European Commission

Future transitions for the Bioeconomy towards Sustainable Development and a Climate-Neutral Economy

Modelling needs to integrate all three aspects of sustainability

Knowledge Synthesis and Foresight Work Package 2 - Network of Experts

The European Commission's Knowledge Centre for **Bioeconomy**

JRC124579

PDF ISBN 978-92-76-32323-5 doi:10.2760/097710

Joint Research Centre

Contact information

KNOWLEDGE CENTRE FOR BIOECONOMY

EC-Bioeconomy-KC@ec.europa.eu

DG Research & Innovation

Contact Information

RTD BIOECONOMY COMMUNICATION

RTD-BIOECONOMY@ec.europa.eu

EU Science Hub

https://ec.europa.eu/jrc

https://knowledge4policy.ec.europa.eu/bioeconomy_en

DG Research & Innovation

https://ec.europa.eu/research/bioeconomy/

Luxembourg: Publications Office of the European Union, 2021

How to cite this report:

Verkerk, P.J., Cardellini, G., van Meijl, H., Pyka, A., Future transitions for the Bioeconomy towards Sustainable Development and a Climate-Neutral Economy – Modelling needs to integrate all three aspects of sustainability, M'barek, R. (editor), Publications Office of the European Union, Luxembourg, 2021, ISBN 978-92-76-32323-5, doi:10.2760/097710, JRC124579.

Contents

Acknowledgements

The authors would like to thank the partners of the BioMonitor consortium for sharing review results on the existing capacity for bioeconomy modelling. The authors also thank Robert M'barek, Marios Avraamides and Sarah Mubareka from the Joint Research Centre of the European Commission and Órlaith Ní Choncubhair from the Directorate-General for Research and Innovation for their critical comments and suggestions.

Authors

Verkerk, P.J., Cardellini, G., van Meijl, H., Pyka, A.

Executive summary and key messages

The updated EU Bioeconomy Strategy aims to develop a sustainable and circular bioeconomy for Europe, strengthening the connection between economy, society, and the environment, thereby addressing global challenges such as meeting the United Nations' Sustainable Development Goals and the climate objectives of the Paris Agreement. To guide policy making in the transition, knowledge and forward-looking capacities are needed. These capacities include quantitative modelling tools, which can support a better understanding of the complexity, trade-offs, and potential pathways to achieve the transition. This report (i) analyses the existing capacity and needs for an improved bioeconomy modelling to integrate all three dimensions of sustainability and (ii) provides recommendations for developing new and improved models that are better suited to assist policy making.

The present review of existing models highlights important gaps in the existing capacity to model the bioeconomy:

- Some existing bioeconomy sectors and products are not well covered. Most of the models reported in the literature have a sectoral focus and only a selected group of models cover all bioeconomy sectors. Especially the aquaculture and fishing sector, as well as the manufacturing of textiles, leather and wearing apparel, pharmaceuticals, plastics, and the chemical sector are not well captured by existing models focusing on bioeconomy products.
- Limited ability of capturing the cross-cutting issues of the bioeconomy transition. Linked to the sectoral scope of most models is their limited ability of capturing the cross-cutting issues of the bioeconomy transition and addressing multiple bioeconomy objectives. Due to the sectoral focus, models do not well cope with the competition between the different (industrial and energy) sectors of the bioeconomy. It is of paramount importance to address these cross-cutting issues if the goal is to secure a successful transition to a sustainable and circular bioeconomy.
- Novel products are not well captured by existing models. Existing models typically focus on products that have established markets and not properly capture the emergence of new or novel products. Similarly, transformative land use practices are not well addressed by existing models.
- Most of the models provide information on the bioeconomy on the national level and a much smaller number of models provide such information at sub-national level. Impacts associated with the development of the bioeconomy are typically occurring at regional or local level and it is important that such impacts are properly understood.

Efforts have been made to develop linkages between models to overcome shortcomings related with the sectoral focus of models and to assess policy questions related to the bioeconomy. Many of these model linkages focused on related economic activities while fewer cover many or all bioeconomy sectors in detail. Integrated Assessment Models are especially important for providing information on different aspects of the bioeconomy, because of their multi-sector and multidisciplinary nature. To improve the bioeconomy modelling capacity, we formulate the following technical recommendations:

- Improve the model coverage of existing bioeconomy sectors and products. To cover the entire bioeconomy with sufficient level of detail, existing models need to be extended, new models need to be developed and/or numerous linked models might be needed to cover all sectors of the bioeconomy.
- Improve the coverage of novel bioeconomy products. Existing models should be expanded to better cover novel products based on available technical, engineering and market information. Availability of appropriate data is a key issue and improved modelling should therefore go hand in hand with improved data collection efforts.
- Improve existing models to better address circularity. Existing (economic) models are generally based on the notion of linear (i.e., produce, use, discard) economies and almost completely ignore material cycles and recycling, as well as co- and by-production of products and materials.
- Improve existing models to better address climate change. Climate change affects natural systems, which are at the heart of the bioeconomy. Another area of attention is the introduction of bioenergy with carbon capture and storage technologies and especially the interaction between forestry and agriculture in terms of land and biomass competition.
- Link existing models with specialised biodiversity models to better address biodiversity. Future assessments should seek to better represent land-management practices as well as additional pressures on land and biodiversity, such as the influence and mitigation of climate change, overexploitation, pollution, and biological invasions.
- Consider the novel possibilities offered by big data and artificial intelligence to detect new developments in bioeconomy sectors which are hidden in traditional industry statistics.
- Improve linkages/integration with other tools and approaches. Linking models with existing and well-established tools and approaches (e.g., Life Cycle Assessment and Material Flow Analysis) can help to efficiently mitigate some of the models' shortcomings building on the know-how already established in other scientific domains.
- Improve the spatial resolution of existing models. Impacts associated with the development of the bioeconomy are typically occurring at regional or local level and it is important that such impacts are properly understood.

- Develop social (SDG) indicators by inclusion of distributional issues between different groups of people or households.

Governance recommendations are:

- Be selective in the models to be further developed for bioeconomy modelling. IAMs are considered especially important, because of their multi-sector and multidisciplinary nature.

- Plan for sufficient time and resources to better link models. Enabling factors for model cooperation are open data and IT infrastructure and model governance structures oriented at long-term maintenance, development, and cooperation.

- Combine bioeconomy modelling with other foresight techniques. This combination will improve the credibility, legitimacy, and relevance of the results with regards to the needs of decision makers.

- Improve quality and transparency of existing models. Quality control of models needs to be better ensured through model documentation, validation, publishing model descriptions and applications in peer reviewed journals and by making models and their code accessible to peers through open access.

To support policymakers in addressing cross-cutting issues, improved modelling approaches need to consider key processes as technological change (or innovation), circularity, consumer behaviour, climate change and biodiversity. Whereas circularity might be included into existing models in the short and medium run, other important concepts require the development of new models building on the emerging modelling techniques. These concepts refer to societal and technological changes associated with the transition to a sustainable and circular bioeconomy and they specifically relate to how innovations affect future development or how consumers learn and change their preferences and what kind of dynamics are to be expected. There are several emerging approaches that try to address complex systems and structural changes, but these new classes of models are likely to be considered as complements to the existing models and not as substitutes. Their justification comes from their long run orientation and does not mean that the existing modelling classes with their higher levels of detail and empirical integration are to be replaced. Instead, the closing of the identified gaps of existing models very likely will be useful and supportive for a future modelling capacity which is prepared for analysing comprehensively the bioeconomy. We thus argue for a modelling approach eclecticism, where established and emerging modelling approaches are combined depending on the questions to be analysed. Developments in big data and artificial intelligence will be valuable guideposts for designing future modelling strategies. Enabling factors are an open data and IT infrastructure and model governance structures oriented at long term maintenance, development, and cooperation.

In the context of bioeconomy modelling, improved modeller cooperation is needed which brings together established and emerging modelling approaches and covers the social, economic, and environmental dimension and disciplines to endogenize some of the variables considered as constants in existing (traditional) modelling approaches. We consider the most promising opportunities for future modelling activities in the exploitation of model cooperation between established and emerging modelling approaches. As this recommendation is focusing on the long-term, we also want to highlight the applicability of the emerging modelling approaches, which are very much driven by technological development in computation and modern data sciences. To facilitate the combined use of existing and emerging modelling approaches, we recommend several actions that could be taken to resolve issues that have so far hampered the uptake of complexity models:

- Facilitate the closer cooperation between the so far mostly separated research communities on established and emerging modelling approaches. This could be achieved by research calls requiring the involvement of relevant research communities to ensure a better understanding of how modelling approaches can support each other.

- Remove barriers to access data and computing infrastructure. Despite major progress in computation and modern data sciences, barriers exist that hamper the uptake of development of emerging modelling approaches. Such barriers could refer to access to already established data and computing infrastructures. Improved access to and improved use of data and computing infrastructures are needed to support a larger uptake of emerging modelling approaches.

- Strengthen the development of complexity models that consider behavioural change. Major developments are being made to capture the behaviour of consumers, with the help of internet, big data, and artificial intelligence algorithms, although there are also privacy concerns. In addition to better understanding consumer behaviour, an improved understanding is also needed for the behaviour of landowners and firms.

- Better address technological development and innovation in future models. New models that address the long-term transformation processes in the bioeconomy need to emphasize the outstanding role of innovation. Major developments have been made to integrate experimental behaviour under true uncertainty, knowledge exchange in networks and learning into agent-based models addressing innovation driven industrial dynamics. These promising approaches and their specific application to analyse endogenous innovation processes in the bioeconomy are to be explored to substantially improve our understanding of the complex transformation processes.

1 Introduction

The updated EU Bioeconomy Strategy adopted in 2018 aims to develop a sustainable and circular bioeconomy for Europe, strengthening the connection between economy, society, and the environment, thereby addressing global challenges such as meeting the Sustainable Development Goals (SDGs) set by the United Nations and the climate objectives of the Paris Agreement. While the bioeconomy can be defined in many ways, the European Commission defines the bioeconomy as: "*all sectors and systems that rely on biological resources (animals, plants, micro-organisms and derived biomass, including organic waste), their functions and principles. It includes and interlinks: land and marine ecosystems and the services they provide; all primary production sectors that use and produce biological resources (agriculture, forestry, fisheries and aquaculture); and all economic and industrial sectors that use biological resources and processes to produce food, feed, bio-based products, energy and services*".

The updated Bioeconomy Strategy shifts the understanding of the concept from substitution towards circularity and sustainability and addresses the competing use of biological resources (animals, plants, micro-organisms, and derived biomass, including organic waste), encompassing multiple sectors and policies with a view to achieving policy coherence and synergies. In view of developing transition pathways for a bioeconomy that contributes to a more sustainable, competitive model of growth and employment in Europe, the European Commission formulated a set of key questions:

1. How sustainable are current biomass supplies and can more biomass than is produced and used today, be sustainably sourced (either internally or from third countries) while fulfilling the need to maintain or even increase carbon sinks and sustainably manage land based and marine ecosystems to secure the long-term provision of ecosystem services?
2. How can the development of the bioeconomy foster climate change adaptation and mitigation and how can negative emissions approaches related to the bioeconomy be optimised (e.g., BECCS, bio-based material use, versus wood buildings, afforestation)?
3. What dietary changes would have a positive impact on climate and on the economic, social, and environmental sustainability of food systems as well as consumer and planetary health?
4. How can sustainable, affordable, and secure bioenergy be delivered where needed in the longer term, while meeting biomass demand for other existing and emerging (material) uses?
5. How can the design and implementation of strategies that limit food losses and waste along the entire supply chain, contribute to the development of sustainable and resilient food systems?

To guide policy making in addressing these questions, knowledge and forward-looking capacities are needed. These capacities include quantitative modelling tools, which can represent the entire bioeconomy, or parts of it, and support a better understanding of the complexity, trade-offs, and potential pathways to achieve the transition to sustainability and climate-neutrality, addressing the economic, social and environmental dimensions. The need for improved modelling tools is highlighted in the Staff Working Document accompanying the updated EU Bioeconomy Strategy (SWD/2018/431), which states that to "*improve the knowledge base (data, information and tacit knowledge) on all areas of the bioeconomy and a forward-looking capacity (modelling, foresight exercises, scenarios), as essential elements for providing the evidence needed to support policy makers and for underpinning policy coherence*".

This call for the use of models and modelling for policy support is not new. Out of 1063 Impact Assessments carried out by the European Commission between 2003 and 2018, 16% relied on the use of models and this share has increased to around 25-30% from 2015 onwards (Acs et al. 2019). Models can support policy making to deal with uncertainty and disentangle complexity. Models are typically used to explore scenarios and develop potential or desirable future states and development pathways. As such, models can reveal and quantify interdependencies and trade-offs between resources, production, consumption, markets and sectors, and the environment. The recent European Commission's 2020 Strategic Foresight Report (European Commission 2020) highlights that strategic foresight and modelling are complementary approaches for anticipatory- and evidence-based policy making.

In this context, the European Commission (Joint Research Centre in collaboration with DG Research and Innovation) created an ad-hoc Network of Experts to contribute to the European Commission's Knowledge Centre for Bioeconomy with forward-looking analysis needed for exploring possible scenarios towards a sustainable, clean, and resource-efficient bioeconomy, with a focus on climate-neutrality and sustainable development. The second work package aims to analyse modelling needs to integrate all three aspects of sustainability (economic, social, environmental). This report is the outcome of the second work package and contains three parts. Firstly, we present an analysis of existing capacity to model transitions for the bioeconomy, focusing on models used in the European Union but covering also reference models used in other countries. Secondly, we present an analysis of emerging approaches to model transitions for the bioeconomy. Thirdly and finally, we provide recommendations how bioeconomy modelling approaches could be improved in the short-medium, and long-term.

2 Existing capacity to model future transitions for the bioeconomy

2.1 What are models and why are they useful?

2.1.1 Role of models in supporting decision-making

Modelling generally refers to the simplification of reality intended to facilitate and promote understanding. The extent to which a model aids in the development of our understanding is the basis for deciding how good the model is. We follow here the definition by Acs et al. (2019), who define a model as "*an analytical representation or quantification of a real-world system, used to make projections or to assess the behaviour of the system under specified conditions*". This definition excludes related methods and approaches, such as for example 'standard cost model', 'lifecycle model', 'analytical model', etc. (Acs et al. 2019).

As a model represents a simplification of reality, certain details are excluded. The risk is that a model represents reality in an over simplistic manner and will not support the development of the understanding desired. In contrast, if too much detail is included, the model may become so complicated that, again, it fails to promote the development of the deeper levels of understanding one seeks. George Box' statements that "*all models are wrong, but some are useful*" recognizes that scientific models always fall short of the complexities of reality but can still be of use.

It is important to distinguish the different purposes of models: some are focusing on short-run adaptations to exogenous shocks and outline the alignment of the system to the new conditions. This class of models usually allows to include a large set of details and depicts the multifaceted reactions and interrelations in the adaptation process. Some other models are designed to develop a better understanding of long-term development driven by co-evolutionary processes and confronted with severe uncertainties concerning the system's architecture and processes. Here, a broader conceptualization of the system modelled (i.e., less detailed descriptions of single system's components) are required to work out the basic mechanisms of qualitative development, e.g., structural changes. There is no better or worse between these different classes of models. The choice of a specific model class depends on the purpose of the analysis and both model classes are to be considered as strongly complementary.

2.1.2 Model typologies

While numerous typologies exist for classifying models, we follow here an existing classification (Smeets et al. 2013; O'Brien et al. 2017; Angenendt et al. 2018) and categorize existing models for assessing the development of the bioeconomy as follows:

1. Economic models
    a. computable general equilibrium (CGE) models
    b. partial equilibrium (PE) models
2. Environmental models
    a. biophysical models
    b. land change models
3. Integrated assessment models (IAMs)
4. Specialist model (or bottom-up models)

Figure 2.1 provides a schematic overview of how different models provide information on the development of the bioeconomy and it illustrates the wide range of models and methods needed to join multiple scales and dimensions of the bioeconomy into one systemic framework. Grouping models is, however, challenging as there are several overlaps among model types and categories and several models address multiple scales of analysis (O'Brien et al. 2017). In the following, the model typologies are discussed, and they are summarized in Table 2.1.

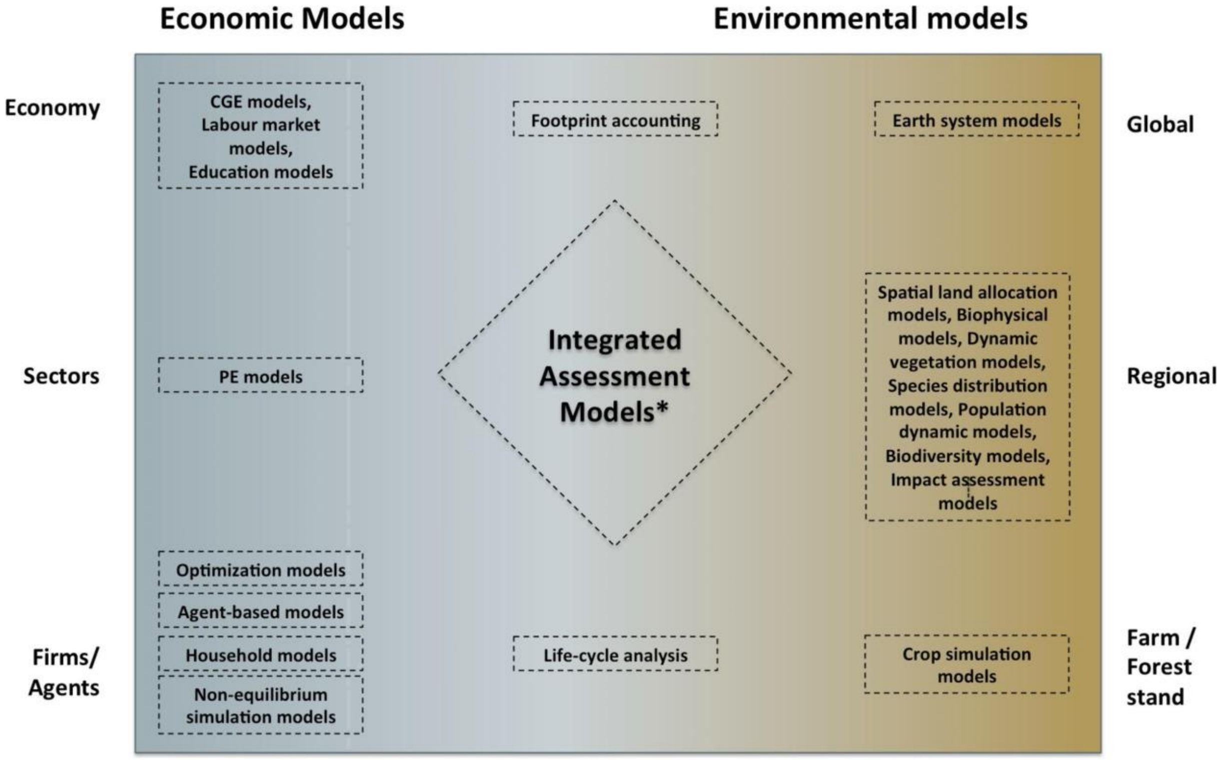

Figure 2.1 Overview of existing types of models and other relevant tools and approaches for assessing the bioeconomy (van Leeuwen et al. 2015; O'Brien et al. 2017)

Global computable general equilibrium (CGE) models are comprehensive market models describing many sectors and the economy as a whole. CGE models are a class of economic models that use actual economic data to estimate how an economy might react to changes in policy, technology, or other external factors. CGEs are especially suitable to evaluate economy-wide impacts of policies related to e.g., agriculture, energy and trade and their subsequent effects on GDP, employment, land-use change, GHG emissions etc. Key strengths are the comprehensive coverage of economic sectors and regions to account for inter-linkages and the explicit modelling of limited economic resources. Limitations are that the CGE models necessitate a simplified representation of agent choices, in particular favouring relatively simple and smooth mathematical forms which help to reduce the number of parameters required to calibrate the models.

Partial equilibrium (PE) models have a more detailed coverage of sectors and often explicitly show biophysical flows and absolute prices. PE models usually also have a high(er) level of detail with respect to regional aspects, policy measures and environmental indicators as well as a higher level of sectoral detail. Disadvantages are that the impacts and economy-wide linkages with other key sectors that are not represented are ignored and that macroeconomic balances are thus not considered. The limited supply of key resources and inputs into productive activities within the economy (such as labour and capital) also tend to be ignored.

Table 2.1. Overview of the bioeconomy modelling approaches with their applications, typical timeframes, key strengths, and limitations. Modified from Wicke et al. (2015)

	CGE Models	**PE Models**	**Environmental models**	**Integrated Assessment models**	**Specialist models**
Application	Economy-wide impacts of biomass and bioenergy policies, including subsequent effects on land-use change and GHG emissions induced by these policies. Indirect substitution, land use and rebound effects due to multiple sectors and production factors	Explicit and detailed sectoral impacts of sectoral policies on agriculture, forestry, land-use change, energy system and GHG emissions Market outlooks for sectors for medium term	Monitoring natural ecosystems and simulations to mimic or predict bio-physical processes. Assessment of availability of raw materials Impacts of (bioeconomy) policies on environment (land use, water, and biodiversity)	Bioeconomy resource potentials under different assumptions (incl. sustainability criteria). Possible contribution of bioenergy to long-term climate policy. Impacts of bioenergy policies on global land use, water, and biodiversity	Wide variety of specific (technical) aspects of biomass production, conversion, and use. Validation of other studies with a broader scope, such as PE and CGE models, and IAMs
Analysis period	~2050, up to 2100	~2050	~2050, up to 2100	~2100	~2050, up to 2100
Strengths	Comprehensive coverage of economic sectors and regions to account for interlinkages. Explicit modelling of limited economic resources. Measuring the total economy wide and global effects of bioeconomy policies (including indirect and rebound effects)	Detailed coverage of sectors of interest with full market representation. Explicit representation of biophysical flows and absolute prices. Usually more details on regional aspects, policy measures and environmental indicators	Detailed understanding of biophysical process (e.g., crop or tree productivity) or land use changes	Integrating different relevant systems in one modelling framework. Possibility to analyse feedbacks between human and nature systems, and trade-offs and synergies of policy strategies. Built around long-term dynamics	Detailed insights into techno-economic, environmental, and social characteristics and impacts of biobased systems
Limitations	Level of aggregation that may mask the variation in the underlying constituent elements. Scope of CGE models necessitates simplified, representation of agent choices, favouring smooth mathematical forms and reduced number of parameters required to calibrate the models. Often no or little explicit representation of quantities for biophysical flows Technological change is ignored or exogenous, and without understanding of stakeholder strategies for innovation and diffusion. No learning or behavioural change on the side of consumers.	Optimization of agent welfare, but only the sectors represented in the model. No consideration of macroeconomic balances and impacts on not-represented sectors. Need large number of assumptions for long-term projections. Technological change is ignored or exogenous, and without understanding of stakeholder strategies for innovation and diffusion. No learning or behavioural change on the side of consumers.	Challenges related to data availability and quality No consideration of feedback loops with the economic system (indirect effects such as price responses, competition, replacement effects as well as technological or structural changes outside the system boundaries are exogenous)	High level of aggregation or too complex systems. Unsuitable for short-term assessments. Large number of assumptions (and the communication of these to the public)	No inclusion of indirect and induced effects outside the boundaries of the study, i.e., often deliberately ignore interactions with other sectors

Environmental models focus on depicting the environment and generally aim to monitor natural ecosystems and run simulations to mimic or predict bio-physical processes and identify problems. Methods include e.g. biophysical modelling, land change modelling and can focus on the micro level (e.g. farms and forest stands with crop simulation models) to the global level (e.g. with Earth system models) (O'Brien et al. 2017). Biophysical models are one class of environmental models, which aim to capture biophysical processes, such as crop or forest/tree growth dynamics, as affected by climate, water and nutrient availability and other environmental conditions. Biophysical models tend to have well-defined system boundaries in terms of geographic scope, sectoral coverage, and technology. Land use and land cover models are another subset of environmental models, designed to describe land use dynamics in a spatially explicit manner using information about land availability, land suitability, proximity to infrastructure, as well as other environmental and socio-economic factors (Smeets et al. 2013; Varacca et al. 2020).

Integrated assessment models (IAMs) are designed to describe the interactions between human activities and (global) environmental change processes (Smeets, et al. 2013). IAMs, therefore, include a description of the human system and environmental system and the interaction between the two. As such, they cover a broad range of disciplines, including energy analysis, economics, agriculture analysis, and biophysical sciences. The models and tools discussed in the previous sections often form a part of an IAM (although often deliberately simplified compared to the stand-alone forms). The agricultural and/or energy economics components are normally represented by a CGE or PE model. However, in IAMs these are combined with a simultaneous representation of the physical system, implying that the model not only describes emissions or agricultural production but also the full chain of climate change (concentrations, temperature change) and a representation of land-use. Disadvantages are the high complexity and the high level of aggregation (or other simplifications) necessary to maintain computational tractability.

Specialist models deal with a wide variety of specific (often technical) aspects of biomass production, conversion, and use. Bottom-up models are used to validate other studies with a broader scope, such as PE and CGE models and IAMs, and tend to be more process-based models with an engineering or biophysical focus. These bottom-up models, or specialist models, typically address very specific themes and/or technological processes. They have normally a deterministic nature and a much narrower geographical scope, but typically can look at a much higher number of dimensions thanks to their detailed nature. In between these two are placed the energy system models, which have a broader array of aspects they try to cover using different methodologies.

2.2 What capacity exists currently to model future transitions of the bioeconomy?

Models have long been used in Europe to monitor how (traditional) sectors of the bioeconomy could develop and how these are affected by policy changes. Models may address the entire bioeconomy, or parts thereof, and may be linked to each other to give a comprehensive view of the bioeconomy (Smeets et al. 2013; Wicke et al. 2015; Angenendt et al. 2018). Within the context of the BioMonitor project[1], a review has been recently conducted of existing models that can be used to analyse the impacts of drivers on the economic, social, and environmental performance of the bioeconomy (Varacca et al. 2020). The study conducted a systematic literature review and compiled an exhaustive inventory of existing bioeconomy-related models that have a clear socio-economic component or provided insight on key market variables (e.g., supply and use of biomass), as well as biophysical models focusing on environmental aspects. The authors conducted their review by first identifying studies published in recent years using relevant bioeconomy keywords. This search yielded a large set of publications, which was then further scrutinized and reduced using a set of selection criteria (Varacca et al. 2020):

- The models should have a clear role in either monitoring the bioeconomy sectors or producing scenarios, projections, foresights on the same sectors.
- The models should have a sufficiently wide geographical coverage (e.g., at least one country as a whole) and be extendable to other countries and regions.
- The models should have been published in peer-reviewed journals or research reports prepared by reputable institutions.

Varacca et al. (2020) identified 33 models and characterized each of these models according to a predefined set of evaluation criteria. The authors reviewed which economic activities are covered by the models in accordance with the Nomenclature of Economic Activities (NACE). Their selected NACE sectors are given in Table 2.2. However, the NACE classification is focused on economic activities and does not well cover ecosystem services and non-market activities. Thus, while NACE classification is the basis for most economic models, it is not directly applicable to environmental models focusing on biophysical processes.

Varacca et al. (2020) focused mainly on bio-based products and less on energy uses. As the bioeconomy includes also energy uses of biomass (see also Box 1), this review was here extended by identifying and characterizing 29 additional models using the methodology by Varacca et al (2020) but focusing on the energy sector. In the next sections, we review what bioeconomic modelling capacity currently exists, both within and outside the European Union, based on a review of 62 of models in total.

[1] http://biomonitor.eu/

Table 2.2. Overview of economic sectors that belong in part or as whole to the bioeconomy in accordance with the Nomenclature of Economic Activities (NACE) (Kardung et al. 2021)

Code	Description
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
C10	Manufacture of food
C11	Manufacture of beverages
C12	Manufacture of tobacco
C13	Manufacture of textiles
C14	Manufacture of wearing apparel
C15	Manufacture of leather and related products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C31	Manufacture of furniture
D35	Electricity, gas, steam and air conditioning supply
D3511	Production of electricity
F41	Construction of buildings
F42	Civil engineering
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
I55	Accommodation
I56	Food and beverage service activities

Box 1. The role of energy models in the bioeconomy

With the transition towards sustainable energy systems, energy models play a prominent role in policy support by providing information to deal with the current variable and mixed energy technologies. These models can be useful also in the context of bioeconomy. A wide range of energy models exists, each using different approaches, and addressing different issues of energy generation and distribution (Ringkjøb et al. 2018). They generally deal with energy questions related to the entire economy, or just specific economic sectors, without focusing in detail on the products these sectors are producing. For the bioeconomy, the relevant energy models are the ones considering bioenergy as a commodity in any of the relevant sectors of the economy.

Following the classification used in this report, energy models do not represent a separate class of models. The two most important families of energy system models are the ones finding their roots in the partial or general equilibrium theories. This family of models is typically used to assess respectively the sectorial or the direct and indirect impact across sectors of specific energy policies. Energy models are here described separately as they can play an important role in addressing key policy issues. In addition, they comprise a well-developed field in bioeconomy modelling with interesting new modelling approaches extendable to the whole bioeconomy context that are useful to further consider and explain in this report. Below the main purpose, strengths, and weaknesses of different categories of energy models are described (modified from Welfle et al. 2020).

	Integrated Assessment Models (IAMs)	**Energy system models**		**Specialist models**
		Computable General Equilibrium (CGE)	**Partial Equilibrium (PE)**	
Application	• Bioenergy resource potentials based on varying assumptions & criteria • Contribution to long term climate policy • Impacts of bioenergy policies on global land use, water and biodiversity	• Economic impacts of biomass & bioenergy policies • Policy Effects such as resulting GHG emissions	• Indirect substitutions such as land use & rebound effects on multiple sectors • Sector impacts of bioenergy policies on agriculture, forestry, land use change, energy system & GHG emissions	• All technical aspects of feedstock supply, conversion & use. • Validation of other studies with broader scopes.
Timeframe	• Long	• Short to Medium	• Short to Long	• Short to Long
Strength of Approach	• Integrating different systems in one modelling framework • Potential for analysing feedbacks between human & natural systems, trade-offs & synergies with political strategies • Developed around long term dynamics	• Comprehensive coverage of economic sectors & regions to account for inter-linkages • Explicit modelling of limited economic resources Measuring economy-wide & global effects of bioenergy policies	• Detailed coverage of interest sectors with full market representation • Explicit representation of biophysical flows & prices	• Typically greater detail on regional aspects, policy measures & environmental indicators • Detailed insights into techno-economic, environmental & social characteristics • & impacts of bio-based systems
Limitations of Approach	• High level of aggregation of highly complex systems • Unsuitable for short term assessments • Large number of assumptions	• Level of aggregation may mask the variation in the underlying elements. • Scope of CGE models necessitates simplified trends and outputs • Few or no explicit representation of quantities for biophysical flows	• Optimisation of agent welfare, but only the sectors represented in the model • No consideration of macro- economic balances & impacts on non-represented sectors	• Needs large number of assumptions for long term projections • No inclusion of indirect & induced effects outside the boundaries of the study - often deliberately ignoring interactions with other sectors
Strong Coverage of Bioenergy Themes	• Forestry & Wood Feedstocks • BECCS & CCS • Emissions & GHGs	• Forestry & Wood Feedstocks • Residue Feedstocks	• Emissions & GHGs	• Forestry & Wood Feedstocks • Emissions & GHGs
No Coverage of Bioenergy Themes	• Bioenergy Processes & • Technologies (other than BECCS + CCS) • Pre-treatment Processes • ILUC • Water Issues • Bio-chemicals	• ILUC Water Issues	• Alternative Transport Biofuels • (non-road) • Pre-treatment Processes	• Coverage of all Bioenergy Themes

2.2.1 Economic models

Computable General Equilibrium models

Computable General Equilibrium Models (CGE) are comprehensive market models describing many sectors and the economy as a whole. CGE models are a class of economic models that use actual economic data to estimate how an economy might react to changes in policy, technology, or other external factors. The core of a CGE model is an input–output model, which links industries in value added chains from primary goods, over continuously higher stages of intermediate processing, to the final assembly of goods and services for consumption. Producers are assumed to choose the cheapest combination of imperfectly substitutable labour, capital, land, natural resources, and intermediates. As such, interlinkages between different markets are provided, so feedback effects can be accounted for when evaluating different policy actions, changes in technology or other exogenous dynamics. Therefore, one of the main advantages of CGEs lies in their breadth of key economic relationships, including market price adjustments, changes in trade, market balances and factor markets.

CGEs account for technological shifts, although this is most of the time achieved without a detailed specification of the technologies involved. The same applies to changes in policies, with CGE models providing a means for assessing medium- and long-term effects in the bioeconomy agenda at the EU or global level. However, the generally higher level of sectoral and regional aggregation (with respect to PE models) is detrimental to modelling sectorial details such as niche markets, regional characteristics, land use restrictions and other lower-level features (Kretschmer et al., 2010). Clearly, the higher the aggregation, the weaker the interactions between the underlying constituent elements, and the lower the chance to include bottom-up information (elasticities and data) (Hoefnagels et al., 2013). Consequently, the representation of technology and technological change is usually rather limited (Smeets et al., 2013).

The GTAP model (Corong et al. 2017) is the mother of most of the CGE models mentioned in the list as it provides the starting template and database provided by the global trade consortium. MIRAGE extended the GTAP database in the direction of biofuels and was actively used in the iLUC debate of biofuels (Laborde et al. 2014, Valin et al. 2015). MAGNET has a focus on the bioeconomy by a split of many agricultural sectors and residues of primary and food processing sectors (including various fisheries and aquaculture sectors), it has extended its coverage to biofuels, bioenergy, and several biobased chemicals (Woltjer et al. 2014, van Meijl et al. 2018a, Philippidis et al. 2019).

GEM-E3, ICES, LIBEMOD and NEWAGE are CGEs with an energy focus. These models generally consider the entire economy and the interactions between economic sectors but focus on energy questions related to the entire economy, or just specific economic sectors, without focusing in detail on the products these sectors are producing.

Table 2.3. Overview of existing Computable General Equilibrium models

Model	Full name	Bioeconomy Sectors	Resolution	Reference
GEM-E3*	General Equilibrium Model for Economy-Energy-Environment	All economic activities (focus on energy) Key strength: D35, D3511, C20	Regional - Continental	Capros et al. 2013
GTAP	Global Trade Analysis Project	All economic activities (no specific focus)	National - Continental	Corong et al. 2017
ICES	Intertemporal Computable Equilibrium System	All economic activities (focus on energy) Key strength: D35, D3511, C20	Regional - Multinational	Eboli et al. 2010
LIBEMOD	LIBEralization MODel for the European Energy Markets	All economic activities (focus on energy) Key strength: D35, D3511, C20	National - National	Aune et al 2008
MIRAGE	Modelling International Relationships in Applied General Equilibrium	All economic activities (no specific focus, used for biofuels)	Regional - Continental	Bchir et al. 2002; Bouët, etal. 2010, 2012
MAGNET*	Modular Applied GeNeral Equilibrium Tool	All economic activities (agriculture and bioeconomy focus)	National - Continental	Woltjer et al. 2014

Model	Full name	Bioeconomy Sectors	Resolution	Reference
		Key strength: A01, A03, C10, C11, C20-C22 (biobased), D2511 (bioenergy)		
NEWAGE	National European Worldwide Applied General Equilibrium	All economic activities (focus on energy) Key strength: D35, D3511, C20	National - Multinational	Montenegro et al. 2019

**Model applied by JRC*

Partial equilibrium models

A fairly large number of partial equilibrium models exist that can model specific sectors of the bioeconomy. PE models are often used to address sector specific questions (e.g., agriculture and energy) and for which interrelation with other parts of the economy are secondary. The models can be roughly grouped in models focusing on the agricultural sector, the forestry sector, or the energy sector (Table 2.2), although there are also models (GLOBIOM and MAGPIE) that cover all these sectors, at least to a certain extent. There are also only few models that cover fisheries and aquaculture.

Partial equilibrium models that focus on the agricultural sector include Aglink-COSIMO, AGMEMOD, CAPRI, IMPACT and MAGPIE. A wide variety of PE models have been identified and classified, as can be seen in Table 2.2. PE models have frequently been used to analyse first-order effects of policy intervention on a feedstock market when using biomass for bioenergy and materials (see e.g., De Gorter and Just (2009) for corn ethanol and Babcock et al. (2011) for second generation). More sophisticated models however exist, such as the Common Agricultural Policy Regionalised Impact (CAPRI) model (Britz et al. 2014), encompassing many sectors and regions, and providing a high level of detail in the supply and demand representation especially within the EU, including a detailed treatment of environmental effects. GlOBIOM moves in the same direction at global level but more aggregated within the EU and linking also to the forest sector. Other examples of PE models that consider the agricultural sector and focus more on market developments (outlooks) are AGMEMOD with EU MS specific country representation, Aglink-COSIMO with global focus (EU is one region), IMPACT with a LDC focus, and MAGPIE (global focus). A similar variety of PE models is available for energy models (e.g., POLES, PRIMES, TIMER). A review of PE models for the energy sector is available from Bhattacharyya (2010) and Ringkjøb et al. (2018), see also section 2.2.4.

Partial equilibrium models that cover the forestry sector include EFI-GTM, GLOBIOM, GFTM and GFPM. All these models contain a module or function to assess forest biomass availability, but they may derive such information also from dedicated environmental models (see section 2.2.6 on model linkages). All these models focus on the traditional economic activities relating to the manufacture of wood and first transformation products of wood and cork, as well as paper and paper products, but they generally exclude second transformation products (e.g., furniture). Links with the energy sector are being developed for several of the models, but these models generally contain limited information on emerging wood products such as engineered wood products, man-made cellulose fibres, or biofuels. The main difference between these models is their scope in terms of products coverage and geographical coverage and spatial resolution. For example, EFI-GTM includes 30 forest industry and energy sector products, five roundwood categories, three categories for forest chips, four recycled paper grades, and the main by-products of the forest industries (black liquor, sawmill chips and sawdust), while GFTM covers 10 final products, 4 intermediate products, and 4 primary products. While all models cover the global forest sector, they differ in how they treat countries or global regions. For example, GFPM covers 180 individual countries, while EFI-GTM and GFTM cover individual EU countries and group countries for the rest of the world.

Table 2.4. Overview of existing partial equilibrium models

Model	Full name	Bioeconomy Sectors	Resolution	Reference
Aglink-COSIMO*	Aglink-COSIMO	A01, C10, C11	Regional - National	OECD and FAO, 2015
AGMEMOD*	Agriculture Member State Modelling	A01, A03, C10	Regional - National	Salamon et al. 2017
CAPRI*	Common Agricultural Policy Regional Impact	A01	Regional - National	Britz et al. 2014

Model	Full name	Bioeconomy Sectors	Resolution	Reference
EFI-GTM	European Forest Institute Global Trade Model	A02, C16, C17	National - Continental	Kallio et al. 2004
ESIM	European Simulation Model	A01, C10	National - National	Grethe et al. 2012
GLOBIOM	Global Biosphere Management Model	A01, A02, C16, C17	Regional - Continental	Ermolieva et al. 2015
GFPM	Global Forest Products Model	A02, C16, C17	National - Continental	Buongiorno et al. 2003; Buongiorno, J., 2014
GFTM*	Global Forest Trade Model	A02, C16, C17	National - Continental	Jonsson et al. 2015; 2017; 2018
IMPACT	International Model for Policy Analysis of Agricultural Commodities and Trade	A01, C10, C11	Regional - National	Robinson et al. 2015
MAGPIE	Model of Agricultural Production and its Impact on the Environment	A01, A02, A03, C10, C11	Regional - Continental	Dietrich et al. 2018
Oemof	Open Energy Modelling Framework	D35, D3511, C20	Local - Multinational	Hilpert et al. 2018
PLEXOS	PLEXOS Integrated Energy Model	D35, D3511, C20	Local - Multinational,Continental	-
POTEnCIA*	Policy Oriented Tool for Energy and Climate Change Impact Assessment	D35, D3511, C20	National - National	Mantzos et al. 2017
PRIMES	Price-Induced Market Equilibrium System	D35, D3511, C20	Regional - National	Capros, 2018
POLES*	Prospective Outlook on Long-term Energy Systems	D35, D3511, C20	National - National	Criqui 1996
TIMES*	The Integrated MARKAL-EFOM System	C19, D35, D3511	Local - National	Loulou et al. 2005
BALMOREL	-	D35, D3511, C20	Local - Multinational	Wiese et al. 2018
PROMETHEUS	-	D35, D3511, C20	Multinational - Multinational	Fragkos et al. 2015

**Model applied by JRC*

Other economic models

There are additional economic models that cannot be classified as a CGE or PE model. Models like FARMIS and MARKAL are bottom-up optimization models for the agricultural and energy sectors, respectively. The models include relatively a lot of biophysical and technical details.

Table 2.5. Overview of other existing economic models

Model	Full name	Bioeconomy Sectors	Resolution	Reference
ENPEP-BALANCE	Energy and Power Evaluation Program	D35, D3511, C20	Regional - Multinational	Energy and Power Evaluation Program 2008
GINFORS	Global INterindustry FORecasting System	D35, D3511, C20	National - Multinational	Lutz et al. 2010
WEM	World Energy Model	D35, D3511, C20	National - Multinational	Kato 2002
FARMIS	Farm Modelling and Information System	A01	Regional - National	Ehrmann 2017; Deppermann et al. 2014
IFM-CAP*	Individual Farm Model for Common Agricultural Policy Analysis	A01	Local - National	Louhichi et al. 2015
MARKAL	MARKet ALlocation	C20, D3511, Others (depending on version): Heat, road transport, aviation, petro-chemical, bio-based chemical, other energy-intensive industries.	Local - National	Loulou et al. 2004; Zonooz et al. 2009

**Model applied by JRC*

2.2.2 Environmental models

Biophysical models

Biophysical models are one class of environmental models, which aim to capture biophysical processes, such as crop or tree growth dynamics, as affected by climate, water and nutrient availability and other environmental conditions. These models generally provide relevant information on crop or tree productivity or biomass availability from agriculture or forestry, but they generally do not address the economic activities themselves. Furthermore, these models often allow for understanding environmental impacts of economic activities, as well as addressing ecosystem services and non-market activities.

EPIC, MITERRA and PRISM-ELM are biophysical models that mostly focus on agricultural soils and crops. They generally consider detailed information on climate and nutrient availability in the soils and provide information on crop productivity.

CBM-CFS3, EFDM, EFISCEN and G4M are biophysical models that mostly focus on forest resources. They generally consider data on forest productivity as input and project the development of forest resources. These models can be used to assess biomass availability from forests, but also provide insight in how policy and management effects may affect carbon stocks and sinks in forests, and other forest-related indicators and ecosystem services (incl. biodiversity).

INVEST is developed to assess how changes in ecosystems are likely to change their benefits to society. The model assesses the impact of a variety of different ecosystems (e.g., carbon and habitat quality) employing a production function approach to quantify and value ecosystem services.

Table 2.6. Overview of existing biophysical models

Model	Full name	Bioeconomy Sectors**	Resolution	Reference
A4a*	Assessment For All	A03	NA (>250 fish stocks)	Millar et al. 2012; Jardim et al. 2014
CBM-CFS3*	Carbon Budget Model of the Canadian Forest Sector	A02	Local - Continental	Kull etal. 2016; Kurz et al. 2009
EPIC*	Environmental Policy Integrated Climate Model	A01	Regional - Continental	Balkovič et al. 2013
EFDM*	European Forest Dynamics Model	A02	Regional - Continental	Vauhkonen and Packalen 2017
EFISCEN	European Forest Information SCENario model	A02	Regional - Continental	Verkerk et al. 2017; 2019
G4M	Global Forest Model	A02	Regional - Continental	Kindermann et al. 2008
INVEST	Integrated Valuation of Ecosystem Service and Tradeoffs	User defined	Local - National	Sharp et al. 2018
MITERRA	Miterra-Europe	A01, A02	Regional - Continental	Lesschen et al. 2011; Velthof et al. 2009
PRISM-ELM	Parameter-elevation Regressions on Independent Slopes Model Environmental Limitation	A01	Local - National	Daly et al. 2018

**Model applied by JRC*

***The NACE classification on economic activities is not directly applicable to environmental models. The NACE classification is here used to broadly indicate which bioeconomy activities are addressed, while acknowledging environmental models address also other activities not covered by NACE*

Land use and cover and other environmental models

Land use and land cover models are designed to describe land use dynamics in a spatially explicit manner using information about land availability, land suitability, proximity to infrastructure, as well as other environmental and socio-economic factors. Existing models include the empirical-statistical model Dyna-CLUE, the dynamic simulation model CLUMondo and the Land-Use based Integrated Sustainability Assessment tool LUISA. The former class of tools attempts to identify explicitly the causes of land-cover changes through regression-like analyses of possible exogenous contributions to empirically derived rates of changes, whereas with the latter type of models, patterns of land-cover changes in time and space are produced by interacting biophysical and socio-economic processes.

Table 2.7. Overview of land use and cover and other environmental models

Model	Full name	Bioeconomy Sectors**	Resolution	Reference
CLUMondo	Conversion of Land Use and its Effects model	A01, A02	Local - Continental	van Asselen and Verburg 2013
Dyna-CLUE	Dynamic Conversion of Land Use and its Effects model	A01, A02	Local - Continental	Verburg and Overmars 2009
LUISA*	Land Use-based Integrated Sustainability Assessment	A01, A02	Local - Continental	Lavalle et al. 2015
ToSIA	Tool for Sustainability Impact assessment	User defined	Local - National	Lindner et al. 2010.
DSK model	Dystopian Schumpeter meeting Keynes model	D35, D3511, C20	Global - Global	Lamperti et al. 2018
MADIAMS	Multi-actor dynamic integrated assessment model	All economy modelled as one aggregated sector	Multinational - Global	Hasselmann et al. 2013

**Model applied by JRC*

***The NACE classification on economic activities is not directly applicable to environmental models. The NACE classification is here used to broadly indicate which bioeconomy activities are addressed, while acknowledging environmental models address also other activities not covered by NACE*

2.2.3 Integrated assessment models

Several IAMs exist, of which few cover all sectors of the bioeconomy (Table 2.8). A well-known IAM is the IMAGE 3.0 model (Stehfest et al. 2014). It embeds many models such as the MAGNET CGE model for agricultural developments, the TIMER energy model and the LPJML crop growth model. The MESSAGE model (Krey et al. 2016) is developed for strategic energy planning and integrated assessment of energy-engineering-economy-environment systems. The model forms the core of the MESSAGEix framework, which can be applied to analyse scenarios of the energy system transformation under technical-engineering constraints and political-societal considerations. The model can be linked to the general-economy MACRO model to incorporate feedback between prices and demand levels for energy and commodities. The Remind model is often used in combination with the Magpie PE model.

The integration of models from different disciplines comes at a price. Linking fundamentally heterogeneous tools poses some serious methodological questions concerning the specification of the underlying models (i.e., the above-mentioned simplifications), how to link model components, overcoming computational complexities, etc. (Varacca et al. 2020). On the other hand, allowing for information exchange between socio-economic and biophysical models provides a means to address trade–offs and synergies of policy strategies at a global scale, over a long period of time. Moreover, the involvement of researchers belonging to different areas could foster interdisciplinary model development and research in general.

Table 2.8. Overview of Integrated Assessment models

Model	Full name	Bioeconomy Sectors	Resolution	Reference
DNE21+	Dynamic New Earth 21	D35, D3511, C20	National - Multinational	Akimoto et al. 2010
E3ME-FTT-GENIE*	-	All economic activities	National - Continental	Mercure et al. 2018
ETSAP-TIAM	The TIMES Integrated Assessment Model	D35, D3511, C20	National - Continental	Loulou et al. 2008
GCAM	Global Change Assessment Model	A01, D35	National - Continental	-

Model	Full name	Bioeconomy Sectors	Resolution	Reference
IMAGE 3.0	Integrated Model to Assess the Global Environment	A01, D35, A02	Local - Regional	Stehfest et al. 2014
IFs	International Futures	All economic activities	Regional - Multinational	Hughes et al. 2019
MEDEAS	Modeling the renewable energy transition in europe	All economic activities	National - Multinational	Capellán-Pérez et al. 2020
REMIND	Regional Model of Investments and Development	All economic activities, but as single sector	Continental - Continental	Leimbach et al. (2010)
WITCH	World Induced Technical Change Hybrid model	All economic activities	Multinational - Multinational	Bosetti et al. 2006
IMACLIM-R	0	D35, D3511, C20	National - Multinational	Sassi et al. 2010

**Model applied by JRC*

2.2.4 Specialist models

Specialist models deal with a wide variety of specific (often technical) aspects of biomass production, conversion, and use. The BeWhere model is a clear example of this group of models. It is a spatially-explicit techno-economic model, which was originally developed for optimizing the capacity and localization of bioenergy facilities. The model minimizes the production cost and the total emissions of the whole supply chain. The model uses input on biomass cost-supply, the conversion technology specifications, the logistical and pre-treatment technologies, and the demand categories. ETM, LEAP, MESSAGE and OSeMOSYS are other specialist models with a focus on energy. SIMFISH is a simulation model for fisheries behaviour that optimises the effort allocation to maximize annual profit for a consecutive number of years. This bio-economic model includes feedback loops between the biology of the stocks represented in the model and the behaviour of fisheries in the short run (effort allocation), as well as in the long run (entry-exit in the fishery).

Table 2.9. Overview of specialist models

Model	Full name	Bioeconomy Sectors	Resolution	Reference
BEWHERE	BEWHERE	D35, D3511, C20	Regional - Continental	Leduc 2009
ETM*	Energy Transition Model	D35, D3511, C20	Local - Continental	van Lelyveld 2010
LEAP	Long-range Energy Alternatives Planning	D35, D3511, C20	Local - Multinational	Heaps 2020
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental impact	C19, D35, D3511	National - Continental	Krey et al. 2016
OSeMOSYS	The Open Source Energy Modeling System	D35, D3511, C20	Local - Multinational	Howells et al. 2011
SIMFISH	Spatial Integrated bio-economic Model for FISHeries	A03	Local - Local	Bartelings et al. 2015

**Model applied by JRC*

Box 2. Overview of bioeconomy applications of existing models

Existing models have been used alone or in cooperation with other models to study different aspects of the bioeconomy transition.

ESIM has been applied to evaluate agricultural market impacts of biomass demand for food, feed, and perennial biomass crops under different bioeconomy scenarios to achieve a 75% GHG-reduction target in the EU until 2050 (Choi and Entenmann, 2019). Focusing on the production of biodiesel in the EU, Junker et al. (2015) used the MAGNET and the CAPRI models to investigate the potential effects of the withdrawal of rapeseed oil from the biodiesel industry in EU Europe. Frank et al. (2016) applied the GLOBIOM model in combination with G4M to estimate current and future CO_2 emissions from LULUCF in the EU used to generate an updated European Reference Scenario. GLOBIOM, G4M and EFISCEN were linked to estimate future CO_2 emissions and removals from forestry activities (Böttcher et al. 2012). The EFI-GTM model was coupled with the FORMIT-M forest growth model to assess the impacts of EU forest management strategies on climate mitigation potential (Härkönen et al., 2019). Jonsson et al. (2018, 2020) combined the GFTM with the CBM models to make an outlook of the European forest-based sector until 2030, considering forest growth, harvest demand, wood-product markets, and forest carbon dynamics. MIRAGE was used by Brinkman et al. (2018) to study the potential ILUC related to rapeseed production for biodiesel conversion in Romania and Gerssen-Gondelach et al. (2016)) the ILUC-risk of miscanthus-based bioethanol in Poland. Somé et al. (2018) combined LCA and EEIO with the GTAP model to evaluate the effect of large-scale biofuel policies in terms of potential indirect environmental effects, including land-use changes. Smeets et al. (2014) used the MAGNET model to assess the macroeconomic impacts of the deployment of second-generation biofuels, biochemicals, bioelectricity and biogas. M'barek et al. (2019) applied the MAGNET model to quantify different medium- to long-term market outlooks for the European and global bioeconomy. The authors designed and simulated transition pathways to 2050 and analysed the contribution of the bioeconomy to the Sustainable Development Goals.

Tsiropoulos et al. (2017) explored potential least-cost pathways to 2030 in the case of the energy system of the Netherlands. This study assesses the potential effects of bioenergy (with and without CCS) on the evolution of the bioeconomy. Schulze et al. (2016) combined a spatially explicit economic simulation model with InVEST to assess the impact of land-use decisions on provisioning and regulating ecosystem services and biodiversity. With regard to the effects of dietary changes on emissions, Westhoek et al. (2014) explored the impact of replacing 25-50% of animal-derived foods with plant-based foods, assuming corresponding changes in production in the EU case. The EFISCEN model was used to assess the potential availability of woody biomass in 39 European countries (Verkerk et al. 2019) and coupled with the EFI-GTM model to develop an outlook of the entire European forest sector (UNECE-FAO 2011). The CBM-CFS3 model has been linked with the GFTM model as well as EVA (forest ownership behavior model), POLES and LUISA to build an integrated forest-based bioeconomy modelling framework (Mubareka et al., 2014). Bertram et al. (2018) introduced a broad suite of mitigation policy options—including direct sector-level regulation, early mitigation action, and lifestyle changes—into the integrated energy-economy-land-use modelling system REMIND-MAgPIE.

2.2.5 Features of existing bioeconomy models

In this section, we summarize the information that is provided by the 62 models that have been reviewed. A suite of model types exist that can model the development of (part of) the bioeconomy (Figure 2.2a). Most of the models reported in the literature are economic models and partial equilibrium models are the most common type of all models identified to model the development of the bioeconomy. Seven CGE models have been identified in the literature that cover the entire economy; three of these provide detailed information on all economic sectors and the other four consider all economic activities but focus on energy. We identified six specialist models and a similar number of environmental models (13) and IAMs (12) and biophysical models are most common in the group of environmental models.

For each of the models, their coverage of bioeconomy sectors has been identified in accordance with the Nomenclatures of Economic Activities (NACE). We focused on 24 economic sectors and activities that are considered to belong to the bioeconomy (Kardung et al. 2021; Varacca et al. 2020). The NACE classification is here used to broadly indicate which bioeconomy activities are addressed, while acknowledging environmental models also address other activities not covered by NACE. The supply and production of (bio-)energy (see also Box 3), the manufacture of chemicals and the agriculture and forestry sectors are the five sectors that are most covered by existing models, followed by the manufacturing of food, wood and paper products (Figure 2.3). The relatively high coverage of the first three sectors in this list is clearly influenced by the large number of energy models included in the review. Many of these models address the chemical sector, but they mostly focus on energy questions related to the sector, rather than the products that are produced. The dominance of models focusing on agro-food most likely relates to the importance of the sector to the bioeconomy. Furthermore, the reviewed models generally poorly covered the aquaculture and fishing sector, as well as the manufacturing of textiles, leather and wearing apparel, as well as the pharmaceuticals and plastics. It must be stressed that this type of analysis can only be used to give a quantitative overview of the covered sectors (i.e., which one are addressed) and not a qualitative indication (how comprehensively each sector is covered). For example, while the number of models covering the chemical sector is relatively high, in the same models this sector is described quite rudimentarily by including just one or a few products (often biofuels). It is also important to note that, firstly, many sectors appear to be addressed by the existing models, but these models often do not capture the sector as a whole, but typically focus on a subset of products. Secondly, environmental models capture important activities related to each sector, but - by their design –do not provide economic information. Thirdly, while many sectors are captured by the models, the models may not distinguish between bio-based products and activities vs. activities based on non-renewable, non-bio-based products.

The existing models vary in terms of their spatial resolution (Figure 2.2b). Almost all existing models could produce outputs at the national level, while about 60% of the models could also deliver results at the sub-national level (regional). Approximately one-third of the models could produce results at a spatial resolution as fine as local.

Figure 2.2c depicts the temporal coverage of the 62 models found in the literature, based on the difference between the base year considered by each model and the maximum temporal horizon each model allowed to consider. The period between 2010 and 2050 are covered by most models, while few covered the longer time horizons (e.g., up to 2100). The models with no bars have a user-defined timeframe, so it is not possible to represent their timespan. Most of the models have a time-step of one or five years.

Another important evaluated feature was the extent of the model accessibility (Figure 2.2d). Accessibility determines to what extent models are made available to other researchers or users and relates to the transparency of the models, when the full source code is made available. It should be noted, however, that when the source code of a model is not available, it does not mean the model is not transparent as its equations may be available from supporting documentation. Figure 2.2d shows that 37% of the models are completely (29%) or partially accessible (8%) to (expert) users. Another 29% of the models have restricted access, which means that only model holders and associated institutions could run the models and had access to the source code. The remaining models were either not accessible or no information was retrievable from the documentation.

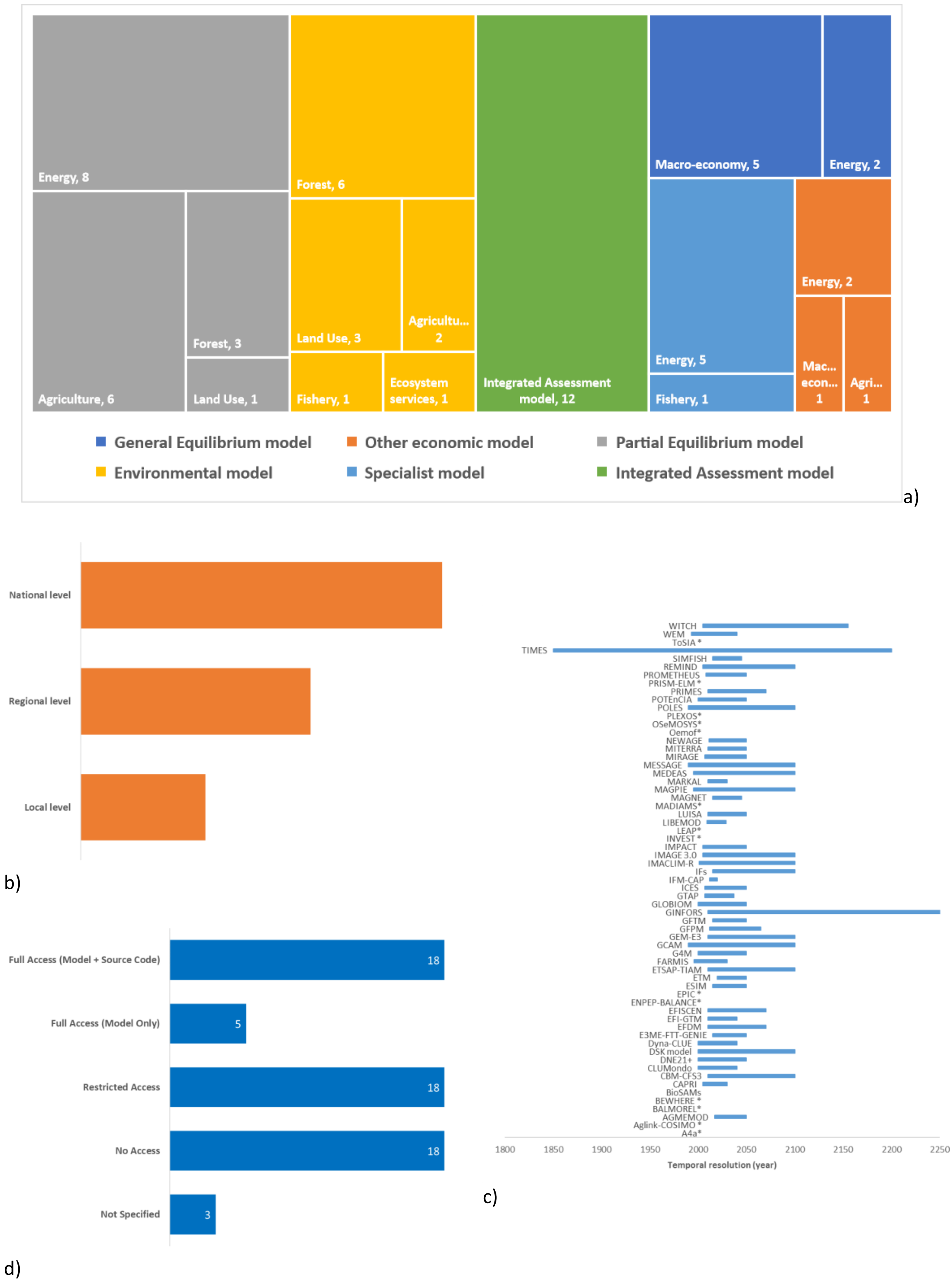

Figure 2.2. Overview of features of existing bioeconomy models (updated from Varacca et al. 2020) based on (a) model types with number of models in each sub-category; (b) models' spatial resolution (local resolution refers to a surface as small as a farm unit, or up to a 10 km x 10 km spatial grid); (c) models' temporal resolution (* indicates that temporal resolution is user-defined); and (d) accessibility of models.

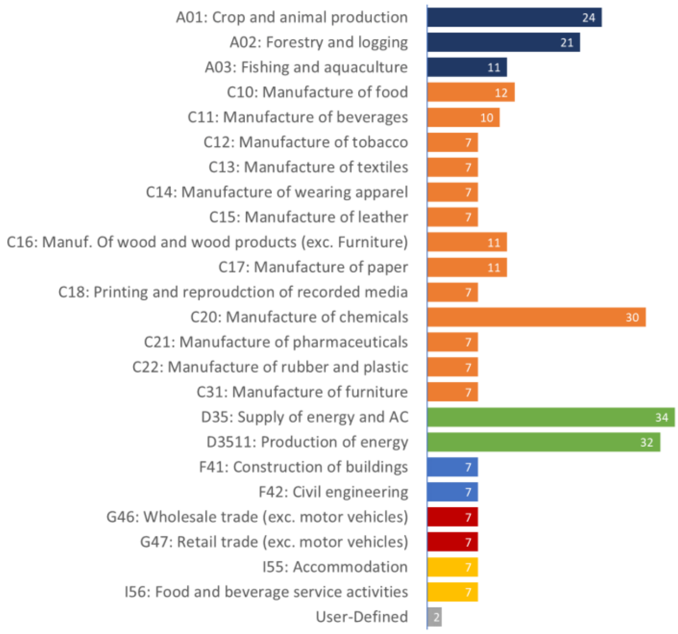

Figure 2.3. Coverage of bioeconomy sectors by models. Note that Computable General Equilibrium models cover all bioeconomy sectors (updated from Varacca et al. 2020).

Box 3. Coverage of key bioenergy issues by different categories of models

Numerous energy models exist and below a summary is provided how different types of energy models address the main bioenergy related themes and thus those relevant for the bioeconomy. From the summary it is clear that each modelling approach suffers from limitations that are intrinsic to their design. For example, the IAMs' strength of capturing as much as possible the interaction between the bio and the ecosphere is counterbalanced by the unavoidable coarser representations of the system, which filter through the generated results. CGE and PE are based on key assumptions (e.g., price changes) and focus on certain specific sectors or economic activities. PE models, for example, cannot analyse the broad interactions caused by new policies due to their sectorial scope. The high focus of the specialist models often also represents their limit since they generally lack the consideration of more macro-scale effects and feedbacks occurring in broader real-life systems. There is no such thing as a model that can cover all the energy-related issues but, the most suitable model family must be chosen based on the main goal of the analysis.

Summary of key bioenergy issues covered by different categories of energy models (Welfle et al. 2020). The summary is based on the abstract of about 124 thousand papers and a keyword search.

Themes	**Keywords**	**Energy System Models***	**IAMs**	**Specialist Models**
Bioenergy Feedstocks	Forestry	●●●	●●●	●●●
	Algae	●●	●	●
	Briquettes	●	X	X
	Pellets	●	●	●
	Chips	●	●	●
	Wood	●●	●●●	●●●
	Wastes	●●	●●	●●
	Residues	●●●	●	●●
	Lignocellulosic	●	●	●●
	Energy Crops	●	●●	●
	1st Generation	X	●	●
	2nd Generation	●	●	●
	3rd Generation	X	●	X
Bioenergy Processes & Technologies	BECCS & CCS	●●	●●●	●●
	Combustion	●	●●	●

	Pyrolysis	●●	●	●
	Gasification	●●	●●	●●
	Torrefaction	X	X	X
	Anaerobic Digestion	●	X	X
	Co-firing	X	●	●
	Thermo-chemical	X	●	X
	Catalysis	●●	●	●
	Bio-chemicals	●●	●	●●
	Fermentation	●●	X	●●
	Drying	●●●	●●●	●●●
	Chipping	X	X	X
	Pelletising	X	X	X
Bioenergy Systems Issues	Bioeconomy	●●	●●	●●
	Environment	●●	●●	●●
	Emissions & GHGs	●●●	●●●	●●
	ILUC	X	X	X
	Sustainability	●●	●●	●●
	Climate Change	●●	●●	●●
	Yields & Productivity	●●	●●	●●
	Trade	●	●	●
	Water	X	X	X
	Deforestation	●	●	X
	Forestation	●	●	●
	Ecosystems & Biodiversity	●●	●	●●
	Jobs, Training & Skills	●	●	●
	Land Use	●●	●●	●●
Bioenergy Vectors	Bio-Power	●●	●●	●●
	Bio-Heat	●	●	X
	Transport Biofuels	●●	●●	●
	Aviation	X	●	X
	Heavy Goods Haulage	X	X	X
	Maritime	X	X	X
	Bio-chemicals	●	X	●
	Bio-Syngas	X	●	X
	Ecosystem Services	●	●	●

Explanation: X: issue not addressed ●●●: issue generally addressed ●●: issue sometimes addressed ●: issue rarely addressed.
*This includes PE and CGE models but also other bottom-up optimization and accounting models

2.2.6 Model cooperation

The cooperation between different approaches (model types) and the linking of models provides a possible way to move beyond the typical sectoral focus of models and platforms are being developed to facilitate such efforts (e.g., Integrated Modelling Partnership (http://www.integratedmodelling.org/). Such cooperation offers possibilities to reduce some of the shortcomings and knowledge gaps in existing models (see also section 2.3) and strengthen the ability to project (both directly and indirectly) the impacts of the emerging bioeconomy. Thereby, model collaboration can aid in improving the quality of information for policymakers and contribute to better-informed decision-making (Wicke et al. 2015). Model cooperation can help assess issues that involve multiple economic sectors, different temporal, and spatial scales and/or various impact categories and their linkages and trade-offs. Wicke et al. (2015) identify three forms of model collaboration (Figure. 2.4).

- Alignment and harmonization of models focus mainly on input data, level of aggregation, and scenario definitions.
- Comparison of models focuses on the methods, representation and parameterization of bioeconomy, assumptions and uncertainties in input data, and/or on results and sensitivities to uncertainties in underlying data and approaches.
- Integration of models takes collaboration a step further and it can thereby provide a more comprehensive picture of the impacts of a certain policy or development. Model linkages can be of a number of forms, including using the results from one model as input to another model, iterating inputs from different models, partially integrating models by using a simplified form of one model in another model or fully integrating models and solving them simultaneously

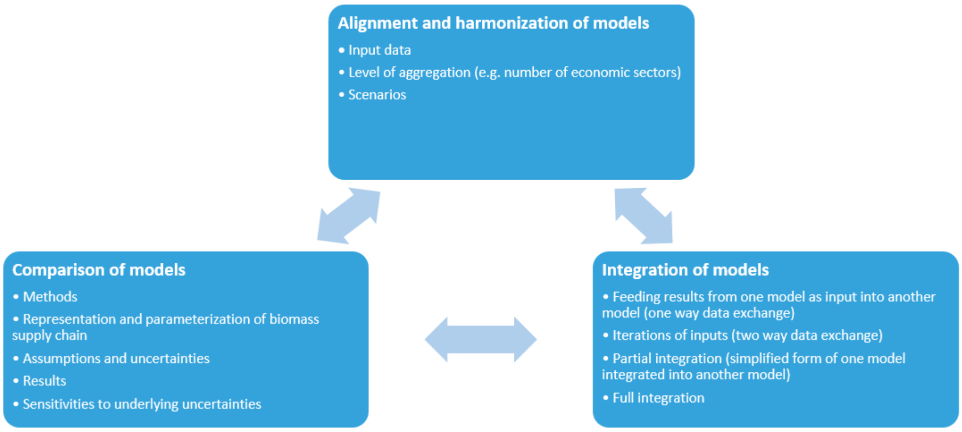

Figure 2.4. Typology of model collaboration. Redrawn from Wicke et al. (2015).

The three forms are interrelated in such a way that, for example, model comparison can guide and improve alignment and harmonization of models. Conversely, under the condition of harmonized input data and scenarios, model comparison allows a better understanding of the results, its drivers and the differences across models. Model cooperation can also reveal information about the robustness of the results when tested under different paradigms, about model biases and artefacts, and about strengths and weaknesses of different approaches (Wicke et al. 2015). Thereby, model comparison can be used to further improve and calibrate the individual models. Model comparison can also help expose the causes of differences and similarities in model output, which is important for interpreting the results for policy making.

Integration of models has also its drawbacks. The linking of different models and sources, for example, can contribute to propagating errors between modelling tools, potentially increasing the uncertainty of the results significantly. It is important to be careful in this exercise and find the proper balance to avoid making the whole effort of limited use due to the excessive uncertainty of results.

As shown in Table 2.10, model integration can be performed in different ways and efforts have been made to develop linkages between models to overcome shortcomings related to the sectoral focus of models and to assess policy questions related to the bioeconomy. IAMs are clear examples of partially or fully integrating different modelling approaches. However, the more generic model collaboration discussed here can also refer to the cooperation between two or more stand-alone models, which does not require the analysis to be conducted in one integrated system. 'Soft linkages' have been developed in the past by harmonizing common input variables to the models and using one model results of one model as input to the other. 'Hard linkages' are of a more systematic nature requiring that model results converge through multiple iterations of exchanging results between models (see e.g., Jansson et al. 2008). The latter approach is quite resource intensive.

Table 2.10. Model integration methods and their advantages and disadvantages. Modified from van Vuuren et al. (2012)

Method	Advantages	Disadvantages
A: Off-line information exchange (one-way)	• Work with existing terminology and tools • Transparent information exchange • Flexibility • Separate research strategies	• Feedback are only captured via (one-single) iterations • Potential inconsistencies
B: Improved socio-economic models)	• Allows for good representation of uncertainty • Model complexity tailored to question • Detail in treatment of socio-economic processes	• Lack of detail in treatment of biophysical processes (often meta-modelling)
C: Improved natural systems models	• Higher resolution analyses than in B • Detail in treatment of biophysical processes	• Lack of detail in treatment of socio-economic processes • Limitation of model runs limits representation of uncertainty
D: Full coupling (two-way)	• Assessment of feedback • Highest degree of consistency	• Technical difficulties • Lack of representation of uncertainty • Inflexibility • Complexity/intransparency • Limitations in knowledge may hamper progress

Several examples exist where sectoral models have been linked to each other, with relevance to bioeconomy modelling. One such example of model cooperation is the agricultural model intercomparison project (Agmip) where various crop models, livestock models, global gridded land use models, regional economic models and global economic models cooperate. CAPRI, MAGNET, Magpie and Globiom participate in the collaboration project. Examples exist also for the forestry sector in which biophysical forest resource models are linked with forest sector partial equilibrium models for example, CBM with GFTM (Mubareka et al. 2014; Jonsson et al. 2015; 2016; 2017; 2018; 2020), EFISCEN with EFI-GTM (UNECE 2011; Verkerk et al. 2014; 2018) and G4M with GLOBIOM (e.g., Böttcher et al. 2012). In another initiative, soft-linkages were realised between a suite of models to cover the entire land use sector (Figure 2.5); CGE models (Remind/MagPie and MAGNET) provided drivers such as economic growth or technology change to PE models (CAPRI and EFI-GTM) and calculated changes in agricultural production were used in Dyna-CLUE to project land use change, which affected forest area in EFISCEN. EFISCEN then provided wood harvesting potentials to EFI-GTM. The modelling framework was used to assess policy impacts (Lotze-Campen et al. 2018) and identify pathways to envisioned, future land uses (Verkerk et al. 2018).

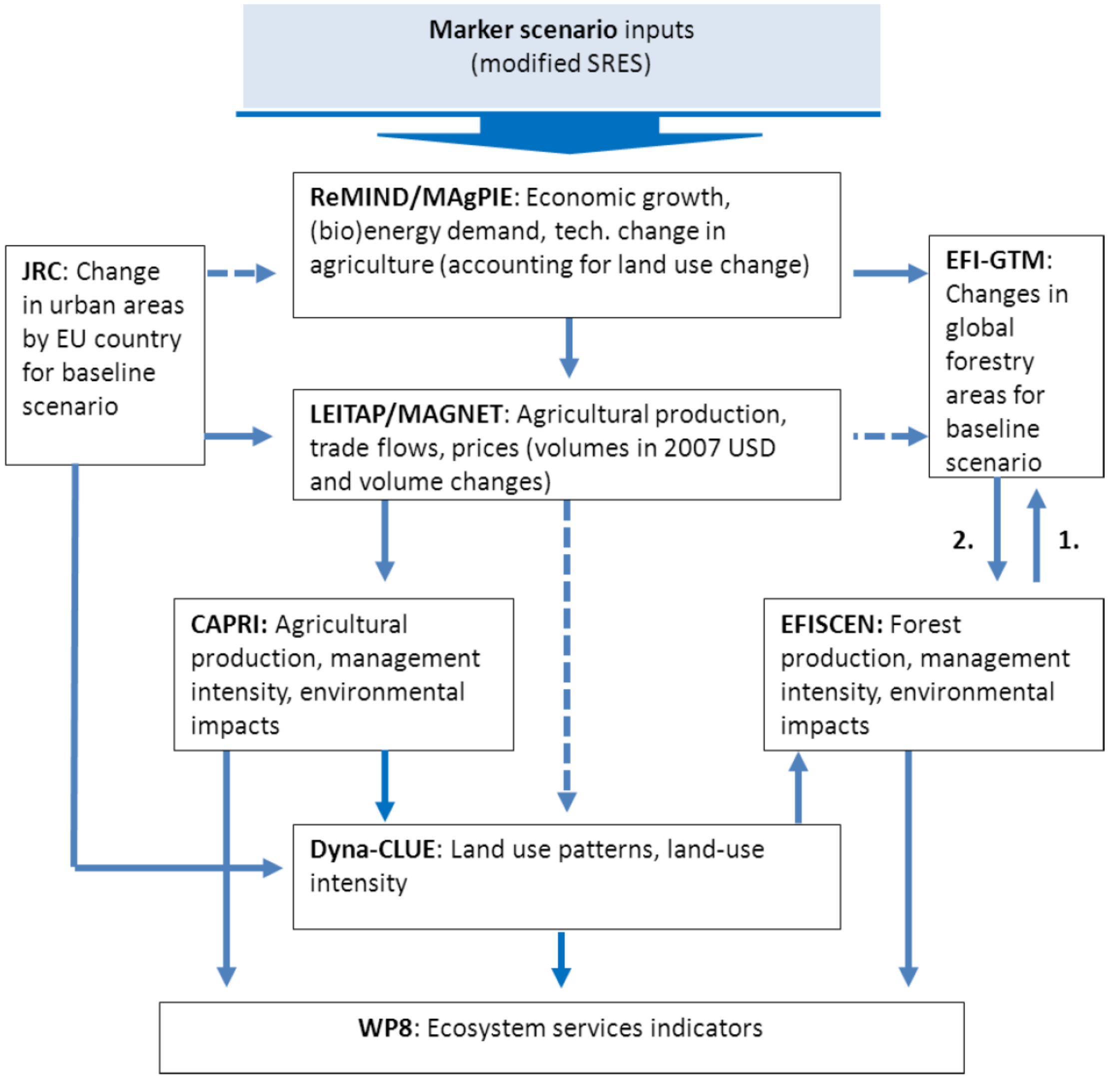

Figure 2.5. Model linkages realised in the VOLANTE project (Lotze-Campen et al. 2018; Verkerk et al. 2018) to capture scenario impacts on land use and their effects of ecosystem service provisioning.

The full coupling of models represents the most advanced type of model cooperation (Calvin and Bond-Lamberty, 2018), allowing for the two-way interaction between the (ensemble of) models and, as such, for the full endogenization of the feedback mechanisms. IAMs are currently mostly one-way coupled models in which resource use and emission levels, which are some of the input of the modelled earth system variables (e.g., temperature) are, among others, determined by the projected socioeconomic variables such as GDP growth. The estimated changes in temperature, resource availability etc. cannot, in turn, affect the modelled socioeconomic sphere, being them exogenous to the models. Two-way coupled modelling, on the contrary, can shed light on complex and, sometimes, also new mechanisms difficult to find when investigated separately. Such a bidirectional modelling can also bring to unexpected and sometimes counterintuitive results consequence of the nonlinear dynamic of feedback, which also represent their real added value. As the same authors found, the feedback effects across the reviewed models are variable, ranging from being very influential to negligible for certain aspects. It must be however noted that the development of such coupled models is complex and extremely expensive, contributing to hinder their widespread development and adoption (Verburg et al., 2016). The computational cost of running this type of integrated analysis can also be prohibitive, limiting their adoption and type of feedback and scenarios studied. Just to give an example, the work of Thornton et al. (2017), which studied how energy, agriculture, land, and carbon will be influenced by the climate-land feedback, required approximately 500,000 processor hours per simulation on a supercomputer. It must be also noted, however, that Thornton et al. (2017), as many other scholars, used earth system models (Flato, 2011) to simulate the environmental component. This family of models are certainly detailed but also complex and computationally expensive. Being important to study the impact of these feedback, but not being the focus of policy-oriented bioeconomy modelling, it would certainly be advisable to use more simplified models. Climate emulators and other types of simplified climate tools such as the BernSCM (Strassmann and Joos, 2018) and the SimMod (Smith et al., 2018) models, are certainly more suitable. In fact, despite being simpler and less computationally expensive, they still allow for the consideration of the two-way feedback of altered anthropogenic emissions in the studies scenarios.

Efforts are ongoing to cover the disconnection between environmental and economic issues. Examples of such efforts are the inclusion of the value of nature in economic modelling or how changes in environmental conditions may affect the economy (e.g., climate change affecting biomass feedstock quantity and quality, Nelson et al. 2013, Van Meijl et al. 2018b). Economic (CGE) and integrated assessment models have recently been combined with biodiversity models to assess the possibility to reverse the trend of decreasing biodiversity by several kinds of measures (nature conservation, reducing food waste, productivity changes and diet shifts) without compromising food security (Leclere et al 2020).

2.2.7 Other relevant tools

The models described above are part of a rich set of tools, approaches and methods to conduct sustainability impact assessments. There is abundant literature on sustainability assessment tools, approaches and methods that are useful to measure the progress towards the UN Sustainable Development Goals (SDGs) and answer other major policy questions. Figure 2.6 summarizes existing tools based on their objectives, temporal focus, and coverage (Ness et al., 2007).

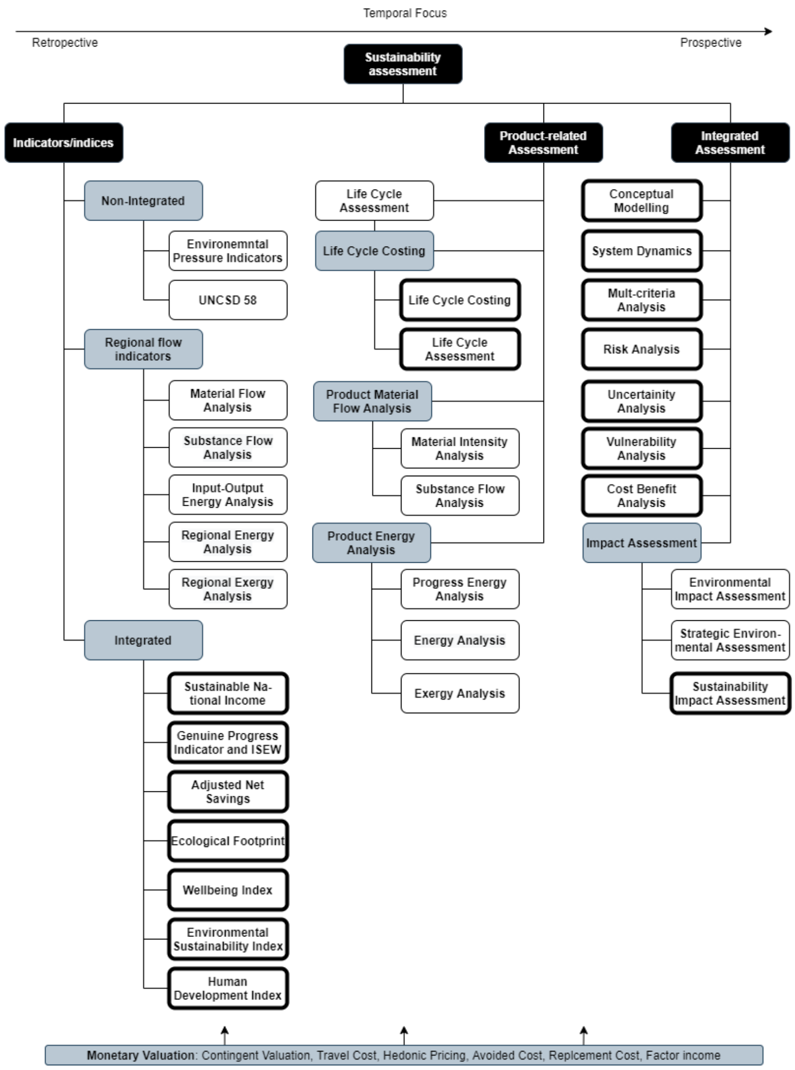

Figure 2.6 Framework for sustainability assessment tools based on the temporal focus of the tool along with the object of focus of the tool. The arrow on the top of the framework shows the temporal focus, which is either retrospective (indicators/indices), prospective (integrated assessment) or both (product-related assessment). The object of focus of the tools is either spatial, referring to a proposed change in policy (indicators/indices and integrated assessment), or at the product level (product-related assessment). The monetary valuation tools on the bottom are used when monetary valuations are needed in the above tools. Thick lines around the boxes mean that these tools can integrate nature–society systems into single evaluation. Redrawn from Ness et al. (2007).

Life Cycle Assessment (LCA)[2], Material Flow Analysis (MFA) and Input-Output Analysis (IOA) are approaches of high relevance in assessing the development of the bioeconomy (e.g., O'Brien et al. 2017) and complement the use of models (Acs et al. 2019). Input-output tables are the backbone of several of the reviewed models (e.g., MEDEAS, GINFORS) and MFA data are often used as primary source of information for materials consumption and extraction data in several models (e.g., E3ME-FTT-GENIE). LCA, MFA and IOA play an important role in helping to evaluate the progress toward the SDGs and how policy actions address sustainability. Box 4 describes how these tools and approaches can supplement bioeconomy modelling.

Process-based LCA is probably the most widely used sustainability assessment tool. LCA is a structured and comprehensive method to assess the sustainability impacts associated with products, processes, and systems throughout their entire life cycle (i.e., from raw materials extraction to the end of life). The holistic nature of the life cycle-based approaches makes them particularly suitable to mitigate the risks of burden-shifting and sub-optimization of the available resources when comparing different options. The method has been, in fact, also used to assess the environmental impact of bioeconomy sectors and commodities, as for example in the JRC biomass study (European Commission and Joint Research Centre, 2018). An interesting example of LCA tool that can be used in the bioeconomy context, also at EU scale, is the Bioeconomy AGE (Air emissions, Greenhouse gas emissions, and Energy consumption) model developed from the Argonne National Laboratory. The model was used to estimate the energy and GHG emissions of the bioeconomy in the US as compared to an all-fossil case (Rogers et al., 2017).

Material flow analysis (MFA) focuses on the systematic tracking of the flows and stocks of material and/or substances from extraction to disposal within our socioeconomic (e.g., productive, economic, or social) systems. By using this methodology, the material or substance flow through the whole economic system can be understood and it can thus help in: (i) determining critical pathways where losses or inefficiencies of resources occur; (ii) optimizing material use and processing and (iii) building meaningful and simple indicators to improve the sustainability of resource extraction and use. This method has already been used to serve the cause of EU bioeconomy transition as a whole (Gurria et al., 2017) or for individual sectors (Mantau, 2015; Cazzaniga et al., 2019) and MFA tools like DPMFA (Bornhöft et al., 2016) exist already.

In Input-Output Analysis[3] (IOA), the structure of the economy is described and analyzed in terms of the interactions, both among industries and between them and households. Compared to MFA, IOA allows not only to illustrate the flows of resources in the economy, but also between the economic and the industrial sectors. Also, the input-output methodology has been directly used to estimate the socio-economic impacts of the bioeconomy transition in the EU (see e.g., Asada et al., 2020; Budzinski et al., 2017). Besides forming the basis of the overall database in General Equilibrium models, Input-Output (I-O) and Social Accounting Matrix (SAM) models are often separately, on an ad-hoc basis, used for assessing the impact of a change in the demand conditions for a given sector in a given regional economy. The Social Accounting matrices for the Bioeconomy (hereafter BioSAMs) (Mainar Causapé and Philippidis, 2018) represent an important tool for understanding the structure and the revenue flows among the commodities, activities, factors, and institutions pertaining to the Bioeconomy (these also include households and governments). In addition, BioSAMs (and SAMs in general) serve as inputs for calibrating most economic equilibrium models and allow multiplier analysis in multi-sector linear models.

The strengths and weaknesses of these four approaches are summarized in Table 2.11. These approaches can be used in combination or even merged, as in the hybrid LCA approaches (Crawford et al., 2018) and sometimes they are even built on top of each other. For example, PIOTs are often built upon MFA (De Marco et al., 2009), EEIOA can rely on the integration of product-based E-LCA data into MIOTs (Merciai and Schmidt, 2018), and S-LCA is built on top of MIOTs (Benoît Norris, 2014).

[2] Comprising Environmental Life Cycle Assessment (E-LCA), Life Cycle Costing (LCC) and Social Life Cycle Assessment (S-LCA)

[3] Including PIOT (Physical Input Output Tables), MIOT (Monetary Input Output Tables), WIOT (Waste Input Output Tables, MRIO (Multi Regional Input Output), SUT (Supply and Use Tables), EE-IOT (Environmentally Extended Input-Output Table) and Social Accounting Matrix (SAM).

Table 2.11. Main sustainability assessment tools relevant for the bioeconomy with their topical orientations, main strengths and weaknesses and examples of their extensions and combinations with other tools. Modified from Karvonen et al. (2017)

Tool	Orientation	Strengths	Weaknesses	Extensions & combinations
Input - output (IO) methods	Economic	Economic tables are commonly available for IO-analysis and are well and reliably documented. Preciseness is better if markets are well-known. Especially suitable for industry once cost structure and profitability is applied.	Assumption of linear market responses. Markets need to be well established and known for higher certainty levels.	Extensions to environmental dimension (EE-IO).
	Environment (environmentally extended IO)	Environmental extension of IO is obtainable from commonly available statistics.	Shares the weaknesses of IO. In addition, EE-IO may produce large datasets which are cumbersome to operate.	LCA databases or MFA calculations may be applied
Life cycle Assessment (LCA) methods	Environment (E-LCA)	Comprehensive consideration of all inputs and emissions of a product during its life cycle. Inclusion of indirect emissions, such as those from steel or fossil fuel production. Standardized methods and comprehensive databases are available.	Highly demanding in data and large data sets are demanding to handle. Datasets not always available, but access only via costly licenses. Datasets are quickly outdated and are not fully transparent in documentation	Combination with material flow analysis possible.
	Social (S-LCA)	Social aspects are often connected to economic and ecological issues. Hence, much data is available.	Methods to assess and derive social impacts from existing data are in infant state. Cannot be directly attached to environmental LCA because of high site-specific nature.	Data from other LCA methods
	Economic (LCC)	Economy is often of high interest to any decision maker and economic information supports social impact assessment too.	Some economic information may be difficult to obtain because of trade secrets. Market price fluctuations and changes in consumption patterns cause uncertainties	Combining with OI, MFA or the other LCA methods is possible.
Material flow analysis (MFA)	Environment	Focus on loads of materials needed in production of a specific (end) product enables identification of inefficient material uses and production phases. Can be comprehensive, yet simple to operate.	May inherit a limited view in respect to inclusion of externalities outside the examined system.	MFA-model tools are capable to add many different indicators if the functional unit permits it. Combination with LCA is possible.

Box 4. Examples of how other tools and approaches can help to improve bioeconomy modelling

Although often applied to fossil-based sectors, examples exist on how tools such as LCA, MFA and I-O analysis can be coupled to models to improve them. Typically, IAMs are not constrained by the supply of mineral resources and are thus unable to address potential material resource scarcity in the future. Boubault et al. (2019) addressed this issue by using life cycle material footprint data in the TIAM-FR model (derived from the ETSAP-TIAM model). To quantify the amount of mineral resources extracted and consumed directly and indirectly by electricity-generating technologies, the authors used process-based life cycle inventories (LCIs) from the Ecoinvent 3 (Wernet et al., 2016) database. The goal was achieved by disaggregating the relevant LCIs into separate life cycle stages (namely construction, operation, and decommissioning) and linking them to the respective TIAM-FR electric outputs (new capacities, electricity production, and end-of-life capacities). Using this method, the authors could demonstrate how the infrastructures for hydro, solar, and wind power generation will drive an increased global demand for minerals within the coming decades.

The proper representation of physical material cycles in IAM, CGE and PE models would help modelling more realistically the effects of e.g., policy measures aiming at increasing the efficiency of biophysical resources use. Linking models from economic to physical material cycles needs two-way "translation" of monetary to physical flows (and stock changes) to ensure the proper representation of physical balances and ensure the development of mass-balance-consistent models. Normally the representation in both physical and monetary units in such models exists only for the use phase of energy conversion and, for some models, for other specific assets in industry, buildings, and transportation). Cao et al (2019) used dynamic MFA to include the physical linkages and stock dynamics into the CGE model enabling both the mass and monetary balance modelling simultaneously. By considering the physical stock dynamics the authors could add new constraints to the CGE model that is merely exogenously driven by e.g., population and GDP growth.

Except for certain products and sectors, existing multi-sectoral (i.e., CGE and IAM) models almost completely ignore material cycles and recycling, as well as co- and by-production of products and materials (Pauliuk et al., 2017; McCarthy et al., 2018). This is because past and present modelling techniques are generally based on the notion of linear (i.e., produce, use, discard) product lifecycle and economies. Input - output methods can help address this gap (Winning et al. 2017). To consider waste management and material recovery and include secondary production sectors in their ENGAGE-Material, Winning et al. (2017) split steel production into one sector using virgin mineral ores and another one using secondary metal scrap, using environmentally-extended, multi-regional input-output tables.

2.2.8 Sustainable Development Goals

The development of the bioeconomy is considered to pave the way for meeting challenges for sustainable development (El-Chichakli et al., 2016; Heimann, 2019). The updated EU Bioeconomy Strategy aims to develop a sustainable bioeconomy for Europe, strengthening the connection between economy, society, and the environment. It also addresses global challenges such as meeting the Sustainable Development Goals (SDGs) set by the United Nations.

The SDG framework explicitly acknowledges interlinkages between the Goals and to achieve all Sustainable Development Goals (SDGs) by 2030, it is necessary to understand how they interact with each other. A recent review of how economic activities affect SDGs (van Zanten and Tulder 2020) finds that studies on agricultural, industrial, and manufacturing activities predominantly report negative impacts on environmental development, while literature on services activities highlight economic and social contributions. The review finds that economic activities are generally considered to positively affect SDG 9 (industrialization, infrastructure, and innovation) and SDG 8 (economic productivity], while meeting basic needs (SDGs 2, 3, 4, 6, 7, 11). However, SDGs 3 (human health), 13 (climate action) 14 and 15 (aquatic and terrestrial ecosystems) are generally negatively affected (van Zanten and Tulder 2020). In general, the entire SDG agenda is threatened as recent assessments show that inequality is widening, hunger is on the rise, ecosystems are eroding at an alarming rate, and climate change is getting worse (Sachs et al. 2019; UN 2019).

Existing bioeconomy models provide only partial insights in these complex relations within and between SDGs. Partial equilibrium models generally focus on one SDG but address implications that affect few other SDGs. For example, the agricultural PE models focus on SDG2 (No hunger) and contribute partially to SDG 13 (climate action). Similarly, energy PE and other energy models focus on SDG7 (Affordable and clean energy) and address implications on SDG13 (climate action). CGE models generally have a broader coverage of SDGs as they focus on the whole economy and contribute therefore especially to SDG8 (decent work and economic growth). Despite the economy wide focus, CGE models have their own strength and specialisation. For example, GEM-E3, ENVISAGE and ENV-linkages have a focus on energy and climate (SDG8 and SDG13) while MAGNET has a focus on agriculture and the rest of the bioeconomy (SDG2). The MAGNET model, using its economy-wide focus, has recently been extended with a SDG indicator module with a broad coverage of SDGs (12 out of 17: SDG 1, 2, 3, 6, 7, 8, 9, 10, 12, 14, 15, 17) encompassing over 60 SDG related indicators, the majority 'inspired' by the 'targets' which appear in each of the goals (Philippidis et al. 2020, van Meijl 2019). Table 2.12 shows the specific targets and SDG addressed in Philippidis et al. (2020).

Table 2.12. Overview of selected SDG targets by sustainable development layers (Philippidis et al. 2020)

	SDG Target	Target Description
Economy	8.1	Sustain per capita economic growth in accordance with national circumstances and, in particular, at least 7 per cent gross domestic product growth per annum in the least developed countries
	8.4	Improve progressively, through 2030, global resource efficiency in consumption and production and endeavour to decouple economic growth from environmental degradation, in accordance with the 10-Year Framework of Programmes on Sustainable Consumption and Production, with developed countries taking the lead
	8.5	By 2030, achieve full and productive employment and decent work for all women and men, including for young people and persons with disabilities, and equal pay for work of equal value
	9.2	Promote inclusive and sustainable industrialisation and, by 2030, significantly raise industry's share of employment and gross domestic product, in line with national circumstances, and double its share in least developed countries
Society	7.1	By 2030, ensure universal access to affordable, reliable and modern energy services
	7.2	By 2030, increase substantially the share of renewable energy in the global energy mix
	2.1	By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round
	2.2	>By 2030, end all forms of malnutrition, including achieving, by 2025, the internationally agreed targets on stunting and wasting in children under 5 years of age, and address the nutritional needs of adolescent girls, pregnant and lactating women and older persons
Biosphere	6.4	By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity
	13.2	Integrate climate change measures into national policies, strategies and planning
	15.2	By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally
	15.3	By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world

Notable is also the work done with the ICES model (Eboli et al. 2010; Campagnolo and Davide, 2019; http://paris-reinforce.epu.ntua.gr/detailed_model_doc/ices) to assess and monitor current well-being and future sustainability. The model has been extended to include 28 indicators related to the 17 SDGs16 of the country level ASDI indicators are based on model results, seven are linked via regression analyses (SDG1, SDG2, SDG3a, SDG3b, SDG4, SDG7a, SDG10), and four remaining (SDG14, SDG15a, SDG15c, SDG16) are kept historically constant.

These examples show that progress is made to include SDGs in modelling, it is complicated to include all SDGs and their targets and variables of interest within a single modelling framework. A model review by Allen et al. (2016) showed that only one of 80 reviewed models included variables relating to all 17 SDGs. The SDGs with the greatest coverage by existing models are economy and employment (SDG 8), energy (SDG7), investment-trade-finance (SDG 17), food-land (SDG 2), climate change (SDG 13), and to a lesser degree, water (SDG 6) and industry-innovation (SDG 9). Policy areas that represent key gaps in modelling capabilities included institutions-governance (SDG 16), gender equality (SDG 5), cities (SDG 11), marine life (SDG 14), education (SDG 4) and, to a lesser degree, poverty (SDG 1), health (SDG 2), inequality (SDG 10) and terrestrial life (SDG 15). Thus, while some existing models are particularly relevant, it is unlikely that a single modelling framework can help to analyse all SDG targets and variables of interest. Instead, combining multiple modelling approaches are considered to provide a robust approach for analysis and decision-making (Allen et al. 2016). Similarly, van Soest et al. (2019) analysed how IAMs can contribute to a wider analysis of the SDGs to inform integrated policies. By design the IAMs cover the SDGs related to climate and most IAMs also cover several other areas that are related to resource use and the Earth system (Figure 2.8). Overall, the analysed IAMs cover 3 SDGs in detail and 10 can at least partly be quantified by IAMs, while 4 are clearly not well covered in these models. Areas identified for model development include oceans, consumption and production patterns, cities (in relation to public transport and buildings, including e.g., compactness/polycentrism), inequalities (especially for national models and CGEs), health (in relation to food, air pollution, climate change, and life below water and on land), poverty, and, to some extent, education (on an aggregated level, and possibly through coupling with specialised education models). To better cover SDGs, it is necessary to facilitate a better representation of heterogeneity (greater geographical and sectoral detail) by using different types of models (e.g., national, and global) and linking different disciplines (especially social sciences) together (van Soest et al. 2019).

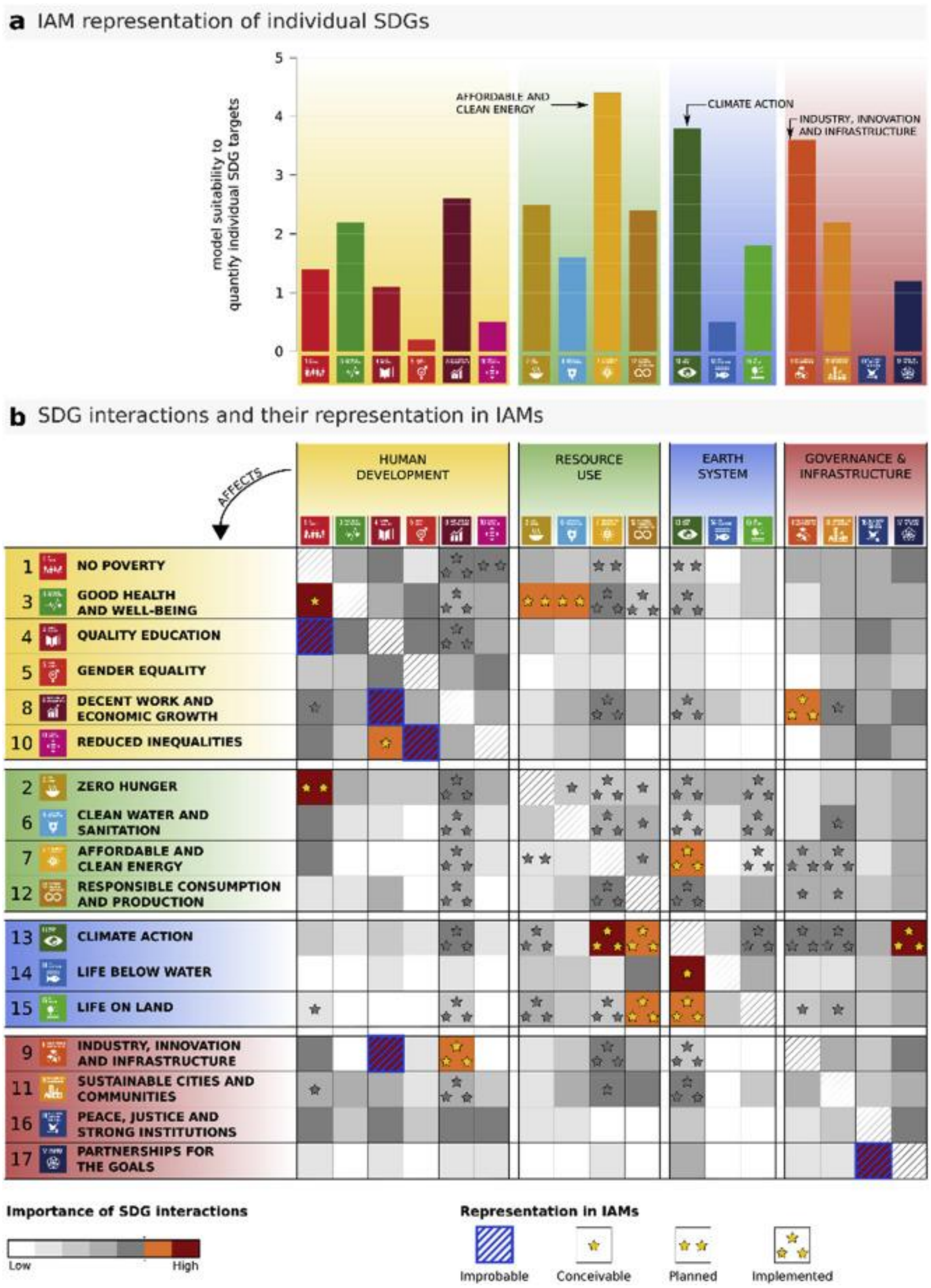

Figure 2.7 The representation of SDGs by IAMs (van Soest et al. 2019; reproduced with permission). (A): Bar height represents the average score for individual target coverage from the model survey. (B): SDG interactions and coverage by IAMs according to the expert and model surveys (the SDG in the column impacts the SDG in the row). The strength dimension of SDG interactions is indicated by grey shading: the darkest shade of grey represents average scores near 3 (strong interactions), while white represents no interactions. The representation of IAMs following the model survey is indicated by asterisks. ***: currently in IAMs, **: planned development, and * conceivable to be represented in the future. Finally, orange cells indicate the highest agreement between the importance of interactions and potential model representation, while blue coloured cells show the most notable important interactions without model representation. Interactions that are marked as currently represented are endogenous, with various levels of process detail. Future modelling of the SDG interactions that have remained unrepresented thus far can be achieved as a part of a consistent set of exogenous assumptions such as, for example, the impact of quality education on reducing poverty.

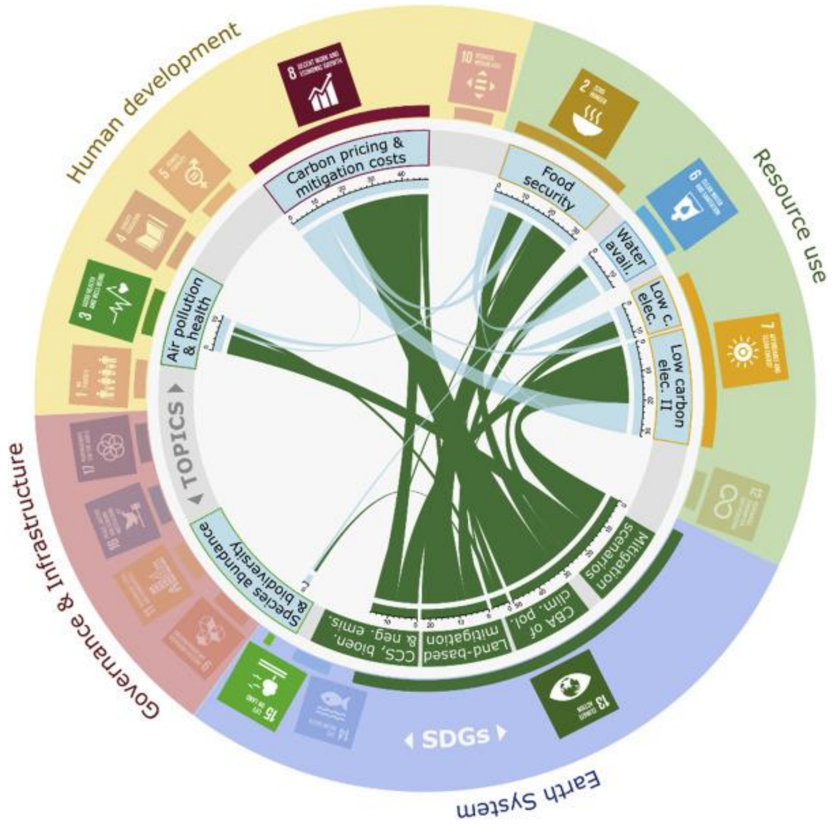

Figure 2.8. SDG interactions in the IAM literature (van Soest et al. 2019; reproduced with permission). Linkages among the topics in the literature (inner circle) have been uncovered endogenously using topic modelling. Topics are manually allocated to SDGs (outer circle). Chord width is proportional to the number of documents that simultaneously feature two topics. Climate topics are in green while non-climate ones are in light blue. Water avail.: Water availability; Low c. elec.: low-carbon electricity; CBA of clim. pol.: cost-benefit analysis of climate policy; CCS: carbon capture and storage; bioen.: bioenergy; neg. emis.: negative emissions.

We can conclude in line with van Soest et al. (2019) that it is necessary to facilitate a better representation of heterogeneity (greater geographical and sectoral detail) by using different types of models (e.g., national, and global) and linking different disciplines (especially social sciences) together. Especially, the social dimension is not well represented and models that can deal with distributional issues need to be included in the model frameworks.

2.3 What are gaps and complementarities in existing capacities for modelling future transitions for the bioeconomy?

2.3.1 Gaps to be addressed in the short to medium term

From the review undertaken in chapter 2.2, it can be clearly seen that most of the available models have a sectoral focus. It is therefore not straightforward to address cross-cutting policy questions (i.e., sustainability of current and future biomass supplies; the contribution of the bioeconomy to climate change adaptation and mitigation; impact of dietary changes on sustainability of food systems and on planetary health; sustainability of bioenergy supply, considering biomass demand for other uses; and the design and implementation of strategies limiting food losses and waste to contribute to a sustainable and circular economy) (see also O'Brien et al., 2017). To fully exploit the potentials of modelling, gaps in the existing modelling capacity need to be addressed.

An obvious gap of most of the existing models (see also Varacca et al. 2020; Lovrić et al. 2020a) is their sectoral focus. Only a few models, falling under the family of IAMs and CGE models, cover all bioeconomy sectors. However, even if all economic sectors are covered, these models may not necessarily capture the bioeconomy itself. That is, sectors that produce or manufacture products from biological resources may not be easily separated from products made from fossil resources. Furthermore, while many models cover most if not all the economic sectors from the demand side, they provide info on the potential impacts of policies for only one or very few sectors. An archetypal example of this behaviour is represented by the family of models with emphasis on energy-related issues (e.g., PRIMES, POTEnCIA, PROMETHEUS etc.). Despite considering the demand of energy from basically all the economic sectors, the impact in terms of consumption, prices, emissions etc. is in these models only given for the energy sector. This limitation makes these models less suitable to address the entire bioeconomy, but only aspects related to the production of energy from bio-based feedstock.

Linked to this incomplete sectoral scope of some models, is their limited ability of capturing the cross-cutting issues of the bioeconomy transition. Being often sectoral, meaning addressing (bio)energy production either or (bio)product manufacturing, they can hardly cope with the existing competition between the different industrial sectors of the bioeconomy. Even deeper are the limitations of the models in dealing with the issue of food-feed-fibres-fuel competition, not only for land, but also for other resources such as water, labour, and capital (Muscat et al., 2020). It is of paramount importance to address these cross-cutting issues if the goal is to secure a successful bioeconomy transition and help the policymakers in addressing cross-cutting issues, which require an integrated modelling approach and consider key process such as technological change (or innovation), circularity, consumer behaviour and climate change. Many of the environmental models, just to give an example, are rather robust in proving sector-specific info on the (potentially) available biomass supply (e.g. EFISCEN, G4M or CBM for forestry, CAPRI for agriculture, SIMFISH for fishery), and many other biomass supply related issues (e.g. GHG emissions from LULUCF sector, biodiversity impact etc.), but they generally fall short in vertical (full supply-chain consideration) or horizontal (competition among different sectors fighting for same resources) integration. In the cases this is done, as in some CGE or IA models, the resulting integration is either at a rather coarse resolution or in a not fully realistic way (e.g., assuming perfect competition between sectors).

Box 5. Model validation

Model validation is a critical issue in which model outputs are (systematically) compared to independent empirical information to evaluate whether the quantitative and qualitative model results correspond with reality. Validation is a key element in the evaluation of environmental models. A mix of methods is generally used for validating environmental models and Augusiak et al. (2014) refer to the term 'evaludation', a fusion of 'evaluation' and 'validation', to describe the entire process of assessing a model's quality and reliability. Evaludation should consider (i) 'data evaluation' for scrutinising the quality of numerical and qualitative data used for model development and testing; (ii) 'conceptual model evaluation' for examining the simplifying assumptions underlying a model's design; (iii) 'implementation verification' for testing the model's implementation in equations and as a computer programme; (iv) 'model output verification' for comparing model output to data and patterns that guided model design and were possibly used for calibration; (v) 'model analysis' for exploring the model's sensitivity to changes in parameters and process formulations to make sure that the mechanistic basis of main behaviours of the model has been well understood; and (vi) 'model output corroboration' for comparing model output to new data and patterns that were not used for model development and parameterization (Augusiak et al. 2014).

Macroeconomic models such as CGEs are often criticized as for being poorly validated. In the literature two approaches have been used to validate CGE models. In the first approach, the price fluctuations projected by the model are compared with historical time series for those commodities showing high price volatility due to shocks in supply and demand (e.g., agricultural ones). Production shocks are introduced in the model and the results of the model are then compared with the real-world data in terms of variance in prices for the commodities chosen. Notable examples of this approach are the works done with GTAP from Valenzuela et al. (2007) and Beckman et al (2011), with both finding the understating of real-world impacts by the models. In the second approach, secondary data sources are used to calibrate an historical simulation. By using actual movements in prices and quantities for consumption, exports, etc. disaggregated by commodity, changes in employment, investment and capital stocks disaggregated by industry, these information are treated as exogenous and those other factors augmenting technical change (changes in consumer preferences and technologies) are endogenized. Projections are then made at the detailed industry level and on consumption and government spending in addition to forecasts on aggregate macro-level variables such as total consumption and GDP assuming that past calibrated changes in preferences and technologies reflect future developments accurately. The model results are eventually compared with actual data. Eventually the impact on the forecast of different exogenous factors can be measured by introducing the 'real' pattern of used exogenous variables such as technology and preferences, trade, and tariffs etc. An example of this validation can be found in Dixon and Rimmer (2010) and van Dijk et al. (2014) with the MESSAGE model.

IAMs suffer from the same challenge. One way used to check IAMs validity is to assess how good is the model in reproducing historical patterns of changes (Wilson et al., 2017). There is one big shortcoming in the approach of using past performance as a proxy of the model quality because the future may not be like the past. Furthermore, errors in the model can cancel out each other, leading to projections apparently accurate.

Box 6. Recommendations for improved agricultural modelling (Jongeneel et al. 2020)

The SUPREMA (SUpport for Policy RElevant Modelling of Agriculture) developed a roadmap for future suggestions for agricultural modelling in the EU. Based on an assessment of both the future policy needs and the strengths and weaknesses of selected agricultural models, Jongeneel et al. formulated the following recommendations:

- The current and upcoming agricultural policy framework, and the notion of 'food system approach' as an overarching framework that covers the food market from a broad perspective require a reconsideration of the EU's modelling strategy in which integrated model use gets a more prominent place.
- The increased emphasis on sustainability, while maintaining the income perspective of farmers, makes that an increased attention has to be paid to the integrated use of environmental and economic modelling approaches to ensure coherence and consistency in the approach to a complex reality. It becomes increasingly unlikely that all these aspects can be in a satisfactory way integrated into one or a few models.
- A drawback might be that the (from a 'control'-perspective) attractive option of having a few 'recognized' models that have an EU wide spatial coverage, and a comprehensive coverage of issues and themes is no longer the only best option. There are two 'answers' to this:
    - Firstly, the EU is already supporting several key models in different domains (economic-policy, environment, climate) and a challenge is to let these models better work together. Additional investments will be necessary into model ensembling and the type of linkages that can be used. In the process of linkages-development, special attention needs to be paid to circularity issues, which are so far under addressed.
    - Secondly, large scale models can never reach the degree of refinement regarding policy representation, spatial granularity, and behavioural responses (e.g., innovation adoption) that is needed for delivering support to EU and national policy makers reflecting the indicated future priorities and the subsidiarity with respect to policy implementation and modality options that are planned to be given to Member States. More effort and support on refined and more 'localized' models (e.g., EDM-models) are welcomed and more pluralistic approaches (e.g., agent-based modelling).
- To get further insights into the impact of policy measures at farm level, more emphasis should be put on understanding and modelling individual farm decision making.
- In the context of both actual economic developments as well as from the perspective of a food systems policy approach, food supply chain modelling needs more attention. Without this a number of insights that are crucial for effective policy making may be missed. It is still an issue how to best approach this, although starting from case studies that concentrates on key sectors seems a good idea.
- With respect to trade modelling a focus on the role of standards and non-tariff measures continues to be important, while the increased attention for 'functional trade' and 'fair trade' (level playing field corrections that account for maybe diverging EU and non-EU standards and requirements with respect to agricultural production and food processing) requires more insight into global value chains and trade linked sustainability indicators.
- Quality control, model (cross)validation, transparency, data management, research networks are crucial and become of increasing importance when more models and a plurality in modelling approaches are allowed for. The EU's role for providing services and platform-function has been recognized in the past and needs to be strengthened for the future.
- More generally, it is welcomed to have more academic publications on models, model applications and modelling results and maybe this also justifies a specialized journal on this as the standard disciplinary journals sometimes lack sufficient openness to such publications.

Existing models cover bioeconomy products and sectors to different levels of detail. It must be underlined that basically none of the models was built with the primary goal of being used in the broader context of bioeconomy (see also Varacca et al. 2020). This makes it difficult to draw a clear boundary between the models that can be directly used to assess the bioeconomy and the models that currently (i) cover the bioeconomy sectors marginally or (ii) not at all. It is important but also difficult to evaluate whether bio-based products (processes) have been or can be potentially assessed using models for these sectors.

The results of the review in section 2.2 clearly evidenced two contrasting features: the model coverage, assessed in terms of spatial resolution, accessibility, and model types, but the same could not be said for sector and bioeconomy objectives covered. This generally reflects a trade-off between generalization and specialization of models. For example, the need for higher resolution hinders the coverage of such activities by models that generally work with aggregated data. This issue also holds true for bioeconomy activities which, for reasons related to data availability and/or relatively low value added, are typically aggregated into larger categories. For example, most models can easily perform analysis of crop productions for plants such as maize, soybean and wheat. However, few models can provide details for smaller bio-based activities such as the manufacturing of crop residues, which might represent an important feedstock for the most innovative bioeconomy sectors. Another reason for bioeconomy objectives not being addressed properly by all models is that currently available statistics struggle to supply detailed data for the innovative part of the bioeconomy, so the models fail to produce outputs on those bioeconomy indicators as well. It must be underlined, however, that efforts are being put in place to integrate innovative bio-based technologies and materials into models (see e.g., van Meijl et al., 2018a and Tsiropoulos et al., 2018). The integration of innovative technologies and feedstocks into models is necessary to estimate sustainable biomass stock available (issue 1), find the best technological mix to mitigate climate change (issue 2) and reduce competition between bioeconomy sectors (issue 4).

There is one additional interesting aspect when considering the relationship between models and their ability to cover the five main objectives of the EU's bioeconomy strategy, namely (i) food nutrition and food security; (ii) sustainable natural resources management; (iii) dependence on non-renewable resources; (iv) mitigation and adaptation to climate change and (v) employment and economic competitiveness. Environmental models address one or few aspects (e.g., climate change mitigation, land use, biomass availability), even if in a more detailed manner, whereas integrated assessment and economic models (both PE and CGE models) encompass a much larger set. With some due exceptions, economic models and IAMs (which often have economic models as backbone) generally encompass more aspects than pure environmental models. Because of their multi-sector and multidisciplinary nature, IAMs typically do a rather good job in providing information on different aspects of bioeconomy. Therefore, it would seem natural to advocate for an even larger and deeper synergy between environmental and economic models compared to what has already been done so far as discussed in section 2.2.5. Such linkages between economic and environmental models will also facilitate the understanding of how developments in natural systems interact with the bioeconomy (e.g., climate change may affect the productivity of agricultural and forestry systems, which will affect the availability and cost of biomass supply. Natural disturbances (e.g., windthrows or pest outbreaks) may disrupt biomass supply and have implications on markets and industry. This integration is needed to ensure the sustained and sustainable supply of biomass for the bioeconomy and help dealing with cross-cutting issue 1. Some of the models included in our review are indeed the result of different levels (and means) of integration between tools designed for different purposes (e.g., E3ME-FTT-GENIE, IMAGE-MAGNET, or IMACLIM-R). Sometimes environmental/economic models can enter economic/environmental models as modules or, more simply, models can work in synergy exchanging inputs and outputs. Economic models tend to be more integrated with biophysical and other non-economic tools than with other categories of models. On the other hand, although there are environmental models that also interface with economic modules, these seem to be less frequent.

With regards to models' objectives, the models assessed are mostly capable of doing and used to perform (forward-looking) impact assessments. This essentially means that models, at least the ones included in this report, primarily focus on policy analysis and deal with other purposes to a much lesser extent. As the transition to a bio-based economy is strongly dependent on the dynamic of the adoption of new technologies, it is of paramount importance that the diffusion of (bio)technology, innovations and practices throughout industries and between households is addressed in the models. With food waste biorefineries (Dahiya et al., 2018), for example, food waste can be valorised (cross-cutting issue 5) and biomass availability for uses other than bioenergy increased (cross-cutting issue 4). The effective potential of this, and of many other innovative (bio)technologies in contributing to the circular bioeconomy goal, cannot be really estimated without understanding and estimating their diffusion dynamic.

Traditional equilibrium and optimisation-based analysis show five important limitations with regard to this aspect (Mercure et al., 2016): (i) they lead to normative rather than positive/descriptive approaches; (ii) the possibility that agents may not behave completely rationally is not sufficiently addressed; (iii) positive feedbacks and increasing returns due to mutual influence among agents is not captured; (iv) path-dependence and multiple solutions are hardly accounted for; (v) as the models are based on the rational expectations of a sole representative agent, agent heterogeneity is not properly accounted for. Unfortunately, only a few of the reviewed models try to model explicitly this phenomenon. One interesting example is the E3ME-FTT-GENIE model, which considers the selection and diffusion of innovations using the so-called Future Technology Transformations (FTT) modelling approach (Mercure, 2012). Despite the valuable effort of the E3ME-FTT-GENIE in considering this crucial aspect, the FTT framework is only used for the power, road transport, household heating and steel sectors, making it not fully capable of capturing the bioeconomy sectors. Other interesting models that explicitly cope with the issue of innovation using Agent Based Modelling are the DSK and MADIAMS models. Despite their interesting goal and approach, both models are quite new in terms of development and cannot compete with well-established IAMs and CGE models when the sectorial and geographical resolution is concerned, at least so far. Innovation and adaptation of new technologies are typically not explicitly considered in traditional economic models (PE and CGE), where technological progresses are generally only incorporated ex-post, e.g., in the form of changes in the production function or cost parameters (Baccianti and Löschel, 2014).

It can be clearly derived from the above discussion that focusing on a specific model family can help to provide insights only on a limited range of issues. Being practically impossible to build the silver bullet model, the combined use of multiple types of models is the best strategy to draw more solid overall conclusions.

2.3.2 Gaps to be addressed in the long-term

The transition for the bioeconomy towards sustainable development and a climate neutral economy strongly depends on structural change and transformations within the economic system. For a better understanding of the dynamics of the transformation process and to identify promising targets for policy interventions, these technology and preference driven changes are to be considered as endogenous. Both fundamentally change the economic behaviour of producers and consumers and the design of value creation chains as well as the value creation networks. The common denominator of these structural changes is their dependence on novelties, both technological and social, and the fundamental uncertainty that limits quantitative forecasting and allows only for more moderate predictions concerning the conditions for change (pattern detection, identification of critical fluctuations, windows of opportunity etc.). Uncertainty and innovation are two faces of the same coin and are widely considered to be the features of complex systems. Table 2.13 summarizes the features of simple and complex systems.

Table 2.13. Comparison of simple and complex systems

	Simple systems	**Complex systems**
Agents and interactions	Homogenous and symmetric	Heterogeneous and asymmetric
Composition	Decomposable, units can be analysed separately	Non-decomposable, can only be analysed as a whole
Innovation	Risky (probabilities are known)	Uncertain (state space is changing)
Processes	Linear, equilibrium-oriented	Non-linear, dynamic
Change	Exogenous (shocks)	Endogenous

There are several emerging approaches that try to address complex systems and structural changes. Emerging approaches (e.g., agent-based modelling (Gilbert and Troitzsch, 2005) together with the application of machine learning (Macal, 2016; Marsland, 2015)) can be summarized under the heading of complex systems modelling (Arthur, 2014). They all emphasize the importance to understand dynamic processes which govern the development of individual and aggregate variables (e.g., the entrepreneurial experimentation with new technology, their adoption by users and finally the emergence of a new bioeconomy industry). This is most important in situations where innovation matters because agents are engaged in learning and adaptation, which includes the possibility of failure (which is absent in optimization approaches). For learning processes, the heterogeneity of agents is essential as a condition for mutual learning (in innovation networks) as well as for the outcome, where non-innovative and innovative agents are to be distinguished.

Already at this point in our report, we want to stress that the new classes of models, which take these complexity considerations as a starting point, are to be considered as complements to the existing models and not as substitutes. Their justification comes from their long run orientation and does not mean that the existing modelling classes with their higher levels of detail are to be replaced. The emerging modelling techniques cannot compete with the existing (or traditional) modelling approaches, as they do not provide information on detailed adaptations in single industries. However, the emerging model classes can help to understand better the conditions for endogenous transitions, i.e., when it is more likely for systems to change and conditions, when it is very unlikely that the system is thrown off course (so-called punctuated equilibria). Finally, as phenomena of crisis are endogenous to complex systems, the emerging class of models might also be considered of help to understand better what is happening in crisis-like situations which shake socio-economic systems from time to time, like the financial crisis at the end of the first decade of the 2000s and the current Corona-pandemic crisis.

The focus on agents' heterogeneity and learning is required not only to better understand how innovations are developed endogenously, but also how consumers learn and change their preferences and what kind of aggregate dynamics like e.g., threshold effects are to be expected in this process. Consumer dynamics and the impact on the overall demand for goods and services will play an important role in the transition for the bioeconomy to reach all three dimensions of sustainability. Minor changes in the preferences of some individuals can swing up to fundamental pattern changes which are behind the emergence of new and the disappearance of mature industries.

In summary, the integration of the new model classes into the existing families of models will likely provide synergies for analysing the transition towards a knowledge-based bioeconomy. We will further discuss the role of new or emerging modelling approaches in the next chapter.

3 Emerging modelling approaches

3.1 Why are new modelling approaches needed?

Quantitative modelling tools can be a key input to facilitate a better understanding of the complexity, trade-offs, and potential future pathways for the bioeconomy to achieve a transition towards sustainability and climate-neutrality, addressing the economic, social and environmental dimensions. To strengthen the use of models and address key policy questions on cross-cutting issues, it is important to look at enabling factors (Fritsche et al. 2020) and include key processes that models need to consider (Figure 3.1).

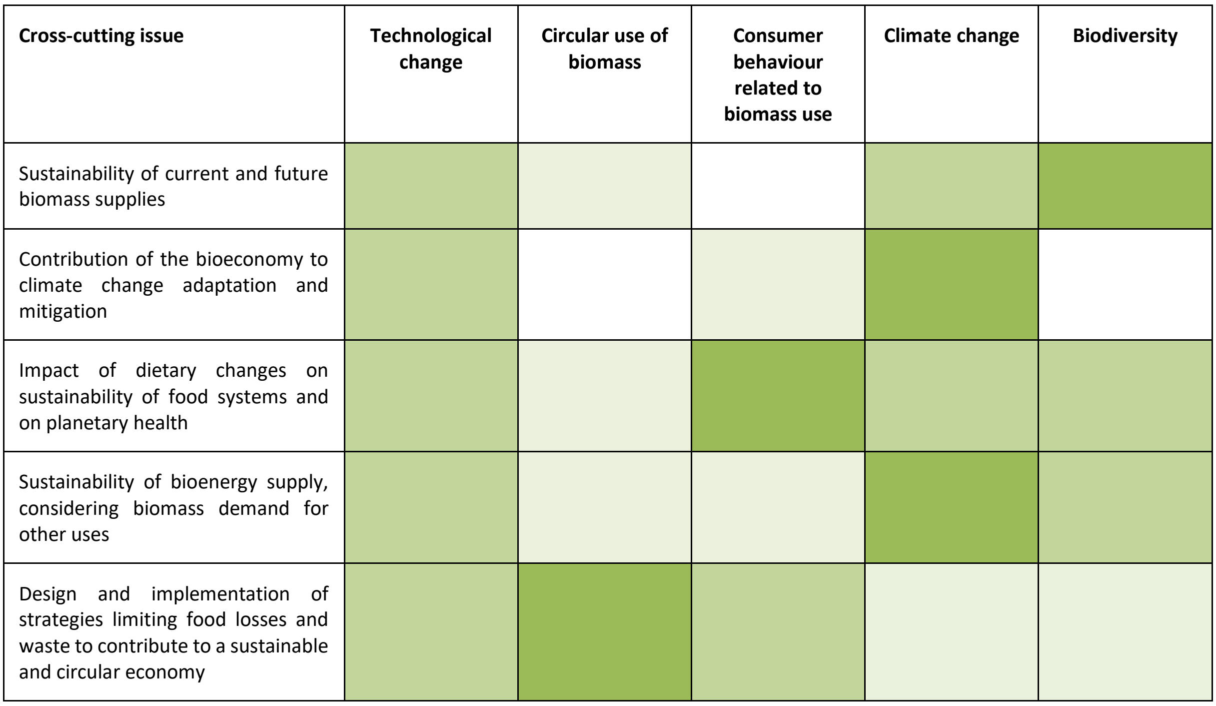

Figure 3.1. Heatmap showing the relevance of key processes that need to be covered by models to address key policy questions (darker shading indicates higher relevance).

To use models for exploring transition pathways for a bioeconomy, it is important to consider enabling factors (Fritsche et al. 2020) and include key processes in models (see heat map in Figure 3.1). **Technological change** (or innovation) can lead to the development of innovative and climate friendly bio-based products and technologies (Lovrić et al. 2020b) and contribute to the production of more sustainable second and third generation bioenergy, which would also help to give food losses a value. Similarly, **circular use of biomass**, namely the adoption of recycling, reusing or repairing practices, can contribute to increasing biomass availability and reducing waste. The possibility of, for example, turning biowaste and residues into valuable bio-based products, as well as the introduction of practices like cascading use of products can, potentially, reduce the demand for virgin biomass feedstock and contribute to lowering the competition for resources (biomass, land etc.) and mitigate climate change (Risse et al. 2017). Demand is affected by **consumer behaviour related to biomass use**, or behavioural changes more generally. For example, consumer preferences with regards to dietary changes are crucial for sustainability of food systems (Sanchez-Sabate and Sabaté 2019; Kause et al. 2019), as well as climate change mitigation (Roe et al. 2020; Gifford et al., 2011). The consideration of consumer preferences and consumption behaviour is fundamental to ensure the effectiveness of policy measures. For example, strategies aiming at an increased use of wood-based materials in construction to mitigate climate change would be confronted with the prejudices of owners about fire security, lifetime, and sound insulation properties of such materials (Gold and Rubik 2009; Lähtinen et al. 2019). **Climate change** is a key factor in driving the development of a bioeconomy, affecting both demand (e.g., feedstock for bioenergy and bioproducts and chemicals) and supply (through climate change impacts) simultaneously. Finally, to preserve **biodiversity** is key by sustainably managing land and marine ecosystems to secure the long-term provision of ecosystem services.

In the following, we review the extent to which these enabling factors and processes are already addressed by extensions to existing models and to what extent emerging modelling approaches can address them.

3.2 What extensions of existing models are in development?

3.2.1 Technological change

Modelling of technological change (TC) in the literature is mainly based on economic methods (Köhler et al. 2018). Technological change is the key component to explain macro-economic growth. Solow (1957) concluded that 87.5% of the increase in gross output per capita was attributable to technological change and the remaining 12.5% due to increased use of capital and labour. As Freeman (1994, p. 463) states: "*one of the continuing paradoxes in economic theory has been the contrast between general consensus that technical change is the most important source of dynamism in capitalist economies and its relative neglect in most mainstream literature*". This paradox now seems to become highly relevant for the attempts to model the transition to a knowledge-based bioeconomy.

In so-called mainstream economic models, TC is historically considered an exogenous, non-economic variable since the emphasis is on understanding their effect rather than how research and development induces these changes. In many top-down models (e.g., several IAM and CGE), autonomous energy efficiency is assumed to capture all non-price driven improvements in technology and is used to model technological change exogenously and represent the decoupling of energy use and economic growth. Another common approach to consider technical progress consists in the semi-exogenous incorporation of discrete, so called backstop, new technologies. These are basically technologies at low technological readiness level that are already known but not yet commercial. Since a while, technology is seen as an important driver of innovation and growth, as such research and learning-by-doing, as well as other technological changes originating within the economic system, are endogenized in economic models. To represent technological progress endogenously, technological changes must be made responsive to the modelled economic conditions.

The new growth theory (Romer 1986; Grosmann and Helpman 1991) endogenized technical change by learning and feedback effects of R&D investments in theoretical models. TC are typically modelled endogenously in economic models using three approaches (see also Table 1, updated from Gillingham et al. (2008) and Löschel and Schymura (2013)): the direct price-induced, the research and development (R&D)-induced and the learning-induced TC. Direct price-induced TC is based on the idea that changes in relative factor prices, typically energy, can stimulate innovation to reduce the input of those factors that became relatively more expensive. This mechanism is normally embedded in models using a productivity parameter derived from energy prices. The R&D-induced approach starts from the idea that R&D increases the stock of knowledge and, consequently, investment in R&D can influence the rate and direction of TC. R&D induced TC is the most widely used way to endogenize TC and the approach showing the greatest diversity in the used modelling approaches (see Gillingham et al. 2008 for an exhaustive overview). Finally, learning-induced TC models rely on the learning-by-doing effect, namely the cost-reduction of technologies based on the experience gained with that technology. A common way used to endogenously model this learning effect is by means of learning curves, which aims at describing the relationship between the cumulative capacity of a technology (a proxy for the accumulated knowledge) and its cost reductions. The stock of knowledge approach is often used to endogenously model investment in R&D. Based on the idea that knowledge accumulation stimulates technological progress and that R&D investments improve the state of knowledge, the stock of knowledge is introduced as an explicit input in production that captures the relationship between investments in R&D and technological progress. Heterogeneous firms (i.e., firms differing in productivity but working with the same production function, Melitz 2003) are an important component in these theories and in the last decade these are introduced in CGE models (Balistreri and Rutherford 2013, Dixon et al. 2018; Akgul et al. 2016). These developments endogenize technological changes partly, but are data intensive, require estimates of parameters which are difficult to assess, and they drive to a large extent the outcomes of models. Some parts are endogenous due to specification of various production technologies to a product (e.g., GLOBIOM) or due to substitution effects (CGE models). Another way to endogenize technological change is to introduce R&D investments explicitly in a model (e.g., Smeets-Kriskova, 2017a, 2017b). Challenges in this approach remain also the estimation of the rate of return to R&D. To summarize, because of the severe difficulties in conceptually integrating technological progress and innovation in current economic models, technological change most often remains exogenous.

In IAM, both static and dynamic technologies are projected. In the former, no temporal changes in the technical characteristics (essentially the conversion efficiency) are modelled, variation of efficiency over time is modelled in the latter. A similar approach is used for modelling capital and operating costs. For example, REMIND, WITCH and IMAGE use learning curves to endogenize the reduction of the capital cost of certain technologies (e.g., renewables) owing to the increased cumulative installed capacity driven by the climate policies stimulating their adoption. Others, such as GCAM and MESSAGE parameterize technological growth exogenously.

Table 3.1. Technological change modelling approaches in some of the reviewed models.

Model	Model type	Representation of technological change*
AGMEMOD	Partial equilibrium model	Exogenous
CAPRI	Partial equilibrium model	Exogenous
GCAM	Integrated assessment model	Exogenous
EFI-GTM	Partial equilibrium model	Exogenous, different technologies to produce a specific product
GEM-E3	Computable general-equilibrium model	Exogenous
GFPM	Partial equilibrium model	Exogenous
GFTM	Partial equilibrium model	Exogenous
GLOBIOM	Partial equilibrium model	Exogenous, price-induced, different technologies to produce a specific product
IMACLIM	Integrated assessment model	Exogenous, learning-by-doing
IMAGE	Integrated assessment model	Exogenous, price-induced, learning-by-doing
MAGNET	Computable general equilibrium model	Exogenous, Option for endogenous tech change by explicit R&D sector, options for CAP driven tech change
MARKAL	Other economic model	Learning-by-doing
MESSAGE	Specialist model	Learning-by-doing
POLES	Partial equilibrium model	Learning-by-doing
PRIMES	Partial equilibrium model	Learning-by-doing
REMIND	Integrated assessment model	Learning-by-doing
TIMES	Partial equilibrium model	Learning-by-doing
WITCH	Integrated assessment model	Research and development, backstop, learning-by-doing

**Not necessarily applied to all technologies/sectors, different approaches can be used depending on the technology/sector.*

Modelling of technological change in environmental models is less common as compared to economic models or IAMs, as they mostly do not cover socio-economic variables endogenously. The effects of technological change may be incorporated in environmental models exogenously through scenarios storylines by which either inputs to the models are changed, or through which model outputs are post-processed. As an example of this approach, Verkerk et al. (2018) considered the technological developments in tree breeding efforts on productivity gains by scaling productivity functions used in the EFISCEN model for estimating potential forest biomass availability. The effects of other technological improvements (e.g., improved harvesting technology and supply chain logistics) were then assessed by modifying the constraints that limit potential biomass availability.

3.2.2 Circular use of biomass

Past and present modelling techniques are generally based on the notion of linear (i.e., produce, use, discard) product lifecycle and economies. Except for certain products and sectors, existing multi-sectoral (i.e., CGE and IAM) models almost completely ignore material cycles and recycling, as well as co- and by-production of products and materials (Pauliuk et al., 2017; McCarthy et al., 2018). It is crucial that recycling, reuse, and cascading of materials are properly addressed and included in bioeconomy models to make them more useful to support policymakers in the transition towards a sustainable and circular bioeconomy. The bioeconomy is characterised by complex interlinkages between land-productivity-management-feedstock choices with multiple-output systems such as biorefineries (especially regarding food residues / waste as feedstock).

Some initial work on addressing such a need exists, though. Although they are often applied to fossil-based sectors, they represent valuable modelling approaches replicable in the bioeconomy context. Concerning the consideration of waste management and material recovery and the inclusion of secondary production sectors, the ENGAGE-Material model (Winning et al., 2017), based on EXIOBASE 2 (Wood et al., 2014) and GTAP-9 (Aguiar et al., 2016), splits steel production into one using virgin mineral ores and another using secondary metal scrap. A similar distinction is made for six metals in EXIOBASE 3 (Stadler et al., 2018), although this version has not been incorporated yet into the EXIOMOD CGE model (Bulavskaya et al., 2016) which uses it as an underlying database. In the MAGNET CGE model two features of the circular economy have been introduced. First, residues are modelled explicitly for agricultural, biofuel and forestry sectors and these residues can be used for feed or bioenergy, or biobased materials (van Meijl et al. 2018a). This embeds multiple-output systems which can be sourced by different inputs (primary products, residues, waste) and are therefore also linked to the land using sectors land market. Secondly, a waste management sector is introduced that collects all kinds of waste from consumers and industry (Bartelings et al.). The fact that, to our knowledge, only these three multi-region CGE models include circularity aspects clearly shows the trade-off between a comprehensive but not explicit representation of all materials and a detailed sectoral and geographical representation. A more detailed approach dealing with secondary production that goes at the expenses of its geographical resolution can be found in some single-region CGE models (Godzinski, 2015; Masui, 2005; Fujimori et al., 2017) in which a waste management sector is introduced. This sector is responsible for the production of a disposal service (split between incineration and landfilling in some cases), and of multiple secondary raw materials which, in downstream manufacturing sectors, substitute the primary ones. Hartley et al. (2016) monetize the recyclable content of 13 waste flows, and they use these figures in the model as an exogenous supply shock for resource availability.

In partial equilibrium models, the use of residues and recycled materials is considered in more detail. For example, PE models for the forestry sector do generally consider recycled paper as feedstock and it is also common practice to consider the use of by-products (i.e., sawdust, black liquor). Similarly, agriculture by- products are often considered in models like CAPRI, Aglink and Agmemod. Nevertheless, these models fall short in considering recycling or cascading of products.

A proper representation of products' lifetime and the role of product-lifetime extending activities (e.g., remanufacturing, repair, and reuse) is clearly relevant to address circularity. However, these are all aspects not well represented so far in all the models with their roots in the economic field. CGE, PE and all IAM models, which start from the economic representations of flows within the society, show little or no inclusion of stock accounting. A simplified approach to model the effect of longer living products could consist in decreasing exogenously the demand for the longer-lived products under study, based on the assumption that such a longer living or reused product determines a reduction in its demand. Another approach is to extend lifetime by increasing the price of the product, based on the assumption that the longer the lifetime the higher the value of the product. The limits of these two approaches are evident, as more realistic representations of the effect of lifetime extensions are needed. A third approach is to introduce an explicit recycling sector.

As highlighted by Pauliuk et al. (2017), an improved representation of physical material cycles in economic modelling (i.e., IAM, CGE and PE) help to increase the policy support relevance of such modelling approaches. This advance would give the opportunity to model more realistically the effects of more efficient use of biophysical resources due to circular and lifetime extending practices in the spectrum of policy options considered. The integration of such models with (dynamic) material flow analysis (see Section 2.2.7), which was developed exactly to track the dynamics of stocks of materials and products, is one of the ways forward and an example on how this integration can be done (Cao et al., 2019) play an important role in potentially increasing biomass availability, sustainability of bioenergy as well as reducing food losses.

3.2.3 Consumer behaviour related to biomass use

Existing models generally depict demand for products as a function of income and prices and preference shifts are driven by external factors. This approach can be useful, for example, to assess how demand varies in function of price and income changes driven by external factors like technology and policy instruments. However, this setup falls short in considering other non-price related demand-side effects and consumers behaviour more generally. The realistic modelling of consumer behaviour, a factor influencing all our economies, of unquestioned importance to address major policy questions. Therefore, it is not surprising that modellers are increasingly confronted with expectations from e.g., the foresight community as well as from policy to consider in more detail the specific roles and effects of different consumer groups as well as the endogenous dynamics generated by learning consumers, leading to the increasing diffusion of new consumer orientations, and adapting lifestyles and strategic re-orientations of firms.

Changes in consumer behaviour are related to changes in preferences or lifestyle. Lifestyle changes are those actions leading, or aiming at, avoiding, or shifting the demand that thus determine a difference in the levels of service output. This type of non-standard decisions[4] by consumers are much more complex to capture in models compared to, for example, those standard, price-induced changes leading to substitution effects between consumer products. As highlighted by van den Berg et al. (2019, see also Table 2), lifestyle changes can be included in models by (i) exogenously including lifestyle changes into the underlying storylines and narratives used; (ii) endogenously modifying assumptions and parameters in the model; and (iii) explicitly modelling the changes in lifestyle in the model.

[4] In behavioural economics, non-standard are considered those decisions and behaviours that deviate from those based on the neoclassical vision of the rational homo economicus.

Table 3.2 Example of how the impact of food lifestyle changes has been performed in the literature. Source: van den Berg et al., 2019

Categories	Measures	Details	Model	Source
Healthier, less meat-intensive diet	Willet diet	Conforming to health recommendations	IAM (GCAM)	van de Ven et al 2018
			IAM (IAM) –(IMAGE)	van Vuuren et al., 2018
		"Healthy eating" recommendations, transitioning from 2010-2030	(IAM) – IAM (IMAGE)	Stehfest et al., 2009
		Based on the relative kg CO2-eq savings from Willet diet	Input-output analysis	Lekve Bjelle et al. 2018
		Based on the relative kg CO2-eq savings from Willet diet in addition to organic farming	Input-output analysis	Lekve Bjelle et al. 2018
	Reduced ruminant meat	Complete protein substitution of cattle, sheep, goats, and buffaloes, by plant-proteins, transitioning from 2010-2030	(IAM) – IAM (IMAGE)	Stehfest et al., 2009
		Beef consumption reduction, substitute beef with pork and poultry	PEM (TIMES)	Frenette et al. 2017
		Dairy and Poultry scenario – ruminants still used for dairy product supply, with culled calves and cows entering the meat chain, with a reduced ruminant meat consumed. It is assumed that animal production efficiencies increase to the North-western European (i.e., Swedish) levels of highly intensive systems.	Energy modelling - spreadsheet model	Röös et al., 2017
	Vegetarian diet	Complete protein substitution of pork and poultry by plant-proteins, transition from 2010-2030	(IAM) – IAM (IMAGE)	Stehfest et al., 2009
		No meat, but includes dairy products and possibly fish products	(IAM) – IAM (GCAM)	van de Ven et al 2018
		Beef, poultry and pork reductions, substitute with an increase in food grains, fruit, vegetables, eggs and dairy	(IAM) – PEM (TIMES)	Frenette et al. 2017
		Dairy and Aquaculture scenario – it is assumed that demand for animal protein continues rapidly, but health consciousness increases combined with high efficiencies by intensive aquaculture systems, by 2050 all animal meat consumed are from aquatic products (20% of aquaculture products are oysters, mussels and other filter feeding and 80% are low trophic-level finfish).	- Custom spreadsheet model	Röös et al., 2017
		Artificial Meat and Dairy scenario – consumer acceptance of in vitro meat matched with production technological breakthroughs (meat and dairy replaced by these	- Custom spreadsheet model	Röös et al., 2017

Categories	Measures	Details	Model	Source
		emerging proteins and those produced from insects and algae), essentially protein production in this scenario is landless.		
	Vegan diet	No animal products, additional protein substitution of eggs and milk by plant-proteins, transition from 2010-2030	(IAM) – IAM (IMAGE)	Stehfest et al., 2009
		No animal products (no meat, dairy, or fish)	(IAM) – IAM (GCAM)	van de Ven et al 2018
		Progressively reduce animal products until 2030 (substitute by grain and vegetable consumption)	(IAM) – PEM (TIMES)	Frenette et al. 2017
		Plant-Based Eating scenario – animal-free (except for a small amount of wild stock seafood). Policy actions discourage the consumption of animal products, in addition to growing environmental concern from the public, and technological developments of plant-based emerging proteins, vegan diets are most common. Assumed that grazing land are used for other activities, and the cropland is used production of foods directly for human consumption	- Custom spreadsheet model	Röös et al., 2017
Food waste reduction and composting		Assumed excess food used for animal feed as food waste, due to a reduction in final calories for humans	IAM (GCAM)	van de Ven et al 2018
		Eliminate food waste and composting	Input-output analysis	Lekve Bjelle et al. 2018
Organic and local foods		Organic and local foods	Input-output analysis	Lekve Bjelle et al. 2018

The first approach is the simplest and, so far, most widely used method out of the three. This approach generally relies on applications of models for different storylines, which include assumptions on lifestyle changes and other non-standard decisions to better represent consumption behaviour in modelling exercises. The Shared-Socioeconomic Pathways (SSPs; Riahi et al., 2017) framework representing undoubtedly its prominent example. Such storylines can draw on qualitative research aiming at understanding how consumers behaviours can change over time. Examples of how food diet-related lifestyle changes have been included exogenously can be found in van Vuuren et al. (2018), van de Ven et al. (2018), van Meijl et al. (2020) and Frank et al. (2019). Interestingly, van de Ven et al. also focused on food waste reduction. In Frank et al. (2019) diet changes were harmonised and exogenously implemented in the PEs CAPRI and GLOBIOM and the GCE MAGNET-IMAGE.

The endogenous representation of consumer behaviour through modified assumptions and parameters in the model is more challenging. Changing consumer behaviour has been a topic of research in modelling demand for forest products. For example, long used relationships between increasing graphic paper production and consumption and consumers' income growth appear no longer valid, as at high enough income levels, further income growth is now associated with decreasing graphic paper production (Chiba et al., 2017; Hurmekoski and Hetemäki, 2013), often explained by the adoption of the Internet and electronic media. This has led to new methods and additional parameters being considered to assess the demand for certain wood products (Chiba et al. 2017; Latta et al. 2016; Rougieux and Damette 2018; Hurmekoski et al. 2014). In general, the endogenous representation of non-standard behaviours is much more difficult, especially for lifestyle changes not related to technologies[5]. One approach consists in the dynamic representation of the social and technological learning of adopter groups' influencing the desired technological transition. An example on how this method can be applied, even if in another context, is provided by Edelenbosch et al. (2018) and McCollum et al. (2017), who explored how the adoption of electric vehicles is influenced by social and technological learning. Also, the studies by van de Ven et al. (2018) and Li (2017) are noteworthy examples that investigated different energy transition pathways modelling the impact of several actors with heterogeneous behaviour. While so far used almost exclusively in the energy modelling domain, the idea of using quantitative modelling approaches for understanding the socio-technical nature of bioeconomy transitions is certainly replicable in the bioeconomy context as well. In addition, van de Ven et al. (2018) and Li (2017) have introduced heterogeneity among decision-making within energy modelling. Cayla and Maïzi (2015) dealt with the same issues building the TIMES-Households model, which considers household behaviour and heterogeneity by modelling both their daily energy consumption and equipment purchasing behaviour. All these are interesting exercises that are worth to be considered as future paths to follow for the modelling of (bio-based) technology diffusion patterns.

A detailed comprehension of future behaviours and the motivations driving them is needed to explicit model lifestyle changes. This is thus the third and most challenging methodological approach to represent lifestyle changes. Edelenbosch et al. (2018) tried to include changing behaviour in the modelling of social learning dynamic in the IAM IMAGE. Similarly, Niamir et al. (2020) proposed a way to integrate the evolutionary dynamics of micro-level behaviourally rich ABMs (see section 2.3.3) into macroeconomic model by scaling up and linking the results of the empirical ABM BENCH-v3 with the EU-EMS (2019) CGE model (Figure 2). These two models are examples of approaches which are used outside the context of bioeconomy modelling but could nonetheless be reproduced in this context.

[5] With the attempt of an endogenous representation of changing consumer behavior new modeling approaches like agent based modelling (see 2.3.3.) are invoked, which shows that the boundaries between established and emerging modelling approaches in many cases is blurred and it is almost impossible to make a clear distinction.

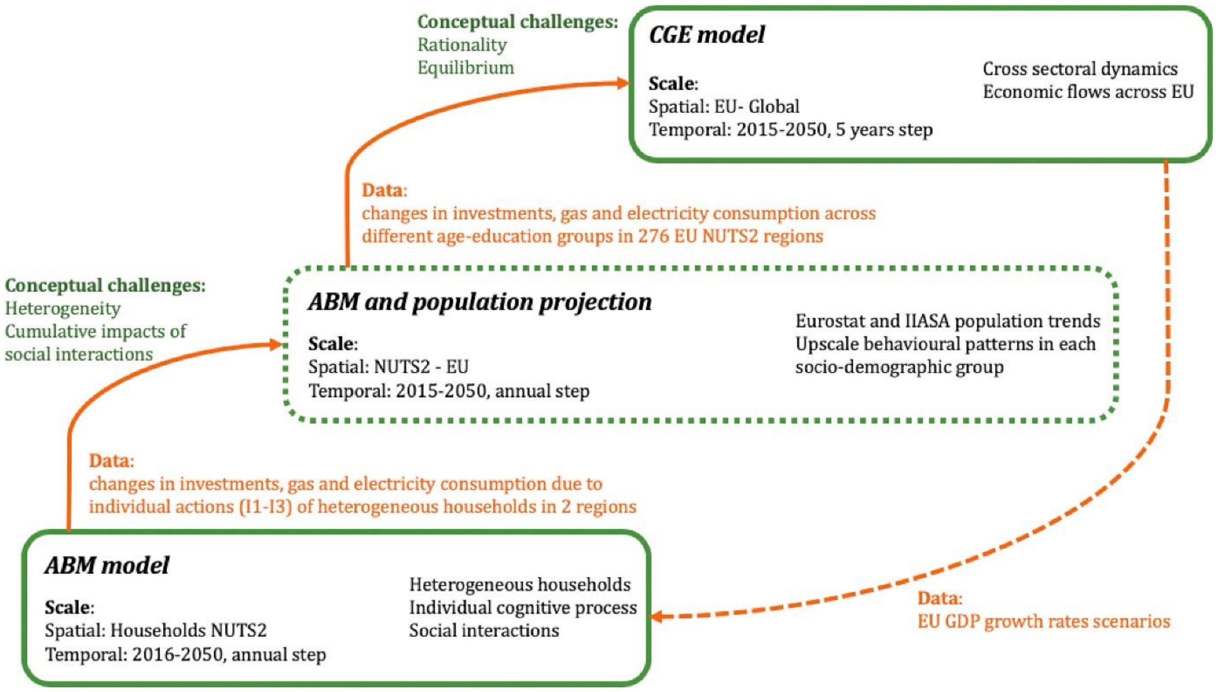

Figure 3.2. Representation of the three-steps approach used to upscale individuals behavioural change by linking the BENCH-v3 ABM with the EU-EMS model (Niamir et al. 2020; reproduced with permission)

3.2.4 Climate change

To mitigate and avoid as much as possible adverse climate effects, Europe strives to become the world's first climate-neutral continent by 2050. Mitigating and adapting to climate change is one of the main objectives of the European Commission's updated Bioeconomy Strategy.

Substantial resources have been invested so far to consider climate change in modelling and significant progress is being made. While these developments have not focused on the bioeconomy per se, they are very important to improve the capacity for bioeconomy modelling and address the aforementioned policy questions.

Climate change impacts and adaptation

Climate change affects agriculture and forestry both directly and indirectly. Changes in mean (and extreme) temperatures and rainfall directly influence productivity and site suitability for crops and tree species and alter the frequency and severity of disturbance events (wildfire, storms, pests, and pathogens) (e.g., Challinor et al., 2014; Lindner et al. 2014; Seidl et al. 2017; Smith and Gregory, 2013). These impacts directly affect sustainable biomass supply and their costs. For example, recent extreme weather events, including heat waves and extended droughts, have led to widespread tree mortality and forest decline even for several commercially important tree species which had not been regarded as particularly vulnerable. Furthermore, natural disturbances can ripple through bioeconomy sectors; for example, storms or pests can disrupt wood markets by first creating a pulse of available timber from salvage harvesting, and later resulting in a shortage of local timber supply.

Improvements to consider the impacts of climate change in modelling bioeconomy sectors is progressing in different lines of research. A major line of research is linked to modelling of the Shared Socio-Economic Pathways (Riahi et al. 2017; o'Neill et al. 2014). The Shared Socioeconomic Pathways (SSPs) are part of the modelling effort adopted by the climate change research community to facilitate the integrated analysis of future climate impacts, vulnerabilities, adaptation, and mitigation. The socio-economic information of the SSPs has been used as input to IAMs (e.g., IMAGE, GCAM, REMIND, AIM) and other economic models (e.g., MESSAGE, MAGNET, GLOBIOM and MAGPIE). These modelling efforts include the land use sector, but with a focus on agriculture, although the SSP scenarios framework is recently being adapted and applied to the forest sector as well (Daigneault et al. 2019; Johnston and Radeloff 2019).

Modelling the impacts of climate change on agriculture has so far focused on yield changes of a small number but important staple crops (Hertel and Lima 2020). Future climate change impact analyses should include the consequences of climate change for labour productivity, as well as for purchased intermediate inputs. Largely overlooked is the impact of climate change on the rate of total factor productivity growth and the potential for more rapid depreciation of the underlying knowledge capital underpinning this key driver of agricultural output growth. Further research is also needed that considers impacts on non-staple crops, which, while less important from a caloric point of view, are critically important in redressing current micronutrient deficiencies in many diets around the world.

Forestry modelling efforts have focused on including climate change impacts in large-scale forest resource modelling. This has typically been done by linking dynamic vegetation models (e.g., LPJ, ORCHIDEE) to empirical growth and yield models such as EFISCEN and EFDM (Eggers et al. 2008; Schelhaas et al. 2015; Vauhkonen and Packalen 2018). These efforts have particularly focused on incorporating climate-induced productivity changes, although some efforts have also been made to include changes in tree species suitability (Hanewinkel et al. 2013). Instead of model linkages, more recently promising progress is being made by developing growth functions (Schelhaas et al. 2018) and models (FORMIT-M; Härkönen et al. 2019) that are sensitive to climate and can be applied to estimate forest resource development and biomass availability at the European level. Natural disturbances are increasingly receiving attention as they have strong impacts on biomass availability, both in the short and long-term. While progress is being made in modelling natural disturbances at landscape level, this has not yet satisfactorily translated into large-scale modelling efforts to assess biomass availability.

With a growing understanding of the impacts of climate change, it is also becoming increasingly clear that adaptation is needed. There is thus a need to adapt to the impacts of climate change in addition to the need to mitigate climate change (Scherr et al. 2012; Verkerk et al. 2020). Adaptation has, however, received substantially less attention in crop modelling so far (Peng et al. 2020). While the understanding is improving on how forest management could be adapted to climate change (Kolström et al. 2011; Jactel et al. 2017), what the behaviour or perception of forest owners is to considering adaptation in their management practices (Sousa-Silva et al. 2018; Vinceti et al. 2020), and how this could be modelled (Yousefpour et al. 2015), this understanding is yet to be translated into large-scale modelling efforts.

Climate change mitigation

Agriculture, together with land use, land use change and forestry (AFOLU), is responsible for about 25% of global GHG emissions and are therefore key sectors for mitigating climate change. For this reason, mitigation is relatively well covered in existing modelling capacities. These analyses are typically done through integrated assessments, either by IAMs or by linking economic models with environmental models. Existing economic models allow exploring how emissions can be reduced by introducing mitigation technologies (incl. land use and management), energy saving, CO_2 taxes and diet changes. Mitigation technologies can be introduced explicitly or can be introduced by a marginal abatement curve. Optimization models and PE models often introduce technologies explicitly while CGE models often rely on marginal abatement curves. Biophysical models can provide insights in sustainable biomass availability for material and energy uses (e.g., Verkerk et al. 2011, 2019; di Fulvio et al. 2016; Jonsson et al. 2018) and provide insight into ecosystem carbon stocks and sinks (e.g., Böttcher et al. 2012; Nabuurs et al. 2018; Forsell et al. 2019; Pilli et al. 2017; Jonsson et al. 2020).

A challenge remains the identification, potential and adoption of new mitigation technologies and negative emission technologies (NETs) deserve particular attention and it is closely linked with modelling technological change. Especially afforestation and bioenergy with carbon capture and storage (BECCS) are currently the most modelled NETs. Modelling BECCS requires the modelling of first- and second-generation bioenergy crops, residues, forestry, bioenergy. Carbon Capture and Storage (CCS) involves injecting CO_2 deep underground. The real utility of BECCS, and more broadly of NETs for addressing climate change, will depend a lot on the speed of the technological progress that will determine when and how they will become commercially available at affordable costs. For BECCS, to become a competitive mitigation strategy the innovation rate is crucial, and it is thus crucial to properly model this aspect.

BECCS technologies for producing hydrogen, liquid fuels, and electricity from biomass are included in most IAMs (Daioglou et al. 2020), while heat and gaseous fuels productions are generally not represented. The production of electricity with CCS is generally included, while BECCS with production of hydrogen and liquid fuels are hardly modelled. BECCs are generally considered to be technologically ready and thus available for significant deployment from 2030 onwards, a questionable assumption since the technology is still in pilot phase. In most IAMs the dynamics of techno-economic performance in terms of evolution of conversion efficiencies and capital costs are exogenously assumed, except for some models (e.g., IMACLIM, IMAGE, and POLES) that treat them endogenously.

3.2.5 Biodiversity

Biodiversity, or the variety of all living things on our planet, has been declining at an alarming rate in recent years, mainly due to human activities. Intensive land use practices, pollution and climate change are major causes for losses in biodiversity, for example through loss and degradation of habitats and overexploitation (Butchart et al. 2010; IBES 2019).

Biodiversity is a key issue in the updated Bioeconomy Strategy, and its importance has been stressed in the recent Biodiversity Strategy linked to the Green Deal. The Biodiversity Strategy includes establishing protected areas for at least 30% of all European lands and 30% of European seas, restore at least 25,000 kilometers of rivers to free-flowing states, reduce the use and harmfulness of pesticides by 50%, plant 3 billion trees, increase organic farming and biodiversity-rich landscape features on agricultural land and reverse the loss of pollinators. As these aims closely relate to agriculture, forestry, and fisheries, they are also of key relevance to the bioeconomy.

Despite some studies that modelled biodiversity in the context of the bioeconomy (e.g., Verkerk et al. 2014; Di Fulvio et al. 2019; Kok et al 2019), most modelling studies that projected future biodiversity at the global level have focused on the future impacts of climate change and largely neglected changes in land use and land cover, although these represent the most significant and immediate threats to biodiversity (Titeux et al., 2016; Titeux et al., 2017; IPBES 2019). Despite many existing specialized biodiversity models, modelling biodiversity in a socio-economic context remains an important challenge. This is due to a lack of integration between ecological and land system sciences which limits the ability to make credible evaluations of the future response of biodiversity to land use and land-cover changes in interaction with climate change (Titeux et al., 2016; Titeux et al., 2017). Improved modelling of biodiversity needs to consider the direct result of human decision making at multiple scales. Improved modelling will also need to consider the modelling of TC and consumer behaviour (Kok et al. 2019) and need to account for the feedback between global change drivers, biodiversity, and socio-economic dynamics (Crossman et al. 2018).

Leclere et al. (2020) recently linked multiple models to explore biodiversity targets to reverse global biodiversity trends by 2050. Here some of the PE, CGE and IAM (land-use) models (AIM, GLOBIOM, IMAGE-MAGNET, Magpie) are connected with specialised biodiversity models (AIM-B, INSIGHTS, LPI-M, BILBI, cSAR_CB17, cSAR_US16, GLOBIO and PREDICTS). Leclere et al. (2020) find that future assessments should seek to better represent land-management practices as well as additional pressures on land and biodiversity, such as the influence and mitigation of climate change, overexploitation, pollution, and biological invasions. The upscaling of new modelling approaches could facilitate such improvements, although such modelling efforts currently face data and technical challenges. In addition, efforts are needed to evaluate and report on the uncertainty and performance of individual models. Such efforts, however, remain constrained by the complexity of natural and human systems and data limitations. For example, the models used in their analysis lack validation, not least because a thorough validation would face data and conceptual limitations. Leclere et al. (2020) state that in such a context, both improved modelling practices (for example, open source and FAIR principles, and community-wide modelling standards) and participatory approaches to validation could have a key role in enhancing the usefulness of models and scenarios. Besides being affected by land use, biodiversity is also important to support a sustainable development of the bioeconomy.

Besides understanding how biodiversity is affected by bioeconomy or socio-economic developments more generally, there is an urgent need to improve our understanding of how economies and societies will be impacted if current trends in biodiversity loss continue. Existing models, data and modelling approaches are currently not ready for estimating impacts to economies from changes to biodiversity. Additional effort is needed to link and integrate existing tools and approaches, incorporate new scenarios, and upscale for a global assessment (Crossman et al 2018).

3.3 What new modelling approaches are needed?

Traditional equilibrium- and optimisation-based models are limited in their capacity to fundamentally shift the modelling of policy interventions for sustainability transitions (e.g., Mercure et al. 2016). The limitations stem from the methodological orientation in neoclassical welfare theory which makes the models normative, while a positive/descriptive orientation would be required to reflect open and non-deterministic developments. The possibility that agents may not behave completely rational is thus not sufficiently addressed, in particular with respect to long-term developments shaped by uncertain innovation. Also, positive feedback and increasing returns due to mutual influence among agents cannot be captured adequately, but that decisively matters for a better understanding of consumer dynamics and knowledge diffusion. This also includes the important role of path-dependencies and multiple solutions which so far are hardly accounted for. Finally, traditional models are based on the idea of the representative agent in situations where the consideration of agent heterogeneity is indispensable for the analytical coverage of the problem. While these limitations are identified for economic models, they may also (partly) apply to environmental models (e.g., with regards to land use practices). In the case of modelling future transitions for the Bioeconomy, the major motive for an increasing interest in alternative modelling approaches, therefore, can be identified in a growing critique concerning two assumptions characteristic for most of the traditional models: (i) the assumption of stable optimal technologies, which excludes innovation, and (ii) the assumption of representative optimizing agents, which excludes dynamics generated by the interaction of heterogeneous actors. If the drivers of transformation processes are innovation and changing behaviours, it is contradictory to exclude them by assumption.

Studies on the bioeconomy applying emerging modelling approaches are almost non existent so far. Timmermans and de Haan (2008) observe that computational models theorizing and investigating structural change of economic systems and transformations of social systems have long been almost absent and - according to our knowledge - this has not drastically changed until today. Models applying emergent methodologies related to evolutionary economics and non-equilibrium complexity sciences, are still more theoretically oriented, demonstrating the principal applicability of the approaches or focusing on very specific (small scale) cases. Nevertheless, we consider emerging modelling approaches, which focus on topics close to the bioeconomy transition (e.g., on transformation processes in general, industrial development with structural change, land use and climate change and sustainability issues) as highly relevant for future bioeconomy models. In principle, the high expectations for the emerging modelling approaches to close the gaps and to solve the issues of traditional modelling approaches are justified, because the raison d'être of complexity sciences is the explicit consideration of non-linearities, which are behind all kinds of transformation processes. However, the general trade-off between generalization and specialization remains also valid for the emerging modelling approaches. Although they push the frontiers of possibilities of modelling outwards, they do not overcome what is discussed as the role and purpose of models: by the very logic of a model, it must remain a simplification and therefore must abstract from reality.

In what follows, we briefly discuss the state of development of four different emerging modelling classes which we consider highly relevant for bioeconomy modelling and outline which gaps they potentially close and where their limitations are. The selection of modelling classes cannot be complete because of the large dynamics in this emerging literature. The selection also cannot be highly selective because there are many overlapping features among the emerging modelling techniques, as well as among the emerging modelling and the established techniques. To structure this scattered and growing literature we suggest distinguishing four modelling classes, namely (1) complexity models, (2) agent-based models, (3) socio-environmental agent-based models, and (4) stock-flow consistent models. Our taxonomy logic takes up the most important traditional model families and set against the corresponding emerging modelling approaches (see Table 3.4).

Table 3.4. Taxonomy of emerging modelling approaches inspired by traditional modelling classes

Focus	Traditional	Emerging
Economy-wide impacts	Computational General Equilibrium Models	Complexity Models
Selected sectoral impacts and phenomena	Partial Equilibrium Models	Agent-Based Models
Interaction between human and natural systems	Integrated Assessment Models	Socio-environmental Models
Changing internal economic interdependencies	Input-Output Matrices	Stock-flow consistent models

3.4 What types of emerging modelling classes could be distinguished?

3.4.1 Complexity models

The principal idea of complexity models is that dynamic system behaviour can only be analysed and understood if systems are treated as a whole. With this regard there is some resemblance with the existing CGE models discussed in Chapter 2. Mutual interdependencies of the system components cause changes and unexpected developments and are responsible for non-linearities in the interaction patterns. Complexity models are traced back to the activities of the Santa Fee Institute starting in the 1990s (e.g., the work on increasing returns by Arthur (1989), complex adaptive systems by Holland (1993), self-organization by Kauffman (1993) and self-organized criticality by Bak 1996), which create this prolific modelling field by exploiting the possibilities from statistical physics, non-linear physics, theoretical biology, and computer science. As an early predecessor of complexity models, the system dynamics model (SDM) approach must be mentioned, in particular because of its large popularity in addressing systemic interactions between socio-economic systems and environmental systems starting already in the 1970s and prominently applied in the early studies of the Club of Rome. From an economic theory point of view, complexity models build in many cases on ideas of evolutionary economics (Safarzynska, Frenken and van den Bergh, 2012) and are often considered as the formal approach in evolutionary economics (Beinhocker, 2006).

As an example, for complexity models, Safarzyńska and van den Bergh (2010) extend Brian Arthur's model of increasing returns to investigate transitions away from environmentally unsustainable activities to sustainable ones, notably in agriculture, energy, and transport sectors. The transition depends on the overcoming of a lock-in in an unsustainable technology. The model describes coevolving populations of bounded rational consumers and innovating firms. On the demand side, attention is laid on the interdependence of consumer preferences. The prevailing lock-in is surmounted only by the synergetic interaction of various actors on both market sides exposed to increasing returns in innovation and network effects large enough to surpass the threshold given by increasing returns in production of the unsustainable technology. The model is then used to identify various targets for policy interventions to support this transition.

Complexity models can also offer an adequate modelling framework for so-called utopia models, which focus on long-term developments of pre-defined (desired and undesired) scenarios, necessarily including large uncertainties and interaction-based complexities. For example, Almudi et al. (2017) address the interaction-based competition between different economic regimes. This modelling study of transition dynamics is based on a co-evolutionary model of differential citizen contributions to competing 'utopias' — market fundamentalism, socialism, and environmentalism. In this battle of ideas, initial distributions and interactions between groups explain the observed transition dynamics. For the transition towards a bioeconomy and unlocking the lock-in in existing fossil-based technologies, similar approaches might explain the temporary co-existence of various sectors from oil-based and bio-based industries as well as their hybrids in a transition period, which might last many years, if not decades.

Similar to computable general equilibrium models, complexity models are often comprehensive and describe economies as a whole. The expressiveness of the complexity models in terms of qualitative structural changes in the economy and the focus on uncertain innovation stems from an explicit account of heterogeneous agents and the non-linearities, which emerge from their interaction. Obviously, the higher expressiveness in these dimensions comes with the price of a lower accuracy concerning a detailed mapping of inter-sectoral relations typical for the CGE models and their large possibilities to align with empirical information.

3.4.2 Agent-Based Models

With their bottom-up approach agent-based models (ABM) (for a general overview see Gilbert and Troitzsch, 2005 and Tesfatsion, 2002) raise the highest expectations within the group of emerging modelling approaches. Macal (2016) concludes from the various attempts to define agent-based modelling, that the consensus seems to be: "*We do not know what agent-based modelling is, … but we know we need it!*". ABMs allow to model and analyse complex adaptive systems consisting of autonomous, decision-making agents that interact with other agents and their environment (Pyka and Fagiolo, 2007). In contrast to other simulation methods, the agent perspective and the inherent bottom-up approach is particular (Axelrod, 1997). ABMs help to understand both agents' and aggregate behaviour and explain how these behaviours lead to large-scale outcomes and emergent phenomena (North and Macal, 2007). ABMs allow the analysis of emergent phenomena, e.g., over time or on a spatial level, from the interactions of agents who follow 'simple' what-if rules. The actors differ in their behaviour and strategies and jointly shape their environment which in turn influences their behaviour. This feature allows the ABM methodology to include dynamics on different scales, in particular the important micro-meso-macro feedbacks, which are lost by applying the idea of the representative actor, which is characteristic for the traditional modelling approaches.

The following thought experiment illustrates the relevance for bioeconomy modelling: Supply side dynamics in bioeconomy sectors stem from the entrepreneurial introduction of a new bioeconomy technology on the micro-level, which eventually is the seed for a new bioeconomy industry on the meso-level and attracts imitating companies. This finally impacts qualitatively on macro-economic growth by lowering CO_2-emissions. This is not yet the end of the dynamic cascade, but these developments are responsible for further feedbacks: The changes on the meso- and macro-levels increases the probability for the development of other bioeconomy technologies because the first feasibility is proven and innovation directions are tried out, which eventually triggers changes in value creation networks on the meso-level, and so on. This beginning transformation is aggravated from similar dynamics shaping the developments on the demand side where new consumption patterns might be developed by avantgarde consumers, which weigh higher ecological-friendly attributes. They eventually are imitated by larger groups and determine the mainstream consumer orientation which then facilitates further pattern changes, both on the demand and the supply side.

This possibility of a flexible representation of human-decision making and the leaving-behind of the *homo oeconomicus* inspires many new modelling initiatives. As an example might serve so-called land use and land cover change models (LUCC), which today reflect on the consequences of considering heterogeneous agents and the consequence for decision making by applying decision heuristics instead of optimization (see Groeneveld et al. 2017 for a survey of LUCCs).

These examples illustrate that the dynamics of complex systems are directly shaped by the heterogeneity of the agents, their interactions, and the adaption of their behavioural rules. Decision rules follow descriptive ideas observed in real decision behaviour (heuristics) instead of the normative optimization idea in mainstream economic models. Agents have incomplete knowledge and competences which opens space for learning and innovation as well as failure. Furthermore, ABMs allow for an explicit consideration of true uncertainty (e.g., Vermeulen and Pyka, 2016) as well as the consideration of values and norms (e.g., Schlaile et al. 2018). For these reasons, ABMs already today enjoy great popularity in so-called neo-Schumpeterian innovation economics and are frequently applied to study innovation, entrepreneurship, technology diffusion or learning in innovation networks (e.g., Pyka et al. 2019; Vermeulen and Pyka, 2018), which all are highly relevant topics in the bioeconomy transformation.

An illustrative set of ABMs focusing on technological transitions towards sustainability was developed in the FP6 project MATISSE. As an example, in a contribution by Bergman et al. (2008) the authors apply their ABM in a so-called *history-friendly-simulation* (Malerba et al. 1999) to reproduce the development of a historical technological transition. In particular, they address the so-called sailing ship effect, which enjoys some popularity in modern innovation economics to explain the acceleration of innovation activities in incumbent technologies due to the challenge of being replaced by the introduction of a new technology. When steamboats appeared on the market in the middle of the 19th century, the sailing ship industry started to innovate again, after not having changed the technology for about a century. Although they could not prevent being finally completely replaced, they considerably delayed the steamboat diffusion. However, their innovation activities also helped the immature steamboats to develop to a reliable and superior technology (see e.g., Mendonca, 2013). A similar situation very likely characterizes several industries, where new bioeconomic approaches challenge the established fossil-based technologies in a substitutive way.

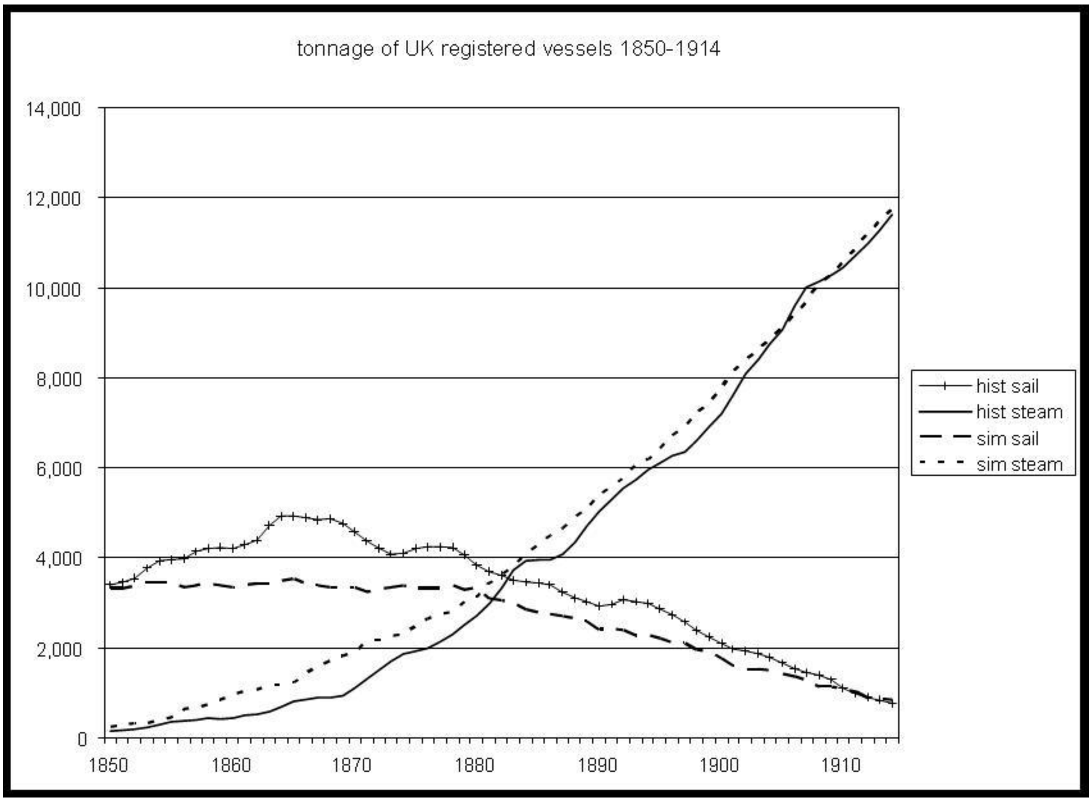

Figure 3.3. Comparison of registered tonnage of sail and steam from historical data with model simulation results (Bergman et al. 2008; reproduced with permission).

Figure 3.3 from Bergman et al. (2008) displays the historical paths and the very similar simulated paths of the invasion of steamboats, the long period of co-existence of steamboats and sailing ships and the final displacement of the older sailing ship technology. This example illustrates the possibilities of *close-to-reality* modelling by the simulation based on the implementation of transition theory together with an empirical calibration of manifold parameters, which are characteristic for ABMs. It must be mentioned here, that in the last 10 years or so, the possibilities to calibrate empirically the parameters of ABMs have improved substantially due to new available data sets. ABMs increasingly rely on the exploitation of big data by machine learning algorithms like deep learning to calibrate the models (for a comprehensive review see Dahlke et al. 2020). This development is supposed to invalidate the reproach towards ABM being arbitrary in parametrization (e.g., Fagiolo et al. 2019).

With respect to the standard modelling approaches, ABMs might be considered as an extension and complement of PE models. They also allow a detailed and less abstract coverage of sectors but compared with PE models their focus is on endogenous innovation, technology transition, learning, consumer behaviour and changing preferences as well as entrepreneurial experimentation. ABMs allow for an explicit representation of heterogeneity, which is a most important feature in transformation processes, which always involve different groups of actors (e.g., incumbents, entrepreneurs, different consumer habits etc.). Because of their orientation to real world decision behaviour, they go beyond the normative application of optimization and allow for learning, experimentation (including failure) and mutual influencing of actors, who are confronted with open developments, i.e., true uncertainty.

3.4.3 Socio-environmental ABMs

Socio-environmental agent-based models are not a completely different emerging modelling approach compared to the above discussed ABMs, but a combination of socio-economic ABMS with ecological models, often also formulated as an agent-based model (N.B. in ecology modelling ABMs are sometimes called individual-based modelling). Socio-environmental ABMs represent the behaviour and interactions of organisms, human actors, and institutions. Feedback effects between the various interactions are responsible for continuous adaptation and change processes on all temporal and spatial scales and make-up the enormous complexity of these systems. A better understanding of the highly dynamic socio-environmental systems is closely connected with the expectation to improve our possibilities for sustainable management of resources and to safeguard the integrity of ecosystems (see Ostrom, 2009). With socio-environmental ABMs large expectations are connected, which are nicely worked out in a recent manifesto-like paper by Elsawah et al. (2020). The authors highlight that socio-environmental ABMs allow for a formal representation of complex adaptive systems and integrate qualitative and quantitative methods and data on: system components, interactions among components, and their responses to changes in the exogenous or endogenous drivers. Finally, socio-environmental ABMs, by their very nature of combining social and natural systems, explore interdependencies among changes in controllable (e.g., policy and its instruments) and uncontrollable (e.g., natural system influences) drivers.

As an example of this fast developing and highly interdisciplinary literature we refer to an agent-based simulation model of human-environment interactions in agricultural systems by Schreinemachers and Berger (2011). This model might serve as an exemplary case for the rich possibilities of this modelling approach. At the core of their model is an agent-based simulation model on farm-decision making in agricultural systems with the aim to better understand how agricultural technology, market dynamics, environmental change, and policy intervention affect a heterogeneous population of farm households and the agro-ecological resources these households command. The microeconomic decision-making and learning socio-economic ABM is coupled with an environmental ABM, which depicts the dynamics of the relevant eco-systems. Figure 3.4 illustrates the interfaces between the socio-economic and the environmental ABM, typical for socio-environmental ABMs models. Besides the respective internal dynamic loops addressing either the economic decision model or the ecosystem dynamics, in socio-environmental models the ecosystem is impacted by the socio-economic-system and delivers information for agents as a basis for decision making. Due to e.g., different time scales in both systems, non-linearities might emerge responsible for surprises or even sudden collapses of the systems. In the example of Berger et al., (2010) the authors analysed the question "*What could be the impact of climate change on land use and farm incomes?*" which includes in its dynamic version the feedback between agricultural production and climate change and vice-versa between climate change and land use.

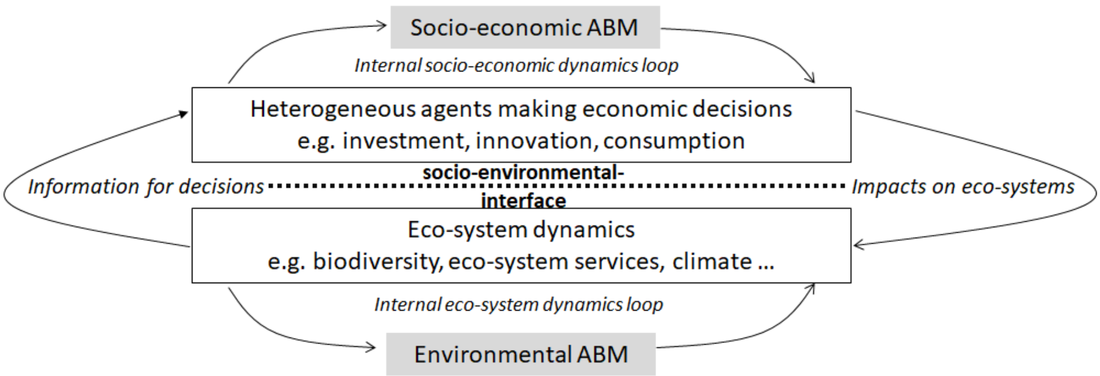

Figure 3.4. Human-environment interactions in socio-environmental models

Brown et al. (2019) developed and used an agent-based model of the European land system, namely the CRAFTY-EU model, to investigate the effects of human behavioural aspects of land management at the continental scale. Their modelling approach is motivated by the observation that established computational models to analyse land use are too narrowly focussing on biophysical changes and do not explore the social dynamics that are a key aspect of future land use. Therefore, established models are suffering from "blind spots" at which individual, social, and political behaviours divert the land system away from forecasted developments. The study by Brown et al. shows the advantages of not being constrained by equilibria nor by optimisation. With exploring a range of potential futures using climatic and socio-economic scenarios, the authors show that deviation from simple economic rationality at individual and aggregate scales, typical for e.g., CGE and PE models, may profoundly alter the nature of land system development and the achievability of policy goals. Their conclusion both underlines the opportunities as well as the challenges of socio-environmental models in general: the integration of socio-economic aspects of future scenarios have a profound impact on environmental developments and require far more detailed and varied treatment. Several other studies also introduced behaviour of forest owners in wood production (e.g., Rinaldi et al. 2015; Sotirov et al. 2019). The study by Rinaldi et al. (2015) introduces a (theoretical) behavioural decision model on wood harvesting to complement a biophysical model and a partial equilibrium model for the forest sector.

The combination of economic and biophysical models in the socio-environmental ABMs is offering large possibilities for modelling the future transition for the bioeconomy towards sustainable development and a climate-neutral economy. This is because it allows, in principle, a comprehensive consideration of the interaction between human and natural systems, as well as the non-linearities which are expected in these complex systems. However, while the advantages of socio-environmental ABMs are their ability to simulate the implications of human-nature interactions explicitly, the methods for providing empirical support for the representation of these interactions are not yet available in a systematic structural form (e.g., Smajgl, et al. 2011). In a critical review on social-ecological ABMs, Schulze et al. (2017) emphasize the arbitrariness to communicate whether the models represent real systems well enough and the massive difficulties in the transparent and systematic analysis of the models, so that output is not only observed but also understood. By their very nature, social-ecological ABMs are following from the beginning the KIDS-strategy in designing the model to allow for a high degree of realistic representations of the various relations, interactions, and interrelations not only in economic systems but in economic and ecological systems as well as in their interrelations. For this reason, Elsawah et al. (2020) state in their manifesto, that despite the large potentials, "*this is not a straightforward endeavour, and both theoretical and methodological challenges abound*".

Social-ecological ABMs, in a way, are in the group of emerging modelling approaches, the approach which extends and develops further the class of IAMs. IAMs also focus on the interactions between human activities and environmental change and include in a multidisciplinary fashion a detailed description of the coupled human and environmental systems as well as the one-way interrelations between the two. Because socio-environmental ABMs displace the standard economic models with their equilibrium-orientation and optimization-based decision rules with ABMs, they combine the advantages of ABMs concerning the representation of learning, innovation and non-linearities with the comprehensiveness intended in IAMs.

3.4.4 Stock-Flow Consistent Models

A final emerging model class, even if only a few applications exist so far, builds on the tradition of models relying on input-output tables (see section 2.2.7). So-called stock-flow consistent (SFC) macroeconomics (Godley and Lavoie, 2007) track financial and physical flows through an economic system and provide a holistic approach that integrates the economic, ecological, and social spheres (for an excellent survey of SFC models see Nikiforos and Zecca, 2017). Stock-flow consistent (SFC) models are based on stocks of assets and liabilities of multiple sectors in the economy, as well as flows between these sectors, and their dynamic interactions in a consistent accounting structure. This logic makes Stock-Flow-Consistent-Input-Output models different from traditional Input-Output models. In the latter, final demand is usually assumed exogenous and given (or is shocked exogenously), while in the former there is an endogenous evolution of income structures, employment levels, and spending on goods through input-output relationships (see e.g., Rezai and Stagl, 2016 and Dafermos et al. 2017).

In Dafermos et al. (2017) a model is introduced which combines the macroeconomy, the financial system and the ecosystem (see Figure 3.5) to simultaneously analyse in a scenario-based approach the dynamic interactions between growth and how it is financed, the natural constraints of resources and how they are degraded and depleted by the economic activities.

Moreover, the SFC approach is also used as the macroeconomic closure of microeconomic agent-based models (e.g., EURACE model by Deissenberg et al. 2008) and therefore offers a promising opportunity for model cooperation. For applications concerning the future transitions for the Bioeconomy towards sustainable development and a climate neural economy, so-called SFC ecological models (e.g., Jackson and Victor, 2015, 2016) are most interesting, where specific conditions for sustainable growth of economic systems are derived.

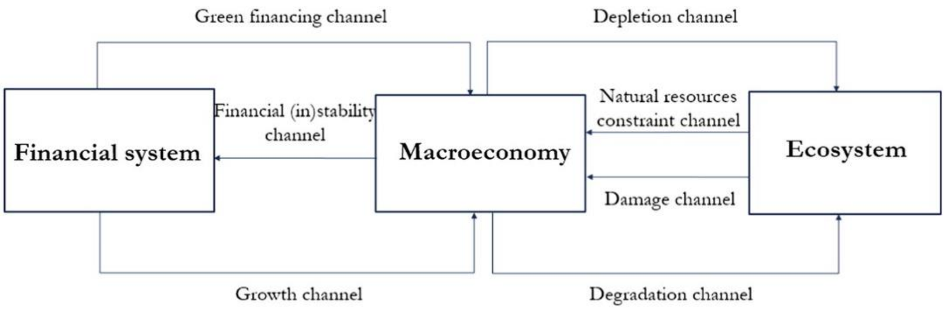

Figure 3.5. Main interactions between the ecosystem, the financial system and the macroeconomy in the model (Dafermos et al. 2017; reproduced with permission)

To summarize: the limitations of traditional models can be addressed by the modelling possibilities of emerging modelling techniques which allow to analyse future transitions towards a knowledge-based bioeconomy. These modelling features are the representation of (i) uncertainties, (ii) heterogeneity, (iii) qualitative different system states, (iv) social values and norms and how they change, (v) non-linear behaviour and (vi) different scales.

The four emerging model classes introduced above all consider these six modelling features at the core of their constitutive principles. The extension to allow for the analysis of real complex systems which do not exclude innovation driven development and qualitative change by assumption but include them as endogenous features allows for a better understanding of dynamic systems and, most important, for an application in the policy realm for experimentation of alternative policy interventions as well as alternative theoretical backgrounds. ABMs, for example, are recently extended to so-called policy laboratories (see e.g., Schilperoord and Ahrweiler, 2014, Ahrweiler et al., 2015 and Pyka et al. 2018), which add a graphical user interface with intervention possibilities and observation monitors, and which are used for an ex-ante evaluation of policy interventions. The integration of the models into the policy laboratories facilitates communication with stakeholders and their experimentation is strengthening their intuition to deal with complex systems. Edmonds et al. (2019) are observing that the purpose of modelling shifts with the emerging modelling approaches from prediction and explanation more and more to description and illustration, theoretical exploration, and analogy to facilitate social interaction among stakeholders and the modelling researchers.

Although the emerging modelling approaches are around for more than two decades now and have found a considerable interest in the literature and progress is made, attempts to develop larger models used to describe whole economies and applied on the bioeconomy transition with a few exceptions are largely absent. Possible reasons for the limited uptake for bioeconomy modelling are the inherent difficulties with dealing with complex systems, hesitation towards emerging modelling approaches in existing models, and the ongoing development on the understanding of the bioeconomy and the required transitions. A promising exception can be found in large-scale models combining land-use change and climate change. For example, Arneth et al. (2014) enrich a global vegetation model with an agent-based model to represent the socio-economic part. The existing models focus on specific problems and show the principal applicability of the emerging modelling approaches but lack developments and applications with regards to bioeconomy transition. Table 3.5 lists examples for each emerging model class and is not claiming for any completeness at all. Instead, we refer to survey papers to give the interested reader access to more examples in this literature: For complexity models see Bruno et al. (2016), for ABM with an ecological focus see Heckbert et al. (2010), for socio-environmental ABMs see Levin et al. (2013) and for stock-flow consistent models see Nikiforos and Zecca (2017). The examples in the table were chosen in a way to cover topics close to bioeconomy and sustainability issues.

Table 3.5. Examples from emerging modelling classes

Emerging modelling approach	Topic	Source
Complexity science	Co-development of energy consumption, knowledge creation and economic growth	Foster 2013
	Overcoming of technological lock-ins in the case of environmental innovations	Zeppini et al. 2011
Agent-based models	Policy instruments and their effects on innovation and industrial dynamics in the case of environmental regulation	Arfaoui et al. 2014
	Combining bounded rational consumers in an ABM with a CGE macro model in the case of energy uses	Niamir et al. 2020
Socio-environmental ABM	Non-linear dynamics in coupled human-nature systems	Crépin et al. 2011
	Ecosystem management of spatial interactions between natural systems (groundwater, biomass) and human systems (myopic optimizing agents)	Brock and Xepapadeas 2010
Stock-Flow Consistent Models	Formal integration of the SFC and the I-O approach, taking energy into account	Berg et al. 2015
	Model to examine policies that address growth, distribution and environmental sustainability	Naqvi 2015

With most recent developments in data science the application to larger real-world systems seems to become possible. Deep learning and other machine learning algorithms increasingly are applied to squeeze out information from big data sets required to capture ongoing, but slow transitions which usually are not visible in e.g., industry statistics. Dahlke et al. (2020) and van der Hoog (2017) provide extensive recent overviews on these developments. Dahlke et al. (2020) conclude their survey with emphasizing the prolific alliance between ABM modelling and big data which requires sophisticated tools to exploit these opportunities. One of the most promising tools is machine learning with its multifaceted possibilities to calibrate agent characteristics, environmental settings, learning strategies and, perhaps most important, endogenous structural breaks. This has the potential of a structural break for modelling on its own and will play a major role in addressing the grand challenges of mankind from a social sciences perspective.

3.5 What new methods and approaches could support bioeconomy modelling?

3.5.1 Big data

Since more than a decade we observe that a huge amount of diverse data from conventional data sources like statistical offices (see for example http://data.un.org/) as well as from unconventional sources, e.g., processed data from large internet companies (see for example https://cloud.google.com/public-datasets) is becoming increasingly available. Another important source of big data directly stems from global climate research and globally widespread in situ observations as well as increasingly available satellite data (e.g., https://www.copernicus.eu/en or https://f-tep.com/). Furthermore, many of these big data sources and derived products are provided on easy accessible platforms (e.g., http://www.globalforestwatch.org/).

Responsible for the advent of 'big data' are the advances in the generation, storage and sharing of data (e.g. sensors, satellites, user behaviour in the internet etc.), the administration of data (e.g. cloud solutions, high performance computing, fast internet etc.) and new possibilities to exploit the large amount of data, in particular the application of methods of artificial intelligence (e.g. machine learning etc.) together with broad available sophisticated competences in data processing which has led to new disciplines (e.g. data sciences). Not surprisingly, these developments are also considered as highly relevant in environmental and economic research. Big data are considered to provide important opportunities for improved understanding of important processes along value chains in agriculture (Coble et al. 2018) and forestry (Rossit et al. 2019; Hasan Shaikh et al. 2019; Zou et al. 2019). Lokers et al. (2015, 2016) describe the possibilities and give examples for Big Data technologies in agriculture and forestry and focus on the complexities of bringing together heterogeneous data from a variety of different sources. The DataBio project developed the DataBio Hub with a big data platform for the bioeconomy with a focus on agriculture, forestry, and fisheries (https://www.databiohub.eu/registry/).

3.5.2 Artificial intelligence

The exploitation of big data sources only became possible with the advent of artificial intelligence which empowered statistical and econometric tools to be applied on the processing of huge amounts of structured and unstructured data. For an overview on the fast and dynamic development of this vibrant field in modern computer science in Europe, see Craglia (2018). Willcock et al. (2018) give examples for machine learning driven empirical modelling approaches which search for correlation in the variables of big data sources to identify unknown interdependencies. Rammer and Seidl (2019) used deep learning to predict both local scale short term infestation risk and landscape level long-term outbreak, obtaining overall performances that are better than those achievable with conventional approaches. Similarly, Senf and Seidl (2020) mapped forest disturbance regimes for Europe using the Google Earth Engine. Artificial intelligence is also used as in the Integrated Modelling Partnership (http://www.integratedmodelling.org/) to link data and models through semantic annotation. Rossit et al. (2019) employ data mining methods like k-means clustering algorithms to analyse data generated in so far unknown quantity and quality by modern forest harvesting technologies equipped with various sensors and online transmission tools combined with common protocols for data storage and data processing. In the context of this report also the United Nations Global Pulse (UN Global Pulse 2017) (https://www.unglobalpulse.org/) initiative must be mentioned, which harnesses big data and artificial intelligence to support the achievement of the sustainable development goals and related policy making.

Concerning the future transitions for the bioeconomy towards sustainable development and a climate-neutral economy these approaches promise prolific applications. As the bioeconomy is not a single sector but has general purpose character and is highly relevant in many different sectors, traditional industry classifications do not allow to portray the ongoing diffusion of the bioeconomy. We observe in many cases an increasing conversion of established industries e.g., when bioplastics and chemicals appear in the portfolio of established chemical companies or when they replace the use of oil-based plastics on a small, but over time increasing share. In such a case relying on the industry classification would simply not allow us to figure out the relevant changes. Exploiting big data sources together with tools from artificial intelligence can be used to recognize these patterns hidden in traditional industry statistics and allow for new and more precise understanding of sectoral developments. To discover the dynamics of these sectoral transitions towards the bioeconomy could support policy to identify most vibrant areas where policy support could create critical mass to accelerate the desired development. The same ideas could be used to detect patterns in databases describing the actors' knowledge bases such as patent data. The new patterns detected in firms' knowledge allow us to figure out which areas of the bioeconomy already are characterized by vibrant dynamics. An improved classification of knowledge fields relevant for the bioeconomy is essential for more accurate innovation policies, e.g., the support of innovation alliances in the bioeconomy. The transformation from a fossil-based to a biobased economy will require time and will thus imply a co-existence between the two for at least some time. A better understanding of the substitutive, complementary, and potential synergetic relations is essential for designing the right policy instruments.

A common feature of models building on traditional as well as emerging modelling approaches is that they use large sets of parameters to distinguish between different sectors and to weigh interrelations among variables. Big data and machine learning offer innovative instruments to substantially improve parametrization of models which often is a theme for strong critique. In this sense, Pereda et al. (2017) argue that "(*i)n general, but particularly in models with high dimensional parameter spaces, machine learning techniques can be usefully applied to analyse ... models*".

Bringing together environmental, social, and economic big data sources also very likely will allow us to discover unknown causalities and interdependencies among different variables. For following the sustainable development goals, this will most likely allow to develop early warning signals, e.g., detecting upcoming crisis (Chatzis et al., 2018; Sevim et al., 2014) and other changes not immediately visible in conventional statistics. In non-linear systems early warning signals are of utmost importance to avoid dynamic developments which cannot be stopped anymore.

Finally, the emerging modelling approaches based on computational approaches are characterized by a large flexibility concerning the use (the implementation) of very different variables which are crucial for the understanding of the ongoing transformation. The consideration of ethical rules, social norms and values is essential for the understanding of consumption behaviour and its development over time. Although in many cases these variables are empirically difficult to be observed and not measurable, they can be simulated. The artificial data generated in the artificial world of the model allows for e.g., a better understanding of the driving motives of consumers and how they change over time. For example, Schlaile et al. (2018) show how responsibility considerations can be integrated in an ABM on consumption behaviour and innovation to analyse changing behavioural modes over time.

The possibilities provided by artificial intelligence, in particular machine learning, are also likely to push forward the limits of emerging modelling approaches like agent-based modelling and socio-environmental agent-based modelling (for a most recent survey see Dahlke et al. 2020). If the size and the complexity of the model is reaching a level where we are no longer able to understand the processes involved and the underlying input-output relationships, we cannot understand these artificial complex systems any better than we understand the real ones (Axtell and Epstein, 1994; Gilbert and Terna, 2000). Especially in highly complex models with many different parameters like in socio-environmental agent-based models, generated output must be stored and prepared in a way that it can be efficiently accessed by a human being or by a computer (Macal 2016). In this context, machine learning tools can be used to improve the understanding of the model by (i) improving the understanding of model behaviours (Perry and O'Sullivan, 2018), and (ii) enhancing the analysis of output data to find important parameters, clusters, conditions, causalities and input-output relationships (Edali and Yücel, 2019).

3.6 How could new model developments help to address new indicators, trade-offs and synergies?

As outlined in chapter 2, existing models mostly cover the SDGs on economy and employment (SDG 8), energy (SDG7), investment-trade-finance (SDG 17), food-land (SDG 2), climate change (SDG 13), and to a lesser degree, water (SDG 6) and industry-innovation (SDG 9). Policy areas that represent key gaps in modelling capabilities included institutions-governance (SDG 16), gender equality (SDG 5), cities (SDG 11), marine life (SDG 14), education (SDG 4) and, to a lesser degree, poverty (SDG 1), health (SDG 2), inequality (SDG 10) and terrestrial life (SDG 15) (Allen et al. 2016).

There is thus a need for quantitative simulation modelling assessments to deepen our understanding of the potential medium- to long-term benefits, synergies and risks associated with alternate narratives of human development. In the next four sections we discuss key challenges in this regard based on Costanza et al. 2016).

3.6.1 Modelling and possible valuation of SDG goals

In general, the social SDGs are not covered or not very well covered in existing bioeconomy models. More abstract "social" concepts described in SDG1 (poverty), SDG3 (good health and wellbeing), SDG4 (quality education), SDG5 (gender equality), SDG10 (reduced inequalities), SDG11 (sustainable cities and communities) and SDG16 (peace, justice, and strong institutions) are not addressed or addressed to a limited extent. All these SDGs cover distributional issues between different groups of people or households. These indicators could partly be quantified and connected to existing modelling platforms by connecting with household and social models or developing complex indicators based on distributional data and econometric analyses that can be added to existing modelling frameworks. Some ABM models could potentially fill the gaps on modelling social issues as they model the individual decision makers and how they interact. Data needs to cover broader areas are currently a challenge in the ABM models. For the short run most promising is to connect existing models with distributional issues. They can be potentially integrated within existing frameworks (i.e., include multi-households instead of one household in CGEs) or by connecting to micro-simulation models. In the longer run when complexity models progress, they might become an alternative option because of their higher flexibility to deal with heterogeneity and endogenous dynamics. As a starting point for covering more SDGs in current frameworks and constructing econometric modelling efforts, the United Nations Global SDG Database (https://unstats.un.org/sdgs/indicators/database/) provides coverage of numerous indicators for 195 regions over the period 2000-2018. See for example the work by Campagnolo and Cian (2020) who employ a mix of econometric and equilibrium modelling work to address changes in the Palma ratio. In the area of health (SDG3), few efforts are taken to connect with existing bioeconomy models. The links are often through detailed modelling of macro and micronutrients (see e.g., Springmann et al. 2018). In general, we can conclude that the coverage of social goals and indicators is weak in current modelling. Including sophisticated indicators based on distributional data might be a first step to take. Another option is to connect with social models although a broad geographical coverage is a challenge.

Environmental models are typically well suited to cover ecosystem services and other environmental indicators related to the SDGs (e.g., biodiversity in the SDGs on life on land and on sea (SDG 14 and SDG 15)). It is, however, challenging to include the services and indicators in economic models. Significant efforts have been made to estimate the economic value of ecosystem services (e.g., Costanza et al. 2014), but has not yet been taken up strongly in economic models.

3.6.2 Complex interconnections between the goals

The interactions between the various SDGs are complex and modelling can shed light on these complex interactions. A recent review (van Zanten and Tulder 2020) finds that studies on agricultural, industrial, and manufacturing activities predominantly report negative impacts on environmental development, while literature on services activities highlight economic and social contributions.

Models are well suited to quantify the complex interaction between SDGs. A prerequisite is of course that a model should be able to model the SDGs at all (see point 1). Then relation between SDGs is another challenge. A first option to address this issue is to extend existing models or modelling frameworks as described above (see point 1). For example, general equilibrium models extended or linked with complex indicators in the field of social and environmental issues could play a role (see for example the ICES model by Eboli et al. 2010). In the field of bioeconomy, agricultural, forestry, food, wood, energy, and chemical PE models could be linked. However, these models remain equilibrium models and for the transition pathways new modelling techniques are needed. Complexity or system dynamics models could play a role here as the existing modelling systems cover only a few SDGs and extensions to a full coverage is not easy. With respect to a comprehensive coverage of the SDGs, recently system dynamics modelling is experiencing a renaissance. The very idea to reflect on complex interactions between various subsystems and its application of the interconnected target system of the SDGs suggests a promising application. Ferri and Sedehi (2018) developed a so-called causal loop diagram of a systemic view of the overall set of SDGs (enlarged by three further goals) by emphasizing the positive and negative feedbacks between the goals (see Figure 6). Zelinka and Amadei (2019) made a step further in using system dynamics to model the time-dependent progress of each one 17 SDGs and analyse the interactions among them.

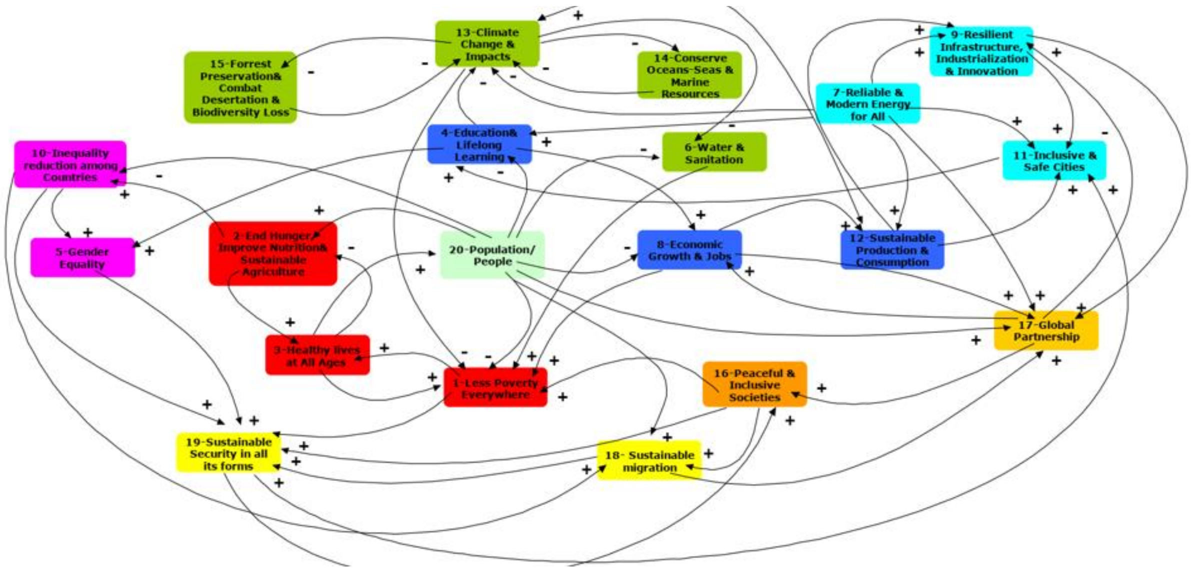

Figure 3.6. A Systemic View of overall Sustainable Development Goals (Ferri and Sedehi 2018; reproduced with permission)

3.6.3 Means-ends continuum toward an overarching goal

Costanza et al. (2016) argue that an overarching goal for the SDGs is needed with clear metrics of progress toward that goal that are geared to integrate the sub-goals. The authors stress that we must first decide where we are going - our overarching goal - to measure progress toward it. The 17 proposed SDGs are best seen as sub-goals or means to this larger end. An aggregate indicator is needed that can assess the relative contribution of each of the SDGs and their interactions with each other to assess overall progress. The dashboard and an aggregated indicator of overall progress toward our shared goal are both necessary if one hopes to achieve the goal. The current models do not cover many SDGs and lack an overarching goal. For a long time, gross domestic product (GDP) has been used as a measure of income in existing models, but it has never been designed as a measure of societal wellbeing. However, from utilitarian philosophy, more consumption leads to higher wellbeing, ceteris paribus, and GDP per capita can be used as a proxy for national wellbeing. This line of reasoning has been challenged for a long time (Stiglitz et al., 2009). Higher GDP can go together without more employment, neglect of civil rights, more income inequality, decline in cultural values, and depletion of natural resources. So, we need better measures and connect these to existing or new model approaches. In particular, the utopia models mentioned in section 2.3.3 suggest a promising model architecture which builds on predefined desired and undesired developments to find out how lock-ins in trodden paths can be left and promising new ones can be taken. Measures to take some of these aspects into account are green growth (Boyd 2007), the Inclusive Wealth Index (UNU-IHDP and UNEP, 2014), and the Genuine Progress Indicator (GPI – Talberth et al., 2007). The GPI takes the impact of inequality (income distribution) into account (Wilkinson and Pickett, 2009) and several positive (family, volunteer work) and negative (depletion of natural capital, pollution, crime). Another possibility is a unit-less indicator based on the SDG indicators. The OECD Better Life index is an example (http://www.oecdbetterlifeindex.org/). However, weighting is a challenge in this approach. This is often based on surveys that are also not readily available in many countries. A third method is to use a subjective measure of wellbeing (SWB) and perform a regression analysis with independent variables. For example, the World Happiness Report (Helliwell et al., 2016) explained 73% of the variation in SWB across countries by developing regressions against a range of independent variables. The challenge with this method is to obtain the dependent variable. Often economic, social, and natural capital are used as independent variables. Costanza et al. (2014) conclude: "*The successor to GDP should be a new set of metrics that integrates current knowledge of how ecology, economics, psychology and sociology collectively contribute to establishing and measuring sustainable wellbeing*". A measure could be constructed based on the methods discussed above.

- Economic contribution: GPI that includes income and considers income distribution and additional positive and negative effects.
- Natural Capital/Ecosystem Services Contribution: valued in monetary units (spatially explicit). Examples are Accounting and Valuation of Ecosystem Services (WAVES) project of the World Bank (https://www.wavespartnership.org/), the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES - http://www.ipbes.net/), and The Economics of Ecosystems and Biodiversity (TEEB - http://www.teebweb.org/), the Economics of Land Degradation initiative (ELD - http://eld-initiative.org/).
- Social Capital Contribution: Could be captured via surveys (e.g., trust), of the various components of life satisfaction (World Values Survey, Eurobarometer, Afrobarometer, etc.).

Again, existing modelling approaches can be extended more and more to include more elements of sustainable wellbeing. Most of these models are especially strong in the field of economic contribution and they could be extended to add distributional issues and positive or negative externalities. Including natural and especially social capital is another bridge away that might be built by connecting with other models. Complexity models could take directly sustainable wellbeing as a starting point and focus on the key concepts and relations such as including the contributions from economic, natural capital/ecosystem services and social capital.

3.6.4 Narrative of change to achieve the SDGs

Measurement of SDGs, the interdependency of SDGs and an overarching goal enable the measurement of the gap between current indicator values and the fulfilment of the SDGs. The gap might be closed by societal shifts (e.g., preference shifts) and policy reforms. Models can be used to identify potential pathways to reach the defined, overall goal using back-casting approaches and thereby providing insight in what societal shifts and policy reforms are needed to achieve the target. A challenge with traditional models is that they poorly address paradigm changes, but emerging model approaches could support this development. The expression of the various SDGs represents the aggregate outcome of environmental systems and social systems as well as the interactions between the two. However, basically individual behaviour in social systems (but also in environmental systems, e.g., invading animal and plant species) responds to the aggregate outcomes which is responsible for the complexity in overall system behaviour. It establishes recursive loops manifested in endogenous adaptation (e.g., changing consumption behaviour and innovation) which again impact on the expression of SDGs on the aggregate level, and so on. This necessity to focus on the endogeneity of changes and the connected complexity is where the emerging approaches step in.

A modelling framework that deals with all these four aspects does not exist. There are pros and cons of the various approaches. System dynamics tools build upon stock and flows which is an interesting feature given the necessity to take stocks into account. They also can cover rather quickly a broad range of indicators. More traditional models have likely much more detail on sectors, their interdependencies, and the impact of policies. There are several options. In System dynamic models the detailed IO structure could be embedded, include non-linearities and follow the flow and stocks. The traditional models, such as PEs and CGEs, could be extended with a broader welfare measurement (wellbeing) and the inclusion of cost and benefits from other stocks such as natural and social capital. A third method mixes these approaches. Anyway, a long-term horizon is needed for these sustainability assessments.

Finally, a very important implication of the importance of the SDG goals is that the SDG framework offers new perspectives on model comparison as now a wide range of models try to model the same set of goals and indicators. This enables a much broader comparison of a much more diverse set of models. Through model comparison the different approaches learn from each other and can complement each other. In this way a much wider perspective can be obtained regarding uncertainties on the future.

4 Conclusions and recommendations

4.1 Existing capacity to model future transitions of the bioeconomy

This report presents **an analysis of the existing capacity for modelling the future transitions to a sustainable and circular bioeconomy**, as well as **an analysis of emerging approaches to model transitions for the bioeconomy**. Modelling this transition is of increasing importance for designing an effective implementation of the Green Deal and related policies of the European Commission. In this respect, modelling is complementary with the large efforts in foresight activities and offers potential to disentangle the complexities of the targeted transformation and to deal with the large uncertainties that is characteristic for envisaged developments which strongly depend on innovation, the exploration of relevant knowledge fields and changing consumer behaviour.

Our review of existing models highlights **important gaps in the existing capacity to model the bioeconomy**:

- **Some existing bioeconomy sectors and products are not well covered**. Most of the models reported in the literature have a sectoral focus and only a selected group of models covered all bioeconomy sectors (i.e., the group of CGE models and IAMs). Especially the **aquaculture and fishing sector, as well as the manufacturing of textiles, leather and wearing apparel, pharmaceuticals, plastics, and the chemical sector are not well captured by existing models** focusing on bioeconomy products. This suggests that to be able to cover the entire bioeconomy with sufficient level of detail, models need to be improved or should be linked to cover all sectors of the bioeconomy in detail.

- **Limited ability of capturing the cross-cutting issues of the bioeconomy transition**. Due to the sectoral focus, models do not well cope with the competition between the different (industrial and energy) sectors of the bioeconomy. **It is of paramount importance to address cross-cutting issues if the goal is to secure a successful transition to a sustainable and circular bioeconomy.**

- **Novel products are not well captured by existing models**. Existing models typically focus on products that have established markets and not properly capture the emergence of new or novel products. Models typically estimate the demand for certain products based on price information, but for novel products there are likely to be other factors that explain their emergence. **Models would need to be extended to capture the developments of new or novel products**.

- Most of the models provide information on the bioeconomy on the national level and **a much smaller number of models provide such information at sub-national level**. Impacts associated with the development of the bioeconomy are typically occurring at regional or local level and it is important that such impacts are properly understood.

Efforts have been made to develop linkages between models to overcome shortcomings related with the sectoral focus of models and to assess policy questions related to the bioeconomy. **Many of the linkages between models focus on related economic activities** (e.g., linkages of an agricultural crop model with an agricultural sector model, or a forest resource model with a forest sector model) **while fewer cover many or all sectors of the bioeconomy in detail**. **IAMs are especially important for providing information on different aspects of bioeconomy, because of their multi-sector and multidisciplinary nature**. To better exploit the advantages of economic and environmental models, it would be important to further **develop linkages and cooperation between environmental and economic models**.

If the goal is to secure a successful bioeconomy transition and help the policymakers in addressing cross-cutting issues, such linkages need to **consider key processes such as technological change (or innovation), circularity, consumer behaviour, climate change and biodiversity**. Whereas concepts like circularity could be included into existing models with reasonable effort in the short and medium run, other important concepts require the development of new models building on emerging modelling techniques. This most likely cannot be achieved quickly but asks for long-term development efforts.

Therefore, and in addition to the gaps that need to be addressed in the short to medium term, there are also tasks that should be addressed in the long-term. They refer to **societal and technological changes associated with the transition to a sustainable and circular bioeconomy**. Specifically, such gaps relate to **how innovations affect future development or how consumers learn and change their preferences** and what kind of dynamics are to be expected. There are several emerging approaches that try to address complex systems and structural changes, but these new classes of models are likely to be considered as complements to the existing models and not as substitutes. Their justification comes from their long run orientation and does not mean that the existing modelling classes with their higher levels of detail and empirical integration are to be replaced. Instead, the closing of the identified gaps in existing models very likely will be useful and supportive for a future modelling capacity.

4.2 Promising developments with relevance to bioeconomy modelling

Modelling has proven to be a strong instrument to analyse complicated interdependencies, to discover relationships between different variables and thereby to improve the prerequisites for our understanding of the world. Models are popular tools for supporting decision makers, in particular in the policy realm, because of their supposed stringency and capacity to focus on the drivers of development and to abstract from the exuberant information which might distract from the core of the relevant question. We observe two interrelated developments triggered by technological and methodological advances:

i. The development of larger and more complicated models crossing disciplinary borders and a topical widening of models to include a larger variety of phenomena as well as interdependencies between them.
ii. The emergence of new modelling approaches basically aims for a new capture of a complex reality in models which includes, most importantly, the endogenous capacity of changing structures and qualitative developments.

The first development can be considered as the most popular in the domain of bioeconomy modelling. It builds on the large experience accumulated in around three decades and can quickly integrate new areas into their core model architecture, which, in most cases, is a model representation of a stable economic system in which several exogenous shocks unfold and are processed and balanced into a new equilibrium state. Concerning short run adaptations of the system this strategy leads to promising results and to a better understanding of the interrelated, not easily disentangled feedback effects. However, when it comes to the analysis of long-term development, characterised by fundamental structural changes driven by changing lifestyles, innovation, or more generally learning and changing knowledge, most of the traditional modelling approaches are insufficient because of their principal optimisation and equilibrium design.

The second line of developments gains its attractiveness exactly from the limitations of the first line of development. The roots of these emerging modelling approaches are in the theory of complex systems. They focus on the endogenous drivers of the co-evolutionary development of social and ecological systems which are considered crucial for the bioeconomy which strongly depends on the introduction of new technologies, the adoption of new consumer behaviours as well as the permanent negotiation between unforeseen and emerging conflicts between the different sustainability goals. The uncertainty of innovation requires experimental behaviour instead of optimisation. The changing lifestyles and consumer behaviours require the consideration of interactions among heterogeneous agents, which are both the ingredients of non-linear interactions responsible for structural changes and unforeseen surprises in socio-ecological development processes. Because of the large number of interdependencies and the immense difficulties in handling the complexity, the emerging modelling approaches today still are very much at the beginning, specifically with regards to modelling the bioeconomy.

As both developments are characterised by strong advantages but also by severe disadvantages, the third development of combining established and emerging modelling approaches might offer a prolific alternative:

iii. combining established and emerging modelling approaches aiming at the exploitation of the advantages from both sides, e.g., combining the comprehensiveness of traditional modelling tools with the fine-grained capture of emerging simulation techniques allowing to represent large numbers of heterogeneous agents.

Few models today are indeed combining the macro-economic structure of an economic system with agent-based models (e.g., Niamir et al., 2020), where agents make decisions on the micro-level which are used as inputs in the CGE model. This combination of traditional and emerging modelling approaches will improve the mutual understanding of the rather dispersed research communities and therefore must be considered as promising and important. However, the attempts existing so far are very likely suited neither to overcome the limitations of the established modelling approaches nor to fully exploit the opportunities of the emerging modelling approaches. The reason is that the structures of the systems analysed are fixed and change is purely exogenous and not the result of the interactions among agents and among agents with their natural environment.

The challenge in combining established and emerging modelling techniques in modelling the bioeconomy stems from a subtle but important difference between two notions which we often used synonymously, namely transition and transformation. Both processes describe a change process but with fundamental different prerequisites and outcomes. In a transition process, e.g., a fossil-based industry replaced by a bio-based industry which takes completely the place of its predecessor offering the same products and services, economic structures are not affected. Thus, in a transition process, we observe a perfect substitution, perhaps even the birth of a new industry, but the overall setting is not affected after the transition period. In a transformation process, e.g., when carbon-based materials are increasingly displaced by biomaterials and consumers increasingly demand less polluting solutions, the economic structures on the supply side as well as the economic behaviour on the demand side fundamentally change (and mutually influence each other). This is not a simple replacement but a complex adaptation of the whole system, which is driven by innovation, new lifestyles, and also potential changes in the governance system, i.e., the economy transformed itself structurally. Whereas a transition process is described by a well-defined decision problem and follows the logic of comparing the relative rate of marginal substitution with relative prices, the transformation process is responsible for an ill-defined decision problem. The actors are confronted with true uncertainty when they try to introduce innovations or try to develop new consumption patterns as a reaction to the observed changes in their surrounding economic and/or natural environment. The reasons behind the transformation can be manifold, e.g. an increasing awareness of sustainability issues with an effect on value and norms which might unfold in a self-organized way from single actors trying to change technologies with an entrepreneurial motive, or from single consumers trying out new lifestyles which become fashionable and are imitated, or from policy strategies emphasizing sustainability, or from civil society organizations which mange to raise the alertness towards certain topics.

To avoid this confusion and the loss of modelling potentials, we emphasize a fourth trajectory for model development, namely:

iv. model cooperation to exploit the benefits of established and emerging modelling approaches.

For the analysis of short-term temporal developments, the fine-grained established modelling approaches are well suited to analyse future transition processes for the bioeconomy towards sustainable development and a climate neutral economy as we can expect that the underlying structures do not change dramatically in the short run. However, the application of the established modelling approaches should reflect from the very beginning the shortcomings and limitations of the validity of their conclusions which determine their scope of application with respect to some of the most urgent questions to be asked today, namely those dealing with transformation. Because of endogenous structural changes due to innovation and changing consumer behaviour, the advantage of a detailed description cannot be maintained when it comes to the analysis of long-term development. This is the place, where the emerging modelling approaches can exert already today their full power concerning the future transformations for the bioeconomy towards sustainable development and a climate-neutral economy. The emerging modelling approaches hint on the drivers of these fundamental changes responsible for the non-linearities and disruptive changes characteristic of and affecting socio-ecological long-term development. From a theoretical point of view an equilibrium state of an established model is one possible outcome out of many predicted by a representative model of the emerging modelling approaches. However, for long run analysis it is not very likely that the system under investigation remains in this equilibrium. But it will take a long period of intensive model development until the emerging modelling approaches will be able to describe economic systems with the same level of details characteristic of many established models. In the interim period, model cooperation to exploit the advantages of established and emerging models is the most promising strategy, as many important decisions to improve on sustainability cannot be postponed. Without doubt, such a model cooperation strategy will not come for free but needs to be accompanied by an open data and IT infrastructure, and governance structures that reduce maintenance and cooperation costs and enable long term cooperation between models or model types. It requires flexible modular structures to link models.

To summarize, **we argue for a modelling approach eclecticism, where we combine established and emerging modelling approaches cooperatively depending on the questions which are to be analysed with the model**. This asks for a better description of modelling targets, a sound reflection on the meaning of time horizons and a closer cooperation between the different research communities. The description of the modelling targets as well as the determination of time horizons will benefit from the developments in big data and artificial intelligence from which we expect valuable guideposts for designing future modelling strategies. Enabling factors are an open data and IT infrastructure and model governance structures oriented at long term maintenance, development, and cooperation.

4.3 Recommendations to improve bioeconomy modelling

The emerging modelling approaches raise high expectations concerning their use in the analysis of future transformations for the bioeconomy towards sustainable development and a climate-neutral economy. Their capacity to analyse complex systems is most promising, this means their capacity to analyse the effects of agents' heterogeneity in decision making, fundamental (endogenous) pattern changes like the overcoming of lock-ins, as well as socio-economic and environment system interaction. There are already approaches that can be used by existing models to support the analysis of key policies issues (e.g., circularity, climate change), but for the emerging approaches we see a complementary role in addressing technological change and behavioural change.

Because of the fast progress in computer sciences and a growing community of researchers from different disciplines working in the field of emerging modelling approaches, modelling activities in bioeconomic realms could develop substantially. Current first steps, however, highlight the difficulties in this process (e.g., that in the complex models we simply do not understand the relationships involved or their consequences, that computational effort and time becomes enormous and severely reduce the practicability of the model) and clearly suggest that this development will demand a longer transition period of at least a decade. Next to the technical capabilities new governance structures and arrangements should be exploited.

4.3.1 Improving the bioeconomy modelling capacity in the short to medium term

For short-term developments, we consider that the fine-grained established modelling approaches are promising in the analysis of transition processes, because we can expect that the underlying structures do not change dramatically in the short run. The established modelling techniques could thus be applied to address so far neglected cross-cutting policy questions and offer a better understanding on how to achieve sustainability e.g., by integrating the concepts of a circular economy, the United Nations' SDGs, biodiversity, etc. However, the application of the established modelling approaches should reflect from the very beginning their shortcomings and limitations in not fully considering the possibilities of structural changes. This determines their scope of application with respect to some of the most urgent questions to be asked today, namely those dealing with transformation, which by nature will not happen overnight, but require a long-term orientation.

The analysis of existing models of the bioeconomy reveals that existing models cover important components of the bioeconomy, but also important gaps exist in current modelling efforts that should be addressed in the short- to medium-term. Building on the gaps and recent developments to close these gaps, we make the following technical and governance-related recommendations to improve bioeconomy modelling, which could be realized in the next 5-10 years. The technical recommendations are:

- **Improve the model coverage of existing bioeconomy sectors and products**. Most of the existing models reported in the literature have a sectoral focus and only a selected group of models covered all bioeconomy sectors (i.e. the group of CGE models and IAMs). Especially the **aquaculture and fishing sector, as well as the manufacturing of textiles, leather and wearing apparel, pharmaceuticals, plastics, and chemical sectors are not well captured by existing models** focusing on bioeconomy products. This suggests that to be able to cover the entire bioeconomy with sufficient level of detail, existing models need to be extended, new models need to be developed and/or numerous linked models might be needed to cover all sectors of the bioeconomy.
- **Improve the coverage of novel bioeconomy products**. Existing models typically focus on products that have established markets and do not properly capture the emergence of new or novel products. Although the inclusion of new products is closely related to technological progress (which may be better addressed by emerging modelling approaches, see section 3.2.2), existing models should be expanded to better cover novel products (for example, bio-based chemicals and plastics, engineered wood products as construction material, wood-based textile fibres, etc) based on available technical, engineering and market information. Models typically estimate the demand for certain products based on price information, but for novel products there are likely to be other factors that explain their emergence. These need to be more systematically studied and used to improve existing models. Availability of appropriate data is a key issue and improved modelling should therefore go hand in hand with improved data collection efforts.
- **Improve existing models to better address circularity.** Circularity is a key process that needs to be addressed by models to model the future transformations for the bioeconomy. Existing (economic) models are generally based on the notion of linear (i.e., produce, use, discard) product lifecycle and economies and almost completely ignore material cycles and recycling, as well as co- and by-production of products and materials. **An improved representation of physical material cycles (material flows) in economic modelling helps to increase the policy support relevance of such modelling approaches**, with regards to increasing biomass availability, sustainability of bioenergy as well as reducing food losses and waste. Key challenges are the explicit modelling of waste and by-products, waste management sector, secondary production sectors, and the explicit modelling of a product lifetime by, for example, dynamic stocks of materials and products.
- **Improve existing models to better address climate change.** Climate change is a key topic and dealt with in many existing models. Climate change affects natural systems, which are at the heart of the bioeconomy. Approaches to consider changes in yield and productivity are already available, but climate change affects biomass availability also through changes in the frequency and extent of extreme events such as droughts and disturbances (storm, fire, pests) and these **extreme events and natural disturbances need to be better addressed in bioeconomy modelling**. Furthermore, the focus of climate change impact modelling in agriculture has so far focused on a small number of staple crops, but future climate change impact analyses should include the consequences of climate change on non-staple crops, but also on e.g., labour productivity. Another area of attention is the field of negative GHG emissions and especially the **interaction between forestry and agriculture and BECCS and CCS technologies in terms of land and biomass competition**.
- **Link existing models with specialised biodiversity models to better address biodiversity.** Biodiversity is a key topic and difficult to deal with in many existing models but can be introduced by connecting to existing biodiversity models. Future assessments should seek to better represent land-management practices as well as additional pressures on land and biodiversity, such as the influence and mitigation of climate change, overexploitation, pollution, and biological invasions. The upscaling of new modelling approaches could facilitate such improvements, although such modelling efforts currently face data and technical challenges.
- **Develop modelling approaches that consider the bioeconomy as a whole and avoid sectoral approaches**. The sectoral focus of many existing models limits their ability of capturing the cross-cutting issues of the bioeconomy. It is of paramount importance to address these cross-cutting issues if the goal is to secure a successful bioeconomy transition. Modelling approaches need to better address competition between the different sectors of the bioeconomy (e.g., competition for biomass use for energy or materials). **This can be achieved by improving models, and by improving collaboration between different disciplines.** Linkages of models also need to be considered in the design of models, for example though a modular design and programming interfaces that allow interactions between multiple software intermediaries.
- **Consider the novel possibilities offered by big data and artificial intelligence** to detect new developments in bioeconomy sectors which are hidden in traditional industry statistics. The possibility of pattern detection of e.g.,

machine learning algorithms together with the expected availability of big data offers a promising opportunity to develop a better understanding of shifts in industrial structures, which by their very nature are in their early stages too small to be observable in conventional statistics. **The capability to detect 'early warning signals' from big data with the help of AI is not restricted to the analysis of industry development but can be applied also to consumption data and environmental data** to find critical fluctuations responsible for potential major changes e.g. by surpassing critical thresholds.

- **Improve linkages/integration with other tools and approaches:** some of the existing limitations in bioeconomy models are well addressed by other communities. **The linking of models with existing and well-established tools and approaches can help to efficiently mitigate some of the models' shortcomings building on the know-how already established in other scientific domains**. Life Cycle Assessment and Material Flow Analysis, for example, can help to better consider indirect emissions and better quantify the direct and indirect (bio)material consumption of alternatives technologies and scenarios as well as extend the range of environmental issues addressed by the models and better consider in-use stocks and material cycles in a mass balanced framework.
- **Improve the spatial resolution of existing models**. Most of the models provide information on the bioeconomy on the national level and **a much smaller number of models provide such information at sub-national level**. Impacts associated with the development of the bioeconomy are typically occurring at regional or local level and it is important that such impacts are properly understood.
- **Improve coverage of sustainability indicators**. Sustainability indicators addressing social aspects are not well covered by existing models. These indicators could partly be quantified and connected to existing modelling platforms by connecting with household and social models or developing complex indicators based on distributional data and econometric analyses that can be added to existing modelling frameworks. Attention is needed for the complex interconnections between the goals (connecting models or new model (e.g. SDM) approaches) and the means-ends continuum toward an overarching goal by valuing (i) economic services: GPI (Genuine progress indicator) that includes income and considers income distribution and additional positive and negative effects; (ii) natural capital ecosystem services (include nature capital stocks) and (iii) social capital contribution (e.g. surveys life satisfaction). Additionally, **the SDG framework offers additional possibilities to compare very different model approaches.**

Governance recommendations are:

- **Be selective in the models to be further developed for bioeconomy modelling.** Many models already exist that can be used to study the bioeconomy but some of these models cover only very specific aspects of the bioeconomy. **IAMs are considered especially important for providing information on a broad range of issues relevant to the bioeconomy, because of their multi-sector and multidisciplinary nature**. Possible criteria for selecting models to be further improved could include their ability to cover bioeconomy sectors, open-access availability, documentation, ability to address technological progress, circularity, consumer behaviour and climate change, scientific publications, policy-oriented contributions, etc.
- **Plan for sufficient time and resources to better link models**. Efforts have been made to develop linkages between models to overcome shortcomings related with the sectoral focus of models and to assess policy questions related to the bioeconomy. To better exploit the advantages of economic and environmental models, it would be important to further **develop linkages and cooperation between environmental and economic models** and modellers. However, the type of coupling needs to be carefully considered. Hard linkages of models are of a more systematic nature and may provide better insights in the questions addressed but are complex and computationally expensive. Enabling factors for model cooperation and linkage are open data and ICT infrastructure and model governance structures oriented at long-term maintenance, development, and cooperation. There is a need for data management plans, modular set up of models directed toward coupling with other modular models, data sharing and model development by (international) cooperation to reduce development and maintenance costs, institutionalise consortia by cooperation agreements.
- **Combine bioeconomy modelling with other foresight techniques.** Models are simplifications of reality, they are hampered by available information, and are often based on relationships that occurred in the past. Furthermore, even if models would be technically improved following our recommendations, the results still depend to a large extent on how the models are applied to address policy questions. To better understand the transition to a bioeconomy, (quantitative) bioeconomy modelling should be combined with other participatory foresight techniques. The combination of modelling with other foresight techniques will improve the credibility (or scientific adequacy), legitimacy (consideration of divergent values and beliefs, treatment of opposing views) and relevance of the results with regards to the needs by decision makers.
- **Improve quality and transparency of existing models.** Our review revealed that only 37% of all reviewed models are completely or partially accessible to (expert) users. Furthermore, we note that some models are poorly model documented, which hampers a good understanding of the functioning of existing models. Quality control of models needs to be better ensured through model documentation, validation, publishing model descriptions and applications in peer reviewed journals and by making models and their code accessible to peers through open

access. **Such measures will likely strengthen the transparency of the models and the trust in the results they produce.** Model **comparison** exercises can enhance the quality of models and provide insight in key uncertainties.

4.3.2 Improving the bioeconomy modelling capacity in the long-term

In addition to gaps that need to be addressed in the short to medium term, there are also gaps that can be mainly addressed in the long-term. They refer to **societal and technological changes associated with the transition to a bioeconomy**. Specifically, such gaps relate to **how innovations affect future development or how consumers learn and change their preferences** and what kind of dynamics are to be expected. There are several emerging approaches that try to address complex systems and structural changes, but these new classes of models are likely to be considered as complements to the existing models and not as substitutes. Their justification comes from their long run orientation and does not mean that the existing modelling classes with their higher levels of detail and empirical integration are to be replaced in the short-term. **We thus recommend a modelling approach eclecticism, which combines established and emerging modelling approaches cooperatively.** To frame it somewhat simplified, after a transformation towards a knowledge-based bioeconomy, we will observe an economy which most likely looks very different from the economy we know now. Periods of drastic change, however, are followed by less turbulent periods where the established modelling approaches together with the suggested extensions will deliver valuable services with their fine-grained resolution and comprehensive coverage of industry structures.

In the transformation to a sustainable and circular bioeconomy, the role of biomass production and addressing sustainability challenges will play an outstanding role. Complexity models in principle are interesting candidates to shed light on the positive and negative feedbacks to be expected when not only the decision process of agents but also their contradictory effects on planetary boundaries are reflected. ABMs will play an outstanding role in the coming years because of their capacity to tackle changes in preferences on the demand side and innovation and diffusion of bioeconomic technologies and knowledge on the supply side. Even broader but also more demanding and time consuming will be the expected increasing application of socio-environmental ABMs in the years to come. With the help of these tools very explicit model representations of e.g., the food-fuel conflict and required behavioural changes can be developed to directly address the interdependencies between SDGs and behaviour.

In the context of bioeconomy modelling, improved model cooperation is needed which brings together established and emerging modelling approaches and covers the social, economic, and environmental dimension and disciplines to endogenize some of the variables considered as constants in existing (traditional) modelling approaches. For example, CGE systems need to be adapted following the insights of complexity models indicating that critical thresholds are surpassed, and economic structures are likely to change. PE-models need to be enriched by considering innovation processes and endogenously created technological change is complementary models based on the emerging modelling techniques. Economic and environmental models need to be improved to better address behaviour of different agents (e.g., consumers, landowners, and managers). More effort is needed to couple economic and environmental models to better capture two-way interactions between the socio-economic and environmental system, considering new data sources on socio-economic and ecological information. Therefore, **we consider the most promising opportunities for future modelling activities in the exploitation of model cooperation between established and emerging modelling approaches**. To facilitate the combined use of existing and emerging modelling approaches, we recommend several actions that could be taken to resolve issues that have so far hampered the uptake of complexity models:

- Although some first attempts are already developed in the scientific literature to combine existing and emerging modelling techniques, **we recommend the facilitation of a closer cooperation between the so far mostly separated research communities on established and emerging modelling approaches.** This could be achieved by research calls requiring the involvement of relevant research communities to ensure a better understanding how modelling approaches can support each other.
- **Remove barriers to access data and computing infrastructure.** Despite major progress in computation and modern data sciences, barriers exist that hamper the uptake of development of emerging modelling approaches. Such barriers could refer to access to already established data and computing infrastructures. **Improved access to and improved use of data and computing infrastructures are needed to support a larger uptake of emerging modelling approaches.**
- **Strengthen the development of complexity models that consider behavioural change.** New models will inevitably need to be supplied with data. Major developments are being made to capture the behaviour of consumers (e.g. behavioural economics), with the help of internet, big data and artificial intelligence algorithms, although there are also concerns on the privacy of consumers. Similar approaches may be explored also to support future bioeconomy modelling, while carefully respecting privacy concerns. In addition to better understanding consumer behaviour, an improved understanding is also needed for the behaviour of landowners and firms. While the availability of farm-level information has generally improved in the case of agriculture, major steps are still to be made with regards to understanding the behaviour of forest owners to be able to include such information in agent-based models. Similarly, it is also crucial to understand the behaviour of firms in the bioeconomy.

- **Better address technological development and innovation in future models**. New models that address the long-term transformation processes in the bioeconomy need to emphasize the outstanding role of innovation. The philosopher Vogt (2020) coined that "*the bioeconomy operationalizes the innovative aspects of sustainability*" and without doubt, modelling should no longer assume innovation to be exogenous. Major developments have been made to integrate experimental behaviour under true uncertainty, knowledge exchange in networks and learning into agent-based models addressing innovation driven industrial dynamics. These promising approaches and their specific application to analyse endogenous innovation processes in the bioeconomy are to be explored to substantially improve our understanding of the complex transformation processes. This will shed light on the role of user-producer interactions, entrepreneurship and knowledge development which are crucial targets for policymakers in their ambitions to support the transformation. There are still many open questions, concerning the calibration and validation of these necessarily large agent-based models. However, together with the developments from AI and big data, major progress must be expected within the next decade. Furthermore, concerning socio-environmental ABMs the additional consideration of environmental dynamics coupled with socio-economic dynamics can be considered as a starting point for improving our knowledge on endogenous adaptation strategies highlighting promising technological directions or at least excluding non-successful paths more easily and earlier.

References

Acs, S., Ostlaender, N., Listorti, G., Hradec, J., Hardy, M., Smits, P., Hordijk, L., 2019. Modelling for EU Policy support: Impact Assessments, EUR 29832 EN, Publications Office of the European Union, Luxembourg, ISBN 978-92-76-09671-9, doi:10.2760/748720, JRC117250

Aguiar, A., B. Narayanan, and R. McDougall, An Overview of the GTAP 9 Data Base, Journal of Global Economic Analysis, Vol. 1, No. 1, 2016, pp. 181–208.

Ahrweiler, P., Schilperoord, M. Pyka, A. and Gilbert, N., Modelling Research Policy: Ex-Ante Evaluation of Complex Policy Instruments. Journal of Artificial Societies and Social Simulation, 18 (4), 2015

Akgul, Z., Villoria N.B., Hertel T.W. 2016. GTAP-HET: Introducing Firm Heterogeneity into the GTAP Model. Journal of Global Economic Analysis 1(1): 111-180.

Akimoto, K., Sano, F., Homma, T., Oda, J., Nagashima, M., & Kii, M. (2010). Estimates of GHG emission reduction potential by country, sector, and cost. Energy Policy, 38(7), 3384-3393. http://jgcri.github.io/gcam-doc/

Allen, C., Metternicht, G., Wiedmann, T., 2016. National pathways to the Sustainable Development Goals (SDGs): A comparative review of scenario modelling tools. Environmental Science & Policy 66, 199-207. DOI: https://doi.org/10.1016/j.envsci.2016.09.008.

Almudi, I., Fatas-Villafranca, F. & Potts, J. Utopia competition: a new approach to the micro-foundations of sustainability transitions. J Bioecon 19, 2017, 165–185. https://doi.org/10.1007/s10818-016-9239-2

Angenendt, E., Poganietz, W.-R., Bos, U., Wagner, S., Schippl, J., 2018. Modelling and Tools Supporting the Transition to a Bioeconomy. In: Lewandowski, I. (Ed.), Bioeconomy: Shaping the Transition to a Sustainable, Biobased Economy. Springer International Publishing, Cham, pp. 289-316. DOI: 10.1007/978-3-319-68152-8_9.

Arfaoui, N., Brouillat, E. and Saint Jean, M., Policy design and technological substitution: Investigating the REACH regulation in an agent-based model, Ecological Economics, Vol. 107, 2014, 347-365

Arneth, A., Brown, C., Rounsevell, M.D.A., 2014. Global models of human decision-making for land-based mitigation and adaptation assessment. Nature Climate Change 4, 550-557. DOI: 10.1038/nclimate2250.

Arthur, B.W., 2014. Complexity and the Economy, Oxford University Press.

Arthur, W.B., Competing technologies, increasing returns, and lock-in by historical events. Econ. J. 99 (394), 1989, 116–131

Asada, R., G. Cardellini, C. Mair-Bauernfeind, J. Wenger, V. Haas, D. Holzer, and T. Stern, Effective Bioeconomy? A MRIO-Based Socioeconomic and Environmental Impact Assessment of Generic Sectoral Innovations, Technological Forecasting and Social Change, Vol. 153, April 2020, p. 119946.

Augusiak, J. A., van den Brink, P. J., & Grimm, V. (2014). Merging validation and evaluation of ecological models to evaluation: a review of terminology and a practical approach. Ecological Modelling, 280, 117-128. https://doi.org/10.1016/j.ecolmodel.2013.11.009

Aune, F. R., Brekke, K. A., Golombek, R., Kittelsen, S. A., & Rosendahl, K. E., 2008. LIBEMOD 2000-LIBEralisation MODel for the European Energy Markets: A Technical Description. Working paper 1/2008. Ragnar Frisch Centre for Economic Research, Oslo.

Axelrod, R., Advancing the Art of Simulation in the Social Sciences. In: Conte, R., Hegselmann, R. and Terna, P. (eds.), Simulating Social Phenomena, Berlin: Springer, pp. 21–40, 1997.

Axtell, R., and Epstein, J., Agent-based modeling: Understanding our creations. The Bulletin of the Santa Fe Institute, 9(4), 1994, 28–32.

Babcock, B., 2011. The impact of US biofuel, policies on agricultural price levels and volatility, Center for Agricultural and Rural Development, Iowa State University, ICTSD, Issue Paper No. 35. June. http://www.ictsd.org/downloads/2011/12/the-impact-of-us-biofuel-policies-on-agricultural-price-levels-and-volatility.pdf.

Baccianti, C., and A. Löschel, The Role of Product and Process Innovation in CGE Models of Environmental Policy, Working paper, WWWforEurope, 2014.

Bak, P., How Nature Works: The Science of Self-Organized Criticality. New York, NY: Copernicus Books, 1996

Balistreri, E. T. Rutherford, 2013. Computing general equilibrium theories of monopolistic competition and heterogeneous firms. Chapter 23 in Dixon P.B. and D.W. Jorgenson (editors), Handbook of Computable General Equilibrium Modeling, Elsevier, pp. 1513-1570.

Balkovič, J., van der Velde, M., Schmid, E., Skalský, R., Khabarov, N., Obersteiner, M., Stürmer, B., Xiong, W., 2013. Pan-European crop modelling with EPIC: Implementation, up-scaling and regional crop yield validation. Agricultural Systems 120, 61-75.

Bartelings, H., Hamon, K.G., Berkenhagen, J., & Buisman, F.C. 2015. Bio-economic modelling for marine spatial planning application in North Sea shrimp and flatfish fisheries. Environmental Modelling & Software, 74, 156 - 172.

Bchir, M.-H., Y. Decreux, J.-L. Guérin and S. Jean, 2002. MIRAGE, A CGE Model for Trade Policy Analysis. CEPII Working Paper 2002-17.

Beckman, J., T. Hertel, and W. Tyner, 2011. Validating Energy-Oriented CGE Models. Energy Economics 33 (5): 799–806.

Beinhocker, E.P., The origin of wealth: Evolution, complexity and the radical remaking of economics, Boston, MA, Harvard University Press, 2006

Benoît Norris, C., Data for Social LCA, The International Journal of Life Cycle Assessment, Vol. 19, No. 2, February 2014, pp. 261–265.

Berg, M., Hartley, B. and Richters, O., A stock-flow consistent input-output model with applications to energy price shocks, interest rates, and heat emissions. New Journal of Physics 17(1): 015011, 2015

Berger, T., Troost, C., Calberto, G., Ingwersen, J., Warrach-Sagi, K., Fine Resolution Modeling of Adaptation to Climate Change in Agriculture, Research Documentation, 2010. Universität Hohenheim, Stuttgart. Available at: https://www.uni-hohenheim.de/mas/Germany/PAK043Public.zip (accessed on August, 14th 2020).

Bergman, N., Haxeltine, A., Whitmarsh, L., Köhler, J., Schilperoord, M. and Rotmans, J., Modelling Socio-Technical Transition Patterns and Pathways. Journal of Artificial Societies and Social Simulation 11(3)7, 2008 http://jasss.soc.surrey.ac.uk/11/3/7.html

Bertram, C., G. Luderer, A. Popp, J.C. Minx, W.F. Lamb, M. Stevanović, F. Humpenöder, A. Giannousakis, and E. Kriegler, Targeted Policies Can Compensate Most of the Increased Sustainability Risks in 1.5\hspace0.167em°C Mitigation Scenarios, Environmental Research Letters, Vol. 13, No. 6, June 2018, p. 064038.

Bhattacharyya Subhes, C., Timilsina Govinda, R., 2010. A review of energy system models. International Journal of Energy Sector Management 4, 494-518. DOI: 10.1108/17506221011092742.

Bornhöft, N.A., T.Y. Sun, L.M. Hilty, and B. Nowack, A Dynamic Probabilistic Material Flow Modeling Method, Environmental Modelling & Software, Vol. 76, February 2016, pp. 69–80.

Bosetti, V., Carraro, C., Galeotti, M., Massetti, E., & Tavoni, M. (2006). A world induced technical change hybrid model. The Energy Journal, (Special Issue# 2).

Böttcher, H., Verkerk, P.J., Mykola, G., Havlik, P., Grassi, G., 2012. Projection of the future EU forest CO2 sink as affected by recent bioenergy policies using two advanced forest management models. GCB Bioenergy. 4, 773-783. DOI: 10.1111/j.1757-1707.2011.01152.x.

Boubault, A., S. Kang, and N. Maïzi, Closing the TIMES Integrated Assessment Model (TIAM-FR) Raw Materials Gap with Life Cycle Inventories, Journal of Industrial Ecology, Vol. 23, No. 3, June 2019, pp. 587–600.

Bouët A, Laborde D, 2010. Why is the Doha Development Agenda Failing? And What Can Be Done? A Computable General Equilibrium–Game Theoretical Approach. The World Economy. Blackwell Publishing, vol. 33(11), 1486-1516.

Bouët A, Laborde D, Debucquet., 2012. Food crisis and export taxation: the cost of non-cooperative trade policies, Review of World Economics (Weltwirtschaftliches Archiv), Springer, vol. 148(1), 209-233."

Boyd, J., 2007. Nonmarket benefits of nature: what should be counted in green GDP? Ecol. Econ. 61, 716–723.

Brinkman, M.L.J., F. van der Hilst, A.P.C. Faaij, and B. Wicke, Low-ILUC-Risk Rapeseed Biodiesel: Potential and Indirect GHG Emission Effects in Eastern Romania, Biofuels, Vol. 0, No. 0, May 17, 2018, pp. 1–16.

Brock, W. and Xepapadeas, A., Pattern formation, spatial externalities and regulation in coupled economic–ecological systems, Journal of Environmental Economics and Management, Volume 59, Issue 2, 2010, 149-164

Brown, C., Seo, B., Rounsevell, M., 2019. Societal breakdown as an emergent property of large-scale behavioural models of land use change. Earth Syst. Dynam. 10, 809-845. DOI: 10.5194/esd-10-809-2019.

Bruno, B., Faggini, M., and Parziale, A., 2016. Complexity Modelling in Economics: the State of the Art. Economic Thought 5(2): 29-43

Budzinski, M., A. Bezama, and D. Thrän, Monitoring the Progress towards Bioeconomy Using Multi-Regional Input-Output Analysis: The Example of Wood Use in Germany, Journal of Cleaner Production, Vol. 161, September 2017, pp. 1–11.

Bulavskaya, T., J. Hu, S. Moghayer, and F. Reynès, EXIOMOD 2.0: EXtended Input-Output MODel: A Full Description and Applications, Den Haag: TNO, 2016.

Buongiorno, J., 2014. Global modelling to predict timber production and prices: The GFPM approach. Forestry 88, 291-303.

Buongiorno, J., S. Zhu, D. Zhang, J.A. Turner, and J. Tomberlin., 2003. The Global Forest Products Model: Structure, Estimation and Applications. Academic Press, San Diego. 301 pp.

Butchart, S.H.M., Walpole, M., Collen, B., van Strien, A., Scharlemann, J.P.W., Almond, R.E.A., Baillie, J.E.M., Bomhard, B., Brown, C., Bruno, J., Carpenter, K.E., Carr, G.M., Chanson, J., Chenery, A.M., Csirke, J., Davidson, N.C., Dentener, F., Foster, M., Galli, A., Galloway, J.N., Genovesi, P., Gregory, R.D., Hockings, M., Kapos, V., Lamarque, J.-F., Leverington, F., Loh, J., McGeoch, M.A., McRae, L., Minasyan, A., Morcillo, M.H., Oldfield, T.E.E., Pauly, D., Quader, S., Revenga, C., Sauer, J.R., Skolnik, B., Spear, D., Stanwell-Smith, D., Stuart, S.N., Symes, A., Tierney, M., Tyrrell, T.D., Vié, J.-C., Watson, R., 2010. Global biodiversity: indicators of recent declines. Science 328, 1164-1168. DOI: http://dx.doi.org/10.1126/science.1187512.

Calvin, K., and B. Bond-Lamberty, Integrated Human-Earth System Modeling—State of the Science and Future Directions, Environmental Research Letters, Vol. 13, No. 6, June 1, 2018, p. 063006.

Campagnolo L., Cian E.D. (2020) Can the Paris Agreement Support Achieving the Sustainable Development Goals?. In: Buchholz W., Markandya A., Rübbelke D., Vögele S. (eds) Ancillary Benefits of Climate Policy. Springer Climate. Springer, Cham. http://doi-org-443.webvpn.fjmu.edu.cn/10.1007/978-3-030-30978-7_2

Campagnolo, L., Davide, M., 2019. Can the Paris deal boost SDGs achievement? An assessment of climate mitigation co-benefits or side-effects on poverty and inequality. World Development 122, 96-109. DOI: https://doi.org/10.1016/j.worlddev.2019.05.015.

Cao, Z., G. Liu, S. Zhong, H. Dai, and S. Pauliuk, Integrating Dynamic Material Flow Analysis and Computable General Equilibrium Models for Both Mass and Monetary Balances in Prospective Modeling: A Case for the Chinese Building Sector, Environmental Science & Technology, Vol. 53, No. 1, January 2, 2019, pp. 224–233.

Capellán-Pérez, I., de Blas, I., Nieto, J., de Castro, C., Miguel, L. J., Carpintero, Ó., ... & Frechoso, F. (2020). MEDEAS: a new modeling framework integrating global biophysical and socioeconomic constraints. Energy & Environmental Science, 13(3), 986-1017.

Capros, P., 2018. PRIMES Model Description. URL: https://e3modelling.com/wp-content/uploads/2018/10/The-PRIMES-MODEL-2018.pdf

Capros, P., Van Regemorter, D., Paroussos, L., Karkatsoulis, P., Fragkiadakis, C., Tsani, S., Abrell, J., 2013. GEM-E3 model documentation. JRC Scientific and Policy Reports, 26034.

Cayla, J.-M., and N. Maïzi, Integrating Household Behavior and Heterogeneity into the TIMES-Households Model, Applied Energy, Vol. 139, February 2015, pp. 56–67.

Cazzaniga, N.E., K. Jonsson, R. Pilli, and A. Camia, Wood Resource Balances of EU-28 and Member States, 2019.

Challinor, A.J., J. Watson, D.B. Lobell, S.M. Howden, D.R. Smith, and N. Chhetri, A Meta-Analysis of Crop Yield under Climate Change and Adaptation, Nature Climate Change, Vol. 4, No. 4, April 2014, pp. 287–291.

Chatzis, S.P., V. Siakoulis, A. Petropoulos, E. Stavroulakis, and N. Vlachogiannakis, Forecasting Stock Market Crisis Events Using Deep and Statistical Machine Learning Techniques, Expert Systems with Applications, Vol. 112, December 2018, pp. 353–371.

Chiba, T.; Oka, H.; and Kayo, C. 2017. Socioeconomic factors influencing global paper and paperboard demand. J. Wood Sci., 63: 539–547. doi:10.1007/s10086-017-1648-x

Choi, H.S., and S.K. Entenmann, Land in the EU for Perennial Biomass Crops from Freed-up Agricultural Land: A Sensitivity Analysis Considering Yields, Diet, Market Liberalization and World Food Prices, Land Use Policy, Vol. 82, March 1, 2019, pp. 292–306.

Coble, K.H., Mishra, A.K., Ferrell, S., Griffin, T., 2018. Big Data in Agriculture: A Challenge for the Future. Applied Economic Perspectives and Policy 40, 79-96. DOI: 10.1093/aepp/ppx056.

Corong, E.L., Hertel, T.W., McDougall, R.A., Tsigas, M.E., van der Mensbrugghe, D., 2017. The standard GTAP model, Version 7. Journal of Global Economic Analysis 2(1): 1-119.

Costanza, R., Daly, L., Fioramonti, L., Giovannini, E., Kubiszewski, I., Mortensen, L.F., Pickett, K.E., Ragnarsdottir, K.V., De Vogli, R., Wilkinson, R., 2016. Modelling and measuring sustainable wellbeing in connection with the UN Sustainable Development Goals. Ecological Economics 130, 350-355. DOI: https://doi.org/10.1016/j.ecolecon.2016.07.009.

Costanza, R., de Groot, R., Sutton, P., van der Ploeg, S., Anderson, S.J., Kubiszewski, I., Farber, S., Turner, R.K., 2014. Changes in the global value of ecosystem services. Global Environmental Change 26, 152-158. DOI: http://dx.doi.org/10.1016/j.gloenvcha.2014.04.002.

Craglia, M. (ed.), Artificial Intelligence - A European Perspective, EUR 29425, EN, Piblications Office Luxembourg, 2018.

Crawford, R.H., P.-A. Bontinck, A. Stephan, T. Wiedmann, and M. Yu, Hybrid Life Cycle Inventory Methods – A Review, Journal of Cleaner Production, Vol. 172, January 2018, pp. 1273–1288.

Crépin, A., Norberg, J. and Mäler, K., Coupled economic-ecological systems with slow and fast dynamics - Modelling and analysis method, Ecological Economics, Vol. 70(8), 2011, 1448-1458

Criqui, P., 1996. Prospective Outlook on Long-term Energy Systems. EUR 17358 EN. European Commission.

Crossman, N.D., Banerjee, O., Brander, L., Verburg, P. and Hauck, J., 2018. Global socio-economic impacts of future changes in biodiversity and ecosystem services: State of play and approaches for new modelling. Report prepared for WWF-UK.

Dafermos, Y., Nikolaidi, M., & Galanis, G. A stock-flow-fund ecological macroeconomic model. Ecological Economics, 131, 2017, pp. 191-207.

Dahiya, S., A.N. Kumar, J. Shanthi Sravan, S. Chatterjee, O. Sarkar, and S.V. Mohan, Food Waste Biorefinery: Sustainable Strategy for Circular Bioeconomy, Bioresource Technology, Vol. 248, January 2018, pp. 2–12.

Dahlke, J., Bogner, K., Mueller, M., Berger, T., Pyka, A., and Ebersberger; B., Is the Juice Worth the Squeeze? Machine Learning (ML) In and For Agent-Based Modelling (ABM), arXiv:2003.11985, 2020.

Daigneault, A., Johnston, C., Korosuo, A., Baker, J.S., Forsell, N., Prestemon, J.P., Abt, R.C., 2019. Developing Detailed Shared Socioeconomic Pathway (SSP) Narratives for the Global Forest Sector. Journal of Forest Economics 34, 7-45.

Daioglou, V., S.K. Rose, N. Bauer, A. Kitous, M. Muratori, F. Sano, S. Fujimori, et al., Bioenergy Technologies in Long-Run Climate Change Mitigation: Results from the EMF-33 Study, Climatic Change, August 24, 2020.

Daly, C., Halbleib, M.D., Hannaway, D.B., Eaton, L.M., 2018. Environmental limitation mapping of potential biomass resources across the conterminous United States. GCB Bioenergy 10, 717-734.

de Gorter, H. and D. R. Just, 2009. The Economics of a Blend Mandate for Biofuels. American Journal of Agricultural Economics 91(3): 738-750.

De Marco, O., G. Lagioia, V. Amicarelli, and A. Sgaramella, Constructing Physical Input-Output Tables with Material Flow Analysis (MFA) Data: Bottom-Up Case Studies, in S. Suh (ed.), Handbook of Input-Output Economics in Industrial Ecology, Vol. 23, Eco-Efficiency in Industry and Science, Springer Netherlands, Dordrecht, 2009, pp. 161–187.

Deissenberg, C., van der Hoog, S. and Dawid, H., 2008. EURACE: a massively parallel agent-based model of the European economy. Applied Mathematics and Computation 204 (2): 541–552.

Delli Gatti, D., Gallegati, M. and Kirman, A., Interaction and Market Structure, Springer, Berlin, Heidelberg, New York, 2000.

Deppermann A, Grethe H, Offermann F (2014) Distributional effects of CAP liberalisation on western German farm incomes: an ex-ante analysis. Eur Rev Agric Econ 41(4):605-626

Di Fulvio, F., Forsell, N., Korosuo, A., Obersteiner, M., Hellweg, S., 2019. Spatially explicit LCA analysis of biodiversity losses due to different bioenergy policies in the European Union. Science of The Total Environment 651, 1505-1516. DOI: https://doi.org/10.1016/j.scitotenv.2018.08.419.

Dietrich, J.P., Bodirsky, B.L., Humpenöder, F., Weindl, I., Stevanović, M., Karstens, K., Kreidenweis, U., Wang, X., Mishra, A., Klein, D., Ambrósio, G., Araujo, E., Yalew, A.W., Baumstark, L., Wirth, S., Giannousakis, A., Beier, F., Chen, D.M.C., Lotze-Campen, H., Popp, A., 2018. MAgPIE 4 - A modular open source framework for modeling global land-systems. Geosci. Model Dev. Discuss. 2018, 1-26.

Dixon, P., Jerie, M., Rimmer, M. T., 2018. Trade Theory in Computable General Equilibrium Models: Armington, Krugman and Melitz. Advances in Applied General Equilibrium Modeling. Springer, Singapore.

Dixon, P.B., and M.T. Rimmer, 2010. Validating a Detailed, Dynamic CGE Model of the USA. Economic Record 86: 22–34.

Eboli, F., Parrado, R., Roson, R., 2010. Climate-change feedback on economic growth: explorations with a dynamic general equilibrium model. Environment and Development Economics 15(5): 515-533.

Edali, M., and Yücel, G., 2019. Exploring the behavior space of agent-based simulation models using random forest meta models and sequential sampling. Simulation Modelling Practice and Theory, 92: 62–81

Edelenbosch, O.Y., D.L. McCollum, H. Pettifor, C. Wilson, and D.P. van Vuuren, Interactions between Social Learning and Technological Learning in Electric Vehicle Futures, Environmental Research Letters, Vol. 13, No. 12, November 23, 2018, p. 124004.

Edmonds, B. Le Page, C., Bithell, M., Chattoe-Brown, E., Grimm, V., Meyer, R., Montañola-Sales, C., Ormerod, P., Root, H. and Squazzoni, F., 2019. Different Modelling Purpose. Journal of Artificial Societies and Social Simulation 22(3): 6.

Eggers, J., Lindner, M., Zudin, S., Zaehle, S., Liski, J., 2008. Impact of changing wood demand, climate and land use on European forest resources and carbon stocks during the 21st century. Global Change Biology 14, 1-16. DOI: http://dx.doi.org/10.1111/j.1365-2486.2008.01653.x.

Ehrmann M (2017) Modellgestützte Analyse von Einkommens- und Umweltwirkungen auf Basis von Testbetriebsdaten. Braunschweig: Johann Heinrich von Thünen-Institut, 250 p, Thünen Rep 48

El-Chichakli, B.; von Braun, J.; Lang, C.; Barben, D.; and Philp, J. 2016. Policy: five cornerstones of a global bioeconomy. Nature, 535: 221-223. doi:10.1038/535221a

Elsawah, S., Filatova, T., Jakeman, A.J., Kettner, A.J., Zellner, M.L., Athanasiadis,I.N., Hamilton, S.H., Axtell, R.L., Brown, D.G., Gilligan, J.M., Janssen, M.A., Robinson, D.T., Rozenberg, J., Ullah, I.I.T., Lade, S.J. Eight grand challenges in socio-environmental systems modeling Socio-Environmental Systems Modelling, vol. 2, 16226, 2020.

Energy and Power Evaluation Program. (ENPEP-BALANCE) - Brief Model Overview - Version 2.25. Argonne: Argonne National Laboratory, Center for Energy, Environmental, and Economic Systems Analysis (CEEESA); 2008.

Erb, K.-H., Lauk, C., Kastner, T., Mayer, A., Theurl, M.C., Haberl, H., 2016. Exploring the biophysical option space for feeding the world without deforestation. Nature Communications 7, 11382. DOI: http://dx.doi.org/10.1038/ncomms11382.

Ermolieva, T.Y., Ermoliev, Y.M., Havlik, P., Mosnier, A., Leclere, D., Kraksner, F., Khabarov, N., & Obersteinera, M., 2015. Systems analysis of robust strategic decisions to plan secure food, energy, and water provision based on the stochastic GLOBIOM model. Cybernetics and Systems Analysis, 51(1), 125-133.

European Commission, 2020. Strategic Foresight Report. Charting the course towards a more resilient Europe. https://ec.europa.eu/info/sites/info/files/strategic_foresight_report_2020_1.pdf

European Commission, and Joint Research Centre, Biomass Production, Supply, Uses and Flows in the European Union: First Results from an Integrated Assessment., 2018.

Fagiolo, G., Guerini, M., Lamperti, F., Moneta, A. and Roventini, A., Validation of Agent-Based Models in Economics and Finance, In: Beisbart C., Saam N. (eds) Computer Simulation Validation. Simulation Foundations, Methods and Applications. Springer, Cham., 2019 https://doi.org/10.1007/978-3-319-70766-2_31

Ferri, G., Sedehi, H., 2018. The System View of the Sustainable Development Goals. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3287918

Flato, G.M., Earth System Models: An Overview: Earth System Models, Wiley Interdisciplinary Reviews: Climate Change, Vol. 2, No. 6, November 2011, pp. 783–800.

Forsell, N., Korosuo, A., Gusti, M., Rüter, S., Havlik, P., Obersteiner, M., 2019. Impact of modelling choices on setting the reference levels for the EU forest carbon sinks: how do different assumptions affect the country-specific forest reference levels? Carbon Balance and Management 14, 10. DOI: 10.1186/s13021-019-0125-9.

Foster, J., Energy, knowledge and Economic Growth, Papers on Economics and Evolution, Max Planck Jena, #1301, 2013

Fragkos, P., Kouvaritakis, N., Capros, P., 2015. Incorporating uncertainty into world energy modelling: the PROMETHEUS Model. Environmental Modeling & Assessment, 20(5), 549-569.

Frank, S., H. Böttcher, M. Gusti, P. Havlík, G. Klaassen, G. Kindermann, and M. Obersteiner, Dynamics of the Land Use, Land Use Change, and Forestry Sink in the European Union: The Impacts of Energy and Climate Targets for 2030, Climatic Change, Vol. 138, No. 1, September 1, 2016, pp. 253–266.

Frank, S., Havlík, P., Stehfest, E., van Meijl, H., Witzke, P., Pérez-Domínguez, I., van Dijk, M., Doelman, J.C., Fellmann, T., Koopman, J.F.L., Tabeau, A., Valin, H., 2019. Agricultural non-CO2 emission reduction potential in the context of the 1.5 °C target. Nature Climate Change 9, 66-72. DOI: 10.1038/s41558-018-0358-8.

Freeman, C., 1994. The Economics of Technical Change. Cambridge Journal of Economics18 (5): 463-514

Frenette, E., O. Bahn, and K. Vaillancourt, Meat, Dairy and Climate Change: Assessing the Long-Term Mitigation Potential of Alternative Agri-Food Consumption Patterns in Canada, Environmental Modeling & Assessment, Vol. 22, No. 1, February 2017, pp. 1–16.

Fritsche, U., Brunori, G., Chiaramonti, D., Galanakis, C., Hellweg, S., Matthews, R. and Panoutsou, C., 2020. Future transitions for the Bioeconomy towards Sustainable Development and a Climate-Neutral Economy - Knowledge Synthesis Final Report. Publications Office of the European Union, Luxembourg.doi:10.2760/667966, JRC121212.

Fujimori, S., T. Hasegawa, and T. Masui, AIM/CGE V2.0: Basic Feature of the Model, in S. Fujimori, M. Kainuma, and T. Masui (eds.), Post-2020 Climate Action, Springer Singapore, Singapore, 2017, pp. 305–328.

Gerssen-Gondelach, S.J., B. Wicke, M. Borzęcka-Walker, R. Pudełko, and A.P.C. Faaij, Bioethanol Potential from Miscanthus with Low ILUC Risk in the Province of Lublin, Poland, GCB Bioenergy, Vol. 8, No. 5, 2016, pp. 909–924.

Gifford, R., C. Kormos, and A. McIntyre, Behavioral Dimensions of Climate Change: Drivers, Responses, Barriers, and Interventions: Behavioral Dimensions of Climate Change, Wiley Interdisciplinary Reviews: Climate Change, Vol. 2, No. 6, November 2011, pp. 801–827.

Gilbert, N. and Terna, P., How to build and use agent-based models in social science. Mind & Society, 1(1), 2000, 57–72.

Gilbert, N. and Troitzsch, K., Simulation for the Social Scientist, Open University Press, McGraw Hill Education, 2nd edition, 2005.

Gillingham, K., R.G. Newell, and W.A. Pizer, Modeling Endogenous Technological Change for Climate Policy Analysis, Energy Economics, Vol. 30, No. 6, November 2008, pp. 2734–2753.

Godley, W. and Lavoie, M. Monetary Economics: An Integrated Approach to Credit, Money, Income, Production and Wealth. Palgrave Macmillan, New York, 2007.

Godzinski, A., Circular Economy and Energy: A Computable General Equilibrium Approach, French Ministry of Environment, https://afse2015. sciencesconf. org/61878 …, 2015.

Gold, S., Rubik, F., 2009. Consumer attitudes towards timber as a construction material and towards timber frame houses – selected findings of a representative survey among the German population. Journal of Cleaner Production 17, 303-309. DOI: https://doi.org/10.1016/j.jclepro.2008.07.001.

Grethe, H (Ed.), 2012. European Simulation Model (ESIM): Documentation (Model Code, Parameterization, Database). (Version of December 11 2012)

Groeneveld, J., Müller, B., Buchmann, C.M., Dressler, G., Guo, C.,Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., Schwarz, N., Theoretical foundations of human decision-making in agent-based land use models – A review, Environmental Modelling & Software, Volume 87, 2017, 39-48

Grossman, G., Helpman, E. 1991. Quality Ladders in the Theory of Growth. The Review of Economic Studies 58(1): 43-61. http://www.jstor.org/stable/2298044

Gurria, P., T. Ronzon, S. Tamosiunas, R. Lopez, S.G. Condado, J. Guillen, N. Cazzaniga, et al., Biomass Flows in the European Union: The Sankey Biomass Diagram - towards a Cross-Set Integration of Biomass, JRC Working Papers, JRC Working Papers, Joint Research Centre (Seville site), June 2017.

Hanewinkel, M., Cullmann, D.A., Schelhaas, M.-J., Nabuurs, G.-J., Zimmermann, N.E., 2013. Climate change may cause severe loss in the economic value of European forest land. Nature Climate Change 3, 203-207. DOI: http://dx.doi.org/10.1038/nclimate1687.

Härkönen, S., Neumann, M., Mues, V., Berninger, F., Bronisz, K., Cardellini, G., Chirici, G., Hasenauer, H., Koehl, M., Lang, M., Merganicova, K., Mohren, F., Moiseyev, A., Moreno, A., Mura, M., Muys, B., Olschofsky, K., Del Perugia, B., Rørstad, P.K., Solberg, B., Thivolle-Cazat, A., Trotsiuk, V., Mäkelä, A., 2019. A climate-sensitive forest model for assessing impacts of forest management in Europe. Environmental Modelling & Software 115, 128-143. DOI: https://doi.org/10.1016/j.envsoft.2019.02.009.

Hartley, F., T. Caetano, and R.C. Daniels, The General Equilibrium Impacts of Monetising All Waste Streams in South Africa, Energy Research Centre, University of Cape Town, 2016.

Hasan Shaikh, S., Zhang, Y., Chu, X., Teng, Y., 2019. The role of big data in Chinas sustainable forest management. Forestry Economics Review 1, 96-105. DOI: 10.1108/FER-04-2019-0013.

Hasselmann, Klaus, and Dmitry V. Kovalevsky. "Simulating animal spirits in actor-based environmental models." Environmental modelling & software 44 (2013): 10-24.

Heaps, C.G., 2020. LEAP: The Low Emissions Analysis Platform. [Software version: 2020.1.8] Stockholm Environment Institute. Somerville, MA, USA. https://leap.sei.org

Heckbert, S., Baynes, T. and Reeson, A., Agent-based modeling in ecological economics. Annals of the New York Academy of Sciences, 1185: 39-53. doi:10.1111/j.1749-6632.2009.05286.x, 2010

Heimann, T. 2019. Bioeconomy and SDGs: does the bioeconomy support the achievement of the SDGs? Earths Futur., 7: 43–57. doi:10.1029/2018EF001014

Hertel, T.W., de Lima, C.Z., 2020. Viewpoint: Climate impacts on agriculture: Searching for keys under the streetlight. Food Policy 95, 101954. DOI: https://doi.org/10.1016/j.foodpol.2020.101954.

Hilpert, S., Kaldemeyer, C., Krien, U., Günther, S., Wingenbach, C., & Plessmann, G., 2018). The Open Energy Modelling Framework (oemof)-A new approach to facilitate open science in energy system modelling. Energy strategy reviews 22, 16-25.

Hoefnafels R, M Banse, V Dornburg, A Faaij. 2013. Macro-economic impact of large-scale deployment of biomass resources for energy and materials on a national level – A combined approach for the Netherlands. Energy Policy, 59: 727-744. http://dx.doi.org/10.1016/j.enpol.2013.04.026.

Holland, J. H., 1992. Complex adaptive systems. Daedalus, 121: 17–30

Howells, M., Rogner, H., Strachan, N., Heaps, C., Huntington, H., Kypreos, S., ... & Roehrl, A. (2011). OSeMOSYS: the open source energy modeling system: an introduction to its ethos, structure and development. Energy Policy, 39(10), 5850-5870.

Hughes, B. B. (2019). International futures: Building and using global models. Academic Press.

Hurmekoski E, L Hetemäki (2013) Studying the future of the forest sector: Review and implications for long-term outlook studies. Forest Policy and Economics 34:17-29. http://dx.doi.org/10.1016/j.forpol.2013.05.005

Hurmekoski, E., Hetemäki, L., Linden, M., 2014. Factors affecting sawnwood consumption in Europe. Forest Policy and Economics. DOI: http://dx.doi.org/10.1016/j.forpol.2014.07.008.

IPBES (2019): Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. E. S. Brondizio, J. Settele, S. Díaz, and H. T. Ngo (editors). IPBES secretariat, Bonn, Germany.

Jackson, T. and Victor, P.A. 2016, Does slow growth lead to rising inequality? Some theoretical reflections and numerical simulations, Ecological Economics 121: 206–219.

Jackson, T. and Victor, P.A., 2015. Does credit create a growth Imperative? A quasi-stationary economy with interest-bearing debt, Ecological Economics 120: 32–48.

Jactel, H., Bauhus, J., Boberg, J., Bonal, D., Castagneyrol, B., Gardiner, B., Gonzalez-Olabarria, J.R., Koricheva, J., Meurisse, N., Brockerhoff, E.G., 2017. Tree Diversity Drives Forest Stand Resistance to Natural Disturbances. Current Forestry Reports 3, 223-243. DOI: 10.1007/s40725-017-0064-1.

Jansson, T., M. Bakker, B. Boitier, A. Fougeyrollas , J. Helming, H. van Meijl, P.J. Verkerk (2008). Cross sector land use modelling framework. In: Helming, K.; Tabbush, P. and M. Perez-Soba (Eds.). Sustainability Impact Assessment of land use policies. Springer-Verlag Berlin. pp. 159-180. http://www.springerlink.com/content/qw336j683t787384/

Jardim, E., Millar, C.P., Mosqueira, I., Scott, F., Osio, G.C., Ferretti, M., Alzorriz, N., Orio, A., 2014. What if stock assessment is as simple as a linear model? The a4a initiative. ICES Journal of Marine Science 72, 232-236. DOI: 10.1093/icesjms/fsu050.

Johnston, C.M.T., 2016. Global paper market forecasts to 2030 under future internet demand scenarios. Journal of Forest Economics 25, 14-28. DOI: https://doi.org/10.1016/j.jfe.2016.07.003.

Johnston, C.M.T., Radeloff, V.C., 2019. Global mitigation potential of carbon stored in harvested wood products. Proceedings of the National Academy of Sciences 116, 14526. DOI: 10.1073/pnas.1904231116.

Jongeneel, R., Gonzalez-Martinez, A., Lesschen, J.P., van Meijl, H., Heckelei, T., Salamon, P., (2020) Deliverable 1.10 The SUPREMA Roadmap exploring future directions for agricultural modelling in the EU. Project Support for Policy Relevant Modelling of Agriculture (SUPREMA). Online: https://www.suprema-project.eu.

Jonsson, K., Rinaldi, F., and San-Miguel-Ayanz, J., 2015. The Global Forest Trade Model - GFTM. EUR 27360. Publications Office of the European Union, Luxembourg.

Jonsson, R., Blujdea, V., Fiorese, G., Pilli, R., Rinaldi, F., Baranzelli, C., Camia, A., 2018. Outlook of the European forest-based sector: forest growth, harvest demand, wood-product markets, and forest carbon dynamics implications. iForest - Biogeosciences and Forestry 11, 315-328. DOI: 10.3832ifor2636-011.

Jonsson, R., Rinaldi, F., 2017. The impact on global wood-product markets of increasing consumption of wood pellets within the European Union. Energy 133, 864-878. DOI: https://doi.org/10.1016/j.energy.2017.05.178.

Jonsson, R., Rinaldi, F., Pilli, R., Fiorese, G., Hurmekoski, E., Cazzaniga, N., Robert, N., Camia, A., 2020. Boosting the EU forest-based bioeconomy: Market, climate, and employment impacts. Technological Forecasting and Social Change, 120478. DOI: https://doi.org/10.1016/j.techfore.2020.120478.

Jonsson, R., Rinaldi, F., Räty, M., and Sallnäs, O. (2016) Integrating forest-based industry and forest resource modeling. iForest - Biogeosciences and Forestry, 9, 743-750.

Junker, F., A. Gocht, S. Marquardt, B. Osterburg, and H. Stichnothe, Biofuel Sustainability Requirements – The Case of Rapeseed Biodiesel, German Journal of Agricultural Economics, Vol. 64, December 1, 2015. https://ageconsearch.umn.edu/record/270185.

Kallio, A.M.I., Moiseyev, A., Solberg, B., 2004. The global forest sector model EFI-GTM– the model structure. Technical report 15. European Forest Institute, Joensuu.

Kardung, M., Cingiz, K., Costenoble, O., Delahaye, R., Heijman, W., Lovrić, M., van Leeuwen, M., M'Barek, R., van Meijl, H., Piotrowski, S., Ronzon, T., Sauer, J., Verhoog, D., Verkerk, P.J., Vrachioli, M., Wesseler, J.H.H., Zhu, B.X., 2021. Development of the Circular Bioeconomy: Drivers and Indicators. Sustainability 13, 413.

Karvonen, J., P. Halder, J. Kangas, and P. Leskinen, Indicators and Tools for Assessing Sustainability Impacts of the Forest Bioeconomy, Forest Ecosystems, Vol. 4, No. 1, December 2017, p. 2.

Kato, H. (2003). World Energy Model 2002.

Kaufmann, S.A. (1993), The Origins of Order: Self-Organization and Selection in Evolution, Oxford University Press, Oxford UK.

Kause, A., Bruine de Bruin, W., Millward-Hopkins, J., Olsson, H., 2019. Public perceptions of how to reduce carbon footprints of consumer food choices. Environmental Research Letters 14, 114005. DOI: 10.1088/1748-9326/ab465d.

Kindermann, G., Obersteiner, M., Sohngen, B., Sathaye, J., Andrasko, K., Rametsteiner, E., Schlamadinger, B., Wunder, S., Beach, R., 2008. Global cost estimates of reducing carbon emissions through avoided deforestation. Proceedings of the National Academy of Sciences 105, 10302-10307.

Köhler, J., de Haan, F., Holtz, G., Kubeczko, K., Moallemi, E., Papachristos, G., Chappin, E., 2018. Modelling Sustainability Transitions: An Assessment of Approaches and Challenges. Journal of Artificial Societies and Social Simulation 21, 8. DOI: 10.18564/jasss.3629.

Kok, M.T.J., Alkemade, R., Bakkenes, M., van Eerdt, M., Janse, J., Mandryk, M., Kram, T., Lazarova, T., Meijer, J., van Oorschot, M., Westhoek, H., van der Zagt, R., van der Berg, M., van der Esch, S., Prins, A.-G., van Vuuren, D.P., 2018. Pathways for agriculture and forestry to contribute to terrestrial biodiversity conservation: A global scenario-study. Biological Conservation 221, 137-150. DOI: https://doi.org/10.1016/j.biocon.2018.03.003.

Kolström, M., Lindner, M., Vilén, T., Maroschek, M., Seidl, R., Lexer, M.J., Netherer, S., Kremer, A., Delzon, S., Barbati, A., Marchetti, M., Corona, P., 2011. Reviewing the Science and Implementation of Climate Change Adaptation Measures in European Forestry. Forests 2, 961.

Kretschmer, S., Geibert W., van der Loeff MMR., Mollenhauer, G. 2010. Grain size effects on Th-230 (xs) inventories in opal-rich and carbonate-rich marine sediments. Earth and Planetary Science Letters, 294(1-2), 131-142, https://doi.org/10.1016/j.epsl.2010.03.021

Krey V, Havlik P, Fricko O, Zilliacus J, Gidden M, Strubegger M, Kartasasmita G, Ermolieva T, Forsell N, Gusti M, Johnson N, Kindermann G, Kolp P, McCollum DL, Pachauri S, Rao S, Rogelj J, Valin H, Obersteiner M, Riahi K (2016) MESSAGE-GLOBIOM 1.0 Documentation. International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria http://data.ene.iiasa.ac.at/message-globiom/.

Kull SJ, Rampley G, Morken S, Metsaranta J, Neilson ET, Kurz WA (2016) Operational-scale Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) version 1.2: users guide. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta. 346 p.

Kurz WA, Dymond CC, White TM, Stinson G, Shaw CH, Rampley GJ, Smyth C, Simpson BN, Neilson ET, Trofymow JA, Metsaranta J, Apps MJ (2009) CBM-CFS3: A model of carbon-dynamics in forestry and land-use change implementing IPCC standards. Ecol. Model. 220(4): 480-504.

Laborde, D., Padella, M., Edwards, R., Marelli, L., 2014. Progress in Estimates of iLUC with MIRAGE Model. Scientific and Policy Reports. Ispra, Italy, International Food Policy Institute (IFPRI), Joint Research Centre of the European Commission. http://iet.jrc.ec.europa.eu/bf-ca/sites/bf-ca/files/documents/ifpri-jrc_report.pdf

Lähtinen, K., Harju, C., Toppinen, A., 2019. Consumers' perceptions on the properties of wood affecting their willingness to live in and prejudices against houses made of timber. Wood Material Science & Engineering 14, 325-331. DOI: 10.1080/17480272.2019.1615548.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., & Sapio, A. (2018). Faraway, so close: coupled climate and economic dynamics in an agent-based integrated assessment model. Ecological Economics, 150, 315-339.

Latta, G.S., Plantinga, A.J., Sloggy, M.R., 2016. The Effects of Internet Use on Global Demand for Paper Products. Journal of Forestry 114, 433-440. DOI: 10.5849/jof.15-096.

Lavalle C, Lopes Barbosa A, Perpiña Castillo C, Vallecillo Rodriguez S, Jacobs C, Mari Rivero I, Vizcaino M, Vandecasteele I, Baranzelli C, Batista E Silva F, Zulian G, Hiederer R, Aurambout J, Ribeiro Barranco R, Arevalo Torres J, Maes J, Marín Herrera M., 2015. LUISA Dynamic Land Functions: Catalogue of Indicators – Release I: EU Reference Scenario 2013 LUISA Platform - Updated Configuration 2014. EUR 27675 EN. Luxembourg: Publications Office of the European Union. doi:10.2788/158546

Leclère, D., Obersteiner, M., Barrett, M., Butchart, S.H.M., Chaudhary, A., De Palma, A., DeClerck, F.A.J., Di Marco, M., Doelman, J.C., Dürauer, M., Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J.P., Hill, S.L.L., Humpenöder, F., Jennings, N., Krisztin, T., Mace, G.M., Ohashi, H., Popp, A., Purvis, A., Schipper, A.M., Tabeau, A., Valin, H., van Meijl, H., van Zeist, W.-J., Visconti, P., Alkemade, R., Almond, R., Bunting, G., Burgess, N.D., Cornell, S.E., Di Fulvio, F., Ferrier, S., Fritz, S., Fujimori, S., Grooten, M., Harwood, T., Havlík, P., Herrero, M., Hoskins, A.J., Jung, M., Kram, T., Lotze-Campen, H., Matsui, T., Meyer, C., Nel, D., Newbold, T., Schmidt-Traub, G., Stehfest, E., Strassburg, B.B.N., van Vuuren, D.P., Ware, C., Watson, J.E.M., Wu, W., Young, L., 2020. Bending the curve of terrestrial biodiversity needs an integrated strategy. Nature 585, 551-556. DOI: 10.1038/s41586-020-2705-y.

Leduc, S. (2009). Development of an optimization model for the location of biofuel production plants. Doctoral Thesis, Luleå University of Technology, Luleå, Sweden

Leimbach, M. Bauer, N., Baumstark, L., Edenhofer, O. (2010): Mitigation costs in a globalized world: climate policy analysis with REMIND-R. Environmental Modeling and Assessment 15, 155-173.

Lekve Bjelle, E., K. Steen-Olsen, and R. Wood, Climate Change Mitigation Potential of Norwegian Households and the Rebound Effect, Journal of Cleaner Production, Vol. 172, January 2018, pp. 208–217.

Lesschen, J.P., Van den Berg, M., Westhoek, H.J., Witzke, H.P., Oenema, O. 2011. Greenhouse gas emission profiles of European livestock sectors. Animal Feed Science & Technology, 166-167: 16-28.

Levin, S., Xepapadeas, T., Crépin, A., Norberg, J., De Zeeuw, A., Folke, C., . . . Walker, B., Social-ecological systems as complex adaptive systems: Modeling and policy implications. Environment and Development Economics, 18(2), 111-132. doi:10.1017/S1355770X12000460, 2013

Li, F.G.N., Actors Behaving Badly: Exploring the Modelling of Non-Optimal Behaviour in Energy Transitions, Energy Strategy Reviews, Vol. 15, March 2017, pp. 57–71.

Lindner, M., Fitzgerald, J.B., Zimmermann, N.E., Reyer, C., Delzon, S., van der Maaten, E., Schelhaas, M.-J., Lasch, P., Eggers, J., van der Maaten-Theunissen, M., Suckow, F., Psomas, A., Poulter, B., Hanewinkel, M., 2014. Climate change and European forests: What do we know, what are the uncertainties, and what are the implications for forest management? Journal of Environmental Management 146, 69-83. DOI: http://dx.doi.org/10.1016/j.jenvman.2014.07.030.

Lindner, M., Suominen, T., Palosuo, T., Garcia-Gonzalo, J., Verweij, P., Zudin, S., Päivinen, R., 2010. ToSIA--A tool for sustainability impact assessment of forest-wood-chains. Ecological Modelling 221, 2197-2205.

Lokers, R., Knapen, R., Janssen, S., van Randen, Y. and Jansen, J., Analysis of Big Data technologies for use in agro-environmental science,Environmental Modelling & Software, Volume 84, 2016, 494-504

Lokers, R., van Randen, Y., Knapen, R., Gaubitzer, S., Zudin, S., Janssen, S., 2015. Improving Access to Big Data in Agriculture and Forestry Using Semantic Technologies. Springer International Publishing. pp. 369-380

Löschel, A., and M. Schymura, Modeling Technological Change in Economic Models of Climate Change: A Survey, SSRN Electronic Journal, 2013.

Lotze-Campen, H., Verburg, P.H., Popp, A., Lindner, M., Verkerk, P.J., Moiseyev, A., Schrammeijer, E., Helming, J., Tabeau, A., Schulp, C.J.E., van der Zanden, E.H., Lavalle, C., e Silva, F.B., Walz, A., Bodirsky, B., 2018. A cross-scale impact assessment of European nature protection policies under contrasting future socio-economic pathways. Regional Environmental Change 18, 751-762. DOI: 10.1007/s10113-017-1167-8.

Louhichi, K., P. Ciaian, M. Espinosa, L. Colen, A. Perni, S. Gomez y Paloma (2015). An EU-Wide Individual Farm Model for Common Agricultural Policy Analysis (IFM-CAP). First application to Crop Diversification Policy. European Commission. Joint Research Centre. Online: https://publications.jrc.ec.europa.eu/repository/bitstream/JRC92574/jrcreport_jrc92574.pdf

Loulou, R., Goldstein, G. and Noble, K. (2004). Documentation for the MARKAL Family of Models. Available at: http://unfccc.int/resource/cd_roms/na1/mitigation/Module_5/Module_5_1/b_tools/MARKAL/MARKAL_Manual.pdf

Loulou, R., Remme, U., Kanudia, A., Lehtila, A., & Goldstein, G. 2005. Documentation for the times model part ii. Energy Technology Systems Analysis Programme.

Loulou, Richard, and Maryse Labriet. ETSAP-TIAM: the TIMES integrated assessment model Part I: Model structure. Computational Management Science 5.1-2 (2008): 7-40.

Lovrić, M., Verkerk, H., Hassegawa, H., Cramm, M., Varacca, A., Sckokai, P., van Leeuwen, M., Salamon, P., Sturm, V., Vrachioli, M., M'Barek, R., Philippidis, G., 2020a. Requirements and priorities for improved bioeconomy modelling. BioMonitor deliverable report 4.2.

Lovrić, N., Lovrić, M., Mavsar, R., 2020b. Factors behind development of innovations in European forest-based bioeconomy. Forest Policy and Economics 111, 102079. DOI: https://doi.org/10.1016/j.forpol.2019.102079.

Lutz, C., Meyer, B., & Wolter, M. I. (2010). The global multisector/multicountry 3-E model GINFORS. A description of the model and a baseline forecast for global energy demand and CO2 emissions. International Journal of Global Environmental Issues, 10(1-2), 25-45.

Macal, C. M., Everything you need to know about agent-based modelling and simulation. Journal of Simulation 10.2, pp. 144–156. DOI: 10.1057/jos.2016.7.

Mainar-Causapé, A.J.; Philippidis, G. (Ed.), BioSAMs for the EU Member States. Constructing Social Accounting Matrices with a detailed disaggregation of the bio-economy, EUR 29235 EN, Publications Office of the European Union, Luxembourg, 2018, ISBN 978-92-79-85966-3, doi:10.2760/811691

Malerba, F., Nelson, R. R., Orsenigo, L., and Winter, S. G., History-friendly models of industry evolution: The computer industry. Industrial and Corporate Change, 8, 1999, 3–40.

Mantau, U., Wood Flow Analysis: Quantification of Resource Potentials, Cascades and Carbon Effects, Biomass and Bioenergy, Vol. 79, August 2015, pp. 28–38.

Mantzos L, Matei N.A., Rózsai M., Russ P., Ramirez A.S., 2017. POTEnCIA: A new EU-wide energy sector model. 2017 14th International Conference on the European Energy Market (EEM), Dresden, 2017, pp. 1-5, doi: 10.1109/EEM.2017.7982028

March, J.G. 1991. Exploration and Exploitation in Organizational Learning. Organization Science 2(1): 71-87

Marsland, S., 2015. Machine Learning: An Algorithmic Perspective. 2nd ed. Chapman and Hall/CRC

Masui, T., 2005. Policy Evaluations under Environmental Constraints Using a Computable General Equilibrium Model. European Journal of Operational Research 166 (3): 843–855.

M'barek, R.; Philippidis, G.; Ronzon, T., 2019 Alternative Global Transition Pathways to 2050: Prospects for the Bioeconomy - An application of the MAGNET model with SDG insights, EUR 29862, Luxembourg: Publications Office of the European Union, ISBN 978-92-76-11335-5, doi:10.2760/594847, JRC118064.

McCarthy, A., R. Dellink, and R. Bibas, 2018. The Macroeconomics of the Circular Economy Transition: A Critical Review of Modelling Approaches, OECD Environment Working Papers, OECD.

McCollum, D.L., C. Wilson, H. Pettifor, K. Ramea, V. Krey, K. Riahi, C. Bertram, Z. Lin, O.Y. Edelenbosch, and S. Fujisawa, Improving the Behavioral Realism of Global Integrated Assessment Models: An Application to Consumers Vehicle Choices, Transportation Research Part D: Transport and Environment, Vol. 55, August 2017, pp. 322–342.

Melitz, M.J. 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71(6): 1695–1725

Mendonça, S., The "sailing ship effect": Reassessing history as a source of insight on technical change. Research Policy, 42(10), 2013, 1724–1738.doi:10.1016/j.respol.2012.12.009

Merciai, S., and J. Schmidt, Methodology for the Construction of Global Multi-Regional Hybrid Supply and Use Tables for the EXIOBASE v3 Database: Methodology of MR-HSUTs for the EXIOBASE Database, Journal of Industrial Ecology, Vol. 22, No. 3, June 2018, pp. 516–531.

Mercure, J. F., Pollitt, H., Edwards, N. R., Holden, P. B., Chewpreecha, U., Salas, P., ... & Vinuales, J. E. (2018). Environmental impact assessment for climate change policy with the simulation-based integrated assessment model E3ME-FTT-GENIE. Energy Strategy Reviews, 20, 195-208.

Mercure, J.-F., FTT:Power : A Global Model of the Power Sector with Induced Technological Change and Natural Resource Depletion, Energy Policy, Vol. 48, September 2012, pp. 799–811.

Mercure, J.-F., H. Pollitt, Andrea.M. Bassi, Jorge.E. Viñuales, and N.R. Edwards, Modelling Complex Systems of Heterogeneous Agents to Better Design Sustainability Transitions Policy, Global Environmental Change, Vol. 37, March 2016, pp. 102–115.

Millar, C., Jardim, E., Mosqueira, I., Osio, C., 2015. The a4a Assessment Model. Model description and testing. Luxembourg: Publications Office of the European Union. doi:10.2788/73856

Montenegro, R. C., Lekavičius, V., Brajković, J., Fahl, U., & Hufendiek, K., 2019. Long-Term Distributional Impacts of European Cap-and-Trade Climate Policies: A CGE Multi-Regional Analysis. Sustainability 11(23), 1-26.

Mubareka, S., Jonsson, R., Rinaldi, F., Fiorese, G., San Miguel, J., Sallnas, O., Baranzelli, C., Pilli, R., Lavalle, C., Kitous, A., 2014. An integrated modelling framework for the forest-Based bioeconomy. IEEE Earthzine 7, 1-17. DOI: http://dx.doi.org/10.1101/011932.

Muscat, A., E.M. de Olde, I.J.M. de Boer, and R. Ripoll-Bosch, The Battle for Biomass: A Systematic Review of Food-Feed-Fuel Competition, Global Food Security, Vol. 25, June 2020, p. 100330.

Nabuurs, G.-J., Arets, E.J.M.M., Schelhaas, M.-J., 2018. Understanding the implications of the EU-LULUCF regulation for the wood supply from EU forests to the EU. Carbon Balance and Management 13, 18. DOI: 10.1186/s13021-018-0107-3.

Naqvi, A., Modeling growth, distribution, and the environment in a stock-flow consistent framework. Institute for Ecological Economics Working Paper 2/2015. Vienna: Vienna University of Economics and Business, 2015

Nelson, G., H. Ahammad, D. Deryng, J. Elliott, S. Fujimori, P. Havlik, E. Heyhoe, P. Kyle, M. von Lampe, H. Lotze-Campen, D. Mason d'Cruz, H. van Meijl, D. van der Mensbrugghe, C. Müller, R. Robertson, R. D. Sands, E. Schmid, C. Schmitz, A. Tabeau, H. Valin, D. Willenbockel, 2013. Assessing uncertainty along the climate-crop-economy modeling chain, Proceedings of the National Academy of Sciences, 111 (9): 3274-3279.

Nelson, R., Dosi, G., Helfat, C., Pyka, A., Saviotti, P.P., Lee, K., Dopfer, K., Malerba, F. and Winter, S.G. (2018), Modern Evolutionary Economics – An Overview. Cambridge University Press, Cambridge, UK.

Ness, B., E. Urbel-Piirsalu, S. Anderberg, and L. Olsson, Categorising Tools for Sustainability Assessment, Ecological Economics, Vol. 60, No. 3, January 2007, pp. 498–508.

Niamir, L., Ivanova, O. and Filatova, T., Economy-wide impacts of behavioral climate change mitigation: linking agent-based and computable general equilibrium models, Environmental Modelling & Software,2020,104839,https://doi.org/10.1016/j.envsoft.2020.104839, 2020

Nikiforos, M. and Zecca, G., Stock-flow consistent macroeconomic models: a survey. Journal of Economic Surveys, Vol. 31(5), 2017, 1204-1239.

North, M. J. and Macal, C. M., Managing business complexity: discovering strategic solutions with agent-based modeling and simulation. Oxford University Press, 2007.

O'Brien, M., D. Wechsler, S. Bringezu, and R. Schaldach, 2017. Toward a Systemic Monitoring of the European Bioeconomy: Gaps, Needs and the Integration of Sustainability Indicators and Targets for Global Land Use. Land Use Policy 66: 162–171.

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Climatic Change 122, 387-400. DOI: 10.1007/s10584-013-0905-2.

OECD/FAO, 2018. *OECD-FAO Agricultural Outlook 2018-2027*, OECD Publishing, Paris/FAO, Rome. DOI: 10.1787/agr_outlook-2018-en. Available at: https://www.oecd-ilibrary.org/agriculture-and-food/oecd-fao-agricultural-outlook-2018-2027_agr_outlook-2018-en

Olhoff, Anne, and John M. Christensen, eds., Lessons from a Decade of Emissions Gap Assessments, United Nations Environment Programme, France, 2019.

Ostrom, E., A general framework for analyzing sustainability of social-ecological systems. Science, 325(5939), 2009, 419–422

Pauliuk, S., A. Arvesen, K. Stadler, and E.G. Hertwich, Industrial Ecology in Integrated Assessment Models, Nature Climate Change, Vol. 7, No. 1, January 2017, pp. 13–20.

Pedell S., Sterling L., Agent-Based Modelling for Understanding Sustainability. In: Kinny D., Hsu J.Y., Governatori G., Ghose A.K. (eds) Agents in Principle, Agents in Practice. PRIMA 2011. Lecture Notes in Computer Science, vol 7047. Springer, Berlin, Heidelberg, 2011. https://doi.org/10.1007/978-3-642-25044-6_32

Peng, B., Guan, K., Tang, J., Ainsworth, E.A., Asseng, S., Bernacchi, C.J., Cooper, M., Delucia, E.H., Elliott, J.W., Ewert, F., Grant, R.F., Gustafson, D.I., Hammer, G.L., Jin, Z., Jones, J.W., Kimm, H., Lawrence, D.M., Li, Y., Lombardozzi, D.L., Marshall-Colon, A., Messina, C.D., Ort, D.R., Schnable, J.C., Vallejos, C.E., Wu, A., Yin, X., Zhou, W., 2020. Towards a multiscale crop modelling framework for climate change adaptation assessment. Nature Plants 6, 338-348. DOI: 10.1038/s41477-020-0625-3.

Pereda, M., Santos, J. I., & Galán, J. M., A brief introduction to the use of machine learning techniques in the analysis of agent-based models. In Advances in Management Engineering (pp. 179–186). Springer, 2017.

Perry, G. L. W., and O'Sullivan, D., Identifying Narrative Descriptions in Agent-Based Models Representing Past Human-Environment Interactions. Journal of Archaeological Method and Theory, 25(3), 2018, 795–817

Philippidis, G., H. Bartelings, J. Helming, R. M'Barek, E. Smeets, H. van Meijl (2019). Levelling the playing field for EU biomass usage. Economic Systems Research, p. 1-20. (doi 10.1080/09535314.2018.1564020)

Philippidis, G., Shutes, L., M`barek, R., Ronzon, T., Tabeau, A. and Van Meijl, H., 2020, Snakes and ladders: World development pathways` synergies and trade-offs through the lens of the Sustainable Development Goals, Journal of cleaner production, ISSN 0959-6526 (online), 267, p. 122147, JRC120499.

Pilli, R., Grassi, G., Kurz, W.A., Fiorese, G., Cescatti, A., 2017. The European forest sector: past and future carbon budget and fluxes under different management scenarios. Biogeosciences 14, 2387-2405. DOI: 10.5194/bg-14-2387-2017.

Pyka, A. and Fagiolo, G., Agent-based modelling: a methodology for neo-Schumpeterian economics in: Hanusch, H. and Pyka, A. (eds.), Elgar companion to neo-schumpeterian economics, Cheltenham: Edward Elgar Publishers, 2007.

Pyka, A., Kudic, M. and Mueller, M., Systemic interventions in regional innovation systems: entrepreneurship, knowledge accumulation and regional innovation, Regional Studies, 53(9), 2019, 1321-1332

Pyka, A., Müller, M. and Kudic, M., Regional Innovation Systems in Policy Laboratories, Open Innovation, 4(4),44, 2018

Rammer, W., and R. Seidl, Harnessing Deep Learning in Ecology: An Example Predicting Bark Beetle Outbreaks, Frontiers in Plant Science, Vol. 10, 2019.

Rezai, A., Stagl, S., Ecological macroeconomics: introduction and review. Ecological Economics, 121, 2016, pp. 181-185;

Riahi, K., D.P. van Vuuren, E. Kriegler, J. Edmonds, B.C. O'Neill, S. Fujimori, N. Bauer, et al. 2017. The Shared Socioeconomic Pathways and Their Energy, Land Use, and Greenhouse Gas Emissions Implications: An Overview, Global Environmental Change 42: 153–168.

Rinaldi, F., Jonsson, R., Sallnäs, O., Trubins, R., 2015. Behavioral Modelling in a Decision Support System. Forests 6, 311-327.

Ringkjøb, H.-K., Haugan, P.M., Solbrekke, I.M., 2018. A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renewable and Sustainable Energy Reviews 96, 440-459. DOI: https://doi.org/10.1016/j.rser.2018.08.002.

Ringkjøb, H.-K., P.M. Haugan, and I.M. Solbrekke, A Review of Modelling Tools for Energy and Electricity Systems with Large Shares of Variable Renewables, Renewable and Sustainable Energy Reviews, Vol. 96, November 2018, pp. 440–459.

Risse, M., G. Weber-Blaschke, and K. Richter, Resource Efficiency of Multifunctional Wood Cascade Chains Using LCA and Exergy Analysis, Exemplified by a Case Study for Germany, Resources, Conservation and Recycling, Vol. 126, November 2017, pp. 141–152.

Robinson, J., Essays in the Theory of Economic Growth, London: Macmillan, 1962.

Robinson, S., Mason d'Croz, D., Islam, S., Sulser, T.B., Robertson, R.D., Zhu, T., Gueneau, A., Pitois, G., and Rosegrant, M.W. (2015) The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model description for version 3. IFPRI Discussion Paper 1483. Washington, D.C.: International Food Policy Research Institute (IFPRI). http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/129825

Roe, S., Streck, C., Obersteiner, M., Frank, S., Griscom, B., Drouet, L., Fricko, O., Gusti, M., Harris, N., Hasegawa, T., Hausfather, Z., Havlík, P., House, J., Nabuurs, G.-J., Popp, A., Sánchez, M.J.S., Sanderman, J., Smith, P., Stehfest, E., Lawrence, D., 2019. Contribution of the land sector to a 1.5 °C world. Nature Climate Change 9, 817-828. DOI: 10.1038/s41558-019-0591-9.

Rogers, J.N., B. Stokes, J. Dunn, H. Cai, M. Wu, Z. Haq, and H. Baumes, An Assessment of the Potential Products and Economic and Environmental Impacts Resulting from a Billion Ton Bioeconomy, Biofuels, Bioproducts and Biorefining, Vol. 11, No. 1, January 2017, pp. 110–128.

Romer, P. M., 1994. The Origins of Endogenous Growth. The Journal of Economic Perspectives. 8 (1): 3–22.

Röös, E., B. Bajželj, P. Smith, M. Patel, D. Little, and T. Garnett, Protein Futures for Western Europe: Potential Land Use and Climate Impacts in 2050, Regional Environmental Change, Vol. 17, No. 2, February 2017, pp. 367–377.

Rossit, D.A., Olivera, A., Céspedes, V. V., and Broz, D., A Big Data approach to forestry harvesting productivity, Computers and Electronics in Agriculture, Vol. 161, 2019, 29-52, https://doi.org/10.1016/j.compag.2019.02.029.

Rougieux, P., Damette, O., 2018. Reassessing forest products demand functions in Europe using a panel cointegration approach. Applied Economics, 1-24. DOI: 10.1080/00036846.2017.1420887.

Sachs, J.D., Schmidt-Traub, G., Mazzucato, M., Messner, D., Nakicenovic, N., & Rockström, J. 2019. Six Transformations to Achieve the Sustainable Development Goals, Nature Sustainability 2(9): 805–814.

Safarzyńska, K., van den Bergh, J.C.J.M., 2010. Demand-supply coevolution with multiple increasing returns: Policy analysis for unlocking and system transitions. Technological Forecasting and Social Change 77 (2): 297-317

Safarzynska,K., Frenken, K. and van den Bergh, J.C.J.M., Evolutionary theorizing and modeling of sustainability transitions, Research Policy, Vol. 41, 2012, 1011-1024.

Salamon, P., Banse, M., Barreiro-Hurlé, J., Chaloupka, O., Donnellan, T., Erjavec, E., Fellmann, F., Hanrahan, K., Hass, M., Jongeneel, R., Laquai, V., van Leeuwen, M., Molnár, A., Pechrová, M., Salputra, G., Baltussen, W., Efken, J., Hélaine, S., Jungehülsing, J., von Ledebur, O., Rac, I., and Santini, F. (2017) Unveiling diversity in agricultural markets projections: from EU to Member States. A medium-term outlook with the AGMEMOD model. *JRC Technical Report*, 29025 EUR, Publications Office of the European Union, Luxembourg, ISBN 978-92-79-77335-8, DOI:10.2760/363389.

Sanchez-Sabate, R., Sabaté, J., 2019. Consumer Attitudes Towards Environmental Concerns of Meat Consumption: A Systematic Review. International Journal of Environmental Research and Public Health 16, 1220.

Sassi, O., Crassous, R., Hourcade, J. C., Gitz, V., Waisman, H., & Guivarch, C. (2010). IMACLIM-R: a modelling framework to simulate sustainable development pathways. International Journal of Global Environmental Issues, 10(1-2), 5-24.

Saviotti, P. P. and Pyka, A., 2004. Economic development by the creation of new sectors. Journal of evolutionary economics 14(1): 1-35.

Schelhaas, M.-J., Hengeveld, G.M., Heidema, N., Thürig, E., Rohner, B., Vacchiano, G., Vayreda, J., Redmond, J., Socha, J., Fridman, J., Tomter, S., Polley, H., Barreiro, S., Nabuurs, G.-J., 2018. Species-specific, pan-European diameter increment models based on data of 2.3 million trees. Forest Ecosystems 5, 21. DOI: 10.1186/s40663-018-0133-3.

Schelhaas, M.-J., Nabuurs, G.-J., Hengeveld, G., Reyer, C., Hanewinkel, M., Zimmermann, N., Cullmann, D., 2015. Alternative forest management strategies to account for climate change-induced productivity and species suitability changes in Europe. Regional Environmental Change 15, 1581-1594. DOI: 10.1007/s10113-015-0788-z.

Scherr, S.J., Shames, S., Friedman, R., 2012. From climate-smart agriculture to climate-smart landscapes. Agriculture & Food Security 1, 12. DOI: 10.1186/2048-7010-1-12.

Schilperoord, M. and Ahrweiler, P., Towards a Prototype Policy Laboratory for Simulating Innovation Networks, in: Ahrweiler, P., Gilbert, N. and Pyka, A. (eds.), Simulating Knowledge Dynamics in Innovation Networks, Springer: Berlin, Heidelberg, New York, 185-198.

Schlaile, M. P., Müller, M., Schramm, M. and Pyka, A., Evolutionary Economics, Responsible Innovation and Demand: Making a Case for the Role of Consumers, Philosophy of Management, 17, 2018, 7-39

Schreinemachers,P. and Berger, T., An agent-based simulation model of human–environment interactions in agricultural systems, Environmental Modelling and Software, 26, 2011,845-859

Schulze, J., K. Frank, J.A. Priess, and M.A. Meyer, Assessing Regional-Scale Impacts of Short Rotation Coppices on Ecosystem Services by Modeling Land-Use Decisions, Edited by B. Bond-Lamberty, PLOS ONE, Vol. 11, No. 4, April 15, 2016, p. e0153862.

Schulze, J., Müller, B., Groeneveld, J. and Grimm, V., Agent-Based Modelling of Social-Ecological Systems: Achievements, Challenges, and a Way Forward, Journal of Artificial Societies and Social Simulation 20(2) 8, 2017, Doi: 10.18564/jasss.3423

Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., Wild, J., Ascoli, D., Petr, M., Honkaniemi, J., Lexer, M.J., Trotsiuk, V., Mairota, P., Svoboda, M., Fabrika, M., Nagel, T.A., Reyer, C.P.O., 2017. Forest disturbances under climate change. Nature Climate Change 7, 395. DOI: 10.1038/nclimate3303.

Senf, C., Seidl, R., 2020. Mapping the forest disturbance regimes of Europe. Nature Sustainability. DOI: 10.1038/s41893-020-00609-y.

Sert, E., Bar-Yam, Y. & Morales, A.J. Segregation dynamics with reinforcement learning and agent based modeling. Sci Rep 10, 11771 (2020). https://doi.org/10.1038/s41598-020-68447-8

Sevim, C., A. Oztekin, O. Bali, S. Gumus, and E. Guresen, Developing an Early Warning System to Predict Currency Crises, European Journal of Operational Research, Vol. 237, No. 3, September 2014, pp. 1095–1104.

Sharp, R., Tallis, H.T., Ricketts, T., Guerry, A.D., Wood, S.A., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J., Cameron, D., Arkema, K., Lonsdorf, E., Kennedy, C., Verutes, G., Kim, C.K., Guannel, G., Papenfus, M., Toft, J., Marsik, M., Bernhardt, J., Griffin, R., Glowinski, K., Chaumont, N., Perelman, A., Lacayo, M. Mandle, L., Hamel, P., Vogl, A.L., Rogers, L., Bierbower, W., Denu, D., and Douglass, J. 2018. InVEST 3.5.0.post284+ug.hf903e6636cca User's Guide. The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund.

Smajgl, A., Brown, D. G., Valbuena, D. & Huigen, M. G. A., Empirical characterisation of agent behaviours in socio-environmental systems. Environmental Modelling & Soware, 26(7), 2011, 837–844

Smeets E., van Leeuwen M., Valin H., Tsiropoulos Y., Moiseyev A., Lindner M., O'Brien M., Schütz H., Schouten M., Verburg P., Verhagen W., Junker F., Msangi S., 2013. Annotated bibliography on qualitative and quantitative models for analysing the bioeconomy. SAT-BBE project deliverable report 2.3.

Smeets, E., C. Vinyes, A. Tabeau, H. van Meijl, C. Brink, A.G. Prins, Institute for Prospective Technological Studies, LEI-WUR, and Netherlands Environmental Assessment Agency (PBL), Evaluating the Macro-Economic Impacts of Bio-Based Applications in the EU., Publications Office, Luxembourg, 2014.

Smeets-Kriskova, Z., van Dijk, M., Gardebroek, K., van Meijl, H., 2017a. The impact of R&D on factor-augmenting technical change – an empirical assessment at the sector level. Economic Systems Research 29 (3): 385-417.

Smeets-Kriskova, Z., van Dijk, M., van Meijl, H., 2017b. Assessing the impact of agricultural R&D investments on long-term projections of food security. Frontiers of Economics and Globalization 17: 1-17.

Smith, C.J., P.M. Forster, M. Allen, N. Leach, R.J. Millar, G.A. Passerello, and L.A. Regayre, FAIR v1.3: A Simple Emissions-Based Impulse Response and Carbon Cycle Model, Geoscientific Model Development, Vol. 11, No. 6, June 18, 2018, pp. 2273–2297.

Smith, P., and P.J. Gregory, 2013. Climate Change and Sustainable Food Production. Proceedings of the Nutrition Society 72 (1): 21–28.

Somé, A., T. Dandres, C. Gaudreault, G. Majeau-Bettez, R. Wood, and R. Samson, 2018. Coupling Input-Output Tables with Macro-Life Cycle Assessment to Assess Worldwide Impacts of Biofuels Transport Policies. Journal of Industrial Ecology 22 (4): 643–655.

Sotirov, M., Sallnäs, O., Eriksson, L.O., 2019. Forest owner behavioral models, policy changes, and forest management. An agent-based framework for studying the provision of forest ecosystem goods and services at the landscape level. Forest Policy and Economics 103, 79-89. DOI: https://doi.org/10.1016/j.forpol.2017.10.015.

Sousa-Silva, R., Verbist, B., Lomba, Â., Valent, P., Suškevičs, M., Picard, O., Hoogstra-Klein, M.A., Cosofret, V.-C., Bouriaud, L., Ponette, Q., Verheyen, K., Muys, B., 2018. Adapting forest management to climate change in Europe: Linking perceptions to adaptive responses. Forest Policy and Economics 90, 22-30. DOI: https://doi.org/10.1016/j.forpol.2018.01.004.

Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B.L., Lassaletta, L., de Vries, W., Vermeulen, S.J., Herrero, M., Carlson, K.M., Jonell, M., Troell, M., DeClerck, F., Gordon, L.J., Zurayk, R., Scarborough, P., Rayner, M., Loken, B., Fanzo, J., Godfray, H.C.J., Tilman, D., Rockström, J., Willett, W., 2018. Options for keeping the food system within environmental limits. Nature 562, 519-525. DOI: 10.1038/s41586-018-0594-0.

Stadler, K., R. Wood, T. Bulavskaya, C.-J. Södersten, M. Simas, S. Schmidt, A. Usubiaga, et al., EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables: EXIOBASE 3, Journal of Industrial Ecology, Vol. 22, No. 3, June 2018, pp. 502–515.

Stehfest, E., L. Bouwman, D.P. van Vuuren, M.G.J. den Elzen, B. Eickhout, and P. Kabat, Climate Benefits of Changing Diet, Climatic Change, Vol. 95, No. 1–2, July 2009, pp. 83–102.

Stehfest, E., van Vuuren, D., Bouwman, L., & Kram, T. (2014). Integrated assessment of global environmental change with IMAGE 3.0: Model description and policy applications. Netherlands Environmental Assessment Agency (PBL).

Stiglitz, J., Sen, A., Fitoussi, J.-P., 2009. Report of the Commission on the Measurement of Economic Performance and Social Progress.

Strassmann, K.M., and F. Joos, The Bern Simple Climate Model (BernSCM) v1.0: An Extensible and Fully Documented Open-Source Re-Implementation of the Bern Reduced-Form Model for Global Carbon Cycle–Climate Simulations, Geoscientific Model Development, Vol. 11, No. 5, May 25, 2018, pp. 1887–1908.

Talberth, D.J., Cobb, C., Slattery, N., 2007. The Genuine Progress Indicator 2006: A Tool for Sustainable Development. Redefining Progress, Oakland, California.

Tesfatsion, L., Agent-Based Computational Economics: Growing Economies: From the Bottom Up. Artif. Life 8, 2002, 55–82.

Thornton, P.E., K. Calvin, A.D. Jones, A.V. Di Vittorio, B. Bond-Lamberty, L. Chini, X. Shi, et al., Biospheric Feedback Effects in a Synchronously Coupled Model of Human and Earth Systems, Nature Climate Change, Vol. 7, No. 7, July 2017, pp. 496–500.

Timmermans, J., de Haan, H., Special issue on computational and mathematical approaches to societal transitions. Computational and Mathematical Organization Theory, 14(4), 263–265, 2008

Titeux, N., Henle, K., Mihoub, J. B., Regos, A., Geijzendorffer, I. R., Cramer, W., Verburg, P. H., & Brotons, L. (2016). Biodiversity scenarios neglect future land-use changes. Global Change Biology, 22(7), 2505–2515. https://doi.org/10.1111/gcb.13272

Titeux, N., Henle, K., Mihoub, J.-B., Regos, A., Geijzendorffer, I. R., Cramer, W., Verburg, P. H., & Brotons, L. (2017). Global scenarios for biodiversity need to better integrate climate and land use change. Diversity and Distributions, 23(11), 1231–1234. https://doi.org/10.1111/ddi.12624

Tsiropoulos, I., R. Hoefnagels, M. van den Broek, M.K. Patel, and A.P.C. Faaij, The Role of Bioenergy and Biochemicals in CO2 Mitigation through the Energy System – a Scenario Analysis for the Netherlands, GCB Bioenergy, Vol. 9, No. 9, 2017, pp. 1489–1509.

Tsiropoulos, I., R. Hoefnagels, S. de Jong, M. van den Broek, M. Patel, and A. Faaij, Emerging Bioeconomy Sectors in Energy Systems Modeling - Integrated Systems Analysis of Electricity, Heat, Road Transport, Aviation, and Chemicals: A Case Study for the Netherlands: Emerging Bioeconomy Sectors in Energy Systems Modelling, Biofuels, Bioproducts and Biorefining, Vol. 12, No. 4, July 2018, pp. 665–693.

UN Global Pulse, Social Media and Forced Displacement, Big Data Analytics & Machine-Learning, White Paper, UNHCR Innovation Service, 2017.

UN, 2019. The Sustainable Development Goals Report 2019. New York: United Nations.

UNECE-FAO, 2011. The European Forest Sector Outlook Study II. 2010-2030. ECE/TIM/SP/28. United Nations, Geneva.

Valenzuela, E., T.W. Hertel, R. Keeney, and J.J. Reimer, 2007. Assessing Global Computable General Equilibrium Model Validity Using Agricultural Price Volatility. American Journal of Agricultural Economics 89 (2): 383–397.

Valin, H., Peters, D., van den Berg, M., Frank, S., Havlik, P., Forsell, N. & Hamelinck, C., 2015. The land use change impact of biofuels consumed in the EU: quantification of area and greenhouse gas impacts, Report to the European Commission, Ecofys, IIASA & E4tech.

van Asselen, S. & Verburg, P.H. 2013. Land cover change or land-use intensification: simulating land system change with a global-scale change model. Global change biology, 19(12), 3648-3667.

van de Ven, D.-J., M. González-Eguino, and I. Arto, 2018. The Potential of Behavioural Change for Climate Change Mitigation: A Case Study for the European Union. Mitigation and Adaptation Strategies for Global Change 23 (6): 853–886.

van den Berg, N.J., A.F. Hof, L. Akenji, O.Y. Edelenbosch, M.A.E. van Sluisveld, V.J. Timmer, and D.P. van Vuuren, Improved Modelling of Lifestyle Changes in Integrated Assessment Models: Cross-Disciplinary Insights from Methodologies and Theories, Energy Strategy Reviews, Vol. 26, November 2019, p. 100420.

van der Hoog, S. (2017), Deep learning in (and of) agent-based models: A prospectus, arXiv:1706.06302v1

van Dijk, M., G. Woltjer, and G. Philippidis, 2014. Validating CGE Models Employing an Historical Approach. www.gtap.agecon.purdue.edu

van Leeuwen M., Smeets, E., O'Brien, M., Tsiropoulos, Y., Lindner, M., Moiseyev A., O'Brien, M., Wechsler, D.,, Valin, H., Verburg, P., van Teeffelen A., Schulp N, Derkzen M, Prestele R, Junker F, Döring R, Msangi S., 2015. Design of a systems analysis tools framework for a EU bioeconomy strategy. Final Report of the SAT-BBE Project.

van Lelyveld, W. (2010). Development of the Energy Transition Model: Introduction of the Object Oriented Modeling method.

van Meijl H. Havlik P., Lotze-Campen H., Stehfest E, Witzke P, Pérez Domínguez I, Bodirsky B, van Dijk M, Doelman J, Fellmann T, Humpenoeder F, Levin-Koopman J, Mueller C, Popp A, Tabeau A, Valin H, van Zeist WJ (2018b) Comparing impacts of climate change and mitigation on global agriculture by 2050, *Environ. Res. Lett.* 13 064021

van Meijl, H. L. Shutes, H. Valin, E. Stehfest, M. van Dijk, M, Kuiper, A, Tabeau, W. van Zeist, T. Hasegawa and P. Havlik, (2020) Modelling alternative futures of global food security: Insights from FOODSECURE. Global Food Security 25: 100358.

van Meijl, H., I. Tsiropoulos, H. Bartelings, R. Hoefnagels, E. Smeets, A. Tabeau, and A. Faaij, 2018a. On the Macro-Economic Impact of Bioenergy and Biochemicals – Introducing Advanced Bioeconomy Sectors into an Economic Modelling Framework with a Case Study for the Netherlands. Biomass and Bioenergy 108: 381–397.

van Soest H.L., van Vuuren D.P., Hilaire J., Minx J.C., Harmsen M.J.H.M., Kreyf V., Popp A., Riahif K., Luderer G., 2019. Analysing interactions among Sustainable Development Goals with Integrated Assessment Models. Global Transitions 1: 210-225

van Vuuren, D.P., E. Stehfest, D.E.H.J. Gernaat, M. van den Berg, D.L. Bijl, H.S. de Boer, V. Daioglou, et al. 2018. Alternative Pathways to the 1.5 °C Target Reduce the Need for Negative Emission Technologies. Nature Climate Change 8(5): 391–397.

van Vuuren, D.P., L. Batlle Bayer, C. Chuwah, L. Ganzeveld, W. Hazeleger, B. van den Hurk, T. van Noije, B. O'Neill, and B.J. Strengers, A Comprehensive View on Climate Change: Coupling of Earth System and Integrated Assessment Models, Environmental Research Letters, Vol. 7, No. 2, June 1, 2012, p. 024012.

van Zanten, J.A., van Tulder, R., 2020. Towards nexus-based governance: defining interactions between economic activities and Sustainable Development Goals (SDGs). International Journal of Sustainable Development & World Ecology, 1-17. DOI: 10.1080/13504509.2020.1768452.

Varacca A, Sckokai P, Chakrabarti A, Verkerk H, Lovrić M, Hassegawa M, van Leeuwen M, Gonzàlez Martinez AR, Banse M, Salamon P, Sturm V, Vrachioli M, Zhu B, Sauer J. 2020. Existing models that investigate the bioeconomy. BioMonitor project deliverable report 4.1. 140 pp.

Vauhkonen, J., Packalen, T., 2017. A Markov Chain Model for Simulating Wood Supply from Any-Aged Forest Management Based on National Forest Inventory (NFI) Data Forests 8, 307.

Vauhkonen, J., Packalen, T., 2018. Uncertainties related to climate change and forest management with implications on climate regulation in Finland. Ecosystem Services 33, 213-224. DOI: https://doi.org/10.1016/j.ecoser.2018.02.011.

Velthof, G.L., Oudendag, D., Witzke, H.P., Asman, W.A.H., Klimont, Z., Oenema, O., 2009. Integrated assessment of nitrogen emissions from agriculture in EU-27 using MITERRA-EUROPE. J. Environ. Qual. 38, 402-417.

Verburg, P.H. & Overmars, K.P. 2009. Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model. Landscape Ecology, 24, 1167. https://doi.org/10.1007/s10980-009-9355-7

Verburg, P.H., J.A. Dearing, J.G. Dyke, S. van der Leeuw, S. Seitzinger, W. Steffen, and J. Syvitski, Methods and Approaches to Modelling the Anthropocene, Global Environmental Change, Vol. 39, July 2016, pp. 328–340.

Verkerk, P.J., Anttila, P., Eggers, J., Lindner, M., Asikainen, A., 2011. The realisable potential supply of woody biomass from forests in the European Union. Forest Ecology and Management 261, 2007-2015. DOI: http://dx.doi.org/10.1016/j.foreco.2011.02.027.

Verkerk, P.J., Ball, I., Dzene, I., Janssen, R., Lindner, M., Moiseyev, A., Michel, J., Witzke, P., Zazias, G., Chartier, O., 2018. Research and Innovation perspective of the mid- and long-term Potential for Advanced Biofuels in Europe. D1.2 Research and innovation scenarios for biomass potential. Directorate-General for Research and Innovation (European Commission). Luxembourg, 104 pp. DOI: https://doi.org/10.2777/557801

Verkerk, P.J., Costanza, R., Hetemäki, L., Kubiszewski, I., Leskinen, P., Nabuurs, G.J., Potočnik, J., Palahí, M., 2020. Climate-Smart Forestry: the missing link. Forest Policy and Economics 115, 102164.

Verkerk, P.J., J.B. Fitzgerald, P. Datta, M. Dees, G.M. Hengeveld, M. Lindner, and S. Zudin, Spatial Distribution of the Potential Forest Biomass Availability in Europe, Forest Ecosystems, Vol. 6, No. 1, February 7, 2019, p. 5.

Verkerk, P.J., Lindner, M., Pérez-Soba, M., Paterson, J.S., Helming, J., Verburg, P.H., Kuemmerle, T., Lotze-Campen, H., Moiseyev, A., Müller, D., Popp, A., Schulp, C.J.E., Stürck, J., Tabeau, A., Wolfslehner, B., van der Zanden, E.H., 2018. Identifying pathways to visions of future land use in Europe. Regional Environmental Change 18, 817-830.

Verkerk, P.J., Mavsar, R., Giergiczny, M., Lindner, M., Edwards, D., Schelhaas, M.J., 2014. Assessing impacts of intensified biomass production and biodiversity protection on ecosystem services provided by European forests. Ecosystem Services 9, 155-165. DOI: http://dx.doi.org/10.1016/j.ecoser.2014.06.004.

Verkerk, P.J., Schelhaas, M.J., Immonen, V., Hengeveld, G., Kiljunen, J., Lindner, M., Nabuurs, G.J., Suominen, T., Zudin, S., 2017. Manual for the European Forest Information Scenario model. Version 4.2.0. EFI Technical Report 99. European Forest Institute, Joensuu, p. 49.

Vermeulen, B. and Pyka, A., Agent-based Modeling for Decision Making in Economics under Uncertainty. Economics: The Open-Access, Open-Assessment E-Journal, 10 (2016-6), 2016, 1-33.

Vermeulen, B. and Pyka, A., The role of network topology and the spatial distribution and structure of knowledge in regional innovation policy. A calibrated agent-based model study, Computational Economics, 52(3), 2018, 773-808.

Vinceti, B., Manica, M., Lauridsen, N., Verkerk, P.J., Lindner, M., Fady, B., 2020. Managing forest genetic resources as a strategy to adapt forests to climate change: perceptions of European forest owners and managers. European Journal of Forest Research, 1-13. DOI: 10.1007/s10342-020-01311-6.

Vogt, M. 2020. Horizonterweiterung zulassen - Bioökonomie aus ethischer Perspektive, in: Oekom and Umweltbundesamt (ed.), Bioökonomie - Weltformel oder Brandbeschleuniger? Oekom Verlag, München.

Welfle, A., P. Thornley, and M. Röder, A Review of the Role of Bioenergy Modelling in Renewable Energy Research & Policy Development, Biomass and Bioenergy, Vol. 136, May 2020, p. 105542.

Wernet, G., C. Bauer, B. Steubing, J. Reinhard, E. Moreno-Ruiz, and B. Weidema, The Ecoinvent Database Version 3 (Part I): Overview and Methodology, The International Journal of Life Cycle Assessment, Vol. 21, No. 9, September 2016, pp. 1218–1230.

Westhoek, H., J.P. Lesschen, T. Rood, S. Wagner, A. De Marco, D. Murphy-Bokern, A. Leip, H. van Grinsven, M.A. Sutton, and O. Oenema, Food Choices, Health and Environment: Effects of Cutting Europe's Meat and Dairy Intake, Global Environmental Change, Vol. 26, May 1, 2014, pp. 196–205.

Wicke, B., F. van der Hilst, V. Daioglou, M. Banse, T. Beringer, S. Gerssen-Gondelach, S. Heijnen, et al., 2015. Model Collaboration for the Improved Assessment of Biomass Supply, Demand, and Impacts. GCB Bioenergy 7(3): 422–437.

Wiese, F., Bramstoft, R., Koduvere, H., Pizarro Alonso, A., Balyk, O., Kirkerud, J.G., Tveten, Å.G., Bolkesjø, T.F., Münster, M., Ravn, H., 2018. Balmorel open source energy system model. Energy Strategy Reviews 20, 26-34.

Wilkinson, R.G., Pickett, K., 2009. The Spirit Level: Why Greater Equality Makes Societies Stronger. Bloomsbury Press, New York.

Willcock, S., Martínez-López, J., Hooftman, D., Bagstad, K., Balbi, S., Marzo, A., Prato, C., Sciandrello, S., Signorello, G., Voigt, B., Villa, F., Bullock, J. and Athanasiadis, I., 2018. Machine learning for ecosystem services. Ecosystem Services 33: 165-174

Wilson, C., E. Kriegler, D.P. van Vuuren, C. Guivarch, D. Frame, V. Krey, T.J. Osborn, et al., 2017. Evaluating Process-Based Integrated Assessment Models of Climate Change Mitigation, International Institute for Applied Systems Analysis. http://pure.iiasa.ac.at/14502

Winning, M., A. Calzadilla, R. Bleischwitz, and V. Nechifor, Towards a Circular Economy: Insights Based on the Development of the Global ENGAGE-Materials Model and Evidence for the Iron and Steel Industry, International Economics and Economic Policy, Vol. 14, No. 3, July 2017, pp. 383–407.

Woltjer G, Kuiper M, A. Kavallari, H. van Meijl, J. Powell, M. Rutten, L. Shutes and A. Tabeau, 2014, The MAGNET model - Module description. LEI Report 14-057. The Hague: LEI - part of Wageningen UR (University & Research centre).

Wood, R., K. Stadler, T. Bulavskaya, S. Lutter, S. Giljum, A. de Koning, J. Kuenen, et al., Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis, Sustainability, Vol. 7, No. 1, December 26, 2014, pp. 138–163.

Yousefpour, R., Didion, M., Jacobsen, J.B., Meilby, H., Hengeveld, G.M., Schelhaas, M.-J., Thorsen, B.J., 2015. Modelling of adaptation to climate change and decision-makers behaviours for the Veluwe forest area in the Netherlands. Forest Policy and Economics 54, 1-10. DOI: https://doi.org/10.1016/j.forpol.2015.02.002.

Zelinka, D., and B. Amadei, A Systems Approach for Modeling Interactions Among the Sustainable Development Goals Part 2: System Dynamics, International Journal of System Dynamics Applications, Vol. 8, No. 1, January 2019, pp. 41–59.

Zeppini, P. and van den Bergh, J., 2011. Competing Recombinant Technologies for Environmental Innovation: Extending Arthurs Model of Lock-In. Industry and Innovation 18(3): 317-334

Zonooz, M.R.F., Nopiah, Z.M., Yusof, A.M. and Sopian, K. (2009). A Review if MARKAL Energy Modelling. European Journal of Scientific Research, 26(3): 352-361.

Zou, W., Jing, W., Chen, G., Lu, Y., Song, H., 2019. A Survey of Big Data Analytics for Smart Forestry. IEEE Access 7, 46621-46636. DOI: 10.1109/ACCESS.2019.2907999.

Annex: model overview

Table A.1. Overview of existing bioeconomy models.

Model Type		Acronym	Name	Holder	Link
Economic Models	Computable General Equilibrium models	GEM-E3*	General Equilibrium Model for Economy-Energy-Environment	European Commission	https://ec.europa.eu/jrc/en/gem-e3/model
		GTAP	Global Trade Analysis Project	GTAP consortium	https://www.gtap.agecon.purdue.edu/models/current.asp
		ICES	Intertemporal Computable Equilibrium System	RFF-CMCC European Institute on Economics & the Environment	https://www.icesmodel.org/
		LIBEMOD	LIBEralization MODel for the European Energy Markets	Ragnar Frisch Centre for Economic Research and the Research Department at Statistics Norway	http://www.frisch.uio.no/ressurser/LIBEMOD/
		MIRAGE	Modelling International Relationships in Applied General Equilibrium	CEPII, IFPRI	http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=14
		MAGNET*	Modular Applied GeNeral Equilibrium Tool	WEcR & MAGNET consortium	https://www.magnet-model.eu
		NEWAGE	National European Worldwide Applied General Equilibrium	Institute of Energy Economics and Rational Energy Use. Unicversity of Stuttgart	https://www.ier.uni-stuttgart. de/forschung/modelle/NEWAGE/index_en.html
	Partial Equilibrium models	Aglink-COSIMO*	Aglink-COSIMO	OECD-FAO	http://www.agri-outlook.org/about/
		AGMEMOD*	Agriculture Member State Modelling	Thünen Institute, Wageningen Economic Research (WEcR)	https://agmemod.eu/
		CAPRI*	Common Agricultural Policy Regional Impact	CAPRI network	https://www.capri-model.org/dokuwiki/doku.php?
		EFI-GTM	European Forest Institute Global Trade Model	European Forest Institute	NA
		ESIM	European Simulation Model	Humboldt University at Berlin	https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=9&ved=2ahUKEwjAtM-B6KfhAhVS-aQKHVmLAYwQFjAIegQIBxAB&url=https%3A%2F%2Fwww.uni-hohenheim.de%2Fqisserver%2Frds%3Fstate%3Dmedialoader%26objectid%3D7530%26application%3Dlsf&usg=AOvVaw1QFXmwPKVcU4kWU88WGJac
		GLOBIOM	Global Biosphere Management Model	IIASA	http://www.globiom.org
		GFPM	Global Forest Products Model	University of Wisconsin	http://labs.russell.wisc.edu/buongiorno/welcome/gfpm/
		GFTM*	Global Forest Trade Model	European Commission	https://forest.jrc.ec.europa.eu/en/activities/forestbioeconomy/modelling/
		IMPACT	International Model for Policy Analysis of Agricultural Commodities and Trade	IFPRI	http://www.ifpri.org/publication/international-model-policy-analysis-agricultural-commodities-and-trade-impact-model-0

		MAGPIE	Model of Agricultural Production and its Impact on the Environment	Potsdam Institute for Climate Impact Research	https://www.pik-potsdam.de/research/projects/activities/land-use-modelling/magpie/magpie-2013-model-of-agricultural-production-and-its-impact-on-the-environment; https://rse.pik-potsdam.de/doc/magpie/4.0/index.htm
		Oemof	Open Energy Modelling Framework	Oemof developing group (currently comprising of Reiner Lemoine Institut / ZNES Flensburg/ University of Magdeburg)	https://github.com/oemof/oemof
		PLEXOS	PLEXOS Integrated Energy Model	Glenn Drayton - Energy Exemplar	https://energyexemplar.com/products/plexos-simulation-software/
		POTEnCIA*	Policy Oriented Tool for Energy and Climate Change Impact Assessment	European Commission	https://ec.europa.eu/jrc/en/potencia#:~:text=POTEnCIA,system%20developed%20by%20the%20JRC.
		PRIMES	Price-Induced Market Equilibrium System	E3MLab/ICCS at the Technical University of Athens	https://ec.europa.eu/clima/policies/strategies/analysis/models_en#PRIMES
		POLES*	Prospective Outlook on Long-term Energy Systems	CNRS (GAEL Energy), Enerdata, European Commission	https://www.enerdata.net/solutions/poles-model.html
		TIMES*	The Integrated MARKAL-EFOM System	IEA-ETSAP (Energy Technology Systems Analysis Program)	https://iea-etsap.org/index.php/etsap-tools/model-generators/times
		BALMOREL	-	Hans Ravn	http://www.balmorel.com
		PROMETHEUS	-	E3MLab/ICCS at the Technical University of Athens	https://e3modelling.com/modelling-tools/prometheus/
	Other economic models	ENPEP-BALANCE	Energy and Power Evaluation Program	Center for Energy, Environmental, and Economic Systems Analysis (CEEESA). Argonne National Laboratory	https://ceeesa.es.anl.gov/projects/Enpepwin.html#balance
		GINFORS	Global INterindustry FORecasting System	The Institute of Economic Structures Research (GWS)	https://www.gws-os.com/de/index.php/global-developments-and-resources/models.html
		IFM-CAP*	Individual Farm Model for Common Agricultural Policy Analysis	European Commission	https://ec.europa.eu/jrc/en/publication/eu-wide-individual-farm-model-common-agricultural-policy-analysis-ifm-cap-v1-economic-impacts-cap
		WEM	World Energy Model	International Energy Agency	https://www.iea.org/reports/world-energy-model
		FARMIS	Farm Modelling and Information System	Thünen Institute	https://www.thuenen.de/en/infrastructure/the-thuenen-modelling-network/models/farmis/
		MARKAL	MARKet ALlocation	IEA for general version. Several holders for different country models	https://iea-etsap.org/index.php/etsaptool/model-generators/markal
Environmental Models	Biophysical Models	A4a*	Assessment For All	European Commission	https://github.com/flr/FLa4a
		CBM-CFS3*	Carbon Budget Model of the Canadian Forest Sector	Natural Resources Canada	https://www.nrcan.gc.ca/forests/climate-

					change/carbon-accounting/13107
		EPIC*	Environmental Policy Integrated Climate Model	USDA (main model) and IIASA (EPICI-IIASA and EU-EPIC)	http://www.iiasa.ac.at/web/home/research/researchPrograms/EcosystemsServicesandManagement/EPIC.en.html
		EFDM*	European Forest Dynamics Model	European Commission	https://ec.europa.eu/jrc/en/european-forestry-dynamics-model https://github.com/ec-jrc/efdm
		EFISCEN	European Forest Information SCENario model	European Forest Institute	http://efiscen.efi.int/
		G4M	Global Forest Model	IIASA	http://www.iiasa.ac.at/web/home/research/researchPrograms/EcosystemsServicesandManagement/G4M.en.html
		INVEST	Integrated Valuation of Ecosystem Service and Tradeoffs	US Natural Capital Project	https://naturalcapitalproject.stanford.edu/software/invest
		MITERRA	Miterra-Europe	Wageningen Environmental Research	http://content.alterra.wur.nl/Webdocs/PDFFiles/Alterrarapporten/AlterraRapport1663.1.pdf
		PRISM-ELM	Parameter-elevation Regressions on Independent Slopes Model Environmental Limitation	PRISM Climate Group at OSU (Oklahoma State University)	http://www.prism.oregonstate.edu/
	Land Use And Cover Models	CLUMondo	Conversion of Land Use and its Effects model	IVM Institute for Environmental Studies, Vrije Universiteit Amsterdam	https://www.environmentalgeography.nl/site/data-models/models/clumondo-model/
		Dyna-CLUE	Dynamic Conversion of Land Use and its Effects model	IVM Institute for Environmental Studies, Vrije Universiteit Amsterdam	https://www.environmentalgeography.nl/site/data-models/data/clue-model/
		LUISA*	Land Use-based Integrated Sustainability Assessment	European Commission	https://ec.europa.eu/jrc/en/luisa
	Other Environmental Models	ToSIA	Tool for Sustainability Impact assessment	European Forest Institute	http://tosia.efi.int/
Integrated Assessment Models		DSK model	Dystopian Schumpeter meeting Keynes model	Sant'Anna School of Advanced Studies	http://www.highendsolutions.eu/page/dsk
		MADIAMS	Multi-actor dynamic integrated assessment model	Max Planck Institute for Meteorology,	0
		E3ME-FTT-GENIE*	-	Cambridge Econometrics	https://www.e3me.com/
		DNE21+	Dynamic New Earth 21	RITE Systems Analysis Group	https://www.rite.or.jp/system/en/global-warming-ouyou/modeltodata/overviewdne21/outline-dne21plusmodel/
		GCAM	Global Change Assessment Model	Pacific Northwest Laboratory (PNNL)	http://www.globalchange.umd.edu/gcam/
		IMAGE 3.0	Integrated Model to Assess the Global Environment	PBL, Netherlands Environmental Assessment Agency	https://models.pbl.nl/image/index.php/Welcome_to_IMAGE_3.0_Documentation
		IFs	International Futures	Pardee Center for International Futures	https://pardee.du.edu/

	MEDEAS	Modeling the renewable energy transition in europe	Spanish National Research Council	https://www.medeas.eu/model/medeas-model
	REMIND	Regional Model of Investments and Development	Potsdam Institute for Climate Impact Research	https://www.pik-potsdam.de/research/transformation-pathways/models/remind https://www.iamcdocumentation.eu/index.php/Model_Documentation_-_REMIND
	ETSAP-TIAM	The TIMES Integrated Assessment Model	ETSAP-IEA	https://iea-etsap.org/index.php/applications/global
	WITCH	World Induced Technical Change Hybrid model	Fondazione Eni Enrico Mattei (FEEM)	http://www.witchmodel.org/
	IMACLIM-R	-	CIRED	http://www2.centre-cired.fr/IMACLIM?lang=en
Specialist Model	BEWHERE	BEWHERE	IIASA	http://www.iiasa.ac.at/web/home/research/researchPrograms/EcosystemsServicesandManagement/BEWHERE/BEWHERE.en.html
	ETM*	Energy Transition Model	Quintel Intelligence	https://energytransitionmodel.com/
	LEAP	Long-range Energy Alternatives Planning	Stockholm Environment Institute	https://www.energycommunity.org/
	MESSAGE	Model for Energy Supply Stratergy Alternatives and their General Enviromental impact	International Institute for Applied Systems Analysis (IIASA)	http://www.iiasa.ac.at/web/home/research/researchPrograms/Energy/MESSAGE.en.html ; https://messageix.iiasa.ac.at/
	OSeMOSYS	The Open Source Energy Modeling System	Energy Systems Analysis Group (dESA), KTH Royal Institute of Technology, Stockholm, Sweden	http://www.osemosys.org/
	SIMFISH	Spatial Integrated bio-economic Model for FISHeries	Wageningen Economic Research, Heinrich von Thünen Institute	https://www.sciencedirect.com/science/article/pii/S1364815215300566?via%3Dihub

**Model applied by JRC*

KJ-02-21-357-EN-N

European Commission's Knowledge Centre for Bioeconomy
https://knowledge4policy.ec.europa.eu/bioeconomy

Contact: EC-Bioeconomy-KC@ec.europa.eu

Publications Office
of the European Union

doi:10.2760/097710

ISBN 978-92-76-32323-5