Pacific Northwest NATIONAL LABORATORY

Agriculture and Land-use system

February 15, 2023

Xin Zhao

U.S. DEPARTMENT OF ENERGY BATTELLE

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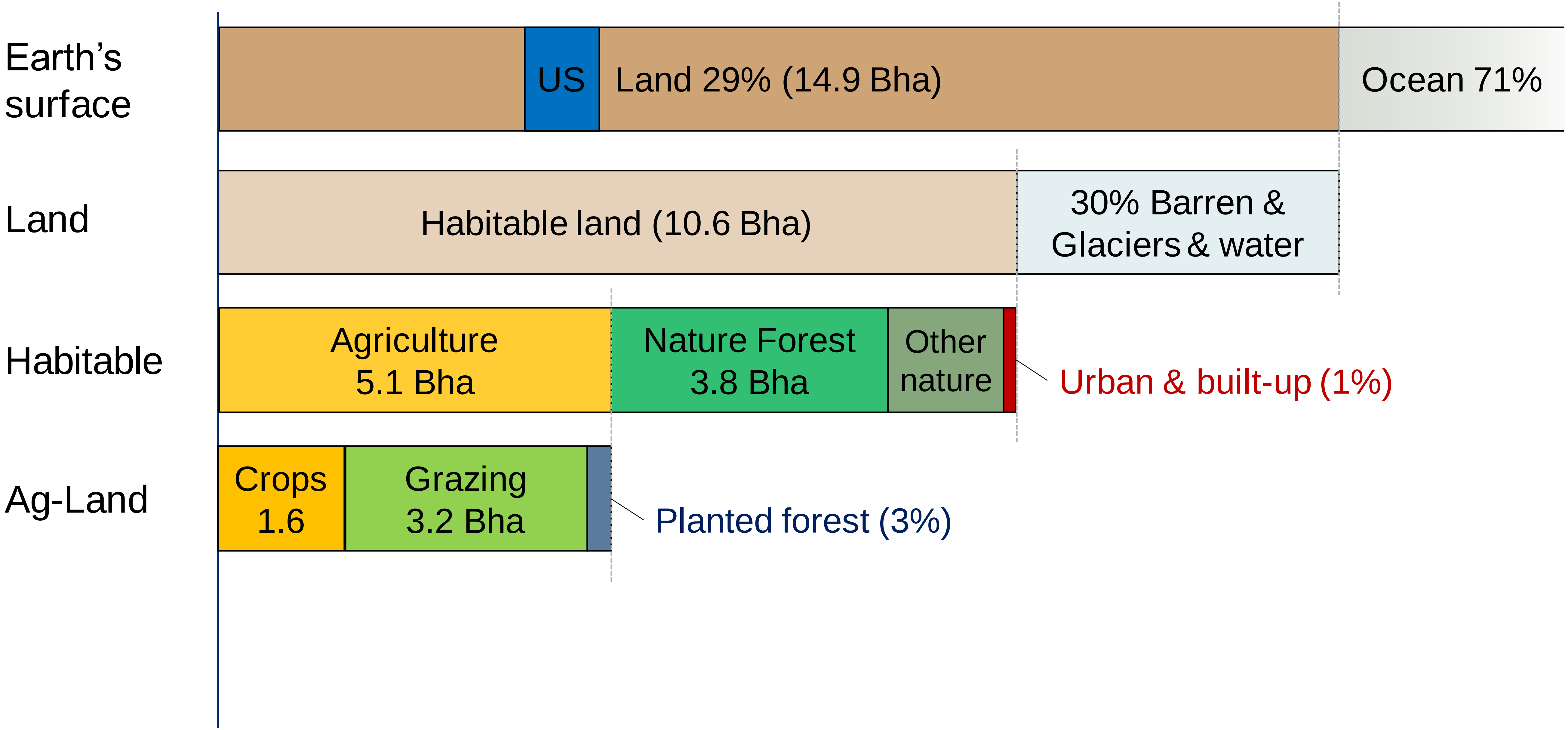
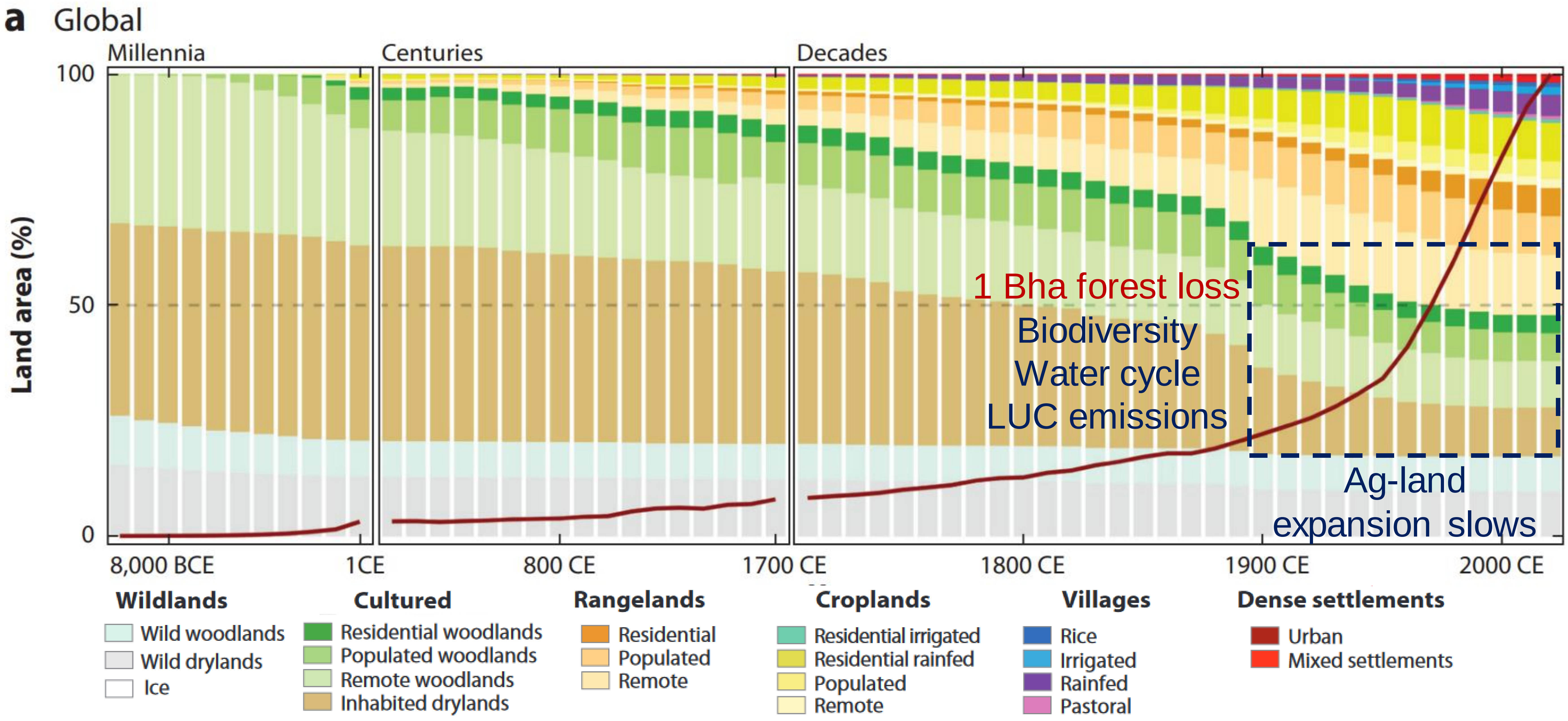
Today’s talk

- Big pictures of land and agriculture
  - Data talk
- Share a framework/method of analyzing ag & land-use related issues from a modeler’s point of view
- Some relevant research questions
  - How to feed 9 billion people in 2050?
  - Climate impacts on agriculture & trade as an adaptation
  - Land-based mitigation measures

Land and how it is used now

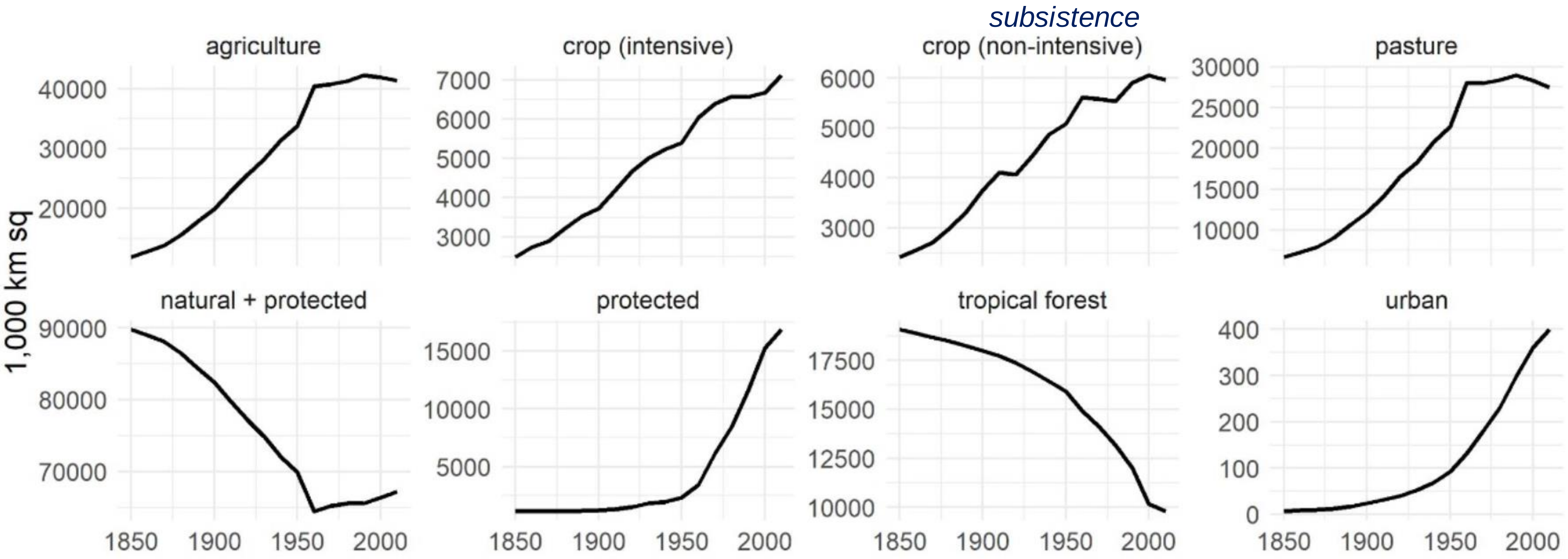


Land use over time: past 12,000 years (HYDE)



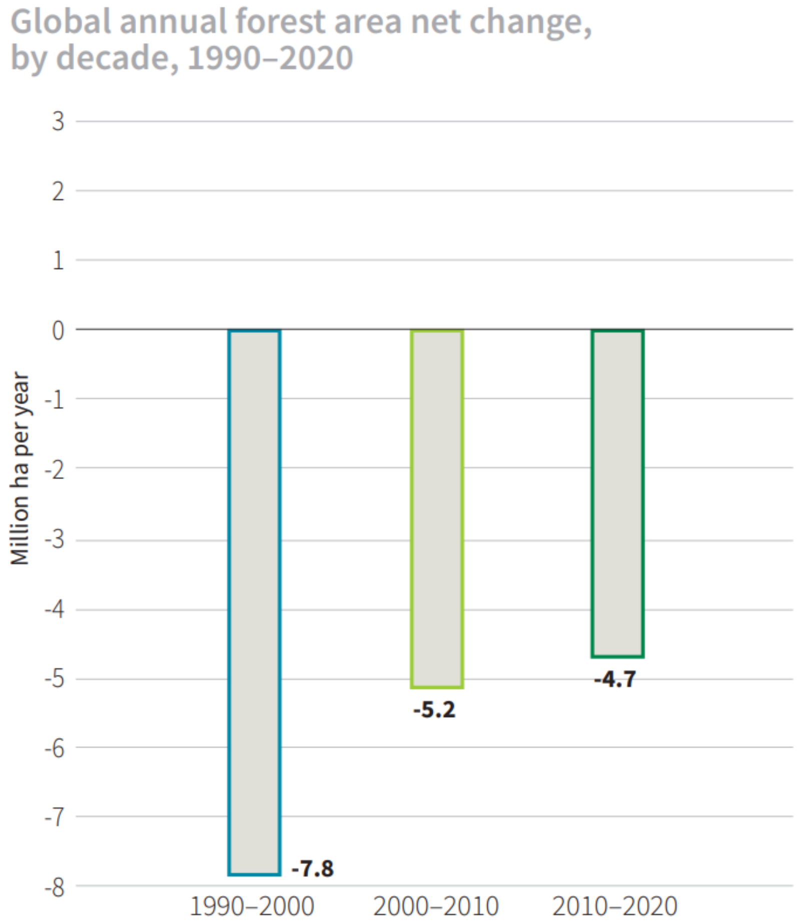
Ellis (2021); Goldewijk et al. (2017)

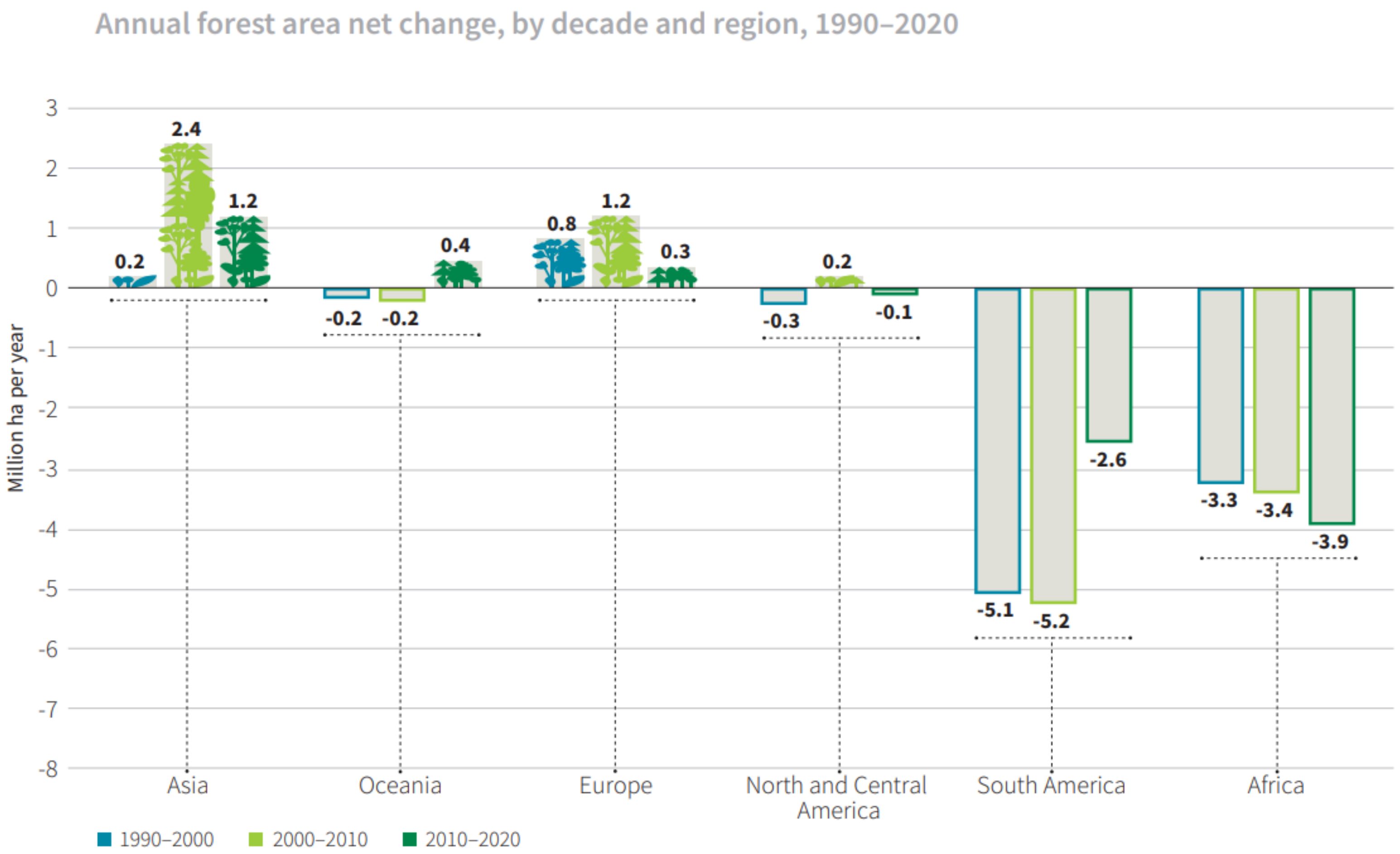
The net total global agricultural land plateaued



Taylor and Rising (2021 ERL);

Recent slower global deforestation

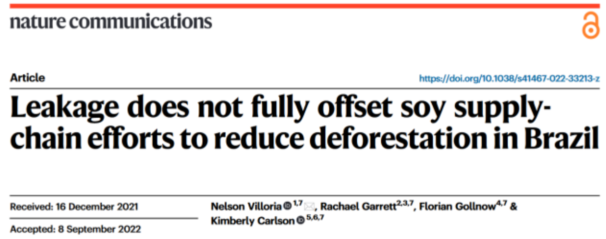




Policy intervention

- REDD+ (UNFCCC)
- Amazon Soy Moratorium
- Zero-deforestation supply chain pledge
- Trade policies

Leakage?


nature communications

Article https://doi.org/10.1038/s41467-022-33213-z

Leakage does not fully offset soy supply-chain efforts to reduce deforestation in Brazil

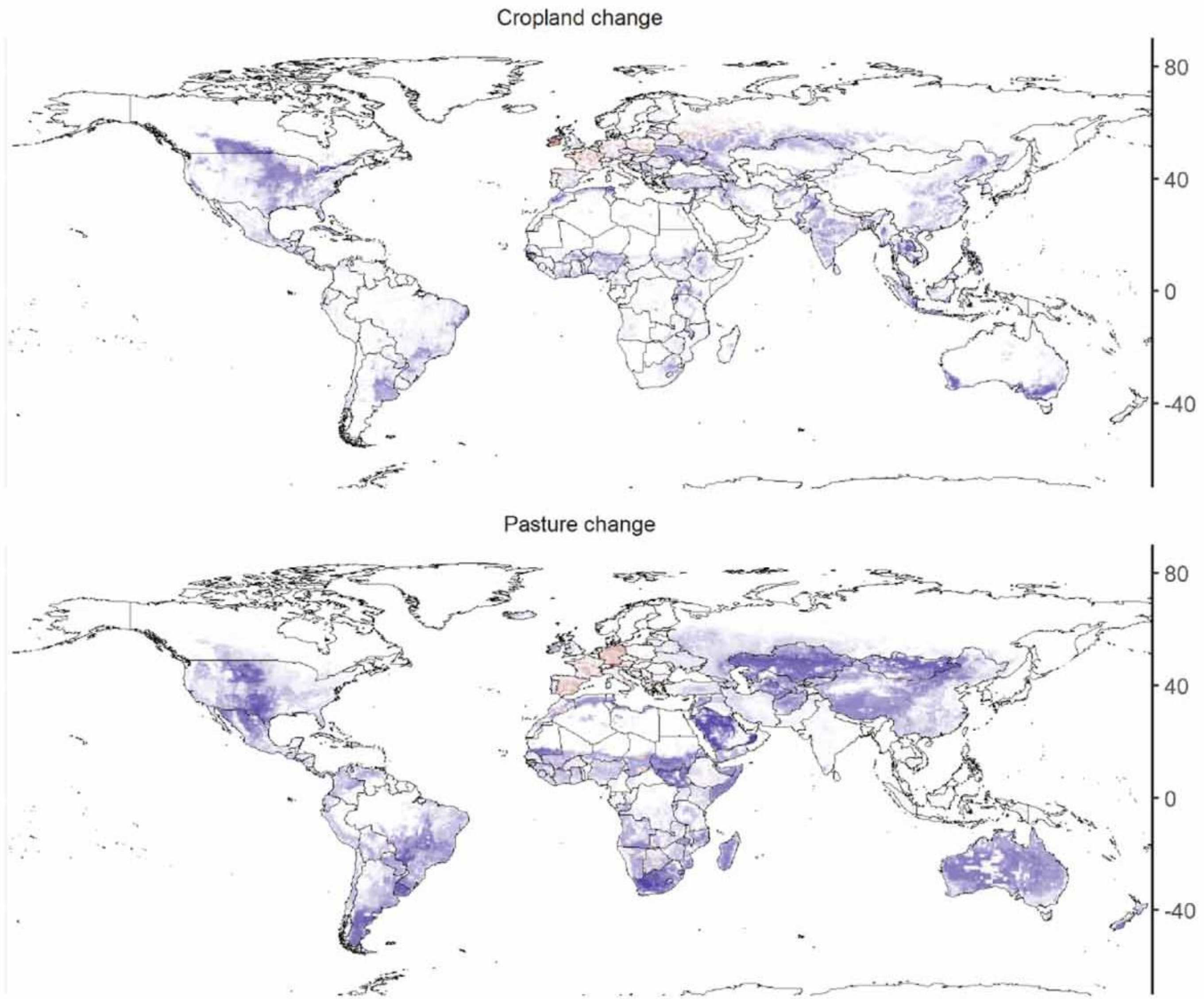
Received: 16 December 2021

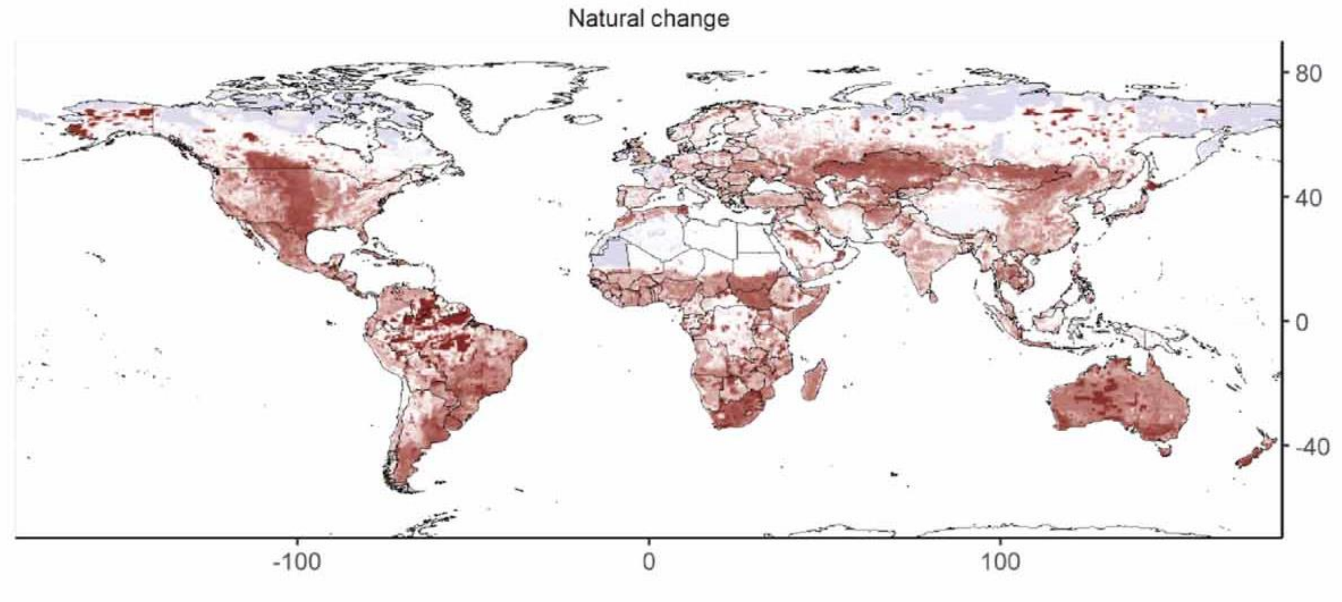
Accepted: 8 September 2022

Nelson Villoria[1,7], Rachael Garrett[2,3,7], Florian Gollnow[4,7] & Kimberly Carlson[5,6,7]

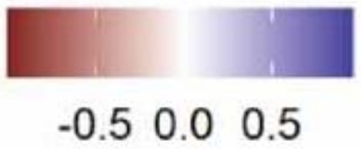
FRA (2020); Villoria et al. (2022 nc)

Where was the land use change?
LUC in 1850 - 2010





Change as a proportion of total land area

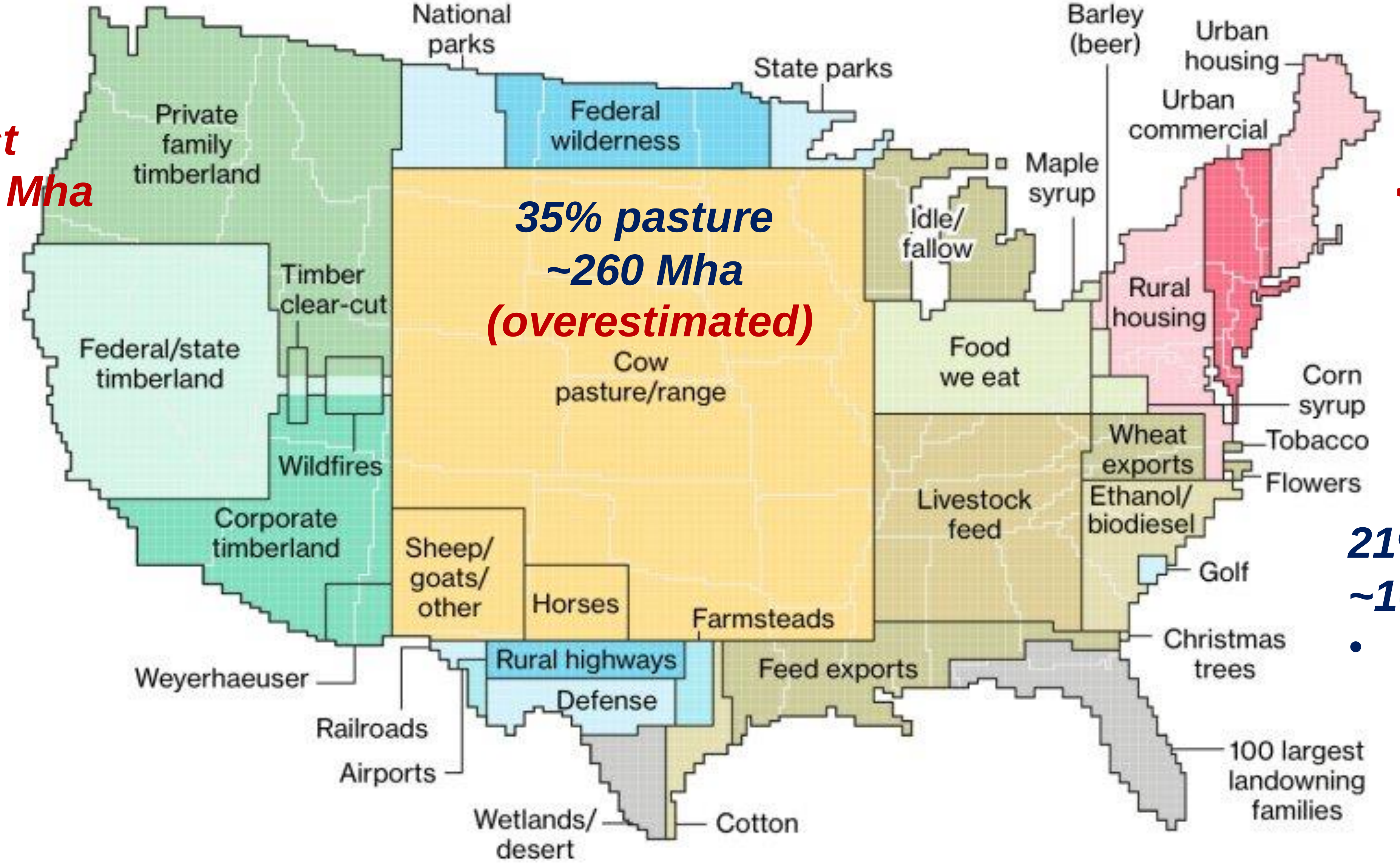


[Taylor and Rising (2021 ERL)]();

How America uses its land?

The contiguous USA: ~766 Mha

29% forest ~220 Mha



35% pasture ~260 Mha (overestimated)

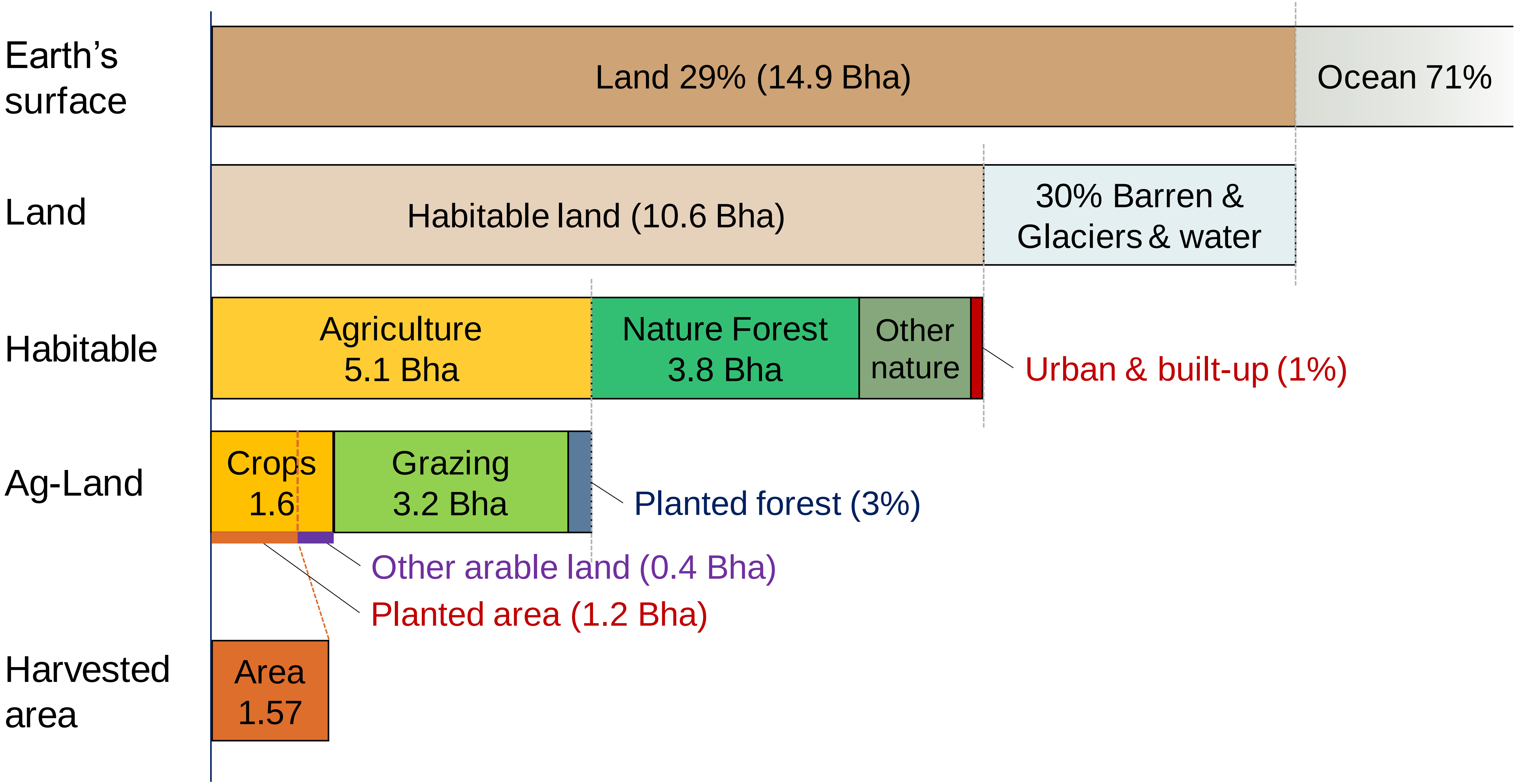
<4% urban

21% cropland ~160 Mha

- *~30 Mha for domestic food*

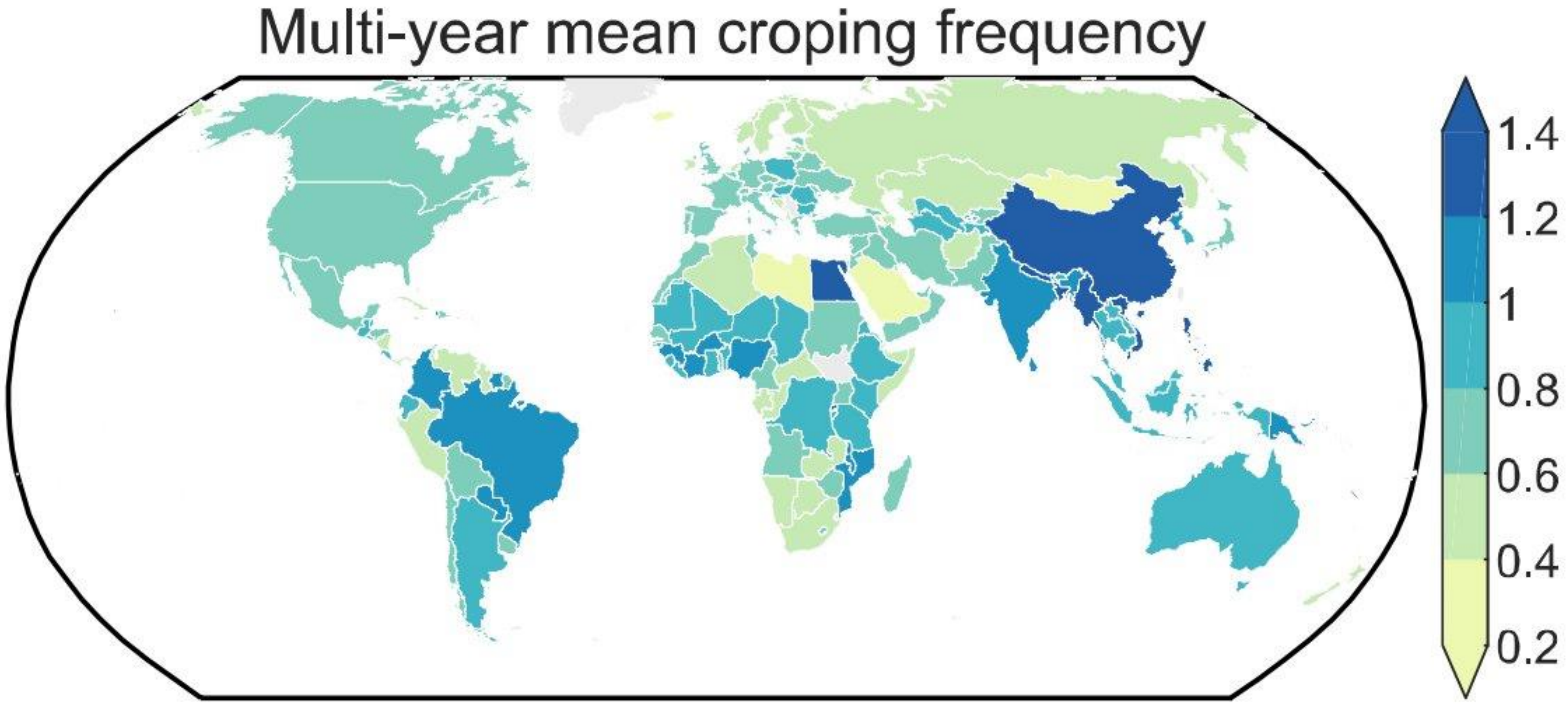
Merrill and Leatherby (2018); DeLong and Hughes (2019 AJAE)

Land and how it is used now



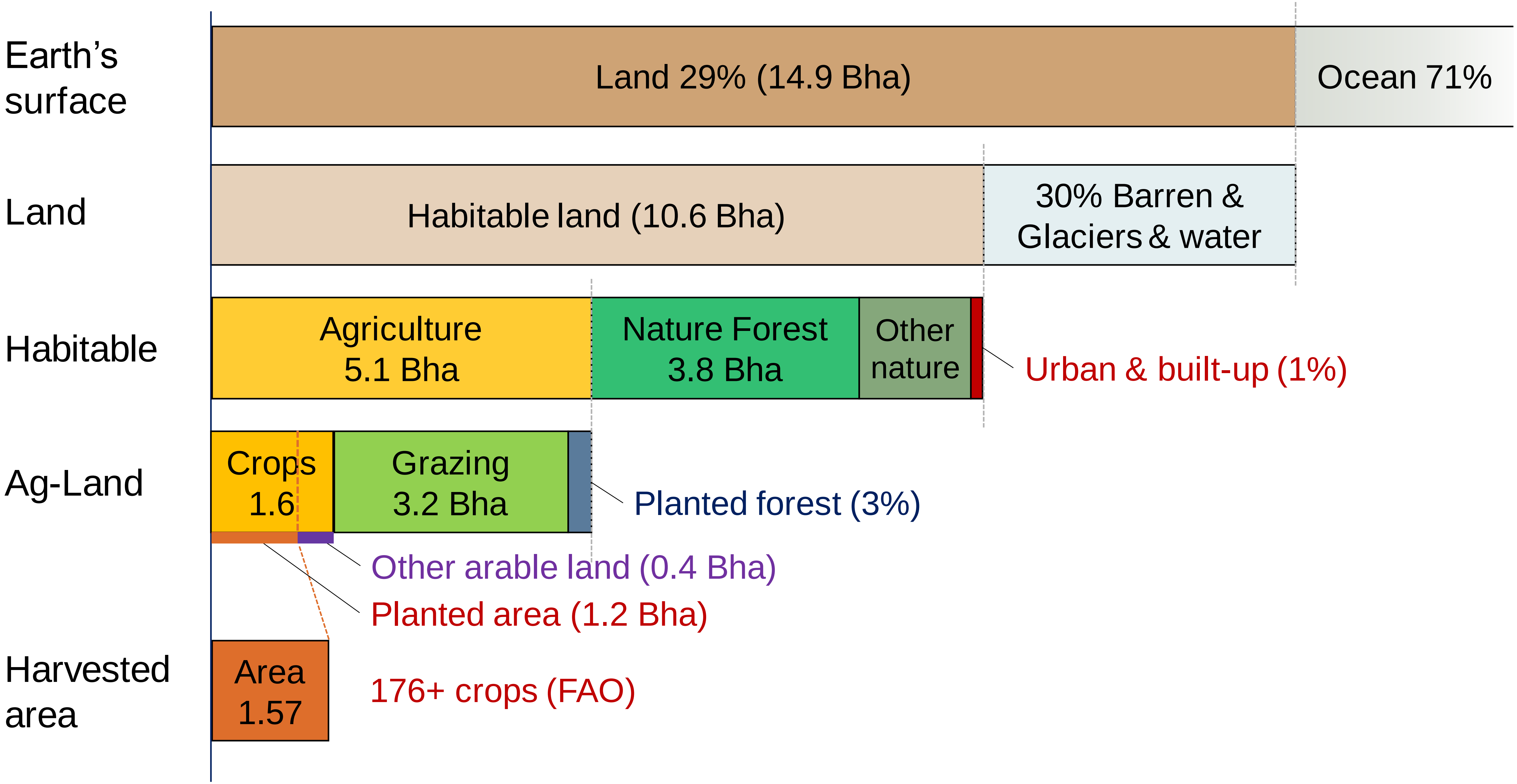
Ritchie and Roser (2021); gcamdata; FAOSTAT

Cropping frequency: harvested area/cropland cover



Supplementary Figure 1 Four decades (1979-2018) of mean cropping frequency in each country.

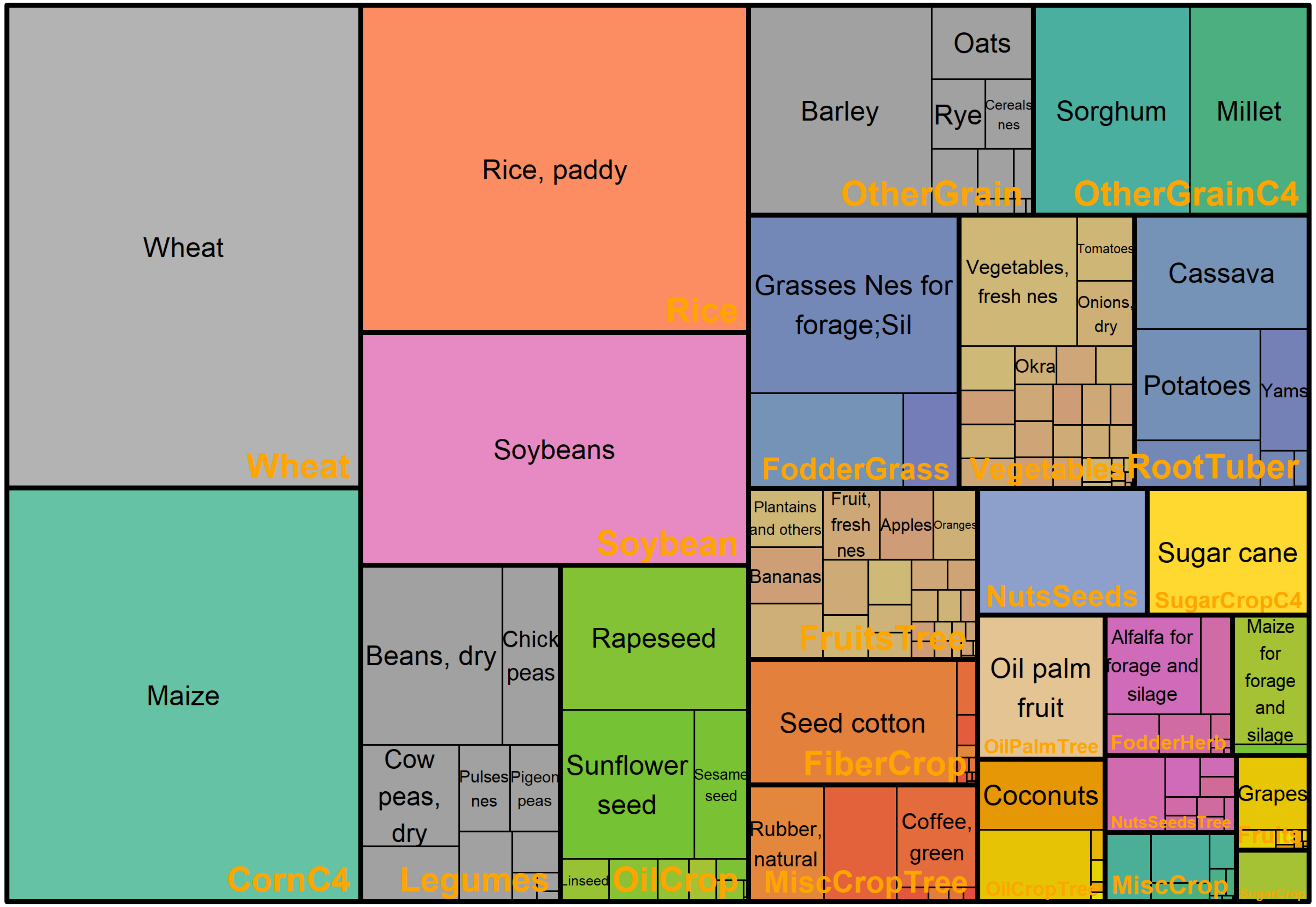
Land and how it is used now



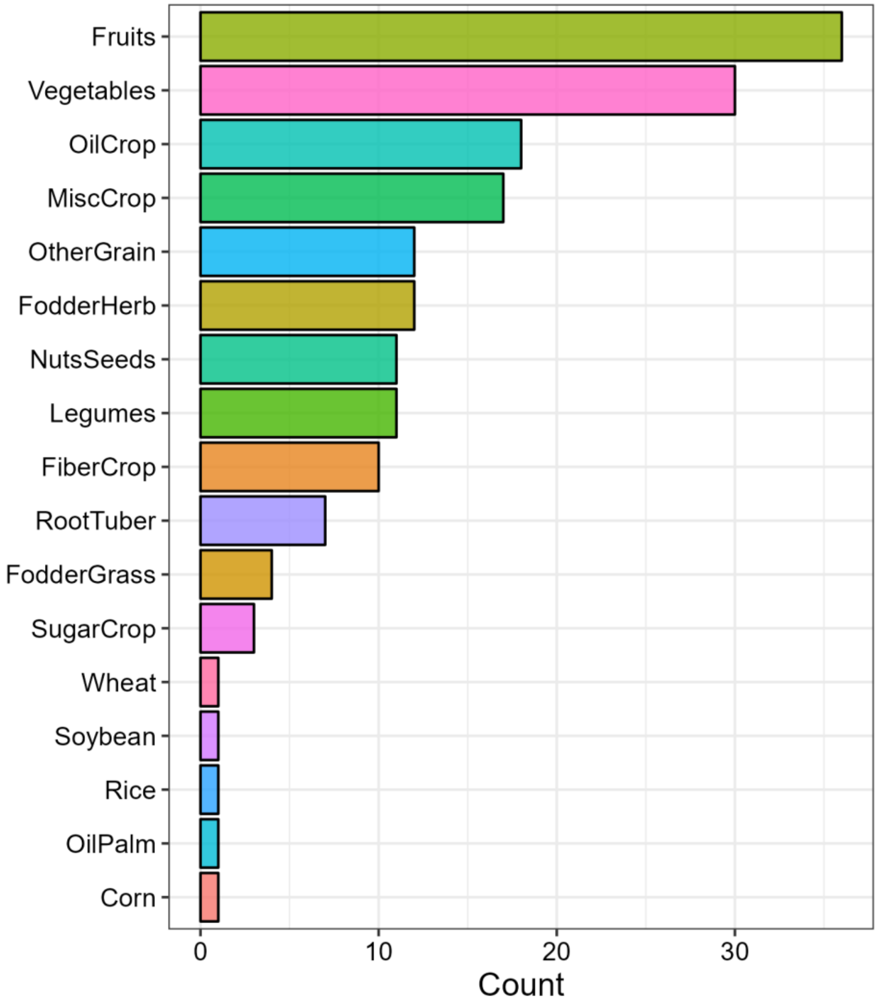
Ritchie and Roser (2021); gcamdata; FAOSTAT

World harvested area in 2010 – 2019
Mean = 1570 Mha

World area harvested share by GCAM-FAO crops in 2010-2019 (mean = 1570 Mha)

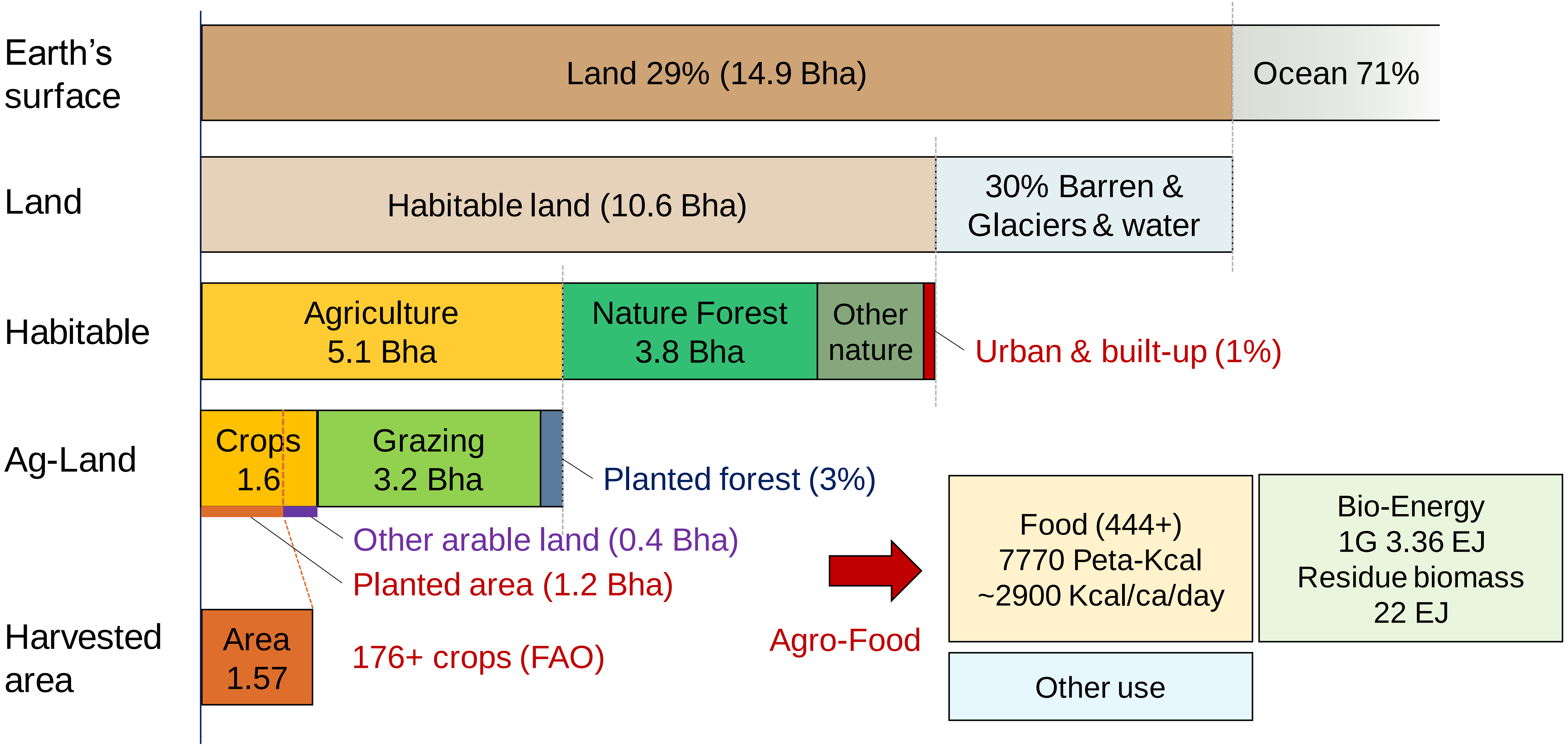


176 FAO food items to 17 GCAM items



gcamdata-faostat; FAOSTAT

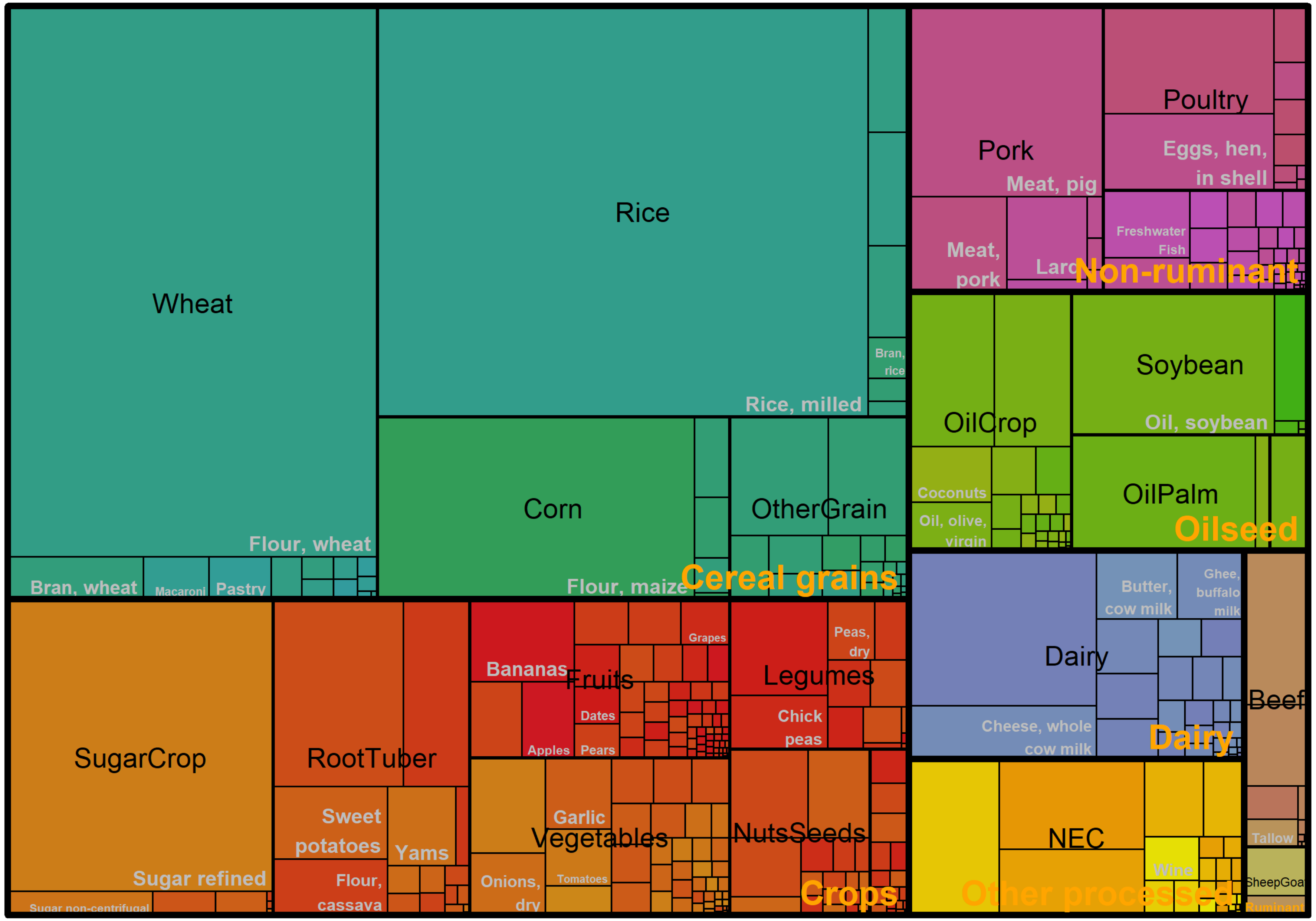
Land for Agro-Food production

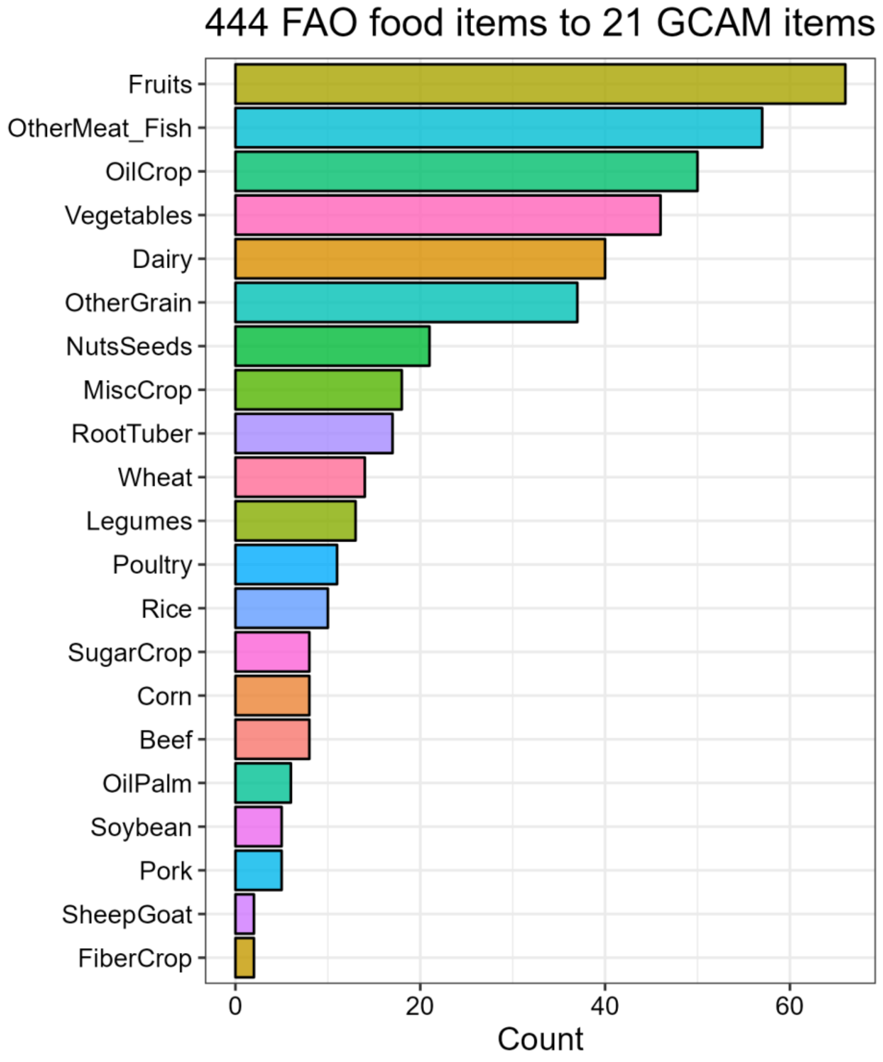


Ritchie and Roser (2021); gcamdata; FAOSTAT

World food availability in 2010 – 2019
Mean = 7770 Peta-Kcal; 2901 Kcal/ca/d

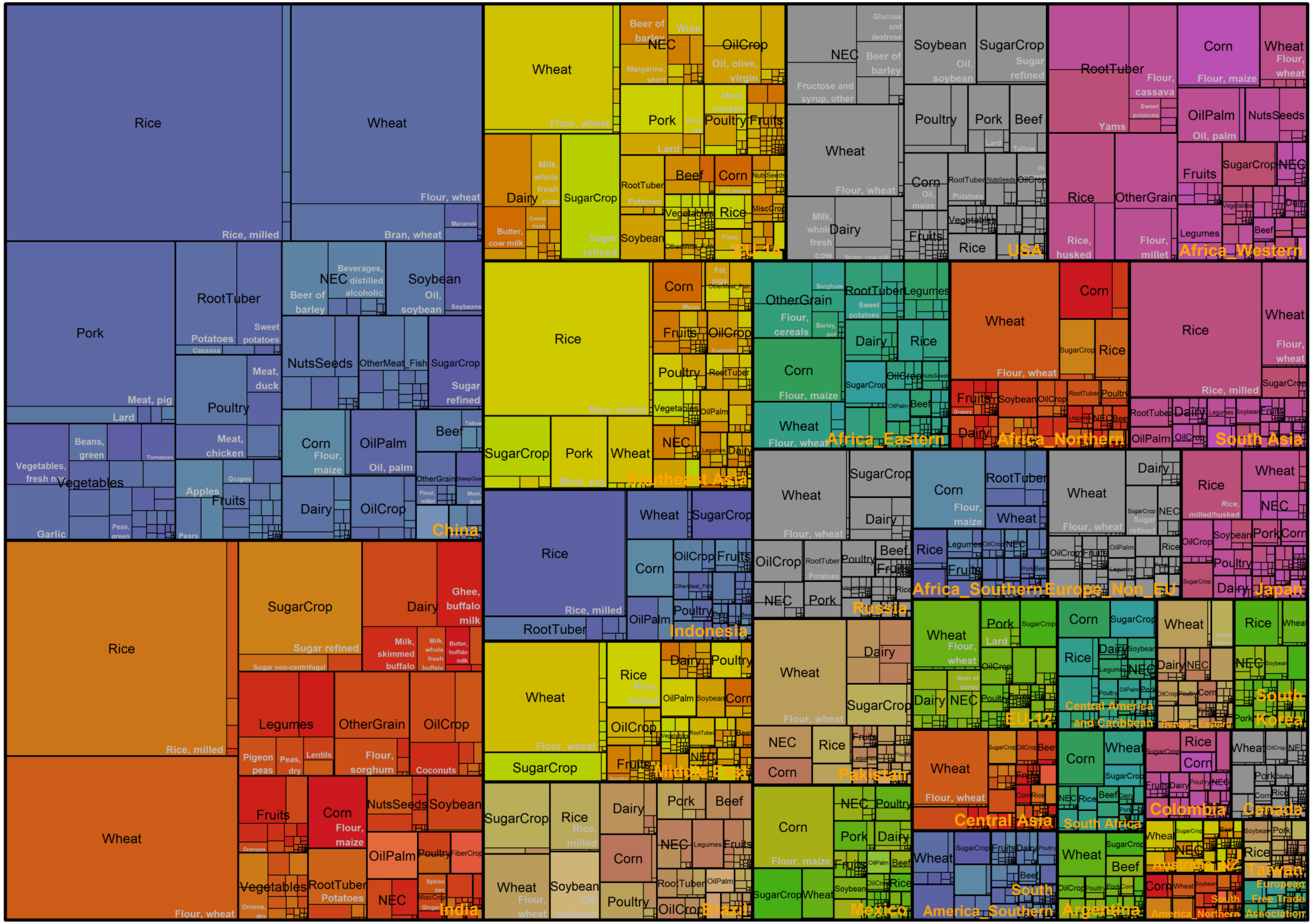
World food consumption (Calories) share by primary product in 2010-2019 (mean = 7770 Peta-Kcal or 2901 Kcal/ca/d)





gcamdata-faostat; FAOSTAT

World food consumption (Calories) share by GCAM regions and FAO items



7770 Peta-Kcal by region

gcamdata-faostat; FAOSTAT

World food consumption (Calories) share by GCAM regions and FAO items

Per capita food

3500 kcal/ca/day

2500 kcal/ca/day

gcamdata-faostat; FAOSTAT

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What the world eats (2011)

Food expenditure per week: $342

Food expenditure per week: $155

Food expenditure per week: $39

Food expenditure per week: $1.23

USA
GDP per ca. in 2011 = $50,000
Wealth rank in 2011 = #7

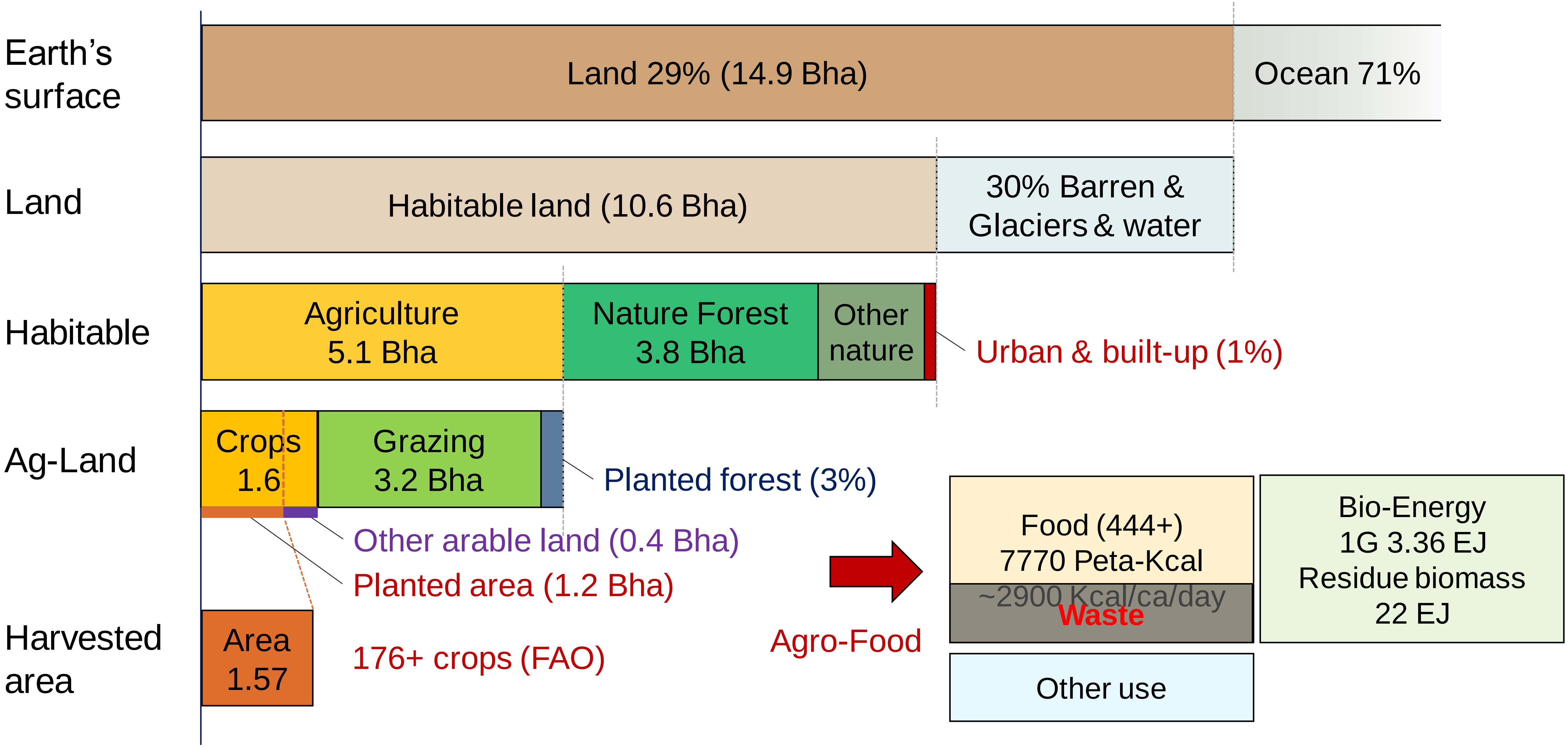
China
GDP per ca. in 2011 = $8394
Wealth rank in 2011 = #90

India
GDP per ca. in 2011 = $3703
Wealth rank in 2011 = #127

Chad
GDP per ca. in 2011 = $1,880
Wealth rank in 2011 = #150

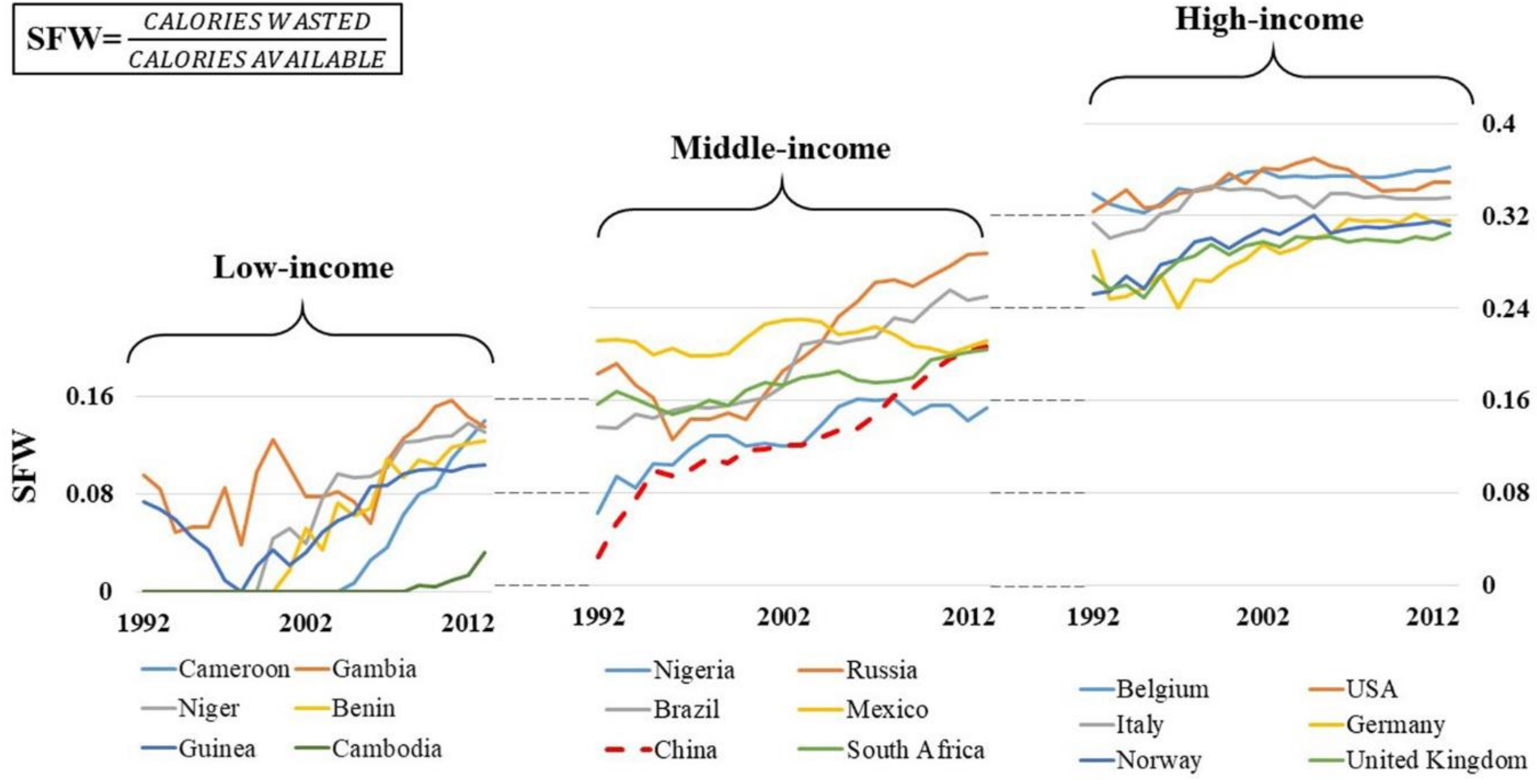
Peter Menzel "Hungry Planet: What The World Eats" (2013);

Land for Agro-Food production



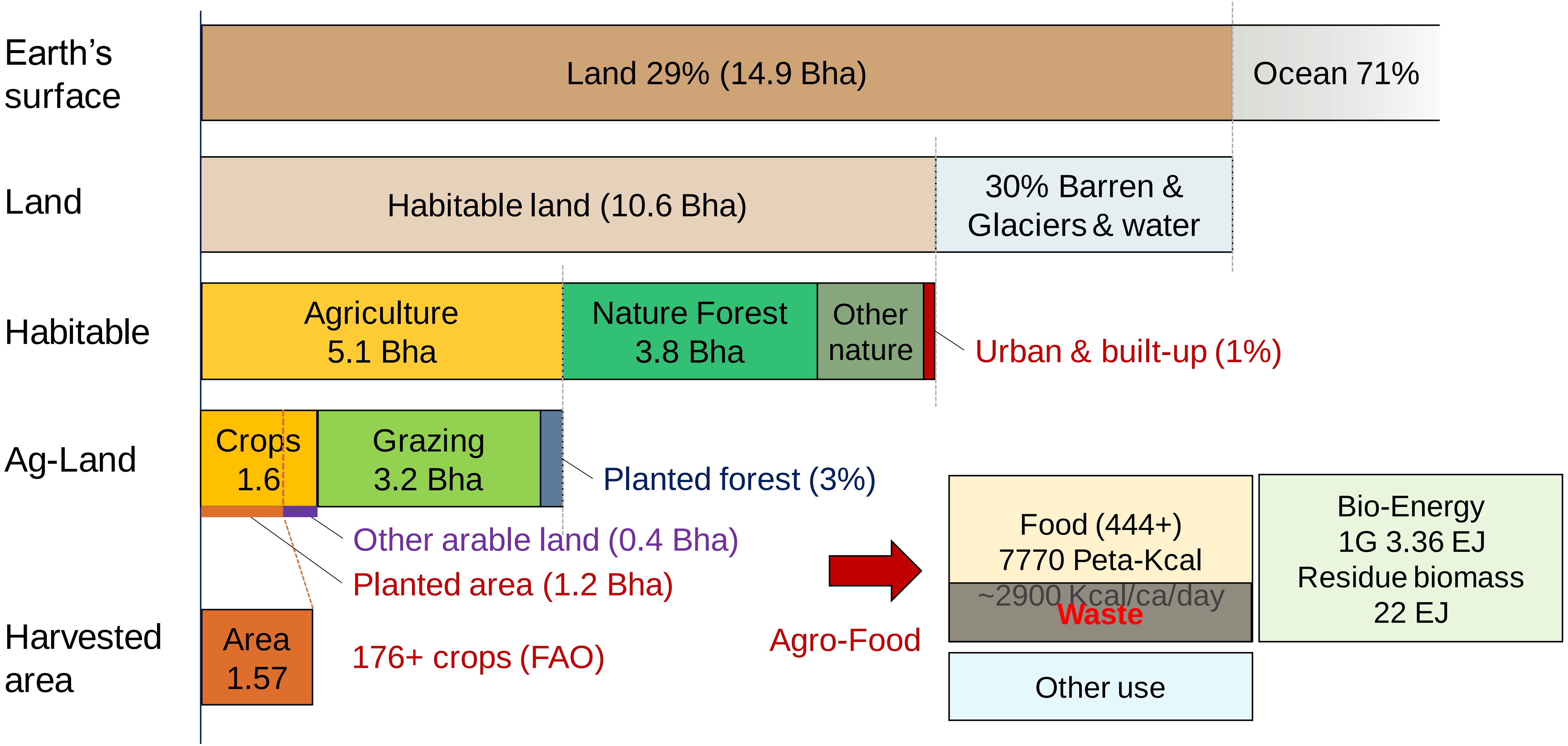
Food waste

$$SFW = \frac{CALORIES\ WASTED}{CALORIES\ AVAILABLE}$$



Barrera and Hertel (2021 Food Policy)

Land for Agro-Food production



Ritchie and Roser (2021); gcamdata; FAOSTAT

Agriculture vs. land by economic value

Ag

Unmanaged Land

Land: Crops 1.6 | Grazing 3.2 Bha | F | Nature Forest 3.8 Bha | Other nature

Land: $0.6 Tril

Labor: $1.4 Tril

Capital: $0.6 Tril

Water

Fertilizer: $0.1 Tril

Others: *$0.9 Tril*

Ag: *$1 Tril*

Inputs

~$4.6 Trillion
Primary Ag output in 2014

Rental profit of Ag land:
~$0.6 Trillion

- 13% of primary output
- <1% of GDP ~($80 Tril.)

Agro-Food Processing 3-4x

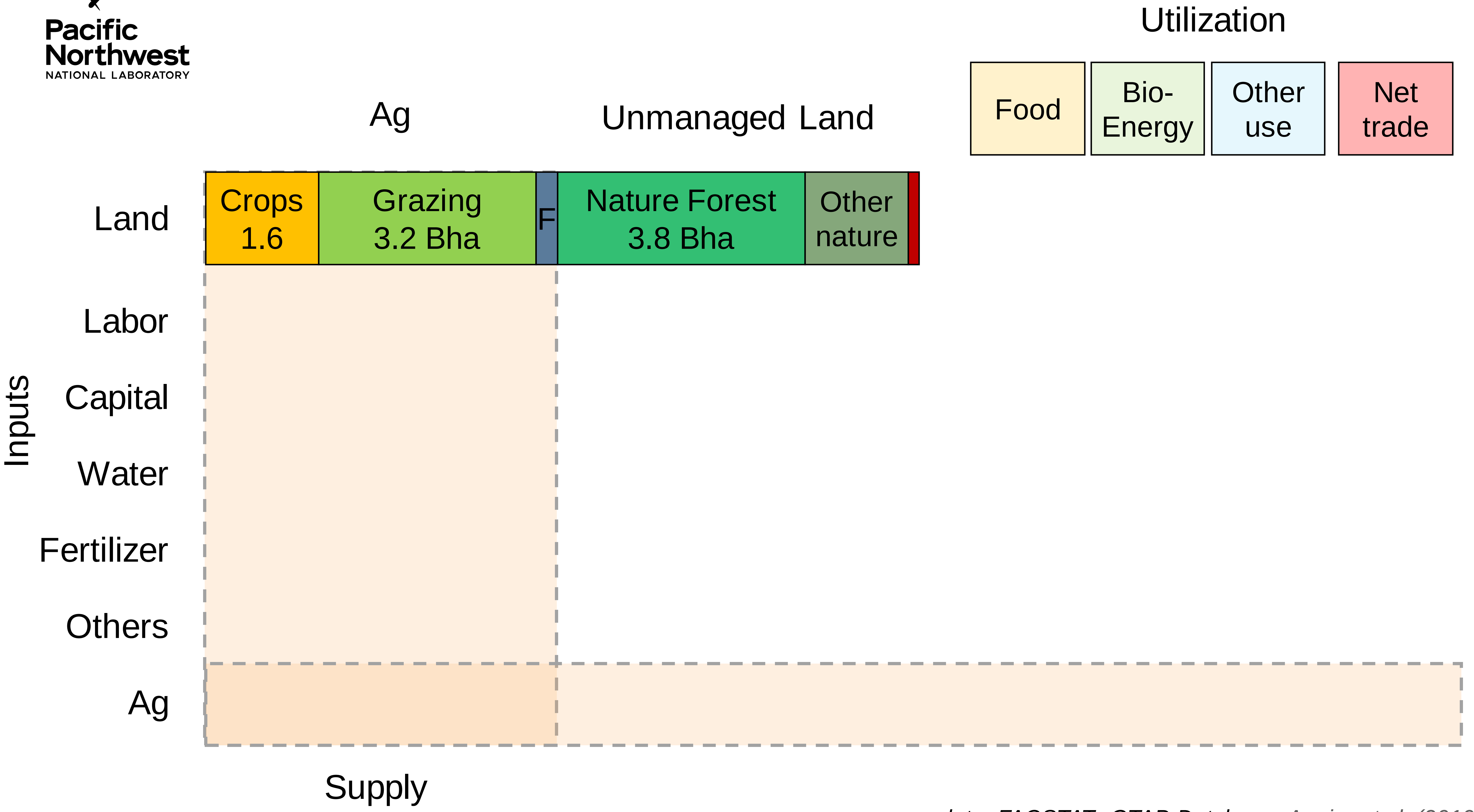
Food (444+)
7770 Peta-Kcal
~2900 Kcal/ca/day

Bio-Energy
1G 3.36 EJ
Residue biomass
22 EJ

Other use

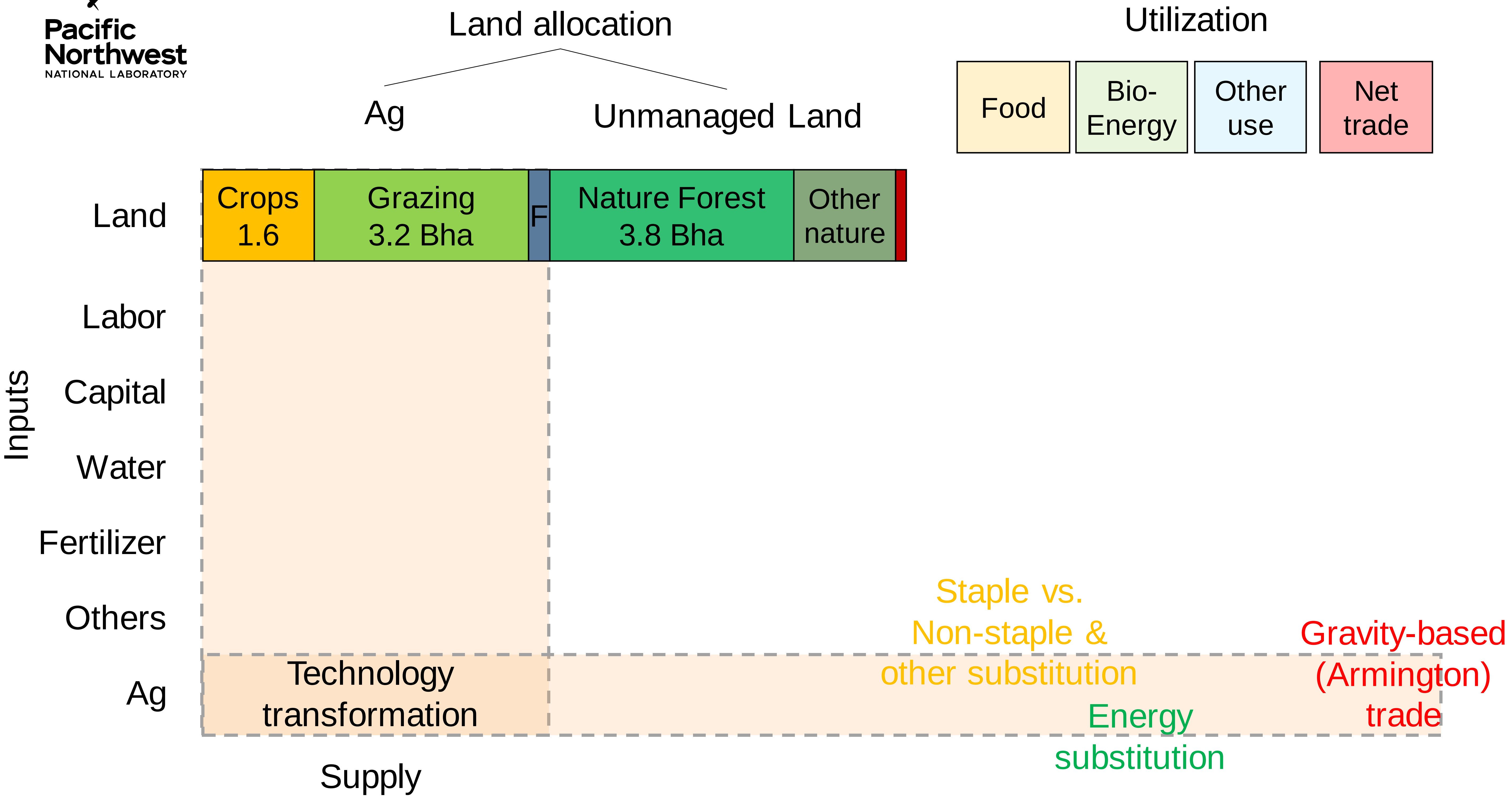
gcamdata; FAOSTAT; GTAP Database; Aguiar et al. (2019)

IO table



gcamdata; FAOSTAT; GTAP Database; Aguiar et al. (2019)

IAM AgLU Modeling



gcamdata; FAOSTAT; GTAP Database; Aguiar et al. (2019)

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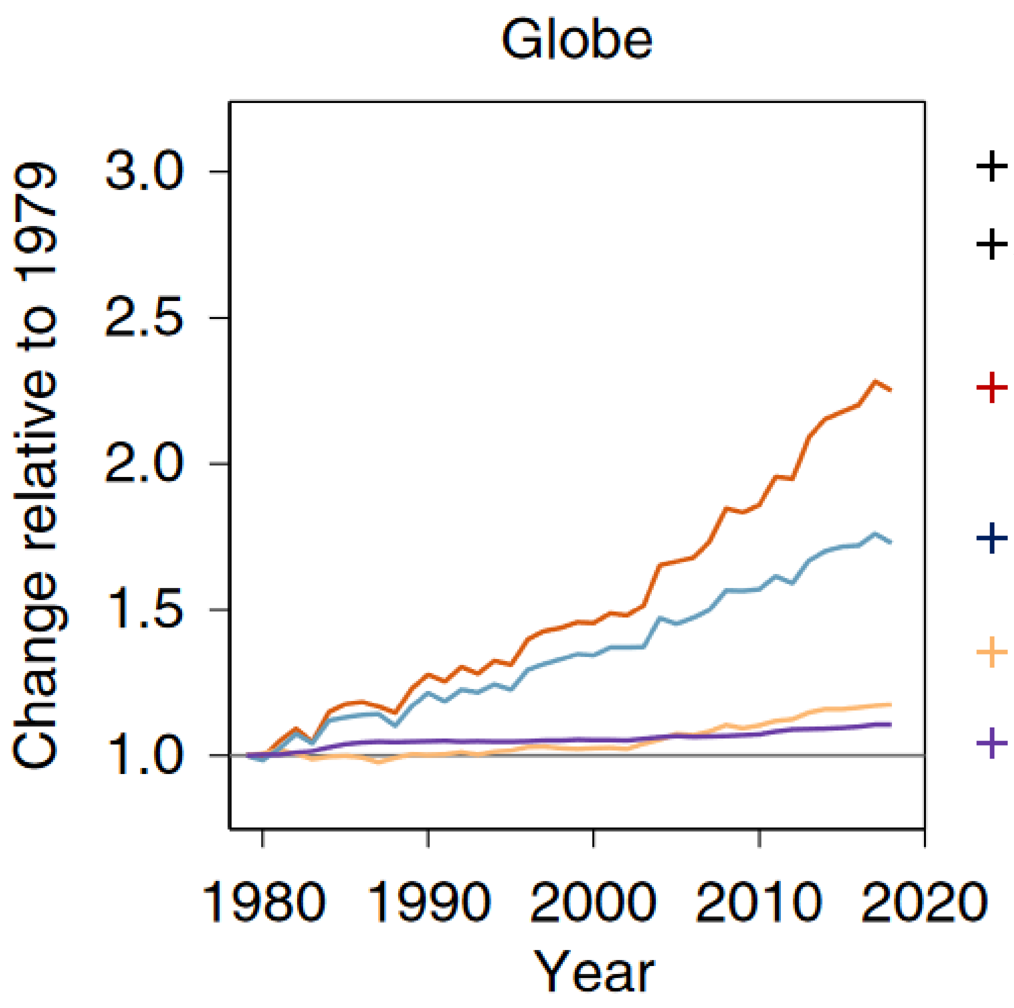
USA 2015 1975B$ Intersectoral Value Flows	Corn	Wheat	Rice	OtherGrain	OilCrop	PalmFruit	FiberCrop	RootTuber	SugarCrop	FodderGrass	FodderHerb	MiscCrop	biomassGrass	biomassTree	Beef	Dairy	Pork	Poultry	SheepGoat	FeedCrops	FodderHerb_Residue	Pasture_FodderGrass	Scavenging_Other	Pasture	Forest	Ethanol	Biodiesel	FoodDemand	NonFoodDemand	Net export	Total
Land	11	2	0	1	9	0	0	0	0	2	2	1	0	0										2	7						37
Water	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0												0
Scavenging_Other_Rsrc																							0								0
Others	10	1	0	0	5	0	1	1	1	4	7	14	0	0	5	7	3	9	0					0	12						80
regional corn																				7						9		0	4	2	22
regional wheat																				0								2	0	2	4
regional rice																												0	0	0	1
regional othergrain																				0								0	1	0	1
regional oilcrop																				1							5	1	0	7	14
regional palmfruit																				0								0	0	0	0
regional fibercrop																				0								0	0	0	1
regional root_tuber																				0								1	0	0	1
regional sugarcrop																				0								0	1	0	1
FodderGrass																						6								0	6
FodderHerb																					4								0	5	9
regional misccrop																				0								16	1	-2	15
regional beef																												17	0	-1	17
regional dairy																												10	1	1	12
regional pork																												6	0	1	7
regional poultry																												11	1	2	13
regional sheepgoat																												0	0	0	0
FeedCrops															3	2	3	4	0											0	12
FodderHerb_Residue															2	1	1	1	0											0	4
Pasture_FodderGrass															6	1			0											0	8
Scavenging_Other															0	0	0	0	0											0	0
Pasture																						2								0	2
Forest																													18	1	19
DDGS and feedcakes																				3											3
N_fertilizer	1	0	0	0	0	0	0	0	0	0	0	0	0	0																	3
Output	22	4	1	1	14	0	1	1	1	6	9	15	0	0	17	12	7	13	0					2	19						292

Drivers to higher agricultural output
Extensification vs. intensification



+70% population
+340% GDP

+125% caloric production

+73% crop yield (production per harvested area)

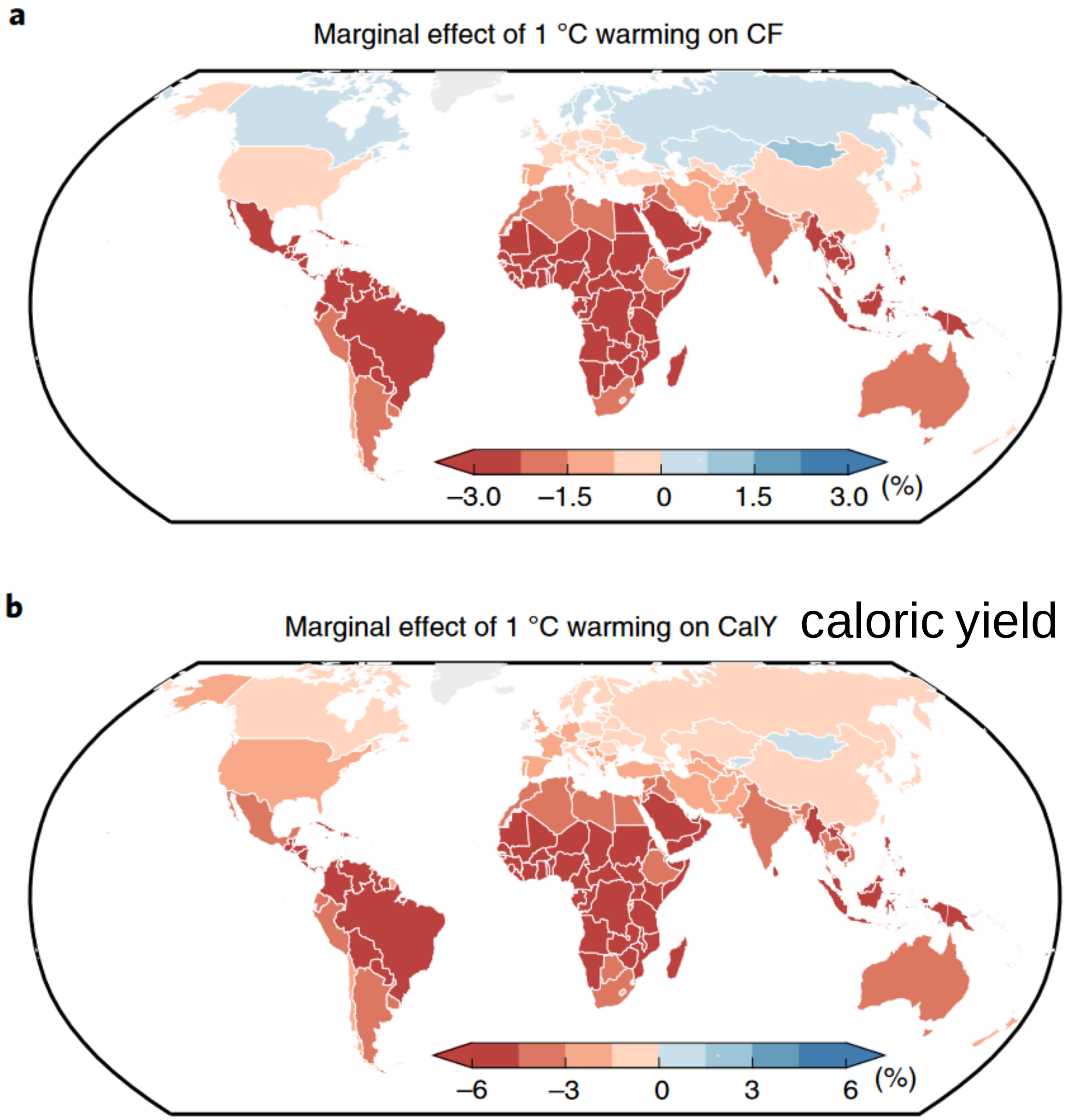
+18% cropping frequency (harvested area per cropland)

+11% cropland cover

Ag production and land are decoupling

FAOSTAT; Zhu et al. (2022 ncc);

Climate impacts on cropping frequency (CF)



caloric yield

nature climate change

Article https://doi.org/10.1038/s41558-022-01492-5

Warming reduces global agricultural production by decreasing cropping frequency and yields

Received: 4 September 2021

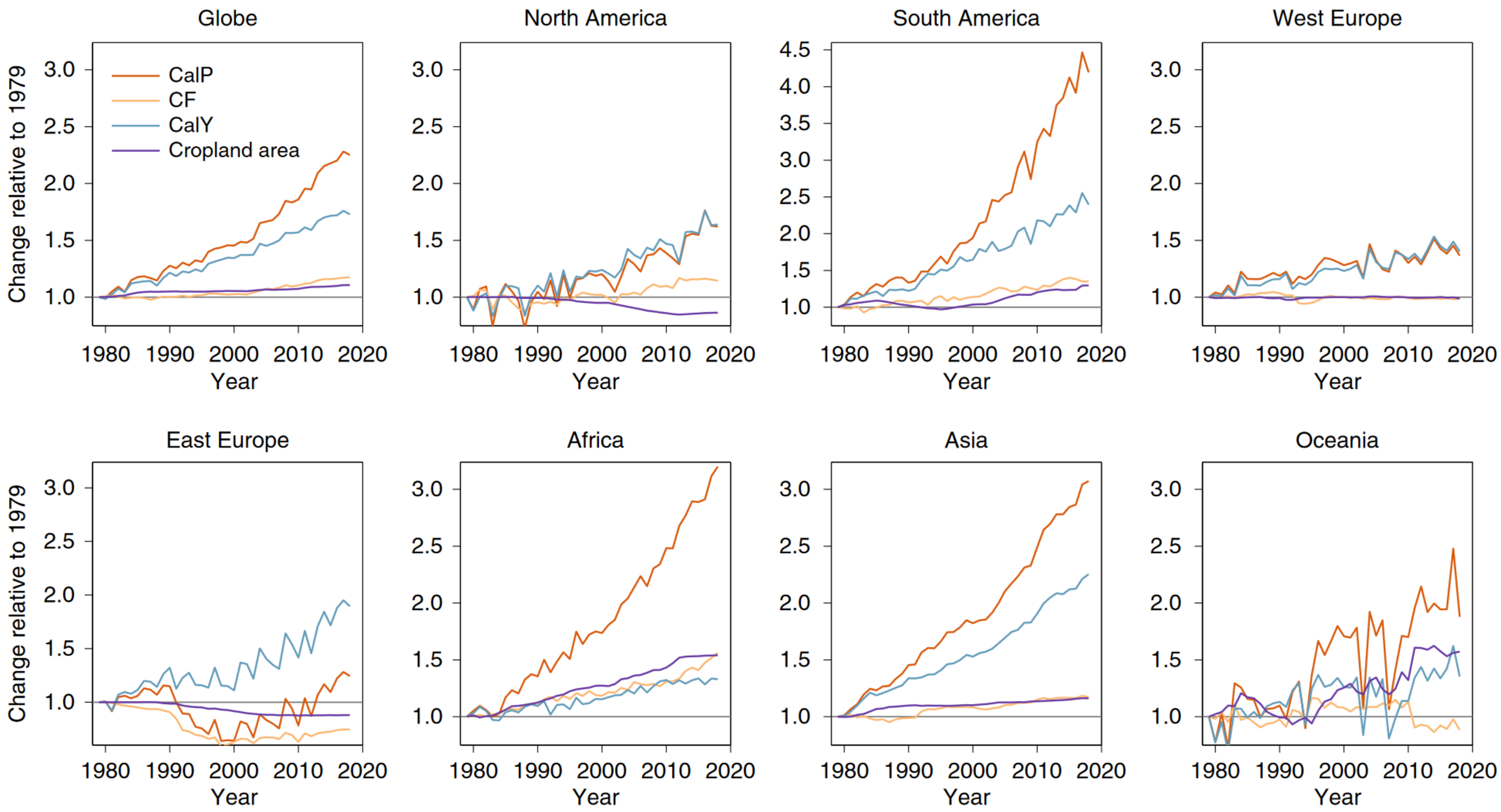
Accepted: 5 September 2022

Peng Zhu[1,2,3], Jennifer Burney[4], Jinfeng Chang[5], Zhenong Jin[6], Nathaniel D. Mueller[7,8], Qinchuan Xin[3], Jialu Xu[9], Le Yu[10,11], David Makowski[12] and Philippe Ciais[1]

- +1 °C warming leads to
  - -3.6% in caloric yield
  - -1.8% in harvest frequency
- The behavior may not be well identified

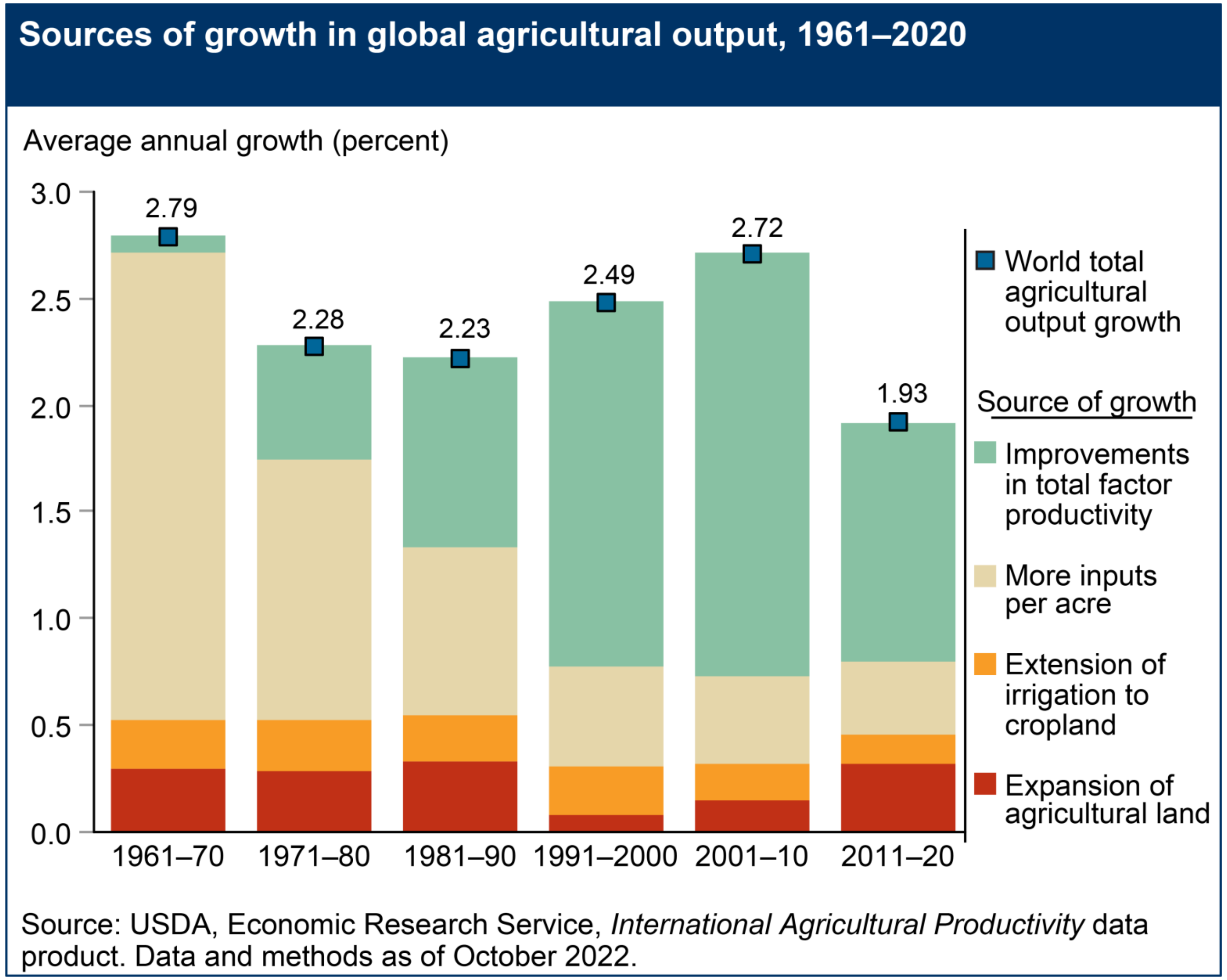
Zhu et al. (2022 ncc);

Regional heterogeneity



FAOSTAT; Zhu et al. (2022 ncc);

Driver of the yield growth



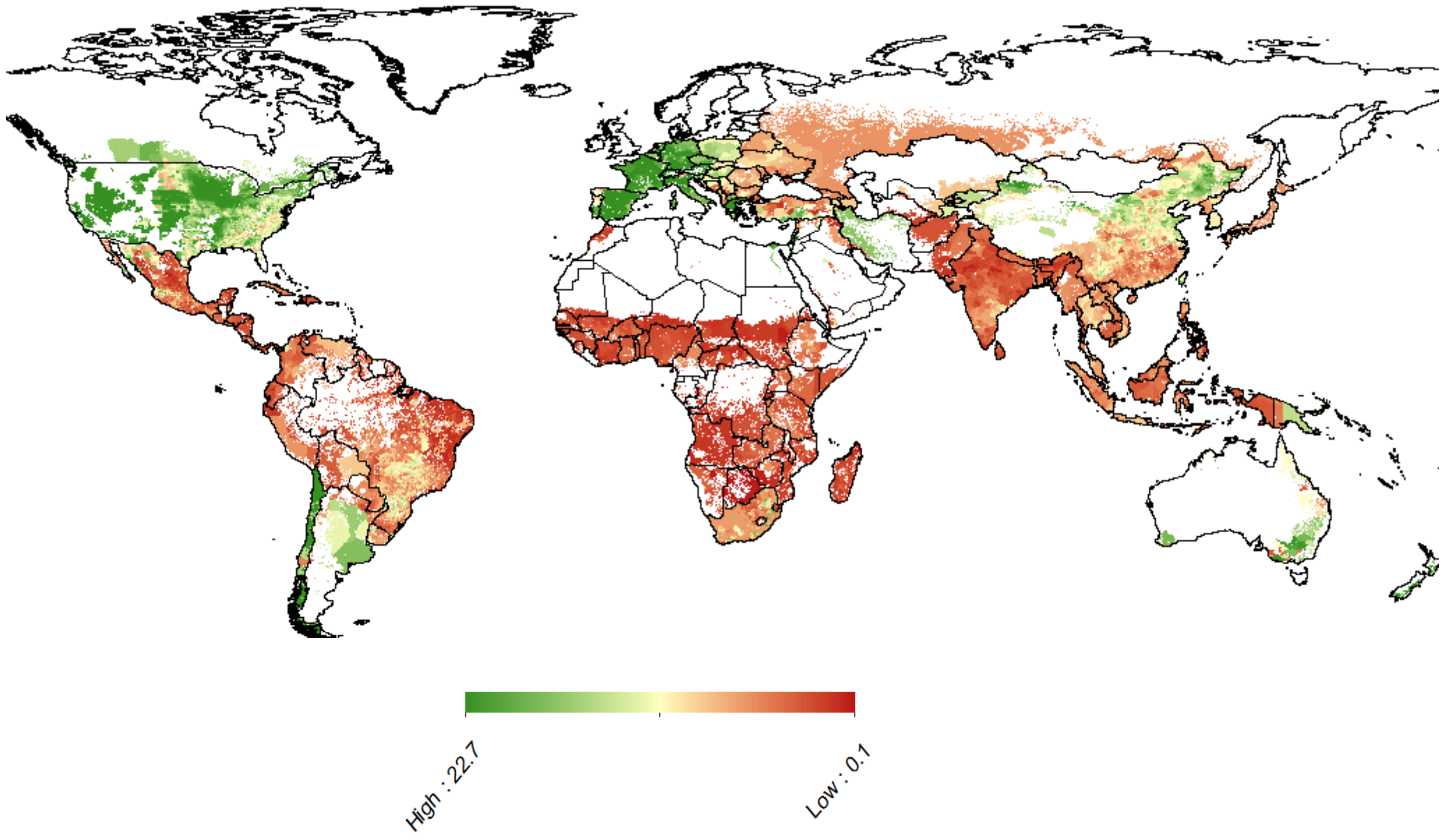
- Total factor productivity (TFP)
  - Partial FPs
  - Technology
  - Climate impacts

USDA (2022)

Yield gap

Corn plots in Africa vs. US Midwest

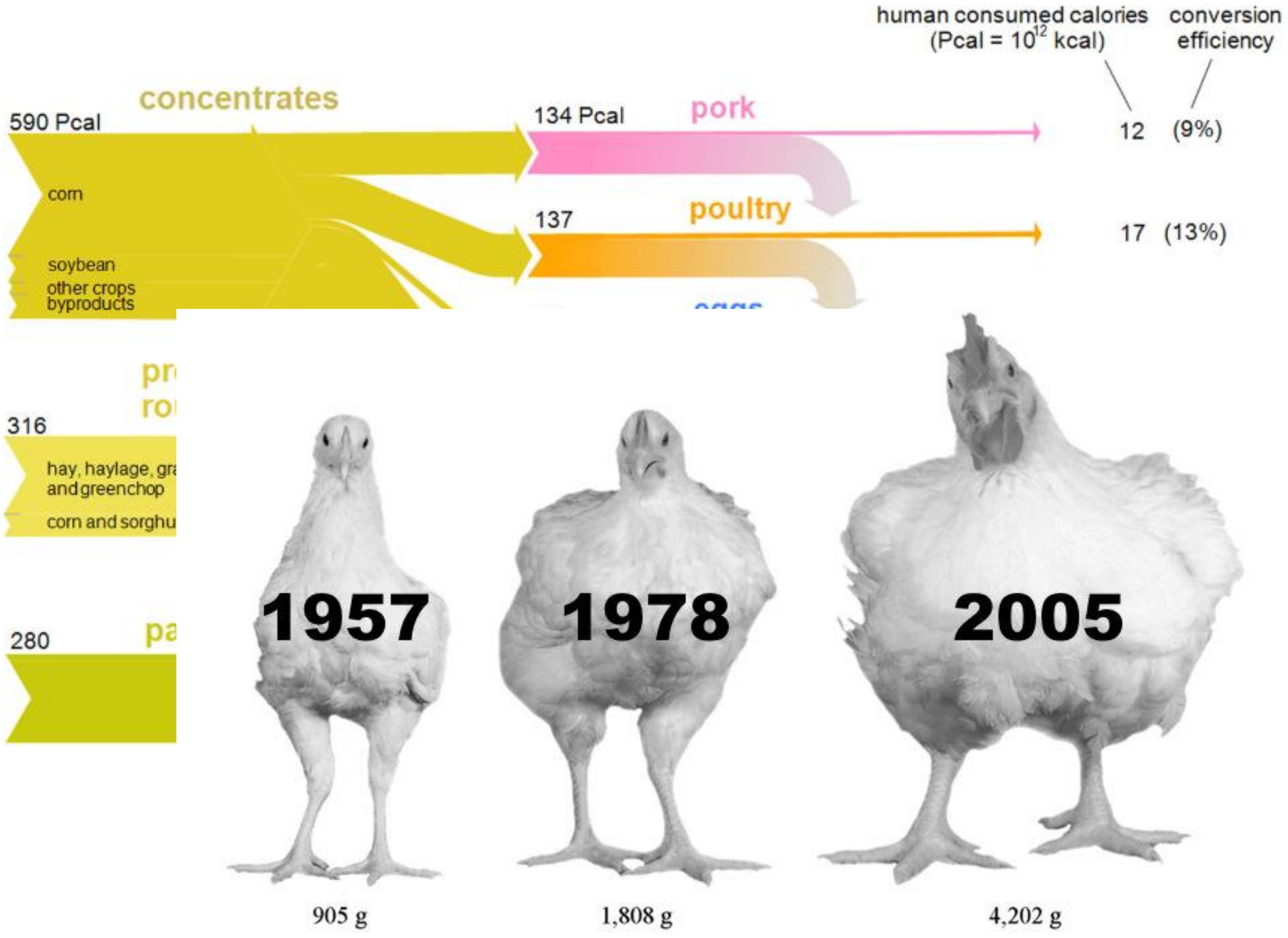
- **Corn yields across the world**



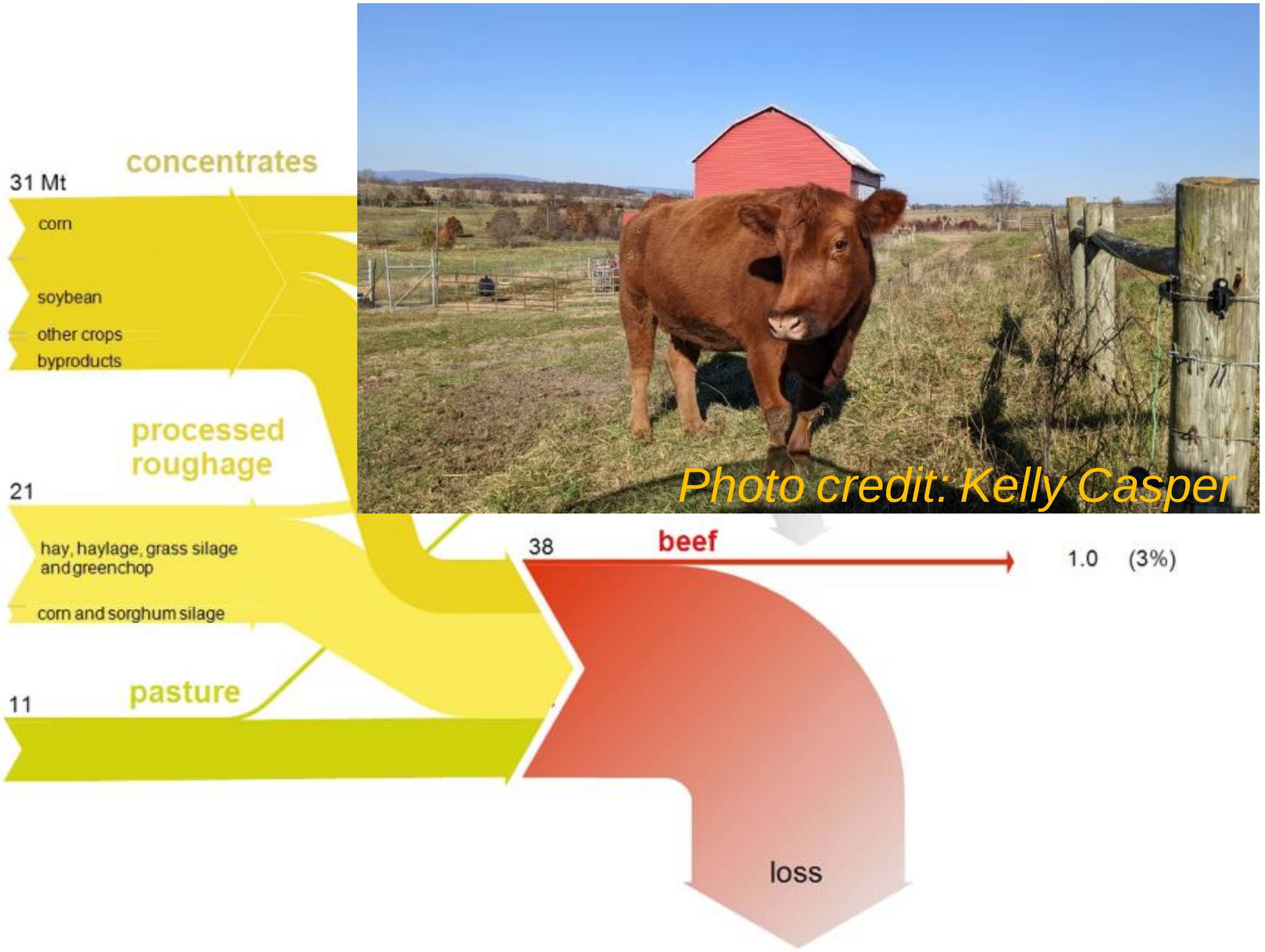
Monfreda et al (2008) & Baldos (2015)

Livestock feed conversion efficiency (US)

- Calorie conversion

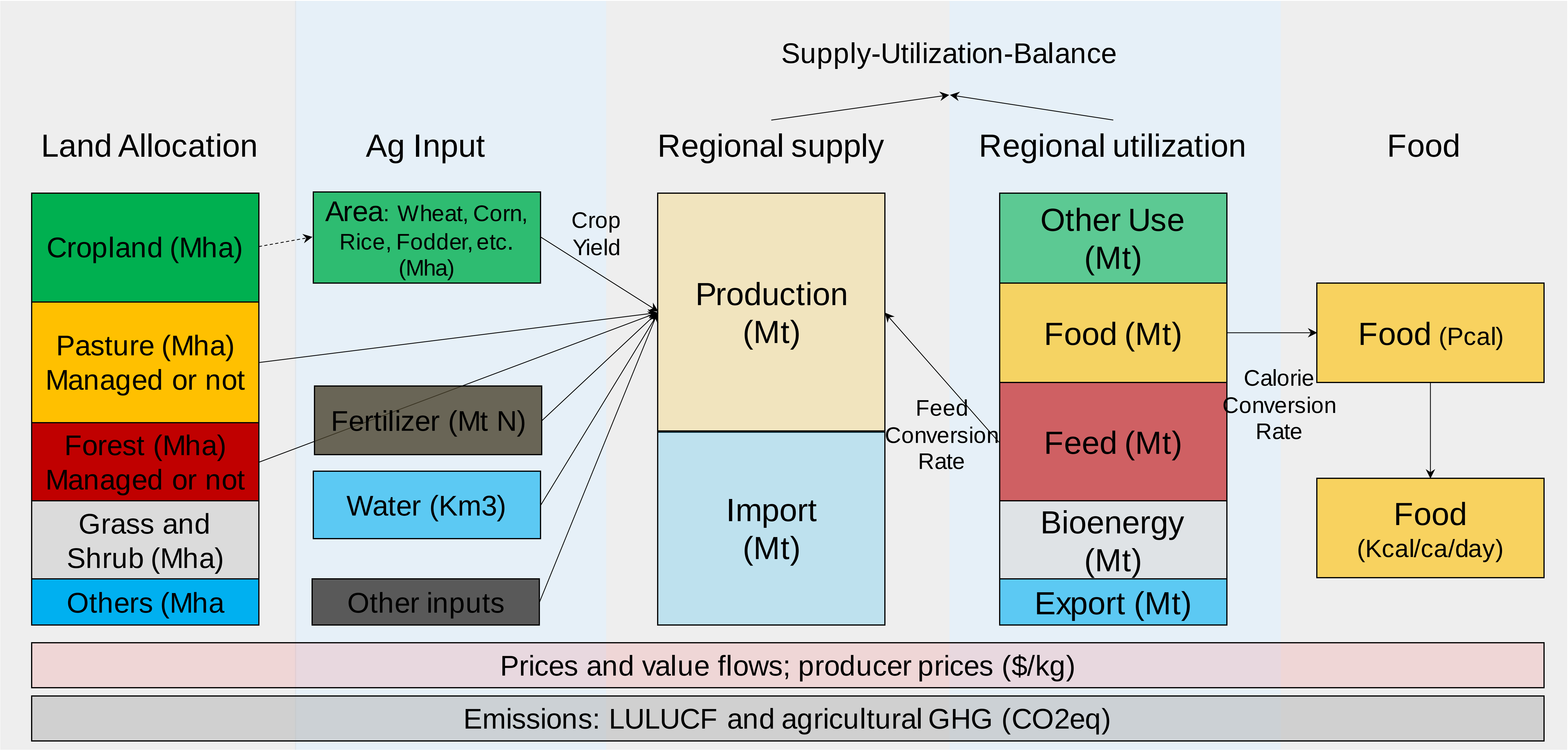


- Protein conversion



Shepon et al. (2016 ERL); Zuidhof et al. (2014 Poultry Sci)

Connect land hectares to food calories



Agriculture, forestry and other land use (AFOLU)

- Land use, land use change, and forestry (LULUCF)
  - Mainly driven by deforestation

IPCC AR6 WG3 chp7 Fig. 7.3 (2022)

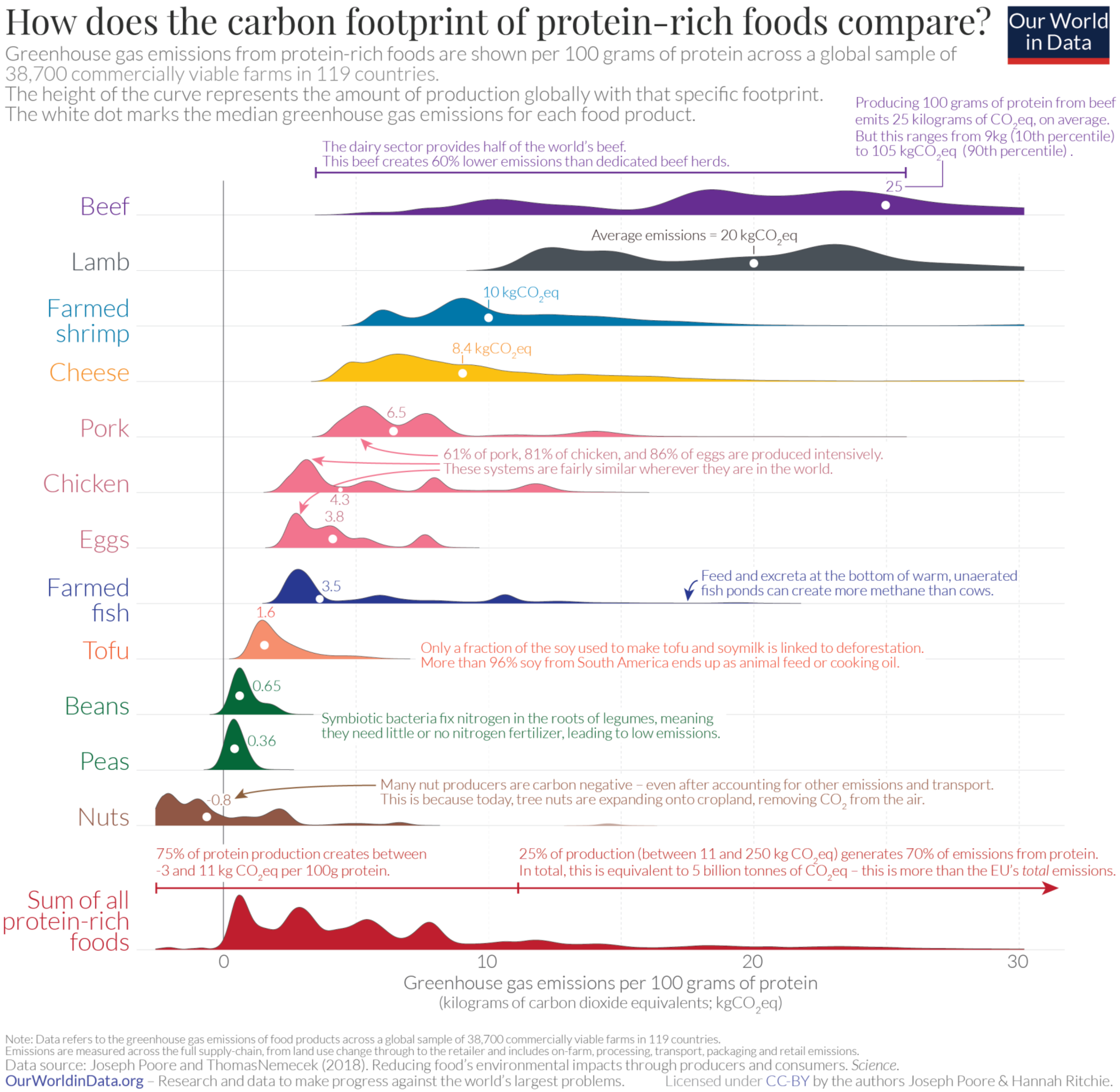
Mapping of emissions across agri-food systems

IPCC		Food Systems Activity	GHG: CH_4	GHG: N_2O	GHG: CO_2	FAO		
AFOLU	LULUCF	Net Forest Conversion	x	x	x	LAND USE CHANGE	AGRICULTURAL LAND	FOOD SYSTEMS
		Tropical Forest Fires	x	x	x			
		Peat Fires	x		x			
		Drained Organic Soils	x		x	FARM GATE		
	AGRICULTURE	Burning - Crop residues	x	x				
		Burning - Savanna	x	x				
		Crop Residues		x				
		Drained Organic Soils		x				
		Enteric Fermentation	x					
		Manure Management	x	x				
		Manure Applied to Soils		x				
		Manure Left on Pasture		x				
		Rice Cultivation	x					
		Synthetic Fertilizers		x				
ENERGY		On-farm Energy Use	x	x	x			
		Transport	x	x	x	PRE AND POST PRODUCTION		
		Processing	x	x	x			
		Packaging	x	x	x			
		Fertilizer manufacturing	x	x	x			
		Household consumption	x	x	x			
		Retail –Energy Use	x	x	x			
Industry		Retail –Refrigeration	x	x	x			
WASTE		Solid Food Waste	x					
		Incineration			x			
		Industrial Wastewater	x	x				
		Domestic Wastewater	x	x				

- GHG Emissions:

  LULUCF < AFOLU < food system

Tubiello et al. (2022 ESSD)



OurWorldinData: Ritchie (2020)

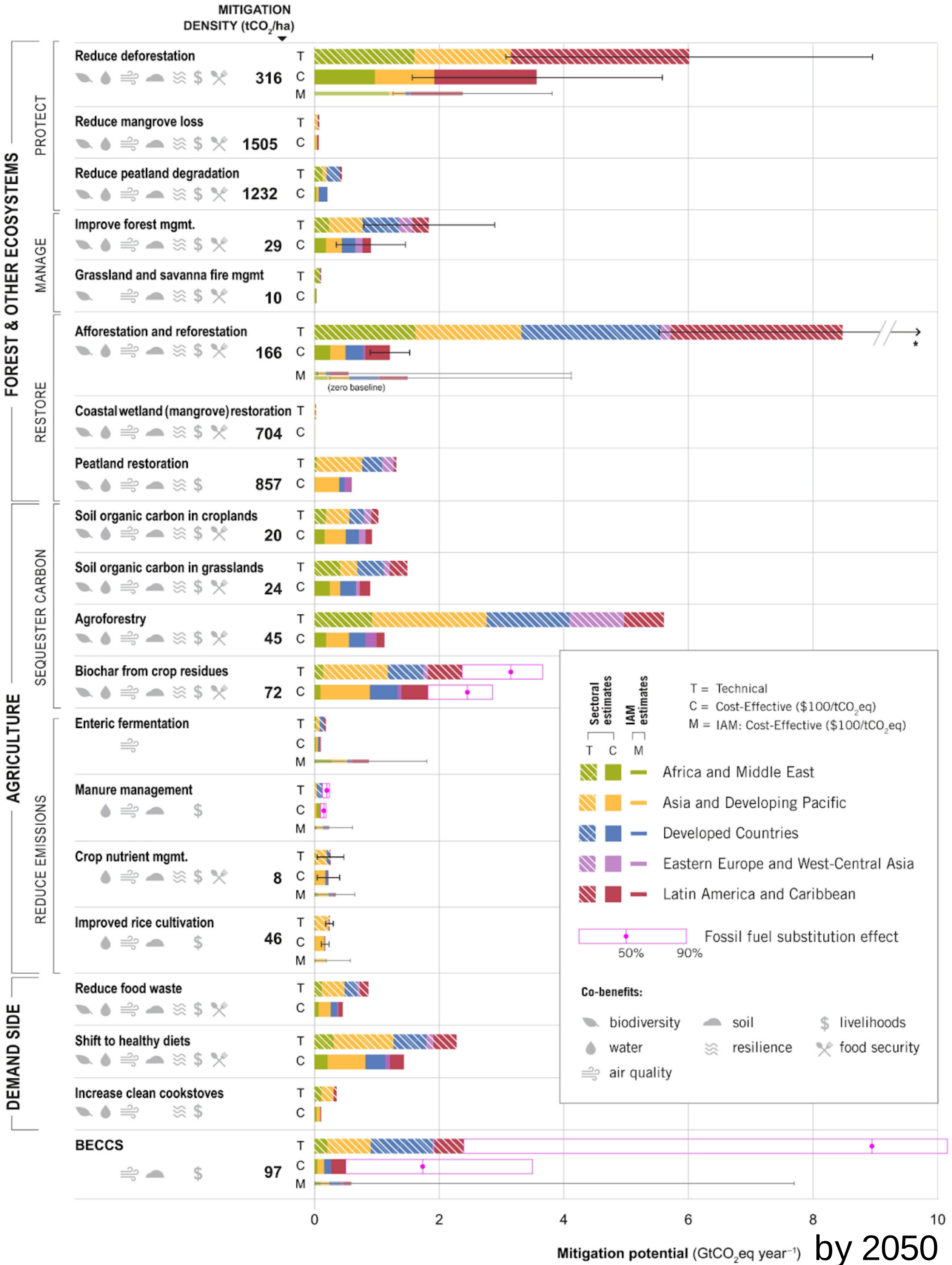
Land-based mitigation

- 20 measures (Roe et al., 2021 GCB) by 2050
  - Sectoral: Technical, Cost-effective <100$/tCO2eq
  - IAM: Median in model intercomparison

- Forest: T 18, C 6.6, M 3.5 GtCO2eq/yr
- Ag: T 11, C 5.3, M 2.7 GtCO2eq/yr
- BECCS: T 2.5, C 0.5, M 0.7 GtCO2eq/yr

- *IAMs expects large BECCS after 2050*

FIGURE 3 Climate mitigation potentials for 20 land-based measures in 2020–2050, by region. Technical and cost-effective ($100/$tCO_2eq$) mitigation potentials are provided for each measure using a sectoral approach according to Table 1 and Figure 1. The 20 measures are grouped into four systems-level mitigation categories, and seven management-level categories. For measures with more than one dataset, the bar graph represents the mean estimate, and the error bars represent the min and max potential range. Global mitigation potentials of substituting fossil fuels were estimated for BECCS, biochar, and manure management, shown in pink outline bars, illustrating the median and 90th percentile values. IAM estimates (range and median, up to $100/$tCO_2eq$) are provided for the seven measures where data are available in the ENGAGE database (Riahi et al., 2021). Potential co-benefits are indicated with icons, and the average global mitigation "density" (cumulative mitigation potential divided by total hectares in 2020–2050) is noted for measures with available data



by 2050

Assessing climate impacts on agriculture and land use

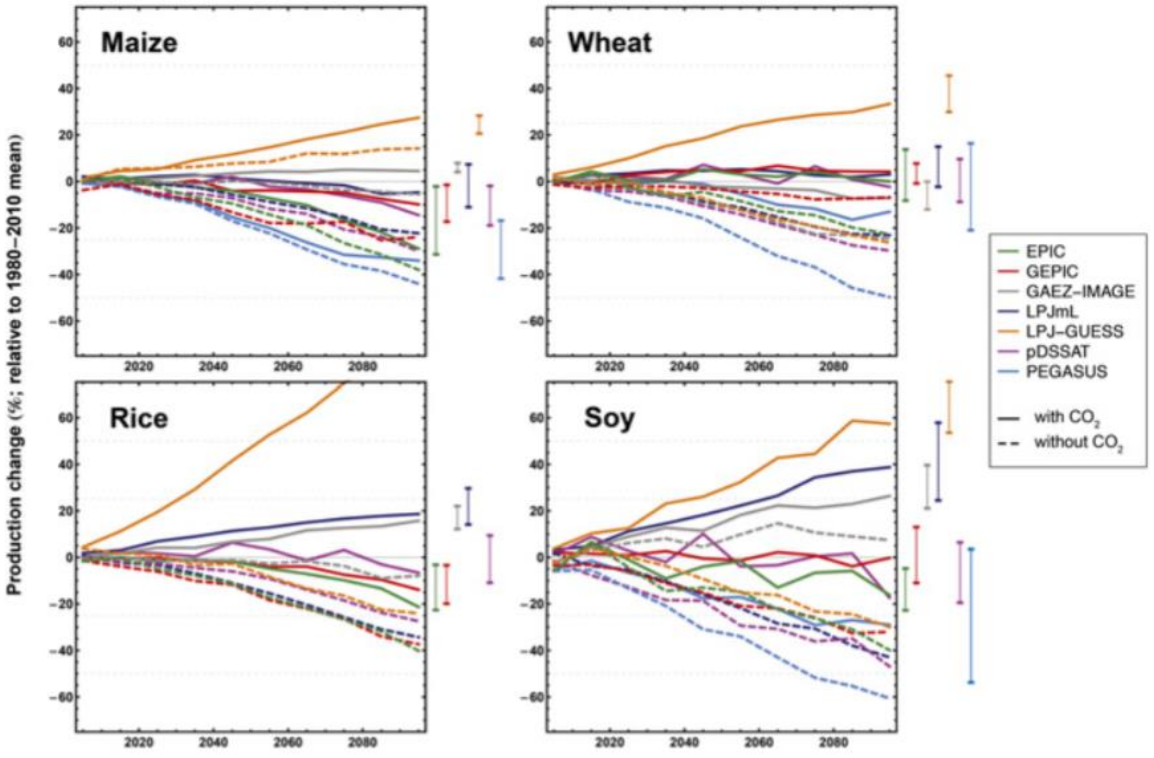
- Relationship between climate variability and economic responses

Modeling chain	Climate model	Crop model	Economic Model (GCAM)
Variable	• Temperature • Precipitation • C concentration • Wind speed • Etc.	• Biophysical yield	• Harvested area • Production • Consumption • Prices • Etc.

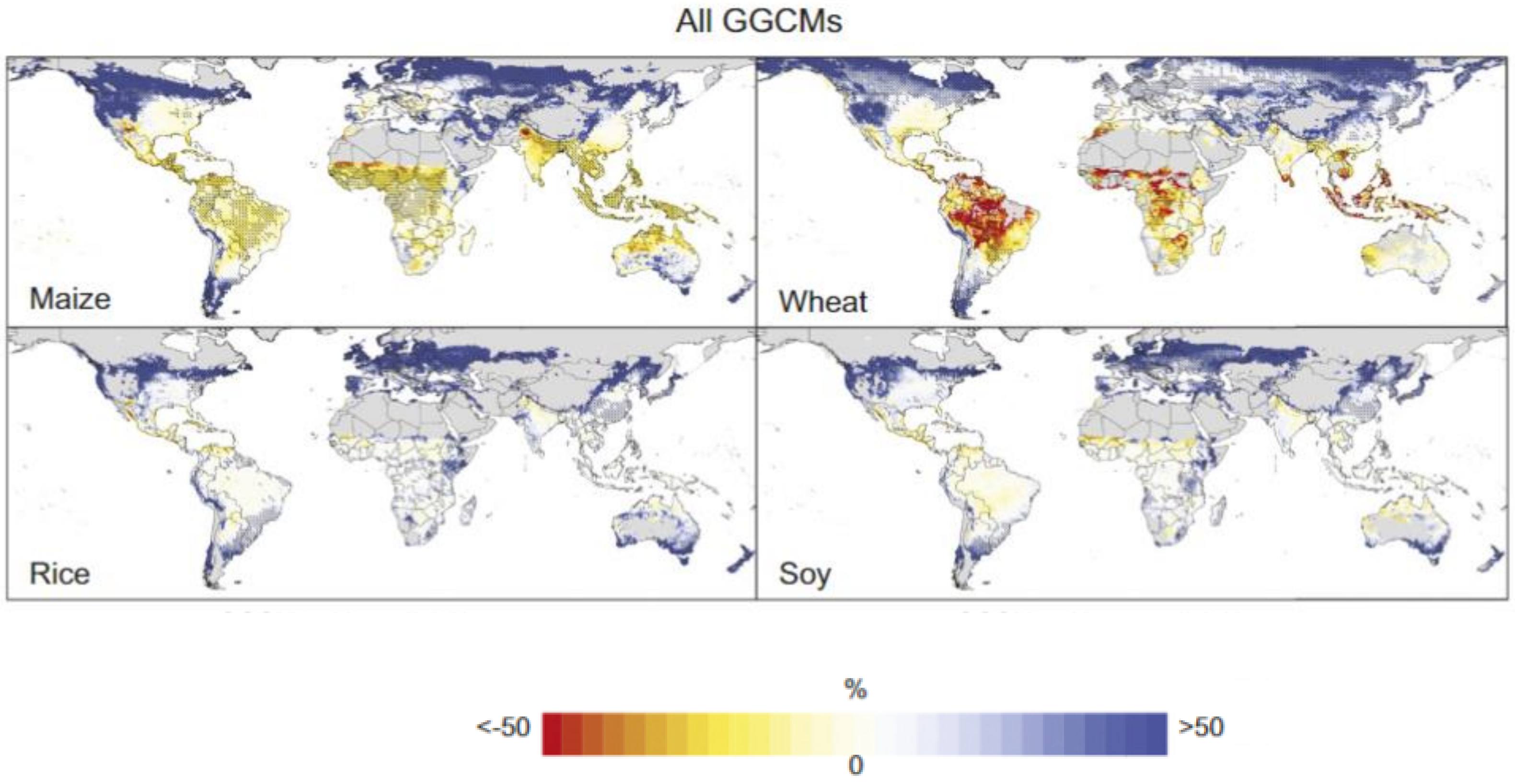
- Biophysical yield is an agronomic representation of all climate variables
- Relationship between climate interannual variability and economic responses
  - ✓ Annual step modeling & separating planting and harvesting decisions

Zhao et al. (2021 ERL)

RCP8.5 model mean crop biophysical yield impact (ISIMIP model intercomparison)

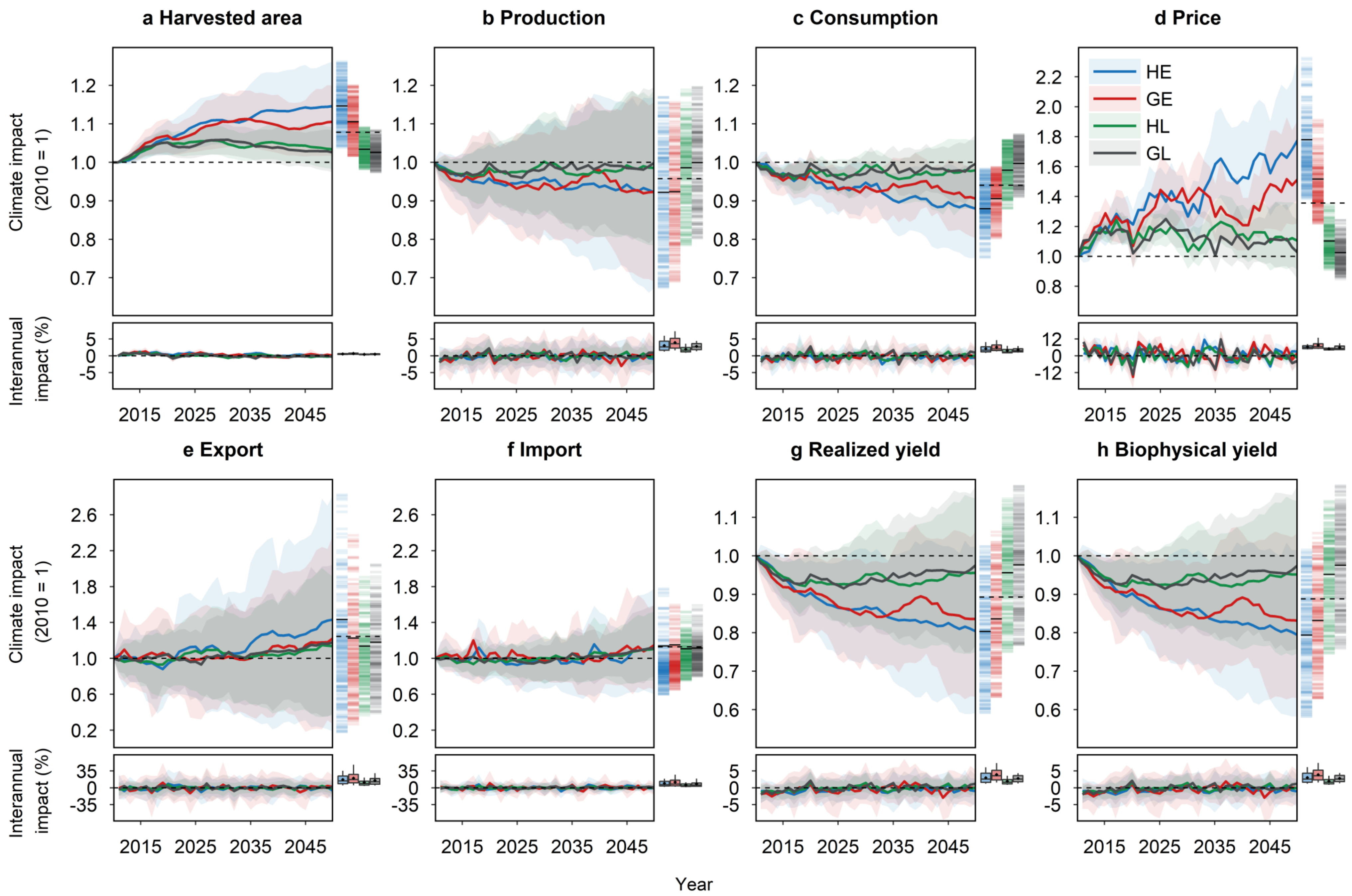


- End of the century impacts
  - Median values
  - Rainfed with carbon fertilization



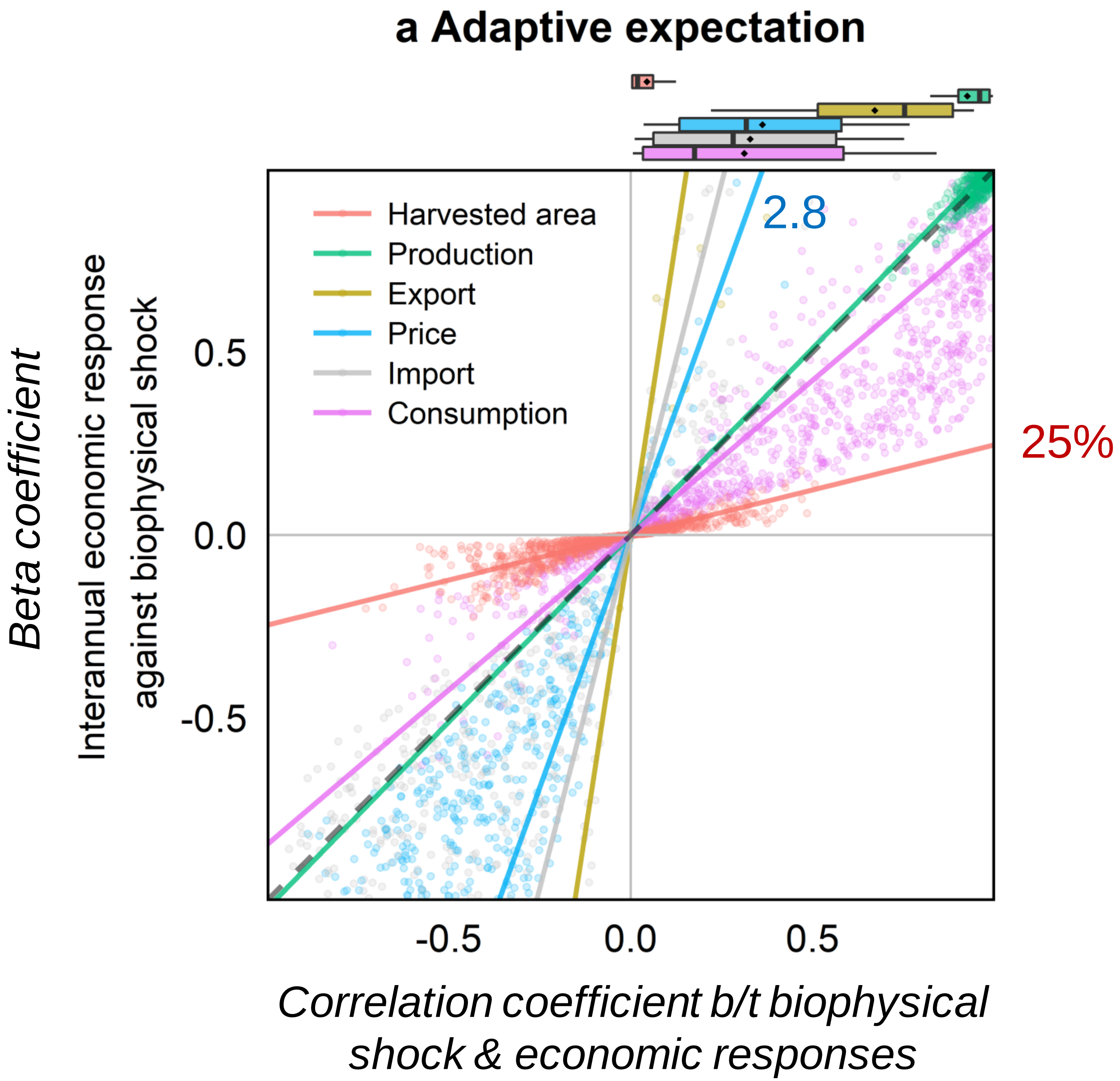
Rosenzweig et al. (2014 PNAS)

Climate impacts on global agriculture to mid-century



Zhao et al. (2021 ERL);

Interannual economic responses and correlations to biophysical yield shocks



- Bigger slope indicates stronger transmission of biophysical yield (climate) variability to the economic response

- Trade reduces and mediate market variability due to climate impacts

Market integration and trade liberalization

- Global agricultural markets became increasingly integrated
  - Industrialization and globalization
  - Trade cost and barrier reductions

- Fix the “**Missing globalization**” issue (Donaldson, 2015)
  - Crop consumption: total (+60%) vs. imported (+150%) in 1995 - 2015
  - Underestimate trade expansions and gains from market integration

- Trade integration scenarios to lower non-economic barriers
  - Global Ag market become 50% more integrated in every 40 years
  - Lower “distance” & higher “gravity”
  - Improves adaptation with the evolution of comparative advantage

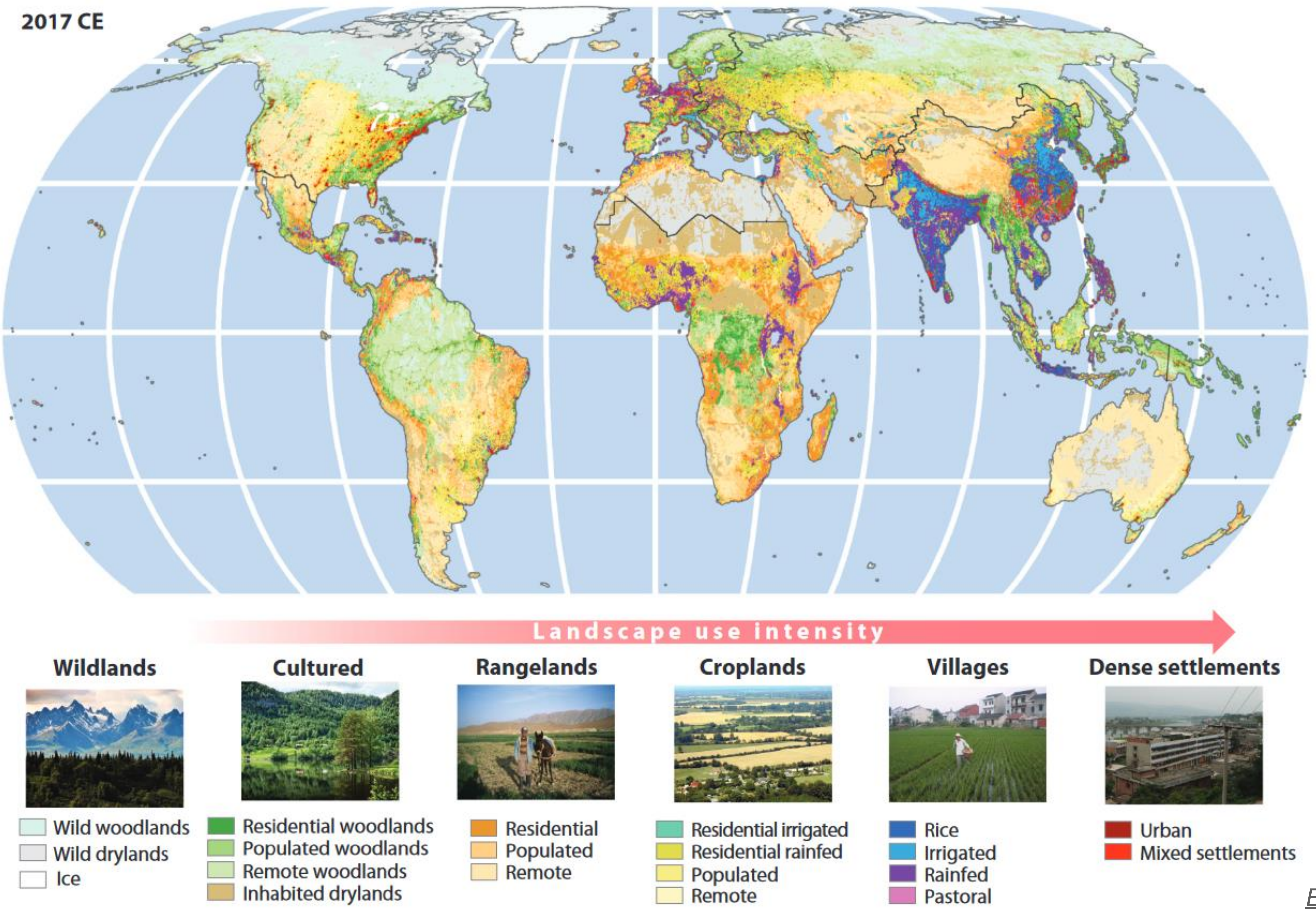
Zhao et al. 2021 EAP & Zhao et al. 2022 GEC

Other AgLU related studies

- Agricultural labor supply & climate impacts
  - Hill et al. (2021 ARRE) & Lima et al. (2021 ERL)
- Biodiversity: Leclère et al. (2020 nature)
- Climate impacts on TFP: Jägermeyr et al. (2021 nfood) & Ortiz-Bobea et al. (2021 ncc)
- Eutrophication: Sinha et al. (2017 science)
- Food demand: Edmonds et al. (2017 CCE)
- Hindcast experiment /historical validation
  - Calvin et al. (2017 CCE) & Calvin et al. (2022 GMD) & Zhao et al. (2021 EAP)
- Land-based mitigation
  - Calvin et al. (2014 CC) & Wise et al. (2009 science) & Fujimori et al. (2022 nfood)
- Nutrient and Health: Willett et al. (2019 Lancet)
- Virtual water & land-use emissions
  - Graham et al. (2020 nc) & Hong et al. (2022 science)

Thank you

Land use over space



Ellis (2021); Goldewijk et al. (2017)

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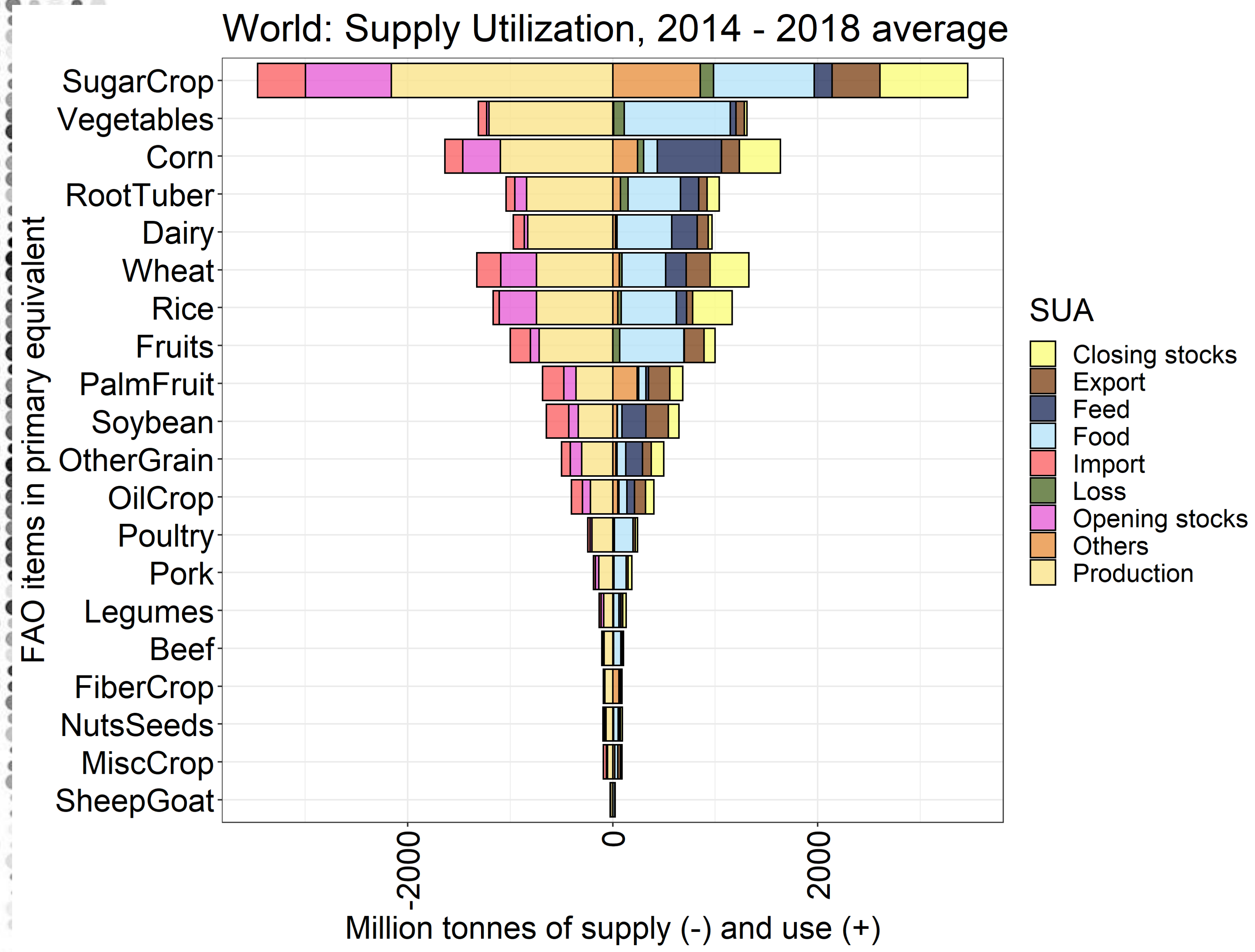
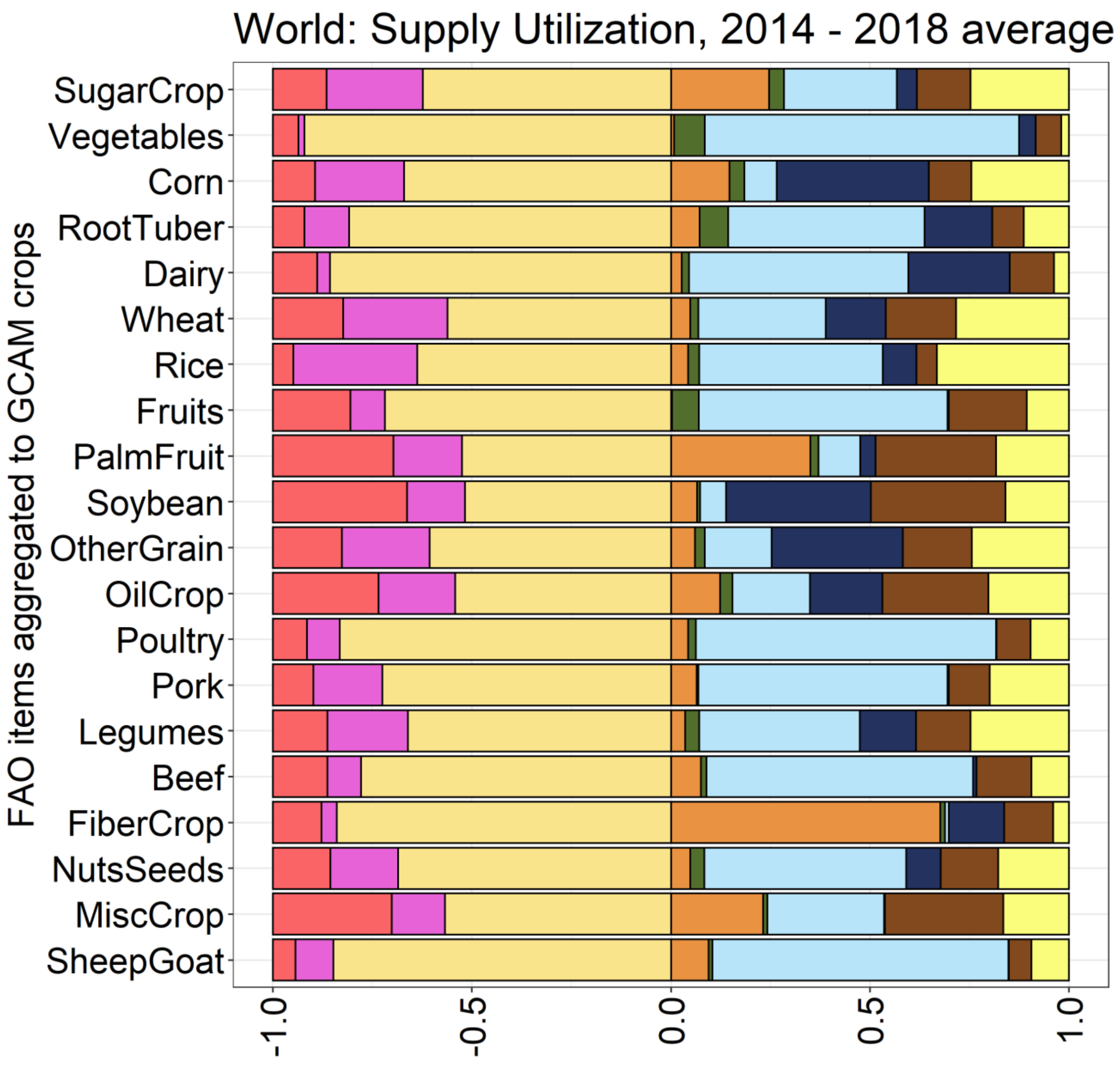
USA 2100 1975B$ Intersectoral Value Flows	Corn	Wheat	Rice	OtherGrain	OilCrop	PalmFruit	FiberCrop	RootTuber	SugarCrop	FodderGrass	FodderHerb	MiscCrop	biomassGrass	biomassTree	Beef	Dairy	Pork	Poultry	SheepGoat	FeedCrops	FodderHerb_Residue	Pasture_FodderGrass	Scavenging_Other	Pasture	Forest	Ethanol	Biodiesel	FoodDemand	NonFoodDemand	Net export	Total
Land	13	3	1	1	13	0	1	0	1	5	3	1	3	1										3	15						64
Water	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0												0
Scavenging_Other_Rsrc																							0								0
Others	12	2	1	0	10	0	1	2	1	6	11	18	2	1	8	11	4	13	0					0	16						118
regional corn																				10						8		0	6	3	27
regional wheat																				1								2	0	3	6
regional rice																												1	0	1	1
regional othergrain																				0								0	1	0	1
regional oilcrop																				1							9	2	1	10	23
regional palmfruit																				0								0	0	0	0
regional fibercrop																				0								0	1	0	1
regional root_tuber																				0								2	0	0	2
regional sugarcrop																				0								0	1	0	1
FodderGrass																						11								0	11
FodderHerb																					7								0	7	15
regional misccrop																				0								22	1	-4	20
regional beef																												28	0	0	29
regional dairy																												16	1	1	18
regional pork																												9	0	1	10
regional poultry																												17	1	2	20
regional sheepgoat																												0	0	0	0
FeedCrops															6	3	5	7	0											0	20
FodderHerb_Residue															4	2	1	1	0											0	7
Pasture_FodderGrass															11	3			0											0	14
Scavenging_Other															0	0	0	0	0											0	0
Pasture																						3								0	3
Forest																													31	0	31
DDGS and feedcakes																				7											7
N_fertilizer	2	0	0	0	0	0	0	0	0	0	0	0	0	0																	4
Output	27	6	1	1	23	0	1	2	1	11	15	20	5	2	29	18	10	20	0					3	31						454

New FAO data


World: Supply Utilization, 2014 - 2018 average
SugarCrop
Vegetables
Corn
RootTuber
Dairy
Wheat
Rice
Fruits
PalmFruit
Soybean
OtherGrain
OilCrop
Poultry
Pork
Legumes
Beef
FiberCrop
NutsSeeds
MiscCrop
SheepGoat
FAO items in primary equivalent
-2000
0
2000
Million tonnes of supply (-) and use (+)
SUA
Closing stocks
Export
Feed
Food
Import
Loss
Opening stocks
Others
Production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SugarCrop
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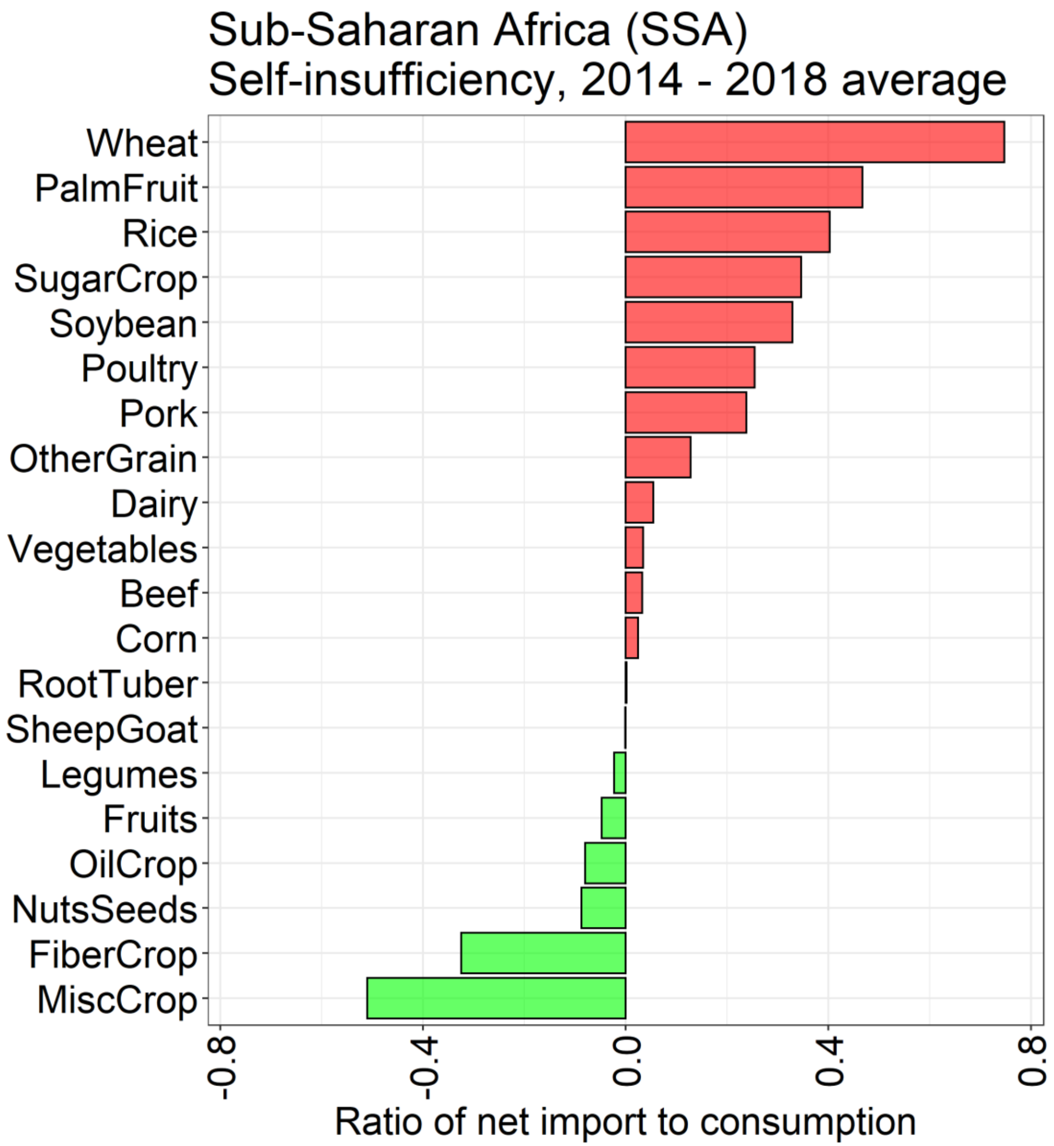
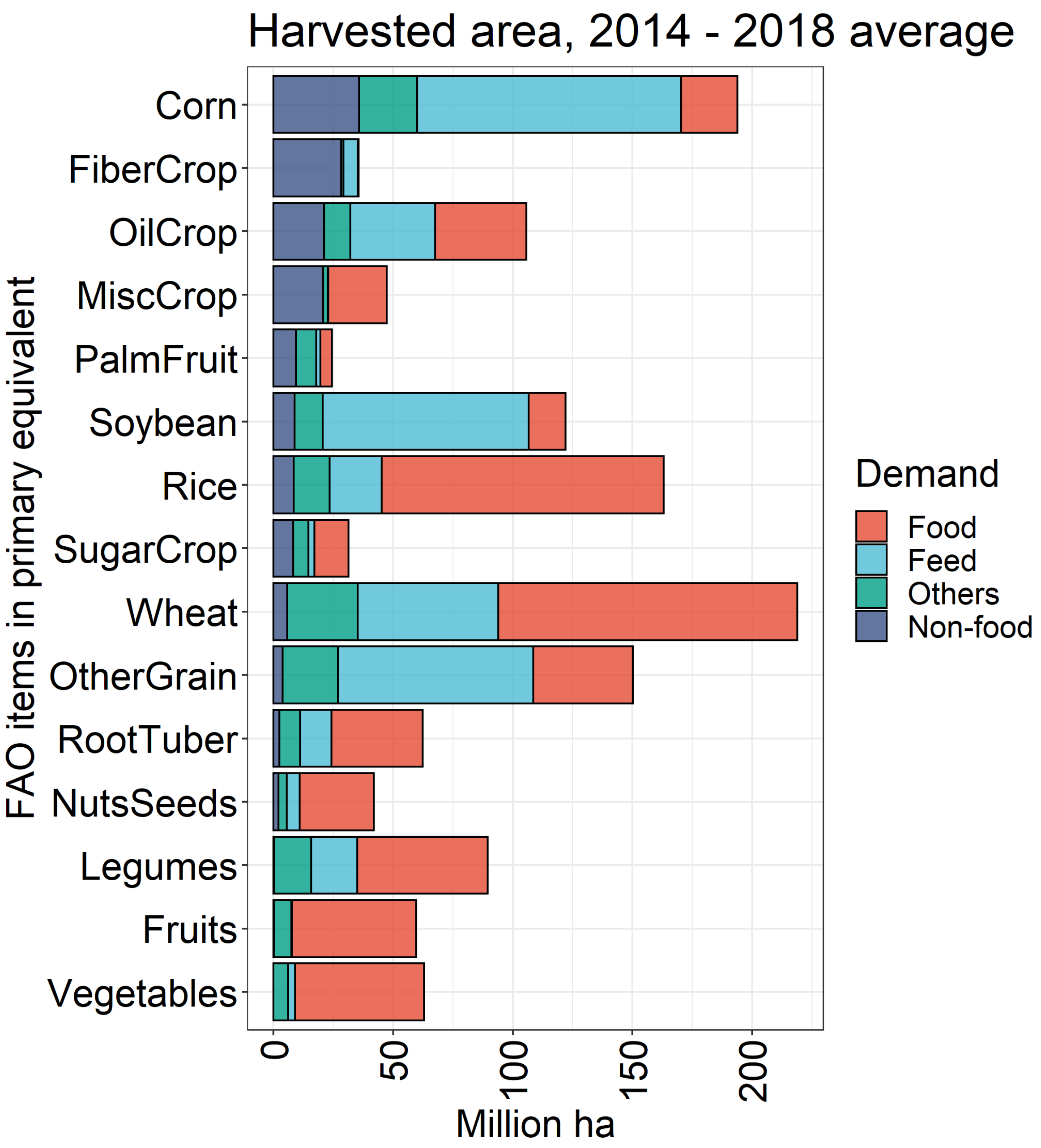
Soybean
OtherGrain
OilCrop
Poultry
Pork
Legumes
Beef
FiberCrop
NutsSeeds
MiscCrop
SheepGoat
FAO items aggregated to GCAM crops
-1.0
-0.5
0.0
0.5
1.0

Self-sufficiency

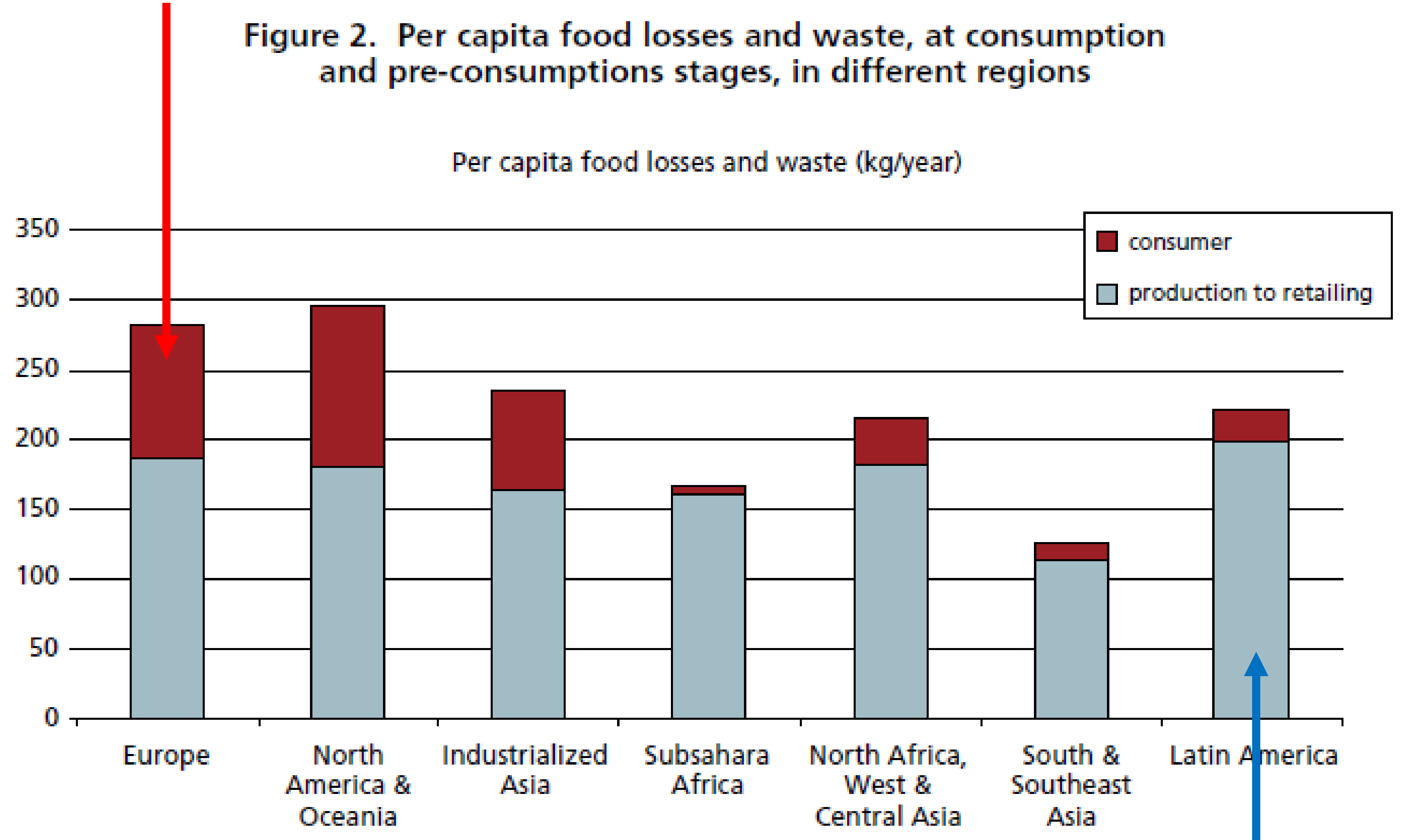


Global harvested area by use



Food waste vs. food loss

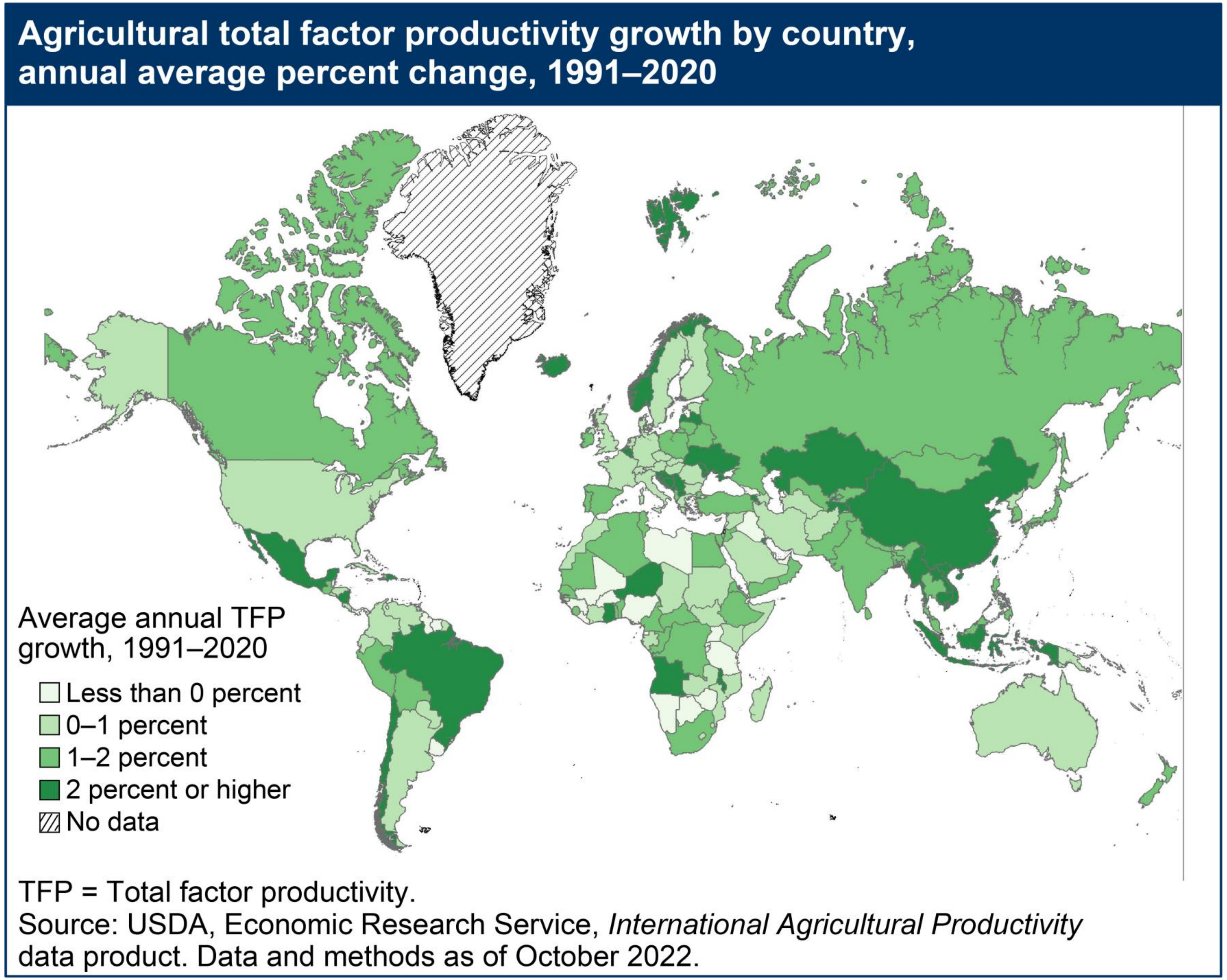
Food Waste



Post-harvest crop losses

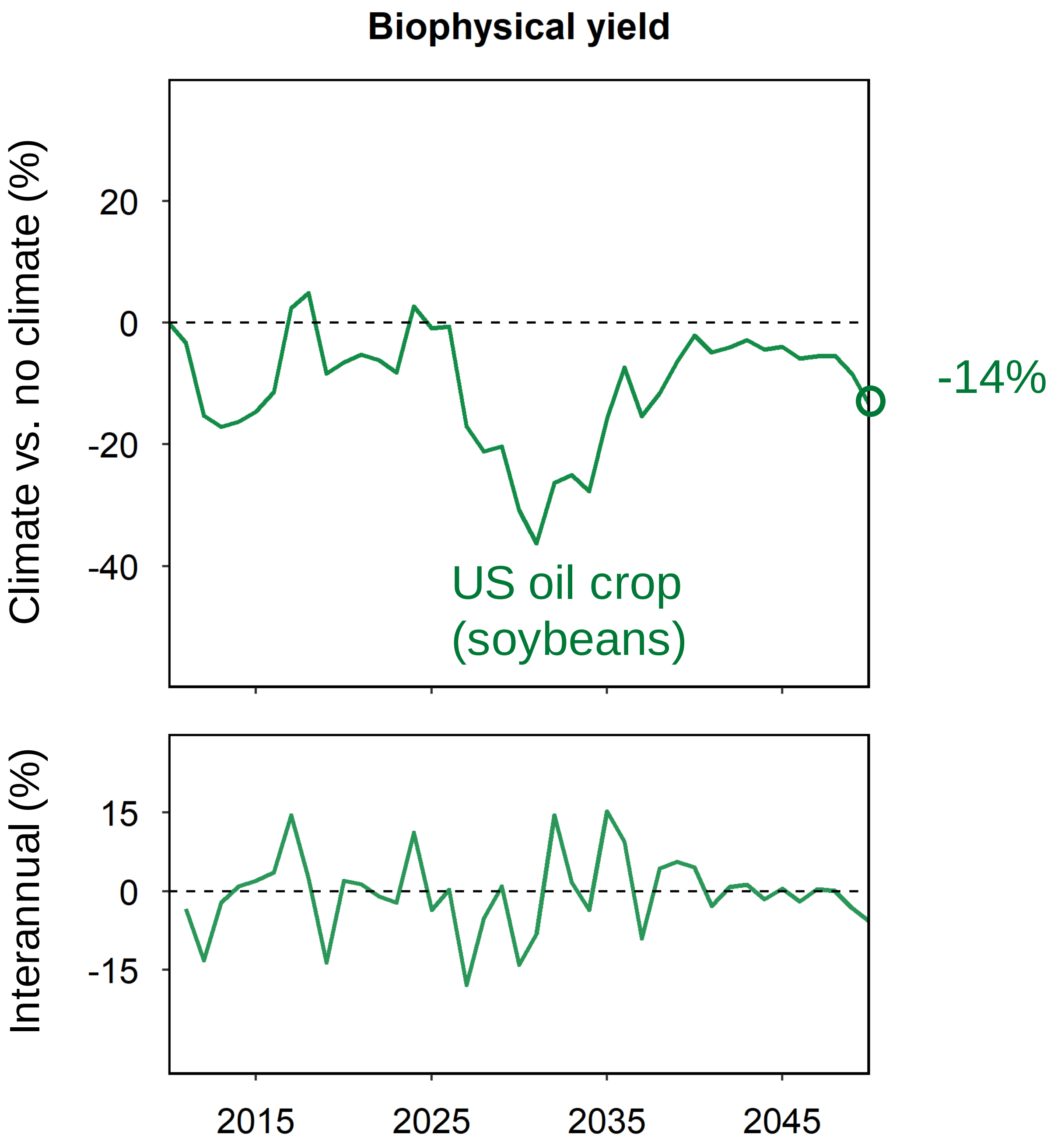
FAO

TFP growth



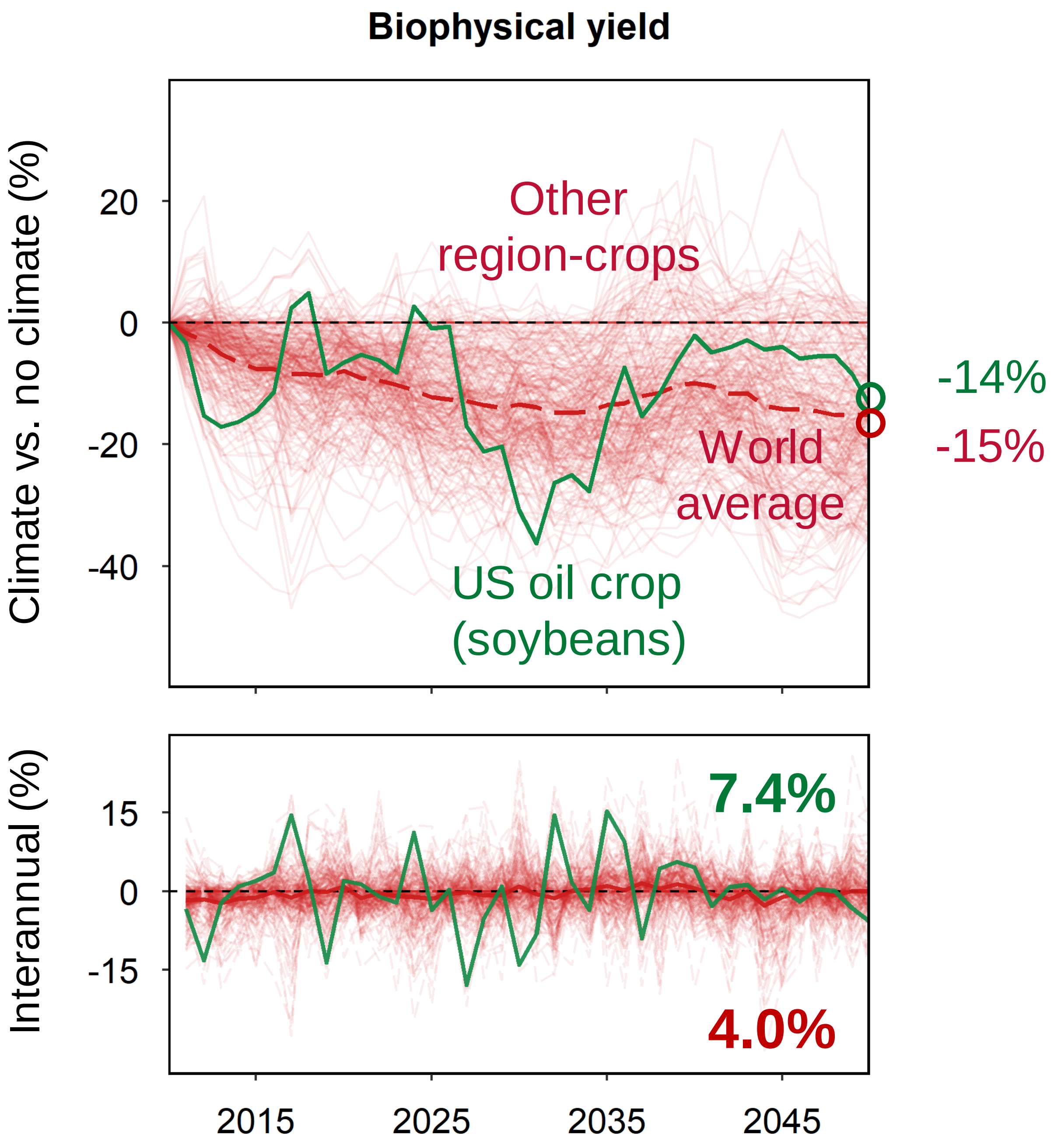
USDA (2022)

Biophysical yield shocks



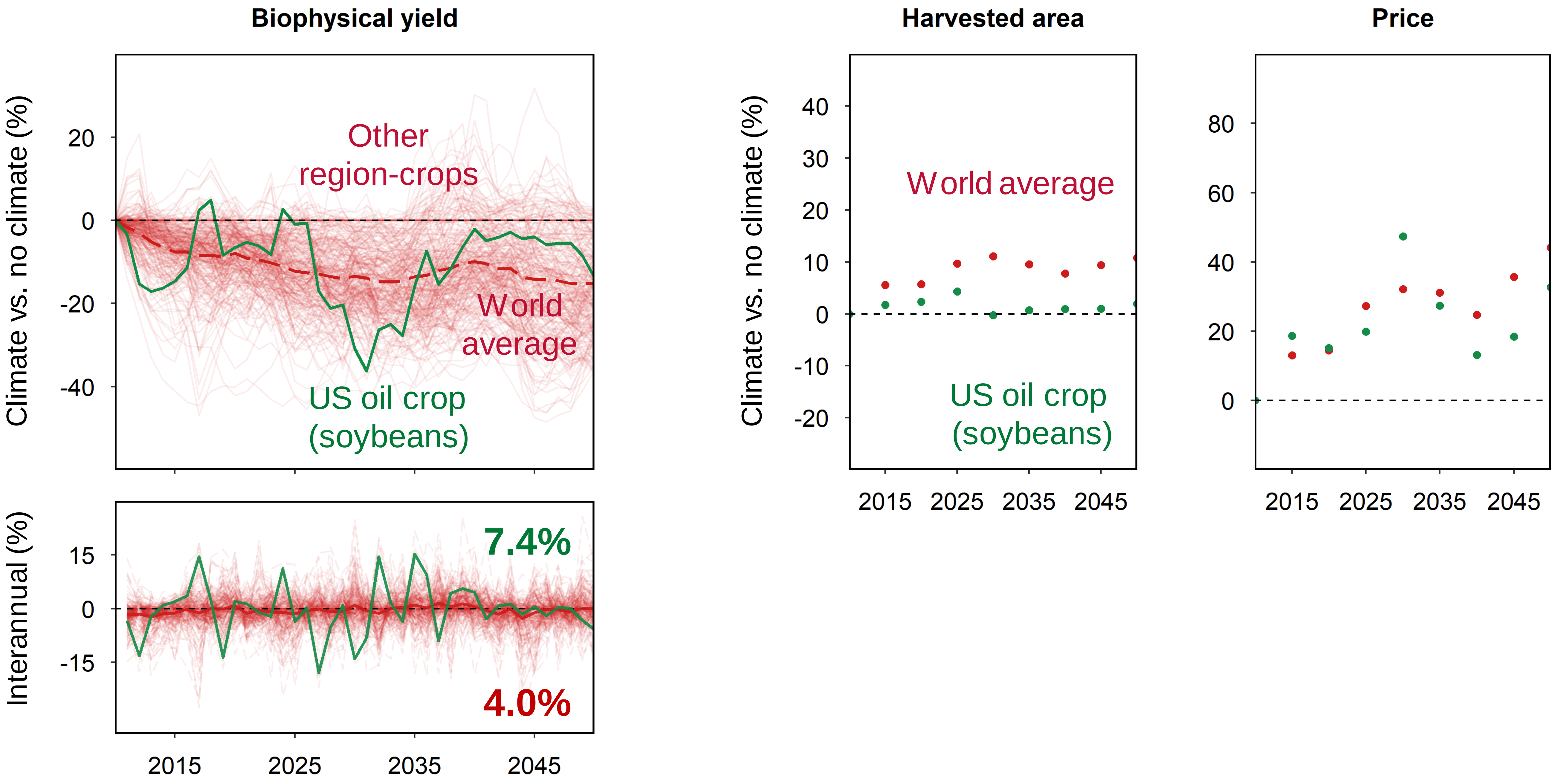
- A high-emissions scenario
  - RCP8.5 & GFDL-EPIC
- Interannual variability
  - SD of annual percent change
  - US oil crop (soybeans): 7.4%

Biophysical yield shocks

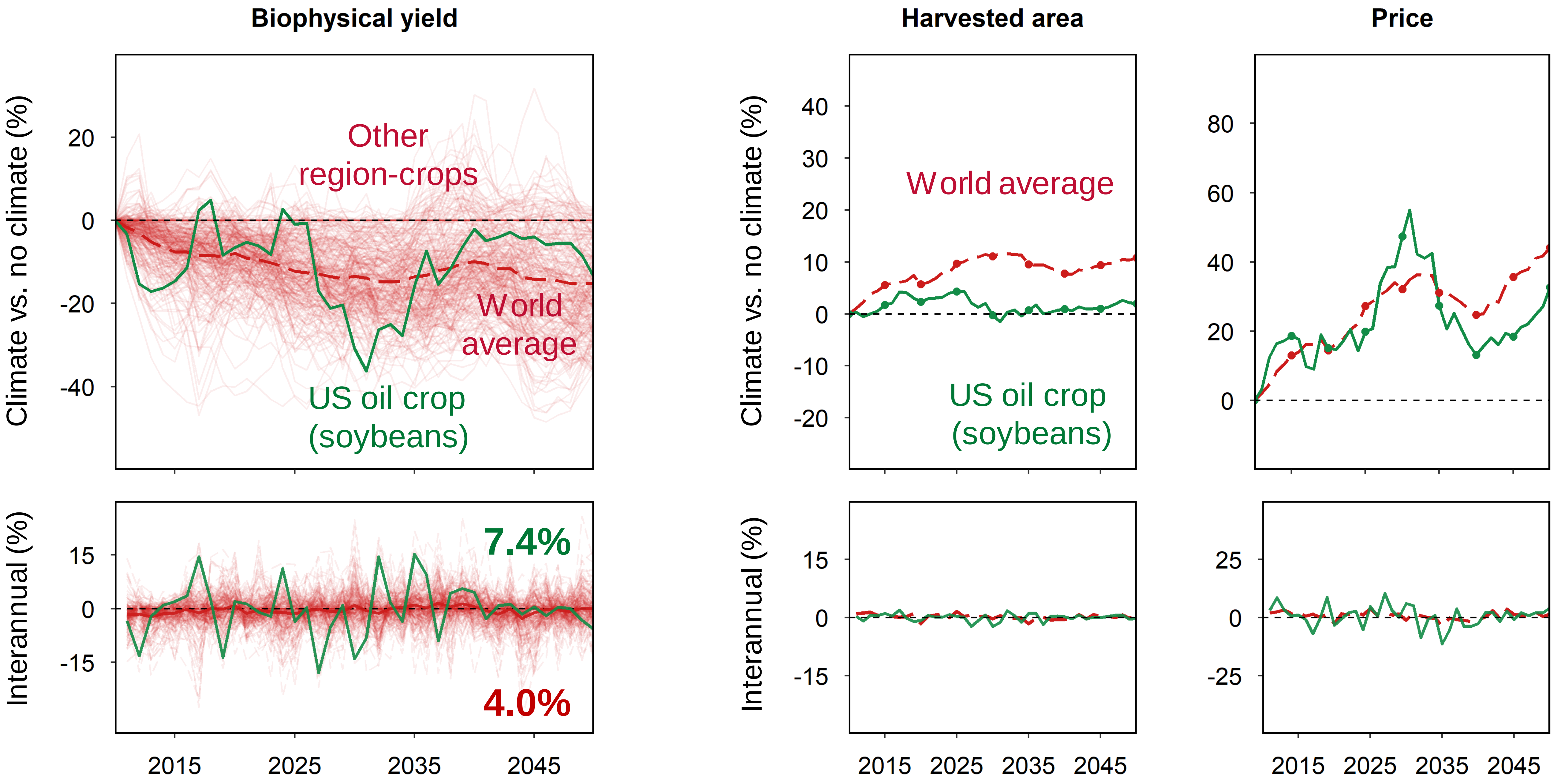


- A high-emissions scenario
  - RCP8.5 & GFDL-EPIC
- Interannual variability
  - SD of annual percent change
  - US oil crop (soybeans): 7.4%
  - World: 4%

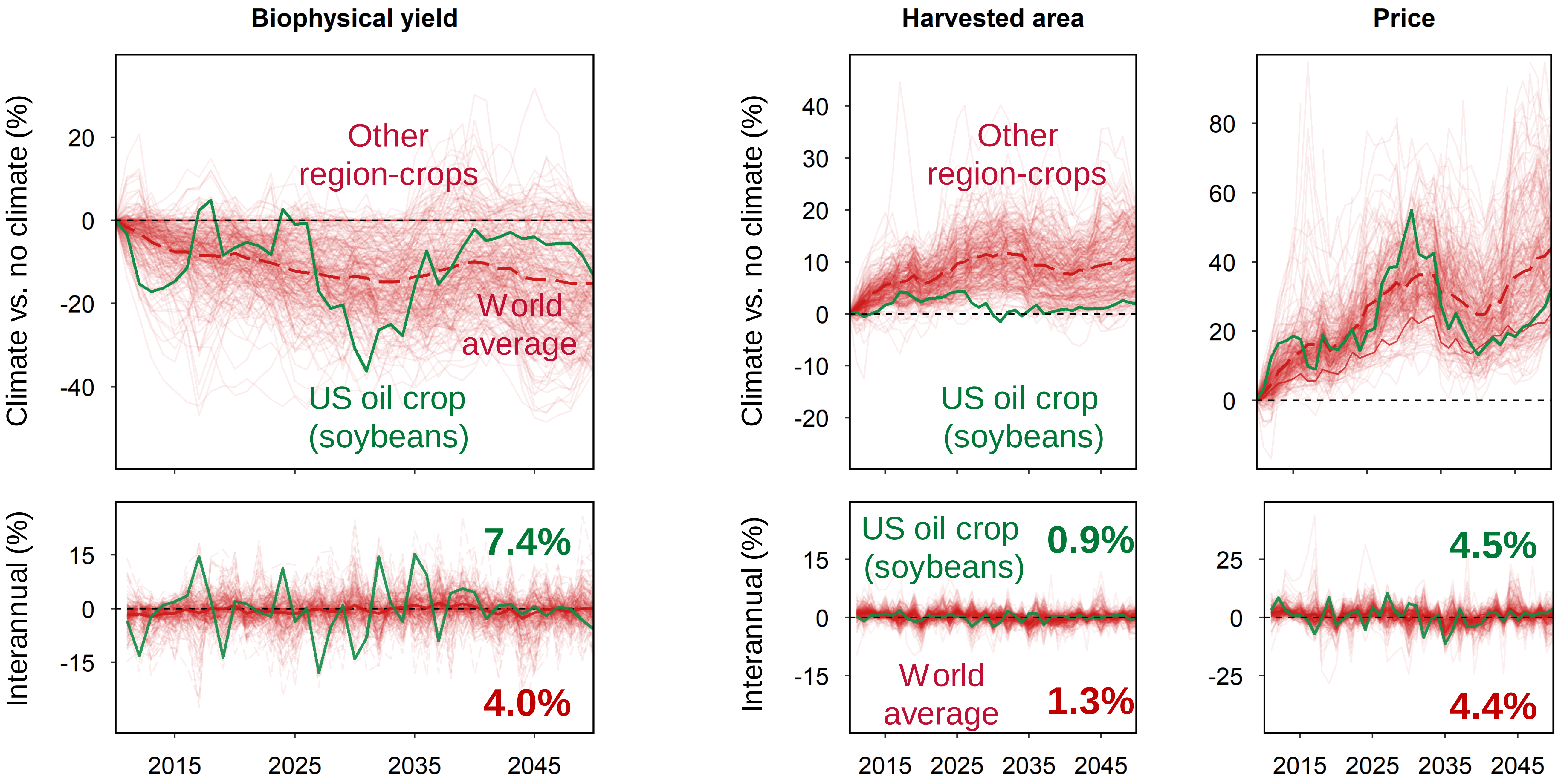
Climate impacts on agriculture
Original GCAM results



Climate impacts on agriculture
Run GCAM annually

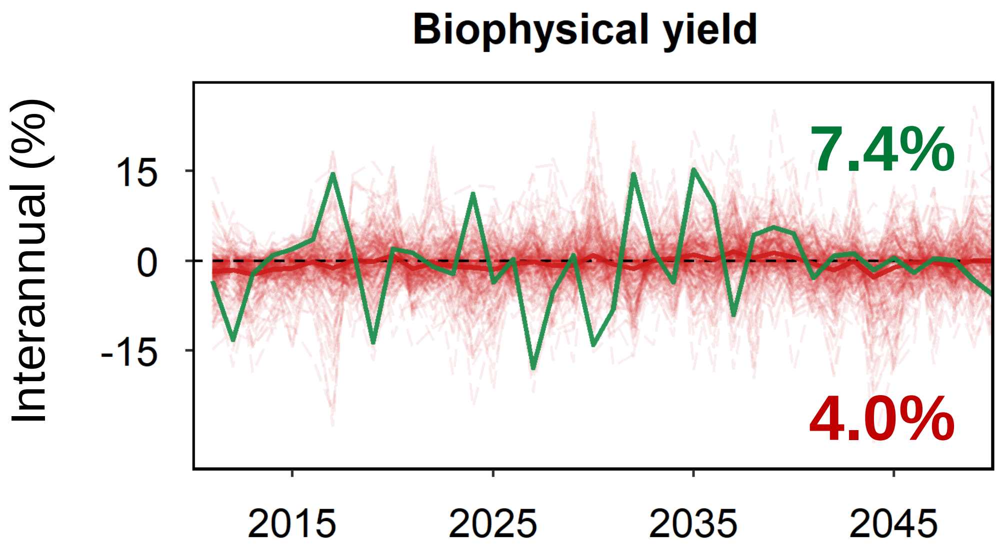


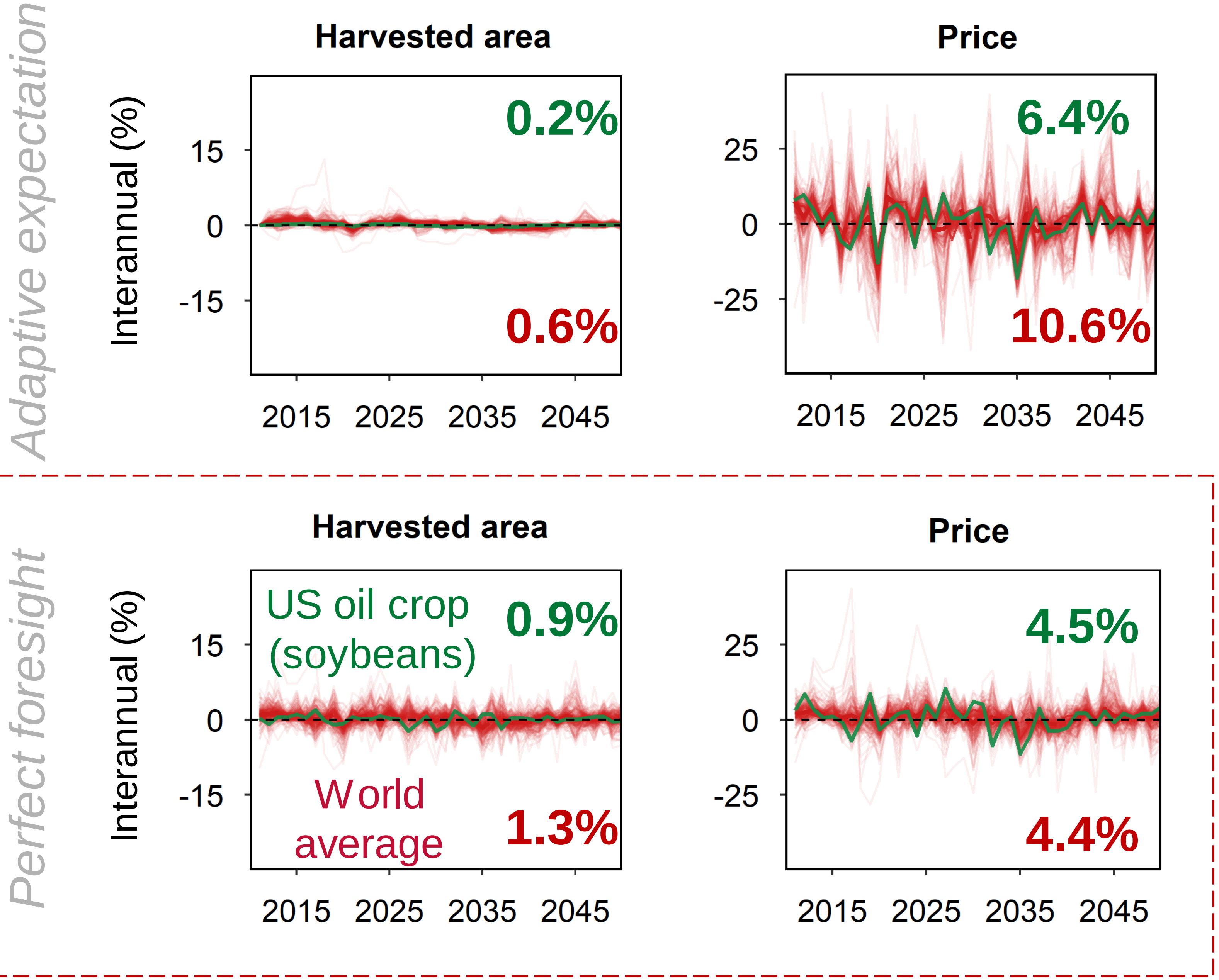
Climate impacts on agriculture
Run GCAM annually + all region-crops



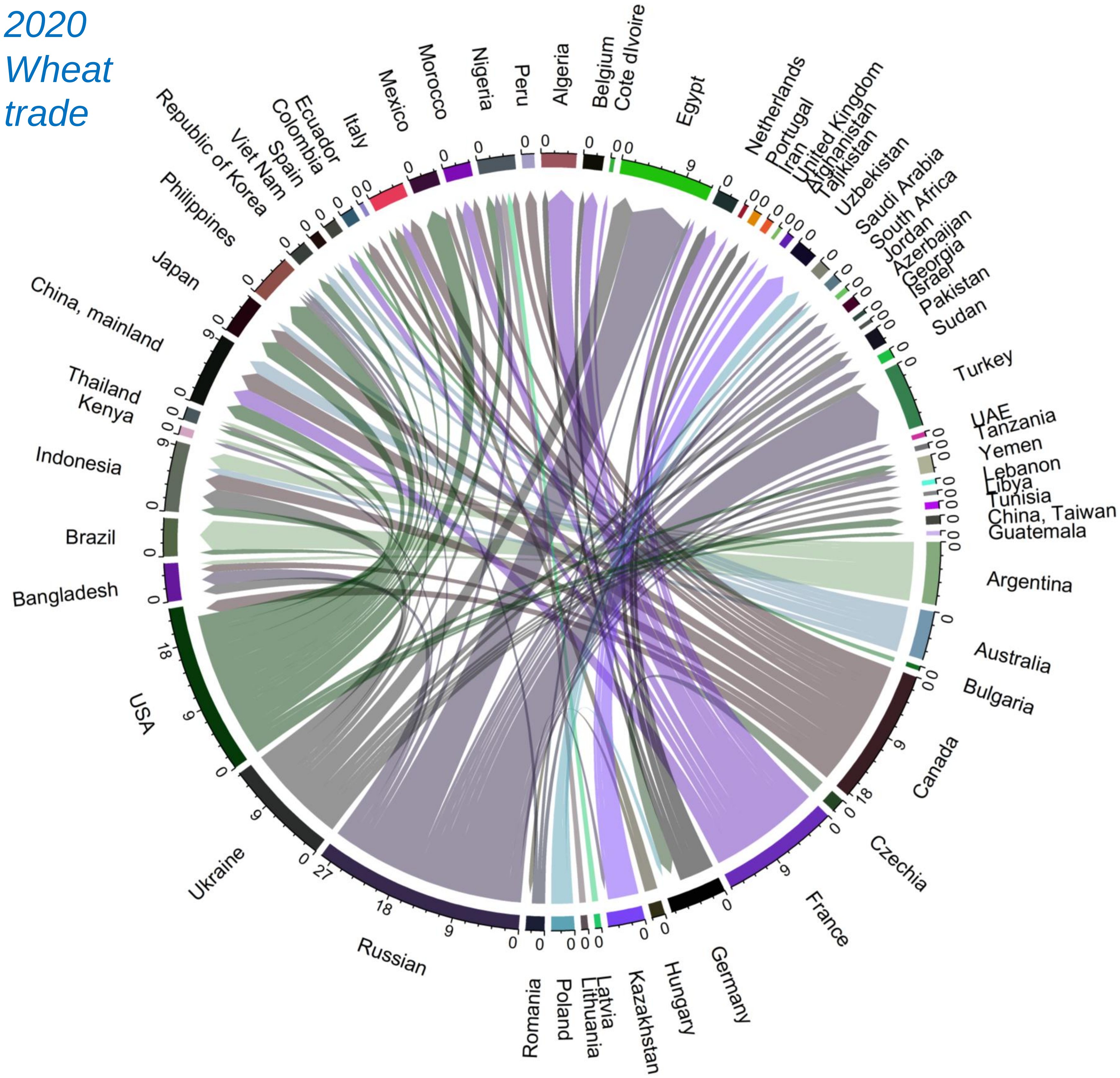
Climate impacts on agriculture
Adaptive expectations

- **Imperfect foresight**
- Smaller variation for area
  - Slower adaptation
  - Effectively more rigid acreage responses
- Higher price volatility
  - Endogenous market fluctuation





2020 Wheat trade

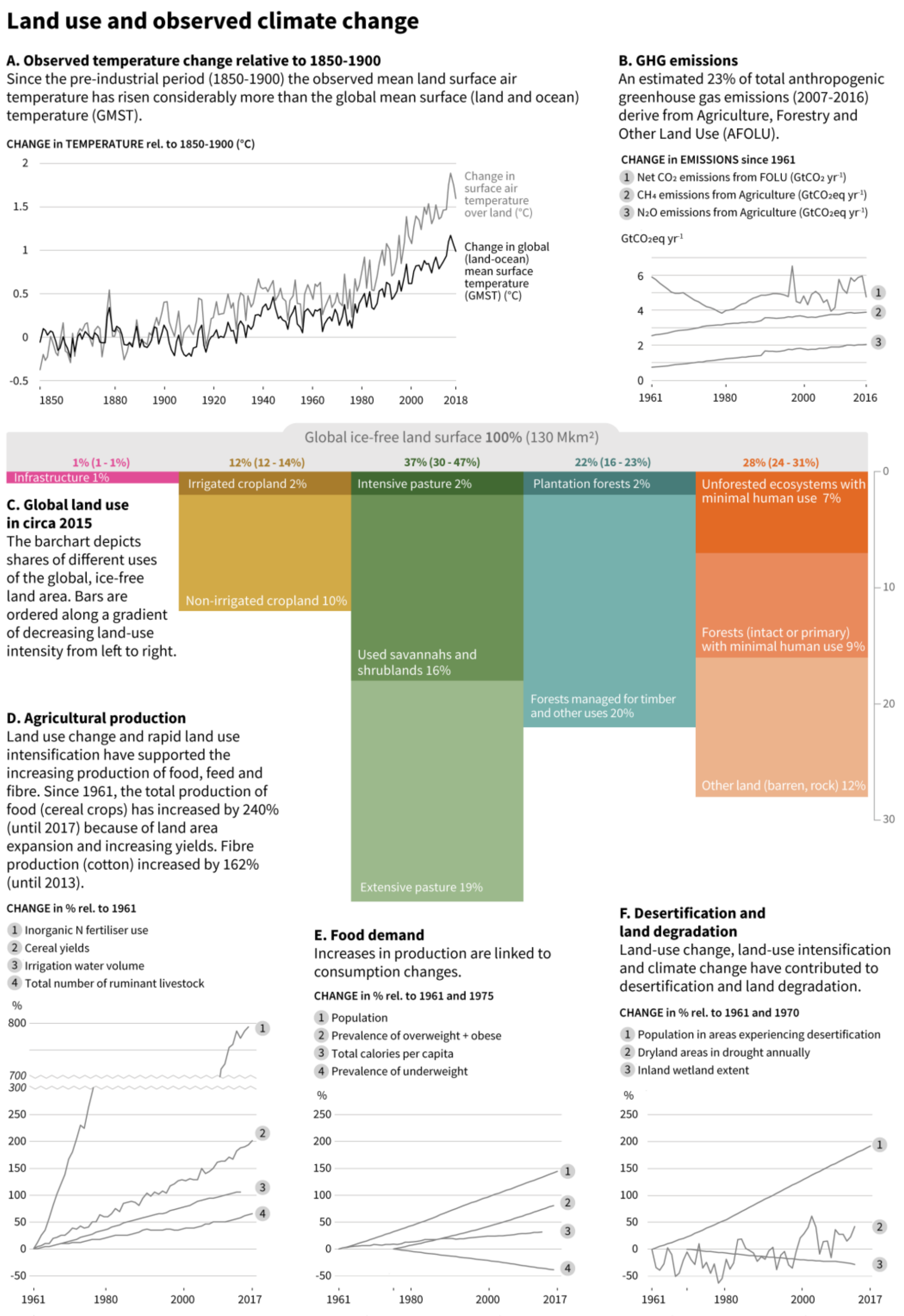


Teleconnected grain markets

- Price transmission in international grain markets

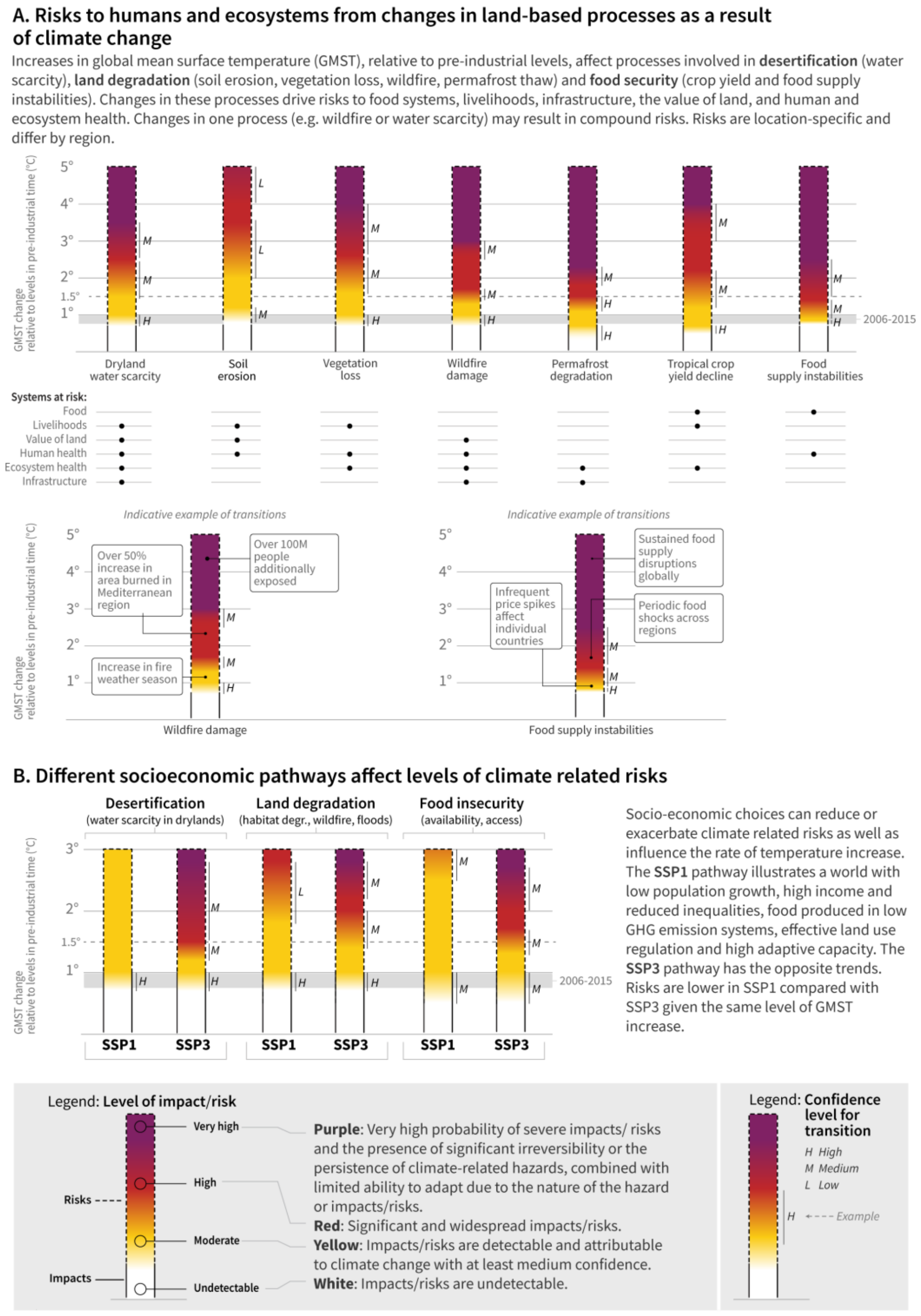
FAOSTAT; Zhao (2022); Rennison (2022);

Land: Past Trends and Current Status



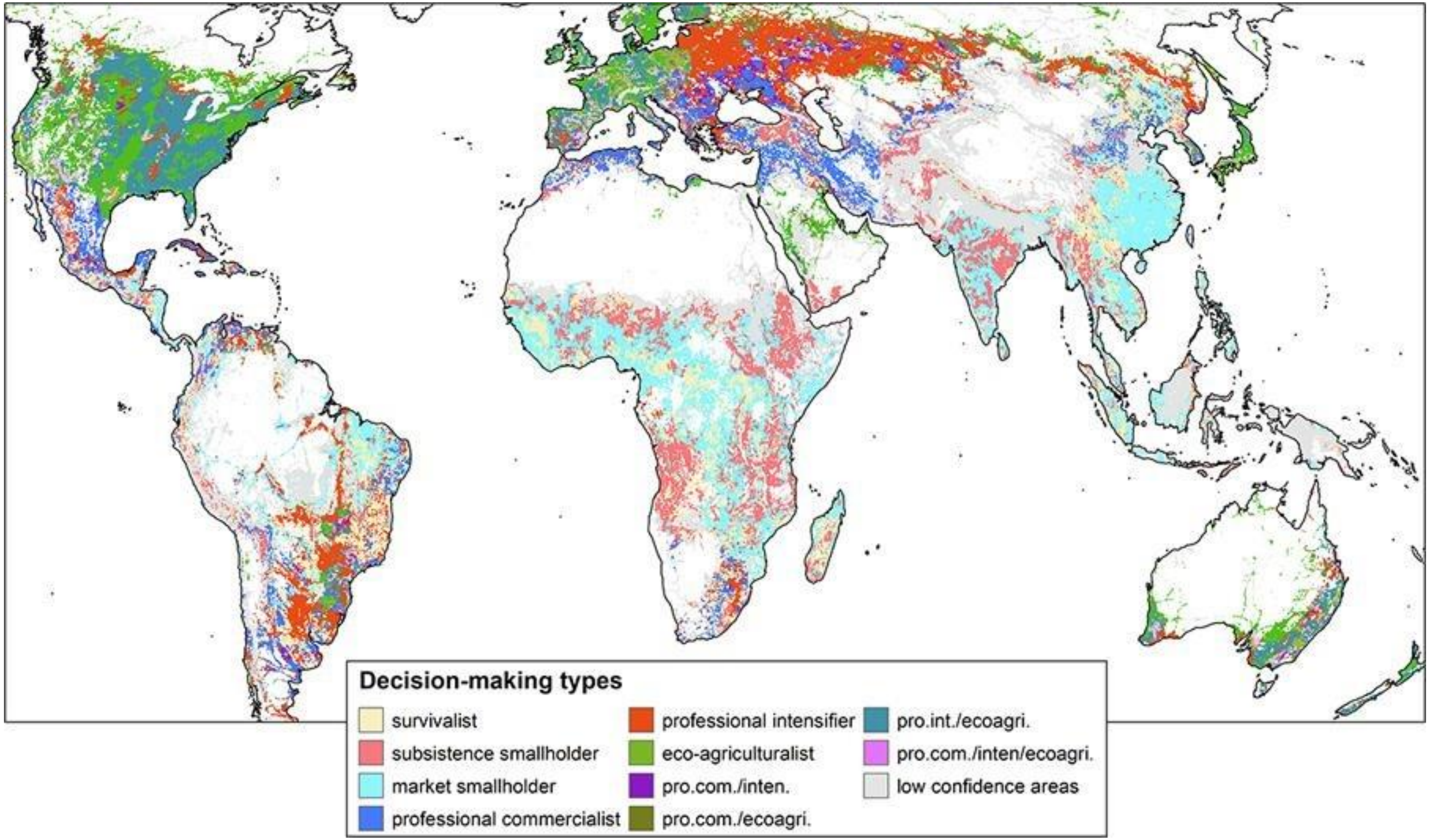
Source: IPCC SRCCL SPM

Land Systems at Risk from Climate Change



Source: IPCC SRCCL SPM Figure 2

Different types of land use decision-making



Source: Malek and Verburg (2020). https://doi.org/10.1016/j.gloenvcha.2020.102170

Different estimates of land cover

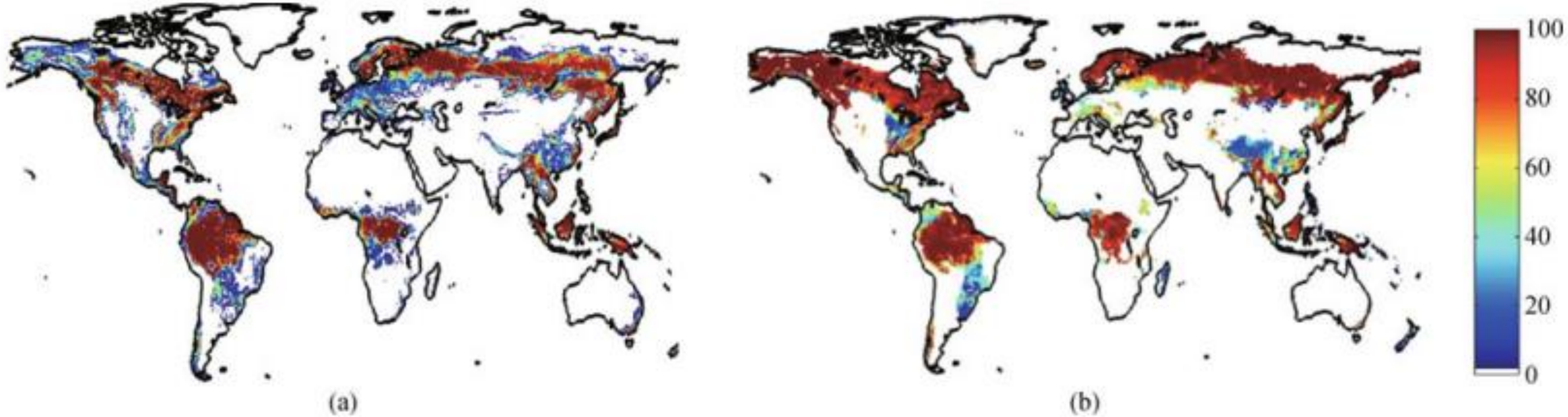
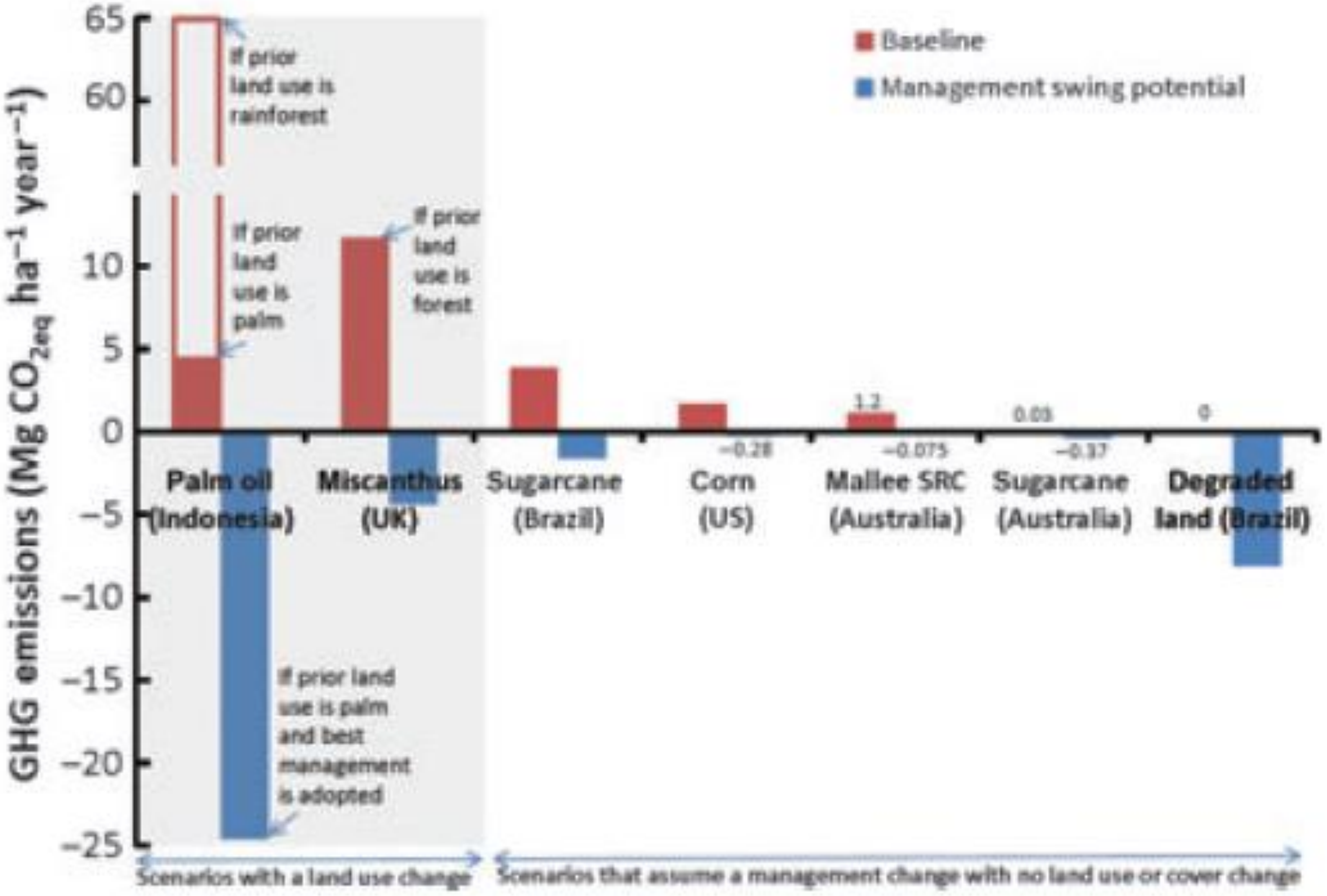


Fig. 1 Global distribution of forest area during 2005 based on (a) MODIS-IGBP data, and (b) estimates by Hurtt et al. (2011) (Unit: % per grid cell area)

Source: Meiyappan and Jain (2012). 10.1007/s11707-012-0314-2

Lots of site-specific information, but globally consistent data sets harder

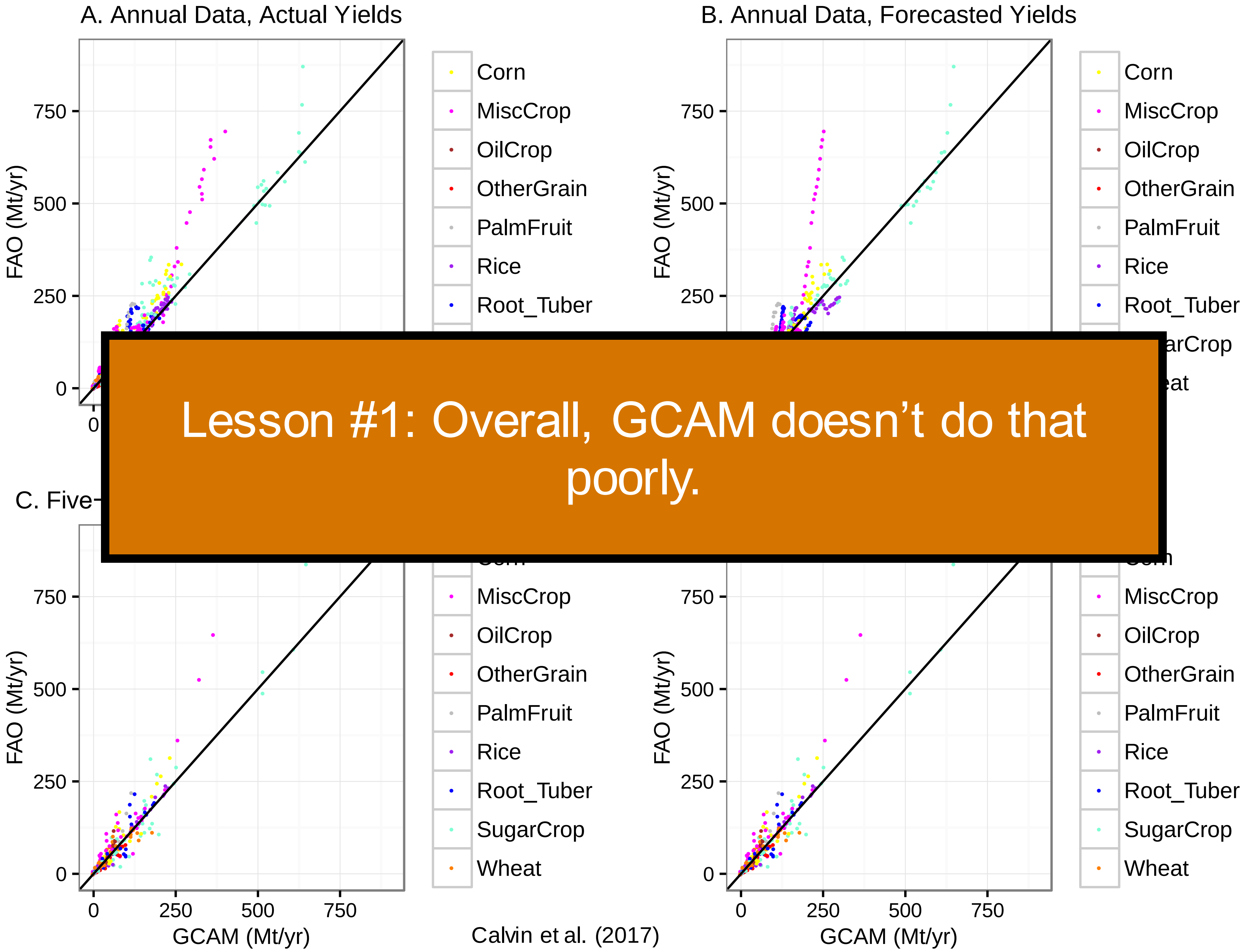


Source: Davis et al. (2013). 10.1111/gcbb.12042

Strengths of IAMs

- Long-term
- Interconnection with other systems
- Interconnection with other regions
- Emission trade-offs
- Help to answer what if questions

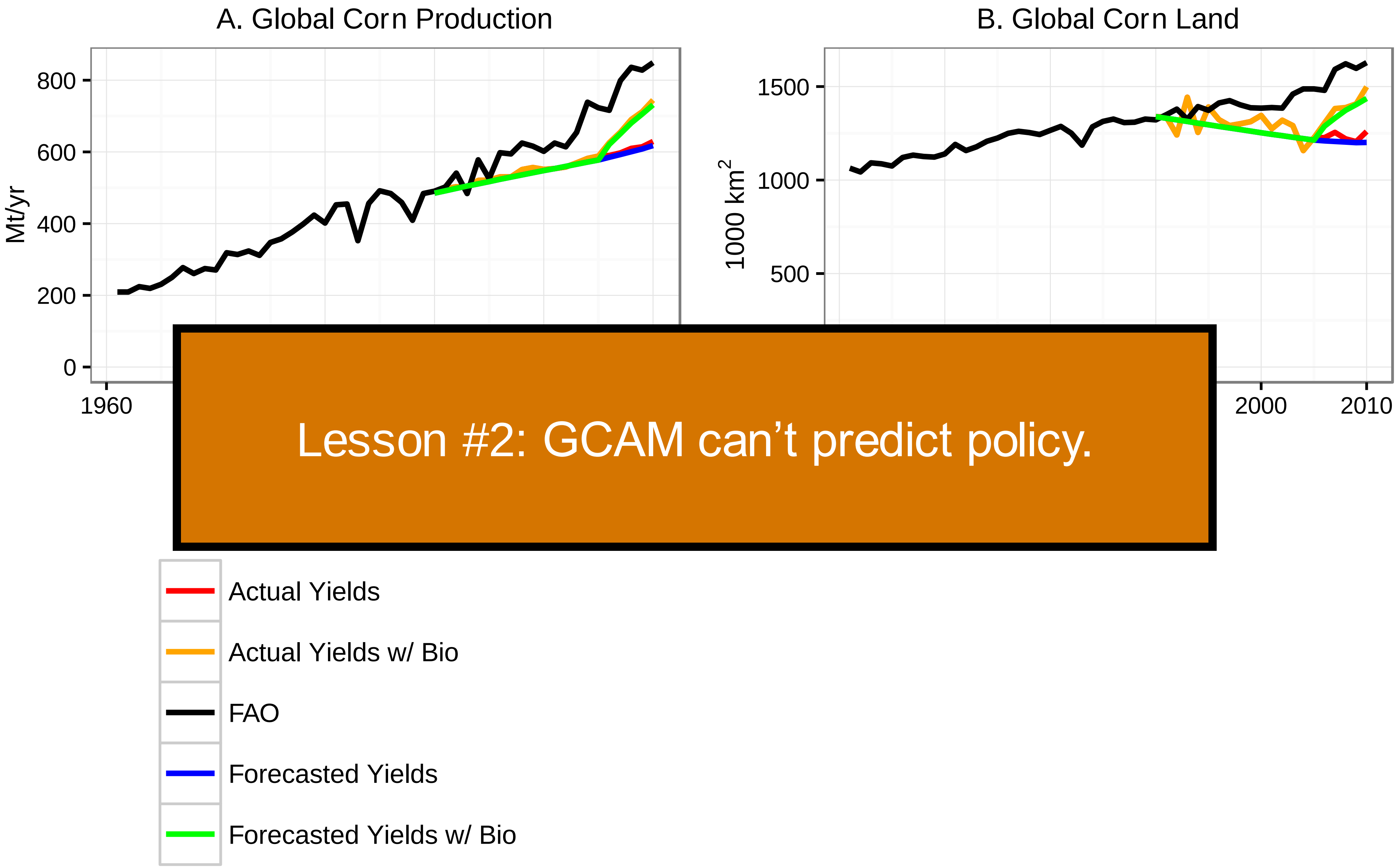
Learning from historical simulations within our own model.



Lesson #1: Overall, GCAM doesn't do that poorly.

Calvin et al. (2017)

Learning from historical simulations within our own model.



Lesson #2: GCAM can’t predict policy.

Calvin et al. (2017)

Learning from historical simulations within our own model.

Lesson #3: We do better at trends than inter-annual variability.

Calvin et al. (2017)

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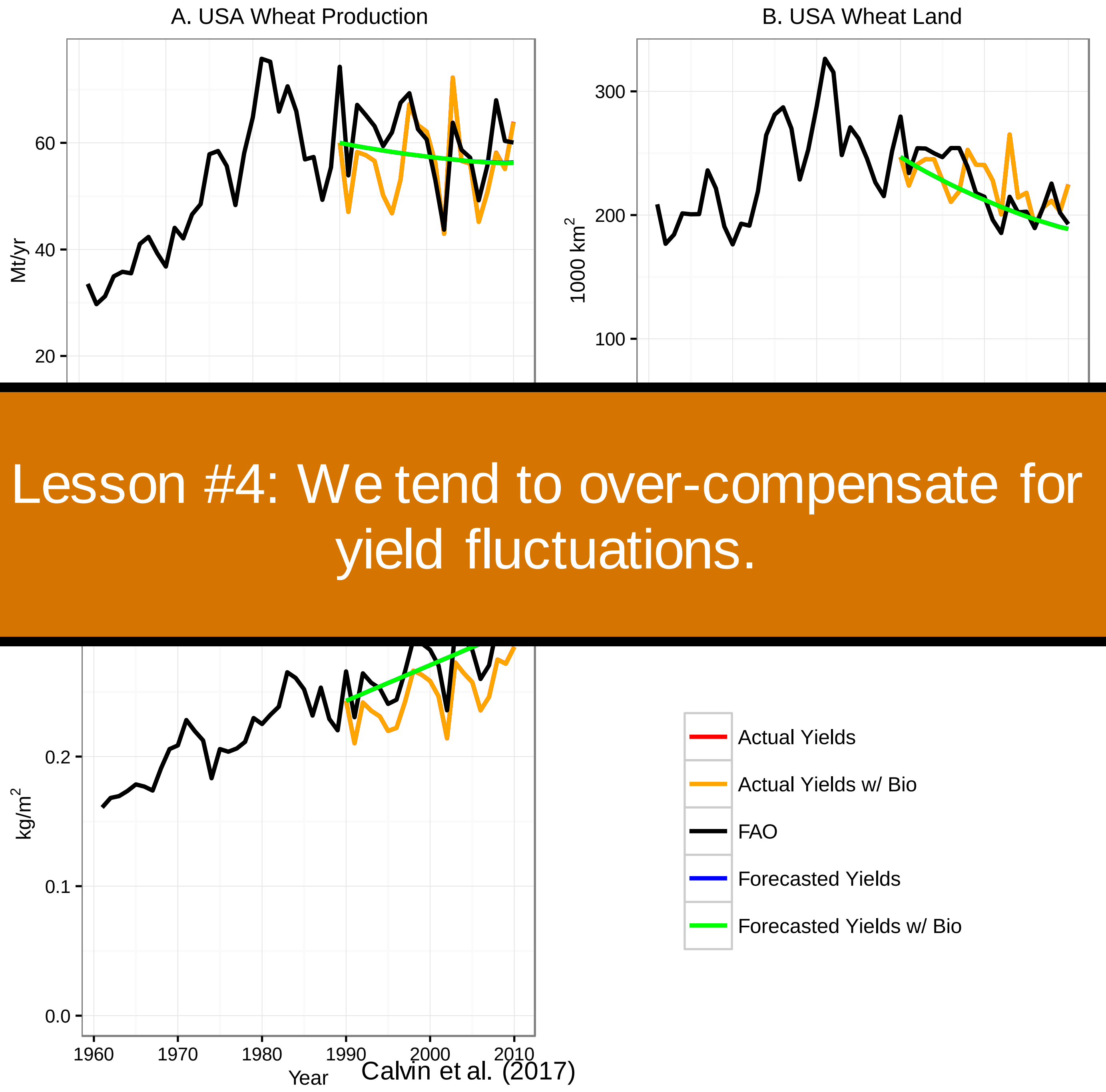
Learning from historical simulations within our own model.



Lesson #4: We tend to over-compensate for yield fluctuations.

Calvin et al. (2017)