

The Future of Food Demand:

Understanding Differences in Global Economic Models

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Abstract

Understanding the capacity of agricultural systems to feed the world population under climate change requires projecting future food demand. This paper reviews demand modeling approaches from ten global economic models participating in the Agricultural Model Intercomparison and Improvement Project (AgMIP). We compare food demand projections in 2050 for various regions and agricultural products under harmonized scenarios of socio-economic development, climate change and bioenergy expansion. In the reference scenario (SSP2), food demand increases by 59 to 98 percent between 2005 and 2050, slightly higher than the most recent FAO projection of 54 percent from 2006 (Alexandratos and Bruinsma, 2012). The range of results is large, in particular for animal calories (between 61 and 144 percent), caused by differences in demand systems specifications, and in income and price elasticities. The results are more sensitive to socio-economic assumptions than to climate change or bioenergy scenarios. When considering a world with higher population and lower economic growth (SSP3), consumption per capita drops on average by 9 percent for crops and 18 percent for livestock. The maximum effect of climate change on calorie availability is -6 percent at the global level, and the effect of biofuel production on calorie availability is even smaller.

Keywords: world food demand, socio-economic pathways, climate change, computable general equilibrium, partial equilibrium.

JEL Codes: C63, C68, Q11, Q54

50 **1. Introduction**

Agriculture has succeeded so far to respond globally to increased food demand from population growth. Food supply has more than tripled since the 1960s and continues to rise everywhere (FAO, 2011). But prospects for the future are uncertain as climate change and natural resource depletion threaten the capacity of agriculture to continue these trends in the long term. Simulating possible
55 agricultural futures requires analytical tools that can represent world agriculture in a comprehensive way and reproduce the main structural drivers of demand and supply.

An important component of such quantitative analysis is modeling of consumer demand. Modelers have different perspectives, captured in their choice of behavioral parameters, on how future food consumption might evolve. But quantitative models also rely on specific mathematical functions to
60 represent consumer behavior. This paper, part of a series comparing results from the initial phase of the global economic model intercomparison of the AgMIP project (von Lampe et al., 2013), examines how model demand specifications influence results. It provides a comparison of food demand projections across eight scenarios that vary by socio-economic assumptions (GDP and population growth), crop productivity, and climate change for major agricultural commodity groups in 13 world
65 regions through year 2050. We consider the use of agricultural products as human food, ignoring crop use for feed and bioenergy.¹

Demand for food is driven mainly by population growth, but also by income growth. Using food expenditure data across countries, Muhammad et al. (2011) find that the marginal share of income spent on food declines with countries ranked from low to high per-capita income. Income growth
70 also leads to a change in consumption to a more diverse diet that includes a larger share of animal

¹ We follow the Food and Agricultural Organization of the United Nations (FAO) standard of reporting. Food demand then corresponds to food supply to households, including both actual food intake and household waste.

protein and fats and oils (a phenomenon known as Bennett's Law, see Bennett, 1941). China is an interesting example of diet transition, with a very rapid growth in per-capita income over the past two decades. Chinese per-capita consumption of livestock products has grown rapidly, while per-capita consumption of rice has declined slightly since the late 1990s, a pattern of consumption
75 change following that of Japan in the latter part of the 20th century.

Commodity affordability also conditions access to food. Therefore, real prices constitute another important driver of food demand. High commodity prices directly impact food consumption in developing regions (Headey and Fan, 2008) but also consumption choices for final products in more advanced countries (Green et al., 2013).

80 Food demand is influenced by many other drivers, such as education, local traditions, degree of urbanization, trade liberalization and development of downstream services such as supermarket chains and dining out (Kearney, 2011). Population, age and gender structure as well as physical activity lead to different metabolic requirements and determine patterns of over- or under-
85 consumption. The share of products wasted also increases food demand, especially in industrial countries (Gustavsson et al., 2011). FAO food balance sheets generally overestimate the amount of food actually consumed when compared to dietary surveys (Kearney, 2010). Most of the food demand systems used by models in this study explicitly consider income and price effects, with limited representation of other drivers.

90 **2. Modeling demand in global models**

Two classes of models have traditionally been used in developing forward looking scenarios for food at the world level: partial equilibrium (PE) and computable general equilibrium (CGE) models. These are reflected in the sample of models studied here (see von Lampe et al. 2013 for an overview of models characteristics). The main characteristics of PE and CGE demand systems are summarized in
95 Table 1. Demand in all CGE models starts with a theoretically consistent utility function from which it

is possible to derive demand functions, and functional forms for income and price elasticities. Demand functions are based on final consumption of household goods. All consumption items are included, exhausting the budget constraint. Because consumer utility is explicitly modeled, it is possible to calculate a change in welfare between scenarios as either compensating or equivalent variation.

[Insert Table 1]

PE models typically use reduced-form demand functions, which can be thought of as a local approximation of the full demand system, and are limited to a narrower set of goods, in their primary product form. They can therefore only compute a partial index of household welfare, such as consumer surplus or simply household food intake. Partial equilibrium models typically have a much greater level of detail at the commodity level (e.g. 26 crops in the IMPACT model), sometimes with a few stages of processing following the traditional supply utilization account structure (e.g. bioenergy in GLOBIOM).

Due to their origins in input-output models, CGE models typically include relatively few commodities but have a more detailed representation of the supply chain through various processing and intermediate activities between the producer and the consumer – restaurants, hotels, tourism or even business or other service expenses such as school and hospital meals. As incomes rise, a growing share of household food consumption no longer relies on commodity consumption and is spent on processed foods and beverages and food consumed outside of the house.

The AgMIP comparison includes six CGE models and four PE models. The characteristics of the food demand systems are summarized in Table 2. All models compute demand using a representative

household for each of the modeled regions.² The behavior of each demand system is then driven by the choice of functional form and its parameterization.

[Insert Table 2]

120 *2.1 Food demand systems in PE models*

Two approaches to modeling food demand in the PE models in this paper are used. The standard approach has per-capita food demand expressed as a function of per-capita income and a vector of all prices (in the IMPACT, GLOBIOM, and GCAM models). Food demand is calculated as follows:

$$D_{r,c,t} = Pop_{r,t} \left(\frac{Y_{r,t}}{Pop_{r,t}} \right)^{\eta_{r,c,t}} \prod_{c'} (P_{r,c',t})^{\varepsilon_{r,c,c',t}} \quad (1)$$

125 where D is food demand for commodity c in region r in year t , Pop is population, Y is total income, P is the vector of commodity prices, η are the commodity specific income elasticities and ε is the matrix of own-price and, for IMPACT, also cross-price elasticities.³ This functional form is based on a representative household model, but it can be readily adjusted to allow for household heterogeneity. In these models, population and income growth are exogenous and prices are endogenous. When
130 looking forward to 2030 or 2050, one of the key questions is how income and price elasticities evolve. For example, there is overwhelming evidence that income elasticities for most food

² A region can be a sub-regional part of a country, a country, or an aggregation of countries, depending on the model and the part of the world. The aggregated regions used in this paper are reported in supplementary information, section 4.2.

³ Neither GCAM nor GLOBIOM have cross-price effects in their standard versions. Further, GCAM has only own-price effects in the livestock sectors with limited cross substitution across crops, using a logit choice function. Some cross-price substitution effects can be obtained in GLOBIOM using an extended version of the model with a hard-link to a non-linear demand module (Valin et al. 2010).

commodities decline as consumer income increases, a relationship known as Engel's Law. Models should therefore have varying income elasticity values depending on the level of development of their countries. This is done by having an exogenous trend depending on time (IMPACT, GCAM) or on income evolution (GLOBIOM).

The second variant, used by MAgPIE is to compute the demand for calories ex-ante and to use it as a constraint for the model optimization (Bodirsky et al., in review). Total calorie demand D in MAgPIE is estimated on the basis of population Pop , income Y and time t for each region r according to the relation:

155 produced and does not consider the effects of supply shocks such as climate change or biofuel policies on food demand.

Models using explicit income elasticities can also use their own estimates of these parameters. For example, income elasticities in GLOBIOM are defined as rational functions that are calibrated to the following constraints: (i) the base year value should match USDA econometric estimates on past data
160 (Muhammad et al., 2011), (ii) the level of total calorie consumption per capita should converge to advanced countries intake when income per capita reaches similar levels of development, and (iii) composition in product consumption should correspond to future diet preferences such as defined for a given scenario (level of red or white meat consumption, share of sugar, fat, etc.). This approach results in the production of a set of Engel curves for each region and associated elasticities for each
165 good, depending on assumptions about future preferences.

2.2 Food demand systems in CGE models

As noted above, food demand in the CGE models of this study is based on utility functions that are consistent with microeconomic theory and thus are consistent with an overall budget constraint (adding up properties). However, without some form of dynamic recalibration process, none are
170 consistent with the stylized facts of consumer behavior over multiple decades with high per-capita growth where the food budget share declines.

The workhorse utility function for CGE models has been the Linear Expenditure System (LES), also referred to as the Stone-Geary utility function.⁴ It is used by three of the AgMIP CGE models (AIM, ENVISAGE, and FARM). The starting point for the LES is the following expression for utility:

$$175 \quad u_{r,t} = \prod_c (d_{r,c,t} - \gamma_{r,c,t})^{\mu_{r,c,t}} \quad (4)$$

⁴ See for example Sadoulet and de Janvry (1995).

where u is utility, d is per capita consumption and μ and γ are parameters of the utility function. The γ parameters are often referred to as the subsistence minima, or floor consumption. Maximizing u subject to the standard budget constraint leads to the following demand function:

$$d_{r,c,t} = \gamma_{r,c,t} + \frac{\mu_{r,c,t}}{P_{r,c,t}} \left[y_{r,t} - \sum_{c'} P_{r,c',t} \gamma_{r,c',t} \right]$$

$$\Downarrow$$

$$D_{r,c,t} = Pop_{r,t} \gamma_{r,c,t} + \frac{\mu_{r,c,t}}{P_{r,c,t}} \left[Y_{r,t} - Pop_{r,t} \sum_{c'} P_{r,c',t} \gamma_{r,c',t} \right] \quad (5)$$

180 where y is per-capita expenditure on goods and services.⁵ Demand is the sum of two components—the subsistence minima γ , and a share μ of residual expenditures after aggregate expenditures on the subsistence minima, often referred to as supernumerary income.

Though the LES is widely used, it has dynamic properties that are clearly contradicted by empirical evidence. As the top equation shows, with constant γ parameters, the LES converges towards a Cobb-
185 Douglas utility function with unitary income elasticities. The LES also has minimal flexibility in determining price elasticities, so even for comparative static exercises it might be less than ideal.

As an alternative, the EPPA model uses a nested constant-elasticity-of-substitution (CES) structure to describe consumption preferences, i.e. a combination of several functions of the form

195 reproduce the dietary changes as indicated by Bennett’s Law (see Lahiri et al., 2000, for a detailed discussion).

Another commonly used utility function—popularized by the wide use of the GTAP model—is the Constant Differences in Elasticities (CDE) utility function.⁶ Starting from an indirect utility function, the CDE demand function takes the following form:

$$200 \quad d_{r,c,t} = \frac{\alpha_{r,c,t} b_{r,c,t} u_{r,t}^{e_{r,c,t} b_{r,c,t}} \left(\frac{P_{r,c,t}}{y_{r,t}} \right)^{b_{r,c,t}-1}}{\sum_{c'} \alpha_{r,c',t} b_{r,c',t} u_{r,t}^{e_{r,c',t} b_{r,c',t}} \left(\frac{P_{r,c',t}}{y_{r,t}} \right)^{b_{r,c',t}}}$$

where d , P , y and u have the same interpretation as above and the key response parameters are represented by b and e . The b coefficients are linked to own- and cross-price substitution effects; the e parameters govern the responsiveness of demand with respect to income. It is still a relatively parsimonious functional form, although it allows for significantly more realistic price elasticity response than the LES. Nonetheless, in the absence of a dynamic recalibration of the price and income parameters, CDE income responsiveness is limited and final-year income elasticities are close to their initial levels. This functional form is used by several of the GTAP-based models participating in AgMIP (MAGNET, GTEM). Preckel et al. (2005) provide extensions to the CDE class of expenditure functions that introduce minimum quantities in the utility function, as in the LES.

210 Although rarely adopted for modeling demand in CGE models, other, more flexible functional forms are also used in the modeling literature. These functions are not directly derived from a utility function but they allow for a broad range of price and income response. Jorgenson and associates

⁶ See for example Hertel (1997).

have made extensive use of the translog functional form and have provided econometric estimates of the various parameters of this function (Jorgenson et al., 2012).⁷

215 Lewbel (1991) has characterized utility functions by their rank number. A utility function of rank 1 has expenditure shares for each good invariant with the level of income. The utility functions described above are all of rank 2, i.e. their expenditure shares vary but Engel curves remain linear. In the absence of adjustments, a utility function of rank 3, i.e. having non-linear Engel curves, is needed to appropriately deal with plausible dynamic behavior.

220 Relatively minor adjustments to the functions above have led to rank 3 demand systems. One, known as AIDADS and first developed by Rimmer and Powell (1996), makes the marginal consumption parameter of the LES a function of utility and no longer constant.

$$d_{r,c,t} = \gamma_{r,c,t} + \frac{\mu_{r,c,t}}{P_{r,c,t}} \left[y_{r,t} - \sum_{c'} P_{r,c',t} \gamma_{r,c',t} \right]$$

where

$$\mu_{r,c,t} = \frac{\alpha_{r,c,t} + \beta_{r,c,t} e^{u_{r,t}}}{1 + e^{u_{r,t}}}$$

AIDADS collapses to the familiar LES when $\alpha=\beta$. Although it has better dynamic characteristics,

225 AIDADS still suffers from the constrained own- and cross-price elasticities compared with other alternative functional forms.

Addition of quadratic terms in per capita incomes to the translog functional form also provides the extra “curvature” needed to make these rank 3 demand systems—though the additional terms do

⁷ Another often-used flexible functional form is the Almost Ideal Demand System (or AIDS), typically used in econometric estimation of price and income responses (Deaton and Muellbauer 1980).

not solve the problem of the domain of applicability, i.e. the budget shares can wander outside the 0-
230 1 range.⁸

Despite recent literature introducing new utility functions with more desirable dynamic properties, their use to date has been relatively limited in empirical models. One of the limiting factors has been the sparseness of available price and income elasticities—needed for the calibration of these functional forms—particularly at the level of disaggregation typically used by a GTAP-style model,
235 both in terms of regional and commodity coverage (see Yu et al., 2003 for an application). A major challenge for the CGE modeling community is to address this gap by providing utility functions that can better track demand behavior over a wide spectrum of income changes, and empirically estimate income and price elasticities to provide a basis for calibration.

Faced with the deficient dynamic behavior of the standard utility-derived demand functions—even if
240 meeting the regularity conditions—most modelers resort to pragmatic approaches that focus on using these simpler utility functions, but shifting the functions' parameters over time to reflect best judgment on the evolution of either budget shares or income elasticities. What this typically involves is some notion of the evolution of income elasticities over time, and then recalibration of functional parameters between solution periods, based on the model solution for the just solved-for period, to
245 line up with a desired path for the income elasticities.

2.3 Commodity supply chain challenges

Partial equilibrium models have a simplified structure of food supply, as they only represent the supply chain through the primary products processing of the FAO supply utilization accounts (oilseed crushing, sugar refining, etc.). In CGE models, the full supply chain representation creates additional
250 challenges when income increases and consumption move to more complex products. For example, in most high-income countries there is very little or no direct consumption of cereal grains—wheat

⁸ See Jorgenson et al. 2012 and Cranfield et al. (2002).

consumption is in the form of bread and other bakery items such as breakfast cereals, pasta and pizza. Reproducing the growth of household demand for wheat from an external projection—such as from the FAO’s long-term scenario reports— would require tracking the indirect consumption of wheat through the input-output table. Moreover, processed goods tend to have higher income elasticities than raw commodities—and thus the derived demand for the raw commodities may lead to higher trend growth than warranted. The problem is exacerbated by the food demand embodied in services demand—where income elasticities are typically greater than 1.

Two solutions can be implemented in CGE models to deal with these problems. The first is to introduce a trend on the input-output coefficient of the relevant commodity. For example, even if the income elasticity for processed foods is relatively high, over time one would expect that a greater portion of the value of that demand will represent the added value to the raw commodity (labor, capital, transport, packaging, advertising, etc.). Thus over time, the input of wheat in the value of baked goods or other wheat-based products declines. A second solution is to re-configure the base data—either partially or wholly. A simple partial re-configuration is to move the food items of the input-output table to household consumption (and reduce the relevant part of household consumption by the same amount).

The ENVISAGE model, for example, incorporates a mix of these strategies. The database reconfiguration moves all food consumed in the service sectors to household demand—and adjusts downwards by the same amount as household demand for services. Food demand on a regional basis (as expressed in raw agricultural commodities) is constrained in the reference scenario to line up with the FAO long-term projections. Two sets of parameters are adjusted to achieve these constraints. Both the LES parameters (the subsistence minima and the marginal budget share parameters) and the agricultural input-output coefficient of processed foods are adjusted. The allocation of the adjustment across these two sets of parameters is driven by an *ad hoc* assumption about the share of direct household consumption of raw agriculture relative to the processed share, with typically the processed share increasing with income.

3. Demand system parameters

Each demand system contains a certain number of parameters that need to be initialized in a calibration phase. The specific functional form chosen for the utility function (and therefore the demand functions) dictates to some extent the requirements needed to calibrate the demand system under the usual assumption that the functional form is able to reproduce some base-year dataset. Thus each demand system has a different degree of freedom for its calibration that can also limit the range of potential behavior. The demand systems can also differ by the type of parameters they are calibrated on. For example, the CES only allows one calibration parameter (the elasticity of substitution), and therefore a nested CES structure such as the one in EPPA will have the same degrees of freedom as the number of nests. The LES has degrees of freedom equal to the number of products included in the demand function. Therefore, when calibrating a LES, a trade-off must be done between fitting a set of price elasticities or income elasticities. The most flexible form in terms of parameterization is the specification found in IMPACT, that allows each product to have unique income, own-price and cross-price elasticities. This approach has the advantage of its large degree of freedom (for n products, $n + n(n+1)/2$ parameters), although substitution patterns can be affected for large shocks if cross price elasticities are kept fixed.⁹ This is also the case with the flexible functional forms found in some CGE models such as the translog and AIDS functions.

In order to calibrate their systems, the different modeling teams have relied on different sources, an overview of which is provided in Table 1. For income elasticities, five out of ten models (two PEs and three CGEs) use the FAO food demand projections (Alexandratos and Bruinsma, 2012) to calculate

⁹ Cross-price elasticities are calculated with respect to an initial structure of food consumption to represent a certain degree of substitution patterns when relative prices are changing. Therefore, these elasticities need to be recalculated when shares of good in final consumption become different.

their income elasticities; hence these models should have relatively similar food demand trends. Among the five other models, FARM uses income and price elasticities from a USDA dataset
300 (Muhammad et al., 2011). IMPACT elasticities rely on a more empirically grounded database from USDA (1998) that compiles a large number of regional econometric studies. Finally, MAGPIE also produces its own elasticities drawing on both the FAO Food Balance Sheet (FBS) database and historical consumption data reported by the World Bank.

Interestingly, only three sources have been used for price elasticities. For PEs, two models used USDA
305 (Muhammad et al., 2011) to target their price responses, although only for livestock in the case of GCAM. IMPACT again relied on the USDA literature survey (USDA, 1998); for CGEs, models with a CDE system have used the GTAP parameterization but adjusted it only with respect to income behavior. In the case of LES-based CGEs, price elasticities are derived endogenously once income elasticities are determined. The two elasticities are therefore structurally correlated and a commodity with a high
310 income elasticity will necessarily have a high price elasticity.

Income and price elasticity magnitudes are reported in Figure 1 for food commodities.¹⁰ EPPA is the model with the largest spread in income elasticities and some of the highest values, in spite of its aggregated product representation. ENVISAGE and MAGNET show less dispersion but have the highest mean value in their elasticity distribution, closely followed by IMPACT. GCAM, FARM and AIM
315 display lower values and dispersion when compared with others. An interesting pattern is that only four of the ten models report some negative income elasticities, mostly PEs and CGEs based on the CDE functional form, as well as EPPA. As expected, price elasticities are correlated in magnitude with income elasticities. This comes as a direct effect of the functional form constraints in degrees of freedom (CES, LES), or from the data used for calibration. Some interesting counter-examples are

¹⁰ For CGEs, these elasticities correspond to direct demand elasticity of commodity products and do not account for the indirect food consumption through the processing chain.

320 found in the group of PE models. Two of them have no sensitivity to prices (MAGPIE and, for crops, GCAM), whereas two others have the highest average values after EPPA (IMPACT, GLOBIOM). We discuss how these patterns can explain differences in projections in the next section.

[Insert Figure 1]

325 **4. Comparison of food demand projections from AgMIP agro-economic models**

We can now compare the food demand results from the ten AgMIP models for the period 2005-2050. Our analysis follows the three dimensions of the AgMIP scenarios: socio-economics, climate change and bioenergy (see von Lampe et al., 2013). Note that climate change and bioenergy results are more extensively explored in separate papers (Nelson et al., 2013, for climate and Lotze-Campen et al, 330 2013, for bioenergy).

4.1 Food projections towards 2050 for a “Middle of the Road” scenario (SSP2)

The reference scenario, S1, uses the GDP and population pathways of the “Middle of the Road” Shared Socio-economic Pathway (SSP2) developed by the climate change impacts research community (O’Neil et al., 2012). This scenario, quantified by OECD and IIASA, leads to a world 335 population of 9.3 billion by 2050 (42 percent higher than the 2005 level) and more than a doubling in average income per capita globally, from 6,700 USD in 2005 to 16,000 USD in 2050.

Global food projections by 2050 associated with SSP2 can be seen in the first column of Table 3. The average volume increase for all models is 74 percent, ranging from 62 to 98 percent. All model projections are higher than the value of +54 percent projected by FAO (labeled ‘AT2050’). This 340 difference cannot be explained by population growth as both FAO and this exercise have similar

population growth assumptions.¹¹ The differences in food consumption are driven in large part by the differences in economic growth assumptions. The SSP2 scenario assumes that income per capita in 2050 will be 50 percent higher than does FAO (16,000 USD per capita as a world average versus 11,000 USD per capita in the FAO scenario, based on World Bank projections). For example, in SSP2
345 China and India per-capita GDP increase 13 and 11 times, respectively whereas FAO assumes 7 times and 4 times increase.

[Insert Table 3]

But the greater income effect in SSP2 only explains a part of the differences observed. To better analyze the source of differences, we can decompose the results between contribution of income
350 effects and price effects for crop and livestock products by adjusting the projections by the price responses and the price demand elasticities reported by the different models. Results are displayed in Table 3. First, for some models the overall high growth in food demand is related to demand for livestock products (+144 percent for GTEM, +136 percent for MAgPIE). Only FARM and EPPA have strong expansion of food consumption in both crops and livestock products. The second interesting
355 source of difference comes from the role of prices. As observed in von Lampe et al. (2013), the models have different price trends for the SSP2 baseline. Some price changes can compensate or exacerbate the effect of income response. For instance, the IMPACT food consumption of crops increases only by 14 percent by 2050, whereas it would have risen by 23 percent without the price effect. ENVISAGE crop and livestock demands reach levels similar to those of AIM, whereas their
360 income responses are initially very different (for livestock, +59 percent for AIM versus +19 percent for ENVISAGE). This is the result of decreasing prices in ENVISAGE and increasing crop prices in AIM.

¹¹ The FAO scenario from AT2050 has a population of 9,150 million by 2050 whereas the IIASA SSP2 scenario projects 9,287 million.

Some models have very little sensitivity to price changes. GCAM and MAgPIE are, by assumption, price inelastic for some or all of their products.

4.2 Product specific and regional differences across models

365 We have so far looked at the differences in results between crop and livestock categories. In fact, five crop aggregates (wheat, rice, other coarse grains, oilseeds, sugar crops) and three livestock sectors (ruminant meat, non-ruminant meat, and dairy) were included in the analysis (see the supplementary information for each model mapping). The product-specific results at the world level are presented in Figure 2.

370 [Insert Figure 2]

Cereals constitute a strong part of global crop consumption and we observe again the pattern mentioned above of greater consumption increase under SSP2 than in the FAO baseline. Food demand for the AgMIP models increases for wheat, corn and rice by an average 53, 106 and 47 percent respectively between 2005 and 2050 in SSP2, whereas it only rises by 34, 68 and 30 percent respectively for FAO.¹² Oilseeds and sugar consumption growth (83 and 75 percent, respectively) are much higher than for wheat or rice, and this holds for most of the models, as well as for the FAO projection. This is consistent with the values of income elasticities in demand systems for these commodities, which are on average higher than for cereals (see Figure 1). The case of coarse grains is interesting as it has the highest growth rate globally of all crop categories but a low average income elasticity. This large global growth is determined in large part by the high share of global maize food consumption (33 percent) in Africa and Middle East and the importance of sorghum and millet in this

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¹² For FAO results, we report the figures obtained by processing FAO detailed projections at product level using the same methodology as for other models. Therefore, results can vary slightly from the published version of FAO projections (Alexandratos and Bruinsma, 2012).

part of the world. This region has the fastest population growth in the SSP2 scenario (+130 percent increase between 2005 and 2050).

385 Livestock products have the largest average income elasticities, which explains the trends observed in Table 3. But the range of values is large across models and associated food projections differ greatly. This is reflected by the large range of income elasticities associated with these different products, for which consumers in many countries have a preference when their budget allows. Model differences reflect this uncertainty with a 50 percent higher dispersion around the mean than for crops.

390 As we have just seen in the specific case of coarse grains, the diversity of results across products is also related to differences in results across regions. Figure 3 presents the results for diet evolution in the different regions, expressed in kcal per capita, aggregated for the crop and livestock categories. We also calculate the implicit income elasticities associated to these estimates for each of the aggregates (Figure 4).¹³

395 [Insert Figure 3 and Figure 4]

As expected, high-income OECD countries and regions in transition (Former Soviet Union, FSU) start from the highest level of intake, which doesn't change much over time. Two notable exceptions are EPPA where crop consumption increases sharply (+34 percent), and for MAgPIE livestock, where a significant decrease of consumption per capita (-13 percent) takes place. MAgPIE's meat decline is 400 the result of the econometric estimates (see above) that lead to implicit income elasticities of -0.37 for Europe and -0.79 for North America. EPPA also has strongly negative values for these regions for both livestock and crops (-0.4 in Europe and -0.5 in North America), resulting from the nested CES

¹³ For the model results, this is calculated by adjusting the projection to remove the effect of price changes. For the FAO results, price projections are not known so the price effects cannot be removed.

recalibration technique. However, on the crop side, the negative income effect in EPPA is counteracted by an implicit income elasticity of 0.75 for FSU, which overall leads to a consumption
405 increase in crops.

For developing regions, the dispersion in results is much wider. This is in part the result of larger income per capita changes for these regions that exacerbate divergence due to income elasticities. Some models reach daily kcal consumption levels in some regions of close to 3000 kcal per capita from crop consumption alone. This level is equivalent to 80 percent of the current caloric intake in
410 the USA. The range of results is the largest for livestock products. This does not come as a surprise considering the large uncertainty about future demand in China, where meat and dairy products are experiencing rapid consumption growth driven by fast economic growth; or in India, where very low consumption of meat and dairy due to traditional culture gives uncertain prospects on the effect of western influence in the future (Alexandratos and Bruinsma., 2012). For instance, for developing
415 regions, average implicit elasticities for livestock products range from 0.1 (EPPA) to 0.6 (MAgPIE). This range seems plausible when compared with values corresponding to Alexandratos and Bruinsma (0.3-0.7 for the 1st–3rd quartile). As average income per capita in developing countries increases by a factor of 4 on average under SSP2, uncertainty for livestock consumption ranges from +15 to +130 percent. And the choice of elasticity is much important for countries such as China or India where
420 income per capita growth is faster (multiplied by 13 and 11 respectively between 2005 and 2050).

4.3 The role of socio-economic assumptions

Results in the previous section were based on GDP and population pathways from SSP2. To illustrate the uncertainty in future demand related to macro-economic drivers, we can contrast these results with those obtained in the SSP3 scenario (“Fragmented world”). The SSP3 scenario generally has
425 greater population growth and slower income growth. The population level in 2050 is 10.2 billion in SSP3 instead of 9.1 in SSP2, with the greatest increases in Africa, India and South-East Asia. World GDP in SSP3 is only two-thirds of that in SSP2 by 2050. The greatest differences in income are in

China, India, Africa and South-East Asia where growth rates in SSP3 are roughly half of those in SSP2. OECD countries also experience lower income growth in SSP3 but their populations grow more slowly, which results in smaller differences in per-capita income than for the non-OECD countries. For example, per capita income in 2050 is 5 percent smaller in SSP3 for the USA but 46 percent smaller in China, 50 percent smaller in India and 52 percent smaller in Sub-Saharan Africa).

Changing the socio-economic scenario has different effects across models. The population increase is similar for all models but the demand response to changes in income per capita depends on income elasticities that vary across the models. Additionally, differences in prices responses can also influence the level of consumption.

The results reflect the differentiated effect of income per capita shocks between developed and developing countries (see Figure 5). Three different patterns are observed for almost all models. In the developed countries, total consumption declines in SSP3 relative to SSP2 (-14 percent), because income and price elasticities are lower and the effect of population decrease dominates.¹⁴ In developing countries, total demand for crops generally increases, but not for all models. Population growth is indeed larger, and remains the dominating effect, except for some models where the income effect is stronger: FARM for example has higher income elasticities on crops in developing countries than other models (Figure 1). Income elasticities in ENVISAGE and EPPA are lower in SSP3 than in SSP2 (see Figure S4 in supplementary information). The third pattern observed is a general

¹⁴ The GTEM crop results for OECD & FSU are outliers. This is due to a different response to the decline in total factor productivity in SSP3 relative to SSP2. The productivity decrease is distributed to uses of intermediate inputs by industries, including the food processing sector. As a consequence, increased inefficiencies in indirect food use of crops and livestock products lead to additional demand for commodity products under SSP3 that offsets the reduction in household use of crops and livestock products.

decrease of total demand for livestock in developing regions, due to the higher income elasticities for these products (Figure 1). The effect of lower economic growth in these regions generally dominates the population effect, and meat and dairy consumption decrease by 11 percent in Asia and by 8 percent in Africa.

450

[Insert Figure 5]

Projection uncertainty therefore depends both on the models and the macro-economic scenario considered. The comparison between these two dimensions of uncertainty can be observed in Figure 6 that shows the standard deviation across models observed at the world level, decomposed by its regional contribution. This information is displayed for each of the food categories and for the two
455 macro scenarios. The span of projections appears rather limited for wheat and rice. The standard deviation is small for these products and contribution to uncertainty is evenly distributed across all regions for wheat and developing regions for rice. Much more uncertainty is associated with coarse grain projections, and this is highly linked to demand in Africa which accounts for more than half the standard deviation in world consumption. For all crops, the uncertainty across models is much higher
460 than the uncertainty across socio-economic scenarios, which is consistent with the previous observation that, for most models, the population and income effects in developing regions tend to compensate for crops between SSP2 and SSP3. FAO projections always appear at the lower bound of projections, except for oilseeds. For livestock products, the standard deviation across models is higher than for crops and the macro assumptions play a more significant role. Most of the
465 uncertainty comes in particular from China and India for non-ruminant meat consumption as well as for dairy products in India due to their high income growth. Scenario and model driven uncertainty are now both comparable for livestock products, and the range of outcomes is a wide band above and below the FAO projections.

[Insert Figure 6]

470 *4.4 Sensitivity of demand projection to climate change*

Using the climate change scenarios (S3-S6), we can illustrate the effect of a pure supply shock on the food demand response. We look at the impact of RCP 8.5, the scenario with the largest greenhouse gas emissions, with outputs from two different general circulation models (IPSL-CM5A-LR and HadGEM2-ES) as inputs into two crop models providing their impact on crop yields (LPJmL and DSSAT). No incremental CO₂ fertilization effect is considered for the crop model runs (see Nelson et al., 2013, for more details).

The climate change shock affects the production side and therefore prices faced by the consumer. For CGE models, they also can impact the representative agent through an income effect but, except in regions where agriculture represents a large share of value added, this feedback is second order.¹⁵

480 Crop demand and price responses to climate shocks are illustrated in Figure 7 for the four climate scenarios. The diversity of demand responses is striking. First, the price-inelastic response of MAgPIE and GCAM is expected because price is not included in their demand functions. GTEM, MAGNET and to some extent FARM, appear as relatively price-inelastic models, with a large number of implied elasticities in the -0.1/-0.2 range. This is consistent with their reported elasticities (Figure 1), except

485 for MAGNET that appears lower than initially expected. ENVISAGE, IMPACT, AIM and GLOBIOM are much more price responsive models, with most elasticities in the -0.5/-0.1 range.

[Insert Figure 7]

¹⁵All climate change scenarios are run under SSP2 that assumes a certain level of GDP growth. For PEs, the income level is exogenous and related to GDP growth. However, the usual practice when running a climate change scenario in a CGE is to set the GDP as endogenous and to set partial or total factor productivity exogenously. Climate change therefore impacts GDP and associated income in each region. This can explain in particular outliers observed in figure 7 in the NE quadrant for some CGEs, because prices are not the only variable interacting with demand.

The implications of model sensitivity to prices appear when looking at the impact on food consumption (see Figure 8; GCAM and MAgPIE, not price responsive for crops, are not considered here). The range of magnitude of climate impact varies significantly depending on input data, in particular on the crop model, but for a given input, economic model results also differ widely. On average, we observe a range of impact from -44 kcal to -77 kcal, i.e. -1.4 to -2.5 percent of the average food consumption, if we compare with FAO trends to 2050 that do not consider climate change. However, if we consider the results from the most responsive models (AIM, GLOBIOM and IMPACT), we obtain a notably larger impact at -6 percent. When we compare with the magnitude of future food demand projections, this would for instance be equivalent to a shift downward in the FAO projection from +54 to +45 percent. This result therefore confirms that integrating climate change in future projections affects the magnitude of future demand. But it also highlights that climate change related uncertainty is much lower than uncertainty from macro-economic scenarios and from model responses. This observation is in line with other studies looking at this question (Easterling et al., 2007; Nelson et al., 2013b).

[Insert Figure 8]

4.5 Sensitivity of model projections to bioenergy policy

The response of agricultural markets to bioenergy policy is the third dimension of AgMIP scenarios (Lotze-Campen et al., 2013). This scenario explores some degree of second generation bioenergy development relying on perennial crops and possibly with limited encroachment from newly cultivated areas on current cropland. Five models out of ten implemented this scenario, but only three are food demand responsive and provide some food consumption results. These three models find the impacts to range from -1.5 percent to no change of the average consumption in 2050 (maximum value for AIM with -33 kcal/cap/day; see detailed results in supplementary information). Unfortunately, no scenario on first generation biofuels was explored in this exercise to compare with the impact of feedstocks competing more directly with food consumption.

5. Conclusion

Many of the underlying drivers of food demand are subject to uncertainty. Demographics are not easily predictable beyond a few decades, and economic growth is even more unpredictable. In this paper, we compared ten global economic models providing projections of future agricultural market conditions under common scenarios. The models used harmonized socio-economic assumptions, providing a convenient platform to investigate other sources of divergence across model projections.

The range of results obtained in our comparison reflects the diversity of demand system specifications and calibration choices. Regional projections and sectoral evolution vary significantly from one model to another for a similar baseline. Overall for the middle of the road scenario (SSP2), the average increase in calories in our sample of models is 74 percent (st. dev. 14 percent) and all models are higher than the value of +54 percent projected by FAO. This finding would probably call into question the usual expectations of a 60 percent increase in world agriculture production by 2050. Even without the leverage effect on feed crops needed for more livestock products, an increase by 20 to 30 percent higher magnitude seems plausible following our analysis, which is in line with some other works (Tilman et al., 2011).

This projection is however dependent on macro-economic assumptions and was obtained under a middle range assumption scenario (SSP2) which supposes higher economic growth than FAO does for its most recent projections. When considering a variant with lower economic growth but higher population increase (SSP3), we find decreased per-capita consumption relative to SSP2 (-12 percent). However, overall food demand remains similar because population is higher, but it is more sourced from crop than from animal products. Demand for livestock products indeed appears very sensitive to change in projected GDP per capita, and large uncertainty is associated with the development of these markets, in particular in developing regions.

We also tested the sensitivity of these projections to future climate change and to a second generation bioenergy scenario. We find that magnitude of change in per-capita demand for the most

dramatic climate change scenario would be in the range of -1.5 to -2.5 percent using model averages, with -6 percent for the most reactive model, whereas the bioenergy option would have at most a 1.5 percent effect on world demand. The related uncertainties are therefore lower than those associated with model specifications and much lower than the usual uncertainty on population and GDP projection drivers.

From a technical point of view, this comparison exercise also provides a first attempt to open the model “black boxes” in order to analyze the origin of their differences. A first important source of divergence comes from the choice of behavioral parameters. Implicit elasticities measured in this exercise often show wide and sometimes fuzzy distributions. The process allowed for significant improvement of assumptions and specifications, and exchange of good practices across modelers. In particular, before reaching the final results presented above, modelers sometimes had to revise some of their specifications (for instance when no dynamic recalibration was present), when not switching to a different demand system more suitable for long term projections. Discussions on most recent estimates of elasticities also allowed some teams to update their parameter choices, in particular with respect to negative income elasticities, often absent in a standard calibration.

However, the limitations from some demand systems and the lack of empirical estimates at a global level pose problems. More serious, the risk of endogeneity is also present as five off ten models calibrated their income elasticities using FAO projections. Only two models used other data sources than FAO: IMPACT relying on expert information for specific countries, and MagPIE using their own panel estimation. This being said, the analysis of their projected patterns also raises questions, and the need for more precise parameter estimates is clearly demonstrated by this analysis. Also usually lacking in the technical debate is the influence of price trends for estimation of projections. FAO reports on the future of agricultural demand remain silent on this point, and models relying on econometric estimations should also acknowledge the role of this parameter for more transparent projections. In an era of economic uncertainty and highly turbulent prices, both drivers could considerably influence the future conditions for food access and food demand.

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Table 1. Main characteristics common to PE and CGE demand systems analyzed in this study.

Demand system	PE	CGE
Theoretical representation	Reduced form	Utility based
Degrees of freedom	Unconstrained	Constrained by functional form
Commodity representation	Commodity	Final consumption good
Consumption metric	Quantity (FAO)	Volume in USD (GTAP)
Welfare approach	Consumer surplus Kilocalorie intake	Compensating or equivalent variation of utility

650 **Table 2 Final demand specifications of the ten global economic models participating to AgMIP**

Model	Type	Demand regions	Food goods			Demand system	Price response	Inc. elast. dyn. adj. ^a	Data source	Parameter or data sources for calibration	
			Crop	Live-stock	Processed					Price	Income ⁱ
AIM	CGE	17	6	2	1	LES	Y	Y	GTAP/FAO	Implicit ^f	FAO proj.
ENVISAGE	CGE	20	7	3	5	LES	Y	Y	GTAP	Implicit ^f	FAO proj.
EPPA	CGE	16	1	1	1	Nested CES	Y	Y	GTAP	GTAP	GTAP
FARM	CGE	13	8	4	8	LES	Y	Y	GTAP/FAO	Implicit ^f	USDA
GCAM	PE	16 ^b	13	5	-	Double-log	Y/N ^e	Y	FAO	USDA ^g	FAO proj.
GLOBIOM	PE	30 ^c	18	6	-	Double-log	Y	Y	FAO	USDA ^g	FAO FBS & FAO proj.
GTEM	CGE	13	6	1	7	CDE	Y	Y	GTAP/FAO	GTAP	GTAP
IMPACT	PE	115 ^b	25	6	8	Double-log	Y	Y	FAO	USDA ^h	USDA ^h
MAGNET	CGE	45	8	3	8	CDE	Y	Y	GTAP	GTAP	GTAP & FAO proj.
MAgPIE	PE	10 ^c	16	5	-	Econometric ^c	N	Y	FAO	-	WB & FAO FBS

^a Income elasticity dynamic adjustment

^b More regions on supply side: GCAM (151 AEZ) and IMPACT (251 FPU)

^c Gridded models for biophysical parameters at 0.5 degree resolution

^d With cross-price effects

655 ^e Price response for livestock products only

^f In a LES calibrated on income elasticities, price elasticity are endogenously determined

^g USDA estimates from Seale et al. (2003) and Muhammad et al. (2011)

^h Sourced from the USDA literature review database (USDA, 1998)

ⁱ For USDA, income elasticities estimate are directly used. GTAP provides calibration parameters for the CDE.

660 For other sources, modelers use their own estimation on past time series of FAO (2011), World Bank (2011) or future projections from FAO (Alexandratos and Bruinsma, 2012).

Table 3. Decomposition of food demand change by 2050 in the SSP2 scenario between price and income effects (percent, except for index).

Model	All	Crops					Livestock				
	Total food change ^a	Total food change ^a	Food per cap change	World price index ^b	Price effect ^c	Income effect	Total food change ^a	Food per cap change	World price index ^b	Price effect	Income effect
	(1)	(2a)	(3a)	(4a)	(5a)	(6a)	(2b)	(3b)	(4b)	(5b)	(6b)
AIM	66	62	13	1.21	-7	22	88	32	1.12	-17	59
ENVISAGE	70	65	15	0.93	6	9	94	36	0.90	15	19
EPPA	79	82	28	0.80	14	12	62	14	0.86	18	-3
FARM	98	97	38	0.85	0	38	102	41	0.97	0	41
GCAM	59	55	8	0.93	0	8	79	25	1.04	0	25
GLOBIOM	62	57	10	1.00	0	11	84	29	1.06	-2	31
GTEM	94	84	29	1.04	0	29	144	71	0.80	1	69
IMPACT	65	63	14	1.31	-7	23	78	25	1.03	-5	31
MAGPIE	83	55	8	1.54	0	8	242	140	1.04	0	140
MAGNET	65	66	16	0.93	1	15	61	12	0.85	5	7
AT2050^a	54	50	8				76	27			

665 ^a"Agriculture Towards 2050" (Alexandratos and Bruisma, 2012)

Calculation method:

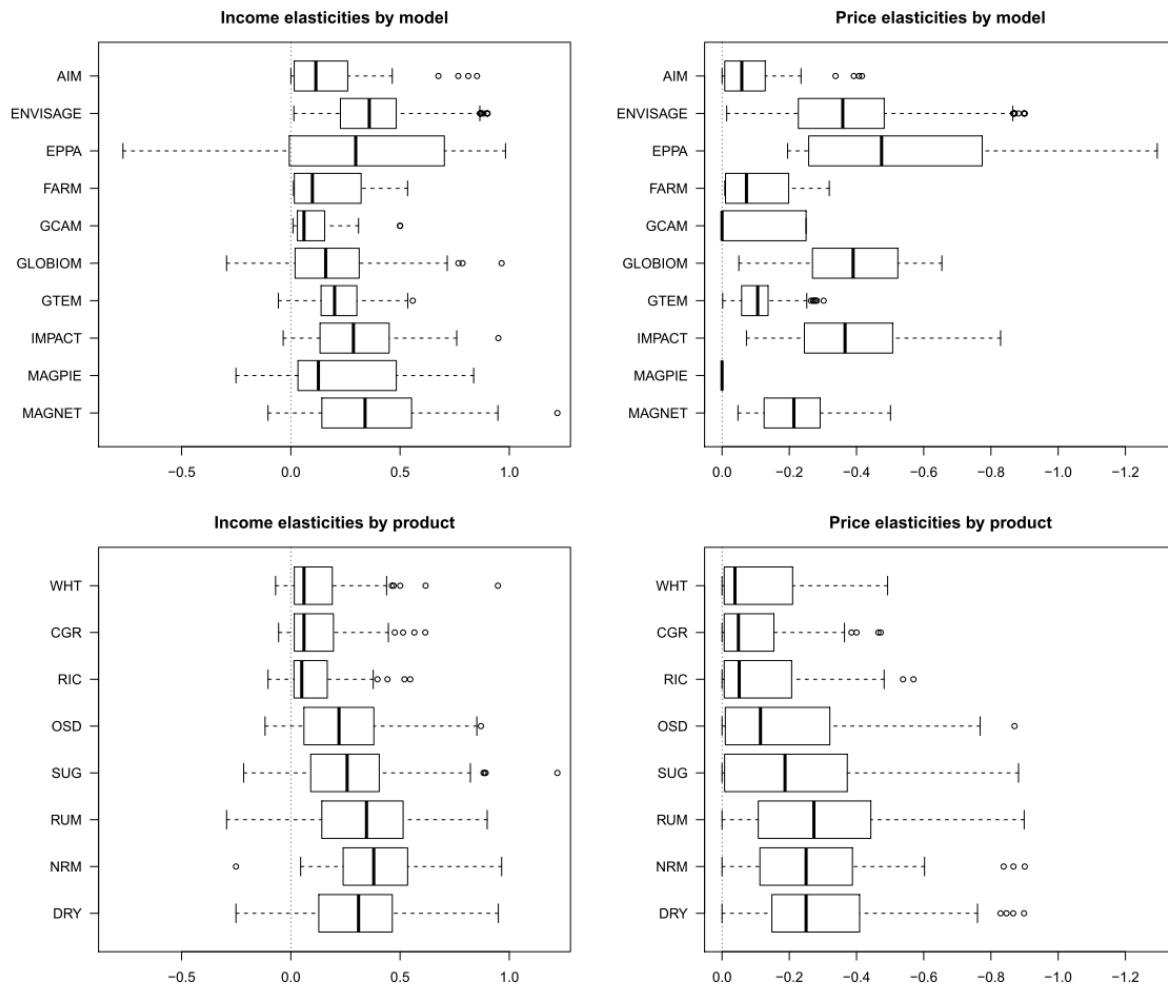
(1), (2a), (3a), (2b), (3b): Aggregated on a calorie basis for the 5 crop categories considered or the 3 livestock products.

(4a), (4b): Based on model reported values. For CGEs, the world price index is deflated by the world consumer price index.

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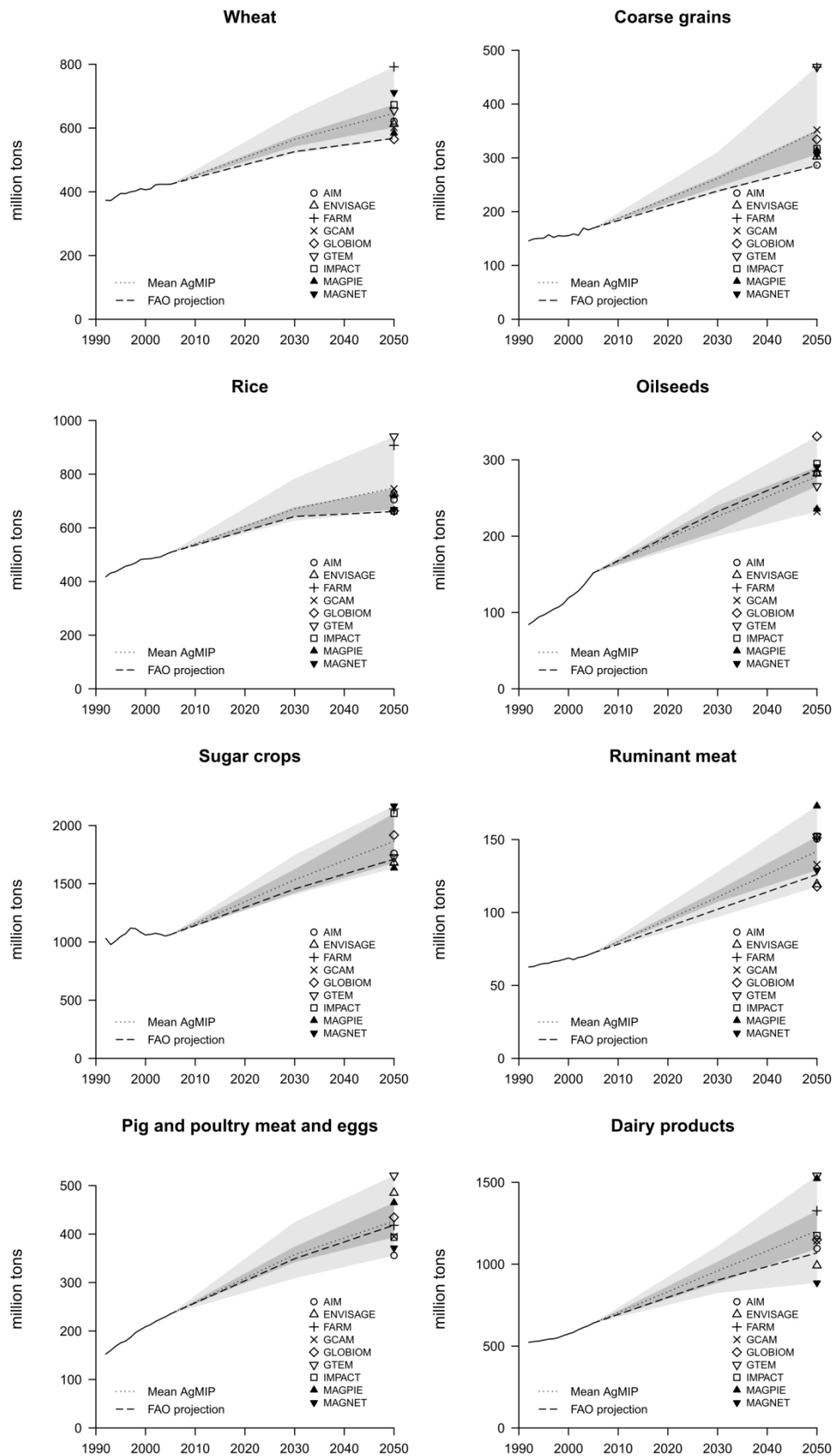
(5a), (5b): Calculated at the product level using the price index and the price elasticities reported by models.

(6a), (6b): Obtained by subtracting the price effect from (5a) and (5b) from the change per capita (3a) and (3b).

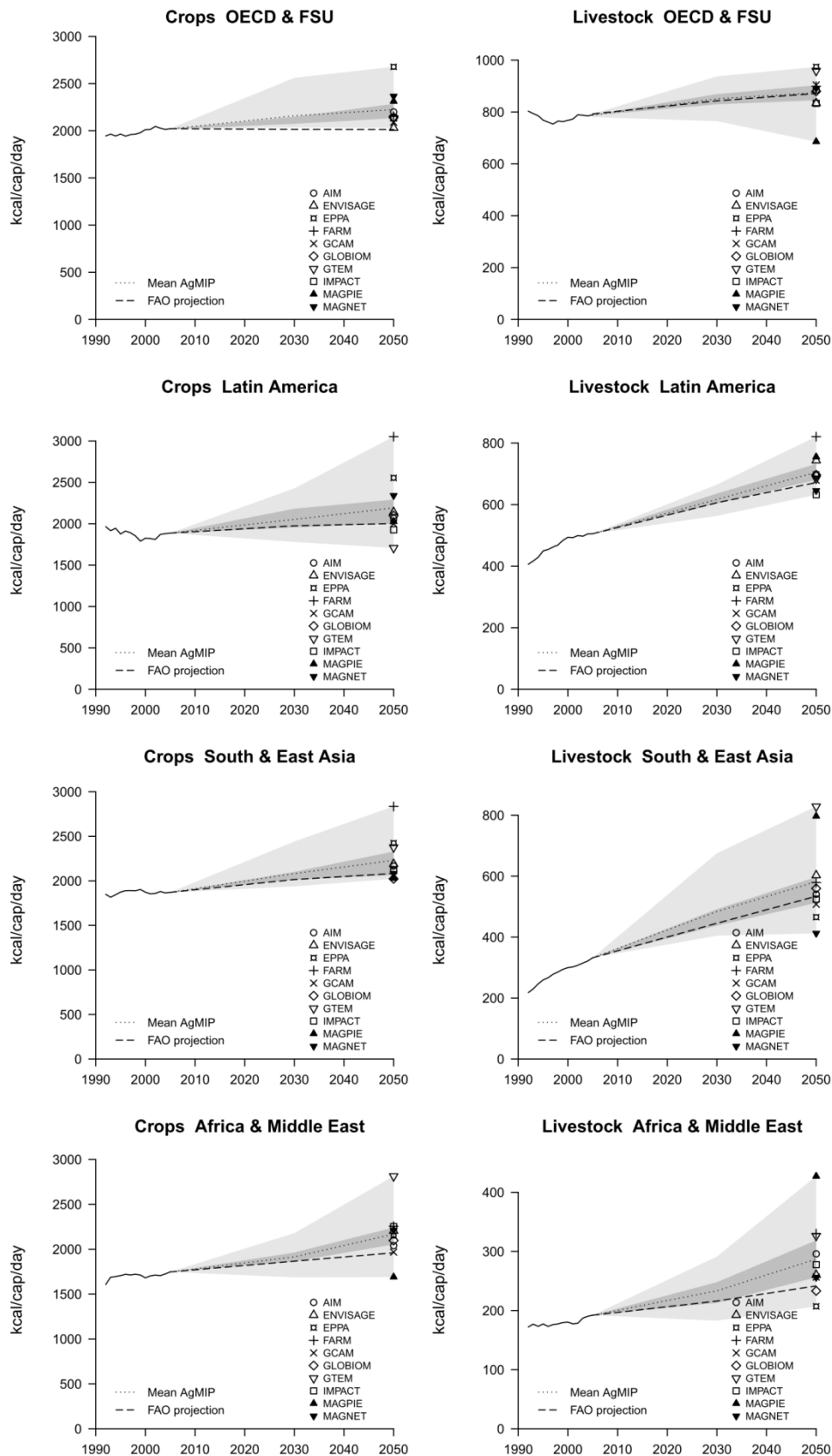


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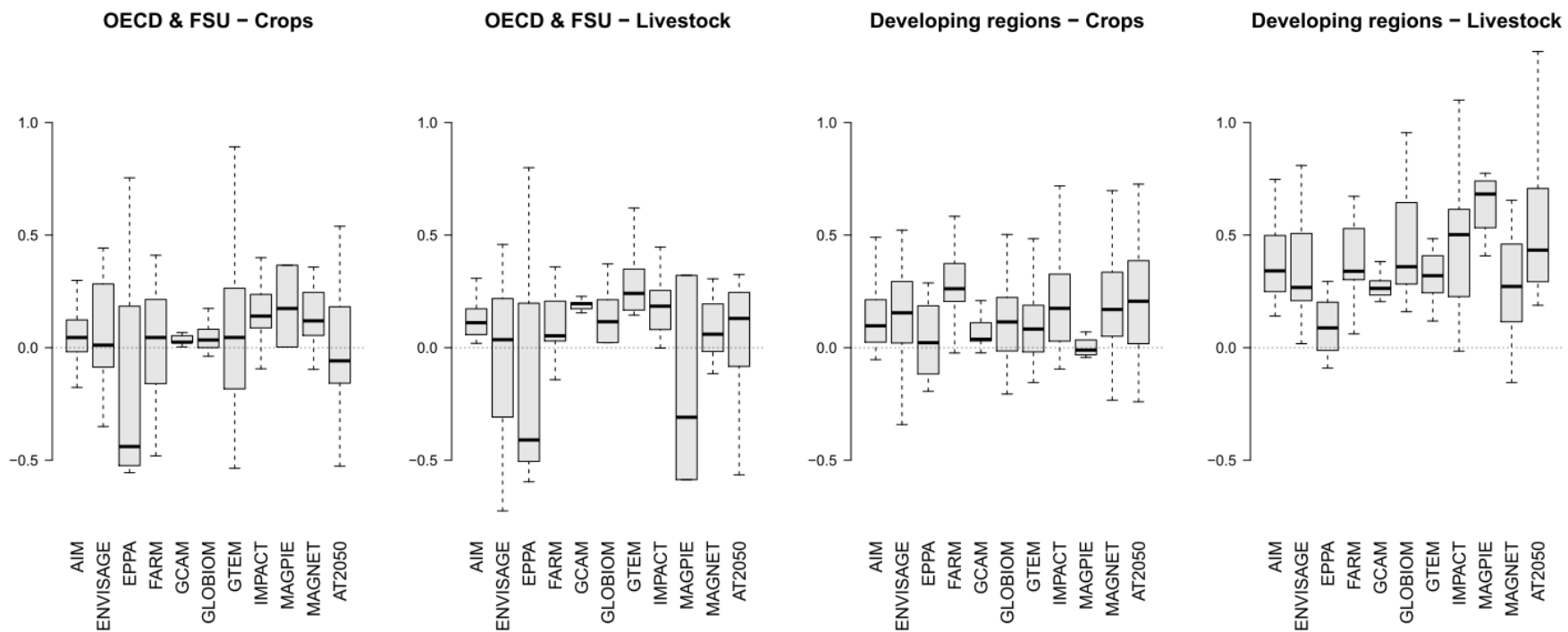
Figure 1. Base year income and price elasticities by model and by product as reported by modeling teams. For PE models, elasticities are reported as they are exogenously fed in the model; for CGEs, elasticities are inferred from formulas based on calibration parameters and estimations can be less accurate. Elasticities of EPPA are not represented for the representation by product because only two aggregates are available for this model. Boxes represent the 1st-3rd quartile range and the plain line indicates the median; dotted lines delineate the 5th and 95th percentile and bullets represent outliers.



685 **Figure 2. World food demand projection for SSP2 scenario by 2050 for AgMIP models, by product category.** Black plain line corresponds to historical data in FAOSTAT. Dashed line corresponds to FAO projections (Alexandratos and Bruisma, 2012). Dotted line corresponds to mean of AgMIP model results. Light grey indicates the span of results and dark grey the 1st-3rd quartile range.



690 **Figure 3. World food demand per capita projection for SSP2 by 2050 for AgMIP models, by region.** The black plain line corresponds to historical data in FAOSTAT. The dashed line corresponds to FAO projections (Alexandratos and Bruinsma, 2012). The dotted line corresponds to the mean of AgMIP model results. Light grey indicates the span of results and dark grey the 1st-3rd quartile range.



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Figure 4. Implicit income elasticities in the SSP2 scenario for the period 2005-2030. Implicit elasticities are defined as the log of food demand divided by the log of change in income per capita, after correction for price effect. For each region group, implicit elasticities are plotted by model for the five crops or the three livestock products. Boxes represent the 1st-3rd quartile range and the plain line indicates the median; dotted lines delineate the 5th and 95th percentile. For clarity, outliers are not represented in this figure.

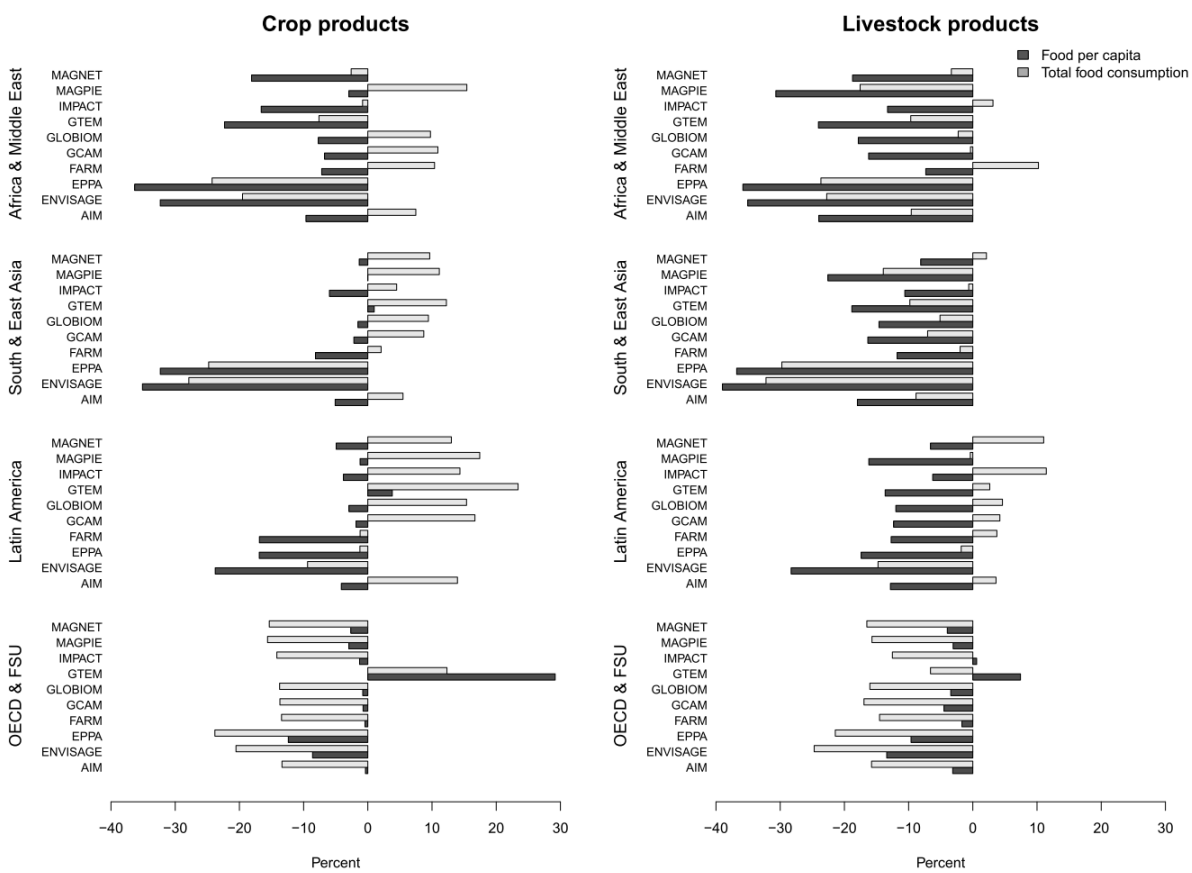


Figure 5. Change in crop and livestock calorie consumption in scenario SSP3 in 2050 when compared with SSP2, by model and region.

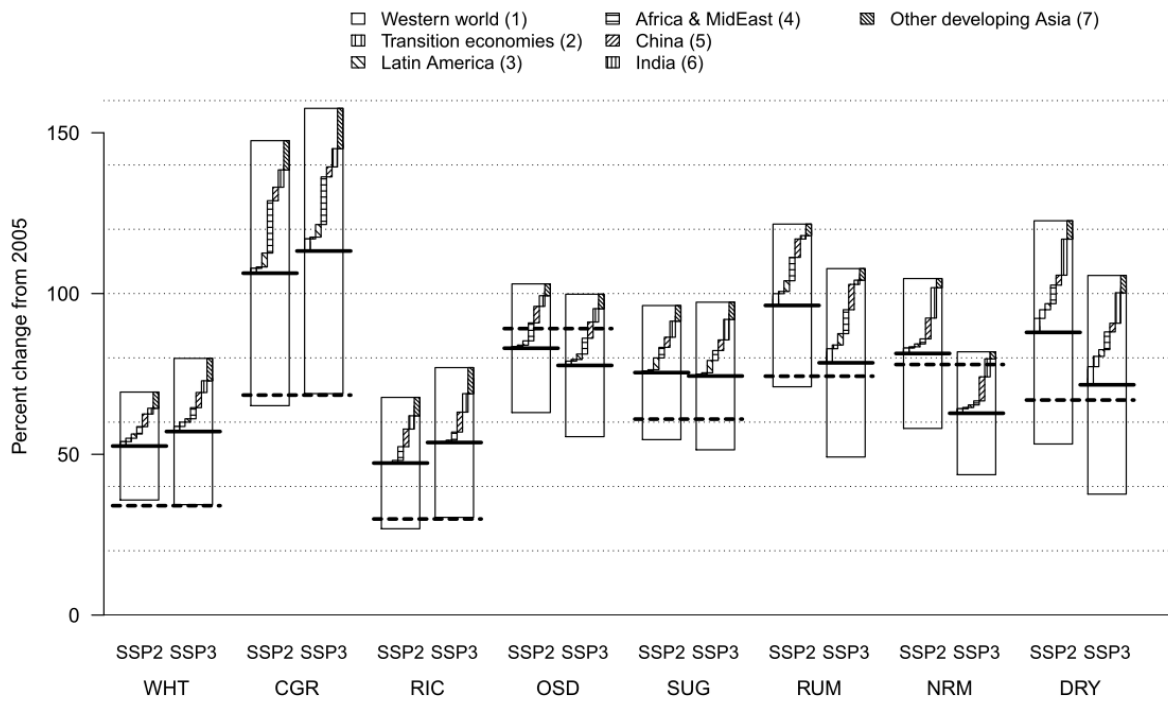
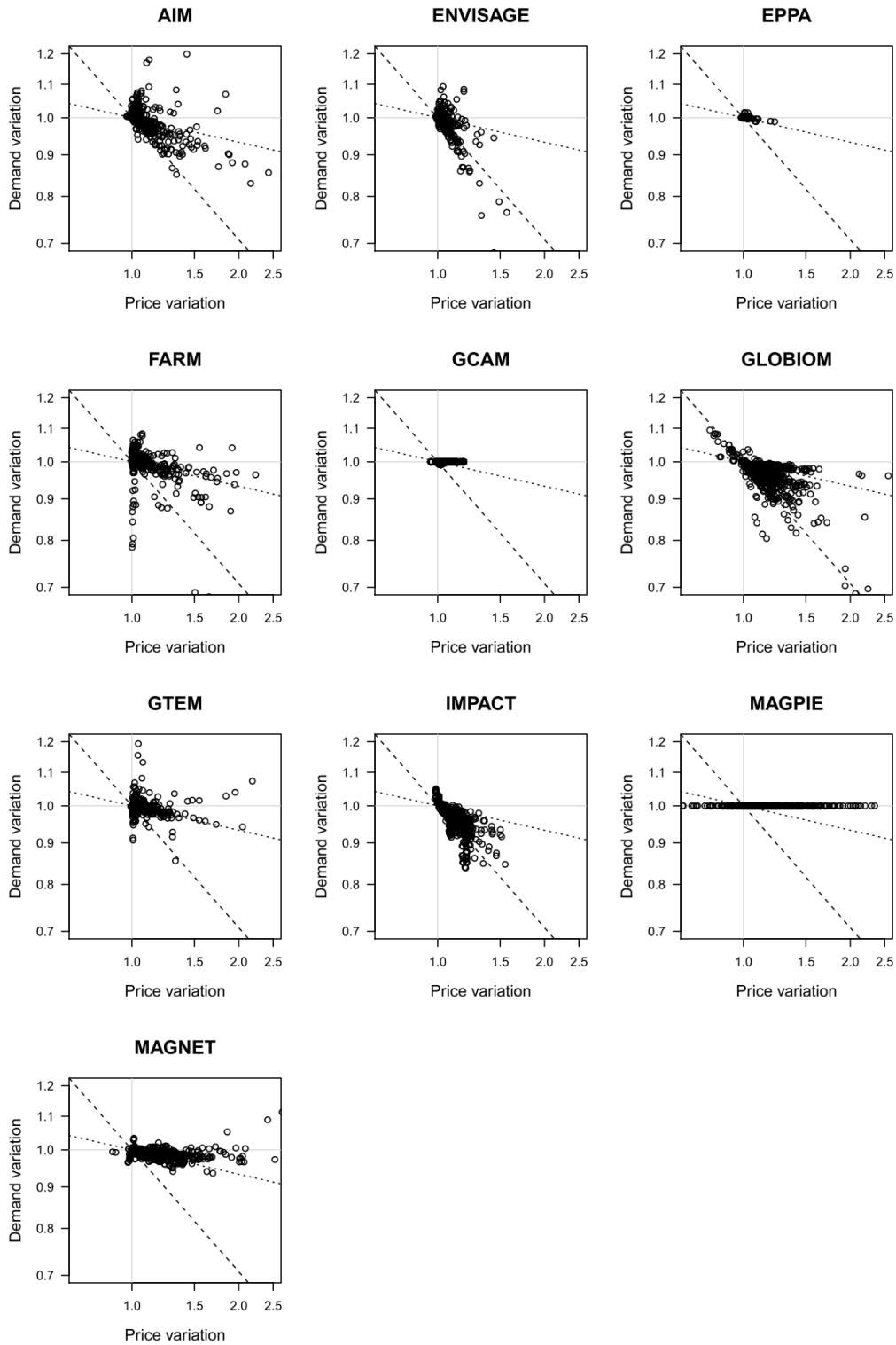
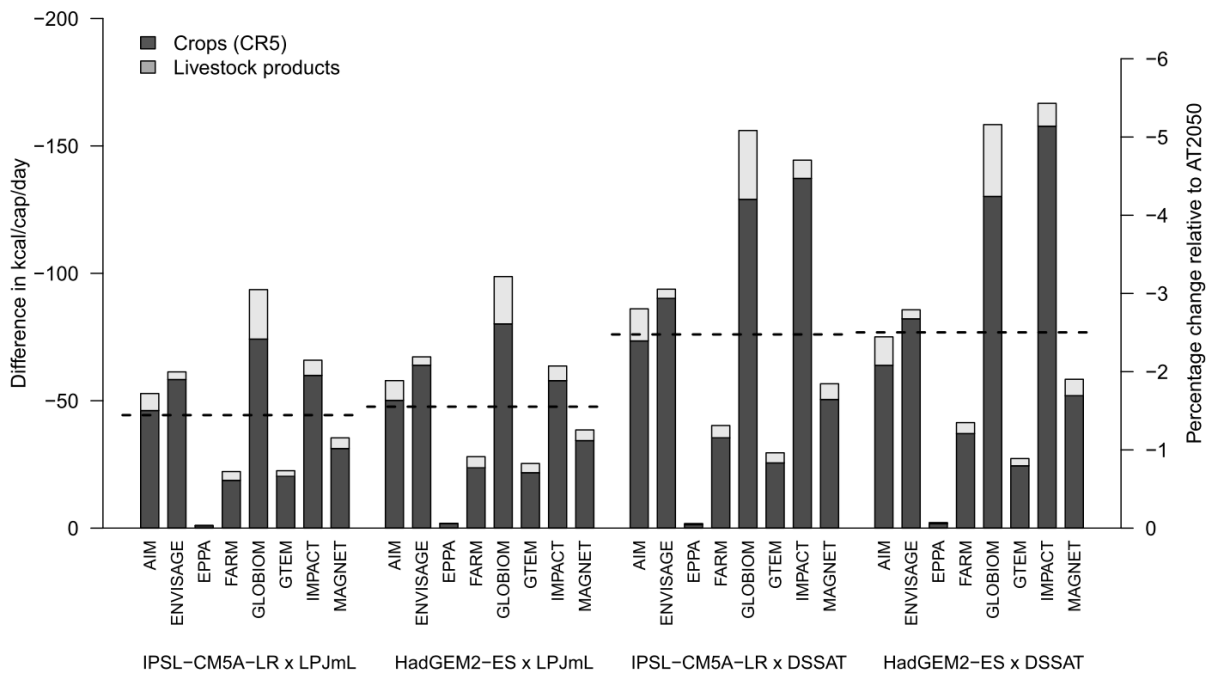


Figure 6. Standard deviation around mean 2050 value of AgMIP models projections, decomposed by region. The black plain line represents the mean of AgMIP model results, the dashed line the FAO projection. White boxes indicate the standard deviation observed across models for variation at the world level. The stacked thin bars represent the decomposition of the world standard deviation. This is performed by splitting the world standard deviation across regions proportionally to standard deviation observed in each region.



715 **Figure 7. Food demand response of AgMIP models to a change in producer prices across the AgMIP**
climate scenarios for single commodity products. Graphs are plotted in log scale. Each dot
 corresponds to a product x region x scenario result; dot superposition areas appear in black. The
 dashed line indicates the response of a price elasticity of -0.5; the dotted line locates is the response
 of an elasticity of -0.1. Both responses for the year 2030 and the year 2050 are displayed, as variation
 720 from the baseline, for the four AgMIP climate scenarios.



725 **Figure 8. Food consumption change with climate change** Left axis indicates the loss in kcal per capita
 730 per day, whereas right axis indicate the results expressed as a percentage of total calorie intake
 according to 2050 FAO estimate in AT2050 (Alexandratos and Bruisma, 2012). Results are calculated
 for two general circulation models (IPSL-CM5A-LR and HadGEM2-ES) using the RCP 8.5 greenhouse
 gas emissions pathway and two crop and vegetation models (LPJmL and DSSAT) with no CO₂
 fertilization (see Nelson et al., 2013 for more details). Dashed lines indicate the mean of the scenario
 considered across economic models.