Integrating System Dynamics and Agent-Based Models for Enhanced Analysis in Sustainable Development

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Abstract

Sustainable development involves complex, non-linear mechanisms within a multidimensional framework integrating natural, social, and economic dimensions. This literature uses both System Dynamics (SD) and Agent-Based models (ABMs). SD models offer a macro perspective with differential equations and graphical representations, while ABMs provide a micro perspective on individual agents' behaviors. These models are complementary: SD models set exogenous conditions for ABMs, aiding their development and validation, while ABMs offer data to validate SD structures by capturing emergent behaviors. Integrating Agent-Based and SD (ABSD) models leverages their strengths, offering a more nuanced analysis of sustainable development despite challenges like complexity and computational demands. We then propose a guideline to address these limitations and two potential applications to provide a detailed analysis of ABSD models in global sustainable development.

Keywords

Hybrid methodology, Complex systems, ABSD models, Sustainability

1. Introduction

Achieving global sustainable development is the primary challenge of this century [1, 2], necessitating collaboration among biologists, economists, sociologists, engineers, urban planners, and computer scientists to achieve this relevant and overarching goal. Indeed, sustainable development is a multidimensional, complex, and interdisciplinary topic [3, 4] that requires the consideration and integration of diverse and essential aspects of natural, social, and economic sustainability. Over time, various tools have been developed to promote a pluralistic, interdisciplinary, and eclectic approach to this field [5, 6].

When sustainability researchers aim to describe and simulate global development mechanisms, they often turn to system dynamics (SD) to incorporate natural, economic, and social dynamics and their complex interactions. SD is a methodology consisting of linked differential equations,

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graphically represented through stock and flow diagrams or causal-loop diagrams, and simulated by algorithms [7, 8, 9, 10]. SD models provide a macro perspective that helps maintain an overarching view of aggregate variables. Moreover, SD models can easily incorporate lags and threshold effects, allowing for a more accurate representation of temporal dynamics and structural changes over time. This capability is essential for analyzing long-term policy impacts and systemic outcomes. Lastly, the aggregate nature of SD models simplifies the integration of composite causality chains due to their focus on population-level mechanisms.

However, relying solely on SD models would mean losing the ability to capture the diverse behaviors and interactions of individual agents, leading to the emergence of novel patterns and trends that might not be predicted by aggregate-level models alone. Agent-based models (ABMs) are particularly effective at modeling heterogeneity and stochasticity within a system, providing insights into micro-level dynamics and agent-based innovations. This micro-level detail is crucial for understanding how innovation, adaptation, and competition mechanisms work within the complex landscape of sustainable development at the global level.

Indeed, ABMs are computational simulations of agents' interactions within an environment that evolves based on the agents' actions and interactions [11, 12]. These models adopt a flexible micro-approach to capture the agents' heterogeneity and their emerging interactions. ABMs simulate complex systems, identifying otherwise unpredictable emergent behaviors. While commonly used in many fields, they require careful design, substantial computational resources, and thorough validation to be effective and reliable simulation instruments.

In this paper, we propose to integrate Agent-Based and SD (ABSD) models to leverage the strengths of both approaches. This integration allows for a more nuanced and accurate analysis of complex systems. However, the ABSD approach presents substantial challenges that limit its widespread application. The increased complexity, significant computational demands, and the necessity for transdisciplinary expertise among computer scientists are among the most relevant obstacles. Nevertheless, careful and precise management of the tool could significantly mitigate these limitations. Therefore, in this paper, we propose to investigate the benefits and drawbacks of the ABSD approach in the context of a potential application to the field of sustainable development.

In addition to the field of sustainable development, this article can provide significant insights into at least three other research areas. Firstly, it contributes to the debate on the micro-macro link [13, 14], which examines how micro and macro levels mutually influence and shape each other. Our work is firmly grounded in this approach, affirming the emergent properties of ABMs and their dependence on macro-level constraints and characteristics that are often predetermined. However, our hybrid approach allows us, in certain circumstances, to propose a macro-founded theoretical framework that incorporates specific micro-level processes, making the entire bidirectional process clearer and more implementable.

Secondly, it engages with the debate on macro-to-micro mapping [15, 16], providing insights into how macro-level models, such as SD, can enhance the understanding of detailed behaviors of individual agents within ABMs. Indeed, macro-to-micro mapping is operationalized in the ABSD model by defining more realistic agent behaviors in ABMs that mirror the real-time environmental dynamics identified by the SD model. This integration can also significantly improve the validation and calibration of the ABSD model. All the same, the ABSD model can be seen as a simulation environment where macro-to-micro mapping facilitates dynamic interactions between the two levels of analysis, enabling an explicit exploration of feedback between macro and micro levels.

Finally, we suggest an alternative approach to macro-programming, where a high-level ABM program integrates low-level equations [17, 18]. Vice versa, the proposed ABSD model organizes high-level equations with low-level ABM programs. Neither methodology is superior to the other; the choice depends on the specific objective. Macro-programming is ideal for optimal coordination of spatially adaptive systems [19]. However, the ABSD model is preferable for describing complex systems of interconnected and micro-founded aggregate variables. Sustainable development depicts this distinction well. If the aim is to propose agent interactions for achieving sustainability, macro-programming offers valuable solutions. Conversely, to illustrate the potential consequences of unsustainable human actions, the ABSD model is more suitable.

The remainder of the article is structured as follows. Section 2 clarifies the contribution of the ABSD model, highlighting the benefits and limitations of a hybrid approach. Section 3 presents some potential applications of the integrated ABSD model in the sustainability literature. Section 4 summarizes the discussion.

2. Simulation Models for Sustainability

2.1. Standard Approaches

According to a recent systematic literature review on sustainability [6], over the past ten years, 49% of the simulation models have used an ABM approach, while 46% have used an SD approach. This paper confirms that SD and ABM are two popular tools for simulating complex and multidimensional systems, such as sustainable development. However, the literature review also reveals that only two articles have been found that combine both tools [20, 21], both specific to water use. Consequently, even in fields where ABMs and SD models are prevalent, their combination, although feasible, is rare and has limited application. Before describing the limitations of the ABSD simulations and proposing a method to integrate both models, it is helpful to briefly describe each of the two simulation models that compose it.

SD models are structural, disequilibrium models characterized by path-dependency, self-organization, historical time, and irreversibility [22, 23]. They feature the non-linear interplay of feedback loops, which enables the emergence of complexity [24] and evolving macro development dependent on systemic interactions. Developed initially by Jay W. Forrester in the 1950s, their non-linear nature allows SD models to simulate the evolution of a system through shifts in the relative strength of positive and negative feedback loops, governed by stock levels and determining systemic outcomes [25]. Like ABMs, the multiple and potentially unstable equilibria follow chaotic trajectories [26]. Consequently, SD models can analyze unintended consequences that may lead to undesirable systemic outcomes, providing decision makers with a flexible tool for evaluating policy options [27]. However, the emergence of novelty is limited to the macro level, as the underlying model of causal relations remains fixed. AnyLogic[1], Stella[2],

[1]https://www.anylogic.com/
[2]https://www.iseesystems.com/

and Vensim[3] are the most popular software tools for developing and simulating SD models.

ABMs simulate novel emerging outcomes and trends arising from the interactions of heterogeneous agents, defined as autonomous entities capable of perceiving and reacting to their environment, incorporating stochastic elements. Among their many applications, this affords a better understanding of micro-level mechanisms, such as innovation-based competition, and their systemic consequences [28]. The concept of emergence, central to ABMs, refers to complex patterns and behaviors that arise from simple interactions among agents, which cannot be predicted by analyzing individual components in isolation [29, 30]. This characteristic enables ABMs to capture the dynamics of systems where agent interactions lead to unexpected macro-level phenomena. Self-organization is another critical feature of ABMs, wherein a system spontaneously forms organized structures without external direction. This occurs through local interactions among agents following simple rules, leading to global order [31, 32]. Similarly, ABMs have been used to model the emergence of cooperation, social norms, and collective behavior in social and economic systems [33, 34].

While behavioral sets in ABMs can vary, they are necessarily exogenous. Agent behavior within the model can change due to evolving environmental variables, but only within the predefined set of behavioral patterns and parameters established during the model's programming phase. This constraint limits the ability of ABMs to capture the adaptive and evolutionary nature of real-world systems fully. While agent interactions can generate emergent novelty, the underlying behavioral structure remains unchanged. Consequently, the dynamics of open systems, characterized by continuous adaptation and innovation, cannot be fully represented by either SD models [35, 36] or ABMs [37, 38]. There are several software tools for developing and simulating ABMs, such as NetLogo[4], AnyLogic[5], and Repast[6].

The choice between the two main non-linear models typically depends on the primary field of research. Economists usually integrate economic, social, and natural aspects using ABMs [39, 40, 41]. In contrast, ecological scholars often use SD models to combine these elements [42, 43, 44]. Certainly, the background and previous skills of the authors play a role in the decision, but the focus of the research issue is also crucial. When the goal is to study the overall system, SD models are the preferable tool. Conversely, when the goal is to analyze human reactions, ABMs are the best choice.

However, exceptions exist. Some ABMs are published in environmental journals, focusing on specific topics [45, 46, 47] or paying limited attention to the complexity of interactions among the economy, society, and nature [48, 49, 50]. Moreover, ABMs have been used in ecological studies, particularly in climate change research [51, 52, 53], and to analyze sustainability through an evolutionary economics lens [54, 55, 56].

Conversely, SD models are rarely published in economic journals. Some exceptions include [57] and [58], who model the relationship between innovation and nature, and [59], who simulate the relationship between sustainable development and human capital investment. A possible explanation for this asymmetry could be the interdisciplinary nature of the topic, often too broad for an economics journal, and the greater flexibility of ABMs, which make them a

[3]https://vensim.com/

[4]https://ccl.northwestern.edu/netlogo/

[5]https://www.anylogic.com/

[6]https://repast.github.io/index.html

more versatile and usable tool than SD models.

However, the SD and ABM approaches can be interpreted as two sides of the same coin. Indeed, both simulation models are useful for analyzing sustainability issues, but SD follows a macroeconomic approach, while ABMs follow a microeconomic approach [60]. SD models focus more on the relevance of time, path dependency, lock-in effects, and the irreversibility of specific trends, while ABMs emphasize agents' heterogeneity, behavior, and bounded rationality. Both ABMs and SD models share three key components: (i) an open interaction space; (ii) the potential for the emergence of constrained novelty; and (iii) an exogenous element. For ABMs, the interaction space is the endogenous environmental component whose actual values influence agent behavior, leading to non-linear dynamics as agents adapt to a changing environment. The exogenous element comprises the behavioral sets of the agents, typically involving randomness, and the given environmental conditions in which they operate. For SD models, positive and negative feedback loops create an interaction space that can produce non-linear dynamics and unexpected systemic outcomes. The exogenous element includes the system structure defined by the designed stocks, their initial values, and the functions governing their flows.

2.2. Hybrid approach

ABMs are described as a micro-modelling approach, focusing on individual agents' behavior sets [12]. In contrast, SD models are defined as a macro-modeling approach, starting from aggregated stocks and flows representing population-level mechanisms [61] embracing systemism [62]. Both tools are relevant and valuable for analyzing sustainability. Therefore, we suggest the use of an ABSD approach capable of combining both analyses. As demonstrated by the two hybrid models on the subject, integration is possible and highly explanatory [20, 21]. Theoretically, a composite model should be considered the best choice for simulating real-world outcomes. A hybrid ABSD model could analyze realistic interaction effects and produce more reliable scenarios.

SD models and ABMs are consistent and complementary to each other [63, 64, 65]. On the one hand, ABMs provide essential data for validating SD model structures by defining the range of novelty arising from micro-level interactions. On the other hand, by identifying the range of macro-level outcomes, SD models can determine the exogenous environmental conditions for ABMs, aiding their development and validation. Combining SD models and ABMs is an effective way to overcome the limitations of both approaches. SD models help ABMs maintain an overarching systemic perspective when reconstructing aggregate variables [66]. Similarly, ABMs contribute by depicting agent reactions as micro-level processes with systemic consequences [67]. However, ABSD models are not exempt from significant limitations.

Firstly, constructing and maintaining a hybrid model necessitates a broad spectrum of expertise spanning both SD models and ABMs. This interdisciplinary nature requires collaboration among specialists proficient in integrating diverse methodologies [68]. Advanced programming skills are crucial for developing complex algorithms and effectively managing the extensive data involved in these models [69]. The need for such a diverse skill set can complicate team assembly and coordination, potentially hindering the practical feasibility of developing and deploying hybrid models in real-world applications. Effective communication and integration among team members from different disciplinary backgrounds are essential yet challenging, as they must align on conceptual frameworks, modeling techniques, and validation methods. Additionally, the iterative nature of model development requires continuous collaboration and adjustment, which can be resource-intensive and time-consuming [70].

Secondly, the development of a hybrid model demands extensive computational resources and meticulous data parameterization. Detailed and comprehensive data are essential to capture the nuanced behaviors and systemic interactions of diverse agents [71]. The computational intensity required to simulate such intricate interactions can be prohibitive, necessitating high-performance computing capabilities [72]. For instance, the need for real-time simulation of thousands or even millions of agents interacting in complex ways requires significant processing power and memory. Additionally, acquiring and processing the necessary data for model parameterization and validation can be resource-intensive. This often involves integrating diverse datasets from multiple sources, cleaning and preprocessing data, and continuously updating the model with new information. The cost and effort associated with these tasks can be substantial, making it a significant barrier for many research teams.

Thirdly, integrating composite mechanisms at the micro level, mainly through heterogeneous agents, significantly amplifies model complexity. This complexity poses challenges in establishing clear causal links between aggregate outcomes and micro-level dynamics. As the number and diversity of heterogeneous agents increase, managing and interpreting the model becomes progressively difficult. This complexity risks obscuring how individual actions translate into macro-level phenomena, thereby complicating the model's explanatory power and usability [70]. Furthermore, the increasing heterogeneity and the need to model diverse agent behaviors add layers of difficulty in defining and tracking the interactions within the system [73]. Studies have shown that this can result in a combinatorial explosion, where the sheer number of possible interactions grows exponentially, making it nearly impossible to simulate all potential scenarios accurately [74].

The relevance of the last limitation depends on the type of ABM used. One pertinent distinction is between collectives and composites ABMs [75, 76]. Collectives ABMs often exhibit greater homogeneity among agents and are studied under the concept of 'collective adaptive systems' [77, 78]. In contrast, composites ABMs involve heterogeneous agents with varied characteristics and behaviors. This distinction underscores the diversity within the framework of multi-agent systems and emphasizes the specific challenges associated with integrating heterogeneous agents in hybrid models like ABSD [69]. The complexity of managing these diverse agents and their interactions often requires sophisticated modeling techniques and substantial computational resources, further complicating the development and deployment of such systems. However, while integrating SD models with collectives should be less challenging than with composites, their utility will also be more modest.

We then propose a roadmap to address these limitations, at least partially, during the projection and development of a hybrid ABSD simulation without sacrificing its strengths. First, choose the SD model tailored to the scope of the simulation as the foundation. This model should be simple enough to facilitate development but widely recognized to support dissemination. In this initial step, it is also essential to adopt a comprehensive and clear theoretical framework. Then, identify variables within the SD model that would benefit most from the incorporation of an ABM. This can be assessed in terms of population-level variance and numerosity and, consequently, the relevance of the missed heterogeneity. Third, search for already validated

ABMs in the literature that are coherent with the SD theoretical framework, prioritizing recent and well-known models that are consistent with the SD model in terms of assumptions and field of application. If no suitable ABMs exist, carefully consider the decision to either omit the ABM or proceed with developing a new one.

The following step is to integrate the selected ABM(s) into the SD model. This process involves careful theoretical and technical analysis to ensure compatibility and coherence between the models. Probably, the best way to integrate two or more simulations is through a macro-to-micro mapping [15, 16] and a parallel approach, where, at each step, the inputs of one model evolve based on the outputs of the others [79, 80]. Finally, the ABM must be fully integrated into the SD model. After a thorough analysis of the already validated tools, continue combining the ABM(s) into the SD model until the complexity becomes unmanageable or all relevant micro-level heterogeneity has been addressed.

The next section proposes two actionable applications of these broad guidelines through a detailed analysis of the integration of SD models and ABMs for global sustainable development.

3. Two Potential ABSD Models in Global Sustainability

3.1. SD model

In this section, we propose to apply the roadmap detailed above with a specific goal: to describe the global trends of sustainable development, considering the main economic and financial reactions. Indeed, the current unsustainable trend of development manifests through a selection process that is often random and disruptive to human activities in a broad sense [81]. However, people are reacting to this situation by proposing technological and financial innovations.

We then propose an ABSD model that adopts a Schumpeterian framework at the macro level of analysis. This theoretical approach combines technological and financial innovations on solid and coherent bases [82, 83]. We will use the SD model called FRIDA (Framework for Integrated Development Assessment), which explicitly employs this theoretical approach [84]. This model is based on the previous Earth4All model [85, 86], and simulates and analyzes the complex interactions between climate, food and land use, society, population, economics, and energy systems. Its primary aim is to provide insights into sustainable development pathways by integrating multiple aspects of human and environmental systems.

FRIDA effectively models atmospheric conditions, greenhouse gas emissions, and climate change impacts, as well as agricultural production, land use changes, and food security. It also includes demographic changes, fertility, mortality, and migration patterns within its societal component. The economic aspect of the model covers GDP, government spending, consumption, investment, and economic growth, while the energy component analyzes energy production, consumption, and transitions to renewable energy sources. The model has been calibrated using historical data from 1980 to 2020 to ensure its accuracy in reflecting past trends. Key data sources for this calibration include the United Nations, IPCC, IEA, FAO, and other reputable databases. To optimize its parameters, FRIDA utilizes Powell's BOBYQA, an efficient gradient descent method. A partial calibration approach is employed, focusing on individual domains before a final whole-model calibration. This approach enhances both computational efficiency and accuracy. The performance of the FRIDA model is robust, with a high correlation between model outputs and historical data. Most variables exhibit correlation coefficients above 0.85. Additionally, Theil Inequality statistics are used to identify and attribute errors, ensuring that the simulations are both reliable and precise.

The next step is to carefully evaluate which areas of the overall SD model would benefit the most from the inclusion of an ABM. This analysis should be conducted by thoroughly assessing the costs and benefits of the tool to achieve the goal. One area where it could be particularly useful is in innovative responses to climate change, as significant heterogeneity across contexts can be expected. Another potentially relevant area is finance, where the response to increased risk and the effort to create more resilient financial systems have a cross-cutting impact on various socioeconomic aspects and can be expected to have relevant interaction effects.

We propose integrating two ABMs into the FRIDA model: one in the innovation domain and the other in the financial domain. In the following subsections, we detail this process.

3.2. ABSD model with innovation dynamics

ABMs of innovation dynamics aim to capture the processes of novelty emergence and diffusion across a population of heterogeneous firm agents. These processes cannot be simulated within the confines of SD sustainability models due to their highly aggregate nature. Innovation can only be implemented within a pure SD model either as an exogenous trend or as the linear outcome of aggregate innovative investments, optionally treated as a policy lever. While stochastic elements may be introduced to simulate the deep uncertainty inherent in innovation processes, they involve two significant costs. First, they complicate the process of calibration significantly. Second, their exogenous nature contrasts with the SD methodology's aim to identify endogenous feedback mechanisms, thus impairing the model's validity.

The integration of an innovation ABM could provide a superior solution to this quandary. The ABM's main aims would be to identify: 1) the shape of the relationship between innovative investment and aggregate technological innovation; 2) the time lag involved; and 3) the possible negative consequences. In this way, the stochastic element related to innovation would be contained in the ABM, a methodological instrument capable of dealing with stochasticity appropriately, without having to resort to heroic assumptions of linearity. Integrating all three elements into the SD model would enable it to depict much more realistic and theoretically satisfying innovation dynamics. Regarding the aspects of innovative firms' reactions, there are several ABMs available, but the "Schumpeter meeting Keynes" family of ABM models is probably the best choice [52, 87].

The integration of the two approaches would yield benefits for the ABM as well. For example, a key limitation of the "Schumpeter meeting Keynes" models lies in the exogenously set number of agents. An unintended consequence of this approach is that corporate bankruptcy becomes an economic boon in the model, as the firm entering default is instantaneously substituted by a fully funded, equipped, and technologically savvy new entrant. Integration with an SD model such as FRIDA would allow relaxation of this methodological constraint through the endogenization of the firm population, using, for example, aggregate real GDP to inform development over time.

3.3. ABSD model with financial dynamics

Another set of dynamics whose modeling could be greatly enhanced by a hybrid ABSD model approach is financial mechanisms. Like innovation, many financial markets are characterized by radical, persistent uncertainty. Therefore, their depiction could be significantly improved by integrating ABMs focused on the consequences of financial agents' interactions, thereby limiting the use of implausible linear functions in SD models of sustainability. Furthermore, ABMs could extend their range of applications to include the interactions between systemic developments and agents' behaviors.

However, finding models that analyze the financial aspect in the sustainable development literature is challenging. To date, the only model that examines these aspects in a clear but simplified way using an ABM is [88]. Nevertheless, some financial aspects have been integrated into the "Schumpeter meeting Keynes" framework by [89]. Unfortunately, the integration of financial dynamics in ABMs suffers from a significant limitation: the impossibility of endogenizing systemic financial conditions. While these models focus on the agents' interactions, it is evident that these interactions both affect and are affected by systemic developments, making the integration of the latter quite desirable.

To achieve significant theoretical coherence within the model, especially if the intention is to integrate both innovation and financial aspects into the FRIDA model, the ABM proposed by [89] is the preferred solution. This model offers a robust framework that effectively addresses the complexities and interactions between these critical elements. Moreover, FRIDA shows that integrating financial and monetary systems with SD models is greatly hampered by the necessity to aggregate financial agents into sector-level entities, thus implicitly assuming a lock-step behavior that greatly increases the financial sector's stability, thereby hindering the capability to simulate financial and monetary crises.

A hybrid approach could alleviate both issues. For ABMs, systemic conditions could be parametrized according to SD output, enabling the modeling of agent-level reactions to a variety of alternative contexts, such as currency crises, production-generated recessions, or public policy-fueled temporary booms. For SD models, ABM-generated scenarios could be used to integrate plausibly calibrated inefficiencies, such as liquidity crises, market-making exits, and bank runs, thus enabling the modeling of fragile financial and monetary sectors and their consequences on the economy at large.

4. Conclusions

ABM and SD models are two complementary tools for simulating complex systems. SD models focus on macro-level structures and feedback loops, while ABMs simulate micro-level interactions and emergent behaviors. Combining these approaches, hybrid ABSD models can provide a more comprehensive analysis by leveraging the strengths of both. However, integrating these models poses significant challenges, including increased complexity, high computational demands, and the need for interdisciplinary expertise. To address these issues, a structured roadmap is proposed, starting with selecting a validated SD model, identifying impactful variables for ABM integration, and carefully incorporating validated ABMs from the existing literature. This approach aims to optimize the benefits while managing the practical challenges of ABSD modelling.

While this article focuses on sustainable development, the ABSD model holds extensive and relevant potential across various fields such as epidemiology, organizational management, urban planning, transportation management, and energy. We aim to establish a robust foundation in these and other disciplines, facilitating clear and systematic coordination of both macro and micro-level analyses to provide practical insights for decision makers. Naturally, improving and integrating this methodology with different tools is crucial to effectively address the complex and interdisciplinary challenges inherent in these areas of research and practice. We hope this paper represents a step in that direction.

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