


NOTES AND INSIGHTS

Commentaries on “what is (quantitative) system dynamics modeling? Defining characteristics and the opportunities they create,” by Naugle et al. (2024)

Tom Fiddaman,^a Josephine Kaviti Musango,^b  Markus Schwaninger^{c*} and Miriam Spano^{d†}

Syst. Dyn. Rev. (2024)

Editor’s note

What are the core characteristics of system dynamics? What is essential to include in a study if it is concerned with or is applying system dynamics? These questions have been asked for decades and probably will continue to keep scholars and practitioners of the methodology busy for many more to come. Naugle *et al.* (2024; this issue) venture to provide an up-to-date answer to these questions, starting from an understanding of system dynamics as a quantitative endeavor and identifying research opportunities from their proposed definition.

System dynamics has a clear starting point and basis regarding content in the seminal works of Forrester (1958, 1961). However, as the field grows and internationalizes, the diversity of its applications and methodological extensions and interpretations have increased (Größler, 2013). To account for this plurality of perspectives, the editor of this journal has invited a diverse group of system dynamicists to provide a commentary on the Naugle *et al.* article, knowing also that the workings of this group only represent a subset of potentially appropriate uses of system dynamics. What unifies all authors in this exchange (of the original article as well as of the comments) is a deep desire to provide high-quality system dynamics studies to address the world’s grand challenges.

References

- Forrester JW. 1958. Industrial dynamics: A major breakthrough for decision makers. *Harvard Business Review* **36**(4): 37–66.
- Forrester JW. 1961. *Industrial Dynamics*. MIT Press: Cambridge.
- Größler A. 2013. The ‘aimless plateau’: A necessary dilemma between growth and coherent identity? *System Dynamics Review* **29**(4): 264–266.
- Naugle A, Langarudi S, Clancy T. 2024. What is (quantitative) system dynamics modeling? Defining characteristics and the opportunities they create. *System Dynamics Review* **40** this issue.

^a Ventana Systems, Bozeman, MT, USA

^b Graduate School of Business, University of Cape Town, 9 Portwood Road, Victoria & Alfred Waterfront, Cape Town, 8002, South Africa

^c Institute of Management, University of St Gallen, St Gallen, Switzerland

^d Monash Sustainable Development Institute, Monash University, Melbourne, Victoria, Australia

* Correspondence to: Markus Schwaninger, Institute of Management, University of St Gallen, St Gallen, Switzerland. E-mail: markus.schwaninger@unisg.ch

† Comments printed and commentators listed in alphabetical order.

Received 8 December 2023; Accepted 22 December 2023

Tom Fiddaman: The essence of system dynamics

I think we should start the process of defining system dynamics (SD) with questions, as we would for a modeling project. Why do we care, who is the audience, and what will they do differently?

I want decision-making to improve, particularly with respect to the intertwined problems on the longest and largest scales, like poverty, war, and overshoot and collapse of the global environment. Quality models that target present decisions as well as methods that build general understanding of complex systems in support of future decisions can serve this goal. I would also like to see the field thrive because it embodies methods and habits that are important to achieving this goal, and I would like to see colleagues succeed. All considerations require better models and evolution of the methods we use to build and explore them, perhaps beyond the original vision of system dynamics.

I don't think there is much leverage in a definition for shared branding; it wouldn't be comprehensible to many prospects and might not match their decision criteria. Polishing our system dynamics "elevator pitch" (*System Dynamics* email archive, 1997) probably has little to do with technical features of models or modeling, and crafting messages is best left to individual customization. I think the benefit of a shared definition is realized when it helps us to work together within the field and build bridges to others.

We should be building models that make the right decisions for the right reasons. This requires models that integrate all available information with an engine that generates replicable predictions about behavior from a realistic structure. This is why we absolutely require adherence to physical laws and avoid heroic assumptions about rationality and foresight, although not all fields share our view.

Different modeling paradigms cause their practitioners to define different problems, follow different procedures, and use different criteria to evaluate the result. In a very real sense the paradigm biases the way the modeler sees the world and thus influences the content and shape of his models.

Donella Meadows, *The Unavoidable A Priori* (1976)

The genius of Forrester's blend of feedback control and simulation is that it inherits good habits from engineers (like dimensional consistency and robustness in extreme conditions), removes unrealistic constraints on form (like linearity or equilibrium), and provides a way to incorporate information about structure from diverse scales, including managerial descriptions of policy and what Barry Richmond (1993) called "operational thinking" about causality.

My interest is in preserving the best parts of the Forrester inheritance, while permitting innovation in productive directions. That means defining SD less by the choices that are frequently made than by the criteria that drive us to those choices. Continuous time is a good example: nearly all SD models are continuous in time and value, and this is good; I've even written that "Discrete Time Stinks" (Fiddaman, 2017). However, this need not be a defining characteristic of SD; it is a technical choice governed by the need to achieve a good representation of a given system. Many SD games run in discrete time steps without harm, and a

discrete interval might be a convenient representation for systems like an hourly electric power market.

Writing about similar phenomena in *Industrial Dynamics*, Forrester advised continuous flows as a starting point,

In formulating a model of an industrial operation, we suggest that the system be treated, at least initially, on the basis of continuous flows and interactions of the variables.”

However, he goes on to admit other possibilities:

These comments should never be construed as suggesting that the model builder should lack interest in the microscopic separate events that occur in a continuous-flow channel....

The preceding comments do not imply that discreteness is difficult to represent, nor that it should forever be excluded from a model....

(1961; Chap. 5, Principles for Formulating Models, 5.5 Continuous Flows)

I think these technical decisions should be left to the modeler, guided by a set of principles of conformance with reality.

Similarly, we all use equations to represent models at present. This doesn’t distinguish SD from other formal modeling methods, yet it is not an absolute requirement. At some level, there have to be some equations, or at least machine code, but this may not be a useful level of description for all approaches. For example, it is possible to imagine equation-free model specifications, where neural networks construct relationships conforming to reality checks in addition to data (Peterson & Eberlein, 1994).

Finally, analysis: certainly feedback is of central importance. However, other features are sometimes critical as well; we are often interested in pure accumulation or the structure of decision rules with their attendant biases. Analyses from other perspectives are also interesting, including exploration of the model’s full policy space, model-data comparisons, and nonlinear dynamic analysis (Mosekilde & Larsen, 1988; Pruyt & Kwakkel, 2012; Rahmandad, Oliva & Osgood, 2015).

With these considerations in mind, I submit a modified definition set:

Definition	Excludes (for example)
Models are based on a priori causal structure with stocks, flows, feedback, and nonlinearities.	Comparative statics; linear regression
Most variables, including the key phenomena of interest, are endogenous and quantified even if they are not measurable.	Dead buffalo diagrams
Models are informed by and tested against a wide variety of formal and informal data.	Purely statistical models
Models represent decision-making behaviorally with realistic cognitive constraints and inputs actually known to agents.	Models with no empirical basis Intertemporal optimization; Computable general equilibrium Causal loop diagramming

Models can be simulated to generate replicable quantitative predictions contingent on model structure, decisions, and environmental conditions.

Analysis seeks understanding of the structural origins of model behavior through broad experimentation. Black boxes

Multiple criteria will also exclude some, but not all, linear and mixed integer programs, discrete event simulations, decision trees, agent-based models, function approximators, and social network analyses.

At the founding of SD, simulation models were essentially unknown. Today they are common, although not yet of great influence in some key decisions. SD can't meet the demand for models today, and SD can't go it alone—we need the collaboration of other methods, and they need us. I hope the criteria above preserve some of the core of the SD genome, while permitting us to inherit new ideas from other domains and to share the best of our work and practices.

References

- Fiddaman T 2017. “Discrete Time Stinks.”. *Metasd blog* <https://metasd.com/2017/11/discrete-time-stinks/>.
- Meadows D. 1976. The Unavoidable A Priori. In *Proceedings of the System Dynamics Conference*. Geilo: Norway.
- Mosekilde E, Larsen ER. 1988. Deterministic chaos in the beer production-distribution model. *System Dynamics Review* 4(1–2): 131–147.
- Peterson DW, Eberlein RL. 1994. Reality check: A bridge between systems thinking and system dynamics. *System Dynamics Review* 10(2–3): 159–174.
- Pruyt E, Kwakkel JH. 2012. A Bright Future for System Dynamics: From Art to Computational Science and Beyond. In *Proceedings of the 2012 Conference of the System Dynamics Society, St. Gallen*. Retrieved October 1, 2023 from <https://proceedings.systemdynamics.org/2012/proceed/papers/P1394.pdf>.
- Rahmandad H, Oliva R, Osgood N. 2015. *Analytical Methods for Dynamic Modelers*. MIT Press: Cambridge.
- Richmond B. 1993. Systems thinking: Critical thinking skills for the 1990s and beyond. *System Dynamics Review* 9(2): 113–133.
- SD 1997. “System dynamics in the elevator,” *SD email discussion list archive*. <http://www.ventanasystems.co.uk/forum/viewtopic.php?t=1787>.

Josephine Kaviti Musango: A better way to characterize system dynamics modeling?

At first glance, Naugle *et al.*'s (2024) stimulating article looks like a proposal for clarifying how system dynamics modeling is defined. At second glance, it still looks the same, but the authors have some notable points to hammer home. This discussion will attempt to reinstate some of the most interesting ones, in my opinion, and to be thought-provoking on some exposed issues.

From the point of view of system dynamics field development, “identity crisis” and “confusion” in defining system dynamics modeling persist. Now, about 65 years since Jay Forrester laid the foundation of the field and prominent scholars contributing to it, the article reminds us of the urgency to define system dynamics modeling to advance its science and practice. Given the advancements in computational capabilities, artificial intelligence algorithms, and data science, this is good evidence, in my view, whether the field should not consider improving itself. In fact, I came across Janet Marjorie Gould’s paper she presented at the International System Dynamics Society Conference in 1985, which discussed artificial intelligence applications for system dynamics (Gould, 1985). Hence, it appears that the need to advance system dynamics modeling in these fields has a long history, which lends to the question, why has it taken so long?

One of the interesting attractions of the paper is the astonishingly different categories used to describe system dynamics modeling. While the authors mention three, there could be more, but I will emphasize one due to limited space. I think system dynamics modeling is also considered a process, with different scholars offering varying steps. Some suggest that it entails a qualitative-quantitative-qualitative process. In my view, it is from this process perspective that much of the debate in defining system dynamics modeling has emerged. Generally, the system dynamics modeling foundations emphasize building quantitative models to simulate problem dynamics and generate insights that help people make better decisions. However, qualitative modeling precedes quantitative modeling.

By contrast, the authors take quantitative modeling as the starting point to define the characteristics of system dynamics modeling. I prefer to encompass the qualitative aspect of system dynamics modeling to help delineate the type of focus problems—the complex ones—constituting a goal, a gap, and a dilemma. Hence, a characteristic of system dynamics modeling could be its problem-oriented perspective. This perspective might help clarify the type of problems analyzed and relevant to system dynamics modeling. However, focusing on the quantitative modeling alone raises puzzles on whether the necessary advancement is only in technical or computing capabilities while ignoring theory development, purpose, and application of system dynamics modeling to inform policy and strategy. In my view, if we need to advance system dynamics modeling, the defining characteristics need to encompass the qualitative-quantitative-qualitative process. Dissociating quantitative modeling from qualitative modeling might imply building models for their own sake without impacting policy and strategy. In addition, applying qualitative and quantitative modeling in isolation undermines the full learning potential of system dynamics modeling in making better decisions. Therefore, the defining characteristics must reflect and constructively advance the qualitative and quantitative core of system dynamics modeling. Nevertheless, on the positive side, the authors’ proposed characteristics might be relevant in improving the technical capabilities in the quantitative modeling phase.

I agree with the authors that clarity in defining system dynamics modeling is essential. However, the authors treat system dynamics, system dynamics modeling, and system dynamics models as synonymous terms when describing the defining characteristics. This got me thinking about whether these terms are synonymous or raising more questions if we truly understand what we are trying to clarify in the definition—a field, a method, approach, structure, and so

on. Hence, clarifying whether these terms are synonymous is also crucial. I think the defining characteristics depicted in the paper reflect system dynamics modeling as a method or approach. In my view, system dynamics may entail the definitions reflecting the field and its theory, system dynamics modeling reflecting definitions of it as a research methodology, and system dynamics models as products of the modeling process. I have had an experience with these unsatisfactory definitions while teaching system dynamics modeling as a research methodology. Thus, in one of the classes I taught, we developed an elevator definition of system dynamics modeling as an “integrated [and quantitative] modeling approach to understand complex real-world issues to guide decision-making over time for achieving sustainable long-term solutions” (SD Class, School of Public Leadership, 2012). I added “and quantitative” at some later stage to emphasize the quantitative core of system dynamics modeling. However, what I’m bringing to the authors attention here is the integrative capability of system dynamics modeling, an important core defining characteristic.

Naugle *et al.* (2024) notably point to four growth opportunities in system dynamics modeling. I think the integrative capability of system dynamics modeling is what offers these opportunities to combine the emerging computational capabilities that the authors propose. All in all, we can hope that the author(s) wrote the paper as an advocacy for the quantitative system dynamics modeling phase without undermining its qualitative phase.

Reference

Gould JM. 1985. Artificial intelligence: A tool for system dynamics. In *Proceedings of the International System Dynamics Society*. Keystone, CO: System Dynamics Society. Available online: <https://proceedings.systemdynamics.org/1985/proceed/gould317.pdf>. [Accessed 1 September 2023].

Markus Schwaninger: Quantitative and qualitative modeling—A complementary set

The article by Naugle and coauthors (2024) focuses on quantitative system dynamics (SD), bracketing out “qualitative System Dynamics,” a notion they use only implicitly, as standing for “systems thinking and other qualitative methods” (p. 2). Qualitative SD should be treated as a methodology¹ in its own right, worthy of purposeful development. Both qualitative and quantitative SD should be used in complementary ways; they should be seen as forming one methodology together.

I concentrate on the most used instruments of qualitative SD, the causal loop diagram (CLD), and the stock-and-flow diagram (SFD). The CLDs are often called “maps” and, in case they represent highly aggregated concepts or variables, as “high-level maps.” The SFDs represent an intermediate component of the SD methodology, between CLDs and the equations level of quantitative models.

Quantitative SD models are laid out in SFDs, which label variables and their relations, all of that are specified rigorously. On the other hand, CLDs depict variables and their causal relationships (arrows), without quantitative assignments.

¹The term “methodology” is used here to denote a set of combined methods, used in a research.

However, the arrows are normally signed with “+” or “-,” —syntactic operators, which enable qualifying the polarity of a relationship and also of a loop. Hence, qualitative SD is not completely devoid of quantitative aspects, as the plus and minus attributes indicate if a dependent variable changes in the same direction (“more”) or opposite direction (“less”) when the independent variable changes. In a loop, these signs are counted, and if multiplied, they result in a polarity, positive for loops with an even number of “-” signs, and negative for loops with an uneven number of “-” signs.

CLDs are applicable to the modeling of dynamic systems, forming networks made up of causal relationships between variables and parameters. The great advantage of CLDs is their universal applicability to dynamic issues and problems. Naugle *et al.*, in their article, have pointed to the importance of validation. A limitation of qualitative models is that instruments for that purpose—i.e. the examination of model quality—are hardly available. Therefore, many CLDs built are spurious representations, which result—as Jay Forrester called it—from a lack of “hard thinking.”

The validation of qualitative models is mostly confined to variants of face validity, such as expert and consensus validity, while statistical methods of validation are excluded. Elsewhere, a proposal for the validation of qualitative systems models and a respective application are documented (Schwaninger, 2004).

Modeling is, in principle, a way of theory building (Schwaninger & Groesser, 2008). This implies that models, both qualitative and quantitative, can play the role of “yet-to-be-tested theory or a particular expert’s point of view” (Naugle *et al.*, 2024).

CLDs and SFDs are valuable tools that help gaining insights into the nature and structure of a system. They are also precursors of a full-fledged quantitative model. One should not forget at least three crucial aspects. First, these diagrams, the CLD in particular, allow for sketching out models with variables that are not operationalized and may even be highly intangible. They may lead the way either into further operationalization or into models that need and should not be quantified. Second, qualitative modeling is often not enough; a quantitative approach is a necessity to enable insight and learning. Third, highly sophisticated quantitative models, which may imply remarkable detail, can often only become valuable by condensing them into highly aggregated qualitative maps—a complement that may become crucial in fostering understanding.

The article commented on here is a call for opportunities opening new paths for research. The agenda is laid out brilliantly by its authors. My contribution here is a plea for recognizing and leveraging the complementarities of qualitative and quantitative SD modeling. System dynamicists should eschew clinging exclusively and obstinately to any one of these two options. Neglect of either must be avoided: despite the prejudices on both sides, each approach is existential, improvable, and in need of development. Serious research into methodological issues is necessary. It has been going on in the quantitative field. In the same vein, a systematic methodological development of qualitative modeling, and also for the integration of both strands, should be pursued. We need more rigor (not rigidity!) in SD modeling. We need it in all three domains: qualitative, quantitative, and integrative. This proposal might open new opportunities for both research and practice in SD.

References

- Schwaninger M. 2004. Methodologies in conflict: Achieving synergies between system dynamics and organizational cybernetics. *Systems Research and Behavioral Science* 21(4): 1–21.
- Schwaninger M, Grösser S. 2008. System dynamics as model-based theory building. *Systems Research and Behavioral Science* 25(4): 447–465.

Miriam Spano: Can we walk the talk when it comes to defining system dynamics?

Thank you for the opportunity to comment on the article by Naugle *et al.* (2024). In the following, I share my thoughts as a practitioner about the broader discussion amplified by this article.

Anecdotally, it appears that the postpandemic world has reignited interest in the systems sciences and its many methods. The increasing impact factor of this journal could be seen as an indicator that the field of system dynamics (SD) also benefits from this increase in interest. Still, it remains difficult to explain SD to others not formally trained in the discipline to highlight its value, its differentiation to other simulation techniques, and its subsequent usefulness. Hence, a debate, via publications and comments about the characteristics, and more so, the identity of a field and related opportunities in the field's own journal, is timely.

However, there might be (side)effects we should consider when discussing what is—or isn't—SD, as opinion pieces will also be read by others who don't (yet) have their own understanding of what SD is. This poses the risk that people that want to know more about the field and search in the core journal will find Naugle *et al.*'s (2024) paper that discusses the “field,” its “philosophy,” and its “processes” but excludes “other techniques involved in the system dynamics process, such as systems thinking and group model building” from the outset. While the authors acknowledge the importance of the latter, sentences like “All models with these characteristics should be considered system dynamics” could, by deduction, render everything else as “not system dynamics.”

The provided overview of the various “identities” of the field of SD covers different epistemological and theoretical concepts and related discussions, addressing paradigms, methodologies, methods, techniques, and tools. Yet, the inherent relationships between these concepts are not explained in detail. Simply listing them side by side could be deduced by an untrained reader to evidence competing definitions. I admit that despite my SD education, I had difficulty to follow the authors' delineation of what exactly they see as “the field” of SD, what SD “modeling” is, and what underpins their choice of quantitative stock-and-flow models as a useful starting point. Most of the citations discuss different parts of the same whole, that (might or might not) form a part of SD's overall identity.

While Naugle *et al.* (2024) extricate the proposed characteristics from such theoretical concepts, they still seek to distinguish SD from other modeling “paradigms”. Applying Pruyt's (2006) paradigmatic approach, the provided characteristics would indeed relate to the technique, i.e. quantitative stock-and-flow models. In a way this shows that the theoretical, or epistemological, frame is helpful when

discussing a scientific field. It connects elements of the debate and facilitates the reader's understanding of Naugle *et al.*'s (2024) perspective onto the (SD) world. Such clarity will not only help the debaters but also those observers and future system dynamicists to gain an informed perspective.

Compartmentalizing a field into “ins” and “outs” might help resolve identity issues, yet to me an identity is all-encompassing, an emerging, complex whole. I would think we system dynamicists in particular would be inclined to accept that there are different perspectives, different purposes, different goals concerning a complex issue such as one's own identity. Separating out quantitative stock-and-flow models, stripping it from the process of building the model, associated methods, and analytical skills of the modeler, feels unnecessarily reductionist. In other words, “dividing an elephant in half does not produce two small elephants” (Senge, 2006: p.66).

What are we solving if we describe a field such as system dynamics by its quantitative technique alone? What or who does it serve? And what does this say about our own ability to do what we urge others to do: to see the whole, the interconnections, appreciate the nonlinearity and complexity of it all?

Lastly, the five defining characteristics were selected through “a deductive process informed by the literature to capture the core philosophy of system dynamics, describe the theoretical and practical principles that make system dynamics modeling unique, and apply to historical work but be flexible enough to hold as technical capabilities progress.” In absence of a detailed process description, this can raise more questions: Why these five characteristics and not others? Why is nonlinearity not one of them? Are the 10 characteristics ChatGPT produces just as plausible?²

While the topic can be messy, the debate doesn't have to be. Embracing the complexity of the evolved SD field and attending to it as we would to a client's problem, focusing on clear boundaries, stakeholder management and precise language, supplemented by relevant and trustworthy research, might help us to keep the elephant intact.

References

- Pruyt E. 2006. What is system dynamics? A paradigmatic inquiry. In *Proceedings of the 2006 Conference of the System Dynamics Society*, 23-27 July 2006, Nijmegen, The Netherlands. System Dynamics Society. Retrieved September 2, 2023 from <https://www.researchgate.net/publication/228925617>.
- Senge PM 2006. *The Fifth Discipline: The Art and Practice of the Learning Organization*. (Rev. and updated ed.). Random House.

²Chat GPT question: What are the characteristics of quantitative system dynamics models? Answer: Quantitative System Dynamics (QSD) models are a type of computational modeling approach used to simulate the behavior of complex systems over time. These models are particularly effective for understanding and analyzing dynamic relationships, feedback loops, and interdependencies within systems. Here are some key characteristics of quantitative system dynamics models: 1. Time Dependency, 2. Causal Relationships, 3. Stocks and Flows, 4. Feedback Loops, 5. Delays, 6. Nonlinear Relationships, 7. Equation and Formulas, 8. Simulation, 9. Policy Analysis, 10. Visualization. Quantitative System Dynamics models are a powerful tool for understanding the behavior of complex systems over time, incorporating elements like time dependency, causal relationships, stocks and flows, feedback loops, delays, and nonlinearities to provide insights into system dynamics and inform decision-making.