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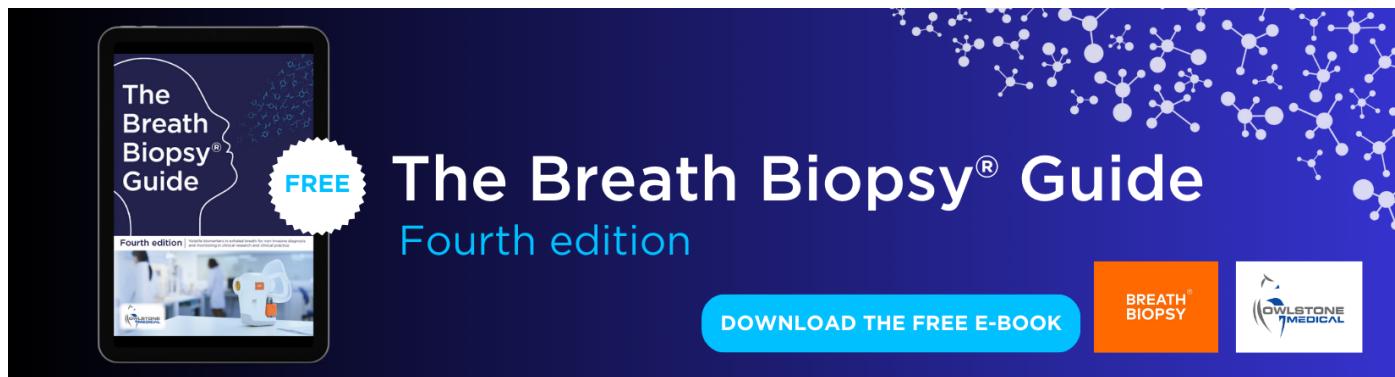
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LETTER

The meso scale as a frontier in interdisciplinary modeling of sustainability from local to global scales

Justin Andrew Johnson^{1,2,*} , Molly E Brown³ , Erwin Corong⁴, Jan Philipp Dietrich⁵ , Roslyn C Henry⁶ , Patrick José von Jeetze⁵ , David Leclère⁷ , Alexander Popp⁵, Sumil K Thakrar^{1,2} and David R Williams⁸

¹ Department of Applied Economics, University of Minnesota, 1994 Buford Ave, Saint Paul, MN 55105, United States of America

² University of Minnesota, Natural Capital Project, 1994 Buford Ave, Saint Paul, MN 55105, United States of America

³ Department of Geographical Sciences, University of Maryland, 7251 Preinkert Drive, College Park, MD 20742, United States of America

⁴ Department of Agricultural Economics, Purdue University, Center for Global Trade Analysis (GTAP), 403 W. State St., West Lafayette, IN 47906, United States of America

⁵ Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, PO Box 601203, 14412 Potsdam, Germany

⁶ The University of Aberdeen, School of Biological Sciences Zoology Building, Tillydrone Avenue, Aberdeen AB24 2TZ, United Kingdom

⁷ Biodiversity and Natural Resources Program, International Institute for Applied System analysis, Laxenburg, Austria

⁸ Sustainability Research Institute, University of Leeds, Leeds LS2 9JT, United Kingdom

* Author to whom any correspondence should be addressed.

E-mail: jajohns@umn.edu

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Abstract

Achieving sustainable development requires understanding how human behavior and the environment interact across spatial scales. In particular, knowing how to manage tradeoffs between the environment and the economy, or between one spatial scale and another, necessitates a modeling approach that allows these different components to interact. Existing integrated local and global analyses provide key insights, but often fail to capture 'meso-scale' phenomena that operate at scales between the local and the global, leading to erroneous predictions and a constrained scope of analysis. Meso-scale phenomena are difficult to model because of their complexity and computational challenges, where adding additional scales can increase model run-time exponentially. These additions, however, are necessary to make models that include sufficient detail for policy-makers to assess tradeoffs. Here, we synthesize research that explicitly includes meso-scale phenomena and assess where further efforts might be fruitful in improving our predictions and expanding the scope of questions that sustainability science can answer. We emphasize five categories of models relevant to sustainability science, including biophysical models, integrated assessment models, land-use change models, earth-economy models and spatial downscaling models. We outline the technical and methodological challenges present in these areas of research and discuss seven directions for future research that will improve coverage of meso-scale effects. Additionally, we provide a specific worked example that shows the challenges present, and possible solutions, for modeling meso-scale phenomena in integrated earth-economy models.

1. Introduction

Humans are radically transforming the environment in ways that harm our wellbeing and the ability of our planet to support life. Understanding how human actions interact with the environment is vital to understand how and where changes can be made to achieve a sustainable future. Reaching this goal relies on understanding a very wide range of complex and interacting phenomena, across many

spatial and temporal scales and different branches of science.

An emerging 'global-local-global' paradigm (GLG) (Hertel *et al* 2019) jointly models how global forces affect local decisions and vice versa. This paradigm is evident in large-scale sustainability assessments (IPBES 2019, IPCC 2022) where it couples economic models of human behavior with biophysical and ecological models of environmental change. The GLG approach considers human

behavior in terms of how it both affects, and is affected by, environmental factors.

Modeling all economic and biophysical phenomena involved in the link between human behavior and environmental change is a hopelessly complex task. Instead, the emerging paradigm of coupled economic and environmental models tends to focus on two distinct levels of explanation. On the one hand, modeling many environmental phenomena depends on understanding processes and variables such as biodiversity, crop yields, carbon storage and sequestration, and pollination services, which occur at, interact at, and vary across spatial scales of 1 km or less (Chaplin-Kramer *et al* 2019, Johnson 2019, Schipper *et al* 2020). Economic impacts and drivers at this scale typically concern landowners or individual private agents making microeconomic decisions. For our purposes, call this the ‘micro-scale’.

On the other hand, much of the economic modeling of human behavior concerns large-scale, national, regional or global forces, such as the actions of governments and multinationals, international trade and macroeconomic policies, technological innovation, and population dynamics (Erickson *et al* 2009). Such forces are important levers for mediating environmental change and following a sustainable pathway (Steffen *et al* 2015). Economic modeling of these forces is not necessarily intrinsically spatial, but can take into account economic parameters that vary across countries or regions (Corong *et al* 2017). Some environmental impact pathways, such as those of climate change, also have large-scale, global effects. Call this the ‘macro-scale’. Macro-scale phenomena will influence the micro-scale, and micro-scale phenomena will combine to affect macro-scale patterns. The GLG approach therefore works to couple the two scales and understand these cross-scale interactions.

As insightful as this emerging paradigm is, a wide range of important phenomena are not captured by it. In particular, there are phenomena that exist at neither the macro- nor the micro-scale, but somewhere in between: what we term the ‘meso-scale’. Meso-scale phenomena are modeled by taking inputs from macro- and/or micro-scale phenomena to determine how meso-scale processes affect those phenomena in a useful, non-trivial way. Not including meso-scale phenomena can lead to incorrect results or modeling artifacts, and constrains what researchers can say. For instance, many policy leverage-points exist at meso-scales, such as national or regional policies, and much of the equity and distributional concerns of sustainability policy operate at the community scale (Roseland 2000).

Incorporating meso-scale phenomena into existing approaches, however, presents additional challenges beyond those of the GLG paradigm. We address these challenges in this paper and argue that important research advances can be made by focusing on this scale. Moreover, we argue that failing to

include relevant meso-scale phenomena in sustainability models will hinder research progress and can result in policy advice that is not relevant or accepted at all scales (Arnott *et al* 2020, Brown *et al* 2022).

We first discuss how the meso-level is represented in five types of sustainability science models: biophysical models, integrated assessment models (IAMs), land-use change (LUC) models, earth-economy models, and spatial downscaling models. The models included were chosen based on our expertise to illustrate a coherent and useful set of interconnections with meso-scale details. We necessarily exclude some models but argue that the models included represent many of the most important and active contributions in the GLG paradigm.

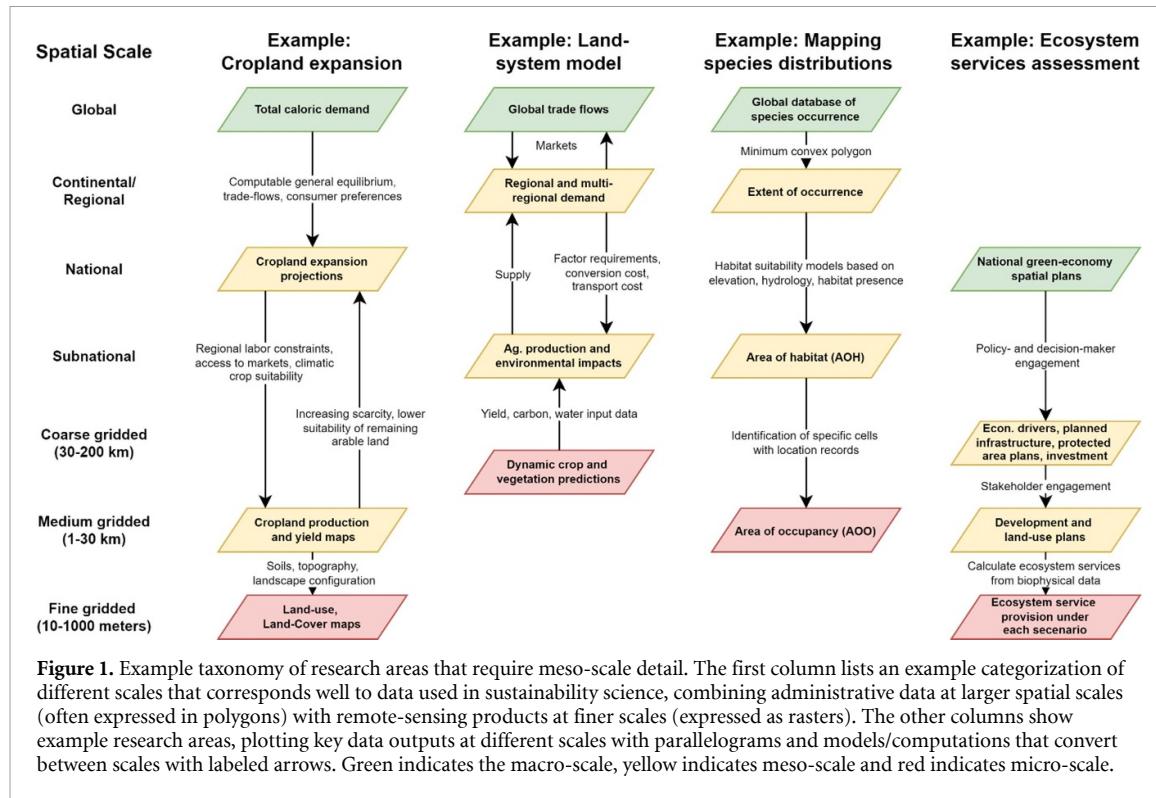
Then, we discuss general challenges that exist in this domain and outline possible avenues for research advance. Finally, we work through one specific example, linking macroeconomic models to ecosystem service models, in order to illustrate specific challenges faced when including the meso-scale. We conclude with ideas for future research and suggestions for improved coordination among modeling groups that work across these spatial scales.

2. The meso-scale in existing sustainability science models

Some form of meso-scale modeling already exists in sustainability science, although it is often rudimentary, it is seldom recognized as meso-scale modeling, and it remains an important frontier for ongoing research. Figure 1 provides an illustration of meso-scale modeling in commonly used environmental modeling approaches. Here, the left column describes the spatial scales of the phenomena being modeled, while the remaining columns illustrate how the modeling approaches (arrows) connect micro-, meso-, and macro-scale data (parallelograms), so as to answer a question relevant to sustainability (e.g. ‘how will projections in caloric demand change global land use?’). Below, we outline how the meso-scale is incorporated in five types of sustainability science models, using figure 1 as a reference.

2.1. Biophysical models

Meso-scale modeling has long been employed in the natural sciences, including in biophysical models that are relevant for sustainability (e.g. dasymetric mapping techniques (Mennis 2008), general circulation models (Sherwood and Huber 2010)) For example, as in other disciplines, the key determinants of hydrological processes vary across scales (Gentine *et al* 2012). At micro-scales (~ 1 km), hydrology is dominated by run-off, with soil properties, land-use and topography being key in determining water flows into and through rivers and soils. At macro-scales



($>10\ 000\text{--}100\ 000\text{ km}^2$), runoff routes and spatio-temporal patterns of and precipitation are dominant (Uhlenbrook *et al* 2004, Gentile *et al* 2012). The meso-scale (usually defined as $10\text{--}10 000\text{ km}^2$) (Uhlenbrook *et al* 2004) is perhaps the key scale for understanding human interactions with hydrological systems. It is at this scale that most decisions are made for water use, and at which many of the impacts of hydrological changes are felt. Decisions in this domain include the regional or even international management of water resources, such as for the Nile (Lawson 2017) or the Rio Grande (Lane *et al* 2015); policy responses to flooding risks; and the regional (as opposed to local) management of water pollution.

Biophysical models are routinely used in sustainability science, but usually only for estimating processes at smaller spatial scales. For example (as shown in figure 1), dynamic crop and vegetation models and ecosystem service models (both of which have biophysical model components) are used to estimate environmental impacts.

2.2. IAMs

IAMs are used to model phenomena at a variety of spatial scales, from trends in demand and growth across at the global scale, down to natural resource supply constraints at high resolution. In IAMs, meso-scale, socioeconomic processes such as demand, processing, trade dynamics and interest rates are at the scale of world regions or countries. IAMs often allow for some flexibility in choosing the level of aggregation depending on the research question; e.g. the

Model of Agricultural Production and its Impact on the Environment (MAgPIE) allows the user to keep single countries as a region, or to group specific countries.

IAMs often require meso-scale modeling to understand the effects of natural resource supply. For example, in MAgPIE, resource quantity and quality for cropland or irrigation water use are simulated on a sub-national scale based on clustered spatial units of similar properties created from a 30 arcmin spatial reference grid (Dietrich *et al* 2019). The two scales are endogenously connected and solved at once via the region-scale aggregated commodity supply curves related to high resolution land and water use. The Global Biosphere Management Model (GLOBIOM) (Havlik *et al* 2011) also relies on similar principles, with the quality and quantity of land and water resources available based on a 5 arcmin reference grid (Skalsky *et al* 2008). Such modeling principles also enable a relatively rich characterization of the land and water resources and the activities they can support (e.g. crop yield and input needs under various management and climate assumptions) based on estimates from biophysical models such as erosion productivity impact calculator (EPIC) (Balkovič *et al* 2014) and lund-potsdam-jena managed land (LPJmL) (Bondeau *et al* 2007). The biophysical models are able to account for the spatial heterogeneities of land and water attributes (e.g. soil type, altitude and slope, climate) that are necessary to accurately model agricultural yield.

Because accounting for micro-scale land and water resources at high spatial resolution comes with

high computational costs and parameter requirements, IAMs often employ meso-scale techniques, such as spatial clustering, to reduce the loss of information (Dietrich *et al* 2013). Both MAgPIE and GLOBIOM typically model land use decisions at a spatial scale coarser than what their biophysical database would allow (e.g. land use decisions are modeled on a 200 km × 200 km regular grid intersected with region boundaries), though they often employ post-hoc downscaling algorithms to generate results at the resolution of their biophysical database (e.g. to 30 arcmin for MAgPIE (Dietrich *et al* 2013) and 5 arcmin for GLOBIOM (Skalský *et al* 2008, Prestele *et al* 2016)). These downscaling approaches include information on the heterogeneity of land resource in terms of land availability (e.g. land available for cropland expansion), quality (e.g. yield) and accessibility (e.g. distance to markets) and neighborhood effects.

2.3. LUC models

LUC models relate macro-scale projections of policies and economic changes to fine-scale representations of LUC. LUC models often explicitly include meso-scale variables that capture human behavior and decision making and variability in their computation.

Meso-scale modeling in LUC models is often explicitly spatial (e.g. concerning spatial competition, adjacency, and clustering). For example, the LandSyMM model (Maire *et al* 2022a) optimizes land use within spatial clusters, using micro-scale biophysical yield data from a dynamic vegetation-terrestrial ecosystem model, LPJGUESS, (0.5° resolution), and macro-scale socio-economic demand and trade processes (for each country). LandSyMM calculates country-scale commodity demand endogenously and therefore demand for commodities responds dynamically to changing commodity prices. This allows for scenarios to explore meso-scale responses to policy or trade changes that affect commodity prices. A recent example of such is Maire *et al* (2022b) who explored the response of different countries to pandemic-related shocks and different policy responses. By focusing on high resolution data, DynaCLUE (Verburg and Overmars 2009). Can capture meso-scale effects such as spatial agglomeration, neighborhood effects, and landscape features and configurations, the latter of which are important both for biodiversity and ecosystem service calculation, and are not easily represented with an approach that relates land-use directly to land-cover, without explicit consideration of the land-system at the meso-scale. As Dou *et al* (2021) show, some phenomena, such as avian species distribution, can better be described with a meso-scale, land-systems based approach to describing land rather than using land-cover as a proxy for more complex land-use dynamics.

The complexity of land-systems can be extended further to cover extremely detailed, farm-scale

decision models. Partial equilibrium models like GLOBIOM and MAgPIE are not able to include high levels of complexity in farm-management decisions, which would be difficult without including mixed-integer and/or nonlinear mathematical programming, along with corresponding increases in computational cost. Phenomena such as farm specialization and the use of off-farm labor are also challenging to include in global, partial equilibrium approaches. Approaches such as the CAPRI model (Britz and Witzke 2014, Barreiro Hurle *et al* 2021) includes detailed market structure and distributed farm models for locations within the European Union but with simpler market structures outside the European Union, as well as an overall simplified representation of non-agricultural land and LUC. There have been attempts (Kleinwechter and Grethe 2012) to explicitly link farm-scale decision making to broader economic forces by defining a village-scale computable general equilibrium model coupled with a national economic model that can trade with the rest of the world, though these models face very significant challenges to generalize their detailed dynamics to broader extents.

Meso-scale modeling in LUC models can employ a wide variety of solution approaches, including agent-based simulation, machine learning, and other non-optimization techniques. For example, the CRAFTY agent-based modeling framework (Murray-Rust *et al* 2014). CRAFTY models the behaviors of simulated agents within a country in response to different scenarios. This approach allows for land use projections at a national and sub-national scale according to, for example, different assumptions regarding human behavior and the valuation of ecosystem services (Blanco *et al* 2017, Brown *et al* 2022, Millington *et al* 2021). Most recently, CRAFTY has been adapted to generate shared socio-economic pathway (SSP) land projections for the UK that incorporate human behaviors and land manager decision-making. This approach was also coupled to LandSyMM, to generate UK demand for food within a global context (Brown *et al* 2022), thus highlighting that computational approaches at different scales need not operate in silo and can be coupled to provide a powerful approach capturing dynamics across scales.

2.4. Earth-economy models

Although relatively newer in the literature, there also are important models in sustainability science that link detailed economic models with high-resolution representations of earth-systems. These 'earth-economy' models place more emphasis on economic equilibrium effects, including a greater range of variables, such as prices, input use, and trade, that are calculated endogenously. Additionally, earth-economy models tend to represent biophysical processes with a higher degree of spatial resolution. Many

of these models take a general-equilibrium approach whereby the whole economy is endogenously linked.

Earth-economy models are well-suited to including meso-scale effect and can evaluate the economic impacts associated with economy and environment interaction at national, regional and global scales. An example is the GTAP-(agro-ecological zones) AEZs model (Hertel *et al* 2009) which facilitates modeling of land use alternatives based on agronomic and climatic information classified into 18 AEZs. To account for the opportunity costs of land uses, GTAP-AEZ restricts which sectors can use different types of land and also specifies land supply competition across crops, pasture and forestry. This is in contrast to standard computable general equilibrium (CGE) models with homogeneous land which can move across land-using sectors regardless of suitability for their use.

Another relevant model with relatively higher spatial differentiation of economic activity is SIMPLE-G. It is a gridded version of the SIMPLE (Simplified International Model of agricultural Prices, Land use and the Environment) partial equilibrium model of global agricultural trade and explicitly accounts for local heterogeneity in crop production, land, water and natural ecosystem services to assess issues associated with food, water and environment nexus at both local and global scales (Baldos *et al* 2020). This granularity comes from gridded data at 5 arcmin resolution for the United States, with ongoing efforts to implement the same resolution for China, Brazil and other regions. Recent studies using SIMPLE-G have addressed meso-scale policies that impact the hypoxic zone in the Gulf of Mexico, including: (a) imposing a leaching tax to reduce nitrogen load in the Mississippi river (Liu *et al* 2022) and (b) the short-term impacts of US renewable fuel standards on nitrogen leaching in the Chesapeake Bay, Great lakes and Mississippi river (Johnson *et al* 2022).

2.5. Spatial downscaling models

The final area of research that we cover is an emergent nexus of scenario planning at the global scale, based on IAMs and broader model-intercomparison projects. The intergovernmental panel on climate change, and subsequent work from the intergovernmental science-policy platform on biodiversity and ecosystem services, has relied heavily on scenarios of representative concentration pathways for climate change and SSPs for other drivers of biospheric change, including LUC (Riahi *et al* 2017). However, one criticism of the widely used SSP framework is the lack of spatial detail, and as such approaches to add a spatial dimension to the SSPs through downscaling has become a focus of research (Estoque *et al* 2020). For example, (Murakami and Yamagata 2019) downscaled the SSP population and GDP data to a gridded 0.5 resolution, while the Coupled Model

Intercomparison Project Phase 6 and other independent modeling efforts (Fujimori *et al* 2018) have added the spatial dimension to the SSPs in terms of emissions and land use. In addition to downscaling the SSPs, recent approaches have combined top-down downscaling with bottom-up stakeholder engagement strategies, such as (Kok *et al* 2018), who extended the global SSPs to create European SSPs and (Pedde *et al* 2021), who created UK SSPs by combining global and European SSPs with national knowledge gathered from stakeholder engagement. While at first glance the SSPs appear to be rooted at the global scale, extensive scenario development work shows that such scenarios can be augmented with meso-scale details to improve their policy relevance.

Even with computational and algorithmic advances discussed throughout this article, the total complexity of models that can be built is still limited. Thus, a sensible approach is to construct meso-scale models that are focused on downscaling specific focal regions and then embedding these more detailed models into the full global model to ensure consistency. This approach also can be used to specify policies, stakeholder preferences, or other nation-specific attributes (such as detailed production relationships) with much more detail than can be included in the full model, increasing policy relevance.

3. Research agenda towards incorporating meso-scale modeling in sustainability science

Below, we present seven directions for future research that overcome the challenges of incorporating meso-scale modeling in sustainability science.

3.1. Developing a diversity of meso-level models with different levels of complexity

The high degree of complexity and computational limits to meso-level modeling present tradeoffs on what can be included in applied models. Making choices about where to spend the model's computational budget is necessary and is subject to the current state of computational methods, with some models opting for more economic detail (e.g. number of sectors, differentiation of inputs, production function detail) and others opting for more biophysical detail (spatial resolution, detail of biophysical processes). Figure 2 illustrates this trade-off: macro-scale models have low spatial resolution but high sectoral and economic detail (top left of the figure), and tend to focus on economic behavior, including general equilibrium (whole economy) approaches in the upper-most area. Micro-scale models have high spatial resolution but are not linked or loosely linked with the economy (bottom right of the figure) and tend to focus on environmental changes. Various meso-scale effects are included, especially in the models clustered in

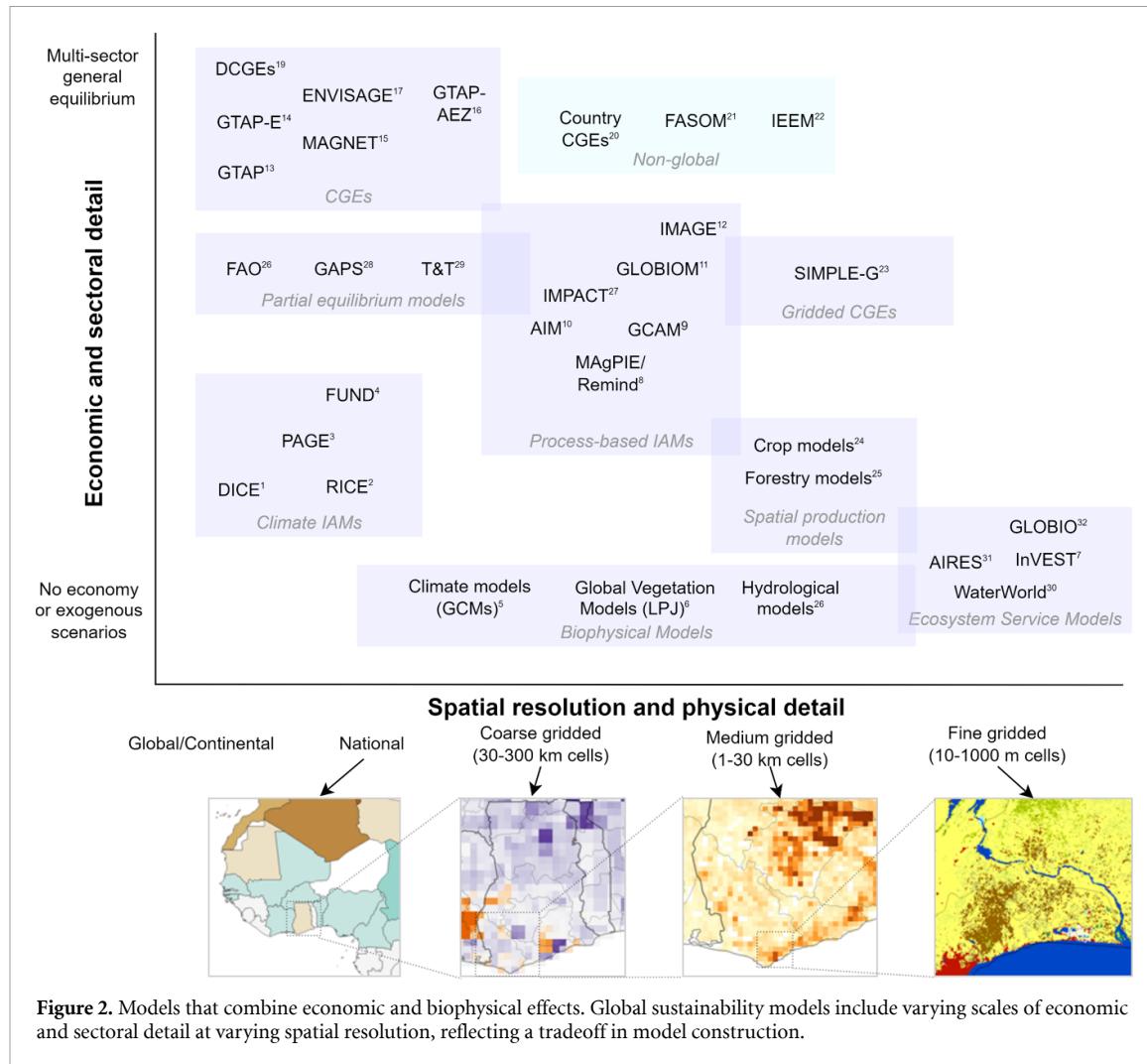


Figure 2. Models that combine economic and biophysical effects. Global sustainability models include varying scales of economic and sectoral detail at varying spatial resolution, reflecting a tradeoff in model construction.

the center of the plot. Additionally, figure 2 includes models in the upper-right that have high levels of both economic and physical detail, though these come at the expense of not being global.

No single model can capture all meso-scale effects, and so a diversity of models is required, each with the fidelity to answer a different set of questions. Significant research advancement could be obtained by creating new models or linking existing models to push further to the upper-right quadrant of the plot while maintaining global extent. However, performing such GLG analyses with meso-scale detail is extremely challenging, due both to requiring advanced computational approaches and the integration of a variety of data sources and processes at multiple scales. Additionally, not all details that are relevant at finer scales are necessarily relevant at coarser scales, suggesting that researchers must carefully choose what details to include at what scales.

3.2. Increasing the availability of high-resolution data

The increase in publicly available satellite data, and the computational capacity to process these data, has been valuable, but it does not *per se* lead to

improved GLG and meso-scale analyses (Hertel *et al* 2019). Specific data gaps persist, including the lack of spatially explicit high-resolution socio-economic data, including factor costs, prices and inputs. More highly resolved socioeconomic data sets are crucial for identifying relationships between outcomes and drivers of change, as well as for the improved assessment of distributional consequences of model outcomes that are obscured in coarser data sets. Broader coordinated efforts are necessary in order to address specific data gaps and issues beyond data availability.

3.3. Standardizing data sources or models, and characterizing uncertainty

Coordinated efforts are required to standardize commonly used datasets, and properly characterize their uncertainty, so that the results of meso-scale modeling can be properly interpreted.

For example, a common requirement for meso-scale modeling is changing model resolution, but doing so requires ensuring that all the affected constraints are still valid on the finer resolution and no implicit assumptions are being violated (e.g. assumptions only valid for big enough sample sizes). This is particularly relevant in the context of IAMs that cover

a wide range of cross-sectoral processes. Furthermore, there is a lack of consistency between satellite-based products such as the ESA CCI land-use, land-cover (LULC) data set (ESA 2017) and other widely-used land-use data sets such as the Land-use Harmonization (LUH2) data (Hurtt *et al* 2020), which is based on the History of the Global Environment database (Klein Goldewijk *et al* 2017). Clarifying the assumptions across models, and standardizing the approaches so that it is clear when it is appropriate to combine models or data, is vital to ensure meso-scale modeling does not produce inaccurate or unphysical results.

Commonly used data and models ought to have their uncertainty characterized, so that it can be propagated through meso-level models to understand how uncertain the results are. Satellite data often exhibit a considerable uncertainty that can sometimes be larger than the land cover changes that are analyzed (Fritz *et al* 2011, Pérez-Hoyos *et al* 2017). There is a lack of consistency and different representations of uncertainty among the available high resolution data sets.

3.4. Developing new, meso-level science that captures important phenomena

Some meso-scale processes, such as those related to the food system, have relatively little formal modeling, and new science is required to incorporate them into sustainability science.

Models that include commercial, globally traded commodities that support animal production often overlook critical smallholder agriculture systems that support large proportions of rural livelihoods (Lowder *et al* 2016). The mix of international versus domestically grown food can be seen in the price of the locally available food, which affects food access across different households. Rural communities that are isolated from international markets are both more vulnerable to domestic availability shocks due to drought (Enenkel *et al* 2020) and more insulated from rapid changes in global prices (Brown and Kshirsagar 2015). Understanding the time lags, transportation costs, diverse supply chains and relative competitive advantage due to geography and labor costs (Mango *et al* 2018) are critical to understanding the probable impact of shocks. The need for meso-scale data, which can capture regional trade as well as local and global supply chains, is central to the ability to model the global food system.

In developing meso-level science, it remains challenging to understand which is the most appropriate scale to model different phenomena, and how to correctly use information across scales. Carefully selecting and aggregating information in a way that appropriately captures the heterogeneity at finer scales can minimize the loss of accuracy while greatly reducing model complexity and the computational resources needed (Dietrich *et al* 2013).

3.5. Applying novel computational techniques for parallelized meso-level modeling

The primary way that computational capacity is increasing lately is through massive parallelization. However, inclusion of meso-scale detail itself can make parallelization much more challenging because it means that spatial units are no longer independent of the outcome of other calculations nearby. For instance, actions of land-owners to deforest their land can affect downstream water quality through export of sediment or nutrients, but this depends on the entire flow-path water within the watershed (Vogl 2016). This spatial endogeneity is one example of where computation cannot trivially be made parallel (and thus, will face more computational limits).

One example approach that overcomes these parallelization challenges uses distributed modeling at the meso-scales. Chaplin-Kramer *et al* (2019), which was the first publication to calculate nutrient retention ecosystem services at the global scale, explicitly uses hydrological information to identify the correct spatial unit for parallelization. By definition, a watershed identifies a contained area where hydrological processes only affect outside areas through outflow to downstream linkages. Chaplin-Kramer *et al* used this fact to define their computations per-watershed, making the spatial endogeneity problem greatly simplified and allowed parallel computation to be done.

Finally, it is worth noting the obvious challenge of parameterizing and validating models that take days or weeks to compute. Slow run-times mean that researchers cannot iterate as quickly, cannot include as many scenarios, and will have challenges in approaching questions of identifying optimal policies (which requires many runs of the model). Modern approaches to computation may alleviate some of these concerns, such as using performant programming languages like Julia, leveraging high-performance computing (supercomputers), and advancement of new algorithms that calculate an existing model more quickly.

3.6. Evaluating whether meso-level science improves prediction accuracy

Meso-scale models require evaluation, even if the micro-scale and macro-scale models are empirically grounded and have been properly evaluated. But evaluating meso-scale models proves difficult, in part, because of the lack of high-resolution historic data sets. Even if data products from new sensors become available, such as the Copernicus CGLS-LC100 collection (Buchhorn *et al* 2020), this may not necessarily improve the availability of high quality time series that can be used to test model behavior before making projections. There must be active research efforts to evaluate meso-scale models, including access to necessary data.

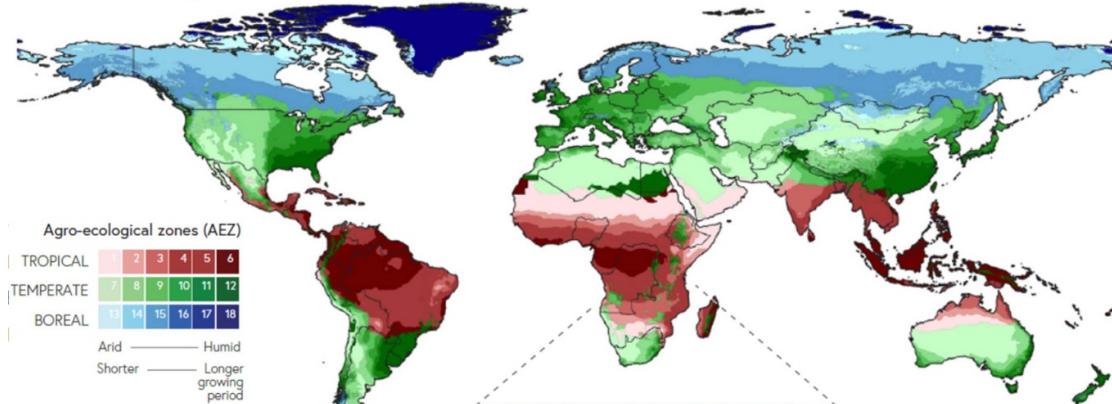
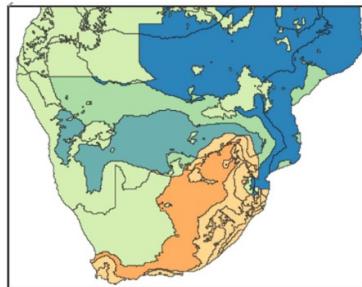
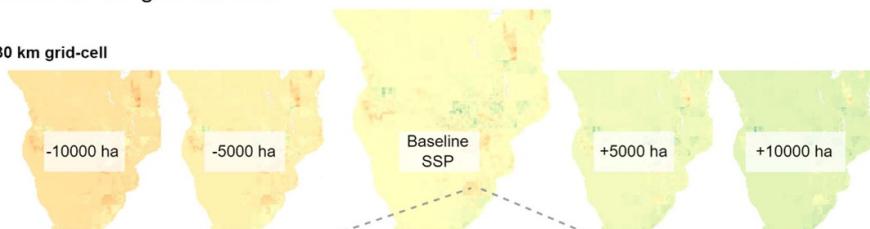
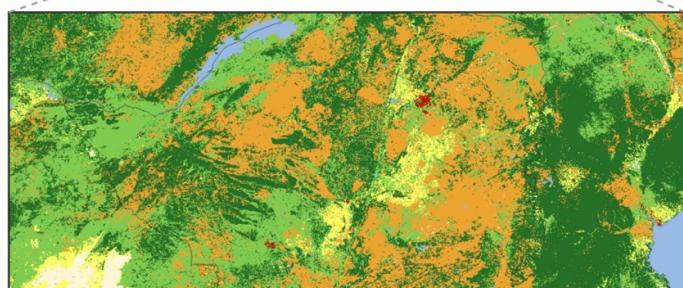
A. Economic regions with agro-ecological zones**B. Agricultural land-cover change projected by GTAP at the AEZ/Region level****C. Agricultural land-cover change projected in SSP2 (GLOBIOM) at the 30 km grid-cell level****D. Downscaled land-use, land-cover data combining information from panels B and C**

Figure 3. Method for downscaling land-use, land-cover data using agroecological zones and integrated assessment models as meso-layers. (A) Macroeconomic model (GTAP-AEZ) generates endogenously calculates land-use change for each AEZ/Region in panel (A). Net cropland change projected is shown in panel (B). Gridded estimates of land-use change from SSP2 (GLOBIOM), panel (C), are used to downscale the AEZ/Region to the coarse grid-cell (30 km) scale by shifting up or down the SSP2 results so they match panel (B) in each AEZ/Region. The 30 km results are then further downscaled to 300 m, shown in panel (D). Including the 30 km meso-layer improves model realism.

3.7. Ensuring consistency of assumptions across integrated models

Scaling up micro-scale, physical-based models is likely to miss non-linearities in processes, and may fail to robustly account for heterogeneity in, for example, soil moisture content without prohibitive data and computational requirements. Meanwhile,

downscaling global/macro models presents major epistemic challenges as downscaling models based on rainfall and run-off results in models that are not based on the physical processes known to dominate at meso-scales. This can lead to a situation where models might work for certain conditions but fail in others (Bierkens *et al* 2015).

4. Detailed example from the Economic Case for Nature (ECN)

One recent study, the ECN (Johnson *et al* 2021) explicitly links global and local effects of policy changes on macroeconomic performance and the provision of ecosystem services and provides a useful example to explore specific challenges faced at the meso-level in this domain. The model created, GTAP-InVEST, estimates how macroeconomic drivers affect the provision of ecosystem services along with monetary estimates of how changed ecosystem services affect overall economic activity. The ECN uses GTAP-AEZ (discussed above) and connects it to a model of ecosystem services (Sharp *et al* 2020). The key methodological challenge address in this work was at the meso-scale: how do we downscale country-level estimates of LUC to a high-resolution land-use, land-cover map for use in ecosystem services models. Here we discuss how meso-scales effects were included in this model to give a practical example of the challenges faced.

4.1. Meso-scale addition #1: GTAP-AEZ with land-supply curves

GTAP-InVEST includes detailed modeling of how increasing demand for food induces expansion of cropland into natural areas. Existing models regard land in relatively simplistic ways, either in monetary terms or in region-level areal change, which do not have enough detail to calculate landscape-scale biophysical models. To address this, GTAP-InVEST uses the most recent GTAP-AEZ database (Baldos and Corong 2020), which combines 36 economic regions (black outlines in figure 3, panel (A)) with 18 AEZs (different colors in figure 3, Panel (A)), to allow for heterogeneous land-supply in each of the 341 generated regions. Additionally, a land-supply curve was added, based on (Woltjer and Kuiper 2014) but specified with high-resolution land-suitability data, to allow for expansion of economic activity onto natural land. The results for cropland expansion are expressed in figure 3, panel B. Without this meso-scale added, all existing models were unsuitable for analyzing policies that have impact through induced LUC.

4.2. Meso-scale addition #2: coarse-gridded results from IAMs

The 341 regions identified above were still very large, and were not suitable for incorporating many of the methodological advances included in IAMs (discussed above) and the scenarios from the SSPs (Riahi *et al* 2017) and their representations in the LUH2 project (Hurtt *et al* 2020). Specifically, downscaling from the region level to the landscape scale (30 m) resulted in edge-effect artefacts, whereby cropland change showed stark discontinuities at region edges, along with remaining spatial artifacts that clustered cropland expansion in a small number of locations. To

address this, GTAP-InVEST incorporated the 30 km representation of LUC used in LUH2, scaling the 30 km SSP2 LUC results up or down so that the aggregate scale of change matched that predicted by the coarser model uniquely for each region (depicted in panel (C) of figure 3). Finally, the results from panel (C) were downscaled to 300 m resolution using the SEALS algorithm (Suh *et al* 2020).

With both of these meso-scales included, few spatial artifacts remained and the overall distribution of changes matched well with the historically observed changes and exhibited improved spatial continuity. However, downscaling algorithms such SEALS introduce new sources of uncertainty and imprecision, thus raising the importance of validation. The underlying models at the coarser scales described above are well validated in the peer-reviewed literature (Hertel *et al* 2009) and the results generated with the algorithm described above match exactly these validated predictions at each input scale. However, validation of the most disaggregated level remains extremely challenging due to widely heterogeneous and complex processes of land-systems transition (Verburg *et al* 2019). Existing validation approaches for SEALS algorithm are presented in Johnson *et al* (2021), which used a cross-validation approach. Specifically, the algorithm was trained on data from 2000 to 2015 but its performance was assessed on fully-withheld data from 2016 to 2019. Ultimately, however, these LULC predictions were used in the GTAP-InVEST CGE model to explore how different, broadly-defined trajectories of future development (Riahi *et al* 2017) might affect ecosystem services (rather than being used to make specific predictions of where LUC will happen).

5. Discussion and conclusion

Using several emergent research areas, we show that meso-scale details are important to sustainability-related questions. The models and methods discussed in this paper were chosen to be illustrative of GLG modeling and are just a subset of the many models we could have included in our selection. Nonetheless, this set of models shows that there are challenges, but also opportunities, in pursuing research in these directions. We argue that this is an important frontier to address in the emergent GLG paradigm. However, we also note that not conducting a systematic review of the literature on meso-scales is a key limitation of this study and we suggest future research should fill in this gap.

In addition to increasing the accuracy of predictions and fidelity of model results, better incorporation of meso-scales is important for analysis of important equity challenges, representation of alternative governance approaches and better inclusion of diverse stakeholders and other challenges that fall beyond the scope of the GLG research

agenda. Further, it is critical that sustainability science increases the use of participatory methods at all of the different scales involved. For example, (Nilsson and Persson 2012) have portrayed the importance of meso-scale agency for earth system governance for identifying problem shifting (rather than solving) and for environmental policy integration, in particular with regard to addressing cross-scale earth system interactions. This is especially important when there are conflicting perceptions of decision-makers at different spatial scales regarding the benefits from a given ecosystem process. Global stakeholders might emphasize the benefit of forest ecosystems with regard to carbon uptake, while the local community might value a forest for its provisioning of fuel (Fisher *et al* 2009). Holzhauer *et al* (2019) have also shown that distinct preferences of land managers and institutional agents at different scales could have a considerable impact on spatio-temporal land-use dynamics, when reacting to supply-demand gaps of ecosystem services. Understanding the behavior of stakeholders at any given scale hence also requires understanding the relevant socioeconomic and political drivers and constraints at neighboring scales (Cash and Moser 2000).

In a recent effort, the nature futures framework has specifically addressed this complexity by formulating integrative multi-scale scenarios for nature that capture the diverse relationships between humans and nature at the meso-scale (Pereira *et al* 2020). The nature futures scenarios can therefore support decision-making, especially at sub-global scales, by identifying policy interventions that promote nature positive futures in different socio-cultural contexts across scales (Kim *et al* 2021). Integrative scenario frameworks such as these that help guide research towards including the details, many of which will be at the meso-scale, that will be useful in complex societal negotiations.

Even with the computational and complexity challenges discussed above, further research advances are possible by linking together such models to further expand the sustainability-relevant phenomena they can assess. Keeping careful track of the meso-scale and how information passes among the different scales of analysis will be important for research within the GLG paradigm to succeed.

Data availability statement

No new data were created or analyzed in this study.

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ORCID iDs

Justin Andrew Johnson  <https://orcid.org/0000-0001-9903-1787>

Molly E Brown  <https://orcid.org/0000-0001-7384-3314>

Jan Philipp Dietrich  <https://orcid.org/0000-0002-4309-6431>

Roslyn C Henry  <https://orcid.org/0000-2942-6753>

Patrick José von Jeetze  <https://orcid.org/0000-0002-1197-4412>

David Leclère  <https://orcid.org/0000-0002-8658-1509>

Sumil K Thakrar  <https://orcid.org/0000-0003-2205-3333>

David R Williams  <https://orcid.org/0000-0002-0379-1800>

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