Impacts of interannual climate and biophysical variability on global agriculture markets

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Abstract (*approximately 150 words*)

Most studies assessing climate impacts on agriculture have focused on average changes in market-mediated responses (e.g., changes in land use, production, and consumption). However, the response of global agricultural markets to interannual variability in climate and biophysical shocks is poorly understood and not well represented in global economic models. Here we show a strong transmission of interannual variations in climate-induced biophysical yield shocks to agriculture markets, which is further magnified by endogenous market fluctuations generated due to producers' imperfect expectations of market and weather conditions. We demonstrate that the volatility of crop prices and consumption could be significantly underestimated (i.e., on average by 55% and 41%, respectively) by assuming perfect foresight, a standard assumption in the economic equilibrium modeling, compared with the relatively more realistic adaptive expectations. We also find heterogeneity in interannual variability across crops and regions, which is considerably mediated by international trade.

Introduction

Climate is essentially an indirect input to agricultural production, and its economic impacts on agriculture have been extensively assessed in the past three decades[1-3]. 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[3,5,6], studies are shifting focus from mean to the variability of future climate and biophysical shocks[7-10]. Interannual variability (IAV), 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[11]. Previous studies focused on assessing economic consequences of climate impacts in 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[12,13]. With perfect foresight, agricultural producers can perfectly predict future climate and market information and make adaptations accordingly and immediately (e.g., adjusting land use and management practices 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 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 undermine the market equilibrium and, thus, generate “endogenous” market fluctuations[14] in addition to the variation stemmed from exogenous climate and biophysical shocks. The assumption of perfect foresight, ignoring the endogenous market fluctuations, may lead to misleading assessments of the IAV of agricultural economic responses[14,15].

Understanding the IAV of the climate impacts on agricultural economics is crucial to formulating agricultural policies that facilitate agricultural adaptation and maintain food security since changes in the variability of climate and weather patterns will have considerable consequences on agricultural production and market fluctuation[7]. In this work, we quantify the IAV of climate impacts on agriculture by incorporating adaptive expectations[16] of annual prices and yield into a well-established global economic model, the Global Change Analysis Model (GCAM). 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 offers an intuitive and effective approach to characterize the "endogenous" market fluctuations in agricultural market equilibrium modeling[12]. Furthermore, we rely on biophysical yield projections estimated from 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. The modeling chain is shown in **Fig. 1**. The climate and agronomic scenarios have been widely used in previous studies[3,17], and they are at the extremes in their respective model intercomparisons[5,18] (see **Methods** for a more detailed description of GCAM and the coupled scenarios). 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. Our results demonstrate that studying IAV provides fundamentally new insights on measuring and understanding climate impacts on global agriculture.

Results

We provide a time-series (annual) evaluation of agricultural economic responses to climate-induced biophysical shocks by mid-century, under the assumption of adaptative expectations (**Fig. 2**). Note that point estimating of the climate impacts by the year 2050 will also indicate the interannual mean impacts over the study period (see density bars in **Fig. 2** top panels). On average across climate scenarios, regions, and crops, by 2050, biophysical yield is estimated to decrease by 11.2%. It results in higher agricultural area expansion (+7.8 %) and yield intensification (+0.5%), which alleviate some of the effects of climate impacts on production. Specifically, production only declines by 4.3% despite the higher decline in 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%). The strong regional heterogeneity in biophysical yield shocks alters comparative advantage across the regions. As a result, trade patterns change, with small exporters being 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. These mean climate impact results are generally consistent with previous studies[3], as the expectation scheme has a fairly small influence on the mean impacts (**SI Section 2.1**).

Throughout this study, we use the standard deviation of logarithmic interannual changes to measure the IAV of climate impacts (boxplot in **Fig. 2** 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 are separate 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.

Our results demonstrate that climate variables are the major sources of variability across time, while agronomic and economic responses contribute relatively more to variability across regions and crops. This is supported by the analysis of variance (ANOVA) conducted for 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 (**Table 1**). For the variability of climate impacts on biophysical yield and economic variables within climate and crop scenarios, year is a significantly more important contributor compared with region and crop, implying relatively higher overall variations across time. When comparing across scenarios, crop model (GGCM) appears to contribute more to the overall variation. However, when it comes to interannual variation, the climate model (GCM) plays a more important role, as implied by the higher interaction with year compared with crop model in the ANOVA (i.e., GCM:Year vs. GGCM:Year).

How farmers form expectations of market and weather conditions plays a key role in making decisions and adapting to a changing climate. We investigate the role of expectation scheme in modeling climate impacts on agricultural markets by comparing the adaptive expectation with the perfect foresight (see **Fig. 3** for results from the GFDL-ESM2M& EPIC scenario). This comparison indicates that the degree to which previous studies using perfect foresight have underestimated the economic responses to climate variability, since adaptive expectations is a relatively more realistic representation of farmer behavior. Conversely, such comparisons also provide insights on to what extent climate impacts can be alleviated by improving farmers' predictions of prices and yield. The expectation scheme has a relatively small

influence on assessing the mean climate impacts (**SI Section 2.1**), while its influence on the IAV of economic responses is considerable. With perfect foresight, the average IAV (across climate scenarios, regions, and crops) of 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 with perfect expectations. However, 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 consumption is more responsive to prices while 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**), that assuming perfect foresight would underestimate market volatility. They also imply that the volatility of prices and consumption induced by climate impacts can be 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, which measures the magnitude of the variance transmission (**Methods**). RIV can be decomposed into a ratio between (1) the magnitude of the interannual economic responses against biophysical yield shocks (measured by the beta coefficient, see y-axis in Fig. 4)) and (2) the correlation coefficient between economic responses and biophysical yield shocks (x-axis in **Fig. 4**). That is, the slope of the lines presented in Fig. 4 represents the average RIV across crop-regions and scenarios, respectively for adaptative expectation (**Fig. 4a**) and perfect foresight (**Fig. 4b**). With adaptive expectations, the results show harvested area and consumption are less responsive to interannual biophysical shocks (i.e., absolute beta coefficient smaller than one) in most crop-regions, compared with production, price, or trade. The magnitude of the economic responses is different across economic variables since the climate and biophysical shocks were transferred to economic variables through different market-mediated responses, e.g., land reallocation, yield intensification, trade responses, and substitutions in consumption in the economic system. The correlation analysis indicates that, under adaptive expectation, biophysical yield shocks explain more interannual variation in crop supply responses (i.e., an R-

squared of on average 92% for production and 67% for export) but less in price and demand responses (i.e., an R-squared of on average 36%, 33%, and 31% for price, import, and consumption, respectively). That is, the correlation between biophysical yield shocks and the economic responses is weaker when the climate variability is transferred from supply to demand variables. Thus, the relatively stronger interannual responses to biophysical shocks along with relatively larger shares of unexplained variations by biophysical shocks determined the more pronounced variance transmission from climate and biophysical variables to prices (with an average RIV of 2.8), under adaptative expectation, compared with other variables.

Area responses, however, only mirrored variations in biophysical shocks about a quarter of the time (RIV is 0.25 on average) under adaptive expectations. Due to the lag between planting and harvesting under adaptive expectations, farmers cannot immediately respond to changes in biophysical shocks by reallocating land, dampening both area responses and its correlation with biophysical shocks. When farmers can adapt immediately (or make better predictions) with perfect foresight (**Fig. 4b**), the magnitude of area responses grows faster than the correlation so that higher variations in biophysical shocks are transferred to area responses (RIV increases to 0.54 on average). Also, the stronger land reallocation and intensification responses under perfect foresight reduce both production responses and its correlation with biophysical shocks at a similar magnitude, which explains the insignificant changes in RIV for production. For prices, consumption, and trade, perfect foresight encourages higher variance transmission compared with adaptative expectation (i.e., the average RIV decreased from 2.8 to 1.1 for prices and decreased from 0.85 to 0.49 for consumption). The reduction in RIV is driven by a combination of reductions in responsiveness to biophysical shocks and increases in the share of explained variations. Note that despite the considerable heterogeneity across regions and crops, the RIV and decomposition are generally consistent across climate scenarios (**SI Fig. S5-S6**).

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. 5 & SI Fig. S7-S9**), as also indicated by the high heterogeneity in RIV (**Fig. 4**). 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 (**Fig. S10**). Despite being subject to barriers and costs, trade plays a unique role in reducing 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 reduction effect, compared with the IAV distributions of biophysical yield shocks (see **SI Fig. S11**). However, the reduction effect was not obvious for price distributions because of the endogenous market fluctuations (see **SI Section 2.3** 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 reduce and mediate market variability due to climate impacts.

Discussion

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. Our sensitivity tests indicate that with faster adjustment in expectation implied by the higher coefficient of expectation, biophysical shock triggered endogenous market fluctuations would become stronger so that the IAV increases for all economic variables, with relatively higher sensitivity for price and harvested area (see supplementary discussions in **SI Section 2.2**). Empirical studies demonstrated incorporating expected prices and yield provided better identifications in evaluating agricultural supply responses[13,19,20], and it is certain that with no endogenous market fluctuations, results from perfect foresight would exaggerate adaptation responses and underestimate market variations.

Furthermore, it has been challenging to include stockholding in global economic models[11,21], which would likely have a moderating impact on market volatility[22,23]. A realistic modeling of storage would also require information on storage cost, government interventions, and stochastic exogenous shocks, which are usually not available at the global scale[22,24]. As with

many studies, we abstract from including a speculative interannual stockholder[11,21]. Nevertheless, the main impacts from including storage implied by a stochastic competitive storage model[15,25], e.g., positively skewed and shifted price distribution, could be mostly reflected in a deterministic adaptative expectation model by adjusting production cost and coefficient of expectation. Thus, we do not investigate the interplay between storage modeling and climate impacts in this paper. Future studies are needed to refine data and parameters to study storage impacts under a changing climate.

This paper focused on four widely used climate scenarios of future biophysical yield shocks and showed relatively consistent economic responses to biophysical interannual variations (i.e., RIV) at the global scale while highlighting the important role of trade in explaining regional heterogeneity in the responses. It is also important to note that the high uncertainty in biophysical yield projections, particularly at the regional scale, would be mirrored in the IAV of their economic responses (See the discussion of regional decompositions in **SI Section 2.3**). More scenarios could be explored in the context of model intercomparison tasks using the framework showcased in this paper. 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 Analysis 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[26] 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[3,27] and widely used for studying climate impacts on agriculture and land use[28,29]. 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 Section 1.2**.

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)[18] and the Agricultural Model Inter-comparison and Improvement Project (AgMIP). We employ the results from the combinations of two Global Gridded Crop Models (GGCMs) , EPIC[30,31] and LPJ-GUESS[32] and two General Circulation Models (GCMs), 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 Section 1.3**).

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[33-35] and also explored in recent studies[12,14,36]. 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 Section 2.2**.

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 GCAM data system is publicly available[26]. The biophysical yield data projected from climate and crop models are publicly available at https://esg.pik-potsdam.de/search/isimip-ft/.

Code availability

The GCAM model is publicly available[37]. The modified version of GCAM created for this study is available upon request. A repository including the data and R code for generating main figures will be made available when published.

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Figures

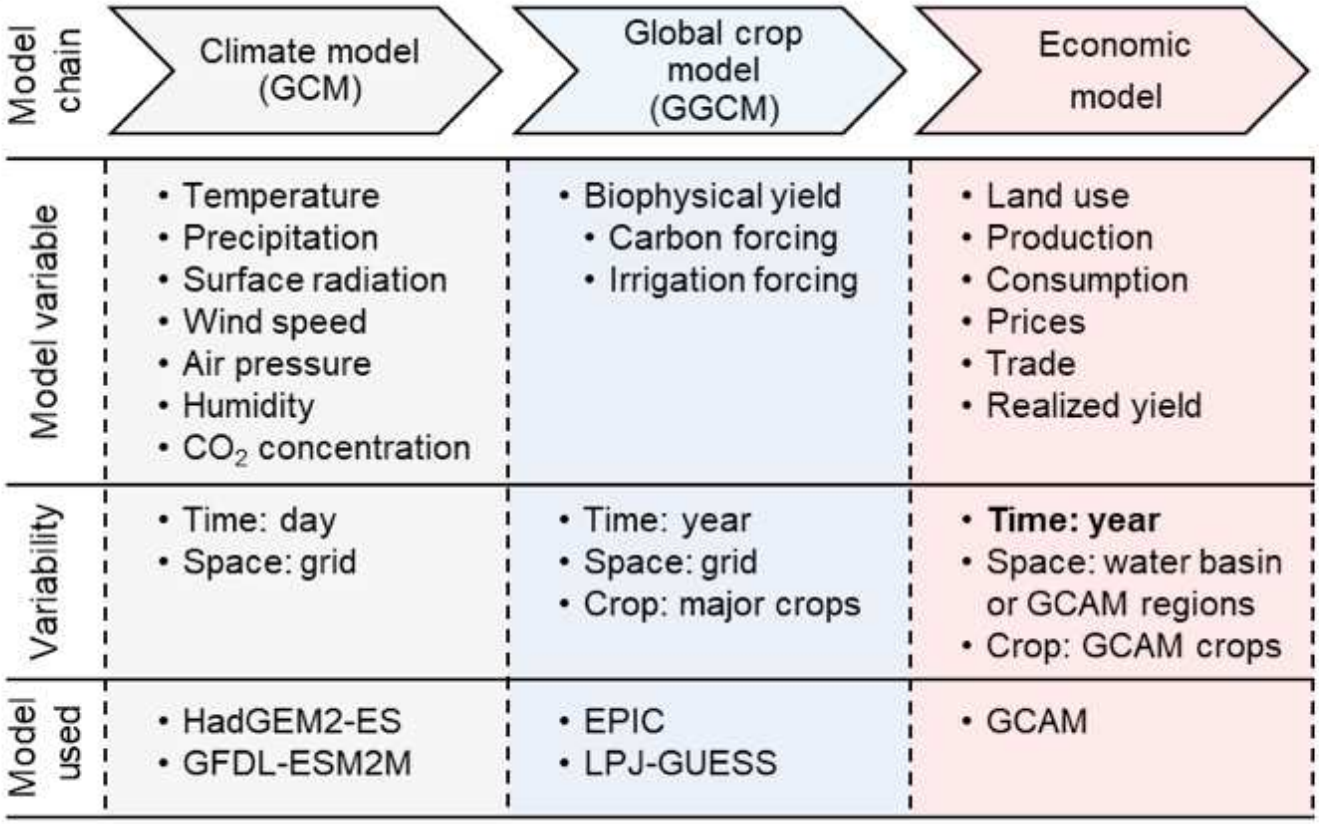

Figure 1

Modeling chain of assessing climate impacts on agriculture

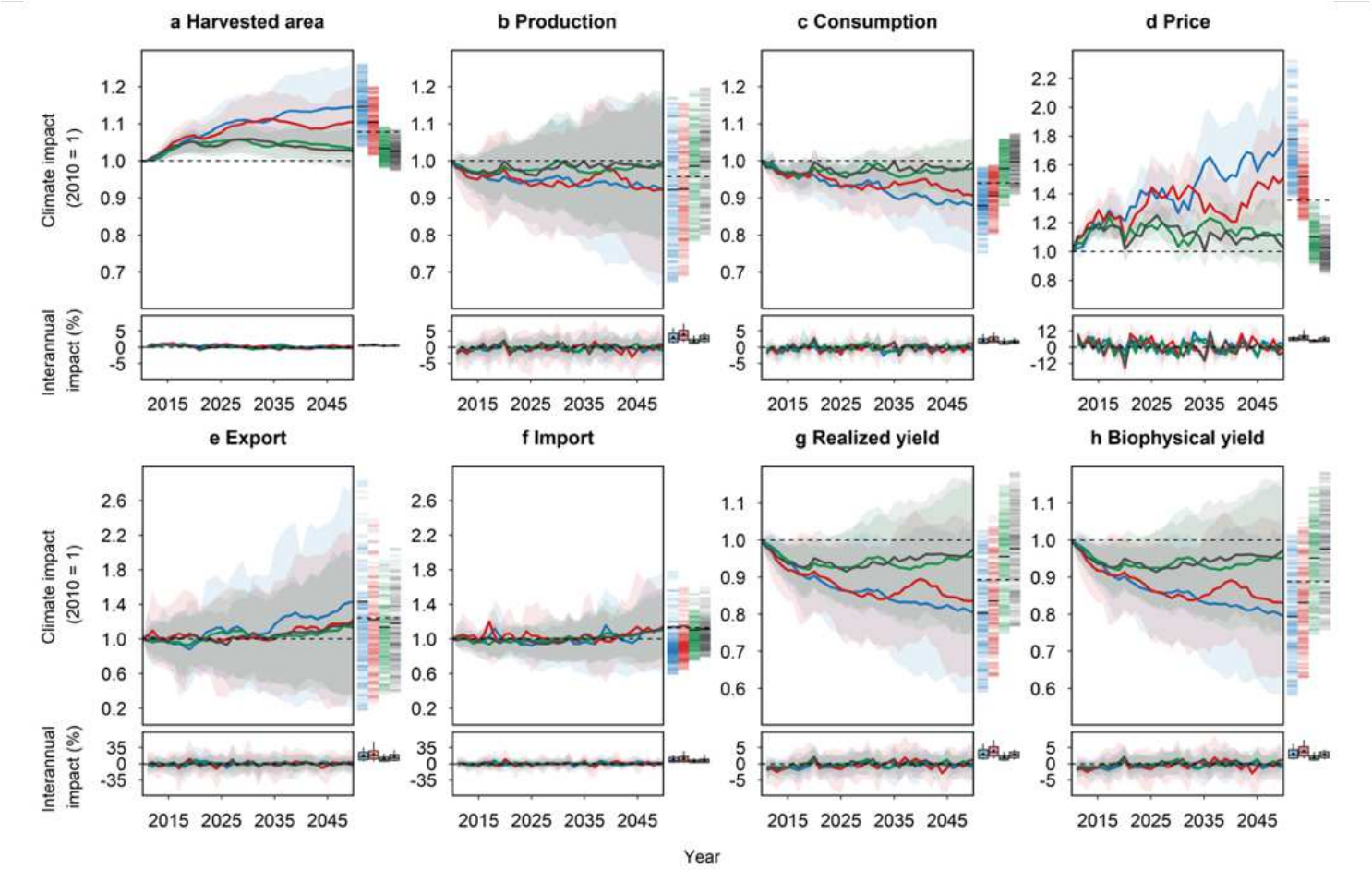

Figure 2

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), price (d), export (e), import (f), realized yield (g) and biophysical yield (h) relative to the GCAM reference scenario, estimated under adaptive expectations. Note that realized yield are results from the model after considering endogenous yield responses. 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 (bottom panels) is calculated as logarithmic changes of cumulative impact (top panels). 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 (i.e., interannual variability) across GCAM crop-region combinations. The summary statistics of the data presented are provided in SI Table S1. Data source: GCAM simulation results

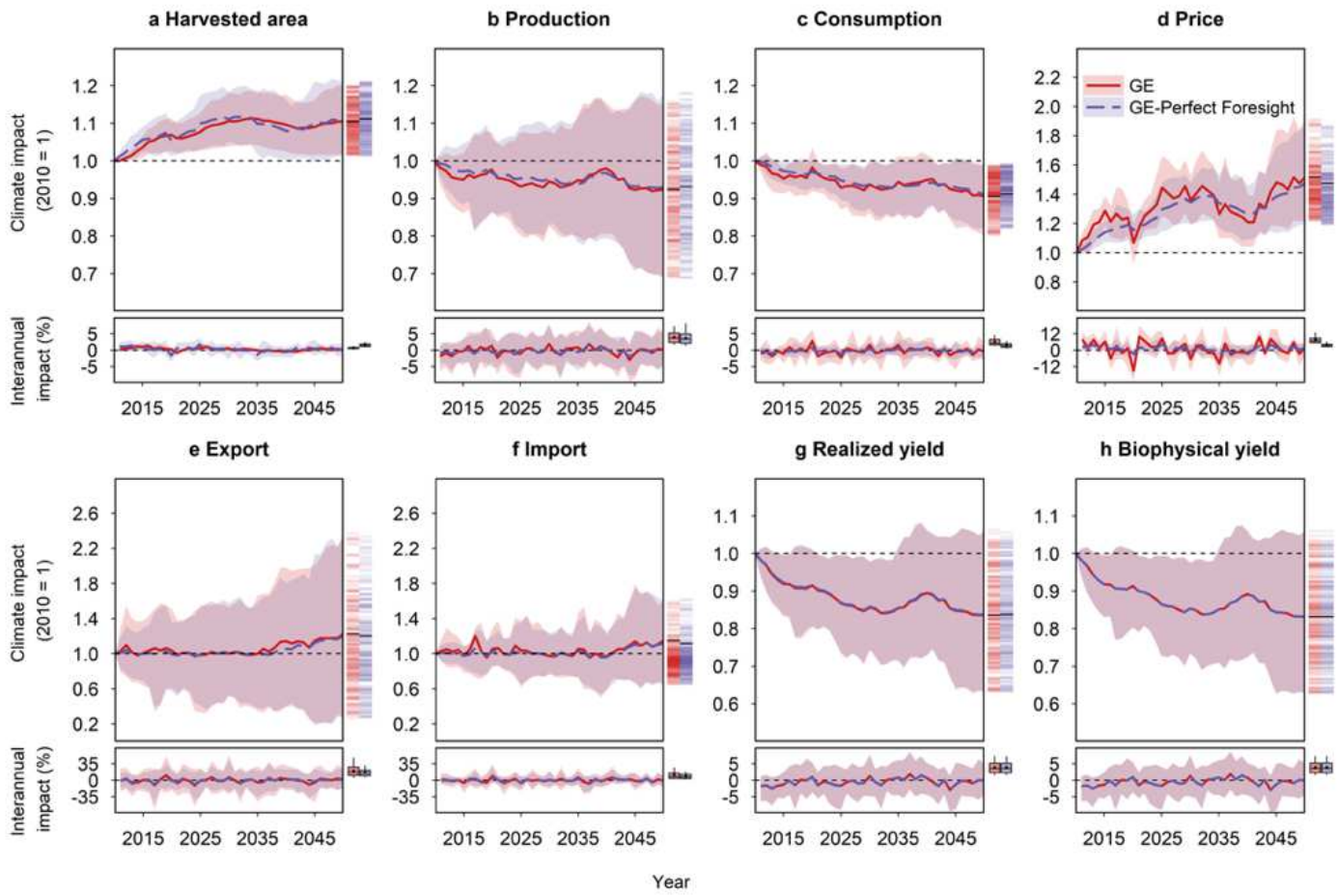

Figure 3

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 harvested area (a), production (b), consumption (c), price (d), export (e), import (f), realized yield (g) and biophysical yield (h) 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. Note that biophysical yield shocks are external drivers in the model so that they are not affected by expectation schemes. 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

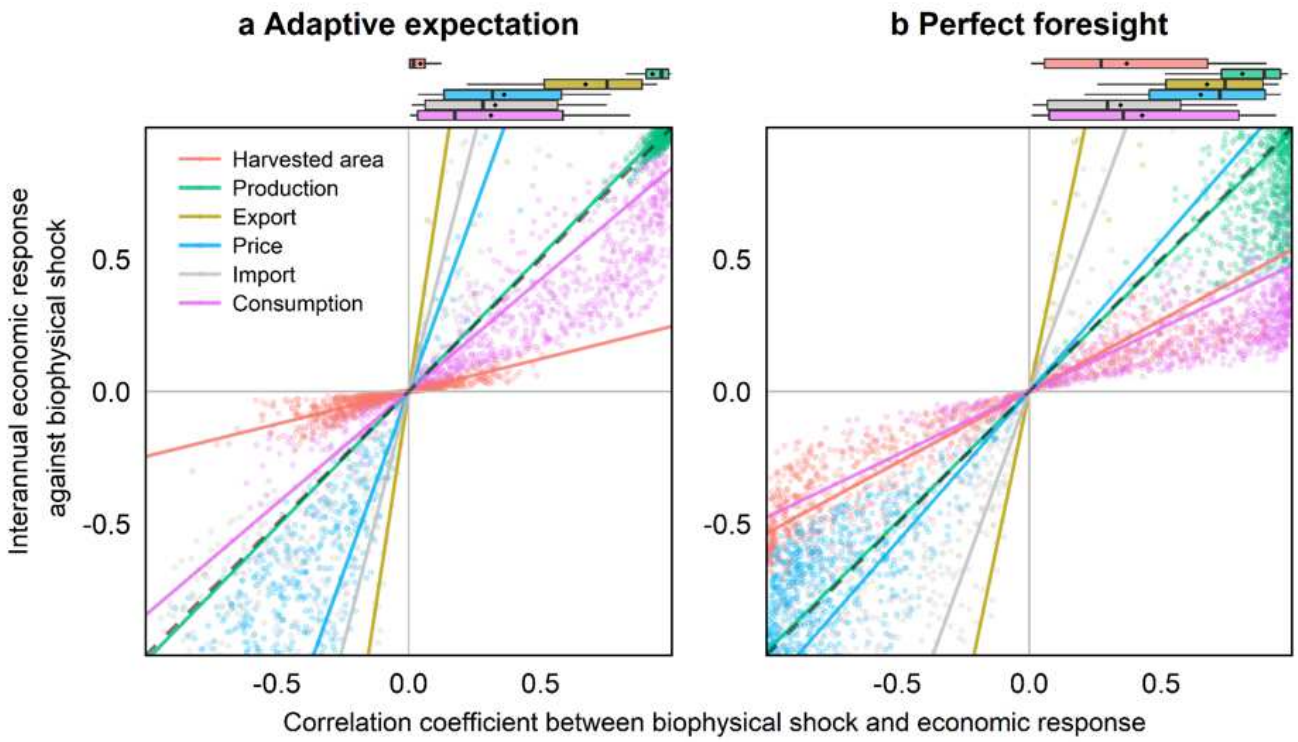

Figure 4

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 SI Fig. S4 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

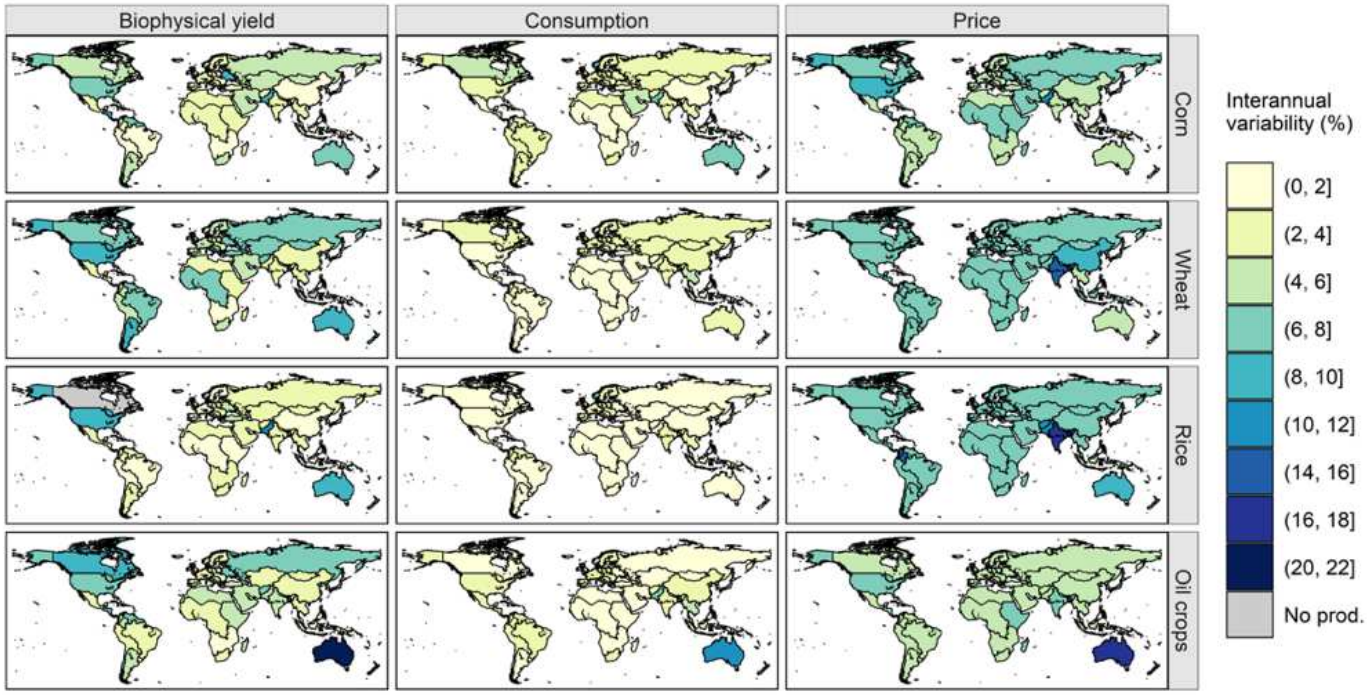

Figure 5

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. S7-S9. Gray areas in biophysical yield maps represent regions with no productions of the crop. Data source: GCAM simulation results

Supplementary Files

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