Energy and Climate Management, 2025, 1(2): 9400005
https://doi.org/10.26599/ECM.2024.9400005

Review

A framework for analyzing climate change impacts on agricultural value chain

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Received: 22 December 2023; Revised: 11 March 2024; Accepted: 29 March 2024

ABSTRACT

In the 21st century, global agriculture faces unprecedented challenges due to the complex interplay between climate change, crop dynamics, and economic factors. Frameworks that integrate climate, crops, and economics models have been instrumental in assessing these impacts. However, these frameworks have some limitations, such as neglecting critical value chain effects. This study aims to bridge this gap by introducing a unique climate-crop-value chain framework that considers the entire agricultural value chain, connecting climate science, agriculture science, and economics. By analyzing the agricultural value chain, this framework captures the interconnectedness and ripple effects of climate impacts beyond the affected crop. Improving modeling frameworks like this contributes to the ongoing dialogue on sustainable agricultural development, guiding future research and policy interventions to ensure global food security in a changing climate. Addressing gaps in understanding the economic consequences on the agricultural value chain is crucial for a more comprehensive and actionable approach to climate resilience in agriculture.

KEYWORDS

Climate-crop-economic modeling, agricultural value chain, climate resilience, sustainable agricultural development.

1 Introduction

Agriculture, a cornerstone of global food security and economic stability, confronts unprecedented challenges in the 21st century due to the intricate interplay of climate change, crop production dynamics, and economic factors. The escalating frequency and intensity of extreme weather events, coupled with shifts in precipitation patterns and temperature fluctuations, pose significant threats to crop yields and, consequently, to global food availability. Concurrently, the economic repercussions of these climate-induced changes reverberate through the agricultural sector. In order to comprehensively address the impact of climate change on agriculture, it is imperative to consider the entire agricultural value chain. The agricultural value chain encompasses the various stages of production, processing, distribution, and consumption of agricultural products.

Climate-crop modeling is essential for grasping climate change impacts on agriculture and has been extensively covered in the literature (e.g., Global Gridded Crop Model Intercomparison (GGCMI)[1]; the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP)[2], and Modelling Agriculture with Climate Change for Food Security (MACSUR)[3]. However, the exclusive use of climate-crop modeling reveals limitations. For example, these models simplify agricultural systems, potentially leading to discrepancies with real-world observations[4]. While proficient in biophysical aspects, they often overlook crucial socioeconomic factors shaping agricultural outcomes, such as economic conditions and policy interventions[5]. Relying solely on climate-crop models may underestimate the role of adaptive strategies and mitigation measures, neglecting the resilience and adaptability of agricultural systems[6]. Uncertainties in climate projections and dynamic feedback loops within agricultural systems further complicate accurate predictions[7, 8]. Acknowledging these limitations is crucial for a more comprehensive and detailed understanding of climate change impacts on agriculture.

The scientific community has endeavored to develop sophisticated modeling frameworks that integrate climate, crop, and economic components in response to these challenges. One pioneering initiative in this domain is the Agricultural Model Intercomparison and Improvement Project (AgMIP). Launched as a collaborative effort among scientists and researchers globally, AgMIP aims to enhance agricultural models and their utility in climate impact assessments[4]. Another prominent player in integrating economic considerations into agricultural modeling is the Consortium of International Agricultural Research Centers (CGIAR)'s Research Program on Climate Change, Agriculture, and Food Security (CCAFS), which collaborates with models such as AgMIP to assess the impact of climate change on crop yields and food security. Additionally, the program incorporates outputs from global climate models and utilizes tools like the IMPACT model to analyze the economic implications of climate change on agriculture and food security[9]. On a national scale, China's CAPSiM model platform (China Agriculture Policy Simulation Model, CAPSiM) plays a crucial role in evaluating climate change effects on the agricultural economy[10].

Many prior studies have focused on the direct effects of climate change on individual crops, such as the ones using the modeling framework mentioned above, overlooking the comprehensive repercussions for the entire agricultural value chain. To fully grasp climate impacts, it is essential to recognize the interdependence of

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different sectors within the economy, allowing for exploration of the economic repercussions on the agricultural value chain and shedding light on the ripple effects on employment, pricing, and market dynamics. This economic-oriented perspective contributes to a more nuanced understanding of the broader implications beyond agricultural production. In addressing this literature gap, our study provides a unique and comprehensive perspective on climate change's impact on agriculture, explicitly emphasizing the agricultural value chain from crop production to the final consumer product. Our study bridges the gap between climate science, agriculture, and economics by adopting a holistic approach and analyzing how climate-related disruptions in crop production could affect the final product and its market dynamics. Moreover, it underscores the importance of cross-sectoral analysis in understanding the full extent of climate change impacts, offering actionable insights for policymakers to address climate-related risks in agricultural and related value chains.

Moreover, technological advancements, such as precision agriculture and genetic modification, play a crucial role in mitigating the adverse effects of climate change on crop yields. Understanding how these technologies interact with natural conditions and market forces and how policy interventions shape their adoption and impact provides valuable insights into building resilient agricultural systems. Additionally, considering the dynamic feedback loops between these factors can elucidate the complex relationships within the agricultural sector and inform more effective policy responses to climate change challenges. By delving into these intricate interactions, the study can offer a richer understanding of the multifaceted nature of climate change impacts on agriculture and pave the way for innovative solutions to address them.

This study contributes to the literature by introducing a unique framework that integrates climate science, agricultural modeling, and economic analysis to understand climate change effects on agriculture comprehensively. Departing from traditional climate-crop-economic models that often oversimplify agricultural systems and neglect downstream economic impacts, this framework offers a holistic perspective on climate change impacts by analyzing the entire agricultural value chain, including the ripple effects on pricing, trade, and market dynamics. Its emphasis on actionable insights for policymakers fills a critical gap in the literature, highlighting the importance of cross-sectoral analysis in addressing climate-related risks and fostering resilience in agricultural systems and related value chains.

The rest of the article is organized as follows. The next section describes a general climate-crop-economic modeling framework commonly used in the literature. Section 3 describes how we incorporate agricultural value chain linkages into a climate-crop-modeling framework. Section 4 elaborates some applications of our framework. The final section concludes the study.

2 A general framework of a climate-crop-economic model

Many previous studies have constructed a climate-crop-economic modeling framework. Of these, AgMIP's framework is an example of the general climate-economic model adopted by several studies[11–14]. This framework aims to assess the impact of climate change on agriculture by combining data from climate, crop, and economic models (Figure 1). In this approach, the general circulation models (GCMs) simulate future changes in climate variables (e.g., temperature and precipitation); the crop models (Biophysical) analyze the biophysical yield effects, while the economic models examine the response of key economic variables.

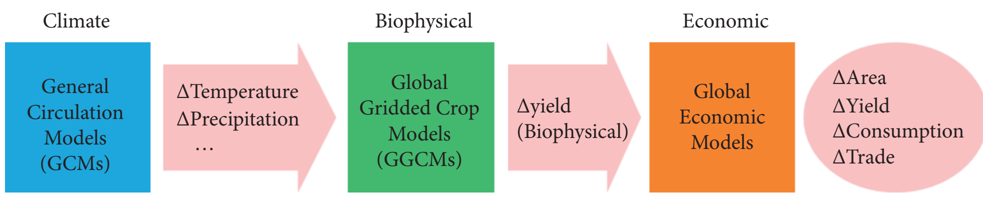

Fig. 1 AgMIP's climate impact modeling framework. Reproduced with permission from Ref. [15], © National Academy of Sciences of the United States of America 2013.

2.1 GCMs

Table 1 summarizes some of the GCMs used in platforms like AgMIP. These models play a pivotal role in simulating and understanding the complex interactions between various components of the Earth system, including the atmosphere, land surface, ocean, and sea ice. HadGEM2-ES, developed by the UK Met Office Hadley Centre[16], and IPSL-CM5A-LR, by the Institute

Table 1 Examples of GCM models used in AgMIP.

Model	HadGEM2-ES	IPSL-CM5A-LR	GFDL-ESM2M	ISI-MIP
General Information	UK Met Office Hadley Centre Global Environmental Model 2	Institute Pierre-Simon Laplace Climate Model 5A - Long Range	Geophysical Fluid Dynamics Laboratory Earth System Model version 2M	Inter-Sectoral Impact Model Intercomparison Project for Integrated Assessment
Spatial Resolution	Medium to High*	Medium to High	Medium to High	-
Components	Atmosphere, Ocean, Land, Ice	Atmosphere, Ocean, Land, Sea Ice	Atmosphere, Lake, Land, Lake Ice	-
Key References	[16, 19, 20]	[17, 21, 22]	[23, 24]	[2, 18, 25]

*High resolution is typically 1.25 × 0.83[26] degrees, and Medium resolution is typically 1.875 degrees in longitude and 1.25 in latitude in the atmosphere[27].

Pierre-Simon Laplace in France[17], are GCMs designed to simulate interactions among the atmosphere, ocean, land surface, and sea ice. HadGEM2-ES comprehensively represents the Earth's climate system, with variable resolutions for different components. IPSL-CM5A-LR operates at a coarser spatial resolution, prioritizing computational efficiency. Both models have been integral to the Coupled Model Intercomparison Project (CMIP) and contribute to climate research, including past climate simulations and future scenarios. Researchers choose between them based on specific strengths for their research questions. ISI-MIP, distinct from climate models, is a project that compares climate impact models using models like HadGEM2-ES and IPSL-CM5A-LR[18]. ISI-MIP assesses climate change impacts on sectors such as agriculture, water, and ecosystems, providing valuable insights for global assessments and policy decisions.

2.2 Crop models

Three main crop model types are used in climate impact assessment studies. Process-based models offer detailed mechanistic insights, statistical regression models leverage historical data for empirical predictions, and field-warming experiments provide real-world validation of model predictions. The choice of model depends on the research goals, available data, and the level of detail required for the analysis.

2.2.1 Process-based crop models

Process-based crop models simulate crop growth by integrating various factors such as climate, soil, agricultural management practices, and crop-specific parameters (Table 2). The goal is to understand the mechanistic relationships between these factors and crop yield. Usually, these models are suitable for small-scale mechanistic studies, especially locally, where interactions between climate, soil, and vegetation are considered. They can enable a comprehensive examination of the complexities of the agricultural system[28]. However, their complex structure requires a large number of input parameters. The accuracy of each parameter directly influences the reliability of the output results. These models may also lack broader applicability beyond the specific conditions of the modeled site.

2.2.2 Statistical regression models

Statistical regression models, on the other hand, rely on historical statistical data to establish relationships between crop yield and climate variables, particularly temperature. Econometric methods are employed to identify these relationships[29]. Their key advantage is the simplicity of their structure, which relies on historical statistical data and provides a practical and efficient way to assess the impact of temperature changes. They can also demonstrate reliability in calculating yield effects caused by temperature increases under existing conditions. On the negative side, they may suffer from potential collinearity issues when multiple climate factors are simultaneously considered, leading to interference and challenges in isolating the effect of temperature. They also have limited credibility in predicting future yield changes based on the current relationship between crop yield and temperature.

2.2.3 Field-warming experiments

Field-warming experiments involve observing crop growth and yield under artificially simulated warming conditions in the field, allowing for a direct examination of the impact of temperature on crops[30]. They provide the most direct method for studying the

Table 2 Major types of crop models used in climate impact analysis.

	Process-based crop models	Statistical regression models	Field-warming experiments
Studies	[4, 28, 31]	[32, 33, 34, 35]	[30, 36, 37]
Mechanism	Simulate the crop growth by inputting data on climate, soil, agricultural management, crop varieties, etc., as well as by adjusting crop parameters and improving the modeling module.	Based on observed crop yields and historical weather records, econometric methods identify the relationship between crop yield and climate. This relationship is then used to evaluate the impact of climate change on crop yield.	Observing the growth and development of crops and changes in final yield under artificially simulated warming environments.
Advantage	The local crop model is a small-scale model based on the conditions of a single experimental site, considering the interactions of climate–soil–vegetation factors, which facilitates small-scale mechanistic studies.The global gridded crop model considers the differences in climate, cultivation, irrigation, and fertilization in different regions, which is conducive to research at different scales.	The model structure is relatively simple and does not need to consider the inherent mechanism of temperature increase affecting yield. The regression functions established based on historical statistical data show strong reliability in calculating the yield effect caused by temperature rise under current conditions.	The most direct method for studying the impact of temperature rise on crop yield only requires manual simulation of future temperature rise conditions at the field scale.
Disadvantage	The structure of the crop model is complex and requires the input of a large number of parameters. The accuracy of each parameter directly affects the reliability of the final output results.There is a lack of extensive warming experiments to verify the impact of simulating future climate change.	When different climate factors enter the statistical model simultaneously, collinearity is prone to occur, leading to interference from other climate factors in the relationship between yield and temperature obtained through statistical regression equations.Due to the possible changes in the correlation between crop yield and temperature, predicting future yield changes based on the current relationship between crop yield and temperature lacks credibility.	The duration of the warming experiment conditions is short, and their representativeness for future long-term (decades to hundreds of years) warming periods is insufficient. The unique characteristics of experimental crop variety types and other growth environments result in insufficient representativeness of experimental results at the regional scale.

impact of temperature rise on crop yield, as it involves manual simulation of future warming conditions at the field scale. They can provide real-world observations of crop responses to temperature changes. One of their shortcomings is that short-duration experiments might not fully capture the long-term impacts of climate change, as decades to centuries of warming cannot be replicated. These models may also suffer from limited representativeness at the regional scale due to specific experimental conditions, including crop varieties and growth environments.

2.3 Economic models

The economic models used by programs like AgMIP represent diverse approaches to modeling environmental and agricultural systems (Table 3). While they share the overarching goal of understanding and predicting complex interactions, their focus, scope, and methodologies differ. Many of these models, such as Asia-Pacific Integrated Model (AIM), Farm Aquaculture Resource Management (FARM), Modular Applied GeNeral Equilibrium Tool (MAGNET), and Common Agricultural Policy Regional Impact (CAPRI), share a regional emphasis, addressing specific geographic areas like the Asia-Pacific region or the European Union. They integrate economic, environmental, and agricultural components to provide a holistic understanding of the systems they model. These models often assess the impact of policies, including agricultural and environmental interventions, on various outcomes like food production, economic indicators, and environmental sustainability.

Among these, ENVISAGE is designed to analyze the relationships between economies and the global environment in response to human-induced greenhouse gas emissions. It incorporates a feedback loop linking temperature variations to economic variables, such as agricultural yields or damages resulting from rising sea levels. Gobal Change Analysis Model (GCAM) takes a global perspective, encompassing economic, energy, land use, and climate components. It is particularly adept at analyzing global challenges like climate change mitigation and energy demand, offering insights into the interconnectedness of these factors worldwide. Global Biosphere Management Model (GLOBIOM), like GCAM, operates at a global level but focuses on the management of biosphere resources. Its integration of economic and biophysical elements makes it valuable for assessing the sustainability of land use in response to varied demands. International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT), another global economic model, is designed to analyze agricultural commodities and trade. It provides policymakers with valuable information on the repercussions of population growth, climate change, and policy decisions on global food and agriculture systems. MAgPIE, developed by the Potsdam Institute, is an integrated model examining agriculture, land use, and the environment globally. It emphasizes the complex relationships between human activities and the environment, offering insights into the broader implications of global change.

Most global modeling frameworks, like AgMIP, are designed to assess the climate change effects on crop sectors. However, a notable limitation in this framework lies in its limited capacity to capture the dynamics of the entire agricultural value chain related to that crop. For instance, when concentrating solely on wheat production and subsequent economic models addressing trade and prices of wheat, these frameworks often neglect crucial elements like the transfer of climate change impacts from wheat to bread price and trade. This oversight hinders a holistic analysis, as the interconnected dynamics of post-harvest processing, distribution, and market factors are not fully considered, resulting in an incomplete representation of the economic consequences of climate change on the agricultural value chain. This holistic approach is essential for facilitating the development of targeted adaptation and resilience strategies, including adopting climate-resilient crop varieties and improving post-harvest technologies. Understanding market dynamics within the value chain context is crucial for making informed decisions about economic policies and interventions in response to climate impacts.

Table 3 Economic models used in AgMIP.

Model	Developer	Economy coverage	Agricultural sectors	Region	Base year
General Equilibrium					
AIM	NIES, Japan	Full economy	8/1	Asia-Pacific, 17	2005
ENVISAGE	FAO/World Bank	Full economy	10/5	Global, 140	2011
FARM	USDA, United States	Full economy	12/8	USA, 5	2004 and 2009
MAGNET	LEI-WUR, The Netherlands	Full economy	10/9	Global, 29/16	2004 and 2007
Partial Equilibrium					
CAPRI	JRC, Belgium	Agriculture	50	EU, 250	1995–2017
GCAM	PNNL, United States	Agriculture, energy	18/0	Global, 32	2005
GLOBIOM	IIASA, Austria	Agriculture, forestry, bioenergy	31/6	Global, 30	2000
IMPACT	IFPRI, United States	Agriculture	32/14	Global, 159	2005
MAgPIE	PIK, Germany	Agriculture	21/0	Global, 10	1995

3 An improved model for climate impacts on agriculture value chain

An improved framework can be used to analyze the climate change effects on crop output and the broader agricultural value chain. Such a framework integrates GCMs, crop models, and global economic models. GCMs simulate future climate changes, while crop models replicate shifts in global yield. Economic models capture consumption and prices, considering shocks to crop yield and the downstream value chain of the crop. To evaluate global crop yield variations due to climate change, simulations compare results with past averages, utilizing rigorously tested crop models. These yield changes from the crop model then inform economic model simulations, exploring variations in production and market repercussions throughout the agricultural value chain. This assessment can be conducted using comparative static or dynamic approaches, with the former projecting impacts on existing economic conditions. The current study introduces this comprehensive framework, evaluating the climate change impact on crop yields and their consequences on this crop's value chain (Figure 2). This approach ensures coverage of climate impacts on the entire agricultural value chain rather than concentrating solely on the affected crop.

To introduce the agricultural value chain impacts of climate change, we consider the impact of climate change on the supply and price of the product of the affected crop (crop product), considering both the direct effects on a crop's production (an ingredient of the product) and the downstream consequences on crop product industry. This approach of examining the entire value chain, from crop production to the final consumer product, provides a more comprehensive understanding of the economic implications of climate change. Some advantages of such a holistic approach may include: By considering the agricultural value chain, the study captures the interconnections and dependencies within the value chain. Climate impacts on crops can have cascading effects on various production, processing, and distribution stages, ultimately influencing the final product's availability and price.

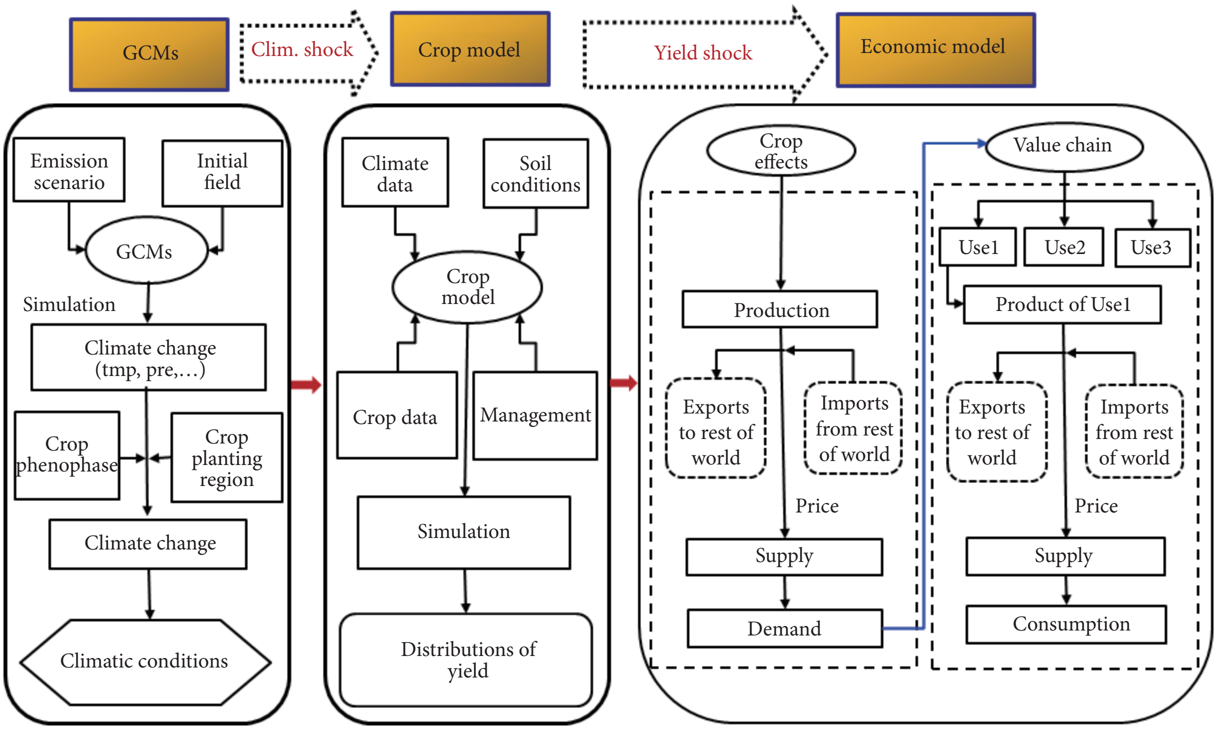

Fig. 2 Modeling framework for climate impacts on the agricultural value chain. Clim. shock means Climate shock.

Analyzing the agricultural value chain allows for a more accurate assessment of the economic ripple effects of climate change. This includes not only the direct impacts on crop yields but also how those impacts propagate through related sectors, potentially affecting employment, investment, and overall economic stability. The study on crop products as consumer products with a well-defined value chain resonates more with people and policymakers. It makes the future climate change effects on everyday items tangible and relatable, enhancing the study's real-world relevance and communication of its findings. Climate change impacts are often cross-sectoral, affecting multiple industries simultaneously. Studying the agricultural value chain acknowledges this complexity and can reveal indirect effects that might be overlooked in studies concentrating solely on the affected crop.

3.1 From climate to crop and crop to economic linkages

In this framework, we start by using different GCMs in conjunction with crop models to translate climate change impacts to crop production. According to the temporal dimension of climate change impacts, we then simulate global crop yield changes due to climate change compared with the average yield during the past period, usually on the grid level, using the crop model. The simulation from the crop model usually requires a considerable amount of data, covering management information, soil parameters, daily weather data, and crop calendar data. The study additionally incorporates data on historical fertilizer use to establish baseline fertilizer application rates.

In our framework, first, crop yields (national/global) from the past periods (30–40 years) will be modeled. Crop yield simulation should also consider possible production systems (for example, early, mid, and late rice) and water management scenarios (usually fully irrigated and rain-fed). Second, accounting for inherent differences in crop varieties might require data on their genetic makeup for the initial parameters, which can be obtained from existing studies. Third, the crop yields will be simulated across the study area. Fourth, global and national yields will be determined by summing data from individual locations at the grid level. Lastly, the framework will help estimate changes in region-specific yields by comparing them to the historical average yield for the corresponding area or the entire globe.

Fertilizer application and other management practices (e.g., irrigation) vary for each crop and crop model. For the case study, the CSM-CERES-Barley model used crop calendar data from various sources that offer planting and harvesting timelines for various crops at different resolutions. Global datasets detailing nitrogen (and other) fertilizer application rates per grid cell are also used. Management information also requires irrigation and other management practices that suit various family-size practices. This information can be sourced from various sources[12, 38, 39] and used in the crop model for each crop.

3.2 Agriculture value chain linkage

3.2.1 *Crop yield shocks*

Next, we will use a specific economic model to simulate crop yield variations resulting from climate change on the crop market and its value chain. There are two main types of economic models, general and partial equilibrium, that employ comparative static or dynamic approaches. General equilibrium models analyze the interdependence of various economic factors across multiple markets, considering simultaneous changes in supply and demand. In contrast, partial equilibrium models focus on the isolated analysis of a specific market, assuming all other markets remain unaffected by changes within that particular sector. Comparative static approaches in economics analyze the changes in equilibrium outcomes resulting from shifts in exogenous variables. In contrast, dynamic approaches focus on studying the evolution of economic systems over time, incorporating considerations of transitions and adjustments in response to endogenous forces. An approach employing a comparative static method can project the climate change impact on the agricultural value chain, i.e., prices and supply of crop products within existing economic conditions. In this approach, one can reduce uncertainties and assumptions related to the model that is run under economic scenarios of the future.

In this framework, the impact of crop yield changes, estimated by the crop model, will be integrated into the economic model by shocking land-use efficiency ("afe" in Eq. (1)) for affected cropland in each region. This is a common approach used to transfer crop yield variations into economic consequences. Eqs. (2) and (3) indicate that changes in the efficiency of land use will consequently change land demand and price. In the economic model, the sectoral/regional price of the primary factors is estimated in Eq. 1 as (equations show percentage changes):

$$\mathrm{pva}_{j,r} = \sum_{k=1}^{n} \left(\mathrm{SVA}_{k,j,r} \times \left(\mathrm{pfe}_{k,j,r} - \mathrm{afe}_{\ k,j,r}\right)\right) \tag{1}$$

here, j indicates production commodity (industry) in region r using endowment commodities k. The firm's price of value-added is pva and price for endowment commodity k is pfe. The share of each endowment commodity (k) in total value added is SVA. Region/sector specific change in primary factor augmenting technology is afe.

Another option would be to incorporate the climate impacts as shocks to total factor productivity (TFP) in a CGE model, as demonstrated by Zhai et al.[40]. In this approach, estimated changes in crop yields due to climate change are translated into a TFP shock within the agricultural sector of the CGE model. This shock captures the overall efficiency with which inputs are transformed into crop outputs, considering the biophysical effects of climate change.

3.2.2 *Input substitutions*

For our improved framework, we surveyed the existing literature on how land and other important inputs (like capital or labor) are substituted under climate change, noticing two main pathways. In the gradual climate change impact assessment, the farmers usually have enough time to respond and adapt to the changing climate. They can adapt by changing their management practices, like using more irrigation to cope with water shortage or to substitute one input with another. In the second pathway, which relates to sudden climate events like drought or extreme heat, farmers find it hard to replace land with other major inputs. To reflect this difficulty, the elasticity of substitution between land and other inputs can be lowered. As an illustration, the model allows us to adjust the responsiveness of crop production to input price changes (elasticity of substitution) under climate change scenarios. We use a 1/10 of the base value of this elasticity (ESUBVA, Eq. (2)), which is based on previous studies[41, 42]. As the value of this critical parameter may also have some inherent uncertainty, we should further analyze the sensitivity of the key parameters in the economic model.

In the economic model, the regional/sectoral input of each endowment commodity is governed by Eq. (2):

$$\mathrm{qfe}_{k,j,r} = -\,\mathrm{afe}_{\ k,j,r} + \mathrm{qva}_{j,r} - \mathrm{ESUBVA}_{j} \times \left(\mathrm{pfe}_{k,j,r} - \mathrm{afe}_{k,j,r} - \mathrm{pva}_{j,r}\right) \tag{2}$$

here, qfe stands for the demand of an endowment commodity k, qva shows the value added to each sector of each region, and the elasticity of substitution among capital, labor, and land in an industry j is denoted by ESUBVA.

Usually, labor and capital factors are mobile among different production sectors in a CGE model setting. However, land and natural resources cannot move that easily (Eqs. (3) and (4)). In the original settings, a crop can change its land demand within a small range, which is set through $\mathrm{ETRAE} = -1$ (i.e., transformation elasticity). However, in contrast to the long-run climate impacts, under extreme climate conditions (e.g., droughts), in response to food security concerns, individuals or regions might prioritize planting more staple food crops that are crucial for their diets. This could lead to an increase in the area dedicated to crops like wheat, potentially at the expense of other cereals such as rice or maize. Consequently, the planted area for these secondary crops might decrease.

Our modeling framework takes a more realistic approach by assuming that total land availability remains constant in the short term during climate events. This means farmers would not be able to simply expand the land dedicated to a specific crop (the affected crop) if faced with climate challenges. Instead, the model considers the possibility of adapting other inputs like labor (through increased work hours) or machinery (through additional investment) to maintain production of the affected crop. In our improved model framework, we assume the amount of land used for the affected crop (or any other crop) remains the same during normal and climate-affected years (achieved by setting $\mathrm{ETRAE} = 0$), even though adjustments might be made to other resources.

Sluggish endowments are allocated across sectors via Eq. (3):

$$\text{qoes}_{k,j,r} = \text{qo}_{k,r} + \text{ETRAE}_k \times \left(\text{pm}_{k,r} - \text{pmes}_{k,j,r}\right) \tag{3}$$

where qoes denotes sluggish endowment supply to sector j in region r and qo stands for the output of endowment k in region r. Sluggish endowments' elasticity of transformation is ETRAE, the market price of endowments is denoted by pm, while the market price of the sluggish endowments is shown by pmes.

Eq. (4) determines sluggish endowments' composite price as

$$\text{pm}_{k,r} = \sum_{j=1}^{n} \left(\text{REVSHR}_{k,j,r} \times \text{pmes}_{k,j,r}\right) \tag{4}$$

In this equation, REVSHR indicates the endowment's share used by each industry j in region r.

Meanwhile, mobile endowments (labor and capital) can act normally (move freely) as sudden climate events can encourage more investment to expand these endowments (Eqs. (5)–(6)).

Mobile endowments are allocated to different sectors as in Eq. (5):

$$\text{qo}_{k,r} = \sum_{j=1}^{n} \left(\text{SHREM}_{k,j,r} \times \text{qfe}_{k,j,r}\right) \tag{5}$$

This shows that mobile endowment's share at market prices = SHREM.

Mobile endowments' composite price is governed as

$$\text{pm}_{k,r} = \text{VFM}_{k,j,r} / \text{ qfe }_{k,j,r} \tag{6}$$

meaning that producer expenditure to purchase endowments at market prices = VFM.

3.2.3 Crop allocation to competing uses

Changes in the affected crop supply due to climate change have diverse effects on downstream industries' production across regions. The crop allocation among various uses will vary due to the elasticity of demand and price in each region as various industries operate under profit maximization conditions. Various downstream users of the crop may consume different shares of the affected crop, and climate change impacts these allocations differentially. As shown in Figure 2, the share of the affected crop to Use1 may contract more/less during climate change than other uses. For example, if wheat supply (the affected crop) is affected by climate change, its allocation to pasta production (Use1) may drop by a higher/lower margin than for bread (Use2), crackers (Use3), or other uses in a given region.

The varying allocation of a climate-affected crop to downstream uses brings forth a complex set of implications. Industries reliant on the affected crop must assess and fortify their supply chains to adapt to changing climate conditions and mitigate potential disruptions in production. Shifting allocations may lead to global trade imbalances, impacting importers and exporters of the downstream products of climate-affected crops. Industries facing altered allocations can find opportunities for innovation, such as developing climate-resilient crop varieties and exploring alternative inputs. Changes in downstream products may influence consumer behavior, leading to shifts in preferences and purchasing patterns. The impacts extend beyond agriculture, emphasizing the interconnectedness of industries in the face of climate-induced challenges.

Here, the allocation of wheat to pasta, bread, and crackers production will depend on region-specific prices and demand elasticities as production sectors operate under the profit maximization principle. For example, if pasta demand is less elastic in one region, its demand for wheat will drop relatively by a lower margin compared to bread or crackers under climate change.

4 Applications of the framework

4.1 Climate-barley-beer application

Several studies have used our introduced framework for climate impact assessment (Table 4). For example, Xie et al.[43] applied this framework to analyze climate change impacts on barley (the affected crop) and beer consumption (barley's primary downstream use). They adopted this employed framework by using different GCMs (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M) and the crop model Decision Support System forAgrotechnology Transfer (DSSAT) to translate climate change impacts into crop production (barley). Changes in barley yield were simulated at a global scale using gridded (0.5° × 0.5°) extreme events through CSM-CERES-Barley within DSSAT. The model was run using gridded formatted inputs, including management information, soil parameters, daily weather data, and crop calendar data. Soil parameters, weather data, and crop calendar data were obtained from various sources, and a crop-specific gridded dataset for nitrogen fertilizer application was used. Barley yields worldwide from 1981–2010 were modeled, considering two production systems for barley (i.e., winter and spring) and rain-fed and fully irrigated water management systems. Changes in regional and global yields were calculated as deviations from the average for 1981–2010. In the agriculture value chain linkage, CSM-CERES-Barley simulated the gridded variations in global barley yield under climate change (from extreme events) in contrast to the past yields (average of 1981–2010). They also considered other related elements of our framework, like input substitutions for barely production and barley allocation to competing uses such as beer, livestock feed, and other uses.

For the final part of the agricultural value chain impact analysis, they found that in most instances, food commodities, particularly animals fed on barley, take precedence over luxury items like beer during climate-related crises (Figure 3(a)). For example, the most intense climatic conditions (i.e., occurring in RCP8.5) will reduce global barley production significantly (15%), and the share allocated to beer would be reduced by a more substantial value of 20%. Different regions would also react differently to barley shortages. For example, the USA's barley consumption will drop by 5% due to climate change (i.e., RCP8.5), with the share of barley for beer production dropping by 10% and exports increasing by 262%. Consequently, future climate change not only diminishes the overall barley availability for key nations but also curtails the proportion allocated to beer production. For example, both the USA and China will face the highest drop in total beer consumption (Figures 3(b) and 3(c)) because they face a disproportionate drop in the supply of barely for beer production.

Other crops like maize or wheat are also viable case study crops. This analysis focused on barley because it is the primary agricultural ingredient in beer production, which stands as the most widely consumed alcoholic beverage worldwide.

In this case study, model validations were performed by testing different factors to see how they affect the global beer market under climate change. By changing each factor by a small amount, how it affected the volume of beer people consume worldwide was observed. It was found that the efficiency of turning barley into

Table 4 Applications of the framework.

Sr. #	Authors	Title	Publication	Year	Geographic coverage
1	Xie et al. [44]	Role of market agents in mitigating the climate change effects on food economy	*Natural Hazards*	2019	Not specified
2	Zhang et al. [45]	Impacts of climate change on self-sufficiency of rice in China: A CGE model-based evidence with alternative regional feedback mechanisms	*Journal of Cleaner Production*	2019	China
3	Huang et al. [46]	Assessment of the economic cascading effect on future climate change in China: Evidence from agricultural direct damage	*Journal of Cleaner Production*	2020	China
4	Wu et al. [47]	Assessing sustainability of soybean supply in China: Evidence from provincial production and trade data	*Journal of Cleaner Production*	2020	China
5	Ignjacevic et al. [48]	Time of emergence of economic impacts of climate change	*Environmental Research Letters*	2021	Global
6	Wang et al. [49]	Modeling the inter-regional economic consequences of sequential typhoon disasters in China	*Journal of Cleaner Production*	2021	China
7	Wang et al. [50]	Economic impacts of climate-induced crop yield changes: evidence from agri-food industries in six countries	*Climatic Change*	2021	Six countries
8	Ali et al. [51]	The Impact of Climate Change on China and Brazil's Soybean Trade	*Land*	2022	China and Brazil
9	Cui et al. [52]	The uncertainty of climate change impacts on China's agricultural economy based on an integrated assessment approach	*Mitigation and adaptation strategies for global change*	2022	China
10	Liu, J. and Li, X. [53]	Impact of Extreme Weather Disasters on China's Barley Industry under the Background of Trade Friction—Based on the Partial Equilibrium Model	*Foods*	2022	China
11	Wei et al. [54]	Dual carbon goals and the impact on future agricultural development in China: a general equilibrium analysis	*China Agricultural Economic Review*	2022	China
12	Qiao et al. [55]	How climate change and international trade will shape the future global soybean security pattern	*Journal of Cleaner Production*	2023	Global

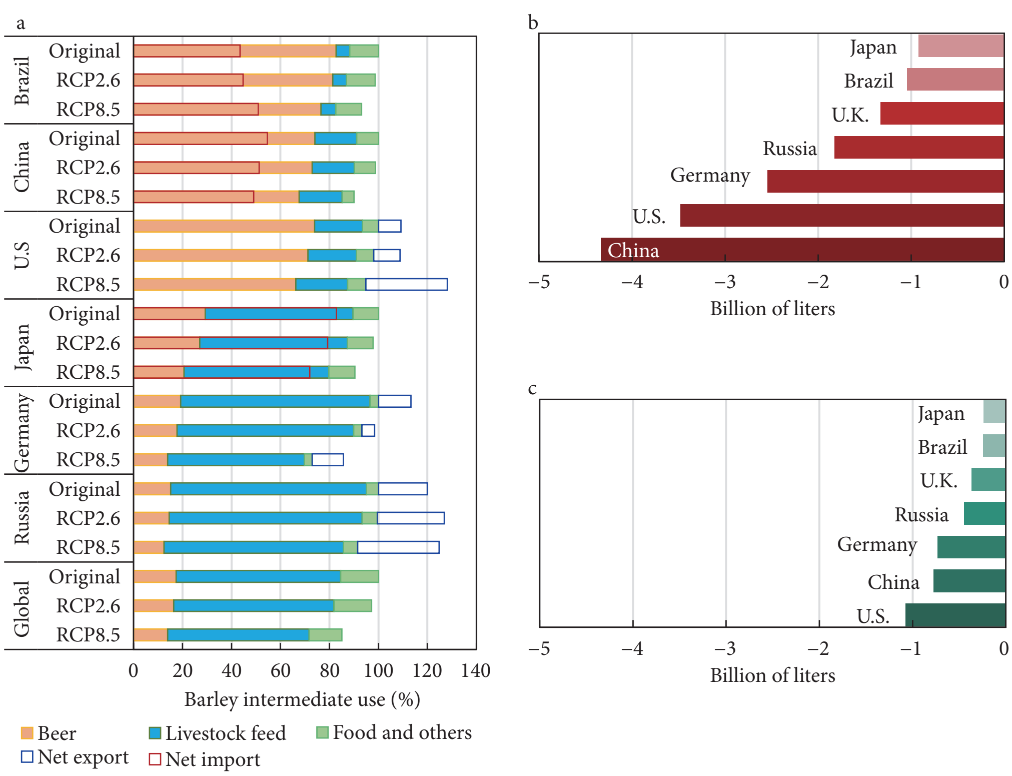

Fig. 3 (a) Shares of barley uses under RCP8.5 and RCP2.6, changes in beer consumption in major countries under (b) RCP8.5 and (c) RCP2.6 due to varying barely consumption by different uses under climate change.

beer had the biggest impact, followed by factors like the severity of climate change and how much barley is stored in each country. These model validations can also be extended to future studies.

Our approach used in the above case study offers a significant advancement over traditional climate impact assessments by considering the entire agricultural value chain rather than concentrating solely on primary crops. By examining downstream uses such as beer production and the allocation of crops to competing uses, this approach provides a more comprehensive understanding of how climate-related disruptions in crop production ripple through the economy and how competing uses of crops compete with each other in times of crop damage. This enables policymakers to make more informed decisions regarding food security, economic stability, and adaptation strategies in the face of climate change.

4.2 Other studies using this framework

Most other studies in Table 4 investigate the intricate relationship between climate change, agricultural sustainability, and economic impacts, predominantly centered around China and global trade. Common themes across these studies include using sophisticated modeling approaches to simulate future scenarios, highlighting the necessity for sustainable agricultural practices. A significant emphasis is placed on the vulnerability of key crops, such as soybeans and rice, to climate change, with an overarching recognition of the role of technological progress in mitigating adverse effects arising from decarbonization efforts on agriculture.

Several studies employ computable general equilibrium models, such as CHINAGEM, Global Trade Analysis Project (GTAP), and Adaptive Regional Input-Output (ARIO), to assess the economic consequences of climate-induced changes in crop yields at various scales. The methodologies include emergy accounting approaches to evaluate sustainability, ensemble modeling coupled with global economic models to assess variations in soybean yields, and probabilistic climate change projections combined with impact functions for identifying the Time of Emergence of Economic Impacts (ToEI).

While some studies analyze the global economic impacts of climate-induced changes in crop yields, others specifically focus on China's self-sufficiency in key crops. The research underscores the importance of understanding the economic repercussions of extreme weather events and trade conflicts on agricultural imports and exports, particularly in the context of China's dependence on soybean imports. The role of international trade policies and market integration emerges as a crucial factor in adapting to climate change and ensuring food security.

Differences among the studies lie in their specific focuses, methodologies, and outcomes. Some concentrate on assessing economic cascading effects due to industrial linkages, while others explore the spatial distribution of soybean security or introduce novel concepts like the Time of Emergence of Economic Impacts (ToEI). Additionally, there are variations in the crops studied, the economic models employed, and the geographic scope, ranging from global assessments to regional analyses.

5 Conclusions

Climate change, crop dynamics, and economic factors pose unprecedented challenges to global food security. While climate-crop models are valuable, they oversimplify real-world systems and neglect socioeconomic factors. Integrative frameworks are crucial for understanding climate impacts but often overlook downstream industry effects.

The comprehensive climate-crop-value chain framework introduced in this study provides a holistic perspective by considering the agricultural value chain. This approach, bridging climate science, agriculture, and agricultural value chains, can offer insights into the broader implications of climate change, resonating with a wider audience. By studying the agricultural value chain, the framework captures the interconnectedness and ripple effects of climate impacts beyond the affected crop.

In navigating the intricate landscape of climate-crop-economic modeling, this study contributes to the ongoing dialogue surrounding improved analytical approaches for attaining sustainable agricultural development. Addressing the gaps identified in existing studies, particularly in understanding the economic consequences on the agricultural value chain, is crucial for a more comprehensive and actionable approach to climate resilience in agriculture. Policymakers must address the differential impacts of climate change on crop allocations, requiring nuanced policies and adaptive strategies for affected industries. Prioritizing research and development is crucial to invest in technologies and practices that enhance the resilience of downstream industries.

This framework has a few limitations. First, it uses just one crop model to predict crop yields, which might not fully account for how climate change affects crop damage. Also, the predictions are based on a static economic approach, indicating current farming methods and global economics and demographic conditions. It does not consider future changes in farming, like new technology or improved crop varieties. Future studies could explore these factors to understand better how climate change affects downstream industries through crop damage.

Acknowledgments

This work was supported by National Key R&D Program of China (No. 2023YFD2300301) and NSFC (Nos. 72261147472 and 72348003).

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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