Impacts of climate and biophysical variability on global agriculture markets

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Summary

Agricultural production is highly sensitive to changes in climate and weather patterns[1,2]. The focus of the great majority of studies assessing climate impacts on agriculture has been on mean changes in agricultural responses[3,4]. However, the manner in which global agricultural markets respond to the interannual variability of the climate and biophysical shocks is poorly understood. Here we show a strong transmission of interannual variations in climate-induced biophysical yield shocks to agriculture markets, which is magnified further by endogenous market fluctuations. We demonstrate the importance of imperfect versus perfect expectations of market and weather in generating the market fluctuations that play a key role in transferring the interannual variations to markets. We find that the volatility of market prices and consumption could be potentially reduced on average by 55% and 41%, respectively, with improved expectations, where agricultural producers make better decisions to adapt to climate and biophysical variability. We also find much heterogeneity in interannual variability across crops and regions, which is considerably mediated by trade as part of the economic response. Our study provides new insights on climate impacts on agricultural market variability and lays a foundation for further investigating the full range of climate impacts on biophysical and human systems.

Climate is essentially an indirect input to agricultural production, and its economic impacts on agriculture have been extensively assessed in the past three decades[3,5,6]. The assessment requires a combined use of climate, crop, and economic models to translate climate and biophysical shocks to changes in economic variables such as agricultural production, price, and land use[3,4]. With the advances in the understanding of the biophysical consequences of changes in temperature, precipitation, and other climate variables on agriculture[1,3], study focuses are shifting from mean to the variability of future climate and biophysical shocks[7-9]. Interannual variability, in particular, is an important characteristic of climate and biophysical shocks. However, how interannual variations in climate and biophysical shocks are transformed and transferred to global agricultural markets has been overlooked[10]. Previous studies focused on assessing economic consequences of climate impacts at a future period (e.g., 2050) as most economic models were designed for mid- or long-term projections. More importantly, perfect foresight has been a standard assumption used in economic modeling even though its lack of realism has been criticized[11,12]. With perfect foresight, agricultural producers could perfectly predict future climate and market information and make adaptations accordingly and immediately (e.g., adjusting land allocation to compensate for changes in productivity). Nevertheless, for understanding dynamics in the agricultural market, it is undisputed that farmers make suboptimal decisions due to the biological time lag between planting and harvesting. In reality, farmers make production, land allocation, and management decisions based on their expectations of future yield and prices. As a result, erroneous expectations of prices and yield due to imperfect foresight could generate endogenous market fluctuations in addition to the variability stemmed from exogenous climate and biophysical shocks. Ignoring endogenous market fluctuations may lead to misleading assessments of the interannual variability (IAV) of agricultural economics[13].

Studying the trend and variability of climate impacts can be more useful than a future time point estimation. On the one hand, changes in the variability of climate and weather patterns will have considerable consequences on agricultural production and market fluctuation[7]. On the other hand, understanding the interannual variability of the climate impacts on agricultural economics is crucial to formulating agricultural policies that facilitate agricultural adaptation and maintain food security. In this work, we develop a modeling framework to quantify the interannual variability of climate impacts on agriculture. We incorporate adaptive expectations[14] of prices and yield into a well-established global economic model, GCAM, and run the model in annual time step (**Method**). That is, agricultural producers make production and land allocation decisions at planting time based on their expectations of prices and yield at harvesting time and adaptively adjust their future expectations with new information. In contrast to perfect foresight, adaptive expectation illustrates endogenous market fluctuations in agricultural markets. We study the impacts of natural climate-induced biophysical yield shocks on agricultural economics to mid-century and assess both mean and IAV of the climate impacts (**Fig. 1** & **Extended Data Fig. 2**). We rely on biophysical yield projections estimated from the combinations of two climate models, HadGEM2-ES and GFDL-ESM2M and two crop models, EPIC and LPJ-GUESS under representative concentration pathway (RCP) 8.5 (see **Extended Data Fig. 1** for modeling chain and **SI** for a discussion of the climate and agronomic scenarios)[1,15].

Our results for the climate impacts on agriculture by mid-century (see density bars in **Fig. 1** top panels) are generally consistent with previous studies[3]. On average across climate scenarios, regions, and crops, by 2050, biophysical yield is estimated to decrease by 11.2%, which encourages higher agricultural area expansion (+7.8 %) and yield intensification (+0.5%), and, thus, alleviates climate impacts on production (-4.3%) relative to the higher impacts on biophysical yield. The negative impact on crop supply leads to significantly higher crop prices (+36%) and lower consumption (-6%). The average impact on consumption tends to be higher than production due to the higher average impact on export (+24%) relative to import (+13%) (**Extended Data Fig. 2**). The strong regional heterogeneity in biophysical yield shocks alters comparative advantage across the regions. As a result, trade pattern changes and traditional small exporters tend to be more responsive. In addition, scenarios with relatively stronger impacts on biophysical yield (i.e., HadGEM2-ES and EPIC scenarios) show more severe climate impacts on the agricultural market by mid-century.

Studying IAV provides important new insights on measuring and understanding climate impacts on global agriculture. Unlike previous climate impacts assessments at one future point, which measure the mean impacts over the study period, we provide a time-series evaluation of agricultural economic responses to climate impacts in order to study IAV. We use the standard deviation of logarithmic interannual changes to measure the IAV of climate impacts (boxplot in **Fig. 1** bottom panels). On average, across climate scenarios, regions, and crops, the IAV of biophysical yield shocks is about 3.05%, which is largely mirrored in the production responses (3.08%). The average IAV of harvested area responses (0.55%) is fairly small as acreage responses are relatively rigid, especially with planting and harvesting decisions separated. The average IAV of crop consumption (2.10%), as mediated by trade and crop substitutions, is considerably smaller than production. Price volatility has been an important characteristic in the agricultural crop market. The average IAV of price responses is 6.33%, which is more than double the average IAV of biophysical yield shocks. Similar to the mean impact, scenarios with higher

IAV in biophysical yield shocks also show higher IAV in the economic responses. However, the mean and IAV of climate impacts imply different measurements, which is important when comparing scenarios. For example, EPIC scenarios have higher impacts in both mean and IAV compared with LPJ-GUESS scenarios, while GFDL scenarios show lower mean impacts but significantly higher IAV compared with HadGEM2-ES scenarios.

Climate variables are the major sources of IAV, while agronomic and economic responses contribute relatively more to variability across regions and crops. This is supported by the analysis of variance (ANOVA) conducted, comparing the relative contribution of variation to climate impacts across five factors, i.e., climate model, crop model, region, year, and crop, and their interactions (**Extended Data Table 1**). For the variability of climate impacts on biophysical yield and economic variables within climate scenarios, year is a significantly more important contributor compared with region and crop. When comparing across climate scenarios, crop model appears to contribute more to the overall variation. However, when it comes to interannual variation, the climate model plays a more important role, as implied by the higher interaction with year compared with crop model in the ANOVA.

How farmers form expectations of market and weather conditions plays a key role in making decisions and adapting to a changing climate. We investigate to what extent climate impacts on agricultural economics can be alleviated by improving farmers' predictions of prices and yield by comparing the adaptive expectation scheme with the perfect foresight scheme (see **Fig. 2** & **Extended Data Fig. 3** for results from the GE scenario). The expectation scheme has fairly small influences on the mean impacts (see discussions in **SI**). Nevertheless, its influences on the IAV of economic responses are considerable. With perfect foresight, the average IAV (across climate scenarios, regions, and crops) of the harvested area increased by a factor of 2.3 compared with adaptative expectation as adaptations through land use change become more responsive to climate variability. The average IAV of price decreases by 55 % with perfect foresight, which reflects the magnitude of endogenous market fluctuations generated under adaptive expectation. In other words, the variation in real shocks of biophysical yield, when transferring to market prices, was magnified (by an average factor of 2.2) due to endogenous market fluctuations. With no endogenous market fluctuations, the average IAV of production (-5%), consumption (-41%), and trade (-25% for export and -29% for import) would also decrease compared with adaptive expectation. Consumption is more sensitive to the expectation scheme than production since it is more responsive to prices. Production is more responsive to biophysical yield shocks. Furthermore, trade responses become relatively less pronounced under perfect foresight as adaptations through land use change and intensification are more accessible compared with adaptive expectations. These results are consistent across scenarios (**SI Fig. S1-S3**). They also imply that the volatility of prices and consumption induced by climate impacts can be significantly reduced if farmers can improve their expectations.

To illustrate how interannual variation is transferred from biophysical shocks to economic variables, we calculate relative interannual variability (RIV) between economic responses and biophysical yield shocks (**Method**), which measures the magnitude of the variance transmission. RIV can be decomposed as the ratio of the magnitude of the interannual economics responses against biophysical yield shocks (or beta coefficient, see **Extended Data Fig. 4**) to the correlation coefficient between economics responses and biophysical yield shocks (**Fig. 3**). With adaptive expectations (**Fig. 3a**), the results demonstrate that, on the one hand, with an absolute beta coefficient smaller than one in most crop-regions, harvested area and consumption are less sensitive to interannual biophysical shocks compared with production, price, and trade. The magnitude of the economics responses is different across economic variables since the climate and biophysical shocks were transferred and transformed to economic variables through different levels of nonlinear market-mediated responses, e.g., land reallocation, yield intensification, trade responses, and substitutions in consumptions in the economic system. On the other hand, as implied by the coefficient of determination, biophysical yield shocks directly explain more interannual variation in crop supply responses (i.e., on average 92% in production and 67% in export) but less in price and demand responses (i.e., on average 36%, 33%, and 31% in price, import, and consumption, respectively). That is, the correlation between biophysical yield shocks, and the economic responses is weaker when the climate variability was transferred from biophysical yield to consumption. Thus, the relatively stronger interannual responses to biophysical shocks along with relatively large shares of unexplained variations by biophysical shocks determined the more pronounced variance transmission from biophysical shocks to prices (with an average RIV of 2.8) compared with other variables. Harvested area responses mirrored about a quarter of variations in biophysical shocks (RIV is 0.25 on average) under adaptive expectations.

Due to the lag between planting and harvesting under adaptive expectations, both economic responses and the explained variation for the harvested area were insignificant while they both increase considerably when farmers can make better predictions with perfect foresight (**Fig. 3b**). The increase in beta was stronger so that the average RIV of the harvested area increased to 0.54 under perfect foresight. Due to stronger land reallocation and intensification responses under perfect foresight, both beta and correlation decreased for production and the average RIV decreased slightly. For prices, consumption, and trade, with no endogenous market fluctuation under perfect foresight, the distribution of coefficient of determination shifted to right while the distribution of beta coefficient shifted to left so that RIV became smaller, e.g., the average RIV decreased from 2.8 to 1.1 for prices and decreased from 0.85 to 0.49 for consumption. Note that despite the considerable heterogeneity across regions and crops, the RIV and decomposition are generally consistent across climate scenarios (**SI Fig. S4-S5**).

The economic responses to biophysical variability, though generally consistent across climate scenarios at the global scale, were considerably heterogeneous across regions and crops within a scenario. Crop-regions with higher IAV of biophysical yield shocks tended to have a higher IAV in economic responses while the relationship was substantially nonlinear, particularly for consumption and prices (**Fig. 4 & SI Fig. S6-S8**), as also indicated by the high heterogeneity in RIV (**Fig. 3**). It was mainly because the IAV of consumption and prices was mediated across crops and regions through crop substitutions and international trade. That is, crop-regions with higher IAV of biophysical yield shocks tend to have a smaller magnitude of variance transmission (smaller RIV) to consumption and price responses. Also, the mediating effects are important regardless of the expectation schemes, while the effects were stronger under adaptive expectation, as implied by the steep slopes compared with perfect foresight (**Extended Data Fig. 5**). Despite being subject to barriers and costs, trade plays a unique role in mitigating agricultural market variability from climate impacts, particularly when consumption is sourced from regions with negatively correlated biophysical yield shocks or crop supply responses. Thus, the IAV distributions of consumption across regions mostly have a smaller dispersion due to the mediation effect, but also shifted to the left due to the mitigation effect, compared with the IAV distributions of biophysical yield shocks (see **Extended Data Fig. 6 & SI Fig. S9**). However, the mitigation effect was not obvious for price distributions because of the endogenous market fluctuations (see **SI** for additional discussions on regional results). This could also be true at the sub-regional level, given the high spatial heterogeneity of climate impacts on crop productivity, that intraregional trade could help mitigate and mediate market variability due to climate impacts.

To our knowledge, this is the first study to systematically examine how global agriculture responds to climate and biophysical variability. However, there are some limitations to our analysis. Although we focused on assessing climate impacts from the natural climate-induced biophysical shocks, other external shocks such as extreme weather events and government policies may further buffer or exacerbate the economic responses, depending on the magnitude of the variation and the extent to which agricultural producers predict these shocks. Also, there could be great uncertainties around endogenous market fluctuations regarding the magnitude of the responses, the heterogeneity of the responses across regions, and crops, and the rationality and heterogeneity of the expectation schemes (see discussions in **SI**). However, empirical studies demonstrated incorporating expected prices and yield provided better identifications in evaluating agricultural supply responses[12,16,17], and it is certain that with no endogenous market fluctuations, results from perfect foresight would exaggerate adaptation responses and underestimate market variations. Furthermore, as with many studies, we abstract from including a speculative interannual stockholder[10,18], which would likely have a moderating impact, with a cost though, on market volatility. These caveats notwithstanding, our study provides fundamental new insights on climate impacts on agricultural market variability and lays the foundation for further investigating the full range of climate impacts on biophysical and human systems.

Methods

Global Change Assessment Model (GCAM). GCAM is a dynamic recursive model that represents the linkages between the energy system, water, agriculture and land use, the economy, and the climate. The model is global in scope and aggregates the world into 31 regions. The base calibration year is 2010. That is, the model and its database represent the technology, factor productivity, socioeconomic conditions, and market equilibrium in 2010. The model is modified to run in annual time steps to 2050 using external drivers of population, GDP, agricultural productivity, and technological progress. The GCAM data system is written in an open-source R package[19] to clean and process source data and parameters into the format required in the model while maintaining transparency and traceability. GCAM was involved in the AgMIP[3,20] and widely used for studying climate impacts on agriculture and land use[21,22]. Note that GCAM version 5.1 with the incorporation of regional agricultural markets is employed in this study. Both the GCAM model and the data system are publicly available. A more detailed description of GCAM is provided in **SI**.

Climate and baseline scenarios. In this study, we rely on future climate scenarios of biophysical yields estimated in the context of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)[15] and the Agricultural Model Inter-comparison and Improvement Project (AgMIP). We employ the results from the combinations of two crop models, EPIC[23,24] and LPJ-GUESS[25] and two climate models, HadGEM2-ES and GFDL-ESM2M. We focus on RCP 8.5 (540 ppm CO_2 concentration in 2050) and allow carbon fertilization. Future biophysical crop yields reported by crop models are mapped and aggregated to GCAM crops and land-water regions. The GCAM reference scenario is used as the baseline in this study. Climate impacts on agricultural economic variables are calculated as the difference between the climate scenarios and the baseline scenario (no climate impacts). Note that the variability in biophysical yield shocks in this study, as detrended by a linear total factor productivity growth implied by the FAO projections in the baseline, mirrors only the natural climate variability implied by variables in the climate model (see discussions in **SI**).

Adaptive expectation in GCAM. We made modifications in the nested logit land allocation framework in GCAM to incorporate adaptive expectations of prices and yield into the model. It is assumed that a representative profit-maximizing agricultural producer of output k makes production and management decisions by determining the uses of land, water, fertilizer, and other inputs, given a vector of input and output prices and a technology that is constant return to scale (CRTS). Instead of perfectly predicting prices and yield, agricultural producers form the expectations of the output price ($p^{\boldsymbol{E}}$) and yield ($g^{\boldsymbol{E}}$) based on existing information. Denote w, f, l, as the price for water, fertilizer, and other inputs, respectively and y^w, y^f, and y^l as the output yield regarding water, fertilizer, and other inputs, respectively. The expected rental profit, $r^{\boldsymbol{E}}$, earned from land use k using irrigation option i (irrigation or rainfed) and fertilizer technology m (high or low fertilizer) for producers in water basin b, region j, and period t can be derived from the zero pure profit condition, as shown in Equation (1).

$$r^{\boldsymbol{E}}_{k,i,m,b,j,t} = \left(p^{\boldsymbol{E}}_{k,j,t} - \frac{w_{k,b,j,t}}{y^w_{k,i,b,j,t}} - \frac{f_{k,b,j,t}}{y^f_{k,m,b,j,t}} - \frac{l_{k,b,j,t}}{y^l_{k,b,j,t}}\right) \cdot g^{\boldsymbol{E}}_{k,i,m,b,j,t} \quad (1)$$

Note that $\frac{w}{y^w}$, $\frac{f}{y^f}$, and $\frac{l}{y^l}$ are input cost per unit output of k for water, fertilizer, and other inputs, respectively. If farmers have perfect foresight on market prices and yield, i.e., $p^{\boldsymbol{E}} = p$ and $g^{\boldsymbol{E}} = g$, Equation 1 becomes the rental profit used in the original GCAM.

We employ the Nerlove Adaptive expectation (Equation 2), which has been extensively studied in the literature[26-28] and also explored in recent studies[11,29,30]. It depicts that the expectation of a variable ($x^{\boldsymbol{E}}_t$) is adaptively revised in proportion to the difference between the previous observation (x_{t-1}) and the previous expectation ($x^{\boldsymbol{E}}_{t-1}$) with a constant coefficient of expectations (α), and $\alpha \in (0, 1]$.

$$x^{\boldsymbol{E}}_t - x^{\boldsymbol{E}}_{t-1} = \alpha(x_{t-1} - x^{\boldsymbol{E}}_{t-1}) \quad (2)$$

Equation 2 can be rearranged to $x^{\boldsymbol{E}}_t = \alpha \cdot x_{t-1} + (1-\alpha) \cdot x^{\boldsymbol{E}}_{t-1}$, which implies that the current expectation is a weighted average of the lagged observation and the lagged expectation. It collapsed into a naïve expectation when α equals one. Further details of expectation schemes and discussions of parameters are provided in **SI**.

Relative interannual variability. The standard deviation of the logarithmic changes of a variable, i.e., $SD[\log(variable_t) - \log(variable_{t-1})]$ is used to measure interannual variability (IAV). Note that the logarithmic changes represent continuously compounded annual growth rates so the IAV has the same unit of percent change. Relative interannual variability (RIV), calculated as the ratio of the IAV of economic responses (a) to the IAV of biophysical yield shocks (b), or $RIV_{a,b} = \frac{IV_a}{IV_b}$, normalizes IAV by biophysical yield so that it can be compared across scenarios, regions, or crops. RIV enhances the explanation of the results since it can be decomposed as the ratio of beta coefficient to the correlation coefficient, both between economic responses and biophysical yield shocks, i.e., $RIV_{a,b} = \frac{cov_{a,b} / IV_b^2}{cov_{a,b} / (IV_a \cdot IV_b)} = \frac{Beta_{a,b}}{Correlation_{a,b}}$. Beta coefficient implies the magnitude of the interannual economics responses against climate impacts on biophysical yield and the correlation coefficient implies the extent to which interannual variation in economic responses is explained by biophysical variability.

Data availability

The biophysical yield data projected from climate and crop models are publicly available at https://esg.pik-potsdam.de/search/isimip-ft/. The GCAM data system is publicly available[19].

Code availability

The GCAM model is publicly available[31]. A repository including the version of GCAM created for this study and the R code for generating main figures will be made available when published.

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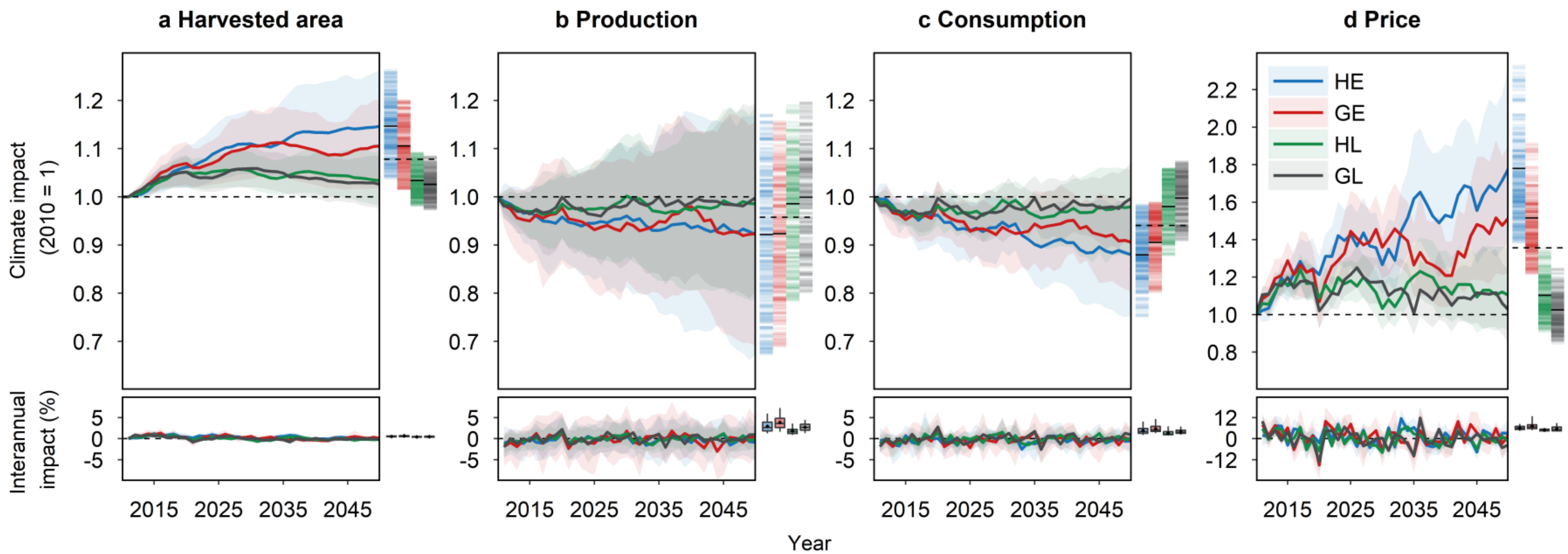


Fig. 1 | Climate impacts on global agriculture to mid-century. Cumulative (top panels) and interannual (bottom panels) climate impacts on agricultural crop harvested area (a), production (b), consumption (c), and price (d) relative to the GCAM reference scenario, estimated under adaptive expectations. Curves and shadows denote average and 10 – 90 percentile ranges of GCAM results across all crop-region combinations (biomass and fodder crops not included), respectively. Climate scenarios (two climate models by two crop models under RCP8.5 and with carbon fertilization), distinguished by color, include HadGEM2-ES & EPIC (HE), GFDL-ESM2M& EPIC (GE), HadGEM2-ES & LPJ-GUESS (HL), and GFDL-ESM2M ES & LPJ-GUESS (GL). The density bars next to plots of cumulative change show heterogeneity across crop-region values in 2050 for the four climate scenarios (with corresponding shadow colors), with the crop-region average in each scenario (solid black lines) and scenario-average (dotted black line) highlighted. Interannual impact is calculated as logarithmic changes of cumulative impact. The boxplot next to plots of interannual impact presents the mean values (points), the median values (line), the first and third quartiles (boxes), and the 10 – 90 percentile ranges (whiskers) of the standard deviations of interannual impact (or the interannual variability) across GCAM crop-region combinations. Climate impacts on additional variables are provided in **Extended Data Fig. 2** and the summary statistics are presented in **SI Table S1**. Data source: GCAM simulation results

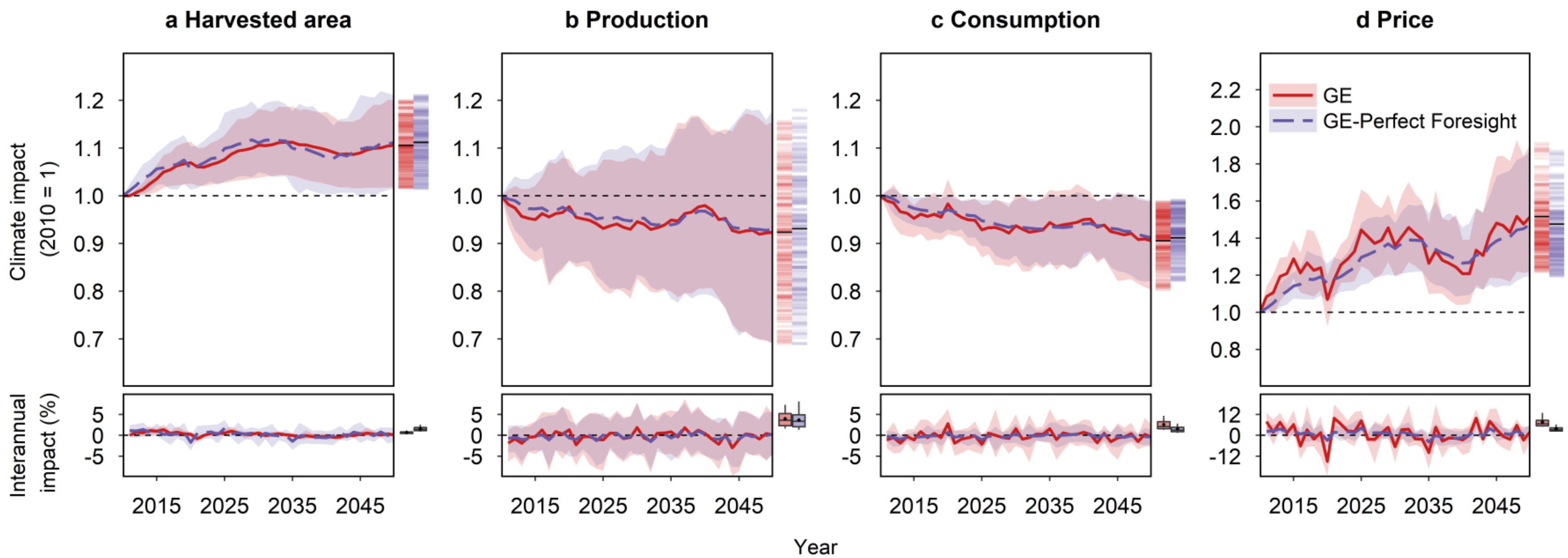


Fig. 2 | The role of expectation scheme in assessing climate impacts on global agriculture to mid-century. Cumulative (top panels) and interannual (bottom panels) climate impacts on agricultural crop harvested area (a), production (b), consumption (c), and price (d) relative to the GCAM reference scenario. Curves and shadows denote average and 10 – 90 percentile ranges of GCAM results across all crop-region combinations (biomass and fodder crops not included), respectively. Adaptive expectation (default) is compared with perfect foresight using the GFDL-ESM2M& EPIC (GE) scenario. The density bars next to plots of cumulative change show heterogeneity across crop-region values in 2050 for the two expectation schemes (distinguished by color). The boxplot next to plots of interannual change presents the mean values (points), the median values (line), the first and third quartiles (boxes), and the 10 – 90 percentile ranges (whiskers) of the standard deviations of interannual impact (interannual variability) across GCAM crop-region combinations. Results for other variables are provided in **Extended Data Fig. 3** and results for other climate scenarios are provided in **SI Fig. S1-S3**. The summary statistics are presented in **SI Table S3**. Data source: GCAM simulation results

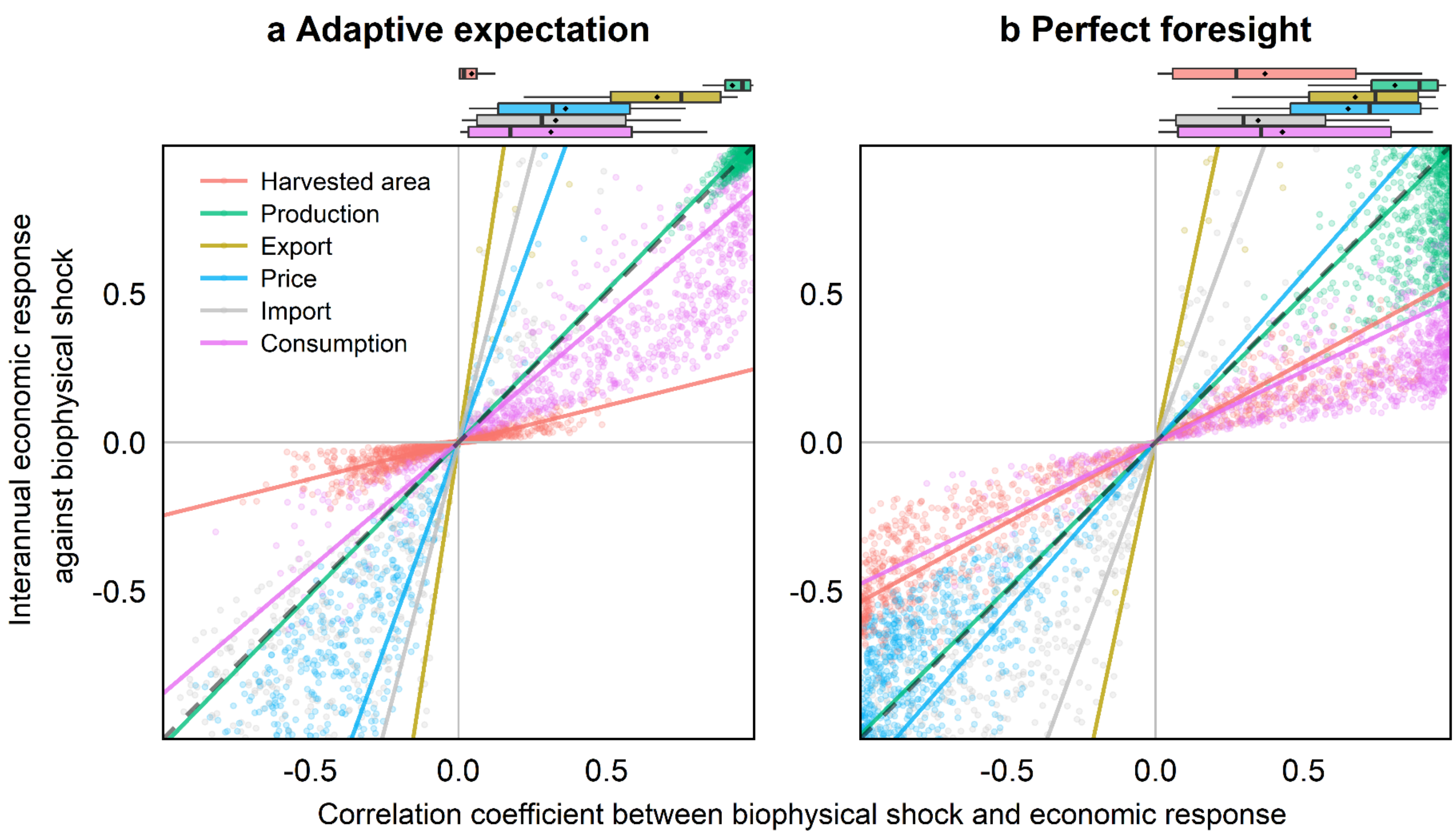


Fig. 3 | Interannual economic responses and correlations to biophysical yield shocks. The beta coefficient and correlation coefficient between economic variables (distinguished by color) and biophysical yield are presented. Each point denotes a crop in a region and a climate scenario, and only crop-regions in 10 – 90 percentile ranges of interannual variability in a climate scenario are presented. Beta coefficients are truncated to [-1, 1] (see **Extended Data Fig. 4** for ranges of Beta). Note that the relative interannual variability between economic variables and biophysical yield (ratio of standard deviations) is equal to the ratio of beta coefficient to the correlation coefficient. The slope of the lines represents the average relative interannual variability between economic variables and biophysical yield. The black dotted line has a slope of one. The boxplot attached above presents the mean values (points), the median values (line), the first and third quartiles (boxes), and the 10 – 90 percentile ranges (whiskers) of the squares of correlation coefficient, namely coefficient of determination (r-squared). Data source: GCAM simulation results

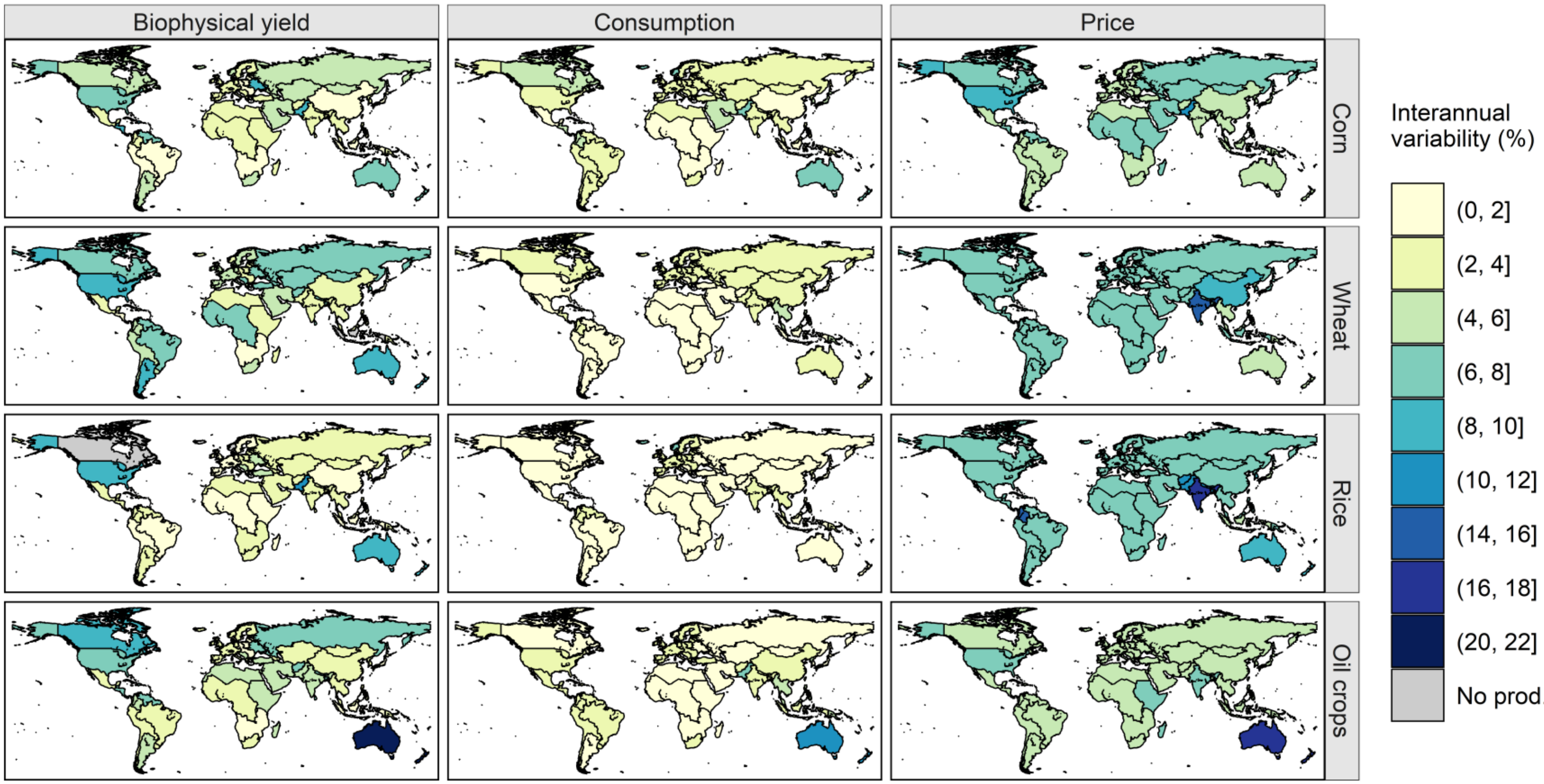


Fig. 4 | Interannual variability in biophysical yield shocks and the economic responses in the GE scenario. Maps of regional interannual variability in biophysical yield shocks and the consumption and price responses for Major crops (corn, wheat, rice, and oil crops) from the GFDL-ESM2M& EPIC (GE) scenario, estimated under adaptive expectations. Results from other climate scenarios are presented in **SI Fig. S6-S8**. Gray areas in biophysical yield maps represent regions with no productions of the crop. Data source: GCAM simulation results

Extended Data Table 1| Analysis of variance for biophysical yield and economic variables. ANOVA is performed for variables and climate scenarios presented in **Fig. 1** across five factors, i.e., climate model (GCM), crop model (GGCM), region, year, and crop, and their interactions. All variables have the same degrees of freedom (Df) across sources presented. The root mean square (RMS), calculated as the square root of Df weighted sum of squares, is used to measure relative contributions of variation. The full ANOVA results with more interactions are presented in **SI Table S2**.

Source of variation	Harvested area		Production	Consumption	Price	Export	Import	Realized yield	Biophysical yield
	Df	RMS	RMS	RMS	RMS	RMS	RMS	RMS	RMS
GCM	1	6***	3	7***	31***	9	8	9***	10***
GGCM	1	24***	23***	29***	114***	19	23**	46***	48***
Region	30	2***	12***	2	12***	56***	27***	12***	13***
Year	39	11***	21***	24***	115***	73***	55***	22***	23***
Crop	9	5***	10***	8***	10***	32***	13*	10***	10***
GCM:Region	30	1***	3**	1	2	13	5	3**	3**
GCM:Year	39	7***	17***	20***	101***	80***	64***	16***	16***
GCM:Crop	9	1***	2	2	4	5	5	1	1
GGCM:Region	30	2***	4***	1	5***	25***	13***	4***	4***
GGCM:Year	39	3***	9***	9***	41***	34***	34***	9***	9***
GGCM:Crop	9	4***	4*	4***	7***	15	12*	5***	5***

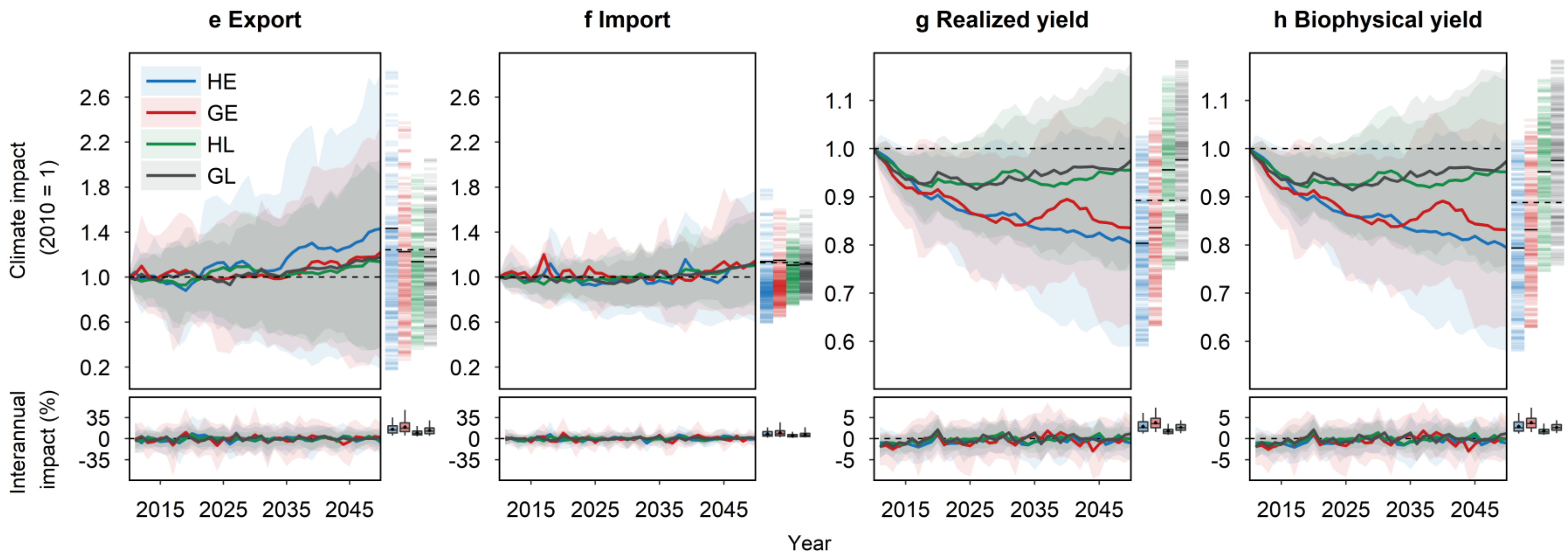
The point (.), single asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance levels of 10%, 5%, 1%, and 0.1%, respectively, from the F test.

Model chain	Climate model (GCM)	Global crop model (GGCM)	Economic model

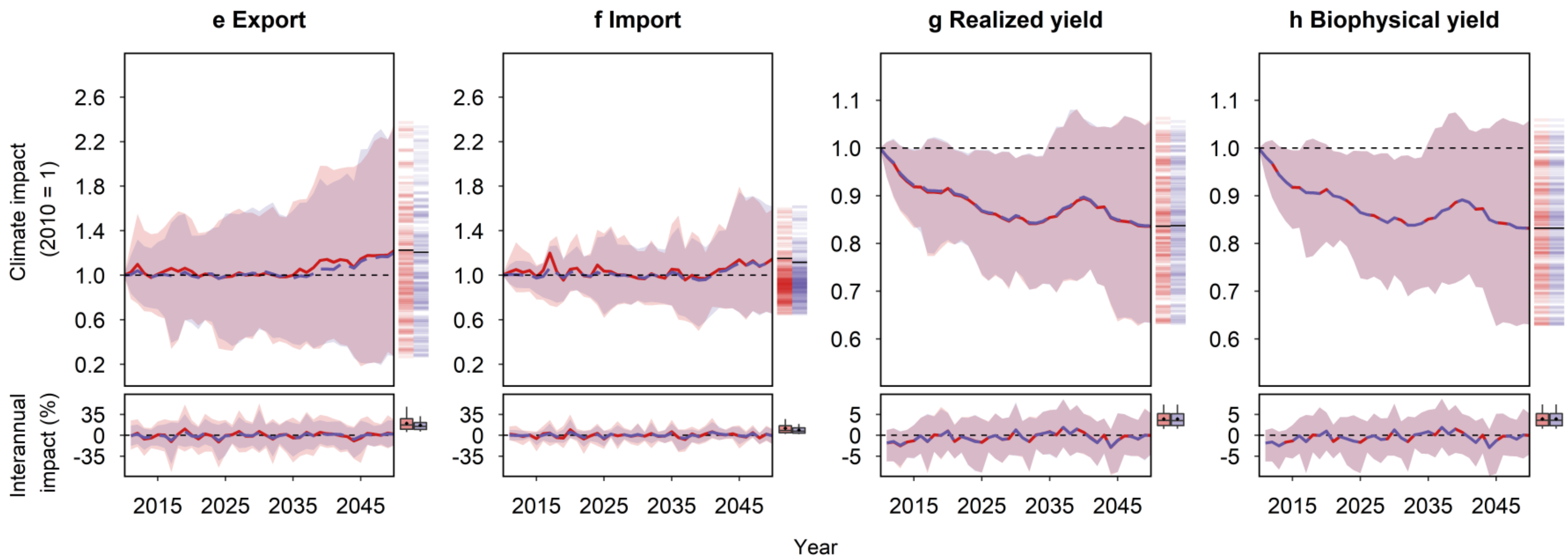
Model variable	• Temperature
	• Precipitation
	• Surface radiation
	• Wind speed
	• Air pressure
	• Humidity
	• CO_2 concentration
		• Biophysical yield
		  • Carbon forcing
		  • Irrigation forcing
			• Land use
			• Production
			• Consumption
			• Prices
			• Trade
			• Realized yield

Variability	• Time: day • Space: grid	• Time: year • Space: grid • Crop: major crops	• **Time: year** • Space: water basin or GCAM regions • Crop: GCAM crops
Model used	• HadGEM2-ES • GFDL-ESM2M	• EPIC • LPJ-GUESS	• GCAM

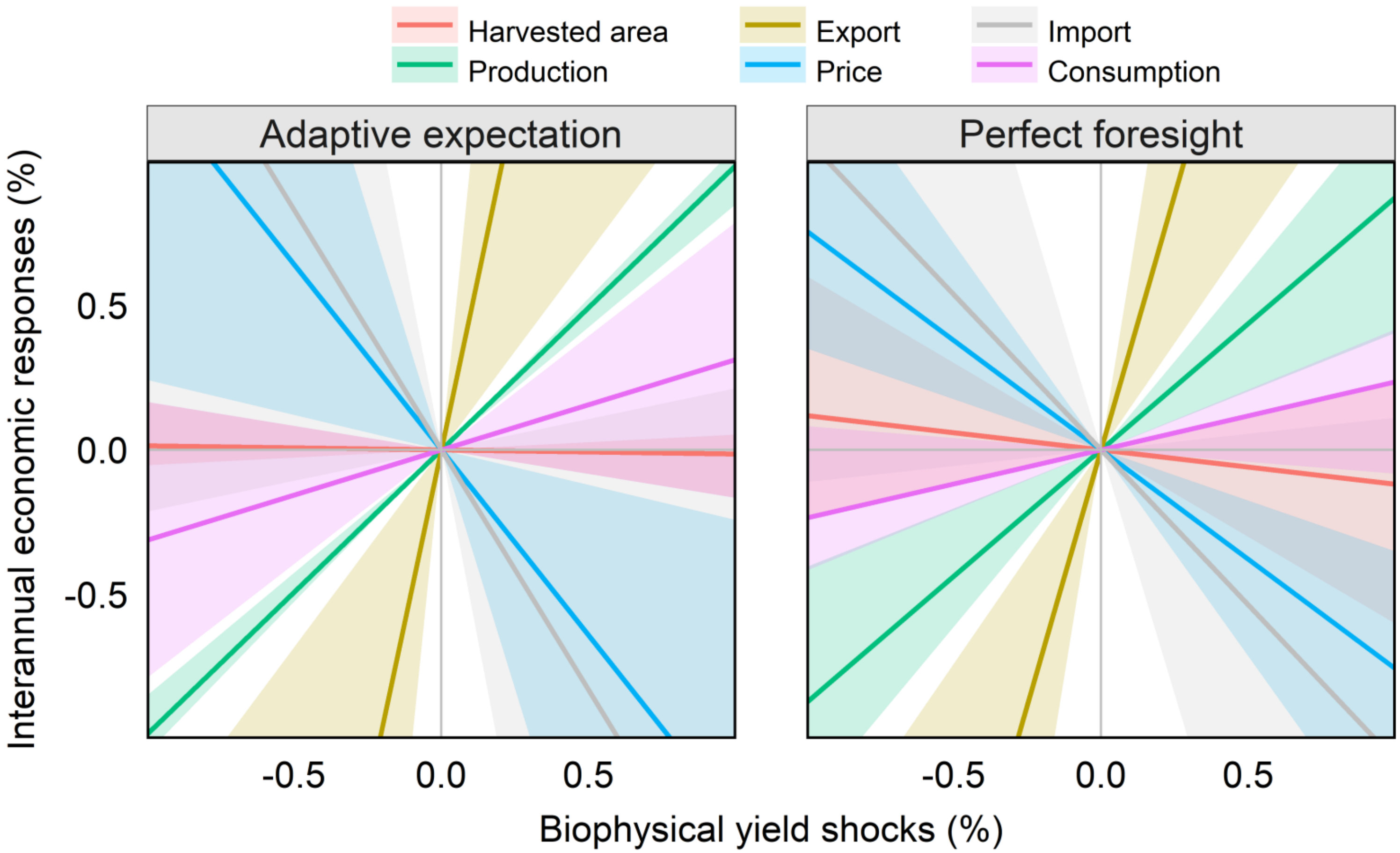
Extended Data Fig. 1 | Modeling chain of assessing climate impacts on agriculture



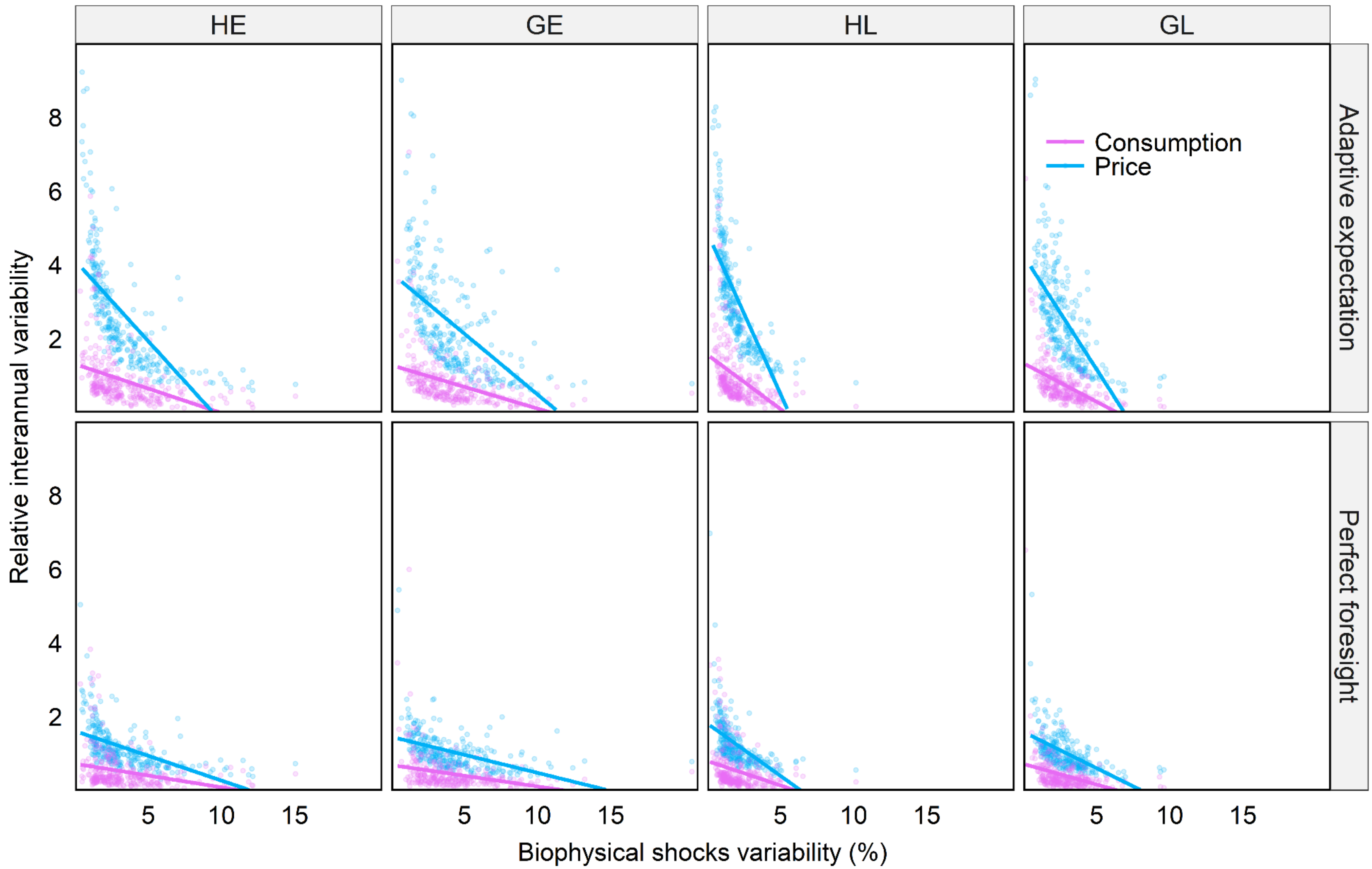
Extended Data Fig. 2 | Climate impacts on agriculture to mid-century. Cumulative (top panels) and annual (bottom panels) climate impacts on agricultural crop export (e), import (f), realized yield (g) and biophysical yield (h) relative to the GCAM reference scenario are presented. This figure supplements **Fig. 1** (see Fig. 1 caption for detailed explanations). Note that realized yield are results from the model after considering endogenous yield responses (see **SI** for discussions). Data source: GCAM simulation results



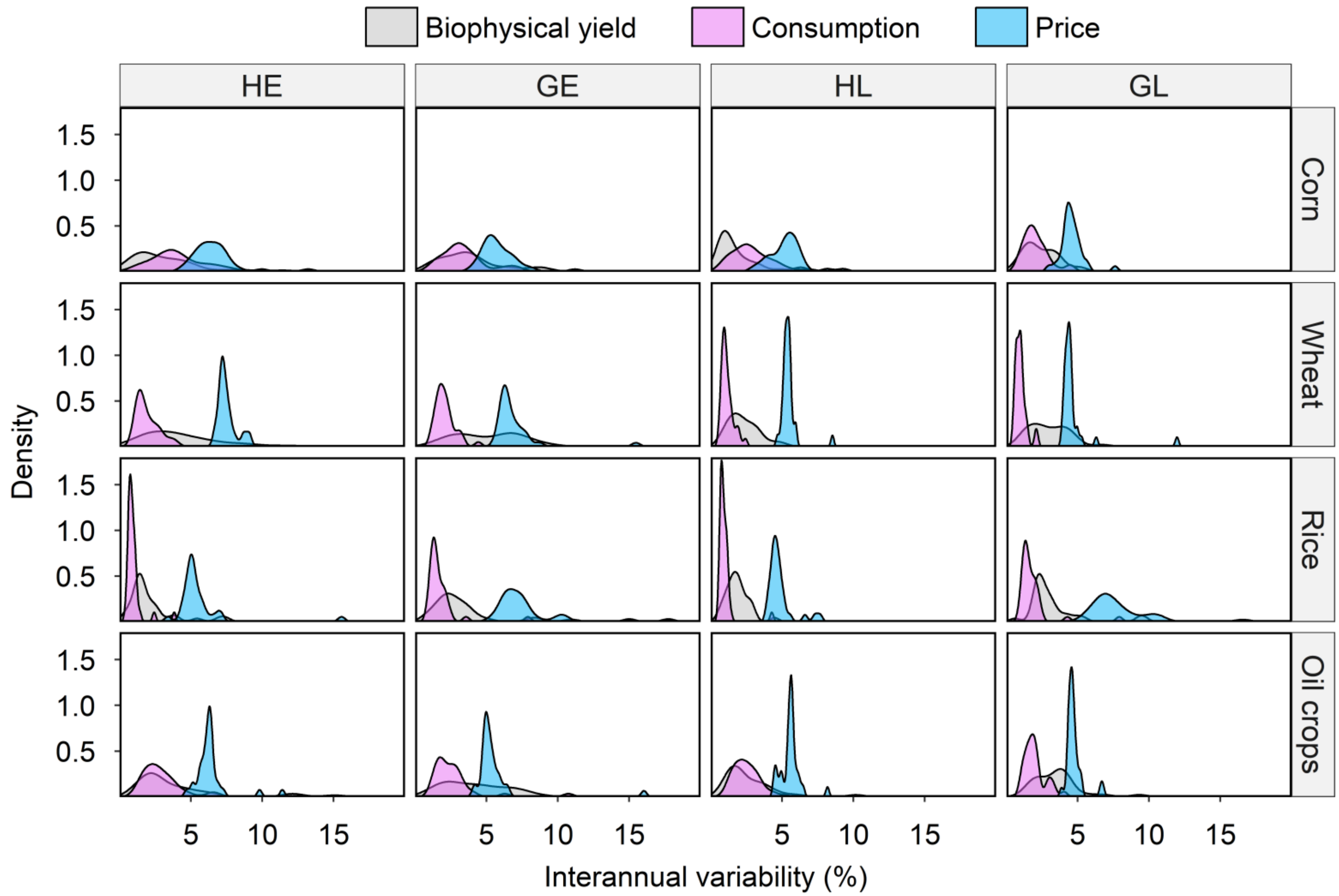
Extended Data Fig. 3 | The role of expectation scheme in assessing climate impacts on global agriculture to mid-century. Cumulative (top panels) and interannual (bottom panels) climate impacts on agricultural crop export (e), import (f), realized yield (g) and biophysical yield (h) relative to the GCAM reference scenario are presented. This figure supplements **Fig. 2** (see Fig. 2 caption for detailed explanations). Note that biophysical yield shocks are external drivers in the model so that they are not affected by expectation schemes. Data source: GCAM simulation results



Extended Data Fig. 4 | Interannual economic responses against biophysical yield shocks. Lines and shadows denote mean and 10 – 90 percentile ranges of the interannual economics responses across scenarios, regions, and crops. The slope of the lines represents beta coefficient between economic variables responses and biophysical yield shocks. Results are provided for two expectation schemes (Adaptive expectation and perfect foresight). Results across different climate scenarios are provided in **SI Fig. S5**. Data source: GCAM simulation results



Extended Data Fig. 5 | Relationship between the RIV of consumption and price and the IAV of biophysical shock. Each point denotes a crop in a region and linear trendlines are provided. Points Results are provided for four climate scenarios (GE, GL, HE, and HL) and two expectation schemes (Adaptive expectation and perfect foresight). Data source: GCAM simulation results



Extended Data Fig. 6 | Distributions of the interannual variability of biophysical yield shocks and their consumption and price responses across regions by scenario and major crops. The results for additional crops are provided in **SI Fig. S9**. Data source: GCAM simulation results