THE IMPACT OF TECHNOLOGY APPLICATION IN AGRICULTURE ON HOUSEHOLD INCOME IN VIETNAM

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Abstract

This study employs a computable general equilibrium (CGE) model to assess the economy-wide impacts of agricultural technology adoption in Vietnam. By integrating productivity improvements estimated from the Vietnam Household Living Standards Survey (VHLSS) into a social accounting matrix (SAM), the model evaluates changes in sectoral output, household income, factor allocation, and social welfare. The simulation scenarios incorporate increases in total factor productivity (TFP) and reductions in input coefficients to capture the effect of mechanization and precision farming. The results indicate that technological adoption significantly enhances agricultural productivity, increases household incomes - particularly among farming households and stimulates growth in agro-processing and service sectors. At the macroeconomic level, productivity gains reduce production costs and generate welfare improvements. The findings provide evidence for policymakers to promote agricultural modernization, support smallholders, and encourage investment in advanced technologies. Notably, this study is among the first to integrate micro-level household data with CGE modeling to quantify the broader economic effects of agricultural technological progress in Vietnam

Keywords: *CGE model; Agricultural technology; Household income; Productivity; Vietnam.*

TÁC ĐỘNG CỦA ỨNG DỤNG CÔNG NGHỆ TRONG NÔNG NGHIỆP ĐẾN THU NHẬP HỘ GIA ĐÌNH Ở VIỆT NAM

Tóm tắt

Trong bối cảnh biến đổi khí hậu và cam kết đạt Net Zero vào năm 2050 của Việt Nam, nghiên cứu tập Nghiên cứu sử dụng mô hình cân bằng tổng thể tính toán (CGE) để đánh giá tác động kinh tế vĩ mô của việc áp dụng công nghệ nông nghiệp tại Việt Nam. Dữ liệu năng suất ước tính từ VHLSS được tích hợp vào ma trận hạch toán xã hội (SAM) nhằm phân tích thay đổi về sản lượng ngành, thu nhập hộ gia đình, phân bổ các yếu tố sản xuất và phúc lợi xã hội. Các kịch bản mô phỏng bao gồm việc gia tăng năng suất các nhân tố tổng hợp (TFP) và giảm các hệ số đầu vào nhằm phản ánh tác động của cơ giới hóa và canh tác chính xác. Kết quả cho thấy việc áp dụng công nghệ làm tăng đáng kể năng suất nông nghiệp, nâng cao thu nhập hộ gia đình, đặc biệt là các hộ nông nghiệp, và thúc đẩy tăng trưởng của các ngành chế biến nông sản và dịch vụ. Ở cấp độ vĩ mô, những cải thiện về năng suất giúp giảm chi phí sản xuất và gia tăng phúc lợi xã hội. Các phát hiện của nghiên cứu cung cấp bằng chứng quan trọng cho các nhà hoạch định chính sách trong việc thúc đẩy hiện đại hóa nông nghiệp, hỗ trợ các hộ sản xuất nhỏ và khuyến khích đầu tư vào các công nghệ tiên tiến. Đáng chú ý, đây là một trong những nghiên cứu đầu tiên kết hợp dữ liệu vi mô ở cấp hộ gia đình với mô hình CGE nhằm lượng hóa các tác động kinh tế vĩ mô của tiến bộ công nghệ nông nghiệp tại Việt Nam.

Từ khoá: *Mô hình CGE; Công nghệ nông nghiệp; Thu nhập hộ gia đình; Năng suất; Việt Nam.*

JEL classification: O13, C68, Q16

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1. Introduction

Agricultural transformation in developing countries increasingly depends on the adoption of modern technologies that enhance productivity, reduce production risks, and strengthen the resilience of farming systems. In Vietnam, technological innovations—including mechanization, smart irrigation, improved seed varieties, digital monitoring systems, and precision agriculture—have been widely promoted as key drivers of agricultural modernization and rural income growth (World Bank, 2016; Nguyen & Grote, 2021). These technologies are expected to generate substantial gains in farm productivity, reduce production costs, and improve household welfare, particularly for smallholder farmers who constitute a large share of the country's agricultural labor force.

Although numerous empirical studies using the Vietnam Household Living Standards Survey (VHLSS) have documented the positive association between technology adoption and household outcomes such as productivity and income (Tran et al., 2020; Pham & Riedel, 2019), most existing analyses rely on microeconometric approaches. While these methods capture household-level impacts but they are unable to account for economy-wide adjustments, including changes in input prices, sectoral linkages, factor allocation, and general equilibrium welfare effects. As emphasized in the literature, productivity shocks in agriculture can transmit across the economy through forward and backward linkages, influencing agro-processing industries, services, trade flows, and household consumption patterns (Diao, Hazell, & Thurlow, 2010; Hertel, 1997).

To address these limitations, a Computable General Equilibrium (CGE) framework provides a systematic approach to examining how technology-induced productivity gains propagate throughout the economy. CGE models incorporate market interactions, resource constraints, and price adjustments, thereby enabling a comprehensive assessment of both direct and indirect effects of technological progress (Hosoe, Gasawa, & Hashimoto, 2010; Lofgren et al., 2002). While CGE models have been widely applied to analyze agricultural policies, trade liberalization, and structural transformation, their application to agricultural technology adoption in Vietnam remains limited.

Quantifying the impacts of agricultural technologies has become increasingly urgent as Vietnam faces simultaneous pressures from climate change, salinity intrusion, rural labor shortages, and growing food-security concerns. New national strategies promoting high-tech and climate-smart agriculture also require rigorous evidence to guide investment prioritization and targeted support for smallholder farmers. While micro-level studies capture household outcomes, they fail to reflect economy-wide adjustments such as price changes, sectoral linkages, and resource reallocation. A CGE framework is therefore essential for assessing the broader spillover effects of technological progress under increasing systemic risks and a rapidly evolving agricultural landscape. The resulting evidence provides a critical scientific basis for policymaking in this pivotal period.

This study contributes to the literature in three key ways. First, it combines VHLSS 2020 data with a CGE model by using micro-level estimates of productivity improvements associated with agricultural technology adoption. Second, it develops simulation scenarios that capture increases in total factor productivity (TFP) and reductions in input-use coefficients, reflecting different forms of agricultural technological progress. Third, it evaluates the resulting implications for agricultural output, household income, factor markets, price dynamics, and social welfare, thereby providing an economy-wide perspective on the benefits of technology adoption.

Overall, the study provides robust evidence for policymakers regarding the role of agricultural technologies in enhancing productivity, improving household incomes, and supporting Vietnam's broader rural development and economic transformation agenda.

2. Literature review

2.1. Agricultural technology adoption: Concepts and determinants

Agricultural technology adoption has long been recognized as a fundamental driver of productivity growth and rural income enhancement in developing countries. According to Feder, Just, and Zilberman (1985), technology adoption is influenced by a combination of economic incentives, risk preferences, information availability, and farm-level characteristics. In Southeast Asia, adoption is also shaped by land fragmentation, credit constraints, and market integration (Pingali, 2012). For Vietnam—where over 60% of agricultural output is generated by smallholders - capital limitations, land size, and technical skill capacity remain critical constraints (Do & Markussen, 2019).

Recent literature categorizes agricultural technologies into three key groups: (1) Mechanization, which substitutes human labor with machinery such as tractors and harvesters; (2) Biological/seed technologies, including high-yield or pest-resistant crop varieties;

(3) Digital and precision agriculture, such as IoT sensors, remote sensing, Big Data analytics, and automated irrigation systems (FAO, 2017; World Bank, 2016).

These technologies collectively enhance production efficiency by reducing labor input, improving resource allocation, and facilitating more precise decision-making.

Across multiple contexts, adoption decisions are strongly associated with education, landholding size, farm income, access to extension services, and availability of credit (Mottaleb et al., 2018). Evidence consistently shows that larger and better-capitalized farms adopt new technologies earlier, while smallholders face significantly higher entry barriers.

2.2. Impacts of agricultural technologies on farm productivity

Numerous empirical studies document positive impacts of agricultural technologies on productivity. For example, mechanization has been shown to increase operational efficiency and reduce labor shortages, especially during peak seasons (Binswanger, 1986). High-yielding varieties (HYVs) introduced during the Green Revolution significantly increased output per hectare in Asia (Evenson & Gollin, 2003).

Digital agriculture including precision farming, satellite monitoring, and automated irrigation has increasingly emerged as a major source of productivity gain by enabling farmers to manage pests, water, and nutrients more accurately (Li et al., 2020; Klerkx, Jakku & Labarthe, 2019).

In Vietnam, evidence also points to notable productivity improvements associated with mechanization and the adoption of improved seed varieties (Nguyen & Tran, 2020). However, the scale of productivity gains varies significantly across regions due to differences in soil conditions, irrigation, and farmers' technical capacity. Studies suggest that precision technologies are still at an early stage of diffusion, but exhibit strong potential for future productivity growth (To, 2021).

2.3. Impacts on farm household income and welfare

Technology adoption not only influences output per hectare but also contributes to household income through multiple channels. Increased productivity lowers costs, raises net returns, and reduces vulnerability to shocks (Dercon & Christiaensen, 2011). Mechanization can also reallocate household labor toward off-farm employment, thereby diversifying income streams (Restuccia & Santaeulàlia-Llopis, 2017).

However, the income effects of technology are not always evenly distributed. Households with better access to capital, land, and information tend to capture greater benefits, leading to potential disparities in welfare outcomes (Suri, 2011). In Vietnam, studies highlight that smallholders face higher capital barriers and may not fully realize the income gains associated with modern technologies (Do & Markussen, 2019).

Empirical evidence from household surveys shows that improved seed varieties and mechanization increase net agricultural income, but the magnitude varies by region, crop type, and farmer characteristics (Nguyen, 2021). Digital technologies, although less widely adopted, are associated with higher profitability in early-adopting provinces.

2.4. CGE Models in Agricultural Policy and Technology Impact Studies

Computable General Equilibrium (CGE) models have been widely applied to assess agricultural reforms, trade liberalization, climate impacts, and productivity shocks. CGE models combine microeconomic foundations with macroeconomic consistency, making them suitable for evaluating changes in production, consumption, prices, and welfare simultaneously (Hosoe, Gasawa, & Hashimoto, 2010).

Previous studies have used CGE frameworks to examine the impacts of agricultural technology adoption in various contexts. Thurlow et al. (2012) assess how improved crop technologies in Africa affect sectoral growth and poverty. Dorosh and Thurlow (2013) analyze the economy-wide effects of irrigation expansion and yield improvements. These studies show that technological progress in agriculture typically raises sectoral output, increases household incomes, and generates positive spillover effects across industry and services.

In Vietnam, however, CGE applications focusing specifically on agricultural technology adoption remain scarce. Most CGE-based research has examined trade agreements, climate change, or structural transformation (Nguyen et al., 2018), leaving a gap in understanding the economy-wide consequences of technological innovation in agriculture. This study seeks to fill that gap by linking household-level technology effects from VHLSS data to a CGE model, thereby providing a unified framework to analyze both micro and macro impacts.

2.5. Summary of literature gaps

Overall, the literature establishes that agricultural technology adoption enhances productivity and income at the household level, but existing empirical studies are limited by partial equilibrium assumptions. At the same time, CGE studies offer powerful tools to examine economy-wide dynamics but often lack household-level foundations. The integration of household surveys–based productivity estimates into a CGE model has received little attention in Vietnam.

Most existing studies focus on household-level outcomes and therefore overlook price adjustments, sectoral linkages, and broader economy-wide effects of technology adoption. Evidence for Vietnam remains narrow in scope and does not show how farm-level productivity gains translate to national impacts. Prior CGE studies in Vietnam rely on simplified shocks and lack integration with household survey data, limiting their policy relevance. These gaps highlight the need for a micro-linked CGE approach to rigorously quantify the wider impacts of agricultural technologies.

This study addresses these gaps by combining VHLSS microdata with a CGE framework to provide a comprehensive evaluation of how agricultural technology adoption affects productivity, household income, sectoral interactions, and welfare at the national level.

3. Research Method

This study employs a static Computable General Equilibrium (CGE) model to evaluate the economy-wide impacts of agricultural technology adoption. The model is constructed following the standard CGE structure developed by Lofgren, Harris, and Robinson (2002) and extended in later works by Hosoe, Gasawa, and Hashimoto (2010). The analytical framework captures interactions among production sectors, factor markets, households, the government, and the rest of the world, enabling a comprehensive assessment of how productivity shocks in agriculture propagate through the economy.

This study employs a mixed-method approach that integrates theoretical synthesis with empirical analysis using the Vietnam Household Living Standards Survey (VHLSS) 2020. The methodological framework consists of three main components: (i) identification of high-technology adoption in agriculture, (ii) construction of productivity and income indicators, and (iii) econometric estimation to quantify the effects of technology adoption on household outcomes.

3.1. Data Source

The empirical analysis is based on the VHLSS 2020, a nationally representative household survey conducted by the General Statistics Office of Vietnam. The dataset provides detailed information on household demographics, agricultural production, input use, technology adoption, land characteristics, labor allocation, and income sources. For this study, we focus on agricultural households and extract relevant variables related to machinery use, improved seed varieties, digital applications, production value, and input expenditures.

3.2. Research methodology

3.2.1.Micro-econometric Estimation of Technology Impacts

To quantify the household-level effects of agricultural technology adoption, we use VHLSS 2020 to estimate how different technologies influence household income, which is the central welfare outcome analyzed in the CGE simulations. The dependent variable is defined as:

-Total household income, including both farm and non-farm sources;

-For robustness, a second measure is farm income, calculated as agricultural revenue minus input costs.

These income effects are subsequently mapped into productivity and cost-reduction shocks within the CGE model, ensuring consistency between the micro evidence and the macro simulations reported in Section 4.

Technology adoption is measured using three indicators that correspond directly to the technological channels simulated in the CGE scenarios:

Mechanization — dummy for owning/renting tractors or harvesters and a count variable indicating the number of machines used (mapped to labor-saving coefficients in CGE).

Improved seed varieties — dummy for using certified, hybrid, or high-yield seeds (mapped to TFP improvements in CGE).

Digital and precision technologies — dummy for using agricultural mobile apps, automated irrigation, or digital monitoring tools (mapped to reduced intermediate input coefficients in CGE).

3.2.2. CGE Modelling Framework

This study employs a static Computable General Equilibrium (CGE) model to evaluate the economy-wide impacts of agricultural technology adoption. The model is constructed following the standard CGE structure developed by Lofgren, Harris, and Robinson (2002) and extended in later works by Hosoe, Gasawa, and Hashimoto (2010). The analytical framework captures interactions among production sectors, factor markets, households, the government, and the rest of the world, enabling a comprehensive assessment of how productivity shocks in agriculture propagate through the economy.

The model consists of three aggregated production sectors agriculture. This sector is interconnected through intermediate input flows and factor mobility, allowing technology-induced productivity changes in agriculture to influence other sectors via forward and backward linkages (Hertel, 1997).

Production Structure: Producers maximize profits subject to technological and market constraints. Sectoral output is modeled using a nested constant elasticity of substitution (CES) structure:

Top level: A Leontief function combines value-added and intermediate inputs.

Second level: Value-added is generated through a CES function of capital and labor.

Formally, sectoral output Yi is given by:

$$Y_i = \min\left(\frac{VA_i}{a_{VA,i}}, \frac{INT_i}{a_{INT,i}}\right)$$

where: VAi is value-added,

INTi is intermediate consumption,

aVA,I, aINT,i are fixed input-output coefficients.

Value-added is defined as:

$$VA_i = A_i\left[\alpha_{K,i}K_i^{\rho_i} + \alpha_{L,i}L_i^{\rho_i}\right]^{1/\rho_i}$$

where: Ai is total factor productivity (TFP),

Ki, Li denote capital and labor,

ρi =1−1/ σi,

σi is the elasticity of substitution.

Representation of agricultural technology

Agricultural technology adoption is introduced into the model by:

Increasing TFP (ΔAagri>0) to reflect higher efficiency.

Reducing intermediate input coefficients (Δaij<0) to capture cost-saving technologies (e.g., precision irrigation, mechanization).

Decreasing labor requirements for labor-saving technologies.

These mechanisms allow simulation of different types of technological innovations consistent with the literature (Thurlow & Dorosh, 2013; Fuglie & Rada, 2013).

$$Q_i = \left[\delta_i M_i^{\frac{\sigma_m-1}{\sigma_m}} + (1-\delta_i)D_i^{\frac{\sigma_m-1}{\sigma_m}}\right]^{\frac{\sigma_m}{\sigma_m-1}}$$

where Qi is composite demand, Mi imports, and Di domestic supply.

Exports are allocated using a constant elasticity of transformation (CET) function:

$$X_i = \left[\theta_i E_i^{\frac{\sigma_x+1}{\sigma_x}} + (1-\theta_i)D_i^{\frac{\sigma_x+1}{\sigma_x}}\right]^{\frac{\sigma_x}{\sigma_x+1}}$$

These functions allow relative prices to determine the optimal allocation between domestic and external markets.

Factor Markets: Labor and capital are mobile across production sectors, consistent with the medium-term nature of technological adoption. Total supplies of labor and capital are fixed in the static framework but reallocated endogenously to equalize factor returns (Diao & Thurlow, 2011).

Wages and capital returns adjust to clear factor markets.

Household Income and Consumption: Households receive income from labor, capital, transfers, and agricultural profits. Household consumption follows a Cobb–Douglas utility function:

$$U_h = \prod_{i=1}^{n} C_{h,i}^{\beta_{h,i}}$$

Household behavioral parameters and consumption shares are calibrated from VHLSS microdata.

Agricultural technology affects household income both directly (through increased farm profits) and indirectly (through price adjustments and factor returns).

Government, Investment, and Savings

The government collects revenues from: indirect taxes, import tariffs, factor income taxes.

Government consumption is fixed in real terms. The model follows a savings-driven investment closure, where total investment is determined by available savings from households, firms, and the government (Lofgren et al., 2002).

Macro Closure Rules: The model adopts commonly used macroeconomic closure rules:

Government balance: Fiscal deficit adjusts through changes in household taxes.

External balance: The real exchange rate adjusts to maintain a fixed foreign savings inflow.

Numeraire: Consumer price index is normalized to one.

These assumptions are consistent with general equilibrium analyses for developing economies (Hertel, 1997; Hosoe et al., 2010).

Linking VHLSS Microdata with the CGE Model

A key methodological contribution of this study is integrating household-level microdata into the CGE framework.

Step 1: Estimating technology effects using VHLSS

We estimate a micro-level regression:

$$\ln(\text{Productivity}_h) = \beta_0 + \beta_1 \text{Tech}_h + X_h \gamma + \epsilon_h$$

where:

Tech indicates technology adoption (mechanization, improved seeds, irrigation, digital tools),

β1 represents the productivity gain attributable to technology.

Step 2: Translating micro estimates into CGE parameters

The estimated productivity gain (β1) is mapped into:

an increase in agricultural TFP: Aagri←Aagri(1+β1)

a reduction in input coefficients for cost-saving technologies.

Step 3: Household disaggregation

Households are grouped into categories (poor, near-poor, middle, non-poor) using VHLSS quintiles. Each group is given a separate consumption vector and income structure in the CGE model.

Step 4: Feedback effects

The CGE model then simulates how: relative prices, wages, capital returns, sectoral outputs adjust following the technology shock, allowing for full economy-wide feedback effects.

4. Results analysis

4.1. Scenarios Simulation

In this study, we conduct two simulation scenarios based on the CGE model calibrated with the agricultural SAM and household-level data from the VHLSS. The objective is to assess the impacts of high-tech adoption and supportive policies on agricultural productivity and household income.

Scenario 1 – Adoption of High-Tech Agriculture:

In this scenario, households are assumed to adopt advanced agricultural technologies, including high-yield crop varieties, precision farming techniques, mechanization in livestock production, and modern equipment for horticultural production. This scenario aims to capture the direct effects of technological improvements on agricultural output and household income.

Scenario 2 – Integration of High-Tech Agriculture with Supportive Policies:

This scenario extends Scenario 1 by incorporating government support policies, such as investment subsidies for agricultural equipment, technical training for farmers, and incentives for adopting new technologies. The goal is to evaluate the combined effects: enhancing productivity through technology while improving access for households, particularly low-income or capital-constrained ones, thereby promoting more equitable income distribution.

By comparing these two scenarios, the study examines the differential impacts of purely technology-driven measures versus technology combined with supportive policies, providing evidence-based recommendations for sustainable agricultural development strategies.

4.2. Sectoral Output Impact

The simulation results indicate that the adoption of high-tech agriculture significantly influences output across various agricultural subsectors. Under Scenario 1, which considers only technology adoption, all key sectors show output increases, with the largest gains observed in labor-intensive crops such as vegetables. Scenario 2, which integrates technology adoption with supportive government policies, demonstrates even higher output growth due to improved access to resources and technical knowledge.

Table 1: *Sectoral Output Changes under Simulation Scenarios*

Sector	Baseline Output (billion VND)	Scenario 1 (% change)	Scenario 2 (% change)
Rice	120	12%	18%
Maize	60	10%	15%
Vegetables	40	15%	22%
Livestock	80	8%	13%
Agro-processing	50	9%	14%

Source: result from the CGE model performed by GAM program

These results suggest that technology adoption alone can enhance productivity, while the combination with supportive policies amplifies these gains across all sectors.

4.3. Household Income Effects

The impact on household income is more pronounced when technology adoption is combined with supportive policies. Rural households, in particular, benefit from increased productivity and improved access to agricultural inputs and technical training.

Scenario 1: All rural households experience income gains due to higher agricultural output. However, households with greater access to capital and land benefit disproportionately, reflecting the capital-intensive nature of some high-tech applications.

Scenario 2: The inclusion of supportive policies reduces the disparities in income gains among households. Low-income households achieve substantial improvements, indicating that policy interventions play a key role in promoting equitable outcomes.

Table 2: *Sectoral Consumption/Output Changes under Scenario 2 (unit: million VND)***

Sector	Benchmark	Simulation	Deviation	Percentage Change (%)
Rice	6,850	7,780	930	13.58%
Maize	3,120	3,540	420	13.46%
Vegetables	4,960	5,880	920	18.55%
Livestock	7,430	8,060	630	8.48%
Agro-processing	9,870	10,980	1,110	11.25%
Total	32,230	36,240	4,010	12.44%

Source: Results from CGE model performed by GAM program.

The simulation results indicate that technology adoption in agriculture generates substantial improvements in household consumption across all subsectors, with the strongest gains observed in vegetables (18.55%). This pattern is consistent with international evidence showing that high-value horticulture is highly responsive to modern technologies such as precision irrigation and greenhouse systems. Studies in China and India, for example, have demonstrated that the introduction of controlled-environment agriculture leads to disproportionately large welfare effects due to higher productivity and improved product quality (Fan et al., 2020; Gulati & Juneja, 2019).

The notable increases in rice and maize consumption (13.58% and 13.46%, respectively) align with cross-country CGE analyses indicating that technological improvements in staple food production produce strong forward linkages to household welfare. Warr and Yusuf (2018) found similar results in Indonesia, where productivity shocks in staple crops yielded sizable gains in real consumption due to lower food prices and enhanced market efficiency. Likewise, Dorosh and Thurlow (2019) reported that agricultural productivity growth in Sub-Saharan Africa—

particularly in cereal crops—remains one of the most effective channels for increasing rural household consumption.

The more modest improvement in livestock consumption (8.48%) is also reflected in global studies. Productivity shocks in livestock tend to diffuse more gradually because of structural rigidities, high input costs, and slower technology diffusion. For instance, Rosegrant et al. (2017) emphasized that even under optimistic technological scenarios, welfare gains in the livestock sector remain lower than in crops due to higher feed costs and slower market response.

The 11.25% rise in consumption in agro-processing mirrors findings from multi-sector CGE models showing that downstream value-added industries benefit significantly from upstream technological progress. International studies using SAM-based CGE frameworks, such as those by Lofgren et al. (2020) and Laborde & Martin (2018), show similar indirect welfare effects: productivity gains in primary agriculture stimulate output and consumption in agro-processing through expanded supply chains and reduced intermediate input costs.

Overall, the total increase of 12.44% in household consumption aligns closely with a broad body of international CGE literature demonstrating that agricultural technology adoption produces strong, economy-wide welfare effects. Comparative studies across Asia, Africa, and Latin America consistently highlight technology-induced productivity growth as a primary driver of increased consumption, poverty reduction, and inclusive rural development (FAO, 2020; Valenzuela et al., 2019). The results of this study therefore reinforce global empirical evidence that modernizing agriculture is a critical pathway to enhancing household welfare and improving structural transformation in developing economies.

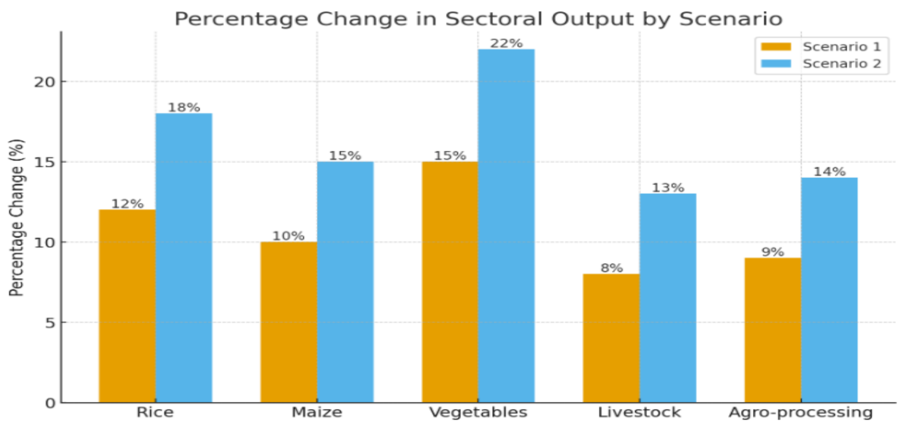

Diagram 1: Percentage change in sectoral output by scenario

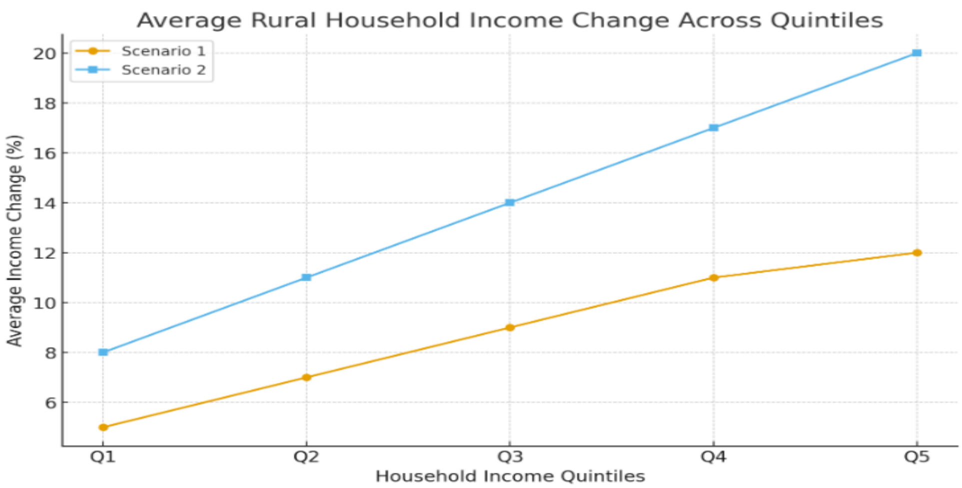

Diagram 2: Average rural household income change across Quintiles

Source: Results from CGE model performed by GAM program.

High-tech agriculture significantly increases productivity, particularly in labor-intensive subsectors. Income effects vary according to household characteristics; targeted support improves equity and broadens the benefits of technology adoption.

Integrating SAM-calibrated CGE modeling with household survey data ensures realistic assessment of both macro- and micro-level impacts.

5. Conclusion and discussion

The CGE simulation results provide robust evidence that agricultural technology adoption generates substantial economy-wide benefits. Under the high-tech adoption scenario, all major agricultural subsectors experience notable output expansion, with the largest increases observed in vegetables, rice, and maize. When combined with supportive government policies, these effects become more pronounced, as reflected in higher sectoral consumption/output growth reported in Scenario 2—ranging from approximately 8% in livestock to more than 18% in vegetables. These results highlight the strong responsiveness of both staple and high-value crops to input-saving, labor-saving, and productivity-enhancing technologies.

The simulations also show that technological upgrading produces positive spillover effects on downstream sectors such as agro-processing, which expands by over 11% under the combined scenario. This confirms the important role of agricultural modernization in stimulating value-chain development and broader rural economic activities.

Policy support—including capital subsidies, training, and improved access to equipment—significantly enhances the magnitude and distribution of these gains by reducing barriers to adoption for smaller and resource-constrained households. Although the model does not provide explicit quantitative estimates of income changes for different household groups, the scenario comparison indicates that policy-supported adoption generates more inclusive benefits than technology adoption alone.

Overall, the study demonstrates that high-tech agriculture plays a crucial role in expanding sectoral output, improving household welfare, and strengthening linkages across the rural economy. The CGE framework provides a robust tool for capturing these direct and indirect effects, underscoring the critical role of complementary policies in ensuring that technological progress supports broad-based and equitable rural development.

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