chapter 10

contents

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chapter 10

The role of international trade under a changing climate: Insights from global economic modelling[1]

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main chapter messages

- The likely impacts of future climate change and socio-economic drivers on international trade in agrifood commodities would vary depending on assumptions regarding how the future will evolve as encapsulated by 'scenarios'.
- The projected agrifood trade impacts are also likely to vary across economic models, depending on model types and underlying theoretical structures.
- To improve understanding on why simulated impacts differ across models under specific 'scenarios', results from a recent AgMIP (Agricultural Model Intercomparison and Improvement Project) economic modelling exercise are used, with particular focus on the agriculture sector.
- The analysis presented in this chapter suggests an increasing role for trade under future climate change but the extent of the change in agrifood trade varies substantially between models.
- Based on the insights from the analysis, a number of potential issues are recommended for future modelling and research.

1 This paper is part of a global economic model intercomparison activity undertaken as part of the AgMIP Project (www.agmip.org). The climate change drivers collectively known as MIP were provided as part of the ISI-MIP model comparison project (www.isi-mip.org). The socio-economic drivers were developed for the Shared Socio-economic Pathways (SSP) as part of a new set of IPCC scenarios for analyses of climate impacts, adaptation and mitigation, and are available at the SSP data portal (https://secure.iiasa.ac.at/web-apps/ene/)

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1. Introduction

International trade plays an important role in improving global wellbeing, by allowing comparative advantages to be exploited. Changing socio-economics can alter comparative advantages and trade flows, and so can climate change. In recent decades, the volume of agricultural trade has grown in response to growing populations and rising incomes, with geographical distribution of this trade favouring certain developing countries. In the future, climate change will potentially have an impact on land productivity globally, altering the relative productivity of land in one region compared with another (see, for example, Nelson *et al*., 2013). In other words, climate change can alter the volumes and patterns of international agrifood trade through its impacts on national comparative and competitive advantages arising from changes in production, transport and distribution chains (see, for example, WTO-UNEP, 2009). Therefore, while the socio-economic drivers of international trade are expected to remain important, climate change can also potentially alter future international competitiveness and agrifood trade patterns.

A number of studies (see, for example, Reilly and Hohmann, 1993; Hertel and Randhir, 2000; and Verburg *et al*., 2008; Nelson *et al*. 2010) have suggested that trade can facilitate “adaptation” to climate change in agriculture and food sectors. The term “adaptation” is amenable to multiple interpretations. To avoid any misinterpretation, trade as an adaptation option should be understood in the following context: climate change causes changes in comparative advantage and exploiting these changes will involve changes in trade flows. That is, changes in trade flows are an “endogenous” response or adaptation to climate change. All economic models considered in this chapter specify “endogenous” responses to changes in socio-economic and climate drivers. Many important research questions are concerned with identifying *how much*, *where*, and *how different* these responses will be, and there is no clear consensus that has yet emerged from the literature in this regard (see also OECD, 2012). Model projections are expected to differ across scenarios, due to differences in the underlying economic, demographic and technology assumptions, and also across models, due to differences in the underlying model structures and base-year databases.

In this chapter, the likely implications of some socio-economic and climate change drivers of trade are examined, using six scenarios involving two alternative assumptions about the socio-economic drivers (GDP, population) with varying climate change impacts on agricultural productivity. These scenarios were designed for a recent AgMIP (Agricultural Model Intercomparison and Improvement Project) exercise, to examine how economic models responded to different kinds of shocks – socio-economic and climate (as well as bioenergy) – and to improve the understanding of *why* simulated impacts differ across models. AgMIP has brought together climate modellers, crop modellers and global economic modellers from across the world and provides a forum for comparison and improved understanding of model results under selected socio-economic and climatic scenarios. The global economic modelling group incorporates both partial equilibrium (PE) models of agriculture and food commodities and global general equilibrium (GE) models (von Lampe *et al*., 2014). The different models used in this joint analysis are described in Table 1a.

This chapter presents a synthesis of modelling results for agrifood trade under the selected socio-economic and climatic scenarios. In particular, the specific objectives of this study are to examine key trends and patterns in projected future agrifood trade under the different socio-economic and climate scenarios and, drawing on the results, to shed some light on the relative importance of socio-economic and climate drivers, as well as the characteristics of the models involved, all of which determine trade patterns.

The following section presents some of the key features of the global economic models that are being used to project international trade.

Section 3 provides an overview of current trends in agrifood trade. Section 4 briefly describes the scenarios simulated for the AgMIP global economic modelling exercise. Section 5 presents and synthesises key agrifood trade results from participating models. The final section draws conclusions on the level of consistency between model results, identifies some key reasons for significant differences across models and suggests potential areas for future model comparison exercises.

2. Modelling international trade

Projections of agricultural trade are dependent on the characterization of trade in the models, which depends on the supply and demand responses specified within the models. These responses depend, in particular, on the capacity of regions to respond to changes in productivity, land-use change and changing input mix, and how price and income changes affect consumption. A series of papers offers some detailed assessment of the specifications of the supply side (Robinson *et al*., 2014), land use change (Schmitz *et al*., 2014) and the demand side (Valin *et al*., 2014) of the AgMIP models.

The specification of international trade varies significantly between model classes – i.e. GE and PE models, as well as between models within each model class. While these differences are important in understanding the model results, for brevity only the broad characteristics of GE and PE modelling of trade are described below. Interested readers are directed to AgMIP papers and/or can further explore individual model documentations cited earlier.

2.1 Modelling trade in a general equilibrium framework

All six GE models utilize the "Armington" approach to modelling international trade (Armington, 1969a, 1969b), which distinguishes domestically produced

table 1a

Partial equilibrium and general equilibrium models used in this analysis

Model category	Model name	Source
Partial Equilibrium (PE)	Global Change Assessment Model (GCAM)	Wise and Calvin, 2011
	Global Biosphere Management Model (GLOBIOM)	Havlík *et al*., 2011; 2013
	International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT)	Rosegrant *et al*., 2012
	Model of Agricultural Production and its Impacts on the Environment (MAgPIE)	Lotze-Campen *et al*., 2008
General equilibrium (GE)	Asian Pacific Integrated Model (AIM)	Fujimori *et al*., 2012
	Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE)	van der Mensbrugghe, 2013
	Predictions and Policy Analysis (EPPA)	Paltsev *et al*., 2005
	Future Agricultural Resources Model (FARM)	(Sands *et al*., 2013)
	Global Trade and Environmental Model (GTEM)	Ahammad and Mi, 2005
	Modular Applied GeNeral Equilibrium Tool (MAGNET)	Nowicki *et al*., 2009

commodities from comparable commodities produced in other countries.[3] By differentiating domestic goods from comparable imports, these models effectively allow for two-way trade flows, preventing the problem of over-specialization that would otherwise occur in computable general equilibrium (CGE) models while also conferring some market power on each open economy.

The two-way trade flows specified in these models can be described by means of a two-level nested constant elasticity of substitution (CES) function, representing a two-level budgeting and decision-making process. The first level distinguishes between imports and domestically produced goods and the second between imports from various sources.

The same "Armington" preference structure is adopted for each model agent: households, government and producers select from domestically produced goods and imports based on the same two-level budgeting and decision-making process. Total demand for imports for each commodity in an economy is the sum of imports by all model agents. Bilateral trade between all model regions is determined through a CES function, as seen in Equation 1.

(1)

$$QMS(i,r,s) = b(i,r).\,QM(i,s).\,\left(\frac{PMS(i,r,s)}{PM(i,s)}\right)^{(1-\alpha(i))}$$

where:

- QMS is bilateral trade in commodity i from region r to region s
- QM is demand for imports of commodity i by region s
- PMS is price of commodity i from region r in region s
- PM is the average price of imports of commodity i in region s
- b is a parameter representing any exogenous preference shift
- α is elasticity of substitution (often referred to as the "Armington elasticity").

Total exports from all regions equal the sum of imports to all regions.

Armington (1969b) lists the characteristics that determine the size of the elasticity, including the commodity composition of trade (i.e. the level of homogeneity within the commodity class), the degree and nature of trade restrictions, the importance of long-term contracts and loyalty to particular sources. The size and diversity of the region can also affect elasticities. For example, the elasticity could be different for large diverse regions compared to single country regions.

One of the most established sets of Armington elasticity estimates is in the Global Trade Analysis Project (GTAP) database (Narayana *et al.*, 2012). Most models used the GTAP database as a starting point for their Armington elasticity estimates (Table 1b). The most recent GTAP database (version 8) has Armington elasticities

table 1b

Description of Armington elasticities from the CGE models

Model	Description of Armington
ENVISAGE	Higher than GTAP
EPPA	Unmodified from GTAP
FARM	Approximately those of GTAP
GTEM	Unmodified from GTAP
MAGNET	Unmodified from GTAP

Note: AIM is a CGE model that does not specify bilateral trade. Therefore, it has a single import/domestic Armington structure, rather than the nested approach adopted in other models. AIM specifies an Armington elasticity of 0.8 for all agrifood commodities across all regions.

[3] An alternative approach to modelling international trade in a GE model is to treat domestic commodities as identical to (or as perfect substitutes for) corresponding imports, and address the issue of complete production or import specialization when constant returns to scale prevail in production – for example, by assuming some sector-specific factors of production (see, for example, Taylor and Black, 1974; Clarete and Whalley, 1988).

between imports and domestically produced goods ranging between 1.3 and 4.5, depending on the level of homogeneity within the commodity class. The elasticity for wheat, for example, is approximately three times that of the "other coarse grains" commodity class. In the standard GTAP database, these elasticities are assumed to be the same for all regions. However, given any difference in a commodity class across regions, the same elasticity value for the class will represent varying levels of product differentiation (or degrees of substitutability) for the commodities in the class across regions. For example, a given elasticity value for the "other coarse grains" commodity class will mean a different degree of substitutability (that is, a different underlying or implied value of Armington elasticity) for corn for different regions, depending on the share of corn in the "other coarse grains" commodity class across regions.

As pointed out earlier, by treating the domestically produced commodity and the comparable commodities produced in other economies as heterogeneous, the Armington approach to modelling international trade confers some market power on each open economy. In other words, this approach allows changes in the international terms of trade of an economy to occur under a scenario simulation. Also, all AgMIP global GE models specify exchange rates. With the choice of particular price indexes – for example, gross domestic product (GDP) deflators – as the numeraires (relative to which all price changes are measured), model simulations will generate changes in real exchange rates. The changes in the international terms of trade and real exchange rates are features of the GE mechanisms that can have dominating effects on trade flows, as compared with PE modelling.

2.2 Modelling trade in a partial equilibrium framework

The four PE models assume that a commodity is homogenous regardless of where in the world it is produced and consumed – i.e. that there is a single world market for each commodity and that consumers do not have a preference for domestically produced commodities over imports. In modelling terms, these models specify net trade by region, rather than in two-way trade flows. In the PE models, trade is calculated as the residual of regional production and consumption, as specified in Equation 2.

(2)

$$QT = QP - QD - QS$$

where:

- QT = volume of net trade
- QP = domestic production of the commodity
- QD = domestic demand for the commodity
- QS = change in held stock of the commodity

The world price (PW) of a commodity is the equilibrating mechanism, such that when an exogenous shock is introduced in the model, PW will adjust and each adjustment is passed through to consumer and producer prices in each region. Producer and consumer prices differ from the PW by transport and other margins and by subsidy equivalents. Changes in domestic prices subsequently affect commodity supply and demand, necessitating their iterative readjustment until world supply and demand are in balance. The PW is set to ensure that global net trade equals zero, representing the market clearing condition, as shown in Equation 3.

(3)

$$\sum_r QT = 0$$

Thus, the net trade projections from these models are directly linked to the demand and supply functions, whereas imports and exports are linked to demand and supply functions, respectively, in the GE models.

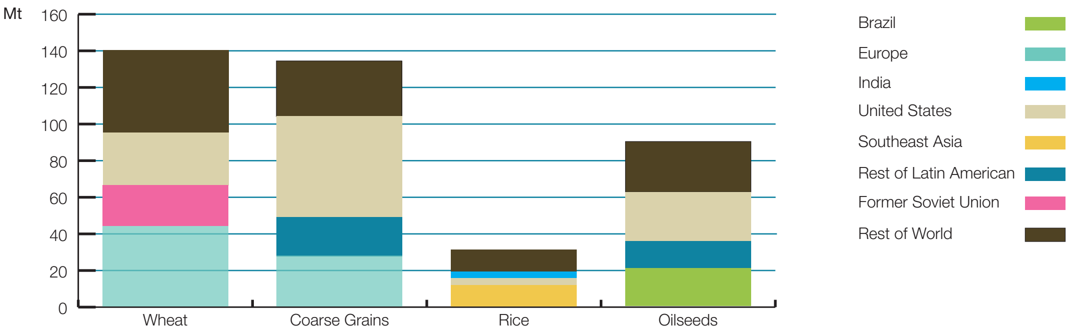
3. Trade in agricultural commodities: Recent trends

Over the past several decades, global agricultural trade has expanded in line with increasing populations, rising incomes, improved technologies and an expansion of agricultural lands. In broad terms, international agricultural trade tends to flow from countries with large, productive land resources and high rates of agricultural mechanization and investment to less-developed countries that are characterized by rising populations and limited productive capacity, such as in sub-Saharan Africa (Figures 1 and 2, USDA ERS, 2013a, 2013b). Some developing countries, such as Brazil and Argentina, export significant quantities of agricultural products. Conversely, some developed countries, such as Japan and Korea, are highly import-dependent.

Wheat is the most widely traded agricultural commodity, with exports totalling around 21 percent of world production (FAOSTAT 2013). Collectively, the European Union (EU), the United

figure 1

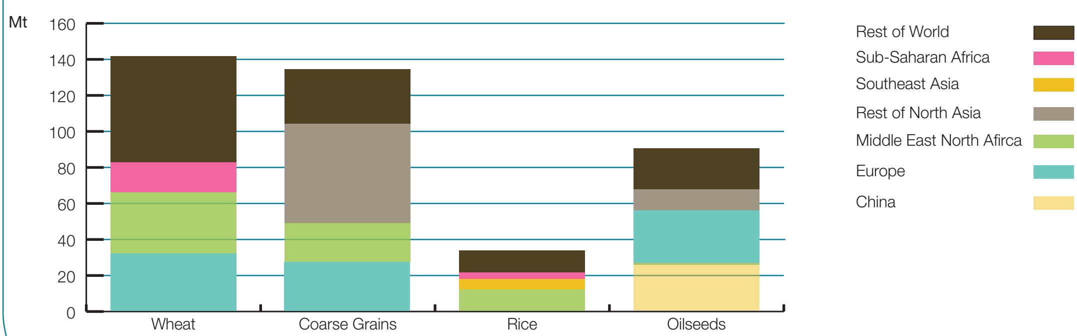
Exports by commodity and region, average over 5 years to 2009, million tonnes (Mt)



Source: FAOSTAT 2013
Note: Trade data for Europe includes intra-EU trade

figure 2

Imports by commodity and region, average over 5 years to 2009, million tonnes (Mt)



Source: FAOSTAT 2013
Note: Trade data for Europe includes intra-EU trade

States of America, the former Soviet Union, Argentina, Australia and Canada account for around 90 percent of world exports. Trade in coarse grains (corn, barley, sorghum and oats) represents around 13 percent of global production. Corn is the main commodity, representing around three-quarters of global coarse grains production. The United States of America is the main exporter of coarse grains, followed by the EU and Latin America. The main importers of wheat and coarse grains are countries in Africa, the Middle East and North Asia. For both wheat and coarse grains, the EU appears to be both a major exporter and importer; however, this is a reflection of significant intra-EU trade (FAOSTAT 2013).

Rice is not heavily traded; exports account for only about 4 percent of global rice production (FAOSTAT 2013). Southeast Asia is the world's largest rice-exporting region, accounting for around 50 percent of world rice exports (Figure 1). Thailand and Viet Nam are the primary exporters, followed by Pakistan, the United States of America and India. The major importers of rice are other countries in Southeast Asia, sub-Saharan Africa, the Middle East and North Africa (FAOSTAT 2013, Figure 2).

Around 29 percent of world oilseed production is exported, with soybeans accounting for half of this trade (FAOSTAT 2013). The United States of America is the world's largest exporter, followed by Brazil and Argentina (which appears as part of Rest of Latin America in Figure 1). China is the world's largest importer of vegetable oil and oilseeds, India is a major importer of vegetable oil, and the EU is the largest importer of soybean meal and second largest importer of soybeans (FAOSTAT 2013).

Trade in meat consists of ruminant (sheep and cattle) and non-ruminant (pigs and poultry) meat and collectively accounts for about 5 percent of global production. The major exporters of meat are the United States of America, the EU, Brazil and Australia, while the major importers are Japan and the Republic of Korea, as well as China, Southeast Asia, the Middle East and North Africa and the former Soviet Union (FAOSTAT 2013).

Trade in dairy products represents around 9 percent of global dairy production. The main exporters of dairy products are the EU, Australia, New Zealand and the United States of America. The main importers are the Middle East and North Africa, China, Japan and the Republic of Korea (FAOSTAT 2013).

4. Description of scenarios

The AgMIP modelling group simulated eight scenarios, each one specified in terms of: socio-economic characteristics (GDP and population); agricultural productivity (based on results of climate and crop modelling); and rate of biofuel penetration. Table 2 lists the key features of each scenario and the following paragraphs briefly describe them. These scenarios are described in more detail in von Lampe *et al*. (2014).

The socio-economic scenarios, SSP2 and SSP3, are the two of the shared socio-economic pathways (SSP) developed for the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC). Broadly described, SSP2 reflects a world in which economic growth is reasonably rapid, sustained by relatively high productivity growth, clean technology development and an integrated global economy. The SSP3 scenario, on the other hand, reflects a world of high population growth in developing countries, combined with slower economic growth, representing a fragmented global economy.

The AgMIP scenarios S1 and S2 represent the SSP2 and SSP3 socio-economic pathways but no allowance has been made for the impacts of climate change on agricultural productivity (Table 2). The AgMIP scenarios S3 to S6 incorporate agricultural productivity affected by climate change, and are derived from a combination of outputs from climate and crop models assuming a Representative [greenhouse gas] Concentration Pathway (RCP) corresponding to a radiative forcing target of 8.5w/m^2 by 2100. More specifically, for scenarios S3 through S6, most AgMIP modellers have implemented agricultural productivity changes generated

table 2

Description of AgMIP scenarios

Scenario code	Socio-economic characteristics	RCP	Climate Model	Crop Model	Bioenergy
S1	SSP 2	Present climate	None	None	Model-specific
S2	SSP 3	Present climate	None	None	Model-specific
S3	SSP 2	RCP8.5	IPSL-CM5A-LR	LPJmL	Model-specific
S4	SSP 2	RCP8.5	HadGEM2-ES	LPJmL	Model-specific
S5	SSP 2	RCP8.5	IPSL- CM5A-LR	DSSAT	Model-specific
S6	SSP 2	RCP8.5	HadGEM2-ES	DSSAT	Model-specific
S7	SSP 2	Present climate	None	None	1st-gen. ca. 6ExaJoule; no 2nd-gen. (2050)
S8	SSP 2	Present climate	None	None	1st-gen. ca. 6ExaJoule; 2nd-gen. ca. 108EJ (2050)

though IMPACT modelling, using the outcomes of the climate models and crop models (Table 2). The only exception is MAgPIE, which has used its own endogenously derived technological change parameters (for details on the MAgPIE methodology, see Dietrich *et al*., 2013).

In simulating these scenarios, no trade policy reforms have been explicitly implemented. Land supply has been determined and implemented independently by individual modellers (Schmitz *et al.,* 2014). Furthermore, the climate change scenarios (S3 through S6) have not accounted for CO_2-fertilization effects of higher atmospheric concentration of carbon dioxide (CO_2). Many other factors, such as extreme events and seasonal variability, sea level rises, population health and labour productivity – through which climate change may affect agriculture and broader economies – have not been considered. In terms of adaptation to climate change, no explicit measures have been considered other than price-driven "endogenous" responses to the input and output mix, supply and demand, and trade structures. In light of these omissions and model implications, the results should be read cautiously as first order approximation that require more follow up investigations where policy issues are factored in.

5. Implications for trade of the "socio-economic and climatic" scenarios

Various models that were included in the AgMIP model comparison exercise differ in their spatial resolution/economic regions and in the level of aggregation of various agricultural sectors, as well as in many other important aspects, such as international trade, as discussed earlier. For comparability of model results, however, the AgMIP exercise involved harmonization of agricultural commodity aggregates, spatial aggregates/economic regions, key model variables and time period across models for reporting and analysis. Furthermore, with the "base" database for these models corresponding to different years, the reported results were re-based to 2005 as the common base year. For further details on the reporting protocol, processes and associated issues, see von Lampe *et al*., 2014 and also Nelson *et al*., 2013.

Given the focus of this paper and for the sake of brevity, the results presented and analysed in this section relate to the AgMIP scenarios S1 ("reference case"), S2 ("fragmented global economy") and an average of the four climate change scenarios (S3 to S6) including, where possible, error bars showing the maximum and minimum of the climate change scenarios. Also, we have focused only on the key trends and on the major exporting and importing economies or regions. A more comprehensive set of results is available from the authors on request.

5.1 Agrifood trade in 2050 under Scenario S1 (the reference case)

Figure 3 presents global exports of major agricultural commodities (wheat and rice) and commodity groups (coarse grains and oilseeds) in 2050 under Scenario S1, simulated by various GE models. (Projected exports from the PE models were not available as these models specify net trade and do not project exports and imports separately.) Exports of these commodities and commodity groups are projected to grow substantially by 2050, relative to the common base year of 2005: by between 50 and 230 percent in the case of wheat; between 50 and 190 percent for rice; between 80 and 140 percent for coarse grains; and between 90 and 210 percent for oilseeds, depending on the model.[4] Most models projected that today's largest exporters of rice, coarse grains and oilseeds would retain their dominance in the world export market in 2050. However, in the case of wheat, Canada is projected by most models to replace the former Soviet Union to become one of the top three exporters in the world.

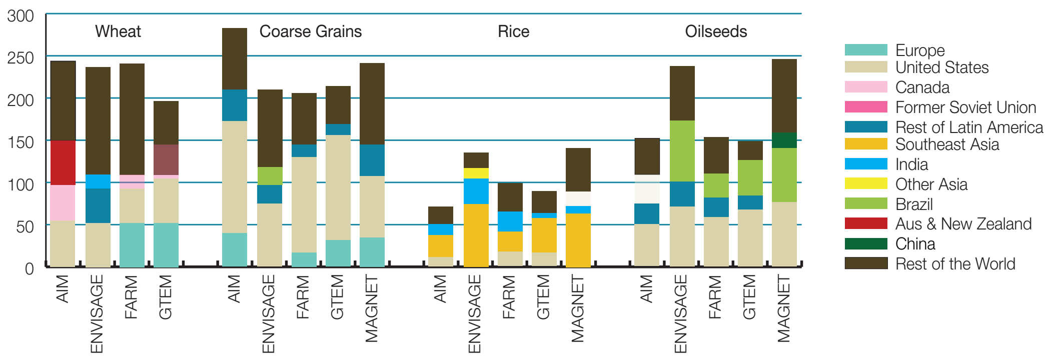
Figure 4 shows the growth in global exports relative to the growth in global production of five commodities and commodity groups (wheat, rice, sugar, coarse grains and oilseeds) under Scenario S1, simulated by the GE models. The solid line indicates equal growth rates in exports and production. As can be seen, exports of most commodities are projected to grow marginally faster than production.

Not all models have simulated exports and imports separately (see Section 2). In what follows, we focus on net trade – measured as exports minus imports, with a positive net trade quantity meaning net exports and negative quantity means net imports.

[4] As already indicated, the base data sets of these models were not harmonized. With GE models drawing on different versions of the GTAP database and PE models calibrated to FAOSTAT data but with different starting years, it proved challenging to harmonize the base data across models and therefore that was not undertaken as part of this AgMIP exercise (Nelson et al., 2013). However, for reporting and analysis, the model results for selected variables, including trade variables, were re-based, post-simulation, to the common base year of 2005.

figure 3

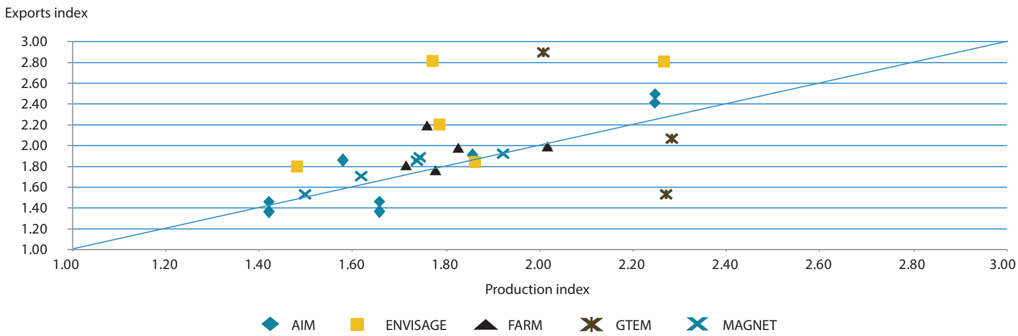
Export by commodity and region in 2050 under Scenario S1, million tonnes (Mt)



Source: AgMIP scenario results
Note: Results are only presented for GE models because PE models specify only net trade

figure 4

Index of export and production growth in 2050 under Scenario S1



Source: AgMIP scenario results

Note: Results are only presented for GE models because PE models specify only net trade

Most models project that the historical net trade status of key regions will be maintained until 2050 under Scenario S1 (Table 3). Countries with large and productive land areas are projected by most models to remain key exporters and most of the less-developed countries are projected to be key importers of agrifood commodities.

According to most models, the United States of America and the former Soviet Union will remain net exporters in wheat, and the United States of America and Latin America will be net exporters in coarse grains at 2050. In the case of rice, Southeast Asia, the United States of America and India are projected to remain net exporting regions. The main net importers of wheat, rice and coarse grains are projected to be countries in the Middle East, North Africa and sub-Saharan Africa. The United States of America and Latin America are projected to remain net exporters in oilseeds, with China a net importer.

5.2 Agrifood trade in 2050: A closer look at model agreement

As discussed above, there is some agreement across models in terms of key exporters and importers by 2050. Here, we explore further agreement among models, focusing on net trade results for key commodities and trading countries.

Most models project that the United States of America will remain a significant net exporter of coarse grains and oilseeds under all AgMIP scenarios in 2050 (Figures 5 and 6). GCAM is the exception, projecting that the United States of America will become a net importer of coarse grains by 2050. This result in GCAM is primarily driven by the assumed corn ethanol production, which would increase corn demand by about 150 million tonnes per year between 2005 and 2050.

The agreement among models with regard to changes in net trade diminishes somewhat for the fast-growing developing economies. Some models project that China will become a net agricultural importer by 2050, whereas other models suggest that low population growth and rapid productivity growth will ensure that China remains a net exporter. Given its growing importance in the global economy, the results for China have a significant impact on global trade.

The projected net trade in coarse grains and oilseeds of China in 2050 are presented in Figures 7 and 8, respectively.

As can be seen from Figure 7, some models project that China will become a net importer of coarse grains by 2050. Others project that China will remain mostly self-sufficient for coarse grains, as in recent years, when net trade was less than *table 3*

Net importers and net exporters under Scenario S1 in 2050, by commodity

Commodity	Net importer	No of models	Net exporter	No of models
Coarse grains	China	5 of 9	Europe	5 of 9
	Middle East; North Africa		India	7 of 8
	Sub-Saharan Africa	All	Rest of Latin America	6 of 9
		6 of 9	USA	7 of 8
Oilseeds	China	7 of 9	Brazil	All
	Europe	All	Rest of Latin America	All
	India	6 of 8	Sub-Saharan Africa	5 of 9
			USA	All
Rice	Europe	7 of 9	China	6 of 9
	Middle East; North Africa	All	India	5 of 8
	Sub-Saharan Africa	All	Southeast Asia	7 of 9
			USA	6 of 8
Wheat	Europe	5 of 9	China	5 of 9
	India	5 of 8	Former Soviet Union	7 of 9
	Middle East; North Africa	All	USA	7 of 8
	Sub-Saharan Africa	All		

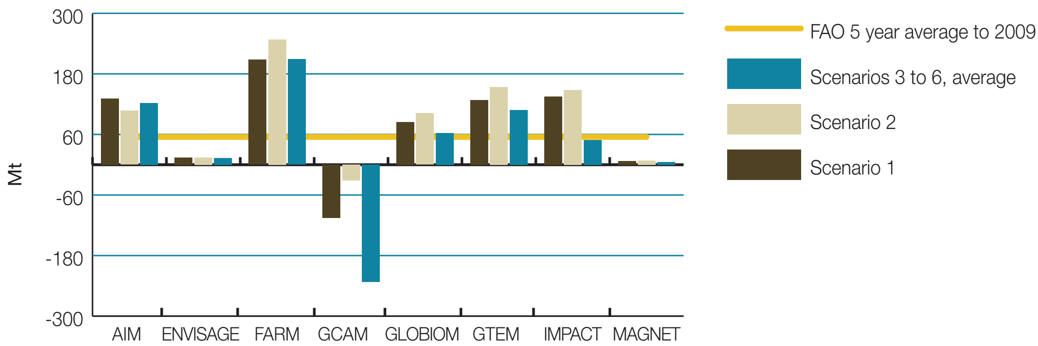
1 percent of domestic supply. For oilseeds, where net imports accounted for about 35 percent of domestic supply in the base year, the models also generally project this pattern to continue, with the exceptions of GCAM, MAgPIE, and MAGNET (Figure 8). However, GCAM projects that China will become a significant net exporter of both coarse grains and oilseeds by 2050.

Notable disagreement among models in projected net trade also appears in the case of rice trade in India (Figure 9). Currently, India is largely self-sufficient in rice. Most of the GE models project relatively small changes in its net rice trade by 2050. Interestingly, among the PE models, GCAM and GLOBIOM project that India will become a significant net importer by 2050, driven by an approximate doubling in food demand over this time, consistent with the assumed population and income growth. In contrast, despite similar assumed growth in food demand, IMPACT projects that India will become a net exporter in the S1 and S2 scenarios. This is because, compared with GCAM and GLOBIOM, IMPACT projects a relatively strong income-related shift from rice towards other commodities, predominantly dairy, wheat and sugar crops (not shown in Figure 9).

Consistent across models is the increasing import dependency of sub-Saharan Africa for staple commodities such as wheat, rice and coarse grains (Figures 10, 11 and 12). Figure 10 shows projections for net imports of wheat into sub-Saharan Africa in 2050, with IMPACT projecting larger and ENVISAGE and MAGNET projecting lower net imports, relative to other models. Sub-Saharan Africa currently imports a large volume of rice and all models project this situation to continue until 2050 (Figure 11). However, IMPACT among the PE models and

figure 5

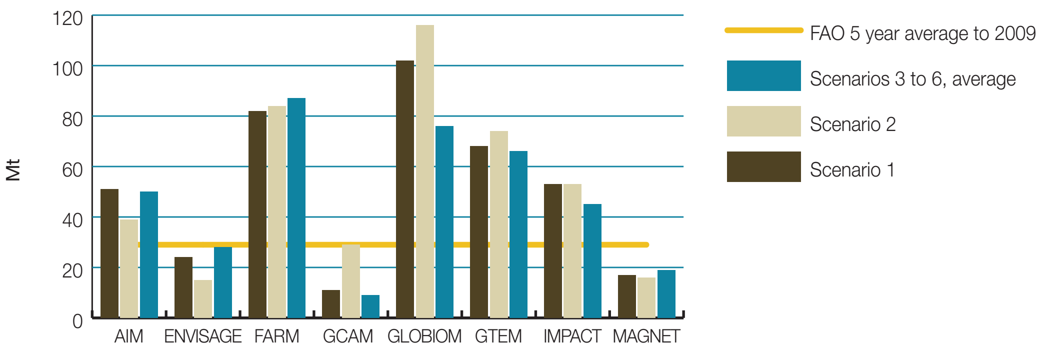
Net trade in coarse grains in 2050, the United States of America



Source: AgMIP scenario results

figure 6

Net trade in oilseeds in 2050, the United States of America



Source: AgMIP scenario results

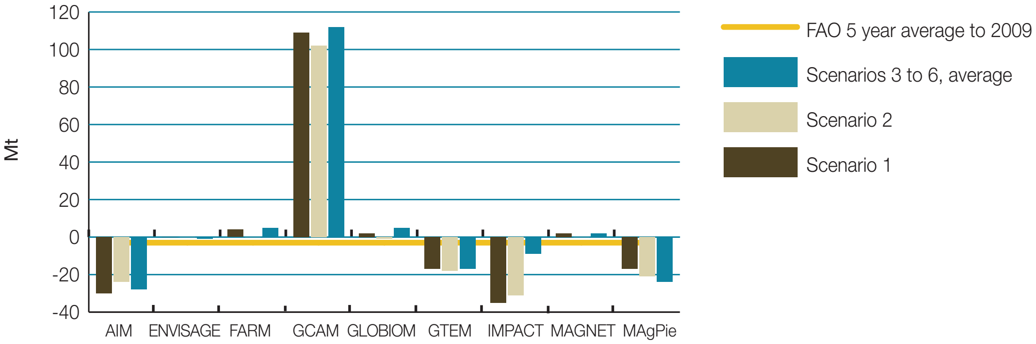
GTEM among the GE models project the largest net import volumes for all AgMIP scenarios under consideration. By 2050, most models project that net imports will make up between 30 and 50 percent of rice consumption in sub-Saharan Africa (with the highest rates projected by IMPACT). As for the coarse grains, a majority of the models suggest that sub-Saharan Africa will remain a net importer in 2050, with the PE models (particularly IMPACT and GCAM) projecting substantial import dependence (Figure 12).

5.3 Key drivers of trade: Degree of model agreement

Most of the projected changes in agrifood production and consumption, and thus changes in international trade in these commodities over the projection period, are driven by economic and population growth. Comparing results for scenarios S1 and S2 also gives some insights into likely implications of lower global economic growth and the distribution of global economic and population growth. While most models show

figure 7

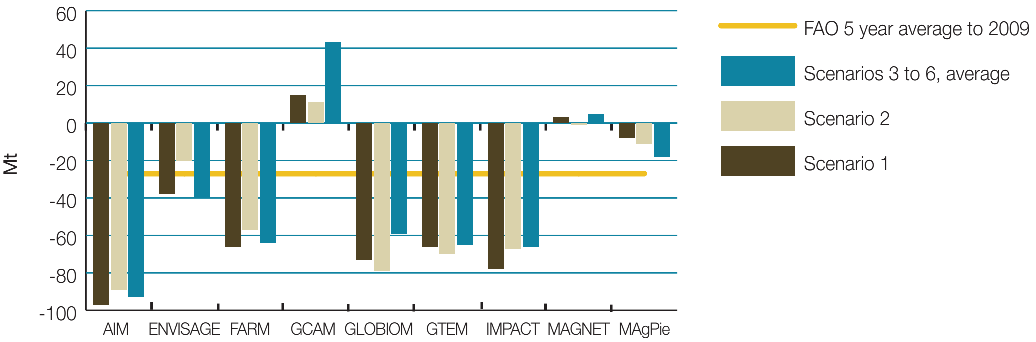
Net trade in coarse grains in 2050, China



Source: AgMIP scenario results

figure 8

Net trade in oilseeds in 2050, China



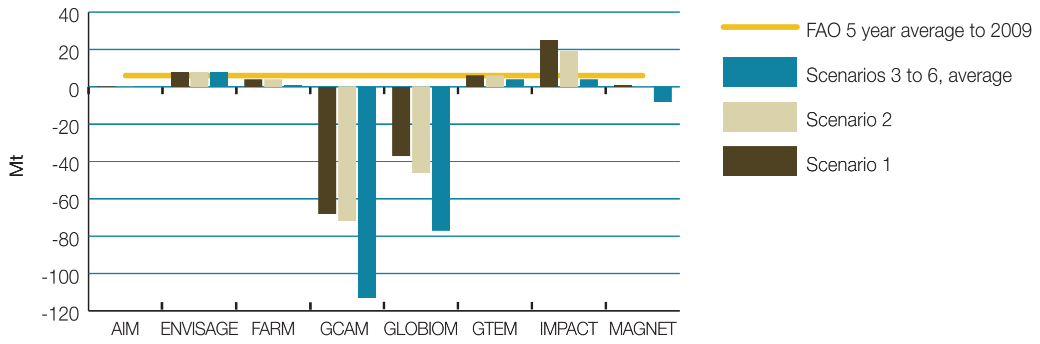
Source: AgMIP scenario results

changes in net trade arising from the changes in key socio-economic drivers, i.e. GDP and population growth (Figures 5 through 12), the magnitude of the change in net trade varies across models. Furthermore, the direction of change is not uniform across models. For GCAM, changes from base-year trade patterns typically arise from relative forces of the assumed demand drivers – i.e. changes in socio-economic drivers and future agricultural productivity, as well as biofuel mandates assumed for GCAM modelling. Model agreement in terms of direction of changes also seems to vary across commodities depending on the size of the net trade volumes in the initial years of the modelled period. More specifically, the degree of model disagreement is found to be high for small net trade volumes (for example, rice trade for India and coarse grains trade for China) compared to large net trade volumes (for example, coarse grains and oilseeds trade for the United States of America and wheat and rice trade for sub-Saharan Africa).

Another key production and trade driver, included in AgMIP scenarios 3 through 6, is

figure 9

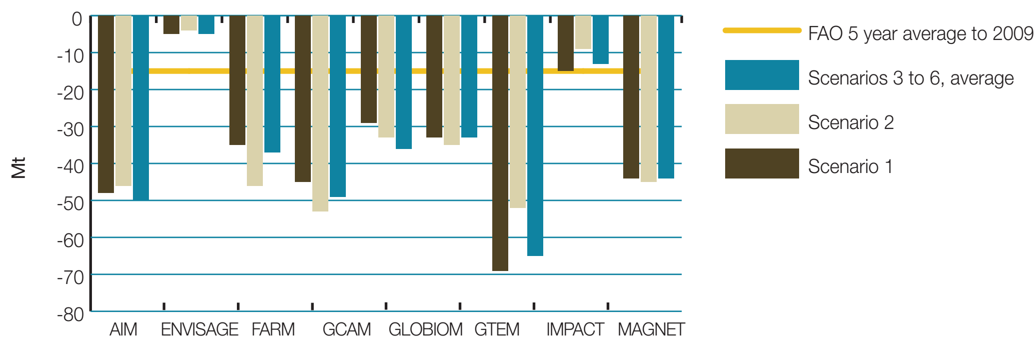
Net trade in rice in 2050, India



Source: AgMIP scenario results

figure 10

Net trade in wheat in 2050, sub-Saharan Africa



Source: AgMIP scenario results

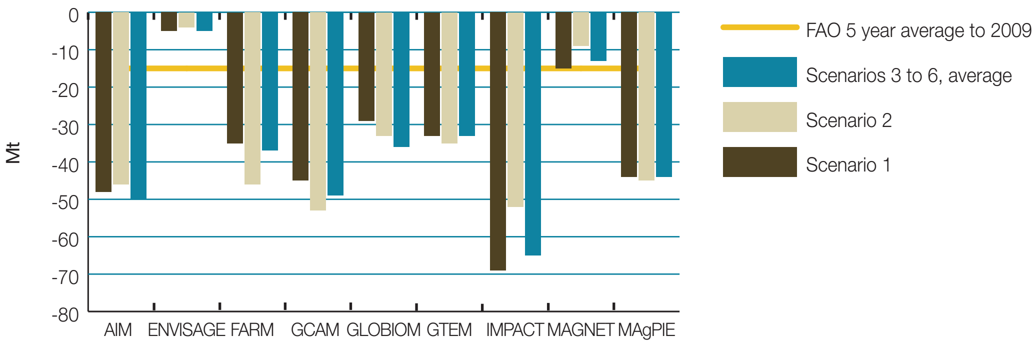
climate change impact.[5] While all models simulate reportable impacts on net trade (with varying directions and magnitudes) associated with climate change, with the exception of a few cases, the models projected no change in the net trade status in 2050 of the key exporting and importing countries and commodities considered in Figures 5 through 12.

Most models have projected that climate change will have some negative effect on coarse grains and oilseeds exports from the United States of America (Scenarios S3 to S6 relative to Scenario S1, Figures 5 and 6). However, according to results from the crop models used in the AgMIP study, crop yields in the United States of America are

[5] It is important to note that, although the implications of the socio-economic and climate change drivers for production and trade have been identified and analysed separately, the model results for the climate scenarios indeed represent outcomes of interactions between these two sets of drivers. In addition, impacts of climate change on GDP and/or population growth were not simulated, given the way the underlying scenarios were modelled. However, the models do generate impacts on food prices and consumption under various scenarios; these have been discussed extensively in von Lampe *et al.* (2014) and are therefore not repeated here.

figure 11

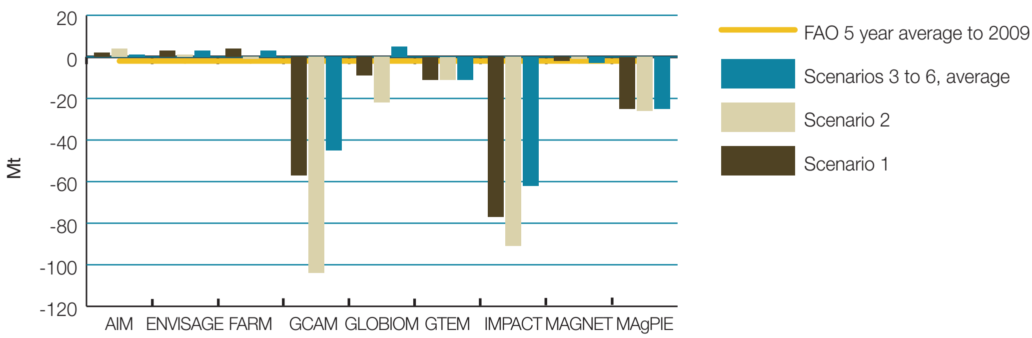
Net trade in rice in 2050, sub-Saharan Africa



Source: AgMIP scenario results

figure 12

Net trade in coarse grains in 2050, sub-Saharan Africa



Source: AgMIP scenario results

generally less affected by climate change than in other countries/regions, and consequently the impacts on the net exports from the United States of America are also projected to be relatively small, with the exception of GCAM and IMPACT models for coarse grains, and GLOBIOM and GCAM models for oilseeds. According to most models, projected impact of climate change on Chinese trade in coarse grains and oilseeds will be a reduction in net imports (Scenarios S3 to S6 relative to Scenario S1, Figures 7 and 8). A majority of models suggest somewhat increased import dependency for rice and wheat in sub-Saharan Africa (Scenarios S3 to S6 relative to Scenario S1, Figures 10 to 11).

The error bars in Figures 5 to 12 reflect the projected minimum and maximum net trade across Scenarios S3 to S6. All the PE models, apart from MAgPIE, show far larger variations in net trade across the various climate change scenarios than the GE models. This may be linked to the ways these two types of model specify international trade.

5.4 Production-exports nexus: Degree of model agreement

Figure 13 shows the difference between Scenario S2 and Scenario S1 in the projected volumes of global production (on the horizontal axis) and exports (on the vertical axis) in 2050 for the following crop commodities: wheat, rice, coarse grains, sugar and oilseeds. Only results from GE models are considered, as PE models only consider net exports for modelled regions (and the global sum of net exports is zero). Modelling results presented show a positive correlation between projected changes in production and projected changes in exports. That is, if global production is projected to rise (or fall) by 2050 under Scenario S2 relative to Scenario S1, then exports are also projected to rise (or fall) by 2050 under Scenario S2 relative to Scenario S1, with the exception of MAGNET projections.

There is no consensus among models on whether global production and exports will be higher under Scenario S2 than under Scenario S1. Relative to Scenario S1, ENVISAGE projects strong declines in global production and exports under Scenario S2, whereas GTEM projects strongly rising production and exports. With faster population growth under Scenario S2 relative to Scenario S1, food consumption and production are expected to increase. A slower income growth under Scenario S2 relative to Scenario S1 would have the reverse effect for most goods. With relatively high income elasticities, slower income growth could drive declining food demand despite increasing population.

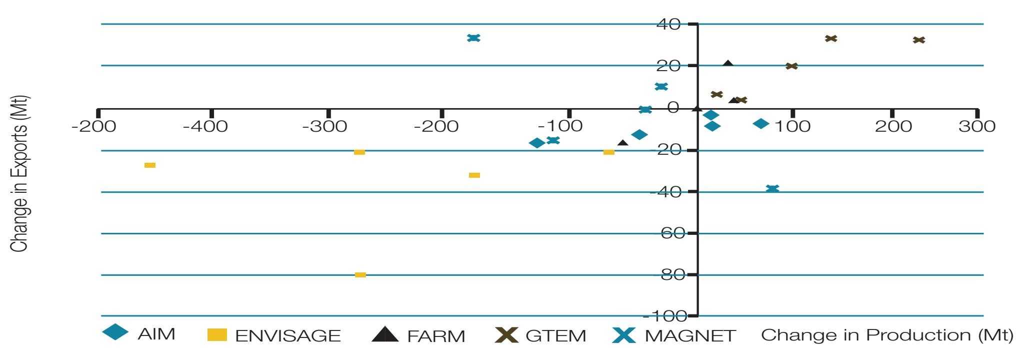
Figure 14 plots the projected changes in global production and exports for all modelled crops in 2050, similarly to Figure 13, but under climate change Scenarios S3 to S6 relative to Scenario S1. Each point in Figure 14 represents the likely impacts of climate change by 2050 on the production and exports of a particular crop projected by a particular GE model. Virtually all models project lower global production for all modelled crops under climate change. Most models project exports to decrease by much less than the projected decline in production or, interestingly, to increase against declining production under Scenarios S3 to S6 relative to Scenario S1. This seems to suggest an increasing role of trade under climate change.

6. Discussion and conclusions

The modelling results confirm that economic growth and population growth will continue to drive

figure 13

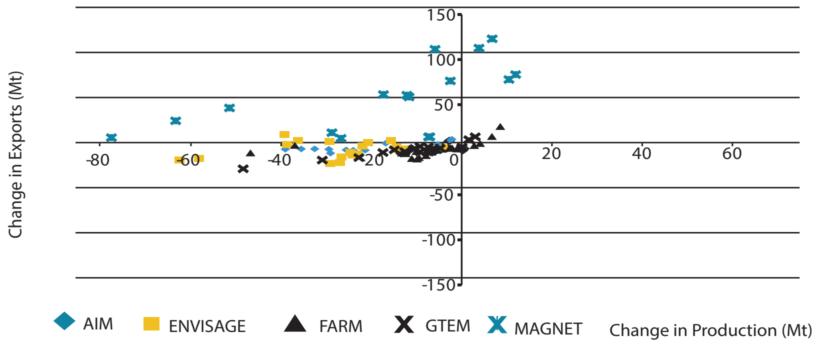
Changes in global production and export volumes in 2050: Scenario S2 relative to Scenario S1



Source: AGMIP modelling results
Note: Results are only presented for GE models because PE models specify only net trade

figure 14

Change in global production and export volumes in 2050: Scenario S3 to Scenario S6 relative to Scenario S1



Source: AGMIP modelling results
Note: Results are only presented for GE models because PE models specify only net trade

international trade. Most models suggest that the net trade status of key exporting and importing countries/regions would remain the same in 2050 under various AgMIP scenarios considered in the paper, even when climate change is taken into account. However, the results have only focused on few important traded commodities and major exporters and importers.

There are significant differences across models in terms of projected trade in key commodities. The differences in model results seem to be somewhat heightened in cases of small trade volumes involving less-developed and/or fast-developing countries. For example, the projected capacity of China and India to meet domestic demand for key commodities varies significantly across models under the scenarios considered. A close assessment of land supply and land use would reveal additional reasons for the lack of model agreement.

PE models and GE models specify and treat trade differently, which seems to influence model results in many cases. In some cases, small initial values for trade can restrict its growth in GE models, to well below estimates from the PE models. In other cases, the "Armington" product differentiation assumption (or the lack of it) can lead to very large differences in projected trade patterns across models. This area of modelling warrants further investigation.

Despite the differences, modelling results in this chapter seem to suggest an enhanced role for international trade under climate change. Virtually all GE models project global production of key crops to be lower under climate change than otherwise. Most models also project exports to decrease by much less than the projected decline in production attributable to climate change. Some even project exports to increase against declining production due to climate change.

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