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Modelling the bioeconomy: Emerging approaches to address policy needs

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ABSTRACT

With its update of the Bioeconomy Strategy and the Green Deal, the European Commission committed itself to a transformation towards a sustainable and climate-neutral European Union. This process is characterised with an enormous complexity, which policymaking needs to acknowledge for designing transition pathways. Modelling can support policymaking in dealing with uncertainty and complexity. This article reviews emerging and new developments and approaches to model the development of the bioeconomy. We focused our review on how bioeconomy modelling addresses key enabling factors related to (i) climate change, (ii) biodiversity, (iii) circular use of biomass, (iv) consumer behaviour related to biomass and bioproducts use, and (v) innovation and technological change. We find that existing modelling frameworks offer large possibilities for extensions and considerations for analysing short-run impacts related to climate change and circularity, and to lesser degree for biodiversity, and we identify possibilities for developing further the existing bioeconomy models. However, addressing key processes related to societal and technological changes is more challenging with existing/conventional modelling approaches, as they specifically relate to how innovations transform economic structures and how consumers learn and change their preferences and what kind of dynamics are to be expected. We indicate how emerging modelling techniques such as Agent-Based Modelling could improve and complement existing bioeconomy modelling efforts by allowing for the consideration of structural change and, more generally, transformation of the economic metabolism. This modelling approach eclecticism 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. Furthermore, it will benefit from the developments in big data and artificial intelligence from which we expect valuable guideposts for designing future modelling strategies.

1. Introduction

The bioeconomy is considered an important means to achieve sustainable development and for tackling the climate and biodiversity crises resulting from overconsumption of and overreliance on non-renewable resources (El-Chichakli et al., 2016; Bell et al., 2018; Birner, 2018; Aguilar et al., 2019). While many, also sometimes conflicting definitions and narratives exist (Kardung et al., 2021; Vivien et al., 2019), the bioeconomy is generally considered to relate to the use of biological resources and their substitution for fossil-based resources and materials to produce energy, food, feed, fibre, and other manufactured goods, and the application of biological processes for manufacturing goods. While the earlier understanding focused more narrowly on resource substitution, bioenergy, and biotechnology (D'Amato et al., 2017; Birner, 2018), the understanding is broadening to also include sustainability and circularity to meet the United Nation's Sustainable Development Goals as well as the objectives of the Paris Agreement (El-Chichakli et al., 2016; Hetemäki et al., 2017; Stegmann et al., 2020; Heimann, 2019; European Commission, 2020; Global Bioeconomy Summit, 2020). Therefore, the substitution perspective is shifting in favour of a much more profound transformation perspective.

Modelling is an important tool to support policy making (Kolkman, 2020) and can facilitate a better understanding of the complexity, trade-offs, and potential pathways to achieve the transition to a bioeconomy (O'Brien et al., 2017). A large number of bioeconomy models already exist (see e.g., van Leeuwen et al., 2013; Angenendt et al., 2018;

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Verkerk et al., 2018; Ringkjøb et al., 2018; Welfle et al., 2020; Nielsen et al., 2018). Many of the existing models have their origin in applied economics and are designed with a sectoral focus (e.g., on agriculture or forestry and their related industries), which limits their ability in capturing cross-cutting issues (e.g., climate change, biodiversity loss, circularity) that are of importance to the bioeconomy transition. Importantly, existing bioeconomy models generally fall short in addressing long-run fundamental paradigm changes as affected by technological progress and behaviour change (Verkerk et al., 2018).

The challenge in bioeconomy modelling stems from a subtle but important difference between the notions of transition and transformation (Pyka and Urmetzer, 2022). In a transition process, e.g., a fossil-based industry is replaced by a bio-based industry which takes completely the place of its predecessor offering the same products and services, while economic structures are not affected. In a transformation process, e.g., when production is re-organizing value creation networks and consumers increasingly develop and change to new and more sustainable lifestyles, 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 and irreversible adaptation of the whole system, which is driven by innovation, new lifestyles, and potential changes in the governance system, i.e., the economy transformed itself structurally (Saviotti et al., 2020). Thus, a transformation towards higher degrees of sustainability involves fundamental pattern changes. We argue that this difference between transition and transformation has profound consequences for modelling. Whereas modelling transitions can be encapsulated in existing approaches with stable structures, modelling transformation requires new or alternative approaches to endogenize changes and complexity.

To capture transition pathways towards a bioeconomy, models should ideally be able to endogenously consider the enabling factors of this transition and their interdependencies. We focus here on the following five enabling factors: (i) climate change, (ii) biodiversity, (iii) circular use of biomass, (iv) consumer behaviour related to biomass and bioproducts use, and (v) innovation and technological change, as we consider these factors will be playing a prominent role in the bioeconomy transition and should thus be prioritized in bioeconomy modelling. First, tackling climate change is one of the key issues behind the development of a bioeconomy and it has been a topic for many developments in modelling. Considering climate change in bioeconomy modelling is a challenging but also a promising task as it affects both demand for biomass (e.g., feedstock for bioenergy, bioproducts and biobased chemicals) and its supply (through climate change impacts on yields, for example) simultaneously. Second, biodiversity is key to secure the long-term provision of ecosystem services that are crucially important to society (IPBES et al., 2019). The positive nexus between biodiversity and ecosystems productivity and resilience is well-established (Liang et al., 2016; Mori et al., 2013; O'Brien et al., 2017; Tilman et al., 2012). Productive and resilient ecosystems are fundamental to ensure the sustained and sustainable biomass supply needed from the bioeconomy, as well as socio-economic sustainability. Third, circular use of biomass, namely the adoption of recycling, reusing or repairing practices, can contribute to increasing biomass availability and reducing waste. In a similar vein, waste reduction strategies contribute to the achievement of this goal and at the same time reduces the necessary throughput of a circular economy. Circularity and waste reduction are increasingly linked to the bioeconomy (e.g., Hetemäki et al., 2017; Stegmann et al., 2020). The possibility of turning biowaste and residues into valuable bio-based products, as well as the extension of practices like cascaded use of products can, potentially, reduce the demand for virgin biomass feedstock and contribute to lower the competition for resources (biomass, land etc.) and mitigate climate change (Risse et al., 2017). Fourth, the consideration of changing consumer preferences and consumption behaviour is fundamental to ensure the effectiveness of policy measures towards a bioeconomy (Davies et al., 2014; Schlaile et al., 2016; Gold and Rubik, 2009; Lähtinen et al., 2019). For example, consumer preferences concerning dietary changes are crucial for sustainability of food systems (e.g., Sanchez-Sabate and Sabaté, 2019; Kause et al., 2019), as well as climate change mitigation (e.g., Frank et al., 2019, Roe et al., 2019). Fifth, technological change and innovation are considered of key importance for the development of innovative and climate friendly bio-based products and technologies (Pyka, 2020; Lovrić et al., 2020) and therefore require major attention in modelling the bioeconomy. For example, the human capacity to breed and utilize new organisms has been sensibly expanded from the modern tools developed in molecular biology. This has led to an increase in productivity of agriculture and fisheries and to the production of a broad range of products that were originally mined (Zilberman et al., 2013).

In this paper, we analyse emerging and new developments and approaches to model the development of the bioeconomy to close the identified gaps of existing models. We looked at models that follow the definition given by Acs et al. (2019), who defined 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". Specifically, we address the questions (1) to what extent do existing bioeconomy models already consider climate change, biodiversity, circularity, consumer behaviour and technological development and where are their limitations, and (2) what alternative modelling approaches potentially close the remaining gaps concerning long run structural change which cannot be closed by further sophistications of existing models.

2. What extensions are in development to model the enabling factors of bioeconomy transition?

Bioeconomy modelling has mostly progressed in established modelling approaches that consider economic modelling (computable general equilibrium (CGE) models, partial equilibrium (PE) models), environmental modelling (biophysical and land change models), Integrated Assessment Models (IAMs) and specialist models (or bottom-up models) (O'Brien et al., 2017). In the following subsections we outline how (i) climate change, (ii) biodiversity, (iii) circular use of biomass, (iv) consumer behaviour related to biomass and bioproducts use, and (v) innovation and technological change are considered in recent model extensions for bioeconomy modelling based on the results of a literature review. The snowballing procedure (Wohlin, 2014) was used to identify the relevant works to be included. An initial literature search has been done in Google Scholar to identify the start set using the results of the cartesian product of the following triple set of keywords: {"climate change", "biodiversity", "circularity", "consumer behaviour", "innovation", "technological change"}; {"economic", "environmental", "energy"} and {"modelling"}. Based on the title and keywords in the first iteration and on the content of the abstract in the second, the number of articles has been reduced in a first step. In the second, the content of the article was analysed to evaluate their relevance and for making sure that the work was following the definition of models given by Acs et al. (2019) and that was applied in the field of economy, environmental science and energy modelling. The results are presented in the following subsections.

2.1. Climate change

Models have been developed to understand how anthropogenic activities contribute to or can mitigate climate change, as well as to understand the impacts and to assess options to adapt to climate change impacts.

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 such as wildfire, storms, pests, and pathogens (Challinor et al., 2014; Lindner et al., 2014; Seidl et al., 2017; Smith and Gregory, 2013), which can ripple through bioeconomy sectors by affecting sustainable biomass supply and its costs thereby disrupting bio-based markets. For example, extended droughts in recent summers in central Europe followed by insect outbreaks have led to widespread tree mortality for commercially important tree species and large volumes of salvaged wood.

Improvements to consider climate change in modelling bioeconomy sectors is progressing in different lines of research. An important line is linked to the development of Shared-Socioeconomic Pathways (SSPs) (Riahi et al., 2017) developed by the climate change research community to facilitate the integrated analysis of future climate impacts, vulnerabilities, adaptation, and mitigation. These scenarios describe how society and economies might develop over the next decades (Wiebe, et al., 2014; Vuuren et al. 2017; Van Meijl et al., 2020b).

Several open questions are currently addressed with model extensions and new identified gaps offer opportunities for further modelling activities: Hertel and de Lima (2020) stress how modelling of climate change impacts on agriculture has so far focused on yield changes of a few important staple crops and that in future the consequences of climate change for labour productivity, as well as for purchased intermediate inputs should be included. 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 (Hertel and de Lima, 2020). 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, so-called *micro-hunger* in many diets around the world. For forestry, including climate change impacts in large-scale applications has typically been done by linking dynamic vegetation models to empirical forest models by incorporating productivity changes (e.g., Eggers et al., 2008; Vauhkonen and Packalen, 2018) and changes in tree species suitability (e.g., Schelhaas et al., 2018; Hanewinkel et al., 2013), or by including forest or land management practices in dynamic vegetation models (Luyssaert et al., 2018). Promising progress is also being made by endogenizing climate change impacts through climate-sensitive growth functions (Schelhaas et al., 2018) and models (Härkönen et al., 2019). While progress is being made in modelling natural disturbances (e.g., Reyer et al., 2017; Dobor et al., 2020; Pugh et al., 2019), this is yet to be translated into bioeconomy modelling, e.g., to assess biomass availability.

Climate change mitigation is receiving a lot of attention in existing modelling efforts due to the relative importance of the bioeconomy sector in this context. Existing economic models and Integrated Assessment Models (IAMs) 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 (as typical for optimization PE models) or by using marginal abatement curves (typical for CGE models). Biophysical models can provide insights in sustainable biomass availability for material and energy uses (Verkerk et al., 2011, 2018; di Fulvio et al., 2019; Jonsson et al., 2020) 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).

Renewable resources' productivity depends on climatic and biophysical conditions. With a growing understanding of the impacts of climate change adaptation, it is also becoming more and more clear that adaptation is needed. Despite some examples (e.g., Alexander et al., 2018), adaptation of complex systems is mostly beyond the scope of the existing models.

2.2. Biodiversity

Most biodiversity modelling studies have focused on assessing the future impacts of climate change, selecting places for biodiversity conservation practices (e.g., establishment of protected areas, habitat restoration, and/or species translocation) and quantifying or forecasting the effects of anthropogenic factors on biodiversity (Araújo et al., 2019). Changes in land use and land cover are largely neglected, although these represent the most significant and immediate threats to biodiversity (Titeux et al., 2016; Titeux et al., 2017; IPBES et al., 2019). A recent study (Leclère et al., 2020b and Leclère et al., 2020) linked multiple PE, CGE and IAM models with specialised biodiversity models to explore biodiversity targets to reverse global biodiversity trends by 2050. The study argues that future assessments should seek to better represent land-management practices as well as additional pressures on land and biodiversity, such as climate change, overexploitation, pollution, and biological invasions.

Future biodiversity modelling should not be limited to assess how anthropogenic activities and climate change affect biodiversity loss. Biodiversity promotes ecosystem functioning and positively affects primary productivity (Liang et al., 2016; O'Brien et al., 2017) and the effects of biodiversity loss on ecosystem functioning should thus be considered in modelling. Furthermore, there is an urgent need to improve our understanding of how economies and societies will be impacted if current trends in biodiversity loss will continue. Continued biodiversity loss could impair the provisioning of important services (e.g., water quality regulation, crop pollination) and thereby negatively affect human wellbeing (Chaplin-Kramer et al., 2019). Existing models, data and modelling approaches are currently not ready for estimating impacts from changes in biodiversity on economies (Crossman et al., 2018). Therefore, modelling biodiversity in a socio-economic context, i.e. including biodiversity aspects in existing models, remains an important challenge as it is difficult and controversial when it comes to commoditization of more and more aspects of nature in its public good dimension (Titeux et al., 2016, 2017; Chaplin-Kramer et al., 2019). In the Dasgupta (2021) review on "the economics of biodiversity" it is stressed that to get nature inclusive decisions, the inclusion of natural capital stocks and related ecosystem services in economic models is difficult but a step in the right direction.

2.3. Circular use of biomass

The established bioeconomy models are mostly based on the notion of linear (produce, use, discard) product life cycles and economies. To increase their effectiveness in the context of bioeconomy, the proper representation of recycling, reuse, cascading of materials as well as waste reduction strategies in models is of outmost importance. With due exceptions, existing multi-sectoral models (CGEs and IAMs) 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).

To our knowledge, three multi-region CGE models include circularity aspects by considering waste management and material recovery and the inclusion of secondary production sectors: The ENGAGE-Material model (Winning et al., 2017) considers waste management and material recovery and includes secondary production sectors for steel. EXIOBASE 3 (Stadler et al., 2018) does the same for six metals. In the MAGNET CGE model (van Meijl et al., 2018) bio-based residues can be used for feed, bioenergy, or biobased materials and a waste management sector is introduced (Bartelings et al., 2004).

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. Hartley et al. (2016) monetized the recyclable content of 13 waste flows, and use these figures in the model as an exogenous supply shock for resource availability. In PE models, the use of residues and recycled materials is typically considered in more detail. For example, in the forestry context recycled paper and by-products (e.g., wood chips, sawdust, black liquor) are generally considered, as are by-products in agricultural models. Nevertheless, these models still fall short in considering recycling (e.g., post-consumer wood) 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 still lacking in all the models with their roots in the economic field. CGE, PE and all IAM models, in fact, show little or no inclusion of stock accounting. As highlighted by Pauliuk et al. (2017), an improved representation of physical material cycles in models gives the opportunity to model more realistically the effects of an efficient use of (bio)physical resources due to circular and lifetime extending practices, increasing the policy relevance of models. The integration of models with (dynamic) material flow analysis is one of the ways forward (Cao et al., 2019).

Circular and lifetime extension practices can play an important role in potentially increasing biomass availability, sustainability of bioenergy as well reducing food losses. Because of the multiple interdependencies between circularity approaches and innovation as well as on consumer behaviour, it is most likely that the prevailing economic structures and value creation networks are affected. Thus, the complexity increases sharply and limits the possibilities of model extensions. Instead, new modelling approaches discussed in section 3 might promise to offer a better fit.

2.4. Consumer behaviour related to biomass and bioproducts use

Changes in consumer behaviour are related to changes in preferences or lifestyle. Lifestyle changes are those actions aiming at fundamental pattern changes in consumption behaviour which for example suggests new modes of diet, leisure activities or mobility to name but a few. This type of non-standard decisions by consumers (i.e., decisions and behaviours that deviate from those based on the neoclassical vision of the rational *homo oeconomicus*) are much more complex to be captured in models compared to, for example, those standard, price-induced changes leading to substitution effects between consumer products. Lifestyle changes can be included in models by (van den Berg et al., 2019, see also Table 1):

- exogenously including lifestyle changes into the underlying storylines and narratives used.
- endogenously modifying assumptions and parameters in the model.
- explicitly modelling the changes in lifestyle in the model.

Table 1
Example of how the impact of food lifestyle changes has been performed in the literature. Modified from 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 to 2030	(IAM) – IAM (IMAGE)	Stehfest et al. (2009)
		Based on the relative kg CO2-eq savings from Willet diet	Input-output analysis	Lekve Bjelle, Steen-Olsen, and Wood (2018)
		Based on the relative kg CO2-eq savings from Willet diet in addition to organic farming	Input-output analysis	Lekve Bjelle, Steen-Olsen, and Wood (2018)
		Compares carbon footprint of user's diet with lower carbon, and lower calorie diet	EIO-LCA model	
	Reduced ruminant meat	Complete protein substitution of cattle, sheep, goats and buffaloes, by plant-proteins, transitioning from 2010 to 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 to 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 emerging proteins and those produced from insects and algae), essentially protein production in this scenario is landless.	- Custom spreadsheet model	Röös et al. (2017)
	Vegan diet	No animal products, additional protein substitution of eggs and milk by plant-proteins, transition from 2010 to 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 (with the exception of 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, Steen-Olsen, and Wood (2018)
Organic and local foods		Organic and local foods	Input-output analysis	Lekve Bjelle, Steen-Olsen, and Wood (2018)

The first approach is the simplest and, so far, most widely used method and generally relies on applications of models for different storylines, with the Shared-Socioeconomic Pathways (SSPs) framework representing its most prominent example. Such storylines can draw on qualitative research aiming at understanding how consumers behaviours can change over time and include assumptions on lifestyle changes and other non-standard decisions. 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. (2020a) and Frank et al. (2019). Changes in preferences might be estimated with econometric methods and by historical simulations to validate economic models (Dixon and Rimmer, 2013). However, obviously this approach is not suited to understand the endogenous and highly interdependent evolution of consumption behaviour.

Existing economic models generally depict demand for products as a function of income and prices. The endogenous representation of consumer behaviour through modified parameters in the model is more challenging but is of crucial importance in the bioeconomy transition. For example, long used relationships between graphic paper demand and consumers' income growth appear no longer valid, as at high enough income levels, further income growth is now associated with decreasing consumption (Chiba et al., 2017; Hurmekoski and Hetemäki, 2013), often explained by the adoption of 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 difficult, especially for lifestyle changes not related to technologies. One promising approach consists in the dynamic representation of the social and technological learning of adopter groups influencing the desired technological transition, but this is already breaking up the tight corset of standard models used in bioeconomy modelling. van de Ven et al. (2018) and Li (2017) have, for example, introduced heterogeneity among decision-makers within energy modelling, Cayla and Maïzi (2015) considered household behaviour and heterogeneity in terms of daily energy consumption and equipment purchasing behaviour in their TIMES-Households model and McCollum et al. (2017) explored how the adoption of electric vehicles is influenced by social and technological learning. All these are exercises done in the energy modelling domain, that are worth to be considered as future paths to follow for the modelling of (bio-based) technology diffusion.

To our knowledge, only Edelenbosch et al. (2018) tried to explicitly model the changes in lifestyle including changing behaviour in the modelling of social learning dynamics in the IAM IMAGE. Similarly, Niamir et al. (2020) proposed a way to integrate the evolutionary dynamics of micro-level behaviourally rich Agent-Based Models (ABM, see section 3.2) into a macroeconomic model by scaling up and linking the results of the empirical ABM BENCH-v3 with the EU-EMS CGE model. These last two are examples of approaches which are used outside the context of bioeconomy modelling but could nonetheless be reproduced in this context. Changing lifestyles is closely related to learning and experimenting which eventually affects economic structures and transforms the whole economic system. Once more the limits of existing models are reached and most recent modelling attempts, at least partially, already refer to the new modelling tools (see section 3.2).

2.5. Innovation and technological change

Modelling Innovation and technological change has been a topic of economic research already for very long time. In the 1940s the linear model of innovation was introduced to model the relationship between science, technology and the economy (Godin, 2006). Still today, the analysis of technological change in bioeconomy models is mostly based on mainstream neoclassical economics methods (Köhler et al., 2018; Arthur, 2021) where the emphasis is on understanding the impact of technological change rather than understanding its drivers such as research and development. It is surprising that although there is wide agreement among economists about the overwhelming importance of technological change for economic growth, in many existing models it is still modelled exogenously and *falls like manna from heaven*. Table 2 gives an overview of existing models with technological change.

In several IAMs and economic models, technological change is assumed to be represented by an exogenous parameter; for example, an autonomous energy efficiency representing the decoupling of energy use and economic growth which is assumed to capture all non-price driven improvements. Another common approach consists in the semi-exogenous incorporation of so-called backstop technologies (i.e., technologies at low technological readiness level) that are already known and completely available as blueprints and which can be unlocked by investing in research and development (R&D). In more recent models, technological change is endogenized as price-induced, R&D-induced and learning-induced. The first is based on the idea that changes in relative factor prices, typically energy or endowment (land, labour, capital) prices, stimulates innovation, namely substitution of those factors that became relatively more expensive. In the second, which is the most widely applied way to endogenize technological change (see Gillingham et al., 2008 for an exhaustive overview in the field of energy), R&D increases the stock of knowledge, which allows for a deterministic introduction of process innovation in a pre-defined technology (see e.g. Smeets-Kriskova et al., 2017a; 2017b). The third approach relies on the learning-by-doing effect, namely the cost-reduction of technologies based on the experience, which is modelled using learning curves.

Modelling technological change in environmental models so far is less common, as they hardly cover socio-economic variables. The effects of technological change may be incorporated in environmental models exogenously through scenarios storylines.

A promising new development on the relationship between investments in R&D and technological progress is the introduction of heterogeneous firms, because in the transition period, introducing bioeconomy innovations will lead to the co-existence of firms still relying on fossil-based technologies and firms which already have switched to bioeconomy technologies. However, the possibilities of these extensions, where the heterogeneity is approximated by productivity differences between firms which apply the same production function (Melitz, 2003) in economic (e.g. CGE) models (Balistreri and Rutherford, 2013; Dixon et al., 2018; Akgul et al., 2016) are limited. Already more than 30

Table 2
How technological change is modelled in some of the most known IAM, CGE and PE models. Adapted and updated from Gillingham et al. (2008) and Löschel and Schymura (2013).

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

years ago, Stiglitz (1987) has emphasized the importance of localized technological progress which rejects the possibilities to model innovation processes of firms as improvements along one production function. In this particular case of the bioeconomy transformation it is evident, that in these models apples are compared with pears and implications stemming from the heterogeneity of technological approaches are faded out.

The modelling of negative emission technologies (NETs) as mitigation strategy represents an interesting example that can further highlight the limitations of the mainstream modelling approaches. The massive reliance on NETs in the mitigation scenarios in line with the Paris Agreement, especially in the form of bioenergy with carbon capture and storage (BECCS), is evident (Lawrence and Schäfer, 2019). In these scenarios BECCS are assumed to be technologically ready and thus available for significant deployment from 2030 onwards. The real utility of these mitigation strategies will depend on the rate of technological progresses that determines when and how they will become commercially available at affordable costs. Modelling NETs' technological dynamics is thus crucial to understand when they can effectively become a viable mitigation strategy. For two reasons this is a questionable modelling strategy: (i) the technology is still in its pilot phase characterized by strong uncertainties which do not allow for the assumption of a deterministic progress trajectory. And (ii) the NETs are introduced to the models as an end-of-pipe technology packed on existing economic structures which do not change over several decades.

In all the aforementioned cases, the rationale is that technological solutions have already been developed, and their use depends solely on cost-benefit considerations of the agents. Technological change is based on existing technologies and provides for efficiency increases. This approach excludes the emergence of new and the disappearance of mature industries, i.e., structural change. Neither true uncertainty, characteristic for innovation, nor potential failures or experimental behaviour and learning are considered. However, these are important features of innovation relevant for long-term development. Instead, innovation is reduced to a deterministic technological change in a well-defined decision problem. Model extensions of existing models therefore are restricted to analyse only short-run adaptations and incremental technological improvements along narrow and well-defined technological trajectories.

3. What alternative modelling approaches are available to address new policy needs?

In section 2 we focussed on efforts and possibilities to extend existing models for bioeconomy modelling. In this section we discuss first the reasons for an urgent need for new modelling approaches, and then highlight promising developments.

3.1. Transformation processes are long-term

While existing models can be extended to analyse short-run re-allocations in the bioeconomy transition processes, they mostly omit developments such as structural change and/or the fundamental reorganisation of the value creation and consumption process. This omission limits their use for a better understanding of the long-term transformation to a sustainable bioeconomy. The reasons for this limitation are of a principal nature and spotlight the limitations of existing models (see Nelson et al., 2018). The methodological orientation of most existing models is in neoclassical welfare theory makes the models normative, while a positive/descriptive orientation would be required to reflect long-term, open and non-deterministic developments: The experimental introduction of innovations, which unavoidably goes hand in hand with failed attempts due to the uncertainty inherent in innovation, is beyond the scope of models which are built on optimal decision making (e.g. Simon, 1991). Further, positive feedbacks and increasing returns due to mutual interdependencies, responsible for the emergence of new behavioural patterns and path dependencies, cannot be captured because of the built-in equilibrium orientation (e.g. Arthur, 2021). While these limitations are identified for economic models, they may also (partly) apply to environmental models (e.g., with regards to land use practices).

The major motive for an increasing interest in alternative modelling approaches in the field of the bioeconomy is a growing critique crystallizing around (i) the assumption of stable optimal technologies, which excludes innovation, and (ii) the assumption of a representative optimizing agent, which excludes dynamics generated by the interaction of heterogeneous actors.

If the drivers of transformation processes are innovation and changing behaviour, it is contradictory to exclude them by assumption. This general critique is not new. For almost 40 years, evolutionary economists (Nelson et al., 2018) are arguing for alternative modelling frameworks when it comes to the analysis of long-term innovation driven developments. Therefore, it is not surprising that from an economic theory point of view, most alternatives concerning the analysis of transformation processes rely on ideas of evolutionary economics (Safarzynska et al., 2012) and complexity models (Arthur, 2021), which can be considered as its formal modelling-oriented branch (Beinhocker, 2006).

More than ten years ago, Timmermans and de Haan (2008) observed that models theorizing and investigating structural change of economic systems and transformations of social systems have been almost absent and - according to our knowledge - this has not drastically changed until today. Only a small number of bioeconomy-related studies exist so far that applied emerging modelling approaches (e.g., Schiller et al., 2014; Mertens et al., 2018; Maes and Van Passel, 2019), with some notable work such as that of Arneth et al. (2014) who coupled a global vegetation model with a socio-economic ABM. Possible reasons for the limited uptake for bioeconomy modelling are the inherent difficulties in dealing with complex systems and hesitation towards emerging modelling approaches in existing modelling communities.

The different focus of existing and emerging modelling approaches corresponds with the difference between simple and complex systems (Arthur, 2021) (Table 3). To apply the rich toolkit of existing models, the inherent complexity of long-term development has to be excluded by a set of assumptions. By removing these assumptions, the analysis of long-term developments becomes possible, but at the price of a lower level of detail, which is undoubtedly one of the merits of existing modelling approaches.

Complexity models do not exclude innovation driven developments and qualitative change by assumption, but allow for their endogenous consideration, and they work neither with a fixed set of preferences nor with exclusive price adjustment in consumption behaviour. Instead learning and experimentation are considered to be relevant on the supply and the demand side and responsible for fundamental pattern changes, e.g. the emergence of new industries or of new lifestyles. This is a condition-sine-qua-non for a better understanding of long-run

Table 3
Comparison of simple and complex systems using the features of a sustainability transformation highlighted by Köhler at al. (2018).

	Simple systems	Complex systems
Agents and interactions	Homogenous and symmetric, optimization	Heterogeneous and asymmetric, learning and experimenting
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)
Dominant theme	Allocation of resources, equilibrium-oriented, reversible	Formation of structures, dynamics, different scales
Change	Exogenous (shocks), the equilibrium shifts	Innovation and learning cause endogenous restructuring

dynamics and, most important, for an application in the policy realm concerning experimentation of alternative policy interventions to influence the desired transformation towards higher degrees of sustainability.

Some of the recent developments also focus on the improvement of the communication between modellers and stakeholders. Agent-Based Models (ABMs), for example, are extended to so-called *policy laboratories* (see e.g., Schilperoord and Ahrweiler, 2014; Ahrweiler et al., 2015; Pyka et al., 2018), which add a graphical user interface with intervention possibilities and observation monitors, and are used for an ex-ante evaluation of policy interventions. Policy laboratories allow for performing experiments to strengthen the intuition of policy makers to deal with complex systems. Edmonds et al. (2019) are observing that the purpose of modelling shifts with the complexity models from prediction and explanation more and more to description and illustration, theoretical exploration, and analogy to facilitate social interaction among stakeholders, e.g., between modelling and foresight.

In principle, the high expectations for complexity models to close the remaining gaps and to overcome the limitations of existing bioeconomy modelling approaches are justified. However, the general trade-off in modelling between generalization and specialization is also valid for complexity models, which are characterised by a significantly lower level of detail compared to existing models.

In the following paragraphs, we briefly discuss the possibilities of complexity models beginning with system dynamics as an early predecessor. Then we focus on agent-based models, which are currently by far the most popular branch of complexity models. Most interesting for bioeconomy modelling are recent attempts to combine socio-economic and environmental ABMs.

3.2. Emerging modelling approaches: from system dynamics to agent-based modelling

The system dynamics model approach must be considered as an early predecessor of complexity models, in particular because of its large popularity in addressing systemic interactions between socio-economic and environmental systems beginning with the work of Meadows et al. (1972). The principal idea of system dynamics is that dynamic system behaviour can only be analysed and understood, if systems are considered as a whole, which resembles to some extent the rationale of CGE models. Mutual interdependencies of the system components, however, cause changes in structures as well as unexpected developments and are responsible for non-linearities in the interaction patterns which are behind surprises and potential system's collapse.

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. In this respect, the system dynamics approach turned out to be unwieldy concerning the heterogeneity of agents in the various subsystems. For this reason and with the increasing availability of computational methods, system dynamics was more and more replaced with ABMs since the early 1990s.

With their bottom-up approach, ABMs (see Gilbert and Troitzsch, 2005; Tesfatsion, 2002) raise the highest expectations within the group of complexity models. ABMs allow the analysis of emergent phenomena 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.

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 further entrepreneurs are attracted, which eventually triggers changes in value creation networks on the meso-level, and so on. This beginning transformation is aggravated from dynamics 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. In this process, at no stage actors are confronted with well-framed decision problems suitable for an optimization approach nor an equilibrium is attained. History matters in form of failed attempts, emerging new attractors, interactions taking place in dynamically changing networks, path dependencies etc.

This possibility of a flexible representation of human-decision making and the leaving-behind of the *homo oeconomicus* inspires many applications of ABMs. Land use and land cover change models (LUCC) might serve as an example, which 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 agent-based LUCCs).

The 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 in ABMs follow descriptive ideas observed in real decision behaviour (heuristics). 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*, which eludes probabilistic considerations, which are only applicable in risky situations (e.g., Vermeulen and Pyka, 2016). Moreover, ABMs allow for the consideration of values and norms (e.g., Schlaile et al., 2018). They are frequently applied to study innovation, entrepreneurship, technology diffusion or learning in innovation networks (e.g., Morone et al., 2013, Pyka et al., 2019; Vermeulen and Pyka, 2018), all highly relevant topics in the bioeconomy transformation. This should illustrate the possibilities of *close-to-reality* modelling by ABMs focusing on the implementation of transformation theory together with an empirical calibration of manifold parameters. It must be mentioned that in the last decade the possibilities to calibrate empirically the parameters of ABMs have improved substantially due to new available data sets and new methodologies for pattern recognition (see also section 3.3). This development is supposed to invalidate the reproach towards ABM being arbitrary in parametrization (Fagiolo et al., 2019).

Concerning bioeconomy modelling, a promising development is the amalgamation of socio-economic and environmental ABMs. 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). 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 (Elsawah et al., 2020). 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 socio-economic ABM is coupled with an environmental ABM, which depicts the dynamics of the relevant eco-systems.

Fig. 1 illustrates the interfaces between the socio-economic and the environmental ABM, typical for socio-environmental ABMs. 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 true uncertainties leading to surprises or even sudden collapses. Berger et al. (2010), 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.

Brown et al. (2019) describe an ABM of the European land system (CRAFTY-EU), 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 focusing on biophysical changes and do not explore the social dynamics that are a key aspect of future land use. Their study shows the advantages of neither being constrained by equilibria nor by optimization. With exploring a range of potential futures using climatic and socio-economic scenarios, they show that deviation from simple economic rationality at individual and aggregate scales 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 ABMs 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.

The combination of economic and biophysical models is offering large possibilities for modelling the bioeconomy transformation. However, while the advantages of socio-environmental ABMs lie in their ability to simulate the implications of human-nature interactions explicitly, the methods for providing empirical support for the representation of these interactions are still on an early stage of development (Smajgl et al., 2011). In their 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. Lamperti et al. (2018) show that socio-ecological ABMs extend and develop further the class of IAMs, which also consider 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 ABMs, they combine the advantages of ABMs concerning the representation of learning, innovation and non-linearities with the comprehensiveness intended in IAMs.

3.3. Big data and artificial intelligence support new modelling approaches

Many of the outlined methodological developments hint on the immense data hunger of new modelling approaches to facilitate parametrization and to link socio-economic with environmental systems. Huge amounts of diverse data are becoming available that include both socio-economic and ecological information.[1]

Therefore, big data is considered to provide important opportunities for improved understanding of important processes along value chains in agriculture and forestry and to support the explanatory power of the new modelling approaches. 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, we refer to Craglia (2018). Of the many examples available, the United Nations Global Pulse (UN Global Pulse, 2017) initiative must be mentioned, which harnesses big data and artificial intelligence to support the achievement of the sustainable development goals and related policy making. Other interesting examples are the works of Rammer and Seidl (2019) that 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 and of Senf and Seidl (2020), who mapped forest disturbance regimes for Europe using the Google Earth Engine.

Exploiting big data sources together with tools from artificial intelligence can be used, for example, to recognize patterns (e.g., the conversion over time of oil-based into bio-based plastics industries) hidden in existing industry statistics and allow for new and more precise understanding of sectoral developments. 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. Something similar has already been done in other sectors, for example in the Cleantech Report 2020 (Cleantech Flanders, 2020) that mapped the ecosystem of companies dealing with innovative clean technologies in Flanders and built an accurate profile of all actors. To do so, data mining was used to analyse all patents released by Flemish companies in the relevant domains and to retrieve other multidimensional data such as financial performance, investments and funding, shareholders, company size, locations, target market etc. Next, machine learning was used to discover trends and relationships in the ecosystem.

A common feature of models building on existing 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. Bringing together environmental, social and economic big data sources also very likely will allow us to discover unknown causalities and interdependencies among different variables and 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.

The possibilities provided by artificial intelligence, in particular machine learning, are likely to push forward the limits of emerging modelling approaches like agent-based modelling and socio-

[1] Just as an example, satellite (e.g., https://www.copernicus.eu/en or https://f-tep.com/) and processed data from large internet companies (e.g. https://cloud.google.com/public-datasets) are becoming increasingly available, and many of these big data sources and derived products are provided on easily accessible platforms (e.g., http://www.globalforestwatch.org/).

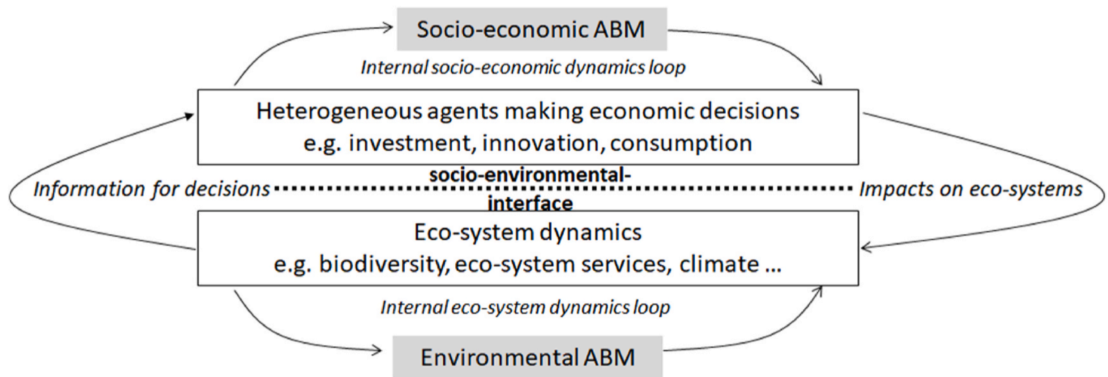

Fig. 1. Human-environment interactions in socio-environmental models.

environmental agent-based modelling (see Dahlke et al., 2020). Especially in highly complex models with many different parameters like in socio-environmental agent-based models, generated output has to 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).

4. Discussion and conclusion

The bioeconomy is considered to play an important role towards sustainable development. Models allow for a better understanding of the complex context in which policy instruments intervene, are important. Therefore, bioeconomy models can be considered valuable instruments to inform policy makers about intervention possibilities and their consequences.

4.1. Exploiting existing models and exploring new modelling approaches

We show that existing modelling frameworks offer large possibilities for extensions and considerations for analysing short-run impacts within the prevailing structural composition of the socio-economic system and we identified possibilities for developing further the existing bioeconomy models. Whereas some key processes focusing on short-run adaptations of the economic system within prevailing economic structures can be included into existing models with reasonable effort, other key processes cannot be integrated and require the development of new models building on emerging modelling techniques. These key processes refer to societal and technological changes associated with the transformation to a bioeconomy and they specifically relate to how innovations transform economic structures and how consumers learn and change their preferences and what kind of dynamics are to be expected. Together with those addressed in depth in in this work, there are several other emerging approaches that try to address complex systems and structural changes, and are likely to be considered as further complements to the existing models. For example, the so-called stock-flow consistent (SFC) macroeconomics 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). The justification of these emerging approaches 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 a knowledge-based and sustainable bioeconomy. In the literature 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 aiming 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 so far can be considered as the most popular in the domain of bioeconomy modelling. 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, for 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 existing modelling approaches are insufficient because of their optimization and equilibrium design.

The second development of applying emerging modelling approaches in the bioeconomy domain gains its attractiveness exactly from the limitations of the first. They focus on the endogenous drivers of the co-evolutionary development of social and ecological systems. 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 in applications like modelling the bioeconomy.

4.2. Modelling eclecticism and/or modelling cooperation

As both developments are characterised by strong advantages but also by severe disadvantages, the third development trend 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.

Few models today are indeed combining the macro-economic structure of an economic system, as done in CGE models, 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 existing 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 not the result of the interactions among agents and among agents with their natural environment. To avoid this loss of modelling potentials, we emphasize a fourth trajectory for future model development:

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

For the analysis of short-term temporal developments within stable structures, the fine-grained established modelling approaches are well suited to analyse future bioeconomy transition processes. However, the application of the established modelling approaches should reflect from the very beginning the shortcomings and limitations concerning their 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. The emerging modelling approaches hint on the drivers of these fundamental changes responsible for the non-linearities and disruptive changes characteristic for and affecting socio-ecological long-term development.

From a theoretical point of view, an equilibrium state of an established model is one possible outcome of a complexity model. However, in a long-run analysis it is not very likely that the system under investigation remains in this equilibrium even without an exogenous shock. But, as 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 for 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.

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.

CRediT authorship contribution statement

A. Pyka: Formal analysis, Writing – original draft. **G. Cardellini:** Formal analysis, Writing – original draft. **H. van Meijl:** Formal analysis, Writing – original draft. **P.J. Verkerk:** Formal analysis, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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