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SCENARIO ANALYSIS OF SDG CO-BENEFITS FROM CLIMATE ACTIONS IN LT-LEDS AND NAPS

GREEN GROWTH SIMULATION TOOL PHASE 2

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A collaborative project between the Global Green Growth Institute (GGGI) and the AbonyiLab

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Scenario Analysis of SDG Co-Benefits from Climate Actions in LT-LEDS and NAPs Green Growth Simulation Tool Phase 2

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2 GGGI staff who supported the collection and validation of data and scenarios as well as coordinating the GGPM team with the government partners for the country-level GGSim applications.

Preface

One of GGGI's main missions is to support its Member Countries in strengthening policy, planning, and regulatory frameworks, as well as institutional capacity, to achieve green growth outcomes. To this end, I advocated for the development of GGGI's in-house policy tools to assess the economic, environmental, and social impacts of climate actions in Long-term Low Emission Development Strategies (LT-LEDS), Nationally Determined Contributions (NDCs), and National Adaptation Plans (NAPs). One such tool is the Green Growth Simulation Tool (GGSim), which GGGI, through the Green Growth Performance Measurement (GGPM) Program and under the leadership of Dr. Lilibeth Acosta, has been developing in phases since 2019. Phase 1, with results published in a 2020 technical report, focused on pilot applications of system dynamics models for key sectors, including energy and transport, agriculture, forestry and other land use (AFOLU), and water and waste. Significant progress since then has improved the interlinkages of these models, enabling assessments of co-benefits across Sustainable Development Goal (SDG) indicators from climate mitigation and adaptation actions. This technical report presents Phase 2 results, covering work from 2021 to 2023, including:

- Linking GGSim's sectoral system dynamics models to the SDG indicators of the Green Growth Index, which measures performance in achieving SDG Targets from 2010 to the present. This linkage allows GGSim to estimate Index scores for these indicators from 2020 to 2050 under business-as-usual and various policy scenarios for climate interventions.

- Interlinking GGSim sectoral system dynamics models for SDG indicators related to efficient and sustainable resource use with those addressing natural capital protection. This enables assessment of co-benefits from climate mitigation actions on SDGs related to GHG emissions, environmental quality, and biodiversity and ecosystem protection.

- Applying GGSim to the LT-LEDS of Burkina Faso, Ethiopia, and Hungary to assess the SDG co-benefits of climate mitigation actions, using national data and validated policy scenarios developed through consultations and participatory approaches in these countries.

- Pilot testing GGSim's application to assess SDG co-benefits of climate adaptation actions in St. Lucia and Senegal, demonstrating GGSim's adaptability in evaluating diverse climate policy interventions for NAPs.

During Phase 2 development and applications, the GGPM encountered two challenges. First, validating the interlinked system dynamics models across economic sectors (e.g., energy, transport, AFOLU, water, and waste) and green growth dimensions (e.g., sustainable resource use, natural capital protection, green economic opportunities, and social inclusion) required a sophisticated approach. Second, a lack of data and models for social inclusion and gender-related SDG indicators hindered assessments of these critical green growth dimensions for developing countries. Artificial Intelligence (AI) offered solutions, with this report presenting pilot results of AI applications. Machine learning validated the system dynamics models, while Shapley-based network and data analysis addressed model and data gaps. In 2022, GGGI partnered with the University of Pannonia, Hungary, to apply AI approaches to GGSim.

GGGI ensured GGSim's credibility through several measures. Interested users can download model descriptions, Python codes, and raw data for Hungary's application via the Green Growth Index website (greengrowthindex.gggi.org). The technical report underwent review by international experts from March to October 2024. The University of Pannonia and GGGI also published the article "Network science and explainable AI-based life cycle management of sustainability models" in PLoS One, showcasing AI applications in GGSim. Additionally, GGGI and the University co-organized a virtual workshop on October 4, 2024, to review the technical report with the Global Green Growth Index International Expert Group that included members from organizations like FAO, UNIDO, UNCTAD, UNDP, the Water Footprint Network, and universities such as Zurich and Western Australia. Their insights are invaluable, as GGSim is intricately linked to the Green Growth Index. Moreover, experts from diverse backgrounds, including AI for Good Global Summit 2024 scholars and authors of winning use cases, contributed reviews.

As a champion of the Green Growth Index and Simulation Tool at GGGI, I am deeply honored by GGSim's achievements, including two prestigious global awards in 2024. GGSim was recognized as a top 20 Winning Use Case at the AI for Good Summit organized by the International Telecommunication Union (ITU) in Geneva on May 30 and a top 30 Elite Project at the World Artificial Intelligence Conference (WAIC) in Shanghai on July 4-6. However, GGSim's journey is far from over. GGGI is committed to further advancing the tool by refining its models and incorporating cutting-edge AI methodologies to address increasingly complex environmental and societal challenges. An international expert group of 20 multi-sectoral modelers and AI specialists from global organizations and academia has been established to support GGSim's progress.

As I prepare to leave GGGI in November to embark on new endeavors, I reflect with pride on the progress achieved and the promising future of GGSim. I extend my heartfelt best wishes to the GGPM Team and the international expert group as they take the lead to propel GGSim into its next development phase. Phase 3 marks an ambitious step forward, transforming GGSim into a comprehensive global online tool capable of offering a "global outlook" on green growth transitions from 2020 to 2050. This progress will complement the insights provided by the Global Green Growth Index, which has tracked green growth performance from 2010 to the present. By integrating AI-driven methodologies, the tool will enhance its capacity to assess complex interlinkages between climate actions and sustainable development outcomes. I am confident that the collective expertise, dedication, and collaboration of the GGPM Team and expert group will ensure GGSim becomes a vital resource for driving sustainable and inclusive global progress.

Dr. Frank Rijsberman
Director General
Global Green Growth Institute

Acknowledgments

The Green Growth Performance Measurement (GGPM) Team extends its heartfelt gratitude to the GGGI country teams and their government partners for facilitating the application of the Green Growth Simulation (GGSim) Tool across various projects from 2021 to 2023. In the Long-term Low Emission Development Strategies (LT-LEDS) projects in Burkina Faso and Kenya, several individuals provided invaluable support: (1) the Climate Action and Inclusive Development (CAID) Team, including Stelios Grafakos, Basil Oberholzer, and Shivenes Shammugam, for technical expertise in LT-LEDS development; (2) the GGGI Country Office Teams, particularly Laura Jalasjoki, Omar Diouf, and Shiferaw Tafesse, for project management; and (3) national experts who facilitated access to national databases, validated international datasets, and aligned GGSim results with sectoral models. For the SDG co-benefits analysis of Hungary's National Clean Development Strategy (NCDS), we are deeply grateful to the Hungary Country Office Team, including Julie Godin and Miklos Szekely, and our government partners, notably the Ministry for Innovation and Technology.

Special thanks go to Dr. Barbara Botos, Ambassador-at-Large for Climate, and Dr. Monika Rabai, Head of the Climate Policy Department, for their contributions during the December 2022 webinar on Hungary's NCDS. This event was facilitated by the Hungarian Academy of Sciences' Regional Committee of Veszprém. We also appreciate the GGGI Caribbean Regional Office, led by Kristin Deason, and the Organisation of Eastern Caribbean States (OECS) Commission, particularly Joan John-Norville and Chamberlain Emmanuel, for supporting the GGSim application to St. Lucia's National Adaptation Plan. Similarly, we thank the Senegal Country Team—Romain Brillie, Aida Diongue Niang, and Assana Magagi-Alio—and the Bureau Opérationnel de Suivi du Plan Sénégal Émergent (BOS PSE) for their assistance in applying GGSim to Senegal's Green Emerging Plan.

The development of GGSim benefited greatly from the National Green Growth Index projects, which identified relevant SDG indicators for model development. In Zambia, Ms. Angela Nantulya and Mr. Hedges Tembo mobilized national experts through webinars and workshops. For Kenya and Ghana, we are grateful to the GGGI Africa Regional Office, including Dr. Malle Fofana, Ms. Nagnouma Kone, and their team, as well as national consultants like Mr. Philip Omondi (Kenya) and Richard Amfo-Out (Ghana). Their collaboration with government representatives, including Peter Odhengo and Hillary Korir (Kenya) and Oliver Boachie and Dr. Felix Addo-Yobo (Ghana), was instrumental. We also recognize the contributions of the Lao PDR team, led by Mr. Rowan Fraser and Mme. Sisavanh Didaravong, for their efforts in organizing successful participatory workshops.

As the GGPM Program Manager, I express my profound gratitude to both former and current GGPM Team members for their unwavering dedication to the development and application of GGSim during Phases 1 and 2. Their efforts have established a strong foundation for Phase 3, which will see GGSim applied globally to assess green growth outlooks, leveraging artificial intelligence (AI) to address data gaps and complexities in modeling. I am deeply honored by the commitment of many members of the Green Growth Index International Expert Group, who continue to support the further development of GGSim models and their application to tackle global environmental and societal challenges. These esteemed contributors include Cornelia Krug from the University of Zurich, Francesco Tubiello and Suyu Liu from the Food and Agriculture Organization of the United Nations, Hitomi Rankine from the United Nations Conference on Trade and Development, Jose Pineda from DevTech Systems Inc., Nicola Cantore and Valentin Todorov from the United Nations Industrial Development Organization, Rick Hogeboom from the Water Footprint Network, Rusyan Jill Mamiit from the United Nations Uzbekistan Office, Shun Chonabayashi from Soka University, and Usman Iftikhar from the United Nations Development Programme.

From 2019 to 2023, during GGSim's development, I encountered significant challenges in applying the tool to assess SDG indicators across the four dimensions of the Green Growth Index: efficient and sustainable resource use, natural capital protection, green economic opportunities, and social inclusion. The lack of models and data for social inclusion indicators—such as access to basic services, gender equality, social equity, and social protection—posed significant obstacles to evaluating the co-benefits of climate mitigation and adaptation actions on these SDGs. Recognizing the potential of AI to address these gaps, the GGPM Team initiated a collaboration with the University of Pannonia to integrate AI approaches into GGSim. This innovative work has been recognized globally, with GGGI's AI-supported Green Growth Simulation receiving two prestigious awards in 2024: the AI for Good Summit Winning Use Case by the International Telecommunication Union (ITU) and the AI Elite Project designation at the World Artificial Intelligence Conference (WAIC).

During the virtual review workshop for this report on October 4, 2024, members of the Green Growth International Expert Group and additional scholars and authors of the AI for Good Summit Winning Use Cases expressed keen interest in joining the Global AI-GGSim International Expert Group. These include Afrah Hussein from Addis Ababa Science and Technology University, Emmanuel Othniel Eggah from the Nigerian Tegan Mosugu Company, Estella Oncins from the Autonomous University of Barcelona, Ferheen Ayaz from the University of London, Shadia Y.M. Baroud from the University of Malaysia, and Vishnu Ram from the Institute of Electrical and Electronics Engineers. I extend my heartfelt gratitude to Mr. Vishnu Ram, coordinator of the Winning Use Cases during the AI for Good Summit, and the selection committee for recognizing AI-GGSim as a transformative use case for advancing the SDGs.

Finally, I am deeply grateful to Dr. Frank Rijsberman for his unwavering support and guidance since 2019. His steadfast belief in the vision of GGSim and its potential to drive meaningful climate action has been a source of immense encouragement. By entrusting me with the responsibility of developing such an ambitious and impactful tool, he not only provided invaluable opportunities for innovation but also inspired confidence in the importance of our work. His leadership and commitment have been instrumental in navigating challenges and ensuring that GGSim evolves as a transformative solution for addressing global environmental and societal challenges.

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Cont


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Acronyms and Abbreviations

AB	Access to Basic Services and Resources
AFD	French Development Agency
AFR100	African Forest Landscape Restoration Initiative
AFOLU	Agriculture, Forestry, and Other Land Use
AGVA	Agricultural Gross Value Added
AIR	Agriculture area actually irrigated
AIRi	Irrigated area per irrigation technology type
AM	Ambitious scenario
APEC	Asia-Pacific Economic Cooperation
AWU	Agricultural Water Withdrawal
AWUE	Agricultural Water Use Efficiency
BAU	Business as usual
BE	Biodiversity and Ecosystem Protection
BOS	Bureau Opérationnel de Suivi du Plan Sénégal Émergent
CA	Cautious scenario
CAID	Climate Action and Inclusive Development
CH_4	Methane
CI	Cropping Intensity
CNG	Compressed Natural Gas
CO_2	Carbon Dioxide
CO_{2eq}	Carbon Dioxide equivalent
COVID-19	Coronavirus disease
Cr	Corrective coefficient
CV	Cultural and Social Value
DALY	Disability-Adjusted Life Year
dm	Dry matter
DMC	Domestic Material Consumption
DRR	Disaster Risk Reduction
EA	Early Action
EE	Efficient and Sustainable Energy
EQ	Environmental Quality
ESRU	Efficient and Sustainable Resource Use
ETa	Actual Evapotranspiration
ETc	Potential Crop Evaporation Vector
ETo	Evapotranspiration
EU	European Union
EW	Efficient and Sustainable Water Use
Ex-ACT	EX-Ante Carbon-balance Tool
F-gas	Fluorinated gases
FAO	Food and Agriculture Organization of the United Nations
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database

FRA	Forest Resources Assessment
GB	Gender Balance
GDP	Gross Domestic Product
GDPc	Gross Domestic Product per capita
GE	GHG Emissions Reduction
GEM	Green Economic Model
GEO	Green Economic Opportunities
gg	gigagram
GGI	Green Growth Index
GGGI	Global Green Growth Institute
GGPM	Green Growth Performance Measurement
GGSim	Green Growth Simulation Tool
GHG	Greenhouse Gas
GIS	Geographic Information System
GJ	Green Employment
GN	Green Innovation
GNI	Gross National Income
GT	Green Trade
GV	Green Investment
GW	Gigawatt
HA	High Ambition
ICU	Irrigation Consumptive Use
IEA	International Energy Agency
IGVA	Industrial Gross Value Added
IIASA	International Institute for Applied Systems Analysis
IPCC	Intergovernmental Panel on Climate Change
IRRTECHi_Drip	Proportion of drip irrigation technology
IRRTECHi_ Sprinkler	Proportion of sprinkler irrigation technology
IWRi	Irrigation Water Requirement per irrigation
IWU	Industrial Water Use
IWUE	Industrial Water Use Efficiency
IWW	Irrigation Water Withdrawal
ktonnes	Kiloton
LA	Late Action
LA	Low Ambition
LCU	Local Currency Unit
LEAP	Low Emissions Analysis Platform
LSU	Livestock Unit
LT-LEDS	Long-term low emissions development strategies
LULUF	Land Use Change and Forestry
LULUCF	Land Use, Land Use Change, and Forestry
LUF	Land-Use Footprint

Acronyms and Abbreviations

m^3	Cubic meter
MA	Moderate Ambition
ME	Material Use Efficiency
MF	Material Footprint
MIT	Ministry for Innovation and Technology
MJ	Megajoule
ML	Machine Learning
MSW	Municipal solid waste
MT	Metric ton
MToe	mega tons of oil equivalent
MW	Megawatt
MWh	Megawatt-hour
MWU	Municipal Water Withdrawal
MWUE	Municipal Water Use Efficiency
N_2O	Nitrous Oxide
NAP	National Adaptation Plan
NCAR	National Center for Atmospheric Research
NCP	Natural Capital Protection
NCDS	National Clean Development Strategy
NDC	National Determined Contributions
NDP	National Development Plan
NÉBIH	National Food Chain Safety Office
NEP	National Electrification Program
NEXT	Nationally Determined Contribution Expert Tool
NGGS	National Green Growth Strategy
NZE	Net Zero Emissions
OECD	Organisation for Economic Co-operation and Development
OECS	Organisation of Eastern Caribbean States
ONEA	Office National de l'Eau et de l'Assainissement
PAIR	Proportion of Irrigated Cropland
pkm	passenger kilometer
PJ	Pentajoules
$PM_{2.5}$	Particulate matter with a diameter of less than 2.5 micrometers
Pop	Population
PPP	Purchasing power parity
PSE	Green Emerging Senegal Plan
r^2	coefficient of determination
RCP	Representative Concentration Pathway
RES	Renewable Energy Sources
SCADD	Strategy for Accelerated Growth and Sustainable Development
SDGs	Sustainable Development Goals

SDSN	Sustainable Development Solutions Network
SE	Social Equity
SEM	Structural Equation Models
SGVA	Service Sector Gross Value Added Resources
SI	Social Inclusion
SL	Sustainable Land Use
SP	Social Protection
SPV	Solar Photovoltaic Systems
SSP	Shared Socioeconomic Pathways
SSP1	Sustainability storyline
SSP2	Middle of the Road storyline
TFA	Total Freshwater Available
TJ	Terajoule
TNCW	Total Non-Conventional Water
TR	Transformative scenario
TRF	Total Renewable Freshwater
TW	Treated Wastewater
TWW	Total Water Withdrawal
UHC	Universal Health Coverage
UN	United Nations
UNCCD	United Nations Convention to Combat Desertification
UNEP	The United Nations Environment Programme
UN-Habitat	United Nations Human Settlements Programme
UNICEF	United Nations International Children's Emergency Fund
UNSTATS	United Nations Statistics Division
USD	United States Dollar
WASH	Water, sanitation and hygiene
WHO	World Health Organization
WSS	Water Supply and Sanitation

01 INTRODUCTION

1.1 Overview of SDG alignment

The 17 Sustainable Development Goals (SDGs)[1], with its global indicator framework of 231 unique SDG indicators[i], provide the 193 UN Member States targets to benchmark their performance in achieving social, economic, and environmental sustainability, with the aim of reducing inequalities and protecting the earth while aspiring for economic growth. It is thus imperative that Governments ensure alignment of the development policies, plans, and strategies with the SDGs. "The 2030 Agenda for Sustainable Development encourages national target-setting and adaptation of the SDGs into national process, policies, and strategies."[2] Consequently, National Development Plans (NDPs)[3], National Green Growth Strategy (NGGS)[4], Nationally Determined Contributions (NDCs)[5], Long-term low emissions development strategies (LT-LEDS)[6], National Adaptation Plans (NAPs)[7], Disaster Risk Reduction (DRR)[8], etc. are being aligned with the SDGs, facilitating the implementation of the 2030 Agenda for Sustainable Development. For example, according to the LT-LEDS Synthesis Report conducted in 2023, 63 percent of the 68 latest available LT-LEDS referred to linkages with the SDGs.[9] SDG alignment ensures tracking performance in achieving the key development, mitigation, and adaptation goals. In most cases, assessing SDG alignment mainly depends on a qualitative approach.[10] However, building quantifiable scenarios on the impacts of mitigation and adaptation measures on achieving the SDG targets will be helpful for policy and planning.

1.1.1 Green growth performance measurement

In 2019, GGGI developed the Green Growth Index and its simulation tool (i.e., Green Growth Simulation (GGSim) Tool) to both qualitatively and quantitatively investigate SDG alignment. The qualitative methods involve using checklist tables to check the relevance of the Green Growth Index indicators to the countries' national policies, sectoral programs, and development priorities.[11] In addition, for a more rigorous qualitative assessment, content analysis is applied to identify patterns and themes within qualitative data, using systematic coding and categorizing contents of policy frameworks and presenting results in Sankey diagrams and frequency tables.[12] The quantitative methods, which are applied in this report, involve the assessments of distance to sustainability targets and SDG co-benefits using the Green Growth Index and Simulation Tool. These are complementary approaches developed through GGGI's Green Growth Performance Measurement (GGPM) Program to measure its Member Countries and Partners' performance in green growth. On the one hand, the Index measures the country-level green growth performance based on a standard set of performance metrics in four green growth dimensions: efficient and sustainable resource use, natural capital protection, green economic opportunities, and social inclusion (Figure 1). On the other hand, the Tool allows the users to enhance their knowledge of how countries' green growth performance can be influenced by different policy and investment options in major economic sectors: energy and transport, agriculture, forest, and land use (AFOLU), and water and waste (Figure 2). By coupling the Simulation Tool with the Green Growth Index, policy and investment scenarios can inform policymakers on how their current decisions will affect their ability to achieve their targets in the future. The Green Growth Index provides a composite index of 48 indicators; 34 (or 71 percent) are from the SDGs, covering 2010-2022, and the Green Growth Simulation Tool provides scenarios for selected SDG indicators (and indicators contributing to the achievement of the SDGs) for the period 2020-2050.

Through the Green Growth Index and Simulation Tool, GGGI aims to:[13]

- **Provide a composite index to measure, track, and communicate green growth performance.** The 2023 Global Green Growth Index covers 157 countries. It can raise awareness and sustain green growth momentum in the public and private sectors. It ranks and benchmarks the countries' green growth performance through a standard set of variables based on publicly available and credible data. Because the Green Growth Index is based on a robust sustainability framework developed with over 300 interdisciplinary experts worldwide, it can highlight the SDGs' achievements linked to green growth. The Green Growth Index is applied at the global, regional, and national levels. (Note: available at https://greengrowthindex.gggi.org/)

- **Improve current knowledge on green growth and its drivers.** The Simulation Tool provides an interactive learning experience and enhances users' knowledge of green growth planning and strategy development. Because the tool can be used to simulate and understand the impacts of different policy and investment measures on green growth performance, it can provide input in planning and supporting the formulation of green growth policies in critical sectors. The Phase 1 Simulation Tool covers its application in three case study countries: Hungary, Mexico, and Uganda.[14] The Phase 2 Simulation Tool covers its application in Hungary, Burkina Faso, and Ethiopia for assessing climate mitigation measures (e.g., LT-LEDS) and St. Lucia and Senegal for assessing climate adaptation measures (e.g., NAP, Green Recovery). (Note: available in this report and online tools: https://ggindex-simtool.gggi.org/SimulationDashBoard/country_level_applications)

- **Foster a data- and evidence-driven approach in identifying and developing strategies for green growth.** The index and tool are linked to an evidence library, allowing users access to the data, models, and empirical evidence underpinning the framework and simulations. This provides credibility to the results and will enable them to inform and guide green growth planning. The evidence library can be a helpful starting point for further studies and analysis of indicators and sectors related to green growth performance. Green Growth Index users can access the evidence library data for indicators unavailable elsewhere, including green employment in manufacturing, green trade, and water

i The total number of indicators listed in the global indicator framework of SDG indicators is 248, but 13 indicators repeat under two or three different targets

Figure 1. Conceptual framework for the Green Growth Index

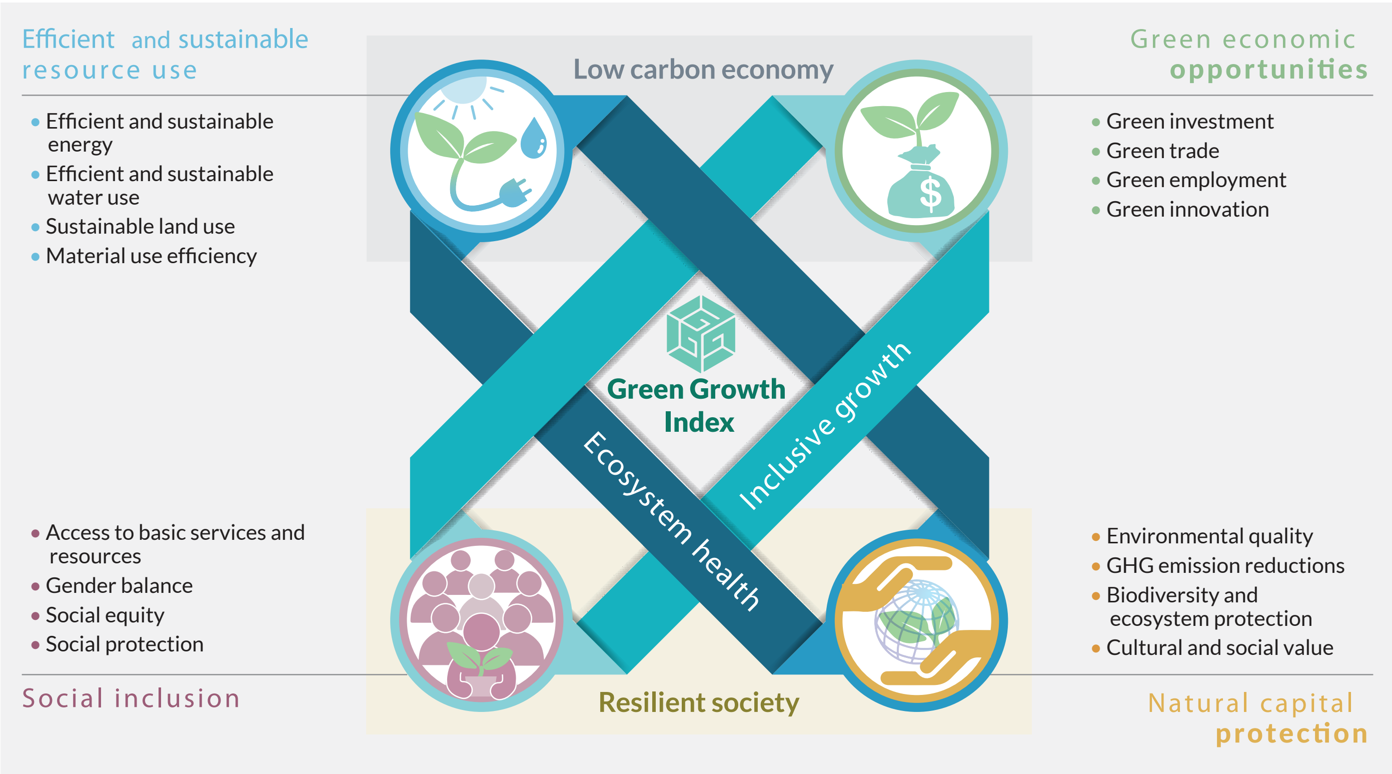
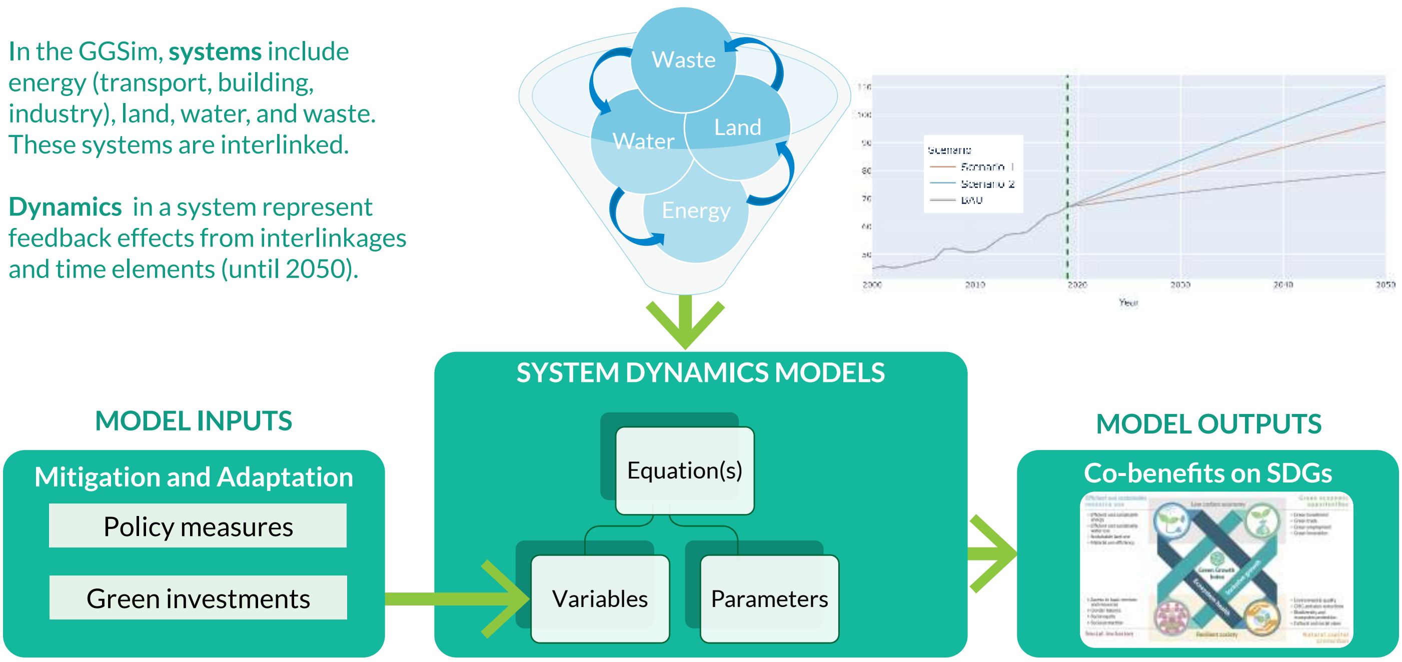


Figure 2. Green Growth Simulation (GGSim) framework for assessing SDG co-benefits



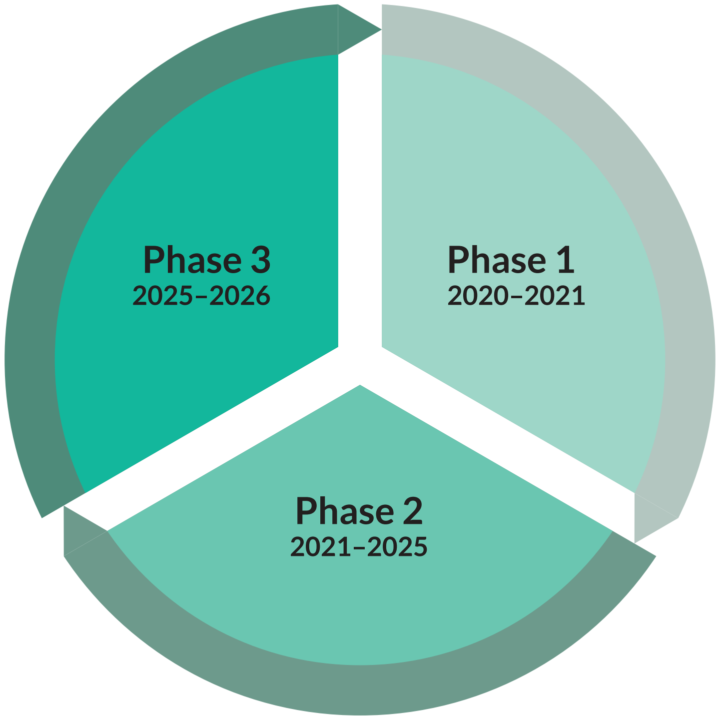
virtual trade flows. (Note: available at https://ggindex-simtool.gggi.org/SimulationDashBoard/data)

1.2 Development phases of the simulation tool

GGGI develops the GGSim Tool in various phases to allow its systematic validation and collaborative applications. In each phase, the design process and the results of the applications are published in a technical report. The GGSim development follows three phases, each phase contributing to the next phase and, thus, representing a continuous process (Figure 3):

Phase 1 (2020-2021) consists of identifying and applying models that provide interlinkages among the indicators and require available data online. Models that require data to be collected from countries were kept for use in Phase 2. A comprehensive review of mathematical models and tools was conducted to identify appropriate models, which were used to develop interlinked system dynamics models for energy, land, water, and waste systems. Details are available in Acosta et al. 2020[15].

Figure 3. Development phases for the Green Growth Simulation (GGSim) framework



Phase 2 (2021-2025) involves conducting stakeholder dialogues to create/identify policy scenarios and collect feedback on the Phase 1 Simulation Tool. It also aims to improve the Phase 1 Simulation Tool by adding models that require data collected from agencies and integrating feedback from stakeholder dialogues. Phase 2 focuses on country applications to support SDG co-benefits assessments in development policies (e.g., NDPs, NGGS), climate mitigation (e.g., LT-LEDS, NDCs), and climate adaptation (e.g., NAPs, DRR). This report presents the first applications of the Phase 2 Simulation Tool.

Phase 3 (2025-2026) consists of refining the models and scenarios by adopting lessons learned from different country applications of the Phase 2 Simulation Tool and standardizing them for more global applications. The Phase 3 Simulation Tool will be interactive with the Global Green Growth Index, comparing distance to sustainability targets from 2020 to 2050. The online tool will allow building scenarios for various climate mitigation and adaptation measures to assess SDG alignment, emphasizing interlinkages between the distance to SDG targets and SDG co-benefits.

1.3 Objectives and structure of this report

This report aims to present to modelers and practitioners the country-level applications of the Phase 2 Simulation Tool, assessing the impacts of climate mitigation and adaptation actions on the SDG co-benefits and distance to targets from 2020 to 2050. The assessments include impacts of mitigation measures in LT-LEDS for Hungary, Burkina Faso, and Ethiopia and adaptation measures in NAP and Green Recovery-related projects in St. Lucia and Senegal.

Chapter 1, this chapter, provides the rationale for using the GGSim Tool in SDG alignment assessments in key national policies, plans, and strategies. It also briefly introduces the complementarity between the Green Growth Index and its GGSim Tool, as well as the phases for developing the latter.

Chapter 2 presents the key assessment findings for distance to targets and SDG co-benefits for the five selected countries, including Hungary, Burkina Faso, Ethiopia, St. Lucia, and Senegal.

Chapter 3 presents the methods and models for the Phase 2 applications. The chapter discusses the mathematical models, including the input and output variables for the equations for the energy and transport, AFOLU, and water use and waste system dynamics models. More details on the equations and data sources are provided in Annexes.

Chapter 4 discusses selected results from the SDG co-benefits scenario analyses for the energy and transport, AFOLU, and water use and waste sectors in Hungary, Burkina Faso, Ethiopia, St. Lucia, and Senegal.

Chapter 5 presents the pilot application of the AI-based network and data analyses in validating GGSim's system dynamics models and its potential to extend SDG co-benefits analysis for SDGs lacking models and data.

Chapter 6 provides conclusions and explains the steps to further develop and apply the Green Growth Simulation Tool Phase 2.

02 KEY FINDINGS

2.1 SDG co-benefits assessments

In this report, the SDG co-benefits assessment identifies the impacts of climate mitigation and adaptation measures on the performance of SDG indicators from 2020 (baseline year) to 2050. The methods for this assessment is discussed in section 3.1.2A. The assessments in Hungary, Burkina Faso, and Ethiopia deal with the mitigation measures in the LT-LEDS, while those in St. Lucia and Senegal focus on adaptation measures in the NAP and Green Recovery. The mitigation measures in the LT-LEDS also vary across countries, depending on the governments' development, sectoral, and investment priorities. For this reason, the SDG indicators included in the assessments vary across the countries (Table 1). Another important reason for the variation in the SDG indicators is data scarcity, limiting the applications of the GGSim models in some countries. Sections 4.1 and 4.2 discuss the results of the SDG co-benefits assessment, and this section provides the highlights of the results and compares performance for the same SDG indicators where available across countries. Except for Hungary, two scenarios are compared with the business-as-usual (BAU) scenario. In this section, however, only the results of the scenario showing the most significant difference from the BAU are presented. The description of these scenarios is given below.

- The **Early Action (EA)** mitigation for Hungary aims to achieve climate neutrality by 2050 by considering the short- and medium-term benefits of implementing the transition. In the EA scenario, emissions follow a linear trajectory from 2030 to net zero in 2050. Among the assumed mitigation measures include increasing renewable power generation capacities (mainly solar PV), increasing electricity generation, shifting transport demand towards electricity and biofuels, and reforestation.

- The **High Ambition (HA)** mitigation for Burkina Faso implements ambitious measures as early as 2022, allowing the country to reach carbon neutrality in 2045 and be a net carbon sink by 2050. Among the assumed mitigation measures include increasing renewable power generation capacities (mainly solar), increasing electricity generation, and reforestation.

- The **Maximum Ambition (MA)** mitigation for Ethiopia represents the maximum potential emissions reduction achievable if strong policies and measures are implemented early on. The MA scenario aims to reach net zero emissions around 2035 and remain below zero onwards. Among the assumed mitigation measures include increasing renewable power generation capacities (mainly hydro, wind, and biomass), increasing electricity generation, and reforestation.

- The **Transformative (TR)** adaptation for St. Lucia assumes that technological and behavioral changes that will reduce trade-offs and ensure sustainable transformations are important priorities for this scenario, while the BAU assumes nothing is done to adapt to climate change. In the TR scenario, social rather than economic costs of no action are more important considerations when addressing the trade-offs. Moreover, the implemented policies and actions also aim to achieve the climate targets and commitments. Among the assumed adaptation measures include increasing agricultural productivity, diversifying agricultural exports, improving manure management, and reforestation.

- The **Moderate Ambition (MA)** adaptation scenario for Senegal ensures that any climate adaptation or mitigation plan is affordable, limiting investments that cannot be supported without collaboration and, therefore, restricting what national governments and local investors can afford. Among the assumed adaptation measures include substituting cattle for poultry, improving manure management, and reforestation.

In contrast to the above scenarios, the BAU assumes that current trends and policies will continue and no climate measures will be implemented. The changes in the values of the indicators in the BAU and selected scenarios (SCE), as described above, are compared for the years 2030 and 2050 (Table 1). Only the direction of change, i.e., → no change, ↑ increase, ↓ decrease, are presented in this section. Details on the value change are presented in sections 4.1 and 4.2, and the corresponding figures are given in Table 1 for reference. This table also provides the relationship of the SDG indicators to green growth, where a negative change (i.e., value reduction) is sought for indicators with a negative relationship. The GGSim consists of different system dynamics models, and the ones applied for the SDG co-benefits assessments depend on policy measures and data availability. The energy and transport model (ENET) was only applied in Hungary because the

Table 1. Co-benefits and trade-offs for SDG indicators from climate mitigation and adaptation measures, with arrows providing direction of change in 2030 and 2050

SDG indicators/relevance to SDGs	Green growth links	Country	Model	Source	BAU		SCE	
					2030	2050	2030	2050
A. Impacts of Mitigation Measures								
A.1 Cross-country comparisons								
Energy intensity (SDG 7.3.1)	Negative	Hungary	ENET	Figure 14	↓	↓	↓	↓
		Burkina	ENE	Figure 29	↓	↓	↓	↓
		Ethiopia	ENE	Figure 41	↓	↓	↓	↓

Table 1. Co-benefits and trade-offs for SDG indicators from climate mitigation and adaptation measures, with arrows providing direction of change in 2030 and 2050 *(continued)*

SDG indicators/relevance to SDGs	Green growth links	Country	Model	Source	BAU		SCE	
					2030	2050	2030	2050
Share of renewables in electricity generation (part of SDG 7.2.1)	Positive	Hungary	ENET	Figure 15	↑	↓	↑	↑
		Burkina	ENE	Figure 30	→	→	↑	↑
		Ethiopia	ENE	Figure 42	↑	→	↑	→
Installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1)	Positive	Hungary	ENET	Figure 16	↑	↓	↑	↑
		Burkina	ENE	Figure 31	→	→	↑	↑
		Ethiopia	ENE	Figure 43	↑	→	↑	↑
Food loss and waste index (SDG 12.3.1.a and b)	Negative	Hungary	AFOLU	Figure 20	↑	↑	↓	↓
		Burkina	AFOLU	Figure 32	↓	↓	↓	↓
		Ethiopia	AFOLU	Figure 44	↓	↓	↓	↓
Nutrient balance (part of SDG 15.3.1)	Negative	Hungary	AFOLU	Figure 21a	→	→	↓	↓
		Burkina	AFOLU	Figure 33	↑	↑	↑	↓
		Ethiopia	AFOLU	Figure 45	↑	↑	↓	↓
Above-ground biomass in forest (SDG 15.2.1)	Positive	Hungary	AFOLU	Figure 23	↑	↑	↑	↑
		Burkina	AFOLU	Figures 34	→	↓	→	↑
		Ethiopia	AFOLU	Figure 46	↓	↓	↑	↑
Share of forest area to total land area (SDG 15.1.1)	Positive	Hungary	AFOLU	Figure 24	→	→	↑	↑
		Burkina	AFOLU	Figure 35	↓	↓	→	↑
		Ethiopia	AFOLU	Figure 47	↓	↓	↑	↑
Water use efficiency (SDG 6.4.1)	Positive	Hungary	WU&W	Figure 26a	↓	↑	↓	↑
		Burkina	WU&W	Figure 38a	↑	↑	→	↑
		Ethiopia	WU	Figure 49	↑	↑	↑	↑
Level of water stress (SDG 6.4.2)	Negative	Hungary	WU&W	Figure 27	↑	↓	↑	↓
		Burkina	WU&W	Figure 37	→	→	↑	↑
		Ethiopia	WU	Figure 48	↑	↑	↑	↑
Treated wastewater (part of SDG 6.3.1)	Positive	Hungary	WU&W	Figure 28	→	→	↑	↑
		Burkina	WU&W	Figure 40a	→	↑	↑	↑
A.2 SDG indicators for a specific country								
Land requirement for SPV installation (link to SDG 7.2.1)	Negative	Hungary	ENET	Figure 17a	↑	↓	↑	↑
Land use change emissions from SPV installation (part of SDG 13.2.2)	Negative	Hungary	ENET	Figure 18a	↑	↓	↑	↑
Emission levels from transport activity (part of SDG 13.2.2)	Negative	Hungary	ENET	Figure 19	↓	→	↓	↓
Crop residue emissions (part of SDG 13.2.2)	Negative	Hungary	AFOLU	Figure 22a	→	↓	↓	↓

Table 1. Co-benefits and trade-offs for SDG indicators from climate mitigation and adaptation measures, with arrows providing direction of change in 2030 and 2050 *(continued)*

SDG indicators/relevance to SDGs	Green growth links	Country	Model	Source	BAU		SCE	
					2030	2050	2030	2050
Non-CO2 emissions in agriculture (SDG 13.3.2)	Negative	Hungary	AFOLU	Figure 25	↑	↑	↓	↓
Bioenergy production (link to SDG 7.1.2)	Positive	Hungary	AFOLU	Figure 22b	→	↓	↑	↑
Proportion of degraded (forest) land (part of SDG 15.3.1)	Negative	Burkina	AFOLU	Figure 36	↑	↑	↑	↓
B. Impacts of Adaptation Measures								
B.1 Cross-country comparisons								
Food waste and loss index (SDG 12.3.1.a and b)	Negative	St. Lucia	AFOLU	Figure 50	↓	↑	↓	↓
		Senegal	AFOLU	Figure 61	↓	↓	↓	↓
Nutrient balance (part of SDG 15.3.1)	Negative	St. Lucia	AFOLU	Figure 52a	↓	→	↑	↑
		Senegal	AFOLU	Figure 63a	↑	↑	↑	↓
Above-ground biomass in forest (SDG 15.2.1)	Positive	St. Lucia	AFOLU	Figure 53	↑	↑	↑	↑
		Senegal	AFOLU	Figure 64	→	↓	↑	↑
Share of forest area to total land area (SDG 15.1.1)	Positive	St. Lucia	AFOLU	Figure 54	→	→	↑	↑
		Senegal	AFOLU	Figure 65	→	↓	→	↑
Managed manure (link to SDG 2.4.1)	Positive	St. Lucia	AFOLU	Figure 51b	→	↑	↑	↑
		Senegal	AFOLU	Figure 62b	↑	↑	↑	↑
Fertilizer use, manure applied to soil (link to SDG 2.4.1)	Negative	St. Lucia	AFOLU	Figure 51c	↑	→	↑	↓
		Senegal	AFOLU	Figure 62c	↑	↑	↑	↓
Emissions from agricultural production (part of SDG 13.2.2)	Negative	St. Lucia	AFOLU	Figure 55	→	↑	↓	↓
		Senegal	AFOLU	Figure 66	↓	↓	↓	↓
B.2 SDG indicators for a specific country								
Cropland area (part of SDG 15.3.1)	Positive	St. Lucia	AFOLU	Figure 52b	↑	→	↓	↓
Water use efficiency (SDG 6.4.1)	Positive	St. Lucia	WU&W	Figure 57a	↑	↑	↑	↑
Level of water stress (SDG 6.4.2)	Negative	St. Lucia	WU&W	Figure 56	↑	↑	↓	↓
Treated wastewater (part of SDG 6.3.1)	Positive	St. Lucia	WU&W	Figure 58	→	→	↑	↑
Emissions from agricultural production (part of SDG 13.2.2)	Negative	St. Lucia	AFOLU	Figure 55	↑	↑	↓	↓
Crop residues left on pastureland (link to SDG 2.4.1)	Positive	Senegal	AFOLU	Figure 62d	↑	↑	↑	↑
CO_2 emissions in agriculture to population (part of SDG 13.3.2)	Negative	Senegal	AFOLU	Figure 66	↓	↓	↓	↓

Model: Energy and transport (ENET), Energy ENE), Agriculture, forest and land use (AFOLU), Water use and waste (WU&W), and Water use (WU)
Scenarios (SCE): Early action (EA) for Hungary, High ambition (HA) for Burkina Faso, Maximum ambition (MA) for Ethiopia, Transformative (TR) for St. Lucia, and Moderate Ambition (MA) for Senegal.
Legend: → no change, ↑ increase, ↓ decrease

mitigation measures focused on reducing emissions in the transport sector. Due to a lack of data, the transport module was excluded from the SDG co-benefits assessment of mitigation measures in Burkina Faso and Ethiopia.
The AFOLU and water use (WU) models were linked to the energy (ENE) model to determine the SDG co-benefits in other relevant sectors. The energy model was excluded from the SDG co-benefits assessments in St. Lucia and Senegal because the policy measures focused on adaptation in the agriculture and forest sectors, respectively.
The water use (WU) or, where data is available, water use and waste (WU&W) models are linked with the agriculture, forest, and land use (AFOLU) model to determine the SDG co-benefits in other relevant sectors.

2.1.1 Climate mitigation

Climate mitigation measures focus on increasing renewable power generation capacities and reforestation to reduce GHG emissions with SDG co-benefits in the agriculture and water sectors. With or without the mitigation measures, energy intensity (SDG 7.3.1), which has a negative relationship to green growth, will improve in Hungary, Burkina Faso, and Ethiopia in 2030 and 2050, as shown by the downward change in the value of this SDG indicator for both the BAU and the selected scenarios (SCE). However, the value of change will be more significant in the SCE than in the BAU scenario in all countries (section 4.1). The changes in the share of renewables in electricity generation (part of SDG 7.2.1) due to mitigation measures will vary between scenarios, years, and countries. In all three countries, performance in this related SDG indicator will be better in the SCE than in the BAU scenario. The share of renewables in electricity generation will continue to increase from 2030 to 2050 in Hungary and Burkina Faso. However, it will level off in Ethiopia as the country reaches 100 percent renewable electricity by 2030. The mitigation measures will improve the performance in installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1) in the SCE vis-à-vis the BAU scenario for all three countries.

The mitigation measures will provide co-benefits for several AFOLU, water, and waste-related SDG indicators. In the agriculture sector, the food loss and waste index (SDG 12.3.1.a and b), which has a negative relationship to green growth, will benefit from the mitigation measures, particularly in Hungary, where this indicator, showing an increase in the BAU, will decrease in the SCE scenario. The significant co-benefits for this indicator in Hungary compared with Burkina Faso and Ethiopia are mainly because an increasing population will offset the BAU trend in the two African countries, while it will be accentuated by a decreasing population in Hungary. Similarly, the nutrient balance (part of SDG 15.3.1), which measures the overuse of fertilizer and thus represents a negative relationship to green growth, will also benefit from the mitigation measures in Hungary, Burkina Faso, and Ethiopia. However, in Burkina Faso, the decline in nutrient balance will only occur after 2030 due to the assumption of livestock substitution and manure management. In the forest sector, the above-ground biomass in the forest (SDG 15.2.1) and the share of forest area to total land area (SDG 15.1.1) are expected to gain from the mitigation measures in the three countries. Ethiopia will have the most visible co-benefit in both SDG indicators, where the negative change in the BAU will be reversed to a positive change in the SCE scenario in the years 2030 and 2050. Another SDG indicator for forests that will benefit from the mitigation measures in Burkina Faso is the proportion of degraded (forest) land (part of SDG 15.3.1). Forest degradation in the BAU will be reversed (or halted) in the SCE scenario, albeit only in 2030. The impacts on this SDG indicator were not modelled in Burkina Faso and Ethiopia due to a lack of data.

The impact of mitigation measures on the water sector depends on the country's available water resources, the water demand to implement the measures, and the assumption of measures to reduce the impact on water withdrawal. For these reasons, the impacts on water use efficiency (SDG 6.4.1) and the level of water stress (SDG 6.4.2) will vary in the three countries. Water use efficiency will improve in Ethiopia's SCE scenario in 2030 and 2050, but in Burkina Faso, it will only improve in 2050. In contrast, in Hungary, it will decrease in 2030 and increase in 2050. The decline in water use efficiency in 2030 is due to a significant increase in nuclear electricity generation, requiring large amounts of cooling water. In the case of water stress, which has a negative relationship to green growth, it will continue to increase in both BAU and SCE scenarios in Ethiopia in 2030 and 2050, while the direction of change will be the same for both scenarios in Hungary (i.e., increasing in 2030 and decreasing in 2050). In Burkina Faso, the mitigation measures will show some trade-offs because the level of water stress will change from a stagnant level in the BAU to an increase in the SCE scenario in 2030 and 2050. The reason for this is the development of the agricultural sector, led by population growth. Developing more efficient irrigation technologies will not be sufficient to offset the increasing cropland demand. The treated wastewater (part of SDG 6.3.1) will benefit from the mitigation measures, increasing in the SCE scenario relative to the BAU in 2030 and 2050.

Additional assessments relevant to the energy and transport mitigation measures were computed for Hungary. The land requirement for SPV installation (link to SDG 7.2.1) will increase in the SCE scenario, resulting in trade-offs for the land use change emissions (part of SDG 13.2.2). In contrast, with the support from SPV for vehicle electrification, the emission levels from transport activity (part of SDG 13.2.2) will decrease in the SCE scenario. Moreover, increased biofuel production from crop residues will reduce crop residue emissions (part of SDG 13.2.2) and non-CO2 emissions in agriculture (SDG 13.3.2).

2.1.2 Climate adaptation

The adaptation measures address sustainability challenges in the AFOLU sector with SDG co-benefits in the water and environment sectors. The food waste and loss index (SDG 12.3.1.a and b), which negatively relates to green growth, will decline in St. Lucia and Senegal in the SCE scenarios in 2030 and 2050. The adaptation measures will reverse the increase in this SDG indicator in the BAU scenario in St. Lucia in 2050. Food loss and waste will also decline in the BAU scenario in Senegal, but the rate of decline will be higher in the SCE scenario (section 4.2). The change in nutrient balance (part of SDG 15.3.1), also with a negative relationship to green growth, will vary in the two countries. It will decline in 2030 and remain stable in 2050 under the BAU scenario but increase in both 2030 and 2050 under the SCE scenario in St. Lucia. This is because of the policies on manure management and the decrease in cropland demand. The increasing trend in nutrient balance in the BAU scenario will be reversed in the SCE scenario in Senegal, albeit only in 2050. The improvement in nutrient balance in this scenario is due to policies on manure, with an increase in the proportion of manure managed but a decrease in the proportion of manure applied to soil. Reforestation as an adaptation measure will support biodiversity and ecosystem protection. Above-ground biomass in forests (SDG 15.2.1) will see an improvement in the SCE scenarios in St. Lucia and Senegal. This is particularly valuable in Senegal, where above-ground biomass and the share of forest area to total land area (SDG 15.1.1) is expected to decline in the BAU scenario in 2050. Manure management (link to SDG 2.4.1) will improve in the SCE scenarios in St. Lucia and Senegal. Consequently, fertilizer use or manure applied to soil (link to SDG 2.4.1), which has a negative relationship to green growth, will decline in the SCE scenarios, albeit only in 2050. An important co-benefit of the adaptation measures will be the reduction in emissions from agricultural production (part of SDG 13.2.2) due not only to reforestation but also better management of manure fertilizer.

Other SDG indicators specific to the SDG co-benefits assessment in St. Lucia include the cropland area (part of SDG 15.3.1), which is expected to decline in the SCE scenario due to the land conversion to forests. The decline in cropland will have an implication on the country's food security, hence representing a trade-off to the adaptation measures. St. Lucia's water use efficiency (SDG 6.4.1) and the level of water stress (SDG 6.4.2) will improve in the SCE scenarios. The co-benefit in the latter SDG indicator is more significant as the increasing water stress trend in the BAU scenario will be reversed. Other co-benefits will be improving the treated wastewater (part of SDG 6.3.1) and reducing the emissions from agricultural production (part of SDG 13.2.2).

2.2 Achieving SDG targets

The distances to targets, representing the Green Growth Index scores, measure a country's performance in achieving sustainability targets, including SDGs, the Paris Climate Agreement, and Biodiversity targets. The values of the SDG indicators calculated from the SDG co-benefits assessment were benchmarked against the targets, generating scores between 1 and 100, where a score of 100 indicates the achievement of the targets. The benchmarking methods are discussed in section 3.1.2B. Table 2 and Table 3 compare the distances to targets for selected SDG indicators from the historical data (i.e., 2010 and 2020) and the BAU and low-emissions scenarios (i.e., 2030 and 2050) for climate mitigation and adaptation. Sections 4.1 and 4.2 provide detailed descriptions of these scenarios. The following will have to be considered when comparing historical and scenario-based distances to targets:

- The historical distances to targets were drawn from the 2023 Global Green Growth Index results, covering 157 countries (cite ref).
- Benchmarking requires global data to make Green Growth Index scores comparable across countries and over time. For this reason, distance to targets can only be computed for the SDG indicators included in the Global Green Growth Index.
- As part of the LT-LEDS assessments, national databases were mainly used for SDG co-benefits assessments for Hungary, Burkina Faso, and Ethiopia. As a result, when national databases used in computing the scenario-based SDG indicators significantly differ from international sources, the distances to targets may diverge a lot from the historical values.

The values and sources of the sustainability targets are presented in Table 2 and Table 3. Although SDG targets are valid for 2030, comparing the distances to targets in 2050 informs whether the 2030 targets can be achieved after another 20 years. For targets not derived from SDGs (e.g., mean top five country performers, FAO targets, etc.), they are not necessarily limited until 2030 but are valid for assessing results for 2050.

2.2.1 Climate mitigation

Hungary

Performance in installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1) will increase considerably in the BAU and low emission scenarios compared to the historical, with distance to targets below 12 in 2010 and 2020. Distances to targets for this SDG indicator will be closer to 100 in the Early Action (EA) scenario than in the BAU scenario (Table 2). Under the EA scenario, the sustainability target will be reached by 2050, mainly due to the installation of SPVs. Additional measures will need to be taken to improve water use efficiency (SDG 6.4.1), as the distances to targets will remain farther away, where the EA scenario results do not show very significant improvement from the BAU and historical values. The slight increase will be driven by the growing importance of the highly efficient municipal sector in the total water use withdrawals. Compared with Burkina Faso and Ethiopia, Hungary has the highest score for the level of water stress (SDG 6.4.2) as it will maintain its water stress level below 25 percent share of freshwater water withdrawal to available freshwater resources. Reducing fertilizer use and manure applied to soil in the EA scenario will help improve performance on the nutrient balance (SDG 15.3.1). Distances to targets in the EA scenario will improve from 83 in 2030 to 87 in 2050, while the BAU scenario will not show any increase. However, relative to historical value in 2010, with a score of 90, performance in the EA scenario is lower at 87. The share of food loss (SDG 12.3.1a) has almost reached the target, with distances to targets between 97 and 99 for the historical values as well as BAU and EA scenarios. The share of the forest (SDG 15.1.1) has already achieved the target, and a further improvement in the performance under the EA scenario due to reforestation measures will not be visible on the score. Compared to historical values, performance in above-ground biomass stock in the forest (SDG 15.2.1) seems to decrease under BAU and EA scenarios. As mentioned above, comparison with historical levels can be a challenge for some SDG indicators, as in the case of SDG 15.2.1, because some data inputs to the GGSim were from national sources, and the historical Green Growth Index scores and targets were based on international databases.

Burkina Faso

Performance in installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1) has been very low and will not improve much by 2050, even under the most ambitious scenarios (Table 2). The distances to targets are below 5 in historical values as well as in the BAU and the three low-emission scenarios. Indeed, while there is some significant development of renewable energy capacities, mainly solar, Burkina Faso still partly relies on fossil fuels to generate electricity. Two-fifths of the country's electricity demand is imported. Performance in water use efficiency (SDG 6.4.1) is also very low, and the BAU scenario will show the most significant increase; however, it will keep a low score. The significant share of agricultural water withdrawals in the low emission scenarios and a corresponding low sectoral water use efficiency explain this. The level of water stress (SDG 6.4.2) shows deteriorating scores, with the worst performance in the High Ambition (HA) scenario attributed to the large amount of water required to develop the agricultural sector. The historical value and BAU scenario show distances to targets of 100 for this SDG indicator but falling to almost half in the HA scenario in 2050. Measures on livestock substitution and manure management will help limit the increase in the nutrient balance (15.3.1), resulting in distances to targets above 90 under the low emission scenarios. However, the historical values were slightly higher at 99 in 2010 and 100 in 2020. The share of forest (15.1.1) is already above the target, and the SDG indicator score will remain at the highest level, with distances to targets of 100, even in the BAU scenario where there will be a non-negligible loss of forest area. Performance in SDG above-ground biomass in forests (15.2.1) will slightly increase in the low-emission scenarios and slightly decrease in the BAU scenario. Overall, distances to targets will remain low at below 30, not only historically but also in the BAU and low emission scenarios.

Ethiopia

Performance in installed renewable energy capacity (SDG 7.b.1 and 12.a.1) has been very low, but the low emission scenarios are showing a significant improvement (Table 2), supported mostly by hydropower capacities, as well as wind and biomass. The highest value on distances to targets will only be 38 for all low-emission scenarios in 2050. As Ethiopia reaches a share of 100 percent renewable electricity, improvement can be achieved by intensifying electricity generation. Improving water use efficiency (SDG 6.4.1) under all scenarios will be challenging due to the large amounts of water required by the agricultural sector. Nonetheless, there will be some improvement in distances to targets compared with the historical values. Performance in the level of water stress (SDG 6.4.2) will worsen with the higher levels of ambition in the low-emission scenarios due to the development of the different water-intensive sectors, particularly the agricultural sector. Not considering any measures to improve water use efficiency and availability in the GGsim models, distances to targets will fall from 100 in 2030 to about 50 in 2050. The low emission scenarios will allow Ethiopia to almost reach the target for the nutrient balance (SDG 15.3.1) due to the reduction in fertilizer use. In contrast, the performance of this SDG indicator will worsen under the BAU scenario because no measure is assumed to be implemented to reduce fertilizer. Historically below the sustainability target for the share of forests (SDG 15.1.1), Ethiopia will reach the target 17 percent target by 2050 in all the low emissions scenarios, hence the scores of 100. The country will continue to experience a loss of forest area in the BAU scenario. The levels of above-ground biomass in forests (SDG 15.2.1) will decrease in the BAU scenario and increase only slightly in the low-emission scenarios, with distances to targets of around 30 in 2050. This is not much higher compared to the historical values.

2.2.2 Climate adaptation

St. Lucia

Due to irrigation technologies and water price measures, a significant improvement in water use efficiency (SDG 6.4.1) will be seen in St. Lucia under the Transformative (TR) scenario, with distance to target of 63 in 2050 compared with 25 in 2030 (Table 3). The country's performance will also increase in the cautious (CA) and ambitious (AM) scenarios but not as much as the TR scenario. The country will remain well below the water stress (SDG 6.4.2) limit in all the scenarios and throughout the period, helping it to achieve the target for this SDG indicator. The nutrient balance (SDG 15.3.1) will be most affected by the policies on manure management and the decrease in cropland area under the Transformative scenario, which will end up performing worse than the other scenarios. The distance to target will be as low as 63 in 2050 compared with 76 in the BAU scenario in the same year and 84 in historical value in 2020. Improvement in the food loss to production (SDG 12.3.1a) under the low emission scenarios can be observed from the increasing scores from 2030 to 2050. The distance to target will be highest for the TR scenario in 2050 at 72. St. Lucia has already achieved the target for the share of forest (SDG 15.1.1). This will be maintained across all scenarios. The performance of above-ground biomass in forests (SDG 15.2.1) will improve under all scenarios supported by policies on fuelwood removals. However, distances to targets will not exceed 80, albeit higher than the historical values of less than 70 in 2010 and 2020.

Senegal

Performance in the nutrient balance (SDG 15.3.1) has been high in Senegal and will only deteriorate slightly due to

Table 2. Distance to sustainability targets from climate mitigation

Hungary

SDG Number*	SDG target**	Historical data		Business-as-usual (BAU) scenario		Low emission scenario*** Early Action (EA)	
		2010	2020	2030	2050	2030	2050
7.b.1, 12.a.1	1460.528 watts per capita [a]	4	11	56	83	83	100
6.4.1	265.76 USD per m^3 [c]	8	10	13	27	13	35
6.4.2	25 Percent [b]	100	100	100	100	100	100
15.3.1	5 Kg per hectare [e]	90	81	80	80	83	87
12.3.1	0.7598 Percent [a]	97	99	98	98	99	99
15.1.1	17 Percent [c]	100	100	100	100	100	100
15.2.1	428.69 Tons per hectare [a]	24	26	7	8	10	11

Burkina Faso

SDG Number*	SDG target**	Historical data		Business-as-usual (BAU) scenario		Low emission scenarios*** High Ambition (HA)		Moderate Ambition (MA)		Low Ambition (LA)	
		2010	2020	2030	2050	2030	2050	2030	2050	2030	2050
7.b.1, 12.a.1	1460.528 watts per capita [a]	1	2	2	2	3	4	3	4	2	4
6.4.1	265.76 USD per m^3 [c]	3	4	5	11	3	3	4	5	4	5
6.4.2	25 Percent [b]	100	100	100	100	93	58	99	81	99	81
15.3.1	5 Kg per hectare [e]	99	100	94	88	96	95	95	94	94	95
15.1.1	17 Percent [c]	100	100	100	100	100	100	100	100	100	100
15.2.1	428.69 Tons per hectare [a]	27	24	24	21	25	28	25	28	24	25

Ethiopia

SDG Number*	SDG target**	Historical data		Business-as-usual (BAU) scenario		Low emission scenarios*** Maximum Ambition (MA)		NDC-aligned 2030 (NDC)		Late Action (LA)	
		2010	2020	2030	2050	2030	2050	2030	2050	2030	2050
7.b.1, 12.a.1	1460.528 watts per capita [a]	2	4	6	8	14	38	13	38	12	38
6.4.1	265.76 USD per m^3 [c]	2	3	7	10	9	10	9	10	9	10
6.4.2	25 Percent [b]	95	86	100	80	100	48	100	49	100	49
15.3.1	5 Kg per hectare [e]	98	96	90	87	97	98	96	96	98	97
15.1.1	17 Percent [c]	93	89	77	58	100	100	98	100	87	100
15.2.1	428.69 Tons per hectare [a]	29	29	28	25	30	32	29	31	29	30

* SDG 7.b.1, 12.a.1 Installed renewable electricity-generating capacity (watts per capita), SDG 6.4.1 Water Use Efficiency (USD per m3), SDG 6.4.2 Freshwater withdrawal as a proportion of available freshwater resources (Percent), SDG 15.3.1 Nutrient balance per unit area (Kg per hectare), SDG 12.3.1. Percentage of food loss to production (Percent), SDG 15.1.1 Forest area as percent of total land area (Percent), and SDG 15.2. 1 Above-ground biomass stock in forest (Tons per hectare).
**Sources of SDG targets: [a]Mean top five country performers, [b]SDG, [c]OECD (2019), [d]FAO (2017), and [e]FAO (2021)
*** Refer to Box 1 for the definition of the low emission scenarios

policies on manure (Table 3). The distances to targets in the High Ambition (HA) scenario will fall from 91 in 2030 to 87 in 2050. These values are slightly lower than the historical values of 93 in 2010 and 94 in 2020. Improvement in the performance of the food loss to production (SDG 12.3.1a) can be observed from the high scores the country will reach by 2050, up to 100 under the HA scenario. The high share of forest (SDG 15.1.1) in Senegal will result in continuously achieving the sustainability target and garnering a score of 100, which will remain constant across scenarios and years. However, the above-ground biomass in forests (SDG 15.2.1) will not perform well, and the various assumptions under the different scenarios will not lead to any significant change. Above-ground biomass indicates the quality of forests, which means that high performance in the share of forest area (i.e., the quantity of forests) does not translate into a high score in above-ground biomass. Forest biomass is assumed to regenerate naturally, causing above-ground biomass to increase over time.

Table 3. Distance to sustainability targets from climate adaptation

SDG Number*	SDG target**	Historical data		Business-as-usual (BAU) scenario		Low emission scenarios***					
						Cautious (CA)		Ambitious (AM)		Transformative (TR)	
		2010	2020	2030	2050	2030	2050	2030	2050	2030	2050
St. Lucia											
6.4.1	265.76 USD per m^3 (c)	---	13	19	28	19	29	23	45	25	63
6.4.2	25 Percent (b)	100	100	100	100	100	100	100	100	100	100
15.3.1	5 Kg per hectare (e)	88	84	76	76	76	75	75	72	73	66
12.3.1.	0.7598 Percent (a)	81	74	47	48	51	56	51	58	55	72
15.1.1	17 Percent (c)	100	100	100	100	100	100	100	100	100	100
15.2.1	428.69 Tons per hectare (a)	61	69	73	79	73	79	74	80	74	80

SDG Number*	SDG target**	Historical data		Business-as-usual (BAU) scenario		Low emission scenarios***			
						High Ambition (HA)		Moderate Ambition (MA)	
		2010	2020	2030	2050	2030	2050	2030	2050
Senegal									
15.3.1	5 Kg per hectare (e)	93	94	92	91	91	87	83	90
12.3.1.	0.7598 Percent (a)	82	85	77	76	90	100	86	93
15.1.1	17 Percent (c)	100	100	100	100	100	100	100	100
15.2.1	428.69 Tons per hectare (a)	11	11	11	11	11	12	11	11

* SDG 6.4.1 Water Use Efficiency (USD per m3), SDG 6.4.2 Freshwater withdrawal as a proportion of available freshwater resources (Percent), SDG 15.3.1 Nutrient balance per unit area (Kg per hectare), SDG 12.3.1. Percentage of food loss to production (Percent), SDG 15.1.1 Forest area as percent of total land area (Percent), and SDG 15.2. 1 Above-ground biomass stock in forest (Tons per hectare).
**Sources of SDG targets: (a)Mean top five country performers, (b)SDG, (c)OECD (2019), (d)FAO (2017), and (e)FAO (2021)
*** Refer to Box 1 for the definitions of low emission scenarios

Box 1. Business-As-Usual (BAU) and low emissions scenarios

The Business-As-Usual (BAU) scenario does not include further interventions than the existing policy strategies and measures; current trends are considered in all sectors. The BAU applies to all countries.

Hungary

- Early Action (EA) scenario - aims to achieve climate neutrality by 2050 by considering the short- and medium-term benefits of implementing the transition. Emissions follow a linear trajectory from 2030 to net zero in 2050.
- Late Action (LA) scenario - aims to achieve climate neutrality by 2050 by implementing a slow emissions reduction trajectory until 2045 and increasing efforts in the last five years of the transition. (Note: not presented in the report due to very negligible impacts).

Burkina Faso

- High Ambition (HA) scenario - implements ambitious measures as early as 2022, allowing the country to reach carbon neutrality in 2045 and be a net carbon sink by 2050.
- Moderate Ambition (MA) scenario - implements slightly lower ambitious efforts than the HA scenario, allowing the country to reach carbon neutrality in 2047.
- Low Ambition (LA) scenario - implements most measures after 2030 to focus on the country's socio-economic development before decarbonization efforts are implemented.

Ethiopia

- Maximum Ambition (MA) scenario - represents the maximum potential emissions reduction achievable if strong policies and measures are implemented early on. It aims to reach net zero emissions around 2035 and remain below zero onwards.
- NDC-aligned (NDC) scenario - aims to achieve the NDC emissions target by 2030, increasing ambitions from 2035 onwards to reach net zero emissions in 2050. It is the most cost-effective net-zero emission (NZE) scenario.
- Late Action (LA) scenario - implements high ambitions between 2040 and 2050 to reach net zero emissions in 2050 but does not reach the NDC targets in 2030.

St. Lucia

- Cautious (CA) scenario - ensures that any climate adaptation or mitigation plan is affordable, limiting investments that cannot be supported without collaboration and, therefore, restricting what national governments and local investors can afford.
- Ambitious (AM) scenario - assumes that adaptation targets require some form of structural change, which will significantly impact resource use. The investment requirements to achieve the targets are not a primary concern, assuming that support from the international community will be available to implement those ambitious targets.
- Transformative (TR) scenario - aims to achieve the climate targets and commitments. Technological and behavioral changes that will reduce trade-offs and ensure sustainable transformations are important priorities for this scenario.

Senegal

- Moderate Ambition (MA) scenario - ensures that any climate adaptation or mitigation plan is affordable, limiting investments that cannot be supported without collaboration and, therefore, restricting what national governments and local investors can afford.
- High Ambition (HA) scenario - requires structural change and investments, assuming support from the international community.

03
METHODS AND MODELS

This chapter discusses the green growth and SDG indicators in the Green Growth Index, which are the focus of the SDG co-benefits and distance to target assessments in the GGSim applications (section 3.1). It also presented the system dynamics models used for the SDG co-benefits from implementing climate mitigation and adaptation measures (section 3.2).

3.1 GGSim methods

3.1.1 Green growth and SDG indicators

The GGSim builds on the four dimensions of the Green Growth Index – efficient and sustainable resource use, natural capital protection, green economic opportunities, and social inclusion (Figure 1). Four pillars, which are essential to transitioning to green growth, define each dimension (Figure 4). The efficient and sustainable resource use covers energy (e.g., transport, industry, residential), water (e.g., freshwater, groundwater), land (e.g., agriculture, forest, cities), and materials (e.g., domestic, imports). The natural capital protection dimension includes improvement of environmental quality (e.g., air, land, water), reduction of GHG emissions (i.e., CO_2 and non-CO_2 emissions), protection of biodiversity and ecosystem (e.g., freshwater, terrestrial, marine, forest), and preservation of cultural and social value (e.g., species and their habitat). Green investment, trade, innovation, and employment create green economic opportunities. The social inclusion dimension includes access to basic services and resources (e.g., water and sanitation, electricity and clean fuels, internet and mobile communications), gender balance (i.e., political representation, equal pay, access to finance), social equity (i.e., income distribution, urban-rural, youth's future), and social protection (i.e., pension, healthcare, adequate housing). Capturing the interlinkages among the indicator categories within and across the green growth dimensions is an important feature of the GGSim Tool. These interlinkages are represented through the simulation models discussed in section 3.2.

Thirty-four (or 71 percent) of the 48 indicators in the 2023 Green Growth Index are from the SDGs (Figure 5). However, the number will continue to increase as databases for relevant SDG indicators improve. Indicators such as ME3 (i.e., food loss and food waste), BE1 (i.e., marine, freshwater, terrestrial, mountain), and AB1 (i.e., water, sanitation, electricity, and clean fuels) indicators combined different SDG indicators in one green growth indicator (i.e., composite indicators). As a result, there are 41 SDG indicators in the Green Growth Index. The natural capital protection dimension has the most significant number of SDG indicators, while the green economic opportunities dimension has the least number. Half of the eight new green economic opportunities' indicators are SDGs, including the degree of integrated water resources management implementation, financing (GV2), total amount of funding to promote environmentally sound technologies per GDP (GV3), employed population below international poverty line (GJ3), and installed renewable energy-generating capacity (GN3). SDG 9 on the industry, innovation, and infrastructure includes SDG 9.2.2 on manufacturing employment as a proportion of total employment. The indicator GJ1 share of green employment in total manufacturing (percent) is thus represented in SDG 9.2.2, albeit focusing on the green aspect of manufacturing employment. Currently, there are 14 (29 percent) non-SDG indicators. However, because they directly support the achievement of the SDGs, they are also considered in the SDG co-benefits assessments (sections 4.1 and 4.2).

3.1.2 SDG alignment approaches

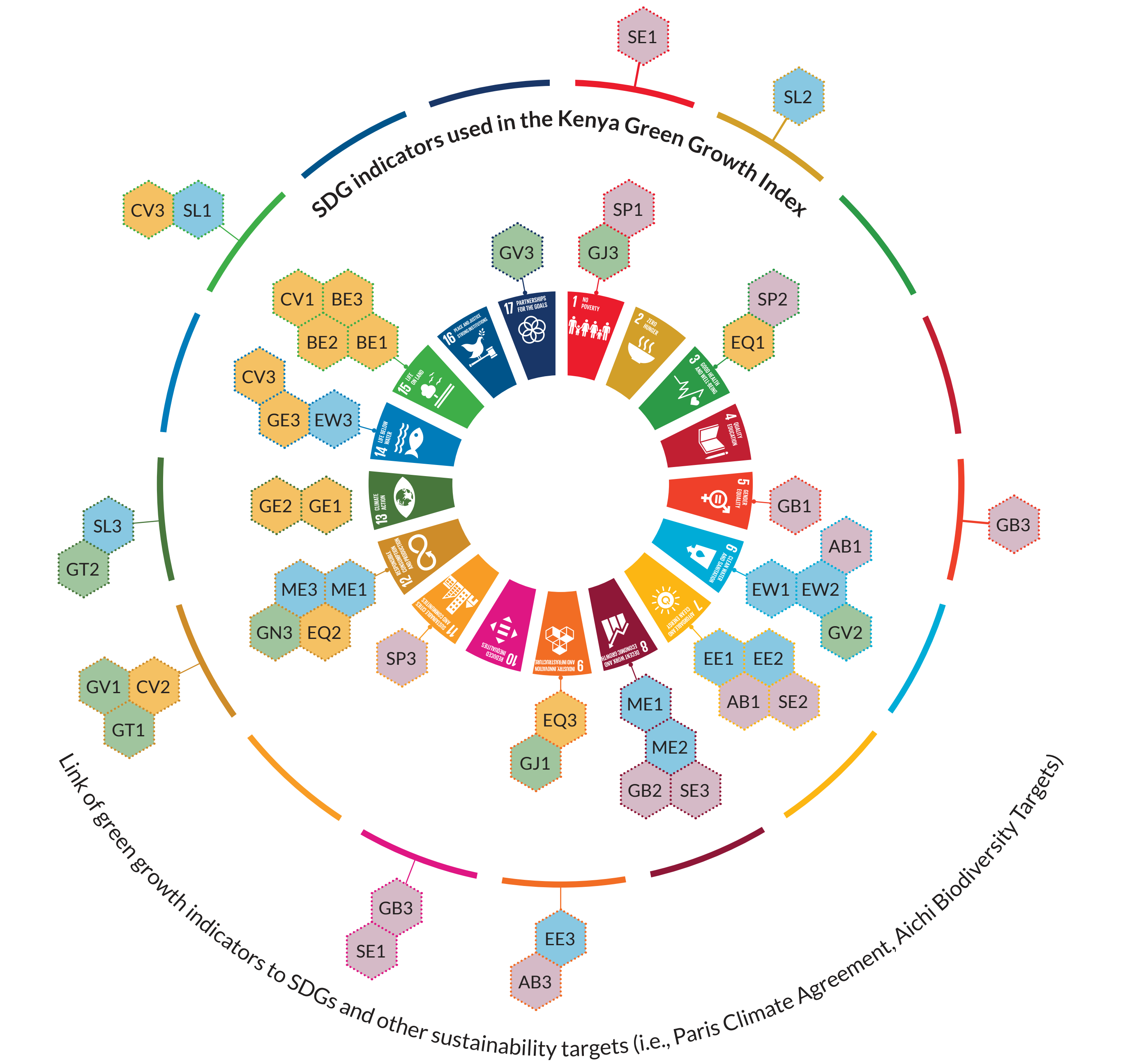
A. SDG co-benefits

In building the Simulation Tool for the Green Growth Index, the indicators provide a quantitative basis (i.e., metrics) for identifying and developing the mathematical models. They determine the implementation of the mathematical models by providing knowledge of the data requirements. Although many mathematical models would be available to describe the indicators' dynamics, data availability could restrict their implementation. Similarly, the integration relation may not be established if the data providing the links between different indicators are unavailable. In some cases, however, the data and mathematical models (due to lack of prior knowledge) are not available to describe the links between indicators in different green growth dimensions. GGSim's objective is to

Figure 4. Indicator framework for the 2023 Green Growth Index

	Dimensions [Goals]	Indicator categories [Pillars]		Indicators [metrics]
Green Growth Index	Efficient and sustainable resource use	Efficient and sustainable energy	EE1	Ratio of total primary energy supply to GDP (MJ per $2011 PPP GDP)
			EE2	Share of renewable to total final energy consumption (Percent)
			EE3	Logistics performance, efficiency in sustainable transport (Score)
		Efficient and sustainable water use	EW1	Water use efficiency (USD per m^3)
			EW2	Share of freshwater withdrawal to available freshwater resources (Percent)
			EW3	Sustainable fisheries as a proportion of GDP (Ratio)
		Sustainable land use	SL1	Nutrient balance per unit area (Tons per hectare)
			SL2	Share agriculture organic to total agriculture land area (Percent)
			SL3	Livestock units per agricultural land area (LSU/ha)
		Material use efficiency	ME1	Domestic material consumption per unit of GDP (Kilograms per constant 2015 USD)
			ME2	Total material footprint (MF) per capita (Tons per capita)
			ME3	Average of food loss to production and food waste to consumption (Percent)
	Natural capital protection	Environmental quality	EQ1	PM2.5 air pollution, mean annual population-weighted exposure (Micrograms per m^3)
			EQ2	DALY rate due to unsafe water sources (DALY lost per 100,000 persons)
			EQ3	Municipal solid waste (MSW) generation per capita (Tons per year per capita)
		Greenhouse gas emissions reductions	GE1	Ratio of CO_2 emissions to population, including AFOLU (Metric tons per capita)
			GE2	Ratio of non-CO_2 (CH4 , N_2O and F-gas) emissions to population, excluding AFOLU (CO_2eq tons per capita)
			GE3	Ratio of non-CO_2 (CH4 , N_2O and F-gas) emissions in agriculture to population (CO_2eq tons per capita)
		Biodiversity and ecosystem protection	BE1	Average proportion of Key Biodiversity Areas covered by protected areas (Percent)
			BE2	Share of forest area to total land area (Percent)
			BE3	Above-ground biomass in forest (Tons per hectare)
		Cultural and social value	CV1	Red List Index (Score)
			CV2	Tourism and recreation in coastal and marine areas (Score)
			CV3	Share of terrestrial and marine protected areas to total territorial areas (Percent)
	Green economic opportunities	Green investment	GV1	Ratio of adjusted net savings to GNI, including particulate emission damage (5 yrs moving ave.)
			GV2	Degree of integrated water resources management implementation, financing (Percent)
			GV3	Total amount of funding to promote environmentally sound technologies per GDP (Ratio)
		Green trade	GT1	Share of export of environmental goods (OECD and APEC classifications) to total export (Percent)
			GT2	CO_2 emissions embedded in trade (Percent)
			GT3	Water virtual trade flows (Tons per hectare)
		Green employment	GJ1	Share of green manufacturing employment in total manufacturing employment (Percent)
			GJ2	Ratio of renewable energy employment to renewable energy production (Ratio)
			GJ3	Employed population below international poverty line (Percent)
		Green innovation	GN1	Development of environment-related technologies, share of patents (Percent)
			GN2	University-industry collaboration in Research & Development (Score)
			GN3	Installed renewable energy-generating capacity (Watts per capita)
	Social inclusion	Access to basic services and resources	AB1	Population with access to basic services, i.e. Water, sanitation, electricity, and clean fuels (Percent)
			AB2	Prevalence of undernourishment (Percent)
			AB3	Universal access to sustainable transport (Score)
		Gender balance	GB1	Proportion of seats held by women in national parliaments (Percent)
			GB2	Gender ratio of an account at a financial institution or mobile-money-service provider (Ratio)
			GB3	Getting paid, covering laws and regulations for equal gender pay (Score)
		Social equity	SE1	Inequality in income based on Palma ratio (Ratio)
			SE2	Population with access to basic services by urban/rural, i.e. electricity (Ratio)
			SE3	Share of youth (aged 15-24 years) not in education, employment or training (Percent)
		Social protection	SP1	Proportion of population above statutory pensionable age receiving pension (Percent)
			SP2	Universal health coverage (UHC) service coverage (Score)
			SP3	Proportion of urban population living in slums (Percent)

Figure 5. SDG indicators in the 2023 Green Growth Index



Note: Refer to Figure 4 for the definitions of the indicator codes

create as many interlinkages as possible among the different indicators across pillars and dimensions (Figure 6), enhancing the Tool's relevance in assessing co-benefits of a given policy or investment decision related to a specific indicator. In the Phase 1 Simulation Tool, interlinkages have been identified for many indicators. A lack of data from online sources and mathematical models from literature often challenged this task. This justifies the development of the Simulation Tool in phases, allowing stepwise identification of solutions to the problems and expert consultations for identifying the most relevant indicators to be interlinked.

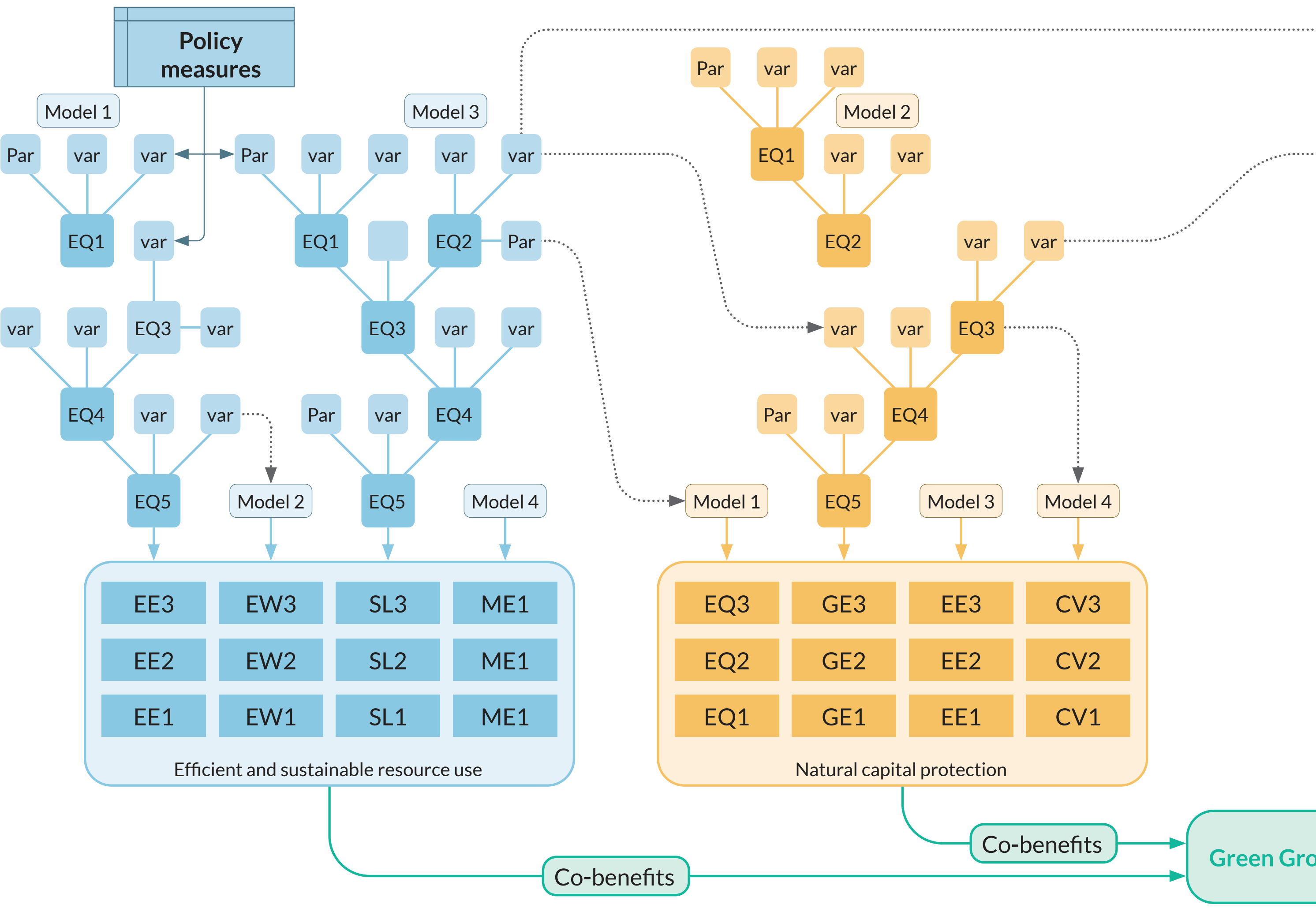
The identification and development of mathematical models require a shared understanding of their basic components based on the objective of the Simulation Tool. As the Tool is aimed to be applied to assess the impacts of alternative policy and investment options on green growth performance in major economic sectors, the mathematical models consist of variables that can link sectoral scenarios to the green growth indicators. A simple representation of mathematical models using equations is as follows:

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_n X_{nt} + \delta_t$$

where $\delta_t = \partial \, (\rho_t / (\rho_{t-1}))$

In these equations, Y represents the green growth indicators, whose values in time t are influenced by the changes in the values of the exogenous variables X_n and their interrelationships. The variable δ, with its equation, represents an endogenous variable whose value depends on the other exogenous variables. The equations for the green growth indicators consist of the following types of variables:

Figure 6. Illustration of interlinkages of the green growth indicators resulting in co-benefits



1. Output variables (i.e., Y, δ) whose values are computed from the equations in the simulation model and depend on the data of the exogenous variables.

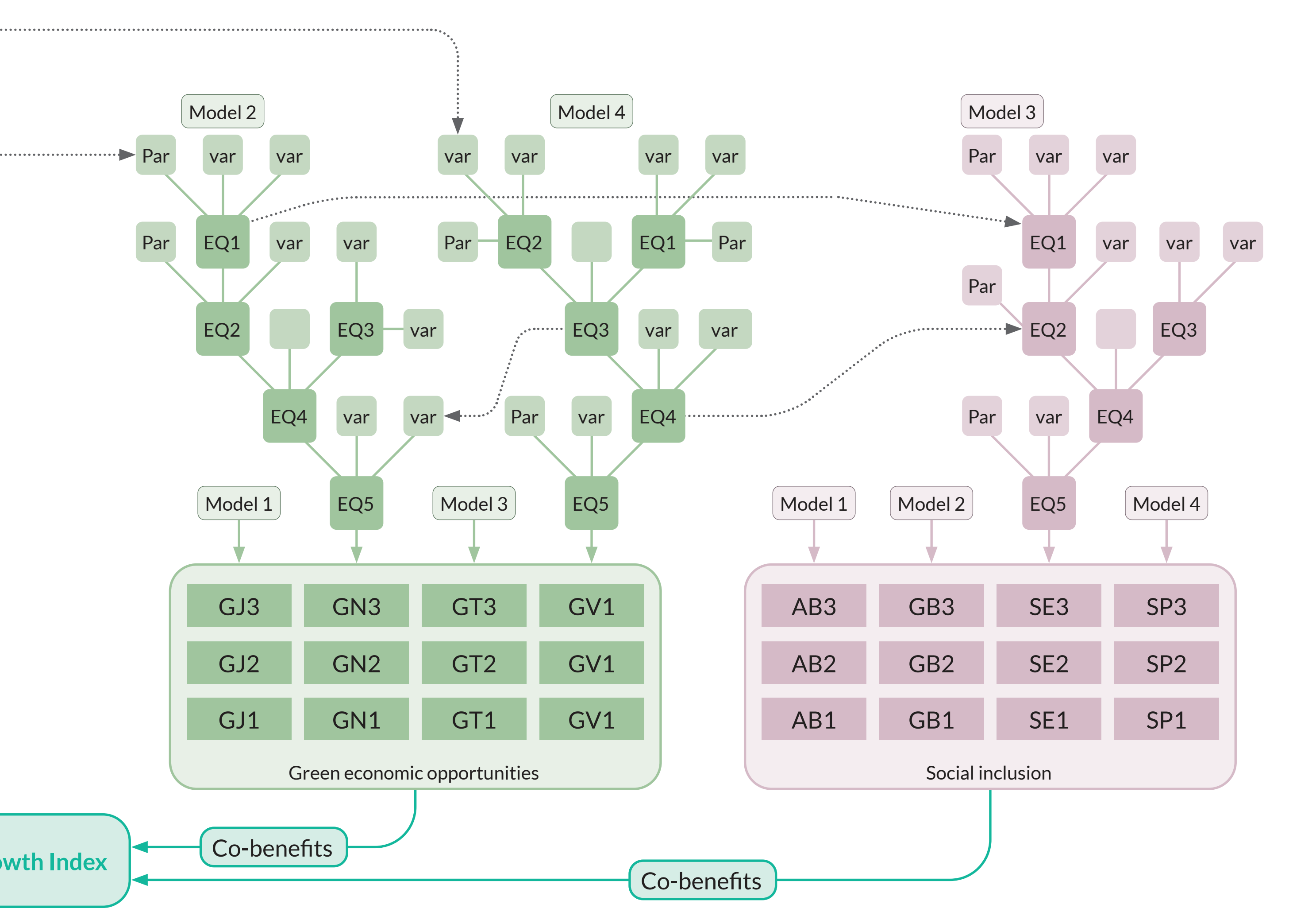
2. Input variables (i.e., χ_n, ρ) are exogenous to the simulation model, and their values are available from the databases and dependent on time t (i.e., time-series data).

3. Input parameters (i.e., β_n, δ) are also exogenous to the simulation model but not dependent on time as they have fixed values (e.g., regression coefficients). They are also referred to as state variables.

In case the equation is linked to the policy or investment options, which represent the scenarios in the simulation model, then input variables are referred to as input scenarios to emphasize the variables that drive the changes in the green growth indicators. In the above equations, if δ represents the equation for the scenarios, then ρ becomes an input scenario. The equations in the Phase 1 Simulation Tool represent the dynamic models, wher e dynamics lie from the time-dependent interrelationships among the variables. Spatial dynamics will be added in developing Phase 2 Simulation Tool, allowing the use of geographic information system (GIS) databases to capture dynamics in land use, biodiversity, and ecosystems. However, many GIS databases are unavailable online and must be collected from government agencies and research institutions.

B. Distance to targets

The distance to targets is based on the normalization and benchmarking methods applied in the Green Growth Index. Normalization is a key method when developing a composite index, particularly when the index builds on multidimensional concepts and covers a large number of indicators. It helps to transform indicators with different units into uniform scales and unitless numbers that allow meaningful comparisons;[16] align indicators with positive and negative relationships to the phenomenon, which, in the case of this report, is green growth;[17] and reduce the uneven influence of indicators with extreme values on the index[18]. The rescaling method, also known as min-max transformation, was chosen to normalize the indicators in the Green Growth Index for the following reasons: (1) It is simple and the most widely used method, allowing governments to replicate the Green Growth Index at the national and sub-national levels; (2) It can integrate upper and lower bounds in the method, reducing the problems of extreme values and partially correcting for outliers; and (3) It allows the application of targets in the method, representing benchmarking of sustainability targets.



Generally, the method rescales a given indicator xi into different intervals with an identical range between 0 and 1 based on a minimum (Xmin) and a maximum (x_{max}).

$$x_i^{norm} = (x_i - x_{min}) / (x_{max} - x_{min})$$

where: x_i^{norm} = normalised *ith* indicator
$x = (x_1, x_2, ..., x_n)$; $n = 1, 2, ...,$ n number of countries

Many sustainability, environmental, and governance indices use the rescaling method to normalize indicators. The range of the indices, however, is often not [0,1] because the rescaling method offers the advantage of setting boundaries.[19] The Green Growth Index uses the range [1,100] (Figure 7). The lower bound of 1 is used because a zero score could be misinterpreted to mean the lack of capacity to perform in a given green growth indicator. The upper bound of 100 is used to imply the achievement of the sustainability target for a given indicator. The following is a more general mathematical function of the rescaling method to include information on lower bound ***a*** and upper bound ***b***.

$$x_i^{norm} = a + ((x_i - x_{min}) / (x_{max} - x_{min}))\,(b - a)$$

where: ***a*** = lower bound
b = upper bound

Integrating the targets into the rescaling method can directly measure the distance to sustainability targets from the indicator scores. This approach is called the benchmarking normalization function, which "depends on indicator values, each being mapped to some value based on a qualitative valuation of their level of sustainability".[20] Organisation for Economic Co-operation and Development's (OECD) Measuring Distance to the SDG Targets[21] and Sustainable Development Solutions Network's (SDSN) SDG Index[22] applied this approach to measure country performance relative to the SDG targets.

In addition to policy relevance, the added value of using SDG indicators in the Green Growth Index is the availability of targets against which to benchmark the green growth indicators. However, there are no globally agreed climate targets for some SDG indicators, including GHG emissions reduction. Governments determine national targets in their National Determined Contributions (NDCs). To allow for cross-country comparisons, national targets are not used. To come up with sustainability targets for all green growth indicators, the following criteria were adopted:

Figure 7. Illustration of distance to targets at the (a) pillar and (b) indicator levels of the Green Growth Index

Note: The figures refer to the 2023 Green Growth Index scores for Hungary, available at https://ggindex-simtool.gggi.org/SimulationDashBoard/country-profile.
The definitions of the indicator codes are available in Figure 4

SDG indicators

1. The SDG targets, both explicit and implicit, which were suggested by the OECD[23] and SDSN[24] reports, were used. If the interpretation of implicit targets differs, the SDSN values applied globally were adopted.

2. The average value of the top five performers was used for SDG indicators not included in the OECD and SDSN reports.

Non-SDG indicators

1. The targets suggested in scientific literature and reports from international organizations were used.

2. The average value of the top five performers was used for non-SDG indicators with no available information from the literature and reports.

3.2 System dynamics models

The GGSim applications in this report includes three models: energy and transport, agriculture, forest, and land use (AFOLU), and water and waste (Figure 7). Each model comprises several components modeled by system dynamics equations and interlinked by shared variables and parameters. The energy and transport model focuses on electricity generation from solar photovoltaic panels and biofuel demand from transport (Annex 1 and Annex 5). It is, therefore, linked to the AFOLU model by the consequent land use changes. The AFOLU model links agriculture and land use and can also provide inputs to the Energy model with the bioenergy potential from agricultural residues and waste (Annex 2 and Annex 6). The water and waste model includes water use from the municipal sector in addition to that from the industry (cooling water for electricity generation) and agriculture (irrigation water) sectors (Annex 3 and Annex 7). It assesses the impacts of water withdrawals on natural resources and the impacts of wastewater treatment on pollution from human waste. Other system dynamics models relevant to energy and transport, as well as AFOLU not applied in countries presented in this report, are presented in Annex 4.

The outputs of the models are mainly SDG indicators, but some other relevant results with links to SDGs are also considered as outputs due to their contribution to achieving the SDGs and other sustainability goals (i.e., the Paris Agreement, Aichi Biodiversity Targets).

3.2.1 Energy and transport

The energy and transport model includes the energy and transport sectors. The International Energy Agency (IEA) estimates that energy accounts for around 75 percent of the world's greenhouse gas (GHG) emissions[25], while transport accounts for more than a third of the emissions from the end-use side[26]. These sectors are expected to experience significant changes to achieve the GHG emissions reduction targets by 2030 and 2050, with measures including electrification, reduction of the share of fossil fuels in energy generation, deployment of bioenergy, and improvement of energy efficiency, etc. This model emphasizes, in particular, the development of solar photovoltaic systems (SPVs) and bioenergy generation, with key links to the AFOLU model due to the implications of land use change. Figure 2 presents the components of the energy and transport model, including the outputs which are mainly SDG indicators.

Energy Intensity (SDG 7.3.1)

Energy intensity is an SDG indicator, indicating how much energy is needed to produce one unit of economic output (Table 3). It is used to assess the progress of energy efficiency. It is computed as the ratio of the primary energy supply over the total gross domestic product.[27] . Annex 1 presents the equations and data inputs to compute energy intensity, particularly primary energy supplies, electricity imports, and total real GDP. While its global value improved by an average annual 1.8 percent from 2010 to 2020, it must improve by an annual 3.4 percent to meet the SDG target by 2030.[28]

Share of renewables in electricity generation (part of SDG 7.2.1)

The share of renewables in electricity generation is part of the SDG 7.2.1 renewable energy share in the total final energy consumption (Table 3). It is computed as the ratio of the sum of the electricity generated by Renewable Energy Sources (RES) over the total electricity generated by all sources. Annex 1 presents the equations and data inputs to compute the share of renewables in electricity generation, including Installed capacities and capacity factors. Fossil fuels still account for more than 60 percent of electricity generation worldwide, with coal supplying more than a third of the total electricity generation.[29] As the electricity share in final energy consumption is projected to increase to 50 percent by 2050 - compared to 20 percent today - the development of renewable electricity generation is indispensable to meet the GHG emissions targets.[30] The model includes biomass, waste, hydropower, solar, wind, and geothermal as renewable energy sources and coal, oil, natural gas, and nuclear as non-renewable energy sources.

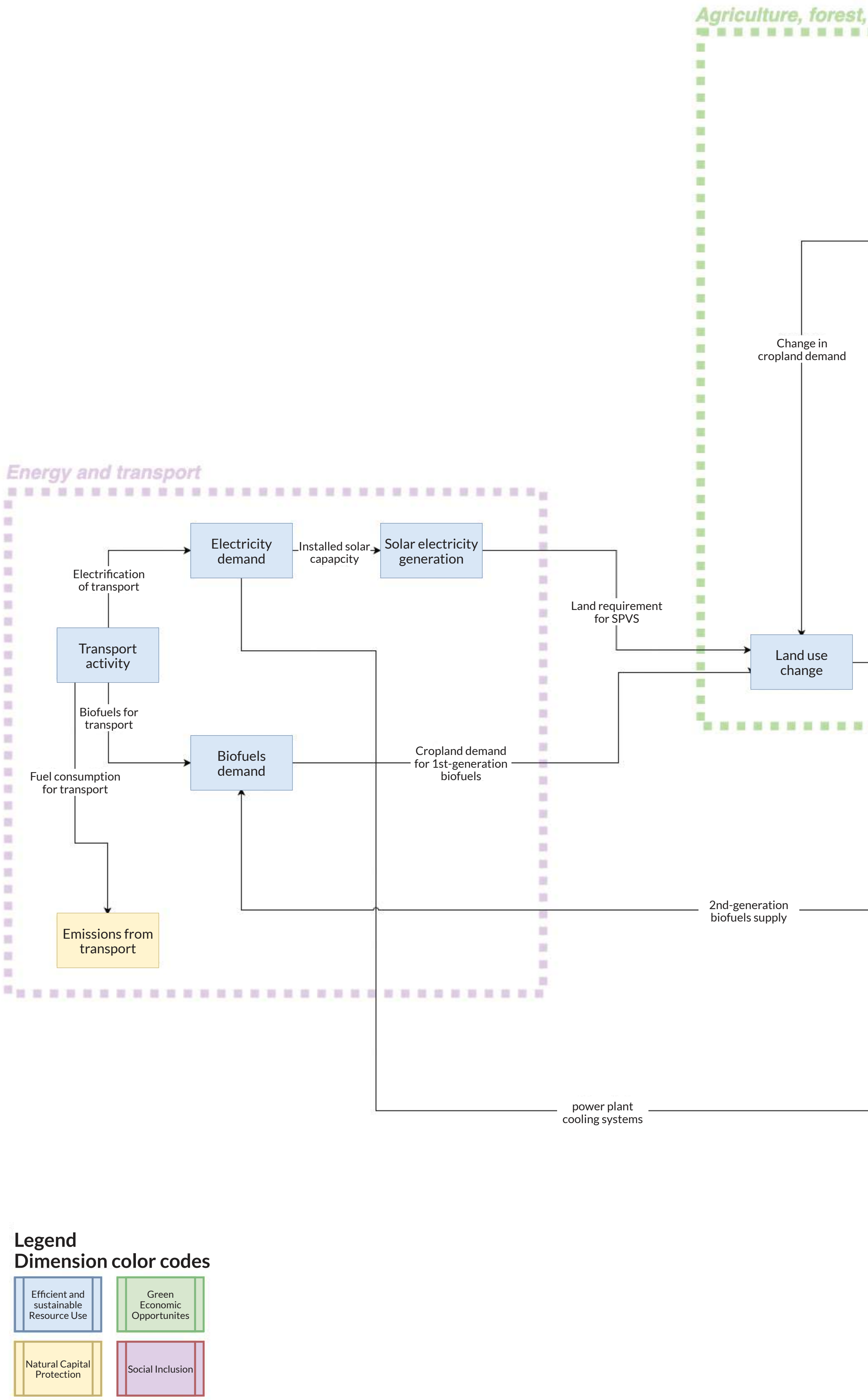
Installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1)

The installed renewable energy capacity per capita is an SDG indicator (Table 1). It is computed as the ratio of the installed renewable capacity over the population. Annex 1 presents the equations and data inputs to compute the installed renewable energy capacity per capita, including installed capacities and population. This indicator focuses particularly on the least developed countries and tracks the progress in the access to clean energy for all.[31]

Land requirement for SPVs (link to SDG 7.2.1)

Solar Photovoltaic (SPV) production is linked to SDG 7.2.1 renewable energy share in the total final energy consumption (Table 1). With the implementation of large-scale SPVs, large areas of land are required. Lakhani et al. use the land-use footprint (LUF) methodology to estimate the land required by SPVS and its impact on land use.[32] Annex 1 presents the equations and data inputs to compute the land requirement for SPVS, including the installed solar capacity and capacity weighted-average area requirement. The land required for SPVS is simply modeled as proportional to the installed solar capacity. Furthermore, the potential of rooftop solar PV can be assessed to relieve the pressure on land. Bodis et al. evaluate the potential of rooftop solar PV in the European Union by developing a geospatial analysis methodology to obtain building stock in the EU and estimate the available rooftop area for SPVs.[33] The model also assesses the potential of brownfields, and the total installed solar capacity on the two alternative surfaces can be discarded from the calculations on the land use demand.

Figure 8. Green Growth Simulation (GGSim) models and their interlinkages



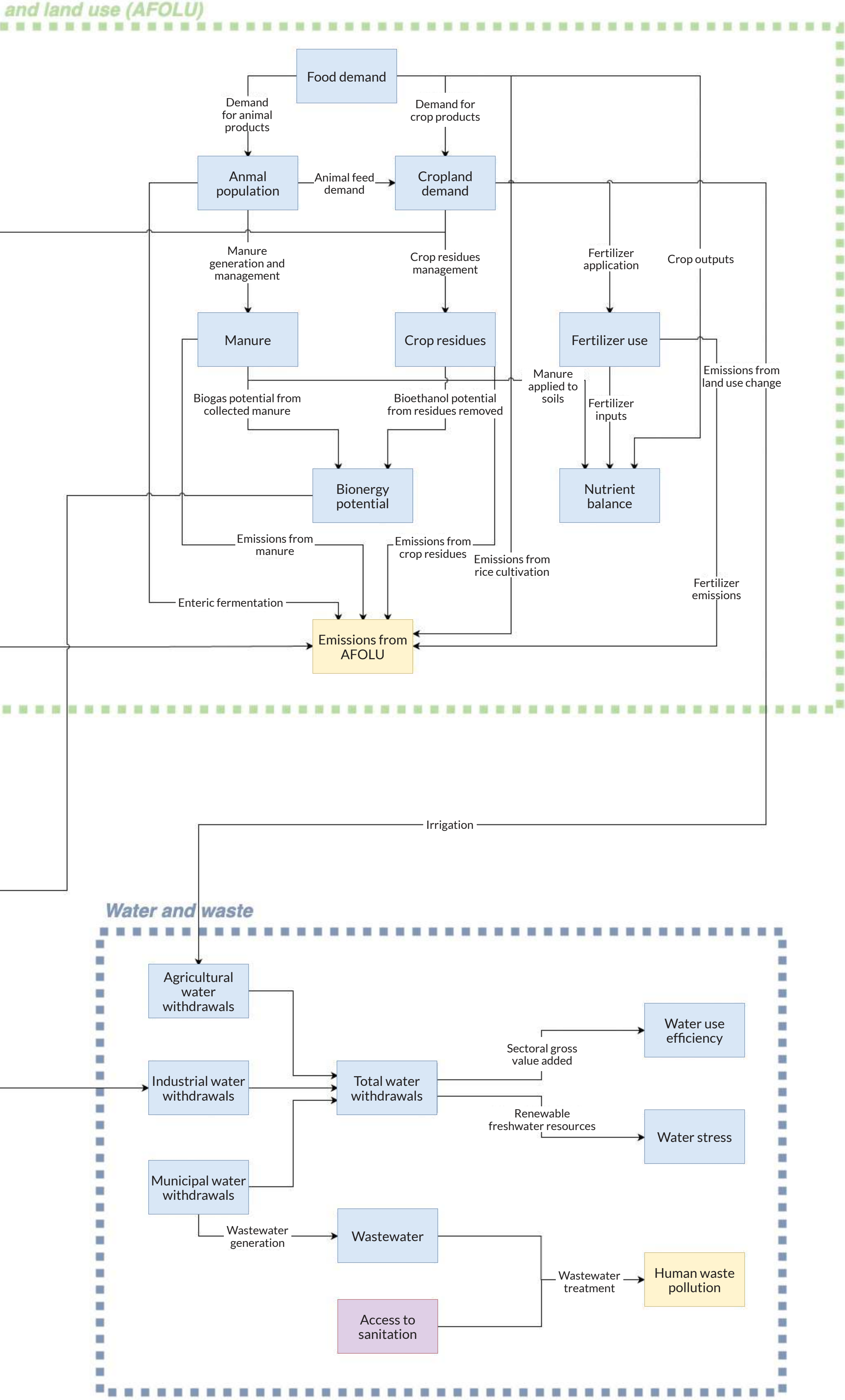
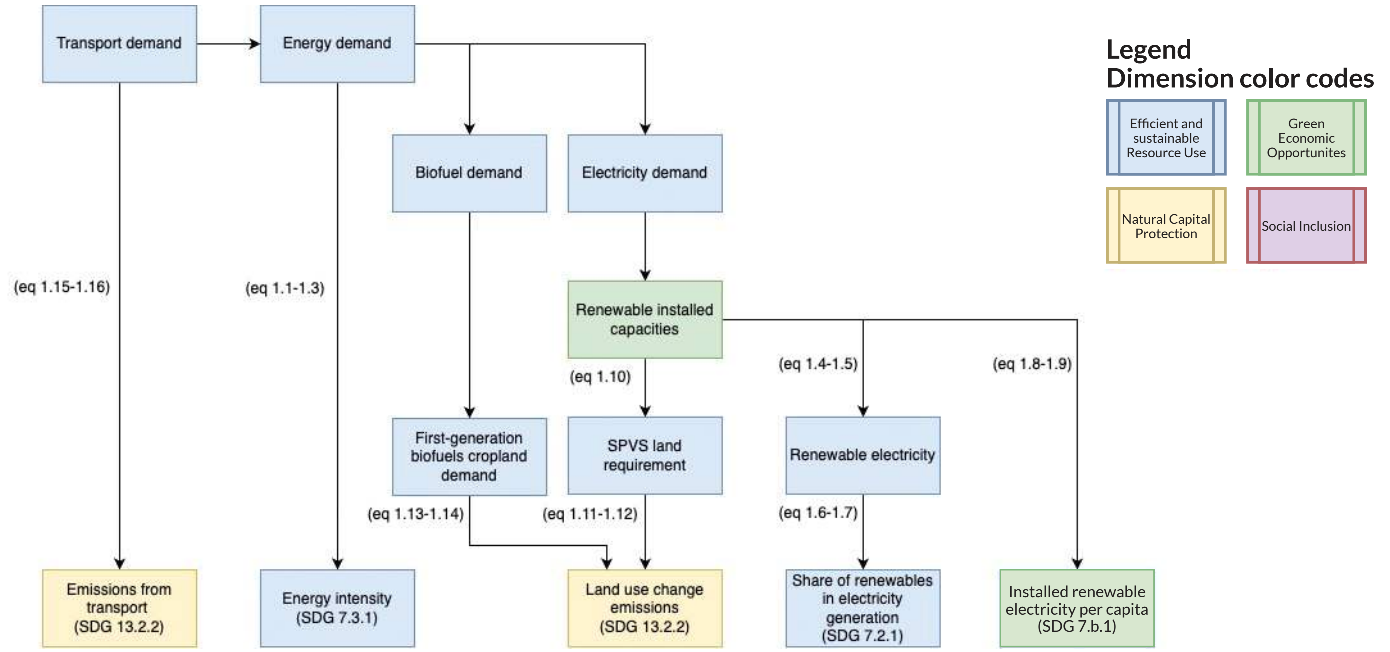

and land use (AFOLU)
Food demand
Demand for animal products
Demand for crop products
Anmal population
Animal feed demand
Cropland demand
Manure generation and management
Crop residues management
Fertilizer application
Crop outputs
Manure
Crop residues
Fertilizer use
Manure applied to soils
Emissions from land use change
Biogas potential from collected manure
Bioethanol potential from residues removed
Fertilizer inputs
Bioenergy potential
Nutrient balance
Emissions from manure
Emissions from crop residues
Emissions from rice cultivation
Fertilizer emissions
Enteric fermentation
Emissions from AFOLU
Irrigation
Water and waste
Agricultural water withdrawals
Water use efficiency
Sectoral gross value added
Industrial water withdrawals
Total water withdrawals
Renewable freshwater resources
Water stress
Municipal water withdrawals
Wastewater generation
Wastewater
Wastewater treatment
Human waste pollution
Access to sanitation

Figure 9. Energy and transport model components and their interlinkages



Note: eq and numbers refer to equations in Annex 1

Land use change emissions from SPV installation (part of SDG 13.2.2)

Land use change emissions are part of SDG 13.2.2 total greenhouse gas emissions per year. Assessing the land requirement for SPVs is important as the competition for land can be followed by land use change emissions. Indeed, if large areas of croplands are used for SPVs, this will lead to the conversion of forest land elsewhere to sustain the cropland demand, resulting in a loss of above-ground carbon stock.[34] The land use change emissions are computed based on a forest land use change emission factor and the land requirement for SPVs (Table 1)). Annex 1 presents the equations and inputs to land use change emissions due to SPVs, including

Table 4. Description of energy and transport model components

	Energy intensity
Equations	Annex 1 eq. 1.1 – 1.3
Inputs	Primary energy supplies [*PJ*] Electricity imports [*PJ*] Total real GDP [*Real million LCU*]
Outputs	Energy intensity[*Real million LCU/capita*]
SDG indicator	SDG 7.3.1 Energy intensity measured in terms of primary energy and GDP
	Share of renewables in electricity generation
Equations	Annex 1 eq. 1.4-1.7
Inputs	Installed capacities [*MW*] Capacity factors [–]
Outputs	Electricity generation [*MWh/y*] Share of renewables in electricity generation [–]
SDG indicator	SDG 7.2.1 Renewable energy share in the total final energy consumption
	Installed renewable energy capacity per capita
Equations	Annex 1 eq. 1.8-1.9
Inputs	Installed capacities [*MW*] Population [*capita*]
Outputs	Installed renewable energy capacity per capita [*W/capita*]
SDG indicator	SDG 7.b.1 and 12.a.1 Installed renewable energy-generating capacity in developing countries (in watts per capita)

Table 4. Description of energy and transport model components *(continued)*

Land requirement for SPVs	
Equations	Annex 1 eq. 1.10
Inputs	Installed solar capacity [*MW*] Capacity weighted-average area requirement [*acres/MWac*]
Outputs	Land requirement for installing SPVs capacity [*acres*]
Related SDG indicator	SDG 7.2.1 Renewable energy share in the total final energy consumption
Land use change emissions due to SPVs	
Equations	Annex 1 eq. 1.11-1.12
Inputs	Carbon stock change in forests [$kgCO_2eq$] Forest land area [*acres*] Land requirement for installing SPVS capacity [*acres*]
Outputs	Emissions from land use change due to the installation of SPVS [$kgCO_2eq$]
SDG indicator	SDG 13.2.2 Total greenhouse gas emissions per year
Land requirements for first-generation biofuels	
Equations	Annex 1 eq. 1.13-1.14
Inputs	First-generation biodiesel demand [*TJ*] Allocation of crop items for biodiesel production [–] Biodiesel yields of crops [*ha/TJ*]
Outputs	Land requirement for first-generation biofuels [*ha*]
Link to SDG indicator	SDG 2.1.2 Prevalence of moderate or severe food insecurity in the population
Emission levels from transport activity	
Equations	Annex 1 eq. 1.15-1.16
Inputs	Energy consumption in transport [*MWh*] Emission factors [$kgCO_2eq$]
Outputs	Emissions from transport [$kgCO_2eq$]
SDG indicator	SDG 13.2.2 Total greenhouse gas emissions per year

carbon stock change in forests, forest land area, and land requirement for installing SPV capacity.

Land requirements for first-generation bioenergy (link to SDG 2.1.2)

Biofuels are projected to have an important role in decarbonizing the transport sector. From accounting for 3.5 percent of the total energy demand for transport, it is supposed to reach a share of 9.0 percent by 2030 to align with the IEA's Net Zero Emissions (NZE) scenario.[35] Biofuels can either be first- or second-generation. First-generation biofuels are produced directly from food crops such as grains and seeds. In contrast, second-generation biofuels are produced from agricultural and crop residues and non-food crops.[36] First-generation biofuel production creates competition on land and water with crops for food use. Land requirement for first-generation biofuels is thus linked to SDG 2.1.2 prevalence of moderate or severe food insecurity in the population (Table 1). Their further expansion must be carefully monitored to minimize the impacts on land use and food systems. Biofuel production is further discussed in the AFOLU model (section 3.2.2). Annex 1 presents the equations and inputs to land requirements for first-generation biofuels, including first-generation biodiesel demand and allocation of crop items for biodiesel production.

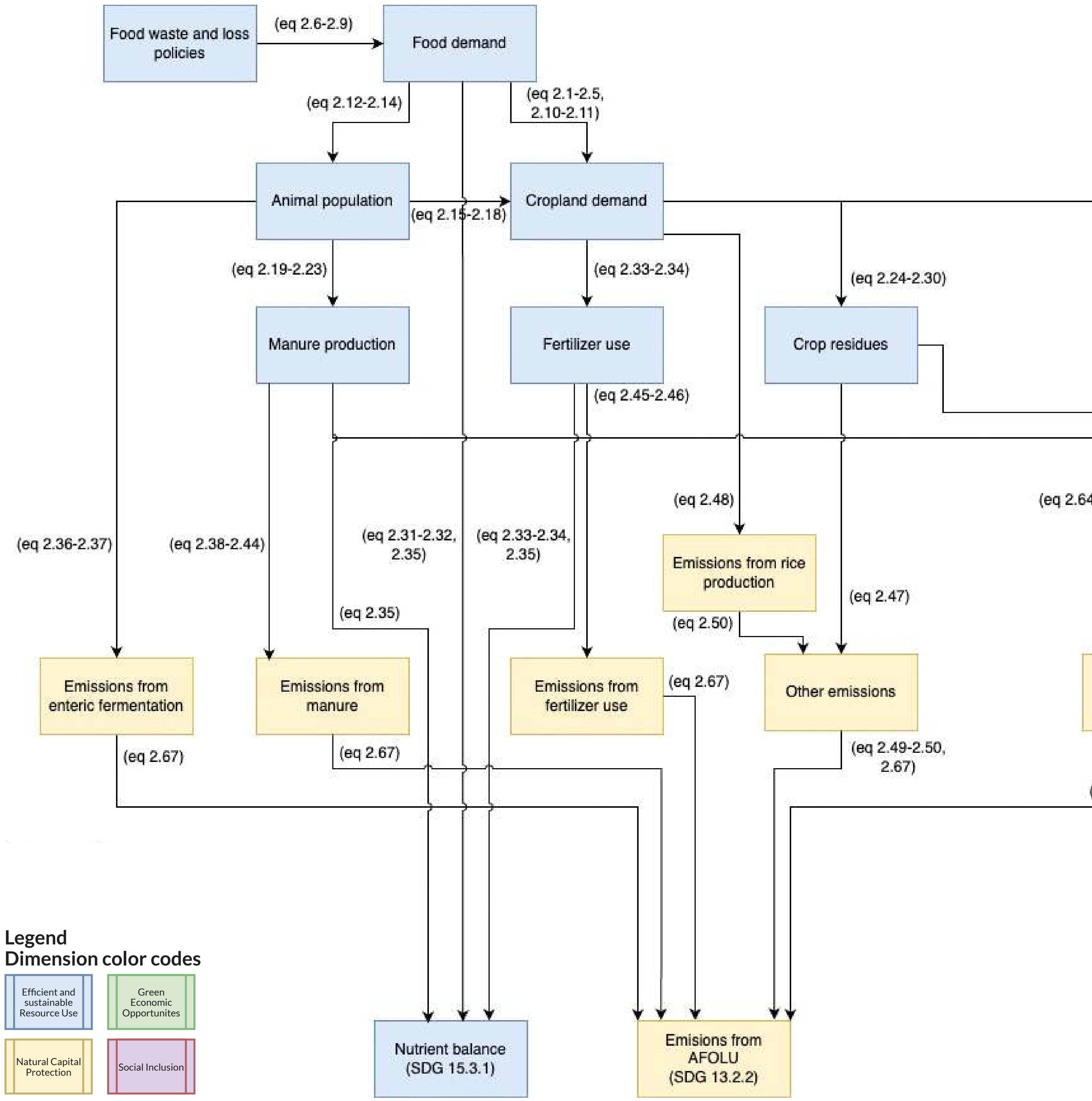
Emission levels from transport activity (part of SDG 13.2.2)

Emission levels from transport activity are part of SDG 13.2.2 total greenhouse gas emissions per year (Table 3). To estimate both CO_2 and non-CO_2 emissions, the energy consumption levels of different transportation modes are multiplied by a specific emission factor according to vehicle and fuel types. Annex 1 presents the equations and inputs to emission levels from transport activity, including energy consumption in transport and emission factors. The transport sector is divided into freight and passenger categories. Freight and passenger transport demands are expected to rise by 59 and 65 percent by 2050 under the Organisation for Economic Co-operation and Development (OECD) High Ambition scenario.[37] There is, therefore, a need to decouple transport activity from transport emissions, as CO_2 emissions from the sector must annually decrease by 3.0 percent by 2030 to achieve the IEA's Net Zero Emissions (NZE) scenario.[38] Even though the focus has been on electrifying private passenger cars, the transition of the sector should not forget to include measures regarding freight and public transport. Moreover, one should acknowledge the significant disparity regarding the transition of this sector. For example, 95 percent of electric vehicle sales in 2022 occurred in China, the USA, and Europe.[39]

3.2.2 Agriculture, forest, and land use (AFOLU)

The AFOLU sector has the particularity that it is both a carbon emitter and a carbon sink. It is estimated to be responsible for around 23 percent of the net anthropogenic GHG emissions.[40] Forests contribute to mitigating carbon emissions by capturing carbon from the atmosphere and stocking in the form of biomass. In addition to its important role in reducing GHG emissions, the AFOLU sector affects significant issues related to climate change mitigation and adaptation, as it is at the center of food systems, biodiversity conservation, habitat, and energy. The AFOLU model links food demand to agricultural inputs and outputs, land use, forest area, emissions, and several indicators related to the Sustainable Development Goals. It is also strongly linked to the water and waste model, as agriculture uses an important share of the water supply – around

Figure 10. Agriculture, forest, and land use (AFOLU) model components and their interlinkages



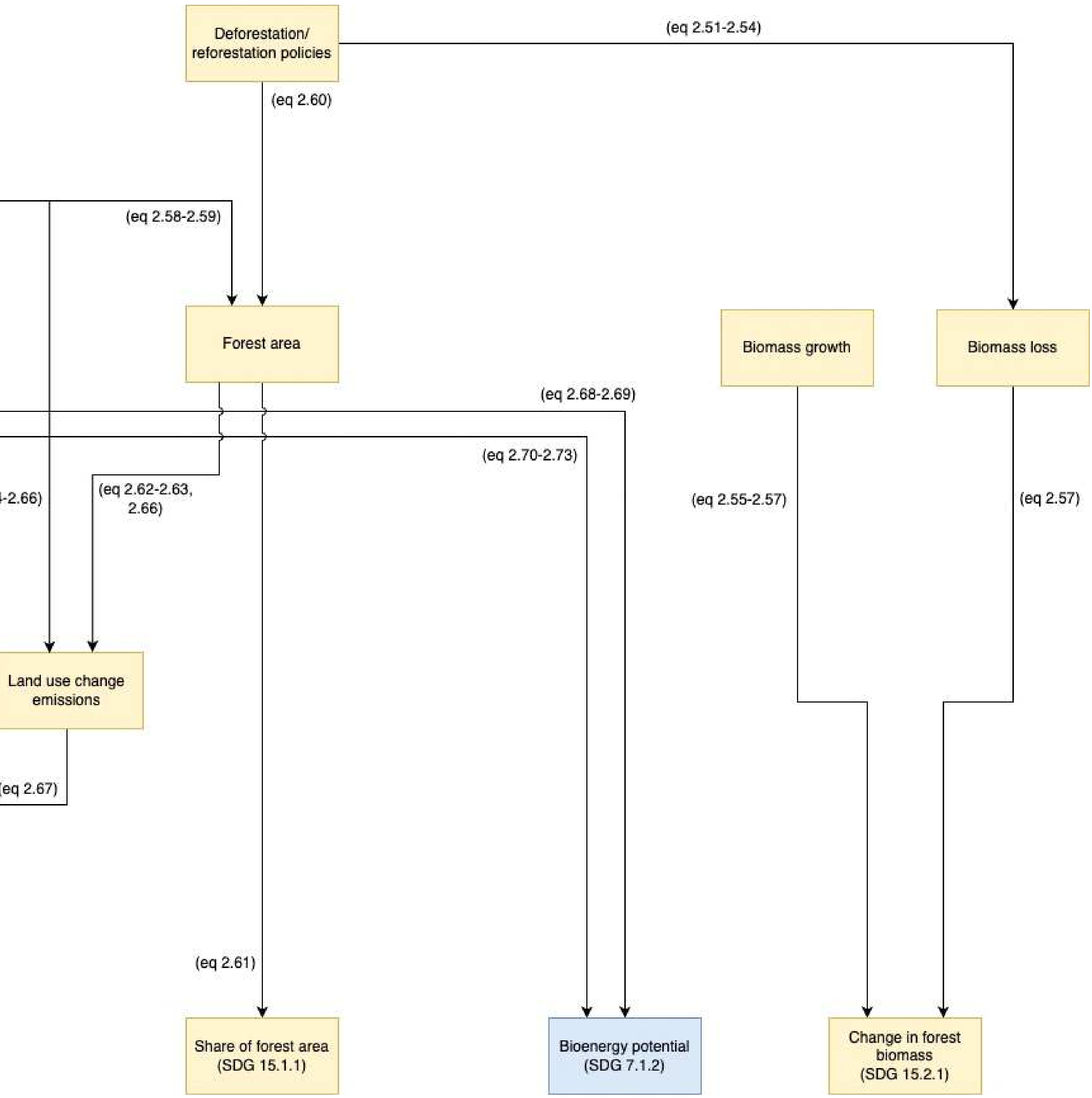
Note: eq and numbers refer to equations in Annex 2

70 percent globally.[41] Figure 3 presents the components of the AFOLU model, including the outputs which are mainly SDG indicators.

Food demand (link to SDG 2.1.2)

Food demand contributes to SDG 2.1.2, the prevalence of moderate or severe food insecurity in the population.

The models for crops and cropland are adapted from Baudry's EU Calculator Agriculture and Land-Use Module[42] and different food groups are defined based on the aggregation made by the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT)[43]. Annex 2 presents the equations and inputs to food demand, including the demand for each commodity group (i.e.,



147 crops and 25 animals). Food demand is calculated by considering human food consumption, seeds, residuals, imports, exports, and non-food use losses. The projections for future food demand are driven by changes in population and user-defined scenarios based on food waste on the consumption side and food losses on the production side (Table 2). A self-sufficiency ratio is defined to compare the domestic production of crops to the imports and exports. This helps determine the impact of a change in food demand on land use and domestic food production. With almost one in ten people in the world not having enough to eat[44] and the food demand projected to increase between 35 and 56 percent over the period 2010-2050,[45] food systems must become resilient and sustainable.

Food loss and waste index (SDG 12.3.1.a and b)

These indicators correspond to SDG 12.3.1 (a) food loss index and (b) food waste index. Food waste and losses, integrated into the total crop demand, represent a potential for reducing GHG emissions from AFOLU. Measures for reducing them will help achieve the implementation of a sustainable food system. It is estimated that around 13 percent of food production is lost on the production side, while about 17 percent is wasted on the consumption side.[46] The food loss index is computed based on the FAO methodology,[47] and the food waste index is computed based on the UNEP methodology[48] (Table 4). Annex 2 presents the equations and inputs to food waste and losses, including food losses, annual food loss reduction, food waste, annual food waste reduction, and population.

Cropland demand (link to SDG 2.4.1)

Cropland demand contributes to SDG 2.4.1 proportion of agricultural area under productive and sustainable agriculture. The demand for cropland is calculated from the total food demand for each food item, using historical specific crop yields (Table 4). Annex 2 presents the equations and inputs to cropland demand, including food production, crop yields, and cropland correction coefficient. The FAO uses the cropland coefficient to account for the difference between the sown and harvested area.[49]

Animal population and feed demand (link to SDG 2.1.2)

Meat products as a food source contribute to SDG 2.1.2 prevalence of moderate or severe food insecurity in the population. Meat is a good source of protein (at least 23 percent depending on the animal type), minerals (i.e., zinc, iron, selenium, phosphorus), and vitamins (i.e., A, B-complex) the human body needs.[50] The total number of animals required for animal-based food items is assessed using the food demand for animal groups and animal yields (Table 2). Population and economic growth, urbanization, and globalization drive the demand for animal-based products. According to 2018 FAO projections, this demand is expected to increase by 80 percent by 2030 and 200 percent by 2050 in low- and middle-income countries,[51] impacting demand for animal feed from crops, pastures, and grasslands. The feed demand is calculated using a feed-conversion ratio for each animal group.[52] Around one-third of the total crop demand comes from animal feed demand.[53] Annex 2 presents the equations and inputs to animal feed demand, including animal yields, total live animals and total number of animals needed for production, food production, feed conversion ratios, crop forage feed ratio, and animal feed demands.

Manure production and crop residues (link to SDG 2.4.1)

Manure production and crop residues contribute to SDG 2.4.1 Proportion of agricultural area under productive and sustainable agriculture, particularly in achieving an acceptable or desirable level of management of fertilizers. Each group of animals produces a certain amount of manure, estimated using their specific manure yields.[54] Once produced, manure can either be left on pasture or collected on the farm, and collected manure can either be applied on soil or used for biogas production. Similarly, crop residues can be left on the farm as organic fertilizer. Crop residues are estimated following the Intergovernmental Panel on Climate Change (IPCC) guidelines for national GHG inventories.[55] The total crop residues lead to residue emissions, and the residues removed are used for biofuel production. Table 4 and

Annex 2 present the equations and inputs to manure production and crop residues.

Fertilizer use and nutrient balance (part of SDG 15.3.1)

Fertilizer use from nitrogen, manure, and crop residues affects soil fertility, measured through nutrient balance, contributing to SDG 15.3.1 proportion of land that is degraded over total land area. The nutrient balance is calculated by subtracting the nitrogen content of crops from the total manure applied to the soil, fertilizer inputs, biological fixation, and atmospheric nitrogen deposition (Table 4). A negative value indicates declining soil fertility, while a positive value indicates a risk of pollution.[56] Annex 2 presents the equations and inputs to nutrient balance, including crop nitrogen content, food production, agricultural use of nutrients, cropland demand, amount of manure applied to soil, nitrogen biological fixation, and nitrogen atmospheric deposition.

Emissions from enteric fermentation, manure, and fertilizer (part of SDG 13.2.2)

AFOLU emissions from enteric fermentation, manure, and fertilizer are part of the SDG 13.2.2 total greenhouse gas emissions per year. Emissions from enteric fermentation due to the ruminants' digestive process are proportional to the number of live animals and are computed based on emissions factors and the IPCC Guidelines.[57] Livestock contributes around 30 percent of global methane emissions and 5.5 percent of total anthropogenic GHG emissions.[58] CH_4 and N_2O emissions from manure are produced from anaerobic decomposition and nitrification-denitrification of nitrogen contained, respectively. They are calculated using emissions and conversion factors,[59] depending on whether the manure is left on pasture, stored on farms, or applied on soils. Manure storage and processing is estimated to account for 10% of the total emissions attributable to livestock.[60] Emissions from fertilizer applications are calculated using emission and conversion factors. Fertilizer production and use are estimated to account for around 5% of total GHG emissions, while about 48% of the world population is estimated to be fed with fertilized crops. Besides GHG emissions, fertilizer use contributes to eutrophication and soil acidification.[61] Other emissions from AFOLU represent emissions from crop residues, cultivation of organic soils, burning savanna and biomass, and rice production. Table 4 and Annex 2 present the equations and inputs to AFOLU emissions from enteric fermentation, manure and fertilizer applications, and other emissions.

Above-ground biomass in forest (SDG 15.2.1)

Above-ground biomass in forests is one of the indicators for SDG 15.2.1 Progress towards sustainable forest management. Based on Marklund,[62] the change in above-ground biomass is the difference between biomass growth and biomass loss. Biomass growth results from a mean annual biomass growth rate, whereas biomass loss can be due to wood removal, fuel wood removals, or disturbances (Table 4). Annex 2 presents the equations and inputs to the above-ground biomass in the forest.

Share of forest area to total land area (SDG 15.1.1)

The share of forest area to total land area is an SDG indicator (i.e., SDG 15.1.1). Land use change is driven by cropland demand based on Baudry.[63] The total agricultural area directly depends on the previously calculated cropland demand. The land requirements for SPVs and first-generation biofuels, defined earlier, are not included in this calculation. By determining the reforestation rate, the forest land stock can be estimated based on the previous forest land stock (Table 4), resulting in the estimates for the share of forest area to total land area. Specifically, Annex 2 presents the equations and inputs to the share of forest area to total land area, including cropland demand, inactive land stock, forest land stock, and reforestation rate.

Emissions from land use change (part of SDG 13.2.2)

In addition to enteric fermentation, manure, fertilizer, and others (i.e., crop residues, cultivation of organic soils, burning savanna and biomass, and rice production), land use change is a source of emissions. Emissions from land use change are part of SDG 13.2.2 total greenhouse gas

emissions per year. They are driven by crop demand and are the combined result of the emissions from a change in forest land and agriculture on organic soils. Table 4 and Annex 2 present the equations and inputs of the emissions from land use change, including forest land stock, forest land emission factor, change in cropland demand, percentage of cropland under organic soils, and emission factor for cropland under organic soils.

Total AFOLU emissions (part of SDG 13.2.2)

The ratio of non-CO_2 emissions in agriculture to population is calculated as the emissions from enteric fermentation, manure stored on farms, manure left on pasture, manure applied to soils, fertilizer application, land use change, and other emissions as defined above, over the population. Table 4 and Annex 2 present the equations and inputs to the Total AFOLU emissions, which are part of the SDG 13.2.2 total greenhouse gas emissions per year.

Bioenergy production (link to SDG 7.1.2)

As already discussed in the energy model (section 1.1.1), bioenergy expansion significantly impacts land use. The model considers the biogas potential from manure and the bioethanol potential from crop residues. The biogas potential from manure results from the available manure and its specific biogas yields.[64] The manure production per animal is estimated following Vermeulen[65] and the IPCC Guidelines[66]. The ethanol produced from residues is estimated by applying a conversion factor to the available amount of residue. Table 4 and Annex 2 present the equations and inputs to the bioenergy production, which contributes to SDG 7.1.2 proportion of the population with primary reliance on clean fuels and technology.

Proportion of degraded (forest) land (part of SDG 15.3.1)

Land degradation is defined as the reduction of loss of biological or economic productivity and complexity of land.[67] The proportion of forest land that is degraded is part of SDG indicator 15.3.1: Proportion of land that is degraded over total land area. This indicator is binary, meaning that an area of land will either be qualified as degraded, or non-degraded. The calculation is based on the Good Practice Guidance from the UNCCD.[68] The area of land degraded at the current period is the area of land that was already degraded, plus the area of land newly degraded, minus the area of land that is newly improved. Land degradation is estimated to adversely affect the well-being of 40 percent of the total population and be responsible for a GDP loss of 10 percent.[69] Table 5 and Annex 2 present the equations and inputs to the proportion of degraded forest land.

Table 5. Description of the AFOLU model components

Food demand	
Equations	Annex 2 eq. 2.1-2.5
Inputs	Population [*capita*] Food demands [(*kg/capita*)/*day*] Food waste [(*kg/capita*)/*day*] Food losses [*ktonnes*] Stock variations, seed, non-food, processed, residual demands [*ktonnes*] Animal feed demands [*ktonnes*] Food production, exports and imports in the base year [*ktonnes*]
Outputs	Self-sufficiency ratios [–] Food production [*ktonnes*]
Related to SDG indicator	SDG 2.1.2 Prevalence of moderate or severe food insecurity in the population
Food waste and loss index	
Equations	Annex 2 eq. 2.6-2.9
Inputs	Food losses [*ktonnes*] Annual food loss reduction [*ktonnes*] Food waste [(*kg/capita*)/*y*] Population [*capita*] Annual food waste reduction [*tonnes*]
Outputs	Food loss index [–] Food waste index [–]
SDG indicators	SDG 12.3.1 (a) Food loss index and (b) Food waste index
Cropland demand	
Equations	Annex 2 eq. 2.10-2.11
Inputs	Food production [*ktonnes*] Crop yields [*hg/ha*] Cropland correction coefficient [–]
Outputs	Cropland demand [*ha*]

Table 5. Description of the AFOLU model components *(continued)*	
Related to SDG indicator	SDG 2.4.1 Proportion of agricultural area under productive and sustainable agriculture
	Animal population and feed demand
Equations	Annex 2 eq. 2.12-2.14 and 2.15-2.18
Inputs	Animal yields [*kg/head*] Total live animals and total number of animals needed for production, in the base year [*head*] Food production [*ktonnes*] Feed conversion ratios [$ktonnes_{feed}/ktonnes_{edible}$] Crop forage feed ratio [–] Animal feed demands in the base year [*ktonnes*]
Outputs	Total live animals and total number of animals needed for production [*head*] Feed-mix fractions [–] Animal feed demands [*ktonnes*]
Related to SDG indicator	SDG 2.1.2 Prevalence of moderate or severe food insecurity in the population
	Manure production
Equations	Annex 2 eq. 2.19-2.23
Inputs	Total manure produced in the base year [*kgN*] Animal populations in the base year [*head*] Fraction of manure left on pasture [–] Fraction of manure applied to soil [–]
Outputs	Total manure produced [*kgN*] Amount of manure that is left on pasture, collected, and applied to soil [*kgN*]
Related to SDG indicator	SDG 2.4.1 Proportion of agricultural area under productive and sustainable agriculture
	Crop residues
Equations	Annex 2 eq. 2.24-2.30
Inputs	Crop yields [*hg/ha*] Dry matter fraction of harvested crops [*kg dm/kg fresh weight*] Regression parameters for computing above-ground residues [–, *Mg/ha*] Ratio of above-ground residues dy matter to harvested yield [–] Ratio of below-ground residues to harvested yield [–] Cropland demand [*ha*] Crop combustion factors [–] Fraction of crop area renewed annually [ ] Fraction of above-ground residues removed annually [–] Nitrogen content of above-ground residues [*kgN/kg dm*] Nitrogen content of below-ground residues [*kgN/kg dm*]
Outputs	Amount of residue removed from cropland [*kg dm*] Nitrogen content from crop residues and forage/pasture renewal [*kgN*]
Related to SDG indicator	SDG 2.4.1 Proportion of agricultural area under productive and sustainable agriculture
	Fertilizer use and nutrient balance
Equations	Annex 2 eq. 2.31-2.35
Inputs	Crops nitrogen content in the base year [*tonnesN*] Food production in the base year [*ktonnes*] Food production [*ktonnes*] Agricultural use of nutrients in the base year [*tonnesN*] Cropland demand in the base year [*ha*] Amount of manure applied to soil [*kgN*] Nitrogen biological fixation [*tonnesN*] Nitrogen atmospheric deposition [*tonnesN*]
Outputs	Nitrogen crop output [*tonnesN*] Agricultural use of nutrient [*tonnesN*] Nutrient balance [*tonnesN*]
Related to SDG indicator	SDG 15.3.1 Proportion of land that is degraded over total land area
	Emissions from enteric fermentation
Equations	Annex 2 eq. 2.36-2.37

Table 5. Description of the AFOLU model components *(continued)*	
Inputs	Animal populations [*head*] Animal CH_4 emissions factors [*$ggCH_4$/head*] CH_4 global warming potential [*$ggCO_2eq/ggCH_4$*]
Outputs	GHG emissions from enteric fermentation [*$ggCO_2eq$*]
SDG indicator	SDG 13.2.2 Total greenhouse gas emissions per year
Emissions from manure	
Equations	Annex 2 eq. 2.38-2.44
Inputs	Animal populations [*head*] Amount of manure left on pasture [*kgN*] Amount of manure managed [*kgN*] Amount of manure applied to soil [*kgN*] NO_2 emission factors for manure left on pasture [*$kgN_2O–N$*] CH_4 and N_2O emission factors for manure management [*$kgCH_4$/head,($kgN_4O–N$)/kgN*] N_2O emission factors for manure applied to soil [*($kgN_2O–N$)/kgN*] CH_4 global warming potential [*$ggCO_2eq/ggCH_4$*] N_2O global warming potential [*$ggCO_2eq/ggCH_4$*] N_2O-N to N_2O conversion factor [–]
Outputs	GHG emissions from manure left on pasture, manure management and manure applied to soil [*$ggCO_2eq$*]
SDG indicator	SDG 13.2.2 Total greenhouse gas emissions per year
Emissions from fertilizer application	
Equations	Annex 2 eq. 2.45-2.46
Inputs	Agricultural use of nutrients [*ktonnes*] N_2O emission factor from fertilizers [*($kgN_2O–N$)/kgN*] N_2O global warming potential [*$ggCO_2eq/ggN_2O$*] N_2O-N to N_2O conversion factor [–]
Outputs	GHG emissions from fertilizer application [*$ggCO_2eq$*]
SDG indicator	SDG 13.2.2 Total greenhouse gas emissions per year
Other emissions	
Equations	Annex 2 eq. 2.47-2.50
Inputs	Nitrogen content from crop residues and forage/pasture renewal [*kgN*] Crop residue emissions factors [*($kgN_2O–N$)/kgN*] Cropland demand for rice [*ha*] Rice cultivation emission factor [*($kgCH_4$–C)/ha*] Biomass burnt [*(kg dm*] N_2O and CH_4 emission factors for burning crop residues [*(($kgN_2O–N$)/CH_4–C)/kg dm*] Emissions from cultivation of organic soils [*$ggCO_2eq$*] Emissions from savanna and forest fires [*$ggCO_2eq$*] CH_4 global warming potential [*$ggCO_2eq/ggCH_4$*] N_2O global warming potential [*$ggCO_2eq/ggN_2O$*] N_2O-N to N_2O conversion factor [–]
Outputs	GHG emissions from crop residues [*$ggCO_2eq$*] GHG emissions from rice cultivation [*$ggCO_2eq$*] GHG emissions from burning crop residues [*$ggCO_2eq$*] Total other GHG emissions from AFOLU [*$ggCO_2eq$*]
SDG indicator	SDG 13.2.2 Total greenhouse gas emissions per year
Above-ground biomass in forest	
Equations	Annex 2 eq. 2.51-2.57
Inputs	Roundwood removals [*m^3*] Biomass conversion and expansion factors [*tonnes dm/m^3*] Ratio of below-ground forest biomass to above-ground biomass [–] Carbon fraction of dry matter [*tonnes C/tonnes dm*] Volumes of fuel wood removals as whole trees and as tree parts [*m^3*] Wood densities [*tonnes dm/m^3*] Areas disturbed [*ha*] Average above-ground biomass of land areas affected by disturbance [*tonnes dm/ha*] Fraction of biomass lost in disturbances [–] Average annual above-ground biomass growth [*tonnes dm/ha*] Area of forest remaining in the same land use category [*ha*]

Table 5. Description of the AFOLU model components *(continued)*

Outputs	Decrease and increase in carbon stocks due to biomass loss and growth [*tonnes C*] Net change in forest biomass [*tonnes C*]
SDG indicator	SDG 15.2.1 Progress towards sustainable forest management (Above-ground biomass in forest)
Share of forest area to total land area	
Equations	Annex 2 eq. 2.58-2.61
Inputs	Cropland demands in the base year [*ha*] Cropland demands [*ha*] Inactive land stock in the base year [*ha*] Forest land stock in the base year [*ha*] Rate of reforestation [–]
Outputs	Change in cropland demand [*ha*] Forest land stock [*ha*] Share of forest area to total land area [–]
SDG indicator	SDG 15.1.1 Forest area as a proportion of total land area
Emissions from land use change	
Equations	Annex 2 eq. 2.62-2.66
Inputs	Forest land stock in the base year [*ha*] Forest land [*ha*] Forest land emission factor [$ggCO_2/ha$] Change in cropland demand [*ha*] Percentage of cropland under organic soils [–] Emission factor for cropland under organic soils [$ggCO_2eq/ha$]
Outputs	Emissions from land use change [$ggCO_2eq$]
SDG indicator	SDG 13.2.2 Total greenhouse gas emissions per year
Total AFOLU emissions	
Equations	Annex 2 eq. 2.67
Inputs	Emissions from enteric fermentation [$ggCO_2eq$] Emissions from manure applied to soils, manure left on pasture and manure management [$ggCO_2eq$] Emissions from fertilizer use [$ggCO_2eq$] Emissions from land use change [$ggCO_2eq$] Other emissions from AFOLU [$ggCO_2eq$]
Outputs	Total AFOLU emissions [$ggCO_2eq$]
SDG indicator	SDG 13.2.2 Total greenhouse gas emissions per year
Bioenergy production	
Equations	Annex 2 eq. 2.68-2.73
Inputs	Amount of residue removed [*kg dm*] Crop Bioethanol yields [*L/kg dm*] Bioethanol conversion factor [*L/TJ*] Animal populations [*head*] Animal average adult body mass [*kg body mass*] Daily manure production [*(kgVS/day)/1000kg body mass*] Fractions of manure left on pasture and applied to soil [–] Methane yields from manure [$m_3/kgVS$] Biogas conversion factor [MJ/m_3]
Outputs	Bioethanol from residue crops [*TJ*] Biogas from manure [*TJ*]
Related to SDG indicator	SDG 7.1.2 Proportion of population with primary reliance on clean fuels and technology
Proportion of degraded (forest) land	
Inputs	Area of forest that was degraded and is still [*ha*] Area of forest that becomes degraded in the current period [*ha*] Area of forest that improves from a degraded state to a non-degraded state in the current period [*ha*] Forest land stock [*ha*]
Outputs	Share of forest that is degraded [–]
SDG indicator	SDG 15.3.1 Proportion of land that is degraded over total land area

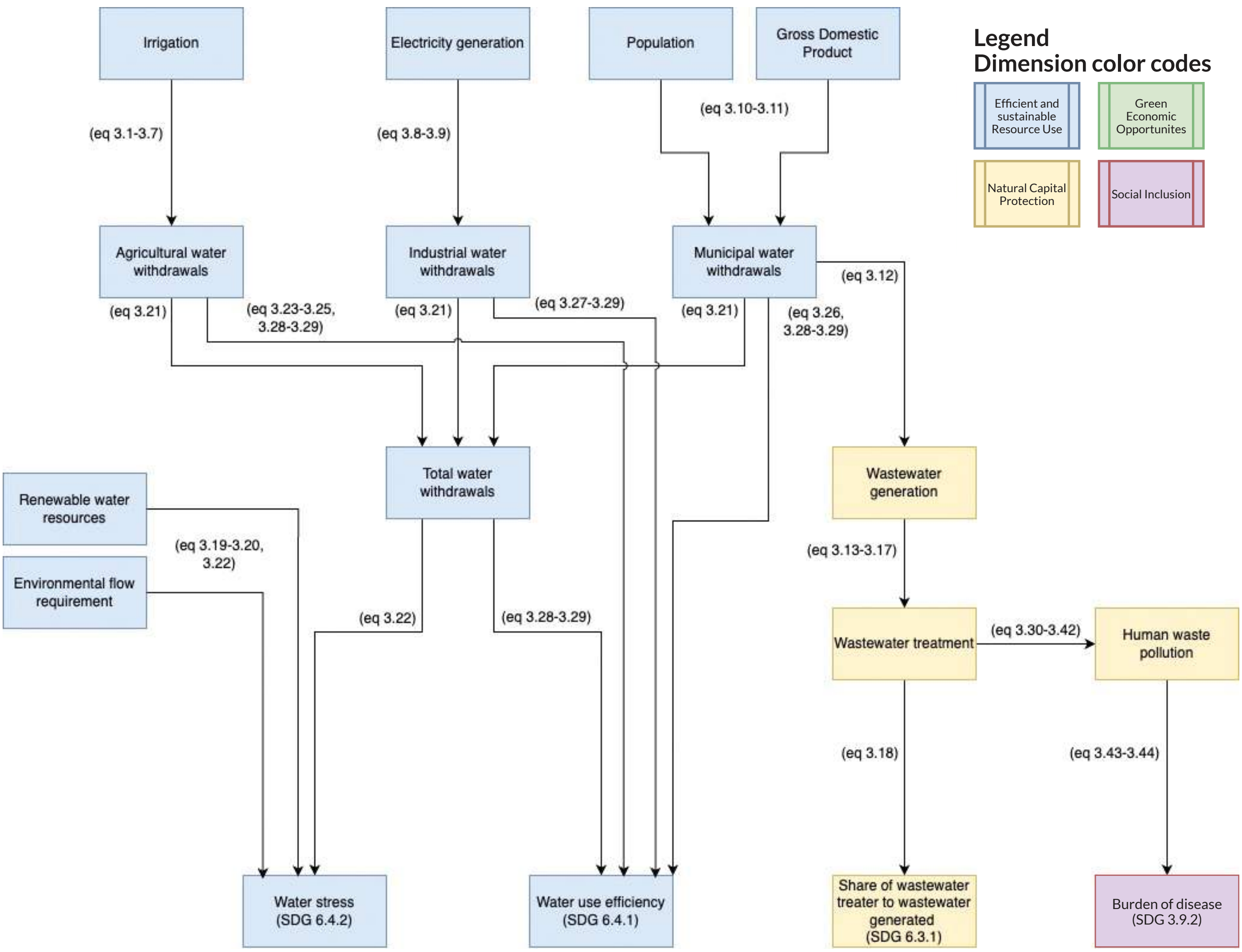
3.2.3 Water use and waste

Water use and wastewater

Agricultural water withdrawals (part of SDG 2.4.1 and 6.4.2)

Agricultural water is represented in two SDG indicators: first is the SDG 2.4.1 Proportion of agricultural area under productive and sustainable agriculture, particularly the proportion of agricultural land area that has achieved an acceptable or desirable level of variation in water availability, and second is the SDG 6.4.2 level of water stress, particularly freshwater withdrawal as a proportion of available freshwater resources. The water withdrawal from the agriculture sector is calculated using the methodology from Allen[72] and Luck[73]. The model estimates the water required and withdrawn for irrigation by considering the impacts of different crops, evapotranspiration, irrigated area, cropping intensity, and irrigation efficiency (Table 3). Three irrigation technologies are considered: drip, surface, and sprinkler. The total irrigation withdrawal is assumed to be equal to the total agricultural water withdrawal, as the livestock and aquaculture sectors are assumed to be insignificant compared to the crop irrigation demand. Annex 3 presents the equations and inputs to the agricultural water, including land irrigated by the different technologies, total arable irrigated land, irrigated crop harvested areas, crop coefficients, crop evapotranspiration

Figure 11. Water use and wastewater model components and their interlinkages



Note: eq and numbers refer to equations in Annex 3 under standard conditions, actual evapotranspiration, and irrigation technology efficiencies.

Industrial water withdrawals (part of SDG 6.4.2)

Industrial water is part of the SDG 6.4.2 level of water stress, particularly freshwater withdrawal as a proportion of available freshwater resources. The model accounts for water use in cooling systems for power generation. Industrial water withdrawals can represent as high as 90 percent of a country's total water withdrawals in Europe and less than one percent in other parts of the world.[74] Thermoelectric water withdrawal and consumption estimates for the different power plants' cooling systems are determined following Flörke[75], using water withdrawal and consumption intensity factors. Thermoelectric water withdrawal and consumption are directly proportional to electricity generation. Table 5 and Annex 3 present the equations and inputs to industrial water, including electricity generation, water withdrawal and consumption intensity factors, and cooling system proportions.

Municipal water withdrawals (part of SDG 6.4.2)

Municipal water is part of SDG 6.4.2 level of water stress, particularly freshwater withdrawal as a proportion of available freshwater resources. Municipal water withdrawal is determined through regression analysis based on the gross domestic product (GDP) per capita, water prices, and population, adapted from Hejazi[76]. Rapid urbanization across the globe is a key factor threatening the municipal water supply. Poor governance of urban water services and unsustainable water management can also add to the issue. An estimated one in four cities worldwide is estimated to be under water stress, with harmful impacts on sanitation and hygiene.[77] . Table 5 and Annex 3 present the equations and inputs to municipal water, including, among others, GDP per capita and water price.

Treated wastewater (part of SDG 6.3.1)

Municipal wastewater is part of SDG 6.3.1 proportion of domestic and industrial wastewater flows safely treated. The model is extended to account for different wastewater flows using the WHO and UN-Habitat framework on municipal wastewater production, collection, and treatment.[78] Water returning to its source from municipal activities is classified as wastewater, assuming it has been used within the sector. The amount of wastewater generated is the difference between municipal water withdrawal and municipal water consumption. Wastewater is either collected or enters surface water. WHO defines two kinds of collection systems: piped sewage networks and septic tanks. Once it is collected, wastewater goes through various sanitation service chain steps. The total amount of wastewater treated is the summation of the amounts of wastewater treated through the different types of treatment. The proportion of wastewater treated to wastewater generated can then be assessed. Table 5 and Annex 3 present the equations and inputs to treated wastewater.

Level of water stress (SDG 6.4.2)

The level of water stress is an SDG indicator, particularly SDG 6.4.2 freshwater withdrawal as a proportion of available freshwater resources. Water scarcity can be due to an excessive demand compared to supply, inadequate infrastructures, or poor institutions. Values of water scarcity vary according to demand and supply variations.[79] It is estimated that 2.3 billion people live in high and critically water-stressed countries.[80] A territory is said to be under water stress when it withdraws more than 25 percent of its renewable freshwater resources.[81] The total renewable freshwater comprises both internal and external renewable water resources, covering both groundwater and surface water. The environmental flow requirement quantifies the amount of freshwater that must be available to support ecosystem functioning as well as human health. Water stress is the total water withdrawal over the total renewable freshwater minus the environmental flow requirement. Table 5 and Annex 3 present the equations and inputs to the level of water stress, including groundwater, surface water, overlap between groundwater and surface water, external renewable water resources, and agricultural, industrial, and municipal water withdrawals.

Water use efficiency (SDG 6.4.1)

SDG 6.4.1 is the water use efficiency over time. Water use efficiency assesses the efficiency of both economic and social uses of water resources. An increase in water use efficiency means a step towards decoupling economic growth from water use. The gross value-added generated using water in agriculture, industry, and municipal sectors are considered, following the UNSTATS' approach.[82] The total water use efficiency is calculated as the sum of all three sectors' efficiencies, weighted according to the proportion of water used by each sector over the total water use (Table 5). Annex 3 presents the equations and inputs to the water use efficiency, including sectoral and total water withdrawals, irrigated land, cropland area, default ratio between rainfed and irrigated yields, and sectoral gross values added.

Human waste pollution (link to SDG 3.9.2)

Human waste pollution is part of SDG 3.9.2 mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene. The amount of pollutant emission input entering surface water systems from different sanitation types and socio-economic factors were estimated to investigate the impacts of sanitation on water quality. Human waste emissions of nitrogen, phosphorus, and Cryptosporidium pathogen inputted to river systems are estimated following Van Drecht[83], Strokal[84], and Hofstra's[85] methodologies. Three main sanitation sources are identified as contributing emissions to river systems: piped sewer systems, hanging latrines (associated with unimproved sanitation[86]), and open defecation. The percentage of the population (urban and rural) with access to sanitation (connected unimproved and open defecation) is determined (Table 3), and the annual emissions input to river systems from both point and diffuse human waste sources is estimated following

Hofstra[87], Mayorga[88], and Vermeulen's[89] methodologies.[90] Annex 3 presents the equations and inputs to human waste pollution, including, among others, national minimum and range protein intake, protein consumption, average nitrogen content of proteins, fraction of population under the different sanitation systems, removal efficiencies, types of wastewater treatment distribution, and wastewater treatment average removal efficiencies. This module needs further development and represents a first attempt to include water quality in the model. Significant limitations such as lack of public data, assumptions and appropriate methods, as well as requirements for spatial modelling, only enabled the production of interim results.

Disease burden due to inadequate sanitation (part of SDG 3.9.2)

The disease burden due to inadequate sanitation is part of SDG 3.9.2 Mortality rate attributed to unsafe water, unsafe sanitation, and lack of hygiene. To consider the impacts of access to sanitation on health, the disease burden attributable to inadequate sanitation is estimated according to Prüss-Ustün's methodology.[91] The population attributable fraction (PAF) is the proportion of the disease or death that could be prevented if exposure were reduced to an alternative or counterfactual scenario. It is estimated as a function of the proportion of the exposed population and the relative risk at the different exposure levels (Table 5).[92] The attributable burden of diarrheal disease from inadequate sanitation is then calculated by multiplying the PAF with the total deaths from diarrheal diseases in the country. Annex 3 presents the equations and inputs to disease burden due to inadequate sanitation. As for the module on human waste pollution this module needs further development and represents a first attempt to include water quality in the model. Significant limitations such as lack of public data, assumptions and appropriate methods, as well as requirements for spatial modelling, only enabled the production of interim results.

Table 6. Description of the water use and waste model components

Agricultural water withdrawals	
Equations	Annex 3 eq. 3.1-3.7
Inputs	Land irrigated by the different technologies [*ha*] Total arable irrigated land [*ha*] Irrigated crop harvested areas [*ha*] Crop coefficients [–] Crop evapotranspiration under standard conditions [*mm/y*] Actual evapotranspiration [*mm/y*] Irrigation technology efficiencies [–]
Outputs	Total irrigation water withdrawals [m^3/y]
SDG indicator	2.4.1 Proportion of agricultural area under productive and sustainable agriculture 6.4.2 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources
Industrial water withdrawals	
Equations	Annex 3 eq. 3.8-3.9
Inputs	Electricity generation [*MWh*] Water withdrawal and consumption intensity factors [$(m^3/MWh)/y$] Cooling system proportions [–]
Outputs	Thermoelectric water withdrawals and consumption [m^3/y]
SDG indicator	6.4.2 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources
Municipal water withdrawals	
Equations	Annex 3 eq. 3.10
Inputs	Gross domestic product per capita [*USD/capita*] Water price [USD/m^3] Population [*capita*] Linear regression constants
Outputs	Municipal water withdrawals [m^3/y]
SDG indicator	6.4.2 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources
Treated wastewater	
Equations	Annex 3 eq. 3.11-3.18

Table 6. Description of the water use and waste model components *(continued)*

Inputs	Consumptive coefficient [–] Municipal water withdrawals [m^3/y] Proportion of the population connected to the different sanitation systems [–] Percentage of wastewater delivered to treatment plants [–] Percentage of population connected to at least secondary wastewater treatment [–] Proportion of wastewater collected [–] Proportion of wastewater not emptied [–]
Outputs	Wastewater generated [m^3/y] Wastewater treated [m^3/y] Proportion of wastewater treated to wastewater generated [%]
SDG indicator	SDG 6.3.1 Proportion of domestic and industrial wastewater flows safely treated
Level of water stress	
Equations	Annex 3 eq. 3.19-3.22
Inputs	Groundwater [m^3/y] Surface water [m^3/y] Overlap between groundwater and surface water [m^3/y] External renewable water resources [(m^3/y] Agricultural, industrial, and municipal water withdrawals [m^3/y]
Outputs	Total water withdrawals [m^3/y] Water stress [–]
SDG indicator	SDG 6.4.2 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources
Water use efficiency	
Equations	Annex 3 eq. 3.23-3.29
Inputs	Sectoral and total water withdrawals [m^3/y] Irrigated land [*ha*] Cropland area [*ha*] Default ration between rainfed and irrigated yields [–] Sectoral gross values added [*USD*]
Outputs	Agricultural, industrial, and municipal water use efficiency [USD/m^3] Total water use efficiency [USD/m^3]
SDG indicator	6.4.1 Change in water-use efficiency over time
Human waste pollution	
Equations	Annex 3 eq. 3.30-3.42
Inputs	National minimum and range protein intake [*kg/capita*] Gross domestic product per capita and maximal gross domestic product per capita amongst available countries [*USD/capita*] Protein consumption [*kg/capita*] Average nitrogen content of proteins [–] Conversion factors [–] Human Development Index [–] Population [*capita*] Fraction of population under the different sanitation systems [–] Proportions of urban and rural population [–] Removal efficiencies [–] Types of wastewater treatment distribution [–] Wastewater treatment average removal efficiencies [–]
Outputs	Direct and diffuse source emissions of nitrogen, phosphorus and Cryptosporidium [*kg/y*] Total emissions of nitrogen, phosphorus and Cryptosporidium [*kg/y*]
Related SDG indicator	SDG 3.9.2 Mortality rate attributed to unsafe water, unsafe sanitation, and lack of hygiene
Disease burden due to inadequate sanitation	
Equations	Annex 3 eq. 3.43-3.44
Inputs	Proportion of the exposed population at the different exposure levels [–] Relative risks at the different exposure levels [–] Total deaths from diarrhoeal diseases [*deaths*]
Outputs	Population attributable fraction [–] Attributable burden of diarrheal disease from inadequate sanitation [*deaths*]
SDG indicator	SDG 3.9.2 Mortality rate attributed to unsafe water, unsafe sanitation, and lack of hygiene

04

GGSIM COUNTRY APPLICATIONS

4.1 Climate mitigation

4.1.1 Hungary

A. Overview of scenarios

Hungary is a landlocked country located in Central Europe, 93,028 km^2 wide, and home to 9.67 million people.[93] Under the Soviet regime after World War II, it became a democratic parliamentary republic in 1989; this regime change induced significant economic and industrial restructuring. It is a member of the European Union since 2004.[94] GGGI assisted the government of Hungary in preparing its National Clean Development Strategy (NCDS),[95] which presents the country's long-term trajectory policies towards 2050, in line with the Paris Agreement and the European Green Deal. It includes discussions and projections for the energy, industrial processes, agriculture, land use, land use change and forestry (LULUF), and waste management sectors. Three scenarios were evaluated:

- The Business-As-Usual (BAU) scenario does not include further interventions than the existing policy strategies and measures; current trends are considered in all sectors.
- The Early Action (EA) scenario aims to achieve climate neutrality by 2050 by considering the short- and medium-term benefits of implementing the transition. Emissions follow a linear trajectory from 2030 to net zero in 2050.
- The Late Action (LA) scenario aims to achieve climate neutrality by 2050 by implementing a slow emissions reduction trajectory until 2045 and increasing efforts in the last five years of the transition.

The BAU scenario does not allow for reaching either climate neutrality in 2050 or the intermediary European target of an emissions reduction of 55 percent compared to 1990 in 2030. Both the LA and EA scenarios allow for reaching these targets. Considering avoided costs and added benefits, the EA scenario brings more economic and employment benefits than the LA scenario. Therefore, the NCDS mostly focused on comparing the BAU and EA scenarios, as does the GGSim application in this report.

B. GGSim model applications

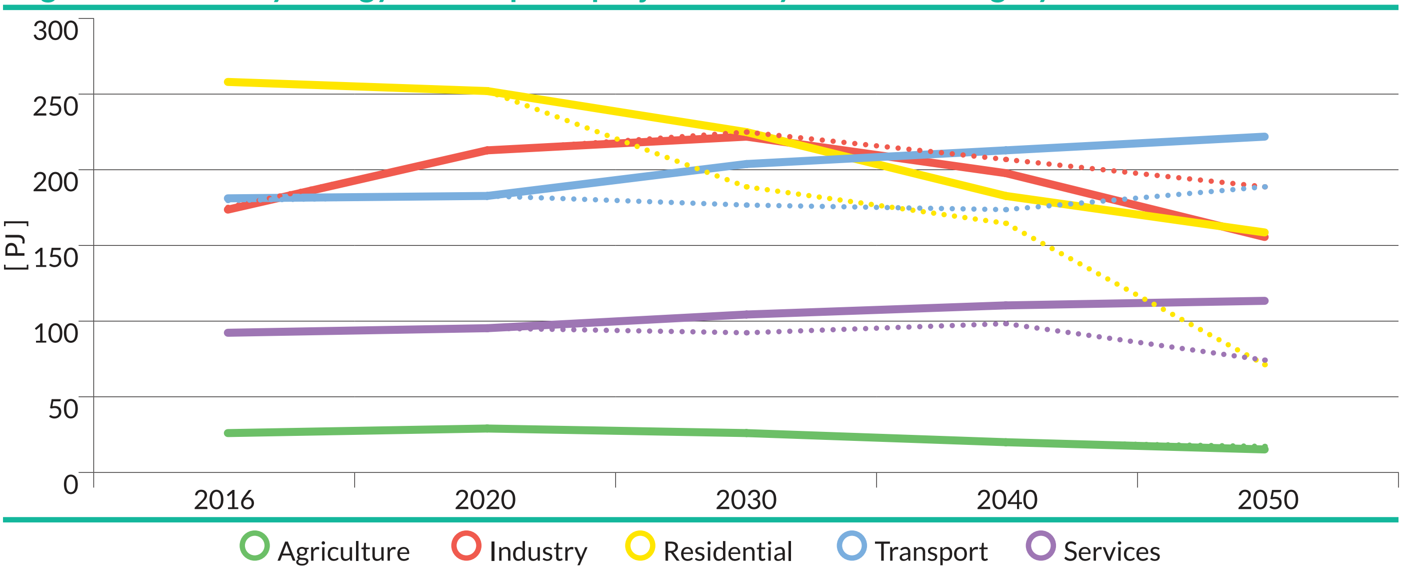
This section presents the results of the GGSim applications for the following models – energy and transport, AFOLU, and water use and waste (Tables 4-6).The applications were based on the GGGI-funded project "The Scenario Analysis for Implementing the European Green Deal and Green Recovery in Hungary," conducted from 2021 to 2022 (Annex 10). In 2021, the Ministry of Innovation and Technology proposed the transport sector as the focus of the scenario analysis. The mitigation measures to achieve climate neutrality cover solar and biofuels, whose impacts can go beyond the energy sector, including AFOLU, water, and waste sectors.

B.1 Energy and transport

The energy sector accounted for 72 percent of Hungary's total GHG emissions in 2018.[96] Increases in renewable energy capacities and energy efficiency in all sectors are at the heart of Hungary's policies on energy. The focus of this application is the increase in installed solar photovoltaic (SPV) capacity to power electric vehicles and the shift in the demand for the transport sector from fossil to biofuels. The impacts will be reflected in terms of land requirements and GHG emissions. The main differences in the assumptions of the BAU and EA scenarios lie in the primary energy consumption, the electricity generation mix, and the energy consumption mix in the transport sector.

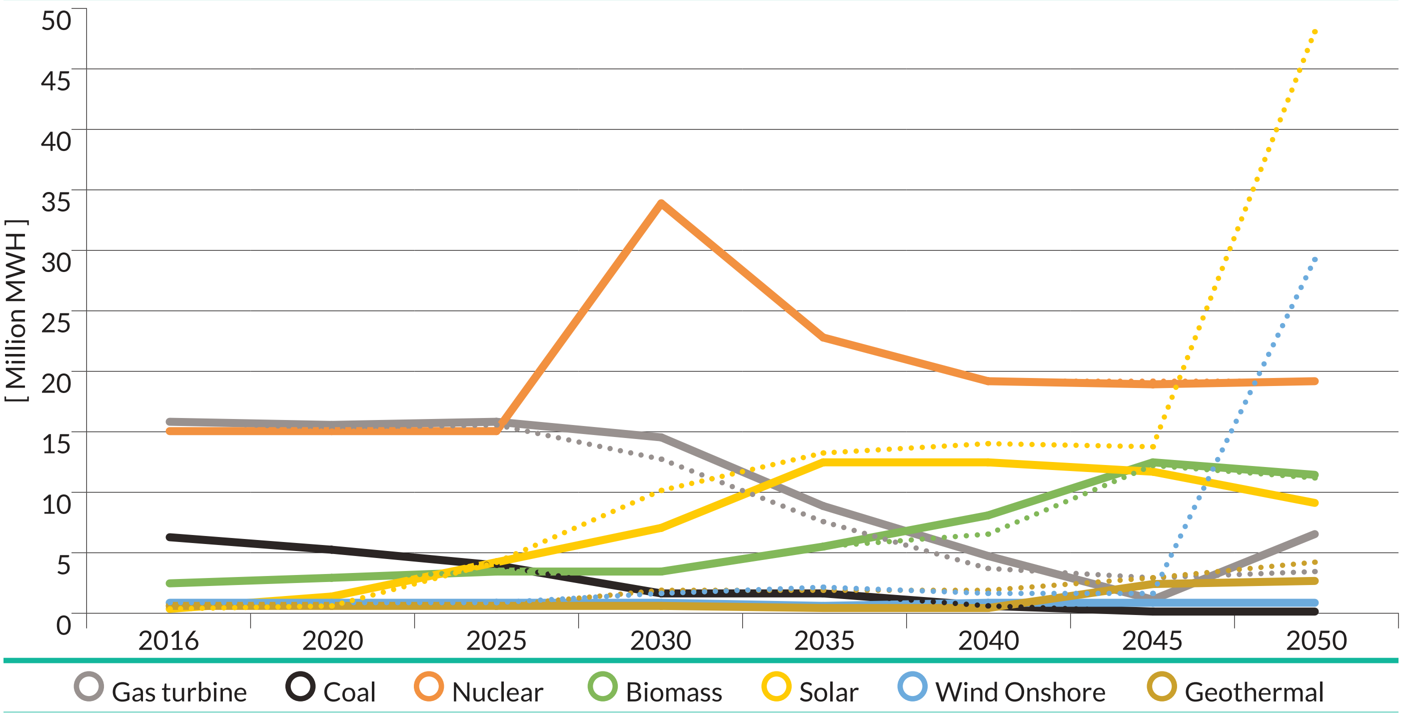
According to the NCDS, the total primary energy consumption decreases from 2016 to 2050 in both scenarios, by 27 percent in the EA scenario and 10 percent

Figure 12. Primary energy consumption projections by sector in Hungary



Note: BAU - plain lines and EA - dashed lines
Data source: National Clean Development Strategy 2020-2050.[97]

Figure 13. Electricity generation projections by source in Hungary



Note: BAU - plain lines and EA - dashed lines
Data source: National Clean Development Strategy 2020-2050.[98]

in the BAU scenario (Figure 12). The residential sector has the most significant potential for decreasing energy consumption due to the energy efficiency of newly built buildings and cost-effective renovations. The higher energy consumption of the industry sector in the EA scenario compared to the BAU scenario is explained by the fact that the green investments made in the EA scenario will lead to an increase in GDP, in turn leading to increased demand on the end-use side and therefore an increase in production.

Electricity generation will be almost three times higher by 2050 than in 2020 under the EA scenario and more than two times higher under the BAU scenario (Figure 12). This is mainly explained by the electrification of the transport sector and the spread of heat pumps in the household sector. The electricity generation mix differs between the scenarios mainly due to solar and wind electricity generation from 2045 when there will be a sharp increase in capacities (Figure 13). In five years, solar electricity generation more than tripled, and wind electricity generation increased by approximately 19 units. Before that, solar electricity generation progresses at almost the same rate in both scenarios. The rest of the transition is also similar under both scenarios, with an important peak in nuclear electricity generation between 2025 and 2035, decreased production from gas turbines, and increased biomass and geothermal electricity generation.

In the transport sector, the BAU scenario relies on an increase in liquefied petroleum gas (LPG) and compressed natural gas (CNG) consumption, while the EA scenario relies on an increase in electricity, biofuel consumption,

Table 7. Scenario assumptions in the GGSim application for Hungary's energy and transport model

Inputs	2016	BAU 2050	EA 2050	Source
Energy consumption				National databases applied in NCDS
Total primary energy consumption [PJ]	733	662	538	
Biofuel consumption in transport [PJ]	4*	2	28	
Electricity consumption in transport [PJ]	4*	29	91	
Power generation capacities				National databases applied in NCDS
Installed solar capacities [MW]	204	8,072	43,606	
Installed wind capacities [MW]	330	330	15,974	
Installed biomass capacities [MW]	511	2,166	1,965	
GDP				National databases applied in NCDS
GDP [real million LCU]	115,251,800,000	252,009,811,013	326,923,943,936	

Note: *Values refer to 2020

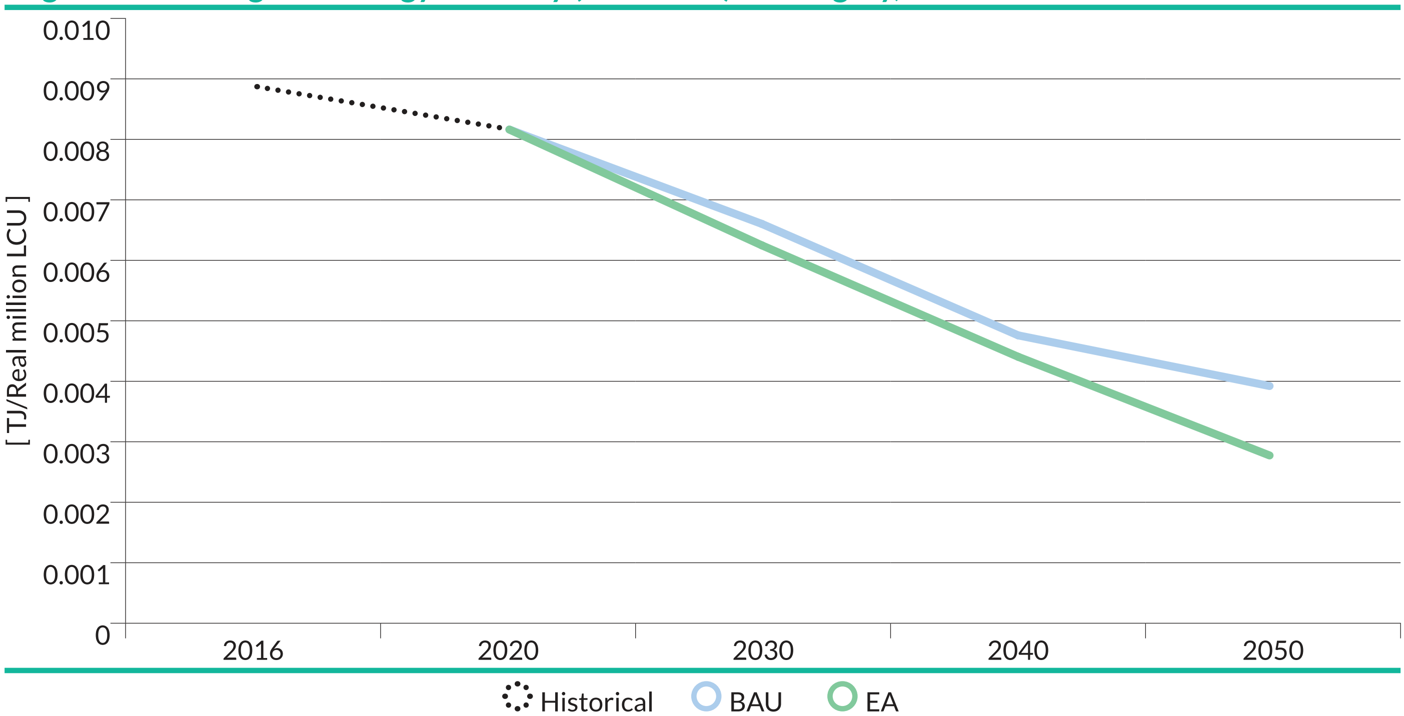
and hydrogen (the latter was not applied in the GGSim model). In both scenarios, there is a decrease in petrol consumption and a more significant decrease in diesel consumption, which will completely disappear from the mix by 2050 in the EA scenario. The scenarios applied for Hungary's GGSim application in the energy and transport model are summarized in Table 7. Following is a discussion of the results for relevant SDG indicators.

Energy Intensity (SDG 7.3.1): In Hungary, efforts to separate energy demand from economic growth have fallen short. In the transport sector, the energy efficiency of passenger transport energy intensity rose from 1.08 MJ/pkm to 1.28 MJ/pkm between 2013 and 2019. As part of the National Transport Strategy to strengthen energy-efficient transport modes, electric vehicle deployment is increasing; however, it still constitutes only 0.5 percent of the total passenger car fleet, below the EU average of 1.5 percent.[99] In the industry sector, energy demand increased by 46 percent from 2010 to 2020, driven by heightened activity, partially offset by efficiency improvements. In 2020, total final consumption from buildings, consisting of residential (75 percent) and service sector buildings (25 percent), amounted to 8.0 Mtoe, showing an 18 percent decline from 2009 levels, attributed to enhanced energy efficiency and reduced activities.[100] Decoupling energy consumption from economic growth can help simultaneously achieve economic and environmental goals. The decoupling may result from reducing the demand for energy services, increasing energy efficiency, or combining the two. The lower energy intensity in the EA scenario is also explained by an increase in GDP compared to the BAU scenario due to the early investments and policies. The GGSim results show an improvement in SDG 7.3.1 energy intensity, with TJ per LCU in the EA scenario decreasing slightly faster than in the BAU scenario (Figure 14).

Share of renewables in electricity generation (part of SDG 7.2.1): In 2016, most of the electricity was generated from non-renewable sources, including gas (37.9 percent), nuclear (35.9 percent), and coal (15.1 percent). In the GGSim energy and transport model, the main renewable sources in 2050 in the EA scenario are solar (41.7 percent), wind (25.3 percent), biomass (9.6 percent), and geothermal (3.5 percent). The rest of the electricity is generated mainly by nuclear (16.4 percent) and gas (2.8 percent). While in the BAU scenario, gas still accounts for 12.8 percent of the total electricity generation, nuclear keeps its historical significance (38.5 percent), there is a noticeable increase in the use of biomass (22.9 percent), and solar is less developed (18.1 percent). Figure 15 presents the GGSim results for the share of renewables in electricity generation. The BAU scenario shows a less steady increase in the share of renewables but reaches the same value as the EA scenario in 2045 before decreasing. However, the amount of electricity generated in the BAU scenario is much smaller than in the EA scenario, meaning the absolute amount of electricity from renewable sources is much more significant in the EA scenario.

Installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1): The GGSim results show that the installed renewable energy capacity per capita increases similarly under both scenarios until 2045, the EA projection being only slightly higher from 2025 onwards (Figure 16). In the BAU scenario, it then increases slightly and decreases between 2045 and 2050. In the EA scenario, there is an acceleration in the installation rate in 2045. The capacity per capita will increase by 294 percent in the last five years of the transition, mainly supported by solar and wind capacities. This acceleration at the end of the transition to net zero will require intense effort for Hungary to sustain this sharp growth in solar capacity.

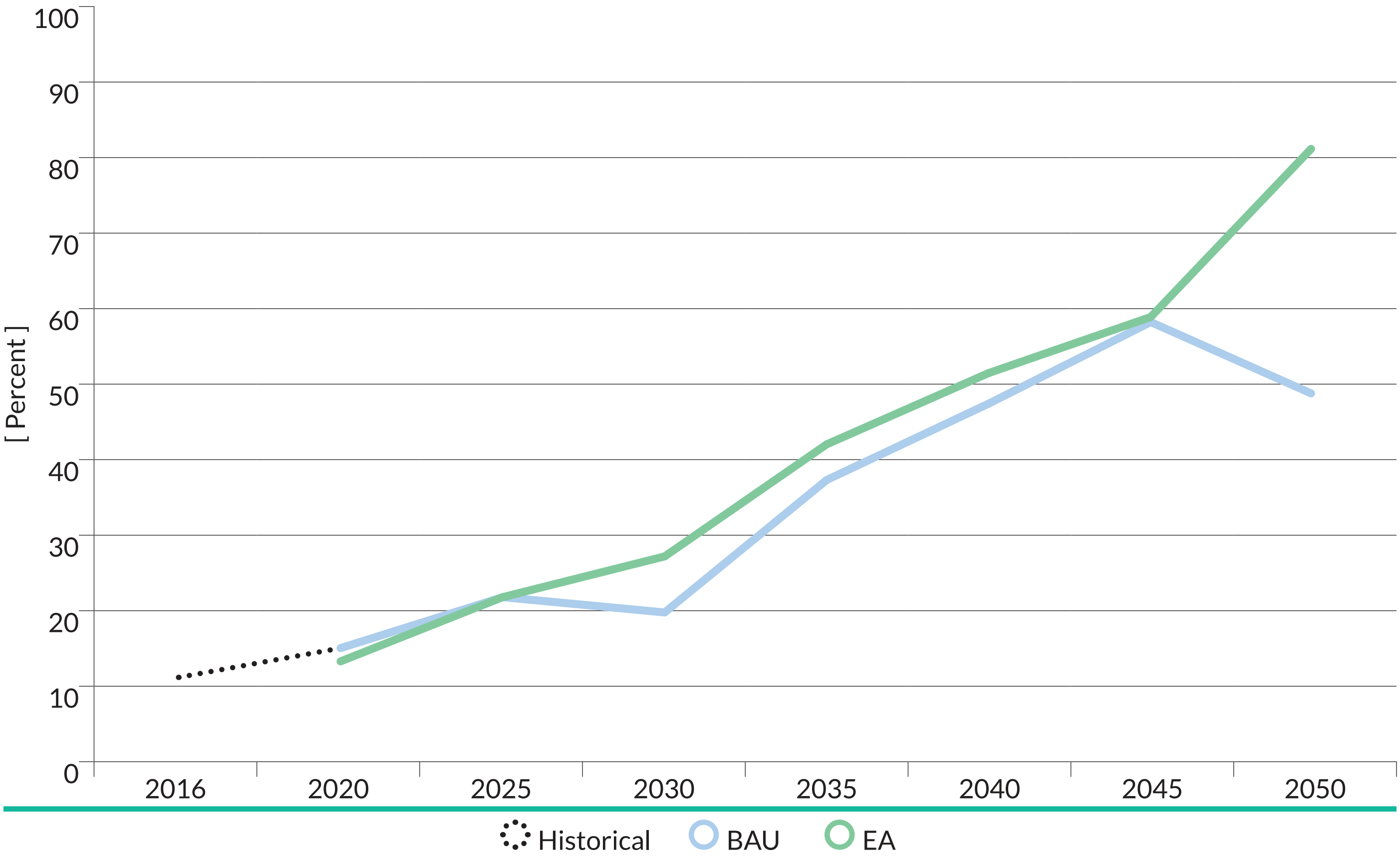
Figure 14. Changes in energy intensity (SDG 7.3.1) in Hungary, 2016-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

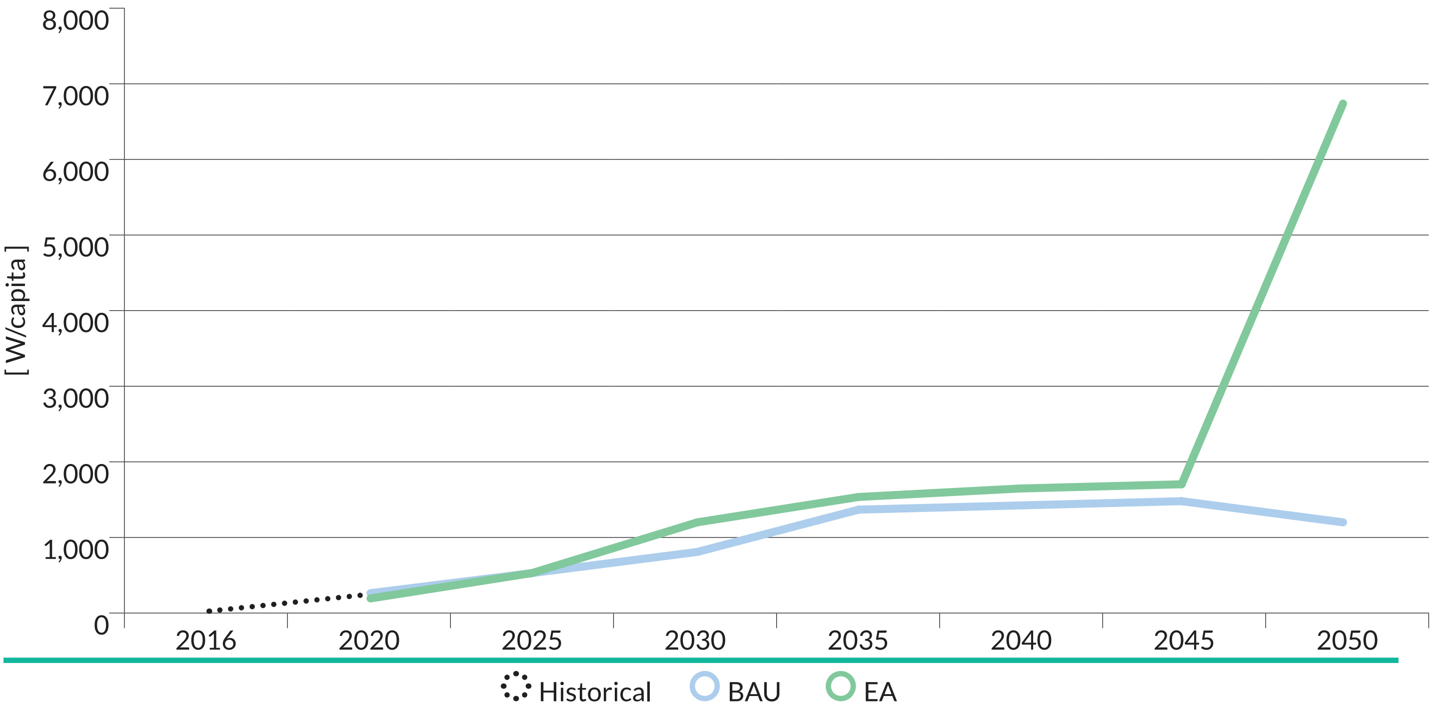
Land requirement for SPV installation (link to SDG 7.2.1) and bioenergy production (link to SDG 2.1.2): The sharp increase in solar capacity between 2045 and 2050 in the EA scenario will impact land requirements for SPVs. In 2050, under the EA scenario, the land occupied by SPVs will represent 1.45 percent of Hungary's total land

Figure 15. Changes in the share of renewables in electricity generation (part of SDG 7.2.1) in Hungary, 2016-2050



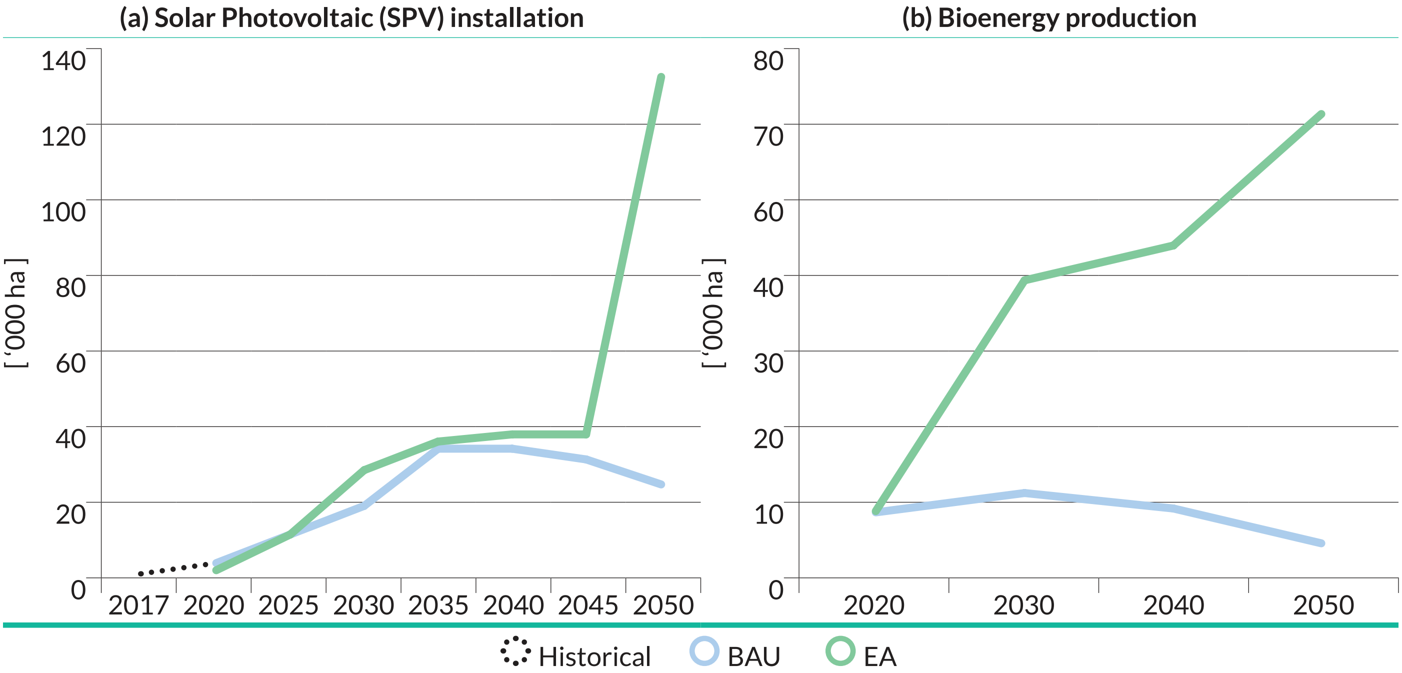
Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

Figure 16. Changes in the installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1) in Hungary, 2016-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

Figure 17. Changes in the land requirements for (a) SPV installation (link to SDG 7.2.1) and (b) bioenergy production (link to SDG 2.1.2) in Hungary, 2017-2050

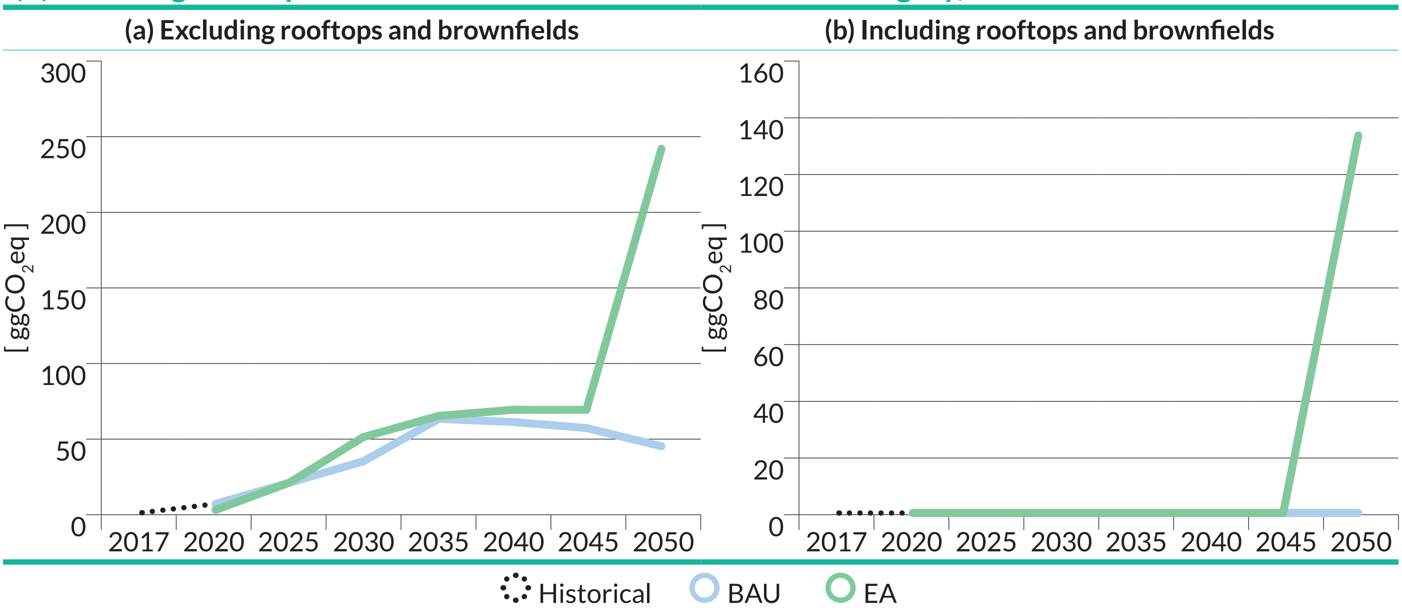


Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

area (Figure 17a). This value falls in the 0.5-5% interval estimated by van den Ven et al.[101] The GGSim results show that improving SDG 7.2.1 renewable energy share in the total final energy consumption would come at a cost, particularly if the land required for installing SPVs will come from forest and/or agricultural lands. The same can be said for bioenergy production when the EA scenario includes increased biofuel demand for the transport sector. Figure 17b shows the land requirement for bioenergy production when crop residues are not used, i.e., when only first-generation biofuels are produced. In the EA scenario, this demand will increase by 600 percent between 2020 and 2050 and represent around 0.8 percent of Hungary's total land area by 2050. This will have an implication on SDG 2.1.2 prevalence of moderate or severe food insecurity in the population due to land conversion from food to bioenergy production.

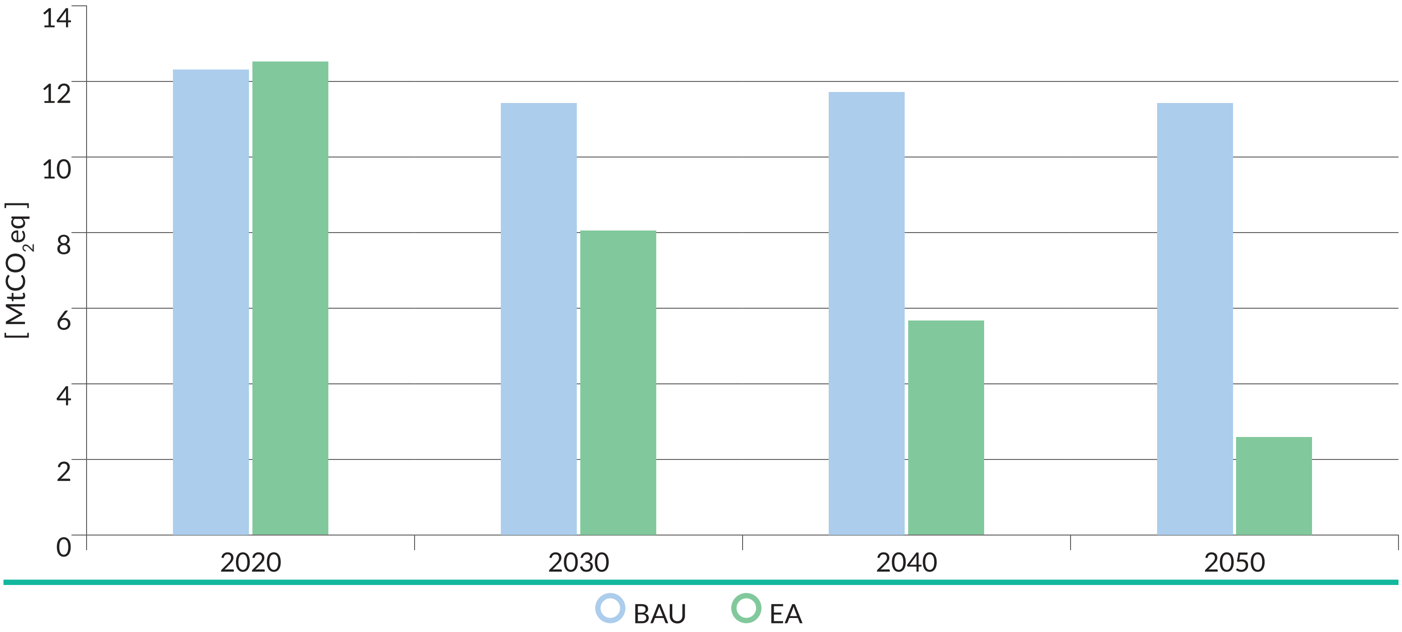
Land use change emissions from SPV installation (part of SDG 13.2.2): Land use change emissions follow the

Figure 18. Changes in land use change emissions from SPV installation (a) excluding and (b) including rooftops and brownfields in the scenarios for Hungary, 2017-2050



Note: BAU Business-as-usual, Early Action (EA)
Source: Authors own.

Figure 19. Changes in GHG emissions from transport activity (part of SDG 13.2.2) in Hungary, 2020-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

same trend in BAU and EA scenarios until 2045, when the solar capacity expansion begins to differ significantly between the two scenarios (Figure 18a). The EA scenario will significantly increase GHG emissions from expanding SPV installation in forest lands. However, when rooftops and brownfields are assumed to be used for SPV installation to reduce pressure on forests (Figure 18b), land use change emissions remain non-existent until the rooftops and brownfields' capacity is reached, and the solar capacity expansion requires forest lands to be used. Rooftop and brownfield capacity estimates for installing solar PV panels are based on Bódis et al.[102] and Dannert and Pirisi[103]. If implemented under the EA scenario, using rooftops and brownfields would save an estimated 1.7 $MtCO_2eq$, equivalent to 83 percent of the emissions from installing SPVs.

Emission levels from transport activity (part of SDG 13.2.2): In the BAU scenario, the transport sector remains dominated by fossil fuels, with only a minimal increase in the number of electric vehicles. Therefore, the emissions in the sector do not show any significant decrease (Figure 19). On the other hand, introducing electric- and biofuel-powered vehicles in the EA scenario will significantly reduce emissions in the sector by nearly 80 percent by 2050. In 2018, the transport sector accounted for 30.6 percent of the total emissions in the energy sector.[104] The GGSim results show that SDG 13.2.2 total greenhouse gas emissions per year will significantly improve from introducing electric vehicles, supported by SPV installation, and using biofuels, supported by bioenergy production, in the EA scenario.

B.2 Agriculture, forest, and land use

In 2018, agriculture accounted for 11 percent of Hungary's GHG emissions and 87 percent of its nitrous oxide emissions. Since 2004, the share of methane emissions has declined in favor of the share of nitrous oxide emissions due to crop production gradually becoming dominant over livestock. Even though the Land Use, Land Use Change, and Forestry (LULUCF) sector has been a GHG sink for a long time, the agricultural output has been more important than the absorption, resulting in net emissions from the AFOLU sector.[105] The EA scenario includes the digitalization and sustainable intensification of the agriculture sector. Expansion of the natural GHG sink capacities is essential to achieve climate neutrality.

Table 8 shows the inputs to the BAU and the EA scenarios of the GGSim AFOLU model. The EA scenario includes changes in food consumption, losses, and waste, a more substantial increase in agricultural productivity, and reforestation and biomass policies. The proportion of manure left on pasture and applied to soil decreases as it is used to produce bioenergy together with crop residues.

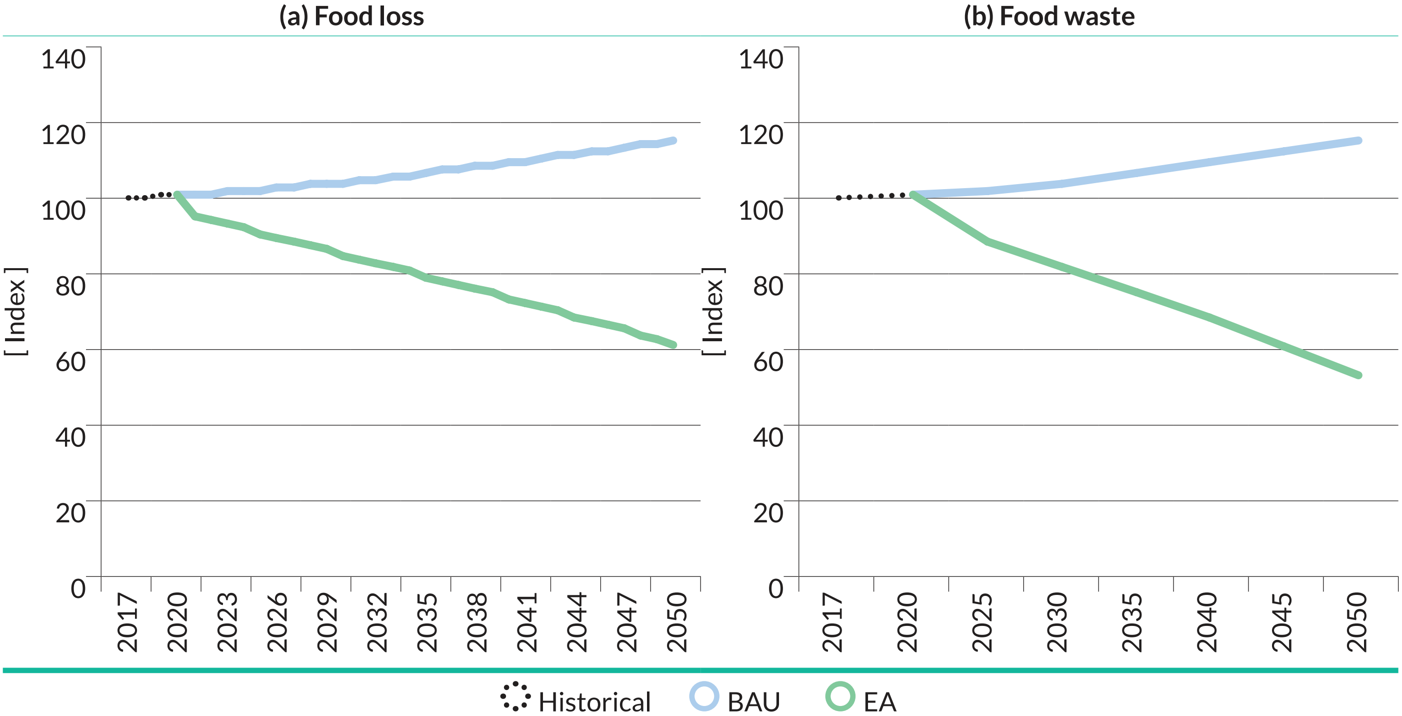
Food loss and waste index (SDG 12.3.1.a and b): According to the National Food Chain Safety Office (NÉBIH), Hungary generates approximately 1.8 million tons of food waste annually (68 kg per capita), of which 50 percent is considered avoidable.[106] Food loss and waste in the supply chain in Hungary are triggered by various factors, including a shortage of field labor for full harvests, inadequate storage and care during transportation, and an excessive emphasis on the visual appearance of food at retail outlets.[107] Without implementing measures reducing food losses and waste, the food loss and waste indices will follow a trend contrary to the desired one, and both food losses and waste will increase by nearly 20 percent by 2050 (Figure 20). The effort made under the EA scenario leads to a declining trend for both indices. However, in 2050, the food losses have only decreased by 40 percent and the food waste by almost 50 percent, while the SDG target is to halve the indices by 2030. This indicates that further efforts will be needed, even under the EA scenario.

Table 8. Scenario assumptions in the GGSim application for Hungary's AFOLU model

Inputs	BAU	EA	Source
Agriculture			
Change in animal-based food consumption [Percent per year]	No increase	-1.5	FAO (2021)
Change in crop-based food consumption [Percent per year]	No increase	+0.75	FAO (2021)
Agricultural productivity	+0.03	+0.2	FAO (2017, 2021)
Decrease in post-harvest food losses [tons per year]	No change	5000	UN (2021)
Decrease in consumer food waste [tons per year]	No change	15000	UN (2021)
Manure left on pastoral land in 2050 [Percent]	80	40	NAP (2013) Historical data
Manure applied to soil in 2050 [Percent]	62	25	FAO (2017, 2021) Historical data
Residues removed from cropland in 2050 [Percent per year]	2	10	FAO (2017, 2021)
Forestry			
Reforestation of fallow agricultural land [Percent per year]	0	1	FAO (2017, 2021)
Change in wood removals for firewood [Percent per year]	No change	-1	FAO (2017, 2021)
Extreme weather events and drought damage on forest biomass	Increasing over the years across all scenarios		

Data source: FAO. (2021). Food and agriculture projections to 2050; UN. (2021). UNEP Food Waste Index Report 2021; NAP (National Adaptation Plan). (2013). Second National Climate Change Strategy (2014-2025); FAO. (2017). FAOSTAT.

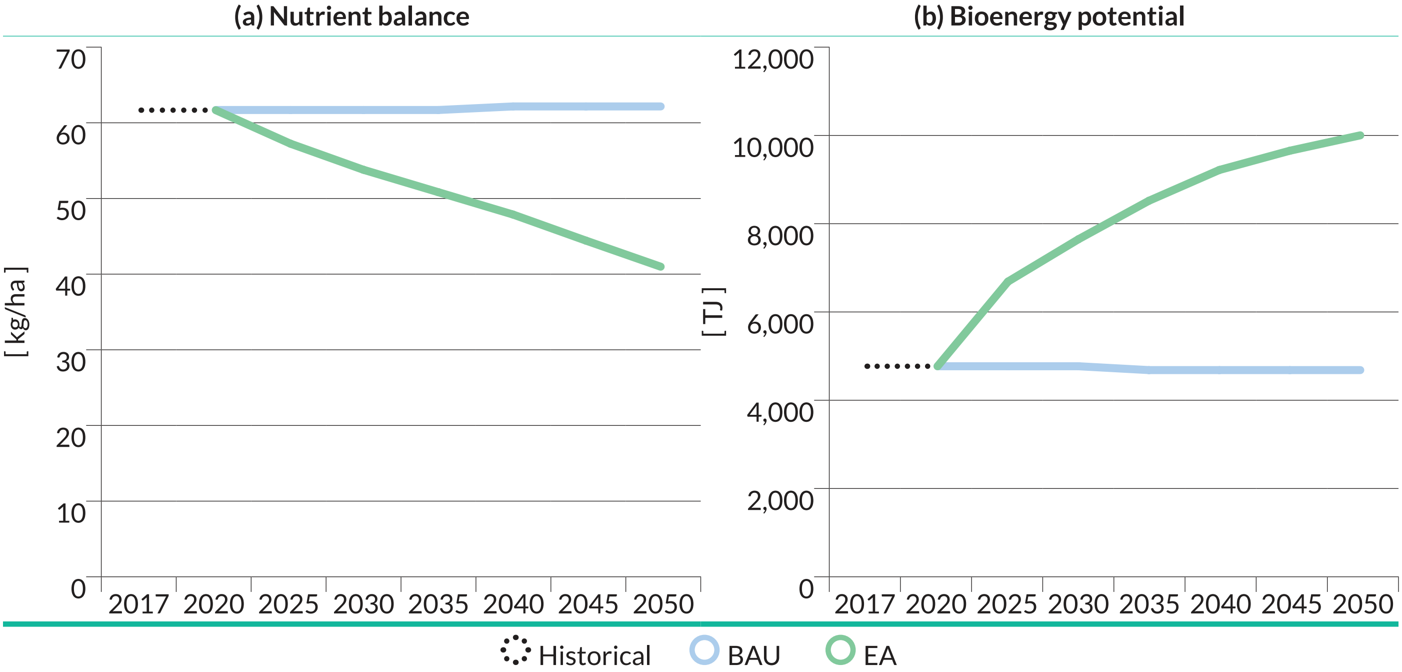
Figure 20. Changes in (a) food loss (SDG 12.3.1a) and (b) food waste (SDG 12.3.1b) index in Hungary, 2017-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

Fertilizer use and nutrient balance (part of SDG 15.3.1): In 2020, fertilizer use and manure applied to soil contributed to around 70 and 14 percent of the nutrient balance inputs, respectively. The increased performance in the nutrient balance indicator in the EA scenario is mainly due to the decrease in fertilizer application and manure applied to soil compared to the BAU scenario (Figure 21a). Reducing nutrient balance to around 5 kg/ha, i.e., which is the sustainability target for this indicator, will improve the soil quality. Moreover, it will have a positive impact on bioenergy potential in Hungary (Figure 21b). By decreasing the amount of manure applied to soil, more manure will be available for biogas production (+112 percent in 2050 compared to 2020). Reducing fertilizer use from manure will thus have positive impacts not only on improving

Figure 21. Changes in (a) nutrient balance (part of SDG 15.3.1) from shifting use of manure to (b) bioenergy production in Hungary, 2017-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

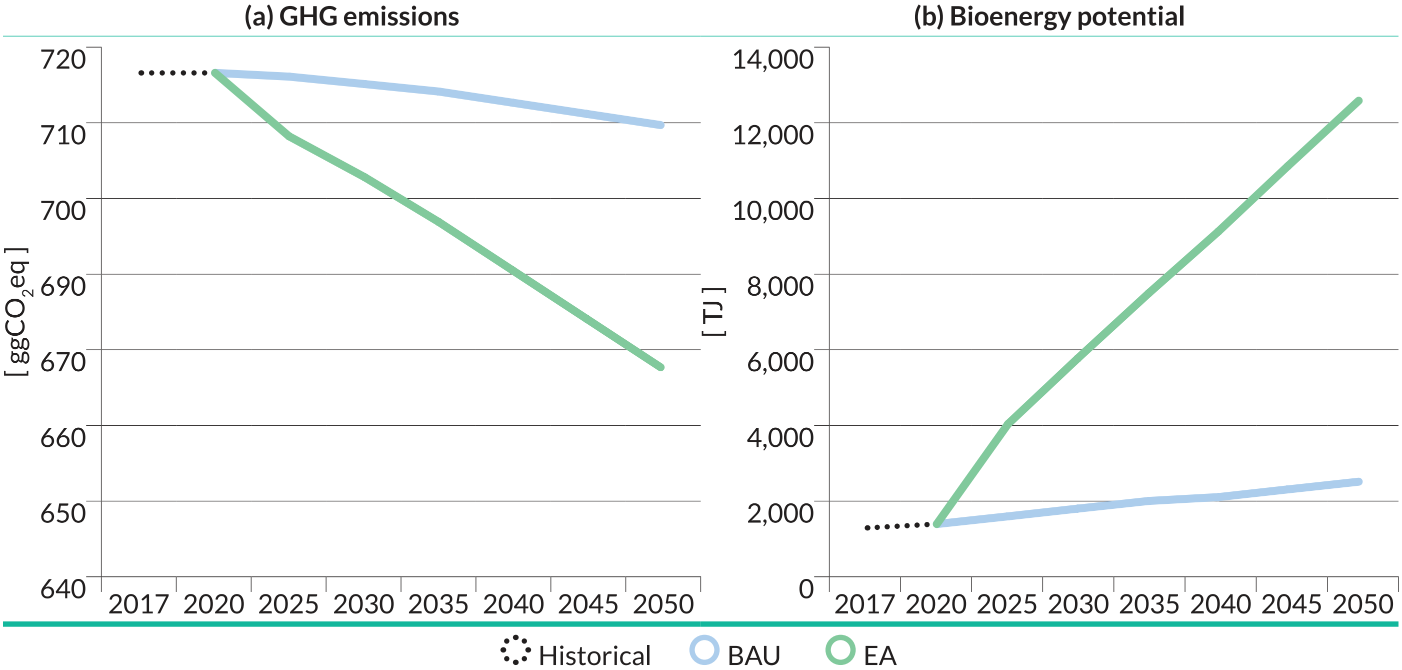
nutrient balance (part of SDG 15.3.1) but also on reducing GHG emissions (SDG 13.2.2) and increasing renewable energy (SDG 7.2.1).

Crop residue emissions (part of SDG 13.2.2) and bioenergy production (link to SDG 7.1.2): While the bioenergy potential from crop residues will remain stable in the BAU scenario, it will increase in the EA scenario by about 896 percent between 2017 and 2050 (Figure 22b). This results from increasing crop residue removal, making the crop residues available for bioenergy production. The slight increase in the bioenergy potential in the BAU scenario is due to the increase in total agricultural production. Consequently, GHG emissions from crop residues will decrease since the residues used for bioenergy production will not be burnt on the farm. By 2050, the total bioenergy potential from manure management (Figure 21b) and crop residues (Figure 22b) will amount to 22.6 PJ in the EA scenario. Manure and crop residues are considered second-generation bioenergy. Using them instead of first-generation biofuels would allow for saving around 57,000 ha, equivalent to 81 percent of the land requirement for first-generation biofuels that year (Figure 17b). However, removing all crop residues will have an impact on soil fertility, decreasing nutrient balance that contributes to SDG 15.3.1 proportion of land that is degraded over total land area. There are, thus, some trade-offs between improving nutrient balance (Figure 21a) and reducing GHG emissions (Figure 22a) when it comes to crop residues.

Above-ground biomass in forest (SDG 15.2.1): Above-ground biomass increases in both scenarios, only slightly more in the EA scenario, due to policies on wood removals and changes in forest areas (Figure 23). In the BAU scenario, industrial wood removals are responsible for 35 percent, fuelwood removals for 36 percent, and disturbances for 29 percent of the annual carbon losses throughout the whole period. In the EA scenario, policies lead to a decrease in annual industrial and fuelwood removals of 27 percent by 2050 compared to 2020. Then in 2050, disturbances become the main cause of carbon losses, with shares of 32 percent for industrial wood removals, 28 percent for fuelwood removals, and 40 percent for disturbances. As for biomass growth, the annual increase will remain constant in the BAU scenario, while it will gradually rise in the EA scenario, getting two times bigger than in the BAU scenario by 2050. This will result in a net annual change of 80 percent, which will be more significant in the EA scenario than in the BAU scenario. This difference is attenuated when dividing above-ground biomass by the total forest area.

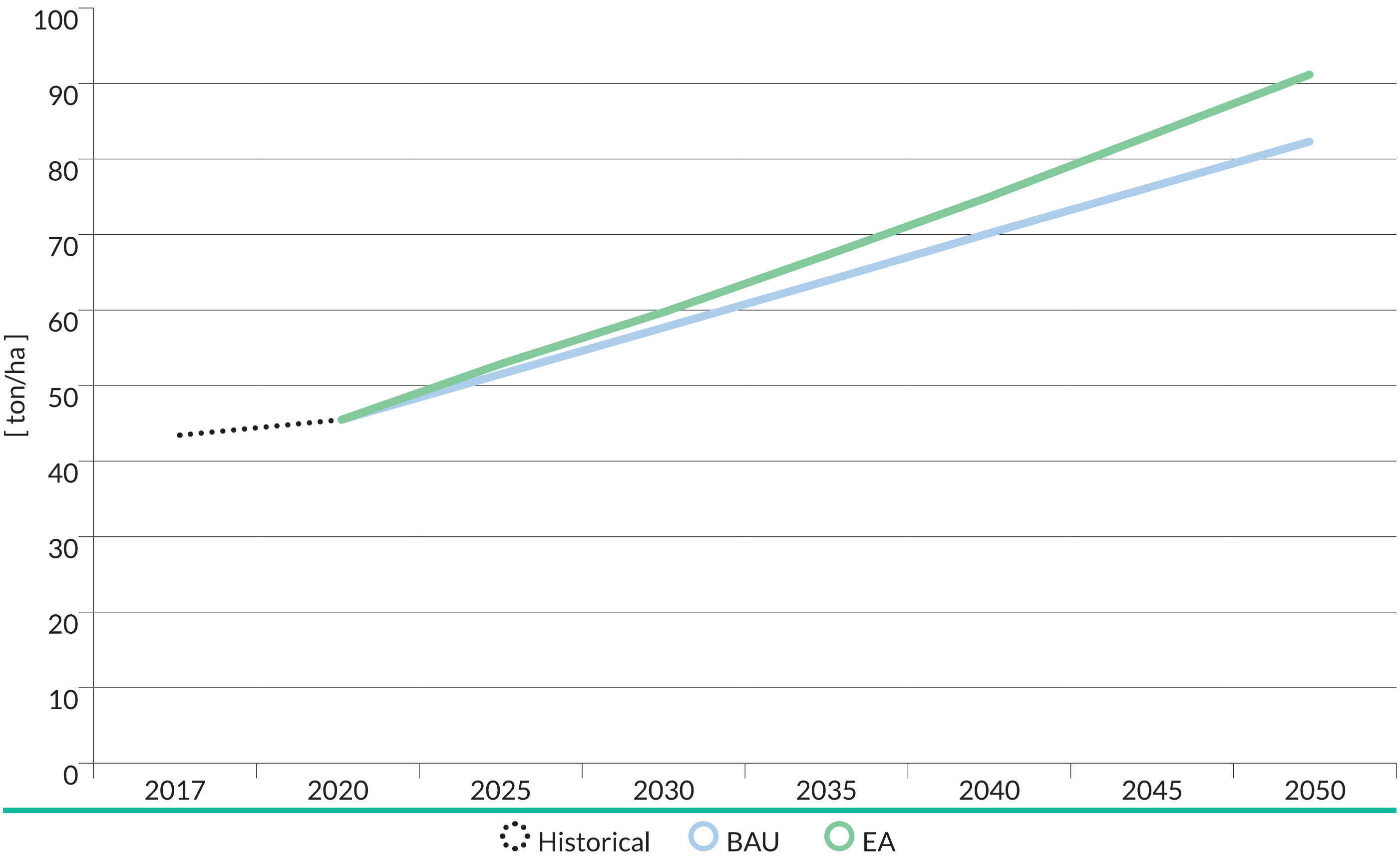
Share of forest area to total land area (SDG 15.1.1): Agricultural expansion and timber harvesting (fuelwood) are two of the key reasons for deforestation in Hungary.[108] To mitigate the impacts of climate change, the Hungarian Government implemented policies such as the National Forest Strategy, aiming to increase forest cover to 30 percent by 2030 through afforestation, conservation, and sustainable forest management practices.[109] The BAU scenario assumes no further deforestation nor reforestation, causing the share of forest area to remain constant throughout the whole period (Figure 24). On the other hand, the EA scenario implements a rate of reforestation of inactive land of one percent per year. The increasing rate of reforestation is also due to increased agricultural productivity, which will decrease the area of land required for crops. Measures on food losses and waste will also help further decrease the cropland demand.

Figure 22. Changes in (a) GHG emissions (part of SDG 15.3.1) from shifting use of crop residues to bioenergy production in Hungary, 2017-2050



Note: BAU Business-as-usual, Early Action (EA)
Source: Authors own.

Figure 23. Changes in above-ground biomass in the forest (SDG 15.2.1) in Hungary, 2017-2050

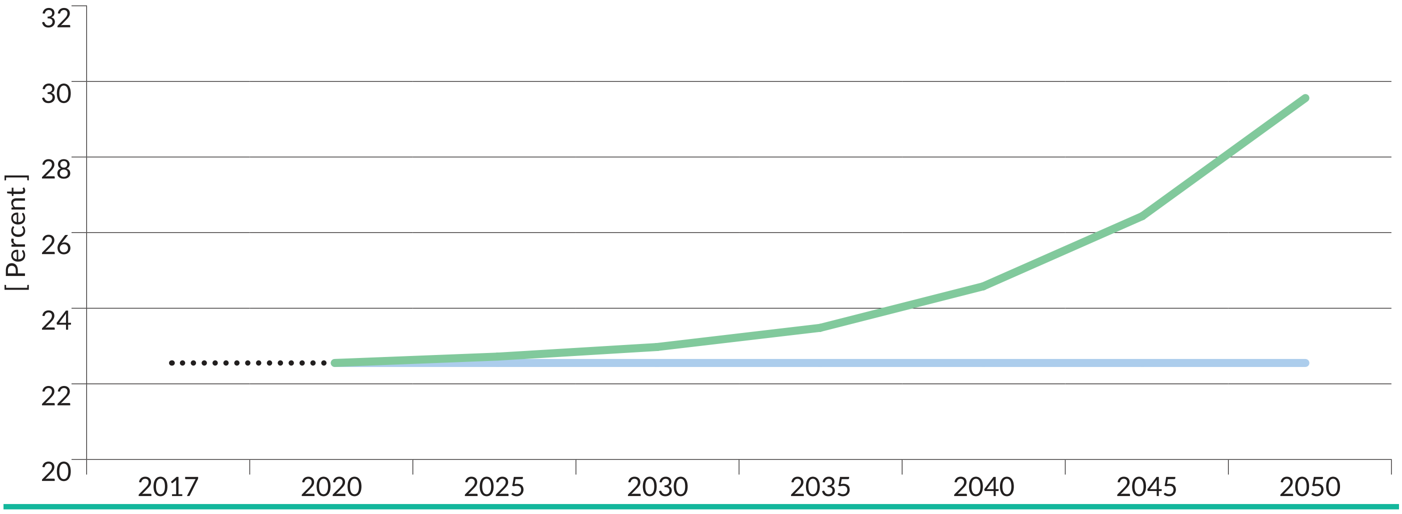


Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

The total forest area will change in the EA, but this will not affect the above-ground biomass by much, as it is not linked to the area. Forest biomass naturally generates, which causes above ground-ground to increase over time, even in the BAU scenario (Figure 23).

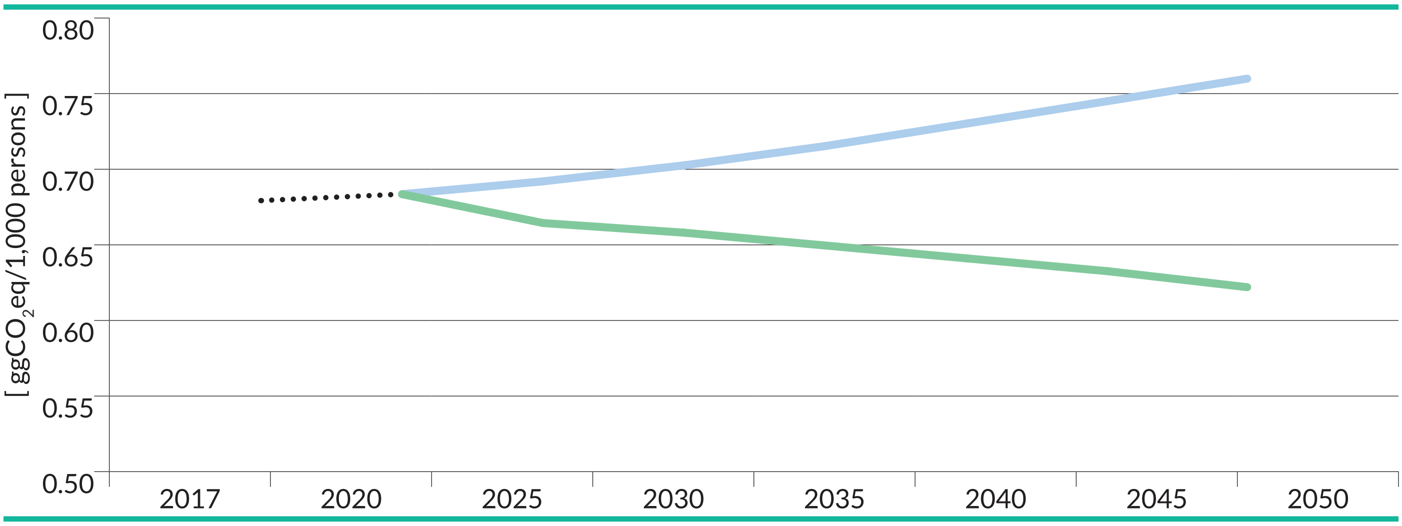
Non-CO_2 emissions in agriculture (SDG 13.3.2): Historically, Hungary's agricultural non-CO_2 emissions have increased over time; for example, Methane (CH4) emissions went up from 2.40 MT CO_2e in 2010 to 2.55 MT CO_2e in 2020. Nitrous oxide (N_2O) also went up from 4.60 MT

Figure 24. Changes in the share of forest area to total land area (SDG 15.1.1) in Hungary, 2017-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

Figure 25. Changes in non-CO_2 emissions in agriculture (part of SDG 13.2.2) in Hungary, 2017-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

CO_2e in 2010 to 5.86 MT CO_2e.[110] The ratio of non-CO_2 emissions in agriculture to population evolves almost symmetrically, opposite to the EA scenario compared to the BAU scenario (Figure 25). From 2017 to 2050, enteric fermentation and fertilizer use are the main contributors, together accounting for around two-thirds of the emissions from the sector in both scenarios. However, the combined set of model drivers and policies on manure use and removal of crop residues (link to SDG 2.4.1), reforestation (SDG 15.1.1), and food waste and loss reduction (SDG 12.3.1.a and b) lead to lower emissions in the agricultural sector under the EA scenario. This shows that improving performance in different SDGs could improve performance in another.

B.3 Water use and waste

The scenarios' assumptions consider the three subsectors of the water use and waste model: agricultural, industrial, and municipal water. The agricultural sector considers the evolution of the shares of irrigation technologies, i.e., sprinkler and surface irrigation shares decrease while drip irrigation takes more importance (projection from the FAO). The electricity generation mix is the main driver of change in the industrial sector. It is assumed that cooling systems are held constant relative to base year values for each scenario. For municipal water, water pricing and GDP per capita differ between scenarios. For sanitation and wastewater, the EA scenario considers measures

Table 9. Scenario assumptions in the GGSim application for Hungary's water use and waste model

	2017	BAU 2050	EA 2050	Source/basis of assumption
Economic				
Water price [$/15m³]	2.89	No increase	+2.5%/y	World Bank (2015)
Industry				
Total power generation capacity [GW]	6*	13	66.5	MIT (2021)
Irrigation				
Surface irrigation [Percent]	13.4	13.4	5	Expert Judgement
Sprinkler irrigation [Percent]	83.7	83.7	65	Expert Judgement
Drip irrigation [Percent]	2.8	2.8	30	Expert Judgement
Sanitation				
Population connected to sewage network [Percent]	81.91	84.42	85.88	WHO & UNICEF (2021)
Population with septic tanks [Percent]	17.34	15.05	13.72	WHO & UNICEF (2021)
Population with wastewater treatment [Percent]	79.0	79.0	87.0	Expert Judgment
Resources				
Freshwater availability [km³/y]	104	100.6	103.9	FAO (2021)

Data source: World Bank (2015). Water and wastewater services in the Danube region – Hungary country note; Ministry for Innovation and Technology (MIT). (2021). National Clean Development Strategy 2020 - 2050. WHO & UNICEF (2021); FAO (2021). AQUASTAT Core Database.
Note: : *Value refers to 2016

leading to more population connected to sewage networks and wastewater treatment than in the BAU scenario. Total freshwater availability will decrease by 3.3 percent by 2050 in the BAU scenario, while it does not decrease significantly in the EA scenario. These projections come from FAO's Global Perspective Studies[111]. To account for climate change, the BAU scenario uses the *Representative Concentration Pathway* (RCP) 4.5, and the EA scenario uses the RCP2.6. Table 9 summarizes the assumptions for Hungary's water use and waste model application.

Water use efficiency (SDG 6.4.1) and water withdrawals (part of SDG 6.4.2): Total water withdrawals will decrease overall in both scenarios by 2050, even though agricultural and municipal withdrawals will increase (Figure 26b-d). This is due to the industry share in the total water withdrawals, accounting for 82 percent of the base year, 70 percent of the BAU scenario, and 73 percent of the EA scenario in 2050 of the total withdrawals. The industry will drive the overall decrease in water withdrawals in 2050. This sector will also be responsible for a significant increase in 2030 due to increased nuclear capacity. Nuclear electricity generation will be the main contributor to industrial water withdrawals and total water withdrawals, accounting for 72 percent of the country's total water withdrawal in 2050 under the EA scenario. This will also cause the industrial water use efficiency to decrease between 2020 and 2030, resulting in a lower total water use efficiency in 2030 (Figure 26a). However, water use efficiency will start to increase afterward and eventually reach, by 2050, a value 88 percent higher than in the base year for the BAU scenario and 142 percent higher for the EA scenario. This rising trend will be due to the increased share of municipal water withdrawals occurring when industrial water withdrawals fall back after the 2030 increase. The municipal sector has indeed the highest sectoral water use efficiency (183$/m³ in 2050, compared to 32 and 0.55 $/m³ for the industrial and agricultural sectors, respectively).

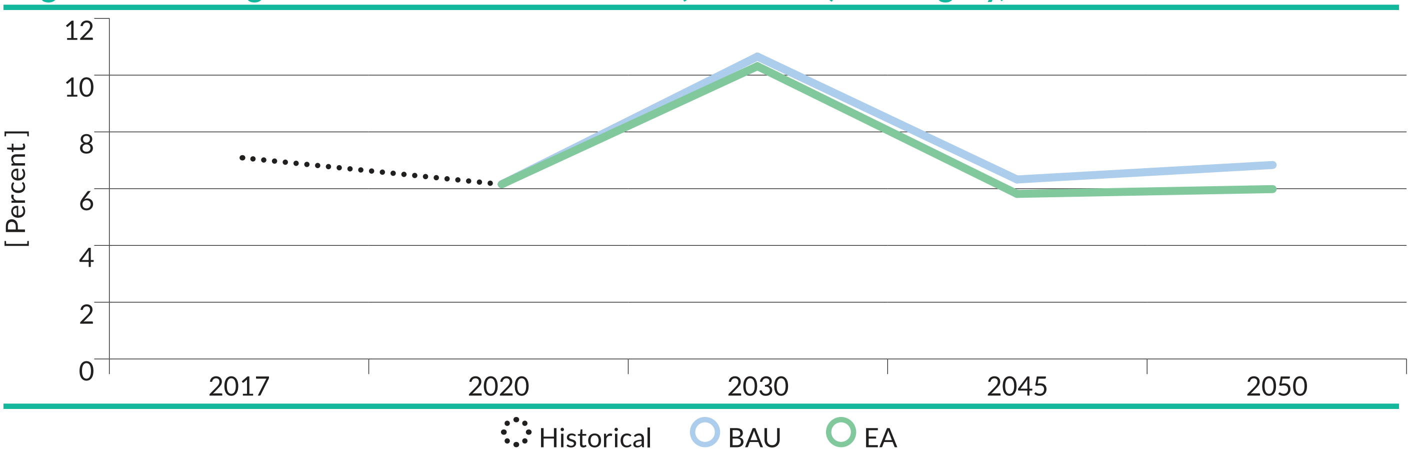
Level of water stress (SDG 6.4.2): Water withdrawals directly affect the level of water stress, particularly if available freshwater resources are scarce. Hungary will remain having a low level of water stress under BAU and EA scenarios. Still, a peak will be observed in 2030 due to the temporary increase in nuclear capacity (Figure 27). As mentioned above, the industry dominates water withdrawal in Hungary, accounting for more than 70 percent of the country's total water withdrawals, which is assumed to hold in the BAU and EA scenarios. Nuclear electricity generation is part of the industry sector. After 2030, the level of water stress will decrease to its initial levels. The slight increase between 2040 and 2050 will be brought about by the fast increase in electricity generation during the same period, with biomass and solar generation mainly contributing to this positive change.

Treated wastewater (part of SDG 6.3.1): Under the EA scenario, connection to tertiary wastewater treatment will be improved, and help gradually to increase performance in the share of treated wastewater from 80 percent in 2017 to about 88 percent in 2050 (Figure 28). The main driver for this change is urbanization. In 2022, around 63.71 percent of rural populations had access to sewage facilities, as compared to 91.67 percent of urban households. Thus, the remaining 36.29 percent of the rural population relies more on septic tanks.[112] While the percentage of the rural population with access to sewage networks does not change over time, the percentage of the urban population does increase, which is more significant in the EA scenario than in the BAU scenario. The improvement in SDG 6.3.1 will thus need to be assessed on the equality of access between urban and rural areas, which is an indicator of social inclusion.

Figure 26. Changes in (a) water use efficiency (SDG 6.4.1) and (b-d) sectoral water withdrawals (part of SDG 6.4.2) in Hungary, 2017-2050

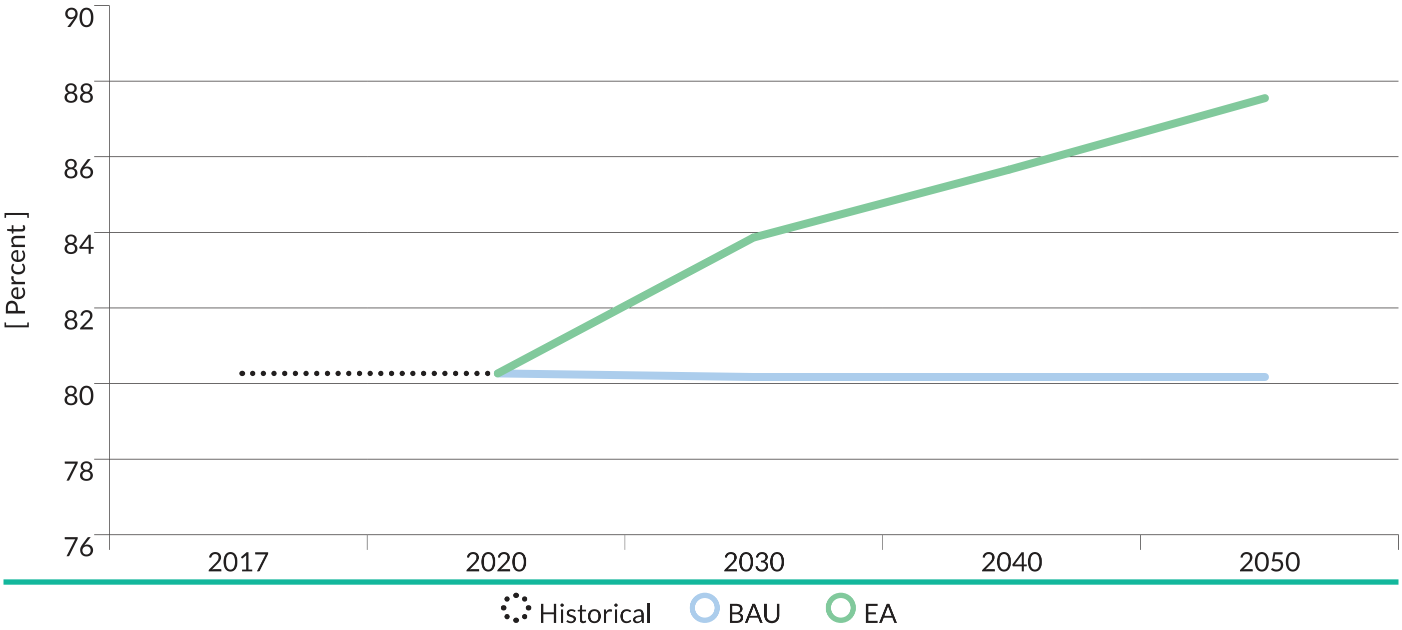
Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

Figure 27. Changes in the level of water stress (SDG 6.4.2) in Hungary, 2017-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

Figure 28. Changes in the share of treated wastewater (part of SDG 6.3.1) from the municipal sector in Hungary, 2017-2050



Scenarios: BAU - Business-as-usual, EA - Early Action
Source: Authors own.

4.1.2 Burkina Faso

A. Overview of scenarios

Burkina Faso is a landlocked country in West Africa, 274,200 km2 wide, and home to 22,489,126 people.[113] It is divided into three climatic zones with different durations of the rainy season: the Sahelian zone (3-4 months), the Sudano-Sahelian zone (4-5 months), and the Sudanian zone (5-6 months). Three-quarters of the population lives in rural areas, and more than 45 percent of the urban population lives in the capital, Ouagadougou. In 2018, 41.4% of the population lived under the national poverty line, and only one in five households had access to electricity.[114]

GGGI collaborated with the Government of Burkina Faso and the French Development Agency (AFD) to prepare the country's LT-LEDS, referred to as Burkina Faso's 2050 Low-carbon and Climate-resilient Development Vision. The BAU scenario was elaborated using different models, including the Ex-ACT model from the FAO[115] and the IPCC Waste model.[116] It includes the energy, transport, agriculture and other land use, waste, industrial processes, and product use sectors. A series of adaptation and mitigation measures were considered in consultation with the national experts. Finally, the Green Economic Model (GEM) was applied to derive three scenarios depending on the level of ambition implemented:

- The High Ambition (HA) scenario implements ambitious measures as early as 2022, allowing the country to reach carbon neutrality in 2045 and be a net carbon sink by 2050.
- The Moderate Ambition (MA) scenario implements slightly lower ambitious efforts than the HA scenario, allowing the country to reach carbon neutrality in 2047.
- The Low Ambition (LA) scenario implements most measures after 2030 to focus on the country's socio-economic development before decarbonization efforts are implemented.

The GEM results provided the scenario inputs necessary to align the GGSim application with the overall assumptions in Burkina Faso's LT-LEDS. Other data inputs to the GGSim models were taken from national data sources. In case not available, data inputs were drawn from international sources and shared with the national experts for validation.

B. GGSim model applications

This section presents the results of the GGSim applications for the following models – energy and transport, AFOLU, and water use and waste (Tables 4-6).The applications were based on the AFD-funded LT-LEDS project for Burkina Faso conducted from 2022 to 2023. The adaptation assessment in the Burkina Faso LT-LEDS mainly applied qualitative assessment. For this reason, the SDG co-benefits assessment using the GGSim focused mainly on the mitigation scenarios and measures with available quantitative data for the simulation.

B.1 Energy

In 2015, the energy sector accounted for 6.1 percent of the total GHG emissions,[117] significantly lower than the world average of around 75 percent[118]. However, the sector's emissions are expected to grow eight times in 2050. The primary energy source is biomass, accounting for about two-thirds of the national energy consumption, with domestic and imported fossil fuels mainly supplying electricity generation.[119] The climate mitigation measures implemented in the three alternative scenarios for the GGSim application are the increase in the share of renewable energy sources, improved access to electricity, and the increase in energy efficiency, particularly for households with alternative fuels for cooking.

The scenario assumptions in Table 10 present the power capacities for electricity generation, the total electricity generation, and the real GDP. Fossil fuel capacities increase in the BAU scenario but also in the alternative scenarios, although the increase is less significant in the latter. Solar capacities witness the most substantial increase, while hydropower capacities slightly decline, and biomass capacities do not reach significant levels. Total electricity generation is multiplied by 7 in the BAU, 18 in the HA, 15 in the MA, and 14 in the LA scenarios. According to the GEM results, the transition to a low-emission economy will positively impact GDP by 2050, it will be higher by 21 percent in the HA, 15 percent in the MA, and 13 percent in the LA scenarios compared with the BAU scenario.

Energy Intensity (SDG 7.3.1): The energy intensity per unit GDP has decreased slightly over the past decade, showing additional decoupling between economic growth and energy consumption since 2010, albeit minimal minimal (Figure 29). The decreasing energy intensity can be attributed to several factors, for example in terms of policy, Burkina Faso has several policies which aim to promote energy efficiency such as the Strategy for Accelerated Growth and Sustainable Development (SCADD 2011-2015) and the Energy Sector Policy 2014-2025.[120] In addition, the gradual shift towards solar, hydro, and other renewable sources also decreased the use for energy-intensive sources like fossil fuels and biomass.[121] The country's GDP growth since 2010 also implies that the country is producing more goods and services in relation to the energy used in the economy.[122] All scenarios, including the BAU, project a more abrupt decline from 2020 onwards. The implemented energy efficiency measures and the increase in GDP under the low emissions scenarios allow a slightly better performance. Burkina Faso will thus continue improving energy intensity performance for all scenarios, including BAU.

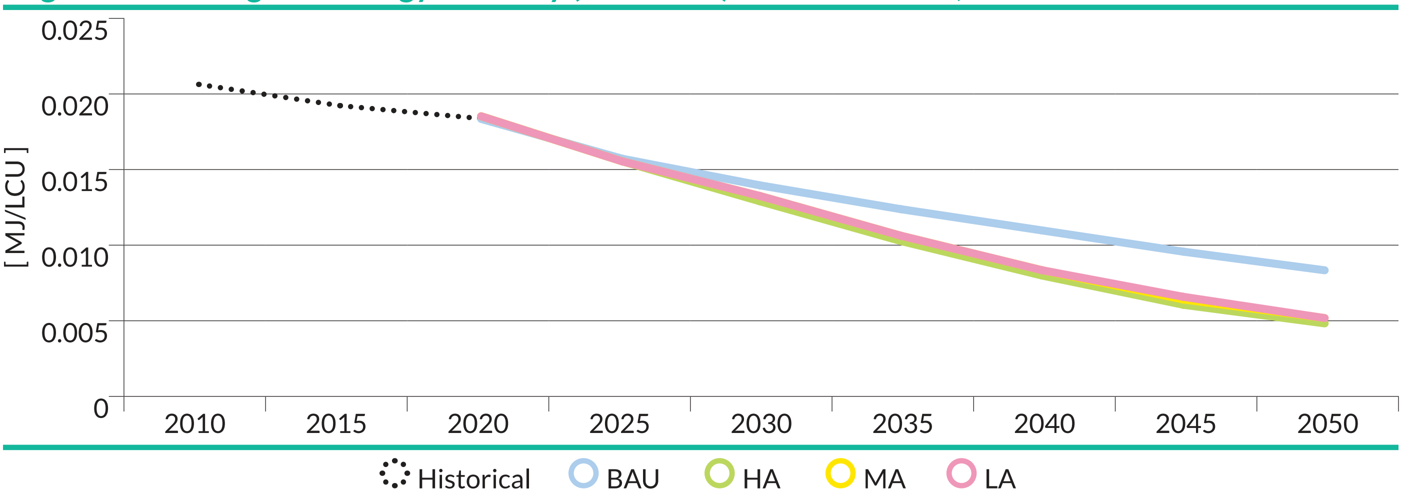
Share of renewables in electricity generation (part of SDG 7.2.1): The electrification of Burkina Faso's energy system will require essential investments in renewable electricity sources. In 2017, the electricity mix was 86 percent oil, 12 percent hydro, and 2 percent solar. Table 11 presents the electricity mix in 2050 for the different scenarios. In the alternative scenarios, the share of oil will decline significantly and reach 7 percent in the most ambitious scenario. By 2050, hydropower will only

Table 10. Scenario assumptions in the GGSim application for Burkina Faso's energy model

Inputs	2017	BAU 2050	HA 2050	MA 2050	LA 2050	Source
Power capacities [MW]						LT-LEDS
Diesel and oil	592	2069	843	1276	1746	
Solar	28	229	6672	5309	4317	
Hydro	56	177	78	62	50	
Biomass	0	0	16	13	11	
Electricity demand						LT-LEDS
Total electricity generation (+ imports) [GWh]	1,380	9,151	24,361	20,444	18,983	
GDP [B FCFA]						LT-LEDS
Real GDP	-	41,220	49,930	47,569	46,570	

Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Data source: Burkina Faso's 2050 Low-Carbon and Climate-Resilient Development Vision, 2022; National databases used for the LT-LEDS.

Figure 29. Changes in energy intensity (SDG 7.3.1) in Burkina Faso, 2010-2050



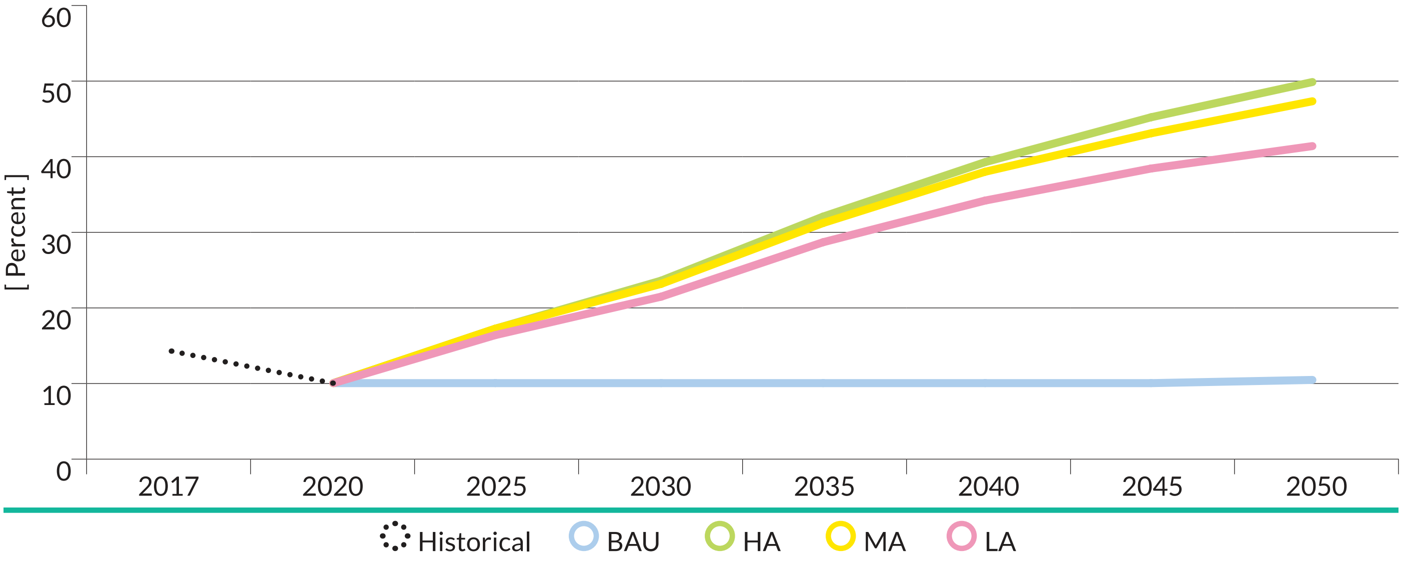
Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

Table 11. Electricity mix in Burkina Faso in 2050, percent.

	BAU 2050	HA 2050	MA 2050	LA 2050
Oil	45	7	12	18
Hydro	6	1	1	1
Solar	4	49	46	40
Imports	45	43	40	40

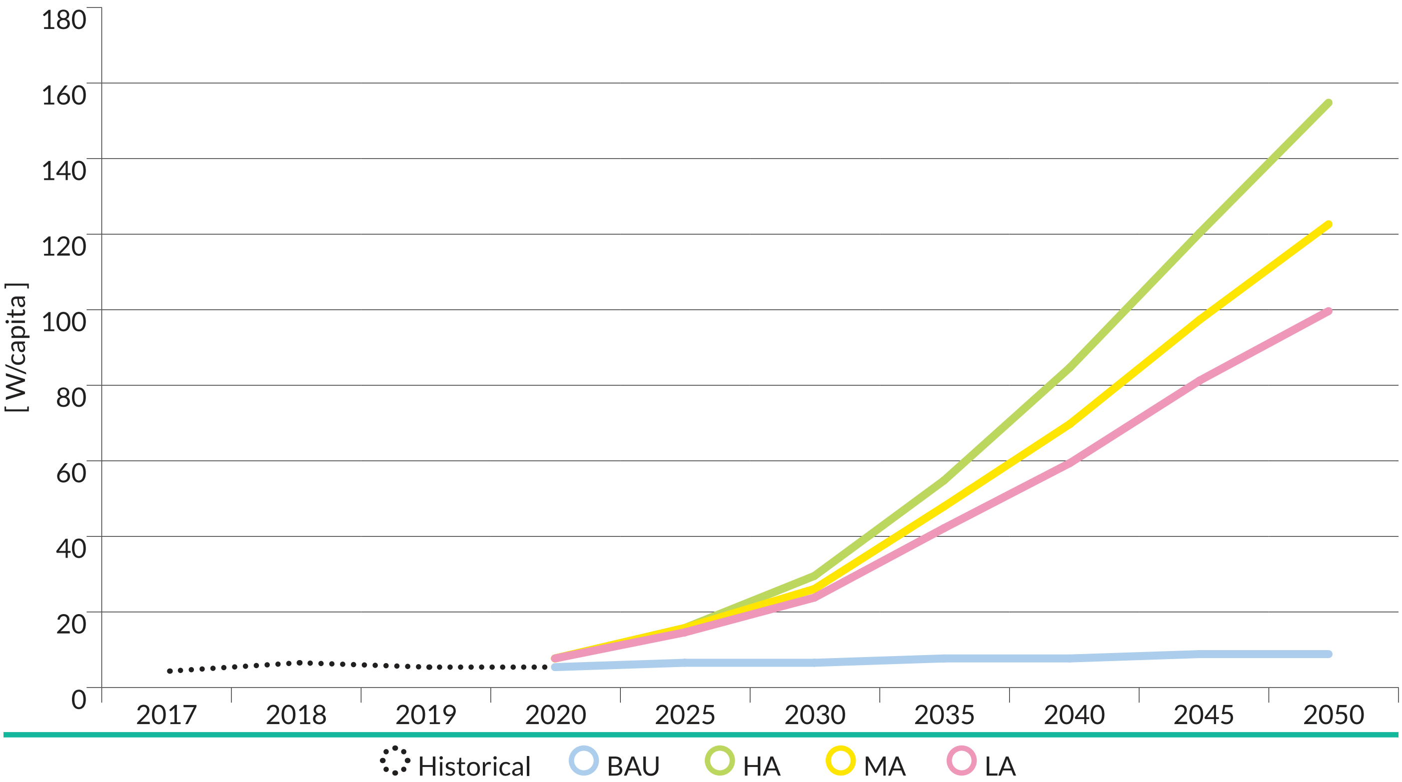
Data source: Burkina Faso's 2050 Low-Carbon and Climate-Resilient Development Vision, 2022

Figure 30. Changes in the share of renewables in electricity generation (part of SDG 7.2.1) in Burkina Faso, 2010-2050



Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

Figure 31. Changes in the installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1) in Burkina Faso, 2016-2050



Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

account for one percent of the mix, while solar generation will expand between 40 and 49 percent. Imports will become the second electricity source, which could alter the country's energy security. On the contrary, the BAU scenario still relies heavily on fossil fuels and does not significantly expand solar capacities. Fossil fuel shares in the mix will decrease, but in favor of imports, assumed to be non-renewable. Despite the significant expansion of renewable electricity capacities and the progress compared to the BAU scenario, the share of renewables in electricity generation will not exceed 50 percent under the alternative scenarios (Figure 30).

Installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1): Performance in the installed renewable capacity has been low in Burkina Faso because, as previously mentioned, electricity generation mostly relies on fossil fuel capacities (86 percent of the total electricity mix). Moreover, only 21 percent of the population had access to electricity in 2020, "making Burkina Faso one of the world's least-electrified countries".[123] The combined factors of low generation capacity and low share of renewables in the electricity sector contribute to very low installed renewable energy capacity per capita, less than 10 Watts per capita from 2017 to 2020 (Figure 31). This will not significantly improve in the BAU scenario due to further development of the fossil fuel capacities and low development of the renewable capacities. On the contrary, the remarkable increase in solar capacities in the NZE scenarios (Table 10) will allow the installed renewable energy capacity per capita to significantly increase in 20050, 100 Watts per capita in the LA scenario, over 120 Watts per capita in the MA scenario, and almost 160 Watts per capita in the HA scenario (Figure 31).

B.2 Agriculture, forest, and land use

The AFOLU sector is the country's most emitting sector, accounting for about 90 percent of the country's total emissions.[124] The country indeed relies heavily on biomass for energy but also on agriculture, employing 73 percent of the workforce in 2021.[125] Moreover, agriculture productivity is limited by the size of the exploitations. The emissions mainly come from deforestation and livestock, and their increase is driven by population economic growth and urbanization.[126] The LT-LEDS plans to create a significant GHG sink out of the forestry subsector. In contrast, due to the emissions from livestock, the agriculture and livestock subsector will not be able to reach carbon neutrality on its own. However, the overall balance will result in net absorptions from the AFOLU sector.

Measures include developing sustainable land management and climate-smart agriculture, sustainable animal production methods, protecting the forest and wildlife resources, and strengthening the AFOLU sector's climate

Table 12. Scenario assumptions in the GGSim application for Burkina Faso's AFOLU model

Input variables	BAU 2050	HA 2050	MA 2050	LA 2050	Source/basis of assumption
Agriculture					
Baseline household food waste per capita [kg/y]	103	103	103	103	UNEP (2021)
Change in animal demand [%]	64.3	104.9	104.9	104.9	GEM model
Livestock substitution [%]	0	-65	-57	-57	Expert judgment
Change in crop demand [%]	41.7	62.5	62.5	62.5	GEM model
Change in crop yields [%]	44.1	59.9	59.9	54.0	GEM model
Change in fertilizer use [%]	-10.3	-83.0	-83.0	-57.7	GEM model
Fraction cropland area burnt [-]	0.1	0.1	0.1	0.1	IPCC, 2006
Annual food waste reduction [kg/capita/y] (value in 2050)	0	85	55	55	BAU: historical trend. Scenarios: Based on the SDG target of 50% reduction of food waste
Annual food loss reduction [t/y]	0	10,000	5,000	10,000 (from 2035 onwards)	BAU: historical trend. Scenarios: Based on the SDG target of 50% reduction of food waste
Atmospheric nitrogen deposition [kg]	10926.2	10926.2	10926.2	10926.2	FAOSTAT (2022)
Forestry					
net above-ground biomass growth in natural forests [t dm/ha]	2.39	2.39	2.39	2.39	FRA (2020)
Fuel wood removals [1000 m^3 / y]	14029882	14029882	14029882	14029882	FAOSTAT (2022)
Industrial roundwood removals [1000 m^3 / y]	1171000	1171000	1171000	1171000	FAOSTAT (2022)

Table 12. Scenario assumptions in the GGSim application for Burkina Faso's AFOLU model *(continued)*

Input variables	BAU 2050	HA 2050	MA 2050	LA 2050	Source/basis of assumption
Deforestation rate [ha/y]	0.745 [%/y]	37,553 (averaged)	37,553 (averaged)	37,553 (averaged)	GEM model
Reforestation rate [ha/y]	0	76,223 (averaged)	76,223 (averaged)	43,158 (averaged from 2030 onwards)	GEM model
Reforestation rate of inactive land [%/y]	0.1895	0.1895	0.1895	0.1895	GEM model

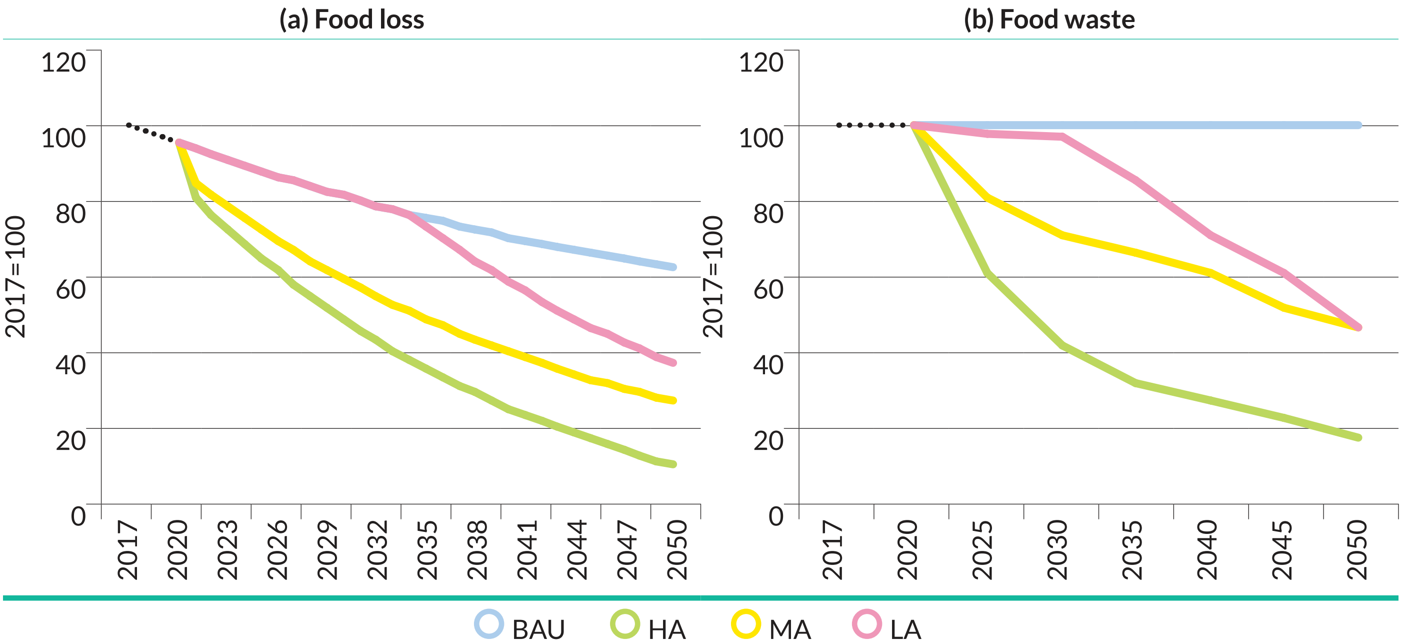
Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Data source: UNEP. (2021). Food Waste Index Report 2021; IPCC. (2006). 2006 IPCC Guidelines for National Greenhouse Gas Inventories; FAOSTAT. (2022). Food and Agriculture Organization Corporate Statistical Database. FRA. (2020). Global Forest Resources Assessment 2020.

resilience.[127] Table 12 presents the assumptions for the agriculture and forestry subsectors.

Food waste and loss index (SDG 12.3.1.a and b): Around 20 percent of the Burkinabè population is estimated to be food insecure.[128] Food insecurity due to the poor development of the agricultural sector is worsened by climate change and the current violence the country is facing.[129] The BAU scenario does not include measures to prevent food waste and losses, yet the food loss index decreases (Figure 32). The reason for this is the increasing population, while the total amount of food lost remains constant. This result, however, does not permit the index to be halved before the end of 2050. The HA scenario performs best in achieving the SDG target of around 50 percent reduction in food loss by 2030. There is no improvement in the BAU scenario for the food waste index as the food waste per capita remains constant. The LA scenario performs worse, but even if the MA scenario addresses the issue sooner and performs better throughout the period, both scenarios end up at the same point in 2050. As for the food waste index, only the HA scenario achieves the SDG target by around 2030.

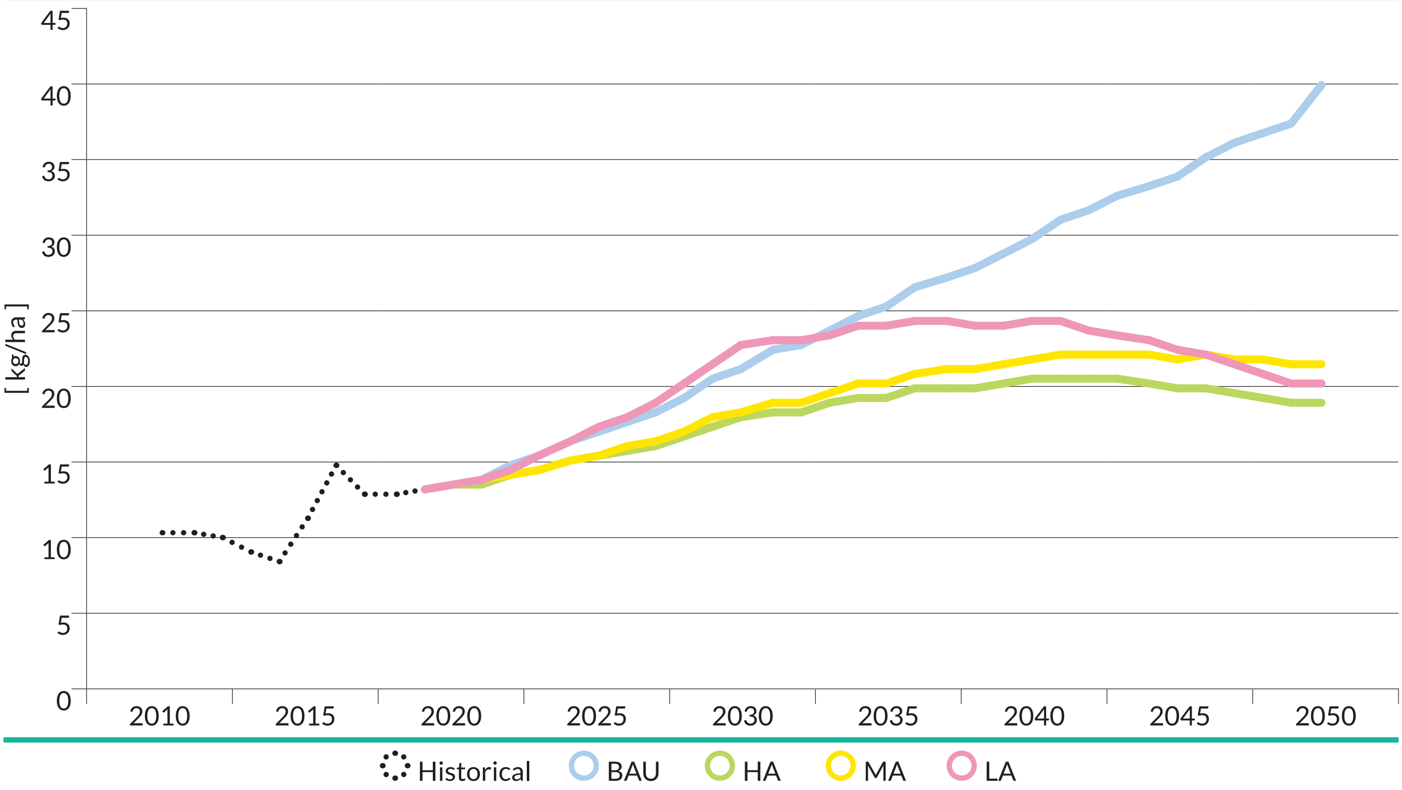
Nutrient balance (part of SDG 15.3.1): Without further interventions (i.e., BAU scenario), the nutrient balance will linearly rise from 2020 to 2050 when it reaches 40kg/ha (Figure 33). This will move the country away from the sustainability target of around 5kg/ha in nutrient balance. The LA scenario will follow the same trend as the BAU scenario until 2030. Afterward, it will start to decrease and end up performing better than the MA scenario, which initially showed a slighter increase. The increase will be restrained by the policies on livestock substitution and manure management, decreasing the manure supply and application. The HA scenario performs best, but none of the scenarios will achieve a nutrient balance as low as in 2015. Yet, the three alternative scenarios seem to reach a

Figure 32. Changes in (a) food loss (SDG 12.3.1a) and (b) food waste (SDG 12.3.1b) index in Burkina Faso, 2017-2050



Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

Figure 33. Changes in nutrient balance (part of SDG 15.3.1) in Burkina Faso, 2010-2050

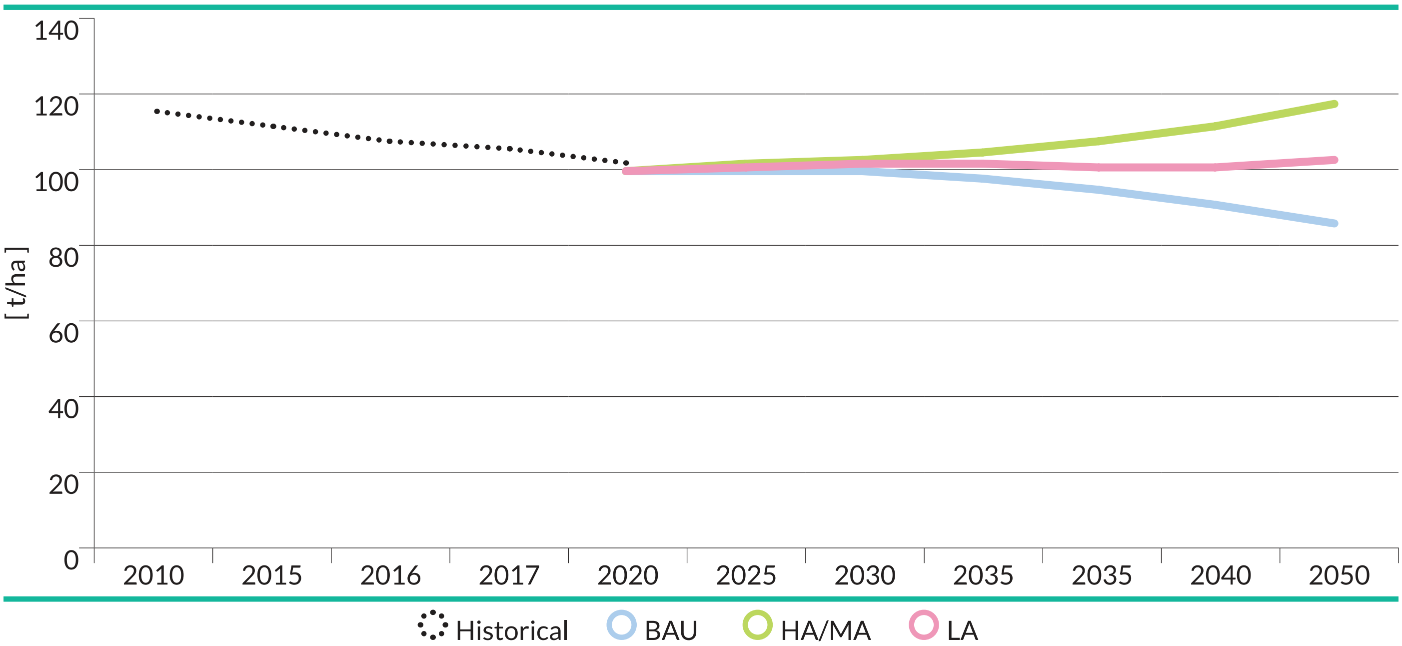


Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

plateau at the end of the transition to 2050, so no further improvement in nutrient balance could be expected.

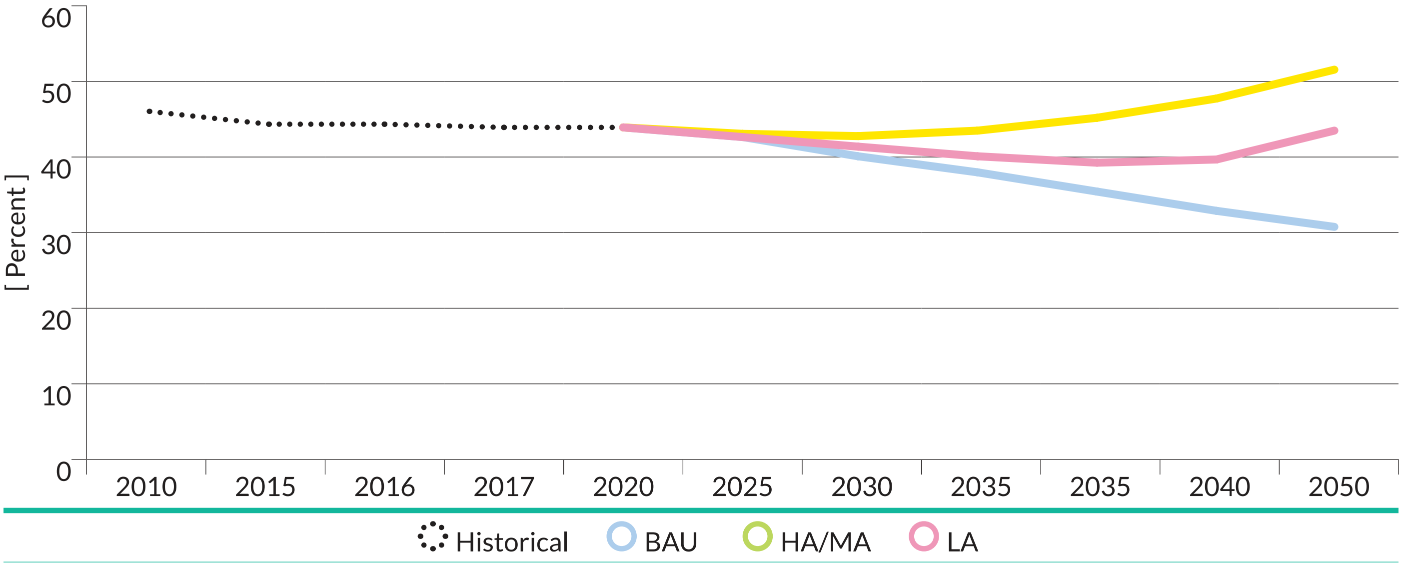
Above-ground biomass in forest (SDG 15.2.1): The evolution of the above-ground biomass follows the same trend as the forest area (Figures 34 and 35), as biomass losses are constant across the whole period and all scenarios. Therefore, the trend in above-ground biomass levels will be driven by biomass growth, which is directly dependent on the forest area. Disturbances account for 64 percent of biomass losses, fuelwood removals amount to 34 percent, and wood removals for the rest. The MA and HA scenarios will achieve an 18 percent increase by 2050 compared to 2020. The LA scenario will not significantly increase, while the BAU will decrease by 15 percent. Higher levels of above-ground biomass will lead to a higher CO_2

Figure 34. Changes in above-ground biomass in the forest (SDG 15.2.1) in Burkina Faso, 2010-2050



Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

Figure 35. Changes in the share of forest area to total land area (SDG 15.1.1) in Burkina Faso, 2010-2050

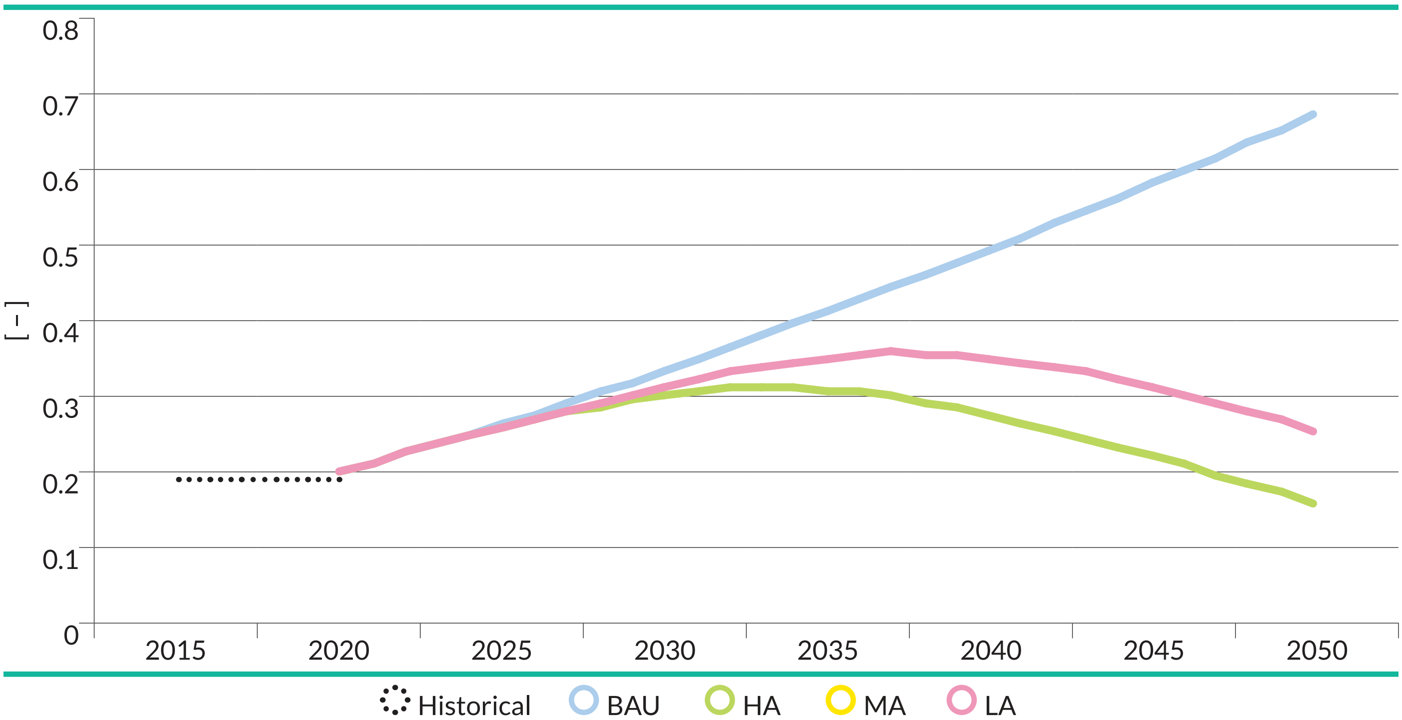


Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

absorption capacity in forests, contributing to the forestry sector mitigation potential.

Share of forest area to total land area (SDG 15.1.1): Deforestation in Burkina Faso is driven by agricultural land expansion, grazing, and overexploitation of forest resources.[130] Forest resources are critical for livelihoods and the economy, especially in the rural areas. In 2018, Burkina Faso committed to restoring 5 million hectares of degraded land by 2030, participating in the African Forest Landscape Restoration Initiative (AFR100), which aims to restore 100 million hectares across the continent. The provision of tree-planting materials was facilitated by institutions such as the government-run National Tree Seed Center of Burkina Faso (World Bank, 2014; Marchant, 2021).[131] Without action to limit deforestation and without implementing reforestation policies, Burkina Faso will lose the equivalent of 13 percent of its forest land between 2020 and 2050, the share of forests falling to 31 percent by 2050 (Figure 35). In both the MA and HA scenarios, reforestation policies were implemented as of 2020, whereas in the LA scenario, reforestation policies

Figure 36. Changes in the proportion of degraded forest land (SDG 15.3.1) in Burkina Faso, 2015-2050



Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

will be implemented only from 2030 onwards. This explains that the two more ambitious scenarios increase the share of forests to total land area by 2050 compared to the historical levels, while the LA scenario only succeeds in going back to similar levels after a temporary decrease.

Proportion of degraded (forest) land (part of SDG 15.3.1): In northern Africa, including Burkina Faso, arable land quality has significantly deteriorated in recent years due to climate change and inadequate land management. About one-third of Burkina Faso's landscape is now degraded. This degradation, expanding at 360,000 hectares per year, threatens over nine million hectares of previously productive agricultural land.[132] To address this issue, the "Great Green Wall" initiative aims to restore degraded land in the Sahel region, including Burkina Faso, through reforestation, sustainable land management practices, and community engagement.[133] The BAU scenario assumes that a constant area of land is degraded yearly during the transition to 2050 and that no reforestation policies are in place. In the alternative scenarios, a continuous land improvement rate is implemented. The degradation rate has slowed down in the MA and HA scenarios as of 2025, while degradation continues at the same rate as in the BAU scenario until 2030 (Figure 36). Degradation will become insignificant in the most ambitious scenarios by 2050 but will not improve further in the LA scenario from 2040 onwards. Without degradation and restoration policies, the proportion of degraded land will rise linearly and reach 67 percent in 2050. The policies implemented in the alternative scenarios, particularly the simultaneous slowing-down of the degradation and acceleration of the improvement of degraded land, limit the degradation rate and then reverse the trend (between 2030 and 2035 for the MA and HA scenario, 2035 and 2040 for the LA scenario). The MA and HA scenarios can reduce the share of degraded forest to a lower level than in the baseline by 2050.

B.3 Water use and waste

Water use is directly related to access to sanitation. The population's access to sanitation remains a critical issue in Burkina Faso, with a high rate of open defecation and poor wastewater management systems due to a lack of infrastructure and investment. With growing urbanization, wastewater generation is expected to increase, and the wastewater sector can, therefore, lead to job creation opportunities.[134] Improving sanitation systems is one of the priorities developed in the low emissions scenarios. In all alternative scenarios, urban open defecation will decrease from 6 percent in 2022 to zero and rural open defecation from 47 percent to zero by 2050.[135] Moreover, secondary wastewater treatment coverage will reach at least 62.3 percent in the LA and MA scenarios and 85.7 percent in the HA scenario.

Burkina Faso's economy is primarily based on agriculture. It is one of the top 10 cotton exporters in the world, with an average export earnings of US$207 million per year.[136] In 2022, the value added of the agriculture, forestry, and fishing sectors contributed to 18.5 percent of its GDP[137] and employed about 73 percent of its population in 2021.[138] Despite a 41.3 percent increase in crop production in Burkina Faso over the last decade (2011-2020), alarming levels of food insecurity persist, affecting more than 3.5 million people, or roughly 20 percent of the population. About 86 percent of the population relies on subsistence agriculture, with only a tiny portion benefiting from higher-value marketed agricultural production.[139] Under the low-emission scenarios, the development of the agricultural sector will significantly impact the indicators related to water use. The irrigated area will be 2.4 times higher in the LA and MA scenarios and 3.2 times higher in the HA scenario than in the BAU scenario in 2050. Table 13 presents the assumptions for the different scenarios, including irrigation technologies. As of the latest FAO estimates in 2020[140], Burkina Faso relies predominantly on

Table 13. Scenario assumptions in the GGSim application for Burkina Faso's water use and waste model

Inputs	BAU 2050	MA 2050	MA 2050	LA 2050	Source/basis of assumption
Irrigation					
Irrigation technology proportions [Percent]	Surface: 85 Sprinkler: 13 Drip: 1	Surface: 27 Sprinkler: 4 Drip: 69	Surface: 36 Sprinkler: 6 Drip: 58	Surface: 36 Sprinkler: 6 Drip: 58	Assumption based on agriculture working group target
Municipal					
Water Tariff [USD /m³]	1.4402	1.4402	1.4402	1.4402	ONEA, 2021;
Sanitation					
Percentage of the population under open defecation [Percent]	Urban: 7.2 Rural: 57.6	Urban: 0 Rural: 0	Urban: 0 Rural: 0	Urban: 0 Rural: 0	Derived from waste working group
Coverage of at least secondary wastewater treatment [Percent]	6.6	85.7	62.3	62.3	Tanoh, 2016 derived from Waste working group
Freshwater					
Total freshwater available [km³]	17	17	17	17	FAO, 2021

Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Data source: ONEA. (2021). Office National de l'Eau et de l'Assainissement ; Tanoh. (2016). Analysis of fecal sludge management in Ouagadougou: Kossodo and Zagtouli Fecal Sludge Treatment Plants; FAO. (2021). AQUASTAT Core Database.

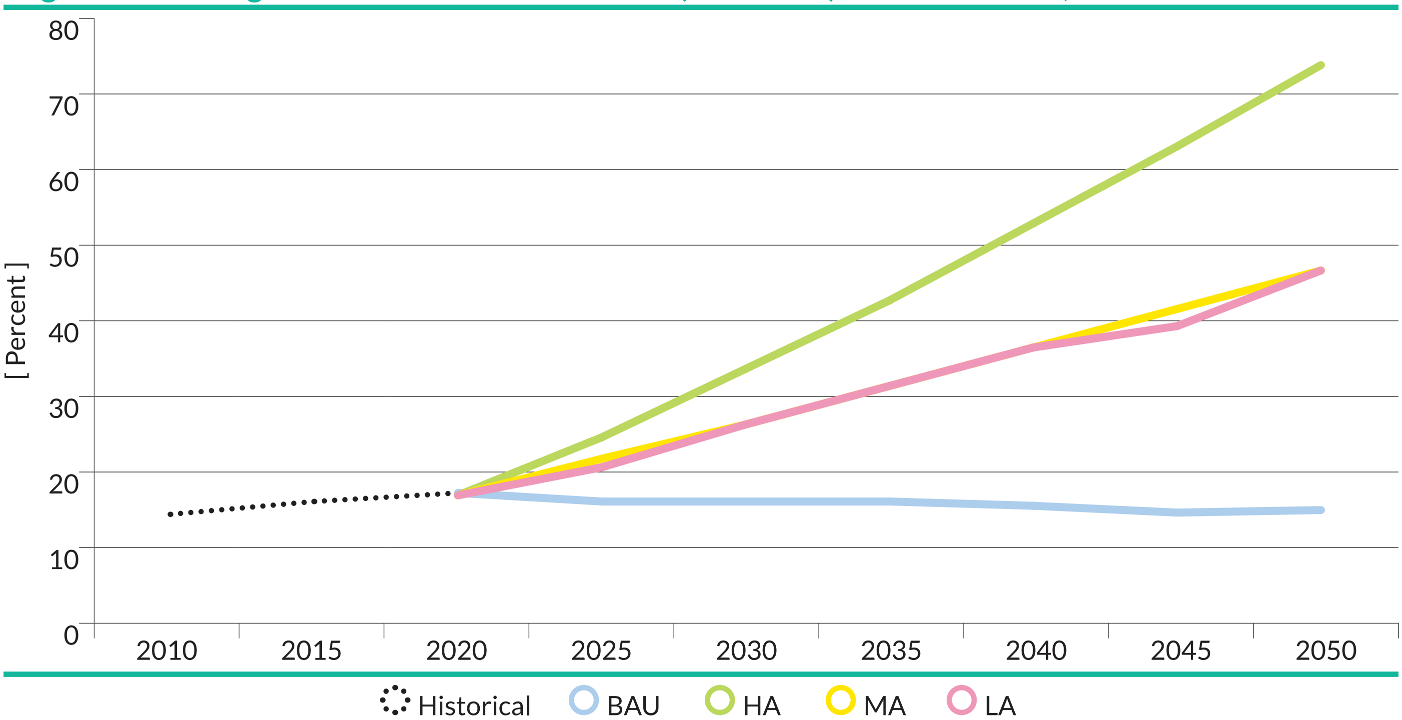
surface irrigation, covering 25,390 hectares (i.e.,85 percent of the total area equipped for irrigation), followed by sprinkler irrigation at 3,900 hectares (13 percent) and localized irrigation, including drip irrigation, at 440 hectares (1 percent). Notably, drip irrigation in Burkina Faso exhibits a field application efficiency of approximately 90 percent, significantly improving over the 50-60 percent efficiency observed in surface irrigation.[141] In the alternative scenarios, drip irrigation becomes predominant compared to traditional surface irrigation.

Level of water stress (SDG 6.4.2): Despite Burkina Faso having one of the lowest per capita water supplies in Sub-Saharan Africa and globally, its water stress values remain low. This can be attributed to the country's comparatively low utilization rate of available water resources. However, the challenge lies ahead as water demand is expected to surpass the country's limited supply, driven by factors such as population growth, urbanization, and the impacts of climate change.[142] Over the past decade, water stress has only slightly increased, and the BAU scenario would allow the indicator to stabilize around its current value (Figure 37). On the contrary, and as a direct result of the development of the agricultural sector requiring higher water withdrawal, the low emissions scenarios will lead to a severe increase in water stress, putting the country well above the water stress limit of 25 percent. Indeed, agricultural water withdrawals contribute to the majority of the total water withdrawals (from 85 to 93 percent throughout the whole period in the HA scenario). And these will increase by 7 times from 2020 to 2050 in the HA scenario. This is due to the increase in cropland demand, led by population increase. Even if this increase in irrigated land is mitigated by the development of more efficient technologies, this is highly insufficient to keep SDG indicator 6.4.2 below acceptable levels.

Water use efficiency (SDG 6.4.1): In contrast to the increasing level of water stress (i.e., freshwater withdrawal as a proportion of available freshwater resources), performance in the BAU scenario regarding water use efficiency will be better. As explained above, the former is due to the further development of the agricultural sector and the resulting increasing share of agricultural water withdrawal in total water withdrawal in the low emissions scenarios. Figure 38b shows the difference in agricultural water withdrawal across the different scenarios. While the share of agricultural water withdrawal will decrease from 85.1 percent in 2020 to 66.9 percent in 2050 under the BAU scenario, it will increase to 88.7 percent in the LA and MA scenarios and 92.7 percent in the HA scenario. In addition, the agricultural sector has a significantly lower water use efficiency than the industry and municipal sectors (Table 14).resulting in a poorer overall performance despite using more efficient irrigation technologies. Figure 38a shows that all sectors' total water use efficiency will be much lower in the low-emission scenarios than in the BAU scenario.

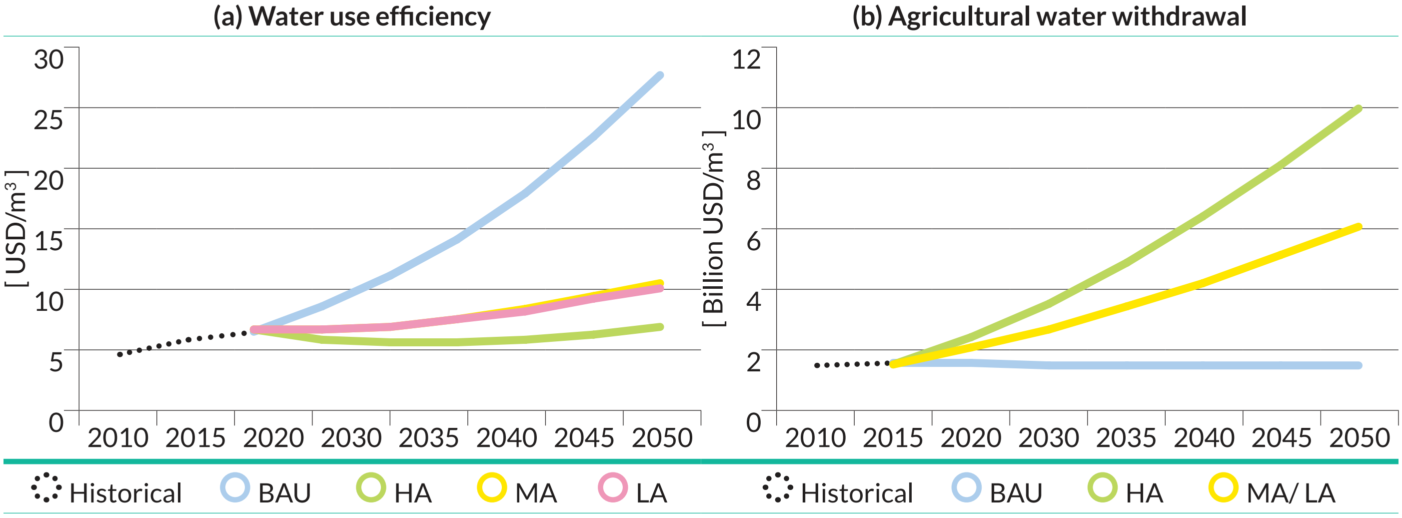
Population with access to sanitation (SDG 6.2.1): In Burkina Faso, disparities regarding improved sanitation access persist. As of 2021, 91 percent of the urban population had access, compared to 40 percent in rural areas.[143] The country's population growth, recorded at approximately 2.6 percent in 2022,[144] continues to exert pressure on water supply and sanitation systems. While the National Office of Water and Sanitation (ONEA) effectively serves urban areas, expanding WSS services to rural and rapidly growing peri-urban regions poses significant challenges.[145] To ensure the success of Burkina Faso's WSS rural sub-sector in its decentralization from the central government to municipalities, there is a critical need for substantial capacity building across operations

Figure 37. Changes in the level of water stress (SDG 6.4.2) in Burkina Faso, 2010-2050



Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

Figure 38. Changes in (a) water use efficiency (SDG 6.4.1) and (b) agricultural water withdrawal (part of SDG 6.4.2) in Burkina Faso, 2010-2050



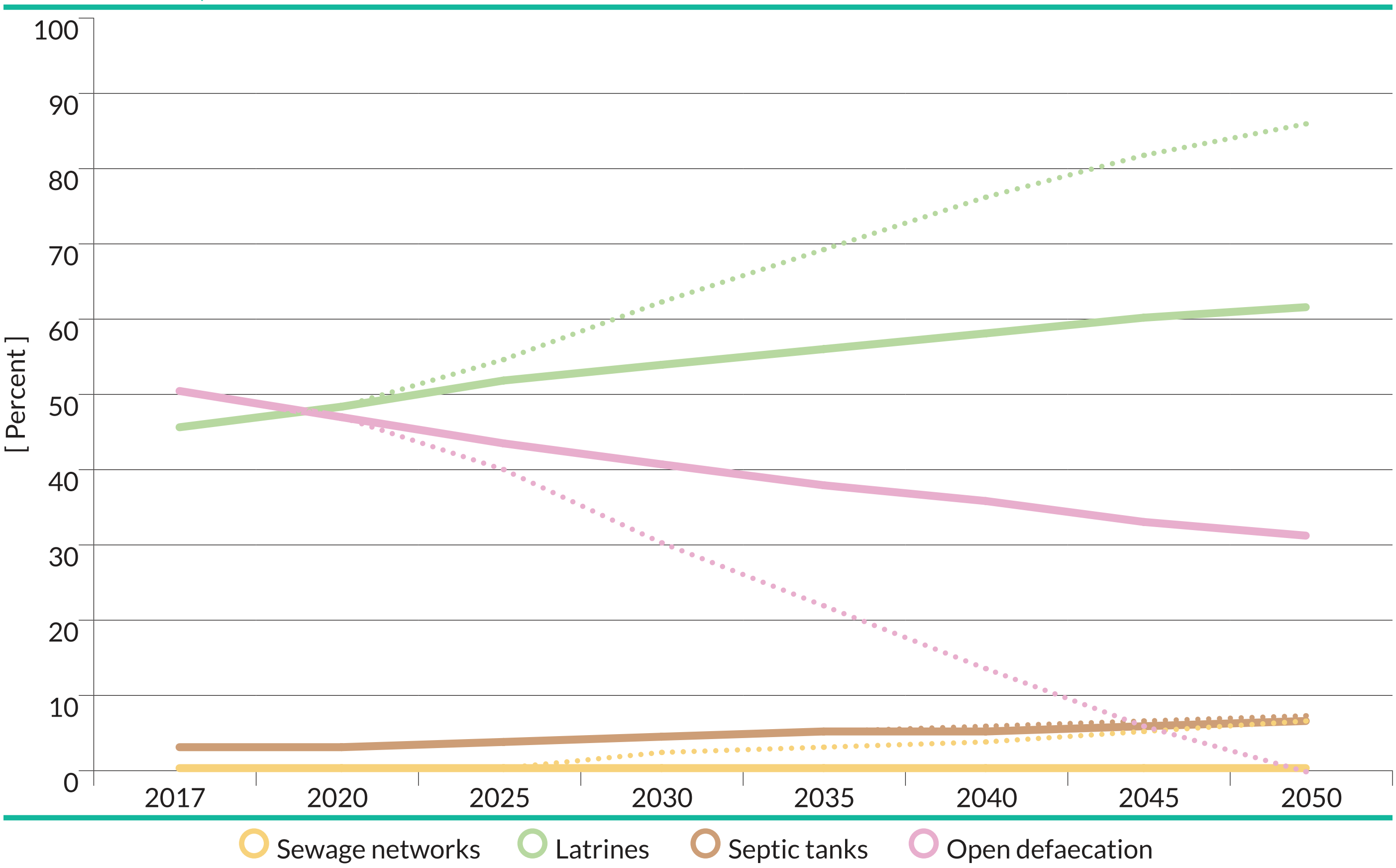
Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

Table 14. Sectoral water use efficiencies ($/m³) in Burkina Faso in 2050

	BAU 2050	LA 2050	MA 2050	HA 2050
AWUE	0.04	0.02	0.02	0.02
IWUE	173.1	205.3	249.3	295.1
MWUE	69.7	73.0	73.0	74.2

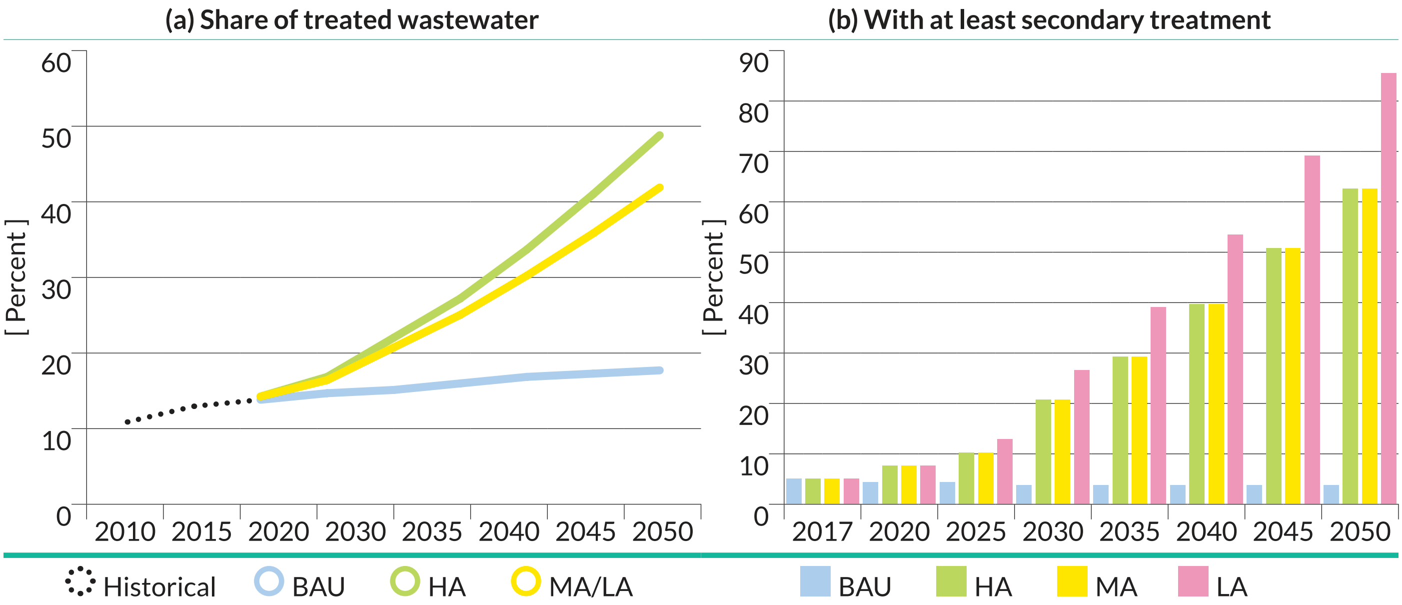
Note: AWUE - Agricultural Water Use Efficiency; IWUE - Industrial Water Use Efficiency; MWUE - Municipal Water Use Efficiency

Figure 39. Changes in the proportion of population with access to sanitation (SDG 6.2.1) in Burkina Faso, 2017-2050



Note: BAU with plain line and Low emissions scenarios with dashed line
Source: Authors own.

Figure 40. Changes in the (a) share of treated wastewater (part of SDG 6.3.1) and (b) wastewater with at least secondary treatment in Burkina Faso, 2010-2050



Scenarios: BAU - Business-as-usual, HA - High Ambition, MA - Moderate Ambition, LA - Low Ambition
Source: Authors own.

and management. The private sector also plays a pivotal role in attracting the necessary financing and technical expertise for WSS reforms.[146] All low-emission scenarios implement sanitation measures allowing the eradication of open defecation by 2050. In contrast, in the BAU scenario, 31 percent of the population will still be under open defecation in 2050 (Figure 39). The discrepancies between rural and urban populations will remain, with 57 percent of the rural population and 7 percent of the urban population having access to sanitation. The development of sewage networks will be slow, so latrines will prevail as the more widespread sanitation system. By 2050, in the alternative scenarios, 86 percent of the population will have access to latrines and the rest to septic tanks and sewage networks. Again, rural populations will not have the same access to better sanitation.

Treated wastewater (part of SDG 6.3.1): Burkina Faso, like many other Sub-Saharan African countries, faces significant challenges in achieving SDGs related to water resources and wastewater. The obstacles include inadequate water resource distribution, insufficient wastewater remediation, ineffective government policies, a lack of institutions, and limited political willpower.[147] According to a 2021 estimate by the World Health Organization, only approximately 2.3 percent of household wastewater in Burkina Faso is safely treated. The main hindrance to addressing these issues is the scarcity of capital, as substantial investments are required to establish and maintain wastewater management and sanitation infrastructure.[148] For example, Burkina Faso received an annual allocation of USD 46 million for urban water and sanitation services in 2019, highlighting the substantial financial demands in this sector.[149] Sewage systems allow the collection and treatment of wastewater. The BAU scenario will not have significant improvement in wastewater treatment, while the low-emission scenarios will improve significantly, reaching 62 percent in the LA and MA scenarios and 86 percent in the HA scenario (Figure 40a). This can be explained by the increasing share of wastewater receiving at least secondary treatment under the low-emission scenarios (Figure 40b). In contrast, the performance in SDG indicator 6.3.1, the share of domestic safely treated wastewater in total wastewater generated, will not improve sufficiently under the BAU scenario. Performances will be significantly better in the alternative scenarios due to the implemented policies, combining access to sanitation and wastewater treatment. These measures will also improve the mitigation of methane emissions from latrines and septic tanks. However, Burkina Faso's performance remains low compared to the SDG target, even under the higher ambition scenario.

4.1.3 Ethiopia

A. Overview of scenarios

Ethiopia is a landlocked country in East Africa, 1,104,300 km^2 wide, and home to 116.5 million people.[150] It is Africa's second most populous country, and its population is expected to reach 200 million by 2050. While it has been experiencing strong economic growth (6.3 percent in 2020), it remains one of the poorest countries in the region.[151] GGGI worked closely with the Ministry of Planning and Development of Ethiopia and the French Development Agency (AFD) to develop the country's LT-LEDS, published as "Ethiopia's Net-Zero and Climate-resilient Development Strategy".[152] Different scenarios were drawn from various models: the LEAP model from the Stockholm Environment Institute, the Green Economy model (GEM), the Ex-ACT and NEXT models from the FAO, and the IPCC Waste Model. The low-emission and climate-resilient scenarios stem from the previously determined BAU scenario and a series of mitigation and adaptation measures selected by sectoral working groups. The GGSim Tool was applied to assess the progress of several SDG indicators, focusing on co-benefits.

Four scenarios were considered in the LT-LEDS: the BAU scenario and three Net Zero Emissions (NZE) scenarios, representing different decarbonization pathways for the country's economy.

- The Business-as-Usual (BAU) scenario does not implement any additional mitigation or adaptation measures. It leads to GHG emissions as high as 559 Mt in 2050, compared to 288 Mt in 2020, or an increase of 94 percent.

- The Maximum Ambition (MA) scenario represents the maximum potential emissions reduction achievable if strong policies and measures are implemented early on. It aims to reach net zero emissions around 2035 and remain below zero onwards.

- The NDC-aligned (NDC) scenario aims to achieve the NDC emissions target by 2030, increasing ambitions from 2035 onwards to reach net zero emissions in 2050. It is the most cost-effective NZE scenario.

- The Late Action (LA) scenario implements high ambitions between 2040 and 2050 to reach net zero emissions in 2050 but does not reach the NDC targets in 2030.

The most important measures considered in the NZE scenarios include the creation of a carbon sink in the land-use sector, the electrification of end-use sectors, and the reduction of emissions from livestock. These interventions will lead to a more substantial increase in GDP in the NZE scenarios compared to the BAU scenario. The MA scenario will witness an average annual increase in GDP of 9.07 percent, the NDC scenario of 9.05 percent, and the LA scenario of 9.02 percent between 2020 and 2050, compared to an average yearly growth of 7.3 percent in the BAU scenario.[153] The GEM and sectoral models' results provided the scenario inputs necessary to align the GGSim application with the overall assumptions in Ethiopia's LT-LEDS. Other data inputs to the GGSim models were taken from national data sources. In case not available, data inputs were drawn from international sources and shared with the national experts for validation.

B. GGSim model applications

This section presents the results of the GGSim applications for the following models – energy, AFOLU, and water use and waste (Tables 4-6).The applications were based on the AFD-funded LT-LEDS project for Ethiopia conducted from 2022 to 2023. The adaptation assessment in the Burkina Faso LT-LEDS mainly applied qualitative assessment. For this reason, the SDG co-benefits assessment using the GGSim focused mainly on the mitigation scenarios and measures with available quantitative data for the simulation.

B.1 Energy

In 2020, the energy sector only accounted for 4 percent of the total GHG emissions in Ethiopia,[154] which was significantly low compared to the world's average (around 75 percent)[155]. However, the energy demand, driven by GDP growth, is expected to rise, and so are the emissions from the sector if fossil fuels increasingly meet this demand, as assumed in the BAU scenario. Electrification is one of the most important measures implemented in the NZE scenarios. While in the BAU scenario, electricity generation will double from 2020 to 2050; it will increase by 26-27 times under the NZE scenarios during the same period. Significant increases in renewable capacities will sustain this large increase. The measures implemented in the NZE scenarios will lead to higher GDP growth. In 2050, the GDP will be 58 percent higher in the MA, 55 percent in the NDC, and 53 percent in the MA scenario than in the BAU scenario. Table 15 summarizes the inputs to the GGSim energy model for the different scenarios in 2050.

Energy Intensity (SDG 7.3.1): Ethiopia's decreasing trend in energy intensity can be attributed to several key factors, including GDP, the share of renewables, and the share of the industry sector to GDP.[156] First, the country had an average annual GDP growth rate of 8.83 percent from 2010 to 2022,[157] meaning it produced more goods and services per unit of energy. Second, around 90 percent of its final energy consumption is from renewable sources.[158]

Table 15. Scenario assumptions in the GGSim application for Ethiopia's energy model

	2017	BAU 2050	MA 2050	NDC 2050	LA 2050	Source
Power generation capacities [MW]						LT-LEDS
Diesel and fuel oil	110	87	87	87	87	
Biomass	140	974	5090	5045	5017	
Hydropower	2401	15,794	83321	82572	82103	
Solar	159	317	1552	1551	1552	
Wind	702	3657	19258	19249	19248	
Geothermal	99	760	4008	3974	3952	
GDP						LT-LEDS
GDP [2017 PPP]	1.66E+12	1.92E+13	3.03E+13	2.97E+13	2.94E+13	

Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Data source: Ethiopia's Net-Zero and Climate-resilient Development Strategy (2023)

Thus, the country is not using energy-intensive resources such as coal. Third, the country still has a relatively low share of energy-intensive sectors, particularly the industry sector, which only contributed 9.4 percent to GDP in 2010 and rose to 22.7 percent in 2022.[159] The energy intensity has been decreasing over the past decade, showing that Ethiopia has been able to use less energy to produce one unit of economic output. The decreasing trend will continue in the BAU scenario, while the three NZE scenarios will show slight additional progress (Figure 41). The country's energy efficiency performance is already high, and there is a narrow window for more progress. Regarding energy intensity, Ethiopia ranks 39th out of 52 ranked countries in Africa and 171st out of 199 ranked countries globally in the Global Green Growth Index in 2023.[160]

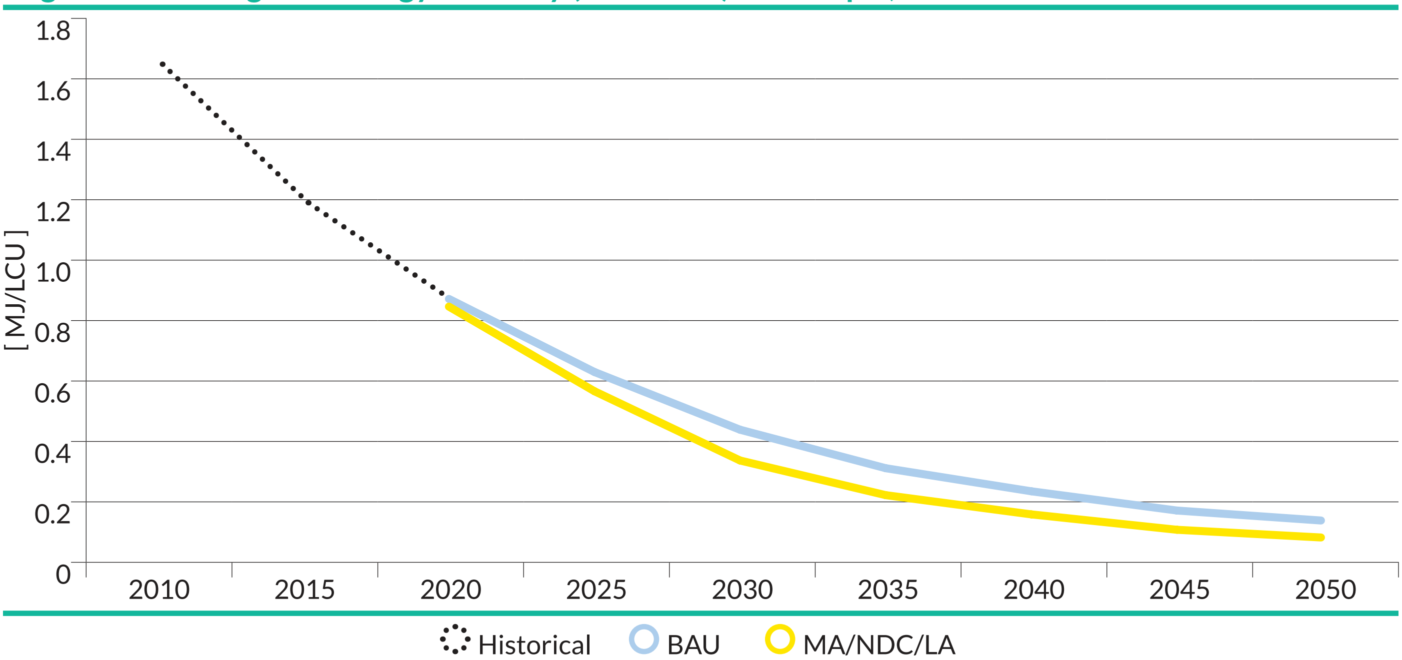
Share of renewables in electricity generation (part of SDG 7.2.1): Ethiopia, a prominent East African nation, is renowned for its ample water resources, with hydropower generating about 95 percent of the electricity.[161] Despite an economically feasible potential of around 30,000 MW, only 8.82 percent of this capacity is currently harnessed.[162] Notably, with just 54.2 percent of the population having access to electricity,[163] there exists substantial untapped potential in hydropower to meet the growing demand for electricity. Acknowledging this concern, the government initiated the National Electrification Program (NEP) in 2017 and 2019. This comprehensive initiative aims to achieve universal electricity access by 2025.[164] Hydropower mainly supports electricity generation in all scenarios, accounting for around 63 percent in 2020 to 73 percent in 2050 in the NZE scenarios and about 70 percent in 2020 to 75 percent in 2050 in the BAU scenario (Figure 46). The two main other electricity sources are (1) onshore wind turbines, increasing from 12 percent in 2020 to 18 percent in 2050 in the NZE scenarios and to 16 percent in 2050 in the BAU scenario, and (2) biomass, increasing slightly from 6 percent in 2020 to 7 percent in 2050 in all scenarios. The MA and BAU scenarios will reach 100 percent green electricity by 2025, while the NDC and LA scenarios, relying on a temporary increase in fossil fuels to meet the demand, will reach it by 2030 and 2040, respectively. Note that the performance of the BAU scenario is explained by the fact that electrification is far less important than in the other scenarios, making it easier to meet the electricity demand without relying on fossil fuels.

Installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1): Ethiopia's energy mix is dominated by biomass and waste, accounting for over 90 percent of the total energy supply.[165] Solid biomass remains the primary fuel for cooking of more than 90 percent of households.[166] The country's per capita energy supply and consumption is thus one of the lowest worldwide. Hydropower, providing 95 percent of the electricity, accounts for less than 2 percent of the total energy supply in Ethiopia.[167] The renewable energy capacity is thus low, less than 50 Watts per capita from 2017 to 2020. The assumptions on strong investments in renewable capacities in the NZE scenarios can be observed in Figure 47, which presents the installed renewable energy capacity per capita. All three NZE scenarios follow the same increasing trend, while the BAU scenario only shows a slight increase. As mentioned above, this increase is largely due to the increase in hydropower capacities. This increase is 2941 percent between 2017 and 2050 in the MA scenario, with hydropower capacities representing 74 percent of the total renewable capacities in 2050. The significant increase in wind, biomass, and geothermal capacities also contributes to Ethiopia's performance in terms of renewable electricity.

B.2 Agriculture, forest, and land use

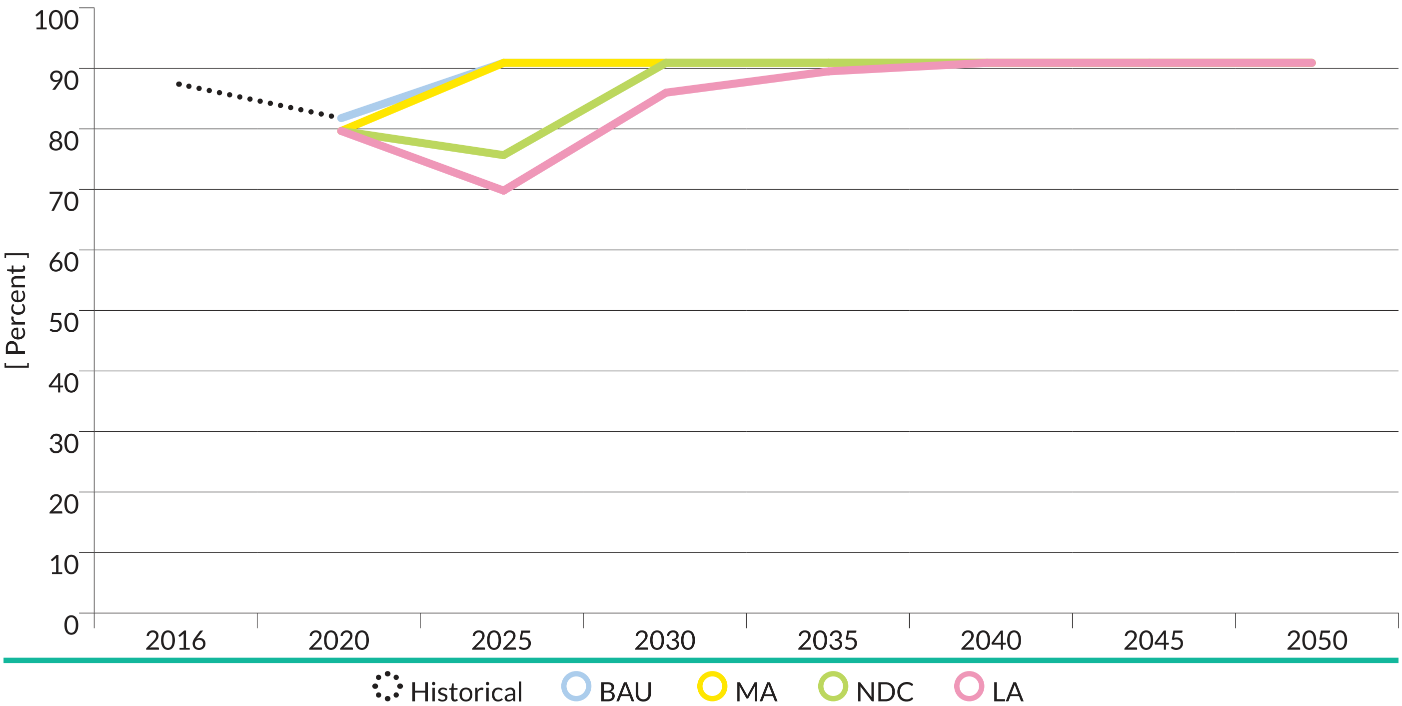
Agriculture has a prominent role in Ethiopia's economy. The sector employed about 70 percent of the workforce

Figure 41. Changes in energy intensity (SDG 7.3.1) in Ethiopia, 2010-205



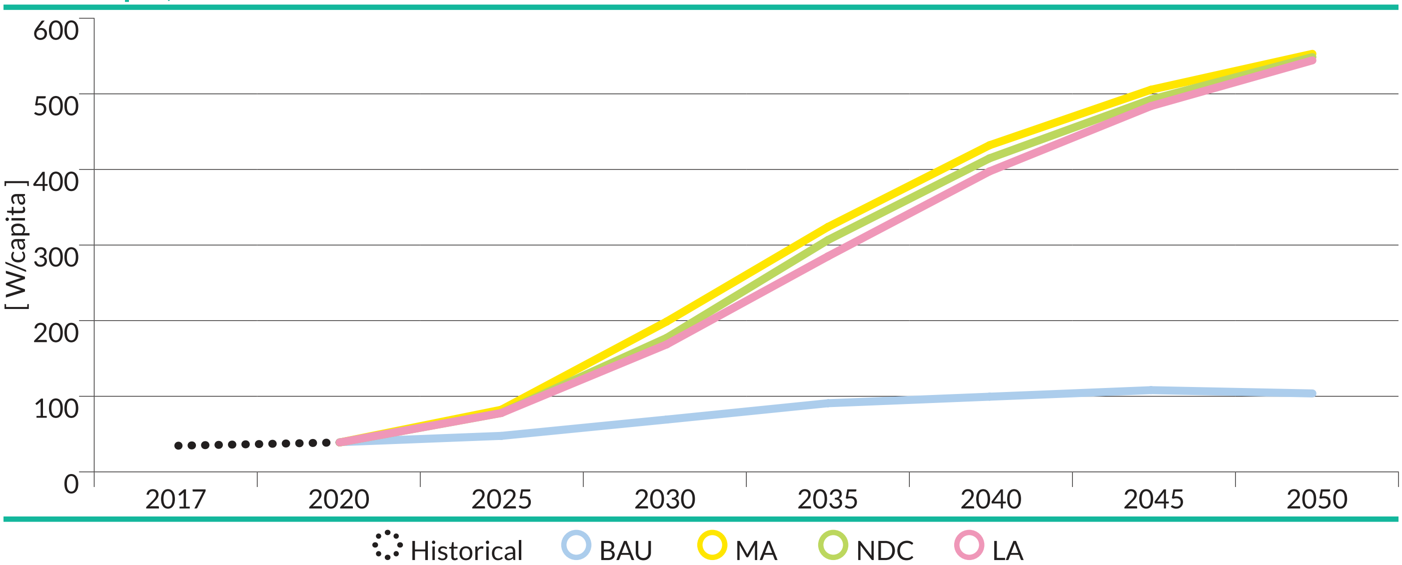
Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

Figure 42. Changes in the share of renewables in electricity generation (part of SDG 7.2.1) in Ethiopia, 2017-2050



Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

Figure 43. Changes in the installed renewable energy capacity per capita (SDG 7.b.1 and 12.a.1) in Ethiopia, 2016-2050



Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

but also contributed 51 percent of the country's total GHG emissions in 2020. Together with land use, the sector's share in the total GHG emissions reaches 92 percent. In the BAU scenario, projections are driven by population growth and include an increase in livestock production, area of land under annual and perennial crops, and use of fertilizers, pesticides, and lime. Livestock will account for around 91 percent of the total GHG emissions from agriculture, while perennial crops can contribute to carbon sequestration.[168] The NZE scenarios include manure and feed management, improved livestock productivity, increased perennial crop production, and food waste reduction. The two main drivers of deforestation are the expansion of agriculture and the use of biomass for energy. Between 1990 and 2020, forest land area has been reduced by 8 percent. Reforestation/afforestation and restoration policies implemented in the NZE scenarios will make the land use sector a significant carbon sink.[169] Table 16 presents the assumptions for the different scenarios in the AFOLU sector in 2050.

Food waste and loss index (SDG 12.3.1.a and b):
In Ethiopia, droughts are the main cause of food insecurity, and post-harvest losses add challenges to the agriculture

Table 16. Scenario assumptions in the GGSim application for Ethiopia's AFOLU model

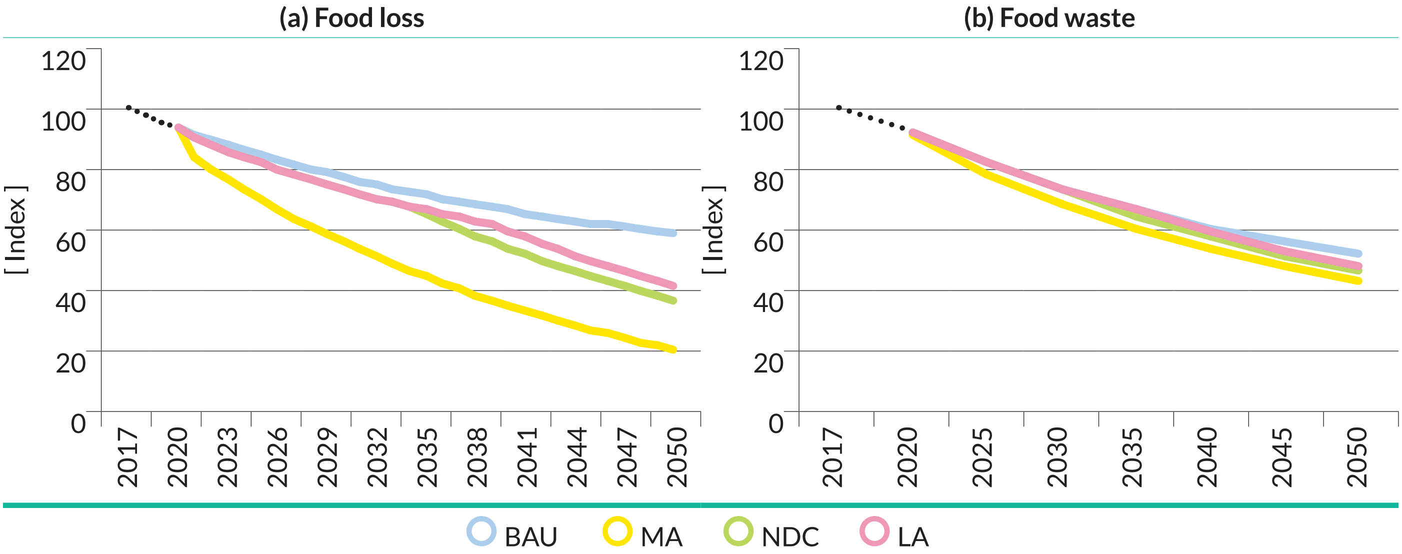
Input variables	BAU 2050	MA 2050	NDC 2050	LA 2050	Source/basis of assumption
Agriculture					
Change demand for livestock products [Percent]	81.85	19.21	19.21	19.21	FAO, 2018
Change demand crop products [Percent]	4.14	4.14	4.14	4.14	FAO, 2018
Change in livestock productivity [Percent]	10.03	40	40	40	BAU: FAO, 2018 Other: Scenario targets
Change in fertilizer use [Percent]	11.62	-34	-24	-22	Expert judgment
Fraction cropland area burned [-]	0.1	0.1	0.1	0.1	Default value IPCC, 2006
Fraction of above-ground residues removed annually [-]	0	0.66	0.66	0.66	Karlsruhe Institute of Technology
Food loss reduction [Tons/year]	-11,257	50,000	50,000 (from 2035 onwards)	50,000 (from 2040 onwards)	Historical trend, targets
Food waste reduction [Tons/year]	0	50,000	50,000 (from 2035 onwards)	50,000 (from 2040 onwards)	Targets
Atmospheric nitrogen deposition [Tons/year]	10926	10926	10926	10926	FAOSTAT, 2022
Forestry					
Net above-ground biomass growth in natural forests (Tons dm/ha/year)	1.19	1.19	1.19	1.19	FRA, 2020
Fuel wood removals (1000 m^3 /5 years)	110622	110622	110622	110622	FAOSTAT, 2022
Industrial roundwood removals (1000 m^3 /5 years)	2935	2935	2935	2935	FAOSTAT, 2022
Deforestation rate [Percent/year]	0.0112	0.0041	0.0041	0.0041	LT-LEDS
Averaged reforestation rate [1000ha/year]	0	273.33	295.78 (from 2025 onwards)	319.72 (from 2040 onwards)	LT-LEDS GEM model

Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Data source: FAO. (2018). The future of food and agriculture – Alternative pathways to 2050. IPCC. (2006). 2006 IPCC Guidelines for National Greenhouse Gas Inventories; FAOSTAT. (2022). Food and Agriculture Organization Corporate Statistical Database; FRA. (2020). Global Forest Resources Assessment 2020.

sector.[170] Moreover, food waste is exacerbated by rapid urbanization.[171] An estimated 29 percent of the population suffers from micronutrient deficiencies,[172] so food waste and loss policies are key to the country's sustainable development. Food loss and waste policies implemented as early as 2020 in the MA scenario will enable Ethiopia to achieve the SDG target of reducing food loss by 50 percent around 2030, while delayed implementation in the NDC and LA scenarios leads to poorer performance. (Figure 44). The declining trend across all scenarios will be caused by an increasing population, explaining the decline in the index despite the annual increase in food loss in the BAU scenario. The food waste index results are similar across the scenarios; reaching the target of 50 percent will be a challenge before 2040. In the BAU scenario, total food waste will remain relatively constant over the whole period, but the food waste per capita will decrease by 49 percent. Food waste and loss policies will help release land pressure from increasing food demand due to population growth.

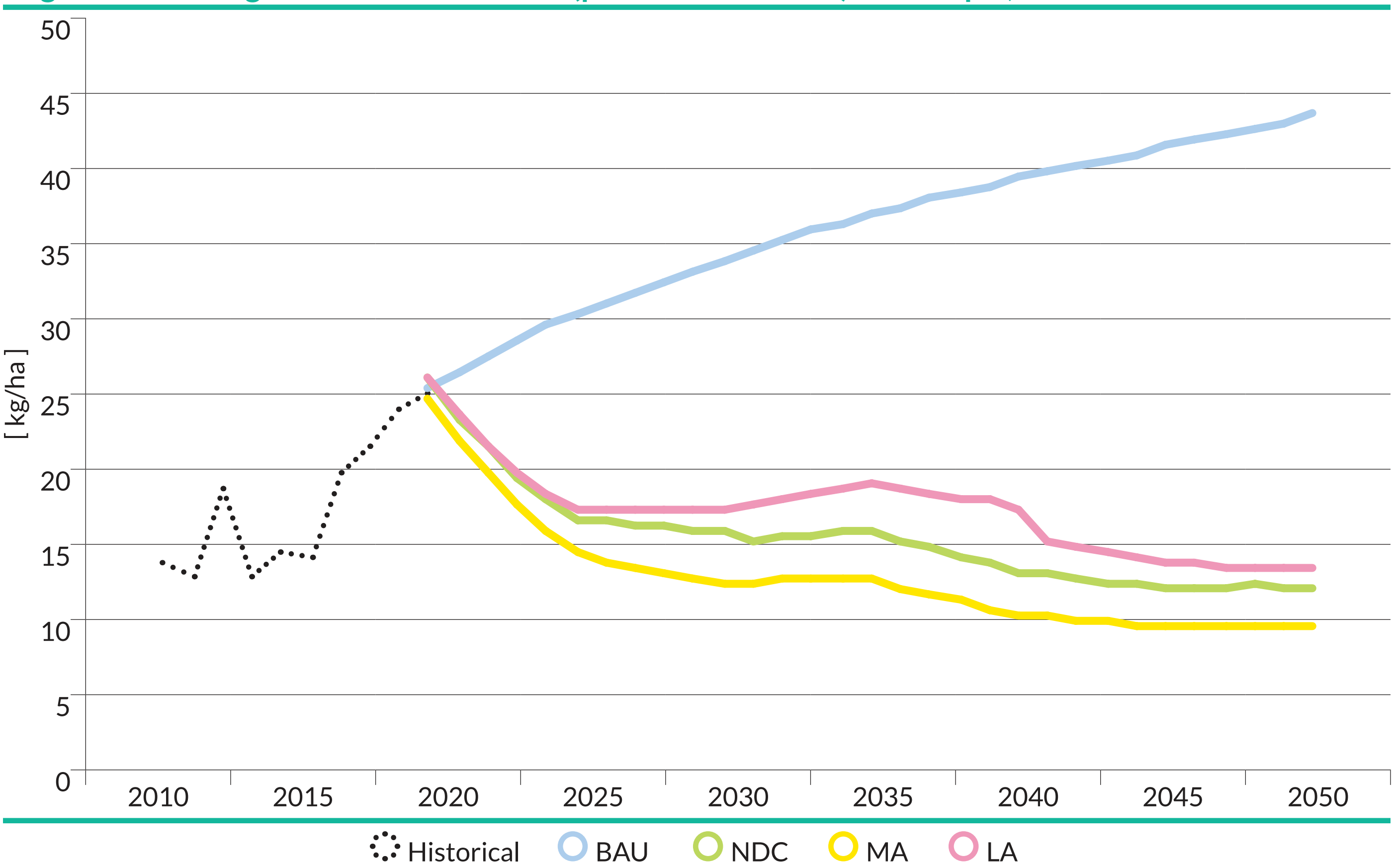
Nutrient balance (part of SDG 15.3.1): The increasing amount of mineral fertilizer use contributed the most to the increase in the nutrient balance scores from 2015. Recent data from FAO raised the value to around 24.62 kg/ha in 2021 from 15.12 kg/ha in 2015. The nutrient balance is expected to follow the overall increasing trend from 2015 in the BAU scenario, reaching 43 kg/ha in 2050 (Figure 45). The additional measures implemented in the NZE scenarios, especially a decrease in fertilizer use, on the contrary, will reverse this trend, reducing the nutrient balance below 15 kg/ha by 2040. To a lesser extent, food loss and waste reduction policies, as well as increased livestock productivity, will lower the livestock requirements and, therefore, lead to less manure applied on soil, also contributing to lower nitrogen balance. Across the NZE scenarios, improvement will be achieved faster in the MA scenario, where the interventions are applied earlier.

Figure 44. Changes in (a) food loss (SDG 12.3.1a) and (b) food waste (SDG 12.3.1b) index in Ethiopia, 2017-2050



Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

Figure 45. Changes in nutrient balance (part of SDG 15.3.1) in Ethiopia, 2010-2050

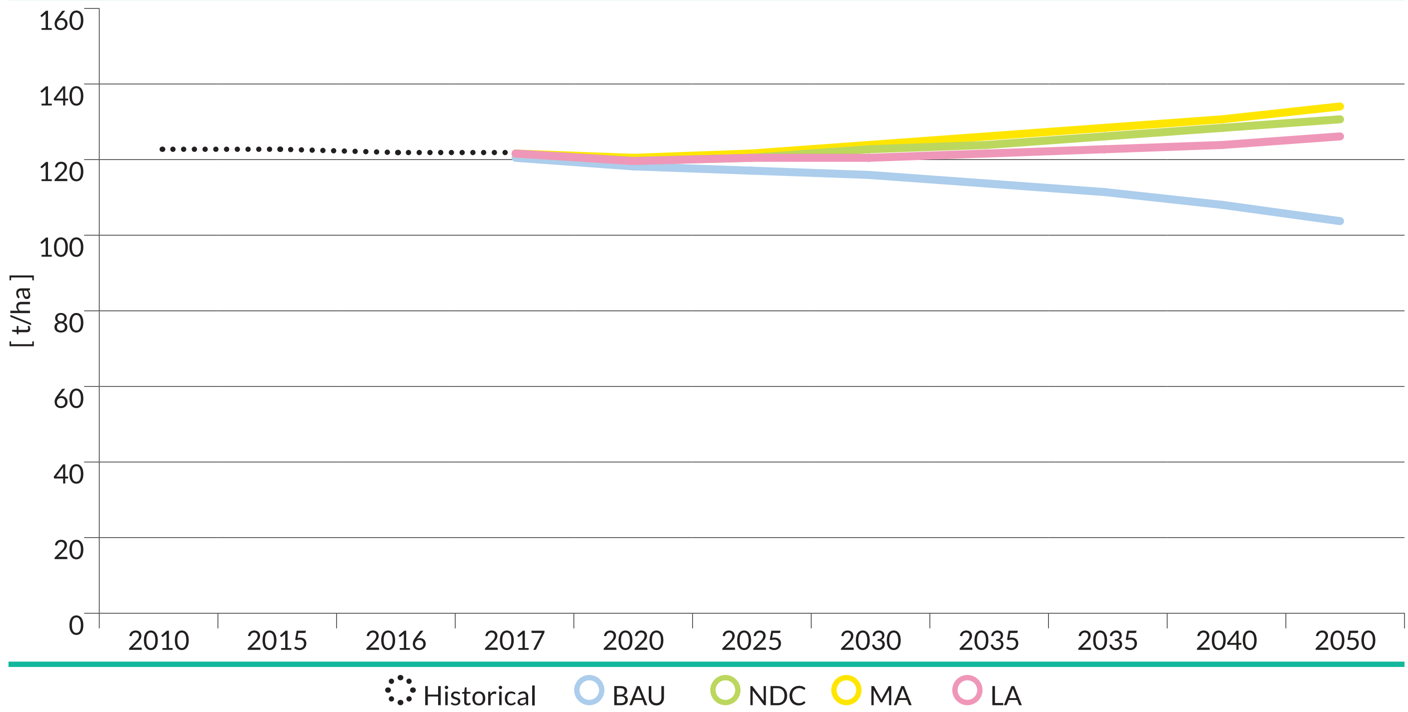


Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

Above-ground biomass in forest (SDG 15.2.1): The above-ground biomass is directly linked to the share of forest area. While it has remained mostly constant over the last decade, the lack of intervention in the BAU scenario will significantly decrease the indicator's performance and make forests less able to capture carbon (Figure 46). Losses in above-ground biomass will remain constant, with fuelwood removals accounting for 64 percent and disturbances for 34 percent. However, biomass growth will decline in the BAU scenario due to the decline in forest area (Figure 47). Reforestation policies implemented in the NZE scenarios will allow net biomass stock growth, enhancing the mitigation potential of the AFOLU sector.

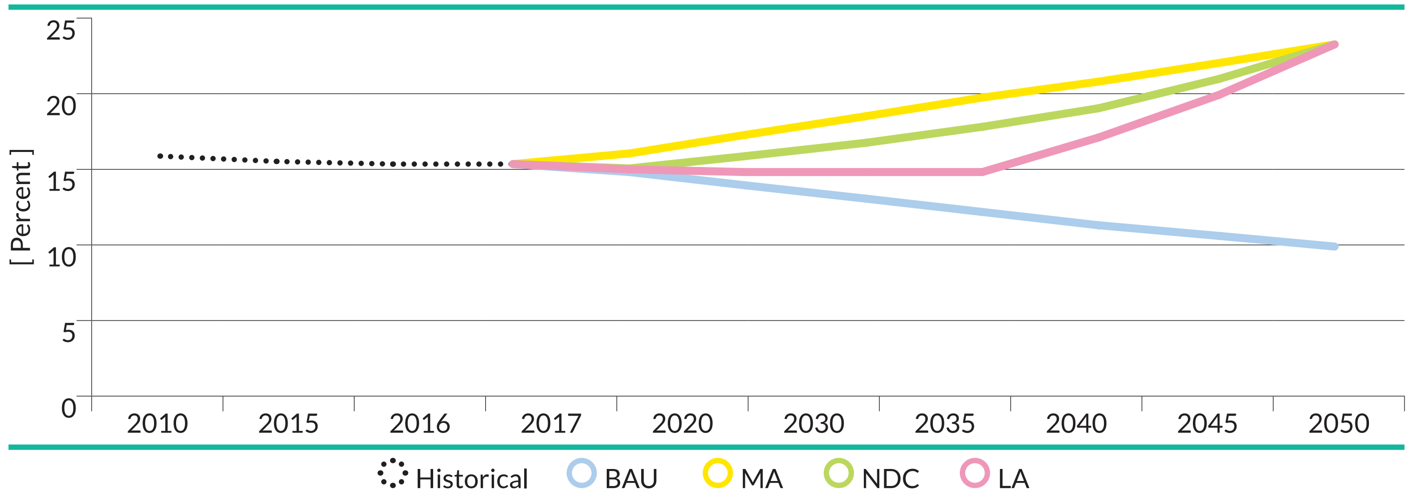
Share of forest area to total land area (SDG 15.1.1): Critical factors for successful forest tree planting and

Figure 46. Changes in above-ground biomass in the forest (SDG 15.2.1) in Ethiopia, 2010-2050



Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

Figure 47. Changes in the share of forest area to total land area (SDG 15.1.1) in Ethiopia, 2010-2050



Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

restoration efforts in Ethiopia include local participation, marketing prospects, socio-economic incentives, and key considerations related to tree and land tenure.[173] Challenges, such as low community engagement in tree planting decisions and limited support, hinder reforestation efforts. The government's inability to enforce regulations and manage forest access, coupled with efforts to assert ownership, has contributed to widespread forest degradation and deforestation.[174] Additionally, issues like tenure insecurity of replanted communal lands, unclear land use rights, and a lack of clarity on tenure rights over planted trees and associated benefits pose significant challenges.[175] Without further intervention, the forest area share will start decreasing sharply and fall below 10 percent in the BAU scenario in 2050 (Figure 47). However, significant progress will be achieved when implementing reforestation policies in the NZE scenario. All NZE scenarios will result in a share of 23 percent by 2050, but which achievement will depend on overcoming the above-mentioned challenges.

B.3 Water use

The Horn of Africa has faced a severe water crisis driven by climate change, lack of infrastructure, population growth, and urbanization[176]. Despite its abundant water resources, Ethiopia is particularly vulnerable to climate change and has low adaptation capacities[177]. Its agriculture is strongly dependent on rainfall, which has high variability[178]. Water scarcity severely threatens Ethiopia's population and the country's growing economy. The latter will require increased amounts of water withdrawals to sustain the development of the agricultural and industrial sectors. Sanitation is also an issue, and the country has one of the continent's lowest access rates to water supply and sanitation[179]. Only 52 percent of the population has access to safe drinking water, and less than 50 percent have access to sanitation[180].

The country's water governance remains a challenge that needs to be addressed to mitigate the water crisis. Water quality is poorly monitored, and the water sector lacks internal coordination. However, the country's recent ten-year development plan (2021-2030)[181] includes a water resource development plan, with the main goals being improving access to good hygiene services and strengthening the operation of the river basin and irrigation resources[182]. Table 17 presents the assumptions relevant to assessing water resource management using the GGSim.

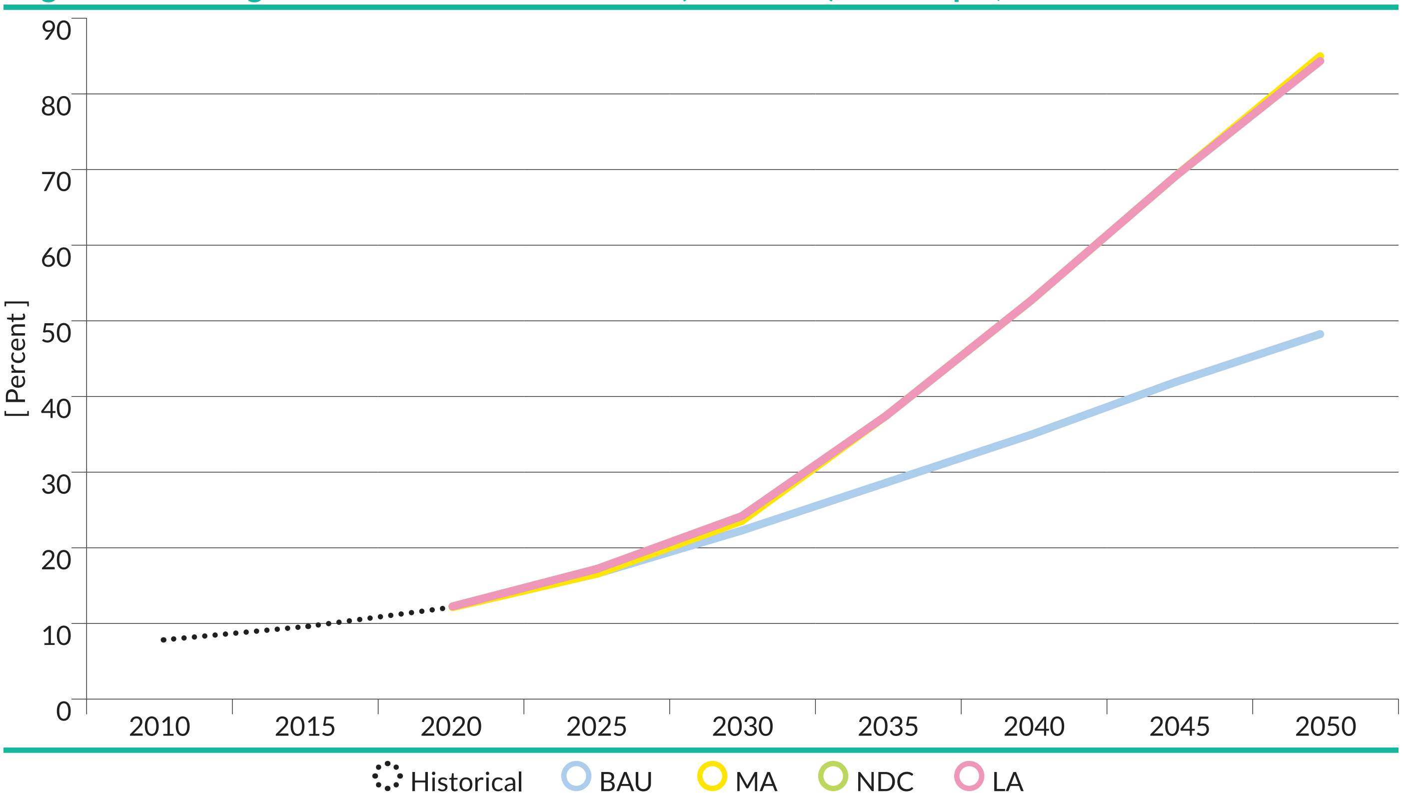
Level of water stress (SDG 6.4.2): Ethiopia has sufficient water resources, but the water crisis in the Horn of Africa is qualified as a deadly risk for children by the United Nations Children's Fund (UNICEF). Increasing variability in rainfall patterns and their distribution and extreme climatic events due to climate change threaten water resources in Ethiopia.[183] Water stress is also caused by the geographical disparity between water resources (in the West) and water demand (in the East), and nearly 25 percent of

Table 17. Scenario assumptions in the GGSim application for Ethiopia's water use model

Input variables	BAU 2050	Low emission scenarios 2050	Source/basis of assumption
Irrigation			
Irrigation Area [1000 ha]	2218.51	3600	BAU: Planning and Development Commission (2020). NZE scenarios: LT-LEDS
Total Cultivated Land [1000 ha]	27447	24656	AFOLU model
Proportion of Irrigation Technological [%]	Surface : 96 Sprinkler : 4 Drip : 0	Surface : 50 Sprinkler : 4 Drip : 46	LT-LEDS
Municipal			
Water Tariff [USD $/m³]	+200%	+200%	Ministry of Water and Energy

Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Data source: Planning and Development Commissions; Ministry of Water and Energy.

Figure 48. Changes in the level of water stress (SDG 6.4.2) in Ethiopia, 2010-2050[ii]



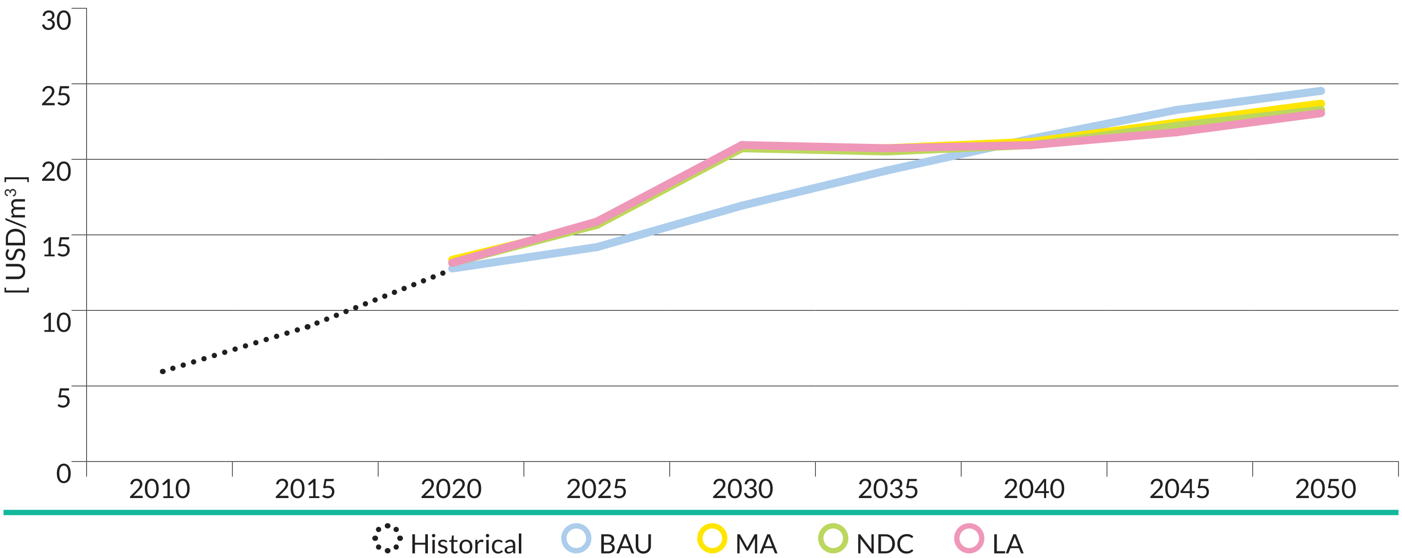
Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

ii Historical data come from national sources and may differ from international databases.

Ethiopians are estimated to live in regions of high water stress.[184] The NZE scenarios will all lead to a dramatic increase in the freshwater withdrawals to freshwater availability (Figure 48), as more water will be withdrawn to sustain the development of the different sectors, including GDP and population growth in the municipal sector, power generation in the industrial sector, and irrigation demand in the agricultural sector. The latter sector is the most water-intensive, contributing to about 65 percent of the total withdrawals in 2050 in the NZE scenarios. These sectoral developments result in an increase in total water withdrawals of about 900 percent between 2020 and 2050 in the NZE scenarios.

Water use efficiency (SDG 6.4.1): Water use efficiency has increased significantly over the past decade. The BAU scenario will follow the increasing trend more or less until 2050 (Figure 49). The water use efficiency trends for the NZE scenarios will be almost identical because the same policy interventions will be implemented, with a slight divergence from 2040 due to the difference in the GDP and population growth. Better performance in NZE scenarios compared to the BAU scenario until 2040 will be attributed to irrigation technology, decreasing surface, and increasing drip/sprinkler irrigation in the former. However, from 2030 to 2040, water use efficiency in the NZE scenarios declined for two reasons. First, the expansion of irrigated areas will cause an increase in water withdrawal in the agricultural sector, increasing the share of this sector to total water withdrawal relative to the municipal sector (Table 19). However, the municipal sector has higher water use efficiency than the agriculture sector so that this shift will reduce the overall efficiency in the country. Second, the level of irrigation technology (i.e., 4% sprinkler, 46 drip) and traditional irrigation (50% surface) will not be sufficient to increase water use efficiency in the larger area of irrigated land. Shifting development priority away from primary (i.e., agriculture) to secondary and tertiary industries in the NZE scenarios in 2040 will not be sufficient to bring water use efficiency level higher or even at par with the BAU scenario until 2050.

Figure 49. Changes in water use efficiency (SDG 6.4.1) in Ethiopia, 2010-2050



Scenarios: BAU - Business-as-usual, MA - Maximum Ambition, NDC - NDC-aligned, LA - Late Action
Source: Authors own.

Table 18. Sectoral water use efficiencies (USD/m³) and shares in total withdrawals (Percent) in Ethiopia, 2050

Sectors	Indicators	BAU 2050	LA 2050	NDC 2050	MA 2050
Agriculture	Water use efficiency	0.24	0.19	0.19	0.22
	Share to total withdrawals	57	65	65	64
Industry	Water use efficiency	1151.77	365.24	367.77	375.03
	Share to total withdrawals	1	3	3	3
Municipal	Water use efficiency	26.76	33.5	33.62	33.94
	Share to total withdrawals	42	32	32	32

Source: Authors own.

4.2 Climate adaptation

4.2.1 Saint Lucia

A. Overview of scenarios

St. Lucia is a volcanic island in the eastern Caribbean Sea, 616 km^2 wide, home to 167,591 people, mainly concentrated around coastal zones. Its economy strongly relies on tourism and agriculture.[185] While the country contributes very little to global GHG emissions, it is highly vulnerable to climate change due to its geographical location and size, bringing disasters to a territory-wide scale and economic reliance on sectors directly impacted by climate change.[186] Protection of the country's natural resources through adaptation measures is, therefore, essential to the country's prosperity. Related to the national climate adaptation strategies, such as the country's Climate Change Adaptation Policy or Nationally Determined Contribution, the Simulation Tool was applied to assess and show the alignment with SDG co-benefits. Three alternative scenarios were analyzed in addition to the BAU scenario. They are characterized by various levels of sectoral policy implementation, green investment, global collaboration, and prioritization of achieving climate adaptation and mitigation plans.

- The Business-as-usual (BAU) scenario assumes nothing is done to adapt to climate change. The world follows a path in which social, economic, and technological trends do not shift markedly from historical patterns, and countries only focus on national economic growth without considering sustainable development or environmental issues. The national government and global institutions' work for adaptation is extremely slow in progress because of the low priority for sustainability.

- The Cautious (CA) scenario assumes that implemented policies and actions aim to perform better than the BAU pathway. It ensures that any climate adaptation or mitigation plan is affordable, limiting investments that cannot be supported without collaboration and, therefore, restricting what national governments and local investors can afford.

- The Ambitious (AM) scenario assumes that implemented policies and actions aim to address climate issues and achieve ambitious adaptation and mitigation targets. These will require some form of structural change, which will significantly impact resource use. The investment requirements to achieve the targets are not a primary concern, assuming that support from the international community will be available to implement those ambitious targets.

- The Transformative (TR) scenario assumes that implemented policies and actions aim to achieve the climate targets and commitments. Technological and behavioral changes that will reduce trade-offs and ensure sustainable transformations are important priorities for this scenario. Social rather than economic costs of no action are more important considerations when addressing the trade-offs.

Quantitative assumptions for the AFOLU, as well as water use and waste models, were identified based on a review of St. Lucia's Nationally Determined Contribution, National Adaptation Plans, and relevant articles and reports. The scenarios were aligned with the Green Recovery measures for St. Lucia, which GGGI identified in consultation with the Organisation of Eastern Caribbean States (OECS) Commission. The shared socioeconomic pathways (SSPs), the most important and recognized environmental scenario frameworks, were applied for socioeconomic data. These include the ***Sustainability*** storyline (SSP1), which assumes the commitment to achieving development goals, and the ***Middle of the Road*** storyline (SSP2), which assumes that trends do not shift markedly from historical patterns. SSP1 was used for the AM and TR scenarios, while SSP2 was used for the BAU and CA scenarios. SSP projections of population and GDP were sourced from the International Institute for Applied Systems Analysis (IIASA)[187] and urbanization rates from the NCAR model.[188]

B. GGSim model applications

This section presents the results of the GGSim applications for the following models – AFOLU and water use and waste (Tables 5 and 6).The applications were based on the GGGI-funded Green Recovery and SDG co-benefits assessment project for St. Lucia, conducted in 2022. It focused on the adaptation measures in a small island developing country, particularly addressing land and coastal degradation vulnerability

B.1 Agriculture, forest, and land use

In 2021, agriculture employed 11 percent of the workforce[189] and accounted for 6.6 percent of St. Lucia's total GHG emissions (excluding LULUCF), of which 63 percent were due to enteric fermentation and 21 percent were due to manure left on pasture[190]. The main contributor to the agricultural economy is banana production, which covers around 45 percent of the total agricultural land.[191] Measures implemented in the alternative scenarios include a zero-grazing policy, indicating that manure is stored on farms and applied to cropland, and diversification in agriculture production with increased cashew nuts and coconut exports. Forests covered 34 percent of the total land area in 2020. The AM and TR scenarios include the phasing out of wood removals for firewood and construction. Increasing agricultural productivity and reducing crop consumption can also lead to reforestation of freed agricultural land. Table 19 presents the assumptions for the GGSim application in St. Lucia for AFOLU model.

Food waste and loss index (SDG 12.3.1.a and b):
The prevalence of severe and moderate food insecurity is around 22 percent in Saint Lucia.[192] High food prices, hazardous weather events, and the economic shift away from agriculture, with a high share of imported food, are contributing factors.[193] Agriculture contributed 1.64 percent to the total GDP in 2022, compared to 3.65 percent in 2009[194], while the value of food imports in total merchandize exports rose from 63 percent (2008-2010 average) to 314 percent (2019-2021

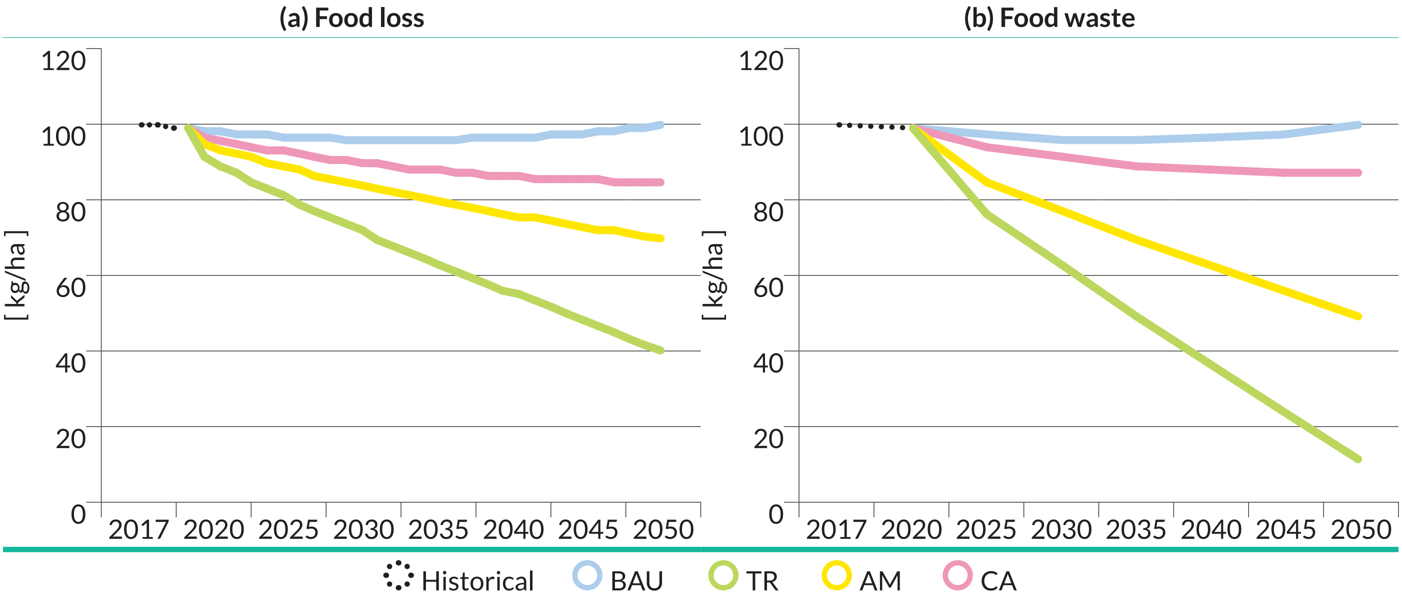
Table 19. Scenario assumptions in the GGSim application for St. Lucia's AFOLU model					
	BAU	CA	AM	TR	Source
Agriculture					
Change in animal-based food consumption [Percent/year]	+0.36	+0.36	0	-0.36	FAO, 2021
Change in crop-based food consumption [Percent/year]	+0.36	+0.36	+0.18	-0.24	FAO (2021)
Change in agricultural productivity	0	+0.06	+0.12	+0.32	FAO (2017)
Decrease in post-harvest food losses [Ton/year]	0	50	100	200	UN (2021)
Decrease in consumer food waste [Ton/year]	0	50	200	350	UN (2021)
Manure left on pastoral land (2050) [-]	0.44*	0.4	0.2	0	NAP (2018)
Manure applied to soil (2050) [-]	0.97*	0.6	0.45	0.4	Expert judgment
Diversifying agricultural exports: cashew nuts [Ton/year]	0	10	25	50	Expert judgment
Diversifying agricultural exports: coconut [Ton/year]	0	10	50	150	Expert judgment
Forestry					
Reforestation of fallow agricultural land [Percent/year]	0	0.1	0.5	1	Expert judgment
Change in wood removals for firewood [Percent/year]	0	-0.5	-1	-3	Expert judgment
Extreme weather events and drought damage on forest biomass	Increasing over the years across all scenarios				

Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Data source: FAO. (2021). Food and agriculture projections to 2050; FAO. (2017). The future of food and agriculture – Trends and challenges; UN. (2021). UNEP Food Waste Report 2021; Government of Saint Lucia. (2018). Government of Saint Lucia. (2018). Saint Lucia's National Adaptation Plan (NAP): 2018-2028.). Government of Saint Lucia. (2018). Saint Lucia's National Adaptation Plan (NAP): 2018-2028.

average)[195]. Food loss and waste policies can help minimize the country's reliance on imports. The food waste and loss indices follow similar trends, with values in the BAU scenario very close to 100 from 2020 to 2050 (Figure 50). The sustainability target for food waste and loss is 50. The AM and TR scenarios will meet the food waste target only around 2050 and 2035, respectively, while the food loss target is only met by the Transformative scenario, only around 2045. The BAU scenario shows no overall improvement in either of the indices.

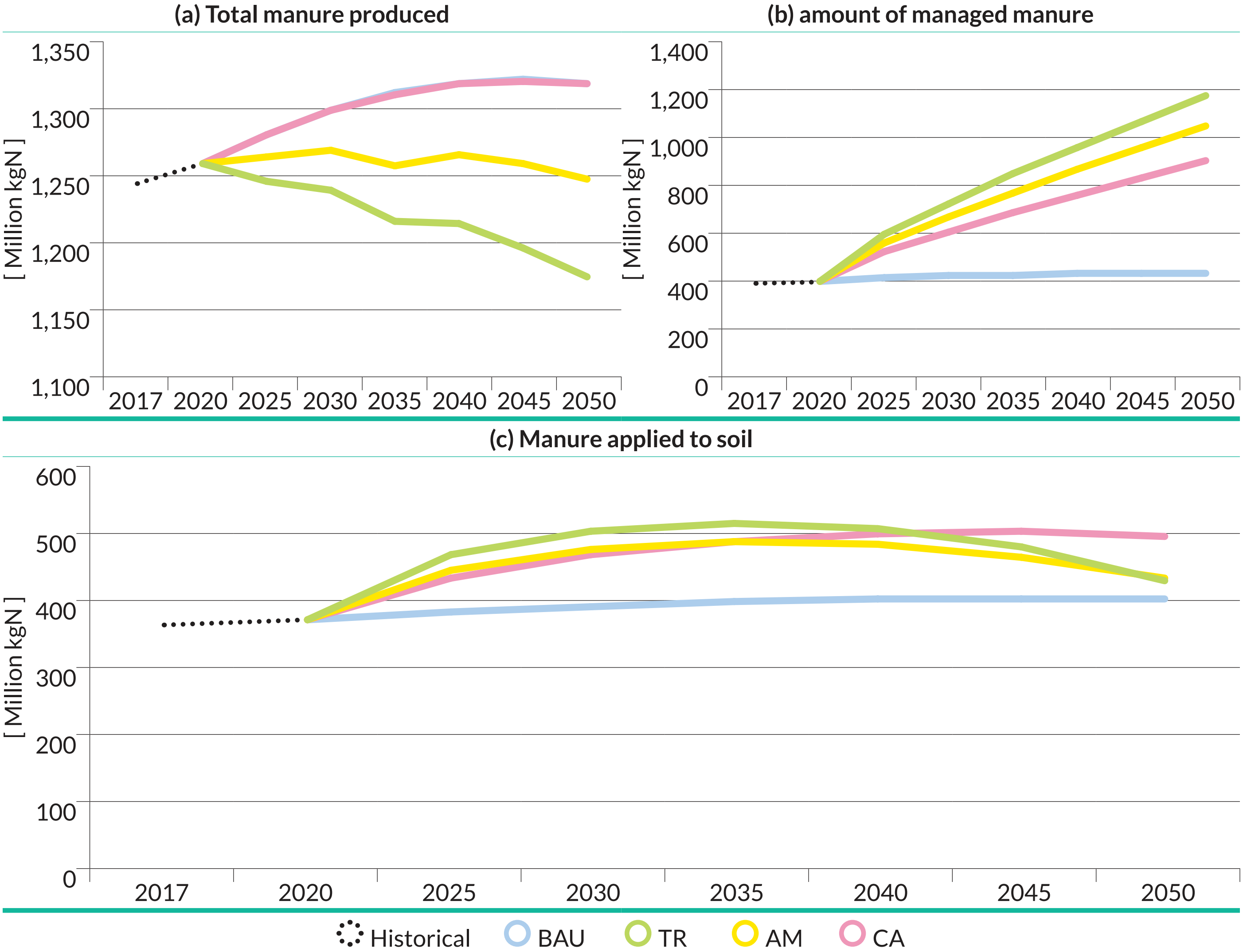
Manure production and fertilizer use (link to SDG 2.4.1): The livestock sector in St. Lucia is relatively small and dominated by poultry and pork.[196] In 2014, it only contributed 14 percent of the total agricultural GDP, compared to 27 percent for fishing and 40 percent for crops. Animal product consumption is assumed to increase under the BAU and CA scenarios and decrease under the TR scenario. The amount of manure generated will increase indistinguishably in the BAU and CA scenarios, which have the same assumptions on animal production

Figure 50. Changes in (a) food loss (SDG 12.3.1a) and (b) food waste (SDG 12.3.1b) index in St. Lucia, 2017-2050



Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR – Transformative
Source: Author's own.

Figure 51. Changes in (a) total manure produced, (b) amount of managed manure, and (c) manure applied to soil (link to SDG 2.4.1) in St. Lucia, 2017-2050



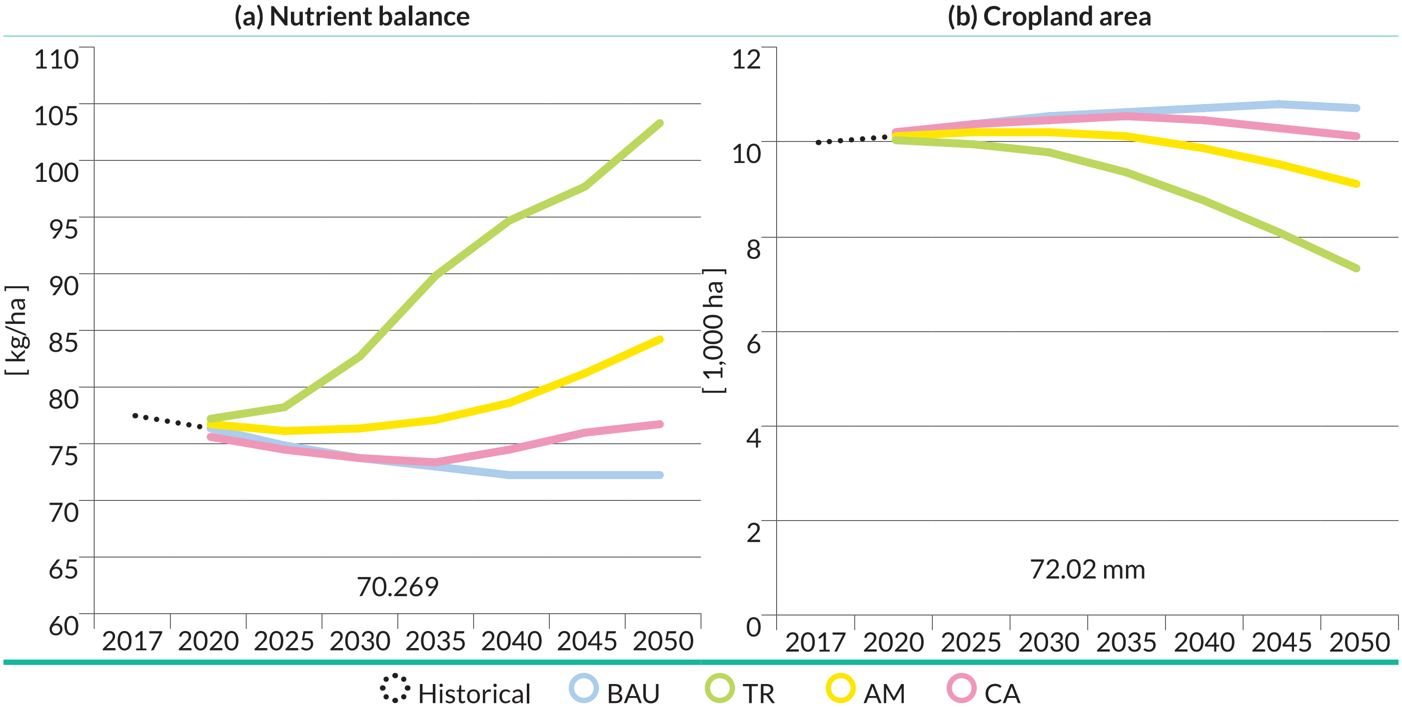
Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

(Figure 51a). The amount of manure produced in the AM scenario will stay constant over the whole period, with only minor variations. It will decrease in the TR scenario due to the decrease in animal product demand. The amount of managed manure will increase linearly under the alternative scenarios, but it will remain almost constant in the BAU scenario (Figure 51b). In the TA scenario in 2050, all the manure produced will be managed. In the two most ambitious scenarios (i.e., MA and TR), the amount of manure applied to the soil first increases due to the increased amount of manure managed, resulting in more manure available to be applied to the soil (Figure 51c). However, this trend is reversed in the second part of the period due to the decreasing share of manure applied to the soil. This result will also be observed in the CA scenario, albeit to a lesser extent. Overall, the proportion of agricultural area under productive and sustainable agriculture (SDG 2.4.1) will improve due to the increased amount of managed manure and the decrease in manure applied to soil in the alternative scenarios.

Nutrient balance and cropland area (part of SDG 15.3.1): The nutrient balance value will decrease in the BAU scenarios and remain overall constant in the CA scenario between 2020 and 2050 (Figure 56a). However, the AM and TR scenarios will perform worse, with the nutrient balance value increasing most significantly in the TR, 43 percent higher than in the BAU scenario in 2050. This observation can be attributed to two main factors: the policies on manure management and the change in cropland demand. The share of manure left on pasture will decrease in the alternative scenarios; in the TR scenario, all the manure will be managed by 2050. Therefore, even if the share of manure applied to soil decreases more with increasingly ambitious scenarios, it will not offset the increase in manure management. On the other hand, fertilizer use policies will contribute to limiting the increase in nutrient inputs. Then, the increase in the nutrient flow is explained by the decrease in cropland area due to the reduction in food demand (Figure 56b). On the contrary, the cropland area increases in the BAU and (only temporarily) in the CA scenario.

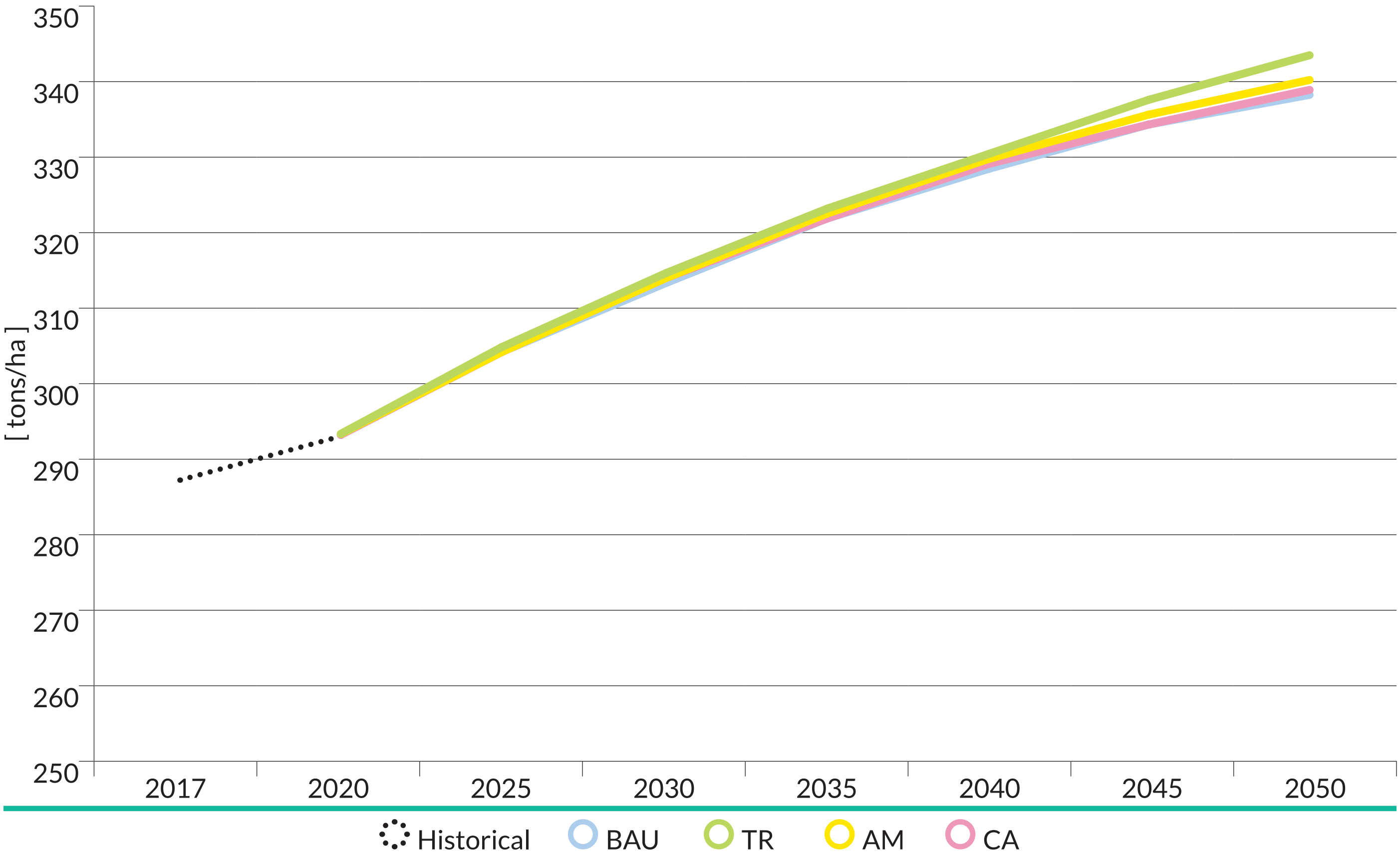
Above-ground biomass in forest (SDG 15.2.1): The level of above-ground biomass increases similarly under all scenarios (Figure 53). Fuelwood removals are reduced throughout the period in the alternative scenarios, reducing the amount of above-ground biomass loss, while differences

Figure 52. Changes in (a) nutrient balance (part of SDG 15.3.1) and (b) cropland area in St. Lucia, 2017-2050



Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

Figure 53. Changes in above-ground biomass in the forest (SDG 15.2.1) in St. Lucia, 2017-2050



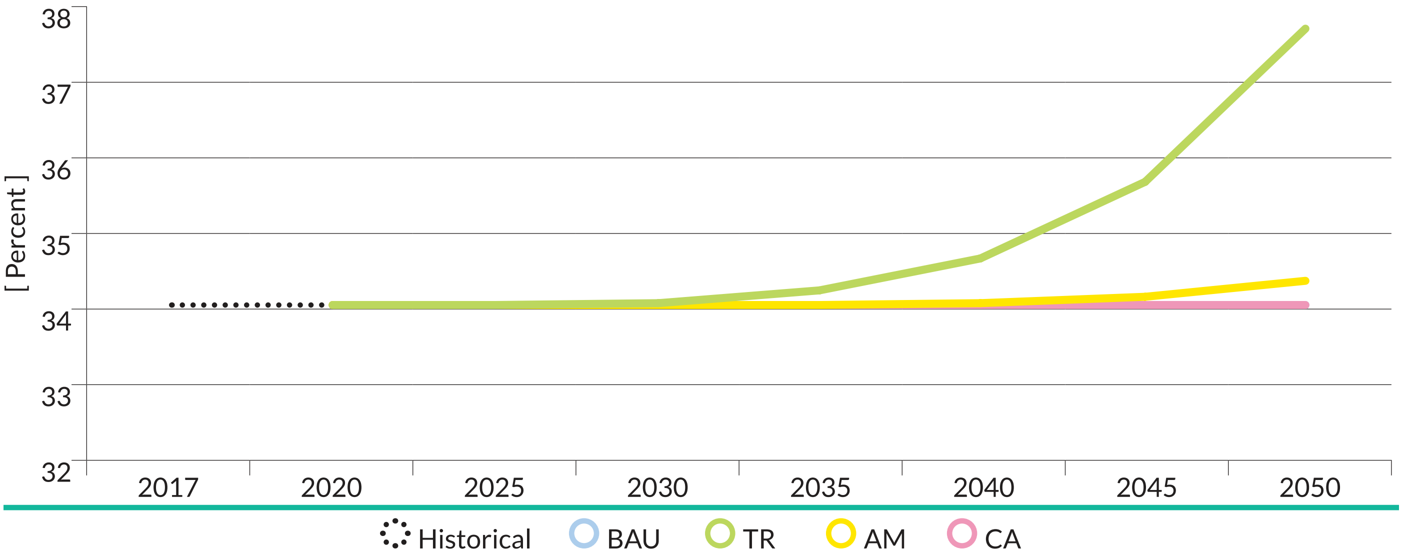
Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

in biomass increase are due to differences in forest land (Figure 54). However, the variation in above-ground biomass levels across the scenarios is insignificant. Two observations can explain this: First, the forest area does not vary much, with only a notable increase of less than 4 percent in the TR scenario (Figure 54), offsetting the variations in the annual change in biomass across the scenarios. Second, annual changes are small compared to the existing levels; from 2045 to 2050, levels increased by 1.2 and 1.8 percent under the BAU and TR scenarios, respectively.

Share of forest area to total land area (SDG 15.1.1): The area of forest lands has remained constant over the last decade.[197] The country recognizes the importance of its forest resources in its Forest and Lands Resources Development Strategy 2015-2025[198] and has been part of the Coalition for Rainforest Nations[199] since 2016. The increase in the share of forest land is only noticeable under the TR scenario (+3.7 percent) due to the reforestation of fallow lands (Figure 54). The other scenarios, however, will not lead to any decrease due to the low reforestation rate or the lack of fallow land. The total forest area will change in the TR scenario, but this will not affect the above-ground biomass because it is not linked to the changes in the area. Forest biomass is assumed to naturally regenerate, causing above-ground biomass to increase over time, even in the BAU scenario (Figure 53).

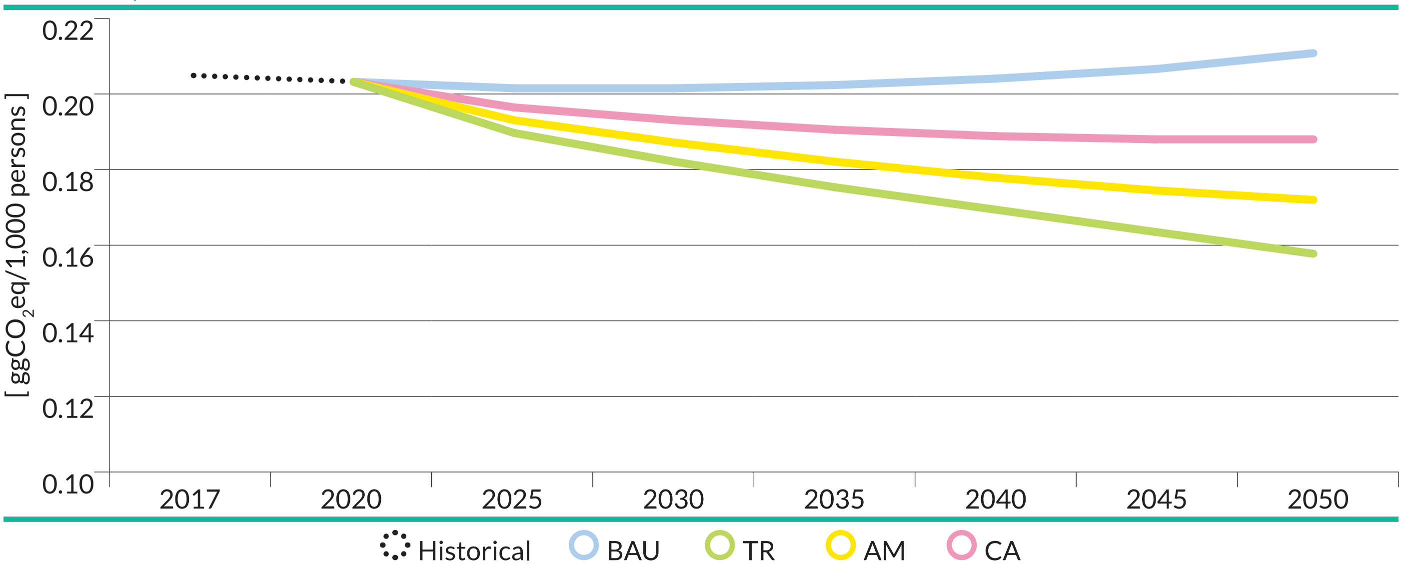
Emissions from agricultural production (part of SDG 13.2.2): Emissions from agriculture have remained constant over the past decade, amounting to about 5 percent of the country's total GHG emissions.[200] Contributions have also remained mostly stable, with livestock being the largest contributor due to enteric fermentation (61 percent), manure left on pasture (21 percent), and manure management (8 percent)[111, 201] The ratio of non-CO_2 emissions in agriculture to population slightly increases in the BAU scenario and decreases in the others, with the best performances achieved with increased

Figure 54. Changes in the share of forest area to total land area (SDG 15.1.1) in St. Lucia, 2017-2050



Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

Figure 55. Changes in the ratio of non-CO_2 emissions (part of SDG 13.2.2) in agriculture in St. Lucia, 2017-2050



Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

iii Shares are averaged over the period 2011-2021.

levels of ambition (Figure 55). The absolute emissions also declined, driven by reduced emissions due to manure left on pasture. The emissions from enteric fermentation, on the other hand, remain mostly constant under all scenarios. The share of emissions varies from 59 percent in 2017 to 74 percent in 2050 in the TR scenario.

B.2 Water use and waste

The water use and waste model in St. Lucia considers the agricultural and municipal sectors. Outputs from the AFOLU model on the irrigated area values were used in the water model, and policy measures for the agricultural sector focused on introducing more efficient irrigation technologies. For the municipal sector, increased water tariffs were implemented as an adaptation measure to improve water efficiency.[202] Prices were based on St. Lucia's National Water and Sewage Commission reviews.[203] St. Lucia has identified that wastewater treatment plants are operating at a lower capacity than the designed capacity would allow.[204] Improving the current wastewater infrastructure to meet existing treatment capacity and repairing the wastewater collection network were therefore assumed to be a priority. Construction of new wastewater treatment plants, which is more costly, was assumed to be implemented only under the AM and TR scenarios. A similar assumption was used for distributing wastewater treatment types (primary, secondary, tertiary), which will impact the pollutant removal efficiencies.

Additionally, the population is mostly rural (81 percent in 2017), and progress was assumed to occur faster in urban areas. Table 20 presents the assumptions for the GGSim application of water use and waste model in St. Lucia.

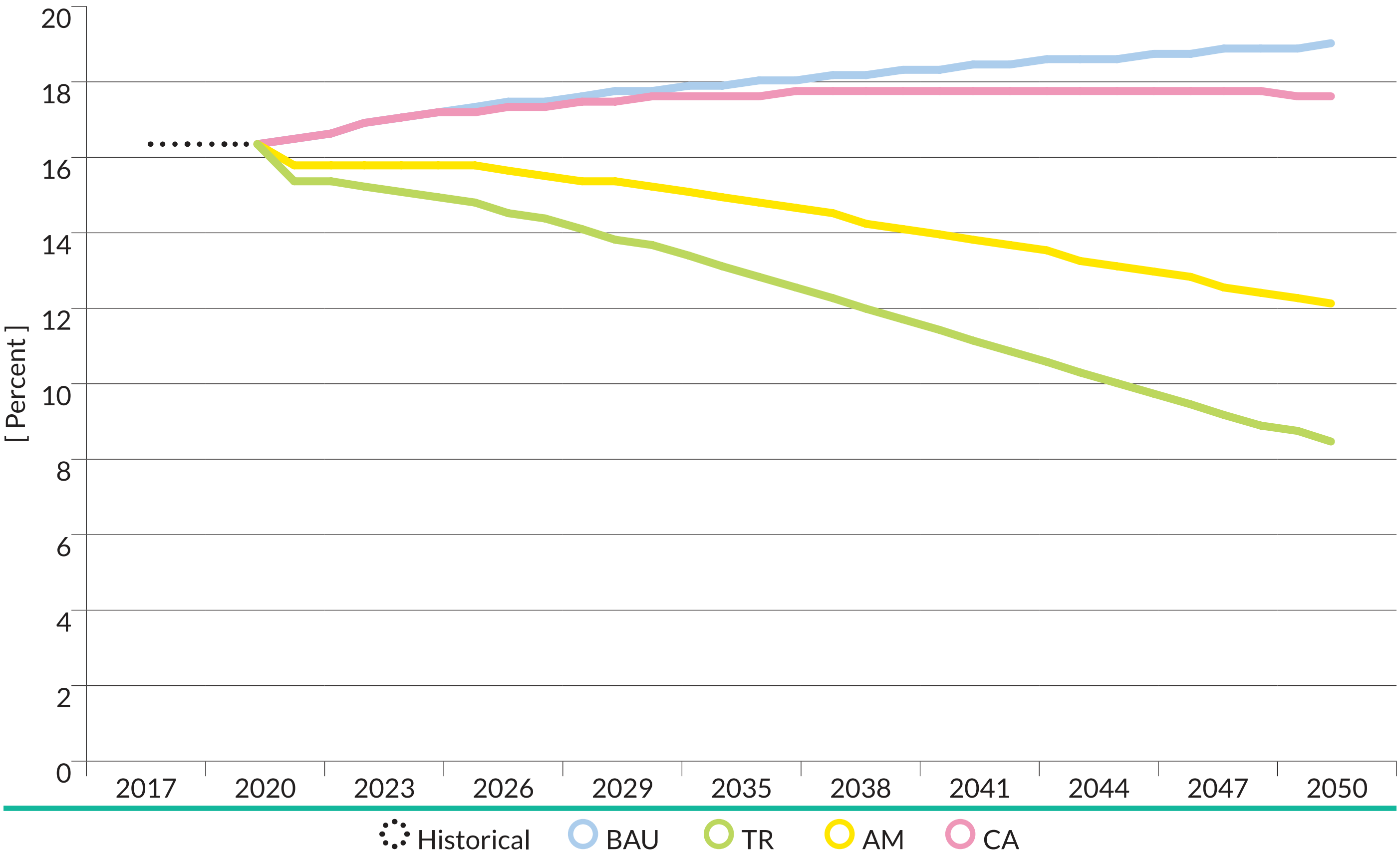
Level of water stress (SDG 6.4.2): In 2017, St. Lucia withdrew approximately 16.3 percent of the total available renewable freshwater resources. Under a BAU scenario, the level of water stress will increase to 19 percent by the end of 2050 (Figure 56), driven by the increase in both municipal and agricultural water withdrawals. The CA scenario will also show an increasing trend in water stress, although the decline in agricultural water withdrawal after 2030 will reduce water stress to 17.6 percent by 2050. However, under BAU and CA scenarios, the water stress level will remain below 25 percent, meaning that the sectoral water withdrawals do not place significant pressure on water resources. Further improvements in maintaining freshwater resources will be observed under the AM and TR scenarios. The AM scenario will result in a decline in water stress to 12 percent and the TR scenario will be 8.3 percent by 2050 due to implementing more efficient technologies within the agricultural sector, leading to more significant water demand reductions. On the other hand, even if there is no substantial reduction in municipal water withdrawals, higher water tariffs within the TR scenario will cause a reduction in the overall water withdrawals, which will be more than in the AM scenario. Hence, the management strategies under the AM and TR scenarios can

Table 20. Scenario assumptions in the GGSim application for St. Lucia's water use and waste model

Inputs	BAU 2050	Cautious 2050	Ambitious 2050	Transformative 2050	Source/basis of assumption
Socioeconomic					
GDP	SSP2 IIASA	SSP2 IIASA	SSP1 IIASA	SSP1 IIASA	SSP IIASA
Population	SSP2 IIASA	SSP2 IIASA	SSP1 IIASA	SSP1 IIASA	SSP IIASA
Urban population [Percent]	51	51	72	72	SSP NCAR
Rural population [Percent]	49	49	28	28	SSP NCAR
Irrigation					
Irrigation technology proportions [Percent]	Surface: 100 Sprinkler: 0 Drip: 0	Surface: 100 Sprinkler: 0 Drip: 0	Surface: 40 Sprinkler: 30 Drip: 30	Surface: 20 Sprinkler: 30 Drip: 50	
Municipal					
Water price [USD/m^3]	12.21	+1%	+2.5%/y	+5%/y	St. Lucia's National Water and Sewage Commission
Wastewater recycling	No	No	Yes	Yes	
Sanitation					
Population connected to sewage [Percent]	8	17	42	86	
Population under open defecation [Percent]	5	1	0	0	
Population connected to septic tanks [Percent]	87	82	58	14	
Wastewater treatment coverage [Percent]	2	22	35	60	

Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative

Figure 56. Changes in the level of water stress (SDG 6.4.2) in St. Lucia, 2017-2050



Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

significantly improve water use efficiency while limiting the over-exploitation of St. Lucia's freshwater availability.[iv]

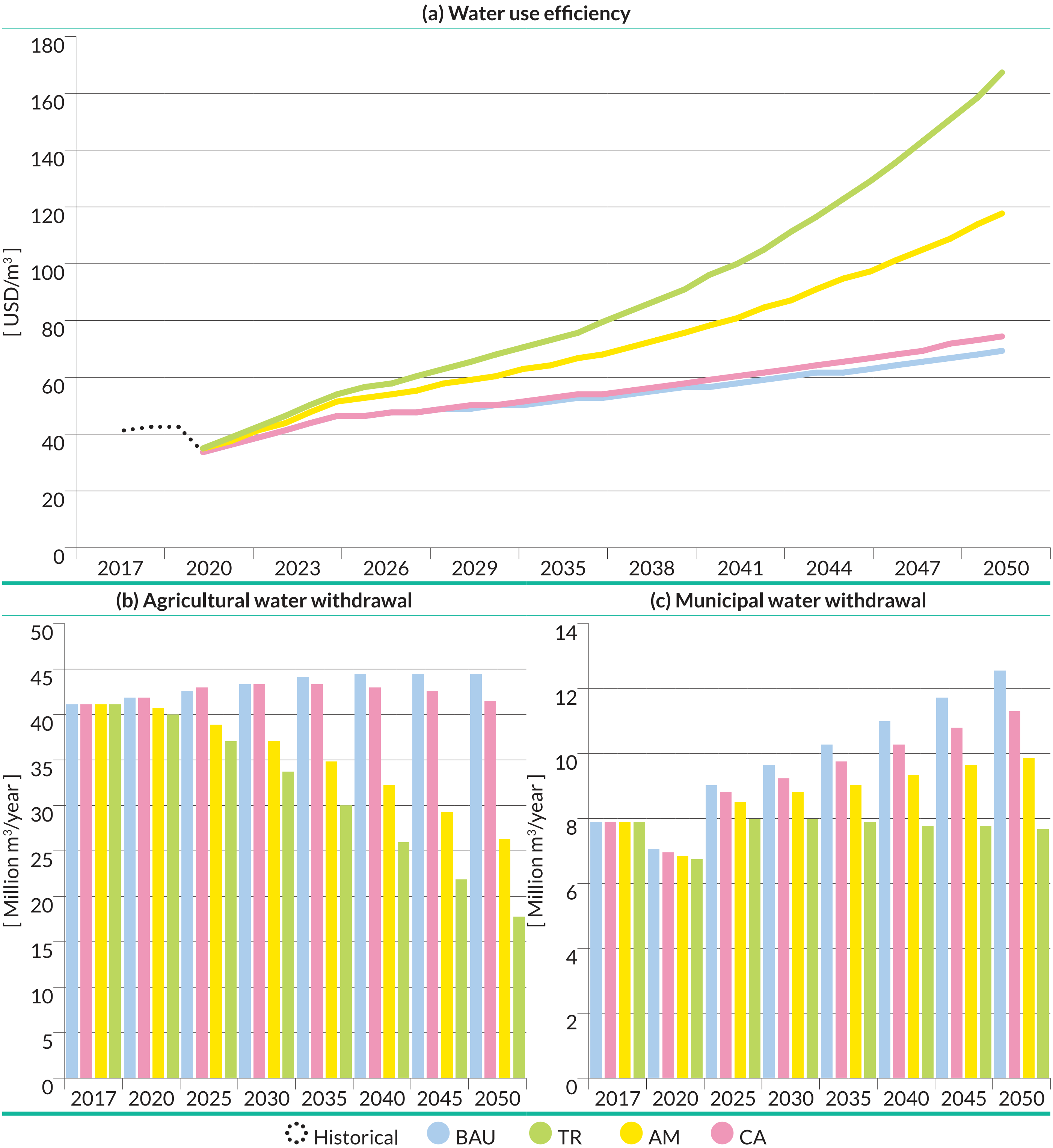
Water use efficiency (SDG 6.4.1): Agriculture is the most water-intensive sector, contributing 70 to 84 percent to the total water withdrawals across all scenarios (Figure 57b). In the BAU scenario, agricultural water withdrawals will steadily grow by 11 percent in 2050. In the AM and TR scenarios, this will decline over time, highlighting the effectiveness of technological innovation in reducing the water demand. Indeed, transitioning to more efficient systems such as sprinkler and drip irrigation leads to a decrease in 36 percent and 54 percent withdrawals under the AM and TR scenarios, respectively. On the other hand, municipal water withdrawals increase under the BAU by 60 percent, the CA scenario by 44 percent, and the AM scenario by 25 percent compared to the base year (Figure 57c). The TR will be the only scenario where municipal water withdrawal does not significantly increase over time. This suggests that the increase in water tariff (5 percent increase per year) will successfully maintain constant levels of water withdrawals. All scenarios showed a decline in municipal water withdrawals in 2020 due to the decline in GDP caused by the COVID-19 crisis. As GDP per capita is an essential driver of the municipal water use sub-model, this impact on income is reflected in the model outputs.

All scenarios show an increase in total water use efficiency as well as per sector for St. Lucia between 2017 and 2050 (Figure 57a and Table 21). The most significant gains in water use efficiency are observed under the TR scenario, with an increase of 306 percent between 2017 and 2050, predominately due to the reduction in agricultural water withdrawals. A similar trend is also observed under the AM scenario, although water use efficiency estimates are not as high as in the TR scenario. The BAU and CA scenarios also show increased water use efficiency while the water withdrawals also increase. This means there is a more considerable increase in sectoral value-added, which depends on the SSP framework's GDP estimates. These estimates increase faster over the modeling period in both the SSP1 and SSP2 narratives than the increase in water withdrawal. Therefore, it suggests that under these scenarios, St. Lucia does not show any decoupling between economic growth and water use, and there is no significant improvement in water use efficiency. This also emphasizes that performance in SDG 6.4.1 should be coupled with other indicators, such as SDG 6.4.2 (Level of water stress), to validate any improvements in water use efficiency.

Treated wastewater (part of SDG 6.3.1): Municipal wastewater flows safely treated have been historically mostly inexistent in St. Lucia. No significant change will be observed in the municipal wastewater treated to wastewater generated in the CA scenario because the main policy intervention will be to improve the connectivity to sewage networks as opposed to wastewater treatment (Figure 58) Therefore, while a higher proportion of wastewater is collected, the amount that undergoes treatment remains relatively small. The UN monitoring guidelines for SDG 6.3.1 also classify safely treated

iv Note that the environmental flow requirements were not included in the analysis due to data and modeling limitations.

Figure 57. Changes in (a) water use efficiency (SDG 6.4.1), (b) agricultural water withdrawal, and (c) municipal water withdrawal in St. Lucia, 2017-2050



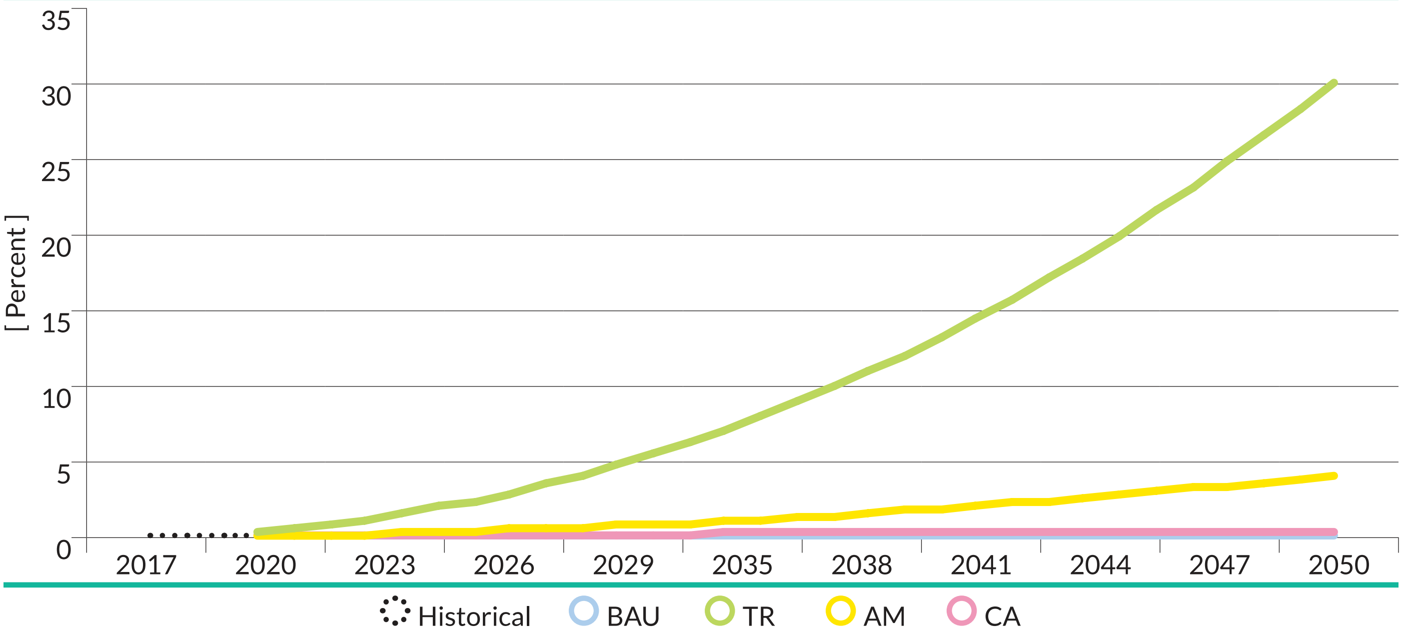
Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

Table 21. Sectoral and total water use efficiencies in St Lucia in different scenarios, 2050

Sector	Base Year (2017)	BAU (2050)	Cautious (2050)	Ambitious (2050)	Transformative (2050)
Agriculture	0.15	0.42	0.44	0.75	1.12
Municipal	256.98	312.43	346.75	430.84	554.54
Total	41.34	69.29	74.44	117.43	167.79

Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

Figure 58. Changes in Treated wastewater (part of SDG 6.3.1) in St. Lucia, 2017-2050



Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

wastewater as water that undergoes at least secondary treatment, such as biological treatment with a secondary settlement process.[205] Hence, improvements in primary treatment, which is the main assumption for this scenario, were not captured by the definition of SDG 6.3.1. This suggests that the interlinkages between access to improved sanitation and water quality are more complex, and policies to support improvements in one indicator will not necessarily result in improvements in the other.

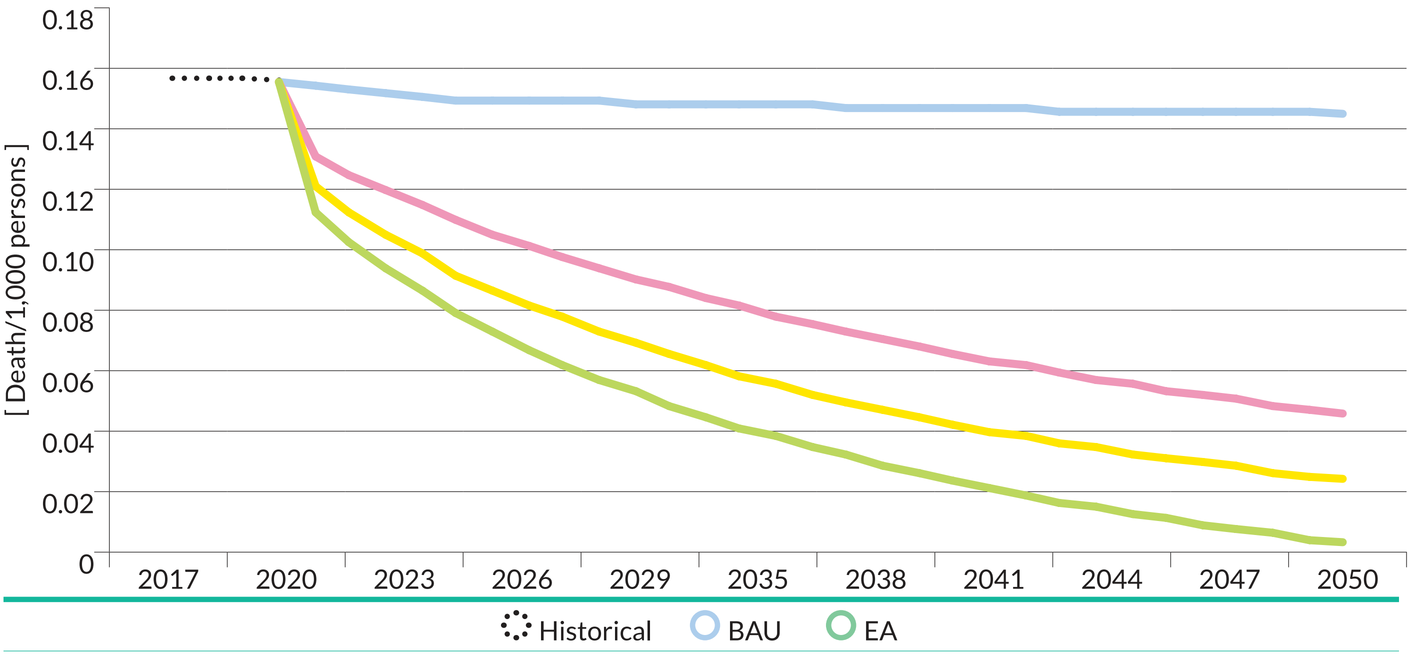
The AM scenario will only increase to 4 percent by 2050 despite the implementation of increased access to secondary wastewater treatment. This can be explained by the increase in municipal water withdrawals and, thereby, generation, offsetting the improvements in wastewater treatment. The TR scenario will reach 30 percent of safely treated wastewater, which will need improvement to meet the 2030 SDG target to halve untreated wastewater.[206] This better performance, however, can be attributed to less municipal wastewater generated. Combining ambitious wastewater strategies, such as high connectivity to sewage networks, with advancements in tertiary wastewater treatment results in a more significant proportion of wastewater treated. Note that this analysis only considers sewage networks as sanitation sources that can undergo safe treatment. This assessment recognizes that independent sanitation sources such as septic tanks can also contribute to the proportion of safely managed wastewater flows. However, this was not included in the analysis due to a lack of data on septic tank performance in St. Lucia. Therefore, with the inclusion of independent treatment, this could result in a higher value for SDG 6.3.1 for St. Lucia.

Disease burden due to inadequate sanitation (part of SDG 3.9.2)[v]: Sanitation is a risk factor contributing to SDG indicator 3.9.2: burden of disease attributable to unsafe water, unsafe sanitation, and lack of hygiene (WASH). The base year values estimated that inadequate sanitation contributed to approximately 0.15 diarrheal deaths per 100,000 people in 2017 (Figure 59). The BAU scenario indicates that without improvements in access to basic sanitation, the number of deaths will remain relatively consistent over time, falling to 0.14 deaths per 100,000 people per year in 2050. As other scenarios include sanitation and wastewater treatment improvements, there will be a gradual decrease in the disease burden from inadequate sanitation over time. As with the other results, the TR scenario will show the most significant progress, with the disease burden falling close to zero by 2050.

Environmental pollution due to nutrient emissions (SDG 6.3.2 and SDG 14.1.1a)[vi]: Nutrient emissions discharged into surface water systems from human waste were estimated to provide preliminary investigations on environmental pollution in St. Lucia. These estimates can be linked to SDG indicators 6.3.2 (proportion of bodies of water with good ambient water quality) and 14.1.1(a) (Index of coastal eutrophication).[vii] The BAU scenario shows a gradually increasing trend, with nutrient emissions being 29 percent higher by 2050 than in the base year (Figure 60). Most of this increase will be due to the increase in point source emissions, with non-point source emissions[viii] staying more or less constant. This contrasts with the alternative scenarios, which all show a similar decreasing trend. The CA scenario will also show an increasing trend, with nutrient emissions being 82 percent higher by 2050 than in the base year due to the increase

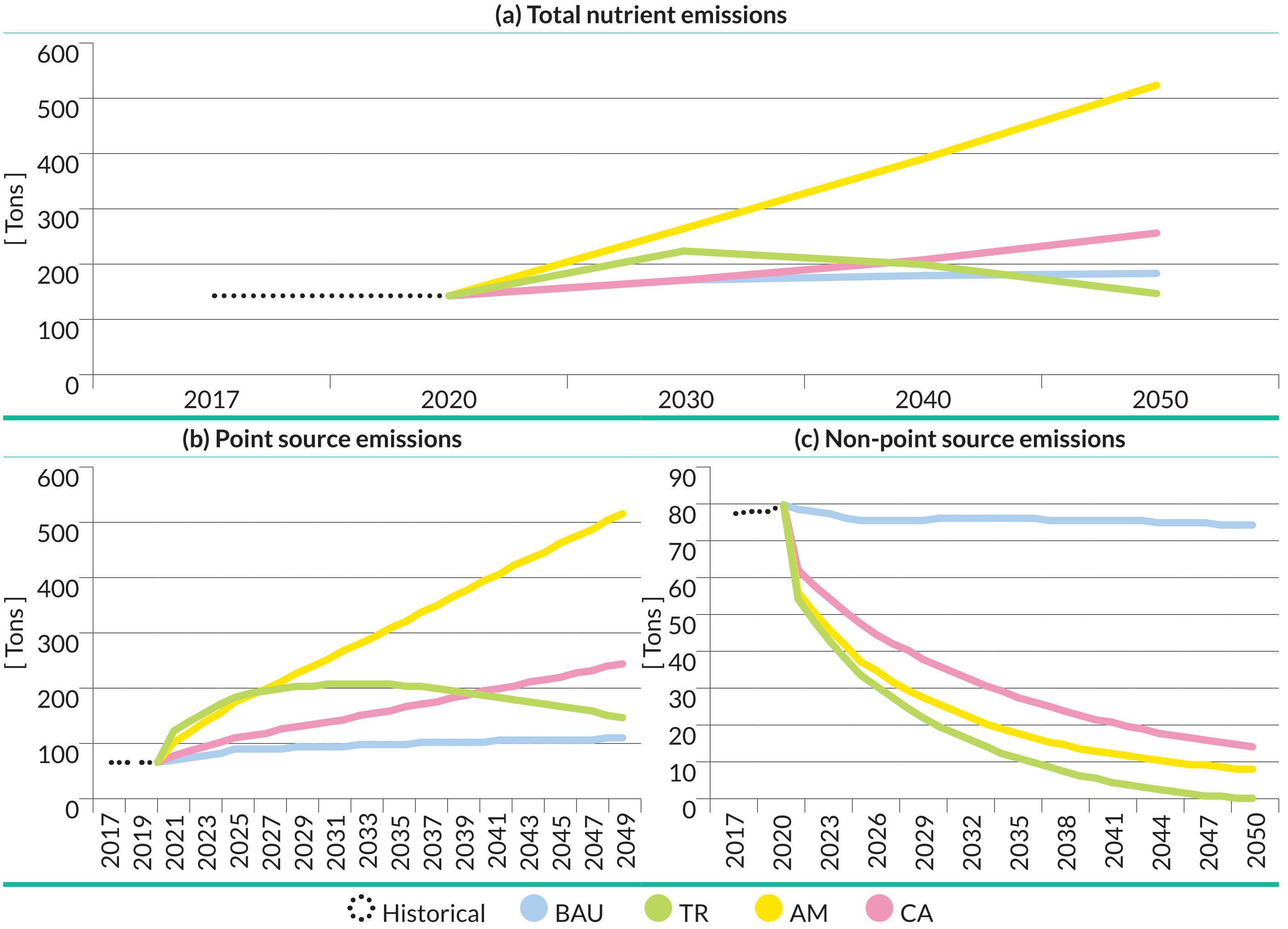
v As mentioned in Section 4.1.3, this module needs further development. The results presented here are initial results and represent an attempt to include water quality into the model.
vi As mentioned in Section 4.1.3, this module needs further development. The results presented here are initial results and represent an attempt to include water quality into the model.
vii As land use and hydrological processes are not included in this analysis, these results will not provide an estimation of basin-level nutrient loads, which are necessary to fully determine the progress of these indicators. This will require additional spatial data and modeling to extend the water quality model for St. Lucia.

Figure 59. Changes in disease burden due to inadequate sanitation (part of SDG 3.9.2) in *St. Lucia*, 2017-2050



Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

Figure 60. Changes in (a) total nutrient emissions (SDG 6.3.2 and SDG 14.1.1a), (b) point emissions, and (c) non-point emissions discharge into surface water in St. Lucia, 2017-2050



Note: Point source emissions refer to emissions from connected sewage systems while non-point source emissions refer to emissions from direct and diffuse sources.
Scenarios: BAU – Business-as-usual, CA – Cautious, AM – Ambitious, TR - Transformative
Source: Authors own.

in point source emissions. The AM scenario results in the most significant increase in emissions discharged, as high as 272 percent by 2050 compared to the base year. The TR scenario, after an increase due to point source emissions, will go back to the base year levels.

Yet, relative to the BAU and CA scenario, the AM scenario will perform better in SDG 6.3.1. As in the other scenarios, the increase in emissions discharged is due to point source emissions significantly rising over time. This finding presents a situation where sewage networks can act as a direct pathway for pollutants into water systems due to the different levels of access to sanitation and wastewater treatment.[207] It implies that the wastewater treatment assumptions in the AM scenario will be insufficient to deal with the large capacity of collected wastewater treatment from increasing connectivity to sewage networks. Therefore, while the AM scenario has improved water quantity when assessing other indicators (SDG 6.4.1 and SDG 6.4.2), it is expected to perform poorly in supporting healthy water quality. The improvement in safely treated wastewater (SDG 6.3.1) is offset by the increased amount of untreated human waste and discharge into water systems, leading to increased nutrient pollution, which can create water quality imbalances and higher risks of eutrophication.[208] These will reduce progress in SDG 6.3.2 and SDG 14.1.1. These results highlight the relevance of SDG co-benefit assessment, as focusing on a single indicator for policy implementation can mask adverse impacts in other sustainable development indicators, resulting in an inaccurate understanding of a country's progress towards green growth.

4.2.2 Senegal

A. Overview of scenarios

Senegal is in Western Africa and borders the Atlantic Ocean. It is 196,722 km2 wide and home to 18.4 million people. The population is predominantly young, with 60 percent of the population under the age of 25, lives mainly in rural areas, with a share of around 70 percent, and suffers a high illiteracy rate of 40 percent.[209] The ***Plan Senegal Emergent (PSE)*** was published in 2014 and aimed to accelerate economic expansion and improve the country's sources of livelihood. The ***Green PSE*** was further adopted in 2021 and ensures environmental recovery and sustainable resource management while enhancing green economic growth. It includes measures to restore degraded natural areas, improve forest management, and increase vegetation cover and carbon sequestration capacity. The GGSim Tool was applied to the AFOLU sector to assess SDG co-benefits from the adaptation measures addressing these environmental issues. Two scenarios were developed to be compared with the BAU scenario based on the policies identified during the LAB[ix] sessions on the Green PSE and the pathway trajectories designed by the FAO[210]:

- The Business-as-usual (BAU) scenario assumes nothing is done to adapt to climate change. Social, economic, and technological development follows historical trends and focuses on national economic growth with little regard for environmental issues.
- The Moderate Ambition (MA) scenario ensures that any climate adaptation or mitigation plan is affordable, limiting investments that cannot be supported without collaboration and, therefore, restricting what national governments and local investors can afford.
- The High Ambition (HA) scenario requires structural change and investments, assuming support from the international community.

The GGSim scenarios focused on agriculture and forest, which are some economic sectors emphasized in the Green PSE.

B. GGSim model applications

This section presents the results of the GGSim applications for the AFOLU model (Table 5). The GGSim application in Senegal was based on the project Fast-tracking investment in nature for the green recovery of Senegal: designing and operationalizing the Green PSE, funded by the MAVA Foundation for Nature in 2022. In this project, GGGI and VividEconomics to support the Bureau Opérationnel de Suivi (BOS) du PSE and the Ministry of Environment and Sustainable Development in designing the Green PSE contents.

B.1 Agriculture, forest, and land use

Agriculture employs half of the population of Senegal, but the sector's productivity is low at 7.6 percent of the GDP.[211] It represents 36 percent of the country's GHG emissions, and the sector's emissions are expected to rise until 2030.[212] The emissions are dominantly due to livestock (enteric fermentation and manure left on pasture) and savanna fires, accounting for an estimated 88 percent of the total agricultural emissions.[213] The Green PSE includes measures to reduce emissions and chemical inputs, restore degraded ecosystems (including forests), and develop sustainable practices. In 2021, forests represented 42 percent of the country's land area, down from 48 percent in 1990.[214] Causes of deforestation include increasing droughts, bushfires, inappropriate farming practices, illegal logging, and biomass extraction for energy purposes.[215] Forestry and land use change accounts for 22 percent of the country's GHG emissions. The scenarios' assumptions include changes in food consumption and food waste and loss, substitution of cattle for poultry, changes in manure management, and deforestation and reforestation policies. Table 22 lists the quantitative measures for the three scenarios. Unless mentioned otherwise, numbers refer to final values in 2050.

viii Point source emissions refer to emissions from connected sewage systems while non-point source emissions refer to emissions from direct and diffuse sources.

ix It is an intensive structuring workshop, which is a structuring framework for technical and financial aspects of priority projects between the state and the private sector under the Green PSE. The LAB is characterized by establishing an intensive framework of high-level participation for five to six consecutive weeks, with the participation of all public structures concerned, private businesses, academia, and interested financial institutions. (Source: GGGI's project proposal submitted to MAVA Foundation).

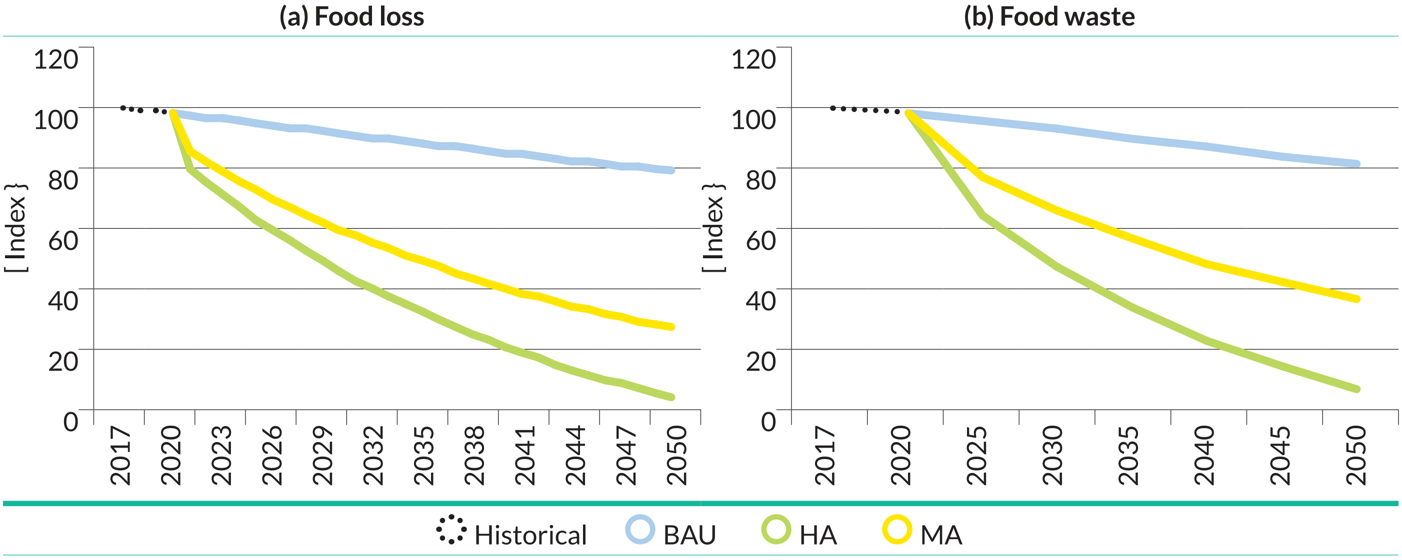
Table 22. Scenario assumptions in the GGSim application for Senegal's AFOLU model

	BAU	HA 2050	MA 2050	Source
Agriculture				
Change in animal-based food consumption [Percent]	+12	+5.96	+5.96	FAO, 2018
Change in crop-based food consumption [Percent]	+18.86	+5.96	+5.96	FAO, 2018
Change in agricultural productivity [Percent]	+34.5	+34.5	+34.5	FAO, 2018
Livestock substitution	No policy	50% substitution of cattle for poultry	25% substitution of cattle for poultry	Expert judgment
Decrease in post-harvest food losses [tons/year]	Historical trend	13000	6000	UNEP, 2021
Decrease in consumer food waste [tons/year]	Historical trend	40000	10000	UNEP, 2021
Manure left on pastoral land [-]	Historical trend	0.9	0.2	Expert judgment
Manure applied to soil [-]	Historical trend	1	0.1	Expert judgment
Forestry				
Reforestation of inactive land [Percent]	Historical trend	30	15	Green-PSE policy
Decrease in wood removals [Percent]	No decrease	20	10	Expert judgment

Scenarios: BAU - Business-as-usual, MA - Moderate Ambition, HA - High Ambition
Data sources: FAO. (2018). The future of food and agriculture – Alternative pathways to 2050; UNEP. (2021). Food Waste Index Report 2021; Marklund, L. G., & Schoene, D. (2006). Global Assessment of Growing Stock, Biomass and Carbon Stock. The Forest Resources Assessment (FRA) Working Paper Series

Food loss and waste index (SDG 12.3.1.a and b): Food security in the country is highly impacted by economic, health, and environmental crises. Senegal, classified as a lower-middle-income country, struggles with high levels of poverty and food insecurity, especially in rural areas.[216] Approximately 16 percent of the population experiences food insecurity, with 2 percent categorized as severe and 14 percent as moderate. This issue is unevenly distributed across the nation, with 15 percent of rural households facing food insecurity compared to 8 percent of urban households.[217] Additionally, as of 2018, 37.4 percent of the population lived below the low-middle income country poverty line of 882.5 CFA franc or US$3.65 per day (World Bank, 2023).[218] The agriculture sector is predominantly subsistence farming, characterized by limited access to essential resources such as quality seeds, fertilizers,

Figure 61. Changes in (a) food loss (SDG 12.3.1a) and (b) food waste (SDG 12.3.1b) index in Senegal, 2017-2050

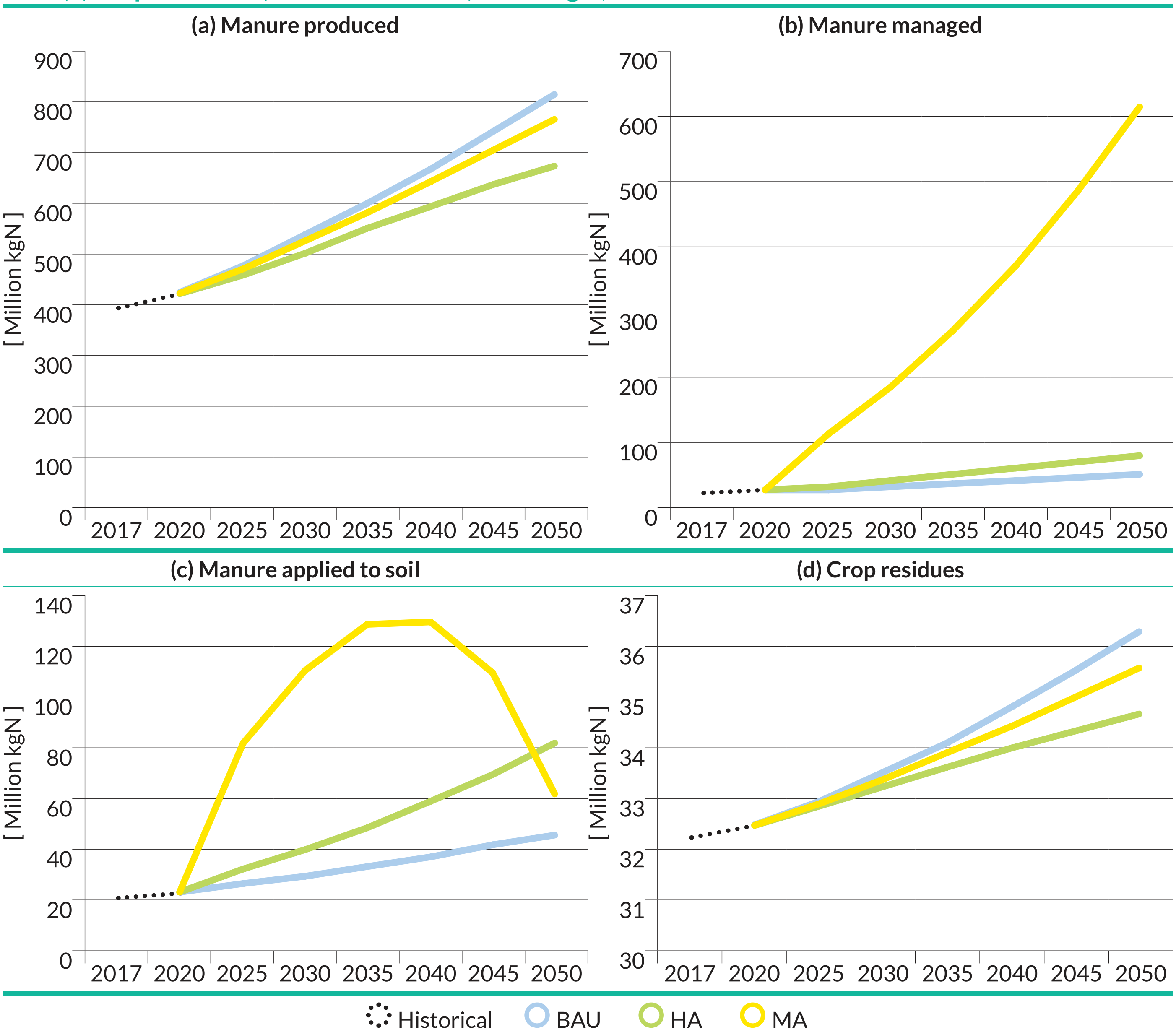


Scenarios: BAU - Business-as-usual, MA - Moderate Ambition, HA - High Ambition
Source: Authors own.

technology, finance, credit, insurance, and post-harvest storage techniques. Traditional and unsustainable practices, including overgrazing and bushfires, contribute to land degradation. Seventy (70) percent of crops are rainfed, which makes the country highly vulnerable to climate shocks, impacting food availability and prices.[219] Food loss and waste policies will help reduce food insecurity and thus poverty. For example, it is estimated that eliminating on-farm postharvest losses could reduce vegetable imports by 22 percent per year.[220] Moreover, reducing postharvest losses will mean more income from farm livelihoods for the farmer. Indeed, marketable surpluses will increase farmer income, but could also lower consumer prices. The total value of supply could increase to up to $72 million. [221] In the BAU scenario, the indices will decrease slightly, although the amount of food loss and waste was assumed to remain constant (Figure 61). This is explained by the increasing population, which results in smaller amounts per capita. The food loss and waste measures implemented in the alternative scenarios will allow Senegal to reduce food loss and waste indices by half before 2040.

Manure production and crop residues (link to SDG 2.4.1): The amount of manure generated will increase in all scenarios due to the increasing demand for animal products (Figure 62). In the case of manure managed and applied to soil, the trends in HA and MA scenarios will vary a lot. The HA scenario will more or less follow the BAU trend, but the former performing better than the latter scenario. The MA will diverge significantly due to a substantial increase in the amount of manure managed, leading to a more significant amount of manure applied to soils in the first half of the period. The increase will be offset by the reduction in the share of manure collected that will be applied to soil in the second half of the period until 2050. The increasing food demand will also drive the amount of crop residues, which explains the increasing trend. No crop residue removals will be implemented in the scenarios,

Figure 62. Changes in (a) manure production, (b) manure managed, (c) manure applied to soil, and (c) crop residues (link to SDG 2.4.1) in Senegal, 2017-2050



Scenarios: BAU - Business-as-usual, MA - Moderate Ambition, HA - High Ambition
Source: Authors own.

so these residues are assumed to be left on pasture. Both manure and crop residues left on land will have implications for the nutrient balance.

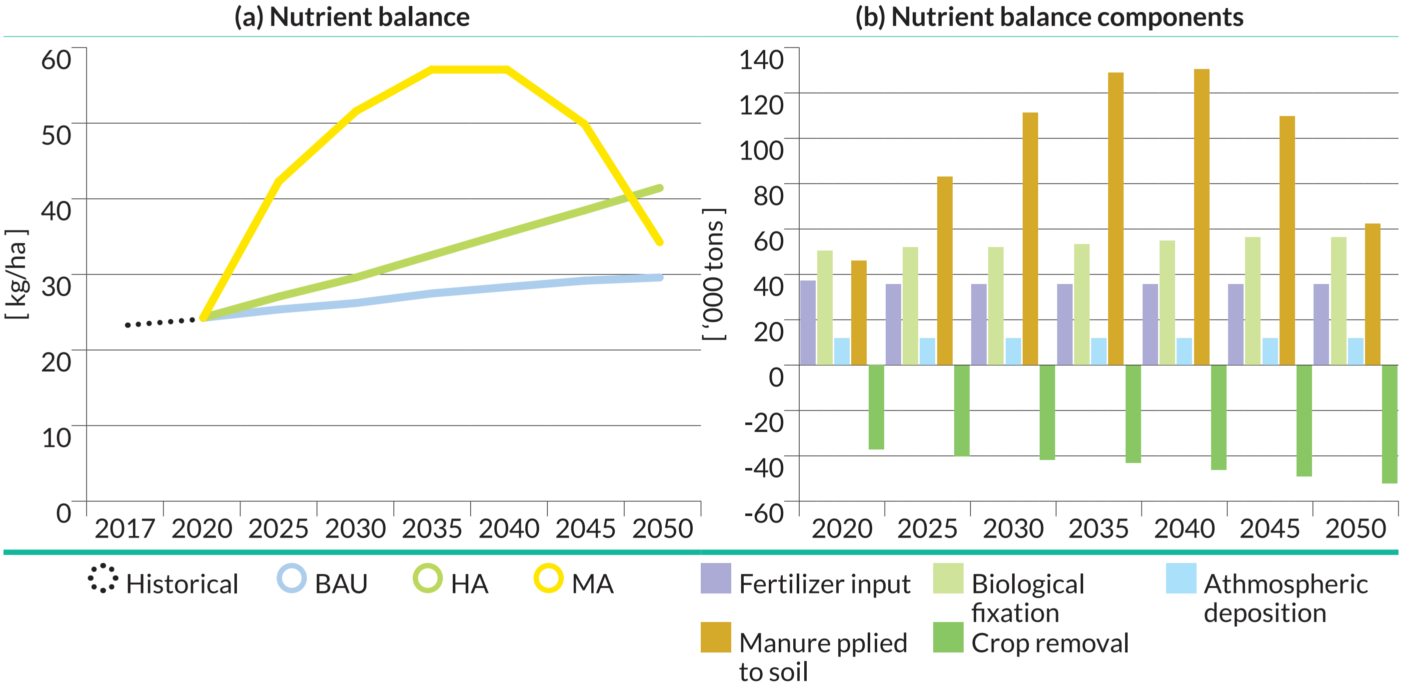
Fertilizer use and nutrient balance (part of SDG 15.3.1): The nutrient balance has been overall constant over the past decade. The BAU scenario will lead to a slight, steady increase (Figure 63a). The nutrient balance in the HA scenario also increases steadily, reaching a value 40 percent higher than the BAU scenario in 2050. In the MA scenario, the nutrient balance will more than double between 2020 and 2030 before decreasing to a level still 16 percent higher than in the BAU scenario by 2050. This aligns with the trend on manure applied to soil (Figure 62c), which can be explained by the policies on manure management. Indeed, while the proportion of manure treated increases, the proportion of manure applied to soil decreases. Figure 63b further reveals the significant impact of manure applied to soil vis-à-vis other nutrient balance components. While crop removal will be slightly decreasing from 2020 to 2050, other components like fertilizer input, biological fixation, and atmospheric deposition were assumed to remain constant.

Above-ground biomass in forest (SDG 15.2.1): Without further interventions, the above-ground biomass will continue to decline, with an accelerating trend in the second half of the transition to 2050 (Figure 64). The HA scenario performs not surprisingly better than the MA scenario due to the stronger objectives of the measures taken on sustainable forest management and reforestation. The trends in above-ground biomass thus align with those in the share of forest area to total land area (Figure 65). Above-ground biomass losses are mainly due to disturbances, accounting for 60 to 66 percent of the losses in 2050, depending on the scenario. Compared to the above-ground biomass value in 2050 in the BAU scenario, the MA and HA scenarios perform 2.5 and 4.2 percent better, respectively, due to the measures decreasing wood removals.

Share of forest area to total land area (SDG 15.1.1): Senegal has experienced only a gradual decline in forest area from 44 percent in 2010 to 41.7 percent in 2021,[222] with deforestation driven by agricultural expansion, unsustainable logging, and land degradation. Senegal has a semi-arid Sahelian climate, with rainfall exhibiting significant variability from year to year. The prolonged periods of drought directly contribute to the degradation of Senegal's natural resources.[223] Human activities, including frequent bushfires, overgrazing, extensive livestock rearing, unsustainable fuelwood extraction, and illegal logging, further exacerbate the degradation of forest ecosystems. To curb this decline in forest share, the government implemented policies such as Senegal's National Forest Policy (2005-2025) to address forest and soil degradation and biodiversity loss while also focusing on livelihood support and poverty reduction. In addition, Senegal has recently approved a new Forest Code and a corresponding decree to regulate the exploitation of forest products.[224] The historical trend in the share of forest area to total land area showed a relatively stable performance at about 42 percent from 2017 to 2020 (Figure 65). The BAU scenario will show a slight declining trend, reaching about 40 percent in 2050. The alternative scenarios will prevent this decline. The land covered by forests in 2050 in the HA scenario will be 8.3 percent more than in the MA scenario and 14.5 percent more than in the BAU scenario.

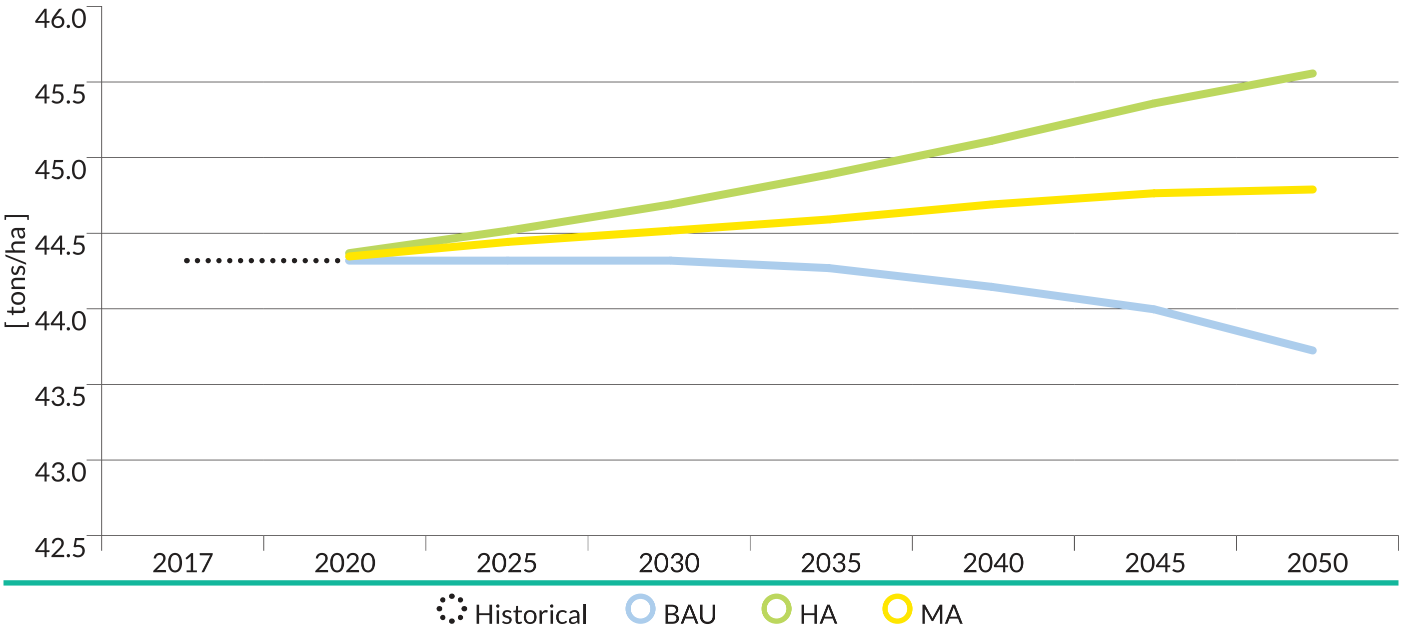
CO_2 emissions in agriculture to population (part of SDG 13.3.2): In 2019, Senegal's carbon emissions were 29.2 million tons of CO_2 equivalent, with agriculture

Figure 63. Changes in (a) nutrient balance (part of SDG 15.3.1) and (b) its components in Senegal, 2017-2050



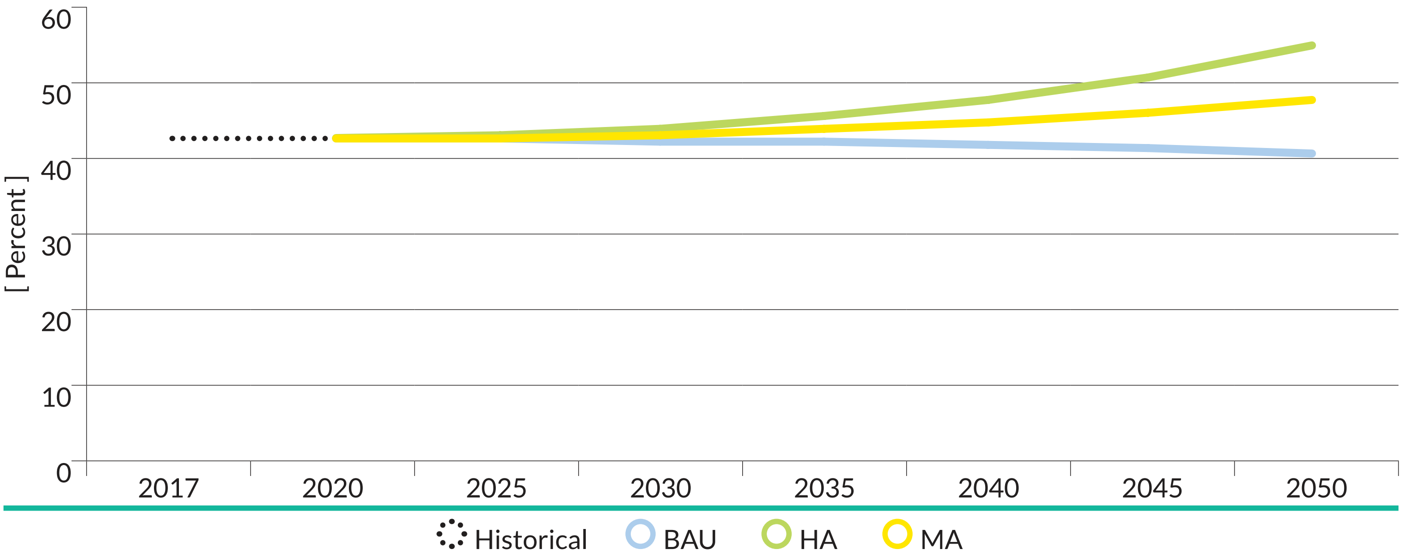
Scenarios: BAU - Business-as-usual, MA - Moderate Ambition, HA - High Ambition
Source: Authors own.

Figure 64. Changes in above-ground biomass in the forest (SDG 15.2.1) in Senegal, 2017-2050



Scenarios: BAU - Business-as-usual, MA - Moderate Ambition, HA - High Ambition
Source: Authors own.

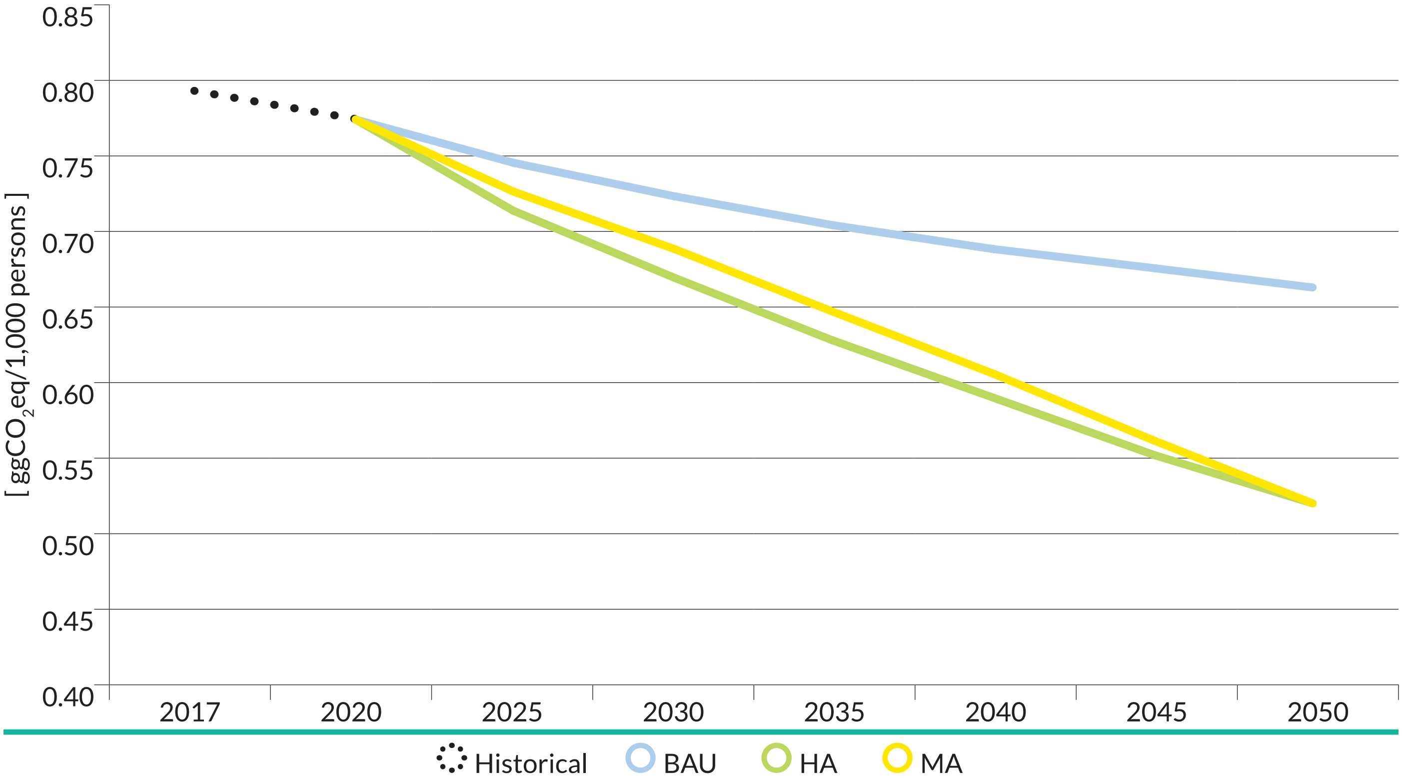
Figure 65. Changes in the share of forest area to total land area (SDG 15.1.1) in Senegal, 2017-2050



Scenarios: BAU - Business-as-usual, MA - Moderate Ambition, HA - High Ambition
Source: Authors own.

contributing 42 percent.[225] Senegal is actively addressing climate change and the Paris Agreement by implementing measures outlined in its NDC, aiming to reduce emissions by 29.5 percent, increase renewable energy to 40.7 percent in the electricity mix by 2035, and secure substantial funding for mitigation and adaptation efforts. The country is mobilizing $8.7 billion and $4.3 billion to fund mitigation and adaptation efforts, respectively, and reducing deforestation by 25 percent from 40,000 to 30,000 hectares/year. Moreover, Senegal is leveraging its Green PSE Plan to develop and invest in green and climate projects, utilizing sovereign wealth funds to explore blue finance, carbon finance, infrastructure, and other development-focused investments.[226] All scenarios show a decline in the ratio of non-CO_2 emissions in agriculture to population. The absolute emissions, however, increased between 2017 and 2050 by 80 percent in the BAU scenario and 41 percent in the alternative scenarios (Figure 66). The main contributors to the emissions are enteric fermentation, manure left on pasture, burning savannas, and manure management. Their shares in the total non-CO_2 emissions from agriculture are presented in (Table 23). The MA scenario projects a more significant share of manure managed by 2050, which explains the increased share of emissions from manure management and the decreased share of manure left on pasture. The substitution of cattle by poultry will limit the increase in the emissions from enteric fermentation, and food loss and waste prevention measures also help decrease the emissions per capita.

Figure 66. Changes in the ratio of non-CO_2 emissions in agriculture to population (part of SDG 13.3.2) in Senegal, 2017-2050



Scenarios: BAU - Business-as-usual, MA - Moderate Ambition, HA - High Ambition
Source: Authors own.

Table 23. Share to non-CO_2 emissions from various sources in the AFOLU sector in Senegal in different scenarios, 2050

[ggCO_2eq]	2017	BAU 2050	HA 2050	MA 2050
Enteric fermentation [Percent]	45.8	53.1	48.6	60
Manure left on pasture [Percent]	23.6	27.5	25.7	6.8
Burning savannas [Percent]	18.5	10.3	13.6	13.4
Manure management [Percent]	2.8	3.2	4.0	12.0
Total contribution [Percent]	90.8	94.1	91.4	92.0

Scenarios: BAU - Business-as-usual, MA - Moderate Ambition, HA - High Ambition
Source: Authors own.

05

COMPLEMENTARY METHODS TO SYSTEM DYNAMICS MODELS

5.1 Overview

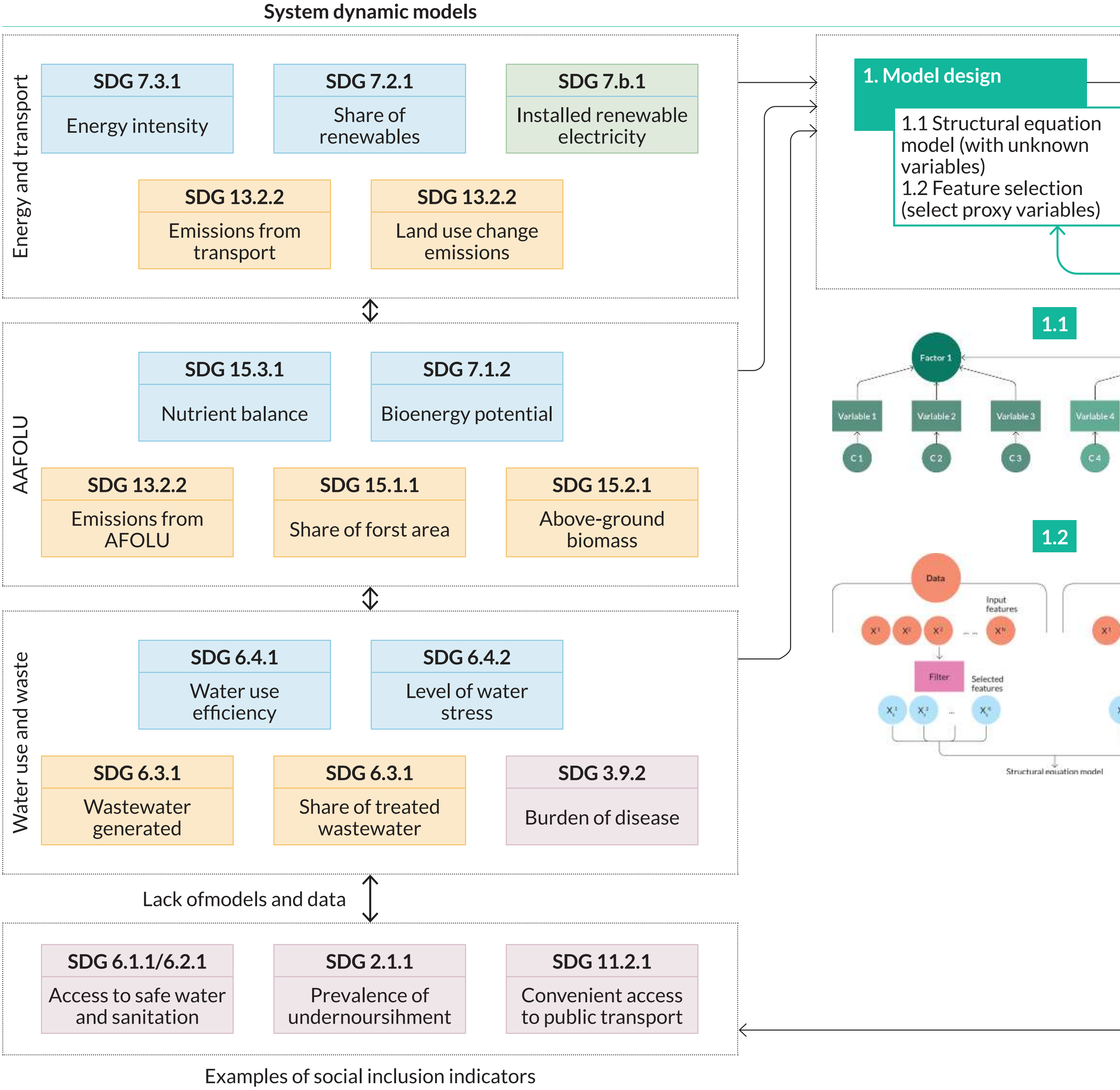
The complex relationships between policies and social, economic, and environmental issues require models and analyses considering each dimension and predicting countries' sustainable development performance.[227] System dynamics models can simulate complex systems and support understanding the potential impacts of changes in the model[228], such as policy interventions with different scenarios. In addition to simulating the impacts of various policies, system dynamics models can also be used to identify key drivers and constraints that affect the achievement of the SDGs. By identifying these key drivers and constraints, system dynamics models can help policymakers and other stakeholders prioritize actions and allocate resources to maximize the chances of achieving the SDGs. However, developing system dynamics models requires broad expertise in modeling techniques and validation methods. It relies highly on data and information and understanding the relationships between variables and how they may change over time.[229] A common challenge in developing system dynamics models is model identification, which refers to accurately representing the complex system in a model. Model identification problems can arise due to the complexity of the modeled system, data and information limitations, and modeling techniques. Furthermore, the country-specific nature of developing system dynamics models for assessing countries' performance on SDG indicators arises because each country has a unique development phase, distinct policies, specific targets to reach, and varying databases with data availability. These challenges restricted the GGSim applications to SDG indicators, whose measurement relies on survey or expert-judgment data or behavioral models, as in the case of most social inclusion indicators. Therefore, a complementary approach has been developed to support system dynamics model-based assessment of SDG co-benefits analysis, validation, and identification (Figure 67). The machine learning (based on artificial intelligence (AI) technique) network and data analyses were identified as the most suitable methods because they:

- support the assessment of alternative models with different structures and unknown variables; representing system dynamics models as structural equation models (SEMs);
- offer a systematic and adaptive approach to identifying proxy variables to represent unknown variables, filling in data gaps;
- allow model representation as networks to measure the connectivity of known and unknown (proxy) variables;
- allow complex model evaluation and validation by subjecting the network's connected elements to sensitivity analysis;
- can be used to generate Shapley values, measuring the contribution of variables from different network connectivity and

Table 24. Summary of the AI-based machine learning network and data analyses to improve the GGsim Tool

Steps	Objectives	Inputs	Outputs
1. Model design			
Structural equation model (SEM)	Integration of system dynamics models and identify latent variables from integrated models	Energy and transport, AFOLU, water use, and waste models; Other models for SDGs with unknown variables and a lack of data	Variable interlinkages across different SDGs
Feature selection	Addition of proxy variables to models lacking data and improve variable interlinkages	Indicators and data relevant to model SDGs	SEM with extended model construct with additional variables
2. Model validation			
Network connectivity	Validation of the variables' causal relationships in the SEM extended equations and latent variables (i.e., conceptual validation)	SEM extended equations and latent variables; time-series data for the observed variables	Validated causal relationships among variables based on the extended model construct
Robustness check	Application of machine learning to generate Shapley values and compare model constructs (i.e., statistical validation)	Network connectivity and time-series data for the latent and observed variables	Validated mean contribution of the variables to the SDGs; GGSim Model statistical fit for scenario analysis
3. Model estimation			
Shapley values	Application of machine learning to identify mean contribution of variables to the SDGs	Validated network connectivity and time-series data for the latent and observed variables	Shapley-based impact value of variables to the changes in SDGs
SDG co-benefits	Changes in the values of the SDGs due to policy measures for different scenarios	Shapley values for the variables impacting the SDGs	Changes in SDGs for different scenarios over time

Figure 67. The framework of applying network and data analysis to complement GGSim's system dynamics models for SDG co-benefits assessment



- assess SDG co-benefits from the changes in relevant variables under different scenarios based on variables' mean contribution over time.

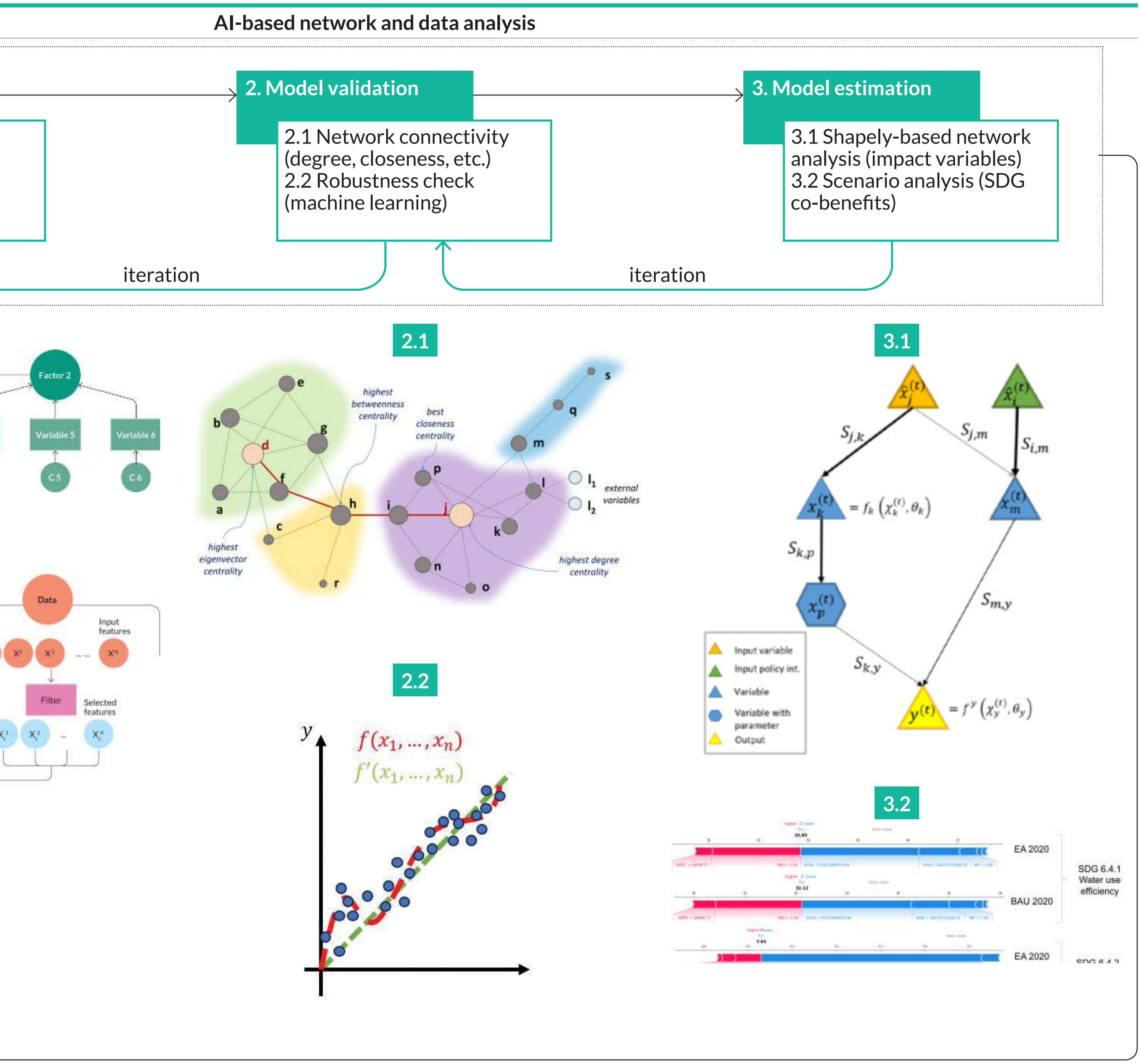
The network and data analyses can extend the system dynamics models, bridging the disconnect between the different SDG indicators, particularly those relevant to social inclusion (Figure 67). The analyses consist of three main steps: model design, validation, and estimation, with a summary provided in Table 24 and the details discussed next. These steps follow an iterative and exploratory approach, requiring re-examination of earlier steps to improve results from the current step.

5.2 Steps for network and data analyses

5.2.1 Model design

A. Structural equation model

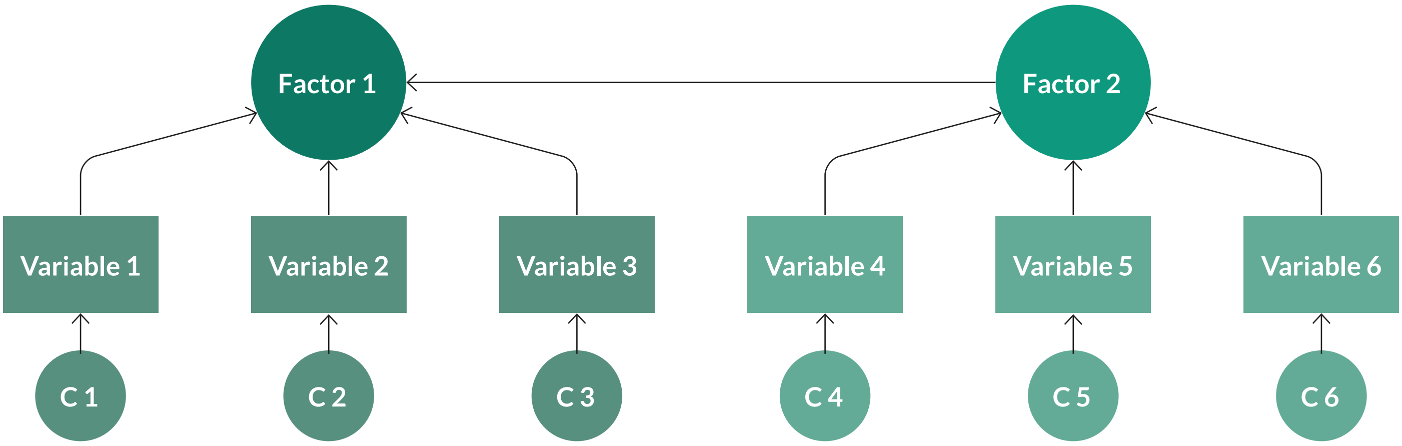
In designing the models for the network and data analyses, the relevant system dynamics models for energy and transport, AFOLU, and water use and waste are combined with the knowledge and variables for the SDG indicators



that lack models and data. Figure 67 provides examples of SDG indicators for social inclusion. The combined models are represented as a structural equation model (SEM), which is a useful method to determine latent variables (i.e., the influence of unobserved variables), provide knowledge of variable interlinkages in equations (i.e., testing hypothetical relationships), analyze data from multiple databases and theoretical constructs,[230] and represent model equations as networks. SEM has two parts[231]: (1) equations that give the causal relations between the latent variables, which are often inaccessible to direct measurement; and (2) linkages of the observed variables to the latent variables, as provided in an example of a two-equation measurement model (Figure 68). "SEM is an inference engine that takes in two inputs, qualitative causal assumptions[x] and empirical data, and derives two logical consequences of these inputs: quantitative causal conclusions and statistical measures of fit for the testable implications of the assumptions."[232] Thus, SEM helps to establish whether the assumptions implied on the causal relationship between the variables exist and to what degree. Causality determines whether one variable causes another to change, informing about the underlying

x SEM does not provide causal relations; rather, the modeler provides causal assumptions to SEM based on the research design, prior studies, scientific knowledge, logical arguments, temporal priorities, and other evidence. (https://ftp.cs.ucla.edu/pub/stat_ser/r393-reprint.pdf)

Figure 68. Illustration of a structural equation model (SEM) with two-equation models



mechanisms that drive the relationships between different variables in a system.

B. Feature selection

Feature selection is a data science tool to identify the most relevant and informative variables (also known as "features") in a data set, helping to identify external variables that fit the model and improve the accuracy and relevance of the predictive model.[233] It is a crucial step when building SEMs, allowing the addition of proxy variables closely representing the missing variables. Among its objectives include selecting from many observed and proxy variables the set of variables that provide the best statistical fit to the model (i.e., reduce model noise), reducing the number of variables (i.e., input data) to ensure model simplicity and interpretability, and achieving most significant variable interlinkages.[234] Unknown interactions in the models for SDGs can be explained by adding relevant variables,[235] and checking relevance of the variables can be supported by machine learning.[236] Various methods are available to support feature selection, including correlation analysis, a statistical technique to assess the relationship between two or more variables. It filters variables that will be used as inputs to the models, in this case, the SEM (Figure 69). Highly correlated variables with coefficients greater than 0.8 can be removed during feature selection.[237]

5.2.2 Model validation

A. Network connectivity

Network analysis is a technique to analyze the relationships between different variables or features in a machine learning model, with the objective of identifying patterns and relationships in the data that may not be immediately apparent. SEM can be represented as networks, and sustainable development-related problems can be evaluated using network science tools.[238] It can be used

Figure 69. Illustration of feature selection using correlation analysis to filter the input variables

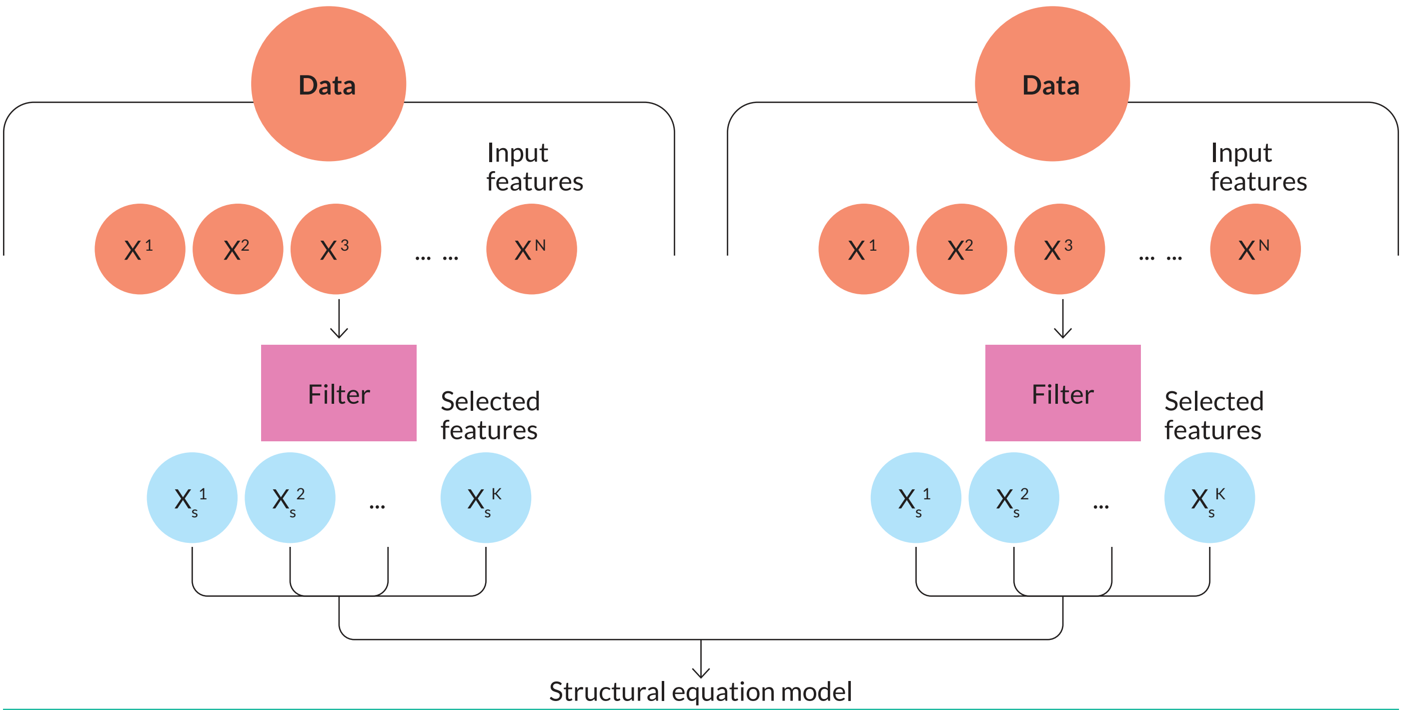
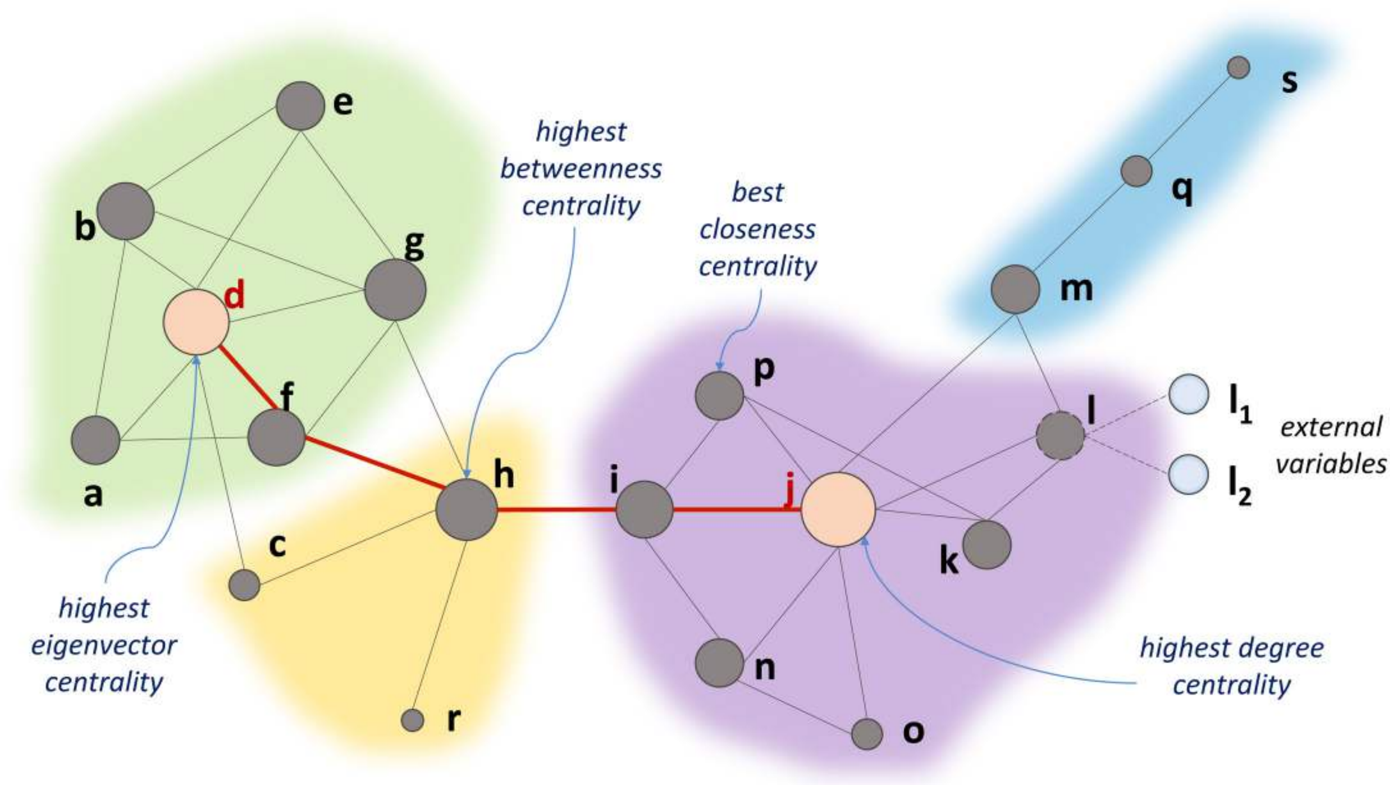


Figure 70. Illustration of network analysis showing different centrality measurements



to understand the relationships between different SDG goals and targets. For example, network tools can help identify the interdependencies between different goals and understand how progress in one area can impact others.[239] The model's critical variables can be identified as possible intervention points (i.e., focus of policy or investment measures). Network analysis identifies critical paths through its different centrality measures, defined by the nodes and edges. Nodes are the objects of analysis (represented by circles), and edges connect the nodes (lines connecting the nodes), as shown in Figure 70. Applied in the SEM, the nodes represent the observed and latent variables, and the edges represent their interlinkages. The relevant centrality (or node connectivity) measures include the following:[240]

- Degree centrality – identifies the most "frequent" connected nodes, measuring the number of edges each node holds.
- Betweenness centrality – identifies the node that 'bridges' between nodes in a network, measuring the number of times a node lies on the shortest path between other nodes.
- Closeness centrality – identifies the "closest" node to all other nodes in a network, measuring the (sum of) shortest paths between all nodes.

While centrality measures provide a structural perspective of the models and are vital for understanding the importance of and relationship between the variables, they do not consider the dynamics, uncertainties, or external factors. However, the causal relationships[241] and complex interactions between the variables, including the SDG indicators, can be mapped through network analysis[242]. Sensitivity analysis can be used to validate the robustness of the network analysis. The points with the most significant potential for improving outcomes can be identified by testing the model's sensitivity to changes in intervention point values. While the nodes and edges' characteristics determine the most important variable, using Shapley values in networks informs about the contribution of the variables to the SDGs.

During the model validation, it is imperative to ensure that only the relevant variables are included in the network analysis.

B. Robustness check

The validity of the connection between independent and dependent variables was assessed by comparing GGSim model results with observed data. Moreover, GGsim model performance was compared to other alternative models, including linear regression and k-th nearest neighbors. Machine Learning (ML), used in network analysis to identify key drivers (i.e., variables with "best" node connectivity), was applied to linear regression and k-th nearest neighbors models (Figure 71). With ML, models are trained over time to adapt to changes, including updating model parameters and incorporating new data and variables to improve the model's predictive capability. ML techniques facilitate the integration of data-driven insights and evidence-based policy assessment. Applying ML in an iterative approach ensures that the models capture the complexity of the sustainability problems and enhance model accuracy and robustness.

Figure 71. Illustration of machine learning in network analysis

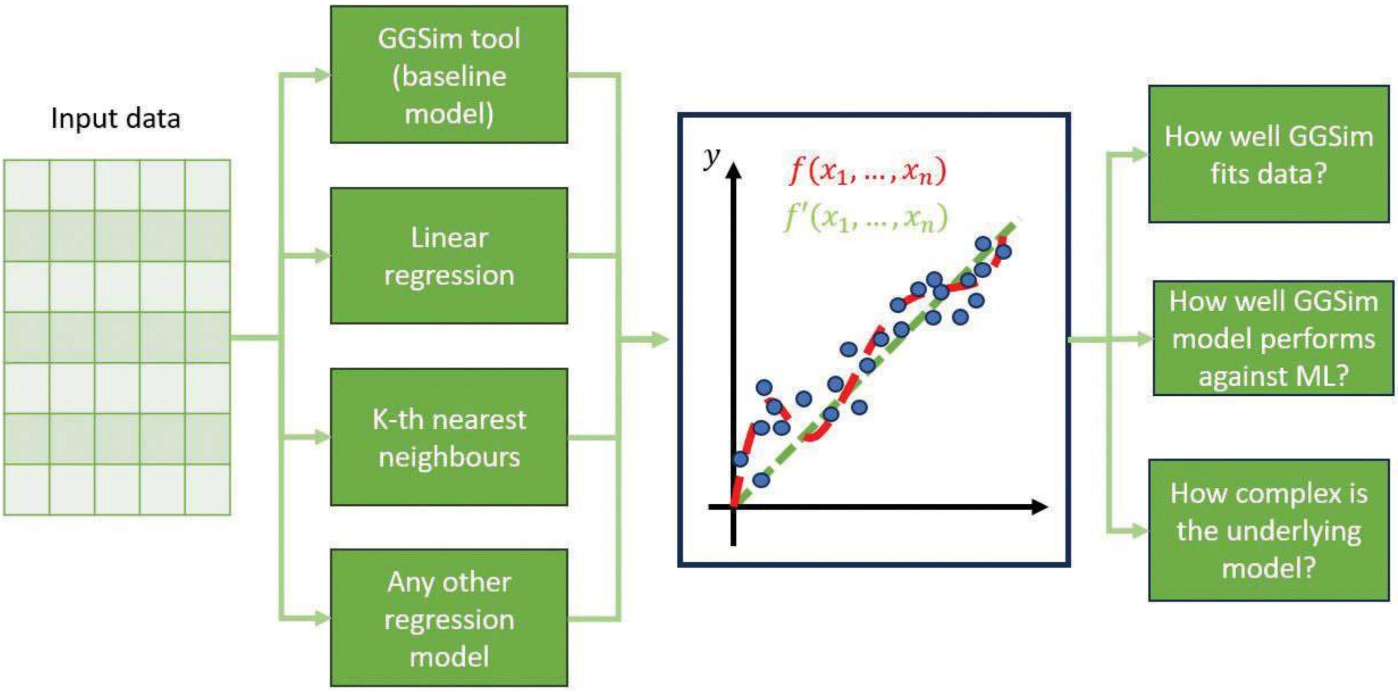
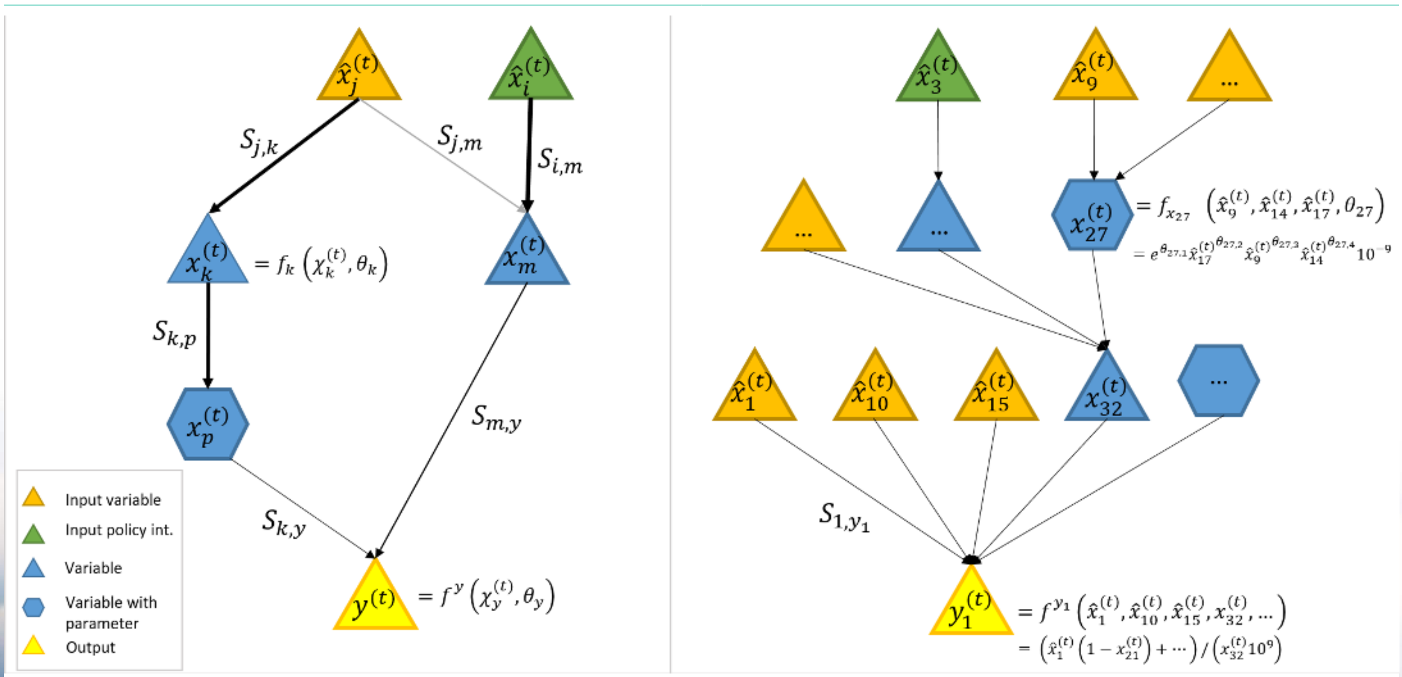


Figure 72. Schematic representation of the Shapley value-based network interpretation of structural equation model and variable contributions.



Source: Source: Ipkovich et al. (2024)[20]

5.2.3 Model estimation

A. Shapley-based network analysis

"Shapley values[xi] can be used to explain the output of a machine learning model"[243], including network analysis. In this report, the utilization potential of the Shapley value[244] to identify the contribution of each input variable to the output SDG indicators is explored (Figure 72). Combining the previously interpreted structural network measures with the Shapley value has great potential to achieve a more complete understanding of the system. Since the Shapley value defines the contribution of the variables, these values can be applied as weights of the network edges (i.e. values on the lines connecting the network nodes). In the Shapley value, the impact of one variable includes all its contributions to the model, including the added value from its connectivity with the other variables. Shapley value heavily relies on the role of the variable in the model and the variance of the data, so ensuring variance may define the importance of a variable. Details on the methods as applied in the Phase 2 Simulation Tool are available in the study by Ipkovich et al. (2024)[245], who emphasize the "significance of combining the Shapley value and network science in identifying key drivers of model behavior" and "great potential to achieve a more complete understanding of the system".

B. Scenario analysis

The Shapley value can be used to measure the impact of policy and investment measures on the SDG indicators. Because it is calculated from the network analysis of the structure equations of the combined system dynamics models (i.e., SEM) (Figure 67), the Shapley value captures the interlinkages of the SDG indicators in the energy and transport, AFOLU, and water use and waste models. The Shapley value can be estimated for different years, including scenarios from 2020 to 2050. As the Shapley value is computationally intensive, particularly when computing for multiple years, Monte Carlo analysis can be used for simulating model scenarios.

5.3 Results from the pilot application

5.3.1 SME latent variables in the water use model

The application of the network and data analysis in the GGSim was piloted using the water use and waste model and time-series data (2000-2019) for Hungary (see section 4.1.1 for the structure of the equations and input variables). Details of the application are available in Ipkovich et al. (2024).[246] This section presents the result highlights of this pilot application, focusing on water use efficiency (SDG 6.4.1) and the share of freshwater withdrawal to freshwater availability (SDG 6.4.2). The latent variables in the SME-defined water use and waste models include the following:

- Irrigated area per irrigation technology type (AIRi)
- Agricultural Water Withdrawal (AWU)
- Cropping intensity (CI)
- Corrective coefficient (Cr)
- Potential Crop Evaporation Vector (ETc)
- Irrigation Consumptive Use (ICU)
- Irrigation Water Requirement per irrigation (IWRi)
- Irrigation Water Withdrawal (IWW)
- Municipal Water Withdrawal (MWU)
- Proportion of Irrigated Cropland (PAIR)
- Total Freshwater Available (TFA)
- Total Non-Conventional Water (TNCW)
- Total Renewable Freshwater (TRF)
- Total Water Withdrawal (TWW)

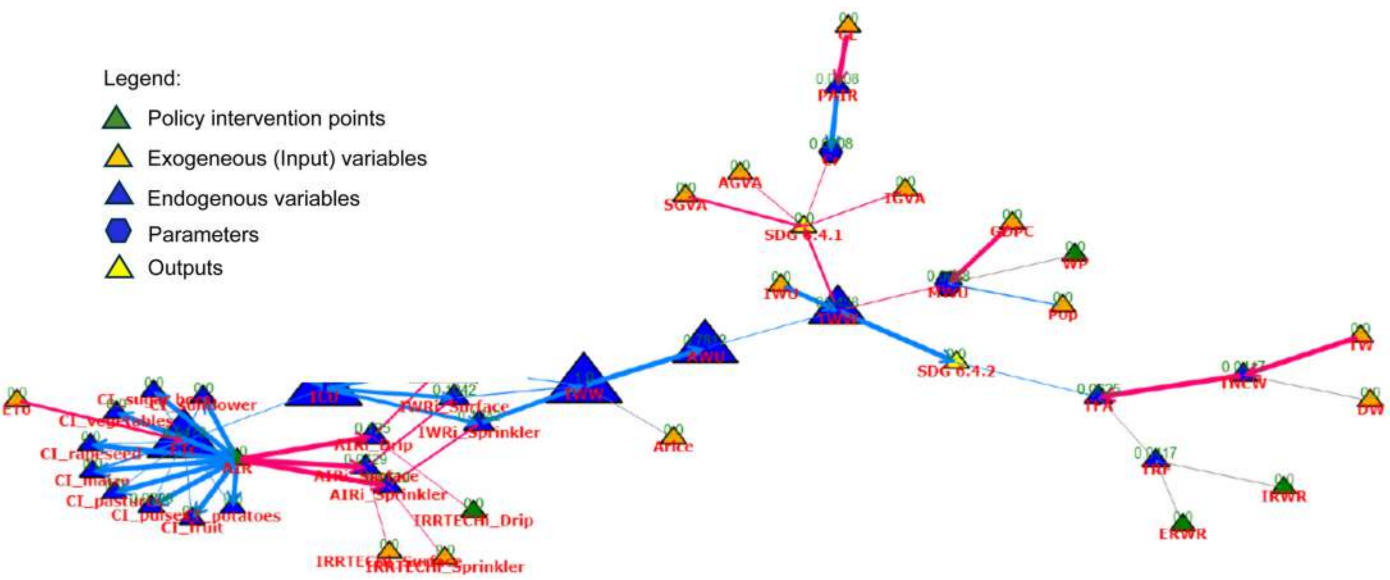
xi The Shapley value is a concept in game theory used to determine contribution of each player in a coalition or a cooperative game. (https://c3.ai/glossary/data-science/shapley-values/)

5.3.2 Model validation results

The sensitivity analysis of the network connectivity was used to validate policy intervention points and support the selection of possible intervention measures. The results help prioritize interventions and focus resources on the most effective intervention points. The tools of network science enable us to identify critical paths and nodes within the water model, based on which information we can focus on the essential variables in the system and identify intervention measures that target these variables. Figure 73 shows the betweenness centrality of network water use efficiency (6.4.1) and level of water stress (6.4.2) SDG indicators. Crop evaporation (Etc), irrigation (ICU, IWW), agricultural water use (AWU), and total water withdrawal (TWW) play a prominent role in the network, so a direct or indirect reduction of these node values indicates potential for targeting intervention measures. The results imply that the model captures areas useful for assessing the impacts of policy measures on SDG co-benefits.

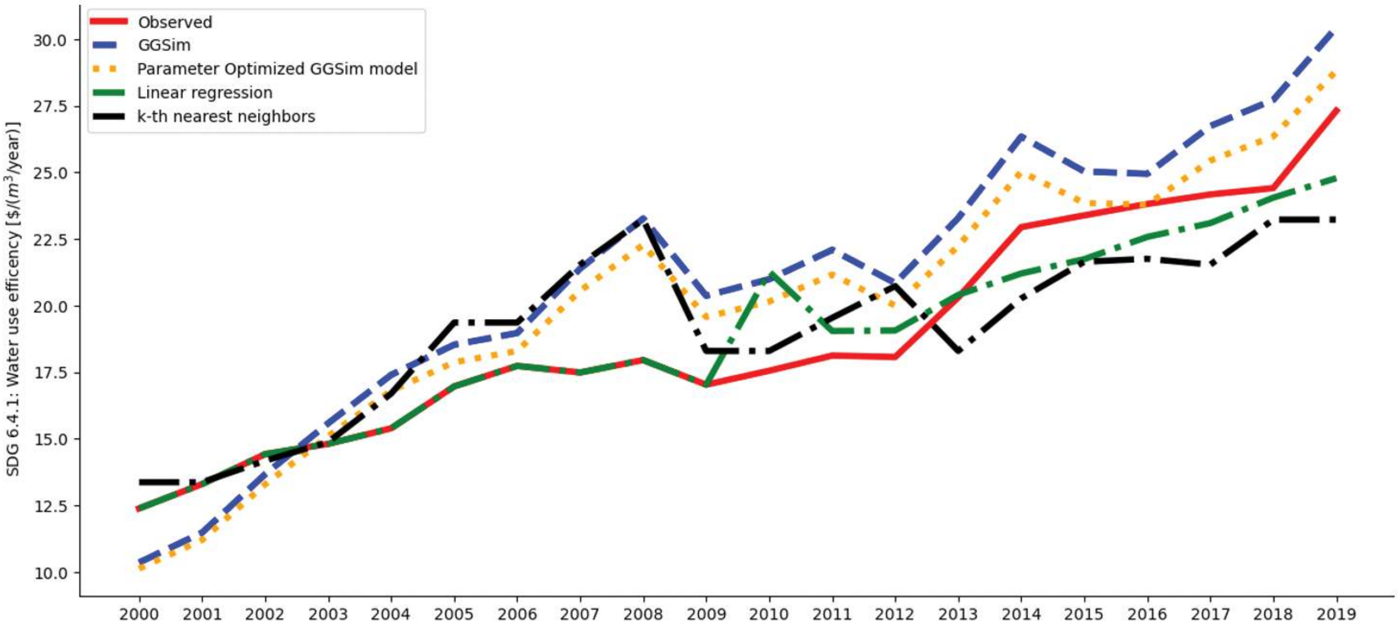
Figure 74 presents the results of the robustness check using network analysis based on machine learning. The predictions are evaluated for the observed data, GGSim model and parameter optimized GGSim model (i.e., parameter optimization of the municipal water withdrawal equation improvement in the model), linear regression, and k-th nearest neighbors. Linear regression and the k-th nearest neighbor models applied machine learning, particularly in the input data, to predict the outputs while leaving out intermediate (latent) variables. Results from machine learning show the most promise but may perform differently based on the number of layers and epochs used, as in the case for the linear regression of SDG 6.4.2. This pilot application revealed the necessity of continuous model development and maintenance through data-driven machine-learning techniques to ensure the quality of model performance. The model accuracy can vary significantly, as shown by the machine learning results of the linear regression and k-th nearest neighbor.

Figure 73. Network representation of the betweenness centralities for the SDG 6.4.1 & SDG 6.4.2 indicators in the water use model



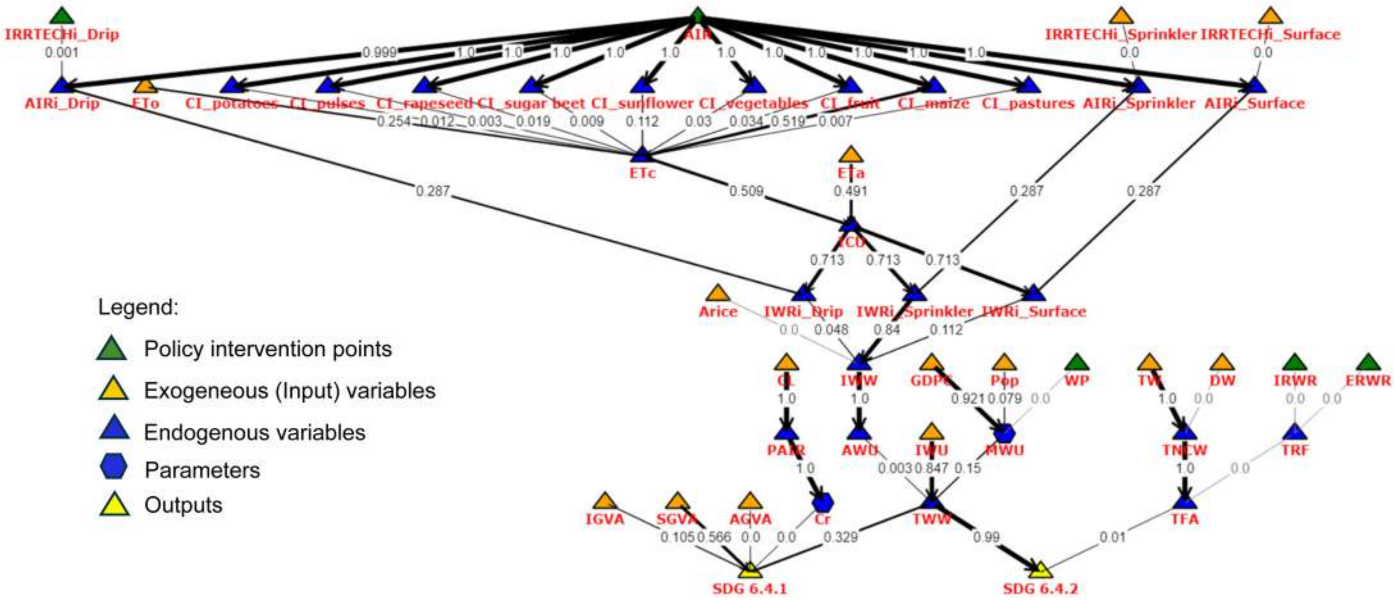
Note: The node colors represent the model elements and the thickness of the edges (i.e., lines with arrows) represents the strength of direct variable contribution.
Codes: Actual Evapotranspiration (ETa), Evapotranspiration (ETo), Potential Crop Evaporation Vector (ETc), Cropping intensity (CI), Irrigated area per irrigation technology (AIRi), Irrigation Consumptive Use (ICU), Irrigation Water Requirement per irrigation (IWRi), Irrigation technology proportion (IRRTECHi), Irrigation Water Withdrawal (IWW), Agricultural Water Withdrawal (AWU), Industrial Water Withdrawal (IWU), Municipal Water Withdrawal (MWU), Total Water Withdrawal (TWW), Agricultural Gross Value Added (AGVA), Service Sector Gross Value Added Resources (SGVA), Cropland (CL), Corrective coefficient (Cr), Proportion of Irrigated Cropland (PAIR), Industrial Gross Value Added (IGVA), GDP per capita (GDPC), Population (Pop), Water Price (WP), Total Freshwater Available (TFA), Total Renewable Freshwater (TRF), External Renewable Water Resources (ERWR), Internal Renewable Water Resources (IRWR), Total Non-Conventional Water (TNCW), Treated Wastewater (TW), Desalination Water (DW)
Source: Source: Ipkovich et al. (2024)[22]

Figure 74. Prediction of the GGSim model against observed data and other models



Statistical fit: GGSim model (SDG 6.4.1 r^2: 0.519, SDG 6.4.2 r^2: 0.639), linear regression model (SDG 6.4.1 r^2: 0.907, SDG 6.4.2 r^2: -20.46), k-th nearest neighbor algorithm (SDG 6.4.1 r^2: 0.91, SDG 6.4.2 r^2: 0.69), parameter optimized GGSim model (SDG 6.4.1 r^2: 0.744, SDG 6.4.2 r^2: 0.65).
Source: Ipkovich et al. (2024)[23]

Figure 75. Direct mean contribution of variables to the change in the SDG 6.4.1 water use efficiency and SDG 6.4.2 level of water stress

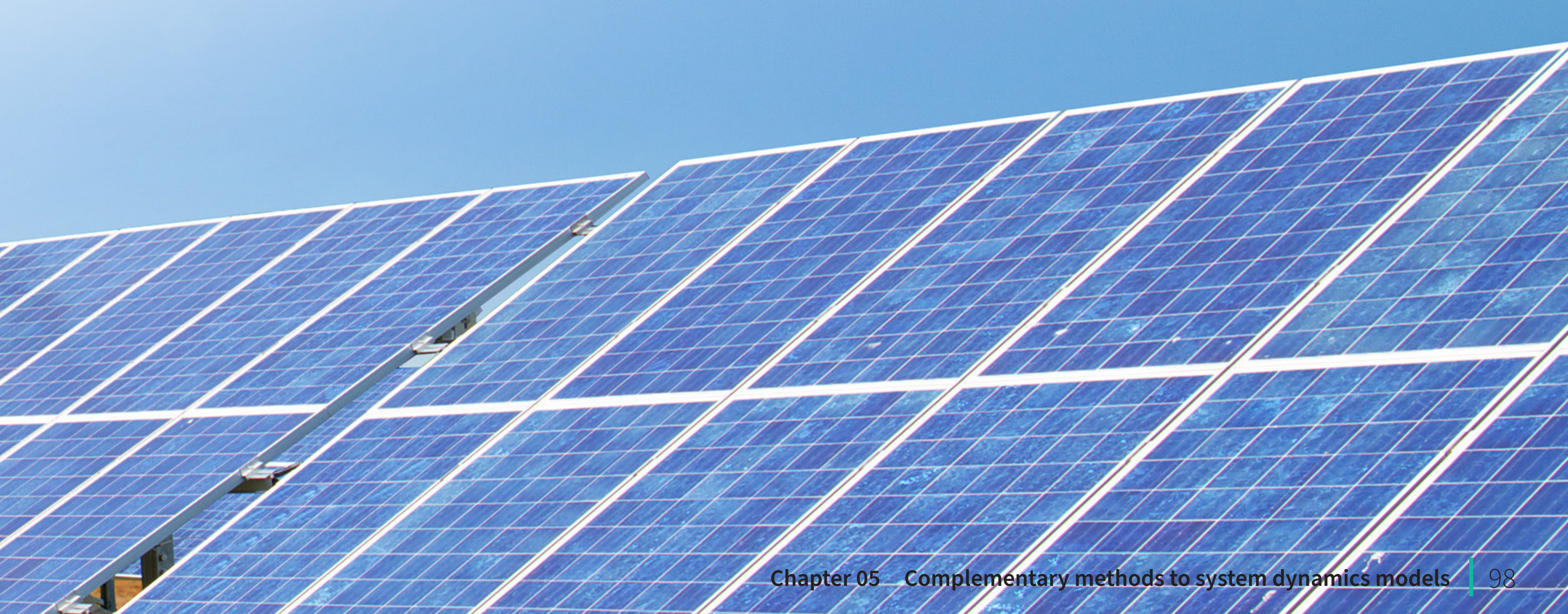


Note: The node colors represent the model elements and the thickness of the edges (i.e., lines with arrows) represents the strength of direct variable contribution.
Codes: Actual Evapotranspiration (ETa), Evapotranspiration (ETo), Potential Crop Evaporation Vector (ETc), Cropping intensity (CI), Irrigated area per irrigation technology (AIRi), Irrigation Consumptive Use (ICU), Irrigation Water Requirement per irrigation (IWRi), Irrigation technology proportion (IRRTECHi), Irrigation Water Withdrawal (IWW), Agricultural Water Withdrawal (AWU), Industrial Water Withdrawal (IWU), Municipal Water Withdrawal (MWU), Total Water Withdrawal (TWW), Agricultural Gross Value Added (AGVA), Service Sector Gross Value Added Resources (SGVA), Cropland (CL), Corrective coefficient (Cr), Proportion of Irrigated Cropland (PAIR), Industrial Gross Value Added (IGVA), GDP per capita (GDPC), Population (Pop), Water Price (WP), Total Freshwater Available (TFA), Total Renewable Freshwater (TRF), External Renewable Water Resources (ERWR), Internal Renewable Water Resources (IRWR), Total Non-Conventional Water (TNCW), Treated Wastewater (TW), Desalination Water (DW)
Source: Ipkovich et al. (2024)[26]

5.3.3 Shapley-based variable contributions

Figure 75 presents the results of the network analysis including Shapley values, measuring the variable contributions to SDG 6.4.1 water use efficiency and SDG 6.4.2 level of water stress. The node colors represent the model elements, and the thickness of the edges (i.e., lines with arrows) represents the strength of direct variable contribution. The Shapley values are the mean contributions of the variables to the SDG indicators over the period 2000 to 2019. The Shapley-based network analysis shows, for example, that irrigated agricultural areas (AIR) influence irrigation water use (IWW) through potential crop evaporation vector (ETc) and irrigation consumptive use (ICU), whose impacts on SDG 6.4.2 level of water stress pass through the total water withdrawal (TWW). However, water price (WP) and renewable water resources do not show significant contributions to the SDGs, with zero Shapley values. Detailed assessment of the network analysis is available in Ipkovich et al.[247], which suggested that "water reuse and water circularity offer a more effective intervention option than pricing and the use of internal or external renewable water resources" to improve performance in SDG 6.4.1 and 6.4.2. Annual Shapley values could support a better understanding of the dynamics of the SDG indicators through the interlinkages of the input variables over time.[248] Figure 76 illustrates changes on selected input variables to the SDG indicators for early action (EA) and business-as-usual (BAU) scenarios in 2020 and 2040. For the following GGSim applications, one of the goals for applying the Shapley-based network analysis will be to translate the variable contributions into comparable measurement units, allowing SDG co-benefits across scenarios and over time.

Figure 76. Changes in the annual contribution of variables to the change in the SDG 6.4.1 water use efficiency and SDG 6.4.2 level of water stress by scenarios



06 CONCLUSIONS AND NEXT STEPS

6.1 Progress and constraints in GGSim Phase 2 (v.1)

6.1.1 Model applications

Developing the model interlinkages between the indicators across the four Green Growth Index dimensions is a challenging scientific task but indispensable for conducting SDG co-benefits assessments. The GGsim interlinked system dynamics models covering energy and transport, AFOLU, and water use and waste components were applied to assess SDG co-benefits of mitigation measures in Hungary, Burkina Faso, and Ethiopia, and adaptation measures in St. Lucia and Senegal. The mitigation measures were aligned with the LT-LEDS scenarios in the former three countries, and the adaptation measures were identified from the NAP and adaptation-related Green Recovery Plan in the latter two countries. Several SDG and SDG-related indicators were covered in the assessments, identifying where gains and trade-offs from alternative scenarios will be expected from 2020 to 2050.

The model applications showed GGSim's flexibility and value when using the GEM and sectoral models' results and scenarios, extending assessments of LT-LEDS mitigation measures on SDG indicators beyond their scopes. This is particularly important for SDGs related to biodiversity protection (e.g., nutrient balance, above-ground biomass, forest degradation) and water resource conservation (e.g., water use efficiency, water withdrawals, wastewater treatment). The GGSim model components are subdivided into modules, allowing the applications of relevant parts according to available data and scenarios. For example, the adaptation measures applied to the SDG co-benefits assessments in St. Lucia and Senegal focused only on the AFOLU sector. The energy and transport models were thus excluded from the assessments, and co-benefits emphasized impacts on the water and waste sectors. Although improved data availability and model constructs will be needed to achieve more reliable results, the GGSim illustrated its potential for assessing relevant social inclusion indicators, such as access to sanitation and disease burden.

6.1.2 Model limitations and validation

During Phase 1 of GGSim development, the comprehensive review of system dynamic models revealed the limited models and information to assess SDG co-benefits in social inclusion relevant SDG indicators. The model applications in this report further confirm this, showing the challenges of linking water use and waste to the population's access to sanitation and the health impacts of waste pollution. These indicators are relevant to assessing the impacts of policy measures on access to basic services and social protection, two of the four sustainability pillars in the social inclusion dimension of the Green Growth Index. The two other pillars, gender balance and social equity, pose even more challenges because models often rely on surveys or primary data that are not readily available at the national level and over time.

Model validation was conducted at the input and output levels, aligning the data inputs used in the GEM and sectoral models and comparing their outputs. The comparison of model results from the BAU scenario with the historical data was another pragmatic approach to validate the GGSim models. During the development of the network models for the GGsim, more systematic validation of the system dynamics models was conducted using correlation and causality analysis. Moreover, the pilot application of AI-based Shapley values for the network analysis of water use and waste model in Hungary allowed the validation of the GGSim results against the observed data and results from other alternative models (i.e., optimized GGsim model, linear regression, k-th nearest neighbor). This validation approach will also be used for all GGSim models in the upcoming country applications.

6.1.3 Data gaps and discrepancies

The model applications revealed data gaps in national databases, restricting the applications of a few GGSim modules in a country. The SDG indicators covered thus vary for different countries, although the climate intervention measures were very similar. The data from national databases and international sources diverged significantly for some model inputs. Because the distance to target assessments required a global database for normalization and benchmarking scores, results for some SDG indicators did not align between the historical values and scenarios. This is the case for the energy intensity (SDG 7.3.1), whose results were not presented in the distance to target assessment of this report.

6.2 Motivations for improving GGSim Phase 2 (v.2)

6.2.1 Exploring AI-based approaches

The pilot application of the Shapley-based network analysis showed that AI or machine learning is a valuable approach for assessing variable contributions to SDG indicators and validating the robustness of complex models. For this reason, the next version (v.2) of the GGSim Phase 2 development will emphasize the application of this approach in both system dynamics and network models. Other AI-based approaches addressing data gaps will also be explored to support the application of additional system dynamics models for SDG indicators lacking time-series data.

6.2.2 Model integration

The pilot application of the Shapley-based network analysis also showed that system dynamics models can be represented as structural equation models (SEMs). The energy and transport, AFOLU, water use, and waste models, as well as available data and model constructs for social inclusion, can thus be transformed into SEMs with the objective of combining them into an "integrated" GGsim model capable of assessing co-benefits for SDGs-related to gender balance and social equity. The next version (v.2) of the GGSim Phase 2 development will focus on this model integration.

6.2.3 Policy applications

The following GGGI projects will have the potential to validate the applicability of AI-based approaches and SEM-based integrated models for SDG co-benefits assessments:

- Assessment of SDG co-benefits of adaptation measures relevant to the NAP and NGGS in Lao PDR, a collaborative project between Lao PDR Ministry of Planning and Investment (MPI), GGGI and OECD with funding from the Korea Green New Deal Fund (KGNDF). The project is an extension of the National Green Growth Index for Lao PDR.

- Assessment of SDG alignment of green growth indicators as part of developing and validating the National Green Growth Index for Togo, a project funded by the GGGI through the African Regional Office.

- Assessment of SDG co-benefits for gender in the Green Recovery Action Plan (GRAP) project, implemented in collaboration with the African Union (AU) and with co-funding of Global Affairs Canada and the Global Green Growth Initiative (GGGI).

6.3 Link to the Green Growth Index

This report presented the results of the distance to targets assessment of the SDG and SDG-related indicators, comparing historical values generated from the Global Green Growth Index with those computed from the scenario-based SDG co-benefits assessment. While data gaps and discrepancies between national databases and international sources hindered the comparative analysis for a few SDG indicators, the applications in this report illustrated how assessments from the GGSim's SDG co-benefits can be interlinked with the Green Growth Index distance to targets. AI-based approaches to improving data inconsistencies will be explored to enhance GGsim and Index's interlinkages in the next version (v.2) of the GGSim Phase 2 development.

ANNEXES

ANNEX 1

Equations and data for energy and transport models

SETS

RES	:	renewable energy sources (biomass, waste, hydro, solar, wind, geothermal)
NRES	:	non-renewable energy sources (nuclear, natural gas, coal, oil)
F	:	fuel types for transport
ALLMODES	:	all modes of transport (cars, two wheels, LCV, HDV, bus, passenger rail, freight rail)
GHGgases	:	greenhouse gases
FOODcrop	:	food items from crops[1]

Energy intensity

1.1 | $Renewables\_Intensity = \sum_{(i \in RES)} PES_i$

1.2 | $TPES = \sum_{(i \in NRES)} PES_i + Renewables\_Intensity + Electricity\_Import$

1.3 | $EnergyI = (TPES) / (Trgdp/1000)$

where:
Renewables_Intensity is the total energy supply from renewables [***PJ***];
PES$_i$ is the primary energy supply of source [***PJ***];
TPES is the total primary energy supply [***PJ***];
Electricity_Import is the import of electricity [***PJ***];
EnergyI is the energy intensity [***TJ*** / (***Real million LCU***)];
Trgdp is the total real gross domestic product [***Real million LCU***].

Share of renewables in electricity generation

1.4 | $EG_i = PGC_i * CAPFACTOR_i * 8760$

1.5 | $Renewables\_EG = \sum_{(i \in RES)} EG_i$

1.6 | $Total\_EG = Renewables\_EG + \sum_{(i \in NRES)} EG_i$

1.7 | $EGC\_Renewables = (Renewables\_EG) / (Total\_EG)$

where:
EG$_i$ is the electricity generation from source ***i*** [***MWh*** / ***y***] ;
PGC$_i$ is the installed capacity of source ***i*** [***MW***];
CAPFACTOR_i is the capacity factor of source ***i*** [**–**];
Renewables_EG is the electricity generation from renewable energy sources [(***MWh***) / ***y***];
Total_EG is the total electricity generation [(***MWh***) / ***y***];
EGC_Renewables is the share of renewable electricity generation in total electricity generation [**–**].

Installed renewable energy capacity per capita

1.8 | $InstalledMW = \sum_{(i \in RES)} PES_i$

1.9 | $Installedwatts = (InstalledMW * 1e6) / (Pop)$

where:
InstalledMW is the total installed energy capacity [*MW*];
Installedwatts is the installed renewable energy capacity per capita [*W* / *capita*];
Pop is the population [*capita*].

Land requirement for SPVS

1.10 | $Area_{PV} = PCG_{solar} * A_{av}$

where:
$Area_{PV}$ is the land requirement for installing the total solar capacity [*acres*];
A_{av} is the capacity weighted-average area requirement [*acres* / *MWac*]

Land use change emissions due to SPVS

1.11 | $EF_{forest} = (\Delta_{(carbon,forest)}) / (Area_{forest})$

1.12 | $GHG_{LUC} = Area_{PV} * EF_{forest}$

where:
EF_{forest} is the forest land use change emission factor [$kgCO_2eq$ / *acres*];
$\Delta_{(carbon,forest)}$ is the carbon stock change in forests [$kgCO_2eq$];
$Area_{forest}$ is the forest land area [*acres*];
GHG_{LUC} is the emissions from the land use change due to the installation of SPVS [$kgCO_2eq$].

Land requirement for first-generation biofuels

For $i \in FOODcrop$:

1.13 | $BioDieselSupply_i = BioCropMix_i * BioDieselDemand$

1.14 | $CroplandBioDiesel = \sum_{(i \in FOODCrop)} (BioDieselSupply_i / BioYields_i)$

where:
$BioDieselSupply_i$ is the first-generation biodiesel demand for crop *i* [*TJ*];
$BioCropMix_i$ is the allocation of crop items for biodiesel production [–];
BioDieselDemand is the total first-generation biodiesel demand [*TJ*];
CroplandBioDiesel is the total cropland demand for first-generation biodiesel [*ha*];
$BioYields_i$ is the biodiesel yields of crops *i* [*TJ* / (*ha*)].

Emissions from transport

For $k \in ALLMODES$, $e \in GHGgases \setminus \{CO_2\}$:

1.15 | $CPE_k = \sum_{(f \in F)} EC_{k,f} * CEF_{k,f}$

1.16 | $NCPE_{k,e} = \sum_{(f \in F)} EC_{k,f} * NCEF_{k,f,e}$

where:
CPE_k and $NCPE_{k,e}$ are respectively the CO_2 and non-CO_2 GHG emissions levels due to mode [$kgCO_2$], [$kgCO_2eq$];
$EC_{k,f}$ is the energy consumption of fuel *f* for mode *k* [*MWh*];
$CEF_{k,f}$ and $NCEF_{k,f,e}$ are respectively the emission factors for CO_2 and non-CO_2 GHG emissions for mode *k* and fuel *f* [$kgCO_2$ / (*MWh*)], [$kgCO_2eq$ / (*MWh*)].

Data sources

Variable/Parameter name	Code	Equation	Data source
Primary energy supply	*PES_i*	Eq. 1	LEDS
Electricity imports	*Electricity_Import*	Eq. 2	LEDS
Total real GDP	*Trgdp*	Eq. 3	LEDS
Electricity generation	EG_i	Eq. 4-6	LEDS
Installed capacity	PGC_i	Eq. 4, 8, 10	LEDS
Capacity weighted average area requirement for SPVs	A_{av}	Eq. 10	BLD Solar Europe
Carbon stock change in forests	$\Delta_{carbon,forest}$	Eq. 11	FAO
Forest land area	$Area_{forest}$	Eq. 11	FAO
Rooftops area available for SPVs	-	-	K. Bodis et. al (2019)
Brownfields area available for SPVs	-	-	?
First-generation biodiesel demand	*BioDieselDemand*	Eq. 13	LEDS
Crop biodiesel yields	$BioYields_i$	Eq. 14	Edenhofer et al. (2011)
Energy consumption in transport	$EC_{k,f}$	Eq. 15-16	LEDS
Emission factors in transport	$CEF_{k,f}$, $NCEF_{k,f,e}$	Eq. 15-16	Ntziachristos, L. & Samaras, Z. (2020)

Note: Commodities considered in the FOODcrop equations

1 Almonds, with shell; Anise, badian, fennel, coriander; Apples; Apricots; Areca nuts; Artichokes; Asparagus; Avocados; Bambara beans; Bananas; Barley; Beans, dry; Beans, green; Berries nes; Blueberries; Brazil nuts, with shell; Broad beans, horse beans, dry; Buckwheat; Cabbages and other brassicas; Canary seed; Carobs; Carrots and turnips; Cashew nuts, with shell; Cashewapple; Cassava; Cassava leaves; Castor oil seed; Cauliflowers and broccoli; Cereals nes; Cherries; Cherries, sour; Chestnut; Chick peas; Chicory roots; Chillies and peppers, dry; Chillies and peppers, green; Cinnamon (cannella); Cloves; Cocoa, beans; Coconuts; Coffee, green; Cow peas, dry; Cranberries; Cucumbers and gherkins; Currants; Dates; Eggplants (aubergines); Figs; Fonio; Fruit, citrus nes; Fruit, fresh nes; Fruit, pome nes; Fruit, stone nes; Fruit, tropical fresh nes; Garlic; Ginger; Gooseberries; Grain, mixed; Grapefruit (inc. pomelos); Grapes; Groundnuts, with shell; Hazelnuts, with shell; Hempseed; Jojoba seed; Kapok fruit; Karite nuts (sheanuts); Kiwi fruit; Kola nuts; Leeks, other alliaceous vegetables; Lemons and limes; Lentils; Lettuce and chicory; Linseed; Lupins; Maize; Maize, green; Mangoes, mangosteens, guavas; Maté; Melons, other (inc.cantaloupes); Melonseed; Millet; Mushrooms and truffles; Mustard seed; Nutmeg, mace and cardamoms; Nuts nes; Oats; Oil palm fruit; Oilseeds nes; Okra; Olives; Onions, dry; Onions, shallots, green; Oranges; Papayas; Peaches and nectarines; Pears; Peas, dry; Peas, green; Pepper (piper spp.); Persimmons; Pigeon peas; Pineapples; Pistachios; Plantains and others; Plums and sloes; Poppy seed; Potatoes; Pulses nes; Pumpkins, squash and gourds; Quinces; Quinoa; Rapeseed; Raspberries; Rice, paddy; Roots and tubers nes; Rye; Safflower seed; Sesame seed; Sorghum; Soybeans; Spices nes; Spinach; Strawberries; String beans; Sugar beet; Sugar cane; Sugar crops nes; Sunflower seed; Sweet corn frozen; Sweet corn prep or preserved; Sweet potatoes; Tallowtree seed; Tangerines, mandarins, clementines, satsumas; Taro (cocoyam); Tea; Tomatoes; Triticale; Tung nuts; Vanilla; Vegetables, fresh nes; Vegetables, leguminous nes; Vetches; Walnuts, with shell; Watermelons; Wheat; Yams; Yautia (cocoyam);

ANNEX 2

Equations and data for agriculture, forest, and land use (AFOLU) model

SETS

FOODcrop : food items from crops
FOODanimal : food items from animals
FOOD = *FOODcrop* ∪ *FOODanimal*
ANIMALS : animal species
$PROD_{(i \in ANIMALS)}$ = {$f \in$ *FOODanimal* | *f* is produced by ***i***}: food items from animal species ***i***
FORESTS : types of forests
DISTURBANCES : types of forest disturbances

Food demand

For ***i*** ∈ *FOOD*:

2.1 | $$FConsumedKG_i = FDKG_i - (FWasteKG_i / 365)$$

2.2 | $$FDP_i = FDKG_i * 365 * Pop * 1e^{-6} + FLO_i$$

2.3 | $$OF_i = SD_i + NFD_i + PD_i + RD_i + SV_i$$

2.4 | $$SSR_i = (100 * FP_{i,baseline}) / (FP_{i,baseline} - FE_{i,baseline} + FI_{i,baseline})$$

2.5 | $$FP_i = \begin{cases} (SSR_i / 100) * (OF_i + FD_i + FDP_i), i \in FOODcrop \\ (SSR_i / 100) * (OF_i + FDP_i), i \in FOODanimal \end{cases}$$

where:
$FConsumedKG_i$ is the amount of item consumed per capita and per day [(***kg/capita***) / ***day***];
$FDKG_i$ is the demand for item per capita and per day [(***kg/capita***) / ***day***];
$FWasteKG_i$ is the amount of item annually wasted per capita [(***kg/capita***) / ***y***];
FDP_i is the total domestic production of item ***i*** [***ktonnes***];
Pop is the population [***capita***];
FLO_i is the amount of item ***i*** lost [***ktonnes***];
OF_i is the other food demand for item ***i*** [***ktonnes***];
SD_i is the seed demand for item ***i*** [***ktonnes***];
NFD_i is the non-food demand for item ***i*** [***ktonnes***];
PD_i is the processed demand for item ***i*** [***ktonnes***];
RD_i is the residual demand for item ***i*** [***ktonnes***];
SV_i is the stock variation of item ***i*** [***ktonnes***];
SSR_i is the self-sufficiency ratio for item ***i*** [%];
$FE_{i,baseline}$ is the export of item in the base year [***ktonnes***];
$FI_{i,baseline}$ is the import of item in the base year [***ktonnes***];
FP_i is the production of item ***i*** [***ktonnes***].

Food waste and losses

2.6 | $$FLO_{tot} = \sum_{i \in FOOD} (FLO_{i,t-1}) - FL_{reduction}$$

2.7 | $$FLossIndex = (FLO_{tot} / Pop) / (FLO_{tot,baseline} / Pop_{baseline}) * 100$$

2.8 | $$FWC_{tot} = (\sum_{i \in FOOD} FWasteKG_{i,t-1} * Pop * 1e^{-3}) - FW_{reduction}$$

$$2.9 \mid \quad FWasteIndex = 100 * (FWC_{tot} / Pop) / (FWC_{tot,baseline} / Pop_{baseline})$$

where:
FLO_{tot} is the total food losses [***ktonnes***];
$FL_{reduction}$ is the annual food loss reduction from policies implementation [***ktonnes***];
FLossIndex is the food loss index [**–**];
FWC_{tot} is the total food waste [***tonnes***];
$FW_{reduction}$ is the annual food waste reduction from policies implementation [***tonnes***];
FWasteIndex is the food waste index [**–**].

Cropland demand

For $i \in FOODcrop$:

$$2.10 \mid \quad TCLD_i = (FP_i * 1e7) / (CY_i)$$

$$2.11 \mid \quad TCLD = \sum_{i \in FOODcrop} TCLD_i * CL\_corr\_coef$$

where:
$TCLD_i$ is the cropland demand for item i [***ha***];
CY_i is the yields of item i [***hg / ha***];
TCLD is the total cropland demand [***ha***];
CL_corr_coef is a correction coefficient [**–**];

Animal population

For $i \in ANIMALS$:

$$2.12 \mid \quad ANP_i = \sum_{j \in PROD_i} (FP_j * 1e6) / (AY_{i,j})$$

$$2.13 \mid \quad PTTA_i = (TA_{i,baseline}) / (ANP_{i,baseline})$$

$$2.14 \mid \quad TA_i = PTTA_i * ANP_i$$

where:
ANP_i is the total number of animals needed for food production i [***heads***];
FP_j is the production of food item i [***ktonnes***];
$AY_{i,j}$ is the yields of animals for food item j [***kg / head***];
$PTTA_i$ is the production-to-total animal ratio [**–**];
TA_i is the total live animals i [***heads***].

Animal feed demand

For $i \in FOODcrop$:

$$2.15 \mid \quad TAFD = \sum_{i \in FOODanimal} FP_i * FeedCR_i$$

$$2.16 \mid \quad FeedD = (TAFD) / (CRFD)$$

$$2.17 \mid \quad FM_j = (FD_{j,baseline}) / (\textstyle\sum_{i \in FOODcrop} FD_{i,baseline})$$

$$2.18 \mid \quad FD_j = FM_j * FeedD$$

where:
TAFD is the total animal feed demand ;
$FeedCR_i$ is the feed conversion ratio for animal product ;
FeedD is the total crop feed demand ;
CRFD is the crop-forage feed ratio ;
FM_j is the feed mix fraction of item ;
FD_j is the total animal feed demand for item .

Manure production

For $i \in ANIMALS$:

2.19 | $MY_i = (TM_{i,baseline}) / (TA_{i,baseline})$

2.20 | $TM_i = TA_i * MY_i$

2.21 | $MLP_i = TM_i * MMLP_i$

2.22 | $MT_i = TM_i * (1 - MMLP_i)$

2.23 | $MAS_i = MT_i * MMAS_i$

where:
MY_i is the manure yields of animal group i [$kgN / head$];
TM_i is the total manure (nitrogen content) production of animal group i [kgN];
MLP_i is the amount of manure left on pasture [kgN];
$MMLP_i$ is the fraction of manure left on pasture [–];
MT_i is the amount of manure treated [kgN];
MAS_i is the amount of manure applied to soils [kgN];
$MMAS_i$ is the fraction of manure applied to soil [–].

Crop residues

For $i \in ANIMALS$:

2.24 | $CropDRY_i = (CY_i * DRY_i) / (10)$

2.25 | $AGDM_i = (CropDRY_i / 1000) * Slope_i + intercept_i$

2.26 | $RAG_i = (AGDM_i * 1000) / (CropDRY_i)$

2.27 | $RBG_i = RBGBIO_i * (((AGDM_i * 1000) + CropDRY_i) / CropDRY_i)$

2.28 | $Areaburnt = TCLD_i * 0.1$

2.29 | $FCR_i = CropDRY_i * (TCLD_i - Areaburnt_i * CombF_i) * Frac_{renew} * (RAG_i * NAG_i * (1 - Frac_{remove}) + RBG_i * NBG_i)$

2.30 | $ResiduesRemoved_i = CropDRY_i * TCLD_i * Frac_{renew} * RAG_i$

where:
$CropDRY_i$ is the dry-weight correction of reported crop yields [$(kg\ dm) / ha$];
DRY_i is the dry matter fraction of harvested crops [$kg\ dm / kg\ fresh\ weight$];
$AGDM_i$ is the above-ground residue dry matter [Mg / ha];
$Slope_i$ and $intercept_i$ [Mg / ha] are default values for computing above-ground residues;
RAG_i is the ratio of above-ground residues dry matter to harvested yield [–];
RBG_i is the ratio of below-ground residues to harvested yield [–];
$RBGBIO_i$ is the ratio of below-ground residues to above-ground biomass [–];
$Areaburnt$ is the area of crop item burnt [ha];
FCR_i is the nitrogen content from crop residues and forage/pasture renewal [kgN];
$CombF_i$ is the combustion factor of item [–];
$Frac_{renew}$ is the fraction of crop area that is renewed annually [–];
NAG_i is the nitrogen content of above-ground residues [$kgN / kg\ dm$];
$Frac_{remove}$ is the fraction of above-ground residues removed annually [–];
NBG_i is the nitrogen content of below-ground residues [$kgN / kg\ dm$];
$ResiduesRemoved_i$ is the amount of residue removed from cropland [$kg\ dm$].

Nutrient balance

1.17 | $CNY_{baseline} = (CNO_{baseline}) / (\sum_{i \in FOODcrop} FP_{i,baseline} * 1000)$

2.31 | $OUT_C = \sum_{i \in FOODcrop} (FP_i * CNY_{baseline}) * 1000$

2.32 | $FUrate = (IN_{F,baseline}) / (TCLD_{baseline})$

2.33 | $IN_F = TCLD * FUrate$

2.34 | $SL1 = \sum_{i \in ANIMALS} ((MAS_i) / 1000) + IN_F + BF + AD - OUT\_C$

where:
$CNY_{baseline}$ is the crop nitrogen yield per unit of output [*tonnesN / tonnes*] ;
$CNO_{baseline}$ is the total nitrogen content of crops in the baseline year [*tonnesN*];
OUT_C is the crop output [*tonnesN*];
FUrate is the cropland fertilizer application rate [*tonnesN / ha*];
IN_F is the agricultural use of nutrients [*tonnesN*];
SL1 is the nutrient balance [*tonnesN*];
BF is the biological N fixation [*tonnesN*];
AD is the atmospheric deposition [*tonnesN*].

Emissions from enteric fermentation

2.35 | $EE_{CH_4} = \sum_{i \in ANIMALS} TA_i * EF_{EE_i}$

2.36 | $TEE_{CO_2eq} = EE_{CH_4} * GWP_{CH_4}$

where:
EE_{CH_4} is the CH_4 emissions from enteric fermentation [$ggCH_4$];
EF_{EE_i} is the implied CH_4 emissions factor of animal group ***i*** [$ggCH_4$ / *head*];
TEE_{CO_2eq} is the CO_2eq emissions from enteric fermentation [$ggCO_2eq$] ;
GWP_{CH_4} is the global warming potential of CH_4 relative to CO_2 [$ggCO_2eq$ / $ggCH_4$].

Emissions from manure

For ***i*** ∈ *ANIMALS*:

2.37 | $EL_i = (EFL_i * MLP_i * WC_{N_2O}) * 1e^{-6}$

2.38 | $TMP_{CO_2eq} = \sum_{i \in ANIMALS} (EL_i * GWP_{N_2O})$

2.39 | $ETCH_{4i} = EFCH_4T_i * TA_i * 1e^{-6}$

2.40 | $ET_i = (EFT_i * MT_i * WC_{N_2O}) * 1e^{-6}$

2.41 | $TMT_{CO_2eq} = \sum_{i \in ANIMALS} (ET_i * GWP_{N_2O}) + \sum_{i \in ANIMALS} (ETCH_{4i} * GWP_{CH_4})$

2.42 | $EAS_i = EFAS_i * MAS_i * WC_{N_2O} * 1e^{-6}$

2.43 | $TMA_{CO_2eq} = \sum_{i \in ANIMALS} (EAS_i * GWP_{N_2O})$

where:
EL_i is the N_2O emissions from manure from animal group left on pasture [ggN_2O];
EFL_i is the implied N_2O emission factor for manure from animal group **i** left on pasture [(kgN_2O - *N*) / *kgN*] ;
WC_{N_2O} is the N_2O-N to N_2O conversion factor [= 44.01 / 17.0076];
TMP_{CO_2eq} is the emissions from manure left on pasture [$ggCO_2eq$];
GWP_{N_2O} is the global warming potential of N_2O relative to CO_2 [$ggCO_2eq$ / ggN_2O];;
$ETCH_{4i}$ is the CH_4 emissions from manure management from animal group ***i*** [*ggCH4*];
$EFCH_4T_i$ is the implied CH_4 emission factor for manure management and animal group ***i*** [$kgCH_4$ / *head*];

ET_i is the N_2O emissions from manure management from animal group ***i*** [ggN_2O];
EFT_i is the implied N_2O emission factor for manure management and animal group ***i*** [$(kgN_2O - N) / kgN$];
TMT_{CO_2eq} is the emissions from manure management [$ggCO_2eq$];
EAS_i is the N_2O emissions from manure applied to soil [ggN_2O];
$EFAS_i$ is the implied N_2O emission factor for manure applied to soil and animal group ***i*** [$(kgN_2O - N) / kgN$];
TMA_{CO_2eq} is the emissions from manure applied to soil [$ggCO_2eq$].

Emissions from fertilizer application

$$2.44 \mid F_{N_2O} = (IN_F * WC_{N_2O} * EF_F) \;/\; 1000$$

$$2.45 \mid FE_{CO_2eq} = F_{N_2O} * GWP_{N_2O}$$

where:
F_{N_2O} is the N_2O emissions from fertilizer application ;
EF_F is the N_2O emission factor from fertilizer ;
FE_{CO_2eq} is the emissions from fertilizer application .

Other emissions

$$2.46 \mid ECR_{CO_2eq} = \sum_{i \in FOODcrop} FCR_i * EF_{cr,i} * WC_{N_2O} * 1e^{-6} * GWP_{N_2O}$$

$$2.47 \mid ERice_{CO_2eq} = TCLD_{rice} * EF_{rice} * 1e^{-6} * GWP_{CH_4}$$

$$2.48 \mid EburnCR_{CO_2eq} = BM_{burn} * ((EFCRBI_{N_2O} * GWP_{N_2O}) \;/\; (WC_{N_2O}) + EFCRBI_{CH_4} * GWP_{CH_4}) * 1e^{-6}$$

$$2.49 \mid OE = ECOS_{CO_2eq} + ECR_{CO_2eq} + ERice_{CO_2eq} + EburnCR_{CO_2eq} + EBS_{CO_2eq} + EBB_{CO_2eq}$$

where:
ECR_{CO_2eq} is the emissions from crop residues [$ggCO_2eq$];
$EF_{cr,i}$ is the crop residue emission factor [$(kgN_2O - N) / kgN$];
$ERice_{CO_2eq}$ is the emissions from rice cultivation [$ggCO_2eq$];
EF_{rice} is the rice cultivation emission factor [$kgCH_4 / ha$];
$EburnCR_{CO_2eq}$ is the emissions from burning crop residues [$ggCO_2eq$];
BM_{burn} is the total biomass burnt [$kg\,dm$];
$EFCRBI_{N_2O/CH_4}$ is the emission factor for burning crop residues [$(kg_{N_2O} - N / CH_4) / kg\,dm$];
$ECOS_{CO_2eq}$ is the emissions from the cultivation of organic soils [$ggCO_2eq$];
EBS_{CO_2eq}, EBB_{CO_2eq} are the emissions from savanna and forest fires, respectively [$ggCO_2eq$];
OE is the total other emissions from AFOLU[$ggCO_2eq$] .

Biomass

$$2.50 \mid L_{wood\text{-}removals} = \sum_{i \in FORESTS} H_i * BCEF_{R,i} * (1 + R) * CF$$

$$2.51 \mid L_{fuelwood} = \sum_{i \in FORESTS} ((FG_{trees,i} * BCEF_{R,i} * (1 + R) + FG_{part,i} * D_i * CF$$

$$2.52 \mid L_{disturbance} = \sum_{i \in DISTURBANCE} A_{disturbance,i} * B_{W,i} * (1 + R) * CF * fd$$

$$2.53 \mid \Delta C_L = L_{wood\text{-}removals} + L_{fuelwood} + L_{disturbance}$$

$$2.54 \mid G_{total} = (G_W * (1 + R))$$

$$2.55 \mid \Delta C_G = A_{remain} * G_{total} * CF$$

$$2.56 \mid \Delta BE3 = \Delta C_G - \Delta C_L$$

where:
$L_{wood\text{-}removals}$ is the biomass loss due to wood removals [$tonnesC$];
H_i is the roundwood removals from forest type ***i*** [m^3];
$BCEF_{R,i}$ is the biomass conversion and expansion factor for forest type ***i*** [$(tonnes\,dm) / m^3$];
R is the ratio of below-ground forest biomass to above-ground biomass [–];

CF is the carbon fraction of dry matter [$(tonnesC) / tonnesdm$];
$L_{fuelwood}$ is the biomass loss due to fuel wood removals [$tonnesC$];
$FG_{trees,i}$ is the volume of fuel wood removal as whole trees from forest type i [m^3];
$FG_{part,i}$ is the volume of wood removal as tree parts from forest type i [m^3];
D_i is the basic wood density for forest type i [$(tonnes\ dm) / m^3$];
$L_{disturbance}$ is the biomass loss due to disturbances [$tonnesC$];
$A_{disturbance}$ is the area affected by disturbance i [ha];
$B_{W,i}$ is the average above-ground biomass of land areas affected by disturbance i [$(tonnes\ dm) / ha$];
fd is the fraction of biomass lost in disturbances [–];
ΔC_L is the decrease in carbon stocks due to biomass loss [$tonnesC$];
G_{total} is the mean annual biomass growth [$(tonnes\ dm) / ha$];
G_W is the average annual above-ground biomass growth [$(tonnes\ dm) / ha$];
ΔC_G is the increase in carbon stocks due to biomass growth [$tonnesC$];
A_{remain} is the area of forest remaining in the same land use category [ha];
$\Delta BE3$ is the net change in forest biomass [$tonnesC$].

Share of forest area to total land area

$$2.57 \mid \Delta TCLD = TCLD - TCLD_{baseline}$$

$$2.58 \mid IL = IL_{baseline} + \Delta TCLD$$

$$2.59 \mid FL\_RF = FL_{baseline} + RRate * IL$$

$$2.60 \mid BE2 = (FL\_RF) / (TLA)$$

where:
$\Delta TCLD$ is the change in cropland demand [ha];
IL is the inactive land stock [ha];
FL_RF is the forest land stock after reforestation policy [ha];
TLA is the total land area [ha];
$FL_{baseline}$ is the forest land stock in the base year [ha];
$RRate$ is the rate of reforestation [–];
$BE2$ is the share of forest area to total land area [–].

Emissions from land use change

$$2.61 \mid chFL = FL\_RF - FL_{baseline}$$

$$2.62 \mid EFL_{CO_2eq} = chFL * EF_{fl}$$

$$2.63 \mid \Delta Clorg = \Delta TCLD * OS$$

$$2.64 \mid EOS_{CO_2eq} = \Delta Clorg * EF_{os}$$

$$2.65 \mid LUC_{CO_2eq} = EFL_{CO_2eq} + EOS_{CO_2eq}$$

where:
$chFL$ is the change in forest land ;
EFL_{CO_2eq} is the emissions from change in forest land ;
EF_{fl} is the forest land emission factor ;
$\Delta Clorg$ is the change in cropland under organic soils ;
OS is the percentage of total cropland under organic soils (histosol) ;
EOS_{CO_2eq} is the emissions from change in agriculture on organic soils ;
EF_{os} is the emission factor for cropland under organic soils ;
LUC_{CO_2eq} is the emissions from land use change .

Total AFOLU emissions

$$2.66 \mid GE3 = [(OE + TEE_{CO_2eq} + TMT_{CO_2eq} + TMP_{CO_2eq} + TMA_{CO_2eq} + FE_{CO_2eq} + LUC_{CO_2eq}) / Pop]$$

where:
GE3 is the ration of non-CO_2 emissions in agriculture to population .

Bioenergy

For $i \in FOODcrop$:

$$2.67 \mid RBioEth_i = ResiduesRemoved_i * EthY_i$$

$$2.68 \mid RBioEthSupply = \sum_{i \in FOODcrop} RBioEth_i * BioEthConversion_{MJ}$$

For $i \in ANIMALS$:

$$2.69 \mid ManureVS_i = (TA_i * BodyMass_i * VSprodDAY_i) * 365 * 1e^{-3}$$

$$2.70 \mid Mbioenergy_i = (ManureVS_i * (1 - MMLP_i)) * (1 - MMAS_i)$$

$$2.71 \mid MBiogas_i = Mbioenergy_i * BiogasY_i$$

$$2.72 \mid MBiogas_{TJ} = \sum_{i \in ANIMALS} (MBiogas_i * BioGasConversion_{MJ} * 1e^{-6})$$

where:
$RBioEth_i$ is the bioethanol from residue crops ***i*** [***L***];
$EthY_i$ is the bioethanol yields from crops ***i*** [***L*** / (***kg dm***)].
RBioEthSupply is the total bioethanol from residue crops [***TJ***];
$BioEthConversion_{MJ}$ is the bioethanol conversion factor[***TJ*** / ***L***];
$ManureVS_i$ is the total manure production from animal group ***i*** [***kg VS***];
$BodyMass_i$ is the average adult body mass of animal group ***i*** [***kg body mass***];
$VSprodDAY_i$ is the manure production of group ***i*** animal per day day [(***kg VS***) / ***day***) / (1000***kg body mass***)];
$Mbioenergy_i$ is the manure from animal group available for bioenergy [***kg VS***];
$MBiogas_i$ is the biogas production from manure from animal group ***i*** [m^3];
$BiogasY_i$ is the methane yields from manure from animal group ***i*** [m^3 / ***kg VS***];
$MBiogas_{TJ}$ is the total biogas production from manure [***TJ***];
$BioGasConversion_{MJ}$ is the biogas conversion factor [***MJ*** / m^3].

Data sources

Variable/Parameter name	Code	Equation	Data source
Types of crops	*FOODcrop*	Eq. 1-6, 8, 10-11, 15, 17-18, 24-32, 47, 68-69	FAO
Animal yields	$AY_{i,j}$	Eq. 12	FAO
Baseline total animals	$TA_{i,baseline}$	Eq. 13, 19	FAO
Baseline total number of animals needed for food production	$ANP_{i,baseline}$	Eq. 13	FAO
Feed conversion ratio	$FeedCR_i$	Eq. 15	Alexander et al. (2016)
Crop-forage feed ratio	*CRFD*	Eq. 16	Calibrated using baseline year data
Baseline animal feed demand	$FD_{i,baseline}$	Eq. 17	FAO
Food demand	$FDKG_i$	Eq. 1	FAO
Food waste	$FWasteKG_i$	Eq. 1, 8	UNEP (2021)
Population	*Pop*	Eq. 2, 7-9, 67	FAO
Food loss	FLO_i	Eq. 2, 6-7	FAO
Seed demand	SD_i	Eq. 3	FAO
Non-food demand	NFD_i	Eq. 3	FAO
Processed food demand	PD_i	Eq. 3	FAO
Residual food demand	RD_i	Eq. 3	FAO

Variable/Parameter name	Code	Equation	Data source
Stock variation	SV_i	Eq. 3	FAO
Baseline food production	$FP_{i,baseline}$	Eq. 4, 31	FAO
Baseline food exports	$FE_{i,baseline}$	Eq. 4	FAO
Baseline food imports	$FI_{i,baseline}$	Eq. 4	FAO
Crop yields	CY_i	Eq. 10, 24	FAO
Baseline manure production	$TM_{i,baseline}$	Eq. 19	FAO
Dry matter fraction of harvested crops	DRY_i	Eq. 24	IPCC (2006)
Regression parameters for computing above-ground residues	$slope_{i,}$	Eq. 25	IPCC (2006)
Crop combustion factor	$intercept_i$	Eq. 29	Dong et al. (2020)
N content of above-ground residues	$CombF_i$	Eq. 29	IPCC (2006)
N content of below-ground residues	NAG_i	Eq. 29	IPCC (2006)
Ratio of below-ground residues to above-ground biomass	NBG_i	Eq. 27	IPCC (2006)
Baseline total crops nitrogen content	$RBGBIO_i$	Eq. 31	FAO
Baseline fertilizer use	$CNO_{baseline}$	Eq. 33	FAO
Biological nitrogen fixation	$IN_{F,baseline}$	Eq. 35	FAO
Atmospheric deposition	BF	Eq. 35	FAO
Implied CH_4 emission factor from enteric fermentation	AD	Eq. 36	FAO
Global warming potential of CH_4	$EF_{EE,i}$	Eq. 37, 42, 48-49	Pachauri et al. (2014)
Implied N_2O emission factor for manure left on pasture	GWP_{CH4}	Eq. 38	FAO
Global warming potential of N_2O	EFL_i	Eq. 39, 42, 44, 46-47, 49	Pachauri et al. (2014)
Implied CH_4 and N_2O emission factors for manure management	GWP_{N_2O}	Eq. 40, 41	FAO
Implied N_2O emission factor for manure applied to soil	$ETCH4,$	Eq. 43	FAO
N_2O emission factor from fertilizers	EFT_i	Eq. 45	FAO
Crop residue emission factor	$EFAS_i$	Eq. 47	FAO
Rice cultivation emission factor	EF_F	Eq. 48	FAO
Emission factors for burning crop residues	$EF_{cr,i}$	Eq. 49	IPCC (2006)
Emissions from forest and savanna fires	EF_{rice}	Eq. 50	FAO
Biomass conversion and expansion factor	$EFCRBI_{N_2O/CH_4}$	Eq. 51, 52	Aalde et al. (2006)
Carbon fraction of dry matter	$EBS_{CO_2eq}, EBB_{CO_2eq}$	Eq. 51-53, 56	Aalde et al. (2006)
Average annual above-ground biomass growth	$BCEF_{R,i}$	Eq. 55	Aalde et al. (2006)
Ratio of below-ground forest biomass to above-ground biomass	CF	Eq. 51-53, 55	Aalde et al. (2006)
Basic wood density	G_W	Eq. 52	Aalde et al. (2006)
Area affected by disturbance	R	Eq. 53	FAO
Average above-ground biomass of land areas affected by disturbances	D_i	Eq. 53	Aalde et al. (2006)
Baseline inactive land	$A_{disturbances,i}$	Eq. 59	FAO
Baseline cropland	$B_{W,i}$	Eq. 58	FAO
Baseline forest land	$IL_{baseline}$	Eq. 60 , 62	FAO
Total land area	$TCLD_{baseline}$	Eq. 61	FAO
Forest land emission factor	$FL_{baseline}$	Eq. 63	FAO

Variable/Parameter name	Code	Equation	Data source
Percentage of total cropland under organic soils	*TLA*	Eq. 64	FAO
Organic soil emission factor	EF_{fl}	Eq. 65	FAO
Bioethanol yields	*OS*	Eq. 68	Kim&Dale (2004)
Bioethanol conversion factor	*EF_os*	Eq. 69	Gnansounou et al. (2018)
Animal average adult body mass	$EthY_i$	Eq. 70	Vermeulen et al. (2017)
Daily animal manure production	$BioEthConversion_{MJ}$	Eq. 70	Safley et al. (1992), Vermeulen et al. (2017)
Manure methane yields	$BodyMass_i$	Eq. 72	Jørgensen (2009)
Biogas conversion factor	$VSprodDAY_i$	Eq. 73	IEA
	$BiogasY_i$		
	$BioGasConversion_{MJ}$		

ANNEX 3

Equations and data for water use and waste model

SETS

FOODcrop : food items from crops
IRRTECH : irrigation technologies
FELEC : fuel types for electricity generation
COOLINGSYSTEMS : cooling systems for electricity generation power plants
WWCOLLECT : wastewater collection systems (sewage network, septic tanks)
POPTYPE : population type (urban, rural)
SANITATION : sanitation categories (connected, unimproved, open defecation)
WWTREATMENT : type of wastewater treatment (primary, secondary, tertiary)
POLLUTANT : types of pollutant from human waste (nitrogen, phosphorus, cryptosporidium)

Agricultural water

For $i \in FOODcrop$, $tech \in IRRTECH$:

3.1 | $AL_{tech} = IRRTECH_{tech} * AL$

3.2 | $CI_i = (IHA_i) \; / \; (AL)$

3.3 | $ET_c = \sum_{i \in FOODcrop} \mathbf{K}_i * ET_{o,i} * CI_i$

3.4 | $ICU = |ET_c - ET_a$

3.5 | $IWR_{tech} = (ICU * AL_{tech} * 10)$

3.6 | $IWW = \sum_{tech \in IRRTECH} (IWR_{tech} \; / \; IRRTECHEFF_{tech}) + 0.2 * IHA_{rice}$

3.7 | $AWU = IWW$

where:
AL_{tech} is the land irrigated by technology tech [*ha*];
$IRRTECH_{tech}$ is the proportion of total irrigated land irrigated by technology tech [–];
AL is the total arable irrigated land [*ha*];
CI_i is the crop intensity of crop ***i*** [–];
IHA_i is the irrigated crop harvested area for crop ***i*** [*ha*];
ET_c is the crop evapotranspiration [*mm / y*];
$\mathbf{K}_i$ is the crop coefficient for crop i [–];
$ET_{o,i}$ is the evapotranspiration of crop i under standard conditions [*mm / y*];
ICU is the irrigative consumptive use [*mm / y*];
ET_a is the actual evapotranspiration [*mm / y*];
IWR_{tech} is the irrigation water requirement for irrigation technology $tech \in \{surface, sprinkler, drip\}$ [m^3 / y];
IWW is the total irrigation water withdrawal [m^3 / y];
$IRRTECHEFF_{tech}$ is the efficiency of irrigation technology tech [–];
AWU is the total agricultural water withdrawal [m^3 / y].

Industrial water

3.8 | $TEWW = \sum_{f \in FELEC, cs \in COOOLINGSYSTEMS} EG_f * WWI_{cs,f} * CS_{cs,f}$

3.9 | $TEWC = \sum_{f \in FELEC, cs \in COOOLINGSYSTEMS} EG_f * WCI_{cs,f} * CS_{cs,f}$

where:
TEWW is the thermoelectric water withdrawal [m^3 / y];
EG_f is the total electricity generated by fuel *f* [*MWh*];
$WWI_{cs,f}$ is the water withdrawal intensity factor for cooling system cs and fuel *f* [$(m^3 / MWh) / (y)$];
$CS_{cs,f}$ is the proportion of cooling system cs for fuel *f* [–];
TEWC is the thermoelectric water consumption [m^3 / y];
$WCI_{cs,f}$ is the water consumption intensity factor for cooling system cs and fuel f [$(m^3 / MWh) / (y)$].

Municipal water and wastewater

For $i \in WWCOLLECT$:

$$3.10 \mid MWU = \alpha GDPC^{\beta 1} * P^{\beta 2} * Pop^{\beta 3}$$

$$3.11 \mid MWC = MWU * C$$

$$3.12 \mid WG = MWU - MWC$$

$$3.13 \mid WC_i = WG * CS_i$$

$$3.14 \mid TW_{sn} = WC_{sn} * DTP * PWT$$

$$3.15 \mid TW_{is} = WC_{st} * collected * NE$$

$$3.16 \mid TW_{fst} = WC_{st} * collected * DTP * PWT$$

$$3.17 \mid TW = TW_{sn} + TW_{is} + TW_{fst}$$

$$3.18 \mid SDG6.3.1 = (TW / WG) * 100$$

where:
MWU is the municipal water use withdrawal [m^3 / y];
GDPC is the gross domestic product per capita [USD/capita];
P is the water price [USD / m^3];
Pop is the population [*capita*];
α [$(capita{*}m^3)/(USD{*}y)$],$\beta 1$ $\beta 2$,$\beta 3$[–] are constants determined by linear regression;
MWC is the municipal water consumption [m^3 / y];
C is the consumptive coefficient [–];
WG is the amount of wastewater generated [m^3 / y];
WC_i is the amount of wastewater collected by system *i*={*sn,sp*}, where *sn* stands for sewage networks and *sp* stands for septic tanks [m^3 / y];
CS_i is the proportion of the population connected to system *i* [–].
TW_{sn} is the total wastewater treated via sewage networks [m^3 / y];
DPT is the percentage of wastewater that is delivered to treatment plants [–];
PWT is the percentage of the population connected to at least secondary wastewater treatment [–];
TW_{is} is the wastewater collected through septic tank that is treated in-situ [m^3 / y];
collected is the proportion of wastewater that is collected [–];
NE is the proportion of wastewater that is not emptied [–];
TW_{fst} is the wastewater collected through septic tank that is treated through faecal sludge treatment [m^3 / y];
TW is the total wastewater treated [m^3 / y];
SDG6.3.1 is the proportion of wastewater treated to wastewater generated [%].

Freshwater availability

$$3.19 \mid IRWR = GW + SW - O$$

$$3.20 \mid TRF = IRWR + ERWR$$

$$3.21 \mid TWW = AWU + TEWW + MWU$$

$$3.22 \mid EW2 = TWW / (TRF - EFR)$$

where:
IRWR is the internal renewable water resources [m^3 / y];
GW is the groundwater [m^3 / y];
SW is the surface water [m^3 / y];
O is the overlap between GW et SF [m^3 / y];
TRF is the total renewable water resources [m^3 / y];
ERWR is the external renewable water resources [m^3 / y];
TWW is the total water withdrawal [m^3 / y];
EW2 is the water stress [–];
EFR is the environmental flow requirement [m^3 / y].

Water use efficiency

3.23 | $A_i = A_{irr} / TCLD$

3.24 | $C_r = 1 / (1 + A_i / ((1 - A_i) * Y_g))$

3.25 | $AWE = (GVA_a * (1 - C_r)) / AWU$

3.26 | $MWE = (GVA_m) / MWU$

3.27 | $IWE = (GVA_i) / TEWW$

3.28 | $P_x = (WU_x) / TWW$

3.29 | $EW1 = AWE * P_a + IWE * P_i + MWE * P_m$

where:
A_i is the proportion of irrigated land (A_{irr}) over the total cropland area (*TCLD*) [–];
C_r is the corrective coefficient identifying the proportion of agricultural GVA produced par rainfed agriculture [–];
Y_g is a generic default ratio between rainfed and irrigated yields [–];
AWE is the agricultural water use efficiency [USD / m^3];
IWE is the industrial water use efficiency [USD / m^3];
MWE is the municipal water use efficiency [USD / m^3];
GVA_x is the gross value added of the sector **x** (excluding fisheries and forestry for agriculture) [*USD*];
P_x is the proportion of water used by sector **x**={***agriculture,industry,municipal***} (WU_x) over the total water use (*TWW*) [–];
EW1 is the total water use efficiency [USD / m^3].

Human waste pollution

For $i \in POPTYPE$, $s \in SANITATION$, $x \in POLLUTANT$:

3.30 | $N_{intake} = N_{protein_{min}} + N_{protein_{range}} * (GDPC / GDPC_{max})^{0.3}$

3.31 | $N_{protein} = [\, Protein * N_{content} \,]$

3.32 | $HE_N = N_{intake} * CF_N$

3.33 | $HE_P = HE_N * (1 / 6)$

3.34 | $HE_C = \{5 \times 10^7 \; if\, HDI \geq 0.78 \; 10^8 \; if\, HDI \leq 0.785$

3.35 | $PC_{s,i} = Pop * S_{s,i} * F_i$

3.36 | $RE_x = \sum_{j \in WWTREATMENT} f_j * ARE_j$

3.37 | $EI_{connect,x} = (1 - RE_x) * \sum_{i \in POPTYPE} PC_{connect,i} * HE_x$

3.38 | $EI_{direct,x,u} = (PC_{open,u} + PC_{ui,u}) * HE_x$

3.39 | $EI_{direct,x,r} = PC_{ui,r} * HE_x$

3.40 | $EI_{direct,x} = EI_{direct,x,u} + EI_{direct,x,r}$

3.41 | $EI_{diffuse,x} = PC_{open} * HE_x$

3.42 | $EI_x = EI_{connect,x} + EI_{direct,x} + EI_{diffuse,x}$

where:
N_{intake} is the nitrogen intake [*kg* / *capita*];
$N_{protein_{min/range}}$ are the minimum and range of national protein intake [*kg* / *capita*];
GDPC is the GDP per capita and GDPC_max is the maximal GDP per capita amongst available countries [*USD* / *capita*];
$N_{protein}$ is the national protein intake [*kg* / *capita*];
Protein is the protein consumption [*kg* / *capita*];
$N_{content}$ is the average nitrogen content of proteins [–];
HE_N is the annual nitrogen emissions from human waste [(*kg* / *capita*];
CF_N is a conversion factor [1 / *y*];
HE_P is the annual phosphorus emission from human waste [(*kg* / *capita*];
HE_C is the annual cryptosporidium emissions [(*oocyst* / *capita*) / *year*] ;
HDI is the Human Development Index [–];
$PC_{s,i}$ is the population of type ***i*** under sanitation category ***s*** [*capita*];
$S_{s,i}$ is the fraction of population of type i under sanitation system ***s*** [–];
F_i is the fraction of population of type ***i*** [–];
RE_x is the removal efficiency for pollutant ***x*** [–];
f_j is the distribution of the type of wastewater treatment ***j*** [–];
ARE_j is the average removal efficiency of wastewater treatment ***j*** [–];
$EI_{connect,x}$ is the emission of pollutant x from connected systems [*kg* / *y*];
$EI_{direct,x,i}$ is the direct source emissions of pollutant x from population type ***i*** [*kg* / *y*];
$EI_{diffuse,x}$ is the diffuse source emissions of pollutant ***x*** [*kg* / *y*];
EI_x is the total emissions of pollutant ***x*** [*kg* / *y*].

Burden of disease attributable to inadequate sanitation

3.43 | $PAF = (\sum_{j=1}^{n} p_j (RR_j - 1)) / (\sum_{j=1}^{n} p_j (RR_j - 1) + 1)$

3.44 | $AB = PAF * B$

where:
PAF is the population attributable fraction [–];
p_j is the proportion of the exposed population at exposure level ***j*** [–];
RR_j is the relative risk at exposure level ***j*** [–];
AB is the attributable burden of diarrhoeal disease from inadequate sanitation [*deaths*];
B is the total deaths from diarrheal diseases [*deaths*].

Data sources

Variable/Parameter name	Code	Equation	Data source
Types of irrigated crops	*FOODcrop*	Eq. 2-3	FAO, Central Statistical Office of Saint Lucia
Crop coefficient	K_i	Eq. 3	FAO
Reference evapotranspiration	$ET_{o,i}$	Eq. 3	LP DAAC (Running et al. 2019)
Actual evapotranspiration	ET_a	Eq. 4	LP DAAC (Running et al. 2019)
Irrigated area	*AL*	Eq. 1-2	FAO
Irrigated crop harvested area	IHA_i	Eq. 2, 6	FAO
Irrigation technology efficiency	$IRRTECHEFF_{tech}$	Eq. 6	Brouwer et al. (1989)
Sectoral value added	GVA_x	Eq. 25-27	World Bank
Generic default ratio between rainfed and irrigated yields	Y_g	Eq. 24	UNSTAT
Electricity generated	EG_f	Eq. 8-9	LEDS

Variable/Parameter name	Code	Equation	Data source
Water withdrawal and consumption intensity	$WWI_{cs,f}$, $WCI_{cs,f}$	Eq. 8-9	Macknick et al (2011-2012)
Proportion of cooling systems	$CS_{cs,f}$	Eq. 8-9	Lohrmann et al. (2019), Florke et al. (2013), satellite image
Water tariff price	P	Eq. 10	World Bank, ONEA, WASCO
GDP per capita	$GDPC$	Eq. 10, 30	World Bank
Population	Pop	Eq. 10, 35	Riahi et al. (2017), World Bank, UN
Population connected to sewage network system, septic tanks, and with access to at least secondary wastewater treatment	CS_i, PWT	Eq. 13 Eq. 14, 16	WHO & UNICEF, LEDS, TANOH
Surface water, groundwater, and overlap	SW,GW,O	Eq. 19	FAO
Internal and external water resources	$IRWR,ERWR$	Eq. 20	FAO
Environmental flow requirement	EFR	Eq. 22	
Protein consumption	$Protein$	Eq. 31	FAO
Nitrogen content of proteins	$N_{content}$	Eq. 31	Strokal et al. (2019)
Human Development Index	HDI	Eq. 34	UNDP
Cryptosporidium excretion rates	HE_C	Eq. 34	Hofstra et al. (2013)
Fraction of urban and rural population	F_i	Eq. 35	Jiang & O'Neill (2017), World Bank
Treatment nitrogen, phosphorus, and cryptosporidium removal efficiencies	ARE_j	Eq. 36	Strokal et al. (2019)
Distribution of wastewater treatment	f_j	Eq. 36	van Puijenbroek et al. (2019)
Exposure levels	p_j	Eq. 43	WHO & UNICEF
Exposure level relative risk	RR_j	Eq. 43	Wolf et al. (2014)
Total deaths from diarrhoeal diseases	B	Eq. 44	Global Health Data Exchange

ANNEX 4

Equations for other models

SETS

NRES	:	non-renewable energy sources (coal, oil, natural gas, nuclear)
SOLARJOBS	:	types of jobs created by the development of SPVS (construction & implementation, manufacturing, operation & maintenance)
PRIVATEMODES	:	types of private transport modes (cars, two wheels)
TRANSPORTFUELS	:	types of fuels used in transport
POW	:	types of powertrains
ALLMODES	:	all modes of transport, including PRIVATEMODES (cars, two wheels, LCV, HDV, bus, passenger rail, freight rail)
RAIL	:	rail transport types (passenger rail, freight rail)
FOODcrop	:	food items from crops
ANIMALS	:	animal species

4.1. Energy

Emissions reduction from transition to clean electricity generation

As defined by the Asian Development Bank (Asian Development Bank, 2017), the emission reduction resulting from a clean energy generation project can be estimated as the difference between the emissions that would have occurred, were the same amount of energy be generated from fossil fuels (baseline emissions), and the emissions generated from the renewable project. The baseline emissions are computed using emission and power plant efficiency factors.

For $i \in NRES \setminus Nuclear$:

4.1 | $$Q_i = (EG_i) \;/\; (\eta_{powerplant,i})$$

4.2 | $$BE = \sum_{i \in NRES \setminus Nuclear} Q_i * EF_i$$

4.3 | $$AE = BE - PE$$

where:

Q_i is the amount of fossil fuel i used to generate the same amount of electricity [TJ / y];
EG_i is the electricity that would have been generated by fossil fuel ***i***;
$\eta_{powerplant,i}$ is the efficiency of a powerplant of fuel ***i*** [TWh / TJ];
BE are the baseline emissions, i.e., emissions generated by the generation of the same amount of electricity from fossil fuels [$kgCO_2eq / y$];
EF_i is the emission factor of fossil fuel ***i*** [$kgCO_2eq / TJ$];
AE are the emissions avoided by the renewable energy projects [$kgCO_2eq / y$];
PE are the emissions generated by the renewable projects [$kgCO_2eq / y$].

Clean energy jobs

The development of the renewable energy sector is expected to create an important number of jobs. The Employment Factor (EF) approach is adapted in this paper to determine employment opportunities resulting from the increase in capacity of SPVS from 2020 – 2050 (Grafakos, Kim, Krispien, Quezada, & Rijsberman, 2021). The different jobs created along the value chain of SPVS can be grouped by categories: Manufacturing, Construction and Implementation (C&I), and Operation and Maintenance (O&M). Employment factors are country-specific and obtained from industrial surveys, Input-Output analyses, and model estimations.

For $i \in SOLARJOBS$:

$$4.4 \mid \quad jobs_i = PCG_{solar} * EmployF_i * M_{country}$$

$$4.5 \mid \quad Jobs = jobs_{C\&I} + jobs_{manu} + jobs_{O\&M}$$

where:

$jobs_i$ is the number of jobs created in category i [–];
PCG_{solar} is the installed solar capacity [MW];
$EmployF_i$ is the employment factor for category i;
$M_{country}$ is the country multiplier [–];
$Jobs$ is the total number of jobs generated by the installation of SPVS [–].

Private passenger transport activity

To model the passenger transport sector, the Gompertz function, widely used in mathematics to model growth in various fields of studies (Kathleen M. C. Tjørve, 2017), is fitted with data on vehicle stocks for passenger cars and two-wheels. Each mode of transport has a different growth rate; hence the model's parameters are estimated separately for each mode. The vehicle stocks are therefore represented as a function of GDP per capita by the Gompertz model (Joyce Dargay, 2007). The stocks can be multiplied by a vehicle utilization rate (Tan, 2018) to yield the vehicle-kilometers travelled annually by each mode of private passenger transport. The vehicle-kilometers demand for each fuel type can then be derived.

For $k \in PRIVATEMODES$, $f \in TRANSPORTFUELS$:

$$4.6 \mid \quad VS_k = \gamma_k e^{\alpha_k e^{(\beta_k Trgd \,/\, Pop)}}$$

$$4.7 \mid \quad V_k = (VS_k * Pop) \,/\, (1000)$$

$$4.8 \mid \quad VDT_k = \lambda_k * V_k$$

$$4.9 \mid \quad VTD_{k,f} = VDT_k * \sum_{pow \in POW} TS_{k,pow} * F_{pow,f}$$

where:
VS_k is the vehicle stock per thousand capita for mode k [($vehicle$) / 1000$capita$];
γ_k is the maximum saturation level of vehicles in a country [($vehicle$) / 1000$capita$];
α_k is a negative parameter determining the midpoint of the regression [–];
β_k is a negative parameter representing the rate of growth [$capita$ / ($Real$ $million$ LCU)];
$Trgdp$ is the total real gross domestic product [$Real$ $million$ LCU];
Pop is the population [$capita$];
V_k is the total vehicle fleet of mode k [$vehicle$];
VDT_k is the vehicle-kilometers travelled for mode k [vkm];
λ_k is the vehicle utilization rate for mode k [km];
$VTD_{k,f}$ is the vehicle-kilometers demand for each fuel type f and mode k [vkm];
$TS_{k,pow}$ is the technology share for mode k and technology pow [–];
$F_{pow,f}$ is the fuel share of fuel f for technology pow [–];

Energy consumption from transport

From the transport activity projections, energy efficiency factors are used to convert the distance travelled into the amount of energy consumed.

For $k \in ALLMODES \setminus RAIL$:

$$4.10 \mid \quad EC_{k,f} = VTD_{k,f} * EE_{k,f}$$

$$4.11 \mid \quad EC_{rp,f} = PTD_{rp,f} * EE_{rp,f}$$

$$4.12 \mid \quad EC_{rf,f} = FTD_{rf,f} * EE_{rf,f}$$

where:
$EC_{k,f}$ is the energy consumption of fuel f for mode k [MWh];
$EE_{k,f}$ is the energy efficiency factor for fuel f and mode k [MWh / vkm];
$EC_{rp,f}$ and $EC_{rf,f}$ are the energy consumption of fuel f for passenger and freight rail transport, respectively [MWh];
$PTD_{rp,f}$ and $FTD_{rf,f}$ are the passenger and freight rail transport demand, respectively [pkm], [tkm];
$EE_{rp,f}$ and $EE_{rf,f}$ are the energy efficiency factors for fuel f for the passenger and freight rail transport, respectively [(MWh) / pkm], [(MWh) / tkm].

4.2. AFOLU

Bioenergy

The biodiesel potential from residue streams is added to the second-generation biofuel potential. The demand for first-generation biofuels is calculated by subtracting the second-generation biofuel potential from the total biofuel demand. Then the cropland demand for biofuel is assessed based on the first-generation biofuel demand.

For $i \in FOODcrop$:

$$4.13 \mid CropBioEthSupply_i = (BioethDemand - RBioEthSupply) * EthCropMix_i$$

$$4.14 \mid RBioDiesSupply = \sum_{i \in FOODcrop} BioDieselResidue_i * BiodieselY_i$$

$$4.15 \mid CropBioDiesSupply_i = (BioDieselDemand - RBioDiesSupply) * BioCropMix_i$$

$$4.16 \mid CropBiogasSupply_i = (BiogasDemand - MBiogas_{TJ}) * BiogasCropMix_i$$

$$4.17 \mid BioEthLand_i = (CropBioEthSupply_i) / (CropBioEthY_i)$$

$$4.18 \mid BioDiesLand_i = (CropBioDiesSupply_i) / (CropBioDiesY_i)$$

$$4.19 \mid BiogasLand_i = (CropBiogasSupply_i) / (CropBiogasY_i)$$

$$4.20 \mid CLBIO = \sum_{i \in FOODcrop} BioEthLand_i + BioDiesLand_i + BiogasLand_i$$

where:
$CropBioEthSupply_i$ is the demand for bioethanol (first generation) from crops i [TJ];
$BioethDemand$ is the total demand for bioethanol [TJ];
$RBioEthSupply$ is the total bioethanol from residue crops [TJ];
$EthCropMix_i$ is the allocation of crop items i for bioethanol production [–];
$RBioDiesSupply$ is the total biodiesel from residue streams [L];
$BioDieselResidue_i$ is the residues for biodiesel from group i [kg];
$BiodieselY_i$ is the biodiesel yields from group i [L / kg];
$CropBioDiesSupply_i$ is the demand for biodiesel (first generation) from crops i [TJ];
$BioDieselDemand$ is the total demand for biodiesel [TJ];
$BioCropMix_i$ is the allocation of crop items i for biodiesel production [–];
$CropBiogasSupply_i$ is the demand for biogas (first generation) from crops i [TJ];
$BiogasDemand$ is the total demand for biogas [TJ];
$BiogasCropMix_i$ is the allocation of crop items i for biogas production [–];
$BioEthLand_i$ is the land for bioethanol crops of group i [ha];
$CropBioEthY_i$ is the bioethanol yields from crops i [TJ / (ha)];
$BioDiesLand_i$ is the land for biodiesel crops of group i [ha];
$CropBioDiesY_i$ is the biodiesel yields from crops i [TJ / (ha)];
$BiogasLand_i$ is the land for biogas crops of group i [ha];
$CropBiogasY_i$ is the biogas yields from crops i [TJ / (ha)];
$CLBIO$ is the total land requirement for first-generation biofuels [ha].

PM2.5 emissions from AFOLU

The fine particulate matter emissions from AFOLU consist in the emissions from agricultural energy use, crop production, live animals and burning of crop residues (Lagerwerf, 2019), using emission factors for the conversion (Ole Kenneth, 2019). This indicator is part of SDG indicator 11.6, aiming to reduce the impact of cities.

4.21 | $PM25_A = \sum_{i \in ANIMALS} TA_i * EFPM25A_i$

4.22 | $PM25_C = \sum_{i \in FOODcrop} TCLD_i * EFPM25C_i$

4.23 | $PM25_E = \sum_{j \in TRANSPORTFUELS} AEU_j * EFPM25E_j$

4.24 | $ECR_{PM25eq} = BM_{burn} * EFCRBI_{PM25}$

4.25 | $PM25 = PM25_A + PM25_C + PM25_E + ECR_{PM25eq}$

where:
$PM25_A$, $PM25_C$, $PM25_E$ respectively are the PM25 emissions from live animals, from crops and from agricultural energy use [*tonnes*];
$EFPM25A_i$ is the live animals PM25 emission factor [*tonnes* / (*head*)];
$EFPM25C_i$ is the PM25 crops emission factor [*tonnes* / (*ha*)];
$EFPM25E_j$ is the PM25 agricultural fuel consumption emission factor for fuel ***j*** [*tonnes* / (*tonnes fuel*)];
AEU_j is the agricultural use of fuel ***j*** [*tonnes fuel*];
$EFCRBI_{PM25}$ is the emission factor for burning crop residues [*tonnes* / (*kg dm*)];
ECR_{PM25eq} is the PM25 emissions from burning crop residues [*tonnes*];
PM25 is the total agricultural PM25 emissions [*tonnes*].

Biodiversity

The biodiversity model is based on (Eppink, 2004) and represents the relationship between urban and agricultural land use change, eutrophication, and biodiversity.

The number of wetland species is modeled as a function of the percentage of wetland area and the number of plant and animal species. The number of plant species is negatively affected by eutrophication, while the number of animal species depends on the available natural land and the agricultural land area. The available natural land is affected by the land dedicated to agriculture and the land dedicated to urban area. The urban area is a function of the willingness to pay for expansionists and the willingness to pay for conservationists. The willingness to pay for urban expansion depends on the population density and the threshold level of population density, and the willingness to pay for wetland conservation is a function of the plant and animal richness species and percentage of wetland area.

4.26 | $WD = f_{wd}(W,R^a,R^p)$

4.27 | $W = f(G)$

4.28 | $NW = f(1 - W)$

4.29 | $G = f(TCLD_i,e)$

4.30 | $R^p = f(SL1)$

4.31 | $R^p = f(TCLD_i,N)$

4.32 | $N = K - U - TCLD$

4.33 | $U = U_{t-1} + \Delta U$

4.34 | $\Delta U = f(WTP^u,WTP^N)$

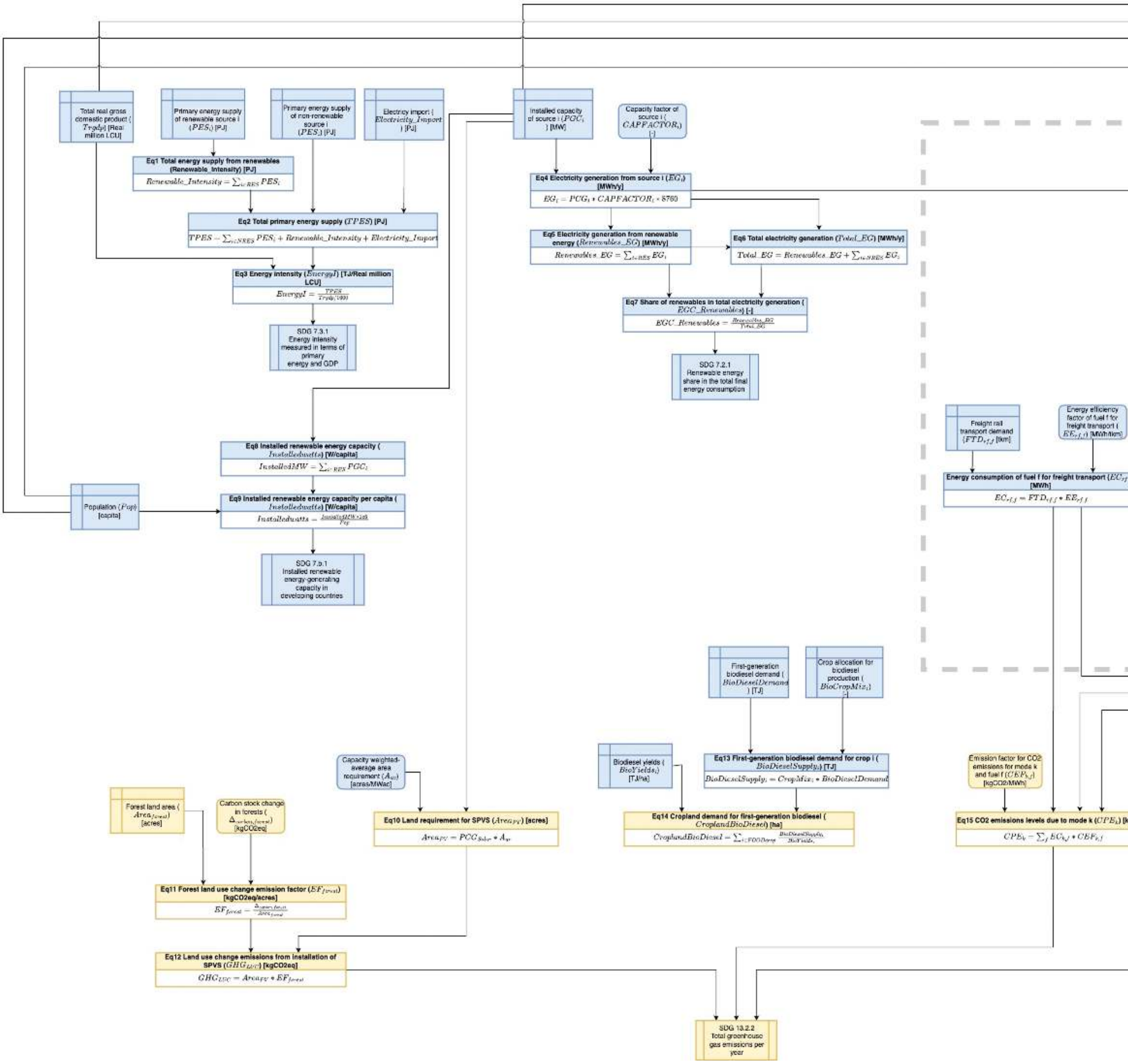
4.35 | $WTP^u = f((Pop / U),TD)$

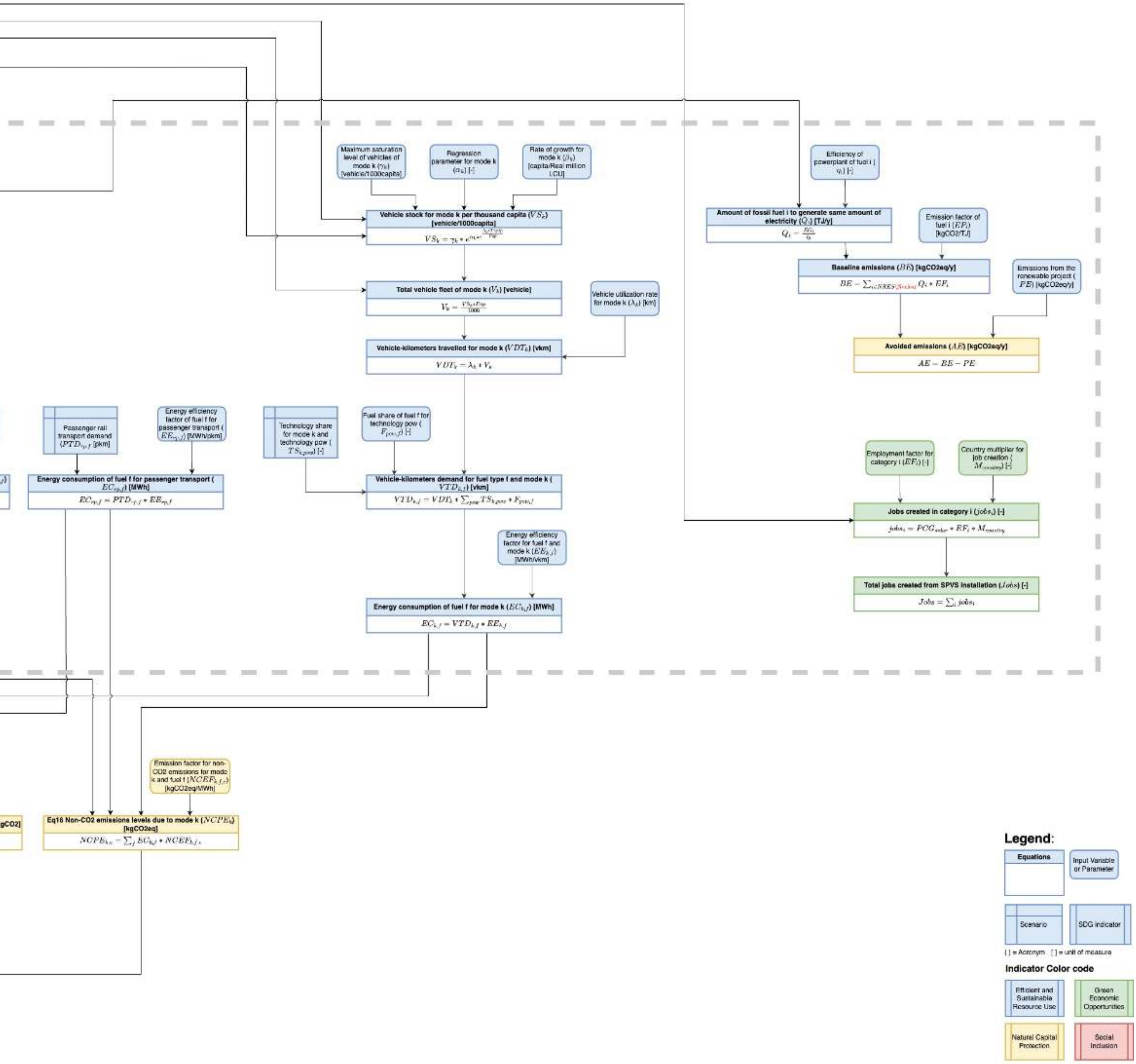
4.36 | $WTP^N = f(R^a,R^p,W)$

where:
WD is the number of wetland species [–];
W is the wetland area as a percentage of the total natural land area [–];
NW is the total natural land area [*ha*];
G is the ground water depth in the surrounding ecosystem [*m*];
e is the level of drainage by farmers [–];
R^p is the number of plant species [–];
R^a is the number of animal species [–];
N is the available natural land [*ha*];
K is the fixed natural land [*ha*];
U is the urban area [*ha*];
ΔU is the change in urban area [*ha*];
WTP^u,WTP^N are the willingness to pay for urban expansion and wetland conservation, respectively [*$*];
TD is the threshold level of urban population density [*capita* / (*ha*)].

ANNEX 5

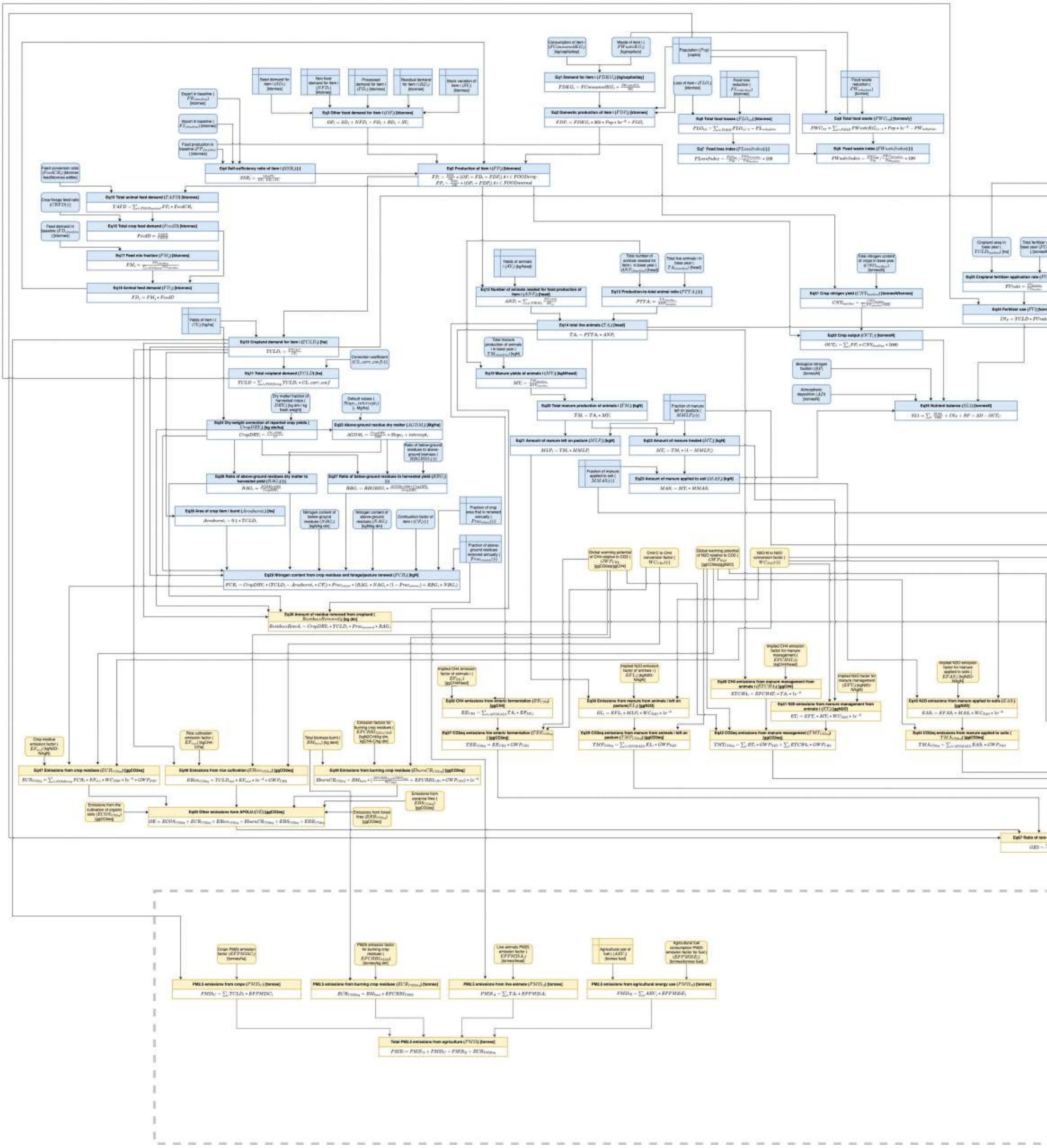
Flow diagram for the energy and transport model

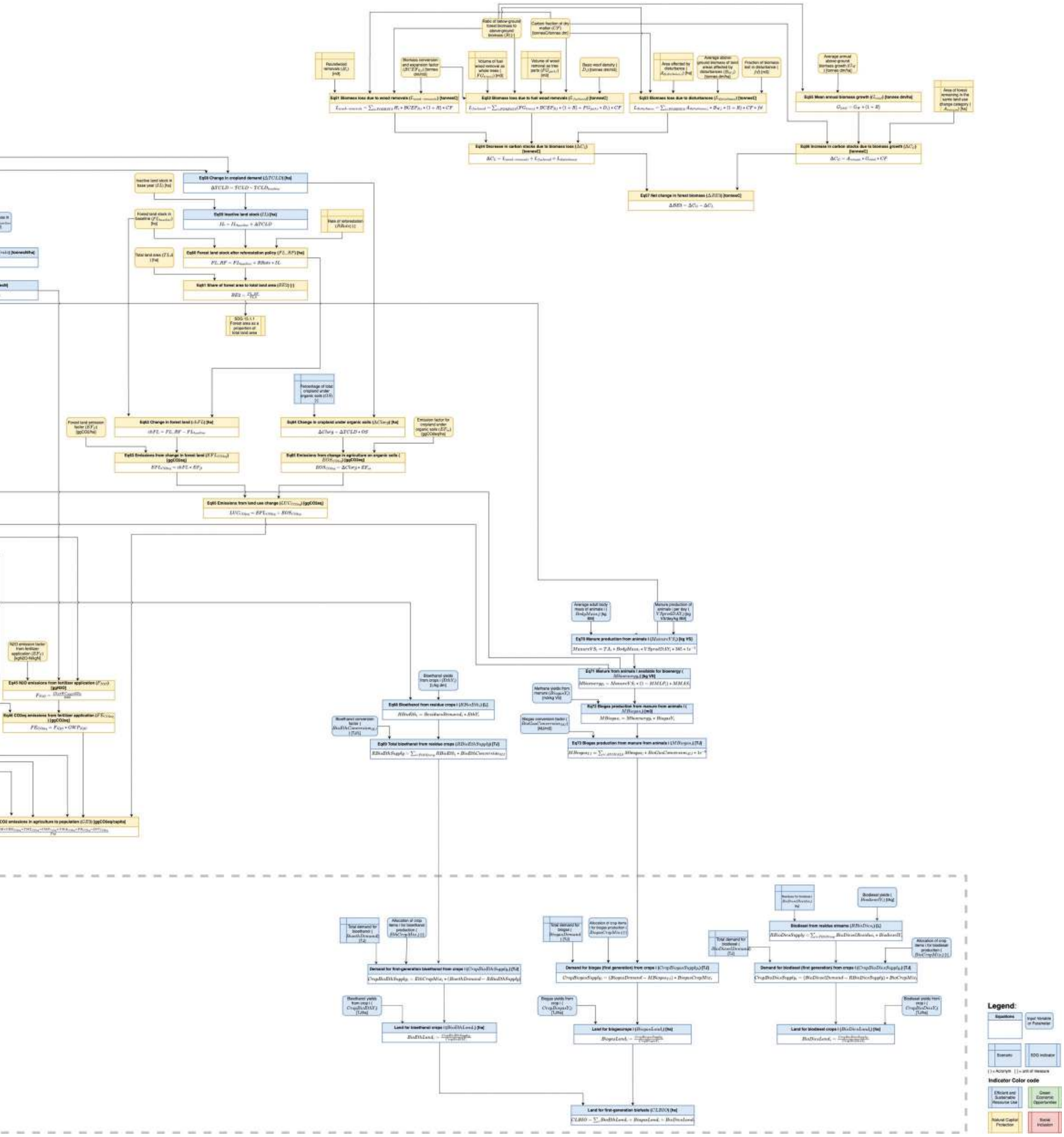



Maximum saturation level of vehicles of mode k (γ_k) [vehicle/1000capita]
Regression parameter for mode k (α_k) [-]
Rate of growth for mode k (β_k) [capita/Real million LCU]
Vehicle stock for mode k per thousand capita (VS_k) [vehicle/1000capita]
Total vehicle fleet of mode k (V_k) [vehicle]
Vehicle utilization rate for mode k (λ_k) [km]
Vehicle-kilometers travelled for mode k (VDT_k) [vkm]
$VDT_k = \lambda_k * V_k$
Passenger rail transport demand ($PTD_{rp,f}$) [pkm]
Energy efficiency factor of fuel f for passenger transport ($EE_{rp,f}$) [MWh/pkm]
Technology share for mode k and technology pow ($TS_{k,pow}$) [-]
Fuel share of fuel f for technology pow ($F_{pow,f}$) [-]
Energy consumption of fuel f for passenger transport ($EC_{rp,f}$) [MWh]
$EC_{rp,f} = PTD_{rp,f} * EE_{rp,f}$
Vehicle-kilometers demand for fuel type f and mode k ($VTD_{k,f}$) [vkm]
$VTD_{k,f} = VDT_k * \sum_{pow} TS_{k,pow} * F_{pow,f}$
Energy efficiency factor for fuel f and mode k ($EE_{k,f}$) [MWh/vkm]
Energy consumption of fuel f for mode k ($EC_{k,f}$) [MWh]
$EC_{k,f} = VTD_{k,f} * EE_{k,f}$
Efficiency of powerplant of fuel i (η_i) [-]
Amount of fossil fuel i to generate same amount of electricity (Q_i) [TJ/y]
Emission factor of fuel i (EF_i) [kgCO2/TJ]
Baseline emissions (BE) [kgCO2eq/y]
Emissions from the renewable project (PE) [kgCO2eq/y]
Avoided emissions (AE) [kgCO2eq/y]
$AE = BE - PE$
Employment factor for category i (EF_i) [-]
Country multiplier for job creation ($M_{country}$) [-]
Jobs created in category i ($jobs_i$) [-]
$jobs_i = PCG_{solar} * EF_i * M_{country}$
Total jobs created from SPVS installation ($Jobs$) [-]
$Jobs = \sum_i jobs_i$
Emission factor for non-CO2 emissions for mode k and fuel f ($NCEF_{k,f,i}$) [kgCO2eq/MWh]
Eq16 Non-CO2 emissions levels due to mode k ($NCPE_k$) [kgCO2eq]
$NCPE_{k,i} = \sum_f EC_{k,f} * NCEF_{k,f,i}$
Legend:
Equations
Input Variable or Parameter
Scenario
SDG indicator
( ) = Acronym [ ] = unit of measure
Indicator Color code
Efficient and Sustainable Resource Use
Green Economic Opportunities
Natural Capital Protection
Social Inclusion

ANNEX 6

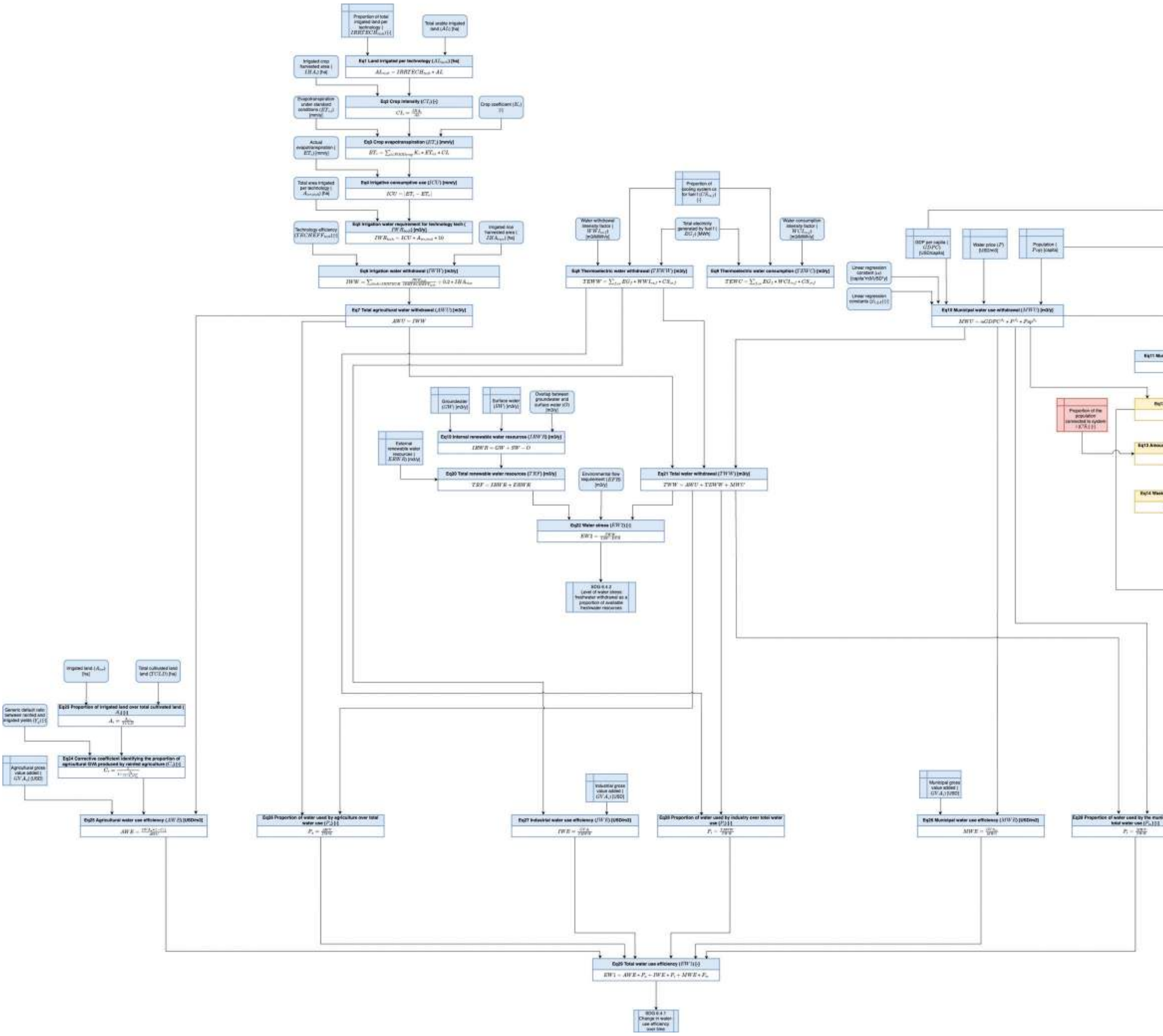
Flow diagram for the agriculture, forest, and land use (AFOLU) model

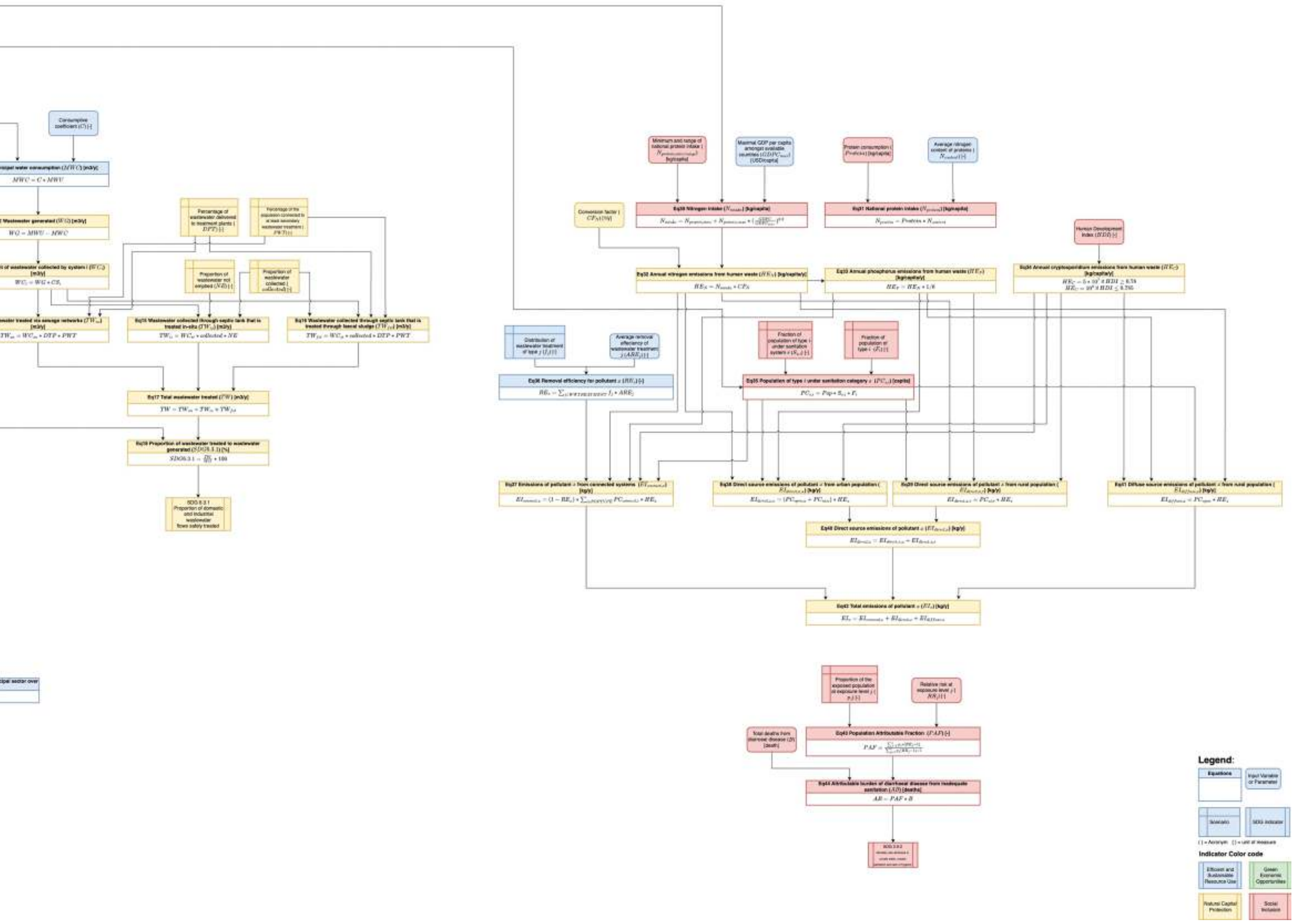




ANNEX 7

Flow diagram for the waste and water use model





ANNEX 8

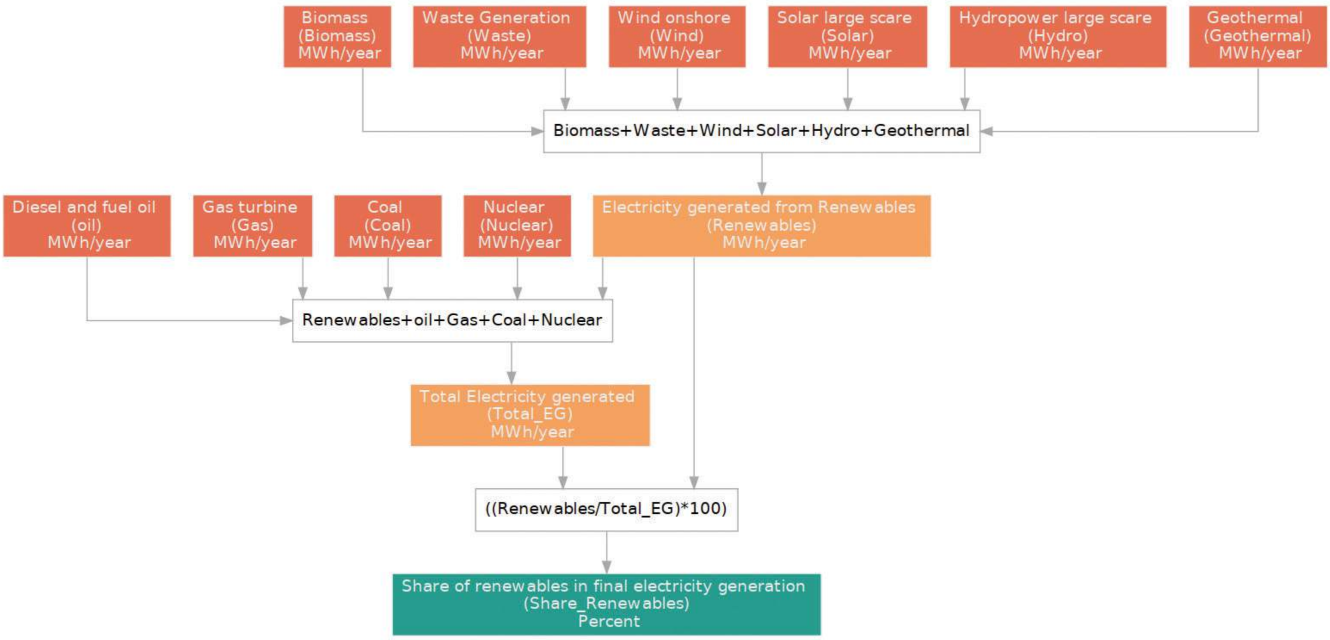
Python codes to implement the system dynamics models for the Green Growth Simulation Tool Phase 2 (V.1) (Hungary, Burkina Faso, and Ethiopia)

1 Energy and Transport

1.1 Simulation model for share of renewables in final electricity generation

```
__Publisher__ = 'Global Green Growth Institute'
__Author__ = 'GGPM Team'
__Model_lead__='P.Godwin'
__Programmers__='I.Nzimenyera & R.Munezero'

from ggmodel_dev.graphmodel import GraphModel, concatenate_graph_specs
from ggmodel_dev.utils import get_model_properties
import numpy as np

Renewables_node = {'Biomass': {'type': 'input', 'unit': 'MWh/year', 'name': 'Biomass'},
                   'Waste': {'type': 'input', 'unit': 'MWh/year', 'name':'Waste Generation'},
                   'Wind': {'type': 'input',
                      'unit':  'MWh/year',
                      'name': 'Wind onshore'
                      },
                   'Solar':{'type': 'input',
                      'unit':  'MWh/year',
                      'name': 'Solar large scale'
                      },
                   'Hydro': {'type': 'input',
                      'unit':  'MWh/year',
                      'name': 'Hydropower large scale'
                      },
                   'Geothermal': {'type': 'input',
                      'unit':  'MWh/year',
                      'name': 'Geothermal'
                      },
                   'Renewables': {'type': 'output',
                      'unit': 'MWh/year',
                      'name': 'Electricity generated from Renewables',
                      'computation': lambda Biomass,Waste, Wind,Solar,Hydro,Geothermal,**kwargs: Biomass+Waste+Wind+Solar+Hydro+Geothermal
                         },
                  }
all_nodes={'Renewables': {'type': 'input', 'unit': 'MWh/year', 'name': 'Electricity generated from Renewables'}, #combine models together

            'oil': {'type': 'input',
                      'unit':  'MWh/year',
                      'name': 'Diesel and fuel oil'
                      },
              'Gas': {'type': 'input',
                      'unit':  'MWh/year',
                      'name': 'Gas turbine'
                      },
              'Coal': {'type': 'input',
                      'unit':  'MWh/year',
                      'name': 'Coal'
                      },
              'Nuclear': {'type': 'input',
                      'unit':  'MWh/year',
                      'name': 'Nuclear'
                      },
              'Total_EG': {'type':'output',
                      'unit': 'MWh/year',
                      'name': 'Total Electricity generated',
                      'computation': lambda Renewables,oil,Gas,Coal,Nuclear,**kwargs:Renewables+oil+Gas+Coal+Nuclear

                  }

                        }
EGC_renewables={'Renewables': {'type': 'input', 'unit': 'MWh/year', 'name': 'Electricity generated from Renewables'},
                'Total_EG': {'type': 'input','unit': 'MWh/year','name': 'Total Electricity generated'},
                'Share_Renewables': {'type': 'output',
                      'unit': 'Percent',
                      'name': 'Share of renewables in final electricity generation',
                      'computation': lambda Renewables,Total_EG,**kwargs:((Renewables/Total_EG)*100)

                  }
```

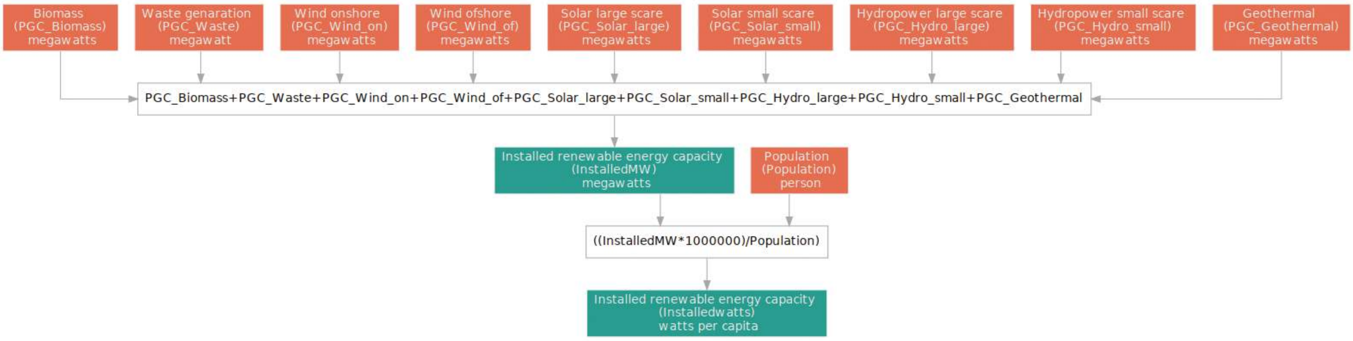
```
            }

Energy1_partial_model = GraphModel(Renewables_node)
Energy2_partial_model = GraphModel(all_nodes)
Energy3_partial_model = GraphModel(EGC_renewables)

Share_model = GraphModel(concatenate_graph_specs(
    [Renewables_node, all_nodes,EGC_renewables]))

# Dictionnary for easier access in the interface
model_dictionnary = {
                    'Electricity generated from Renewables (MWh/year)': Energy1_partial_model ,
                    'Total Electricity generated(MWh/year)': Energy2_partial_model ,
                    'Share of renewables in final electricity generation(%)':Energy3_partial_model ,
                    'Share_model': Share_model,
                    }
model_properties = get_model_properties('models/Energy/Energy_properties.json')
```



1.2 Simulation model for installed renewable energy capacity.

```
Installed_nodes = {'PGC_Biomass': {'type': 'input', 'unit': 'megawatts', 'name': 'Biomass'}, #Electrical generation from renewables
             'PGC_Waste': {'type': 'input', 'unit': 'megawatt', 'name': 'Waste genaration'},

             'PGC_Wind_on': {'type': 'input',
                     'unit':  'megawatts',
                     'name': 'Wind onshore'
                     },
            'PGC_Wind_of': {'type': 'input',
                     'unit':  'megawatts',
                     'name': 'Wind ofshore'
                     },
            'PGC_Solar_large': {'type': 'input',
                     'unit':  'megawatts',
                     'name': 'Solar large scare'
                     },
            'PGC_Solar_small': {'type': 'input',
                     'unit':  'megawatts',
                     'name': 'Solar small scare'
                     },

            'PGC_Hydro_large': {'type': 'input',
                     'unit':  'megawatts',
                     'name': 'Hydropower large scare'
                     },
            'PGC_Hydro_small': {'type': 'input',
                     'unit':  'megawatts',
                     'name': 'Hydropower small scare'
                     },

            'PGC_Geothermal': {'type': 'input',
                     'unit':  'megawatts',

                     'name': 'Geothermal'
                     },
```

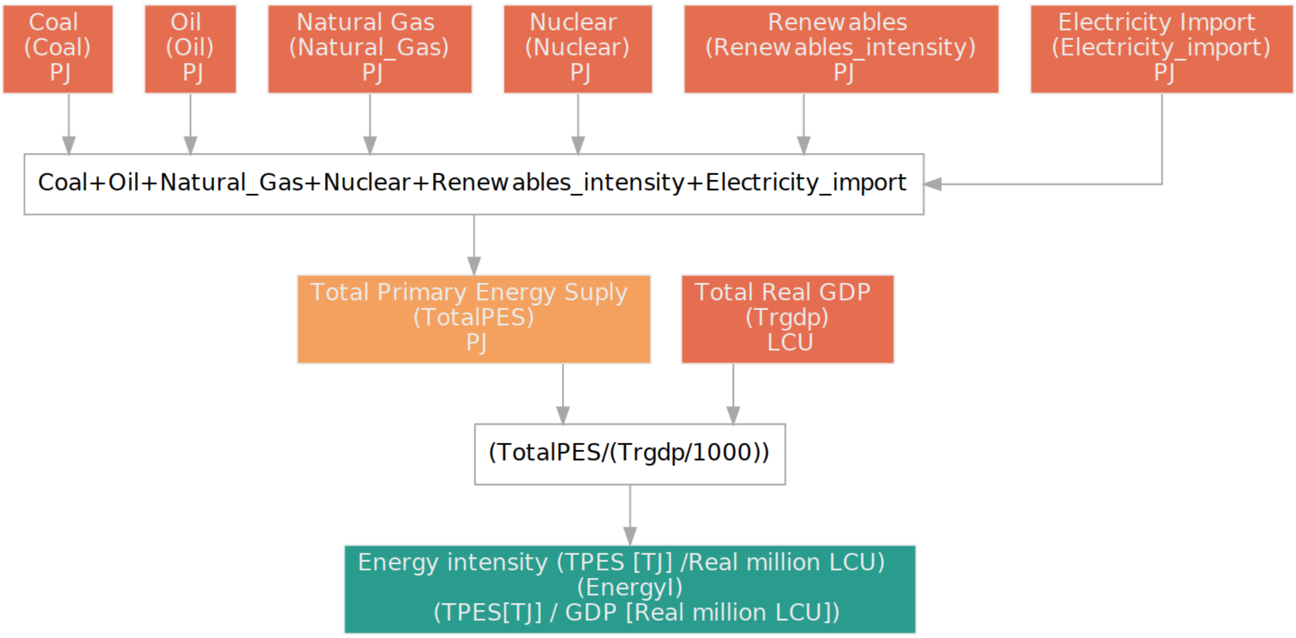
```
           'InstalledMW': {'type': 'output',
                     'unit': 'megawatts',
                     'name': 'Installed renewable energy capacity',
                     'computation': lambda PGC_Biomass,PGC_Waste,
PGC_Wind_on,PGC_Wind_of,PGC_Solar_large,PGC_Solar_small,PGC_Hydro_large,PGC_Hydro_small,PGC_Geothermal,**kwargs:
PGC_Biomass+PGC_Waste+PGC_Wind_on+PGC_Wind_of+PGC_Solar_large+PGC_Solar_small+PGC_Hydro_large+PGC_Hydro_small+PGC_Geothermal

                },
           'Population': {'type': 'input',
                     'unit':  'person',
                     'name': 'Population'
                     },
          'Installedwatts': {'type': 'output',
                     'unit': 'watts per capita',
                     'name': 'Installed renewable energy capacity',
                     'computation': lambda InstalledMW,Population, **kwargs: ((InstalledMW*1000000)/Population)

                }

                      }
Installed_model = GraphModel(Installed_nodes)


# Dictionnary for easier access in the interface
model_dictionnary = {'Installed_model': Installed_model}

model_properties = get_model_properties('models/Energy/Installed_properties.json')
```



1.3 Simulation model for energy intensity (TPES [TJ] /Real million LCU)

```
TotalPES_node = {'Coal': {'type': 'input', 'unit': 'PJ', 'name': 'Coal'},
                   'Oil': {'type': 'input', 'unit': 'PJ', 'name':'Oil'},
                   'Natural_Gas': {'type': 'input',
                      'unit':  'PJ',
                      'name': 'Natural Gas'
                     },
                   'Nuclear':{'type': 'input',
                      'unit':  'PJ',
                      'name': 'Nuclear'
                     },
                   'Renewables_intensity': {'type': 'input',
                      'unit':  'PJ',
                      'name': 'Renewables'
                     },
                   'Electricity_import': {'type': 'input',
                          'unit':  'PJ',
                      'name': 'Electricity Import'
                     },
                   'TotalPES': {'type': 'output',
                      'unit': 'PJ',
                      'name': 'Total Primary Energy Suply',
                      'computation': lambda Coal,Oil, Natural_Gas,Nuclear,Renewables_intensity,Electricity_import,**kwargs:
Coal+Oil+Natural_Gas+Nuclear+Renewables_intensity+Electricity_import
                         },
                }
TotalRGDP_node={'Trgdp': {'type': 'input', 'unit': 'LCU', 'name': 'Total Real GDP'},

                }

EnergyI_node={'TotalPES': {'type': 'input', 'unit': 'PJ', 'name': 'Total Primary Energy Suply'},
                'Trgdp': {'type': 'input','unit': 'LCU','name': 'Total Real GDP'},
                'EnergyI': {'type': 'output',
                      'unit': ' (TPES[TJ] / GDP [Real million LCU])',
                      'name': 'Energy intensity (TPES [TJ] /Real million LCU) ',
                      'computation': lambda TotalPES,Trgdp,**kwargs: (TotalPES/(Trgdp/1000))

                }
             }
```

```
TotalPES_model = GraphModel(TotalPES_node)
TotalRGDP_model = GraphModel(TotalRGDP_node)
EnergyI_model = GraphModel(EnergyI_node)

Intensity_model = GraphModel(concatenate_graph_specs(
    [TotalPES_node, TotalRGDP_node,EnergyI_node]))

# Dictionnary for easier access in the interface
model_dictionnary = {
                    'Total Primary Energy Suply': TotalPES_model ,
                    'Total Real GDP': TotalRGDP_model ,
                    'Energy intensity (TPES [TJ] /Real million LCU)':EnergyI_model ,
                    'Intensity_model':Intensity_model,
                    }
model_properties = get_model_properties('models/Energy/Intensity_properties.json')
```



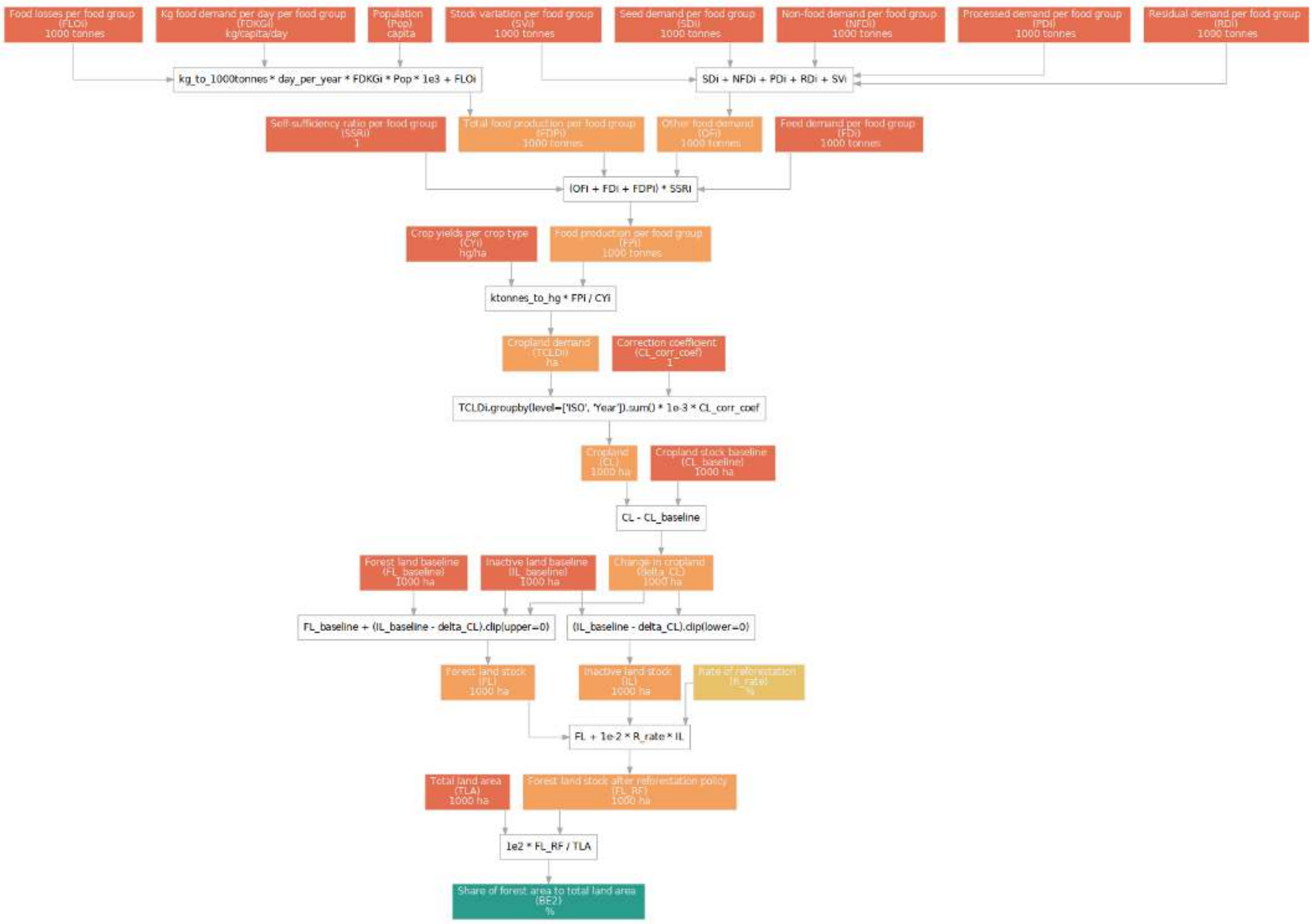
2. Agriculture, forest, and land use (AFOLU)

2.1 Simulation model for share of forest area to total land area

```
__Publisher__ = 'Global Green Growth Institute'
__Author__ = 'GGPM Team'
__Model_lead__='H.Luchtenbelt'
__Programmers__='I.Nzimenyera & R.Munezero'

from ggmodel_dev.graphmodel import GraphModel, concatenate_graph_specs
from ggmodel_dev.utils import get_model_properties
import pandas as pd

# To check naming, confusing with demand/prod + total not total
kg_to_1000tonnes = 1e-6
day_per_year = 365
ktonnes_to_hg = 1e7

FPi_nodes = {'FLOi': {
    'type': 'input',
    'unit': '1000 tonnes',
    'name': 'Food losses per food group'
},
    'FDKGi': {
    'type': 'input',
    'unit': 'kg/capita/day',
    'name': 'Kg food demand per day per food group'
},
    'SSRi': {
    'type': 'input',
    'unit': '1',
    'name': 'Self-sufficiency ratio per food group',
},
    'FDPi': {
    'type': 'variable',
    'unit': '1000 tonnes',
    'name': 'Total food demand per food group',
    'computation': lambda FDKGi, Pop, FLOi, **kwargs: kg_to_1000tonnes * day_per_year * FDKGi * Pop * 1e3 + FLOi
},
    'OFi': {
    'type': 'variable',
    'unit': '1000 tonnes',
    'name': 'Other food demand',
    'computation': lambda SDi, NFDi, PDi, RDi, SVi, **kwargs: SDi + NFDi + PDi + RDi + SVi
},


    'SDi': {
    'type': 'input',
    'unit': '1000 tonnes',
    'name': 'Seed demand per food group'
},
    'NFDi': {
    'type': 'input',
    'unit': '1000 tonnes',
    'name': 'Non-food demand per food group'
},
    'PDi': {
    'type': 'input',
    'unit': '1000 tonnes',
    'name': 'Processed demand per food group'
},
    'RDi': {
    'type': 'input',
    'unit': '1000 tonnes',
    'name': 'Residual demand per food group'
},
    'SVi': {
    'type': 'input',
    'unit': '1000 tonnes',
    'name': 'Stock variation per food group'
},
    'FPi': {
    'type': 'output',
    'name': 'Food production per food group',
    'unit': '1000 tonnes',
    'computation': lambda SSRi, OFi, FDi, FDPi, **kwargs: (OFi + FDi + FDPi) * SSRi
},
    'FDi': {
    'type': 'input',
    'unit': '1000 tonnes',
    'name': 'Feed demand per food group'
},
    'Pop': {
    'type': 'input',
    'unit': 'capita',
    'name': 'Population'
}
}
```

```
TCLDi_nodes = {'TCLDi': {
     'type': 'output',
     'name': 'Cropland demand',
     'unit': 'ha',
     'computation': lambda CYi, FPi, **kwargs: ktonnes_to_hg * FPi / CYi
},
     'CYi': {
     'type': 'input',
     'unit': 'hg/ha',
     'name': 'Crop yields per crop type'
},

     'FPi': {
     'type': 'input',
     'name': 'Food production per food group',
     'unit': '1000 tonnes'
},
}

CL_nodes = {'TCLDi': {
     'type': 'input',
     'name': 'Cropland demand',
     'unit': 'ha',
},
     'CL_corr_coef': {
     'type': 'parameter',
     'name': 'Correction coefficient',
     'unit': '1',
},
     'CL': {
     'type': 'output',
     'name': 'Cropland',
     'unit': '1000 ha',
     # Strange to check !
     'computation': lambda TCLDi, CL_corr_coef, **kwargs: TCLDi.groupby(level=['ISO', 'Year']).sum() * 1e-3 * CL_corr_coef
},
}

IL_FL_nodes = {'CL': {
     'type': 'input',
     'name': 'Cropland',
     'unit': '1000 ha',
},
     'CL_baseline': {
     'type': 'input',
     'name': 'Cropland stock baseline',
     'unit': '1000 ha',
},
     'delta_CL': {
     'type': 'variable',
     'name': 'Change in cropland',
     'unit': '1000 ha',
     'computation': lambda CL, CL_baseline, **kwargs: CL - CL_baseline
},
     'IL_baseline': {
     'type': 'input',
     'unit': '1000 ha',
     'name': 'Inactive land baseline'
 },
     'FL_baseline': {
     'type': 'input',
     'unit': '1000 ha',
     'name': 'Forest land baseline'
 },
     'IL': {
     'type': 'output',
     'name': 'Inactive land stock',
     'unit': '1000 ha',
     # to double check
     'computation': lambda delta_CL, IL_baseline, **kwargs: (IL_baseline - delta_CL).clip(lower=0)
 },
     'FL': {
     'type': 'output',
     'name': 'Forest land stock',
     'unit': '1000 ha',
     # to double check
     'computation': lambda delta_CL, FL_baseline, IL_baseline, **kwargs: FL_baseline + (IL_baseline - delta_CL).clip(upper=0)
 }
 }

 BE2_nodes = {'TLA': {
     'type': 'input',
     'unit': '1000 ha',
     'name': 'Total land area'
 },
     'FL': {
     'type': 'input',
     'unit': '1000 ha',
     'name': 'Forest land stock'
```

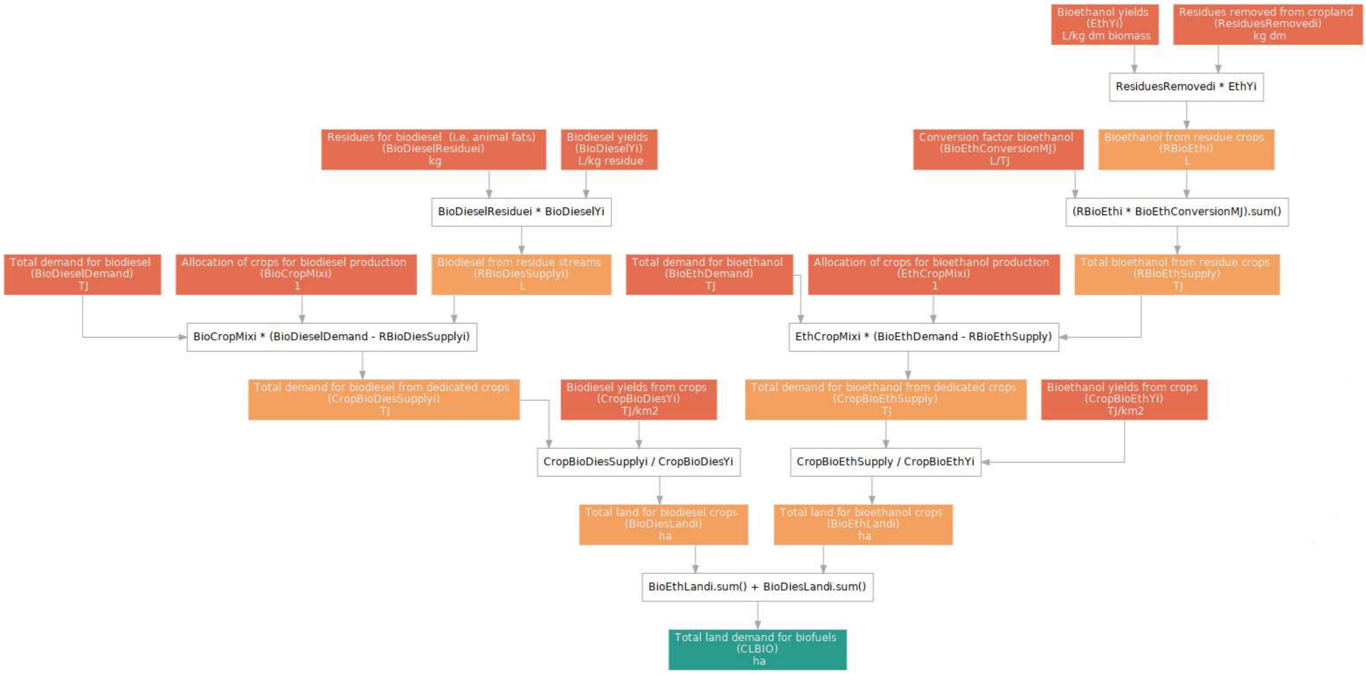
```
},
    'IL': {
    'type': 'input',
    'unit': '1000 ha',
    'name': 'Inactive land stock'
},
    'R_rate': {
    'type': 'input',
    'unit': '%',
    'name': 'Rate of reforestation'
},
    'FL_RF': {
    'type': 'variable',
    'name': 'Forest land stock after reforestation policy',
    'unit': '1000 ha',
    'computation': lambda FL, R_rate, IL, **kwargs: FL + 1e-2 * R_rate * IL
},

    'BE2': {
    'type': 'output',
    'name': 'Share of forest area to total land area',
    'unit': '%',
    'computation': lambda FL_RF, TLA, **kwargs: 1e2 * FL_RF / TLA
}
}


FPi_model = GraphModel(FPi_nodes)
TCLDi_partial_model = GraphModel(TCLDi_nodes)
TCLDi_model = GraphModel(concatenate_graph_specs([TCLDi_nodes, FPi_nodes]))
IL_FL_model = GraphModel(IL_FL_nodes)
BE2_partial_model = GraphModel(BE2_nodes)
BE2_model = GraphModel(concatenate_graph_specs(
    [BE2_nodes, IL_FL_nodes, CL_nodes, TCLDi_nodes, FPi_nodes]))

model_dictionnary = {
    'TCLDi_model': TCLDi_model,
    'TCLDi_partial_model': TCLDi_model,
    'FPi_model': FPi_model,
    'IL_FL_model': IL_FL_model,
    'BE2_partial_model': BE2_partial_model,
    'BE2_model': BE2_model
}

model_properties = get_model_properties('models/landuse/BE2_properties.json')
```



2.2 Simulation model for total land demand for biofuels

```
BIOGAS_nodes = {
    "BioCropMixi": {
        "name": "Allocation of crops for biodiesel production",
        "type": "input",
        "unit": "1"
    },
    "BioDiesLandi": {
        "name": "Total land for biodiesel crops",
        "type": "variable",
        "unit": "ha",
        "computation": lambda CropBioDiesSupplyi, CropBioDiesYi, **kwargs: CropBioDiesSupplyi / CropBioDiesYi
    },
    "BioDieselDemand": {
        "name": "Total demand for biodiesel",
        "type": "input",
        "unit": "TJ"
    },
    "BioDieselResiduei": {
        "name": "Residues for biodiesel  (i.e. animal fats)",
        "type": "input",
        "unit": "kg"
    },
    "BioDieselYi": {
        "name": "Biodiesel yields",
        "type": "input",
        "unit": "L/kg residue"
    },
    "BioEthConversionMJ": {
        "name": "Conversion factor bioethanol",
        "type": "parameter",
        "unit": "L/TJ"
    },
    "BioEthDemand": {
        "name": "Total demand for bioethanol",
        "type": "input",
        "unit": "TJ"
    },
    "BioEthLandi": {
        "name": "Total land for bioethanol crops",
        "type": "variable",
        "unit": "ha",
        "computation": lambda CropBioEthSupply, CropBioEthYi, **kwargs: CropBioEthSupply / CropBioEthYi
    },

    "BiogasConversionMJ": {
        "name": "Conversion factor biogas",
        "type": "parameter",
        "unit": "m3/MJ"
    },
    "BiogasYi": {
        "name": "Methane yields from manure",
        "type": "input",
        "unit": "m3/kg VS"
    },
    "BodyMassi": {
        "name": "Average adult body mass of animal",
        "type": "input",
        "unit": "kg"
    },
    "CLBIO": {
        "name": "Total land demand for biofuels",
        "type": "output",
        "unit": "ha",
        "computation": lambda BioEthLandi, BioDiesLandi, **kwargs: BioEthLandi.sum() + BioDiesLandi.sum()
    },
    "CropBioDiesSupplyi": {
        "name": "Total demand for biodiesel from dedicated crops",
        "type": "variable",
        "unit": "TJ",
        "computation": lambda BioDieselDemand, RBioDiesSupplyi, BioCropMixi, **kwargs: BioCropMixi * (BioDieselDemand - RBioDiesSupplyi)
    },
    "CropBioDiesYi": {
        "name": "Biodiesel yields from crops",
        "type": "input",
        "unit": "TJ/km2"
    },
    "CropBioEthSupply": {
        "name": "Total demand for bioethanol from dedicated crops",
        "type": "variable",
        "unit": "TJ",
        "computation": lambda BioEthDemand, RBioEthSupply, EthCropMixi, **kwargs: EthCropMixi * (BioEthDemand - RBioEthSupply)
    },
    "CropBioEthYi": {
        "name": "Bioethanol yields from crops",
        "type": "input",
        "unit": "TJ/km2"
    },
    "EthCropMixi": {
        "name": "Allocation of crops for bioethanol production",
        "type": "input",
        "unit": "1"
```

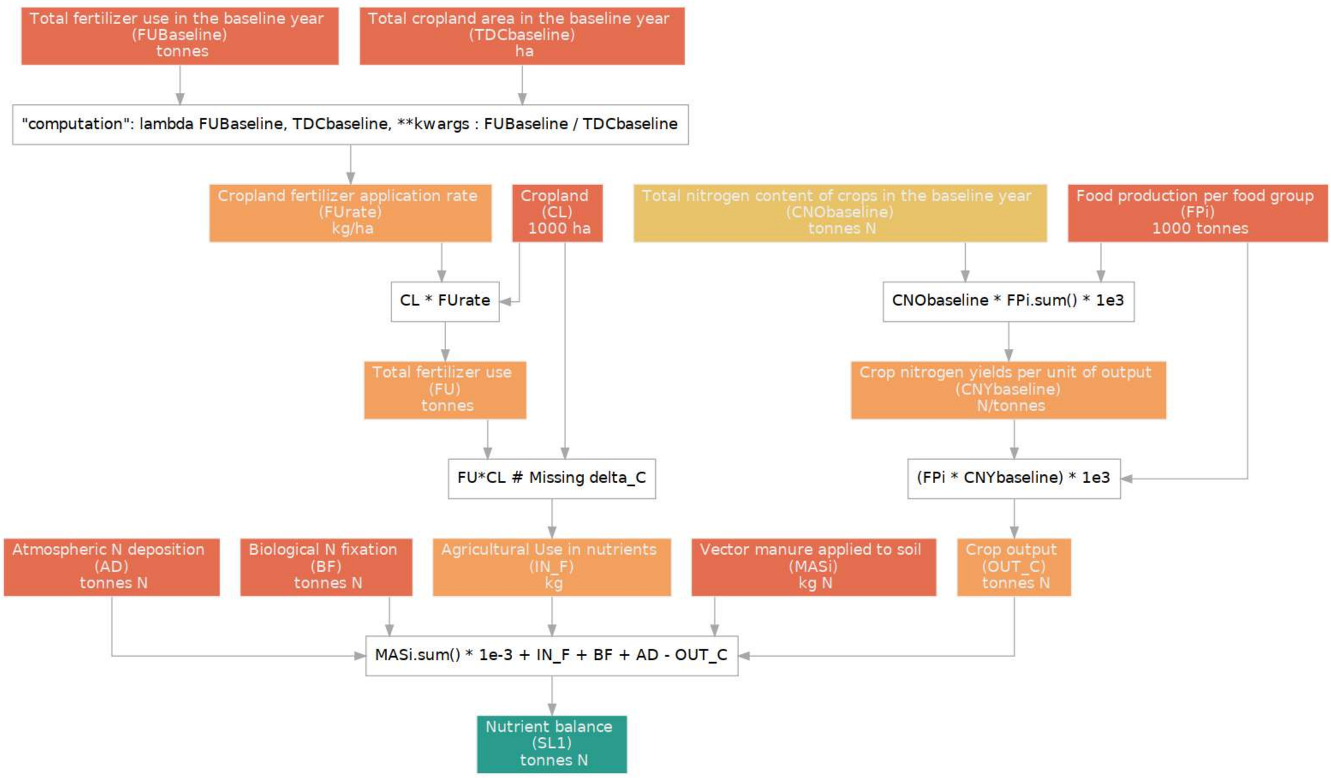
```
    },
    "EthYi": {
        "name": "Bioethanol yields",
        "type": "input",
        "unit": "L/kg dm biomass"
    },
    "MBiogasTJ": {
        "name": "Total biogas production from manure",
        "type": "variable",
        "unit": "TJ",
        "computation": lambda Mbiogasi, BiogasConversionMJ, **kwargs: (Mbiogasi * BiogasConversionMJ).sum()
    },
    "MMASi": {
        "name": "% of total manure applied to soils",
        "type": "input",
        "unit": "%"
    },

    "MMLPi": {
        "name": "Fraction of manure left on pasture",
        "type": "input",
        "unit": "%"
    },

    "ManureKGi": {
        "name": "Total manure production in kg",
        "type": "variable",
        "unit": "kg",
        "computation": lambda TAi, BodyMassi, MprodDAYi, **kwargs: (TAi*BodyMassi*MprodDAYi)/1000
    },
    "ManureVSi": {
        "name": "total manure production in kg volatile solids",
        "type": "variable",
        "unit": "kg",
        "computation": lambda TAi, BodyMassi, VSprodDAYi, **kwargs: TAi * BodyMassi * VSprodDAYi * 365 * 1e-6
    },
    "Mbioenergyi": {
        "name": "Manure available for bioenergy",
        "type": "variable",
        "unit": "kg VS",
        "computation": lambda ManureVSi, MMLPi, MMASi, **kwargs: ManureVSi * (1 - MMLPi) * (1-MMASi)
    },
    "Mbiogasi": {
        "name": "Total biogas production from manure",
        "type": "variable",
        "unit": "m3",
        'computation': lambda Mbioenergyi, BiogasYi, **kwargs: Mbioenergyi * BiogasYi
    },
    "MprodDAYi": {
        "name": "Manure production per day",
        "type": "input",
        "unit": "kg / day per 1000 kg body mass"
    },


    "RBioDiesSupplyi": {
        "name": "Biodiesel from residue streams",
        "type": "variable",
        "unit": "L",
        "computation": lambda BioDieselResiduei, BioDieselYi, **kwargs: BioDieselResiduei * BioDieselYi
    },
    "RBioEthSupply": {
        "name": "Total bioethanol from residue crops",
        "type": "variable",
        "unit": "TJ",
        "computation": lambda RBioEthi, BioEthConversionMJ, **kwargs: (RBioEthi * BioEthConversionMJ).sum()
    },
    "RBioEthi": {
        "name": "Bioethanol from residue crops",
        "type": "variable",
        "unit": "L",
        "computation": lambda ResiduesRemovedi, EthYi, **kwargs: ResiduesRemovedi * EthYi
    },
    "ResiduesRemovedi": {
        "name": "Residues removed from cropland",
        "type": "input",
        "unit": "kg dm"
    },
    "TAi": {
        "name": "Total animal population",
        "type": "input",
        "unit": "head"
    },
    "VSprodDAYi": {
        "name": "Manure production per day in Volatile solids",
        "type": "parameter",
        "unit": "kg VS / day per 1000 kg body mass"
    }
}

BIOGAS_model = GraphModel(BIOGAS_nodes)

model_dictionnary = {'BIOGAS_model': BIOGAS_model}

model_properties = get_model_properties('models/landuse/BIOGAS_properties.json')
```



2.3 Simulation model for Nutrient balance

```
NUTRIENT_nodes = {
    "AD": {
        "name": "Atmospheric N deposition",
        "type": "input",
        "unit": "tonnes N"
    },
    "BF": {
        "name": "Biological N fixation",
        "type": "input",
        "unit": "tonnes N"
    },
    "CL": {
        "name": "Cropland",
        "type": "input",
        "unit": "1000 ha"
    },

    "CNObaseline": {
        "name": "Total nitrogen content of crops in the baseline year",
        "type": "parameter",
        "unit": "tonnes N"
    },

    "CNYbaseline": {
        "name": "Crop nitrogen yields per unit of output",
        "type": "variable",
        "unit": "N/tonnes",
        "computation": lambda CNObaseline, FPi, **kwargs: CNObaseline * FPi.sum() * 1e3
    },
    "FPi": {
        "name": "Food production per food group",
        "type": "input",
        "unit": "1000 tonnes"
    },
    "FU": {
        "name": "Total fertilizer use",
        "type": "variable",
        "unit": "tonnes",
        "computation": lambda CL, FUrate, **kwargs: CL * FUrate
    },
    "FUBaseline": {
        "name": "Total fertilizer use in the baseline year",
        "type": "input",
        "unit": "tonnes"
    },
    "FUrate": {
        "name": "Cropland fertilizer application rate",
        "type": "variable",
        "unit": "kg/ha",
        "computation": lambda FUBaseline, TDCbaseline, **kwargs : FUBaseline / TDCbaseline
    },
    "IN_F": {
        "name": "Agricultural Use in nutrients",
        "type": "variable",
        "unit": "kg",
        "computation": lambda FU, CL, **kwargs: FU*CL # Missing delta_C
    },
    "MASi": {
        "name": "Vector manure applied to soil",
        "type": "input",
        "unit": "kg N"
```

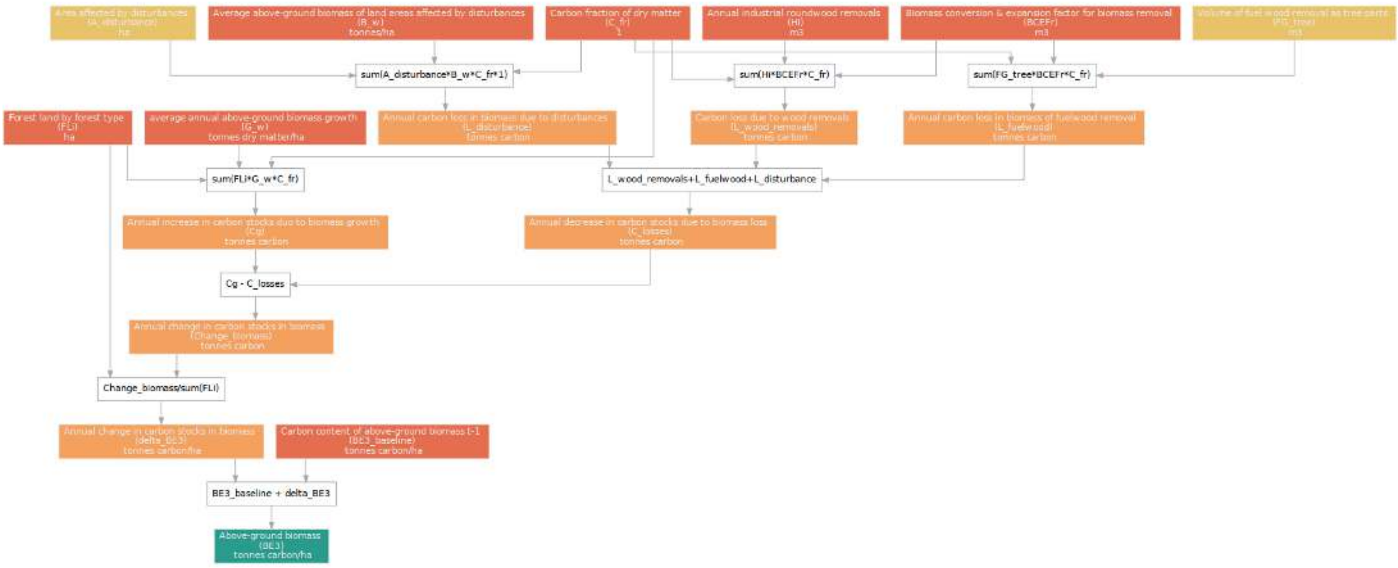
```
    },
    "OUT_C": {
        "name": "Crop output",
        "type": "variable",
        "unit": "tonnes N",
        "computation": lambda FPi, CNYbaseline, **kwargs: (FPi * CNYbaseline) * 1e3
    },

    "SL1": {
        "name": "Nutrient balance",
        "type": "output",
        "unit": "tonnes N",
        "computation": lambda MASi, IN_F, BF, AD, OUT_C, **kwargs: MASi.sum() * 1e-3 + IN_F + BF + AD - OUT_C
    },
    "TDCbaseline": {
        "name": "Total cropland area in the baseline year",
        "type": "input",
        "unit": "ha"
    }
}

NUTRIENT_model = GraphModel(NUTRIENT_nodes)

model_dictionnary = {'NUTRIENT_model': NUTRIENT_model}

model_properties = get_model_properties('models/landuse/NUTRIENT_properties.json')
```



2.4 Simulation model for Above-ground biomass

```
BIOMASS_nodes = {
    'C_fr': {'type': 'parameter',
             'unit': '1',
             'name': 'Carbon fraction of dry matter'},
    'G_w': {'type': 'input',
            'unit': 'tonnes dry matter/ha',
            'name': 'average annual above-ground biomass growth'},
    'Cg': {'type': 'variable',
           'name': 'Annual increase in carbon stocks duo to biomass growth',
           'unit': 'tonnes carbon',
           'computation': lambda G_w,FLi,C_fr, **kwargs: sum(FLi*G_w*C_fr)
           },
    'FLi': {'type': 'input',
            'unit': 'ha',
            'name': 'Forest land by forest type'},
    'Hi': {'type': 'input',
           'unit': 'm3',
           'name': 'Annual industrial roundwood removals'},
    'BCEFr': {'type': 'parameter',
              'unit': 'm3',
              'name': 'Biomass conversion & expansion factor for biomass removal'},
    'L_wood_removals': {'type': 'variable',
              'name': 'Carbon loss due to wood removals',
              'unit': 'tonnes carbon',
              'computation': lambda Hi,BCEFr,C_fr, **kwargs: sum(Hi*BCEFr*C_fr)
```

```
            },
    'L_fuelwood': {'type': 'variable',
            'name': 'Annual carbon loss in biomass of fuelwood removal',
            'unit': 'tonnes carbon',
            'computation': lambda FG_tree,BCEFr,C_fr,  **kwargs: sum(FG_tree*BCEFr*C_fr)
            },
    'FG_tree': {'type': 'input',
            'unit': 'm3',
            'name': 'Volume of fuel wood removal as tree parts'},
    'A_disturbance': {'type': 'input',
            'unit': 'ha',
            'name': 'Area affected by disturbances'},
    'B_w': {'type': 'parameter',
            'unit': 'tonnes/ha',
            'name': 'Average above-ground biomass of land areas affected by disturbances'},
    'L_disturbance': {'type': 'variable',
            'name': 'Annual carbon loss in biomass due to disturbances',
            'unit': 'tonnes carbon',
            'computation': lambda A_disturbance,B_w,C_fr, **kwargs: sum(A_disturbance*B_w*C_fr*1)
            },


    'C_losses': {'type': 'variable',
            'name': 'Annual decrease in carbon stocks due to biomass loss',
            'unit': 'tonnes carbon',
            'computation': lambda L_wood_removals,L_fuelwood,L_disturbance,  **kwargs: L_wood_removals+L_fuelwood+L_disturbance
            },

    'Change_biomass': {'type': 'variable',
            'name': 'Annual change in carbon stocks in biomass',
            'unit': 'tonnes carbon',
            'computation': lambda Cg, C_losses,  **kwargs: Cg - C_losses
            },
    'delta_BE3': {'type': 'variable',
            'name': 'Annual change in carbon stocks in biomass',
            'unit': 'tonnes carbon/ha',
            'computation': lambda Change_biomass,FLi,  **kwargs: Change_biomass/sum(FLi)
            },


    'BE3_baseline': {'type': 'input',
            'unit': 'tonnes carbon/ha',
            'name': 'Carbon content of above-ground biomass t-1'},
    'BE3': {'type': 'output',
            'name': 'Above-ground biomass',
            'unit': 'tonnes carbon/ha',
            'computation': lambda BE3_baseline, delta_BE3,  **kwargs: BE3_baseline + delta_BE3
            },
}

BIOMASS_model = GraphModel(BIOMASS_nodes)

model_dictionnary = {'BIOMASS_model': BIOMASS_model}

model_properties = get_model_properties('models/landuse/BIOMASS_properties.json')
```



3. Waste and water use

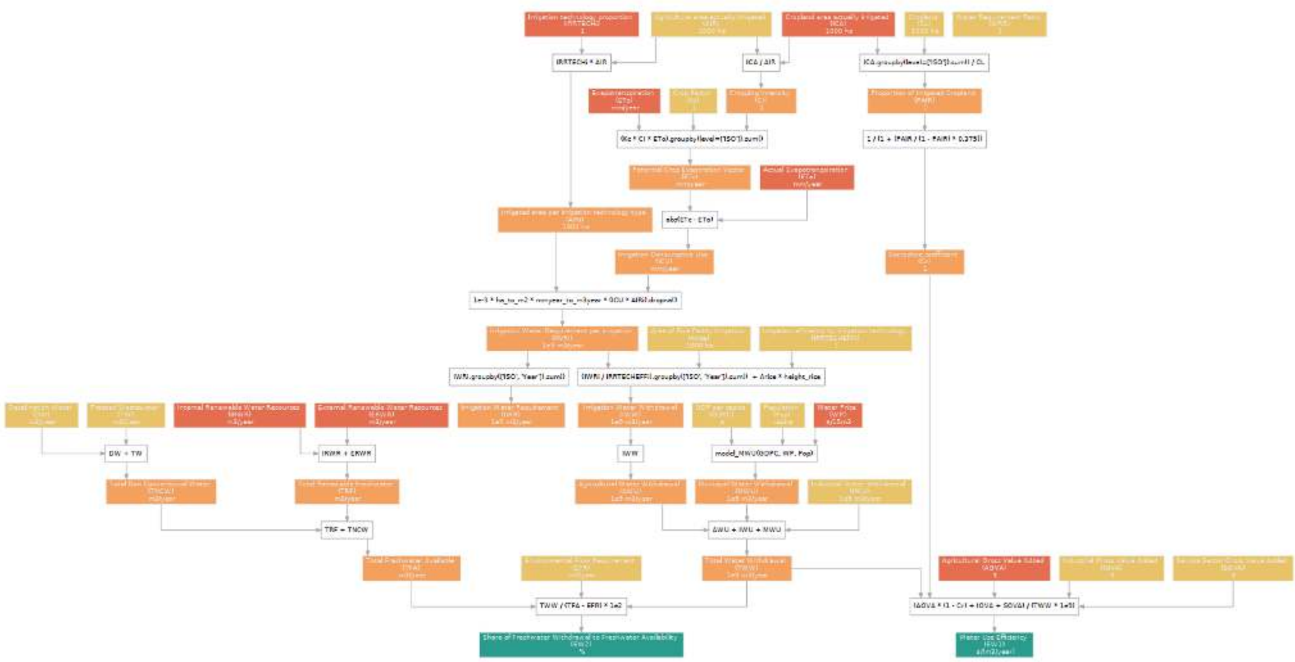
3.1 Water Use Efficiency

```
__Publisher__ = 'Global Green Growth Institute'
__Author__ = 'GGPM Team'
__Model_lead__='Sanga Lee'
__Programmers__='I.Nzimenyera & R.Munezero'

from ggmodel_dev.graphmodel import GraphModel, concatenate_graph_specs
from ggmodel_dev.utils import get_model_properties

import numpy as np

# Conversions
height_rice = 0.2  # meter height of rice
ha_to_m2 = 1e4  # * 1e3
mm_to_m = 1e-2  # 1e-3 TO CHECK
mmyear_to_m3year = 1e-2  # from mm/year to m3/year as 1mm = 10m3/ha \n",

IWW_nodes = {'Kc': {'type': 'parameter', 'unit': '1', 'name': 'Crop Factor'},
             'ICA': {'type': 'parameter', 'unit': '1000 ha', 'name': 'Cropland area actually irrigated'},
             'CI': {'type': 'variable',
                    'unit': '1',
                    'name': 'Cropping Intensity',
                    'computation': lambda ICA, AIR, **kwargs: ICA / AIR
                    },
             'ETo': {'type': 'input', 'unit': 'mm/year', 'name': 'Evapotranspiration'},
             'ETc': {'type': 'variable',
                     'name': 'Potential Crop Evaporation Vector',
                     'unit': 'mm/year',
                     'computation': lambda Kc, CI, ETo, **kwargs: (Kc * CI * ETo).groupby(level=['ISO']).sum()
                     },


             'ETa': {'type': 'input',
                     'unit': 'mm/year',
                     'name': 'Actual Evapotranspiration'},
             'ICU': {'type': 'variable',
                     'name': 'Irrigation Consumptive Use',
                     'unit': 'mm/year',
                     # bug to fix
                     'computation': lambda ETc, ETa, **kwargs: abs(ETc - ETa)
                     },
             'AIR': {'type': 'input',
                     'unit': '1000 ha',
                     'name': 'Agriculture area actually irrigated'},
             'Arice': {'type': 'input',
                       'unit': '1000 ha',
                       'name': 'Area of Rice Paddy Irrigation'},
             #'WRR': {'type': 'parameter', 'name': 'Water Requirement Ratio', 'unit': '1'},
             'IWW': {'type': 'variable',
                     'name': ' Irrigation Water Withdrawal',
                     'unit': '1e9 m3/year',
                     'computation': lambda IWRi, Arice, IRRTECHEFFi, **kwargs: (IWRi / IRRTECHEFFi).groupby(['ISO', 'Year']).sum()  + Arice
* height_rice
                     },
             'IRRTECHi':{
                 'type': 'input',
                 'name': 'Irrigation technology proportion',
                 'unit': '1'
             },
             'IRRTECHEFFi':{
                 'type': 'parameter',
                 'name': 'Irrigation efficiency by irrigation technology',
                 'unit': '1'
             },
             'AIRi':{
                 'type': 'variable',
                 'name': 'Irrigated area per irrigation technology type',
                 'unit': '1000 ha',
                 'computation': lambda IRRTECHi, AIR, **kwargs: IRRTECHi * AIR
             },

             'IWRi':{
                 'type': 'variable',
                 'name': 'Irrigation Water Requirement per irrigation',
                 'unit': '1e9 m3/year',
                 'computation': lambda AIRi, ICU, **kwargs: 1e-9 * ha_to_m2 * mmyear_to_m3year * (ICU * AIRi).dropna()

             },
            'IWR':{
                 'type': 'variable',
                 'name': 'Irrigation Water Requirement',
                 'unit': '1e9 m3/year',
                 'computation': lambda IWRi, **kwargs: IWRi.groupby(['ISO', 'Year']).sum()
             },
             'AWU': {'type': 'variable', 'unit': '1e9 m3/year',
                     'name': 'Agricultural Water Withdrawal',
                     'computation': lambda IWW, **kwargs: IWW
                     },
             }
```

```
def model_MWU(GDPC, WP, Pop):
    '''Find alternative to hard coding,
    also find way to link the regression data to those coefficient to improve reproducability
    '''
    return np.exp(-0.9522 - 0.3174 * np.log(WP) + 0.5918827 * np.log(GDPC) + 0.9859812 * np.log(Pop)) * 1e-9


MWU_nodes = {'WP': {'type': 'input', 'name': 'Water Price', 'unit': '$/15m3'},
             'GDPC': {'type': 'input', 'name': 'GDP per capita', 'unit': '$'},
             'Pop': {'type': 'input', 'name': 'Population', 'unit': 'capita'},
             'MWU': {'type': 'variable',
                     'name': 'Municipal Water Withdrawal',
                     'unit': '1e9 m3/year',
                     'computation': lambda GDPC, WP, Pop, **kwargs: model_MWU(GDPC, WP, Pop)
                     }
             }

EW1_nodes = {'IWU': {'type': 'input',
                     'name': 'Industrial Water Withdrawal',
                     'unit': '1e9 m3/year'},
             'ICA': {'type': 'input',
                     'unit': '1000 ha',
                     'name': 'Cropland area actually irrigated'},
             'MWU': {'type': 'input',
                     'name': 'Municipal Water Withdrawal',
                     'unit': '1e9 m3/year'},
             'AWU': {'type': 'input',
                     'name': 'Agricultural Water Withdrawal',
                     'unit': '1e9 m3/year'},
             'TWW': {'type': 'variable',
                     'name': 'Total Water Withdrawal',
                     'unit': '1e9 m3/year',
                     'computation': lambda AWU, IWU, MWU, **kwargs: AWU + IWU + MWU
                     },
             'AGVA': {'type': 'input',
                      'name': 'Agricultural Gross Value Added',
                      'unit': '$',
                      },


             'CL': {'type': 'input',
                    'unit': '1000 ha',
                    'name': 'Cropland'},
             'PAIR': {'type': 'variable',
                      'name': 'Proportion of Irrigated Cropland',
                      'unit': '1',
                      'computation': lambda ICA, CL, **kwargs: ICA.groupby(level=['ISO']).sum() / CL
                      },

             'Cr': {'type': 'variable',
                    'name': 'Corrective coefficient',
                    'unit': '1',
                    'computation': lambda PAIR, **kwargs: 1 / (1 + (PAIR / (1 - PAIR) * 0.563))
                    },


             'IGVA': {'type': 'input',
                      'name': 'Industrial Gross Value Added',
                      'unit': '$'},

             'SGVA': {'type': 'input',
                      'name': 'Service Sector Gross Value Added',
                      'unit': '$'},
             'EW1': {'type': 'output',
                     'name': 'Water Use Efficiency',
                     'unit': '$/(m3/year)',
                     'computation': lambda TWW, AGVA, IGVA, SGVA, Cr, **kwargs: (AGVA * (1 - Cr) + IGVA + SGVA) / (TWW * 1e9)
                     },
             }
```

3.2 Share of Freshwater Withdrawal to Freshwater Availability

```
EW2_nodes = {
    'IRWR': {'type': 'input',
                 'name': 'Internal Renewable Water Resources',
                 'unit': 'm3/year'},
    'ERWR': {'type': 'input',
             'unit': 'm3/year',
             'name': 'External Renewable Water Resources'},
    'TRF': {'type': 'variable',
            'name': 'Total Renewable Freshwater',
            'unit': 'm3/year',
            'computation': lambda IRWR, ERWR, **kwargs: IRWR + ERWR
            },
    'DW': {'type': 'input', 'unit': 'm3/year', 'name': 'Desalination Water'},
    'TW': {'type': 'input', 'unit': 'm3/year', 'name': 'Treated Wastewater'},
    'TNCW': {'type': 'variable',
             'name': 'Total Non Conventional Water',
             'unit': 'm3/year',
             'computation': lambda DW, TW, **kwargs: DW + TW
             },
    'TFA': {'type': 'variable',
            'name': 'Total Freshwater Available',
            'unit': 'm3/year',
            'computation': lambda TRF, TNCW, **kwargs: TRF + TNCW
            },
    'TWW': {'type': 'input', 'unit': '1e9 m3/year', 'name': 'Total Water Withdrawal'},
    'EFR': {'type': 'parameter',
            'unit': 'm3/year',
            'name': 'Environmental Flow Requirement'},
    'EW2': {'type': 'output',
            'name': 'Share of Freshwater Withdrawal to Freshwater Availability',
            'unit': '%',
            'computation': lambda TWW, TFA, EFR, **kwargs: TWW / (TFA - EFR) * 1e2
            },
}

# models
IWW_model = GraphModel(IWW_nodes)
MWU_model = GraphModel(MWU_nodes)
EW1_partial_model = GraphModel(EW1_nodes)
EW2_partial_model = GraphModel(EW2_nodes)

EW1_model = GraphModel(concatenate_graph_specs(
    [IWW_nodes, MWU_nodes, EW1_nodes]))
EW2_model = GraphModel(concatenate_graph_specs(
    [IWW_nodes, MWU_nodes, EW2_nodes]))
EW_model = GraphModel(concatenate_graph_specs(
    [IWW_nodes, MWU_nodes, EW1_nodes, EW2_nodes]))

# Dictionnary for easier access in the interface
model_dictionnary = {'IWW_model': IWW_model,
                     'MWU_model': MWU_model,
                     'EW1_partial_model': EW1_partial_model,
                     'EW2_partial_model': EW2_partial_model,
                     'EW1_model': EW1_model,
                     'EW2_model': EW2_model,
                     'EW_model': EW_model,
                     }
model_properties = get_model_properties('models/water_model/EW_properties.json')
```



3.3 Municipal wastewater collected (by sewage network) -Ethiopia

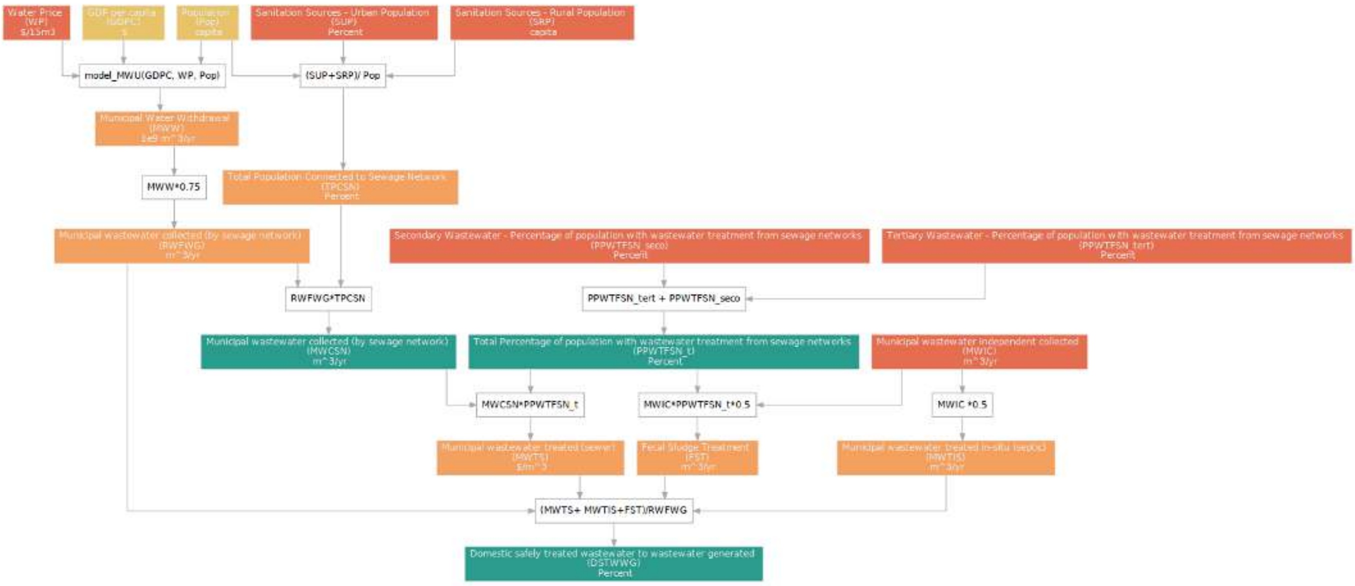
```
MWTIS_nodes = {

    'MWIC':{'type': 'input',
            'name': 'Municipal wastewater independent collected',
            'unit': 'm^3/yr'
             },

    'MWTIS': {'type': 'output',
             'name': 'Municipal wastewater treated in-situ (septic)',
             'unit': 'm^3/yr',
             'computation': lambda MWIC , **kwargs: MWIC *0.5
            },
}

FST_nodes = {
    'MWIC':{'type': 'input',
            'name': 'Municipal wastewater independent collected',
            'unit': 'm^3/yr'
             },

    'PPWTFSN_seco': {'type': 'input',
            'name': 'Secondary Wastewater - Percentage of population with wastewater treatment from sewage networks',
            'unit': 'Percent',
            },

    'PPWTFSN_tert': {'type': 'input',
            'name': 'Tertiary Wastewater - Percentage of population with wastewater treatment from sewage networks',
            'unit': 'Percent',
            },


    'PPWTFSN_t': {'type': 'output',
            'name': 'Total Percentage of population with wastewater treatment from sewage networks',
            'unit': 'Percent',
            'computation': lambda PPWTFSN_tert , PPWTFSN_seco , **kwargs: PPWTFSN_tert + PPWTFSN_seco
            },

    'FST': {'type': 'output',
            'name': 'Fecal Sludge Treatment',
            'unit': 'm^3/yr',
            'computation': lambda MWIC, PPWTFSN_t, **kwargs: MWIC*PPWTFSN_t*0.5
                }
}

def model_MWU(GDPC, WP, Pop):
    return np.exp(-0.9522 - 0.3174 * np.log(WP) + 0.5918827 * np.log(GDPC) + 0.9859812 * np.log(Pop)) * 1e-9

MWU_nodes = {'WP': {'type': 'input', 'name': 'Water Price', 'unit': '$/15m3'},
             'GDPC': {'type': 'parameter', 'name': 'GDP per capita', 'unit': '$'},
             'Pop': {'type': 'parameter', 'name': 'Population', 'unit': 'capita'},

             'MWW': {
                'type': 'variable',
                'name': 'Municipal Water Withdrawal',
                'unit': '1e9 m^3/yr',
                'computation': lambda GDPC, WP, Pop, **kwargs: model_MWU(GDPC, WP, Pop)
                }
             }
```

3.4 Total Percentage of population with wastewater treatment from sewage networks-Ethiopia

```
RWFWG_nodes = {

        'MWW': {'type': 'input',
                'name': 'Municipal Water Withdrawal',
                'unit': '1e9 m^3/yr',
                },

        'RWFWG': {'type': 'output',
                'name': 'Municipal wastewater collected (by sewage network)',
                'unit': 'm^3/yr',
                'computation': lambda MWW, **kwargs: MWW*0.75
                }

}

MWTS_nodes = {
    "SUP":{'type': 'input',
            'name': 'Sanitation Sources - Urban Population',
            'unit': 'Percent'
             },

    "SRP":{'type': 'input',
                'name': 'Sanitation Sources - Rural Population',
                'unit': 'capita',
            },


    'Pop': {'type': 'parameter', 'name': 'Population', 'unit': 'capita'},

    'TPCSN': {'type': 'variable',
                'name': 'Total Population Connected to Sewage Network ',
                'unit': 'Percent',
                'computation': lambda SUP,SRP,Pop, **kwargs: (SUP+SRP)/ Pop
             },


    'MWW': {'type': 'input',
                'name': 'Municipal Water Withdrawal',
                'unit': '1e9 m^3/yr',
                },

    'RWFWG': {'type': 'variable',
                'name': 'Municipal wastewater collected (by sewage network)',
                'unit': 'm^3/yr',
                'computation': lambda MWW, **kwargs: MWW*0.75
                },

    'MWCSN': {'type': 'output',
            'name': 'Municipal wastewater collected (by sewage network)',
            'unit': 'm^3/yr',
            'computation': lambda RWFWG,TPCSN, **kwargs: RWFWG*TPCSN
            },

    'PPWTFSN_seco': {'type': 'input',
            'name': 'Secondary Wastewater - Percentage of population with wastewater treatment from sewage networks',
            'unit': 'Percent',
            },

    'PPWTFSN_tert': {'type': 'input',
            'name': 'Tertiary Wastewater - Percentage of population with wastewater treatment from sewage networks',
            'unit': 'Percent',
            },


    'PPWTFSN_t': {'type': 'output',
            'name': 'Total Percentage of population with wastewater treatment from sewage networks',
            'unit': 'Percent',
            'computation': lambda PPWTFSN_tert , PPWTFSN_seco , **kwargs: PPWTFSN_tert + PPWTFSN_seco
            },
```

3.5 Domestic safely treated wastewater to wastewater generated Ethiopia

```
WasteWater_nodes = {
    'MWTS': {'type': 'input',
            'name': 'Municipal wastewater treated (sewer)',
            'unit': '$/m^3'},

    'MWTIS': {'type': 'input',
             'name': 'Municipal wastewater treated in-situ (septic)',
             'unit': 'm^3/yr'},

    'FST': {'type': 'input',
            'name': 'Fecal Sludge Treatment',
            'unit': 'm^3/yr'},

    'RWFWG': {'type': 'input',
              'name': 'Municipal wastewater collected (by sewage network)',
              'unit': 'm^3/yr'},

    'DSTWWG': {'type': 'output',
            'name': 'Domestic safely treated wastewater to wastewater generated',
            'unit': 'Percent',
            'computation': lambda MWTS, MWTIS, FST, RWFWG, **kwargs: (MWTS+ MWTIS+FST)/RWFWG
            },
}

# models
MWTIS_model = GraphModel(MWTIS_nodes)
FST_model = GraphModel(FST_nodes)
RWFWG_model = GraphModel(RWFWG_nodes)
MWTS_model = GraphModel(concatenate_graph_specs([MWTS_nodes, MWU_nodes]))
Wastewater_model = GraphModel(concatenate_graph_specs([RWFWG_nodes, MWTS_nodes,FST_nodes,MWTIS_nodes, MWU_nodes, WasteWater_nodes]))

# Dictionnary for easier access in the interface
model_dictionnary = {
                    'RWFWG_model':RWFWG_model,
                    'MWTS_model': MWTS_model,
                    'FST_model': FST_model,
                    'MWTIS_model': MWTIS_model,
                    'Wastewater_model': Wastewater_model,
                     }

model_properties = get_model_properties('models/water/Wastewater_properties.json')
```



ANNEX 9

Python codes to implement the network, causality, and correlation analyses in the Green Growth Simulation Tool Phase 2

1. Network Analysis

```
__Publisher__ = 'Global Green Growth Institute'
__Author__ = 'GGPM Team'
__Model_lead__='A.Lilibeth'
__Programmers__='A.Ipkovich'

import dash_core_components as dcc
import dash_html_components as html
import plotly.express as px
import dash_table
import dash
from dash.dependencies import Input, Output
from app import app, data
from pages import model_overview
from utils import Header, Footer
import numpy as np
import pandas as pd
import pages.network_analysis_tool as nat
import plots.network_analysis.igraph_to_plotly as itop
import data_utils as du
from utils import is_btn_clicked
from ggmodel_dev.models.greengrowth import GGGM
import plotly.graph_objects as go
import json

# set the figure size
fig_network1=go.Figure()
fig_network1.update_layout(width=700,height=700)

#%% Import the models, and their properties.
prop_files = ["Energy/Energy_properties.json", "Energy/Installed_properties.json", "Energy/Intensity_properties.json",
"landuse/BE2_properties.json", "landuse/BIOGAS_properties.json", "landuse/BIOMASS_properties.json", "landuse/NUTRIENT_properties.json",
"water_model/EW_hungary_properties.json"]
all_props = {}
for i in prop_files:
    f = open('ggmodel_dev/models/' + i,encoding="utf8")
    props_dummy = json.load(f)
    f.close()
    #all_props = {key: value for (key, value) in (all_props.items() + props_dummy.items())}
    for key, vals in props_dummy.items():
        all_props[key] = vals


networks = GGGM.all_model_dictionary

network_names = {}
# We will use this to generate the options for the networks...
model_list = all_props.keys()
for model_name, model in networks.items():
    mds = [model_name == i for i in model_list]
    if any(mds):
        network_names[model_name] = model

network_names_dropdown = []
for y in network_names.keys():
    try:
        network_names_dropdown.append({'label': all_props[y]["display_name"], 'value': y})

    except:
        network_names_dropdown.append({'label': y, 'value': y})

network_mode = [{'label':"Direct", 'value': "Direct"}, {'label':"Indirect", 'value': "Indirect"}]


size_labels = []
for i in nat.n_measures:
    size_labels.append({'label':i, 'value': i})
```

```
node_color_labels = []
for i in nat.node_color_labels:
    node_color_labels.append({'label':i, 'value': i})


edge_color_labels = []
for i in nat.edge_color_labels:
    edge_color_labels.append({'label':i, 'value': i})

na_settings = { 'network' : [],
                'network_mode' : [],
                'node_size' :  [],
                'node_size_slider' : INDEX_YEAR,
                'node_color' : [],
                'edge_color' : []
}

na_set_desc = {"Direct" : "Direct mode: Only the predefined connections are seen between nodes.",
            "Indirect" : "Indirect mode: A node is connected to the variables it has an impact on.",
            "Degree" : "A centrality measure that calculates how many neighbors a node has, which may show how important the node is.
Relevancy: One can find the major variables that play an important role in the ecosystem. (e.g. renewable, non-renewable energies)",
            "Betweenness" : "A centrality measure that calculates the shortest paths between the nodes. The more of the shortest paths go
through the node, the higher the centrality is. Relevancy: How important",
            "Closeness" : "Measures how close can one node be found to the other nodes. Reveals the nodes with the most (indirect)
connections.",
            "Clustering": "",
            "GGI" : "The standard color scheme of GGGI's graphs.",
            "Louvain Community" : "Detects communities in the networks thorugh the Louvain greedy optimization method.",
            "Edge Community": "Detects communities in the networks based on the connections between the nodes.",
            "Edge Betweenness" : "Calculates the shortest paths between edges. Groups similar edges.",
            "Infomap": "Partitions the edges into different groups. Groups similar edges.",
            "Walktrap": "Finds densely populated subnetworks through random walks."
             }

#%% Layouts

layout = html.Div(
    [
        html.Div([
            Header(app, 'Network Analysis')
        ]),
        html.Div(
            [
                html.Div(
                    [
                        html.Div(
                            [
                                html.H5("Highlights"),
                                html.Br([]),
                                html.P("Network analysis is a set of integrated techniques to depict relations among actors and to analyze
the social structures that emerge from the recurrence of these relations.",
                                    style={"color": "#ffffff", 'font-size': '15px'},),
                                html.Br([]),
                                html.P("Network Analysis converts the GraphModel to Networkx and igraph networks, and calculates the
centality measures of the direct graph (degree,closeness,betweenness). It also clusters the graphs,and calculates the correlation matrix of
the given and calculated data.",
                                    style={"color": "#ffffff", 'font-size': '15px'})

                            ],
                            className="product"
                        ),


                        html.Div(
                            [
                                html.Br([]),
                                html.Div(children='Select Network'),
                                dcc.Dropdown(id='network_sel_dropdown',options=network_names_dropdown, value =
list(GGGM.all_model_dictionary.keys())[0]),
                                html.Div(id='network_desc', children=["Network Description"]),
                                html.Br([]),
                                html.Div(children='Network Mode'),
                                dcc.Dropdown(id='network_mode_dropdown', options = network_mode, value = network_mode[0]['value'],
placeholder=network_mode[0]['value']),
                                html.Div(id='network_mode_desc', children=["Network Mode Description"]),
                                html.Br([]),
                                html.Div(children='Node Size'),
                                dcc.Dropdown('variable_size_dropdown', options = size_labels, value =size_labels[0]['value'],
 placeholder=size_labels[0]['value']),

                                html.Div(id='node_size_desc', children=["Node Size Description"]),
                                html.Br([]),
                                html.Br([]),
                                html.Div(children='Node Color'),
                                dcc.Dropdown(id='node_color_dropdown', options = node_color_labels, value = node_color_labels[0]['value'],
placeholder=node_color_labels[0]['value']),
                                html.Div(id='node_color_desc', children=["Node Color Description"]),
                                html.Br([]),
                                html.Div(children='Edge Color'),
                                dcc.Dropdown(id='edge_color_dropdown', options = edge_color_labels, value = edge_color_labels[0]['value'],
```

```
placeholder= edge_color_labels[0]['value']),
                                html.Div(id='edge_color_desc', children=["Edge Color Description"]),
                                html.Br([]),
                                html.Button('Run', id='btn-run', n_clicks=0,
                                style={'font-size': 20,
                                       'font-weight': 'normal',
                                       'color': '#ffffff',
                                       'background': '#14ac9c',
                                       'border': '#14ac9c',
                                       })

                            ], className="na_ui"

                        )
                    ],
                    className="pretty_container four columns"
                ),
                html.Div(
                    [
                        html.H5("Network Analysis results:"),
                        html.Br([]),
                        dcc.Graph(id='network',figure=fig_network1)

                    ],
                    className="pretty_container eight columns"
                ),

@app.callback(
    Output("download-netw", "data"),
    Input("btn-run", "n_clicks"),
    Input('network', 'figure'),
    prevent_initial_call=True
)
def down_network(n_clicks, fig):
    if(is_btn_clicked('btn-dwn')):
        fig.write_html("./images/export.html")
        return dcc.send_file("./images/export.html")

###
@app.callback(
    #Output('network_desc', 'children'),
    Output('network_mode_desc', 'children'),
    Output('node_size_desc', 'children'),
    Output('node_color_desc', 'children'),
    Output('edge_color_desc', 'children'),
    Input('network_sel_dropdown', 'value'),
    Input('network_mode_dropdown', 'value'),
    Input('variable_size_dropdown', 'value'),
    Input('node_color_dropdown', 'value'),
    Input('edge_color_dropdown', 'value')
)
def change_network_setting(net, net_mode, node_size, node_col, edge_col):

    na_settings['network'] = networks[net]
    na_settings['network_mode'] = net_mode
    na_settings['edge_color'] = edge_col
    na_settings['node_size'] = node_size
    na_settings['node_color'] = node_col
    return na_set_desc[net_mode], na_set_desc[node_size], na_set_desc[node_col], na_set_desc[edge_col]


@app.callback(
    Output("index-table", "style_data_conditional"),
    Input("index-table", "active_cell"),
)
def style_selected_rows(active_cell):
    if active_cell is None:
        return dash.no_update

    css = [
        {'if': {'row_index': 'odd'},
    'backgroundColor': 'rgb(0, 0, 0, 0.1)',
        },
        {"if": {'row_index': active_cell['row']},
            "backgroundColor": "rgba(45, 178, 155, 0.3)",
            "border": "1px solid green",
            },
           {
        # 'active' | 'selected'
        "if": {"state": "selected"},
        "backgroundColor": "rgba(45, 178, 155, 0.3)",
        "border": "1px solid green",
    },

    ]
    return css
```

```
def update_variable_network(n_clicks):
    if(is_btn_clicked('btn-run')):

            #print("Button Pressed")

            variable_size_dropdown = na_settings['node_size']
            #variable_size_slider =[2000, 2005, 2010, 2015, 2020]
            network_mode_dropdown = na_settings['network_mode']
            sel_model = na_settings['network']
            node_col = na_settings['node_color']
            edge_col = na_settings['edge_color']

            dat = []

            G, _, cm, cl, e_cl, labels, results, lbl = nat.Network_Analysis_Tool(sel_model, dat, network_mode = network_mode_dropdown,
edge_mode=edge_col)
            mark_sc ={}
            dis_slider = True

            if node_col == "Louvain Community":
                cl = nat.GetLouvainCommunity(G)
            elif node_col == "Edge Community":
                cl = nat.GetEdgeCommunity(G)

            for i in labels:
                    mark_sc[i] = cm.loc[variable_size_dropdown, i]
            dat = pd.DataFrame.from_dict(mark_sc, orient='index')
            pd_mark_sc = []



            if dat.sum().sum() != 0:
                pd_mark_sc = (dat/dat.max()).to_numpy().tolist()
            else:
                pd_mark_sc = np.zeros((len(labels), 1)).tolist()
            mark_sc = [float(x[0]) for x in pd_mark_sc]

            fig1 = itop.Vizualize_iGraph_Plotly(G, labels, cl, edge_colors = e_cl, marker_scaler = mark_sc, names = lbl)

    else: fig1 = go.Figure()
    return  fig1# dis_slider
```

2. Causality Analysis

```
__Publisher__ = 'Global Green Growth Institute'
__Author__ = 'GGPM Team'
__Model_lead__='A.Lilibeth'
__Programmers__='A.Ipkovich'

import dash_core_components as dcc
import dash_html_components as html
import plotly.express as px
import dash_table
import dash
from dash.dependencies import Input, Output
from app import app, data
from utils import Header, Footer
import numpy as np
import pandas as pd
import pages.network_analysis_tool as nat
import plots.network_analysis.igraph_to_plotly as itop
import data_utils as du
from utils import is_btn_clicked
from ggmodel_dev.models.greengrowth import GGGM
import plotly.graph_objects as go
import plotly.express as px
from sklearn.manifold import trustworthiness
from sklearn.neighbors import KNeighborsRegressor as KNN
import json
networks = GGGM.all_model_dictionary

f = open('data/causal_data.json')
data = json.load(f)
f.close()
c_data = [] #current data

# We will use this to generate the options for the networks...
network_names = []
network_names = list(data.keys())

network_names_dropdown = []
for y in network_names:
    network_names_dropdown.append({'label': y, 'value': y})

#%% Layouts

layout = html.Div(
    [
        html.Div([
            Header(app, 'Causality Analysis')
        ]),
        html.Div(
```

```
                html.Div(
                    [
                        html.Div(
                            [
                                html.H5("Highlights"),
                                html.Br([]),
                                html.P("Causality analysis may indicate which variables are controllable in the model (according to its
output). Causal interference is capable of measuring how significantly one variable distort the function shape of the output. The current
method features a machine learning algorithm that is trained on the inputs and outputs. One input is selected and imputed random values (500
times), from which the output is predicted. The random and the original models change in function determines how well one variable fits. Due
to the method's heuristic nature, the results must be evaluated statistically.",
                                    style={"color": "#ffffff", 'font-size': '15px'},),
                                html.Br([]),
                                html.P("The results show the functions projection's difference between the original and imputed method. If
the mean is more than 0.1, there may not be a causal relation.",
                                    style={"color": "#ffffff", 'font-size': '15px'})

                            ],

                            className="product"
                        ),


                        html.Div(
                            [
                                multi=True),

                                html.Div(id = "caus_obj", children = [
                                    html.Div(children='Select Network'),
                                    dcc.Dropdown(id='qa_network_sel_dropdown',options=network_names_dropdown, value =
network_names_dropdown[0]['value']),
                                    html.Div(id='network_desc', children=["Network Description"]),
                                    html.Br([]),
                                    html.Div(children='Select variables for causal interference'),
                                    dcc.Dropdown(id='outp_dropdown',options=[], value = None, clearable=True),
                                    html.Div(id='out_vars', children=["Description"])

                                ])

                            ], className="na_ui"

                        )
                    ],
                    className="pretty_container four columns"
                ),
                html.Div(
                    [
                        html.H5("Causality Analysis results:"),
                        html.Br([]),
                        html.Div(id = "results_id", children = dcc.Graph(id='caus_fig',figure=go.Figure()))
                    ],
                    className="pretty_container eight columns"
                ),

            ],
            className="row",
        ),
        Footer(),
    ],
    className="page",
)
@app.callback(
    Output('outp_dropdown', 'options'),
    Output('outp_dropdown', 'value'),
    Input('qa_network_sel_dropdown', 'value')
)
def SetNodes(input):
    sel_vars = []
    vs = list(data[input].keys())
    for y in vs:
        sel_vars.append({'label': data[input][y]['name'], 'value': y})

    sel_var_lab = None

    if len(sel_vars) != 0:
        sel_var_lab = sel_vars[0]["value"]

    return sel_vars, sel_var_lab


@app.callback(
    Output('caus_fig', 'figure'),
    Input('outp_dropdown', 'value'),
    Input('qa_network_sel_dropdown', 'value')
)
def ModCausalInterference(inputs, model):
        figa =go.Figure()
        if inputs != None:
            figa = go.Figure(data=[go.Histogram(x=np.array(data[model][inputs]["sim"])[:, 2])])
            figa.update_layout(
                title=inputs,
                xaxis_title="Projection Difference",
```

```
                yaxis_title="Count",
                font=dict(
                size=20
            ))
        return figa
```

3. Correlation analyses

```
__Publisher__ = 'Global Green Growth Institute'
__Author__ = 'GGPM Team'
__Model_lead__='A.Lilibeth'
__Programmers__='A.Ipkovich'

import dash_core_components as dcc
import dash_html_components as html
import plotly.express as px
import dash_table
import dash
from dash.dependencies import Input, Output
from app import app, data
from utils import Header, Footer
import numpy as np
import pandas as pd
import pages.corr_analysis_tool as cat
import plots.network_analysis.igraph_to_plotly as itop
import data_utils as du
from utils import is_btn_clicked
from ggmodel_dev.models.greengrowth import GGGM
import plotly.graph_objects as go
import plotly.express as px
from sklearn.manifold import trustworthiness
from openpyxl import load_workbook

networks = GGGM.all_model_dictionary

#%%
corr_types = []
corr_types.append({'label': 'Direct', 'value': 'Direct'})

wb = load_workbook("./data/causal_data.xlsx", read_only=True, keep_links=False)
imp_models = wb.sheetnames

network_options = []

for i in imp_models:
    network_options.append({"label" : i, "value" : i})
layout = html.Div(
    [
        html.Div([
            Header(app, 'Correlational Analysis')
        ]),
        html.Div(
            [
                html.Div(
                    [
                       html.Div(
                            [
                                html.H5("Highlights"),
                                html.Br([]),
                                html.P("Correlational analysis measures the relationship between input and output variables. Generally
speaking, the higher the correlation is, the more similarly change two variables. However, it is important to note that correlation is not
causality.",
                                       style={"color": "#ffffff", 'font-size': '15px'},),
                                html.Br([]),
                                html.P("This page vizualizes the correlations as direct networks. The direct correlation measures the
correlation between the input and output variables.",
                                       style={"color": "#ffffff", 'font-size': '15px'},)

                            ],
                            className="product"
                        ),
                        html.Div(
                            [
                                html.Div(children='Select Correlation Mode'),
                                dcc.Dropdown(id='ca_corr_sel_dropdown', options=corr_types, value = corr_types[0]['value']),
                                html.Br([]),
                                dcc.Dropdown(id='ca_network_sel_dropdown', options=network_options, value = network_options[0]['value']),
                                html.Br([]),
                                html.Div(id="placeholder"),
                                html.Button('Run', id='btn-run-ca', n_clicks=0,
                                style={'font-size': 20,
                                       'font-weight': 'normal',
                                       'color': '#ffffff',
                                       'background': '#14ac9c',
                                       'border': '#14ac9c',
                                       }) #,

                            ], className="na_ui"

                        )
```

```
                    )
                ],
                className="pretty_container four columns"
            ),
            html.Div(
                [
                    html.H5("Correlational Analysis results:"),
                    html.Br([]),
                    html.Div(id = "c_results_id", children = dcc.Graph(id='corr_fig',figure=go.Figure()))
                ],
                className="pretty_container eight columns"
            ),

        ],
        className="row",
    ),
    Footer(),
],
className="page",
)

@app.callback(
    Output('corr_fig', 'figure'),
    Input('ca_corr_sel_dropdown', 'value'),
    Input('ca_network_sel_dropdown', 'value')
)
def DirectCorrelationVizualization(corr_typ, model):

    data = pd.read_excel("./data/causal_data.xlsx", engine='openpyxl', index_col =0, sheet_name =model)

    rem_vars = data[data.isna().all(axis=1)].index.tolist()
    data.drop(rem_vars, axis = 0, inplace=True)
    data.dropna(inplace=True, axis = 1)

    var_types = data.loc[:, 'Type']
    data.drop(labels = 'Type', axis = 1, inplace=True)

    X = data.transpose()
    X = (X - X.min(axis=0)) / (X.max(axis=0) - X.min(axis=0))

    figa =go.Figure()
    if corr_typ == 'Direct':
        G, cl, labels, ann_text  = cat.DirectCorrelation(X, rem_vars, var_types)
        figa = itop.Vizualize_iGraph_Plotly(G, labels, cl, annotation_text=ann_text)
    return figa
```

Annex 10

Scenarios analysis for implementing the European Green Deal and Green Recovery in Hungary

Background

GGGI believes that robust modeling is a powerful tool to support decision-making and prudent planning in the context of carbon neutrality. With this background, GGGI proposes to assess a set of policies and measures identified under Hungary's National Clean Development Strategy (NCDS)[1] using the Green Growth Index Simulation (GGSim) Tool to further assess co-benefits, with a focus on the Sustainable Development Goals (SDGs).

The COVID-19 pandemic has negatively affected all economies in the world, including the European Union (EU). The crisis has deeply impacted employment, with about 2.6 million workers losing their jobs in the EU (ages 15 to 64)[2]. In response to the economic crisis, the EU provides massive economic stimulus while placing the European Green Deal (EGD) at the heart of the economic recovery.

The EGD is the EU's new growth strategy. It sets the blueprint for the EU's climate neutrality by 2050. It puts the building blocks for tomorrow's economy in place with landmark strategies on biodiversity, circular economy, sustainable and smart mobility, zero pollution, renovation wave, sustainable food, hydrogen, batteries, offshore renewable energy, and many others.

In the context of the EGD and Hungary's national climate neutrality commitment, GGGI has delivered various low-carbon scenarios, such as the late action (LA) and early action (EA) climate neutrality scenarios, using the Green Economy Model (Box 1). According to these scenarios, significant climate action positively impacts the GDP and green employment.

The work to be carried out will further assess and show the alignment of SDG co-benefits with the climate neutrality goals. After consultation with the Ministry of Innovation and Technology in 2021, the SDG co-benefits assessments should focus on the transport sector. GGGI suggested two policy measures for this sector, solar and biofuels, as sustainable solutions to achieve climate neutrality and whose impacts can go beyond the energy sector.

Objectives

The project will provide answers to this question: How are the EA low-carbon scenarios aligned with the SDGs? This is a critical question that could further motivate the uptake of EGD proposals that reduce not only greenhouse gas (GHG) emissions but also biodiversity loss and social inequality. By assessing co-benefits, it will be possible to determine the EGD's potential contribution to reducing biodiversity loss and enhancing social inclusion. These co-benefits are added social, economic, or environmental benefits above and beyond the direct benefits of reducing GHG emissions and the economic indicators already covered in the analysis performed with GEM. They can include, for example, access to basic services, management of natural resources, etc.

Policy measures[1]

The project will assess SDG co-benefits of policy measures relevant to energy, the sector that contributed the most significant (72 percent) to total GHG emissions in Hungary in 2018. These measures will focus on two energy sources – solar and biofuels, which could have the most significant impacts on reducing emissions in the energy sector, including (i) transport, (ii) electricity and district heating, and (iii) energy use in buildings and agriculture. Within the energy sector, transport accounts for 30.6 percent of the GHG emissions, electricity and district heating 28.8 percent, and energy use in buildings and agriculture 27.1 percent. Solar photovoltaic energy and second-generation biofuels, in particular, are expected to play an important role in Hungary's energy mix in 2050 under the EA scenario. However, the specific SDG targets and scale of co-benefits will depend on measures (or strategy) to implement their production and consumption policies.

1 Unless otherwise cited, statistics presented in this section were drawn from the NCDS report.

1. Solar energy

Hungary has, at present, a solar power capacity of 2 GW, which the government aims to achieve a two to three-fold increase by 2030[3]. According to the NCDS, solar photovoltaics will contribute 51 GW (or 78 percent) of the total 65 GW renewable energy production capacity required to achieve the 2050 climate neutrality target in the EA scenario. Electrification will significantly contribute to decarbonizing the energy sector due to its essential role in transport (i.e., demand for electric vehicles) and household (i.e., use of heat pumps) sectors. The EA scenario estimated that 56 percent of electricity will be generated by solar energy, compared to only 22 percent from wind and 11 percent from biomass. The solar panel program will be part of the energy transformation, using decentralized, small-scale solar utilization (rooftop) and brownfield sites to ensure sustainable land use for the scenarios.

The co-benefits from solar energy on achieving sustainability targets on other SDG indicators will depend on specific policy measures that will be implemented to reduce GHG emissions. For example, producing 51 GW from photovoltaics can be possible by generating electricity from either a few large solar plants or many smaller solar farms or combining both. But the generation of one megawatt (or 0.0010 GW) of solar power would require one hectare of land, and most solar farms are 40.5 hectares or less in size[4].[2] A minimum of 20,000 hectares and a maximum of 40,000 hectares of brownfields are estimated to exist in Hungary, which will not be sufficient to cover the generation of 51 GW of solar energy, not to mention that 52.7% of the areas are actually protected or worthy of protection due to their ecological value or elements of architectural heritage[5]. Finding suitable land areas for solar plants/farms could be challenged by the potential negative impacts on biodiversity and the ecosystem. Solar panels installed on buildings, which produce between 250 and 400 Watts of power depending on shading, orientation, and sun hours, can contribute to achieving the 51 GW as estimated in the EA scenario by 2050[6]. Installation of solar panel systems for residential and agricultural use will improve the population's direct access to renewable electricity-generating capacity. Solar energy can supply the electricity needed to run household heat pumps, or solar thermal heaters can be installed to reduce emissions in the residential sector. Moreover, integrating solar panel systems on buildings into the on-grid electricity supply will allow residents to contribute to generating renewable electricity.

More recently, installing solar panel systems to generate electricity for agriculture, e.g., solar irrigation, has received government policy support. The use of solar energy will be helpful in countries like Hungary, particularly where fragmented and small-scale farms exist. At the farm level, solar for irrigation provides a reliable water source at reduced costs in pumping water from the ground. In addition, it also improves access to water all year round in farm areas where rainfall is scarce, groundwater is available, or surface water is far away[7]. However, if not appropriately managed, solar irrigation could cause over-withdrawal of freshwater resources due to low energy costs and unregulated water use, which will pose challenges in the future due to an increase in water demand in agriculture and a decrease in water supply from climate change impacts[8]. But if coal disappeared from the energy mix and old nuclear power plant units were closed down, as estimated in the EA scenario, then freshwater withdrawal could be reduced since the operation of coal and nuclear power plants requires large water withdrawal[9].

To sum up, specific policy measures related to solar energy programs, such as the size and location of solar plants, policy incentives, consumer-producer models (household level, community level, etc.), and support for installing solar panel systems in buildings and farms, and amount of non-renewable energy to be replaced by solar energy, will determine the co-benefits of achieving the SDGs.

2. Biofuels

In addition to electrification, second-generation biofuels[3] are expected to decarbonize and modernize the transport sector significantly. Unlike first-generation biofuels, generally produced from edible biomass, second-generation biofuels are based on non-food feedstock and have little impact on food security, a long-term priority for Hungary. In the EA scenario, the share of biofuels in energy consumption in the transport sector is expected to increase from 4 percent in 2020 to 28 percent in 2050, but this is due mainly to the increase in second-generation biofuels. Feedstock from second-generation biofuels ranges from lignocellulosic feedstocks (including forest and crop residues) and livestock manure to municipal solid wastes. The price for the second-generation feedstock is significantly less than that of the first-generation, but the former feedstock is "generally more complex to convert, and its production is dependent on new technologies"[10]. Depending on the feedstock, using biofuels to decarbonize the transport sector will have different impacts on society and the environment and, thus, on the SDG co-benefits.

Forest residues, which include byproducts from forest harvesting (i.e., thinning, cutting stands for timber or pulp), clearing lands for construction, and stands damaged by insects, diseases, or fire, usually have "low density and heating values with

2 But the size of solar farms has been increasing in recent years, with Bhadla Solar Park in India being the world's largest with an installed capacity of 2.25GW, and it spans 14,000 acres in 2020 (https://www.nsenergybusiness.com/features/largest-solar-power-plants/).

3 Like the second-generation biofuels, carbon-free hydrogen is also expected to contribute to decarbonization only from 2040s, with the share increasing to 8 percent by 2050 (LTS report). For this reason, only biofuel technologies will be considered in this project.

high transportation costs"[11]. The transport of forest residues to biofuel processing plants alone contributes to emissions. The same can be said for crop residues, which can vary in bulk density, moisture content, particle size, and distribution depending on geographical location[12]. However, since biomass production is the largest consumer of water, using forest and crop residues, which will be otherwise wasted, provides more value for water use. In practice, the use of crop residues for bioenergy can compete with sustainable land use practices, including, for example, using them as fertilizer for crops and fodder for livestock, preventing erosion, and mitigating soil carbon depletion. Similarly, forest residues from felling trees for timber return carbon and nutrients to the soil to support future tree growth[13]. Hence, using forest and crop residues for biofuel production would require appropriate management (e.g., fertilizer application, cover crops, etc.).

Like crop residues, when properly managed and used, livestock manure is a good source of fertilizer because it contains nitrogen, phosphorus, and other nutrients for growing crops. However, intensive livestock production has contributed to pollution because excessive use of manure in agriculture caused nitrogen and phosphorus runoffs into water bodies. Using manure for biofuel production can help not only reduce this environmental problem but also provide renewable sources of power and electricity for on-farm production or sale to the electricity grid. Various technologies are available to produce biofuels from manure - anaerobic digestion that uses microbes to process manure into biogas, thermal processes to produce biodiesel, and gasification to convert to syngas[14]. An on-site, manure-based energy system can help farmers generate significant annual savings in energy costs and more stable sources of heat and electricity compared to solar and wind[15], whose availability is influenced by nature.

Among the sources of second-generation biofuels, municipal solid waste (MSW) is the cheapest but more expensive and complex due to the required operation before processing and conversion technologies. "A 1,000-ton-per-day waste-to-biofuel facility can cost over $500 million to construct, so these technologies are generally economically feasible only at sizes of 1,000 tons per day or more."[16] The management of wastes involves separation at source into recyclable materials (e.g., metals, paper, and plastics), non-recyclable materials, or solid recovered fuel that can be combusted to syngas (e.g., shredded textiles, wood, paper, card, and plastics), and organic fraction that can be converted to biogas (decayable food waste)[17]. Among these three waste components, food waste, which accounts for about 70 percent of the overall weight of MSW, is one of the most viable biomass feedstock for biofuel production[18]. Unlike forest and crop residues, which are not available in adequate quantities throughout the year and which could result in supply challenges for biorefineries during some months[19], biomass from food waste has been increasing at an environmentally unsustainable level due to the increase in population and urbanization. The common approaches for waste management, like landfilling, composting, and incinerating, have adverse environmental impacts, including GHG emissions and water pollution. There is evidence that converting MSW to biofuels could deliver the highest GHG emission reduction by avoiding decomposition to methane in landfill sites.[20] Using food waste to produce biofuels offers both environmental benefits and alternative use of land instead of dumpsites, generation of renewable energy, and savings in feedstock costs.[21]

To sum up, specific policy measures related to the amount of first-generation biofuel to be replaced by second-generation biofuels, the types and amount of feedstock to be used for second-generation biofuels, and the sectors that will be aimed to benefit from second-generation biofuel supply will determine the co-benefits of achieving the SDGs.

SDG co-benefits

Based on the policy measure that will be specified for solar energy and biofuels for the different NCDS scenarios, SDG co-benefits can be assessed using the GGSim Tool. Table 25 below provides examples of relevant SDGs that can be influenced by policy measures for these two renewable energy sources. Other sustainability indicators that can be included in the assessment, which are not yet part of but can contribute to achieving the SDGs, will consist of, for example, soil nutrient budget (nitrogen kilogram per hectare), DALY rate due to unsafe water sources (DALY lost per 100,000 persons), non-CO_2 emissions per capita (Mt CO_2 equivalent), etc.

Table 25. SDG indicators that can be included in the co-benefits assessment

Number and description of SDG indicators	Policy relevance	
	Energy sources	Sectors/Areas
2.4.1 Proportion of agricultural area under productive and sustainable agriculture	Solar & Biofuels	Agriculture
3.9.1 Age-standardized mortality rate attributed to ambient air pollution (deaths per 100,000 population)	Biofuels	Demographic/Health, Transport
6.3.1 Total wastewater generated (million m3/year)	Solar & Biofuels	Waste, Water
6.3.2 Proportion of bodies of water with good ambient water quality	Biofuels	Waste, Water
6.4.2 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources (%)	Solar	Water

Table 25. SDG indicators that can be included in the co-benefits assessment *(continued)*

Number and description of SDG indicators	Policy relevance	
	Energy sources	Sectors/Areas
7.1.2 Proportion of population with primary reliance on clean fuels and technology (%)	Solar & Biofuels	Energy and Health
7.b.1 and 12.a.1 Installed renewable energy-generating capacity (watts per capita)	Solar & Biofuels	Energy
7.2.1 Renewable energy share in the total final energy consumption (%)	Solar & Biofuels	Energy, Transport, Buildings
9.4.1 Carbon dioxide emissions from fuel combustion (millions of tons)	Solar & Biofuels	Energy
11.6.1 Municipal Solid Waste collection coverage by cities (%)	Biofuels	Waste
11.6.2 Annual mean levels of fine particulate matter (population-weighted) by location (micrograms per cubic meter)	Biofuels	Demographic/Health
12.3.1 Food waste per capita (KG)	Biofuels	Agriculture, Waste
12.4.2 Municipal waste generated (tons); Municipal waste treated, by type of treatment (%)	Biofuels	Waste
13.2.2 Total greenhouse gas emissions per year (Mt CO_2 equivalent)	Solar & Biofuels	Energy
15.3.1 Proportion of land that is degraded over total land area (%)	Biofuels	Agriculture
15.1.1 Forest area (thousands of hectares); Forest area as a proportion of total land area (%)	Solar & Biofuels	Forest
15.1.2 Average proportion of Terrestrial Key Biodiversity Areas (KBAs) covered by protected areas (%)	Solar	Forest
15.2.1 Above-ground biomass stock in the forest (tonnes per hectare); Forest area annual net change rate (%); Proportion of forest area within legally established protected areas (%)	Biofuels	Forest

Box 2. Description of the relevant NCDS scenarios

BAU scenario: The emission trajectory of the scenario follows current trends. The scenario does not include energy efficiency, renewable energy, or GHG emission reduction targets for 2030 and 2050. It, therefore, does not include the targets set in the NECP and the new NES. Current trends have been considered in all sectors without further efforts to reduce emissions.

LA climate neutrality scenario: This scenario aims to achieve net climate neutrality by 2050 by reducing emissions in the energy sector at a slower pace by 2045 and then with an increased effort until 2050. This allows the lower cost levels of low and zero-emission technologies to be exploited. The scenario assumes that, in line with the targets set in the climate action, final energy consumption could reach a maximum of 785 PJ in 2030, with the share of renewable energy increasing to at least 21 percent. After 2030, non-waste sectors will be on the lowest cost trajectory toward climate neutrality, resulting in accelerated emission reductions by the end of the period due to the postponement of investments pending a decrease in technology costs. In the case of waste management, the model assumes a higher level of ambition by 2030 to meet the EU targets for reducing landfill use (circular economy).

EA climate neutrality scenario: the EA approach envisages achieving climate neutrality by 2050 while considering the short- and medium-term benefits of job creation and the reduction of environmental externalities, the economic potential of the first mover, improved productivity, and higher GDP growth. The scenario assumes that Hungary's final energy consumption in 2030 will be a maximum of 734 PJ and that renewable energy penetration will reach 27 percent. The emission reduction trajectories for industry, LULUCF, waste management, and agriculture are the same as in the LA scenario. Between 2030 and 2050, emissions will follow a linear trajectory to reach net zero emissions. CCUS technologies will become commercially viable in the energy and industrial sectors after 2030 in both the LA and EA scenarios.

Source: National Clean Development Strategy 2020-2050, Ministry for Innovation and Technology, Government of Hungary 2021.

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