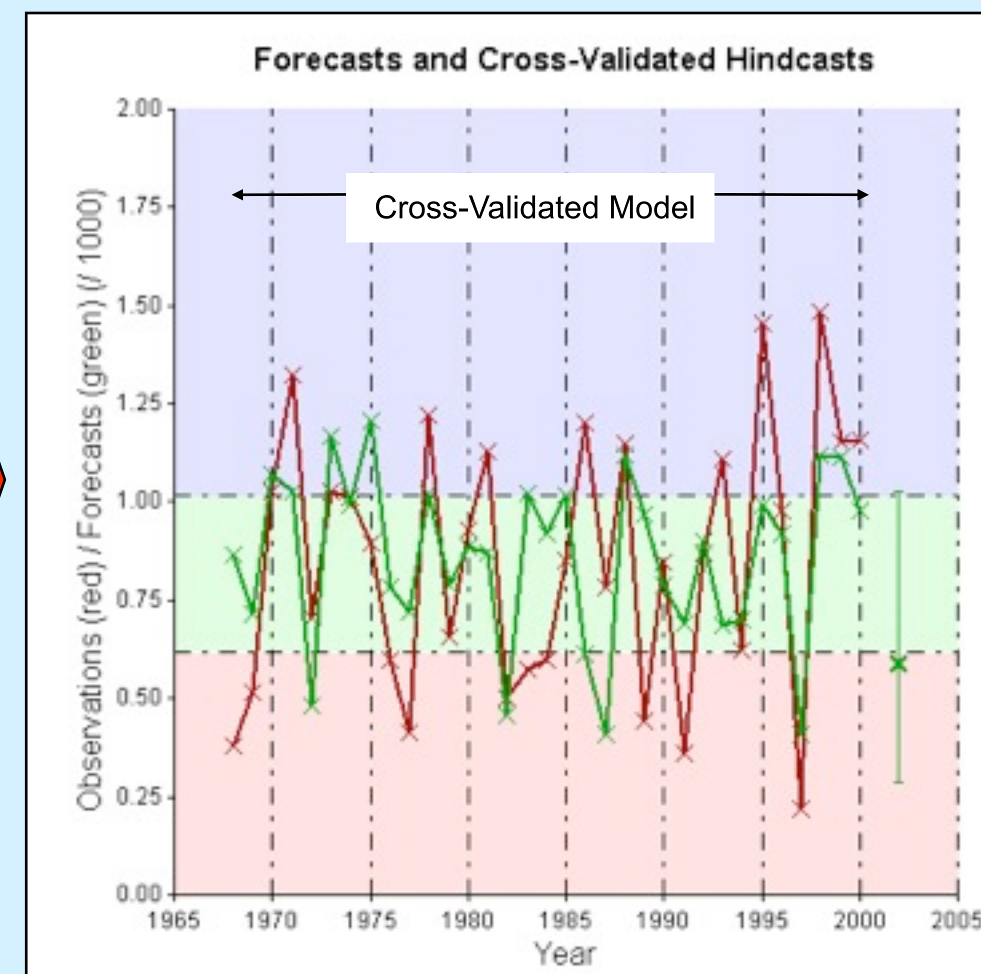

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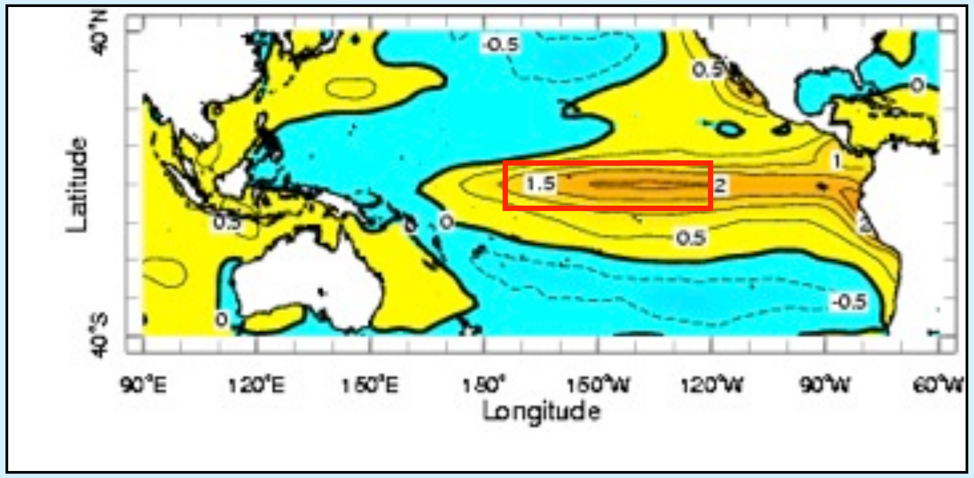

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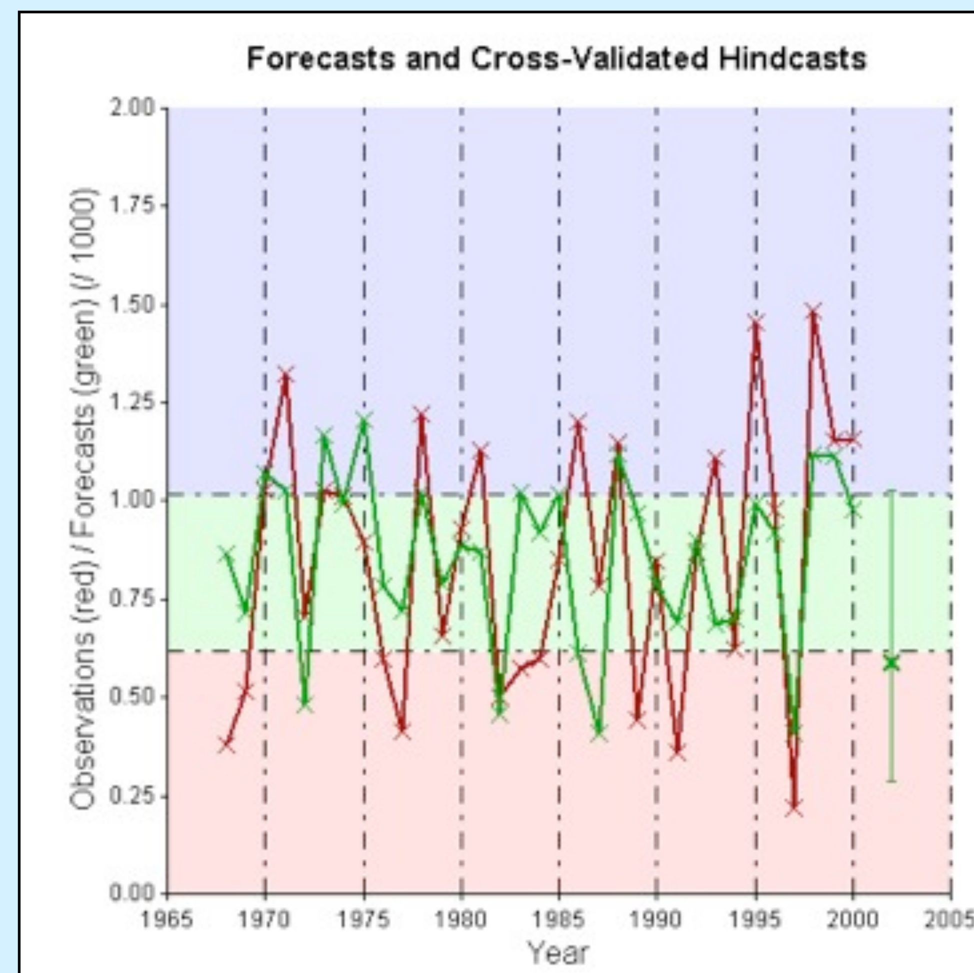

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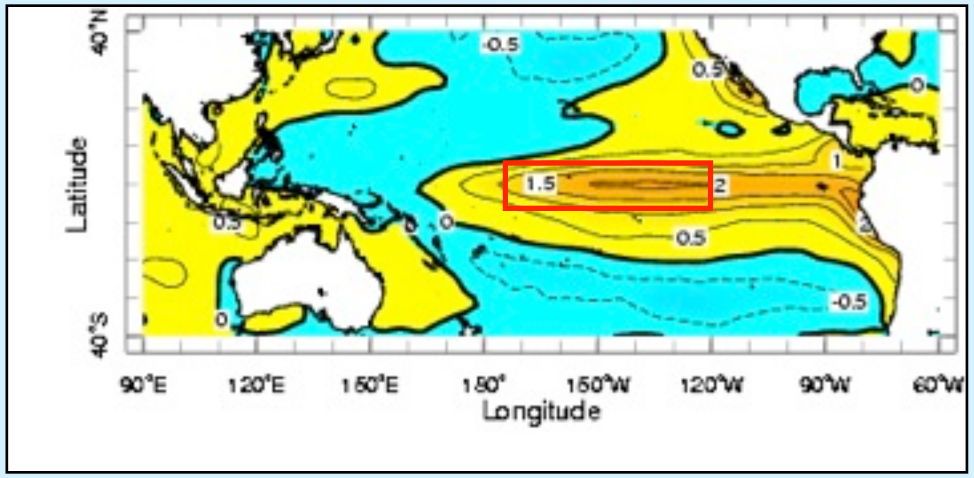

Historical Angat Inflow Observations (1968–2000)

Statistical Model

Tailoring seasonal forecasts for reservoir inflow

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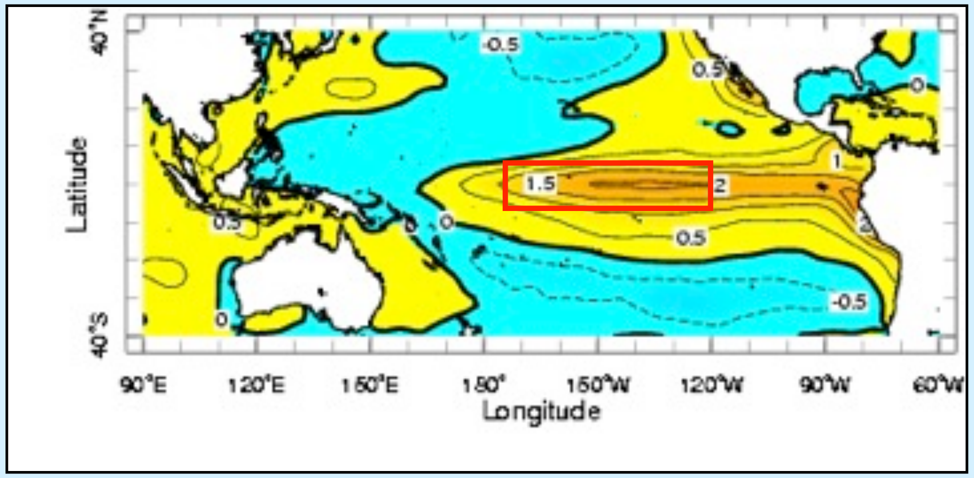

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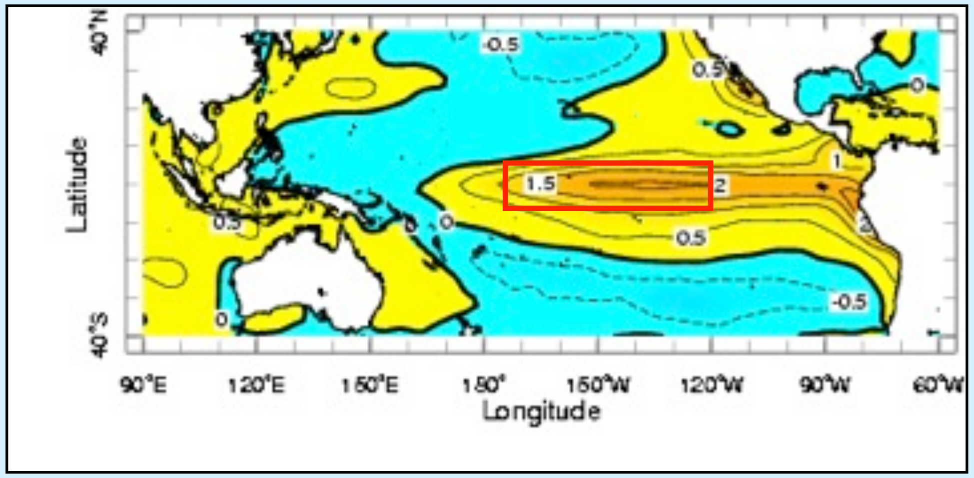
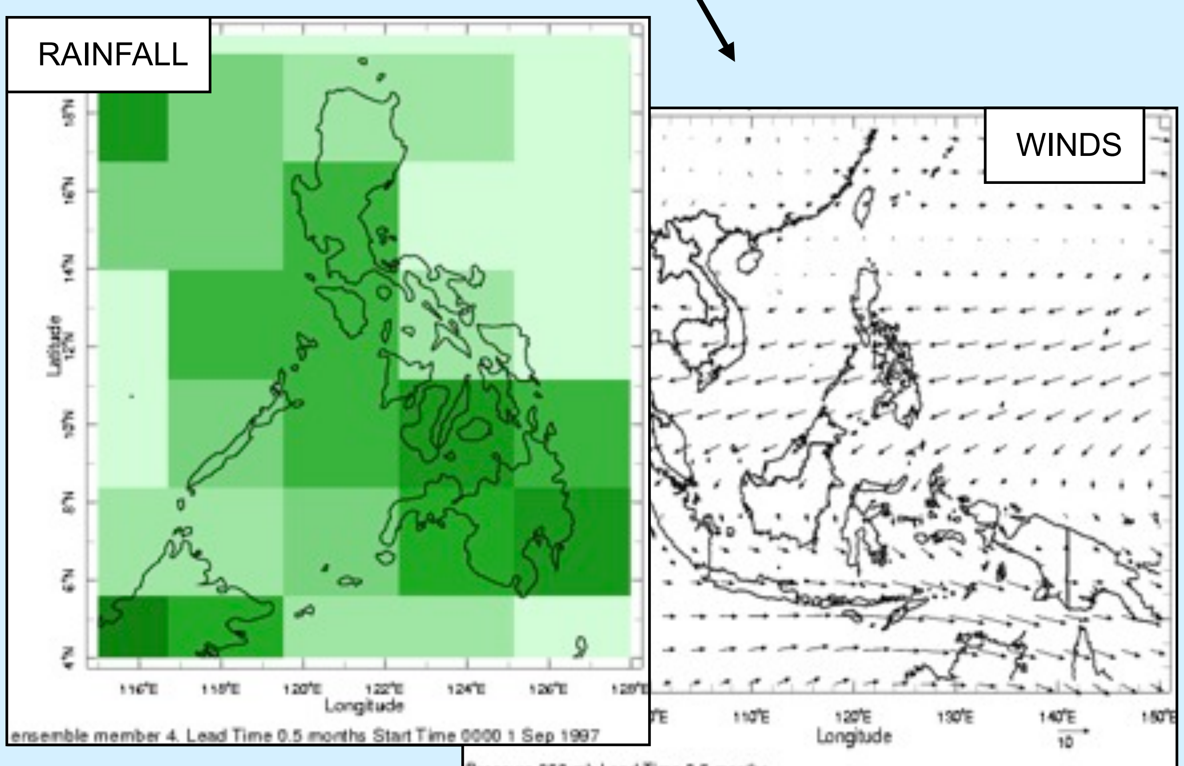


Global Climate Model



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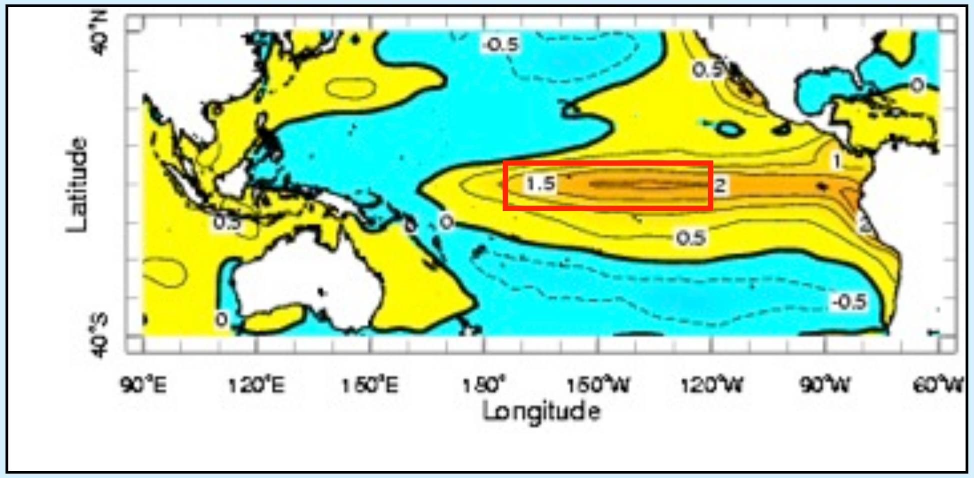

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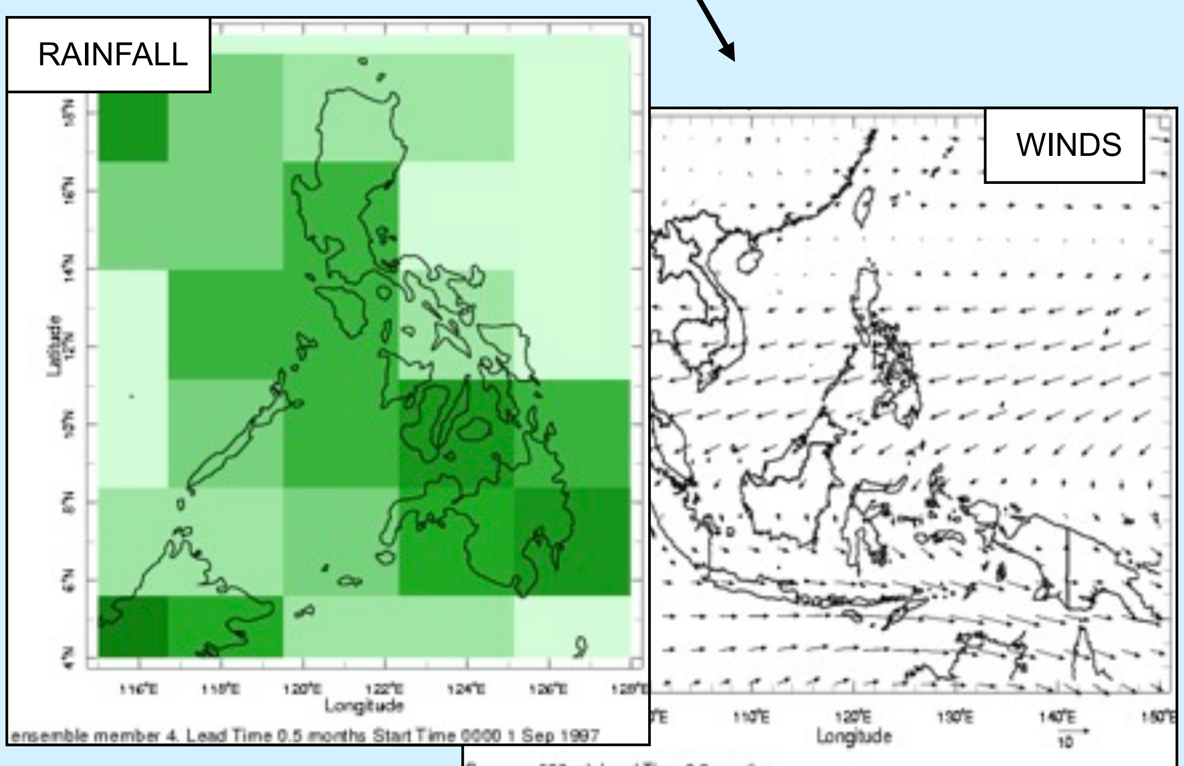

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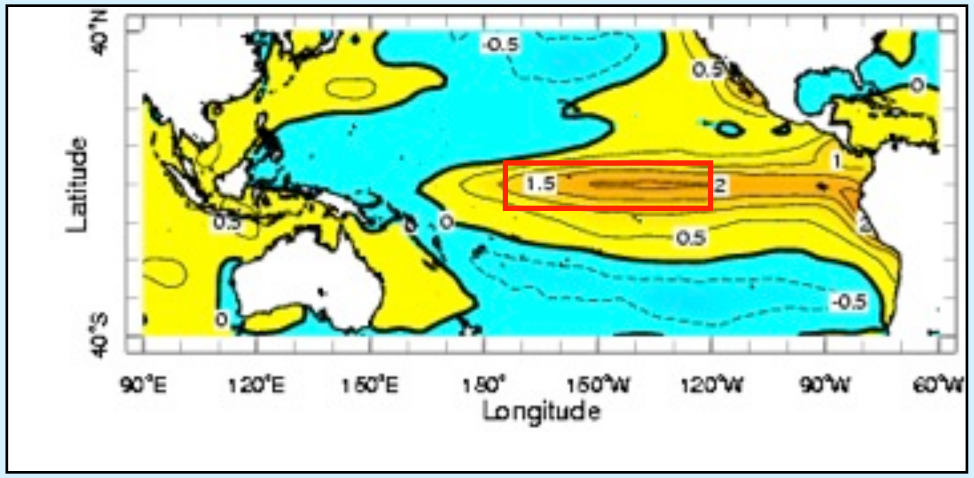

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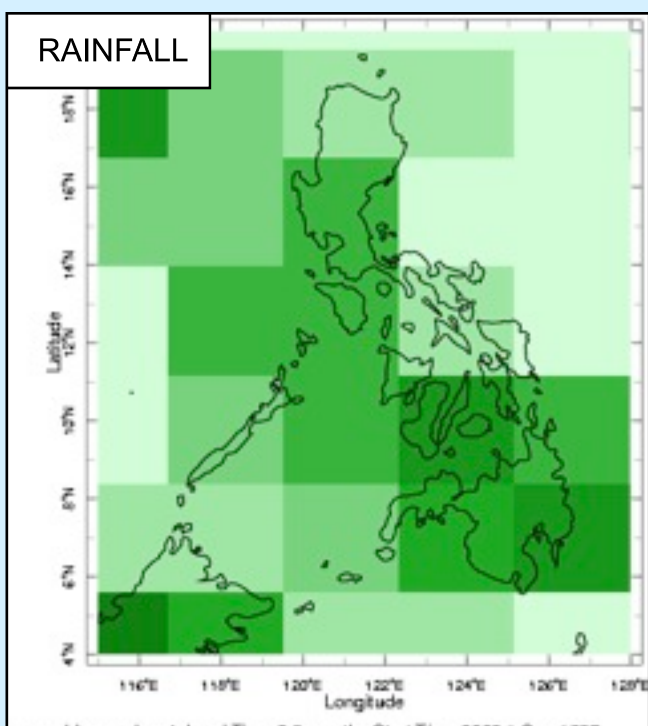

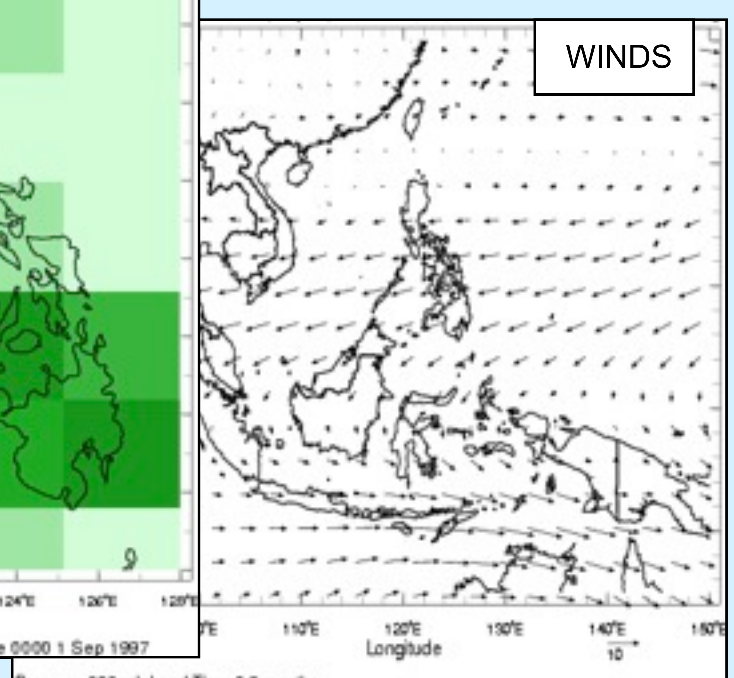

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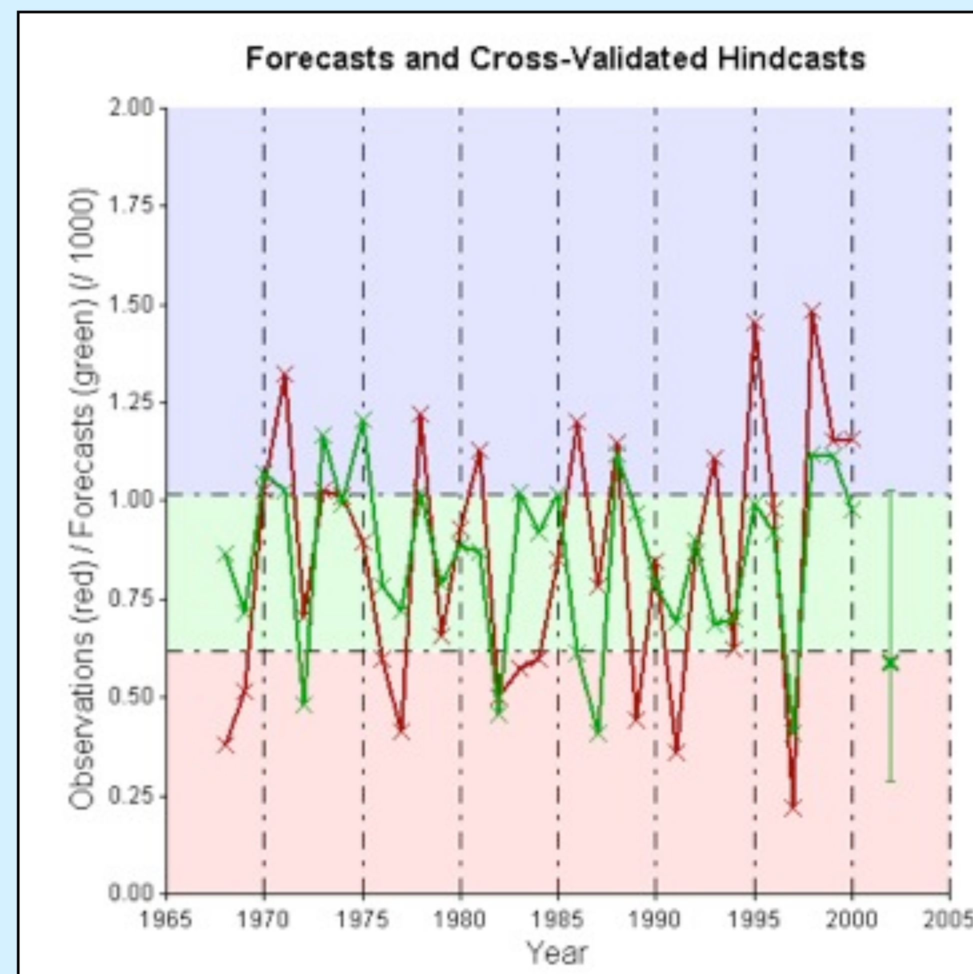

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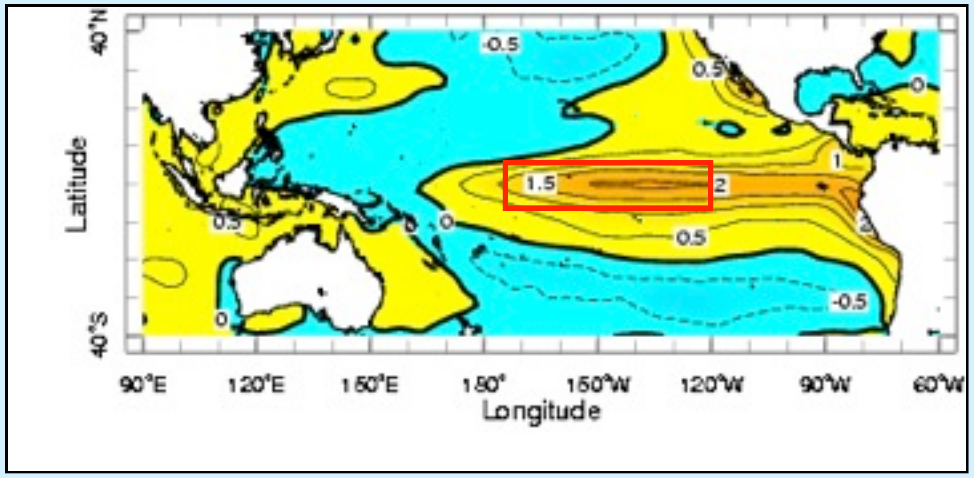

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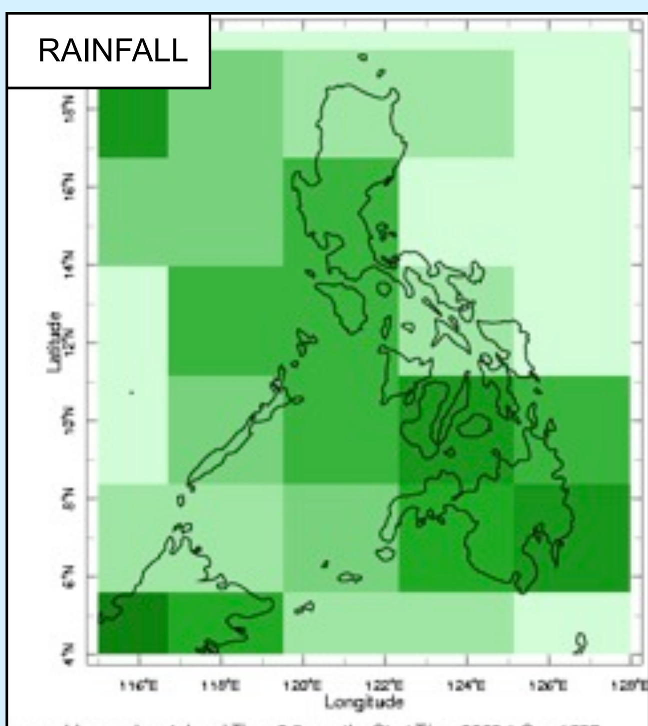

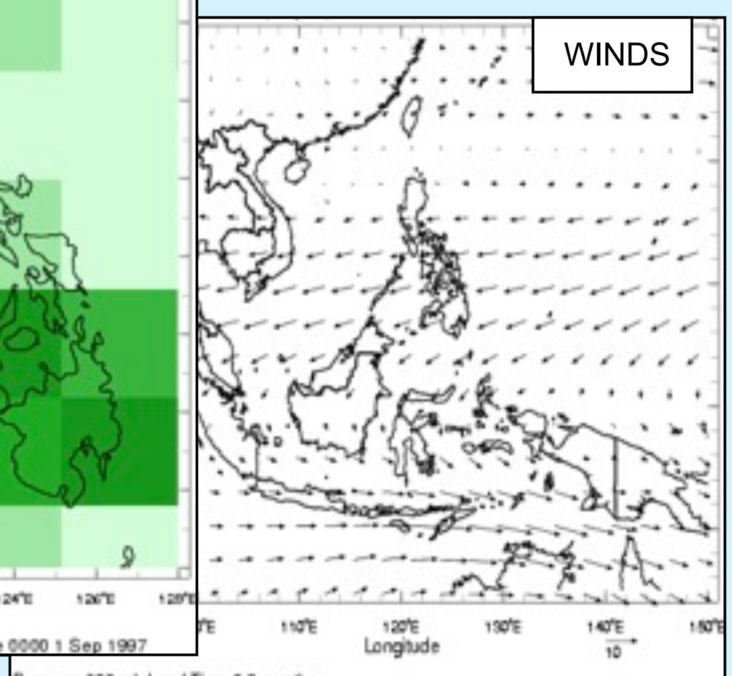

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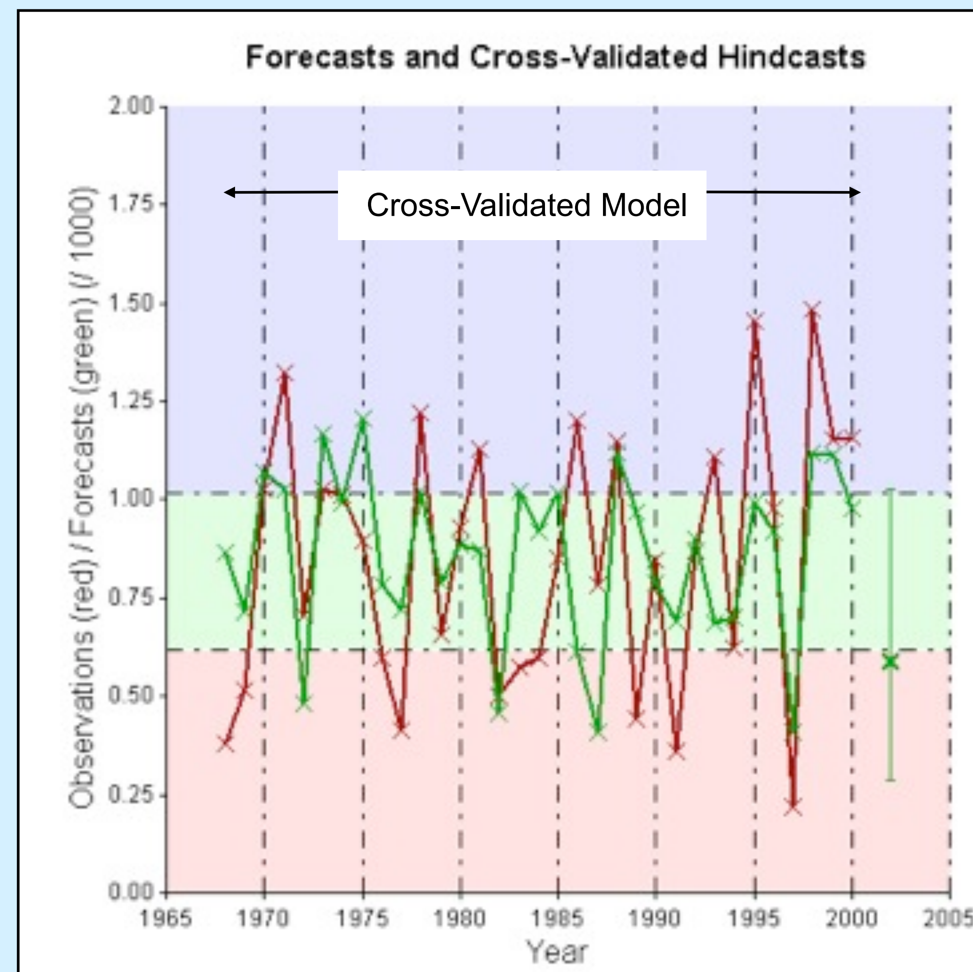

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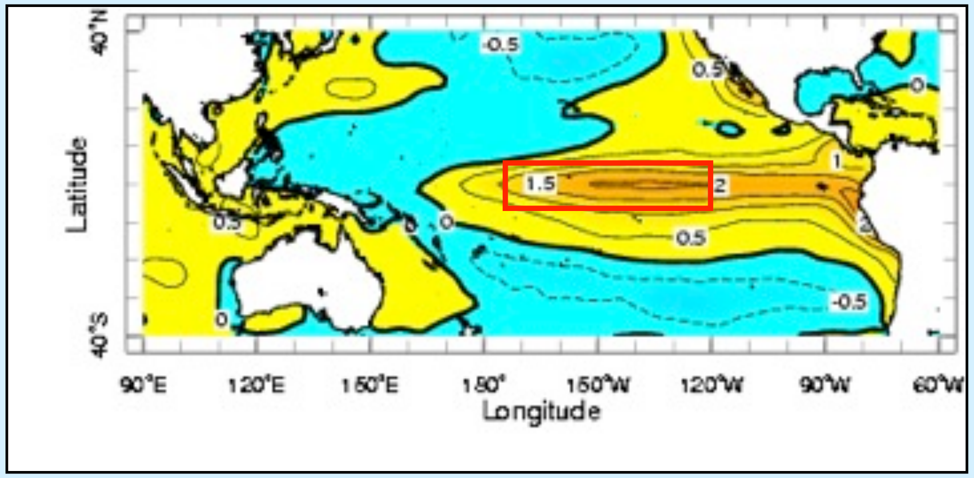

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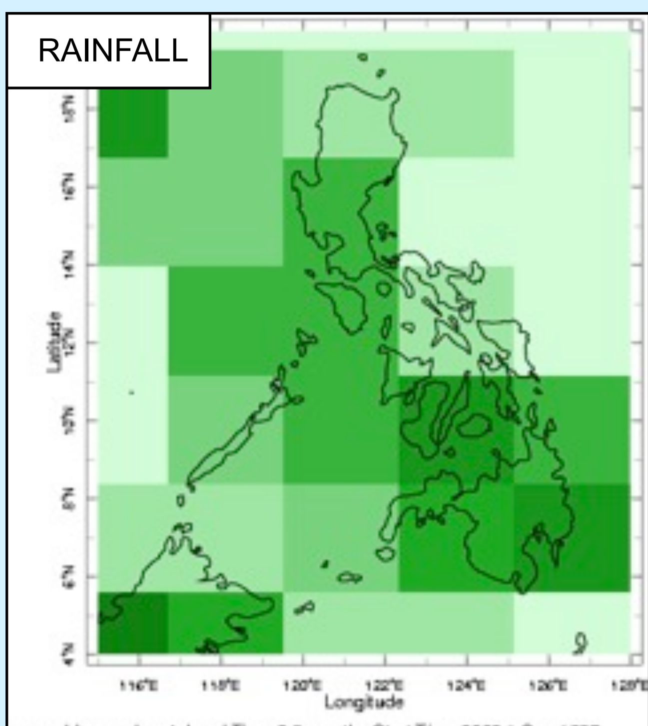

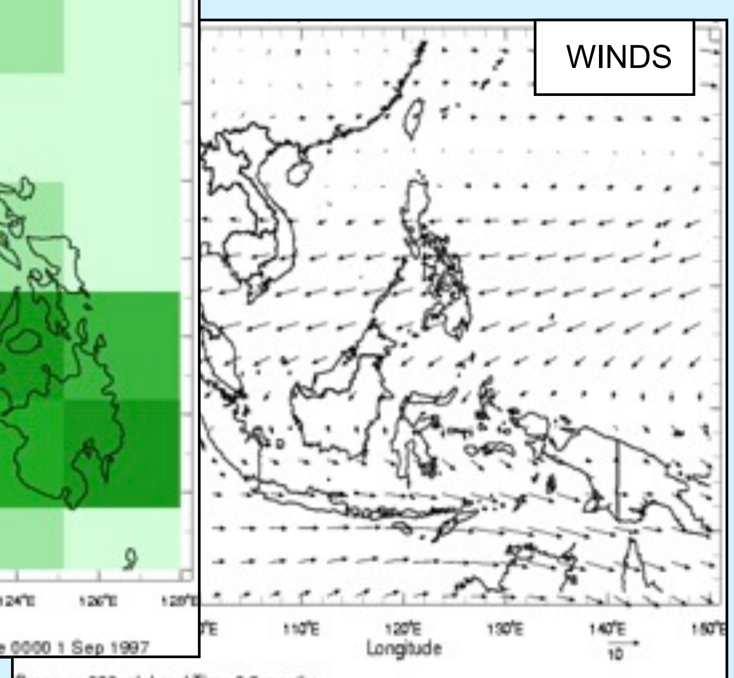

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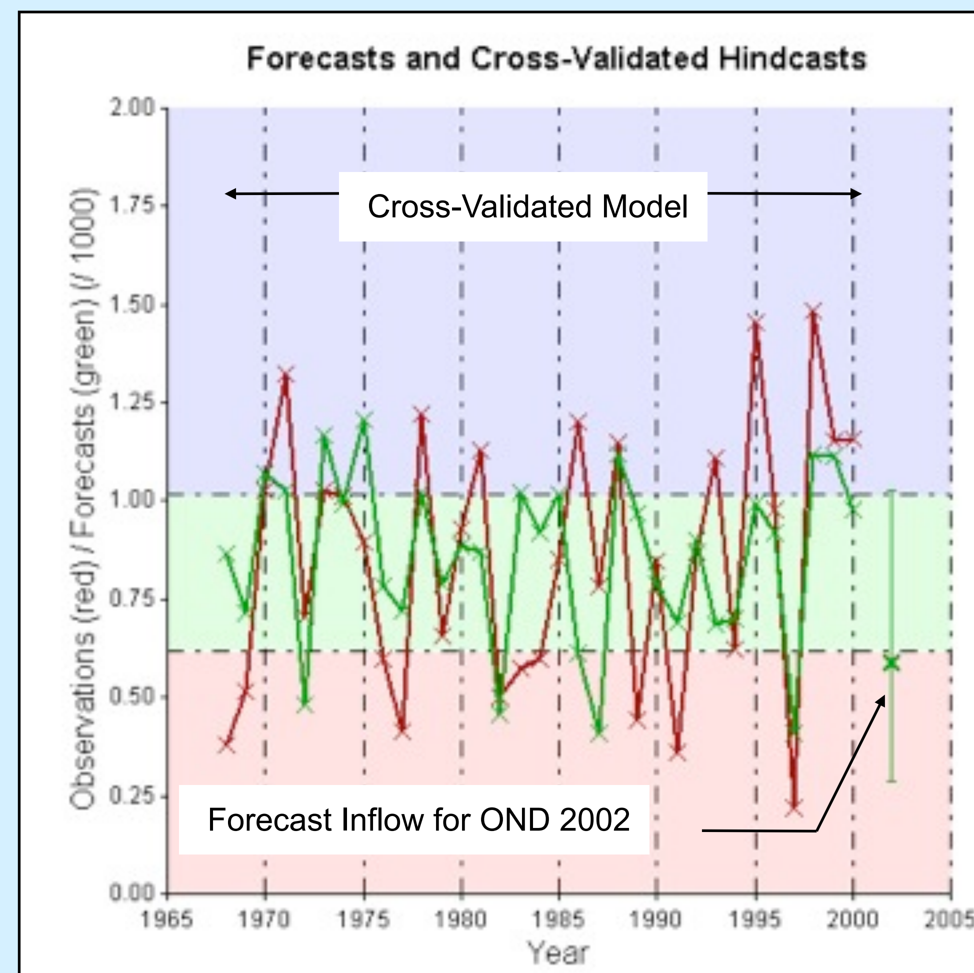

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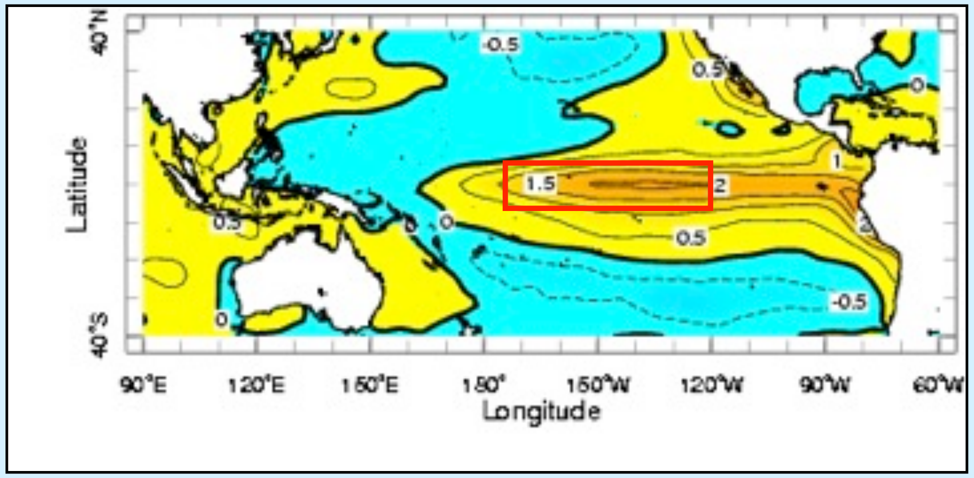

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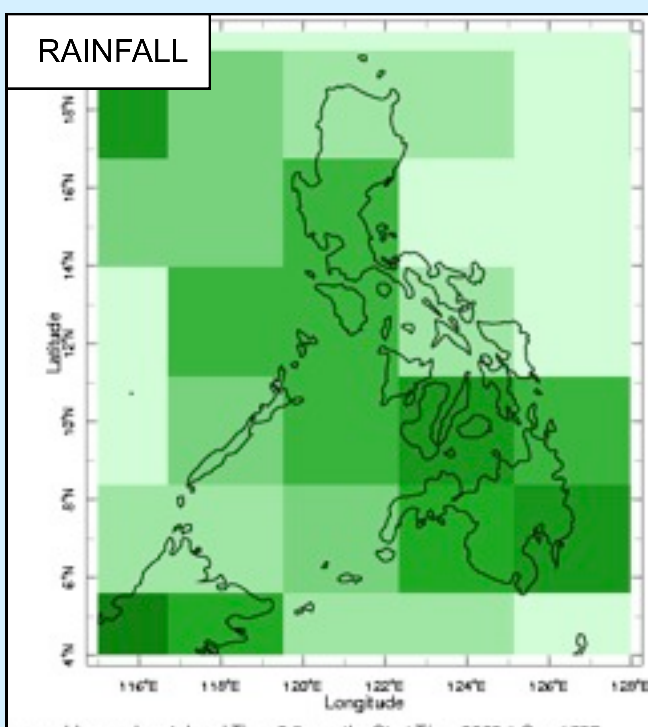

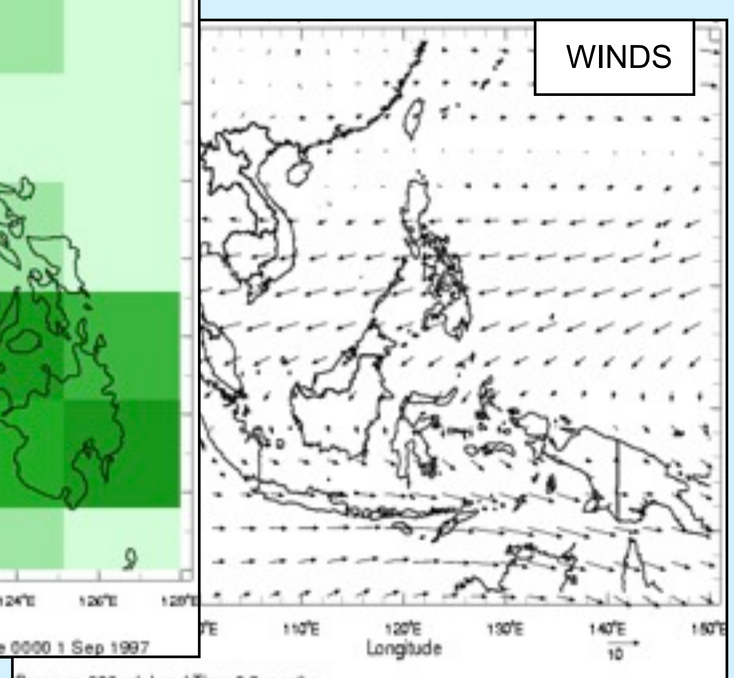

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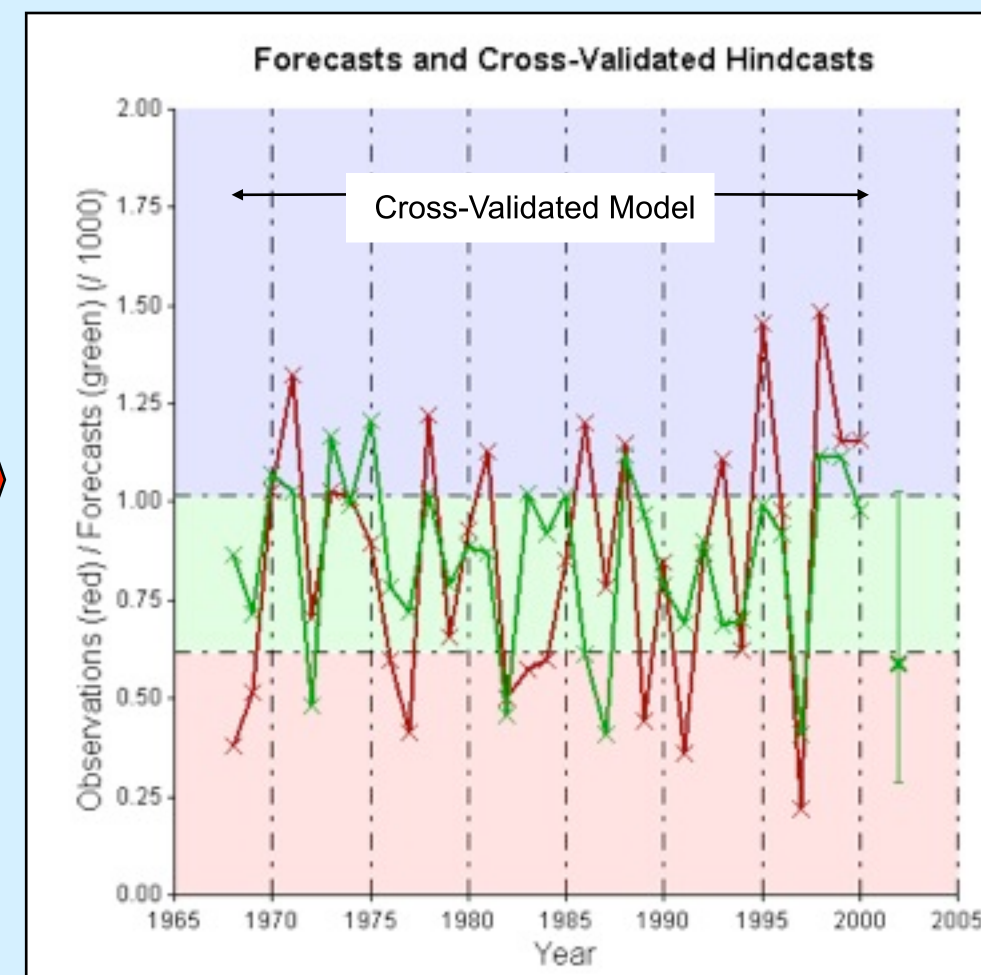

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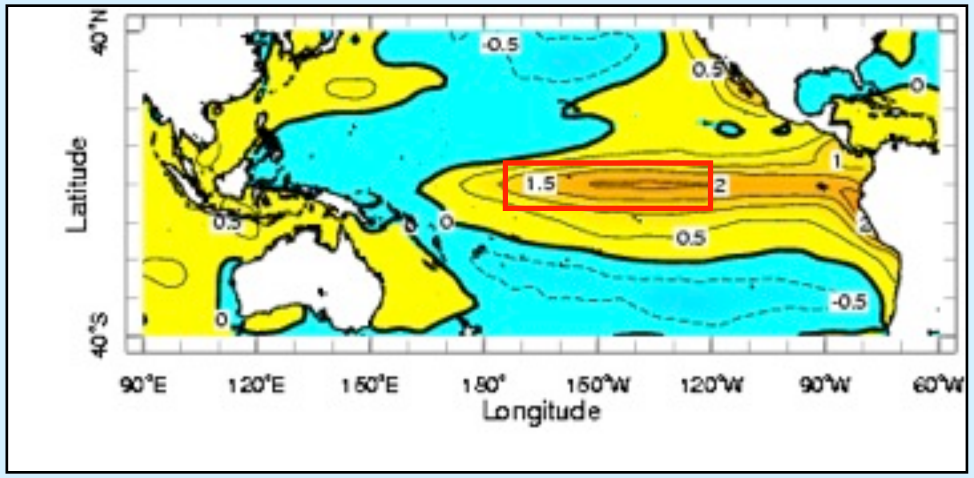

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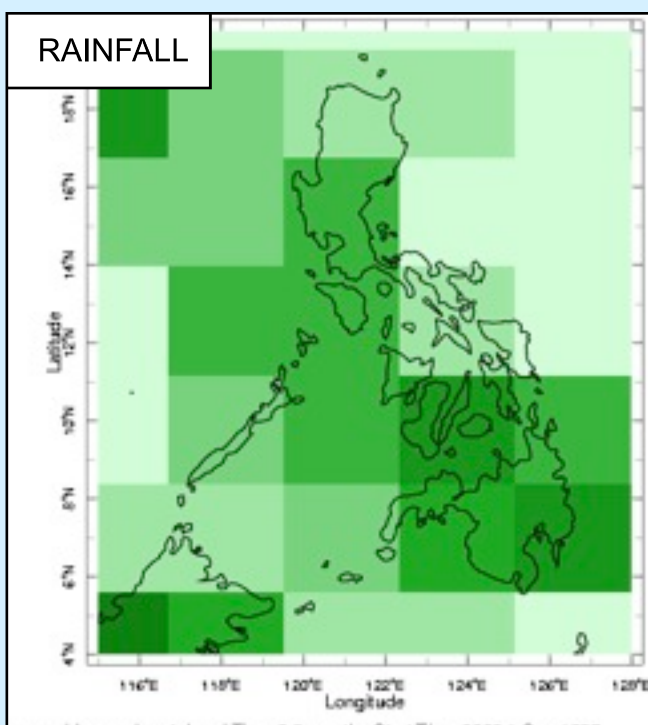

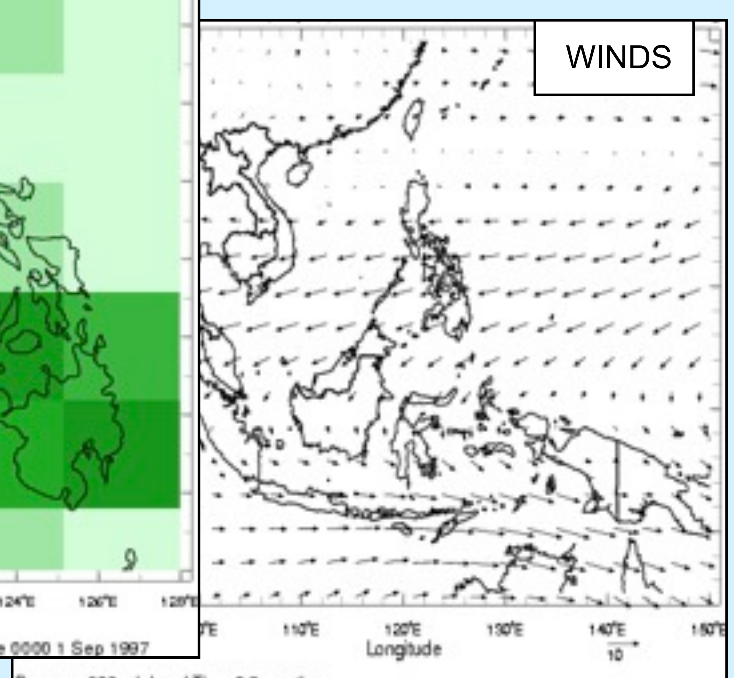

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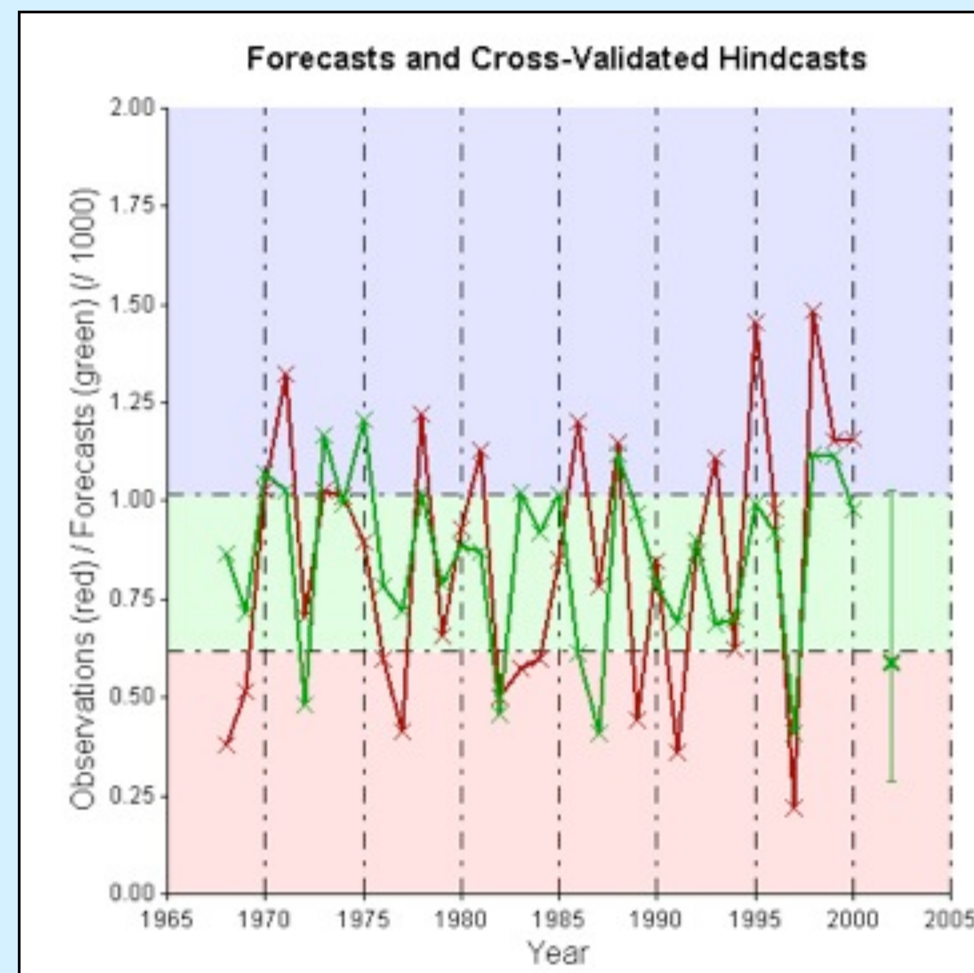

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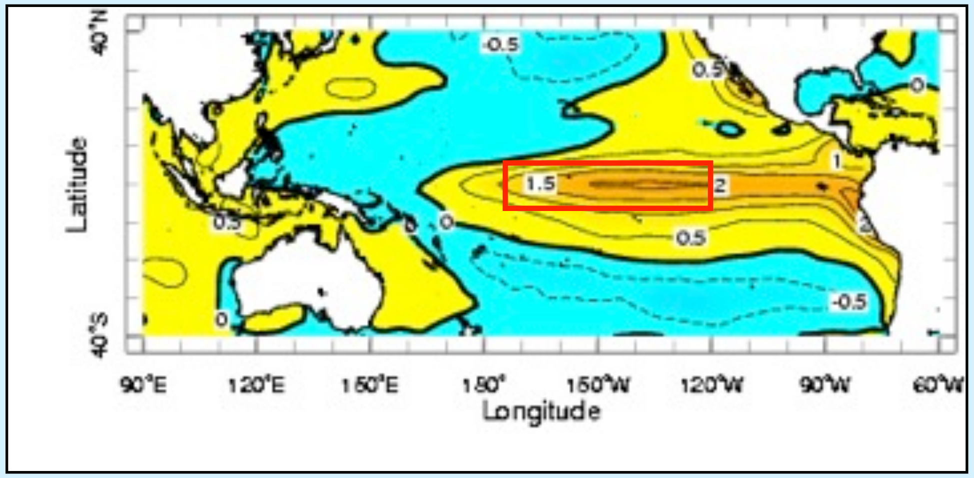

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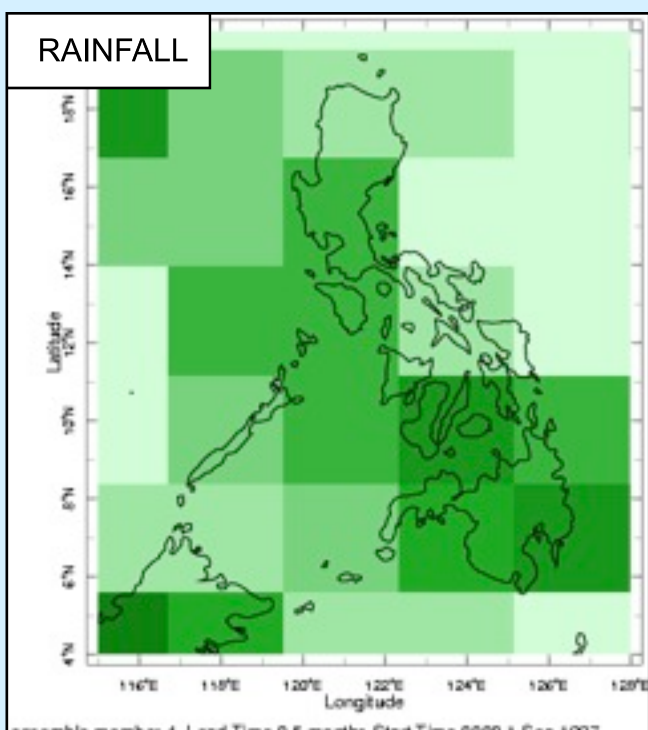

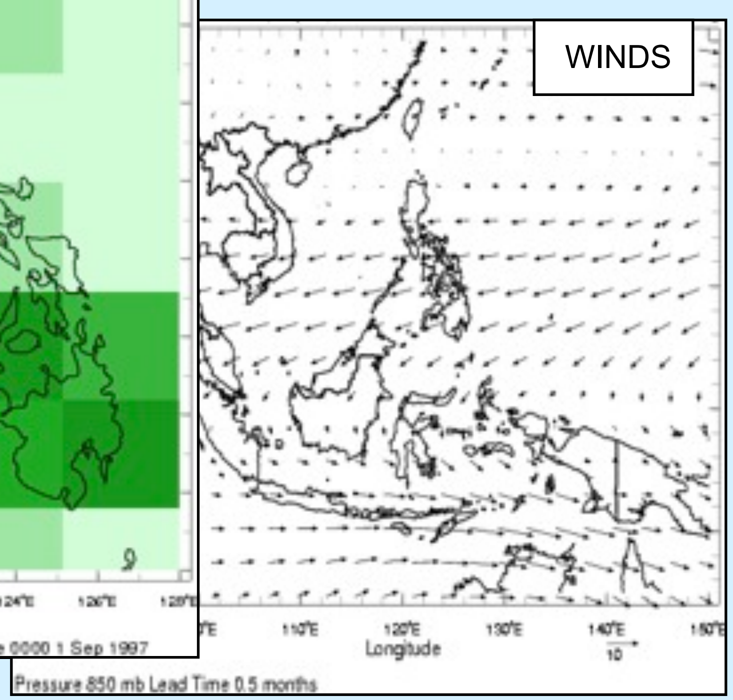

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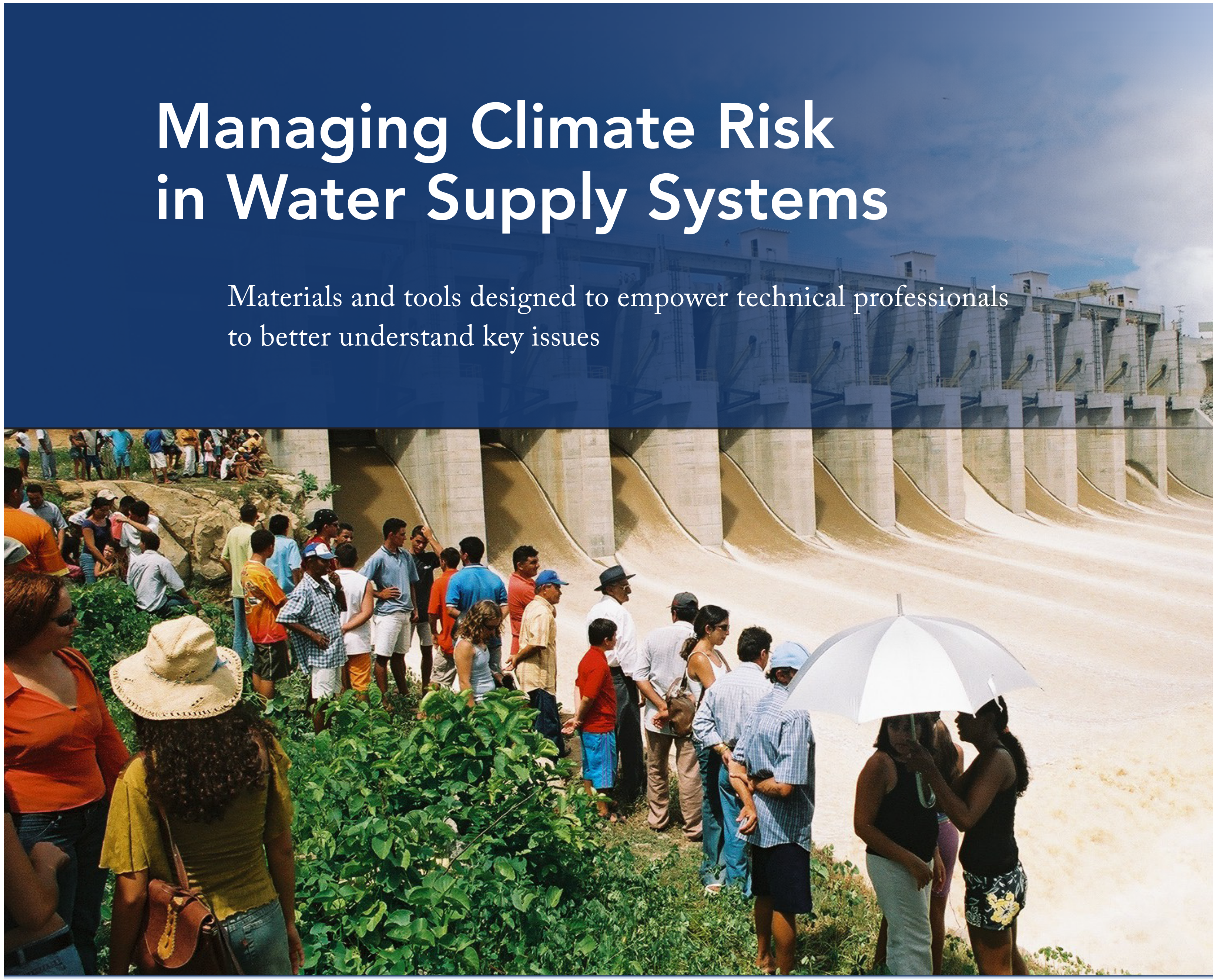

[Link to Water CRK manual](http://crk.iri.columbia.edu/)

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ENSO Phase composites

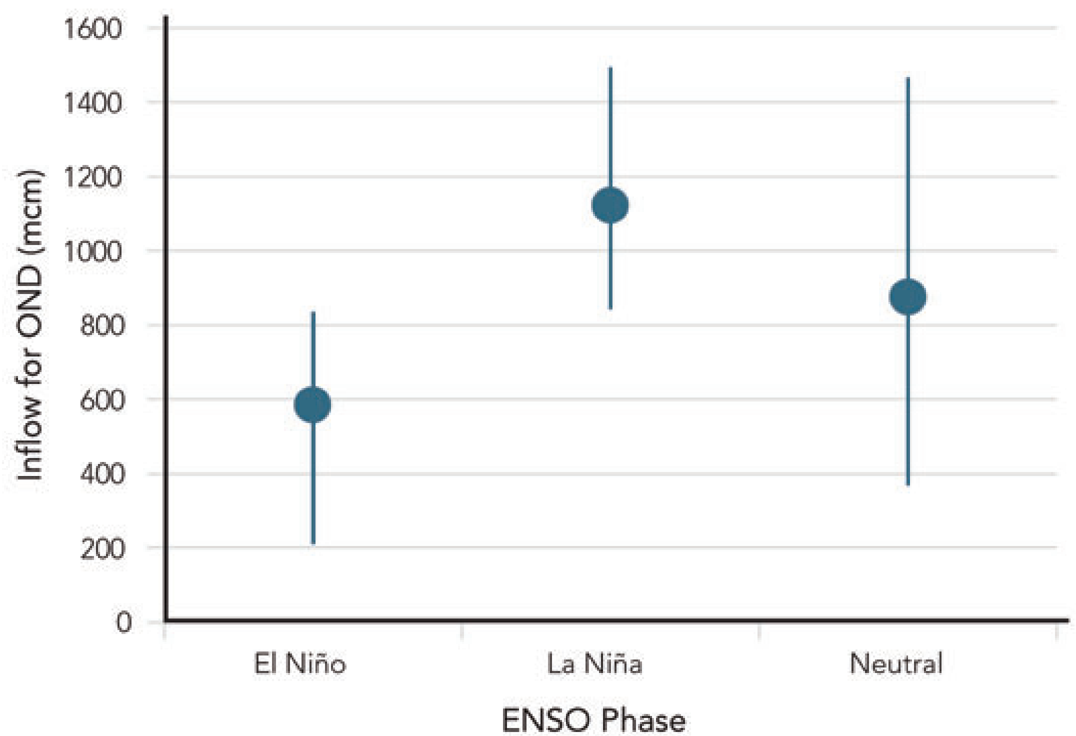


Figure 5.6
Partitioning approach for identifying relationships.
Shown are the ranges of historical OND Angat Reservoir inflows corresponding to three categories of ENSO conditions during the preceding July-August-September. The horizontal bar shows the mean inflow, while the length of the vertical bars represents the full range of inflow values. Note the significant difference between inflows during El Niño and La Niña events and the very limited overlap.
Source: SST data from NOAA NCDC ERSST v.2 (Smith and Reynolds, 2004); Angat inflow data from Philippines National Power Corporation

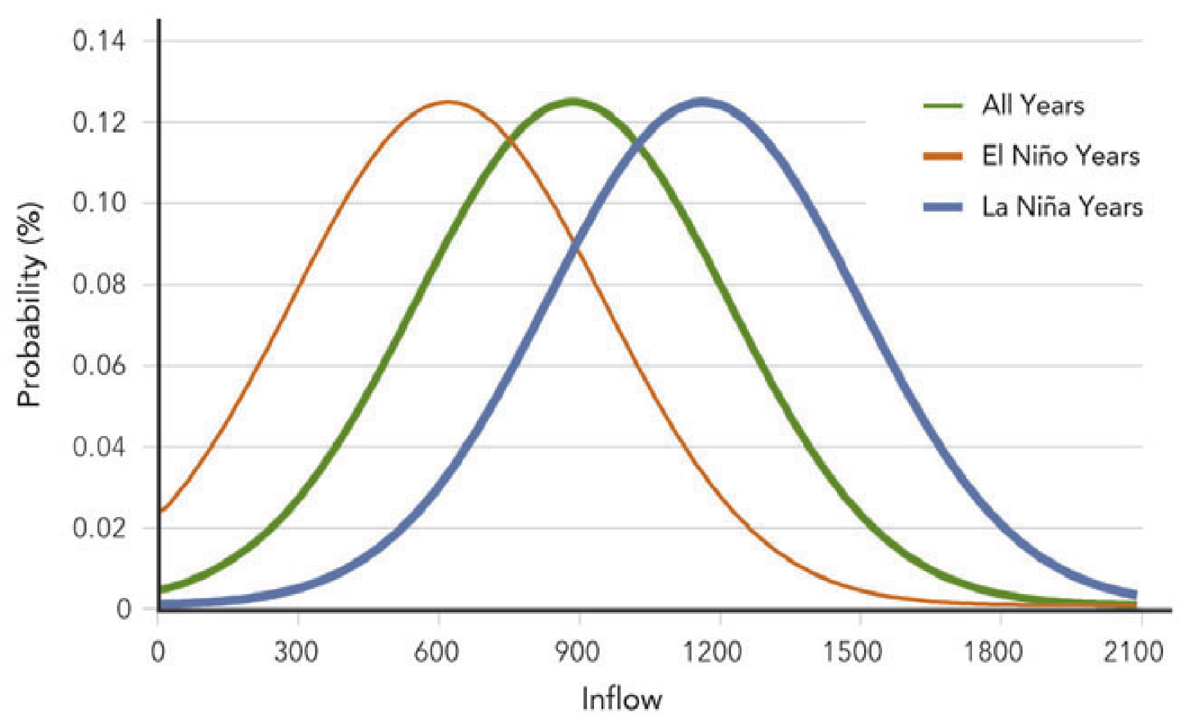
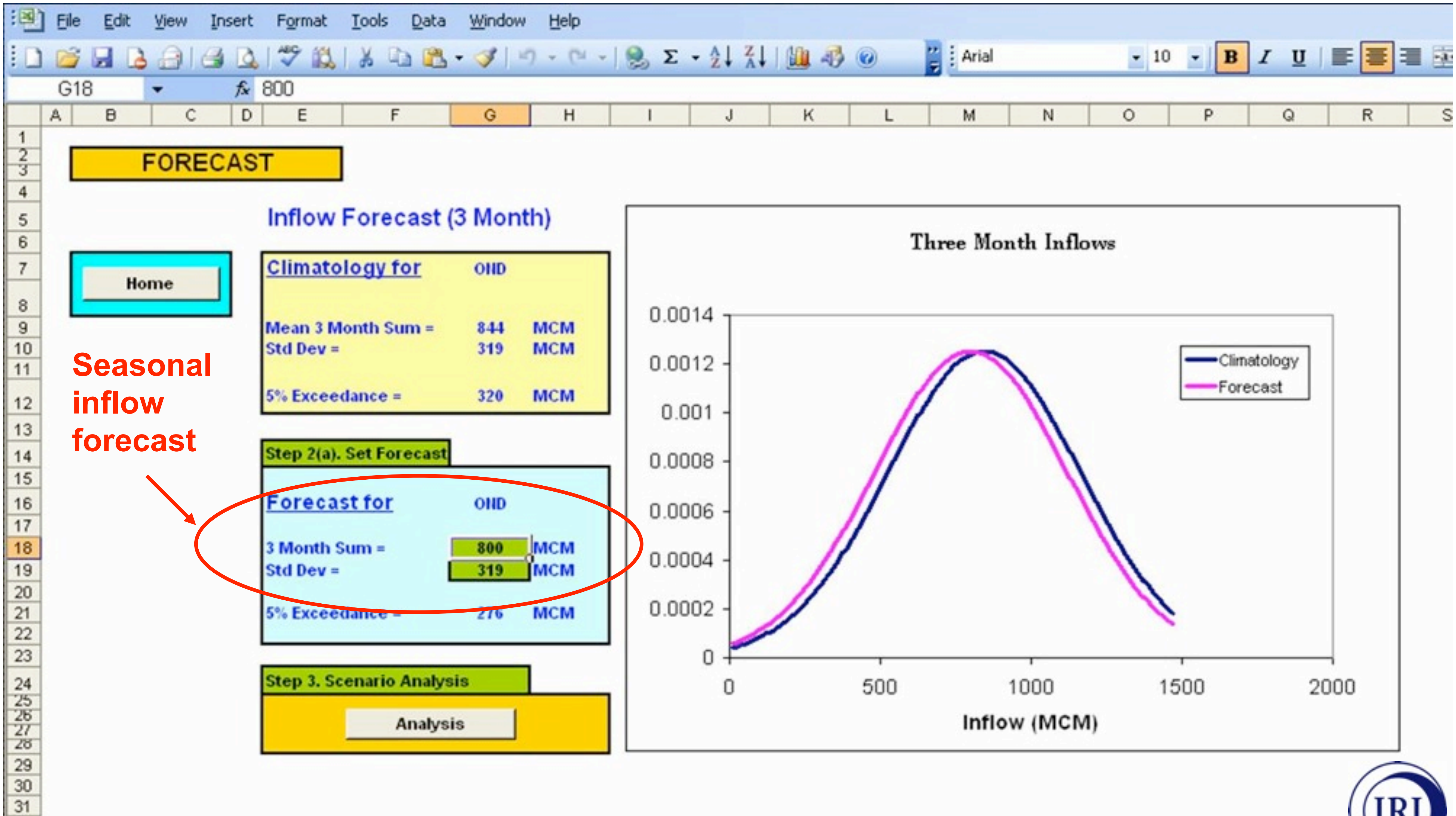


Figure 5.7
Probabilistic three-month (October-November-December) inflow distribution for the Angat Reservoir based on mean inflow across all years, in El Niño years, and in La Niña years.
Each distribution is constructed using the mean across appropriate years and the standard deviation for the entire historical period. Although there is overlap, the El Niño conditions result in reduced average precipitation and inflow, while La Niña conditions result in higher average inflows.

Source: SST data from NOAA NCDC ERSST v.2 (Smith and Reynolds, 2004); Angat inflow data from Philippines National Power Corporation

[Link to Water CRK manual]

Integration of Climate Forecasts into Reservoir Management Tool



Tool: shows probability associated with particular allocations and forecasts

STEP 3(d)

Forecast

Probabilistic

Deterministic Scenario

80 % of Mean

STEP 3(e)

Reliability

Based on whether above

Lower Rule Curve

190.4

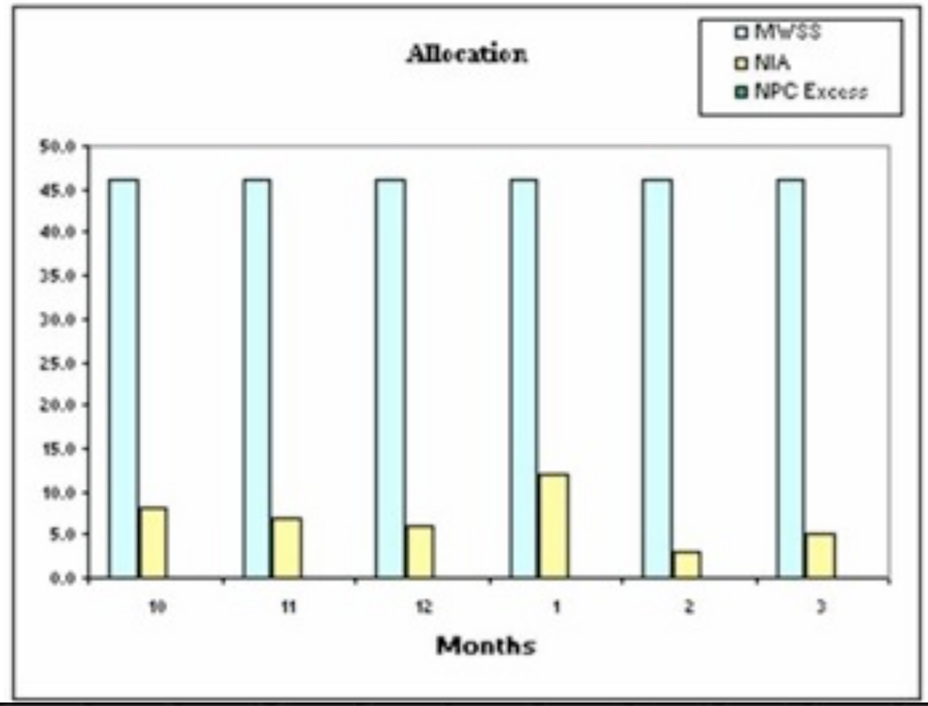
at the end of

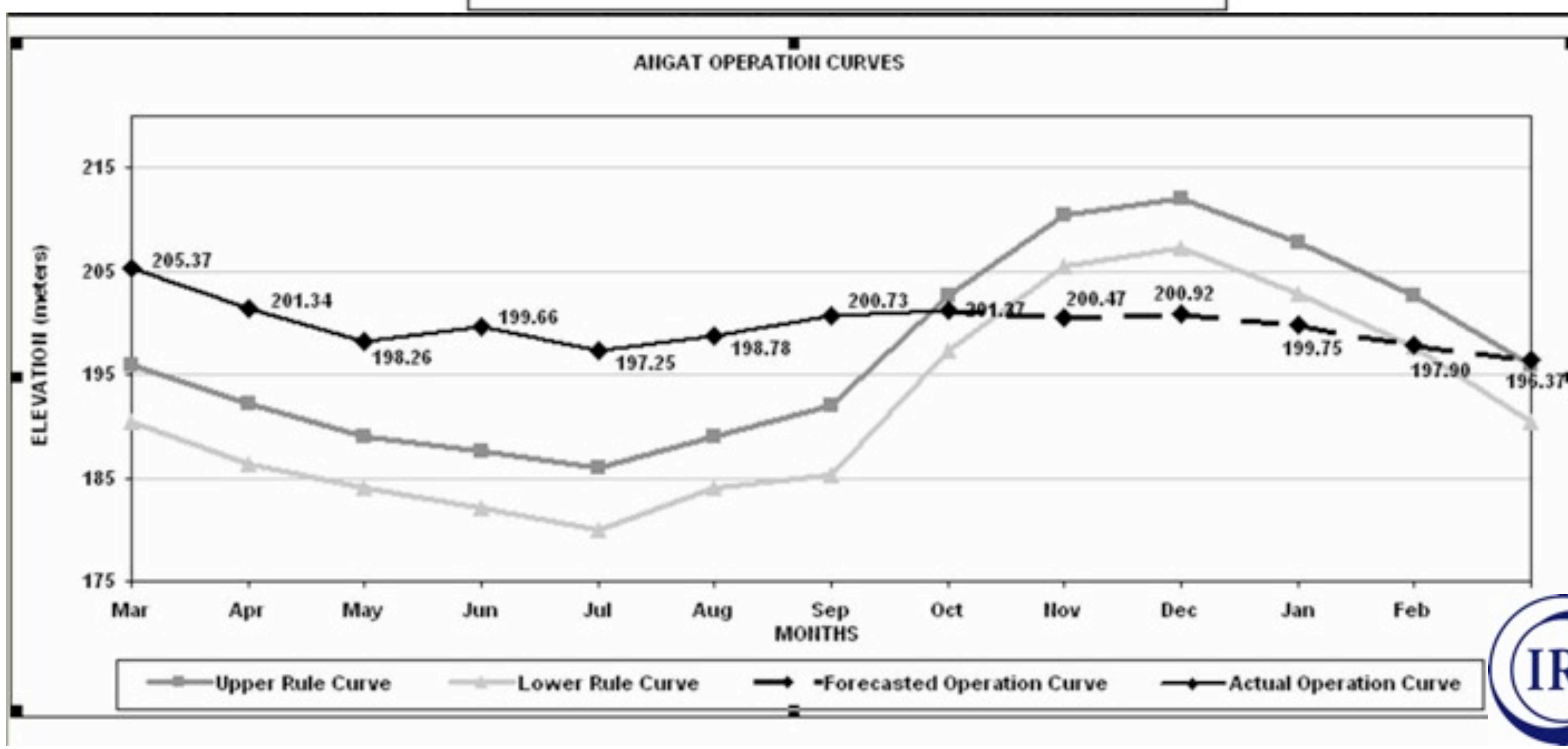
Mar

97%

Probability of Failure

3%





Approaches for longer timescales

A stochastic simulation approach

A stochastic simulation approach

- Concept:
    - given the large uncertainty of climate change projections, one approach is to test the sensitivity of water-allocation reliability to synthetic scenarios of inflow to the reservoir, based on the statistics of historical data and some possible scenarios

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  - A first-order auto-regressive model

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$$X_t = c + \varphi X_{t-1} + \varepsilon_t$$

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  - Superimpose linear trends c=c(t)

Simulated flow traces:
Historical interannual variability + long-term trend

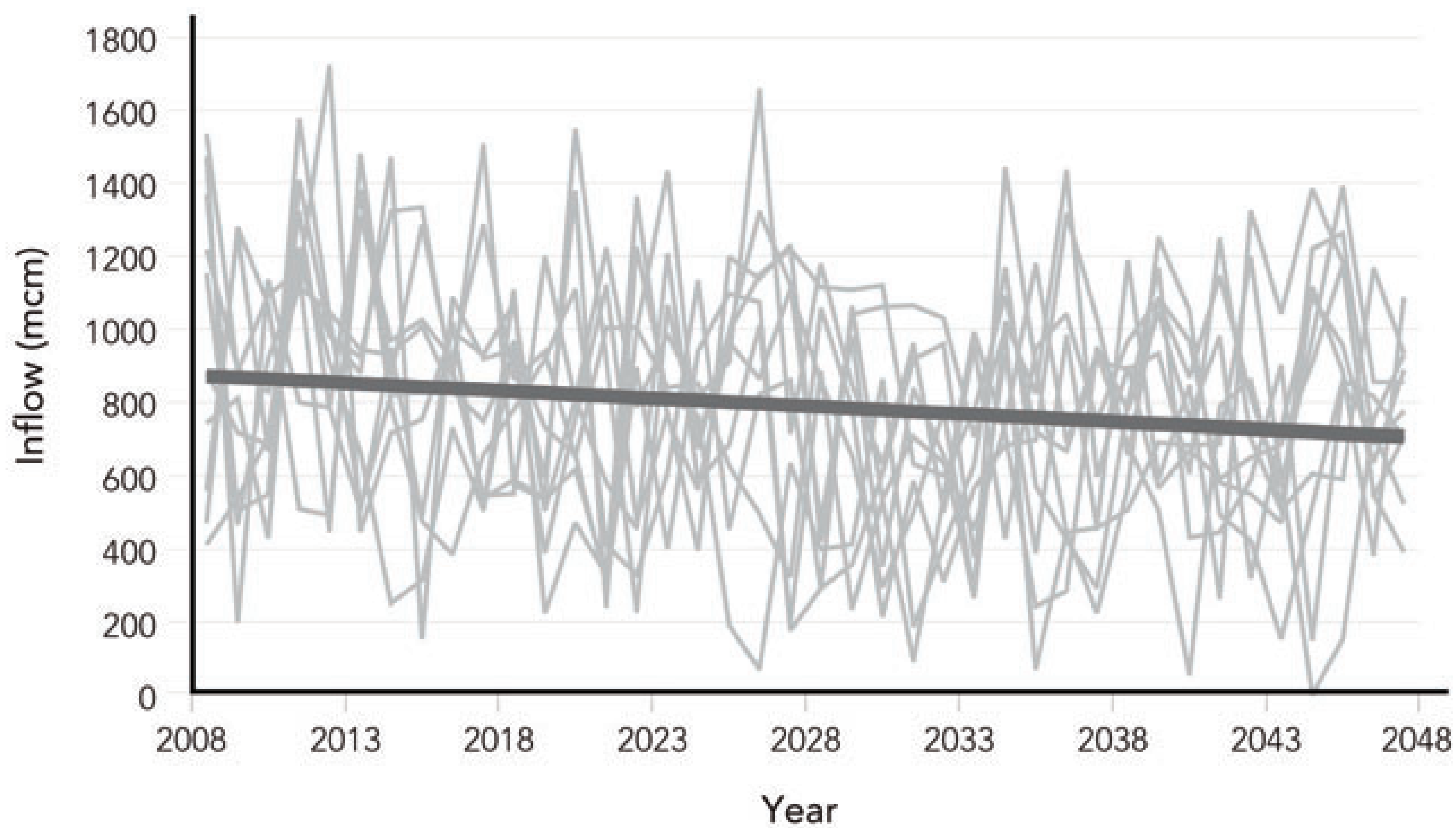


Figure 5.9 (a)
Projected inflow traces with a long-term trend of -20%, interannual variability consistent with the historical record, and no systematically imposed multidecadal variability. Traces sampled from 100 simulations by selecting every 10th trace after ranking by average inflow. Includes trendline average for all inflow traces (4.2mcm/year decrease)

Source: Simulated traces from IRI; Angat inflow and storage level data from Philippines National Power Corporation

Simulated flow traces:
Interdecadal variability, NO long-term trend

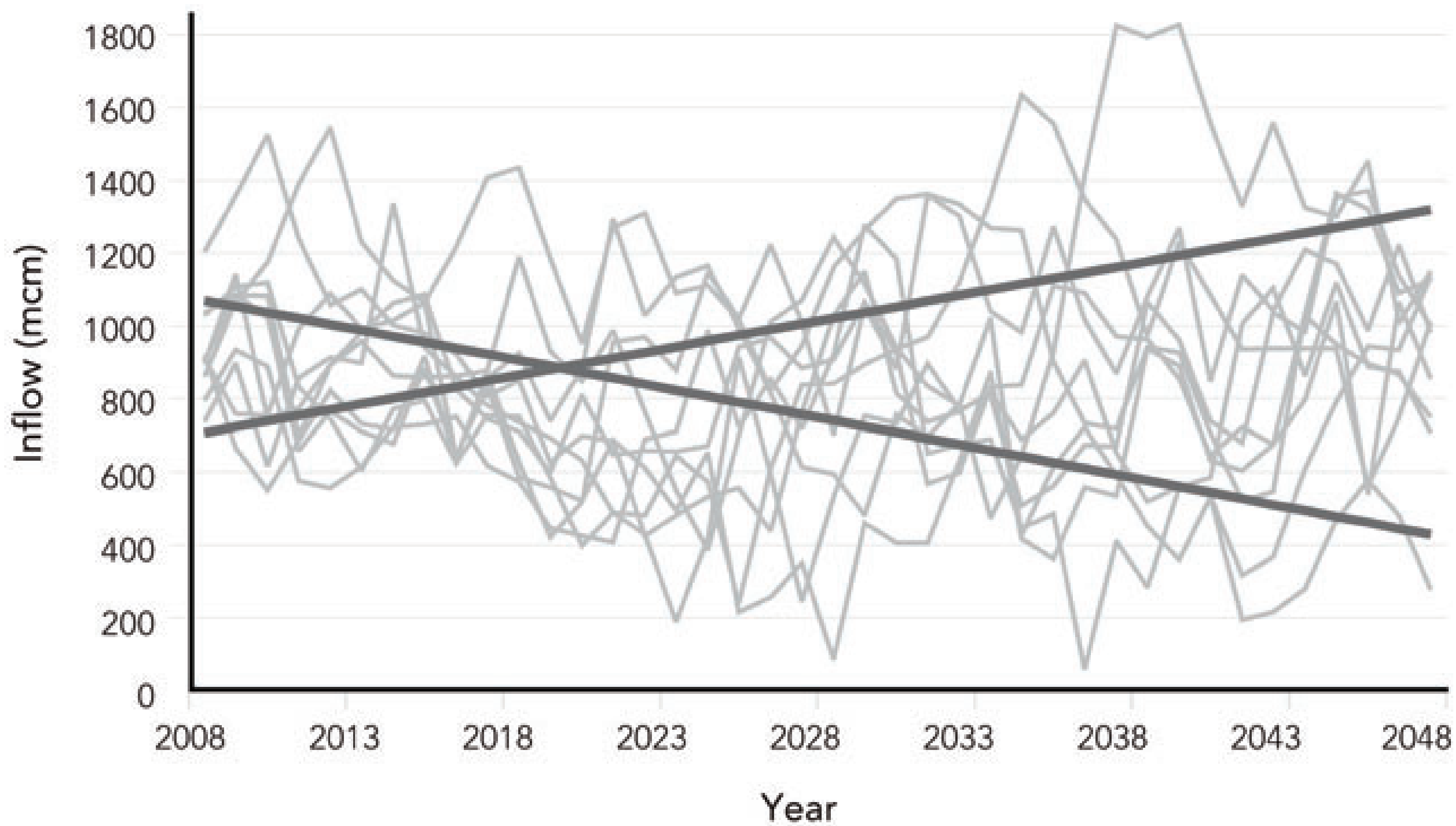


Figure 5.9 (b)
Projected inflow traces with no systematically imposed long-term trend, but with a randomly imposed multidecadal variability (imposed lag 1 autocorrelation, r=0.8). Traces sampled from 100 simulations by selecting every 10th trace after ranking by slope of trace trendline (derived using ordinary least squares regression). Includes trendlines for inflow traces with 10th highest (15.7mcm/year increase) and 10th lowest (16.4mcm/year decrease) slope.

Source: Simulated traces from IRI; Angat inflow and storage level data from Philippines National Power Corporation

Simulated flow traces:
Interdecadal variability AND long-term trend

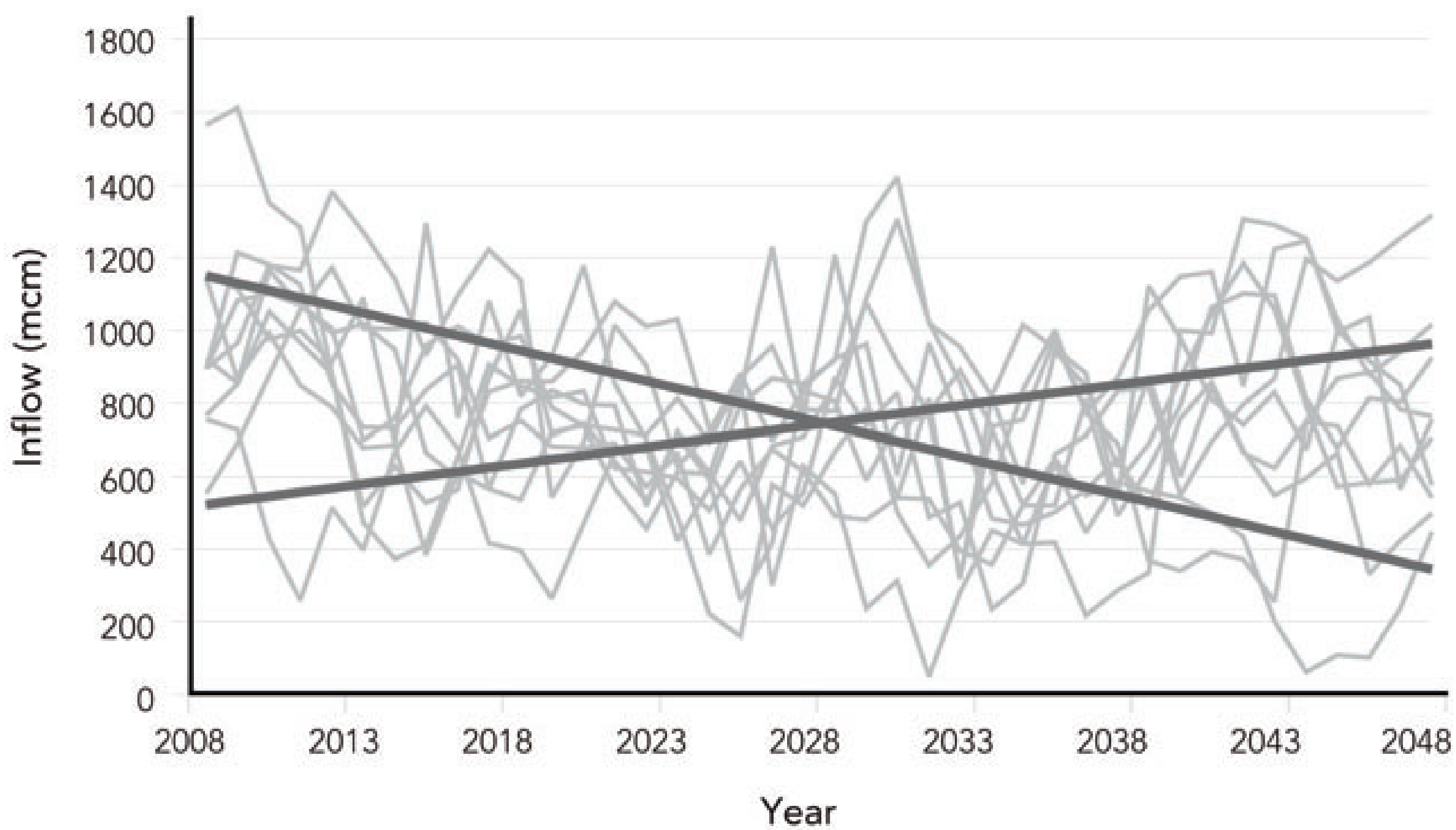


Figure 5.9 (c)
Projected inflow traces with a long-term trend of -20 and a randomly imposed multidecadal variability (imposed lag 1 autocorrelation, r=0.8).
Traces sampled from 100 simulations by selecting every 10th trace after ranking by slope of trace trendline (derived using ordinary least squares regression). Includes trendlines for inflow traces with 10th highest (11.3mcm/year increase) and 10th lowest (20.7mcm/year decrease) slope.

Impact of linear trend on reliability

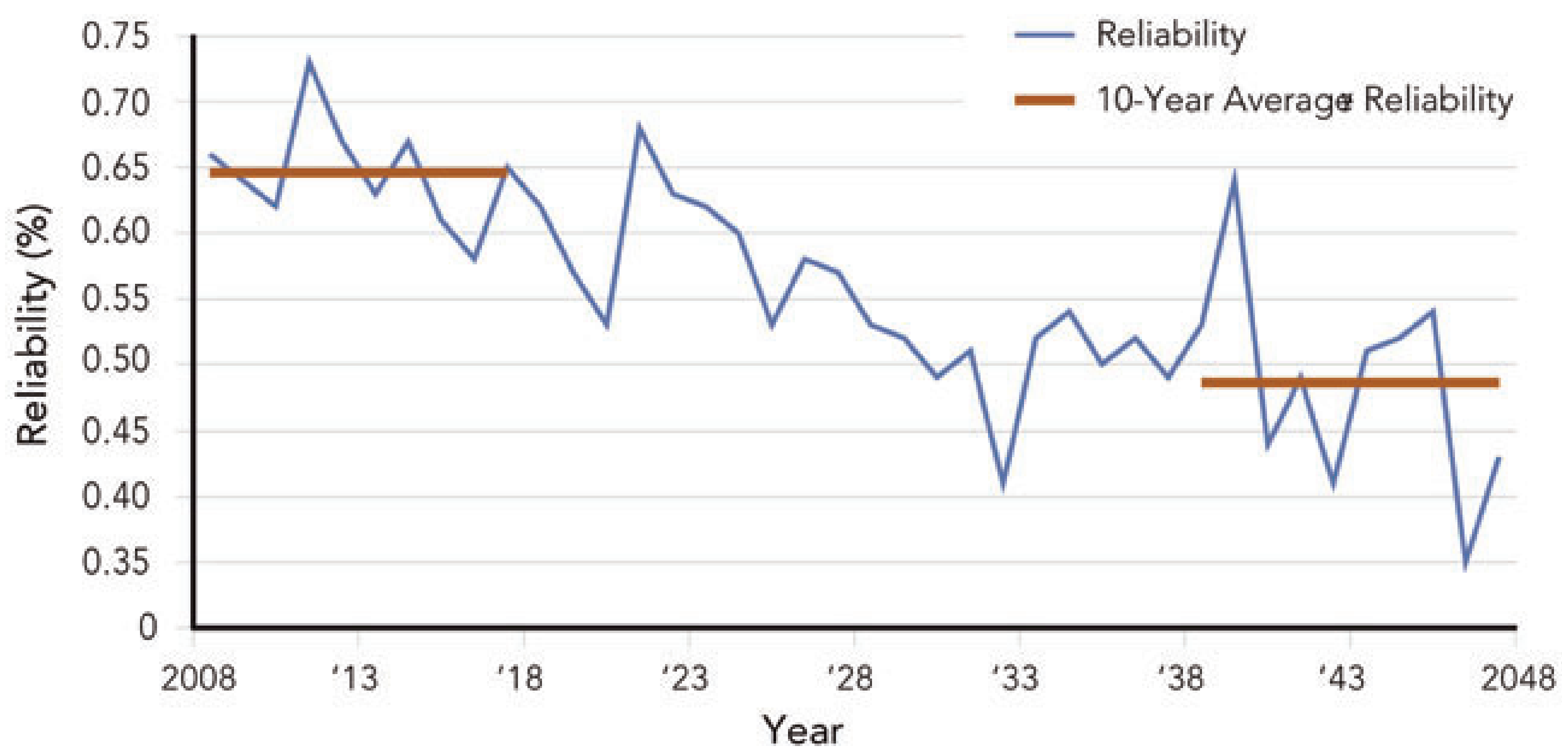


Figure 5.10
Reliability based on average of 100 simulated projections of inflow traces with a long-term trend of -20% and no multidecadal variability (the type illustrated in Figure 5.9a).
The reliability is calculated as the percent of simulations in which the reservoir level is above a given threshold (lower rule curve) at the end of March each year. The solid brown lines indicate the average of the reliability values for the first and last 10-year period (i.e., 2008-2017 and 2038-2047).

Scenario	Cumulative deficit statistic (mcm)	Average reliability first 10 years	Average reliability last 10 years
No trend and no multidecadal signal	59	64%	65%
Trend of +20% and no multi-decadal signal	33	68%	82%
Trend of -20% and no multi-decadal signal	94	65%	49%
Trend of +20% with multidecadal signal	64	70%	79%
Trend of -20% with multidecadal signal	198	65%	46%
No trend, but with multidecadal signal	145	64%	62%

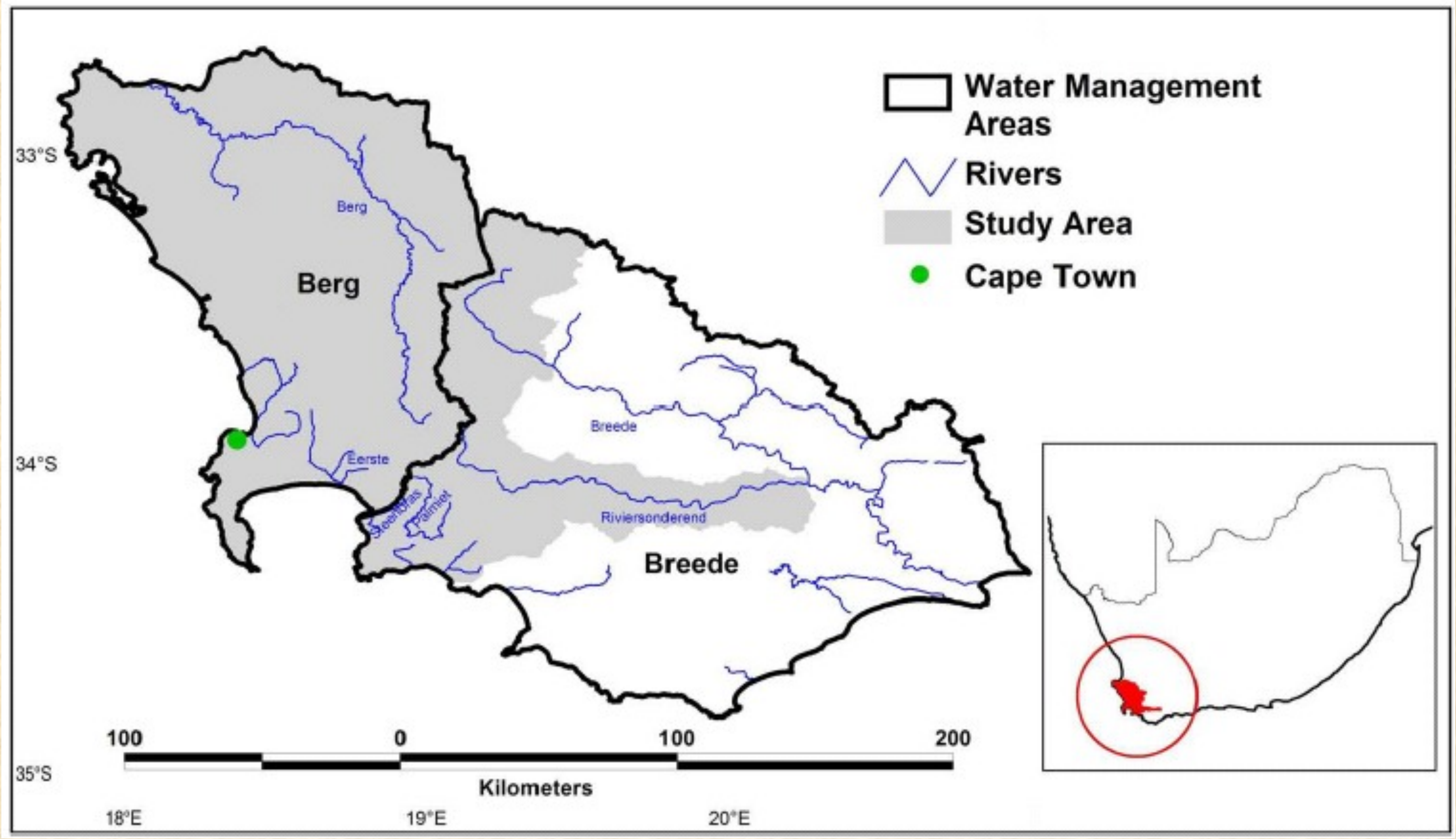
Table 5.2
Sensitivity metrics for reservoir system based on simulated climate scenarios.
Reliability based on average of 100 simulated projections of inflow traces under various scenarios (with or without a long-term trend of +/-20% and with or without a multidecadal signal introduced by adding autocorrelation with a lag1 correlation of .8). Cumulative deficit statistic is the maximum cumulative shortfall for consecutive shortfall years (over the last ten years) that would be expected to be exceeded 10% of the time, where the shortfall (deficit) is the difference between the threshold level and the simulated reservoir level at the end of the period. No shortfall is experienced if the reservoir level meets or exceeds the lower rule curve at the end of the period. The reliability is calculated as the percent of simulations in which the reservoir level is above a given threshold (lower rule curve) at the end of the period. Average reliability for first 10 years based on 2008-2017, for last 10 years based on 2038-2047. The results reveal the significant effect of multidecadal variability on the cumulative deficit statistic; even when there is no systematically imposed long-term trend, the existence of the multidecadal variability results in a significant increase in the possible cumulative deficits that must be planned for.

The results in Table 5.2 reveal the significance of the multidecadal signal. Because a certain phase of a multidecadal signal might lead to dry conditions over several years, this will increase the likelihood of consecutive shortfalls and shortfalls of greater severity. This will not usually be captured in changes in simulated average reliability, so it is important to develop metrics that capture such sensitivity in the system and provide a comprehensive risk assessment.

Toward greater realism – Incorporating IPCC Scenarios

Slides from Arthur Greene

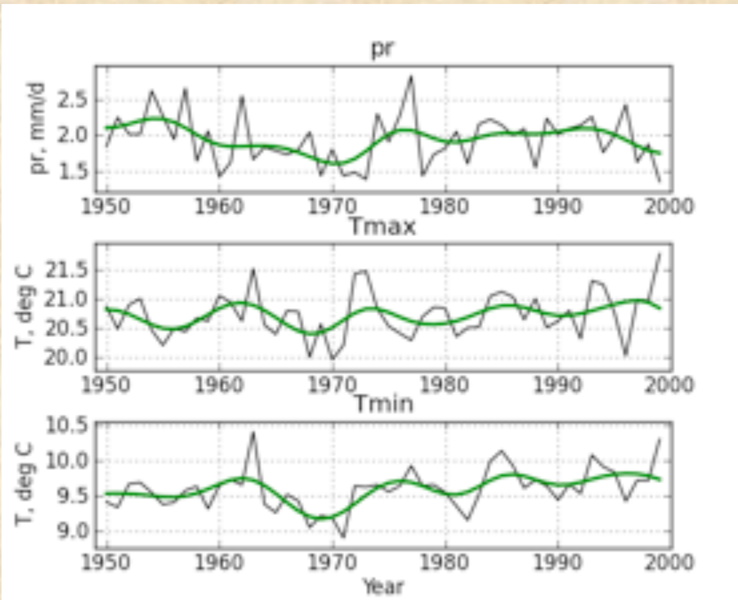
A region of interest: The Western Cape, South Africa



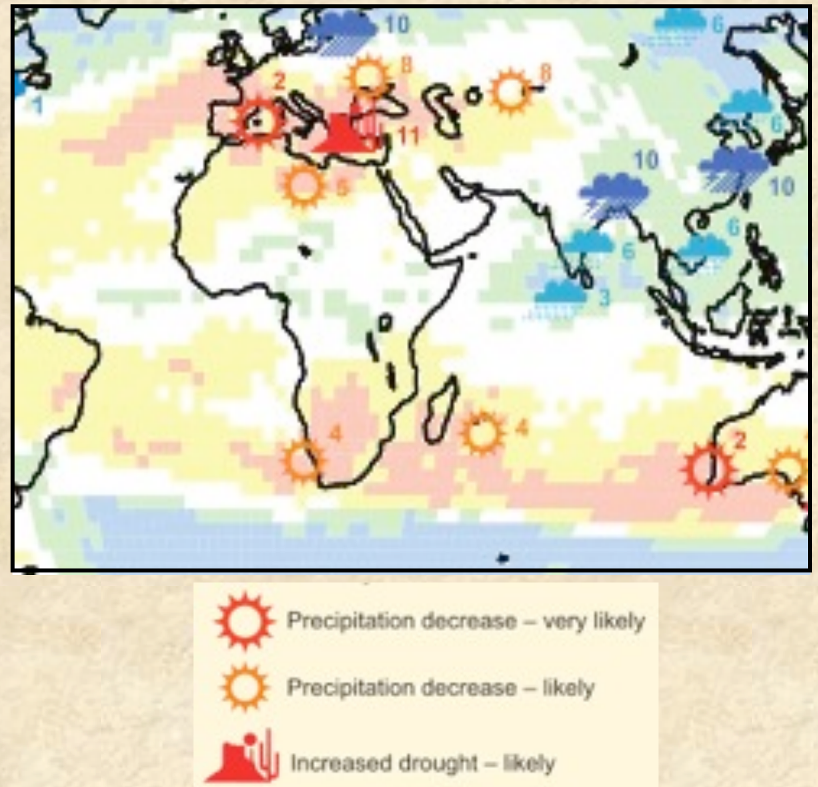
High economic value: Agriculture, urban water (principal supply for Cape Town)
Population increase + projected rainfall decline: Collision trajectory…
Problem: How to anticipate potential climatic stresses – and their socioeconomic consequences.
The decadal scale becomes important for longer-range planning.

Future of the Western Cape: Lines of evidence

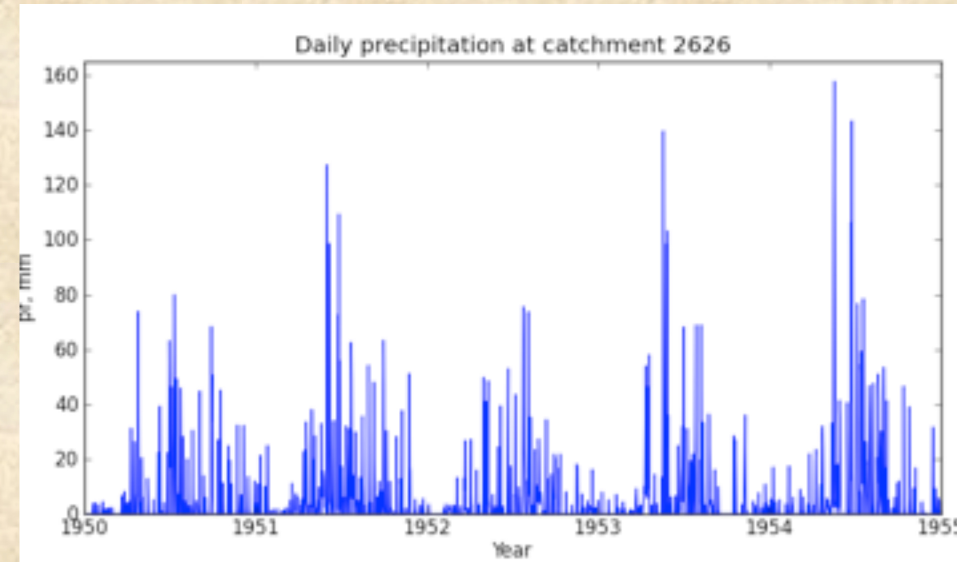
Annualized regional data



IPCC: Climate change



Observed daily variability



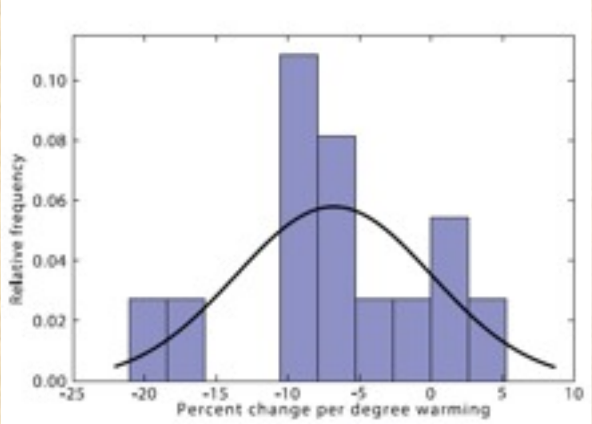
- To generate future climate outlooks, **information from a variety of sources** is synthesized, including climate change projections from IPCC models, the characteristics of observed variability and theoretical expectations.
- Salient question: Can climate models predict variations on the decadal scale?

Elements of a simulation model

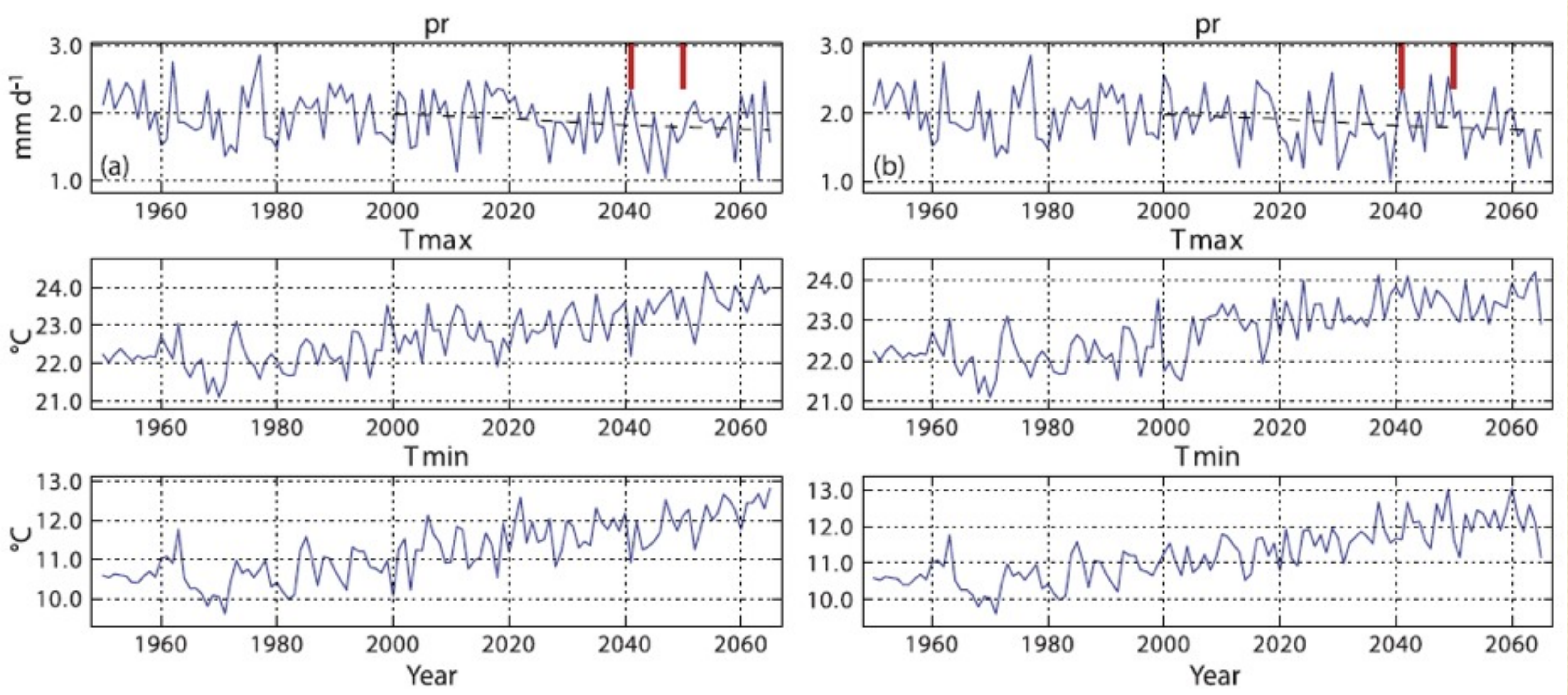
Component	Source	Model
Climate change (trend-like)	IPCC and local observations	IPCC (pr) / linear regression (T)
Annual-to-decadal	Regional-mean observations	Vector autoregressive – VAR(1)
Subannual (seasonal to daily)	Local obs, regional coherence	K-NN resampling

The table describes elements of a complex simulation scheme, designed to reproduce important characteristics of the observed climate while also incorporating IPCC-based climate change information. Some important points:

- The climate change element varies among IPCC models (see plot); the distribution is sampled in order to generate simulations.
- The three components (table, above) are not assumed to be independent.
- Given the absence of demonstrated decadal prediction skill, a “VAR(1)” model is used to *simulate* variations on the annual-to-decadal scale. This model takes into account the simultaneous variations of precipitation and temperature.
- Subannual variations are resampled coherently across the domain.

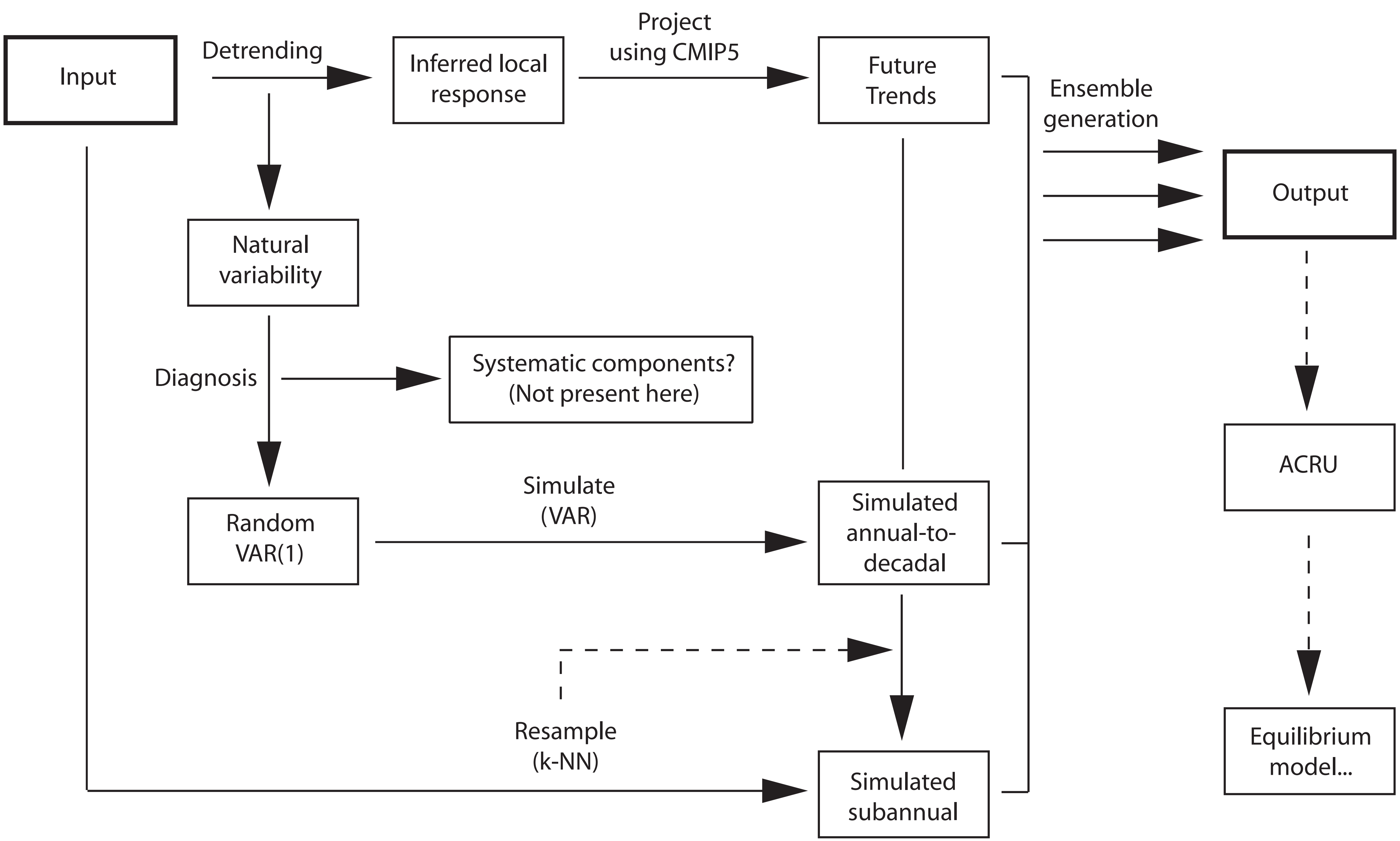


Example simulations



Two simulations for the same catchment are shown, including observed values during 1950-1999. At left the 2041-2050 decade is unusually dry; at right it is wet. The median precipitation trend from the IPCC distribution is used. At left, the drying due to this long-range trend is *doubled* by the decadal fluctuation; at right it is *cancelled.* Trend alone causes drying of about 10% for the 2041-2050 decade.

Incorporating IPCC Scenarios

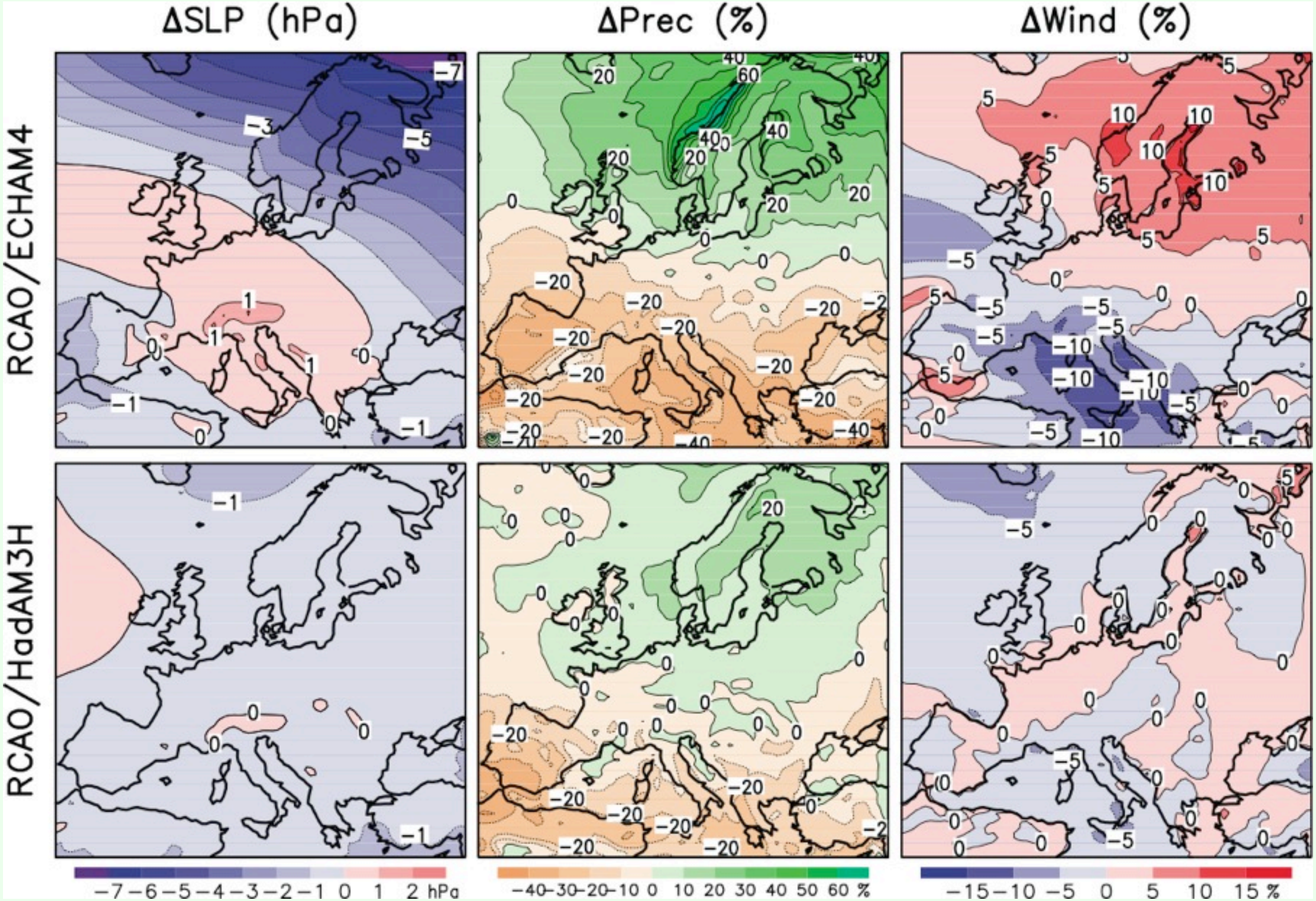


Important Issues

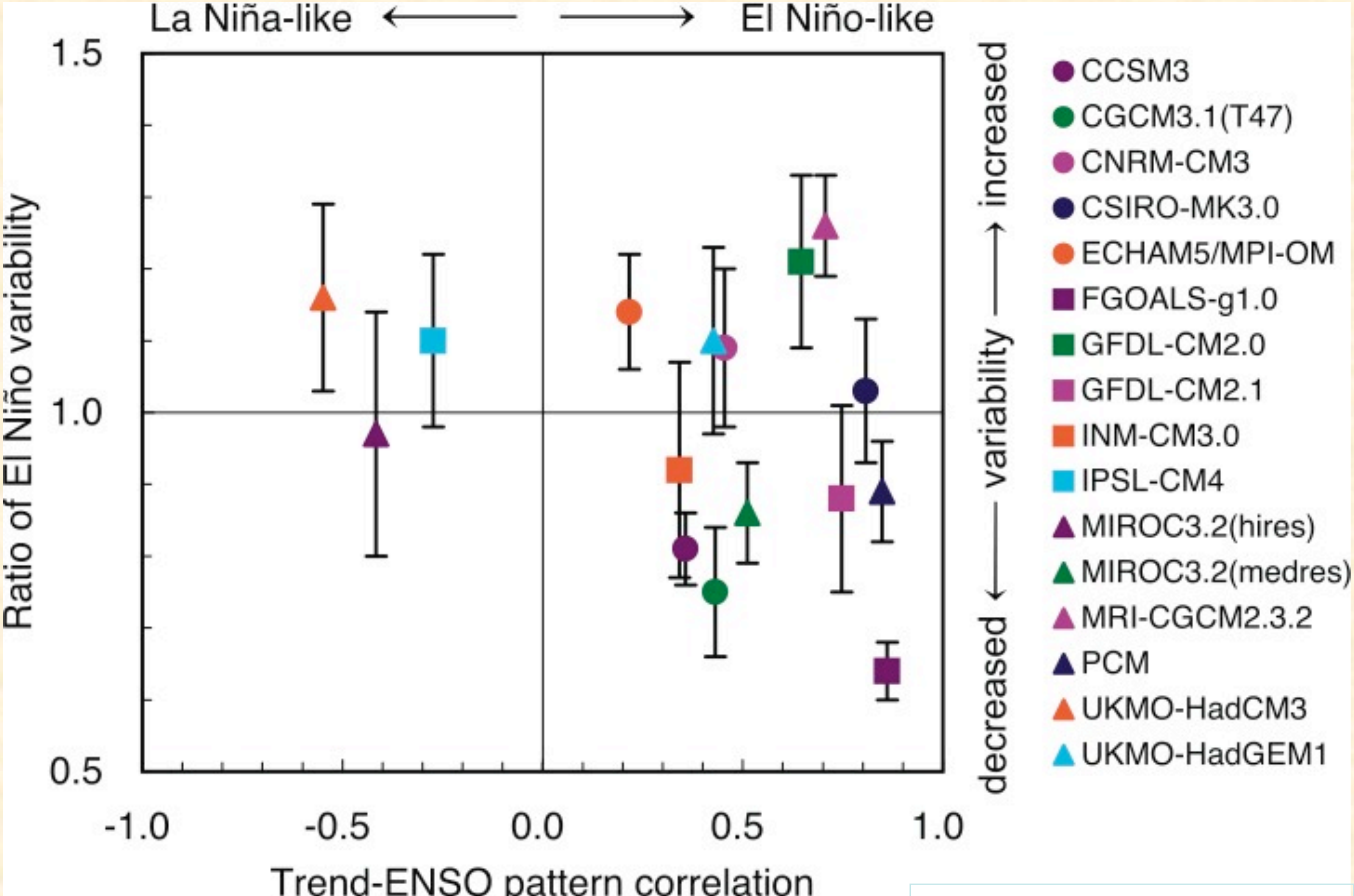
- Are the relevant climate processes represented in the simulations?
- Do known modes of climate variability (ENSO, SAM, IPO) impact the region?
- How may different anthropogenic forcings play a role in the region, such as aerosols, stratospheric ozone?

Dynamical Downscaling?

<u>Example</u>: 2 IPCC CGCMs, both downscaled with same regional model (RCM).



Tropical Pacific Trend Pattern vs ENSO Variability



Source: IPCC AR4 WG1, Chp 10

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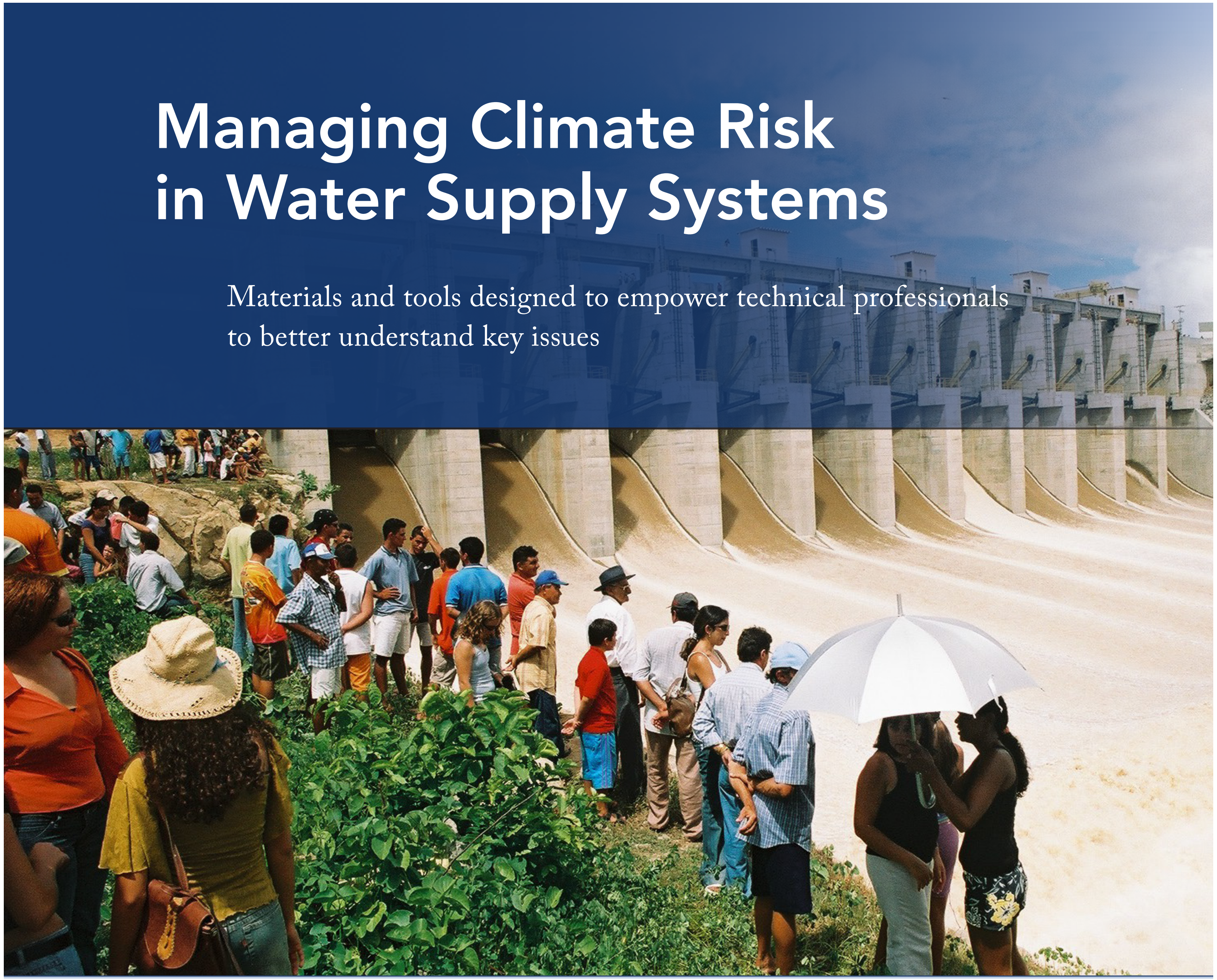
- Need interdisciplinary partnerships!

Ultimately, successful climate risk management relies on:
1) the quality of the climate information;
2) successful integration of this information into relevant decision tools (such as reservoir models); and
3) incorporation of the information into decision making, including relevant policies, regulations, and other institutional processes.

Make your own seasonal forecasts of reservoir inflow, manage water allocations, and explore climate change sensitivities!



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