

The Financial Toll of Climate-Induced Crop Losses



STEP 1

Fit statistical model

Panel regression model with T_{\max} and SPEI as independent predictors

$$Y_{ct} = \beta_T f_T(T_{ctg}) + \beta_S f_S(S_{ctg}) + \lambda_c + \alpha_{ct} + \epsilon_{ct}$$

STEP 2

Calculate yield impact

Grid-level yield impact calculated as the difference between the estimated and baseline yield

STEP 3

Get production & economic impact

Convert yield impact to production and economic impact using FAO producer price data

STEP 4

Get warming due to emitters

Get local growing season temperature increase due to Emitters' CO2 using rTCRE framework

$$dT_{ie} = E_e \Phi_i rTCRE$$

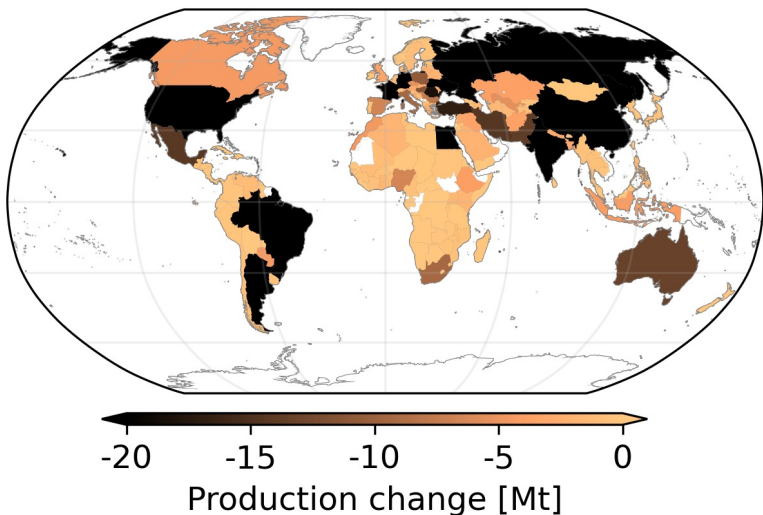
STEP 5

Attribute impacts to emitters

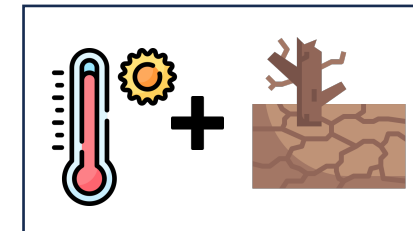
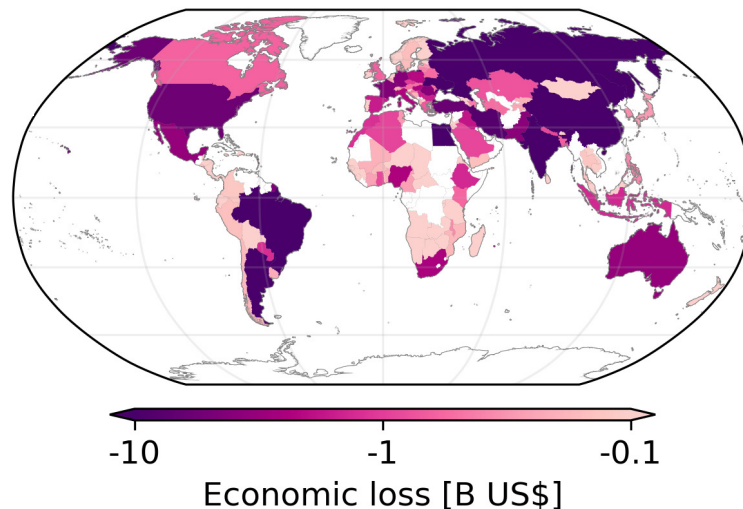
Apply fitted coefficient to estimate yield impact due to emitter-attributable warming; convert to economic impact

$$dy_{ite} = \beta_T f_T(T_{ig,base} + dT_{iet}) - \beta_T f_T(T_{ig,base})$$

Production impact [Mt]

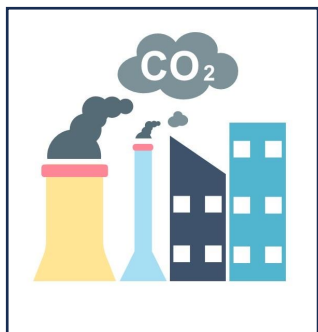


Economic impact [US\$]



- **855 Mt** of global crop losses
- **\$251 billion** in aggregated economic loss

Carbon Majors



- **427 Mt** global crop losses
- **\$119 billion** in heat-induced crop losses



Top 10% richest people

- **277 Mt** global crop losses
- **\$78 billion** in heat-induced crop losses

Preprint:



PICO screen

PICO2.11

The Financial Toll of Climate-Induced Crop Losses

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Background

- Detrimental impacts of **heat and drought** on global agriculture are well documented, but their **economic consequences** are underexplored.

Research Objectives

- Provide an estimate of future **climate driven financial impacts** from **global** agricultural losses using a statistical model based on heat and water stress.
- **Attribute heat-induced losses** to top **emitting** individuals and Carbon Majors.

Preprint:



Data

Source	Variable	Resolution
ISIMIP3a, 3b	T_{\max} , SPEI-3	0.5° × 0.5° grid-point cubic expansion, averaged over growing season, aggregated to national scales using national harvested-area weights
FAO	Crop yield, production, harvested-area for maize, wheat, and soybeans	National
	Producer prices [US\$/tonne]	National
	Irrigation fraction	5 arc-minute, coarsened to 0.5° × 0.5°
World Bank	GDP (historical)	National
Koch & Leimbach (2023)	GDP (SSP projection)	National

Time periods

- Model **fitting** and **study** period: 2007-2019
- SPEI-3 **calibration** reference period: 1974-2004
- Historical and SSP impact **baseline** period: 1974-2004

Statistical Model

- Statistical model (**panel regression**) with **climate** variables (T_{\max} and SPEI-3) as independent predictors, controlling for country-specific fixed effect and long-term time trend (Proctor et al., 2022)

$$Y_{ct} = \beta_T f_T T_{ctg} + \beta_S f_S S_{ctg} + \lambda_c + \alpha_c t + \epsilon_{ct} \quad (1)$$

Y_{ct}

Crop yield for country c and year t

T_{ctg}, S_{ctg}

mean **growing season** T_{\max} and SPEI-3 for country c and year t

β_T, β_S

Regression coefficients

$f_T(\cdot), f_S(\cdot)$

Cubic expansions of grid-point values, spatially averaged to country-level using HA weighting

λ_c

Fixed effect for **time-invariant** differences between countries (e.g., soil type)

$\alpha_c t$

Within-country linear **time trend** (e.g., technological adoption)

Complementary Statistical Models

- Panel regression model including **irrigation** terms (I_c)

$$Y_{ct} = \beta_T f_T T_{ctg} + \beta_S f_S S_{ctg} + \beta_{TI} f_T(T_{ctg} I_c) + \beta_{SI} f_S(S_{ctg} I_c) + \lambda_c + \alpha_c t + \epsilon_{ct} \quad (2)$$

- Panel regression model including **interaction** terms between T_{\max} & SPEI-3

$$Y_{ct} = \beta_T f_T(T_{ctg}) + \beta_S f_S(S_{ctg}) + \beta_{TS} f_{TS}(T_{ctg} \cdot S_{ctg}) + \lambda_c + \alpha_c t + \epsilon_{ct} \quad (3)$$

$f_T(\cdot), f_S(\cdot)$
 $f_{TS}(\cdot)$

Quadratic expansions of grid-point values
Quadratic polynomial TS, T²S, TS², T²S²

Model Evaluation

- Model evaluation: out-of-sample (**OOS**) cross-validation **within- R^2**
 - **within- R^2** : share of yield variation explained solely by **climate** variables after removing fixed effects and time trends
- **Two** methods to estimate within- R^2 :
 - Random 10-fold CV
 - Blocked leave-one-year-out (LOYO) CV

Crop	Model	Overall adjusted R^2	Random CV R^2	Blocked CV R^2
Maize	t3s3	0.96	0.030	0.019
	t3s3_irr	0.96	0.021	0.018
	t2s2_int	0.96	0.018	0.003
Wheat	t3s3	0.93	0.064	0.059
	t3s3_irr	0.93	0.063	0.062
	t2s2_int	0.93	0.068	0.062
Soybeans	t3s3	0.89	0.077	0.053
	t3s3_irr	0.89	0.077	0.033
	t2s2_int	0.89	0.072	0.052
All	t3s3	0.70	0.057	0.047
	t3s3_irr	0.70	0.058	0.048
	t2s2_int	0.70	0.052	0.042

Impact Calculations (1)

- Yearly grid-level yield impact (dy_{it}) [%]: change in yield relative to **baseline** yield, using the **β coefficients** from the fitted model

$$dy_{it} = [\beta_T f_T T_{itg} + \beta_S f_S S_{itg}] - [\beta_T f_T T_{ig,base} + \beta_S f_S S_{ig,base}] \quad (4)$$

- Aggregated to **country** level using **harvested-area** (HA) weighting:

$$dy_{ct} = \sum_{i \in c} dy_{it} \frac{HA_i}{\sum_{i \in c} HA_i} \quad (5)$$

- National **production** impact (dp_{ct}) [ton]:

$$dp_{ct} = dy_{ct} y_{ct} HA_{ct} \quad (6)$$

Impact Calculations (2)

- Production losses (dp) are converted to **economic** impacts (de) [US\$] using crop-specific **producer prices** PP [US\$/ton] from FAO:

$$de_{ct} = dp_{ct}PP_{ct} \quad (7)$$

- Economic losses **relative** to national economies ($degdp$)[%]:

$$degdp_{ct} = \frac{de_{ct}}{GDP_{ct}} \quad (8)$$

Impact Attribution to Emitters

- Use nonlinear β_T coefficients of temperature from the fitted model to estimate yield impacts of warming induced by emissions from groups of emitters:

$$dT_{ie} = E_e \cdot \Phi_i \cdot rTCRE \quad (9)$$

$$\Phi_i = \frac{dT_{ig}}{dT_i} \quad (10)$$

- Grid-point yield impact due to emitter-attributable warming (dT_{ie}):

$$dy_{ite} = \beta_T f_T(T_{ig,base} + dT_{iet}) - \beta_T f_T(T_{ig,base}) \quad (11)$$

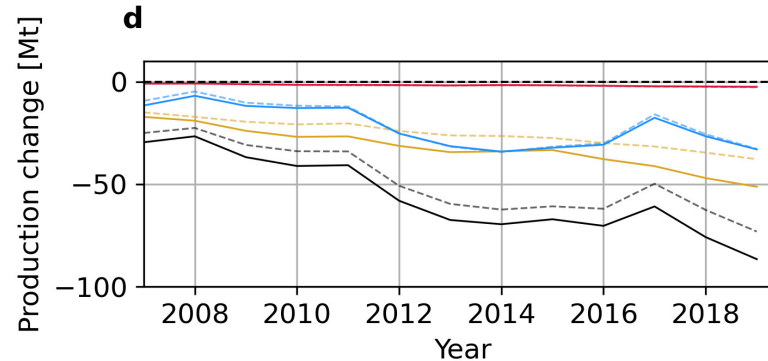
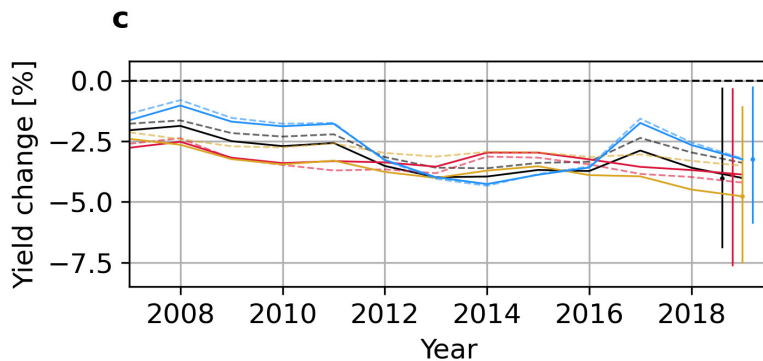
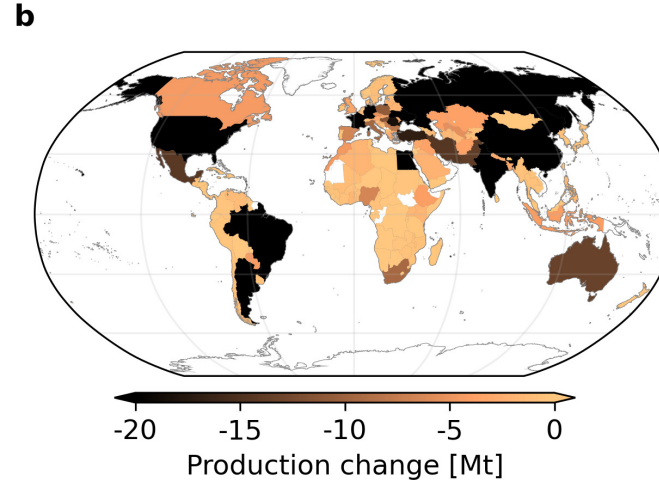
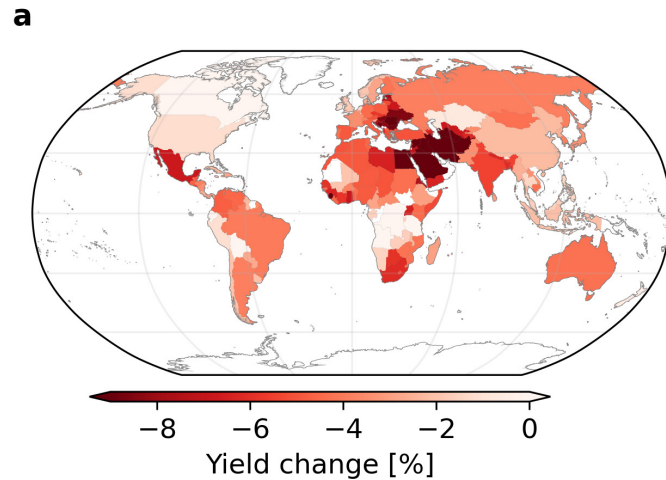
- Corresponding country-level, emitter-attributable yield, production and economic impact calculated using equations 5-8

For country c, what are the yield, production and economic losses of a given crop, attributable to the warming caused by emissions from emitter E_e ?

Results

Historical Crop Yield and Production Impact

- **Global** losses from extreme heat and drought:
 - 3.48% of baseline
 - 855 Mt
- **LDCs** comparable yield losses ([%]) with developed nations, despite smaller production losses

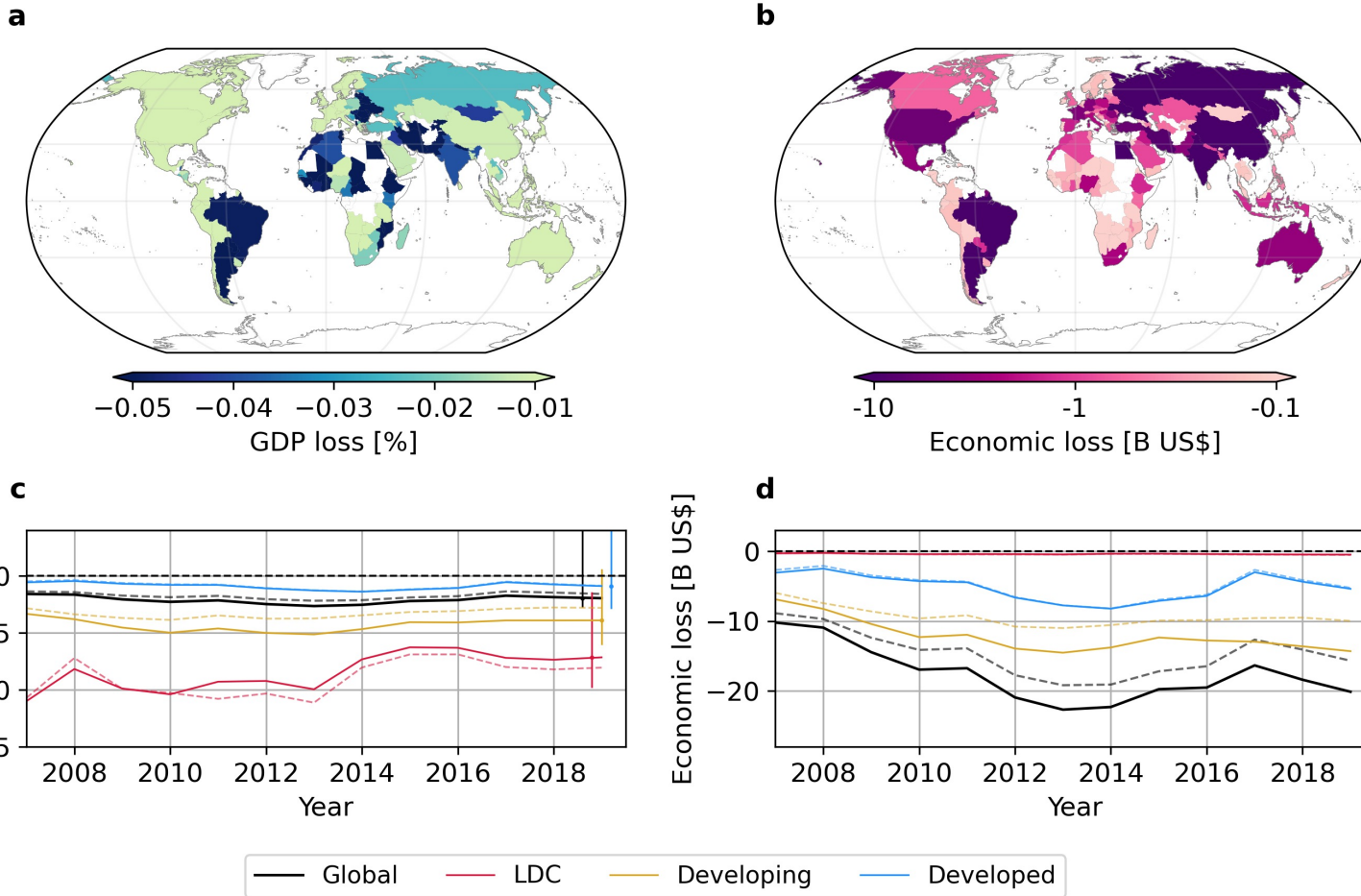


— Global — LDC — Developing — Developed

*Solid lines = main model; dashed lines = model with irrigation terms

Historical Economic Impact

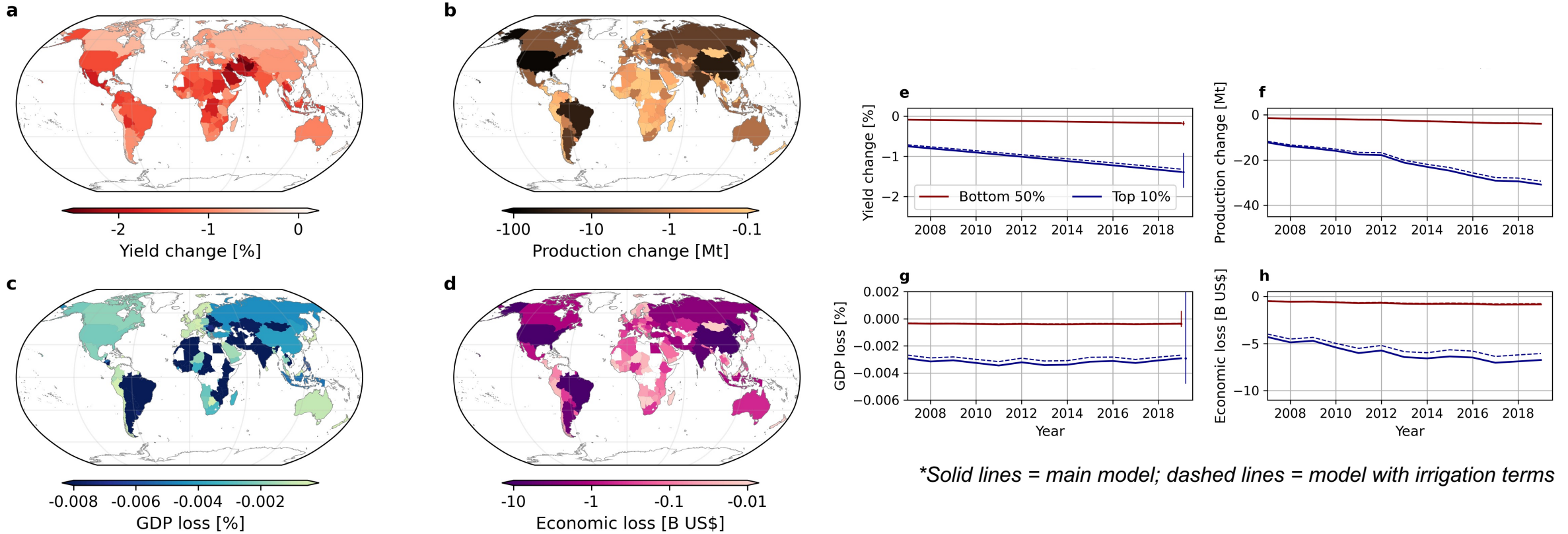
- **Global** economic losses
 - 0.04% of GDP
 - \$251 billion
- Much more severe **relative** consequences for LDCs



*Solid lines = main model; dashed lines = model with irrigation terms

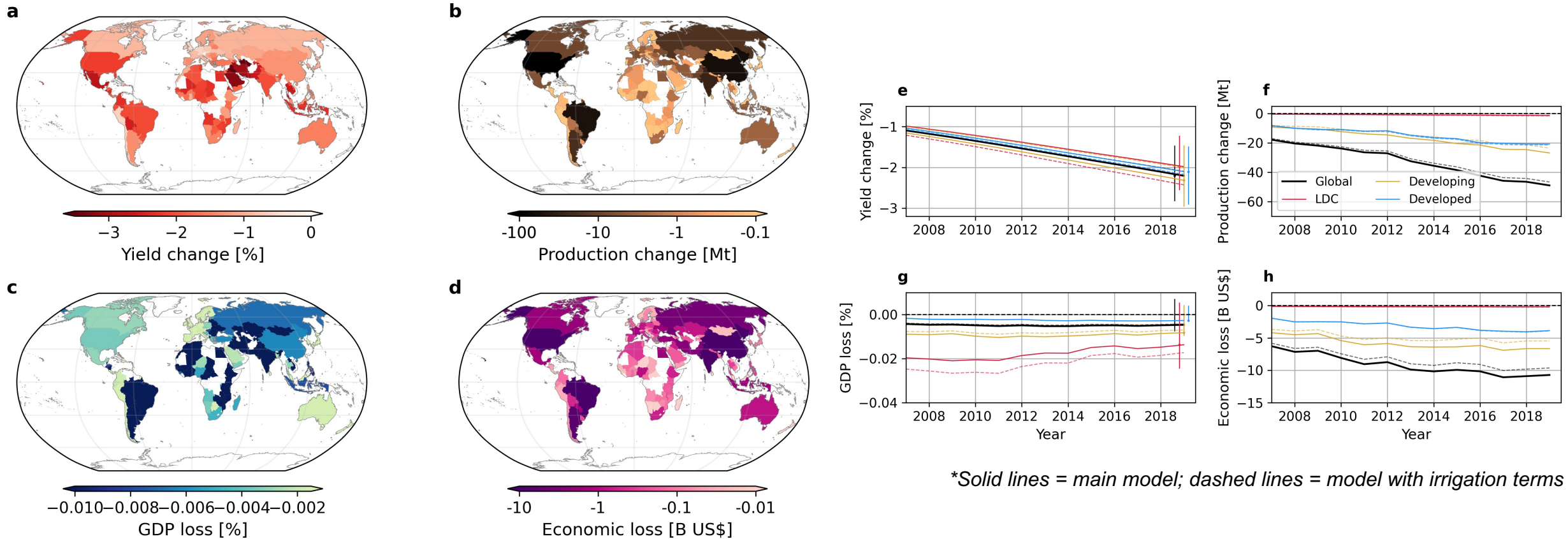
	USA	Malawi
de	\$6 billion	\$0.2 billion
degdp	0.001 %	0.34 %
pop in agri.	2 %	65 %

Losses Attributable to Richest Individuals



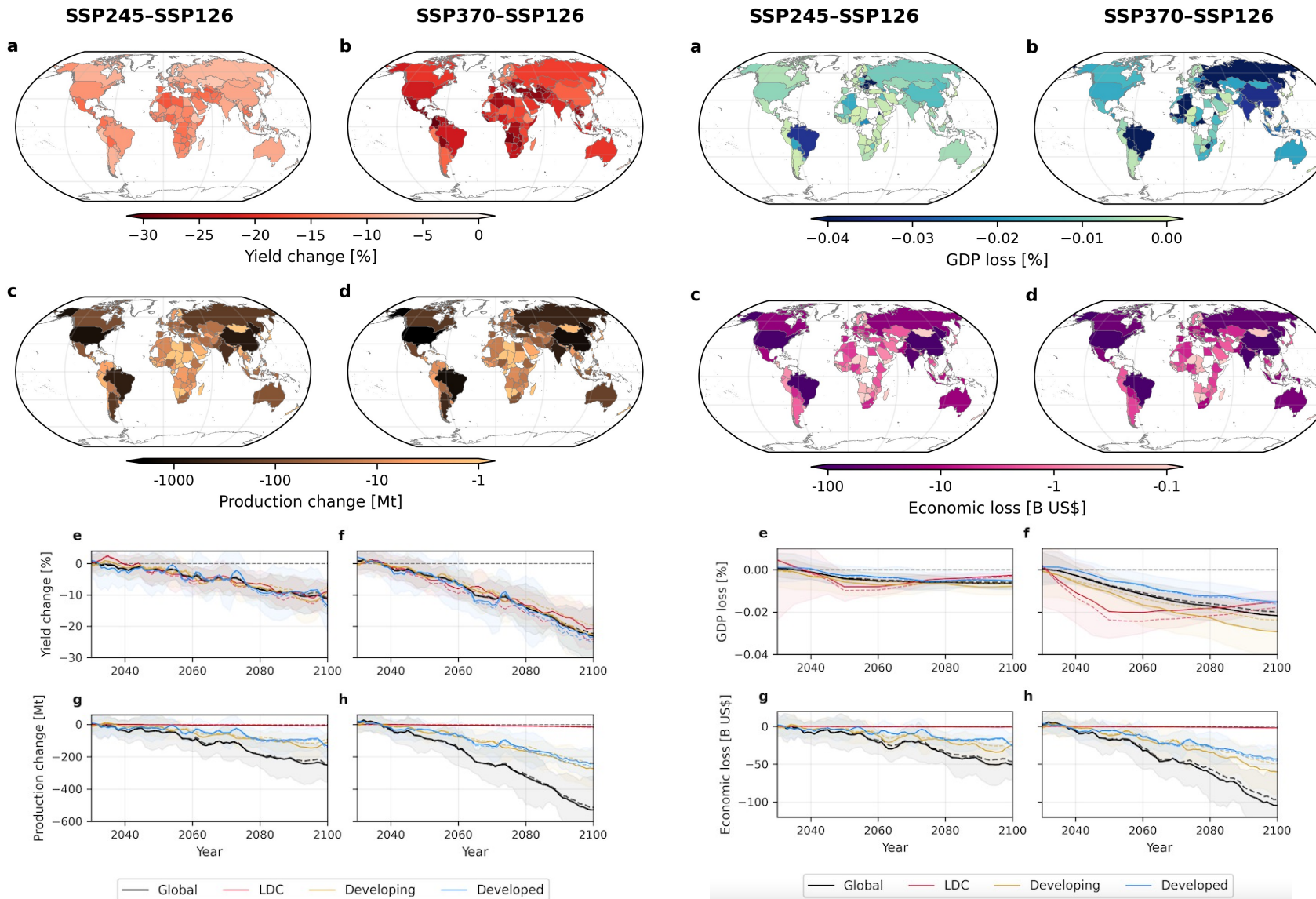
- CO₂ emissions from the **richest 10%** (232.6 GtCO₂) accounted for over **eight times** more of the global production and economic losses (54.2% vs. 6.6% of total) than those from the **poorest 50%** (32.6 GtCO₂).

Losses Attributable to Carbon Majors



- CO₂ emissions from the **Carbon Majors** (322.9 GtCO₂) linked to **427 Mt (\$119 billion)** in crop losses

Projected Crop Losses from Heat and Drought



- **Global** economic losses could increase from \$20 billion (2019) to **\$161 billion** (2100) under SSP3-7.0

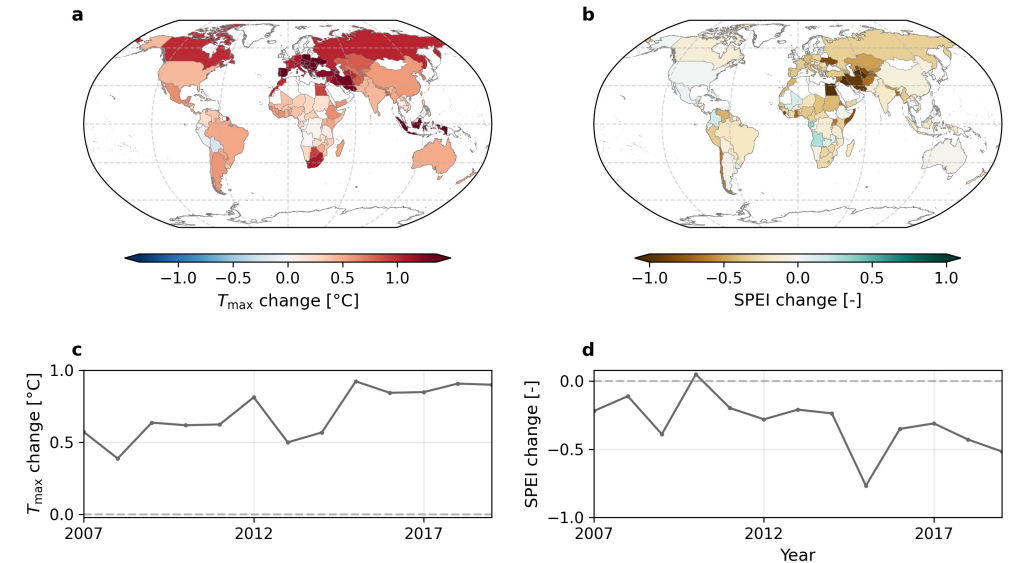
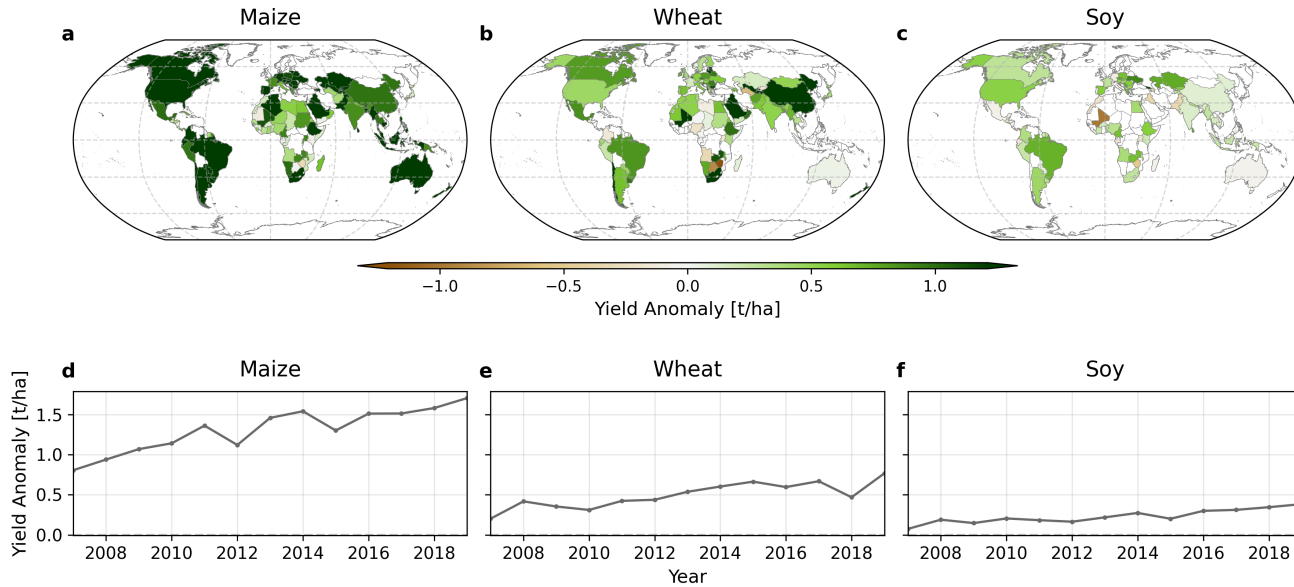
- Following **SSP1-2.6** could avoid **\$105 billion** of these damages

Summary

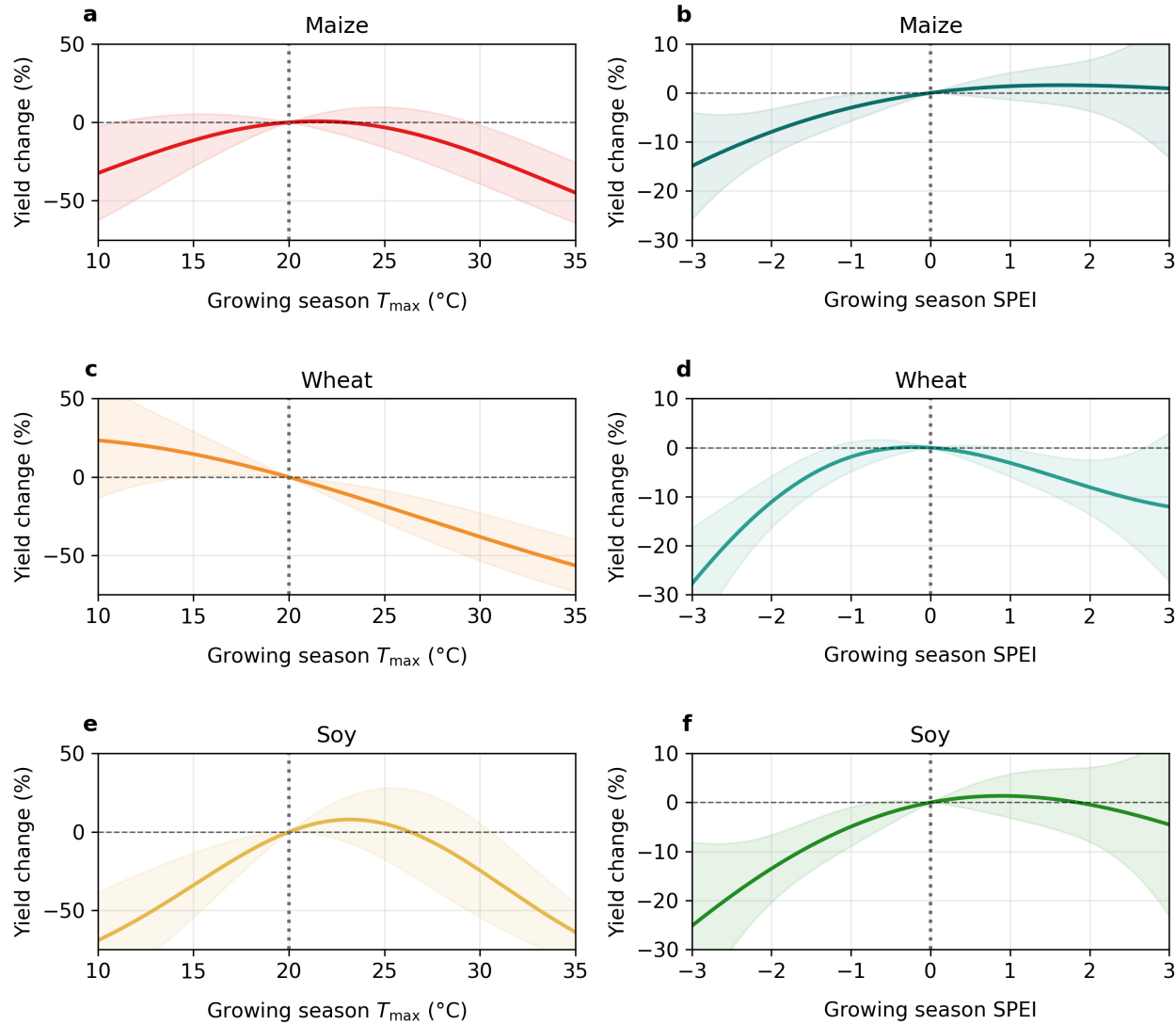
- We develop a statistical model to assess the impact of extreme **heat and drought** on crop yield, and estimate the resulting **economic losses**
- As a percent of GDP, **less-developed** countries experience the **highest economic losses**, despite their absolute losses in US dollars being much smaller than those of developed countries.
- The **richest 10%** caused **over 8x** the economic damage of the poorest 50%, while **Carbon Majors'** emissions are linked to \$119 billion in economic losses
- The world stands to **save** approximately **\$105 billion** annually by 2100 when following SSP1-2.6 compared to SSP3-7.0

Additional Results

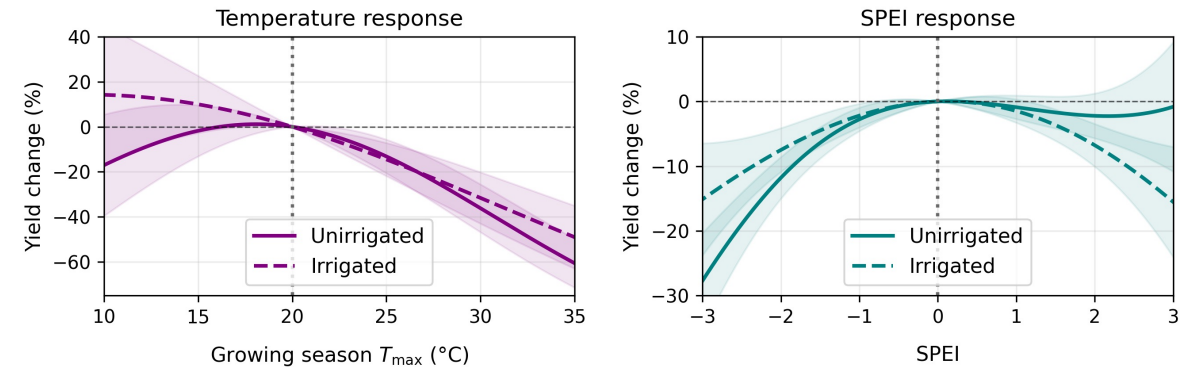
Historical Crop Yield and Climate



Response Curves of Fitted Model

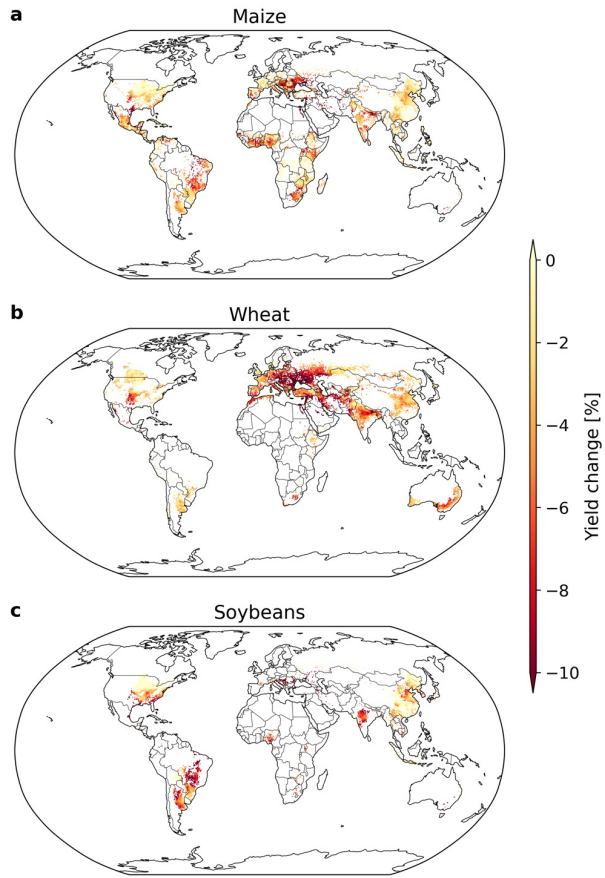


Irrigated vs. un-irrigated

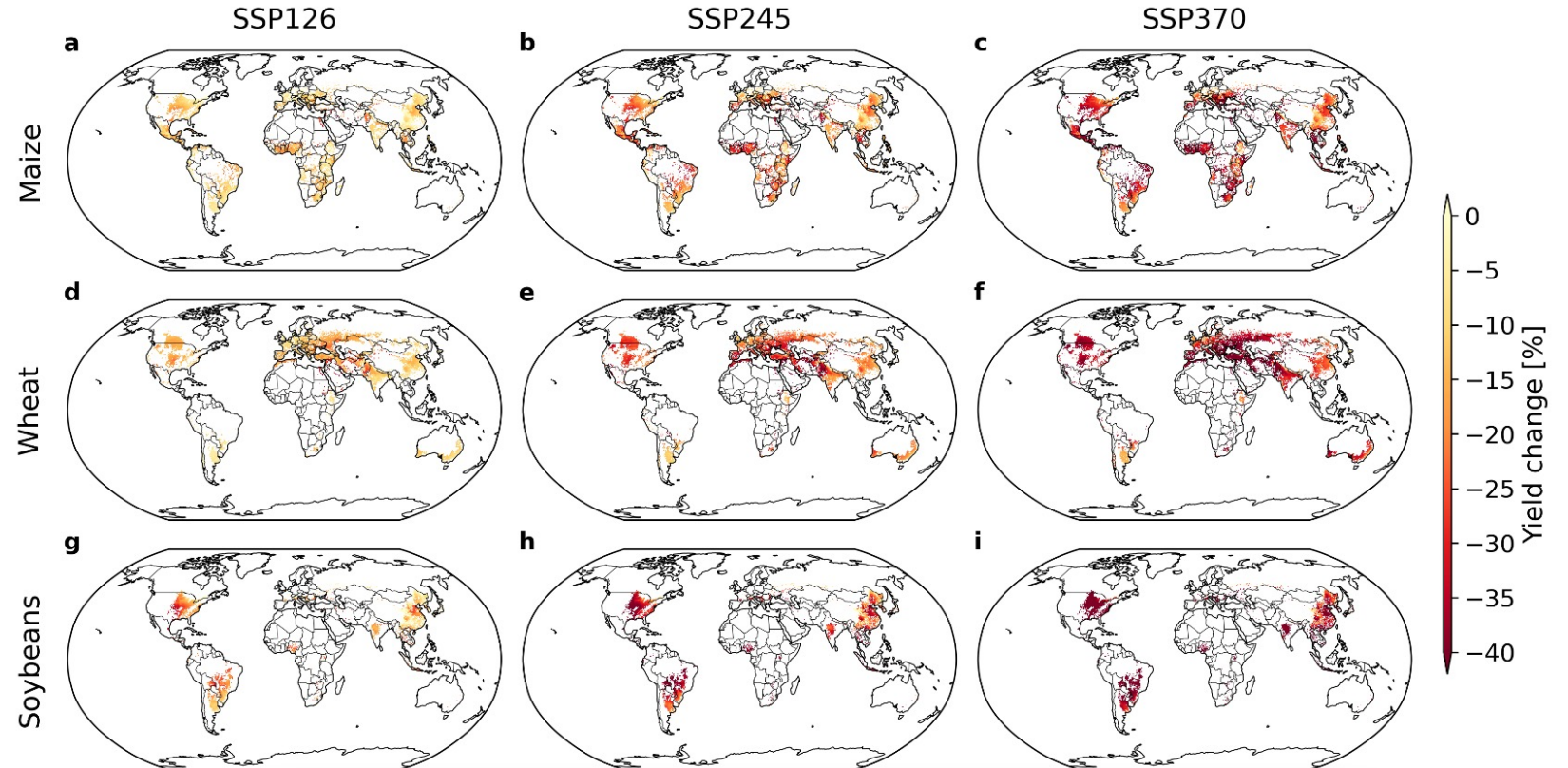


Gridded Yield Loss

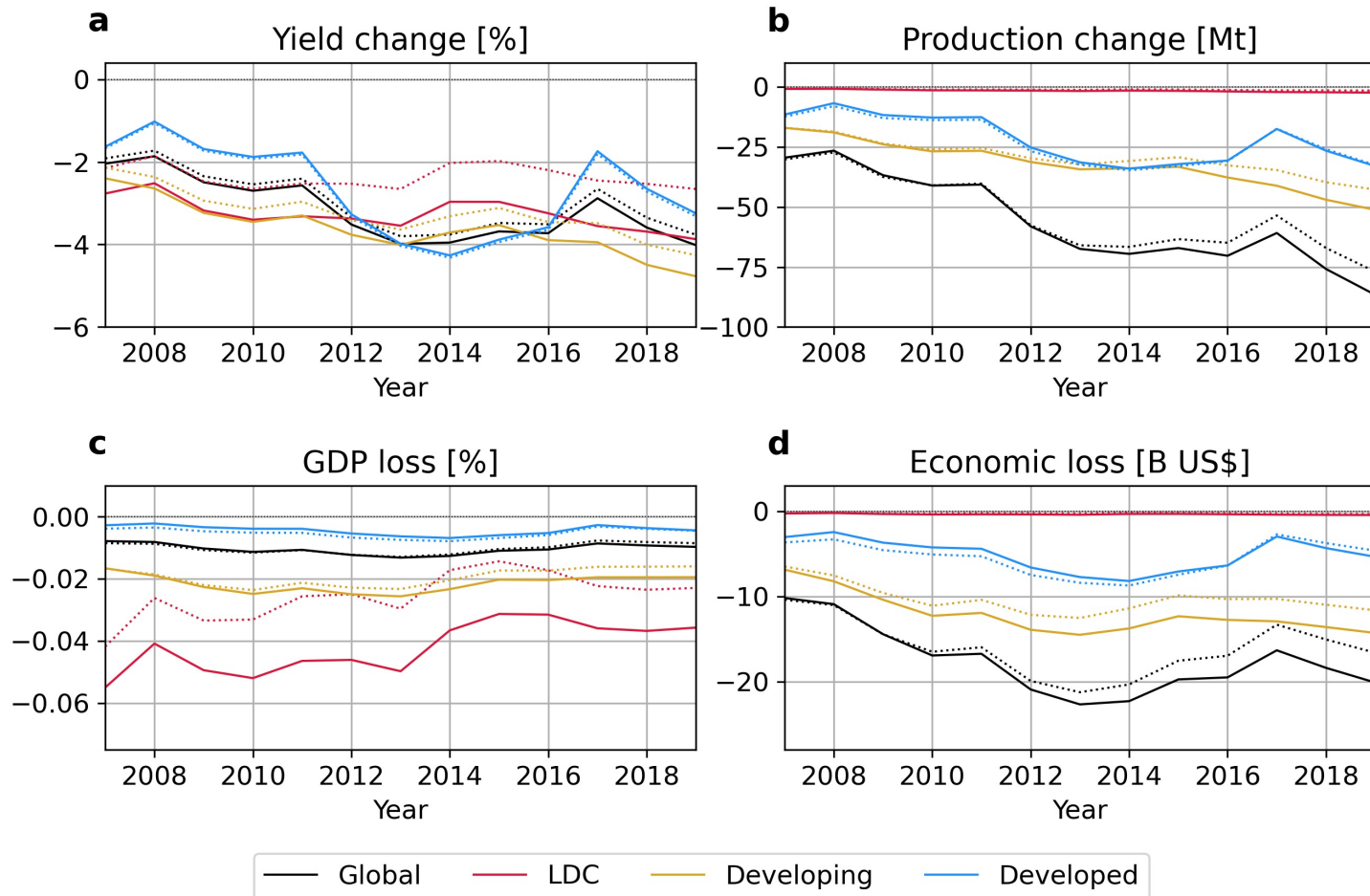
Historical



Future SSPs



CO₂ Fertilization Effect



- Post-hoc adjustment for **CO₂ effect** using CO₂ fertilization meta-regression analysis coefficients from Zhu et al. (2023)

*Solid lines = main model; dotted lines = with post-hoc CO₂ effect correction