Predicting Long Term Food Demand, Cropland Use and Prices

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Abstract: This paper seeks to survey, understand and reconcile the widely divergent estimates of long run global crop output, land use and price projections in the current literature. We begin by reviewing the history of such projections and the different models and assumptions used in these exercises. We then introduce an analytical partial equilibrium model of the global crops sector which provides a lens through which we can evaluate this previous work. The resulting decomposition of model responses into demand, extensive supply and intensive supply elasticities offers important insights into the diversity of model parameterizations being employed by the existing models. This, along with the methodology for implementing productivity growth, helps explain some of the divergences in results. We conclude the review by employing a numerical version of the analytical model, which serves as an emulator of this entire class of models, in order to explore how uncertainties in the common underlying drivers and economic responses contribute to uncertain projections of output, prices and land use in 2050. We place each of the published estimates reviewed within this paper into the resulting empirical distribution of outcomes at mid-century. In addition, we quantify the sensitivity of these projections to model inputs. Our findings suggest that the top priority for future research should be improved estimation of agricultural factor supply elasticities – a topic which has been largely neglected in recent decades.

Keywords: Agricultural output, crop prices, land use, projections, total factor productivity, food security

Glossary

AgMIP	Agricultural Model Intercomparison and Improvement Project
AIM	Asian-Pacific Integrated Model
CGE	Computational General Equilibrium Model
CR5	Cereals/Oilseeds/Sugar composite
ENVISAGE	Environmental Impact and Sustainability Applied General Equilibrium Model
FARM	Future Agricultural Resources Model
GCAM	Global Change Assessment Model
IAM	Integrated Assessment Model
IFPRI	International Food Policy Research Institute
IIASA	International Institute for Applied Systems Analysis
LEITAP	Landbouw Economisch Instituut Trade Analysis Project
MAGNET	Modular Applied GeNeral Equilibrium Tool
MAgPIE	Model of Agricultural Production and its Impact on the Environment
MMT	Million Metric Tons
SIMPLE	Simplified International Model of agricultural Prices, Land use and the Environment
SSP	Shared Socio-economic Pathways
TFP	Total Factor Productivity
USDA	US Department of Agriculture

1. Introduction

1.1. Motivation

The sharp spikes in international crop prices since 2006 have led to a resurgence of interest in global food security. This has, in turn boosted concerns about the implications of expanding cropland cover and deforestation for the terrestrial environment as well as greenhouse gas emissions. What will be the environmental cost of feeding 9+ billion people in 2050? How much land will be required? In light of current and anticipated adverse climate impacts, concerns have also been raised about the long run trajectory of food prices. Given the importance of these issues, the wide range of projections of global crop output growth from 2005 to 2050 is rather disturbing, ranging from a modest 60% rise (Alexandratos and Bruinsma, 2012) to more than 100% (Tilman et al., 2011). Projected changes in crop prices are similarly diverse, ranging from a doubling under adverse climate impacts (Nelson et al., 2010) to a resumption of the historical, post-WWII downward trend (Baldos and Hertel, 2014). What is behind these divergent estimates for output growth and prices? What are the key drivers behind the long run agricultural trends and what can we say about their likely paths in the coming decades? How does underlying uncertainty in drivers and response parameters translate into uncertainty in long run output and prices? The goal of this paper is to review the literature and competing estimates of crop output, price and land use in 2050, evaluate this work within the context of a consistent, analytical framework, and establish a likely distribution for these variables at mid-century. We conclude the review by proposing a set of research priorities designed to facilitate improved predictions of long run agricultural output and prices at global scale.

1.2 Past as Prologue to the Future

Modern day concerns about the ability of the world to feed itself trace back at least to the end of the 18th century, when Malthus predicted widespread famine based on his assumption that agricultural production, growing linearly, would be unable to keep up with geometric growth in population (Malthus, 1888). His prediction was subsequently contested by Ricardo's more sanguine predictions based on rising productivity of land. Since then, there has been ongoing debate between the Malthusian and Ricardian views of the ability of the planet to feed an ever-growing population. In the latter half of the 20th century, the debate was highlighted by influential publications by the Club of Rome (Meadows et al., 1972), *The Population Bomb*, (Ehrilch, 1970), and *By Bread Alone* (Brown and Eckholm, 1974) among others, all taking a Malthusian view of the future. Ironically, these publications emerged during a period of rapid crop yield growth in important parts of the world, an outcome of the so-called 'green revolution.'[2] A relatively long period of robust yield growth and mildly declining prices was abruptly interrupted in 2006/2007 (e.g., online appendix Figure A1) and gave a stronger, and more recent, voice to the Malthusian view.

There are many factors behind the recent price surges (Abbott et al., 2011). During the two year period from 2005/6 to 2007/8, half of the global growth in cereals demand can be attributed to increased ethanol production in the US (Westhoff, 2010). With biofuels drawing down stocks of grains and oilseeds, the world was left vulnerable to supply side shocks (Abbott et al., 2011, 2009). This 'perfect storm' placed the future of food and agriculture back on the

[2] Attributed to William Gaud in 1968, then Administrator of the U.S. Agency for International Development (http://www.agbioworld.org/biotech-info/topics/borlaug/borlaug-green.html).

policymakers' radar screens. The UK government initiated the Foresight Project that commissioned a substantive set of papers on various aspects of the future of food and agriculture summarized in its final report (Foresight, 2011). Several agencies issued major reports with conflicting views of long-term agricultural trends as reflected in agricultural price projections. On the 'pessimistic' side were IFPRI and Oxfam. IFPRI's 2010 report (Nelson et al., 2010) predicted increases of maize, rice and wheat prices of between 18 and 32 percent in the absence of any impacts from climate change by 2050, and between 31 and 106 percent with climate change, with particularly large increases for maize. Oxfam issued a report in 2011 (Oxfam, 2011) with much higher predicted price increases—close to a doubling by 2030 for maize, rice and wheat and substantially more incorporating climate impacts—an increase of nearly 180 percent in the case of maize.

Other institutions continued to be more sanguine. The World Bank's 2009 annual Global Economic Prospects Report (World Bank, 2009), with a focus on commodities, projected a continuation in the declining price trends through 2030. However, in keeping with the Malthusian spirit of the times, the report also explored alternative scenarios including a slowdown in productivity growth which led to modest price growth. Projections from the Netherlands based on the LEITAP model (see Prins et al. (2011)), were also suggesting price declines in their baseline through 2030—some 24-25 percent for temperate cereals and maize. These wildly divergent estimates precipitated establishment of the global economic analysis component of the Agricultural Model Intercomparison and Improvement Project (AgMIP) – results of which will be summarized below.

Before turning to a comprehensive review of crop output projections to 2050, it is useful to pause and reflect on historical projections of global crop output for which we can compare predictions to actual realizations. The first such comparison was undertaken at the request of the International Food Policy Research Institute (McCalla and Revoredo (2001)) and focused on past projections by FAO, IFPRI and USDA. As one would hope for with ‘learning by doing’, they find that the efforts associated with FAO’s projections of wheat production and consumption did, in fact, improve over time. In the appendix to this review (Appendix Table A2), we have updated/extended the McCalla-Revoredo evaluation of FAO forecasts. The FAO projections of global cereals production in 2000, made sixteen years earlier, in 1984, were just 2 percent over the actual value. Cereals output projected for 2015 in the year 1998 were just 7 percent below actual observation with the difference likely accounted for by the strong growth in corn ethanol production in the US. Of course, cereals demand has been the most stable type of food demand. Oilseeds have been far more dynamic and therefore more difficult to predict (Appendix Figure A2).

In their review of the performance of IFPRI and USDA projections, the findings of McCalla and Revoredo (2001) are less favorable. Here, the size of the errors seem to get larger, rather than declining with additional agency experience. They attribute this in part to the mandate for further detail in these models, as forecast errors appear to increase with greater disaggregation. Not surprisingly, McCalla and Revoredo (2001) also find that forecast errors were largest for small economies with low quality data and limited in-country expertise. However, there were also large errors in projections of North American and EU production and consumption changes. The authors attribute this to the challenge of modeling agricultural policies in those regions. McCalla and Revoredo (2001) conclude their report by cautioning against the use of global models to reach definitive conclusions about specific countries or regions. In keeping with their admonition, this review will focus primarily on global aggregates.

2. Overview of the Modeling Landscape

Table 1 lists the models encompassed by this review, and their key characteristics. Perhaps the most obvious distinction across models is whether the framework covers just the food sector (partial equilibrium: PE – top panel of Table 1) or whether it encompasses the full economy (general equilibrium: GE – bottom panel of Table 1), but many within each of the two categorizations are hybrids of standard formulations. For example, many of the partial equilibrium models have different spatial resolution between production and demand units, and this even exists to some extent in some of the general equilibrium models. Two of the frameworks are not truly equilibrium models at all. The FAO and Tweeten and Thompson frameworks are in the tradition of simple accounting frameworks with trend analysis that rely strongly on expert judgment.

The spatial dimension is categorized across both supply and demand sides. All of the GE models rely on some aggregation of the GTAP database (see Narayanan et al. (2015)) that may include large countries individually, but typically collapse global activity to between 20 and 30 regions. Using GTAP's supplemental Agro-Ecological Zones database (see Monfreda et al. (2009)), production within a region can be distinguished across up to 18 AEZs. The PE models specify demand at either an aggregate regional or country level. Supply, on the other hand, varies from the grid-cell level (MAgPIE, GLOBIOM), to sub-regional (that may be defined by AEZ or water basin), to national. For example, IFPRI's IMPACT model has a country resolution for demand (and trade), but sub-regional Food Production Units (which tend to follow major river basins) for production.

Figure 1 helps to conceptualize the major drivers of change on the demand and supply sides of the models listed in Table 1 by providing an overview of a generic model of long run global crop output, prices and land use. Starting at the top of Figure 1, we see that income per capita, population and biofuels are key drivers of change on the demand side. All of the models in Table 1 include population as an exogenous driver of the demand for food (hence the 'X' in the population column of Table 1). However, not all the models include an explicit representation of the links between income per capita, prices and food consumption – a point which deserves further discussion.

In some notable cases (FAO, GCAM), food consumption is specified exogenously, based on the idea of eventual convergence of caloric consumption. This means that food demand is unresponsive to the economic forces which may vary across scenarios. In the case of the FAO projections led by Alexandratos and Bruinsma (see for example Bruinsma 2003 and Alexandratos and Bruinsma 2012), the authors have made extensive use of in-house and external expertise in formulating these projections.[3] The final result can be usefully summarized in the form of an *arc elasticity* measuring the growth in global food demand for each one percentage point growth in global GDP (as a proxy for income). These are reported in the final column of Appendix Table A3 and suggest an arc-income demand elasticity for agricultural output between 0.15 and 0.24, depending on the time period considered. The most recent FAO estimates, from

[3] A core guiding principle of the reports has always been "… to describe the future as it is likely to be, not as it ought to be."

Kavallari et al. (2016), serve to reinforce the importance of the anticipated saturation effect.[4] With daily caloric intake of nearly 3,400 in developed countries there is not much room for increasing demand without exacerbating the obesity crisis or increasing the level of wasted food. Some developing countries are also approaching saturation levels—even if the dietary transition to more proteins (dairy and meats) is yet to be completed. In China, the world's largest food market, the FAO estimates daily per capita caloric intake at 3,108 in 2013, for example, but there is no doubt a wide household distribution underpins this figure.

Other models take the more conventional, top-down approach to determining consumer demands for food, using price and income elasticities of demand (Figure 1). Empirical evidence suggests that both the price- and income-responsiveness of consumers' demand for food becomes smaller in absolute value as households become wealthier (Muhammad et al., 2011) Some of the models in Table 1 seek to take this into account through a series of *ad hoc* parameter adjustments over the course of their simulation.

Of course it is not just final demand that is potentially responsive to prices. Intermediate demands by the livestock and food processing sectors are also potentially quite important. All of the GE models have both of these channels for determining aggregate agricultural demand. None of the PE models have food manufacturing sectors; a few incorporate the livestock sector and price sensitive feed demand (e.g., GLOBIOM, GAPS, IMPACT). Biofuel demand is included in most of the models as a long run driver. In the case of the partial equilibrium models, this source

[4] Despite the relatively large increase in rate of growth of per capita income, 0.6 percentage points (annualized basis) higher than the growth rate assumed in Alexandratos and Bruinsma (2012), the associated increase in the production growth rate predicted by Kavallari et al. (2016) is just 0.1 percentage points higher on an annualized basis than the earlier estimates.

of demand is typically exogenously specified, whereas in the general equilibrium models this may be related to the price of oil, as well as to government mandates which may, or may not be binding, depending on the oil price scenario (e.g., LEITAP). When these other sources of demand are also price responsive, we expect a larger farm level price elasticity of demand and a more muted market price responses to supply side shocks – particularly when the biofuel mandates are not binding.

The next set of columns of model characteristics identified in Table 1 are those associated with the price responsiveness of crop supply (see also the bottom portion of Figure 1). This depends critically on the scope for endogenous intensification – represented here was the potential for substituting non-land inputs for land, thereby increasing yields in response to scarcity (or the reverse in the case of crop surplus). In most cases, this intensification is viewed simply as increased application of variable inputs per hectare. However, in the case of the MAgPIE model, land scarcity engenders increased investment in agricultural R&D which, in the longer run, can generate higher yields (Dietrich et al., 2014). As shown in Table 1, several of the PE models *do not allow for such endogenous intensification* (FAO, GCAM, IMPACT, GAPS and T&T) – although some models allow for the choice between alternative fixed-proportion technologies thus exhibiting some substitution in the aggregate factor proportions (e.g., GCAM). As we will see below, these fixed proportions models tend to favor land conversion as an avenue for responding to scarcity in global food markets.

Virtually all of the market models in Table 1 rely on endogenous land supplies as a key factor in equilibrating long run supply with growing demands. However, as we will see below, the magnitude of this component – the extensive margin – of supply response varies greatly across models. The bottom portion of Figure 1 also highlights the role of non-land factor supply response to the crops sector. This is a largely overlooked constraint on long run crop output. Yet the supply of labor, capital, fertilizer and other non-land inputs to the farm sector can play an important role in constraining crop output expansion in response to food scarcity. Nearly all of the PE models ignore this element, thereby overstating the importance of land (and possibly water) as the sole constraining factors on the supply side. The fact that they explicitly incorporate non-land factor supplies is a strength of the GE models – although as we will see, the empirical basis for these non-land input supply elasticities is quite limited.[5]

The models listed in Table 1 also vary in the way they treat productivity. Some (most of the PE models) treat productivity growth as a shifter in the yield equation (YS in Table 1). Others (most of the GE models) treat productivity growth as a change in the parameters of the underlying crop production function (PF), in which case it becomes important to distinguish between input-augmenting and factor-neutral technological change. As we will see in Section 3, these differences can give rise to significant differences in long run output growth despite authors' assuming a common annual rate of crop productivity growth.

There are two broad strategies for specifying trade – and hence the equilibration of supply and demand at regional and global levels (center portion of Figure 1, see also final column in Table 1). The first is the homogeneous goods assumption (also known as Heckscher-Ohlin, or HO), where markets clear at the global level and changes in global prices are reflected

[5] An additional strength of GE models, of which not enough is exploited, is that changes in market prices are necessarily reflected by changes in the cost structure. For example, if agriculture is small relative to the overall economy, and non-land factors and goods are mobile, price rises will be embedded in the non-mobile factor, i.e. land.

in equi-proportionate changes in domestic prices (in the absence of variable tariffs to neutralize changes in global prices). However, this type of model is also prone to large swings in individual commodity trade balances. As a consequence, two of the PE models impose assumptions on the degree of self-sufficiency required in each region. In the case of the FAO framework, projections are adjusted iteratively to maintain a relatively high-degree of self-sufficiency. This implies, for example, that Europe's potentially declining future demand will lead to declining production rather than an increased exportable surplus. MAgPIE incorporates exogenous assumptions on future food self-sufficiency ratios as a fundamental feature in the determination of agricultural trade.

The GE models listed in Table 1 implement the differentiated goods, or Armington (ARM) assumption. In this case, changes in the 'world' price of imported goods are typically fully transmitted into the domestic market. However, the domestic goods are assumed to be imperfect substitutes for the imported good (Figure 1, center section), and so their price will change less than proportionately with the international price. The precise outcome depends on the share of imports in domestic absorption and the degree of product differentiation. If goods, such as wheat, are close substitutes globally, then there is a high degree of price co-variance across regions.

A final difference between the PE and GE models is worthy of note and this has to do with the distinction between primary and processed goods. The PE models mostly focus on the production and consumption of primary agricultural goods. This has some appealing features, including the ability to more readily measure the availability of calories. The down-side is that in most cases producer prices are assumed to be the same as consumer prices and may overstate the impact of changes in food prices on household patterns of consumption. All of the GE models incorporate the processed food sectors. In the higher income countries, where much of the food consumption is based on processed foods, consumers are somewhat ‘insulated’ from changes in agricultural prices, provided the prices of non-farm, processing inputs do not also change. However, this framework makes it more difficult to measure food consumption at the household level (without supplemental information). This challenge is rendered even more difficult since a significant proportion of household consumption occurs outside the household (i.e. is embedded in the consumption of services—such as restaurants).

Having surveyed the modeling landscape, we are now in a position to begin to compare 2050 projections from these different models. However, given the wide differences in model structures, we find it useful to develop a common lens through which to view these results. We seek to boil their behavior down to a few key summary statistics which can be elicited from the models and compared to obtain insights about their different behaviors. The next section introduces this theoretical framework.

3. Theoretical Framework

In order to understand numerical differences across the diverse models and projections reviewed in this paper, it is helpful to collapse the conceptual model in Figure 1 down to simpler framework which can be manipulated and solved analytically. Here, we follow Hertel (2011) and aggregate the individual supply and demand responses up to the global level. This eliminates the role of international trade, and focuses attention on the global drivers and elasticities of supply and demand. We ignore intermediate crop demands, tracing all final demand back to the farm-gate. The other key simplification imposed here is the assumption that, in the spirit of the PE models, non-land factors of production are in perfectly elastic supply.

The associated behavioral equations are presently in differential form in Box 1. When filtered through the global economy back to the farm-gate, the price responsiveness of this global food demand is reflected in an iso-elastic demand curve with own-price elasticity $-\varepsilon^D < 0$/The system is subject to exogenous demand-side output shocks which we characterize in percentage change form as Δ_O^D (biofuels, income and population), as well as shocks to the supply of land for agriculture, Δ_L^S. Box 1 allows for three alternative types of productivity shocks, each of which has quite different consequences for long run output growth. These differences will prove important as we seek to reconcile results across global models. The following analysis tackles each of these, in turn.

3.1. Traditional supply-shifter approach to technological change

We begin with a commonly employed technological change assumption in agricultural economics which involves an exogenous trend in yields (output/hectare), Δ_L^D, which serves to dampen the derived demand for land (Box 1, equation 4). When combined, and solved for the equilibrium cumulative percentage growth in crop output over the projections period, we obtain:

$$q_O^* = \frac{-(\Delta_O^D + \Delta_L^S - \Delta_L^D)}{\varepsilon^{S,I} / \varepsilon^D + \varepsilon^{S,E} / \varepsilon^D + 1} + \Delta_O^D = -\varepsilon^D \frac{\Delta}{\eta} + \Delta_O^D \qquad (1)$$

Where $\eta = \varepsilon^{S,I} + \varepsilon^{S,E} + \varepsilon^D$ is the *aggregate economic response* to scarcity as evidenced through 'net demand growth' which is defined as $\Delta \equiv (\Delta_A^D + \Delta_L^S - \Delta_L^D)$, i.e. the rate at which growth in farm level demand, combined with land removals from agriculture, outstrip the exogenous trend yield growth. The crop commodity supply elasticity is broken into two components (Box 1; also recall Figure 1): the extensive margin $\varepsilon^{S,E}$ which summarizes the response of farmland to a rise in commodity prices, and the intensive margin: $\varepsilon^{S,I}$ which captures the potential for yields to rise endogenously in response to higher farm level prices.

Subtracting Δ_O^D from both sides of (1), it can be seen that, for positive net demand growth, $\Delta > 0$, output will grow more slowly than predicted by the exogenous outward shift in net demand, i.e. $q_O^* - \Delta_O^D = -\varepsilon^D(\Delta / \eta) < 0$, provided the combined supply response is positive, i.e. $\varepsilon^D / \eta > 1$. Conversely, when net demand growth is negative, the opposite will be true. These relationships are important when one seeks to compare projections of models in which economic forces are active, vs. those from models which are purely biophysical (e.g., FAO). Overall, in the period from 1961-2006, crop commodity prices fell by nearly one-third, suggesting that *purely biophysical models of this historical period would have understated observed output changes* – due to the fact that they ignored economic responses to this price decline. Indeed, this systematic under-prediction of output growth by the FAO is one of the central findings in the McCalla-Revoredo (2001) review discussed above. Our analytical framework explains why this result is expected. We summarize this important insight as follows: *Purely biophysical models of long run output determination will overstate output growth when net demand growth is positive, and understate output growth when yields are growing faster than the combined food demand and cropland supply shifts.*

In addition to the expression for the change in output, it will be useful to have at hand the companion expressions for the change in crop prices and land use as a function of the exogenous perturbations to this system:

$$p_O^* = \frac{\Delta_A^D + \Delta_L^S - \Delta_L^D}{\varepsilon^{S,I} + \varepsilon^{S,E} + \varepsilon^D} = \frac{\Delta}{\eta} \tag{2}$$

$$q_L^* = \varepsilon^{S,E} \frac{\Delta_A^D + \Delta_L^S - \Delta_L^D}{\varepsilon^{S,I} + \varepsilon^{S,E} + \varepsilon^D} - \Delta_L^S \tag{3}$$

In the next section, we will use the system of equations (1) – (3) in order to evaluate the behavior of the existing global economic models being used to project agricultural prices, output and land use.

As we saw in Table 1, it is not uncommon in the partial equilibrium models to omit one of the three key margins of economic response highlighted in this framework. Based on equations (1) and (2), we expect the models with endogenous supply response, but negligible demand response, might have an exaggerated price reaction to scarcity, while the output response will be muted. On the other hand, by equation (3), models which omit the intensive margin of supply response will have a tendency to convert more cropland.

3.2 Hicks-neutral production function approach to technological change

The preceding discussion was based on the common approach, in partial equilibrium commodity models, of including an exogenous yield trend in the model. However, this is inconsistent with the production function approach to long run projections. Indeed, simply inserting a shifter into the yield function ensures that the resulting evolution of output will be no longer lie on the underlying production function. Therefore, instead of an exogenous yield shifter, we introduce technological progress directly into the crop production function itself.

In the case of factor-neutral technological improvement ($a_O > 0$), solving the long run model in Box 1 for the percentage change in output as a function of this technology shock yields:

$$q_O^* = (\varepsilon_S + 1)\varepsilon^D a_O / \eta \tag{4}$$

This may be contrasted with the output impact of trend yield growth from the supply-shifter model in equation (1) which is: $q_O^* = \Delta_L^D \varepsilon^D / \eta$. Note that a one percent exogenous rate of growth in Hicks neutral technological change, $a_O = 1$, *is not equivalent* to a one percent rate of growth in yields. To we why, refer to the model of long run output growth in Box 1. The Hicks-neutral technological change, a_O, appears in two places in this model. Firstly, it appears in the derived demand equations for land and non-land inputs. Since non-land inputs do not constrain long run output growth, it is the derived demand for land equation which is of primary interest. In this case, a_O plays the same role as Δ_L^D. Both are subtracted from output growth, allowing for more output from the same amount of land.

However, note that a_O also plays another role in the model of long run output determination. In the first and second equations of Box 1, a_O is added to the percentage change in price, *thereby enhancing profitability in the sector*. Indeed, at constant prices for both output and non-land inputs $(p_O = p_N = 0)$, this technological innovation will result in positive profits, thereby encouraging entry into the sector. In long run equilibrium, with limited land, these enhanced profits will translate into higher returns to land $(p_L = \theta_L^{-1} a_O)$, where θ_L^{-1} is the inverse cost share of land. Of course with less than perfectly elastic demand for output, some (perhaps most) of these gains will be transmitted forward to consumers in the form of lower output prices. The fact that a Hicks-neutral productivity gain also affects profitability in the sector, means that we must factor in the sector's ability to respond to this change in profitability by boosting output, which explains the presence of an additional supply elasticity term in the numerator of (4). These theoretical insights may be summarized as follows: *In the presence of positive supply response, a Hicks-neutral shock to technology will always give a larger rate of long run output growth than an equi-proportional shift in the supply schedule. The larger the sectoral supply response, the larger will be this difference.*

3.3 Land-augmenting production function approach to technological change

In addition to Hicks-neutral technical change, the production function imbedded in the model in Box 1 also offers the possibility of biased, factor-augmenting technical change. In the context of the long run output projections discussed below, it is most common to utilize *land-augmenting* technical change, or, in terms of the equations in Box 1: $a_L > 0$. Solving the model for output growth as a function solely of this form of technological progress gives the following expression:

$$q_O^* = (\nu_L + 1)\varepsilon^D a_L / \eta \tag{5}$$

where ν_L is the area supply response to a one percent change in the land rental rate. As with the Hicks-neutral technical change, the land-augmenting perturbation affects not only the direct amount of input required (land in this case), but also the profitability of land use in the sector, thereby boosting the output response beyond that achieved with a simple supply shift.

Comparison with this Hicks-neutral outcome is facilitated by noting that the aggregate supply response is given by $\varepsilon_S = \theta_L^{-1}\nu_L + \sigma(\theta_L^{-1} - 1)$, where $\sigma \geq 0$ is the elasticity of substitution between land and non-land inputs. It is possible that a one percent rate of land-augmenting technological progress could result in the same long run output growth as the same rate of change in Hicks-neutral technology; however, this only arises in the unlikely case that land is the only input in production ($\theta_L = 1$). These insights may be summarized as follows: *Equi-proportional shocks to the Hicks-neutral and land-augmenting parameters in the agricultural production function will only give rise to equal rises in long run output when non-land inputs are negligible. In general, the Hicks-neutral shock will give rise to a larger change in output, with the difference increasing in both the cost share of non-land inputs rises and the elasticity of substitution between land and non-land inputs. When compared to output growth under the supply shifter approach, land-augmenting technical change will give a larger response, with the magnitude of this difference depending on the elasticity of cropland supply with respect to land rents.*

It will also be useful to have analogous expressions to equations (2) and (3) for long run changes in crop price and land use in the presence of both biased and neutral technological change. These are developed in the appendix and are used in the next section to back-out global supply and demand responses from the various models. Having these theoretical insights at hand, we are now ready to turn to a rigorous evaluation of the family of quantitative economic models currently being used to project long run changes in output, land use and prices to mid-century.

4. Global projections for crop output, prices and land use

Table 2 summarizes published projections to 2050 from the models discussed in Table 1. The first line reports FAO projections made in 2012. Here, total crop output is projected to grow by 52% over the 2005-2050 period. However, cereals output growth is just 41% over this period. The CR5 aggregate reported here includes oilseeds and sugar crops and shows a considerably higher cumulative growth rate (58%). This is all accomplished with very modest net growth in cropland (just 4%). As noted previously, the FAO approach to projections does not rely on market equilibrium and therefore does not generate a price change. More recent work at the FAO (GAPS) predicts a somewhat higher growth rate for global crops (60%). And, once the FAO approach is adjusted for more recent projections of global GDP growth (SSP2—see below), cereals growth rise to 57% period.) These estimates are broadly consistent with the projections by Tweeten and Thompson presented as ranges in the third row of Table 2. These depend on assumptions about underlying drivers of change. The lack of harmonization on these drivers has previously made comparison across model projections difficult.

The next set of entries in Table 2 are drawn from the models involved in the AgMIP global economic model comparison exercise. This effort was undertaken to highlight differences in projections across models, and to *improve* the models in terms of specification, parameterization, as well as implementation of assumptions on the evolution of technology and preferences over time. *To begin with, all models were harmonized to the same set of key drivers.* Population and GDP projections were taken from a preliminary version of the so-called shared socio-economic pathways (SSPs). The SSPs have been developed by the Integrated Assessment Modeling (IAM) community and are intended for broad use by all scientific groups working on long run analysis of climate change.[6] For the AgMIP exercise, SSP2—the so-called middle of the road scenario—was used as the baseline using the population projections from IIASA and the GDP projections of the OECD. The SSP2 projections have population increasing by about 40% between 2005 and 2050, and global GDP more than tripling (see Figure A3 in the Annex). The modeling teams also harmonized on a third set of drivers—IFPRI's so-called intrinsic productivity rates (IPRs). These were used as shifters (Δ_L^D) to yield functions in the partial equilibrium models and land-augmenting technological shocks (a_L) in the crop production functions of the general equilibrium models.[7]

The first three columns in Table 2 report indexes of the growth in global supply of cereals, a cereals/oilseeds/sugar composite (CR5), and total crops, from 2005-2050. When converted to levels, the first column may be compared with FAO's 2012 projection of around 3,000 MMT of cereal output in 2050.[8] The range of AgMIP outcomes for cereals production are relatively narrow, with the exception of the MAGNET model which predicts significantly higher growth (86%). It is perhaps not surprising that many of the projections are broadly consistent with the SSP2-adjusted FAO cereals projection of 57% growth.[9] This consistency is partly by

[6] A preliminary version (0.53) of the SSP projections were available at the start of the model comparison exercise. A newer version is now available.

[7] PIK's MAgPIE model only loosely calibrated to the exogenous yield shifters for specification reasons. As well, several of the CGE models also shocked labor-augmenting technical change. We will discuss this below.

[8] Taking into account the relative growth in agricultural production with the FAO's new model (GAPS) and the SSP2 projections, the current FAO projection is likely between 3,200 and 3,300 MMT.

[9] Almost all also show a declining demand growth trend—to be expected from a deceleration in population growth and declining income elasticities with income growth. On the other hand, greater feed requirements (driven by dietary shifts) and higher bio-energy demand could counteract the former effects.

design, as half of the modeling groups loosely calibrated their model's response to reproduce the FAO's arc elasticity of demand discussed above (Valin et al., 2014).

Comparison of column two, CR5 output growth, in Table 2, with the cereals output growth, clearly reveals that the strong historical growth in oilseeds is expected to continue. The growth rate in this broader composite is markedly higher than for staple grains alone – reaching more than 100% (an index of 208) in the case of MAGNET and a near doubling of CR5 output in most of the other models. Broadening the definition of output to *all crops* (third column of results in Table 2) introduces much greater variation in output growth. This is likely due to differing definitions of what is included in the crop aggregate, and less harmonization of underlying parameters for these other commodities.

Despite the apparent harmonization with respect to total output growth, there is less agreement on the evolution of prices across the AgMIP models (second to last column in Table 2). The median value for all crops in these simulations suggests a modest rise by 2050, which, if realized, would signify a reversal of the long run declining price trend over the last century (Appendix Figure A1). However, the range for the aggregate price index is very wide, extending from a decline of 16 percent to a rise of 46 percent, with half of the AgMIP models showing a price decline and half predicting a price rise over the 2005-2050 period, under SSP2, and in the absence of climate change impacts.

Turning to net cropland expansion, it is surprising that, for broadly comparable increases in crop production, changes in cropland over this period are surprisingly varied – ranging from a modest decline, in the case of the FARM model, to a large increase in the case of AIM and MAGNET. A number of the models are within range of the latest projections from the FAO, which suggest an increase of some 70 million hectares at the global level—to a total of 1,661 million hectares[10]—but half of the models are above this level, with the highest (MAGNET) projecting an increase of nearly 400 million hectares!

Some of these differences across projections can be readily explained by the differing assumptions about the underlying drivers of demand. Clearly slower income growth, compared with SSP2, plays a role in explaining the more modest growth in crop output under the FAO projections. However, this does not explain the differences across the model projections drawn from the AgMIP exercise as these drivers of demand have been harmonized. Understanding the remaining differences requires us to dig more deeply into the models' assumptions about supply and demand behavior (recall Figure 1). This is normally quite difficult to do. However, in the case of the AgMIP models, we are fortunate to have access to results from a series of exogenous, climate-motivated yield shocks which all of the modeling teams implemented. This allows us to back-out the implicit demand and supply elasticities for global crop output, which should aid in explaining some of these model differences.

Table 3 reports the implied, global supply and demand elasticities for each of the models in the AgMIP effort. In the case of the partial equilibrium models, all of which used the supply-shifter approach to technical change, this involved solving equations (1) – (3) for the underlying elasticities, given observed changes in output, prices and land use. (Since the technology shocks were only implemented for the CR5 crops, we use the results from the CR5 composite in these calculations.) In the case of the general equilibrium models, since the shock was applied to land-

[10] Alexandratos and Bruinsma (2012) use an adjusted number for the 2005/07 period that may not line up directly with the official FAO statistics.

augmenting technical change, the resulting equations are slightly different. (Compare, for example, equations (1) and (5). See the Online Appendix for detailed derivations and the algorithm for solving for the values in Table 3.)

Table 3 permits a number of important observations about these diverse models. First of all, the aggregate response of these models to economic scarcity varies greatly. With the exception of GCAM, which is a hybrid model designed as part of an Integrated Assessment modeling system and seeks to cover all land uses, the partial equilibrium models tend to have a much smaller elasticity total (first column). This point has been made previously by Hertel (2011) who hypothesizes that these settings may reflect the evolution of these agricultural commodity models from near term forecasting to long term projections frameworks. The only way to obtain the kind of crop price volatility observed on an inter-annual basis is to have a relatively low value for η, the total price elasticity (recall equation (2)). This is obtained in the commodity models by having small supply elasticities at the intensive margin – a point consistent with short run analysis. By contrast, the CGE models are not used for year-on-year forecasting, and price volatility is a lesser point of emphasis. Furthermore, the supply elasticities are functions of deeper parameters (Robinson et al., 2014) which are consistent with longer run, equilibrium assumptions. Thus we see in the CGE models larger aggregate responses to scarcity, with the supply side of the market dominating the overall price responsiveness.

As we look through specific models in Table 3, a number of points stand out. MAgPIE, for example, has, by design, exogenously specified demand. Based on equation (1), this means that output growth will not respond to scarcity, being driven instead by the exogenous demand shocks. Overall, the CGE models appear to have relatively small farm-level price elasticities of demand. This is likely a function of the fact that very little of the crop commodity is sold directly to consumers in a CGE model. Rather, it must first pass through multiple processing activities, which tend to mute the farm-level price responsiveness of final demand.

There are also a number of counter-intuitive signs in Table 3. (Due to our definition of the demand margin, all expected signs are positive.) This is presumably due to compositional effects. For example, the MAGNET model has very large land supply elasticities and relatively small intensification elasticities, suggesting that the main response to adverse technological change (i.e., a negative climate change impact) will be to bring in more cropland area. Given the trade specification (segmented markets via the Armington assumption), if the adverse climate shocks are largest in regions with relatively low yields, this is where the price rises will be largest. If, in addition, these regions also have large land supply elasticities (e.g., Africa), then we expect strong expansion in low-yielding land areas. This would result in a decline in global average yields for grains and oilseeds in MAGNET. This outcome is observationally equivalent to a negative intensive margin when viewed at global scale through our conceptual lens, which is why we see the negative entries in the final column of Table 3. AIM and FARM (also Armington models) show negative intensive margins at global scale, as do IMPACT and GCAM. In these cases, this is due to the absence altogether of intensification possibilities, combined with a compositional effect.

With this information from Table 3 in hand, we can now return to Table 2 and explain why the ENVISAGE model has the strongest output growth. Despite a modest price rise, crop output expands by 108% over the projections period. This is consistent with the very strong supply response in this model. It is also now clear why MAGNET, AIM and ENVISAGE predict so much cropland conversion between 2005 and 2050. These are all models where the extensive margin of supply dominates the total economic elasticity. By the same token, this comparison raises a puzzle with respect to GCAM, and especially the FARM model. In both cases, the extensive margin dominates the total elasticity, yet cropland growth is more muted – indeed cropland is lower in 2050 than in 2005 in the case of FARM. This may be due to the assumptions about land mobility within AEZs which is quite different from the other models (Sands, Jones and Marshall, 20014).

The preceding discussion highlights the challenges of obtaining a consensus from the global models currently in use. Despite the involvement of top flight researchers in the AgMIP model inter-comparison exercise, and the expenditure of significant resources by ten[11] different modeling teams over several years, the final set of projections for prices and cropland use remain quite different, and, more importantly the differences cannot be fully explained. We are left wondering: How great is the underlying uncertainty about total crop output in 2050? In order to advance the science in this area, we return to the stylized framework outlined in Figure 1 and Box 1 and develop an emulator[12] which provides a numerical lens through which to view the interplay of drivers and economic responses in determining global crop output, price and land use projections to 2050.

5. Emulator analysis of cropland, output and prices

[11] We report the results from 9 of the 10 teams that participated. The 10th model, EPPA based at MIT, did not have the agricultural resolution for a full model comparison.

[12] Emulators are common in climate science, where it can take months to complete a full scale simulation experiment. They typically comprise a few key equations which are capable of broadly replicating key relationships in the detailed models, but at global scale.

Return for a moment to Box 1 which offers a simple, theoretical framework for thinking about the long run evolution of the global crops sector. With a few modifications, this can be expanded to reflect the key features of the projections problem as identified in Figure 1. This includes: (a) adding a regional index, (b) including a specification for trade – here we choose to follow the Armington (segmented markets) hypothesis, and (c) allowing for the less than perfectly elastic supply of non-land inputs. In addition, to adequately emulate the models used in this area, we separate out three sources of farm level demand for crops: livestock feed, processed foods and direct crop consumption. Such a model can be readily calibrated to the same international data sets as used for the models in Table 1 (Baldos and Hertel, 2013) and its simplicity allows for a more comprehensive uncertainty quantification of long run projections for the global crops sector.

All of the emulator's elasticities and demand drivers are summarized in Table 4. These are drawn from the same basic sources as the global models listed in Table 1 (see online Appendix for additional details). In addition to the most likely values for each parameter (the mode – listed first), we also provide likely maximum and minimum values in each case. This permits us to consider the full distribution of results for 2050. (For the sake of consistency, we have adopted the same population and income growth rates as used in the AgMIP inter-comparison study, namely those from SSP2.) Unlike the AgMIP partial equilibrium models, productivity growth is treated through shifts in the production function rather than in yields. In order to shed additional light on the CGE results which also incorporate such production function shifts, we explore two alternative simulations in the online appendix, in the first case, in the second to last row (EMULATOR*) we follow the lead of the AgMIP CGE models and interpret the intrinsic rate of productivity growth as a shock to land-augmenting technical change. In order to ensure an overall rate of TFP growth consistent with historical experience, we also shock non-land augmenting technical change using the global projections from Ludena et al (2007), along with regional scaling factors from Fuglie (2012). This is roughly consistent with several of the AgMIP/CGE studies which also shocked some elements of non-land factor productivity. (This aspect of their experiments was not harmonized.) In this case, crop output is projected to grow by 79%, while crop prices fall and cropland expands by 19%. Compared to the AgMIP models, these projections are most similar to those of MAGNET, although crop land expansion is less dramatic in the Emulator, due to that model's relatively greater reliance on the intensive margin of supply (Table 3, bottom row).

The final row in Table 2 (Emulator**) shows the outcome if non-land inputs do not experience productivity growth. As anticipated by our theoretical analysis, the projections are now dramatically different. Output growth is 18 percentage points lower, crop prices rise by 26% and cropland expansion is much higher when non-land factors do not become more productive. This makes it very clear why the CGE modelers in the AgMIP exercise chose to increase non-land as well as land productivity in their 2050 projections. However, since those shocks were not harmonized across GE models, it is difficult to say much more about this important aspect of the projections.

The objective of introducing this emulator is to explore the interplay between the uncertainties in economic drivers, supply and demand parameters, and the crop sector outcomes in 2050. We begin this uncertainty quantification with a Monte Carlo analysis, for which we run the model 5,000 times, each time drawing a different combination of parameters from the distributions outlined in Table 4. Given the straightforward nature of this methodology, it is perhaps surprising that there are not more such analyses already available in the literature.

However, most global models of agriculture are quite large, with many parameters, and the computational burden is therefore significant – hence the value of the emulator approach.

Figure 2 reports the distributions for key model outputs at global scale based on the 5,000 simulation samples. Note that the distributions of these global changes are skewed to the right, highlighting the fact that there are critical combinations of external drivers and economic parameters which could give rise to extremely high values in these global variables. For example, in the few emulator's simulations which predict a 50% increase in global crop prices, population and income projections are at the upper end of their distribution while crop TFP growth and non-land supply elasticities are at the lower end. Mean values from the Monte Carlo analysis are reported with the dashed line. They predict output growth and cropland expansion over the 2006-2050 period of 102% and 20%, respectively. The expected value for the change in crop price is virtually flat at -3% with 66% of the simulated price changes predict falling or declining crop prices and 34% predicting price rises. However, if we only rely on the modal input values from Table 4, we see more modest changes in global crop production and cropland use (85% and 12%, respectively), while crop prices are expected to fall by 13%. These results highlight the importance of estimating the full distribution of outcomes if one wishes to obtain an accurate estimate of the expected values of key variables. Simply projecting modal outcomes does not factor in the long right-hand tail in these figures.

We have super-imposed the model projections from Table 2 onto the distributions in Figure 2 in order to see where they fall within this distribution of emulator outcomes. From this, it is immediately clear that the emulator framework is potentially consistent with nearly all of the individual predicted outcomes from all of the different models. For example, both the 16% crop price decline projected by MAGNET and the 46% price rise from AIM fall within the overall distribution of price outcomes in Figure 2. However, this distribution also suggests that the AIM results is an extreme outcome –lying outside the emulator's 95% confidence interval denoted by the red bars. With the exception of the early FAO estimate (slow GDP growth), AIM, MAgPIE and GAP, , all of the other models fall within the 95% confidence interval of outcomes from the emulator. As noted above, cropland results are the most diverse. This is likely due to the diversity of approaches in modeling technological progress, which, as we have seen from Section 3, has critical implications for the derived demand for land. Nonetheless, six of the nine model projections fall within the 95% confidence interval. (The negative growth in cropland from FARM is not shown in the Figure.)

The real payoff from developing this global crop model emulator is that it allows us to undertake comprehensive screening of the role of underlying parameters in determining uncertainties in 2050. Figure 3 reports the relative importance of each uncertain model input (recall Table 4) in the determination of the final changes in crop price, production and land use. These have been computed using the Morris Method, which perturbs individual drivers and economic parameters one-at-a-time across their full distribution in order to elicit the impact of elementary effects of each model input, allowing identification and ranking of critical model variables (Morris, 1991). In light of the theoretical discussion above, it is hardly surprising that crop TFP growth is the most important input in driving future crop price uncertainty. If we wish to improve our understanding of the long run trajectory of food prices, we must focus on improving the accuracy of our projections of future TFP growth (Dietrich et al., 2014). This must begin by focusing on the determinants of agricultural productivity, which are closely tied to research and development expenditures (Alston et al., 2009; Fuglie, 2012). Improved understanding of future TFP growth will also play a significant role in dictating future crop production and cropland where it ranks 6th and 8th in importance.

More surprising is the second-most important contributor to global price change uncertainty in Figure 2 – the elasticity of supply of non-land inputs to crop production. This is a parameter which receives almost no attention in the contemporary agricultural economics literature, yet it ranks 2nd, 5th and 6th in relative importance in driving future changes in price, production and land use. As noted previously, the relative sizes of the land and non-land elasticities of factor supply used here are obtained from a series of literature reviews commissioned by the OECD (OECD, 2001). Those studies cite mostly much older literature. Labor supply to agriculture was a central issue for Nobel Laureate T.W. Schultz (Schultz, 1951) and his students at the University of Chicago (Tyrchniewicz and Schuh, 1966; Sumner, 1982). As Schultz anticipates in his 1951 paper, titled "The Declining Importance of Agricultural Land" (Schultz, 1953), non-land inputs – in particular labor and capital – have become the dominant inputs in the global agricultural production function (see also Just and Pope, 2001). It is high time that the economics profession revisits the problem of measuring the responsiveness of non-land input supply to agriculture.

Equations (1) – (3) highlight the critical role of demand growth determining the long run evolution of the crops sector. From Figure 3 it is clear that demand growth is driven by income per capita (ranking 2nd – 3rd in Figure 3) and population (ranking from 4th – 7th in relative importance), as well as the economic responsiveness of demand to income growth. The elasticity of land supply is also a key parameter – particularly when it comes to cropland expansion (1st in relative importance). The intensification parameter (elasticity of substitution between land and non-land inputs in the crop sector) ranks 2nd to 11th in relative contribution to changes of the variables reported in Figure 3. However, the other variables are typically in the bottom half of the relative importance plots for global outcomes in Figure 3 and appear to be factors which should attract lesser priority if the goal is to reduce uncertainty about long run crop production, prices and land use.

5. Summary and Conclusions

This paper has reviewed the literature on long run projections of global crop output, prices and land use, begun nearly half a century ago in the midst of an earlier 'food crisis'. The world has recently been through another period of high and volatile food prices which has precipitated a flurry of new projections to 2050. Of particular note is the AgMIP effort which sought to harmonize inputs into ten global economic models, comparing the resulting projections. However, the projections for the global crops sector nonetheless vary quite widely. We trace part of this variation back to the underlying supply and demand responses in these models, as well as their treatment of technical change which proves to be a critical driver of future crop output and prices.

In an effort to better understand the sources of uncertainty in crop output, prices and land use in 2050, we create an emulator, designed to capture key features of the models reviewed in this paper. This allows for a comprehensive uncertainty quantification which reveals a very broad distribution of potential outcomes for these global variables. Importantly, the distributions are all rightward-skewed, such that *the expected values for global crop output, price and land use in 2050 are all higher than the point estimates obtained by simply using the most likely input values for the underlying drivers and economic response parameters*. Based on the mean outcomes from these distributions, crop prices are expected to be at roughly the same level in 2050 as in 2006, while overall crop production is expected to double. (Although growth in cereals output will be much slower.) Cropland conversion is expected to continue at roughly the same rate as in the 1961-2006 period.

We also highlight the critical drivers of uncertainty in crop production, output and land use. Improvement in future predictions will benefit most from greater attention to TFP projections. This is followed closely by the need to provide improved estimates of the elasticities of supply of labor and capital to agriculture. The latter has been a neglected area of research over the past thirty years and deserves far greater attention in the future.

Summary Points:

1. This paper reviews the literature on long run projections of global crop output, prices and land use, begun nearly half a century ago in the midst of an earlier 'food crisis' and which has been stimulated by the recent period of high and volatile food prices.

2. The AgMIP model comparison effort is noteworthy for harmonizing inputs into ten global economic models but their projections vary widely due to differences in the underlying supply and demand responses, as well as their treatment of technical change.

3. We undertake a comprehensive uncertainty quantification using an emulator of the reviewed family of global crop models which reveals a very broad distribution of potential outcomes for output, prices and land use in 2050.

4. The distributions of all three variables are rightward-skewed, such that the expected values are all higher than the point estimates obtained by simply using the most likely input values for the underlying drivers and economic response parameters.

5. Based on our analysis, crop prices are expected to be at roughly the same level in 2050 as in 2006, while overall crop production is expected to double and cropland conversion is expected to continue at roughly the same rate as for 1961-2006.

Future Issues:

1. Improvement in future predictions will benefit from greater attention to TFP projections.

2. Global economic modelers must give more thought to the way they incorporate productivity growth into their framework, since this is an important source of difference across model projections.

3. Future research should focus on the relatively neglected topic of labor and capital supply to agriculture, as this is a key parameter governing the long run evolution of the crops sector.

Box 1: A simple model of long run demand and supply for agricultural land

(1) $qo = -\varepsilon^{D} p_O + \Delta_O^D$	: demand for agricultural output
(2) $p_O + a_O = \sum_j \theta_j (p_j - a_j)$	: agricultural entry/exit; zero profits
(3) $q_N + a_N = q_O - a_O - \sigma(p_N - a_N - p_O - a_O)$	: demand for non-land inputs
(4) $q_L + a_L = q_O - a_O - \sigma(p_L - a_L - q_O - a_O) - \Delta_L^D$	: demand for land input
(5) $p_j = 0, \forall j \neq L$	: supply of non-land inputs
(6) $q_L = v_L p_L - \Delta_L^S$	: supply of land to agriculture

Notation: all price and quantity variables represent percentage changes in the underlying indexes

q_O , q_j : % change in long run agricultural output and input j

a_O, a_j : cumulative output-augmenting and input-*j* augmenting technical change in agriculture

p_O, p_j : % change in the price of agricultural output and input *j*

$\sigma \geq 0$: elasticity of substitution between land and non-land inputs

$v_j \geq 0, \theta_j \geq 0$: elasticity of supply to agriculture and cost share of input *j*

$\varepsilon_D \geq 0$: price elasticity of demand for agricultural output

$\Delta_L^S, \Delta_L^S, \Delta_O^D$: *ad hoc* shifters in land supply, land demand and output demand

$\varepsilon^{S,E} \equiv \theta_L^{-1} v_L$: the extensive margin of supply response (area elasticity wrt commodity price)

$\varepsilon^{S,I} \equiv \sigma(\theta_L^{-1} - 1)$: the intensive margin of supply response (yield elasticity wrt commodity price)

CES production function (upper case variables are *levels* of corresponding lower case variables):

$$Q_O \equiv A_O((-\rho A_L)(Q_L)^{-\rho} + (-\rho A_N)(Q_N)^{-\rho})^{-1/\rho}$$

Where: $\sigma = 1/(1+\rho)$ and $\rho > -1$

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Online Resources

Agricultural Model Intercomparison and Improvement Project: www.agmip.org

Shared Socio-economic Pathways Database: https://secure.iiasa.ac.at/web-apps/ene/SspDb

Model Applications and Teaching Materials related to the theoretical framework and model emulator: https://mygeohub.org/courses/global_change

Figure 1: A framework for analyzing long run growth in crop output, land use and prices

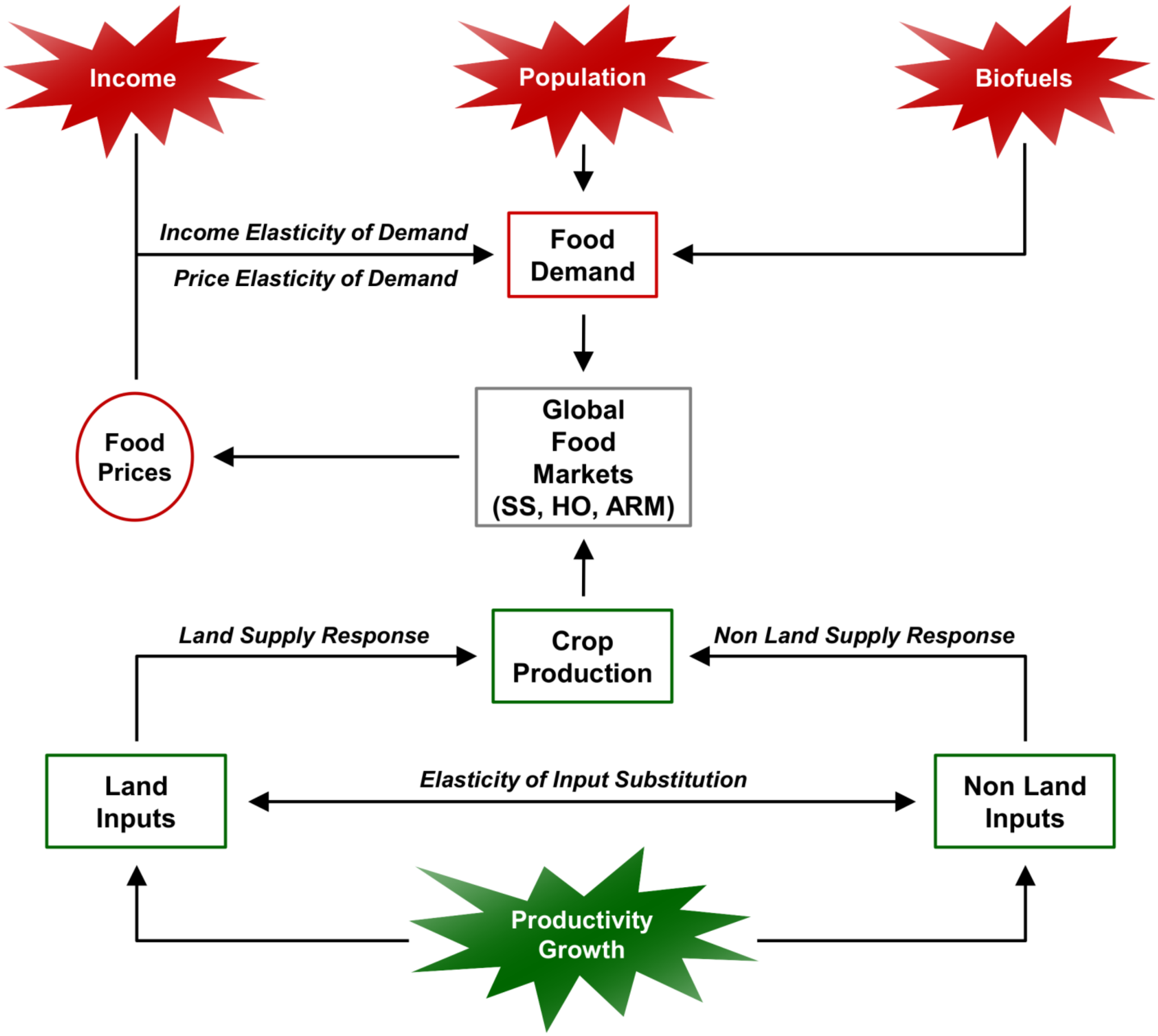

Figure 2. Monte Carlo results for 2050 (n=5000)[a]. Dotted line denotes mean outcome, red bars represent 95% CI. Individual model predictions labeled one vertical lines.

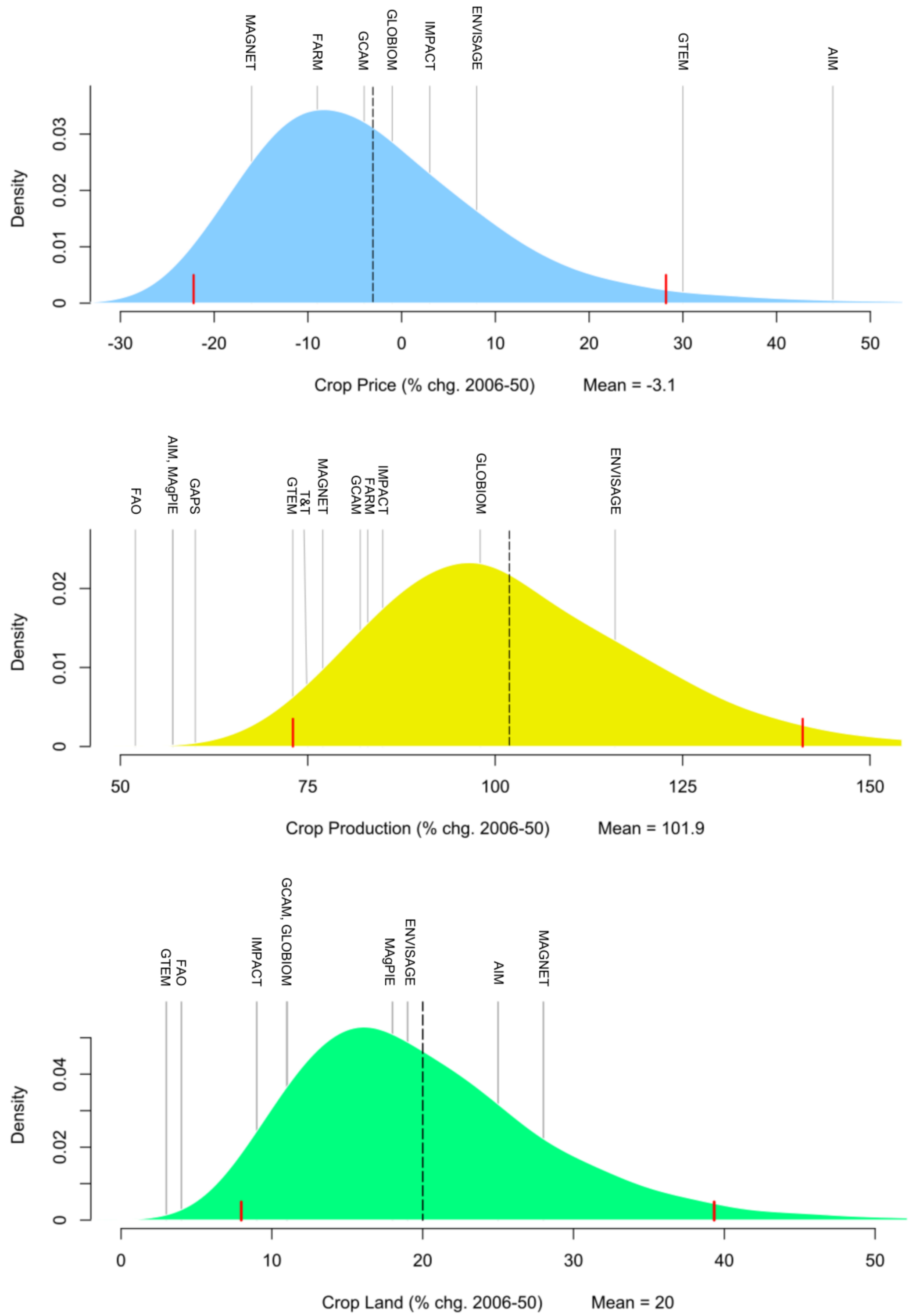

Figure 3. Relative importance of model inputs for future projections based on the Morris Method under segmented markets (n=360)

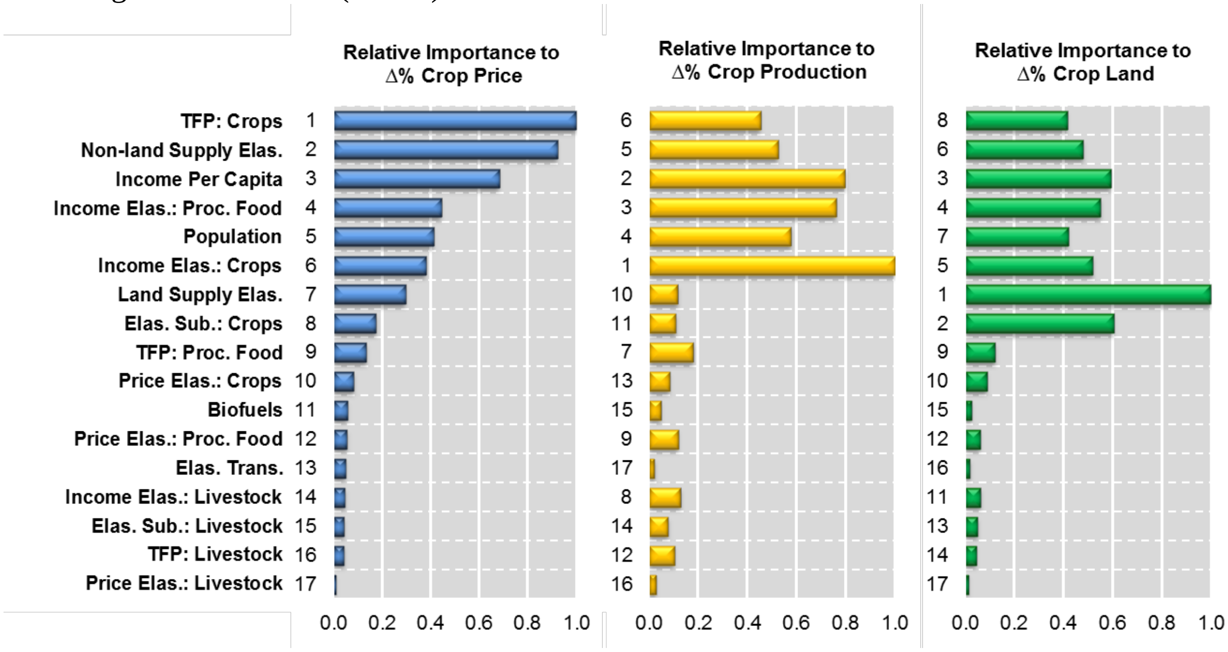

Table 1. Overview of the models

Models	Source	Spatial Resolution		Global Drivers				Price Responsiveness					Productivity Growth	International Trade
		Demand	Agricultural Production	Population	GDP	Income Elasticity	Biofuels	Demand	Intermediate	Supply: Intensive	Supply: Extensive	Nonland Supply		
Partial Equilibrium Models														
FAO	FAO	Country	Country	X[a]	X	-	X	-	-	-	-	-	YS[d]	SS
GCAM	PNNL	Regional	Sub-regional[g]	X[b]	X[b]	-	✓	X	-	-	✓	-	YS	HO
GLOBIOM	IIASA	Regional	Gridded	X	X	-	✓	✓	✓[e]	✓[e]	✓	-	YS	HO
IMPACT	IFPRI	Country	Sub-regional	X	X	✓	X	✓	-	-	✓	-	YS	HO
MAgPIE	PIK	Regional	Gridded	X	X	-	✓	-	-	✓[e]	✓	-	YS[h]	SS/HO[f]
GAPS	FAO	Country	Country	X	X	✓	X	✓	-	-	✓	-	YS	HO
T & T	OSU	Global	Regional	X	X	✓	X	-	-	-	-	-	YS	HO
General Equilibrium Models														
AIM	NIES	Regional	Regional	X	✓	✓	✓	✓	✓	✓	✓	✓	PF	ARM
ENVISAGE	FAO/WB	Regional	Regional	X	✓	✓	-	✓	✓	✓	✓	✓	PF	ARM
EPPA	MIT	Regional	Regional	X	✓	✓	✓	✓	✓	✓	✓	✓	PF	ARM
FARM	ERS/USDA	Regional	Regional/AEZ	X	✓	✓	✓	✓	✓	✓	✓	✓	PF	ARM
GTEM	ABARES	Regional	Regional	X	✓	✓	✓	✓	✓	✓	✓	✓	PF	ARM
MAGNET	LEI/WUR	Regional	Regional	X	✓	✓	✓	✓	✓	✓	✓	✓	PF	ARM

Model References: FAO: Alexandratos and Bruinsma (2012), GCAM: Wise and Calvin (2011), GLOBIOM: Valin et al. (2013), IMPACT: Robinson et al (2015), MAgPIE: Lotze-Campen et al. (2008) GAPS: Kavallari et al. (2016), T & T: Tweeten & Thompson (2008), AIM: Fujimori et al. (2012), ENVISAGE: van der Mensbrugghe (2008), EPPA: Chen et al. (2015), FARM: Sands et al. (2014), GTEM: Pant (2014), MAGNET: Woltjer and Kuiper (2014).

Notes:
[a] Population is a key driver in FAO projections, but requires fine-tuning by expert judgment
[b] GCAM calibrates food demand to FAO's projections.
[c] FAO has fertilizer projections and differentiates between rainfed and irrigated land
[d] FAO uses expert judgment to drive growth in yields.
[e] Non-land input prices are exogenous, Leontief technologies are used. Substitution occurs across discrete technologies
[f] Self sufficiency targets are met first, net trade balances based on HO basis
[g] Agricultural production is based on some 151 AEZs that align with the demand regions
[h] Yields in MaGPIE are endogenous and reflect price sensitive changes to the cost of improving yields.

Table 2. AgMIP global economic comparison for 2050 (2005=100) [a]

Models	Cereals output	CR5 output	Crop output	Crop price	Cropland
FAO[b]	141	158	152	NA	104
GAPS[c]	NA	NA	160	NA	NA
Tweeten & Thompson[d]	160-175	158-184	154-173	>100	NA
AIM	169	182	157	146	125
ENVISAGE	164	191	216	108	119
FARM	169	193	183	91	94
GCAM	159	195	182	96	111
GLOBIOM	164	197	198	99	111
GTEM	164	175	NA	130	103
IMPACT	157	193	185	103	109
MAGNET	186	192	177	84	128
MAgPIE	168	208	157	NA	118
Emulator*	NA	NA	179	86	119
Emulator**	NA	NA	161	126	132

Sources: Alexandratos and Bruinsma (2012) with additional calculations by authors, Kavallari et al. (2015), Tweeten & Thompson (2008) with additional calculations by authors, von Lampe et al (2014) and Schmitz et al (2014) including supplemental materials. Emulator (SIMPLE) results are based on the authors' calculations: Emulator* corresponds to the case of both land and non-land augmenting technical change, whereas Emulator** only has land-augmenting technical change.

[a] Based on SSP2. (1) Models had different base years, but were interpolated to a common base year of 2005. (2) Models reported results in different units so figures in table represent growth relative to 100 in 2005. (3) Commodity aggregations were done by individual modeling teams. (4) Prices reflect percent change relative to GDP deflator (for CGE models). The Emulator* results are generated using population and income growth from SSP2, land-augmenting technical change calibrated to intrinsic yield projection from the IMPACT model and non-land augmenting technical change which targets future crop TFP growth based on global projection from Ludena et al (2008) and regional rates from Fuglie (2012). The final row, Emulator**, omits the non-land augmenting technical change.

[b] FAO scenario was based on population and GDP projections available circa 2010. Population increases by 41% and GDP by a factor of 2.6—compared with the AgMIP figures of 40% for population and a factor of 3.1 for GDP. Note that global growth rates are influenced by base year prices and exchange rates. Production growth rates are based on 2005/07 constant price weights. The growth in crop land represents the growth in arable land, not harvested land.[c] Results from GAPS are only provided in summary form. Global agricultural production increases by 68% under SSP2 compared to 60% under the Alexandratos & Bruinsma (2012) scenario. If we assume the same proportion of crop to global production, the index of global crop production is 160 compared to the 2012-based projection of 152.

[d] Tweeten and Thompson provide population and GDP projections from 1994 to 2050. With interpolation to 2005, global population growth is 42%, similar to FAO and SSP2. GDP grows by a factor of only 2, much lower than either FAO or SSP2. However, this largely reflects the significant differences in weights between 1994 and 2005/07. For example, their GDP in low income countries increases by a factor of over 5. They provide two different scenarios for yield growth that affects supply growth—these ranges are provided in the table (after interpolation from 2000 to 2005). The budget shares (from their table 4) are used to aggregate the individual commodity groupings.

Table 3. Implied Demand and Supply Elasticities for the AgMIP Global Economic Models[a]

Model	Total	Demand	Extensive	Intensive
Partial equilibrium models				
IMPACT	0.58	0.24	0.37	-0.03
GCAM	2.80	0.63	2.52	-0.36
GLOBIOM	0.49	0.28	0.08	0.13
MAgPIE[b]	0.36	0	0.18	0.18
General equilibrium models				
AIM	0.85	0.10	0.92	-0.17
ENVISAGE	3.22	0.47	1.57	1.18
FARM[b]	1.33	0.07	1.30	-0.04
GTEM[b]	0.96	0.07	0.52	0.36
MAGNET	0.93	-0.04	1.23	-0.26
Emulator				
	1.16	0.29	0.36	0.51

[a] Elasticities for the PE models are computed by solving equations (1) - (3) using model results for 2050 changes in grains and oilseeds output, land use and prices, based on four different yield shocks, thereupon taking the average of these four elasticity estimates. Results for the CGE models require modified formulae (production function approach) as discussed in the text. Emulator elasticities are obtained via model perturbations.

[b] Denotes case where global shock is taken from IMPACT calculations.

Table 4. Uncertainty ranges for global drivers and economic parameters

Exogenous Shocks (p.a. rates)	Mode	Max	Min
Population	0.78	1.02	0.56
Per capita income	1.9	2.8	0.73
Biofuels	3.88	4.72	3.04
Total Factor Productivity			
Crops	0.94	1.14	0.5
Livestock	2.11	2.49	0.78
Processed Foods	0.89	1.05	0.33
Parameters	Mode	Max	Min
Demand Elasticities			
Future Price Elasticities			
Crops	-0.10	-0.02	-0.31
Livestock	-0.34	-0.29	-0.5
Processed Foods	-0.38	-0.29	-0.65
Future Income Elasticities			
Crops	-0.06	0.26	-0.17
Livestock	0.2	0.49	0.1
Processed Foods	0.21	0.55	0.1
Land supply response	0.28	0.56	0.11
Non-land supply response	1.34	2.68	0.49
Elasticity of substitution: Crop	3	4.5	0.24
Elasticity of substitution: Livestock	1.16	1.51	0.81
Elasticity of Transformation: Local and Global Markets	3	3.9	2.1

Notes: For each driver and parameter, we postulate a global triangular distribution using scalars to convert some of these global shocks to regional values (Appendix Table A2). Sources of exogenous growth rates for global drivers are as follows.

Population and per capita incomes: SSP Projections Database v0.5 (Kriegler et al., 2012; O'Neill et al., 2014) for population and per capita income growth rates. The modal values are based on SSP2 projections which are built on the assumption that current trends continue. We construct the max and min growth rates for population using SSP3 and SSP1, and SSP5 and SSP3 for income growth, respectively. Note that these SSP combinations encompass the full range of expected global population and income growth in the SSP database.

Biofuels: The max and min for global biofuel growth is taken from IEA (2014) *New Policies* scenario 2012-40 p.a. rate and *Current Policies* scenario 2030-40 p.a. rate while the mode is calibrated to *Current Policies* scenario 2012-40 p.a. rate. Under the IEA scenarios, *Current* policies reflect projections given governmental energy and emissions policies enacted as of mid-2014 while *New* policies build on this projection albeit with cautious implementation of future policies that have not been fully developed at the moment (IEA, 2014).

Total Factor Productivity: Productivity growth is based on TFP estimates. For the crop and livestock sectors, we rely on projections by Ludena et al (2007) which assumes eventual convergence of productivity growth across regions. Max and min TFP growth rates are based the periods: 2001-20 (the two decades of most rapid projected global growth) and 1961-80 (the slowest historical TFP decades) while modes are based on 2001-2040 rates. Lacking data for processed foods TFP growth, we impose the normalized range of livestock TFP growth using estimate from Griffith et al (2004) as the mode.

Demand Elasticities: Max and min values of future global average demand elasticities reported in the table are based on the full range of predicted regional demand elasticities in SIMPLE at base year 2006. Note that demand elasticities in SIMPLE are calculated from OLS regressions linking the natural log of adjusted per capita incomes to country-level demand elasticities computed by Muhammed et al. (2011) in order to capture the declining responsiveness of consumers to food price change and increased food spending on livestock and processed foods at higher income levels.

Supply and Substitution Elasticities: The range of global land supply response is based on the 5-year and 45-year own-price elasticities of U.S. cropland from Ahmed et al. (2008) which incorporates information on the response of land to economic markets as well as the natural transition of land across uses overtime. Lacking data, we impose the same range for the global non-land supply response albeit normalized to modal value. The max and min values of input substitution elasticities for crops are calibrated using the range of estimates of U.S. corn yield price response assembled by Keeney and Hertel (2009) as a guide. Finally, we do not have sufficient data to compute for the ranges of the input elasticity of substitution in the livestock sector and the elasticity of transformation between local and global markets. For these parameters, we simply assume that the max and min values are +/- 30% of modal values.