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Computable General Equilibrium assessment of Sustainable Development Goals in low-income countries with household detail

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Rienne Wilts

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Referent:	PD Dr. Wolfgang Britz
Korreferent:	Prof. Dr. Jan Börner

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Kurzfassung

Aktuelle Krisen, wie Klimawandel, Hunger, politische Spannungen und Armut, sind über verschiedene Kanäle wie Krankheiten, Märkte und Emissionen verbunden. Dadurch haben sie Ursachen und Auswirkungen sowohl auf lokaler als auch auf globaler Ebene. Die Ziele für nachhaltige Entwicklung (SDGs), die unter anderem dieser Herausforderungen adressieren, sind eine beispiellose Vereinbarung, für eine nachhaltigere und gerechtere Zukunft bis 2030. Mit 17 Zielen und 169 Vorgaben sind die SDGs durch Synergien und Konflikte eng verknüpft. Daher ist es eine gewaltige, aber entscheidende Aufgabe bei künftigen Maßnahmen, ihrer Multidimensionalität und ihr zentrales Versprechen, niemanden zurückzulassen, Rechnung zu tragen.

Länder stehen bei den Krisen und der Erreichung der SDGs vor unterschiedlichen Hürden, wobei Länder mit niedrigem Einkommen am vulnerabelsten sind. Auch nationale Ungleichheit führt zu diversen Reaktionen der Bevölkerung auf exogene Schocks. Daher wird in dieser Dissertation das allgemeine Gleichgewichtsmodell CGEBox in drei dynamischen Analysen erweitert und angewendet, um sowohl die Auswirkungen auf Länder- als auch auf Haushaltsebene zu beleuchten.

Da Menschen unterschiedlich stark vom Klimawandel betroffen sind, werden in Kapitel 2 neun Haushaltstypen in Vietnam, Äthiopien und Bolivien untersucht, um festzustellen, wie anfällig sie für Ertragsänderungen im Jahr 2050 sind. Die Ergebnisse zeigen, dass Haushalte mit einem geringeren Einkommen und geringerem Einkommensanteil aus landwirtschaftlichen Tätigkeiten am stärksten betroffen sind, was die Bedeutung von Landbeßitz verdeutlicht. Ein weiterer wichtiger Faktor für den Effekt, sind Klimawandel induzierte Ertragsänderungen bei Getreide, die durch den Vergleich von drei verschiedenen Ertragsschocks ermittelt wurden, um Unsicherheiten hinsichtlich der Auswirkungen des Klimawandels zu berücksichtigen. Dies unterstreicht die Bedeutung einer diversifizierten Ernährung.

Um die Abbildung der SDGs in dynamischen Analysen zu verbessern, wird in Kapitel 3 ein Indikatorrahmen entwickelt, der 15 der 17 SDGs durch 68 Indikatoren abdeckt. Der Rahmen legt einen Schwerpunkt auf Agraraspekte und erfasst Verteilungseffekte auf Haushaltsebene durch eine dem Model angeknüpfte Mikrosimulation. Die Berechnung der Indikatoren in drei Zukunftspfaden bis 2050 für zehn Länder mit niedrigem Einkommen zeigt, dass nicht alle Ziele erreicht werden und dass keines der Szenarien nachhaltiger ist als die anderen. Zwischen Haushalten nimmt die Ungleichheit teilweise auf der Einkommens- und Konsumseite zu. Weitere Schritte werde benötigt um Zielkonflikte zwischen und innerhalb der SDGs, sowie auf Haushaltsebene zu vermeiden.

Maßnahmen wie die EU-Bioökonomie-Strategie haben globale Auswirkungen. In Kapitel 4 werden daher die Effekte von drei EU-Bioökonomiepolitiken auf EU eigene SDGs und die von zehn Ländern mit niedrigem Einkommen analysiert. Technologischer Fortschritt bei Biomasse-Inputs führt zu mehr Zielkonflikten in der EU als eine Steuersenkung, während die Förderung vegetarischer Ernährung teilweise gegensätzliche Auswirkungen hat, was mögliche Vorteile einer kombinierten Umsetzung verdeutlicht. Keine Politik hat ausschließlich positive Effekte für die zehn Länder, was auf Konflikte mit deren Entwicklung hinweist. Die Ausweitung der Politik auf alle OCED-Länder unterstreicht die Relevanz der EU für die Nebeneffekte.

Insgesamt leistet die Dissertation einen Beitrag zur Literatur, indem sie das Wissen über Unterschiede in der Reaktion auf Schocks erweitert und die politische Notwendigkeit unterstreicht, (Neben-)Effekte politischer Interventionen sowie Entwicklungsprozesse auf verschiedenen Ebenen zu berücksichtigen.

Abstract

The major crises of our time, such as climate change, hunger, political tensions, and poverty, are linked by various channels, such as diseases, markets, and emissions. Through these connections, they have causes and implications both at the local and the global level. Targeting among others these challenges, the Sustainable Development Goals (SDGs) are an unprecedented common agreement to reach a more sustainable and equal future by 2030. With 17 single goals and 169 specifying targets, the SDGs are closely connected through synergies and trade-offs. Therefore, accounting for their multi-dimensionality and complying with their central pledge to leave no one behind in future actions is a daunting yet crucial task.

Countries face different hurdles in tackling the crises and reaching the SDGs, with low- and lower-middle income countries being among the most vulnerable. However, also within-country inequality leads to varying responses to exogenous shocks of their population. Thus, this dissertation applies and extends the Computable General Equilibrium model CGEBox in three dynamic assessments to shed light on both country- and household-level effects.

As people experience diverse impacts from climate change, Chapter 2 assesses nine different household types in Vietnam, Ethiopia, and Bolivia to determine the channels of vulnerability to crop yield changes in 2050. The results demonstrate that households with lower absolute income and income sourcing from agricultural activities are most affected and, thus, underline the im-portance of land ownership. Another driver of the effect on households is changes in cereal yields, revealed by a comparison of three different yield shocks to account for uncertainties about climate change effects, stressing the importance of diversified food consumption.

To improve the quantification of SDGs in dynamic analysis, in Chapter 3, an indicator framework is developed that captures 15 of the 17 SDGs. The total of 68 indicators put a special focus on agricultural aspects and incorporate distribution at the household level through a post-model micro-simulation. Employing the indicators in three development pathways until 2050 for ten low- and lower-middle income countries reveals that the indicators are not reached in unison and that none of the scenarios outperforms the others with regard to its sustainability. Also, at the household level, inequality partly increases both on the income and consumption side, indicating the need to implement measures to overcome central trade-offs among and within SDGs, but also across households.

Mitigation policies, such as the EU Bioeconomy Strategy, have global spillovers. Therefore, Chapter 4 focuses on the effects of three EU bioeconomy policies on their SDGs and those of ten low- and lower-middle income countries. Fostering a technological shift in biomass inputs in three sectors triggers more trade-offs between selected indicators and the Strategy's objectives in the EU than a tax reduction. Promoting vegetarian diets causes partly opposing effects, highlighting potential benefits from combined implementation. None of the policies induce purely positive spillovers for the ten countries in focus, highlighting conflicts with their development. Ex-tending the assessment to all OCED countries underlines the relevance of the EU for global spillovers.

Overall, the dissertation contributes knowledge about differences in the response of countries and households to shocks and highlights the political need to take (side-)effects of political interventions and development processes at different levels into account.

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Abbreviations

ACRONYM	Definition
aCET	additive Constant Elasticity of Transformation
AEZ	Agro-Ecological Zones
AIDADS	An Implicitly Additive Demand System
BAU	business as usual
BOL	Bolivia
BOP	Balance of Payments
BOT	Balance of Trade
CET	Constant Elasticity of Transformation
CGE	Computable General Equilibrium
CO_2	Carbon dioxide
COVID-19	Coronavirus disease 2019
CSA	Central Statistical Agency of Ethiopia
EC	European Commission
ETH	Ethiopia
EU	European Union
EV	Equivalent variation
FAO	Food and Agricultural Organization
GAMS	General Algebraic Modeling System
GHG	Greenhouse gas emissions
GDP	Gross Domestic Product
GTAP	Global Trade Analysis Project
IAM	Integrated Assessment Model
ICSU	International Council for Science
IIASA	International Institute for Applied Systems Analysis
iLUC	indirect Land Use Change
INE	Instituto Nacional de Estadística
IPCC	International Panel of Climate Change
ISSC	International Social Science Council
LDC	Least developed countries
LES	Linear Demand System
LLMICs	Low- and Lower-middle income countries
LICs	Low-income countries
LMICs	Lower-middle-income countries
LUC	Land Use Change
MAIDADS	Modified An Implicitly Additive Demand System
ND	no date
NH_3	Ammonia
NOx	Nitrogen oxides

NUTS2	Nomenclature des unités territoriales statistiques 2
OECD	Organisation for Economic Co-operation and Development
RCP	Representative Concentration Pathway
Ref	Reference
ROW	Rest of the world
SDG	Sustainable Development Goal
SO_2	Sulfur dioxide
SSS	Stratified society scenario
SSP	Shared Socio-Economic Pathway
TSS	Towards sustainability scenario
UN	United Nations
USA	United States of America
USD	United States Dollar
VNM	Vietnam

Chapter 1
Introduction

Humanity faces major parallel challenges and crises to be solved in the upcoming years. Among the most pressing issues are anthropogenic climate change, poverty, hunger, and environmental damage through increasing pollution, over-exploitation of natural resources, and intensive agricultural production (Godfray et al., 2010; Springmann et al., 2018; Lenton et al., 2023; Vousdoukas et al., 2023). At the same time, inequality and tensions between countries have been rising in recent years (Miranda et al., 2023; Davies et al., 2023). The described crises entail not only local but also global causes and implications, transmitted by markets and emissions (Raleigh et al., 2015; Laber et al., 2023; Lapola et al., 2023). Through these and other linkages such as diseases, agricultural production shocks, and threats to peoples' livelihoods, the challenges are intertwined and have strong potential to aggravate each other if untargeted (Siddiqui et al., 2020; Hallegatte et al., 2020; Nguyen et al., 2023). The lack of a legally binding global institution makes enforcement of agreed commitment on changes and political interventions difficult. Given the global dimensions and linkages of the crises, however, strong cooperation and efforts are needed to address this institutional gap for a more sustainable and resilient future.

Recognizing this need, the United Nations' (UN) Member States have agreed in 2015 on the Agenda 2030 which includes common goals for the next 15 years to tackle the major challenges of humanity. These so-called Sustainable Development Goals (SDGs) with their cornerstone *'leave no one behind'* apply since 2016 and set the stage for sustainable actions (UN, 2015). Addressing the multi-dimensionality of sustainability, they consist of 17 goals specified by 169 targets to be reached until 2030. Among these 17 SDGs, a wide range of environmental and economic problems are addressed, as well as manifold social issues such as lack of access to basic services, impoverished living conditions, (gender) inequality and discrimination. Through these comprehensive goals an unprecedented internationally agreed commitment for future decision taking is achieved, standing out compared to preceding efforts (Biermann et al., 2022a) such as the Millennium Development Goals.

The goals and targets are inseparable and have no hierarchical order, rather they are indivisible and integral (UN, 2015). Nevertheless, agricultural- and environmental-related SDGs (SDG6 'Clean Water and Sanitation', SDG13 'Climate Action', SDG14 'Life below Water', SDG15 'Life on Land') are seen as their foundation (Griggs et al., 2013; Folke et al., 2016) underlining the central role agri-food sectors play in sustainable development (Crippa et al., 2021; Viana et al., 2022; Ivanovich et al., 2023). The breadth of the SDGs, with a strong nexus between the single goals and their targets (ICSU and ISSC, 2015; Nilsson et al. 2016; McCollum et al., 2018; Scherer et al., 2018; Warchold et al., 2021), entails the challenge to reach all targets in unison. Achieving such an extensive set of goals and targets encompasses a large degree of complexity and interactions. These linkages can result in synergistic effects, such as reduced poverty and increasing health, but also in trade-offs, like higher food security and rising pressure on land. While synergies are found to predominate, many critical trade-offs arise partly due to historical lock-in relationships which may seem inevitable (Pradhan et al., 2017); however, in general, interactions are non-static. That is, they can evolve over time even at unchanged circumstances (Nilsson et al., 2018) and can be actively transformed through new technologies and policies (Kroll et al., 2019; Zimm et al., 2018).

To quantify these interactions and the status quo of SDG performance, data and commonly used indicators are required. For this purpose, the official SDG indicator framework was published in 2017 by the General Assembly (UN, 2017) and subsequently updated, encompassing a catalogue of 231 unique indicators to quantify every target by at least one indicator. Applying these and further suitable indicators, several reports on the performance of single countries have been published, including the Sustainable Development Report 2022 by Sachs et al. (2022) and The Sustainable Development Goals Report 2024 by the UN (2024). In these reports and other literature (Zimm et al., 2018; Soergel et al., 2021a), major sustainability gaps between the achieved indicator values and their targets have been identified, with their magnitude differing by country. To narrow these gaps, massive annual investments are required (Schmidt-Traub, 2015; Kulkarni et al., 2022) but thus far often lacking (Leal Filho et al., 2022). Likewise, the impact of SDGs on political and societal transformation has been limited until now (Biermann et al., 2022b) even if some policies and strategies have been designed to contribute to the SDGs, such as, for example, in Europe the European Union (EU) Bioeconomy Strategy (EC, 2018) and the European Green Deal (EC, 2019).

Recent global shocks, such as COVID-19, have widened these sustainability gaps, pushing back efforts on SDG achievements by several years or even decades (Laborde et al., 2021; Osandarp et al., 2021; UN, 2022). This step backwards, however, is unevenly distributed across the world (Yuan et al., 2023), reflecting the fact that countries react differently to the same shock due to their respective circumstances. For one, countries differ in terms of their vulnerability to climate change owing to their geographical location and socioeconomic parameters (IPCC, 2022). Addressing these country-specific challenges and tackling remaining sustainability gaps through policies can have adverse effects on other countries and regions due to complex integrations in global networks (Soergel et al., 2021b). As policies are often defined for a specific context (Nilsson et al., 2016), interactions at sectoral and country level can be overlooked. However, not only at country level, responses to shocks and policies can be diverse. The occurrence of unequal effects is also determined for single households (Ahmed et al., 2009; Winsemius et al., 2018; Guan et al., 2023). Such distributional effects are specifically addressed in several targets of the SDGs, as reflected in the pledge to '*leave no one behind*'.

1.1 **Motivation**

Being more than halfway to 2030 together with the lagging action and thus deficient status of the SDGs globally, underlines the immense effort required for the remaining time frame. Given the trade-offs and challenges to be addressed in the upcoming six years and beyond, it is decisive to find solutions and sustainable future pathways. The identification of synergies and trade-offs can help to reduce investment burdens when negative impacts are prevented and co-benefits are fostered (McCollum et al., 2011). Knowing, however, which pathway to follow and how sustainability dimensions (i.e., SDGs and targets) interact as a result of a policy or socioeconomic change is a daunting task.

The effects of anthropogenic climate change, caused by the combustion of fossil fuels, for example, strongly interlink with the SDGs (Laumann et al., 2022) as it can increase hunger, poverty and health risks while jeopardizing biodiversity. Currently, often discussed climate mitigation strategies such as a bioeconomic transition can also have (unforeseen) trade-offs at several dimensions. With the aim to substitute non-renewable resources by renewable ones, bioeconomic sectors are new competitors for local biomass but can also affect foreign markets through rising imports. An expansion of the bioeconomy, thus, has the potential to increase land, water, carbon (Bringezu et al., 2021) and timber (Egenolf et al., 2022) footprints of production. Therefore, the Global Sustainable Development Report 2023 (Miranda et al., 2023) strongly emphases the importance of SDG-related science to provide evidence and help understand crucial channels of change.

To advance here, it is important to identify the countries or households most vulnerable to different shocks, to understand how SDGs develop over time and how potential mitigation technologies or policies affect different actors. In the context of evidence-based policy-making, quantitative ex-ante assessments are valuable as they provide information on (undesired) effects of policies and other changes prior to their occurrence. Especially, tools such as Computable General Equilibrium (CGE) models have useful advantages because they allow for global coverage. With the endogenous links between economic sectors, regions and actors, they contribute a sound methodological framework and a holistic perspective for these assessments. CGE models are typically comparative static, i.e., they perform policy analysis without modeling the dynamic path that led to the change or without incorporating changes in other (demographic) variables. The transformative process of relationships between SDGs and their time frame until 2030, however, demand for a long-term perspective that captures related adjustment processes and thus for a dynamic CGE framework. For this purpose, a common methodology is to use projections from five Shared Socioeconomic Pathways (SSPs) in dynamic CGE models to solve long-term simulations and construct baselines. The different SSPs describe consistent qualitative narratives about the global socioeconomic developments (Riahi et al., 2017) that are translated into quantitative macro-economic projections (such as Gross Domestic Product (GDP), demographics and education levels (Dellink et al., 2017; KC and Lutz, 2017)) up to 2100 and vary regarding their challenges for mitigation and adaptation of climate change.

A detailed differentiation of inequality at various levels is critical to quantify just and sustainable pathways that '*leave no one behind*'. Such a distinction can determine the most affected countries and households to target policies towards their well-being. As CGEs can provide a global coverage and allow for country-specific assessments they are well suited for this task at country level. In general, the Agenda 2030 addresses all countries alike, but a strong emphasis is made on the support of developing countries including particularly least developed and landlocked developing countries (UN, 2015). These low-income countries are also especially vulnerable in terms of certain crises such as climate change (Méjean et al., 2024) and face major challenges to close their sustainability gap. This motivates a regional focus on low- and lower-middle income countries.

At household level, however, standard CGE models lack the ability to depict distributional effects such as poverty due to their aggregated nature at country level with one representative consumer. Advancing here poses several challenges as it requires to capture effects at very disaggregated levels which is data intensive and can incorporate numerical challenges, especially in dynamic long-run settings (van Ruijven et al., 2015). Various options are discussed to capture this differentiation in dynamic models, including to split the representative consumer to several (thousands of) households or to link different types of microsimulations to the model (van Ruijven et al., 2015). Thus far, the interactions and consequences of policies and development pathways at household level, however, remain a research gap (Philippidis et al., 2020; Verkerk et al., 2021).

Further, to study and compare SDG outcomes of different (long-term) scenarios, quantifiable indicators are required. The official indicator list published by the UN is, however, not directly transferable to CGE models due to their partly qualitative nature and additional data requirements, as indicators need to be linked to endogenous variables in the model (Campagnolo et al., 2018), to determine changes over time or as a consequence of a shock. A comprehensive framework for the SDGs that incorporates the relevant sector- and household-differentiation for indicators is, however, lacking for CGE models.

1.2 Research objectives and structure of thesis

The dissertation at hand pursues the overall research objective to better understand differences in terms of the vulnerability to shocks and policy interventions with a long-term perspective. Further, it focuses on the development of SDGs and their representation in ex-ante assessments. By analyzing impacts at different levels of aggregation, including single countries and various households, it aims to assess the pledge of the SDGs to '*leave no one behind*'.

To this end, the CGE model CGEBox (Britz and van der Mensbrugghe, 2018) is applied and extended taking both among and within country inequalities into account. CGEBox is an open-source and open-access model that enables to incorporate use-case-specific components due to its modular structure. With its long-run recursive dynamic extension G-RDEM (Britz and Roson, 2019), it includes methodological features to simulate future developments, with crucial economic adjustment processes and demographic changes that permit baseline constructions for example up to 2030 or 2050. In terms of household differentiation, CGEBox allows for two ways: (1) to differentiate household groups based on a combination of their characteristics, such as income per capita, source of income or gender; or (2) to represent the population with a post-model microsimulation. The underlying database of the model (Global Trade Analysis Project (GTAP) Database) depicts a snapshot of the global economy in the respective base year and has a global coverage that enables to analyze global impacts, while focusing on specific single countries and their specific circumstances.

To fulfill the overall research objective, the first publication presented in Chapter 2 of this thesis applies CGEBox to analyze determinants of vulnerability to crop yield changes induced by climate change at household type level. To this end, the representative consumer in the countries at focus is differentiated to capture nine household types distinguished by a combination of income per capita and share of agriculturally-sourced income. Specifically, Vietnam, Ethiopia, and Bolivia are chosen, due to data availability of household surveys and to represent examples from different continents. Considering the uncertainties about climate change effects, three different yield shocks (FAO, 2018) are applied to the same baseline in a sensitivity analysis. These baselines follow the SSP2 projections, which represent a 'Middle of the road' development, in line with historical trends. To determine the added value of incorporating a long-term set up until 2050, a comparative static analysis in the base year 2011 of the GTAP database Version 9 (Aguiar et al., 2016) is conducted for comparison. Therefore, the aim of this study can be defined as:

Assessing differences in household level vulnerability to climate change induced yield changes in low-income countries in a long-term and comparative static model set up.

Given the integrated nature of the SDGs, a framework that quantifies a large number of targets and indicators is critical to perform relevant ex-ante CGE sustainability assessments, motivating the development of an extensive indicator framework in Chapter 3. As household level data and distributional aspects are largely incorporated in the SDGs, information from a post-model microsimulation is extracted in the framework. This methodology allows to better capture distribution and household heterogeneity by increasing the number of households per country, which are represented in 500 percentiles (FAO, 2017). In addition to households, also larger detail in production is required than provided by the standard GTAP Version 10 database (Aguiar et al., 2019) with 65 different sectors. Especially, food is of central importance to the SDGs rendering a split of the related sectors to higher level of detail useful. This database with extensive agri-food detail (Britz, 2022) is further extended in this study by adding irrigation water and aquacultural production. To quantify developments of the SDGs for ten low- and lower-middle income countries[1] under different socioeconomic conditions, three baselines are simulated with the indicator framework until 2050 following SSP1, SSP2 and SSP3 assumptions. These projections span a broad range of population and GDP growth outcomes and provide the base for the research aim of the analysis presented in Chapter 3:

Development of an extensive SDG indicator framework for CGE models to assess long-run baselines with a special focus on household-level inequality.

The EU Bioeconomy Strategy 2018 has the dedicated aim to address some of the aforementioned challenges, including climate change, food security and sustainable

[1] The ten countries encompass: Bangladesh, Bolivia, Ethiopia, Ghana, Indonesia, Kenya, Malawi, Nicaragua, Nigeria, and Vietnam.

production, and are linked to the SDGs. Therefore, Chapter 4 assesses the effects of bioeconomic developments as a transition strategy on the SDG performance of different countries. For this purpose, different EU bioeconomy policy scenarios are developed and projected up to 2050. To quantify the effects of bioeconomy policies on both national and foreign SDG performances, the indicator framework developed in the Chapter 3 is applied to CGEBox. The assessment focuses on the EU and the same ten low- and lower-middle income countries as in Chapter 3 with different levels of EU-trade integration to capture potential spillovers of the EU bioeconomy policies. For comparison, the same policies are also applied to other OECD countries, to show how effects change if more countries follow a similar path and to determine EU's importance in this context. The aim of this study can therefore be summarized as:

Quantification of effects of EU bioeconomy policies on their Member States and on low- and lower-middle income countries in terms of their SDG performance.

Chapter 5 summarizes the contributions of this thesis and discusses the methodology also in terms of limitations while presenting a research outlook. Eventually, the policy implications of the thesis are derived.

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Chapter 2
Who is most vulnerable to climate change induced yield changes? A dynamic long run household analysis in lower income countries[1]

Abstract

Climate change impacts on agricultural production will shape the challenges of reaching food security and reducing poverty across households in the future. Existing literature lacks analysis of these impacts on different household groups under consideration of changing socio-economic developments. Here, we analyze how crop yield shifts induced by climate change will affect different household types in three low- and lower-middle-income countries, namely Vietnam, Ethiopia and Bolivia. The long-run analysis is based on a recursive-dynamic Computable General Equilibrium model. We first construct a baseline scenario projecting global socio-economic developments up to 2050. From there, we implement business-as-

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usual climate change shocks on crop yields. In the baseline, all households benefit from welfare increases over time. Adding climate change induced yield changes reveals impacts different in size and direction depending on the level of the households' income and on the share of income generated in agriculture. We find that the composition of the factor income and the land ownership are of large importance for the vulnerability of households to climate change, since the loss for non-agricultural households is highest in absolute terms. The complementary comparative static analysis shows smaller absolute and relative effects for most households as the differentiated factor income growth over time is not considered, which makes household types more or less vulnerable. A sensitivity analysis varying the severity of climate change impacts on yields confirms that more negative yield shifts exacerbate the situation (especially) of the most vulnerable households. Furthermore, it underlines that yield shocks on staple crops are of major importance for the welfare effect. Our findings reveal the need for differentiated interventions to mitigate consequences especially for the most vulnerable households.

Keywords: Climate Change, Long run analysis, Low Income Country, Household effect, Computable General Equilibrium Model

2.1 Introduction

Vulnerability to climate change is one of the main challenges faced by humankind in the 21st century (Godfray et al., 2010). Many low-income countries (LIC) are expected to face high vulnerability due to large population shares in high risk areas, poorly developed health infrastructure and weak adaptation capacities (Haines et al., 2006). Within countries, climate change vulnerability differs across population strata, for instance, depending on income sources and levels (e.g. Winsemius et al., 2015), and between rural and urban regions (e.g. Pandey et al., 2015; Ahmed et al., 2009). Farmers are often identified as especially vulnerable to direct impacts (Deressa et al., 2008) due to reduced average crop yields or more frequent crop failures. Market feedbacks from reduced production can, however, increase prices and thus (partially) offset income effects of yield losses, as seen during the food price crises around 2007 (Cohen and Garrett, 2010). Higher crop prices harm households that are poor net buyers of food, which are rural non-agricultural households (Aksoy and Isik-Dikmelik, 2008) and also urban residents (Cohen and Garrett, 2010). As net sellers and net buyers of food face different repercussions, distributional effects of agricultural climate change impacts need to be considered.

Some studies have addressed this by introducing household types in climate change assessments. Hertel et al. (2010) studied effects of climate change driven productivity shifts of six crops on seven household groups in fifteen developing countries. A similar study by Skjeflo (2013) for Malawi, with a focus on maize, differentiated eight household types. Both papers assess impacts of likely future crop yield changes in consequence of decades of climate change in the economic setting of today. This disregards that macro-economic and population dynamics happen in parallel to climate change and affect income levels, earning and consumption patterns, which determine vulnerability to changes in crop productivity.

Thus, a holistic forward-looking perspective in climate change assessments is needed as provided by the five Shared Socio-Economic Pathways (SSPs), developed for integrated long-term analyses of climate change mitigation and adaptation (Riahi et al., 2017). Each SSP describes a different qualitative narrative about the global socioeconomic developments with SSP2 depicting a “Middle of the Road” development. The narratives were the basis to develop long-term macro-economic projections of population dynamics and income growth (Dellink et al., 2017; KC and Lutz, 2017). These projections in combination with the narratives have been used for assessments in terms of e.g. climate change (Leimbach and Giannousakis, 2019) or land use change (Popp et al., 2017), or have been refined with sub-national detail (Dong et al., 2018; Britz et al., 2019). Studies based on the SSPs draw on various model types including dynamic computable general equilibrium (CGE) models as an established method for long-run economic analysis with sectoral detail (Fujimori et al., 2017; Doelman et al., 2018; Britz et al., 2019).

Direct impacts of climate change differ across crops, and their consequences for food availability depend on factors such as global market integration and regional diets. Existing work based on the SSPs does not combine macro-economic mechanisms including agri-food detail with household differentiation. A study from Hallegatte and Rozenberg (2017) assesses household level effects of climate change using a microsimulation approach under SSP4 and SSP5. However, in this study neither trade, nor investment changes over time are considered. We address these gaps by carrying out an ex ante assessment of climate change induced yield shifts based on dynamic global CGE modeling. To this end, we incorporate detail for nine different household types, grouped by income per capita and share of agricultural income, for Vietnam, Ethiopia, and Bolivia as low- and lower-middle-income countries (LMICs). With this framework, we can model crucial developments over time such as income dependent household demand curves, sector specific productivity growth, and endogenous national saving rates, which depend on demographics and income. The baseline draws on projections of population, educational levels and GDP for SSP2 until 2050. It captures increasing demographic pressures on cropland resources and the changing importance of the agri-food sector in the overall economy as GDP rises, which shape the impacts from crop yield changes. In order to isolate the effect of climate change on different household types, we compare our baseline without explicit climate change assumptions on agricultural production to a scenario in which we consider climate change induced yield shifts for eight crop aggregates globally. In addition, we run a comparative static analysis to show the added value of the dynamic analysis applied here i.e. revealing the relevant driving dynamics explicitly. These are ignored in a comparative static setting which can result in over- and underestimation of the effects. The uncertainty of the yield shocks is assessed as part of a sensitivity analysis varying crop yield changes in the recursive dynamic analysis by considering projections under different future atmospheric CO_2 concentrations.

Detailed information about the approach is provided in Section 2.2, which includes the model description, household representation, yield shift assumptions and the scenario design with the indicator descriptions. Section 2.3 then presents the results by describing country specific effects both economy wide and at household level. It further includes the results of the comparative static analysis and the sensitivity analysis. In Section 2.4, the results are compared to previous studies' findings in tandem with a discussion of relevant limitations and uncertainties. Finally, a conclusion is drawn in Section 2.5.

2.2 **Methods**

2.2.1 *Model description*

We employ a recursive dynamic global CGE model implemented in the flexible and modular modeling framework CGEBox (Britz and van der Mensbrugghe, 2018), which takes as its core the standard GTAP model (Hertel and Tsigas, 1997) in its current version 7 (van der Mensbrugghe, 2018). It depicts constant-returns-to-scale industries without market power, revenue maximizing factor suppliers and utility maximizing consumers. Moreover, it comprises various exhausting conditions and macro-economic balances such as investments equal savings, and international capital flows offsetting the balance of trade (B.O.T.). The analysis employs the so-called "global bank" mechanism of the GTAP standard model where a global agent distributes all savings to equilibrate expected returns to capital in each region. The parameters that govern this distribution, as reported in the GTAP database, are set at the benchmark such that the in- and outflows of foreign savings from this "global bank" are equal to the B.O.T., after accounting for remittances. During simulation, changes in expected returns alter the balance of payments (B.O.P.) and thus the B.O.T. such that the latter changes endogenously. Bi-lateral trade is represented in two stages based on the 'Armington assumption' (Armington, 1969), which differentiates products by origin, considering transport margins, export taxes (or subsidies) and import tariffs. Various further subsidies and taxes in input and output markets are considered in prices for producers, factor suppliers and consumers.

We extend this core by the recursive-dynamic G-RDEM model (Britz and Roson, 2019) combined with elements of the GTAP-E (McDougall and Golub, 2009), GTAP-AGR (Keeney and Hertel, 2005) and GTAP-AEZ (Lee, 2005) modules, to consider detail for energy, agriculture and land use. G-RDEM is designed for the construction of internally consistent and detailed scenarios of long-run economic development (Britz and Roson, 2019). Besides the capital accumulation component typically applied in recursive dynamic CGEs, G-RDEM adds five features, capturing key adjustment processes in the long run: (1) an econometrically estimated implicitly directly additive demand system (AIDADS) with non-linear Engel curves to depict income dependent variations in household consumption patterns, (2) sectoral differentiated total factor productivity growth depending on GDP growth, (3) endogenous national aggregate saving rates driven by demographic and income dynamics, (4) time-varying and income dependent industrial input–output parameters, and (5) debt accumulation generated from foreign savings and trade imbalances (Britz and Roson, 2019, p. 69ff). This extends the "global bank" mechanism by assuming that the "global bank" will charge interest to foreign savings (= a negative B.O.T) and that the resulting debt has to be paid back. The interest received and the debt servings accrue to the regions with positive trade balances (i.e. net lenders), reflecting their share on total global foreign savings in each year. A feedback mechanism driven by outstanding debts relative to GDP prevents ever increasing negative B.O.T. for a region.

G-RDEM uses exogenous projections of real GDP and population by age and educational level provided by the SSP database (Riahi et al., 2017) during baseline construction. At each period t, the model is solved for a simultaneous equilibrium in all commodity and factor markets globally. Endogenous aggregate factor productivity adjusts in accordance with the exogenous GDP changes and drives the sector-specific productivity shifters (Britz and Roson, 2019). Real GDP per capita in each region is fixed during baseline construction to given exogenous projections, by adjusting endogenously an economy wide total factor productivity shifter (Britz and Roson, 2019). This shifter changes total factor productivity differently in the primary, secondary and tertiary sector (Britz and Roson, 2019, p. 61ff.) depending on the GDP per capita growth rate. The faster the GDP growth, the faster industry sectors and the slower services grow compared to primary sectors. The functional relation is based on empirical work by Roson (2019). Before each iteration, net investments define the capital stocks at t + 1, whereas population and labor stocks, saving rates and input–output coefficients are exogenously updated. In our counterfactual scenario runs we include climate change assumptions. Here productivity shifters turn exogenous and are taken from the baseline run, while GDP now reacts endogenously.

We add some features of the GTAP-E model, which provides detail in depicting the demand for energy carriers by industries and final households to better capture technical substitution. Similarly, the GTAP-AGR model depicts substitution among feedstuffs in livestock production, as well as specific groups of food products to capture cross-price effects in the top-level final demand for food. The GTAP-AEZ model disaggregates land into specific uses across different agro-ecological zones (AEZs). There are 18 AEZs in total, which result from differentiating tropical, temperate, and boreal zones further by the length of growing seasons. We extend the GTAP-AEZ formulation by considering land supply from natural vegetation. As land expansion to forestry and agriculture mostly serves to increase cropland, we use the remaining available cropland buffers as an estimate for the maximal area, which can be converted from natural vegetation. The land supply elasticities are adjusted to match forecasts by FAO (2018) from which we also take yield trends.

We draw on version 9 of the GTAP database (Aguiar et al., 2016), which provides a snapshot of the global economy for 2011. We keep the full differentiation of 57 sectors, which comprise, inter alia, 12 agricultural, 6 energy and 3 transport sectors. In Section 2.3, the results of the detailed agricultural sectors are often aggregated into a ‘grains and crops’ and a ‘livestock and meat’ sector. In addition, the processed food sector is studied, which is also contained when referred to the overall ‘agri-food sector’ in the following. All monetary values are presented in USD 2011 in line with the model database. We aggregate the 140 countries or country blocks included in GTAP 9 into 15 regions. This includes one LIC (Ethiopia) and two LMICs (Bolivia and Vietnam) considered with household details as well as China and the USA, and 10 country aggregates (see in Table A.2.1 for detail). We opted for the three case study countries as they are located in different regions around the world and thus face different conditions, both climatic and economic. In addition, the choice reflects data availability, i.e. we need LICs or LMICs represented as a single region in GTAP 9 for which a FAO household survey is available, see Section 2.2.2.

2.2.2 *Household representation*

As the standard GTAP model, G-RDEM normally considers only one representative consumer in each country or region. Here, we instead exploit information from a set of household surveys (FAO, 2017a), which provide, inter alia, information on income composition for selected LICs and LMICs, with detail and focus on farming households. The Ethiopian survey is called Ethiopian Rural Socioeconomic Survey and was constructed for rural areas and small towns. The surveys for Bolivia and Vietnam are representative for the whole population (FAO, 2017a). Besides data on household size and their weight in the population, we include information on the size of factor income, differentiating (self-) employment in ten different sectors. Furthermore, we take government or intra-household transfers, remittances and other income sources into account.[2] In the underlying survey data, both monetary and in kind (e.g. own produced food) receipts are used to depict income (ILO, 2003). Thus, also products that do not enter the market are valued as income. All flows are measured in real terms at the benchmark 2011.

We group the households into nine household types using the above-mentioned information. Specifically, we group the households into three quantiles by per capita income: poor (I30: 30% quantile), middle (I70: 30% up to 70%) and rich (I100: rest), considering their different weights in the total population given in the

[2] For details, see the chapter on the myGTAP module in the CGEBox documentation, Britz (Britz, 2019), p. 58 ff.

database. In doing so, we account for the unequal shares that these households represent in the population in the quantile definition process. Moreover, we use the share of their income generated in agriculture as second dimension for the household type aggregation. This allows to capture the distinction between net sellers and net buyers of food among the households. Again, we use the same percentage allocation, resulting in three quantiles encompassing the households with the lowest 30% (A30), the middle (A70: 30% up to 70%) and the highest 30% of the shares of agricultural in total income (A100). The combination of these quantiles results in the nine household types shown in Fig. 2.1. Table 2.1 reports the population shares represented by each household type. The household types are named according to the total income per capita quantile and the share of agricultural income quantile that they represent, as indicated in the brackets above. For instance, the poor non-agricultural household is named I30_A30, represented by the lower right dark blue shaded square in Fig. 2.1.

We employ the myGTAP module in CGEBox to introduce income and consumption related data from the household surveys in the social accounting matrix ensuring consistency with the aggregated GTAP data. Each household is assumed to own property rights to primary factors (skilled and unskilled labor, land, capital, and natural resources), which are allocated to the different sectors subject to the revenue maximization objective based on a Constant Elasticity of Transformation function.

For the integration of multiple household types into the accounting framework of the CGE model, the single representative consumer is disaggregated (with fixed weights obtained by the survey data) in each country. Household specific saving rates are updated based on a regression analysis underlying the saving rate dynamics (driven by demographic and income dynamics) in G-RDEM (Britz and Roson, 2019). Vectors of income from different sources are disaggregated based on income shares provided by the surveys. On the consumption side, the vector of final consumption is split down to the household types by using marginal budget shares from the AIDADS demand system, to determine fitting baskets as the surveys do not report household consumption patterns. The AIDADS (Rimmer and Powell, 1996) can be understood as an extended Linear Demand System (LES) where marginal budget shares are a function of the utility level. Britz and Roson (2019) perform a global cross-sectional estimation for the parameters of this demand system (see Table 1 in Britz and Roson, 2019), which includes a regression of the utility level on GDP per capita (Britz and Roson, 2019, p. 60). This regression is here applied to the per capita income level of the households at the base year, which allows estimating their utility level and from there their demand. A follow-up balancing step ensures that each household exhausts its spending on final consumption, while the sum of their demand exhausts given economy totals. During this step, the AIDADS parameters are adjusted to match the per capita demand, by minimizing squared deviations against the empirical parameter estimates. Further insight on how the estimated AIDADS system changes baseline outcomes compared to other solutions can be found in Ho et al. (2020). Consumption baskets vary in this study across household types, such that, for instance, poor households have higher expenditure shares for food.

Population development projections are available at country level only, so that we update all household types proportionally to total population. Capital income is assigned to the households on the basis of fixed ownership shares, which implies that household specific capital stocks vary proportionally. There is no migration from one household category to another and the proportion of skilled versus unskilled workers varies with the same rates across all households, reflecting projections of education levels.

2.2.3 *Scenario design*

To assess impacts of yield shifts, we first construct a baseline scenario upon 2050 using GDP, population and workforce assumptions from SSP2 from the IIASA database. We choose SSP2 for the assessment as it consists of narratives that build on historical development patterns for future trends and thus represent on average a medium challenges scenario. Yield developments are taken from country specific yield shifts from FAO (2018), available for different scenarios. Following SSP and

Representative Concentration Pathways (RCP) assumptions[3], they differentiate the impact of technology and climate change on yield shifters for 36 crops. The SSP assumptions here determine the framework of technological change over time, while RCP assumptions form the basis for the climate change shifter. Like all other scenarios we develop here, our baseline includes yield changes that reflect evolving technology from the Business As Usual (BAU) scenario in FAO (2018) which matches SSP2. However, as the original SSP scenario narratives do not consider climate change feedbacks (Riahi et al., 2017), yield shifts induced by climate change are not incorporated in our baseline scenario.

We then compare the baseline to a counterfactual scenario (bau_CC), which considers impacts of climate change on yields at unchanged technological change. Both types of yield changes are taken from the BAU scenario of FAO (2018). Yield projections for the scenarios are incorporated by aggregating the productivity shifts from FAO (2018) to the available crops in the GTAP database and to model regions, using the crop acreage projections of the FAO as weights. The resulting shocks are depicted in Fig. 2.2, with rest of the world (ROW) representing the unweighted average of the shocks implemented in the regions which are not in the focus of the analysis. In the bau_CC scenario, the workforce and population data used in the baseline are adopted, while GDP adjusts endogenously.

We provide new insights as to how climate change induced yield shifts affect the equilibria in primary factor and product markets, and prices, considering bi-lateral trade to ultimately assess income effects on specific household types. To this end, we make a detailed comparison of the bau_CC scenario to the baseline. We use the equivalent variation (EV) as a welfare indicator for the household types, which can be interpreted as the income change needed to reach the new welfare level at old

[3] The scenarios contain of a "business as usual scenario" (BAU), a "stratified society scenario" (SSS), and a "towards sustainability scenario" (TSS). The climate change impacts are associated with the so-called Representative Concentration Pathways (RCP): RCP 6.0 (BAU), RCP 8.5 (SSS) and RCP 4.5 (TSS), while the socio-economic and technology developments draw on the SSPs (BAU: SSP2, TSS: SSP1, SSS: SSP4).

prices (Bockstael and McConnell, 1980). The EV is expressed in monetary units, allowing for an intuitive interpretation. Furthermore, as an ordinal welfare indicator, the EV enables to rank counterfactual prices and quantities to a given base price as a benchmark - as it is applied in our simulation (McKenzie, 1988). Additionally, we present the EV change induced by the yield shift relative to the real income of each household type in the baseline, which represents the total income deflated with the GDP price index, to illustrate the importance of the respective change for a household's welfare.

Complementary to the dynamic analysis, we perform a comparative static analysis similar to those used in previous studies (e.g. Skjeflo, 2013). Through comparison of both analyses, it is possible to determine the additional contribution of considering long-run global economic changes. Using the same model on the same database enables us to pinpoint the impact of considering long-term dynamics. In

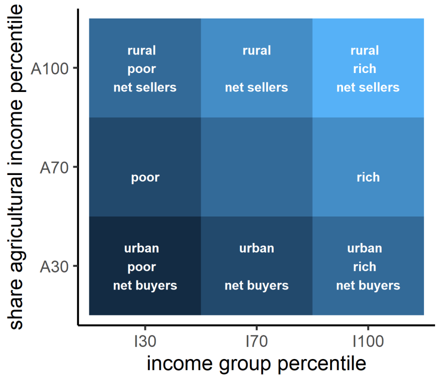

Figure 2.1. Household types aggregated by income per capita and share of agricultural income as used in this study.

both experiments, we implement the same yield shock, while we do not consider inter alia GDP development or population growth over time in the comparative static run.

Table 2.1. Share of each household type in the population (%).

	I30_A30	I30_ A70	I30_A100	I70_ A30	I70_A70	I70_ A100	I100_A30	I100_A70	I100_A100
VNM	9	12.5	17.1	8.9	15.2	8.8	13.5	9.8	5.1
ETH	6.5	8.7	12.3	5.1	20.7	15.9	6	13.8	10.9
BOL	11.4	1.6	15.2	27.3	3.2	8.9	27.4	2.5	2.4

Remark: VNM = Vietnam, ETH = Ethiopia, BOL = Bolivia, Household type (e.g. I30_A30) are named according to the total income per capita quantile (e.g. 30% quantile of total income: I30) and share of agricultural income (e.g. 30% quantile of agricultural income: A30) that they represent. *Source: Model simulation based on data from FAO (2017a)*

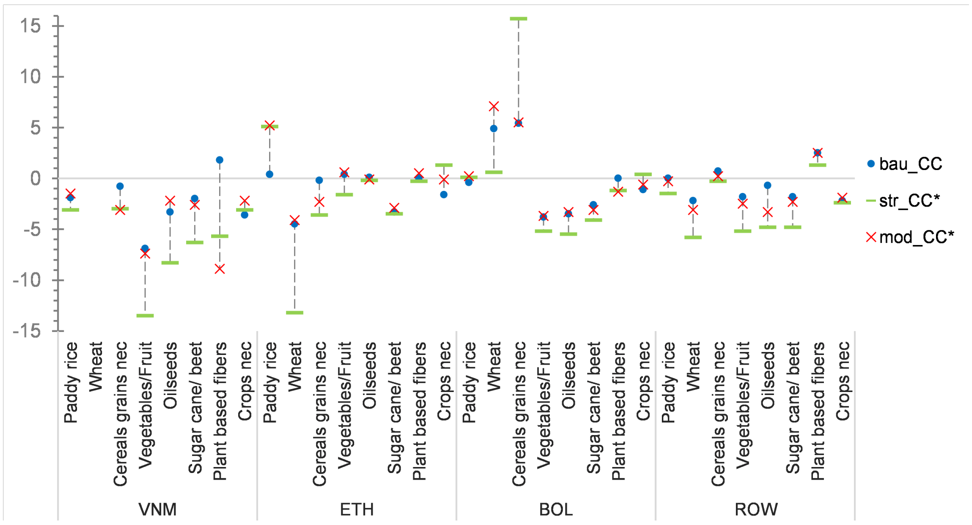

Figure 2.2. Percentage yield changes induced by climate change, as implemented in scenarios until 2050.

Remark. bau_CC = business as usual Climate change scenario, str_CC = strong climate change scenario, mod_CC = moderate climate change scenario, * = sensitivity analysis scenarios, VNM = Vietnam, ETH = Ethiopia, BOL = Bolivia, ROW = unweighted average of the rest of the world, nec = not elsewhere classified. Source. Based on data from FAO (2018)

Finally, as part of a sensitivity analysis, we vary the severity of climate change impacts on crop yields in our two additional scenarios str_CC (based on rather strong climate change effects (RCP 8.0)) and mod_CC (based on moderate climate change effects (RCP 4.5)), see Fig. 2.2, by using the respective climate change yield shifters from FAO (2018). All scenarios are constructed on the basis of the baseline scenario. This includes the SSP2 assumptions on population and education, along with total factor productivity changes and other parameter updates derived in the baseline as well as the SSP2 technology shifters on yield from FAO (2018). In the scenarios, GDP adjusts endogenously driven by climate change induced yield shifts of FAO (2018) aiming to disentangle the consequences of climate change severity ceteris paribus. As shown in Fig. 2.2, the yield shocks are not always in a linear order from lower (mod_CC), to moderate (bau_CC), to strong climate change assumptions (str_CC). This nonlinearity reflects simulations with crop growth models that account for regional climatic differences and specific crop growth requirements. However, CO_2 fertilization is not considered in these yield projections, in order to compensate for other negative temporary and small-scale climate phenomena that are not accounted for (FAO, 2018).

2.3 **Results**

2.3.1 *Baseline development*

The SSP2 projections imply that until 2050 global population grows by 32% and real GDP by 186%, resulting in a considerable GDP per capita growth (117%) compared to 2011. For the study countries, even higher changes in real GDP are projected over time increasing approximately by factor six in Vietnam and Bolivia and by factor eleven in Ethiopia (‘solid lines’ Fig. 2.3 A). Combined with population increases of 18% in Vietnam, of 42% in Bolivia and of 87% in Ethiopia until 2050 (‘dashed lines’ Fig. 2.3 A), this implies strong GDP per capita increases (Fig. 2.3 B). These exogenous trends require considerable endogenous adjustments such as massive capital accumulation and sizable improvements in factor productivity in the baseline, and imply strong structural change in the economies. This relates, for instance, to the composition of consumption and production, primary factor endowments and their relations, and prices of inputs and outputs.

2.3.1.1 *Economy wide effects*

The combination of a growing world population and increases in per capita purchasing power let global economic output increase by 217% from 2011 to 2050. Compared to the overall global economic output increase, output growth of the agri-food sectors is more modest (see Table 2.2), reflecting mostly lower income elasticities for these products. Thus, the share of agricultural and processed food outputs in total output decreases from 4% to 2%, respectively. An even stronger trend of falling agricultural importance is observed in the study countries. Ethiopia faces the largest decrease (by -17 percentage points), resulting from the strong GDP increase over time (Fig. 2.3). Yet, the share of agriculture in the overall economy still remains largest. Likewise, the importance of the processed food sector decreases in all three countries, by at most 5 percentage points. For the three countries in focus, output developments differ substantially from global averages, as summarized in Table 2.2. While growth rates vary, output of all crops is projected to increase in all three countries until 2050.

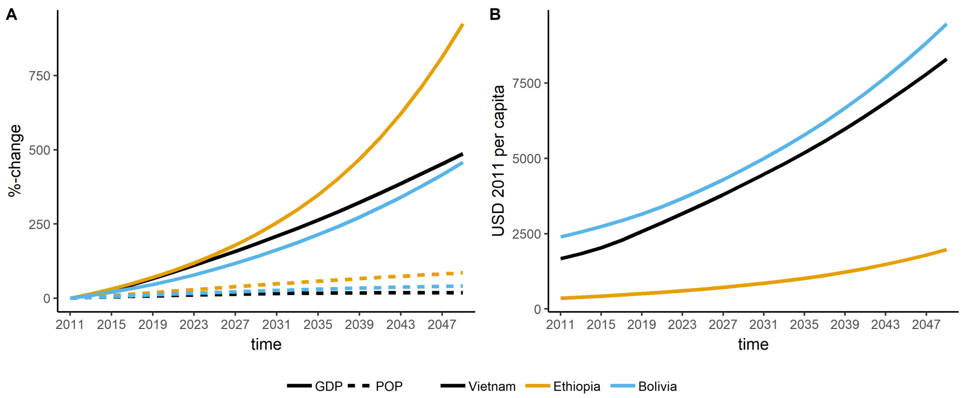

Figure 2.3. (A) Percentage change of population and GDP relative to 2011 and (B) GDP per capita development until 2050 in the study countries in USD 2011. Source: Based on data from Riahi et al. (2017).

Due to the improvements in factor productivity, which imply falling production costs, average product prices tend to decrease globally and in the three countries. Large decreases are especially visible in the livestock sector and the processed food sector, while the prices for grains and crops increase on average. The overall increase in prices of the latter reflects strong demand growth meeting limited land reserves.

Table 2.2. Output changes for the total economy and for agri-food sectors in all study regions and globally from 2011 to 2050 (%).

	Total output	Grains and crops	Livestock and meat	Processed food
Global	217	59	120	74
VNM	608	43	491	151
ETH	1293	198	1334	349
BOL	549	47	217	120

Remark: VNM = Vietnam, ETH = Ethiopia, BOL = Bolivia. *Source: Model simulations*

Globally trade becomes more important as the share produced for domestic use decreases, and the importance of imports for consumption increases. In line with this trend, approximately 29% of the final demand of agricultural products in Vietnam are supplied by imports in 2050, whereas in the two other study countries imports are of negligible importance for livestock products and make up at most 10% for grains and crops. With respect to processed food, a large share of the demand is covered by imports in Vietnam (29%) and Bolivia (22%), while Ethiopia relies mainly on domestic production. These differences are to a lesser extent already found in 2011. In Vietnam agri-food systems are highly integrated in global markets in terms of exports. In Ethiopia and Bolivia, they are again of less importance, except for the Ethiopian meat sector, where export dependency strongly increases.

In response to the previously described changes, factor demand adjusts. The global factor demand for land increases only little over time, both overall and in the grain and crops sector. In Bolivia, similar trends are observed while in Vietnam decreases in the land use of the livestock sector overshadow extension in the grains and crops sector. In contrast, in Ethiopia demand for land increases substantially. Thus, rapid cropland expansion is projected in Africa including Ethiopia. Expansions are projected to be smaller in South America (including Bolivia), and even smaller in

Asia (including Vietnam). These changes are also determined by the remaining suitable land available. They originate mainly from conversion of unmanaged forests, while in Ethiopia conversion of savanna is more important. In all regions, relative cropland expansion is below population growth, such that the available cropland per capita is reduced. Cropland use adjusts to meet changes in yields, i.e. generally more land is allocated to crops with reduced yields and vice versa. In line with the strong output increase (Table 2.2), the land devoted to the livestock and meat production increases substantially in Ethiopia, while it decreases or remains unchanged globally and in the other study countries. The capital stock increases substantially in all study countries. However, the capital employed in the grains and crops sector falls, expressing its shrinking importance in the overall economy. Increasing scarcity, lets land prices rise on average over all sectors and in the agricultural sectors in Ethiopia and Bolivia, while in Vietnam they increase only in the grains and crops sector. This relative increase is especially large in Ethiopia in the grains and crops sector. The output increases (Table 2.2) substantially outweigh factor demand change in all study countries, reflecting strong technological progress. These economic developments shape the impacts of crop yield changes: on the one hand, sensitivity to changing yields increases as less land is available for food production per capita while, on the other hand, relatively less people draw income from agriculture.

2.3.1.2 *Household effects*

As seen from Fig. 2.4 below, all households in our study countries benefit from the projected GDP increase under SSP2. However, how much a household gains in absolute terms depends strongly on its initial income level and its sourcing. Absolute gains are larger for richer households in all three study countries and, in tendency, decrease with the higher share of agricultural income. The latter can be explained by the fact that the agricultural sectors show more limited output growth (Table 2.2) such that capital and labor demand in agriculture increase slower compared to the rest of the economy. Households therefore shift capital and labor towards other sectors with higher wages and returns to capital. This reallocation comes, however, at the cost for the households that remain in the agricultural sector, as a specialization into a shrinking sector implies lower income increases. The negative impact of a specialization into agriculture is true for all household types in Vietnam and Ethiopia, while in Bolivia this is not entirely true for the lower income households (I30 and I70), as for them the A70 households benefit most over time instead of A30. In fact, for I30 the household type A30 also gains slightly less than A100 in this income group. Furthermore, for the rich households (I100) in Bolivia the welfare gain strictly increases with increasing share of agricultural income, such that A100 benefits most.

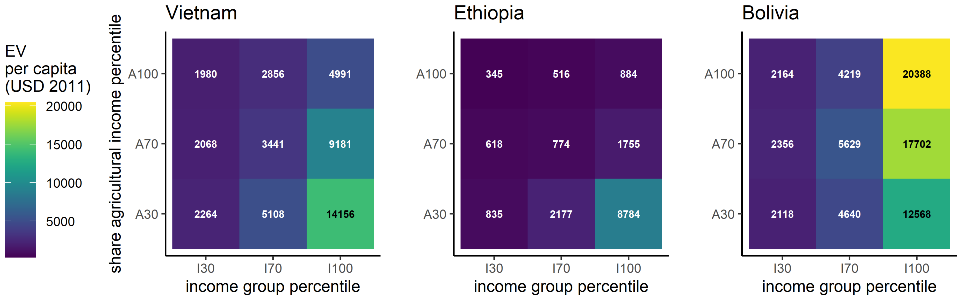

Figure 2.4. Absolute welfare (EV) change in USD per capita up to 2050 by household type and study country. Source. Model simulations.

One reason for the lower EV over time for farmers (A100) compared to the other household types is the absolutely lower change in real total income for these households (Table 2.3). The absolute increase in factor income is lower for these households as they have a lower factor income from capital compared to other households (Table 2.3). Factor income stemming from capital increases most until 2050, reflecting the strong capital accumulation mentioned before in Section 2.3.1.1. This benefits households with a higher initial share of capital income. Thus, the income of non-agricultural households, that tend to have larger shares of income from capital, increases in absolute terms more than for other households. In Bolivia, the divergent total real income changes (higher increases for richest agricultural household) also explains the deviations in the EV change over time. Here, land endowment is very unequally distributed across households. According to the Agricultural Census in 2013 of the National Institute of Statistics (INE = Instituto Nacional de Estadística) in Bolivia, more than 50% of the agricultural land is cultivated by less than 1% of the total numbers of farms (INE, 2015). Thus, the agricultural household types (especially the richest agricultural household type) collect almost all factor income from land, benefitting strongly from land price increases. This overcompensates for lower capital endowments and results overall in a higher income increase over time. Furthermore, the richest agricultural household type has further important income sources, especially its income shares from skilled labor exceeds the ones of other agricultural household types in Bolivia. In the other countries, the highest income shares from skilled labor are found in the A30 household types, instead. This results in the inverted increase of income in Bolivia, increasing most for A100 and least for A30, which explains the divergent EV change pattern. Similar reasoning applies to a smaller extent also to the other household types that show exceptional behavior.

The difference in income also results in different expenditure shares. In Ethiopia, the households' income is lower compared to Vietnam and Bolivia (Table 2.4), such that the share of income spent on food remains on average largest. In all three study countries, the share decreases on average over time, making them all less vulnerable to price increases for food. Farmers (A100) have in tendency a lower income, which leads to higher expenditure shares for food compared to other household types in all three study countries. Farmers in Bolivia do not always have the highest share of expenditure for food as their income is higher compared to other households.

Household demand per capita increases over time for all commodities on average, by 358%, 781% and 458% in Vietnam, Ethiopia and Bolivia, respectively. In contrast, the value of the demand for food increases only by 34% in Vietnam, 162% in Ethiopia and 125% in Bolivia. Decreasing demand for grains and crops is observed on average only in Vietnam, while demand for processed food increases on average in all three study countries. Comparing all food products, the demand for meat and livestock products increases in all three study countries at the strongest rate being about twice as high as for processed food products on average, reflecting the development of the economic output increase described in Section 2.3.1.1. In

Ethiopia and Vietnam, the agricultural households (A100) always change demand less than the other households in the same income group. In contrast, in Bolivia this observation holds for the non-agricultural households.

2.3.2 *Climate change effect*

2.3.2.1 *Economy wide impact*

The *bau_CC* scenario reveals that, up to 2050, impacts of macro-economic growth outweigh by far the effects of climate change induced yield shifts. The latter reduce GDP per capita by less than 0.01% on global average and at most by 0.8% in the three study countries compared to the baseline scenario in 2050. The importance of the agri-food sectors also remains mainly unchanged. Thus, the simulated climate change effects on crop yields generate only slight feedbacks in aggregated indicators for the overall economy. The production of livestock increases globally (+0.1%) through the climate change induced yield shifts, whereas the production of grains and crops (-0.4%) and processed food (-0.2%) shrinks. In the three study countries, the output of all three sectors declines, with Vietnam showing the largest reduction. As expected, the production of crops with positive yield shifts tends to increase and vice versa, leading, for instance, to an increase of the wheat production in Bolivia. Prices for grains and crops increase globally (+2%) and in the three study countries (+4% in Vietnam, +1% in Ethiopia, +3% in Bolivia). For single crops, price increases can be more substantial, as for instance for sugar cane and beet in Ethiopia (+8%). Prices for crops with positive yield shifts tend to fall.

Table 2.3. Real total and factor income changes per capita in USD, by household type and country over time.

	Real total income change									
	average	I30_A30	I30_A70	I30_A100	I70_A30	I70_A70	I70_A100	I100_A30	I100_A70	I100_A100
VNM	5653	2720	2556	2483	5630	3900	3304	15,068	9809	5405
ETH	1500	934	762	502	2402	893	633	9085	1861	936
BOL	6845	2481	2710	2564	4968	6038	4614	11,851	17,489	19,905
	Factor income change									
	average	I30_A30	I30_A70	I30_A100	I70_A30	I70_A70	I70_A100	I100_A30	I100_A70	I100_A100
VNM	1644	300	257	271	1564	922	672	5640	3554	1704
ETH	483	209	147	50	772	287	167	3245	696	317
BOL	2327	377	479	506	1468	1948	1457	4485	6953	8408

Remark: VNM = Vietnam, ETH = Ethiopia, BOL = Bolivia. *Source: Model simulations*

Table 2.4. Real income per capita in 2050 in USD, by household type and country.

	Real total income									
	average	I30_A30	I30_A70	I30_A100	I70_A30	I70_A70	I70_A100	I100_A30	I100_A70	I100_A100
VNM	7106	3193	3149	3014	6886	5140	4470	18,517	12,282	7975
ETH	1824	1065	915	646	2639	1162	903	9827	2381	1466
BOL	9010	3204	3481	3234	6590	7625	5900	16,005	21,354	25,074

Remark: VNM = Vietnam, ETH = Ethiopia, BOL = Bolivia. *Source: Model simulations*

Import dependency increases for grains and crops both globally and in Vietnam and Ethiopia, whereas in Bolivia it decreases. For single crops, import changes follow the exogenous yield shifts as they counterbalance the resulting domestic production impacts. In Vietnam only, an increase in import dependency is visible for livestock and meat production. Likewise, in Vietnam, exports relative to production are reduced most in all three agri-food sectors, while this relation increases in Ethiopia for grains and crops and processed food.

Negative yield shifts trigger cropland expansion and thus render land scarcer. Overall, the three study countries show small expansions about 0.1%. The area allocated to crops varies in accordance with the yield shock and trade changes. For instance, cropland used for plant based fiber decreases in Vietnam, while production increases as the positive yield shift (1.8%) allows to produce more on the same area.

Overall, global factor demand remains unchanged while it slightly decreases through climate change in Vietnam and Bolivia, and slightly increases in Ethiopia. In contrast to the other two agri-food sectors, in the grains and crops sector factor demand increases on average in the study countries and globally. In this sector, the percentage increase is lowest in Vietnam compared to the other study countries and to the global average, as in Vietnam demand for all other factors than land decreases. In Ethiopia (0.3%) and Bolivia (0.4%), the lowest increase in demand occurs for land in this sector. Factor prices decrease in all regions on average. However, as land gets scarcer, it is the only factor that faces increasing prices in the grains and crops sector through climate change, besides unskilled labor in Ethiopia of which prices increase by 0.1%.

2.3.2.2 *Household effects*

The difference between the baseline and the *bau_CC* scenario reveals that the climate change impact on yields leads on average to a welfare loss for households in all three study countries. The highest losses on average per capita are visible for households in Vietnam (-43 USD), followed by Bolivian households (–22 USD), while Ethiopian households lose on average less (-4 USD). This ranking persists also when comparing single household types between countries. Large variances within one country can emerge when comparing the effect on single household types, as shown in Fig. 2.5. However, all study countries reveal the same pattern, namely that the higher the share of agricultural income is in the total income, the lower is the projected loss resulting from climate change. Conversely to Vietnam and Ethiopia, in Bolivia the household type that already showed the highest positive effect over time in the baseline (I100_A100) even benefits (+108 USD) from the yield shift. Apart from this, in most cases the absolute welfare loss is higher for richer households in all three study countries. The household type I100_A70 in

Bolivia (-42 USD) and I100_A30 in Vietnam (-82 USD) and Ethiopia (-9 USD), respectively, faces overall the highest EV reduction.

These differences in EV result, inter alia, from changes in household's factor returns. In contrast to the EV, factor returns slightly increases on average per capita in Ethiopia (+0.1%), while it decreases in Vietnam (-0.6%) and Bolivia (-0.2%). Similar to the EV, factor income change rises with increasing agricultural share at constant income per capita level, see Table 2.5. In fact, it increases most for farmers (A100) or decreases least in all three study countries compared to the other households in the same income per capita quantile. This is because factor returns to land increase through climate change, while other returns that are most relevant for non-agricultural households tend to decrease overall. Land rents increase through climate change, as demand for food is rather inelastic such that overall demand for food adjusts only slightly, even if production costs rise. The fact that households in Vietnam face comparably larger absolute welfare losses than the same household types in the other study countries can be explained by lower increases in factor returns to land and, as a result, higher factor income reductions. As mentioned in the baseline run, the Bolivian household type I100_A100 owns a very large share of the land, which results in an overall EV rise through climate change. For this household type the benefits from the land price increase are not offset by higher spending on foods, due to its high income and the resulting low share spent on food. Households with higher per capita income and the same share of agricultural income face more negative factor income changes in absolute terms. Hence, as for the EV, the household types I100_A30 in Vietnam and Ethiopia, and I100_A70 in Bolivia face the largest reduction in factor income through climate change. The exceptional outcome of household type I100_A70 reflects reduced factor returns to capital which are its main source of income.

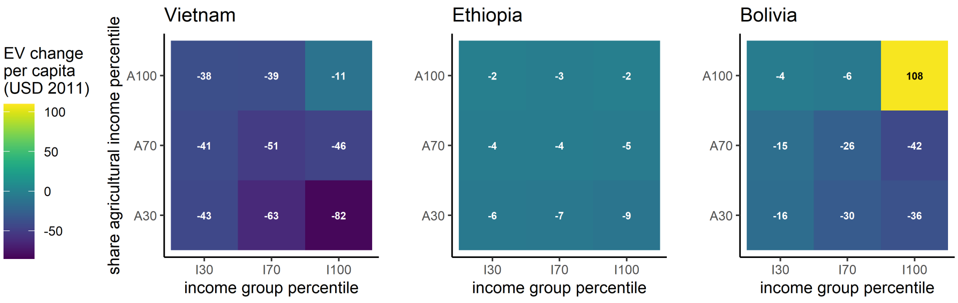

Figure 2.5. Absolute welfare (EV) change through climate change in 2050 in USD, by household type and study country. Source: Model simulations.

Table 2.5. Absolute change in factor income per capita in USD through climate change by household and country.

	average	I30_A30	I30_A70	I30_A100	I70_A30	I70_A70	I70_A100	I100_A30	I100_A70	I100_A100
VNM	-16	-3	-2	0	-16	-9	-1	-66	-30	-4
ETH	0	0	0	0	-1	1	1	-5	1	2
BOL	-7	-2	-1	5	-8	-7	10	-24	-30	48

Remark: VNM = Vietnam, ETH = Ethiopia, BOL = Bolivia. *Source: Model simulations*

Average demand per capita decreases in all three study countries. The demand for the agri-food products is reduced through climate change. In Ethiopia and Bolivia, overall demand increases for some A100 households only, while their demand for agricultural products decreases. These households are thus able to consume more from other sectors, whereas the other households consume overall less. Induced by price increases for all three agri-food sectors, the expenditure shares for grains and crops, livestock and meat, and processed food remain nearly unchanged on average through climate change, despite the overall demand decrease.

Setting the absolute welfare loss in 2050 expressed by the EV in USD in relation to the total real income deflated by the GDP price index under the baseline scenario in 2050 (Fig. 2.6) shows that richer households, despite higher absolute EV changes, lose less relative to their income. In all income groups, agricultural household types are never the most affected ones. In contrast, mainly non-agricultural (net food buying) households (A30) are identified as most vulnerable to yield shocks. This shows decreasing vulnerability with increasing agricultural share of income. It results from the higher absolute EV change for non-agricultural households combined with decreases in real income per capita. In contrast, A100 households face lower absolute EV changes and slightly increasing real incomes per capita. As an exception, in Ethiopia, two of the three A70 household groups are the most affected households, namely in the I70 and I100 income quantile, while then the A100 households are the second most affected. The A30 household in Ethiopia is considerably richer than the other households in the I70 and I100 quantiles (see Table 2.4), which leads albeit the absolute highest EV change (see Fig. 2.5) to the lowest relative importance. Hence, besides this, farmers face mostly the lowest relative effect. The rich agricultural household in Bolivia is the only household type showing welfare gains, due to its positive absolute EV change and the increase in real income, reflecting a high income share from land combined with a low expenditure share for food.

Additionally, the shares that each household represents in the total population are relevant for the interpretation of the distribution of the welfare changes (see Table 2.1). For instance, the household that gains from climate change (I100_A100) represents only 2.4% of the Bolivian population in 2050, while the household type that loses most relative to their initial consumption (I30_A30) represents 11.4% of the total population. Similarly, in Vietnam, the poor (I30) household types represent in sum about 38% of the population, such that the most affected encompass more than one third of the population. In Ethiopia, the relatively most affected household type encompasses 6.5% of the population.

2.3.3 *Comparative static analysis*

Existing studies analyzing climate change induced yield shift introduced the resulting crop productivity changes in a comparative static setting, i.e. into the currently observed global economy. In order to highlight the contribution of our long-run perspective presented in the previous section, we also conduct a comparative static analysis where population, GDP, demand and production pattern reflect a snapshot of the global economy in 2011. As expected, the comparative static analysis shows that, on average, households would face a welfare loss if the cumulative yield changes through climate change up to 2050 would instead happen immediately. However, size and order of welfare changes by household type partly differs from the dynamic analysis. The household type that gained from the simulated climate change effects in Bolivia (I100_A100) in the dynamic assessment faces a welfare loss in the comparative static case, see Fig. 2.7. In addition, the I30_A70 household now loses more than the I30_A30 in Vietnam. Besides this, the direction of welfare changes and the ranking of households are unchanged from the dynamic analysis and show again that absolute losses in EV are higher for richer households and, in tendency, lower for agricultural households. For Bolivia, the divergent results from this general pattern also found in the long-run analysis, are again observed under the comparative static analysis. However, absolute changes in EV under a comparative static setting are considerably smaller than in the recursive dynamic analysis for all household types.

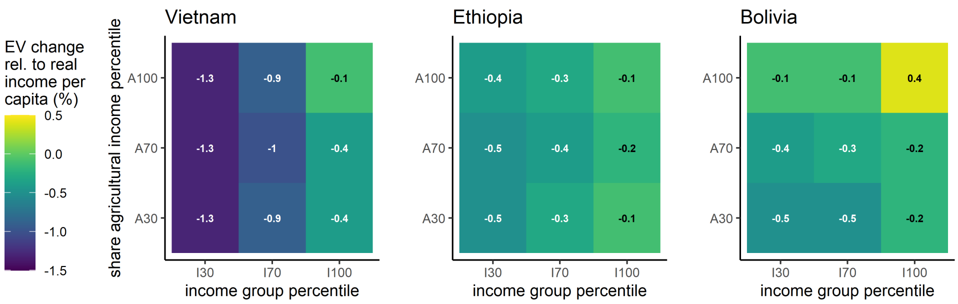

Figure 2.6. Absolute welfare (EV) change in 2050 (bau_CC) relative to the real income in 2050, by household type and study country. Source: Model simulations.

The trend of decreasing relative EV change with increasing agricultural income share is also observed here (Fig. 2.8) as absolute and relative EV show the same trend in the comparative static analysis (besides I30_A70 in Vietnam). Thus, it would also result in an identification of non-agricultural households as more vulnerable than others, besides in Bolivia where the A70 household is always most affected. The comparative static analysis does not show that the effect decreases with increasing income per capita, as also many I70 households are among the most affected when comparing households with the same agricultural share on income.

In comparison to the dynamic assessment, the relative EV changes are smaller for most households in the comparative static analysis, i.e. it might underestimate the economic importance of these yield shifts. This might come at a surprise given a decreasing weight of the agri-food sector in the global economy over time, considered in the dynamic analysis. Only some (rich) households, especially in Bolivia, show higher relative effects under a comparative static setting, as summarized in Table 2.6.

However, the comparative static analysis cannot consider that the income of the different household types changes at a different pace over time, depending on their respective income sources, which can make households over time relatively more or less vulnerable. Therefore, especially for poor non-agricultural households, the welfare effect is thus underestimated in the comparative static analysis, while for rich households it is overestimated compared to the recursive dynamic approach. Since the comparative static analysis does not consider GDP growth over time, the importance of the agricultural sector is larger in all three study countries than in the dynamic analysis while total factor productivity remains unchanged. The latter causes overall prices to be higher than in the dynamic analysis. Additionally, income remains at 2011 level and thus lower than the 2050 income level, resulting together with the higher prices in larger agri-food expenditure shares. For some household types, especially in Ethiopia, the shares are twice as high as in the dynamic analysis in 2050. As income over time increases most for non-agricultural households, their income shares for grains and crops show the largest positive difference in the comparative static analysis. Hence, the prices of agri-food are still of larger importance for these households in a comparative static setting. Only the two household types in Ethiopia that have a higher relative negative effect (Table 2.6: I70_A30 and I100_A30) spend less on grains and crops in the comparative static analysis than in the dynamic analysis. In terms of their real income per capita, they lose substantially more than other households, as private transfers sent to both households decline through climate change and their factor income decreases. This effect can be explained by decreasing returns to capital, which is the main income source of these two household types. Thus, also the slight increase in factor returns to land does not compensate the loss of these households, as it does for all other (A70 and A100) households.

In contrast to the dynamic analysis, factor returns to land decrease through climate change in Vietnam and Bolivia as less pressure (also demographic) is on land and more land is still available, making it less scarce, such that land price changes are more muted. In both countries, this results together with the stronger decreasing returns to capital in a relatively higher reduction in factor income for all households. In Vietnam, it decreases percentagewise largest for all rich households. Together with the large EV change this leads to the higher relative effect compared to the dynamic analysis. Since, in Bolivia also factor returns to land decrease for all households, the agricultural households' factor income declines through climate change. As they already had lower income levels on average per capita compared to the other households in the same income quantile, the reduction leads to a relatively higher EV change than in the dynamic analysis, where their income increases. Increases in factor returns over time in the dynamic analysis result in strong income growth for the agricultural household types (A100) and also for type I70_A70, and I100_A30 and A70. Thus, the EV change is of higher relative importance in the comparative static analysis, even if it is absolutely lower, due to the lower real income per capita underlying in the static analysis, as this income rise is not considered.

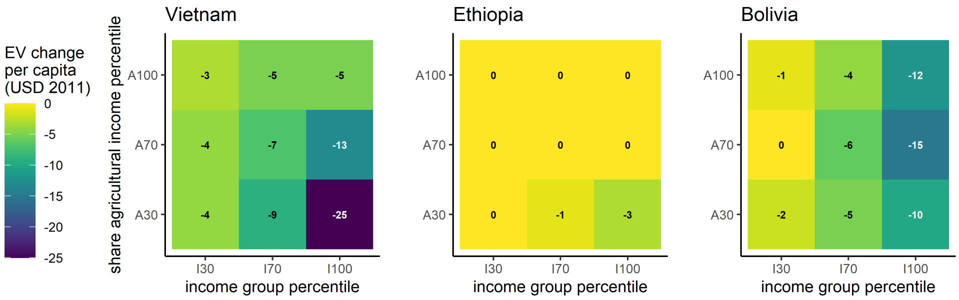

Figure 2.7. Absolute welfare (EV) change in USD in the comparative static analysis by household type and study country. Source: Model simulations.

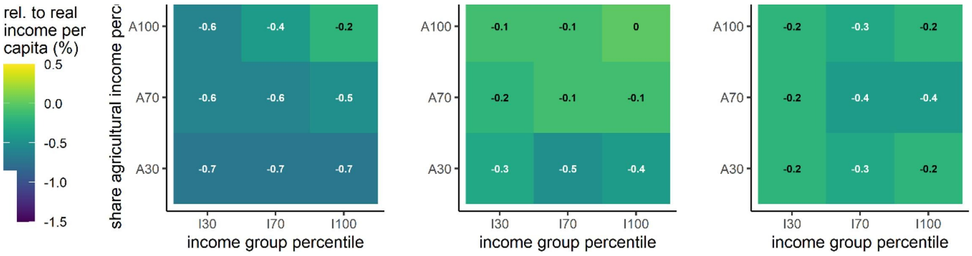

Figure 2.8. Absolute welfare (EV) change relative to the real income in 2011, by household type and study country. Source: Model simulations.

Table 2.6. Absolute difference in relative EV change between the comparative static and recursive dynamic analysis, by household type and country.

	average	I30_ A30	I30_ A70	I30_A100	I70_ A30	I70_A70	I70_ A100	I100_ A30	I100_A70	I100_A100
VNM	-0.02	-0.6	-0.68	-0.69	-0.18	-0.42	-0.48	0.28	0.16	0.05
ETH	-0.09	-0.25	-0.32	-0.28	0.2	-0.27	-0.24	0.29	-0.12	-0.11
BOL	0.03	-0.32	-0.21	0.09	-0.12	0.08	0.22	0.02	0.18	0.67

Remark: VNM = Vietnam, ETH = Ethiopia, BOL = Bolivia. *Source: Model simulations*

2.3.4 *Sensitivity analysis*

The two additional scenarios developed for the sensitivity analysis generally support the previous results of the economic development change induced by climate change. The *mod_CC* scenario results often into a slightly stronger effect than the *bau_CC* in the study countries while the *str_CC* scenario provokes the strongest effect on economic indicators. Here, it is recalled, that the yield shocks displayed in Fig. 2.2 are not always in a linear order from *mod_CC* (RCP4.5) to *bau_CC* (RCP6.0) to *str_CC* (RCP8.5) for all regions and crops.

2.3.4.1 *Household effects*

The *mod_CC* and *str_CC* scenario result on average in household welfare losses compared to the baseline, which are higher in both scenarios than in the *bau_CC* scenario in Vietnam and Ethiopia, while they are only larger on average in the *str_CC* scenario in Bolivia. More precisely, comparing the single household types between the scenarios shows that the *mod_CC* scenario results in a lower welfare loss only for household I100_A100 in Vietnam and all I100 households in Ethiopia.

In Bolivia, only the (poor) non-agricultural households (I30_A30, I30_A70 and I70_A30) lose more of their welfare. As in the *bau_CC* scenario, households with a higher share of agricultural income face lower welfare reductions in the sensitivity scenarios. Again, the exception among the I100 households in Bolivia emerges, so that household type I100_A30 is better off than I100_A70. Furthermore, in the *mod_CC* not only the I100_A100 household gains but also the I70_A100 household faces a welfare gain. In the *str_CC*, in addition household I30_A100 increases its welfare.

The mod_CC yield shock is more negative for 4 of the 8 crop aggregates in Vietnam (see Fig. 2.2), explaining the reduction in EV compared to the bau_CC scenario. The decrease in total real income exceeds on average and for all non-agricultural households under the bau_CC scenario. Thus, most households increase expenditure for the agri-food sectors due to higher prices, an effect which is negligible or even reversed only for a few households.

In Ethiopia, the yield shock under *mod_CC* is less negative for all crop aggregates but cereal grains nec, which decreases by 2.1 percentage points. This aggregate includes main staple crops of Ethiopian diets such as maize and sorghum, which remain besides 'vegetables, fruits and nuts', and 'food products nec' the agri-food products that are most demanded in 2050. Given the large demand, the price increase (+5%), which is considerably stronger than for all other crops, affects household expenditure visibly. Even if factor income rises for all households, improving their real income compared to the *bau_CC* (besides A30 households), nearly all households increase their expenditure for grains and crops in both scenarios, while for meat it is mainly reduced. The discussion underlines the importance of a disaggregated analysis of several food products, as staple crops matter more in poorer countries and household groups and can be differently affected by climate change.

Poor non-agricultural households and the I70_A30 lose more in the *mod_CC* than in the *bau_CC* scenario in Bolivia. This is caused by increasing prices for most crops compared to the *bau_CC* scenario. This increase lets poor non-agricultural households increase their expenditure share for grains and crops, and processed food more than in the *bau_CC* scenario. Whereas, the majority of the households change expenditure for food like in the *bau_CC* scenario, especially for meat. Agricultural households slightly lower their food expenditure because of their increasing income. For richer households, price increases in grains and crops are of less importance as they consume more processed food and livestock.

Setting the EV change in relation to the real income of each household type in 2050 shows in both scenarios mainly the same effects as in the bau_CC scenario. In Ethiopia, some deviations from the bau_CC arise in both additional scenarios, as among the poorest households (I30), the A70 household is most vulnerable, followed by the A30 household. The same is observed among the I100 households, opposite to the bau_CC scenario. In Vietnam and Ethiopia, all households are worse off in the mod_CC and the str_CC, besides rich households which partly face an absolute welfare gains in the mod_CC scenario (Vietnam: I100_A100 and Ethiopia all I100). In Bolivia, in both scenarios, some households are better off and others are worse off compared to the bau_CC. On average though, in the mod_CC households are better off, while in the str_CC they are worse off.

2.4 **Discussion**

The baseline constructed using the SSP2 data for GDP and demographic developments are in line with Popp et al. (2017). Most prices for agricultural products fall in the baseline until 2050. Furthermore, the trade with agricultural products increases in the baseline as also found in their analysis. Similarly, the authors find additional cropland to result from conversion of unmanaged forest, which is also found in our study. The locations of cropland expansion are similar in both analyses, being largest in Latin America and Africa. Consequently, our results show similarities with the Fricko et al. (2017), who study SSP2 developments. They find livestock demand to increase globally which can also be seen here, as production and consumption increase.

The effect of the yield shift induced by climate change on different household groups are similar to results found by previous studies. Hertel et al. (2010) analyze the agricultural impacts of climate change in 2030 on global commodity prices, national economic welfare, and the incidence of poverty of 7 household strata in 15 developing countries in the economic setting of 2001. The effects are simulated using the static GTAP model, by including low, medium, and high productivity shifts for six commodities in the developing countries and the rest of the world by 2030. The authors determine costs of living and earnings as two channels of poverty impacts. Thus, increasing food prices result in falling poverty rates for households specialized in agriculture and rising rates for non-agricultural households (especially urban wage earners). This is in line with our results, where farmers are absolutely less affected through climate change. Similarly, our results align with Skjeflo (2013), who simulates the importance of access to the markets on household vulnerability to climate change in 2000 in a CGE model for Malawi by inducing productivity shocks and an exogenously adjusted global price for maize from 2030. Skjeflo (2013) finds that large farms with access to markets can actually benefit from the yield reduction through increased maize prices. According to her analysis, urban poor and small-scale farmers are most vulnerable. This is because these households do not exploit increasing returns to land and agricultural labor while they have high expenditures for food and face increasing food prices. This is in line with our results of the dynamic analysis that show that some farmers even gain, and the other agricultural households at least lose less than the other households in their income group. While the analysis by Skjeflo (2013) is focused on Malawi only, our study assesses further countries, applying country specific climate change shocks with global coverage. Thus, our analysis verifies that the patterns are transferable to other LICs and LMICs. However, the size of the effects deviates from our analysis, our findings being considerably smaller in both the comparative and the recursive dynamic analysis. Differences emerge inter alia as the price and yield shocks are higher in Skjeflo (2013) and the EV is calculated relative to the initial household expenditure while we use the total real income. Hallegatte and Rozenberg (2017) study the effects of climate change on households in 92 countries using a bottom up approach (microsimulation). The analysis is based on SSP4 and SSP5 upon 2030. Hallegatte and Rozenberg (2017) find that impoverished people are relatively more affected than the population average and that alleviate poverty is a good way to reduce future impacts. However, they name as a limitation of their study that they do not consider investments and trade. The latter is identified by Xie et al. (2019) to have a large impact on food security (especially if distorted) as it transmits price signals.

The sensitivity analysis shows that the results are robust and that not only the severity of the yield shock matters but also which crops are affected. Hirvonen et al. (2015) find that cereals account on average for 60% of the energy intake of Ethiopian households. Thus, the small variety of staple crops in their diets makes Ethiopian households especially vulnerable to the yield shock. This is in line with Aksoy and Isik-Dikmelik (2008), who state, that a more diverse food basket decreases vulnerability to price changes. Since, this increases substitutability and flexibility to adjust.

For the assessment, we used a recursive dynamic CGE model which depicts adoption processes in the long term and reflects changes in demography and income, along with some core structural change processes. However, projecting possible future scenarios requires various assumptions strongly shaping baseline outcomes, but linked to uncertainties (Dellink et al., 2020). Elasticities and regressions build on data from past years and might not account for all potential future behavioral changes (Bijl et al., 2017). Still, the applied model reflects the state-of-the-art in this field by depicting important dynamic development processes in the overall economy and at household level (as discussed in Section 2.2).

The integration of yield shifts as the only impact of climate change on the agricultural sector in the model misses other potential impact channels of climate change in the agri-food nexus. Consequences on health, migration and food security stemming from catastrophic climate change events such as extreme weather events, weed and disease pressures, tropospheric ozone, and sea-level rise, are not captured in our model assessment. Catastrophic climate change events might exacerbate losses in land productivity, as pointed out by FAO (2018). For instance, sea-level rises could affect arable land near coastlines. Thus, better quantification of impacts on crop yields and including more climate change impacts such as for instance sea level rise (see Nauels et al. (2017)) will improve the representation of climate change in this analysis. In our simulation, this could be especially relevant for Vietnam as a country with long sea borders. Furthermore, rising temperatures might decrease labor productivity especially in the agricultural sector, as this work is carried out mainly on the field, exposed to the weather (Kjellstrom et al., 2009).

We assess average yields over a year. However, interannual scarcities in crops as, for instance, before each harvest (Vaitla et al., 2009) are also of large importance for vulnerability. Similarly, local differences in yields among regions in a country can result in differentiated effects for households depending on their residence. Wossen et al. (2018) find poor households to be especially vulnerable to price and climate variability, aggravating poverty and inequality, in their assessment for Ethiopia and Ghana. Likewise, Ahmed et al. (2009) determine urban employees to be most vulnerable to volatile climatic events and Ahmed et al. (2011) find overall large increases in Tanzanians poverty if precipitation gets more volatility. Furthermore, climate variability increases uncertainty. Nevertheless, we do not consider risk and risk behavior of firms which could especially in LICs play a crucial role in production decisions under climate change and how this affects markets, and households' income. We assume that land is owned by households working in agriculture. This ignores the actual institutional settings in different countries, which make households owning property rights to land benefit from increases in land rents rather than those producing with this factor. However, for instance, in Vietnam, the percentage of households that rented out (some of) their land between 2008 and 2016 averaged only 21% and 16% for female and male headed households, respectively. Of this total land rented out, 44% (female headed) and 54% (male headed) were even rented out for free (Ayala-Cantu and Morando, 2020). Renting land for production plays a minor role in Bolivia, where only about 1.4% of the land is rented and 0.4% is lend in exchange of a share of the production (INE, 2015). In Ethiopia, land rental is restricted by a law implemented in 2006 which does not allow to rent out more than 50% of the household's land (Holden and Ghebru, 2016). Yet, many households rented out more than the allowed share of their land in 2010, as sharecropping is the predominant rental concept that the households did not consider to be covered by the law (Holden and Ghebru, 2016).

We assume complete access to the market for all households. The underlying household data is built such that goods are accounted for as income (based on the market price of the products), which is then spent on these goods, even if they are produced for own consumption. Thereby, we assume that all goods dedicated to consumption are sold and bought from the market. In case of subsistence farmers, the interpretation of our results can thus be misleading. In reality, for subsistence farmers with no access to markets, a negative yield change would directly affect the amount harvested while they do not benefit from increasing prices, threatening their food security. The number of small-holders makes up about 75%, 88% and 93% in Ethiopia, Vietnam and Bolivia, respectively. The share of agricultural products sold from these farms equals on average 21%, 47% and 34%, respectively, in the years the surveys were conducted (FAO, 2017b), illustrating especially the higher share of subsistence farmers in Ethiopia and Bolivia. Furthermore, catastrophic events can reduce food availability as transport is distorted impeding households from selling or buying products (Ziervogel and Ericksen, 2010). Additionally, pressure on land can be raised through land-based mitigation efforts (Doelman et al., 2018) affecting the wellbeing of households. We refrain from including mitigation and adaptation strategies and their consequences in order to focus on an unmitigated shock on crop yields. Due to data availability, the Ethiopian households represent mainly rural households, thus urban households are underrepresented for this study country. However, according to the census 2007, more than 83% of the population lived in rural areas (CSA, 2008). In 2019, it was still 79% of the population according to World Bank (2020), such that this survey still represents a large part of the population.

This study provides new insights in the context of vulnerability assessments of households regarding climate change effects. The sole assessment of the effects on macroeconomic indicators (GDP) can be misleading, as its response to the limited crops yield shocks is small. Previous assessments which have considered households level effects of yield shifts used mainly comparative static modeling frameworks. However, for such climate change assessments the demographic dynamics are of large importance as over time consumption patterns change and the importance of agricultural sectors decrease. Furthermore, pressure on land increases and thus mitigation options are reduced, and intensification potentials decrease. In addition, income develops differently over time depending on the source of income, determining vulnerability. This study determined again the importance of disaggregation of different household types, as on average all households lose through climate change, which does not represent the variances between household types and would not reflect that some even gain from climate change. Yet, this is important to target climate change vulnerability policies to the households most in need.

2.5 Summary and conclusion

We assess the effects of yield shifts induced by climate change on low and lower-middle-income countries in terms of the economic changes (production, trade, demand) and of the welfare of nine household types distinguished by level and source of income in 2050. To this end, we apply a recursive dynamic CGE model with household detail, which draws on the SSP2 projections for GDP per capita, population and workforce data, and include yield shifts for 8 crop aggregates. Additionally, we perform a sensitivity analysis to test the robustness of the results, considering the uncertainty of the effects of the climate change on yields and a comparative static analysis to disentangle the difference to our dynamic long run model. The results show that effects vary between the nine household types and that not only the level of income is of relevance for the vulnerability to climate change but also the factor endowment. We show that agricultural households are both absolutely and relative to their income in most cases the least affected ones and that richer households face absolutely larger effects; while relative to their income the poor are the most affected. The sensitivity analysis shows that results are robust and that the yield shock on the staple crops largely determine the effect on the households (especially for the poor).

Thus, it is important to disaggregate the yield shifts and different household types and to take not only income levels, but also other aspects such as agricultural income share into account. Various studies have identified that higher food prices can benefit agricultural households. In addition, our modeling framework gave new insides, especially into the long run development. It shows both under- and overestimations of vulnerability for some household types in a comparative static analysis with an otherwise identical model set-up. This is a consequence of missing key dynamic developments in comparativestatics, such as varying importance of sectors, sector specific productivity growth, and income dependent consumption change.

Our results stress the need for a differentiated assessment of climate change impacts, considering regional and household differences. The results, even if limited to three countries and to nine household groups, emphasize quite divergent income impacts of climate change induced yield shifts across households, with ownership to land as one key determinant. Across countries, consequences were found to be comparable, while remaining differences show the need for country- and household-specific strategies and support, considering regional priorities for mitigation and land reforms.

2.6 Acknowledgement

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Chapter 3
Distribution matters: Long-term quantification of the Sustainable Development Goals with household detail for different socio-economic pathways[1]

Abstract

Knowledge about upcoming sustainability challenges is crucial to tackle them by political incentives, not at least to reach the United Nations' 17 Sustainable Development Goals (SDGs). SDGs are multidimensional and require detail beyond an aggregate household approach to assess income inequality and other differences across households in transformative processes. Incorporating these aspects, we develop an SDG indicator framework for dynamic Computable General Equilibrium Models with a total of 68 endogenous indicators related to 15 SDGs. This enables a more differentiated assessment of the SDGs in forward looking analysis compared to existing approaches, by considering additional SDG indicators and household level detail based on micro-simulation. We apply the

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indicator framework in a global analysis of 3 Shared Socioeconomic Pathways (SSPs) until 2050 with a focus on selected low- and lower-middle income countries from different continents. The analysis finds sustainability gaps by 2030 and 2050 for all focus countries, especially in the environmental domain. In none of the analyzed SSPs, all indicators develop in the desired direction, underlining trade-off among and within SDGs, but also across the SSPs. Based on household detail, we find increasing inequality over time for several indicators regardless of developments at average aggregate household level, pointing at the need for targeted redistribution and compensation policies. These results highlight the importance of including distributional aspects and disaggregated data in policy and socioeconomic development studies.

Keywords: Sustainable development goal, Computable general equilibrium model, household level detail, microsimulation, indicator quantification

3.1 Introduction

To address multidimensional aspects of human and planetary well-being, the United Nations' (UN) Member States agreed in 2015 on the so-called Agenda 2030 with 17 Sustainable Development Goals (SDGs) to be reached in 2030. These goals and their associated targets are strongly interlinked, leading to synergies and trade-offs among them (e.g., Refs. [1-5]). A wider range of literature assesses the advancements towards these goals (e.g., Ref. [6]), or develops approaches for their quantification (e.g., Refs. [7-9]). The degree to which the SDGs will be reached depends on complex interactions, including socio-economic and demographic dynamics, governance and climate change. Modelling these dynamics in ex-ante assessments can inform society how policies affect the different SDGs. Suitable tools need to capture interactions between economic variables including production, demand, income and prices, to acknowledge global interrelations and to quantify indicators for the different SDGs. For this task, multi-regional dynamic Computable General Equilibrium (CGE) models are well suited due to their multi-sectoral and global perspective. Furthermore, their recursive-dynamic nature permits them to capture relevant societal and economic adjustment processes in the long-run following exogenous macro-economic projections such as the shared Socioeconomic Pathways (SSPs [10]).

For quantification of SDGs in CGE analysis, indicator frameworks processing model outcomes are partly available. For example, Campagnolo et al. [11] quantified 23 individual indicators based on the results of their CGE model, from which they calculated country-level composite indicators (FEEM SI) to assess progress toward the SDGs. Philippidis et al. [12] used a CGE model to depict synergies and trade-offs between SDGs under different development pathways. Using the MAGNET SDG Insights Module (that captures indicators linked to 13 SDGs), they selected 12 indicators related to 7 SDGs for this assessment. Liu et al. [13] conducted a CGE analysis on the potential achievement of SDGs using the SSPs projections combined with climate policy assumptions, quantifying indicators related to 5 SDGs.

While CGE models will never capture the full multi-dimensionality of the SDGs, existing indicator work still misses some SDGs and targets that can be quantified from model results. To the authors knowledge, distributional impacts regarding income, food security and equality, have not yet been covered in SDG-related CGE model analysis. This reflects that suitable household level data are often scarce and their consistent link to CGE modelling challenging. However, several SDG indicators specifically focus on the distributional aspects (e.g., SDG1 “No Poverty”, SDG2 “Zero hunger”, SDG10 “Reduced inequalities”). To advance here, we develop and apply a post-model micro-simulation approach, on harmonized household level data from FAO [14] available for low- and lower-middle income countries. This data fits the special attention paid to low- and lower-middle income countries in the Agenda 2030 and allows to cover countries from different continents.

In addition to the household heterogeneity, this work addresses research gaps by adding more detail in the sectoral coverage and by quantifying results for single countries in a global model [15] rather than regional aggregates. Specifically, we disaggregate the agri-food sectors and incorporate nutrient accounting in diets to address substitution and to capture aspects in many SDGs [16] where detail so far was missing. Another contribution of this work consists of adding heterogeneity gender differentiated labor categories in the model allowing for further extension of the SDG coverage in the developed indicator framework.

The extended indicator framework is applied to the three baselines SSP1, SSP2, and SSP3 to quantify developments of the SDGs for selected low and lower-middle income countries. We link our work to the SSPs which provide narratives of broad future scenarios of the global economy, focusing on developments relevant for climate change [10]. These narratives are quantified into projections of income (real Gross Domestic Product, GDP) [17], demography and educational attainment levels and made available to the international research community[2]. Applying this data with further scenario specific assumptions, we assess the SDG achievement both until 2030 and 2050.

3.2 Methodology

3.2.1 *Database development*

We depart from the GTAP-Power Data Base Version 10 [18] which extends the GTAP Data Base [19] commonly used for global CGE analysis with detail for power generation[3], which allows quantifying the contribution of renewable energy production and improves climate change emission accounting. With 76 sectors, it presents a snapshot of the entire global economy in 2014, reporting economic transactions in USD for a total of 141 countries and regional aggregates. Available extensions such as greenhouse gas (GHG) emissions factors [20] and air pollution [21] linked to production and trade are also incorporated in the database. To provide further detail for our SDG indicator framework presented in Section 3.2.4, we extend this database by splitting the initial data in three steps as depicted in Fig. 3.1 drawing on the method developed in Britz [22]. In the first step ("Split 1"), we introduce high detail for agri-food sectors based on the FABIO MRIO [23] and FAO [24] data as detailed in Britz [25]. This adds 34 agri-food sectors, improving the assessment related to food security, nutrition and land use. In parallel, we add data on gender differentiated labor, provided from the World Bank [26], to differentiate labor by male and female for skilled and unskilled, respectively. 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 (Table A.3.1

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

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

lists the regional aggregation). To set the regional focus on countries that are specifically targeted in the Agenda 2030, ten of the single countries represent low- and lower-middle income countries for which uniformly structured household surveys are available (see subsection 3.2.3). This step results in the intermediate data base termed FABIO_DB in Fig. 3.1.

Detailed references to the sources can be found in the text. Source: authors own.

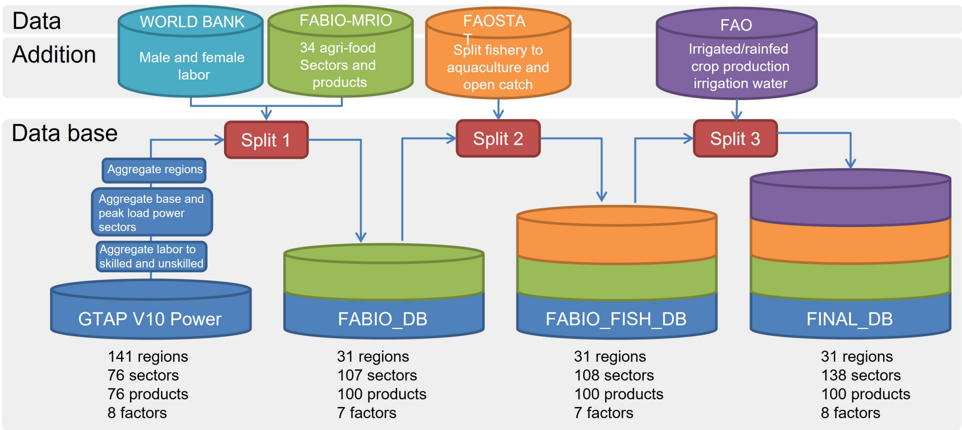

Figure 3.1. Overview on the generation of the final database.

The second step ("Split 2") splits the fisheries sector into open catch and aquaculture using FAOSTAT [27] data on production quantities of open catch and aquaculture, providing the second intermediate database FABIO_FISH_DB. A final third step ("Split 3") introduces irrigation water as a production factor and related resource depletion. It uses a data set by the [24] to split up crop activities into a rainfed and irrigated variant, similar to earlier work by Ref. [28]. This provides the final data base (FINAL_DB) with 100 products, 138 activities and 8 primary factors (capital, male/female skilled labor, male/female unskilled labor, natural resources, land, irrigation water) for 31 regions.

3.2.2 *CGE modelling framework and model set-up*

The model employed is configured in the flexible and modular platform for CGE modelling CGEBox [29-30]. Its core consists of the widely used GTAP Standard Model version 7 [31] realized in GAMS by van der Mensbrugghe [32]. It employs the usual assumptions of CGE analysis: competitive markets for products and factors, utility-maximizing consumers, cost-minimizing firms operating under constant returns-to-scale and revenue-maximizing factor supply. Drawing on the modularity of CGEBox, we add further model components relevant to quantifying SDG indicators. This includes detail in land use, incorporated based on the GTAP-AEZ (agro-ecological zones) data [33] and model [34]. Elements of the GTAP-E model [35] improve the presentation of energy use, while features from GTAP-AGR [36] consider specifics of agri-food sectors. More detail on CGEBox can be found in the Annex A3.1.1.

While income and population growth broadly shape many SDGs, details depend on structural changes. Addressing these details requires a framework that considers besides broad macro developments also relevant structural change processes and its consequences for agri-food sectors, here provided by the G-RDEM module [37] realized in CGEBox. It reflects the interaction of multiple supply and demand side drivers, including changes in primary factor stocks, technology, and final demand patterns. G-RDEM is specifically developed for long-term baseline construction and analysis, and extends the standard GTAP model [38] by the following features.

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 [37, p. 64-69], and its debt accumulation mechanism from foreign investments [37, p. 69-70]. The used stock of labor by skill force follows projections provided for each SSP taken from the IIASA SSP portal.

During the constructions of our three baselines (see Fig. 3.2), G-RDEM uses exogenous projections for real GDP, population, demography, and workforce based on the narratives of SSP1, SSP2 and SSP3 [10]. Based on these exogenous developments, the model is solved for a simultaneous equilibrium in all commodity and factor markets globally at each period t. As it is typical of recursive dynamic models, net investments from step t update the capital stocks at t+1. Extending this, saving rates, input-output coefficients, population size and labor stocks by skill level are also updated between periods depending on income and demographic developments. During the process, sector-specific productivity shifters adjust, reflecting the change in aggregate total factor productivity needed to replicate the given trajectory of real GDP. 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 [37, p. 61-63]. Specific productivity changes for crop and livestock products recover crop yield and crop land forecasts by FAO [24], while built-up land is driven by GDP growth and changes by urbanization and population density, based on empirical work similar to Chen et al., [39]. Additionally, input-output coefficients in G-RDEM are not static, but are updated instead depending on projected income growth [37, 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 [40] which motivates the use of the rank 3-MAIDADS (Modified An Implicit Additive Demand System) demand system estimated by [41]. 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 [42]. Equally, expenditure shares for investment and government demand are rendered income dependent in G-RDEM which is solved in bi-yearly steps from the 2014 benchmark year until 2050.

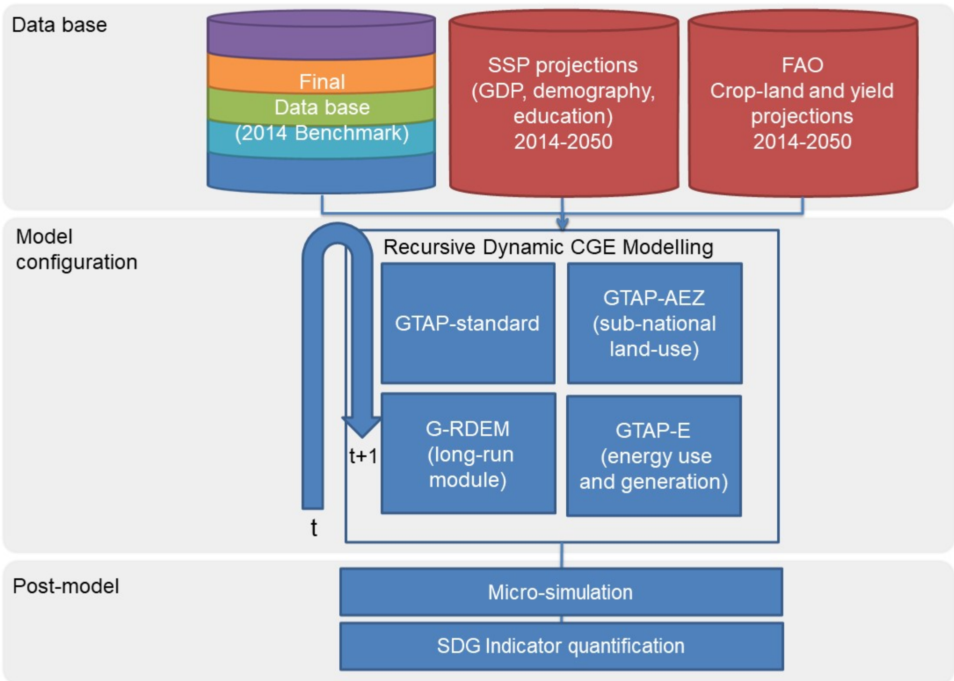

Figure 3.2. Overview on the recursive dynamic modelling approach. Source: authors own.

3.2.3 *Post-model micro-simulation: adding household level detail*

CGEBox, as the standard GTAP model, considers only one representative household in each model region. Using multiple ones instead can better inform on links between economic growth, structural change, and well-being [43]. Households can, for instance, be differentiated by urban and rural as well as the size of owned land [44], income levels and the households' links to agricultural and non-agricultural sectors [45] or by a combination of income, rural or urban and gender [46]. Micro-simulation allows for a far richer analysis by depicting many different households of a population, revealing detail beyond average effects at country or aggregate household level.

Structural change affects households both on the income and consumption side. Top-down micro-simulation consists of projecting earnings and spending for each household in the survey based on aggregate model results. The "Data Portrait of Small Family Farms" [14] is used here. It provides data for 19 low- and lower-middle income countries from which ten (Nigeria, Ghana, Kenya, Nicaragua, Bolivia, Vietnam, Indonesia, Malawi, Ethiopia, and Bangladesh) are chosen to keep the assessment manageable. The selection covers different continents and the latter three countries are classified as least developed countries (LDCs; [47]) for which partly more ambitious SDG targets are defined. Each survey covers tens of thousands of households along with their aggregation weights.

The income positions provided by the FAO [14] for the base year are updated post-model for each report year and individual household until 2050, based on simulated changes in factor stock, prices, transfers, and taxes. The household survey data provides besides income levels also income shares for self-employment and wages by different sectors and skill levels, from crop and livestock production, from public and private transfers, plus a residual category. As a first step, initial FAO income shares of the first four income sources are used to derive share parameters of a CET (Constant Elasticity of Transformation) function, from which price and quantity indices are calculated. These are then updated based on CGE model results. To do this, the definitions of sectors and skills from the household survey are mapped to the more detailed ones in the CGE model to update single household results (see Table A.3.2 in the Annex). Here, for wages, changes in factor returns to labor by skill category are used. For example the skilled wage income category stemming from agricultural production is linked to the respective labor category of all agricultural sectors in the Social Accounting Matrix. For other sectors a direct mapping to the skill category of a single GTAP sector is made. The same sectoral mapping holds for the other factor incomes (i.e., self-employment and crop and livestock production), while here changes in all factor returns are considered, i.e., labor, land, capital, and natural resources. From there, the CET function determines each household's new factor allocation, assuming a transformation elasticity of five [30]. Resulting incomes by factor are then scaled, considering household-specific aggregation weights, to exhaust economy-wide totals (see Annex A3.1.2).

The remaining sources of income are updated as follows: Income derived from public transfer at country level are linked to changes in total tax income; Income derived from private transfer, including remittances are shifted in line with country level changes in total private consumption; Income derived from the 'other' position, are adjusted following changes in regional income [30]. Finally, we assign to each household a share of total government consumption according to the number of household members while household specific saving rates are estimated based on the regression coefficient used in the G-RDEM excluding negative savings or values that exceed 50% of income.

Since the household survey misses information on spending, consumption patterns are estimated and updated based on the exponential Engel curves of the MAIDADS demand system as applied in CGEBox [41]. Specifically, an estimated relation derives a utility metric from each household's income in every year. This metric determines household-specific parameters of the demand system, which estimate the demands at given prices and the household's income. Demands are then multiplied by nutrient contents to derive daily per capita calories, protein, and fat intakes.

For reporting, we aggregate the micro-simulation results for the several thousand households in each country to 500 percentiles based on income per capita, to calculate metrics such as the Gini Index to characterize the income distribution. Further detail on the micro-simulation provides the model documentation ([30], pp. 109-116).

3.2.4 *Indicator collection and implementation*

The starting point for the indicator development and choice in this study provides a literature review of the studies [11-13] that used CGE models to measure SDG indicators in future pathways provides. Not all indicators found in these studies could be quantified based on our database[4]. Others were dropped as they are exogenous to our model; some were excluded due to the different focus of this study. We also explored potential indicators in studies that quantify SDGs in other model types, such as Integrated Assessment Models (e.g., Refs [48-49]).

The next step scanned the 169 SDG targets and the related indicators (231) published by the UN [50], the indicators used by the FAO to measure food security [51] and the ones applied by Sachs et al. [52]. Our study excludes targets that are qualitative, addressing inter alia means of implementation, such as legal frameworks. Remaining indicators were checked for data availability and compatibility with CGEBox. We discard indicators solely based on exogenous drivers, following Campagnolo et al. [11].

In total, our indicator framework, quantified based on results from CGEBox, covers 68 indicators linked to 15 SDGs. Here, we briefly discuss the additional indicators not found in the CGE-based SDG studies so far, see also in Fig. 3.3, with a focus on their data requirements. The complete list of 68 indicators can be found in the annex (Table A.3.3). Employing the GTAP standard model and using the GTAP V10 Data Base allows to quantify two indicators so far not calculated in CGE analysis, which are "Proportion of total government spending on essential services" (UN indicator 1.a.2, SDG1 'No Poverty') and the FAO Food Security Indicator: Cereal Import Dependency Ration (Stability Domain) for SDG2 'Zero Hunger' [51].

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[4] These include for example corruption, waste and the share of endangered animals or plants from Campagnolo et al. [11] or the ration of rural wages to cereal prices and the difference between agricultural and non-agricultural wages from Philippidis et al. [12].

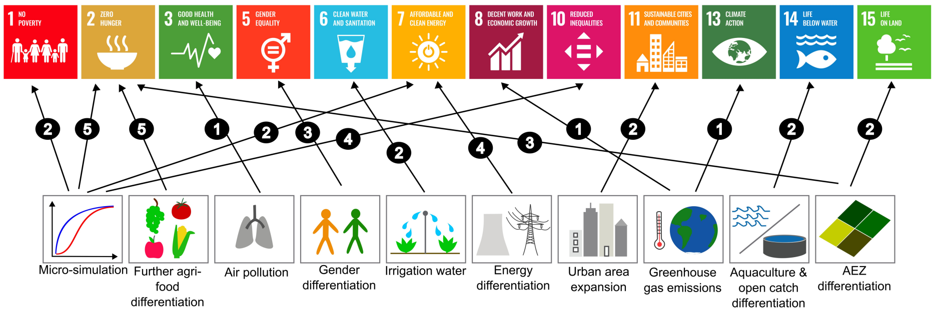

Figure 3.3. Number of new indicators by data source and link to the respective Sustainable Development Goal.

The arrows indicate the link between the data and the Sustainable Development Goal with which the indicators are associated. The number in the black circles represents the new indicators calculated from the data source. The total number of indicators quantified is sometimes larger. Source: authors own.

Adding the auxiliary data available from the GTAP Center (AEZ, non-CO2 emissions, air pollution) as well as the details in electricity generation from GTAP V10 Power allows to quantify (additional) indicators for six SDGs. Specifically, we add (1) partial productivity for different crop groups, linked to SDG2 ‘Zero Hunger’, (2) a human health hazard indicator, calculated from 4 different air pollutants,[5] following the characterization factors for human health of ReCiPe [53], linked to SDG3 ‘Good Health and Well-being’, (3) the share of total biomass that flow into energy production, linked to SDG7 ‘Affordable and Clean Energy’, (4) the decoupling of GHG emissions growth and environmental degradation of economic activity, linked to SDG8 ‘Decent Work and Economic Growth’, (5) the CO_2 emissions embodied in fossil fuel exports, linked to SDG13 ‘Climate Change Action’, and (6) the share of unmanaged forest and the intensification (stocking rate) of grassland, linked to SDG15 ‘Life on Land’.

The additional detail in our base (FINAL_DB in Fig. 3.1) allows quantification of indicators for five additional SDGs and additional ones related to three SDGs (see Fig. 3.3), drawing on gender-differentiated labor and its agri-food detail, including the differentiation into rain-fed and irrigated crops and the disaggregation of fisheries to open catch and aquaculture. Micro-simulations deliver indicators for five SDGs by assessing distributional impacts, adding indicators not found in

[5] With the pollutants being Ammonia (NH3), Sulfur dioxide (SO2), Nitrogen oxides (NOx) and Particulate matter 2.5.

existing CGE analysis. For the representation of SDG1, for instance, we quantify indicators that address income distribution, namely household income per capita and the share of the population living below international poverty lines ($1.90 and $3.20), included in the UN official indicators (1.1.1). Concerning SDG2 'Zero Hunger', the share of total expenditure spent on food per household per capita links to food security, while calories, protein and fat consumed per capita per household indicate the level of malnutrition. Dietary diversity, i.e., the share of different food groups in total food consumption, further quantifies SDG2. Food groups from Kennedy et al. [54][6], here slightly adopted, allow to calculate the Shannon Index both for the income spent on these food groups and the calories derived from their consumption. Further, we implement as indicators for SDG7 'Affordable and Clean Energy' the households' budget share spend on energy and electricity. To address equality issues, we apply the SDG10 'Reduced Inequalities' 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, as well as the share of the population living below 50% of the national median income (listed as indicator 10.2.1). Regarding SDG5 'Gender Equality', the gender labor price gap and the share of female versus male labor per sector serve as indicators. For SDG6 'Clean Water and Sanitation', the water use per total output of agricultural production links to the target of increased water use efficiency. The nutrient information also allows to calculate the share of total calories used as input for energy production linked to SDG7. Addressing SDG11 'Sustainable Cities and Communities', the "ratio of land consumption rate to population growth rate" (UN indicator 11.3.1) is calculated. From the differentiation of open catch and aquaculture production, we finally calculate the share of fish demand derived from open catch for SDG14 'Live below Water'. Solely, SDG4 'Quality Education' and SDG16 'Peace, Justice and Strong Institutions' could not be quantified.

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[6] 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.

3.2.5 *Scenario definition until 2050*

The baselines for SSP1, SSP2, and SSP3 incorporate the projections of demographics and GDP, educational attainment, and the urbanization rate by Riahi et al. [10], and consider matching crop yield projections from technological progress by FAO [24]. Furthermore, in line with the underlying narratives, we add own assumptions for each SSP on meat consumption as well as on CO_2 prices and related energy-saving technical progress (see Table A.3.4 for detail). Given the sustainability narrative of SSP1, CO_2 price assumptions and percentage meat consumption reduction are higher than in SSP2 as the business-as-usual scenario. Our SSP3 baseline does not comprise changes compared to the 2014 benchmark for these exogenous drivers but considers increases in tariffs (except for intra-EU trade) and a preference shift towards domestic production, reflecting the 'regional rivalry' character of SSP3. To capture the first order effect of these differences in baseline developments, we refrain from including any redistribution policies in the three baselines. The given projections and these assumptions drive the baselines in CGEBox at the full level of the final database in bi-yearly steps from 2014 until 2050. These model outcomes allow us to calculate the 68 indicators which assess how SDG achievement develop until 2030 and 2050.

3.3 **Results**

This section is structured along the so-called SDG 'wedding cake' [55], which groups the SDGs into the economy, society, and biosphere-related goals, with SDG17 being described here in the 'economy' subsection, see Table 3.1. SDG indicators outcomes are presented under the assumptions of SSP1, SSP2 and SSP3, and where available, compared to target values or ranges in 2030 and 2050 from the UN [50] and other literature [49, 52]. Results for 2030 can be found in Figure B.3.1-B.3.3, target values applied are listed in Table A.3.3. Result graphics show an improvement in an indicator always as green, irrespective of whether this implies a reduction (as for emission) or an increase (as for income) in the indicator value, shown by the two scales of the color bar. All indicators are additionally marked with an arrow indicating the desired direction. If indicator outcomes fall outside the color range of the heatmaps, values are shown as annotations, i.e. as numbers in the respective cell.

Table 3.1. SDGs grouped following the ‘wedding cake’ scheme as presented graphically in Folke et al. [55].

SDG17: ‘Partnership for the Goals’		
Biosphere	Society	Economy
SDG6: ‘Clean Water and Sanitation’ SDG13: ‘Climate Action’ SDG14: ‘Live below Water’ SDG15: ‘Life on Land’	SDG1: ‘No Poverty’ SDG2: ‘Zero Hunger’ SDG3: ‘Good Health and Well-being’ SDG4: ‘Quality Education’ SDG5: ‘Gender Equality’ SDG7: ‘Affordable and Clean Energy’ SDG11: ‘Sustainable Cities and Communities’ SDG16: ‘Peace, Justice and Strong Institutions’	SDG8: ‘Decent Work and Economic Growth’ SDG9: ‘Industry, Innovation and Infrastructure’ SDG10: ‘Reduced Inequality’ SDG12: ‘Sustainable Consumption and Production’

3.3.1 *Biosphere results*

Fig. 3.4 maps the relative change from the base year 2014 to2050 for biosphere-related indicators per study country and SSP. They show similar trends across the three SPPs, but of different magnitudes. Regarding SDG6 ‘Clean Water and Sanitation’, increases in water demand for irrigation in 2050 are projected for all countries and SSPs, driven by growing food production. However, as factor productivity improves, less water is generally needed per agricultural output over time, implying a positive development towards Target 6.4, addressing water use efficiency in all sectors.

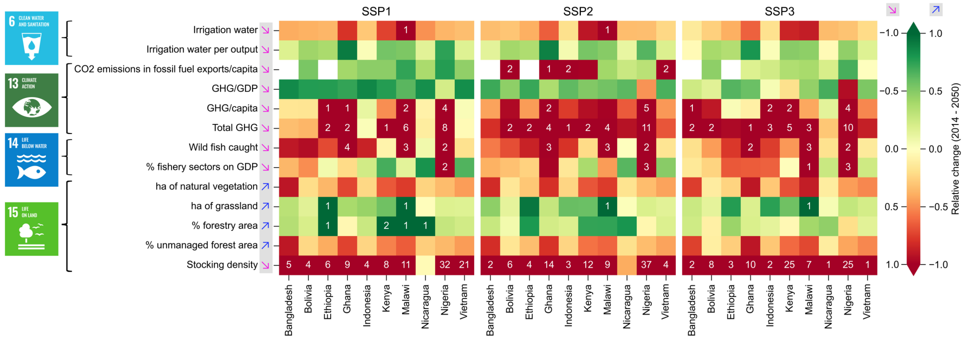

Figure 3.4. Heatmap of Sustainable Development Goal indicators quantified in the biosphere layer in terms of their change until 2050.

Indicators are abbreviated for better readability; complete full information can be found in Table A.3.3 in the annex. The color bar is fixed to values between 1 and -1; exceeding values are shown as numbers in the respective cell. All indicators show improvements as green and regressions as red, while the pink and blue arrows indicate the desired direction. Source: model results.

Strong output expansion in all SSPs and countries translates into higher total and per capita GHG emissions associated with SDG13, ‘Climate Action’. SSP1 results in the lowest increases, with substantial deteriorations only observed for the five African countries. In the other two SSPs, most countries’ total GHG emissions increase strongly. Exemptions exist, in Nicaragua where emissions decrease most per capita in SSP3. The GHG emission intensity per unit of GDP tends to decrease, with only Nigeria (SSP2 and SSP3) and Kenya (SSP3) showing increasing intensities. Likewise, lower CO_2 emissions linked to fossil fuel exports per capita are found for most countries, except for SSP2, however they missing the target value of zero set by Sachs et al. [52] in 2050. The medium-term prospects are even bleaker, as in 2030 some countries show deteriorations in all three SSPs (Figure B.3.1). The strong increase in total GHG emissions stands in contrast to current ambitions to limit climate change and overshadows improvements on a per capita or GDP basis.

The two indicators linked to SDG14: ‘Live below Water’ generally worsen. Especially, for three African countries, namely Ghana, Malawi, and Nigeria wild fish catch keeps on expanding strongly until 2030 and 2050, which would hamper the targeted reduction to prevent overfishing. Solely Nicaragua in SSP1 and SSP2 shows the desired trend of reduced open catch. Surprisingly, despite the assumed preference shift away from fish and meat consumption in SSP1, it does not show the lowest levels of open catch. The reason is that solid income elasticities for fish and meat dominate over the preference shifts, as SSP1 projects the smallest population in tandem with the highest GDP growth for most countries. However, the lowest share of fishery sectors on GDP over time is found under SSP1 assumptions for most countries, with some countries even reducing the share, as other economic sectors grow stronger.

Similarly, adverse developments for indicators associated with SDG15 ‘Life on Land’ emerge. While directions are similar among SSPs, changes differ in magnitude mainly for forestry shares and stocking densities. Total hectares of natural vegetation show downwards trends in all countries and SSPs. Substantial percentage reductions are observed predominantly in Bangladesh, Ghana, and Malawi, also due to their low initial area. Conversion of natural land is funneled by the increased food and feed demand of a growing and richer world population. It is mainly observed in the five African countries where population growth is much higher than in the other countries. To meet rising meat demand in all countries and SSPs, grasslands expand and are managed more intensively as seen from higher stocking densities, rendering a positive contribution of these areas to biodiversity conservation unlikely. The share of unmanaged forest as part of natural vegetation decreases while managed forestry mainly expands in all SSPs (Indicator 15.1.1).

3.3.2 *Society results*

As seen from the first line of Fig. 3.5, the macro projections assume growing average incomes per capita for all regions, especially in SSP1. To assess if this improves SDG1 ‘No Poverty’, the shares of households living on less than 1.9$ per day per capita and less than 3.2$ per day per capita are quantified. In SSP1, we project the best progress. All countries except Malawi reduce the population share below the poverty line of 1.9$ by more than 90% to (almost) zero by 2050, reaching the goal to eradicate extreme poverty (Target 1.1), however, mostly not yet in the target year 2030. Solely Malawi and Ethiopia do not reach zero households living below 3.2$ per day per capita by 2050 under SSP1. In SSP2, more countries miss the targets, with meager improvements in poverty shares for the three LDCs, while SSP3 generally leads to the highest shares of poor, with only two countries (Bolivia and Indonesia) achieving the target in 2050, however, not yet in 2030.

Figure 3.5. Heatmap of Sustainable Development Goal indicators quantified in the society layer in terms of the relative change to 2050.

Indicators are listed in a brief form, for better readability, full information can be found in Table A.3.3 in the annex. The color bar is fixed to values between 1 and -1, exceeding values are shown as numbers in the respective cell. All indicators show improvements as green and regressions as red, while the pink and blue arrow indicate the desired direction. Source: model results.

Total governmental expenditure on essential services (including the health, security and education sectors) rises over time, while their budget shares remain constant in all SSPs, except for minor improvements observed in Vietnam and Kenya. However, in 2014, these sectors already encompass the major share of the government expenditure in all countries, indicating that the UN target for SDG1 to “ensure significant mobilization of resources” for these essential services would be met by 2030 and 2050. Thus, in terms of SDG1 we see a clear positive trend until 2050 in all SSPs.

Trends of indicators related to SDG2 ‘Zero Hunger’ are more ambiguous. Higher food prices, except for Nigeria and Vietnam in SSP2, reflect strong demand growth per capita in tandem with limited land resources. Nevertheless, food budget shares decline primarily due to the higher income per capita, especially in SSP1. In terms of eradicating hunger, we observe the desired increase in food consumption for almost all income quantiles in the distributional graphs (see Figure B.3.4). In general, SSP1 results in the highest consumption per household with the lowest budget shares for food, while SSP2 and SSP3 lag. The graph also indicates that the inequality of food consumption is simulated to increase. This is especially found for some outliers in the upper values in SSP1 for the majority of the countries. Figure B.3.5 showing the distribution of the budget shares indicates mostly higher equality. Regarding food security, advances are projected since more nutrients are consumed per capita in all countries, except for slight decreases in calories intake in Bangladesh and Ghana in SSP3. By 2030, calories intake is higher on average in all countries, compared to 2014, developing towards eradicating undernourishment. At household level, the distributional graphs (Figure B.3.6-B.3.8) show that the scenarios develop similarly regarding the rising nutrient intake, with SSP3 showing the lowest nutrient uptake in most countries and some strong outliers in the upper right end of the distribution. For some countries, we observe lower calorie intake in the left end of the distribution than in 2014, especially in SSP3, indicating a shift towards less calorie-intensive food consumption. In contrast, average expenditure-weighted food diversity is generally lower in 2050 in all SSPs, with SSP1 projecting the smallest shares for seven countries. Thus, households distribute food expenditure more unequally, focusing their income on fewer food groups. The related distributional graphs (Figure B.3.9) reveal that food diversity values mostly become more equal and that, in six countries, parts of the households still diversify food consumption in terms of expenditure over time. Regarding calorie-weighted food groups most countries diversify consumption, with Bolivia showing a decline. Again, the distributional graphs (Figure B.3.10) suggest higher equality is achieved over time, particularly in SSP1. As an additional aspect of food security, the share of imported cereals on total cereal demand is assessed. Most countries become more dependent on imports in all SSPs thus more vulnerable to trade shocks. Under SDG2 ‘Zero hunger’, also goals for agricultural productivity are set, which show improvements in all SSPs, as depicted in Fig. 3.5. However, Target 2.3, to double the average productivity of food producers by 2030, is met by Nigeria for the aggregate ‘export crops’ and Bolivia for ‘other crops’ only in SSP1 (Figure B.3.2).

By 2050, more countries reach the target for other crop groups as well, in particular in SSP1.

Air pollution related to domestic and imported products strongly increases over time. Of the air pollutants mapped in Fig. 3.5, the strongest deteriorations are projected for Ethiopia, Kenya, and Malawi, under SSP1. While for the other countries (except for Ghana), it generally rises least in SSP1. Likewise, the indicators of human health hazards (results for Ammonia, Sulfur dioxide, Nitrogen oxides, and particulate matter 2.5 can be found in Figure B.3.11**)** develop negatively, compared to the base year for all countries and SSPs, indicating a development away from achieving SDG3 'Good Health and Well-being'.

The gender wage gap, associated with gender equality under SDG5 'Gender Equality', shrinks until 2050 for the skilled labor category, except for Nicaragua, Malawi, and Bangladesh in SSP3, meaning that wages of female workers increase more vital towards 2050. This reflects that male skilled labor, owing to higher years of schooling, is growing stronger. In terms of the unskilled labor, the projections show instead a higher gender wage gap for the majority of the countries in all three SSPs. The ratio between female and male workers decreases over time because the share of the male population with no education decreases faster until 2050, thus, more male labor generally is available over time.

Energy gets more affordable over time, which relates to SDG7 'Affordable and Clean Energy', with only four countries in SSP3 projecting higher prices by 2050. Nevertheless, half of the average households spend a higher budget share on energy over time, especially in SSP1. The distributional graphs (see Figure B.3.12) show more similar budget shares across the household percentiles compared to 2014. The energy budget share is still less relevant than the food budget share for all households. From a sustainability perspective, energy sourcing is of great relevance. While shares of renewables in the energy mix should increase (Target 7.2), the opposite is found for SSP1 where the share of electricity from renewables in total electricity consumption shrinks and more is produced from fossil fuels (Fig. 3.5). This is also primarily found in SSP2. In contrast, in SSP3, developments are (mostly) in line with the target. However, Ethiopia, as the sole country, reaches the optimal value listed in Sachs et al. [52] with a share above 51% (but here it is calculated for total electricity, not total energy).

Similar trends among the SSPs are observed for the share of fossil fuels in total energy demand in the three scenarios. It might be seen as positive that a larger share of total biomass produced tends to flow into the energy sector over time. In SSP1, despite this trend, a smaller proportion of the total calories produced flow into the energy sector in Indonesia and Vietnam, while Bolivia is projected to expand the share. In contrast, in SSP3, for all countries, stronger competition between food and energy production is projected in 2050, while in SSP2 the calorie share used in the energy sector declines in Indonesia. For most countries and SSP1, a higher share of electricity and energy is produced domestically, indicating less dependency on energy imports which is interpreted as a positive development towards energy self-sufficiency. SSP1 is generally the least energy-intensive scenario of all three SSPs, with the lowest mega tons of oil equivalent per real GDP. This reflects the assumption of strongly increasing carbon taxes over time which provoked additional energy savings in SSP1. In this scenario and SSP3, the target proposed by ICSU and ISSC [1] of improving energy intensity of GDP by at least 2.9% annually would be met by four countries over the 36 years.

Urban area expands over time in all countries and SSPs, with some countries doubling urban area until 2050 (see Fig. 3.5) due to the projected exogenous GDP and population growth, and the rising share of urban population projected for all SSPs. However, the urban area grows generally less than overall population growth (Indicator 11.3.1, SDG11 'Sustainable Cities and Communities'), both until 2030 and 2050, representing higher population densities in cities. In particular, under SSP1 assumptions, since here, none of the countries shows a contra-trend.

3.3.3 *Economy results*

Fig. 3.6 summarizes the SDG indicators linked to the economic layer of the 'wedding cake'. Following the exogenous SSP projections, real GDP per capita and per employed person rise over time, indicating progress towards SDG8 'Decent Work and Economic Growth'. However, Target 8.1 states that in LDCs real GDP per capita should grow by at least 7% annually through 2030, which none of the SSPs would accomplish, although SSP1 is closest to the target. GDP growth is accompanied by at least half of the countries in all SSPs by a decreasing share of total agricultural labor, which is associated with economic development and depicts technological progress. Furthermore, decoupling GHG emissions growth (included in Target 8.4) from economic growth in 2050 for six countries in SSP1 and SSP2 adds a further positive dimension to this development. Nevertheless, for the others, we observe substantial intensification in terms of GHG emissions. In SSP3, none of the countries decouples economic growth from emissions, which generally matches the results of SDG13 in Subchapter 3.3.1.

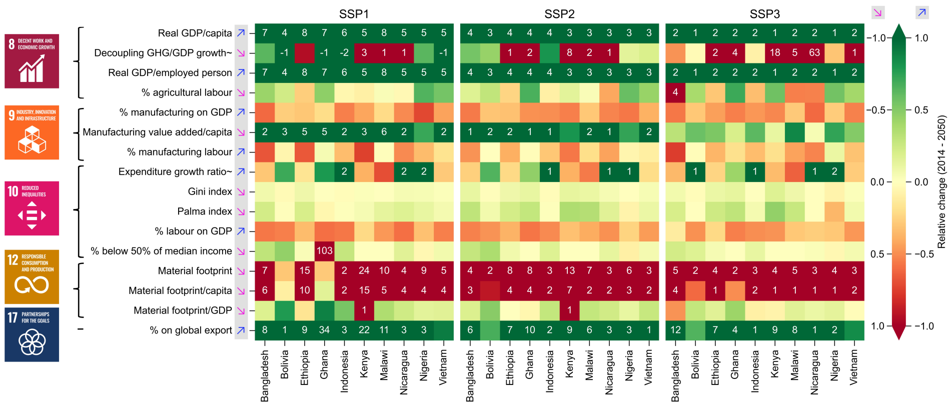

Figure 3.6. Heatmaps of Sustainable Development Goal indicators quantified in the economy layer in terms of the relative change to 2050.

Indicators are abbreviated for better readability; complete full information can be found in Table A.3.3 in the annex. The color bar is fixed to values between 1 and -1; exceeding values are shown as numbers in the respective cell. All indicators show improvements as green and regressions as red, while the pink and blue arrows indicate the desired direction. Source: model results.

The targets of SDG9 ('Industry, Innovation and Infrastructure') indicators "manufacturing value added as a proportion of real GDP and per capita" and "manufacturing employment as a proportion of total employment", are to increase the shares substantially and to double them in LDCs by 2030. In all three baselines, both the shares of manufacturing on GDP and total employment regress from these targets over time in all countries. Since, in general, the service sectors, the grains and crops sectors, and the meat and livestock sectors contribute, on average, larger shares to the total value-added. In turn, the manufacturing value added per capita shows a positive trend in all countries and SSPs (most in SSP1) up to 2050, reaching the target for all three LDCs in SSP1 and SSP2 albeit not by 2030.

We observe from Fig. 3.6 that countries mostly become more equal over time (focused on SDG10: 'Reduced Equality'). For example, a lower share of the people lives below 50% of the median income in 2050 for all countries but Nigeria in all SSPs, both until 2030 and 2050, with Bolivia improving only until 2050. A strong outlier is Ghana in SSP1 and 2050 only. Given this strong regression in Ghana in SSP1, here the Palma Index (i.e., the share of income owned by the bottom 40% relative to the one owned by the upper 10%) also worsens over time until 2050, while in the other two SSPs a rising Palma index is projected. Improvements are generally highest in SSP3 per country, with the lowest changes being projected for SSP1. Until 2030, considerably more countries show a higher Palma Index. Despite the improvements observed in most countries until 2050, none reaches the target value set by Sachs et al. [52] of a Palma index of 0.9. Similarly, the Gini coefficient also improves over time for most countries, with none reaching the optimal value for this indicator set by Sachs et al. [52] to 27.5 neither in 2030 nor in 2050. In fact, under some SSPs in Bolivia, Indonesia and Nigeria, the Gini index even worsens until 2050. Similar countries already develop away from the target until 2030 (Figure B.3.3). Target 10.1 addresses household expenditure growth rates and aims to achieve higher growth for the bottom 40% of the population compared to the national average through 2030, which in all three scenarios, shows positive trends for five countries until 2050. Nevertheless, some countries with a reduction in this ratio still realize faster expenditure growth of the bottom 40% of the population by 2050. Consequently, several countries achieve this target, while until 2030 this is the case for fewer countries only. In SSP3, the indicator outcome is worse with only five countries succeeding. In summary, SSP2 and SSP3 generally show the lowest Gini and Palma values, which contrasts with higher inequality in terms of expenditure growth also observed in both SSPs. Thus, the strongest increase in per capita income under SSP1 projections would worsen inequality. This is also reflected by a decline in the labor income share on GDP over time in all SSPs and countries, especially in SSP2 and SSP1, which disadvantages households mainly depending on labor income. In contrast, factor returns to land grow substantially in all countries (particularly in SSP1) to the benefit of households with larger property rights to land. The related income distribution graphs are in the annex (Figure B.3.13).

Production increases over time are found in all SSPs, however, at different magnitudes, and increase the domestic extraction of natural resources, linked to SDG12 ‘Responsible Consumption and Production’, also at a per capita level. Thus, the so-called material footprints widen, especially in SSP1, except for Ghana which shows a per capita reduction in SSP1. However, GDP creation relies less on the exploitation of natural resources for most countries. As no quantitative target exists for SDG12, the improvement cannot be further evaluated.

This overall production increase comes with higher global market integration for the focus countries, linked to Target 17.11 of SDG17 ‘Partnership for the Goals’, which aims to double the LDCs’ share on global exports and to significantly increase developing countries’ share by 2020. All countries in all SSPs expand their export shares with most countries even more than doubling it by 2050. Except for Bangladesh, SSP1 has the highest trade participation for the countries. Already, by 2030, the three LDCs (Bangladesh, Ethiopia and Malawi) double their export shares (see Figure B.3.1), indicating that these countries could achieve the goal (at least) by 2030 under the baseline assumptions.

3.3.4 *Aggregated results*

The aggregated summary graph (Fig. 3.7) shows the unweighted average effect per SDG and SSP. It confirms again that general trends for the SDGs are similar across SSPs. Nevertheless, when findings for each SSP are ranked by the number of countries that show the highest relative change in the underlying indicators per SDG compared to the other SSPs, differences in magnitude and sometimes also in direction become visible. SSP1 tends to have the highest number of countries with the highest changes over time compared to the other SSPs, with only three cases of the largest adverse developments. This implies that no SSP outperforms the other SSP in all SDGs without further weighting.

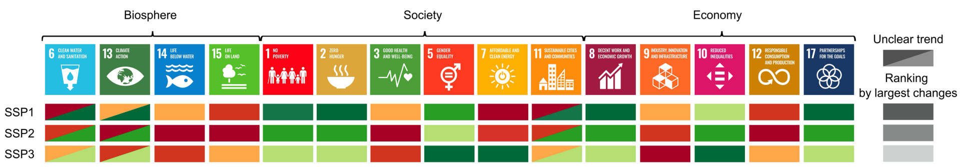

Figure 3.7. Simplified unweighted summary over indicators per Sustainable Development Goal in the three Shared Socioeconomic Pathways (SSP), grouped by the three layers Biosphere, Society, and Economy.

Shared Socioeconomic Pathways are ranked by the numbers of countries with the largest relative change compared to the other Shared Socioeconomic Pathways. Green square = only/predominantly positive trends, red square = only/predominantly negative trends, divided squares = half of the indicators show positive/negative trend, darkest color = highest number of countries with strongest positive/negative change. Source: model results.

Summarizing the detailed description in Subchapter 3.3.1-3.3.3, we observe predominantly positive developments for several SDGs under the Economy and the Society layer, with negative trade-offs to the Biosphere layer where either all indicators or some show adverse developments. Positive trends associated with SDG6 'Clean Water and Sanitation' and SDG13 'Climate Action' in the Biosphere layer relate to per capita or GDP indicators, while total demand for irrigation water and total GHG emissions continue to rise.

Trade-offs are also found inside the Economy and the Society layer, based on unsustainable energy generation (SDG7, Society Layer), stronger air pollution (SDG3, Society Layer) and the increasing material footprint (SDG12, Economy Layer). However, SDG8, SDG10, and SDG17, relating to economy, income equality, and trade integration in the Economic Layer, show a synergetic development funneled by economic growth. Similarly, primarily positive improvements for SDG1, SDG2, and SDG5, relating to reduced poverty, eradication of hunger and increases in gender equality in the Society Layer benefit from overall economic growth, and thus show synergies with positive trends for SDG8, SDG10, and SDG17 under the Economic Layer.

3.4 **Discussion**

The 68 indicators in the framework allow for a detailed assessment, depicting heterogeneity in response to the three pathways, both at country and household level. Regardless of the differences between the SSP scenarios, none of them is able to achieve the SDGs in unison by 2030 or 2050. While no clearly dominant scenario emerges here due to trade-offs between underlying model assumptions, we often find the best results projected under SSP1 assumptions. This fits to the results of previous studies, which find even most optimistic SSP1 scenarios to be not fully sustainable according to the SDGs by 2030 [13,49,56].

Generally, our projected SDG developments between the SSPs are similar, while they differ in magnitude and sometimes directions of trends depending on the layer of the 'wedding cake' and single SDGs or indicators. Confirming existing literature, in all SSPs, the prevalence of undernourishment or risk of hunger relating to SDG2 decreases [13,56]. With the microsimulation applied here, however, we observe partly lower calorie intake for the households that already consumed the lowest amount in 2014. Even if food consumption increases for all, trends still imply higher inequality in 2050. Philippidis et al. [12] also found average improved calorie availability, but our results differ from theirs in other aspects: for instance, we find manufacturing shares of employment to decrease against the desired development, while they determine increasing shares. Campagnolo et al. [11] and Philippidis et al. [12] also confirm the general improvements in social indicators found in the underlying study.

Addressing the three layers of the ‘wedding cake’, trade-offs within the SSPs emerge between Society and Economic SDGs, which improve towards or even reach the target, and adverse developments for the Biosphere layer. We thus confirm trade-offs between environmental and economic goals found in previous studies [11,12] and determine them for societal SDGs and the Biosphere [5]. The relevance of these trade-offs is underlined by the findings of Campagnolo et al. [11], as their composite indicator suggests that these conflicts could even reduce the overall sustainability at global level.

What interactions a study can highlight depends on the included indicators and SDGs [57]. While our developed indicator framework quantifies many indicators and SDG, beyond what previous CGE modelling approaches provide, it still lacks indicators for SDG4 and SDG16. Assumptions on SDG4 (‘Quality Education’) are currently taken as exogenous and drive the development of the labor force by skill level. Interlinkages between SDG4 and others are hence not endogenously modelled, while they have been analyzed previously using other methodologies [3,58]. Changes in education could be treated as endogenous in follow-up work, for instance, driven by the development of spending on education as in Roson [59], an approach partly already incorporated in the latest version of the CGEBox modelling framework. Endogenous indicators relating to SDG16 ‘Peace, Justice and Strong Institutions’ are challenging, while its basal for the achievement of the SDGs [60]. Numerous synergies and trade-offs were found among SDGs, also supporting other literature, such as trade-offs among parts of the biosphere SDGs [12] or trade-offs for economic growth (SDG8), industry (SDG9), consumption and production (SDG12) and terrestrial resources (SDG15) with other SDGs [3].

For SDGs for which indicators are available in the framework, the CGE model cannot address all aspects. SDG14 ‘Life on Land’ is quantified here only by assessing fish extractions from the sea and the economic importance of the fishery sectors, while other issues, such as lowering plastic exposure under Target 14.1 and reducing ocean acidification under Target 14.3, are not covered. Similarly, for SDG3 air pollution risks to human health are captured; however, other SDG3 targets, such as relating to maternal mortality (Target 3.1), or road injuries and deaths (Target 3.6), remain unexplored. Rather, demography and thus birth and death rates are exogenous and their development is thus not further described here in detail. SDG3 is highlighted to have synergetic relationships with many other SDGs and is therefore a strong determinant of development processes [61] which we could not show. Similarly, we find smaller intra-SDG8 'Decent Work and Economic Growth' trade-offs in contrast to Pradhan et al. [3] since the indicators of 'Material Footprint' are double assigned in the UN Indicator framework (both to SDG8 and SDG12) and were here only considered under SDG12. Nevertheless, we confirm intra-SDG trade-offs for SDG7 [3] since rising biomass use in the energy sectors under SDG7 'Clean Water and Sanitation' develop in tandem with increasing calorie shares flowing into these sectors. In addition, several indicators provided context for other indicators and allowed for further evaluation of the developments. For example, the undesired development of increasing irrigation water use (SDG6, 'Clear Water and Sanitation') is put into context as its increase is below production growth in sector using irrigation. In fact, exclusively positive trends in the depicted indicators were observed for 'No Poverty' (SDG1) and 'Partnership for the Goals' (SDG17) alone, underling the complexity of achieving sustainability both among and within SDG.

Most omitted indicators in this study are 'non-marketed', reflecting the limits of economic modeling. Here, linkages with other models or incorporating equations capturing relationships of non-marketed indicators to economic variables could help [62], as often done in Integrated Assessment Models. However, as Zimm et al. [56] discussed, comparing different SDG indicator frameworks of models that exploit their respective strengths might be more fruitful than continuously increasing the model boundaries.

The discussion of the 68 indicators covered in the study underlines the challenges of analyzing and presenting findings of detailed indicator frameworks. Composite indicator development, such as in Campagnolo et al. [11], could condense the information of our framework but implies a loss of information and asks for sensitive decisions on indicator normalization and their weighting [63]. Especially synergies and trade-offs among different SDGs, indicators and households remain visible when the full set of indicators is used. As Philippidis et al. [12], we refrain therefore from weighting indicators, SDGs or layers. Finding a comprehensive set of SDG indictors that is both manageable and detailed enough is thus crucial [56].

The graphs showing distributions based on the micro-simulation provide further insights beyond average effects. They reveal that most indicators grow unevenly among the population, leading to higher inequality (e.g., income per capita), while others converge (e.g., energy budget shares). For some indicators, parts of the population even develop in opposite directions (such as increases in food diversity in terms of expenditure against the average negative trend), rendering such an assessment crucial for sustainability analysis. Findings on distributional impacts are not reported in the existing literature and underline the study's novelty. Regarding SDG10 'Reduced Inequality', generally higher equality is projected for all indicators under all SSPs. Compared to the empirical analysis of the Gini index for the SSPs [64], we did not always find the lowest Gini values under SSP1 assumptions due to the uneven increase in income among the population.

The described effects are generally similar for the ten countries, with some country-specific differences. As we focus here on low- and lower-middle income countries, which are found to have the highest trade-offs and distances to targets [6,11,48,65], an assessment of middle- and high-income countries could reveal whether our methodological approach also determines a lower sustainability gap for the latter two country categories.

Our results suggest that many SDGs would not be reached in 2030 and 2050 in the assessed countries under the given SSP-specific exogenous projections of economic growth and demography, complemented by own assumptions. Thus, additional societal action is needed to meet the SDGs as the projected economic growth and slowing population increases are insufficient. Trade-offs and synergies within and among SDGs are transformative processes that can switch over time due to changing conditions [50,65]. Changing governance is essential for SDG achievement [2,58], as improving institutions and other dimensions of governance can boost SDG progress and determine positive or negative linkages between goals and targets. Given the trade-offs with the Biosphere layer and resource extractions, stronger food consumption shifts and lower household waste rates [66] could play an essential role in achieving economic growth that does not compromise environmental boundaries, as do higher sustainability in production techniques through higher circularity in the bioeconomy [67,68]. Also, further increasing land productivity could alleviate pressures from population growth [12]. Policies can foster these developments when taking current lock-in relation among SDGs into account [2,3] by targeted subsidization or taxation and support to develop more sustainable technologies, also taking the social dimension of political change into account [69]. However, Biermann et al. [70] found that, to date, the impact of SDGs on profound changes in policies is limited and that they mainly have changed political institutions and raised discussions. The required investments toward achieving the SDGs are probably large for some SDGs [71], such that finding and exploiting synergies between SDGs is crucial [72].

The indicator framework can be directly applied to counterfactual scenarios against any of the developed (or other) baselines, for instance, to analyze actions that tackle the determined trade-offs. All indicators used and discussed are linked to endogenous variables via the model results and thus change also in counterfactual scenarios. In this regard, the only exception is SDG8 'Decent Work and Economic Growth' which mainly depicts GDP developments exogenously provided by the SSP database during baseline generation. This changes in counterfactual runs where GDP turns endogenous. Counterfactuals could also assess options for global burden sharing, where especially high-income countries contribute to reduced resource extractions and lower emissions.

A drawback of the methodological approach is the missing feedback of induced environmental impacts on economic performance. As climate change damages can exacerbate conflicting targets and destroy or weaken synergies [3], they could be integrated into counterfactual runs to depict sector-differentiated impacts and results on the SDG indicator framework. For instance, climate change induced yield changes led to quite differentiated impacts for household aggregates with the same model as used here [45]. Additional channels of damages are, for instance, found in Ref. [73].

Assuming fixed emission factors, our study might overestimate the link between output increases and emissions. While the model considers different power generation technologies that reduce emissions per unit of electricity produced, such differentiation is missing for other sectors, such as transport, where low-emission technologies exist today. Moreover, future technologies might allow to reduce emission factors. Equally, while we consider future carbon tax increases that generate incentives to reduce GHG emissions, such an instrument is missing for health-relevant air emissions.

Using a recursive dynamic CGE model allows the depiction of long-term structural change. However, it requires exogenously projected changes in income and demography for baseline construction, which are surrounded by uncertainties [74]. This is partially addressed by applying three different sets of projections. Inevitably, however, parameterization and other decisions in setting up the model introduce further uncertainties. Following the categories of Allen et al. [75] specifying models suitable for SDG analysis, CGEBox fulfils several of their prerequisites. As a simulation model, it allows to generate long-term scenarios up to 2030 or 2050 at a flexible geographical coverage, including single countries (or even the option to disaggregate to NUTS2-level) and their global feedbacks building on a highly disaggregated database. They also found social dimensions to be least addressed by models, which find the largest coverage compared to the other two layers in our framework.

The extension of the CGE with a post-model micro-simulation allows for a rich assessment of distributional effects at the household level. Yet, the methodology also comes with some weaknesses. The model addresses only two of three channels of adjustment proposed by van Ruijven et al. [43]: heterogeneous factor endowments, heterogeneous preferences and savings. Unemployment or leisure categories for labor or different labor markets as the third channel are not captured. However, wages are differentiated by the disaggregated labor categories, namely skilled and unskilled labor, as well as gender categories. Furthermore, the average of the micro-simulation results does not always perfectly resemble the model average due to the nonlinearity of the demand function. As a result, for a few indicators, both averages showed opposite trends over time. For consistency, therefore, all results for average indicators, for which household-level results exists, are taken from the micro-simulation. The heatmap with the model averages can be found in Figure B.3.14-B.3.16 for comparison. Lastly, the quality of the micro-simulation results strongly relies on the underlying data. The FAO [14] data set mainly focuses on farming households, and in Ethiopia, predominantly rural households are represented due to missing data from surveys. Repeating the assessment, thus, with household data with other focus could provide further insights, also how the already now differentiated income growth, being most pronounced for large land lords, would evolve and affect equality.

Previous work that used similar micro-macro linkage approaches with GTAP models applied these for other contexts. While the general idea is the same, the design and focus of the micro-simulations differs among these assessments. For example, compared to Bussolo et al., [76] and Laborde et al., [77] the update mechanisms for income per capita level applied at household-level reflect differences in data availability and methodological choices. While these two papers focus on a larger data set, assessing global income distribution, we selected here ten countries to assess the full set of SDG indicators. A key addition of our approach lies on the expenditure side, where we model explicitly a demand system for each household to better depict changes in the demand structure across countries at household level as relevant for several SDGs. Drawing on the employed MAIDADS demand system and the extended database, a special focus lies on depicting food consumption and related realistic nutrient intakes at household level as well as on differences in energy expenditures in the long run.

The SSP projections were published in 2017 [10], so that underlying data are by now almost a decade old. An update of the SSP data is currently in process and will reflect besides newer data the likely consequences of shocks such as the global COVID-19 crisis. These shocks probably imply less optimistic projections of economic growth, which shape many of the indicators discussed here. Moreover, we observe currently that advances towards SDG targets, for instance, regarding poverty or hunger reduction or health, have stalled or even been eroded by recent developments [78-81]. Furthermore, the pandemic entailed a decline in life expectancy for many countries [82]. Thus, repeating the assessment with the updated SSP and updated GTAP data could reveal new information on the sustainability issues of recent developments.

Beyond the SSPs, Sustainable Development Pathways are required to extend the narratives of SSPs to derive scenarios capable of reaching the SDGs. Not at least because even the most optimistic scenario of the SSPs does not reach all SDGs, it is clear that we need a set of projections and narratives that are more comprehensive than what is captured to study climate change scenarios. Soergel et al. [48] provide a first quantification of Sustainable Development Pathways that add different narratives to the set of SSP1 in an Integrated Assessment Model. Their study shows that the additional interventions enable improvements in different dimensions while sustainability gaps remain. Thus, the findings of the study at hand contribute to this field of research and highlight the need to incorporate distributional effects in narratives to analyze the required redistribution of wealth but also governance.

3.5 Conclusion

Economic modelling frameworks linked to further accounting, such as on emissions, land use or nutrition, can provide information on synergies and trade-offs between SDGs from policy changes and socioeconomic developments. However, most SDG-related CGE analysis have been based on aggregate household effects, missing distributional aspects, and using rather aggregated agri-food sectors. This limited the details in related SDG indicators. Therefore, this study extends existing SDG indicator frameworks for recursive dynamic CGE models by adding, among other things, distributional effects through a post-model micro-simulation linked to different SDGs and great detail for the agri-food sector. The framework is then applied to three different SSP baselines up to the year 2050 to provide an assessment for the years 2030 and 2050 for the different dimensions of sustainability, grouped by the three layers of the wedding cake (i.e., Economy, Biosphere, and Social). Drawing on 68 indicators, trade-offs both between and within SDGs can be determined. The combination of long-term CGE analysis and the sustainability indicator framework introduced in this study proofs beneficial for a multifaceted comparison of scenario outcomes. In particular, the integration of micro-simulation allows the quantification of indicators associated with distributional aspects that remain otherwise hidden behind average effects.

Of the three scenarios assessed here, none outperforms the others, preventing a clear ranking and emphasizing the complexity of sustainable development. None of the scenarios improve indicators fast enough to reach goals in their targeted timeframe (mostly by 2020 or 2030), and goals for many SDGs might not even be reached by 2050. Consequently, counterfactual analyses, incorporating policies that tackle remaining challenges and trade-offs, could help determine decisive action points. Our analysis found negative trends mainly in the Biosphere layer for resource extraction and emissions. Accordingly, policies and technologies should target a decoupling of economic growth from environmental pollution and exploitation of natural resources, for example, by providing sustainable energy resources that do not compromise food production. The results suggest the importance of incorporating distributional aspects in policy-making to initiate socially just transitions when solving the trade-offs. The indicator framework can hence serve as a toolbox to study specific effects of novel policies and socio-economic developments on SDG targets and beyond. Furthermore, the results of this study can be used for the further scenario development process of Sustainable Development Pathways.

Follow-up work could perform such counterfactual analysis. It might also add indicators for SDG4 ‘Quality Education’ and SDG16 ‘Peace, Justice and Strong Institutions’ and broaden the indicators coverage of some SDGs where currently only some dimensions are addressed. Moreover, climate change damages and technological progress linked to update of emissions factors could be integrated into such analysis.

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Chapter 4
European Bioeconomy Policy: Spillovers on low-income countries in light of the Sustainable Development Goals[1]

Abstract

The EU's Bioeconomy Strategy seeks to foster more sustainable production and consumption to ensure food security and respect planetary boundaries in line with the Sustainable Development Goals (SDGs) of the United Nations. A progress report published in 2022 identified implementation gaps linked to consumption patterns in the EU and related demand for land and biomass within and outside EU member states. In support of efforts towards closing these gaps, this paper provides a comprehensive assessment of interactions between the strategic goals of the EU Bioeconomy Strategy and the achievements of the SDGs at global scale. Our analysis is based on a recursive-dynamic global Computable General Equilibrium (CGE) analysis extended by an SDG indicator framework. Impacts of three EU bioeconomy policy scenarios are compared against a baseline until 2050 drawing

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CRediT Statement: Rienne Wilts: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Visualization; Jan Börner: Conceptualization, Writing - Original Draft, Writing - Review & Editing; Wolfgang Britz: Conceptualization, Methodology, Software, Writing - Review & Editing, Supervision

on assumptions matching the Shared Socioeconomic Pathway 2 for the EU and ten low- and lower-middle income countries. Results suggest that bioeconomy expansion scenarios and reduced meat consumptions lead to trade-offs with the SDGs and thus the Strategy's objectives. Technological advancements can provoke more desirable outcomes regarding the objective of climate change mitigation and EU competitiveness while a subsidy on biomass use improves parts of the economic indicators. With regard to the spillovers of the EU policies on the ten low- and lower-middle income countries, none of the scenarios is purely positive for any of the ten countries in focus. Especially, in critical economic domains, the subsidy scenarios increase pressure, reducing income and widening wage gaps.

Keywords: Sustainable Development Goal, Computable General Equilibrium Model, Bioeconomy, Micro-simulation, Spillover

4.1 **Introduction**

Fossil fuel use is a main driver of climate change increasing the likelihood of catastrophic compound events (Zscheischler et al., 2018). As population and economic growth will likely expand fossil fuel extraction and related environmental impacts (OECD, 2019), we need renewable alternatives such as substitutes drawing on biomass feedstocks. The European Union (EU) as well as other countries are, therefore, developing strategies to promote their bioeconomy (Teitelbaum et al., 2020). However, some elements in these strategies may also result in adverse effects on different dimensions of sustainability (Stark et al., 2022).

The United Nations (UN) developed the Sustainable Development Goals (SDGs) in 2015 as comprehensive framework to measure progress towards multiple dimensions of sustainability. El-Chichakli et al. (2016) emphasize strong interlinkages between certain SDGs and bioeconomic growth. For example, some studies found that an expanding EU bioeconomy potentially involves undesirable trade-offs exacerbating food security, pressure on land, forests, and water as well as other environmental impacts (Bringezu et al., 2021; Egenolf et al., 2022).

Multiple studies analyzed connections between the SDGs and bioeconomy strategies (Calicioglu and Bogdanski, 2021), relating specific SDGs to national bioeconomic strategies (Linser and Lier, 2020) or to alternative concepts of the bioeconomy (Heimann, 2019; Nazari et al., 2021) and analyzing their observed ex post developments (Ronzon and Sanjuan, 2020). Ex-ante assessments of planned bioeconomy strategies with Computable General Equilibrium (CGE) in a comparative static setting, found sustainability issues related to the bioeconomy (e.g. Escobar and Britz, 2021; Haddad et al., 2019). Recursive-dynamic analysis, partly using CGE models, assessed future bioeconomy pathways, for example, with regard to pressure on land, especially forests (Buongiorno et al., 2011), effects of advanced biomass usage on the Dutch economy in 2030 (van Meijl et al., 2018) and increasing global biomass efficiency in chemicals (Nong et al., 2020). Taking the five goals of the EU's Bioeconomy Strategy into account, Philippidis et al. (2023) assessed effects at EU Member State level of an expansion of bio-based chemical sectors. Yet only few studies so far specifically incorporate SDG indicators for assessing European and global bioeconomy baselines until 2050 (M'Barek et al., 2019; Többen et al., 2024), however at a higher regional and sectoral aggregation. Summarizing, existing studies find selected environmental and social trade-offs arising from the EU bioeconomy strategy, but a holistic long-run assessment of multidimensional effects on the SDGs is missing, specifically with regard to low- and lower-middle income countries (LLMICs) exporting biomass.

Already now, the EU imports large amounts of biomass from other continents (Bringezu et al., 2012), including from LLMICs (Weinzettel et al., 2013). Scaling-up the EU bioeconomy will, thus, likely affect natural resources of these biomass-exporting countries, especially land, adding to growing pressures under future projections of socioeconomic changes (Popp et al., 2017). These dynamics let land rents rise, benefitting land owners, while a rising demand for biomass of industry competes with its use for food and feed and raises food prices, hitting especially poor households. These changes affect also further economic and social dimensions of biomass exporting countries.

Taking these spillovers into account in policy measures and governance mechanisms can shape the sustainability of bioeconomic developments (Dietz et al., 2018). El-Chichakli et al. (2016), for instance, therefore advocates to better reflect the international dimension in national strategies and policies. In 2017, the EU reiterated its commitment to policy coherence for development in its European Consensus for Development (Ahlström and Sjåfjell, 2023). This is increasingly reflected in a number of EU policy initiatives, including the amended Renewable

Energy Directive (REDII), the Green Deal, and the Directive on Corporate Sustainability Due Diligence. Also the update of the EU Bioeconomy Strategy in 2018 emphasizes the need to account for sustainability impacts outside the EU (EC, 2018). Research on some of these initiatives, however, points to considerable gaps in external policy coherence with implications for development and the environment outside the EU (Häbel and Hakala, 2021; Koch and Keijzer, 2021; Oliveira et al., 2024).

Current events such as escalating oil prices and interrupted natural gas supplies spurred the search for bioeconomy-based alternatives and narrowed related gaps in competitiveness. This makes an informed discussion about trade-offs even more relevant. Thus, we aim to quantify the effect of an expanded European bioeconomy under three different potential policy scenarios on selected SDG indicators in ten LLMICs as well as EU Member States. Drawing on an agricultural and food extended database (Britz, 2022), a special version of the dynamic CGE model CGEBox (Britz and van der Mensbrugghe, 2018) is employed, exploiting its global coverage and its ability to depict long-term economic adjustment processes. The scenarios build on a baseline constructed up to 2050 using economic and demographic projections from the Shared Socioeconomic Pathway 2 (SSP2; Riahi et al., 2017) together with further scenario assumptions matching the narratives of SSP2. The EU bioeconomic strategy might have a pioneering role, encouraging other countries to follow which lets us also analyze a scenario where OECD countries employ similar policies.

4.2 **Methodology**

4.2.1 *CGE Model*

Given its global and intersectoral focus, this study employs the flexible and modular CGE modelling platform CGEBox (Britz and van der Mensbrugghe, 2018). It draws on the latest Global Trade Analysis Project (GTAP) Standard Model version 7 (Corong et al., 2017) including a two-stage Armington representation of bilateral trade with an agent-specific differentiation of products by origin. To this core model, several extensions are added, including the GTAP-E and GTAP-Power models drawing on Peters (2016), GTAP-Agri-Environmental-Zone (AEZ) data (Baldos and Corong, 2020) and model (Lee, 2005) and the GTAP-

AGR model (Keeney and Hertel, 2005) as summarized in Figure 4.1, to improve the modelling of energy and agri-food market specifications. The extended version of the GTAP-AEZ model employed considers land supply from natural vegetation

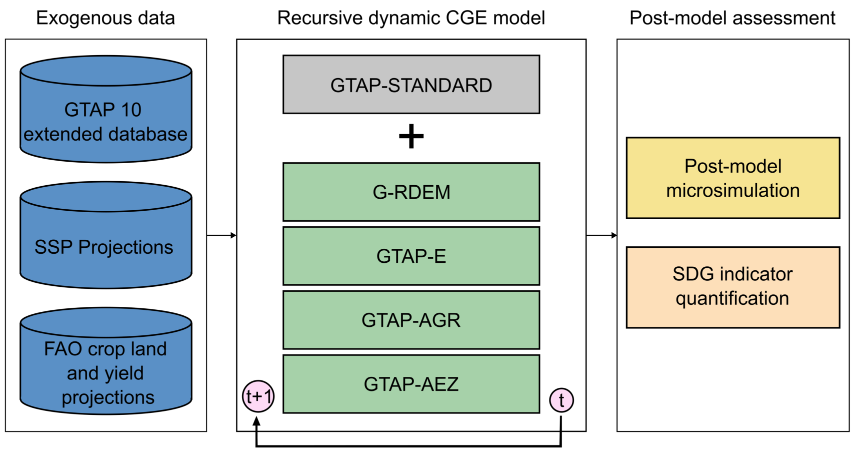

Figure 4.1. Schematic overview of the CGE model approach. Source: Authors own.

to land in economic use, draws on additive Constant Elasticity of Transformation (aCET) functions (proposed by van der Mensbrugghe and Peters (2020)) to guarantee physical balances and adds aCET nests for annual and permanent crops to further differentiate substitution between land uses.

The forward-looking perspective of this study considers changing socio-economic conditions, such as demographic developments and economic growth, based on the long-run extension G-RDEM (Britz and Roson, 2019). G-RDEM captures different demand and supply side drivers of structural change, including a non-linear rank 3-MAIDADS demand system (Britz, 2021a) to better address income dynamics in consumption including consumption saturation for specific food groups. More detail on all features can be found in Britz and Roson (2019).

The baseline construction builds on exogenous SSP2 projections for real GDP, population, demography and education (Riahi et al., 2017). Given these projections and the G-RDEM mechanism, the model updates quantities, prices, income and other variables in each year such that all product and factor markets are in simultaneous equilibrium, combined with macro-economic closures such as investments equal savings, and a closed balance of payments. An economy-wide total factor productivity shifter in each region adjusts to recover the exogenous real per-capita GDP projections (Britz and Roson, 2019).

Land use change (LUC) is driven by the exogenous projections of cropland and crop yield changes from FAO (2018), reflecting ex-post estimated relations between changes in cropland, pasture and natural vegetation. Built-up land develops based on empirical estimations considering population density, urbanization rates (also provided by the SSP database) and GDP growth (similar to Chen et al., 2020). Counterfactual scenarios take over the productivity shifters from the baseline and render GDP endogenous to analyze changes in equilibria due to political interventions or economic shocks.

Several of the employed SDG indicators reflect distributions of variables in a country's population, such as income or nutrient supply while the model depicts solely one regional representative consumer. We therefore disaggregate selected results in a post-model micro-simulation to 500 income quantiles per country, drawing on the FAO (2017) household surveys for selected LLMICs. The survey provides for each observed household among others information on their income sources and levels, household size, and an aggregation weight to total population. Sources of income encompass sector- and skill-differentiated self-employment and wage income, as well as crop and livestock production, public and private transfers and an additional 'others' category. This information is matched to the model's sector detail to update the income positions of each household from the base year until 2050 using model results.

Households can change the income sourcing by allocating labor and other production factors to sectors with higher returns, represented by Constant Elasticity of Transformation functions. For the remaining income sources (public and private transfers, others), other updating mechanisms are chosen. As the survey does not report consumption patterns, the MAIDADS demand system is used to estimate consumption by product for the base year for each household and to update it dynamically. From there, calories, proteins and fat intake per capita and day are obtained by multiplying final demand by product with nutrient contents. The 500 income quantiles per country used in the analysis are aggregated from the several thousand households in each survey to facilitate further assessment. Additional information on the micro-simulation is detailed in Wilts and Britz (2024).

4.2.2 *Database*

The data base employed departs from the GTAP-Power Data Base Version 10 (Chepeliev, 2020a) which provides a snapshot of the global economy in 2014. It covers output, primary factor use and intermediate demand by each industry, final demand and bilateral trade by product, returns for eight primary factors, and related tax/subsidy rates for 141 countries and 76 sectors, including detail on electricity generation and distribution. Drawing on the methodology of Britz (2021b), we disaggregate it further for higher product and sector detail on the bioeconomy, to in total 110 products and 141 activities (see Table A.1 for detail), comprising 45 agri-food products of which 26 are crops with their production split into rainfed and irrigated activities. Equally, the fishery sector distinguishes open catch and aquaculture. Some biomass related cost shares for the bioeconomy sectors ‘rubber and plastic’, ‘chemicals’, and ‘petroleum and coal’ in the focus of this study were manually adjusted for the EU and OECD countries (see also the argumentation of Avitabile et al., 2023). For the sustainability assessment, the data base covers CO_2 and non-CO_2 (Chepeliev, 2020b) and air pollution emission factors (Chepeliev, 2020c), linked to production and consumption. Gibbs et al. (2014) provides data for the assessment of the carbon stock changes, of which some implausible ones for pasture in Germany are replaced by EU averages. Gender differentiated labor categories (Worldbank, ND) are created for skilled and unskilled labor, such that the data base covers eight primary factors (capital, male/female skilled labor, male/female unskilled labor, natural resources, land, irrigation water). The approach follows largely Wilts and Britz (2024), see there for detail.

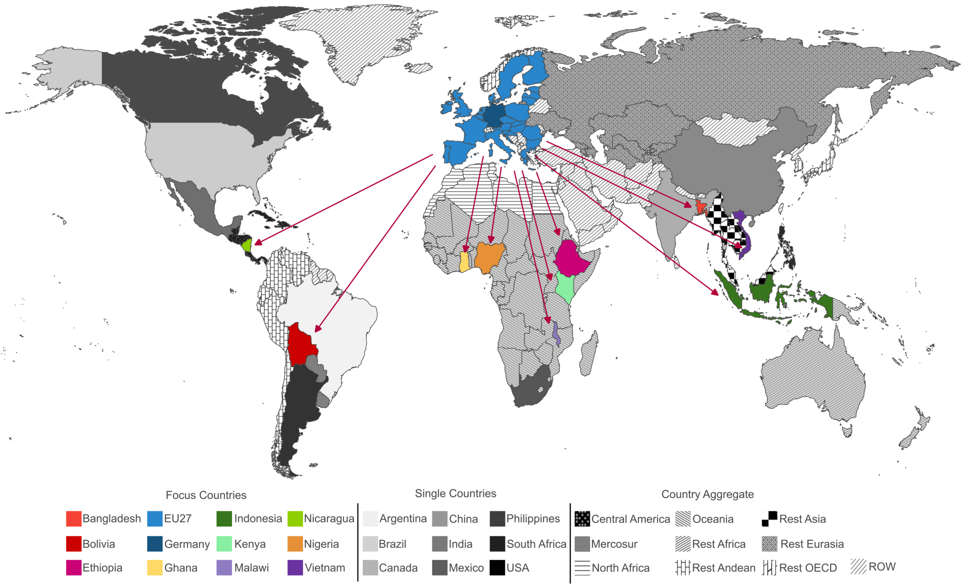

Figure 4.2. Regional aggregation.

Remark: Colored countries are in the regional focus of the study. Grey shaded areas are single countries while countries with grey patterns depict regional aggregates. The red arrows represent the direction of the effect the study focuses on. Source: Authors own.

To assess impacts of EU policies on LLMICs across the world, a regional aggregation is chosen which comprises Germany, some larger biomass producers and ten LLMICs as single countries, and EU27 and ten other countries as aggregates (see Figure 4.2 and Annex (Table A.4.2) for detail).

4.2.3 *EU Bioeconomy Strategy*

In 2018, the European Commission (EC) updated its Bioeconomy Strategy from 2012 to put greater emphasis on sustainable developments in all dimensions, i.e., economy, society and environment. This new strategy (EC, 2018) addresses explicitly multiple challenges of an expanded bioeconomy, such as increasing future demand for feed, food, biomass based industrial products and energy, and defines five related objectives, namely (1) food and nutrition security, (2) sustainable management of natural resources, (3) climate change mitigation and adaptation, (4) reduced reliance on unsustainable resources, and (5) competitiveness and job opportunities (EC, 2018).

The strategy underpins other EU key policy priorities including the Green Deal, the Paris Agreement, and the UN Agenda 2030 with the SDGs. Interlinkages with established policy objectives are also foreseen, among others to the Common Agricultural Policy and the Biodiversity Strategy (EC, 2018), such that the strategy stresses the need of a sustainable, circular bioeconomy. Since the bioeconomy is not necessarily sustainable by nature, the strategy identifies three main areas of action, namely (1) to expand the bio-based sectors among others by capitalizing related research grants, (2) to support local bioeconomy deployment in Europe by fostering training and pilot actions in different areas, and (3) to scrutinize the ecological boundaries of bioeconomy (EC, 2018). The underlying comprehensive definition of the bioeconomy covers the use of biological resources in all sectors (Bell et al., 2018), excluding, however, biomedicines and health biotechnology sectors (EC, 2018).

4.2.4 *Scenarios*

GDP and population growth, changes in urban population shares and demographics from the SSP2 projections data base are exogenous elements of the baseline. Additional elements comprise a 10% reduction of preferences for animal-based food, moderately increasing carbon prices and related matching assumptions on technical progress in energy use and power generation. Land use is largely driven by FAO 'BAU' cropland and yield projections. The constructed baseline (for further detail, see Subsection 4.2.1) serves as backbone and comparison point for the policy counterfactuals (Figure 4.3). These counterfactuals take over baseline productivity and preference shifters and let GDP adjust endogenously. They employ land supply elasticities from Miranda et al. (2024) to steer changes in land supply compared to the baseline. Regarding elasticities of substitution for fossil and biomass feedstock, we follow Nong et al. (2020). More detail also on the nestings can be found in the annex (Figure A.4.1).

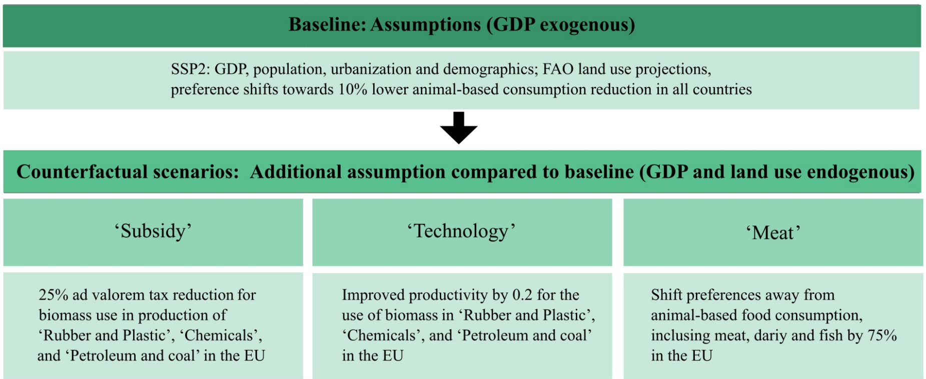

Figure 4.3. Definition of baseline and scenarios against baseline definition for the assessment. Source: Authors own.

The EU Bioeconomy Strategy described in Subsection 4.2.3 is translated into three policy scenarios (see Figure 4.3). Scenario 1 ('Subsidy') incentivizes intermediate use of biomass by applying a subsidy in selected value chains. Specifically, domestic and import ad-valorem tax for biomass inputs are reduced by 25% for the 'rubber and plastic', 'chemicals' and 'petroleum and coal' sectors, as mentioned in Subsection 4.2.2. The second scenario ('Technology'), in contrast, analyzes productivity gains for biomass use in these sectors, as the likely consequence of fostering research and development by the EU. It increases productivity of biomass intermediate input use by 20%, while simultaneously decreasing the productivity of fossils to offset an overall increase in intermediate demand. Finally, Scenario 3 ('Meat') analyzes changes induced by a strong further reduction of 65% in preferences for animal-based products in the EU. This links to the EU Bioeconomy Strategy by analyzing options to reduce pressure on land and thus to facilitate the sustainability of bioeconomic developments. These three counterfactuals are discussed in terms of their increase in biomass use in the three sectors, their SDG effects in the EU and the SDG synergies and trade-offs for LLMICs.

Additional scenarios apply the elements of the three scenarios to all OECD countries to analyze consequences if such strategies are more widely applied. All scenarios are solved until 2050 in bi-yearly steps from the base year 2014. The shocks are applied in equal steps over the time horizon, such that the final values are reached in 2050.

4.2.5 *Indicators*

Interlinkages between SDGs and the bioeconomy are widely discussed in research, given the bioeconomy's complex integration into the global economic system. Robert et al. (2020) therefore ask for a commonly agreed approach to monitor the sustainability of the bioeconomy. Here, indicators are inevitable to assess both current status and advancements and to determine potential trade-offs and synergies. Although not always explicitly using the SDG terminology, national bioeconomy strategies are associated with a large number of SDGs (Heimann, 2019; Linser and Lier, 2020; Ronzon and Sanjuán, 2020; Robert et al., 2020). Assessed linkages differ by study, depending on national context and approach, but none finds impacts of bioeconomic developments on SDG5 ('Gender Equality') and SDG16 ('Peace, Justice and Strong Institutions') while potential interlinkages might exist.

The focus of this paper is both on the EU's own SDG performance after the implementation of the different bioeconomy policies and on global spillover effects on LLMICs. Accordingly, all SDGs quantifiable with the CGEBox are considered, whether or not directly targeted by the EU Bioeconomy Strategy. To avoid being lost in detail, mostly one key indicator per SDG is selected (Egenolf & Bringezu, 2019). Building on the SDG indicator framework by Wilts and Britz (2024), the assessment encompasses 18 indicators related to 15 SDGs as summarized in Figure 4.4. Some indicators rely on household surveys not available for EU countries and are available for analysed LLMICs, only. Greenhouse gas (GHG) emissions per capita are derived according to IPCC guidelines and thus exclude emissions embodied in imports. Effects on carbon stocks through LUC are discussed separately, as an additional indicator associated to SDG13 ('Climate Action').

The SDGs are grouped to the five objectives of the EU Bioeconomy Strategy, following mostly Robert et al. (2020). However, we add SDG3 and relate each SDG to one bioeconomy strategy objective, only.

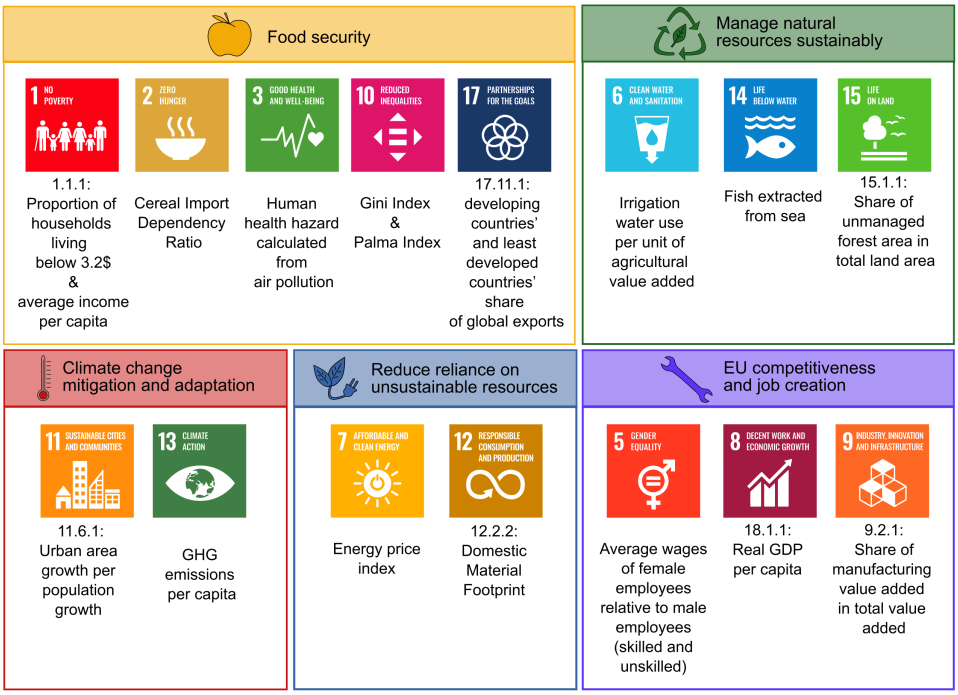

Figure 4.4. Matching of the SDGs and their selected indicators to the five Bioeconomy Strategy Goals. Source: broadly based on grouping from Robert et al.

4.3 Results

We start with the results of the baseline and the three scenarios focusing only on the EU. Here we also compute the 'level' of bioeconomy using the share of biomass input in the shocked sectors and their ratio to fossil inputs as indicators. We use 'the EU', when referring to both the Rest-of-the EU aggregate ('EU27') and Germany, otherwise, their respective name is used.

4.3.1 *Results inside the EU*

Baseline and general spillovers

The baseline results paint a relatively positive picture in terms of the development of selected SDG indicators for the EU (Figure 4.5a). Our results suggest improvements in 11 of the studied SDGs, reflecting changes in total factor productivity and demography together with assumptions quantifying SSP2 scenario narratives (Figure 4.3). However, SDG9 ('Industry, Infrastructure and

Innovation'), SDG15 ('Live on Land') and SDG17 ('Partnership for the Goals') are adversely affected, as indicated by the red colored cells in Figure 4.5a.

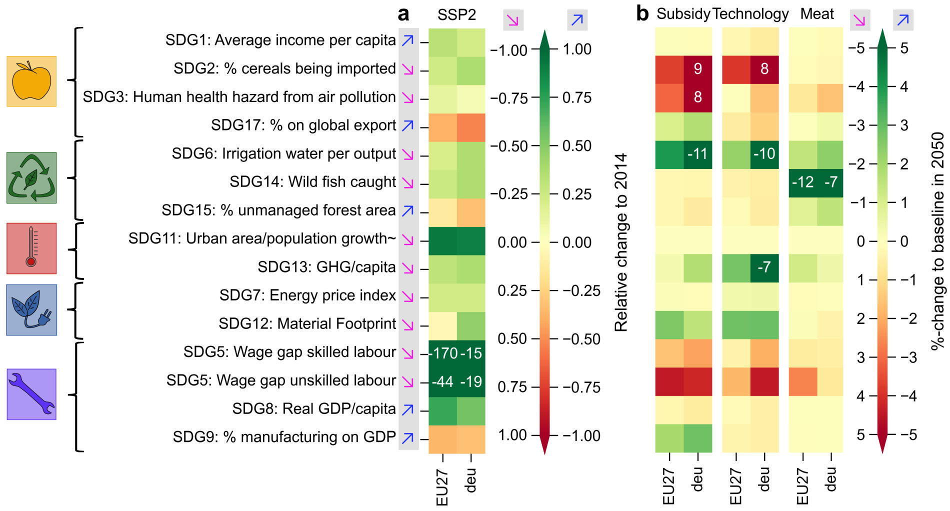

Figure 4.5. Heatmap showing the (a) relative change in baseline from 2014 to 2050 and (b) % changes induced by the different policy scenarios for the SDGs in EU27 and Germany.

Remark: Indicators are abbreviated for better readability and grouped by the bioeconomy objectives (pictograms on the left); complete information can be found in Figure 4.4. The color bar is fixed to values between (a) 100% and -100%, (b) 5% and -5%; exceeding values are shown as numbers in the respective cell. All indicators show improvements as green and regressions as red, with the pink and blue arrows next to the label indicating the desired direction and the applied side of the color bar scale. Source: Model results.

The policy scenarios produce co-benefits and trade-offs for certain SDGs, as depicted in percentage deviations from the baseline in Figure 4.5b. Tax reductions on biomass use ('Subsidy') and technical progress ('Technology') in the three considered sectors show mostly the same directions of impacts on the selected indicators, whereas the meat demand reduction scenario ('Meat') partly diverges.

Table 4.1. Changes in (a) economic variables relative to the baseline in the three targeted sectors in 'Subsidy' and 'Technology' (%) and (b) demand for biomass and fossils, and their ratio to the baseline over the three targeted sectors (%)

(a)		**Subsidy**			**Technology**		
		p&c	chem	rpp	p&c	chem	rpp
Price	EU	-1	-5	-7	-1	3	1
	D	-	-4	-3	-1	2	1
Output	EU	-1	66	29	-9	-24	3
	D	-5	53	+	-26	-17	-4
Export	EU	-2	83	38	-4	-30	-5
	D	-2	67	1	-9	-21	-5
Import	EU	-1	6	-	-17	-	+
	D	-4	13	4	-25	-3	+

(b)		**Subsidy**			**Technology**		
		biomass	fossil	ratio	biomass	fossil	ratio
Demand[1]	EU	60	0.06	22*	35	-14	24*
	D	185	-0.01	84*	137	-30	108*

Note: p&c = 'petroleum and coal' sector, rpp = 'rubber and plastics products' sector, chem = 'chemicals nec' sector, D = Germany, EU = European Union. [1] = the total demand is calculated as sum over the three shocked sectors. * = these values are given in percentage point change. +/- = indicate direction of effect for changes that round to zero. Source: Model results.

For the Technology and Subsidy scenario, effects in the EU on the three sectors differ, with the chemical sector's output being most responsive (see Table 4.1a), following higher initial cost shares for biomass. While the tax reduction for biomass produces mostly positive output effects, the technology shifter causes shrinking outputs, due to substitution of petroleum and coal products in the three sectors and declining export demand induced by rising prices. Both scenarios lead to an improvement of the ratio between biomass and fossil feedstocks, however induced in the Subsidy scenario by massive increases in biomass demand and in the Technology scenario due to desired substitution of fossils with biomass (see Table 4.1b).

Food security

The first row of Figure 4.5b shows slight decreases in average income per capita (SDG1: ‘No Poverty’) in the two biomass scenarios, stemming mainly from dropping returns to natural resources mostly compensating for the increase in land returns and water provoked by the expansion of primary biomass production. In Germany, mainly rape seed areas rise (112 Mha (Mega hectare) and 82 Mha, respectively) and displace other crops, while in EU27 more crops expand their acreages, the largest being also rape seed with 259 Mha (18%) and 182 Mha (13%) for the Subsidy and Technology scenario, respectively. Besides expanded domestic production, imports cover higher demands for biomass in both scenarios, resulting in an undesired reduction in the self-sufficiency of cereals (SDG2: ‘Zero Hunger’) and rising food prices for grains and crops and processed food products. Increasing human health hazard from air pollution (SDG3: ‘Good Health and Well-being’) are found in both biomass scenarios due to rising ammonia emissions. However, in the Subsidy scenario only higher total air pollutions are emitted, for example, in Germany by 155 Mt caused by increased production of chemicals and crops. In the Meat scenario, effects on SDG indicators related to the food security objective are more muted. Total air pollution (41 Mt and 184 Mt in Germany and EU27, respectively) health hazards rise, despite lower output of animal-based products, reflecting higher pollution from crops, fruits and vegetable production. Like in the biomass scenarios, cereal self-sufficiency decreases as more cereals are imported, however to a lower degree, as decreasing pasturelands frees land for cereal production. Due to expanded exports of chemicals in the Subsidy scenario (see Table 4.1a) and of livestock and vegetable products in the Meat scenario, EU’s trade integration increases (SDG17: ‘Partnership for the Goals’), reverting a trend found in the baseline. Declining exports of all shocked sectors due to rising prices in the Technology scenario, causes a reinforcement of the baseline trend. We observe, hence, for the Meat scenario the same trade-offs as in the Subsidy scenario with improvements for SDG17 and deteriorations for SDG1, SDG2 and SDG3, with the Technology scenario showing adverse effects only.

Sustainable natural resource management

All policy scenarios induce increased irrigation water use efficiency (SDG6: 'Clean Water and Sanitation'), as rising demand from expanded crop production pushes water prices up and triggers substitution with capital. For the other two indicators related to natural resources, namely wild fish caught (SDG14: 'Live below Water') and share of unmanaged forest area (SDG15: 'Life on Land'), strong positive trends are observed in the Meat scenario, only. Less fishing (e.g. -4 bill. $ in the EU) reflects scenario assumptions on lower consumption of animal-based products by up to 48%. Less meat consumption also reduces expansion of grassland areas (-5% and -8% less in EU27 and Germany, respectively) causing lower deforestation (429 Mha and 72 Mha in EU27 and Germany, respectively). In contrast, in the biomass scenarios, cropland expands by about 3% and 5% and lets unmanaged land shrink (-0.2% and -0.6%), in EU27 and Germany, respectively. The meat reduction scenario thus contributes to the objective of sustainable resource management, while the biomass scenarios generate again trade-offs among the associated SDGs.

Climate change mitigation and adaptation

The urban area growth relative to population change (SDG11: 'Sustainable Cities and Communities') remains almost unaffected in all scenarios due to limited GDP changes which drive changes in urbanized areas in the model. GHG emissions per capita (SDG13: 'Climate Action'), however, fall in all three scenarios, due to the decarbonization of the shocked sectors and, in the case of the Meat scenario, due to shrinking livestock production. The strongest reductions are found for the Technology scenario, where 7% or 35 Mt CO_2-eqv and 3% or 75 Mt CO_2-eqv of the emissions are mitigated in Germany and EU27, respectively. Considering, however, also emissions form LUC partly reverses these findings, as shown in Figure 4.6. The biomass scenarios induce considerable LUC, as crop and pastureland expand to the detriment of natural vegetation, especially unmanaged forest. This conversion combined with shifts from pastureland to cropland induce carbon stock reductions by -47 Mt CO_2-eqv and -606 Mt CO_2-eqv in the Subsidy (Figure 4.6a) and -37 Mt CO_2-eqv and -308 Mt CO_2-eqv in the Technology scenario (Figure 4.6b), in Germany and EU27, respectively. These emissions clearly balance out the GHG savings. In contrast, the Meat reduction scenario results in a higher carbon stock than in the baseline for EU27, (+274 Mt CO_2-eqv) and Germany (+36

MT CO_2-eqv) as shown in Figure 4.6c, in line with the overall lower GHG emission from production and consumption. In terms of the climate mitigation objective, the Meat scenario again generates more favorable results, whereas the biomass scenarios deteriorate considering LUC emissions.

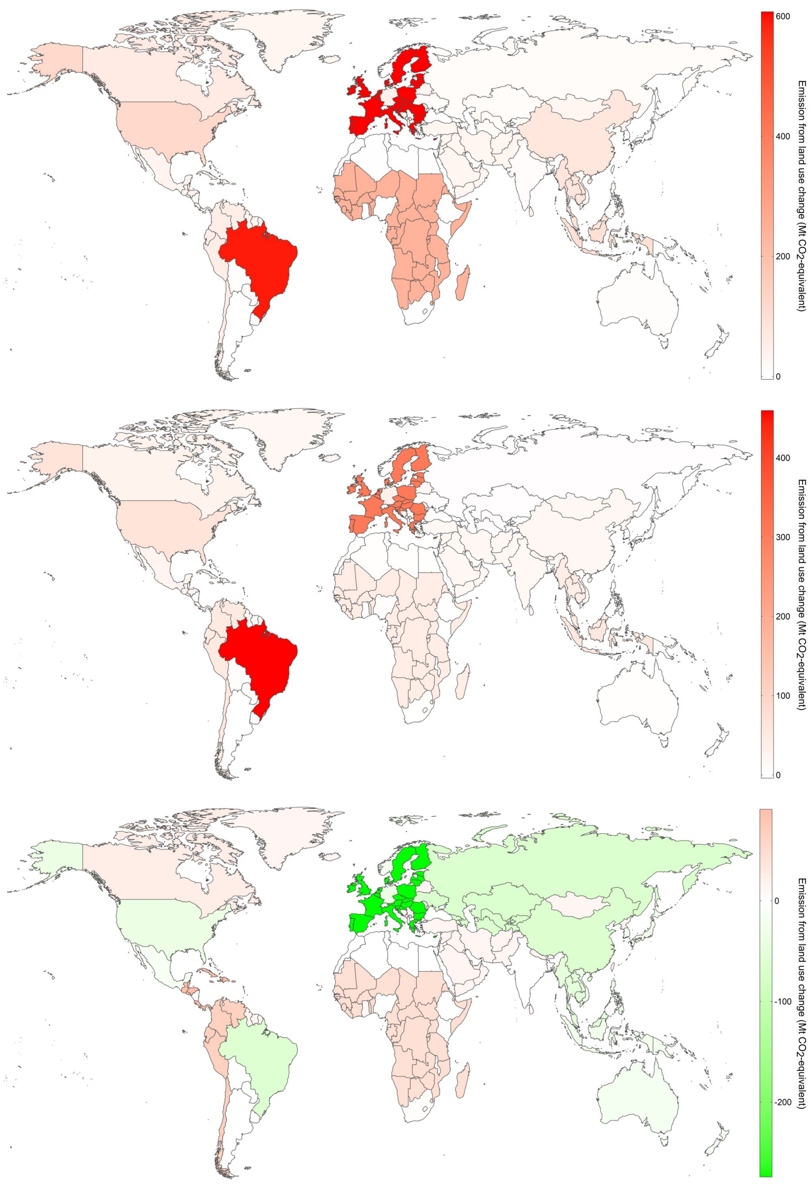

Figure 4.6. GHG emissions from changes in carbon stock (million tons (Mt)) for (a) Subsidy, (b) Technology and (c) Meat scenario. Source: Model results.

Reduced reliance on unsustainable resources

Changes in the energy price index (SDG7: 'Affordable and Clean Energy') in the EU from all policy scenarios are marginal. In the Technology scenario only, prices drop due to the decarbonization of the shocked sectors. In contrast, we observe strong improvements in the domestic material footprint (SDG12: 'Sustainable Consumption and Production') in both biomass scenarios, since the demand for domestic materials such as coal, oil and gas declines. However, forestry products demand increase in the shocked sectors both from domestic and imported origin indicating spillover of deforestation and extraction. The Meat scenario results in a slightly higher material footprint in Germany, despite lower meat production and oil, gas and coal demand, driven by rising demand for domestic forest products. In contrast to the biomass scenario, here total demand for forestry declines, as less wood is imported. Given the strong declines in both domestic and imported demand for coal, oil and gas in the Technology scenario it performs best regarding the objective to reduce dependence on unsustainable resources.

EU competitiveness and job creation

The gender wage gap both in skilled and unskilled labor (SDG5: 'Gender Equality') widens in the three scenarios, driven by higher labor demands for agricultural production as a mainly male dominated sector, which drive up male wages. Regarding GDP per capita (SDG8: 'Decent Work and Economic Growth'), all policies show only small effects (for example -0.6% or -434$ in Germany under Subsidy). The share of manufacturing on GDP (SDG9: 'Industry, Innovation and Infrastructure') is positively affected only in the Subsidy scenarios. Here, the increase in vegetable oil and cake production for the chemical sector is of importance. In contrast, the Technology scenario leads to a decline of the shocked sectors, causing the share to shrink. In summary, the Technology scenario reveals the most adverse effects on indicators for EU competitiveness and job creation.

4.3.2 *Results outside EU*

Baseline and general spillovers

The baseline scenario shows more undesirable trade-offs over time for the ten LLMICs (Figure 4.7a) compared to EU (Figure 4.5a). While effects partly differ by country, some common patterns emerge. Overall positive trends are found for eight SDGs, but at the expense of most biosphere related SDGs (SDG13: ‘Climate Action’, SDG14: ‘Life below Water’, SDG15: ‘Life on Land’), cereal imports (SDG2: Zero Hunger’), air pollution (SDG3: ‘Good Health and Well-being’), share of manufacturing on GDP (SDG9: ‘Industry, Innovation and Infrastructure’) and their material footprint (SDG12: ‘Sustainable Consumption and Production’).

Spillovers of the three EU policies on the selected LLMICs are generally smaller than direct effects in the EU. In contrast to effects in the EU, the Technology and Subsidy scenarios show partly opposing spillovers, while again the Meat scenario shows the smallest spillovers, with some countries diverging from common patterns.

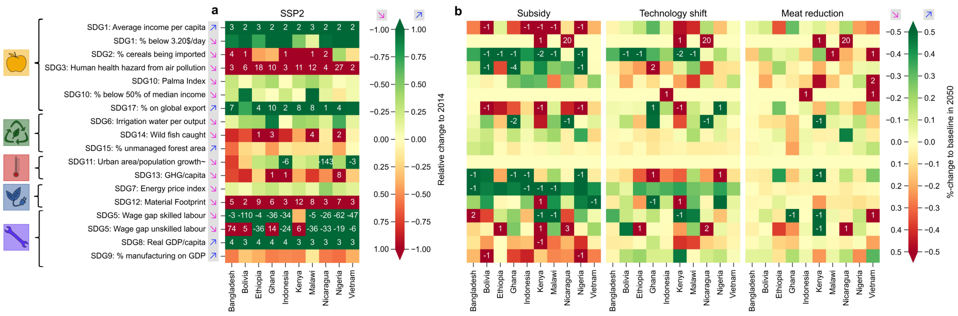

Figure 4.7. Heatmap showing the (a) relative change in baseline from 2014 to 2050 and (b) % changes induced by the different policy scenarios applied in the EU for the SDGs in ten low and lower-middle income countries in 2050.

Remark: Figure follows the design of Figure 4.5, only that the color bar of (b) is fixed to 0.5% and -0.5%. Source: Model results.

Food security

With regard to average per capita income (SDG1: ‘No Poverty’), associated to the food security objective (see Figure 4.7b), the generally negative effect for the Subsidy scenario is driven by decreasing factor returns especially to natural resources, due to declining export demand. In the Technology scenario, increasing income is induced by overall rising factor returns except for natural resources. Lower income for four countries, in the Meat scenario, is driven by reduced land rents. The remaining six countries show income increases, stemming from rising land returns and higher agricultural labor demand. Due to the differentiated changes in factor prices, impacts on households vary, as reflected in the increasing inequality (SDG10 ('Reduced Inequality'), Palma index and share of households living below 50% of median income) in the Technology and the Meat scenario, and declining inequality in the Subsidy scenario. The share of households living below the poverty line of 3.20$ rises in all three scenarios for two countries.

Induced by expanding cereal demand of the EU in the biomass scenario, the share of imported cereal on total cereal demand declines (SDG2: 'Zero Hunger'), increasing self-sufficiency. In the Meat scenario, however, cereal imports partly increase as rising imports of fruits and vegetables to the EU displace domestic production. Kenya forms an exception here, as paddy rice imports are strongly reduced. For a detailed discission, see Annex (B.4.1). The net effects are overall higher exports in the Technology and Meat scenario and lower ones in the Subsidy scenario (SDG17: 'Partnership for the Goals'), reverting the effects within the EU. In contrast to the effects in the EU, air quality (SDG3: 'Good Health and Well-being') improves mostly through the Subsidy scenario due to lower domestic production of chemicals displaced by EU imports. Whereas the opposite is observed for the Technology scenario, from shrinking EU production. The Meat scenario also causes generally higher air pollution, triggered by expanded production of vegetables for export to the EU.

Summarizing the effects for the Subsidy scenario, it leads to overall positive spillovers on the food security objective related SDGs, except for declining income and lower exports. More diverse but yet predominantly positive effects are induced by the Technology shift while negative spillovers are projected for the Meat reduction scenario.

Sustainable natural resource management

Spillovers of the EU policies on irrigation water use rises its efficiency per unit of output (SDG6: 'Clean Water and Sanitation') in all scenarios, predominantly in the two biomass scenarios, triggered as in the EU by increasing irrigation water rents which stimulates some substitution with capital. Desirably, open catch fishery (SDG14: 'Live below Water') is reduced, except for in the Technology scenario, in contrast to the baseline trend, shifting in the Meat scenario partly towards aquaculture. Like in the EU a positive trend for SDG15 ('Life on Land') is observed in the Meat scenario only, as there is less expansion of pasturelands into natural vegetation compared to the baseline in the Meat scenario. One exception here is

Ghana, which drastically expands its production of other vegetables for export to the EU and thus increases its cropland cover, rising also demand for water. The two biomass scenarios in contrast, cause higher deforestation in most LLMICs, to make room for agricultural land for production for the EU. In summary, while the effects are partly small, they indicate generally desirable trends in terms of the sustainable management of natural resources in the Subsidy scenario only.

Climate change mitigation and adaptation

For the SDG indicators associated to climate change, the policies affect GHG emissions, only, as small changes in GDP keep the urban area (SDG11: 'Sustainable Cities and Communities') at baseline level, as also observed for the EU. GHG emissions per capita (SDG13: 'Climate Action') reduce predominantly in the Subsidy scenario, stemming from reduced domestic production of petroleum, chemicals and plastics, displaced by EU imports, where sector emissions per unit of output are lower, compensating increases in GHG emissions from agricultural production. In the Technology scenario in contrast, the EU decreases their exports of these products, boosting local production of the shocked sectors associated with higher emissions. Interestingly, in the Meat scenario, emission savings from lower meat production for export to the EU are overshot by higher vegetable production for five countries. These negative developments for consumption- and production-based GHG emissions per capita stand in contrast to the effect of the policies in the EU. When taking the indirect LUC (iLUC) emissions into account (see Figure 4.6), also the slight positive trends are partly offset. Globally and in the EU, higher emissions from LUC and iLUC clearly overshoot emission savings induced by the biomass policies. The same can be observed for some of the LLMICs in the Subsidy and Meat scenarios, where for 4 and 3 countries, respectively, emission reductions are (partly) offset. These increasing emissions stem from higher conversion of forestry as well as natural vegetation such as unmanaged forest and savanna grassland to cropland for increased vegetable and fruits production. The reduction of pastureland in the Meat scenario, however, is the main driver in Ethiopia, where actually less conversion of natural vegetation takes place. However, especially in the Meat scenario, we also observe lower emissions from iLUC to compensate for higher GHG emissions or decrease them further, as declining expansion of managed forestry leaves more unmanaged forest, while cropland expands from pastureland, if at all. In the Technology scenario, emissions from iLUC overall reinforce higher total GHG emissions, and offset them in case of mitigated emissions in Malawi. Kenya alone shows lower carbon stock emissions, yet too small to compensate for the higher GHG emissions under this scenario (see Annex B.4.1). However, in general iLUC emissions are lower than in the Subsidy scenario. Thus, while the Subsidy scenario leads to lower emission from production and consumption, higher iLUC changes this trend, threatening its positive contribution to climate change mitigation. In contrast, the Meat scenario is overall more desirable, even at higher GHG emissions from production, due to higher carbon stocks from less deforestation. The Technology scenario is the least desirable, despite lower iLUC, as the EU alone benefits from the decarbonized bioeconomy sectors.

Reduced reliance on unsustainable resources

The EU policies cause decreasing energy price indices (SDG7: 'Affordable and Clean Energy') for the ten LLMICs in the two biomass scenarios, due to lower demand for energy, among others as the results of the declining production of the shocked sectors or lower demand for coal, oil and gas from the EU. In the Meat scenario, however, energy demands increase due to extended agricultural production and inputs thereof and cause slight increase in energy prices for all countries. The same directions of change and reasoning are observed for the material footprint (SDG12: 'Sustainable Consumption and Production') which decreases in the biomass scenarios, while it increases in the Meat scenario, as also found in the EU. The biomass scenarios, thus, lead to more desirable outcomes with regard to the dependence on unsustainable non-renewable resources, with mainly positive effects on the selected SDG indicators, while the Meat reduction provokes negative effects through strongly increasing agricultural production.

Competitiveness and job creation

The two biomass scenarios, cause opposing effects in the LLMICs compared to the outcome in the EU, with real GDP per capita (SDG8: Decent Work and Economic Growth') and the share of manufacturing on GDP (SDG9: 'Industry, Innovation and Infrastructure') being negatively and positively affected for most countries in the Subsidy scenario and the Technology scenario, respectively. The effects are driven mainly by changes in export competitions by the EU which pressures/relieves domestic production. Impacts on wage gaps (SDG5: ‘Gender Equality’) are heterogeneous, but widen predominantly in the Subsidy scenario only. The narrower wage gap is induced by, for example, declining extraction of naturel resources in the Technology scenario, a mainly male dominated sector. In contrast, we observe more desirable effects for the share of manufacturing on GDP and the wage gaps in the Meat scenario, while GDP also declines, due to shrinking livestock sectors. In summary, the Subsidy scenario has negative effects on the competitiveness and economic indicators of the LLMICs, whereas the Meat scenario and the Technology scenario show some desirable effects except for the declining GDP.

The comparison of the magnitudes of the effects for an implementation in the EU only or all OECD countries (see Annex B.4.2) shows that the EU is of major importance for the effects of some countries, as it largely determines the size of the effects.

4.4 Discussion

To determine the impacts of EU bioeconomy-specific policies on SDGs, this study quantifies both the direct (national/regional) and the indirect (foreign) effect for specific countries. Indirect effects are often disregarded or captured without regional detail at global or ‘rest-of the world’ level in CGE analysis (Hertel et al., 2019). We add to the existing literature on bioeconomy impacts by providing a more detailed look at these indirect effects for ten LLMICs and our approach allows for a differentiated comparison of the SDG outcomes within and outside of the main target area of the policy.

For comparison to our Meat scenario, we consider recent studies implementing the EAT-Lancet diet in their assessments which recommends, beyond reduction of animal-based products as considered by us, also lower total calorie intake from the consumption of sugars and fats. Humpenöder et al. (2024) implement the EAT-Lancet diet globally in REMIND_MAgPie and find global reductions in GHG emissions, which matches our findings for the Meat scenario in the EU. However, Gatto et al. (2023) find that without further measures, the income gains from implementing the EAT-Lancet diet causes a rebound effect, eventually rising total emissions at global level. Using the CGE model MAGNET, they also find negative social impacts in non-EU regions, for example, an increasing wage gaps for unskilled labour which we also find for some countries. Our analysis adds indicators related to income distribution, such as the Palma index, which also worsen in the Meat scenario. Rieger et al. (2023) analysed changes towards the EAT-Lancet diet for the EU27, only. They find increased emissions for the Rest-of-the-World, however without considering carbon stock changes from iLUC. In contrast, we find the opposite for the majority of the ten LLMICs in the focus, partly, however, only if carbon stock changes are taken into account.

For the two bioeconomy expansion scenarios, our results are supported by Nong et al. (2020), studying bio-chemicals, Escobar and Britz (2021), focusing on bio-plastics, and Philippidis et al. (2023), covering three chemical sectors similar to our study, who find carbon stock losses to offset GHG emission savings inside and outside of the EU. However, our more disaggregated analysis for single non-EU countries finds the opposite for certain countries, especially as we find GHG emission spillovers in most LLMICs in the Technology scenario, in addition to the iLUC emissions, due to falling EU exports of the bioeconomic sectors and, thus, expanded production in the LLMICs. The latter indicated the importance of international competitiveness of the bioeconomic sectors to prevent shrinking exports and higher emissions from more carbon intensive production outside of the policy target area. However, the lower exports of the bioeconomic sectors have positive implications for economic indicators, highlighting the inherent trade-offs to be targeted when expanding the bioeconomy. More generally, studies such as by Escobar et al. (2018) on biofuels indicate that first-generation bioeconomic products are not necessarily more sustainable in terms of climate change mitigation compared to fossil-based ones. For example, the degree of circularity plays a central role in alleviating negative effects on the SDGs in the EU and at global level (Többen et al., 2024).

Previous studies differ in regional focus, sectoral coverage as well as scenario assumptions, and none matches exactly our analysis. For example, we find mostly smaller effects than Sinkko et al. (2023), which could reflect that their analysis covers additionally food, textiles, furniture, and bio-based energy, while we focus on the three bio-economy related sectors, only. While we maintain the original sector definitions and model the bioeconomy transition trough changes in the input composition, Escobar et al. (2018), Escobar and Britz (2021) and Philippidis et al. (2023) split their focus sectors into bio-based and fossil-based ones to define directly the level of bio-based production. However, Philippidis et al. (2023) point out that data on production and more so on trade to support this distinction are available for a few countries, only. Accordingly, the three studies aggregate the output of the split-up sectors to one consumed and traded product without differentiation between bio- and fossil-based, as in our study. As results at the EU level are comparable to their findings and results for spillovers stem from trade effects, the demanding disaggregation of the production side might not be necessary for the indicators assessed by us. To improve the representation of substitution possibilities between different types of biomasses, we instead opted for splitting the initial GTAP 10 data base to higher agri-food detail, covering more than 40 sectors. This disaggregation is also of relevance for the Meat scenario, where cross-price effects and demand shifts can be depicted more accurately with higher detail in vegetables, fruits and crops as well as products from animal production.

One key objective of bioeconomy policies is to reduce extraction of fossil resources. Here, we find relatively modest impacts in the two EU biomass policy scenarios, especially on the global petroleum and coal sector. This is mostly driven by small cost share of biomass compared to fossil-based inputs in the three shocked sectors at the benchmark, and reflects the often raised “small shares stay small” critique on the functional forms used in CGE models. Here, also the statistical time gap might play a role as our base year of 2014 might miss recent increasing contributions of the bioeconomy to value-added, a problem also discussed by Cingiz et al. (2021). The CES functional form with its “small shares stay small and zero shares stay zero problem” is also employed in basically all CGE models to depict substitution between import partners and imports and domestic production, excluding emerging production or trade, which could be challenged given our time horizon of 36 years. We might therefore underestimate impacts on countries which produced initially not all crops demanded by a growing EU economy or exported them not or only in small quantities to the EU.

Despite these limitations, CGE models provide a useful basis for policy analysis as they capture global value chains which allows to quantify global spillover effects and to consider limits of natural resource extraction and land expansion (Verkerk et al., 2021). Nevertheless, modelling bioeconomic transitions remains challenging due to their comprehensive nature which let O'Brien et al. (2017) argue that a single model cannot capture all aspects of the bioeconomy. We advance here by increasing the sectoral detail of the CGE analysis to the one found in more specialized agri-food partial equilibrium models, and integrate the G-RDEM extension to capture relevant dynamics over time, which are often omitted (Pyka et al., 2022). Combined, this allows to generate baselines and conduct counterfactual analysis up to 2050 to assess bioeconomic developments alongside other influential socio-economic drivers. Such scenario assessment in quantitative model allows to compare different potential futures and the effect of policies in the bioeconomic context, as discussed by Angenendt et al. (2018).

In addition, CGEBox allows to assess distributional impacts induced by the EU bioeconomy policies which were not considered in similar analysis. For this purpose, we apply a micro-simulation for the selected ten LLMICs, capturing heterogeneities in factor income and other income sources based on household surveys and differences in budget shares through an econometrically estimated MAIDADS demand system. However, we cannot model changes in labor participation rates, neither economy-wide nor at household level, such that we miss impacts on unemployment. As such, our micro-simulation represents only two of the three impact channels discussed by van Ruijven et al. (2015) in their method review. While we consider that households re-allocate their labor and capital endowments as part of structural change, the weights of the individual households stay unchanged such that we cannot consider, for instance, impact of demographic trends on household size.

In terms of the SDG coverage in CGEBox, the extended indicator framework provides a large set of indicators to quantify impacts of an expanded EU bioeconomy of which solely a selection was discussed in detail. Still, we miss indicators available ex-post, such as qualitative ones, or indicators where we cannot model changes endogenously, such as those related to governance. Moreover, we exclude potential future developments in the bioeconomy not covered by the EU Bioeconomy Strategy, such as progress in bio-based pharmaceutics. Other literature, such as OECD (2010), discusses potential positive impacts for SDG3 (health) which is our analysis is driven by changes in air pollution, only, with partly negative impacts. In case of the Meat scenario, additional health indicators could be helpful as well, as higher levels of meat consumption increase the likelihood of certain diseases.

To quantify global spillovers of EU policies on the SDGs of ten LLMICs, bioeconomic developments outside the EU are solely driven by model mechanisms and the same exogenous assumptions as in the SSP2-related baseline. Countries such as Ethiopia, Ghana, Kenya, Malawi, Nigeria and Indonesia have developed their own bioeconomy strategies (Teitelbaum et al., 2020). Additional analyses could assess how these strategies interact with the EU's own, for instance, by further pressures on land and agri-food markets. However, especially in Sub-Saharan Africa, the effectiveness of measures to support and regulate the bioeconomy has so far been considered relatively low (Dietz et al., 2023). Still, it is crucial to consider that direct effects of any domestic measure on the SGDs interact with indirect ones induced by foreign policies. Our findings, therefore, support previous calls to design bioeconomy and accompanying policies such that both direct and indirect sustainability trade-offs are considered.

Bioeconomy technologies based on waste or new-technologies such as algae or other third generation biomass are currently captured by a limited number of models, only, as discussed by Christensen et al. (2022). As such technologies could deliver biomass for specific bioeconomy applications without using (additional) land, less or lower negative impacts might emerge than found in our study under existing technologies. Another way to advance our analysis is to model in more detail policies that target arising trade-offs, for instance certification initiatives for production on land not stemming from deforestation. This could improve the understanding of how an effective policy design can increase the sustainability of the bioeconomy.

4.5 Conclusion

This paper assesses the sustainability impacts of policy and technology induced expansion scenarios of EU bioeconomy sectors versus a reduced meat consumption scenario on national SDG outcomes and spillovers on ten selected LLMICs. We use the global CGE model CGEBox and evaluate three different scenarios vis-à-vis a SSP2 baseline in 2050. The selected SDG indicators are linked to the five strategic objectives of the EU Bioeconomy Strategy. Our results suggest critical trade-offs in the expansion scenarios, whereas SDG outcomes are largely positive under reduced meat consumptions regarding the objectives ‘Sustainable natural resource management’ and ‘Climate change mitigation and adaptation’. In comparison between the two expansion scenarios, i.e., a tax reduction (Subsidy) and a technological shift (Technology), the latter leads to the more desirable outcomes regarding the objective of ‘Climate change mitigation and adaptation’, while declining production and exports of the bioeconomy sectors cause further adverse effects, for example on ‘EU competitiveness and job creation’. The five objectives of the EU Bioeconomy Strategy quantified here by matching SDG indicators thus likely imply trade-offs both internally but also across objectives.

The spillovers of the EU policies on each of the ten LLMICs are smaller than both the baseline developments and the direct effects in the EU. However, considering the effects on the whole Rest-of-the-World remains important, especially as spillovers can offset positive developments in the region where a policy is implemented, such as repeatedly found in studies with regard to global GHG emissions for bioeconomy related domestic policy measures. Generally, none of the scenarios is purely positive for any of the ten selected countries outside of the EU. For example, our study finds that the policy driven expansion of the EU bioeconomy increases pressure on natural vegetation, and can reduce income and widen wage gaps in certain countries. EU policies related to the bioeconomy, hence, threaten the success of other EU countries’ policies, for instance, related to development cooperation or to biodiversity. Both direct and indirect effects of the reduced meat consumption scenario are more positive in terms of certain SDG outcomes and could eventually alleviate trade-offs and create synergies if jointly implemented with an expansion scenario. While general trends can be deduced from the spillovers, the effects are country-specific and depend, among others, on initial trade relations, also for products that are not directly demanded for bioeconomic production. The applied micro-simulation shows that bio-economy related policies have distributional impacts in other countries, with mainly negative ones in Meat and Technology scenario and positive one in the Subsidy scenarios of the EU.

A comparison of the EU-level implementation to a hypothetical OECD-wide effort suggests that the EU is the core driver for most countries analyzed in detail, especially in the expansion scenarios. While the effects of an OECD-wide implementation are somewhat larger, the socioeconomic developments in the long-run remain the far more decisive factor for the SDG outcomes, as seen when comparing the changes between 2014 and 2050 to the changes in 2050 from implementing the bio-economy related policies on top of the baseline.

Importantly, this study highlights the complexity of bioeconomic transitions and corroborates conjectures put forward in prior theoretical and expert-based research on the impacts of bioeconomic transformation (e.g., Dietz et al., 2023; Stark et al., 2022). First, absent appropriate regulatory safeguards and measures to balance distributional outcomes, policies aimed at promoting the use of biomass, even if directly targeted at improving the efficiency of biomass use, can produce unexpected negative environmental rebound effects or socially undesirable impacts. And second, unilateral implementation of measures to promote bioeconomic transformation, especially in large economic blocks like the EU, implies both desirable and undesirable impacts in multiple SDG dimensions for third countries. As such, our results call for a careful selection and design of the policy mix used to implement the EU Bioeconomy Strategy. A particular focus is warranted on regulations to mitigate rebound effects and alleviate undesirable spillover effects, as well as on measures to support the most vulnerable world regions in the development and implementation of safeguards to render their own bioeconomies sustainable. Beyond conventional means of technical and financial cooperation, this may involve international agreements for the development of coherent bioeconomy policy frameworks and programs to accelerate knowledge and technology transfer from both public and private-sector based research in biotechnology and process engineering.

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Chapter 5
Contribution and conclusion

5.1 Major contributions

In general, thus far, studies have mostly employed static CGE models when analyzing distributional and poverty issues (van Ruijven et al., 2015). In contrast, the three case studies presented in this dissertation explicitly focus on long-run developments incorporating adjustment processes and demographic changes. Focusing on sustainable development, this thesis shows that a detailed differentiation of aggregation levels provides useful information on synergies and trade-offs of development pathways. In the following, the different contributions of each chapter to the state-of-the-art are discussed.

The analysis in Chapter 2 contributes to existing literature by taking changing socioeconomic conditions into account when analyzing the effect of climate change-induced yield changes on household welfare. Differentiating nine household types by income characteristics, specifically, absolute income and income share sourcing from agricultural activities in three low- and lower-middle income countries, this study assesses aspects that determine vulnerability to these climate change effects. First, households working in the agricultural sector are overall less vulnerable than non-agricultural households. Some farmers even gain from the yield changes, while others lose less relative to other households in their income quantile. These findings underline the importance of land ownership in the context of vulnerability levels as increasing returns to land due to scarcity can (partly) compensate rising food prices. Besides the composition of the factor income, the level of income clearly is of importance, as richer households spend a smaller share on food, which makes them relatively less vulnerable to the increasing food prices.

Second, the comparison to a comparative static approach allows to disentangle the added value of a dynamic approach. The findings reveal that the static analyis tends to underestimate the effect sizes since differentiated factor income growth over time and other crucial dynamics (e.g., sector varying productivity changes and population growth) are disregarded. Third, the sensitivity analysis applying different yield shocks underlines that impacts on staple crops are of major importance for the welfare change. Where cereals constitute the largest share of household consumption, as currently still in many low-income countries, changes in their yield and thus prices are critical for the wealth of these households. The results indicate the need for diversification of food consumption to buffer increasing food prices as a diverse food basket provides substitution options and leads to a higher flexibility regarding food choices.

Another major contribution of this thesis is the development of an indicator framework in Chapter 3 that enables the quantification of SDGs. In this process, the SDG indicators are built-in to CGEBox and customized for long-term assessments. This methodological contribution allows to assess baseline and counterfactual scenarios in terms of their sustainability and achievement of SDG targets. With its 68 endogenous indicators, the new framework represents 15 out of the 17 SDGs, in particular, those relevant to the agri-food sector, various distributional aspects and gender equality. The framework builds on the (endogenous) model outcomes to calculate a varying number of indicators per SDG. A post-model microsimulation that calculates income and expenditure effects on the initial data of household surveys available for selected low- and lower-middle income countries, provides the 500 household quantiles underlying the indicators for the distribution-related SDGs. Through this extended indicator coverage, the framework specifically improves the assessment of social SDGs which were thus far underrepresented in modelling approaches (Allen et al., 2016) and adds a strong focus on agri-food.

Employing this indicator framework to simulate scenarios for ten low- and lower-middle income countries, Chapter 3 contributes different aspects to the literature. First, it adds a quantification of SDGs for single low- and lower-middle income countries in long-term scenarios both until 2030 and 2050 in a global model. This regional focus addresses a research gap as existing literature has analyzed mainly aggregated world regions. The representation of single countries provides high level of detail and allows to take country-specific circumstances into account. Second, it emphasizes the importance of household level detail when assessing scenarios regarding their SDG performance as it permits to quantify distributional effects. For the baseline studied in Chapter 3, this reveals that inequality increases for some indicators as parts of the population benefit more than others, but also as parts develop in undesired directions (i.e., deteriorate). Third, a comprehensive coverage of the different aspects of the SDGs is crucial to identify trade-offs and synergies among and between the single goals. For very few SDGs all indicators improve unidirectionally. Fourth, the baseline quantification of the indicators shows that current baseline narratives are not capable of reaching all SDGs in unison by 2030 and 2050, as sustainability gaps remain, especially in the environmental domain. Further, none of the three SSPs studied in Chapter 3 with scenario-specific baseline assumptions clearly outperforms the others, emphasizing the complexity of sustainable development and the inherent trade-offs. Thus, the combination of long-term CGE analysis and the sustainability indicator framework introduced in this study proves useful for a multifaceted comparison of scenario outcomes.

The assessment presented in Chapter 4 quantifies the effects of sustainable development policies, in the context of the EU Bioeconomy Strategy. Simulating three scenarios in the long-run, the impacts induced by EU bioeconomy policies are assessed regarding their SDG implications. Therefore, the five objectives of the EU Bioeconomy Strategy are linked to specific SDG indicators. The results indicate, that a subsidy on biomass inputs in the petroleum and coal, chemical, and rubber and plastic sectors leads to similar trade-offs on the SDGs as an increase in biomass-use-efficiency in the same three sectors. Negative effects mainly emerge across indicator evaluating the Strategy’s objectives to increase food security, foster EU competitiveness and sustainably manage natural resources. As expected, indicators linked to climate mitigation and reduced reliance of fossil fuels such as GHG savings, improve through substitution of fossil fuel inputs. However, these emission savings in production are offset by emissions from land use change. Through the third scenario a shift towards a less animal based-diet, i.e., dairy, meat and fish is assessed, showing that general spillovers are mostly smaller and in contrast to the two aforementioned biomass scenarios, purely beneficial regarding environmental indicators and the objective to manage natural resources sustainably. Thus, a reduction in meat consumption provides options to compensate for negative impacts resulting from expanding bioeconomic sectors. Through the revealed trade-offs, this assessment underlines the importance to account for adverse effects both within and among the objectives to derive actual sustainable solutions across social, environmental and economic dimensions.

In addition to the direct effects, the assessment in Chapter 4 contributes to the literature by deriving indirect effects of the policies on ten low- and lower-middle income countries' SDGs. These spillovers from the EU are, thus far, mostly assessed at an aggregated rest of the world level in modelling exercises. The effects of the three policies are generally smaller than the direct effects in the EU and predominantly opposing. Thus, also for the spillovers, trade-offs with the Strategy's objectives can be emphasised. Specifically, comparing the three policy scenarios, the effects differ as, for example, the technology shift for more biomass-use-efficiency leads to a reduction of exports from the three bioeconomic sectors in the EU, causing partly opposite spillovers compared to the subsidy on biomass for the ten focus countries. Regarding GHG emissions this is problematic, as the low-income countries increase their own, more carbon intensive production. In contrast, rising imports from the bioeconomic sector in the subsidy scenario, link to negative economic outcomes for these countries. Disentangling policy spillovers for single trade partners of the EU underlines that they are country-specific and driven by trade relations to the EU. Phenomena such as increasing emissions from land use change offsetting partly emission savings from the import of decarbonized bioeconomic products or reduced meat demand, are found at global level and for some of the countries. For other focus countries where conversion does not occur from natural land covers but managed pastureland this effect cannot be observed. The assessment indicates also that products that are not directly demanded for bioeconomic production, such as livestock, can drive effects, when these are displaced for the production of biomass inputs and thus outsourced to other countries.

Finally, the comparison to scenarios where OECD countries obtain the same policies, shows that general directions of effects for the low-income countries remain the same as in the EU-only implementation. This additional scenario, provide also insights on the importance of the EU for the overall spillover, as the effect size is determined by a large share from the employment of the policy in the EU.

5.2 Methodological discussion and outlook

In this thesis, the CGE model CGEBox is applied and extended to assess different global long-term scenarios that differ in their socioeconomic, policy and climate change assumptions and are analyzed regarding the achievement of SDGs and distributional impacts. In the following, six arguments are discussed why CGEBox (and a CGE model in general) is particularly suitable for this kind of assessment: First, CGE models excel at representing the global economy due to their consistent foundation following microeconomic theory (Borges, 1986). Compared to partial equilibrium models, which often focus with high detail on specific markets or products, global CGE models account for interconnections across all sectors and regions while all (factor) markets are in equilibrium through price mechanisms. This allows to also take macroeconomic changes into account. These advantages are especially relevant in the context of this dissertation as it aims to study interlinkages at different levels (i.e., households, sectors, and countries). For the representation of the bioeconomy capturing global value chains as well as limits of natural resource extraction and land expansion is of crucial relevance (Verkerk et al., 2021). Such global feedbacks would be missing when relying on household models alone, such as dynamic micro simulations or agent-based models, which incorporate a large detail on household level often at a regional scale however disregard market clearing and supply side effects (Klevmarken, 2022) and provide less details than CGE models (Pyka et al., 2022).

Second, long-term dynamics can be captured in CGE models. Quantifying sustainable development pathways requires a long-term perspective, as the impacts of climate change and bioeconomic transformation both depend on and affect socioeconomic development. Furthermore, the time frame of the SDGs until 2030 demands for a long-term consideration, which makes for example static input-output models less suitable (Allen et al., 2016). Initially, CGE models were developed for the implementation in a comparative static configuration, addressing short-term policy shocks, which would fall short of depicting the relevant adjustment processes in the long-term (Britz and Roson, 2019). The complementary comparative static assessment of the climate-induced yield changes in Chapter 2 shows that in this setting effects are underestimated due to the neglect of increasing pressures on natural resources induced by population and economic growth over time. Changing population and GDP development exogenously while maintaining the economic structure of the base year over time is not sufficient here, as changes in preferences, productivity, sector composition and factor endowment need to be considered (Pyka et al., 2022). In this dissertation, CGEBox is therefore implemented in a recursive dynamic setting, through the model G-RDEM, which allows to construct baselines and counterfactuals until 2050, capturing crucial structural changes and transformative dynamics, such as sector-specific productivity growth, debt accumulation, and changing industrial cost shares (Britz and Roson, 2019).

Third, the model applied in this dissertation enables to investigate several parallel scenarios, which allows to reveal externalities, undesired outcomes and sustainability gaps through the assessment of consequences for different economic agents and indicators. In Chapter 2-4, different baselines and counterfactuals are compared regarding their distributional effects and performance in light of the SDGs. For this task, economic models require exogenous projections of macro-economic parameters to solve the model iteratively for succeeding years. As common in long-term projection literature, G-RDEM relies on exogenous projections from the SSPs (Riahi et al., 2017). The option to solve the model along exogenous projections of macro-economic variables permits to construct different parallel baselines. These projections applied in all three chapters were recently updated (IIASA, 2024). Thus, repeating the assessments with the newly released pathways might enable a more accurate representation of current events and their effects on the respective study such as, for example, the progress towards the SDGs. Beyond these projections, several assumptions are required for the construction of consistent baselines and for modelling their development. This baseline definition process is therefore crucial for the analysis. From the findings in Chapter 3 it is clear that none of the three baselines is yet able to reach all SDGs in unison. Thus, more elaborated assumptions need to be developed to construct Sustainable Development Pathways, as initialized by Soergel et al. (2021). For example, including policies for changing wealth redistribution, and governance in counterfactual analyses could deliver interesting insights for the upcoming years.

Already in comparative static analyses, behavioral parameters are subject to uncertainty, which is often addressed through sensitivity analysis. Projecting future scenarios adds further dimensions of uncertainty, as it is unknown how societies develop. Socioeconomic parameters including GDP, population, and education might change in many possible ways in the next decades. To deal with uncertainty about future developments, the construction of several plausible scenarios is useful to characterize a results space of possible outcomes (Angenendt et al., 2018). Building on established exogenous projections from the SSPs or scenario assumptions allows to compare model results among studies and to identify differences arising from the respective model coverage and assumptions (Schmitz et al., 2014; von Lampe et al., 2014; Popp et al., 2017; Dekker, et al., 2023). Therefore, in Chapter 2, a sensitivity analysis is performed to assess uncertainty about the changes in yield induced by climate change and to test the robustness of the distributional results. In contrast, in Chapter 3, baselines constructed following different SSPs are compared to capture the effect of changes in varied socioeconomic conditions. Finally, in Chapter 4, three policies increasing biomass demand are compared to understand differences in their local and global effects.

Fourth, incorporating climate change effects and policies that tackle remaining sustainability gaps in counterfactual analyses allow to determine decisive action points. With the aim to disentangle differences in climate change effects for household groups, Chapter 2 incorporates induced yield changes. However, effects of climate change are manifold and include among others sea level rise, extreme weather events, disease outbreaks and biodiversity loss. While some of these drivers were considered in the quantification of the yield changes taken from FAO (2018), their impacts exceed yields, affecting, inter alia, energy demand, labour productivity and health. Future research could incorporate further channels of effects on the economy. One approach is to estimate and include a climate damage function as found in Roson and Sartori (2016). Extending the current representation of climate change in the study of Chapter 2 would permit a more nuanced assessment of household vulnerability. While in Chapter 2, mitigation policies are disregarded, such policies can have great impact on different household categories, potentially changing the distributional impacts found in this dissertation (Emmerling et al., 2024).

In Chapter 4, different EU bioeconomy policies are assessed in terms of their contribution to the SDGs, also in low- and lower-middle income countries. The representation of bilateral trade in global CGE models permits to capture changes in trade relations of the EU and other geographical regions as a result of the policies. However, representing the bioeconomic developments in CGE raises some challenges due to the complexity of this transformative process (Pyka et al., 2022). Therefore, O'Brien et al. (2017) conclude that all aspects of the bioeconomy cannot be depicted in detail in a single model. Linking different models to extend model boundaries at sectoral level and to capture other environmental interactions are, however, time consuming and require extensive harmonization processes (Delzeit et al., 2020). In this dissertation, we, therefore, increase the sectoral detail of the CGE analysis, including also aquaculture, to better represent substitution and cross-price effects when demand for feedstocks rises. However, a full distinction of bio-based and fossil-based sectors has not been implemented due to data limitations, especially regarding trade flows. A comparison to other model exercises applying this distinction at EU-level showed, however, that the effect size for EU outcomes lies in a similar range. Further sectoral disaggregation could be incorporated in future studies, to model, for example, separate by-product sectors (Verkerk et al., 2021). Capturing technologies that utilize waste or innovations processing algae or other third generation biomass could deliver further insights (Christensen et al., 2022) and improve the representation of circularity, which is a central way forward for achieving sustainability (Risse et al., 2017). Future research could assess these new technologies in tandem with policies targeting remaining sustainability gaps to expand knowledge on effective policy and pathways aligned with the SDGs.

Fifth, the quantification of the 17 SDGs for future scenarios requires several model features to comprehensively represent the different components of the integrated and indivisible policy agenda of human and planetary well-being. CGE models are not capable of capturing all aspects relevant for the SDGs, as no other single model can depict their full multi-dimensionality. Nevertheless, CGE models are useful for sustainability assessments (Böhringer and Löschel, 2006) and CGEBox fulfils prerequisites for the quantification of SDGs discussed by Allen et al. (2016) like projections of long-term scenarios as outlined above, global linkages and (flexible) quantification at country level. Other models used for a comprehensive coverage of SDGs are Integrated Assessment Models (IAM), which often incorporate CGE models. While they partly reach coverage of all 17 SDGs and incorporate different aspects of environmental modelling, these models tend to aggregate other dimensions, such as sectoral detail or spatial coverage lacking detail on other parts. Yet, country-level assessments are required to quantify the national SDG performance, while sufficient sectoral detail is needed to capture cross-price and substitutional behavior in consumption and to properly depict changes in nutritional outcomes. In the context of SDG indicator quantification, there is thus a clear trade-off between breadth and detail. The structure of CGEBox and the underlying extended (agri-food) database allows for broad coverage of relevant sectors and the flexible simulation of several single countries at a time. The developed indicator framework (Chapter 3) is very detailed in certain SDGs and quantifies indicators for 15 of the 17 SDGs, however, it is not exhaustive. Again, the link of other (sectoral) models to CGEBox can extend its coverage while leveraging the strength of the respective models. Missing non-market indicators could thereby be linked to the economic framework of CGE. However, the disadvantages of such linkages were mentioned in the previous paragraph.

Sixth, CGEBox allows for a representation of household detail. While generally CGE models represent interactions among regions and sectors of (different) economies, intra-national household distributions are also relevant to find sustainable development pathways and effective policies. As CGE models typically fall short in addressing distributional aspects, incorporating household level detail creates large added value. In the literature, different approaches are established to assess household inequalities with macroeconomic models: Specifically, (i) a "disaggregation approach", disaggregating multiple household types (up to the full population) in the CGE model, (ii) a "microsimulation approach", coupling microsimulation models in a layered or integrated manner, and (iii) a "ex-post distribution approach", modelling income distributions provided by ex-post data (van Ruijven et al., 2015). As these approaches differ in terms of their behavioral assumptions, the level of captured household heterogeneity and the way the additional detail is linked to the CGE, the decision on how to incorporate households depends on a study's objective weighting the advantages and limitations of each approach (Cockburn et al., 2014).

Full integration of the household surveys ("full population disaggregated approach") into the CGE model seems the most desirable solution as it is theoretically sound and allows for mutual feedback channels. However, it comes with several challenges which made it unsuitable for the conduction of the three studies in the thesis at hand. The size of the model increases with every additional household, raising convergence problems and computational time considerably which makes it especially in long-run simulations difficult to solve (van Ruijven et al., 2015).

This could be partially compensated for by disregarding detail in other parts of the model, however, aggregating sectors and products restricts SDG quantifications, while regional aggregation hinders the assessment of cross-country inequality as discussed above.

With the aim to determine differences in vulnerability of household types to crop yield changes, the case study in Chapter 2 therefore relies on the "representative disaggregated approach". Here, the single representative consumer is split down to household types in CGEBox, while the remainder of the model maintains the initial structure. The main drawback of these multiple representative household types in the representative disaggregated approach compared to microsimulations and the full population disaggregated approach is that it disregards intra-group distributional effects, since, as in the ex-post distribution approach, they would be assumed a priori (Hertel and Reimer, 2004). Therefore, changing distributions of the total populations is not depictable in this chapter. However, in contrast to the ex-post distribution approach it allows to differentiate endogenous expenditure and income effects for household types (van Ruijven et al., 2015) revealing vulnerability patterns of parts of the population depending on certain (economic) characteristics, which was the main focus in Chapter 2.

To be able to measure distributional effects endogenously, as required for several SDGs, a high number of households is, however, needed in Chapter 3 and 4, reaching the bounds of the disaggregation approach. Thus, an alternative approach, namely microsimulations, is chosen in these studies. This top-down linkages to the CGE model belong to the most applied techniques (Cockburn et al., 2014). In this approach, certain linkage variables (for example, prices or factor returns) from the CGE results are used to quantify the distributional effects of these macro changes on households. As such, it delivers distributions, that are crucial for several SDGs (SDG1 "No Poverty", SDG2 "Zero Hunger", SDG7 "Affordable and Clean Energy", SDG10 "Reduced Inequality") and their endogenous changes over time or as a result of a shock, as employed in Chapter 3 and 4. However, this method disregards the feedback or second-order effects to the macro level (Bourguignon and Bossolo, 2013). Thus, effects calculated by the microsimulation have no effects on the CGE simulations in contrast to the representative household approach or fully integrated (microsimulation) approach. This results however only into an information loss if the 'aggregation error' (Savard, 2010) arises, which means that the average effect of the microsimulation does not resemble exactly the CGE results. This error was identified in Chapter 3, due to the non-linearity and varying fixed commitment terms of the MAIDADS[1] demand function applied in CGEBox and the microsimulation. While the aggregated microsimulation results partly differ from the macro-model outcomes, the difference is rather small, rendering the bias neglectable in terms of poverty and inequality outcomes (Hertel and Reimer, 2004). An iterative approach where both models are solved sequentially in feedback loops until both models converge (van Ruijven et al., 2015) would address this gap. However, again, convergence can be challenging, already in a single country CGE (Beņkovskis et al., 2023) making it especially daunting in a global CGE with the extensive database applied in Chapter 3 and 4. Within these limitations, post-model top-down coupling of CGE with microsimulation models can leverage the strengths of both model types (Peichl, 2016).

In recent literature, estimated income (decile) effects of different drivers such as climate change (Gilli et al., 2024), climate policies (Emmerling et al., 2024) and changing socioeconomic conditions (Rao et al., 2019) have been implemented to investigate changes in inequality. While these approaches deliver distributional insights, they fall short in providing sufficient detail to investigate household-level implications for SDG targets that go beyond income inequality. The post-model microsimulation applied in Chapter 3 and 4 captures household responses to the macro changes through two of the three channels of adjustment discussed in van Ruijven et al. (2015). First, we allow for changes in income source incorporating heterogeneity in factor endowments and through a MAIDADS demand system to reflect income-dependent preferences and savings. This allows to quantify changes in income, food consumption and nutritional intake, and other consumption shares. Second, unemployment or leisure categories for labor, as a third channel of adjustment and heterogeneity, are not specified. Household vulnerability to certain shocks can furthermore vary by various other (qualitative) factors such as religion, age or health (Emmerling and Tavoni, 2021) which is not covered in CGEBox to date. The incorporation of those factors is partly limited due to data availability and due to the missing knowledge about their effects on household responses. Nevertheless, at country-level the demand system incorporates for example differences in demand due to religious restriction.

[1] Modified An Implicit Directly Additive Demand System

In general, data availability is a challenge when linking household surveys to CGE models, as micro data need to fit to the structure of the CGE or be party extensively reconciled (Bourguignon and Bossolo, 2013). The household data applied in all three case studies of the thesis is derived from surveys with a focus on farming households in terms of the data collected, while it is nationally representative, with the exception of Ethiopia (FAO, 2017). These surveys were conducted in different years which partly differ from the base year of the GTAP database. With the updated database of GTAP (GTAP Version 11) released, the integration of more recent household datasets can improve the representation of distributions of income sources and levels in the respective countries for the new base year in 2017. Further research could also be conducted collecting and applying data for other countries, as for example for EU Member States, to capture distributional impacts of bioeconomic policies also within these countries. The focus in Chapter 2-4 was laid on low- and lower-middle income countries due to their special attention on the SDGs and their vulnerability to climate change.

While this dissertation focuses on inter-country and household inequality through a comparison of country-level outcomes and household distributional analysis, differences among subregions are not considered. However, (historical) intra-country differences due to regional specialization in fossil-fuel intensive industries, natural resource endowments and geographical conditions can have strong effects on their vulnerability to climate change and policies. Likewise, the progress towards the SDGs can differ among these regions and, thus, their explicit representation would provide more targeted insights into another level of distribution effects. Currently, CGEBox can operate at NUTS2 level, differentiating production activities by subregion. The SDG framework, however, relies to a large extend on demand-side and income variables. Household surveys applicable for this disaggregated assessment would need to provide the economic as well as spatial information to match the data to the respective model subregion to enable a full integration with the microsimulation. Such an assessment would deliver novel insights into differences in vulnerability at regional level.

5.3 Policy implications

Overall, this dissertation highlights the political need to take (side-)effects and linkages of political interventions as well as development processes at different tiers into account. In the context of climate change, it underlines that households face different repercussions depending on their respective characteristics. Against the background of SDG Target 13.3 (“strengthen resilience and adaptive capacity to climate-related disasters”), a central point that determines vulnerability is the level of income through its link with the share dedicated to food consumption. Thus, enacting policies that tackle poverty and reduce inequality is of great relevance in this context. Another point of political action is land reforms, as the results from Chapter 2 spotlight the importance of access to land for vulnerability. Improved land titles and institutions in low-income countries can allow agricultural households to actually benefit from increasing crop prices through higher income. Well-targeted land reforms could improve the living conditions for socioeconomic groups with little access to land and increase efficiency and resilience, when investments are taken (Bambio and Agha, 2018; Makate et al., 2019). Cautiously, the environmental external effects from deforestation need to be considered in this process (Liscow, 2013; Pacheco and Meyer, 2022). While some general patterns persist, household situations are very diverse. Thus, there is a need for policy strategies considering regional priorities and household type-specific needs while working towards climate resilience and adaptation.

In light of these impacts especially for poor households and SDG Target 13.2 (“Integrate climate change measures into policy and planning”), climate change mitigation policies are of great importance. Political attention should however focus on a just transition to distribute burdens across society. Like climate change also mitigation policies can have diverse effects on different households depending on their circumstances. Thus, differentiated interventions to mitigate consequences especially for the most vulnerable households are needed. Designing climate policies that overlook such social inequalities risks exacerbating them (Markkanen and Anger-Kraavi, 2019). One policy option is to implement carbon pricing schemes and redistribute the resulting tax income within the population to balance households’ shares on financial burden and pollution. Such a lump-sum payment can improve the economic situation of low-income households (Emmerling et al., 2024). Within the EU, the Social Climate Fund was established with this purpose to strive for compensation of low-income household for increasing cost due to the rising carbon price for the period of 2026 to 2032 (EU, 2023). As Member States are still formulating their national strategies about how to distribute this budgetary resource, a holistic and circumspect definition of the most effective pattern should play a pivotal role in the process.

Results of the baseline assessment until 2030 and 2050 in Chapter 3 showed that all three scenarios fall short of achieving the SDGs in their target time frame and beyond. As the developments towards the SDGs are off-track, in September 2024 the ‘Summit of the Future’ will be held to find ways to still achieve the SDGs and other international commitments. Politicians should take this as an incentive to increase their efforts to achieving the SDGs by implementing relevant policies and transformation strategies. Chapter 3 underlines that tackling the economic and social trade-off with the environmental dimensions is crucial for the achievement of the SDGs in unison. At the same time, inequality rises in these baselines even without considering climate change impacts. Thus, filling the environmental sustainability gap, policies and technologies should target a decoupling of economic growth from environmental pollution and exploitation of natural resources taking the effect on distributional issues into account. To prevent undesired effects of political decisions addressing these sustainability gaps, ex-ante assessments allow to disentangle the massive interactions of SDGs. Quantitative studies can help policy makers to find priorities in the jungle of SDG targets and indicators and to make more holistic policies in times of polycrisis[2]. This can help to do justice to the indivisibility concept of the SDGs while acknowledging the limited resources and capacities that policy makers are facing.

Through Target 17.14 “Enhance policy coherence for sustainable development” the Agenda 2030 stresses the need for partnership and holistic policies to achieve the SDGs. Beyond national policy coherence, the aspect becomes more relevant at an international dimension as well. In recent years, several EU policies incorporate the need to account for global spillovers, such as the Renewable Energy Directive

[2] The term polycrisis is revered to “*when crises in multiple global systems become causally entangled in ways that significantly degrade humanity’s prospects. These interacting crises produce harms greater than the sum of those the crises would produce in isolation, were their host systems not so deeply interconnected.*” (Lawrence et al., 2022, p.2).

(REDII), the Green Deal, and the EU Bioeconomy Strategy. For free trade agreements, sustainability assessments are increasingly demanded to better reflect the international impacts in national policies. As Browne et al. (2023) concluded, however, it is relevant to assess for whom the policies are coherent to contribute to SDG10 ("Reduced inequality"). This can also be translated to the findings of Chapter 4, were the coherence of policies linked to the EU Bioeconomy Strategy are assessed in light of global spillovers on the SDGs which can compromise the overall sustainability of bioeconomic developments. The results highlight that EU bioeconomy policies affect the selected SDG indicators and partly interfere with the Bioeconomy Strategy's goals at national and international level. The findings call for policy makers to incorporate the complexity of bioeconomic transformation beyond the local level, avoiding to define policies in silos, i.e. without cooperating with other policy areas and regions. Recognize these trade-offs at different levels and dimensions of sustainability in a policy mix, could eventually allow to reach Target 12.2 "By 2030, achieve the sustainable management and efficient use of natural resources". Finally, it is also of relevance that low-income countries transform their fossil fuel-based sectors, making international cooperation through knowledge transfers but also technical capacity building particularly relevant (Dietz et al., 2023).

Performing ex-ante assessments before implementing such a policy mix can help to understand how an effective policy design can increase the sustainability of the bioeconomy to reach the SDGs globally and in their country-specific contexts. This dissertation, thus, highlights the importance to incorporate beyond local effects also spillovers at global level in ex-ante assessments to derive coherent policies and development pathways that enable sustainable development *leaving no one behind*.

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Chapter 6 Appendix

Appendix Chapter 2

Table A.2.1: country aggregation

Aggregate	Country
Vietnam	Vietnam
Ethiopia	Ethiopia
Bolivia	Bolivia
ASIAN	Brunei Darussalam, Cambodia, Indonesia, Lao People's Democratic Republic, Malaysia, Philippines, Singapore, Thailand Rest of Southeast Asia
Rest_COMESA	Egypt, Kenya, Madagascar, Mauritius, Rwanda, Uganda, Zambia, Zimbabwe, Rest of Eastern Africa
Mercosur	Argentina, Brazil, Paraguay, Uruguay,
Rest_ANDEAN	Chile, Colombia, Ecuador, Peru, Venezuela
REST_CAFTA	Costa Rica, Guatemala, Honduras, Nicaragua, El Salvador, Dominican Republic, Rest of North Africa
ROW	Oman, Israel, Rest of Oceania, Hong Kong, Taiwan, Rest of East Asia, Bangladesh, India, Nepal, Pakistan, Sri Lanka, Rest of South Asia, Rest of North America, Rest of South America, Panama, Rest of Central America, Jamaica, Puerto Rico, Trinidad and Tobago, Caribbean, Belarus, Russian Federation, Ukraine, Kazakhstan, Kyrgyzstan, Rest of Former Soviet Union, Armenia, Azerbaijan, Georgia, Bahrain, Islamic Republic or Iran, Jordan, Kuwait, Qatar, Saudi Arabia, Turkey, United Arabic Emirates, Rest of West Asia, Morocco, Tunisia, Rest of the world
USA	United States of America
Rest_OECD	Australia, New Zealand, Japan, Korea, Canada, Mexico, Switzerland, Norway, Rest of EFTA
EU28	Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom, Bulgaria, Croatia, Romania
Rest_Sub-Saharian Africa	Benin, Burkina Faso, Cameroon, Cote d'Ivoire, Ghana, Guinea, Nigeria, Senegal, Togo, Rest of Western Africa, Central Africa, Southern Central Africa, Malawi, Mozambique, Tanzania, Botswana, Namibia, South Africa, Rest of South African Costums
China	China
CEFTA	Albania, Rest of Eastern Europe, Rest of Europe

Source: Data from Aguiar et al. (2016).

Appendix Chapter 3

A Method

Table A.3.1: List of country aggregation

Aggregate	Country
Vietnam	Vietnam
Ethiopia	Ethiopia
Bolivia	Bolivia
Malawi	Malawi
Ghana	Ghana
Indonesia	Indonesia
Nicaragua	Nicaragua
Nigeria	Nigeria
Bangladesh	Bangladesh
Kenya	Kenya
South Africa	South Africa
India	India
USA	United States of America
Canada	Canada
Mexico	Mexico
Bolivia	Bolivia
Brazil	Brazil
Argentina	Argentina
China	China
Germany	Germany
Philippines	Philippines
Oceania	Australia, New Zealand, Rest of Oceania
ASIAN	Brunei Darussalam, Cambodia, Lao People's Democratic Republic, Malaysia, Singapore, Thailand, Rest of Southeast Asia
CentralAm	Costa Rica, Guatemala, Honduras, Panama, El Salvador, Dominican Republic, Jamaica, Puerto Rico, Trinidad and Tobago, Rest of Central America
XANDEAN	Chile, Colombia, Ecuador, Peru, Venezuela
MERCOSUR	Paraguay, Uruguay
EU28	Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom, Bulgaria, Croatia, Romania

XEurasia	Russian Federation, Ukraine, Kazakhstan, Kyrgyzstan, Tajikistan, Rest of Former Soviet Union, Armenia, Azerbaijan, Georgia
NorthAfrica	Egypt, Morocco, Tunisia, Rest of North Africa
RestOfAfrica	Benin, Burkina Faso, Cameroon, Cote d'Ivoire, Guinea, Senegal, Togo, Rest of Western Africa, Central Africa, Southern Central Africa, Madagascar, Mozambique, Mauritius, Tanzania, Rwanda, Uganda, Zambia, Zimbabwe, Rest of Eastern Africa, Botswana, Namibia, Rest of South African Customs Union
ROW	Oman, Israel, Hong Kong, Taiwan, Rest of East Asia, Nepal, Pakistan, Sri Lanka, Rest of South Asia, Rest of North America, Rest of South America, Caribbean, Belarus, Bahrain, Islamic Republic or Iran, Jordan, Kuwait, Qatar, Saudi Arabia, Turkey, United Arabic Emirates, Rest of West Asia, Morocco, Rest of the world, Albania, Rest of Eastern Europe, Rest of Europe, Rest of EFTA
XOECD	Japan, Korea, Switzerland, Norway

A3.1.1 CGE modelling framework and model set-up

The model employed is configured in CGEBox[3] (Britz and van der Mensbrugghe, 2018), a flexible and modular platform for CGE modelling. Its core draws on the GTAP Standard Model version 7 (Corong et al., 2017) realized in GAMS by van der Mensbrugghe (2018). It employs the usual assumption found in CGE analysis: 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 defines 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. Foreign savings as the difference between regional and total savings define the balance of payment (BOP) and render trade balances (BOT) endogenous as BOP equals BOT.

Drawing on the modularity of CGEBox, further model components are added which are relevant to quantify SDG indicators. The study's focus on agri-food sectors asks for detail in land use, incorporated based on the GTAP-AEZ (agro-ecological zones) data (Baldos and Corong, 2020) and model (Lee, 2005). This

[3] 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

extension disaggregates land demand and supply at model region level to up to 18 different spatial sub-units with more homogenous bio-physical properties. These AEZs distinguish three climate zones (tropical, temperate, and boreal) further by 6 different lengths of the growing season. Land is immobile across these spatial units. Competition between different land uses at the level of the AEZ is depicted by nestings of the Additive Constant-Elasticity-of-Transformation (aCET) functional form proposed by van der Mensbrugghe and Peters (2020) which guarantees physical balancing. Moreover, the original nesting from Lee (2005) is extended by two further nests which depict more flexible substitution between major annual crops and less flexible one between others. CGEBox adds to this substitution between different types of natural land cover and land in economic use (see Figure A.3.1 and A.3.2 for detail).

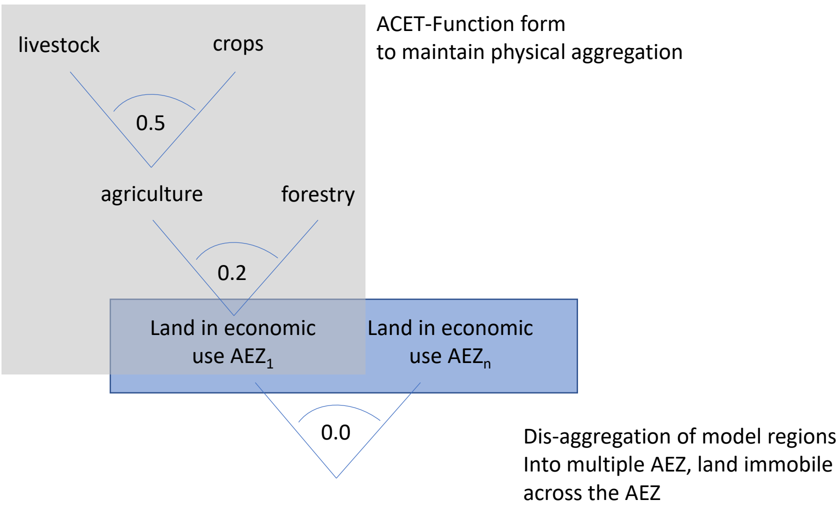

Figure A.3.1: CET nesting in the GTAP-AEZ model from Lee 2005 and extension by ACET

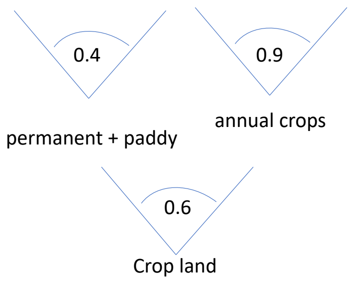

Figure A.3.2: Additional CET nesting in the GTAP-AEZ model

Elements of the GTAP-E model (McDougall and Golub, 2009) improve the presentation of energy use, by allowing for substitution between different energy commodities, while features from a module drawing on GTAP-AGR (Keeney and Hertel, 2005) consider specifics of agri-food sectors. High detail for crop and livestock products implies that the assumption of additive utility cannot be defended and care must be given to properly reflect Hicksian cross-price effects. This is reflected in a top-level demand nesting structure which bundles nests comprising more closely substitutable food products such as vegetable oils, cereals or meat and dairy, see Figure A.3.3. For these product groups, also higher substitution possibilities in intermediate demand in the feed use and the food industry is assumed, see Figure A.3.4 and A.3.5 in the annex. Trade is depicted by a two-stage Armington presentation with identical domestic and import shares for all agents, simplifying the GTAP standard model.

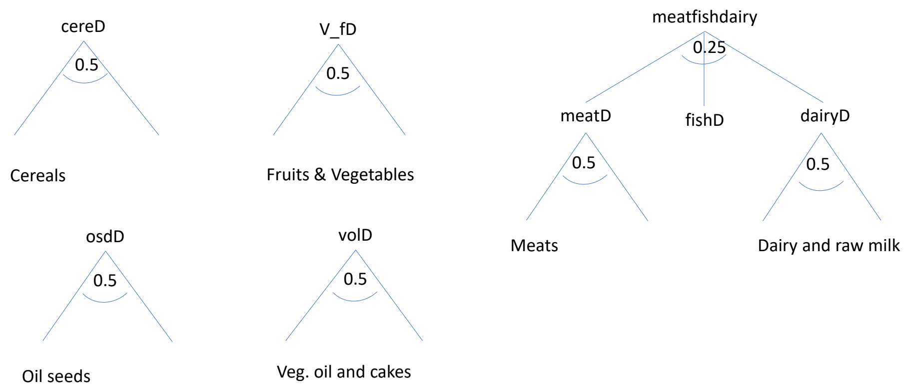

Figure A.3.3: CES-sub nests relating to agri-food used for private, government and investment demand

Note: 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).

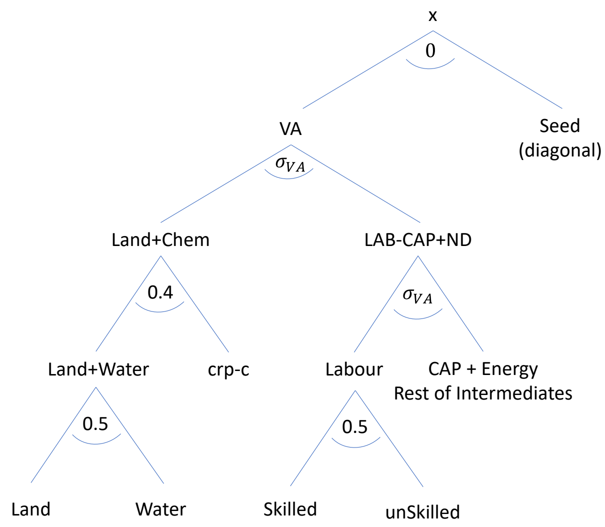

Figure A.3.4: CES-Nesting for crop production activities

Note: 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.

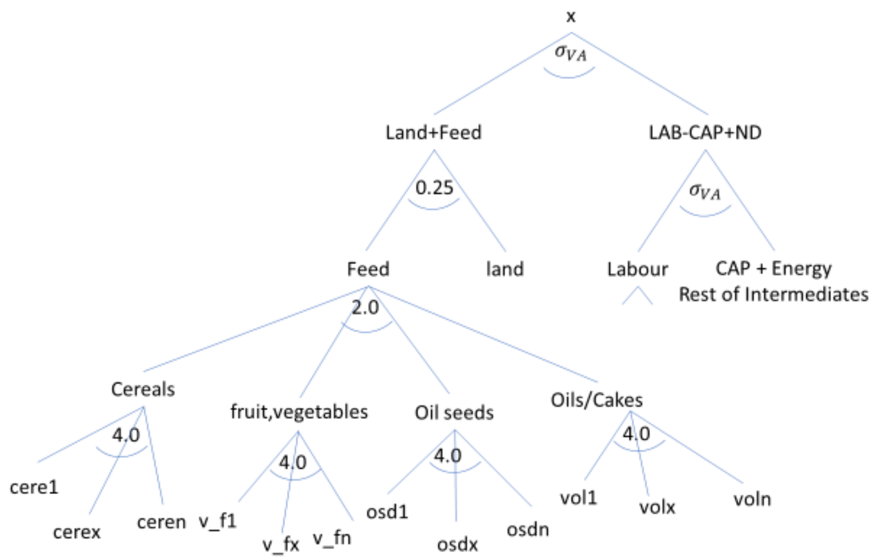

Figure A.3.5: CES-Nesting for livestock production activities

Note: The parameters for the substitution between importer regions are taken from Fontagné 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.

Table A.3.2: List of mapping between sectors of the FAO database (FAO, 2017) and the GTAP sectors

* = for these wage income categories the two unskilled categories (_2 & _3) are also available, which are shown for the first category only, sector names are taken from GTAP (Aguiar et al., 2019) and the GTAP AGROFOOD (Britz, 2022) database.

Income category	FAO sectors	GTAP (AGROFOOD) mapping
Self-employment (all factors are mapped)	sh1Self2	coa, oil, gas, oxt
	sh1Self3	frs, ctlMeat, orumMeat, Pigmeat, othMeat, olivOil, palmOil, soyCake, soyOil, rapCake, rapOil, volo, mil, pcr, sgr, ofdAnim, ofdOther, b_t, tex, wap, lea, lum, ppp, p_c, chm, bph, rpp, nmm, i_s, nfm, fmp, ele, eeq, ome, mvh, otn, omf, cns, dwe, fsh_catch, fsh_aqua
	sh1Self4	gdt, wtr, TnD, NuclearBL, CoalBL, GasBL, WindBL, HydroBL, OilBL, OtherBL, GasP, HydroP, OilP, SolarP
	sh1Self5	cns
	sh1Self6	trd
	sh1Self7	otp, wtp, atp, cmn, whs
	sh1Self8	ofi, rsa, ins
	sh1Self9	obs, ros, osg, afs, hht, edu
	sh1Self10	All sector with the exception of agricultural sectors (which are mapped to sh1Crop1, sh1LiveStock, see below)
Wage income (labour only is mapped)	sh1wge1_1	(male and female) SkLab as mapped to sh1Crop1 and sh1LiveStock
	sh1wge1_2	(male and female) unSkLab as mapped to sh1Crop1 and sh1LiveStock
	sh1wge1_3	(male and female) unSkLab as mapped to sh1Crop1 and sh1LiveStock
	sh1wge2_1*	(male and female) SkLab as mapped to sh1Self2
	sh1wge3_1*	(male and female) SkLab as mapped to sh1Self3
	sh1wge4_1*	(male and female) SkLab as mapped to sh1Self4
	sh1wge5_1*	(male and female) SkLab as mapped to sh1Self5
	sh1wge6_1*	(male and female) SkLab as mapped to sh1Self6

	sh1wge7_1*	(male and female) SkLab as mapped to sh1Self7
	sh1wge8_1*	(male and female) SkLab as mapped to sh1Self8
	sh1wge9_1*	(male and female) SkLab as mapped to sh1Self9
Agricultural income (all factors are mapped)	sh1Crop1	pdr, wht, sorg, barl, rye, oat, maiz, ocer, olv, soy, palm, rape, oso, pota, rttb, leg, toma, oveg, citr, banp, appl, grap, ofru, v_fo, c_b, pfb, coco, teas, coff, ocro (these crop activities are all split by irrigated and rainfed profuction)
	sh1LiveStock	orum, pig-a, poul, oapo, rmk, wol

A3.1.2 Microsimulation

This CET function is part of the post-model micro-simulation and applied for each household in the sample. Its main purpose is to ensure coherence between total factor and transfer income in the CGE model on the one hand and the aggregate of all households in the micro-simulation on the other hand, and at least directional coherence with regard to the re-allocation of factors across sectors. The approach is applied for the different simulated time points including the benchmark where also the share parameters are determined.

As usually, the CET depicts a revenue maximization problem, here for the total factor stock (sum of labor, land, capital, natural resources) of each household. It uses the broader income source groups (crop, livestock, different types of self-employed and wage incomes) as found in the household sample as the CET components. The household will re-direct its efforts (stock of assets) towards those broader income source groups where per unit revenues increase. The per unit revenues are calculated as a Laspeyres price index for all production factors for self-employed categories, including livestock and crops. For dependent labor income from broader sectors, only after-tax wage changes are considered and define the per unit revenue. Multiplying the updated factor allocation with the per unit price index gives the new income flow for such a broader income category if the per capita factor stocks of the factors would be unchanged. But unchanged per capita factor use is assumed for labor stocks, only, as discussed next.

We assume that labor participation rates do not change, neither economy-wide nor at household level. At unchanged household composition, this implies that per capita income from wages for each household would be determined by changes in the wages only, not from changes in the labor stock. This is different for capital, land and natural resources where the per capita stock in the economy changes, for instance due to capital accumulation. To capture this effect, a Laspeyres quantity index is calculated for the self-employed categories including crops and livestock. It measures the change in total factor use, using benchmark prices as weights corrected for the change in population growth. This implies that a household, for instance, involved in crop production, would see the same relative increase in its land stock as the sum of crops at economy-wide level. Without the CET function, household income would hence change according to economy wide changes in assets per capita in the income category and the income category specific returns to factors. This are the two multipliers PIndex and QIndex below

$$PIndex_{r,Inc,t} = \frac{\sum_{a,f}\left(xf_{r,f,a,t0} * pf_{r,f,s,t} * \left(1 - \kappa f_{r,f,t}\right)\right)}{\sum_{a,f}\left(xf_{r,f,a,t0} * pf_{r,f,s,t0} * \left(1 - \kappa f_{r,f,t0}\right)\right)} \tag{1}$$

$$QIndex_{r,Inc,t} = \frac{\sum_{a,f}\left(xf_{r,f,a,t} * pf_{r,f,s,t0} * \left(1 - \kappa_{r,f,t0}\right)\right)}{\sum_{a,f}\left(xf_{r,f,a,t0} * pf_{r,f,s,t0} * \left(1 - \kappa_{r,f,t0}\right)\right)} \tag{2}$$

$$CETInc_{r,hhid,t} = \gamma_{r,hhid,Inc,t} * TotInc_{hhid} * \left(\frac{PIndex_{r,Inc,t}}{CETp_{r,hhid,t}}\right)^{5} * PIndex_{r,Inc,t} * QIndex_{r,Inc,t} \tag{3}$$

$$CETp_{r,hhid,t} = \left(\sum_{Inc} \gamma_{r,hhid,Inc,t} * PIndex_{r,Inc,t}{}^{5}\right)^{\frac{1}{5}} \tag{4}$$

Where formula (1) calculates the factor allocation (CETInc), through γ, the household specific share parameters, calculated from the initial income share divided by the total sum of CET income share, TotInc is the household's total factor stock, derived from the initial total income, and (PIndex/(CETp_hhid)) gives the transformation effect, derived from the price indices and the household specific price index. The latter is calculated in formula (2) by multiplying the price indices and γ, assuming a transformation elasticity of 5.

Figure A.3.6 below represents a schematic overview of the different income categories that are updated.

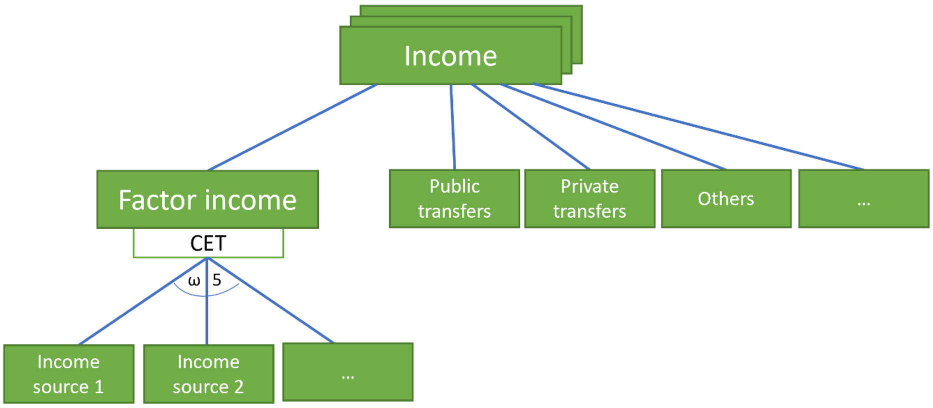

Figure A.3.6: Income update including the CET function

Table A.3.3: List of SDG indicator implemented to CGEBox,

N = number, D = desired direction: ↗ (increase) and ↘ (decrease), * = distributional information; [1]= UN quantitative target, [2]= Sachs et al (2021), [3]= van Vuuren et al (2022), [2020, 2030, 2050] = target years

	SDG indicators implemented	N	D	target
SDG1	Proportion of population living below poverty line ($3.20)	1	* ↘	0[1, 2030]
	Proportion of population living below poverty line ($1.90)	2	* ↘	0[1, 2030]
	Income per household per capita (Average and at household level)	3	* ↗	
	1.a.2 Proportion of total government spending on essential services (education, health and social protection)	4	↗	
SDG2	Food price index	5	↘	
	FAO Food Security Indicator: Cereal Import Dependency Ration (Stability Domain)	6	↘	
	Food consumption per capita (average and at household level)	7	* ↗	
	Dietary diversity, Shannon index in terms of total calories	8	* ↗	

	Dietary diversity, Shannon index in terms of total expenditure		9	* ↗	
	Share of food expenditure in total income (average and at household level)		10	* ↗	
	Calories per capita (average and at household level)		11	* ↗	
	Protein per capita (average and at household level)		12	* ↗	
	Fat per capita (average and at household level)		13	* ↗	
	Partial productivity by staple crops		14	↗	double[1, 2030]
	Partial productivity by export crops		15	↗	double[1, 2030]
	Partial productivity by other crops		16	↗	double[1, 2030]
SDG3	Health hazard from air pollution Air pollution	Air pollutants considered separately: Black carbon, OC, PM2.5, PM10, NH3, NMVOC, NOX, SO2	17 18-25	↘ ↘ ↘	
SDG5	Gender wage gap for skilled labour		26	↘	0[3, 2030]
	Gender wage gap for unskilled labour		27	↘	0[3, 2030]
	Share of female relative to male labor		28	↗	
SDG6	Irrigation water use		29	↘	
	Irrigation water use per output of agricultural products		30	↘	
SDG7	Energy price index		31	↘	
	Share of energy imported on total energy consumed		32	↘	
	Share of electricity imported on total		33	↘	

	electricity consumed			
	Share of renewable electricity on total electricity consumption	34	↗	51%[2, 2030]
	Share of fossil fuel energy on total energy consumption	35	↘	
	Share of fossil fuel electricity on total electricity consumption	36	↘	
	Share of other (biomass) electricity in total electricity consumption	37	↗	
	Share of transmission and distribution on total energy consumption	38	↘	
	Share of total biomass output used in energy sector	39	↗	
	Share of calorie input in energy sector on total calories in consumption	40	↘	
	Share of spending on electricity (average and at household level)	41	↘	
	Share of spending on energy (average and at household level)	42	* ↘	
	Energy intensity measured in terms of primary energy per GDP (Mtoe/GDP)	43	* ↘	half[1]
SDG8	8.1.1 Real GDP per capita	44	↗	+7% annual[1, 2030]
	8.2.1 Real GDP per employed person	45	↗	
	Share of agricultural labor on total employment	46	↘	
	Decoupling of GHG emissions growth and economic activity (GDP) growth	47	↘	
	Money metric per capita per households	48	* ↗	
SDG9	9.2.1 Manufacturing value added as proportion of GDP	49	↗	double[1, 2030]
	9.2.1 Manufacturing value added per capita	50	↗	double[1, 2030]

	9.2.2 Manufacturing employment as a % of total employment	51	↗	double[1, 2030]
SDG10	Palma Index (income % of top 10% / income % of bottom 40%)	52	* ↘	0.9[2, 2030]
	Gini index	53	* ↘	27.5[2, 2030]
	10.1.1 Growth rates of household expenditure per capita among the bottom 40 % and the total population	54	* ↗	
	10.2.1 Proportion of people living below 50 per cent of median income	55	* ↘	15%, 10%[,3 2030, 2050]
	10.4.1 Labor share of GDP, comprising wages and social protection transfers	56	* ↗	
SDG11	Land demand of cities	57	↘	
	11.3.1 Ratio of land consumption rate to population growth rate	58	↘	
SDG12	Domestic Material Footprint	59	↘	
	Domestic Material Footprint per capita	60	↘	
	Domestic Material Footprint per GDP	61	↘	
SDG13	Total GHG emissions per year	62	↘	
	Total GHG emissions per capita	63	↘	
	Total GHG per GDP	64	↘	
	CO_2 emissions embodied in fossil fuel exports	65	↘	0[2, 2030]
SDG14	Share of fish output extracted from open catch	66	↘	
	Fisheries as a value share of GDP	67	↘	
SDG15	Share of forestry area on total land area	68	↗	
	Share of unmanaged forest area on total land area	69	↗	no loss[2, 2030]
	Total area covered with natural vegetation	70	↗	
	Total area of grassland	71	↗	
		72	↘	

	Intensification of grassland use (stocking rate)			
SDG17	Developing countries' and least developed countries' share of global exports	73	↗	double[1, 2020]

Table A.3.4: List of SSP specific assumptions

LIC = low middle income country, MIC = middle income country, HIC = high income country

	SSP1	SSP2	SSP3
CO2 price (Average in 2050 over single countries in the respective category)	HIC: 587.3 MIC: 416.17 LIC: 224.24	HIC: 61.61 MIC: 47.68 LIC: 37.71	-
Meat consumption	25%	10%	-
Energy efficiency	HIC: 113.47 MIC: 50.46 LIC: 24.37	HIC: 5.58 MIC: 3.93 LIC: 3	-
Trade change	-	-	Tariff increase (except for intra EU trade), increasing preference for domestic production

B Results

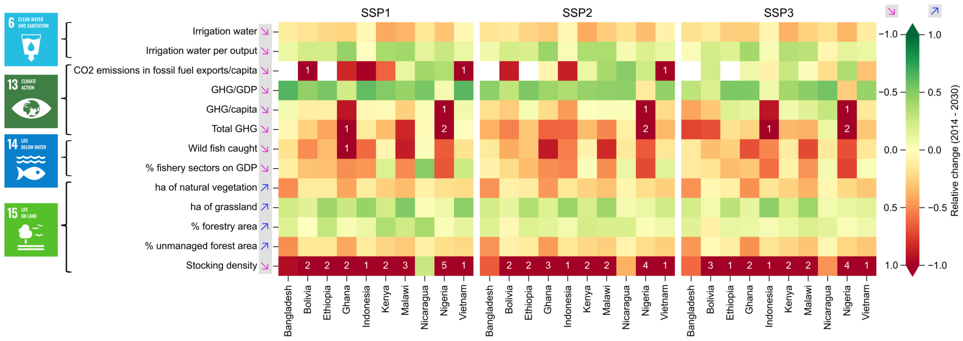

Figure B.3.1: SDG indicators quantified in the biosphere layer in relative change to 2030

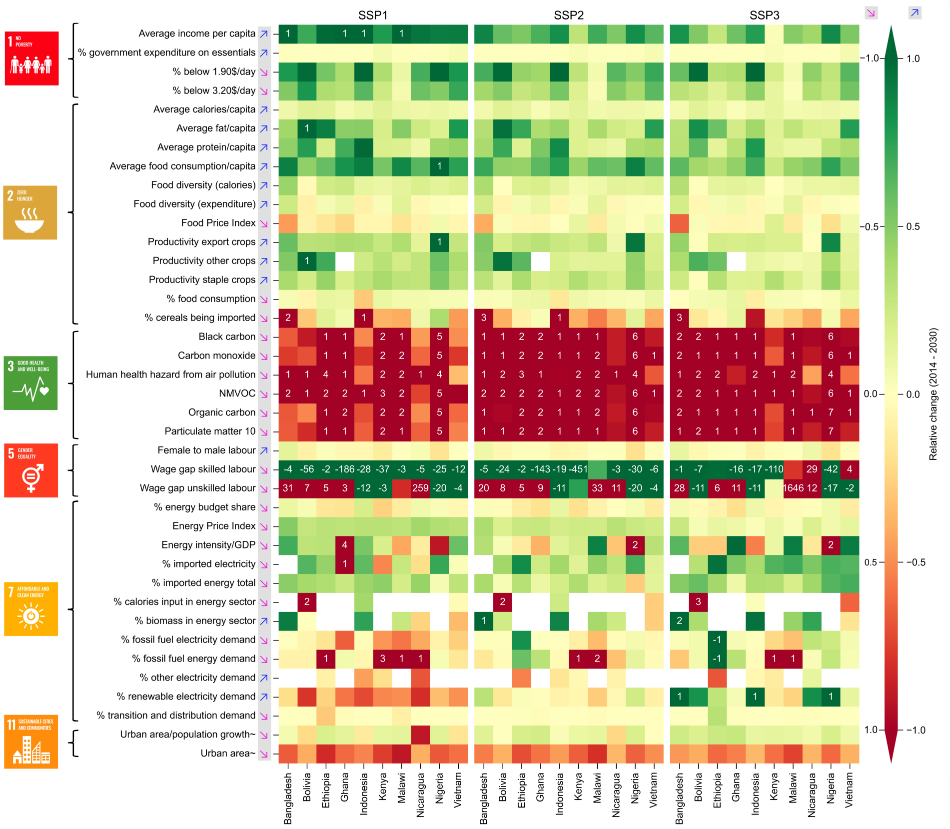

Figure B.3.2: SDG indicators quantified in the society layer in relative change to 2030

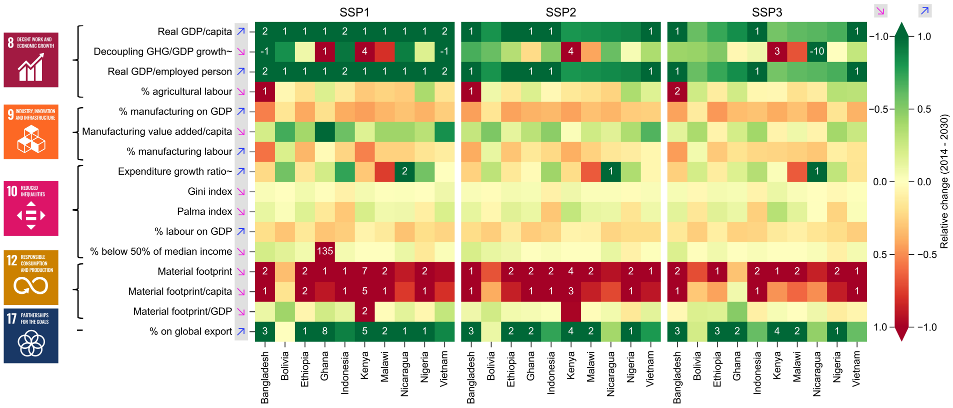

Figure B.3.3: SDG indicators quantified in the economy layer in relative change to 2030

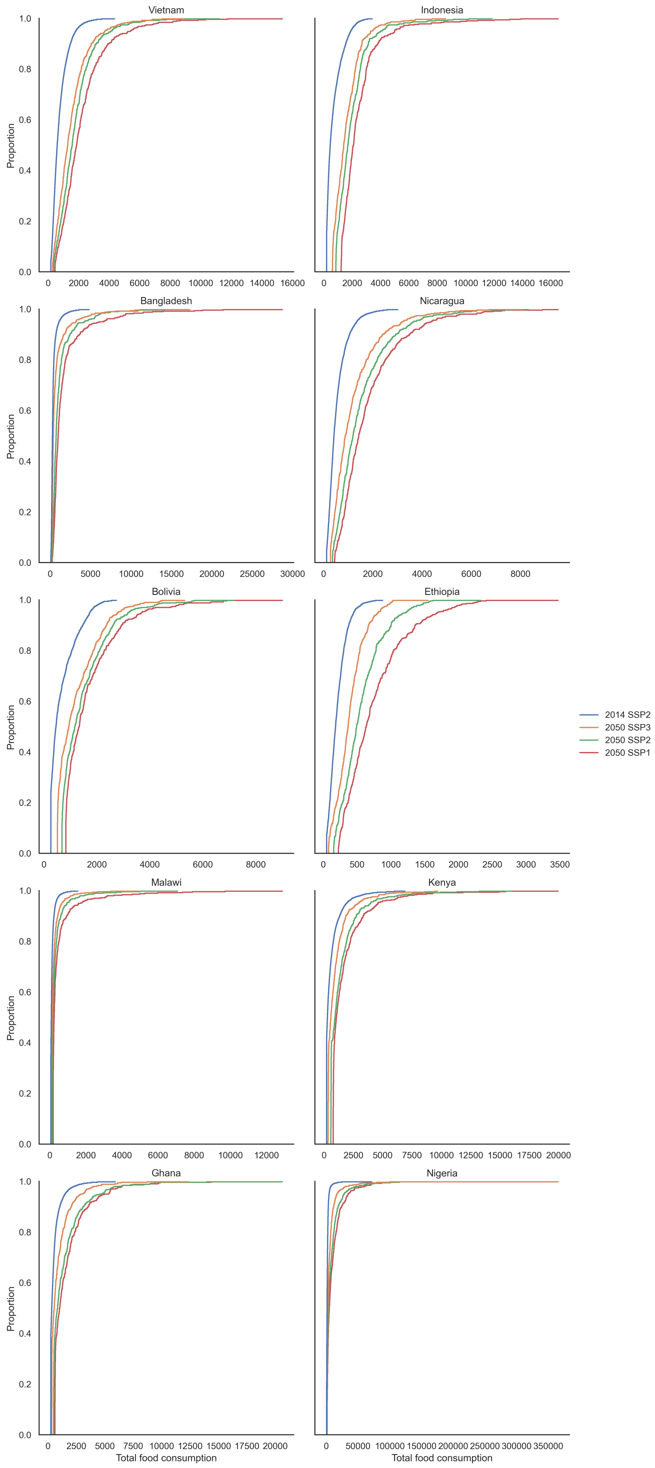

Figure B.3.4: Total food consumption distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

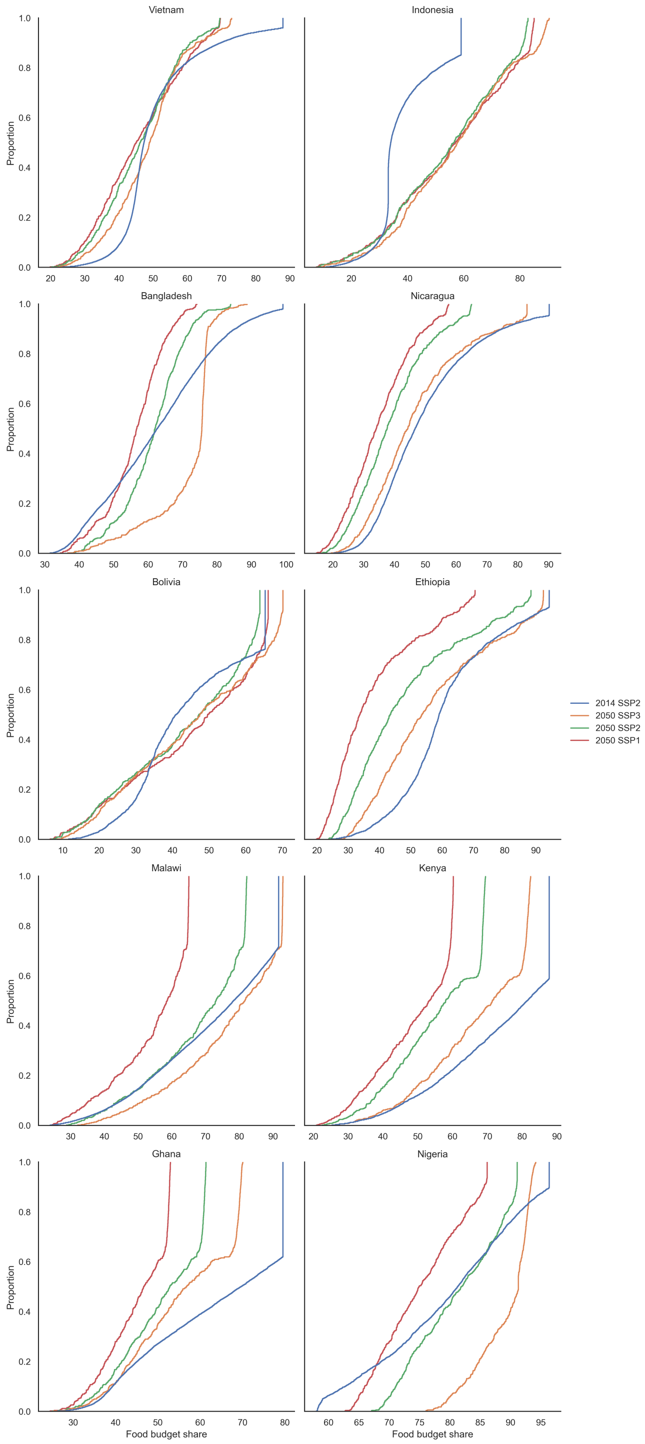

Figure B.3.5: Food budget share distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

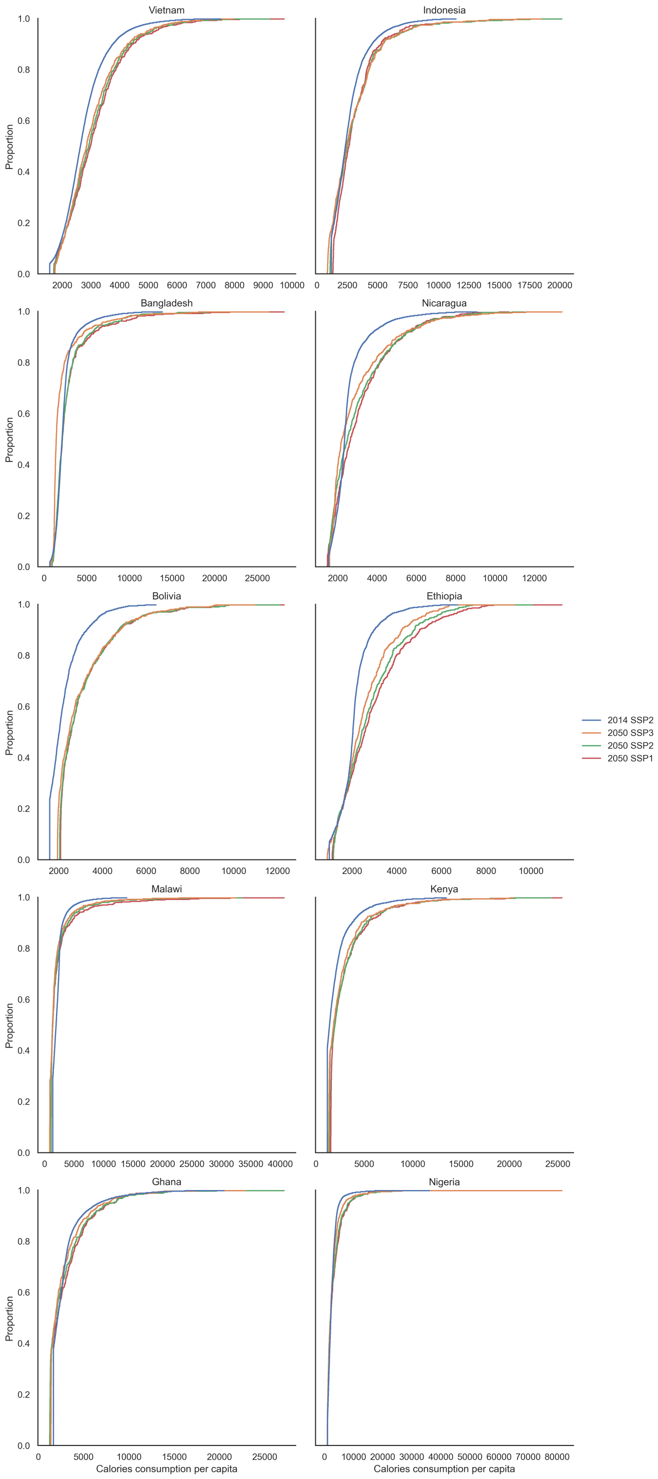

Figure B.3.6: calories distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

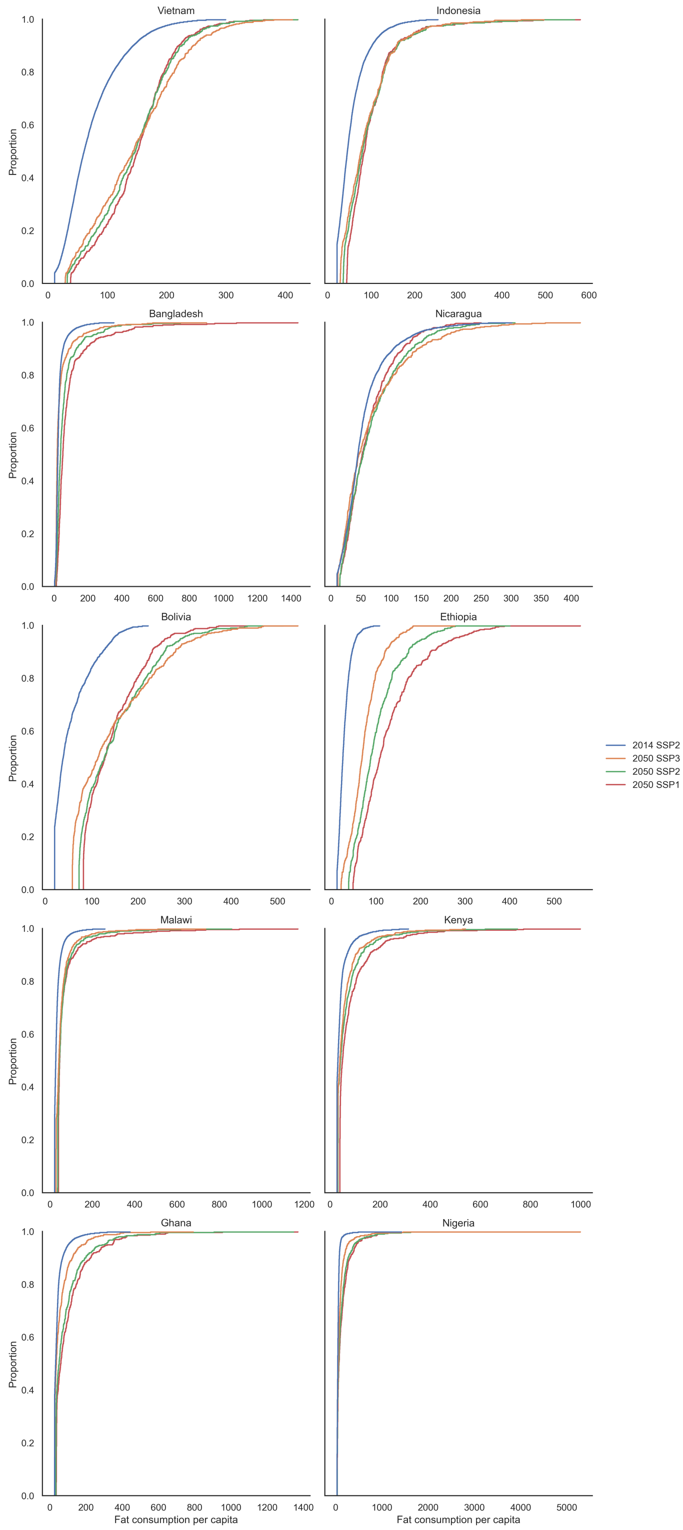

Figure B.3.7: fat distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

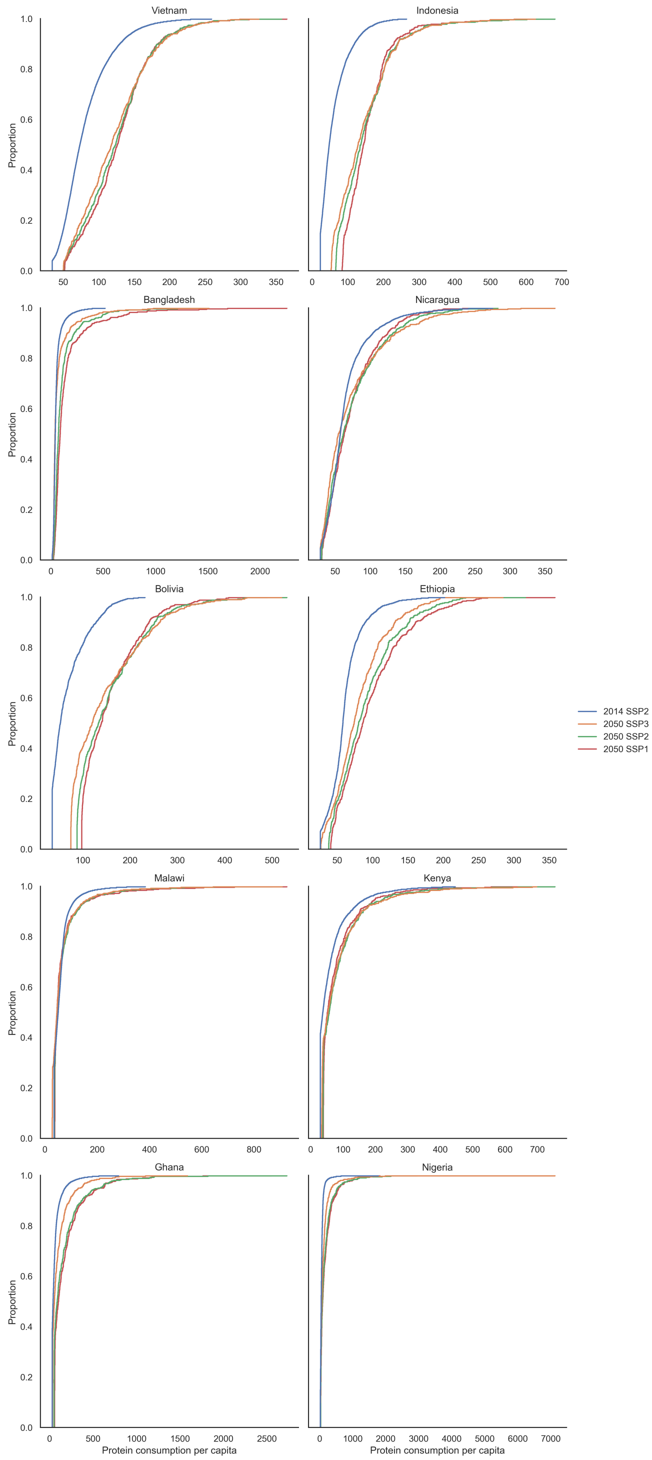

Figure B.3.8: protein distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

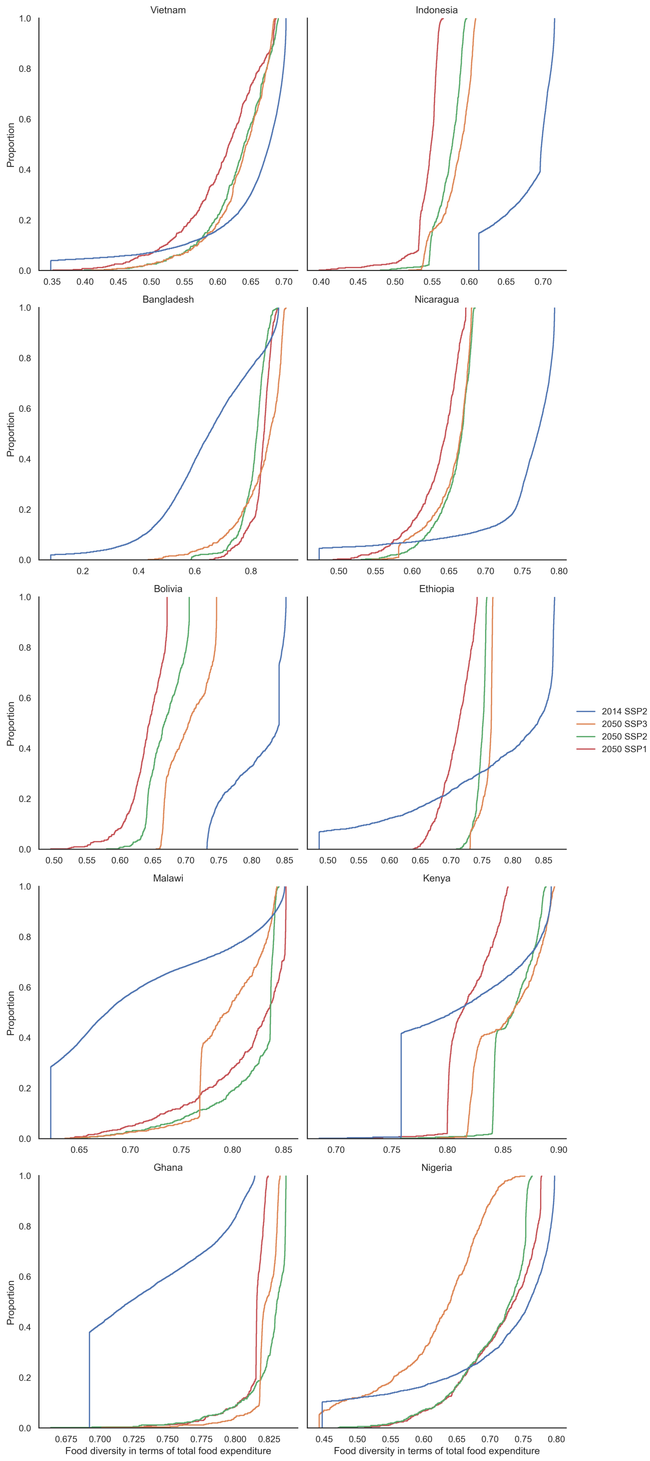

Figure B.3.9: Food diversity in terms of total food expenditure distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

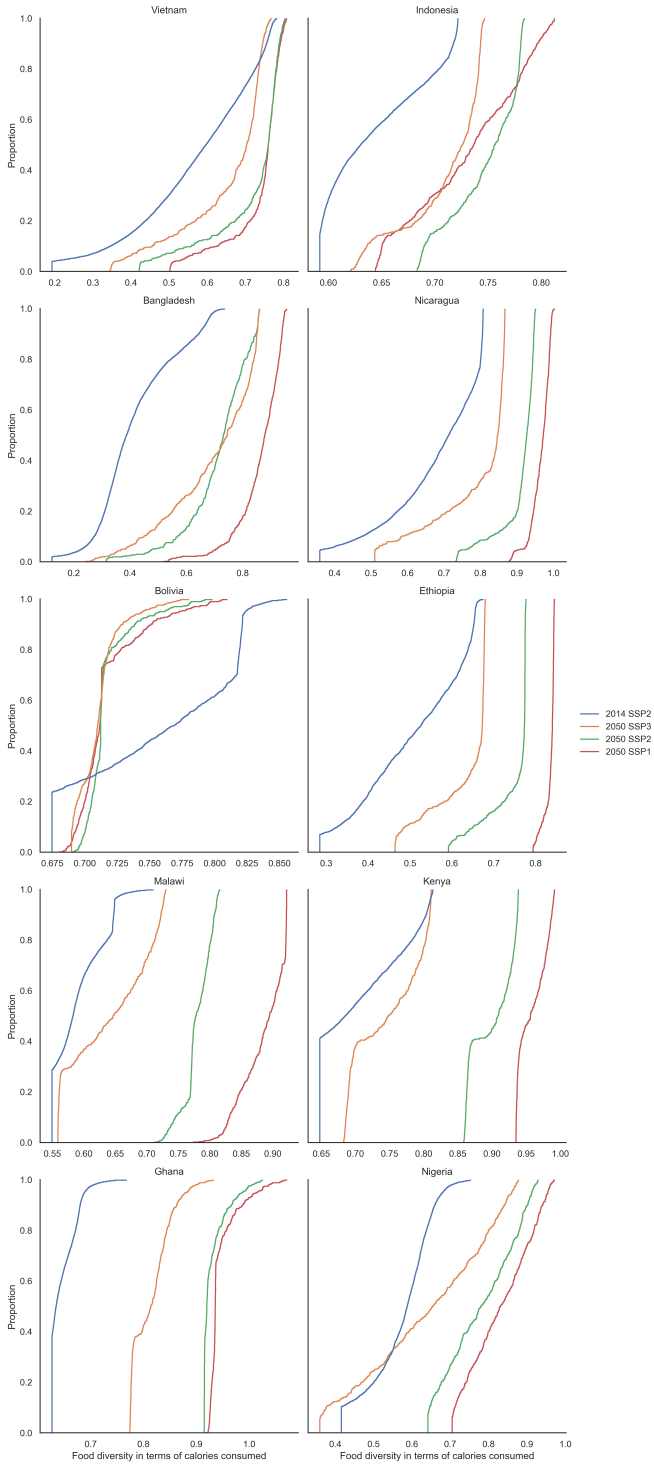

Figure B.3.10: Food diversity in terms of total calories consumed distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

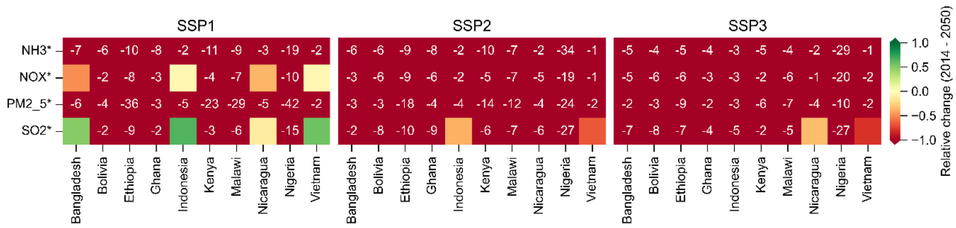

Figure B.3.11: Percentage change for air pollution results for NOx, SO2, SH3 and PM2.5 between 2050 and 2014

Note: SO_2 = Sulfur dioxide, NH_3 = Ammonia, NOx = Nitrogen oxides, PM2.5 = Particulate Matter 2.5,

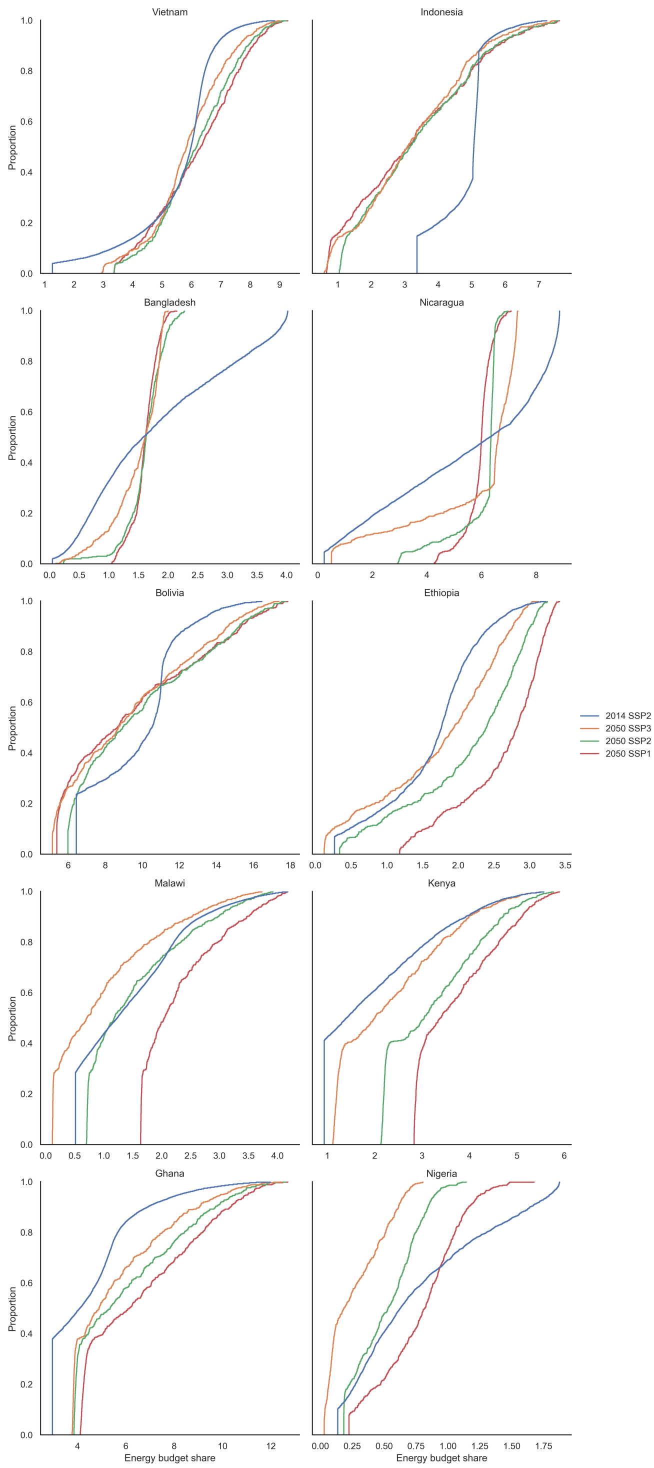

Figure B.3.12: Energy budget share distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

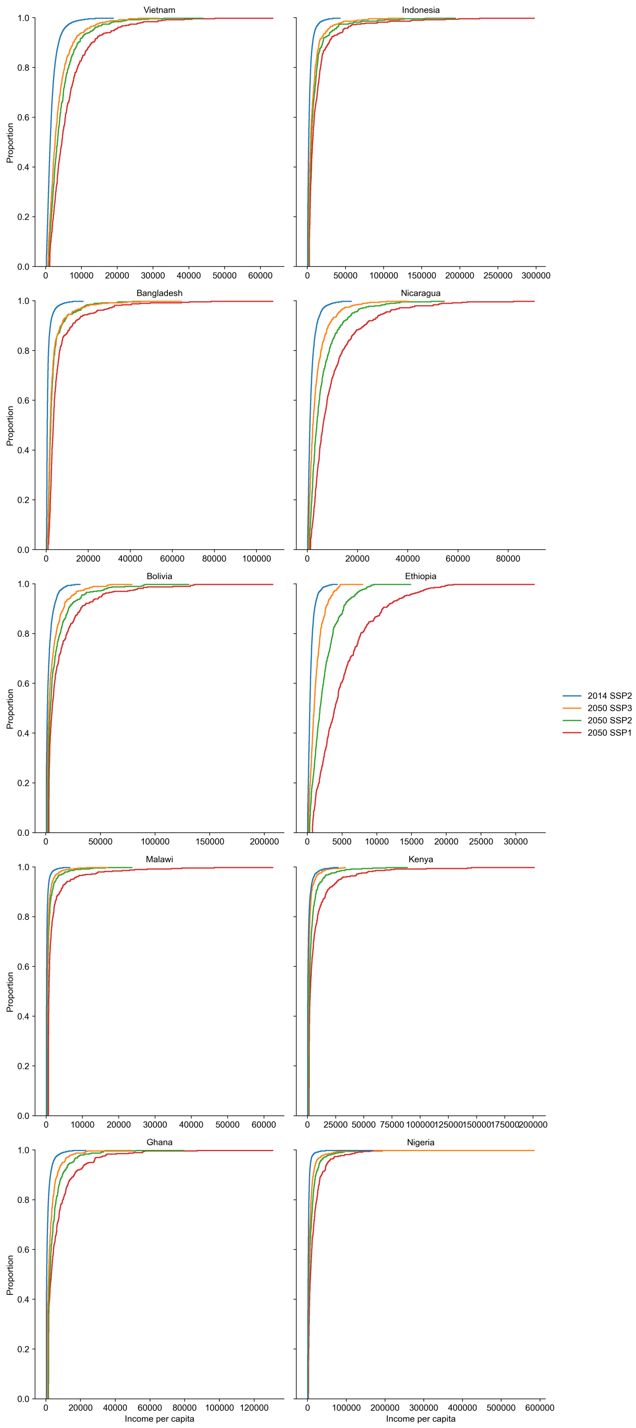

Figure B.3.13: income distribution for SSP1, SSP2 and SSP3 in 2050 for all countries

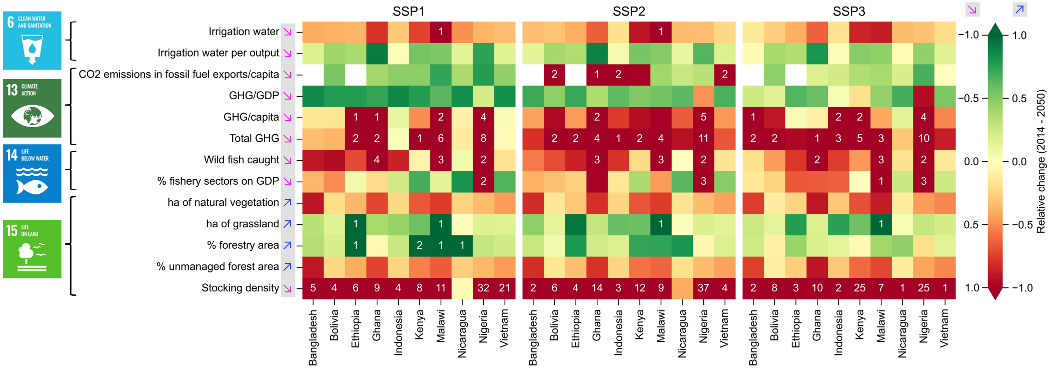

Figure B.3.14: SDG indicators quantified in the biosphere layer in relative change to 2050 with model averages for microsimulation results

Figure B.3.15: SDG indicators quantified in the social layer in relative change to 2050 with model averages for microsimulation results

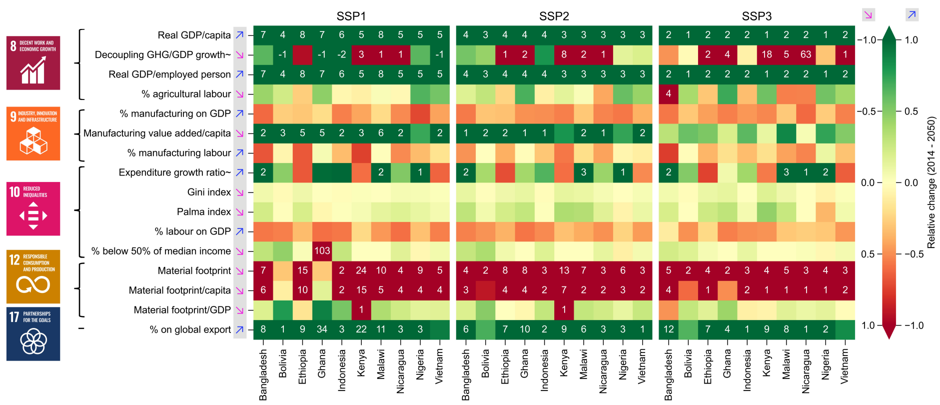

Figure B.3.16: SDG indicators quantified in the economy layer in relative change to 2050 with model averages for microsimulation results

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Appendix Chapter 4

Annex A methods:

Table A.4.1 Sectoral Disaggregation from GTAP 10 sectors

GTAP10 sector	Database in analysis split	Differentiation in production only	In biomass nest
Pdr	Paddy price	Irrigation/rainfed	*
Wht	Wheat	Irrigation/rainfed	*
gro	maize, barley, oat, rye, sorghum, other cereal	Irrigation/rainfed	*
osd	olive, soy, palm oil fruit, rape seed, other oilseeds	Irrigation/rainfed	*
v_f	Citrus fruits, banana & plantain, apple, grape, other fruits, tomato, other vegetables, rest of vegetables and fruits, potato, legumes, other roots and tubers	Irrigation/rainfed	*
ocr	coco, coffee, teas, other crops	Irrigation/rainfed	*
ctl	cattle, other ruminants		
oap	pig, poultry, other animal products		
vol	olive oil, palm oil, soy cake, soy oil, rape cake, rape oil, other vegetable oil		*
ofd	Feed concentrates, other food processing		*
cmt	cattle meat, other ruminant meat		
omt	pig meat, other meat		
c_b-c	Sugar cane, sugar beet	Irrigation/rainfed	*
pfb-c	Plant-based fibers	Irrigation/rainfed	*
rmk-c	Raw milk		
wol-c	Wool, silk-worm cocoons		
frs-c	Forestry		*
fsh-c	Fishing	Aquaculture/open-catch	

Remark: All other sectors not listed in the table are kept in the GTAP 10 standard sector differentiation and can be found here: *https://www.gtap.agecon.purdue.edu/databases/v10/v10_sectors.aspx#Sector65*

Table A.4.2 Regional Aggregation of GTAP 10 regions

Model region	Single Countries
Australia and New Zealand	Australia, New Zealand, Rest of Oceania
China	China
Philippines	Philippines
Vietnam	Vietnam
Indonesia	Indonesia
Bangladesh	Bangladesh
India	India
ASEAN	Brunei Darussalam, Cambodia, Lao People's Democratic Republic, Malaysia, Singapore, Thailand, Rest of Southeast Asia
USA	United States of America
Canada	Canada
Mexico	Mexico
Nicaragua	Nicaragua
Central America and Carribean	Dominican Republic, Costa Rica, Guatemala, Honduras, Panama, El Salvador, Rest of Central America, Jamaica, Puerto Rico, Trinidad and Tobago, Caribbean
Bolivia	Bolivia
Rest_ANDEAN	Chile, Colombia, Ecuador, Peru, Venezuela
Brazil	Brazil
Argentina	Argentina
Mercosur	Paraguay, Uruguay
Germany	Germany
EU27	Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom, Bulgaria, Croatia, Romania
Former Soviet Union	Russian Federation, Ukraine, Kazakhstan, Kyrgyzstan, Tajikistan, Rest of Former Soviet Union, Armenia, Azerbaijan, Georgia
Northern Africa	Egypt, Morocco, Tunisia, Rest of North Africa
Ethiopia	Ethiopia

Malawi	Malawi
Kenya	Kenya
Ghana	Ghana
Nigeria	Nigeria
South Africa	South Africa
RestOfAfrica	Burkina Faso, Cameroon, Cote d'Ivoire, Guinea, Senegal, Togo, Rest of Western Africa, Central Africa, South Central Africa, Madagascar, Mauritius, Mozambique, Rwanda, Tanzania, Uganda, Zambia, Zimbabwe, Rest of Eastern Africa, Botswana, Namibia, Rest of South African Customs
ROW	Hong Kong, Mongolia, Taiwan, Rest of East Asia, Nepal, Pakistan, Sri Lanka, Rest of South Asia, Rest of North America, Rest of South America, Rest of EFTA, Albania, Belarus, Rest of Eastern Europe, Rest of Europe, Bahrain, Islamic Republic of Iran, Israel, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Turkey, United Arab Emirates, Rest of Western Asia, Rest of the World
Rest_OECD	Japan, Korea, Switzerland, Norway

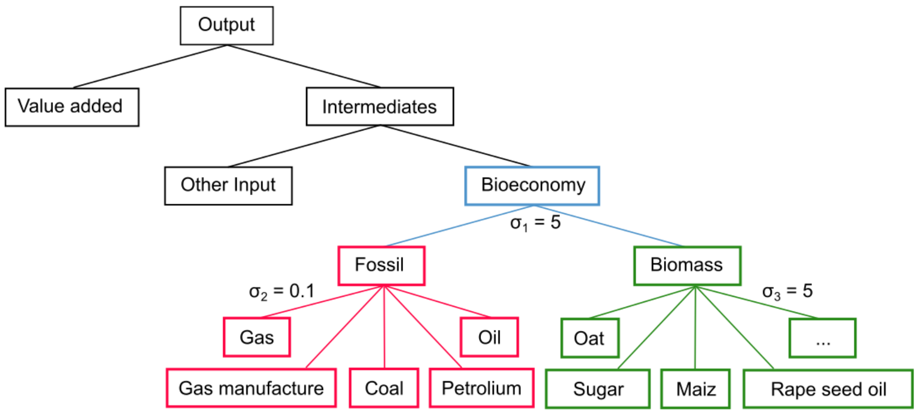

Figure A.4.1 Nestings and substitution elasticity chosen for the bioeconomy sectors. Source: based on Nong et al., 2020.

Remark: Representation is simplified, to focus on the bioeconomy nest. σ is the substitution elasticity in the respective nest. "…" in the biomass nesting refers to the biomass products listed in Table A.4.1.

Annex B results:

B.4.1 The case of Kenya

Kenya shows partly the strongest effect, especially in the Meat scenario, and is among the countries that show opposing trends in the Subsidy and Technology scenario. Illustrating how country specific circumstances drive the results, Kenya is the only of the ten countries, that does not expand crop land as a result of both bioeconomy policies, while expanding pasture land to produce more livestock products for export. Most of the primary products imported by the EU due to the policies are not produced in Kenya, thus it shifts towards crops displaced in other countries to cultivate crops that are increasingly demanded from EUs bioeconomy sectors. The rising livestock production explains the increase in GHG emissions and in material footprint, due to intermediates demanding coal and other extractions, in contrast to the general trend in the Subsidy scenario. Thus, while the livestock products, especially pig meat, are not directly demanded by the three shocked sectors in the EU, their production is reduced, also in most of the other low and lower-middle income countries, to specialized in the input crops. In the Meat scenario, pig meat exports to the EU are again the main driver of the effect, which occupied a place in the top five trading commodities terms of export volume to the EU in 2050 and accounted for 35% and 14% for EU27 and Germany, respectively, of the total pig meat export by Kenya.

B.4.2 Global spillovers if all OECD countries apply the analysed EU strategies

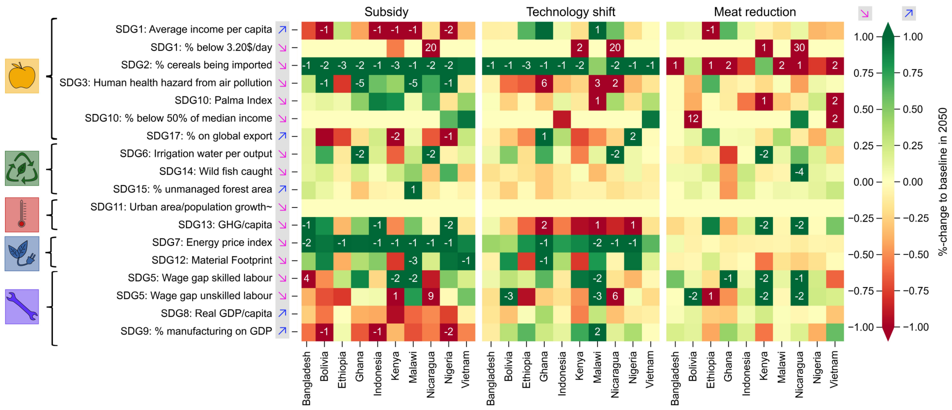

Figure B.4.1: Heatmap showing the percentage changes induced by the different policy scenarios applied in the OECD for the SDGs in ten low and lower-middle income countries in 2050. Indicators are abbreviated for better readability; complete information can be found in Figure 4.4. The color bar is fixed to values between 100% and -100%; exceeding values are annotated in the respective cell. All indicators show improvements as green and regressions as red, with the pink and blue arrows next to the label indicating the desired direction and the applied side of the color bar scale. Source: model results.

Figures 4.7 (all OECD countries) and 5 (EU only) reveal quite similar trends for the focus countries, but an application to all OECD countries drives up the size of the impacts compared to an EU only implementation. Accordingly, synergies and trade-offs persist as discussed for the EU case. Malawi only seems to be exceptionally more effected if the Subsidy is expanded to all OECD countries as its forest sector is hit by the side effects. Global forestry production shrinks due to the policy and thus production drops drastically in Malawi, as export to the other countries declines. In rare cases, the effect is turned from positive to negative or vice versa. This occurred for example for the change in average income and the GHG emissions per capita in Malawi in the Technology scenario as here factor returns increase, especially for natural resources (i.e. coal) and capital due to increasing domestic production of the shocked sectors in the OECD, which were covered before by more than 60% by imports.

The comparison of the magnitudes of the effects in the EU and OECD implementations show that the EU is of major importance for the effects of some countries, in the biomass scenarios, as it determines more than half of the effect size. For example, for countries such as Ghana, Nigeria, Bolivia and Indonesia, most of the indicators are predominantly driven by the change induced by the EU implementation of the biomass policies.

References

Nong, D., Escobar, N., Britz, W., & Börner, J. (2020). Long-term impacts of bio-based innovation in the chemical sector: A dynamic global perspective. *Journal of Cleaner Production*, 272, 122738.