

Climate variability, climate change, and food security: the role of more targeted seasonal climate forecasting – opportunities and challenges

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Climate variability, climate change, and food security: the role of more targeted seasonal climate forecasting – opportunities and challenges

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GRDC

Grains
Research &
Development
Corporation



Grains Research
UPDATE



International conference on 'FOOD, WATER, ENERGY Nexus in Arena of Climate Change' Anand Agricultural University, Anand (India) 14-16 October, 2016.



ECOM

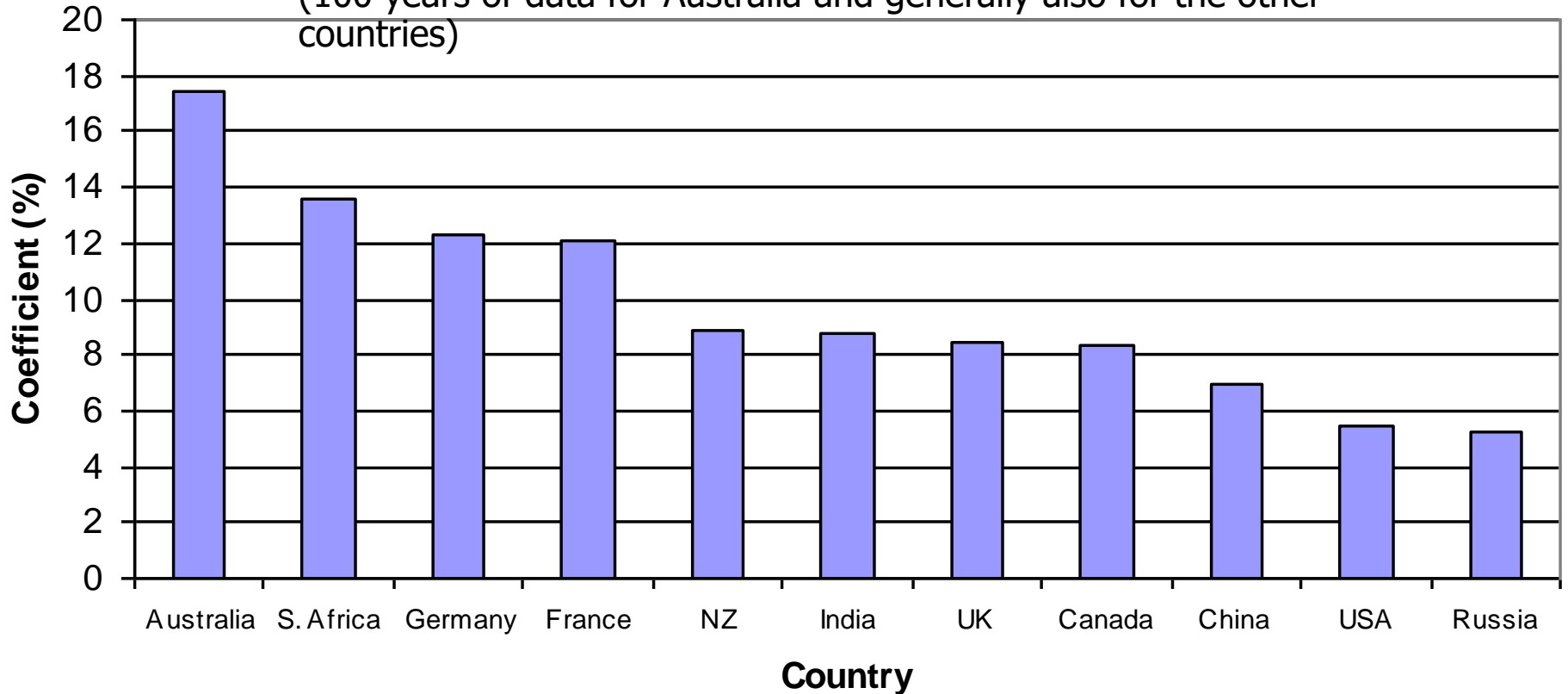


Research
International Centre for
Applied Climate Sciences

The world's highest levels of year-to-year rainfall variability

Variability of Annual rainfall

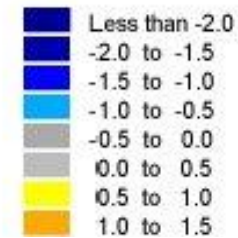
(100 years of data for Australia and generally also for the other countries)



(Love, 2005)

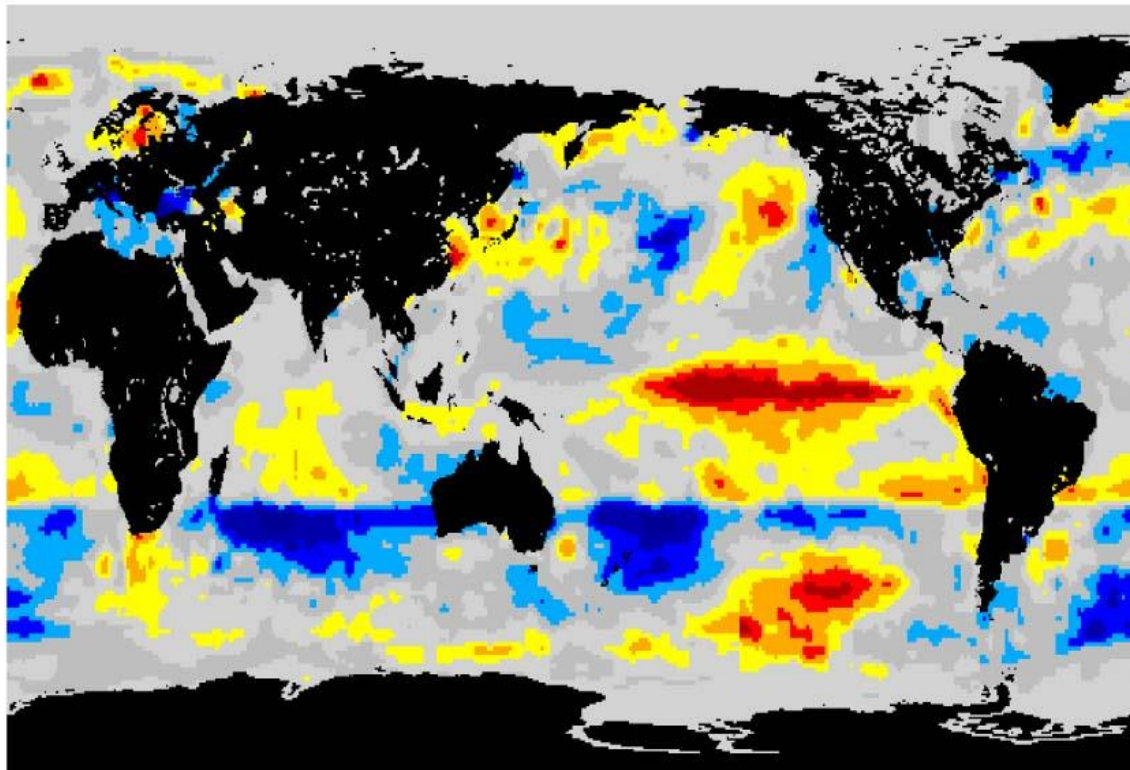
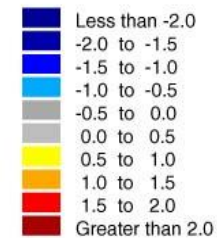
SST Anomaly (degrees C)

ENSO the main contributor. Conditions in the Tropical Pacific Ocean (example from October 1982)



SST Anomaly (degrees C)

December 1991



Produced by R
Data courtesy of

Produced by Queensland Center for Climate Applications, Toowoomba
Data courtesy of National Oceanographic and Atmospheric Administration, USA

Consider Agricultural Management Decisions and Climate Systems that operate at various time scales across the industry value chain (Meinke and Stone, 2005).

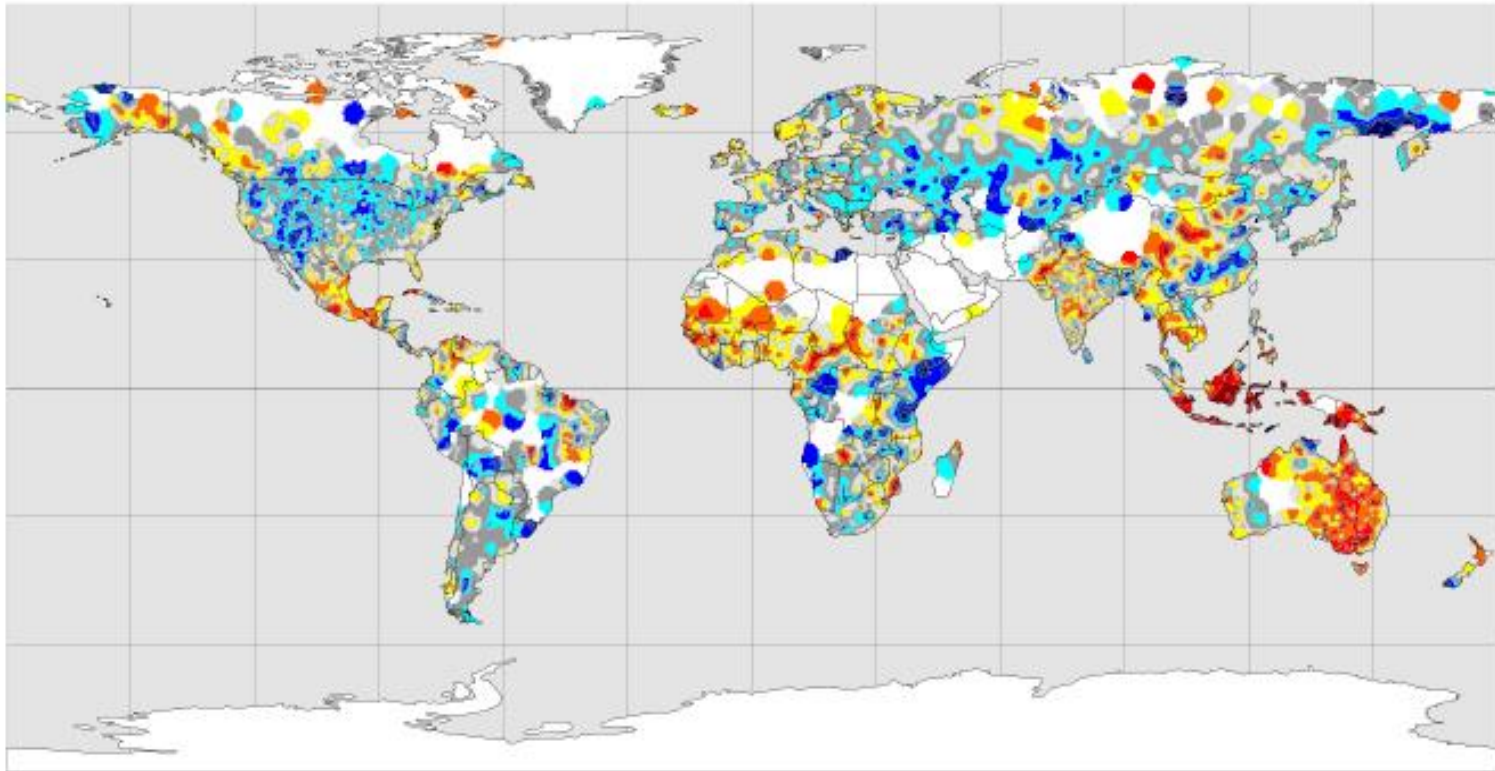
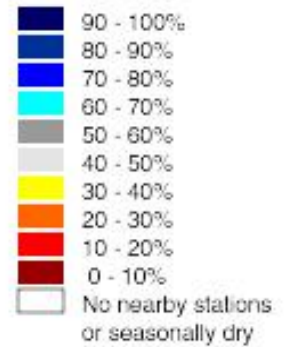
Decision type (eg. only)	Climate period
Logistics (eg. scheduling of planting / harvest operations; short-term buying decisions (stock))	Intraseasonal (>0.2) MJO
Tactical crop management (fertiliser/pesticide use)	Intraseasonal (0.2-0.5)
Crop type/area/fertiliser app (wheat/chickpeas); stocking rates; agistment planning; grain supply.	Seasonal (~1.0) ENSO
Crop sequence (eg. long or short fallows); agistment	Interannual (1-2.0) SAM
Crop rotation (eg. winter or summer crop); selling due to likely drought in QBO West Phase +STR	Annual/biennial (2) QBO
Industry issues(eg. grain/cotton); land purchase	Decadal (~10) +STR
Agricultural industry (eg. crops or pasture)	Interdecadal (10-20) IPO
Landuse (eg. Agriculture or natural system)	Multidecadal (20+)
Landuse and adaptation of current systems, etc	Climate change

Probability of exceeding Median Rainfall

for August / October

based on consistently negative phase during June / July

Seasonal climate forecasting - globally



Produced by Queensland Centre for Climate Applications, Toowoomba, 1999



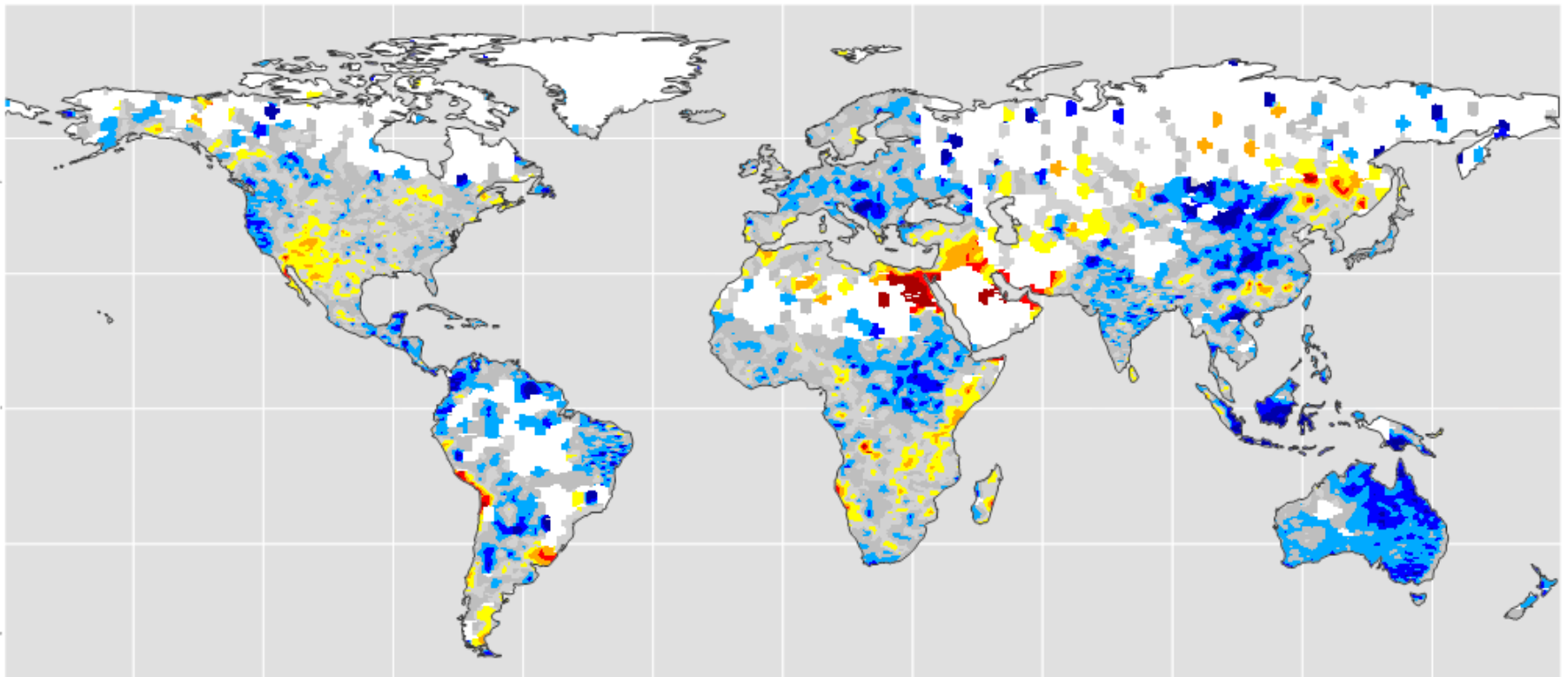
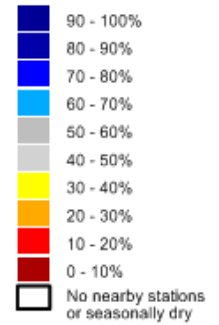
example of forecast of El Niño/negative SOI phase influence - value to agricultural commodity trading (Stone et al, *Nature* 1996)

Probability of Exceeding Median Rainfall

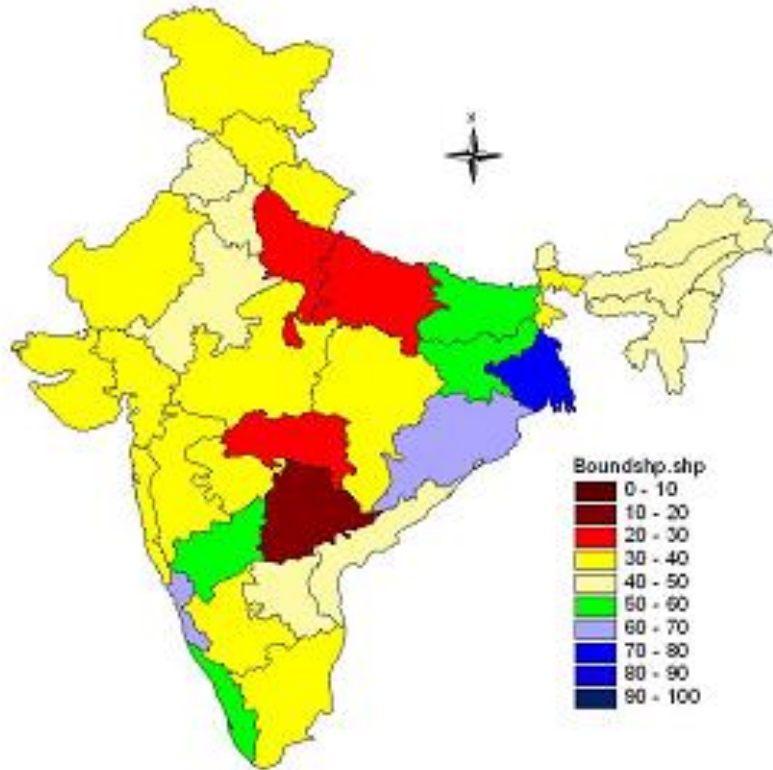
August / October

Based on Consistently Positive phase during June / July

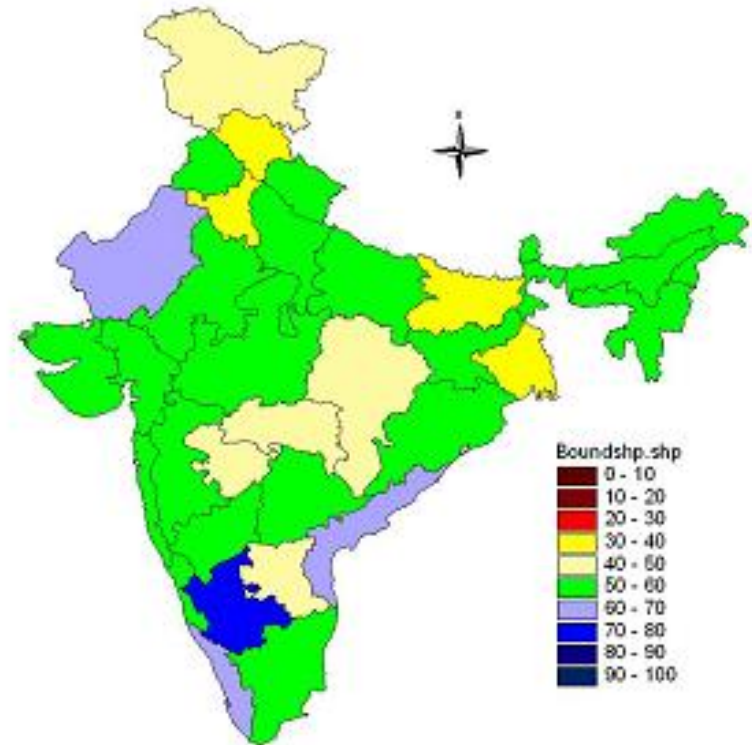
Seasonal climate forecasting



Negative Apr/May SOI phase



Positive Apr/May SOI phase

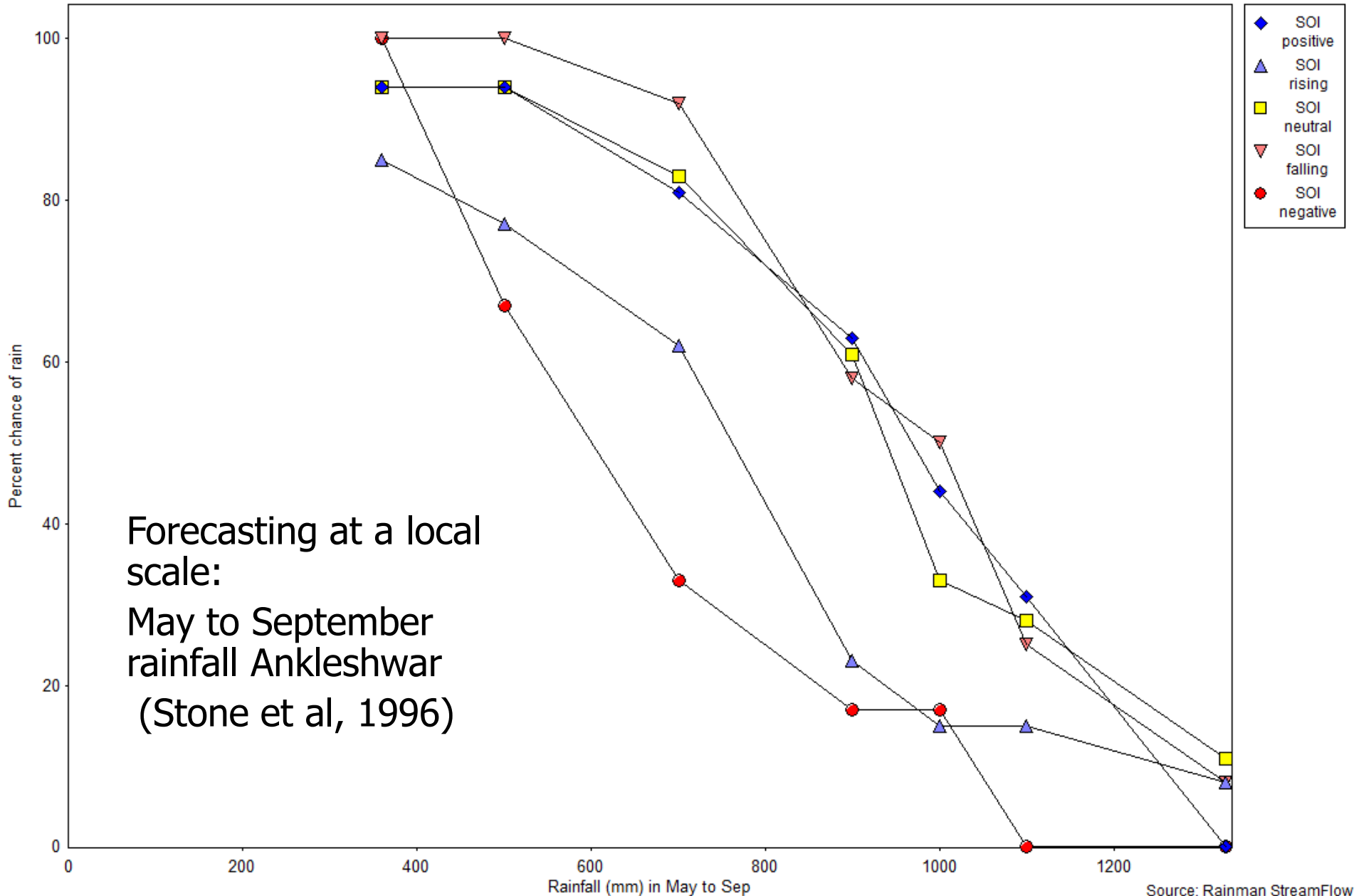


Example for the June to September period: Probability of exceeding long-term (1901-2000) median rainfall during summer monsoon (Jun-Sep) for meteorological subdivisions of India following SOI phases of Apr/May (from Selvaraju et al (2004) and after Stone et al, 1996)

Chance of rainfall at ANKLESHWAR GUJA

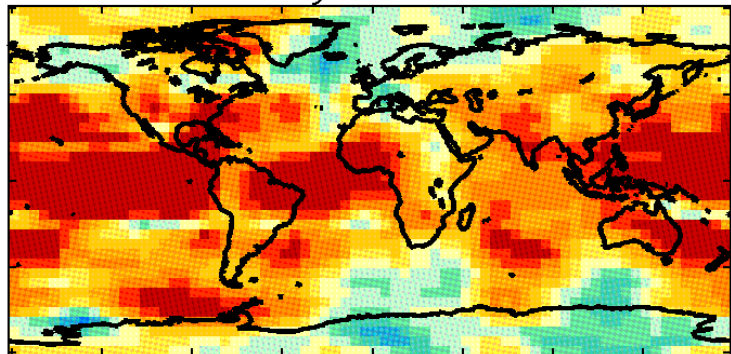
Analysis of historical data (1901 to 1969) using SOI Phases: Mar to Apr Leadtime of 0 months Rainfall period: May to Sep

The SOI phases/rainfall relationship for this season is statistically significant because KW test is above 0.9, and Skill Score (15.6) is above 7.6 ($p = 0.99$).

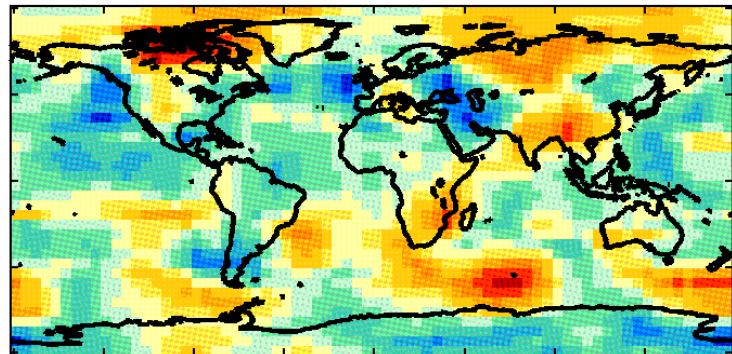


Decadal forecasting Precip anomaly correlation (35x35° lat/long boxes
– (high potential skill for 2 years – courtesy UKMO Hadley Centre for
Climate Research, Exeter)

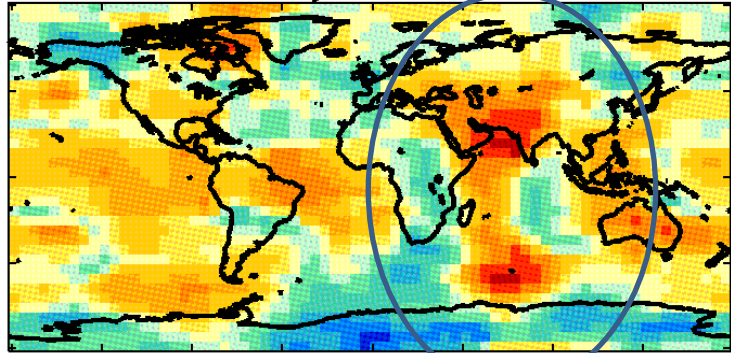
DePreSys : Year 1



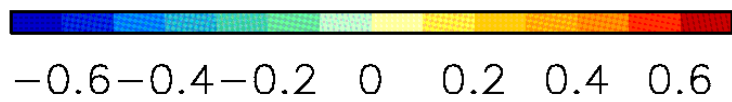
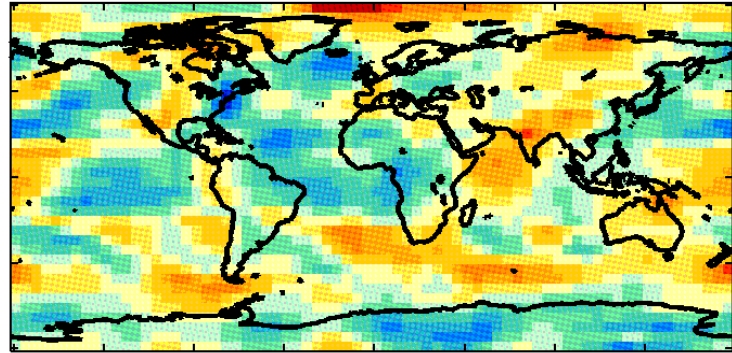
NoAssim : Year 1

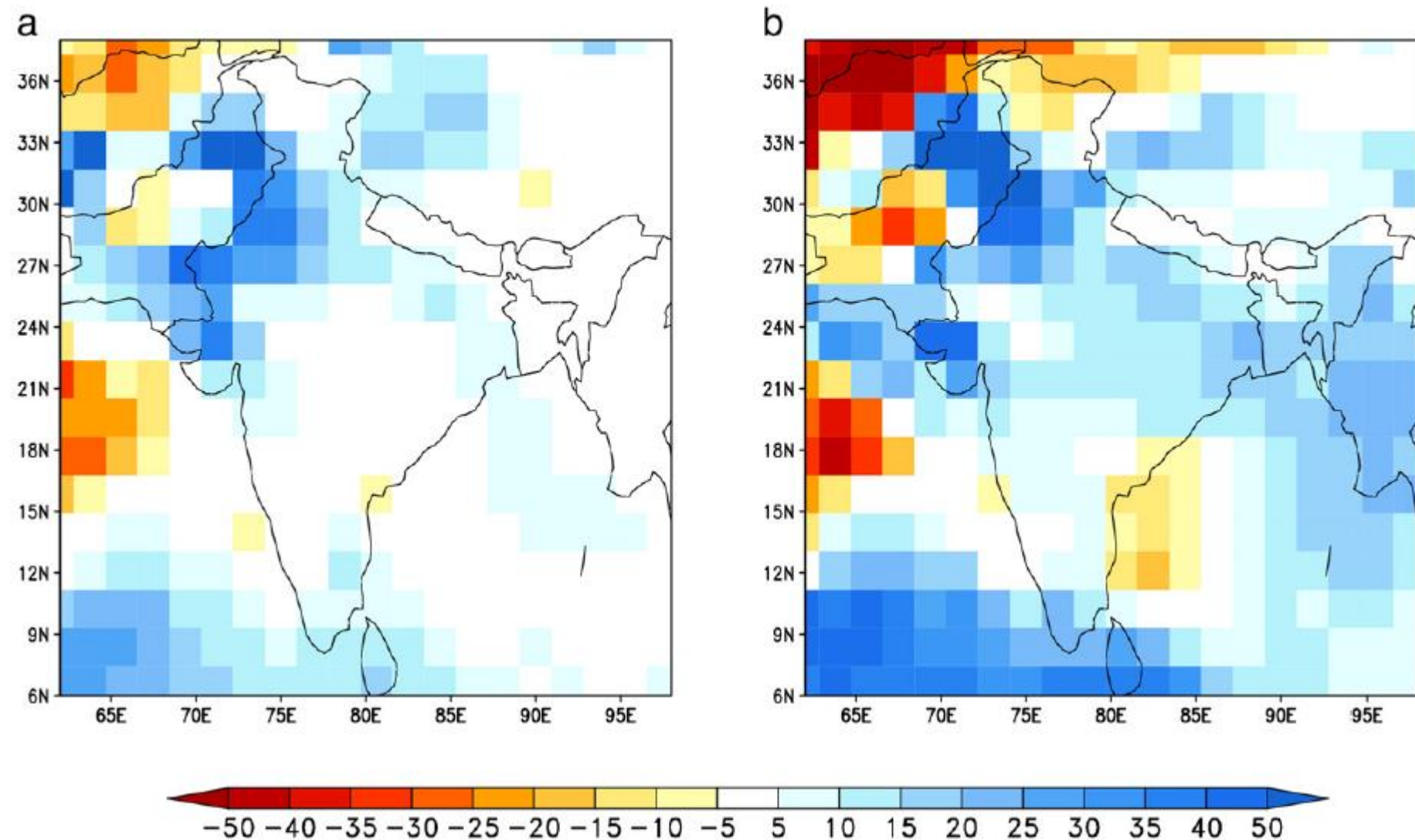


DePreSys : Year 2

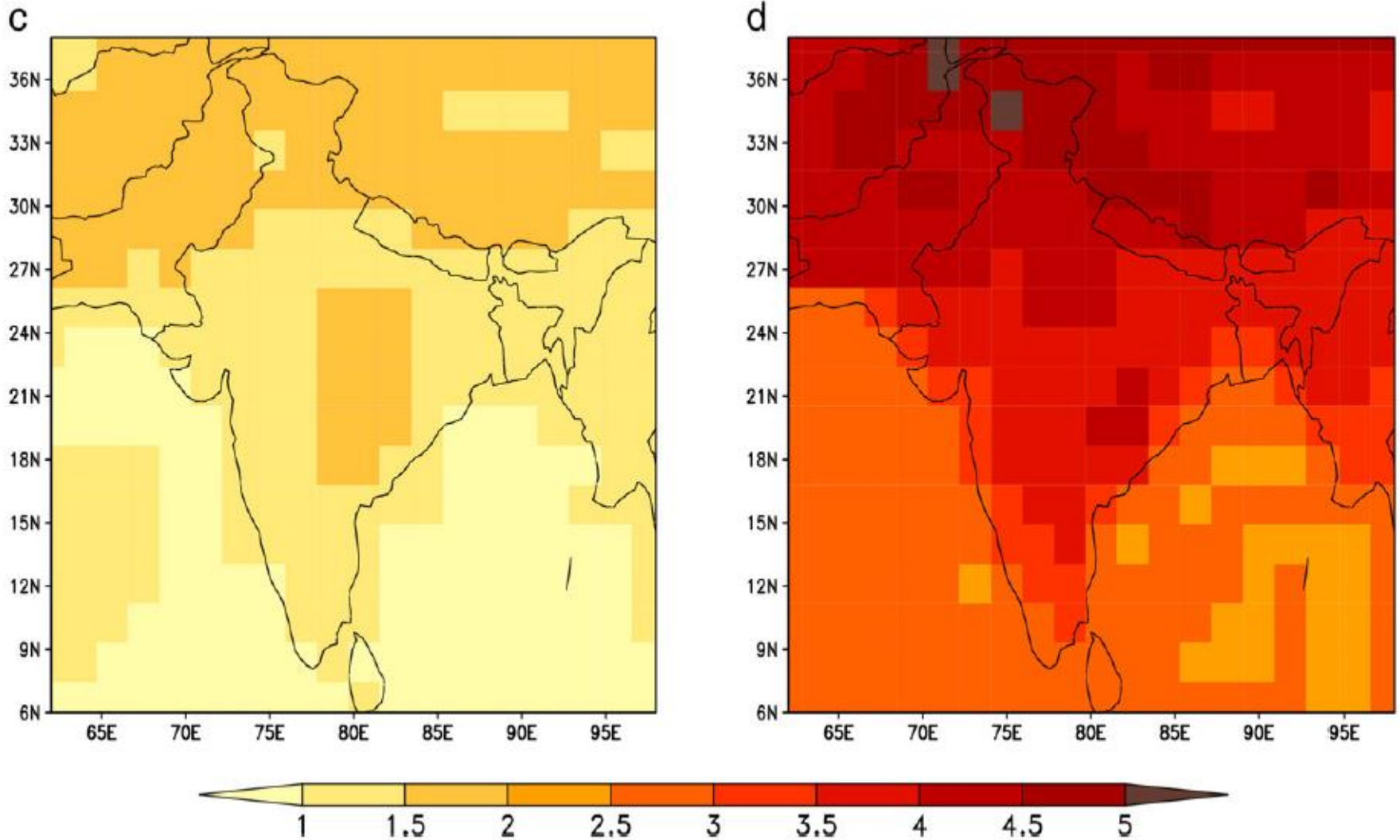


NoAssim : Year 2





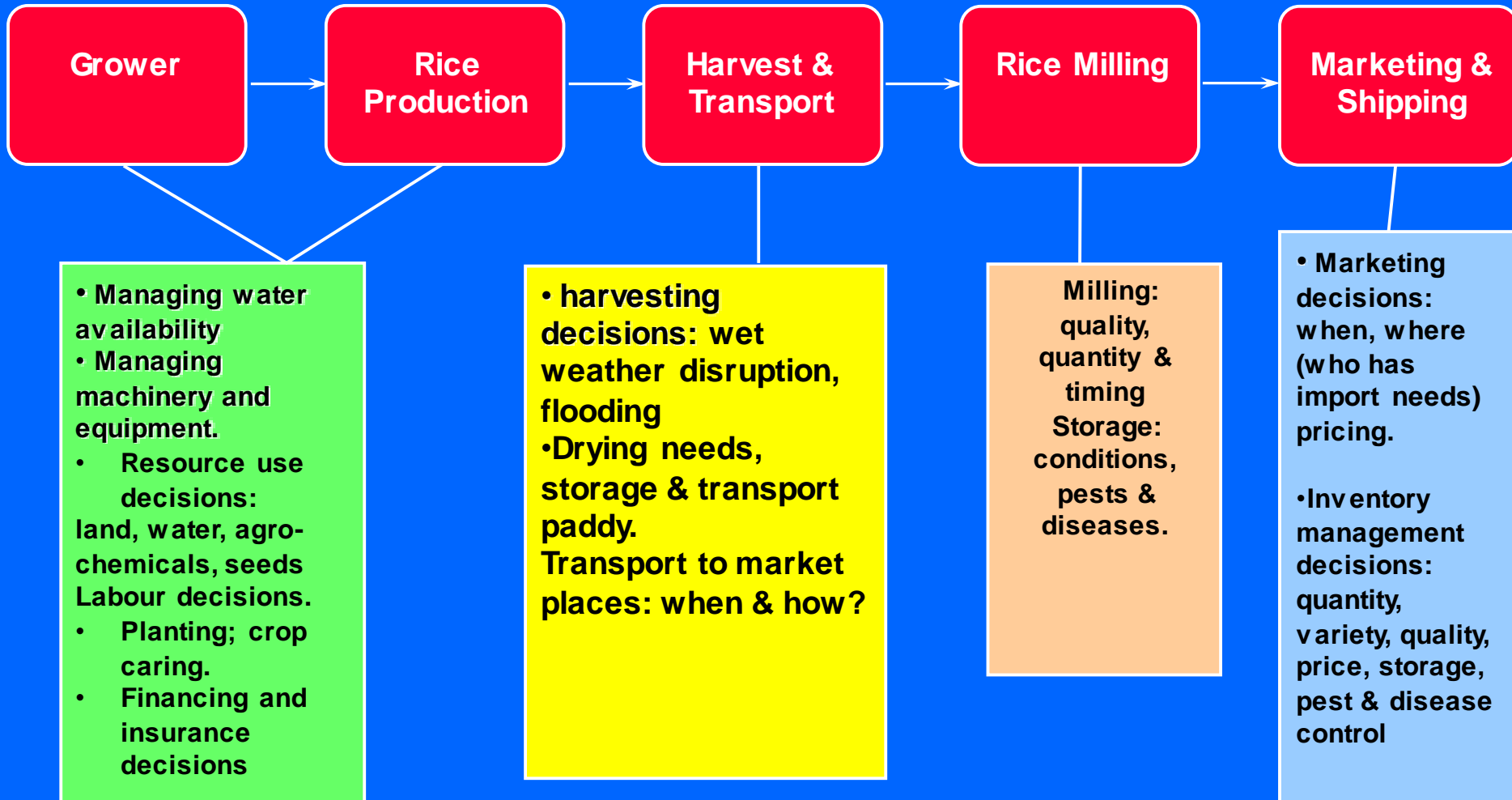
Climate Change projections: GCMFEM change in precipitation (%) from 1970–1999 to (a) 2020–2049 (b) from 2070–2099, over south Asia (Kumar et al, 2013)



GCMFEM change in temperature (%) from 1970–1999 to (c) 2020–2049 (d) from 2070–2099, over south Asia (Kumar et al, 2013).

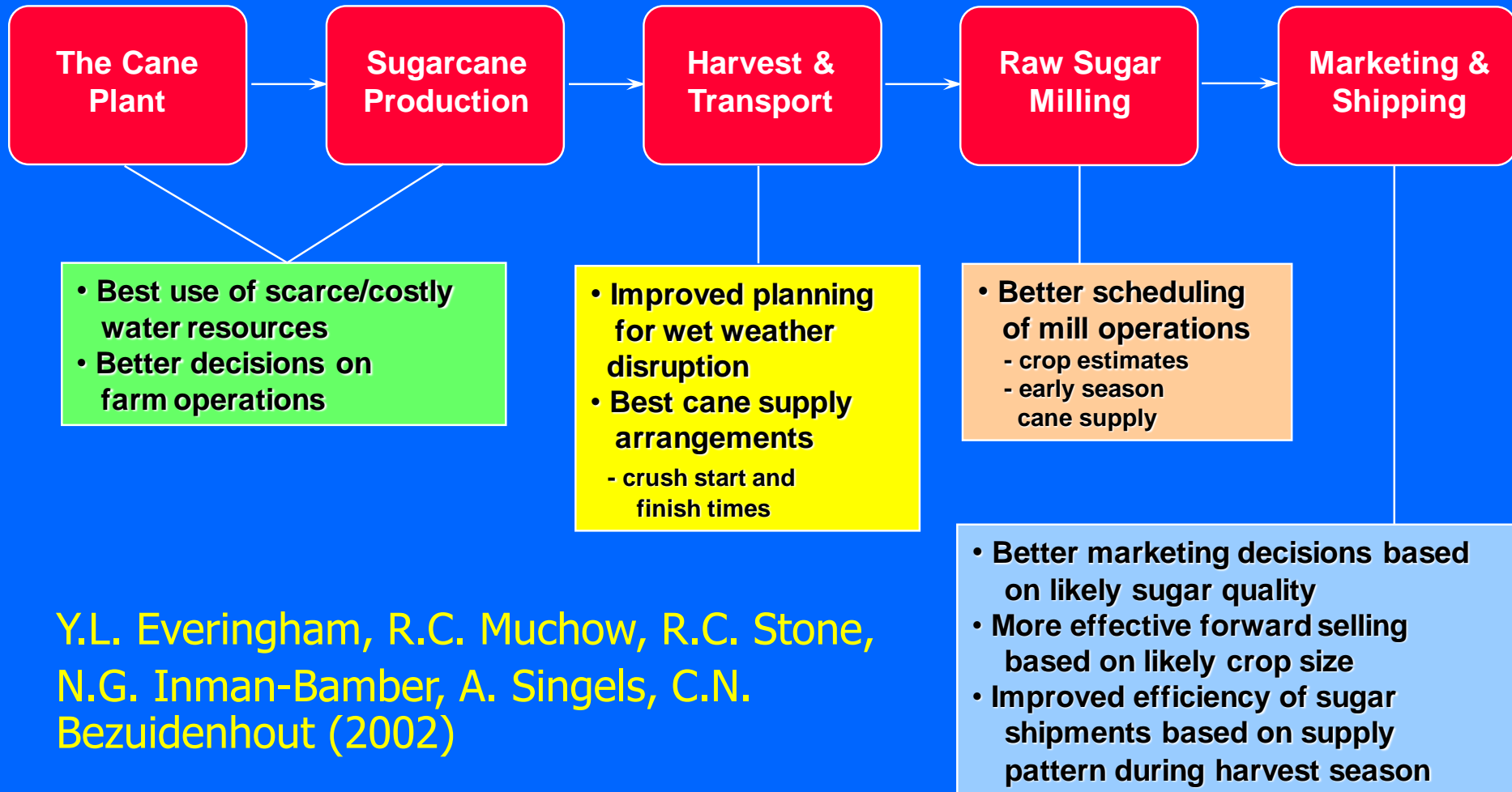
Key point: Seasonal climate forecasting has no value unless it changes a management decision:

Understanding decisions across the (rice) value chain

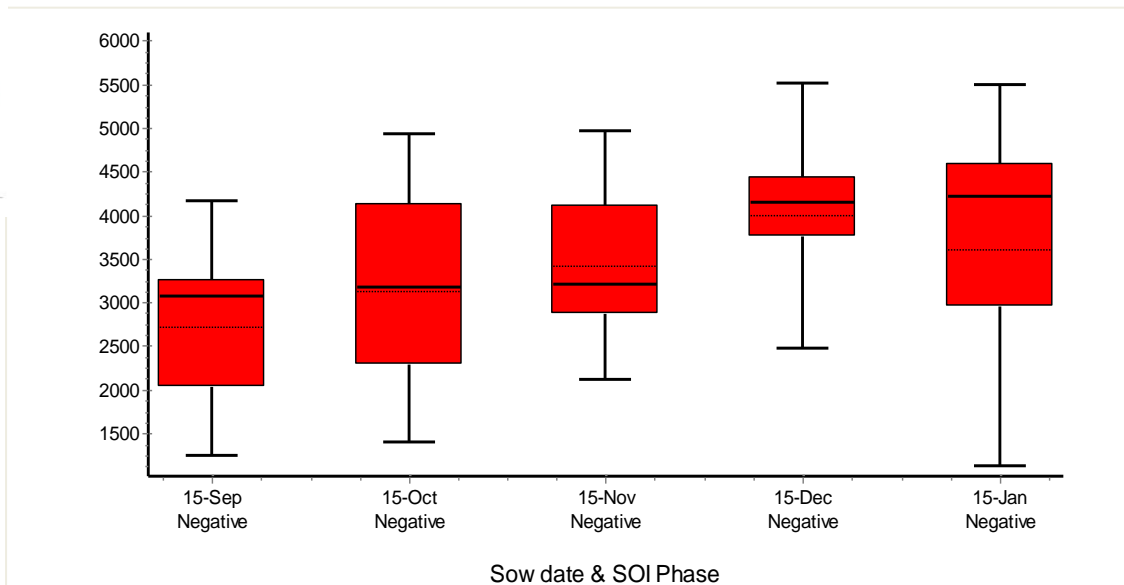
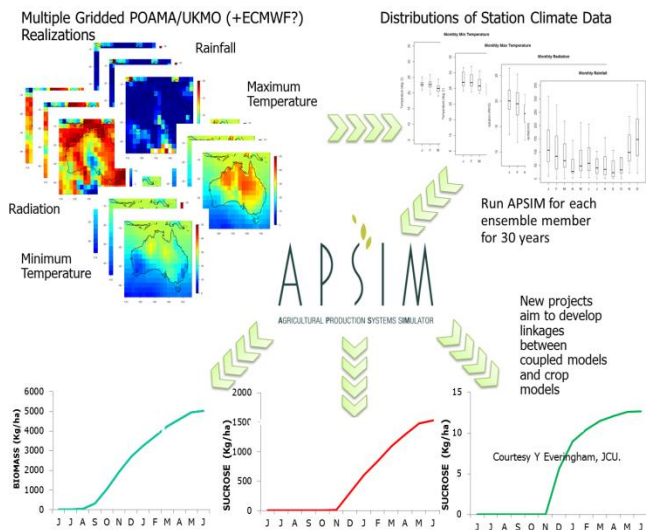


Climate forecasting has no value unless it changes a management decision

Understanding climate related issues across the (sugar) value chain



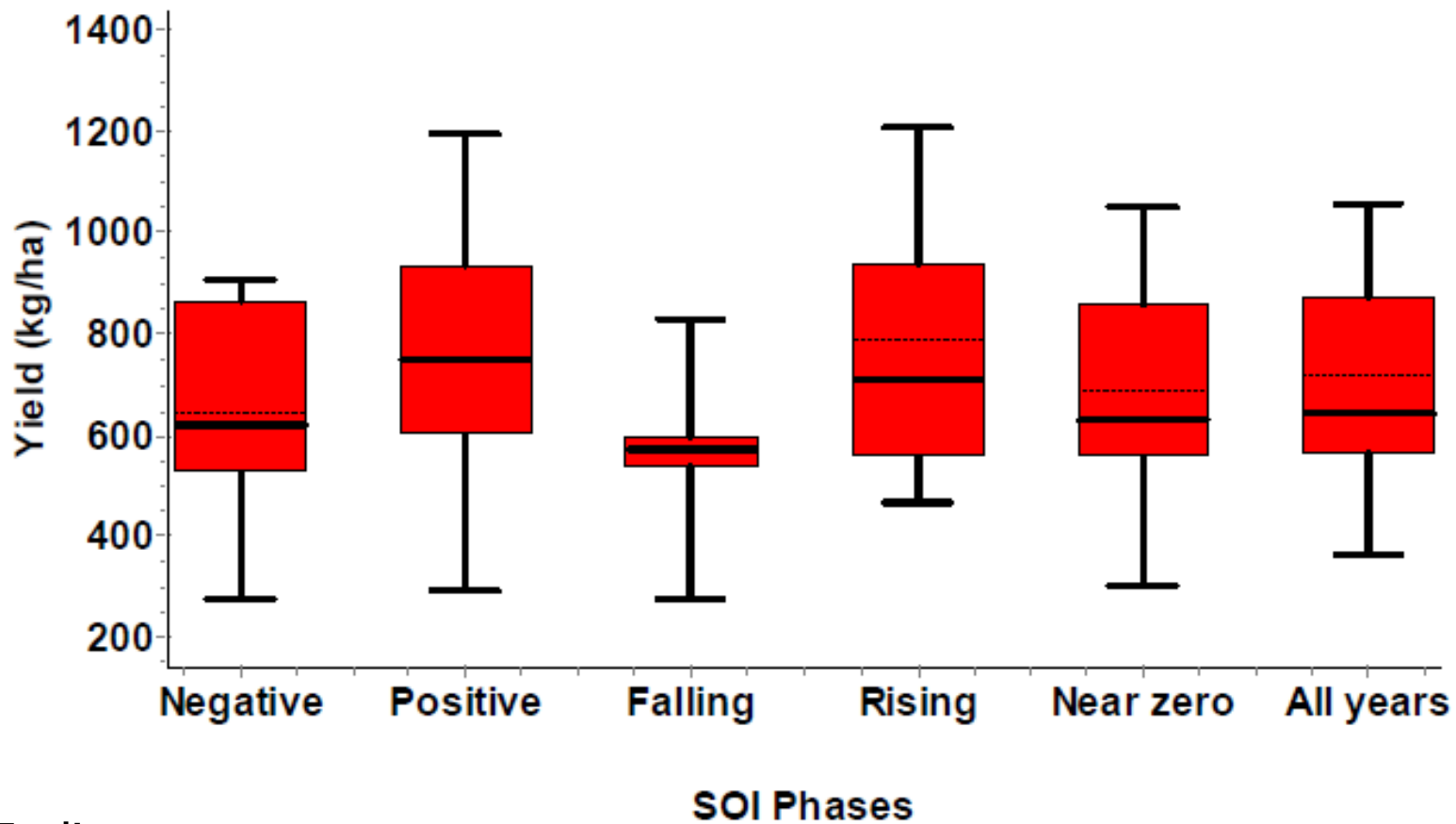
Y.L. Everingham, R.C. Muchow, R.C. Stone,
N.G. Inman-Bamber, A. Singels, C.N.
Bezuidenhout (2002)



Farm-level decisions - Australia - Utilising seasonal climate forecasts in management and adaptation – integrating seasonal climate forecasting into crop simulation models –

forecasts of potential sorghum yields associated with varying climate regimes (example for a 'consistently negative SOI phase') – varying management decisions (sowing dates) : example for Miles, Australia.

Effect of sowing date on sorghum yield at Miles South QLD with a 'consistently negative' SOI phase for September/October (Other parameters - 150mm PAWC, 2/3 full at sowing, 6pl/m2, medium maturity (WhopperCropper)

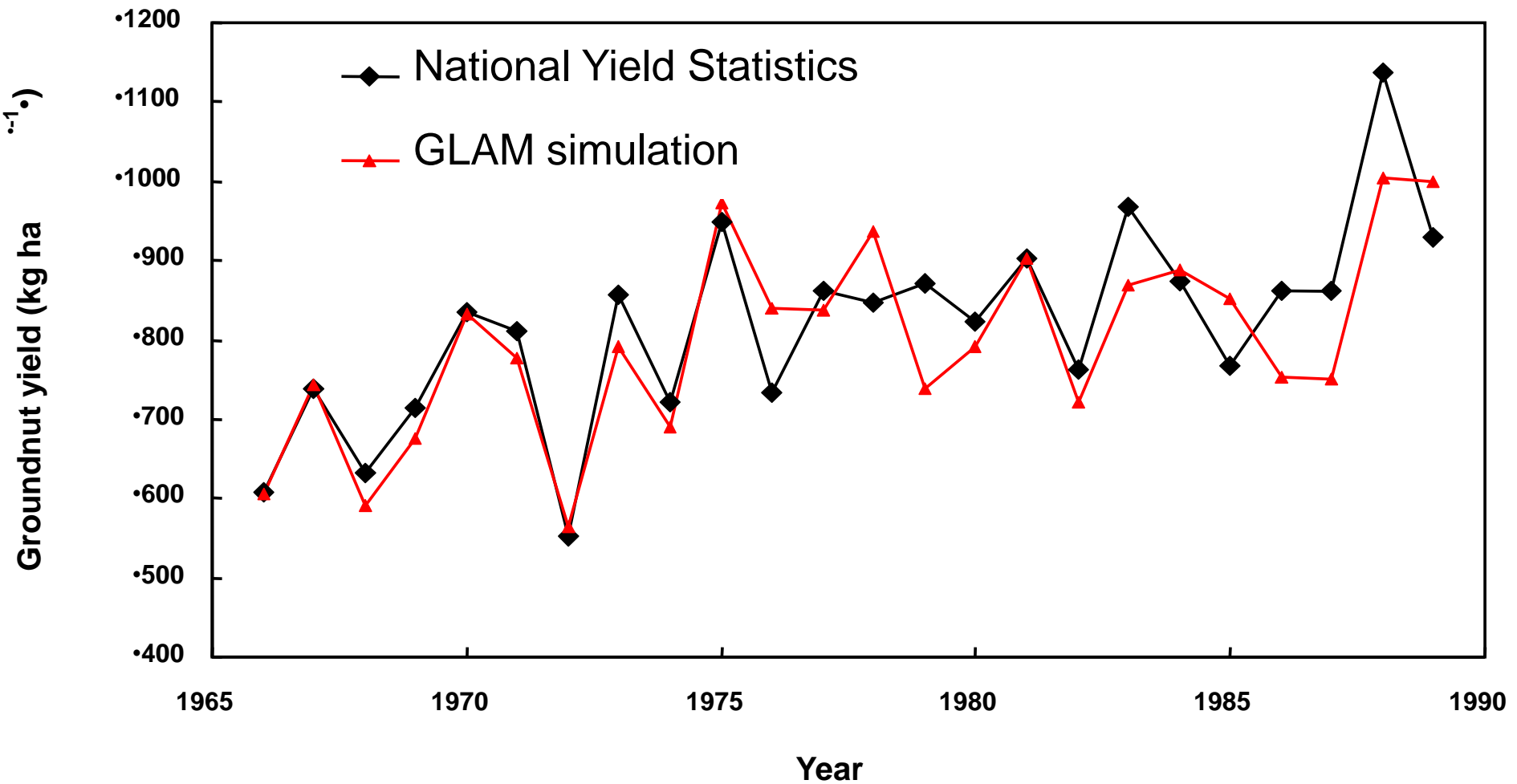


India

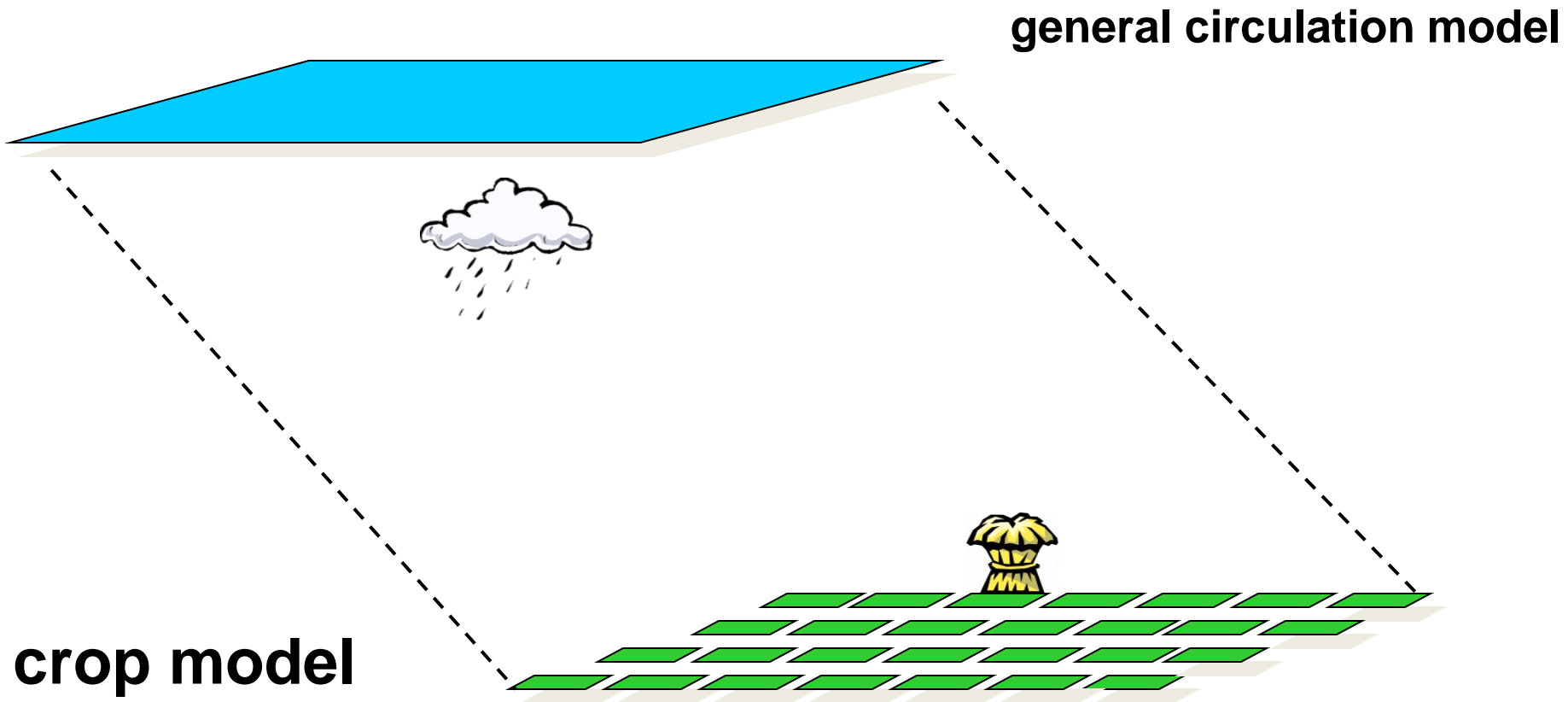
SOI Phases

Figure 3. Distributions of simulated cotton yield (kg ha^{-1}) for an early sowing window (June 1- July 31) at Avinashi for years associated with each of the five April-May phases of the SOI and for all years

Another approach using seasonal climate forecasts – example of all-India groundnut yield using the ‘GLAM’ coupled climate model
(Challinor et al, 2004)



**Key – to effectively link the ‘new generation’ of
general circulation climate models in climate
prediction to agricultural models (Challinor et al)**



At what scale should information pass between models?

WHAT DOES IPCC SAY more broadly about climate change?

- **“Decline in productivity (*medium confidence*) {24.4.4}** This is evident in the case of rice production. Most models, using a range of General Circulation Models (GCMs) and *Special Report on Emission Scenarios* (SRES) scenarios, show that higher temperatures will lead to lower rice yields as a result of shorter growing periods.
- There are a number of regions that are already near the heat stress limits for rice.
- Issues with grain quality need to be addressed?
- However, carbon dioxide (CO₂) fertilization may at least in part offset yield losses in rice and other crops. exacerbate desertification).
- In the Indo-Gangetic Plains of South Asia there could be a decrease of about 50% in the most favourable and high-yielding wheat area as a result of heat stress at 2 x CO₂.
- Sea level rise will inundate low-lying areas and will especially affect rice growing regions. Many potential adaptation strategies are being practiced and proposed but research studies on their effectiveness are still few”.

Summary:

- India shares with Australia the 'distinction' of having some of the world's highest levels of year to year rainfall variability.
- Much of this variability, globally, can be linked back to the El Nino/Southern Oscillation (ENSO) in the tropical Pacific Ocean (through teleconnections).
- Based on ENSO, seasonal (3 to 6 month) climate forecasting shows skill in many regions of India – depending on the particular season in question.
- Seasonal to decadal climate forecasting may provide *an incremental capability* to link to practical agricultural management decisions and also assist with long-term management of climate change.
- Need to address the whole value/supply chain in agricultural production when utilising climate forecasting.
- Climate change modelling provides much more effective outputs when only those models that capture the dynamics of the monsoon are utilised.



Summary: A systematic approach in applying climate forecasts to agricultural decision-making

- **Seasonal (and decadal) climate forecasting may be able to provide an incremental approach in managing longer-term climate change in agriculture – at a variety of scales.**
- **Need to understand the agricultural system and its management:** it is essential to understand the system dynamics and opportunities for management intervention i.e. ***identify those decisions*** that could influence desired systems behaviour or performance;
- **Understand the impact of climate variability (seasonal to decadal to climate change):** it is important to understand *where in the (ag)-system climate is an issue;*
- **Determine the *opportunities* for tactical/strategic management in response to the forecasts.** If forecasts are now available, what possible options are there at relevant decision-points? How might decisions be changed in response to forecasts? What nature of forecast would be most useful? and - what lead-time is required for management responses?



•**Evaluate the worth of tactical or strategic decision options:** the quantification and clear communication of the likely *outcomes* e.g. economic or environmental, *and associated risks of a changing a management practice* are key to achieving adoption of the technology.

•**Implement participative implementation and evaluation: working with managers/decision makers generates valuable insights and learning** throughout the entire process: i.e. identifying relevant questions/problems and devising suitable technologies and tools.

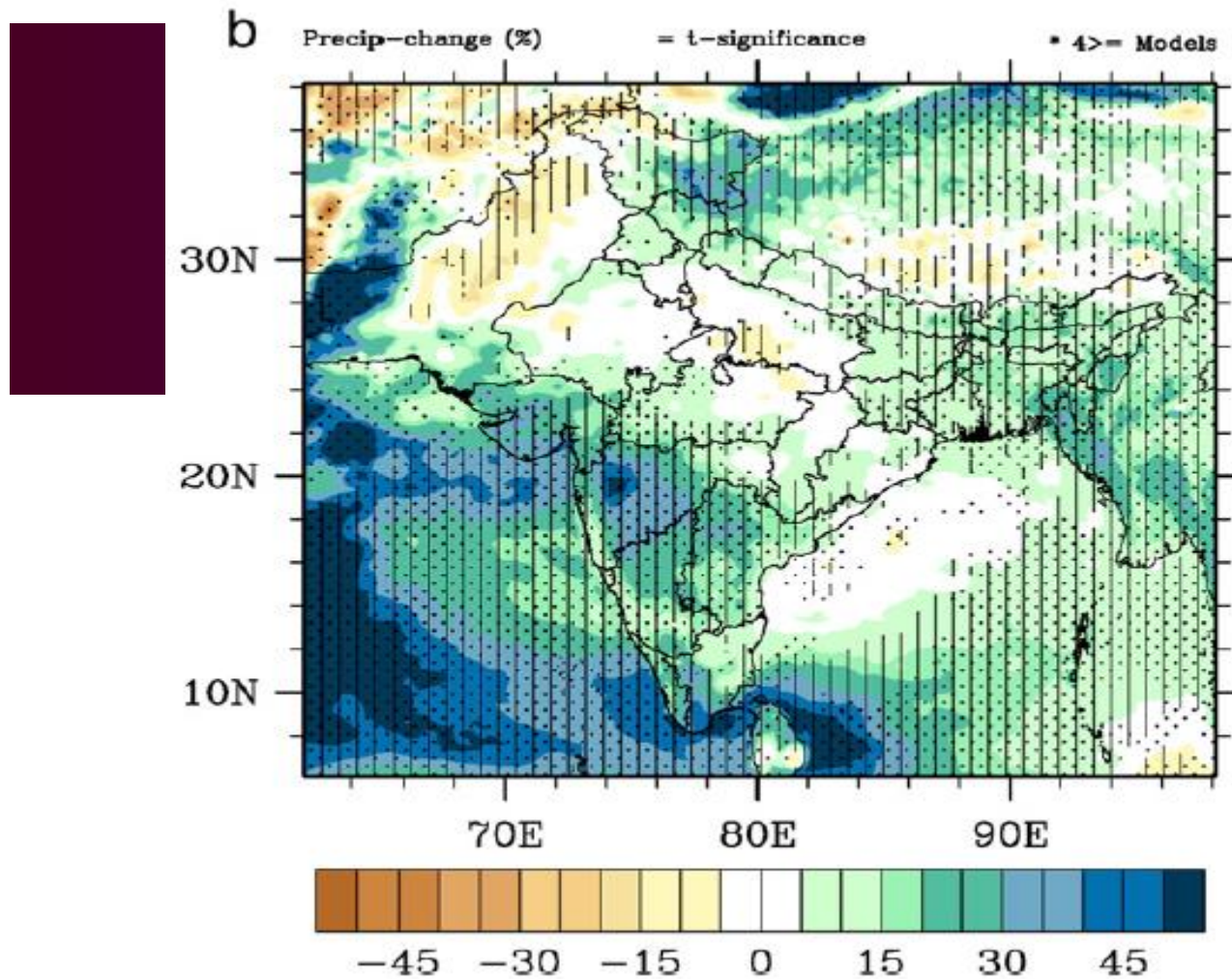
•**Provide feedback to climate forecasting research in the NMHS/ State Agency/university: rather than just accepting a given climate forecast**, consider what specific improvements would be of greatest value in the agricultural/hydrological/financial/industry system. This can provide some direction for the style of delivery of forecasts and for climate research of value for the particular sector.

•**“Climate forecast information doesn’t have to be perfect to be useful; it just needs to support a decision”** (Hammer, 2000; Hammer *et al.*, 2001; Stone and Meinke, 2007; Rodriguez, 2010; Stone, 2012).

McARTHUR'S UNIVERSAL CORRECTIVE MAP OF THE WORLD

This map is intended to be a corrective to the distortions of the Mercator map, which is the most widely used map in the world. It is based on the 'Universal Corrective' map of the late 19th century, which was the first map to show the world as a whole. The map is based on the 'Universal Corrective' map of the late 19th century, which was the first map to show the world as a whole. The map is based on the 'Universal Corrective' map of the late 19th century, which was the first map to show the world as a whole. The map is based on the 'Universal Corrective' map of the late 19th century, which was the first map to show the world as a whole.





Spatial plots for RCMEM for change in precipitation (%) compared to 1970–1999 and 2070–2099 over south Asia. Vertical lines represent regions where the climate change signal is statistically significant and the symbol * denotes regions where 4 or more members out of five RCM simulations agree the sign of change.

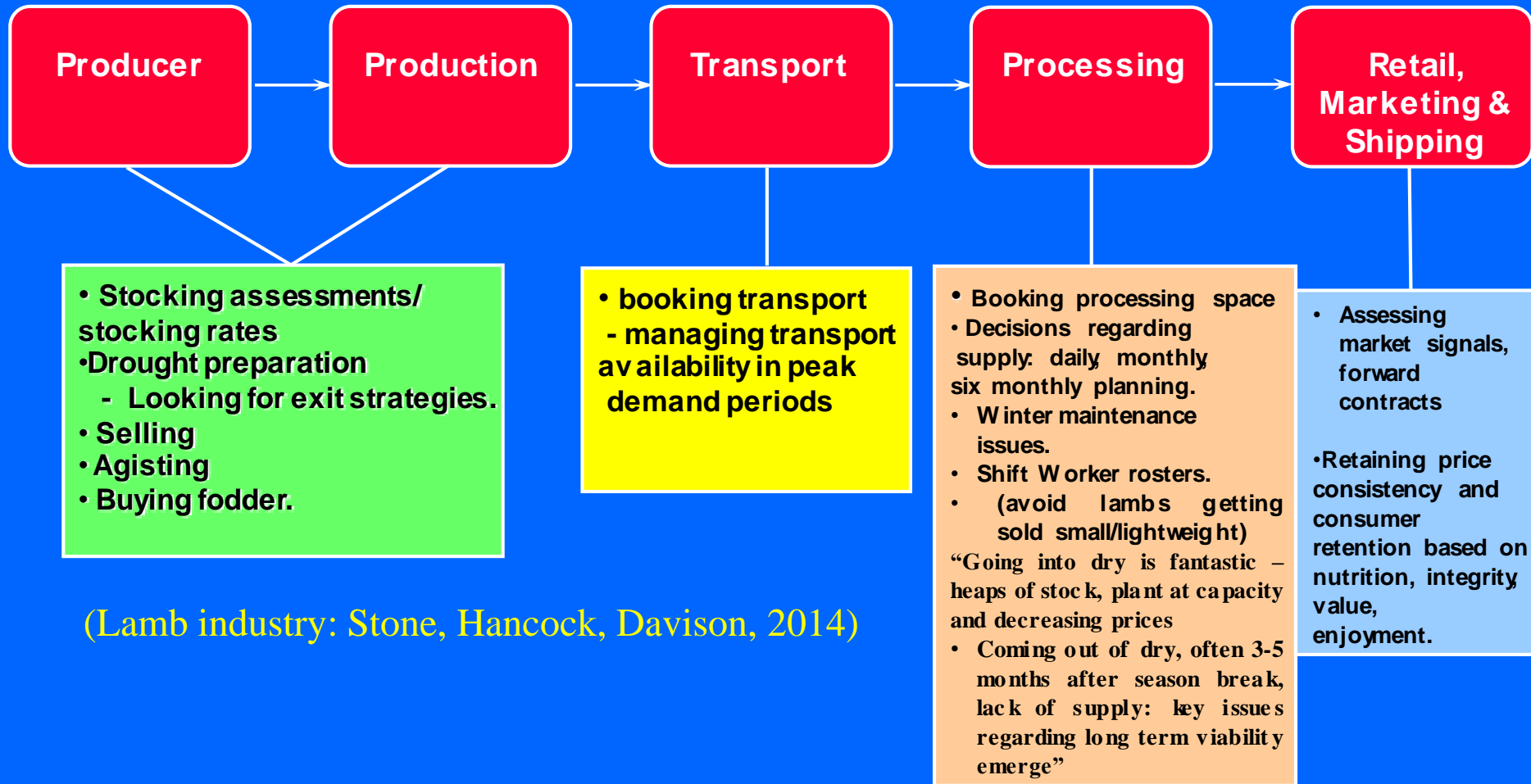


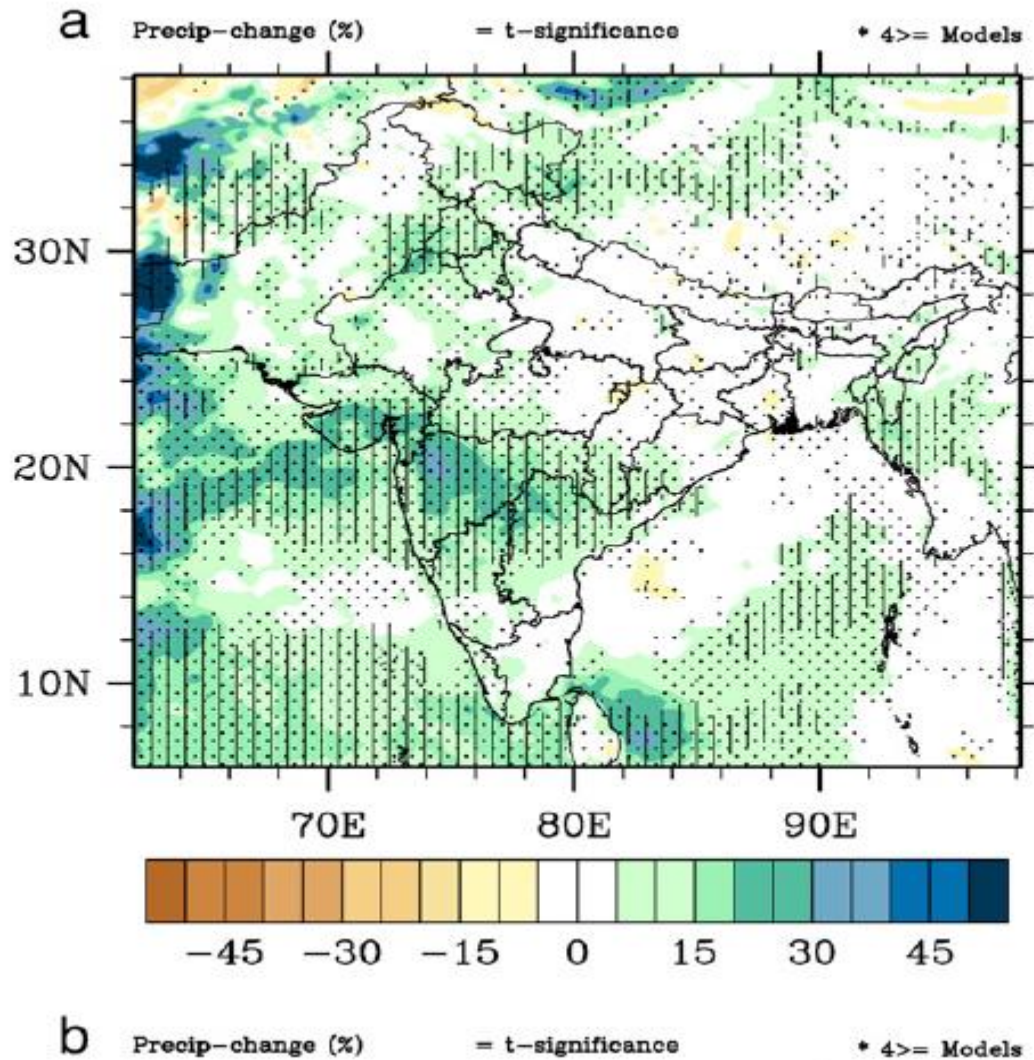
The value of climate forecasts to users will depend not only on climate forecast accuracy *but also on the management options available to the user to take advantage of the forecasts*" (Nicholls, 1991).



Seasonal climate forecasting needs to connect to management decisions...

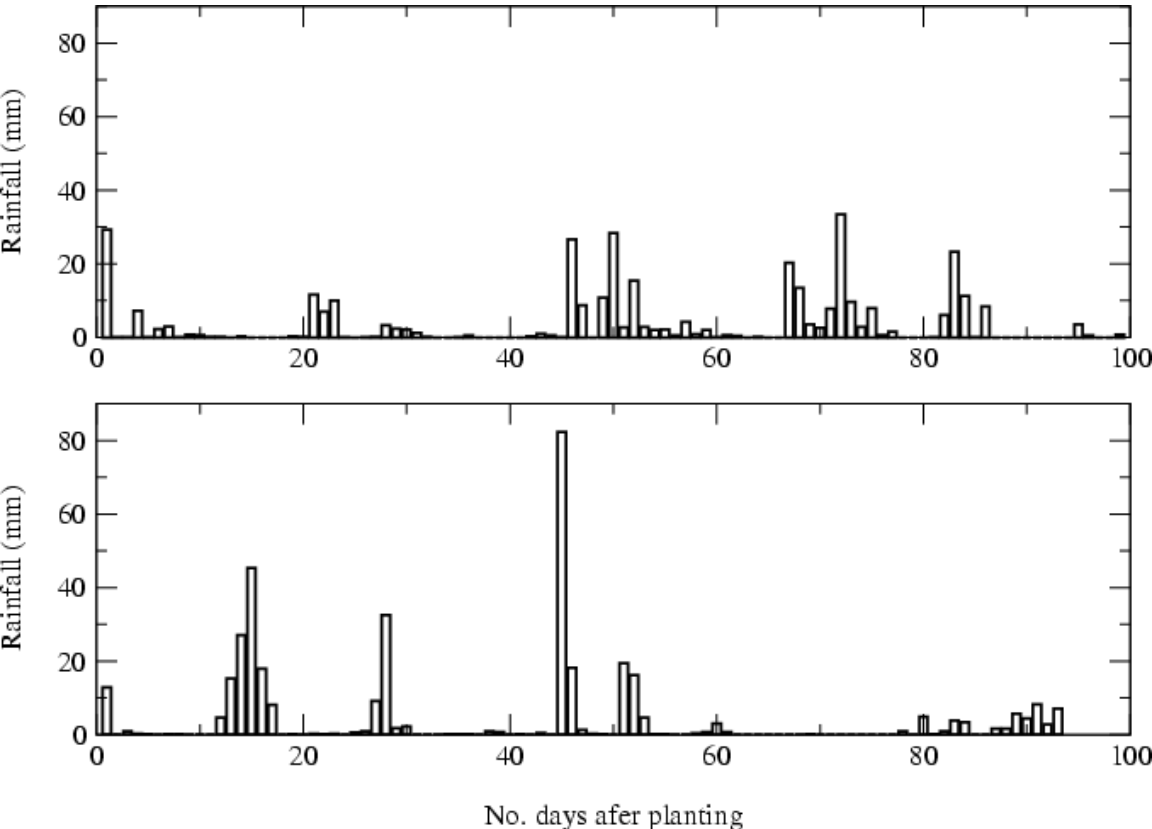
The grazing industry - climate issues across the supply chain





Spatial plots for RCMEM for change in precipitation (%) compared to 1970–1999, 2020–2049 over south Asia. Vertical lines represent regions where the climate change signal is statistically significant and the symbol * denotes regions where 4 or more members out of five RCM simulations agree the sign of change.

The need to capture the effects of intra-seasonal variability



1975

Total rainfall: 394mm

Model: 1059 kg/ha

Obs: 1360 kg/ha

1981

Total rainfall 389mm

Model: 844 kg/ha

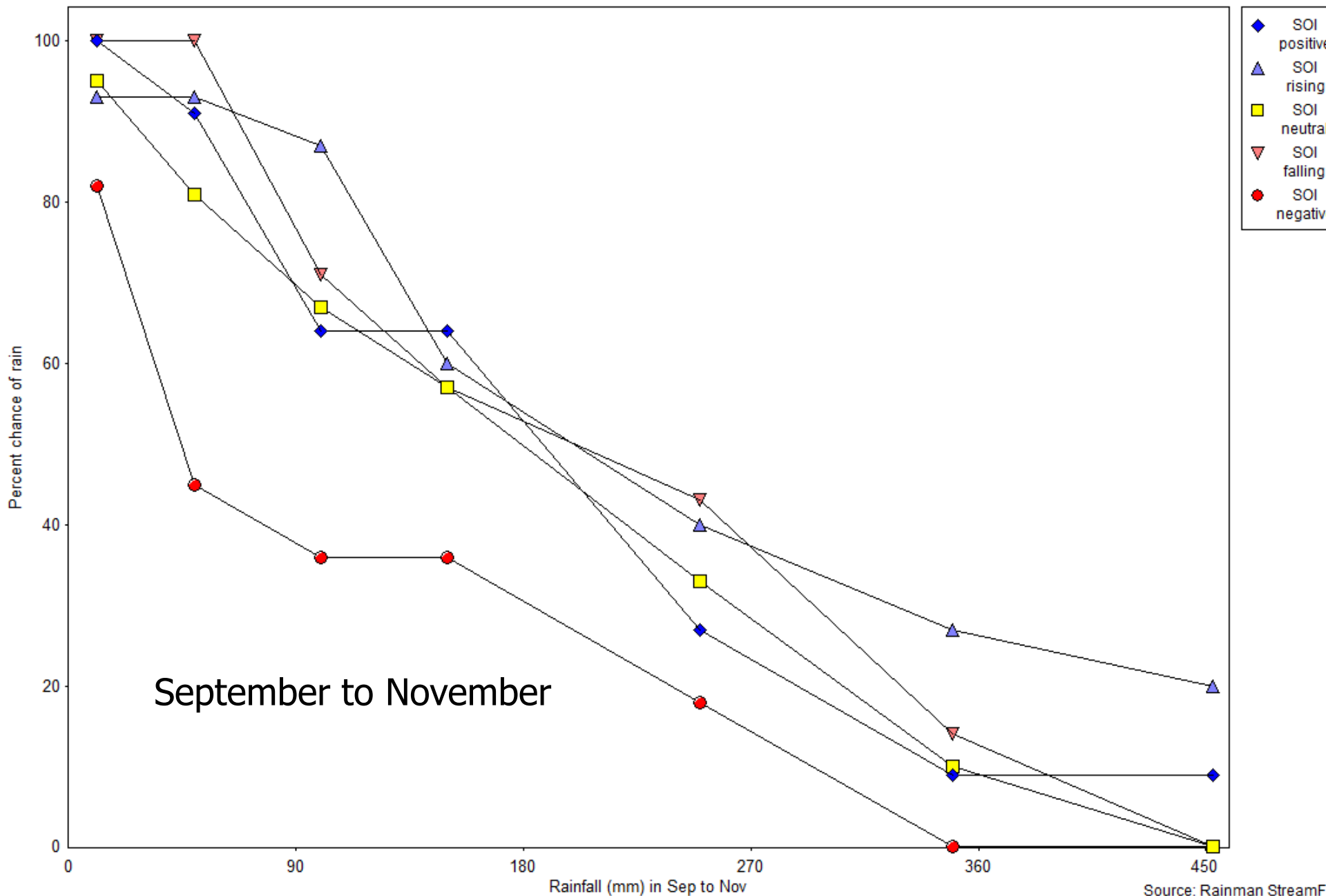
Obs: 901 kg/ha

“While these models provide probabilistic predictions of the seasonal mean climate they also produce daily time series of the evolution of the weather and therefore provide information on the statistics of the weather during the crop growing season. Of prime importance is that these daily time series can be used to drive crop simulation models” (Challinor et al. 2003).

Chance of rainfall at ANKLESHWAR GUJA

Analysis of historical data (1901 to 1969) using SOI Phases: Jul to Aug Leadtime of 0 months Rainfall period: Sep to Nov

The SOI phases/rainfall relationship for this season is not significant because KW test is below 0.9 and Skill Score (2.9) is below 7.6 ($p = 0.72$).

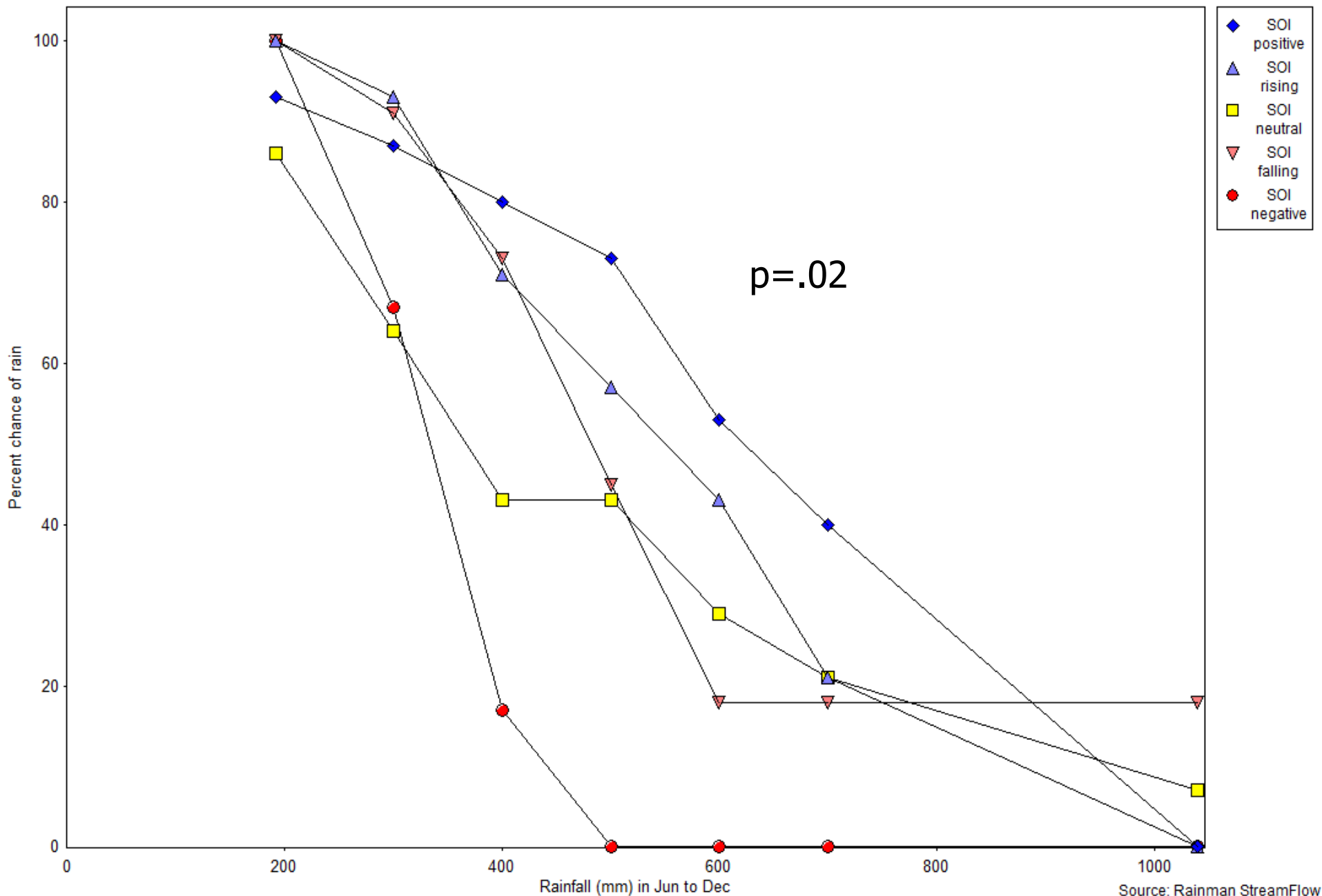


Chance of rainfall at BASAUNTI U.P.

Analysis of historical data (1901 to 1961) using SOI Phases: Apr to May Leadtime of 0 months Rainfall period: Jun to Dec

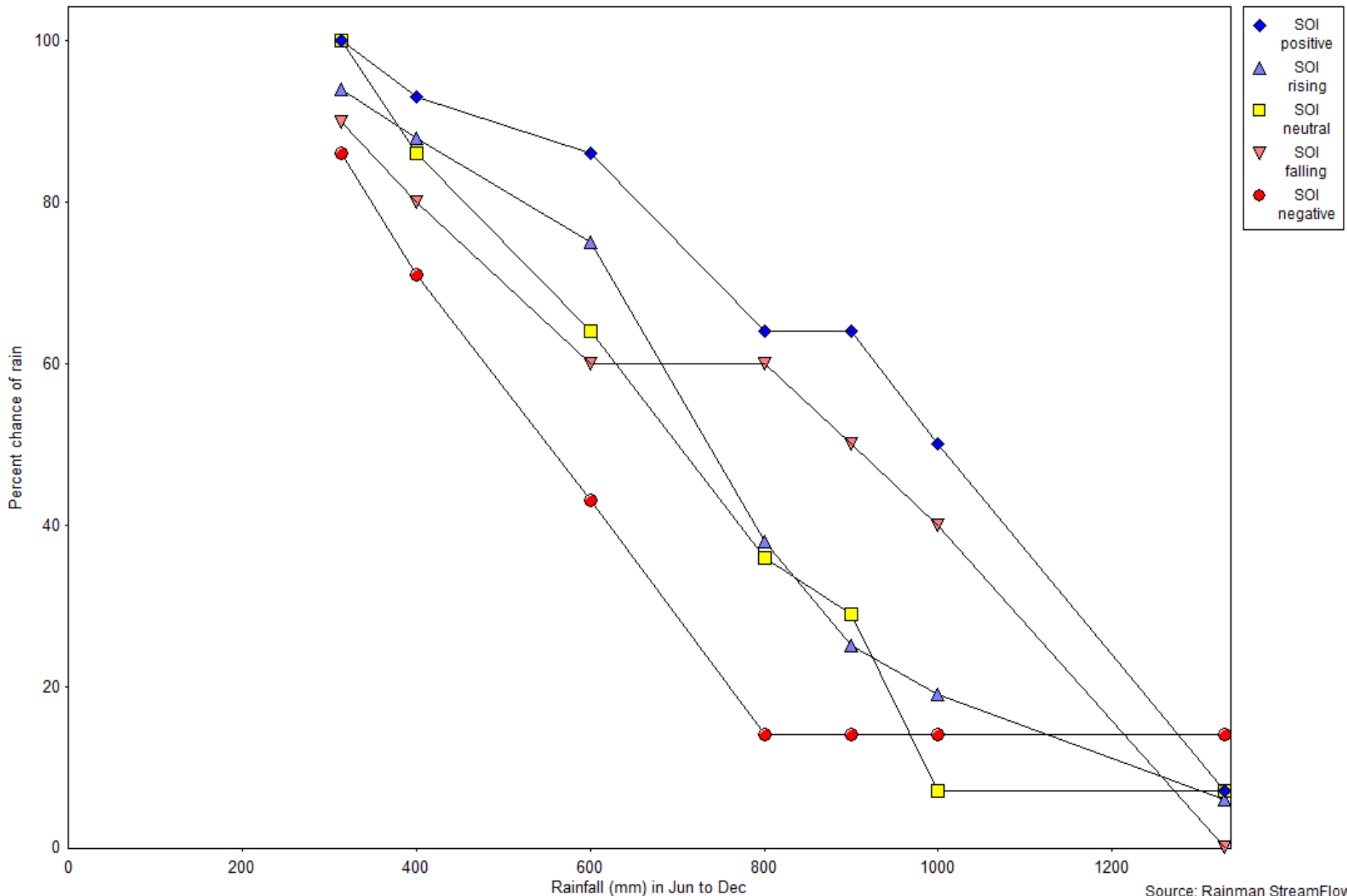
The SOI phases/rainfall relationship for this season is statistically significant because KW test

is above 0.9, and Skill Score (9.7) is above 7.6 ($p = 0.94$).



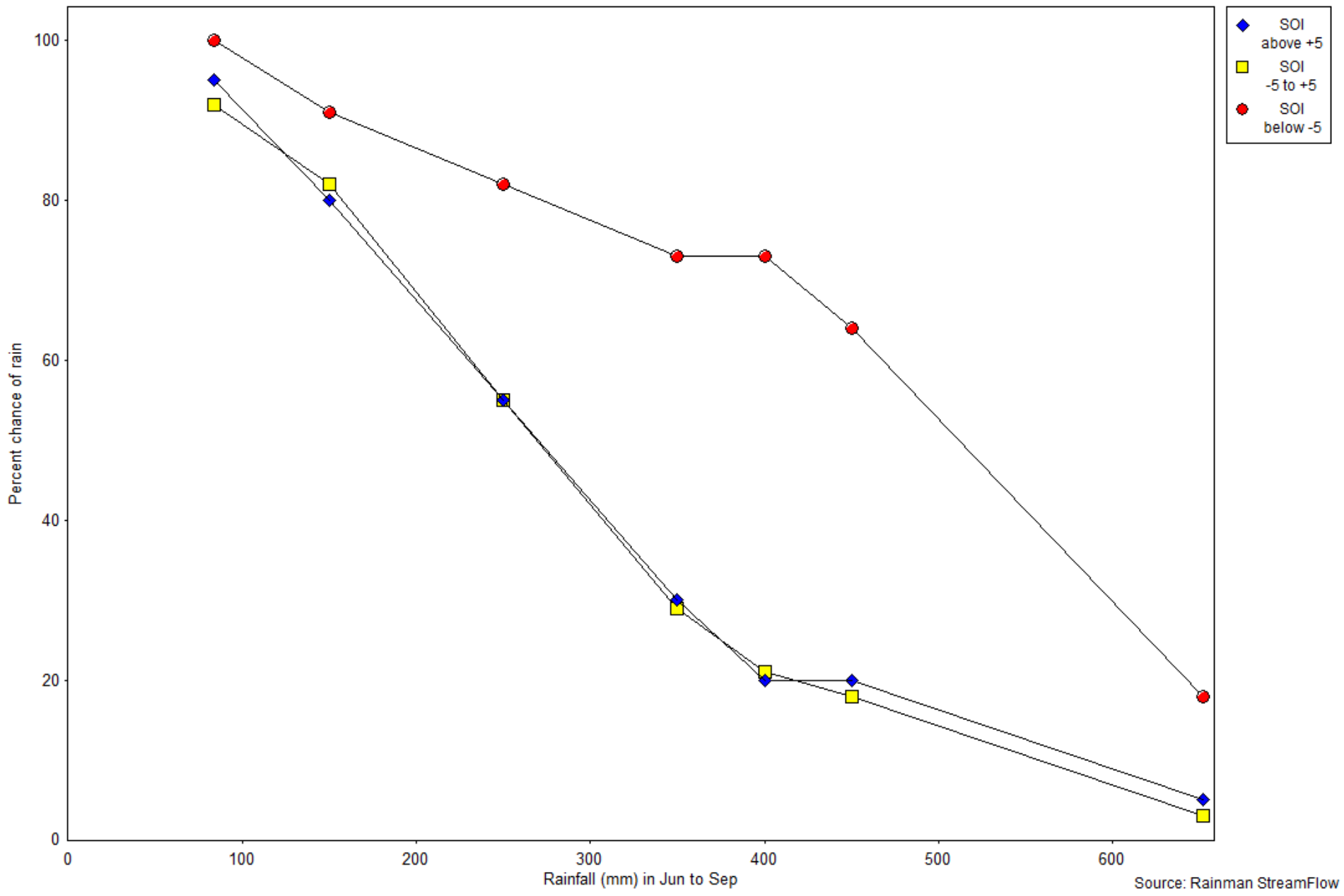
Chance of rainfall at ANTAH RAJA

Analysis of historical data (1901 to 1970) using SOI Phases: Apr to May Leadtime of 0 months Rainfall period: Jun to Dec
The SOI phases/rainfall relationship for this season is not significant because KW test is below 0.9 and Skill Score (4.6) is below 7.6 ($p = 0.80$).



Chance of rainfall at ANJAR GUJA

Analysis of historical data (1901 to 1970) using Average SOI: Mar to May Leadtime of 12 months Rainfall period: Jun to Sep
The average SOI/rainfall relationship for this season is statistically significant because KW test is above 0.9, and Skill Score (10.5) is above 7.6 ($p = 0.95$).



A core challenge

Challinor et al 2003

Country +

district

field



Spatial scale →

annual +

seasonal

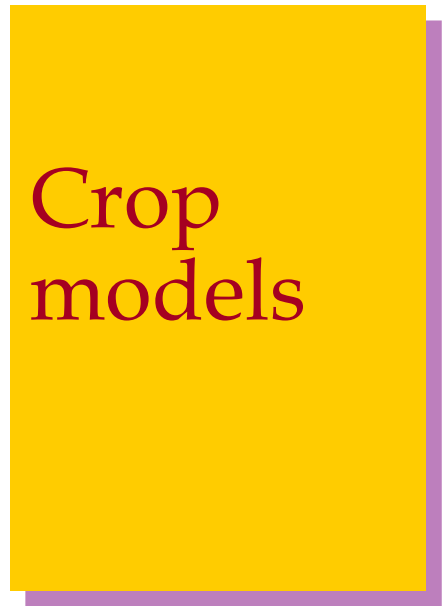
monthly

daily

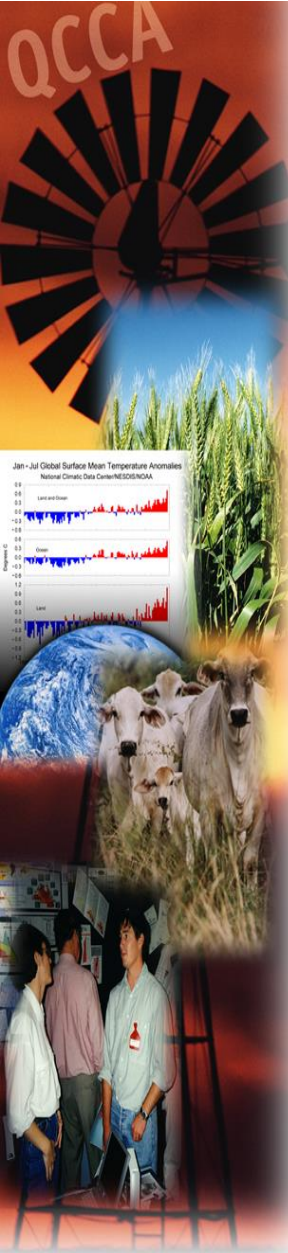
Time scale ↓



GCM



Crop models

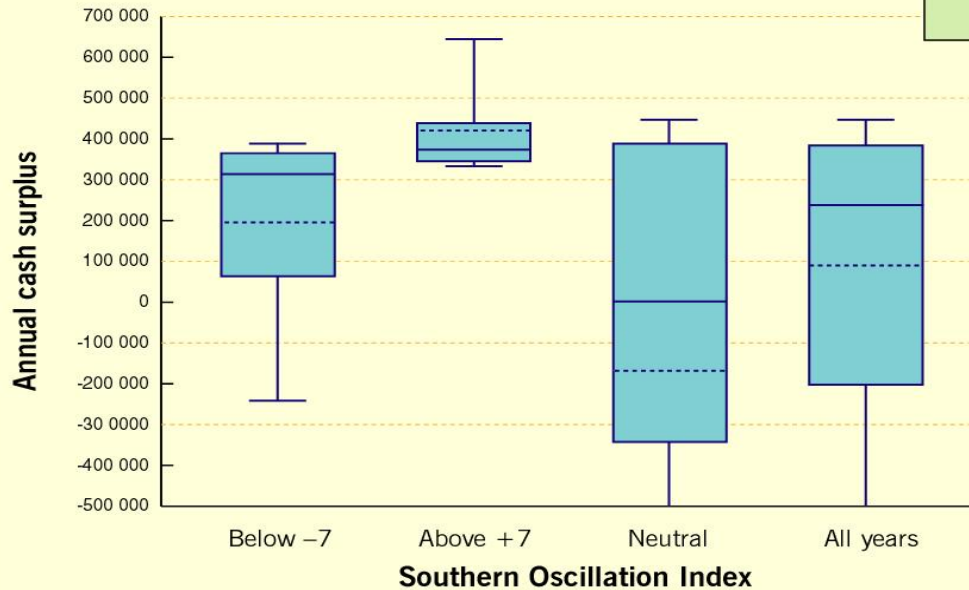


Impact of ENSO

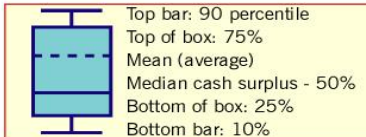
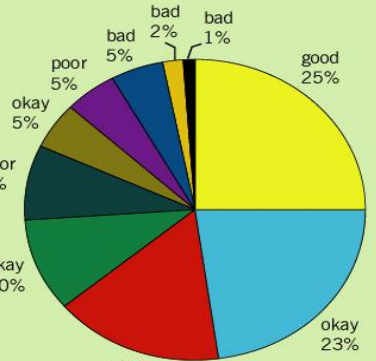
Profit

Does the SOI affect wool production in western Queensland?

Effect of SOI on Cash Surplus



Proportion of annual cash surplus and total annual cash surplus in 10 years. Season type is shown.

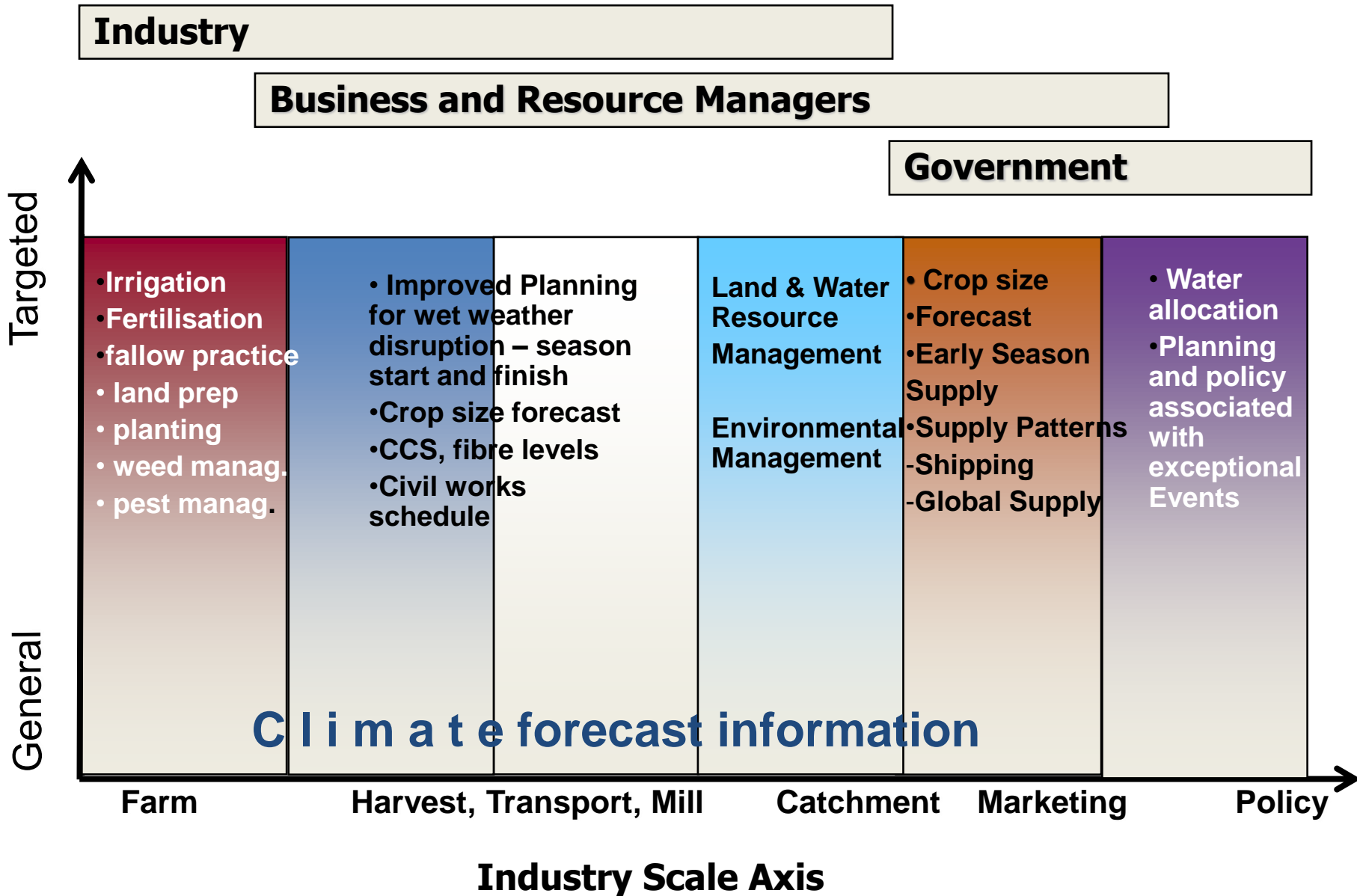


© Queensland Centre for Climate Applications 1999

Courtesy D Cobon – 4 month lead time forecasts



What are the decisions? Linking climate information to stakeholder decisions – complex issues of scale – targeting seasonal forecasts (example for the sugar industry)



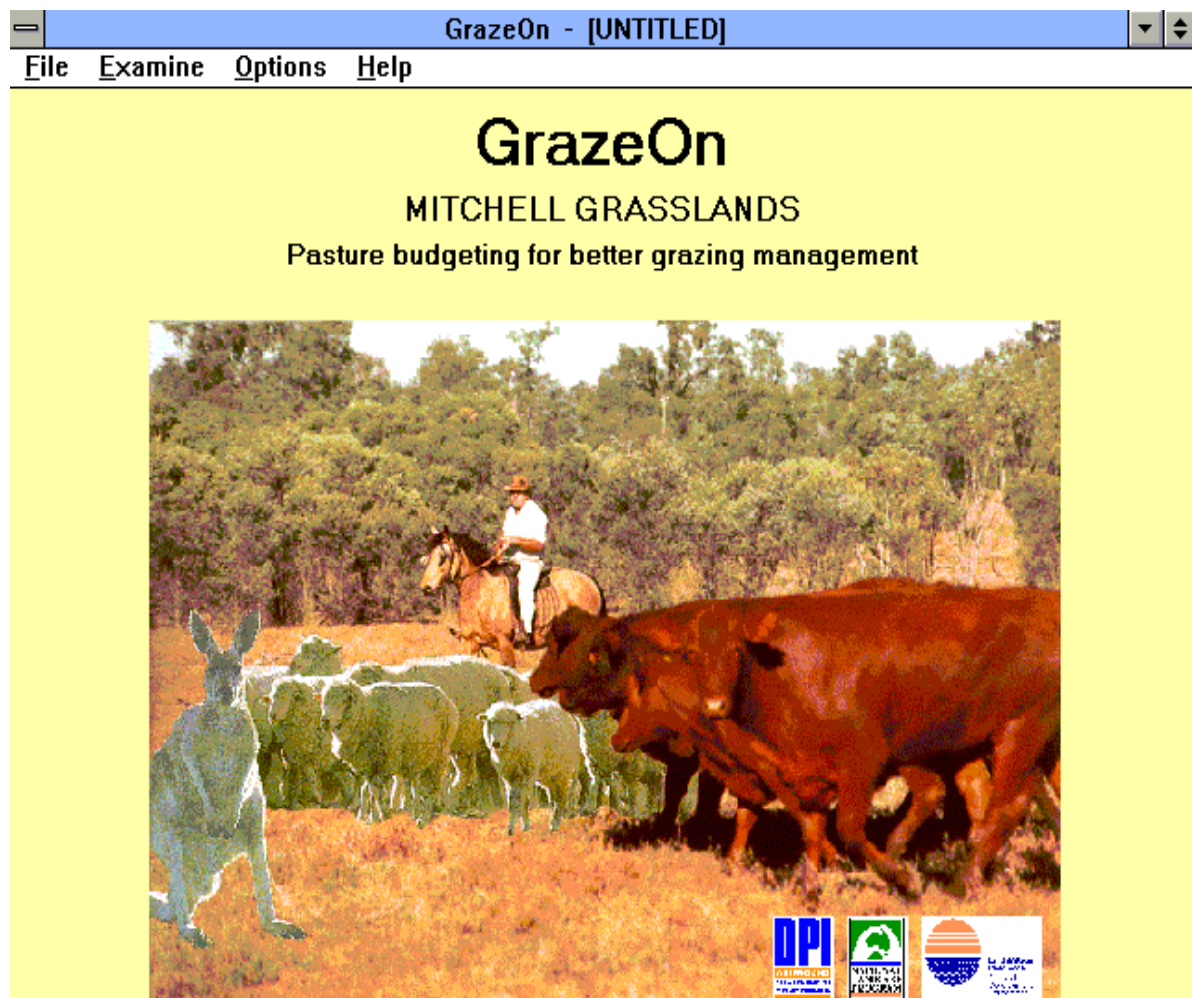
Assisting decision processes for stakeholders? – developing decision-support systems that link climate information, agricultural models and user decisions – make sure they actually add value ...

Decisions related to estimation of future stocking rates

Decisions related to pasture budgeting monitoring

Decisions related to total grazing pressure

Decisions related to drought preparation.



ఎన్.ఎ 1037

ఆచార్య ఎన్.జి. రంగా ఆగ్రికల్చరల్ యూనివర్సిటీ హైదరాబాద్
ఎంటర్ప్రైజీస్ ద్వారా వాతావరణ ఆధారిత పునరుద్ధరణ పు
చేర్చా కార్యక్రమం
తేదీ: 29-09-2010
స్థానం: హనుమాన్ జూ, వరంగల్
ప్రొ.పాణిగ్రామం, బీ.సి. కాలనీ, హనుమాన్ జూ, వరంగల్



A useful aim is to do a complete research analysis utilising the linking role of crop simulation modelling in the application of climate forecasting (example for cotton production modelling)

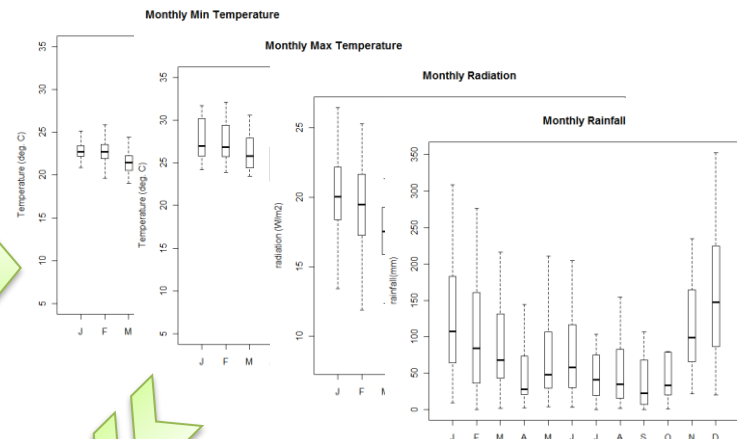
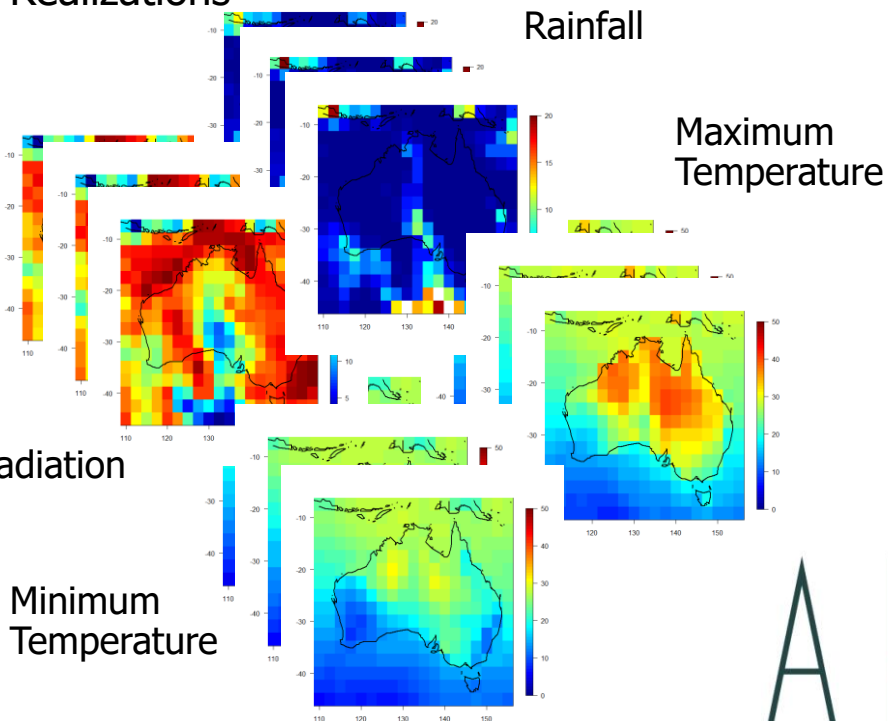
- Simulate management scenarios
- **Evaluate outcomes/risks relevant to decisions**
- Agricultural Production Systems Simulator (APSIM) simulates



- **yield of crops (potential yield is the key output),**
- key soil processes (water, N, carbon)
- surface residue dynamics & erosion
- range of management options
- crop rotations + fallowing
- short or long term effects

Multiple Gridded POAMA/UKMO (+ECMWF?) Realizations

Distributions of Station Climate Data

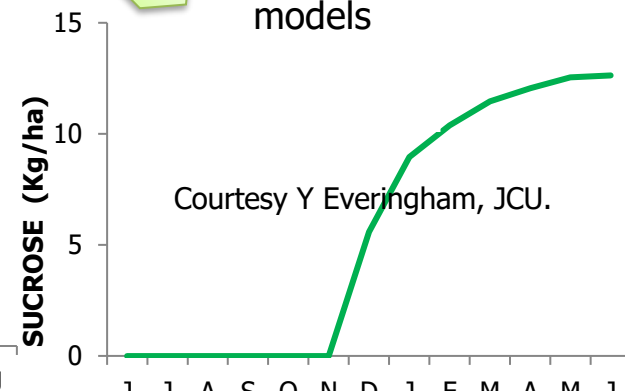
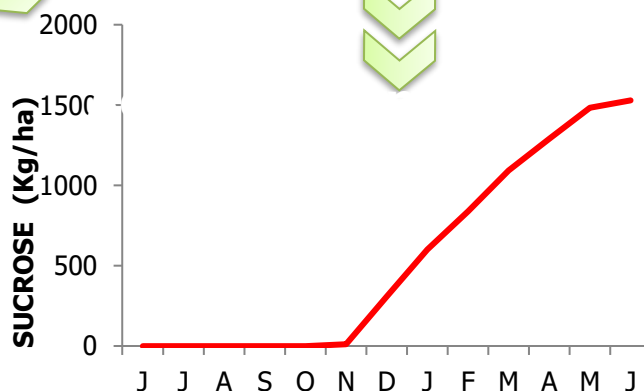
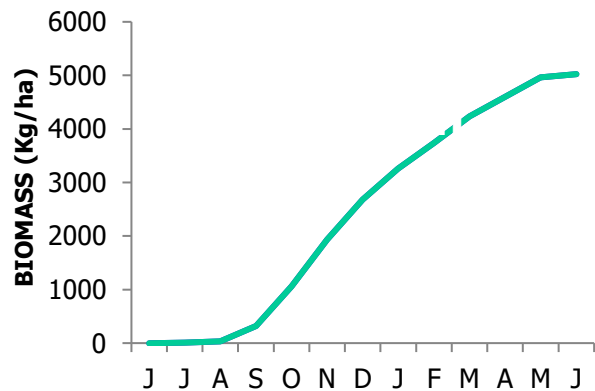


APSIM

AGRICULTURAL PRODUCTION SYSTEMS SIMULATOR

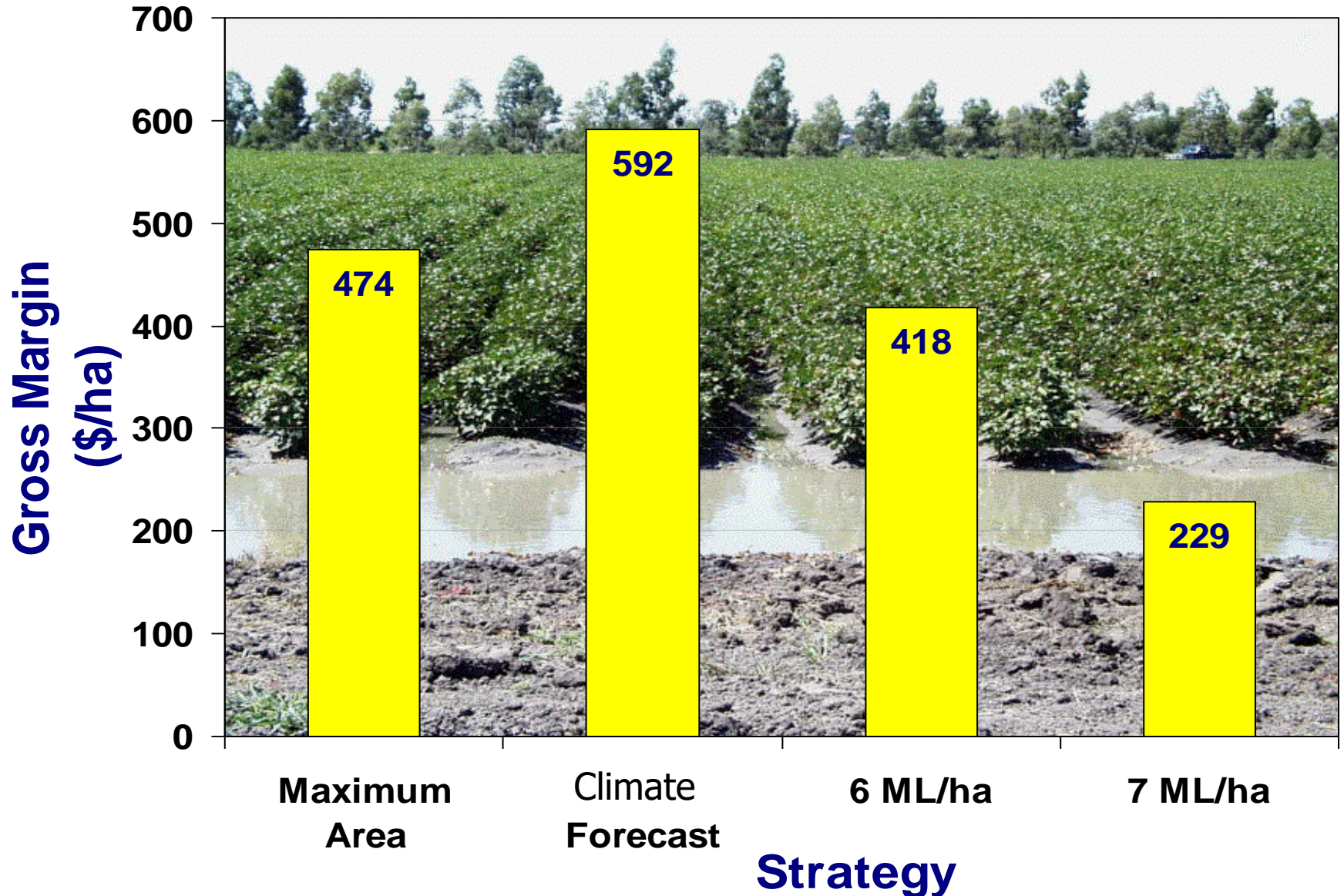
Run APSIM for each ensemble member for 30 years

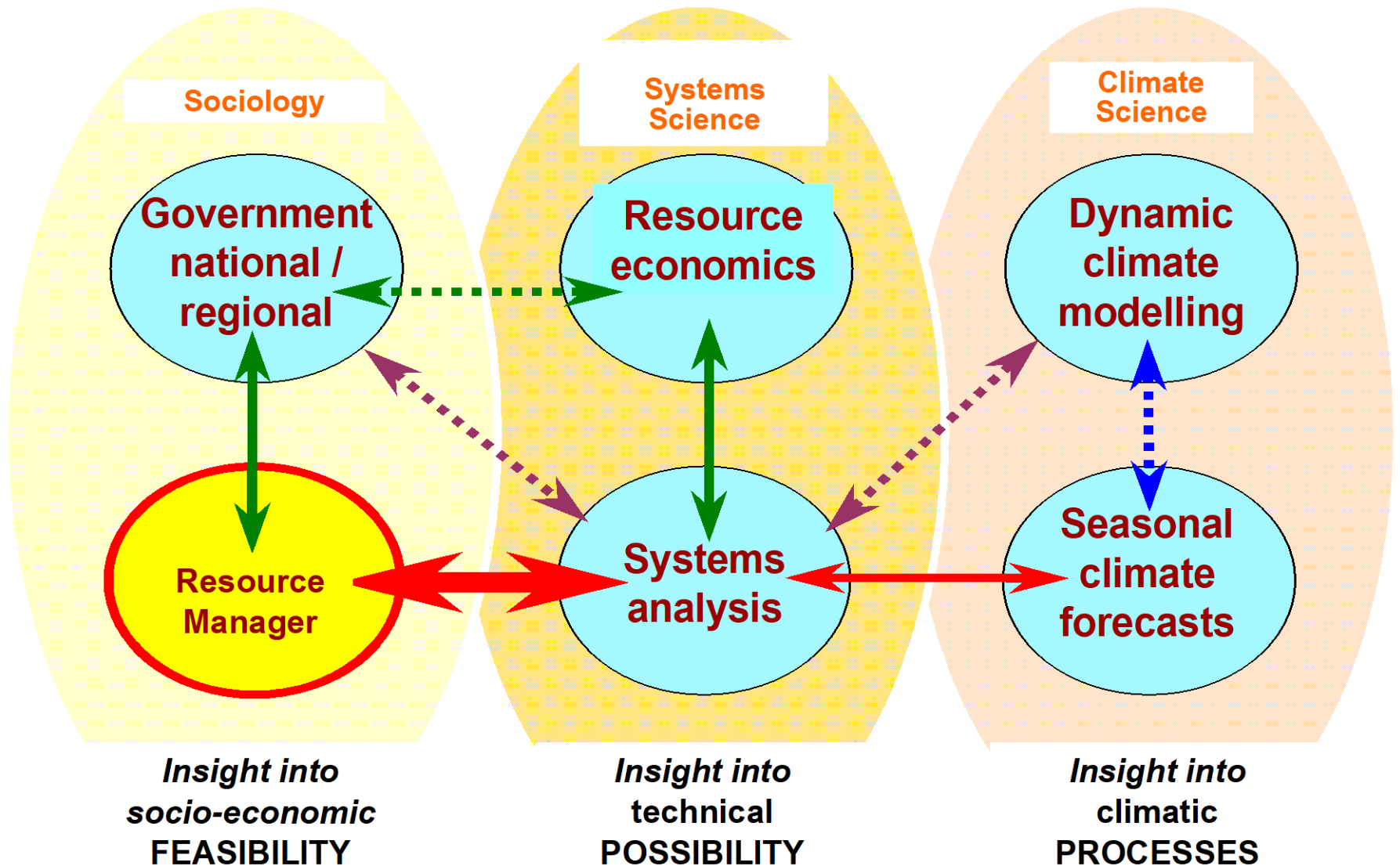
New projects aim to develop linkages between coupled models and crop models



Courtesy Y Everingham, JCU.

Demonstrating economic pay-offs in applying climate information to agricultural production—the value of seasonal climate forecasting in irrigated cotton production (Abawi)





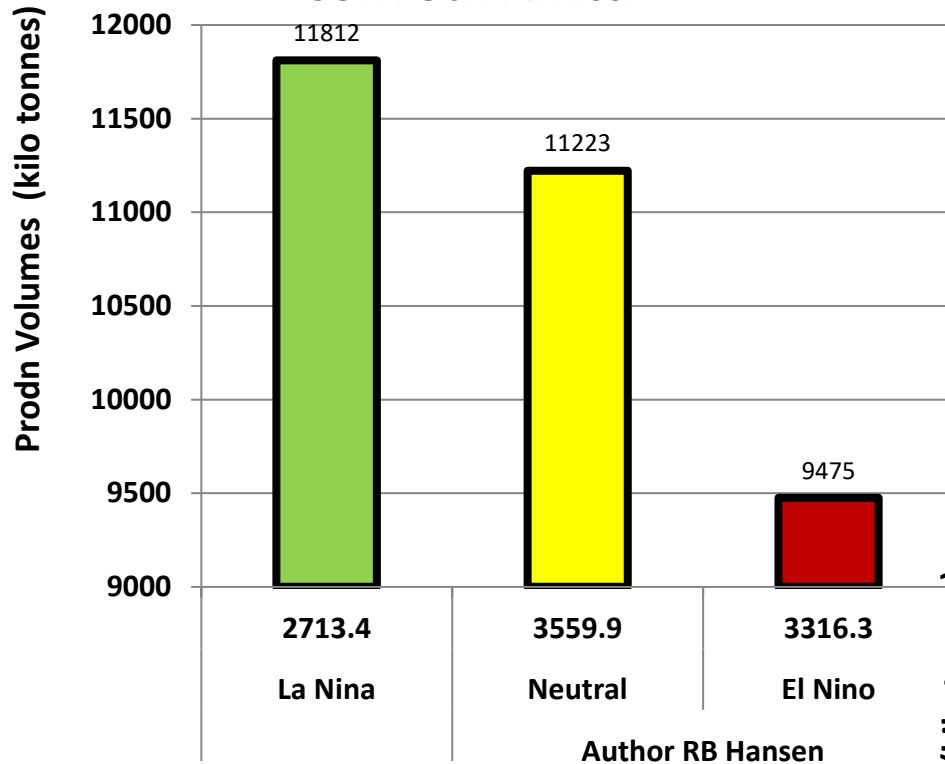
The need for an interdisciplinary approach :The RES AGRICOLA concept (Meinke *et al.*, 2001). Aim to convert insights gained into climatic processes via systems analysis and modelling into the socio-economic feasibility of decision options (after Meinke and Stone, 2005).

Conclusions...

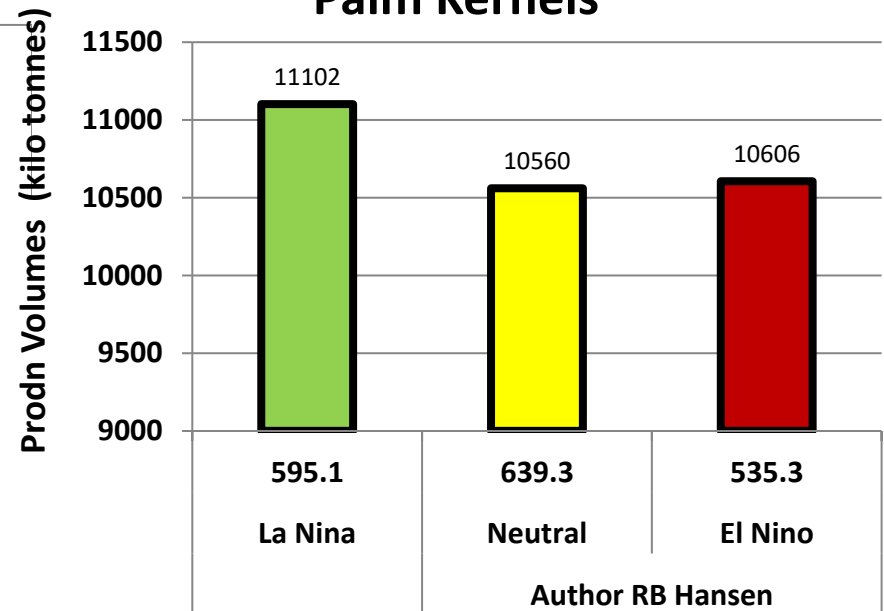
- Climate forecast information has reached a mature stage in Australia care still must be taken in relation to scale issues – spatial but especially temporal (eg: 3 month seasonal or intra-seasonal?)
- Useful to provide information on forecast skill to users but the key aspect will always be whether the SCF can fit the management options available to the user...if we miss this point the entire system can be seen by the user to fail..
- Seek out as many key decision-points as possible for a particular industry enterprise – and aim to meet these points with fully relevant information...
- Decision-support systems (DSS) and tools are useful but often more valuable to the scientist than to the user: the best application of DSS maybe as a tool to be used within a broad discussion environment (workshops – even electronic media).
- Provide as much information as possible back to the climate/ocean modellers/forecast agencies (also good to have them all working together).
- Aim to give as much 'ownership' as possible of the climate forecast system to the user – create a sense of empowerment!



Corn Sth Africa

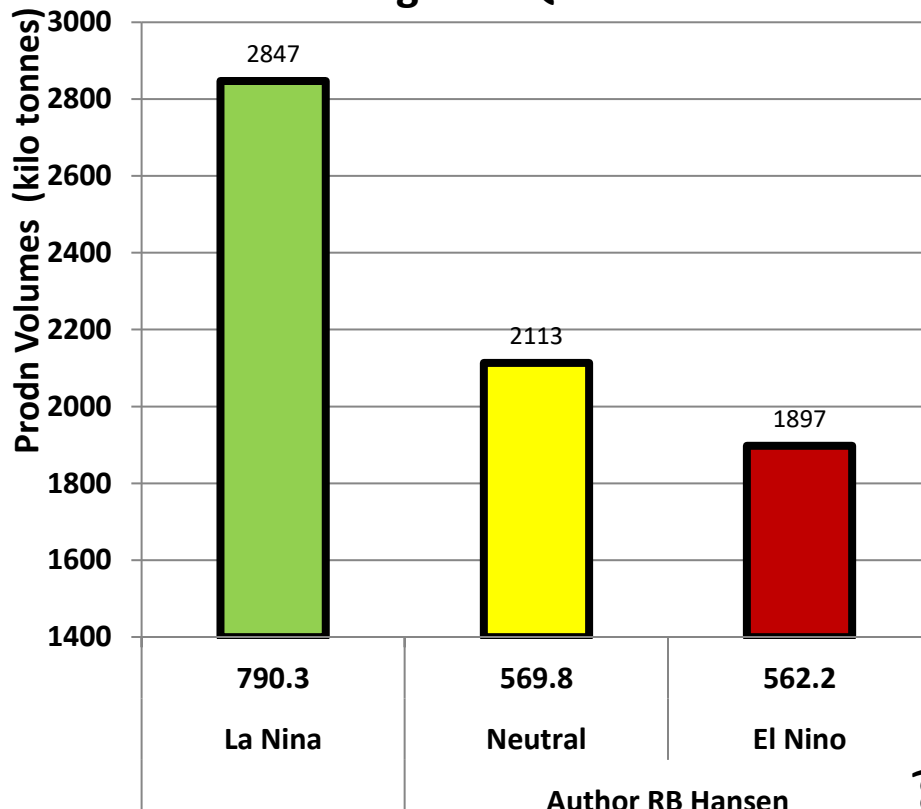


Palm Kernels



Mean/std Corn production RSA and Palm Kernels (global) associated with ENSO (Hansen and Stone, 2012)

Sorghum Qld & NSW

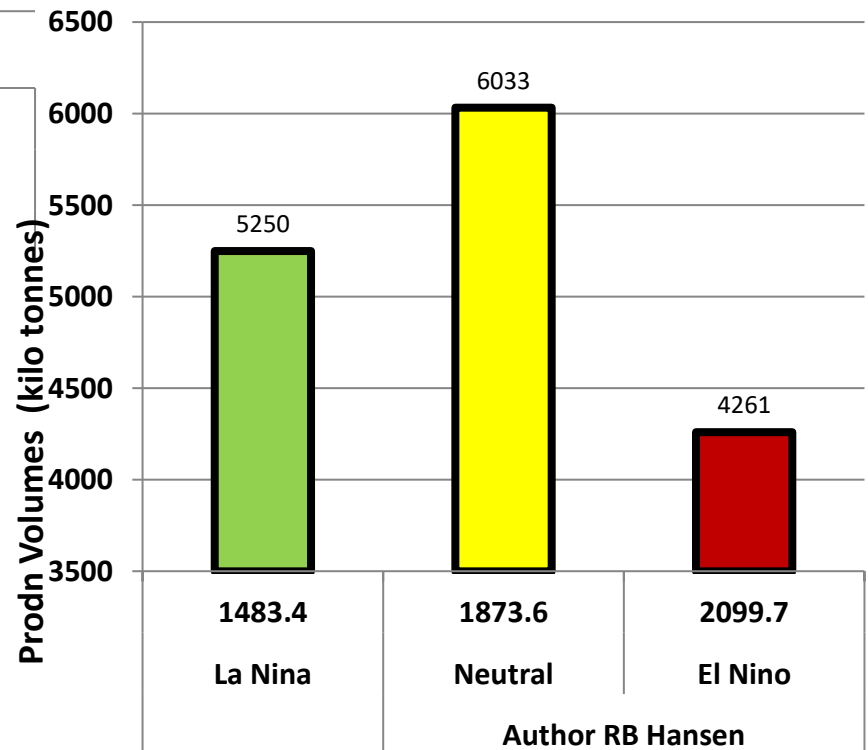


Author RB Hansen

Detailed climate indicator/yield relationships:

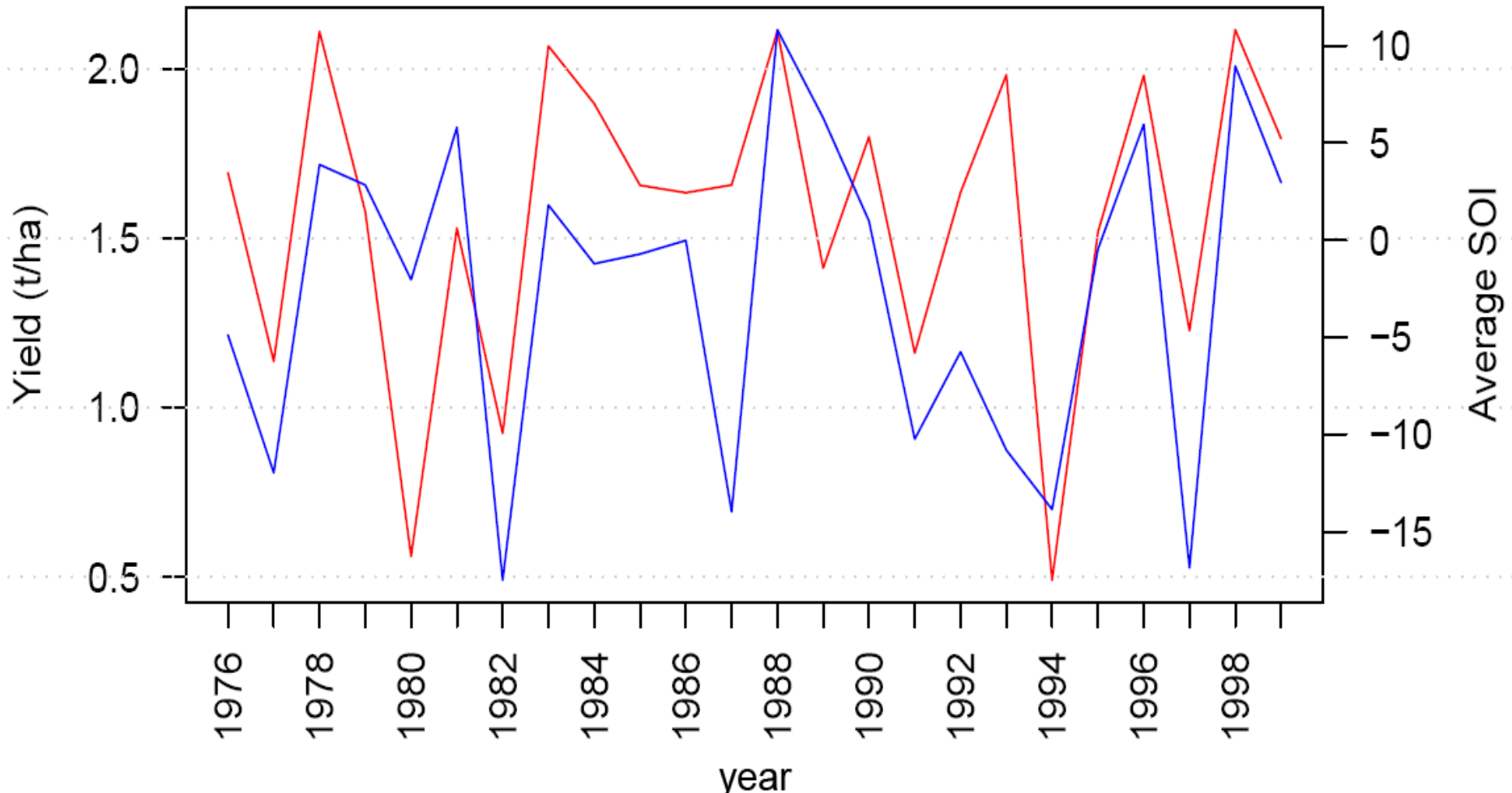
Mean /std production levels associated with ENSO – example for sorghum and wheat /Australia (Hansen and Stone, 2012)

Wheat NSW

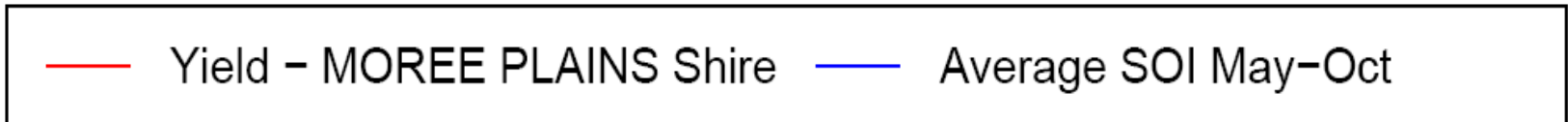


Author RB Hansen

Wheat Yield – Average In Season SOI Value



Local scale issues - relationship between annual variation in the SOI and annual Moree Plains wheat yield (Stone and Donald, 2007)
- **the key is the need to modify actions ahead of impacts.** .



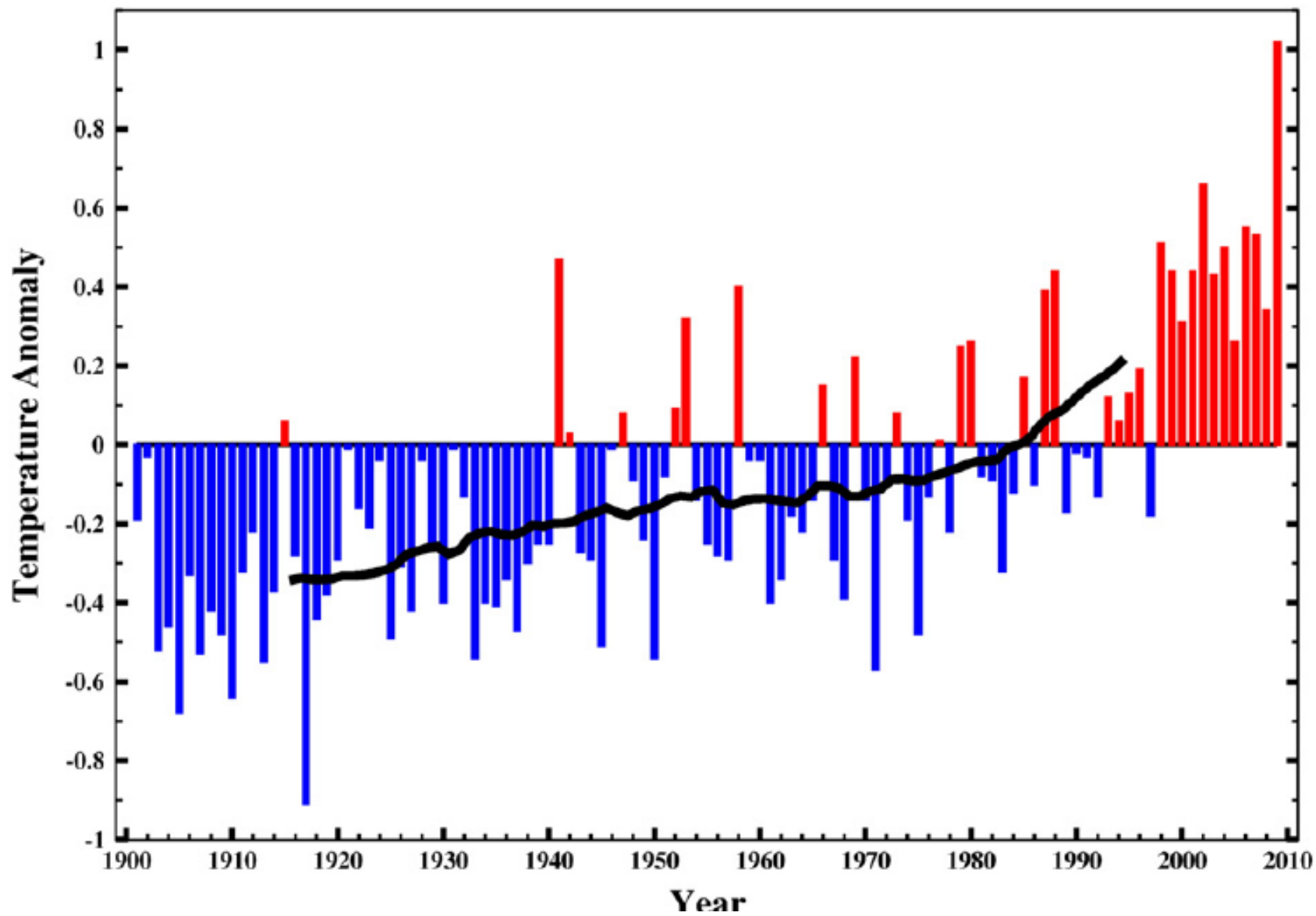
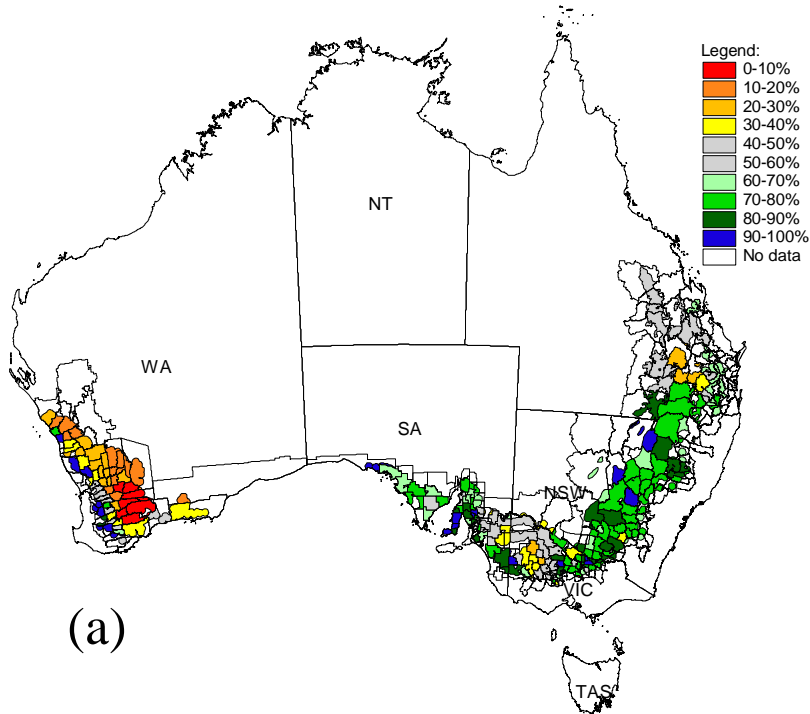


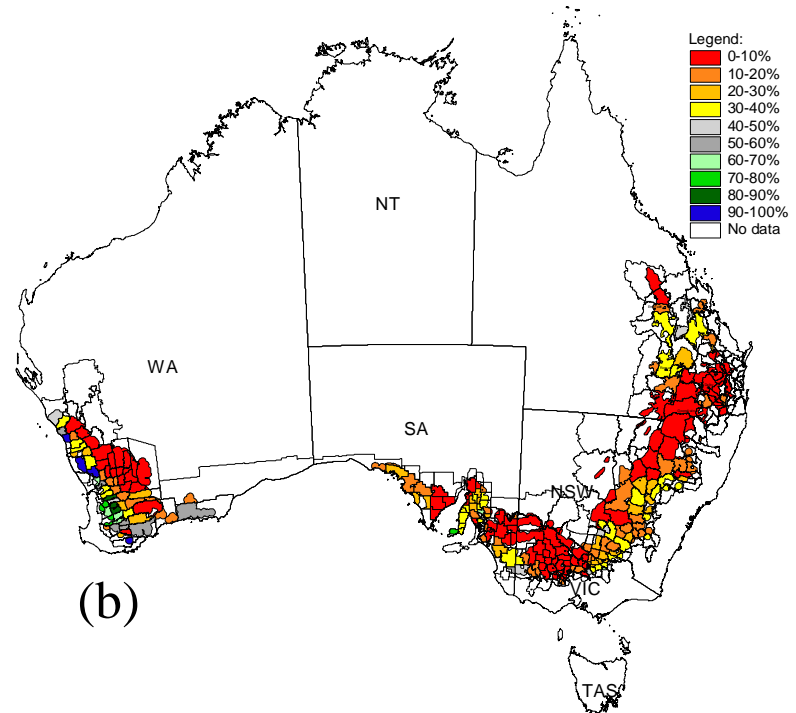
Fig. 2. Observed (CRU) temperature anomaly over India for the period 1901–2009, with respect to present day climate (normal: 1970–1999). The black line shows the 30 year running mean.

July 2001



(a)

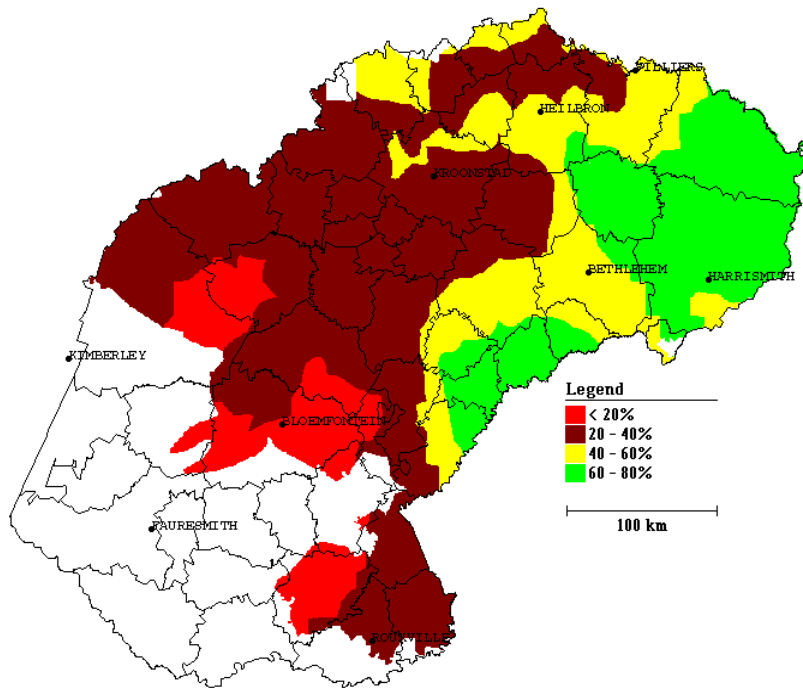
July 2002



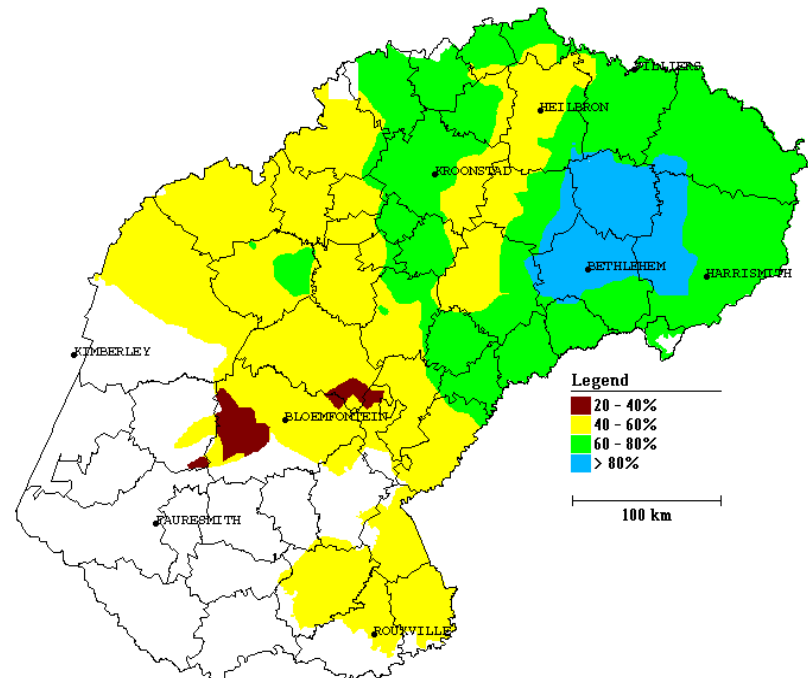
(b)

Decisions being made by grain exporting authority: forecasting agricultural commodities: Use of the larger spatial scale model - 'OzWheat' - to produce probabilistic of exceeding long-term median wheat yields for every wheat producing district in Australia issued in July 2001 and July 2002, respectively - (2002 was an 'El Niño year') (Potgieter, 2010).

Probabilities of exceeding long-term median maize yields for Free State, RSA, associated with a consistently negative SOI phase and a consistently positive SOI phase – output provides the probability (%) of exceeding maize yields of 2.5 t/ha



Planting date: 1 November
(Cons -ve SOI phase)



Planting date: 1 November
(Cons +ve SOI phase)



the CMIP3 GCMs over South Asia shows that only 6 GCMs of a subset of 18 are able to capture the pattern correlation of precipitation between models and observed precipitation with a relatively small root mean square difference compared to observations over India (7N–30N & 65E–95E) and a larger monsoon domain (25S–40N & 40E–180E)

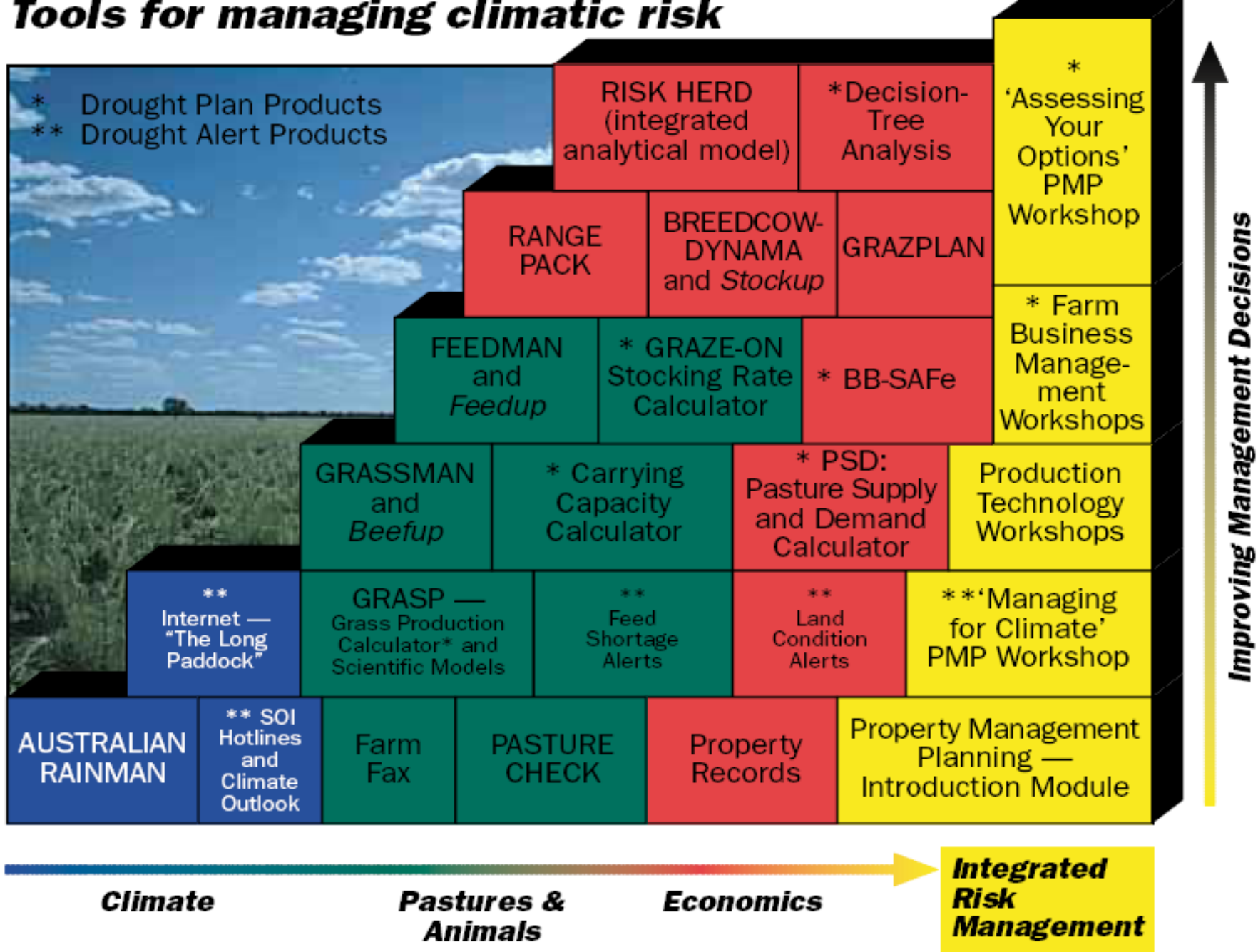
(Annamalai et al., 2007). Kripalanai et al. (2007) show that only 6 models of a subset of 22 CMIP3 GCMs over India (5N–35N & 65E–95E) are able to simulate the monsoon interannual variability.

- So far over south Asia, climate change studies are very limited and are based on only single RCM forced with one GCM. In the present study multi model approach is applied for more robust signal. For the first time, results from RCM simulation are presented that we produce by three RCMs forced with two GCMs. In this paper using ensemble approach, we explore climate variability and change, and its predictability at the seasonal and decadal time scales over India. The ensemble approach (Jacob et al., 2007; Reichler and Kim, 2008) should improve the reliability of the projections and the uncertainty can be estimated quantitatively. We argue that an adequate awareness of tools and knowledge concerning the seasonal time scale may increase our ability to deal with climate variability at longer time scales.

Section 2

- will address the data sets and the model used in the study. Experiment
- design and the methods used are discussed in Section 3. Results of general
- and seasonal predictability in the CMIP3 GCM ensemble and the
- RCM ensemble simulated for this study are presented in Section 4 and
- discussed in Section 5. Finally summary is given in Section 6.
- 2. Datasets and models
- 2.1. Observations and GCM data
- Two sets of observational precipitation and temperature data
- (Table 1) have been used to analyze the robustness of the model simulation
- results:
- The observational data

Tools for managing climatic risk



Developing targeted decision support tools - examples for the cattle industry