Climate change impacts on agriculture using improved multi-region input-output framework

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1. Introduction

The agricultural sector plays a central role in the climate change adaptation and mitigation strategies. As one of the key global emitters of greenhouse gasses (GHGs), much effort has to be put in order to reduce its carbon footprint (Smith el al., 2014). At the same time, according to many studies, it is arguably the most vulnerable sector to face the impacts of global warming with both land and water availability, as well as yields productivity, being under pressure (Porter et al., 2014; Fischer et al., 2005). One of the approaches that attempts to consistently account for the global interactions between climate-related adaptation and mitigation strategies in the agricultural sector is the multi-region input-output (MRIO) framework (von Lampe et al., 2014).

In particular, several modelling tools reported within the Agricultural Model Intercomparison and Improvement Project (AgMIP, 2014) are based on the input-output framework. In this study, we use a computable general equilibrium (CGE) model ENVISAGE (van der Mensbrugghe, 2017), which is based on the latest Global Trade Analysis Project (GTAP) Data Base (Aguiar et al., 2016), to provide an assessment of climate change impacts on agricultural sectors under the set of economic, climate change and adaptation scenarios within the AgMIP protocols.

To this end, we dramatically improve the agricultural representation of the GTAP Data Base. This database can be considered an MRIO, which when reconciles its data inputs focuses on international datasets more than in the various Input-Output (IO) tables at its core.

Any MRIO framework usually faces several limitations mostly driven by data availability issues. These include both low regional coverage and/or insufficient level of agricultural sector disaggregation (Lenzen et al., 2013; Mengo et al., 2013; Wood at al., 2015; Timmer et al., 2015). Moreover, even if an IO table has the required level of sectoral representation, it may be outdated and thus in need for updates. Several approaches are applied to overcome these issues. In particular, the GTAP Data Base, which sectoral classification includes 12 agricultural and 8 processed food sectors for 121 countries and 20 aggregate regions, uses a two-step procedure.

First, a special agricultural and food IO table is developed to split up agricultural sectors and related activities in the IO tables that require disaggregation. This is based on the set of IO tables from representative countries as well as Food and Agricultural Organization (FAO) data. Second, selected countries are subjected to an agricultural production targeting (APT). While providing a valuable contribution to the GTAP Data Base development framework, the current approach to the APT targeting has some limitations and potential for further improvements.

First, following the OECD agricultural commodity classification, input data includes high share of unclassified/undistributed (non-MPS) commodities, which should later be distributed among agricultural sectors. According to 2011 data, an average share of the non-MPS commodities for 25 non-EU regions represented in OECD database was 27%. Second, while covering 46 regions (corresponding to the 70% of global agricultural output), the APT process used in latest available GTAP version 9 (released in 2015) still missed most developing countries and some major agricultural producers, like India. Finally, because the OECD data does not cover all agricultural commodities, some food commodities output are used to complement the dataset.

Such limitations of the agricultural sector representation in the GTAP MRIO potentially have a significant impact on the results of the climate change policy simulations, influencing both sectoral and regional distribution of outcomes. In an attempt to overcome these shortcomings and provide a more consistent assessment of climate change impacts on global agriculture, we develop an approach to APT values estimation, which is based on the FAO database and some additional data sources. The 5-step approach used in our study allows us to estimate the APT values for 133 regions of the GTAP MRIO.

The newly developed APT targets are used to revise the GTAP Data Base in order to explore the impacts of climate change. We focus on the comparisons of climate change assessment scenarios under different input agricultural data.

This paper hopes to contribute to the ongoing efforts on improving the representation of the agricultural sector in the MRIO framework by taking advantage of the international datasets. Utilizing the benefits of agricultural sector representation, our study also intends to extend the literature on the assessment of long-term climate change impacts on agriculture.

The rest of the paper is organized as follows. Section 2 provides an overview of the approach currently used in the GTAP database for agricultural sector disaggregation. Section 3 discusses a newly developed approach for the agricultural production targeting in GTAP, as well as comparisons with the current methodology. Section 4 presents methodological framework for the assessment of climate change impacts on agriculture. This Section also discusses policy scenarios and assessment results. Finally, Section 5 concludes.

2. Agricultural sector representation in GTAP

One of the main features of the GTAP Data Base is a detailed sectoral classification of agricultural and food products. This level of detail evolved over time, although from the start it included the paddy rice and wool sectors, which were inherited from the SALTER project, which focused in Australia and its trading partners (SALTER, 1991).

Currently, twelve sectors within agriculture and eight sectors within the area of food, beverages, and tobacco are identified. This level of detail is readily available from our trade and protection (i.e., tariff and agricultural domestic support) data but such detailed representation is not available for all countries' input-output (I-O) statistics.[2] Therefore, we need to implement a disaggregation procedure as part of the development of the GTAP Data Base. In addition, during the database construction, agricultural production is targeted in order to improve the representation of agricultural sectors. The next subsection presents these two procedures.

2.1 Agricultural sectors disaggregation

In order to disaggregate agriculture, one needs to account for geographic factors such as climate and soil that heavily influence the industry structure. Accordingly, we use country-specific data, from the Food and Agriculture Organization (FAO) of the United Nations to determine the value of production and trade, valued at producer prices, and a collection of country I-O tables using a sectoral classification heavily oriented toward agriculture, for details please refer to Peterson (2016). In version 9.2, 71 countries required agricultural disaggregation, these are listed in Table 1. Countries requiring food sectors disaggregation are Laos, Colombia, Guatemala, Belarus, Morocco, and Nigeria.

We use the FAO data to develop an Agricultural I-O table, that is rich in agricultural detail. This table is rebalanced to match every single table that requires agricultural disaggregation. Then for each country, we disaggregate the original table by pro-rating with the rebalanced table weights (McDougall, 2009).

Table 1. Countries requiring agricultural disaggregation in GTAP 9.2

No.	Country	No.	Country	No.	Country
1	Australia	**26**	Nicaragua	**51**	United Arab Emirates
2	New Zealand	**27**	Panama	**52**	Egypt
3	China	**28**	El Salvador	**53**	Tunisia
4	Hong Kong	**29**	Dominican Republic	**54**	Benin
5	Mongolia	**30**	Jamaica	**55**	Burkina Faso
6	Brunei Darussalam	**31**	Puerto Rico	**56**	Cote d'Ivoire
7	Indonesia	**32**	Trinidad and Tobago	**57**	Ghana
8	Malaysia	**33**	Switzerland	**58**	Guinea
9	Philippines	**34**	Norway	**59**	Senegal

[2] Certain contributors undertake this disaggregation, but when they do not, we perform the disaggregation.

No.	Country	No.	Country	No.	Country
10	Singapore	**35**	Russian Federation	**60**	Togo
11	Thailand	**36**	Ukraine	**61**	Ethiopia
12	Viet Nam	**37**	Kazakhstan	**62**	Kenya
13	India	**38**	Kyrgyzstan	**63**	Malawi
14	Pakistan	**39**	Tajikistan	**64**	Mauritius
15	Sri Lanka	**40**	Armenia	**65**	Mozambique
16	Canada	**41**	Azerbaijan	**66**	Rwanda
17	Mexico	**42**	Bahrain	**67**	Tanzania
18	Bolivia	**43**	Iran	**68**	Uganda
19	Brazil	**44**	Israel	**69**	Zambia
20	Chile	**45**	Jordan	**70**	Namibia
21	Ecuador	**46**	Kuwait	**71**	South Africa
22	Paraguay	**47**	Oman		
23	Peru	**48**	Qatar		
24	Venezuela	**49**	Saudi Arabia		
25	Honduras	**50**	Turkey		

2.2 Agricultural production targeting

Agricultural production targeting (APT) arose from concerns that EU member countries encountered with considerable inaccuracies in levels and international distribution of agricultural production, and, consequently, in the budgetary cost of assistance, which led to problems in analysis of EU agricultural reform (Hussein et al. 2016). Since GTAP 6, this procedure, supplements the updating of I-O tables with information at the sectoral level.

Under the current procedure, the values of agricultural production are based on two sources: the OECD Producer and consumer support estimates (PCSE) database (OECD, 2017) and JRC estimates, which are also based on the OECD data[3] (Boulanger et al., 2016). Both sources are also used in the GTAP build process to estimate the level of agricultural domestic support by countries and commodities. Thus, keeping consistency with domestic support data. Table 2 list the 46 countries for which we impose APT.

[3] The OECD reports data for the EU only; Boulanger et al. (2016) are using extended OECD dataset, which reports data for all EU member states. As stated in Boulanger et al (2016), such data was received from OECD upon request.

Table 2. Countries and regions subject to APT in GTAP 9.2

No.	Country	No.	Country	No.	Country
1	Australia	**8**	United States	**15**	Russian Federation
2	New Zealand	**9**	Mexico	**16**	Ukraine
3	China	**10**	Brazil	**17**	Kazakhstan
4	Japan	**11**	Chile	**18**	Turkey
5	Korea	**12**	EU27	**19**	Israel
6	Indonesia	**13**	Switzerland	**20**	South Africa
7	Canada	**14**	Norway		

While the current approach to the APT in general serves its purpose, there are several limitations of the current set up, which can be further addressed. As the main goal of the PCSE database is to provide agricultural support estimates by countries and commodities, values of the agricultural output are derived as an accompanying estimates. In particular, OECD distinguishes country-specific market price support (MPS) commodities and reports values of agricultural production for each type of such commodity. All other commodities are treated as non-MPS, they are allocated to the one aggregate group and their output value is estimated as a difference between total agricultural output and sum of the outputs for MPS commodities. On average non-MPS commodities share is 27% with EU-28 being the only region with “0” non-MPS share. In some countries, the share of non-MPS commodities is over 40%, like in case of China. In such cases, additional assumptions should be made to redistribute the non-MPS associated agricultural output between GTAP agricultural sectors, which includes a certain level of uncertainty.

Another issue is that non-MPS commodities in the PCSE database include some support estimates (and correspondingly commodity outputs) for food products and other sectors (e.g. forestry), which are not in the set of 12 GTAP agricultural sectors. Current mapping to GTAP sectors is designed to gap-fill the values of production for agricultural commodities, by using some food products’ output values. In general, this is an acceptable approach to gap-fill some output values, but this is a potential source for double counting (like in case of grapes and wine) and/or discrepancies in output value estimates.

Finally, while under the current APT approach production values represent around 70% of global agricultural output, a large number of developing countries, including some large agricultural producers, like India, are still not included into targeting procedure.

3. Agricultural production targeting using FAO data

In this Section, we discuss the way the FAO data is used to address some of the highlighted shortcomings of the currently used approach to agricultural production targets estimation, as well as help to expand regional coverage. The latter one can be particularly useful in case of developing countries with outdated IO tables (like in most African and some South American countries) and/or large agricultural producers (like India). Second part of the Section 3 provides an overview of the FAO-sourced and currently used in GTAP agricultural production targets. We also discuss some observed differences and sources of uncertainties. While this Section provides an overview of the new approach to APT, for more details an interested reader is referred to Chepeliev and Aguiar (2018).

3.1. General methodology

The approach for the new APT estimation includes 5 steps (Figure 1). In the ***first step***, we source the values of agricultural production from FAOSTAT database[4] (FAO, 2017) and map them to the GTAP country list. We add 3 countries represented in the FAOSTAT to the standard 244 GTAP country list.[5] In particular, additional countries included are Serbia and Montenegro (disaggregated into two countries in GTAP), South Sudan (aggregated within Sudan in GTAP) and China (ISO3 code CPR, in addition of CHN).[6]

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[4] http://www.fao.org/faostat/en/#data/QV

[5] https://www.gtap.agecon.purdue.edu/databases/regions.asp?Version=9.211

[6] FAOSTAT reports data both for China, mainland (ISO3 code CHN) and China (ISO3 code CPR). We use China, mainland (CHN) for accessing Chinese data. China (CPR) in FAOSTAT is used additionally to CHN and only for reporting output quantities.

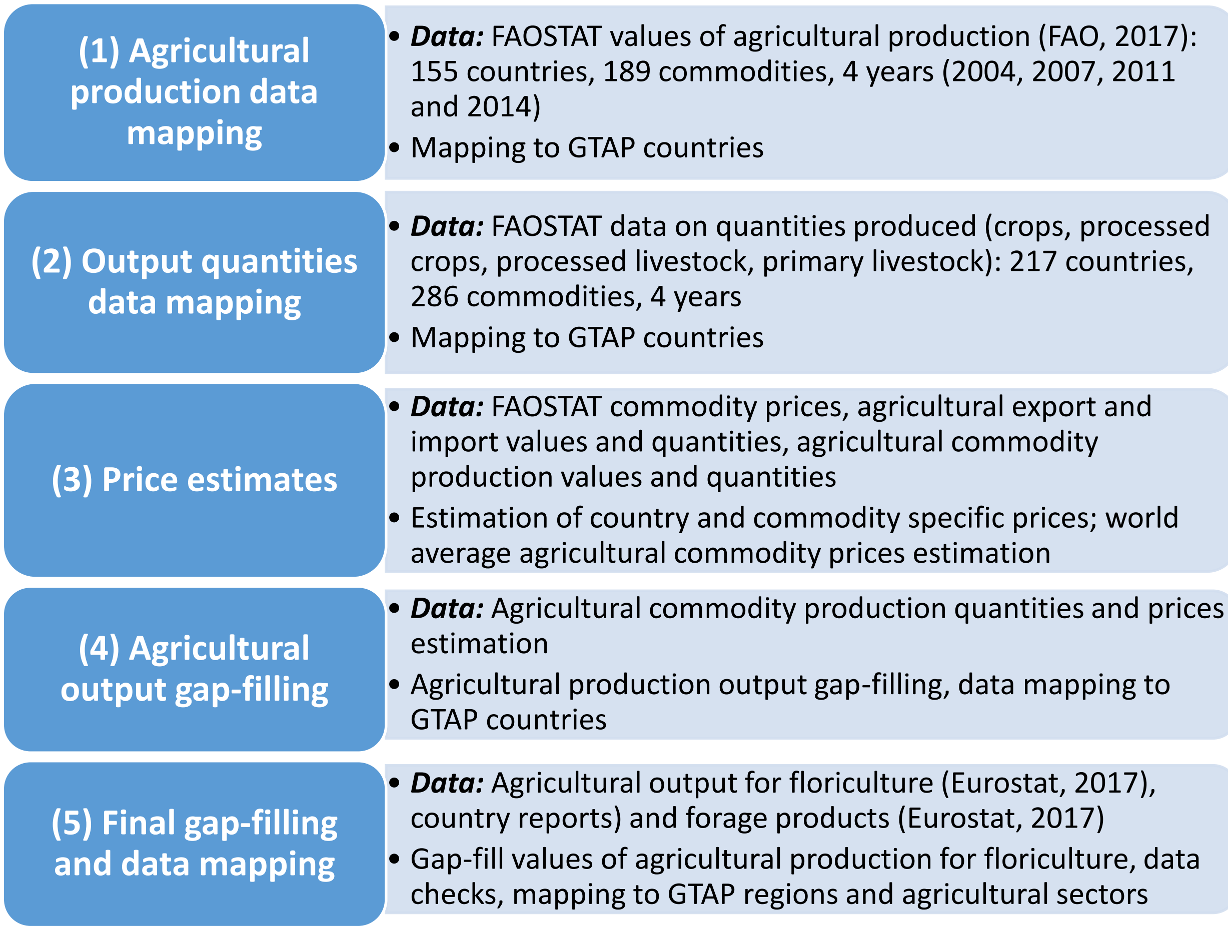

Figure 1. Steps to estimate agricultural production targets from FAO data for GTAP Data Base
Source: Authors

In the ***second step***, we source agricultural production quantities for crops[7], processed crops[8], processed livestock[9] and primary livestock.[10] As in the case of the agricultural output values, sourced on the first step, production quantities are also available for all 4 reference years: 2004, 2007, 2011 and 2014.

One of the identified limitations of the FAOSTAT database is the under-representation of several agricultural commodities. In particular, they include "Forage products" (CPC 2.1 code 0191) and "Living plants; cut flowers and flower buds; flower seeds" (CPC 2.1 code 0196). To gap-fill the first commodity group[11] (Forage products) we use the Eurostat data for EU countries.

[7] http://www.fao.org/faostat/en/#data/QC
[8] http://www.fao.org/faostat/en/#data/QD
[9] http://www.fao.org/faostat/en/#data/QP
[10] http://www.fao.org/faostat/en/#data/QL
[11] Approach to the gap-filling of floricultural products is discussed later.

Third step includes sourcing of the annual producer prices from the FAOSTAT database (FAO, 2017)[12] and their further gap-filling. In case of APT estimation we are focusing on the 12 agricultural sectors of the GTAP 9 Data Base (sectors No. 1-12 in Appendix A).

Out of 286 commodities initially sourced for APT targeting, 203 are mapped to the 12 GTAP agricultural sectors. We first map all 286 commodities to the 20 GTAP sectors (both agricultural and non-agricultural) based on the CPC and GTAP sector correspondences (GTAP, 2017; UNSD, 2017; Chepeliev and Aguiar, 2018). We further exclude commodities, which may contribute to double counting in the FAO data (e.g. if FAO reports output for an aggregate commodity and then for sub aggregate) and commodities, which do not have an associated output values (e.g. live animals with only stock data reported).

In case of cattle (ctl) and other animal products (oap) we gap-fill the agricultural output values by using output data for primary livestock. Therefore, we remap most commodities, which are initially mapped to the cattle meat (cmt) and other meat (omt) sectors to the "ctl" and "oap" correspondingly. While such mapping is not based on the direct CPC and GTAP sectors correspondence (GTAP, 2017; UNSD, 2017), we consider this approach acceptable, taking into account the availability of data.

To gap-fill the prices for agricultural commodities we additionally source the FAOSTAT trade data on crops and livestock products (FAO, 2017)[13], in particular import/export quantities and values. FAO trade data is provided in the FAOSTAT commodity list (FCL) classification. Therefore, we use correspondence tables between CPC 2.1 and FCL classifications. Figure 2 depicts general approach to the country/commodity price estimates and gap-filling. It should be noted that latest available year for the FAO trade data is 2013, therefore in case of 2014 price estimates we apply FAO Food Price Index to inflate price data from 2013 to 2014 (FAO, 2018).

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[12] http://www.fao.org/faostat/en/#data/PP

[13] http://www.fao.org/faostat/en/#data/TP

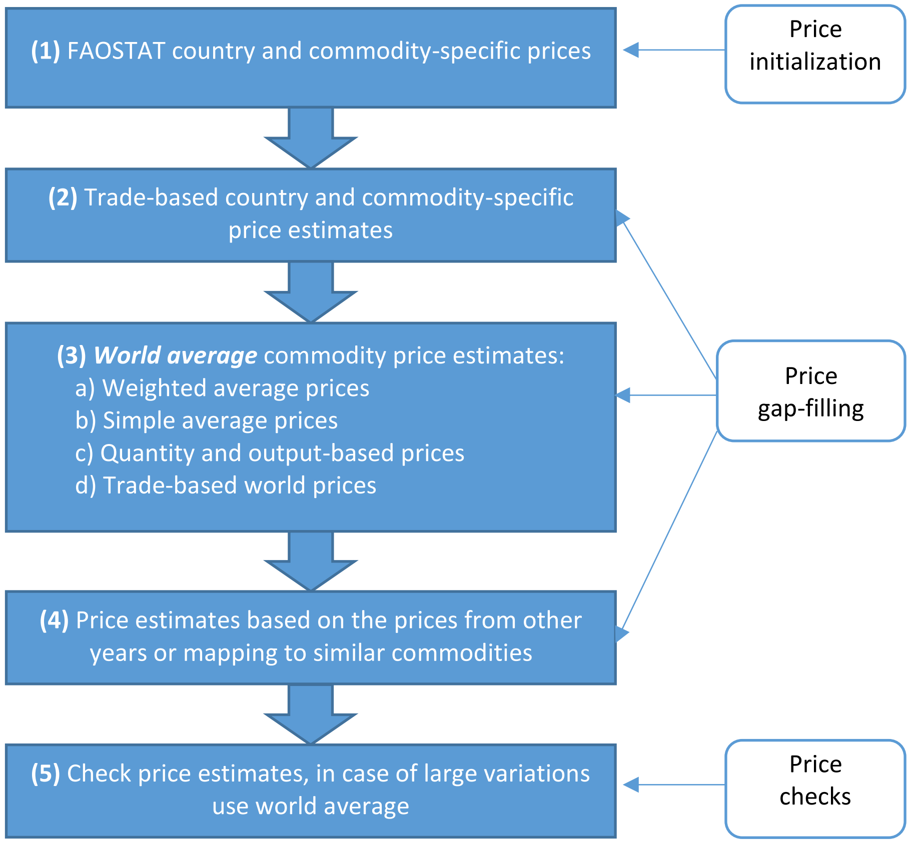

Figure 2. Steps to estimate and gap-fill agricultural commodity prices

Source: Authors

On the ***fourth step,*** we use quantities and prices to gap-fill values of agricultural production for FAO commodities, which are associated with GTAP agricultural sectors. We also provide mapping from extended 247 country list to the GTAP 244 standard country list. In particular, South Sudan from FAO data is mapped to Sudan (SUD) in GTAP country list. Aggregate data for Serbia and Montenegro from FAOSTAT for 2004 (before country's separation into the Republic of Serbia and Montenegro) is shared between the Republic of Serbia (SRB) and Montenegro (MNE) proportionally to the corresponding commodities output in 2007, 2011 and 2014 (3-year average shares are used).[14] To avoid double counting, additionally reported by FAOSTAT data for China (coded as CRP) is ignored.

Finally, on the ***fifth step***, we provide additional agricultural output data gap-filling before moving to final regional and sectoral mappings. In particular, as discussed at the beginning of this Section, FAO does not report values and/or output quantities for floricultural commodities. To fill this gap we use several additional data sources. First, we source agricultural output data from Eurostat database

[14] Under the current regional aggregation of the GTAP Data Base, such data split would not have any impact, as the Republic of Serbia and Montenegro are combined into one aggregate region – "Rest of Europe" – together with 11 other countries.

(Eurostat, 2017), in particular, data for the “Plant and flowers production”, which includes output of “Nursery plants” (Eurostat code 4210), “Ornamental plants and flowers (including Christmas trees)” (code 4220) and “Plantations” (code 4230). This data is available for 32 countries and all 4 benchmark years – 2004, 2007, 2011 and 2014. Following GTAP sectoral classification (GTAP, 2017) floricultural output is mapped to “Other crops” (ocr) sector.

While Eurostat database covers all large European floricultural producers, it does not report production data for non-European countries. According to available reports, apart from EU countries (Netherlands, France, Italy, Germany, Spain) largest world floricultural producers also include USA, China and Japan (Ierugan, 2010; Hanks, 2015). For these three countries, we use a country-specific sources to estimate the floricultural output.

In case of USA, data is sourced from US Census of agriculture and Crops outlook (Jerardo, 2005; USDA, 2014; USDA, 2015). In case of China, we use domestic floricultural sales estimates (Jia et al., 2016; ITC, 2016) and convert them to US dollars (OECD, 2016). Considering that the value of commodity sales can be much larger than production values (as the former one are measured at the farm gate, while the latter one include trade and transport margins, sales margins etc.), we use the USA data to estimate the ratio between the value of production and sales. In case of Japan, floricultural output values are based on the USDA Report (USDA, 2010). Finally, we map the agricultural output estimates to the 12 GTAP sectors and 141 GTAP regions.[15]

3.2. Agriculture output comparisons

Using an approach discussed in Section 3.1, we estimate agricultural production targets for 141 GTAP regions and 12 agricultural sectors. Below, we provide a sectoral overview and comparisons with existing APT estimates for the 46 regions, which are currently targeted in the GTAP APT and represent around 70% of global agricultural output. For all comparisons we focus on the year 2011, which is the latest available year for all 46 regions in GTAP APT. For more details on the APT values comparison and verification an interested reader is referred to Chepeliev and Aguiar (2018).

On the ***aggregate level***, FAO agricultural production targets for 46 regions are 15.6% higher than targets currently used in GTAP APT (Appendix B). In most country cases relative difference is below 10%, while mapping of raw

[15] Compared to the version 9 of the GTAP Data Base, which has 140 regions, GTAP 9.2 adds Tajikistan as a separate region.

OECD/Eurostat-sourced agricultural production data gives estimate much closer to the FAO-derived value (9% difference – see Appendix B). Largest absolute differences arise for China (over 300 bn USD). Both Chinese national statistics (NBSC, 2013) and OECD dataset (OECD, 2017) report larger agricultural output values than currently used in GTAP APT, but lower than FAO-based estimates (absolute difference reduces to 137 bn USD). As was further verified on the sectoral level, FAO may be over reporting production values for China in some commodity cases by around 30 bn USD (e.g. cane and beet production, plant fibers).

In the case of ***paddy rice***, on average FAO reports 22.5% larger paddy rice production than GTAP APT data. In case of 5 countries (New Zealand, Canada, Norway, Switzerland and Israel) GTAP APT has small output values, while FAO reports "0" value of paddy rice production, which are further supported by Eurostat/OECD data. The largest absolute difference (27.3 bn USD) is observed for Indonesia (accounts for 80% difference on the global level). Verification of paddy rice production in Indonesia using additional national (Sudaryanto, 2016) and international sources (IRRI, 2017) gives more support to the FAO data.

GTAP APT and FAO-based data for ***wheat production*** differs by only 2.4% on the aggregate level. All 7 cases of relative large[16] country-specific differences are associated with small wheat producers.

Other grains aggregate output difference is also relatively small – less than 4%, while 10 cases with identified large differences are all minor producers. In case of several European countries, like Belgium, Latvia and Netherlands, Eurostat/OECD-sourced data reports closer values to the FAO data than the GTAP APT. OECD data has much lower other grains commodity coverage than FAO dataset. This can contribute to the underreporting of other grains production in some country cases.

Vegetables and fruits is sector with the largest absolute difference between GTAP APT and FAO-sourced output data. Total vegetable and fruits output for 46 countries according to FAO is over 246 bn USD or 37.7% larger than in case of GTAP APT. Two countries – China and Brazil – contribute over 80% to this underrepresentation, while 70% is associated with China alone. Further verification of FAO-sourced estimates using additional sources for Brazil (MAPA, 2012) and China (OECD, 2017) gives more support to the FAO data. It was also identified that one of the issues in the Eurostat vegetables and fruits data reporting for EU countries (which is in line with GTAP APT data) is significant underrepresentation of the grapes production, which contradicts both FAO data (FAOSTAT, 2017) and International organization of vine and wine statistics (OIV, 2016).

[16] Differences of over 30% w.r.t. GTAP APT values are considered high (relatively large).

In case of ***oil seeds***, FAO reports 31% larger output for 46 countries than GTAP APT. Further commodity specific comparisons have revealed that Eurostat and OECD data is significantly underrepresenting olives production in EU countries, including such large olives producers as Greece, Spain and Italy. Substantial differences are also observed for China and Indonesia. But as long as OECD includes large portion of the oil seeds output data to the non-APT commodities, it is hard to verify this statistics.

In case of ***sugar cane and beets,*** FAO dataset reports 27% larger aggregate production for 46 countries than the GTAP APT. This difference is by and large driven by the Chinese data. Other 14 cases of large differences include mainly middle size and small producers. Further verification of Chinese data (Li and Yang, 2015; USDA, 2016) suggests that in case of cane and beet output, GTAP APT data should be considered more accurate than FAO-sourced.

In case of ***plant fibers***, FAO-derived data reports on aggregate 33% larger output than corresponding GTAP APT values. Country cases with the largest differences and high output values include Australia (140%), China (50%) and Indonesia (14 times). Comparison of GTAP APT, FAO-based and international cotton statistics (ICAC, 2012; USDA, 2017) for selected countries revealed that in case of Australia and China, FAO data seems to report larger values than suggested by international statistics. At the same time, FAO-based data is more accurate in cases of "0" output identification.

Other crops is the only sector with much smaller FAO-based output for the 46 country aggregate compared to the GTAP APT data. On the country level most differences occur for non-EU countries (Australia, Japan, Korea, Canada, Mexico, China, Indonesia etc), while most EU countries data is within 30% difference range. Key driver behind such differences between GTAP APT and FAO-reported data is that in most non-EU cases OECD data does not have explicit representation of other crops in general and feed crops in particular. To gap-fill this data GTAP APT reallocates share of the non-MPS commodities to the other crops output (see Section 3.1 for more details), which includes high level of uncertainty.

In case of ***cattle output***, FAO dataset reports on aggregate 23.5% larger production than GTAP APT current values for 46 countries. In both GTAP APT and FAO data there is no explicit representation of cattle production (as only cattle stock is reported), therefore fresh cattle meat output values are used to gap-fill the data. In case of FAO, there is a larger set of commodities that are mapped to cattle sector than in OECD data, as apart from sheep, beef and veal meat represented in OECD dataset, FAO also reports output of goat, camel, horse, mules and some other types of meat, as well as hides and skins output.

In case of ***other animal products*** output, discrepancies between FAO and GTAP APT data on aggregate for 46 countries are lower than for cattle meat, as FAO reports only 12% larger production value. Out of 46 countries only 9 have differences over 30% between GTAP APT and FAO-based data, in addition out of top 10 other animal products producers only two (Brazil and Indonesia) experience large differences. As in case of cattle meat, both GTAP APT and FAO data does not have explicit representation of production and corresponding fresh meat output values are used to gap-fill the data.

In case of ***raw milk*** production, there is not much discrepancy between GTAP APT and FAO data. An aggregate difference for all 46 countries is 4.5%. Only 4 countries have relative difference larger than 30% (Switzerland, Romania, Latvia and Indonesia) – all of them are not large milk producers. In case of Switzerland and Latvia, if raw Eurostat/OECD data is used instead of GTAP APT, difference falls below 30% threshold.

Wool and silk-worm cocoons is the sector with largest relative difference on the aggregate level. In particular, GTAP APT provides output estimates over 3 times higher than FAO-based data. Further verification of the wool and silk cocoons output estimates on the country level, based on different international data sources, provide much more support for the FAO data.

Based on the whole set of GTAP agricultural commodities and regions, in most cases, further data verification provides more support to the FAO-sourced estimates, which in general can be considered more consistent than currently used in the GTAP APT data sourced from OECD dataset. At the same time, some country cases, e.g. China, may require further data verification and comparisons, as FAO-sourced data is not fully in line with national statistics.

For a more consistent treatment of the FAO data, additional step may include further gap-filling of the forage commodities output for non-EU countries, although in general this should not significantly impact sectoral output values. In terms of the currently used GTAP APT data, more attention should be payed to the cases of under reported commodities in the OECD database (e.g. olives, grapes etc). While data for EU countries (currently used in GTAP APT) is provided together with producer and consumer support estimates, some country and sector specific cases experience large under reporting, which may also introduce inconsistencies for the agricultural support levels interpretation. Such country and commodity cases require additional verification and/or correction. At this stage, we may continue using JRC-provided GTAP APT data for EU countries (after additional verification/correction of specific commodity cases) and use FAO-sourced targets for all available non-EU countries.

4. Climate change policy simulations

In this section, we discuss the details of the policy simulation. We use an MRIO framework to provide and assessment of the climate change impacts on agriculture. We first discuss relevant input data treatment, assumptions on technological change and preference shifts of the model. We further describe policy scenarios and provide assessment of the climate change impacts on the global agriculture.

4.1. Methodological framework

To provide an assessment of the climate change impacts on agriculture, we use the ENVISAGE model (van der Mensbrugghe, 2017). ENVISAGE is a global recursive dynamic CGE model with a focus on environmental and climate change analysis, that we calibrate to the revised GTAP Data Base.

While the revised GTAP Data Base was produced at the full disaggregation level (i.e. with 141 regions and 57 sectors), for the purpose of this paper, we are working with a regional and sectoral aggregation. In particular, 141 GTAP regions are mapped to the 20 aggregate regions (Appendix C), while 57 GTAP sectors are aggregated to 27 categories with rich representation of agricultural and food activities (Appendix D). GTAP's eight factor accounts are aggregated into five categories: capital, land, natural resources and unskilled and skilled labor. The latter two represent an aggregation of the five labor types available in the GTAP database (Appendix E).

For the baseline scenario we assume GDP and population growth rates consistent with the SSP2 scenario from the Share Socioeconomic Pathways database (IIASA, 2016), which represents "middle of the road" pathway with intermediate socio-economic challenges for mitigation and adaptation. Appendix F outlines key macroeconomic and demographic assumptions of different SSP scenarios.

In terms of technological and productivity changes, we assumed that agriculture labor productivity growth is one percentage point higher than in services for the period 2011-2040, and then drops to half percentage point. Manufacturing labor productivity growth is assumed to be two percentage points higher over the full time horizon.[17]

We incorporate three key additional productivity factors in agriculture—crop yields, feed efficiency, and improvements in meat yields. All three of these are provided as calibrated based on the GAPS partial equilibrium model developed by FAO (Kavallari et al., 2016). In the case of crop yields, this is applied to the land

[17] While these assumptions line up with some of the stylized facts, work is ongoing to improve these assumptions by looking at past country trends and historical validation exercises.

factor. In the absence of changes in the relative prices of inputs, this would result in yield growth equal to that emerging from FAO's model. Similarly, the growth in meat yield is applied to the capital stock in livestock that represents the size of herds. The improvements in feed efficiency are applied to the feed bundle in livestock.

Improvements in energy efficiency is captured in the so-called autonomous energy efficiency improvement parameter (or AEEI). We assume AEEI to be differentiated by countries and changing over time. In the benchmark year, it is set at one per cent per annum across all activities, energy sources, and vintages (old vintage represents installed capital, while new vintage represents most recent supply of capital). AEEI values are further linked to the GDP growth rates and assume to increase with higher per capita GDP growth. For instance, if GDP growths at two per cent per annum, AEEI equals one per cent per annum, while if GDP increase at the rate of eight per cent per annum, AEEI equals four per cent per annum. We use a power function with defined elasticities to establish such link between GDP growth and AEEI values and use lower (0.5 per cent) and upper (4.5 per cent) bounds to cap AEEI levels. Fixed AEEI values are used for coal consumption (one per cent in developing countries and 0.5 per cent in developed).

The final dynamic source of technological change is an exogenous improvement in international transport costs. It is assumed that costs decline by one per cent per annum.

To further provide a more realistic representation of the baseline scenario, we use several assumptions regarding preferences related to food demand. A first assumption regards dynamic changes to the preferences in the constant difference of elasticities (CDE) function. The CDE is a relatively flexible functional form in prices, but not with respect to income. Income elasticities, unless the income parameters of the CDE are re-calibrated, stay relatively close to their base year levels. For food and agriculture, this is typically implausible because as incomes grow food and agriculture elasticities decline towards zero. Based on a suggestion by Wolfgang Britz, a functional form is estimated that links the CDE's income parameter to real per capita consumption. The estimation uses the base year information contained in the GTAP database, i.e. it is a cross-section estimation. This may not be perfectly satisfactory for out of sample projections, though we are mainly concerned with food growth demand in developing countries. The estimated equation is a quadratic functional form. The CDE income parameters are then re-calibrated between periods for each region.

A second potential source of over-projecting food demand comes from the indirect demand implicit in an input-output framework that underlies CGE models. As countries become wealthier, they tend to consume more processed foods and more foods outside of the home—this indirect food demand is embedded in the input-output relations. In the case of meals outside of the home, these are typically linked to demand for services that are highly income elastic, i.e. as incomes rise, the demand for services rise at the same or higher pace and thus so does indirect food demand in the absence of re-calibration. One can assume that as demand for services rises, the demand for the non-food component of services rises considerably more rapidly than the demand for food—better restaurants, improved quality, etc. In order to capture these phenomena, the input-output coefficients of food demand are exogenously adjusted over time.

4.2. Climate change impacts on agriculture under different agricultural targets

With two alternative GTAP Data Bases at hand – original and revised agricultural production targets, we use a methodological framework described in Section 4.1 to provide an economic assessment of climate change impacts on agriculture. As input shocks, we use AgMIP scenarios and focus on the case with SSP2 baseline and median climate change impacts from RCP6.0[18] without CO_2 fertilization (Scenario SSP2_C6, Table 3). We further map climate change impacts on agriculture to the developed regional and sectoral aggregation (Appendix C, Appendix D). Climate change shocks represent impacts of the increase in temperature on changes in the agricultural productivity/yields (with respect to the baseline case with no climate impacts).

Table 3. Matrix of the climate change scenarios

	Climate	Focus	SSP1 'Sustainability'	SSP2 'Middle of the Road'	SSP3 'Fragmentation'
			Adaptation challenge: low	Adaptation challenge: medium	Adaptation challenge: high
A	NoCC	No climate change	SSP1_NoCC	SSP2_NoCC	SSP3_NoCC
B	RCP6.0	Climate change impacts	SSP1_CC6	**SSP2_CC6**	SSP3_CC6
C	NoCC	Mitigation measures for 2°C stabilization without residual climate change impacts	SSP1_NoCC_m	SSP2_NoCC_m	SSP3_NoCC_m
D	RCP2.6	Mitigation measures for 2°C stabilization + residual climate change impacts	SSP1_CC26_m	SSP2_CC26_m	SSP3_CC26_m

Source: AgMIP protocols

[18] RCP stands for Representative concentration pathways. RCP6.0 corresponds to the +6.0 W/m^2 change in radiative forcing in the year 2100 relative to pre-industrial levels.

The economic assessment of the climate change impacts on agriculture does not show significant negative implications on the macro level (Figure 3). Even by 2050, in the most severely impacted regions (India and South Asia) GDP reduces by less than 0.2% relative to the baseline scenario. Most of the developed countries do not experience any GDP deviations. As other studies show, in a longer run, for instance by 2100, we can expect much more severe agricultural-related climate change impacts on macro variables (Eboli et al, 2010; Matsumoto and Masui, 2011).By 2050, our macroeconomic results are comparable with available studies (Eboli et al, 2010; Matsumoto and Masui, 2011), although more deep comparison with decomposition analysis would be highly beneficial.

It could be also the case that agricultural-related climate impacts are not the most influential at the macro level compared to other impact factors, like sea level rise, tourism, water scarcity and overall labor productivity. According to some studies, the latter one may be a key determinant of the aggregate impacts (Roson and van der Mensbrugghe, 2010).

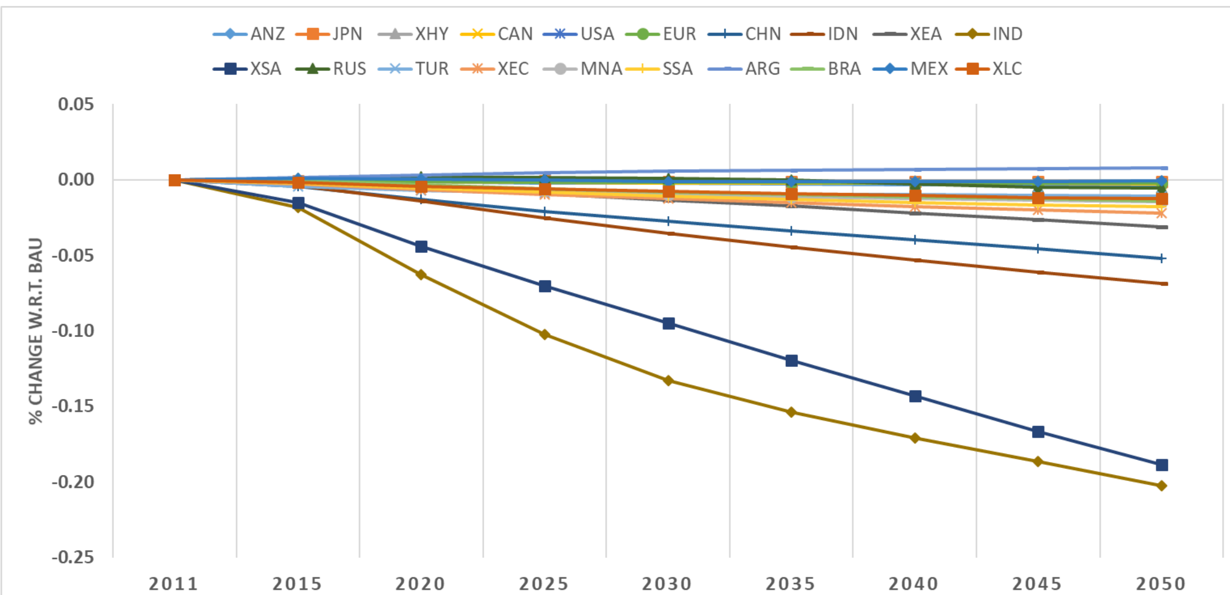

Figure 3. Deviation of regional GDP from baseline due to climate change impacts on agriculture, %

Impacts of the same order of magnitude as GDP are observed for the changes in real households' income (Figure 4). Although, in this case results are more uniformly distributed between regions with South Asian countries being the most severely impacted. In both cases (GDP and real households income), Argentina seems to be the key gainer, as both rice and oil seeds production increase in this country.

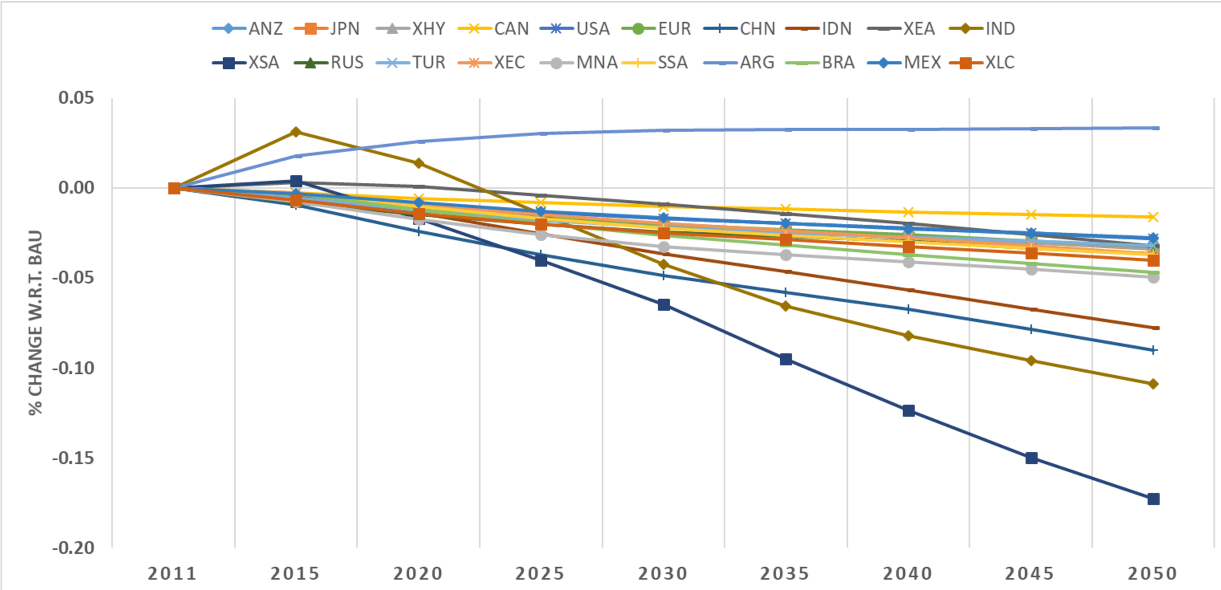

Figure 4. Deviation of real households' income from baseline due to climate change impacts on agriculture, %

While on the aggregate level, agricultural-related climate change impacts show extremely low order of magnitude, sectoral-level picture is much more differentiated by regions, as agricultural commodity output deviates from -10% to +20% relative to BaU in 2050 (Figure 5). On the global level, wheat experiences the largest negative impacts as its output decreases by over 1%. And while some regions, like East Asia, Mexico and Sub-Saharan Africa show sharp wheat output reduction (up to 10%), on the global level such trends are compensated by the wheat output increase in high income countries and South Asia (Figure 5). Mexico and some other Latin America countries experience significant drop in the oil seeds production, which at the global level is almost fully outstated by output in high-income countries, East Asia, Russia and Argentina.

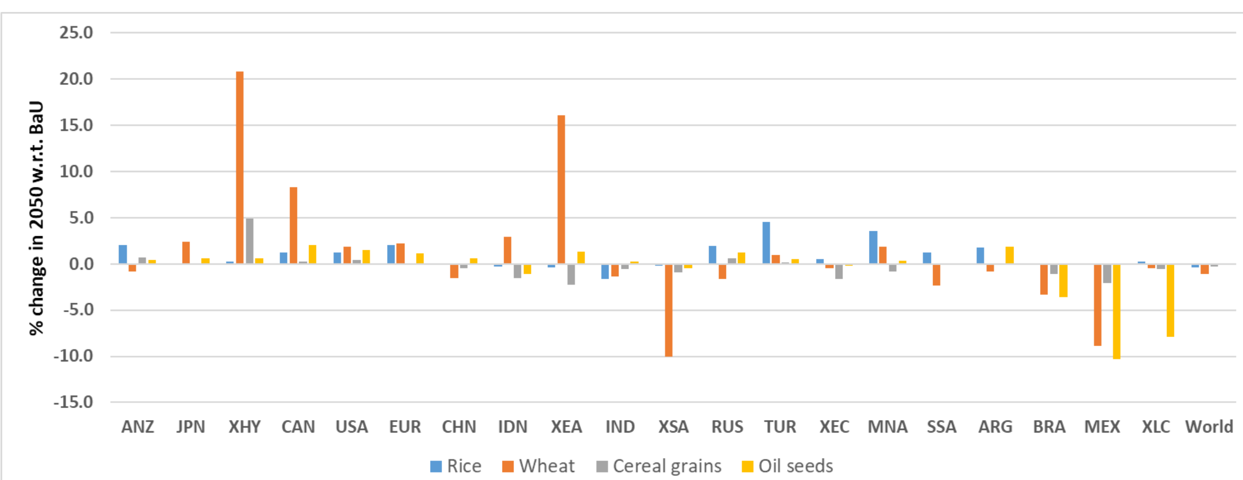

Figure 5. Deviation of agricultural output by sectors in 2050 from baseline due to climate change impacts, %

Comparison of the agricultural-related climate change impacts for the GTAP Data Base with initial and revised agricultural output targets is provided in Appendix G. With initially lower agricultural output values in the default GTAP dataset, results show less negative macroeconomic impacts, although qualitatively distribution of impacts between regions does not change significantly. On the sectoral level, results proof to be very similar with average lower magnitude changes, especially in case of rice output. Although some region-specific cases deviate from this general case.

5. Discussion

Agricultural sector plays a central role in the climate change adaptation and mitigation strategies. As it is one of the key global emitters of GHGs, much effort has to be put in order to reduce its carbon footprint. At the same time, according to many studies, it is arguably the most vulnerable sector to face the impacts of global warming with both land and water availability, as well as yields productivity, being under pressure. One of the approaches that attempts to consistently cover the global interactions between climate-related adaptation and mitigation strategies in the agricultural sector is based on an MRIO framework.

In particular, several modelling tools reported within AgMIP (2014) are based on the input-output framework. At the same time, any MRIO framework usually faces several limitations mostly driven by data availability issues. These include both low regional coverage and insufficient level of agricultural sector disaggregation (Lenzen et al., 2013; Mengo et al., 2013; Wood at al., 2015; Timmer et al., 2015; Aguiar et al., 2016). Moreover, even if an IO table has the required level of sectoral representation, it may be outdated and thus in need for updates.

In this paper, we contribute to the ongoing efforts on improving the representation of the agricultural sector in the MRIO framework by taking advantage of international datasets with an emphasis on agriculture. In particular, we update an agricultural production targeting approach within the widely used GTAP Data Base. We show that updated agricultural output targets, mainly based at the FAO data, increase the consistency with national data sources and international statistics.

The economic assessment of the climate change impacts on agriculture does not show significant negative implications on the macro level by 2050. The most severely impacted regions (China, Indonesia, India and South Asia) decrease their GDP by utmost 0.2% in 2050 relative to the baseline path. Impacts of the similar magnitude are observed for the households' real income. In general, our macro results are consistent with previous studies with comparable timeframe (Eboli et al, 2010; Matsumoto and Masui, 2011). As other studies show, more severe agricultural-related climate change impacts can be expected by 2100 (Eboli et al, 2010).

On the sectoral level, the most impacted agricultural sectors include rice, wheat, cereal grains and oil seeds with wheat experiencing the largest negative impacts. Although wheat output reduction in 2050 barely exceeds 1% globally relative to the baseline.

Comparison of the agricultural-related climate change impacts for the GTAP Data Base with initial and updated agriculture output targets on average shows less regressive outcomes in case of the default GTAP Data Base, as the latter one has on average lower agricultural output in the benchmark year. Sectoral-level impacts also show lower magnitude of changes. In general, initial and updated GTAP Data Bases show consistent climate change impact assessment outcomes.

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Appendix A. GTAP 9 Data Base sectoral breakdown

No.	Code	Description
1	pdr	Paddy Rice: rice, husked and unhusked
2	wht	Wheat: wheat and meslin
3	gro	Other Grains: maize (corn), barley, rye, oats, other cereals
4	v_f	Veg & Fruit: vegetables, fruitvegetables, fruit and nuts, potatoes, cassava, truffles,
5	osd	Oil Seeds: oil seeds and oleaginous fruit; soy beans, copra
6	c_b	Cane & Beet: sugar cane and sugar beet
7	pfb	Plant Fibers: cotton, flax, hemp, sisal and other raw vegetable materials used in textiles
8	ocr	Other Crops: live plants; cut flowers and flower buds; flower seeds and fruit seeds; vegetable seeds, beverage and spice crops, unmanufactured tobacco, cereal straw and husks, unprepared, whether or not chopped, ground, pressed or in the form of pellets; swedes, mangolds, fodder roots, hay, lucerne (alfalfa), clover, sainfoin, forage kale, lupines, vetches and similar forage products, whether or not in the form of pellets, plants and parts of plants used primarily in perfumery, in pharmacy, or for insecticidal, fungicidal or similar purposes, sugar beet seed and seeds of forage plants, other raw vegetable materials
9	ctl	Cattle: cattle, sheep, goats, horses, asses, mules, and hinnies; and semen thereof
10	oap	Other Animal Products: swine, poultry and other live animals; eggs, in shell (fresh or cooked), natural honey, snails (fresh or preserved) except sea snails; frogs' legs, edible products of animal origin n.e.c., hides, skins and furskins, raw , insect waxes and spermaceti, whether or not refined or coloured
11	rmk	Raw milk
12	wol	Wool: wool, silk, and other raw animal materials used in textile
13	frs	Forestry: forestry, logging and related service activities
14	fsh	Fishing: hunting, trapping and game propagation including related service activities, fishing, fish farms; service activities incidental to fishing
15	coa	Coal: mining and agglomeration of hard coal, lignite and peat
16	oil	Oil: extraction of crude petroleum and natural gas (part), service activities incidental to oil and gas extraction excluding surveying (part)
17	gas	Gas: extraction of crude petroleum and natural gas (part), service activities incidental to oil and gas extraction excluding surveying (part)
18	omn	Other Mining: mining of metal ores, uranium, gems. other mining and quarrying
19	cmt	Cattle Meat: fresh or chilled meat and edible offal of cattle, sheep, goats, horses, asses, mules, and hinnies. raw fats or grease from any animal or bird.
20	omt	Other Meat: pig meat and offal. preserves and preparations of meat, meat offal or blood, flours, meals and pellets of meat or inedible meat offal; greaves
21	vol	Vegetable Oils: crude and refined oils of soya-bean, maize (corn),olive, sesame, ground-nut, olive, sunflower-seed, safflower, cotton-seed, rape, colza and canola, mustard, coconut palm, palm kernel, castor, tung jojoba, babassu and linseed, perhaps partly or wholly hydrogenated, inter-esterified, re-esterified or

No.	Code	Description
		elaidinised. Also margarine and similar preparations, animal or vegetable waxes, fats and oils and their fractions, cotton linters, oil-cake and other solid residues resulting from the extraction of vegetable fats or oils; flours and meals of oil seeds or oleaginous fruits, except those of mustard; degras and other residues resulting from the treatment of fatty substances or animal or vegetable waxes.
22	mil	Milk: dairy products
23	pcr	Processed Rice: rice, semi- or wholly milled
24	sgr	Sugar
25	ofd	Other Food: prepared and preserved fish or vegetables, fruit juices and vegetable juices, prepared and preserved fruit and nuts, all cereal flours, groats, meal and pellets of wheat, cereal groats, meal and pellets n.e.c., other cereal grain products (including corn flakes), other vegetable flours and meals, mixes and doughs for the preparation of bakers' wares, starches and starch products; sugars and sugar syrups n.e.c., preparations used in animal feeding, bakery products, cocoa, chocolate and sugar confectionery, macaroni, noodles, couscous and similar farinaceous products, food products n.e.c.
26	b_t	Beverages and Tobacco products
27	tex	Textiles: textiles and man-made fibres
28	wap	Wearing Apparel: Clothing, dressing and dyeing of fur
29	lea	Leather: tanning and dressing of leather; luggage, handbags, saddlery, harness and footwear
30	lum	Lumber: wood and products of wood and cork, except furniture; articles of straw and plaiting materials
31	ppp	Paper & Paper Products: includes publishing, printing and reproduction of recorded media
32	p_c	Petroleum & Coke: coke oven products, refined petroleum products, processing of nuclear fuel
33	crp	Chemical Rubber Products: basic chemicals, other chemical products, rubber and plastics products
34	nmm	Non-Metallic Minerals: cement, plaster, lime, gravel, concrete
35	i_s	Iron & Steel: basic production and casting
36	nfm	Non-Ferrous Metals: production and casting of copper, aluminium, zinc, lead, gold, and silver
37	fmp	Fabricated Metal Products: Sheet metal products, but not machinery and equipment
38	mvh	Motor Motor vehicles and parts: cars, lorries, trailers and semi-trailers
39	otn	Other Transport Equipment: Manufacture of other transport equipment
40	ele	Electronic Equipment: office, accounting and computing machinery, radio, television and communication equipment and apparatus
41	ome	Other Machinery & Equipment: electrical machinery and apparatus n.e.c., medical, precision and optical instruments, watches and clocks
42	omf	Other Manufacturing: includes recycling

No.	Code	Description
43	ely	Electricity: production, collection and distribution
44	gdt	Gas Distribution: distribution of gaseous fuels through mains; steam and hot water supply
45	wtr	Water: collection, purification and distribution
46	cns	Construction: building houses factories offices and roads
47	trd	Trade: all retail sales; wholesale trade and commission trade; hotels and restaurants; repairs of motor vehicles and personal and household goods; retail sale of automotive fuel
48	otp	Other Transport: road, rail ; pipelines, auxiliary transport activities; travel agencies
49	wtp	Water transport
50	atp	Air transport
51	cmn	Communications: post and telecommunications
52	ofi	Other Financial Intermediation: includes auxiliary activities but not insurance and pension funding (see next)
53	isr	Insurance: includes pension funding, except compulsory social security
54	obs	Other Business Services: real estate, renting and business activities
55	ros	Recreation & Other Services: recreational, cultural and sporting activities, other service activities; private households with employed persons (servants)
56	osg	Other Services (Government): public administration and defense; compulsory social security, education, health and social work, sewage and refuse disposal, sanitation and similar activities, activities of membership organizations n.e.c., extra-territorial organizations and bodies
57	dwe	Dwellings: ownership of dwellings (imputed rents of houses occupied by owners)

Appendix B. Comparison of APT targets for total agricultural production in 2011, mn USD[19]

No.	Country	GTAP APT[20]	FAO	Ord	GTAP/ FAO (%)	Eurostat, OECD[21]	OECD/ FAO (%)
1	Australia	49577	50166	-590	-1.2	48940	-2.5
2	New Zealand	17824	19152	-1328	-7.5	17795	-7.6
3	Japan	102664	103281	-617	-0.6	103458	0.2
4	Korea, Republic of	37451	35839	1613	4.3	37350	4.0
5	United States of America	379486	385717	-6231	-1.6	379486	-1.6
6	Canada	48272	48913	-641	-1.3	46664	-4.8
7	Mexico	51002	48994	2008	3.9	49776	1.6
8	Brazil	208507	224311	-15804	-7.6	188217	-19.2
9	Norway	4378	5242	-864	-19.7	5435	3.5
10	**Switzerland**	**7513**	**10872**	**-3359**	**-44.7**	**10196**	**-6.6**
11	Turkey	77841	82481	-4640	-6.0	79211	-4.1
12	South Africa	21221	24066	-2845	-13.4	20341	-18.3
13	Bulgaria	5123	5192	-69	-1.4	5124	-1.3
14	Romania	22923	25752	-2830	-12.3	23185	-11.1
15	Belgium	10599	12504	-1905	-18.0	10839	-15.4
16	Czech Republic	6288	7253	-965	-15.3	6355	-14.1
17	Denmark	13790	12319	1471	10.7	13981	11.9
18	Germany	68430	77156	-8727	-12.8	74587	-3.4
19	Estonia	1002	1050	-48	-4.8	1002	-4.8
20	**Greece**	**12424**	**19554**	**-7130**	**-57.4**	**12718**	**-53.8**
21	Spain	49910	54699	-4789	-9.6	52360	-4.5
22	France	78614	92409	-13794	-17.5	91644	-0.8
23	Ireland	8770	9825	-1056	-12.0	8695	-13.0
24	**Italy**	**52706**	**69747**	**-17041**	**-32.3**	**61353**	**-13.7**
25	Cyprus	906	893	13	1.4	936	4.6
26	**Latvia**	**940**	**1774**	**-834**	**-88.8**	**1337**	**-32.7**
27	Lithuania	3052	3321	-269	-8.8	3053	-8.8
28	Luxembourg	410	414	-4	-1.0	447	7.3
29	Hungary	9716	9270	446	4.6	9718	4.6
30	Malta	167	190	-24	-14.2	163	-16.6
31	Netherlands	30741	29470	1270	4.1	31176	5.5

[19] All numbers are in mn USD unless otherwise noted. Countries with differences (between GTAP APT and FAO-based data) over 30% are highlighted bold. “Ord” stands for ordinary difference.
[20] Value used in GTAP APT procedure.
[21] Direct mapping of agricultural output data from Eurostat/OECD datasets.

No.	Country	GTAP APT[20]	FAO	Ord	GTAP/ FAO (%)	Eurostat, OECD[21]	OECD/ FAO (%)
32	Austria	8106	10036	-1929	-23.8	8182	-22.7
33	Poland	29334	30455	-1121	-3.8	29340	-3.8
34	Portugal	7017	8754	-1737	-24.8	7748	-13.0
35	Slovenia	1475	1509	-33	-2.2	1673	9.8
36	Slovakia	2823	2871	-48	-1.7	2824	-1.7
37	Finland	5359	4477	882	16.5	4940	9.4
38	Sweden	7250	7163	87	1.2	7127	-0.5
39	United Kingdom	33996	35314	-1319	-3.9	34204	-3.2
40	**China**	**885003**	**1185383**	**-300381**	**-33.9**	**1048391**	**-13.1**
41	Indonesia	128366	152183	-23817	-18.6	119509	-27.3
42	Kazakhstan	16938	14545	2393	14.1	15592	6.7
43	Russian Federation	100385	99623	762	0.8	93357	-6.7
44	Ukraine	38056	38152	-96	-0.3	37400	-2.0
45	Israel	7989	8855	-866	-10.8	5985	-47.9
46	Chile	13040	11847	1194	9.2	12868	7.9
Total		**2667383.5**	**3082994.2**	**-415610.8**	**-15.6**	**2824681.2**	**-9.1**

Appendix C. Regional aggregation

Aggregate region	GTAP region
Australia & New Zealand (anz)	Australia (AUS), New Zealand (NZL)
Japan (jpn)	Japan (jpn)
Rest of high-income (xhy)	Hong Kong (HKG), Japan (JPN), Korea (KOR), Taiwan (TWN), Singapore (SGP), Rest of North America (XNA), Switzerland (CHE), Norway (NOR), Rest of EFTA (XEF), Israel (ISR)
Canada (can)	Canada (CAN)
United States (usa)	United States of America (USA)
EU28 (eur)	Austria (AUT), Belgium (BEL), Cyprus (CYP), Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Malta (MLT), Netherlands (NLD), Poland (POL), Portugal (PRT), Slovakia (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), United Kingdom (GBR), Bulgaria (BGR), Romania (ROU)
China (chn)	China (CHN)
Indonesia (idn)	Indonesia (IDN)
Rest of East Asia (xea)	Rest of Oceania (XOC), Mongolia (MNG), Rest of East Asia (XEA), Brunei Darussalam (BRN), Cambodia (KHM), Laos (LAO), Malaysia (MYS), Philippines (PHL), Thailand (THA), Viet Nam (VNM), Rest of Southeast Asia (XSE)
India (ind)	India (IND)
Rest of South Asia (xsa)	Bangladesh (BGD), Nepal (NPL), Pakistan (PAK), Sri Lanka (LKA), Rest of South Asia (XSA)
Russia (rus)	Russian Federation (RUS)
Turkey (tur)	Turkey (TUR)
Rest of Europe & Central Asia (xec)	Kazakhstan (KAZ), Tajikistan (TJK), Azerbaijan (AZE), Albania (ALB), Belarus (BLR), Croatia (HRV), Ukraine (UKR), Rest of Eastern Europe (XEE), Rest of Europe (XER), Kyrgyzstan (KGZ), Rest of Former Soviet Union (XSU), Armenia (ARM), Georgia (GEO)
Middle East & North Africa (mna)	Bahrain (BHR), Iran (IRN), Kuwait (KWT), Oman (OMN), Qatar (QAT), Saudi Arabia (SAU), United Arab Emirates (ARE), Rest of Western Asia (XWS), Rest of North Africa (XNF), Jordan (JOR), Egypt (EGY), Morocco (MAR), Tunisia (TUN)
Sub-Saharan Africa (ssa)	Benin (BEN), Burkina Faso (BFA), Cameroon (CMR), Côte d'Ivoire (CIV), Ghana (GHA), Guinea (GIN), Nigeria (NGA), Senegal (SEN), Togo (TGO), Rest of Western Africa (XWF), Central Africa (XCF), South-Central Africa (XAC), Ethiopia (ETH), Kenya (KEN), Madagascar (MDG), Malawi (MWI), Mauritius (MUS), Mozambique (MOZ), Rwanda (RWA), Tanzania (TZA), Uganda (UGA), Zambia (ZMB), Zimbabwe (ZWE), Rest of Eastern Africa (XEC), Botswana (BWA), Namibia (NAM), South Africa (ZAF), Rest of South African Customs Union (XSC), Rest of the World (XTW)
Argentina (arg)	Argentina (ARG)
Brazil (bra)	Brazil (BRA)
Mexico (mex)	Mexico (MEX)
Rest of Latin America & Caribbean (xlc)	Bolivia (BOL), Colombia (COL), Ecuador (ECU), Venezuela (VEN), Chile (CHL), Paraguay (PRY), Peru (PER), Uruguay (URY), Rest of South America (XSM), Costa Rica (CRI), Guatemala (GTM), Honduras (HND), Nicaragua (NIC), Panama (PAN), El Salvador (SLV), Rest of Central America (XCA), Dominican Republic (DOM), Jamaica (JAM), Puerto Rico (PRI), Trinidad and Tobago (TTO), Rest of Caribbean (XCB)

Appendix D. Sectoral aggregation

No.	Aggregate sector	GTAP sector[22]
1	Rice (ric)	pdr, pcr
2	Wheat (wht)	wht
3	Other grains (gro)	gro
4	Vegetables & fruits (v_f)	v_f
5	Oil seeds (osd)	osd
6	Sugar (sug)	c_b, sgr
7	Other crops (ocr)	pfb, ocr
8	Cattle (ctl)	ctl, wol
9	Other livestock (oap)	oap
10	Raw milk (rmk)	rmk
11	Forestry (frs)	frs
12	Coal (coa)	coa
13	Oil (oil)	oil
14	Natural gas (gas)	gas, gdt
15	Other mining (omn)	omn
16	Red meat (cmt)	cmt
17	Other meat (omt)	omt
18	Vegetable oils (vol)	vol
19	Dairy products (mil)	mil
20	Other food (ofd)	fsh, ofd, b_t
21	Textile wearing apparel & leather goods (twp)	tex, wap, lea
22	Energy intensive manufacturing (ke5)	ppp, crp, nmm, i_s, nfm
23	Other manufacturing (xmn)	lum, fmp, mvh, otn, ele, ome, omf
24	Refined oil products (p_c)	p_c
25	Electricity (ely)	ely
26	Construction (cns)	cns
27	Services (srv)	wtr, trd, otp, wtp, atp, cmn, ofi, isr, obs, ros, osg, dwe

[22] For the detailed description of GTAP sectors please see https://www.gtap.agecon.purdue.edu/databases/contribute/detailedsector.asp

Appendix E. Factor aggregation

Aggregate factor	GTAP Concordance
Capital (cap)	Capital (capital)
Land (lnd)	Land (land)
Natural resources (nrs)	Natural resources (NatlRes)
Unskilled labor (nsk)	Agriculture and other low-skill workers (ag_othlowsk),Service shop (service_shop), Clerical workers (clerks)
Skilled labor (skl)	Technical & professional workers (tech_aspros), Management (off_mgr_pros)

Appendix F. Macroeconomic and demographic assumptions of the Shared Socioeconomic Pathways

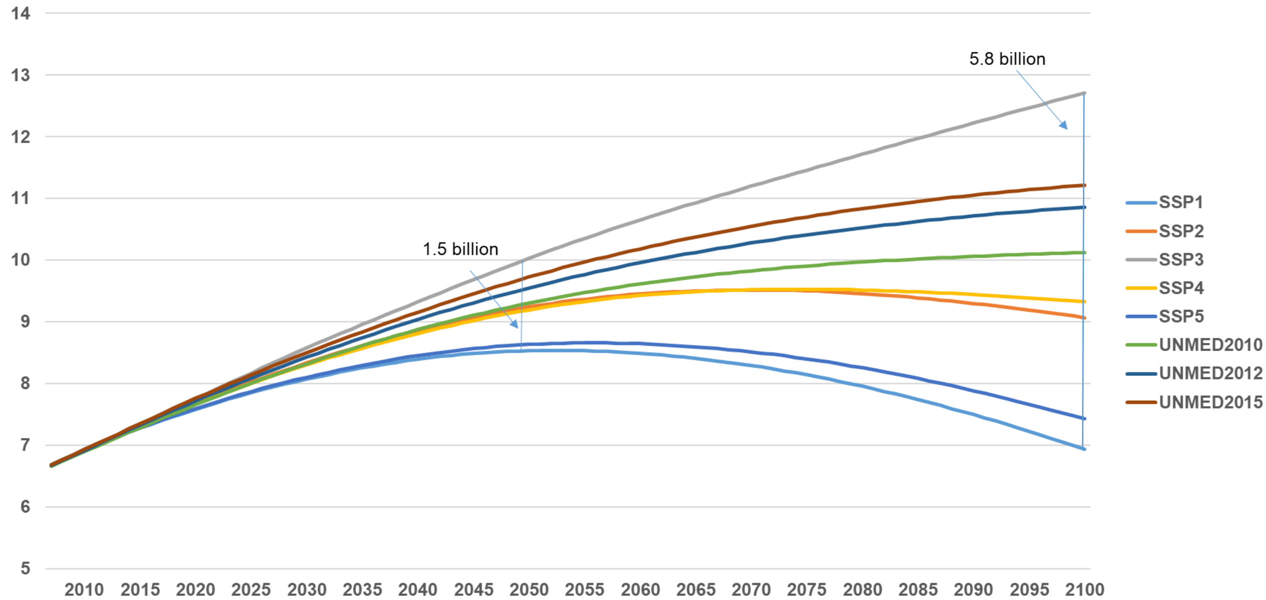

Figure F.1. Global population by SSP and UN scenarios, billion people
***Source*:** IIASA (2016); UN Population Division (2010, 2012, 2015).

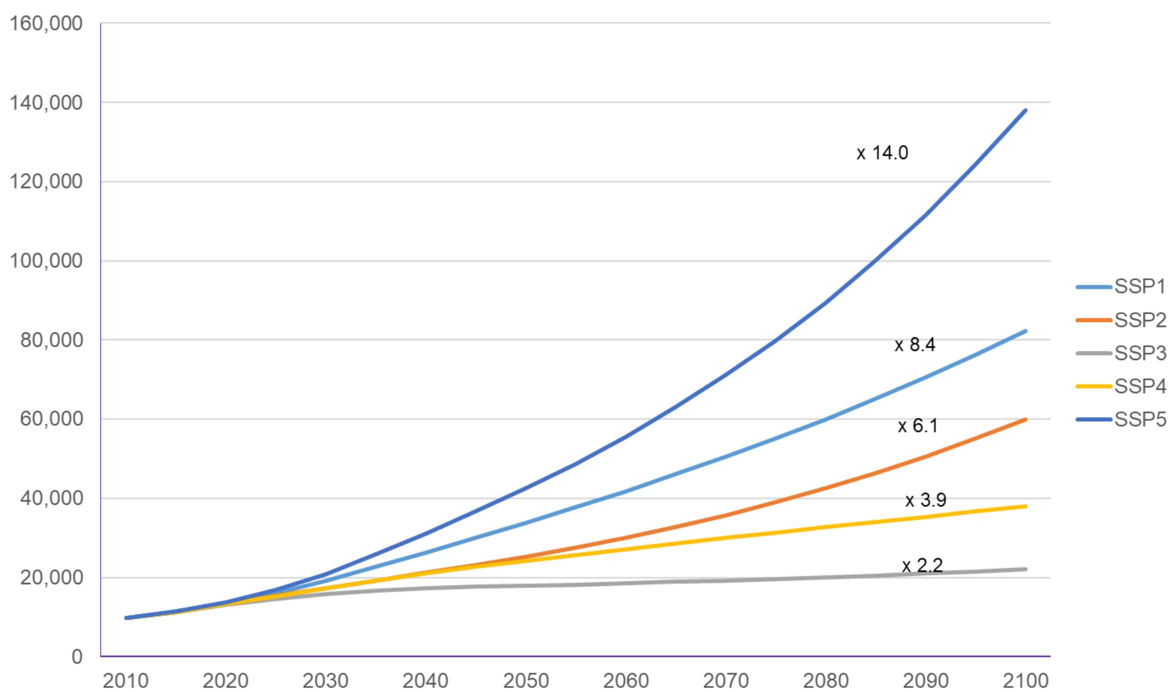

Figure F.2. Global per capita GDP by SSP scenarios, $2005 PPP
***Source*:** IIASA (2016)

Appendix G. Comparison of the agricultural-related climate change impacts for the GTAP Data Base with default and updated agricultural output targets

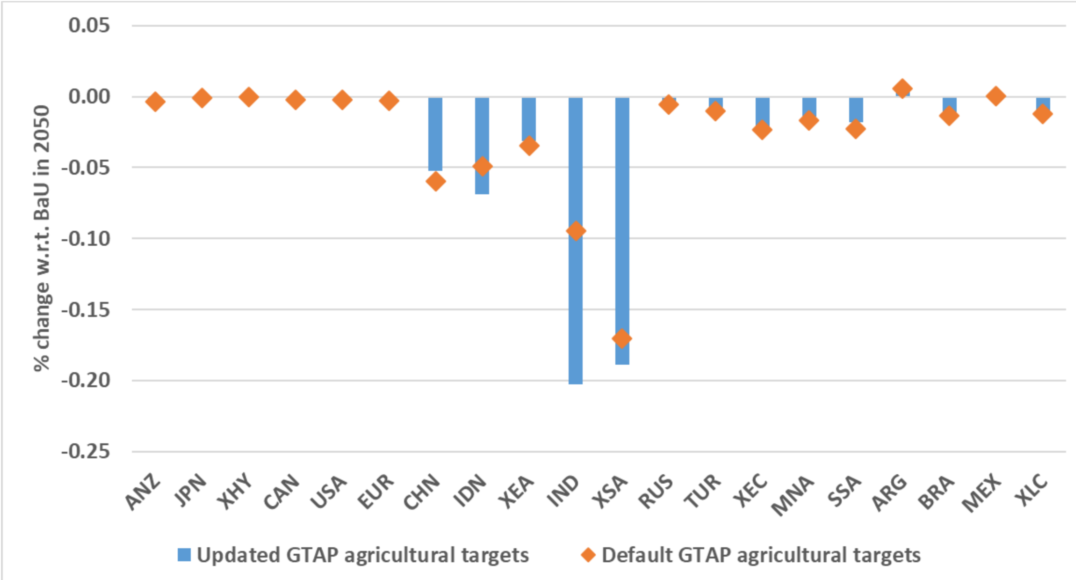

Figure G.1. Deviation of regional GDP from baseline in 2050 due to climate change impacts on agriculture, %

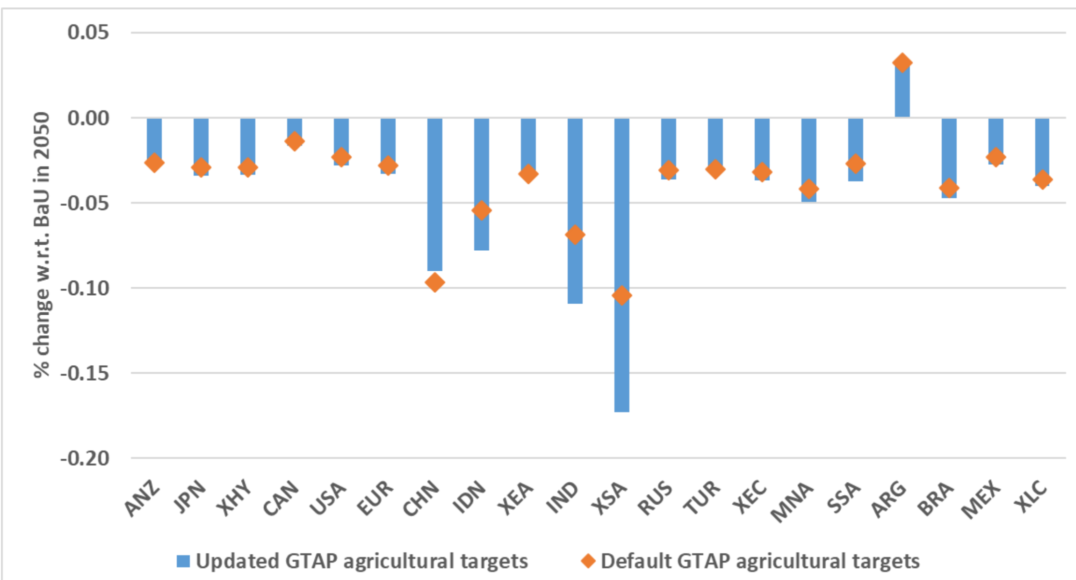

Figure G.2. Deviation of real households' income from baseline in 2050 due to climate change impacts on agriculture, %

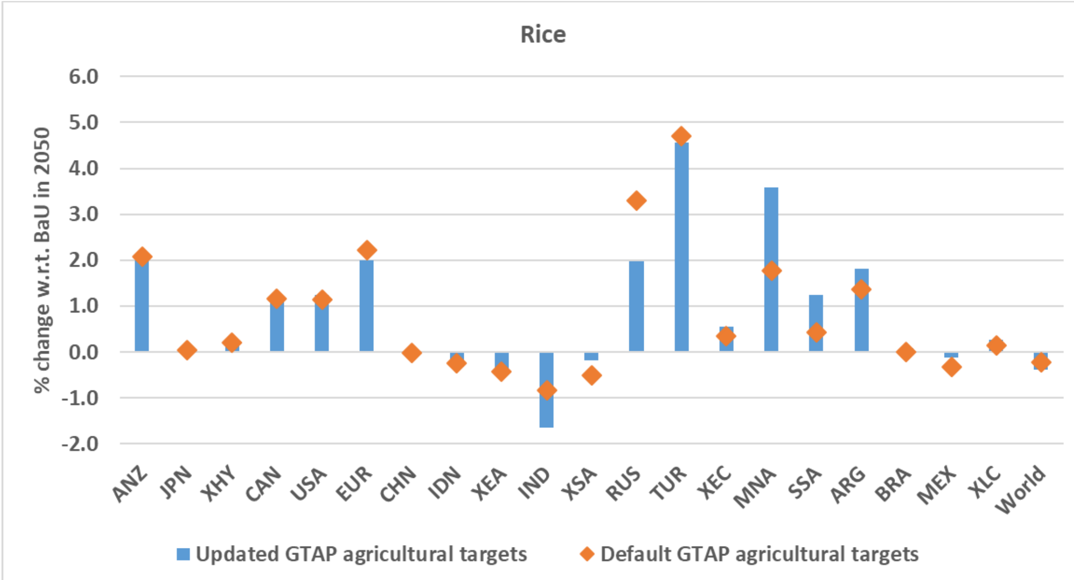

Figure G.3. Deviation of rice output in 2050 from baseline due to climate change impacts, %

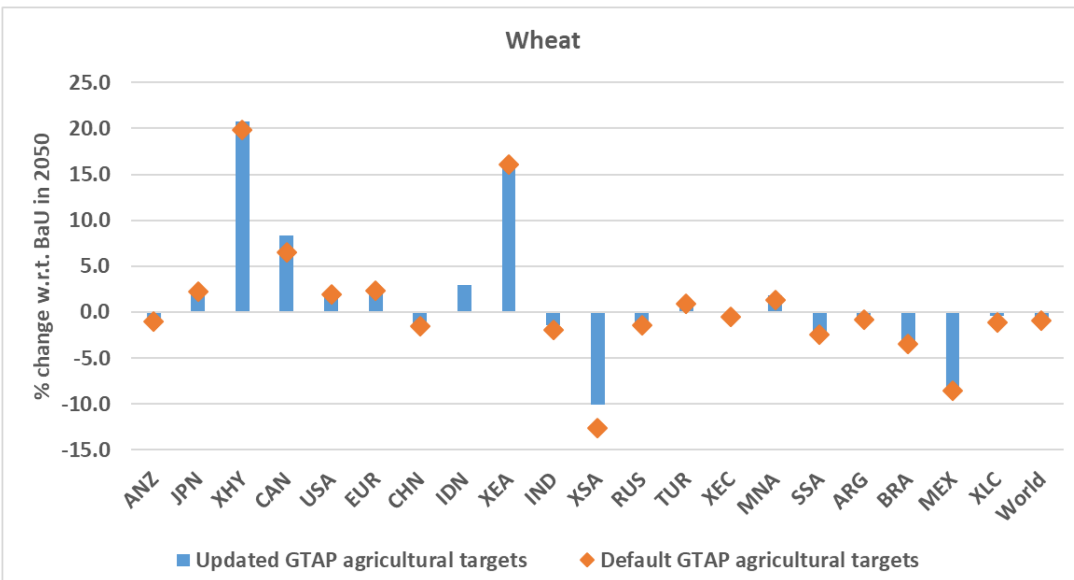

Figure G.4. Deviation of wheat output in 2050 from baseline due to climate change impacts, %

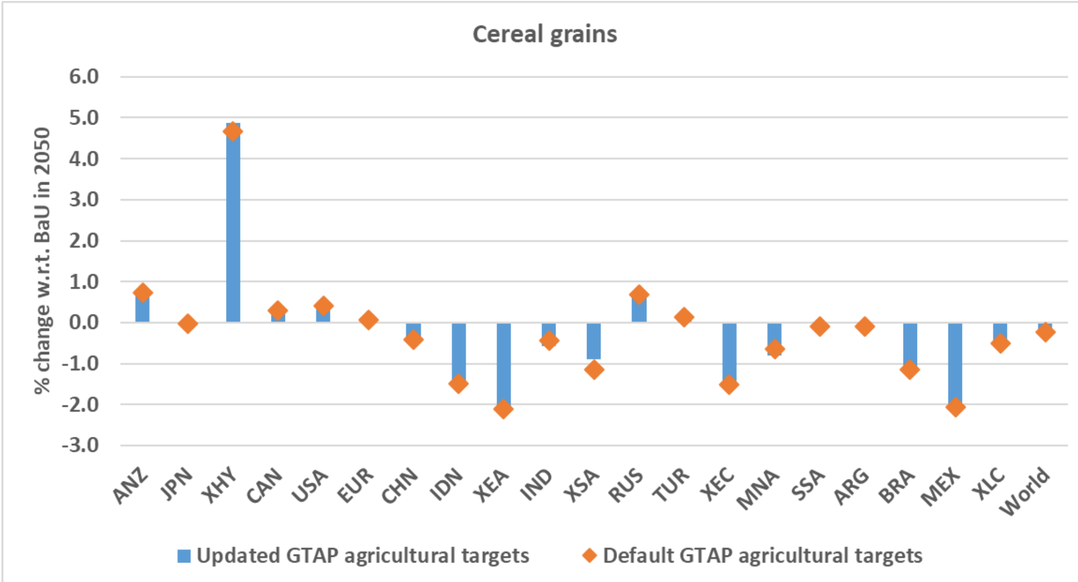

Figure G.5. Deviation of cereal grains output in 2050 from baseline due to climate change impacts, %

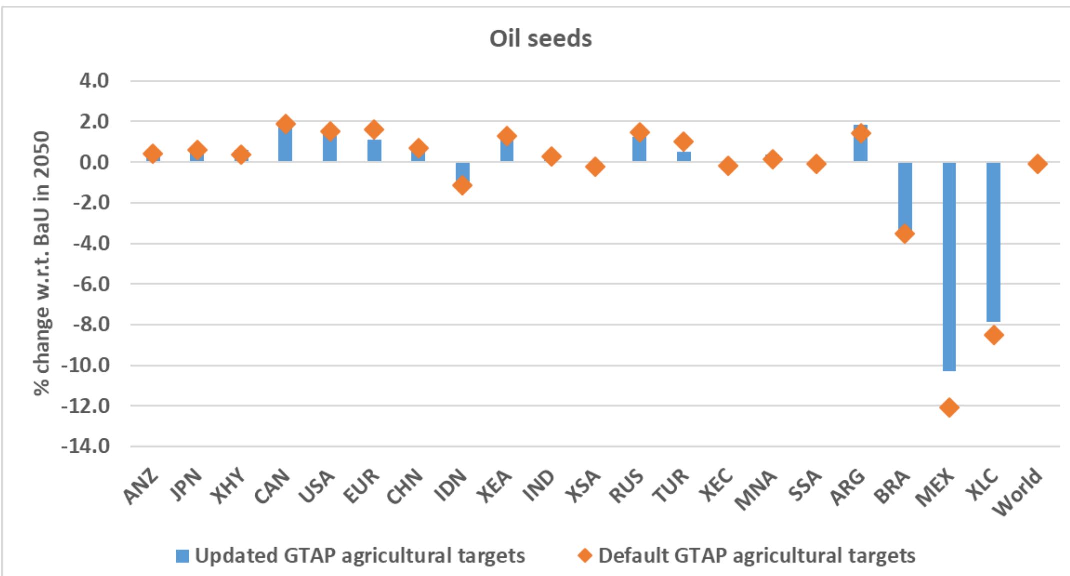

Figure G.6. Deviation of oil seeds output in 2050 from baseline due to climate change impacts, %