Seasonal prediction at IRI for managing climate risk

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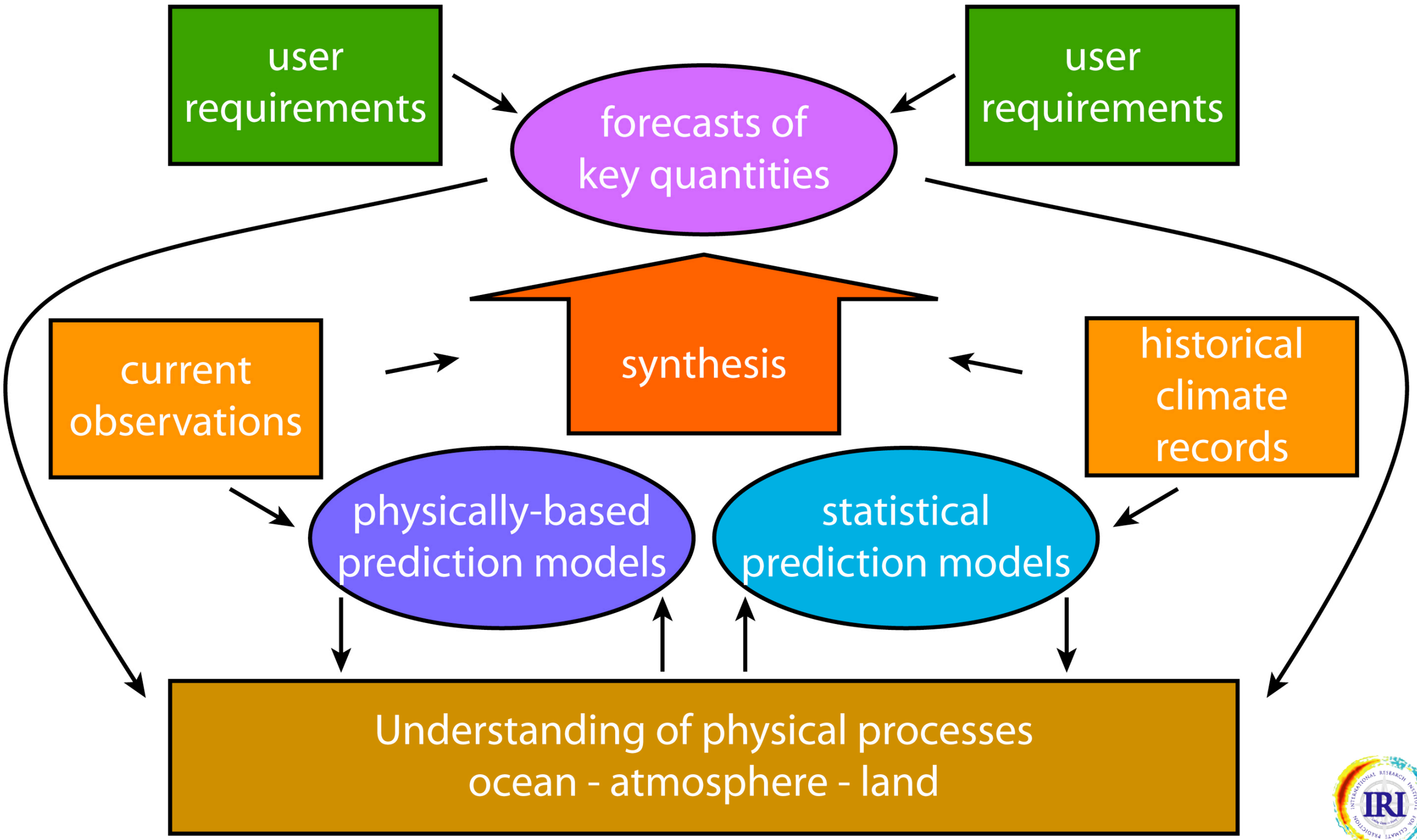
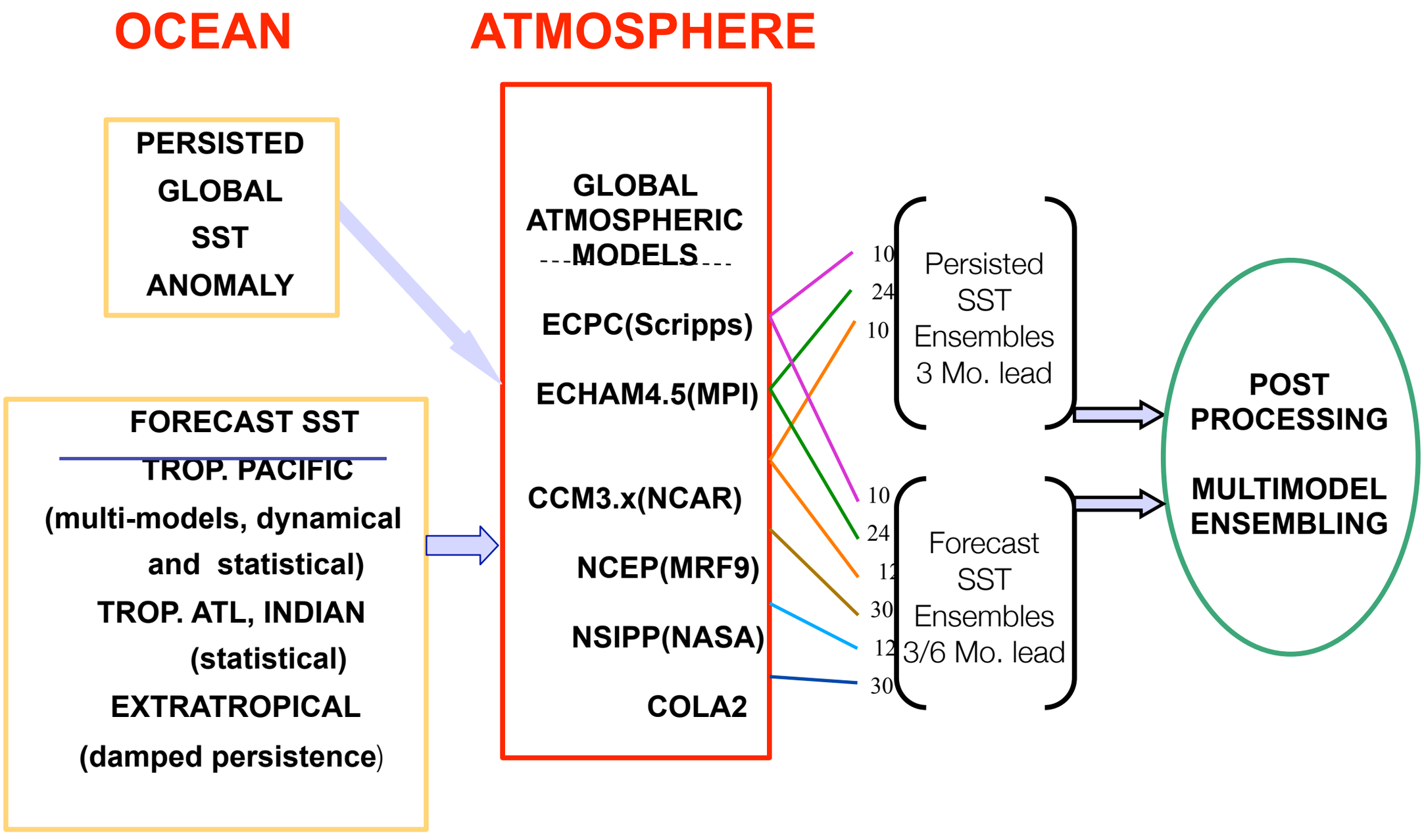
to be useful to decision makers, climate forecasts must:

- be probabilistic
- be reliable
- contain some resolution
- address relevant scales and quantities

Demand-driven climate prediction



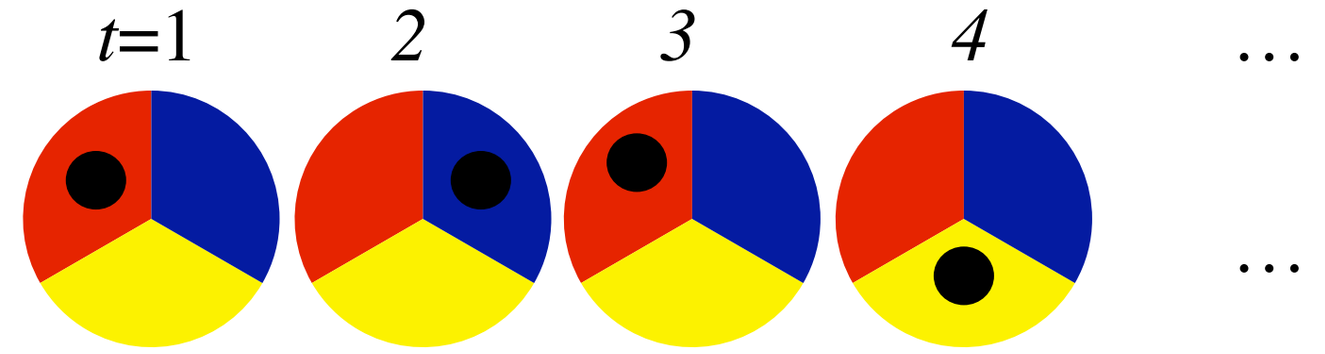
IRI Operational Dynamical Forecast System



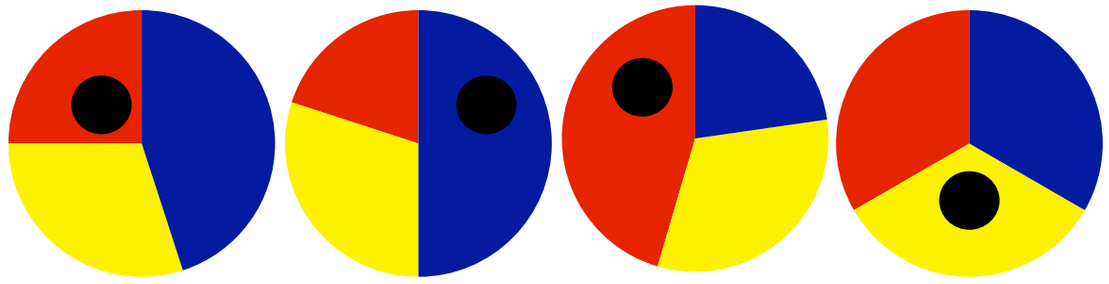
forecast calibration

- multi-model ensembling
  - a Bayesian method for combining multiple atmospheric GCM ensembles for seasonal prediction
  - discriminant analysis
- statistical downscaling
  - MOS
  - stochastic weather models

Combining forecast distributions



Climo Fcst
"Prior"



GCM Fcst
"Evidence"

posterior distribution of forecast probabilities:

$$f[\mathbf{Q}_t|\mathbf{P}_t(y)] = D(\mathbf{a}+\mathbf{b})$$

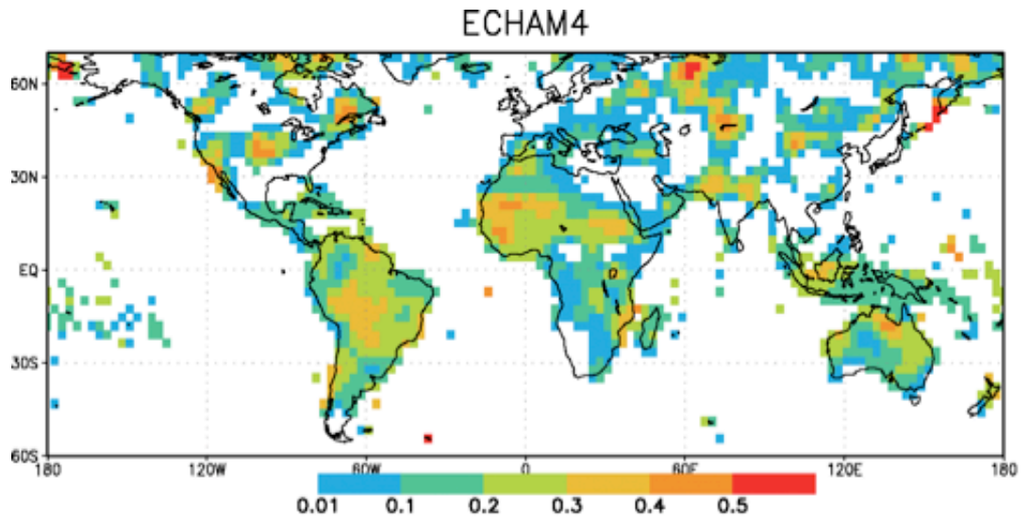
sum of Dirichlet distributions
for climo. and GCM

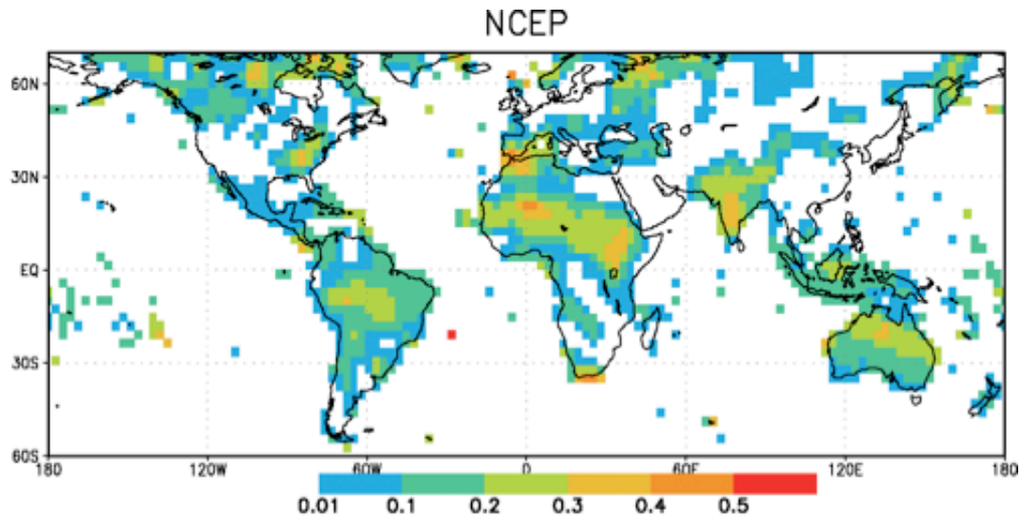
Reducing sampling variability

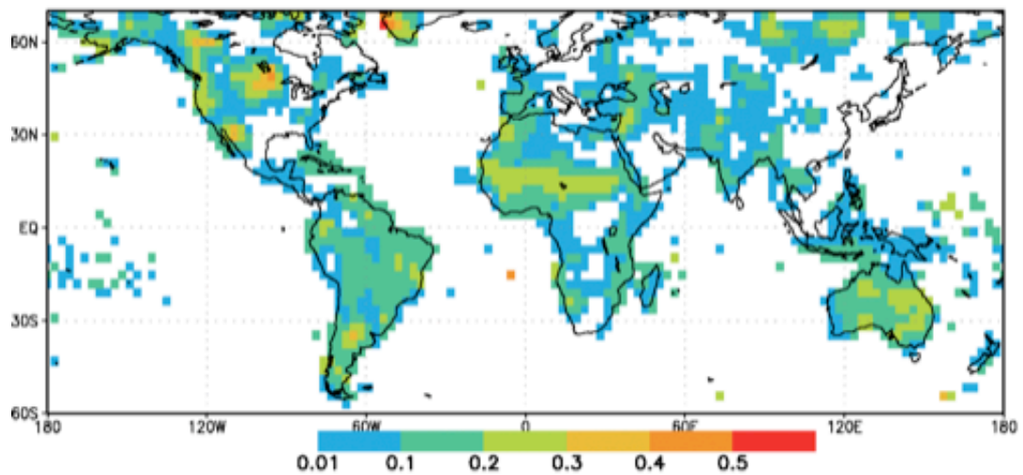
- Temporal smoothing: bootstrap the optimization, omitting contiguous 6-year blocks
  - average the weights across the samples
- Spatial smoothing: introduce 9-point binomial spatial smoother into the likelihood optimization

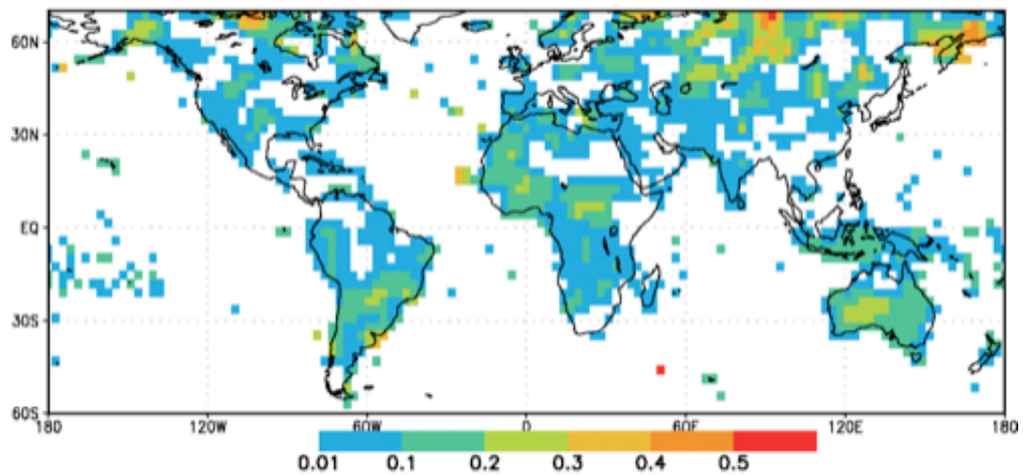
$$L(w) = \prod_{i=1}^{9} \prod_{t=1}^{N} E[Q_{itk^*}]$$

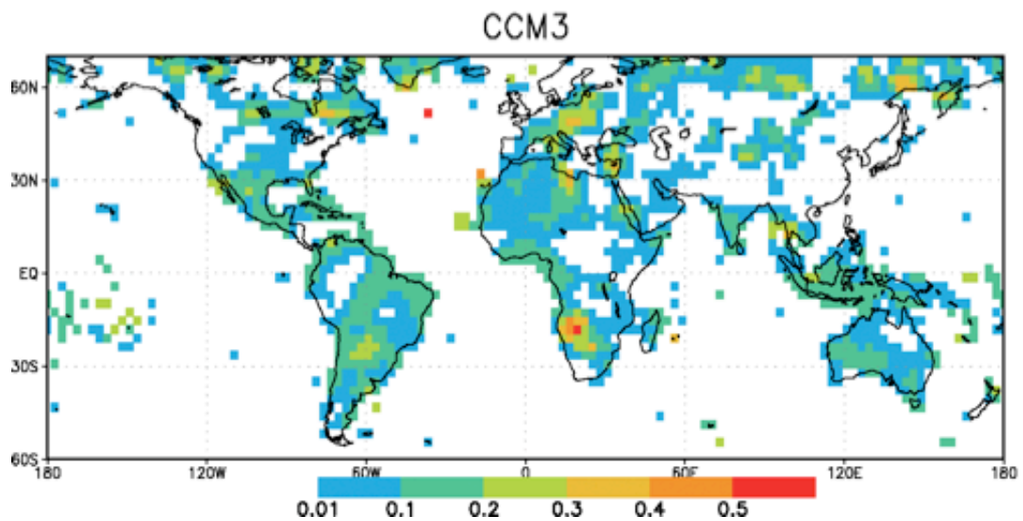
Model weights: JAS Precip.

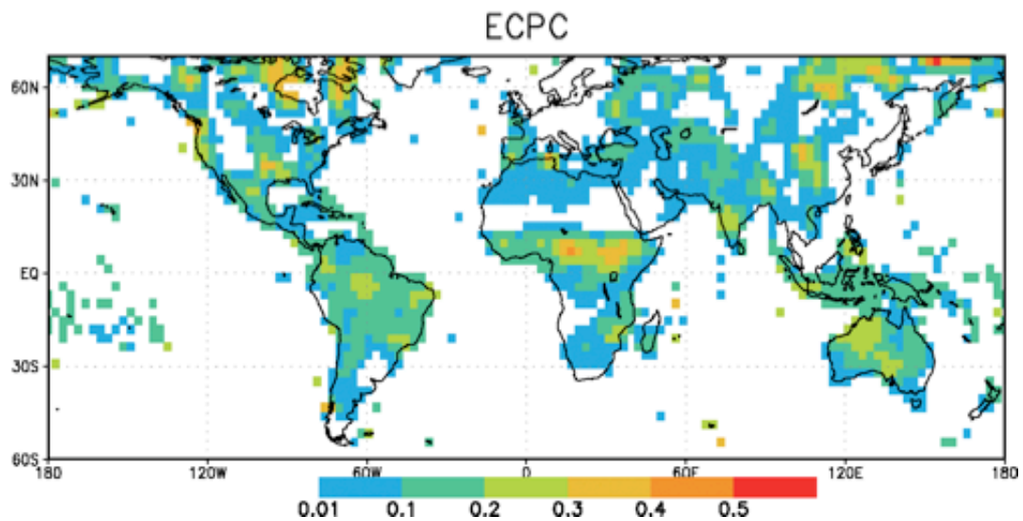




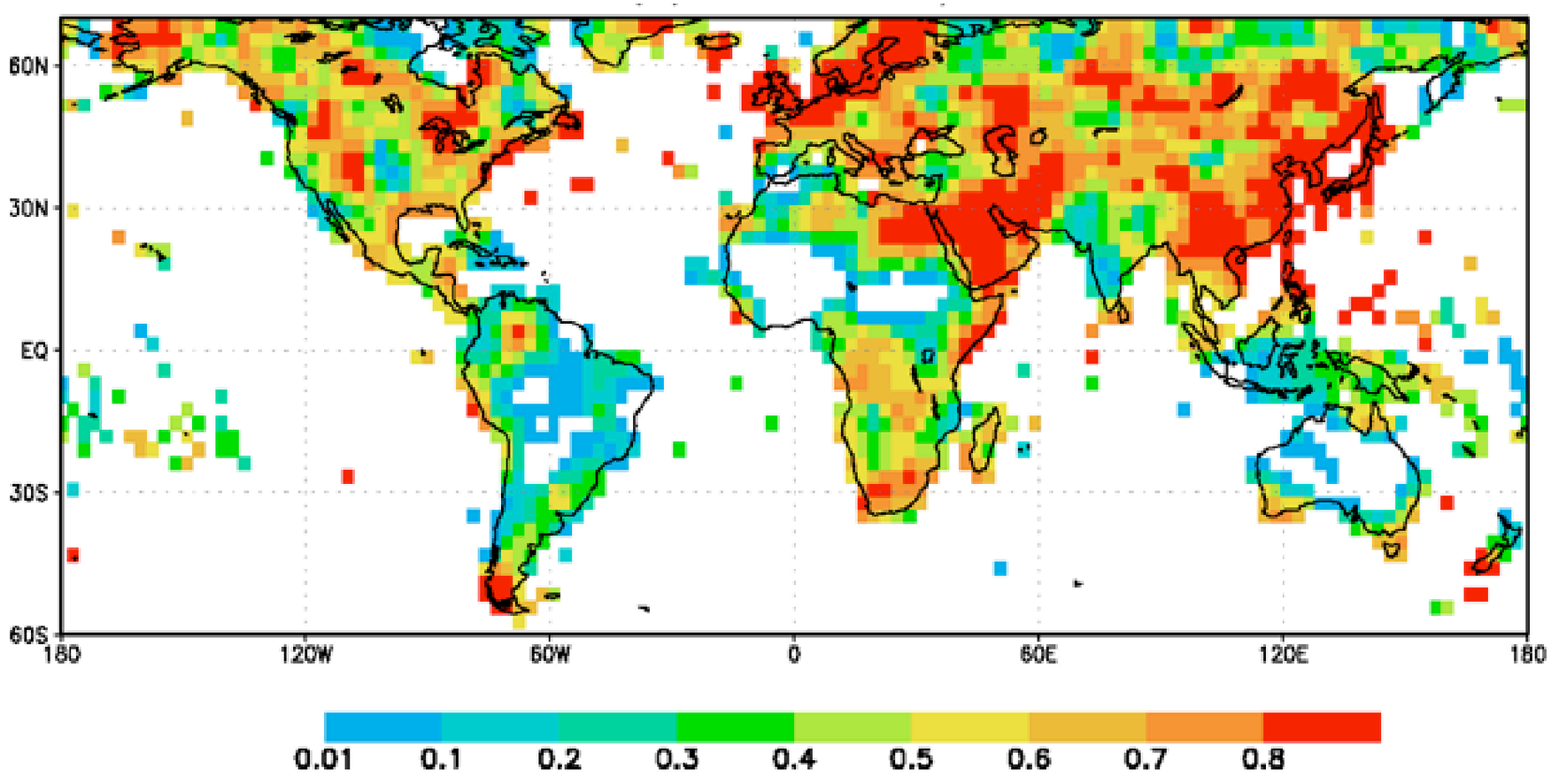








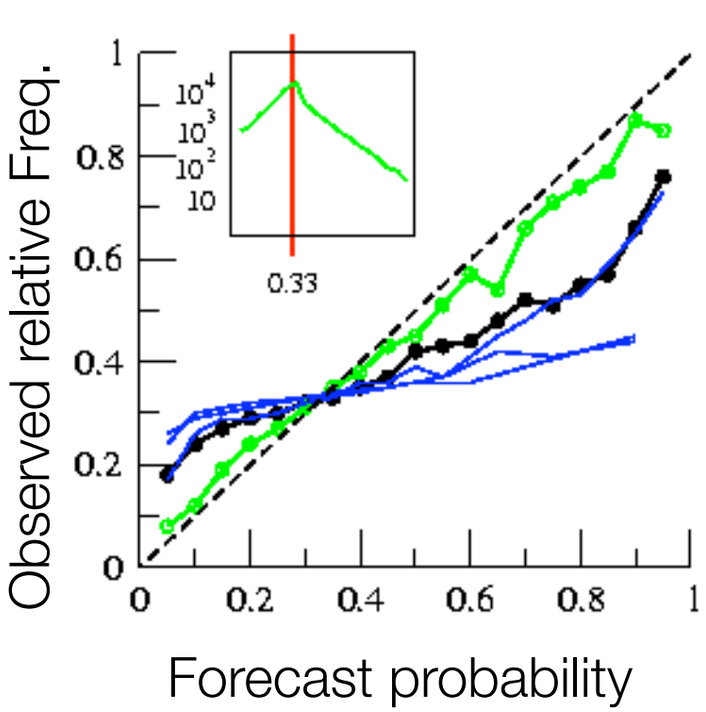
Climatological weights:
JAS Precip.



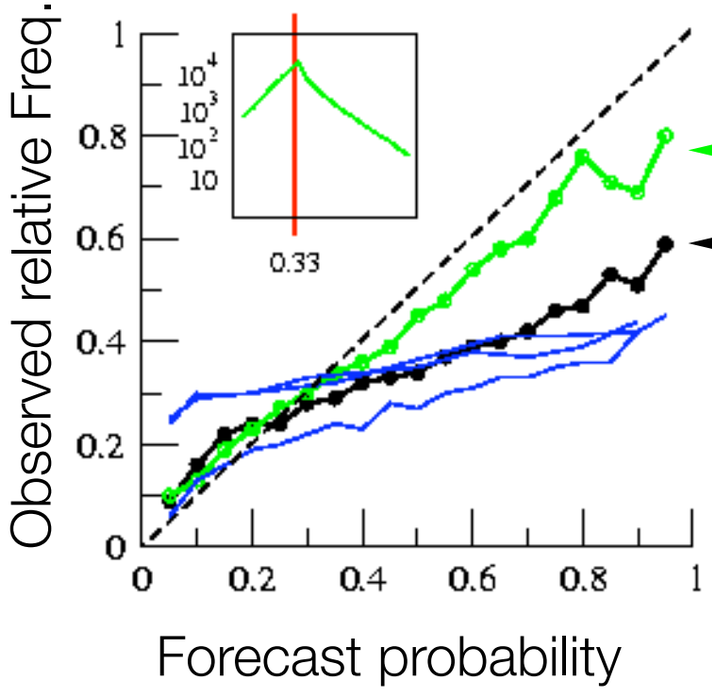
Reliability

JAS Precip., 30S-30N (3-model)

Above-Normal

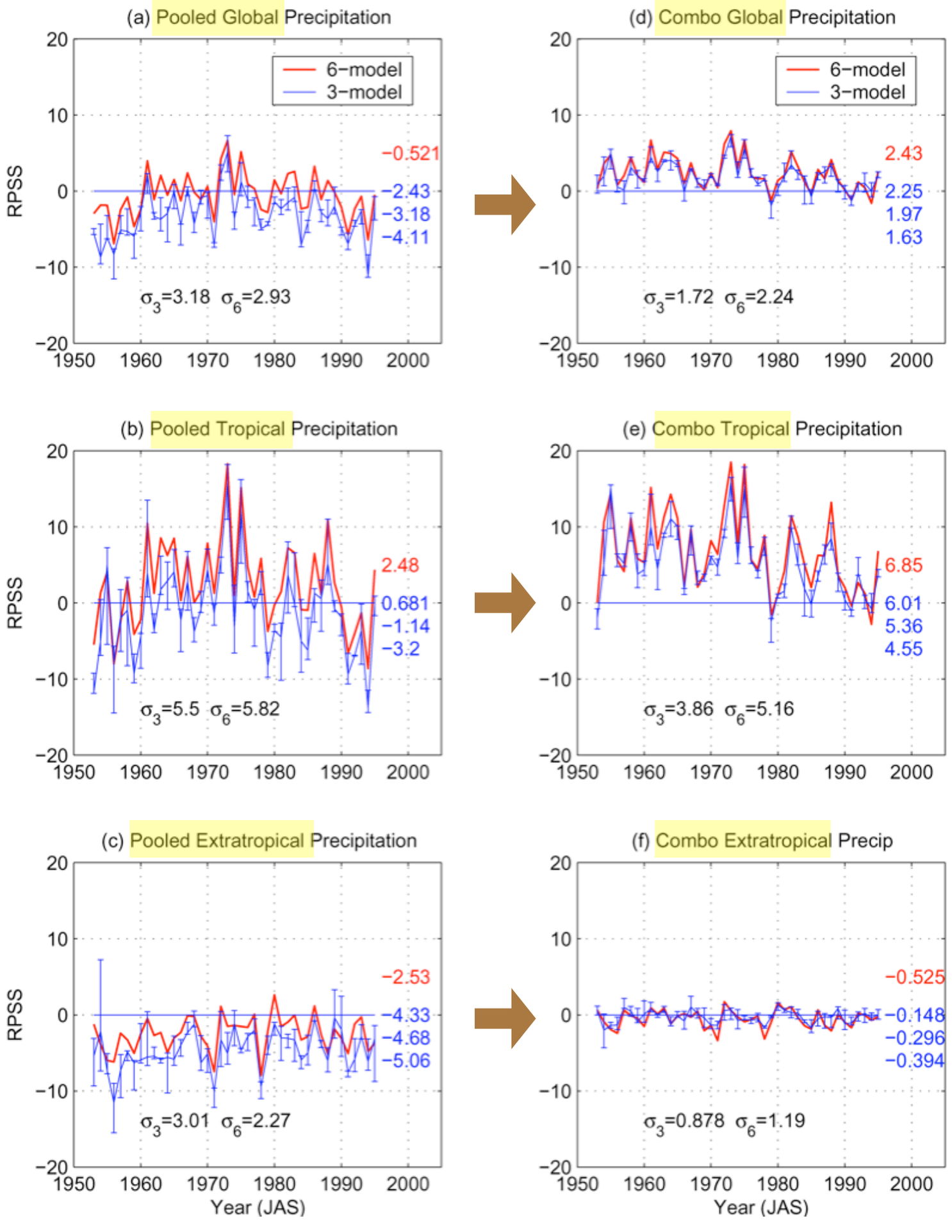


Below-Normal

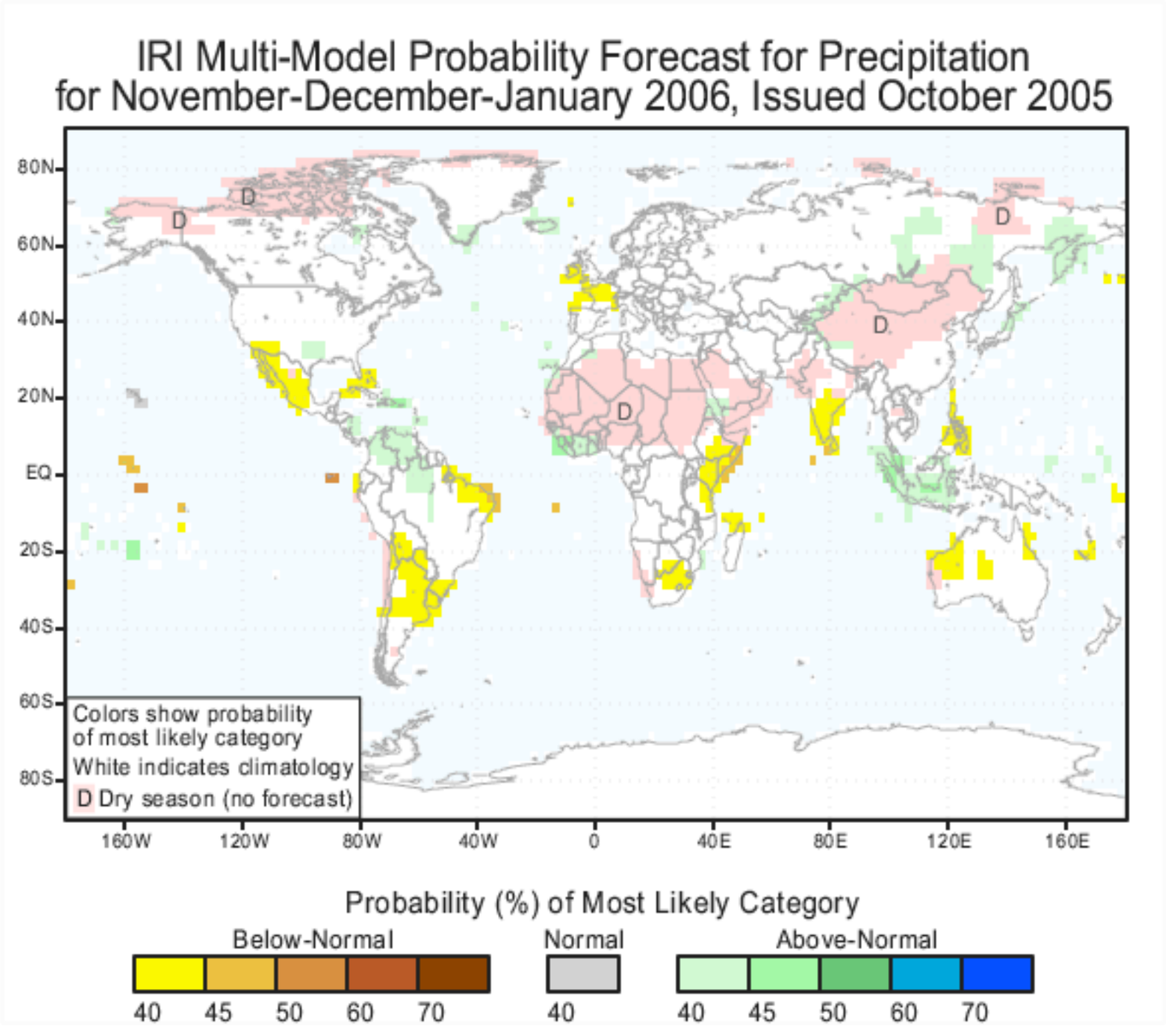


Rank probability skill score

JAS Precip.



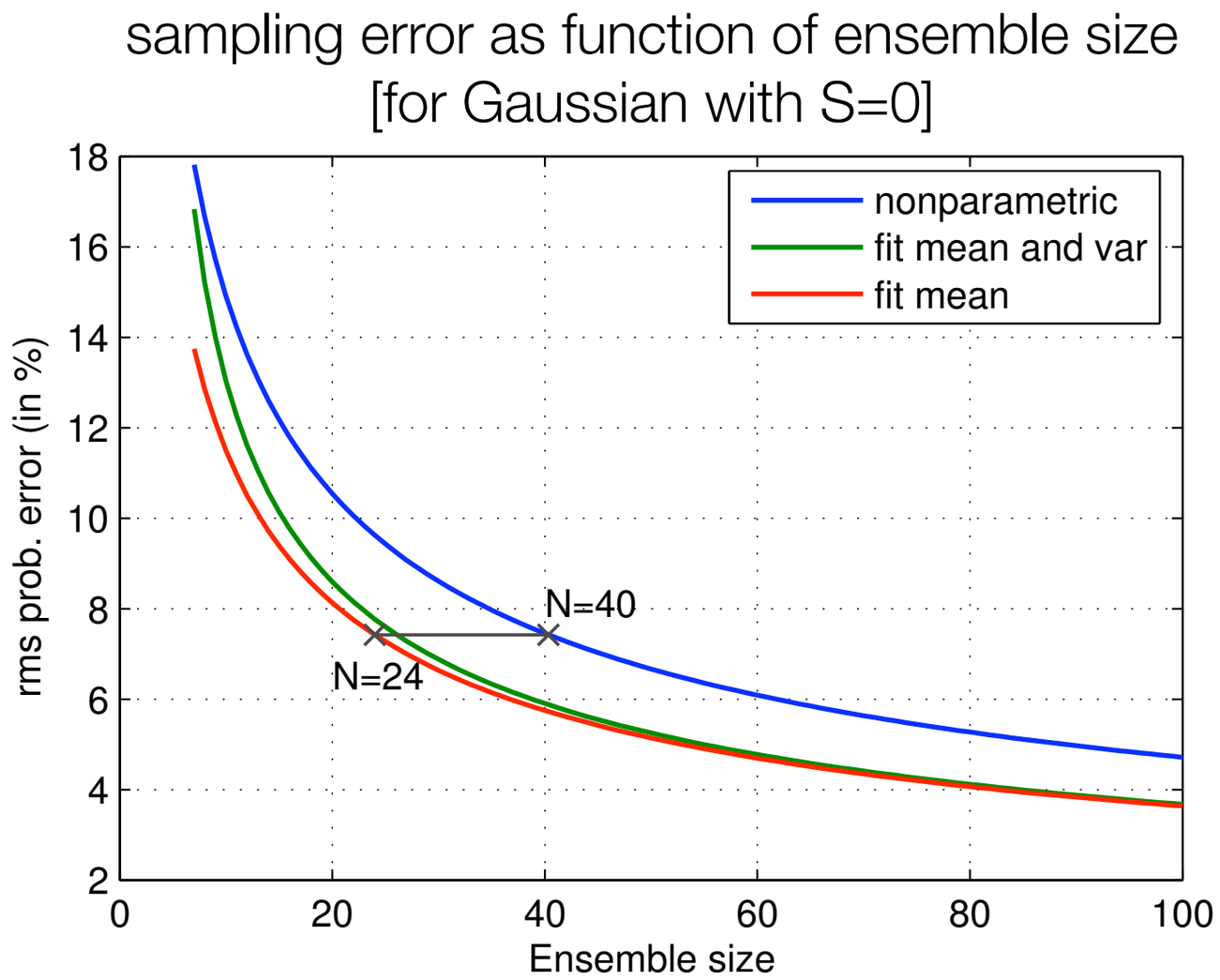
IRI global forecasts
– issued monthly –



what size ensembles for estimating tercile probabilities?

variance of counting estimate p_N as function of ensemble size N and S/N ratio S:

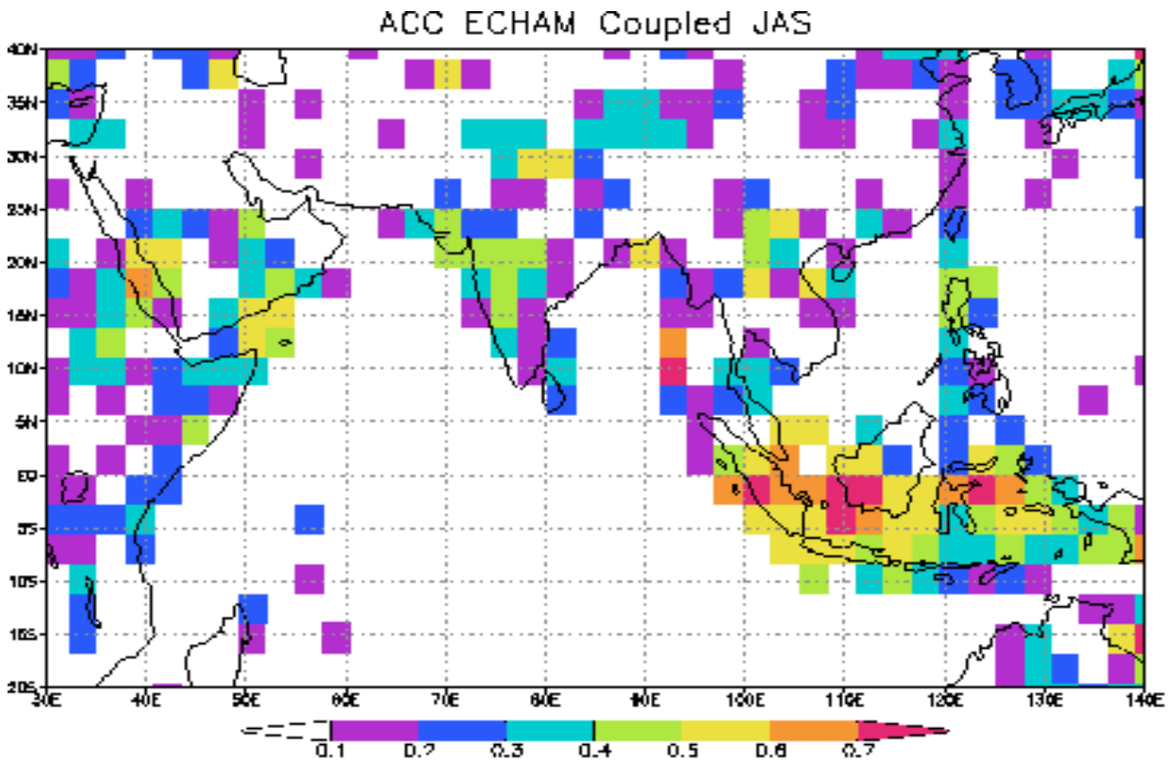
$$\left\langle (p - p_N)^2 \right\rangle \approx \frac{2}{9N\sqrt{1+S^2}}$$

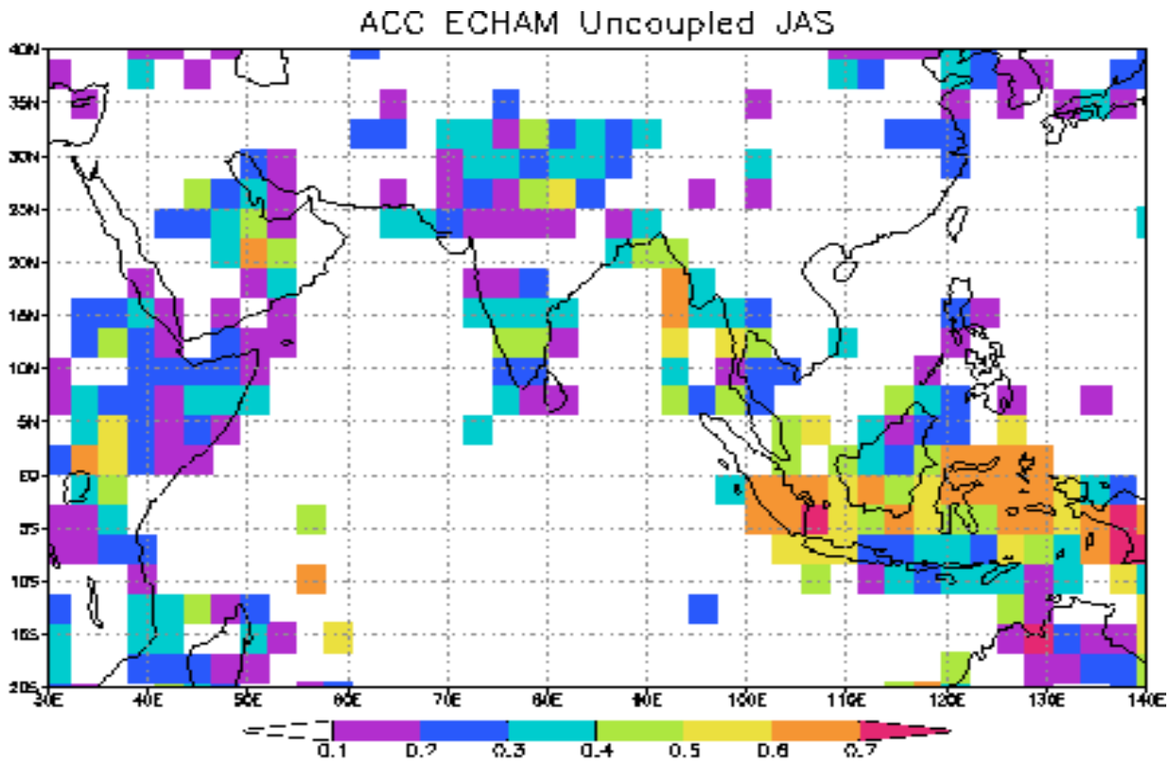


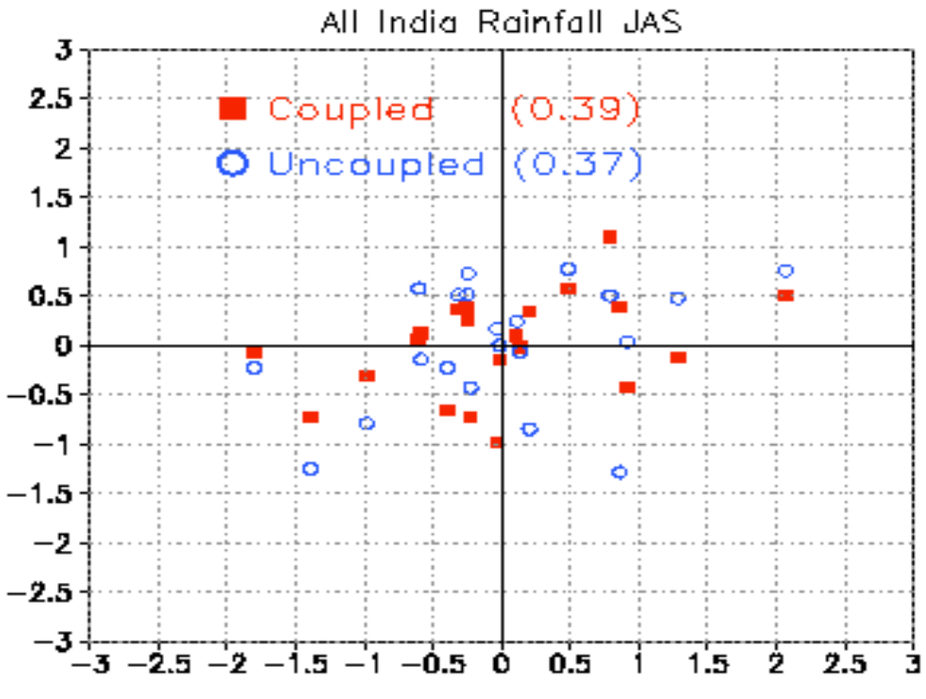
M. Tippett

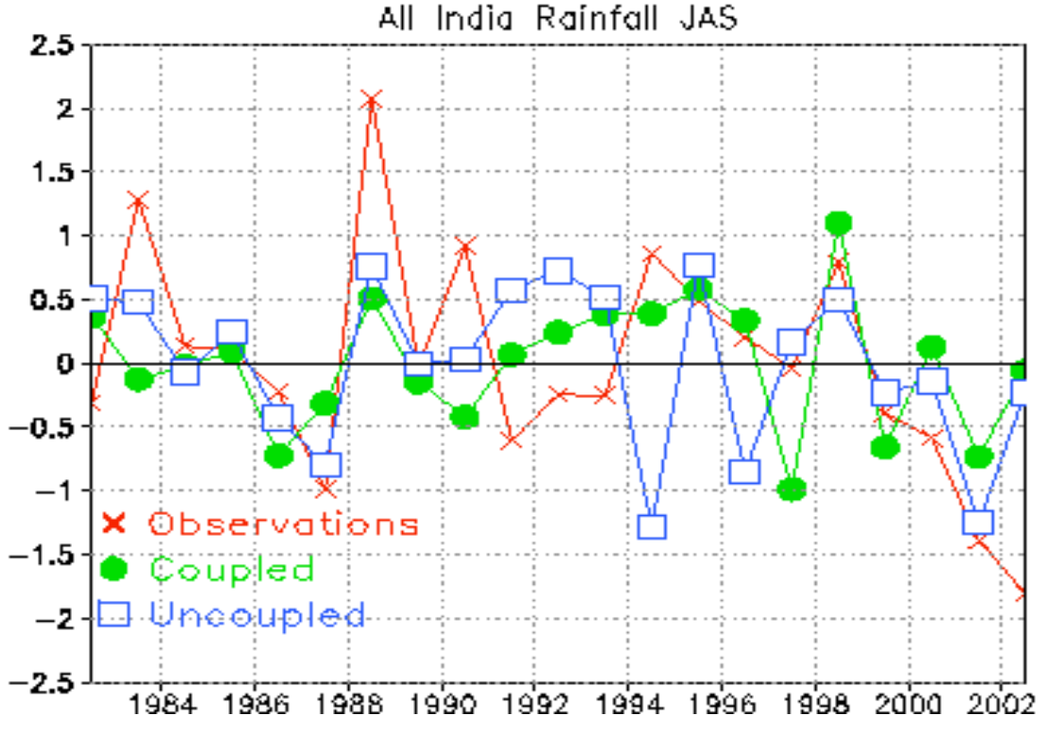
Effect of Coupling on Simulated Indian Monsoon

D. DeWitt









“downscaling” climate forecasts

- regional dynamical models
- stochastic daily rainfall modeling
- crop model downscaling example

Dynamical downscaling

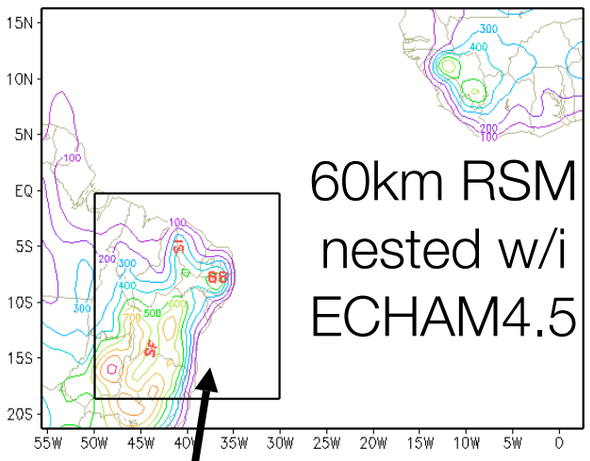
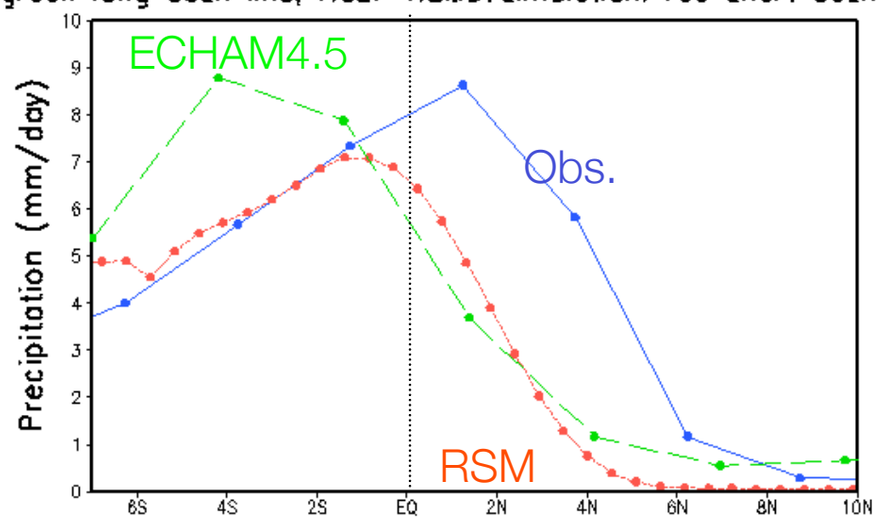
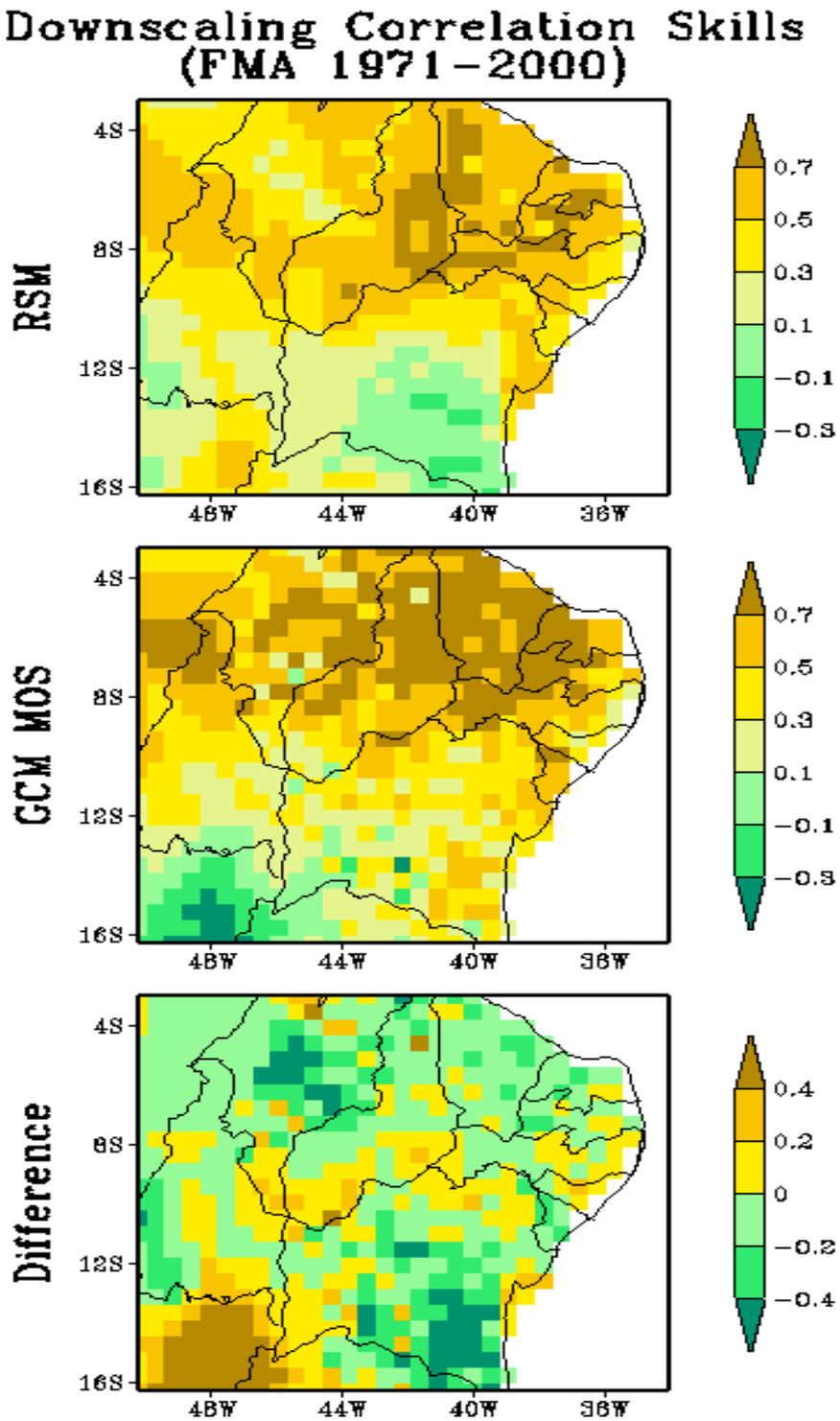


Fig. 4. Precipitation climatology for February–March–April season
longitude 35W. Observation: blue solid line; ECHAM4.5 AGCM simu
green long dash line; NCEP RSM97simulation: red short dash



L. Sun

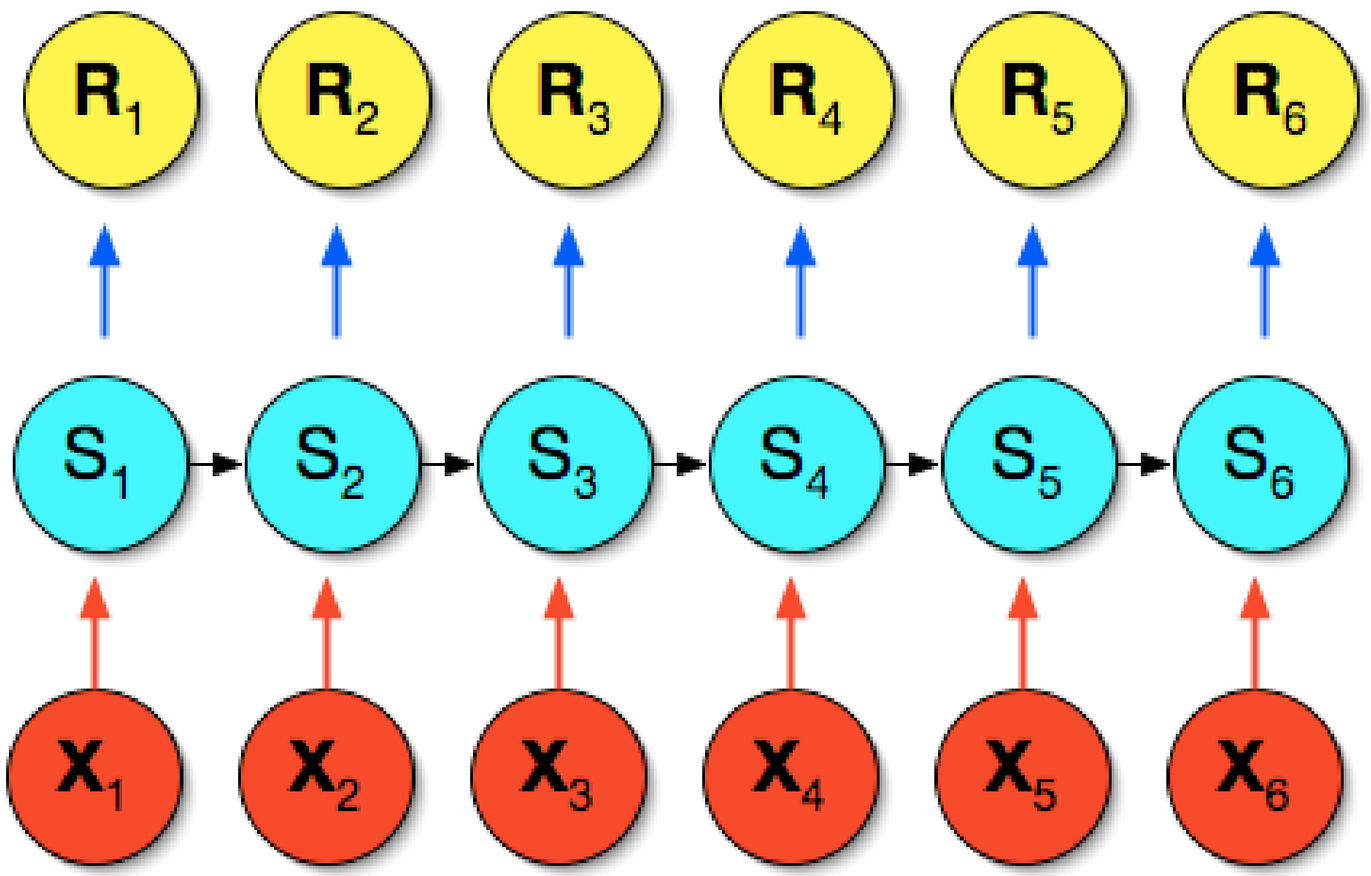


Statistical downscaling
Non-homogeneous HMM

$P(\mathbf{R}_t)$

$P(\mathbf{R}_t|S_t)$

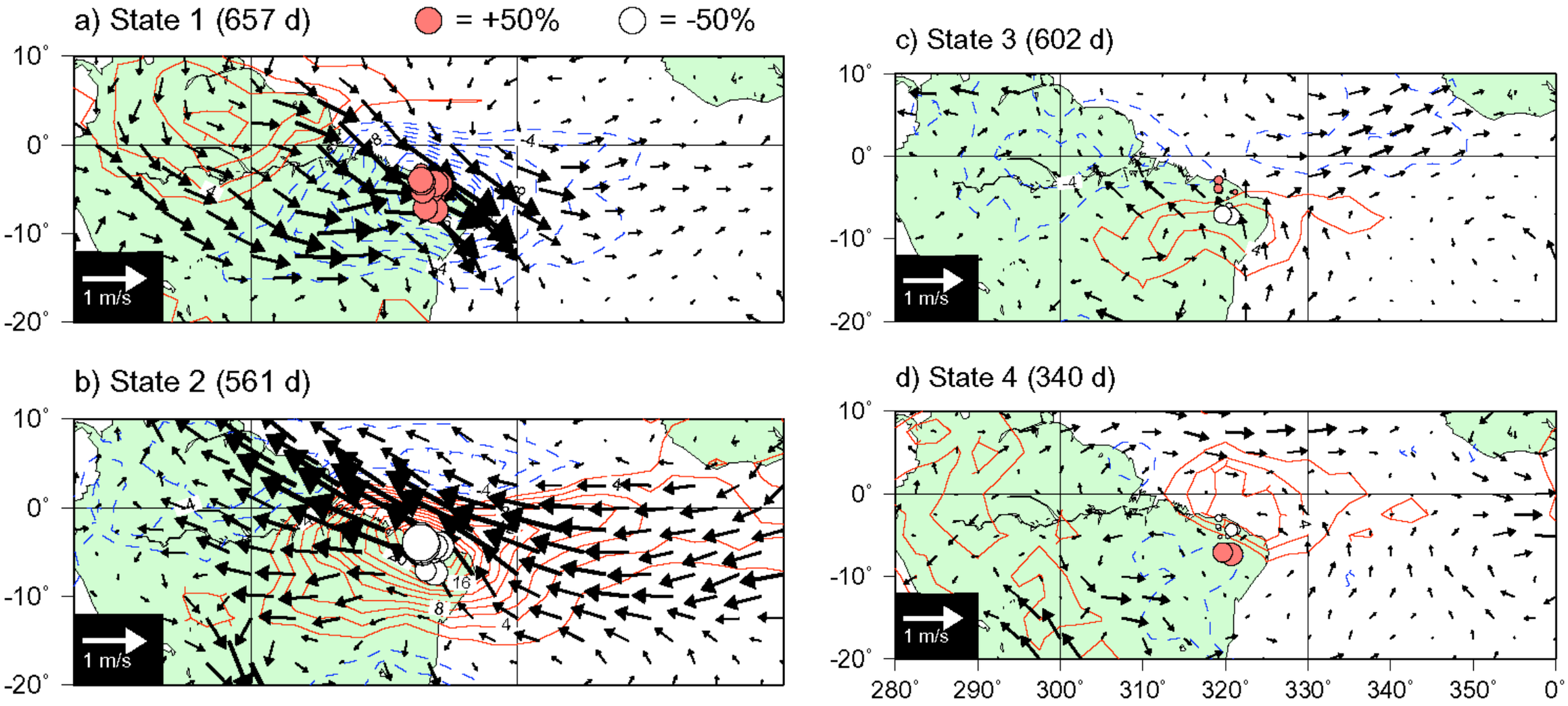
$P(S_t|S_{t-1})$



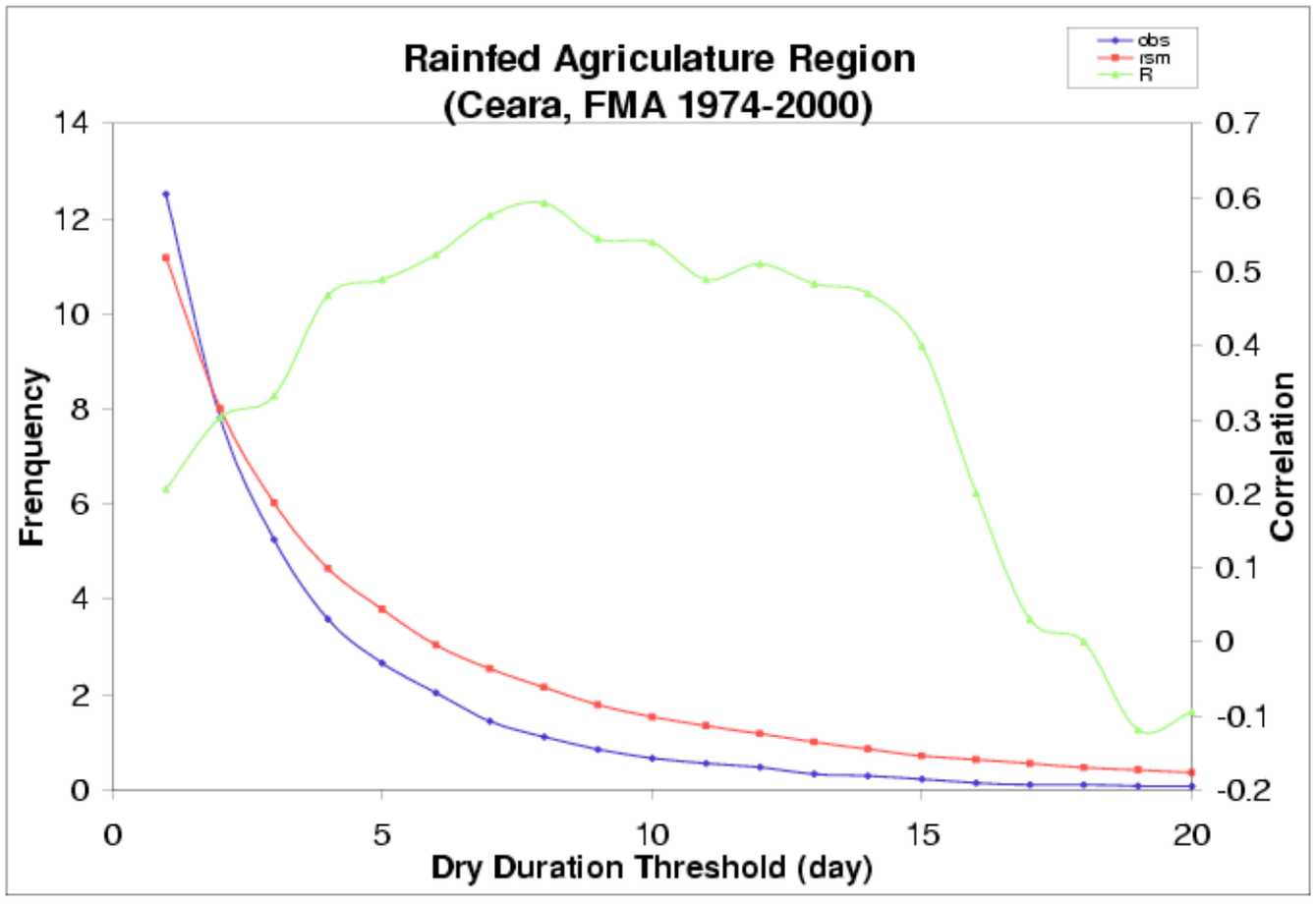
$$P(S_t|S_{1:t-1}, \mathbf{X}_{1:T}) = P(S_t|S_{t-1}, \mathbf{X}_t)$$

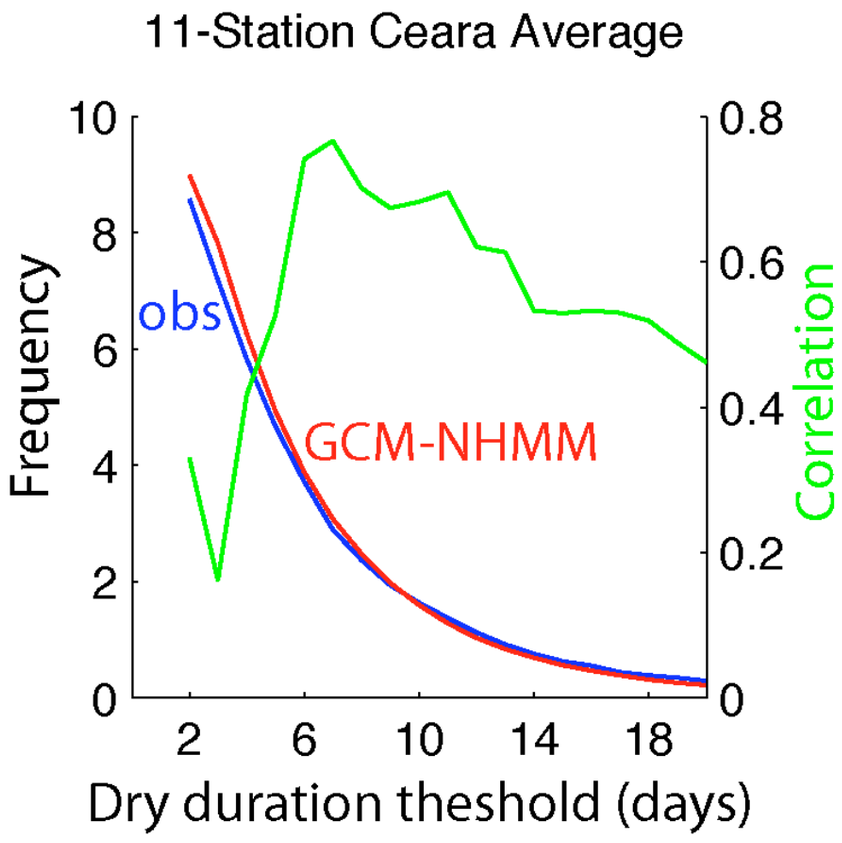
logistic regression

HMM States: Composites of 850-hPa wind and OLR Anomalies



Downscaling of Dry-Spells over NE Brazil from GCM Simulations

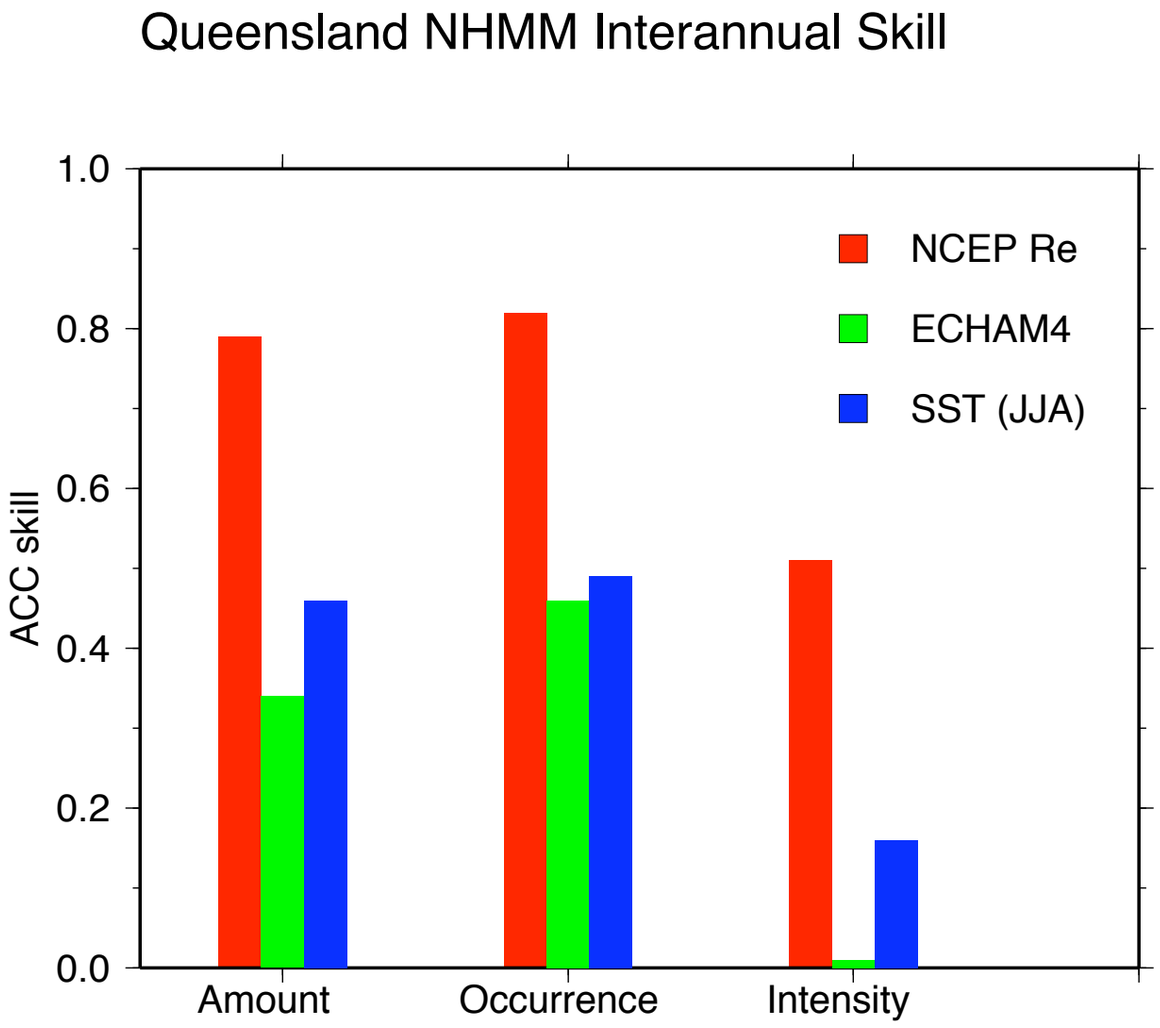


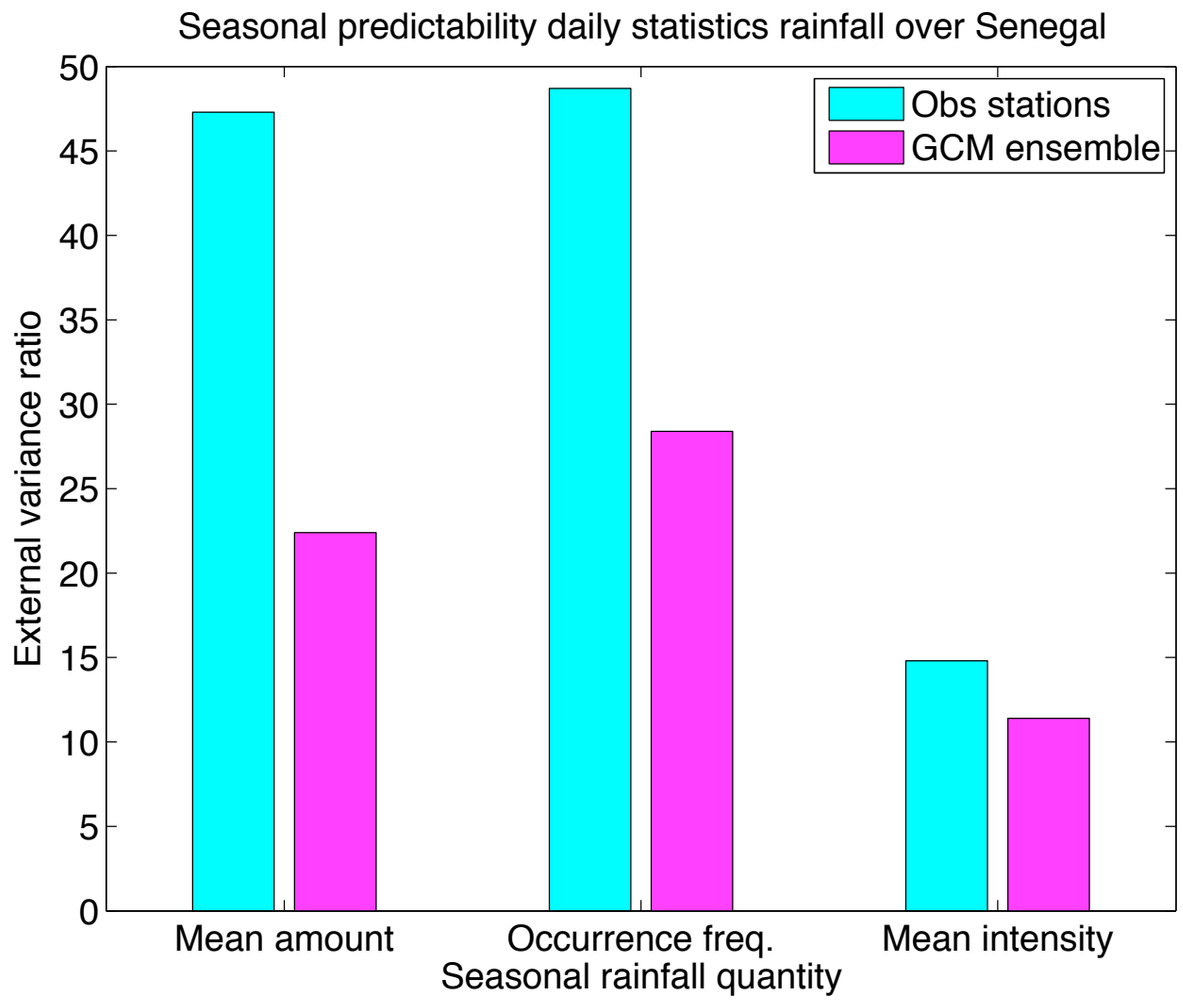


Dynamical model (RSM)

Statistical (NHMM)

seasonal predictability of daily rainfall statistics

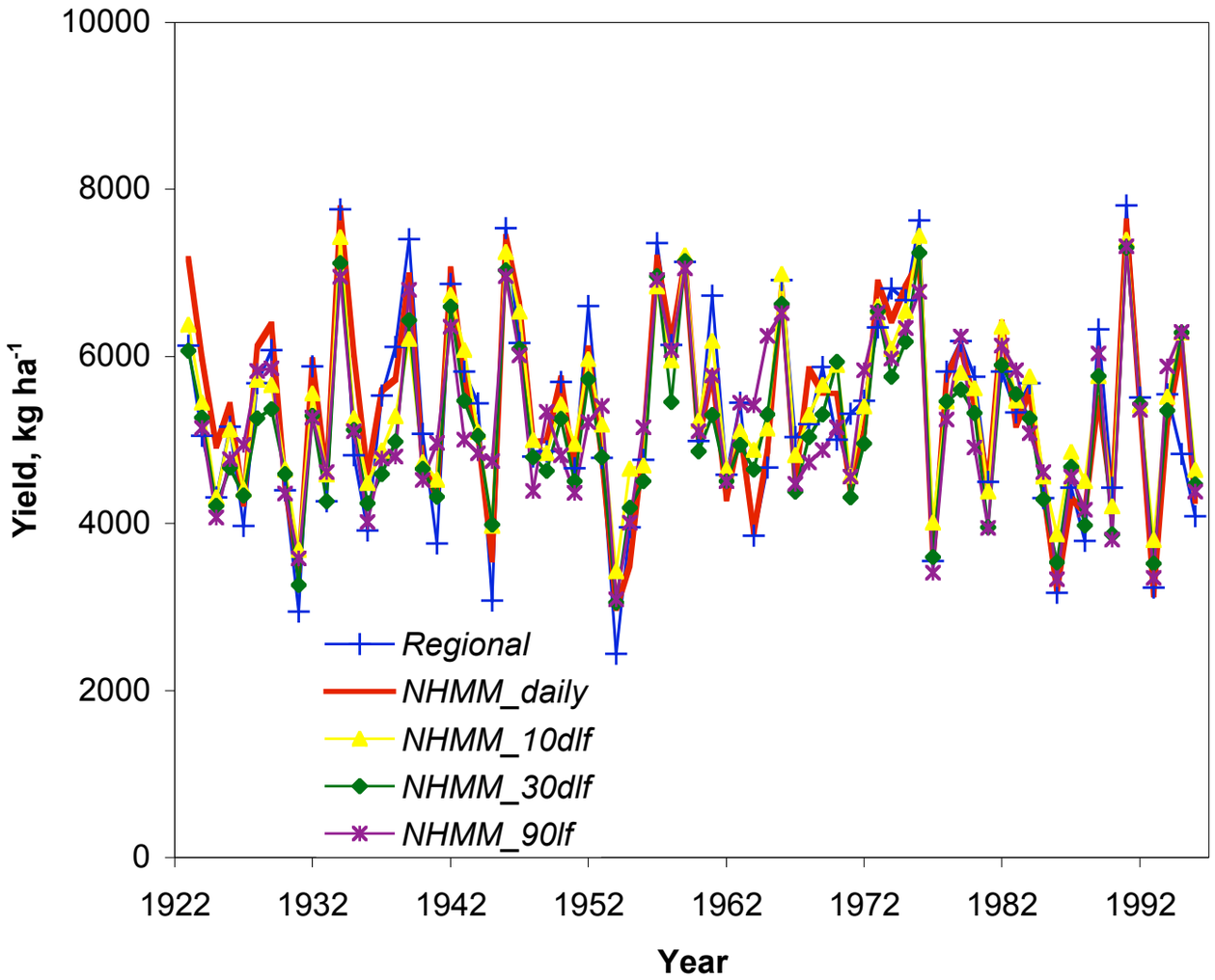




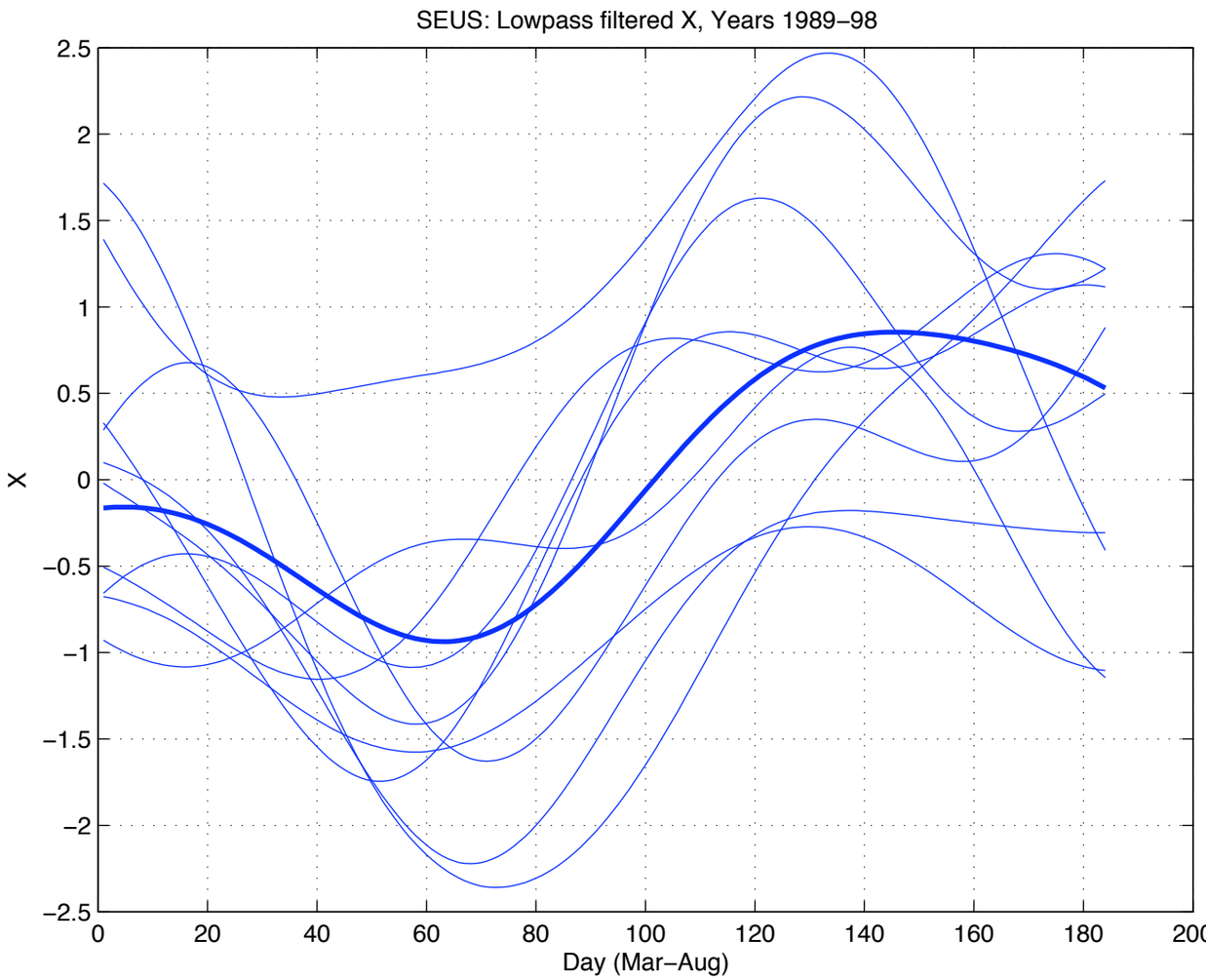
V. Moron

regional crop yield predictability

maize yields from HMM downscaling of regional rainfall



low-pass filtered regional rainfall



summary

- seasonal forecasts must be reliable to be useful
- multi-model ensembles can reduce variance and bias in GCM seasonal forecasts
- downscaling using a combination of dynamical and statistical models gives best hope of gaining improved understanding of regional climate predictability and tailoring forecasts to sectoral needs