

Article

Global Land Use Impacts of Bioeconomy: An Econometric Input–Output Approach

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Abstract: Many countries have set ambiguous targets for the development of a bioeconomy that not only ensures sufficient production of high-quality foods but also contributes to decarbonization, green jobs and reducing import dependency through biofuels and advanced biomaterials. However, feeding a growing and increasingly affluent world population and providing additional biomass for a future bioeconomy all within planetary boundaries constitute an enormous challenge for achieving the Sustainable Development Goals (SDG). Global economic models mapping the complex network of global supply such as multiregional input–output (MRIO) or computable general equilibrium (CGE) models have been the workhorses to monitor the past as well as possible future impacts of the bioeconomy. These approaches, however, have often been criticized for their relatively low amount of detail on agriculture and energy, or for their lack of an empirical base for the specification of agents' economic behavior. In this paper, we address these issues and present a hybrid macro-econometric model that combines a comprehensive mapping of the world economy with highly detailed submodules of agriculture and the energy sector in physical units based on FAO and IEA data. We showcase the model in a case study on the future global impacts of the EU's bioeconomy transformation and find small positive economic impacts at the cost of a considerable increase in land use mostly outside of Europe.

Keywords: bioeconomy; global macro-econometric model; land use change; multiregional input–output



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1. Introduction

The bioeconomy (BE) is seen as an important way to promote sustainable development and achieve ambitious climate change goals [1,2]. Since COP26 in Glasgow, most major GHG-emitting countries have committed to becoming climate neutral by 2050 (EU, USA), 2060 (China, Russia) or 2070 at the latest (India). Several countries have developed policies to promote the development of the bioeconomy as a key building block for decarbonizing the economy and shifting to a renewable resource base while, at the same time, promoting jobs, innovation and economic competitiveness (see Dietz et al. [3] for a review). The International Energy Agency (IEA) sees huge potential in bioenergy, in particular for long-haul road transport, water transport and aviation, but does not expect substantial contributions to decarbonization from substituting fossil feedstocks in the chemical industry with biomass [4]. The EU, by contrast, emphasizes the substitution of plastic with bio-based materials in its plastic strategy and Circular Economy Action Plan, which is part of the Green Deal [5,6]. Schipfer et al. [7] found that up to 75% of fossil inputs of the EU's chemical industry could be substituted by 2050.

However, as a consequence of human biomass consumption, land use-related environmental impacts such as the loss of carbon stocks and biodiversity, over-nutrition and

freshwater withdrawal [8–11] already exceed planetary boundaries [12,13]. The amount of additional suitable and unprotected land is limited and increasingly threatened by climate change [14,15]. For this reason, the biomass demand of a large-scale expansion of bioenergy and advanced biomaterials together with the need to feed a growing and increasingly affluent world population is one of the challenges for reaching the global Sustainable Development Goals [16]. There are initial programs in place to develop monitoring frameworks for the bioeconomy transformation [17–20].

A major challenge for monitoring the environmental, economic and social impacts of the bioeconomy transformation as well as for policy design is that a substantial fraction of these impacts occur along increasingly complex global value chains [21]. Several accounting approaches have been developed to link the demand for biomass in one country to production and related environmental impacts in other countries via international trade flows. Global environmentally extended multiregional input–output models (EE-MRIO) rely on national accounts and bilateral trade data in monetary units with environmental metrics such as GHG emissions or agricultural land use. They provide a comprehensive mapping of the linkages between consumption and global environmental impacts scattered across the global supply chain network [22]. A major drawback, however, is that these frameworks typically offer only a low amount of detail in terms of agricultural products, energy carriers and, partly, e.g., in the case of using the EXIOBASE database, country coverage. Furthermore, accounting based on monetary values bears the risk of biased footprint results if price differences across different uses of a product are large, thus violating the homogenous price assumption [23]. Biophysical accounting methods based on the FAO's supply utilization accounts and bilateral trade in physical units, by contrast, are of a much higher product and country resolution, but at the cost of truncation errors, especially those of non-food use of biomass [24–26]. In recent years, hybrid accounting frameworks combining physical flows of biomass with monetary input–output relations have been developed by several authors with the objective to have the best from both worlds [27–30].

A similar trade-off can be observed for projection models used to assess the wider impacts of the future bioeconomy transformation under climate change scenarios. Partial equilibrium (PE) models such as GLOBIUM [31] or MagPie [32] offer a high amount of detail on underlying mechanisms that drive agricultural land use and land use change, but they do not take general equilibrium effects and feedback from the wider economy into account [33]. Taking this feedback into account is particularly important as non-food use of biomass is expected to tremendously increase in the future. Computable general equilibrium (CGE) models, by contrast, are based on the same data as EE-MRIOs and, thus, share their shortcomings when it comes to assessing impacts of the bioeconomy transformation [34–36]. As a consequence, many recent publications favor a combination of PE and CGE approaches such as MAGNET [37–39]. In recent years, a growing interest in simpler models allowing better transparency and traceability of the impacts of exogenous scenario parameters on impact results has been observed [33,40–42]. This development is also a response to criticisms of a lack of empirics in many CGE models. Their model parameters such as elasticities of substitution typically result from model calibration rather than econometric estimates [43].

In this paper, we combine a global macro-econometric input–output model (GINFORS-E) for mapping macro-economic developments and the evolution of global supply chain networks, with specific modules based on physical flows describing developments in critical sectors such as energy or agriculture in greater detail. This allows addressing two shortcomings. First, a major advantage of the econometric approach compared to CGE models is that behavioral parameters are empirically validated. Second, in contrast to PE models, macro-economic feedback mechanisms are accounted for. In the following, we describe the development of an econometric agriculture module mapping the consumption, trade, production and land use of 28 crops and livestock products and show how this new module interacts with both the economic core and an econometric energy module within the GINFORS-E framework. Our approach follows a similar philosophy to the hybrid

accounting approaches mentioned above in that commodity flows measured in physical and monetary units are linked within a combined modeling framework. Thereby, a key objective of our approach is to map all relevant economic channels based on empirical data while keeping the overall model transparent and traceable.

The remainder of this paper is organized as follows: Section 2 describes how agriculture is modeled in GINFORS-E (Section 2.1), how the demand for biomass is modeled (Section 2.2), how agriculture, production and trade interact with each other (Section 2.3) and, finally, how the feedback between GINFORS_E and the agriculture module works (Section 2.4). In Section 3, a case study is described with details of the scenario settings in Section 3.1 and general scenario specifications referring to the GINFORS-E model settings in Section 3.2. Section 4 provides results for land use (Section 4.1), GDP per capita and employment (Section 4.2) as well as production by production sectors (Section 4.3). Section 5 concludes the paper.

2. Materials and Methods

The assessment of the global environmental and economic impacts of the future development of the bioeconomy under climate scenarios was based on the Global Inter-Industry Forecasting System-Energy (GINFORS-E, [44]) linked to a newly developed global partial model of agricultural production, consumption and trade.

GINFORS-E is a global econometric input–output model covering 64 countries and one “Rest of World” region with 36 industries each. The model is designed for the assessment of economic, energy, climate and environmental policies up to the year 2050. The GINFORS-E modeling setup is shown in Figure 1 and consists of, first, the economic core, in which 64 country-specific macro and input–output models are linked via a world trade model, and, second, modules linked with the economic core providing further detail on sectors of high importance, such as energy and agriculture. The arrows show which variables in each model block are determined by another model block or which variables are entered as exogenous scenario parameters. The bioeconomy-related scenario parameters are marked gray and are explained in greater detail below. For example, sector prices are calculated in the input–output model. The aggregate price is entered into the macro model. In contrast, the final demand for the components private consumption, government consumption and investment is determined at the macro-economic level in the macro model and then allocated to the individual sectors in the input–output model.

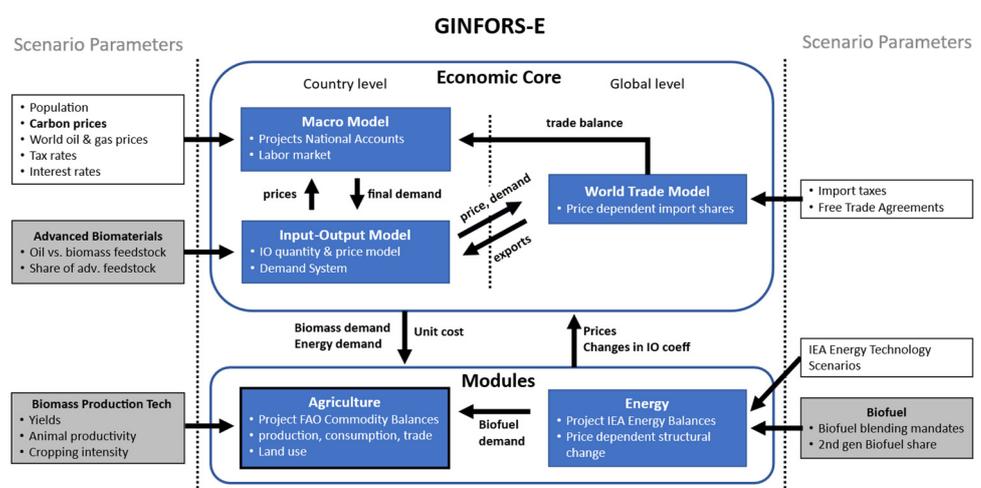


Figure 1. Model structure of GINFORS-E. Source: own elaboration.

GINFORS-E’s economic core is based on post-Keynesian economics, which means that markets, especially labor markets, are not assumed to be cleared [43]. It is assumed that economic agents have myopic expectations and follow past behavioral routines. Most

of the parameters of these behavioral equations are estimated econometrically based on time series data from Eurostat, OECD.Stat, the World Bank, the UN and IEA for 1990 up to 2018 [45–53]. As shown in Figure 1, each country model has two main components: (1) The macro model that projects, on the one hand, the main components of the consumption side of GDP (household and government spending, capital formation) and, on the other hand, labor supply and demand, as well as wage rates [54]. (2) Based on the growth paths of aggregate GDP components and the development of the labor market, the input–output core projects structural changes in the economies.

The economic core is linked to further modules that project satellite accounts in physical units, most notably the energy module that is based on IEA energy balances [52]. Demand for energy carriers is driven by economic activities of industries, households and the government in the economic core. The structural changes in energy generation (e.g., expansion of renewables) and consumption (e.g., shift to electric vehicles) of 18 energy carriers are modeled based on energy and carbon prices including assumptions on price dependency of clean technologies such as renewable energies and electric vehicles. For some technologies such as nuclear and renewable energy deployment, additional assumptions are made in line with the recent IEA Stated Policies Scenario [55]. This approach is typically used in E3 models [56,57] and has similarities to the way hybrid multiregional input–output models combine data in monetary and physical units, but without econometric specifications for the behavior of agents [28,29,58].

Almost all model variables are determined endogenously via identity or econometrically estimated behavioral equations. For this reason, GINFORS-E scenario runs are controlled by only few exogenous variables that drive the model. These are population growth and demographic changes, international energy prices, interest rates, exchange rates and tax rates, as well as monetary and non-monetary trade barriers. Additionally, further scenario-specific parameters are used to model energy and climate policy scenarios, in particular carbon prices, electric vehicle shares or expansion targets for renewables.

Thus far, GINFORS-E has been used for answering various research questions, such as for simulations of macro-economic impacts of different electricity price scenarios calculated for the German Ministry of Economic Affairs and Energy [59], economic impacts of different international climate regimes [60] and peak oil [61], or explicit modeling of learning curves for renewable energy technologies [62]. The model was also applied to inform the EU on the impacts of the GEAR 2030 strategy [63]. In a parallel research activity [64], the GINFORS-E model serves as a socioeconomic driver to inform a detailed material flow accounting model that uses EXIOBASE [65] as the main data source.

Therefore, the model is well suited for the projection of the drivers of the bioeconomy, such as the increased use of biofuels in transportation or the bioplastic/biomass substitute inputs based on crude oil as the feedstock. However, the model severely lacks detail on agriculture, which is represented by a single sector in the national IO tables. In the following, we develop a new partial model describing the production, consumption and trade of 20 crops and 8 animal products (see list in the appendix) in physical quantities and integrate it into the existing GINFORS-E modeling framework. The list of 20 crops resulted from the differentiation of aggregated items in FAO statistics (cereals, sugar crops, starchy roots, pulses, tree nuts, oil crops, vegetables, fruits, stimulants, spices, fiber crops) and added more details for those crops that are—from a global perspective—most relevant economy wise and land use wise. A similar approach for animal products resulted in a differentiation of four types of meat. In the following sections, we first discuss how the agriculture module conceptionally fits into the GINFORS-E framework. Afterwards, in Section 2.2, we discuss how demand quantities for agricultural products are derived by means of a hierarchical approach, followed by a discussion about how corresponding international trade, production and land use are modeled (Section 2.3). Finally, in Section 2.4, we describe the iterative solution process of the module and its interaction with the economic core and the energy module.

2.1. Modeling Agriculture within the GINFORS-E Framework

The newly developed agriculture module was built on the same theoretical background as the economic core of GINFORS-E. As shown in Figure 2, the agriculture module consists of two components. Firstly, the demand block derives demand quantities for 28 crops and livestock products from the intermediate and final consumption expenditures for food and agriculture in the IO core. Here, we distinguish the expenditures of households (H; food use), agriculture (1; feed and seed use) and the chemical and textile industries (6,9,10; other industrial use), which correspond to the utilization categories distinguished in the FAO's commodity balance sheets.

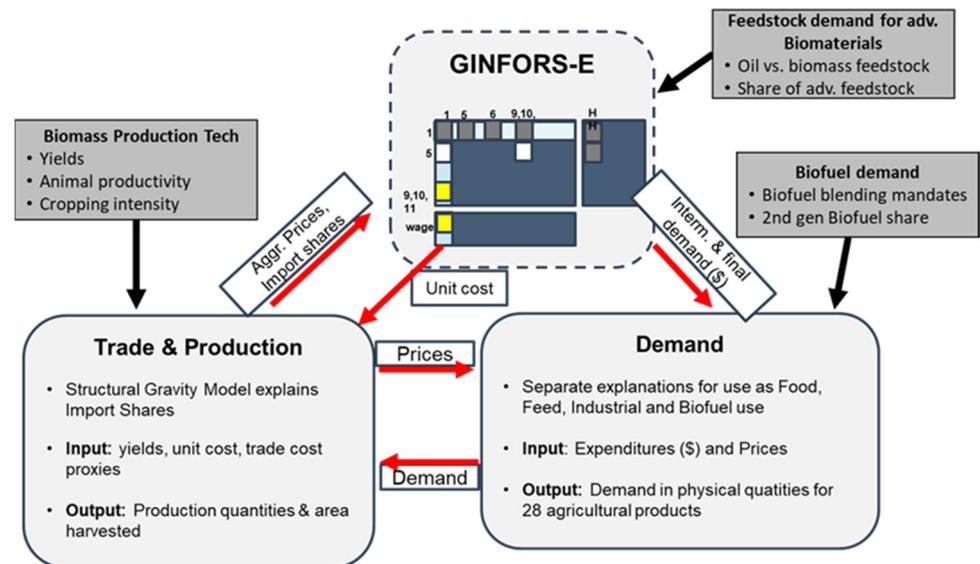


Figure 2. Components of the agriculture module and their interaction with GINFORS-E. Source: own elaboration.

The demand for biofuel feedstocks, by contrast, is driven by the demand for biofuels in caloric values modeled in the energy module. The second component of the agriculture module is the trade and production block. It takes the quantities from the demand block as an input and allocates them across producing countries via import shares, which depend on the exporter's competitiveness (measured by unit costs and yields) and trade cost between the origin and destination country. Afterwards, consumer prices and structural changes in agriculture markets are fed back into the IO core.

The IO core is, by itself, demand driven in that, first, aggregate GDP components are broken down into demand for products of the 36 industries. In the default case, the product structure of government spending as well as of capital formation remains fixed or is adjusted exogenously, depending on the scenario specifications. The product structure of household consumption, however, is based on the demand system from Muhammad et al. [66] and, therefore, depends on the development of income and relative prices (see Section 2.2). This is particularly important, as especially the budget share of food is expected to decrease considerably in many fast-growing emerging countries following Engel's law.

For a given vector of final demands, $\mathbf{y}^c(t)$ with the generic element $y_i^c(t)$ denoting the demand in country c for product i in year t , the total output required from industry j can be computed by the demand-driven quantity input–output model

$$\mathbf{x}^c(t) = \mathbf{L}^c(t) \mathbf{y}^c(t) = (\mathbf{I} - \mathbf{A}^c(t))^{-1} \mathbf{y}^c(t) \quad (1)$$

where $\mathbf{x}^c(t)$ denotes a vector of gross output by the industry in country c and year t and $\mathbf{L}^c(t) = (\mathbf{I} - \mathbf{A}^c(t))^{-1}$ is the Leontief inverse of country c and year t , with $\mathbf{A}^c(t)$ being a

matrix of technical coefficients showing the input required from industry i to produce a unit of output in industry j . Based on total output, value added, labor compensation and demand for domestic and imported intermediates are computed taking the cost structures of the industries into account [67]. The resulting final and intermediate demands for agricultural products then enter the demand side of the agriculture module.

Making use of the duality between the IO quantity and price models [68], the inter-industry relations are also used to determine how changes in unit cost of production, $uc_i^c(t)$, influence output prices, $p_i^c(t)$. It is assumed that the output price of an industry increases compared to the previous year with the same rate as the total unit cost of production. This is consistent with the assumption that profits per unit are given by a fixed markup on production costs. Using the input–output relations, we can express the total unit costs of production as a weighted average of the price changes of domestic inputs, imported inputs and labor, i.e.,

$$uc_j^c(t) = \sum_i a_{ij}^{cc} p_j^c + \sum_i a_{ij}^{rc} p_j^r + v_i^c wage_i^c, \quad (2)$$

where a_{ij}^{cc} and a_{ij}^{rc} denote the input requirements from industry i produced domestically (c) or abroad (r), respectively, per unit output of industry j in country c ; p_j^c and p_j^r denote the prices for domestic and imported intermediates, respectively; and v_i^c and $wage_i^c$ are the labor input requirements and the wage rate, respectively.

2.2. Modeling Household Consumption

Growth in household income affects consumption levels and patterns, depending on whether the good is normal, inferior or luxury. According to Engel's law, the share of food expenditure in total consumption decreases as income increases, as food is an inferior good [69]. This effect is of particular importance for studying the global development of food consumption across countries in the long run, as in many major economies, affluence is expected to increase tremendously up to 2050.

The relationship between private consumption patterns and changing income and relative prices is typically modeled using demand systems, which are simultaneous equation systems that explain how households allocate their budget to different consumption purposes. In GINFORS-E, final consumption expenditures of households are modeled by means of the Florida Demand System [70], which allows for flexible budget shares under changing income levels. We used the estimates from Muhammad et al. [66], which are based on cross-country data from the World Bank's International Comparison Program. These estimates, especially the income and own-price elasticities, have been widely used among researchers to parameterize global economic models, and particularly those models with a focus on modeling the global demand for food and agricultural products [15,33,41]. In the first stage, the demand system distinguishes nine different product groups, namely, food (1), clothing (2), housing (3), furnishings and appliances (4), health (5), transport (6), recreation (7), education (8) and other (9).

To capture the decline in income elasticities for food as income increases, Hertel et al. [33] and the FAO [15], among others, regressed per capita income on income elasticities and projected them into the future. Here, we took a different approach: we used the estimation equations of Muhammad et al. [66] in combination with the parameter estimates and projected the data, i.e., income and prices, directly into the future. The demand system has the following form:

$$w_i^c = (\alpha_i + \beta_i y^c) + (\alpha_i + \beta_i y^c) \left[\log \frac{p_i^c}{\bar{p}_i} - \sum_j (\alpha_j + \beta_j y^c) \log \frac{p_j^c}{\bar{p}_j} \right] + \phi (\alpha_i + \beta_i (1 + y^c)) \left[\log \frac{p_i^c}{\bar{p}_i} - \sum_j (\alpha_j + \beta_j (1 + y^c)) \log \frac{p_j^c}{\bar{p}_j} \right], \quad (3)$$

where w_i^c denotes the budget share of product group i in country c ; y^c denotes the log of per capita income; p_i^c denotes the price of product group i in country c ; \bar{p}_i denotes the global average price of i ; and α_i , β_j and ϕ_i are the estimated parameters. Index j is used to refer to prices of another product group. The first term in Equation (3) captures the linear effect of real income, the second quadratic term captures the pure price effect and, finally, the third cubic term captures the substitution effects.

The predicted budget shares for a country in a future year are used to compute total expenditures by product group. The budget shares are multiplied by total household expenditures and further broken down into the 36 products distinguished in the GINFORS-E IO core, assuming constant shares.

2.3. Modeling Demand for Biomass

In this section, we describe the estimation and projection of total domestic consumption of agricultural products in physical units, which is mainly based on the FAO's commodity balance sheets (CBSs). In each CBS, the utilization side consists of three main use categories, namely, food, feed and industrial use. From OECD/FAO data [71], it is possible to further split industrial use into biofuels and other industrial uses (e.g., feedstock for chemicals). Primary commodities that go into the production of another commodity (e.g., soybeans into vegetable oil) are captured in the category processing. To avoid too many units of measurement, we decided to express all physical flows of processed agricultural commodities (especially vegetable oil and sugar) as primary crop equivalents using the FAO's technical conversion factors [72].

As shown in Figure 3, the estimation and projection were carried out using a two-step approach: In the first stage, we modeled the consumption separately for aggregate agricultural commodities that share similar use characteristics, e.g., oil crops used for fodder. In the second stage, we modeled the substitutions between individual products in the aggregate category, e.g., soybeans versus rapeseed used as fodder.

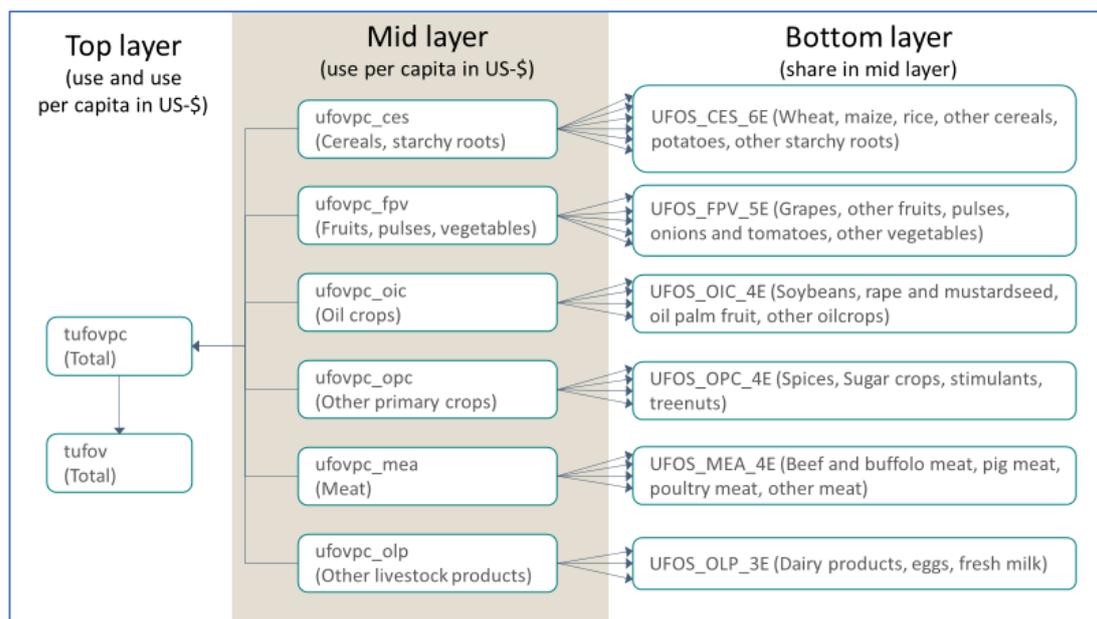


Figure 3. The system of food use explanation in GINFORS-E (BEST). Source: own elaboration.

In Stage 1, we distinguish 10 different aggregate product groups, as shown in Table 1. The first six aggregate categories comprise products that are (almost) exclusively used for human food consumption. These are basic food crops, fruits and vegetables, spices and stimulants, meat, milk and eggs. By contrast, feed and fodder crops, comprising maize and other cereals, are used for feeding animals, for human consumption and, to a much lesser extent, as a feedstock for biofuels. Oil crops and sugar crops show a highly mixed pattern with relatively high shares in all four use categories. Finally, fiber crops are only used by industries, especially the textile industry.

Table 1. Product groups and their assignment to aggregates, utilization categories and input–output (IO) components.

Aggregate (l')	Product Group (l)	Utilization (k)	IO Table Element (i)
Basic food crops	Wheat, rice, pulses, potatoes, other starchy roots	Food	Food industry and households
Fruits and vegetables	Grapes, other fruits, onions and tomatoes, other vegetables, nuts	Food	Food industry and households
Spices and stimulants	Spices and stimulants	Food	Food industry and households
Meat	Cattle and buffalo meat, pig meat, poultry meat, other meat	Food	Food industry and households
Milk	Milk	Food	Food industry and households
Eggs	Eggs	Food	Food industry and households
Feed and food crops	Maize, other cereals	Food, feed, other industrial use	Food industry and households, agriculture, chemicals
Oil crops	Soybeans, rapeseed and mustard seed, palm fruit oil, other oil crops	Food, feed, other industrial use	Food industry and households, agriculture, chemicals
Sugar crops	Sugar crops	Food, feed, other industrial use	Food industry and households, agriculture, chemicals
Fiber crops	Fiber crops	Other industrial use	Textiles

Source: own elaboration.

For each of the 16 combinations of aggregate product groups and utilizations (except biofuels), we fitted an econometric demand equation, where quantities demanded depend on total expenditures for agricultural products by the IO sector corresponding to the utilization, as well as on prices. In addition, we tested further explanatory variables in each equation, such as price–income interaction terms or share of pigs in a country’s animal herd for fodder demand. The final specifications included all that were found to be statistically significant and had the expected sign, i.e., negative for prices and positive for expenditures in monetary units. The demand equations were specified as follows:

$$u_{lk}^c(t) = \alpha_{lk} + \vartheta_{lk}^c + \beta_{lk} \log y_{lk}^c(t) + \gamma_{lk} \log p_l^c(t) + \tau \mathbf{X} + \varepsilon_{lk}^c(t), \quad (4)$$

where $u_{lk}^c(t)$ denotes the per capita consumption of aggregate product group l for utilization k in country c and year t ; $y_{lk}^c(t)$ denotes total expenditures for agricultural products by IO sectors belonging to utilization category k ; and $p_l^c(t)$ denotes the aggregate product group l in country c and year t . The matrix \mathbf{X} represents additional covariates that are used for specific categories, such as the number of pigs for estimating fodder demand, and α_{lk} , ϑ_{lk}^c , β_{lk} and γ_{lk} and τ are the coefficient to be estimated. The variables used in each demand equation and the estimation results are shown in Table S4 in the Supplementary Information. Overall, the goodness of fit measures show a strong statistical relationship between the demand quantities and the explanatory variables. The lowest R^2 is about 0.83 and found for feed use of oil seeds. For most combinations of aggregate commodity groups and utilizations, the R^2 's are greater than 0.9.

For the demand equations, we loosely followed Muhammad et al. [73] in using panel specifications to capture country-specific differences in traditions, tastes, etc. However,

unlike these authors, we did not include squared expenditures or price–expenditure interaction terms, as these were found to be either insignificant or to cause consistency issues in combination with other parameters (i.e., positive responses to price increases).

Thus, the per capita consumption quantities depend on relative prices, the intermediate and final expenditures on agricultural products from the IO core of the sectors corresponding to the utilization categories and further context-specific covariates. The growth in demand for biofuel feedstocks, by contrast, is assumed to be proportional to the demand for biofuels and directly linked with the energy module of GINFORS.

The expenditures of the IO sectors for agricultural products constitute one of the main links between the input–output core of GINFORS-E and the agriculture module. For the category food, the expenditures used in Equation (4) are the sum of households' final consumption and food industries' intermediate consumption of agricultural products. We chose this specification rather than the total of agriculture and food consumption of households, as it is closer to the raw crop equivalents used to measure the physical flows. For the utilization as feed, we used the within-sector intermediate transactions of agriculture, whereas for biofuels and other industrial uses of feed and food, and of oil and sugar crops, we used the intermediate consumption of agricultural products by the chemical industry. The consumption of fiber crops is mainly driven by the demands of the textile industry. The prices for each aggregate product group l are measured as dollars per ton and are computed as a weighted average of the price of domestic products derived from the FAO's production statistics and those of imports computed from the FAO's bilateral trade matrices, which are both available in weight and value.

In Stage 2, the consumption quantities of aggregate products in each utilization category $u_{lk}^c(t)$ are further broken down into consumption quantities of individual agricultural products $u_{lk}^c(t)$. For example, oil crops are broken down into soybeans, rapeseed and mustard seed, palm fruit oil and other oil crops. At this stage, we are particularly interested in capturing substitution possibilities between the different products within an aggregate group and how these depend on relative prices. As in Stage 1, the effect of relative prices was modeled econometrically, and we used separate panel specifications with country fixed effects for each combination of agricultural product and utilization.

The estimation equations are specified as

$$\frac{u_{lk}^c(t)}{u_{l'k}^c(t)} = \alpha_{lk} + \vartheta_{lk}^c + \gamma_{lk} \log\left(\frac{p_l^c(t)}{p_{l'}^c(t)}\right) + \varepsilon_{lk}^c(t), \quad (5)$$

where, on the left-hand side, we have the share of product l in the consumption quantity of aggregate product group l' by utilization category k in country c and year t and, on the right-hand side, we have the price per ton of product l relative to the average price of the aggregate product group. α_{lk} , ϑ_{lk}^c and γ_{lk} are coefficients to be estimated. The estimation results are shown in Table S3 in the Supplementary Information. We found strong statistically significant (at the 10% level) relationships between a product's share in the basket and the relative price, all of them also showing the expected negative sign. The R^2 's of at least 0.78 (found for soybeans) indicate a high goodness of fit.

For prediction of demands for future years, we use Equations (4) and (5) in combination with the covariates for the respective year from the GINFORS IO core. The shares from Equation (5) are then scaled such that they add up to one. As a last step, for each agricultural product, we compute total domestic use of product l in country c and year t , $d_l^c(t)$, as the sum of use quantities across utilization categories:

$$d_l^c(t) = \sum_k u_{lk}^c(t) \quad (6)$$

In the following section, we link these demands to production in the same or another country via bilateral trade flows.

2.4. Agricultural Production and Trade

Bilateral trade flows and production levels required to satisfy the domestic consumption quantities resulting from the previous section are derived from a structural gravity model [74]. In this model, bilateral trade flows between an exporting country r and an importing country c , t^{rc} are modeled as a function of total demand of the importer d^c , total supply of the exporter x^r and trade cost for shipping one unit of the product from country r to country c , φ^{rc} :

$$\pi^{rc} = G \frac{S^r D^c}{\Omega^r \Phi^c} \varphi^{rc} \quad (7)$$

where G is a constant, and Ω^r and Φ^c denote the multilateral resistance terms (MRTs) of the exporting and the importing country. The term φ^{rs} is typically a linear combination of variables that describe the bilateral (monetary and non-monetary) trade cost between each pair of two countries such as distance, common language, colonial ties or free trade agreements and can be interpreted as bilateral trade cost elasticities.

The MRTs take the form of

$$\Omega^r = \sum_{c \neq r} \frac{\varphi^{rc} d^c}{\Phi^c} \text{ and } \Phi^c = \sum_{r \neq c} \frac{\varphi^{rc} x^r}{\Omega^r}, \quad (8)$$

and describe the relative competitiveness of the exporter compared to all other exporting countries or the relative attractiveness of the importing country, respectively. They were introduced by Anderson and van Wincoop [74] in order to give the empirically successful classical gravity model of international trade a theoretical foundation that explains the spatial allocation of the importing countries' expenditures as well as the market clearing conditions for the exporters, arguing that their omission leads to omitted variable bias. For the estimation of model parameters, exporter and importer fixed effects are commonly used as proxies for the MRTs [75].

However, as Fally [75] pointed out, the use of exporter and importer fixed effects, though econometrically convenient, has a significant shortcoming, as they absorb the effects of other variables that apply to all sales of an exporting country (e.g., production cost) or to all purchases of an importing country (e.g., per capita income). This means that a two-step approach must be taken if the effects of supply-side productivity changes were to be taken into account, such as unit costs of agriculture as an endogenous variable from GINFORS-E's IO core, or yields as an exogenous scenario parameter [76,77]. In the first step, we estimated a gravity equation with importer-time and exporter-time fixed effects (FEs) for each agricultural product to distinguish between the effects of bilateral trade barriers and general characteristics of countries in their role as exporters or importers. Then, in the second step, we regressed yields and unit costs as productivity measures on the exporter FEs and total domestic consumption as a measure for market size (attractiveness) on the importer FEs.

In Stage 1, the gravity equation was specified as follows:

$$\pi_l^{rc}(t) = e f_l^r(t) i f_l^c(t) \exp \left\{ \theta_l^1 z1^{rc} + \theta_l^2 z2^{rc} + \theta_l^3 z3^{rc} \right\} \varepsilon_l^{rc}(t) \quad (9)$$

where $\pi_l^{rc}(t)$ denotes the quantity of product l produced in country r and consumed in country c in year t , and $e f_l^r(t)$ and $i f_l^c(t)$ denote exporter-time and importer-time fixed effects, respectively. In the third term, the log of the population-weighted distance between country r and country c , $z1^{rc}$, as well as dummies for common language, $z2^{rc}$, and intra-country trade, $z3^{rc}$, was used as a proxy for bilateral trade barriers. θ_l^1 , θ_l^2 , and θ_l^3 are the corresponding coefficients to be estimated. Data for the trade barrier proxies come from CEPII.

Note that we included within-country trade, i.e., domestic consumption, in our setup, which avoided a further nest for the consumers' choice between domestic products and imports. Domestic consumption for each product was computed as the difference between total supply (production quantity plus total imports) and total exports. For some countries

and products, this difference was negative, suggesting the existence of re-exports (export of imported goods). We corrected for this assuming that the import shares for exports were the same as for domestic consumption.

We followed the estimation strategy of Santos Silva and Tenreyro [78] and estimated Equation (9) in its multiplicative form using the Poisson pseudo-maximum likelihood estimator rather than using OLS on the log transformation. The main reason for this approach was that the log transformation would require omitting observations when two countries were not trading, which would lead to biased results. Since we estimated Equation (9) at the product level, the case of zero trade flows should be quite common.

The estimation results are shown in Table S4 in the Supplementary Information. As goodness of fit measures, we used McFadden's pseudo- R^2 . The results show a very high goodness of fit across all commodity groups. Whereas the coefficients for distance and the intra-country trade dummy all have the expected sign and are highly significant in all gravity equations (except for sugar crops, where all variables except fixed effects are insignificant), the dummy for common language is insignificant in the gravity equations for other rice, palm fruit oil, starchy roots, sugar crops and wool and silk. For wool and silk, we observed a negative sign for the effect of common language.

In Stage 2, we estimated the product-specific exporter–time and importer–time fixed effects, which measure the temporal development of the relative competitiveness of exporting countries, and the market attractiveness of importing countries. On the supply side, it was assumed that an exporter's relative competitiveness in the world market increases if yields in a country (or animal productivity) increase relative to the global average but decreases if unit costs of production increase. We followed Reimer and Li [77] and used the relative yields instead of absolute ones. The estimation equation is

$$ef_l^r(t) = \alpha + \beta yield_l^r(t) + \gamma uc^r(t) + \delta t + \varepsilon_l^r \quad (10)$$

where $yield_l^r(t)$ denotes the yield (tons per area harvested) or animal productivity (tons per herd size) of exporting country r and product l , and $uc^r(t)$ denotes the unit cost of the agriculture sector from the OECD's STAN database. We also included a linear time trend.

On the demand side, we regressed total demand by country and product on the importer–time fixed effects, assuming that market attractiveness increases with market size. The estimation equation is

$$if_l^c(t) = \alpha + \beta d_l^c(t) + \varepsilon_l^c \quad (11)$$

The estimation results for Equations (7) and (11) are shown in Tables S5 and S6 in the Supplementary Information. In the regression the exporter fixed effects (Equation (10)), we found that, as expected, relative yields have a positive effect on the exporter's competitiveness, while the effect of the unit costs of production is negative. Both estimates are significant at the 1% level, and the R^2 of about 0.9 shows a high goodness of fit. For the importer's market attractiveness, total demand quantities have a highly significant impact and explain about 88% (adj. $R^2 = 0.8763$) of the variance in the importer fixed effects.

2.5. Interaction between GINFORS-E and the Agriculture Module

GINFORS-E solves iteratively for each year, with ten within-year iterations. As shown in Figure 1, the agriculture module takes information demand for agricultural products and production costs from GINFORS-E and feeds back on consumer price indices and updated trade shares to GINFORS-E. Each iteration involves the following steps:

On the demand side:

1. Computation of new final and intermediate demands in monetary terms for agricultural products in each country using the projection from the demand system (Equation (1)) and the IO quantity model (Equation (2));
2. Computation of new total demand quantities for each crop and animal product using Equations (3)–(5);
3. Computation of the new importer–time fixed effects using Equation (11).

On the supply side:

4. Computation of unit costs using the IO price model;
5. Computation of new exporter–time fixed effects using Equation (10).

International trade:

6. Computation of new import shares using Equation (9), and production quantities using import shares and total demand quantities;
7. Computation of output prices for each crop and animal product by assuming that they change anti-proportionally with the exporter–time fixed effect $\Delta p_i^c = -\Delta e f_i^c$;
8. Computation of new consumer prices using import shares and output prices;
9. Return to Step 1 until the ten within-year iterations are completed and start with the next projection year until the end of the projection horizon is reached.

3. Case Study

As a first application of the new model, we considered comparatively simple scenarios to understand general impact mechanisms and inter-relationships. In this case study, we analyzed the impacts on cropland use, GDP and employment in two different scenarios: a “business as usual” scenario with rather low market penetration rates of biofuels and advanced biomaterials, and an alternative scenario, where market penetration rates were high. The specification of the main scenario variables is shown in Table 2.

3.1. Scenario Specifications for Bioeconomy

The bioeconomy scenarios were specified via three exogenous variables reflecting technological change on the supply and demand sides of the bioeconomy: firstly, on the supply side, the impacts of technological and climate change on yields and animal productivity; secondly, on the demand side, the share of biofuels in the transportation sector; and thirdly, the share of advanced biomaterials versus fossil-based materials in the chemical industry. The increased use of biomass in traditional applications, e.g., paper or construction, is not within the scope of this paper. Hence, our scenario results show the impacts on the use of cropland (area harvested) and GDP under the assumption that the respective exogenously set scenario pathways for these drivers are followed. Generally, the pathways may reflect policy targets or can be the outcome of another model. For this test case, we used outcomes from the FAO [15] and IEA scenarios [4], as well as from the literature [7].

Technological change in agriculture and climate change impacts on productivity were captured via yields or animal productivity, respectively. Future pathways for both variables were taken from the FAO [15] and are compound variables reflecting technological change, such as farming practices, as well as the impacts of climate change. For the reference scenario, we used the developments of yields and animal productivity from the FAO “business as usual” scenario, which assumes that yield improvements are limited in the future, as land degradation is only partially handled. On the other hand, the bioeconomy scenario takes the developments from the FAO’s “towards sustainability scenario”, where it is assumed that land degradation is stopped through sustainable farming practices.

Table 2. Specification of main scenario variables.

Variable/Country Group	Reference		Bioeconomy	
	2030	2040	2030	2040
Share of biofuels in road transport [%]				
Africa	3.17	4.99	9.01	19.39
Asia and Pacific	5.19	7.70	13.57	26.79
Brazil	22.95	25.32	36.14	45.57
China	3.26	5.28	10.11	23.93
Europe	6.78	9.75	13.64	30.37
India	5.58	7.89	12.44	24.01
North America	4.83	7.31	12.41	27.88
Russia	2.98	4.79	9.09	20.72
South America	6.97	9.22	14.41	27.59
Share of advanced biofuels in conventional biofuels [%]				
Africa	36.73	57.47	36.73	57.47
Asia and Pacific	36.73	57.47	36.73	57.47
Brazil	36.73	57.47	36.73	57.47
China	36.73	57.47	36.73	57.47
Europe	36.73	57.47	36.73	57.47
India	36.73	57.47	36.73	57.47
North America	36.73	57.47	36.73	57.47
Russia	36.73	57.47	36.73	57.47
South America	36.73	57.47	36.73	57.47
Share of biomass in the chemical industry [%]				
Europe	-	-	12.00	36.00
Share of advanced biomass to conventional biomass in chemical industry [%]				
Europe	-	-	36.73	57.47

Source: own elaboration, based on data from the IEA and Schipfer et al. (2017).

The biofuel settings were based on the Energy Technology Perspectives 2017 (ETP 2017) report of the IEA. We distinguished two main scenario variables: firstly, the blending share and, secondly, the market share of second-generation biofuels. Both determined the demand for fresh biomass inputs in the agriculture module. The ETP 2017 report considers three scenarios showing different energy technology and policy pathways until 2060: a baseline scenario (Reference Technology Scenario (RTS)), a central climate mitigation scenario (2 °C Scenario (2DS)) and a more ambitious climate mitigation scenario (Beyond 2 °C Scenario (B2DS)) [4]. For this case study, we used the RTS for the reference scenario and the B2DS for the bioeconomy scenario. The RTS includes countries' current ambitions and commitments to limit emissions and improve energy efficiency and requires significant policy and technology changes by 2060 and further subsequent emission cuts, resulting in an average temperature increase of 2.7 °C by 2100 [4]. This scenario can be interpreted as the most probable development under the status quo and was therefore integrated in the reference scenario. The B2DS attempts to estimate what would happen if known clean energy technologies were pushed to the limit to achieve carbon neutrality by 2060. The result is a 50% chance of limiting the average future temperature increase to 1.75 °C by 2100 [4]. The role of bioenergy in the transport sector is of major importance in this scenario. Biofuels decarbonize long-haul transport and complement the role of electrification

in short-haul transport applications. Furthermore, biofuel production is shifting towards advanced biofuels. The IEA provides scenario data for the following countries and country groups from 2025 to 2060: ASEAN, Brazil, China, the European Union, India, Mexico, Russia, South Africa and the United States, as well as OECD and non-OECD countries.

Similarly, the development of advanced biomaterials in the chemical industry was modeled via, firstly, the share of fossil feedstocks that were substituted by biomass feedstocks and, secondly, the share by which these feedstocks came from fresh biomass versus the use of advanced feedstocks. In Schipfer et al. [7], the authors identified five groups of chemical products where biomass can substitute fossil feedstocks to a large extent: these were surfactants and lubricants based on vegetable oil, plastics and solvents based on glucose from sugar or starchy crops and bio-bitumen based on lignin from wood. The first four product groups were integrated in the bioeconomy scenario setting. Bio-bitumen was not considered. More precisely, we assumed that the shares of fossil feedstocks substituted by biomass were 12% by 2030 and 36% by 2040 for all EU28 countries. These assumptions were in the range of the two scenarios in Schipfer et al. [7]. For the shares of advanced feedstocks, we assumed they are the same as for advanced biofuels.

3.2. Remaining Scenario Specifications for the GINFORS-E—Baseline

The bioeconomy development occurred within the broader GINFORS-E scenario framework, which reflected global population growth, economic development and climate policy. Assumptions for exogenous variables for the baseline stemmed from population projections. For the EU28 member states, the 2018 Ageing Report [79] was used. Developments of other countries including world totals were provided by the UN World Population Prospects 2019 [51]. Projections of international energy prices were taken from the IEA World Energy Outlook 2018 [80].

GDP development is endogenous in GINFORS-E. Developments were, however, calibrated to match long-term projections of economic development from the IEA [80]. For EU countries, projections from the 2020 EU [81] Reference Scenario were used. Calibration means that mainly gross fixed capital formation, which is modeled endogenously, is adjusted through a multiplicative adjustment so that GDP is close to the target values.

Regarding energy-related GHG emissions, we applied a baseline scenario with low ambition to mitigate climate change. The EU reached its old NDC target (−40% against 2005) with the policies in place. NDC targets from 2020 were also reached by major emitting countries and regions including China, India and Russia due to their low ambition. Climate protection efforts were not intensified after 2030.

4. Results

4.1. Agricultural Land Use

The bioeconomy scenario affected the land use of the country groups in three different ways: (1) an intensification of the already increasing area harvested, (2) a continuous decline in land use to a lesser extent and (3) an inversion of the declining trend. According to Figure 4, the first effect applies to the country groups Africa and Asia and Pacific. In 2040, the area harvested was 7 and 54% higher than in the reference scenario (for the numbers, see also Table S8 in the Supplementary Information). This means an extra need for 2 and 93 million hectares of land in 2040. The second effect could be observed for Europe, India and Russia. Even though the area harvested diminished as in the reference scenario, the area needed was 15, 6 and 2% higher in 2040, representing an increase of 14, 11 and 1 million hectares. The third effect was present for Brazil, China, North America and South America. Here, the declining demand for land in the reference scenario was more than offset in the bioeconomy scenario. In 2040, the area needed for harvesting crops was 19, 29, 24 and 53% larger than under the reference scenario. This corresponds to an increase of 10, 59, 26 and 13 million hectares in 2040.

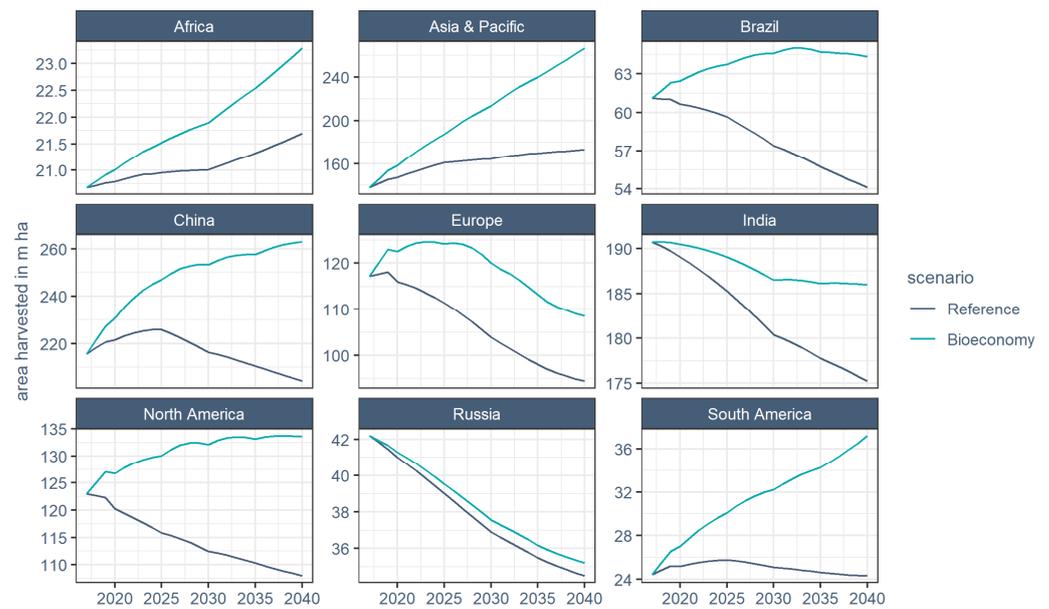


Figure 4. Area harvested for crops in million hectares in the reference and bioeconomy scenarios for 2017–2040. Comment: Due to data limitations, the country groups do not encompass all countries of the respective continent, e.g., Africa only consists of 3 out of 55 countries. The complete list of countries considered in the estimations can be found in Table S7. In general, a comparison with other model results is difficult and only possible to a very limited extent. Popp et al. [82] compared three models and their calculated impacts of bioeconomy production land use. The authors found that disparities in the projection of bioenergy cropland mostly resulted from plausible model assumptions regarding agricultural yields, economic growth, available technologies, etc. Additionally, the initial amount of land use in the base year can vary considerably depending on the data source, definitions and categorizations [82]. However, one important result was that “bioenergy croplands expands significantly” [82] (p. 504), supporting our scenario results.

The high increase in land use in the Asia and Pacific country group was mainly attributable to New Zealand, Malaysia, Korea and Indonesia: 285, 132, 85 and 69% more land was cultivated in the bioeconomy scenario compared to the reference. This additional land use added up to 74 million hectares, or 80% of the additional harvested area needed in the Asia and Pacific country group.

In total, an area of almost 1120 million hectares was cultivated in the bioeconomy setting in 2040. Compared to a total land use of less than 900 million hectares in the reference scenario, 300 additional million hectares were needed, or 26%.

The estimated percentage differences in land use for crops are considerably larger than those in Nong et al. [35], whose results suggest relative changes between -0.3 and 7.9% . However, Nong et al. [35] only focused on biochemical production. Including other components of the bioeconomy as in this study would most probably lead to higher percentage deviations in their study as well.

A comparison with ten different models conducted by Schmitz et al. [83] showed that cropland would increase by an average of 200 million ha between 2005 and 2050, although the individual results were subject to a very high range and could deviate from the mean by between -40 and $+100$ million ha. The high standard deviation was explained by the model structure and assumptions regarding trade, elasticities of substitution, available land restrictions, substitution possibilities, bioeconomy, climate change and socioeconomic developments [83]. A direct comparison with the results is not possible for several reasons: The cropland 2005 reference value in Schmitz et al. of about 1500 million hectares represented physical area. The land values used here were measured in harvested area and had a value of about 1250 million hectares in 2005. For the projection, we excluded the “Rest of the World” aggregate, which reduced the value for 2005 to 904 million hectares. Until 2040,

the area harvested in our model remained almost stable in the reference (-1.5% 2005–2040). In the bioeconomy scenario, land use increased by 24% between 2005 and 2040. In Schmitz et al. [83], the land use values of 2040 showed a broad range of behavior including decreasing and stable. Thus, the findings of Schmitz et al. [83] at least support the plausibility of our results.

The additional hectares in the bioeconomy scenario are not equally needed for different groups of crops. As can be seen in the additional charts in Figures S1–S3 in the Supplementary Information, the area harvested with sugar plants only showed comparably minor changes in land use between the reference and the bioeconomy scenario. The absolute differences were below one million hectares for all countries. The only exception was the country group Asia and Pacific, with a maximum difference of 6 million hectares in 2040. Compared to that, the differences in area harvested for grains and oleiferous fruits yielded much higher effects, with mean values of about 6 million hectares. Again, the results could be split into two different cases: while Asia and Pacific, Europe and South America showed high absolute differences for oleiferous fruits, in China and North America, the absolute effects were particularly high for grains.

4.2. GDP per Capita and Total Employment

The higher need for land and the increase in harvesting activities do not necessarily translate into additional growth for a country group. Nevertheless, some countries would profit from a change towards a bioeconomy: Asia and Pacific, North America, South America and Europe would have a higher GDP per capita in a bioeconomic world; in 2030, the GDP per capita in these country groups would be between 0.1 and 0.4% higher than in the reference scenario (see Figure 5 and Table S9 in the Supplementary Information). In 2040, the positive difference even increased for Asia and Pacific, North America and Europe, reaching 1, 0.4 and 0.1%. For South America, the percentage difference between the reference and the bioeconomy scenario remained at 0.3% between both years. In China, the bioeconomy only developed positive effects at a late stage: In 2030, there was almost no difference in GDP per capita between the reference and the bioeconomy scenario. In 2040, however, the GDP per capita was 0.1% higher with a bioeconomic structure in China.

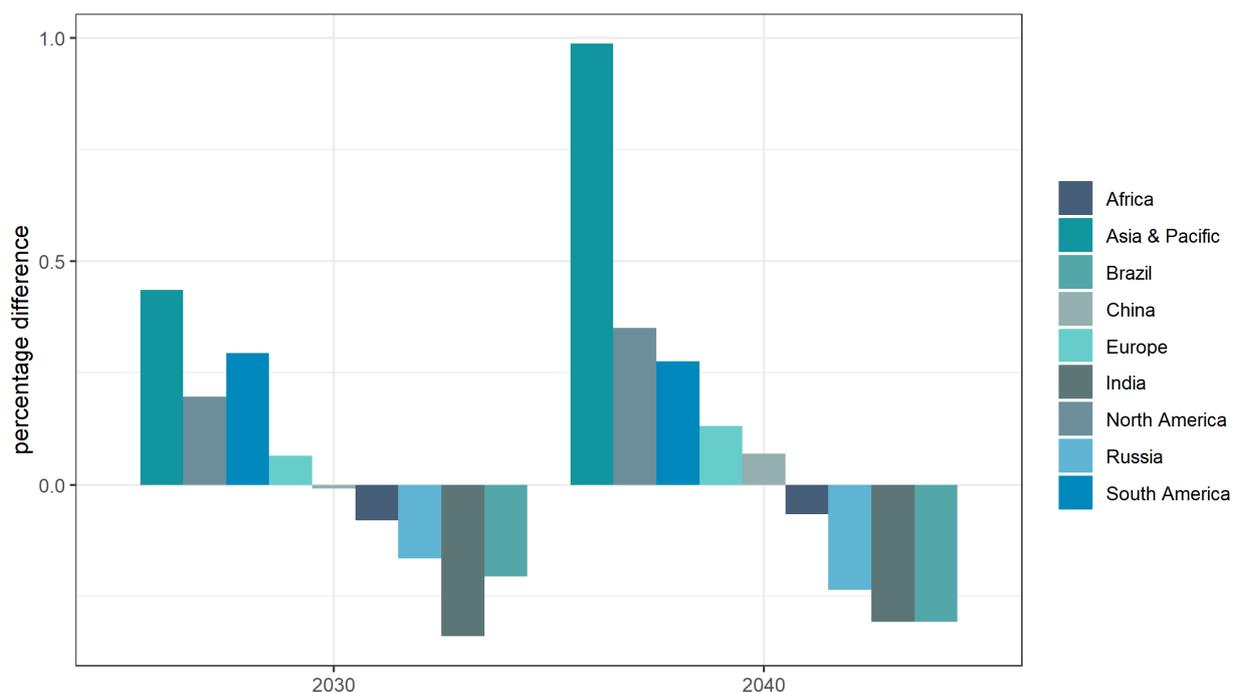


Figure 5. Percentage difference in real GDP per capita between the reference scenario and the bioeconomy scenario in 2030 and 2040. Source: own calculation and figure.

Africa, Russia, India and Brazil would be worse off in a bioeconomic world in terms of GDP per capita. In 2030, their GDP per capita was 0.1 to 0.3% lower than in the reference scenario. The range of the negative percentage difference does not change until 2040, i.e., it remained between 0.1 and 0.3%, even if the negative difference in GDP per capita became somewhat larger for Russia and Brazil.

The magnitudes of the percentage differences are similar to the scenario outcomes published by Nong et al. [35]. In their study, the percentage difference varied between -0.3 and 0.4% . The results only differ at the country level. In contrast to the findings at hand, Nong et al. [35] found a (very low) negative percentage deviation from the reference scenario for the European countries, the North American countries and China. The reverse applies to Africa, being positively affected in Nong et al. [35].

The level and direction of the differences in total employment displayed in Figure 6 corresponded, in most parts, to the results for GDP per capita. The relative differences were slightly smaller, but the composition of the groups with positive and negative effects stayed the same.

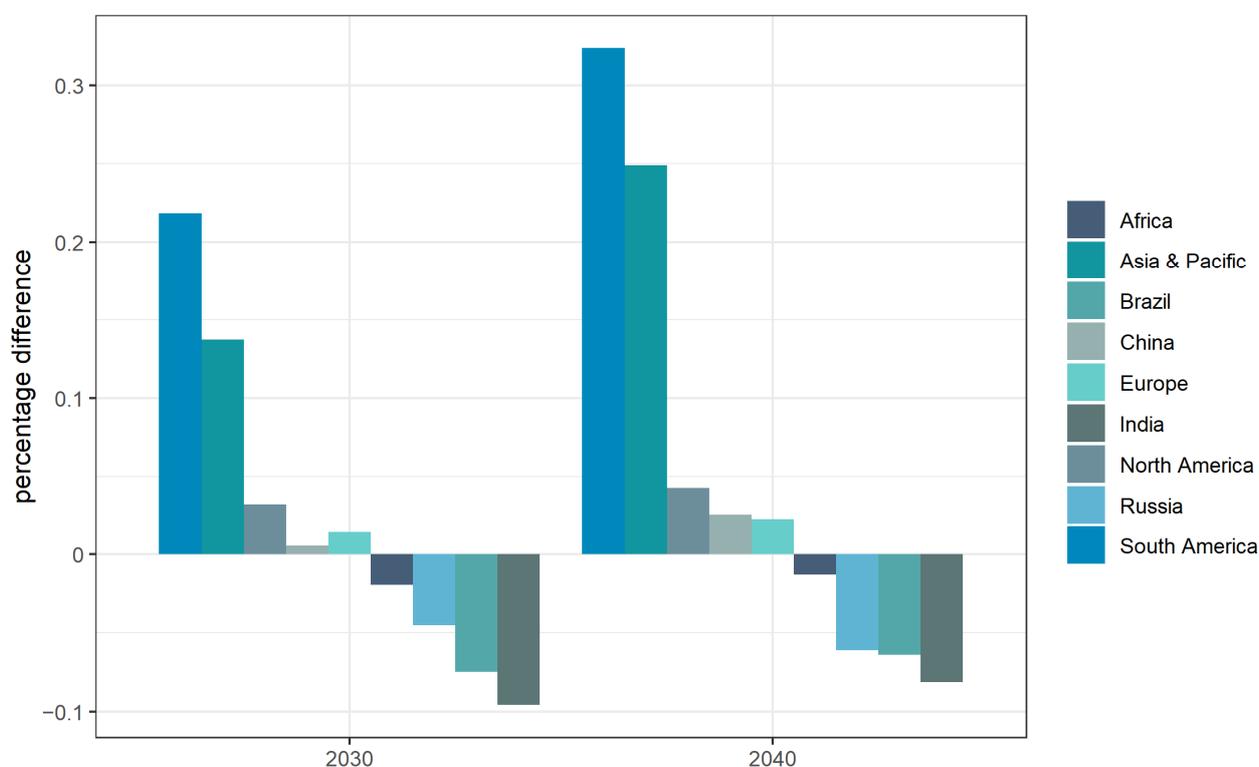


Figure 6. Percentage difference in total employment between the reference scenario and the bioeconomy scenario in 2030 and 2040. Source: own calculation and figure.

4.3. Production by Production Sectors

The reason for the partly negative effects in GDP per capita and employment lies in the different country-specific production structures, the composition of intermediate demand, import shares, price elasticities and feedback effects between the production sectors.

Figure 7 shows the effect of the bioeconomy relative to the reference for different production sectors. In general, the total effects were larger in 2040 than in 2030. Sectors not directly affected by the bioeconomy were aggregated to “other industries” and “other services”. These sectors displayed only minor changes in production output in all country groups, with less than 0.4% on average (more details can be found in Table S10 in the Supplementary Information).

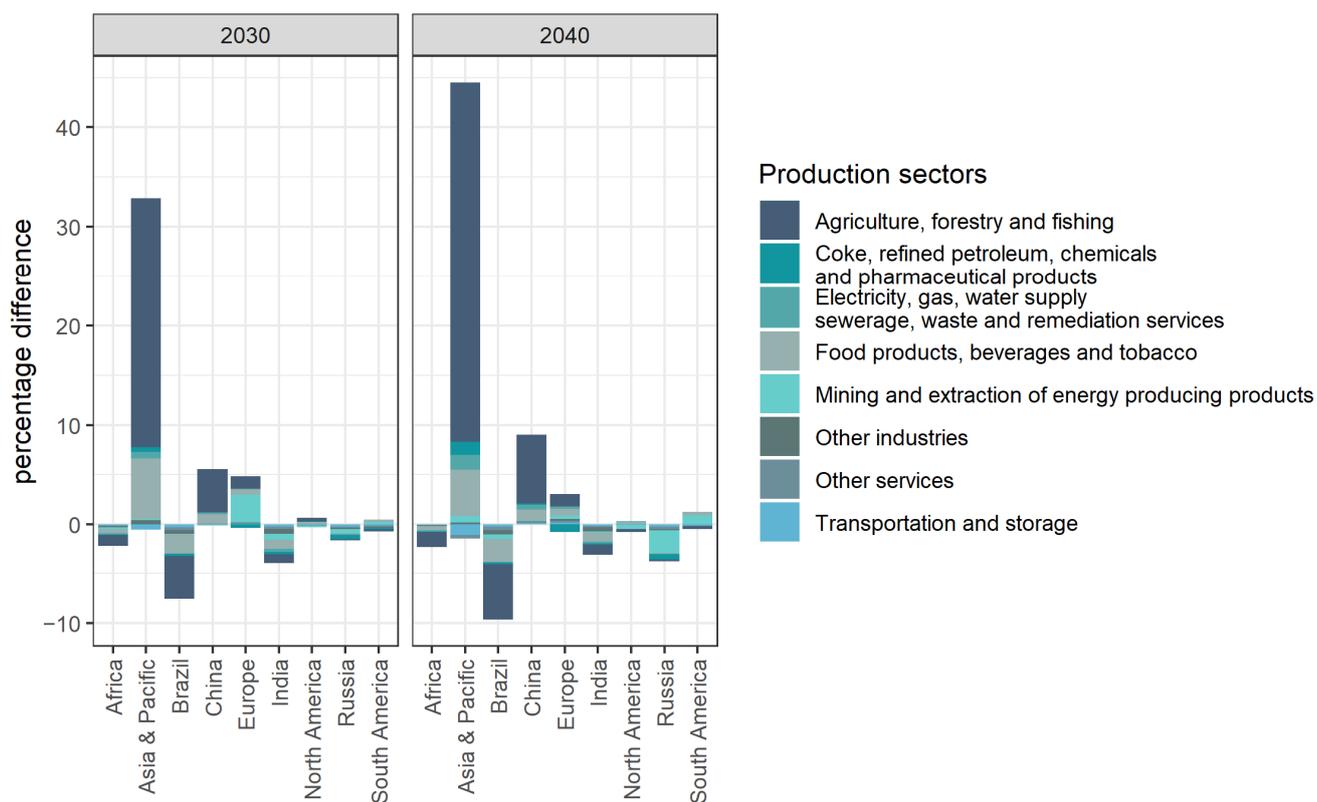


Figure 7. Percentage difference in production between the reference scenario and the bioeconomy scenario in 2030 and 2040. Source: own calculation and figure.

The highest percentage differences between the reference and bioeconomy scenarios could be found for the production sector “Agriculture, forestry and fishing” due to the higher demand for these products. In total, in the bioeconomy scenario, production was 25% (2030) and 36% (2040) higher than in the reference scenario. The output increased in a bioeconomy setting in Asia and Pacific, China and Europe, whereas Africa, Brazil and India produced less output. The production in North America, Russia and South America stayed almost unaffected with deviations of less than 1%.

Related to this, the food industry represented by “Food products, beverages and tobacco”, as a downstream sector with a high degree of interdependence with “Agriculture, forestry and fishing”, also showed corresponding deviations (at a lower level) in production. In 2030, the total percentage deviation summed up to 6%, and in 2040, to 5%. The highest relative differences between the scenarios could be found for Asia and Pacific (6% in 2030 and 5% in 2040) and Brazil (−2% in 2030 and 2040).

Production in the sector “Mining and extraction of energy producing products” was, in total, 0.2% higher in 2030 and 0.1% lower in 2040. At the country level, the effects had a range of −1% (India) to 3% (Europe) in 2030 and −2% (Russia) to 1% (South America) in 2040.

The remaining production sectors “Coke, refined petroleum, chemicals and pharmaceutical products”, “Electricity, gas, water supply, sewerage, waste and remediation services” and “Transportation and storage” showed only minor changes in production compared with the reference scenario, both overall and for most country groups, with values of up to 1%. An exception was Asia and Pacific, where the bioeconomy had notable (positive and negative) effects between 1 and 2% on the aforementioned production sectors. Additionally, effects of −1% in 2040 could be found for Europe in the production of “Coke, refined petroleum, chemicals and pharmaceutical products”, which are partly substituted by biomass.

4.4. Discussion of the Results

The estimated increase in agricultural land use will have a considerable impact on biodiversity, biogeochemistry, biogeophysics and ecosystem functioning [84]. According to Usubiaga-Liaño et al. [85], the findings of other studies suggest that the maximum allowable area of cropland is 13 to 15% of the terrestrial area. Their more pessimistic results suggest much lower admissible values. With a current value of 12% [85,86], there is little scope left. Dinerstein et al. [87] even came to a more rigid conclusion that at least half of the global natural habitat needs to be conserved to guarantee biodiversity and a resilient climate. Though the effects of less biodiversity could not be considered in the model, the increasing demand for harvested area in the bioeconomy scenario already suggests massive drops in biodiversity with the associated consequences for ecosystem functioning.

However, Heck et al. [86] showed that a cropland of 2000 Mha combined with low carbon losses and a low risk to biodiversity can be achieved under certain conditions, such as a massive reduction in grazing land and abandoning of crop and pasture land in tropical and boreal zones. In the bioeconomy scenario at hand, the harvested land summed up to 1300 Mha. Thus, consequent policy interventions complementing the transition towards a bioeconomy could prevent losses in biodiversity.

Put differently, our results suggest that based on biofuels and advanced biomaterials, the goals of decarbonization, green job creation and reduced import dependence can only be achieved at the expense of increased land use, especially in Brazil, China and North and South America. Without additional policy measures, this would mean the destruction of valuable land areas such as the Amazon Forest. Thus, in order to achieve the optimal result suggested by [86], far-reaching international coordination is necessary, which can certainly be viewed skeptically. Against this background, the bioeconomy scenario must be evaluated quite critically. In particular, the economic benefits in terms of GDP growth are quite low in almost all countries, while, at the same time, the expansion of the bioeconomy leads to a strong increase in cropland use and associated environmental impacts. In regions and countries such as Asia and China, the bioeconomy promotes the expansion of the agricultural sector and thus tends to inhibit the country's progressive development. In other words, these countries are making little economic progress with the bioeconomy, as they primarily remain biomass producers but need significantly more land than before to satisfy the additional demand from other countries, and, to a large extent, are endangering their ecosystems.

Although not explicitly modeled, the results also provide evidence of a possible conflict with the achievement of the Sustainable Development Goals (SDG) against the background of the resource nexus. As land is addressed in SDG 7 (affordable and clean energy), SDG 2 (zero hunger), SDG 11 (sustainable cities and communities) and SDG 13 (climate action) [88], the high increase in land use for energy in the scenario outcomes suggests an aggravating competition for land if natural habitat should not be transformed into agricultural land.

5. Conclusions

In this paper, we presented a hybrid approach to model the global environmental and economic impacts of the future transformation of the bioeconomy under climate mitigation scenarios. Similar to hybrid accounting models that simultaneously map commodity flows in physical and monetary units, our approach aims at combining the comprehensiveness of global economic models, such as CGE or econometric input–output models, with the high degree of detail in the mapping of agricultural consumption, trade, production and land use typical for partial equilibrium models. The integration of the agriculture module into a broader multisectoral economic model is implemented in the Global Inter-Industry Forecasting System-Energy (GINFORS-E). The GINFORS-E already features a detailed energy module based on IEA energy balances, which makes the overall system ideal for projecting the future biomass demand of increased bioenergy and biochemical production.

Nonetheless, the approach presented here is generally applicable to a broad range of multisectoral global models.

One of the main advantages of the agricultural module developed here and its integration in the GINFORS-E is the parsimonious and transparent specification of scenarios for the bioeconomy transformation. This was achieved by focusing on the future development of four key variables, namely, (1) the share of biofuels in total fuel consumption for transportation, (2) the share of fossil feedstocks in chemicals replaced by biomass, (3) the share of fresh biomass through which these additional demands are satisfied and (4) yields and animal productivity determining the market share of a country in the global market for agricultural products.

Finally, we showcased these features in a scenario experiment, where we assessed the impacts of a rapid expansion of biofuel and biochemical production in the EU27 on global land use, GDP, employment and production by industries. Our findings suggest that, while the impacts on GDP and employment are positive for the EU, its increased biomass demand would lead to a tremendous increase in agricultural land use outside of Europe, especially in Latin America and the Asia-Pacific region. Although not directly comparable due to differences in the scenario settings, our results are essentially in line with those of other authors (e.g., Nong et al. [35]) who found that savings in GHG emissions from substituting fossil feedstocks with biomass in industry would be more than offset by land use- and land use change-related emissions. Certainly, appropriate scenarios can be refined in the future, and appropriate policies should be considered that limit land use and reduce GHG emissions. In this respect, it is important to warn against making too great demands on the bioeconomy from a silo perspective. The limits of the bioeconomy must be considered holistically. The bioeconomy will have to be prioritized in the face of limited land also in other parts of the world and will not be able to serve all demands.

As mentioned in Section 3, the estimated scenario was a first case study to test the model behavior. The results therefore show the implications of a bioeconomy without any further policy measures and stress the need for additional policy interventions when the bioeconomy is pursued as a decarbonization strategy.

For future research, we aim at increasing the scope of more models in two directions: Firstly, we aim to add modules for forestry as well as fisheries and aquaculture, in order to cover a wider range of biomass applications and impacts. Secondly, the model results will be evaluated in more detail with respect to the SDGs, to the extent that they are quantified in the model. This would make it easier to identify synergies and trade-offs between different policy measures and objectives. The absolute planetary boundaries make it necessary for institutions and stakeholders to better coordinate their goals with regard to limited biomass in order to prevent the shifting of burdens from one policy area to another. For future research, model comparisons on a set of common bioeconomy scenarios represent an important undertaking for finding common ground across different model philosophies and identifying best practices. In particular, the impact of assumptions about the economic behavior of agents and market imperfections on the scenario outcomes has already been identified as critical in other contexts (see [43]) (Table S1).

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su14041976/s1>. Table S1: Crops and livestock products distinguished in the agriculture module. Table S2: Mid-layer coefficients of the agriculture module. Table S3: Bottom-layer coefficients of the agriculture module. Table S4: Estimation results of the structural gravity model. Table S5: Estimation results of the exporter fixed effects. Table S6: Estimation results of the importer fixed effects. Table S7: List of countries and country groups used in the model. Table S8: Area harvested for crops in million hectares for 2017 and 2040 (including absolute and relative differences between the bioeconomy and reference scenarios). Table S9: GDP per capita for 2017, 2030 and 2040 (including absolute and relative differences between bioeconomy and reference scenarios). Table S10: Percentage difference between the bioeconomy and reference scenarios for 2030 and 2040 for different aggregate production sectors and country groups. Figure S1: Absolute difference in area harvested for sugar between the reference and bio-economy scenarios in million

hectares. Figure S2: Absolute difference in area harvested for oleiferous fruits between the reference and bioeconomy scenarios in million hectares. Figure S3. Absolute difference in area harvested for grains between the reference and bioeconomy scenarios in million hectares.

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References

1. De Besi, M.; McCormick, K. Towards a Bioeconomy in Europe: National, Regional and Industrial Strategies. *Sustainability* **2015**, *7*, 10461. [[CrossRef](#)]
2. Meyer, R. Bioeconomy Strategies: Contexts, Visions, Guiding Implementation Principles and Resulting Debates. *Sustainability* **2017**, *9*, 1031. [[CrossRef](#)]
3. Dietz, T.; Börner, J.; Förster, J.; von Braun, J. Governance of the Bioeconomy: A Global Comparative Study of National Bioeconomy Strategies. *Sustainability* **2018**, *10*, 3190. [[CrossRef](#)]
4. IEA. *Energy Technology Perspectives 2017*; IEA: Paris, France, 2017. [[CrossRef](#)]
5. European Commission. *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of The Regions: A European Strategy for Plastics in a Circular Economy, COM (2018) 28 Final*; European Commission: Brussels, Belgium, 2018.
6. European Commission. *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: A New Circular Economy Action Plan for a Cleaner and More Competitive Europe, COM (2020) 98 Final*; European Commission: Brussels, Belgium, 2020.
7. Schipfer, F.; Kranzl, L.; Leclère, D.; Sylvain, L.; Forsell, N.; Valin, H. Advanced biomaterials scenarios for the EU28 up to 2050 and their respective biomass demand. *Biomass Bioenergy* **2017**, *96*, 19–27. [[CrossRef](#)]
8. Mekonnen, M.M.; Hoekstra, A.Y. The green, blue and grey water footprint of crops and derived crop products. *Hydrol. Earth Syst. Sci.* **2011**, *15*, 1577–1600. [[CrossRef](#)]
9. Bouwman, L.; Goldewijk, K.K.; van der Hoek, K.W.; Beusen, A.H.W.; van Vuuren, D.P.; Willems, J.; Rufino, M.C.; Stehfest, E. Exploring global changes in nitrogen and phosphorus cycles in agriculture induced by livestock production over the 1900–2050 period. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 20882–20887. [[CrossRef](#)]
10. Tilman, D.; Clark, M. Global diets link environmental sustainability and human health. *Nature* **2014**, *515*, 518–522. [[CrossRef](#)]
11. Poore, J.; Nemecek, T. Reducing food's environmental impacts through producers and consumers. *Science* **2018**, *360*, 987–992. [[CrossRef](#)]
12. Rockström, J.; Steffen, W.; Noone, K.; Persson, Å.; Chapin, F.S., III; Lambin, E.; Lenton, T.M.; Scheffer, M.; Folke, C.; Schellnhuber, H.; et al. Planetary boundaries: Exploring the safe operating space for humanity. *Ecol. Soc.* **2009**, *14*, 32. [[CrossRef](#)]
13. Steffen, W.; Richardson, K.; Rockström, J.; Cornell, S.E.; Fetzer, I.; Bennett, E.M.; Biggs, R.; Carpenter, S.R.; de Vries, W.; de Wit, C.A.; et al. Sustainability. Planetary boundaries: Guiding human development on a changing planet. *Science* **2015**, *347*, 1259855. [[CrossRef](#)]
14. Lambin, E.F.; Meyfroidt, P. Global land use change, economic globalization, and the looming land scarcity. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 3465–3472. [[CrossRef](#)] [[PubMed](#)]
15. FAO. *The Future of Food and Agriculture—Alternative Pathways to 2050*; FAO: Rome, Italy, 2018.
16. Philippidis, G.; Shutes, L.; M'Barek, R.; Ronzon, T.; Tabeau, A.; van Meijl, H. Snakes and ladders: World development pathways' synergies and trade-offs through the lens of the Sustainable Development Goals. *J. Clean. Prod.* **2020**, *267*, 122147. [[CrossRef](#)] [[PubMed](#)]
17. Bringezu, S.; Distelkamp, M.; Lutz, C.; Wimmer, F.; Schaldach, R.; Hennenberg, K.J.; Böttcher, H.; Egenolf, V. Environmental and socioeconomic footprints of the German bioeconomy. *Nat. Sustain.* **2021**, *4*, 775–783. [[CrossRef](#)]

18. Ronzon, T.; Piotrowski, S.; M'Barek, R.; Carus, M.; Tamošiūnas, S. Jobs and Wealth in the EU Bioeconomy/JRC-Bioeconomics. European Commission, Joint Research Centre (JRC). 2020. Available online: <http://data.europa.eu/89h/7d7d5481-2d02-4b36-8e79-697b04fa4278> (accessed on 29 November 2021).
19. Lier, M.; Aarne, M.; Kärkkäinen, L.; Korhonen, K.T.; Yli-Viikari, A.; Packalen, T. *Synthesis on Bioeconomy Monitoring Systems in the EU Member States—Indicators for Monitoring the Progress of Bioeconomy*; Natural Resources Institute Finland: Helsinki, Finland, 2018.
20. Robert, N.; Giuntoli, J.; Araujo, R.; Avraamides, M.; Balzi, E.; Barredo, J.I.; Baruth, B.; Becker, W.; Borzacchiello, M.T.; Bulgheroni, C.; et al. Development of a bioeconomy monitoring framework for the European Union: An integrative and collaborative approach. *New Biotechnol.* **2020**, *59*, 10–19. [[CrossRef](#)] [[PubMed](#)]
21. Ronzon, T.; Sanjuán, A.I. Friends or foes? A compatibility assessment of bioeconomy-related Sustainable Development Goals for European policy coherence. *J. Clean. Prod.* **2020**, *254*, 119832. [[CrossRef](#)] [[PubMed](#)]
22. Wiedmann, T.; Lenzen, M. Environmental and social footprints of international trade. *Nat. Geosci.* **2018**, *11*, 314–321. [[CrossRef](#)]
23. Weisz, H.; Duchin, F. Physical and monetary input–output analysis: What makes the difference? *Ecol. Econ.* **2006**, *57*, 534–541. [[CrossRef](#)]
24. Kastner, T.; Rivas, M.J.I.; Koch, W.; Nonhebel, S. Global changes in diets and the consequences for land requirements for food. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, 6868–6872. [[CrossRef](#)]
25. Hubacek, K.; Feng, K. Comparing apples and oranges: Some confusion about using and interpreting physical trade matrices versus multi-regional input–output analysis. *Land Use Policy* **2016**, *50*, 194–201. [[CrossRef](#)]
26. Kuempel, C.D.; Frazier, M.; Nash, K.L.; Jacobsen, N.S.; Williams, D.R.; Blanchard, J.L.; Cottrell, R.S.; McIntyre, P.B.; Moran, D.; Bouwman, L.; et al. Integrating Life Cycle and Impact Assessments to Map Food's Cumulative Environmental Footprint. *One Earth* **2020**, *3*, 65–78. [[CrossRef](#)]
27. Bruckner, M.; Fischer, G.; Tramberend, S.; Giljum, S. Measuring telecouplings in the global land system: A review and comparative evaluation of land footprint accounting methods. *Ecol. Econ.* **2015**, *114*, 11–21. [[CrossRef](#)]
28. Bruckner, M.; Wood, R.; Moran, D.; Kuschig, N.; Wieland, H.; Maus, V.; Börner, J. FABIO-The Construction of the Food and Agriculture Biomass Input-Output Model. *Environ. Sci. Technol.* **2019**, *53*, 11302–11312. [[CrossRef](#)]
29. Többen, J.; Wiebe, K.S.; Veronesi, F.; Wood, R.; Moran, D.D. A novel maximum entropy approach to hybrid monetary–physical supply-chain modelling and its application to biodiversity impacts of palm oil embodied in consumption. *Environ. Res. Lett.* **2018**, *13*, 115002. [[CrossRef](#)]
30. Ye, Q.; Bruckner, M.; Wang, R.; Schyns, J.F.; Zhuo, L.; Yang, L.; Su, H.; Krol, M.S. A hybrid multi-regional input-output model of China: Integrating the physical agricultural biomass and food system into the monetary supply chain. *Resour. Conserv. Recycl.* **2022**, *177*, 105981. [[CrossRef](#)]
31. Valin, H.; Peters, D.; van den Berg, M.; Frank, S.; Havlik, P.; Forsell, N.; Hamelinck, C.; Pirker, J.; Mosnier, A.; Balkovic, J.; et al. *The Land Use Change Impact of Biofuels Consumed in the EU: Quantification of Area and Greenhouse Gas Impacts*; ECOFYS Netherlands B.V.: Utrecht, The Netherlands, 2015.
32. Lotze-Campen, H.; Müller, C.; Bondeau, A.; Rost, S.; Popp, A.; Lucht, W. Global food demand, productivity growth, and the scarcity of land and water resources: A spatially explicit mathematical programming approach. *Agric. Econ.* **2008**, *39*, 325–328. [[CrossRef](#)]
33. Hertel, T.W. Economic perspectives on land use change and leakage. *Environ. Res. Lett.* **2018**, *13*, 75012. [[CrossRef](#)]
34. Escobar, N.; Haddad, S.; Börner, J.; Britz, W. Land use mediated GHG emissions and spillovers from increased consumption of bioplastics. *Environ. Res. Lett.* **2018**, *13*, 125005. [[CrossRef](#)]
35. Nong, D.; Escobar, N.; Britz, W.; Börner, J. Long-term impacts of bio-based innovation in the chemical sector: A dynamic global perspective. *J. Clean. Prod.* **2020**, *272*, 122738. [[CrossRef](#)]
36. Escobar, N.; Britz, W. Metrics on the sustainability of region-specific bioplastics production, considering global land use change effects. *Resour. Conserv. Recycl.* **2021**, *167*, 105345. [[CrossRef](#)]
37. Philippidis, G.; Bartelings, H.; Helming, J.; M'Barek, R.; Ronzon, T.; Smeets, E.; van Meijl, H.; Shutes, L. *The MAGNET Model Framework for Assessing Policy Coherence and SDGs: Application to the Bioeconomy*; Publications Office of the European Union: Luxembourg, 2018. [[CrossRef](#)]
38. Philippidis, G.; Bartelings, H.; Helming, J.; M'Barek, R.; Smeets, E.; van Meijl, H. The Good, the Bad and the Uncertain: Bioenergy Use in the European Union. *Energies* **2018**, *11*, 2703. [[CrossRef](#)]
39. Sturm, V.; Banse, M. Transition paths towards a bio-based economy in Germany: A model-based analysis. *Biomass Bioenergy* **2021**, *148*, 106002. [[CrossRef](#)]
40. Wiebe, K.S.; Bjelle, E.L.; Többen, J.; Wood, R. Implementing exogenous scenarios in a global MRIO model for the estimation of future environmental footprints. *Econ. Struct.* **2018**, *7*, 20. [[CrossRef](#)]
41. Saget, C.; Vogt-Schilb, A.; Luu, T. *Jobs in a Net-Zero Emissions Future in Latin America and the Caribbean*; BID: Washington, DC, USA; Geneva, Switzerland, 2020. [[CrossRef](#)]
42. Asada, R.; Krisztin, T.; Di Fulvio, F.; Kraxner, F.; Stern, T. Bioeconomic transition?: Projecting consumption-based biomass and fossil material flows to 2050. *J. Ind. Ecol.* **2020**, *24*, 1059–1073. [[CrossRef](#)]
43. Meyer, B.; Ahlert, G. Imperfect Markets and the Properties of Macro-economic-environmental Models as Tools for Policy Evaluation. *Ecol. Econ.* **2019**, *155*, 80–87. [[CrossRef](#)]

44. Lutz, C.; Meyer, B.; Wolter, M.I. The global multisector/multicountry 3-E model GINFORS. A description of the model and a baseline forecast for global energy demand and CO₂ emissions. *Int. J. Glob. Environ. Issues* **2010**, *10*, 25–45. [CrossRef]
45. Eurostat. Annual National Accounts (Nama10). 2019. Available online: <https://ec.europa.eu/eurostat/web/national-accounts/data/database> (accessed on 14 January 2022).
46. OECD. Average Annual Wages. 2019. Available online: https://stats.oecd.org/Index.aspx?DataSetCode=AV_AN_WAGE (accessed on 14 January 2022).
47. OECD. Structural Analysis (STAN) Databases. 2019. Available online: <https://www.oecd.org/sti/ind/stanstructuralanalysisdatabase.htm> (accessed on 14 January 2022).
48. OECD. Input-Output Tables. 2019. Available online: <https://www.oecd.org/sti/ind/input-outputtables.htm> (accessed on 14 January 2022).
49. World Bank. World Development Indicators (WDI). 2019. Available online: <https://databank.worldbank.org/source/world-development-indicators> (accessed on 14 January 2022).
50. United Nations Statistics Division. *National Accounts—Analysis of Main Aggregates (AMA)*; United Nations Statistics Division: New York, NY, USA, 2019.
51. United Nations. World Population Prospects 2019: Medium Variant. 2019. Available online: <https://population.un.org/wpp/Download/Standard/Population> (accessed on 14 January 2022).
52. IEA. World Energy Balances; 2019. Available online: <https://www.iea.org/data-and-statistics/data-product/world-energy-balances> (accessed on 14 January 2022).
53. IEA. CO₂ Emissions from Fuel Combustion. 2019. Available online: <https://www.iea.org/data-and-statistics/data-product/greenhouse-gas-emissions-from-energy> (accessed on 14 January 2022).
54. Großmann, A.; Mönnig, A.; Wolter, M.I. TINFORGE—Trade in the INterindustry FORecasting GErmany Model. In Proceedings of the 23rd International Input-Output Conference, Mexico City, Mexico, 22–26 June 2015.
55. IEA. *World Energy Outlook 2020*; OECD Publishing: Paris, France, 2020. [CrossRef]
56. Mercure, J.-F.; Knobloch, F.; Pollitt, H.; Paroussos, L.; Scricciu, S.S.; Lewney, R. Modelling innovation and the macroeconomics of low-carbon transitions: Theory, perspectives and practical use. *Clim. Policy* **2019**, *19*, 1019–1037. [CrossRef]
57. Lutz, C.; Becker, L.; Kemmler, A. Socioeconomic Effects of Ambitious Climate Mitigation Policies in Germany. *Sustainability* **2021**, *13*, 6247. [CrossRef]
58. Wiebe, K.S.; Lutz, C.; Bruckner, M.; Giljum, S. The Global Resource Accounting Model (GRAM). In *The Sustainability Practitioner's Guide to Multi-Regional Input-Output Analysis*; Murray, J., Lenzen, M., Eds.; Common Ground Research Networks: Champaign, IL, USA, 2013; ISBN 9781612291918.
59. Lutz, C.; Lehr, U.; Ulrich, P. Economic Evaluation of Climate Protection Measures in Germany. *Int. J. Energy Econ. Policy* **2014**, *4*, 693–705.
60. Lutz, C.; Meyer, B. Environmental and economic effects of post-Kyoto carbon regimes: Results of simulations with the global model GINFORS. *Energy Policy* **2009**, *37*, 1758–1766. [CrossRef]
61. Lutz, C.; Lehr, U.; Wiebe, K.S. Economic effects of peak oil. *Energy Policy* **2012**, *48*, 829–834. [CrossRef]
62. Wiebe, K.S.; Lutz, C. Endogenous technological change and the policy mix in renewable power generation. *Renew. Sustain. Energy Rev.* **2016**, *60*, 739–751. [CrossRef]
63. European Commission. *Commission Staff Working Document Impact Assessment Report SWD (2021) 25 Final*; European Commission: Brussels, Belgium, 2021.
64. Hennenberg, K.J.; Gebhardt, S.; Wimmer, F.; Distelkamp, M.; Lutz, C.; Böttcher, H.; Schaldach, R. Germany's Agricultural Land Footprint and the Impact of Import Pattern Allocation. *Sustainability* **2022**, *14*, 105. [CrossRef]
65. Stadler, K.; Wood, R.; Bulavskaya, T.; Södersten, C.-J.; Simas, M.; Schmidt, S.; Usubiaga, A.; Acosta-Fernández, J.; Kuenen, J.; Bruckner, M.; et al. EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *J. Ind. Ecol.* **2018**, *22*, 502–515. [CrossRef]
66. Muhammad, A.; Seale, J.L.J.; Meade, B.; Regmi, A. *International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data*; Technical Bulletin, No. 1929; United States Department of Agriculture: Washington, DC, USA, 2011.
67. Miller, R.E.; Blair, P.D. *Input-Output Analysis: Foundations and Extensions*, 2nd ed.; Cambridge University Press: Cambridge, NY, USA, 2009; ISBN 0511651031.
68. Oosterhaven, J. Leontief versus Ghoshian Price and Quantity Models. *South. Econ. J.* **1996**, *62*, 750–759. [CrossRef]
69. Chakrabarty, M.; Hildenbrand, W. How should Engel's law be formulated? *Eur. J. Hist. Econ. Thought* **2016**, *23*, 743–763. [CrossRef]
70. Seale, J.L.J.; Regmi, A.; Bernstein, J. *International Evidence on Food Consumption Patterns*; Technical Bulletin, No. 1904; United States Department of Agriculture: Washington, DC, USA, 2003. [CrossRef]
71. OECD/FAO. *OECD-FAO Agricultural Outlook 2020–2029*; OECD Publishing: Paris, France, 2020; ISBN 9789264317673. [CrossRef]
72. FAOSTAT. *Technical Conversion Factors for Agricultural Commodities*; Food and Agriculture Organization of the United Nations, Statistics Division: Rome, Italy, 1972.
73. Muhammad, A.; D'Souza, A.; Meade, B.; Micha, R.; Mozaffarian, D. *The Influence of Income and Prices on Global Dietary Patterns by Country, Age, and Gender*; United States Department of Agriculture: Washington, DC, USA, 2017. [CrossRef]

74. Anderson, J.E.; van Wincoop, E. Gravity with Gravitas: A Solution to the Border Puzzle. *Am. Econ. Rev.* **2003**, *93*, 170–192. [[CrossRef](#)]
75. Fally, T. Structural gravity and fixed effects. *J. Int. Econ.* **2015**, *97*, 76–85. [[CrossRef](#)]
76. Eaton, J.; Kortum, S. Technology, Geography, and Trade. *Econometrica* **2002**, *70*, 1741–1779. [[CrossRef](#)]
77. Reimer, J.; Li, M. Yield Variability and Agricultural Trade. *Agric. Resour. Econ. Rev.* **2009**, *38*, 258–270. [[CrossRef](#)]
78. Santos Silva, J.; Tenreyro, S. The Log of Gravity. *Rev. Econ. Stat.* **2006**, *88*, 641–658. [[CrossRef](#)]
79. European Commission. Directorate General for Economic and Financial Affairs. In *The 2018 Ageing Report: Economic & Budgetary Projections for the 28 EU Member States (2016–2070)*; Publications Office of the European Union: Luxembourg, 2018. [[CrossRef](#)]
80. IEA. *World Energy Outlook 2018*; OECD Publishing: Paris, France, 2018. [[CrossRef](#)]
81. European Commission, Directorate General for Energy; European Commission, Directorate General for Climate Action; European Commission, Directorate General for Mobility and Transport. *EU Reference Scenario 2020: Energy, Transport and GHG Emissions: Trends to 2050*; Publications Office of the European Union: Luxembourg, 2021. [[CrossRef](#)]
82. Popp, A.; Rose, S.K.; Calvin, K.; van Vuuren, D.P.; Dietrich, J.P.; Wise, M.; Stehfest, E.; Humpenöder, F.; Kyle, P.; van Vliet, J.; et al. Land-use transition for bioenergy and climate stabilization: Model comparison of drivers, impacts and interactions with other land use based mitigation options. *Clim. Chang.* **2014**, *123*, 495–509. [[CrossRef](#)]
83. Schmitz, C.; van Meijl, H.; Kyle, P.; Nelson, G.C.; Fujimori, S.; Gurgel, A.; Havlik, P.; Heyhoe, E.; d’Croz, D.M.; Popp, A.; et al. Land-use change trajectories up to 2050: Insights from a global agro-economic model comparison. *Agric. Econ.* **2014**, *45*, 69–84. [[CrossRef](#)]
84. Hurtt, G.C.; Chini, L.; Sahajpal, R.; Frolking, S.; Bodirsky, B.L.; Calvin, K.; Doelman, J.C.; Fisk, J.; Fujimori, S.; Klein Goldewijk, K.; et al. Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6. *Geosci. Model Dev.* **2020**, *13*, 5425–5464. [[CrossRef](#)]
85. Usubiaga-Liaño, A.; Mace, G.M.; Ekins, P. Limits to agricultural land for retaining acceptable levels of local biodiversity. *Nat. Sustain.* **2019**, *2*, 491–498. [[CrossRef](#)]
86. Heck, V.; Hoff, H.; Wirsenius, S.; Meyer, C.; Kreft, H. Land use options for staying within the Planetary Boundaries—Synergies and trade-offs between global and local sustainability goals. *Glob. Environ. Chang.* **2018**, *49*, 73–84. [[CrossRef](#)]
87. Dinerstein, E.; Vynne, C.; Sala, E.; Joshi, A.R.; Fernando, S.; Lovejoy, T.E.; Mayorga, J.; Olson, D.; Asner, G.P.; Baillie, J.E.M.; et al. A Global Deal for Nature: Guiding principles, milestones, and targets. *Sci. Adv.* **2019**, *5*, eaaw2869. [[CrossRef](#)]
88. Bleischwitz, R.; Spataru, C.; VanDeveer, S.D.; Obersteiner, M.; van der Voet, E.; Johnson, C.; Andrews-Speed, P.; Boersma, T.; Hoff, H.; van Vuuren, D.P. Resource nexus perspectives towards the United Nations Sustainable Development Goals. *Nat. Sustain.* **2018**, *1*, 737–743. [[CrossRef](#)]