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Global-to-local-to-global interactions and climate change

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Abstract

Climate change by its very nature epitomizes the necessity and usefulness of the global-to-local-to-global (GLG) paradigm. It is a global problem with the potential to affect local communities and ecosystems. Accumulation of local impacts and responses to climate change feeds back to regional and global systems creating feedback loops. Understanding these complex impacts and interactions is key to developing more resilient adaptation measures and designing more efficient mitigation policies. To this date, however, GLG interactions have not yet been an integrative part of the decision-support toolkit. The typical approach either traces the impacts of global action on the local level or estimates the implications of local policies at the global scale. The first approach misses cumulative feedback of local responses that can have regional, national or global impacts. In the second case, one undermines a global context of the local actions most likely misrepresenting the complexity of the local decision-making process. Potential interactions across scales are further complicated by the presence of cascading impacts, connected risks and tipping points. Capturing these dimensions is not always a straightforward task and often requires a departure from conventional modeling approaches. In this paper, we review the state-of-the-art approaches to modeling GLG interactions in the context of climate change. We further identify key limitations that drive the lack of GLG coupling cases and discuss what could be done to address these challenges.

1. Background and motivation

Climate change by its very nature epitomizes the necessity and usefulness of the global-to-local-to-global (GLG) paradigm. Climate change is a global problem with the potential to affect people and their livelihoods, ecosystems and bio-diversity. No individual can escape contributing to climate change, even if there are vast differences in each individual's contribution to the problem. Because of the global significance of climate change, this is one area that almost from the beginning has been characterized by GLG-type analysis—albeit often at very different scales, and it has seen the emergence of so-called integrated assessment that captures the complex interactions between human societies and their impacts on atmospheric chemistry, energy balance and temperature, and the resulting effects on these same human societies and the bio-physical world (Weyant *et al* 1996, Nordhaus and Boyer 2000). More recently, studies have also started to stress the importance of recognizing the GLG nature of climate change in the context of policy responses (Gupta *et al* 2007, Gupta 2014), as well as to emphasize the value of GLG approach within other socio-economic spheres (Hertel *et al* 2019).

Climate change is one of the global forces that shape the dynamics of socio-economic and biophysical systems (Tol 2018, Piontek *et al* 2021). In combination with other global drivers, such

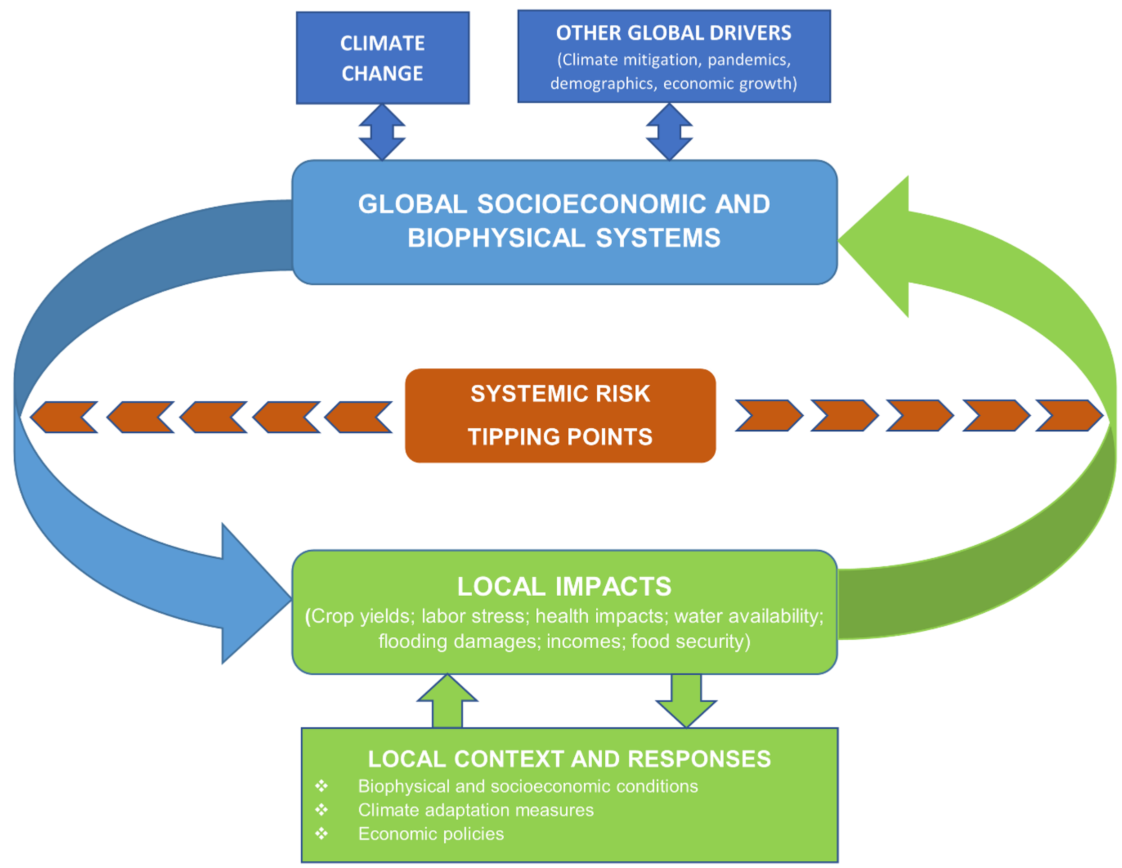

Figure 1. Schematic of the GLG linkages in the context of climate change.

as climate mitigation policies, changes in demographic patterns, pandemics and economic development policies, they form impact channels on the local systems (figure 1). Local impacts are further shaped by the local context, such as specific biophysical and socio-economic conditions, as well as local policy responses. The latter might include climate adaptation measures, and economic or environmental policies. Interaction between global and local channels is further complicated by the presence of systemic risk (Simpson *et al* 2021) and tipping points (Franzke *et al* 2022). The first concept (systemic risk) tries to explain how various impacts across systems and scales can interact with each other and potentially compound leading to outcomes that were hard to anticipate under conventional (linear) assessment approaches. The concept of tipping points helps to identify cases when small perturbations generate abrupt, often irreversible changes to the future of the system (Lenton *et al* 2008). Examples of tipping points in the case of climate systems include permafrost carbon feedback, the Amazon dieback and weakening of the Indian summer monsoon (Dietz *et al* 2021).

All the aforementioned points combined define local impacts of climate change in the context of policy responses and interaction with other systems. Examples of local impacts include implications on crop yields, labor productivity due to heat stress, water availability, flooding damages, incomes and food security. After the first round of impacts, local authorities might implement adjustments to their responses also considering changing local biophysical and socio-economic conditions (e.g. changes in local environmental regulations). These responses, combined with local impacts, further feed back to the global system. The impact of compound risk and tipping points can be distinguished as a meso-level phenomenon that lies between global and local layers, bringing additional uncertainty into multi-scale interactions.

The discussed GLG interactions of climate impacts are revealed in the real world in various forms. One recent example is the Russian invasion of Ukraine, which has put major pressure on global agricultural markets and food security. While the Black Sea Region is a major supplier of grains to the global market and thus export disruptions from the region are expected to have substantial implications for global agricultural trade and food supply (Jagtap *et al* 2022) (*local-to-global-to-local impacts*), actually observed impacts have been exacerbated by a number of interacting factors across global and local scales, including climate change. First, representing a spillover from other commodity markets, rising energy prices have impacted the cost of fertilizer and other agricultural inputs (Chepeliev *et al* 2022b) (*global-to-local impacts*). Second, in response to the war in Ukraine, countries have imposed sanctions on Russia and Belarus, including restrictions on fertilizer imports, further pushing up prices of this important commodity (Behnassi and El Haiba 2022) (*global-to-local impacts*). Third, being concerned with domestic food security, selected producers have imposed agricultural export restrictions to protect domestic consumers (Osendarp *et al* 2022). This has further jeopardized global food security and impacted malnutrition in the most vulnerable localities (*local-to-global-to-local impacts*). Finally, climate impacts and adverse weather events, including droughts in North America, Europe, Brazil and East Africa, have substantially limited possibilities of expanding food supply in the rest of the world (WFP 2022a) (*global-to-local impacts*). As a result, it is estimated that when combined with other stressors, including climate change, the war in Ukraine could increase acute hunger by up to 323 million people worldwide (WFP 2022b). Furthermore, a recent study by Chepeliev *et al* (2023) shows that the food security implications of interacting factors discussed above (rising energy prices, sanctions, trade restrictions and climate impacts) are much more substantial than the direct impacts of disrupted agricultural exports from Ukraine, thus stressing on the importance of accounting for GLG linkages in this particular example.

The discussed GLG interactions of climate impacts are revealed in the real world in various forms. One recent example is the Russian invasion of Ukraine, which has put major pressure on global agricultural markets and food security. While the Black Sea Region is a major supplier of grains to the global market and thus export disruptions from the region are expected to have substantial implications for global agricultural trade and food supply (Jagtap *et al* 2022) (*local-to-global-to-local impacts*), actually observed impacts have been exacerbated by a number of interacting factors across global and local scales, including climate change. First, representing a spillover from other commodity markets, rising energy prices have impacted the cost of fertilizer and other agricultural inputs (Chepeliev *et al* 2022b) (*global-to-local impacts*). Second, in response to the war in Ukraine, countries have imposed sanctions on Russia and Belarus, including restrictions on fertilizer imports, further pushing up prices of this important commodity (Behnassi and El Haiba 2022) (*global-to-local impacts*). Third, being concerned with domestic food security, selected producers have imposed agricultural export restrictions to protect domestic consumers (Osendarp *et al* 2022). This has further jeopardized global food security and impacted malnutrition in the most vulnerable localities (*local-to-global-to-local impacts*). Finally, climate impacts and adverse weather events, including droughts in North America, Europe, Brazil and East Africa, have substantially limited possibilities of expanding food supply in the rest of the world (WFP 2022a) (*global-to-local impacts*). As a result, it is estimated that when combined with other stressors, including climate change, the war in Ukraine could increase acute hunger by up to 323 million people worldwide (WFP 2022b). Furthermore, a recent study by Chepeliev *et al* (2023) shows that the food security implications of interacting factors discussed above (rising energy prices, sanctions, trade restrictions and climate impacts) are much more substantial than the direct impacts of disrupted agricultural exports from Ukraine, thus stressing on the importance of accounting for GLG linkages in this particular example.

Understanding these complex impacts and interactions is key to developing more resilient adaptation measures and designing more efficient mitigation policies. However, until now, the GLG interactions have not yet been an integrative part of the decision-support toolkit. Embracing such complexity requires the development of appropriate modeling approaches with a careful design of data exchanges across different types of modeling tools, spatial and temporal scales. This represents a major challenge. The current paper contributes to the literature on the following three points: (a) reviews state-of-the-art approaches to modeling GLG interactions in the context of climate change; (b) identifies and discusses key challenges that are faced in the context of model coupling in this field of research; and (c) provides guidelines on how these challenges can be addressed and discusses future directions for this field of research in this context.

The rest of the paper is organized as follows. Section 2 provides an overview of the integrated assessment of climate change, reviewing key modeling frameworks that are being used by researchers worldwide. Section 3 discusses two key areas that could particularly enrich the representation of GLG linkages in the climate change research—systemic risk and climate-induced socio-economic tipping points. Selected challenges of coupling models in the context of GLG assessment of climate change are discussed in section 4. Section 5 showcases how GLG perspective can help in improving our modeling approach. Finally, section 6 concludes and provides a discussion of future research directions in this area.

2. Integrated assessment of climate change

The integrated assessment of climate change is often described as a sequence of four 'modules': (1) the socio-economic sphere that describes human actions and institutions and their interactions with

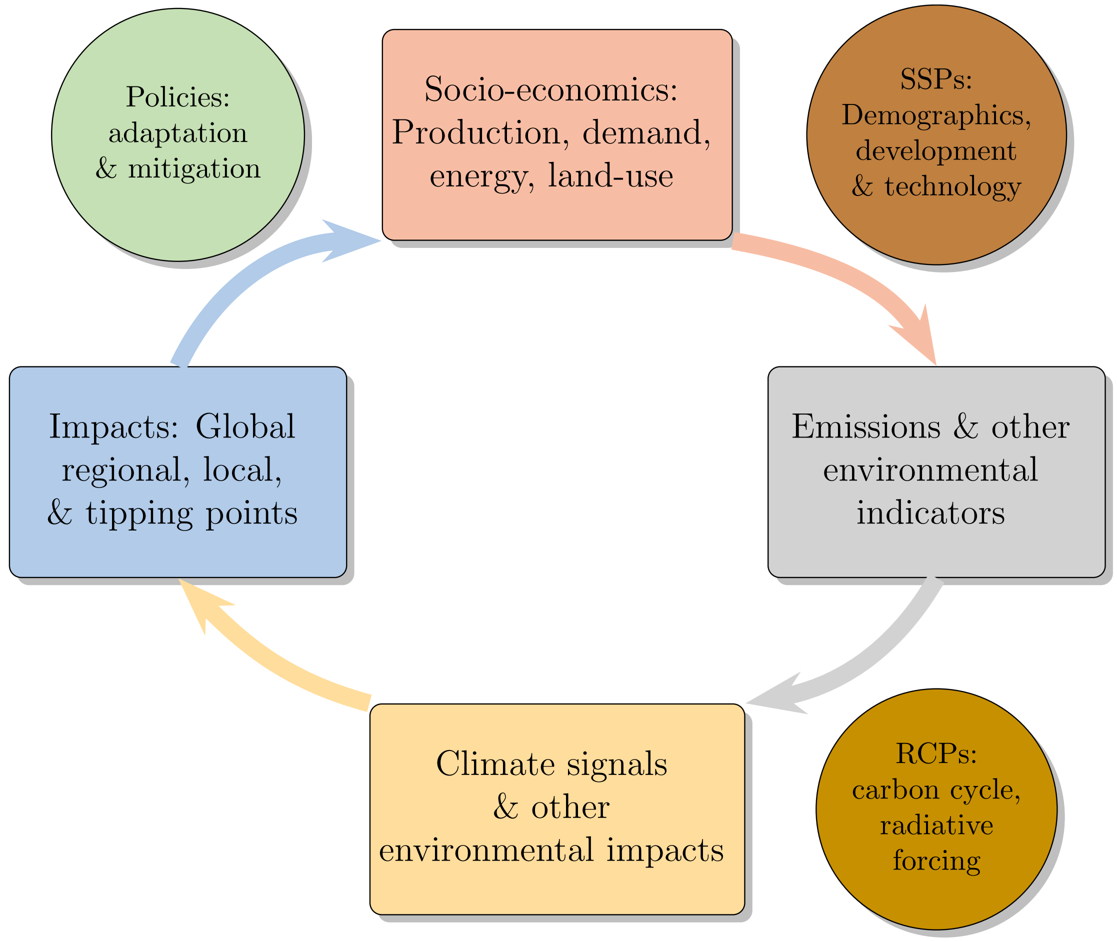

Figure 2. Integrated Assessment Schema.

the physical sphere, which leads to (2) emissions of greenhouse and non-greenhouse gases (GHGs) and other effluents (for example into waters or the ground) and impacts on other environmental indicators, which leads to (3) changes in atmospheric chemistry and the planet's net absorption of solar radiation that impacts local, regional and global climate, which leads to (4) a potentially vast quantity of impacts also at the local, regional and global scales. The loop is closed as these impacts eventually affect socio-economic relations, for example, rising temperatures can impact agricultural yields, sea-level rise will affect coastal economies. The cycle is illustrated in figure 2, which also highlights some components which influence the integrated assessment model (IAM) cycle: (1) the shared socio-economic pathways (SSPs) and other drivers that influence the long-term shape of the future economy; (2) the representative concentration pathways (RCPs) that provide the potential changes to climate across a wide span of emission trajectories; and (3) the policies that will be deployed to adapt to the unavoidable changes due to climate change and policies enacted to move economies towards zero- or negative-emissions.

2.1. Socio-economic module

Socio-economic models describe the 'human' system (HS): demographics, income, essential needs (food, shelter, clothing), critical services (education, health, transportation, security), and income elastic goods (leisure, comfort- and luxury-goods). The HS describes demand and supply, the latter often represented as production processes that require inputs: material, energy, labor, capital and resources (land and water). HS is influenced by 'drivers': demographics, technology, preferences, initial conditions (e.g. the capital stock, infrastructure, natural resources). These are most often seen as exogenous, but can also be endogenous (e.g. investments in education and health can influence fertility and mortality rates, economic conditions can influence cross-border migration). Most global IAMs start from the SSPs[7], which are a set of five scenarios that describe possible pathways for population and income (or gross domestic product (GDP)). Each has a distinct set of narratives and they have been framed along two-axes: one

[7] See O'Neill et al (2015), Riahi et al (2016)and Dellink et al (2017).

that sees increasing emissions of GHGs and thus challenges for mitigation policies, and the second which sees increasing challenges for adaptation policies.

For global-level analysis, models in socio-economic module can be categorized in a 2×2 table. One dimension is spatial that is either national and/or regional[8], or gridded. The other dimension reflects the breadth of economic activities: either partial or focused economic activities (for example agriculture and/or energy) or general, which includes all economic activities. One special case of the latter are the so-called benefit-cost analysis (BCA) models, where economic activity is collapsed into one, i.e. these are purely macro-economic models. Many of the BCA models also model the globe as a single region, these would be termed as 1×1 models: one region and one economic activity. The other models will be designated as detailed process (DP) models[9]. Almost all examples of gridded models are partial equilibrium models and they mostly focus on agriculture. Key examples include MAgPIE[10], GLOBIOM[11] and SIMPLE-G[12]. There are a number of global partial equilibrium energy models that include REMIND[13] and MESSAGE[14], but these normally operate at the national or regional level given the lack of gridded-level economic data, with the exception of agriculture. There are also hybrid models, such as the Global Change Analysis Model (GCAM), which focuses on both energy and agriculture with a mix of national and sub-regional spatial units.

The general equilibrium models generally define spatial units in terms of nations or an aggregation of nations. Many rely on a reference database maintained by the Center for Global Trade Analysis at Purdue University, known as the GTAP Data Base. The most recent publicly available version, V10, divides economic activity into 65 activities across 141 countries/regions[15]—and typically models will aggregate the database to some more limited set of activities and regions. Many of the models operate in isolation, but a number may be linked to other economic models—mostly soft-linked. For example, they may be linked to a macro model for some of the drivers such as GDP and population. The IMAGE model[16]—most likely one of the most complex HS models—is a hybrid with agricultural production represented at the grid-cell level, but with links to a macro-computable general equilibrium (CGE) model (MAGNET[17]) and energy model with country/regional level spatial definition.

2.2. Emissions and other environmental indicators

Production and consumption are typically associated with undesirable outputs such as air emissions or water-borne effluents. The macro-CGE/energy models largely focus on CO_2 emissions from the combustion of fossil fuels, but in many cases can also trace the emissions of other GHGs related to both industrial processes as well as agriculture-based emissions of methane and nitrous oxides. Some are also able to trace non-GHG air emissions. Few of these assess emissions from changes in land-use (e.g. conversion across crop, pasture and forestry), or water-borne effluents. The gridded crop models, on the other hand, can assess land-use based emissions, but typically not those related to energy use.

2.3. Climate module

The changing composition of atmospheric chemistry generated by emissions is linked to changes in radiative forcing and eventually to temperature change. Models with a relatively full accounting of atmospheric emissions can be coupled with general circulation (GCM) or earth system models. These are large and complex numerical models of the climate—covering the global atmosphere (and oceans) with time steps potentially measured in hours. Many take several months for a single run and thus not often used in an integrated framework. The most frequent substitute is to use much simpler climate emulators such as MAGICC[18], HECTOR[19] or FaIR[20]. These take the emissions from the macro-CGE or energy models and provide a profile for concentrations, radiative forcing and global mean temperature change. The latter can be down-scaled spatially using pattern matching algorithms[21]. The climate emulators are relatively simple to integrate in an IAM and run very quickly[22]. The emulators, on the other hand, do not produce changes in precipitation patterns. Analysts can extract

[8] We will use the term regions (or regional) for an aggregation of countries, for example, the European Union or Sub-Saharan Africa. The term sub-regional will be reserved for sub-national spatial units, such as a grid-cell, a district, or a province or state.

[9] Weyant (2017).

[10] www.pik-potsdam.de/en/institute/departments/activities/land-use-modelling/magpie.

[11] https://previous.iiasa.ac.at/web/home/research/GLOBIOM/GLOBIOM.html.

[12] https://mygeohub.org/resources/simpleg.

[13] www.pik-potsdam.de/en/institute/departments/transformation-pathways/models/remind.

[14] https://pure.iiasa.ac.at/id/eprint/1542/.

[15] Aguiar et al (2019).

[16] https://models.pbl.nl/image/index.php/Welcome_to_IMAGE_3.2_Documentation.

[17] www.magnet-model.eu/.

[18] https://magicc.org/.

[19] https://jgcri.github.io/hector/.

[20] Leach et al (2021).

[21] See for example the IMAGE model.

[22] MAGICC is provided as an executable, and thus requires an iterative method to get full model consistency. HECTOR is currently only available in C++. FaIR is available in Python, AMPL and GAMS and could readily be translated to other systems. N.B. There is a version of FaIR in Excel (Dietz et al 2021).

detailed information on temperature change and precipitation from a repository[23] that contains results from a number of GCMs under a range of future conditions—often referred to as the RCPs. There are a limited set of RCPs that range from a low temperature signal, RCP 1.9, to a very high temperature signal, RCP 8.5.

2.4. Impacts of climate change

The climate signals are inputs to the 'impact' module. The literature on the impacts of climate change is vast and forms the bulk of the substance of Working Group II of the Intergovernmental Panel on Climate Change (IPCC), see for example IPCC (2022). The impacts can be described at the global, regional, country and sub-regional levels, as well as cover a broad range of economic and biophysical channels. From the perspective of the IAM community, the scope is narrower as the impact module is necessarily directly linked to the HS module. For the DP models focused on agriculture, the main channel is the impact of changing temperatures, precipitation and rising carbon dioxide concentrations on yields and water resource demands[24]. These effects may reflect changes in long-term average conditions as well as the effects of changing extreme events such as heatwaves, droughts or floods[25]. Agricultural models may also include the impacts of changing heat stress on worker productivity (de Lima *et al* 2021 and livestock Grotjahn 2021). For the energy models, the impacts may include changes in energy demand related to increased demand for cooling and decreased demand for heating, and water availability to cool thermal and nuclear power plants. In addition to these, the broader economic models may include additional impacts such as human health and morbidity, sea-level rise, extreme weather events, tipping points, ecosystems, water resources (quantity and quality) and the impacts on tourism flows (Roson and van der Mensbrugghe 2012, Roson and Sartori 2016). The BCA models typically operate on a single channel—the impact on GDP, with various estimates available in the literature (Burke *et al* 2015, Nordhaus 2017, Newell *et al* 2021).

2.5. Connecting the modules

In most cases, each of the four boxes and the three 'influencers' operate at different scales and it is a challenge to 'connect'. Interactions between impact sectors are also challenging (e.g. water resource competition between agriculture, industrial, municipal and ecosystem demands).

Truly integrated modeling systems are those that can be solved simultaneously, or nearly simultaneously[26]. Perhaps the best-known example is Nordhaus' DICE model (Nordhaus 2017)—one global economy, emitting carbon, and a simple climate model that produces temperature change that impacts economic productivity. With a given parameterization, it calculates a carbon price that maximizes (discounted) social welfare. Some of the key parameters include the discount rate, the price of the 'clean' backstop, and climate sensitivity. It can allow for tipping points, downscaling of the temperature signal, uncertainty and adaptation (de Bruin *et al* 2009, Gillingham *et al* 2018, Dietz *et al* 2021). Nordhaus has also extended DICE to be multi-regional, the RICE model (Nordhaus and Boyer 2000). Similar IAMs include Hope's PAGE model (Hope 2011) and the FUND model (Anthoff and Tol 2014)—with DICE, these models formed the core of the analytical tools used by the U.S. government to develop the social cost of carbon (Interagency Working Group on Social Cost of Carbon 2010). There are a limited set of other DP models that are fully integrated including AIM[27], GCAM[28] and ENVISAGE[29]. There is a broader set of DP models that are nearly integrated such as IMAGE, which uses the MAGICC climate emulator. Many other DP models, which have formed the core of the work on the economics of mitigating GHGs only have two or three components of the full IAM cycle—stopping either with emissions or the climate signal, but not closing the loop with impacts. Their focus has been on the cost of mitigation, and not its benefit from avoided damages from climate change.

3. What is missing in current GLG coupling

Underplaying the importance of GLG linkages in the climate-related assessments could lead to misrepresentation of several important interactions between human and natural systems across multiple scales. In this section we discuss two key areas that could particularly enrich the representation of GLG linkages in the climate change research—systemic risk and climate-induced socio-economic tipping points.

3.1. Systemic risk

There are various types of complex risk in climate change research that may be addressed with improved

[23] https://pcmdi.llnl.gov/CMIP6/.
[24] See for example Ruane *et al* (2017), Snyder *et al* (2019), Franke *et al* (2020).
[25] A core set of estimates of climate change impacts on crop yields can be found at https://agmip.org/aggrid-ggcmi/. See also Jägermeyr *et al* (2021).
[26] Nearly simultaneous systems would include IAMs that use iteration to converge to a consistent solution across all modules. For example, IAMs that use MAGICC, are likely to embed MAGICC in an integrated workflow that solves iteratively—typically in a limited number of steps.
[27] www-iam.nies.go.jp/aim/index.html.
[28] www.globalchange.umd.edu/gcam/.
[29] https://mygeohub.org/groups/gtap/envisage-docs.

global-to-local scale modeling approaches. The IPCC defined two types of complex risk: (1) compound risk that results from an interaction of extremes and (2) emergent risk that results from interactions in a complex system (IPCC 2012, Simpson *et al* 2021). More recently, systemic risk has been described as a type of complex risk associated with the potential for compounding or cascading climate impacts within and across systems attributed to interaction between spatial scales, network relationships, transboundary effects, and harmful outcomes (Simpson *et al* 2021, Sillmann *et al* 2022). In this context, the relationship between risk types requires greater detail to understand if the risk has the potential to simply interact or if the risk has the potential to compound. This additional level of detail about risk had led researchers to explore other types of complex risk, including aggregate risk, amplified risk, interdependent risk, and multi-risk (Simpson *et al* 2021). A recent study by de Lima *et al* (2021) looks into a compound risk for the case of economic impacts of heat stress on plants and people (Box 1).

For multiple-risk assessment to be effective, the complex nature of interacting and interconnected relationships between different triggers needs to be integrated into a holistic framework. Climate risk and socio-ecological outcomes interact across spatial scales (e.g. global climate events transferring risk of severe, local socio-economic consequences), and as such, risk can be understood as the result of dynamic spatial interactions between changing physical systems and society (Weichselgartner 2001, Pescaroli and Alexander 2018). Understanding mechanisms of risk transfer across scales was explored by Simpson *et al* (2021), who created a framework to categorize climate change risk by the mechanisms that create risk, determinants of risk (e.g. hazards, vulnerabilities, responses), types of risk, and their interactions, which include: (1) a single mechanism for each determinant of risk, (2) interactions among multiple mechanisms within and between determinants of risk, and (3) interacting risk. When risk is realized and harmful outcomes occur, spillovers across spatial scales may materialize through direct and indirect interactions via spatial, temporal, or network relationships. Recent literature has focused on the instances in which these harmful outcomes have the potential to permanently alter socio-ecological systems—these instances are often referred to as tipping points.

3.2. Climate-induced socio-economic tipping points

Understanding the complexity of mechanisms for risk transfer across various spatial scales that lead to tipping points has faced challenges in articulating its underlying theory and modeling its complexity. In mathematics and physics, a tipping point is often referred to as a 'critical threshold' or a 'bifurcation point' (Scheffer *et al* 2001). A mathematical definition of a tipping point often involves the use of functions and their derivatives to describe the behavior of a system (Kuznetsov 1998). For example, a system can be described by a function $f(x)$, where x is a control parameter that can be adjusted to change the state of the system (Lenton *et al* 2008). The derivative of the function, $f'(x)$, gives the rate of change of the function with respect to x, and at the tipping point, the derivative of the function changes sign, indicating a change in the stability of the system (Scheffer *et al* 2009). The tipping point can also be identified as the value of x where the derivative of the function becomes zero, indicating a critical threshold beyond which even small changes in x can have large effects on the behavior of the system (Strogatz 2018).

The mathematical definition emphasizes that a tipping point is the critical parameter at which a bifurcation occurs and that it can apply to various types of systems, including social, natural, ecological, and climate systems. Climate scientists have spent many years developing a theoretical framework for climate tipping points, simply concerned with physical Earth systems (Lenton 2011, Lontzek *et al* 2015). Researchers have long recognized the interconnectedness of physical, ecological, social, and economic systems that contribute to climate change, and have now developed frameworks that include tipping points that occur within socio-ecological or socio-economic systems.

A climate-induced, socio-economic tipping point is defined as the case where quantitative climate change triggers a non-linear (abrupt) change in the socio-economic components of the social-ecological systems (stable states). This subsequent change includes feedback mechanisms (mechanism) that lead to a new equilibrium state of the socio-economic system with limited reversibility over the long run (Kopp *et al* 2016, Milkoreit *et al* 2018, van Ginkel *et al* 2020, Franzke *et al* 2022). The rate of change and the magnitude of change are both important considerations in quantifying abruptness of the transition between stable states (van Ginkel *et al* 2020, Stadelmann-Steffen *et al* 2021). Social tipping "dynamics" is believed to give a more realistic representation of transitioning between stable states, and includes the sub-dynamics of technology, politics, and behavior (Olsson *et al* 2004, Folke *et al* 2005, Westley *et al* 2011, Scoones *et al* 2020, Stadelmann-Steffen *et al* 2021).

There are elements essential to complex systems analysis, including documenting the interaction between the biophysical climate and socio-economic systems. Policymakers, researchers, and advocates are concerned about the differences in resiliency across

Box 1: Economic impacts of heat stress on plants and people

de Lima *et al* (2021) estimates the impacts of climate change on plants and people and analyzes their consequences for the world economy. In the study, the authors use fine-scale climate model outputs from the Coupled Model Intercomparison Project Phase 5 (CMIP5), (Taylor *et al* 2012). The impacts of heat stress on people are measured using the simplified wet bulb globe temperature (sWBGT) and the environmental stress indices (ESI). These are calculated using data on temperature, humidity, pressure and solar radiation from CMIP5. Each measure of heat stress is then linked to a labor response function (i.e. ESI-Dunne and sWBGT-NIOSH) in order to estimate changes in farm labor capacity due to climate change.

Gridded predictions of crop yields for maize, rice, wheat and soybeans are based on statistical response functions, which are taken from a meta-analysis of climate change yield impact studies, (Moore *et al* 2017), and on local temperature changes from CMIP5 mean outputs under RCP 8.5. The economic impacts of climate change on crop yields and agricultural labor capacity are then estimated using the GTAP CGE model. To link fine-scale changes in farm labor capacity and crop yields to national economies, data on gridded crop outputs, (Monfreda *et al* 2008) are used to create crop production weights by grid. These weights are then used to aggregate the local impacts of climate change on plants and people at the national level.

The results suggest that agricultural labor capacity is substantially reduced by increased heat stress with around a 30%–50% decline in tropical regions. Reduction in labor capacity diminishes agricultural production. To compensate for the loss of labor productivity, employment in the agricultural sector expands substantially drawing workers away from the non-farm economy. Combining both impacts on plants and people exacerbates economic losses from climate change. Looking at economic welfare, climate change impacts on plants alone are expected to generate global welfare loss at around 78 billion USD at 3 °C warming. However, when both crop and labor impacts are considered, the resulting global welfare loss almost doubles to 136 billion USD. Overall, the compounding impacts of climate change on plants and people results in greater welfare losses in many of the most vulnerable regions, which are already expected to be hard-hit by climate change impacts on staple crop yields.

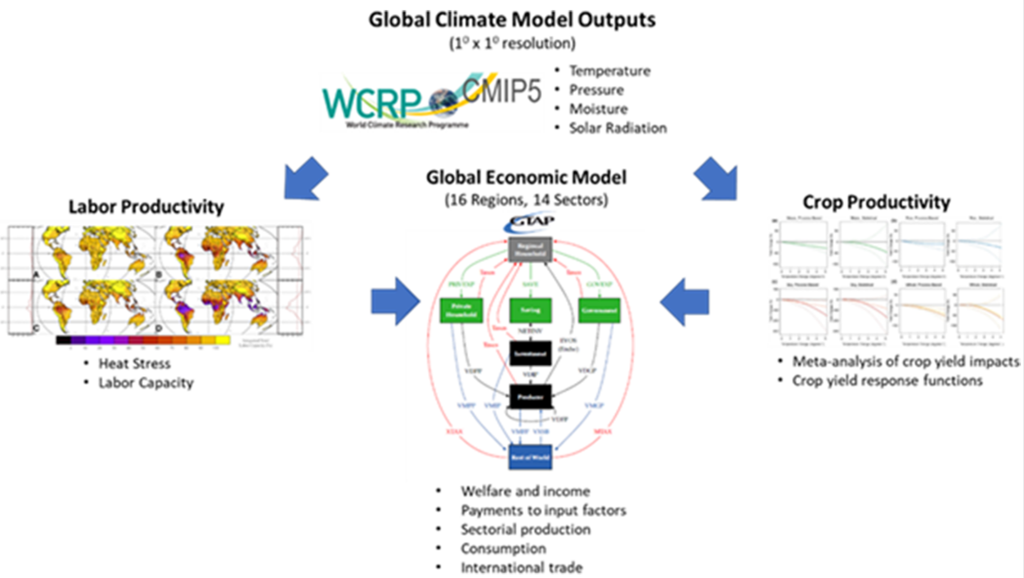

Figure 3. Climate change and heat stress—an example of a coupled system. (left) Reproduced from Moore *et al* (2017). © The Author(s). Published by IOP Publishing Ltd. CC BY 3.0 (right) Reproduced from de Lima *et al* (2021). © The Author(s). Published by IOP Publishing Ltd. CC BY 4.0

spatial scales, given risk mechanisms, network interactions, and harmful climate outcomes leading into tipping points with distributional impacts. Social tipping points, climate tipping points, climate policies that impact global consumer prices may affect the risk of inequitable economic outcomes, particularly for low-income households in certain regions of the world (Ohlendorf *et al* 2018, Dietz *et al* 2021). Positive tipping points have been proposed as a mitigation tool with a variety of climate responses, policy interventions, and feedback mechanisms to positively affect socio-ecological systems that lead to desirable outcomes (Otto *et al* 2020, Lenton *et al* 2022, Tàbara *et al* 2022). Adaptation tipping points have been proposed in cases where adaptation is no longer effective and a new mechanism is necessary to continue dynamic adaptation (Haasnoot *et al* 2013). For the purpose of IAMs, these interconnections and hierarchical complexities imply that the responsiveness of various modeling units (e.g. administrative units, urban areas, grid cells) to external shocks might vary widely based on the local context and existing institutions of coordination, governance, and social organization (Folke *et al* 2005, Westley *et al* 2011). Socio-ecological systems can vary tremendously in their resiliency and transformability (e.g. the ability to manifest new, untried responses in response to shocks (Olsson et al 2006, Westley et al 2011, Scoones et al 2020)). It is also important to note that a resilient system is not a static one. Resiliency can be defined as the capacity of a system to absorb disturbance and reorganize while undergoing change. The capacity of systems to respond to global shocks is constantly in flux, as are the global and local regimes in which this capacity is developed and maintained (Westley et al 2011).

Local tipping points are not always equivalent to global tipping points. van Ginkel et al (2020) argue that tipping points are more difficult to discern at regional and global scales because of substitution effects and policy responses compared to the local scale, but (Scheffer et al 2012) believe that homogeneous, interacting systems might show larger scale tipping points. Beyond the physical, ecological, and economic science of socio-economic tipping points, researchers have grappled with determining the functional relationship between local tipping points and global regimes and vice versa. There is decision-making agency and institutional capacity at different spatial scales but while these scales are organized hierarchically with local institutions likely embedded in regional or global systems (e.g. socio-economic tipping points at local scales can be redressed or enhanced due to governance scales), it has been argued that global governance is ineffective given the complexity of climate systems (Obersteiner et al 2001). FridaysForFuture[30] is an example of how a transition from the local to global spatial scale can occur.

3.3. Limitations in coupled modeling of risks and tipping points across spatial scales

Kwadijk et al (2010) argue that current reliance on climate projections may not be appropriate for the scale of the problem or how policymakers might intervene. Thus far, it has been difficult to model dynamics of change across spatial and temporal scales in a social-ecological system given the complex interactions between biophysical and social systems (Milkoreit et al 2018, Franzke et al 2022). More localized, granular data might be useful in informing soft-coupled energy-economy models (Fragkos et al 2018). However, it is important to consider data and modeling needs for different applications, where data collection and analysis of climatic and social risk must translate into the potential for policy intervention (Sillmann et al 2022). Obersteiner et al (2001) argue that climate risk management research, as a first step, needs to accurately identify, assess, and model climate risk and risk-reducing strategies.

At present, researchers argue for greater empirical evidence on the mechanisms that create socio-economic tipping points as a result of climate science (Russill 2015, Dietz et al 2021, Tàbara et al 2022). A study by Russill (2015) recommends a better understanding of the mathematics and theory of dynamic systems to model and address policy options to avoid climate and socio-economic tipping points. Models need to represent non-linear dynamics, feedbacks between the global socio-economic system and climate change, and socio-economic tipping point thresholds[31] (van Ginkel et al 2020, Ritchie et al 2021, Franzke et al 2022, Lenton et al 2022). Another important component of coupled modeling would be to determine if all costs and benefits of social tipping points can be monetized for economic modeling and that stakeholders agree on these values (Drouet et al 2006). The nexus of adaptive governance systems, social connectivity, and state capacity determines how actors respond to shocks and relate to the socio-economic systems they are embedded within (Folke et al 2005); this implies impacts on measurable outcomes such as economic growth or ecosystem service generation, but this nexus is complex and difficult to measure in its own right, creating both conceptual and computational difficulties in IAM implementation (van Ginkel et al 2020). "A crucial question for further research is whether adaptation turning points are an appropriate concept for assessing and communicating the implication of climate change and prioritize adaptation actions" (Werners et al 2013). Nonetheless, a limited number of existing IAMs incorporate how positive tipping points can occur to the benefit of societies in the context of socio-ecological systems impacted by climate change via the enhancement of resiliency capacity or transformability (Lenton et al 2022).

4. Challenges in coupling of models

Existing efforts to connect climate model outcomes to sectoral models (e.g. ISIMIP see Frieler et al 2017 and Warszawski et al 2014) and to crop models (e.g. Agricultural Model Intercomparison and Improvement Project (AgMIP), see Elliott et al 2015 and Müller et al 2017) illustrate the challenge of coupling climate-biophysical-economic models. Most models have been developed to analyze issues within their own respective disciplines making it difficult to link these frameworks together. To solve this challenge, model comparison activities develop and adopt common protocols for documenting climate and socio-economic input data, model outcomes and methods for output comparison. These protocols make it easier to understand how to couple these models and assess the impacts of different assumptions embedded in each model. But these activities often require consistent feedback and revisions among working groups as

[30] https://fridaysforfuture.org/.

[31] Tipping point threshold refers to threshold or inflection point before a tipping point is reached.

well as significant computational resources, funding, and manpower.

Differences in spatial resolution and time scale across models also present significant barriers to model coupling especially for economic models. Climate change impact assessments using partial or general equilibrium models face this limitation since most economic models have low geospatial (country or regional units) and temporal resolution (annual) (Nelson *et al* 2014 and Piontek *et al* 2021). However, aggregation of high resolution outcomes ignore heterogeneous sub-national impacts and could result in positive outcomes offsetting negative impacts within a region (Piontek *et al* 2021). Integrated assessment models which use highly aggregated regions might fail to capture unequal risks from climate change particularly in developing countries (Rising *et al* 2022). A potential solution to increase the resolution of climate change impact studies is to use spatial dynamic models which account for economic production and consumption as well as temperature feedbacks at the fine scale (Cruz and Rossi-Hansberg 2021).

Some biophysical and economic models do not fully capture climate tipping points and extreme effects. For example, Heinicke *et al* (2022) finds that a few crop models could estimate observed decline in crop yields due to droughts and heat waves. Dietz *et al* (2021) argue that most studies which examine climate tipping points within an integrated assessment framework focus on one or a few tipping points thereby ignoring the interactions effects. Economy-wide computational models—which are typically calibrated and parameterized using historical data and current technologies—often lose their predictive power when projected too far from their base year (Bardazzi and Bosello 2021). Given this, it is likely that economic models cannot capture drastic changes in the global economy given future climate tipping points.

Most studies focus on one-way coupling wherein climate model outcomes are passed to biophysical and economic models. There is a need to move towards tight model coupling wherein simulation outcomes are passed across models and allowing feedback effects. Robinson *et al* (2018) argue that incorporating feedback effects could alter outcomes of coupled human and biophysical process models. Reviewing the literature, the authors find that allowing two-way feedback effects between models could produce non-linear outcomes and expand the range of model results. However, including feedback loops increases uncertainty of model outcomes and further tests are needed to assess the consistency of these feedback effects. Analysis of climate change impacts should also go beyond sector by sector and instead account for different sectors simultaneously to properly account for the observed linkages and feedbacks in the Earth's systems (Frieler *et al* 2017). A recent study by Chepeliev *et al* (2022a) implements such cascading impacts while looking at the local consequences of U.S. climate mitigation policies and their feedbacks onto the world market (Box 2).

5. How can GLG perspectives improve our modeling approach?

There are several dimensions over which GLG perspective can contribute to the improvement of the current modeling efforts. First, it can help researchers to better design inputs and outputs from each model to support coupling across scales. Second, the GLG perspective can facilitate the development of storyline narratives and scenarios that are consistent across levels. One such example is the concept of representative agricultural pathways (RAPs) (Valdivia *et al* 2015), further discussed below. Finally, an important benefit of using the GLG perspective in climate analyses is that it allows to cross-validate impacts and interactions across multiple scales. In this section we discuss examples of some recent studies that showcase an application of GLG perspective for climate change-related modeling.

Agricultural applications within the AgMIP (Rosenzweig *et al* 2013 and Ruane *et al* 2017) underscore the need to appropriately scale models and scenarios across scales to match decision contexts. Stakeholder planning for agricultural development, farmland mitigation, adaptation and risk management need to be tailored to the context of particular farming systems. These include highly-localized characteristics including soil properties, seed selection, and management (e.g. planting dates, row spacing) as well as climate conditions that can vary dramatically especially around coastlines and mountains. Generic approaches that do not recognize these factors are less likely to be a credible or robust foundation for climate action.

Crop models typically simulate a one hectare field (100 m across) but are constrained by the lack of high quality configuration and climate information at that scale as well as the computational resources that would be required to run at high-resolution across large domains. For global simulations this has led to a practical compromise utilizing representative farming conditions for multiple farm systems (e.g. rain-fed maize, irrigated wheat) on a grid scale matching bias-adjusted climate information ($0.5° \times 0.5°$) (Müller *et al* 2017). AgMIP's Global Gridded Crop Model Intercomparison has conducted a series of protocol-based multi-model simulations to provide a solid grounding for application within global integrated assessment modeling. These include benchmarking the performance of models against

Box 2: Multi-scale analysis of U.S. climate policy

A study by Chepeliev *et al* (2022a) looks into local consequences of U.S. climate mitigation policies and their feedbacks onto the world market. To capture the GLG interactions and identify solutions, the authors link four existing models: the integrated assessment ENVISAGE model, the agro-ecosystem model Agro-IBIS, the water balance model WBM and the partial equilibrium SIMPLE-G model.

The analysis starts with the ENVISAGE integrated assessment model and considers a U.S.-only climate mitigation policy, represented in the form of carbon pricing within a set of exploratory scenarios, starting at \$50/tCO_2 and rising to \$200/tCO_2. The main consequence of this climate policy is to raise the price of energy, with natural gas prices rising steeply. The most important impact on the food, energy and water system is the ensuing change in the price of nitrogen fertilizer, for which natural gas is a major ingredient. As a consequence, at \$100/tCO_2, it is estimated that the price of ammonia fertilizer could rise by more than 60% on a permanent basis.

Within this global/national context, the study examines the likely consequences for fine-scale agriculture within the continental U.S. To do so, the authors feed the change in the national price of fertilizer into the SIMPLE-G model of gridded crop production. They assess the impact on N fertilizer applications via yield response curves obtained from the Agro-IBIS ecosystem model. Nitrogen applications fall by 5.4% per annum (at \$50/tCO_2) to 16.1% (at \$200/tCO_2), which results in reduced leaching from 7.6 to 21.8%. The changes in rates vary widely across grids depending on local soils, weather and crops. Having ascertained the reduction in leaching out of the root zone, the study then tracks the leachate movement through the river system using the WBM hydrological model, determining export to the Gulf of Mexico based on natural removal rates within the river system. At a carbon price of \$200/tCO_2, it is found that leachate export to the Gulf could fall by nearly 16% per annum.

The local-to-global feedbacks are explored using the international trade dimension of the SIMPLE-G model. With increasing cost of fertilizer and energy inputs, a decline in U.S. corn and soy production is observed. These reductions in U.S. crop output are only partially offset by responses in the rest of the world. While global crop output falls in this case, global GHG emissions from agriculture rise, due to the relatively high emission factors in the rest of the world. Diminished production also raises prices and pushes 700 thousand people in developing countries into undernourishment. South Asia and Sub-Saharan Africa together account for almost 70% of all the additional undernourished population.

An applied GLG interactions approach reveals unanticipated consequences of a U.S. climate policy—both in terms of local and global environmental quality as well as food security.

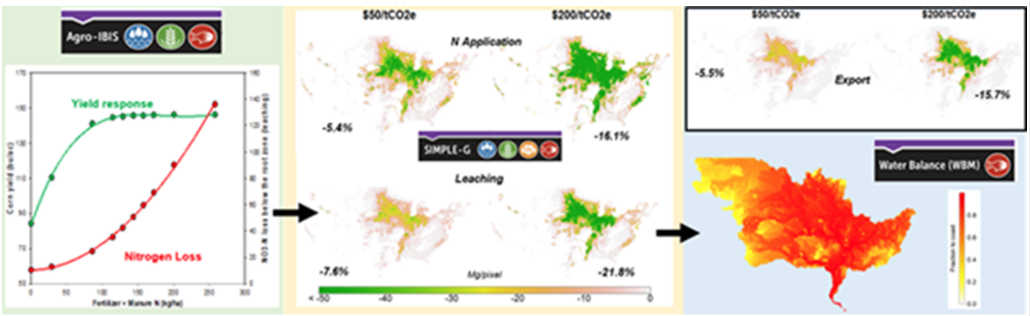

Figure 4. Climate policies and hypoxia—an example of a coupled system.

historical production (Müller *et al* 2017), quantifying fundamental crop system sensitivities to nitrogen fertilizers and core climate change factors of CO_2, temperature and water (Franke *et al* 2020), and simulating the latest climate projections (Jägermeyr *et al* 2021).

Regional and national-scale crop modeling applications add information on more diverse farming systems and can connect to household-level socio-economic information for regional integrated assessment (Freduah *et al* 2019, Rosenzweig *et al* 2021). This requires additional details on agricultural conditions and further bias-adjustment and downscaling of climate information to represent household conditions Ruane *et al* 2015. AgMIP is also developing protocols for crop models ($\sim$30 m) at very high resolution in order to incorporate fine-scale remote sensing information, although this requires development of novel information technologies to utilize high-performance computational systems. Finer resolution information and detailed configurations are appealing to support stakeholder decisions for adaptation strategies particularly when tied to socio-economic analysis capable of evaluating distributional outcomes across households with varying levels of exposure and vulnerability.

Consistent local-to-global story-lines and scenarios are needed to underpin agricultural simulations as mitigation, adaptation and risk management actions do not occur only at a single scale. AgMIP developed the concept of RAPs to reflect the common landscape in which food systems will develop in response to socio-economic, policy, dietary and technological pressures (Valdivia *et al* 2015). RAPs are effectively elaborations of the global SSPs, providing additional insights into trends and tipping points that will shape the future of agricultural systems independent of climate change. At finer scales more elaboration is needed to match the heterogeneity of local policies, markets and supply chains as well as shifts in farm practices and household vulnerability and exposure across diverse populations. Coordination of RAPs across scales allows agricultural model applications and broader IAM applications to be internally consistent while reflecting decision makers' ability to affect their own decision domain without being drowned out by larger global trends and more powerful actors.

AgMIP developed a Coordinated Global and Regional Assessment Protocol to enable consistent simulations at both local and global scales (Rosenzweig *et al* 2016). This allows the simultaneous evaluation of global agricultural production, trade and markets while also using RAPs to recognize regional decisions by stakeholders who have little ability to influence global markets (e.g. due to lower production, market and geopolitical influence). In a pilot investigation of the implications of 1.5 °C and 2.0 °C global warming levels, Ruane *et al* 2018 noted the interplay of local and global production trends illustrated by cotton-wheat systems in Pakistan under the 2.0 °C world. Cotton prices were projected to decrease slightly given increases in global production, indicating that most cotton-growing regions would see yield gains that at least partially offset price declines. Cotton yields in Pakistan decline dramatically (−20%); making it a particularly vulnerable region where profits are hit by both decreased yield and decreased prices.

6. Concluding thoughts

The most recent report of the IPCC, the Sixth Assessment Report, weighs in at well over 7000 pages, covering in-depth virtually every aspect of climate change[32]. Yet there are still relatively few studies that successfully capture the complex nature of GLG linkages in the context of climate change—the full potential of the GLG paradigm in supporting the decision-making process in this area remains largely under exploited. This situation is driven by a number of limitations, addressing of which would help move forward this important agenda. Some of the key limitations are addressed in the body of the paper—notably the interactions of GLG perspectives with risk analysis in its various forms and tipping points. Though these may reflect the most glaring limitations, there are others that are long-standing and yet remain to be addressed, even if there has been some progress over time.

First, despite intensification of efforts on the implementation of multi-disciplinary research in recent years, climate policy field continues to be largely dominated by disciplinary-focused studies, remaining a prisoner of over-specialization. Even with full-hearted efforts at working across disciplines, communication across multi-disciplinary teams is a challenge, where vocabulary, specialized knowledge and modeling paradigms are barriers to model coupling. In many cases models are too complicated to handle by outside users and/or are based on proprietary data without public access to the source code. Unfortunately, there are very few journals in the field of climate change studies or economics that support full replication of published results[33]. An area that still needs substantial improvement (Hoffmann *et al* 2021). Though replicability is the ultimate 'holy grail', there has been important progress in terms of transparency and model availability. Among the complex IAMs, several prominent ones are available for download, for example MESSAGE, REMIND, GCAM, and ENVISAGE—though the ability to successfully run simulations with these requires significant efforts. The macro IAMs, such as DICE and FUND are readily accessible and easier to use—and ongoing efforts to modularize these with other components of a complete, though simple, IAM are underway[34].

Second, linking across global and local modeling frameworks with varying geospatial and temporal resolution is often complicated by the absence of harmonized multi-level assumptions and storylines. Several earlier studies have looked into downscaling of global/national-level scenarios to a more refined level, such as emission and socio-economic dimensions of the SSPs (Murakami and Yamagata 2019, Gütschow *et al* 2021). However, there are very few examples where local and global scenarios are developed using harmonized storylines (Valdivia *et al* 2015), rather than mechanic downscaling techniques. The former is important, since it is vital to properly recognize highly-localized characteristics, such as socio-economic conditions, soil properties, seasonal patterns, demographic characteristics and agricultural management practices for a consistent modeling of local policies and their feedback loops. To facilitate the harmonized storylines' development process, it is important to set up coordinated assessment protocols that would enable consistent simulations across scales. The latter though might often require substantial computational resources and manpower (Rosenzweig *et al* 2016).

Third, motivation for linking models across multiple scales is often downplayed by the monetary valuation fallacy. It is widely believed that to support

32 Available at www.ipcc.ch/report/sixth-assessment-report-cycle/.

33 In the field of economics, the *Journal of Global Economic Analysis* is one notable exception that requires the ability of the reviewers to replicate results of a study.

34 See www.mimiframework.org/.

the decision-making process, the monetized values of environmental costs and benefits should be assessed (Temel *et al* 2018), as the market-oriented approaches are reaching areas that traditionally have been governed primarily by non-market norms (Sandel 2012). And while the added value of monetizing nature is often criticized (Victor 2020), in many cases the inability to provide monetary assessment of specific nature- or human-related implications substantially reduces the potential validity and impact of the study, thus impacting the motivation for the corresponding research. Addressing this fallacy would open a space for a wider variety of applications within the GLG linkages and climate mitigation field, though would require substantial multi-stakeholder efforts.

Fourth, GLG coupling is often complicated by the fact that many channels and feedback loops are still being explored and quantified, as this field is undergoing rapid development. Only recently have studies started to provide the economic parameterization of climate tipping points (van Ginkel *et al* 2020, Dietz *et al* 2021), while many other aspects, such as the potential for positive tipping points, are still under development (Lenton *et al* 2022). New contributions in this area would be key in moving forward the agenda of GLG linkages in the context of climate change.

Finally, it should be stressed that while the development of more comprehensive and advanced GLG modeling solutions in the context of climate change assessment is a necessary step in supporting the decision-making process, this is not the ultimate goal by itself. The science-policy interface is complex and the most advanced modeling approaches might not always be best suited to address the specific policy question at stake. As there are no one-size-fits-all solutions, it is important to consider the feedback from policymakers and stakeholders as an additional driver that shapes the future direction of the development of GLG modeling solutions. The former could also provide an important local context for the customization of the GLG channels allowing better navigate the science-policy landscape.

Data availability statement

No new data were created or analyzed in this study.

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