Quantifying SDG indicators for multiple SSPs up to 2050 with a focus on selected low and middle- income countries and the bio-economy based on CGE analysis

Rienne Wilts[1], Wolfgang Britz[1]

[1] Institute for Food and Resource Economics, University of Bonn, Nussallee 21, D-53115 Bonn, Germany

Abstract

A wide range of indicators beyond gross domestic product growth is necessary to measure progress towards more sustainability as reflected by the 17 multi-dimensional Sustainable Development Goals (SDGs) of the United Nations. Still, such progress builds on its core on economic development and related structural change. Given its multi-sector and global perspective, dynamic Computable General Equilibrium (CGE) analysis depicts these key processes and thus offers a starting point to quantify various SDG indicators. Multiple scholars have therefore developed SDG indicator frameworks which fit their CGE models. For the purpose of increasing the quantification of SDG indicators in CGEs, we reviewed existing studies and the United Nations SDG indicator framework and developed additional indicators. Existing auxiliary data available from GTAP, such as CO_2, non-CO_2 and air emissions data already help to assess important aspects of environmental sustainability and to relate emissions to human health in a CGE. Further indicators require partly sector and product detail beyond the GTAP Data Base which motivates the development of more detail data base in this study. Distributional aspects of economic growth, also beyond income distribution, remain a challenge in CGE analysis, and are addressed in this study by post-model micro-simulations. Extending existing work in this field, we propose to quantify 77 indicators relating to 13 of the 17 SDGs to assess sustainable developments up to 2050 for different Shared Socio-Economic Pathways.

Keywords: Sustainable Development Goal, Low (-Middle) Income Countries, Household data, dynamic Computable General Equilibrium Model, microsimulation

Introduction

In 2015, the United Nation Member States have agreed on 17 Sustainable Development Goals (SDGs) to be reached until 2030. These goals address multi-dimensional aspects of human and planetary well-being. Since the entry into force of the Goals, several analyses have been conducted assessing the advancements of the goals (e.g. Moyer and Hedden, 2020), their interactions (e.g. ICSU and ISSC, 2015; Nilsson et al., 2016; Pradhan et al., 2017; McCollum et al., 2017; Scherer et al., 2018) and measurement techniques (e.g. Hák et al., 2015; Allen et al., 2017; Guppy et al., 2019). The degree to which the SDG will be reached depends on a number of complex interactions, including socio-economic and demographic dynamics, governance and other influences such as climate change. Ex-ante assessments reflecting these interactions can help to inform society about fields where policy actions are required and how policy options affect the different SDGs. Suitable frameworks to do so need to model interactions between many economic sectors, to acknowledge global interrelations and to quantify indicators for the different SDGs. Here, analyses with global dynamic Computable General Equilibrium (CGE) models can be helpful given their multi-sectoral and global design. Furthermore, they can rely on projections for future developments, such as the Shared Socioeconomic Pathways (SSPs) (Riahi et al., 2017) allowing for long term ex ante scenario assessments.

In order to incorporate the effects of future conditions on SDGs, it requires the development of an SDG indicator framework based on model outcomes. Previous studies have already developed such frameworks for CGE model assessments. For example, Campagnolo et al. (2018) used 23 individual indicators from which they calculated a composite indicator (FEEM SI) to assess advancement with SDGs at country level. Zimm et al. (2019) address changes in nine SDGs in their analysis, quantified by baseline development for the different SSPs. They found that even in the most optimistic scenario (SSP1 + RCP 2.6), not all assessed targets can be met, not even by 2100. Philippidis et al. (2020) also used a CGE model to depict synergies and trade-offs between SDGs under different global development pathways. Using the MAGNET SDG Insights Module (that captures about 71 indicators), they selected 12 indicators linked to 7 SDGs and grouped them by three different layers of economy, society and biosphere. Liu et al. (2020) conducted an analysis on the achievement of SDGs using the Socio-Economic Pathways (SSP, Riahi et al., 2017) projections and additionally climate policy assumptions. Their CGE analysis draws on indicators related to 5 SDGs.

Taking the multi-dimensionality of SDG into account an increasing quantification of SDG Indicators for ex-ante CGE model assessments supports to study interactions and assess future pathways and policy decisions. Especially, distributional effects regarding income, food security and equality were not yet covered in CGE models as household level data is often scarce and remain a challenge in CGE modelling. Yet, several SDG Indicator specifically focus on the distribution among the population (e.g. SDG1, SDG2, SDG10). This study, therefore, aims to develop additional SDG indicators for CGE model analysis, with focus on SDGs linked to agro-food sector and land use aspects. It further aims to contribution by providing household level detail, as to the best of the authors knowledge, thus far no study has been published that depicts household level indicators with a CGE model and is thereby able to analyse distribution effects of future developments. To this end, we apply here a post-model micro-simulation approach to analyse household level data from FAO (2017) for 10 low and low-middle income countries.

Like previous studies, we also link our work to the SSPs which describe broad scenarios for the future of the global economy with a focus on developments relevant for climate change (Riahi et al., 2017). Demographic and macro-economic models have been used to map these scenarios into quantified projections of income (real Gross Domestic Product, GDP), demography and educational attainment levels (Dellink et al., 2017) which have been made available to the international research community[1]. Drawing on these projections, global recursive-dynamic CGE models are regularly used to provide structural change projections with sectoral detail. G-RDEM (Britz and Roson, 2019, Roson and Britz, 2021), used in here, is a model specifically developed for this purpose, as a module of the modular and flexible CGE modelling platform CGEBox (Britz and Van der Mensbrugghe, 2018). G-RDEM uses these projections as boundary conditions to develop long-term baselines with high sectoral and regional detail. In this assessment, we develop three baselines based on SSP1, SSP2, and SSP3 to analyse the achievement of the SDGs. In doing so, we draw on the extended indicator framework and, where possible, provide household details from a micro-simulation for selected low and low-middle income countries.

Methodology

Model configuration

The CGE model used in this study is realized in CGEBox[2] (Britz and Van der Mensbrugghe 2018), a flexible and modular platform for CGE modelling realized in GAMS (see Figure 1), complemented by a Graphical User Interface realized in GGIG (GAMS Graphical User Interface Generation, Britz 2014). The core of the model configuration used in this study draws on the GTAP Standard Model version 7

[1] http://www.iiasa.ac.at/web/home/research/researchPrograms/Energy/SSP_Scenario_Database.html

[2] A full documentation of CGEBox is available as Wolfgang Britz (2021), CGEBox – a flexible and modular toolkit for CGE modelling with a GUI, https://www.ilr.uni-bonn.de/em/rsrch/cgebox/CGEBox_GUI.pdf

(Corong et al. 2017) as realized in GAMS by van der Mensbrugghe (2018). It employs the usual assumption found in CGE models: competitive markets for products and factors, utility maximizing consumers, cost minimizing firms operating under constant-returns-to-scale and revenue maximizing factor supply. The GTAP standard model adds two distinct mechanisms. First, according to the so-called regional household approach, primary factor earnings plus indirect tax income minus depreciation define jointly regional income which is distributed based on a Cobb-Douglas utility function to regional savings, private and government demand. Second, a so-called global bank collects all regional savings and distributes them based on expected returns to capital to the regions. The difference between regional and total savings defines foreign savings as the sole element of the balance of payment (BOP). As the BOP is equal to the balance of trade, trade balances are endogenous under the global bank mechanism. Changes to the layout of the GTAP Standard Model used in this study are discussed next. The model is solved in bi-yearly steps from the 2014 benchmark year until 2050.

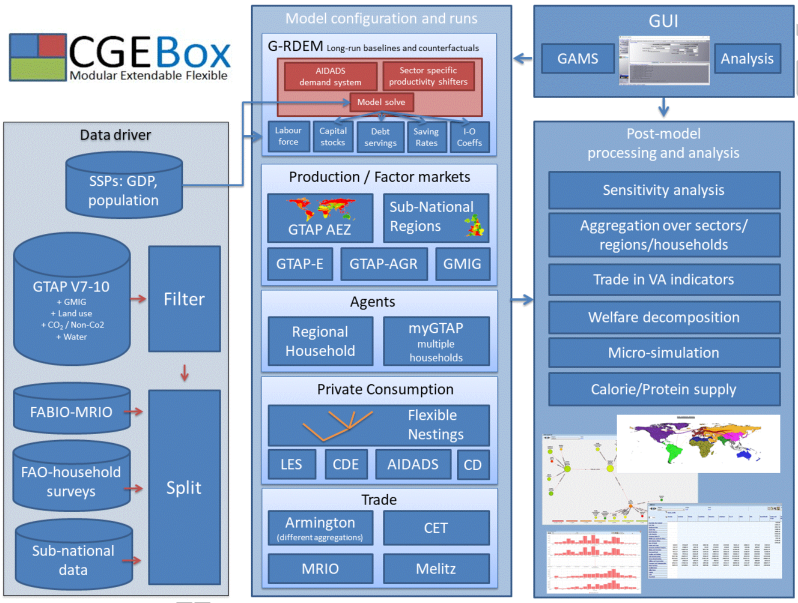

Figure 1: Overview on modular structure of CGEBox

The long-term perspective of the study requires a proper reflection of structural change and its consequences for the agricultural sector. Structural change reflects the interaction of multiple supply and demand side drivers, including changes in primary factor stocks, technology and final demand patterns. Changes in these drivers are captured by the G-RDEM module of CGEBox (Britz and Roson 2019, Roson and Britz 2021), a modular extension of CGEBox for long-run baseline construction and counterfactual analysis.

Changes in primary factor stocks reflect firstly capital accumulation which interacts with the endogenous updates of macro-saving rates in G-RDEM, depending on changes in income per capita and demography (Britz and Roson 2019, p. 64-69), and its debt accumulation mechanism from foreign investments (Britz and Roson 2019, p. 69-70). Secondly, the used stock of labor by skill force follows projections provided for each SSP taken from the IIASA SSP portal[3]. Thirdly, the stock of natural resources in use (oil wells, mines, fish stocks etc.) is depending on the development of rents for such resources with an elasticity for oil, gas and coal of 0.01 and 0.25 otherwise. The supply elasticity for irrigation water is chosen as 0.20. The elasticities are chosen to given plausible changes in prices for natural resources over time and changes in return to irrigation water similar to the development of land rents. In order to avoid infeasibilities, a quite small land supply elasticities of 0.05 is added on top of the projected crop land changes, from which changes in total land in economic use are used based on empirical estimated relation ex-post for individual countries from FAO land cover data. From some

[3] http://www.iiasa.ac.at/web/home/research/researchPrograms/Energy/SSP_Scenario_Database.html

regions, higher land supply elasticities are introduced to avoid infeasibilities when using the uncorrected FAO cropland projections. We add an estimate of how built-up land develops based on empirical work which links it to GDP growth, urbanization and population density (similar to Dong et al., 2018), and drive total land expansion by the given FAO crop land projections based on a factor from country specific regressions using past land use data developments.

Natural resources are considered as immobile, while capital and labor are considered as fully mobile. Irrigation water is assumed to be sluggish with a transformation elasticity of unity. Likewise, land allocation to different land uses is sluggish at the level of the AEZ sub-regions as discussed below. Considering labor and capital fully mobile reflects the quite limited changes simulated in between periods where only moderate changes in the distribution of primary factors occur combined with the long-run horizon of this study.

Detailed changes of technology in the decades ahead are hard to project. Instead of having uniform change in total factor productivity across sectors driven by the exogenous given income dynamics, G-RDEM employs empirical estimates to render productivity changes in three broad sectors group depending on the speed of economic growth (Britz and Roson 2019, p. 61-63). To this, specific productivity changes for crop and livestock products are added to recover crop yield and crop land forecasts by FAO (2018). Using projections from more detailed sector models is the current state-of-the art in linking them to CGE models (Delzeit et al. 2020). Additionally, input coefficients in G-RDEM are not static, but are updated instead depending on projected income growth (Britz and Roson 2019 p. 71-70).

These supply side drivers interact with changes in demand. Especially budget shares for food in total and individual food items are quite sensitive to income developments (Ho et al. 2020) which motivates the use of the rank 3-MAIDADs demand system estimated by Britz (2021b). Its exponential Engel curves capture for instance saturation effects with regard to the consumption of certain food categories. To improve here further, calorie intakes follow an empirically estimated relation to income changes (Britz 2020). Equally, expenditure shares for investment and government demand are rendered income dependent in G-RDEM.

The further configuration of CGEBox for this study reflects the high detail for agro-food (see next Section on Data Base) combined with the necessary coverage of SDG indicators. High detail for crop and livestock products implies that the assumption of additive utility underlying the MAIDADS demands system cannot be defended and care must be given to properly consider Hicksian cross-price effects. This is reflected in a demand nesting structure which bundles nests comprising more closely substitutable food products: cereals, oilseeds, vegetable oils, fruits and vegetables, livestock products (fish, meat, dairy) and introduces further sub-nests for meat and dairy, see Figure 2. For these product groups, also higher substitution possibilities in intermediate demand in the feed use and the food industry is assumed.

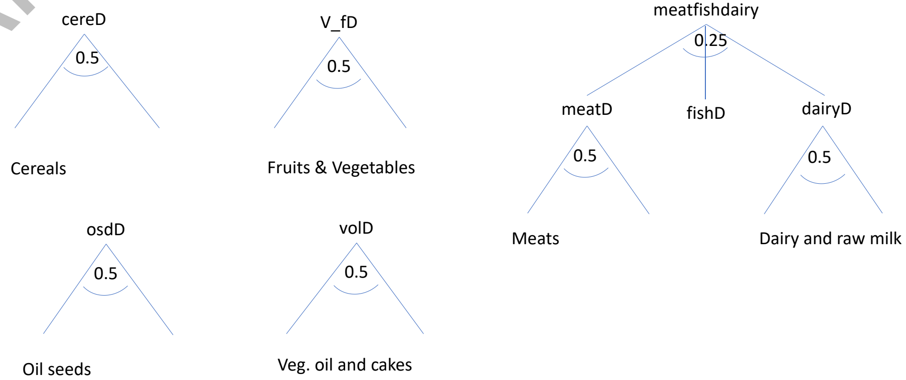

Figure 2: CES-sub nests relating to agri-food used for private, government and investment demand

Substitution possibilities between capital and energy and different energy carriers in intermediate and final demand follow Peters (2016) and are one key element to let the model react to carbon taxes:

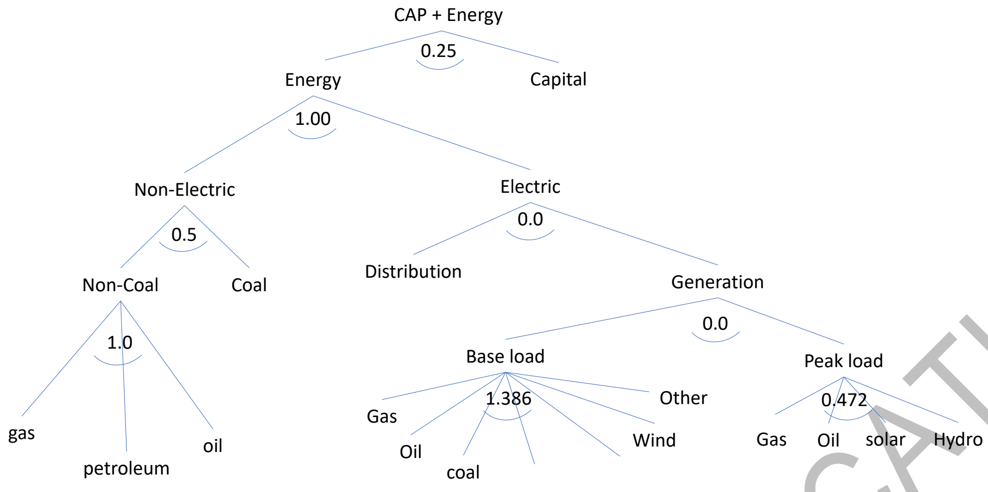

Figure 3: CES-Nesting for energy and capital and different energy carriers

The focus on the agricultural sector asks for detail in land-use, realized based on the GTAP-AEZ (Agri-Envionmental Zone) data (Baldos et al. 2020) and model (Lee 2005). The AEZ model dis-aggregates the land demand and supply at regional level to sub-regional units with more homogenous bio-physical properties. Land is immobile across these units. Inside each unit, competition between different land uses is depicted by a nested Constant-elasticity-of-transformation (CET) functions which employ the Additive CET functional form proposed by van der Mensbrugghe and Peters (2016), see Figure 4. This modification of the CET guarantees physical balancing. Moreover, the original nesting from Lee (2005) is extended by two further nests (Figure 5) which depict more flexible substitution between annual crops and less flexible one between permanent ones. CGEBox adds to this substitution between different types of natural land cover and land in economic use.

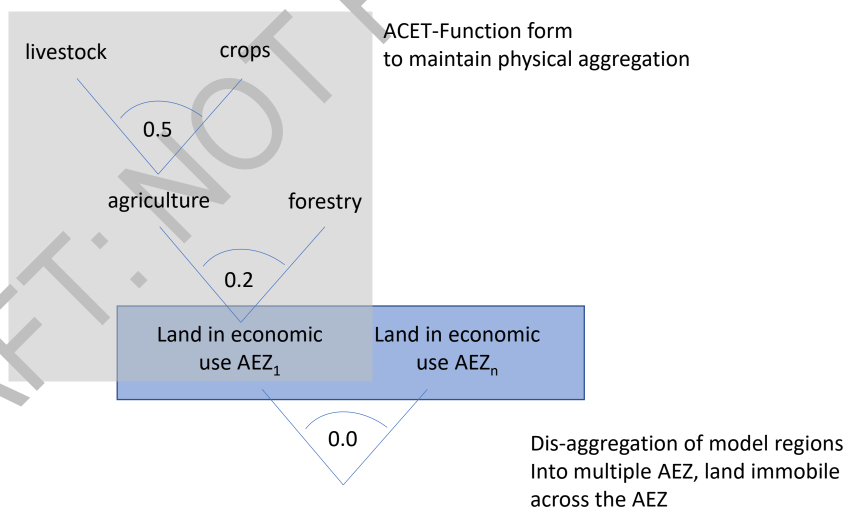

Figure 4: CET nesting in the GTAP-AEZ model from Lee 2005 and extension by ACET

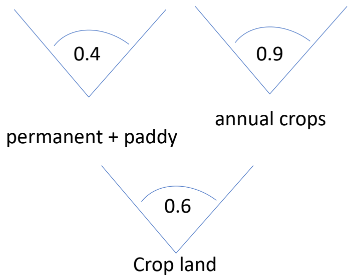

Figure 5: Additional CET nesting in the GTAP-AEZ model

Additional nestings in the production function provide a more realistic depiction of substitution possibilities in agricultural production, drawing on a similar layout in the ENVISAGE model (van der Mensbrughe, 2008).

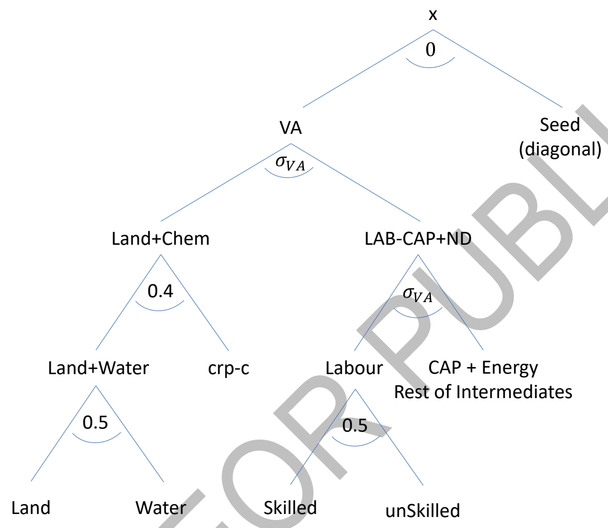

Figure 6: CES-Nesting for crop production activities

In case of livestock production activities, feed from pastureland and concentrates are treated as imperfect substitutes. Sub-nests describe substitution elasticities in the feed composition.

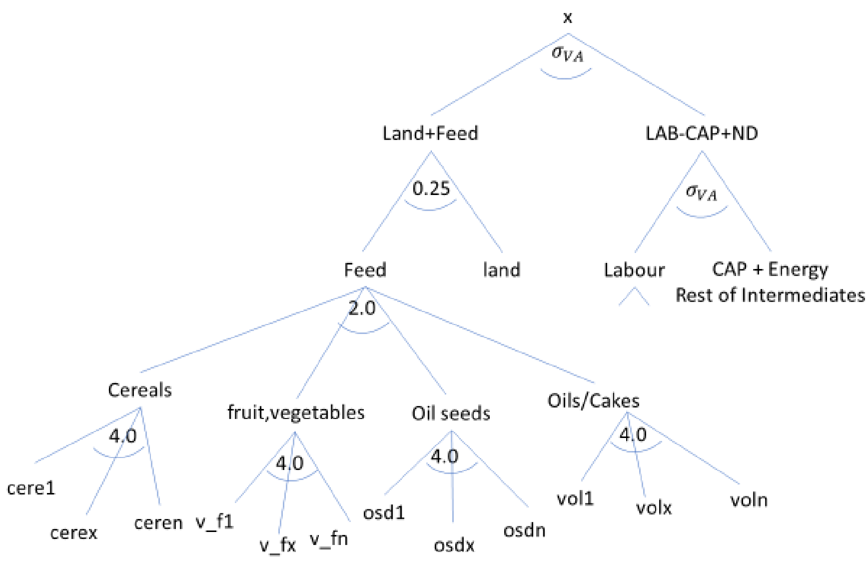

Figure 7: CES-Nesting for livestock production activities

Of the different possibilities to depict international trade, the simplest version available in CGEBox is used which employs a two-stage Armington presentation with identical domestic and import shares for all agents, differently from the GTAP Standard model where these shares are allowed to vary across demanders. This Armington representation is usual in single-country CGE models, but also found, for instance, in the multi-regional GLOBE CGE model (McDoland and Thierfelder, 2014).

The parameters for the substitution between importer regions are taken from Fontagne et al. (2019) which estimate elasticities at HS6 tariff line level. These estimates are aggregated based on trade weights to the product detail of the data base. Substitution elasticities between the imported and domestic origin use half of the ones between individual importers in the lower nest.

Post-Model Micro-simulation

Using multiple household types during baseline construction can already inform on important links between economic growth, structural change and the well-being by, for instance, considering income levels and the households' links to agricultural and non-agricultural sectors (Wilts et al. 2021). Micro-simulation allows for a far richer analysis of distributional issues, since, the it provides insights into a large number of different households of a population, revealing detail beyond country level or household aggregate average effects. Future developments as well as policies can affect households both on the income and consumption side. Thus, the post-model micro-simulation consists of household specific earnings and spending adjustment steps and a final results preparation step.

The income position of each household provided by the FAO (2017) household survey data is updated using changes of different factor prices and quantities as well as tax and regional income from the model simulation. The income sources provided by the data set, including wage categories, self-employment, crop and livestock production, and public and private transfers are updated using matching variables from the model simulation. The spending side is updated using the MAIDADS demand system that estimates the committed and non-committed income term and specific budget shares. Household specific saving rates are estimated based on the regression coefficient used in the G-RDEM for the saving rates. Saving rates above 50% and negative costs shares (credits) are excluded. Additionally, we assign to each household a share of total government consumption. From there we can calculate the money metric for each household. In a final step the results are summarized based on a regression of the money metric on income composition. 500 percentiles are calculated 50 of key results and household features, sorted by the money metric. For the SDG assessment the percentiles where sorted by income per capita, in order to calculate especially income (distribution) related indicators such as the GINI Index. For more detail on the micro-simulation it is referred to the model documentation (Britz, 2021d).

Data base

The recursive dynamic global CGE model implemented in the flexible and modular modeling framework CGEBox draws on the GTAP Data Base Version 10 (Aguiar et al., 2016). The quantification of SDG indicators requires partially product, sector and factor detail beyond what is offered in this Data Base. In order to better assess aspects related to food security, nutrition and land use, we provide further detail for agriculture and food processing. We, therefore, subsequently dis-aggregate the product and sector detail of this data base further in three steps. We depart from the GTAP-Power Data Base Version 10 (Chepeliev, 2020c) which extends the GTAP Data Base with detail on electricity generation and distribution based on eleven additional sectors and products[4]. In the first step, we introduce high detail for agro-food sectors based on the FABIO MRIO (Bruckner et al., 2019) and FAO data, drawing on Britz (2022). The second step splits the fisheries sector into open catch and aquaculture using FAOSTAT (FAO, 2021) data, followed by a third step, that introduces a differentiation between irrigated and non-irrigated crop variants drawing on FAO (2018). This step also dis-aggregates land rents into land and irrigation water. These dis-aggregation steps draw on the methodology by Britz (2021a). The resulting data base comprises 141 sector, 110 products and 6 primary factors (capital, skilled labor, unskilled

[4] base load: nuclear, coal, gas, oil, hydro, wind, other; peak load: gas, oil, hydro, solar; transmission and distribution

labor, natural resources, land and irrigation water). CO_2 and non-CO_2 emissions factors are derived from the GTAP emission Data Base (Chepeliev, 2020c). Additionally, air pollution data is derived from the GTAP air pollution Data Base (Chepeliev, 2020b).

We aggregate the 141 single countries and regions encompassed in the GTAP 10 Data Base to 31 model regions, of which fifteen are individual countries. For ten of those, representing low and low-middle income countries, household surveys by the FAO (2017) allow to use the micro-simulation extension of CGEBox (Britz, 2021, p. 109-116) to provide results which feed specific SDG indicators. Specifically, we assess Nigeria, Malawi, Ethiopia, Ghana, Kenya, Nicaragua, Bolivia, Vietnam, Indonesia, and Bangladesh as separate regions in our analysis.

SDG indicator framework

Multiple studies have developed SDG indicators for CGE analysis. For example, Philippidis et al. (2020) depict synergies and trade-offs between SDGs under different global development pathways using the MAGNET SDG Insights Module which captures about 71 indicators. They selected for their assessment 12 indicators linked to 7 SDGs. Liu et al. (2020) conducted an analysis on the achievement of SDGs using the SSP projections and additional climate policy assumptions. Their CGE analysis draws on indicators related to 5 SDGs. These references provided a first list of candidate indicators for which we checked compatibility to CGEBox (Britz and Van der Mensbrugghe, 2018). In order to quantify additional SDG indicators, we assessed the 169 targets and the related 231 indicators published by the UN (2021). First, qualitative targets and such addressing means of implementation (e.g. legal frameworks) were excluded. Second, we checked for data availability and compatibility to CGEBox. Many indicators in the official UN list had to be excluded as they require detail beyond what our model database offers. Finally, we discarded indicators which could not be calculated from endogenous variables in the model following Campagnolo et al. (2018). The remaining candidates were then implemented in the model.

In total, we implement 75 indicators into the post-model assessment of CGEBox. A key element for new indicators not found in existing CGE analysis of the SSPs is the use of micro-simulations using household surveys (FAO, 2017). Such indicators assessing distributional effects where implemented for 5 SDGs. For the representation of SDG1, we measured for example indicators that address household level income distribution. Here, we use the household income per capita and the share of population living below international poverty lines ($1.25, $3.20 and $1.90), proposed by the UN official indicator (1.1.1). Addressing SDG2, we assess the food consumption represented by the share of total expenditure spend on food per household per capita. Additionally, to measure malnutrition, we use the calories, proteins and fats consumed per capita per household as indicator. Here, we use the inherent calories, proteins and fat of the consumed commodities (Britz, 2020). The post-model module estimates protein, calories and fat per capita supply in-line with the FAO Food Balance Sheets based on a Leontief-Inverse. Another indicator we utilize to measure the food security is the dietary diversity, i.e. the share of different food groups on the total food consumption. We apply slightly adopted food groups from Kennedy et al. (2011)[5] and calculate the Shannon Index both for the money spent on these food groups and the calories derived from their consumption over one year. Further, we implemented for SDG 7 the budget share on energy and on electricity spend by households as indicators. As indicator for decent economic growth, referring to SDG8, we calculate the money metric per capita for the household. In order to address equality issues, we apply the SDG 10 indicator (10.1.1) “Growth rates of household expenditure or income per capita among the bottom 40 per cent of the population and the total population”. The Palma and Gini index are calculated from the model results for target 10.2 which addresses to empower and promote the social, economic and political inclusion of all. As well as the share of the population living below 50% of the national median income (listed as indicator 10.2.1).

[5] We differentiate 11 food groups adopted to our sector differentiation, namely cereals; roots and tubers; legumes, nuts and seeds; other vegetables; fruits; meat; raw milk and dairy; fish; Veg. oils and cakes; sugar and rest.

Results

Preliminary results of the scenarios show a mix picture with regard to reaching the SDG targets up to 2050 if not further targeted policy changes are considered. For example, in SSP2 we observe in all 10 countries in the focus, that real income per capita likely rises for all households until 2050, which is an improvement in SDG2 target 2.1. However, looking at the share of households living below the 1.25$, 1.9$ and 3.2$ per day thresholds, we observe for instance in Ethiopia a decrease by about 1-2 percent points, which is a marginal change considering the time frame of 36 years. Concerning SDG3, we observe that air pollution per capita at unchanged emission factors strongly increases in all countries, suggesting higher risk to human health and a potential increase in related mortality as quantified in indicator 3.9.1 "Mortality rate attributed to household and ambient air pollution". Water use for irrigation increases in all study countries, especially in Ethiopia, potentially jeopardizing sustainable irrigation water withdrawal (target 6.4).

The energy price index decreases in all study countries over time, indicating the target of achieving affordable energy (target 7.1) might be reached. Yet, the share of renewable energy remains in some of these countries close to the initial share in 2014, such that they will not make improvements under SSP2 assumptions toward target 7.2 of increasing the share of renewables. Likewise, GHG emissions per capita increase in all study countries strongly over time, which is in contrast with target 13.2, in most of them even beyond the growth in GDP. The opposite is found only in Nicaragua and Bolivia, however at modest rates, which is in line with target 8.4.

Summary and conclusion

We combine a highly detailed data base with a focus on agriculture and food with CGE analysis to quantify SDG indicators under three different SSPs. We add further mechanisms to the G-RDEM model relevant for SDG assessments, namely, controlling calorie intakes depending on income levels, and integrating crop yield and cropland forecasts from a FAO study. To improve projections of land use, we link cropland forecasts to total land expansions and project built-up areas. In order to reflect distributional effects of structural change, we employ micro-simulations for ten low and low-middle income countries. This allows to quantify based on model results indicators relating to 13 of the 17 SDGs.

Acknowledgement:
This research was supported by the *Förderschwerpunkt „Bioökonomie als gesellschaftlicher Wandel“* of the Federal Ministry of Education and Research under the project *BEST: Bioökonomie in Europa und SDGs: Entwicklung, Beitrag, Trade-offs*.

SPONSORED BY THE
Federal Ministry of Education and Research

References

Aguiar, A., Chepeliev, M., Corong, E., McDougall, R., & van der Mensbrugghe, D. (2019). The GTAP Data Base: Version 10. *Journal of Global Economic Analysis, 4(1)*, 1-27

Allen, C., Nejdawi, R., El-Baba, J., Hamati, K., Metternicht, G., & Wiedmann, T. (2017). Indicator-based assessments of progress towards the sustainable development goals (SDGs): a case study from the Arab region. *Sustainability Science*, *12*(6), 975-989.

Baldos, U. L., & Corong, E. (2020). Development of GTAP 10 Land Use and Land Cover Data Base for years 2004, 2007, 2011 and 2014, GTAP Research Memorandum No. 36, https://www.gtap.agecon.purdue.edu/resources/download/10283.pdf

Britz, W. (2014): A New Graphical User Interface Generator for Economic Models and its Comparison to Existing Approaches, German Journal of Agricultural Economics 63(4): 271-285

Britz, W. (2020): Maintaining plausible calorie intakes, crop yields and crop land expansion in long-run simulations with Computable General Equilibrium Models. Discussion Paper 2020:2

Britz, W. (2021a): Comparing Penalty Functions in Balancing and Dis-aggregating Social Accounting Matrices, Journal of Global Economic Analysis 6(1): 34-81

Britz, W. (2021b): Estimating a global MAIDADS demand system considering demography, climate and norms, Bio-based and Applied Economics, online available 19 July 2021

Britz, W. (2021c): Introducing about fifty additional agro-food sectors in the GTAP V10 database: the GTAP-AGROFOOD database, under review in Journal of Global Economic Analysis

Britz, W. (2021d): CGEbox – a flexible and modular toolkit for CGE modelling with a GUI, Institute for Food Resource Economics, University Bonn. Available at: http://www.ilr.uni-bonn.de/em/rsrch/cgebox/cgebox_GUI.pdf.

Britz, W., Roson, R. (2019): G-RDEM: A GTAP-Based Recursive Dynamic CGE Model for Long-Term Baseline Generation and Analysis, Journal of Global Economic Analysis 4(1): 50-96

Britz, W., van der Mensbrugghe, D. (2018): CGEBox: A Flexible, Modular and Extendable Framework for CGE Analysis in GAMS, Journal of Global Economic Analysis 3(2): 106-176

Bruckner, M., Wood, R., Moran, D., Kuschnig, N., Wieland, H., Maus, V., & Börner, J. (2019). FABIO—the construction of the food and agriculture biomass input–output model. *Environmental science & technology*, *53*(19), 11302-11312

Chepeliev, M. (2020a). Development of the Non-CO2 GHG Emissions Database for the GTAP Data Base Version 10A (No. 5993). Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University.

Chepeliev, M. (2020b): Development of the Air Pollution Database for the GTAP 10A Data Base, Research Memorandum No. 33, Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University

Chepeliev, M. (2020c): GTAP-Power Data Base: Version 10. Journal of Global Economic Analysis, 5(2), 110-137

Corong, E. L., Hertel, T. W., McDougall, R., Tsigas, M. E., & van der Mensbrugghe, D. (2017). The standard GTAP model, version 7. *Journal of Global Economic Analysis*, *2*(1), 1-11

Dellink, R., Chateau, J., Lanzi, E., & Magné, B. (2017): Long-term economic growth projections in the Shared Socioeconomic Pathways. *Global Environmental Change*, 42: 200-214

Delzeit, R., Beach, R., Britz, W., Chateau, J., Freund, F., Lefevre, J., Schuenemann, F., Sulser, T., van Ruijven, B., Weitzel, M., Willenbockel, D., Wojtowicz, K. (2020): Linking Global CGE Models with Sectoral Models to Generate Baseline Scenarios: Approaches, Challenges, and Opportunities, *Journal of Global Economic Analysis* 5(1): 162-195

Dong, N., You, L., Cai, W., Li, G., & Lin, H. (2018). Land use projections in China under global socioeconomic and emission scenarios: Utilizing a scenario-based land-use change assessment framework. *Global Environmental Change*, *50*, 164-177

FAO - Food and Agriculture Organization (2017): Small family farms data portrait. Basic information document. Methodology and data description. FAO, Rome

FAO - Food and Agriculture Organization (2018): The future of food and agriculture – Alternative pathways to 2050. Rome. 224 pp. Licence: CC BY-NC-SA 3.0 IGO.

FAO (2021). FAO Aquaculture, Capture and Global production databases – Online Query Panels. Available online: http://www.fao.org/fishery/topic/16140/en, last accessed 08.07.21

Fontagné, L., Guimbard, H., & Orefice, G. (2019). Product-level trade elasticities, CEPI working paper No. 2019-17, https://hal.archives-ouvertes.fr/hal-02444897/document

Guppy, L., Mehta, P., and Qadir, M. (2019). Sustainable development goal 6: Two gaps in the race for indicators. *Sustainability Science*, *14*(2), 501-513.

Hák, T., Janoušková, S., & Moldan, B. (2016). Sustainable Development Goals: A need for relevant indicators. *Ecological indicators*, *60*, 565-573.

Ho, M., Britz, W., Delzeit, R., Leblanc, F., Roson, R., Schuenemann, F., Weitzel, M. (2020): Modelling Consumption and Constructing Long-Term Baselines in Final Demand, *Journal of Global Economic Analysis* 5(1): 63-80

Lee, H. L. (2005). The GTAP Land Use Data Base and the GTAPE-AEZ Model: incorporating agro-ecologically zoned land use data and land-based greenhouse gases emissions into the GTAP Framework, http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.452.8725&rep=rep1&type=pdf

Liu, J. Y., Fujimori, S., Takahashi, K., Hasegawa, T., Wu, W., Geng, Y., Takakura, J. & Masui, T. (2020). The importance of socioeconomic conditions in mitigating climate change impacts and achieving Sustainable Development Goals. Environmental Research Letters, 16(1), 014010.

Kennedy, G., Ballard, T. & Dop, M. C. 2011. Guidelines for Measuring Household and Individual Dietary Diversity. Rome: Nutrition and Consumer Protection Division, FAO.

McDonald, S. and Thierfelder, K. 2014. Globe v2: A SAM Based Global CGE Model using GTAP Data

Moyer, J. D., and Hedden, S. (2020). Are we on the right path to achieve the sustainable development goals?. *World Development*, 127, 104749.

Peters, J. C. (2016). GTAP-E-Power: an electricity-detailed economy-wide model. *Journal of Global Economic Analysis*, *1*(2), 156-187

Philippidis, G., Shutes, L., M'Barek, R., Ronzon, T., Tabeau, A., & Van Meijl, H. (2020): Snakes and ladders: World development pathways' synergies and trade-offs through the lens of the Sustainable Development Goals. Journal of cleaner production, 267, 122147.

Riahi, K., Van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K.V., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L. A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D.E.H.J., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A. and Tavoni, M. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Global Environ. Change*, 42: 153-168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Roson, R., Britz, W. (2021): Simulating long run structural change with a dynamic general equilibrium model, *Int. J. Computational Economics and Econometrics* 11(4): 368-404

Scherer, L., Behrens, P., de Koning, A., Heijungs, R., Sprecher, B., and Tukker, A. (2018). Trade-offs between social and environmental Sustainable Development Goals. *Environmental science & policy*, *90*, 65-72.

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C. J., Simas, M., Schmidt, S., ... & Tukker, A. (2018). EXIOBASE 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. *Journal of Industrial Ecology*, *22*(3), 502-515.

UN – United Nations (2021): Global indicator framework for the Sustainable Development Goals and targets of the 2030 Agenda for Sustainable Development, E/CN.3/2021/2. https://unstats.un.org/sdgs/indicators/indicators-list/

Van Der Mensbrugghe, D. (2008). The environmental impact and sustainability applied general equilibrium (ENVISAGE) model. *The World Bank, January*, 334934-1193838209522

Van der Mensbrugghe, D. (2018). The Standard GTAP Model in GAMS, Version 7. *Journal of Global Economic Analysis* 3(1), 1-83

Van der Mensbrugghe, D., & Peters, J. C. (2016). Volume preserving CES and CET formulations, https://www.gtap.agecon.purdue.edu/resources/download/8380.pdf

Wilts, R., Latka, C., Britz, W. (2021): Who is Most Vulnerable to Climate Change Induced Yield Changes? A Dynamic Long Run Household Analysis in Lower Income Countries, Climate Risk Management 33(100330)