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Earth's Future

REVIEW ARTICLE

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Key Points:

- Heterogeneity in ecologically consequential production inputs are rarely represented in temporally dynamic studies
- Spatial aggregation disproportionately affects low income countries, notably Central America, Africa, the Middle East, and Central Asia
- Key socioeconomic drivers within global socioeconomic scenarios have largely not been implemented within equilibrium studies

Supporting Information:

Supporting Information may be found in the online version of this article.

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Equilibrium Modeling for Environmental Science: Exploring the Nexus of Economic Systems and Environmental Change

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Abstract Equilibrium models (EMs) are frequently employed to examine the potential impacts of economic, energy, and trade policies as well as form the foundation of most integrated assessment models. Despite their central role coupling economic and environmental systems, environmental scientists are largely unfamiliar with the structure and methodology underpinning EMs, which serves as a barrier to interdisciplinary collaboration and model improvement. In this study we systematically extract data from 10 years of published EMs with a focus on how these models have been extended beyond their economic origins to encompass environmentally relevant sectors of interest. The results indicate that there is far greater spatial coverage of high income countries compared to low income countries, with notable gaps in Central America, Africa, the Middle East, and Central Asia. We also find a high degree of aggregation within production inputs and sectoral outputs, particularly within the context of global socioeconomic scenarios. For example, we were unable to identify a single temporally dynamic study that distinguished between products arising from managed versus natural forest, or pastures relative to natural grasslands. Due to the necessary breadth and associated knowledge gaps within a model of the entire global economy, we see considerable potential for cross-disciplinary innovation as natural scientists gain familiarity into the role these models play in bridging the nexus between socioeconomic systems and environmental change.

Plain Language Summary This analysis of studies using equilibrium models provides an introduction to how they have been employed across a wide range of disciplines with an emphasis on their application within environmental analyses. We find that many model components are represented in a highly aggregated form, hampering their usefulness in policy-making. This problem is particularly acute in low income geographic areas as well as within key production inputs.

1. Introduction

Addressing current and future global environmental change requires an understanding of the complex interactions between human and natural systems (Díaz et al., 2019; Mastrángelo et al., 2019). Equilibrium models (EMs) enhance our understanding of these interactions by simulating change in sectoral demand according to a wide range of scenarios, making them an essential component of most integrated assessment models (IAMs). IAMs are coupled modeling frameworks that have been developed over the last 30 years to simulate environmental change by linking models of anthropogenic and biophysical systems (Weyant, 2017). Driven in part by the need to account for societal and biophysical drivers in climate change analysis (e.g., IPCC AR5, Stocker, 2014), IAMs have progressed from relatively “simple” spreadsheet-based models (e.g., DICE, Nordhaus, 1992) to high dimensional and integrated approaches encompassing demographic, economic, agriculture, forestry, and energy sectors (e.g., IMAGE, Stehfest et al., 2014).

With greater modeling coverage of socioeconomic and biophysical sectors, IAMs have been embraced as a potential tool to evaluate anthropogenic impacts on biodiversity and ecosystem services beyond climate change (Harfoot et al., 2014; IPBES, 2016; H. Kim et al., 2018). Although IAM sub-models vary considerably in terms of sectoral and system coverage, all major IAMs utilize one or more EMs (e.g., A. Popp et al., 2017; Riahi et al., 2017). Despite the widespread use of EMs in policy analysis and within IAMs, the underlying

structure, behavior, and methodology of these models has received scant attention outside of economics. This gap is compounded by the perception of EMs as “black boxes,” a reputation exacerbated by the proprietary nature of prevalent global data sources and solution software as well as reproducibility barriers due to incomplete provision of model parameters (Böhringer et al., 2003). The mathematical complexity of solving these models through optimization methods (Horridge & Pearson, 2011) further reinforces the perception that the methodology underpinning EMs is not transparent or open to scrutiny and testing.

EMs are optimization models frequently employed to examine the potential impacts of economic and trade policies on national economies (e.g., T. Hertel et al., 2007) as well as to examine the impacts of energy policies on greenhouse gas emissions (e.g., Babatunde et al., 2017). In addition to their role in informing policy assessments, they have been applied to a lesser extent in evaluating the ex-post impacts of policies and counterfactual “what-could-have-been” scenarios (e.g., Jean et al., 2014; Stevenson et al., 2013). EMs also provide the economic foundation for IAMs by simulating sector- and region-specific consumption change according to primary factor provision (land, labor, and capital), energy supply, and technological assumptions (Fujimori et al., 2017). More recently, EMs have been used to quantify the economic impacts of climate change (e.g., Dellink et al., 2019; Kompas et al., 2018; Takakura et al., 2018; van Meijl, Havlik, et al., 2018).

In this study, we investigate the use of EMs through a fully reproducible and cross-disciplinary systematic review of literature published over the last 10 years (Data Set S1). We examine implications for their application to environmentally relevant analyses by extracting and analyzing a wide range of information pertaining to the spatial, sectoral, temporal, and technical aspects of EMs. Our review aims to provide environmental scientists with an accessible and comprehensive overview of the use of EMs across multiple disciplines. We start with an examination of the theory underpinning EMs and how they have been applied in extant literature. We then summarize existing literature to reveal where and how these models have been applied and identify potential areas of improvement for environmental applications. In orienting this study toward an environmental science audience, we hope to enable further improvement of EMs to better capture the complex interactions between socioeconomic and biophysical systems at a global scale, and ultimately facilitate more rigorous environmental decision-making and policy toward achieving global and local sustainability goals.

2. A Brief Introduction to Equilibrium Models

EMs represent the global economy by simulating value flows among foreign and domestic agents which include households, private firms, and a government representative of a country or region (Corong & Tsigas, 2017; Pearson et al., 2014). Agent behavior is modeled based on microeconomic behavioral (supply and demand) and accounting equations. These equations represent an optimization problem that seeks to maximize utility by regional households and producers (Bröcker & Korzhenevych, 2013) under constraints such as capital availability and technology (Burfisher, 2017; Pearson et al., 2014). In other words, agent behavior is assumed to be perfectly rational and self-maximizing. Variables within the model are designated as either endogenous (estimated within the model) or exogenous (explicitly specified by the modeler).

The baseline equilibrium state is determined by base year data derived from input-output tables produced by national statistical offices (e.g., Y. Liu et al., 2017), standardized global databases such as Global Trade Analysis Project (GTAP) (Aguiar et al., 2019), or global sources such as the Food and Agriculture Organization (FAO). Policy changes or alternative scenarios are represented as shocks (i.e., changes) to the exogenous variables. The models are then solved using a range of software and methods, with for example GEMPACK using the Euler multistep method of solving differential equations and GAMS using a range of solvers (e.g., PATH, Newton-Raphson method, Horridge & Pearson, 2011). In the course of solving the model, changes applied to exogenous variables cause endogenous variables to adjust in order to find the new optimal solution, yielding a deviation from the baseline that represents the impact of the implemented policy or scenario.

Within economic applications, EMs have been frequently oriented towards evaluating the impacts of trade policies such as the removal of taxes on specific imported goods and implications of regional free trade agreements (e.g., Jafari & Britz, 2018). Energy applications have focused on the role of carbon pricing and energy demand (e.g., Huang et al., 2019; Grubler et al., 2018) as well as emissions abatement costs within

the context of climate change scenarios (e.g., Su et al., 2017; Vandyck et al., 2016; Vrontisi et al., 2020). Sectoral coverage within EMs is broadly indicated by the distinction between computable general equilibrium (CGE) and partial equilibrium (PE). “Computable” indicates that a model can be solved numerically while “general equilibrium” is often used to refer to the underlying theoretical framework. Whereas CGEs represent a wide variety of goods produced by different economic sectors in an effort to encompass the entire global economy, PE models cover a specific economic sector of interest (e.g., agriculture and forestry) and can be linked to a macroeconomic model to ensure consistency with change in overall economic trends (e.g., GLOBIOM, Havlík et al., 2011). Another key difference is the absence of primary factors (see Section 2.2) within PE models, necessitating that supply side constraints are simulated through other means. As such, PE approaches require less data and allow computational resources to be allocated to more disaggregated subsectors such as individual crops and forestry products, at the cost of simplifying feedbacks between factors of production and sectors which would be modeled within general equilibrium.

EMs are often used within coupled or integrated model ensembles consisting of multiple models linked to perform multisectoral analysis (Harfoot et al., 2014). Within a coupled or integrated model framework, links between models can be classified according to the direction of information flows between the respective models. Unidirectional coupling implies a one-way flow of information from the output of one model to the input of a subsequent model(s) (e.g., EPIC, GLOBIOM, Fuss et al., 2015). Multidirectional coupling entails information flows in multiple directions between multiple models, simulating feedbacks between submodel components which can be continuously updated throughout the model run (e.g., GTEM-C/GIAM, Cai et al., 2015).

2.1. Temporal Dynamics

The temporal dynamics of CGE models fall broadly into two categories, static and dynamic. Static models represent the impact of a policy change on a single point in time which is typically the base year of the data used. Static models may also explore the impact of future policies by updating base year data to depict a future baseline, from which policy scenarios can then be simulated (e.g., Bhattacharyay & Mukhopadhyay, 2015). Where static models implement a shock to the baseline data, dynamic models implement multiple time steps simulating potential paths to a time horizon at which point the model terminates.

The choice between recursive and intertemporal dynamic methods depends on the focus of the analysis as well as the extent to which agents within the model should be able to realistically anticipate future shocks (Babiker et al., 2009). Dynamic “recursive” models are solved sequentially for each time step based on intratemporal (between time step) equations determining capital flows in the form of savings and investment, with the dynamic portion of the model effectively carried out between isolated static runs (Féménia & Gohin, 2011). Deviations to the baseline are applied as shocks to exogenous variables at the current time step, hence shocks to be implemented at future time steps will have no effect on agent behavior in the current time step. Consequently, while the initial time step ($t = 0$) represents an equilibrium state, the path to a shock at a future time step (e.g., $t = 2$) is to a certain extent arbitrary and not necessarily optimal, while the ensuing path ($t > 2$) may be unstable. Further, if recursive models are used to simulate long-term time horizons (e.g., 2100), convergence is not guaranteed and models may fail as variables have a tendency to “drift” toward zero or infinity.

In contrast, intertemporal models are forward-looking since current agent behavior takes into consideration the future state of the economy including any shocks (Kompas & Van Ha, 2019). Within an intertemporal simulation, for example, agents representing firms will adjust their investment behavior in anticipation of a shock to carbon pricing at a future time step, while firms within a recursive model will approach the imposition of a carbon price with zero informational foresight until the actual shock takes place. Intertemporal models therefore optimize within each time step and across all time steps simultaneously, maintaining an equilibrium throughout the entire model run (Pearson et al., 2014). This has led to the critique that the “perfect foresight” of intertemporal models is unrealistic and fails to account for real world uncertainties. However, it should be emphasized here that the model is optimizing according to a perceived future and unanticipated shocks can be implemented by recasting the target time step as ($t = 0$) and implementing a shock on this initial time step.

2.2. Primary Factors

Within CGE models, production of goods and services is constrained by the availability of primary factors (also known as endowments), which are components (e.g., capital, labor, land, and natural resources) that serve as necessary inputs for the production of intermediate goods (i.e., goods consumed in the production of final goods) and final goods consumed by private households and governments, domestic and foreign. As with all other CGE components, primary factors are represented in terms of monetary value flows (e.g., USD) rather than in their physical quantities (e.g., labor force, hectares of land) although there have been efforts to track both value and physical flows simultaneously in the course of solving the model (e.g., Zhao et al., 2020).

Primary factors vary in terms of the ease with which they can be redeployed toward production of different goods and services (known as factor mobility). For example, capital and labor are often modeled as perfectly mobile within a region, meaning that the movement of capital or labor from one domestic economic activity to another can occur immediately following a perturbation of the system which alters relative economic returns (e.g., workers move to a sector experiencing growth to maximize utility). In the case of labor, this mobility is often constrained by disaggregating labor supply into “skilled” and “unskilled” components, indicating greater factor mobility within skill-level appropriate economic activities. Where data are available, further disaggregation is possible according to demographic factors such as educational attainment, occupation, urban/rural, domestic/foreign, formal/informal, and gender (Boeters & Savard, 2011).

Land, on the other hand, is a partially mobile or “sluggish” factor, indicating that mobility can take place if the relative monetary gain of a change in production surpasses a specific threshold. These thresholds are usually established by a “transformation frontier” such as the commonly employed Constant Elasticity of Transformation (CET) function. The CET function constrains the degree to which land can be repurposed toward the production of a different good (e.g., grain to vegetable production) although conversions between disparate crop types are considered equally likely regardless of biophysical feasibility (Palatnik & Roson, 2012). This particular shortcoming has been addressed in many CGEs used for environmental analyses (e.g., MAGNET, Woltjer et al., 2014) through disaggregating the land primary factor into nested hierarchies (e.g., land to cropland and forests, cropland to grains and oil seeds). By nesting production structures, differential constraints on land conversion can be simulated according to the specific subgroup under consideration. In doing so, these models specify factor mobility to more accurately simulate the economic and biophysical conditions under which a new activity (e.g., coarse grain production) would displace a current production activity (e.g., wheat production), compared to an activity considered less likely (e.g., sugar crops).

The interface between equilibrium modeling and land use and land cover (LULC) modeling is a focus of considerable scholarship, and represents one of the most tangible links to environmental science. Prominent advances include implementation of land supply curves (Baltzer & Kloverpris, 2008; van Meijl et al., 2006); additive CET functions (ACET) and logit functions for tracking physical land flows (Fujimori et al., 2014; van der Mensbrugghe & Peters, 2016; Zhao et al., 2020); and more ecologically relevant spatial delineations based on agro-ecological zones (AEZs) (Baldos & Corong, 2020) and water basins (e.g., GCAM Calvin et al., 2019), as well as detailed grid cell level information (e.g., GLOBIOM, Havlik et al., 2011; Johnson et al., 2020). Despite extensive work on improving land-use representation within EMs, considerable uncertainties related to input data, LULC type definitions, scenario quantification, and model structure remain—to the extent that greater similarity is often found among disparate scenarios produced by the same model compared to results for a single scenario across different models (Prestele et al., 2016; Stehfest et al., 2019). Choice of spatial delineation directly impacts many of the aforementioned sources of uncertainty and varies considerably among EMs (Schmitz et al., 2014), with AEZs widely used among GTAP-based (CGE) model variants.

AEZs are constructed through classification of land area by length of growing period and thermal climate at the five arc minute grid cell level, yielding 18 zones (Baldos & Corong, 2020). Total land rent (value returned to land in exchange for a production activity) is then shared out according to estimated productivity yields by crop and AEZ (T. W. Hertel et al., 2009), constraining land competition for a specific production activity to within individual AEZs (Lee, 2005). In the context of long-term simulations, however, AEZs are

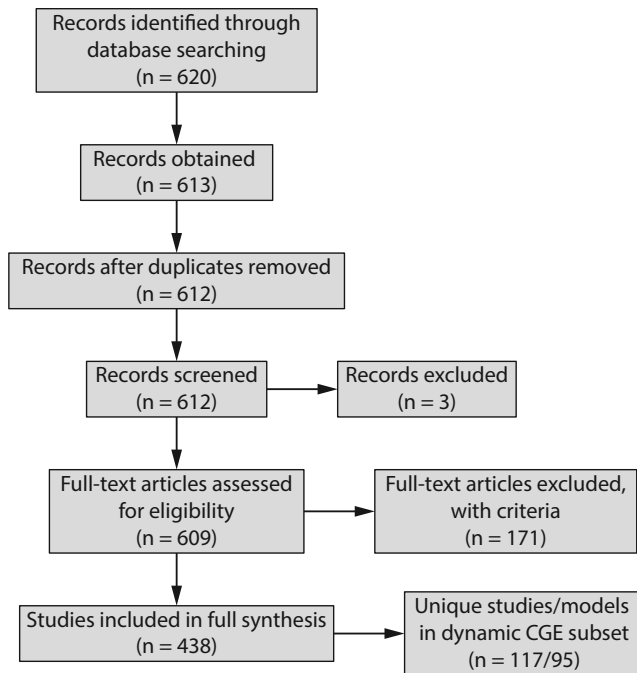


Figure 1. Summary of document selection.

likely to experience heterogeneous climate impacts which introduce spatial uncertainty into global cropland projections, indicating that climate invariant delineations are preferable (Di Vittorio et al., 2016). Beyond the AEZs, gridded approaches are often used in what are referred to as process-based IAMs (Wilson et al., 2021), both within the equilibrium model itself (e.g., landscape parameters) as well as coupled biophysical models (Schmitz et al., 2014).

3. Methods

A systematic and reproducible review was conducted on peer-reviewed English language articles within the Scopus database over the last 10 years (2009–2018) using the following query: *(TITLE-ABS-KEY(("partial equilibrium" OR "general equilibrium" OR cge OR gtap) AND ("trade" AND NOT "trade-off") AND model*) AND ALL (scenario* OR projecti* OR predicti* OR simulati*) AND PUBYEAR >2008 AND PUBYEAR <2019 AND LANGUAGE(english) AND DOCTYPE(ar) AND SRCTYPE(j))*. The search query ensured maximum coverage of EM applications within scenario studies across all relevant disciplines including economic, energy, and environmental themes. The search query did not however target IAM studies which often do not explicitly refer to their EM components. Scopus has a wide range of coverage relative to comparable databases and is appropriate given the time span under consideration (Falagas et al., 2008).

Six hundred and twenty studies resulted from the initial search query (conducted January 15, 2020), with 11 articles either unobtainable, misclassified by the database, or provided in duplicate—yielding 609 articles prior to the application of inclusion criteria (Figure 1).

Three criteria were established for inclusion within the review. The full text of all articles was reviewed to ensure that the article (a) was not a literature review, (b) included an analysis using a CGE or PE model with empirical data (articles using simulated data were excluded), and (c) included scenarios or simulations that represented alternative futures or the impact of policies. Theoretical, methodological, and model intercomparison studies largely failed to meet these criteria.

Of the studies which met all inclusion criteria ($n = 438$, see List S1), data was extracted pertaining to 21 fields including theme, scenarios, and a wide range of technical details pertaining to the model(s) used (Table S1). In addition to the thematic focus of each article, the extracted data can be grouped into five broad categories: Model type; spatial and sectoral coverage; primary factor and energy supply nesting hierarchies; model coupling; and scenario, data, and solution methods.

The distinction between CGE and PE models as well as the associated degree of sectoral coverage provides insight into the trade-offs between the explicit modeling of the entire economy and a more granular focus on a specific sector. Since some sectoral categories common among CGE models (e.g., forestry and fish) are too aggregated to draw ecological inferences, we may expect that PE models are favored within environmental science applications. As with the increased model size and associated computational requirements of general equilibrium, temporally dynamic models are most useful where focus is on the pathway to a potential future state (e.g., atmospheric GHG concentrations). The breadth and resolution of spatial coverage is particularly pertinent within ecological studies examining biodiversity hot spots, many of which exist in low income regions where the data underpinning EMs is either nonexistent or incomplete.

Due to their essential role within environmental analyses, we also extracted the hierarchical data in primary factor production and energy supply nests from a subset of 117 studies containing all unique dynamic CGE models ($n = 95$, Data Set S2). The range of primary factor categories and transformation/substitution between these categories is potentially the most relevant within IAM and coupled modeling applications where change in both constraints (e.g., agricultural land productivity) and enhancements (e.g., technology)

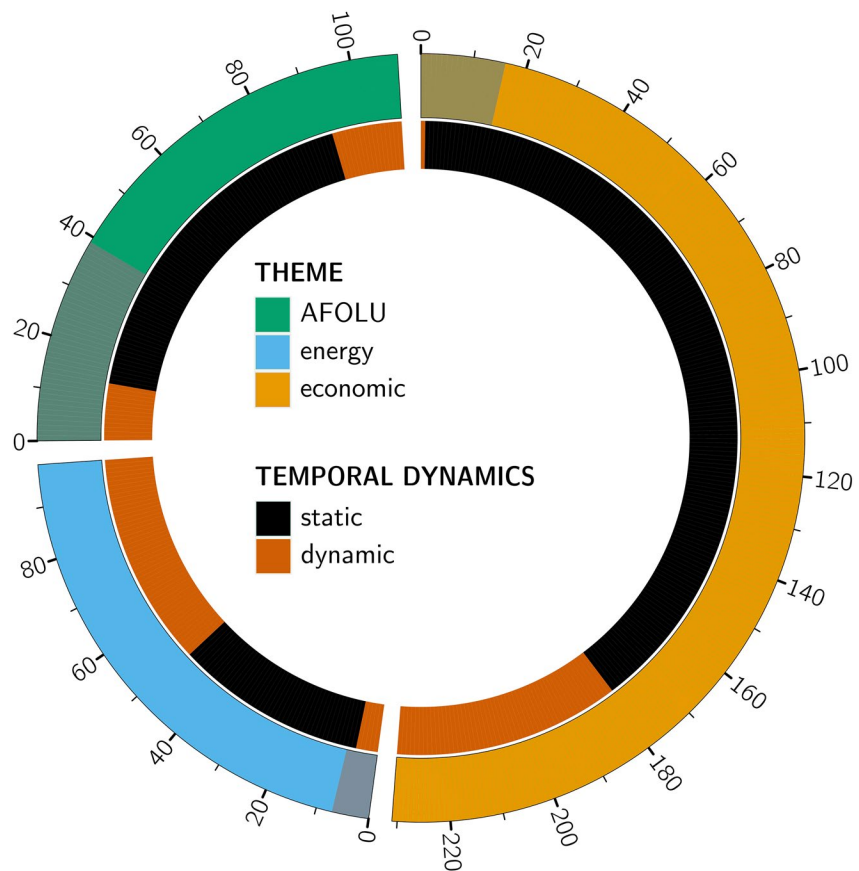


Figure 2. Circos plot (Krzywinski et al., 2009) summarizing articles by theme, general/partial, and temporal dynamics. Full thematic color indicates general equilibrium; gray shade indicates partial equilibrium. Inner black spans indicate static models while red spans indicate dynamic models. AFOLU consists of studies focusing on agriculture, forestry, and other land use.

are expected to impact the provision of land, energy, and labor over long-term periods. Finally, software and solution information is extracted to highlight diverse technical approaches as well as identify reproducibility related gaps within this field.

4. Results

About half of all studies in the review were primarily economic focused, with the remaining equally split among energy and agriculture, forestry, and other land use (hereafter referred to as AFOLU) related studies (Figure 2).

Agriculture ($n = 71$) was the dominant subtheme within AFOLU. A majority of studies used CGE models (86%). PE models were well represented within AFOLU, particularly among agriculture (41%) and forestry (38%) focused articles. More than half (69%) of studies used static models. Dynamic models were most prevalent within energy studies (55%), with the majority of these studies employing recursive dynamics—only 20 intertemporal models were identified over 438 studies. Within dynamic models, only 10 studies modeled scenarios through or beyond 2100, with 2030 as the most prevalent time horizon ($n = 33$).

4.1. Spatial and Sectoral Coverage

The regional and sectoral dimensions included within EMs varied considerably among studies. In terms of spatial coverage, China (210), the United States (205), Europe (194), Japan (157), and India (137) were the most widely represented (Figure 3).

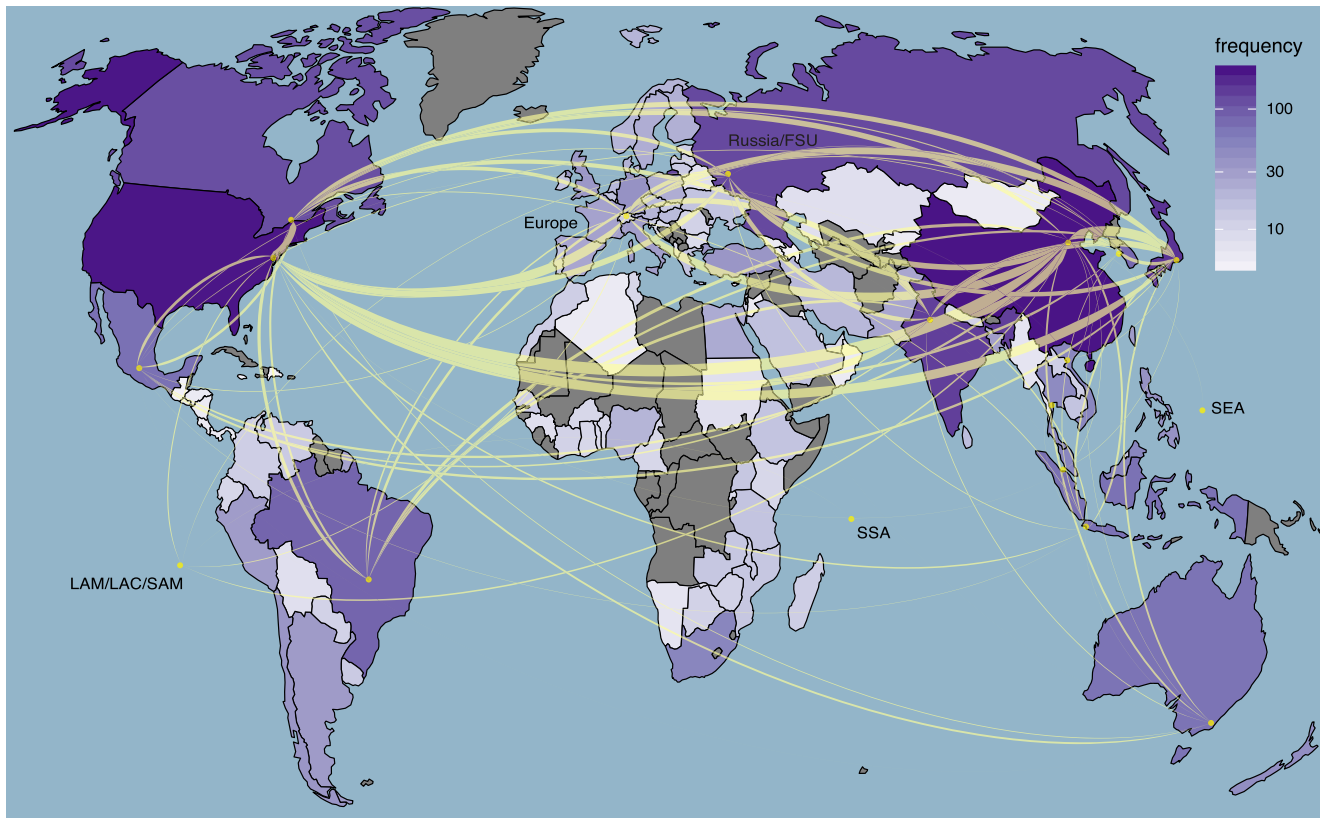


Figure 3. Network heatmap showing frequency of country/region representation within studies. Heatmap indicates frequency of inclusion across all studies (greater than or equal to 5), plotted to a base-10 log scale. Link width between select nodes indicates pairing frequency (inclusion within same study, greater than or equal to 40). LAM includes all combinations of Latin America, South America, and the Caribbean. SEA includes Southeast Asia and ASEAN aggregations. Europe includes all EU and Europe aggregations. Russia/FSU includes all Russia and Former Soviet Union aggregations. South Africa includes the South African Development Community and South African Customs Union.

Although EU and European aggregates were common, individual European countries—Germany (38), UK (34), Italy (30)—were not. Central Asian countries were often included within a Former Soviet Union aggregate, however they were rarely represented as individual countries. South and Southeast Asia were well-represented with the exception of Afghanistan, Nepal, Bhutan, and Myanmar. Brazil (85) and Mexico (72) were the most frequently modeled countries in Latin America with the aggregate Latin America (including South America and Caribbean combinations) appearing in 74 studies. Suriname and Guyana as well as individual countries in Central America and the Caribbean were rarely represented. With the exception of South Africa (47) and Egypt (24), African and Middle Eastern countries were most frequently represented as sub-Saharan Africa and Middle East and North Africa (MENA) regional aggregates, used in 48 and 38 studies respectively. Some countries were frequently represented at the subnational level including China (e.g., Cui et al., 2018; Lin & Jia, 2017; Z. Liu et al., 2018), the United States (e.g., Feijoo et al., 2016; Oliver & Khanna, 2018; Rausch & Mowers, 2014), and Canada (Ochudho et al., 2016; Withey et al., 2016). In order to identify potentially underrepresented countries, we compared the frequency of the top 15 countries and regions within each AR5 region with their respective cumulative GDP over the review period (Table S2). Here we found that Vietnam and New Zealand were the most represented within the review while Romania was the least represented.

The greatest number of modeled regions (173) (Felbermayr et al., 2015) and sectors (135) (Y. Liu et al., 2017) were accomplished within static model runs using World Trade Organization and China Input-Output data respectively. Within dynamic modeling applications, Kompas et al. (2018) employed the greatest number of regions (139) while Mahadevan et al. (2017) employed the greatest number of sectors (95) (Figure 4). The largest model in terms of both regional and sectoral dimensions (139 regions by 57 sectors) was a fully

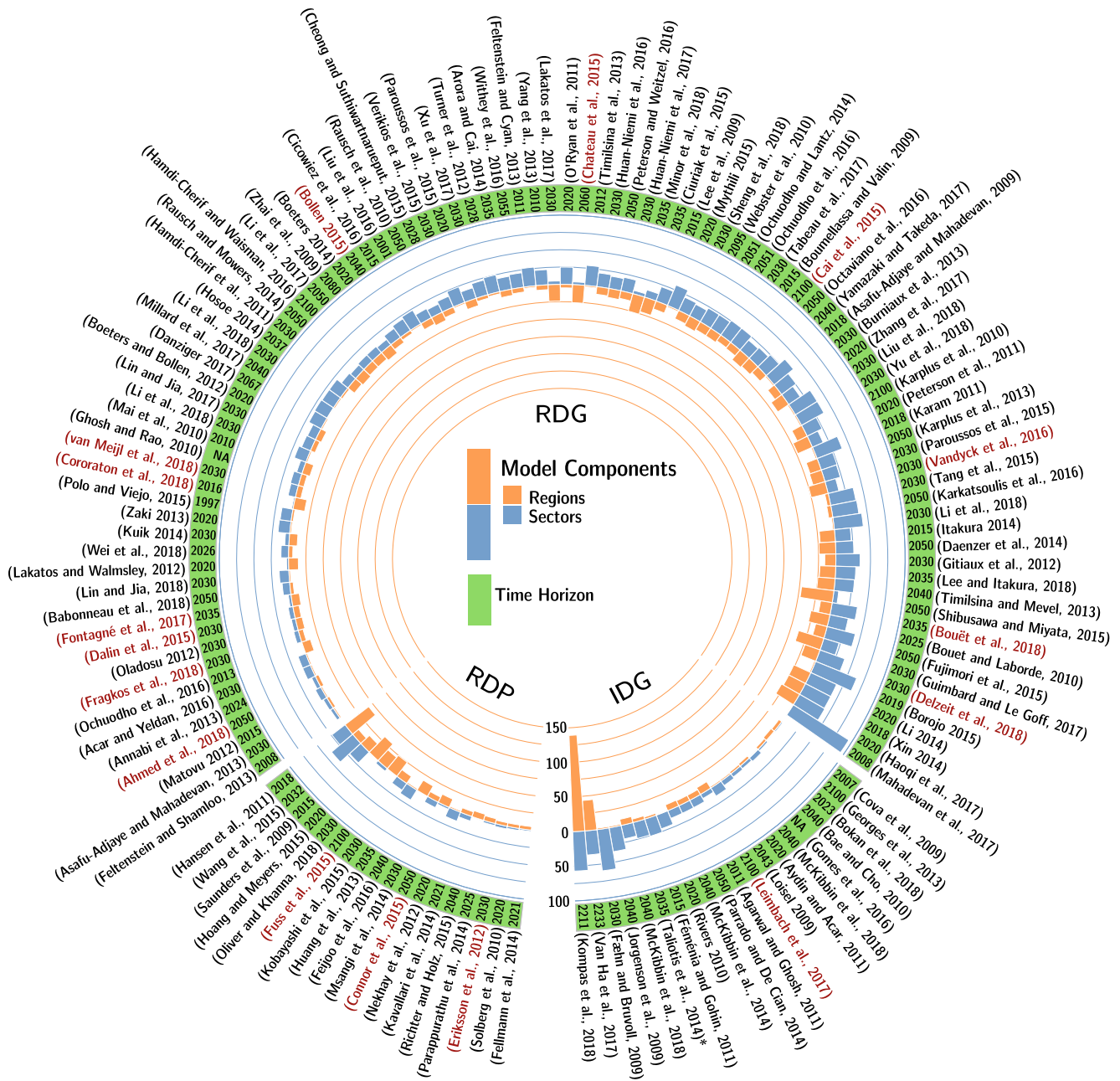


Figure 4. Circos plot of dynamic models arranged by temporal dynamics—recursive dynamic partial (RDP), recursive dynamic general (RDG), and intertemporal dynamic general (IDG). Detailing [from the outside], (a) citation (red color indicates model coupling), (b) numbers (in green band) indicate time horizon, and (c) bars indicate number of modeled regions (in orange) and sectors (in blue). *intertemporal partial equilibrium.

disaggregated dynamic intertemporal run using the GTAP 9 Database (Kompas et al., 2018), followed by a full resolution run of the GTAP 8 Database (Britz & van der Mensbrugghe, 2016). The average model size in terms of the matrix containing the number of regions by number of sectors steadily increased over the 10 years span from 112 in 2009 to 334 in 2018.

Sectoral detail in CGE models was demonstrably higher among agriculture and livestock sectors compared to forestry and fisheries. In fact, most forestry and fishery focused analyses employed PE modeling using FAO data (e.g., Global Forest Sector Model, Mansikkasalo, 2012; Moiseyev et al., 2010) and/or national level statistics (e.g., SF-GTM, A. Kallio, 2010), allowing for greater sectoral detail than what is available in many data sets used by CGE models. Within forestry oriented studies, the Global Forest Sector Model (PE) and

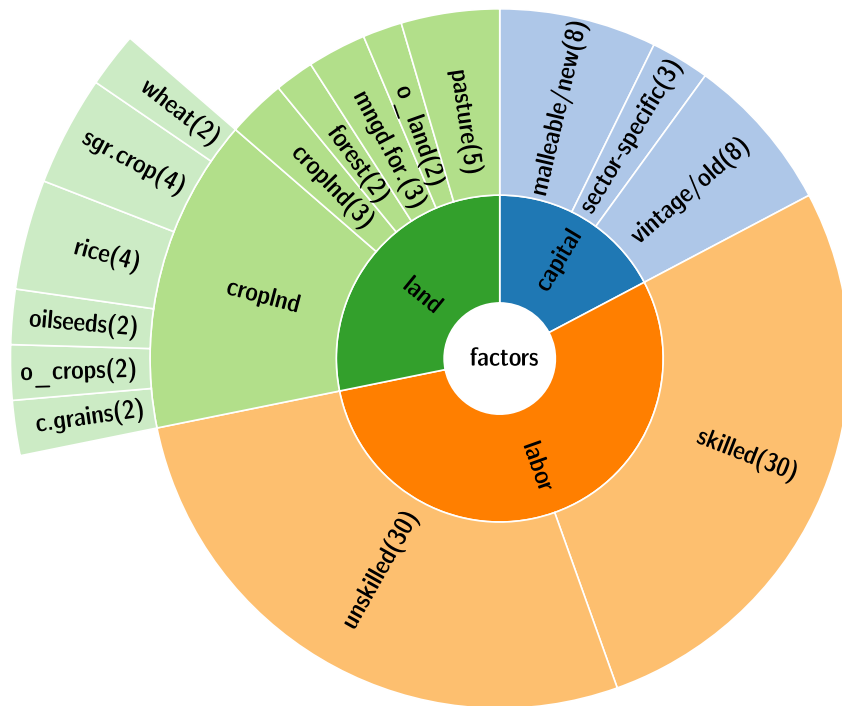


Figure 5. Aggregate capital, labor, and land production nests with at least two identical nestings (same parent to terminal node). Inner ring represents factors in upper level nests and outer ring representing sublevels. Upper tier composites (e.g., capital-labor) and middle tier (e.g., cereals) were excluded. c.grains is coarse grains while “o” indicates other.

associated variants were the most common—The European Forestry Institute Global Trade Model (EFI-GTM) includes 61 global regions and has sectoral coverage of six timber types, 26 forestry products, and four paper grades (A. M. I. Kallio et al., 2004). EFI-GTM was also coupled to regional and stand-level models (e.g., Eriksson et al., 2012) as well as CGE models simulating the rest of the economy (e.g., GTAP-AEZ-GHG, Golub et al., 2009). In terms of fisheries coverage, the IMPACT model stood out with PE trajectories through 2030 for 18 fish and fish products in 115 countries using FAO data (Kobayashi et al., 2015).

4.2. Primary Factor and Energy Supply Production Nests

The dynamic CGE subset consisted of 95 unique models from 117 studies. Within this subset, a total of 143 unique primary factors and sublevel disaggregations were identified after excluding all top level composites (e.g., capital-energy). Commonly used primary factors included labor (93), capital (91), and land (48); energy supply was present in 43 studies. Disaggregation of the most prominent primary factors varied considerably; 88% of models with an energy supply also included sublevel nestings compared to 42% of labor, 15% of land, and 11% of capital.

Three unique subfactors were noted within the capital primary factor nests: malleable/new and vintage/old capital (e.g., Fujimori et al., 2015) and sector-specific capital (e.g., Timilsina et al., 2013) (Figure 5). Labor contained 24 unique subfactors, with unskilled and skilled labor being the most common (33 studies). The TurGEM-D model considered the greatest number of subfactors within labor by including skilled/unskilled, rural/urban, and domestic/foreign workers categories (Aydin & Acar, 2011). Few studies considered age cohorts (e.g., Fehr et al., 2010; Georges et al., 2013) and educational attainment was only modeled in a single national-level ex-post study (Polo & Viejo, 2015).

The most prevalent crop types within the land primary factor were sugar crops, rice, wheat, oilseeds, and coarse grains, with a total of 26 unique subfactors identified. The MAGNET model underpinning IMAGE had the most detailed land disaggregation and distinguished between cropland, forest, and pasture land uses at the upper level (Tabeau et al., 2017; van Meijl, Tsiropoulos, et al., 2018). Forests were included as a

Table 1
Top 10 Scenarios by Theme

Rank	Economic	Energy	AFOLU
1	Liberalization (76)	Emissions related (69)	Agricultural (16)
2	FTA related (66)	Border adjustment (7)	Hydrological (16)
3	Import related (35)	Other energy (7)	SRES (16)
4	Non-tariff barrier (11)	Fuel related (6)	Biofuel related (14)
5	Tax related (11)	Subsidy related (6)	Liberalization (13)
6	Emissions related (9)	Demand change (5)	Demand change (10)
7	Export related (9)	Regulations (5)	Export related (10)
8	Other energy (8)	Export related (4)	Import related (9)
9	Protectionism (7)	RCP scenario (4)	Productivity (8)
10	Technological change (7)	Import related (3)	Other energy (7)

Note. AFOLU includes agriculture, forestry, and other land use.

category distinct from cropland in only five models (Cororaton et al., 2018; Delzeit et al., 2018; Kuik, 2014; Octaviano et al., 2014; Timilsina & Mevel, 2013) while natural grasslands were never represented as a distinct land-state. AEZs were used in several studies (e.g., Delzeit et al., 2018; Timilsina & Mevel, 2013).

There were 83 unique energy subfactors with the most prevalent distinction between electric and non-electric supply. GTAP-DEPS had the most detailed energy disaggregation with nine levels, the majority of which pertained to biofuel production (Oladosu, 2012). Most energy subfactors focused on substitution among various fossil fuels, with only 16 models including a renewable energy source, the most common of which was hydroelectric (e.g., Babonneau et al., 2018; Daenzer et al., 2014).

4.3. Model Coupling

Of the 45 studies that were classified as coupled, only five studies employed multidirectional feedbacks between EMs and coupled models (Cai et al., 2015; I. Kim et al., 2013; Ronneberger et al., 2009; Verburg et al., 2009; Wolf et al., 2011). Multidirectional coupled models included two IAMs (Cai et al., 2015; Hoefnagels et al., 2013) as well as agriculture and land-use (I. Kim et al., 2013; Ronneberger et al., 2009) and an input-output model (Wolf et al., 2011). Within unidirectional coupled frameworks, outputs from upstream models were used as inputs in EMs (23 studies, e.g., J. Liu et al., 2014) or EM output was used as input in downstream models (16 studies, e.g., Henseler et al., 2013). Often, upstream PE models were used to provide enriched data pertaining to hydrology, energy, and forestry to a CGE (e.g., Calzadilla et al., 2013; Fragkos et al., 2018; Golub et al., 2009). CGEs were also in some cases coupled to downstream economic microsimulations models (six studies) and upstream macroeconomic growth models (two studies, Braymen, 2011; Fontagné et al., 2017). In addition to linkages with economic models, other coupled models encompassed air pollution impacts (e.g., GAINS, Bollen, 2015), climate change impact adaptation (e.g., DIVA, Bosello et al., 2012), demography (e.g., PHOENIX, Delzeit et al., 2018), land use (e.g., LUTO, Connor et al., 2015), crop productivity (e.g., DSSAT, Gbegbelegbe et al., 2014), climate (e.g., ECHAM5, Schenker, 2013), hydrology (e.g., H08, Dalin et al., 2015), and forestry (e.g., SMAC, Eriksson et al., 2012).

4.4. Scenario, Data, and Solution Methods

Global multisectoral energy scenarios such as the Special Report on Emissions Scenarios ($n = 21$) and Representative Concentration Pathways ($n = 15$) were used across all themes; however, the Shared Socioeconomic Pathways (SSPs) were only found in four studies (Cai et al., 2015; Countryman et al., 2016; Fragkos et al., 2018; Lee et al., 2018), all of which used the “middle-of-the-road” SSP2 scenario (see Fricko et al., 2017). The most prevalent sector-specific scenarios covered were associated with liberalization and free trade agreements (economic), GHG emissions (energy), and agriculture and hydrology (AFOLU) (Table 1).

Excluding GTAP databases which were explicitly included within the search query, the most frequently used data were from the FAO (24), World Bank (14), OECD (13), and Comtrade (12) databases. Within energy themed studies, however, the International Energy Agency databases were the most prevalent (e.g., Li et al., 2017). Two-thirds of all studies did not specify the software or programming language that was used to solve the model. Of the studies that did provide this information, 71% used GAMS (Rosenthal, 2004) and 25% used GEMPack (Harrison & Pearson, 1996). Within those studies explicitly using GAMS, only 34 studies provided information regarding the specific optimization solver used (e.g., CONOPT3, Moore et al., 2017). One-third of studies conducted a sensitivity analysis, primarily in the form of alternative elasticities.

5. Discussion

Our work highlights that the resolution of primary factors within temporally dynamic CGE models severely limits their application in environmental analyses. In particular, we find considerable variation in the modeling of heterogeneity within energy supply (Figure S1) compared with capital, land, and labor primary factors (Figure 5). The challenge of parameterizing production constraints represents a highly consequential barrier for EM application to environmentally relevant analyses, particularly in the context of integrated assessment modeling and long-term global scenario simulation. Primary factors moderate the link between biophysical and socioeconomic production inputs and sectoral output within the equilibrium modeling framework, and are themselves subject to a wide variety of impacts including technological shifts, natural resource management, and climate change (Bergman, 2005). Disaggregation of primary factors enriches this link by simulating constraints on the substitution and transformation of different production inputs consistent with their underlying heterogeneous nature. Conversely, the absence of a primary factor disaggregation implies an assumption of homogeneity within the supply of a specific factor.

A lack of detail in environmentally relevant primary factors diminishes the ability to accurately model the implications of consumption change on environments critical to the survival of species or provision of ecosystem services, or to simulate how changing land endowments limit economic growth. Simulating varied production inputs homogeneously inhibits an adequate understanding of how an increase or decrease in the consumption of a particular commodity impacts natural ecosystems that may be aggregated with managed land or completely ignored. Throughout the review we found that no dynamic CGE model distinguished between products arising from managed versus natural forests, or pastures compared to natural grasslands. Where forests were included within a dynamic CGE land factor disaggregation, approaches included using a single category for all forestry related products (Timilsina & Mevel, 2013), omitting natural/unmanaged forests (Delzeit et al., 2018; Octaviano et al., 2014), and simulating deforestation through conversion of an unmanaged forest reservoir into managed forests (Kuik, 2014). We also noted that temporally dynamic approaches were more common among energy studies compared to other fields (Figure 2). We surmise that this can be attributed to the importance of path dependence within the context of modeling emissions pathways over longer term time horizons (Table 1).

In addition to homogeneity within primary factors, the link between land and sectoral output is also limited by the degree of aggregation within key production sectors, which varied considerably across dynamic studies (Figure 4). A lack of sectoral detail poses an immediate barrier to examining the impact of policies on specific products linked to environmental degradation (e.g., soybeans, palm oil) when these products are commonly aggregated within broader sectors (oil seeds, vegetable oils). Although PE models have traditionally been used for in-depth analyses of agriculture and forestry sectors (e.g., Latta et al., 2013), greater sectoral detail within CGE models enables simulation of economy-wide feedbacks without the need for coupling disparate models. Modeling such feedbacks is an essential component of simulating both direct and indirect land use competition between bioenergy and food sectors under long-term, global socioeconomic and climatic scenarios (Hasegawa et al., 2018; Obersteiner et al., 2016; J. Popp et al., 2014).

The uncertain future role of bioenergy with carbon capture and storage (BECCS) further illustrates the need for integrated approaches capable of modeling tradeoffs and synergies between agricultural, hydrological, and energy systems within the context of achieving the Sustainable Development Goals (Biggs et al., 2015). If BECCS is implemented at levels necessary to limit warming to 2°C, as in the majority of IPCC scenarios (Fuss et al., 2014), additional land and water requirements are estimated at 380–700 Mha and 720 km³yr⁻¹

in 2100 (Smith et al., 2016). Even under increased crop yield scenarios with no BECCS, global food demand is projected to drive agricultural expansion through 2050 (Bajželj et al., 2014). Given demand increases of this magnitude and the overarching role of international trade, CGE models are uniquely placed to illustrate telecoupled linkages (Millington et al., 2017) as well as the central role of sustainable consumption and production (Akenji & Bengtsson, 2014).

Unsurprisingly, we found that uneven spatial coverage due to data paucity issues and pre-model aggregation bias represents a challenge to modeling ecologically rich, low-income regions. We identified a clear pattern of geographic aggregation affecting countries across Central Asia, sub-Saharan Africa, the Middle East, and Central America (Figure 3). Surprisingly, we found that select high income countries (e.g., France and the United Kingdom) are disproportionately aggregated relative to their economic output due to frequent inclusion within a European Union aggregate (Table S2). While seemingly harmless, evidence suggests that the geographic scale of CGE models has a considerable effect on policy impacts, even when comparing national with subnational resolutions (Standardi et al., 2017). Future integrated assessments focusing on the environmental implications of trade and consumption would benefit by refraining from spatial aggregation when computationally feasible, particularly when the underlying countries have diverse sectoral specializations and primary factor compositions despite geographic proximity. Fortunately, aggregation may no longer be necessary in the near future if computational gains out-pace provision of more granular data. Indeed, existing methods already allow for full scale model runs depending on the temporal dynamics of the model in question (Britz & van der Mensbrugge, 2016; Kompas & Van Ha, 2019).

We also noted the relative absence of key socioeconomic components, both in terms of capital and labor supply heterogeneity (Figure 5) as well as simulation of socioeconomic scenarios (Table 1). Modeling the differential impacts of education and age at the level of sectoral detail common within CGEs is vital for accurately simulating socioeconomic drivers and global scenarios such as the SSPs (Kc & Lutz, 2017; Riahi et al., 2017). Recent work indicates progress toward the development of more sophisticated long-term baseline scenarios such as the SSPs within CGE models (Ho et al., 2020). In terms of labor, while the proportion of models with an extended labor factor nest exceeded that of capital and land, only seven dynamic CGE studies included a distinction other than skilled/unskilled (e.g., Karam, 2011) and no study dynamically incorporated change in demographic traits (e.g., age, gender, and educational attainment) at the global scale. Labor disaggregation beyond the skilled/unskilled distinction is limited primarily by a lack of sufficient data to estimate the degree of substitutability between more granular demographic categories (e.g., male/female) and therefore most global models assume perfect substitutability (Boeters & Savard, 2011).

One approach to representing divergent socioeconomic trajectories has been to calibrate CGE and particularly PE models to GDP projections produced by macroeconomic growth models that have simulated the impact of more detailed demographic characteristics such as age and educational attainment (e.g., Crespo Cuaresma, 2017; Dellink et al., 2017; Leimbach et al., 2017), albeit at a very coarse sectoral detail and subject to considerable uncertainties (Christensen et al., 2018). Despite incorporating demographic trajectories through their aggregate effect on GDP, this method fails to capture the differential impacts demographic change is expected to have on sectoral outputs. For instance, rapid increases in educational attainment have been found to have a differential impact on sectoral production growth according to whether the underlying sectors are unskilled labor-intensive or skilled labor-intensive (Marouani & Nilsson, 2016). Simulating the impact of long-term scenarios of educational attainment (e.g., Lutz et al., 2018) at the sectoral level would require further specification of sector-specific technological change. Without such specification, regions constrained by a single exogenous GDP trajectory into the future will optimize largely according to sectoral specialization in the base year, which does not take into account the sectoral implications of larger macroeconomic trends such as educational attainment, automation, and labor force participation (cf., Costantini & Sforza, 2020).

Although full EM reproducibility is not yet achievable, greater transparency into associated methods is possible by providing more detailed information pertaining to the data, software, and modeling techniques used. We found large gaps in the provision of software and solution methods as well as choice of endogenous and exogenous variables (i.e., model closure). For the uptake of these models in the environmental sciences, clear specification of key aspects and assumptions are required, including data set(s), data processing (i.e., pre-model and post-model aggregation of both regions and sectors), primary factors of production

including disaggregation details and associated elasticities, choice of endogenous and exogenous variables, solution methods employed, and the software used. Ideally, the supporting information for temporally dynamic models would also include a full accounting of all variables at each time step.

The sheer size and complexity of a large-scale model run is testament to the difficulty of achieving greater reproducibility. For example, an intertemporal GTAP-based model run with 112 regions, 57 commodities, and 47 time steps results in over 750 million data points (Kompas & Van Ha, 2019). With the current GTAP LULC database (147 regions, 65 sectors, and 18 AEZs per region), long-term intertemporal runs could easily surpass several billion data points. Efforts to establish good practice guidance and publication transparency standards will facilitate interdisciplinary collaboration and ultimately better science at this crucial nexus between human and biophysical systems. Finally, recent harmonization efforts (e.g., Hurtt et al., 2020; H. Kim et al., 2018) are an important step toward establishing common initial conditions and identifying sources of uncertainty (Eyring et al., 2016).

Limitations to the current study include the absence of sectoral qualitative data analogous to that of spatial units, which proved too laborious to retain within the study protocol. Rather than manually extract such information as we have done here, future efforts may benefit from text data mining to automatically extract relevant tables and deduce sectoral aggregation. The inability to systematically log EM closures also represents an important gap. In this case we found that where closures were provided, they were often ambiguously referred to (e.g., “macro” or “neoclassical”) while a complete list of exogenous and endogenous variables was rarely provided. Finally, studies which include PE and CGE models do not always explicitly use keywords such as “equilibrium” or “CGE” and were therefore not captured in the systematic review. This practice is particularly prevalent within studies using IAMs and coupled model frameworks where the analytical focus is elsewhere.

Due to the considerable scope of EMs and economic background of most equilibrium modelers, model improvement efforts may be best focused on collaboration across the social and natural sciences in addition to well-established intercomparison projects. Knowledge sharing among the former will be vital to better represent natural ecosystems as well as dynamics within production sectors with relatively established modeling frameworks outside of equilibrium modeling (e.g., fisheries). Advances in EM reproducibility would benefit from open-source models comprising both data and solution software. Fortunately this may eventually become possible with the continued development of global, highly disaggregated input-output databases covering value flows (e.g., Lenzen et al., 2013) as well as biomass flows (Bruckner et al., 2019). In terms of currently available open-access resources, detailed macroeconomic data can be found in the World Bank World Development Indicators database and the source code for several well-known models can be found on the GTAP website.

The results of this analysis have revealed that greater disaggregation of primary factor inputs, sectoral outputs, and the spatial units under consideration will be key to improving trajectories of anthropogenic land-use and land cover change. We expect that advances in computational power coupled with remote sensing will enable more explicit spatial modeling of land economics in the near future to account for climate change feedbacks and biomass interpretations of change in land demand. Finally, the low number of global socioeconomic scenarios such as the SSPs outside of their initial IAM interpretations (A. Popp et al., 2017; Riahi et al., 2017) was unanticipated and highlights the need for greater attention to long-term simulation of socioeconomic drivers.

6. Conclusions

The knowledge gained through this study provides a comprehensive accounting of equilibrium modeling across multiple disciplines over the last 10 years. We anticipate that greater adoption of existing methods and improvements made available by future computational advances will facilitate more granular spatial and sectoral resolution and subsequently less uncertainty propagated to coupled models. We also expect that as protection of existing urban centers against sea level rise and climate related extreme weather events becomes increasingly expensive, significant efforts will be devoted toward representing climate change feedbacks on socioeconomic systems beyond agricultural impacts. Finally, reconciliation of CGE value flows with physical units and greater heterogeneity within primary factors will enable simulation of long-term

global socioeconomic scenarios which include changes in demography, natural resource availability, and technological trajectories. We are hopeful that greater transparency into modeling methods will foster advances within equilibrium modeling as well as facilitate their use and development within environmental science where they are an invaluable tool for linking human systems to environmental impacts.

Data Availability Statement

Data Sets S1 and S2 (Cantele et al., 2021) can be obtained at <https://zenodo.org/badge/latestdoi/377695472>, <https://doi.org/10.5281/zenodo.5039905>. The following software and library packages were used in the data wrangling, analysis, and visualizations of this paper: RStudio Team (RStudio Team, 2021); R Core Team (R Core Team, 2020) and the following packages: countrycode (Arel-Bundock et al., 2018), data.table (Dowle & Srinivasan, 2021), jsonlite (Ooms, 2014), plyr (Wickham, 2011), rColorBrewer (Neuwirth, 2014), reshape (Wickham, 2007), rnatuarearth (South, 2017), sf (Pebesma, 2018), and tidyverse (Wickham et al., 2019); Circos (Krzywinski et al., 2009); Gephi (Bastian et al., 2009); and D3.js, node.js, renderHTML.js, and phantom.js.

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