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Analysis of long-term challenges for agricultural markets

John T. Saunders,
Marcel Adenäuer,
Jonathan Brooks

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ANALYSIS OF LONG-TERM CHALLENGES FOR AGRICULTURAL MARKETS

John T. Saunders (Lincoln University, New Zealand)
Marcel Adenauer, Jonathan Brooks (OECD)

The Long-term Agricultural Outlook model (LAO) is a long-run partial equilibrium trade model developed by the OECD as a complementary modelling tool to AGLINK-COSIMO, a more detailed partial equilibrium model used to develop ten-year projections for agricultural markets, as reported in the annual *OECD-FAO Agriculture Outlook* publication. LAO describes the drivers of structural changes in global supply and demand, provides a baseline of real agricultural prices, and can be used to situate short and medium term price projections in a longer-term context. The model is also suitable for performing scenario analysis of long-term issues concerning agriculture, such as the links between food security and climate change. The model structure is similar to that of AGLINK-COSIMO, which enhances comparability, but much simpler, with highly aggregated commodity and regional groupings. The simplified structure makes it possible to make use of data on productivity growth in a way not possible in more complex models, and to investigate the role of long term drivers of productivity growth, in particular research spending. It also facilitates a focus on key macro-economic drivers of agricultural market developments. This report details the motivation, structure, and development of the model, alongside initial outputs. The baseline results indicate a lowering of real agricultural prices in the long run, as growth in global supply outpaces growth in global demand.

Key words: Agricultural productivity; partial equilibrium; long-run analysis; agricultural prices; total factor productivity; climate change; food security; trade modelling

JEL codes: C6, C69, F1, F7

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Executive Summary

This report presents a simple Long-term Agricultural Outlook model (LAO) to describe the potential evolution of agricultural markets over a period of decades. The model is designed as a complement to Aglink-Cosimo, a partial equilibrium model of global agriculture maintained by OECD and FAO, which provides a more detailed description of potential agricultural market developments, but over a medium-term (ten-year) time horizon.

The simplicity of the LAO model derives from the high level of aggregation, with five commodity categories (crops, ruminant livestock, non-ruminant products, capture fish, and fish from aquaculture) and seven continental regions. A principal benefit of this more aggregated specification, which takes its inspiration from Baldos and Hertel's SIMPLE model, is that it is easier to specify the long-term drivers of supply and demand growth than with a more complex model.

On the supply side, a key driver of production growth is improvements in total factor productivity (TFP). Yet TFP is typically estimated at an aggregate level for the agricultural sector, and becomes much more difficult to measure and interpret at a commodity-specific level. A general finding is that detailed models that do not incorporate TFP growth endogenously have tended to under-estimate the responsiveness of production to higher prices (the elasticity of supply). Moreover, a core determinant of TFP growth is agricultural research, which typically yields returns over a period of decades. This provides a further rationale for developing a model with a long-term perspective.

On the demand side, the per capita consumption of food tends to taper off as incomes rise. Moreover, that tapering occurs sooner for crops than for livestock as peoples' demand for calories satiates before their demand for animal protein. Models that operate over a shorter time horizon and are extrapolated over decades do not capture this tapering. As a result, they may over-estimate the price and income elasticity of demand.

Overall, LAO projects faster growth in supply relative to demand than models that do not have endogenous productivity growth. As a result, the LAO model tends to project lower real agricultural prices.

The results of LAO are compared with those from some of the *Agricultural Models used in intercomparison and improvement project* (AgMip), under common scenario assumptions specified in the OECD report "Alternative Futures for Global Food and Agriculture" (OECD (2016_[1])). In general, the projections for real prices are at the lower end, even after allowing for the fact that the AgMip models were calibrated during a period when food prices were relatively high. However, the ranking of the three alternative future scenarios in terms of their effects on prices is similar when applied to LAO, as when implemented in the models used in OECD (2016_[1]). Alignment of three key variables (population, GDP, and oil price) appears to be sufficient to explain this.

An important use of the LAO is to improve medium-term outlook projections by anchoring them to a better understanding of long-term drivers. Each *OECD-FAO Agricultural Outlook* baseline starts from exogenous price assumptions that are then revised when the model resolves trade imbalances globally. However, the initial projections of supply and demand reflect expert judgement, not just the explanatory variables in the model. As a result, final prices are not fully endogenous and the initial price assumptions are important.

LAO provides a useful starting point for establishing initial price assumptions, from which revised medium-term price projections can be calculated.

The core LAO drivers can be linked to simple metrics of food security (calories and protein), resource use (land allocated to crops, pasture and forests), and climate change (emissions from agricultural production and land use change). Thus, LAO has the potential to give a broad assessment of progress on some of the core challenges facing global agriculture.

The model can also be used to assess the implications over decades of changes in those core drivers. On the supply side, those changes would include the implications of faster productivity growth deriving from higher levels of investment in research and innovation. On the demand side, they could include the implications of faster income growth, particularly in Africa where per capita incomes remain far behind averages in other regions. Faster income growth is typically associated with slower population growth, and such interactions can be explored in the model.

More generally, all the core drivers of LAO are subject to a wide range of uncertainty. LAO should be viewed not as a forecasting tool, but rather one with which to explore the markets developments associated with a range of different assumptions on productivity growth and resource constraints, and on population and income trends. The range of possible outcomes can be potentially examined as well via stochastic analysis, and with alternative supply and demand parameter assumptions.

Because LAO is highly aggregated, and most of the supply and demand aggregates are derived from FAOSTAT and data in the Aglink-Cosimo model, additional data needs are modest and easily obtained from other sources. A key piece of information is the global estimates of total factor productivity growth, computed by USDA-ERS on the basis of FAO data.

LAO provides a benchmarking tool that makes it possible to situate both the medium term *OECD-FAO Agricultural Outlook* and the LAO itself relative to other modelling efforts; in particular those in the AGMIP project which have their own strengths, especially with regard to their spatial depiction of resource use. This, in turn, can foster a better-shared understanding obtained from diverse models of some of the long-term challenges facing global agriculture.

1. Background and motivation for the development of the Long-Term Agricultural Outlook model

The Long-Term Agricultural Outlook (LAO) model was developed to represent the core long-term drivers of world agriculture, to facilitate an examination of long-term policy issues that extend beyond the ten-year horizon of the annual *OECD-FAO Agricultural Outlook*, and to provide a benchmark by which the OECD can situate its own modelling analysis relative to other long-term modelling efforts.

A key motivating factor is that although the detailed Aglink-Cosimo model is useful for medium-term analysis, it is less well adapted to capturing the impacts of fundamental forces that evolve over a period of decades. These forces include population and income growth, and changing dietary preferences on the demand side, and productivity growth, land use, and the application of non-land inputs on the supply side. These drivers are all subject to considerable uncertainty. Indeed, the spread of possible outcomes is so wide that LAO, like any other projection model, should not be viewed as a forecasting tool, but as a coherent framework for drawing out the market implications of core drivers evolving in different ways.

The broad aim of the model is to provide a bridge between medium- and long-term market projections so that policy makers can gain insight into the long-term implications of policies that are enacted over the medium term, in particular those related to global food security and climate change (Box 1).

Box 1. Policy analysis across the medium- and long-term

The OECD undertakes research to help inform government policies. Policies can be designed in response to short-term temporary shocks, medium-term cyclical factors, and to address long-term structural challenges such as climate change. However, policies enacted to address short- or medium-term market issues may have consequences across a longer time horizon, while measures addressing long-term challenges will typically have short- and medium-term impacts. A basic aim of OECD's forward-looking analysis is to ensure that policies are informed by a consistent perspective on their impact over time.

The Aglink-Cosimo model, which underpins the *OECD-FAO Agricultural Outlook's* ten-year projections, provides a useful tool for gauging the medium-term impacts of policy changes. It is less well adapted for understanding core long-term drivers such as total productivity growth, which is typically measured at a broad level of aggregation, and the impacts of research and development.

Analysis of medium- and long-term issues has rarely been interlinked. The medium-term outlook process seeks to incorporate expert market knowledge into the first years of the projections, and thus represent a mix of fundamental factors and temporary disturbances that are identified by market experts. A link to long-term analysis can help situate how this expert view of the trend of the medium term outlook fits onto a long term structural path driven by market fundamentals. Some projections are available from the literature, especially from the Agricultural Model Intercomparison and Improvement Project (AgMIP), but there is little coherence across medium- and long-term market assessments, and the assumptions that lead to differences in results are not always clear. The LAO model seeks to help redress this deficiency.

The UN World population prospect's medium fertility variant (Figure 1) shows global population reaching over 10 billion by 2055, and stabilising at just over 11 billion by the 22nd century. This implies that the global population peak would occur within the next century. Alternatively, the high fertility variant sees global population more than doubling by 2100, and continuing to increase, while the low fertility variant predicts the population peaking by mid-century before falling to near its current level. This is a variance of 9.3 billion people (in 2100) between the high and low fertility scenarios, highlighting the potential uncertainty in future demand for food.

It is also expected that as incomes increase, demand preferences for food will change. Consumption of meat and dairy products is expected to grow over the next century to satisfy a demand for protein in today's lower income countries (Bodirsky et al., 2015^[2]), although the 2018 *OECD-FAO Agricultural Outlook* (OECD/FAO, 2018^[3]) sees few signs of a convergence towards western diets. Such a demand, however, will present an additional strain on land-use and greenhouse-gas inventories as livestock sources calories are generally more land- and emission-intensive than the equivalent from crop production. Furthermore, the OECD/FAO (2018^[3]) foresees limited increases in per capita demand in Sub-Saharan Africa, essentially because real income growth is not much higher than population growth. This prognosis could change within the coming years.

The negative impacts of anthropogenic climate change on agriculture are expected to intensify over the next century, although remaining relatively minor up to 2050 (Van Meijl et al., 2017^[4]). Such impacts include changes in crop-growing regions and an increase in severe weather events. The implementation of climate change mitigation policies would also impact on agricultural production (Hasegawa et al., 2018^[5]). This represents another layer of uncertainty that will shape agriculture over the next century.

Figure 1. UN projection of population growth

Note: +/- 0.5 child projection represent the high and low population variant scenarios.

Source: United Nations, Department of Economic and Social Affairs, Population Division (2017).

Lastly, demand for bioenergy with the advent of second generation biofuels may increase competition for land-use, creating further pressure on agricultural production and raising real food prices.¹

On the supply side, the key component in the ability of the agricultural sector to respond to these demand changes is productivity growth. Historically, agricultural supply has grown faster than demand, leading to a long-term declining trend in real agricultural prices, interrupted by price spikes as shown for wheat in Figure 2.

Before and throughout the first half of the 20th century, increases in agricultural production were overwhelmingly the result of increases in agricultural area. As of 1950, increases in yields became the main source of production growth. Since the 1990s, increases in total factor productivity (TFP) – that part of yield increases that are not attributable to increased input use – have become the dominant source of production gains (Figure 3).

Many economic models fail to capture these dynamics because the parameters are estimated based on short-term price responses rather than long-run price dynamics, and because their complexity means that broad drivers cannot be well described.

In general, partial equilibrium models are dependent on exogenous projections or non-agricultural factors, while assumptions often need to be made with respect to model parameters in each model. As these models increase in complexity, so does the number of exogenous inputs and assumptions. This can be detrimental to long-term analysis, in so far as the uncertainty surrounding each element increases as the time horizon becomes longer.

Figure 2. Real prices for wheat

¹ This is only the case when second generation technologies use feedstocks that have that are produced on land. Fast rotation plantations, where trees are grown for the purpose of energy are one example.

Figure 3. Composition of cereal production

Source: Own calculations based on FAOSTAT database.

One approach to reduce this uncertainty is to make the model less complex. In this way, less external data is required, and the amount of testing and analysis on the key variable can be increased. This approach is taken by Baldos and Hertel (2012^[6]) in their SIMPLE model:

“SIMPLE has been developed under the principle that a model should be no more complex than is absolutely necessary to understand the basic forces at work. SIMPLE can be used to assess the relative contribution of each of the individual drivers to the endogenous changes in world agriculture...”

The SIMPLE model was developed to assess long-term dynamics and provides a key reference to understanding the potential evolution of agriculture in the long term as used in Hertel (2011^[14]), Baldos and Hertel (2013^[15]), as well as Hertel, et al. (2016^[16]). A core finding is that the majority of agricultural sector models have under-estimated supply response in the agricultural sector, and hence tended to over-estimate developments in price levels, by not including TFP explicitly in the supply equations. Yet TFP is typically estimated at the sector, rather than the commodity-specific, level.

A general advantage of such approaches is that a model of lesser complexity can provide analysis faster, has greater transparency, facilitates replication of model output, and is a good communication tool for non-specialists and specialists in other disciplines.

Each model has its strengths and weaknesses (Box 2). As far as results across models differ, it is important to be able to distinguish the extent to which these differences are due to exogenous assumptions, model parameters, or the basic structure of the model and the interactions they are capable of capturing. This distinction is not always straightforward for very complex models. The LAO model builds on the philosophy of SIMPLE and has three major aims:

- *Enhance medium-term projections by better describing long-term drivers:* The Aglink-Cosimo model is used to construct an expert validated baseline of agricultural markets over a ten-year range. This same validated baseline process cannot be performed over a 25-50-year horizon as the value of expert opinion diminishes. However, medium-term

trends depend to a certain extent on assumptions on long-term issues: How and when might the implementation of the Paris COP21 agreement impact on agricultural prices? Will the long-term trend of decreasing prices for agricultural commodities be overturned due to more binding resource constraints? Such questions can be addressed more easily in a simpler model with fewer assumptions, and where alternative assumptions on supply and demand shifters can be implemented directly into the model. The result of a wider analysis of the long-term drivers with such a simple model can then be used to further validate the Aglink-Cosimo medium-term baseline² and related scenario work.

- *Perform independent analysis of long-term supply and demand shifters:* The proposed model can also be used to perform scenario analysis either to test the bounds of various macro-economic predictions, and drivers of supply and demand, or to specify paths that would be consistent with meeting specific long-term challenges. Some issues that can be examined are: the productivity impacts of climate change;³ changes in greenhouse gas emissions implied by different scenarios; price developments in production inputs; demands for bio-fuels; and the effects of demographic shifts.
- *Address the determinants of agricultural productivity shifts:* A focus of the model is to incorporate total productivity growth within the model. Endogeneity of productivity is the major aspect that distinguishes LAO from other modelling approaches.

Box 2. Models performing long-term economic analysis

There are several economic models used for long-term analysis (in addition to long-term climate and biophysical models which do not have a primary economic focus). Many are part of the AgMip project, which aims to improve comparability across the outputs of various models, and to test their relative findings, and sensitivities across various parameters. Some relevant studies based on the AgMip project are von Lampe (2014^[7]); Muller & Robertson (2014^[8]); Robinson et al. 2013; Schmitz et al (2014^[9]); Valin et al. (2014^[10]); and Wiebe et al. (2015^[11]). These models generally fall into two categories: Computable General Equilibrium (CGE) and Partial Equilibrium (PE) models.

The strength of CGE models is the incorporation of the entire economy and hence inter-sectoral linkages. They usually are quite complex, have typically more aggregate commodity coverage and are characterised by large data requirements. Many CGE models still struggle with biophysical accounting because they define their variables in value terms. For example, land markets are typically implemented with CET-Nests that do not guarantee that the physical sum over all land types stays constant. CGE models applied in long term analyses suffer from the fact the Social Accounting Matrices on which they are based are static, while in reality many structural changes occur over time. The MAGNET model (Woltjer et al., 2014^[12]) is one of the frequently used CGE models in long-term analysis while the MIT EPPA model (Chen et al., 2016^[13]) has CGE components.

PE models focus on a subset of sectors and are often used for agricultural analysis, with the assumption that this sector is relatively self-contained and linkages to other sectors can be treated exogenously. PE frameworks are usually more flexible and allow for a greater level of detail.

CGE approaches are helpful to understand some aspects of growth dynamics. However, in the context of agriculture-specific developments, the requirement of verifying and testing economy-wide parameters for growth and development over the long-term are costly, and arguably not necessary

² LAO results could be used as a complement to expert information, e.g. on price developments.

³ Even though the model equations have no direct link to a climate change variable, scenarios can be performed that assume different TFP trends mimicking the impact climate change can have on yields.

if the main feedback is from the rest of the economy to agriculture. There are several examples of linking CGE and PE models but this is in most cases only a top down linkage, where the CGE model delivers macroeconomic variables to the PE model. Rarely, the more explicit cost structure of an agricultural PE model is taken into account in CGE models by bottom up linkages as for example in Britz and Hertel (2011^[8]).

There are various PE models with an agricultural focus used for long-term analysis, such as GLOBIOM, MAgPIE, IMPACT (Batka et al., 2012^[9]), CAPRI (Britz and Witzke, 2014^[10]) or SIMPLE. GLOBIOM (Havlík et al., 2014^[11]), (Schneider et al., 2011^[12]) and MAgPIE (Lotze-Campen et al., 2008^[13]) are spatial PE models which simulate supply in detail on a geographic grid. These simulations take into account various biophysical conditions (altitude, slope, and soil type) to determine the suitability for different land use. These models appear to have many of the properties necessary to address long-term agricultural issues, especially with respect to the impact of climate change and mitigation assessments. Yet the high degree of detail and the general complexity make scenario analysis more time and resource intensive than a simpler approach. Overall, the existing alternatives to address outcomes for agriculture over the long-term tend to be complex or are difficult to align with medium-term analysis.

In addressing the supply-side drivers over the long-term, a European Commission report analysed the lack of integration in the approaches to technological change between many long-term models (Van Meijl et al., 2017^[4]). Productivity is often only partially specified in models, especially with regard to total factor productivity growth, and the impact of investment in research and development.

2. Model structure

The LAO model is a recursive dynamic, partial equilibrium model, which solves a world market clearing equilibrium. Demand is divided into five components: consumption as food and feed, waste, other-use, and biofuel use.⁴

The majority of data used in the model and for parameter estimation comes from the FAOSTAT database, which provides a general comparability between country-level data with a wide range of coverage for crops and animal products. This database is largely aligned with the data used in the Aglink-Cosimo model, ensuring further cohesion between the two models. Data for fish commodities was taken from the OECD.stat and from the FAO FIGIS database.

The model has seven regions broadly reflecting the regional composition used in the SIMPLE model and the UN regional groups. The full country composition of these regions is detailed in Table A B.1.

The model currently has five mapped aggregate commodities (Table 2). Animals have been separated into ruminant and non-ruminant categories, primarily due to the large (even at an aggregate level) difference in feeding systems and greenhouse gas outputs between ruminants and non-ruminants. Owing to the difference in production methods, fish production has been split into fish from capture and that from aquaculture. This also allows for constraints on global fish stocks to be simulated. As aquaculture is predicted to play an increasing role in food supply over the long term, this separation is important for understanding food security.

⁴ There are three core elements that distinguish LAO from the SIMPLE model: LAO is recursive dynamic; it has a more explicit endogenous TFP representation; and it has greater commodity coverage.

On the supply side, the most important shifter can be summarised in the productivity measure. Hertel et al. (2016^[16]) identify the response of productivity to agricultural research and development spending as a key factor in understanding market outcomes and the implications for food prices and food security. Accordingly, the structure of the LAO model accounts for several aspects of productivity and inputs.

Productivity in agricultural modelling is typically treated as an externally sourced input, often loosely based on projected GDP growth. In cases where productivity growth is considered internally, this is usually simplified as a single growth rate based on historic growth in production (Robinson et al., 2014^[17]). For the two fish commodity groups (fish from aquaculture and that from capture) the LAO model also uses such exogenous TFP assumptions.

Figure 4. LAO flowchart

Table 1. Aggregate regions in the LAO model

Code	Description
EuCA	Europe & Central Asia
OcSEA	Oceania & South-East Asia
NoAWA	North Africa & West Asia
NoA	North America
SA	South Asia
SsA	Sub-Saharan Africa
LAC	Latin America and Caribbean

Note: Full country composition in Table A.B.1.

Table 2. Commodity composition in LAO Model

Code	Description
CR	All land based plant agriculture (i.e. arable, fruit & vegetables, coffee, etc.)
RA	All ruminant animal production (i.e. meats, wool, raw milk)
AN	All non-ruminant animal production
AQ	Fish from aquaculture
FS	Fish from capture (no shellfish, aquatic mammals or plant-life)

For agricultural commodities, the LAO model seeks to include productivity as an internally calculated endogenous and dynamic measure. As a first step, the TFP measures derived in Fuglie (2015^[18]) were used to estimate a TFP index, which in turn was used to calibrate TFP in LAO's yield equation. This TFP index is endogenous in the model and depends on four major elements (equation 5 in Annex A):

- *R&D investments*: The first variable influencing TFP is returns to agricultural research as described in Alston et al. (2011^[19]). This study and a study by Huffman and Evenson (2006^[20]) find that returns on agricultural R&D have a very long lag period, estimated at between 35 and 50 years. A long-term model with long lags on contemporary investment rates can assess implied TFP growth in a way that is not possible with medium- and short-term models. These lags are implemented using the method described in (Alston et al., 2011^[19]) where a gamma lag distribution is based on the fit of the data (rather than at a static rate taken from the literature). Agricultural R&D investment is estimated from UNESCO agricultural GERD indicators, OECD agricultural science domestic investment data, and USDA data.
- *Productivity spill over between regions*: The method applied by (Alston et al., 2011^[19]) also calculates spill over rates from other regions based on the similarity of their agricultural outputs, i.e. R&D spending in a region with a high production of wheat will be more relevant to other regions with high wheat production.
- *Technology adaptation*: Technology adaptation in periods when market prices are high, and thus revenue prospects are good, results in a positive investment response. Investments can be made by farmers improving their farm machinery because of available cash flow, as well as by multinational enterprises that invest in agriculture (domestic or foreign). To capture this effect, the TFP equation in LAO has an element that shifts TFP in periods of high prices.
- *Exogenous trend*: The equation includes a trend variable.

The yield equation depends on TFP, but also incorporates an index of costs to separate changes in inputs from technological growth. Sourcing consistent input prices for agriculture is a difficult task, especially at the global level. Thus the inputs given by Fuglie's measures for TFP (sourced from FAOSTAT's input and investment indicators) have been used to construct a cost index following Peterson (1988^[21]) to derive marginal cost shares as a factor of multiple inputs. This latter method ensures that various inputs into agriculture are accounted for without the need to source input prices or to estimate shadow prices.

The LAO model has constraints on total water use by sector, total availability of land-use, and on fish stocks for fish from capture. Due to the high level of country aggregation, these limits are rarely reached as resource shortages often occur at a finer geographic level (OECD, 2017^[22]). These limits, however, can be manipulated to perform scenario analysis and have been implemented to allow future model variations to account for more detailed analysis.

Shifters also exist on the demand side. Demand is specified in a log-log form, with demand elasticities taken from the USDA ERS food elasticities (Seale et al. (2003_[23]) and Muhammed et al., (2011_[24])). These elasticities have been weighted and aggregated into the regional groups used in the LAO model. However, income elasticities are not static in the long run as the relative preference for food products associated with marginal increases in income decreases as incomes rise. In addition, the dietary share of plant-based food products usually decreases in comparison to animal-based food. With rising national incomes predicted over the long run, we expect income elasticities for food to decrease.

To account for this effect, a logarithmic trend has been created from the relationship between income elasticities for each food group and individual countries' current national per capita incomes (Figure 5). As a region's income increases over the projected period, their income elasticities progress along the trend, progressing to the levels currently seen in higher income nations. This ensures that demand growth for food does not simply grow in direct proportion with income growth, but also that per capita consumption becomes less sensitive to income growth, as incomes increase.

The LAO model does not use a single year as the basis of its projections. Even though it is a recursive dynamic model that simulates yearly projections, a long-term model represents more a medium-term equilibrium in each reported year. The average of the last five years with available data (2008-12) is used, therefore, to calibrate the model.

Figure 5. Income elasticities relative to income for major food groups

Note: Each point represents a national level income elasticity.
Source: Own calculations based on Muhammed et al. (2005).

World prices in the model are calculated as a weighted average producer price across all regions. The weighting is determined by a region's share of total exports for each commodity. Price transmission is determined by the difference between this synthetic world price and the producer price for each region, and is held constant throughout the modelled period. This price wedge reflects transaction costs as well as possible producer support measures. A similar price wedge exists for consumer prices, reflecting additionally processing margins and potential consumer price support.

3. Scenario analysis

Reference scenario

In general, a baseline projection attempts to describe a “business as usual” reference scenario, using the most-likely outcomes of exogenous variable as input. For long-term analyses it is unusual to define a baseline as the expression most-likely outcomes becomes less stable the further away the final simulation year is. Instead, many long-term analyses use future scenarios, e.g. the five Shared Socio-economic Pathways (SSPs)⁵ which have become a standard set of scenarios for the international global long-term modelling community. The SSP2, a middle of the road scenario, has become a reference scenario in many publications and it is used in the presentation of results as a benchmark to compare with changes in other scenarios. It is in this spirit that the LAO reference run uses the following key drivers of changes over time:

- *Population*: Taken from the UN population prospects 2017 revision: medium variant.
- *GDP*: A linear extrapolation of real GDP per capita for each country from the World Bank GDP data 1961-2012, compiled into the regional aggregations used in the LAO model.
- *Index of non-energy input costs*: Constructed from Peterson (1988), FAOSTAT input data, and a logarithmic trend for projections.
- *Oil price*: A linear extrapolation of the IEA oil prices used in the Aglink-Cosmo model.

As mentioned above, the LAO model has exogenous limits to some production resources incorporated into its structure across three key areas: land use, water use, and fish stocks. The land and water use modules are populated with the FAOSTAT Agri-Environmental Indicators datasets. In the current reference scenario, the limits on land and water use are not significant at the levels of the regional aggregation, although water use limits in the North Africa & West Asia regions are almost binding in 2050, the final year of the current projections.

The constraints on fish from capture, however, are relevant. These constraints are used to simulate the limits of global fish stocks. The total additional capacity for global fishing is thought to be 16.5 million tonnes over the current level of production (FAO, 2014^[25]). This potential for supply has been allocated according to the percentage of under-fished stocks by ocean area (FAO, 2011^[26]) and current capture rates in those areas. All regional limits for production are reached within the time range of the projections by 2040. This results in an increase in the price of fish, incentivises growth in aquaculture, and places increased pressure on crops and animal products to satisfy increases in food demand, leading to higher world prices for other commodities.

⁵ The SSPs are part of a recent framework that the climate change research community has adopted to facilitate the integrated analysis of future climate changes. The different pathways examine how global society, demographics, and economics might change over the next century.

The assumptions for the future of global fisheries can have a significant impact on the outcomes of world prices for other commodities. Using a total additional capacity as the limit for global fisheries assumes global fisheries will be maintained at a sustainable level, whereas if over-fishing is the global norm, higher production of fish from capture would be expected, followed by declining production over-time, and ultimately higher prices for other food commodities. The reference scenario assumes a rapid increase in the share of fish originating in aquaculture production systems in total fish consumption (Figure 6).

Figure 6. Percentage of total fish production from aquaculture

Source: LAO simulation results.

The growing importance of fish from aquaculture is visible in Figure 7, which displays the consumption shares of the five commodity groups used in LAO into perspective. In general, total per capita food demand is expected to increase by 10% from 2012 to 2050. The share of fish in total consumption remains more or less stable. A major shift can be observed historically from crop commodities toward non-ruminant commodities, and this is projected to continue. Ruminant meat consumption is expected to increase slightly by share and on a per capita basis for all regions except North America. At the regional level, while decreasing in total shares, per capita consumption of crops increases in Oceania and South East-Asia, Latin America and Caribbean, South Asia, and Sub-Saharan Africa regions. Additionally the per capita consumption of non-ruminant animals decreases in the high income regions (North America, Europe, and Central Asia).

Biofuel demand quantities for food commodities in the model are determined by historic demand for biofuels, crop and oil prices. There is a biofuel policy parameter in the model which can set a minimum level of consumption for biofuels by region. In the current reference scenario, no changes to biofuel mandates from current levels are assumed and the minimum level is fixed at the biofuel use in the base period. Consequently, biofuels are not assumed to be a major driver of demand in the LAO projections.

Figure 7. Global food consumption shares

Source: LAO simulation results.

In Figure 8, the world prices simulated by the LAO model are compared to those from OECD/FAO (2018_[3]). The prices are presented as an index of the base period, the average of world prices from 2008 to 2012. For a better comparison, the single commodity prices in Aglink-Cosimo have been aggregated to the LAO commodity definition, crops, ruminants and non-ruminants, but the single product prices are also shown as dotted lines.⁶

For crops, the historic real price from the LAO model tracks the aggregate from Aglink-Cosimo well. For the projection period (which starts in 2013 for LAO) one can see that the model properly projects a strong price decrease, but earlier and not to the same extent as prices actually reached in the past few years. One should not place too much emphasis on the actual level of projected prices with LAO as these are dependent on the calibration point and concentrate more on the comparison of price trends. It seems that the LAO model projects a stronger rate of annual decrease in real prices compared to OECD/FAO (2018_[3]). While both models confirm that supply growth will continue to outpace demand growth, supply growth in LAO is relatively stronger.

For ruminant products, the comparison is similar although this time the absolute level of the LAO price is below the specific product prices given by OECD/FAO (2018_[3]). In contrast to crops, however, the medium-term annual price decrease in real terms is similar in both cases, indicating that the assumptions on market fundamentals are similar. In the case of non-ruminant products, the fit between the two models is the best as even the absolute levels are comparable.

Such comparisons will enrich the OECD/FAO agricultural baseline process in the future as the OECD will be able to feed different assumptions on macro drivers into the LAO model and examine the effects on world market price levels. This, in turn, can inform the price generation process.

⁶ Historical differences in the price indices presented might be the result of different aggregation weights. LAO uses the FAO Food Price Index.

Figure 8. World prices for crop, ruminant and non-ruminant products

Comparison between the LAO reference scenario and the Aglink-Cosimo baseline

Source: (OECD/FAO, 2018_[3]).

Demand shift scenario

The reference scenario for the LAO model uses the medium variant from the UN population prospects dataset. To illustrate the impacts of the different population projections, the model was simulated with the high and low variants of the UN population prospects. As seen in Figure 1, there is a variance of roughly two billion people between the high and low scenarios by 2050.

Population dynamics in the model are critically interlinked with GDP predictions. In these scenarios it is assumed that GDP per capita is not dependent on the population projections. Naturally, population changes strongly impacts on demand and on commodity prices (Figure 9).

In the low population variant, crop prices are projected to be about 15% lower than in the high population scenario. The difference in demand also leads to differences in crop areas (Figure 10). In the low population scenario, pressure is taken from the land resource as 100 Mha less area is required, while the high population scenario requires an additional 130 Mha, increasing the pressure on land balance. In the medium variant, total crop areas remain at similar levels as in 2012.

This relatively simple scenario demonstrates one ability of the LAO model: to be able to alter major drivers of demand systematically. The next section will look into changes of supply shifters, but rather than simply altering the TFP measure exogenously, the endogenous representation of TFP is illustrated.

Figure 9. World prices for crop products (real)

Source: LAO simulation results.

Figure 10. Development of harvested areas

Source: LAO simulation results.

Productivity shift

In order to illustrate the endogenous TFP representation in LAO, a scenario that increases GDP in Sub-Saharan Africa (SSA) was simulated. It assesses what would happen if this region were to become considerably richer, similar to the development in China as of 1990. Specifically, GDP growth between 2030 and 2040 was increased to 15% pa, before returning to 1.6% pa from 2040 onwards.

This scenario was run twice; once with the standard TFP implementation as in the reference scenario and again with an exogenous measure of TFP. For the latter, a logarithmic extrapolation from historical TFP between 1961 and 2012 was used. The TFP development between the two versions mainly differs during the first projected years. Here, the endogenous TFP version begins with a stronger growth in TFP because the model begins from a period with high prices that subsequently raises TFP. After the first years, the TFP growth rates are similar between the two model versions in the reference scenarios.

Yet in the GDP shock scenario, TFP picks up from 2030 onwards in the endogenous version as prices increase, induced by additional demand from stronger income growth. The price effect is illustrated for ruminant animal products in Figure 12. Two observations can be made. First, the reference scenario using exogenous TFP growth has generally higher price levels, as TFP is lower. Secondly, the GDP shock leads to stronger price increases compared to the endogenous TFP version, where TFP reacts to the higher prices and thus mitigates the price shock. This brings the price level back to the level of the reference scenario after 2040, when the GDP boost in SSA is effectively over. The continuing increases in TFP are also maintained by ongoing returns to increased agricultural R&D spending, stimulated by the GDP shock.

Figure 11. Total factor productivity for ruminant animal products in Sub-Saharan Africa

Source: LAO simulations.

Figure 12. Real world price for ruminant animal products

Source: LAO simulations.

Alternative futures for global food and agriculture

This OECD (2016^[11]) report developed three contrasting scenarios to illustrate alternative futures based on several global economic models and extensive discussions with relevant stakeholders. It outlines policy considerations to help ensure that future needs are met in an economically, environmentally, and socially sustainable manner. The scenarios highlight the fundamental uncertainties surrounding forward-oriented decision making and point to the crucial importance of international co-operation across multiple policy areas (Box 3).

Box 3. Alternative futures for global food and agriculture

In 2016, the OECD published a study which aimed to provide essential insights into the possible futures, challenges and opportunities facing the food and agriculture systems, and to challenge assumptions regarding the development of, and linkages between, the different drivers and outcomes towards the middle of this century. Three alternative scenarios are presented in the report, each of which depicted alternative pathways which the world may follow in the period leading up to 2050:

- *Individual, Fossil Fuel-Driven Growth* portrays a world driven by sovereignty and self-sufficiency, characterised by the strong focus of individual countries and regions on economic growth and relatively less emphasis by governments or their citizens on environmental or social questions. Co-operation is limited to regional alliances and is driven by national interests rather than long-term geo-political visions. Technological developments are based on fossil fuel extraction.
- The *Citizen-Driven, Sustainable Growth* world, in which consumers and citizens drive individual countries to emphasise environmental and social protection. Global co-operation is relatively limited. Technologies are focused on natural resource savings and the preservation of the environment.
- The *Fast, Globally-Driven Growth* scenario illustrates a future which is characterised by a strong focus on international co-operation to achieve economic growth. Environmental issues receive less attention from governments or their citizens. Technologies flourish in many domains, particularly in the areas of food, feed and energy production, and are easily shared internationally.

These scenarios do not aim to portray the “most likely” outcomes, but rather to present plausible global narratives of alternative responses by private actors (including consumers and business) and governments to the broad challenges facing the global food and agriculture sector. The study found that food prices could well continue to rise and that farm incomes would also increase, while the agricultural sector’s contribution to GDP and employment would fall. The report recommended that versatile, comprehensive and robust strategies are required to exploit the benefits associated with alternative pathways and contain adverse impacts.

This section applies the scenario assumptions made in OECD (2016_[1]) to the LAO model and compares the results with those coming from the other models used in the 2016 study to gauge where results converge and where they diverge with those coming from larger and more complex models.

The three scenarios analysed in OECD (2016_[1]) differ mainly in three dimensions: global co-operation, energy usage, and technological growth (Box 3). In this application of the LAO model, the following input variables were taken from the OECD futures scenarios study:

- population change (aggregated to the LAO region groups)
- GDP change (aggregated to the LAO region groups)
- projections of future world oil prices
- demand profiles for food consumption change (aggregated to the LAO region groups; uniform across the three future’s scenarios).

The different macro variable assumptions are presented in Figure 13. Several additional assumptions were made in OECD (2016) which could not be incorporated into the LAO model as the respective variables do not exist (e.g. infrastructure development or trade integration). The endogenous (internally derived) function for technological growth in the LAO model has also been used for these scenarios leading to potential deviations from the specified growth rate used as inputs.

Figure 13. Macro variable assumption per scenario

Source: LAO input data based on assumptions in OECD (2016).

Figure 14. Production projections from OECD and the LAO model

Source: LAO simulation results and OECD (2016[1]).

Finally, the constraints for existing fish stocks, water-use and land-use, which are incorporated into LAO, have remained at the level set in the reference run. If these limits are more restrictive than those used for the other models, we expect higher prices in the results from LAO due to restricted production.

Production projections of the LAO model broadly fall in the range of the simulated combinations of scenarios and models in OECD (2016[1]) as far as the categories can be compared. To obtain a certain level of comparability, the cereals projections from OECD (2016[1]) are compared to the crop commodity aggregate in LAO, and the non-ruminant products from LAO are compared to the meat projections in OECD (2016[1]). Figure 14 shows those comparisons.

In the case of the cereals/crop comparison, the results from the LAO model are similar. In the *Individual* scenario, LAO projects global crop production to increase by about 60% by 2050 while the different models in OECD (2016[1]) show a range between 45% and 80% for cereals. In the *Fast* scenario, OECD (2016[1]) shows a range of between 40% and 85%, where LAO sees an increase of about 50% – closer to the lower end of the range. In the *Sustainable* scenario, LAO projects an increase in crop products by 40%, in the middle of the OECD (2016[1]) range of 25% to 60%.

For the meat/non-ruminant product comparison it can be observed that LAO projections range at the upper end of the total range simulated in OECD (2016_[1]) and the *Fast* scenario even exceeds that range. This can partly be explained by the differences in variable definition as the non-ruminant projections show stronger increases than ruminant products.

An advantage of the LAO model's simple structure is that it allows for quick testing and analysis of key parameters in scenarios. As an example of this, the three OECD future's scenarios were split into two sub-scenarios to test the main contributor to consumption growth in the period examined. By keeping either population or income at base year levels in the sub-scenarios, we can assess the contribution of the two drivers to growth in demand. Some results of these sub-scenarios are presented in Figure 15.

Figure 15. Contribution of population and GDP per capita to food demand growth, relative changes from base year to 2050

Note: EuCA = Europe & Central Asia, OcSEA = Oceania & South-East Asia, NoAWA = North Africa & West Asia, NoA = North America, SA = South Asia, SsA = Sub-Saharan Africa, LAC = Latin America and Caribbean
Source: LAO simulation results.

Generally speaking, results across all scenarios suggest that population growth is the main component of demand growth for crops across all regions. This is reasonable as growth in per capita demand for crops is expected to be limited in most regions. In Sub-Saharan Africa and Oceania/South-East Asia, aggregate income also contributes considerably to crop demand growth.

With regard to food availability, changes in income for low-income regions, such as South Asia and Sub-Saharan Africa, create significant impact on demand levels, implying that consumers in these areas are held back from their ideal level of consumption by income constraints. Similarly, demand growth for animal products in the two poorest regions – South-East Asia and Sub-Saharan Africa – is largely driven by income growth.

Figure A.B.1 provides a more complete summary of the contribution of GDP growth and population increases to demand changes. These figures present the percentage change in demand from the respective base scenarios in the final year of the projections (2050). In the base scenario, both income and population are altered while in the sub-scenarios it is either population or income. The greater the disparity between the base scenario and the sub-scenario indicates larger contributions to growth.

For the vast majority of regions and products in the “individual” scenario, population growth is the largest component of demand growth. This is, in part, due to the “individual” scenario having the lowest income growth of the three scenarios (coupled with the highest population growth). Interestingly some scenarios with constant income have a higher growth than the base scenario. This is because, in general, individual consumption of certain food items over a certain income level decreases in response to higher incomes, which offsets any demand growth from population increase. These results occur in the higher income regions, such as North America and Europe and West Asia.

In Figure 16, a world market price index for total agriculture is presented comparing LAO simulation outcomes to those of OECD (2016_[1]). The key difference between the findings of the LAO model and the other models is that the LAO model shows a sharp decline in prices in the first years of the modelling period, which was already discussed before. This correction of the base period price levels leads also to all simulated prices from LAO falling outside the range of modelled results from OECD (2016_[1]). In addition, the spread between scenarios is smaller in the LAO results compared to the mean values of the other models. There is, however, consistency in relative performance of the price indices across scenarios: the *Fast* scenario has the highest prices and the *Sustainability* scenario the lowest.

Figure 16. World market price developments

Total Agricultural Price Index

Source: LAO simulation results and OECD (2016_[1]).

While OECD (2016_[1]) sees agricultural prices rising in real terms for most of the scenario/model combinations, LAO projects decreasing prices in real terms, broadly in line with the long term price development (Figure 2) and the general observation that supply growths outpaces demand growth over the medium term. It is worth noting that without the lower prices in the first years of the modelling period as simulated by LAO (due to its later base year and the endogenous productivity element), the simulated prices would fall into the range of OECD (2016_[1]) at the lower end.

OECD (2016_[1]) identifies four main uncertainties behind much of the differences in the model results: i) the development of food demand as incomes continue to grow; ii) the technical possibility and costs of bringing additional land into agricultural use; iii) the role and modelling of labour productivity in the context of growing economies; and iv) prospects of productivity responses to agricultural prices. While LAO incorporates assumptions of the first and the last item, it is relatively easy in the current specification of the model to bring additional land into production, while labour is not tackled at all.

To summarise, this comparison has shown that the ranking of the three alternative future scenarios in terms of their effects on prices is similar when applied to LAO as when implemented in the models used in OECD (2016_[1]). Alignment of three key variables (population, GDP, and oil price) appears to be sufficient to explain this.

4. Discussion

The scenario analysis has demonstrated that the LAO model can deliver results at a highly aggregated level that can give insights into the global challenges that agriculture faces in the coming decades. Compared to other models, the advantages of LAO are its simplicity which incorporates key determinants of supply and demand response over time.

The downside is the potential for key variables to be excluded, leading to misleading results or incomplete identification of key drivers. Close collaboration and comparison with other long-term models would mitigate some of these risks, as well as help validate the model's outputs.

The highly aggregate approach also restricts the level of policy analysis which can be performed. Any analysis at the product or country level cannot be performed without specific calibration of the base data and parameters. Similarly, this limitation restricts the way in which resource constraints, many of which are binding at the sub-regional level, can be implemented within the model.

5. Areas for future development

Land use in the model is currently specified as an input into crop production. Adding a land-use module would allow for explicit land-use change to be modelled and for a more complete account of greenhouse gas emissions.

There are grounds for further disaggregation to align broadly with the commodities in Aglink-Cosimo. However, the trade-offs between simplicity and detail must be carefully assessed. The strength of the current approach can vanish if the complexity of the model increases.

A feature of the Aglink-Cosimo model not currently represented in the LAO model is the ability to perform stochastic analysis. Stochastic simulations on the variability of key parameters is an effective way to address uncertainty in projections. As this is the aim of the LAO model, the use of

stochastic analysis would further elucidate the sensitivity of long-term projections to macro-economic changes.

Situating the findings of the LAO model with those deriving from the AgMIP project, and improving the comparability of sources and methods is another goal and part of the OECD's contribution to a wider public good.

The overall aim is to retain LAO as a low cost complement to Aglink-Cosimo in order to provide consistent analysis of policies needed in order to meet the “triple challenge” of ensuring global food security, contributing to peoples' livelihoods while conserving natural resources, and contributing to climate change mitigation. The model will be available in the future to a wider public and training for its use provided so that simulation analysis can be undertaken via a user-friendly model interface.

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Annex A. Equation structure

In the following, Greek letters denote model coefficients.

Producer and Consumer prices

$$pp_{r,c,t} = wp_{c,t} \cdot sp_{r,c,t} \quad (1)$$

$$pc_{r,c,t} = wp_{c,t} \cdot cp_{r,c,t} \quad (2)$$

pp – producer price	r – region
wp – world price	c – commodity
sp – producer price wedge	cp – consumer price wedge
pc – consumer price	t – period

Prices in the model are linked to a world market price for each commodity, with a second modifier of price transmission specific to each country, period and commodity. Consumer price in the model is expressed with a similar equation (2), with a measure of consumer price support. These price support mechanisms represent the price wedge in supply and demand pricing and are used to simulate all government support, duties and tax effects on price transmission.

Domestic supply (crops)

$$QP_{r,t} = AH_{r,t} \cdot YD_{r,t} \quad (3)$$

$$\log(AH_{r,cr,t}) = \min(a_{r,cr}^{AH} + \sum_c \beta_{r,cr,c}^{ppAH} \log(pp_{r,c,t}) + \beta_{r,cr}^{rap} \log(rap_{r,cr,t}), WATERMAX_r, LANDMAX_r) \quad (4)$$

$$\log(YD_{r,cr,t}) = a_{r,cr}^{YD} + \beta_{r,cr}^{YDpp} + \log(pp_{r,cr,t}) + (\beta_r^{ci} \log(ci_{r,cr,t}) + \beta_{r,cr}^{tfp} \log(tfp_{r,cr,t}) + \beta_{r,cr}^{op} \log(op_t)) \quad (5)$$

AH – area harvested	rap – 5-year average producer price (t to t-4)
YD – yield	op – world oil price (index)
QP – quantity produced	tfp – total factor productivity (index)
r – region	ci – cost index
cr – crops	pp – producer price
WATERMAX – max area allowed by freshwater required	t – period
LANDMAX – max area available for crops	c – commodity

The supply-side equations (3-5) are split into an area component and a yield component. The area component accounts for the own- and cross- price elasticities, and a lagged average price variable. Area harvested is also constrained by the available renewable freshwater by region and the available cropland. The yield equation combines response to a cost index, total factor productivity (equation 9) and a global oil price.

Domestic supply (animal products)

$$QP_{r,ac,t} = AN_{r,ac,t} \cdot YD_{r,ac,t} \quad (6)$$

$$\log(AN_{r,ac,t}) = a_{r,ac}^{AN} + \sum_c \beta_{r,ac,c}^{ppAN} \log(pp_{r,c,t}) + \beta_{r,ac}^{rap} \log(rap_{r,ac,t}) \quad (7)$$

$$\log(YD_{r,ac,t}) = a_{r,ac}^{YD} + \beta_{r,ac}^{YDpp} + \log(pp_{r,ac,t}) + \beta_{r,ac}^{ci} \log(ci_{r,ac,t}) + \beta_{r,ac}^{tfp} \log(tfp_{r,ac,t}) + \beta_{r,ac}^{op} \log(op_t) \quad (8)$$

AN – animal numbers

YD – yield

QP – quantity produced

r – region

ac – animal commodities

c – commodity

rap - 5-year average producer price (t to t-5)

op – world oil price (index)

tfp – total factor productivity (index)

ci – cost index

pp – producer price

t – period

The supply equations for animal products (6-8) are equivalent to the supply equations for crops (3-5), with animal numbers replacing the equation for area harvested in the case of crops.

Total factor productivity

$$\begin{aligned} \log(tfp_{r,c,t}) &= a_{r,c}^{tfp} + \\ &\beta_{r,c}^{TFPrd} \log(rd_{r,c,t-\gamma l}) + \beta_{r,c}^{rds} \log(rds_{r,c,t-\gamma l}) + \beta_{r,c}^{hp} \log(hp_{r,c,t-2}) + \beta_{r,c}^{tv} \log(tv_{r,c}) \\ hp_{r,c,t} &= hp_{r,c,t-1} \text{MIN} \left(1.03, \text{MAX} \left(1, pp_{r,c,t-2}^{AV3} / pp_{r,c,t-5}^{AV10} \right) \right) \end{aligned} \quad (9)$$

tfp – total factor productivity (index)

r – region

c – commodity

yl – gamma lag distribution

pp^{AV3} – Average producer price in past 3 years

rd – Ag. R&D investment (as proportion of GDP)

rds – Ag. R&D investment spill-over

hp – period of high prices

tv – trend variable

pp^{AV10} – Average producer price in past 10 years

t – period

TFP (equation 9) is calculated as a function of previous research spending (using a gamma lag distribution) and the spill-over of research spending in other regions. The “hp” variable depends on the ratio of the average own-price of the three years t-2, t-3, t-4 and the average over a ten-year period ending in t-5. This variable simulates the investment and transmission of new technologies. hp only changes if that price ratio is greater than 1 and the MIN condition assures that the annual shift of this variable does not exceed 3%. This is to simulate that periods of higher prices will lead to potentially higher liquidity of farmers which in turn stimulates investments and thus increases productivity. It assumes however, that existing technologies are not reduced during periods of lower prices. A trend variable is included as well.

Research spill-overs

$$rds_{r,c,t} = \sum_{r1 \neq r2}^{nr-1} rd_{r,c,t-\gamma l} \cdot \left(\frac{\sum_{m=1} f_{r1m} f_{r2m}}{(\sum_{m=1} f_{r1m}^2)^{1/2} (\sum_{m=1} f_{r2m}^2)^{1/2}} \right) \quad (10)$$

$$0 \leq f_{rnm} \leq 1; \sum_{m=1} f_{rnm} = 1$$

rds – Ag. R&D investment spill-over

rd – Ag. R&D investment (as proportion of GDP)

f – value of output (as a proportion of total Agricultural output)

m – different agricultural commodities

c – commodity

r – region

t – period

Domestic supply (fish and aquaculture)

$$\log(QP_{r,aq,t}) = a_{r,aq}^{aq} + \sum_c \beta_{r,aq,c}^{aq,pp} \log(pp_{r,c,t}) + \beta_{r,aq}^{aq,op} \log(op_t) + tv_{r,aq,t} \quad (11)$$

$$\log(QP_{r,fs,t}) = MIN(a_{r,fs}^{fs} + \sum_c \beta_{r,fs,c}^{fs,pp} \log(pp_{r,c,t}) + \beta_{r,fs}^{fs,op} \log(op_t) + tv_{r,fs,t}, maxfs_r) \quad (12)$$

QP – quantity produced

pp – producer price

op – world oil price (index)

r – region

aq – aquaculture

fs – capture fish

tv – trend variable

maxfs – maximum regional fish stocks

t – period

Production for aquaculture (equation 11) is a simplified version of the standard supply equation, using a trend variable to simulate productivity growth. Own-price, cross-prices, and the oil price are also accounted for. The production equation for fish from capture (equation 12) is the same as that for aquaculture with a maximum limit given to regional potential fish stocks.

Domestic demand

$$\log(QC_{r,c,t}) = a_{r,c}^{QC} + \sum_{cc} \beta_{r,c,cc}^{QCpc} \log(pc_{r,cc,t}) + \beta in_{r,c,t} \log(GDP_{r,t}/pop_{r,t}) + \log(pop_{r,t}) \quad (13)$$

$$\beta in_{r,c,t} = a_{r,c}^{in} + \beta_{r,c}^{in} \log(GDP_{r,t}/pop_{r,t}) \quad (14)$$

QC – quantity consumed as food

pc – consumer price

GDP – gross domestic product

βin – income elasticity

pop – population

r – region

c, cc – commodity

t – period

Demand (equation 13) is foremost a function of its own price and cross prices with a growth rate. Demand is also a function of per capita income; the income elasticity defined in equation 14 ensures that quantity demanded is responsive to changes in domestic population and income over time. This component is key, as exogenous changes in population and income are the prime driver of the LAO model. Further, to ensure that food expenditure shares are decreasing with increasing incomes, the income elasticity itself depends on the income level (decreasing with increasing incomes).

$$\log(QF_{r,c,t}) = a_{r,c}^{QF} + \beta_{r,c}^{QFpc} \log(pc_{r,c,t}) + \sum_c \beta_{r,c}^{QFqp} \log(QP_{r,c,t}) + tv_{r,c} \quad (15)$$

QF – quantity consumed as feed
 pc – consumer price
 QP – quantity produced
 ac – animal commodities
 r – region
 c – commodity
 tv – trend variable
 t – period

Demand for feed use (equation 13) differ from the generic consumption equation as the component accounting for income per capita is replaced with the sum of animal production, linking demand for feed to the production of animal products.

$$\log(QB_{r,c,t}) = \text{MAX} (a_{r,c}^{QB} + \beta_{r,c}^{QBpc} \log(pc_{r,c,t}) + \beta_{r,c}^{QBop} \log(op_t), \text{Minbio}_r) \quad (16)$$

QB – quantity processed for biofuel-use
 pc – consumer price
 op – world oil price (index)
 r – region
 Minbio – policy defined minimum biofuel-use
 t – period

Demand for biofuels is expressed in equation 16, where the quantity of crops is defined as a function of the current world oil price, and the consumer price of crops, unless this amount is below the threshold defined by policy minimums.

$$\log(QW_{r,c,t}) = a_{r,c}^{QW} + \beta_{r,c}^{QWpc} \log(pc_{r,c,t}) + \beta_{in,r,c,t} \log(GDP_{r,t}/pop_{r,t}) + \log(pop_{r,t}) \quad (17)$$

QW – quantity waste/consumed in other uses
 pc – consumer price
 GDP – gross domestic product
 β_{in} – income elasticity
 pop – population
 r – region
 c – commodity
 t – period

Quantity wasted (equation 17) is expressed in the same manner as quantity consumed as food, except there is no specification of cross-price elasticities. Consumption for other uses (QO) is treated in an identical way to quantity waste, just the elasticities and data differ.

Domestic stocks

$$QS_{r,c,t} = a_{r,c}^{QS} \cdot pc_{r,c,t}^{\beta_{r,c}^{QSpc}} \cdot (QP_{r,c,t} + QC_{r,c,t})^{\beta_{r,c}^{QS}} \quad (18)$$

QS – quantity held as stocks
 pc – consumer price
 QP – quantity produced
 QC – quantity consumed as food
 r – region
 c – commodity
 t – period

Net Trade

$$QT_{r,c,t} = QP_{r,c,t} - QF_{r,c,t} - QC_{r,c,t} - QB_{r,t} - QW_{r,c,t} - QO_{r,c,t} + QS_{r,c,t-1} - QS_{r,c,t} \quad (19)$$

QT – quantity net trade	QB – quantity processed for biofuel-use
QP – quantity produced	QS – quantity held as stocks
QF – quantity consumed as feed	r – region
QC – quantity consumed as food	c – commodity
QW – quantity wasted	t – period
QO – quantity consumed in other uses	

The net trade equation (19) specifies the remainder of domestic supply, expended in different demand channels, or taken from changes in domestic stocks. The surplus or deficit implied by the domestic supply and demand is satisfied by trade from the world market.

World market clearing

$$\sum_r QT_{r,c,t} = 0 ; \quad (20)$$

QT – quantity net trade	c – commodity
r – region	t – period

Equation 20 sets net trade between all regions at zero, ensuring global supply and demand is equal for each commodity, and forcing an equilibrium world price.

Returns to research investment gamma lag

$$\gamma_t = \frac{(t-g+1)^{(\delta/1-\delta)\lambda^{(t-g)}}}{\sum_{t=0}^L [(t-g+1)^{(\delta/1-\delta)\lambda^{(t-g)}}]} \quad (21)$$

$$\sum_{t=0}^L \gamma_t = 1$$

γ – share of total returns	λ – determinate of lag shape
L – total length of lag	δ – determinate of lag shape
g – gestation lag	

Input cost index

$$ci_{r,c,t} = \sum_{i=1}^n \omega_{i,r} P_{i,r} \quad (22)$$

$$\omega_{r,i1} = a \cdot X_{r,i1} \cdot \bar{X}_{i2} \cdot \dots \bar{X}_{in} \quad (23)$$

$$\sum_{i=1}^n \omega_{r,i} = 1$$

ci – input cost index	X – observed level of input
ω – factor share of input	$\bar{X}$ – mean observed level of input
i – input (1,2...n)	c – commodity
P – index of input/output price ratio	

Annex B. Tables and Figures

Table A B.1. Country composition

LAO aggregate	Single countries				
EuCA	Albania	Czechoslovakia	Ireland	Norway	Sweden
	Armenia	Denmark	Italy	Poland	Switzerland
	Austria	Estonia	Kazakhstan	Portugal	Tajikistan
	Azerbaijan	Faroe Islands	Kyrgyzstan	Republic of Moldova	North Macedonia
	Belarus	Finland	Latvia	Romania	
	Belgium	France	Liechtenstein	Russian Federation	Turkmenistan
	Belgium-Luxembourg	Georgia	Lithuania	Serbia	Ukraine
	Bosnia and Herzegovina	Germany	Luxembourg	Serbia and Montenegro	United Kingdom
	Bulgaria	Greece	Malta	Slovakia	
	Croatia	Hungary	Montenegro	Slovenia	Uzbekistan
	Czech Republic	Iceland	Netherlands	Spain	Yugoslav SFR
LaC	Antigua and Barbuda	Cayman Islands	French Guiana	Mexico	Saint Vincent and the Grenadines
	Argentina	Chile	Grenada	Montserrat	
	Bahamas	Colombia	Guadeloupe	Nicaragua	Suriname
	Barbados	Costa Rica	Guatemala	Panama	Trinidad and Tobago
	Belize	Cuba	Guyana	Paraguay	United States Virgin Islands
	Bolivia (Plurinational State of)	Dominica	Haiti	Peru	Uruguay
		Dominican Republic	Honduras	Puerto Rico	Venezuela (Bolivarian Republic of)
	Brazil	Ecuador	Jamaica	Saint Kitts and Nevis	
	British Virgin Islands	El Salvador	Martinique	Saint Lucia	
NoA	Bermuda	Canada	Saint Pierre and Miquelon	United States	
NoAWA	Algeria	Iraq	Libya	Saudi Arabia	United Arab Emirates
	Bahrain	Israel	Morocco	Sudan	Western Sahara
	Cyprus	Jordan	Occupied Palestinian Territory	Syrian Arab Republic	Yemen
	Egypt	Kuwait	Oman	Tunisia	
	Iran (Islamic Republic of)	Lebanon	Qatar	Turkey	
OcSEA	American Samoa	Guam	Micronesia (Federated States of)	Pacific Islands Trust Territory	Timor-Leste
	Australia	Indonesia		Papua New Guinea	Tokelau
	Brunei Darussalam	Kiribati	Myanmar	Philippines	Tonga
	Cambodia		Nauru	Samoa	Tuvalu

LAO aggregate	Single countries				
	Cook Islands	Lao People's Democratic Republic	New Caledonia	Singapore	Vanuatu
	Fiji	Malaysia	New Zealand	Solomon Islands	Viet Nam
	French Polynesia	Marshall Islands	Niue	Thailand	Wallis and Futuna Islands
SA	Afghanistan	Hong Kong, China	Democratic Korea	Maldives	Korea
	Bangladesh	Macao, China		Mongolia	Sri Lanka
	Bhutan	People's Republic of China	India	Nepal	
	China	Chinese Taipei	Japan	Pakistan	
SsA	Angola	Côte d'Ivoire	Guinea	Namibia	Somalia
	Benin	Democratic Republic of the Congo	Guinea-Bissau	Niger	South Africa
	Botswana		Kenya	Nigeria	South Sudan
	Burkina Faso	Djibouti	Lesotho	Réunion	Swaziland
	Burundi	Equatorial Guinea	Liberia	Rwanda	Togo
	Cabo Verde	Eritrea	Madagascar	Saint Helena, Ascension and Tristan da Cunha	Uganda
	Cameroon	Ethiopia	Malawi		United Republic of Tanzania
	Central African Republic	Ethiopia PDR	Mali	Sao Tome and Principe	Zambia
	Chad	Gabon	Mauritania	Senegal	Zimbabwe
	Comoros	Gambia	Mauritius	Seychelles	
	Congo	Ghana	Mozambique	Sierra Leone	

Note by Turkey: The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Turkey shall preserve its position concerning the "Cyprus issue".

Note by all the European Union Member States of the OECD and the European Union: The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus

Figure A B.1. Consumption in OECD futures scenarios, compared to base scenario in 2050

Note: CR = crop commodities, AN = non ruminant animals, RA = ruminant animals
Source: LAO simulation results.

Table A B.2. Model parameters of LAO

		Supply-side elasticities					Demand-side elasticities				
		Production own-price	Oil price cross-price	Technical growth rate	Cost index	R&D	Feed own-price	Food own-price	Waste and Other-use own-price	Biofuel-use own-price	Income elasticity
Region	Commodity	$\beta_{r,c}^{AHpp}$ $\beta_{r,c}^{ANpp}$ $\beta_{r,c}$	$\beta_{r,c}^{op}$	$\beta_{r,c}^{tv}$	$\beta_{r,c}^{ci}$	$\beta_{r,c}^{TFPrd}$	$\beta_{r,c}^{FEpc}$	$\beta_{r,c}^{Qcpc}$	$\beta_{r,c}^{WSpC}$ $\beta_{r,c}^{OUpc}$	$\beta_{r,c}^{QBpc}$	$\beta_{r,c}^{in}$
Europe & Central Asia	cr	0.89	0.00		-0.95	0.16	-0.25	-0.29	-0.29	-0.29	-0.150
	ra	0.40	0.03		-0.14	0.15	-0.30	-0.40	-0.40		-0.094
	an	0.90	0.01		-0.13	0.13	-0.30	-0.40	-0.40		-0.091
	aq	0.38		0.05			-0.73	-0.30			-0.086
	fs	0.38		0.02				-0.30			-0.086
Oceania & South-East Asia	cr	1.50	0.07		0.48	0.09	-1.48	-0.35	-0.35	-0.35	-0.150
	ra	1.45	-0.09		-0.01	0.17	-1.74	-0.51	-0.51		-0.094
	an	0.62	0.02		0.35	0.14	-0.51	-0.50	-0.50		-0.091
	aq	3.25		0.03			-0.64	-0.44			-0.086
	fs	0.10		0.02				-0.44			-0.086
North Africa & West Asia	cr	0.80	0.02		0.15	0.15	-1.44	-0.33	-0.33	-0.33	-0.150
	ra	1.20	0.00		0.04	0.17	-0.23	-0.51	-0.51		-0.094
	an	0.62	0.00		-0.07	0.16		-0.50	-0.50		-0.091
	aq	1.12		0.04				-0.42			-0.086
	fs	0.05		0.02				-0.42			-0.086
Latin America & the Caribbean	cr	0.80	0.00		0.22	0.19	-0.04	-0.31	-0.31	-0.31	-0.150
	ra	0.55	0.02		0.04	0.15		-0.50	-0.50		-0.094
	an	0.64	0.02		0.14	0.12	-1.74	-0.50	-0.50		-0.091
	aq	1.41		0.05			-0.45	-0.40			-0.086
	fs	0.10	-0.06	0.01				-0.40			-0.086
North America	cr	1.75	-0.01		-0.52	0.21	-1.37	-0.21	-0.21	-0.21	-0.150
	ra	1.30	-0.01		0.03	0.20		-0.26	-0.26		-0.094
	an	0.35	-0.05		0.61	0.18		-0.26	-0.26		-0.091
	aq	0.06		0.01			-0.63	-0.20			-0.086
	fs	0.84		0.04			0.00	-0.20			-0.086
South Asia	cr	1.75	-0.03		0.62	0.29	-1.66	-0.36	-0.36	-0.36	-0.150
	ra	0.64	0.07		-0.17	0.15		-0.55	-0.55		-0.094
	an	0.64	-0.03		0.03	0.14		-0.54	-0.54		-0.091
	aq	0.12		0.01			-0.06	-0.31			-0.086
	fs	0.12		0.01				-0.31			-0.086
Sub-Saharan Africa	cr	1.41	0.07		0.66	0.10	-0.12	-0.42	-0.42	-0.42	-0.150
	ra	0.62	0.01		-0.11	0.21	0.66	-0.57	-0.57		-0.094
	an	0.62	0.00		0.38	0.19	-0.52	-0.56	-0.56		-0.091
	aq	0.00		0.00				-0.48			-0.086
	fs	0.03		0.02				-0.48			-0.086

Note: Elasticities are subject to change with calibration and validation of the original model parametrisation. Supply elasticities were estimated with a two-stage log-log regression incorporating the cost index component as the initial stage of estimation. Demand elasticities (excluding income elasticity) are taken from Muhammed et al. (2011), weighted to the LAO regions. The income elasticity was estimated in a linear-log model, using the income elasticities from Muhammed et al. (2011), and IMF (2018) GDP and population data.

Table A B.3. Non-regionally specific LAO model parameters

	Description	Name	Commodity				
			cr	ra	an	aq	fs
Supply elasticities	Yield own-price	$\beta_{r,c}^{YDpp}$	0.10	0.10	0.10		
	Rolling average price	$\beta_{r,c}^{rap}$	0.02	0.02	0.02		
	Total factor productivity	$\beta_{r,c}^{tfp}$	0.45	0.55	0.55		
	Period of high prices	$\beta_{r,c}^{hp}$	0.40	0.88	0.88		
	Research spillover	$\beta_{r,c}^{rds}$	0.01	0.01	0.01		
Stock elasticities	Stocks own price	$\beta_{r,c}^{QSpC}$	0.10	0.10	0.10	0.10	0.10
	Net consumption balance	$\beta_{r,c}^{QS}$	-0.20	-0.20	-0.20	-0.20	-0.20

Note: Elasticities are subject to change with calibration and validation of the original model parametrisation.

The above are synthetic non-region specific elasticities taken from the literature or due to the practicality the fit. Though these elasticities are currently not regionally specific, the regional index is kept, to allow specificity in future.