Methods for Predicting Rainfall Impacts on Crops at a Long Lead Time

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AMMA 1st International Conference

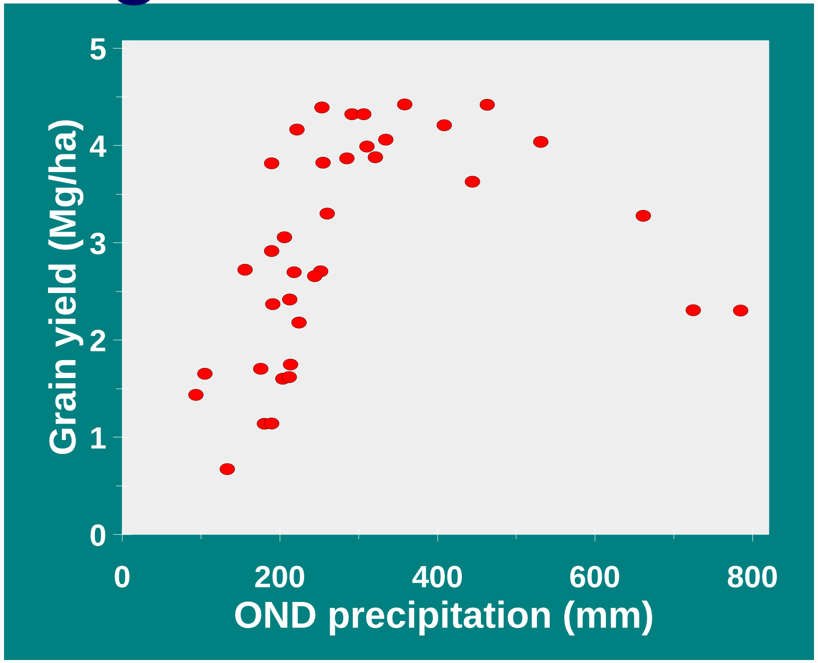
Dakar, Senegal, 1 December 2005

Motivation

- Potential to anticipate conditions, crop response early enough to adjust decisions
- Link climate forecasts with crop models for:
  - Information relevant to decisions
  - Ex-ante assessment for credibility and targeting
  - Fostering and guiding management

The Challenge

- *Nonlinearity*. Crop response to environ-ment nonlinear, non-monotonic.



The Challenge

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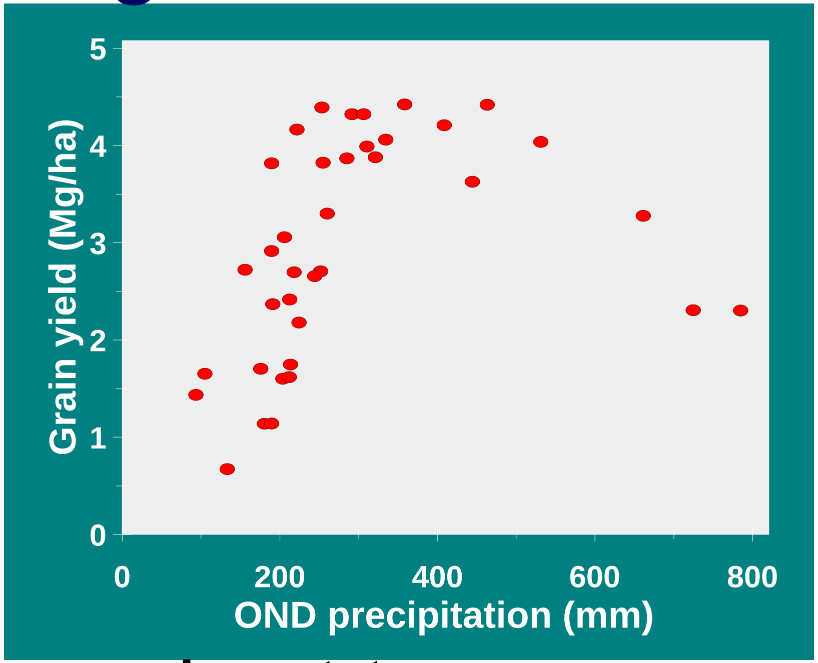
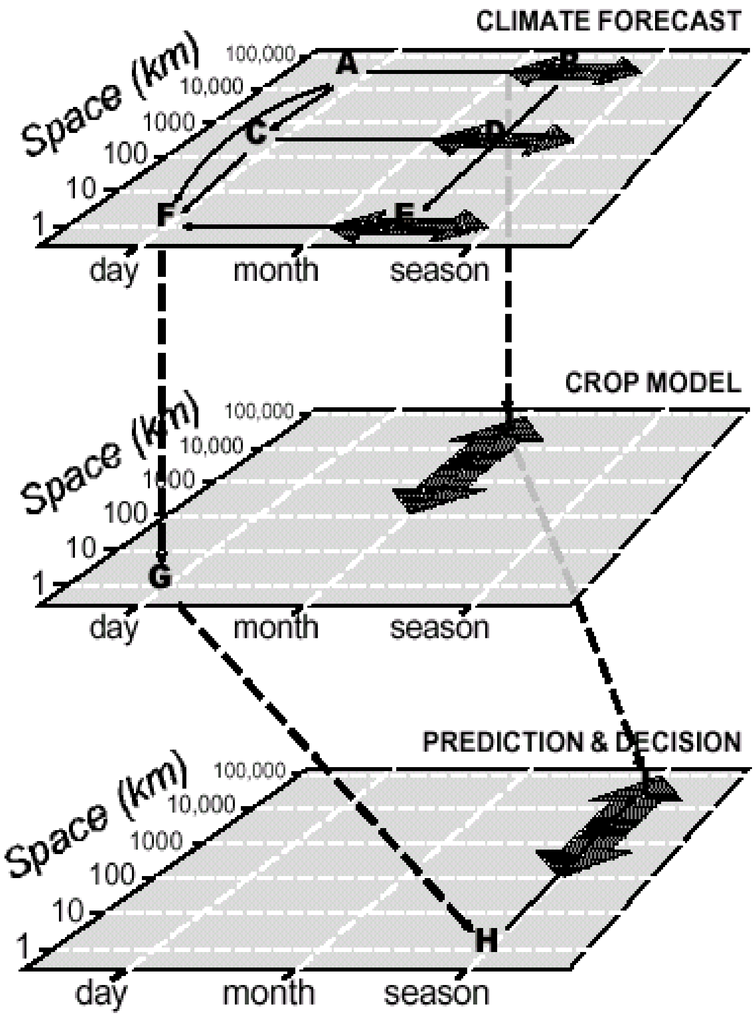


- *Dynamics*. Crops respond not to mean conditions but to dynamic interactions:
  - Soil water balance
  - Phenology

The Challenge: The Scale Mismatch Problem

- Crop models:
  - Homogeneous plot spatial scale
  - Daily time step (w.r.t. weather)
- GCMs:
  - Spatial scale 10,000-100,000 km^2
  - Sub-daily time step, BUT... Output meaningful only at (sub)seasonal scale
- Spatial averaging within GCM distorts daily variability important to crop response
- Temporal scale problem more difficult than spatial scale



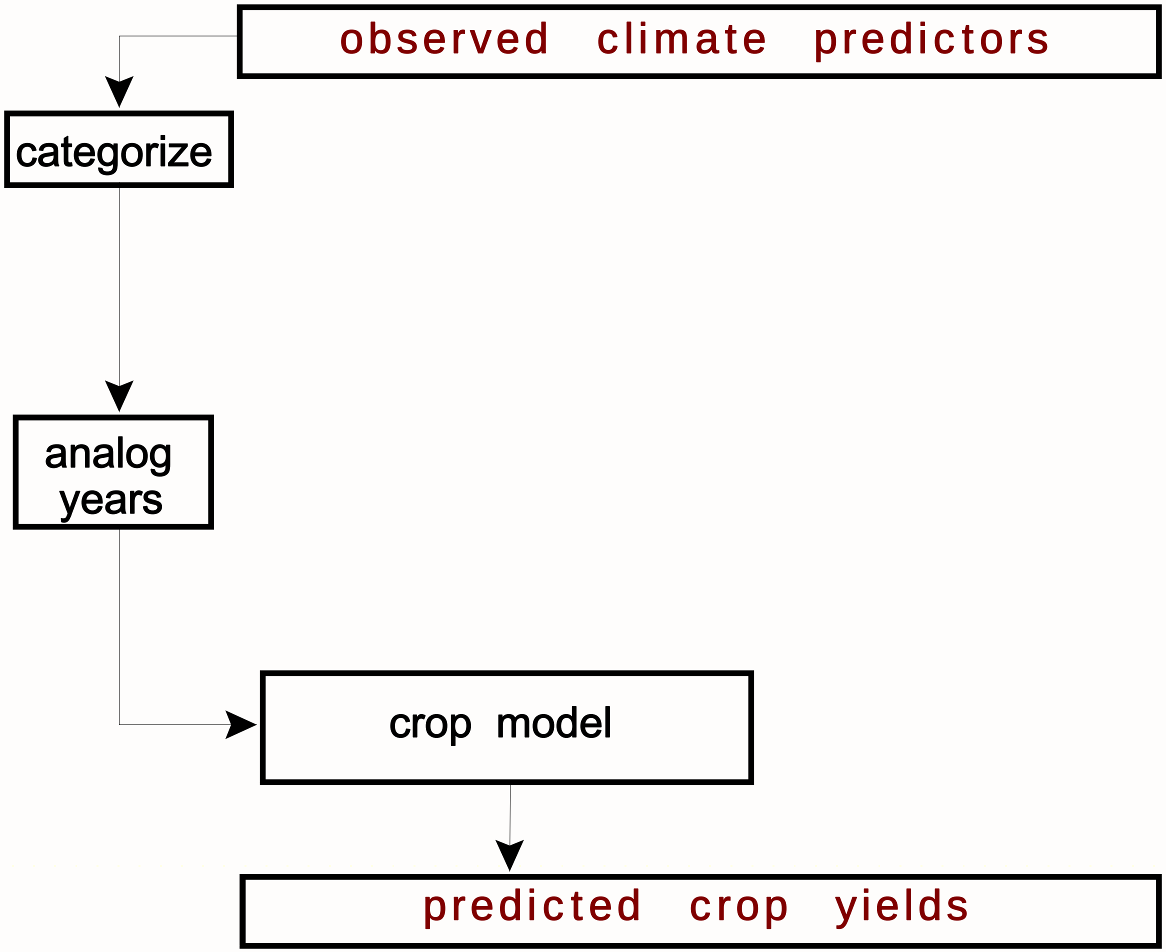
Information Pathways

observed climate predictors

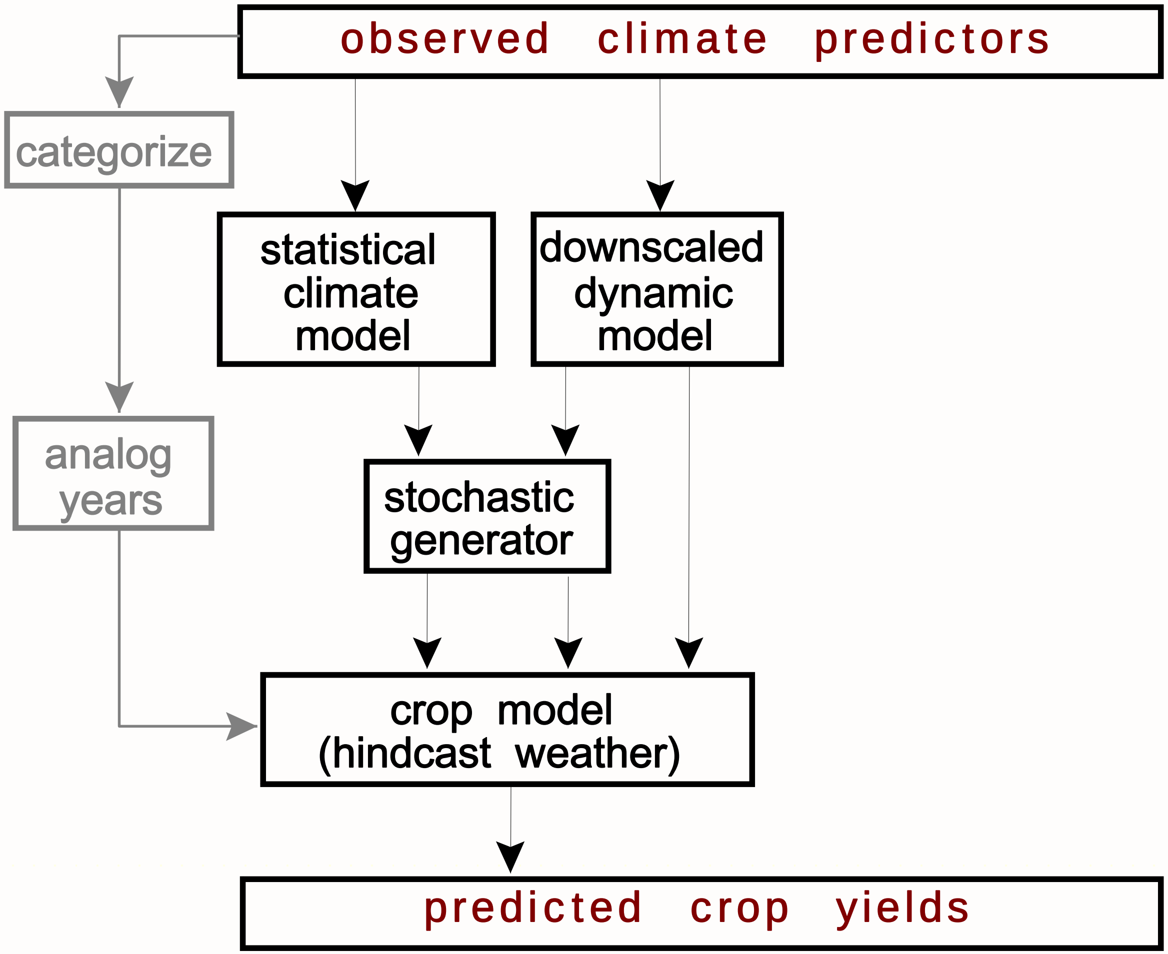
?

predicted crop yields

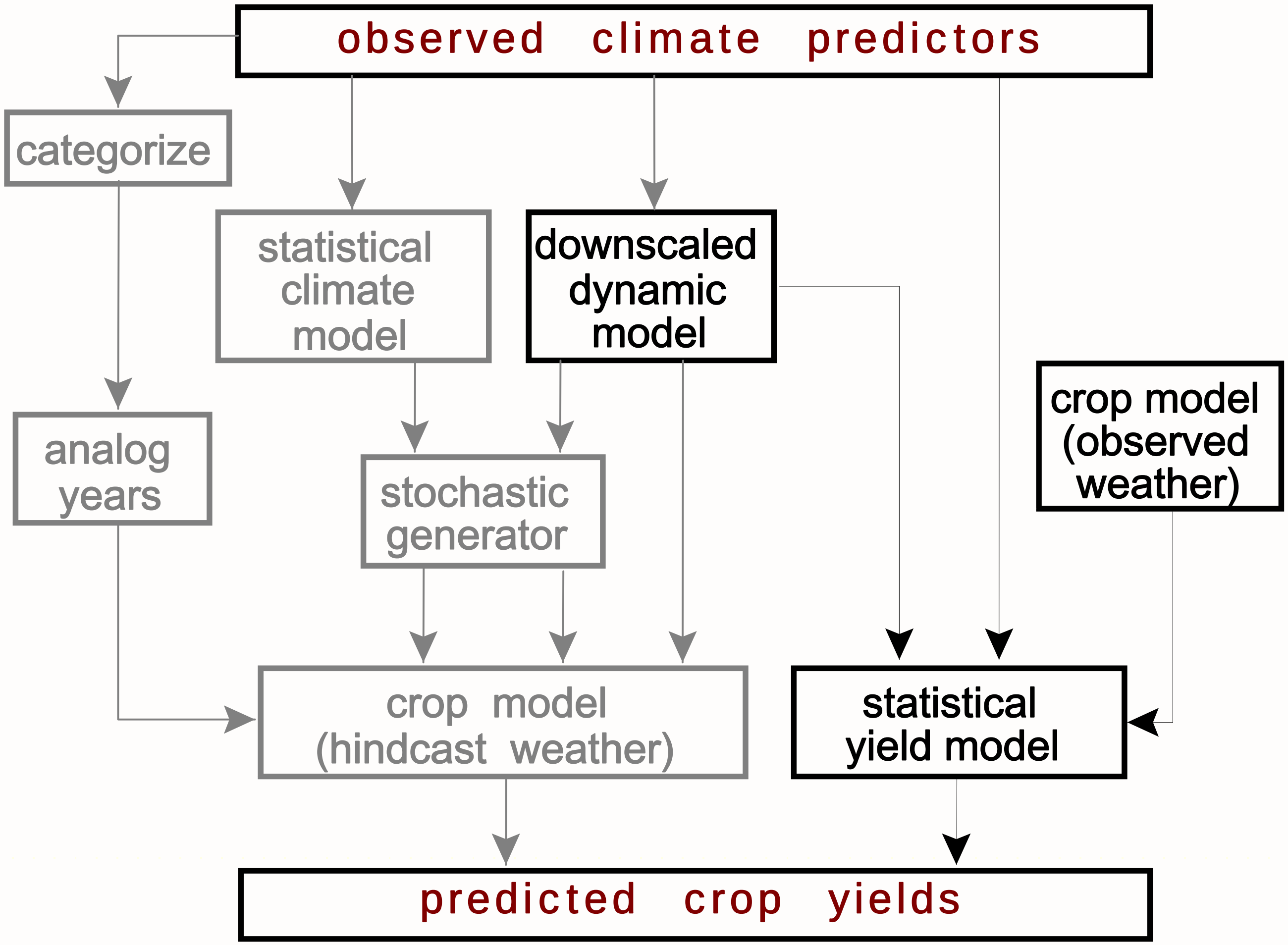
Information Pathways



Information Pathways



Information Pathways

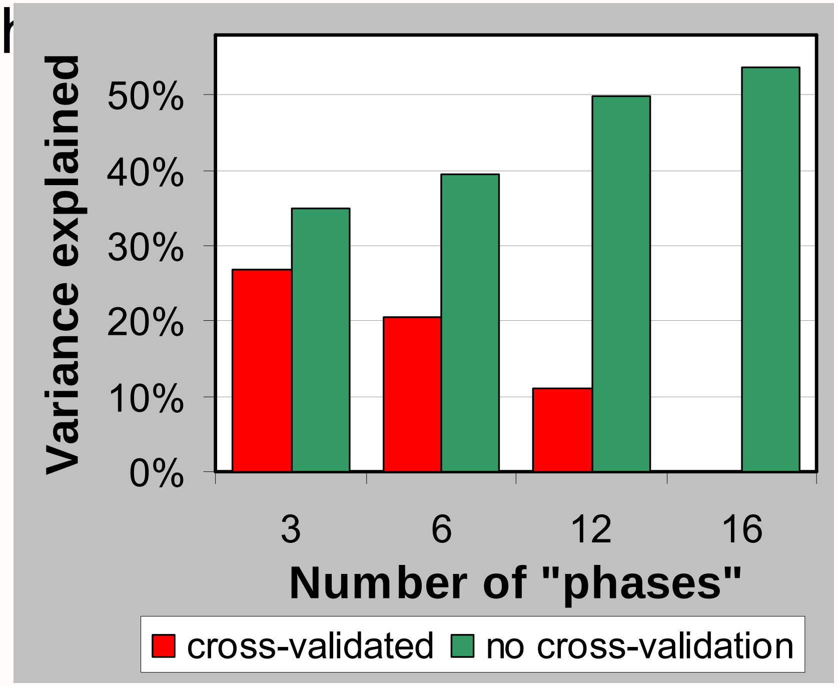


Approaches

- Classification and analog methods (e.g., ENSO phases)
- Synthetic daily weather conditioned on forecast: *stochastic disaggregation*
- (Corrected) daily climate model output
- Statistical function of simulated response

Historic Analogs

- Dominant approach
- Advantages
  - Intuitive probabilistic interpretation
  - Accounts for any differences in “signal strength”
  - May incorporate useful high
- Concerns
  - Small sample size, confidence, artificial skill
  - Are differences in distribution real?
  - How to use with dynamic prediction systems without discarding information?



Synthetic Weather Inputs

Two Approaches:

- Adjusting generator input parameters:
  - Well developed in climate change studies
  - Flexibility to produce statistics of interest
  - Assumed role of intensity vs. frequency
- Constraining generator outputs:
  - No assumptions re. frequency vs. intensity

Synthetic Weather Inputs
Option 2. Constraining generated output

- Approach:
  - Rainfall:
    - Sample stochastic month until total ≈ target
    - Multiplicative rescaling to match target
  - T, H: Additive shift

Hansen & Ines, 2005. *Agric. For. Meteorol.* 131:233-246

Synthetic Weather Inputs
Option 2. Constraining generated output

- App
  – Ra
    •
    •
  – T,

	Tifton, Georgia			Gainesville, Florida		
Scenario	R_M vs. π	R_M vs. μ_I	μ_I vs. π	R_M vs. π	R_M vs. μ_I	μ_I vs. π
Observed daily rainfall						
	0.649	0.577	-0.165	0.668	0.706	0.046
Disaggregated monthly rainfall						
constrain R_M	0.681	0.676	-0.004	0.649	0.697	0.014
condition π	0.822	0.473	0.013	0.831	0.121	0.052
condition μ_I	0.491	0.856	0.071	0.458	0.837	0.052

- Reproduces frequency-intensity correlations better than Option 1 (adjusting inputs)

Hansen & Ines, 2005. *Agric. For. Meteorol.* 131:233-246

Synthetic Weather Inputs
Option 2. Constraining generated output

- Appr
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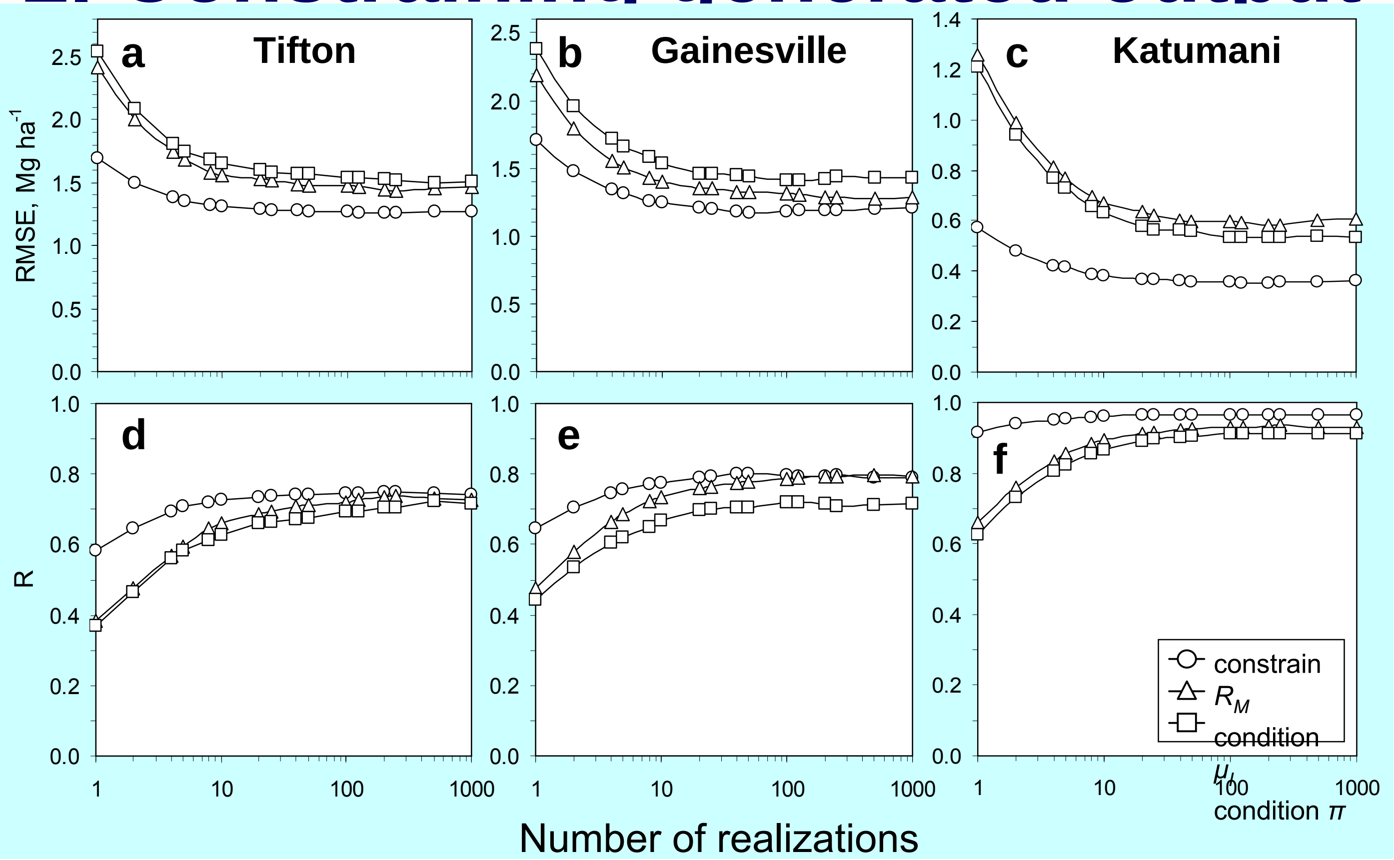
  - T, H
- Repro better



- Requires fewer replicates for given level of accuracy

Hansen & Ines, 2005. *Agric. For. Meteorol.* 131:233-246

Use of Daily Climate Model Output

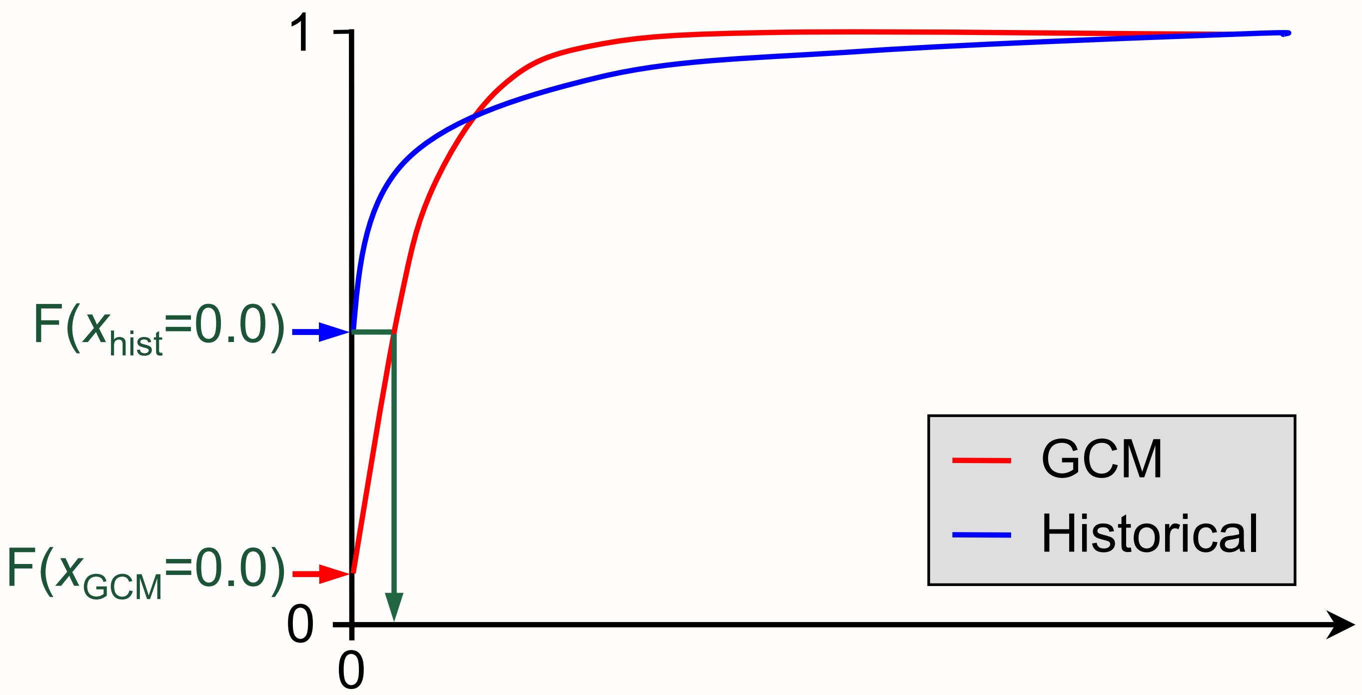
Dealing with Distortion

- Calibrate simulated yields

Challinor et al., 2005. *Tellus* 57A:198-512

- Correct GCM mean bias
  - Additive shift for temperatures
  - Multiplicative shift for rainfall
- Rainfall frequency-intensity correction

Correcting Bias in Daily GCM Output: Rainfall Frequency

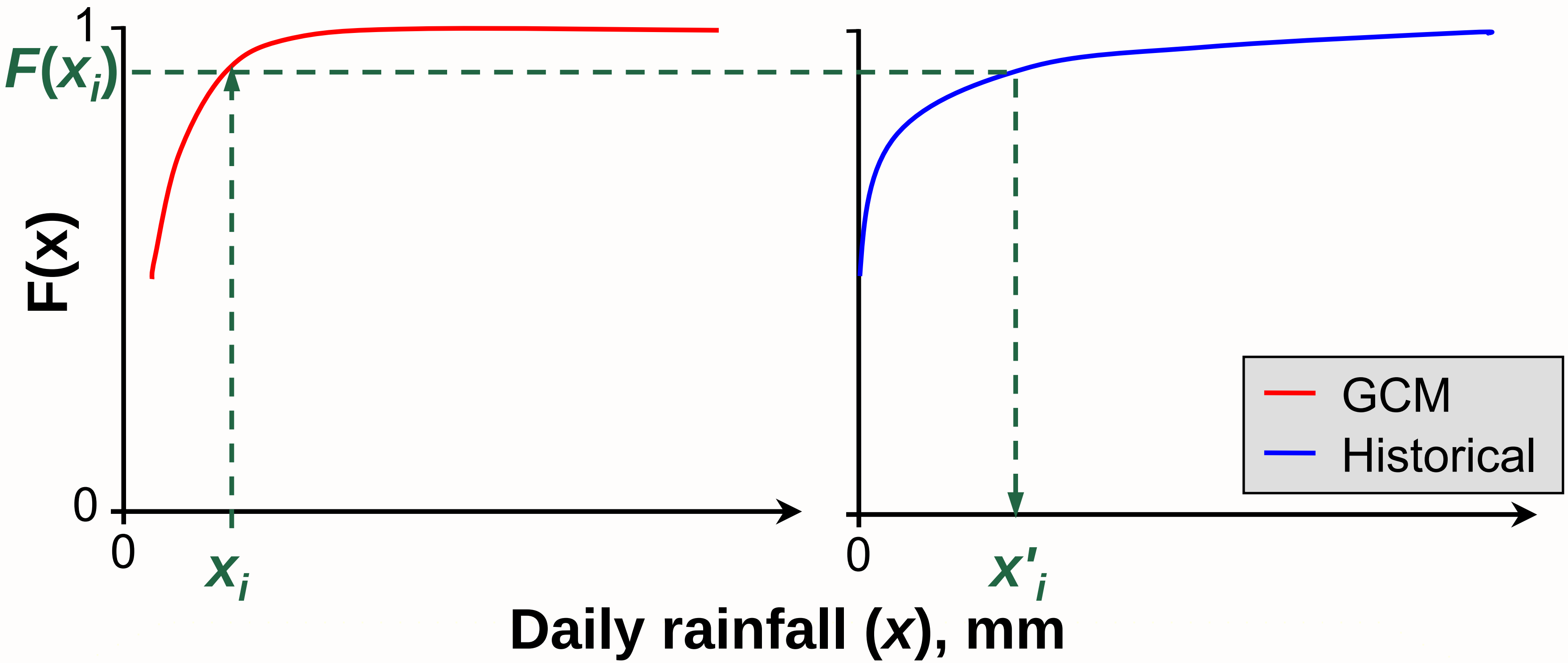


calibrated threshold

Ines & Hansen, *Agric. For. Meteorol.* submitted

Correcting Bias in Daily GCM Output: Rainfall Intensity

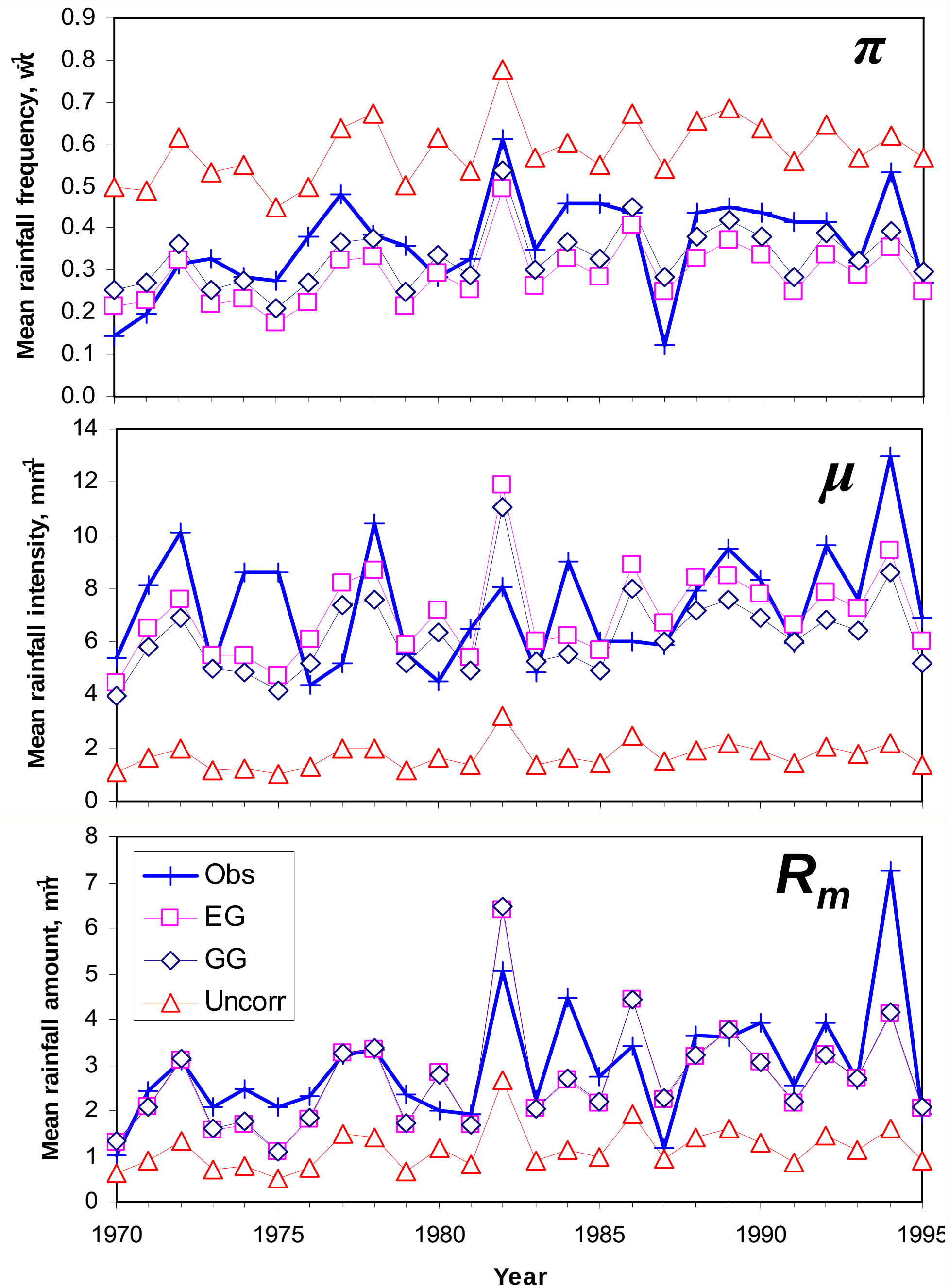
$$x_i' = F^{-1}_{obs,m}(F_{GCM,m}(x_i))$$



Ines & Hansen, *Agric. For. Meteorol.* submitted

Corrects rainfall total, frequency, intensity

- Katumani, Kenya
- ECHAM4 & observed OND daily rainfall (1970-95)
- Intensity corrections:
  - *EG*: empirical (GCM) to gamma (observed)
  - *GG*: gamma (GCM and observed)



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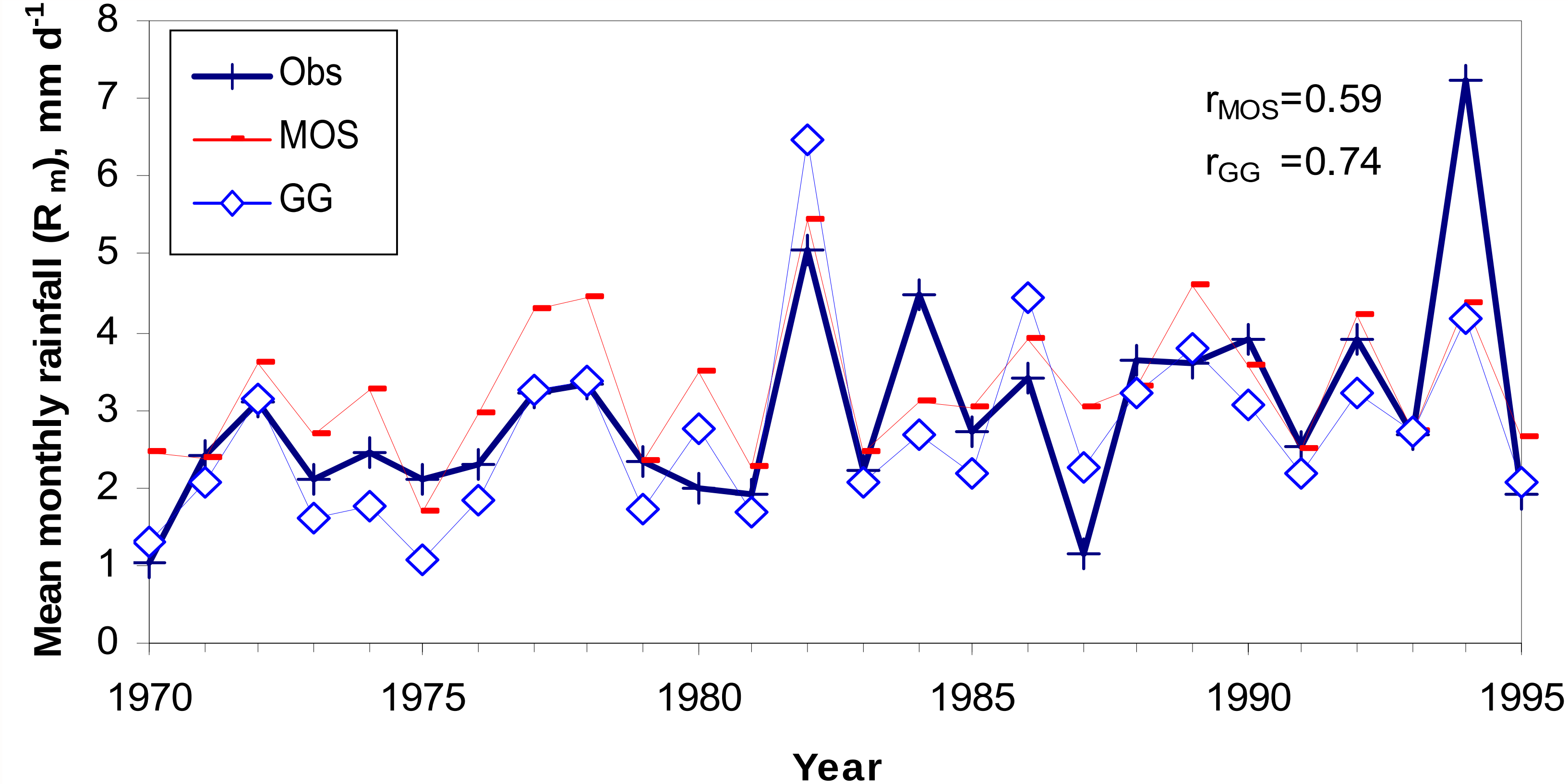
Predicts yields from GCM, perhaps better than stochastic disaggregation



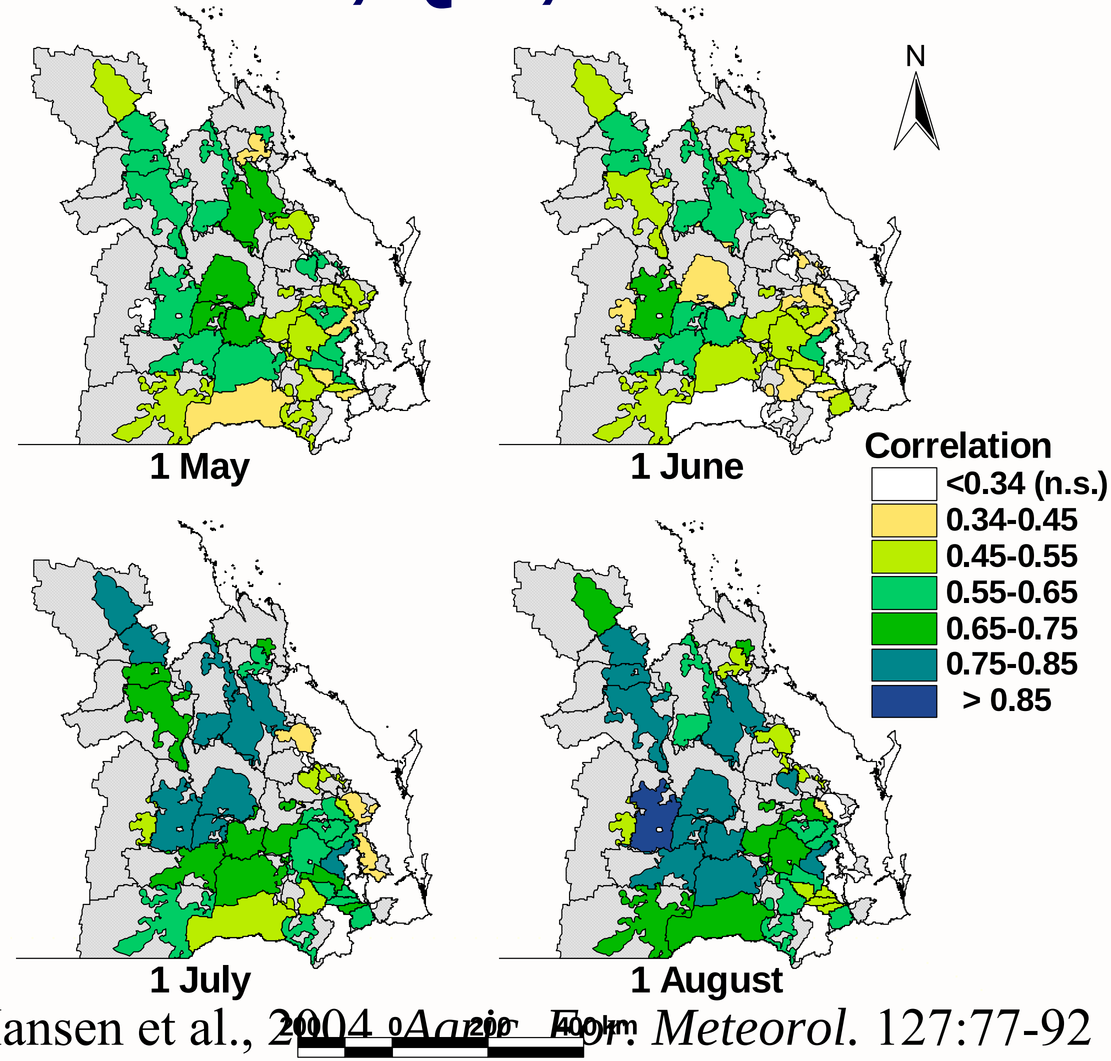
- CERES-Maize simulated with:
  - Disaggregated MOS-corrected monthly hindcasts
  - Gamma-gamma transformation of daily rainfall

Statistical Prediction of Crop Simulation

- Seasonal predictors of local climate potential predictors of crop response
- Predictand: Yields simulated with observed weather
- Eliminates need for daily weather conditioned on climate forecast
- Static relationship to seasonal predictors
- Poor statistical behavior

Linear Regression & Transformation: Regional-Scale Wheat, Qld, Australia

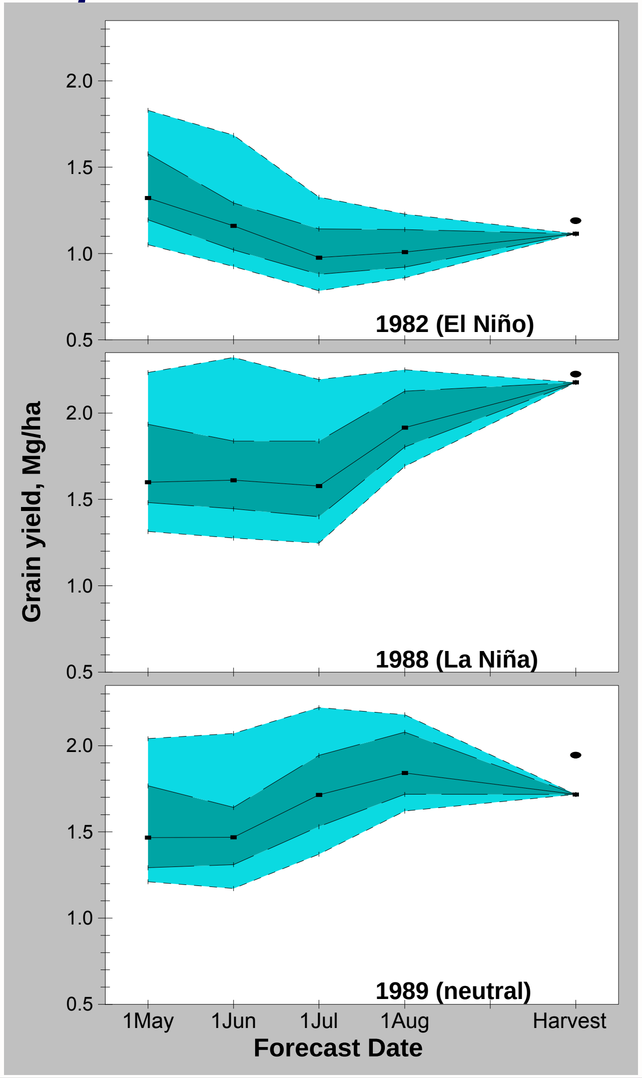
- District yield from water satisfaction index
- ECHAM4.5, persisted SSTs, optimized (MOS)
- Yield prediction by c-v linear regression
- Box-Cox transformation



Hansen et al., 2004 *Agric. For. Meteorol.* 127:77-92

Linear Regression & Transformation: Regional-Scale Wheat, Qld, Australia

- Observed rain & GCM forecast updated monthly
- Forecast distribution:
  - Regression residuals in B-C transformed space
  - *n* antecedent X *n* within-season weather years



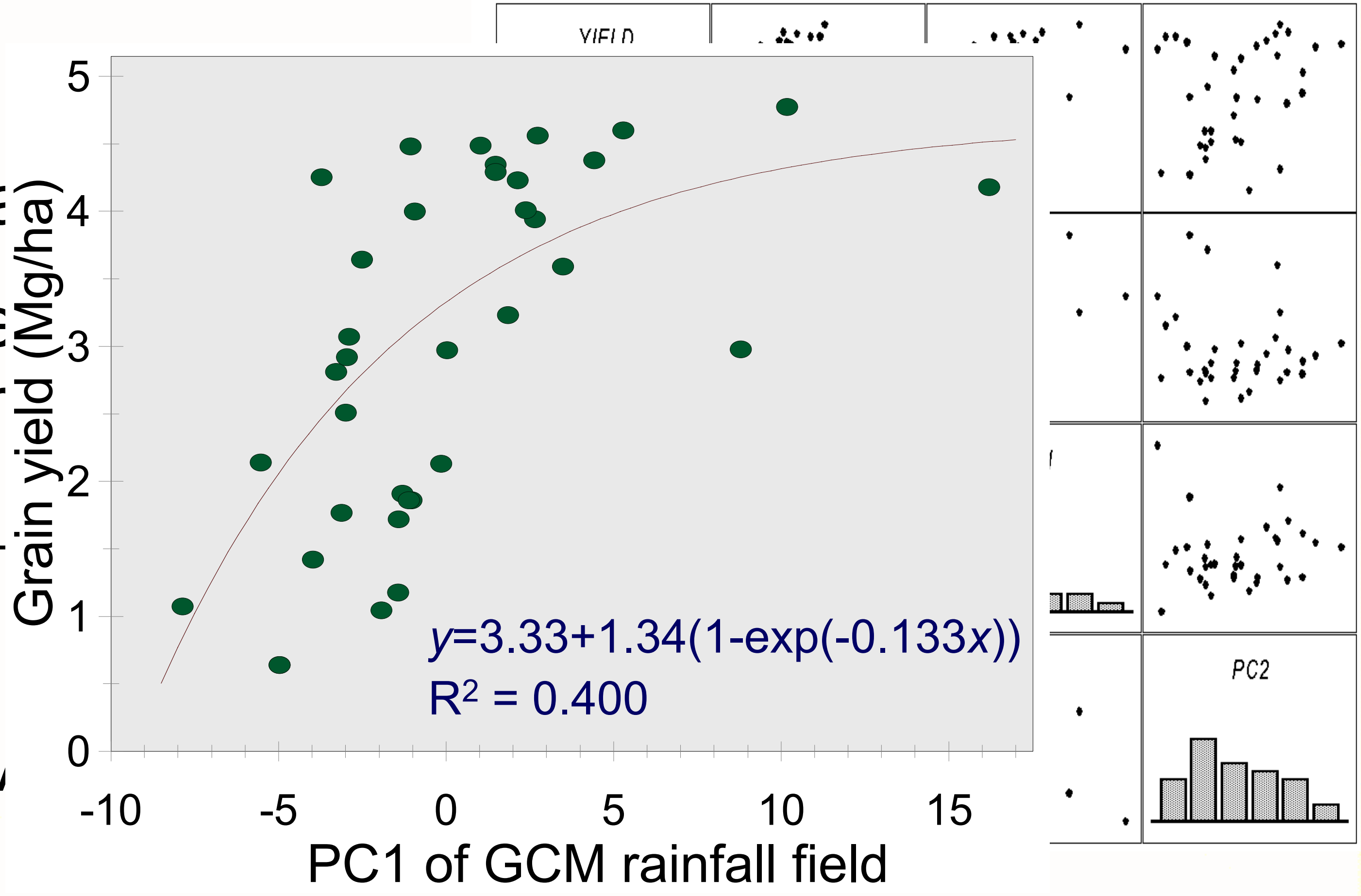
Statistical Prediction of Crop Simulation: Nonlinear Regression

Katumani maize prediction example:

- Yields a
- Mitsche functior

$$\hat{y} = a + b(1 -$$

- Cross-v



Statistical Prediction of Crop Simulation: *K* Nearest Neighbor

- Unequally-weighted analogs
- Weights *w*:
  - Based on rank distance (predictor state space)
  - Interpreted as probabilities

$$w_j = \frac{1/j}{\sum_{i=1}^{k} 1/i}$$

- Forecast $\hat{y}$ a weighted mean:

$$\hat{y}_t = \sum_{i=1, i \neq t}^{n} w_i y_i$$

- Optimize *k*
- A non-parametric regression

Future Opportunities & Challenges

- Expand evaluation of alternative methods
- Embed crop models within climate models
- Enhance use of remote sensing and spatial data
- New avenues of climate prediction research – *“weather within climate”*


THANK YOU