

Ex-Ante Evaluation of Climate-Smart Agriculture Options

Global Yield Gap Atlas (GYGA) Team
(www.yieldgap.org)

Global Yield Gap Atlas Team

University of Nebraska, USA

Ken Cassman, Patricio Grassini, , Nicolas Guilpart,
Justin Van Wart, Haishun Yang

Wageningen University, the Netherlands

Martin van Ittersum, Hendrick Boogaart, Hugo de
Groot, Lenny van Bussel, Joost Wolf

ICRISAT and AfricaRice, CGIAR

Lieven Claessens, Pepijn van Oort, Kazuki Saito

CSIRO, Australia

Zvi Hochman, Peter McIntosh

Global Yield Gap Atlas (GYGA): coordinating team

University of Nebraska (UNL)



Kenneth Cassman



Patricio Grassini



Justin van Wart



Haishun Yang

Wageningen University & Alterra



Martin van Ittersum



Lenny van Bussel



Joost Wolf



Hendrik Boogaard



Hugo de Groot

Regional coordinators and partners



Lieven Claessens (ICRISAT)



Kazuki Saito (Africa Rice)

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Water for Food Institute**



Climate Smart Agriculture (CSA) Involves:

- **Sustainably increasing agricultural productivity and incomes**
- **Greater adaptive capacity and resilience**
- **Reducing or removing greenhouse gas emissions (where feasible)**

FAO, 2013

Enormous number of CSA options

- Tactical: All aspects of crop and soil management
---tillage method, nutrient management, time of sowing, crop maturity, pest and disease management
- Strategic: crop selection, crop rotations, spatial pattern of cropping (intercrops), investment in irrigation, soil conservation structures (bunds, terraces)
- For efficient field testing, must narrow the options to “best bets”; crop simulation provides an essential tool
- Key issue for ex-ante assessment of climate change impact: **what are best sources of long-term weather data?**

Weather Data for Crop Simulations

- **First choice: Observed, high quality, 20+ years**
 - Tmin, Tmax, solar radiation, relative humidity, precipitation
 - See van Ittersum et al. 2013, Field Crops Res. for justification of the 10-yr minimum for duration of weather data for simulating crop performance with regard to climate
- **Acceptable: Observed, 3+ years of Tmin, Tmax**
 - Long-term database “propagated” (detailed explanation in following slides)
- **Last resort: gridded data (NASA-POWER Agro-Climatic Data, CRU, NCEP)**

Major constraint: Availability of long-term daily weather data (since 1971)

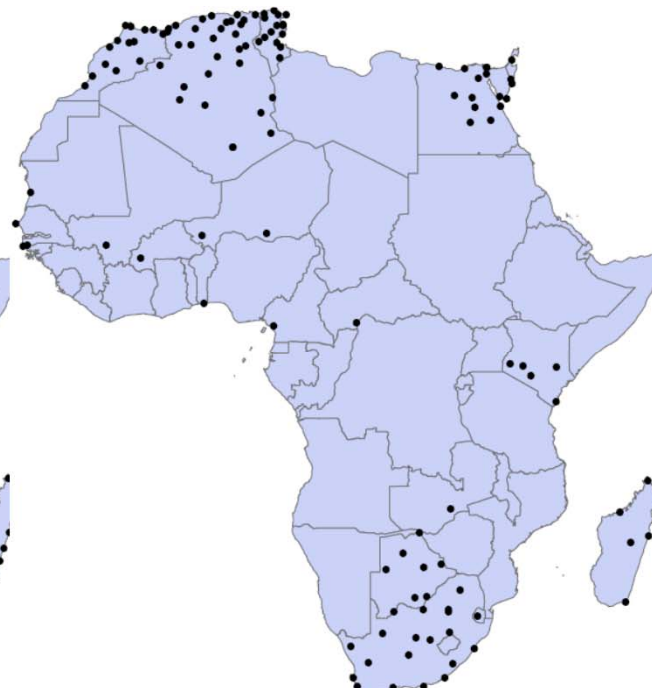
Source: World Meteorological Organization and NOAA Global Summary of the Day database



1048 stations with at least
3-yrs daily weather data

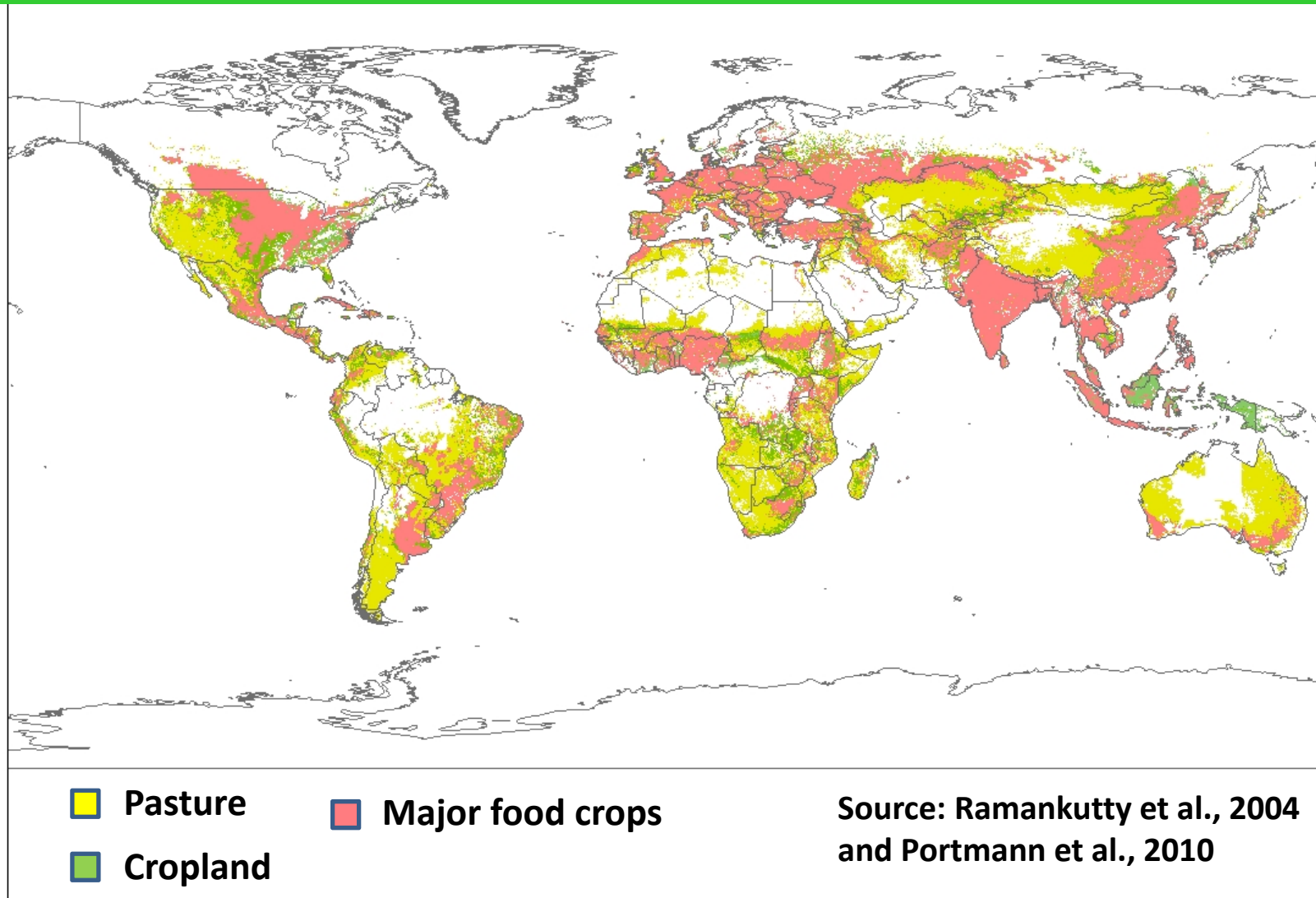


706 stations with at least
15-yrs daily weather data



126 stations with 15-yrs
daily weather data with
< 10% missing days and
< 30-consecutive day gap

Terrestrial coverage of agriculture: major food crops



*Food crops include wheat, maize, rice, barely, rye, millet, sorghum, soybeans, sunflower, potatoes, cassava, sugar cane, sugar beet, oil palm, rape seed/ canola, groundnuts/peanuts, pulses

Crops are grown on relatively small portion of global terrestrial area

	Global coverage		% of total land area
	million km ²	billion ha	
Land area	134.0	13.4	
Agricultural land	49.6	5.0	37%
Pasture/fodder crops	35.0	3.5	26%
Cropland	14.6	1.5	11%
Food Crops*	9.5	0.9	7%

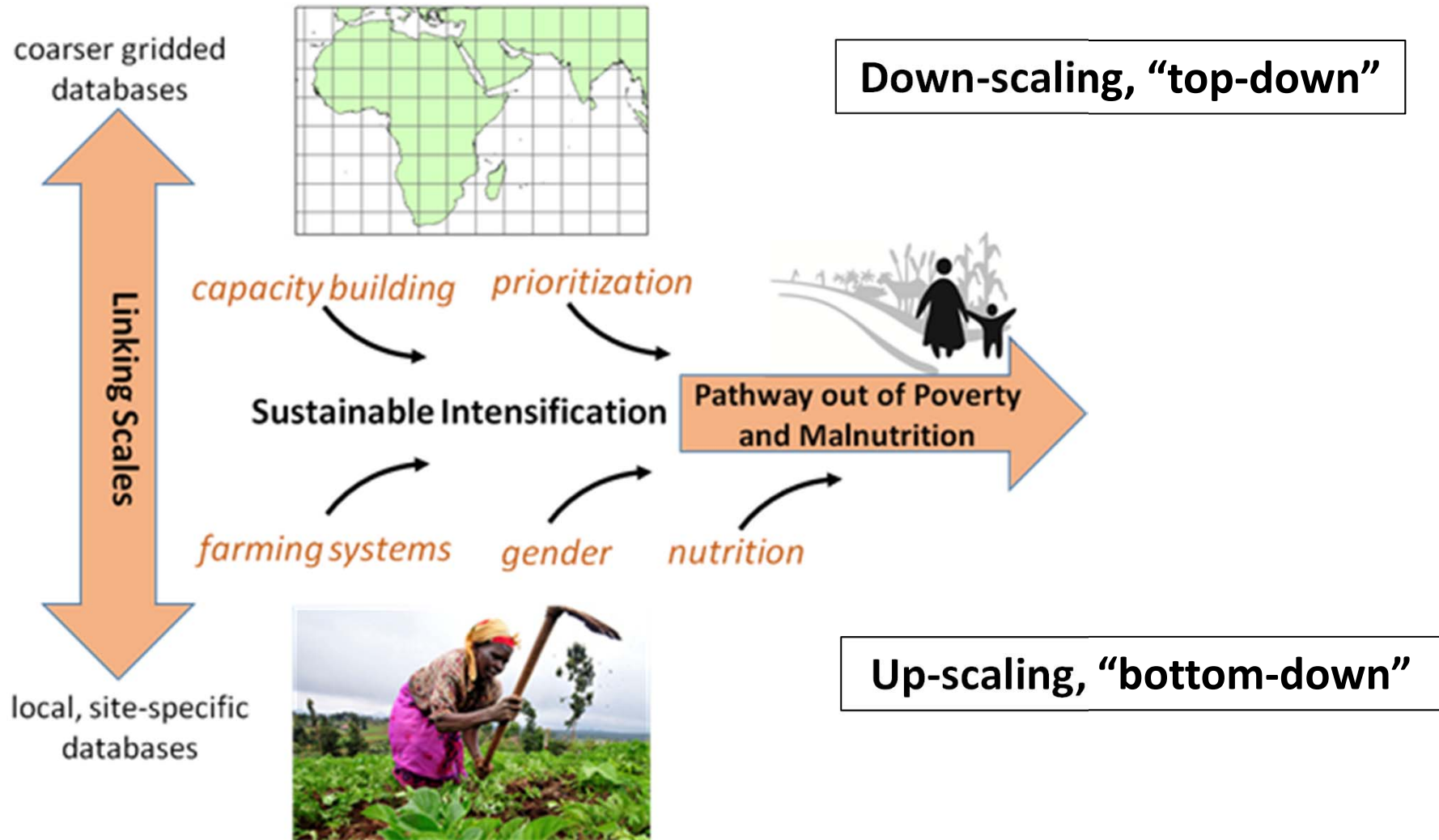
Source: **FAOSTAT** and Portmann et al., 2010 based on the year 2000

*Food crops include wheat, maize, rice, barely, rye, millet, sorghum, soybeans, sunflower, potatoes, cassava, sugar cane, sugar beet, oil palm, rape seed/ canola, groundnuts/peanuts, pulses

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- For efficient field testing, must narrow the options to “best bets”; crop simulation provides an essential tool
- Key issue for ex-ante assessment of climate change impact: **what are best sources of long-term weather data? Top down versus bottom up.....**

Top-Down versus Bottom-Up



Impact of derived global weather data on simulated crop yields

JUSTIN VAN WART, PATRICIO GRASSINI and KENNETH G. CASSMAN

Department of Agronomy and Horticulture, University of Nebraska-Lincoln, Lincoln, NE 68583-0915, USA

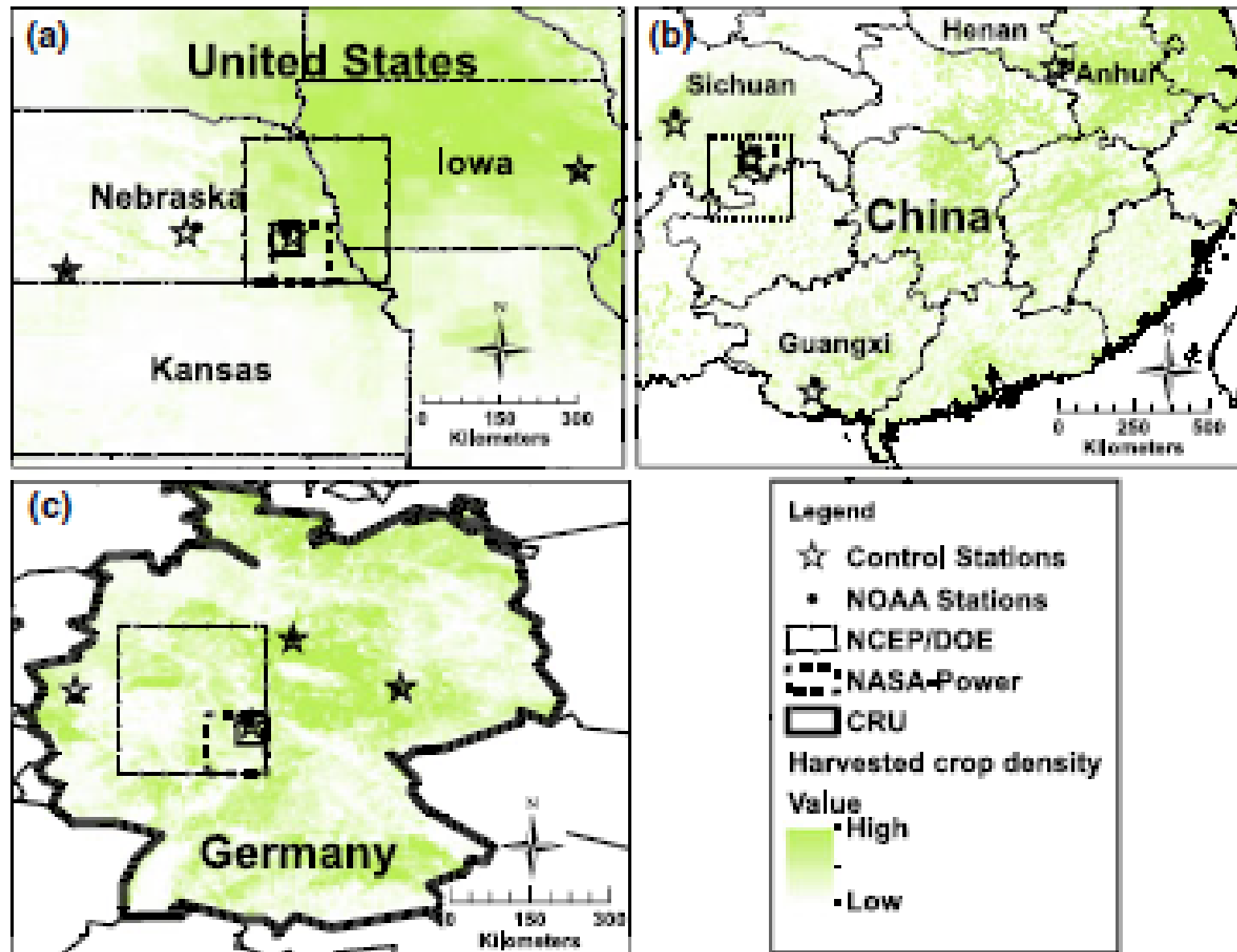
Abstract

Crop simulation models can be used to estimate impact of current and future climates on crop yields and food security, but require long-term historical daily weather data to obtain robust simulations. In many regions where crops are grown, daily weather data are not available. Alternatively, gridded weather databases (GWD) with complete terrestrial coverage are available, typically derived from: (i) global circulation computer models; (ii) interpolated weather station data; or (iii) remotely sensed surface data from satellites. The present study's objective is to evaluate capacity of GWDs to simulate crop yield potential (Y_p) or water-limited yield potential (Y_w), which can serve as benchmarks to assess impact of climate change scenarios on crop productivity and land use change. Three GWDs (CRU, NCEP/DOE, and NASA POWER data) were evaluated for their ability to simulate Y_p and Y_w of rice in China, USA maize, and wheat in Germany. Simulations of Y_p and Y_w based on recorded daily data from well-maintained weather stations were taken as the control weather data (CWD). Agreement between simulations of Y_p or Y_w based on CWD and those based on GWD was poor with the latter having strong bias and large root mean square errors (RMSEs) that were 26–72% of absolute mean yield across locations and years. In contrast, simulated Y_p or Y_w using observed daily weather data from stations in the NOAA database combined with solar radiation from the NASA-POWER database were in much better agreement with Y_p and Y_w simulated with CWD (i.e. little bias and an RMSE of 12–19% of the absolute mean). We conclude that results from studies that rely on GWD to simulate agricultural productivity in current and future climates are highly uncertain. An alternative approach would impose a climate scenario on location-specific observed daily weather databases combined with an appropriate upscaling method.

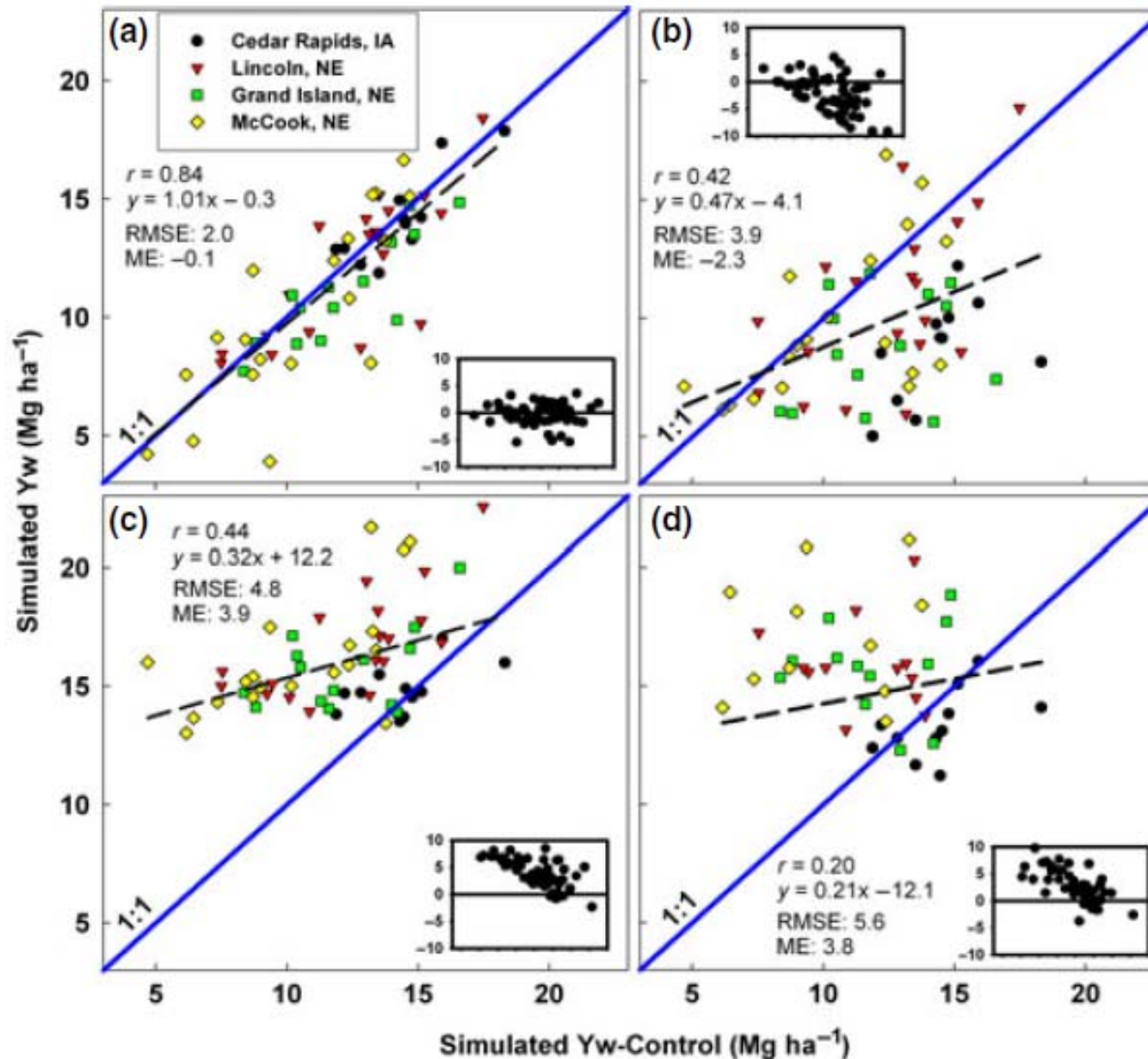
Table 1 Classification of global weather databases and examples of published studies using these databases to understand current and future agricultural productivity. Weather databases used in the present study have been underlined

Classification	Source	Time step	Reference and time interval	Geospatial coverage	Reported variables*	Examples
Point-based data	Weather stations	Daily	<u>HPRCC†, CMA†, DWD§</u> (1983–2010)	Regional	T_{min} , T_{max} , precip, wind speed, Tdew Temp, RH, vapor pressure, radiation	Sinclair & Rawlins (1993), Wang & Connor (1996), Peng <i>et al.</i> (2004), Grassini <i>et al.</i> (2009), Cassman <i>et al.</i> (2010)
			<u>NOAA¶</u> (1900–2010)	Global	T_{min} , T_{max} , precip, Tdew, wind speed, RH, vapor pressure	
Gridded data	Interpolated and generated based on data from weather stations, satellites, ocean buoys, etc.	Daily	<u>NCEP/DOE Reanalysis II </u> (1979–2010)	Global ($2.5^\circ \times 2.5^\circ$) (ca. 70 000 km ²)¶¶	T_{min} , T_{max} , wind speed, precip, RH, wind speed, radiation	Lobell & Asner (2003), Nemani <i>et al.</i> (2003), Schlenker & Roberts (2009), Twine & Kucharik (2009)
			ERA-Interim Reanalysis (1989–2013)**	Global ($1.5^\circ \times 1.5^\circ$) (ca. 25 000 km ²)	T_{min} , T_{max} , wind speed, precip, RH, wind speed, radiation	Rötter (1993), de Wit <i>et al.</i> (2010)
	Interpolated from weather stations	Monthly	<u>CRU05 (3.10)††</u> , Univ. Delaware Climate Dataset (1961–2009)	Global ($0.5^\circ \times 0.5^\circ$) (ca. 3000 km ²)	T_{min} , T_{max} , total precip, no. of wet days, vapor pressure	Fischer <i>et al.</i> (2002), Foley <i>et al.</i> (2005), Bondeau <i>et al.</i> (2007), Lobell (2007), Lobell <i>et al.</i> (2008), Battisti & Naylor (2009), Licker <i>et al.</i> (2010), Lobell <i>et al.</i> (2011)
		Average 50-year monthly mean	WorldClim‡‡ (1950–2000)	Global (ca. 1 km ²)	T_{min} , T_{max} , total precip, no. of wet days	Ortiz <i>et al.</i> (2008), Nelson <i>et al.</i> (2010)
	Satellite	Daily	<u>NASA-Power§§</u> (1983–2010) except precip (1997–2010)	Global $1^\circ \times 1^\circ$ (ca. 12 000 km ²)	T_{min} , T_{max} , precip, Tdew, radiation, RH	Lobell <i>et al.</i> (2010)

Compared simulation of crop yields with good quality weather station data versus gridded weather data for rainfed Maize (USA), irrigated rice (China), and rainfed wheat (Germany); 19 years, four sites in each country. Fig. 1, Van Wart et al., 2013



Control data on X-Axis, versus: (A) NOAA “real” + NASA-SR, and three gridded sources (B) National Center for Environmental Prediction--DOE, (C) Climate Research Unit—Univ. East Anglia, and (D) NASA-POWER dataset. Fig. 2, Van Wart et al. 2013.



Impact of derived global weather data on simulated crop yields

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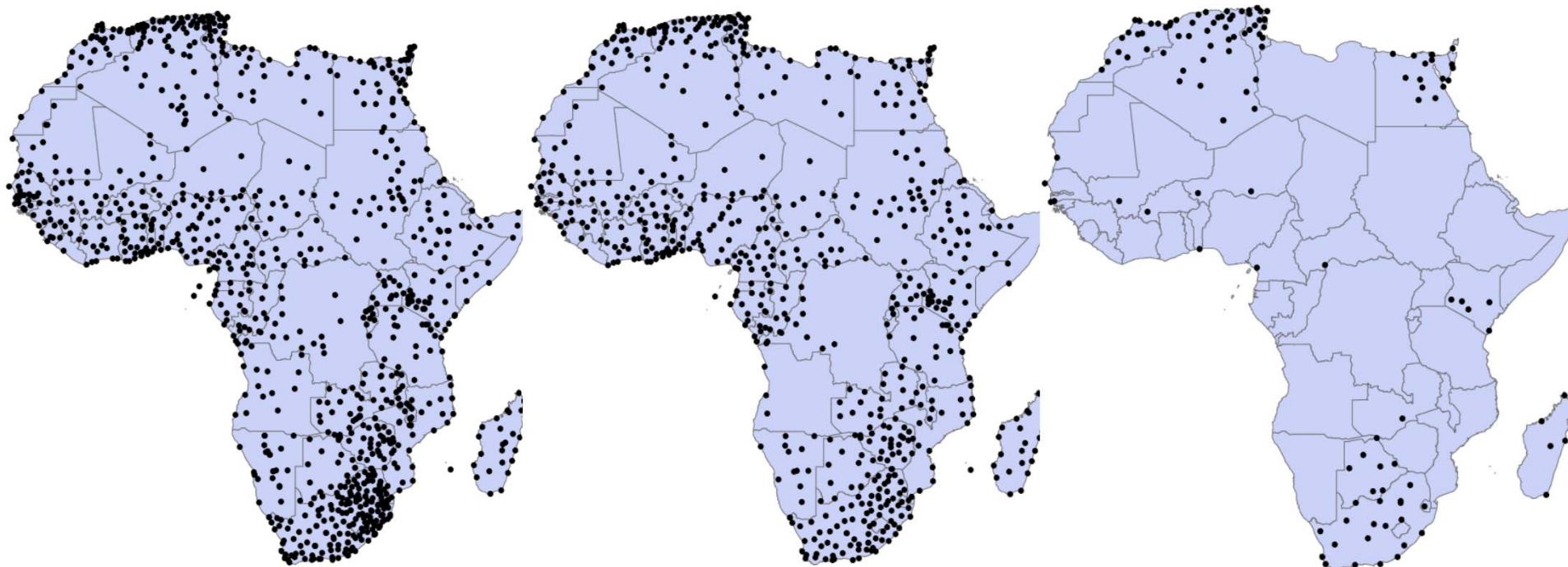
Department of Agronomy and Horticulture, University of Nebraska-Lincoln, Lincoln, NE 68583-0915, USA

We conclude that results from studies that rely on gridded weather databases to simulate agricultural productivity in current and future climates are highly uncertain. An alternative approach would be to impose a climate scenario on location-specific weather databases combined with an appropriate upscaling method.

(CRO, NCEP/DOE, and NASA POWER data) were evaluated for their ability to simulate Yp and Yw of rice in China, USA maize, and wheat in Germany. Simulations of Yp and Yw based on recorded daily data from well-maintained weather stations were taken as the control weather data (CWD). Agreement between simulations of Yp or Yw based on CWD and those based on GWD was poor with the latter having strong bias and large root mean square errors (RMSEs) that were 26–72% of absolute mean yield across locations and years. In contrast, simulated Yp or Yw using observed daily weather data from stations in the NOAA database combined with solar radiation from the NASA-POWER database were in much better agreement with Yp and Yw simulated with CWD (i.e. little bias and an RMSE of 12–19% of the absolute mean). We conclude that results from studies that rely on GWD to simulate agricultural productivity in current and future climates are highly uncertain. An alternative approach would impose a climate scenario on location-specific observed daily weather databases combined with an appropriate upscaling method.

What can be done for regions without long-term weather data?

Source: World Meteorological Organization and NOAA Global Summary of the Day database



**1048 stations with at least
3-yr daily weather data**

**706 stations with at least
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How to obtain long-term weather data where no observed data exist, or only a few years of weather data?

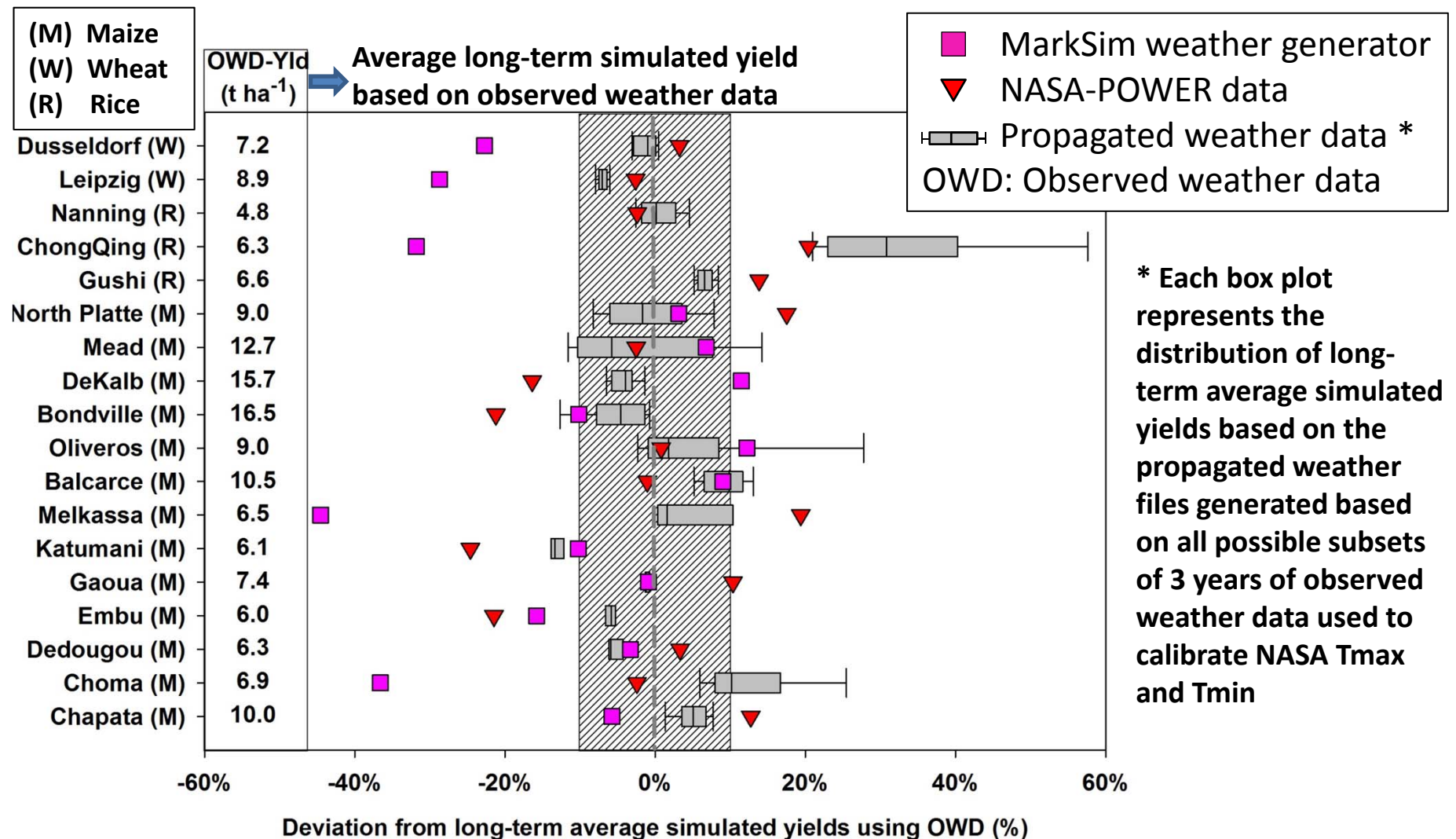
1. Use the best available existing gridded weather data (*not robust for simulating crop yields*)
2. Commercial sources of weather data (*sources unknown and often a black box*)
3. Propagation of long-term weather data for locations with only a few years of observed weather data (*how many years? How well do propagated weather data work?*)

Robust propagation of long-term daily weather data for crop simulation

- Location-specific calibration of NASA Tmax and Tmin based on correlations with ground-measured Tmax and Tmin for at least 3 years
- Solar radiation from NASA-POWER
- Humidity is derived from NASA Tdew (unless measured Tdew or RH are available)
- TRMM rainfall data

Van Wart J, Grassini P, Yang HS, Claessens L, Jarvis A, Cassman KG. 2015. Creating long-term weather data from thin air for crop simulation modelling. *Agricultural and Forest Meteorology, In Press*

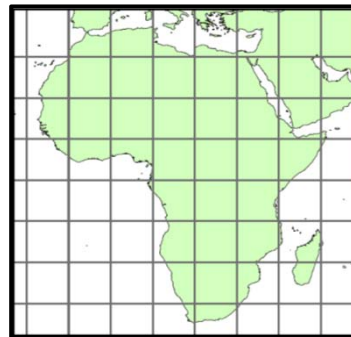
Simulations of yield potential based on propagated *versus* observed and gridded weather data



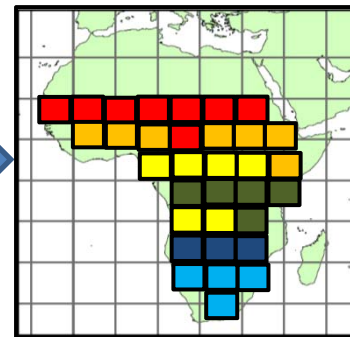
Van Wart J, Grassini P, Yang HS, Claessens L, Jarvis A, Cassman KG. 2015. Creating long-term weather data from thin air for crop simulation modelling. *Agricultural and Forest Meteorology, In Press*

With options for long-term weather data, how to upscale?

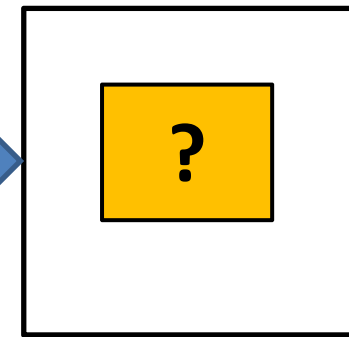
'top-down' approach



Gridded weather, soil, and crop data allows full coverage but has large uncertainty

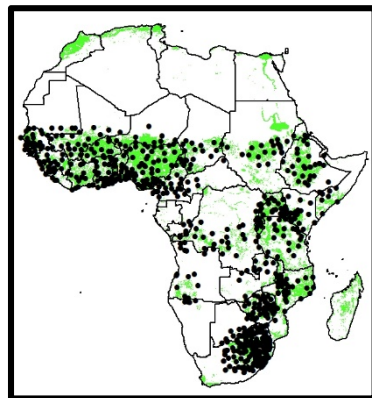


Simulation unit: grid

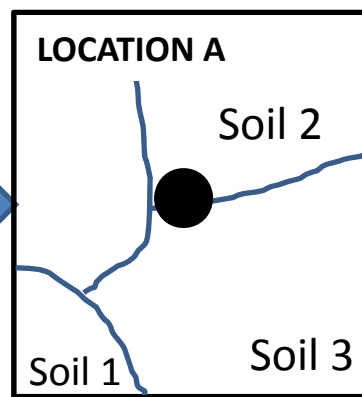


Too coarse to be locally relevant and difficult to validate

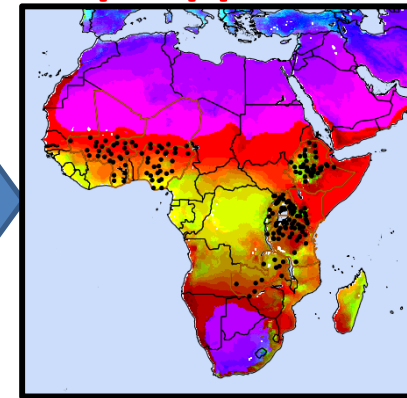
GYGA 'bottom-up' approach



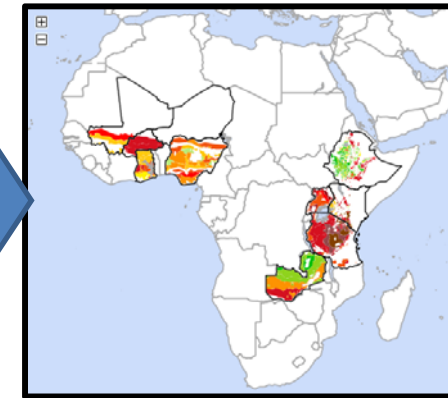
Targeting a tractable number of locations for data collection



Simulation unit: location x soil x crop system combination within a climate zone

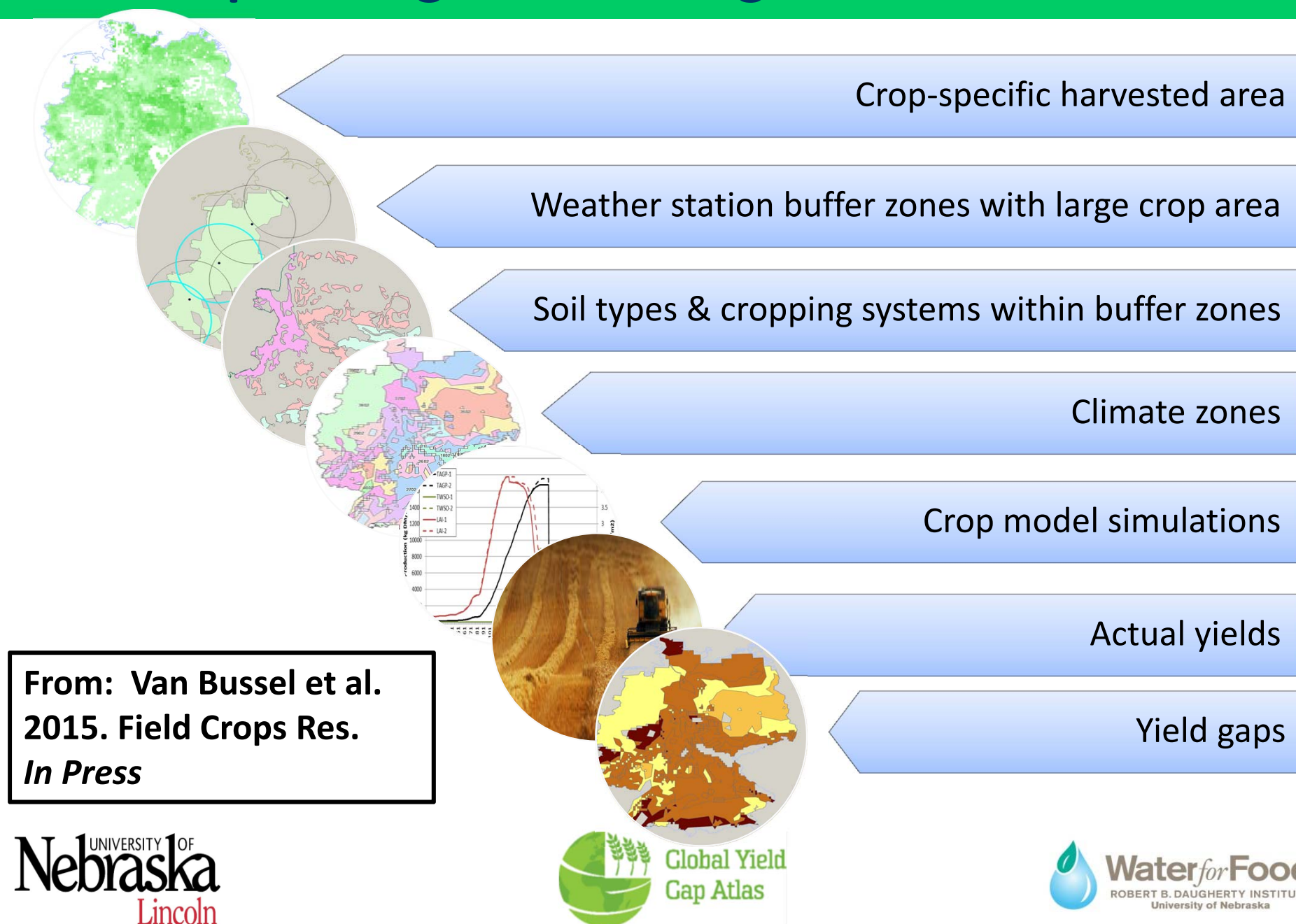


Upscaling from location to region or country by a robust CZ scheme



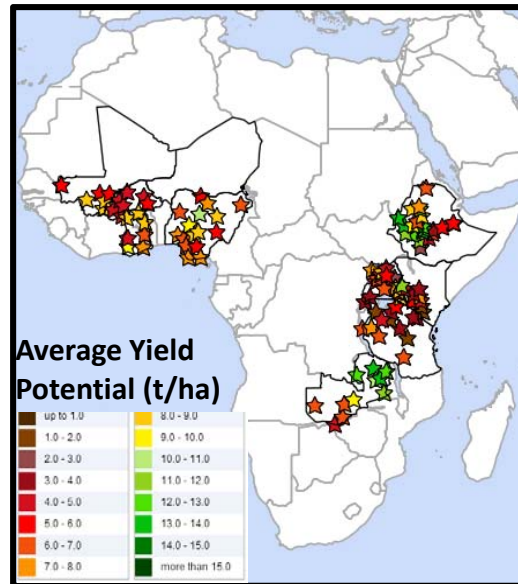
Full coverage without losing local relevance

Up-scaling for local to global relevance

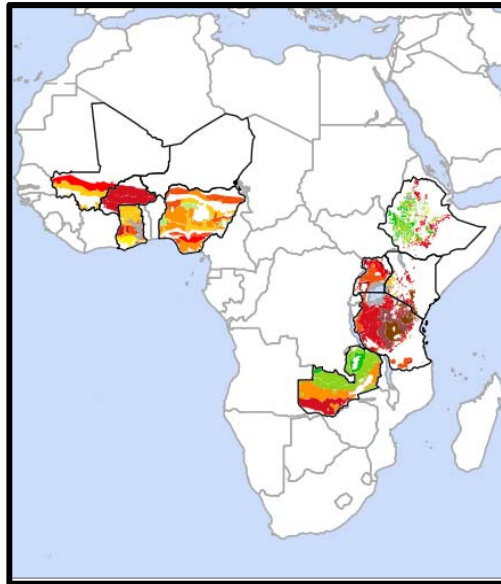


GYGA geospatial upscaling platform for *ex-ante* & *ex-post* impact assessment: sustainable intensification, CSA, climate change

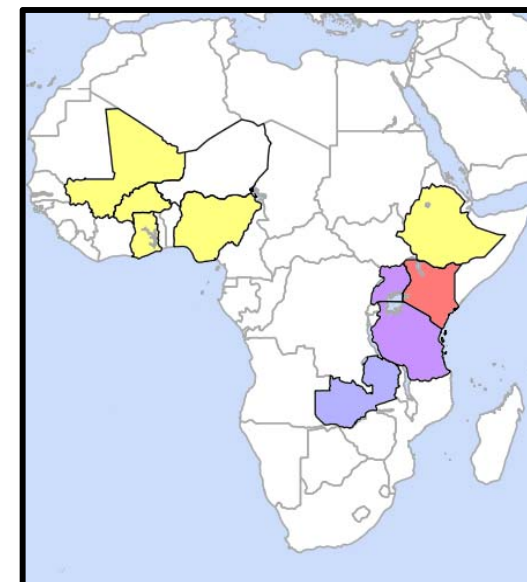
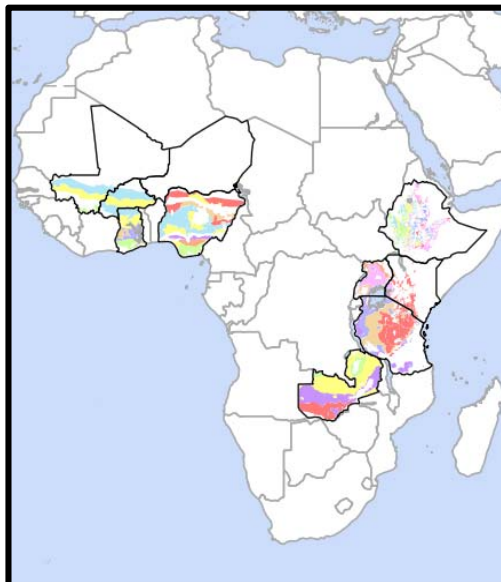
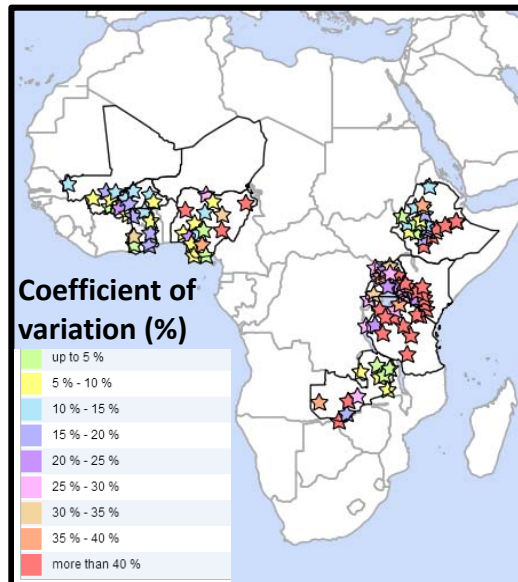
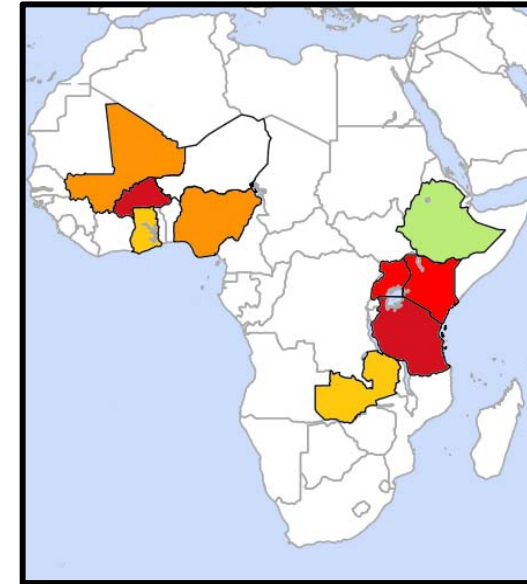
Location



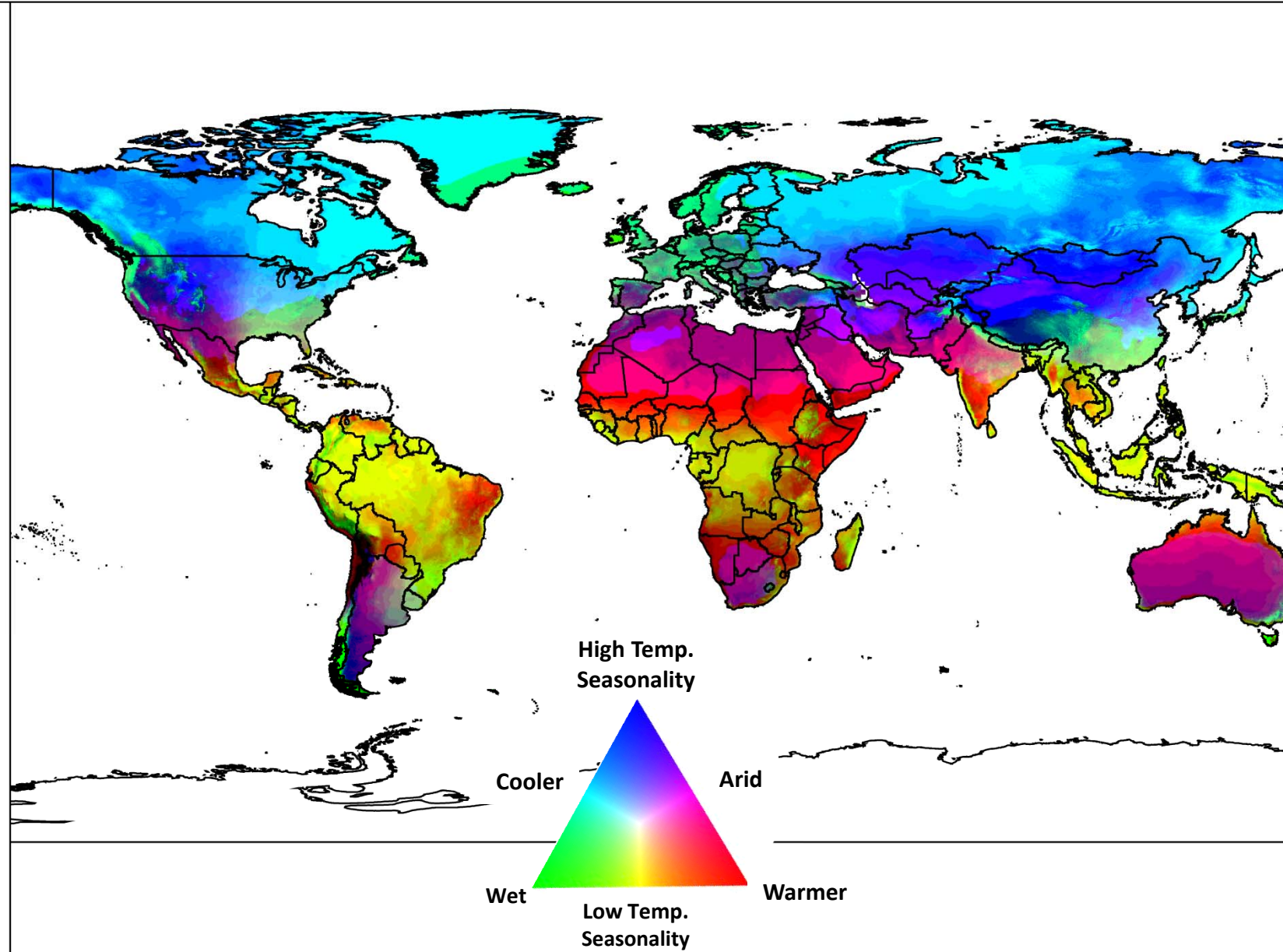
Climate zone



Country



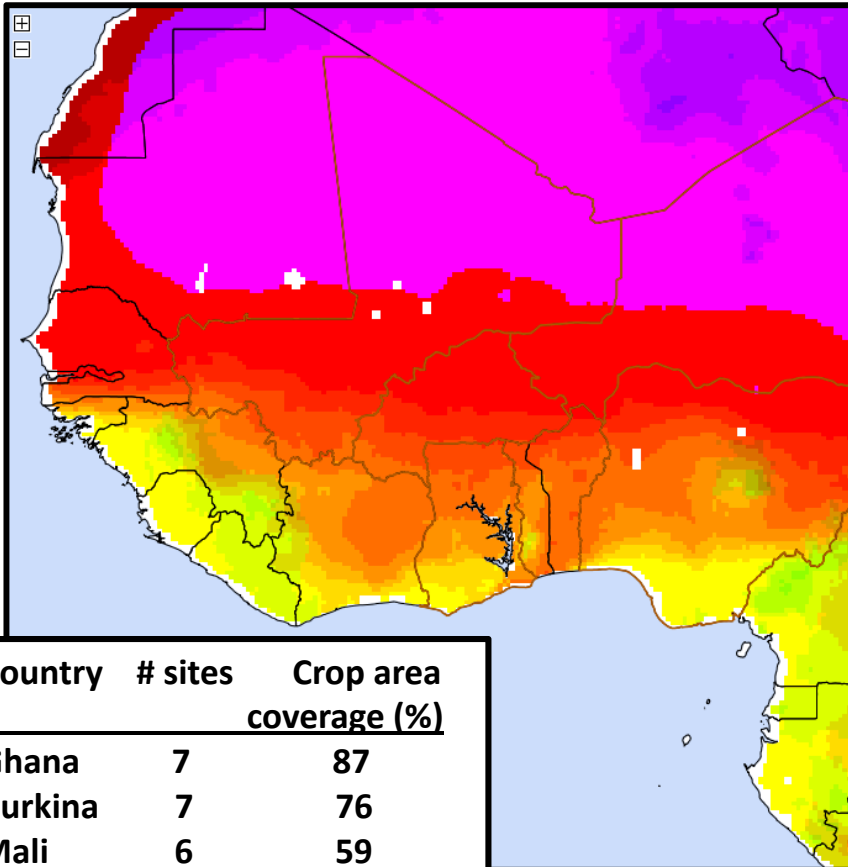
Van Wart et al., 2013. Use of agro-climatic zones to upscale simulated crop yield potential. *Field Crops Research* 143, 44-55.



Upscaling: capturing spatial weather patterns most relevant for evaluating crop production and technology options

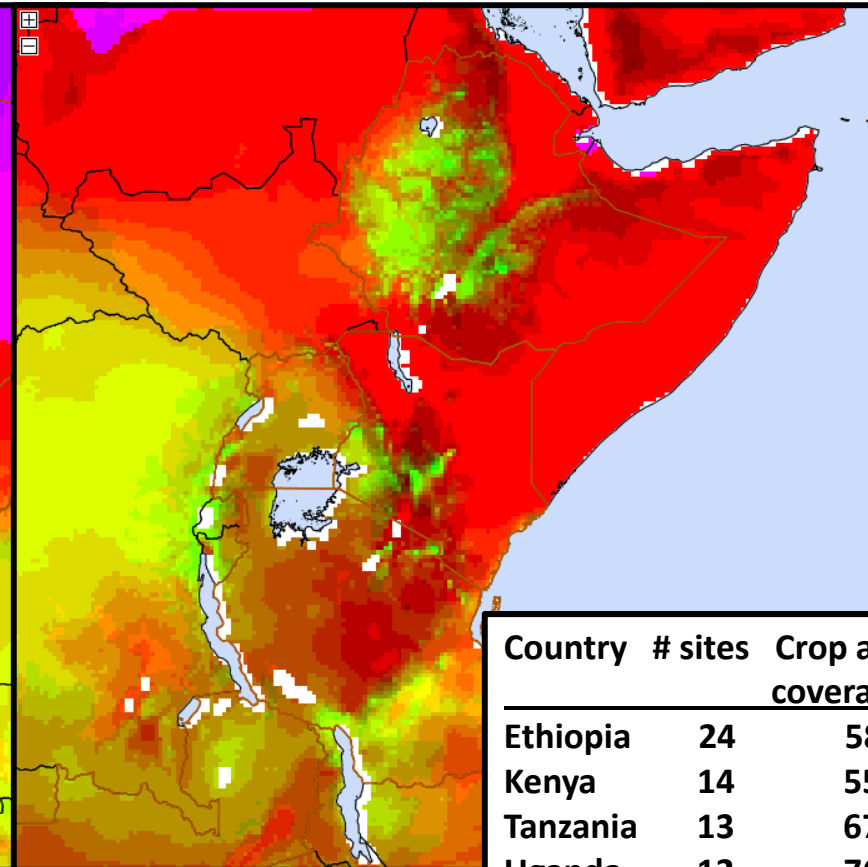
GYGA climate-zone scheme captures spatial weather variation with a tractable number of climate zones to allow focus on the most relevant areas for crop production to upscale results

West Africa: latitudinal rainfall gradient leads to well-defined climate zones



Country	# sites	Crop area coverage (%)
Ghana	7	87
Burkina	7	76
Mali	6	59
Nigeria	16	65

East Africa: complex topography leads to small climate zones of irregular shapes



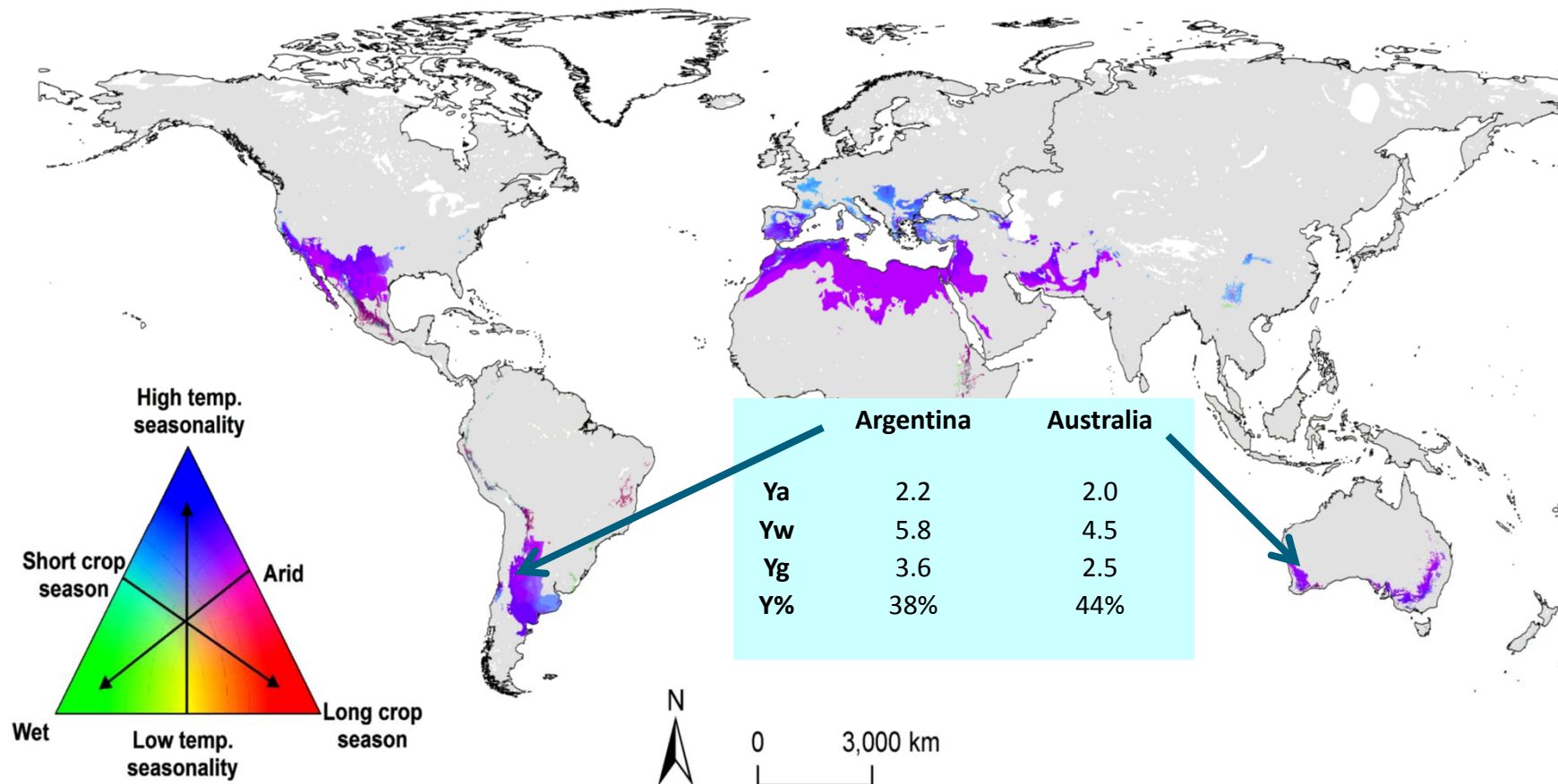
Country	# sites	Crop area coverage (%)
Ethiopia	24	58
Kenya	14	55
Tanzania	13	67
Uganda	12	76
Zambia	11	85

How to determine if a climate zonation scheme is robust?

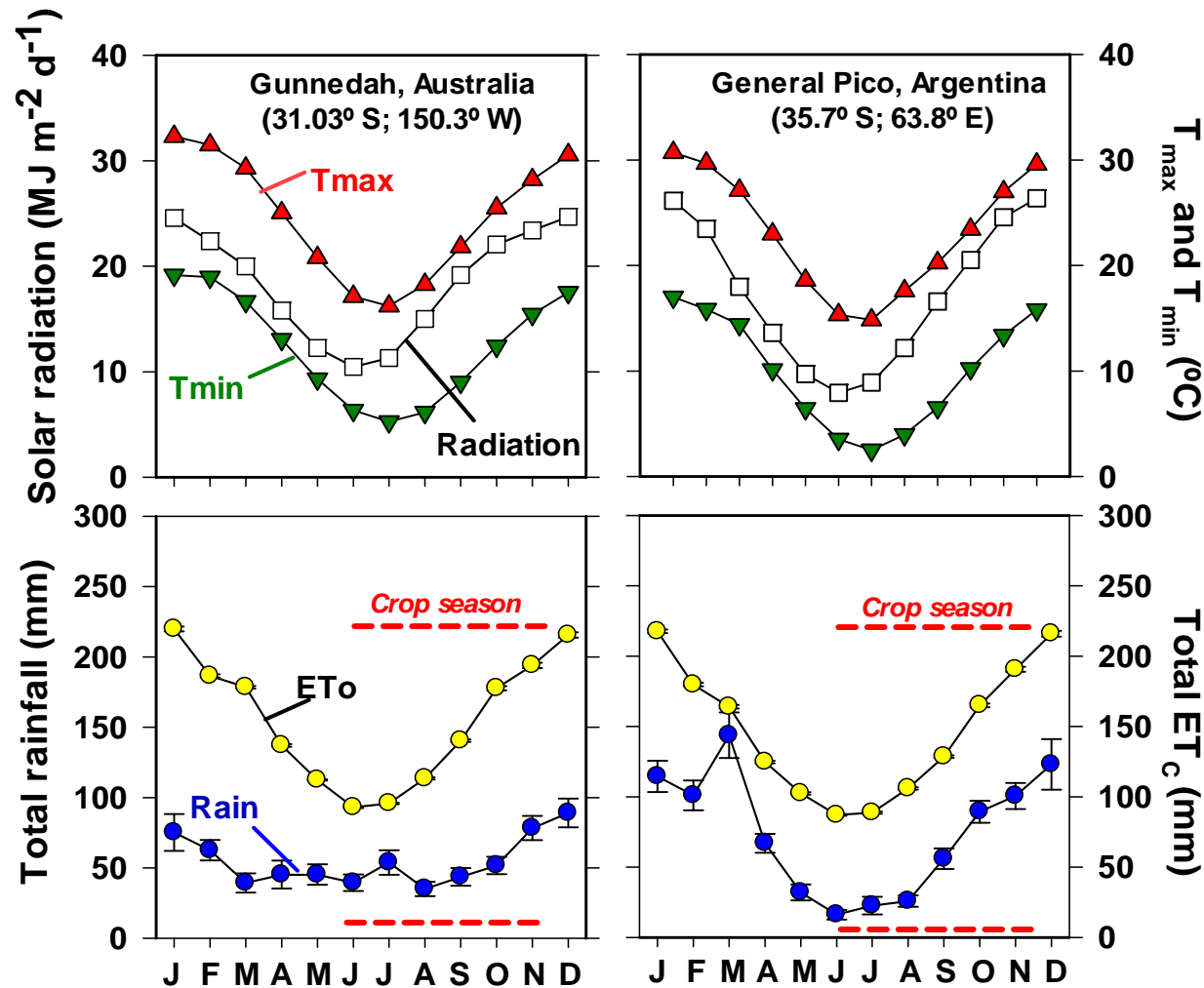
- Uniformity of climate variables governing crop growth, development and yield
- Not too fine (too many), not too coarse (too few)
- Climate zone units can facilitate technology evaluation and extension (extrapolation domains)
- **GYGA climate zonation scheme: example from Australia and Argentina**

Australian wheat yield gaps in a global context: Global Yield Gap Atlas (GYGA) Project

GYGA climate zones used in Australian wheat GYGA analysis: CZ #6202 contains 7% of total Australian cereal area, and has a homologue in Argentina where they also grow wheat and other crops (Source: Hochman and Gobbett, CSIRO; Grassini et al., Univ. Nebraska)



Weather comparison between analogous climate zones: Australia and Argentina



Source: Hochman and Gobbett, CSIRO; Grassini et al., Univ. Nebraska

Can Australia emulate Argentina in CZ 6202?

Candidate Systems for Australia:

1. Continuous wheat
2. Continuous maize
3. Opportunity wheat –maize double cropping (60 mm PAW for each crop)
4. Opportunity wheat –maize double cropping (90 mm PAW for each crop)
5. Wheat-mungbean double cropping
6. Opportunity wheat-mungbean double cropping (60 mm PAW for mungbean)

System	Wheat yield and StDev (t/ha)	Maize yield and StDev (t/ha)	Mungbean yield and StDev (t/ha)	Annual average income (AUD)	Income CV (%)	Gross Margin (AUD/ha/yr)
1	4.82 (0.65)	-	-	1204	14	404
2	-	4.76 (2.34)	-	1572	49	692
3	4.03 (1.11)	3.76 (2.71)	-	2125	39	369
4	4.24 (1.27)	4.58 (2.60)	-	2556	37	739
5	4.55 (0.72)	-	1.49 (0.47)	2008	20	833
6	4.57 (0.76)	-	1.62 (0.29)	2133	14	799

Source: Hochman and Gobbett, CSIRO



How to determine if a climate zonation scheme is robust?

- Uniformity of climate variables governing crop growth, development and yield
- Not too fine (too many), not too coarse (too few)
- Climate zone units can facilitate technology evaluation and extension (extrapolation domains)
- **GYGA climate zonation scheme appears to be robust!**

Protocol for bottom-up ex-ante assessment

- Identify minimum number of weather stations (WS) and associated 100-km buffer zones within a robust climate zone (CZ) framework
- Obtain data required for crop or cropping system simulation within selected WS buffer zones (soil types, crop calendars, sowing rules)
- Impose climate change scenario, including differences in max/min temps, seasonality, variability
- Using a well-validated crop model, simulate current and potential CSA alternatives; minimum 30 yr weather data to also estimate yield variability
- To estimate production potential on existing crop land within each weather station buffer zone, assume 85% and 75% of potential yields for irrigated and rainfed systems, respectively
- Upscale using the GYGA scaline approach (weighted for crop area):
WS buffer zones → climate zones → country → region → global

Proposed upscaling approach for ex-ante assessment of climate change impact on crop yields and CSA options

- **Strengths**

- Provides direct evaluation of temperature and [CO₂] effects
- Results can be validated for ex-ante evaluations in current climate, or in climate zone analogs
- Avoids use of gridded weather data (CRU, NCEP, NASA-POWER) which are not robust for simulation of crop yields

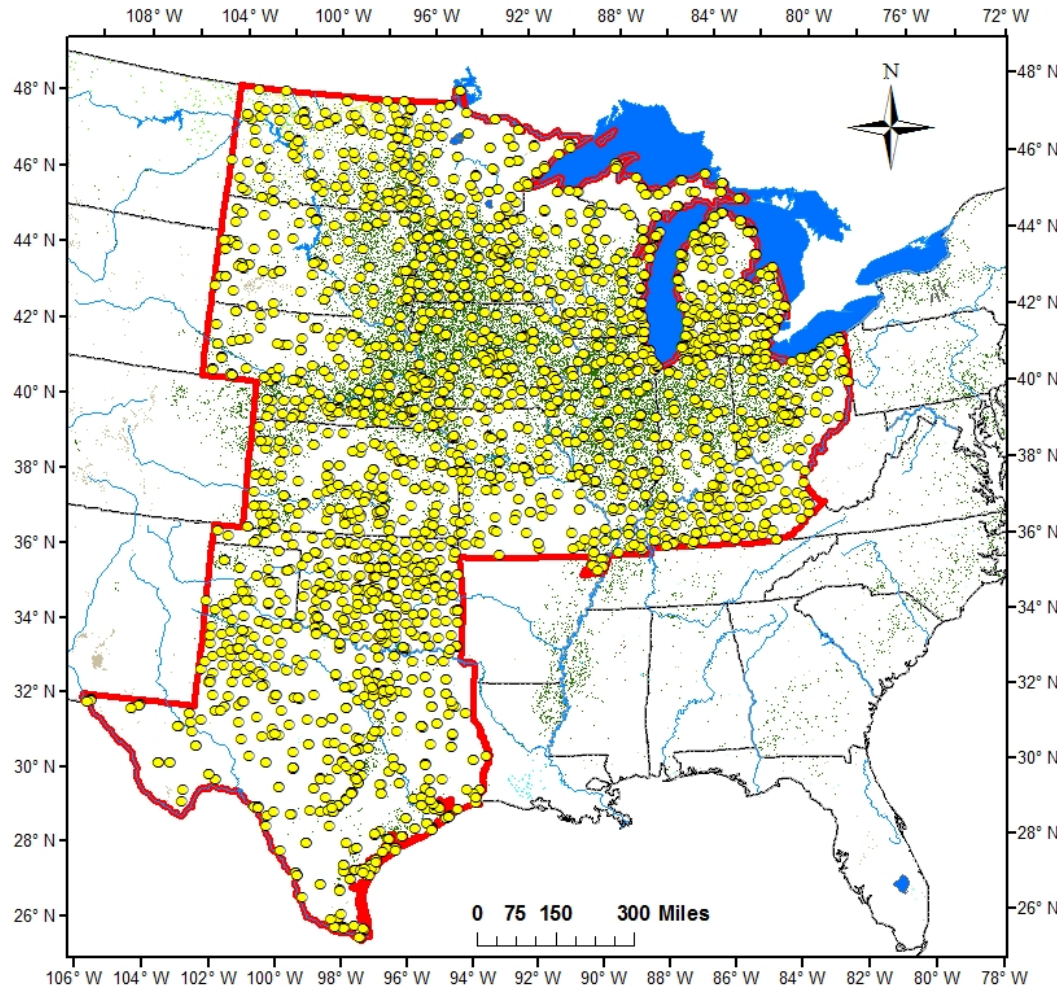
- **Weaknesses**

- Cannot account for changes in rainfall (sensitivity analysis?)
- Difficulty in accounting for changes in variability of temperature and rainfall due to climate change
- Cannot estimate agricultural potential of non-cultivated areas

Highest priority for public sector investment in Climate Smart Agriculture:

- Global coverage of existing farm land with open access to high long-term daily weather data suit of sufficient quality to support tactical and strategic decisions on crop, soil, and farming system management
 - max/min temperature, rainfall, solar radiation, humidity, wind speed
 - 30-years minimum, since 1980
 - Publicly available, no cost

All weather stations with daily data (n=2825)

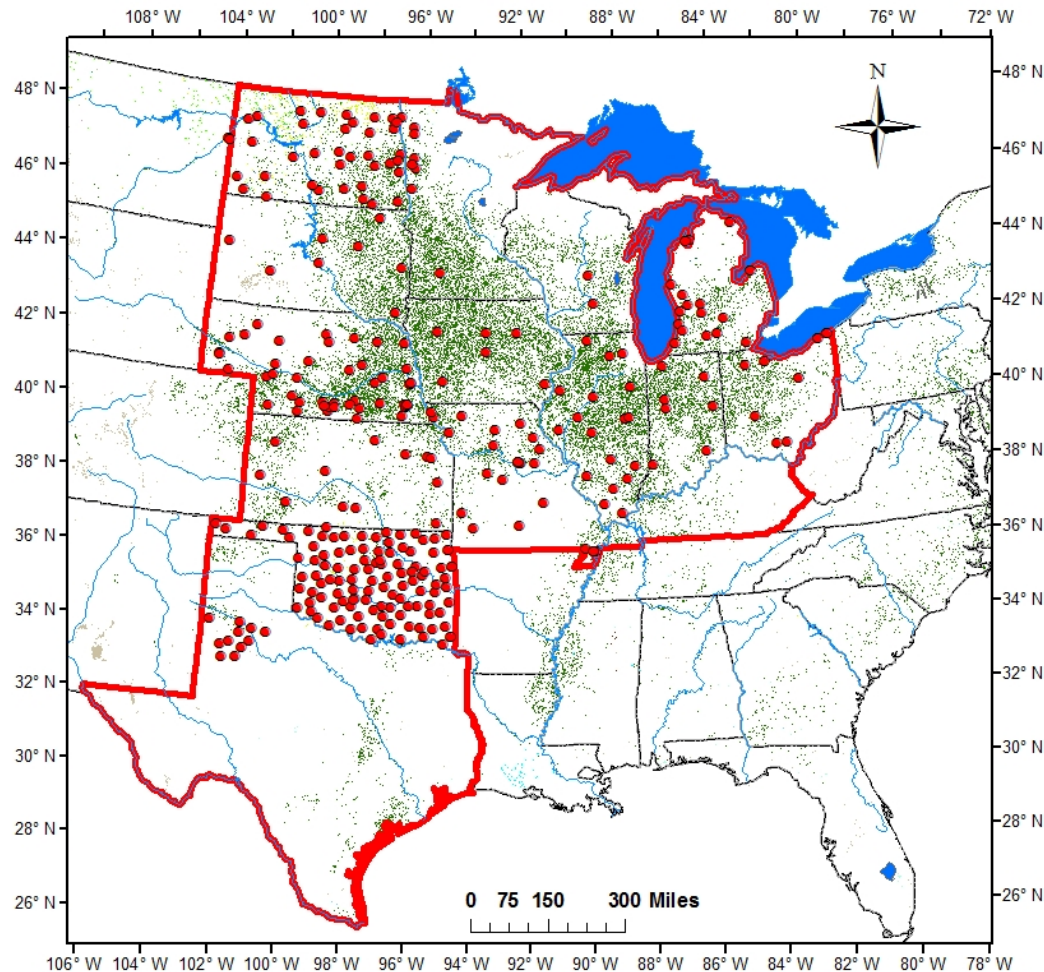


Both NOAA and MESONET:

- *National Oceanic and Atmospheric Administration (NOAA):* Stations are typically located in cities and airports and only record daily temperature and precipitation
- *State MESONET systems:* Developed for agriculture and located in agricultural areas with all required variables for crop simulation (daily radiation, temperature, precip, humidity, wind speed)

Courtesy of: F. J. Morell, Univ. of Nebraska

Active MESONET stations with >15 years data



Spatial Coverage by state:

- 316 stations total (11%)
- Only *Oklahoma* has excellent coverage
- Three states have reasonable coverage (IL, NE, ND)
- Most states have poor coverage (IA, IN, KS, KY, OH, MI, MN, MO, SD)

Courtesy of: F. J. Morell, Univ. of Nebraska

Major constraint: Availability of long-term daily weather data (since 1971)

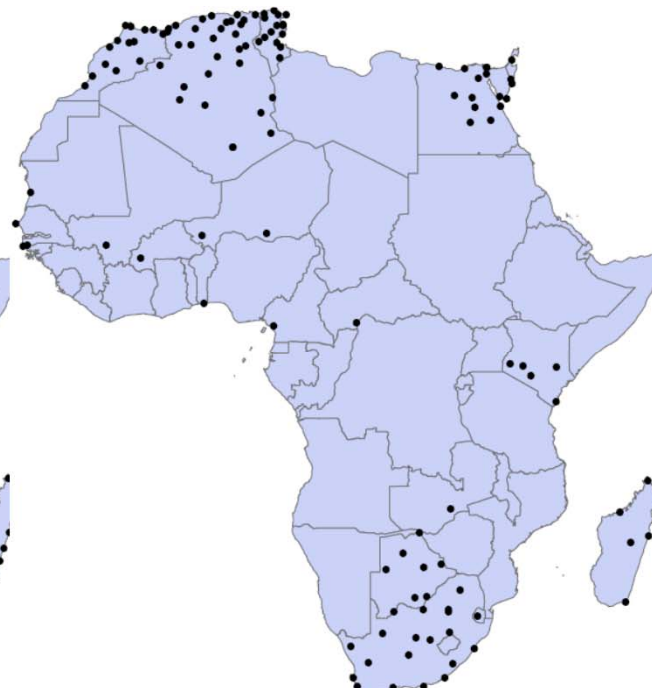
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Conclusions and Recommendations

- A “bottom-up” scaling approach should be a complement to current reliance on “top-down” assessment of climate change impact on crop production and CSA options
 - GYGA geospatial approach appears to be robust
- Investment in good quality weather data in agricultural regions and open access for farmers worldwide is the single most important priority for enhancing capacity to deal with climate change
 - Good news, relatively low cost and getting cheaper!

Citations

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