Chapter 10
The R&D Cost of Climate Mitigation in Agriculture

Keith Fuglie, Srabashi Ray, Uris Lantz C. Baldos, and Thomas W. Hertel

1 Introduction

According to the International Panel on Climate Change (IPCC 2014), agriculture is responsible for about one-quarter of total global emissions of greenhouse gases (GHGs). According to FAOSTAT (FAO 2020), agriculture accounted for 7.21 Gt CO2e of emissions at the farmgate (i.e., from ongoing production and energy use) and another 3.50 Gt CO2e in net emissions from land-use changes in 2019.[1] Supply-side approaches for reducing agricultural emissions include investing in emissions-saving technological change and protecting carbon-rich natural lands from conversion. While technological and productivity improvements can reduce emissions intensity (GHG per unit of output) and save land overall, it could also lead to increased land conversion in some areas through competitiveness effects (Villoria 2019). If these local areas held large carbon sinks, then net emissions from land-use conversion could remain large even if the amount of agricultural land held globally

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Data availability statement: The files needed to replicate this application are available at https://gtap.agecon.purdue.edu/simple-g/

[1] 1 Gt CO2e = 109 or one billion metric tons of CO2 equivalents (CO2e).

K. Fuglie (✉)
Economic Research Service, United States Department of Agriculture, Washington, DC, USA
e-mail: keith.fuglie@usda.gov

S. Ray · U. L. C. Baldos · T. W. Hertel
Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University, West Lafayette, IN, USA

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remained unchanged or declined. Environmental policies can target and protect carbon-rich areas from conversion. However, the drawbacks of these policies include cost (assuming that landowners are compensated for forgone income from other land uses), lack of permanence, higher food prices, and possibly worsening global food insecurity (Baquedano et al. 2022).

This study uses a global economic model of the agri-food system (the Simplified International Model of agricultural Prices, Land use and the Environment, or SIMPLE) to compare outcomes from productivity policies in the form of higher agricultural research and development (R&D) spending and environmental policies that restrict agricultural land supply in the carbon-rich land most at risk to land-use change. Lobell et al. (2013) use SIMPLE model simulations to conclude that an additional US$225 billion in agricultural R&D might save 15 Gt CO2e from avoided land-use change by 2050. However, they used a simplified framework to link R&D to productivity growth and did not include the effects of agricultural productivity growth on farmgate emissions. Our model linking R&D spending to productivity growth also takes into account time lags between R&D spending and the adoption of new technology by farmers, variation in the marginal response of productivity to R&D spending in different regions of the world, and possibilities for international technology spillovers, as informed by empirical studies (Fuglie 2018). This framework has been used to explore the R&D costs of adapting agriculture to climate change (Baldos et al. 2020) and potential gains from liberalizing trade in agricultural commodities and technology to improve global food security (Hertel et al. 2020).

For our policy simulations, the outcomes of interest are changes in global agricultural GHG emissions, land use, agricultural production, food prices, and the prevalence of undernutrition relative to policy cost. Simulations of the world agricultural economy over 2017–2050 are run for a set of policy scenarios involving R&D spending and land-use restrictions that compensate landowners for forgone income from avoided land-use change. We consider scenarios that target actions in less developed countries as well as some that include developed countries. In particular, we examine how more stringent environmental restrictions on agriculture envisioned by the European Union (EU) Green Deal could affect global outcomes and how unintended outcomes might be offset through accelerated R&D spending by EU countries.[2] We find that more R&D spending to accelerate productivity growth reduces GHG emissions from land-use change less effectively than targeted environmental policies. However, accelerated productivity growth also reduces the cost of environmental policies (by effectively making land less scarce and therefore compensation cheaper). Moreover, higher levels of productivity permanently lower farmgate GHG emission intensity and, by lowering global food prices, generally improve global nutrition and food security.

[2]The European Green Deal lays out specific targets for fertilizer and pesticide reductions in EU agriculture by 2030. Beckman et al. (2020) examine the productivity and market impacts of these input reductions but do not quantify how much R&D spending might be needed to offset anticipated productivity losses.

2 Agricultural Production, Productivity, and GHG Emissions Since 1990

Before presenting our model formulation and results, we first describe global and regional patterns of agricultural GHG emissions and output growth over the past three decades. Two types of GHG emissions are associated with agriculture: (1) GHGs released when forests are cut down, peatlands drained, or grasslands plowed to make way for more agricultural land and (2) direct "farmgate" emissions from existing agricultural production (e.g., methane from livestock and rice paddies, nitrous oxide from fertilizer applications, carbon dioxide from decomposition or burning of crop residues, and use of fossil fuels to power machinery and to light, heat, and cool farm buildings).

Figure 10.1 shows agricultural GHG emissions and outputs in 1990 and 2019 for major world regions. Sources of GHG emissions include land-use change and crop-related and animal-related production (Fig. 10.1a and c). Agricultural output is composed of crops, animal products, and products from aquaculture (Fig. 10.1b and d). Between 1990 and 2019, agricultural emissions intensity (i.e., kilograms of emissions per dollar of output) fell in all regions, but the total amount of emissions increased in Sub-Saharan Africa (SSA), South Asia, Northeast Asia, and Central and West Asia and North Africa (CWANA), while decreasing in Latin America (LAC), Southeast Asia, Europe, and other developed countries (other DC). Globally, emissions per unit of output (at constant prices) fell by nearly half between 1990 and 2019, as total emissions remained about constant while world agricultural output increased by 92%. This decline in global agricultural emission intensity was due to slowing rates of deforestation, a slowing rate of growth in emission-intensive factor inputs, and possibly to general improvements in agricultural total factor productivity (TFP). In this chapter, agricultural TFP is defined as the ratio of aggregate agricultural output to aggregate factor inputs (i.e., land, labor, capital, and intermediate inputs) as measured by the US Department of Agriculture Economic Research Service (USDA-ERS 2021).

The level and intensity of emissions from agriculture vary widely across the global landscape. GHG emissions per unit of output are exceptionally high in regions where forestland is being converted to agriculture (Sub-Saharan Africa, Latin America, and Southeast Asia). In Latin America, agricultural GHG emissions declined by nearly 20% between 1990 and 2019 (due to a decline in the rate of land-use change), even as output more than doubled. In Sub-Saharan Africa, both output and emissions increased, driven by an increase in land-use change. Remarkably, Northeast Asia was able to nearly triple agricultural output while increasing emissions by only 9%. The dramatic fall in emissions intensity of agricultural output in Northeast Asia was accompanied by rapid growth in TFP and a relatively small share of emission-intensive inputs—such as ruminant livestock—in production.

In developed country (DC) regions (i.e., Europe and other developed countries, including North America, Oceania, Japan, and South Korea), ruminant livestock account for the bulk of GHG emissions from agriculture. In Europe, there has been

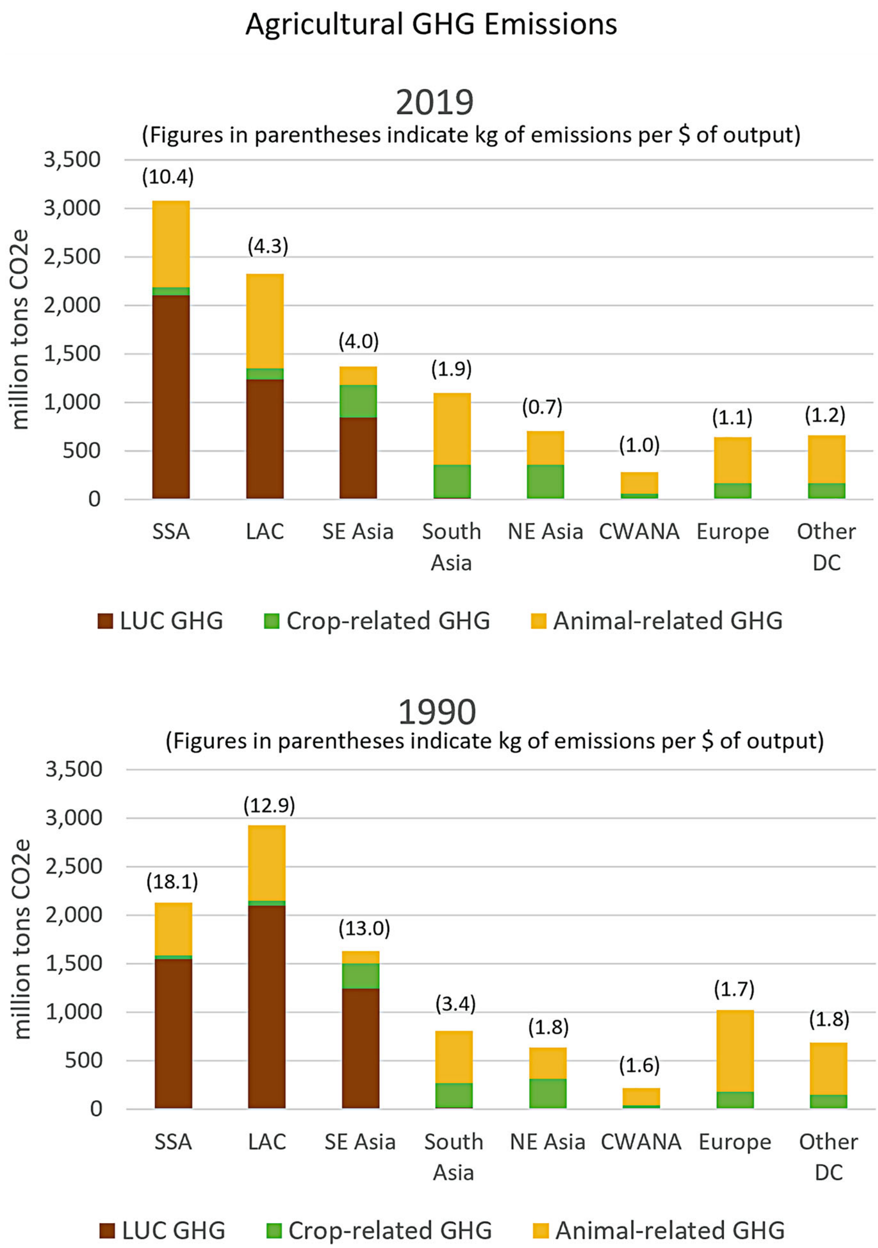

Fig. 10.1 Agricultural greenhouse gas emissions and output in world regions, 1990 and 2019 SSA, Sub-Saharan Africa; LAC, Latin America and Caribbean; CWANA, Central, West Asia, and North Africa; NE Asia, China, Mongolia, and North Korea; Europe includes all of Europe, the Russian Federation, and Kazakhstan; Other DC, North America, Oceania, Japan, and South Korea; and LUC GHG, GHG emissions from land-use change. Crop-related GHG emissions include emissions from rice cultivation, drained organic soils, fertilizer use, crop residue decomposition and the burning of crop residues; animal-related GHG emissions include emissions from enteric fermentation in ruminant livestock, manure, and savanna fires

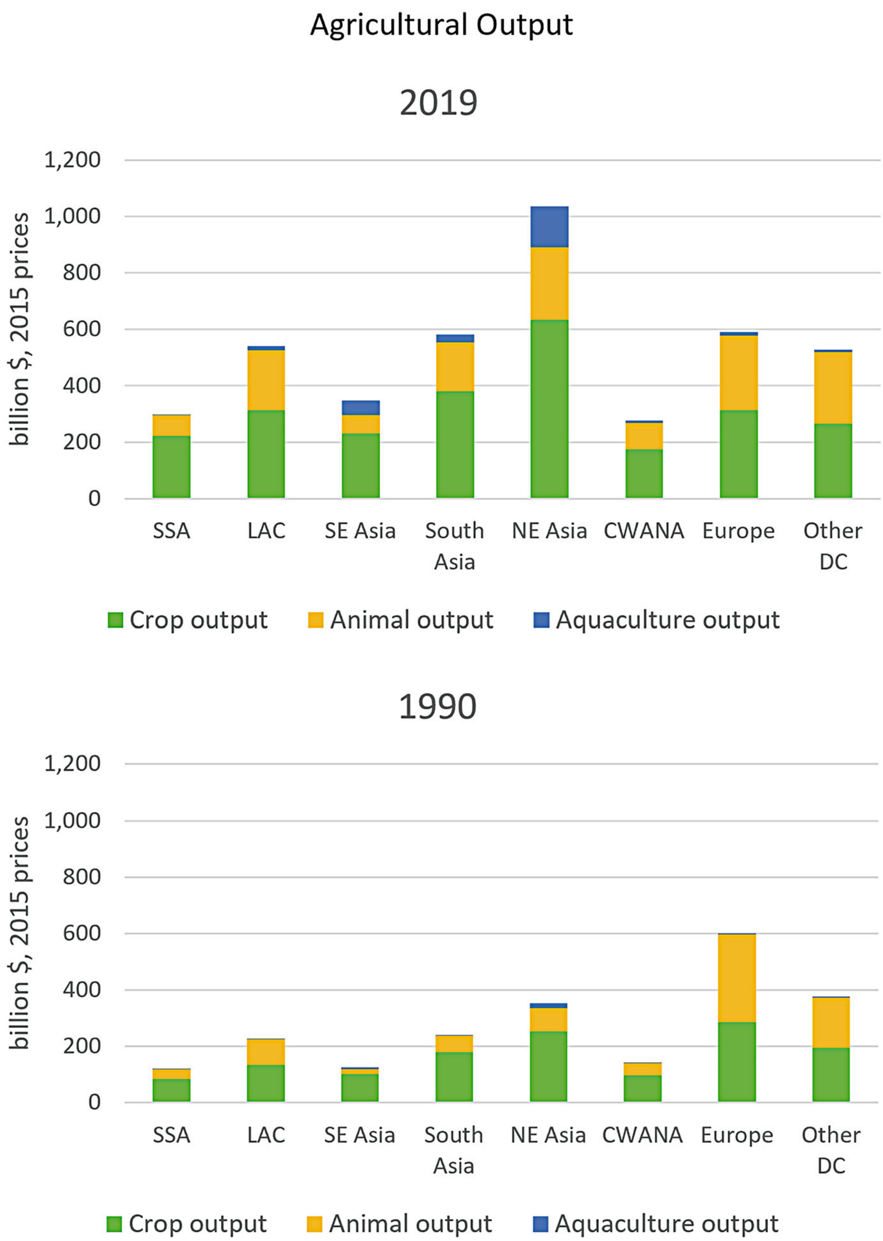

Fig. 10.1 (continued)

Table 10.1 Population and income growth assumptions (2017–2050)

Region	Population growth (% per year)	Income growth (% per year)
Eastern Europe	−0.16	2.59
North Africa	0.77	3.34
Sub-Saharan Africa	1.83	4.00
South America	0.59	2.47
Brazil	0.36	2.11
Australia + New Zealand	1.07	1.20
European Union	0.19	1.40
South Asia	0.82	4.01
Central America + Caribbean	0.57	2.32
South Africa	0.52	2.64
Southeast Asia	0.52	3.71
Canada	0.80	1.09
United States	0.62	1.07
China	−0.25	3.79
Middle East	1.13	2.05
Japan + Korea	−0.37	1.56
Central Asia	0.40	4.23

Growth is shown as compounded annual growth rates
Source: Middle-of-the-road shared socioeconomic pathway (SSP 2) projections, SSP database v2.0 (Riahi et al. 2017)

very little change in agricultural output over the past three decades, but productivity improvement has led to fewer inputs in the sector and less GHG emissions from agriculture. In other DC regions, total emissions (and total factor inputs) have remained roughly constant, while productivity improvement has expanded output. Thus, in both Europe and other developed countries, increases in TFP have led to reductions in GHG emissions intensity from agriculture.

The trends depicted in Fig. 10.1 strongly suggest that agricultural TFP growth has reduced agricultural GHG emission intensity. In existing agricultural areas, TFP growth reduces emissions intensity because fewer factor inputs are required to produce a given level of output. The relationship between agricultural TFP growth and land-use change is more nuanced. At the global level, TFP growth in agriculture almost certainly curtails land expansion into agriculture, but at the local level, it could increase incentives to expand agricultural land if local TFP growth improves trade competitiveness. This land expansion may arise in countries that achieve high TFP growth (relative to the global average) and are integrated into global markets so that their production costs fall relative to global commodity prices (Villoria 2019). But agricultural TFP is hardly the sole determinant of deforestation. National environmental policies also have a strong influence on land use, and recent policy changes in countries like Brazil and Indonesia may account for a significant part of those countries' reductions in GHG emissions from land-use change over the last three decades. Finally, consumer demand for agricultural products exerts an influence on emissions. The growing demand for meat and milk as populations and per capita incomes rise may shift the agricultural product mix toward more emissions-intensive ruminant livestock production.

3 Version of SIMPLE Used in This Application

To simulate how R&D and environmental policies could influence future GHG emissions from agriculture, we employ a nongridded version of the SIMPLE model (recall Part III).[3] The version of SIMPLE used here has a base year of 2017. Population and income growth to 2050 are assumed to follow the middle-of-the-road shared socioeconomic pathway (SSP 2) assumptions developed for integrated assessments of climate change (Riahi et al. 2017). Table 10.1 provides details on the population and income growth assumptions by global region used for this analysis. Based on estimated behavioral parameters, consumers in wealthy regions are assumed to be less responsive to price and income changes than those residing in low-income regions. Aggregated food commodities in SIMPLE include crops, livestock products, and processed foods, and consumption patterns evolve to reflect observed shifts in dietary preferences—moving away from crops toward livestock and processed foods as incomes rise. Population-wide caloric distributions (characterized by a lognormal distribution) in each region are calibrated to data from the Food and Agriculture Organization of the United Nations (FAO 2020) and shift over time based on prices and per capita incomes. The estimates of caloric consumption levels for different segments of a population permit us to estimate the proportion of a region's population that remains undernourished (i.e., minimum daily caloric intake of 1700–2000 kcal/day/person, depending on the age and gender structure of the population).

In this study, we pay attention to the effects of climate mitigation policies on both food and environmental security. By tracking impacts on food prices, we are able to estimate changes in the adequacy of dietary energy consumption in a given region (Baldos and Hertel 2014). Per capita food consumption is converted to caloric consumption equivalents. By applying minimum daily dietary energy requirements, it is possible to calculate hunger in terms of the average shortfall in caloric consumption among the undernourished population, given food prices and per capita income (FAO 2020). Lower food prices (resulting from greater R&D investment in response to climate change) reduce this shortfall and provide a food security benefit.

Environmental benefits are measured as avoided cropland expansion and carbon stock losses associated with the conversion of natural lands into cropland and

[3] Alternatively, a general equilibrium model could be used, which would give more explicit attention to how agricultural growth affects the rest of the economy. See Sands and Suttles (2022) for a recent example that explores questions similar to our own. A partial equilibrium approach is generally more tractable, however, and in this application gives similar results.

reduced emissions intensity from agricultural production. We rely on the global carbon stocks calculated by West et al. (2010) to quantify GHG emissions when cropland expands into natural lands. West et al. (2010) estimate these carbon stocks using spatially explicit datasets on potential vegetative and soil carbon. These are considered as one-time carbon emissions associated with bringing that land into crop production. The data on GHG emissions from agricultural production is based on the GTAP v.10 standard database (Aguiar et al. 2019), which reports CO_2 emissions from fossil fuel combustion and non-CO_2 GHG emissions, which rely on FAO (2020) for methane and nitrous oxide agricultural emissions (Chepeliev 2020).

4 Experimental Design

We turn now to the experimental design of this application of the SIMPLE model. This entails the construction of alternative future scenarios for R&D investments, the ensuing productivity growth, and policies aimed at achieving sustainability.

4.1 Constructing R&D Scenarios for Projections of Future Productivity Growth

R&D policy is modeled as the amount of government spending on agricultural R&D. This generates new technologies that, once adopted by farmers, raise agricultural TFP (Wang et al. 2022). As informed by past empirical studies (Fuglie 2018), the efficiency with which R&D generates TFP growth varies by region. In addition, R&D in developed countries may generate international technology spillovers—mostly to other developed countries but also to less developed countries—although this has historically been rather limited due to ecological and institutional constraints. The model also incorporates the effects of private sector R&D on TFP growth, although the growth rate in private R&D spending is held constant in the policy simulations.

Spending on agricultural R&D is assumed to affect agricultural TFP. We incorporate a lag to account for technology development and diffusion, with effects persisting for several years before eventually depreciating through technological obsolescence (Alene 2010; Alston et al. 2011; Andersen and Song 2013; Jin and Huffman 2016). We use historical R&D spending and capital stock estimates from Fuglie (2018), who assembles data on public and private agricultural R&D expenditures starting from the 1960s. We then project these spending pathways forward to 2050 under various R&D policy scenarios. The historical patterns of agricultural R&D spending show a sustained shift in the global total from developed to less developed countries and from the public to the private sector (Pardey et al. 2016). Since 2000, public agricultural R&D spending in high-income countries as a whole has been essentially flat in real terms (Heisey and Fuglie 2018), while it has continued to grow in less developed countries (LDC).

In this framework, growth in a region's agricultural TFP comes from technologies developed from four independent R&D sources (designated by the subscript s in Eqs. 10.1–10.3): public agricultural R&D by countries within a region, private R&D, R&D by the CGIAR (Consultative Group on International Agricultural Research), and technology spill-ins from public R&D done in other regions. Equations 10.1–10.3 summarize the key linkages under this framework:

$$\mathrm{RDSTOCK}_{s,t} = \sum_{i=0}^{L} \beta_i (\mathrm{RDEXPEND}_{s,t-i}) \tag{10.1}$$

$$\beta_i = \frac{(i+1)^{\delta/(1-\delta)}\lambda^i}{\sum_{i=0}^{L}(i+1)^{\delta/(1-\delta)}\lambda^i}, \text{ where } \sum_{i=0}^{L}\beta_i = 1 \tag{10.2}$$

$$\%\Delta\mathrm{TFP}_t = \sum_{s=1}^{S} \alpha_s (\%\Delta\mathrm{RDSTOCK}_{s,t}) \tag{10.3}$$

Starting with Eq. 10.1, the stock of R&D from source s at time t ($\mathrm{RDSTOCK}_{s,\,t}$) is built up from the past L years of annual R&D expenditures ($\mathrm{RDEXPEND}_{s,\,t}$), where β_i is the R&D lag weight at period i and total lag length L is the number of years in which R&D contributes to productivity until the R&D capital stock has fully depreciated. Equation 10.2 specifies a gamma distribution for the structure of the R&D lag weights (Alston et al. 2010). According to this distribution, R&D spending at time t initially contributes little to new R&D capital stock or TFP growth, but its effect builds over time as technology arising from that research is developed and disseminated to farmers. Eventually, the effects peak when technology is fully disseminated and then diminish due to technology obsolescence. We utilize separate R&D lag distributions for DC and LDC regions. For public R&D in developed countries, we impose an R&D lag structure of 50 years. The peak impacts of R&D spending on knowledge stocks (and productivity) occur after 26 years (δ, λ = (0.90, 0.70) in Eq. 10.2). For R&D by less developed countries, the private sector, and the CGIAR, a total lag length of 35 years is imposed, with peak effects occurring at year 10 (δ, λ = (0.80, 0.75) in Eq. 10.2). The longer lag structure for public R&D in developed countries reflects a greater focus on discovery R&D to push the science and technology frontier. The shorter lag length for less developed countries and private R&D reflects a greater emphasis on adaptive R&D, borrowing from global knowledge capital to close existing yield gaps.

Once the R&D capital stock is constructed from historical and projected future R&D spending by each R&D source, we link these stocks to future growth in agricultural TFP growth via elasticities (α_s) that describe the percentage rise in TFP given a 1% increase in R&D capital stock from source s (Eq. 10.3). The estimates of α_s are based on Fuglie's (2018) review of more than 40 studies that empirically estimated α_s from historical R&D spending and agricultural TFP growth

Table 10.2 Elasticities of agricultural research and development (R&D) capital stock, by region and technology provider (Fuglie 2018)

	Technology provider				
Region	Total—R&D from all sources	National public R&D	Private R&D	CGIAR R&D	Spill-ins from DC regions
Developed countries (DC)	0.67	0.27	0.20		0.21
Transition economies	0.07	0.07			
Less developed countries					
Latin America	0.77	0.23	0.13	0.05	0.36
East and South Asia	0.30	0.21	0.01	0.08	
West Asia & North Africa	0.19	0.15		0.04	
Sub-Saharan Africa	0.17	0.13		0.04	

Elasticities give the percentage change in agricultural total factor productivity (TFP) resulting from a 1% change in R&D capital stock

in various countries and regions, mostly using data since 1980 (see Table 10.2). The estimates vary by R&D source and by region, and the values of these elasticities are generally lower for LDC regions than for DC regions. Public R&D in DC regions is also more likely to generate international technology spillovers, but mainly to other developed countries.

4.2 *Environment Policy*

For this analysis, environmental policies are defined as land policies that restrict land areas rich in carbon stocks from agricultural use. The cost of this environmental policy is the amount of compensation paid to landowners to replace forgone income from agricultural uses of the land. We call this a land set-aside payment; it is equivalent to an annual rental payment for agricultural land. Environmental policy is modeled as a backward shift in the land supply function in regions where there is considerable potential for agriculture to expand into carbon-rich natural areas (i.e., forests and grasslands). These areas are identified from global grid cells of areas (1) in the top 80th percentile of carbon intensity (West et al. 2010) and (2) in which less than 70% of the area is currently in cropland. This scheme assures that land restriction policies are imposed in areas with high carbon sinks near agricultural frontiers. The policy removes a specified share of land from agricultural production in these areas.

4.3 Policy Scenarios

Table 10.3 describes a set of R&D and environmental policy scenarios for reducing GHG emissions from agriculture that form the basis for the SIMPLE model simulations of the global agricultural economy from 2017 to 2050. Scenario S1 is the business-as-usual (BAU) case and assumes that public and private spending on agricultural R&D will continue at the same (real) annual growth rate over 2017–2050 as it did in 2000–2017. For DC regions as a whole, the growth rate in public agricultural R&D was virtually zero (Heisey and Fuglie 2018), while the annual growth in public R&D spending in less developed countries averaged 4.6%, ranging from 2.1% in Sub-Saharan Africa to 9.1% in China (Fuglie 2018). The BAU case assumes that these rates will continue into the future except for in China, which is scaled down to 3% annual growth in R&D spending, since it is unlikely to continue at such a high rate indefinitely. In the BAU case, R&D spending in less developed countries would more than double over the simulation period and would increase as a percentage of gross agricultural output from 1.0% to 1.5%. R&D spending by the private sector is assumed to grow at 4% per year, and CGIAR spending is assumed to grow by 5.8% per year (reflecting their respective 2000–2017 average growth rates).

Scenario S2:ENV adds an environmental policy that places limits on agricultural land use in frontier areas where forests, peatlands, and grasslands provide carbon-rich sinks. In this scenario, we target a 5% reduction in cropland in areas with high potential to serve as carbon sinks and provide compensation to landowners for forgone income from agricultural uses of this land. Compensation costs are estimated from regional average agricultural land rental rates derived from SIMPLE. Most of the set-aside area lies on the agriculture–forest fringe in less developed countries but also includes some areas in developed countries, such as the southeastern United States (Fig. 10.2).

Under scenarios S3, S4, and S5, growth in public agricultural R&D spending is accelerated beyond that in the BAU case for the 2017–2040 period. Due to lags between R&D spending and TFP growth, higher spending during 2017–2040 will begin to nudge TFP growth rates upward in the late 2020s, with effects persisting for several decades; however, R&D spending beyond 2040 will not have much effect on TFP growth before midcentury, so only R&D costs between 2017 and 2040 are considered. Under Scenario S3:LDC, agricultural R&D spending is assumed to grow uniformly in all LDC regions by 6.3% per year but is held at BAU levels (zero growth) in DC regions. At this aggressive rate of growth, R&D spending in less developed countries would grow from US$28.0 billion per year in 2020 to US$126.1 billion per year by 2040 (or to 3.2% of the projected value of agricultural output, compared to 1.5% of the output in the BAU case). Scenario S4:ENV-LDC combines this R&D growth path with the environmental policy under S2:ENV, which protects carbon-rich land from conversion to cropland. Finally, under scenario S5:GLOBAL, R&D spending is accelerated in both LDC and DC regions but for the same global total as S3 and S4. For S5:GLOBAL, we assume that R&D spending in LDC regions

Table 10.3 Research and development (R&D) and environmental policy scenarios for the simulations

Policy scenarios		Total global agricultural R&D spending in 2040 (billion PPP$)	Public agricultural R&D spending in 2040[a]: Less developed countries (LDC) (billion PPP$)	Public agricultural R&D spending in 2040[a]: Developed countries (DC) (billion PPP $)	Total global agricultural R&D spending, 2017–2040 (billion PPP$)	Total global land set-aside payments, 2017–2050 (billion PPP$)	Total global policy cost, 2017–2050 (billion PPP $)
Global policy scenarios S1 to S5							
S1:BAU	Business-as-usual (BAU) case: continue current spending growth in global agricultural R&D	131.7	59.1	19.6	2296	0	2296
S2:ENV	Enact environmental policies that protect carbon-rich land from conversion with BAU R&D growth	131.7	59.1	19.6	2296	1113	3409
S3:LDC	Accelerate public agricultural R&D spending in LDC	199.5	126.5	19.6	2907	0	2907
S4:ENV-LDC	Combines S2 & S3: Accelerate R&D spending in LDC and protect carbon-rich land from conversion	199.5	126.5	19.6	2907	1041	3948
S5: GLOBAL	Accelerate public agricultural R&D spending in both LDC to DC (for same global total as S2 and S3)	192.6	99.9	40.2	2907	0	2907
Regional policy scenario S6 EU "Green Deal"							
S6A:EU-ENV	S5 plus EU imposes reduction of nonland agricultural inputs by 20%	192.6	99.9	40.2	2907		
S6B:EU-RD	S6A plus additional increase in EU R&D spending	203.1	100	50.5	2999		

Dollar amounts are measured in purchasing power parity (PPP)

[a]R&D policy is set by assuming annual growth rates in spending over 2017–2040 and projecting total factor productivity (TFP) growth to 2050. Due to the R&D lag structure, R&D spending after 2040 has minimal effect on TFP growth before 2050 so only R&D costs over 2017–2040 are considered. Total global R&D spending includes private and CGIAR R&D

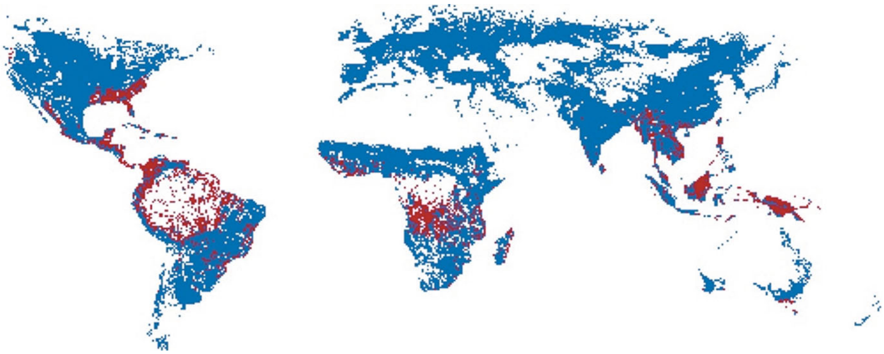

Fig. 10.2 Areas targeted for cropland restrictions in the policy simulations (5% of global cropland area)
Red grid cells lie on or above the 80th percentile in carbon intensity and presently have 70% or less area in cropland

grows by 5.4% per year, while R&D spending in DC regions grows by 3.1% per year. Public R&D as a percentage of agricultural output would reach 3.6% in developed countries and 2.8% in less developed countries by 2040. This scenario exploits the greater efficiency of R&D systems in developed countries to push out the science and technology frontier and produce international R&D spillovers. In all the scenarios, private R&D grows at a constant rate of 4.1% per year (the BAU rate), while under scenarios S2 through S5, CGIAR spending is assumed to grow at the same rate as LDC public R&D.

Finally, scenario S6:EU considers policies that seek to reduce the environmental footprint of agriculture in a developed region. Modeled loosely on the EU Green Deal and its agricultural Farm to Fork Strategy, scenario S6A:EU-ENV deintensifies agricultural production in the European Union by imposing a 20% reduction in the use of nonland inputs.[4] Scenario S6B:EU-RD adds additional R&D spending to offset production losses from the input-use restriction. While we are not able to present the full cost of these policies (in Table 10.3 we show only R&D cost and not the environmental policy cost), scenario 6 is nonetheless useful for exploring the effects of regional policies on global environmental and food security outcomes.

[4]The EU Green Deal policy (European Commission 2020) lays out specific goals for agricultural input use reduction by 2030: reduce pesticide use by 50%, fertilizer use by 20%, sales of antimicrobials in farmed animals and aquaculture by 50%, and place 25% of total farmland under organic farming. Given that nonland inputs account for about 90% of total agricultural costs and material inputs about half of nonland costs (Ball et al. 2010; Fuglie 2015), it is reasonable to assume that these restrictions might mean a 20% overall reduction in nonland inputs. The EU Green Deal policy also commits €10 billion to research and innovation related to food, bioeconomy, natural resources, agriculture, fisheries, aquaculture, and environment. However, our policy scenarios are not directly comparable to the EU Green Deal since our scenarios envision agriculture supplying global demand in 2050 rather than 2030. Given R&D lags, our scenarios also give a more reasonable timeframe for modeling the effects of new R&D spending on productivity growth.

5 Results

Table 10.4 summarizes the implications of the policy scenarios for global agricultural production and prices, GHG emissions from agriculture and land-use change, and the number of undernourished people. Under scenario S1:BAU, the projected growth in agricultural TFP over 2017–2050 is 42.3% (for an average annual rate of 1.07%), and global agricultural output rises by 51.6%. Our finding that output will grow more than TFP indicates that the use of agricultural (land and nonland) inputs also increased. The increase in TFP causes average global crop prices to fall by an average of 21.6% (but regional price changes vary due to market segmentation, as seen in Fig. 10.3). Global cropland expands by 6%, or by about 95 million hectares. This land-use change causes a release of 31.8 Gt CO2e of terrestrial GHGs into the atmosphere. At the same time, farmgate GHG emissions rise to 8.3 Gt CO2e per year, an increase of nearly 3.0 Gt CO2e over 2017 farmgate emissions. Exogenous growth in per capita income and the fall in crop prices reduce the undernourished population by 146 million compared to 2017 levels.

Under Scenario S2:ENV, imposing an environmental policy that protects carbon-rich land from agricultural use reduces the increase in global cropland from 6% to just 1.4%. Net GHG emissions from land-use change are only 2.9 Gt CO2e (compared to 31.8 Gt CO2e under S1:BAU). The increase in global cropland masks a larger shift in cropland from areas with high carbon sink potential to other parts of the world. Even though there is no extra gain in productivity compared with S1: BAU, the projected farmgate GHG emissions in 2050 are cut from 8.3 to 7.4 Gt CO2e. A major contributing factor to the reduction in farmgate emissions is the avoidance of crop production in former peatlands, which continue to emit GHG emissions from peat decomposition as they are farmed. Imposing land-use restrictions without adding productivity growth, however, exacerbates global food insecurity: There are four million more undernourished people compared with the S1: BAU scenario (i.e., the number of undernourished people falls by 142 million under S2:ENV compared to 146 million under S1:BAU).

Increasing R&D spending in less developed countries (scenario S3:LDC) above BAU levels accelerates global growth in agricultural TFP and output while further lowering crop prices. Global cropland expansion falls by nearly half (from 6.0% to 3.4%), but not by as much as the environmental policy under S2:ENV (1.6%). GHG emissions per unit of output are lower under S3:LDC than S2:ENV (see Fig. 10.4); however, total farmgate emissions are higher under S3:LDC than under S2:ENV because output is larger. Lower crop prices under S3:LDC have major benefits for global food security: The prevalence of undernutrition falls by 208 million people by 2050.

Scenario S4:ENV-LDC, which combines increased R&D spending with environmental policies that protect carbon-rich land, has the largest impact among these scenarios at curtailing GHG emissions from agriculture while preserving gains in global food security. In fact, global cropland declines by 1.2% under this scenario. This represents a reduction of 18 million hectares of cropland from 2017 levels and

Table 10.4 Effects of research and development (R&D) and environmental policy scenarios on global agricultural greenhouse gas (GHG) emissions, prevalence of malnutrition, food prices, cropland, and agricultural production

	World agricultural TFP in 2050	World agricultural output in 2050	Average annual GHG emissions from land-use change, 2017–2050	Average annual farmgate GHG emissions	Total GHG emissions from land-use change, 2017–2050	Total change in agricultural GHG emissions, 2017–2050	Difference between 2050 and 2017 global levels			
							Farmgate GHG emissions	Under-nutrition	Crop price	Crop land
Policy scenario	(Index, 2017 = 100)	(Index, 2017 = 100)	million tons CO2e/year	million tons CO2e/year	million tons CO2e	million tons CO2e	million tons CO2e/year	million persons	(%)	(%)
S1:BAU	142.3	151.6	963	8258	31,764	272,510	2985	−146	−21.6	6.0
S2:ENV	142.3	151.4	86	7357	2851	242,791	2060	−142	−20.8	1.4
S3:LDC	156.8	157.7	649	7719	21,403	254,733	2221	−208	−32.2	3.4
S4:ENV-LDC	156.8	157.4	−205	6842	−6756	225,787	1320	−205	−31.4	−1.2
S5: GLOBAL	164.8	159.5	463	7446	15,264	245,703	1860	−212	−42.1	1.9
S6A:EU-ENV	164.8	159.2	499	7479	16,462	246,798	1890	−210	−41.1	2.2
S6:EU-RD	171.1	161.4	337	7251	11,111	239,280	1597	−223	−46.7	0.9

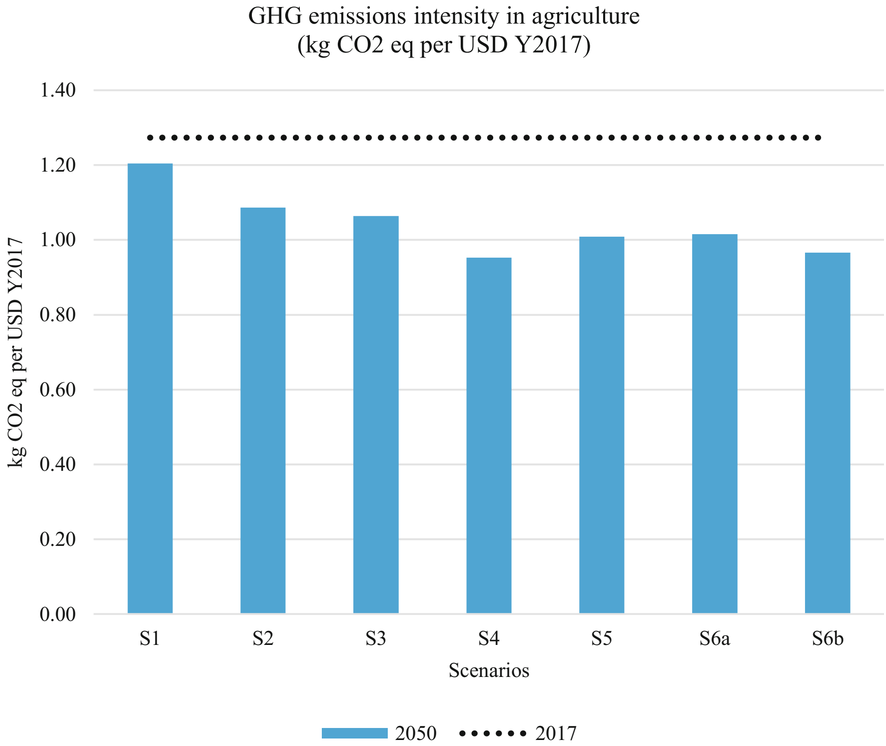

Fig. 10.3 Effect of research and development and land policy scenarios on farmgate greenhouse gas emissions intensity (kg CO2e per constant 2017 USD)
Results for S1:BAU, S2:ENV, S3:LDC, S4:ENV-LDC, and S5:GLOBAL are displayed left to right in the bar graphs

113 million hectares less cropland in 2050 than under S1:BAU projections. The reduction in cropland (and the accompanying expansion of forest area) sequesters 6.8 Gt CO2e. A further advantage of S4:ENV-LDC is that it lowers the cost of the environmental policy. Because faster productivity growth reduces commodity prices, which in turn reduces land rents, compensation to landowners for forgone earnings from agricultural land use also falls (from US$1113 billion to US$1041 billion over the 2017–2050 period, see Table 10.3). Under S4:ENV-LDC, farmgate emissions are also considerably lower compared with those under other scenarios due both to the rise in productivity of existing farmland and the prevention of agricultural expansion into environmentally sensitive peatlands, which continue to emit GHGs for decades following land-use change.

Scenario S5:GLOBAL illustrates the efficiency gains that could be achieved under an R&D strategy that includes additional investments in both DC and LDC regions. Using the same global R&D spending as S3:LDC, this scenario demonstrates that shifting some of this spending from less developed to developed

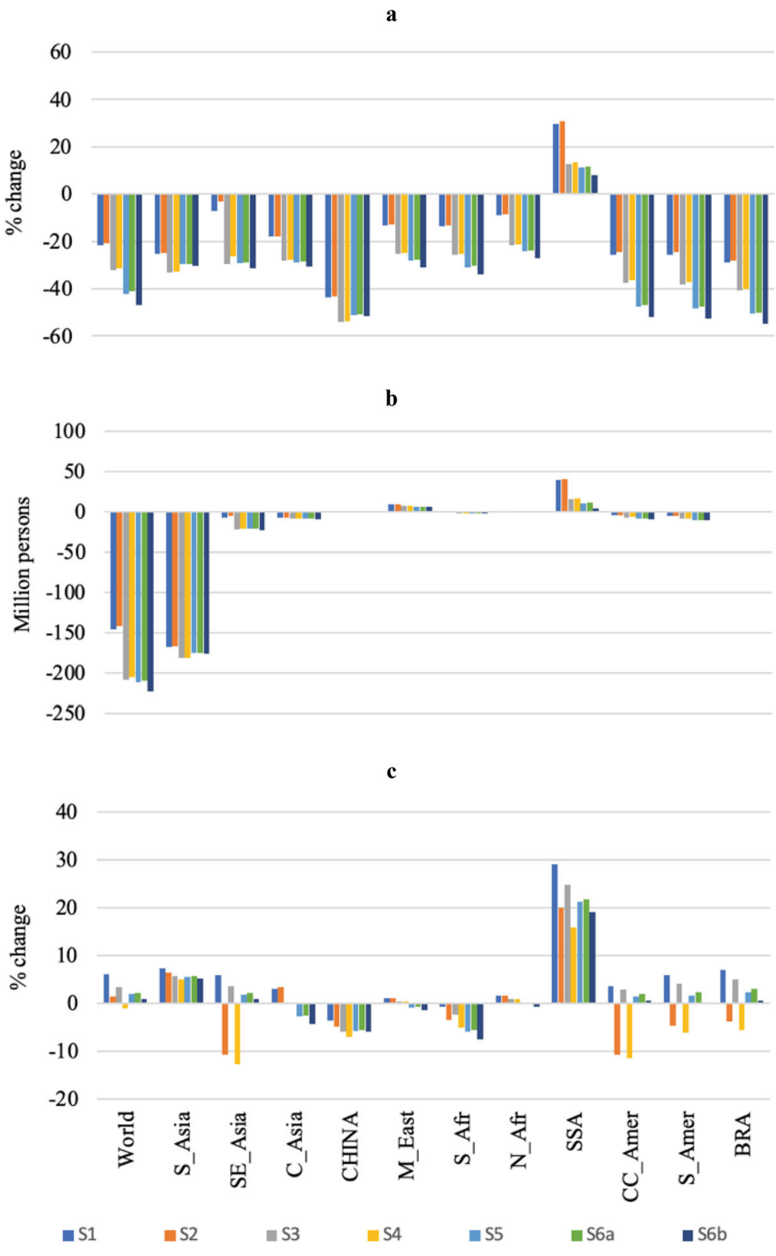

Fig. 10.4 Change in (**a**) crop prices, (**b**) undernutrition, and (**c**) cropland use as a result of global policy scenarios: differences between 2017 and 2050, by region

countries achieves more rapid gains in global agricultural TFP and output. This further reduces food prices, GHG emissions, and undernutrition. Even without the environmental policy, global cropland expands by only 1.9%. The higher return on R&D in DC regions stems from the assumption, based on historical evidence, that these R&D systems generate more technological breakthroughs with potential for international spillovers.

Figure 10.4 illustrates the regional implications of policy scenarios S1–S5 for crop prices, undernutrition, and cropland use. In all policy scenarios, crop prices and undernutrition are projected to decline between 2017 and 2050 except in Africa, especially sub-Saharan Africa (SSA). SSA is the region least integrated into global agricultural markets; as a result of slow agricultural productivity growth coupled with rapidly rising population, the model projects that food prices, cropland use, and the total number of undernourished people in this region will increase even as they fall in other parts of the world. In all regions, the policy scenarios that increase R&D spending (S3:LDC, S4:ENV-LDC, and S5:GLOBAL) have the largest impact on reducing crop prices and undernutrition, while the scenarios with environmental policies (S2:ENV and S4:ENV-LDC) have the largest impact on reducing cropland and therefore avoiding GHG emissions from land-use change. Not shown in Fig. 10.3 are impacts on developed countries. Under BAU productivity gains, cropland is projected to fall in Europe and rise in North America and Oceania. With accelerated R&D in developed countries, cropland is projected to decline in all DC regions except the United States, where cropland is projected to remain unchanged.

The estimates of policy costs and GHG emissions in Tables 10.3 and 10.4 can be used to approximate the marginal cost of GHG abatement. Table 10.5 shows the estimated total costs of R&D and environmental policies incurred over the 33 years from 2017 to 2050, in constant 2017 (undiscounted) dollars, and total agricultural GHG emissions over the same period. Marginal abatement costs are found by comparing the differences in emissions and policy costs with those under the BAU scenario (S1). The ratio of the increase in policy cost to the reduction in emissions then gives an approximate marginal abatement cost in USD per metric ton of CO2e emissions averted. These estimates are approximate because they do not account for the time path of policy costs and environmental benefits but simply make a static comparison of total costs (in constant dollars) and emissions changes over 2017–2050. They also ignore post-2050 benefits from productivity gains due to R&D spending in 2017–2040. The results suggest abatement costs of US$19–US $22 per ton of CO2e for policies S2:ENV, S3:LDC, and S4:ENV-LDC and a substantially lower abatement cost of US$14 per ton for S5:GLOBAL due to the efficiency gains from shifting some R&D spending from LDC to DC regions. By comparison, Lobell et al. (2013) estimate that using greater agricultural R&D spending to mitigate GHG emissions from land-use change would cost about US $15 per ton of CO2e. Our results consider not only emissions saving from avoided land conversion but also changes in farmgate emissions. We also use a more refined model of R&D spending in which the lag between investments and productivity realizations is taken into account. Nonetheless, our results are quite similar to those of Lobell et al. (2013).

Table 10.5 Marginal costs of agricultural greenhouse gas (GHG) emissions abatement costs from the global policy scenarios

	R&D policy cost (2017–2040)	Environmental policy cost (2017–2050)	Total policy cost (2017–2050)	Cost change from BAU	Total agricultural GHG emissions (2017–2050)	GHG emissions change from BAU (2017–2050)	Approximate marginal cost of GHG abatement
Policy scenario	billion PPP$	billion PPP$	billion PPP$	billion PPP$	Gt CO2e	Gt CO2e	PPP$/ton CO2e
S1:BAU	2296	0	2296	0	304	0	–
S2:ENV	2296	1113	3409	1113	246	−59	18.97
S3:LDC	2907	0	2907	611	276	−28	21.71
S4:ENV-LDC	2907	1041	3948	1652	219	−85	19.38
S5: GLOBAL	2907	0	2907	611	261	−43	14.11

Table 10.6 Effects of regional European Union (EU) policy scenarios on agricultural productivity, cropland, and greenhouse gas (GHG) emissions

Policy scenario		Agricultural total factor productivity, 2050 (Index, 2017 = 100)		Change in cropland, 2017–2050 (%)		Agricultural GHG emissions, 2017–2050 (million tons CO2e)	
		EU	Global	EU	Global	EU	Global
S5: GLOBAL	Accelerate public agricultural R&D spending in both less developed and developed countries	164.6	164.6	(1.3)	1.9	15,544	245,703
S6A:EU-ENV	S5 plus EU imposes reduction of nonland agricultural inputs by 20%	164.6	164.8	(1.3)	2.2	15,232	246,798
S6B:EU-RD	S6A plus additional increase in EU R&D spending	195.5	171.1	(0.9)	`0.9	14,938	239,280

Finally, Table 10.6 reports the implications of policy scenarios that focus on developed countries. Here, we consider a policy imposed on EU countries that deintensifies the use of nonland inputs to reduce emissions and other environmental costs from agriculture. Using the productivity growth assumed under scenario S5: GLOBAL, scenario S6A:EU-ENV adds a mandate to reduce nonland inputs in EU agriculture by 20%. This reduces EU GHG emissions but also reduces output and raises global prices (see Table 10.4). More cropland enters agriculture in other parts of the world and total global GHG emissions increase. However, additional R&D spending by the European Union (scenario S6B:EU-RD) could offset these adverse global outcomes. This would raise EU agricultural production and keep more area in cropland in the European Union while reducing the growth in cropland area in the rest of the world. Higher R&D spending by the European Union would also raise agricultural productivity in other parts of the world due to international technology spillovers.

6 Discussion

This chapter has investigated the role of productivity investment policies in reducing GHG emissions from agriculture and compares these outcomes with those obtained through environmental policies that restrict agricultural land and input use. Using the SIMPLE partial equilibrium model of the global agri-food economy, we carried out a series of simulations of world agricultural supply and demand to 2050 that included various combinations of R&D spending and environmental restrictions on agriculture in LDC and DC regions. Our baseline, or business-as-usual (BAU), scenario assumes that R&D spending patterns continue on their present trajectory and that world population and income grow according to SSP 2 middle-of-the-road assumptions. Under the BAU scenario, global cropland increases by 6% (about 95 million hectares) from 2017 levels and agriculture releases a total of 272.5 Gt CO2e from land-use change and farmgate production. A simulation of an environmental policy that reduces agricultural cropland by 5% in carbon-rich areas reduces overall agricultural emissions by 29.7 Gt CO2e but causes food prices to rise and malnutrition to increase. It is also costly: We estimate that compensation to landowners for forgone income will total US$1.11 trillion over 2017–2050 (and continue indefinitely after that). A simulation with a productivity policy scenario that adds US$0.61 trillion to R&D spending in LDC regions over 2017–2050 results in lower food prices and reduces the number of undernourished people worldwide but is only about 60% as effective as the environmental policy in reducing emissions. A simulation that combines these approaches cuts global agricultural emissions by 46.7 Gt CO2e and preserves the reduction in undernutrition at a cost of US$1.65 trillion. Higher productivity results in lower land rents (because output prices are lower) which reduce the cost of the environmental policy by about US$100 billion. All three policy options imply roughly the same marginal abatement cost of US$19–US$22 per ton of CO2e.

A further scenario considers a variation in productivity policy that shifts part of the US$0.61 trillion increase in R&D spending from LDC to DC regions. Because R&D systems in DC regions are assumed, based on historical evidence, to be more efficient at generating international technology spillovers, this scenario achieves more rapid gains in global agricultural productivity and reduces total GHG emissions from agriculture by 27 Gt CO2e, for a unit abatement cost of US$14 per ton CO2e. This scenario also achieves a greater reduction in the size of the undernourished population. A final scenario imposes more stringent environmental restrictions on developed countries—in this case, it targets a 20% reduction in the use of nonland inputs in EU agriculture (roughly what the EU Green Deal envisions). While this reduces GHG emissions in the European Union, it slightly raises agricultural emissions worldwide because lower agricultural outputs in the European Union raise world prices and cause agriculture to expand in the rest of the world. However, an aggressive EU policy of R&D spending could offset those effects by further increasing agricultural productivity not only in the European Union but also in other countries through international technology spillovers.

It is important to note that none of the policy scenarios considered in this chapter resulted in an actual reduction in global GHG emissions from agriculture by 2050. Rather, they curbed the growth in emissions as agricultural output expanded to better nourish the growing world population. Another aspect of our modeling approach is that improvements in productivity are assumed to be factor neutral, meaning that they reduce the amount of all factor inputs (e.g., land, labor, capital) required to produce a unit of output in equal proportions. Because it unambiguously reduces unit costs of production, factor-neutral technical change is profitable for farmers and thus can be expected to face few hurdles to widespread adoption. A suggestion for future work is to consider factor-biased technical change, wherein technologies are designed to save the production factors most closely associated with GHG emissions. Factor-biased technologies that target emissions reductions may require fewer R&D expenditures than factor-neutral technologies for similar savings in farmgate emissions intensity. However, factor-biased technical change may increase the use of other inputs and may not be profitable for farmers to adopt without additional incentives.

Generally, it appears that productivity and environmental policies to curb GHG emissions from agriculture are likely to complement each other. As Stevenson et al. (2013) note, higher agricultural productivity by itself is likely to be too blunt an instrument for protecting environmentally sensitive land from conversion to cropland. However, environmental policies that protect such land from agricultural use may be difficult to monitor and enforce, lack permanence, and exacerbate hunger. Combining these policies may better achieve the dual societal goals of climate change mitigation and global food security.

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