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Towards modelling the World-Earth System: A Systematic Literature Review of the State of the Art and Ways Forward

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Abstract. Understanding coupled World-Earth system dynamics is central to navigating the Anthropocene, yet global social and environmental systems are still predominantly modelled separately. Bidirectionally coupled models of global scale that represent both subsystems as endogenous components are increasingly developed, but the field remains fragmented across disciplines, modelling traditions, and epistemological assumptions.

This study presents a systematic review of global social-environmental modelling approaches, drawing on 314 peer-reviewed studies identified through a comprehensive database search and the usage of a newly developed, Large-Language Model assisted approach.

We propose a typology of three model groups - Goal-Oriented models, Structural Feedback models, and Dynamic Co-evolutionary approaches - that can help to navigate the diverse landscape of this research field and assess them against the design principles for World-Earth Models proposed by Donges/Heitzig et al. (2020).

Our analysis shows characteristic strengths and limitations tied to each typical model group. Across all, socio-cultural processes beyond economic optimization, diverse bidirectional feedback, endogenous tipping dynamics, and cross-scale interactions remain systematically underrepresented. A collaboration analysis further confirms the conceptional difference between the proposed groups and highlights the strong fragmentation of the field along the model groups.

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These findings suggest that future modelling efforts towards a better understanding of Anthropocene dynamics and World-Earth System resilience should prioritize broader actor representation, more diverse feedback structures, and explicit coupling of social and biophysical tipping processes, ideally through hybrid modelling formats - while remaining grounded in the specific research question rather than aiming for universal coverage.

1 Introduction

Today, humans have become the most important determinant of environmental degradation and changes in the Earth System (Crutzen, 2002; Zalasiewicz et al., 2024; Rockström et al., 2026). Besides causing the climate crisis, we have altered global ecosystems by introducing the 6^{th} mass extinction, directly impacted the water cycle, introduced novel entities in the biosphere and are responsible for the increasing acidification of the oceans, breaching the majority of the Planetary Boundaries (Richardson et al., 2023). Anthropogenic perturbations of the Earth system have reached a level at which they can fundamentally alter planetary processes. Consequently, the Earth System is being pushed beyond the relatively stable dynamics of the Holocene and into the Anthropocene. This shift threatens Earth System resilience, defined as the capacity of the planet to absorb disturbances and maintain the conditions that have historically enabled environmental stability and human development (Gleeson et al., 2020; Rockström et al., 2024; Ripple et al., 2026).

Understanding those dynamics is inherently challenging due to the complexity of the relevant biophysical and socio-economic dynamics as well as their interrelations. Many of these interactions operate across multiple spatial and temporal scales, making them difficult to observe directly or investigate through controlled experiments (Schellnhuber, 1999). Consequently, computational models have become indispensable tools for Earth System science (Schellnhuber, 1999; Steffen et al., 2020). In providing a means to investigate system dynamics, evaluate future scenarios, and assess the resilience of the planet under increasing anthropogenic pressures, they help to foster a system understanding that cannot be reached empirically at the planetary scale.

Despite increasing recognition of the interconnectedness of social and environmental systems, both are still predominantly studied and modelled separately at the global scale (Beckage et al., 2018; Obradovich et al., 2019; Moore et al., 2022; Tan et al., 2023). Most environmental models focus on biogeochemical, ecological and biogeophysical (e.g. carbon cycle, vegetation dynamics, ice sheets, or ocean-atmosphere interactions) dynamics and represent human activities, if at all, as solely economic dimension and as external drivers rather than endogenous system components (Beckage et al., 2022). Beyond these biophysical representations, many modelling approaches further emphasize the need to incorporate socio-cultural processes such as learning, norms, and non-rational behavioural dynamics, which are key characteristics of the Anthropocene and may give rise to nonlinear phenomena, including social tipping processes (Bury et al., 2019; Beckage et al., 2020; Farahbakhsh et al., 2022).

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A recent development addressing these limitations is the emergence of so-called World–Earth Modelling approaches (WEMs). These approaches aim to explicitly represent social and environmental systems as dynamically coupled components and focus on their bidirectional co-evolution (Donges/Heitzig et al., 2020; Donges et al., 2021). In contrast to traditional modelling approaches, WEMs move beyond one-way forcing relationships and provide a conceptual framework for studying integrated global social-environmental system dynamics that shape the Anthropocene. For the development of such models, Donges/Heitig et al. (2020) propose five design principles (WEM design principles).

Despite this development, the field remains highly fragmented across research communities, methodologies, and disciplinary perspectives, and significant diversity persists in how social-environmental couplings are implemented across different modelling traditions. This fragmentation limits comparability and makes it difficult to obtain a coherent overview of existing approaches, including their strengths, limitations, and underlying assumptions about human–environment interactions.

Despite a growing number of reviews on social-environmental system interactions, existing syntheses remain largely paradigm-specific or conceptually bounded. Integrated Assessment Model (IAM) reviews (e.g. Krey, 2014; Weyant, 2017; Johnson et al., 2025) primarily focus on energy-economy-climate representations and often exclude broader socio-cultural or system dynamics-based modelling traditions. Reviews of coupled social-environmental systems (Calvin et al., 2018; Farahbakhsh et al., 2022; Tan et al., 2023; Perera et al., 2024) highlight increasing model coupling and bidirectional feedback yet typically remain within specific modelling traditions or focus on selected interaction mechanisms. Similarly, sectoral syntheses (Tachiiri et al., 2021) and extensions towards wellbeing or socio-economic outcomes (Schrijver et al., 2025) broaden the set of impact pathways but do not provide a unified cross-paradigm comparison of model structures. Conceptual contributions such as Anthropocene oriented critiques (Verburg et al., 2016) and human behaviour integration frameworks (Müller-Hansen et al., 2017) further emphasize missing feedbacks and heterogeneity but remain largely descriptive rather than providing a structured model classification.

Against this background, no existing review offers a systematic, paradigm-spanning synthesis of global social-environmental modelling approaches that jointly covers IAMs, integrated Earth System models, System Dynamics approaches, and socio-cultural or Agent-Based models. Existing work either focuses on specific modelling families, individual coupling mechanisms, or conceptual critiques, but lacks a comparative structural mapping of which modelling paradigms exist and how they represent global social-environmental coupling, feedback complexity, and co-evolutionary dynamics.

To fill this lack of a comprehensive, structured overview that integrates different approaches in the highly fragmented field, we present a systematic review of global social-environmental modelling approaches. We develop a structured typology of modelling traditions, assess them through the lens of the WEM design principles and conduct a bibliometric analysis of existing approaches. This allows us to identify systematic differences in how models represent social dynamics, environmental complexity, feedback processes, and cross-scale interactions. By doing so, we provide an integrated map of the field, reveal

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key trade-offs between modelling philosophies, and identify structural blind spots and opportunities for next-generation global social-environmental modelling efforts.

This study is structured as follows. Section 2 describes the systematic review methodology. Section 3 presents the results of the review, including an induction-based classification and grouping of all included studies (3.1), an analysis of their common characteristics and differences (3.2), an assessment of their alignment with the World–Earth Model design principles proposed by Donges/Heitzig et al. (2020) (3.3) and a bibliometric analysis (3.4). Section 4 discusses these findings in the context of the existing literature, identifies key research gaps, and outlines possible directions for future model development. Section 5 concludes the review.

2 Methods

2.1 Research objective

This study aims to systematically identify and analyse global models that represent coupled social-environmental systems, with a specific focus on approaches that explicitly incorporate both environmental and social processes as endogenous components. We further aim to assess how these models conceptualize and implement interactions between these subsystems, and how they align with the WEM design principles (Donges/Heitzig et al. 2020).

In this context, we consider simulation models that include (i) environmental and biophysical processes relevant at the planetary scale, such as climate dynamics, hydrological systems, and ecosystem processes, and (ii) representations of social systems, including economic and socio-cultural dimensions of human behaviour. Furthermore, we only include approaches that (iii) explicitly implement bidirectional coupling between social and environmental subsystems and (iv) operate at the global scale.

2.2 Search strategy and record collection

To identify relevant publications, we conducted a systematic literature search in two major academic databases: Elsevier's Scopus and Clarivate Analytics' Web of Science (WoS). The use of multiple databases is recommended to improve coverage and reduce database-specific bias in literature retrieval (Mongeon and Paul-Hus, 2016; Cheung and Vijayakumar, 2016).
Both databases were queried on June 25, 2025, using a structured search string designed to capture simulation-based studies that represent global social-environmental systems according to the inclusion criteria defined in Section 2.1. The search string combined five conceptual components: social systems, environmental systems, coupling mechanisms, simulation modelling, and global-scale framing.

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The final query was defined as follows:
(social OR socio OR human* OR society OR individual)
AND (earth OR climate OR biosphere OR nature OR ecological OR ecology OR environment*)
AND (coupled OR "system dynamics" OR feedback* OR link*)
AND (model*)
AND (global OR planetary OR world OR macro)

In Scopus, the search was applied to titles, abstracts, and keywords. In WoS, the equivalent “Topic” field was used, covering title, abstract, author keywords, and Keywords Plus (automatically assigned keywords by WoS). The search was limited to English-language, peer-reviewed journal articles, excluding grey literature. The initial search resulted in 10 885 records in Scopus and 11 114 records in Web of Science (see Figure 1).

In a second step, a snowballing procedure was applied to the set of studies identified in the initial search. Specifically, we conducted backward snowballing by screening all references cited within the provisionally included articles and forward snowballing by identifying all publications in WoS that cited these articles. Following the snowballing procedure, the selection of studies from the initial search was further refined by applying the eligibility criteria. All records identified through snowballing were assessed using the same eligibility criteria. In total, the snowballing procedure yielded an additional 9 163 records, resulting in a combined dataset of 31 162 records prior to screening.

2.3 Record screening and inclusion using a Large-Language Model assisted approach

This study follows the PRISMA guidelines (Page et al., 2021) for systematic reviews, with the screening process summarized in the PRISMA flow diagram shown in Figure 1. In the first step, all identified records were merged, and duplicate removal was semi-automatically performed using the software Rayyan (Ouzzani et al., 2016). Remaining ambiguous duplicates were manually verified and removed. After this stage, 16 526 records remained in the first and 7 473 records in the snowball round.

Given the large number of retrieved records, an initial screening of titles and abstracts was conducted using large language models (LLMs) (OpenAI’s Chat GPT 4.o) to efficiently identify studies that met the inclusion criteria defined in Section 2.1. Specifically, three criteria were operationalized into structured prompts for automated screening: (i) the presence of a simulation-based modelling approach, (ii) the explicit representation of a social subsystem, and (iii) a global-scale system framing.

For each criterion, 50 records were initially screened and classified by two independent human reviewers, and their results were compared to the LLM outputs. As a quality control measure, we ensured that agreement between the LLM and each

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human reviewer was not lower than the agreement between the two human reviewers. In addition, we evaluated false exclusion rates and recall, prioritizing the minimization of missed relevant studies.

To further ensure the reliability of the screening process, a set of benchmark articles identified from a prior scoping review was used as a continuous validation set throughout all screening stages. All prompts, validation metrics as well as the list of benchmark articles are provided in the Supplement.

Furthermore, to account for potential variability in LLM outputs - even under deterministic settings (temperature set to zero and top-p fixed) - we implemented an ensemble approach in which each article was classified seven times independently by the LLM. The probability of inconsistent future outcomes can be approximated using Laplace's rule of succession, which suggests that 99 repeated runs would be required to reach 99 % confidence in full consistency across runs. Since this is computationally infeasible, we empirically tested whether increasing the number of runs from seven to 99 affected classification outcomes on a subset of 50 articles. This comparison showed no change in majority decisions. Based on these results, we adopted an ensemble size of seven runs for the full screening. After each ensemble classification, results were additionally checked against a benchmark set of articles that resulted from a scoping review. This procedure resulted in 1 082 records from the initial search and 1 008 records from the snowballing round progressing to the next stage of analysis.

These records were screened at abstract level by the first author (human reviewer), resulting in 384 records in the first and 631 records in the snowball round that were retrieved as full texts. The full texts were then independently screened twice by a human reviewer, and overall, 314 records were classified as fitting the inclusion criteria and included in the final dataset.

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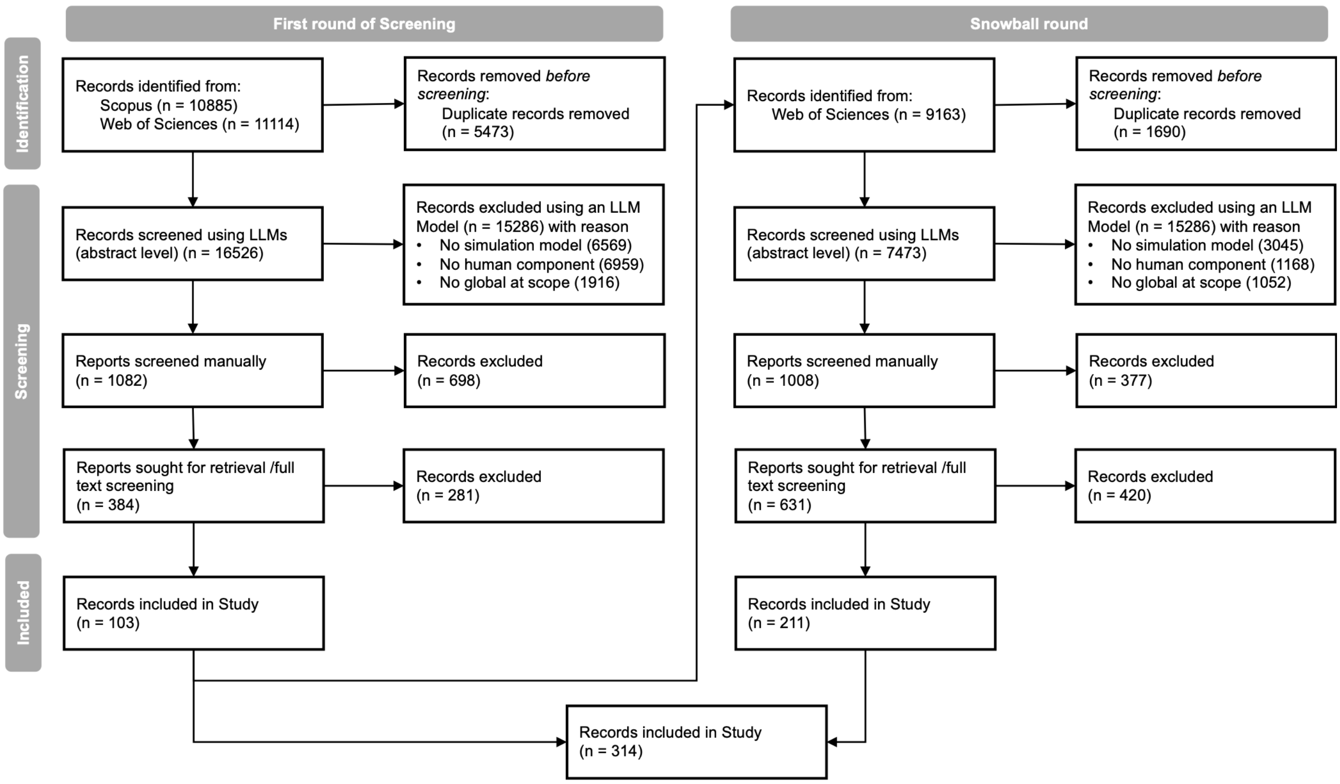

Figure 1: PRISMA flow diagram (Page et al. 2021) depicting the two-stage selection process. The left side shows the initial database search and screening, while the right side illustrates the subsequent snowballing round.

2.4 Record screening and inclusion

To systematically compare and analyse the included, heterogeneous modelling approaches, we adopt the World-Earth Model (WEM) framework proposed by Donges/Heitzig et al. (2020). The authors define five key design principles that are relevant to capture Anthropocene global, coupled social-environmental dynamics: (i) social representations beyond pure economic optimization, (ii) bidirectional coupling between social and environmental systems, (iii) the ability to represent nonlinear dynamics and tipping processes, (iv) cross-scale interactions, and (v) systematic exploration of state and parameter spaces.

In this study, we operationalize the first four of these principles into a structured classification scheme. The fifth criterion - systematic exploration of state and parameter spaces - was excluded from the formal scoring scheme, as its implementation varies substantially across modelling traditions and is not consistently reported in a comparable manner across studies.
Each model was evaluated along the four dimensions based on a clear operationalisation of the principles (see Table 1).

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Table 1: Operationalization of World-Earth Model Design Principles proposed by Donges/Heitzig et al. (2020)

WEM Design Principle	**Score**	Operationalization
WEM1: Socio-cultural processes	0	Representative agent without social dynamics
	1	Multiple agents/groups without interaction beyond a strategic game between them (e.g. overlapping generations, North–South wage differences)
	2	One process of social-cultural interaction (e.g. imitation learning, opinion contagion), or social-cultural aspect aggregated modelled (e.g. social norms, well-being, risk perception)
	3	More than one interacting social process
WEM2: Bidirectional coupling	0	One bidirectional loop (between social and environmental dynamics), but at least one side is very abstract represented (e.g. one simple ODE for emissions to temperature relation)
	1	One bidirectional loop (between social and environmental dynamics) with both sides, physically and socially grounded
	2	Multiple bidirectional loops but only one is physically and socially grounded on both sides
	3	Multiple fully grounded bidirectional loops of qualitatively different types
WEM3: Nonlinearities and Tipping dynamics	0	No nonlinearities or thresholds
	1	Mainly exogenous nonlinearities or hard-coded thresholds not emerging from system structure
	2	One nonlinearity emerging from endogenous system structures
	3	Multiple endogenous non-linearities that mutually reinforce each other and jointly produce emergent system instability
WEM4: Cross-scale interactions	0	No explicit scale structure (fully aggregated system)
	1	One dimension with limited scale structure (social or spatial, two levels)
	2	One dimension with multiple levels (3+) or both dimensions with limited levels
	3	Both social and spatial dimensions with multi-level interactions

The classification was conducted based on human interpretation of the model descriptions and supported by LLM assisted validation. Final decisions were made by the authors, with LLM outputs used as an additional consistency check. This hybrid approach helped ensure robustness across a heterogeneous and often diversely documented modelling literature. As a quality control measure for the WEM classification, only studies providing sufficient methodological detail on model structure and

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system representation were included in the final analytical sample. Studies lacking the necessary information to reliably assess the WEM criteria were excluded from the classification step.

For classical models that appear numerous times in the sample (e.g. the DICE model (Nordhaus 1992), the analysis was based on the basic model version, and records classifications were only adjusted based on the additions made to the basic model. Records which aimed at comparing different models results (typical Model Intercomparison Studies) were excluded from this study.

2.5 Bibliometric analysis

To quantitatively assess the degree of intellectual and social separation between the identified model groups, we conducted a bibliometric community analysis using the R package bibliometrix (Aria & Cuccurullo, 2017). For each included record, we downloaded the full reference lists as well as the corresponding keywords listed by WoS, combining author-defined keywords and automatically generated Keywords Plus into a single keyword set per record. Based on this data, we constructed an author collaboration network from co-authorship relations across all included records. For visualization purposes, we retained all authors with high numbers of publications within their respective model group, reflecting natural breaks in the publication frequency distributions (resulting in top 20-30 publications per group). We choose this approach as these authors are most likely to appear as co-authors and thus drive the observable collaboration structure. To measure conceptual overlap between model groups, we calculated pairwise Jaccard similarity indices for both cited references and keywords. The Jaccard index is defined as the size of the intersection divided by the size of the union of two sets, ranging from 0 (no overlap) to 1 (complete overlap) (Jaccard, 1912).

3 Results

This section presents the main results of the systematic review. In Section 3.1, we develop a structured typology of global social-environmental models, using an inductive approach for grouping the identified models into three typical families based on their modelling philosophy and primary purpose. This typology provides a descriptive map of the modelling landscape and serves as the basis for the subsequent analysis. In Section 3.2, we further characterize these model groups along key dimensions such as model purpose, methodological approach, empirical grounding, and representation of environmental and social processes. In Section 3.3, we then assess all included models using the WEM design principles, enabling a systematic comparison of their representation of socio-cultural dynamics, bidirectional coupling, non-linearities, and cross-scale interactions. Section 3.4 adds a bibliometric analysis to investigate the degree of separation within the research field. Together, these steps provide a combined structural and functional characterization of the coupled global social-environmental system modelling literature.

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3.1 Model Groups

To classify the identified models into a broader model typology, as a first step, we first developed three model groups and nine sub-groups based on their underlying modelling philosophy, system representation, and primary analytical purpose (Figure 2). These groups should rather be understood as ideal types (employing a Weberian ideal-typical approach) and are not mutually exclusive but emerge as dominant structural patterns across the global coupled social-environmental system modelling literature, providing a coherent way to organize a highly heterogeneous field.

Goal-Oriented models focus on achieving predefined objectives such as cost-optimal climate change mitigation pathways, equilibrium states, or policy-relevant targets. While this includes models that follow a typical intertemporal optimization approach, this group also contains models that primarily pursue a rule-based target tracking. This group consists of three subgroups: those which focus on market structures and typically a general or partial equilibrium (Market Targeted), those which are characterized by a macroeconomic structure and single social planners, typically optimizing mitigation pathways (Aggregated Targeted), and those which focus on a limited number of sectors (Sectoral Targeted).

The second group, **Structural Feedback** models typically focus on interactions and feedback between different subsystems. Models in this group are often characterized by system thinking and couple several sub models. The focus here is much more on the interplay of those subsystems than their detailed characteristics. The three subgroups here contain of models focusing on several sectors and social and ecological processes (Comprehensive Feedback), those models which focus on feedback in one specific sector (Sectoral Feedback) and models that follow the typical WORLD dynamics as proposed by Meadows et al. (1974) and focus on the limits to posed by human appropriated natural resources (World Feedback).

The third group, **Adoptive Co-evolutionary** models, focuses on the joint evolution of social and environmental systems and the emergence of interaction dynamic patterns over time. These models typically do not assume optimization behaviour and instead emphasize adaption, heterogeneity and evolving system structures. The three subgroups here contain models, focusing on the overall carrying capacity of the planet for a human population (Carrying Capacity Co-evolutionary), those which focus on socio-cultural dynamics and interactions (Socio-Cultural Co-evolutionary) and those which focus on economic dynamics (Economic Co-evolutionary).

Figure 2 also shows the number of reviewed publications per sub-group over time. Overall, the results indicate a strong increase in publications over the last 30 years. Models in the Goal-Oriented group appear early and dominate the overall sample. Structural Feedback models begin to emerge in higher numbers around 2008, with a relatively stable number of publications per year thereafter. Around 2010, Dynamic Co-evolutionary models appear and show a steady increase in publications over time.

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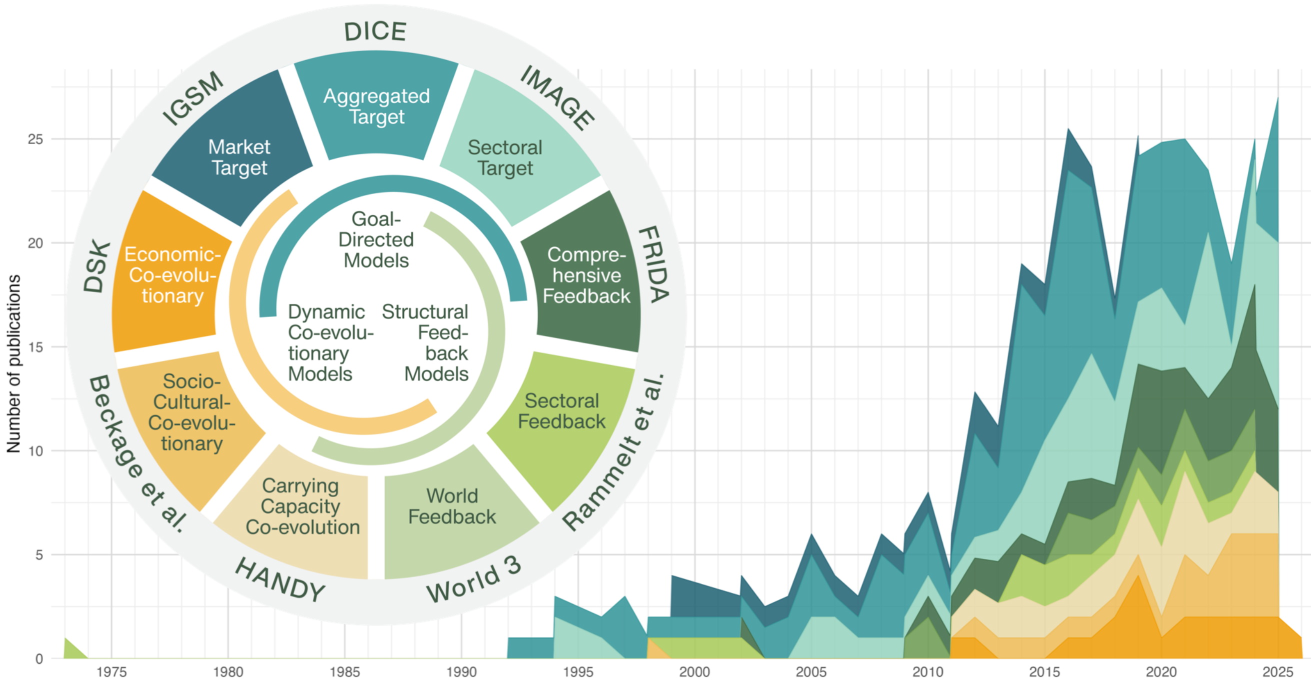

Figure 2: Overview of the proposed model groups and sub-groups (Round circle), with one respective example per sub-group (grey ring) (left). Number of included records per model group over time (right).

3.2 Characteristics of the model groups

Despite considerable overlap between individual models, the three model groups differ systematically in their analytical purpose, methodological structure, representation of social and environmental processes, and degree of empirical grounding. Together, these dimensions reveal a characteristic trade-off between environmental realism, social complexity, and the exploration of emergent dynamics.

Goal-Oriented models primarily serve optimization and projection purposes, such as identifying cost-efficient mitigation pathways or equilibrium outcomes. Structural Feedback models are more commonly used for scenario exploration and understanding system dynamics, whereas Dynamic Co-evolutionary models emphasize theory-building and the study of emergent socio-environmental processes.

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These differences are reflected in their methodological foundations. Goal-Oriented models typically rely on optimization or equilibrium frameworks, Structural Feedback models are predominantly based on stock-flow structures, system dynamics methodology and differential equations, while Dynamic Co-evolutionary models employ a broader range of approaches, including aggregate dynamic models, agent-based models, and network approaches.
A clear gradient is visible in social representation: Goal-Oriented models predominantly rely on representative agents or highly aggregated regions, Structural Feedback models introduce limited heterogeneity through sectoral or regional disaggregation, while Dynamic Co-evolutionary models include the widest range of actor representations, from aggregate populations to heterogeneous interacting agents.

Regarding environmental dimensions and planetary boundaries represented (Figure 3), climate change is represented across nearly all groups, though with vastly different levels of detail - from simple two-box models in many Aggregated Target models to full Earth system models (iESM (Collins et al. 2015), IGSM (Monier et al. 2013), BNU-HESM (Yang et al. 2015)) in the different Goal-Oriented subgroups. Novel entities, ozone depletion, and ocean acidification are rarely explicitly modelled across all groups. Sectoral Target models achieve the broadest environmental coverage, integrating land use, hydrology, biosphere integrity, aerosol emissions, and in some cases marine ecosystems. Within the group of Structural Feedback models, Comprehensive Feedback models represent multiple environmental dimensions simultaneously but emphasize interlinkages over process detail and World Feedback models reduce the environment to (non-)renewable resource stocks. Dynamic Co-evolutionary models show the lowest environmental complexity overall: Economic Co-evolutionary models typically use simplified carbon stocks or emulators; Socio-Cultural Co-evolutionary models often treat climate as a simple temperature or pollution variable and Carrying Capacity Co-evolutionary models proxy the environment typically through carrying capacity or natural land cover.

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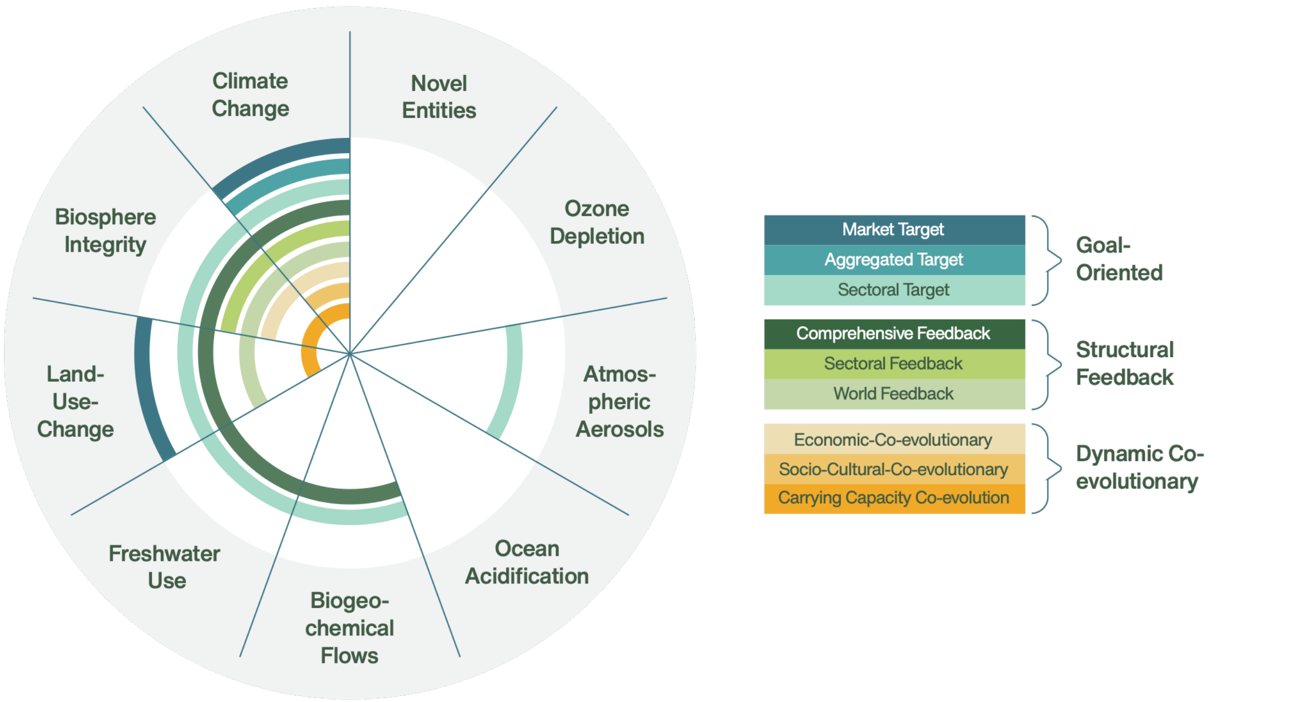

Figure 3: Planetary Boundaries represented per model group (marked for sub-groups if the respective Planetary Boundary is represented in three or more models within the groups).

Empirical grounding is strongest in Goal-Oriented and selected Structural Feedback models, which frequently rely on calibrated datasets and validated biophysical modules. Dynamic Co-evolutionary models are more heterogeneous, ranging from empirically grounded economic approaches to largely theoretical Socio-Cultural or Carrying Capacity-based approaches.

3.3 Analysis of the model groups along the design principles for World-Earth Models (WEMs)

To be able to assess the identified models with respect to the design principles for WEMs proposed by Donges/Heitzig et al. (2020), all records have been classified according to the operationalization of these principles as described above (Section 2.4). Figure 4 depicts this assessment by showing the distribution of the results per model group before the results for each design principle is presented in detail. To make sure that the results are not only dependent on dominant model families (e.g. DICE and IMAGE), a second analysis only including models that implement structural changes to the basic models was conducted and the results can be found in the Supplement. Overall, the results only very little from the here shown, full sample.

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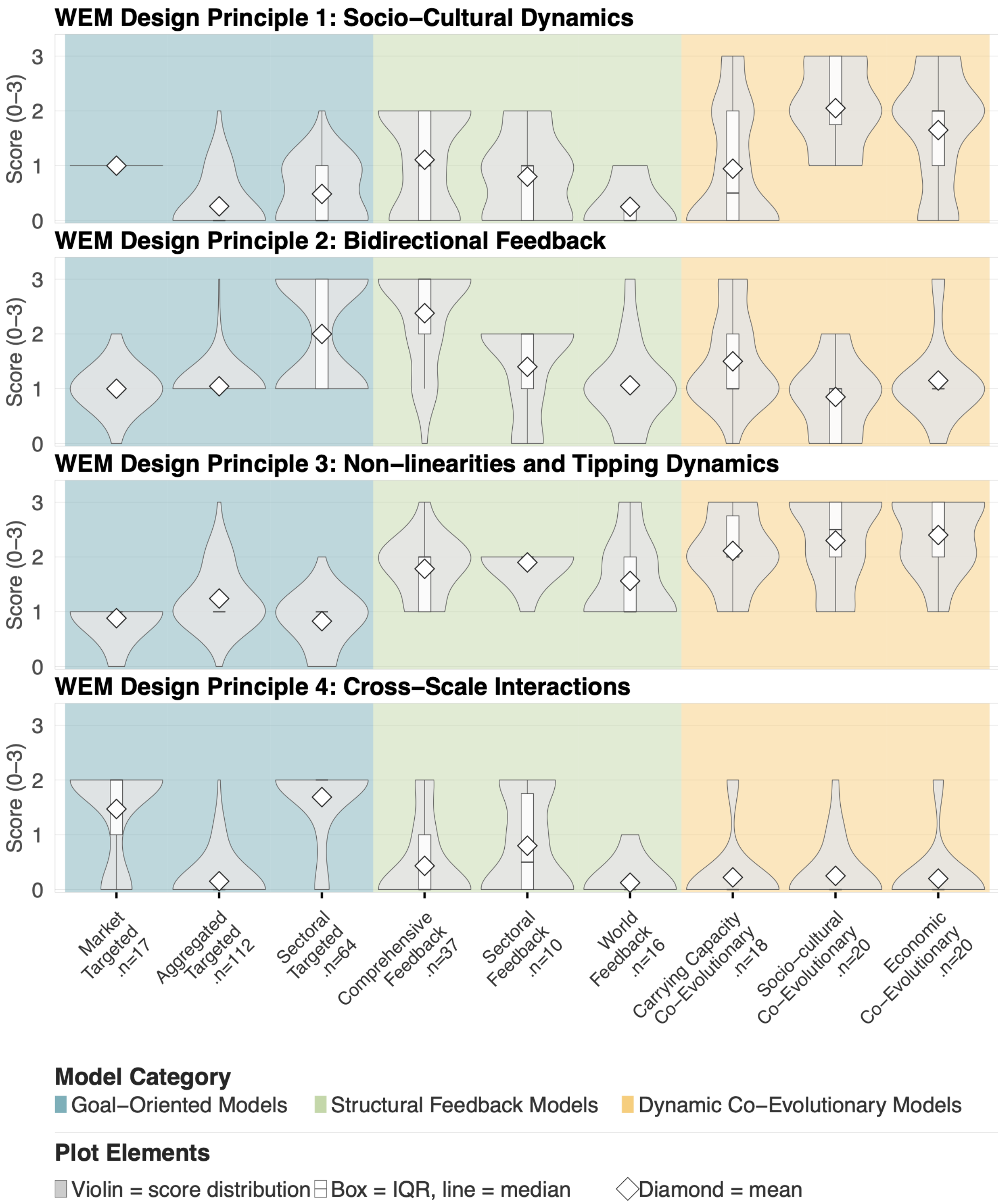

Figure 4: Overview of model groups and the degree to which they match the World-Earth Model design principles, according to the operationalisation described in Table 1.

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3.3.1 Socio-Cultural dynamics

Across model groups, the representation of social dynamics varies systematically (see first panel in Figure 4). Goal-Oriented Models typically do not represent socio-cultural processes explicitly; social behaviour is largely reduced to representative agents or aggregate optimization. Exceptions exist in Sectoral Target models where heterogeneous consumers and social influence are occasionally introduced (e.g. transport technology adoption in IMAGE (Pettifor et al., 2017)).

Comprehensive Feedback models show an overall high variety within this category and regularly include stylized socio-cultural processes such as norms, trust, and risk perception, but mostly in aggregated form. FELIX for instance represents consumers dietary change based on perceived climate risks and social norms (Eker et al. 2019), the GUMBO model (Boumans et al. 2002) includes social capital (modelled as trust, institutions and norms) which can reduce transaction costs and thus increase the modelled welfare and the Earth4All model includes social trust, tensions and reform capacity (Feder et al. 2024).

Dynamic Co-evolutionary models provide the richest representation of social-cultural dynamics, where social influence, learning, norm diffusion, and political dynamics are often explicitly modelled (e.g. Beckage et al., 2018; Bury et al., 2019; Menard et al., 2021; Müller et al., 2021; Frieswijk et al., 2023; Ecotière et al., 2023) over social learning (e.g. Donges et al., 2021), social values and environmental awareness (e.g. Roos, 2018), socio-political acceptance (Perri et al., 2023) to voting dynamics (e.g. Donges et al., 2020). However, most models still focus on a limited subset of behavioural mechanisms, and fully integrated multi-process representations remain rare. Moore et al., (2022) represented an exception to this as the authors combined several socio-cultural processes such as opinion formation, social conformity and political interest feedback in one model.

Overall, actor representation is strongly constrained, and most modelling approaches rely on representative agents or highly aggregated populations. An exception within Goal-Oriented models is the Market Targeted subgroup, where actors such as firms, households, banks, and governments are more explicitly represented, albeit within equilibrium-based structures and typically as one representative agent for each. Structural Feedback models occasionally introduce heterogeneity through population segmentation, for example by age cohorts (e.g. ANEMI3 (Breach et al., 2021)), and in some cases extend this to additional socio-demographic dimensions such as gender or education (e.g. FELIX (Ye et al., 2024)). Within Dynamic Co-evolutionary models, actor representation varies substantially across subgroups, ranging from highly aggregated formulations to more explicit agent-based approaches. While some models remain population-level representations (e.g. Beckage et al., 2018), others introduce limited group structures or game-theoretic interactions (e.g. Menard et al., 2021). Agent-based Dynamic Co-evolutionary models may explicitly represent heterogeneous actors such as firms, households, and banks and capture their interactions. Nevertheless, only a subset of co-evolutionary and market-based models includes explicit heterogeneous agents and interaction structures (e.g. ABM-IAM (Safarzyńska et al. 2022), DSK (Lamperti et al., 2024)).

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3.3.2 Bi-directional Feedback

Feedback structures between social and environmental systems differ in complexity and aggregation level (see second panel in Figure 4). Market and Aggregated Target models within the group of Goal-Oriented approaches typically represent a single dominant feedback loop linking emissions, temperature change, and economic damages via aggregate damage functions affecting GDP or welfare. One exception is the coupled model BNU HESM (e.g. Yang et al., 2015) which represents not only climate but also biosphere dynamics and can represent more than one qualitative bidirectional feedback. Sectoral target and Comprehensive Feedback models extend this structure by introducing sectoral and biophysical feedback (e.g. land use, resource availability, ecosystem services), allowing for more differentiated interactions between subsystems. Dynamic Co-evolutionary models often simplify environmental dynamics again, introducing behavioural feedbacks driven by perceived risks, costs, or social influence, which affect mitigation decisions and aggregate emissions but regularly focusing on one bidirectional feedback loop.

3.3.3 Non-linearities and Tipping Dynamics

The ability to represent non-linear and tipping dynamics varies strongly across model types (see third panel in Figure 4). Goal-Oriented models are generally limited due to smooth functional forms, equilibrium assumptions, and weak representation of interaction networks. While they often aim to include non-linear and tipping dynamics, those are mostly exogenously set by the introduction of thresholds or stochastic shocks (e.g. Bahn et al. 2008; Lontzek et al. 2015).
Structural Feedback models show more non-linear dynamics and regularly include emerging, feedback-driven non-linearities and thresholds (see e.g. Ye et al., 2024; Schoenberg et al., 2025). Such thresholds need not be hard-coded: bifurcations and regime shifts can emerge endogenously from macroscopic feedback structures alone, without requiring micro-level interaction or agent heterogeneity. These are typically social-ecological in nature, arising from the coupled dynamics between economic, social, or behavioural variables and the biophysical system itself. Dynamic Co-evolutionary models show the highest number of non-linear dynamics overall, and feedback-driven thresholds of this same macroscopic kind regularly emerge in them as well. In addition, some Dynamic Co-evolutionary models further incorporate explicit network and agent-based structures, which can give rise to non-linearities and tipping dynamics emerging more distinctly from micro-level interactions: social or economic tipping points arising from network effects, agent heterogeneity, and behavioural or structural cascades (e.g. Lamperti et al. 2018; Müller et al. 2021), although many such implementations remain stylized.

3.3.4 Cross-scale interactions

Cross-scale interactions remain a major limitation across modelling approaches (see fourth panel in Figure 4). Aggregated Target models typically rely on highly aggregated regional or global representative agents, limiting both spatial and social scaling. Market Targeted models such as IGSM (e.g. Prinn et al., 1999) introduce cross-scale dynamics through a combination of socioeconomic regional disaggregation (16 world regions in EPPA) and a finer-grained biophysical grid (latitudinal climate and ecosystem zones), explicitly coupled through emissions mapping procedures; however, the social dimension itself remains flat, with a single representative consumer per region. Sectoral Targeted models instead typically achieve spatial disaggregation on the ecological side, through gridded representations of land use and biophysical processes, while relying on comparatively aggregated social and economic structures. Some Structural Feedback models occasionally capture spatial heterogeneity in a similar way, through regional or gridded disaggregation (e.g. MIMIES (Boumans et al., 2015), WILIAM (Calheiros et al., 2024)), but still mainly rely on aggregated social structures. Dynamic Co-evolutionary models sometimes introduce micro-macro linkage through agent-based or network approaches (e.g. Bechthold et al., 2025; Moore et al., 2022), but these remain exceptions rather than the dominant design. Overall, true multi-level representation of interacting societal scales with heterogeneous actors (households, firms, regions, global system) remains rare.

3.4 Intellectual and social distance between model groups

The conducted author collaboration network shows clear separations between author groups (Figure 5, top panel). While the analysis of the top authors (at least three publications in the sample for Structural Feedback (22), at least two publications in the sample for Dynamic Co-evolutionary models (27), and at least five publications for Goal Oriented models (25)) shows one main and one side cluster for the group of Goal-Oriented models, author interactions within the groups of Structural Feedback and Dynamic Co-evolution remain also fragmented within their larger model group. The analysis shows multiple distinct communities within the network, each containing authors exclusively or predominantly from one model group, with very little cross-paradigm collaborations observed among the top authors of each group. We found no author contributing to all three groups, three authors with publications in the groups of Structural Feedback and Dynamic Co-evolution, five authors with publications in the groups of Structural Feedback and Goal-Oriented models and 13 with publications in the groups of Dynamic Co-evolutionary Goal-Oriented model, each showing less than 2 % pairwise Jaccard similarity between the authors. Pairwise Jaccard similarity of cited references was also consistently low across all model group pairs (between 3.4 % and 3.6 %), indicating that the three model groups draw on largely separate scientific literatures. Keyword overlap was higher but still limited (between 10 % and 13.2 %), suggesting greater conceptual overlap than the citation analysis alone would indicate (Figure 5, bottom panel).

To assess whether the observed paradigm separation is driven by applied studies rather than structural contributions, we repeated the analysis excluding papers that apply existing model frameworks without introducing structural innovations. The results only show minor differences, showing that both application and development of the models seem to be conducted in silos. Detailed results of this additional analysis can be found in the Supplement.

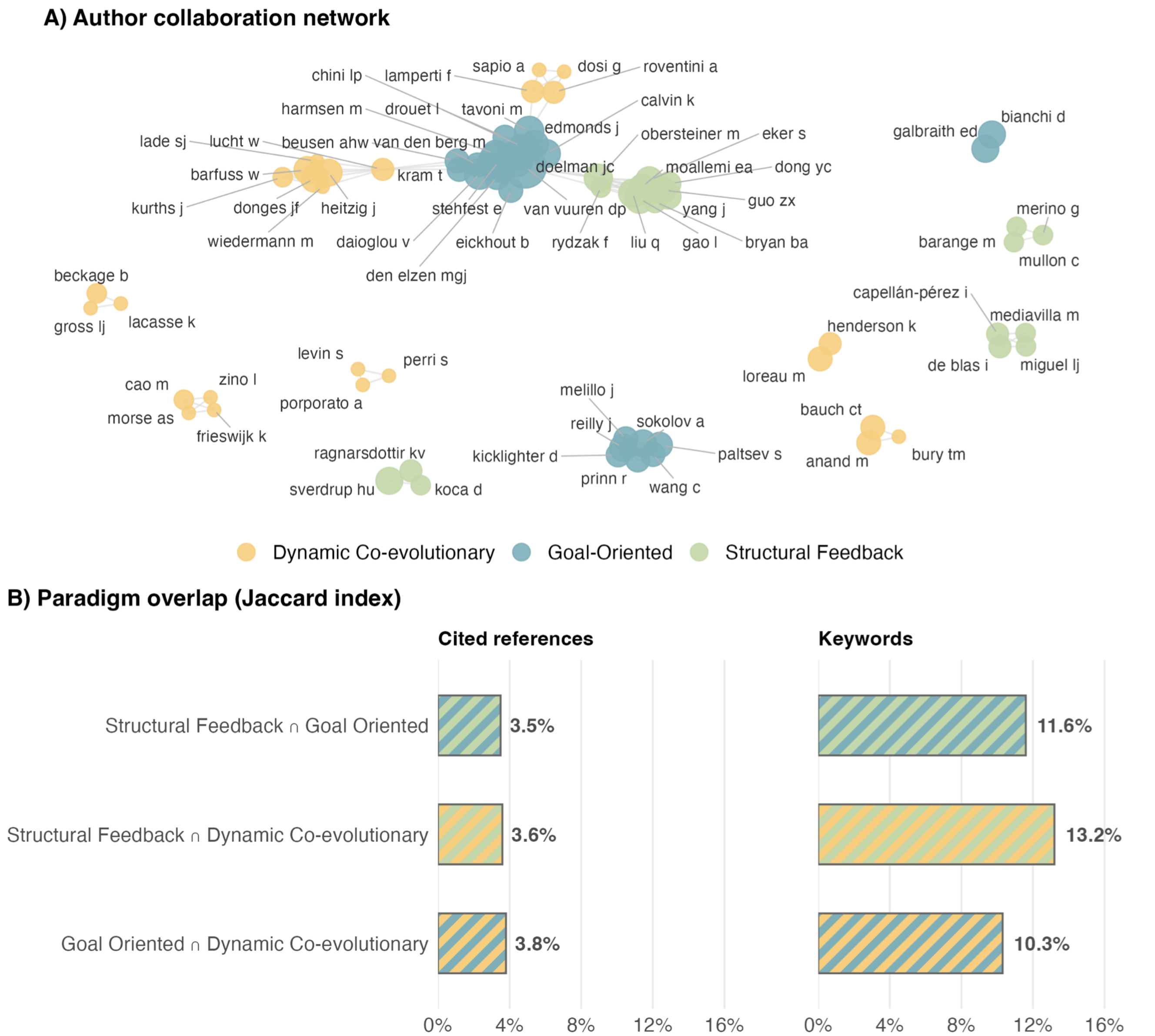

Figure 5: Collaboration network of top authors per group (top panel) and shared references and keywords (pairwise Jaccard similarities) between the model groups (lower panel).

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4 Discussion

4.1 Model groups

Using a systematic review approach, a broad search strategy, and LLM-assisted screening, this study synthesizes a highly diverse body of global social-environmental modelling literature and proposes a typology to structure the field. While the resulting groups provide a useful lens for navigating this landscape, they should be understood as idealized ideal types (in the Weberian sense) rather than strictly separated categories. Several approaches share characteristics across group boundaries, indicating that the modelling landscape is better understood as a set of overlapping modelling traditions rather than as a collection of discrete classes. Nevertheless, the classification reveals fundamentally different ways of conceptualizing social-environment interactions, and its structure is also supported by the conducted bibliometric analysis. Goal-Oriented approaches typically frame environmental systems in relation to predefined objectives such as cost minimization, equilibrium states, or policy targets. Structural Feedback models instead focus on causal relationships and feedbacks between coupled subsystems, emphasizing how changes in one part of the system propagate through others. Dynamic Co-evolutionary approaches view social and environmental systems as jointly evolving, emphasizing adaptation, heterogeneity, and the emergence of system dynamics over time.

While this field was initially dominated by Goal-Oriented modelling approaches in the 1990s (building on early system dynamics modelling in the 1970s), the increasing presence of Structural Feedback and Dynamic Co-evolutionary models suggests a growing heterogeneity in modelling perspectives and objectives, possibly driven by advances in computational capacity and interdisciplinary exchange.

The review shows that no single modelling approach simultaneously combines high environmental realism, rich social representation, strong empirical grounding, and the ability to capture emergent dynamics. Instead, different model families emphasize different aspects of the system, reflecting inherent limits to representational completeness. Future progress may therefore depend less on identifying a superior modelling paradigm than on developing hybrid approaches that integrate the complementary strengths of different model families: While Goal-Oriented models focus on identifying optimal transformation pathways or target achievement, Structural Feedback models emphasize how system components are interconnected, and Dynamic Co-evolutionary approaches explore how interacting dynamics and transformations emerge over time. These differing perspectives reflect the characteristic model purposes, methodological choices, and representations of social and environmental complexity across the three groups and should not be understood as competing, but as complementary.

This typology also provides a structural explanation for the patterns observed in the WEM design principals assessment. The systematic differences between model groups translate directly into differences in their ability to represent social-cultural

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dynamics, feedback complexity, non-linear behaviour, and cross-scale interactions. Rather than being independent model features, these WEM dimensions reflect underlying modelling paradigms, with each group exhibiting characteristic strengths and limitations that emerge from its core conceptual design.

4.2 Covering of the design principles for World-Earth Models and research gaps

Regarding the representation of **social-cultural dynamics**, our results show that most Goal-Oriented models still reduce human behaviour to representative agents, social planners, or other aggregate economic actors. While some Sectoral Targeted models have begun to incorporate heterogeneous consumer preferences and technology adoption dynamics, broader socio-cultural processes remain largely absent. Some Structural Feedback and most Dynamic Co-evolutionary models generally provide richer social-cultural representations, yet most focus on only one or two mechanisms, such as norm diffusion, social learning, or risk perception, rather than capturing a broader diversity of societal processes and actors.

This limited representation constrains the ability of current models to address key Anthropocene challenges such as inequality dynamics, adaptive societal responses to environmental changes and social tipping dynamics (Søgaard Jørgensen et al., 2024; Lawrence et al., 2024). While increasing actor heterogeneity is frequently proposed as a solution implementable in most models (Rao et al., 2017; Lamperti et al., 2018; Mathias et al., 2020), greater complexity should not be treated as an end in itself, as it also raises challenges related to adequate data collection (Rao et al., 2017), computational costs (Keppo et al., 2021), and interpretability of simulation outcomes. Instead, the required level and type of heterogeneity should be guided by the research question and model purpose of interest in a particular study or context.

Interestingly, models that explicitly incorporate socio-cultural dynamics predominantly focus on consumers and households, whereas institutions, governance systems, and businesses remain comparatively underrepresented. This observation is consistent with previous assessments of IAMs and coupled human–Earth system models (Rao et al., 2017; Mathias et al., 2020; Keppo et al., 2021; Schulte et al., 2024). Future modelling efforts may therefore benefit not only from simply increasing the number of agents but also from broadening the range of societal actors and processes represented.

The limited representation of social processes is not merely a modelling challenge but also reflects deeper disciplinary divides. Many of the reviewed models originate from the physical sciences, where human behaviour is often represented in a highly aggregated manner (Yoon et al., 2022). Likewise, optimization-based approaches are strongly rooted in neoclassical economic traditions that differ substantially from contemporary social science understandings of behavioural change and collective action (Mathias et al., 2020; Niamir et al., 2025). As a result, integrating richer socio-cultural dynamics requires not only methodological innovation but also stronger interdisciplinary collaboration. Yoon et al. (2022) therefore argue for a shift

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towards exploratory modelling approaches that treat models less as predictive tools and more as instruments for investigating alternative human-environment futures.

Bidirectional Feedback structures vary in complexity and level of aggregation across model groups. While more disaggregated approaches in Sectoral Targeted and Comprehensive Feedback modelling groups allow for a richer set of sectoral and biophysical interactions, all other model groups mainly rely on simplifications by focusing on one bidirectional feedback loop.

This pattern is consistent with Tan et al. (2023), who identify four dominant feedback types in coupled human-environment systems, based on land-use and land-cover change, greenhouse gas emissions, extreme weather events, and the water–energy–food nexus. More nuanced and heterogeneous feedback are often absent, possibly due to missing social and environmental complexity within the proposed model structures, as well as limited knowledge of feedback strengths and interaction effects.

This limitation is particularly challenging in models integrating socio-cultural dynamics, where behavioural responses are often reduced to risk perception as a closing feedback loop. However, risk perception and resulting behaviour are shaped by multiple socio-economic factors, for which only limited data is available, and which are not solely based on direct economic costs.

This limitation in feedback representation has been identified as highly relevant before, as it may lead to over- or underestimation of plausible emission scenarios (Tebaldi et al., 2026) and can significantly affect the occurrence of tipping dynamics in both social and natural subsystems (Farahbakhsh et al., 2024).

The representation of **non-linear and tipping dynamics** varies strongly across model types, from externally imposed non-linearities in many Goal-Oriented models to feedback-driven regime shifts in Structural Feedback models and agent-based and network-based Dynamic Co-evolutionary approaches which can capture emergent social tipping dynamics through heterogeneous interactions and cascading effects.

This pattern is consistent with earlier studies showing that most IAMs struggle to represent nonlinear events such as extreme floods or droughts and their system-wide consequences (Lamperti et al., 2018; Tebaldi et al., 2026). In many cases, nonlinearities are only included through exogenous threshold functions or non-linear damage specifications. To address this limitation, integrated frameworks combining IAMs, computational general equilibrium models, and agent-based models have been proposed (Filatova et al., 2025), potentially enabling a better representation of emerging nonlinear dynamics.

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Overall, higher structural model complexity is generally associated with a greater capacity to represent tipping elements (Farahbakhsh et al., 2024), which explains why Comprehensive Feedback and Dynamic Co-evolutionary models show the highest frequency of non-linear dynamics.

One example of explicit social tipping representation is Müller et al. (2021), who show how anticipation of future ecological states can induce metastability and trigger social tipping. However, such models typically simplify environmental dynamics and do not fully integrate natural tipping processes. This is notable given that capturing uncertainty and nonlinear ecosystem responses is considered essential for improving system understanding and predictive capacity (Johnson et al., 2025).

The incorporation of **cross-scale interactions** differs widely between model groups but remains overall limited. Only very few exceptional approaches combine both spatial and social scale dimensions. Sectoral Targeted models regularly include spatial linkages, while Market Targeted models combine spatial with some socioeconomic disaggregation, but typically without a deeper social actor layer; both groups thus emphasise one scale dimension over the other rather than integrating both fully. Structural feedback and Dynamic Co-evolutionary models also vary in their treatment of cross-scale interactions, with some representing spatial or social scale interactions, although most models present a globally aggregated approach.

To better integrate social cross-scale interactions, agent-based as well as multi-scale network approaches are often proposed (Lamperti et al., 2018; Niamir et al., 2020; Yoon et al., 2022; Cultice et al., 2023; Schulte et al., 2024). While such approaches are already used within Co-evolutionary modelling frameworks (e.g. ABM-IAM (Safarzyńska et al. 2022)), they may still represent limited societal heterogeneity on each level and can miss spatial heterogeneity.

One reason for the dominant absence of cross-scale interactions are substantial computational and conceptual challenges (Cultice et al., 2023), as well as strong data requirements (Cultice et al., 2023; Eker et al., 2024). To bridge this gap, hybrid approaches have again been proposed that combine fine-grained modelling where necessary with more aggregated representations elsewhere (Niamir et al., 2020; Yoon et al., 2022; Schulte et al., 2024). For example, Filatova et al. (2025) propose coupling IAMs with Computational General Equilibrium and Agent-Based models, enabling the analysis of how global environmental change and policy interventions affect individual and meso-level dynamics. Similarly, Eker et al. (2024) suggest combining agent-based models with system dynamics approaches to better capture cross-scale processes. However, such coupling efforts may introduce additional challenges, including mismatched temporal resolutions and differing modelling logics.

Thus, integrating cross-scale interactions requires careful selection of relevant scales, interactions, and granularity depending on the research question. Nevertheless, this review shows that most models still lack consistent cross-scale representations, highlighting the need for further development of modelling approaches that fulfil this design principle for World-Earth models.

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4.3 Collaboration analysis

The bibliometric analysis shows that the Goal-Oriented, Structural Feedback, and Dynamic Co-evolutionary modelling communities operate in largely separate scientific silos. The rareness of cross-paradigm authors and the very low overlap in cited references (3.5 % – 3.8%) suggest that these communities have developed largely independently from one another, drawing on distinct scientific traditions and literatures. The results also show that the two groups of Structural Feedback and Dynamics Co-evolution remain internally fragmented. At the same time, the higher keyword overlap (10.3 % - 13.2 %) indicates that the three model groups address partly similar research questions. Those findings point to a high separation of the different groups as well as opportunities for collaboration. While each research community may be developing solutions to similar problems in isolation, they might be missing opportunities for cross-fertilization and methodological learning. These findings suggest that meaningful exchange between the three modelling communities captured by this literature review is unlikely to emerge organically, given the degree of structural fragmentation observed. Dedicated efforts to bridge paradigm boundaries - for example through targeted sessions at conferences or structured model intercomparison exercises - could foster mutual learning while preserving the productive plurality of approaches.

4.4 Limitations

While this study was conducted with much care, several limitations apply that should be considered when interpreting the results. Potential bias from the LLM-assisted screening process, as well as from the screening by the first author, cannot be fully excluded. Additionally, not all included studies could be analysed in full depth due to their high number, which, despite utmost care, could have led to occasional interpretation errors or misclassification. One additional limitation of our search strategy is that the scope of eligible model families was refined during the review process. As a result, one model family (GCAM) that had initially been excluded was subsequently included after the snowballing stage had already been completed. Consequently, studies from this model family may be underrepresented in the final sample, despite the complementary snowballing procedure. At the same time, other model families (e.g. the IMAGE and DICE families) dominate the overall sample. Nevertheless, the conducted analyses of only those records that implement structural changes to the basic models show qualitative similar results and we are confident that the included sample of records can represent dominant trends within the field. Moreover, the classification along the WEM Design Principles can sometimes be ambiguous. This is especially the case for WEM3 (Non-linearities and tipping dynamics) as this criteria is challenging to operationalise and a mixture of the analysis of the model structure and publication results were used. Finally, the proposed classification should be understood as a set of idealized types rather than strict categories, as some models may fit multiple groups and the boundaries are inherently continuous.

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5 Conclusion

Understanding the global coupled social-environmental system dynamics that shape the Anthropocene is inherently challenging: the relevant, nonlinear biophysical and socio-economic processes operate across multiple spatial and temporal scales and societal levels, making them difficult to observe directly or study through controlled experiments (Schellnhuber 1999). Thus, computer simulation models are increasingly used to create system understanding. Bidirectionally coupled models, endogenously modelling social and environmental dynamics as well as their interactions are increasingly developed, however the research field remains rather fragmented, spanning many different disciplines, modelling approaches and epistemological assumptions.

This systematic review provides a structured overview of this new and evolving research field, provides a lens for classification of different modelling types and uses the World-Earth Model design principles proposed by Donges/Heitzig et al. (2020) to analyse the state of the art and suggest ways forward.

We propose to structure the field among three major ideal groups (in the Weberian sense): Goal-Oriented models, mainly focusing on cost-effective achievements of certain set targets; Structural Feedback models, focusing less on detailed processes but on the interactions and feedbacks between different sub-systems; and Dynamic Co-Evolutionary approaches focusing on evolving dynamics that arise from the interplay of social and environmental dynamics, including process-detailed representations. While the distinction between the groups is supported by the conducted bibliographic analysis, it should be seen as a continuum, rather than strictly separated categories, they set different foci and should be understood as complementing rather than competing approaches.

The analysis of those groups along the World-Earth Model design principles shows characteristic strengths and weaknesses tied to each paradigm but also highlights limitations that persist across all model groups. Socio-cultural processes beyond economic optimization remain underrepresented even in Dynamic Co-evolutionary approaches, which tend to focus on single mechanisms and miss actor heterogeneity. Bidirectional feedback diversity is similarly limited, with most models focusing on one dominant loop and often strongly simplifying either the social or environmental side. Non-linearities and tipping dynamics are widely aimed at but rarely emerge endogenously from model structure - and cross-scale interactions, both spatial and social as well as their interplay, remain the most consistently underrepresented dimension across all groups. The bibliometric analysis further confirms that the field remains highly fragmented along paradigm and disciplinary boundaries, limiting knowledge transfer between research communities.

This systematic review thus suggests that future research should particularly focus on four priorities. First, broadening the representation of socio-cultural processes and actor types beyond households and consumers, explicitly including institutions, governance systems, and their interactions. Second, exploring more diverse bidirectional feedback and their interplay, shifting

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attention beyond climate change towards a broader set of planetary boundaries. Fourth, developing modelling approaches that can explicitly represent the emergence coupling of social and biophysical tipping dynamics and their cross-scale interactions - for example through hybrid formats combining agent-based and system dynamics approaches. At the same time, no model should aim to be a jack-of-all-trades: model complexity should be guided by the research question and grounded in existing empirical and theoretical knowledge across disciplines and approaches, spanning social sciences, and psychology, environmental sciences and physics, as well as place-based and context focused research and global system thinking. Lastly, the high fragmentation and segregation of the field seems to currently inhibit cross-community interactions and learning. Fostering scientific exchange between the research communities could help to increase the understanding of global Anthropocene social-environmental dynamics from the combination of different perspectives.

Thus, this systematic review can provide a useful compass, helping researchers to navigate the different model groups and paradigms within the field of global coupled social-environmental modelling and provide a context to complement and learn from each other to foster a better understanding of Anthropocene dynamics and to explore the resilience of a human-shaped earth system.

Code and data availability

All data that support the findings of this study are included within the article and the Supplement.

Author contributions

HP and JFD conceptualised and designed the study, HP developed the design of methodology, HP and LS conducted the study and literature screening, HP conducted the formal analysis, visualised the results and prepared the manuscript with contributions from all co-authors.

Competing interests

At least one of the (co-)authors is a member of the editorial board of Earth System Dynamics. Besides, the authors declare that they have no affiliations with or involvement in any organization or entity with any financial interest in the subject matter or materials discussed in this manuscript.

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