Yield & Climate Variability: Learning from Time Series & GCM

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June 7, 2011

AGRODEP Members’ Meeting and Workshop

Dakar, Senegal

Outline

- General discussion on statistical models of crop response & climate
- Illustrations & insights from recent research
- Understanding implications of tool
- Uncertainties
  – Obtaining bounded results and robust conclusions

Climate and CO_2 Changes

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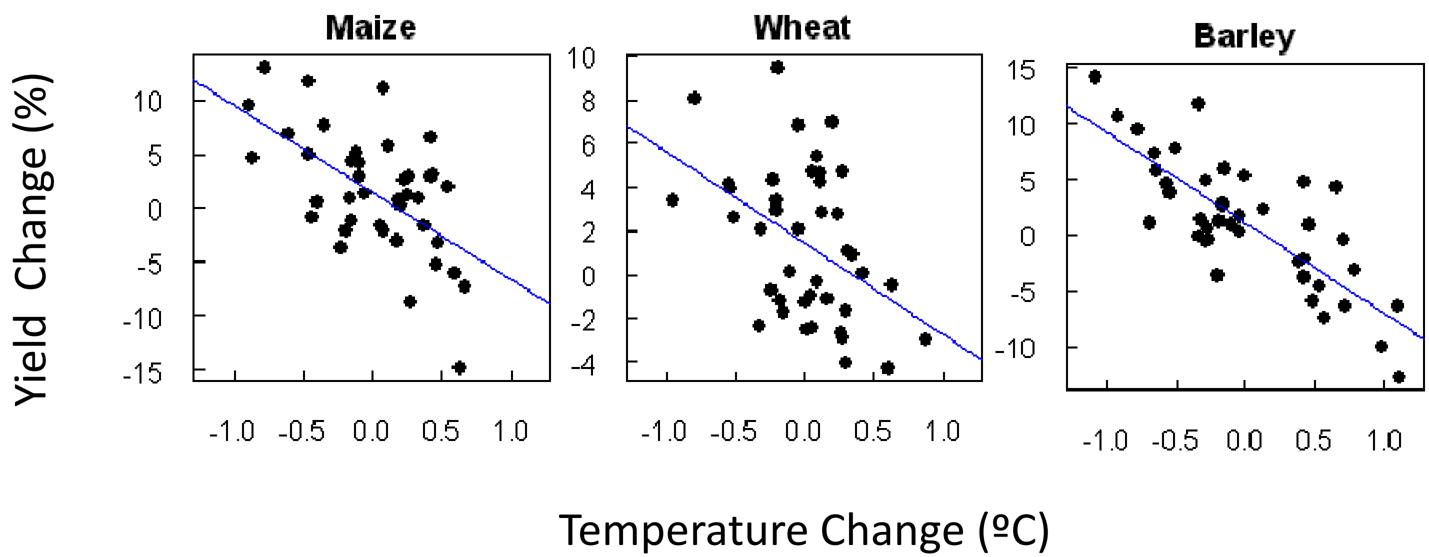
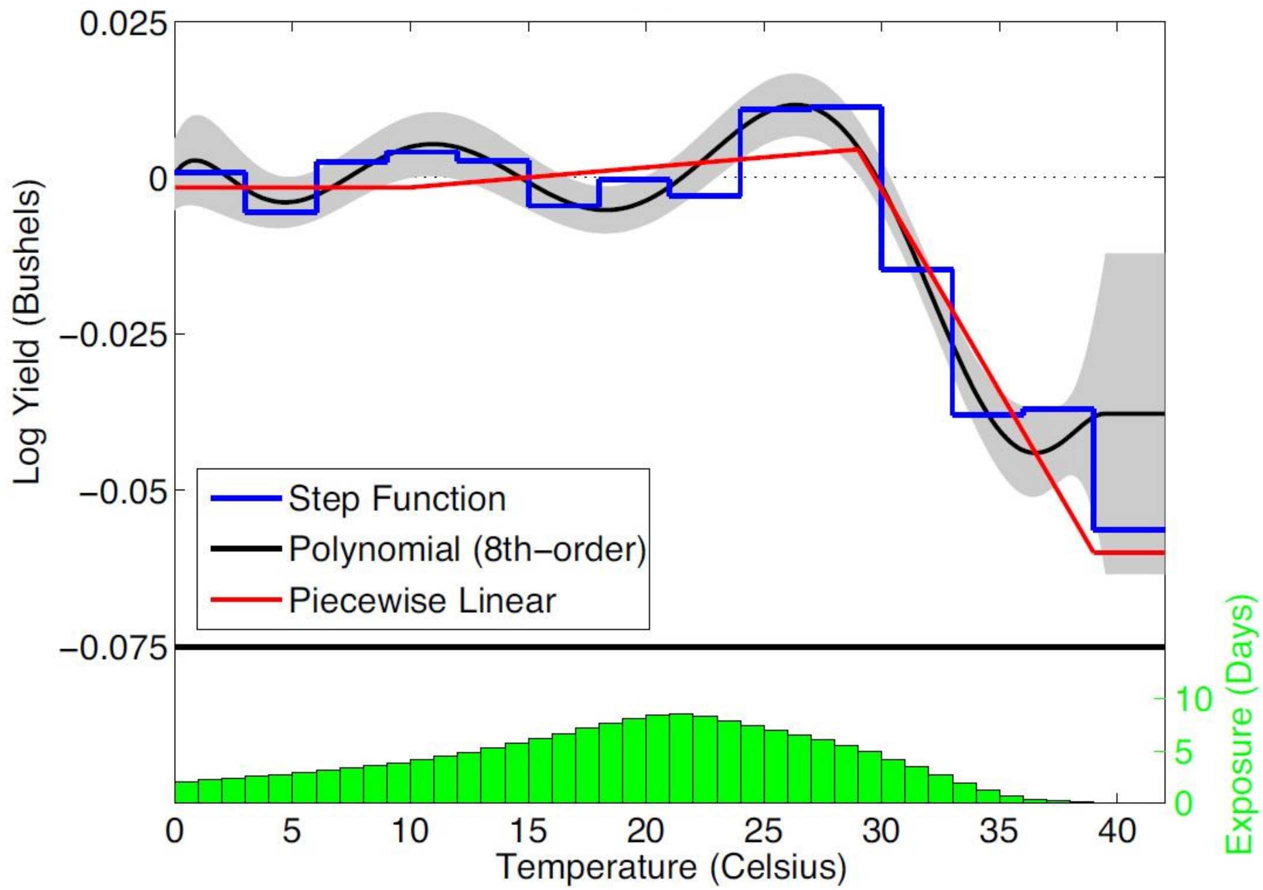
Agricultural productivity

Average Global Yields vs. Temperatures, 1961-2002

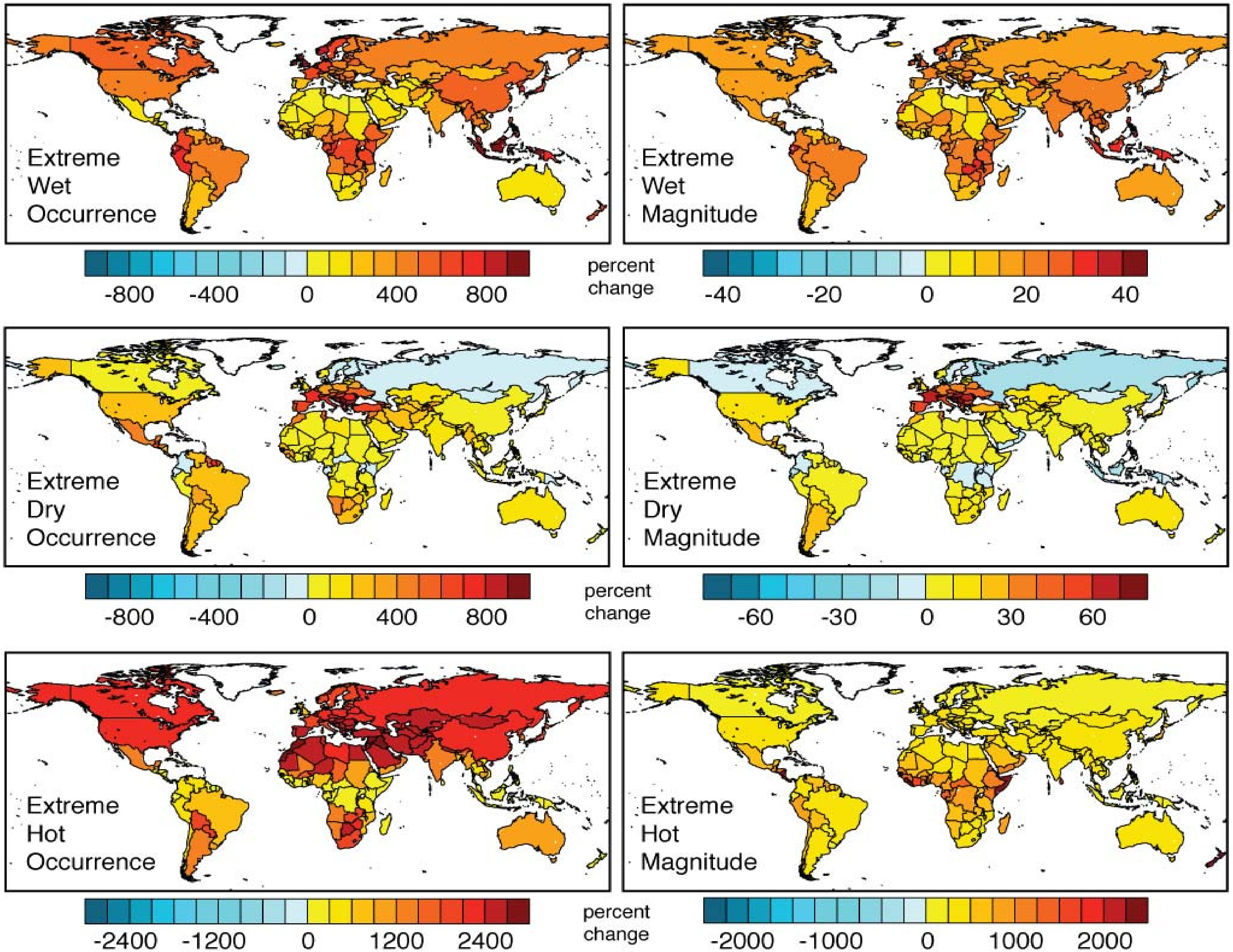


Lobell and Field (2007)

US Maize Yield Response to Temperature



Schlenker and Roberts (2008)



Ahmed et al. (2009)

Changing Climate Volatility

- Extreme outcomes may be particularly important for agriculture (White et al, 2006; Mendelsohn et al, 2007)
- Climate volatility is already changing (Easterling et al, 2000)
  - Higher temperature and precipitation extremes in the future (IPCC, 2007)

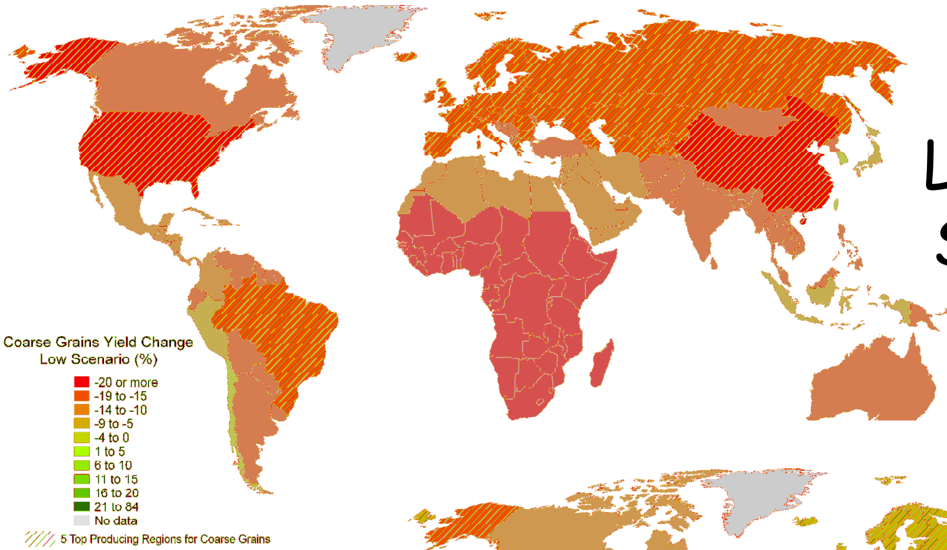
Synthesis of statistical studies

- Undertaken by David Lobell (Stanford) based on work published in *Science* as well as a survey of other published work
- Relatively near term time horizon: 2030
- Estimates for 6 crop categories:
  - Tropical maize adversely affected due to low responsiveness to CO2 fertilization, greater sensitivity to heat stress
  - Consider most-likely case, as well as 5^{th} percentile (pessimistic scenario) and 95^{th} percentile (optimistic scenario) values in distribution of potential yield impacts

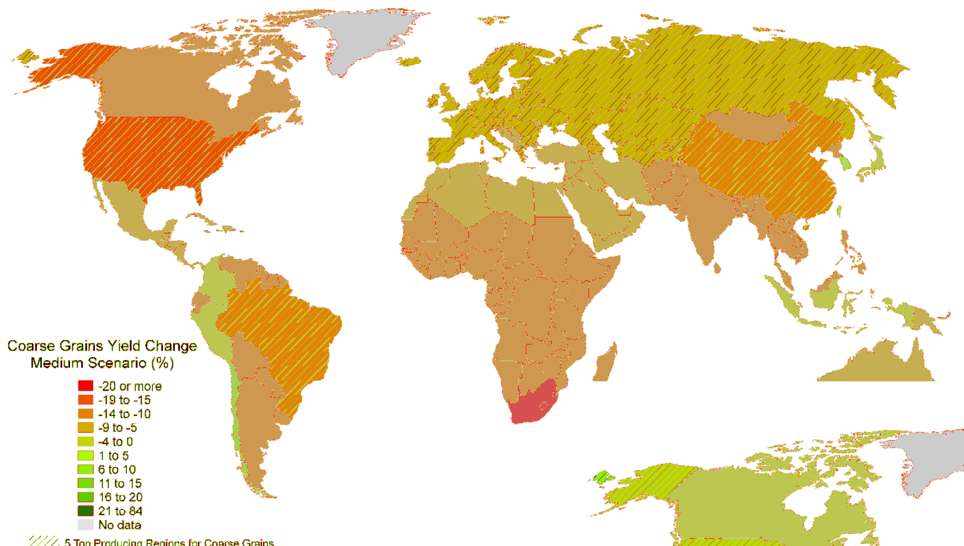
Projected Maize Yield Change (%)

-20 or more
-19 to -15
-14 to -10
-9 to -5
-4 to 0
1 to 5
6 to 10
11 to 15
16 to 20
21 to 84
No data
5 Top Wheat Producing Regions

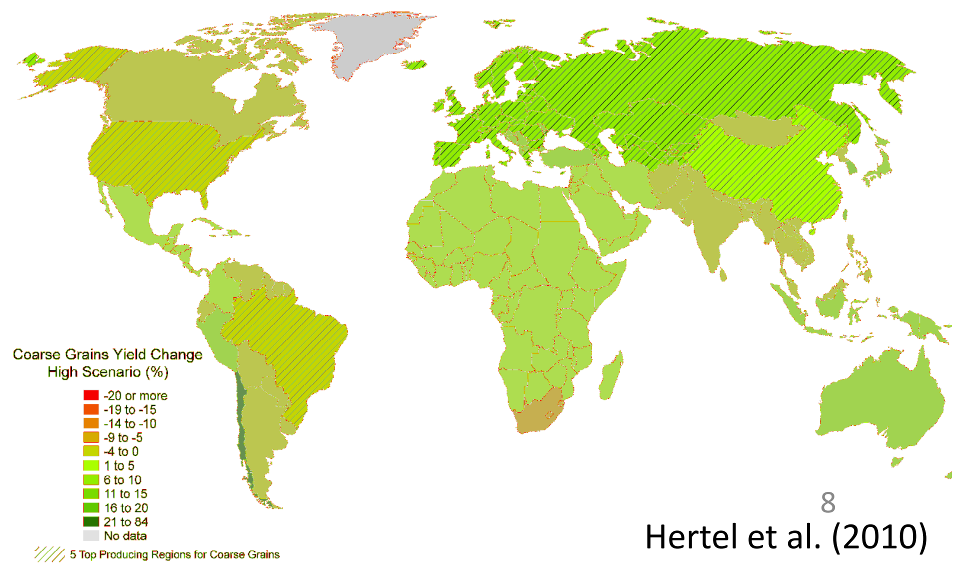
Low Yield Scenario



Medium Yield Scenario



High Yield Scenario



Hertel et al. (2010)

Illustration: Sensitivity of Tanzanian Grain to Climate Volatility

- Ahmed et al. (GEC, 2011)
- Econometric estimation using panel data from 17 administrative regions: 1992-2005
  - Maize, rice, and sorghum yields (tonnes/ha)
  - Temperature (growing season mean in degrees C)
  - Precipitation (growing season mean in mm/month)
- Use yield equation to translate historical and future climate into output changes

Insights (I)

- Interpretation is important
  - Forecasts will be climate-instrumented since climate variables only explain part of the variation in annual yield
  - These are annual yields as explained only by climate variables so technology, policy, & other factors not considered
  - Yield is dependant variable, NOT production
    - Production would depend on yields + area harvested, another source of variation

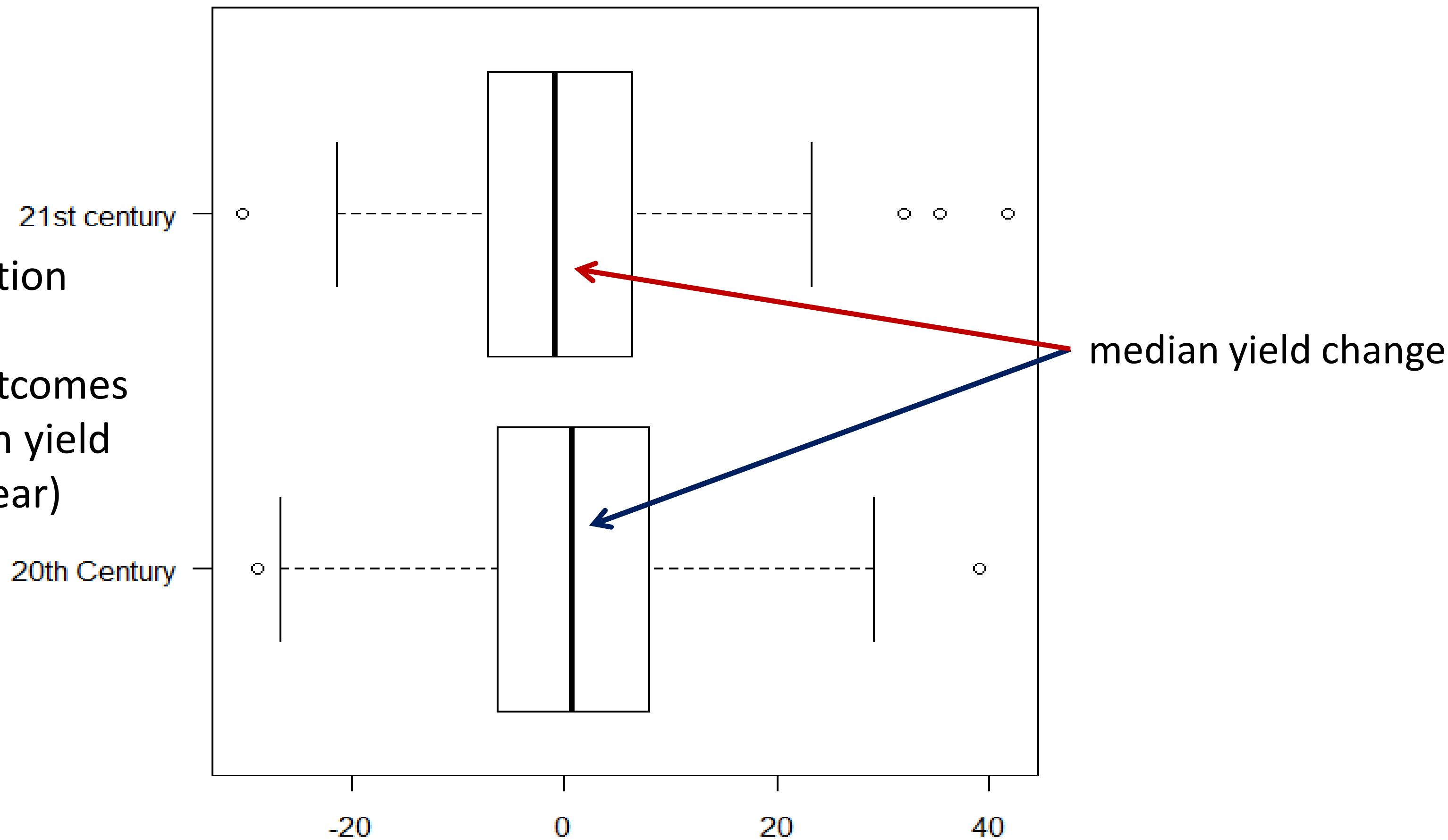
GCM Name	GCM Code	Percent Difference in the Average Value in the 21st Century from the Average Value in the 20th Century (%)			Percent Difference in the Standard Deviation in the 21st Century from the Standard Deviation in the 20th Century (%)		
		Bias-Corrected Average Monthly Growing Season Temp.	Bias-Corrected Average Monthly Growing Season Precip.	Annual Average Grains Yield	Average Monthly Growing Season Temp.	Average Monthly Growing Season Precip.	Annual Average Grains Yield
I	II	III	IV	V	VI	VII	VIII
bccr_bcm2_0	01	1.20 (0.27)	7.21	11.72	-21.46	-4.54	-11.90
cccma_cgcm3_1	02	1.68 (0.38)	20.86	15.81	-29.40	28.09	3.28
cccma_cgcm3_1_t63	03	3.52 (0.80)	11.11	6.78	4.72	1.97	5.05
cnrm_cm3	04	3.52 (0.80)	1.99	3.17	43.29	24.37	34.21
csiro_mk3_0	05	1.17 (0.26)	3.38	10.28	37.60	14.45	18.72
gfdl_cm2_0	06	2.67 (0.60)	11.02	9.12	45.14	12.28	19.04
gfdl_cm2_1	07	1.72 (0.39)	0.12	7.46	-14.89	-19.68	-17.91
giss_aom	08	3.82 (0.86)	3.14	2.78	-8.07	-28.34	-22.84
giss_model_e_h	09	3.69 (0.83)	6.06	4.31	31.72	16.43	21.61
iap_fgoals1_0_g	10	1.70 (0.38)	0.32	7.59	-6.40	-7.60	-2.74
ingv_echam4	11	2.13 (0.48)	1.89	7.00	-8.90	7.47	5.07
inmcm3_0	12	3.53 (0.80)	11.12	6.76	9.87	6.87	-23.27
ipsl_cm4	13	3.34 (0.76)	5.13	4.91	10.33	0.93	9.69
miroc3_2_hires	14	4.90 (1.11)	8.12	1.75	19.35	7.07	5.06
miroc3_2_medres	15	2.33 (0.53)	3.74	7.18	26.51	1.31	-14.85
miub_echo_g	16	1.71 (0.39)	1.81	8.15	-3.58	-15.23	-7.32
mpi_echam5	17	0.88 (0.20)	-1.74	9.06	25.84	-6.18	1.50
mri_cgcm2_3_2a	18	1.99 (0.45)	-1.26	6.15	32.97	-8.10	-0.11
ncar_ccsm3_0	19	4.07 (0.92)	17.18	7.67	4.21	-10.38	-25.56
ncar_pcm1	20	2.80 (0.63)	-0.64	4.14	-5.64	-18.57	-13.84
ukmo_hadcm3	21	2.01 (0.45)	-10.42	2.46	-2.98	-10.95	-16.56
ukmo_hadgem1	22	3.20 (0.72)	-4.54	1.47	29.98	-14.63	-4.58
Average		2.62 (0.59)	4.35	6.62	10.01	-1.04	-1.74
Average Absolute		2.62 (0.59)	6.04	6.62	19.22	12.06	12.94
Sign Consistency		1.00	0.72	1.00	0.52	-0.09	-0.13

Insights (II)

- Climate model data need to be bias-corrected before use
  - Calibrating GCM data to have same 1st and 2nd moments as historical data used in estimation
- Yield forecasts may differ widely based on GCM that are used as inputs
- Challenging to interpret
  - Solution: bounded envelope
  - Pool forecasts based on most volatile GCMs

Distribution of Interannual % Changes in Tanzanian Grains Yield due to Climate

Mass of distribution shifting left (more/larger outcomes with % decline in yield from previous year)



Outcomes within box represent 75% of all predicted outcomes

Ahmed et al. (2011)

Strengths

- Avoids biophysical modeling
- Statistical measures of accuracy (e.g. model fit)
- (Potentially) fewer data demands
- Does not need calibration
- Endogenously captures farmer adaptation (to an extent)

Weaknesses

- Avoids biophysical modeling
- Forecasting limitations
- Difficult to model counterfactual adaptive behavior
- Does not account for Ricardian responses
- Sensitive to data