Journal of Innovative Science

ISSN(Online): 3082- 4435

Volume- 01| Issue- 02| 2025

Research Article

Received: 15-08-2025 | Accepted: 05-09-2025 | Published: 02-10-2025

Exploring How System Dynamics Models Can Be Adapted to Analyze Climate-Related Feedback Loops and Policy Impacts

Eunice Abena Lettu[1], *and Fayowole David Ayadi* [2]

[1] *Department of Mathematics, Kwame Nkrumah University of Science and Technology, Ghana*
[2] *Department of Mathematics, University of Tennessee, Knoxville, U.S.A.*

Abstract: The growing urgency of climate change has intensified the need for robust modeling tools capable of capturing complex, dynamic interactions across environmental, economic, and social systems. System Dynamics (SD) models have emerged as a powerful framework for simulating climate-related feedback loops and informing long-term policy decisions. This scoping review critically examines the current state of SD modeling in climate policy, with a particular focus on its strengths, limitations, and potential for integration with other modeling paradigms. While SD models excel at illustrating dynamic processes and system-wide interactions, they still have limitations in representing nonlinear feedback, tipping points, and cross-sectoral dependencies. Recent advancements have improved the modeling of complex climate feedback and scenario exploration; however, challenges persist in terms of model transparency, empirical data integration, and stakeholder inclusivity. The review identifies key opportunities to enhance SD models through modular design, better parameterization, and hybridization with agent-based and Earth system models. It also underscores the importance of interdisciplinary collaboration and the development of open-access model libraries. By addressing these gaps, SD modeling can play a more prominent role in shaping resilient and adaptive climate policies. This work contributes to a growing body of literature advocating systems-based approaches to climate governance, highlighting actionable pathways to enhance the credibility, utility, and impact of SD models in climate research and decision-making.

Keywords: System Dynamics Modeling, Climate Feedback Loops, Climate Policy, Integrated Assessment Models, Sustainability Transitions

INTRODUCTION

Climate change is governed by a complex network of interdependent feedback mechanisms that can either amplify or mitigate warming. One prominent positive feedback is the ice–albedo effect, where melting ice reduces the Earth's reflectivity (albedo), leading to increased absorption of solar radiation and further ice melt, thereby intensifying warming. This process significantly contributes to Arctic amplification, with the Arctic warming nearly four times faster than the global average between 1979 and 2021 (FasterCapital, 2024; Steffen *et al.*, 2018).

Similarly, the carbon cycle feedback involves the release of greenhouse gases such as carbon dioxide and methane from natural reservoirs, like thawing permafrost, as global temperatures rise, which in turn accelerates the pace of climate change. Permafrost regions store vast amounts of organic carbon, and their thawing can lead to significant greenhouse gas emissions (Schuur *et al.*, 2015).

Understanding such dynamic processes is essential for developing effective climate policy and interventions. In recent decades, system dynamics (SD) modeling has emerged as a powerful tool for analyzing the behavior of complex systems over time. Rooted in the work of Forrester (1971) and later developed in global sustainability contexts by Meadows et al. (1972), SD models use feedback loops, causal loop diagrams, and stock-and-flow structures to simulate interactions within environmental, social, and economic systems. In the context of climate change, SD modeling allows researchers to explore long-term outcomes of policy choices under varying scenarios and assumptions (Meadows, 2008).

Despite the growing application of SD models in climate science, challenges remain. Climate systems are inherently nonlinear, marked by feedback-rich structures, thresholds, and tipping points that are difficult to model comprehensively. Existing SD models often struggle to represent the full range of interdependence and feedback dynamics, limiting their predictive utility for policymaking. For example, many models lack spatial or temporal granularity to assess region-specific impacts or account for uncertainty in feedback intensities (Martínez-Hernández, 2022, Bastiaansen *et al.*, 2023).

This study investigates how System Dynamics models can be adapted to more effectively capture climate-related feedback loops and evaluate the impacts of various policy interventions. The primary research questions guiding this inquiry are: (1) How can System Dynamics modeling be tailored to analyze climate-related feedback loops? and (2) What are the strengths and limitations of SD models in climate policy impact assessment? Addressing these questions through a literature-focused investigation contributes to both climate modeling research and the formulation of data-

*Corresponding Author: Eunice Abena Lettu

DOI- https://doi.org/10.5281/zenodo.17247221

informed, dynamic policy strategies. It also highlights the importance of refining SD models to better align with the evolving scientific understanding of climate feedback and the demands of environmental governance.

LITERATURE REVIEW

System Dynamics in Climate Studies

System Dynamics (SD) modeling, pioneered by Jay Forrester in the 1960s, provides a framework for understanding the behavior of complex systems over time using feedback loops, accumulations (stocks), and causal relationships. Forrester's early work culminated in *Industrial Dynamics* (Forrester, 1961), which introduced SD principles later applied to environmental systems in *World Dynamics* (Forrester, 1971). The application of SD to climate science gained prominence with large-scale models such as World3, developed by Meadows et al. (1972) for the Club of Rome's *The Limits to Growth*. These models revealed how interactions among population growth, industrialization, pollution, and resource depletion shape environmental trajectories under different scenarios.

Over time, SD modeling evolved into a robust tool for environmental decision-making, enabling researchers to test climate policy interventions in systems with nonlinear feedback. For example, Sterman and Wittenberg (1999) applied SD modeling to analyze global climate policy, considering public understanding of the carbon cycle. SD models are particularly valuable in representing long-term consequences of decisions and capturing delays between policy actions and environmental effects, making them relevant for climate governance (Sterman, 2008).

Climate Feedback Loops

Climate feedback loops are processes that can either amplify or dampen initial changes in the Earth's climate system. A prominent positive feedback mechanism is the ice–albedo effect: as reflective ice surfaces melt, darker ocean or land surfaces are exposed, absorbing more solar radiation and leading to further warming and accelerated ice loss. This phenomenon significantly contributes to Arctic amplification, with studies indicating that the Arctic has warmed nearly four times faster than the global average between 1979 and 2021 (Rantanen, 2022).

Negative feedback, such as increased cloud cover reflecting more sunlight, can moderate warming to some extent; however, the net effect and magnitude of such feedbacks remain areas of active research and are not yet fully understood.

Permafrost-carbon dynamics represent one of the most critical types of feedback in the climate system. Permafrost regions store vast amounts of carbon, estimated at approximately 1,600 petagrams (1.6 trillion metric tons) of soil organic carbon. Abrupt thawing processes, such as thermokarst lake formation, can rapidly release significant quantities of carbon dioxide and methane, potent greenhouse gases. Research indicates that accounting for emissions from abrupt thaw more than doubles previous estimates of warming caused by northern permafrost thaw this century (Yi *et al.*, 2024, U.S. Global Change Research Program, n.d).

Steffen et al. (2018) introduced the concept of a "Hothouse Earth" scenario, wherein surpassing critical thresholds, such as the collapse of the Greenland or West Antarctic ice sheets, could trigger self-reinforcing feedback and tipping cascades, potentially leading to runaway climate change. These processes are highly nonlinear and difficult to predict, presenting significant calibration and communication challenges for system dynamics (SD) models, which must remain both scientifically rigorous and policy relevant.

Policy Analysis Through System Dynamics

System dynamics has been widely used in climate policy evaluation, particularly through simulation platforms such as C-ROADS and En-ROADS. Developed by Climate Interactive, MIT Sloan, and Ventana Systems, these tools allow users to explore the impacts of global policy measures on temperature rise, emissions, energy use, and sea level (Climate Interactive, 2024; Sterman *et al.*, 2012). En-ROADS, in particular, is designed for accessibility, running in real-time on standard devices and supporting multiple languages, making it an effective tool for both expert and public engagement.

Despite their widespread use, critiques highlight some limitations. Ford (2010) argues that SD models like En-ROADS may oversimplify spatial heterogeneity and sectoral variability, limiting their fidelity in certain policy contexts. Furthermore, integration with real-time climate data or more complex models, such as General Circulation Models (GCMs), remains limited.

Gaps in Current Research

Despite the demonstrated utility of system dynamics (SD) modeling in climate research,

Publisher: SARC Publisher

significant gaps persist in how feedback mechanisms are incorporated and how these models engage with stakeholders. A major limitation is that many SD models rely on aggregated parameters or assumed feedback strengths without sufficient empirical validation. This simplification often overlooks the spatial heterogeneity and complex dynamics inherent in climate feedback processes. Moreover, comprehensive sensitivity and uncertainty analyses remain underutilized in many SD applications. For instance, while probabilistic climate-risk modeling frameworks such as CLIMADA v.3.1.0 have demonstrated the importance of global uncertainty quantification (Kropf *et al.*, 2022), similar rigorous approaches are not yet standard practice within SD modeling of climate systems.

Another critical challenge is the inadequate representation of tipping elements and cascading feedback across Earth system subsystems. Interactions among tipping points, such as the Greenland Ice Sheet melt influencing the Atlantic Meridional Overturning Circulation (AMOC), which in turn affects regional rainfall patterns, are highly nonlinear and can trigger domino effects that destabilize the climate system. Wunderling et al. (2021) emphasize that these interconnected tipping elements significantly increase the risk of abrupt climate transitions. However, most existing SD models do not fully capture these cascading feedbacks, limiting their ability to simulate realistic climate trajectories and associated risks.

Furthermore, the co-production of SD models with policymakers and stakeholders remains limited, which constrains the practical relevance and impact of these tools. Participatory system dynamics modeling (PSDM) exercises, such as those conducted in West Africa, have revealed challenges in translating conceptual models into actionable simulations and achieving consensus among diverse stakeholders (Kotir, 2004). This gap underscores the need for more inclusive modeling processes that integrate local knowledge and policy priorities to enhance model legitimacy and usability.

Finally, integration of SD models with other modeling approaches, such as agent-based models or integrated assessment models (IAMs), is still in its infancy. Modular frameworks that combine the strengths of SD's feedback representation with the detailed socio-economic and spatial resolution of other models could provide more comprehensive insights. For example, the ANEMI model version 2 represents progress by linking energy-economy sectors with hydrologic cycles, offering a more holistic view of climate system interactions (Akhtar, 2011).

METHODOLOGY

This study adopts a scoping review methodology to investigate how System Dynamics (SD) models have been used to analyze climate-related feedback loops and inform policy decisions. Scoping reviews are well-suited for broad, interdisciplinary topics, especially where the body of literature is heterogeneous and evolving. This approach draws on the framework proposed by Arksey and O'Malley (2005), which provides a structured process for mapping key concepts, identifying research gaps, and summarizing evidence.

The literature search was conducted across major academic databases, including ScienceDirect, SpringerLink, Wiley Online Library, and Google Scholar, focusing on peer-reviewed studies and relevant grey literature published between 2010 and 2023. Foundational works published before 2010 were also included where necessary to provide historical context on the development of SD modeling in climate research. Keywords such as *"system dynamics," "climate feedback," "policy impact," "climate modeling,"* and *"tipping points"* were used in various combinations to identify relevant sources.

Studies were selected based on a set of inclusion criteria that considered both contextual relevance (focusing on climate feedback loops or climate policy), and methodological relevance (explicit application of SD modeling techniques such as stock-flow structures or causal loop diagrams). Grey literature, such as policy reports and technical documents from governmental and research organizations, was reviewed to capture practical insights and applications not yet formalized in peer-reviewed literature. The review process emphasized descriptive mapping of key trends in the use of SD models within climate-related research. Rather than conducting a formal thematic analysis, studies were grouped based on shared features such as modeling scope, feedback types examined, sectoral application (e.g., energy, agriculture, water), and policy relevance. This approach allowed for a high-level synthesis of how SD models are applied, the types of feedbacks they capture, and the kinds of policy scenarios tested.

Publisher: SARC Publisher

Preliminary findings highlight a concentration of SD applications in specific sectors, such as energy and agriculture, with relatively fewer studies addressing long-term or cross-sectoral feedback dynamics. Additionally, most reviewed studies focused on short- to medium-term climate processes, with limited coverage of deep-time or planetary-scale tipping mechanisms.

HOW SD MODELS CAN BE ADAPTED FOR CLIMATE FEEDBACK ANALYSIS

System Dynamics (SD) models have long been used to simulate complex interactions within global systems, including those that drive climate change. Foundational works such as Forrester's *World Dynamics* (1971) and the *World3* model described in *The Limits to Growth* by Meadows et al. (1972) offered a high-level, systems-thinking approach to understanding global sustainability and the role of feedback structures in shaping long-term outcomes. These early models identified the importance of feedback loops, such as those involving population growth, resource depletion, and pollution, but often did not incorporate detailed empirical climate feedback data or capture the full range of nonlinear system behaviors observed in the Earth's climate system (Sutton, 2023).

For example, the interaction between temperature T(t), ice extent I(t), and albedo A(t) can be expressed as:

$$\frac{dI}{dt} = -\alpha T(t), \quad A(t) = \beta I(t), \quad \frac{dT}{dt} = \gamma(1 - A(t)) + \delta C(t)$$

where (t) is carbon feedback from permafrost, and the constants α, β, γ, δ reflect system sensitivity parameters. This illustrates how a temperature rise reduces ice cover, lowers albedo, and further amplifies warming—a classical positive feedback loop.

Recent literature emphasizes the need for SD models to better represent the complexity and nonlinearity of climate feedback. For example, research highlights that the climate system is highly nonlinear, with abrupt transitions and multiple equilibria possible when certain thresholds are crossed, such as those associated with ice sheet collapse or rapid changes in ocean circulation (Rial *et al.*, 2004). These nonlinearities and feedbacks are critical for understanding tipping points and abrupt climate events, yet traditional SD models often lack the flexibility to simulate such dynamics in detail.

Contemporary SD models, such as the C-ROADS simulator developed by Sterman and colleagues, have advanced the field by incorporating more detailed representations of climate system feedbacks, including carbon cycle interactions and thermal inertia (MIT, 2024). These models allow users, including policymakers and negotiators, to explore the implications of different emissions scenarios and policy interventions, providing immediate feedback on likely climate outcomes. Nevertheless, challenges remain in capturing the full range of feedback-rich processes, particularly those involving abrupt or cascading changes across subsystems (e.g., atmosphere-ocean-biosphere interactions) (Moore et al. 2022, Rial *et al.*, 2004).

To address these limitations, recent studies call for the development of more modular and adaptable SD architectures. This includes integrating SD models with other approaches, such as agent-based modeling or machine learning, to better capture the stochastic and path-dependent nature of climate feedbacks. Additionally, there is a need for greater empirical grounding and scenario testing, as well as for models that can be iteratively refined based on new data and stakeholder input (Martínez-Hernández, 2022).

EFFECTIVENESS AND LIMITATIONS OF SYSTEM DYNAMICS (SD) MODELS IN CLIMATE POLICY EVALUATION

System Dynamics (SD) models have proven valuable tools in supporting climate policy evaluation, offering decision-makers a means to simulate the long-term impacts of emissions scenarios, mitigation strategies, and adaptation policies. One of the primary strengths of SD models lies in their capacity to represent causal relationships and feedbacks transparently, enabling users to visualize the systemic consequences of decisions and compare alternative policy pathways over extended time horizons (Martínez-Hernández, 2022; VITO, n.d.). These features make SD models especially effective for scenario analysis, where different combinations of climate and energy policies can be tested under diverse assumptions.

In most SD models, climate variables are represented through differential relationships between state variables (stocks) and their rates of

Publisher: SARC Publisher

change (flows). For instance, a simplified carbon accumulation model may follow:

$$\frac{dC}{dt} = E(t) - R(t)$$

where *C(t)* is atmospheric carbon, *E(t)* is anthropogenic emissions, and *R(t)* is natural carbon removal (e.g., via sequestration or ocean uptake). This stock-flow logic underpins most climate-economy SD simulations.

Despite their strengths, SD models also face several limitations that have been documented across literature. A major challenge is the uncertainty associated with parameter estimation, particularly in feedback-sensitive systems where small changes can lead to significantly different outcomes. As noted by Pindyck (2013, 2015) and Weyant (2017), Integrated Assessment Models (IAMs) and SD-based approaches often depend on arbitrary or weakly constrained parameters, which can undermine confidence in model predictions. Freeman (2021) further highlights how these uncertainties complicate efforts to simulate political and societal responses, particularly in models addressing energy transitions.

Another persistent limitation is the tendency of traditional SD models to oversimplify socio-political dynamics. Institutional inertia, public resistance, and the political feasibility of certain climate interventions are often underrepresented, despite their influence on the implementation and success of policies. Comprehensive representation of these factors remains a critical area for model refinement (Freeman, 2021; Martínez-Hernández, 2022).

Additionally, recent studies call for the incorporation of multi-sectoral and cross-system feedbacks into SD simulations, particularly those involving marine ecosystems and biodiversity. Oceans play a key role in climate regulation through carbon sequestration, yet their contributions and vulnerabilities are frequently omitted or underrepresented in policy models. Research by Elsler et al. (2022) and the National Science and Technology Council (2024) emphasizes the importance of integrating ocean-based processes such as carbon transport, coastal habitat conservation, and sustainable fisheries management into climate governance frameworks. These interactions are essential for aligning mitigation strategies with biodiversity conservation goals.

Finally, the participatory use of SD models—where stakeholders are actively involved in the design, testing, and refinement of models—has been shown to improve relevance, transparency, and legitimacy. Yet this approach remains underutilized in many applications (André, 2023).

To address these issues, scholars recommend refining SD models by:

- Enhancing calibration against real-world observational data,
- Providing transparent documentation of assumptions and uncertainties,
- Broadening sectoral coverage (e.g., oceans, biodiversity, socio-political systems), and
- Promoting stakeholder engagement throughout the modeling process.

Such advancements can significantly improve the robustness, credibility, and policy relevance of SD-based climate evaluations.

CONCLUSION & RECOMMENDATIONS

System Dynamics (SD) models offer significant potential for analyzing climate-related feedback loops and informing policy decisions. Nonetheless, existing limitations, particularly in representing nonlinear feedbacks, tipping points, and cross-sectoral dynamics, constrain their effectiveness in high-resolution climate policy scenarios. Recent advancements have improved the integration of complex feedback structures and scenario analysis tools, yet challenges persist, notably in model transparency and the incorporation of empirical data.

Enhancing SD model design through modular architecture and improved parameterization can bolster its applicability. Integrating stakeholders' perspectives is also crucial for developing models that are both scientifically robust and policy-relevant. Combining SD models with other modeling approaches, such as agent-based models and Earth system models, can provide more granular and context-sensitive outputs (González-Rosell *et al.*, 2020).

Future research should focus on developing standardized frameworks for modeling climate feedbacks within SD systems, creating open-access model libraries for iterative improvement, and fostering interdisciplinary collaborations among climate scientists, engineers, policymakers, and system modelers. These efforts will ensure that SD models continue to evolve as powerful

Publisher: SARC Publisher

tools for simulating climate dynamics and shaping sustainable policy interventions.

REFERENCES

1. Akhtar, M. K. "A system dynamics based integrated assessment modelling of global-regional climate change: a model for analyzing the behaviour of the social-energy-economy-climate system." *The University of Western Ontario (Canada)* (2011).
2. André, K., Swartling, Å. G., Englund, M., Petutschnig, L., Attoh, E. M., Milde, K., ... & Rome, E. "Improving stakeholder engagement in climate change risk assessments: insights from six co-production initiatives in Europe." *Frontiers in Climate* 5 (2023): 1120421.
3. Arksey, H., & O'Malley, L. "Scoping studies: towards a methodological framework." *International Journal of Social Research Methodology* 8.1 (2005): 19–32.
4. Bastiaansen, R., Ashwin, P., & von der Heydt, A. S. "Climate response and sensitivity: time scales and late tipping points." *Proceedings of the Royal Society A* 479.2269 (2023): 20220483.
5. Climate Interactive. "Climate Interactive: The C-ROADS climate policy model." *Climate Interactive* (n.d.). https://www.climateinteractive.org/tools/en-roads/
6. FasterCapital. "Feedback loops: System Dynamics: Exploring the Impact of System Dynamics on Feedback Loops." *FasterCapital* (2024). https://fastercapital.com/content/Feedback-loops--System-Dynamics--Exploring-the-Impact-of-System-Dynamics-on-Feedback-Loops.html
7. Ford, A. *Modeling the Environment.* Washington, DC: Island Press, 2010.
8. Forrester, J. W. *World Dynamics.* Cambridge, MA: Wright-Allen Press, 1971.
9. González-Rosell, A., Blanco, M., & Arfa, I. "Integrating stakeholder views and system dynamics to assess the water–energy–food nexus in Andalusia." *Water* 12.11 (2020): 3172.
10. Kotir, J. H., Jagustovic, R., Papachristos, G., Zougmore, R. B., Kessler, A., Reynolds, M., Ouedraogo, M., Ritsema, C. J., Aziz, A. A., & Johnstone, R. "Field experiences and lessons learned from applying participatory system dynamics modelling to sustainable water and agri-food systems." *Journal of Cleaner Production* 434 (2023): 140042.
11. Martínez-Hernández, A. G. "System dynamics modelling and climate change adaptation in coastal areas: A literature review." (2022).
12. Meadows, D. H. *Thinking in Systems: A Primer.* Chelsea Green Publishing, 2008.
13. Meadows, D. H., Meadows, D. L., Randers, J., & Behrens, W. W. III. *The Limits to Growth.* Universe Books, 1972.
14. MIT Sloan. "This tool is pushing people to take action on climate change (C-ROADS model and World Climate simulation)." *MIT Sloan* (2024).
15. Moore, F. C., Lacasse, K., Mach, K. J., Shin, Y. A., Gross, L. J., & Beckage, B. "Determinants of emissions pathways in the coupled climate–social system." *Nature* 603.7899 (2022): 103–111.
16. Rantanen, M., Karpechko, A. Y., Lipponen, A., Nordling, K., Hyvärinen, O., Ruosteenoja, K., ... & Laaksonen, A. "The Arctic has warmed nearly four times faster than the globe since 1979." *Communications Earth & Environment* 3.1 (2022): 168.
17. Rial, J. A., Pielke, R. A., Beniston, M., Claussen, M., Canadell, J., Cox, P., ... & Salas, J. D. "Nonlinearities, feedbacks and critical thresholds within the Earth's climate system." *Climatic Change* 65 (2004): 11–38.
18. Sterman, J. D. "Risk communication on climate: Mental models and mass balance." *Science* 322.5901 (2008): 532–533.
19. Sterman, J. D., & Wittenberg, J. "Path dependence, competition, and succession in the dynamics of scientific revolution." *Organization Science* 10.3 (1999): 322–341.
20. Sterman, J. D., Fiddaman, T., Franck, T., Jones, A., McCauley, S., Rice, P., Sawin, E., & Siegel, L. "Climate Interactive: The C-ROADS climate policy model." *System Dynamics Review* 28.3 (2012): 295–305.
21. Steffen, W., Rockström, J., Richardson, K., Lenton, T. M., Folke, C., Liverman, D., ... & Schellnhuber, H. J. "Trajectories of the Earth system in the Anthropocene." *Proceedings of the National Academy of Sciences* 115.33 (2018): 8252–8259.
22. Wunderling, N., Donges, J. F., Kurths, J., & Winkelmann, R. "Interacting tipping elements increase risk of climate domino effects under global warming." *Earth System Dynamics* 12 (2021): 601–619.

Publisher: SARC Publisher

Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:

Lettu, E. A. and Ayadi, F. D." Exploring How System Dynamics Models Can Be Adapted to Analyze Climate-Related Feedback Loops and Policy Impacts." *Journal of Innovative Science* 1.2 (2025): pp 9-15.

Publisher: SARC Publisher