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# CGIAR modeling approaches for resource-constrained scenarios: II. Models for analyzing socioeconomic factors to improve policy recommendations

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**Abstract**

International crop-related research as conducted by the CGIAR uses crop modeling for a variety of purposes. By linking crop models with economic models and approaches, crop model outputs can be effectively used as inputs into socioeconomic modeling efforts for priority setting and policy advice using ex-ante impact assessment of technologies and scenario analysis. This requires interdisciplinary collaboration and very often collaboration across a variety of research organizations. This study highlights the key topics, purposes, and approaches of socioeconomic analysis within the CGIAR related to cropping systems. Although each CGIAR center has a different mission, all CGIAR centers share a common strategy of striving toward a world free of hunger, poverty, and environmental degradation. This means research is mostly focused toward resource-constrained smallholder farmers. The review covers global modeling efforts using the IMPACT model to farm household bio-economic models for assessing the potential impact of new technologies on farming systems and livelihoods. Although the CGIAR addresses all aspects of food systems, the focus of this review is on crop commodities and the economic analysis linked to crop-growth model results. This study, while not a comprehensive review, provides insights into the richness of the socioeconomic modeling endeavors within the CGIAR. The study highlights the need for interdisciplinary approaches to address the challenges this type of modeling faces.

## 1 | INTRODUCTION

International agricultural research for development through the CGIAR focuses on achieving and maintaining global

**Abbreviations:** APSIM, Agricultural Production Systems Simulator; CGE, Computable General Equilibrium; CSA, climate-smart agriculture; DREAM, Dynamic Research EvaluAtion for Management; DSSAT, Decision Support System for Agrotechnology Transfer; GFSF, Global Futures and Strategic Foresight; IGRM, International Rice Research Institute Global Rice Model; IMPACT, International Model for Policy Analysis of agricultural Commodities and Trade; IPCC, Intergovernmental Panel on Climate Change; RCP, Representative Concentration Pathway; RT&B, root, tuber, and banana; TOA-MD, Tradeoff Analysis Model for Multidimensional Impact Assessment.

food and nutrition security (CGIAR, 2015). The CGIAR is a global research partnership for a food secure future dedicated to reducing poverty, enhancing food and nutrition security, and improving natural resources (CGIAR, 2015). This is a daunting task because changes in climate, population, income, and food distribution, among others, make the efforts to achieve food security solutions challenging (Burke & Lobell, 2010; Grassini, Eskridge, & Cassman, 2013; Islam et al., 2016; Robinson et al., 2014). Contributing to the transformation of dynamic complex agri-food systems requires a close collaboration between the different actors to assess these threats and weighing possible solutions using either multidisciplinary, interdisciplinary or transdisciplinary approaches as appropriate.

Generating new technologies takes time, whether this refers to new varieties of key crops or management practices that improve the sustainability and resilience of farming systems. Typically, the development of new technologies takes at least five to seven years, but can easily take much longer when the issues addressed are more challenging (Li et al., 2018; Voss-Fels, Stahl, & Hickey, 2019; Watson et al., 2018; Yigezu et al., 2018). Example of challenging technologies to develop are C4 rice (*Oryza sativa* L.) (Lin, Coe, Quick, & Bandyopadhyay, 2019) and incorporating biological nitrification inhibition traits in wheat (*Triticum aestivum* L.) (Subbarao et al., 2007), research that is currently a topic of socioeconomic ex-ante impact assessment studies.

Agri-food systems evaluated by the different CGIAR centers produce a range of products that generate positive environmental, social, and economic impacts at different scales (Bobojonov & Aw-Hassan, 2014; CGIAR Independent Science and Partnership Council, 2011). The socioeconomic impacts of CGIAR–generated activities can be evaluated and predicted using different socioeconomic modeling tools such as foresight analysis of agricultural systems under global change scenarios and the consequences of potential food system and farming system shocks, among others (Godfray et al., 2016; Komarek, Thurlow, Koo, & De Pinto, 2019; Komarek et al., 2019; Komarek & Msangi, 2019; Boussios et al., 2019; Yigezu, Aw-Hassan, Shideed, Sommer, & El-Shater, 2014; Ates et al., 2018; Frija & Telleria, 2016; Reynolds et al., 2018). Simulation and scenario analysis (IPCC, 2019; Riahi et al., 2017) either focus on what the future has in store for humanity to identify research priorities today or look at (potential) emerging technologies to assess how they fit into dynamic complex agri-food systems including the analysis of the appropriateness of technology for farming systems and livelihood strategies (Rosegrant et al., 2017).

The objective of this review is to present an overview of the main modeling activities and the outcomes generated by different CGIAR centers that combine socioeconomic analysis, models, and tools with crop modeling or crop modeling results. In this overview, which is not a systematic review, we present some key examples and their impacts. Big-picture modeling goals that could have a positive impact across research areas, cropping systems, and rural communities, among others, are presented together with the needs and next steps to be taken to ensure global food security.

The scope of the work we discuss in this review relates to modeling efforts related to crops in terms of varieties and management practices and related policies, interventions, and institutional change. While we address models that combine crops and livestock, we purposely ignore models that are focused exclusively on livestock systems, aquaculture, and fisheries. We also ignore studies that focus exclusively on either forestry or plantations.

## 2 | SCOPE AND PURPOSE OF BIO-ECONOMIC MODELING AT CGIAR CENTERS

### 2.1 | Foresight versus ex-ante impact assessment

Very often, strategic foresight and ex-ante impact assessment are used interchangeably. However, we make a clear distinction between the two concepts. We define these concepts in the context of international agricultural research for development.

- Strategic foresight looks at the future and determines what that means for the type of action we need to take today in terms of policy making, research priority setting, and other actions.
- Ex-ante impact assessment looks at how technologies in the research and development continuum fit into farming systems, livelihood strategies, and agri-food systems in general.

The former concept starts in the future and looks back at the present, whereas the latter projects from the present into the future. Both approaches involve the definition and use of scenarios for the assumptions about the future based on major drivers of change such as population growth, economic developments, and climate change.

Foresight and ex-ante research within the CGIAR use a range of interdisciplinary modeling approaches to guide the technology improvement process in each center. Foresight evaluation looks at potential system performance, using both qualitative and quantitative data, in a way that facilitates the examination of different potential future scenarios because of major drivers of change and their interactions leading to rural transformation, urbanization, and food system transformation. For example, foresight models look at the association between past and current income and consumption patterns and make projections on what to expect in the future under various policy, institutional, technological, and climate change scenarios. Ex-ante impact assessment starts from the present and analyzes the potential futures mainly using modeling tools. One example of ex-ante assessment can be the evaluation of how technological and policy changes can influence the future income of smallholder farmers. Within the CGIAR the focus is on the farming systems producing main food crops of resource poor farmers in low- and middle-income countries where food security is of concern.

Global Futures and Strategic Foresight (GFSF, http://globalfutures.cgiar.org/) is a CGIAR-wide initiative led by the International Food Policy Research Institute (IFPRI) in which all 15 CGIAR centers are working together to improve the understanding of future challenges to agricultural productivity, food security, and environmental sustainability especially in developing countries and to explore options to address these future challenges. At its inception in 2010, GFSF was funded through the Bill and Melinda Gates Foundation for five years. Then, the CGIAR Research Program on Policies, Institutions and Markets and the CGIAR Research Program on Climate Change, Agriculture, and Food Security have been funding the initiative for the past five years. Using various quantitative modeling techniques, the GFSF focuses on evaluating the economic viability and biophysical sustainability of promising technologies in their recommendation domains globally as well as the associated research investments and policy reforms. Much of the foresight work carried out in the context of GFSF is based on a structural modeling approach since the suite of tools consists of different interlinked models (more information in Section 3). As of 2019, the collaborative effort is being renamed the CGIAR foresight team.

The main policy and socioeconomic modeling activities performed within CGIAR centers are focused on issues such as scenario development, policy analysis, decision support, and assessment of potential impacts in general and potential economic returns in particular. Specific examples, drawing on the work of the different CGIAR centers, are presented in the next sections.

## 2.2 | Purpose of using crop modeling in socioeconomic research

As mentioned earlier, the purpose of doing specific research is crucial for understanding model choices. The purposes for using crop modeling in a socioeconomic research context are varied and include, among other possibilities, research priority setting, policy analysis, decision support with the scaling of new technologies, and determining the economic returns of new technologies. One reason crop models are needed for the above purposes is that we often do not have enough observation data from agronomic field trials or farmer surveys of crop yields under a range of technologies and across a range of biophysical environments (with heterogenous soils and weather, among others), therefore, models allow for a convenient way to explore a range of scenarios related to crop yields accounting for spatial and temporal variability.

Research priority setting draws heavily on foresight analysis and builds on a long history of studying science under scarcity especially where it concerns the mid- and long-term projections that guide decisions concerning prebreeding strategies and trait discovery decisions. The obvious example is climate change. By adding an economic component to the analysis of climate change, the economic and biophysical effects of climate change on specific crops and technologies in specific geographies can be assessed. In fact, Petsakos, Hareau, Kleinwechter, Wiebe, and Sulser (2018) argue that foresight modeling can add substantial value when setting priorities for international agricultural research, as it can quantify the effect of uncertainty on the performance of the agricultural sector especially related to climate change and socioeconomic variables such as income and population. The analysis of climate-resilient crops includes drought-tolerant rice (*Oryza sativa* L.) varieties (Mottaleb, Rejesus, Murty, Mohanty, & Li, 2017), drought-tolerant common bean (*Phaseolus vulgaris* L.) varieties (Álvarez et al., 2016), drought-tolerant sorghum [*Sorghum bicolor* (L.) Moench] (Nedumaran, Bantilan, Abinaya, Mason-D'Croz, & Kumar, 2014), drought- and heat-tolerant maize (*Zea mays* L.) varieties (Tesfaye et al., 2018). Bobojonov and Aw-Hassan (2014) analyzed the effect of climate change on farm income in central Asia, finding that impact can be either positive or negative depending on situations especially when risk is increased because of biophysical constraints including climate change.

The effect of potential adoption of new technologies under climate change is a key topic, which has become even more relevant with the publication of the latest IPCC report (IPCC, 2019). Examples include the analysis of how climate change may affect world supply of agricultural commodities and thus the prices of commodities and therefore also the ability of consumers to afford food (Rosegrant et al., 2014). Other examples relate to crop yields and food security impact under different scenarios of climate change (Islam et al., 2016; Komarek, Thurlow, et al., 2019; Tesfaye et al., 2018; Chung et al., 2014; Gbegbelegbe, Chung, Shiferaw, Msangi, & Tesfaye, 2014).

Another purpose for using crop models in socioeconomic research is to design scenarios to study crop demand, supply, and trade and is served by coupling economic decision tools with results from crop models (mainly crop yields). An example is the analysis of potato supply in India by 2030 by Scott, Petsakos, and Juarez (2019). Given the predominantly vegetarian diets in India, the authors show that potato (*Solanum tuberosum* L.) production in the country can even double compared with 2010 under a foresight scenario that posits rapid economic and technological growth and milder climate change assumptions (RCP 4.5 vs. RCP 8.5). Another study by Hoang and Meyers (2015) analyzed price stabilization and impacts of trade liberalization in Southeast Asia rice markets. The simulation results suggested that the removal of state trading enterprises in Indonesia, Malaysia, and the Philippines would lower their domestic prices by as much as 34% but increase the world prices by ∼20%. Seck et al. (2013) simulated future rice supply and demand at the global level. The authors projected that by 2035, an additional 116 million t of rice will be required to meet the growing global demand, of which, around one-quarter demand will be from Africa. Therefore, to meet this global demand, ∼0.6 t $ha^{-1}$ more rice will be required to produce annually without any expansion of the rice area. Closing yield gaps and expanding mechanization in rice farming could help achieve this goal (Seck et al., 2013).

Policy analysis is another major purpose for models that combine biophysical relationships or results of crop models and economic optimization (bio-economic models). Some of the policies that can be analyzed are closely related to management practices such as use of water for irrigation (Yigezu et al., 2014). Crop modeling combined with economic analysis can be used to determine of intraseasonal policy actions related to weather changes needed to induce changes in management practices within the cropping season (Boussios et al., 2019) to enhance the effectiveness of the watershed approach (Nedumaran, Shiferaw, Bantilan, Palanisami, & Wani, 2014) and for resolving land ownership disputes to reduce deforestation rates and forest-based carbon emissions in armed-conflict areas (Castro-Nunez, Mertz, Buritica, Sosa, & Lee, 2017).

Bio-economic modeling is also a useful tool for the ex-ante impact assessment of planned or contemplated policies. It allows the analysis of key technological and policy interventions on for instance the socioeconomic wellbeing of rural households and the natural resources (Nedumaran, Shiferaw, et al., 2014). It is also used to assess changes in the price of mineral fertilizer on different household indicators like mineral fertilizer demand, land use, crop yield and production, total calories consumed, household income for smallholder farmers in central Malawi (Komarek et al., 2017), and subsidizing crop production costs on land use and household caloric intake in Sierra Leone (Chenoune et al., 2017).

Bio-economic modeling is also used for food security assessment. The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) model (Rosegrant et al., 2014), which is a partial equilibrium bio-economic model has also been used for analysis of changes in food systems and impacts on producers, consumers, and the environment at different scales (CIAT, 2017). Food security has four dimensions: availability, access, use, and stability. Though they have the potential for application at larger scales, most past applications of bio-economic models were farm-scale scenario simulations using mathematical programming like the ones discussed in several reviews (Janssen & Van Ittersum, 2007; Brown, 2000; Oriade & Dillon, 1997; Castro et al., 2018).

Another key purpose of bio-economic modeling is determining the economic returns of new technologies. The wide range of cases include the following: (a) the analysis of gains in productivity and economic effects of conservation agriculture in Zambia (Komarek et al., 2019); (b) household welfare and poverty distribution when relaxing cash constraints and increasing the off-farm income opportunities in the White-Volta Basin of Ghana (Nedumaran & Berger, 2009); (c) developing and disseminating drought-tolerant rice in southern Asia (Mottaleb et al., 2017); (d) use of biomass-enhancing technologies {conservation agriculture, maize–mucuna [*Mucuna pruriens* (L.) DC.] rotation} in the context of mixed farming systems in semi-arid Zimbabwe (Homann-Kee Tui et al., 2015); (e) preparing a payment for environmental services schemes in the Andes identifying watersheds biophysically critical areas and compare services for current land uses under changing scenarios (Quintero, Wunder, & Estrada, 2009); and (f) restoring degraded land in Latin America through, for instance, the WRI 20 × 20 Initiative (https://www.wri.org/our-work/project/initiative-20%20%EF%82%B4%2020) also requires ex-ante impact assessment (Vergara et al., 2016).

## 2.3 | Key topics

Socioeconomic pressures, such as population growth, changes in income, changes in preferences for food, market access, availability, and access to technology and development, clearly affect crop production and productivity. How these current and projected trends in socioeconomic factors will affect agricultural productivity and food security remains unclear and is being widely studied by different research groups within the CGIAR centers using a combination of tools and methodologies. For example, Petsakos et al. (2019), in a joint study by multiple CGIAR centers, examine how climate and socioeconomic changes could affect root, tuber, and banana (RT&B) crops by 2050. Based on the analysis by Rosegrant et al. (2017), the authors conclude that the diet contribution of RT&Bs in terms of calorie intake is likely to increase in developing countries in the future. Petsakos et al. (2019) also argue that targeted investments on productivity improvements can further strengthen the role of RT&Bs in global food systems.

Forecasting of plausible and probable upcoming events is a crucial step to avoid or reduce the magnitude of future problems, thus enabling better decision making on strategic issues. A good way of examining potential future scenarios is by using agronomic and socioeconomic modeling approaches (Reynolds et al., 2018; Rosegrant et al., 2017). Modeling socioeconomic factors may help provide information for supporting decisions and policies that are beyond the information available only from crop models. This is because, for example, socioeconomic modeling considers the suitability of technologies to different contexts and goes beyond the field or laboratory where technologies were initially innovated and tested.

The key topics addressed by CGIAR economic models, ranging from global integrated assessment models to socioeconomic and bio-economic models at the farm scale, that are informed by crop models depend in part on the scope and purpose. They include economic aspects of climate change and weather variability (including extreme weather events), new and emerging pests and diseases, besides the longstanding analysis of how different farm management practices and genotype affect crop productivity and farm income (Archontoulis et al., 2020; Cooper et al., 2020; Hammer et al., 2020).

Climate change is a key topic for which foresight modeling that combines economic and crop growth models is especially suitable. Crop models, such as Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2019; Jones et al., 2003), ORYZA (Li et al., 2017), and Agricultural Production Systems Simulator (APSIM) (Holzworth et al., 2014) are able to calculate likely productivity outcomes under a variety of climate scenarios (Hammer et al., 2020). The impact in the use of new technologies and agronomic practices for adapting to climate change has been widely evaluated among CGIAR centers as a decision support tool (Li, Angeles, Radanielson, Marcaida, & Manalo, 2015a; Li et al., 2015b). Different research groups have evaluated the ex-ante economic benefits of developing and disseminating drought-tolerant crops under different climate scenarios. Some examples include the evaluation of the development of drought-tolerant crops such as rice in South Asia (Mottaleb et al., 2012, 2017), bean varieties on the Latin America and the Caribbean region and Africa (Álvarez et al., 2016), sorghum in target countries of Asia and Africa (Nedumaran, Bantilan, et al., 2014) and maize in Africa (La Rovere et al., 2014; Setimela et al., 2018; Steward, Thierfelder, Dougill, & Ligowe, 2019). All the analyses show that the development and adoption of new drought-tolerant crop varieties would help to increase crop production and reduce consumer prices, outweighing the research investment needed to develop a new variety (Evenson & Gollin, 2003; Raitzer & Kelley, 2008; Renkow & Byerlee, 2010). The high returns to investment in wheat are well-documented (Lantican et al., 2016). Some studies also suggest combining this varietal replacement with changing crop water and fertilizer management (Komarek et al., 2017; La Rovere et al., 2014) or rotations (Yigezu et al., 2019).

Moreover, there is research focusing on the effect of climate change on crop commodity quality. For example, investigating how carbon dioxide ($CO_2$) affects global nutrition via effects on agricultural productivity and nutrient content of food crops, Beach et al. (2019) found that the effect of increasing $CO_2$ concentrations will slow progress in decreasing global nutrient deficiencies.

## 3 | DATA AND TOOLS USED

An array of tools are used within the CGIAR to do the types of analyses discussed above. These tools range from simple trend analysis to complex dynamic integrated assessment modeling using a variety of interlinked process-based models. In trend analysis, the main focus is to forecast the most likely outcome extrapolating from historical data. This strategy is losing its applicability because of its limitations, as it offers a rather simplified vision and ignores the nonlinearities inherently present in complex systems (Tilman, Balzer, Hill, & Befort, 2011).

The economic models we discuss here are more complicated than simple trend analysis, although some do make use of trend analysis as part of model parametrization procedures. Before we discuss some of the models and model types in more detail, we need to clarify that many models are fit for specific purposes and also for specific temporal and spatial scales. The temporal scales are related to the time frames mentioned earlier when discussing the difference between foresight and ex-ante impact assessment. The spatial scales range from the basic socioeconomic unit of a farm enterprise through all the intermediate levels to the global level.

Special attention needs to be placed on spatial scales. Very often with bio-economic models and interlinked process models from different scientific domains, models are combined that may not be completely compatible in terms of their scales. While this is not necessarily a major problem, it is important to assess the consequences of using models that are optimized for different scales. We recognize that this assessment of scale difference between biophysical and socioeconomic is often missing.

### 3.1 | Models

In our brief model discussion, we start with the integrated assessment models. These include the IFPRI–led IMPACT model and other integrated assessment models at the global level. These models make use of crop modeling results for future scenarios.

#### 3.1.1 | IMPACT model

The IMPACT is a global partial equilibrium model that was first developed in the early 1990s to consider the long-term challenges facing policymakers in reducing hunger and poverty in a sustainable fashion. The IMPACT model has

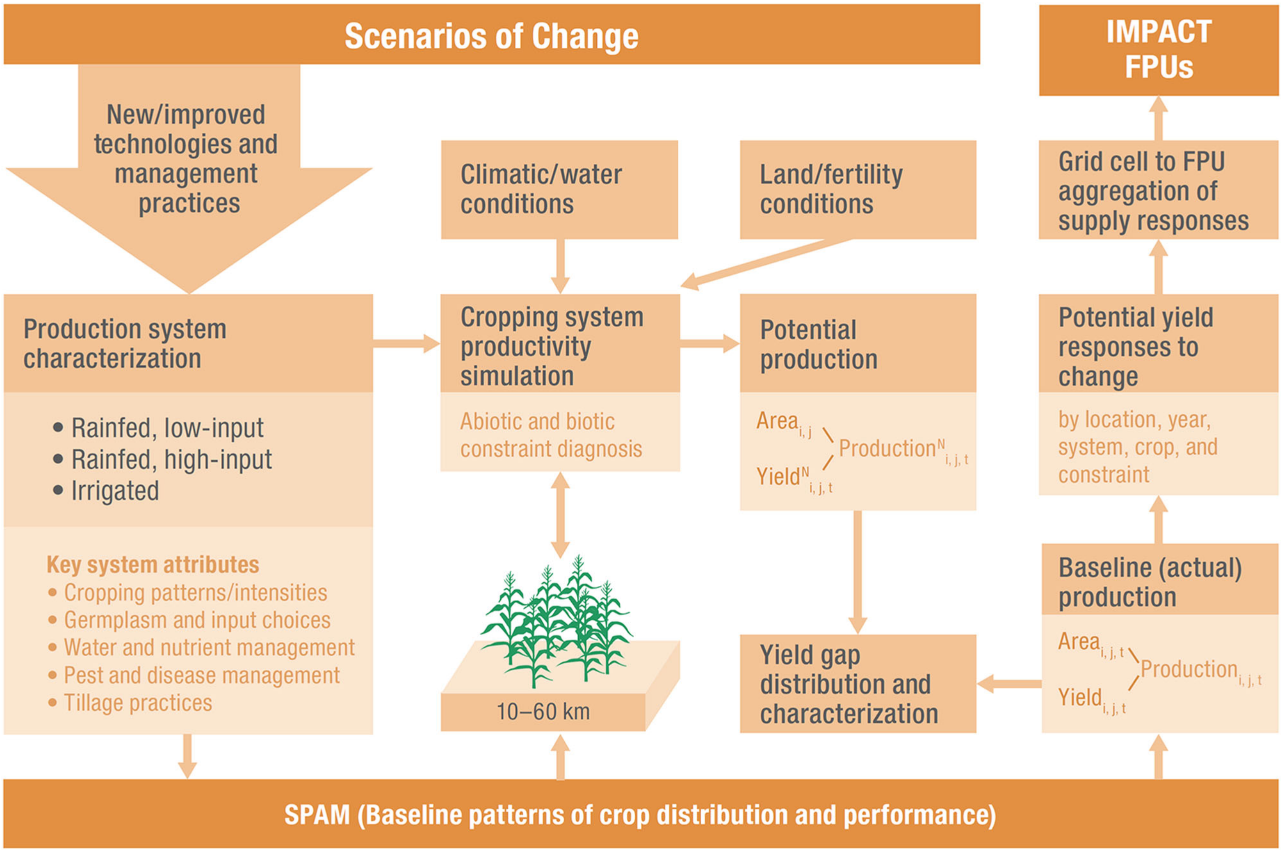


**FIGURE 1** Modeling system for estimation of impacts of agricultural technologies. FPU, food production unit; IMPACT, International Model for Policy Analysis of Agricultural Commodities and Trade; SPAM, spatial production allocation model. Source: Rosegrant et al. (2014).

been expanded and improved repeatedly to respond to increasingly complex policy questions and state-of-the-art modeling (Robinson et al., 2015). The current version of IMPACT is a suite of models including a multimarket economic model; a gridded crop model, the DSSAT; climate models; and a water model. The IMPACT model can calculate the direct effects of and indirect interaction effects of agricultural productivity change under different economic, climatic, and demographic scenarios. The partial equilibrium effects capture the interactions between different commodities in terms of supply, demand and trade, and market clearing prices. Figure 1 illustrates an example of how new technology or management practices can be simulated with IMPACT.

Figure 1 illustrates the relationship between scenario assumptions, technical coefficients related to crop production that are used in crop growth models, and model outputs. While crop production is calculated at a gridded level, the overall outcomes are presented at a higher level of aggregation, the food production unit, and there are 320 food production units in the current version of IMPACT.

The IMPACT model has been used for policy analysis with respect to many commodity systems including but not limited to oil palm (Wiebe et al., 2019), fish (Chan et al., 2019), livestock products (Enahoro et al., 2019), rice (Pradesha et al., 2019), and roots and tubers (Petsakos et al., 2019), to name a few recent studies. IMPACT model results have been used to inform policy decisions in, for instance, the Philippines (Rosegrant & Sombilla, 2018).

### 3.1.2 | Crop-specific global models

Other global models have been developed focusing on a specific crop such as the International Rice Research Institute Global Rice Model (IGRM) and the ORYZA model. The IGRM is a multicountry partial equilibrium model, which can be used for rice-related policy and technology foresight analysis (Hoang & Meyers, 2015; Mottaleb et al., 2017; Seck, Diagne, Mohanty, & Wopereis, 2012). Figure 2 illustrates how the IGRM works.

### 3.1.3 | Economy-wide models at national level

Another group of models is the economy-wide models at national level. Capturing general equilibrium effects of

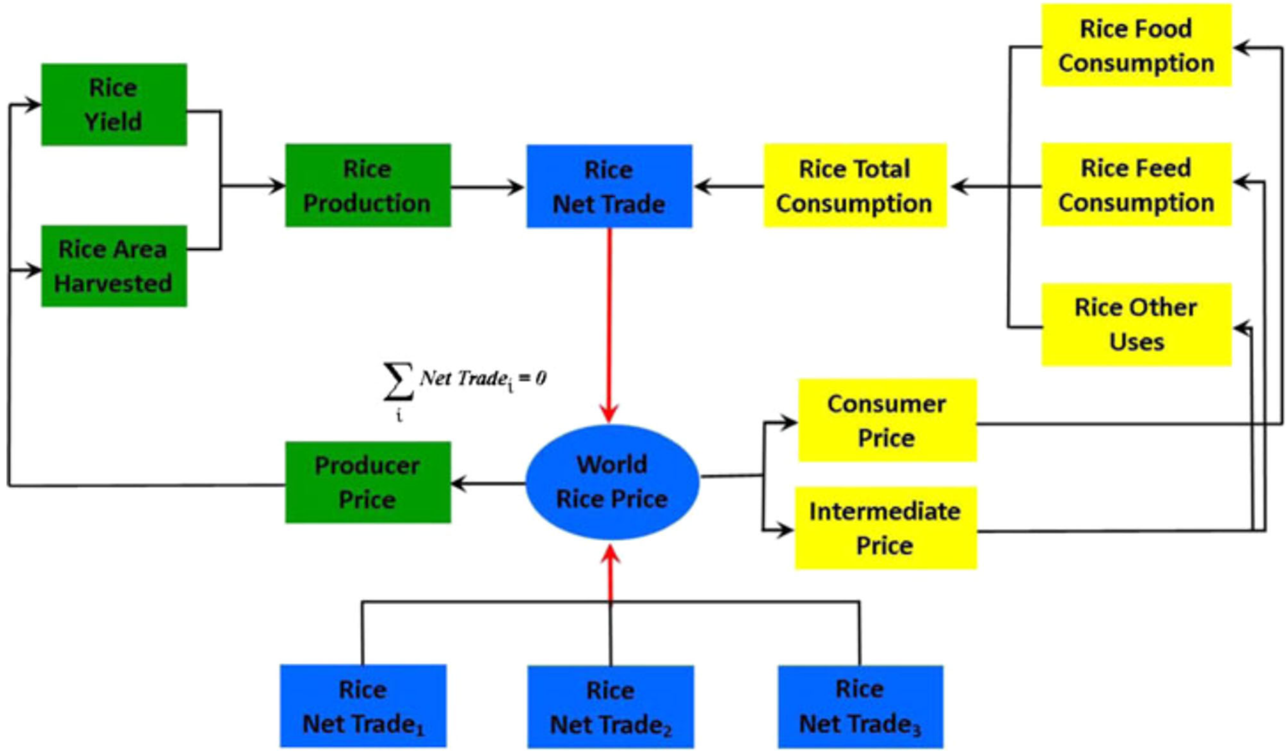


**FIGURE 2** Structure of IRRI Global Rice Model. Source: Hoang and Meyers (2015), Mottaleb et al. (2017).

technology change as predicted by the IMPACT model or assumed using expert opinion may have general equilibrium effects. Computable general equilibrium (CGE) models consider the interactions between agriculture and other economic sectors are affecting the supply, demand, and price formation of crops. An example is Mason-D'Croz et al. (2019) who linked IMPACT with a CGE model (GLOBE) to examine how increased investment in agricultural research, resource management, and infrastructure can help developments in agricultural production systems, offset the adverse effects of climate change, and improve food security and hunger in Africa by 2030. Mason-D'Croz et al. (2019) found that increased investments, US\$15 billion yr$^{-1}$ between 2015 and 2030, may boost crop and livestock productivity by 50% in Africa vs. 2010 productivity levels. As a result, food prices will decline and household incomes will increase; therefore, the large share and number of hungry people in Africa could decline by 2030 under increased investment.

Several other studies also used CGE models to study the general equilibrium effect of maize and wheat technology change in different settings. For instance, using a dynamic CGE model along with a microsimulation model, impacts of promising maize and wheat varieties are evaluated on future food security and poverty and economic performance by Sahoo, Shiferaw, and Gbegbelegbe (2016) in Kenya, Beyene, Shiferaw, Sahoo, and Gbegbelegbe (2016) in Ethiopia, and Ghosh, Shiferaw, Sahoo, and Gbegbelegbe (2016) in India. All of these studies found positive impacts of introducing promising wheat and maize technologies on the respective country's gross domestic product growth and poverty reduction. Lastly, Komarek, Thurlow, et al. (2019) simulated the effects of climate-smart agriculture (CSA) in Ethiopia linking a crop model with a CGE model. The authors found that CSA is more effective than doubling fertilizer use on the same area. Adopting CSA in Ethiopia, the national gross domestic product could increase by US\$33 million and, importantly, it could assist >75,000 people out of poverty. Therefore, to capture general equilibrium effects of technology change, as predicted by partial equilibrium economic models such as the IMPACT or assumed using expert opinion, integrating partial and general equilibrium models is crucial.

### 3.1.4 | DREAM

In 1995, IFPRI researchers developed DREAM (Dynamic Research EvaluAtion for Management), a software to evaluate agricultural research and development projects based on an economic surplus partial equilibrium model. Over the years, this menu-driven software package has been widely used in the evaluation and priority setting of agricultural projects (https://www.ifpri.org/publication/dreampy-evaluation-and-priority-setting-agricultural-research-and-development-projects). Being a partial equilibrium model, a feature of

DREAM is its ability to capture the output price effect of technology adoption, which is often missing in farm-scale models that assume farmers are price takers. Several studies used DREAM to assess technology adoption. For example, Shiferaw, Kebede, and You (2008) evaluated the adoption and impact of disease-resistant pigeonpea (*Cajanus cajan* L. Huth) varieties that were developed and disseminated in Tanzania. Komarek, Koo, Wood-Sichra, and You (2018) used DREAM to examine the effects of adopting improved maize seed cultivars and increasing mineral fertilizer application rates in Tanzania. The authors found that maize farmers' benefits could be US$697 million over five years with a 39% adoption rate.

### 3.1.5 | TOA-MD

The Tradeoff Analysis Model for Multidimensional Impact Assessment (TOA-MD) is a generic model for adaptation strategies related to technology adoption; impact assessment of, for instance, climate change; and ecosystem services analysis. The TOA-MD model simulates technology adoption and its impact in a population of heterogeneous farms (Antle, 2011; Stoorvogel & Antle, 2001). The TOA-MD model has been employed within the CGIAR to analyze the trade-offs at local scale related to potential new technologies (Claessens et al., 2012; Homann-Kee Tui et al., 2015).

### 3.1.6 | Farm household-level bio-economic models

To capture the effects of productivity change and changes in input requirements of different technologies, partial budget analysis is commonly conducted to show the cost–benefit ratio of a technology package. The foresight team at CIMMYT advocates the use of an expanded version of partial budget analysis. The expanded partial budget analysis looks at the intrinsic risk of different technology packages instead of just the average case. Using subjective time preferences, the approach calculates how well new technology packages fit into risk management strategies of farm households (Tesfaye et al., 2018).

Farm household-level bio-economic modeling often combines information from biophysical process models with socioeconomic models that capture farm household decision making including goals and aspirations, risk management, and preferences. This is a powerful tool for ex-ante impact assessment of pipeline technologies that can readily capture climate change and weather variability scenarios to see how pipeline technologies fit into present and future farming systems and livelihood strategies.

Within this domain there are two strands of work. The first is focused on farming systems research and its link with livelihood strategies, and much of this research within the CGIAR is led by the scientists in the Sustainable Intensification Program at CIMMYT. The second is bio-economic household modeling focused on household decision making processes (Kruseman & Bade, 1998; Kruseman, 2000, 2007) and lead by a range of researchers throughout the CGIAR; this includes the Dynamic Agricultural Household Bio-economic Simulator (DAHBSIM) model (Komarek et al., 2017) and earlier work both within the CGIAR and with partners linked to the CGIAR (Reynolds et al., 2018). Both approaches have synergies with each other and only differ in where the primary focus is. A specific strand of modeling relevant in this setting is agent-based modeling (Berger et al., 2017).

Especially for bio-economic models and partial budget analysis models, they are used for very specific purposes and geographies, and therefore do not have specific dedicated model names. Models from different domains are often soft coupled, this includes passing yield simulations from DSSAT to DREAM or IMPACT or other purpose-built models.

## 3.2 | Data sources

Different models have different data sources. The integrated assessment models use aggregate open-source data such as those available from FAO's FAOstat and the World Bank Indicators, amongst others. Important sources of data are the results taken from various climate models and the Shared Economic Pathway scenarios that are widely used as benchmarks for future developments (Riahi et al., 2017).

Many farm household-level and landscape or community-level models make use of farm household surveys to calibrate, evaluate, and validate the model parameters and outputs. The data sources can be both primary data collected by the research teams or secondary household data. The World Bank LSMS-ISA datasets (http://surveys.worldbank.org/lsms/programs/integrated-surveys-agriculture-ISA) and the data available through Africa Rising (https://africa-rising.net/) are examples of widely used secondary farm household data.

The crop models used in the bio-economic modeling frameworks depend critically on the advancement of crop science; the CGIAR centers have a demonstrated record of significant contributions. These models also use a variety of climate model outputs as model parameters to simulate productivity under climate change and weather variability.

The higher aggregation-level models often require gridded information about cropping patterns. Using a variety of inputs, the Spatial Production Allocation Model (SPAM, http://mapspam.info/) uses a cross-entropy approach to make plausible estimates of crop distribution within disaggregated units. Moving the data from coarser units, such as countries and subnational provinces, to finer units, such as grid cells, reveals spatial patterns of crop performance, creating a global gridscape at the confluence between geography and agricultural production systems.

## 4 | COLLABORATION, OPPORTUNITIES, AND NEXT STEPS

As mentioned before, the GFSF project is an excellent platform of CGIAR research centers that focuses on evaluating promising technologies, investments, and policy reforms with various quantitative methods for strategic foresight to inform policy decisions (http://globalfutures.cgiar.org/). Since linking crop modeling and economic modeling is complicated and requires an interdisciplinary approach, more impact can be achieved through such collaboration than through the sum of individual modeling activities. Another example of effective collaboration is the CGIAR Platform for Big Data in Agriculture (https://bigdata.cgiar.org/) hosting two relevant communities of practice in the context of the current review: one on crop modeling and one on socioeconomic data. The community of practice on socioeconomic data supports increasing availability of interoperable data sets at farm household level based on surveys (Van Wijk et al., 2019).

There are significant benefits of modeling collaboration. For instance, keep updating the bio-economic household models to ensure that they fit into the changing farming systems and livelihood strategies and making them accessible so that the models can readily be applicable for assessing pipeline technologies. This includes combining efforts of economists and agronomists regarding farming systems and bio-economic modeling at the household, community, and landscape levels. As far as we are aware, within the CGIAR there is capacity for household-level bio-economic modeling in order to assess pipeline technologies in terms of how they fit into farming systems and livelihood strategies at different centers. ICRISAT, for example, continues using the calibrated and validated models to evaluate the competitiveness of alternative productivity enhancing technologies and management practices and the socioeconomic processes that can facilitate sustainable intensification of mixed crop–livestock systems particularly in semi-arid environments. At CIMMYT, the FarmDesign model developed by Wageningen University (Groot, Oomen, & Rossing, 2012), which is deployed by researchers to analyse the potential impacts of new technology packages linked to farm typologies (Ditzler et al., 2018, 2019; Estrada Carmona, 2019). Both ICARDA and CIMMYT are currently engaged in research projects related to using bio-economic household models.

Across the different CGIAR centers, there is a clear willingness for continued deployment of the IMPACT model, while there is also an interest to actively pursue collaboration with other advanced research institutes and academia regarding alternate integrated assessment models, for example, through Agricultural Model Intercomparison and Improvement Project (AgMIP) (https://agmip.org/). Various centers foster interdisciplinary approaches. At CIMMYT, for instance, crop modelers and economists are working in a dedicated team on ex-ante impact assessment. To foster the link between the structural models' outcomes with the crop improvement programs to better target the technologies to achieve greater impacts, ICRISAT encourages more multidisciplinary collaboration among modelers, crop physiologists, and key stakeholders. These efforts offer clear opportunities to build up cross-discipline collaborations and experiment with soft and hard coupling of different tools and methods. Bringing together modelers, economists and people from other disciplines and across organizations to work synergistically offers an opportunity to leverage diversity of thought and skills to accelerate progress. However, participatory approaches have not always been incorporated into the economic simulation models. Moreover, many of the higher aggregation levels models have difficulty capturing key components of the economy such as the labor market. Market imperfections are usually not represented adequately. Labor demand for specific technologies or practices, while a major issue for sustainable development is difficult to address because of poor data, among others, inadequate data on quantity of labor used in crop production, price of labor, and gender disaggregation.

Modeling the risk of new and emerging pests and diseases on production, productivity, and food security is an important topic that is getting more attention (Duku, Sparks, & Zwart, 2016; Mottaleb, Loladze, Sonder, Kruseman, & San Vicente, 2019; Mottaleb et al., 2018; Yigezu et al., 2010; Yigezu & Sanders, 2012). However, for most crops, there is a lack of integrated crop–pest models or even data on the effect of pests and diseases on yields to calibrate and evaluate models. Therefore, the impact of pests and diseases on crop production cannot be easily quantified with current modeling capacities. It is crucial to bring together pathologists, entomologists, and agronomists to understand and model the interrelation between the pest and disease lifecycle and the growth of its host plant. This effort could be based on the integrated crop–pest model for rice (Duku et al., 2016). Coupling two spatial models, EPIRICE and RICEPEST, the authors quantified the rice yield losses from two important diseases (leaf blast and bacterial leaf blight) under a changing climate in Tanzania. Linking the integrated crop–pest disease models with the economic models will provide foresight of emerging pests and diseases and its impact on crop production. Therefore, policymakers can take necessary actions to avoid such future uncertainties.

There is an opportunity to take advantage of a new data paradigm in traditionally data-poor regions. This ranges from georeferenced household surveys to remotely sensed satellite imagery and scenario modeling analyses. Better data allows

CGIAR centers to better bridge the divide between research output and policy guidance and decision making. Finding alternatives to costly and time-consuming household surveys can enhance the use of bio-economic models especially at lower aggregation levels. Through the communities of practice of the CGIAR Platform for Big Data in Agriculture, efforts are underway to enhance data findability, accessibility, and interoperability to enhance the reuse of data, essential for the type of modeling discussed in this review. Some of this work is done in close collaboration with the Excellence in Breeding Platform of the CGIAR ensuring more synergies.

## 5 | CONCLUDING REMARKS

The combination of crop modeling and economic modeling offers scope and opportunity for both foresight analysis and ex-ante impact assessment. For complex dynamic agri-food systems, various models provide insights into key parts of the system under various scenarios. Bio-economic models are used for exploratory studies to understand the potential impacts of drivers, for instance climate change and alternative crop management practices. The information can be used for priority setting within international agricultural research, for a better understanding of agricultural households, and agri-food systems outcomes under changing circumstances and uncertain conditions. This can be used for policy advice and decision support for various stakeholders. The increasing availability of interoperable data sets at farm household level based on surveys offers scope to use existing tools with these data sets in combination of more readily available crop modeling results.

The value of crop model outputs, and underpinning crop science knowledge and data, is greatly enhanced by adding the socioeconomic context irrespective of the scale at which this occurs. As our study highlights, there is a clear distinction between foresight and ex-ante impact assessment even though the terms are often used interchangeably in the literature. Amongst the wide variety of topics that can be addressed with bio-economic modeling approaches, climate change is arguably the most noteworthy. Bio-economic modeling approaches tackle complex challenges and hence can benefit tremendously from interdisciplinary and interinstitutional collaboration.

The possibility of smart phones for getting GPS coordinates and the feasibility of using Google Maps to locate villages, obtain their GPS coordinates, and linking them to global soil and historical weather data are now advantages that bio-economic modeling work can use. We can now use this information for various purpose, for example, yield gap analysis using data that was collected a few years ago that did not contain weather and soil data that is now available. We are in the middle of a data revolution, with new data sources coming available regularly, the use of new data sources, and new techniques to enhance data operability offer scope for using existing models in new and exciting ways. This includes but is not limited to reusing models in new locations, on larger sets of information, and allowing the results to be analyzed with big data analytics tools. Enhanced data interoperability also allows multiple models to be used on the same data set.

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## CONFLICT OF INTEREST

The authors declare no conflict of interest in the presented work.

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## REFERENCES

Álvarez, P., Fischer, M., González, C., Mason-D'Croz, D., Moreno, P., Robertson, R., … Prager, S. D. (2016). *Ex-ante assessment of drought tolerant bean technology. A case study in the series: Economic foresight for understanding the role of investments in agriculture for the global food system* (CIAT Working Paper). Cali, Colombia: Centro Internacional de Agricultura Tropical (CIAT).

Antle, J. M. (2011). Parsimonious multi-dimensional impact assessment. *American Journal of Agricultural Economics*, *93*, 1292–1311. http://doi.org/10.1093/ajae/aar052

Archontoulis, S. V., Castellano, M. J., Licht, M. A., Nichols, V., Baum, M., Huber, I., … Lamkey K. R. (2020). Predicting crop yields and soil-plant nitrogen dynamics in the US Corn Belt. *Crop Science*, *60*, this issue. https://doi.org/10.1002/csc2.20039

Ates, S., Cicek, H., Gultekin, I., Yigezu, Y. A., Filley, S. J., & Keser, M. (2018). Bio-economic analysis of dual-purpose management of winter cereals in high and low input production systems. *Field Crops Research*, *22*, 56–66. https://doi.org/10.1016/j.fcr.2018.08.003

Beach, R. H., Sulser, T. B., Crimmins, A., Cenacchi, N., Cole, J., Fukagawa, N. K., … Ziska, L. H. (2019). Combining the effects of increased atmospheric carbon dioxide on protein, iron, and zinc availability and projected climate change on global diets: a modeling study. *The Lancet Planetary Health*, *3*, e307–e317. https://doi.org/10.1016/S2542-5196(19)30094-4

Berger, T., Troost, C., Wossen, T., Latynskiy, E., Tesfaye, K., & Gbegbelegbe, S. (2017). Can smallholder farmers adapt to climate variability, and how effective are policy interventions? Agent-based simulation results for Ethiopia. *Agricultural Economics*, *48*), 693–706. https://doi.org/10.1111/agec.12367

Beyene, L. M., Shiferaw, B., Sahoo, A., & Gbegbelegbe, S. (2016). Econo my-wide impacts of technological change in food staples in Ethiopia: A macro-micro approach (PEP Working Paper Series 2016–17). Nairobi, Kenya: Partnership for Economic Policy (PEP). https://doi.org/10.13140/RG.2.2.16086.65608

Bobojonov, I., & Aw-Hassan, A. (2014). Impacts of climate change on farm income security in central Asia: An integrated modeling approach. *Agriculture, Ecosystems and Environment*, *188*, 245–255. https://doi.org/10.1016/j.agee.2014.02.033

Boussios, D., Preckel, P. V., Yigezu, Y. A., Dixit, P., Akroush, S., M'hamed, H. C., … Ayad, J. A. (2019). Modeling producer responses with dynamic programming: A case for adaptive crop management. *Agricultural Economics*, *50*, 101–111. https://doi.org/10.1111/agec.12469

Brown, D. R. (2000). A review of bio-economic models. Paper prepared for the Cornell African Food Security and Natural Resource Management (CAFSNRM) Program. Ithaca, NY: Cornell University.

Burke, M., & Lobell, D. B. (Eds.). (2010). *Climate change and food security: Adapting agriculture to a warmer world*. New York: Springer.

Castro, L. M., Härtl, F., Ochoa, S., Calvas, B., Izquierdo, L., & Knoke, T. (2018). Integrated bio-economic models as tools to support land-use decision making: A review of potential and limitations. *Journal of Bioeconomics*, *20*, 183–211. https://doi.org/10.1007/s10818-018-9270-6

Castro-Nunez, A., Mertz, O., Buritica, A., Sosa, C. C., & Lee, S. T. (2017). Land related grievances shape tropical forest-cover in areas affected by armed-conflict. *Applied Geography*, *85*, 39–50. https://doi.org/10.1016/j.apgeog.2017.05.007

CGIAR. (2015). CGIAR strategy and results framework 2016–2030: Redefining how CGIAR does business until 2030. Retrieved from https://cgspace.cgiar.org/bitstream/handle/10947/3865/CGIAR%20Strategy%20and%20Results%20Framework.pdf

CGIAR Independent Science and Partnership Council. (2011). *Measuring the environmental impacts of agricultural research : Theory and applications to CGIAR research*. Rome, Italy: Independent Science and Partnership Council Secretariat.

Chan, C. Y., Tran, N., Pethiyagoda, S., Crissman, C. C., Sulser, T. B., & Phillips, M. J. (2019). Prospects and challenges of fish for food security in Africa. *Global Food Security*, *20*, 17–25. https://doi.org/10.1016/j.gfs.2018.12.002

Chenoune, R., Allen, T., Komarek, A. M., Gomez y Paloma, S., Flichman, G., … Belhouchette, H. (2017). Assessing consumption-production-resources nexus decisions for rice-focused agricultural households in Sierra Leone. *Land Use Policy*, *67*, 597–607. https://doi.org/10.1016/j.landusepol.2017.06.014

Chung, U., Gbegbelegbe, S., Shiferaw, B., Robertson, R., Yun, J. I., Tesfaye, K., … Sonder, K. (2014). Modeling the effect of a heat wave on maize production in the USA and its implications on food security in the developing world. *Weather and Climate Extremes*, *5–6*, 67–77. https://doi.org/10.1016/j.wace.2014.07.002

CIAT. (2017). CIAT strategic initiative on sustainable food systems. Retrieved from https://cgspace.cgiar.org/bitstream/handle/10568/79795/SUSTAINABLE_FOOD_SYSTEMS_CIAT_STRATEGY_DOCUMENT.pdf

Claessens, L., Antle, J. M., Stoorvogel, J. J., Valdivia, R. O., Thornton, P. K., & Herrero, M. (2012). A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data. *Agricultural Systems*, *111*, 85–95. https://doi.org/10.1016/j.agsy.2012.05.003

Cooper, M., Tang, T., Gho, C., Hart, T., Hammer, G., & Messina, C. (2020). Integrating genetic gain and gap analysis to predict improvements in crop productivity. *Crop Science*, *60*, this issue. https://doi.org/10.1002/csc2.20109.

Ditzler, L., Klerkx, L., Chan-Dentoni, J., Posthumus, H., Krupnik, T. J., Ridaura, L. S. … Groot, J. C. (2018). Affordances of agricultural systems analysis tools: A review and framework to enhance tool design and implementation. *Agricultural Systems*, *164*, 20–30. https://doi.org/10.1016/j.agsy.2018.03.006

Ditzler, L., Komarek, A. M., Chiang, T. W., Alvarez, S., Chatterjee, S. A., Timler, C., … Groot, J. C. (2019). A model to examine farm household trade-offs and synergies with an application to smallholders in Vietnam. *Agricultural Systems*, *173*, 49–63. https://doi.org/10.1016/j.agsy.2019.02.008

Duku, C., Sparks, A. H., & Zwart, S. J. (2016). Spatial modeling of rice yield losses in Tanzania due to bacterial leaf blight and leaf blast in a changing climate. *Climatic Change*, *135*, 569–583. https://doi.org/10.1007/s10584-015-1580-2

Enahoro, D., Kozicka, M., Pfeifer, C., Jones, S., Tran, N., Chan, C. Y., … Rich, K. M. (2019). Changing demand for animal source foods and their effects on the provision of ecosystem services (ILRI Research Brief 93). Nairobi, Kenya: International Livestock Research Institute (ILRI). Retrieved from https://cgspace.cgiar.org/bitstream/handle/10568/106431/Research_brief_93.pdf

Estrada-Carmona, N., Raneri, J. E., Alvarez, S., Timler, C., Chatterjee, S. A., Ditzler, L., … Talsma, E. F. (2019). A model-based exploration of farm-household livelihood and nutrition indicators to guide nutrition-sensitive agriculture interventions. *Food Security*, *12*, 59–81. https://doi.org/10.1007/s12571-019-00985-0

Evenson, R. E., & Gollin, D. (2003). Assessing the impact of the Green Revolution, 1960 to 2000. *Science*, *300*, 758–762. https://doi.org/10.1126/science.1078710

Frija, A., & Telleria, R. (2016). Country-level bio-economic modeling of agricultural technologies to enhance wheat-based systems productivity in the dry areas. *Sustainable Agriculture Research*, *5*, 113–123. https://doi.org/10.5539/sar.v5n3p113

Gbegbelegbe, S., Chung, U., Shiferaw, B., Msangi, S., & Tesfaye, K. (2014). Quantifying the impact of weather extremes on global food security: A spatial bio-economic approach. *Weather and Climate Extremes*, *4*, 96–108. https://doi.org/10.1016/j.wace.2014.05.005

Ghosh, J., Shiferaw, K., Sahoo, A., & Gbegbelegbe, S. (2016). A CGE analysis of the implications of technological change in Indian agriculture. (Working Paper Series 2016-16). Nairobi, Kenya: Partnership for Economic Policy (PEP).

Godfray, H. C. J., Mason-D'Croz, D., & Robinson, S. (2016). Food system consequences of a fungal disease epidemic in a major crop. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *371*, 20150467. https://doi.org/10.1098/rstb.2015.0467

Grassini, P., Eskridge, K. M., & Cassman, K. G. (2013). Distinguishing between yield advances and yield plateaus in historical crop production trends. *Nature Communications*, *4*, 2918. https://doi.org/10.1038/ncomms3918

Groot, J. C., Oomen, G. J., & Rossing, W. A. (2012). Multi-objective optimization and design of farming systems. *Agricultural Systems*, *110*, 63–77. https://doi.org/10.1016/j.agsy.2012.03.012

Hammer, G. L., McLean, G., van Oosterom, E., Chapman, S., Zheng, B., Wu, A., Doherty, A., & Jordan, D. (2020). Designing crops for adaptation to the drought and high temperature risks anticipated in future climates. *Crop Science*, *60*, this issue. https://doi.org/10.1002/csc2.20110.

Hoang, H. K., & Meyers, W. H. (2015). Price stabilization and impacts of trade liberalization in the Southeast Asian rice market. *Food policy*, *57*, 26–39. https://doi.org/10.1016/j.foodpol.2015.07.009

Holzworth, D. P., Huth, N. I., deVoil, P. G., Zurcher, E. J., Herrmann, N. I., McLean, G., … Keating, B. A. (2014). APSIM—Evolution towards a new generation of agricultural systems simulation. *Environmental Modelling & Software*, *62*, 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009

Hoogenboom, G., Porter, C. H., Shelia, V., Boote, K. J., Singh, U., White, J. W., … Jones, J. W. (2019). *Decision support system for agrotechnology transfer (DSSAT) Version 4.7.5*. Gainesville, FL: DSSAT Foundation.

Homann-Kee Tui, S., Valbuena, D., Masikati, P., Descheemaeker, K., Nyamangara, J., Claessens, L., … Nkomboni, D. (2015). Economic trade-offs of biomass use in crop-livestock systems: Exploring more sustainable options in semi-arid Zimbabwe. *Agricultural Systems*, *134*, 48–60. https://doi.org/10.1016/j.agsy.2014.06.009

IPCC. (2019). Climate change and land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems (Approved Draft). Retrieved from https://www.ipcc.ch/site/assets/uploads/2019/08/4.-SPM_Approved_Microsite_FINAL.pdf

Islam, S., Cenacchi, N., Sulser, T. B., Gbegbelegbe, S., Hareau, G., Kleinwechter, U., … Wiebe, K. (2016). Structural approaches to modeling the impact of climate change and adaptation technologies on crop yields and food security. *Global Food Security*, *10*, 63–70. https://doi.org/10.1016/j.gfs.2016.08.003

Janssen, S., & Van Ittersum, M. K. (2007). Assessing farm innovations and responses to policies: A review of bio-economic farm models. *Agricultural Systems*, *94*, 622–636. https://doi.org/10.1016/j.agsy.2007.03.001

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., … Ritchie, J. T. (2003). The DSSAT cropping system model. *European Journal of Agronomy*, *18*, 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Komarek, A. M., Drogue, S., Chenoune, R., Hawkins, J., Msangi, S., Belhouchette, H., & Flichman, G. (2017). Agricultural household effects of fertilizer price changes for smallholder farmers in central Malawi. *Agricultural Systems*, *154*, 168–178. https://doi.org/10.1016/j.agsy.2017.03.016

Komarek, A. M., Koo, J., Wood-Sichra, U., & You, L. (2018). Spatially-explicit effects of seed and fertilizer intensification for maize in Tanzania. *Land Use Policy*, *78*, 158–165. https://doi.org/10.1016/j.landusepol.2018.06.033

Komarek, A. M., Kwon, H., Haile, B., Thierfelder, C., Mutenje, M. J., & Azzarri, C. (2019). From plot to scale: *ex-ante* assessment of conservation agriculture in Zambia. *Agricultural Systems*, *173*, 504–518. https://doi.org/10.1016/j.agsy.2019.04.001

Komarek, A. M., & Msangi, S. (2019). Effect of changes in population density and crop productivity on farm households in Malawi. *Agricultural Economics*, *50*, 615–628. https://doi.org/10.1111/agec.12513

Komarek, A. M., Thurlow, J., Koo, J., & De Pinto, A. (2019). Economywide effects of climate-smart agriculture in Ethiopia. *Agricultural Economics*, *50*, 765–778. https://doi.org/10.1111/agec.12523

Kruseman, G. (2000). Bio-economic modelling for agricultural intensification. (Thesis, Wageningen University, Netherlands). Retrieved from https://edepot.wur.nl/139103

Kruseman, G. (2007). Farm household behaviour and agricultural resource degradation: Using econometric and simulation approaches for policy analysis. In E. Bulte, & R. Ruben (Eds.), *Development economics between markets and institutions incentives for growth, food security and sustainable use of the environment* (pp. 151–166). Wageningen, Netherlands: Manshold Publication Series No. 4. https://doi.org/10.3920/978-90-8686-618-2

Kruseman, G., & Bade, J. (1998). Agrarian policies for sustainable land use: bio-economic modelling to assess the effectiveness of policy instruments. *Agricultural Systems*, *58*, 465–481. https://doi.org/10.1016/S0308-521X(98)00041-9

Lantican, M., Braun, H. J., Payne, T. S., Singh, R. G., Sonder, K., Baum, M., … Erenstein, O. (2016). *Impacts of international wheat improvement research: 1994–2014*. Mexico: CIMMYT.

La Rovere, R., Abdoulaye, T., Kostandini, G., Guo, Z., Mwangi, W., MacRobert, J., & Dixon, J. (2014). Economic, production, and poverty impacts of investing in maize tolerant to drought in Africa: An ex-ante assessment. *The Journal of Developing Areas*, *48*, 199–225. https://www.jstor.org/stable/23612178

Li, H., Rasheed, A., Hickey, L., & He, Z. (2018). Fast forwarding genetic gain. *Trends in Plant Science*, *23*, 184–186. https://doi.org/10.1016/j.tplants.2018.01.007

Li, T., Angeles, O., Marcaida, M., Manalo, E., Manalili, M. P., Radanielson, A., & Mohanty, S. (2017). From ORYZA2000 to ORYZA (v3): An improved simulation model for rice in drought and nitrogen-deficient environments. *Agricultural and Forest Meteorology*, *237–238*, 246–256. https://doi.org/10.1016/j.agrformet.2017.02.025

Li, T., Angeles, O., Radanielson, A., Marcaida, M. & Manalo, E. (2015a). Drought stress impacts of climate change on rainfed rice in South Asia. *Climatic Change*, *133*, 709–720. https://doi.org/10.1007/s10584-015-1487-y

Li, T., Hasegawa, T., Yin, X., Zhu, Y., Boote, K., Adam, M., … Bouman, B. (2015b). Uncertainties in predicting rice yield by current crop models under a wide range of climatic conditions. *Global Change Biology*, *21*, 1328–1341. https://doi.org/10.1111/gcb.12758

Lin, H. C., Coe, R. A., Quick, W. P., & Bandyopadhyay, A. (2019). Development of C4 rice. In A. Sarkar, S. R. Sensarma, & G. W. vanLoon (Eds.), *Sustainable solutions for food security: combating climate change by adaptation* (pp. 111–124). Switzerland: Springer Nature.

Mason-D'Croz, D., Sulser, T. B., Wiebe, K., Rosegrant, M. W., Lowder, S. K., Nin-Pratt, A., … Robertson, R. D. (2019). Agricultural investments and hunger in Africa modeling potential contributions to SDG2—Zero hunger. *World Development*, *116*, 38–53. https://doi.org/10.1016/j.worlddev.2018.12.006

Mottaleb, A. K., Rejesus, R. M., Mohanty, S., Murty, M. V. R., Li, T., Valera, H. G., & Gumma, M. K. (2012, August). *ex ante impact assessment of a drought-tolerant rice variety in the presence of climate change*. Paper presented at the annual meeting of the Agricultural and Applied Economics Association (AAEA), Seattle, WA.

Mottaleb, K. A., Loladze, A., Sonder, K., Kruseman, G., & San Vicente, F. (2019). Threats of tar spot complex disease of maize in the United States of America and its global consequences. *Mitigation and Adaptation Strategies for Global Change*, *24*, 281–300. https://doi.org/10.1007/s11027-018-9812-1

Mottaleb, K. A., Rejesus, R. M., Murty, M. V. R., Mohanty, S., & Li, T. (2017). Benefits of the development and dissemination of climate-smart rice: *ex ante* impact assessment of drought-tolerant rice in South Asia. *Mitigation and Adaptation Strategies for Global Change*, *22*, 879–901. https://doi.org/10.1007/s11027-016-9705-0

Mottaleb, K. A., Singh, P. K., Sonder, K., Kruseman, G., Tiwari, T. P., Barma, N. C. D. … Erenstein, O. (2018). Threat of wheat blast to South Asia's food security: An *ex-ante* analysis. *PloS ONE*, *13*, e0197555. https://doi.org/10.1371/journal.pone.0197555

Nedumaran, S., Bantilan, M. C. S., Abinaya, P., Mason-D'Croz, D., & Kumar, A. A. (2014). *ex-ante* impact assessment of drought tolerant sorghum cultivars under future climates: integrated modeling approach. In M. Behnassi, M. Syomiti Muteng'e, G. Ramachandran, & K. N. Shelat (Eds.), *Vulnerability of agriculture, water and fisheries to climate change: Toward sustainable adaptation strategies* (pp. 167–190). Dordrecht: Springer Netherlands.

Nedumaran, S., & Berger, T. (2009, April). Impacts of small scale irrigation on poverty dynamics in the White-Volta Basin of Ghana: An integrated multi-agent simulation approach. Paper presented at the 7th International Science Conference on Human Dimensions on Global Environmental Change (IHDP Open Meeting), Bonn.

Nedumaran, S., Shiferaw, B., Bantilan, M. C. S., Palanisami, K., & Wani, S. P. (2014). Bioeconomic modeling of farm household decisions for ex-ante impact assessment of integrated watershed development programs in semi-arid India. *Environment, Development and Sustainability*, *16*, 257–286. https://doi.org/10.1007/s10668-013-9476-7

Oriade, C. A., & Dillon, C. R. (1997). Developments in biophysical and bioeconomic simulation of agricultural systems: a review. *Agricultural Economics*, *17*, 45–58. https://doi.org/10.1111/j.1574-0862.1997.tb00463.x

Petsakos, A., Hareau, G., Kleinwechter, U., Wiebe, K., & Sulser, T. B. (2018). Comparing modeling approaches for prioritization in international agricultural research. *Research Evaluation*, *27*, 145–156. https://doi.org/10.1093/reseval/rvx044

Petsakos, A., Prager, S. D., Chibwana Gama, A., Gonzalez, C. E., Sulser, T. B., Gbegbelegbe, S., … Hareau, G. (2019). Understanding the consequences of changes in the production frontiers for root, tuber and banana crops. *Global Food Security*, *20*, 180–188. https://doi.org/10.1016/j.gfs.2018.12.005

Pradesha, A., Robinson, S., Rosegrant, M. W., Perez, N., & Thomas, T. S. (2019). Exploring transformational adaptation strategy through rice policy reform in the Philippines (IFPRI Discussion Paper 1865). Washington, DC: International Food Policy Research Institute (IFPRI).

Quintero, M., Wunder, S., & Estrada, R. D. (2009). For services rendered? Modeling hydrology and livelihoods in Andean payments for environmental services schemes. *Forest Ecology and Management*, *258*, 1871–1880. https://doi.org/10.1016/j.foreco.2009.04.032

Raitzer, D. A., & Kelley, T.G. (2008). Benefit–cost meta-analysis of investment in the International Agricultural Research Centers of the CGIAR. *Agricultural Systems*, *96*, 108–123. https://doi.org/10.1016/j.agsy.2007.06.004

Renkow, M., & Byerlee, D. (2010). The impacts of CGIAR research: A review of recent evidence. *Food policy*, *35*, 391–402. https://doi.org/10.1016/j.foodpol.2010.04.006

Reynolds, M., Kropff, M., Crossa, J., Koo, J., Kruseman, G., Molero Milan, A., Rutkoski, J., … Vadez, V. (2018). Role of modeling in international crop research: Overview and some case studies. *Agronomy*, *8*, 291. https://doi.org/10.3390/agronomy8120291

Riahi, K., Van Vuuren, D. P., Kriegler, E., Edmonds, J., O'neill, B. C., Fujimori, S., … Lutz, W. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Robinson, S., Mason-D'Croz, D., Islam, S., Robertson, R., Gueneau, A., Cenacchi, N., … Mottaleb, K. (2014). Promising technologies and climate change: ex ante scenario analysis of adaptation strategies (Note prepared as an output of the Global Futures & Strategic Foresight (GFSF) program). Washington, DC: International Food Policy Research Institute (IFPRI). Retrieved from https://globalfutures.cgiar.org/files/2014/06/Two_pager-10-31.pdf

Robinson, S., Mason-D'Croz, D., Islam, S., Sulser, T. B., Robertson, R., Zhu, T., … Rosegrant, M. (2015). The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model description for Version 3. (IFPRI Discussion Paper 1483). Washington DC: International Food Policy Research Institute (IFPRI).

Rosegrant, M. W., Koo, J., Cenacchi, N., Ringler, C., Robertson, R., Fisher, M., … Sabbagh, P. (2014). *Food security in a world of natural resource scarcity—The role of agricultural technologies*. Washington, DC: International Food Policy Research Institute (IFPRI).

Rosegrant, M. W., & Sombilla, M. A. (2018). *The future of Philippine agriculture under a changing climate: Policies, investments and scenarios*. Singapore: ISEAS Yusuf Ishak Institute.

Rosegrant, M. W., Sulser, T. B., Mason-D'Croz, D., Cenacchi, N., Nin-Pratt, A., Dunston, S., … Willenbockel, D. (2017). Quantitative foresight modeling to inform the CGIAR research portfolio (Project Report for USAID). Washington, DC: International Food Policy Research Institute (IFPRI). Retrieved from http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/131144

Sahoo, A., Shiferaw, B., & Gbegbelegbe, S. (2016). Economy-wide impacts of promising maize and wheat technologies on food security and welfare in Kenya (PEP Working Paper Series 2016-14). Nairobi, Kenya: Partnership for Economic Policy (PEP).

Scott, G. J., Petsakos, A., & Juarez, H. (2019). Climate change, food security, and future scenarios for potato production in India to 2030. *Food Security*, *11*, 43–56. https://doi.org/10.1007/s12571-019-00897-z

Seck, P. A., Diagne, A., Mohanty, S., & Wopereis, M. C. S. (2012). Crops that feed the world 7: Rice. *Food Security*, *4*, 7–24. https://doi.org/10.1007/s12571-012-0168-1

Seck, P. A., Touré, A. A., Coulibaly, J. Y., Diagne, A., Wopereis, M. C. S., Johnson, D. E., … Jalloh, A. (2013). Africa's rice economy before and after the 2008 rice crisis. In M. C. S. Wopereis, D. E. Johnson, N. Ahmadi, E. Tollens, & A. Jalloh (Eds.), *Realizing Africa's rice promise* (pp. 24–34). Wallingford, UK: CAB International.

Setimela, P., Gasura, E., Thierfelder, C., Zaman-Allah, M., Cairns, J. E., & Boddupalli, P. M. (2018). When the going gets tough: Performance of stress tolerant maize during the 2015/16 (El Niño) and 2016/17 (La Niña) season in southern Africa. *Agriculture, Ecosystems & Environment*, *268*, 79–89. https://doi.org/10.1016/j.agee.2018.09.006

Shiferaw, B. A., Kebede, T. A., & You, L. (2008). Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in Tanzania. *Agricultural Economics*, *39*, 309–323. https://doi.org/10.1111/j.1574-0862.2008.00335.x

Steward, P. R., Thierfelder, C., Dougill, A. J., & Ligowe, I. (2019). Conservation agriculture enhances resistance of maize to climate stress in a Malawian medium-term trial. *Agriculture, Ecosystems & Environment*, *277*, 95–104. https://doi.org/10.1016/j.agee.2018.07.009

Stoorvogel, J., & Antle, J. M. (2001). Regional land use analysis: The development of operational tools. *Agricultural Systems*, *70*, 623–40. https://doi.org/10.1016/S0308-521X(01)00062-2

Subbarao, G. V., Tomohiro, B., Masahiro, K., Osamu, I., Samejima, H., Wang, H. Y., … Tsujimoto, H. (2007). Can biological nitrification inhibition (BNI) genes from perennial *Leymus racemosus* (Triticeae) combat nitrification in wheat farming? *Plant and Soil*, *299*, 55–64. https://doi.org/10.1007/s11104-007-9360-z

Tesfaye, K., Kruseman, G., Cairns, J. E., Zaman-Allah, M., Wegary, D., Zaidi, P. H., … Erenstein, O. (2018). Potential benefits of drought and heat tolerance for adapting maize to climate change in tropical environments. *Climate Risk Management*, *19*, 106–19. https://doi.org/10.1016/j.crm.2017.10.001

Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences*, *108*, 20260–20264. https://doi.org/10.1073/pnas.1116437108

Van Wijk, M., Alvarez, C.; Anupama, G., Arnaud, E., Azzarri, FC., Burra, D., … Kruseman, G. (2019). Towards a core approach for cross-sectional farm household survey data collection: a tiered setup for quantifying key farm and livelihood indicators. Community of Practice on Socio-economic Data report COPSED-2019-001. CGIAR Platform for Big Data in Agriculture. https://cgspace.cgiar.org/handle/10568/105714

Vergara, W., Gallardo Lomeli, L., Rios, A. R., Isbell, P., Prager, S., & De Camino, R. (2016). *The economic case for landscape restoration in Latin America*. Washington, DC: World Resources Institute (WRI).

Voss-Fels, K. P., Stahl, A., & Hickey, L. T. (2019). Q&A: Modern crop breeding for future food security. *BMC Biology*, *17*, 18. https://doi.org/10.1186/s12915-019-0638-4

Watson, A., Ghosh, S., Williams, M. J., Cuddy, W. S., Simmonds, J., Rey, M. D., … Hickey, L. T. (2018). Speed breeding is a powerful tool to accelerate crop research and breeding. *Nature Plants*, *4*, 23–29. https://doi.org/10.1038/s41477-017-0083-8

Wiebe, K. D., Sulser, T., Pacheco, P., De Pinto, A., Mason d'Croz, D., Dermawan, A., … Dunston, S. (2019). The palm oil dilemma: Policy tensions among higher productivity, rising demand, and deforestation (IFPRI Policy Brief). Washington, DC: International Food Policy Research Institute (IFPRI). Retrieved from http://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/133321/filename/133532.pdf

Yigezu, Y. A., Alexander, C. E., Preckel, P. V., Maier, D. E., Woloshuk, C. P., Mason, L. J., … Moog, D. J. (2010). Economics of integrated insect management in stored corn. *Journal of Economic Entomology*, *103*, 1896–1908. https://doi.org/10.1603/EC09390

Yigezu, Y. A., Aw-Hassan, A., Shideed, K., Sommer, R., & El-Shater, T. (2014). A policy option for valuing irrigation water in the dry areas. *Water Policy*, *16*, 520–535. https://doi.org/10.2166/wp.2014.141

Yigezu, Y. A., El-Shater, T., Boughlala, M., Bishaw, Z., Niane, A., Maalouf, F., … Aw-Hassan, A. (2019). Legume-based rotations have clear economic advantages over cereal monocropping in dry areas. *Agronomy for Sustainable Development*, *39*, 58. https://doi.org/10.1007/s13593-019-0602-2

Yigezu, Y. A., El-Shater, T., Mugera, A., Aw-Hassan, A., Piggin, C., Haddad, A., Khalil, Y., Loss, S. (2018). Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting & Social Change*, *134*, 199–206. https://doi.org/10.1016/j.techfore.2018.06.006

Yigezu, Y. A., & Sanders, J. H. (2012). Introducing new agricultural technologies and marketing strategies: A means for increasing income and nutrition of farm households in Ethiopia. *African Journal of Food, Agriculture, Nutrition and Development*, *12*, 6365–6384.

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