

Perspectives on confronting issues of scale in systems modeling

Takuya Iwanaga^{1*}, Patrick Steinmann², Amir Sadoddin³, Derek T. Robinson⁴, Val Snow⁵, Volker Grimm⁶, and Hsiao-Hsuan Wang⁷

¹ Institute for Water Futures, The Australian National University, Australia

² Biometris, Wageningen University & Research, The Netherlands

³ Department of Watershed Management, Gorgan University of Agricultural Sciences & Natural Resources, Iran

⁴ Department of Geography & Environmental Management, University of Waterloo, Canada

⁵ AgResearch Ltd, New Zealand

⁶ Helmholtz Centre for Environmental Research - UFZ, Department of Ecological Modelling, Leipzig, Germany

⁷ Department of Ecology & Conservation Biology, Texas A&M University, USA

Abstract

Issues of scale pervade every aspect of socio-environmental systems (SES) modeling. They can stem from the context of both the modeling process, and the purpose of the integrated model. A webinar hosted by the National Socio-Environmental Synthesis Center (SESYNC), The Integrated Assessment Society (TIAS) and the journal Socio-Environmental Systems Modelling (SESMO) explored how model stakeholders can address issues of scale. Four key considerations were raised: (1) being aware of our influence on the modeling pathway, and developing a shared language to overcome cross-disciplinary communication barriers; (2) that localized effects may aggregate to influence behavior at larger scales, necessitating the consideration of multiple scales; (3) that these effects are “patterns” that can be elicited to capture understanding of a system (of systems); and (4) recognition that the scales must be relevant to the involved stakeholders and decision makers. Key references in these four areas of consideration are presented to complement the discussion of confronting scale as a grand challenge in socio-environmental modeling. By considering these aspects within the integrated modeling process, we are better able to confront the issues of scale in socio-environmental modeling.

Keywords

Socio-environmental modeling; integrated modeling; interdisciplinary scale; patterns

1. Introduction

Socio-environmental systems (SES) modeling is a key tool for understanding the complexities of human-environment interactions. Like many types of models, SES models simplify the real world to isolate processes and behaviors for experimentation and interrogation. However, what sets SES models apart from others is their focus on interaction among human and natural systems (e.g., Elsawah et al., 2020; Iwanaga et al., 2021a; Musters et al., 1998; Schlüter et al., 2019), the identification of thresholds causing system level shifts (e.g., Egli et al., 2019; Lade et al., 2020; Steinmann et al., 2020), and a degree of heterogeneity that is both difficult to represent in statistical modelling (e.g., different heterogeneous actors) and where tails of the distributions can drive the system (e.g., Cirillo and Taleb, 2020). With a focus on the creation of models with these characteristics,

Correspondence:

Contact T. Iwanaga at iwanaga.takuya@anu.edu.au

Cite this article as:

Iwanaga, T., Steinmann, P., Sadoddin, A., Robinson, D.T., Snow, V., Grimm, V., & Wang, H.-H. Perspectives on Confronting Issues of Scale in Systems Modeling *Socio-Environmental Systems Modelling*, vol. 4, 18156, 2022, doi:10.18174/sesmo.18156

This work is licensed under a [Creative Commons Attribution-NonCommercial 4.0 International License](https://creativecommons.org/licenses/by-nc/4.0/).



Socio-Environmental Systems Modelling

An Open-Access Scholarly Journal

<http://www.sesmo.org>

SES models are firmly situated in Complexity Science as these themes associated with the study of complex systems have been around since the 1970s (cf. Vemuri, 1978).

In an effort to assist those seeking to understand SES modeling, and drive the science of SES modeling forward, Elsworth et al., (2020) identified eight grand challenges facing SES modeling: bridging epistemologies across disciplines; multi-dimensional uncertainty assessment and management; scales and scaling issues; combining qualitative and quantitative methods and data; furthering the adoption and impacts of SES modeling on policy; capturing structural changes; representing human dimensions in SES; and leveraging new data types and sources. The National Socio-Environmental Synthesis Center (SESYNC), The Integrated Assessment Society (TIAS), and the board of the journal Socio-Environmental Systems Modelling (SESMO) organized a series of webinars and tutorials dedicated to these grand challenges.

The third webinar¹ in the eight-part series on grand challenges in SES modeling dealt with questions of scale, highlighted recent papers (Iwanaga et al., 2021a, 2021b; Wang and Grant, 2021), and provided a tutorial on the topic of confronting scale issues (The National Socio-Environmental Synthesis Center, 2021). The webinar was led by Hsiao-Hsuan Wang (Texas A&M University, USA) and brought together three panelists to provide perspective and experience about how scale affects their work on SES modeling and how these are managed were provided from various aspects of socio-environmental research. The panelists were Val Snow (AgResearch, New Zealand), Derek T. Robinson (University of Waterloo, Canada) and Volker Grimm (Helmholtz Center for Environmental Research – UFZ, Germany).

Scale can be used as an expansive term, since the term includes not only spatial and temporal aspects, but also levels and aspects of organization, including system-level vs. agent-level, and social, legal, and technical aspects. Issues of scale has been a historical and contemporary challenge across many areas of research, albeit one that is often couched in disciplinary-specific terminologies and perspectives. Within the *Confronting Issues of Scale* webinar, four distinct considerations emerged as being especially relevant to scale challenges in modeling socio-environmental systems. What follows is a synthesis of these considerations of confronting scale, which combines the talking points of the panelists and subsequent discussion, and key references mentioned, supported by existing literature. We also connect the considerations to broader themes in SES modeling.

2 Perspectives and Discussion

2.1 Scale decisions as a socio-technical process

The development of an SES model should be a collaborative process involving a larger group of actors than occurs when a single or linked systems model is developed, including local knowledge holders, interest groups and disciplinary experts, as well as those commissioning the modeling. Using this holistic and collaborative approach – referred to here as a socio-technical process – to choose what scales to represent, and how to represent them, enables actors to influence what is endogenous and exogenous to the model: the system boundaries, the process representations to consider, the scenarios to explore, the model outputs of concern, and the methodologies and technologies used.

There is currently no generic (computational) framework that can model all systems and their interactions. Indeed, such a framework is unlikely. Instead, SES models are constructed to be purpose and context specific. In the decision-support setting, this focused purpose ensures relevance to decision-makers (Will et al., 2021) at the cost of generality. Model construction can occur through a composition process, wherein pre-existing and bespoke models are coupled together. There are now many frameworks to aid in the development and integration of models (e.g., Castronova et al., 2013; David et al., 2013; Hutton et al., 2020; Peckham et al., 2013) and the dissemination of their components as building blocks for alternate purposes (e.g., Bankes, 1993; Whelan et al., 2014; Zhang et al., 2021). Modelers are then able to construct distinct representations and views of an SES that target specific scales to interrogate different questions of the same SES.

Modelers may prefer specific methods, approaches or a given modeling framework (computational or other). It is important to recognize this implicit bias may create a path dependency as the investments in model

¹ The webinar is accessible at: <https://www.youtube.com/watch?v=q5H7jdahJyc>

production (e.g., time, budget, familiarity) persist through time (Iwanaga et al., 2021b; Zare et al., 2021). Modelers should therefore exercise care to avoid limiting the available pathways and applications explored. The socio-technical process should drive decisions on what representations are “hard-wired” in an SES model or those that are simply left unexplored in the model application (Fielke et al., 2018; Iwanaga et al., 2021a, 2021b). Among many benefits of this process are having the actors map the system, justification of the scale of representation, and using inputs and outputs that match actor concerns and decision making.

Over-reliance on existing models can also affect the appropriateness of subsequent model applications due to the “hard-wiring” of system representations and thus the level of knowledge sharing or coalition- and consensus-building activities with those who could benefit from model outputs. Even if the individual models or sub-models were tested and found to be useful on their own, they might fail when integrated. In practice, each model that is integrated should, in principle, be fully tested and parameterized from scratch so as to reduce the risk of ‘integronsters’ – integrated models that are difficult to apply and reason about such that they are no longer fit-for-purpose (Voinov and Shugart, 2013) – arising from their complicated and complex interactions.

From a different perspective, such choices act to embed structural uncertainties into the overall model architecture (e.g., Walker et al., 2003). Depending on the level of accessibility in terms of documentation, code, and the domain knowledge to understand both, a constituent, component, or sub-model, may be opaque to the modeler. On the other hand, it is acknowledged that legacy, budgetary, institutional, and sometimes regulatory, issues may require use of existing models to be considered.

There is a need to harmonize the different perspectives and knowledge, considering the cultural context and background (both organizational and individual; Wang and Grant, 2021) throughout the integration process. Harmonization is required for comparative analyses as well as to develop a shared language to better capture and incorporate the different perspectives and knowledge in the modeling, and for this shared understanding to be documented (Grimm et al., 2020; Iwanaga et al., 2021b). Incorporating a variety of perspectives and acknowledging alternate conceptualizations can also aid in the characterization of the uncertainties involved.

In the conceptual modeling stage (see Hamilton et al., 2015) modelers and stakeholders decide which aspects of the real system to represent in the model, and at what resolution. While in principle the key decision criterion should be that aspects included are relevant to answering the question, often other factors play a role, in particular: the methodological preferences of the modeler; the specific point of view, or worldview, of the stakeholders and experts involved; and the data and knowledge available along with the associated uncertainties. Another important criterion often applied is parsimony so that if in doubt, a certain aspect is ignored or aggregated, rather than included to reduce effort for parameterization and analysis. Most modelling communities develop a culture of tacitly agreeing on ignoring certain important aspects of the real world, simply because a lack of data or knowledge; in vegetation modelling, for example, belowground processes are usually ignored.

To support the recommendations given above regarding scale decisions, it would be useful to make this process of conceptual modelling explicit, for example by using the Overview part of the ODD protocol (Grimm et al., 2020), which requires listing the entities, state variables, scales, and processes to be represented in a model. Ideally, all stakeholders involved would first come up with their own (e.g., ODD) list, and then jointly discuss what to include. It is also important to keep things that are initially omitted, but where arguments exist that they might be important under certain circumstances, on a “reserve list”, otherwise they are easily forgotten. If arguments remain that conditions might exist under which a certain factor becomes key for predicting the systems behavior, this factor should be included, even if under “normal” conditions it does not matter much (Topping et al., 2015). One further note is that it has long been known that the lessons learned while developing a model can be as important and useful than the final model and its output, sometimes even more so (Penning de Vries, 1977). The model may simply be a means to an end and the real value lies in the experience from the process of modeling an SES. Thus, it is important to keep track of these lessons.

2.2 Use patterns to understand and consider scales

Researchers have long searched for patterns to explain observed system behavior as they inform and guide model development; these models reproduce the patterns we observe (Meadows, 2008; Wang and Grant, 2021). There is, however, a tendency to think of SESs as being made of separate – and separable – constituent

systems which are “linked” together in some way. A more holistic approach is to conceptualize these “individual” systems as part of an intertwined whole. Pattern-oriented modeling (POM) offers one approach to identifying the processes, actors, and relevant scales in order to characterize system behavior (Grimm and Railsback, 2012). The challenge with complex systems, such as an SES, is that system structure cannot be inferred from a single pattern at a single scale. Multiple patterns are necessary to characterize the system, and these may be hard to discern as they may occur across scales, and may not be independent from one another (i.e., they interact). Multiple patterns that are “weak” by themselves, such as localized farm management preferences, may aggregate up to a “strong” pattern which explain, for example, basin-scale erosion processes, farm labor movement and influence town planning processes (Grimm and Railsback, 2012; Jafino et al., 2019; Rounsevell et al., 2012).

A variety of perspectives, data and models at the appropriate scales is necessary to understand the inter-related processes and emergence of observed patterns (Grimm et al., 2020). Modeling always involves “tweaking” in the sense of varying model structure, process models, and parameters until the model reproduces a certain observation. If only a single observation, or pattern, is used as a criterion for a model’s realism, the risk is high that the model was tweaked to produce the right patterns, but for the wrong reasons. In a sense, the level of uncertainty regarding the model’s predictive behavior is always high or at the very least difficult to discern. Using entire sets of patterns - combining observations at different scales - reduces this risk and thus its predictive uncertainty, while also making the model “mechanistically rich” (DeAngelis and Mooij, 2003). The model can then be validated by comparing the emerging patterns generated by the model at a range of scales separate from what was used for model development or calibration. The focus is then on reproducing system behaviors (the patterns) more so than matching specific observations, although these are not mutually exclusive. A further step would be to build an ensemble of models with different structures, thus making the influence of the “structural uncertainties” explicit (e.g., Kwakkel et al., 2013).

In System Dynamics, general recurring patterns which characterize system behavior are referred to as “archetypes” (Braun, 2002; Senge, 1990; Špicar, 2014). Such archetypes are used to describe and identify commonly occurring issues and potential solutions across systems. A separate but conceptually identical practice in software engineering is the use of design patterns (Gamma, 1994) to characterize commonly encountered issues and the approaches to resolving these. So-called “community models” developed by the various environmental modeling communities could be described as a concerted effort at identifying effective patterns to represent common system behaviors across a wide range of SES contexts (cf. David et al., 2013). Identifying a pattern of patterns from these somewhat disparate efforts could further improve model development and validation when dealing with multiple interacting scales. Uncertainty can also be managed or characterized in a similar vein. Highly uncertain scenarios, data, or model structures should at least reproduce known patterns somewhere in their pattern space (Chérel et al., 2015), indicating the influence the choice of scale may have on the represented systems.

2.3 Emergent interactions across multiple scales

A growing trend in SES modelling is to see SES as systems of systems (Eusgeld et al., 2011; Iwanaga et al., 2021a; Little et al., 2019). A hallmark of this approach is that events and processes at one system or scale level can create emergent behavior (Bar-Yam, 1997) at other levels. Agricultural systems are one example where multiple systems and scales interact. Conversion of grazing land to forestry to take advantage of carbon offset incentives can significantly influence soil erosion processes and farm labor requirements. These may then impact seasonal labor demand and town population, thus affecting local economies. Yet most models poorly represent the scales at which both environmental and social systems interact. Speaking to the temporal aspect of scale specifically, models of land use change tend to operate at annual time frames, yet social systems, such as town planning and farm management, often make decisions at supra- and sub-annual time frames, respectively.

The choice to align a model with the available data is often a pragmatic decision. It can, however, severely constrain the available modeling pathways and thus the outcomes achieved, as emergent behavior can only occur at and between the scales chosen to represent the problem. Modelers are advised not to be hesitant to move across scale representations as needed. Multiple scales could, and should, be considered even with highly uncertain (or lacking) data (Koo et al., 2020). As many models can map to only one system, the process of modeling for multiple scales, or developing models for different scales, can help identify model structure issues, and aid in model validation and uncertainty assessment (Walker et al., 2003).

A variety of approaches can aid discussions with local knowledge holders and interest groups as it provides a more holistic characterization of the system of systems, and the behaviors that may emerge from it. Documenting the decisions, and explicitly considering alternative scale representations, can further improve understanding across disciplines and stakeholder groups (Ayllón et al., 2021; Grimm et al., 2020, 2014). Some indication of possible mutually beneficial outcomes could at least be obtained by going through this process.

2.4 Select scales appropriate for the model's end users

Earlier we described scale decisions as being made through a socio-technical process, through which modelers influence how an SES is represented. Overly constraining the scales considered or ignoring system behavior at the scales most relevant to stakeholders can limit, or compromise, the outcomes achieved (Meinen and Robinson, 2021). The need to explore as diverse a set of pathways as possible must be balanced with due consideration of the pressures which drive scale selection. The possible level of complexity able to be represented can be directly tied to the available data or computational resources. Legislative requirements can determine what can be done, when and how, which may constrain what patterns can be established, framing the system boundaries and the emergent behavior represented. Effective solutions and the inherent risks may be mis-stated or not be visible if a constrained view of a system is taken, or the scales are otherwise mismatched (Bryant et al., 2020; John et al., 2021).

Stakeholders can aid in identifying appropriate scales, so it is important to incorporate many perspectives to allow consideration of a broad range of patterns and their scales (cf. Hamilton et al., 2015). Neglecting these perspectives can affect the appropriateness and/or acceptability of subsequent model applications, risk normalizing the perspectives of those already the most privileged, and close off future actions that might well be viable. As a consequence, the available decision pathways are collapsed down to a handful of “dominant pathways” (West et al., 2014) that may not be robust or resilient to future uncertainties (Lade et al., 2020).

Involvement of multiple stakeholders can introduce differing views on the modeling process, however, is itself a source of uncertainty. In particular, stakeholders may disagree on a number of aspects related to the “correct” representation of the studied system, including the probabilities related to uncertain events, the structural cause-and-effect mechanisms, and the metrics and methods by which the desirability of alternative futures can be compared (Lempert et al., 2003). For example, stakeholders living in headwater vis-a-vis downstream areas of a river catchment could have different notions on how future hydrologic conditions may change, where water is introduced to and extracted from the river, and how their livelihoods are dependent on future developments. These concerns may all require different scales to integrate and address stakeholder views and concerns.

Ideally, an analysis of the uncertainties involved and the conditions to which outcomes are sensitive would be conducted. Such analyses can aid in identifying the level of influence that modeling choices have and how these may influence outcomes. There are of course many possible approaches to sensitivity analysis, which themselves have many variations that are context dependent (Ligmann-Zielinska et al., 2020). Different, but equally acceptable, configurations could be explored to characterize these effects. Contrasting spatial resolutions, for example, could affect outcomes or highlight the inappropriateness of selected metrics (Koo et al., 2020). Incorporating stakeholder views (and their uncertainties) can aid in identifying consensus and level of disagreement amongst stakeholders (cf. Potter et al., 2016) and simultaneously better align the modeling process with the purpose of the modeling (cf. Noble et al., 2021).

3. Conclusion

Computational modelling of socio-environmental systems represents a powerful tool for understanding their complexities and improving their governance. Deciding on the appropriate scales to represent such systems is a crucial step in this process. The SESYNC/TIAS/SESMO webinar on scale issues was a timely and fruitful effort to bring together experts from multiple fields. Four key themes emerged from their contributions and discussions:

- scale choices are not given, but emerge from a socio-technical process among stakeholders
- system processes are observable as patterns, and can be used to inform scale choices
- processes can transcend scales, necessitating multi-scale representation
- scale choices should match stakeholder and decision-maker requirements

These themes represent valuable guiding principles when dealing with issues of scale. We encourage all SES modelers to reflect on them throughout their work, promoting the explicit and inclusive treatment of scale issues in SES modelling. This will improve research outcomes and enable a better understanding of the crucial human-environment interactions governing our planet's future. Finally, we observe that questions of uncertainty pervade all four themes, suggesting that uncertainty-centric approaches such as ensemble modelling, sensitivity analysis, or group model building may be able to act as a lens with which scale decisions can be inspected and refined.

Acknowledgements

The authors would like to thank The National Socio-Environmental Synthesis Center (SESYNC), The Integrated Assessment Society (TIAS), and the journal Socio-Environmental Systems Modeling (SESMO) for organizing the webinar. The work was also supported by SESYNC under funding received from the National Science Foundation (DBI-1639145). The authors would like to also thank Prof. Sondoss El Sawah for comments provided on an early copy of the manuscript.

References

- Ayllón, D., Railsback, S.F., Gallagher, C., Augusiak, J., Baveco, H., Berger, U., Charles, S., Martin, R., Focks, A., Galic, N., Liu, C., van Loon, E.E., Nabe-Nielsen, J., Piou, C., Polhill, J.G., Preuss, T.G., Radchuk, V., Schmolke, A., Stadnicka-Michalak, J., Thorbek, P. & Grimm, V. (2021). Keeping modelling notebooks with TRACE: Good for you and good for environmental research and management support. *Environmental Modelling & Software*, 136, 104932. <https://doi.org/10.1016/j.envsoft.2020.104932>
- Bankes, S. (1993). Exploratory Modeling for Policy Analysis. *Operations Research*, 41, 435–449. <https://doi.org/10.1287/opre.41.3.435>
- Bar-Yam, Y. (1997). *Dynamics of complex systems*. Perseus Books, USA.
- Braun, W. (2002). The System Archetypes. *System*, pp. 1–26. Available at: https://www.albany.edu/faculty/gpr/PAD724/724WebArticles/sys_archetypes.pdf
- Bryant, R.H., Snow, V.O., Shorten, P.R., & Welten, B.G. (2020). Can alternative forages substantially reduce N leaching? findings from a review and associated modelling. *New Zealand Journal of Agricultural Research*, 63, 3–28. <https://doi.org/10.1080/00288233.2019.1680395>
- Castronova, A.M., Goodall, J.L., & Ercan, M.B. (2013). Integrated modeling within a Hydrologic Information System: An OpenMI based approach. *Environmental Modelling & Software*, 39, 263–273. <https://doi.org/10.1016/j.envsoft.2012.02.011>
- Chérel, G., Cottineau, C. & Reuillon, R. (2015). Beyond Corroboration: Strengthening Model Validation by Looking for Unexpected Patterns. *PLoS ONE*, 10, e0138212. <https://doi.org/10.1371/journal.pone.0138212>
- Cirillo, P. & Taleb, N.N. (2020). Tail risk of contagious diseases. *Nature Physics*, 16, 606–613. <https://doi.org/10.1038/s41567-020-0921-x>
- David, O., Ascough, J.C., Lloyd, W., Green, T.R., Rojas, K.W., Leavesley, G.H. & Ahuja, L.R. (2013). A software engineering perspective on environmental modeling framework design: The Object Modeling System. *Environmental Modelling & Software*, 39, 201–213. <https://doi.org/10.1016/j.envsoft.2012.03.006>
- DeAngelis, D.L. & Mooij, W.M. (2003). In praise of mechanistically rich models. In: C.D. Canham, J.J. Cole, & W.K. Lauenroth (Eds.), *Models in Ecosystem Science*. Princeton University Press, Princeton, New Jersey, pp. 63–82.
- Egli, L., Weise, H., Radchuk, V., Seppelt, R. & Grimm, V. (2019). Exploring resilience with agent-based models: State of the art, knowledge gaps and recommendations for coping with multidimensionality. *Ecological Complexity*, 40, 100718. <https://doi.org/10.1016/j.ecocom.2018.06.008>
- Elsawah, S., Filatova, T., Jakeman, A.J., Kettner, A.J., Zellner, M.L., Athanasiadis, I.N., Hamilton, S.H., Axtell, R.L., Brown, D.G., Gilligan, J.M., Janssen, M.A., Robinson, D.T., Rozenberg, J., Ullah, I.I.T. & Lade, S.J. (2020). Eight grand challenges in socio-environmental systems modeling. *Socio-Environmental Systems Modelling*, 2, 16226. <https://doi.org/10.18174/sesmo.2020a16226>
- Eusgeld, I., Nan, C. & Dietz, S. (2011). “System-of-systems” approach for interdependent critical infrastructures. *Reliability Engineering & System Safety*, 96, 679–686. <https://doi.org/10.1016/j.ress.2010.12.010>
- Fielke, S.J., Kaye-Blake, W., Mackay, A., Smith, W., Rendel, J. & Dominati, E. (2018). Learning from resilience research:

- Findings from four projects in New Zealand. *Land Use Policy*, 70, 322–333. <https://doi.org/10.1016/j.landusepol.2017.10.041>
- Gamma, E. (Ed.) (1994). *Design patterns: elements of reusable object-oriented software*, Addison-Wesley professional computing series. Addison-Wesley, Reading, Mass.
- Grimm, V., Augusiak, J., Focks, A., Frank, B.M., Gabsi, F., Johnston, A.S.A., Liu, C., Martin, B.T., Meli, M., Radchuk, V., Thorbek, P. & Railsback, S.F. (2014). Towards better modelling and decision support: Documenting model development, testing, and analysis using TRACE. *Ecological Modelling*, 280, 129–139. <https://doi.org/10.1016/j.ecolmodel.2014.01.018>
- Grimm, V. & Railsback, S.F. (2012). Pattern-oriented modelling: a ‘multi-scope’ for predictive systems ecology. *Philosophical Transactions of the Royal Society B*, 367, 298–310. <https://doi.org/10.1098/rstb.2011.0180>
- Grimm, V., Railsback, S.F., Vincenot, C.E., Berger, U., Gallagher, C., DeAngelis, D.L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., Johnston, A.S.A., Milles, A., Nabe-Nielsen, J., Polhill, J.G., Radchuk, V., Rohwäder, M.-S., Stillman, R.A., Thiele, J.C. & Ayllón, D. (2020). The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism. *Journal of Artificial Societies & Social Simulation*, 23, 7. <https://doi.org/10.18564/jasss.4259>
- Hamilton, S.H., ElSawah, S., Guillaume, J.H.A., Jakeman, A.J. & Pierce, S.A. (2015). Integrated assessment and modelling: Overview and synthesis of salient dimensions. *Environmental Modelling & Software*, 64, 215–229. <https://doi.org/10.1016/j.envsoft.2014.12.005>
- Hutton, E.W.H, Piper, M.D. & Tucker, G.E. (2020). The Basic Model Interface 2.0: A standard interface for coupling numerical models in the geosciences. *Journal of Open Source Software*, 5, 2317. <https://doi.org/10.21105/joss.02317>
- Iwanaga, T., Wang, H.-H., Hamilton, S.H., Grimm, V., Koralewski, T.E., Salado, A., ElSawah, S., Razavi, S., Yang, J., Glynn, P., Badham, J., Voinov, A., Chen, M., Grant, W.E., Peterson, T.R., Frank, K., Shenk, G., Barton, C.M., Jakeman, A.J. & Little, J.C. (2021a). Socio-technical scales in socio-environmental modeling: Managing a system-of-systems modeling approach. *Environmental Modelling & Software*, 135, 104885. <https://doi.org/10.1016/j.envsoft.2020.104885>
- Iwanaga, T., Wang, H.-H., Koralewski, T.E., Grant, W.E., Jakeman, A.J. & Little, J.C. (2021b). Toward a complete interdisciplinary treatment of scale: Reflexive lessons from socioenvironmental systems modeling. *Elementa: Science of the Anthropocene*, 9(1), 00182. <https://doi.org/10.1525/elementa.2020.00182>
- Jafino, B.A., Haasnoot, M., Kwakkel, J.H., 2019. What are the merits of endogenising land-use change dynamics into model-based climate adaptation planning? *Socio-Environmental Systems Modelling*, 1, 16126. <https://doi.org/10.18174/sesmo.2019a16126>
- John, A., Horne, A., Nathan, R., Stewardson, M., Webb, J.A., Wang, J. & Poff, N.L. (2021). Climate change and freshwater ecology: Hydrological and ecological methods of comparable complexity are needed to predict risk. *WIREs Climate Change*, 12, e692. <https://doi.org/10.1002/wcc.692>
- Koo, H., Iwanaga, T., Croke, B.F.W., Jakeman, A.J., Yang, J., Wang, H.-H., Sun, X., Lü, G., Li, X., Yue, T., Yuan, W., Liu, X. & Chen, M. (2020). Position Paper: Sensitivity Analysis of Spatially Distributed Environmental Models- A pragmatic framework for the exploration of uncertainty sources. *Environmental Modelling & Software*, 134, 104857. <https://doi.org/10.1016/j.envsoft.2020.104857>
- Kwakkel, J.H., Auping, W.L. & Pruyt, E. (2013). Dynamic scenario discovery under deep uncertainty: The future of copper. *Technological Forecasting & Social Change*, 80, 789–800. <https://doi.org/10.1016/j.techfore.2012.09.012>
- Lade, S., Walker, B. & Haider, L. (2020). Resilience as pathway diversity: linking systems, individual, and temporal perspectives on resilience. *Ecology & Society*, 25(3), 19. <https://doi.org/10.5751/ES-11760-250319>
- Lempert, R., Popper, S. & Bankes, S. (2003). *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis*. RAND Corporation. <https://doi.org/10.7249/MR1626>
- Ligmann-Zielinska, A., Siebers, P.-O., Magliocca, N., Parker, D.C., Grimm, V., Du, J., Cenek, M., Radchuk, V., Arbab, N.N., Li, S., Berger, U., Paudel, R., Robinson, D.T., Jankowski, P., An, L., Ye, X., 2020. ‘One Size Does Not Fit All’: A Roadmap of Purpose-Driven Mixed-Method Pathways for Sensitivity Analysis of Agent-Based Models. *Journal of Artificial Societies & Social Simulation*, 23, 6. <https://doi.org/10.18564/jasss.4201>
- Little, J.C., Hester, E.T., ElSawah, S., Filz, G.M., Sandu, A., Carey, C.C., Iwanaga, T. & Jakeman, A.J. (2019). A tiered, system-of-systems modeling framework for resolving complex socio-environmental policy issues. *Environmental Modelling & Software*, 112, 82–94. <https://doi.org/10.1016/j.envsoft.2018.11.011>
- Meadows, D.H. (2008). *Thinking in Systems: A Primer*. Chelsea Green Publishing.
- Meinen, B.U. & Robinson, D.T. (2021). Agricultural erosion modelling: Evaluating USLE and WEPP field-scale erosion estimates using UAV time-series data. *Environmental Modelling & Software*, 137, 104962.

<https://doi.org/10.1016/j.envsoft.2021.104962>

- Musters, C.J.M., de Graaf, H.J. & ter Keurs, W.J. (1998). Defining socio-environmental systems for sustainable development. *Ecological Economics*, 26, 243–258. [https://doi.org/10.1016/S0921-8009\(97\)00104-3](https://doi.org/10.1016/S0921-8009(97)00104-3)
- Noble, M.M., Harasti, D., Pittock, J. & Doran, B. (2021). Using GIS fuzzy-set modelling to integrate social-ecological data to support overall resilience in marine protected area spatial planning: A case study. *Ocean & Coastal Management*, 212, 105745. <https://doi.org/10.1016/j.ocecoaman.2021.105745>
- Peckham, S.D., Hutton, E.W.H. & Norris, B. (2013). A component-based approach to integrated modeling in the geosciences: The design of CSDMS. *Computers & Geosciences*, 53, 3–12. <https://doi.org/10.1016/j.cageo.2012.04.002>
- Penning de Vries, F.W.T. (1977). Evaluation of simulation models in agriculture and biology: Conclusions of a workshop. *Agricultural Systems*, 2, 99–107. [https://doi.org/10.1016/0308-521X\(77\)90063-4](https://doi.org/10.1016/0308-521X(77)90063-4)
- Potter, S., Doran, B. & Mathews, D. (2016). Modelling collective Yawuru values along the foreshore of Roebuck Bay, Western Australia using fuzzy logic. *Applied Geography*, 77, 8–19. <https://doi.org/10.1016/j.apgeog.2016.09.016>
- Rounsevell, M.D.A., Robinson, D.T. & Murray-Rust, D. (2012). From actors to agents in socio-ecological systems models. *Philosophical Transactions of the Royal Society B*, 367, 259–269. <https://doi.org/10.1098/rstb.2011.0187>
- Schlüter, M., Müller, B. & Frank, K. (2019). The potential of models and modeling for social-ecological systems research: the reference frame ModSES. *Ecology and Society*, 24, art31. <https://doi.org/10.5751/ES-10716-240131>
- Senge, P.M. (1990). *The Fifth Discipline*. Currency.
- Špicar, R. (2014). System Dynamics Archetypes in Capacity Planning. *Procedia Engineering*, 24th DAAAM International Symposium on Intelligent Manufacturing and Automation, 2013, 69, 1350–1355. <https://doi.org/10.1016/j.proeng.2014.03.128>
- Steinmann, P., Auping, W.L. & Kwakkel, J.H. (2020). Behavior-based scenario discovery using time series clustering. *Technological Forecasting and Social Change*, 156, 120052. <https://doi.org/10.1016/j.techfore.2020.120052>
- The National Socio-Environmental Synthesis Center (2021). *Confronting Issues of Scale in Socio-Environmental Modeling*, Socio-Environmental Systems Modeling Series. 25 June 2021. Available at: <https://www.youtube.com/watch?v=q5H7jdahJyc>
- Topping, C.J., Alrøe, H.F., Farrell, K.N. & Grimm, V. (2015). Per Aspera ad Astra: Through Complex Population Modeling to Predictive Theory. *The American Naturalist*, 186, 669–674. <https://doi.org/10.1086/683181>
- Vemuri, V.R. (1978). *Modeling of complex systems: an introduction*, Operations research and industrial engineering. Academic Press, New York.
- Voinov, A. & Shugart, H.H. (2013). “Integronsters”, integral and integrated modeling. *Environmental Modelling & Software*, 39, 149–158. <https://doi.org/10.1016/j.envsoft.2012.05.014>
- Walker, W.E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P. & Kreyer von Krauss, M.P. (2003). Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. *Integrated Assessment*, 4, 5–17. <https://doi.org/10.1076/iaij.4.1.5.16466>
- Wang, H.-H. & Grant, W.E. (2021). Reflections of two systems ecologists on modelling coupled human and natural (socio-ecological, socio-environmental) systems. *Ecological Modelling*, 440, 109403. <https://doi.org/10.1016/j.ecolmodel.2020.109403>
- West, S., Haider, L., Sinare, H. & Karpouzoglou, T. (2014). *Beyond Divides: Prospects of Synergy between Resilience and Pathways Approaches to Sustainability*. STEPS Working Paper.
- Whelan, G., Kim, K., Pelton, M.A., Castleton, K.J., Laniak, G.F., Wolfe, K., Parmar, R., Babendreier, J. & Galvin, M. (2014). Design of a component-based integrated environmental modeling framework. *Environmental Modelling & Software*, 55, 1–24. <https://doi.org/10.1016/j.envsoft.2014.01.016>
- Will, M., Dressler, G., Kreuer, D., Thulke, H.-H., Grêt-Regamey, A. & Müller, B. (2021). How to make socio-environmental modelling more useful to support policy and management? *People & Nature* 3, 560–572. <https://doi.org/10.1002/pan3.10207>
- Zare, F., Guillaume, J.H.A., ElSawah, S., Croke, B., Fu, B., Iwanaga, T., Merritt, W., Partington, D., Ticehurst, J. & Jakeman, A.J. (2021). A formative and self-reflective approach to monitoring and evaluation of interdisciplinary team research: An integrated water resource modelling application in Australia. *Journal of Hydrology*, 596, 126070. <https://doi.org/10.1016/j.jhydrol.2021.126070>
- Zhang, F., Chen, M., Kettner, A.J., Ames, D.P., Harpham, Q., Yue, S., Wen, Y. & Lü, G. (2021). Interoperability engine design for model sharing and reuse among OpenMI, BMI and OpenGMS-IS model standards. *Environmental Modelling & Software*, 144, 105164. <https://doi.org/10.1016/j.envsoft.2021.105164>