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Agricultural Productivity and Climate Mitigation

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Abstract

Agriculture will play a central role in meeting greenhouse gas (GHG) emission targets, as the sector currently contributes ~22% of global emissions. Because emissions are directly tied to resources employed in farm production, such as land, fertilizer, and ruminant animals, the productivity of input use tends to be inversely related to emissions intensity. We review evidence on how productivity gains in agriculture have contributed to historical changes in emissions, how they affect land use emissions both locally and globally, and how investments in research and development (R&D) affect productivity and therefore emissions. The world average agricultural emissions intensity fell by more than half since 1990, with a strong correlation between a region's agricultural productivity growth and reduction in emissions intensity. Additional investment in agricultural R&D offers an opportunity for cost-effective (<US$30 per ton carbon dioxide) and large-scale emissions reductions. Innovations that target specific commodities or inputs could even further reduce the cost of climate mitigation in agriculture.

1. INTRODUCTION

Agriculture, forestry, and land use change were responsible for 22% of global anthropogenic emissions of greenhouse gases (GHGs) in 2019 (IPCC 2023).[1] Carbon dioxide (CO_2) from land conversion and cultivation, methane from rice paddies and livestock (both manure and enteric fermentation), and nitrous oxide from fertilizers are some of the main pathways through which agriculture contributes to GHG emissions and climate change.

Given its large GHG footprint, agriculture has a central role to play in moving toward a carbon-neutral economy. Golub et al. (2012) suggest that substantial GHG mitigation in agriculture and forestry is feasible at modest carbon prices. Agriculture is an enormously heterogeneous sector with large differences in emissions intensities, or the quantity of emissions (measured in the quantity of CO_2 equivalent[2] per volume or dollar of commodity output) across geographies, by commodities and farm practice. Moreover, productivity growth in agriculture has led to falling emissions intensity over time. Because most agricultural GHG emissions are directly tied to resources employed in farm production (the amount of land, number of livestock, and quantity of fertilizer applied, etc.), emissions intensity tends to be inversely related to productivity. As productivity raises the output from a given set of resources, it reduces the amount of GHG emissions associated with each unit of output since fewer inputs are used. Policies aimed at raising agricultural productivity can thus serve as an important tool for climate change mitigation.

This article reviews economic and empirical analyses of the relationship between agricultural productivity and GHG emissions. Section 1 lays out evidence at the global and regional levels on general trends in GHG emissions from agriculture over the past three decades (1990–2020), how agricultural emission intensity varies across world regions, and how it has changed over time. Impressively, over the past three decades, agricultural GHG emissions intensity has been cut in half, due to improved farm efficiency and reduced rates of land conversion. This section also discusses concepts of agricultural productivity and how growth in total factor productivity (TFP) can serve as a broad indicator of the rate of agricultural technical change. However, the extent to which TFP growth will result in reduced GHG emissions intensity depends on whether technical change is factor-neutral or factor-biased toward or against the inputs most responsible for emissions. Section 2 reviews the findings from economic models of global land use change and how land use is affected by growth in agricultural productivity once behavioral responses to productivity's effect on prices and trade competitiveness are taken into account. Importantly, these models address the Jevons paradox, the notion that higher productivity—by boosting profitability—could expand rather than save farmland use and GHG emissions. In the case of agriculture, empirical modeling finds that over the last few decades, agricultural TFP growth affected the distribution of the world's agricultural land, increasing it in some areas while reducing it in others, for an overall significant net savings in global agricultural land and GHG emissions.

Section 3 briefly reviews results from a suite of global economic models of the global agri-food economy that project commodity demand, supply, prices, land use, and agricultural emissions out to mid-century and beyond. These models are unanimous in finding that outcomes depend critically on assumptions of future growth in crop and livestock productivity, with more rapid productivity growth leading to reduced land use in agriculture, fewer emissions, and a more food secure world. Section 4 reviews findings from recent studies that have examined agricultural

[1] The larger agri-food economy, including postharvest processing, packaging, and transport, and prefarming manufacture of chemical fertilizers, along with farm production, accounts for approximately one-third of global GHG emissions (FAO 2023). The focus of this review is on the agriculture (farm) component, including land use conversion from forests and grasslands to agricultural land.

[2] CO_2 equivalents weight various GHGs by their relative contribution to global warming.

productivity policy for climate mitigation, namely, investments in agricultural research and development (R&D) that can accelerate productivity growth over the long term. This literature finds that R&D investments can be an economically viable climate mitigation strategy. Based on historical returns to agricultural R&D, productivity policy compares favorably to many other environmental policies in terms of the estimated cost of GHG abatement. Section 5 concludes and presents suggestions for future research areas.

2. AGRICULTURAL PRODUCTIVITY AND GREENHOUSE GAS EMISSIONS

2.1. Concepts of Agricultural Productivity

At its most basic level, productivity is simply the ratio of outputs divided by inputs in a production process. Higher productivity reflects more output per unit of input. Probably the most widely used indicator of agricultural productivity is yield, typically measured as crop output per acre or meat or milk output per animal. These single-factor productivity measures focus on just one of several economic inputs (factors). As increases in yield can arise when other factors increase (say, more fertilizer is added to an acre of cropland), yield is deemed an imperfect measure of overall productivity.

TFP is a more comprehensive measure, defined as the ratio between economic output (which may include several commodities from a farm or region) and the whole set of economic inputs (land, labor, capital, and intermediate inputs like fertilizers and feed) used to produce them. Changes in TFP are a better reflection of changes in technology than single-factor productivity, as the influences on output from changes in other inputs are taken into account. TFP can change owing to many factors, such as adoption of new technologies and practices, attainment of scale efficiencies, and specialization. New technologies are often embodied in purchased inputs such as seed, chemicals, and machinery. TFP is also affected by the quality of the natural resources used in production. Long-term processes like soil erosion, ground water degradation, and climate change can affect TFP over time. Such changes may occur very gradually, and these deleterious effects may go unnoticed if other technologies are simultaneously changing and boosting output.

While an increase in TFP means that fewer total inputs are used to produce a given amount of output, it is possible that adoption of new technologies and practices involves a change in the mix of inputs applied, with the use of some increasing and others decreasing. On the one hand, productivity increases are factor-neutral if they reduce all the inputs needed to produce a given level of output at about the same rate. Factor-biased productivity growth, on the other hand, alters the proportion of inputs used in production. Hayami & Ruttan (1985) found that agricultural technical change in North America and Western Europe tended to be biased in a labor-saving direction, while the Asian Green Revolution technologies were land-saving and fertilizer-using. They interpreted these technology biases as being induced by relative resource scarcities—rising costs of labor relative to other inputs in North America led to labor-saving technologies, while rising relative costs of land in Asia led to technologies that replaced land with other inputs, such as new crop varieties that had greater yield response to fertilizers. Acemoglu (2023) concluded that directed technical change (another term for induced innovation) has been a key feature of productivity growth in many economic sectors in addition to agriculture.

Whether, or to what extent, increases in agricultural TFP result in fewer GHG emissions per unit of output depends critically on the nature of the input savings induced by the new technologies and farming practices that drive TFP growth. If TFP growth reflects factor-neutral technical change, then it is likely that GHG emissions intensity (emissions per unit of output) will decline at about the same rate that TFP increases, because emissions are closely associated with the land, livestock, and fertilizer inputs used in agricultural production. Factor-biased technical change, on the other hand, may lead to situations where TFP growth leads to rapid reductions in emissions intensity (i.e., if it reduces the inputs tied most closely to emissions), or even an increase in emissions intensity if it is biased toward the use of inputs that are heavily associated with emissions. Such technology and resource biases can be quite significant in agriculture. In an assessment of potential impacts of a uniform 30% increase in commodity yields in developing countries between 2015 and 2030, Fuglie et al. (2022b) found that because cereal crops make much greater use of land in production, higher cereal yields were likely to give 40 times the savings in GHG emissions as similar yield improvements to fruits and vegetables, even though both commodity groups had similar aggregate production values.

2.2. Global Agricultural GHG Emissions, 1990–2020: Declining Resource-Use Intensity

In 2020, agriculture production, land use change, and on-farm energy use together were responsible for approximately 10.5 gigatons of CO_2-equivalent (CO_2e) GHG emissions (FAO 2023). According to Food and Agriculture Organization (FAO) estimates, there was a slight downward trend in total global agricultural GHG emissions over 1990–2020 (**Figure 1*a***) due entirely to lower annual rates of land use change; GHG emissions from farm production and on-farm energy use continued to grow over this period, though modestly, at ~0.5% per year. In contrast, agricultural output roughly doubled over these three decades (from US$2.2 trillion in 1990 to $4.3 trillion in 2020, measured using constant 2015 prices), or by approximately 2.3% per year. As a result, agricultural emissions intensity, or the quantity of GHGs emitted per constant-dollar value of agricultural output, declined. In fact, over the 1990–2020 period, the world average agricultural emissions intensity fell by more than half, from 5.1 kg of CO_2e per $1 of agricultural output in 1990 to 2.4 kg CO_2e per $1 output by 2020 (**Figure 1*b***). Although a substantial share of

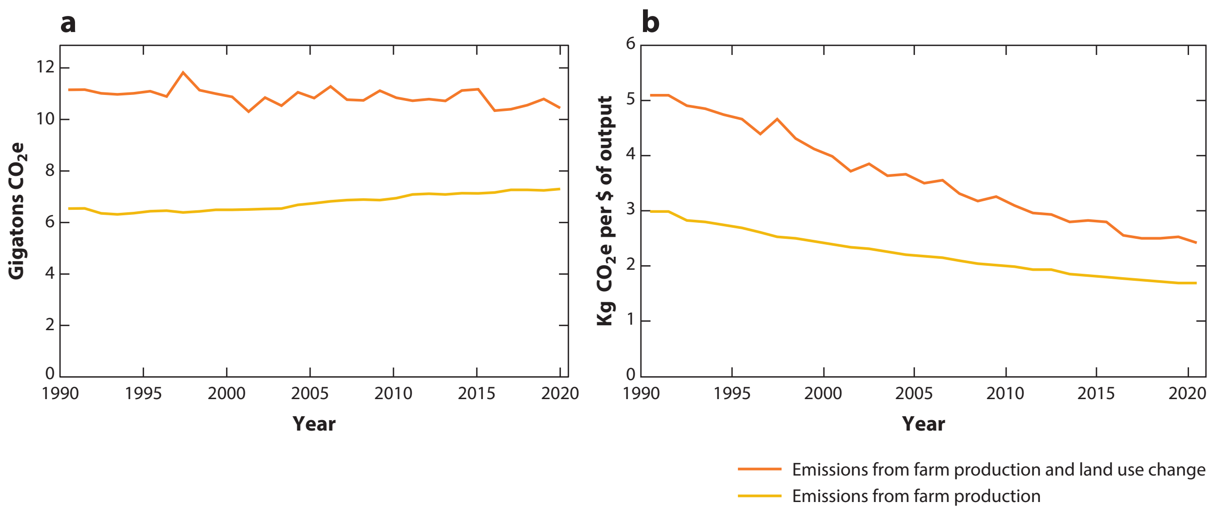

Figure 1

(*a*) World agricultural GHG emissions (CO_2e), 1990–2020. (*b*) World average agricultural GHG emissions intensity, 1990–2020. Agricultural GHG emissions intensity is the quantity of GHG emissions divided by the gross value of farm crop, animal, and aquaculture output (valued at constant 2015 prices). GHG emission data from FAO (2023), and agricultural output is from USDA-ERS (2022). Abbreviations: CO_2e, CO_2-equivalent; GHG, greenhouse gas.

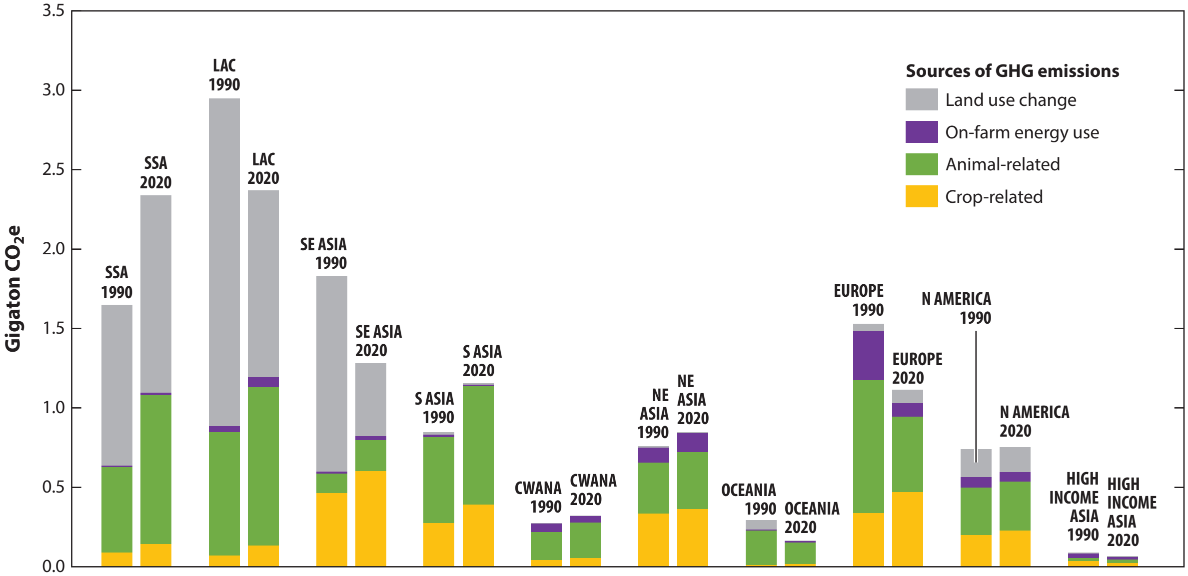

Figure 2

Agricultural GHG emissions across global regions in 1990 and 2020. GHG emission data from FAO (2023). Crop-related emissions include emissions from drained organic soils, synthetic fertilizers, crop residue and burning of crop residues, and rice cultivation. Animal-related emissions include emissions from manure left on pasture, manure applied to soils, manure management, controlled savanna fires, and enteric fermentation. Abbreviations: CO_2e, CO_2-equivalent; CWANA, Central/West Asia and North Africa; EUROPE, Europe, Russia, and Kazakhstan; GHG, greenhouse gas; HIGH INCOME ASIA, Japan, South Korea, and Taiwan; LAC, Latin America/Caribbean; N AMERICA, Canada and the United States; NE ASIA, China, Mongolia, and North Korea; OCEANIA, Australia and New Zealand; S ASIA, South Asia; SE ASIA, Southeast Asia and Pacific; SSA, Sub-Saharan Africa.

this was due to reductions in the rate of land use change, emissions intensity from farm production also declined by 44%, from 3.0 kg to 1.7 kg CO_2e per $1 of output.

The global picture of agricultural emissions intensity depicted in **Figure 1*b*** hides vast regional differences in both the levels and rates of change in GHG emissions and emissions intensity. **Figure 2** compares aggregate agricultural emissions in 1990 and 2020 for 10 world regions and further breaks down emissions into those arising from land use change, crop production, animal production, and on-farm energy use.[3] Agricultural emissions rose in Sub-Saharan Africa (SSA), South Asia, Central/West Asia and North Africa, Northeast Asia and North America, but fell in Latin America/Caribbean (LAC), Southeast Asia, Oceania, Europe, and High Income Asia (Japan, South Korea, and Taiwan). The decline in emissions in LAC and Southeast Asia was entirely due to lower rates of land use change. Land use changes in SSA, LAC, and Southeast Asia were a major cause of agricultural GHG emissions; not only was agricultural area expanding in these regions but also many of these areas contained dense carbon stocks in tropical forests and peatlands, which

[3]We use the FAO estimates of agricultural GHG emissions, which for non-Annex I countries (i.e., most developing countries) are more complete and consistent than national estimates submitted to the United Nations Framework Convention on Climate Change (UNFCCC) (Dittmer et al. 2023). Farm GHG emissions consist of crop-related emissions, animal-related emissions, and emissions from on-farm energy use. We define crop-related emissions as those arising from synthetic fertilizer use, crop residues and residue burning, rice cultivation, and farming on drained organic soils. Animal-related emissions are from enteric fermentation, controlled savanna burning, manure left on pastures and soils, and manure management.

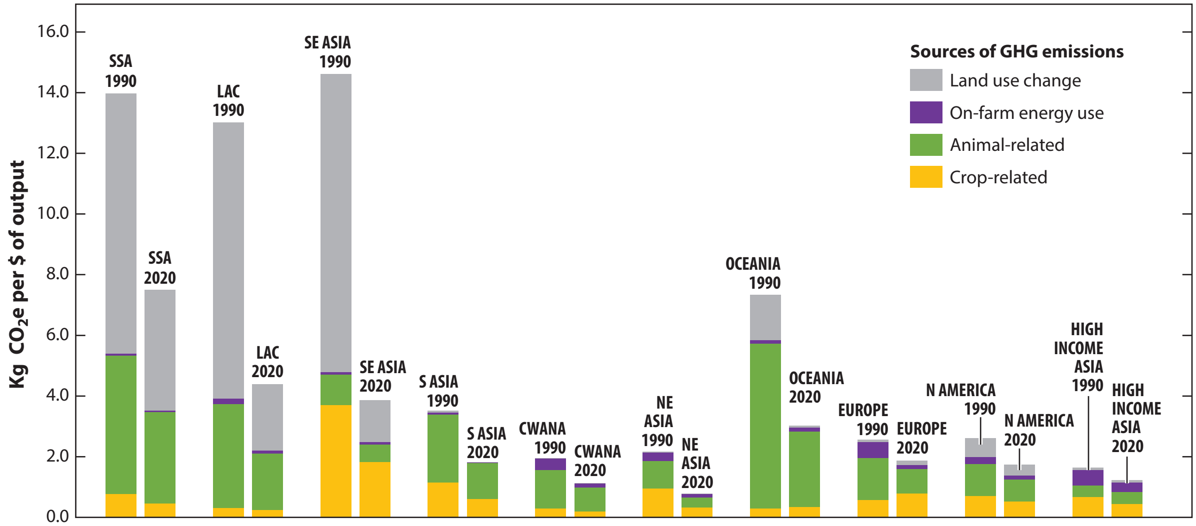

Figure 3

Agricultural GHG emissions intensity by region, 1990 and 2020. GHG emissions intensity is the quantity of GHG emissions from **Figure 2** divided by the gross value of farm crop, animal, and aquaculture output (valued at constant 2015 prices). It does not indicate commodity-specific intensities. GHG emission data from FAO (2023), and agricultural output from USDA-ERS (2022). Abbreviations: CO_2e, CO_2-equivalent; CWANA, Central/West Asia and North Africa; EUROPE, Europe, Russia, and Kazakhstan; GHG, greenhouse gas; HIGH INCOME ASIA, Japan, South Korea, and Taiwan; LAC, Latin America/Caribbean; N AMERICA, Canada and the United States; NE ASIA, China, Mongolia, and North Korea; OCEANIA, Australia and New Zealand; S ASIA, South Asia; SE ASIA, Southeast Asia and Pacific; SSA, Sub-Saharan Africa.

were released when the land was cleared for cropland and pastures. In addition, peatlands continue emitting significant CO_2 and nitrous oxide GHGs for many years following their conversion to cropland. In **Figure 2**, these subsequent emissions are denoted as crop-related once these lands have been cleared and are in crop production.

Figure 3 compares emissions intensities across these regions and between 1990 and 2020. The large regional differences in emissions intensities are due to a combination of factors, including (*a*) rates of land use change, (*b*) commodities produced, and (*c*) productivity. The tropical regions responsible for most of the emissions from land use change (SSA, LAC, and Southeast Asia) achieved very substantial reductions in emissions intensity between 1990 and 2020, mostly due to reductions in land use change relative to farm output. All regions achieved reductions in farm emissions per unit of output between 1990 and 2020, due primarily to gains in productivity. However, commodity mix also plays a role in explaining differences in regional emissions intensity. For example, the high farm emissions intensities in SSA and Oceania are due in large part to their large ruminant livestock sectors that rely heavily on extensive grazing (though Oceania achieved significant reductions in livestock emissions intensities between 1990 and 2020). Southeast Asia's high emissions intensity from crops reflects the large area in rice cultivation in this region. Northeast Asia had the lowest overall emissions intensity; this region has a relatively small share of output from ruminant livestock and large output shares from horticultural crops and aquaculture. These are activities that use relatively little land and produce relatively few emissions per unit of output.

As discussed above, factor-neutral agricultural TFP growth reduces the amounts of land, labor, capital, and material inputs used to produce a given amount of output in roughly equal proportions. In this case, a 1% increase in agricultural TFP should reduce GHG emissions intensity by approximately 1%. Factor-biased technical change, on the other hand, could produce the same rate of TFP

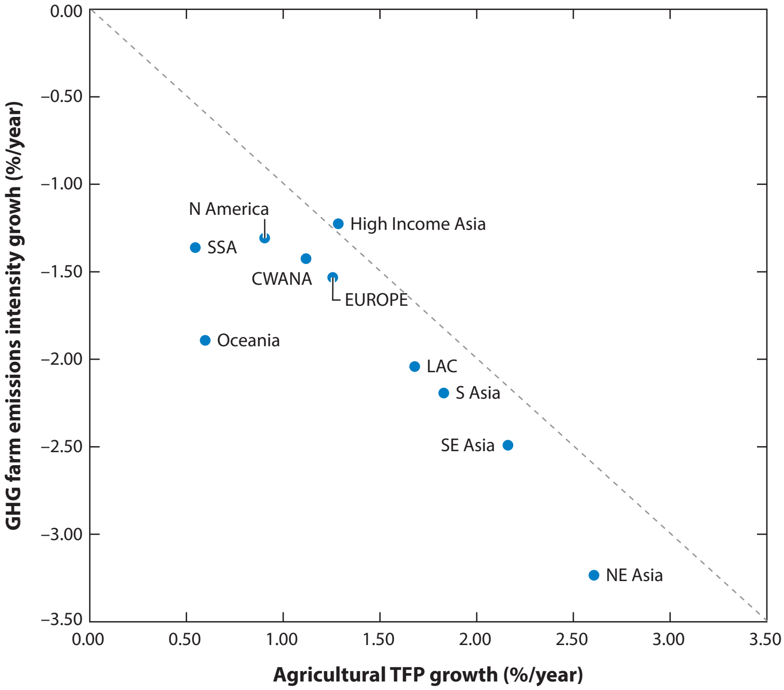

Figure 4

Growth rates in agricultural TFP and GHG-farm emissions intensity, 1991–2020. The dots compare the average annual percent change in agricultural TFP with the average annual percent change in the GHG emissions intensity of farm production over 1991–2020. The dashed line has a slope of −1 so that for points on or near this line, a 1% increase in agricultural TFP is associated with a 1% decrease in emissions intensity. For points below (above) this line, a 1% increase in agricultural TFP is associated with a greater than (less than) 1% decrease in emissions intensity. Agricultural GHG emission data from FAO (2023), and agricultural TFP indexes from USDA-ERS (2022). Abbreviations: CWANA, Central/West Asia and North Africa; EUROPE, Europe, Russia, and Kazakhstan; GHG, greenhouse gas; High Income Asia, Japan, South Korea, and Taiwan; LAC, Latin America/Caribbean; N America, Canada and the United States; NE Asia, China, Mongolia, and North Korea; Oceania, Australia and New Zealand; S Asia, South Asia; SE Asia, Southeast Asia and Pacific; SSA, Sub-Saharan Africa; TFP, total factor productivity.

growth but change the input mix disproportionally. Therefore, GHG emissions intensity could fall by more or less than the rate of TFP growth depending on whether the inputs most closely associated with emissions (the number of livestock, the amount of fertilizers applied, the area in rice cultivation, etc.) change more or less than the average. **Figure 4** compares regional-level growth rates in agricultural TFP and farm GHG emissions intensity over the period 1991–2020. There is a strong negative correlation between the average annual growth rates of these two measures: Regions achieving more rapid TFP growth such as Northeast Asia and Southeast Asia show faster reduction in emissions intensity. For all regions except High Income Asia, the rate of decline in emissions intensity was slightly faster than TFP growth [i.e., the points in the chart fall below the dashed 45-degree line, where (positive) TFP growth = (negative) GHG emissions intensity growth]. It appears that technical change has been either factor-neutral or slightly biased toward saving the factors that cause the most emissions.

The emission intensities shown in **Figure 4** refer to the whole agricultural sector. The FAO also estimates emissions intensities for some select groups of commodities (rice, other cereals, meat, milk, and eggs). There are large variations in emissions intensities across commodities and countries and over time. For example, in 2020 the world average emissions intensity for beef (kg of CO_2e per kg of product) was 27 times higher than that of rice, and the emissions intensity of rice was more than 6 times higher than that of other cereals. Between 1990 and 2020, the global average emissions intensity of dairy milk, rice, and beef declined at an average annual rate of 1.3%, 0.8%, and 0.5%, respectively. This partly reflects differences in rates of productivity growth: It has generally been easier to obtain more rapid productivity gains in confined animal production systems such as dairy and poultry where animals can be more intensively managed than in extensive systems such as pasture-fed beef (Ludena et al. 2007).

3. HOW HAS AGRICULTURAL TOTAL FACTOR PRODUCTIVITY GROWTH AFFECTED LAND USE CHANGE, LOCALLY AND GLOBALLY?

3.1. Productivity, Prices, and Indirect Land Use Effects

Whether agricultural productivity growth reduces or increases cropland has received considerable attention (e.g., Angelsen & Kaimowitz 2001). Most studies only consider partial productivity measures like crop yield and their relation to local land use; results tend to be heterogeneous and context-specific (Villoria et al. 2014). For example, a few studies have used longitudinal data to examine the effects of changes in national crop yields on national harvested area (Ewers et al. 2009, Rudel et al. 2009, Ceddia et al. 2013). These studies have found little correlation between yield increases and reductions in harvested area. This lack of evidence has been interpreted as supporting a land use Jevons paradox, which suggests that improvements in agricultural land productivity could lead to increased land in the sector globally (Rudel et al. 2009). However, Hertel et al. (2014) argue that these studies are insufficient to draw such a conclusion. They note that the studies lack a clear counterfactual, fail to account for other drivers of global land use besides yield growth (an exception includes the study by Ceddia et al. 2013), and do not consider how changes in prices induced by productivity improvement might affect land use in other locations with different productivity levels.

Hertel et al. (2014) develop a theoretical framework for understanding how TFP-driven price changes affect the farm sector's use of land and associated GHG emissions. They develop a two-region, one-sector model of agricultural trade in which innovations occur in only one of the regions. They find that the elasticity of excess demand farmers face in the innovating region determines whether TFP growth reduces or expands local land use. This excess demand elasticity depends on global demand conditions as well as supply response in the rest of the world (the noninnovating region). When the excess demand is elastic, as would be the case for innovations in a small, relatively open economy, increases in revenue outweigh input savings, resulting in an expansion of land use in the innovating region. In contrast, if the excess demand is inelastic, as would be the case for a large, relatively closed economy, TFP growth reduces farmers' revenues, thus reducing farmland use.

Hertel et al. (2014) also examine the impact of TFP growth in one region on outcomes in the rest of the world. They show that the price reduction stemming from TFP growth confers increased competitiveness to the innovating region, which displaces other suppliers from world markets, thereby reducing agricultural production and land use outside of the innovating area. In contrast to the ambiguous effects of TFP growth on land use in the innovating region discussed above, these indirect land use changes are unambiguously land-saving.

A consequence of taking indirect land use effects into account is that, even if TFP growth leads to land expansion in the innovating region, the land savings associated with indirect land use savings could result in global land savings. Hertel et al. (2014) show that for land to expand globally, crop yields in the innovating region need to be initially relatively low so that cropland expansion in the innovating region comes at the expense of higher yield in the rest of the world. Such a possibility hinges strongly on the assumption that only one region innovates. In practice, most countries show some degree of TFP growth, resulting in increased output and lower prices against a counterfactual of no TFP growth. Given the inelastic nature of global demand for most foods, worldwide land use in agriculture is likely to decrease in the presence of broad-based, global growth in agricultural TFP.

3.2. Local and Global Effects of Agricultural Total Factor Productivity Growth on Agricultural Land Use

Villoria (2019b) uses an econometric model to quantify the effects of agricultural TFP growth over 1991–2010 on both local and global demands for cropland. His model took into account the main drivers of global land use, allowing for counterfactual estimation of the amount of cropland needed to satisfy income and population growth in the absence of TFP growth. The demand for cropland was derived from a multicountry spatial equilibrium model of bilateral trade flows specialized in the agricultural sector. The model follows Armington's (1969) approach of differentiating products by country of origin. The model tracks land use spillovers using the degree of connectivity between producers in any two countries by theoretically consistent competition indices based on trade, consumption, and production shares in every country where they compete (Villoria & Hertel 2011).

Villoria's (2019b) model estimates country-level cropland elasticities with respect to changes in both domestic and foreign TFP growth for 70 countries representing 74% of global cropland and more than 90% of agricultural output and exports. Consistent with Hertel et al.'s (2014) conceptual framework, the elasticities of cropland with respect to domestic TFP growth are a function of the excess demand elasticity facing each country. The model includes a set of extensive controls for other drivers of land use such as income and population growth, constraints to land use, and trading costs, among others. Robustness of the main estimates to biases induced by common shocks affecting TFP growth and unexplained drivers of cropland is examined using historical expenditures on agricultural research and development (Fuglie 2018) as instrumental variables for TFP growth rates.

Villoria (2019b) found that in land-constrained countries (China, India, Nigeria, and Nepal), domestic TFP growth was statistically associated with domestic land saving. In relatively land-abundant countries (the United States, Canada, and most countries in Latin America and the European Union), increases in TFP growth led to domestic land expansion. However, in each case, domestic TFP growth contributed to land contraction in other countries. Adding foreign effects to the domestic effects, Villoria (2019a) found that domestic land expansion associated with domestic TFP growth is more than offset by reductions in land elsewhere (**Figure 5**). He estimates that a 1% uniform increase in TFP across the world leads to a 0.34% reduction in global cropland. Moreover, he estimated that without TFP growth between 1991 and 2010, global agriculture would have required an additional 173 million hectares of land.

3.3. Implications of Agricultural Productivity Growth for Greenhouse Gas Emissions

If TFP growth in agriculture causes cropland to expand in some regions and contract elsewhere, the net effect on GHG emissions will depend on the relative size of the CO_2 stocks in those land areas. In related work, Villoria (2019a) estimated that without the improvements in global

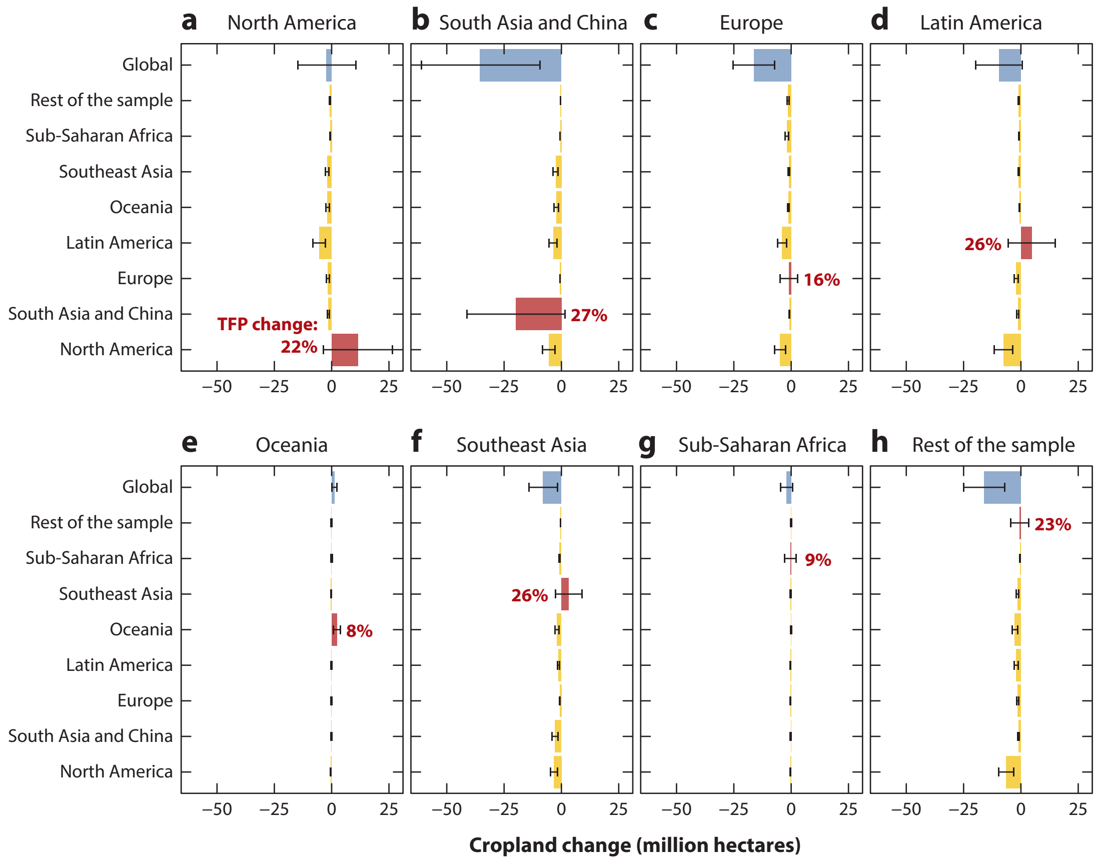

Figure 5

Direct and indirect regional land use effects of total factor productivity (TFP) growth during 2001–2010. Regional changes in cropland resulting from the percentage change in TFP during 2001–2010 in the regions colored in orange (as defined by Villoria 2019a). Positive values represent increased land use from TFP growth. Blue bars represent each region's aggregate global land use effects of TFP growth. Bar heights are median estimates with whiskers indicating 5–95% confidence intervals based on 10,000 bootstrap crop-area responses to TFP by Villoria (2019a). The plot assumes that only the region identifying each panel (*a*–*h*) experienced TFP growth during the period. The regional percentage changes in TFP from 2001 to 2010 are 2004–2006 constant US$ output value-weighted averages of country-level percentage changes in TFP from USDA-ERS (2017). Figure adapted from Villoria (2019a) (CC BY 4.0).

agricultural TFP over 1991–2010, global GHG emissions from conversion of natural lands to cropland would have been up to 5.6 times larger than observed, assuming that all conversion came from forests. Much of these increases in emissions are explained by the fact that most of the land savings associated with TFP growth occurred in Latin America and developing countries in Asia, regions where tropical forests hold relatively large carbon stocks (Villoria 2019a, figure 1).

One limitation of Villoria's (2019b) analysis is that it does not distinguish between TFP growth in crops, livestock, or specific commodities. Because agriculture is a multiproduct sector, it is often difficult to allocate the land, labor, and capital inputs to the different commodities, which is necessary for the estimation of subsector TFP. However, given the importance of livestock production as a driver of methane emissions as well as tropical deforestation (Gibbs et al. 2010), research focused on understanding the sources and dynamics of how productivity growth in animal production affects global land use would help to better gauge the potential of climate mitigation policies in this sector. In one of the few studies that derived separate estimates of global and regional TFP growth for crops and ruminant and nonruminant livestock, Ludena et al. (2007) found significant differences in TFP growth across these subsectors (as well as regional differences for each subsector). For example, animals such as poultry and dairy grown in confined systems generally achieved more rapid TFP growth than animals raised in pasture-based systems such as beef cattle and small ruminants. Not only can animals be more intensively managed in confined systems, but technologies may also be easier to transfer across geographies given greater environmental controls afforded by confined systems.

An example of this type of analysis is that of Cohn et al. (2014), who use a partial-equilibrium, grid-resolved, economic model of global land use (GLOBIOM) to explore the impact of adopting semi-intensive pasture systems in Brazil on global land use changes and GHG emissions. They investigated the effects of a subsidy for adopting semi-intensive pasture systems and a tax on conventional livestock production. They found that both policies resulted in increased cattle density, lower deforestation rates, and reduced agricultural and land use emissions in Brazil by 41–52%, as well as lower global deforestation emissions by approximately 25%.

Environmental policies like those investigated by Cohn et al. (2014) may also affect the rate of agricultural technical change. Nepstad et al. (2014) show how enforcement of the Amazonian Forest Code coincided with significant intensification of crop and livestock production and less agricultural land expansion in Brazil after 2004. The growth in stocking density due to pasture improvements was particularly striking and very likely a result of the higher premium on land as a result of the enforcement of conservation policies. This is an example of how governance can spur technologies and practices that conserve scarce natural resources.

Recent evidence on the geography of land use emissions embodied in international trade suggests that the indirect land use effects of TFP growth may continue to have an important role in global emissions reductions. According to Hong et al. (2022), in recent years, the percentage of land use emissions embodied in international commodity trade is comparable to that of fossil fuel emissions (27% and 21%, respectively, in 2017). However, in contrast to fossil fuel emissions, the largest net exporters of land use emissions are primarily located in the agricultural frontiers of the southern hemisphere (e.g., Brazil, Argentina, Indonesia). Moreover, a substantial portion of these emissions come from products that compete with temperate-climate producers. Cereals and oil crops accounted for 45–54% of embodied deforestation in trade, while animal products accounted for 14–19%. This implies that emissions from land-rich regions in the tropics compete directly with those of temperate exporters such as Canada, the United States, and the European Union, making land use in the southern hemisphere exporters highly susceptible to technological developments in temperate-climate exporters. Therefore, the land-saving effects of TFP growth in North America and Europe could help counteract global land expansion in regions like Latin America and other tropical areas that tend to have higher carbon emissions.

4. THE ROLE OF PRODUCTIVITY IN GLOBAL ECONOMIC MODELS WITH FUTURE PROJECTIONS OF AGRI-FOOD SYSTEMS EQUILIBRIA

Productivity growth is a key driver of changes in agricultural output, prices, and land use in long run, global economic models of the food system. In a prior review for this journal, Hertel et al. (2016) considered predictions from 13 global economic analyses of long-run agricultural growth, including both partial and general equilibrium models. The partial equilibrium models treat productivity improvements as exogenous perturbations to yield, whereas the general equilibrium models treat crop productivity improvements as partial factor augmentation of land productivity

(PFP). These both differ from the approach taken by Fuglie et al. (2022a), who model productivity growth as an augmentation of all inputs used in agriculture (factor-neutral TFP growth). Hertel et al. (2016) show that, for a given perturbation in productivity (e.g., 10% growth), the TFP shock will yield the largest output and price response, followed by the PFP approach, with the yield shift giving the smallest commodity market response to a 10% productivity improvement. This is because the yield augmentation approach does not factor in the impact of enhanced profitability on supply response. The difference between the PFP and TFP approaches is proportional to the relative significance of the nonland inputs, which do not receive a productivity boost under the PFP (land augmenting only) approach. Therefore, the way in which productivity is incorporated into the global model is critically important. In principle, it should correspond to the methodology used in studying historical trends, which, in turn, should mirror the approach to undertaking future projections (Fuglie et al. 2022a).

Hertel et al. (2016, table 2) summarize key results from nine models participating in the AgMIP Economic Model Intercomparison (Lampe et al. 2014) (the models include IMPACT, GCAM, GLOBIOM, MAgPIE, AIM, ENVISAGE, FARM, GTEM, and MAGNET) for growth in output, price, and land use over the 2006–2050 period. Population and income drivers are common across these models and are based on the business-as-usual Shared Socioeconomic Pathway developed by the Integrated Assessment (of Climate Change) Modeling community. Given the differences in how productivity growth is modeled as well as the wide range of assumptions in these models about key economic responses (price and income elasticities), it is hardly surprising that the long-run projections vary widely, even once the authors have harmonized the demand-side drivers. Expected production growth over this 45-year period ranges from 57% (MAgPIE) to 116% (ENVISAGE), while cropland change ranges from −6% (FARM) to 28% (MAGNET). The differences in crop price projections are also quite dramatic, ranging from an expected price decline of 16% (ENVISAGE) to an increase in crop price of 46% (AIM). This wide variation raises the question: What is the source of this variation? Hertel et al. (2016) leverage information from a set of standardized sensitivity analyses undertaken by the AgMIP modeling teams to shed light on this issue. They find that the implied supply and demand elasticities vary widely across the different models, with some having very strong supply response to prices, whereas others are much less responsive.

To further examine the impact of model parameterizations and productivity growth on long-run economic projections, Hertel et al. (2016) built a simple emulator model to mimic the behavior of the AgMIP models. They treat all the key parameters and external drivers (including productivity growth) as uncertain, based on a literature review. They then sample from those distributions, performing a Monte Carlo analysis of projected crop growth over the 2006–2050 period. This allows for a characterization of probability distributions for future crop output, prices, and global land use in 2050. In addition, they utilize the Morris method (Morris 1991) to identify the relative importance of each factor in driving future uncertainty in global crop price, output, and land use. They conclude that the most important factor driving global crop price uncertainty is the rate of TFP growth, thereby underscoring the critical importance of this supply side driver in global food security. TFP uncertainty ranks lower as a driver of uncertainty in future crop output and land use change (sixth and eighth, respectively, in the set of 17 different drivers and parameters in the long-run projections). Not surprisingly, uncertainty in cropland supply elasticities is the most important driver of long-run cropland change and hence terrestrial carbon fluxes. Uncertainty in global crop output is dominated by uncertainty in the income elasticities of demand for food, highlighting the key role of future income growth as a driver of crop production and associated output-related GHG emissions.

5. INVESTMENT IN AGRICULTURAL PRODUCTIVITY AND CLIMATE CHANGE ABATEMENT

The work cited in prior sections focused on the relationship between TFP and emissions but did not consider the cost of achieving higher rates of TFP growth. This begs the question, is investing in agricultural TFP growth cost-effective relative to other mitigation options? Lobell et al. (2013) tackle this issue by formulating a model that links investment in agricultural research and associated GHG emissions. They find that investing $225 billion in R&D would offset the negative effects of climate change on yield growth (to 2050) while avoiding land conversion of 61 million hectares and reducing GHG emissions by 15 gigatons. These estimates imply mitigation costs between $11 and $22 per ton of CO_2e, which is cheaper than most alternatives in other sectors such as energy and transportation (Gillingham & Stock 2018). Subsequent work has refined these initial estimates by incorporating more evidence on the relationship between R&D investment and TFP growth. In this section, we first review that evidence before returning to the question of the overall cost-effectiveness of mitigation through R&D investment.

5.1. R&D Investment and Agricultural Total Factor Productivity Growth in the Long Run

To assess the potential for productivity policy to affect climate change mitigation, one needs an explicit model linking R&D investment to TFP growth (and then as a second step a representation of how TFP growth affects emissions). R&D investment has some similar features with investment in physical capital such as machinery and structures (**Figure 6**): A one-time investment in R&D or physical capital can raise productive capacity for many years, but eventually it depreciates (due to wear and tear in the case of physical capital and technological obsolescence in the case of R&D capital). However, an important distinction between investments in physical and R&D capital is there is likely to be a fairly long gestation lag between when R&D investment is

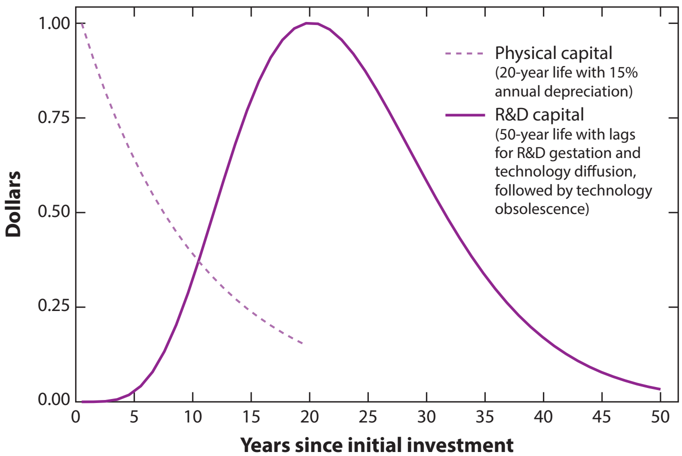

Figure 6

Illustrative time path for research and development (R&D) investment to affect R&D capital stock and productivity. Capital investment in year zero adds to capital stock each year of the operation life of the investment. When an investment of $1 is fully operational, it adds $1 to capital stock. Before it is fully diffused and after it has begun to depreciate, its contribution to capital stock is less than $1. For comparative purposes, a typical life span of an investment in physical capital is also shown.

made and when technologies based on that investment are ultimately adopted, thereby affecting productivity. Alston et al. (2023) review the concepts and empirical measures of R&D lag structures for agriculture. Statistical estimates of the agricultural R&D lag structure and case histories of specific technologies that were widely adopted show that it may take a decade or more for R&D investment to begin to noticeably affect TFP. The peak impact occurs when technology adoption reaches a maximum, which may require a decade or two from the initial R&D investment. R&D capital also tends to have a longer life than physical capital; while tractors typically last for 10–15 years and farm structures around 30 years, agricultural R&D capital may still have noticeable effects on productivity after 50 years (Baldos et al. 2019).

A graphical depiction of how publicly funded R&D investment effects R&D capital stock and productivity (based on estimates from Baldos et al. 2019 for US agriculture during the latter part of the twentieth century) is given in **Figure 6**. In the figure, an initial investment in R&D of $1 in year 0 only contributes to R&D capital stock when technologies developed from that R&D enter commercial use. Its contribution to R&D capital (and productivity) grows as the technology becomes more widely adopted, with peak effects occurring around year 20. After that, the technology becomes less effective (pests and disease may evolve) or is replaced with other technologies and practices. The figure contrasts the typical life span assumed for R&D capital with that of physical capital such as a farm tractor or livestock facility. Physical capital investments are typically assumed to have peak efficiency when purchased (year 0) and then depreciate through wear and tear until being scrapped at the end of their effective life.

In contrast to studies on R&D and agricultural TFP growth, Alston et al. (2023) note that most empirical studies on economic returns to industrial R&D have assumed, rather implausibly, a model like the one for physical capital in **Figure 6**: no or 1-year gestation lag, 15% depreciation rate, and a relatively short life span. Such a mis-specification of the effect of R&D on long-run productivity growth in an economy can give misleading results for productivity policy. First, it would imply that accelerated investment in R&D could significantly boost TFP growth in the short run, whereas in fact it may take a decade or two to produce any noticeable effects on productivity. Second, R&D capital is likely to have much more persistent effects on productivity over the long term. The empirical estimates on the cost of climate mitigation from accelerated spending on agricultural R&D discussed in the next section are all based on the R&D lag structure depicted in **Figure 6**. Results are given in terms of present values, where impacts further into the future are more heavily discounted than benefits obtained nearer to the present.

With an appropriate R&D lag structure for constructing measures of R&D capital stock, the effect of TFP is quantified using an R&D elasticity or the percent change in TFP given a 1% change in R&D capital stock. The R&D elasticity provides a unit-free measure of the long-run impact of R&D spending on TFP growth. Moreover, assuming a constant R&D elasticity implies a log–log relationship: To maintain a constant rate of TFP growth requires a constant rate of growth in the R&D capital stock and thus in R&D spending.

Of course, projecting future TFP growth from past, present, and future spending on R&D involves making assumptions about the likelihood that research will be successful in creating technological breakthroughs. A priori, we do not know which R&D projects, if any, will be successful. Empirical estimates of R&D-to-TFP elasticities are typically based on national- or program-level funding of R&D and thus represent an average success rate across all funded projects (including failures). Using these elasticities to make TFP projections implicitly assumes that an R&D program will continue to be as productive, on average, in the coming few decades as it was in the past.

Fuglie (2018) reviewed more than 40 studies that provided estimates of agricultural R&D elasticities for different countries and regions of the world, most using data from the post-1980s. These studies considered technologies coming out of not only public R&D investments but also international R&D spillins (technology imports), the private sector, and the CGIAR system of international agricultural research centers, which focuses on developing countries. For North America, the average elasticity for public agricultural R&D was 0.30, meaning that each 1% increase in R&D capital would increase TFP by 0.30%. This was the highest R&D elasticity for any region. On the low end, the elasticity for public agricultural R&D in SSA was 0.13, implying a less-effective innovation system for agriculture. In addition, countries in North America, Western Europe, and Oceania were more likely to import technologies from each other and get innovations from R&D conducted by private manufacturers of agricultural inputs like pesticides and machinery. One general characteristic of these R&D elasticities is that they are less than 1, implying that R&D spending will tend to rise faster than productivity growth. A second characteristic of R&D elasticities is that there is significant variation across countries and regions. In particular, agricultural R&D elasticities appear to be higher in developed countries than in developing ones, primarily because of greater technological contributions from the private sector and ability to absorb technology imports.

5.2. Agricultural R&D and Greenhouse Gas Emissions Abatement

Given the evidence on TFP responses to R&D investment, several studies have estimated the cost-effectiveness of climate mitigation through R&D investment (**Table 1**). While estimates vary by roughly an order of magnitude ($4–22 per ton CO_2e) due to various assumptions, they all indicate a cost that is below the cost of many other mitigation options (Gillingham & Stock 2018) and well below most estimates of the social cost of CO_2 emissions, which the US Environmental Protection Agency recently proposed as $190 per ton CO_2e (NAS 2017). A major policy challenge, however, is that many of the emissions benefits accrue outside of the countries in which the TFP increases occur (**Figure 5**), which disconnects who benefits most from, and who pays for, the R&D.

Table 1 The estimated cost-effectiveness of R&D investments for reducing agricultural emissions

Study	Time period	Method	Estimate of abatement cost ($/ton CO_2)	Notes
Burney et al. (2010)	1961–2005	CO_2 from simple counterfactuals of LUC in absence of yield progress For cost of yield gains, assumes 70% of R&D devoted to yields, 1/3 of yield gains from R&D	US$4–8	Estimate for past investments, using counterfactual land use scenarios
Lobell et al. (2013)	2006–2050	Based on SIMPLE Model Uses elasticity of crop total factor productivity with respect to R&D	$11–22	Estimate for future investments, distributed across the world in order to offset climate damages in each region
Fuglie et al. (2022a)	2020–2050	Based on SIMPLE Model	$22	$611 billion in extra world R&D over 20-year period Spending only in LDCs, no protection of carbon-rich lands
Fuglie et al. (2022a)	2020–2050	Based on SIMPLE Model	$19	Spending only in LDCs, with protection of carbon-rich lands
Fuglie et al. (2022a)	2020–2050	Based on SIMPLE Model	$14	Some spending in developed countries, no protection of carbon-rich lands

Abbreviations: LDC, lesser-developed country; LUC, land use change; SIMPLE, Simplified International Model of agricultural Prices, Land Use and the Environment.

The study of Fuglie et al. (2022a) also points to two other important aspects of R&D investments. First, investments are much more cost-effective for emissions when coupled with policies that protect carbon-rich lands from development, as these policies reduce effects of local agricultural land expansion in response to TFP gains. Second, R&D spending and agricultural TFP growth in temperate-zone countries reduce land pressure in tropical-zone countries with relatively carbon rich lands, thus further reducing global emissions.

Importantly, existing studies of R&D effects on emissions consider TFP changes that are both sector-wide and factor-neutral. Because some commodities such as livestock and rice are higher sources of emissions, R&D focused on these commodities could disproportionately affect emissions. Similarly, innovations that are factor-biased can have higher or lower effects on emissions than factor-neutral changes, depending on which inputs are being reduced (see Section 2.1). Innovations that specifically target emissions, which are not traditionally considered in TFP measures because they represent nonpriced externalities, can also have outsized effects. For example, a vaccine or new feed that greatly reduced methanogenesis in ruminant animals could result in a modest change in TFP (by reducing feed inputs) but a dramatic reduction in emissions (Reisinger et al. 2021).

Investment in specific commodities or in specific technologies could therefore offer more cost-effective emissions reductions than the already attractive returns from factor-neutral TFP gains. Moving beyond this qualitative statement, however, will require new research on the returns on investment in specific domains. For example, existing management and technology options for reducing methane and nitrous oxide from agriculture are generally viewed as expensive, with reductions of more than 1 gigaton CO_2e hard to achieve at less than \$100 per ton (Harmsen et al. 2019, Roe et al. 2019). Yet little is known about how quickly the costs could come down with dedicated research investments aimed at a goal of reducing the cost of non-CO_2 emissions from agriculture. Gains could come from lowering the cost of options considered in current assessments, such as feed additives for animals or nitrification inhibitors for fertilizer, or from relatively new options, such as sex-sorted semen (Holden & Butler 2018).

5.3. Other Policy Drivers of Total Factor Productivity

Policies regarding R&D investment are an important lever that governments can use to influence TFP and, indirectly, agricultural emissions. Yet as our understanding of both the drivers and consequences of TFP has advanced, an important role for policies beyond those related to investments has also emerged. Subsidies, for example, can play a significant role in decisions by farmers to switch into and out of certain commodities and to adopt or abandon certain practices. The resulting effects on TFP are typically unintended by-products of the policy and can be either positive or negative depending on the nature of the subsidy. In a recent study, Lobell & Villoria (2023) considered the example of policies promoting the adoption of cover cropping during the winter months in the United States. Both state and federal subsidies have actively promoted cover crop adoption in the recent decade, leading to rapid increases in cover crop area. The goals of the subsidy are generally laudable and include reduced nutrient runoff, reduced soil erosion, and increased soil carbon accumulation. Unfortunately, multiple studies have indicated that, as currently practiced by most farmers, the adoption of cover crops can lower the productivity of the subsequent cash crop. This TFP decline for a major agricultural producing country then reverberates around the world, as described in Section 4. Lobell & Villoria (2023) estimate that the resulting emissions from land conversion are capable of counteracting 70% of the potential carbon benefits from soil accumulation on US farms.

Although this one study provides a cautionary tale, it is equally the case that policies that encourage increased TFP offer the potential to incur significant emissions benefits. Some examples could include policies that limit emissions of pollutants that harm crop and animal productivity, policies that subsidize costs of coatings that make fertilizer application more efficient, or policy reforms that remove subsidies from fertilizer prices. More generally, Lobell & Villoria (2023) demonstrate that it is now possible to quickly assess the indirect emissions effects of any policy that could influence TFP, thus allowing these effects to be more thoroughly considered in policy deliberations.

6. SUMMARY AND CONCLUSIONS

Improvements in global agricultural productivity over the past three decades have allowed agricultural output to double, while GHG emissions from the sector have remained essentially flat, even declining in some regions. By boosting crop and livestock yields, innovations have resulted in reduced emissions intensities and curbed farmland expansion into carbon-rich landscapes. Even when viewed strictly from a climate mitigation perspective (i.e., ignoring economic benefits to farm profitability and lower food prices), investments in agricultural R&D appear to be quite cost-effective when compared to other mitigation options. In addition, by facilitating output growth at lower unit cost of production, these knowledge-facilitated TFP improvements moderate food prices in the face of significant additions to world population.

There are some limitations to an R&D-based productivity policy to reduce GHG emissions from agriculture. (*a*) There is likely to be a long time lag between R&D investments and acceleration in productivity growth. (*b*) The productivity of R&D itself is variable and uncertain, as high past returns are not a guarantee of future returns, and even past returns have varied by region and by commodity. (*c*) The impact of R&D on emissions will depend on the extent to which it stimulates technical change that is directed toward saving the resources most tied to emissions, although even factor-neutral technical change will likely lead to significant reductions in emissions from agriculture. (*d*) Productivity is an important but somewhat blunt policy for curbing emissions from agricultural land use change, and environmental policies that protect the most carbon-rich lands from agricultural conversion can complement investments in productivity. Such joint interventions may offer even lower-cost emissions abatement than either policy alone. Environmental policies that raise the cost of emissions-intensive agricultural inputs such as land can raise the demand for technologies that substitute for them.

Given the extreme heterogeneity of agriculture, future research must move beyond aggregate findings and delve more deeply into the potential for cost-effective investments in innovations for specific products being produced in specific locations under specific socioeconomic systems. This calls for mitigation-oriented investments that are informed by analytical databases and empirical models that account for differences in physical and economic geographies, biophysical potentials, local governance, and past track records.

Future research on the TFP–GHG linkage should seek to identify investment opportunities that are both inexpensive and scalable. In this regard, an interesting open question is whether there are significant economies of scale in agricultural technology: Do marginal costs of abatement fall as the technologies are more widely adopted? If so, this would point to the desirability of large-scale efforts in particular regions and specific agricultural systems.

Our review suggests that directing more, not less, R&D toward emissions-intensive commodities such as livestock would be warranted, as raising their productivity would save on the inputs driving emissions. There is also enthusiasm for developing alternative foods that would redirect consumers away from products such as beef (Smith et al. 2021). This is another area where R&D could play a role in reducing costs and improving quality, thereby expanding the potential market for these GHG-friendly food products. However, as our focus is on agriculture, food manufacturing interventions are beyond the scope of this review. In any case, they would likely be complementary to boosting agricultural productivity in achieving emissions reductions.

In summary, past investments in productivity-enhancing agricultural R&D have proven to be a cost-effective means of reducing GHG emissions. These investments have also served to boost food affordability, a factor that is once again becoming a significant concern in some parts of the world, as conflict and climate change contribute to a renewed food security crisis.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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