APEC Climate Symposium 2018

Global crop yield forecasting using seasonal climate information from a multimodel ensemble

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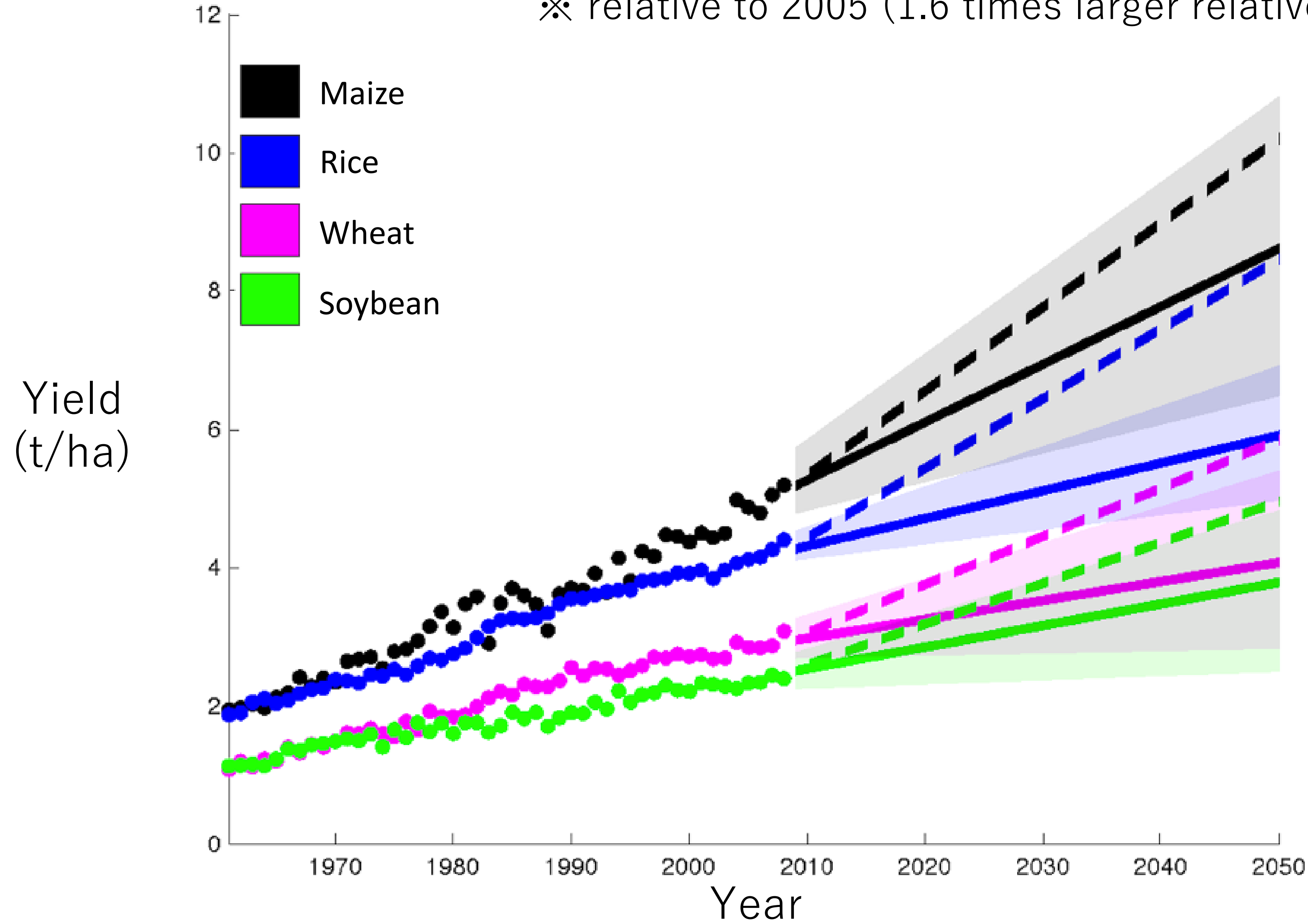
National Agriculture and Food Research Organization (NARO), Japan

August 22, 2018

International Convention Center,
Port Moresby

Global demand for food would double in 2050

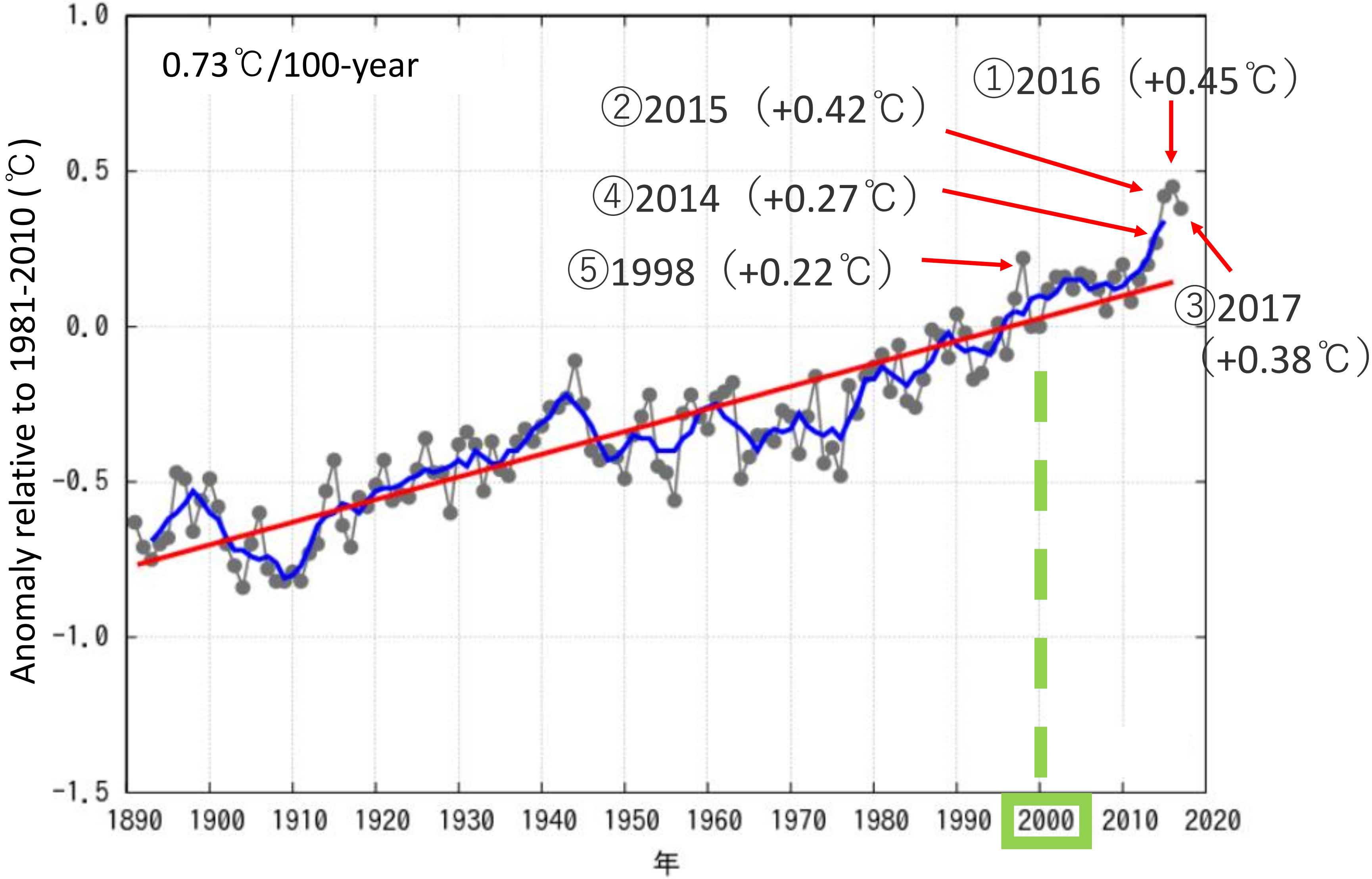
※ relative to 2005 (1.6 times larger relative to 2016)



Ray et al. (2013) PLOS ONE, doi:10.1371/journal.pone.0066428.

Climate change is an additional burden to achieve the supply goal

Global annual mean surface temperature anomaly

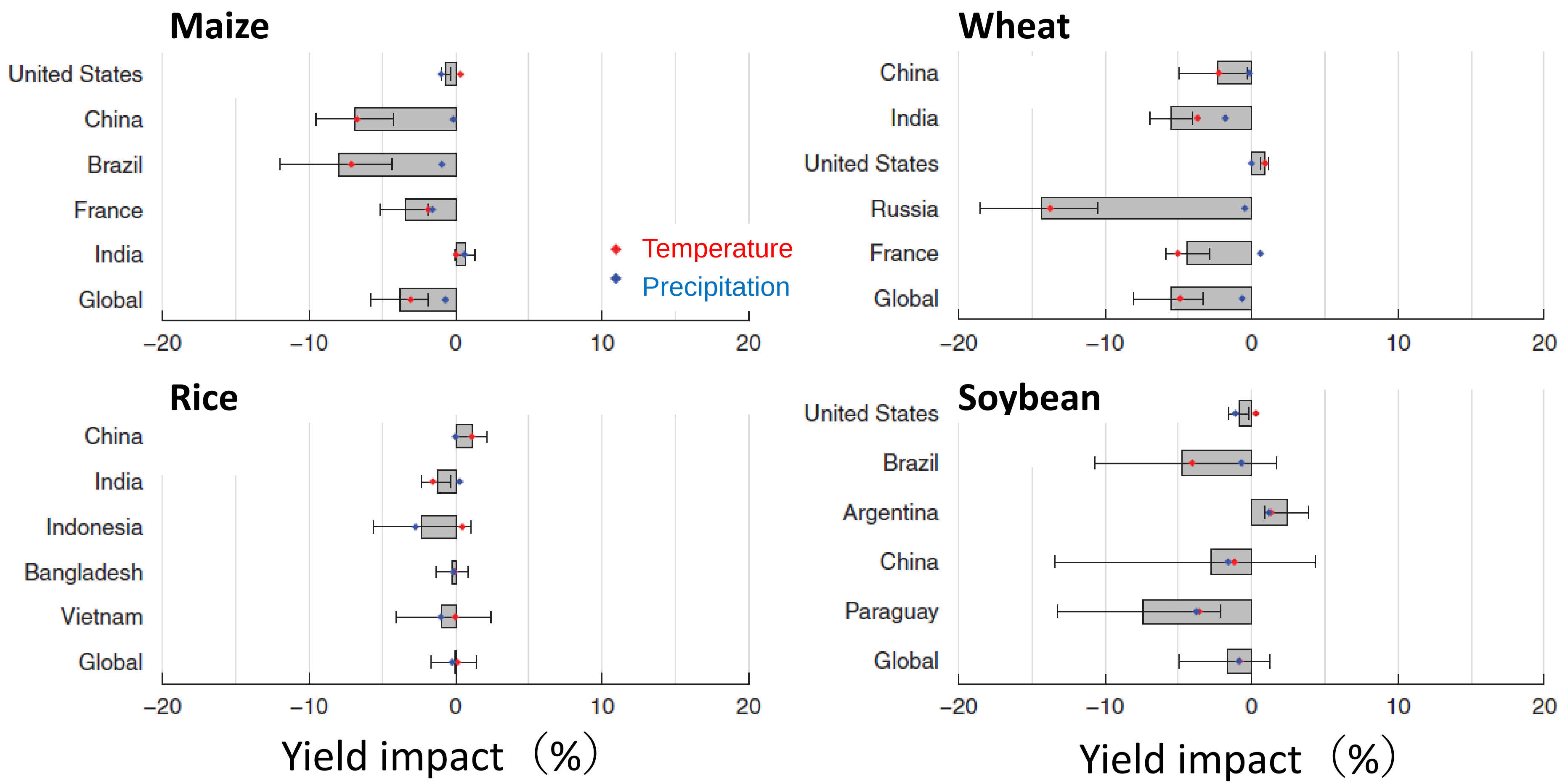


Japan Meteorological Agency, http://www.data.jma.go.jp/cpdinfo/temp/an_wld.html

3.8～5.5％ of global production was lost for the 29 years

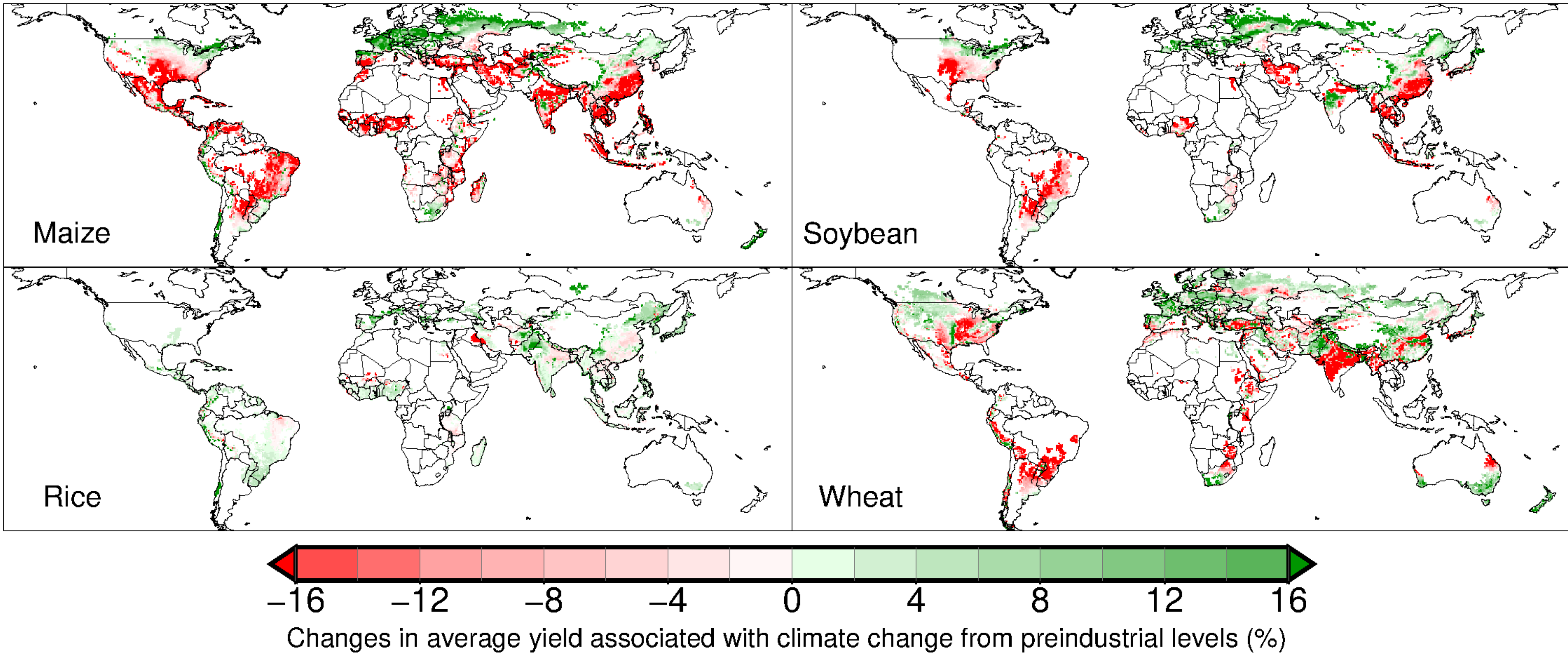
※ It corresponds to ~23 Mt in Mexico and ~33 Mt in France, respectively

※ 1980 to 2008



Lobell et al., 2012, *Science*, http://science.sciencemag.org/content/333/6042/616

Estimated impacts on average yield in 1981-2010



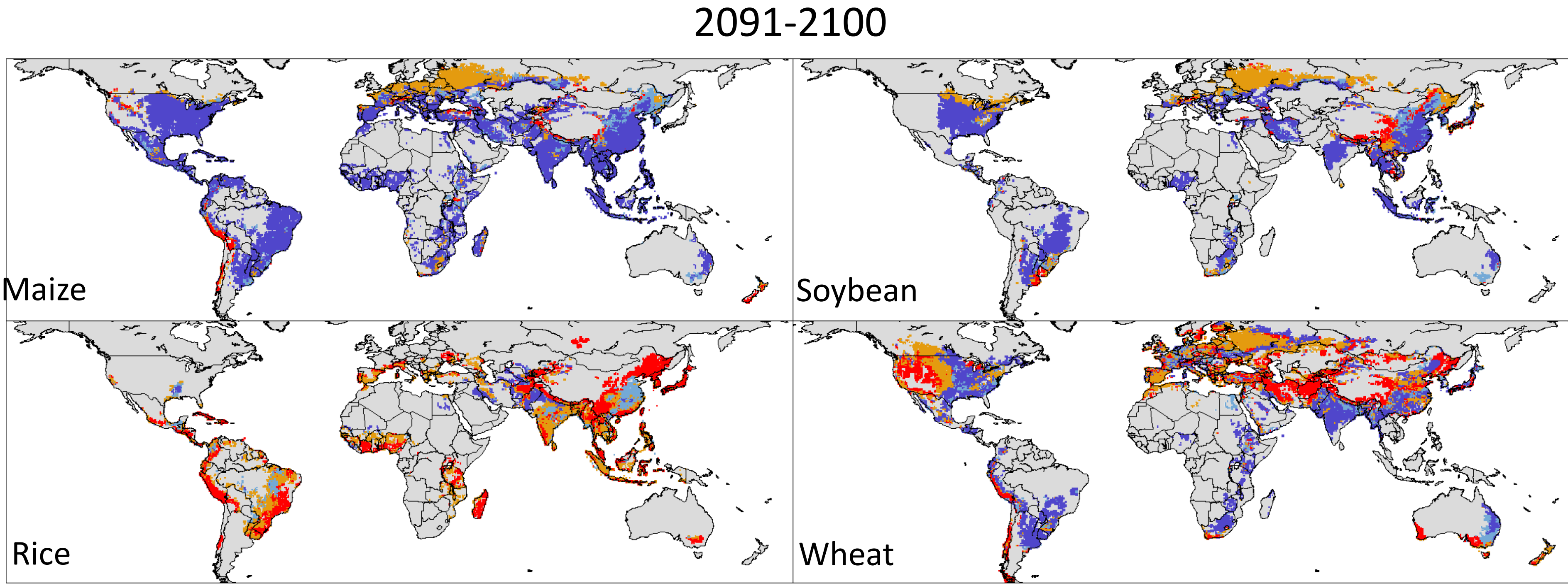
Climate change decreased yield

(Yield_historical – Yield_non-warming) / Yield_non-warming * 100

Climate change increased yield

Iizumi et al., 2018, *Int J Climatol*, doi:10.1002/joc.5818

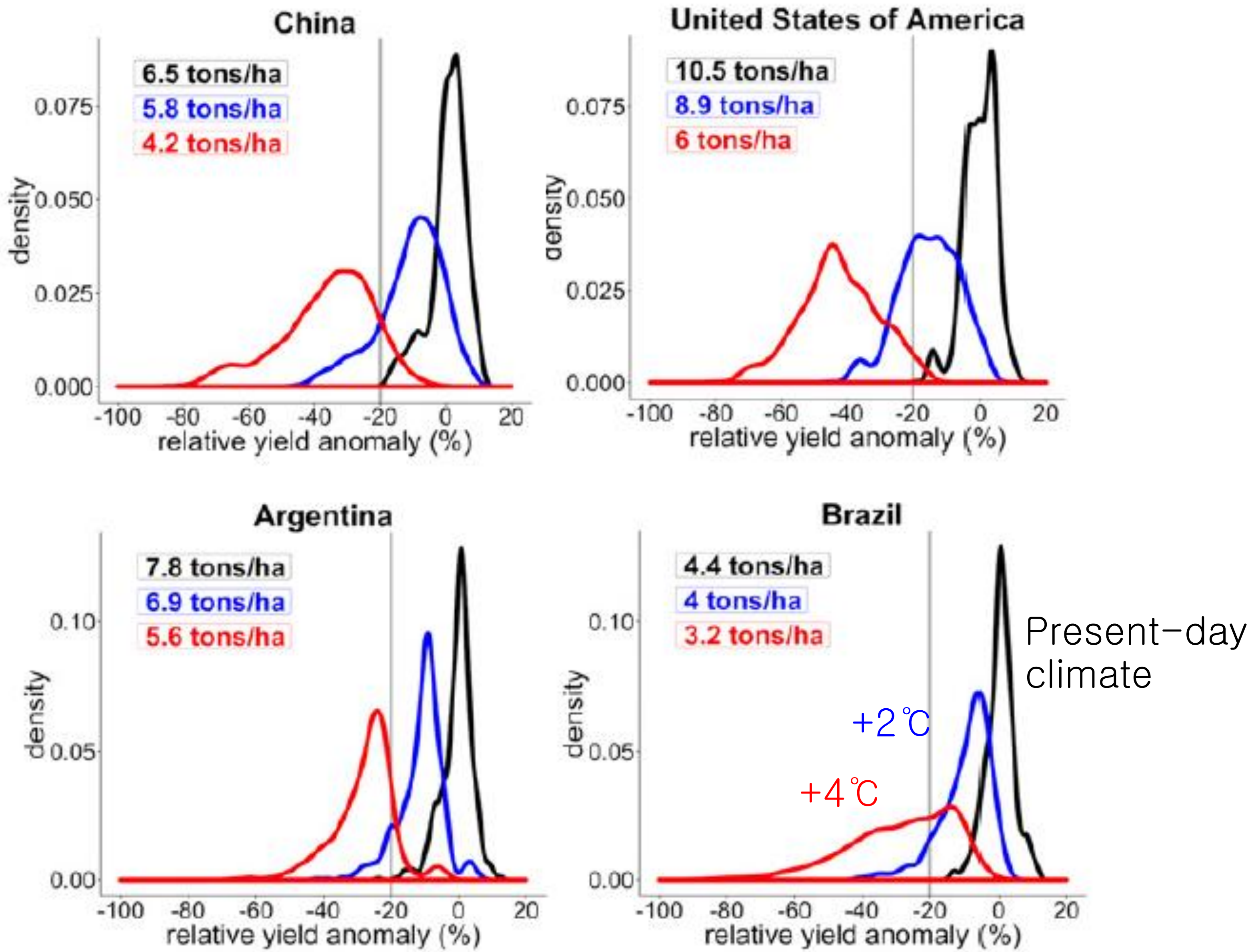
Future yield growth would stagnate with warming



Yield starts stagnating when warming >1.8℃	Yield starts stagnating when warming >2.7℃	Yield starts stagnating when warming >3.2℃	Yield starts stagnating when warming >4.9℃

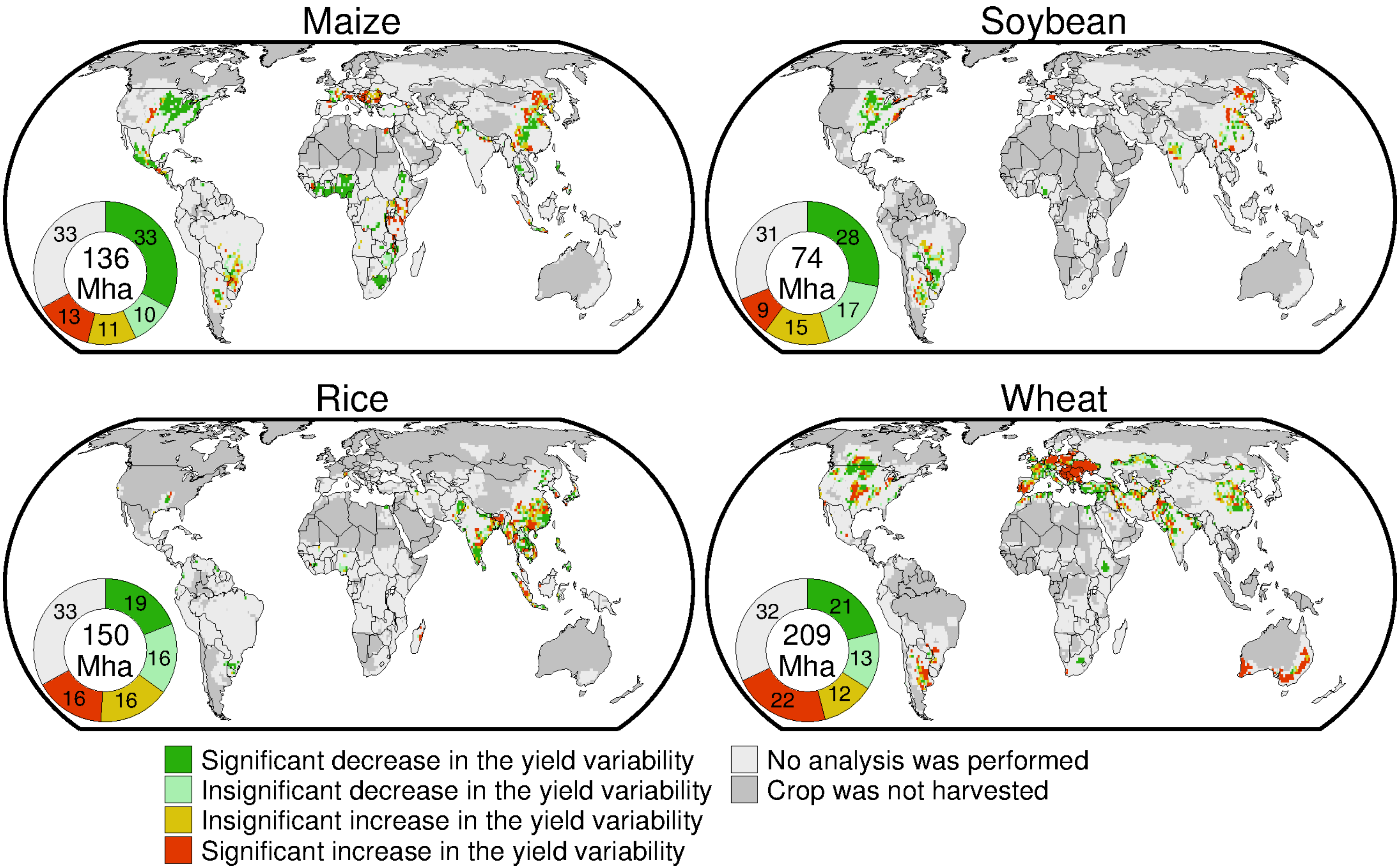
Iizumi et al. (2017), *Sci Rep,* doi:10.1038/s41598-017-08214-4

Warming would lead to increased yield variability



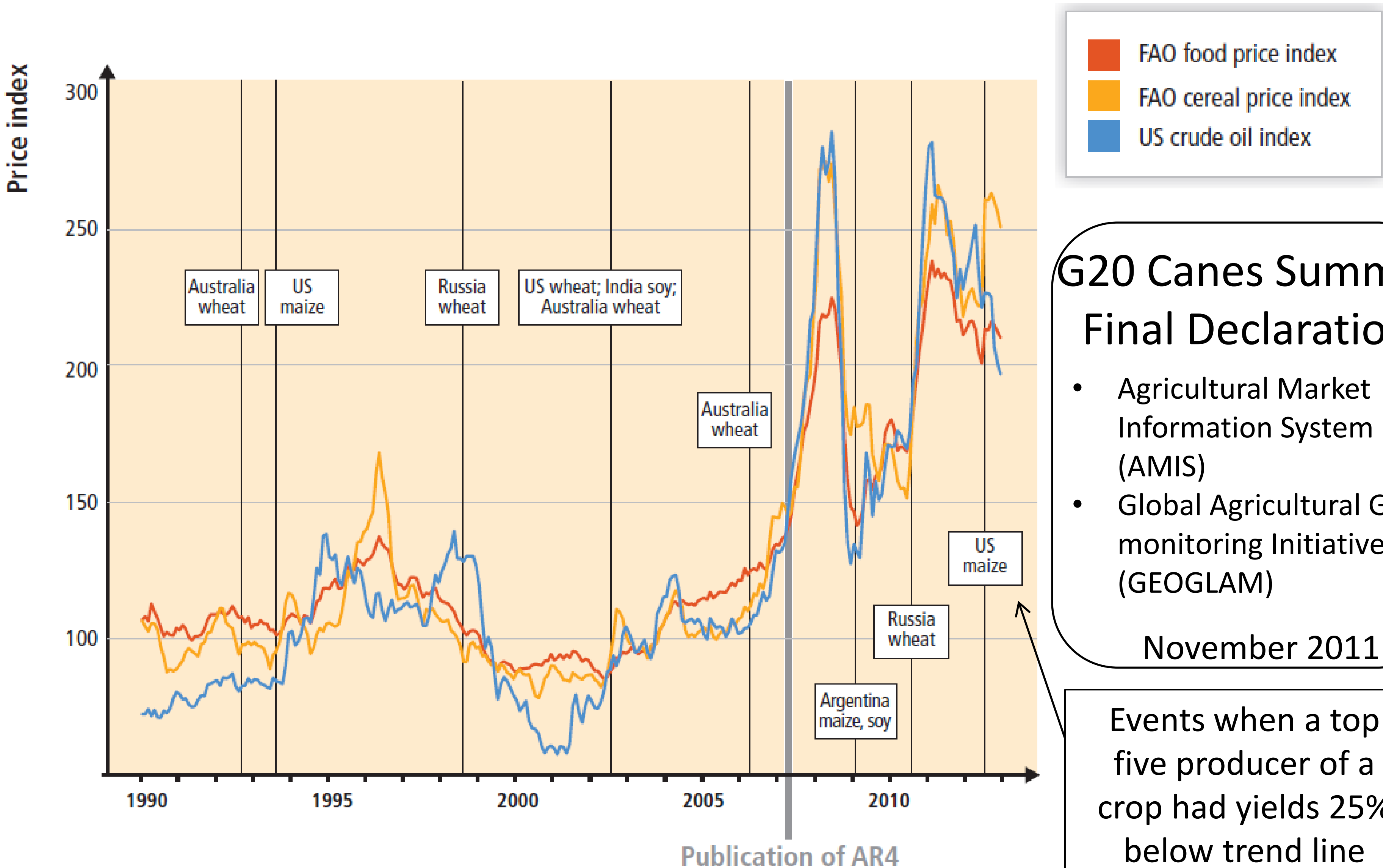
Tigchelaar et al. (2018), *Proc Natl Acad Sci USA*, https://doi.org/10.1073/pnas.1718031115

Yield variability has modulated during the last decades



Iizumi & Ramankutty (2016) *Environ Res Let*, doi:10.1088/1748-9326/11/3/034003

Climate extremes could be a trigger of food price spike



G20 Canes Summit Final Declaration

- Agricultural Market Information System (AMIS)
- Global Agricultural Geo-monitoring Initiative (GEOGLAM)

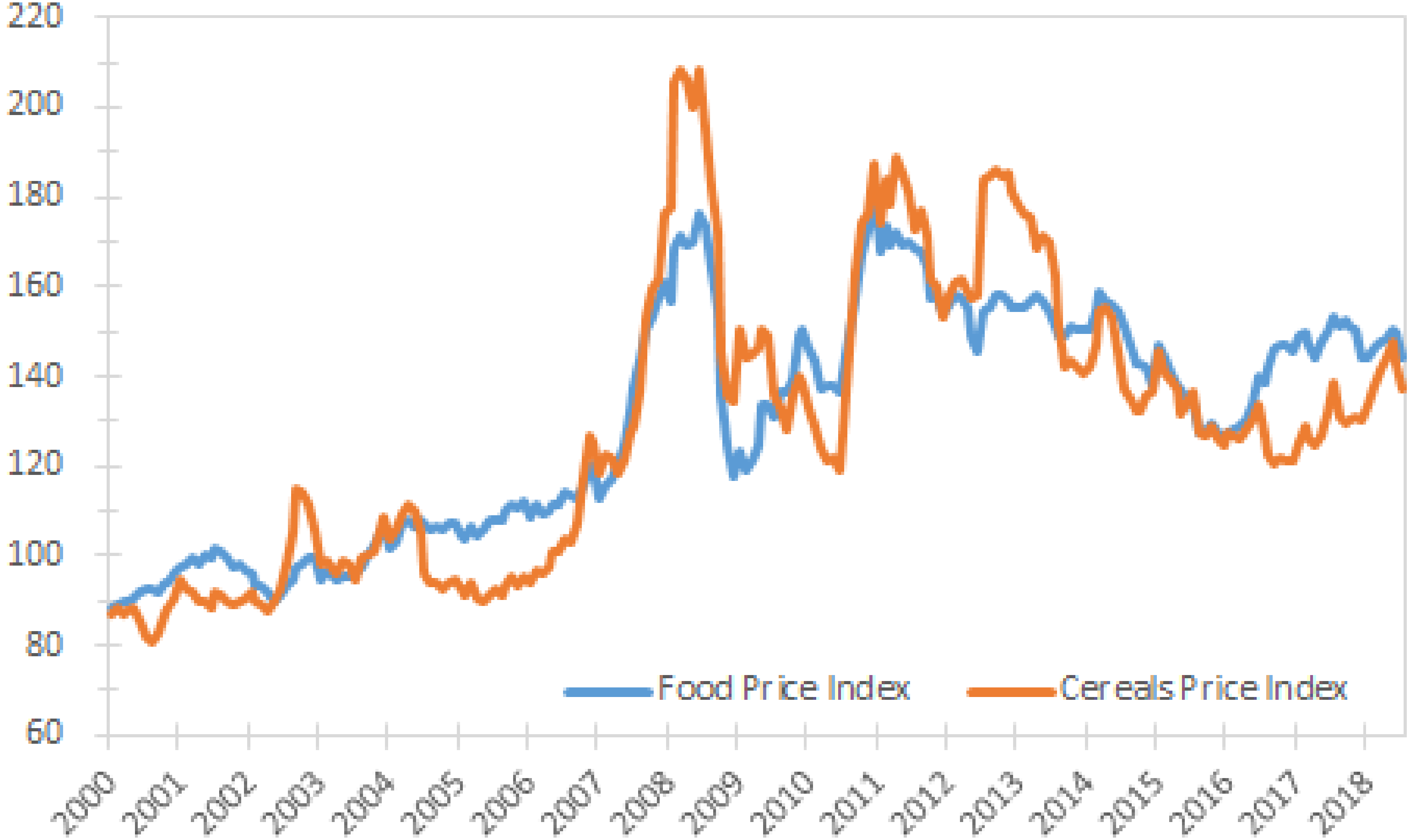
November 2011

Events when a top five producer of a crop had yields 25% below trend line

IPCC WG2 AR5 Ch.7 (2014)

Relatively high food price is persistent

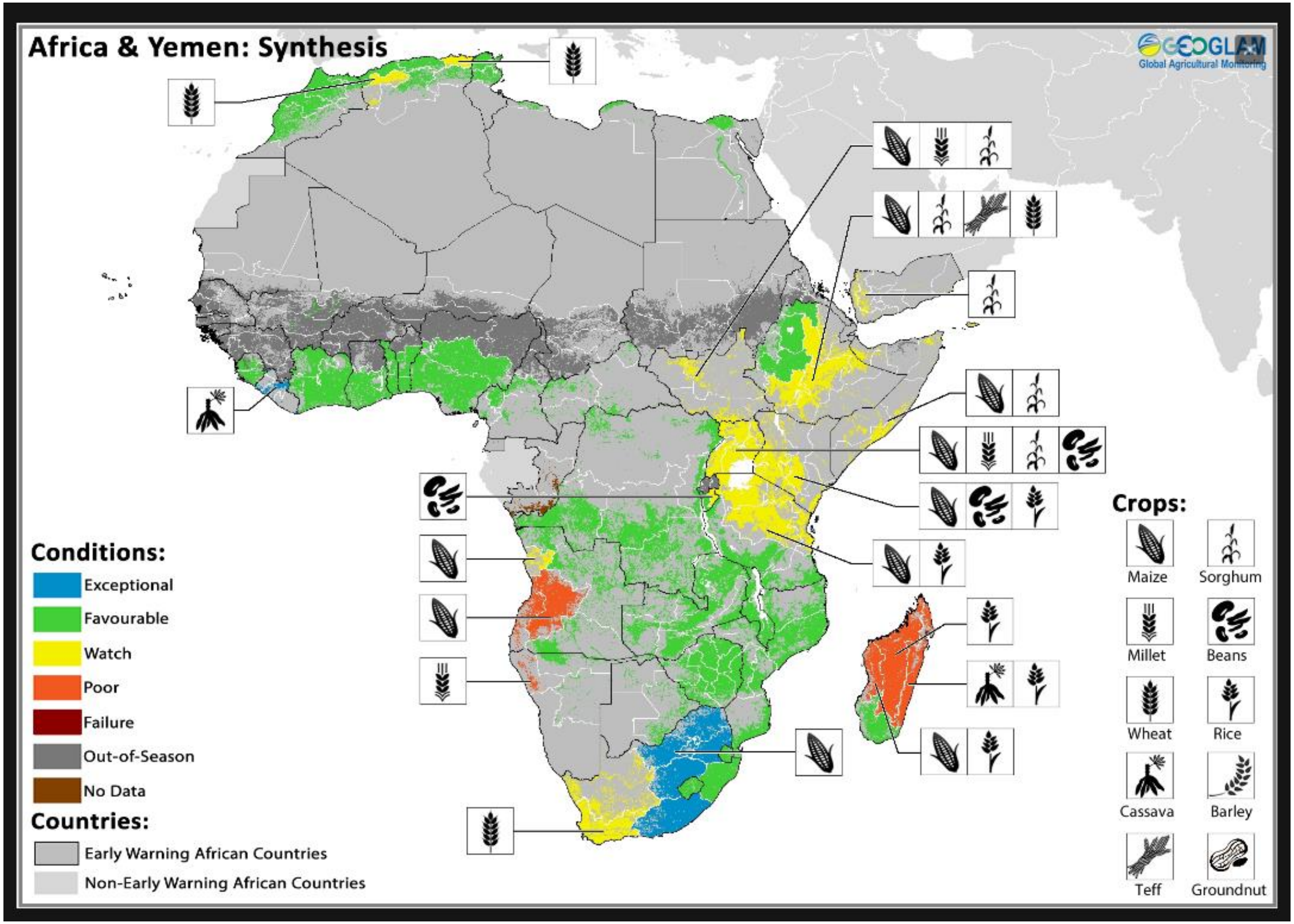
Monthly deflated data; 2002-2004=100



FAO, http://www.fao.org/worldfoodsituation/foodpricesindex/en/

Satellite-based global agricultural monitoring

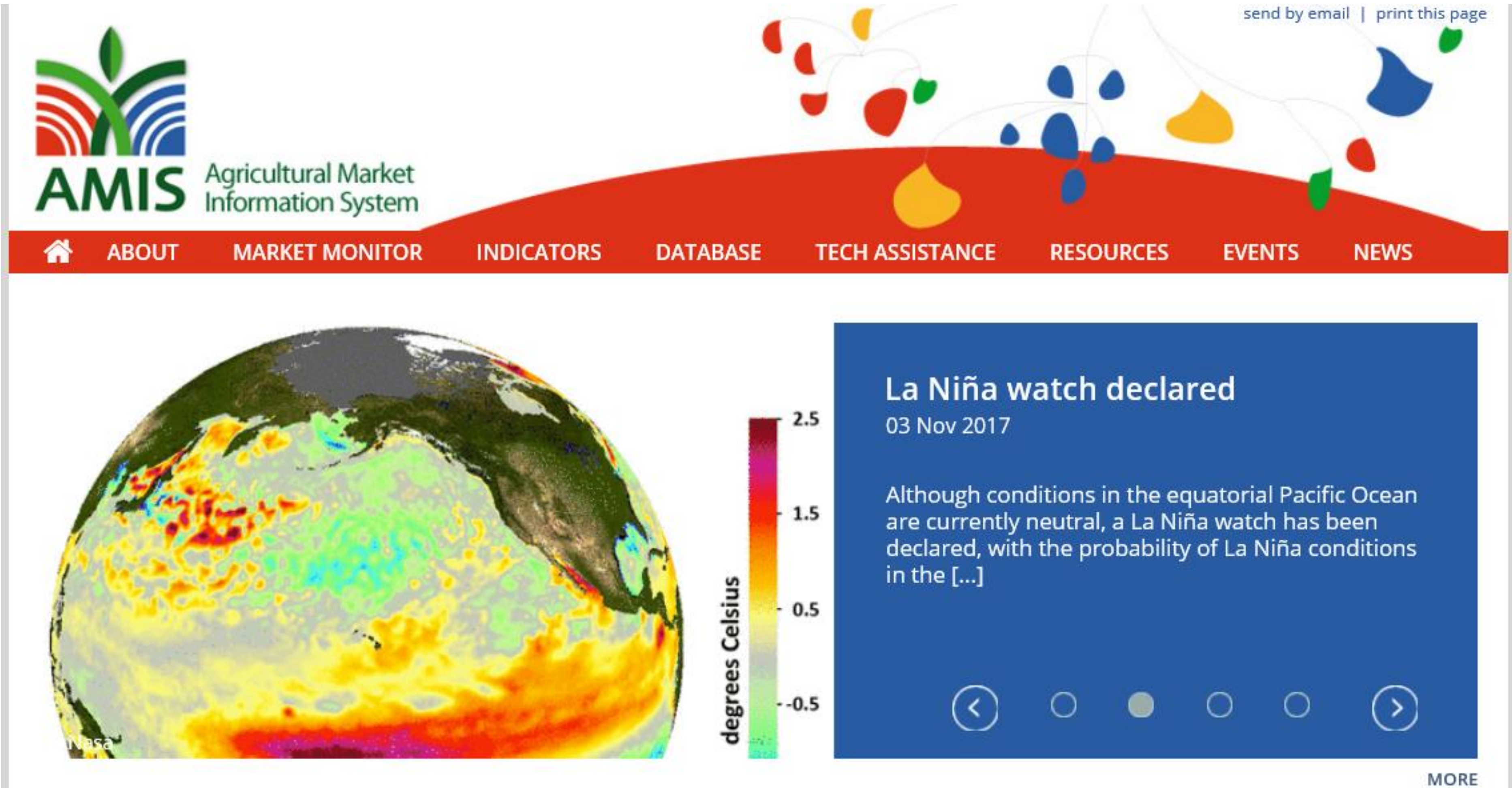
Group on Earth Observations Global Agricultural Monitoring Initiative (GEOGLAM)



https://cropmonitor.org/index.php/2017/05/04/crop-monitor-for-early-warning-may-2017/

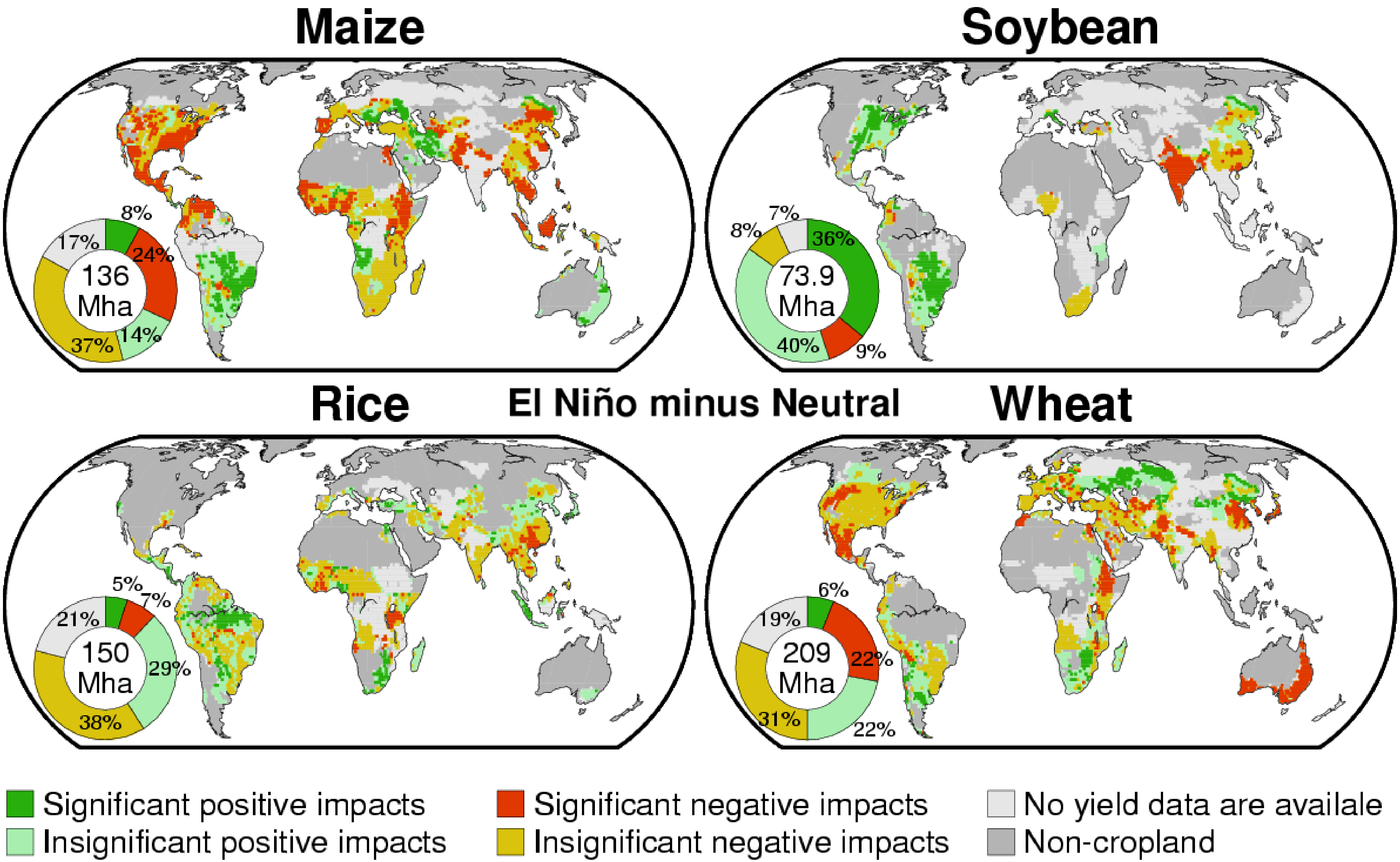
Agricultural market monitoring

The Agricultural Market Information System (AMIS)



http://www.amis-outlook.org/

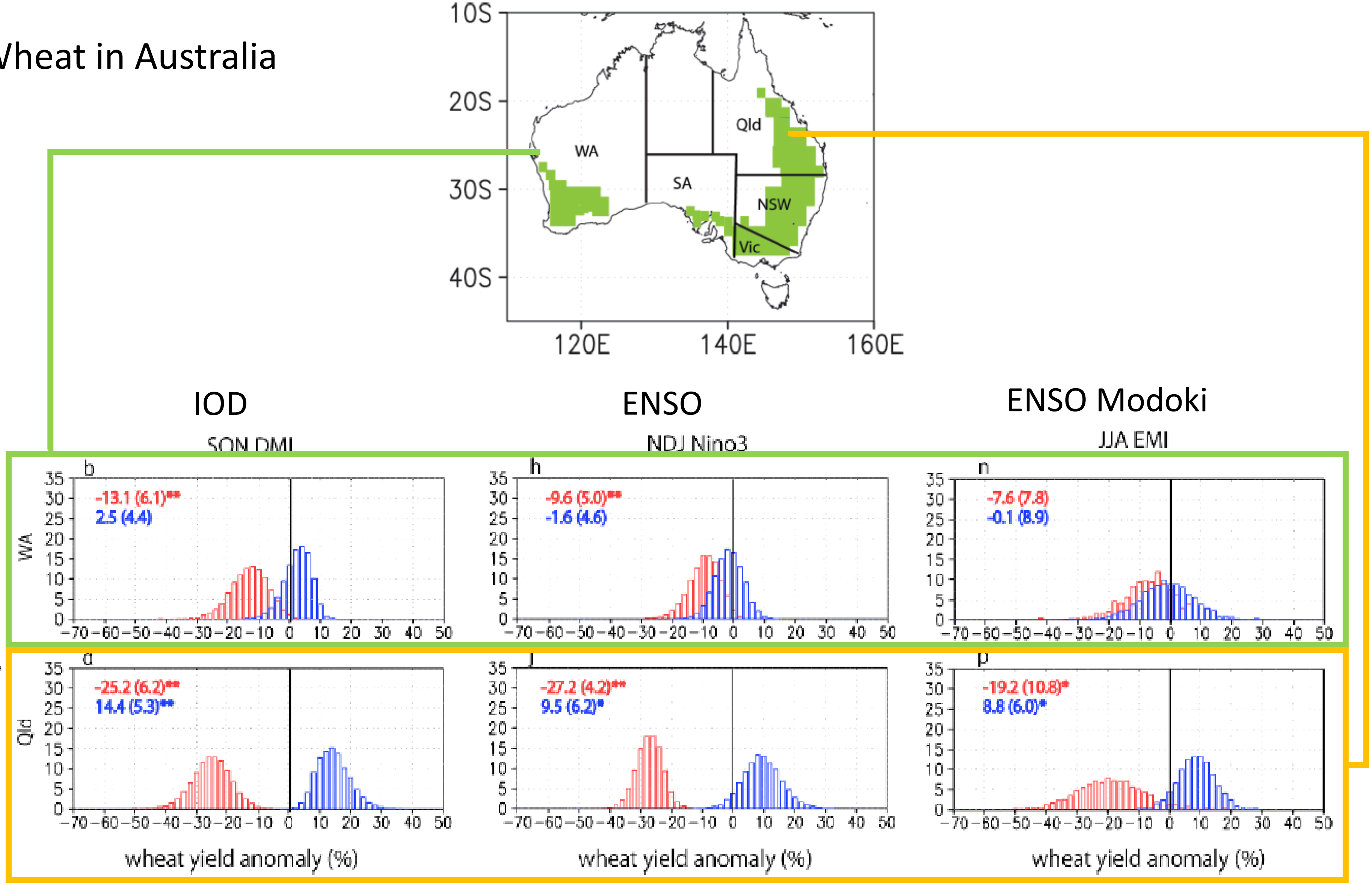
ENSO is a major driver of yield variability



Iizumi et al. (2014) Nature Commun, doi:10.1038/ncomms4712

IOD also contributes to yield variability

Wheat in Australia



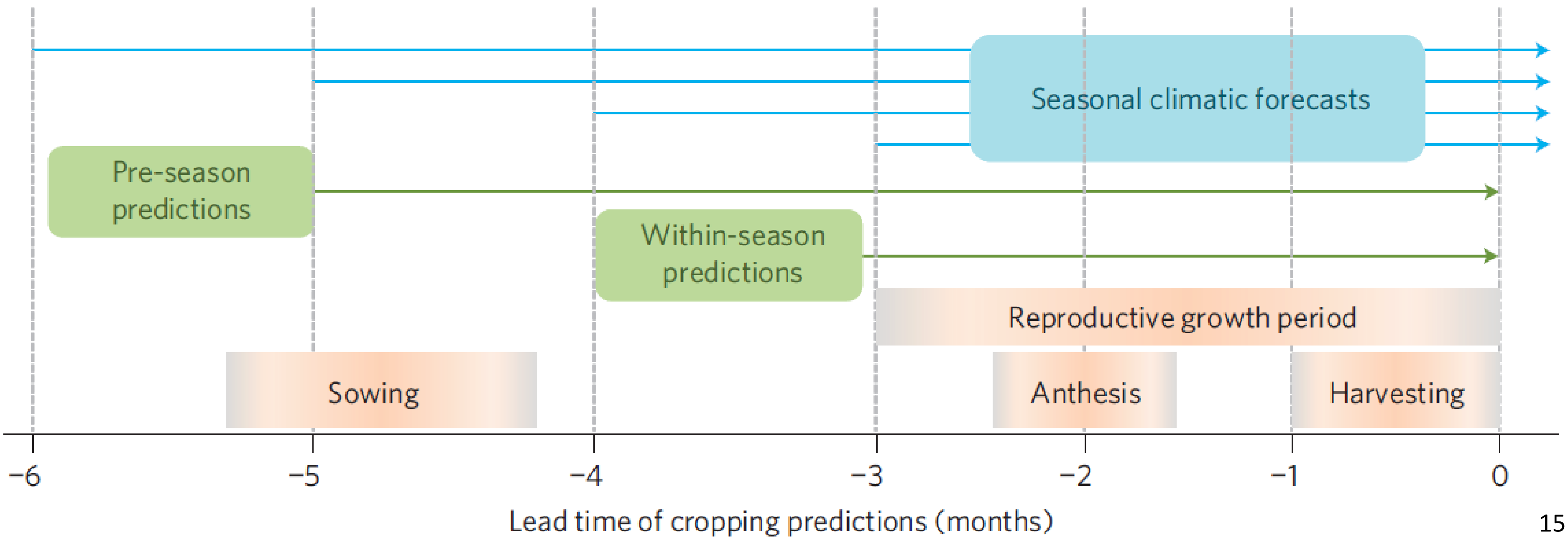
Yuan & Yamagata (2015) *Sci Rep*, doi:10.1038/srep17252

Seasonal crop forecast is another source of information

nature climate change
LETTERS
PUBLISHED ONLINE: 21 JULY 2013 | DOI: 10.1038/NCLIMATE1945

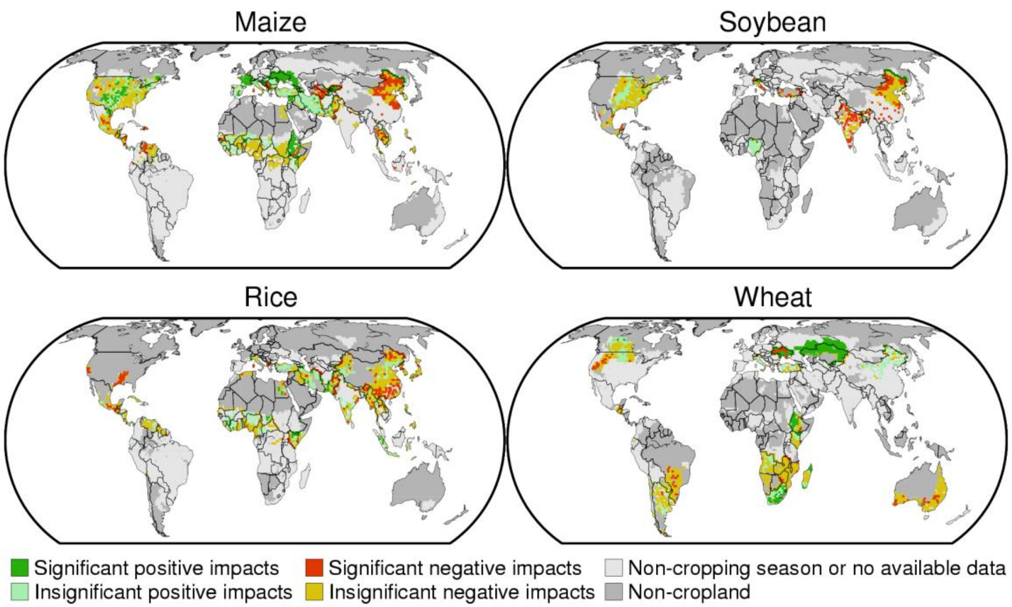
Prediction of seasonal climate-induced variations in global food production

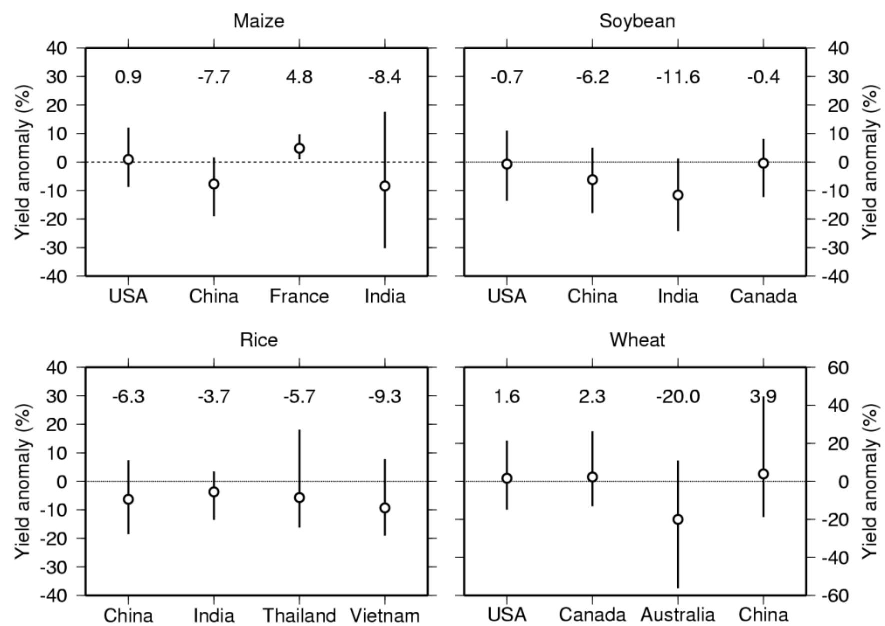
Toshichika Iizumi[1]*, Hirofumi Sakuma[2,3], Masayuki Yokozawa[1], Jing-Jia Luo[4], Andrew J. Challinor[5,6], Molly E. Brown[7], Gen Sakurai[1] and Toshio Yamagata[3]



Crop forecast for 2014 El Nino

- The incidence of El Nino was predicted by weather centers in spring 2014.
- Forecasts on possible variations in 2014-fall yields (lead time of +1 to +6 months) were released in July 31, 2014 via the *Monthly Oversea Food Demand & Supply Report* of MAFF.



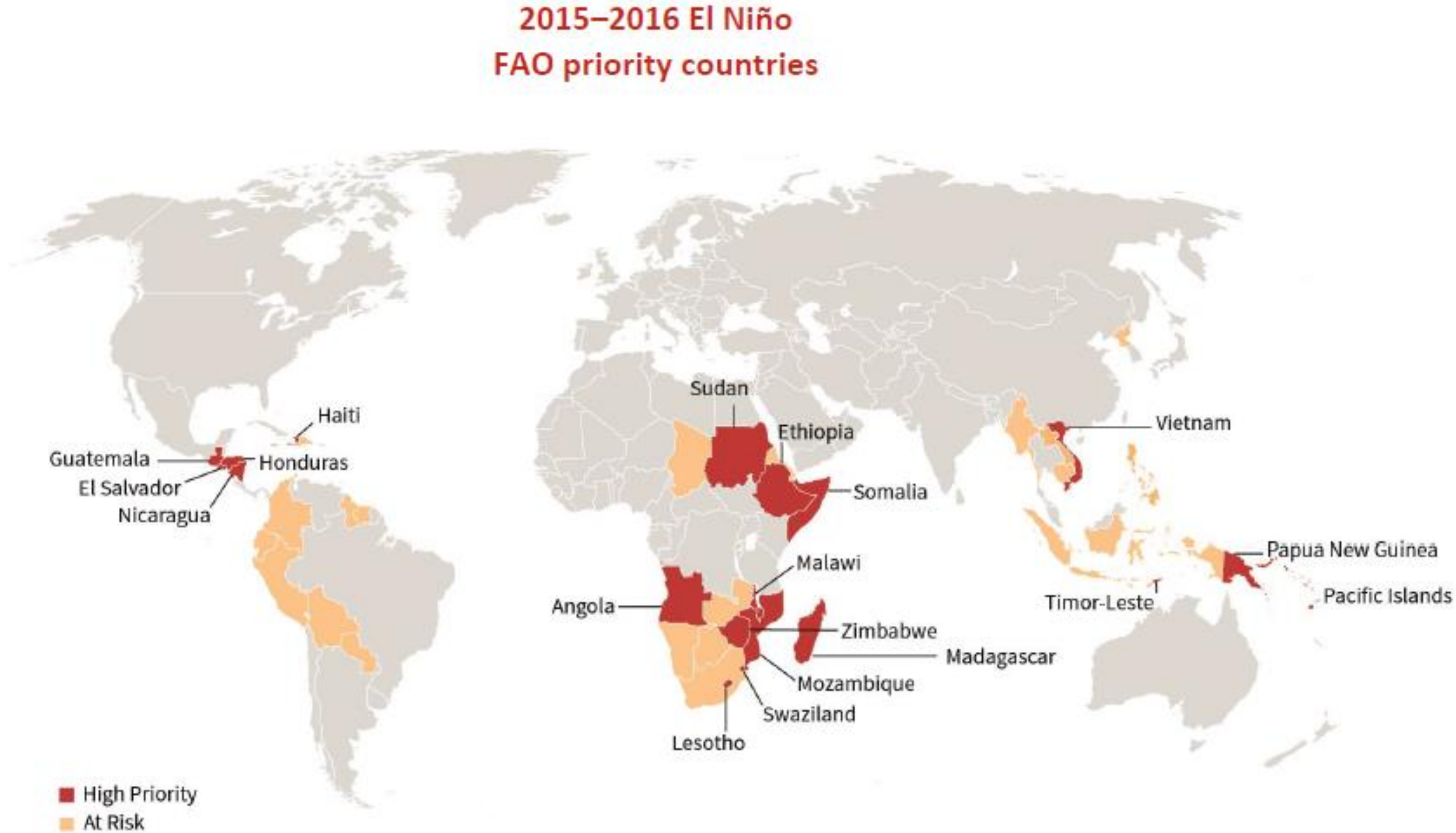


Full text (in Japanese) is available:
http://www.maff.go.jp/j/zyukyu/jki/j_rep/monthly/201407/pdf/21_monthly_topics_1.pdf

2015–2016 El Niño

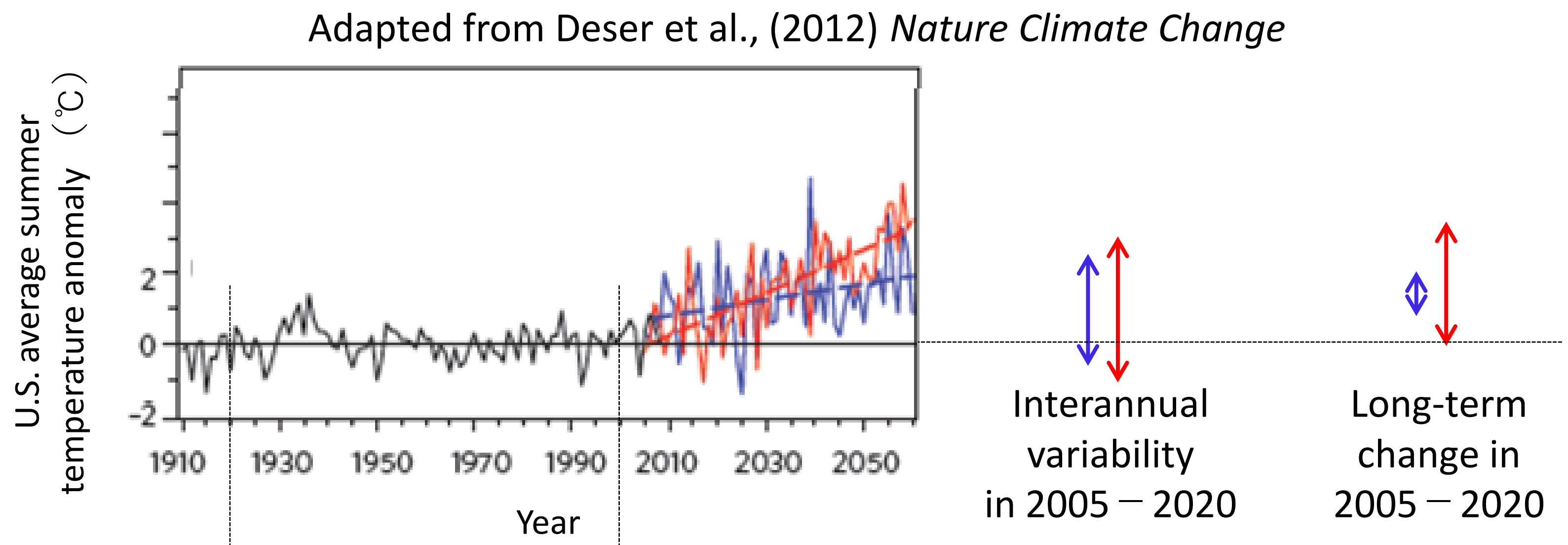
Early action and response for agriculture, food security and nutrition

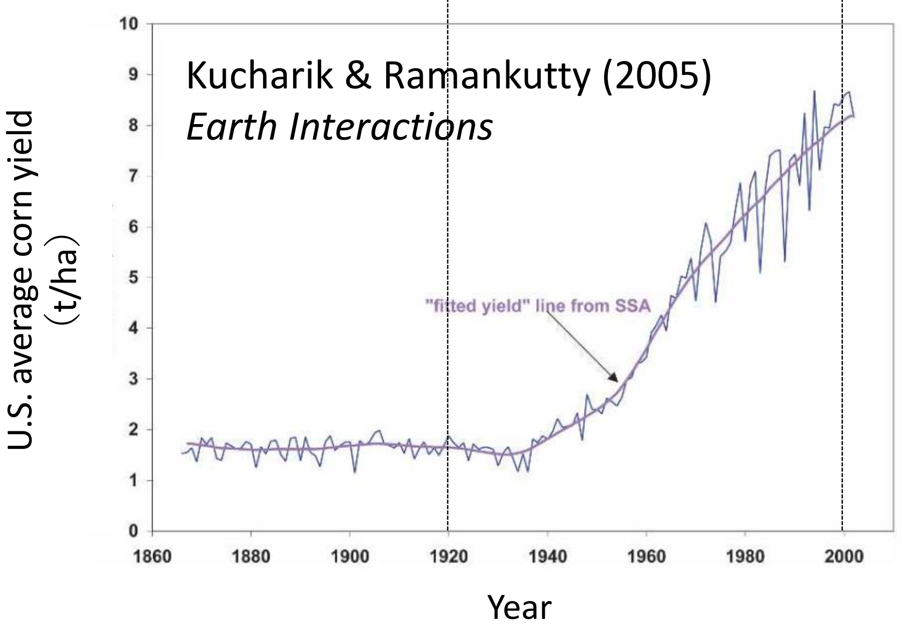
Food and Agriculture Organization of the United Nations



http://www.fao.org/emergencies/resources/documents/resources-detail/en/c/340660/

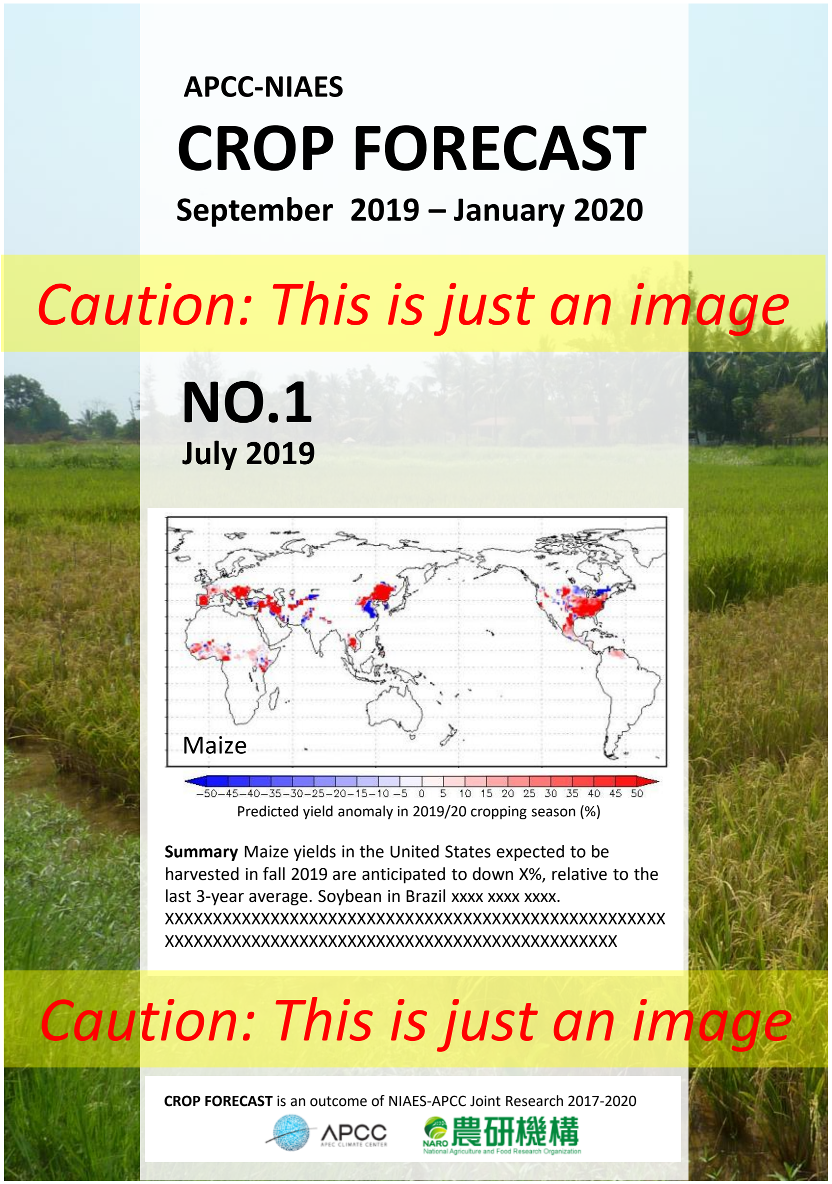
Climate variability is the best test bed toward adaptation





- The amplitude of interannual temperature variability is in general larger than long-term temperature change.
- Responding better to seasonal climate-induced supply shocks will increase society's capability to adapt climate change.

Toward operational crop forecasting service



GEOGLAM CROP MONITOR

https://cropmonitor.org/index.php/2017/05/04/crop-monitor-for-early-warning-may-2017/

The first step to achieve this goal

ARTICLE IN PRESS

Climate Services xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Climate Services

journal homepage: www.elsevier.com/locate/cliser

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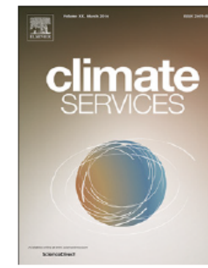


Original research article

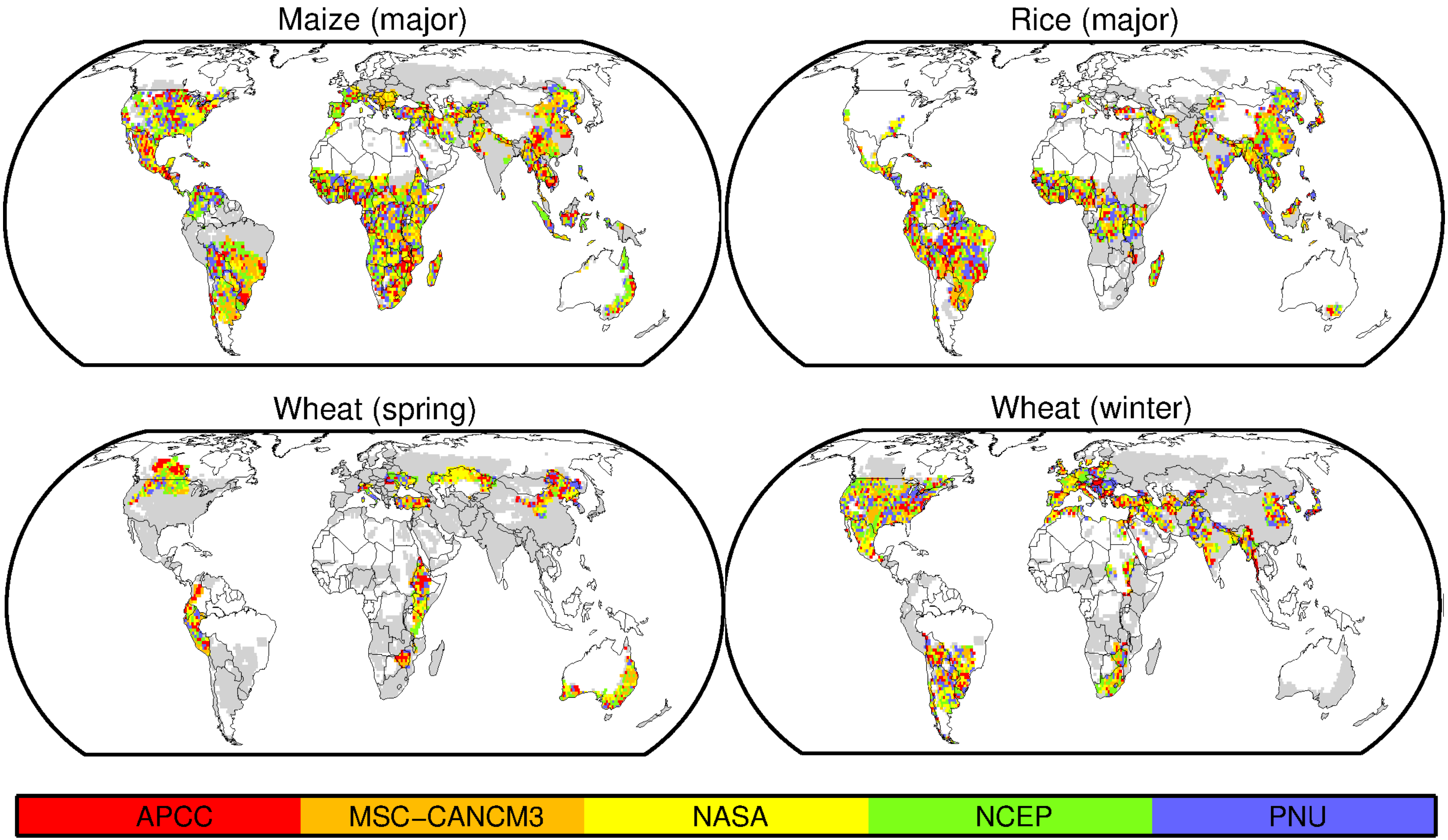
Global crop yield forecasting using seasonal climate information from a multi-model ensemble

Toshichika Iizumi[a,*], Yonghee Shin[b], Wonsik Kim[a], Moosup Kim[b], Jaewon Choi[b]

[a] *Institute for Agro-Environmental Sciences, National Agriculture and Food Research Organization, 3-1-3 Kannondai, Tsukuba, Ibaraki 305-8604, Japan*
[b] *APEC Climate Center, 12, Centum 7-ro, Haeundae-gu, Busan 48058, Republic of Korea*

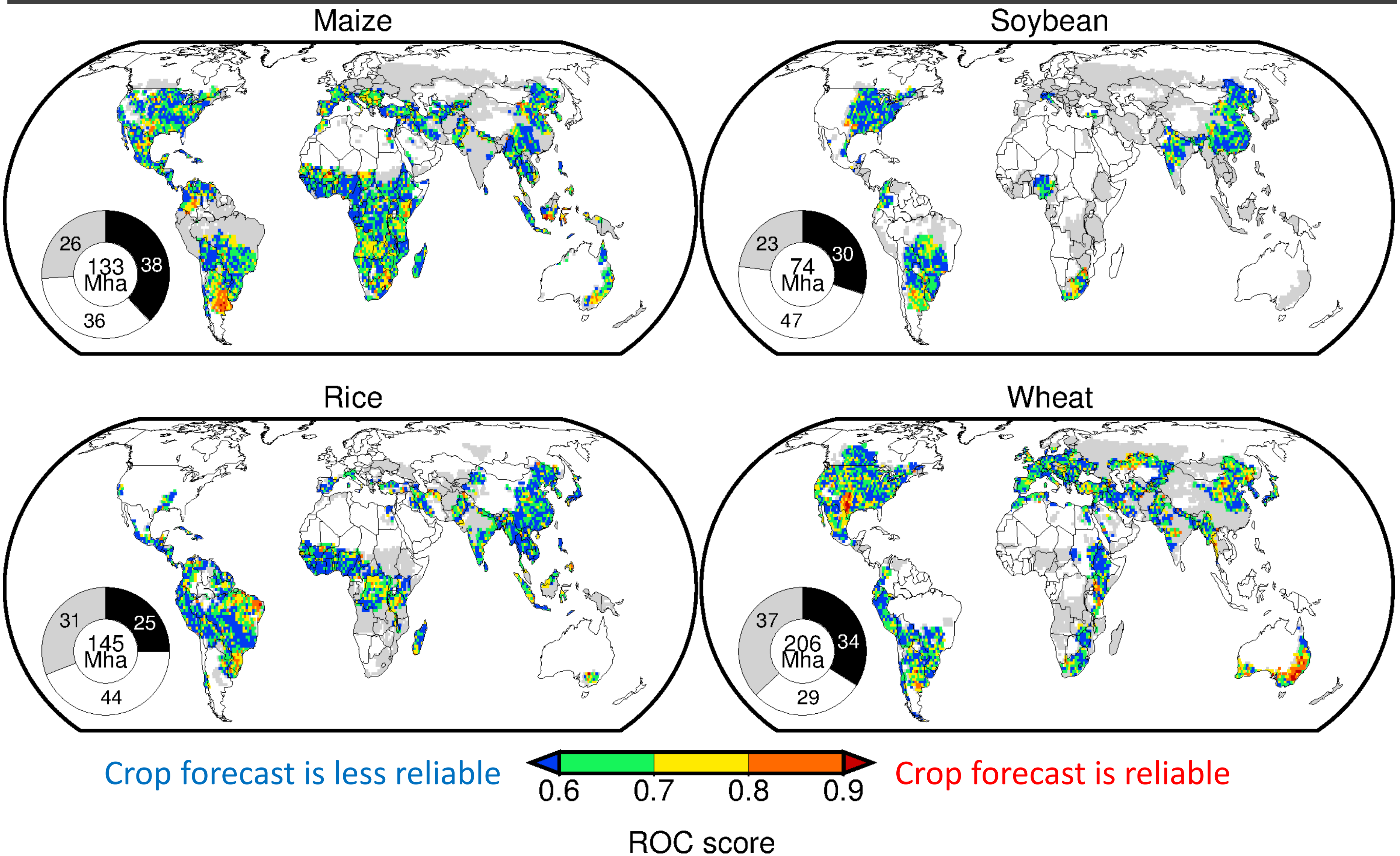
Iizumi et al. (2018) *Clim Serv,* https://doi.org/10.1016/j.cliser.2018.06.003

Utilizing the best-performing GCM from a multimodel ensemble by location and cropping season (mosaic)



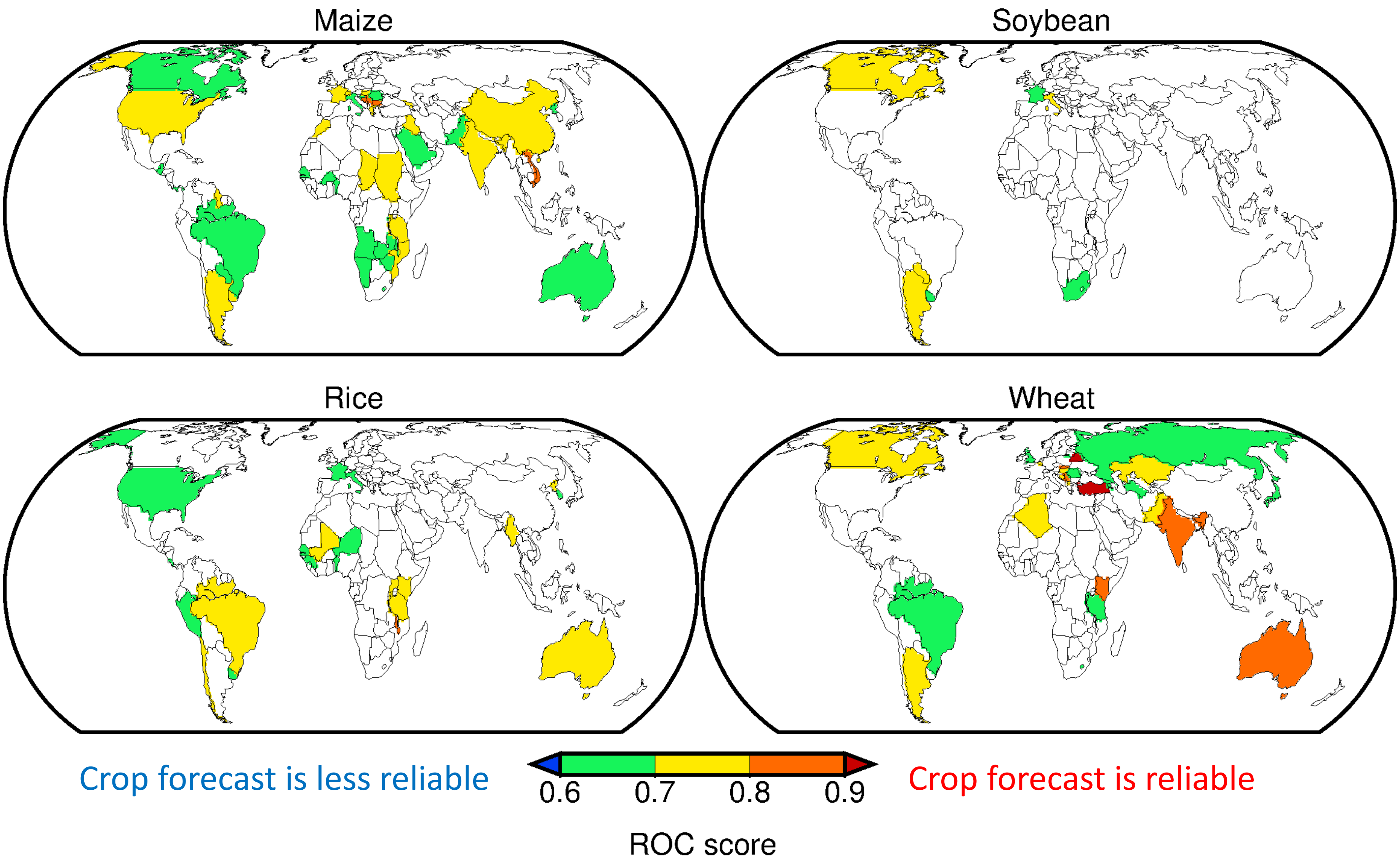
Note: the GCM selection is based on the independent data

Skill score for predicting yield variability (3-mon lead)

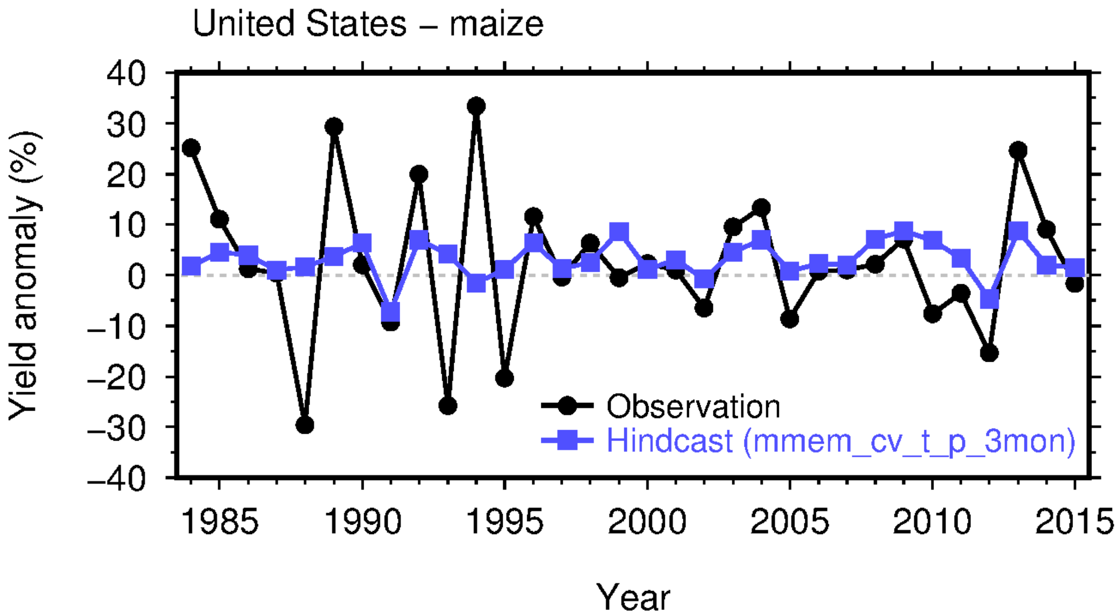


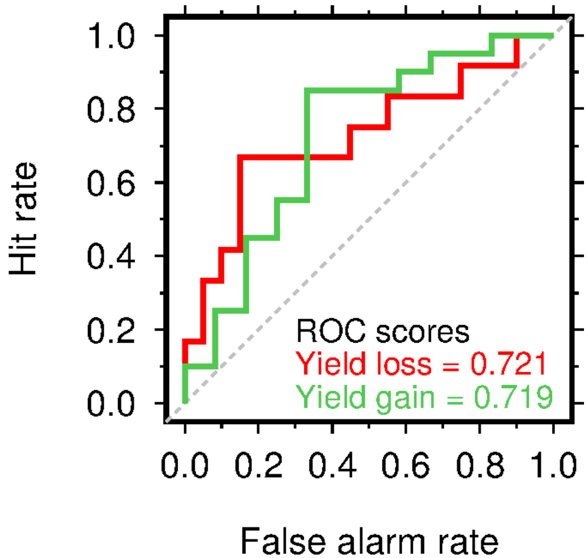
■ Good skill in predicting yield variability □ No skill ■ No data available

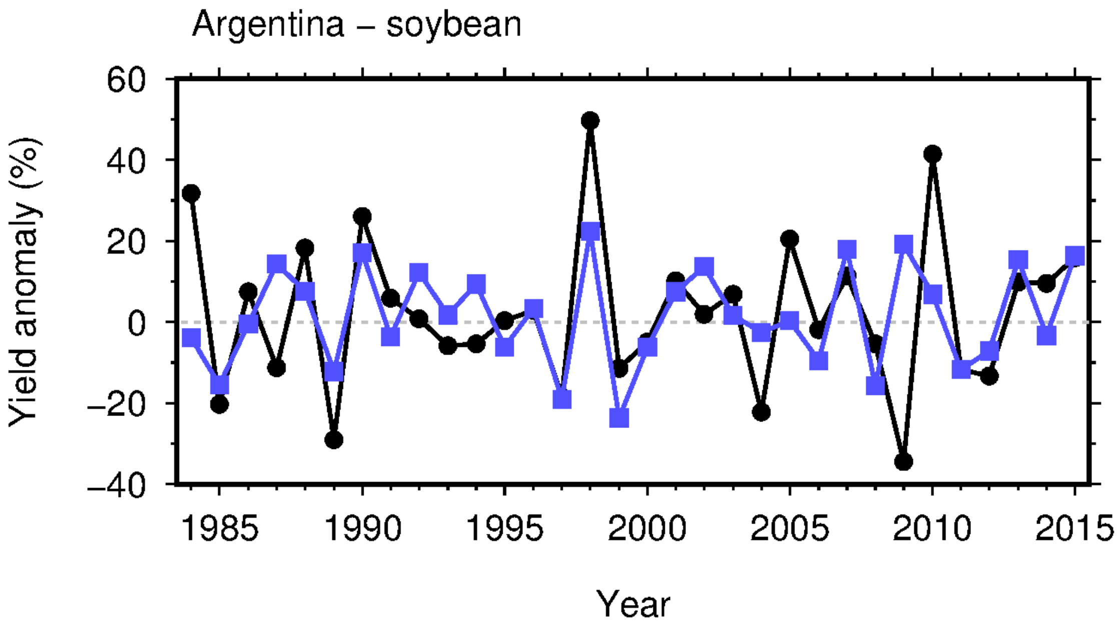
Countries where national average yield variability is reliably predictable at 3-month lead

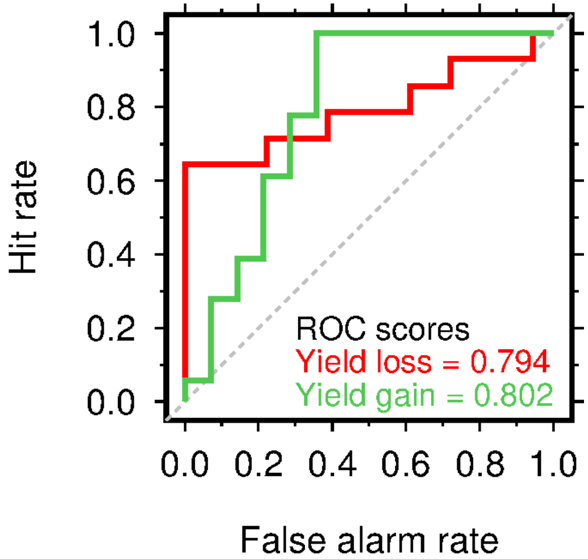


Predicted national average yield variability (3-mon lead)

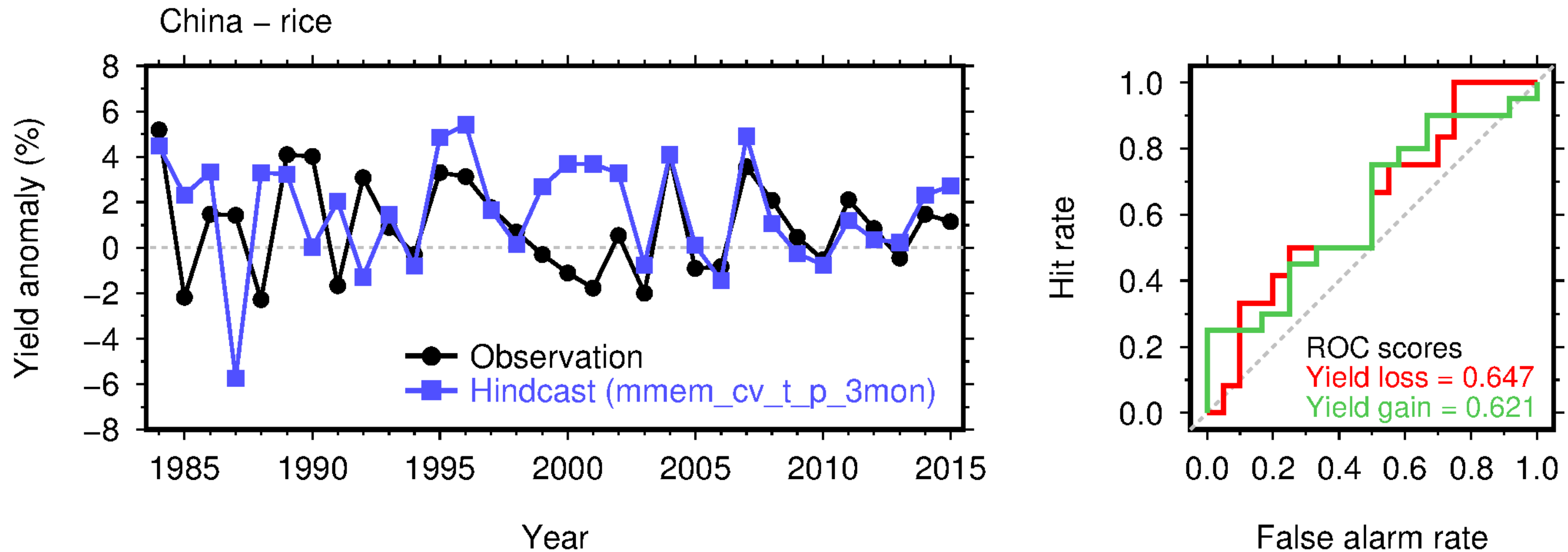


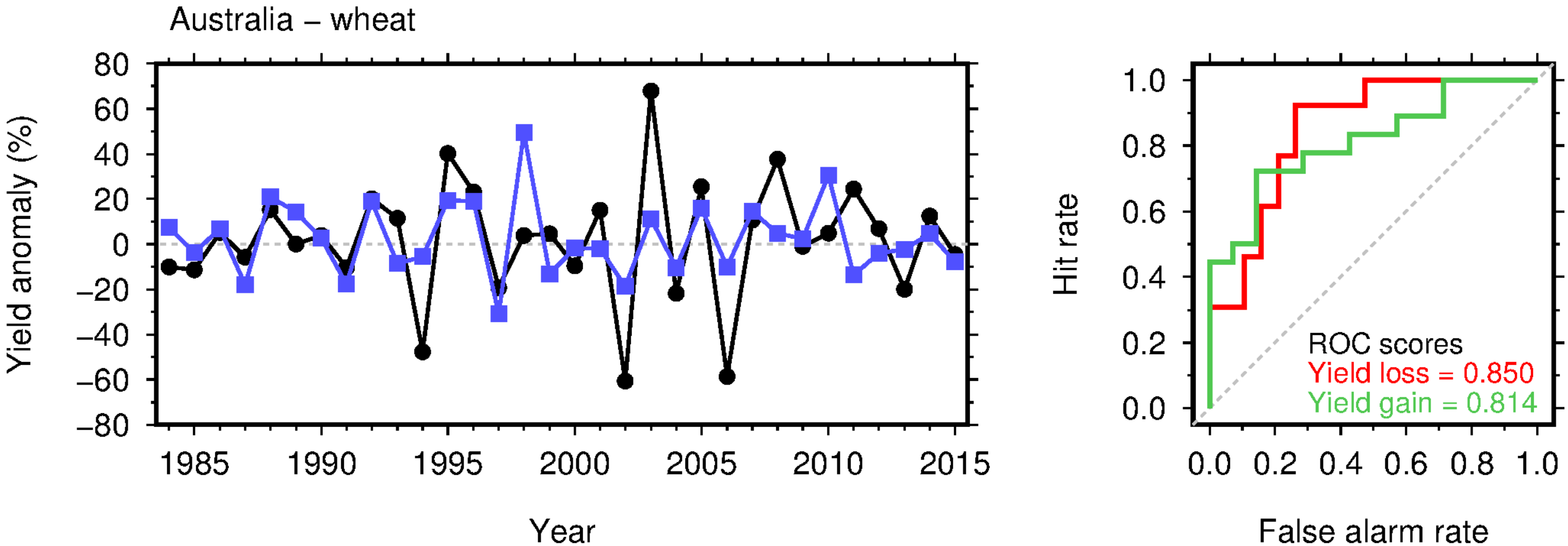




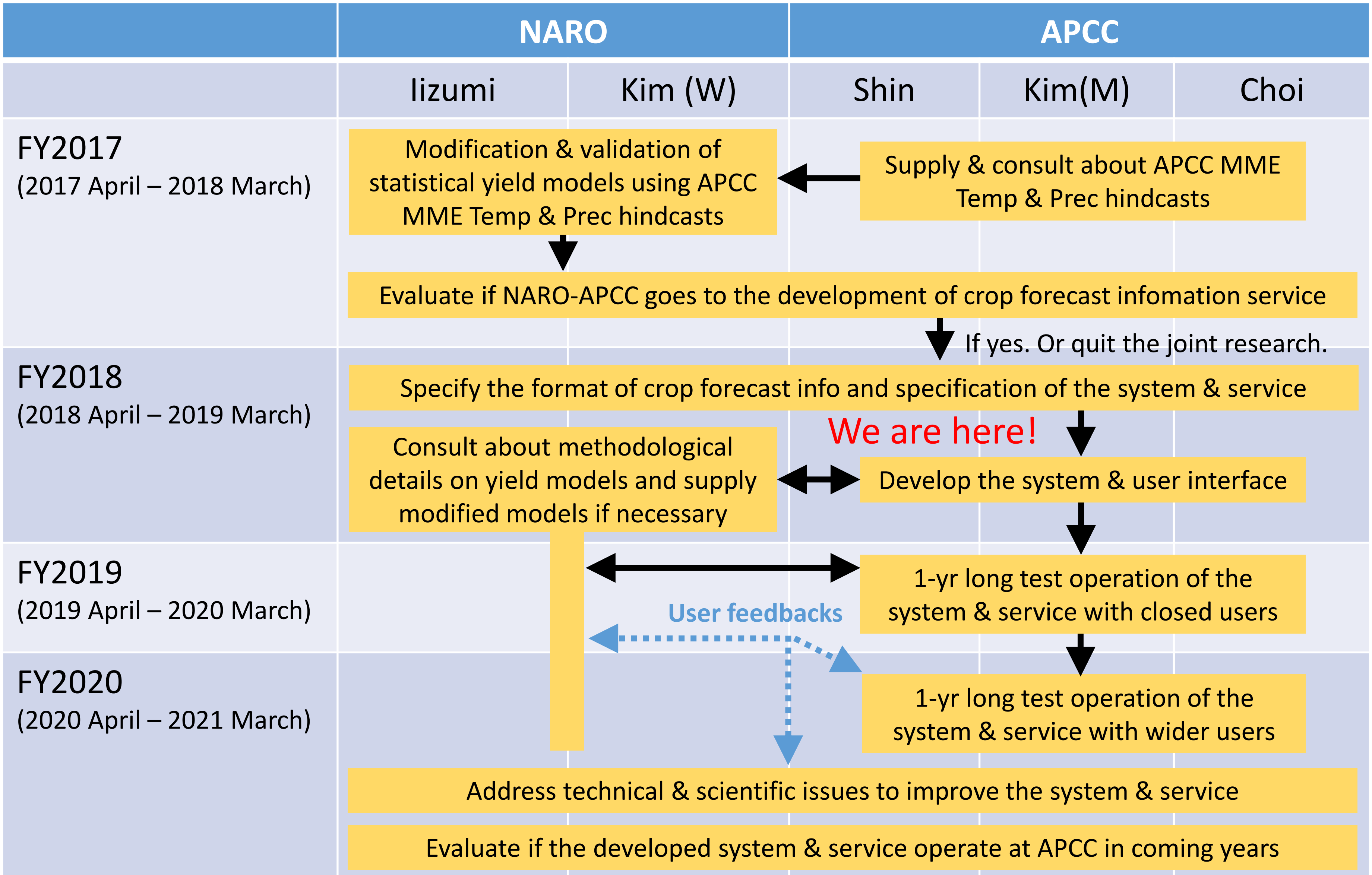


Predicted national average yield variability (3-mon lead)





Timeline of NARO-APCC joint research

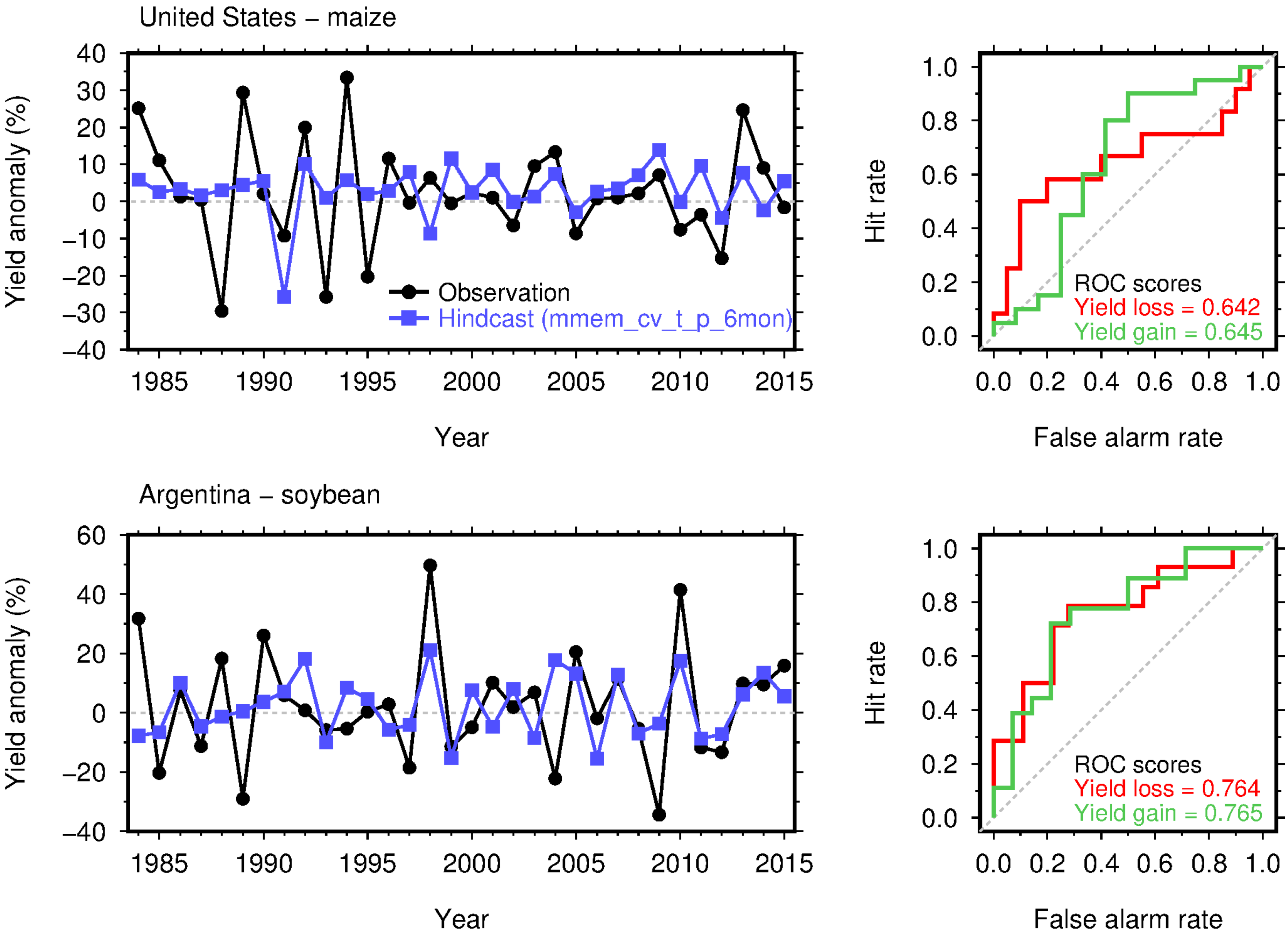


Summary

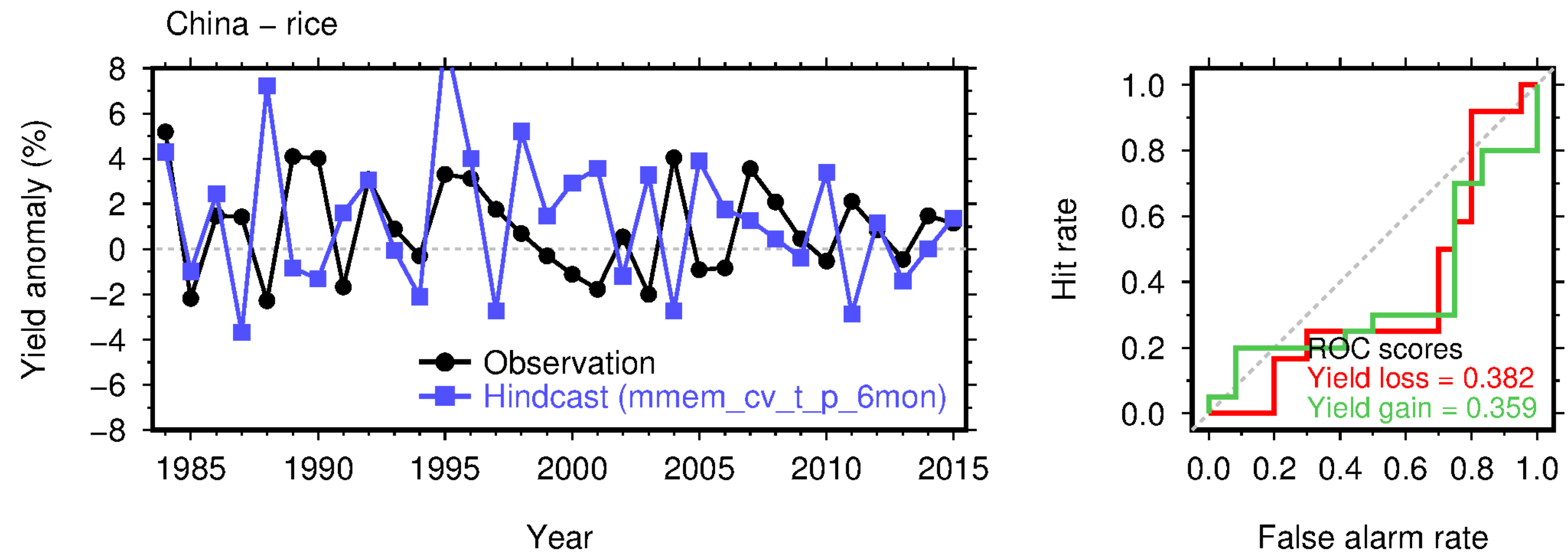
- Crop production has being affected by climate change.
- Crop forecasting is a means for climate change adaptation as well as for climate variability.
- NARO and APCC is conducting a joint research to utilize seasonal climate forecast data for global crop forecasting.
- The research reveals that reliable within-season predictions of yield variability are feasible in 25—38% of global harvested area, enabling us predicting national average yield variability for a substantial portion (24—36%) of the crop-producing countries.
- Based on these findings, NARO and APCC are preparing for test operation of crop forecast in 2019/2020 which is a basis for operational global crop forecasting services.

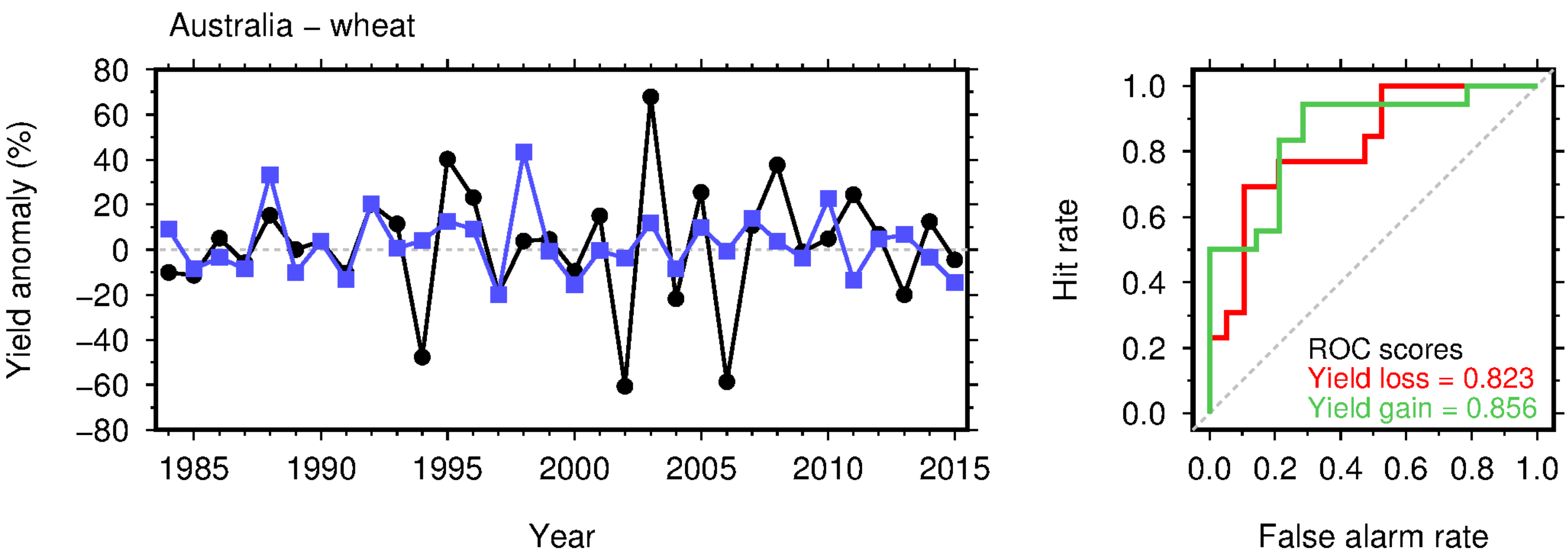
Questions?

Predicted national average yield variability (6-mon lead)



Predicted national average yield variability (6-mon lead)





Settings of statistical yield models

	Iizumi et al (2013)	This study
Period	1983-2006 (24yr)	Grid, 1984-2010 (27yr) Country, 1984-2015 (32yr)
Yield anomaly (normalization)	First difference (average yield t-3:t-1)	Same as I13
Climatic variables	T & S	T & P
Crop calendar	SAGE (Sacks et al., 2010)	Same as I13
Calibration	MCMC	Same as I13
Skill score	R^2	ROC
Yield dataset	Global dataset of historical yields (GDHY) version 1	GDHY version 1.1
Climate model(s)	SINTEX-F1 (average over 9 ensemble members)	5 GCMs & 2 MME methods
Bias correction	Yes (CDFDM)	Same as I13

Statistical yield model (T-P)

$$\Delta Y_t = \frac{(Y_t - Y_{t-1})}{\bar{Y}_{t-3:t-1}} \times 100 \quad (1)$$

$$\Delta T_t = T_t - T_{t-1} \quad (2)$$

$$\Delta P_t = P_t - P_{t-1} \quad (3)$$

$$\Delta Y_t = a_0 + a_1 \cdot \Delta T_t + a_2 \cdot \Delta P_t + \varepsilon \quad (4)$$

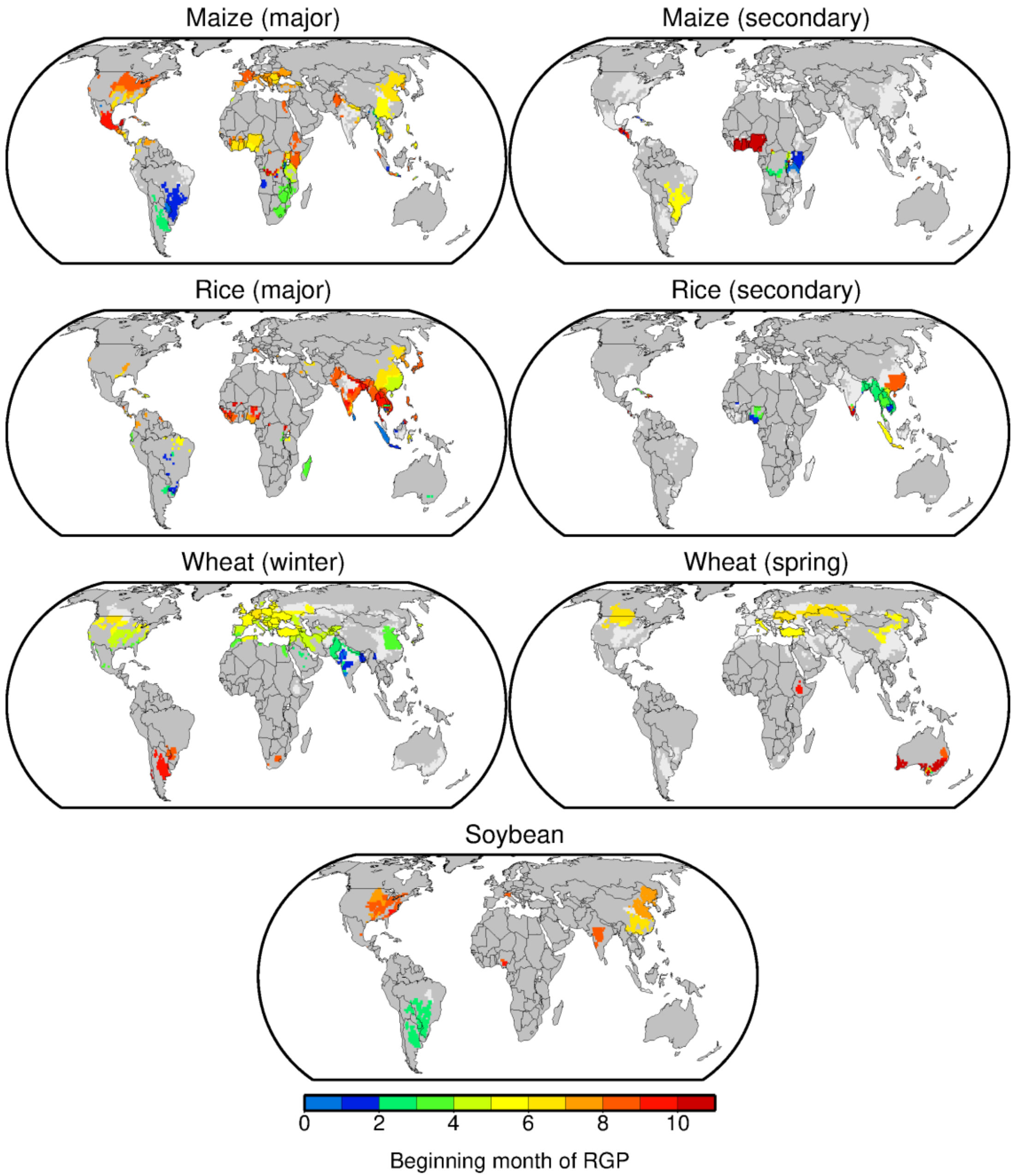
ΔY, yield anomaly (%); Y, yield (t/ha); $\bar{Y}$, average yield (t/ha)

ΔT, RGP mean T anomaly (°C); ΔP, RGP mean P anomaly (mm/d)

a_0, a_1, a_2, regression coefficients; ε, error term

Subscript: t, year; Regression coefficients were estimated by crop, cropping season and grid cell.

Reproductive growth period (RGP)



SAGE global crop calendar (Sacks et al., 2010, GEB)

$$m_{\text{end}} = \begin{cases} 12 & d_{\text{h}} \le 15 \text{ and } m_{\text{h}} = 1 \\ m_{\text{h}} - 1 & d_{\text{h}} \le 15 \text{ and } m_{\text{h}} \ge 2 \\ m_{\text{h}} & d_{\text{h}} > 15 \end{cases}$$

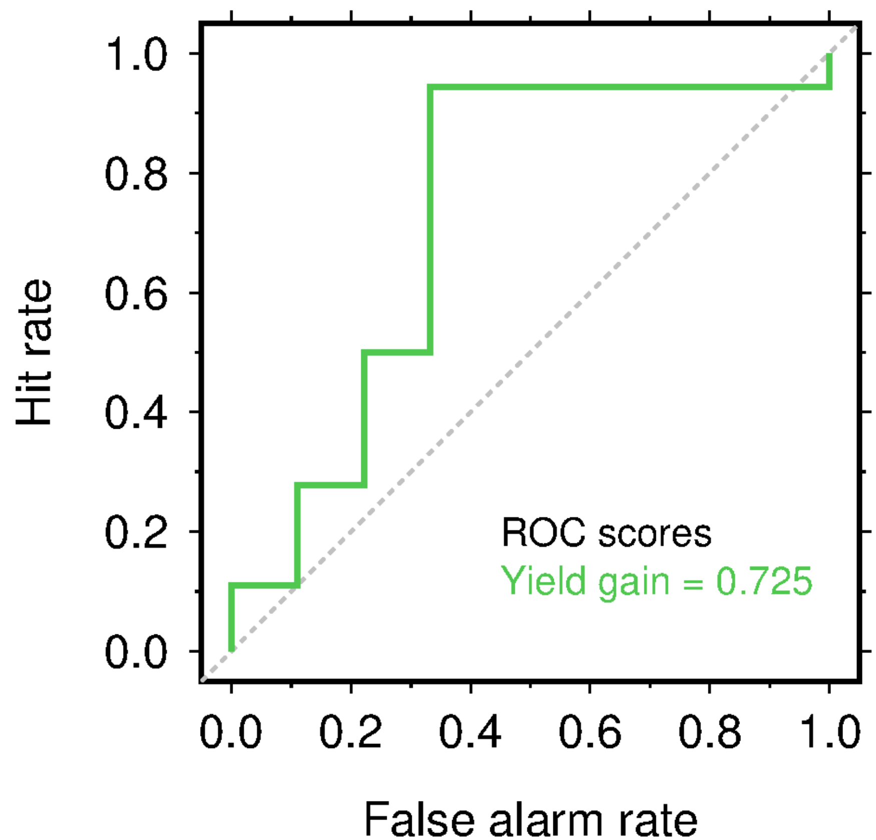
$$m_{\text{start}} = \begin{cases} m_{\text{end}} - 2 + 12 & 1 \le m_{\text{end}} \le 2 \\ m_{\text{end}} - 2 & 3 \le m_{\text{end}} \le 12 \end{cases}$$

m_{start} & m_{end}, the month in which RGP starts and ends, respectively.
m_h & d_h, harvesting month and date.

ROC (Receiver Operatorating Characteristic) score for yield gains

Year	Observed yield anomaly (%)	Hindcasted yield anomaly (%)
1984	25.144	2.52
1985	11.087	4.187
1986	1.338	5.048
1987	0.41	1.201
1988	-29.589	-1.987
1989	29.325	4.822
1990	2.09	5.527
1991	-9.29	0.6
1992	19.979	7.427
1993	-25.745	3.989
1994	33.36	1.1
1995	-20.324	0.607
1996	11.579	6.867
1997	-0.321	0.616
1998	6.325	2.619
1999	-0.497	5.357
2000	2.338	2.386
2001	0.971	3.677
2002	-6.493	-1.845
2003	9.534	5.355
2004	13.288	7.364
2005	-8.615	-0.05
2006	0.768	1.955
2007	1.054	3.816
2008	2.148	6.805
2009	7.143	-2.354
2010	-7.591	7.363

N=27	False N=9	True N=18
Negative (<1.100) N=7 陰性	True negative 0.667 (6/9)	False negative 0.056 (1/18)
Positive (≥1.100) N=20 陽性	False positive 0.333 (3/9)	True positive 0.944 (17/18)



ROC score for yield losses

Year	Observed yield anomaly (%)	Hindcasted yield anomaly (%)
1984	25.144	2.52
1985	11.087	4.187
1986	1.338	5.048
1987	0.41	1.201
1988	-29.589	-1.987
1989	29.325	4.822
1990	2.09	5.527
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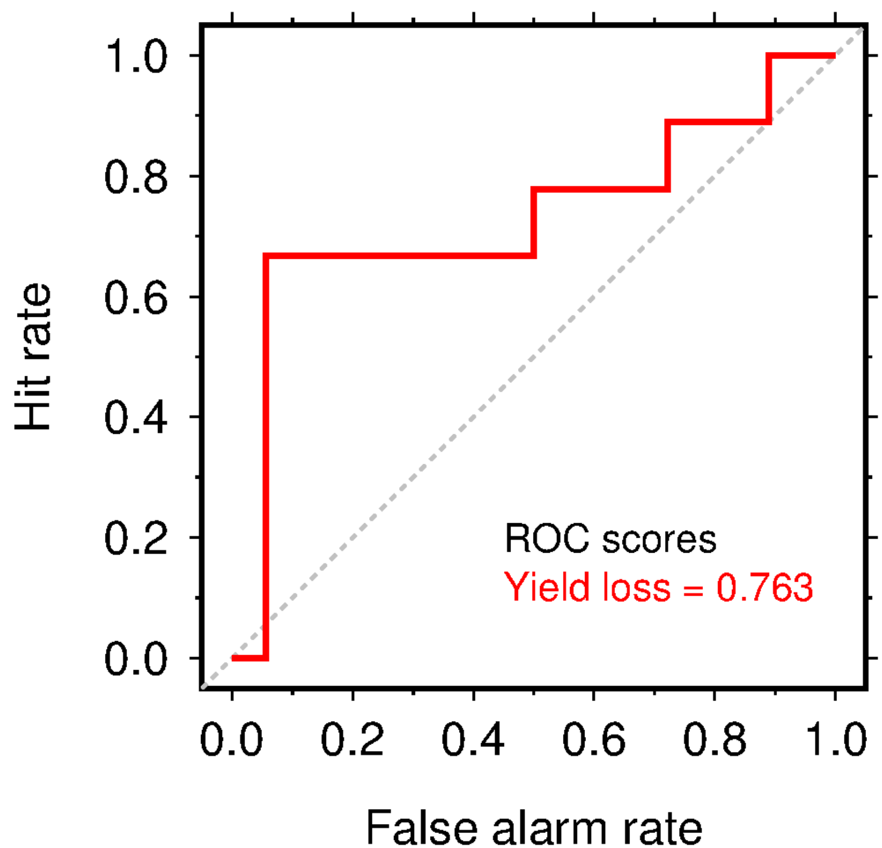
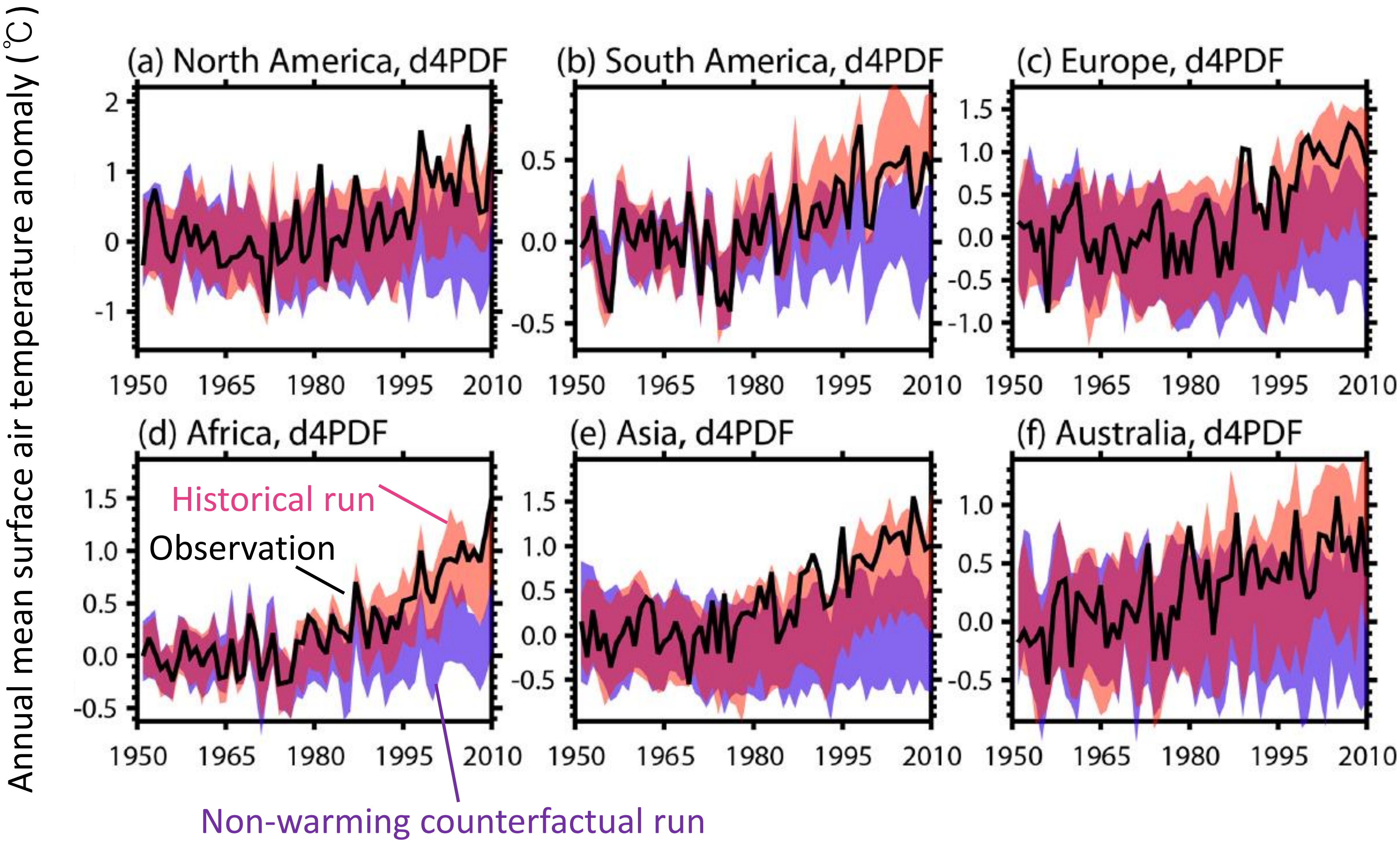
N=27	False N=18	True N=9
Negative (>0.616) N=20 陰性	True negative 0.944 (17/18)	False negative 0.333 (3/9)
Positive (≤0.616) N=7 陽性	False positive 0.056 (1/18)	True positive 0.667 (6/9)

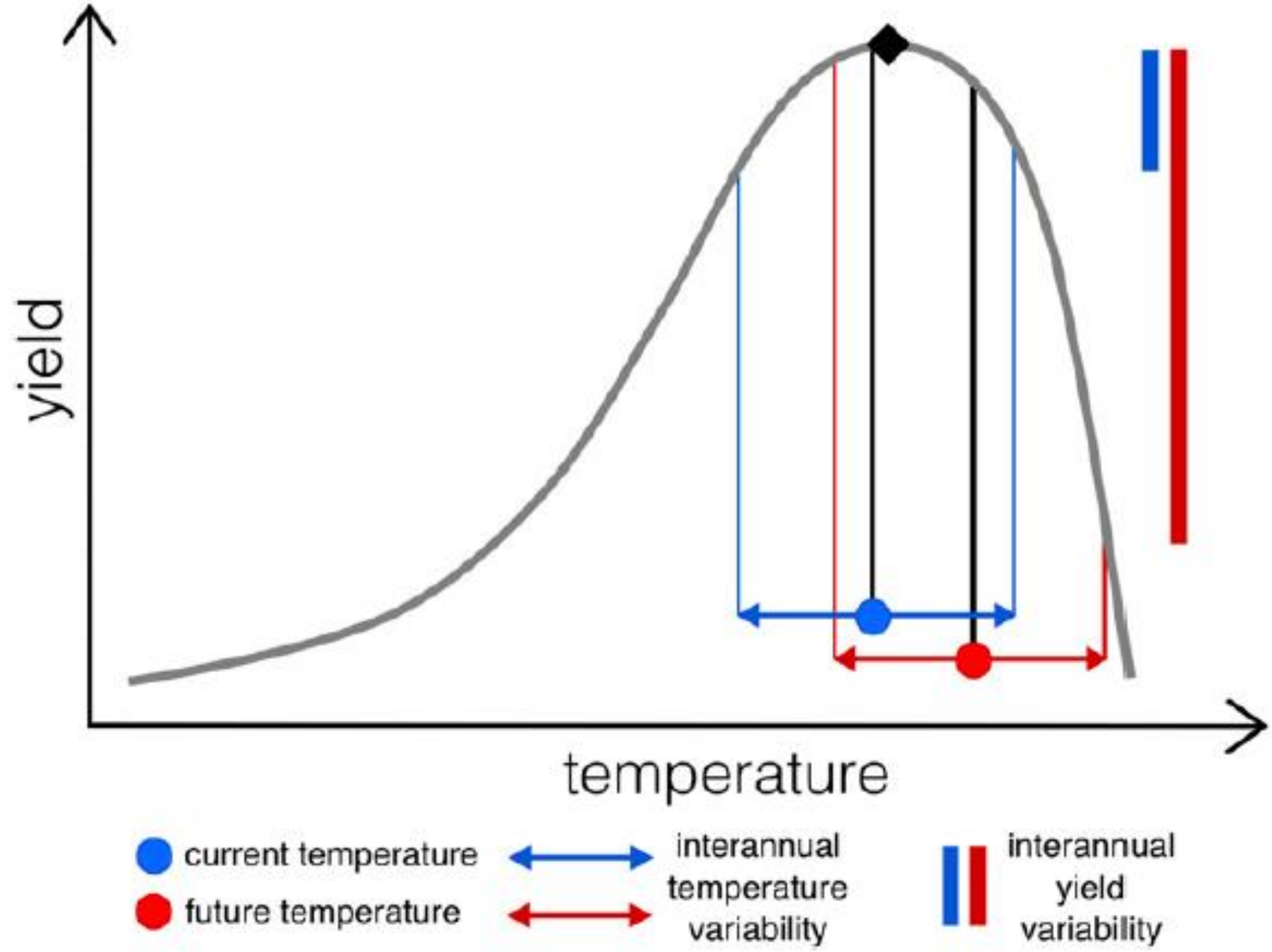


d4PDF historical & non-warming counterfactual climate database



Shiogama et al. (2016) SOLA, doi:10.2151/sola.2016-045

Warming would lead to increased yield variability



Tigchelaar et al. (2018), *Proc Natl Acad Sci USA*, https://doi.org/10.1073/pnas.1718031115