

REVIEW

Model collaboration for the improved assessment of biomass supply, demand, and impacts

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Abstract

Existing assessments of biomass supply and demand and their impacts face various types of limitations and uncertainties, partly due to the type of tools and methods applied (e.g., partial representation of sectors, lack of geographical details, and aggregated representation of technologies involved). Improved collaboration between existing modeling approaches may provide new, more comprehensive insights, especially into issues that involve multiple economic sectors, different temporal and spatial scales, or various impact categories. Model collaboration consists of aligning and harmonizing input data and scenarios, model comparison and/or model linkage. Improved collaboration between existing modeling approaches can help assess (i) the causes of differences and similarities in model output, which is important for interpreting the results for policy-making and (ii) the linkages, feedbacks, and trade-offs between different systems and impacts (e.g., economic and natural), which is key to a more comprehensive understanding of the impacts of biomass supply and demand. But, full consistency or integration in assumptions, structure, solution algorithms, dynamics and feedbacks can be difficult to achieve. And, if it is done, it frequently implies a trade-off in terms of resolution (spatial, temporal, and structural) and/or computation. Three key research areas are selected to illustrate how model collaboration can provide additional ways for tackling some of the shortcomings and uncertainties in the assessment of biomass supply and demand and their impacts. These research areas are livestock production, agricultural residues, and greenhouse gas emissions from land-use change. Describing how model collaboration might look like in these examples, we show how improved model collaboration can strengthen our ability to project biomass supply, demand, and impacts. This in turn can aid in improving the information for policy-makers and in taking better-informed decisions.

Keywords: biomass supply and demand, bottom-up modeling, impacts, integrated assessment, model collaboration, top-down modeling

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Introduction

Bioenergy is often mentioned as an important element of a more sustainable future global energy supply (IPCC, 2011; GEA, 2012). Biomass for the production of biochemicals, bioplastics, and modern biomaterials has also received increased attention given its potential for reducing the products' carbon footprints and the dependence on finite and increasingly costly fossil fuels (e.g., EC, 2012). The economic activities related to biomass production and subsequent conversion into energy, chemicals, materials, and other products are termed biobased economy (also called bioeconomy). It aims at reducing the dependence on fossil fuels and differentiates itself from the traditional uses of biomass by applying advanced biological knowledge and tools (OECD, 2009; Zilberman, 2013). However, the sustainability of a biobased economy has been debated in recent years because of the impacts on the economy, environment, and society such as the competition with food production, and land-use change (LUC)-related greenhouse gas (GHG) emissions (Mitchell, 2008; Searchinger *et al.*, 2008; Tilman *et al.*, 2009; Fritsche *et al.*, 2010; Hertel & Tyner, 2013). The large diversity of opinions and positions on the sustainability of the biobased economy can partly be explained by different perceptions and interests of actors involved, but also by a lack of data and comprehensive understanding of underlying processes (and how these are translated into modeling terms), and by different approaches used to model the supply of biomass and its impacts (Dornburg *et al.*, 2010; Haberl *et al.*, 2010; Batidzirai *et al.*, 2012; Creutzig *et al.*, 2012). Another factor is whether approaches used tend to be mono- or multi-disciplinary where for example a narrow perspective can yield misleading information about problems with broad systemic effects.

It is important to recognize that projecting the future is inherently uncertain, and the purpose of a modeling exercise is to gain insights into the processes of change in response to actions that occur because of external factors such as a policy change. As we will argue in this paper, reducing some of the uncertainties surrounding the biobased economy could be achieved through model collaboration. This may or may not lead to an ultimate consensus, but can at least help improve the understanding of the processes of change and impacts, and as a consequence make more informed decisions.

The already large body of literature provides important insights into the potential size and sustainability of a biobased economy. However, these studies faced various types of limitations and uncertainties, partly due to the type of tools and methods applied (e.g., partial representation of sectors, lack of geographical details, and aggregated representation of technologies involved). Thus, recent scientific literature (Nassar *et al.*, 2011;

Creutzig *et al.*, 2012; Wicke *et al.*, 2012) suggests further developing and improving modeling toolboxes – especially through better integration of detailed bottom-up information and improved cooperation between the different modeling approaches (hereafter referred to as model collaboration). Model collaboration can take the form of aligning and harmonizing input data, detailed model comparison and/or model linkages. Model collaboration in its various forms can facilitate understanding of discrepancies in results and underlying factors, provide information about the robustness of results, and strength and weaknesses of different approaches, and improve validation and calibration of models. As a result, it can provide new and more comprehensive insights into biomass supply, demand and impacts, and allows assessing the effects of policy and regulation. In doing so, it can help in identifying necessary conditions for the development of a sustainable biobased economy.

The main objective of this paper is to assess how model collaboration can contribute to improved assessment of biomass supply, demand, and their impacts. To do so, a thorough understanding of existing approaches is needed. Thus, we first characterize the applications, strengths, and limitations of the main modeling approaches, and then formulate key questions that remain to be answered by any approach (Section 2). In Section 3, we focus on model collaboration, the different types, and opportunities and limitations it presents. This is followed by three examples of key research areas that can benefit from model collaboration and a description of what model collaboration might look like in these cases (Section 4). The three examples relate to (i) developments in the livestock production; (ii) availability, use and impacts of agricultural residues; and (iii) GHG emissions from land-use change. In Section 5, we draw conclusions on model collaboration and other necessary steps to enhance the assessment of biomass supply and demand and their impacts.

Strengths and limitations of existing approaches

Existing approaches for assessing biomass supply, demand, and impacts can be broadly categorized into the following categories: (i) computable general equilibrium (CGE) models, (ii) partial equilibrium (PE) models, (iii) bottom-up models and analyses, and (iv) integrated assessment models (IAM). As the following sections also indicate, the categorization of models is to some degree artificial because each model tends to have individual characteristics and often includes elements of more than one category [an overview of such integration activities related to energy-environment models is given in the Energy Journal special issue 'Hybrid modeling of energy-environment policies: reconciling

bottom-up and top-down' (Hourcade *et al.*, 2006)]. Still, such a categorization is useful for defining strengths and limitations of existing approaches. We discuss the main applications and insights of these four approaches, and their strengths and limitations for assessing biomass supply, demand, and impacts (Section 2.1 to 2.4). The key aspects of this discussion are presented in Table 1. In addition to uncertainties and shortcomings specific to the four approaches, there are also those that are common to all approaches. These are presented in Section 2.5.

Computable general equilibrium models

Computable general equilibrium models have been used to analyze macro-economic consequences of different

types of policies over the last 25 years. Models were initially used to analyze policies related to taxation and trade (Shoven & Whalley, 1984), but progressively expanded to analyses of diverse topics such as spread of human diseases (Kambou *et al.*, 1992), international labor migration (Borjas, 2004), climate change adaptation (Block *et al.*, 2006), and land-use change (van Meijl *et al.*, 2006). In recent years, CGE models have also been used to analyze the implications of biomass and bioenergy policies. For example, Taheipour & Tyner (2012) have studied the implications of the United States' (US) Energy Independence and Security Act of 2007, Banse *et al.* (2008) and Laborde & Valin (2012) have analyzed land-use changes and greenhouse gas emissions resulting from European biofuels policies, and van Meijl *et al.* (2012) have analyzed the macro-economic impacts of a biobased economy in

Table 1 Overview of the four modeling approaches for assessing biomass supply, demand and impacts: Their applications, typical timeframes, key strengths, and limitations

	CGE model	PE model	Bottom-up analysis	IAM
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	Sectoral impacts of bioenergy policies on agriculture, forestry, land-use change, energy system and GHG emissions	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	Bioenergy 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
Typical timeframe	Short to medium term	Short to long term	Short to long term	Long term
Strengths	Comprehensive coverage of economic sectors and regions to account for interlinkages. Explicit modeling of limited economic resources. Measuring the total economy wide and global effects of bioenergy 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 insights into techno-economic, environmental and social characteristics and impacts of biobased systems	Integrating different relevant systems in one modeling framework. Possibility to analyze feedbacks between human and nature systems, and trade-offs and synergies of policy strategies. Built around long-term dynamics
Limitations	Level of aggregation that may mask the variation in the underlying constituent elements. Scope of CGE models necessitates simplified, representation of agent choices, in particular favoring smooth mathematical forms and reduced number of parameters required to calibrate the models. Often no or little explicit representation of quantities for biophysical flows	Optimization of agent welfare, but only the sectors represented in the model. No consideration of macro-economic balances and impacts on not-represented sectors. Need large number of assumptions for long-term projections	No inclusion of indirect and induced effects outside the boundaries of the study, i.e. often deliberately ignore interactions with other sectors	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)

Malaysia. CGE models have often been used for analyzing the agricultural market adjustments and land-use change at global scale, thanks to the Global Trade Analysis Project (GTAP) research consortium that provides a general global CGE framework and database (Narayanan & Walmsley, 2008). Hertel *et al.* (2011) have provided multiple examples of how the land-use representation of the GTAP database was expanded with the agro-ecological zones (AEZ) framework and applied in various CGE assessments.

A key insight from CGE studies into biofuels is the strong impact of the use of first-generation biofuels on national and international food markets, and the associated total net impacts on land use and greenhouse gas emissions. Biofuels increase the link between energy and agricultural market prices that may affect welfare and trade patterns (Bouet *et al.*, 2010; Hertel & Beckman, 2010; Hertel *et al.*, 2010). For example, domestic production of biofuels can decrease foreign oil imports, while the use of crops for biofuels may lead to lower exports of agricultural products. Results from CGE models also show that the effects on land use will depend on trade policy scenarios. For instance, Laborde (2011) calculated for the EU biofuels mandate that with liberalization of trade barriers, more cropland is needed than without liberalization. This is primarily due to a shift in production to regions with lower crop yields and also reduced intensification resulting from lower prices.

The principle strength of CGE-based studies is their comprehensiveness in terms of key economic relationships, including market price adjustments and associated changes in terms of trade, market balances, and factor markets. The CGE models are 'deep' structural models in that they explicitly solve the maximization problem of consumers and producers, assuming utility maximization and profit maximization with production/cost functions that include factor inputs [see Robinson *et al.* (2014)]. CGE models are capable of informing policy-makers of the overall economic effects of existing and potential policies. For example, Taheipour & Tyner (2012) investigated the economic impacts of biofuel use in the United States. The results show the importance of considering interaction between biofuel policies and other economic sectors via impacts on petrol tax, income tax, and agricultural subsidies. Furthermore, there is an obvious strong relationship between first-generation biofuels and food crops, and thereby food security and land-use changes. However, there are less obvious links between the prices of biofuels, fossil fuels, and governmental support policies. They are nevertheless critical for policy impacts. For instance, Laborde (2011) shows that the leakage effect of the EU biofuel policy is significant: for 1 MJ of fossil fuel saved

in the EU, thanks to the biofuel consumption, only 0.7 MJ is saved at a global level. CGE models can account for such interlinkages by their comprehensive coverage of sectors, production factors, and regions. In addition, measuring the overall welfare effects of bioenergy support programs in specific countries can only be understood when viewed in conjunction with the entire set of support programs of these countries. CGE models make this possible because they encompass the entire range of economic activity rather than particular markets, and they explicitly model the fact that economic resources (such as labor, land, and capital) are limited (Banse *et al.*, 2008; Taheipour & Tyner, 2012). The comprehensive coverage of sectors, production factors, and agents then allows assessing (i) production factor and market price adjustments and associated changes in trade and market balance, (ii) economy-wide accounts and consumer welfare indicators that are used to derive the full cost/benefit of a bioenergy policy, (iii) consequences on income, growth, and job markets, and (iv) the distribution of benefits and burdens of policies on consumers and producers both within and among countries. CGE models are particularly useful for studying the impacts of significant bioenergy deployment in the short/medium term, especially when they are used and designed with a high level of disaggregation, and when sectoral and regional interlinkages are relevant.

However, there are also many important uncertainties and limitations to CGE modeling analyses (Hertel, 1999). The price for their comprehensiveness is in general a high level of aggregation, which masks variation in and economic interactions between the underlying constituent elements, and limits the degree to which bottom-up information and data can be effectively integrated within the larger model (Hoefnagels *et al.*, 2013). The same is true for temporal aggregation: CGE models provide a new equilibrium after a certain 'shock', and usually do not provide a temporal trend. Also, the representation of technology and technological change is usually limited; especially advanced options of the biobased economy (e.g., modern biomaterials) or alternative feedstocks and land resources (such as production on degraded land or residues) have hardly been assessed in CGE studies. However, recent advances with regard to a broader representation of bioenergy have been made in some GTAP model versions, introducing ethanol, biodiesel and their by-products (Banse *et al.*, 2011; Laborde, 2011), the agricultural residue corn stover, and the energy crops switchgrass and miscanthus for second-generation ethanol production (Taheipour & Tyner, 2013b) and palm oil residues (van Meijl *et al.*, 2012). There is a trend of disaggregating agricultural, forestry and energy sectors within a CGE

model to obtain the needed detail for policy questions (Woltjer, 2013). The scope of CGE models also necessitates simplified, behavioral assumptions to be able to represent aggregated behavior using smooth mathematical functions and to be able to calibrate the models with limited datasets. Although, it is possible to add data and behavioral detail to a CGE model in terms of new sectors and more complex relationships, in practice, mathematical relationships in CGE models remain highly aggregated and simplified. For example, Laborde (2011) acknowledges limitations that affect the substitution of proteins and carbohydrates and the inability to provide an entirely correct substitution matrix across crops and their yield consequences – a problem shared by most CGE models. He therefore calls for the use of more flexible functional forms and sensitivity analyses. In addition, the uncertainties related to CGE modeling increase in case of major structural and technological changes, which makes them more suitable for short- to medium-term assessments than longer timeframes as described above.

Partial equilibrium models

Partial equilibrium models are economic models following the same neo-classical framework as CGE models, but in which not all economic sectors and factors are represented. PE models are often adopted to address questions specific to some sectors (e.g., agriculture and energy) and for which interrelation with others parts of the economy are secondary. As for CGE models, the main characteristic of PE models is the assumption that markets are at equilibrium and return to equilibrium after an economic shock, i.e. at any time, demand price adjusts to equal marginal producer cost. The simplest form of PE models is the stylized single product demand–supply model generally used to analyze welfare and other impacts of a policy or technology change. PE models have largely been used to analyze first-order effects of policy intervention on a feedstock market when developing bioenergy [see, for example, De Gorter & 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 (Shrestha *et al.*, 2013), encompassing a large number of sectors and regions, and providing a high level of detail in the supply and demand representation. In the context of bioenergy, typically two sets of PE models are relevant: (i) food market models and (2) energy system models. Examples of the first set are the POLYSYS model (De La Torre Ugarte & Ray, 2000) and the FASOMGHG model (Beach *et al.*, 2012), and an example of technology-rich PE models in the energy arena is MARKAL-TIMES (originally from IEA; Clarke *et al.*, 2009), but there are many others. Here, we focus mostly on the food market category.

Although many PE models share some characteristics, their structure can vary strongly depending on their economic assumptions. The biggest difference comes from the formulation of the welfare function to optimize. Some models represent agents' behavior around the equilibrium under the form of reduced top-down functions similar to CGE ones, without explicit representation of the technology and production costs. In that case, quantities are adjusted in response to variation of relative prices with respect to certain price elasticities. For instance, the IMPACT model (Rosegrant *et al.*, 2012) has been used to assess the effect of first-generation biofuel development on world food prices (Msangi *et al.*, 2007). The multi-commodity market model FAPRI-CARD uses an approach where supply functions are precisely derived for each raw agricultural market, as well as for the biofuel sectors (Elobeid & Tokgoz, 2008; Fabiosa *et al.*, 2010). The FAPRI-CARD model in particular has been used in the seminal raising awareness of indirect land-use change through Searchinger *et al.* (2008).

Some other PE models follow linear optimization techniques to determine the level of production on the basis of explicit production cost calculation using bottom-up information and explicit prices with a much more detailed geographic representation [for the US, ASMGHG and BEPAM, see Schneider *et al.* (2007) and Chen *et al.* (2012), respectively; or at the world level GLOBIOM, see Havlík *et al.* (2011)]. In this latter category of PE models, supply functions for biomass distinguish a wide variety of feedstocks sourced from agricultural crops or perennials and forest products, with different management approaches. Depending on the production costs and policy incentives, the models allocate the production across regions and products along structurally bottom-up supply curves that are very close to the ones produced by engineering models. This allows determining the optimal portfolio of GHG emission mitigation measures for a certain carbon price (Schneider *et al.*, 2007) or comparing the projected GHG emission effect of different feedstocks under different land-use change policies (Havlík *et al.*, 2011). The impact of the US Energy Independence and Security Act has, for example, been investigated with FAPRI-CARD and FASOMGHG. Chen *et al.* (2012) investigated land-use impacts in the United States at county level and Mosnier *et al.* (2013), the overall land-use GHG emissions at international level. Both of these analyses in particular allowed comparing different shares of second-generation biofuels in detail; pathways that have little been studied by CGE models because they are not present in the initial state of the economy (Taheripour & Tyner, 2013b).

The advantage of PE models comes from their high level of flexibility in incorporating a large amount of detail in process representation and input data. While CGE models require a large quantity of information (in particular for the input–output tables), this information is only needed for sectors covered in the PE models, which removes the need for lengthy and distortive full rebalancing of the dataset [although procedures are developed to automatize these processes in CGE models (see, e.g., Woltjer, 2013)]. Additionally, in the case of linear optimization models, the performance of solvers allows incorporating a very large number of technologies at a detailed grid-cell level (e.g., up to 200 000 spatial units in GLOBIOM). These models are particularly well fitted for a fully, spatially explicit representation of sector dynamics and particularly adapted to land use-related questions. Depending on their design and calibration elasticities, PE models can be well fit for short- to medium-term analyses (for instance, market outlook models such as FAPRI-CARD or AGLINK from OECD) or long-term analyses (e.g., GLOBIOM applies a time horizon up to 2050 or even 2100).

However, PE models also have some limitations. The first one comes from the absent links with other sectors. Bioenergy being at the nexus between agricultural/forestry and energy sectors, models only focusing on one of the two groups of sectors miss feedbacks from the other group. There are attempts to circumvent this issue by incorporating two PE models and solving them simultaneously (Msangi *et al.*, submitted), by extending their model to a simplified representation of fossil fuel markets (Chen *et al.*, 2012), or by establishing links between the various model approaches (see Section 2.4 on integrated assessment models and Section 3 on model collaboration). Another issue is the absence of macro-economic closure, which can introduce some bias when sectors have a big role in an economy. For example, in developing countries, the link between agricultural income and the final consumer demand is generally missing because the supply and the demand side are not linked by the revenue cycling; a PE model is therefore more limited to study food security benefits for smallholders to develop bioenergy projects. Additionally, for oil-exporting countries, the effect of production and trade on the exchange rates and the feedback from government revenues on welfare and consumption are often neglected, which prevents PE models from a full welfare analysis of biofuel policy impacts.

Bottom-up analyses and models

Bottom-up analyses and models begin with detailed descriptions and modeling of technologies, processes, agents, or resources. They include a wide variety of

analyses that can entail detailed assessments of current conditions as well as long-term projections. As opposed to the CGE and PE models described in the previous sections, they do not model economic markets or calculate market prices endogenously. Various subgroups of bottom-up assessments have been developed for assessing biomass supply potentials and impacts, for example:

- Process-based technical models (including life-cycle analysis), such as the GREET model (Wang *et al.*, 2012) or the BioGrace model (BioGrace, 2011);
- Process-based biophysical models to assess crop suitability and growth (Fischer *et al.*, 2010; Trabucco *et al.*, 2010) or impacts [erosion risk evaluation tools (Muth & Bryden, 2012)], water impact evaluation analysis (Berndes, 2002), land use/management emission analysis [e.g., with the MITERRA model, see de Wit *et al.*, 2014)], or a combination of these (Marohn & Cadisch, 2011);
- Land-use allocation models that combine land availability, land suitability and land-use change at a spatially detailed level (Cai *et al.*, 2010; van der Hilst *et al.*, 2012; Kurka *et al.*, 2012);
- Bioenergy supply and demand mapping (Masera *et al.*, 2006);
- Statistical scenario analyses of biomass resource availability (Smeets *et al.*, 2007);
- Cost–benefit analysis (Wiskerke *et al.*, 2010);
- Multi-criteria assessments (Scott *et al.*, 2012);
- Prospective studies (e.g., learning curve studies [de Wit *et al.*, 2010; van den Wall Bake *et al.*, 2009]).

Many more, both simple and complex bottom-up models and tools are directly or indirectly relevant when evaluating (sustainable) biomass supply, demand and impacts.

A key characteristic of bottom-up models and tools is the focus on specific aspects, processes, technologies, or agents. As a result, these models typically have a well-defined system boundary in terms of geographic scope, sectorial coverage, and technology. They typically take advantage of up-to-date data and detailed parameters, which make them suitable to conduct prospective analyses of latent technologies. Bottom-up models provide detailed information involving specific technologies and their performances (e.g., energy use, emissions, and environmental impacts) within their system boundary. Disadvantages of this type of models are that they typically do not take into account indirect and induced effects outside the boundaries of the system under investigation, such as price responses, competition and replacement effects, as well as technological or structural changes outside the system boundaries (e.g.,

Britz & Delzeit, 2013). This makes bottom-up tools less suitable for policy impact assessments.

The advantages and disadvantages of bottom-up studies can be illustrated by the analysis of GHG emissions of bioenergy systems. A large number of bottom-up life-cycle analysis (LCA) studies have been carried out, which include detailed assessments and comparison of different bioenergy systems and provide thorough understanding of the factors that determine life-cycle emissions, such as the fertilizer application rate and nitrous oxide emissions, the assumed crop yields, the transportation distance from field to factory, etc. (Macedo *et al.*, 2008; Kendall *et al.*, 2009; Smeets *et al.*, 2009; Hoefnagels *et al.*, 2010). These results provide important information on how to differentiate good vs. bad performers, and to improve the GHG balance and sustainability performances of bioenergy through policy regulations and sustainability certification systems. However, the narrow system boundary of bottom-up LCAs also means that indirect effects are ignored, such as indirect land-use change and leakage effects of biofuels. This means that bottom-up LCAs need to be supplemented with economic models and approaches when evaluating the total net impact of bioenergy systems [see also Creutzig *et al.* (2012)].

Integrated assessment models

Integrated assessment models (IAMs) are designed to describe the interactions between human activities and (global) environmental change processes. They, therefore, include a description of the human system and natural system and the interaction between the two. For their application in assessments of a biomass supply, demand and impacts, the results of IAMs not only cover the energy system implications (e.g., which energy sources are replaced?) but also point out the limitations and implications with respect to natural systems such as water use, land use (e.g., where is bioenergy produced and what could be the consequences?), and the interactions with the global carbon cycle in the atmosphere, oceans, and biosphere in a complete, integrated manner. As such, they cover a broad range of disciplines, including energy analysis, economics, agriculture analysis, and biophysical sciences. The approaches discussed in Section 2.1 to 2.3 often form a part of an IAM (although often deliberately simplified compared to the stand-alone forms to allow for integration). The agricultural and/or energy economic 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 IAMs not only describe emissions of agricultural production but also land use and the full chain of climate change (GHG

concentrations, temperature change). This also means that, to some degree, IAMs are already representative of the model collaboration that we are investigating in this paper. But, given their special role in the literature and their focus on simplification, it is still useful to take stock of the current status of this model category. For the model integration referred to in Section 3, we focus on the cooperation between different stand-alone models allowing their representation in their original forms.

Much of the development and application of global IAMs has been in the context of global climate change assessment, where for example the emissions scenarios used by climate models were developed by IAMs (IPCC SRES, 2000; van Vuuren *et al.*, 2011). However, many global IAMs have also been used to study global land use and land-use change [see e.g., overview by Smith *et al.* (2010)], bioenergy supply potentials (Hoogwijk *et al.*, 2005; van Vuuren *et al.*, 2009; Acosta-Michlik *et al.*, 2011; GEA, 2012), and water and biodiversity consequences of biomass production (e.g., Chaturvedi *et al.*, 2013). Often, IAMs have a global coverage and focus on long-term processes in the order of decades to a century.

In general, IAMs deliberately aim to simplify the representation of individual model components to prevent the model as a whole becoming too complex. Most IAMs used to support bioenergy policies, however, tend to be among the more complex IAMs. This is because they need to have a more detailed representation of the human and earth system processes relevant to assess global environmental change. As discussed earlier, this means that IAMs often include CGE or PE models to represent (parts of) the economy. For example, IIASA's integrated assessment modeling framework involves the PE model GLOBIOM, connected to several activity models for agriculture (EPIC, RUMINANT) and forestry (G4M) and is further linked to the energy model MESSAGE for full integrated assessment (Reisinger *et al.*, 2013). The IMAGE model uses results of the CGE model LEITAP (now called MAGNET) or the PE model IMPACT, and integrates the PE energy model TIMER; other model components include the climate model MAGICC and carbon cycle and land-use representations (PBL, 2014). Other examples of model clusters include AIM (Kainuma *et al.*, 2003), REMIND-MAGPIE-LPJmL (Popp *et al.*, 2011) and GCAM (Wise *et al.*, 2009).

The obvious strength of IAMs is that they integrate information on the different relevant systems in a comprehensive modeling framework. In such a framework, trade-offs and synergies of policy strategies can be assessed, and feedbacks between different domains can be studied. Such feedbacks, for instance, relate to the climate impacts on crop growth or the GHG emissions associated with bioenergy production and use. However, there are also some limitations to this approach.

The broad and interdisciplinary coverage can go at the expense of detail (but this is only a problem where details matter, while a high level of detail may also only provide a false sense of precision). Too complex IAMs (that include considerable detail) may in fact lose transparency. Finally, most IAMs are built to capture long-term dynamics, and are therefore less suitable for short-term policy assessments. As in other models, assumptions on technical change in the energy and agricultural system form a key input and uncertainty in IAMs. However, due to the long-time horizon, these assumptions are even more important in IAMs than in studies with short-time horizons, and much of the technical potential of future biomass supply depends on the assumed technical change in agriculture and livestock management (Dornburg *et al.*, 2010).

In the context of bioenergy studies, IAMs have mostly been used to assess the possible contribution of bioenergy to global climate strategies (see for instance Rose *et al.* (2012)). In such studies, information on the technical potential (based on biophysical parameters) is combined with data on technology development, the costs of other energy sources, and the climate policy regime. Due to its focus on a long-time horizon, IAM results typically show low or no use of first-generation bioenergy crops, but instead project large use of agricultural residues, dedicated woody or herbaceous energy crops, and forest residues (Kraxner *et al.*, 2013; Rose *et al.*, 2013). Other reasons for the low application of first-generation biofuels in IAM studies is the carbon tax-driven application of biofuels, which does not stimulate biofuels that result in only a small greenhouse gas saving compared to fossil fuel use.

A second application of IAMs is the estimation of biomass potentials. In these studies, IAMs mostly try to estimate sustainable supply potentials. Typically, it is assumed that bioenergy crops can be grown when land is not used for food or fiber production or is not restricted by sustainability constraints like high-carbon content of natural vegetation or high biodiversity (van Vuuren *et al.*, 2009; Beringer *et al.*, 2011). The main sources of land-based bioenergy resources in such studies are dedicated production of energy crops on surplus agricultural land or abandoned land, and agricultural residues with a total global potential of 50–1000 EJ yr⁻¹ (Chum *et al.*, 2011). According to several studies, the high end of that range is inconsistent with sustainability criteria and a value of 100–150 EJ in 2050 seems more realistic (van Vuuren *et al.*, Schubert *et al.*, 2009; Haberl *et al.*, 2010). Some IAMs apply a ‘food/fiber first’ principle, which represents the possible effects of sustainability criteria on biomass resource availability and its impacts. But this ignores interaction with the food markets and competition for land.

Key research areas across approaches

In addition to the limitations and uncertainties specific to the different modeling approaches described in the previous sections, there are key uncertainties that are common to these different approaches and there are important questions that remain to be answered by any approach. These uncertainties and questions are described extensively in the literature (Schubert *et al.*, 2009; Dornburg *et al.*, 2010; Edwards *et al.*, 2010; Chum *et al.*, 2011; Batidzirai *et al.*, 2012). Here, we only provide an overview of key questions to be answered to better understand a biobased economy and its impacts:

- Can large-scale biomass production and supply be organized over time, in a way that unsustainable price impacts on food markets or undesired LUC are avoided? And if so, how?
- What are the impacts of different degrees of ambitiousness of sustainability targets on future biomass availability and costs?
- How do the various applications of biomass for a biobased economy compete with each other and with (fossil) alternatives, now and in the future?
- What are the effects of different trajectories of developments in agricultural crop and livestock production (e.g., intensification vs. extensification, fertilizer application, irrigation) on biomass supply and its impacts over time?
- What is the net potential contribution of biobased products in mitigating GHG emissions when including emissions related to changes in land use, agricultural production, and the energy system?
- What is the energetic potential of agriculture and forestry residues? What and how large are the competing uses? What are possible changes in agricultural and forestry technologies, and management over time and how would these affect the potential? What are the impacts (especially for soil conditions but also current uses and users) of extracting residues for energy use?
- What are the GHG emissions of LUC induced by a biobased economy? And how does it affect or is affected by other drivers?
- How may climate change affect the potential for bioenergy production?

Some of these questions relate to factors that include some fundamental uncertainties (such as the rate of technological development or future governance structures). But, as will be shown in the following sections, the better use and collaboration of models (while being aware of their limitations) allow exploring these questions in a

meaningful way primarily because different approaches can provide complimentary information.

Addressing open questions with model collaboration

Improved cooperation between the different approaches described in Sections 2.1 to 2.4 offers possibilities to reduce some of the shortcomings of the different modeling types, narrow the knowledge gaps highlighted above (Section 2.5) and strengthen our ability to project (both direct and indirect) the impacts of given bioenergy policies. Thereby, model collaboration can aid in improving the quality of information for policy-makers and contribute to better-informed decision-making.

Model collaboration can come in a number of forms (Fig. 1). Alignment and harmonization of models focus mainly on input data, level of aggregation, and scenario definitions. Model comparison focuses on the methods, representation and parameterization of biomass supply chains, assumptions and uncertainties in input data, and/or on results and sensitivities to uncertainties in underlying data and approaches. 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 (Lotze-Campen *et al.*, 2014). It can also reveal information about the robustness of the results when tested under different paradigms, about model biases and artifacts, and about strengths and weaknesses of different approaches. 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.

Linking or integrating models takes collaboration a step further and 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. It can thereby provide a more comprehensive picture of the impacts of a certain policy. 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 (Fig. 1). IAMs (Section 2.4) are examples of partially or fully integrating different modeling approaches. However, the more generic model collaboration discussed here can also refer to the cooperation between two stand-alone models and does not require the analysis to be conducted in one integrated system.

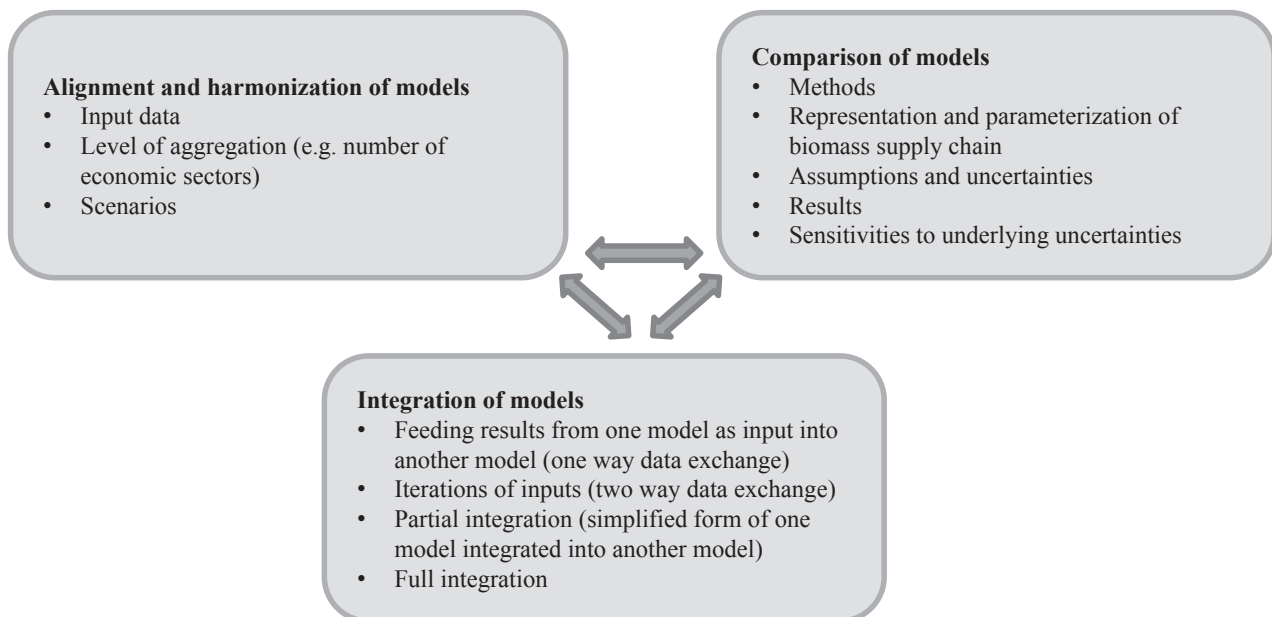


Fig. 1 Typology of model collaboration. Model collaboration can come in a number of forms, here three categories are distinguished: alignment and harmonization of models, comparison of models, and integration of models. Bullets present examples of how models can be aligned, harmonized, compared or linked. Each type of model collaboration can benefit from the others. For example, a basic alignment and harmonization of scenarios is needed to allow comparison of models, while a comparison or integration of models can identify the factors that require alignment.

An alternative distinction in linking models is often made between so-called soft links (models are connected exogenously by transferring the outcomes of scenario model runs from one component or model to another) and hard links (in which models exchange information and solve iteratively, so the solutions are internally consistent between models). Each type of link has its own advantages and disadvantages: hard links allow more consistent representation of the systems but increase complexity and reduce transparency, while soft links allow linking more components but data flows must be very carefully coordinated otherwise inconsistencies between models can either go unnoticed and not reported (Leimbach *et al.*, 2011).

Collaborations will not be ideal for every application. It is sometimes difficult to achieve full consistency or integration in assumptions, structure, solution algorithms, dynamics, and feedbacks. Also, since models are built around a certain paradigm (e.g., economic or engineering), especially hard-linking them may be methodologically inconsistent due to different use of definitions and semantics, and 'double-counting' some subsystems by representing them in both models in different ways. Although internal consistency may be essential for some applications, having internal consistency frequently implies a trade-off in terms of resolution (spatial, temporal, and structural), and/or computation. Furthermore, inconsistency may also arise when data exchanged between models is dependent on a set of criteria, which are not applied consistently across the models. Also, if one of the models produces poor results, the projections of the other model might be worse instead of better than stand-alone projections.

On the contrary, exchange of good data can improve coupled models. If the first of the coupled models is calibrated with real data, its outcomes are improved and might become more accurate than the input data that the second model uses when running independently. This is especially true when the first model, after it is calibrated, is used to project outcomes for future scenarios. This is because these are impossible to measure and are harder to estimate than present-day variables. The same applies for the exchange of information on uncertainty. Running the first of the coupled models stochastically, e.g., using Monte Carlo simulation (Verstegen *et al.*, 2012), provides the second model with confidence intervals for its input data. This information can be used for error propagation through the coupled models.

Key research areas that can benefit from model collaboration

We selected three key research areas from the list of open questions (Section 2.5) to illustrate how model

collaboration can provide additional ways for tackling some of the shortcomings and uncertainties in existing assessments of biomass supply, demand, and impacts: (i) developments in livestock production and impacts on land availability for bioenergy crop production, (ii) availability, use, and impacts of agricultural residues for energetic purposes, and (iii) GHG emissions from land-use change induced by bioenergy crop production. These areas are important for defining biomass resource availability and performance. The importance of each research area is explained in more detail in the following sections.

Given that there are many different types of bottom-up assessments and models (Section 2.3), in the following sections, we refer to the subtypes of bottom-up approaches (such as land-use allocation models or biophysical assessments) rather than using the more generic, overarching term of bottom-up assessment.

Developments in livestock production

Several studies have emphasized the importance of agricultural crop productivity (developments) for the assessment of biomass for energy or material purposes (Keeney & Hertel, 2009; Dornburg *et al.*, 2010; Mosnier *et al.*, 2013). But also livestock productivity (and its developments over time) is a key factor influencing the biomass resource availability. This is because much larger areas of land are needed for feed than for food crop production. Still, livestock has received much less attention than agricultural crops.

Several studies have shown that large areas of land can be freed through livestock management system transitions, particularly from a pasture- to a crop-based feeding system (Bouwman *et al.*, 2005; Smeets *et al.*, 2007; Lapola *et al.*, 2010; Martha *et al.*, 2012; Havlík *et al.*, 2013). Such changes will impact production costs, efficiency, animal welfare and the environment in different ways (also depending on the type of management applied), and conditions necessary for such changes are poorly studied. Also, where the intensification is likely to take place and what the impacts would be is not well understood. An improved analysis of developments in livestock production and their consequences for bioenergy would need to include two components. First, the understanding of current livestock system and the options for further intensification and its impacts need to be improved. This entails improvement of current assessments of pasture use and management (Robinson *et al.*, 2011). It also entails a spatially specific assessment of where and to what degree pasture productivity and/or livestock density can be increased, what the drivers are and what the environmental and socio-economic impacts of the intensification are (Neumann *et al.*, 2011).

Results from this analysis can be used, for example, to provide better information on the drivers of change in pasture productivity, and the relationship with prices.

Second, the representation of substitution between pasture- and crop-based feeding systems in existing model frameworks still needs to be improved because the current approaches do not guarantee that the energy and protein balances in animal feeding are satisfied (Stehfest *et al.*, 2013). This entails primarily more and improved bottom-up data on feed requirements, feed compositions and substitution possibilities between different types of feed. Some PE models have already incorporated a high level of detail on livestock system description (Havlík *et al.*, 2014), but it might be useful to apply their results to determine how changes in livestock production can be better modeled in the more aggregated CGE models. Applying these improvements also to CGE models or linking the PE to the CGE model, it becomes possible to (i) assess how increased pressure on land through bioenergy mandates affects the livestock sector and what the necessary conditions are under which changes in the livestock sector can minimize undesired LUC, and/or (ii) investigate the economy-wide impacts of bioenergy mandates under different livestock (productivity) development scenarios. Given variable impacts of the intensification of the livestock sector, additional environmental indicators based on bottom-up and biophysical models, such as GHG emissions, would also be needed to assess the full impact from pasture intensification and change in feeding systems.

Availability, use, and impacts of agricultural residues for energy purposes

Many studies have indicated that residues from agriculture and forestry activities form a significant part of the total primary biomass resource base and may play a crucial role in bioenergy supply (Smeets *et al.*, 2007; Dornburg *et al.*, 2010; Haberl *et al.*, 2010; Chum *et al.*, 2011). Residues are an attractive source of biomass since they are a by-product of other activities and are often considered underutilized. Thus, in principle, they do not require additional land use or interfere with the production of other commodities. Furthermore, IAMs have indicated the large deployment of residues in scenarios with large GHG emission reductions due to their assumed low costs and large supply (Rose *et al.*, 2013). The projected use of residues is based on a primary potential whose availability and low cost is assumed as a matter of fact. However, the potential sources, technical and economic aspects of supply, competition with other uses or services, and environmental impacts of residue removal (particularly of soil organic carbon levels

and soil erosion) are still not well understood (Schubert *et al.*, 2009; Dornburg *et al.*, 2010; Chum *et al.*, 2011; Kenney *et al.*, 2014). With different agricultural/forestry techniques or economic conditions, the fraction of residues available for a biobased economy without negatively affecting the environment and livelihood of communities is likely to vary (Haberl *et al.*, 2010). This leads to an inadequate and highly variable assessment of the technical, economic and sustainable potential of residues and, in turn, results in a large range of residue use in different studies.

Model collaboration for better assessing residue availability could take the following forms. Bottom-up, process-based technical assessments can identify and parameterize the factors that define residue removal rates under different climate conditions, crop or forest management systems [e.g., the combination of cover crops with residue removal (Pratt *et al.*, 2013)] and sustainability constraints. Biophysical models can use this information to determine the residue potential under different scenarios for these factors. Determining collection costs structures in bottom-up assessments [see e.g., Leal *et al.* (2013) for sugarcane residues in Brazil] and linking this with removal potentials from biophysical models allow calculating the economic residue potential (including cost-supply curves specified e.g., per region and per agro-ecological zone). Next, PE, CGE, and IAM models could assess the commodification and usage of residues from a systems perspective. This would include assessment of the impacts on agricultural and energy systems as well as the social/economic effects of their diversion from current uses. More specifically, in CGE or PE model application one could look into the potential effects of diverting residues to energetic uses, be it reduction in land requirement due to an apparent land-free resource, or expansion of land use due to commodification of residues. This can also help with the assessment of crop prices under a certain biofuel target, and the role residues can play in this setting. Output from this analysis (e.g., amount and types of residues that can be used economically, region of origin, and effects on fertilizer use and costs) can be fed into an IAM, which can then determine the broader, long-term implications for the sustainability of climate mitigation strategies of residue use for energetic purposes, including GHG emissions and nutrient and erosion dynamics. Combining environmental and economic assessments of large-scale residue use for energy, including different scenarios on residue removal restrictions, could thus give a more comprehensive picture of the effects of energetic use of residues than is currently available. In addition, the combination of different models as proposed here also allows assessing effects at multiple timeframes, with e.g., CGE models' main strength at

short- to medium-term and IAMs at long-term assessments (Section 2).

GHG emissions from land-use change

Land-use change induced by bioenergy feedstock production and associated GHG emissions have fueled a heated debate about the sustainability of bioenergy (Searchinger *et al.*, 2008). Several methodologies and models have been developed to explore LUC-related GHG emissions. Approaches based on CGE models have received much attention because they capture the intersectoral and inter-regional market linkages within an integrated economy (Section 2.1). This enables the assessment of shifts in production of commodities toward other regions as a result of the expansion of bioenergy production. However, the results of these modeling efforts entail large uncertainties related to the magnitude, type [referring to the conversion from one type of land use to another (e.g., forest to agriculture; grasslands to agriculture; or more detailed from one crop to another)], timing and location and therefore also the impacts of LUC (Yeh & Witcover, 2010; Wicke *et al.*, 2012).

Computable general equilibrium model estimates of LUC and related GHG emissions are heavily dependent on the assumptions on yield levels (how much land is required to meet the supply of commodities), land supply functions (how much land is available), conversion elasticities (how easily one type of land use is converted to another), and GHG emissions per conversion type. CGE models generally apply regional aggregates for land productivity, and are therefore not able to differentiate the yield response to less or more suitable biophysical conditions. Although for a given agro-ecological zone (AEZ) and country, the representation of average productivities of cropland and other land uses in CGE models might provide a reasonable estimate, more research is needed to assess how accurate these aggregates are for assessing LUC induced by bioenergy. The land availability in CGE models takes into account the land that is not suitable for agricultural land use and land that is excluded for conversion because of policy reasons (e.g., conservation). However, several categories of land that should be excluded may spatially overlap (e.g., a conservation area on steep slopes) which can be missed when assessing land availability in a statistical way. Despite recent refinements to differentiate conversion elasticities for different regions and types of LUC (Laborde & Valin, 2012; Taheripour & Tyner, 2013a), these models cannot account for the complex interactions driving LUC between social, economic and biophysical drivers (such as neighboring land use, access to infrastructure, distance to markets, and land suitability) operating at multiple temporal and spatial

scales and varying for different crops (Verburg *et al.*, 1999). Thus, the ability to project LUC from a sole economic driver, as is currently done in CGE models, may be limited (Plevin *et al.*, 2010).

Spatially disaggregated modeling of LUC (e.g., land-use allocation models based on cellular automata) are not only spatially but often also temporally more detailed than CGE models. These types of models are used to allocate the different land uses (including those for energy crop production) over time, applying several biophysical and socio-economic drivers. Given the spatial variation in biomass and soil carbon stocks, spatial and bottom-up models are in many ways better tools to assess the impacts of LUC on carbon stocks. The use of this type of model could result in drastically different land-use conversion patterns and related GHG emissions compared to models at spatially more aggregated levels (van der Hilst *et al.*, 2014; Yui & Yeh 2013). However, our understanding of the drivers of LUC and how they vary across time and space is still limited (Lambin *et al.*, 2001; Versteegen *et al.*, 2012). In addition, the finest spatial resolution is not always the best, as this depends on the scale of the modeled processes, and the properties and quality of the input data (Hengl, 2006; Kim, 2013). A potential solution is multi-scale modeling, which links models with different scales to account for feedbacks between different scales, for example the effect of global developments on local level impacts (e.g., Verburg & Veldkamp, 2004; Hellmann & Verburg, 2011).

Model collaboration of economic, land-use allocation and biophysical models and better integration of bottom-up information can help to reduce (some of) these shortcomings and uncertainties and could therefore improve the estimations of LUC-related GHG emissions. For example, the CGE and land-use allocation models could be compared in terms of land excluded from LUC, average yield levels, and average GHG emissions per type of land conversion. A next step could be to align and harmonize these key features in the models. Thereafter, a comparison could be made on the aggregated results of the models on amount and type of land-use change and the related GHG emissions. A more advanced way of model collaboration is the integration and iteration between models by exchanging data between CGE, land-use allocation, and process-based biophysical models and bottom-up assessments of economic performance. An illustration of how models can collaborate to achieve a more accurate estimation of biofuels-induced LUC and related emissions is depicted in Fig. 2. Such a modeling framework would also allow assessing how a limitation to carbon stock changes (such as a carbon policy) can affect LUC and its emissions.

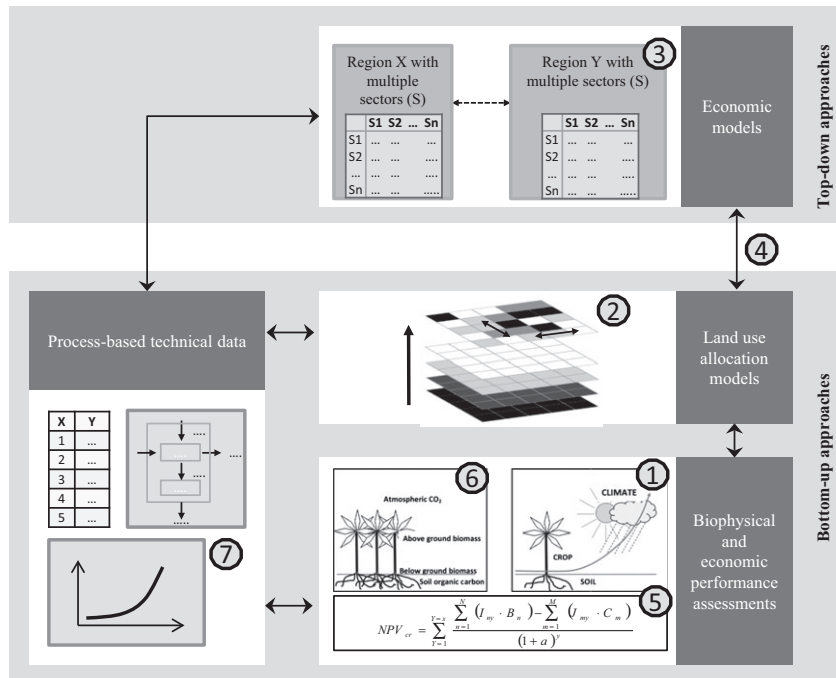


Fig. 2 Illustration of model integration for the assessment of GHG emissions from land-use change. Data exchange can occur in several ways. A crop growth model (1) can provide information on the spatial variation in yield levels. This information can be used in a land-use allocation model (2), as it is essential for calculating the amount of hectares required to meet the demand [which is derived from the CGE model (3)]. Iteration (4) between the land-use allocation model and the CGE model can be applied to harmonize the average yield level to account for crop productivity that changes for the specific land allocated for conversion. A bottom-up economic assessment (5) addressing the spatial variation in production costs could be used as an input for the land-use allocation model and for the CGE model to assess the competition between land uses in every location. Also, calculated prices from CGE models could be used as inputs to the land-use allocation model. A bottom-up model to calculate the change in carbon stocks (6) could be linked to a land-use allocation model. It could be used to exclude land with high-carbon stocks for land conversions, which determines the land availability in the land-use allocation model and the land asymptote in the CGE model. It could also be linked to the land-use allocation model, calculating the GHG emissions resulting from land-use change over time as demonstrated by van der Hilst *et al.* (2014). Process-based technical data and other bottom-up information (7), for example, on crop productivity, economic performance of land uses (cost-supply), transportation costs and GHG emissions related to the change in soil and biomass carbon emissions and costs of production and transportation, feed into various other models.

Conclusions

This article assesses model collaboration as one option for improved assessments of biomass supplies and their impacts. Existing modeling approaches adopt different perspectives (e.g., short term, long term; local, global; and economic, physical) and have unique applications and strengths. However, limitations specific to the modeling approaches exist, which are partly related to the type of tools and methods applied (e.g., partial representation of sectors, lack of geographical details, and aggregated representation of technologies involved). At the same time, key questions related to a biobased economy also remain to be answered in more comprehensive ways than has so far been possible. Model collaboration is an important method for addressing these limitations and open questions. For example, model comparison can reveal new insights into the drivers and

differences in results across approaches. However, model comparison may not always be sufficient in the case of major structural and technological change concerning the agricultural system, land use, and the economy. Model integration is taking collaboration between models a step further and can help provide more comprehensive insights into linkages, feedbacks and trade-offs between different systems and impacts (e.g., economic and natural). But ensuring consistency of data and methodology within models, and balancing the complexity of model integration, collaboration and validation on the one hand and credibility of results on the other hand are examples of key challenges for this type of work.

Given the different types of model collaboration and their opportunities and limitations outlined in this paper, for the specific question being asked, it must be evaluated if and in what form model collaboration is an

appropriate and useful tool. In those cases that full integration is considered useful, a key research challenge relates to developing these coupled models. Such coupled model systems most likely need to include functionality for disaggregation or aggregation of information (as socio-economic information might be presented at a different spatial and/or temporal resolution than, for instance, land use information). Tools to couple different models are under development, but using them in an effective way is still a challenge. First, there are quite some technical obstacles in coupling models from different disciplines as described in this paper. Second, modelers might want to reconsider how to best communicate their results of increasingly complex tools to policy-makers. This is especially important in the multifaceted and political debate about bioenergy. Now policy-makers are often confronted with seemingly contrasting results of different studies. At least partly, these differences originate from key assumptions made in the analysis regarding, for instance, society's ability to implement sustainability criteria. Only if modelers are successful in communicating how their results and assumptions fit into the larger picture, will they contribute to the debate and decision-making in a constructive manner.

Three examples of research areas that can benefit from model collaboration are presented in this paper (developments in the livestock production; availability, use and impacts of agricultural residues; and GHG emissions from land-use change) and show how this cooperation between models can strengthen our ability to project biomass supply, demand, and impacts. This in turn can aid in improving the information for policy-makers and in taking better-informed decisions. The examples also indicate that improved assessments necessitate (i) a better understanding of underlying processes to ensure proper representation of these processes in the models, (ii) increased calibration and validation of models to increase accuracy and reliability, and (iii) extended uncertainty analysis (including uncertainty propagation throughout the whole modeling chain) to identify and quantify the key input uncertainties, interpret the model results, and prioritize future research activities.

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