Enhancing food security through the use of biophysical, climate modelling and sensing technologies

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The University of Queensland Australia | Queensland Alliance for Agriculture & Food Innovation | Queensland Government | ARC Centre of Excellence for translational photosynthesis

Overview

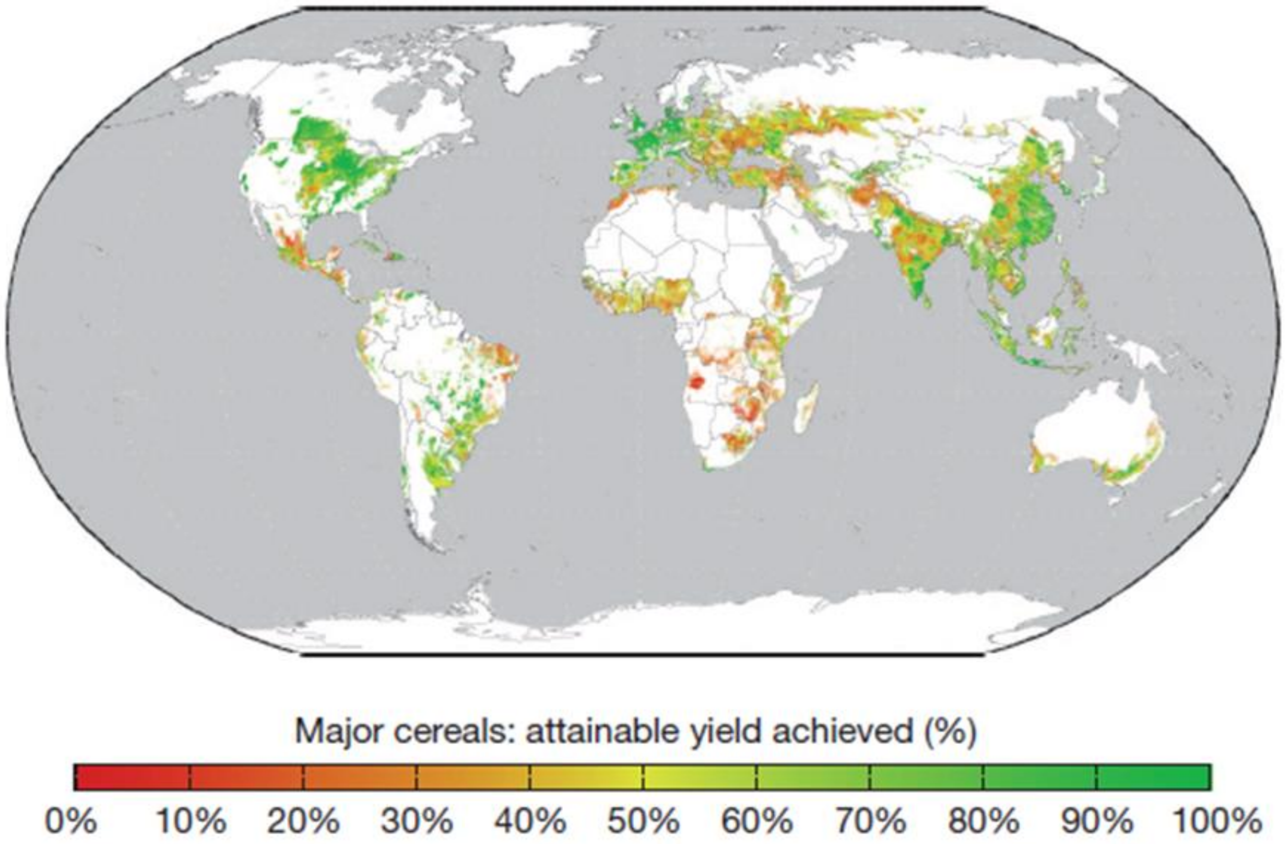
- The global picture
- Impact of climate variability on food security
- Biophysical modelling approach
- Predicting crop Yield, Area & Production
- Increasing the Lead-time of crop yield forecasts
- Crop yield prediction at Field and pixel scales

Food security

Significant advance in productivity needed to meet population growth and increased affluence of emerging economies

Opportunities via crop improvement and removing yield gaps but climate risks interfere

Is it possible to enhance productivity given existing and changing climate risks?



Average yield gaps for maize, wheat and rice

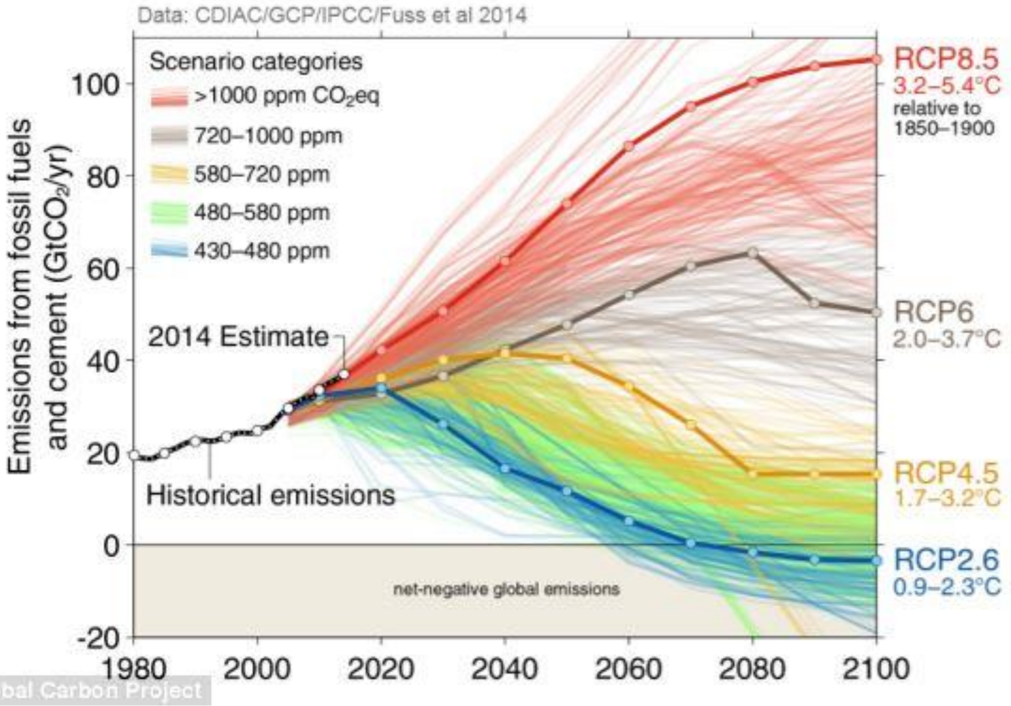
Mueller et al (2012) Nature

Climate Risks

Climate trends introduce more uncertainty and reduce the relevance of experience

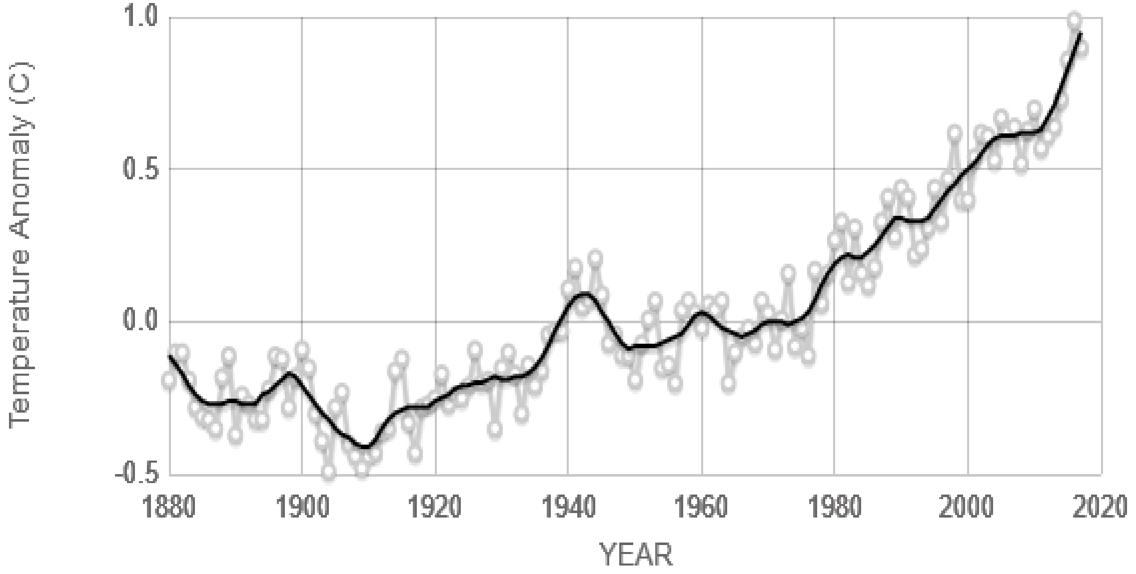
CO_2 emissions and global temperature

Observed CO_2 emissions and future scenarios



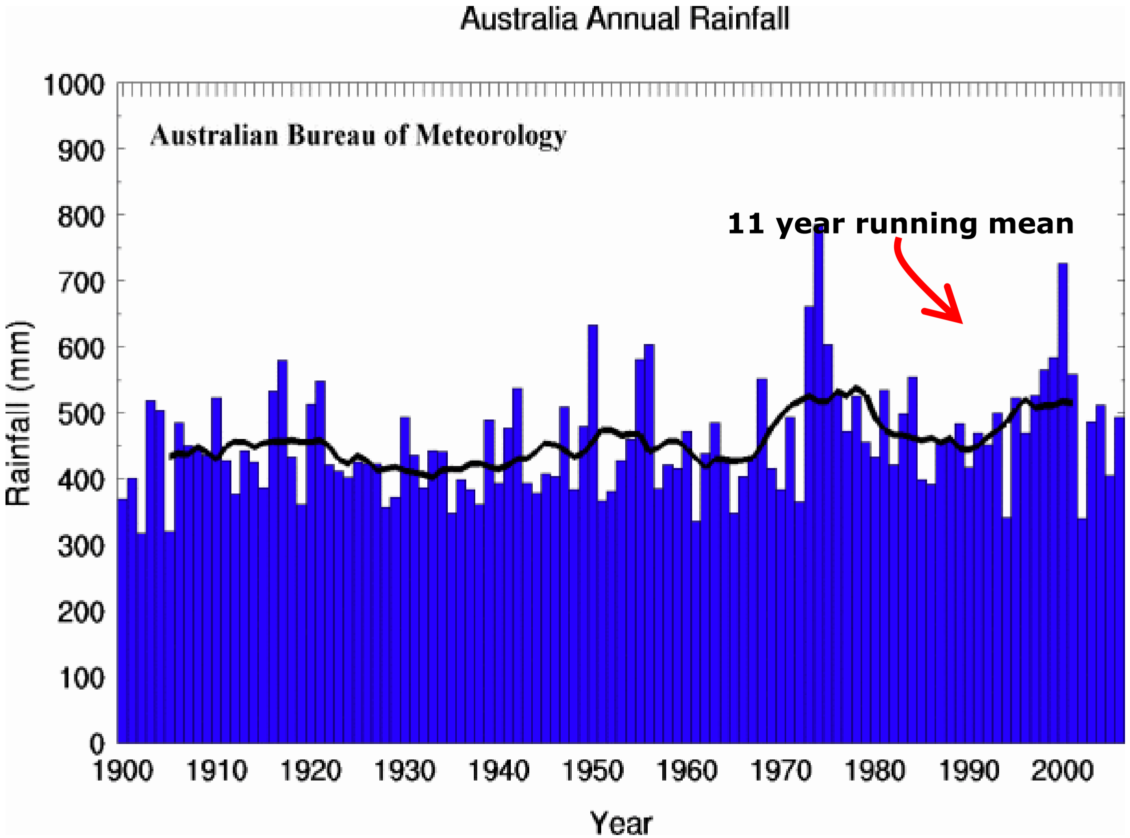
Update - 2017 estimate 36.8 Gt

Observed global temperature anomaly

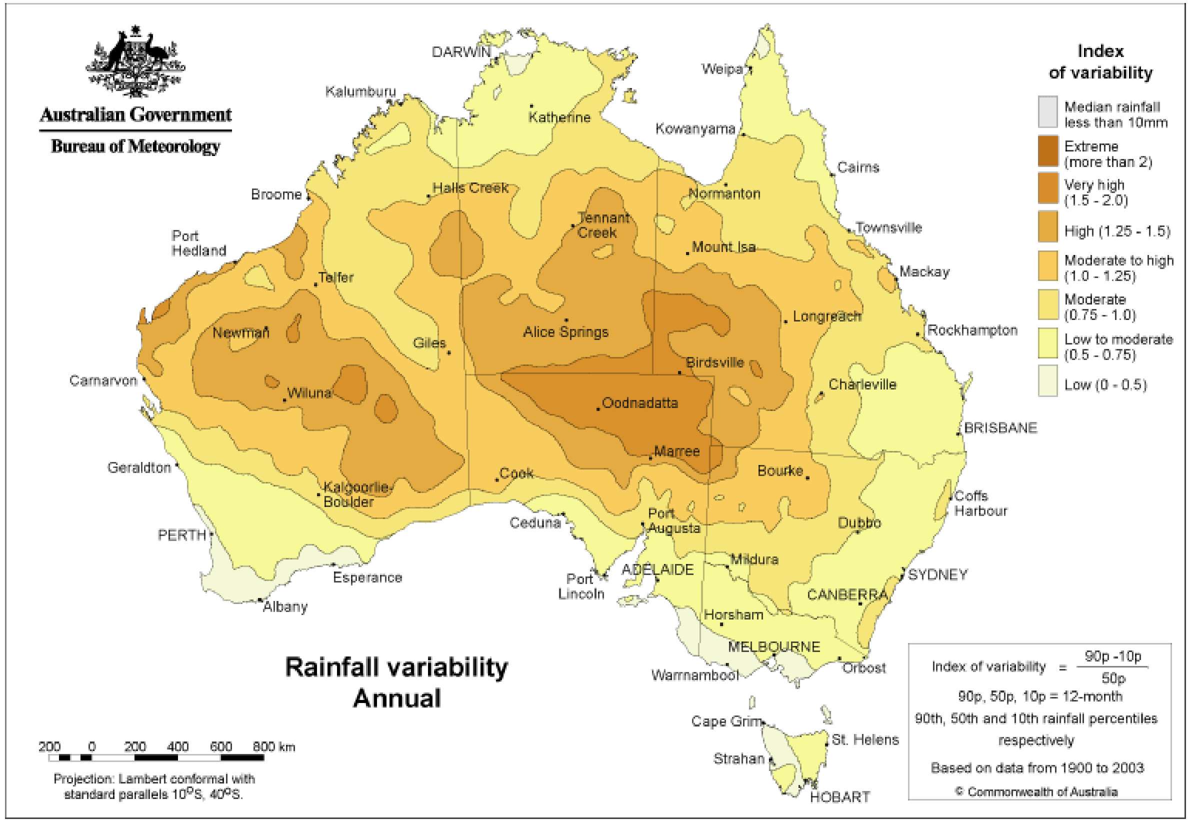


Source: climate.nasa.gov

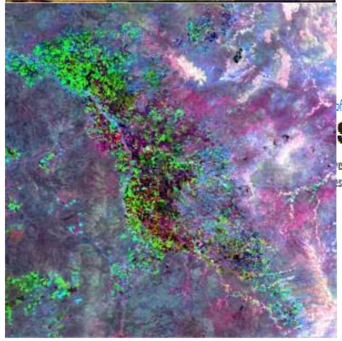
Climate variability - Australia

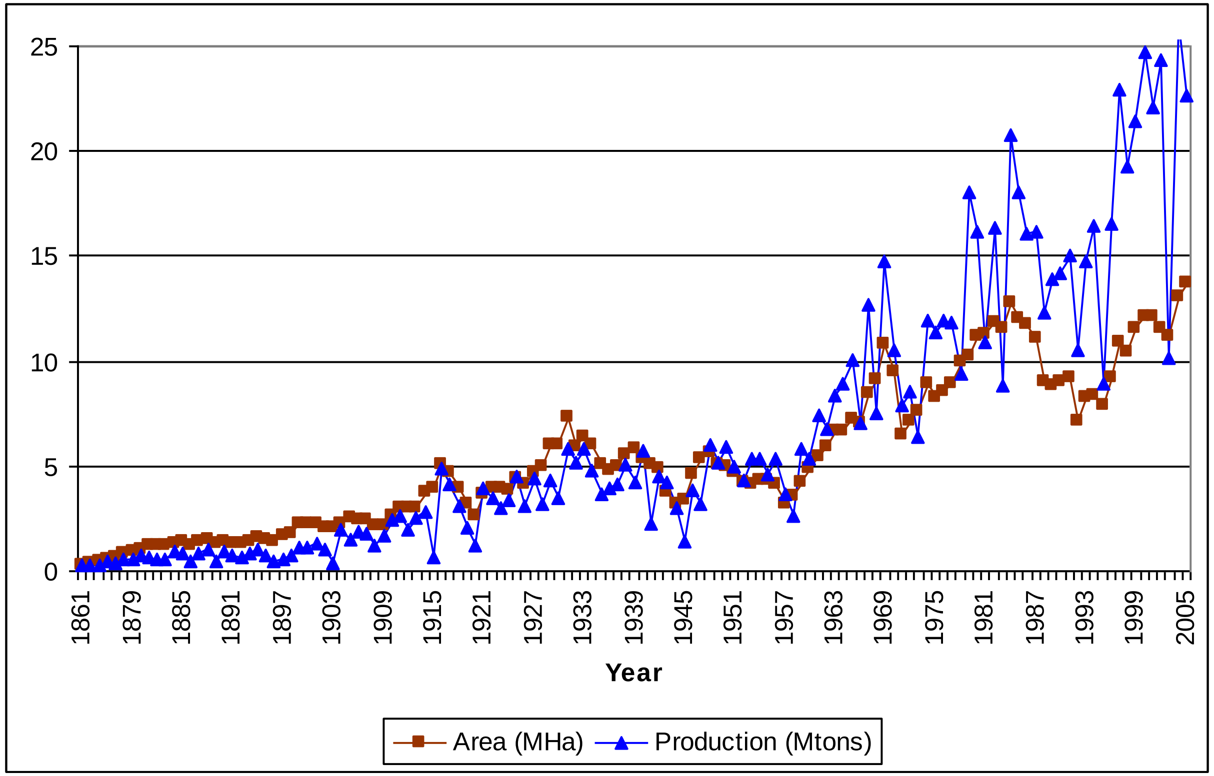


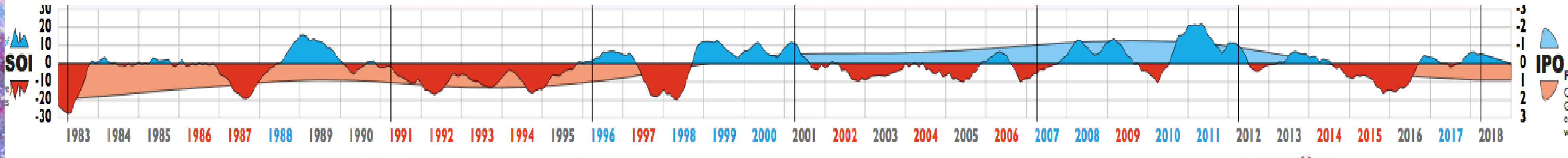
Huge variability at temporal & spatial



Impact (Economic, Natural & Social)







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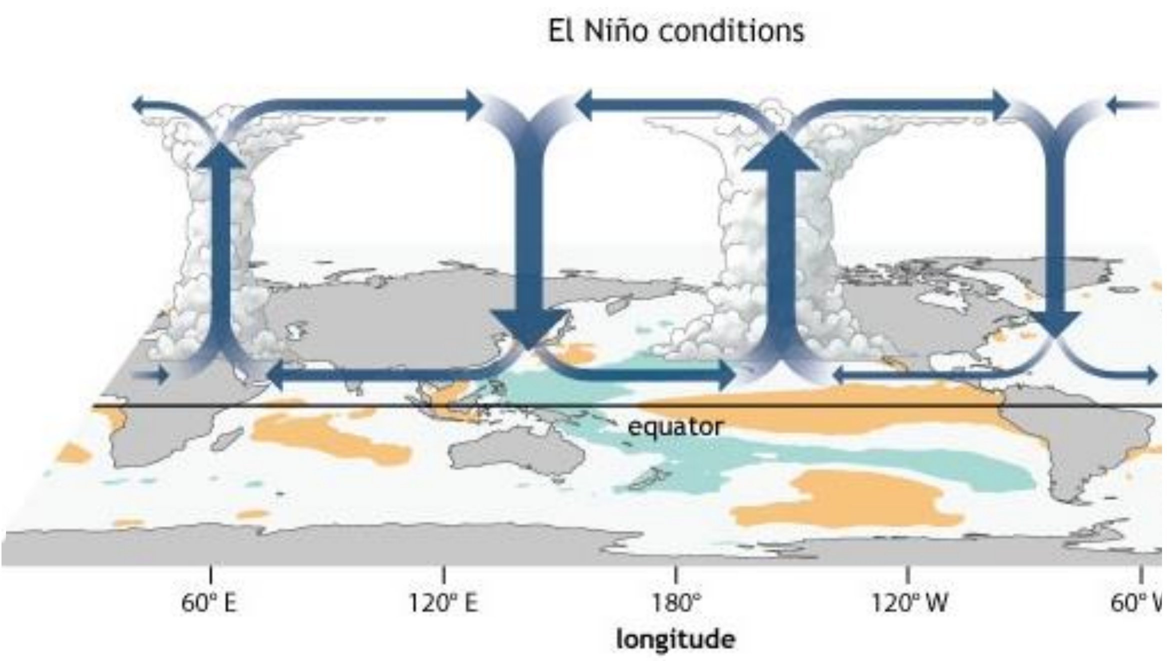
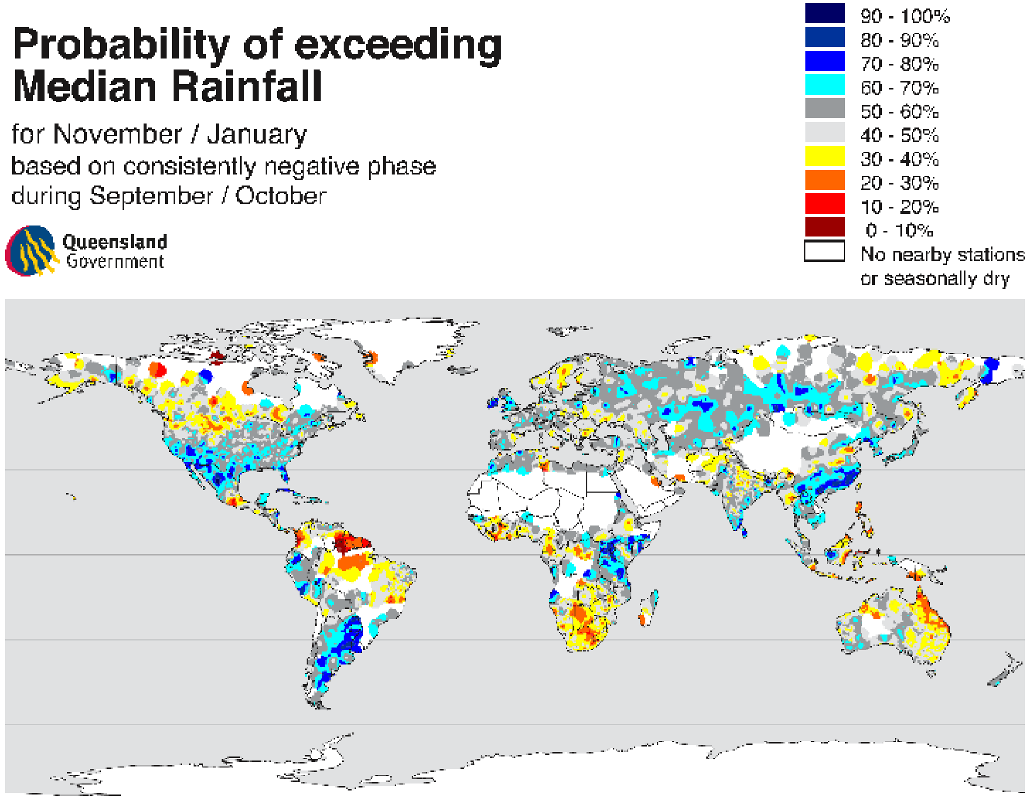
The Nature of Climate Risks

Seasonal climate variability components have some degree of predictability

I. ENSO and interannual





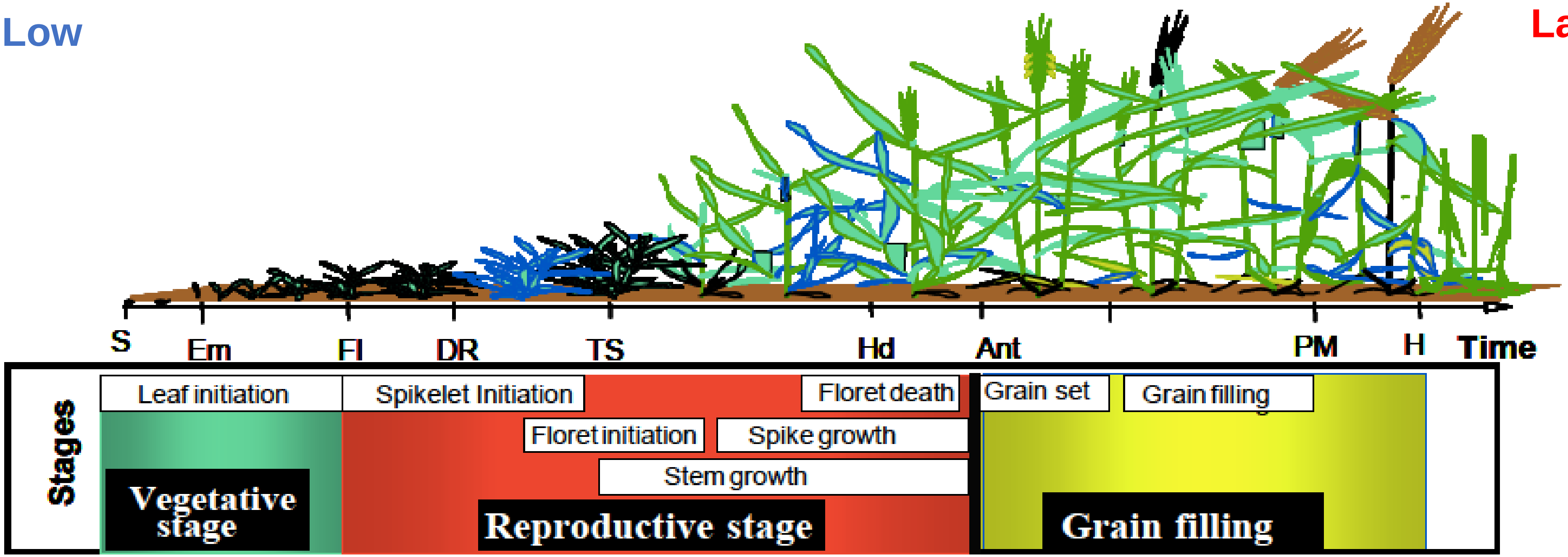
Stone et al (1996) Nature, 384

Utility

Utility of crop predictions is a function of timing and accuracy

Early / Low

Late / High



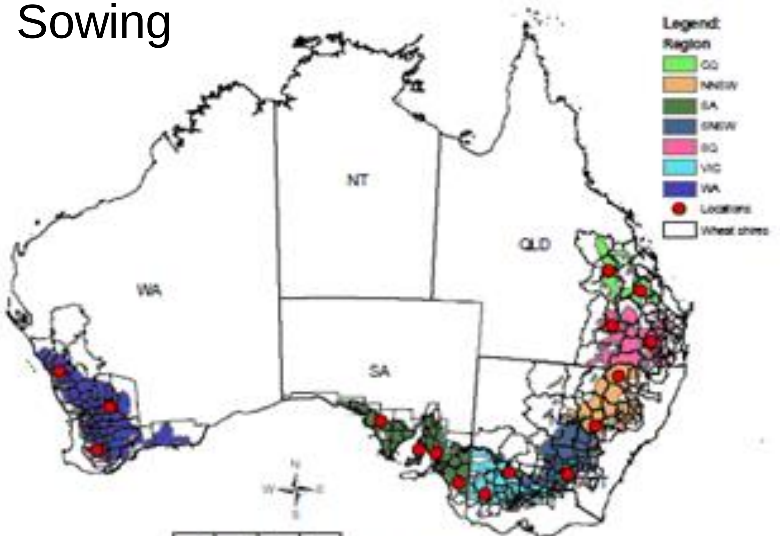
(Slafer, 1999)

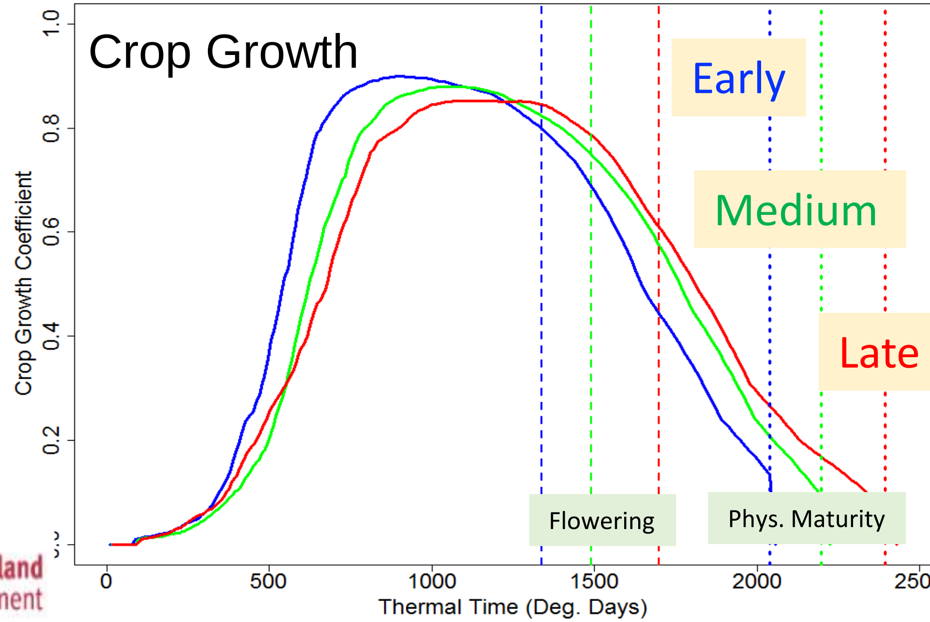
Crop life cycle duration is closely associated with temperature

Biophysical Crop Modelling

- Integrating climate prediction and biophysical modelling (1982-2001,2005, 2010 & 2015)
- Developed wheat & sorghum models:

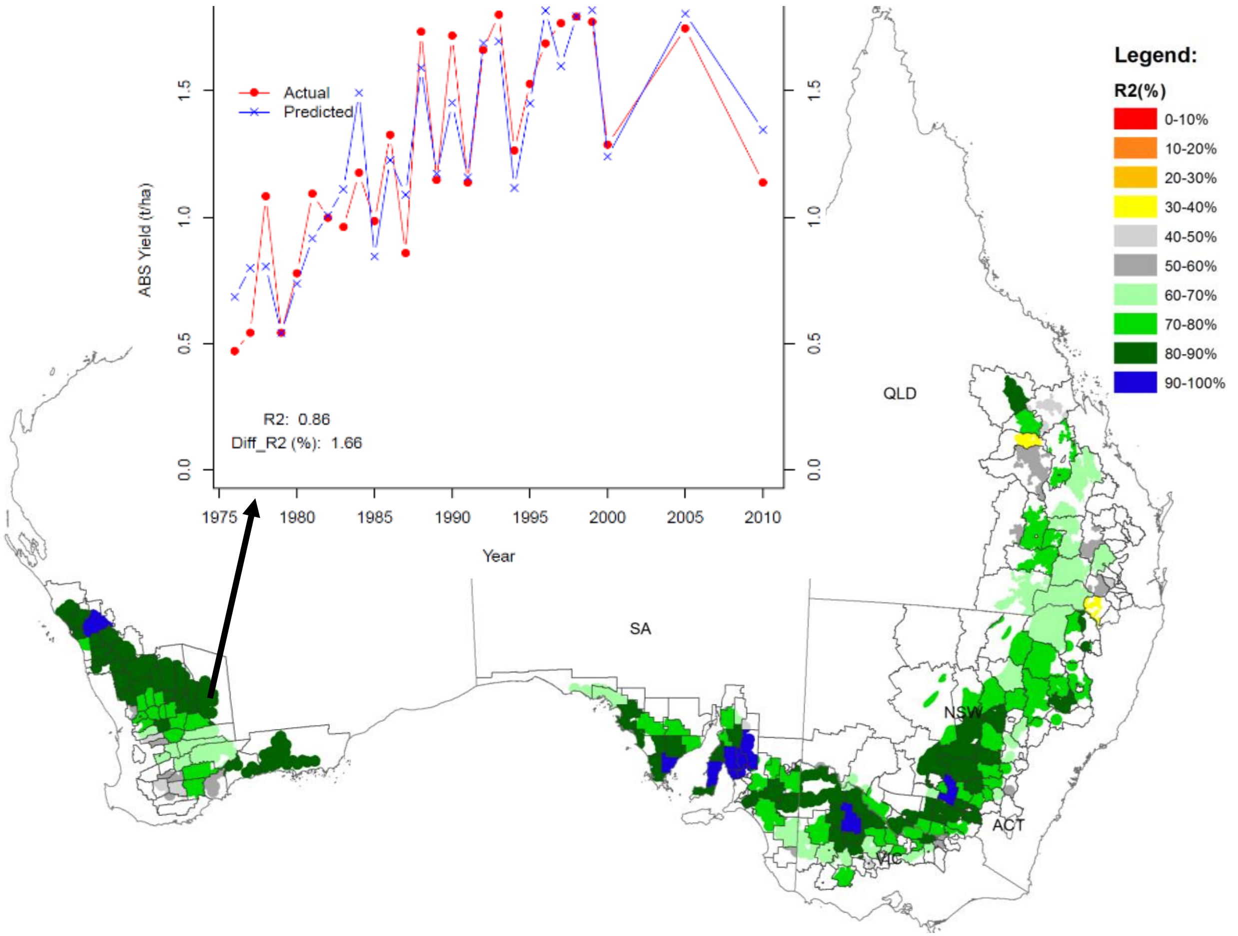
  Yield = f(Year, Stress Index)
- SI simulated daily at weather station level driven by thermal time & aggregated to shire
- Models are trained on actual shire scale data
- Model does not account for pest, diseases and losses due to extreme events (e.g. floods, heat wave)

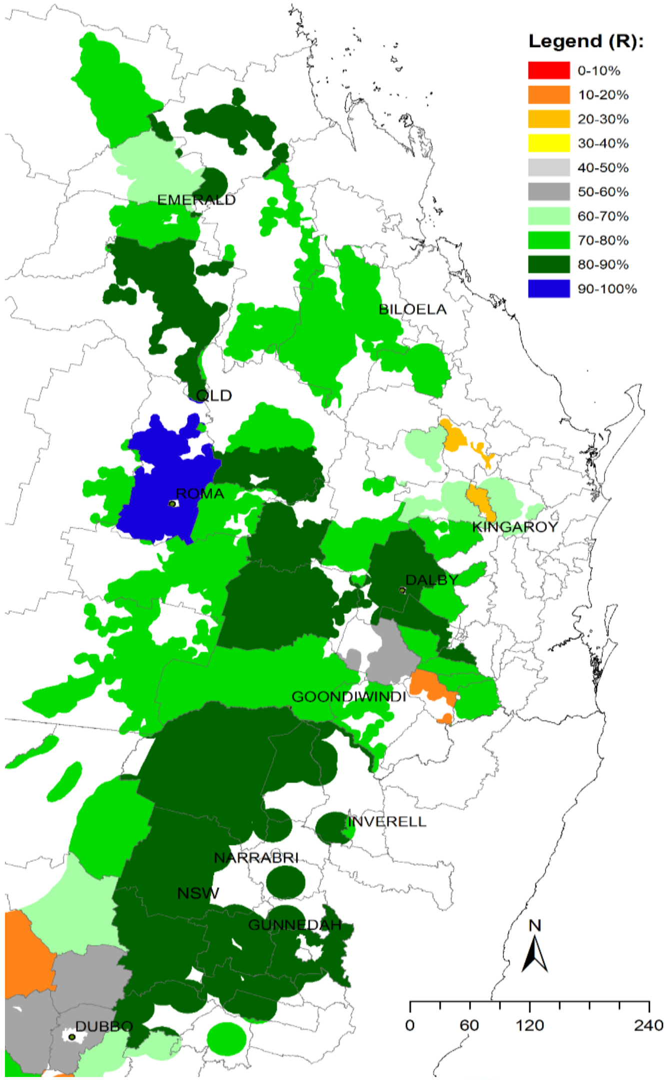




Validation

Significantly high correlations across Australia wheat & sorghum cropping region





Operationally

Generating Yield Forecast Data Plumes – Climate Forecast Set (e.g. at 1 June 2004)

Start of fallow

1 October 2003 to 31 May 2004

1 Jun 19?? to 31 Dec 19??

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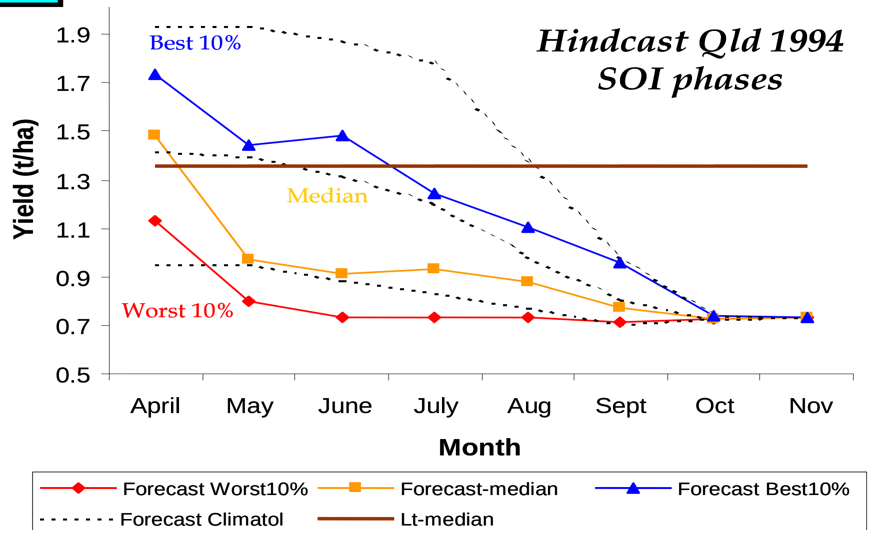
•
•
•

1 Jun 19?? to 31 Dec 20??

Forecast distribution based on climate forecast

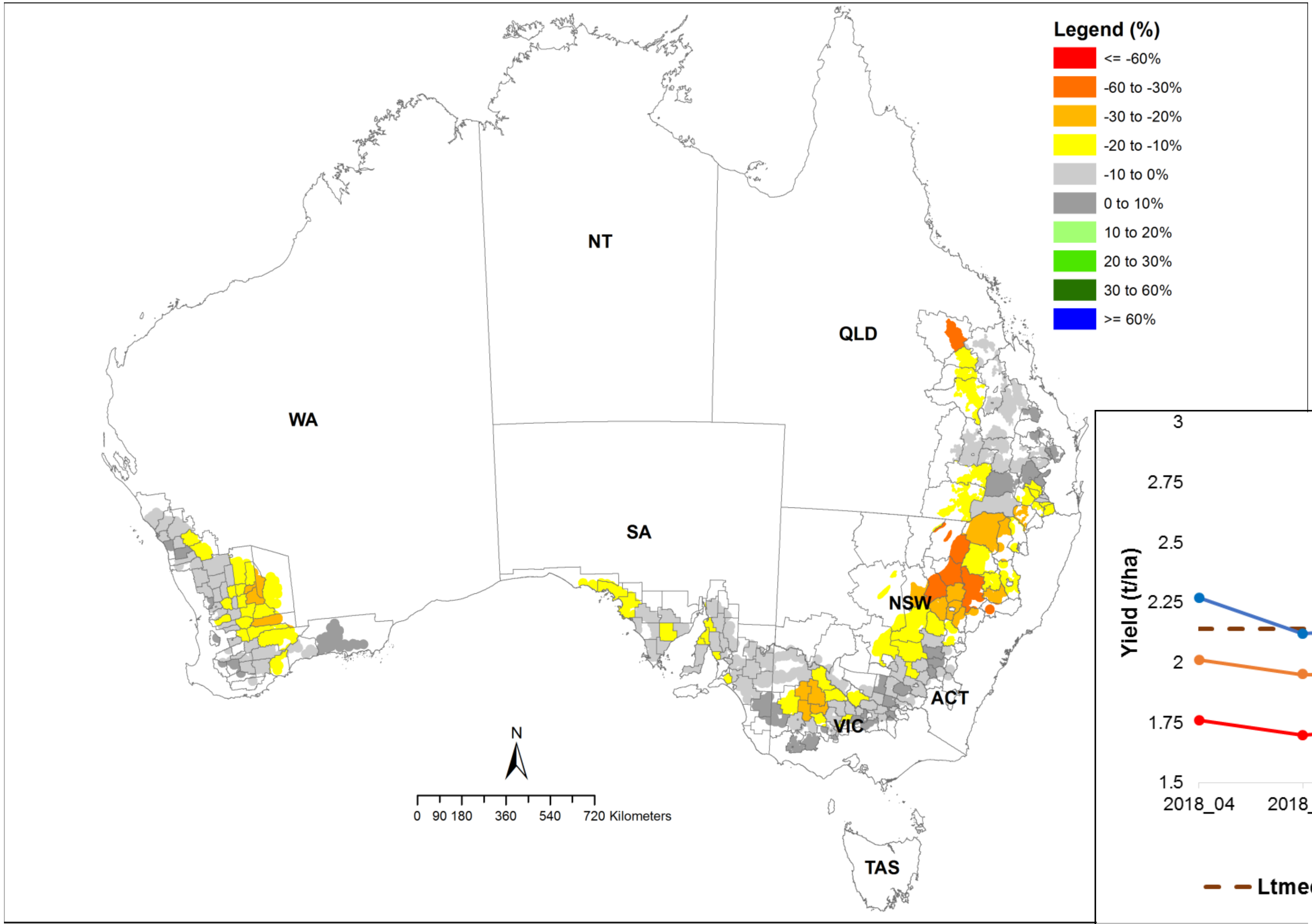
Run model using weather data to date for current season

Run model projections on subset of historical analogues from climate forecast to complete season



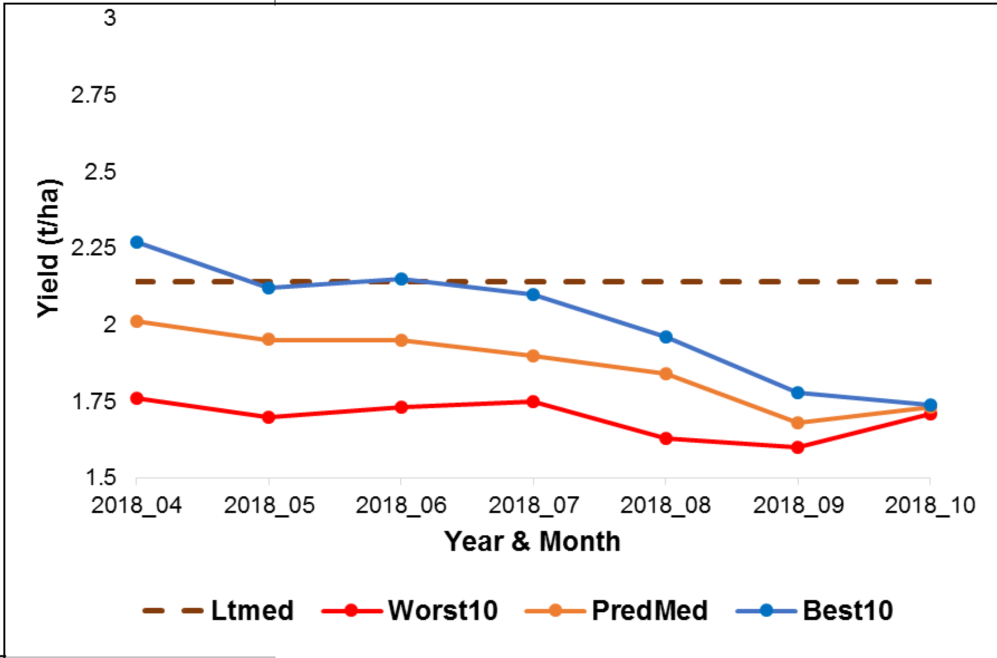
Potgieter et. al. 2003, 2005, 2006

Predicting crop yield at regional and national levels

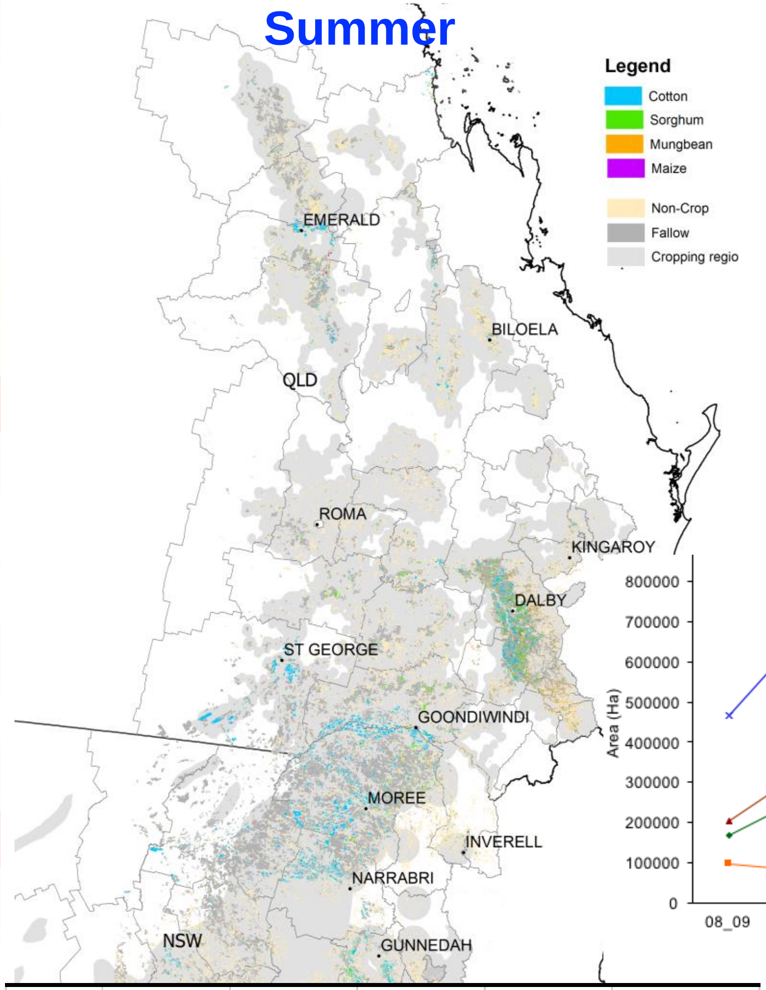


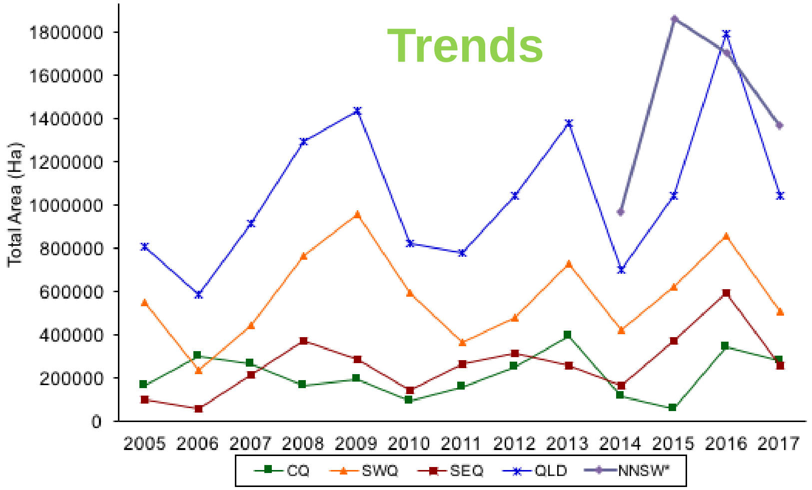
Deviation of forecast median wheat yield from long term median

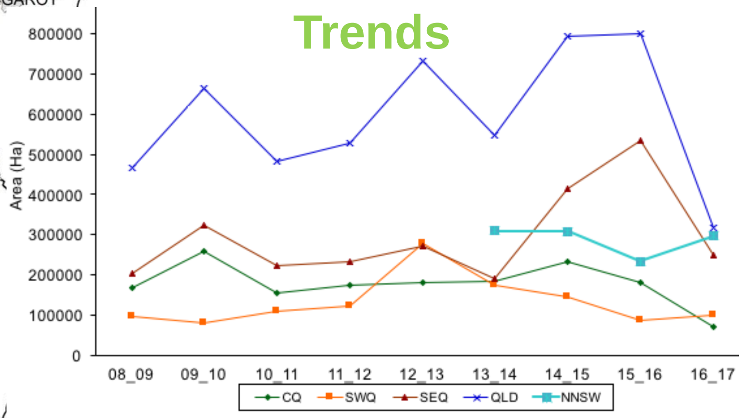
1st July 2018

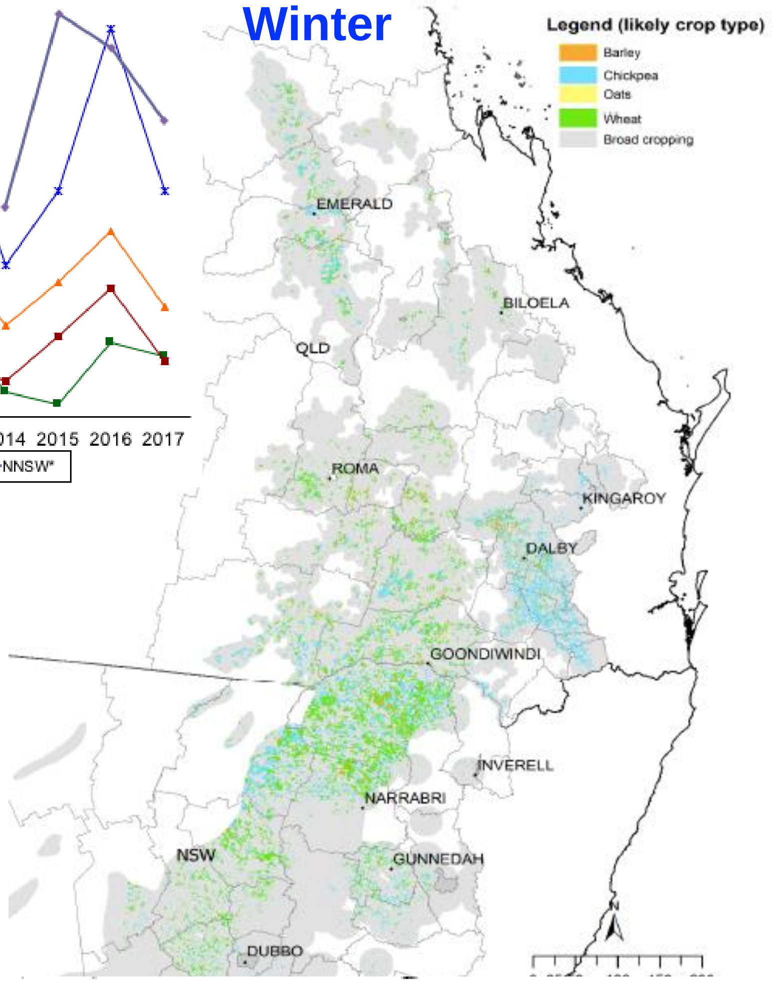


Crop Area, Trends & Production









Region	Cotton (ha)	Maize (ha)	Mung (ha)	Sorghum (ha)	Prod (Sorghum)
CQ	59,531	4,269	4,085	2,135	4,821
SEQ	90,718	12,896	97,507	47,018	162,877
SWQ	79,156			21,477	51,954
NNSW	263,245		10,436	40,379	195,394
Total	492,650	17,166	112,027	111,009	415,046

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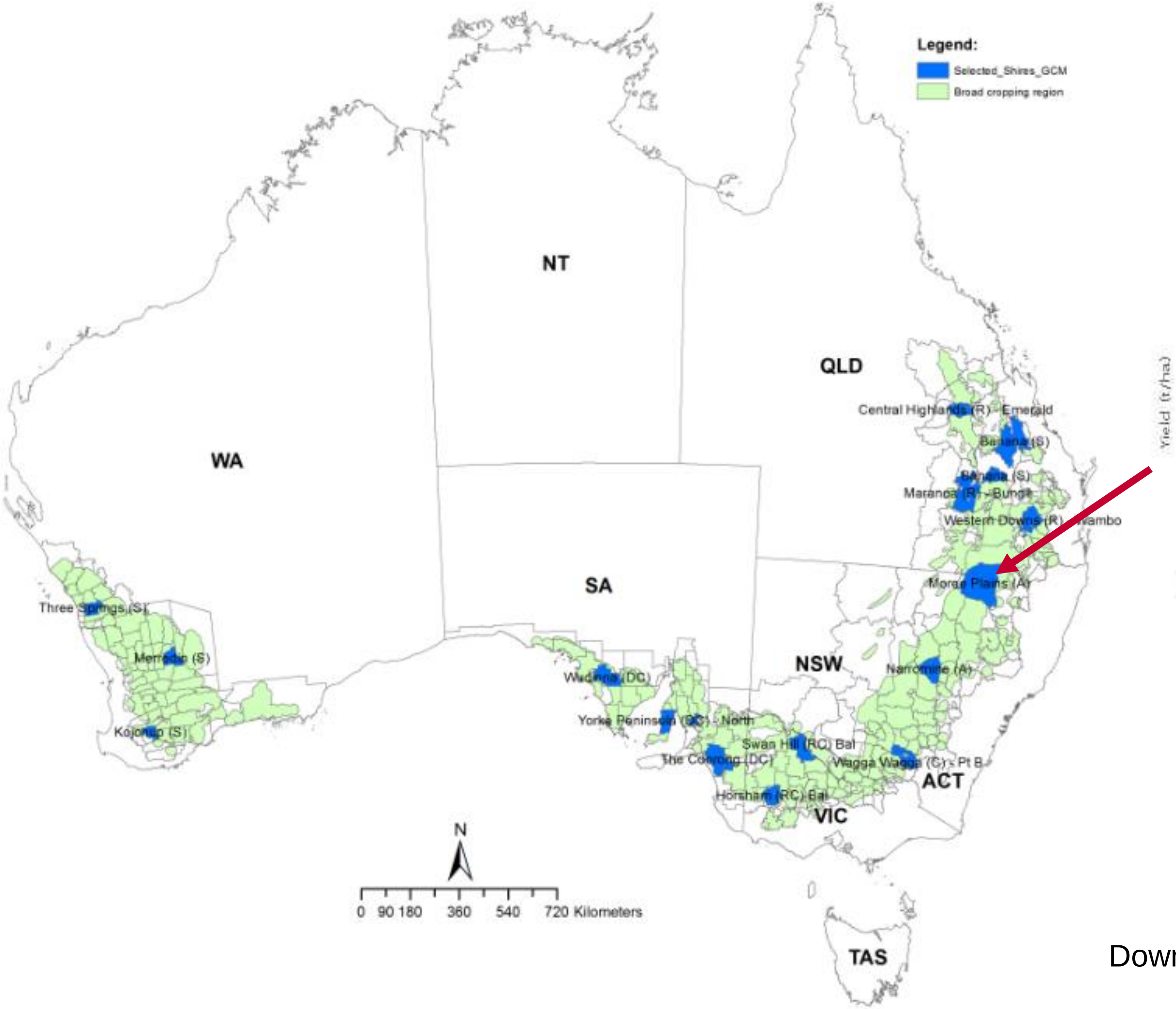
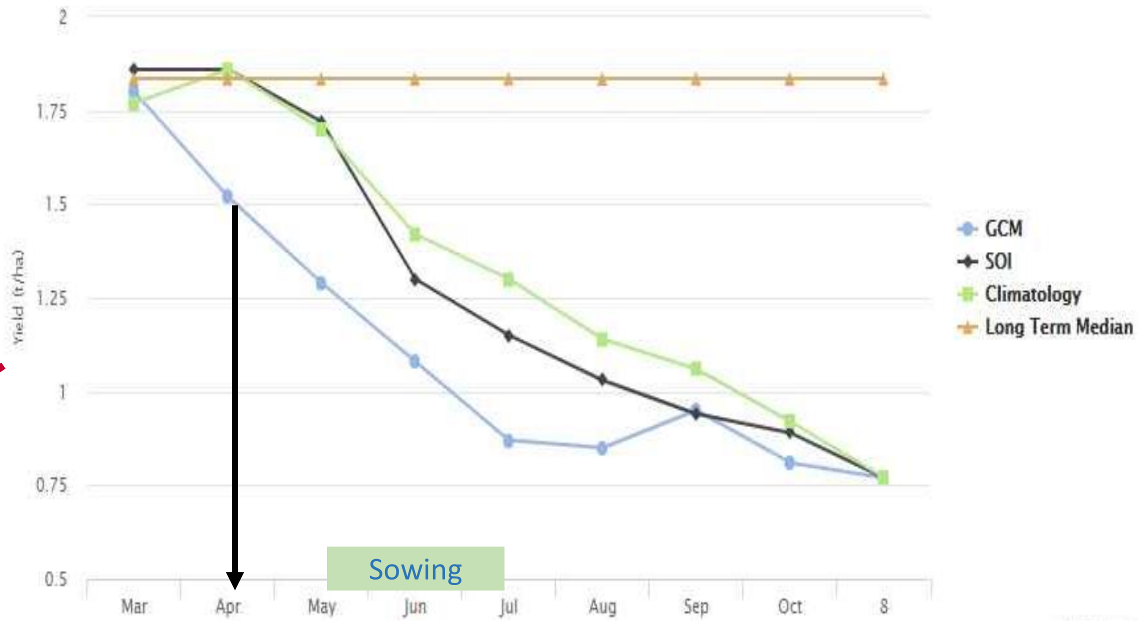
Region	Barley (Ha)	Chickpea (Ha)	Oats (Ha)	Wheat (Ha)	Total (Ha)	Prod (wheat-Tons)
CQ	33,468	182,036	827	125,047	341,377	267,720
SEQ	53,911	484,218	na	51,364	589,493	115,910
SWQ	89,103	326,042	39,961	401,501	856,607	750,791
NNSW	73,286	710,823	na	914,880	1,698,989	2,472,133

Long-lead crop yield forecasting

- Current research shows high potential to predict crop yields well before sowing (funded by Queensland Government)





Downscaling of climate : Dr Andrew Schepen (CSIRO)

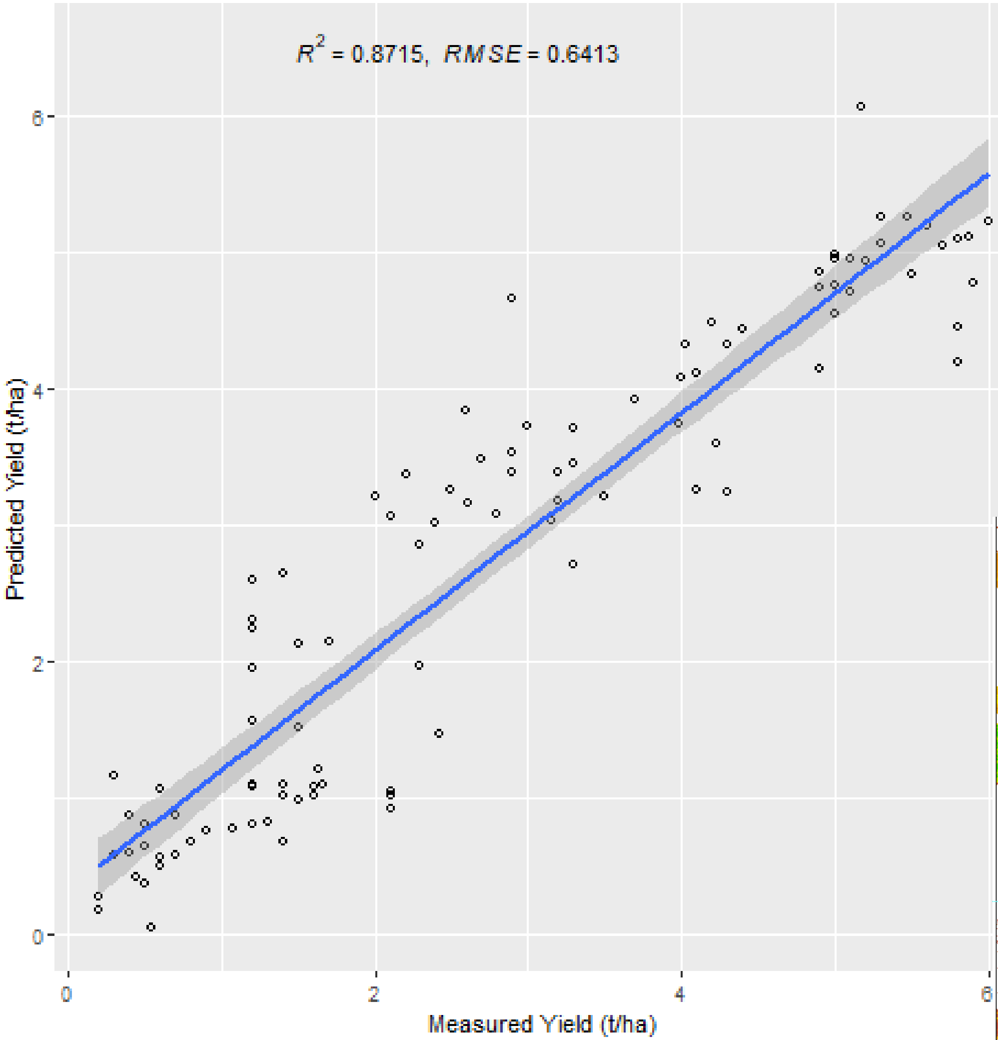
Queensland Government

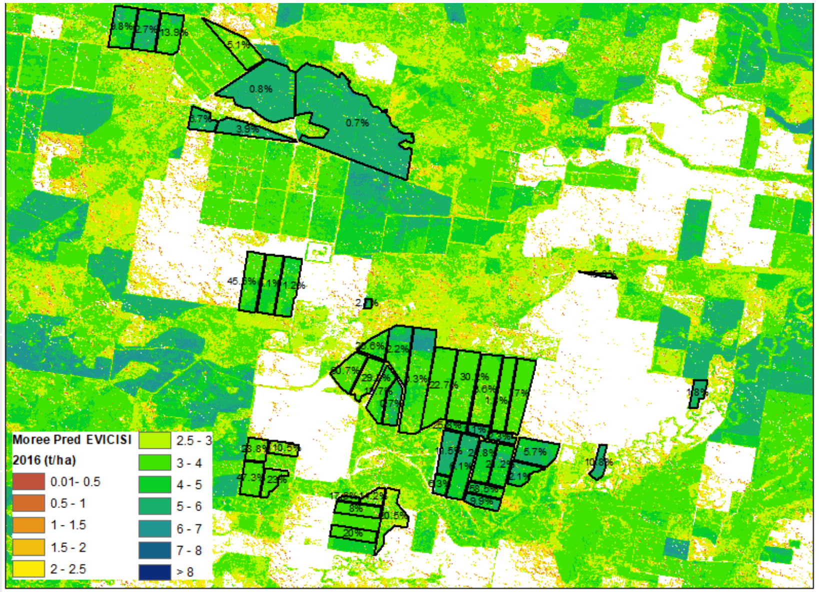
Predicting crop yield at field & pixel scales

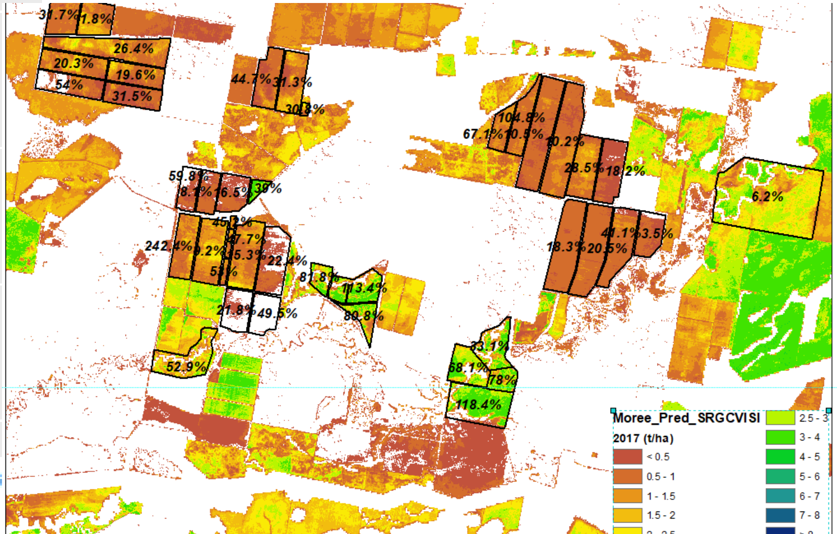
Sentinel 2 satellite (10m pixel); Model: Using indices relating to canopy structure and Chlorophyll

Field (101 fields) MAPE = 30.5%

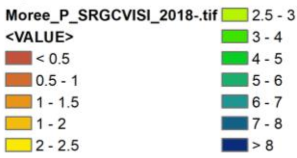
Yield ~ f[$VI\ indices$; Stress Index(shire)]

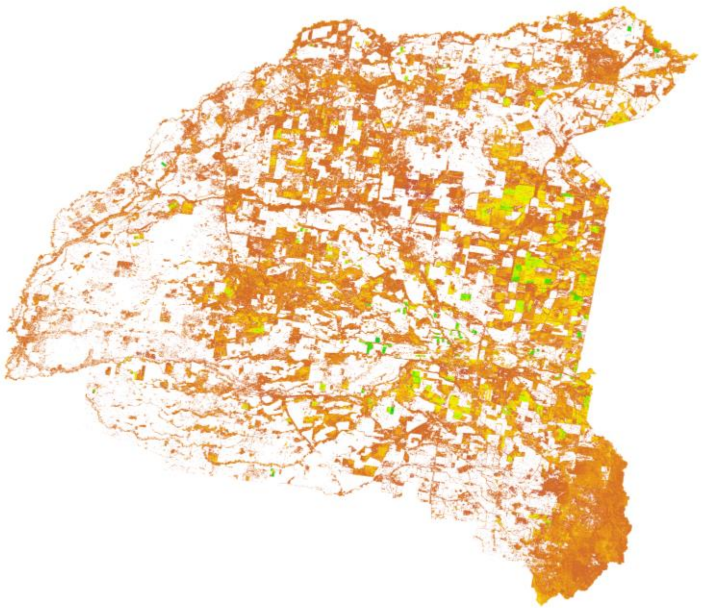






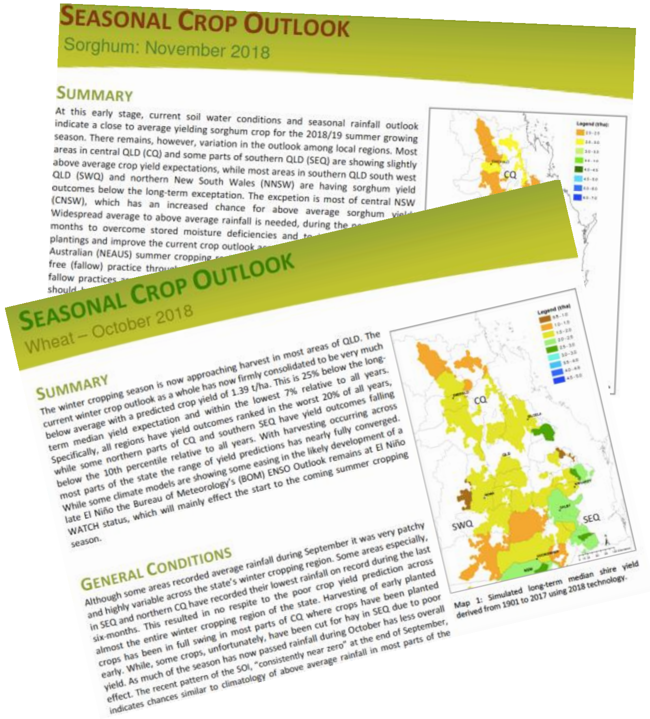
Shire 2018 winter season prediction

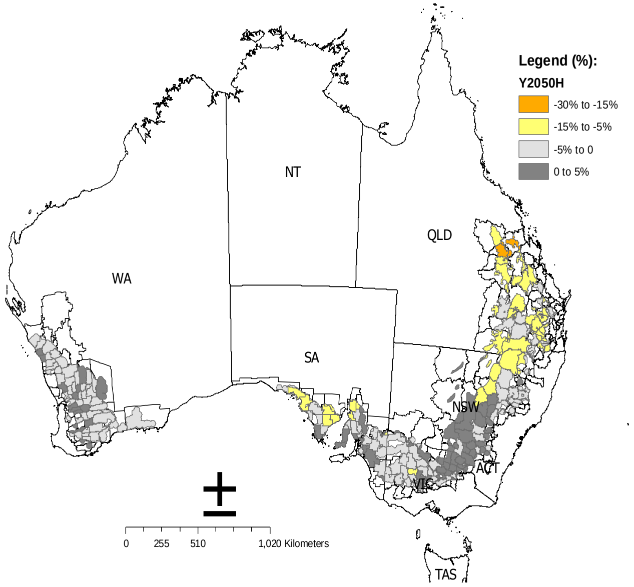




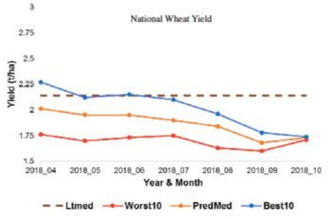
Applications

- National and state level crop outlooks (monthly)
- Impact analysis of climate change and variability
- Production and resource risk management
- Exceptional circumstances
- Insurance against crop losses due to in-season water stress
- Land use & Resource planning



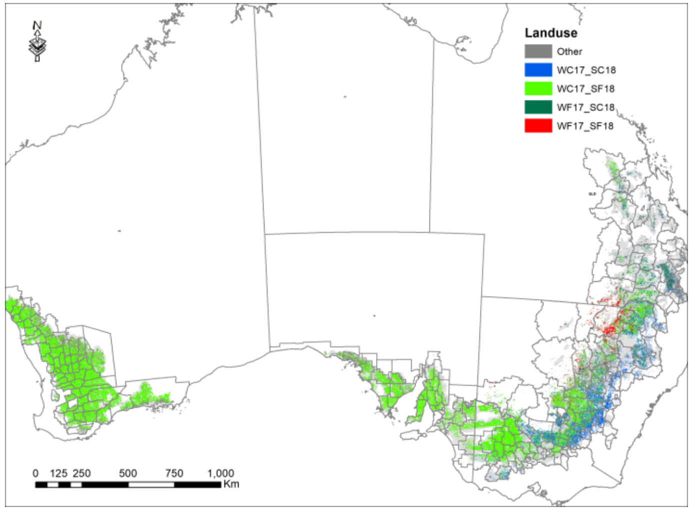


Potgieter et. al. 2003, 2005, 2006 & 2013

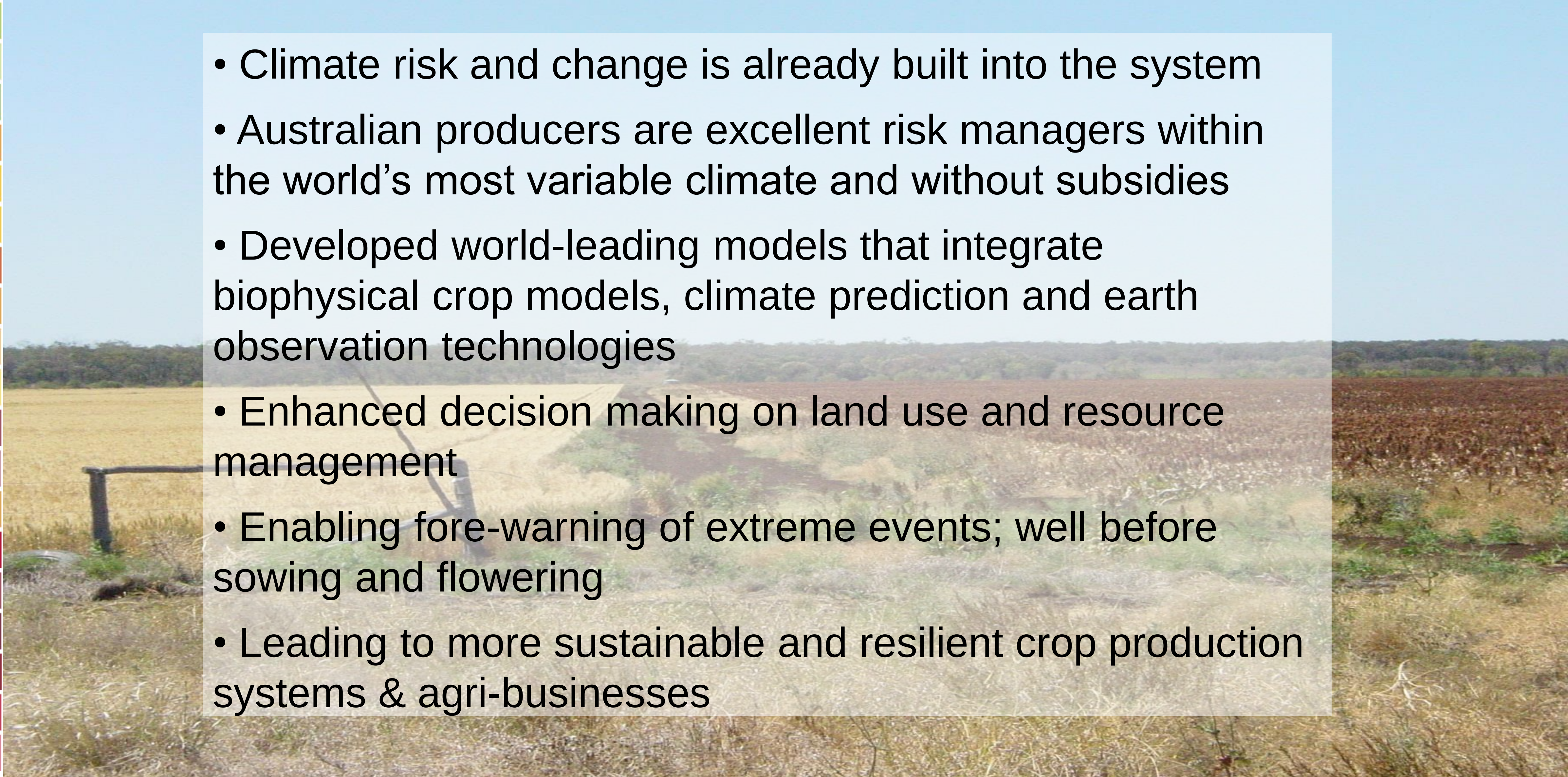


1st November 2018 – State and National wheat outlook range (Worst10 and Best10) and forecast median (PredMed) while Ltmed = Long-term median yield; Pred% = Predicted Percentile ranking of PredMed; DFY= Deviation Percentage of Forecast median from Long-term Median.

Region	Worst10	PredMed	Best10	NoP10	NoP50	NoP90	Ltmed	Pred%	DFY%
AUS	1.71	1.73	1.74	1.71	1.72	1.74	2.14	6%	-19
NSW	1.73	1.77	1.78	1.72	1.75	1.8	2.46	7%	-28
QLD	1.46	1.46	1.46	1.46	1.46	1.46	1.86	9%	-22
SA	1.81	1.82	1.84	1.81	1.82	1.83	2.41	3%	-24
VIC	1.45	1.48	1.54	1.44	1.46	1.52	2.44	3%	-39
WA	1.77	1.78	1.8	1.77	1.77	1.8	1.91	23%	-7



Take Home Message



• Climate risk and change is already built into the system

• Australian producers are excellent risk managers within the world's most variable climate and without subsidies

• Developed world-leading models that integrate biophysical crop models, climate prediction and earth observation technologies

• Enhanced decision making on land use and resource management

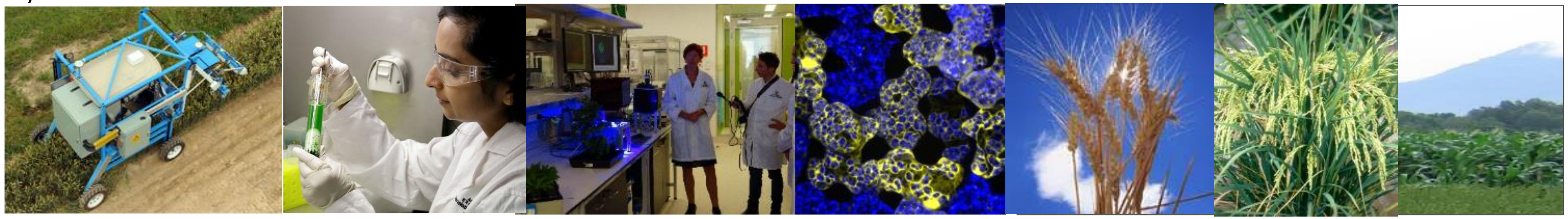
• Enabling fore-warning of extreme events; well before sowing and flowering

• Leading to more sustainable and resilient crop production systems & agri-businesses

Thank you

Contributors:

James Watson, Mark Eldridge, Barbara George-Jaeggli, Kenneth Laws, Greg Mclean, Colleen Hunt, Andrew Borrell, Emma Mace, Scott Chapman, David Jordan, Graeme Hammer, Andrew Schepen, Jason Brider, Yan Zhao



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