An introduction of GTEM-Food: A baseline calibration with a focus on food

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Abstract

There is limited understanding of the level of impact on food systems globally, particularly the interaction between climate change and mitigation and adaptation strategies and policies. To address this limitation, and to improve future analysis of climate change and climate mitigation policies we have extended GTEM-C to become GTEM-Food. First, we used multiple data sources to update the model database with more agriculture and food sectors/commodities. Second, we updated the production and consumption structures for many food sectors and commodities. Finally, we revised and updated the baseline SSP2 GTEM-Food projections considering a new starting point and trends. Results show that most world output levels increase in 2014-2060, except coal and natural gas. Vegetable and fruit double their output level ($1434 billion) in 2060 compared to the level ($779 billion) in 2014. Dairy milk also follows the same pattern, reaching $1447 billion in 2060 compared to $797 billion in 2014. Cattle meat also increases significantly in 2014-60, reaching $1362 billion in 2060 relative to $709 billion in 2014. Coal-fired electricity substantially reclines from 8.6 million GWh in 2014 to 3.4 million GWh in 2060. Solar and geothermal power increase their output significantly in 2014-60 and become main sources of power by 2060, reaching 6.5 and 5.2 million GWh in 2060. From an Australian perspective, agricultural output increases by up to 68% in 2060 compared to the 2014 level. The ratio of food output relative to non-food keep constant in 2014-2060 at 0.043. Shares of agriculture sectors in Australia stay stable at 6.3%, while shares of agricultural emissions in Australia relative to the total Australian emissions increase from 25% in 2030 to 32% in 2060 because emissions from fossil-based electricity generation decline. In general, agricultural emissions in Australia only increase slightly reaching 108 MtCO2e in 2030 and 129 MtCO2e in 2060.

Keywords: Food security; nutrition and diet; agriculture; climate change; dynamic computable general equilibrium (CGE) modelling; electricity or power.

1. Introduction

Agriculture research has been developed significantly in recent decades to increase labour and capital productivity (Bárány & Siegel, 2021; Ortiz-Bobea et al., 2021), to improve irrigation systems (Mpanga & Idowu, 2021; Zinkernagel et al., 2020), fertiliser utilisation efficiency (Lyu et al., 2021), and to control pests and diseases (Laothawornkitkul et al., 2008; Wingfield et al., 2013). As a result, agricultural outputs have increased remarkably.[1] At the same time, the world population has also increased, for example, by 45% from 5.28 billion people in 1990 to 7.67 billion in 2019[2], indicating higher levels of consumption for foods. During this period, higher incomes representing by increased GDP per capita (from $4300 in 1990 to $11,400 in 2019[3]) also boost food consumption levels. However, future global agriculture and food systems will be under higher pressures since population and economics continue to grow, with population expected to reach 9.8 billion in 2050 and 11.2 billion in 2100.[4] In this context, global warming causes more frequent and intensive extreme weather events, such as drought, typhoons, flash floods, etc., which also substantially downgrade land productivity and irrigation systems (Ortiz-Bobea et al., 2021; Steensland, 2019). Global warming also causes sea-level rise, which significantly reduce agricultural land, particularly in pacific islands and nations (Jamero et al., 2017; Minderhoud et al., 2019). All of which threaten agriculture and food production systems and associated natural resources.

Agriculture and food production systems thus face both opportunities and threats in future development, which will affect all their components including land, water, and labour with significant implications for environmental and resources management. Potential impacts of policies and changes in population, technologies, economic conditions, and environment on such systems would be complex, but foreseeing these impacts are important and highly demanded to have timely and efficient intervention to maintain sustainable development of the agriculture and food systems while supplying adequate foods and feeds for growing population and reserving ecological systems. As a result, foresight modelling has become a crucial tool for such impact assessments. One of these tools includes the computable general equilibrium (CGE) modelling approach, which allows to assess impacts on various sectors (i.e., households, industrial sectors, investors, and traders) and overall economies. In this context, significant efforts have been facilitated for decades by various research institutes, universities and experts all around the world to improve such a modelling tool. To address global issues in various countries and regions, global CGE models have been constructed, including GTAP-based models (GTAP, GTAP-E, GTAP-E-Power, GTAP-W, GTAP-POV, GTAP-AEZ, and others), AIM,

[1] https://ourworldindata.org/crop-yields
[2] https://data.worldbank.org/indicator/SP.POP.TOTL
[3] https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
[4] https://www.un.org/development/desa/en/news/population/world-population-prospects-2017.html

ENVISAGE, FTAP, G-Cubed, GEM-E3, GLOBE, GTEM, ICES, Linkage, MAGNET, Mirage, and WorldScan.

Since GTAP database, a global economic database, is often updated and enriched to include more country regions and industrial sectors, many multi-country CGE models have been constructed to use such a database. CSIRO and ABARES[5] have followed this pathway to develop the Global Trade and Environmental Model (GTEM) for policy assessment purposes (Jakeman & Fisher, 2006; Tulpule et al., 1999), which has been applied to inform the Australian Government such as in the Australian National Outlook 2011 and 2015. Over a decade, GTEM has been developed to improve its analysis capacity, for example, to include detailed steel manufacturing, road and rail transportation, and electricity generation technologies (Y. Cai et al., 2015), and to include material flows (Schandl et al., 2020).

The current CSIRO-ABARES Collaboration Project aims to develop an integrated modelling approach that facilitates detailed and insightful analyses of global and regional agricultural and food systems subject to climate variability, as well as public policies. These efforts look to build on and extend further the GTEM model to become GTEM-Food, which has a range of model and data improvements to enhance the representation of global food systems. First, we use multiple data sources to update the model database, and to update both the regional and sector aggregation. Second, we update the production and consumption structures for many food sectors and commodities. Finally, we revise and update the baseline SSP2 GTEM-Food projections considering this new starting point, and changes in trends since the previous baseline projections were calibrated for the Australian National Outlook in 2011.

2. Review of agri-food-energy modelling development

3. Development of GTEM-Food

3.1. Database Update and Extension

GTEM uses GTAP database version 8 with the base year in 2007. For GTEM-Food, we employ the newest GTAP database version 10a with the base year in 2014, which has 65 industrial sectors and 141 countries/regions. We use the most disaggregated level of the GTAP database v10a with respect to agricultural commodities. However, there are several cases where we need a greater detail. To further disaggregate the GTAP database we use multiple sources, which has a simple description and framework provided in Figure 1 to ease the understanding of the whole process.

[5] CSIRO stands for the Commonwealth Scientific and Industrial Research Organisation and ABARES refers to

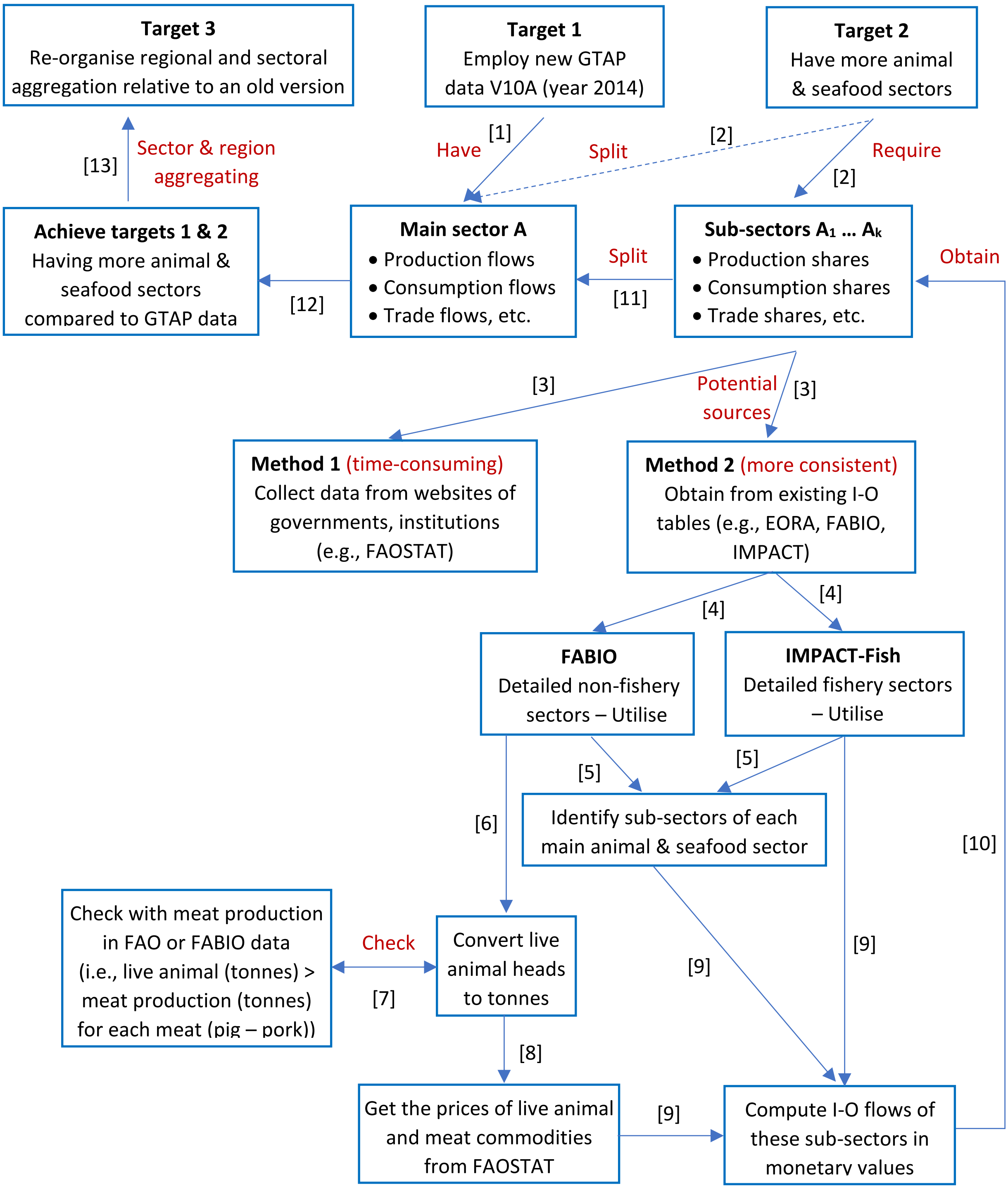

Figure 1: Data compilation processes

In GTAP database V10A, the following are four main agri-food sectors/commodities that we target to disaggregate into sub-sectors/commodities (**Target #1**).

- Live animal sector (GTAP code: ctl);
- Bovine meat sector (cmt);
- Pork, poultry, and other meats sector (omt); and
- Fishery sector (fsh).

Target #2 requires having the monetary value shares of sub-commodities within each of the four main commodities (e.g., the production shares of aquaculture (S1) and wild capture (S2) fishery within the main fishery sector, S1 = 0.3 and S2 = 0.7 for Australia). Since there are many flows of supply of and demand for commodities in GTAP V10A, an ideal method is to have as many shares of flows as possible so that each flow uses a specific share for disaggregation. These shares might include the shares of production, import, export, final use of commodities subject to sources (e.g., import or domestic), etc. There are often two ways to have data generating the shares.

- First, we can collect data from the websites of governments, non-profit organisations, institutions, etc. FAOSTAT can be a useful source to get such data; however, data from this source contains numerous commodities and flows, which require to select all sub-commodities of a main targeted commodity in each flow (e.g., production, consumption, import, export, etc) and process it manually. In addition, one data source often does not provide adequate data for all countries. Consequently, the process to get adequate data of sub-commodities for all countries is particularly time-consuming (e.g., 6-12 months).
- Second, we can use existing multi-region I-O tables that have details of agricultural and food commodities. One major advantage of these data sets is that data flows are well processed and organised. From these I-O tables, we can process to have the expected shares for the selected sub-commodities. This way is more efficient as these tables might contain different groups of commodities (e.g., a meat group that has different meat commodities) so that we are able to select sub-commodities we expect to achieve. There are three potential I-O tables that would fit our requirements/needs. They are the (1) Eora Global supply chain database (Lenzen et al., 2013), (2) FABIO – Food and Agricultural Biomass Input-Output (Bruckner et al., 2019), and (3) IMPACT – Fish data (Msangi & Batka, 2015; Chan et al., 2017).

The main features of the EORA data set are summarised in Figure 2. This data set offers one major advantage of having data flows measured in monetary values so that we can have the shares directly. However, after considering the drawbacks of this data set, which are particularly difficult and time-consuming to organise and have the same names of sectors across the 190 regions, we do not use this data set to process further.

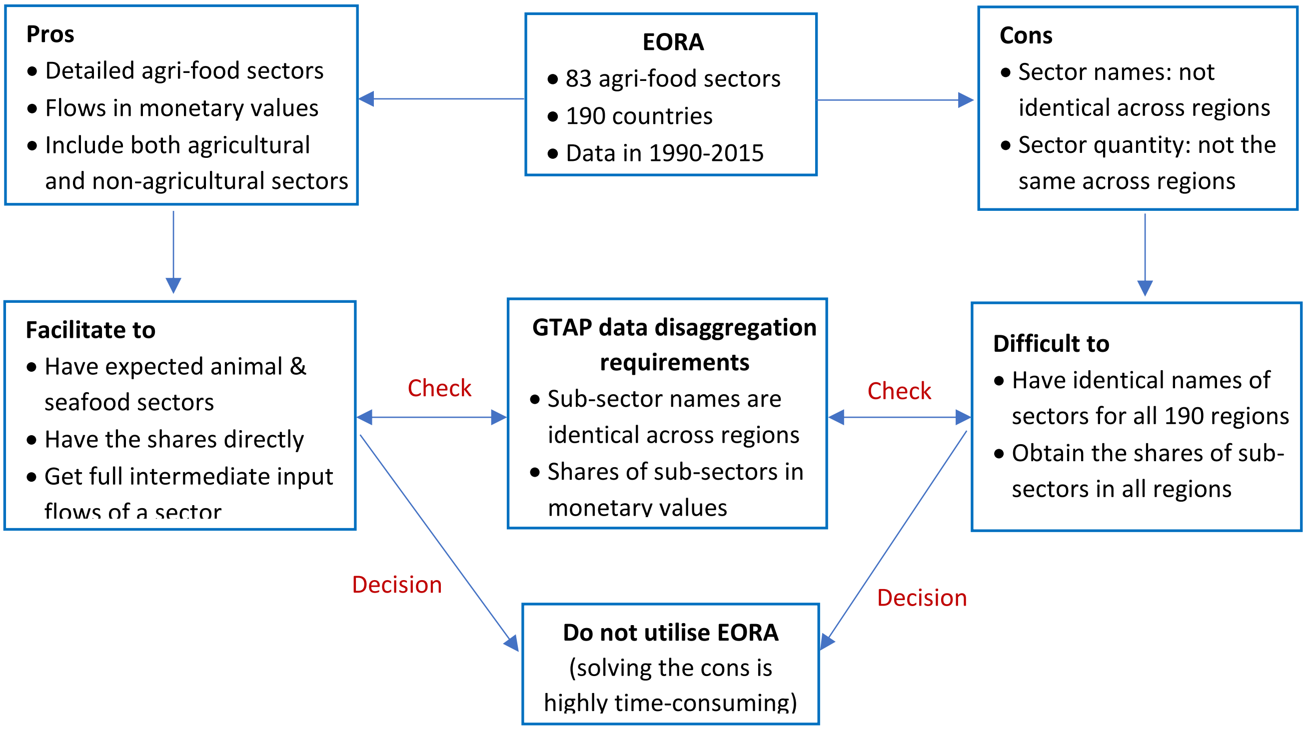

Figure 2: The main features of the EORA data set

The main features of the FABIO data set are summarised in Figure 3. Like EORA, this data set also has detailed information of agricultural and food sectors/commodities, providing the possibilities for GTAP sector disaggregation. One major advantage of this data set is present of the same number of sectors across regions and their names are identical, which ease the process to select sectors in all countries that are sub-sectors of the main GTAP sectors. Although values in this data set are measured in physical units (e.g., tonnes and heads), FAOSTAT provides prices per tonne of these agricultural and food commodities so that the transformation of the physical values to monetary values are straightforward, enabling the calculation of the shares. As a result, we employ this data set to calculate the shares for live animal and meat sectors to disaggregate the live animal sector and the meat sectors in GTAP database V10A as shown in the lower part of Figure 3. It is also noted that this data set does not have details of the fishery sector. In other words, there is only one fishery sector in FABIO, which is similar to the fishery sector in GTAP database V10A. Hence, we seek another data set that has details of the sub-fishery sectors to enable the disaggregation of the fishery sector in GTAP database V10A. One appropriate data source is the IMPACT-Fish model.

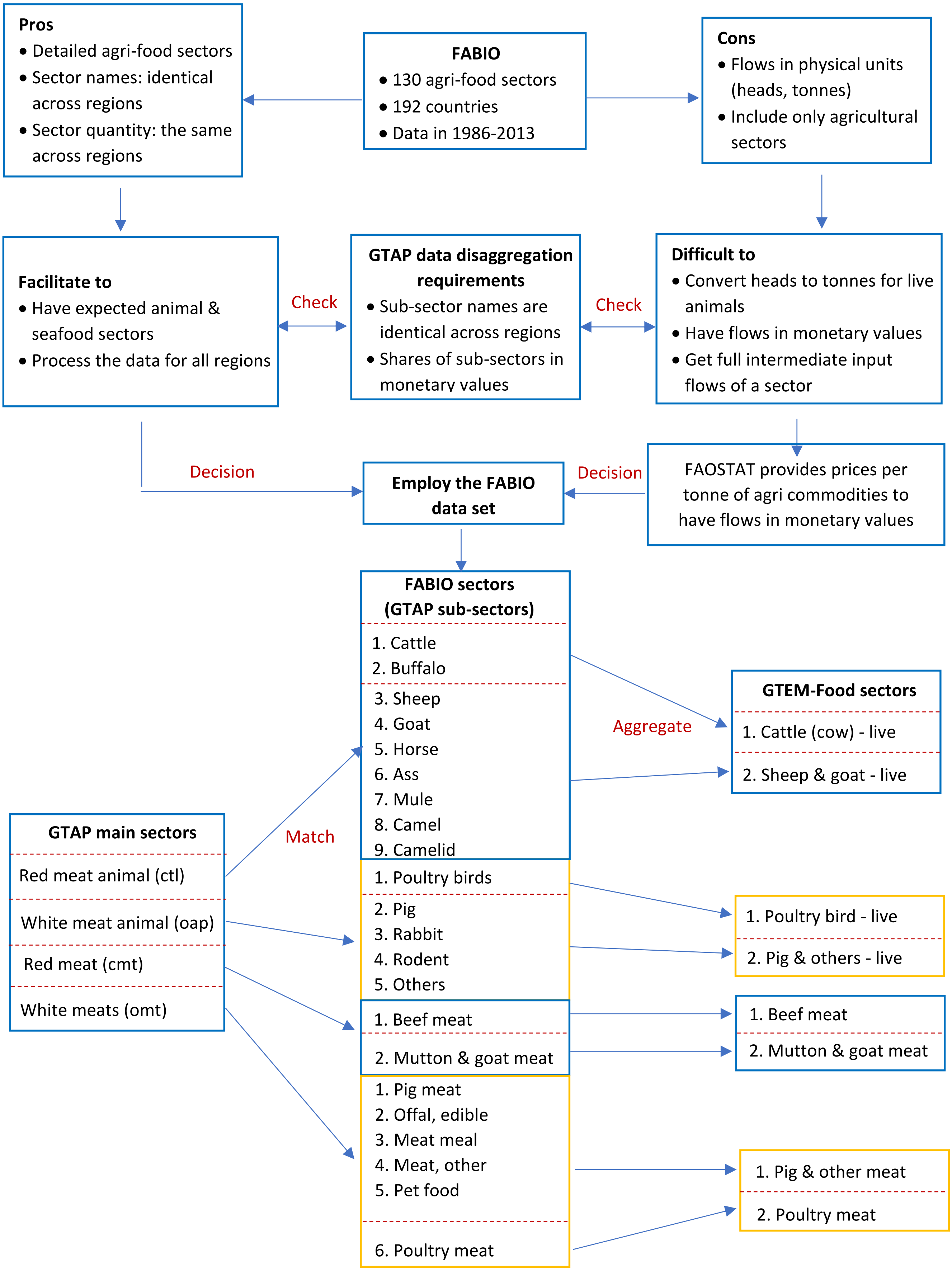

Figure 3: The main features of the FABIO data set and its application for GTEM-Food data

The main features of the IMPACT-Fish data set are summarised in Figure 4. This data set has details of fishery commodities (16 species for each wild capture and aquaculture categories). Values are provided in tonnes; however, it also provides the world prices of each species by year to enable to the conversion of physical values to monetary values. Since consumption of fish is not separated between wild capture and aquaculture, such information is useless. Similarly, only net trade of fish for each country if provided, no information of exports and imports of wild capture and aquaculture fisheries are extracted from this data set. In other words, only the production shares can be derived from this data set to use for disaggregation of the fishery sector in GTAP database V10A. Since this data set provides the most complete data of wild capture and aquaculture fisheries by country and the flows can be transferred to monetary values, we employ this data set to get the shares to split the fishery sector in GTAP V10A into aquaculture and wild capture fishery sectors/commodities.

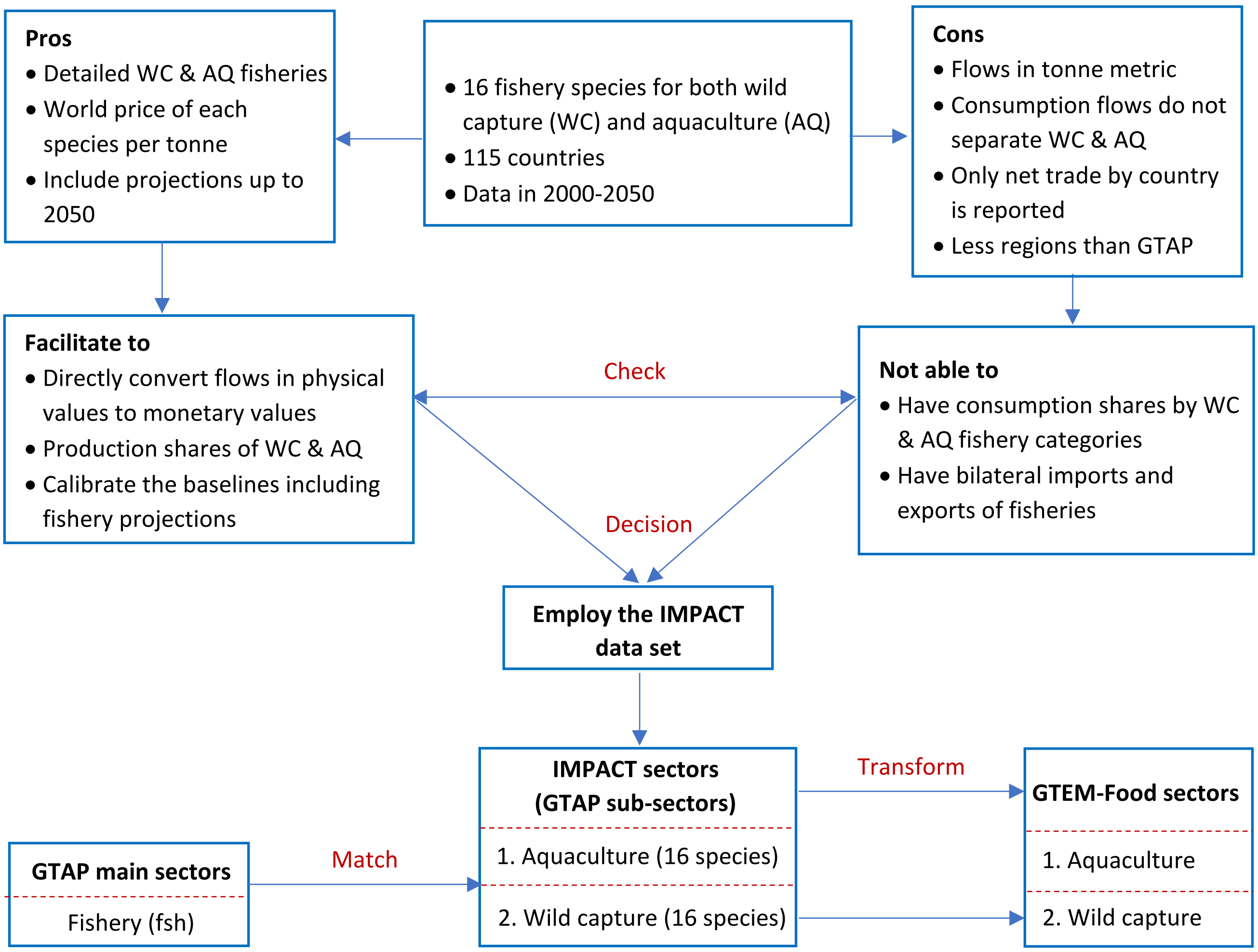

Figure 4: The main features of the IMPACT-Fish data set and its application for GTEM-Food data

The world economy is finally divided into 35 countries/regions and 39 industrial sectors.

3.2. Updated Model Structure

Detailed production and consumption structures of GTEM are provided in Cai et al. (2015) and originally in Pant (2007). There are currently three 'technology bundle' industries in GTEM-C. They are the electricity, land transportation, and steel manufacturing sectors. There are 15 technologies in the electricity generation sector, 5 technologies in the land transportation sector, and 2 technologies in the steel manufacturing sector. Although these three sectors use different technologies in their processes, they only produce unique commodities (i.e., electricity, land transportation services, and steel).

Here, we outline how we develop/modify the production and consumption structures of GTEM-C to become GTEM-Food, which improve the capacities for agriculture and food studies. GTEM-Food will remain the production structure of the 'technology bundle' industries (electricity, land transportation, and steel manufacturing industries) compared to GTEM-C. In addition, we add two more 'processing bundle' industries (ruminant meat processing and fishery processing sectors) to GTEM-Food. We apply the same mechanism of the 'technology bundle' industries existing in GTEM-C. That is, these two processing sectors will have the same structure as a 'technology bundle' industry and use processing-specific inputs. There will be 'ruminant meat processing' output commodity and 'fishery processing meat' output commodity. Below we outline the production structure of key sectors in GTEM-Food based on the new disaggregated database.

Figure 5 outlines the production structure of all industries, excluding ruminant meat and fish processing sectors and the three 'technology bundle' industries that have different structures. For these industries, we keep the production structure as same as for 'non-technology bundle' industries in GTEM-C. That is, all non-energy inputs are at the same level subject to the Leontief function, which are demanded without any substitution.

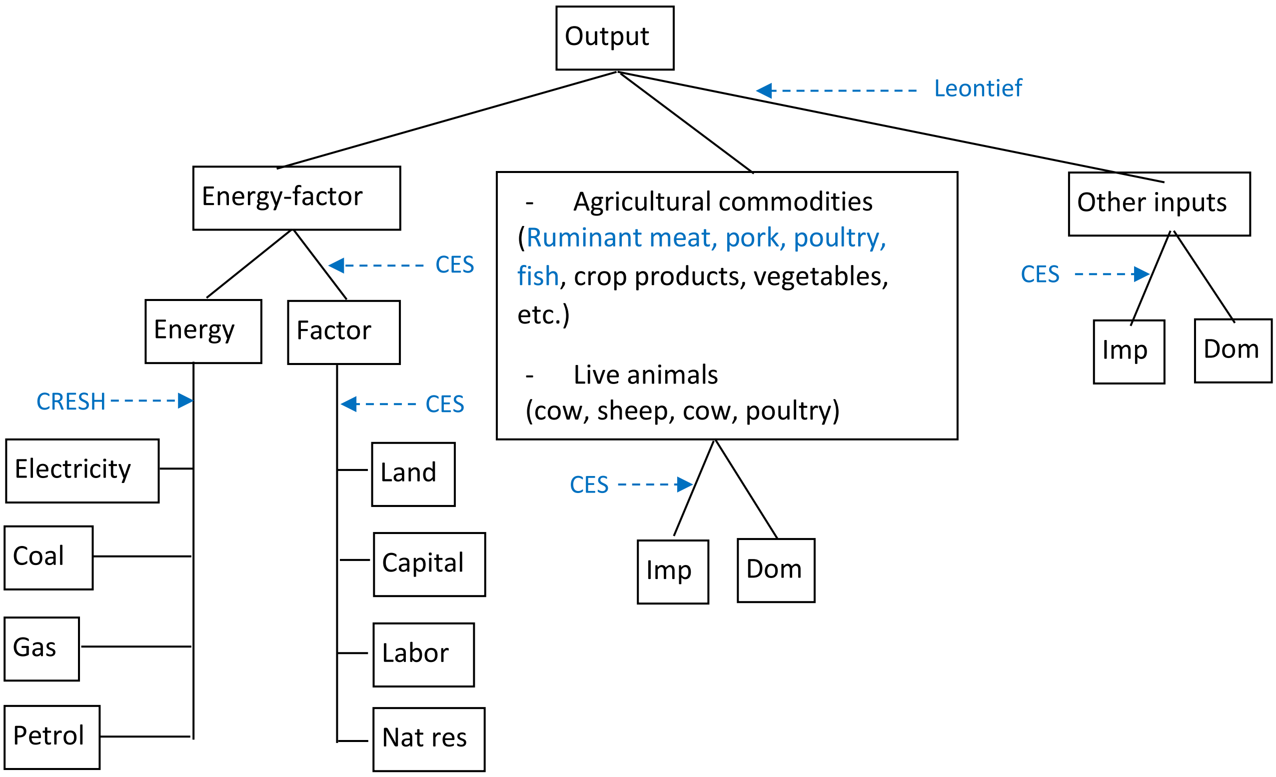

Figure 5: The Production structure of all sectors proposed in GTEM-Food, excluding ruminant meat and fish processing sectors and the three 'technology bundle' industries

Figure 6 provides an example of the ruminant meat processing sector developed in GTEM-Food, which follow the structure of the 'technology bundle' industries in GTEM-C. The ruminant meat processing bundle industry is formed by two processing components (cow-related and sheep-related), which are substitutable for each other. These two processing inputs are formed by specific inputs, which are not substitutable for each other. For example, the cow-related processing is formed by beef meat processing input, live cattle animal input and other processing-specific inputs.

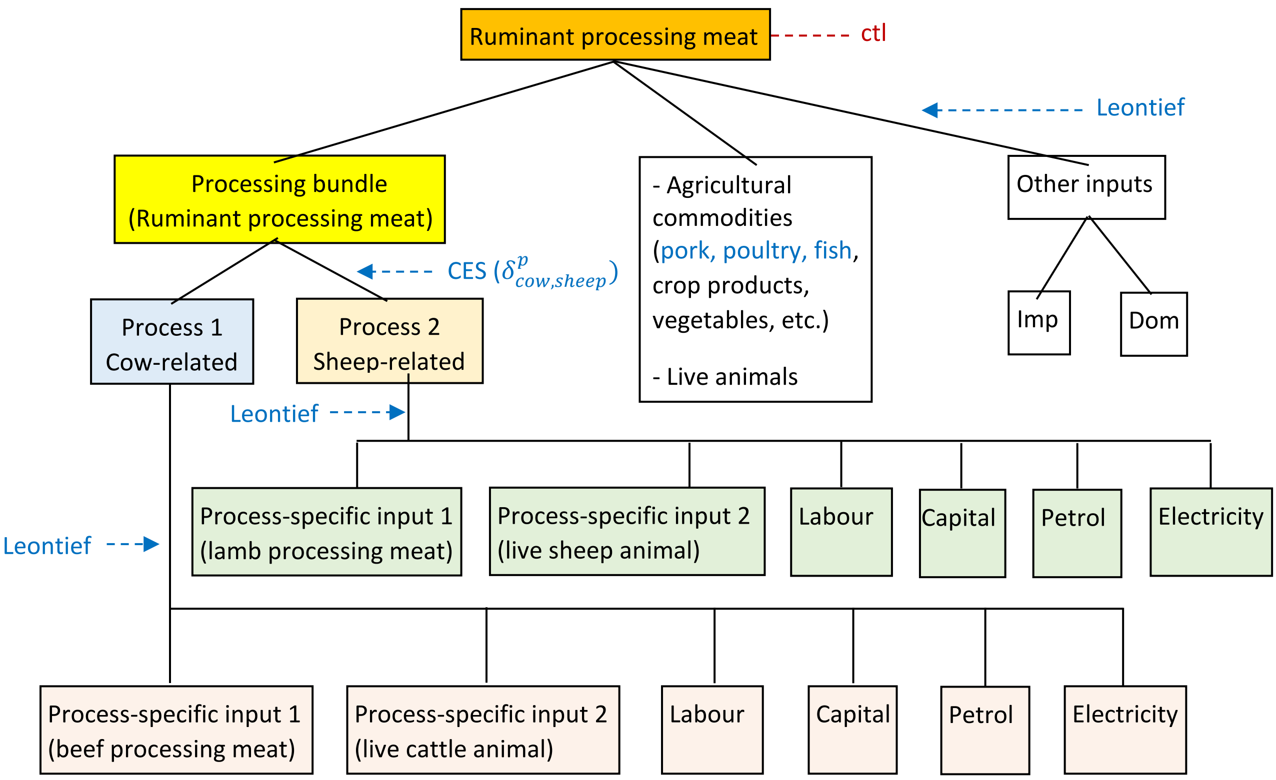

Figure 6: The production structure of the 'technology bundle' ruminant processing meat sector proposed in GTEM-Food

Note: ctl is the code in GTAP sector data. Lamb meat also includes goat meat, and live sheep animal also includes live goat animal.

Figure 7 outlines the production structure of the fishery processing meat sector proposed in GTEM-Food. It applies the same logic as for the ruminant meat processing sector in Figure 5. However, each processing only has one specific input (aquaculture or wild capture fishery) and other processing-specific inputs.

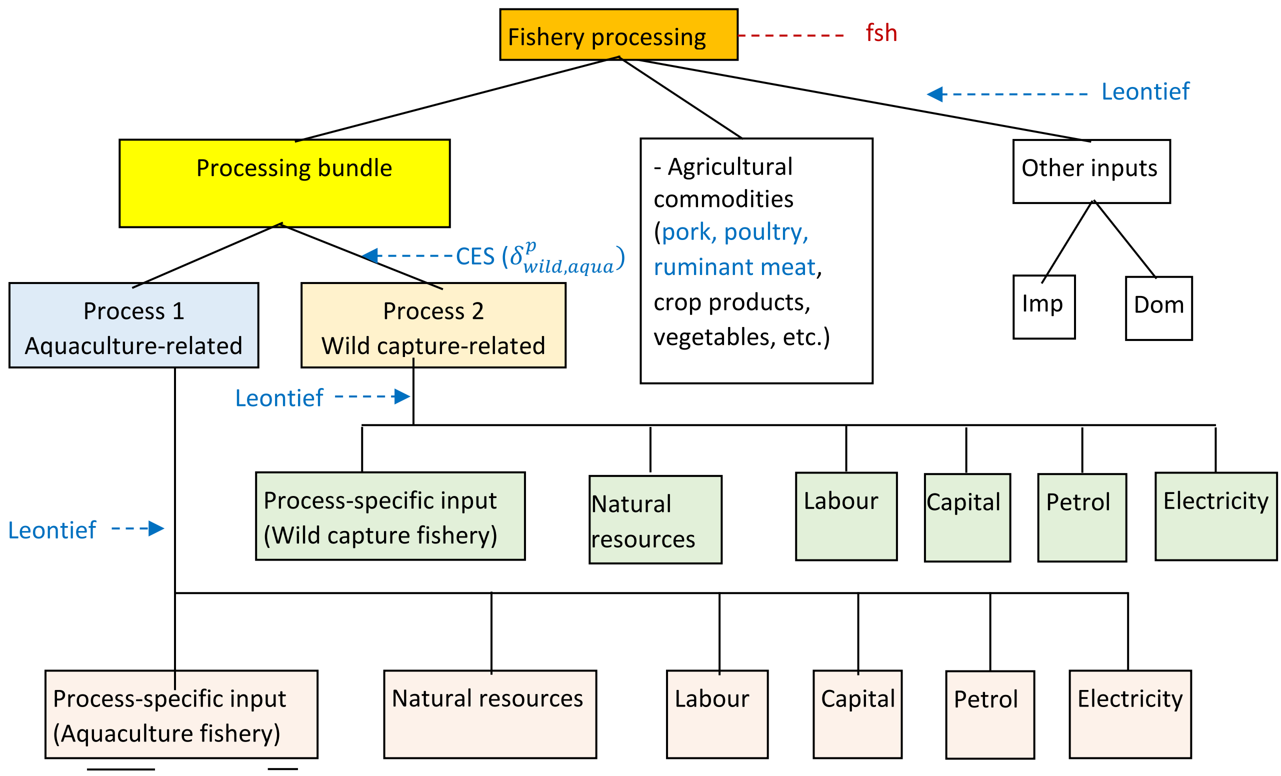

Figure 7: The production structure of fish processing meat sector in GTEM-Food
Note: fsh is the code in the GTAP data sector.

Figure 8 outlines the private consumption structure proposed in GTEM-Food. In this structure, the energy bundle, agricultural and food bundles, and all other commodities are demanded via the CDE function. We group agriculture and food commodities into different bundles of which commodities in each group are substitutable via CES functions.

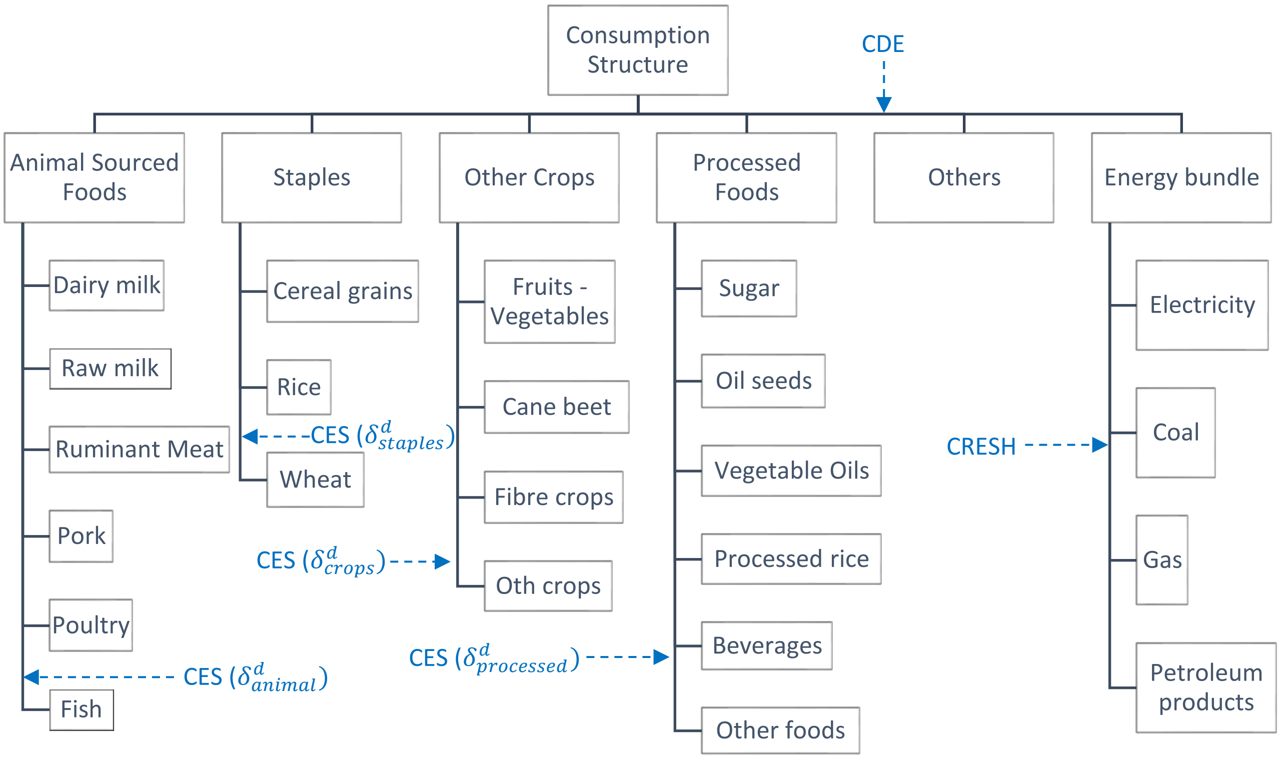

Figure 8: Private consumption structure developed in GTEM-Food

3.3. SSP2 calibration with GTEM-Food

After we completed these model and database improvements, we calibrate a baseline SSP2 scenario in GTEM-Food from 2014 to 2060 (simulated in five-year increments). The calibration of SSP2 is relatively important as SSP2 can be viewed as a 'historical trend' scenario where the world would go on following the historical trends. As a result, the SSP2 scenario is considered a central or reference scenario relative to the other SSP scenarios. Once we have a good calibration of SSP2, the other SSP scenarios would just be based on it and vary the assumptions in certain aspects which reflect the storyline of each SSP.

Since GTEM-Food is more focused on agriculture and food systems, the calibration of SSP2 focuses on two major areas: the agriculture and food sectors, and the energy related sectors. With these two areas well calibrated we will also have a sensible projection of greenhouse gas (GHG) emissions. In SSP2, we assume that the world trade would go as usual and no extra trade conditions would be imposed. However, in the other SSPs we may need to relax or tighten trade conditions. As mentioned before, GDP and population are model inputs which constraint the model to have the same GDP and population growth rate as the markers projection of SSP GDP and population.

3.3.1. Agriculture and food sectors

Our calibration involves eight crop sectors, three livestock sectors, one fishery sector (with two processing technologies), one forestry sector corresponding to one processing sector using forestry product, and eight food processing sectors. The assumptions for these sectors are detailed in Table 1.

Table 1: Assumptions for agriculture and food sectors.

Sectors	Assumptions	GTEM-Food shock variables
Crop sectors	Used pure exogenous productivity assumptions from IMPACT SSP2 projection to approximate the land productivity shocks in GTEM-Food.	af_generic("land", "crop sectors name", REG)
Livestock sectors	Used percentage change of total output (in tonnes) of live animal sectors from IMPACT SSP2 projection to approximate the output efficiency (TFP) in the three livestock sectors.	ao_generic("livestock sectors name",REG)
Forestry sector	Shock the input efficiency from "Forestry" sector into "Farm_Forest" sector (sector which produce paper and wood products) by using the values that were estimated by Tim Baynes from literature when doing IRP project (Hatfield-Dodds et al., 2017).	af_generic("Forestry", "Farm_Forest", REG)
Fishery sector	Use the IMPACT fishery production data on Aquaculture and Wild Capture as the input efficiency shocks from fishery sector to the two processing technologies.	aft("Fishery","t1/t2","Fishery",REG)
Food processing sector	Shock eight food processing sectors output efficiency by using the values that were estimated by Tim Baynes from literature when doing IRP project (Hatfield-Dodds et al., 2017).	ao_generic("food processing sectors name",REG);

3.3.2. Energy related sectors

Calibration of energy sectors is not unique to GTEM-Food, but a standard practice for all GTEM-based models. The calibration approach is developed in Y. Y. Cai et al. (2015).

Input efficiency of coal, oil, gas and electricity in energy-intensive sectors, transportation sectors and household sector as well as input efficiency of fossil fuel in the power generation sector are calibrated by following the IEA historical trend of energy efficiency in the report of *Energy Efficiency*, and the energy mix of current policy scenario in the report of *World Energy Outlook*. The detailed calibration variables and shocks are described in Table 2.

Table 2: Energy related assumptions.

Sectors	Assumptions	GTEM-Food shock variables
Transport	Coal, gas, petroleum and electricity input efficiency into two transport sectors are shocked by using the efficiency improvement in transport by fuel from IEA's *Energy Efficiency* report.	af_generic ("col/gas/p_c/ely","otp/Oth_trans",REG)
Electricity	Coal, gas, petroleum input efficiency into corresponding generation technologies in the electricity sector are shocked by using the efficiency improvement in electricity generation by fuel from IEA's *Energy Efficiency* report.	aft("col","t1","ely",REG)
Electricity output	Output of 15 electricity generation technologies following output projections provided by CSIRO Energy Business Unit	f_qtech(tech,"ely",REG)
Energy-intensive sectors	Coal, gas, petroleum and electricity input efficiency into 2 energy-intensive sectors (Iron and steel production, other energy intensive sector) are shocked by using the efficiency improvement in transport by fuel from IEA's Energy Efficiency report.	af_generic(FUEL,"Ene_Intens",REG) af_generic(FUEL,"i_s",REG) FUEL = (COL,GAS,P_C,ELY)
Others	• We apply a uniform shock to fuel input efficiency in all the other sectors are shocked uniformly by a world aggregate improvement rate. • We also apply a uniform fuel efficiency for final demand (household fuel efficiency) are shocked uniformly by a world aggregate improvement rate. • Emission intensity of fuels are shocked uniformly by a world aggregate improvement rate.	af_generic(FUEL,NON_SHK_IND,REG) fuel_economy f_eo

4. Results

Most world output levels are projected to increase in 2014-2060, except coal and natural gas (Table 3). Vegetable and fruit double their output level ($1434 billion) in 2060 compared to the level ($779 billion) in 2014. Dairy milk also follows the same pattern, reaching $1447 billion in 2060 compared to $797 billion in 2014. Cattle meat also increases significantly in 2014-60, reaching $1362 billion in 2060 relative to $709 billion in 2014. Crude oil only slightly increases its output level from $2458 billion in 2014 to $2523 billion in 2060. They are $3975 billion and $4119 billion for petroleum products. At the world level, only output levels of natural gas and coal reduce in 2014-60 of which natural gas slightly decreases from $881 billion to $757 billion in 2014-2060. Coal experiences relatively high contraction in its output level with decreases from $537 billion to $310 billion in 2014-2060.

Results are mainly driven from the assumptions on electricity output. We assume electricity generation from fossil-based resources gradually reduces in most countries, while renewable-based electricity grows substantially in the study period. As the electricity generation sectors are the main consumers of fossil fuels, lowering demands from these sectors results in lower output supply from the mining and extraction sectors.

Table 3: The world output level (2014 US$ billion).

Commodities	2014	2020	2030	2040	2050	2060	CAGR
Paddy rice	311	331	359	385	409	431	0.0071
Wheat	209	222	235	248	260	270	0.0056
Vege & fruit	779	856	992	1134	1281	1434	0.0134
Oil seeds	286	299	314	330	347	364	0.0052
Fibres crop	92	102	116	132	147	163	0.0125
Live cattle	383	423	485	541	590	634	0.0110
Live pig	398	436	489	526	542	543	0.0068
Live poultry	266	300	357	405	442	472	0.0125
Meat cattle	709	793	944	1086	1217	1362	0.0143
Meat pork	336	370	432	486	529	570	0.0115
Meat poultry	279	312	373	430	477	524	0.0138
Fishery	392	416	454	484	507	529	0.0066
Wool	56	63	74	83	89	93	0.0112
Forestry	349	362	373	390	411	447	0.0054
Vegetable oils	520	546	579	615	649	677	0.0057
Dairy milk	797	872	1025	1175	1309	1447	0.0131
Processed rice	458	498	563	617	658	692	0.0090
Sugar	219	233	252	272	291	309	0.0075
Coal	537	478	424	379	344	310	-0.0119
Oil	2458	2451	2475	2493	2511	2523	0.0006
Natural gas	881	867	851	779	720	757	-0.0033
Petroleum	3975	3988	4047	4085	4103	4119	0.0008
Electricity	2909	2990	3138	3280	3367	3492	0.0040

Figure 9 outlines the output levels of electricity from different resources/technologies. Coal-fired electricity substantially reclines from 8.6 million GWh in 2014 to 3.4 million GWh in 2060. Solar and geothermal power increase their output significantly in 2014-60 and become main sources of power by 2060. In particular, solar power reach 6.5 million GWh, gas-based and geothermal power reach 5.2 million GWh each in 2060.

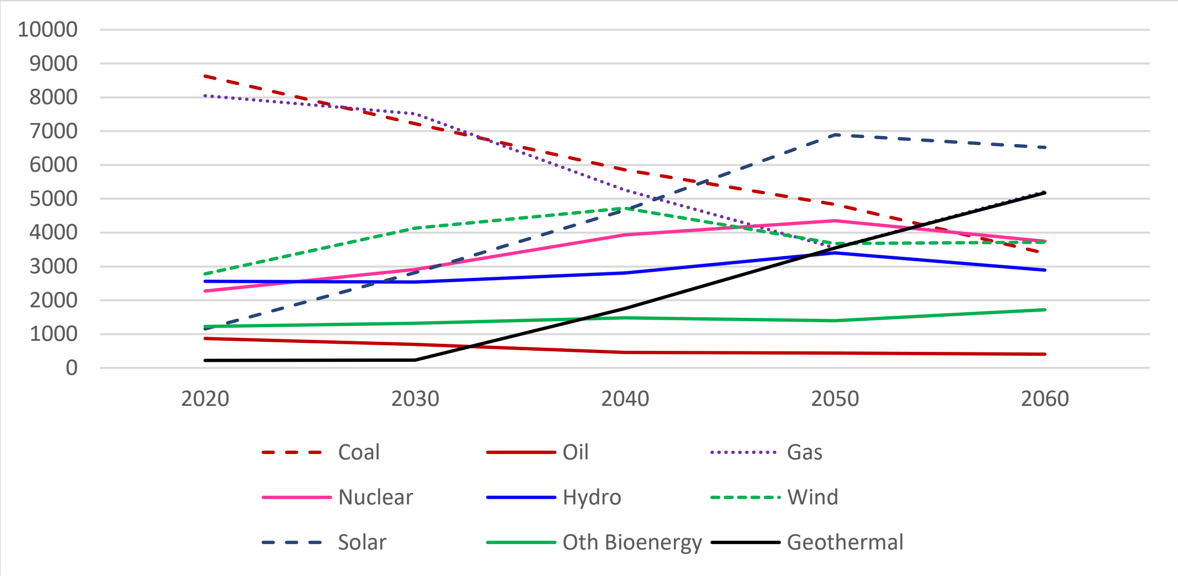

Figure 9: Output of electricity from different resources/technologies.

Table 4: Output of wheat in major producing regions (2014 US$ billion).

Countries	2014	2020	2030	2040	2050	2060	CAGR
Australia	7	8	9	10	11	12	0.0112
China	48	48	48	48	47	47	-0.0007
India	19	21	23	24	26	27	0.0080
France	7	7	7	8	8	8	0.0047
Russia	10	11	12	12	12	11	0.0017
USA	11	12	12	13	14	16	0.0079
South Asia	13	15	17	19	21	23	0.0122
Middle East	26	28	32	35	37	39	0.0092
Africa: North	13	15	18	20	22	24	0.0130

Table 5: Output of processed rice in major producing regions (2014 US$ billion).

Countries	2014	2020	2030	2040	2050	2060	CAGR
China	214	227	240	245	241	231	0.0016
India	59	67	84	98	111	123	0.0162
Japan	20	19	19	18	17	16	-0.0039
Indonesia	22	26	33	38	42	45	0.0154
Brazil	12	12	13	14	14	14	0.0042
Southeast Asia & Pacific	51	55	65	73	79	85	0.0114
South Asia	33	38	51	66	82	101	0.0243

Table 6: Output of live cattle in major producing regions (2014 US$ billion).

Countries	2014	2020	2030	2040	2050	2060	CAGR
Australia	13	15	18	20	23	25	0.0136
China	86	96	107	114	118	118	0.0068
USA	60	64	71	75	78	80	0.0061
Brazil	27	31	36	39	43	46	0.0115
Central Asia	12	13	16	19	21	22	0.0141
Middle East	20	24	31	39	49	61	0.0247
Tropical America	11	13	15	17	19	21	0.0133
Africa: West	15	18	23	29	37	47	0.0246

Note: * the values are measured by using market prices.

Table 7: Output of meat cattle in major producing regions (2014 US$ billion).

Countries	2014	2020	2030	2040	2050	2060	CAGR
Australia	15	18	22	26	30	33	0.0164
China	131	151	176	190	195	192	0.0083
South Korea	12	13	16	19	19	20	0.0113
France	22	23	25	27	29	31	0.0070
Germany	14	13	13	12	12	13	-0.0017
Italy	15	15	15	17	18	19	0.0056
UK	13	13	14	15	16	17	0.0056
Russia	76	83	94	103	108	113	0.0087
Canada	15	16	17	19	21	22	0.0090
USA	135	147	169	186	193	198	0.0084
Argentina	10	13	19	26	31	37	0.0289
Brazil	43	51	63	72	80	87	0.0155
Middle East	18	22	31	39	48	56	0.0256
Tropical America	17	19	24	28	32	35	0.0162
EU Atlantic	16	15	16	17	19	22	0.0071
EU Mediterranean climate	12	12	12	13	13	14	0.0035
Africa: West	44	56	86	123	171	233	0.0370

Table 8: Output of fishery in major producing regions (2014 US$ billion).

Countries	2014	2020	2030	2040	2050	2060	CAGR
China	161	170	182	188	188	183	0.0028
India	20	22	25	28	31	32	0.0105
Japan	14	14	14	14	14	14	0.0001
Indonesia	17	18	20	22	23	24	0.0081
Southeast Asia & Pacific	38	40	44	46	49	50	0.0059
South Asia	14	15	17	19	21	23	0.0108
European FTA	12	12	13	13	13	14	0.0035
Africa: West	11	13	17	20	24	28	0.0196

Table 9: Macroeconomic results in Australia (2014 US$ billion).

Year	2014	2020	2030	2040	2050	2060	CAGR
Real investment	389	591	977	1485	2322	3526	0.0491
Real public consumption	254	278	326	369	402	432	0.0116
Real private consumption	789	872	1022	1163	1271	1369	0.0121
Real import	268	292	326	362	393	425	0.0100
Real export	291	319	366	408	441	468	0.0104
Consumer price index*	n/a	-1	0	0	-1	-2	
Terms of trade*	n/a	-1	-5	-6	-6	-5	
Real wage rate*	n/a	2	6	8	9	8	
labour supply	731	800	910	1011	1109	1198	0.0108

Note: * indicates cumulative % change compared to 2014.

Table 10: Key agriculture results in Australia

Variables	2030	2040	2050	2060
Total emissions, IND + PRI + GOV (Mt CO2e)	438	408	396	406
Aggregate Agricultural sector emission (Mt CO2e)	108.1	114.5	122.1	128.9
Share of agricultural emissions of the total emissions	0.247	0.281	0.309	0.318
Real aggregate agricultural output (cumulative % change compared to 2014)	26.380	41.610	55.380	68.240
Output of food versus output of non-food	0.043	0.042	0.041	0.041
Share of agriculture sector to all sectors	0.063	0.062	0.063	0.063
Agricultural export share of total agricultural output	0.208	0.213	0.216	0.215
Agricultural export share of all commodity exports	0.016	0.016	0.016	0.015
Ratio of aggregate import by agriculture sector to its production level	0.061	0.061	0.061	0.061
Agricultural productivity measured by real output per real input	1.022	1.023	1.023	1.023
Shares of aggregate agricultural product consumption of the total expenditure (household)	0.093	0.090	0.089	0.089
Share of food expenditure of total expenditure (household)	0.070	0.067	0.066	0.066
Share of staple food expenditure of total food expenditure (household)	0.001	0.001	0.001	0.001

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