Institute for Atmospheric Science

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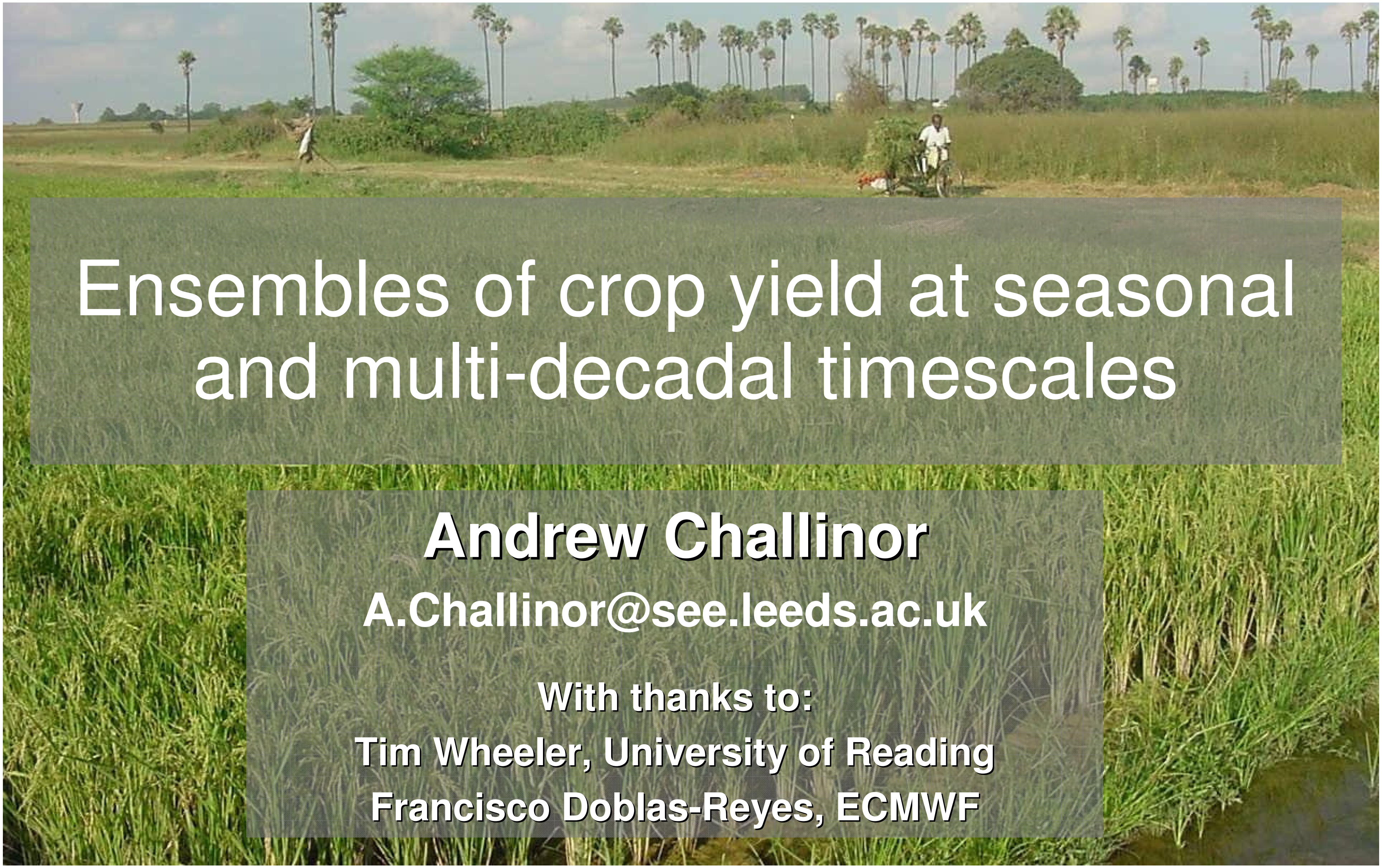

Ensembles of crop yield at seasonal and multi-decadal timescales

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With thanks to:

Tim Wheeler, University of Reading

Francisco Doblas-Reyes, ECMWF

Menu

1. Seasonal forecasting of crop yield
   - Bias correction, calibration and multi-model ensembles
   - Inverted ROC curves
   - ‘Applications’ as a measure of skill

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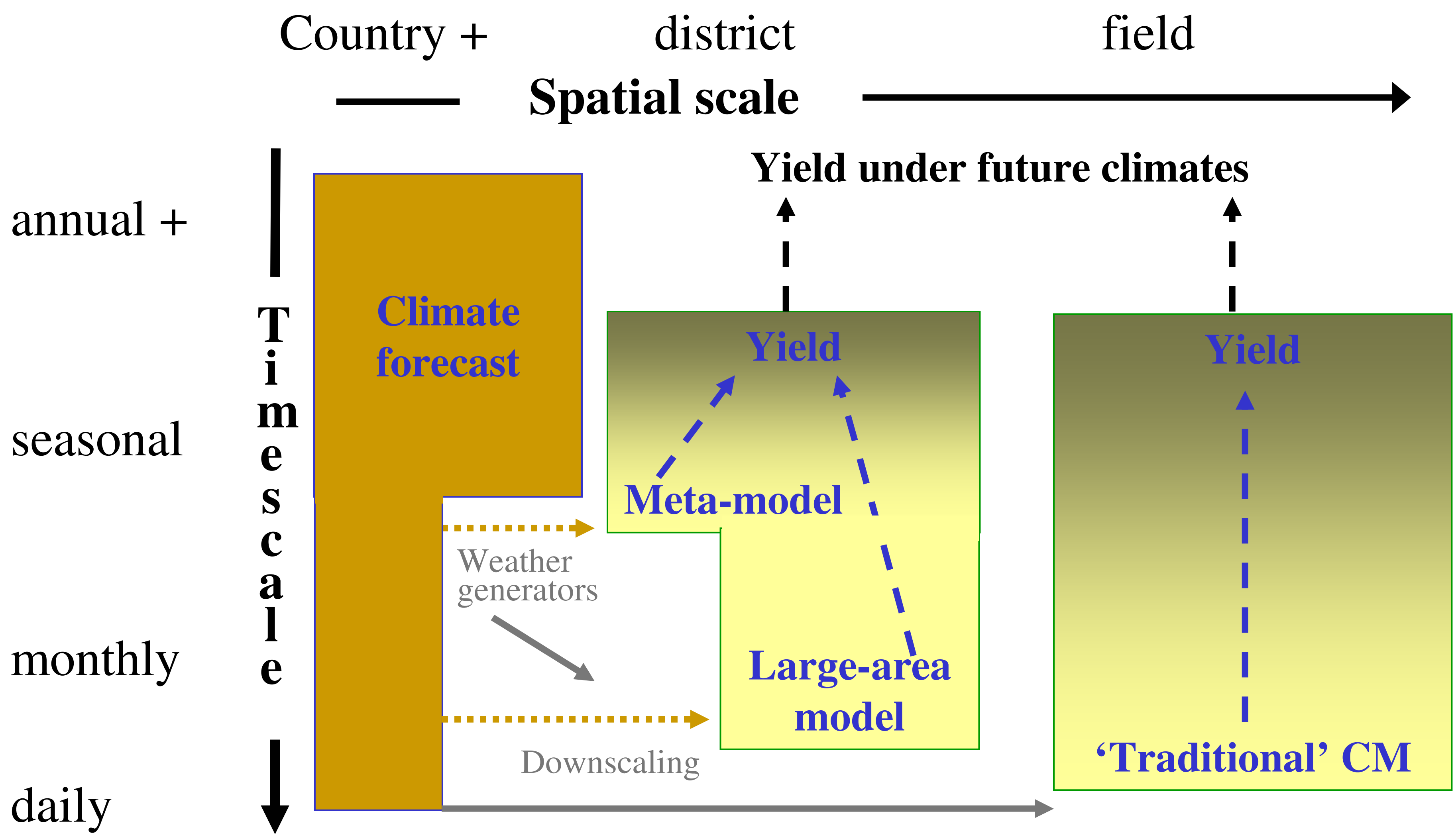
2. Climate change
   - Relevance to seasonal forecasting
   - An ensemble of crop yield simulations for doubled CO2

Combining crop and climate models



Seasonal forecasting of crop yield using the DEMETER hindcasts

- Multi-model ensemble: 7 (models) * 9 ensemble members

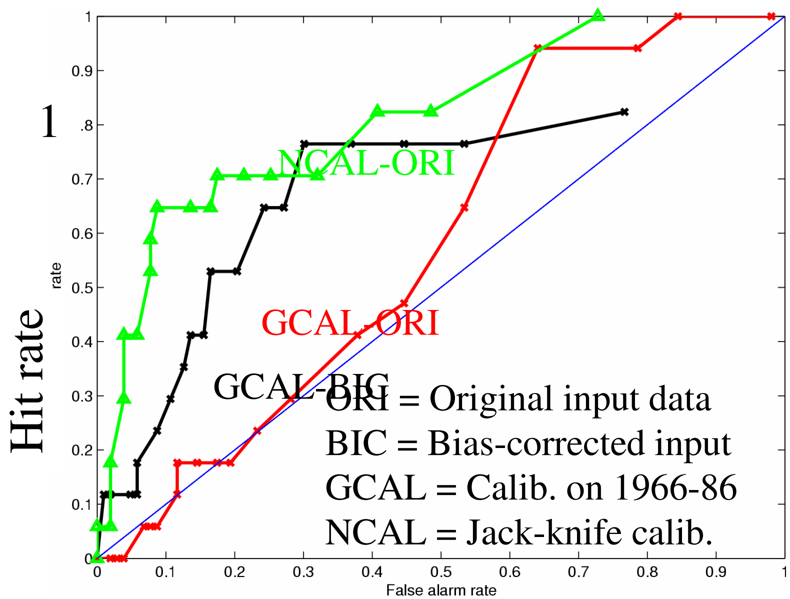
- Run each seasonal hindcast realisation through GLAM to create an ensemble of crop yields

- Try various bias-correction and calibration options

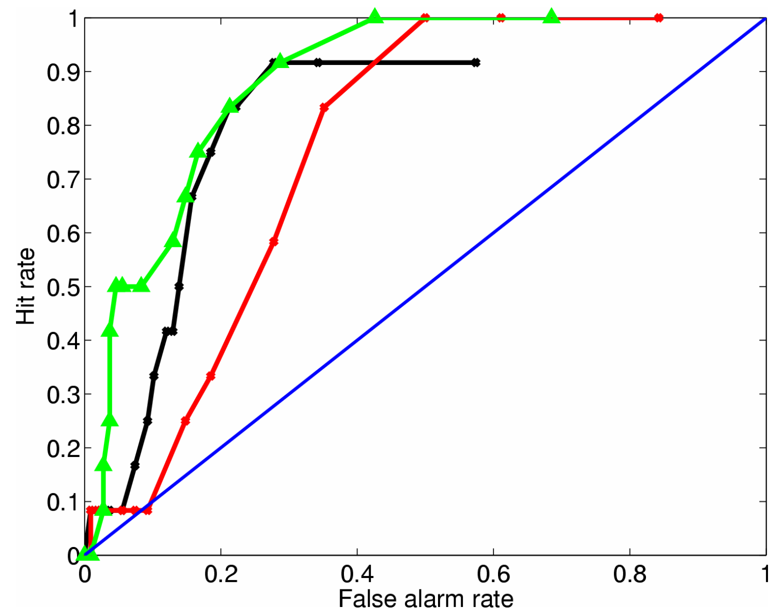
Challinor, A. J., J. M. Slingo, T. R. Wheeler and F. J. Doblas-Reyes (2005). Probabilistic hindcasts of crop yield over western India. Tellus 57A 498-512.

Probabilistic forecasting of crop failure: ROC curves

Failure: Y<500kg/ha (Rao et al. 2000)



Y<400kg/ha



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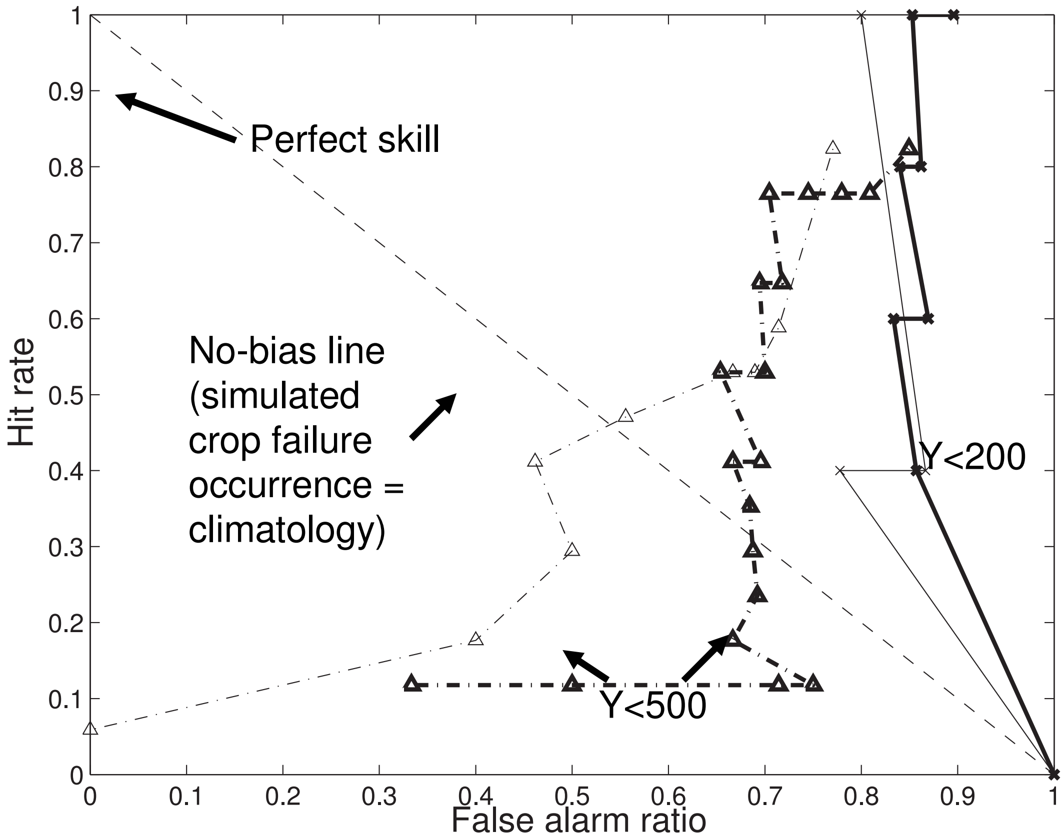
- N 0 AL an False alarm rate skillful 1
- BIC tends to perform less well than NCAL; some failures never simulated by BIC

Hit rate = POD = H/(H+M)

False alarm rate = FA/(FA+CR)

Challinor, A. J., J. M. Slingo, T. R. Wheeler and F. J. Doblas-Reyes (2005). Probabilistic hindcasts of crop yield over western India. Tellus 57A 498-512.

Inverted ROC curves



Thin lines show multi-model ensemble;
Thick show single-model ensemble

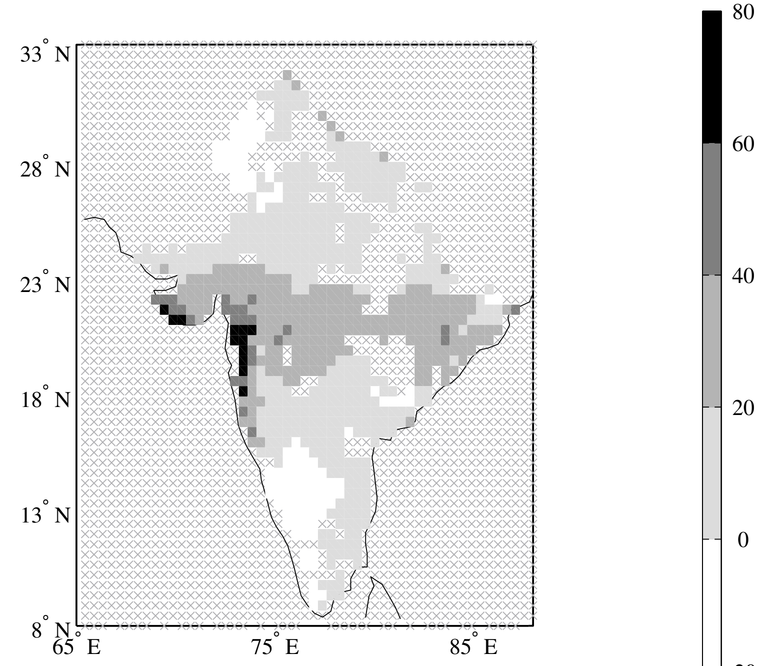
- Cannot directly compare the predictability of Y<500 with Y<400, as they occur with different frequencies (Lalaurette, 2004)
- =>IROC: as ROC, but false alarm ratio on the x-axis.
- As with the ROC curve, skill is greater when the area under the curve is greater.

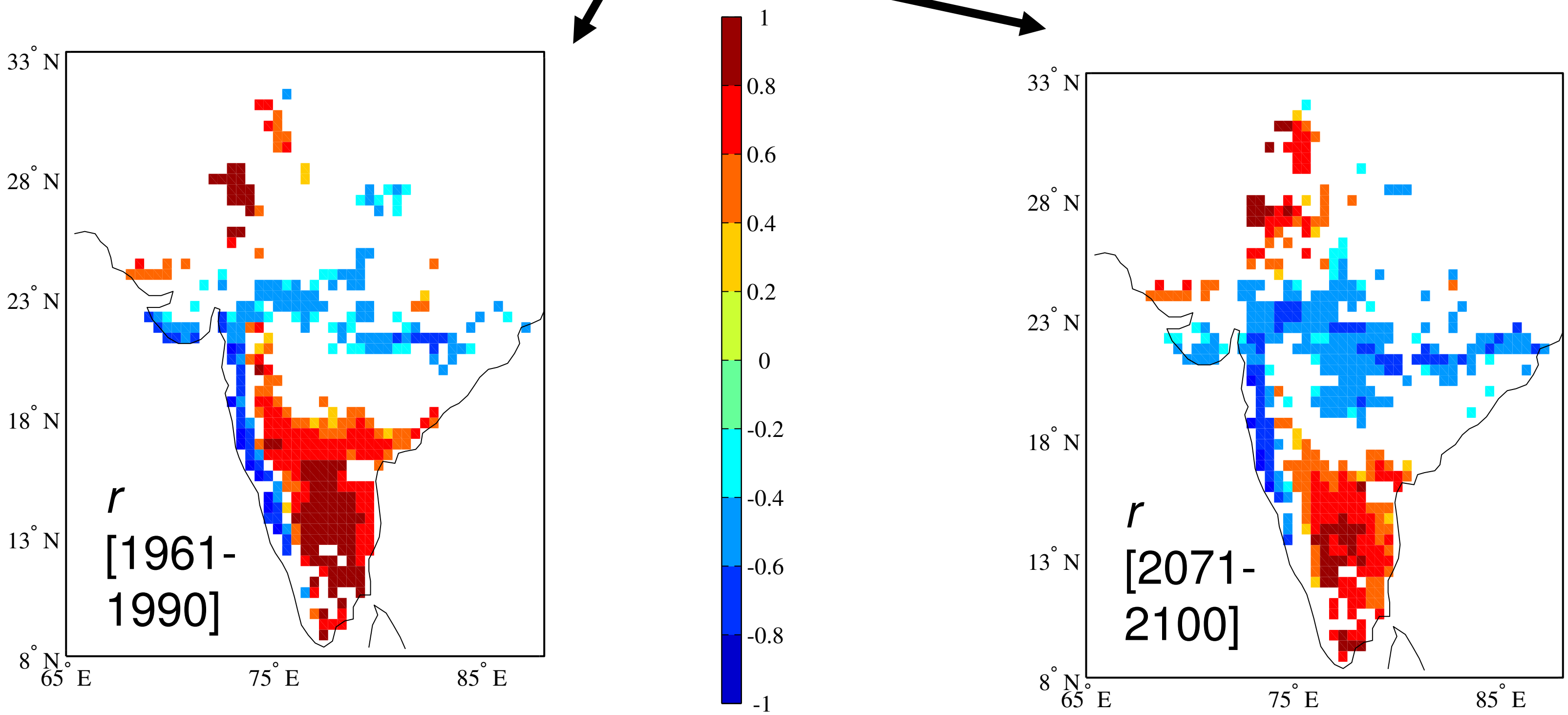
Yield is another metric of SF skill

From Hansen, J., A. J. Challinor, A. Ines, T. R. Wheeler and V. Moron (2006). Translating climate forecasts into agricultural terms: advances and challenges. Climate Research, 33 (3) 27-41.

Non-linearity between climate and derived variables

Changes in rainfall will change the mean and the variability of yield, as well as the nature of the relationship between yield and rainfall





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Seasonal forecasting as a testbed for climate change

SF is relevant to climate change studies:

- Evaluating applications models
- Some commonality/similarity in methods
  - Quantification of uncertainty (e.g. multi-model ensembles)
  - Communication of uncertainty and probabilities
  - Down/up scaling

Seasonal forecasting in a changing climate

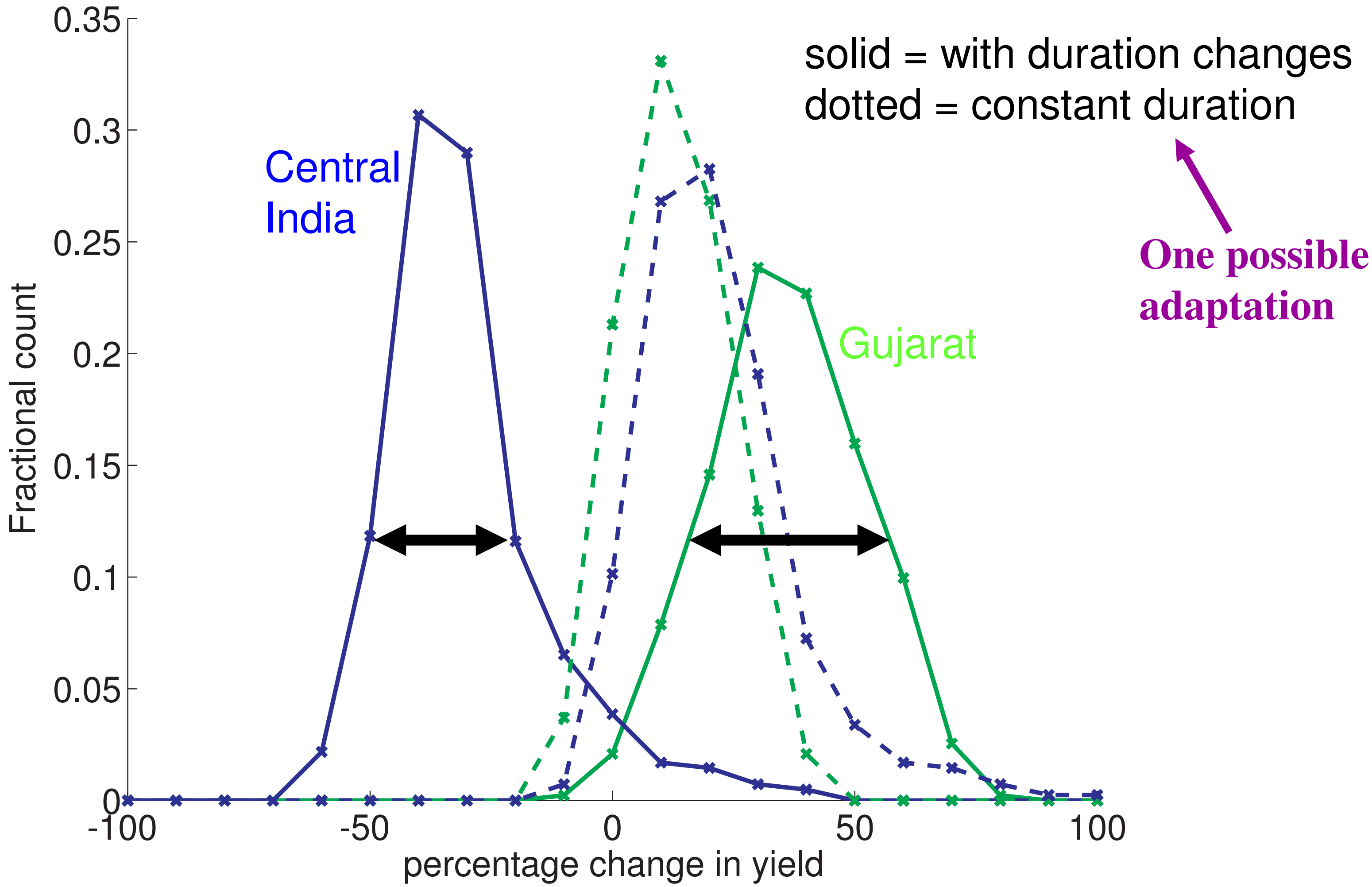
What is the relevance of climate change for SF?

- ‘Taking the shorter route’
- But climate change is not just a 2100+ problem
  - We need to capture changes in interannual variability associated with climate change
  - Means are also important
    - Signal already seen in agricultural yield; CO_2 and warming roughly cancel (Lobel and Field, 2007)
    - Adaptation will mean likely changes in crop variety
- Opportunities associated with climate change (cf Oxfam)
- As ‘climate change processes’ become increasingly important
  - $2*CO_2$ to look at processes (and projections of impacts)
  - Shorter timescales, where uncertainty is less, to look at prediction

An ensemble of crop yield simulations for doubled CO_2

- Run GLAM 2.0 using
  - One baseline climate scenario (PRECIS)
  - 28 parameter sets, varying the response of leaves, biomass and transpiration to elevated CO2
- Compare simulated yields, water-use and LAI to FACE and controlled environment data
  - 18 ensemble members produced realistic results
- Run future climate scenario (A2 2071-2100) with only those 18 members and examine output
- Identify key processes and associated uncertainties
- Sensitivity tests on DSSAT and Qnut models to assess level of consensus on these processes and uncertainties

Quantifying uncertainty for prediction and adaptation



Interaction between water stress and assimilation

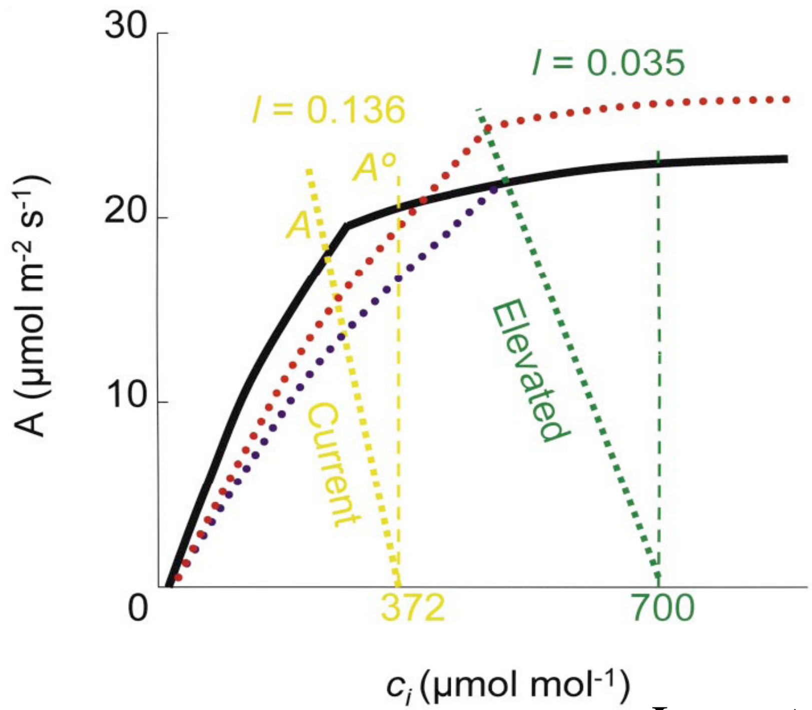
Standard wisdom:

"Droughted plants take better advantage of high CO_2 because they are at a point in the photosynthesis curve that is more CO2-sensitive." (TAR WGII)

What do:

- Models
- FACE

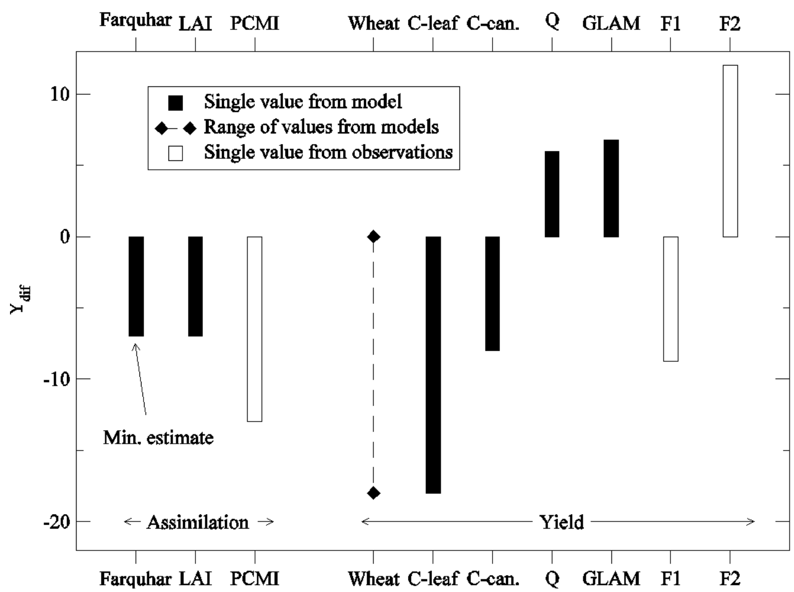
say?



Long, et al., 2004

Interaction between water stress and assimilation

y: yield change for well-watered crop (%) minus yield change for stressed crop (%)
x-axis shows, roughly, increasing level of organisation from left to right



Key result

Effect of elevated CO_2 on stressed versus irrigated crops:

- Leaf-level: greater benefit for stressed crops
- Canopy-level: greater benefit for irrigated crops?
  - But FACE inconclusive
- Implications for rainfed vs irrigated agriculture

Conclusions

Need to account for:

- The emerging impacts of climate change
  - CO_2 fertilisation and interaction with water stress
  - Changes in mean temperature
  - Incidence of heat stress events
- The effect of adaptation, and other social and management factors
- Errors in observations and simulations – Bayesian framework?

Conclusions

To do this we need:

- Robust process-based applications models
  - Note usefulness of upscaled applications models, especially as computer power and resolution increase
- Data for calibration and evaluation of application models
- Consensus on calibration techniques for application models?
  - Probably quite application/model dependent, so we should avoid being too prescriptive.
  - e.g. GLAM has a simple process-based calibration parameter that can correct some bias in mean rainfall