# Towards normalizing good practice across the whole modeling cycle: its instrumentation and future research topics

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## Abstract

Choices made in modeling matter and demand more explication since they determine how much we can trust modeling insights and predictions within their social, political and ethical contexts. Good Modeling Practice (GMP) is a key research area for strengthening and maturing the modeling field and community, through identifying, formulating and sharing knowledge about the *craft* of modeling. This craft represents the knowledge that modelers learn *in practice* about how they get things done, and how they adapt their practices to new situations. This Joint Special Issue is motivated by the importance of sharing good modeling practices from a whole modeling lifecycle viewpoint. We attempt to add conceptual clarity to this research area by defining the plethora of concepts and decision points used to characterize the choices to be made throughout the modeling process, and by synthesizing some of the existing efforts on GMP. We characterize a broad list of articles in the literature on GMP and identify a list of essential topics demanding more attention. This list is only a preliminary one as we anticipate that a more comprehensive list of knowledge gaps will be unearthed from the submissions to the Joint Special Issue collection on GMP, of which this is an introduction. We also propose a vision for GMP and suggest instrumental ways that good practice can become not just well-known but normal practice. This instrumentation focuses on journal standards, collective commitment and culture especially by research community societies, early career awards for advancing GMP, and legal requirements or accreditation. A vital instrument in all this is the design and development of a modeling curriculum that distills core requisite knowledge about modeling, as well as proven-to-work routines and practices that can be scaled up in different contexts.

## Keywords

Good modeling practice, modeling lifecycle, modeling choices, fit for purpose

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**Cite this article as:**
Jakeman, A.J., Elsawah, S., Wang, H.-H., Hamilton, S.H., Melsen, L., & Grimm, V.
Towards normalizing good practice across the whole modeling cycle: its instrumentation and future research topics.
*Socio-Environmental Systems Modelling, vol. 6, 18755, 2024, doi:10.18174/sesmo.18755*



**Socio-Environmental Systems Modelling**
An Open-Access Scholarly Journal
http://www.sesmo.org

# 1. Introduction

Modeling is a semi-structured and knowledge-intensive activity, where the modeling process and achieved outcomes depend largely on the experience and knowledge of individuals and teams (Glynn et al., 2017; Melsen, 2022). While there are well-established modeling theories and methodologies to provide guidance for modelers on how to design and implement a modeling project, much of the modeling business remains a craft mastered through years of experience and exposure to diverse projects and problem situations. This craft represents the knowledge that modelers learn in practice about how they get things done, and how they adapt their practices to new situations (Jones et al., 2020). Several studies have even shown that the experience of the modeler is more relevant for the result than the model structure itself (Holländer et al., 2009; Henckens & Engel, 2017).

Good Modeling Practice (GMP) is an essential endeavor when the system and issues of interest are complex and defy accurate representation in a model, such as those that occur in modeling socio-environmental systems (SES) problems (Elsawah et al., 2020). For most environmental problems this complexity exists and is exacerbated by one or more of several features. Uncertainty tends to be rife in that (Beven, 2018; Maier et al., 2016): observational data are scant and error-ridden; model structure may contain many assumptions with respect to process knowledge, process detail and interactions, and scale treatments; and parameters largely cannot be measured and require calibration, albeit with all the above errors and assumptions. Another attendant feature is the contested nature of the issues and the existence of multiple perspectives on the problem, even what to model (Lempert & Turner, 2021). After all, the model serves certain interests better than others, and makes some factors explicit while hiding others (Melsen et al., 2018; Saltelli et al., 2020a).

Despite the plethora of modeling guidelines that exist (see Section 3), good overall ‘practice’ in environmental and socio-environmental systems modeling remains largely deficient. Common inadequacies include:

- poor scoping with regard to model purpose, objective functions, system boundaries and scales (Wang et al., 2023);
- insufficient consideration of assumptions, especially when applying models to new contexts or scenarios (Di Fiore et al., 2023);
- incomplete uncertainty assessment in particular and model evaluation in general, with the latter tending to be focused predominantly on fit to historic data;
- limited consideration of the socio-technical aspects of modeling (Elsawah et al., 2020);
- weak documentation of decisions made in the modeling process, and associated reporting on model strengths, limitations and assumptions (Grimm et al., 2014; Jakeman et al., 2006; Zare et al., 2021); and
- lack of reflection on the social and political context in which the model is shaped (Saltelli & Di Fiore, 2023; ter Horst et al., 2023).

A worrisome consequence of these deficiencies is that often, for a given system and question, the insights and predictions gained from models depend more on the very team of modelers involved than on the scenarios analyzed. This was for example the case for global and European land cover projection models (Alexander et al., 2017). Likewise, predictions of the growth of the Antarctic krill in the Southern Ocean made by eight different models contradicted each other in many regions (Bahlburg et al., 2023; Grimm, 2023), and the causes underlying the dynamics and collapse of the Baltic cod inferred from 15 models were not compatible (Banitz et al., 2022). While modelers still learn a lot about the system during the modeling process, well-designed GMP, established across disciplines, could lead to more coherent results and help us to document and deal with the remaining, irreducible path and choice dependency of modeling.

In recognition of the criticality of GMP to address SES problems, the three journals, Socio-Environmental Systems Modelling (SESMO), Environmental Modelling and Software (EMS), and Ecological Modelling (ECOMOD) are collaborating to publish this Joint Special Issue (JSI) on GMP. In this article, we aim to motivate this JSI by presenting an overview of the topic, highlighting the current state of the art, and identifying where we see the challenges and opportunities to advance the topic and build social capacity in it.

With this aim in mind, we review the phases and steps in a modeling process and indicate the main decision points in the modeling lifecycle in Section 2. We then review the GMP in Section 3. In Section 4 we canvass a list of essential topics that warrant more attention to progress and build capacity and capability in GMP. Most of these topics will be covered in the accompanying JSI on Good Modeling Practice. We raise two key challenges for GMP in Section 5 and suggest that the JSI is a step in overcoming them. In Section 6 we address ways to instrument GMP so as to enhance practice and build capacity in it.

## 2. The modeling process and decision points in the modeling cycle

The modeling process can be broken down into the following main phases (e.g. Badham et al., 2019; Hamilton et al., 2015; Hamilton et al., 2022) as portrayed in Figure 1:

1. *Problem scoping*– this initial phase involves defining the problem to be addressed and its scope, including the function or purpose of the modeling, the system boundaries, the issues or questions to be addressed, and the stakeholders to be engaged. This planning phase should also clarify the end-user context (user and management needs), problem context (nature of the problem and how well it is understood) and project context (resources available such as time, funding, skills and data) (Hamilton et al., 2022). This is a critical phase because it determines which interests are addressed and who is allowed to be involved in the formulation of the problem.
2. *Problem conceptualization* – this phase involves building the evidence base (e.g. expert and stakeholder knowledge, and relevant literature, data, models and hypotheses) to conceptualize the problem or system, generally in a qualitative sense. This includes identifying key variables, indicators, processes, relationships, entities and scales, as well as metrics around model performance (Bennett et al., 2013)
3. *Model formulation and evaluation* – this model set-up phase is typically the main focus of the model development process as it includes the formal description of the model, its implementation as some computer software, and the software testing; however, as argued in this paper, the other phases can be equally critical to the outcomes of the modeling process. This third phase includes selection of the modeling approach (i.e., the model type used such as in Kelly et al., 2013 for SES), construction of the model structure, calibration of its parameters, uncertainty analysis, and model testing and evaluation.
4. *Model application* – the application of the model involves experimenting with or running the model using, for example, scenarios of interest, followed by analyzing the model outputs and results. This phase also includes appropriately communicating and interpreting model insights to the end user.
5. *Model perpetuation* – this final phase is relevant for models that will be used to support ongoing decision making or operational processes to ensure continuous improvement and their long-term adoption. It involves providing documentation to users in running the model and interpreting its outputs, as well as ensuring that plans and mechanisms are in place for appropriately monitoring, maintaining and updating the model. The iterative revision of the model is achieved through ongoing collaboration between modelers and end users.

These five phases are iterative and do not necessarily follow a linear feed-forward path, with activities from multiple phases often occurring concurrently and decisions made in earlier phases being revisited. While the existence of such phases in the "modeling cycle" (Grimm & Railsback, 2005) is evident, the number of phases distinguished, what they include and how they are named differ widely in the literature (see Table 1 and the Supplement of Schmolke et al., 2010). Still, the main point is that existing suggestions of GMP tend to focus on the model set up (phase 3), whereas the other phases are at least equally important if we want to make the practice of modeling more transparent, coherent and indeed just.

Each phase requires support from both modeling tools and stakeholder engagement processes, albeit at different levels, as indicated in Figure 1. Notably, any or all phases could be political for a specific modeling project, due to, for example, an imbalance of stakeholder representation (Macpherson et al., 2024). This could then lead to gender-related or other biases in the model (Packet et al., 2020), time-place-funding dependent variables (Melsen, 2022; Sanz et al., 2019), or the outright requirement that the model results should align with certain interests. Thus, appropriate engagement of stakeholders is critical throughout the process from problem definition and conceptualization, all the way through to model development, testing, its application and model maintenance. Their engagement ensures the model is fit for purpose, represents multiple perspectives, and subsequently used and adopted as intended (Hamilton et al., 2022).

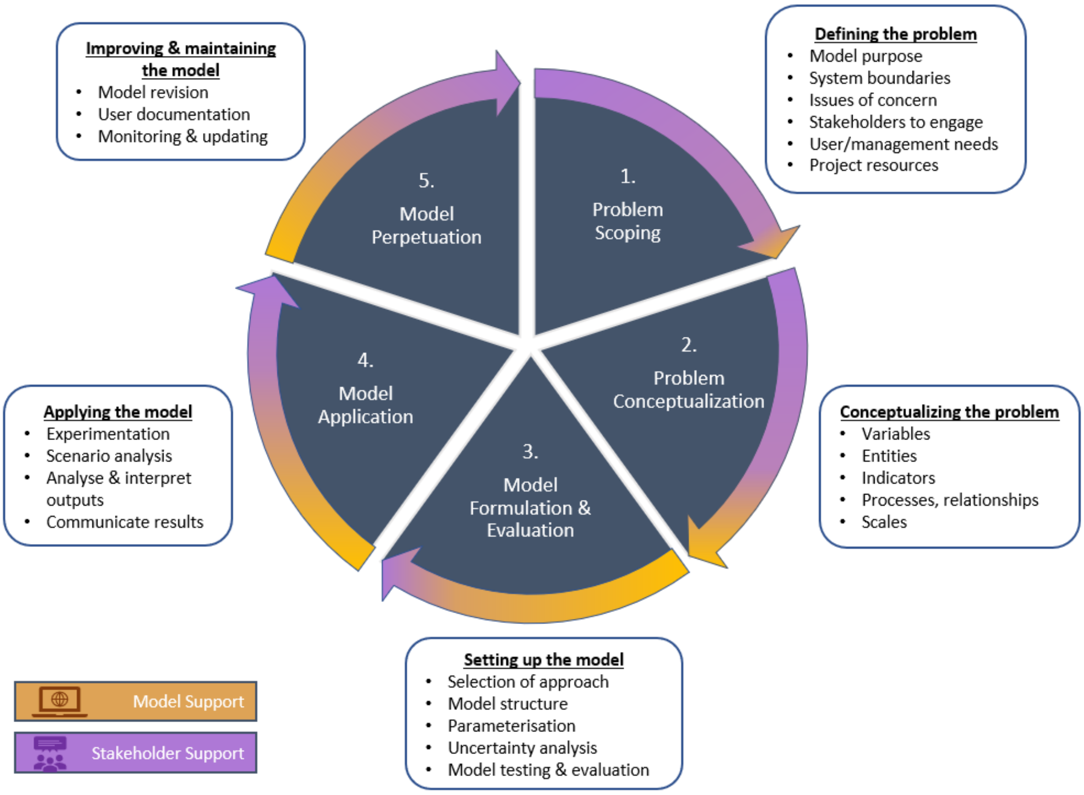


Figure 1: The five main phases of the modeling process. Each phase requires both model and stakeholder support at various levels, indicated by the color shading of the arrows. (Adapted from Hamilton et al., 2015; Rosello et al., 2022)

There are many decision points throughout the lifecycle of the modeling process including: selecting the bounds of the modeling (i.e., model purpose, problem definition and system boundaries); the evidence base (what data, and whose knowledge or perspective); the model features such as the variables, outputs and scales; the modeling approach; and the model testing and evaluation methods (Hamilton et al., 2022). Different choices at any one of these decision points can result in different modeling pathways, leading to different models and modeling outcomes (Grimm & Berger, 2016; Lahtinen et al., 2017). This highlights the inherent subjectivity of modeling practices (Voinov et al., 2014), and the need for ongoing reflexivity along the whole modeling pathway (Zare et al., 2020).

## 3. A review of articles on good modeling practice

There have been many efforts scattered throughout the literature addressing the issues of GMP from a range of perspectives and application domains. A list of some major past efforts to identify and formulate modeling practices is presented in Table 1. Thus, the modeling community has already made some good progress on common principles and methods.

**Table 1:** Non-exhaustive list of existing studies that outline good modeling practices, principles and/or methods, and the phases addressed.

| Publication | Scope of modeling process | Application domain | Modeling Phases |
|---|---|---|---|
| van Waveren et al. (1999) | Whole modeling process | Dutch water management | Phases 1-4 |
| Hulsbeek et al. (2002) | Whole modeling process | Dynamic modeling of activated sludge systems | Phases 1-4 |
| Walker et al. (2003) | Uncertainty in the modeling process | System model based decision support activities | Phases 1-5 |
| Jakeman et al. (2006) | Whole modeling process | Environmental modeling | Phases 1-5 |
| Boorman et al. (2007) | Model code selection | Water management | Phase 3 |
| Glaser & Bridges (2007) | Use of the modeling (process-level view) in decision support | Quantitative modeling for environmental decision support | Phase 4 |
| Refsgaard et al. (2007) | Uncertainty in the modeling process | Environmental modeling | Phase 3 |
| Robinson (2008a, 2008b) | Conceptual modeling | General modeling and simulation | Phase 2 |
| Gaber et al. (2009) | Development, evaluation, and application of models | Environmental modeling | Phase 3 |
| Rietveld et al. (2010) | Whole modeling process | Drinking water treatment | Phases 1-5 |
| Voinov & Bousquet (2010) | Stakeholder engagement in modeling | Environmental modeling | Phases 1-5 |
| Schmolke et al. (2010); Grimm et al. (2014) | Documenting whole modeling process | Ecological models for decision support | Phases 1-4 |
| McIntosh et al. (2011) | Model design and development for improved use and adoption | Environmental decision support systems | Phase 4 |
| Waltemath et al. (2011) | Documenting model experimentation | General modeling and simulation | Phase 4 |
| Barnett et al. (2012) | Whole modeling process | Groundwater modeling | Phases 1-5 |
| Chen & Pollino (2012) | Model development and evaluation in Bayesian networks | Environmental modeling | Phases 2, 3 |
| Kelly et al. (2013) | Model selection | Integrated environmental assessment modeling | Phase 3 |
| Vanwindekens et al. (2013) | Conceptual modeling | Socio-environmental modeling | Phase 2 |
| Harmel et al. (2014) | Evaluating, interpreting and communicating model performance | Hydrological and water quality modeling | Phase 4 |

(*continued next page*)

Table 1 (*continued*)

| Publication | Scope of modeling process | Application domain | Modeling Phases |
|---|---|---|---|
| Black et al. (2014) | Whole modeling process, scenario-based models | Water management modeling | Phases 1-5 |
| HM Treasury (2015) | Whole modeling process | Quality assurance of government models | Phases 1-5 |
| Rose et al. (2015) | Whole modeling process | Ecological modeling | Phases 1-5 |
| Argent et al. (2016) | Conceptual modeling | Environmental modeling | Phase 2 |
| Pianosi et al. (2016) | Sensitivity analysis | Environmental modeling | Phases 3,4 |
| van Vliet et al. (2016) | Model calibration and validation | Land use change | Phase 3 |
| Elsawah et al. (2017) | Whole modeling process in system dynamics | Environmental modeling | Phases 1-5 |
| Badham et al. (2019) | Whole modeling process | Modeling for integrated water resource management | Phases 1-5 |
| Schuwirth et al. (2019) | Whole modeling process | Ecological modeling | Phases 1-5 |
| Grimm et al. (2006, 2010, 2020) | Model documentation | Ecological modeling | Phase 5 |
| Saltelli et al. (2020b) | Whole modeling process | Mathematical modeling | Phases 1-5 |
| Zurell et al. (2020) | Model documentation | Species distribution models | Phase 5 |
| Iwanaga et al. (2021a) | Whole modeling process | Socio-environmental modeling | Phases 1-5 |
| Planque et al. (2022) | Model evaluation | Ecological modeling | Phase 3 |
| Wang et al. (2023) | Conceptual modeling | Socio-environmental modeling | Phase 2 |
| Jacobs et al. (2024) | Model evaluation; linking error measures to model questions | Ecological modeling | Phase 3 |
| Klein et al. (2024) | Whole modeling process | Socio-ecological modeling | Phases 1-5 |

A major challenge in synthesizing aspects of GMP is the obvious lack of a consistent approach to characterize and organize this body of literature. As distilled in Section 2, there are different concepts and approaches for framing the advice given to modelers regarding the choices to be made through the modeling process. Also, there is still much missing in common practice. Most importantly, a major general deficiency in existing suggestions of GMP is that they attend more comprehensively to the technical basics, such as model implementation, calibration and evaluation. A more balanced GMP requires being more thorough and socially-minded throughout the whole modeling cycle - especially but not only in achieving a satisfactory problem framing and conceptualization - by way of recognizing and justifying the many decision choices we make. Human factors in the modeling process are often overlooked, including social, political and ethical considerations in problem scoping, assumptions and choices made by the modeler(s), as is the consideration of how consequent biases or uncertainties can be reduced. These points are even relevant for simple problems but especially for SES problems that require more attention to GMP due to their complexity and uncertainty issues as well as the presence of multiple social perspectives and values.

Another major challenge is evaluating the degree to which the proposed GMP is adopted. The purpose of this evaluation is to measure the outcomes and impacts of the proposed GMP to determine how well the GMP is implemented and served its goal. The evaluation can also identify the strengths and weaknesses of the proposed GMP and provide valuable information that can be used to make necessary changes to the GMP to improve its effectiveness. Even though TRACE provides a positive example (Schmolke et al., 2010; Grimm et al., 2014), there are limited effectiveness evaluations based on experience in GMP. One simple but effective approach for monitoring and evaluating the adoption of a GMP is to require that the publication that presents the GMP is cited if it is being used. This made it possible, for example, to check misunderstandings of the ODD protocol for documenting agent-based models (Grimm et al., 2006, 2010) and for extending its scope (Grimm et al., 2020).

# 4. Enhancing the literature on GMP

To move forward and scale up the practice of good modeling, there are many elements and topics that need to be given attention and appreciated more widely. Although it should be noted that it is impossible for every modeling exercise to cover all the elements and topics because of limited time and resources. A list of topics that relate to steps in the modeling process includes but are not limited to the following:

1) **Developing modeling conceptual maps, protocols and workflows.**
   - (1.1) Including stakeholders. Evaluating the social, political and ethical context in which the problem is scoped and the model is developed.
   - (1.2) Making sure the questions that the model is to address are meaningful, tangible and specific.
   - (1.3) Critically evaluating decisions that determine the boundaries of the system under study.
   - (1.4) Recognizing the importance of formulating a verbal model describing the system to be modeled and hypotheses about the dynamic behavior of the system.
   - (1.5) Being wary of allowing preconceived ideas about the system to be modeled to influence definition of the questions to be addressed by the model or initial model formulation.
   - (1.6) Recognizing the importance of identifying key decision points within the system from a holistic perspective.
   - (1.7) Being wary of including excessive detail during model formulation, but also keeping track of those aspects that are not represented in the model, despite arguments to include them.
   - (1.8) Ensuring all model parameters and variables are assigned specific meanings.
2) **Transparently considering and justifying scale and preprocessing choices for inputs, models and outputs, and their impacts.**
3) **Attending to errors in observational data and their representation.**
4) **Dealing with model structural uncertainty including using multiple models and ensembles.**
5) **Developing robust parameterization, calibration and evaluation frameworks.**
   - (5.1) Recognizing the value of descriptive knowledge about the system being modeled as a source of information for model quantification and qualification.
   - (5.2) Recognizing the importance of distinguishing short-term versus long-term cause-effect mechanisms and the relative lengths of delays and time constants.
   - (5.3) Being wary of relying on automated evaluation procedures with the intent of implying an unwarranted rigor and certainty in the process.
   - (5.4) Being cautious when ascribing permanence to our models or their outputs.
6) **Evaluate strategic use of uncertainty, for example, not inflating it or toning it down, to represent certain interests.**
7) **Going beyond common metrics in assessing model performance and realism, including qualitative methods.**
8) **Evaluating implications of model limitations and identifying priorities for ongoing model development.**

(8.1) Providing a written (non-technical) model description that would allow for a full, independent re-implementation.
(8.2) Providing and documenting all workflows, source code, executables, simulation parameter settings, data files, and scripts for input and output data processing.

In addition to the topics above relating to steps in the lifecycle of the modeling process, a second list of topics emerging from recent research trends and warranting more attention includes:

9) **Advancing project-specific engagement practices with end users and interest groups, including defining model scope, through to communicating model results and their uncertainty to end users, and methods like gamification and serious gaming to help bridge the gap between modelers and end-users with respect to decision support tools.**

10) **Eliciting and capturing stakeholder needs and modeling requirements in a systematic and formalized way to enable validation, traceability and model auditing.**

11) **Benchmarking model results.**

12) **Conducting controlled model intercomparison studies.**

13) **Investigating subjectivity and reflexivity along the modeling chain.**

14) **Data acquisition planning for reducing uncertainty.**

15) **Examples of developing FAIR principles for digital assets in the modeling chain (Findable, Accessible, Interoperable and Reusable – see https://www.comses.net/education/responsible - practices/).**

16) **Improving software quality, through approaches such as test-driven development, paired programming, more rigorous documentation, and better and broader user acceptance testing through the model building chain.**

17) **Developing documentation to serve the purpose of transparency and responsibility of democratic decision making; from documenting model information, to modeling decisions made and their justification.**

18) **Contextualizing model reuse to achieve fitness for purpose.**

19) **Addressing ethical and democratic points of view in modeling and GMP.**

20) **Identifying the nature of team science and collaborative modeling issues required for meeting and/or escalating GMP.**

21) **Instrumenting and scaling up good practice in modeling.**

If we want a general, overarching GMP meta-discipline to emerge and be established, modelers should be aware of all these elements and topics. While addressing all of them seems like a daunting task, the good news is that experienced modelers address most of them anyway, as they are known or have been recognized for their importance. A first step to getting a general GMP established is doing a better job in documenting all the quality-assuring things we are doing anyway in a coherent way, using the same terminology (Schmolke et al., 2010; Grimm et al., 2014), even if we have not yet addressed all of the above elements. “All or nothing” would not be a good strategy for getting GMP established: it is better to explicitly follow at least some elements of GMP than keeping silent about it altogether. Moreover, different scopes, or application classes, of a model will require different levels of comprehensiveness. The effort spent in following GMP should be “proportionate in response to the risks associated with the intended use of the analysis” (HM Treasury, 2017). At the same time, some of the topics above will require the modeler to step out of their comfort zone, by not only reflecting on the technical, but also the social aspects of modeling.

## 5. More on the Joint Special Issue

The ability of the modeling community to share, discuss and exchange knowledge about the practices employed throughout the modeling process is essential for growing the field and expanding its interdisciplinary applications. This knowledge about how to solve a particular problem and perform a particular activity (i.e., knowledge-in-use) is valuable for beginners learning the craft of modeling, distilling information about lessons learned and promoting ideas about new solutions. However, the transfer of this knowledge encounters several challenges. First, this knowledge is largely tacit and subjective, which means it is difficult to articulate. Second, it is scattered among experts in the field. It is also largely embedded in the day-to-day routines (i.e., knowledge-in-use) performed during a modeling exercise, which makes it difficult to abstract.

This Joint Special Issue on Good Modeling Practice attempts to contribute to tackling these challenges. Each paper attempts to cover one or more of the above topics, such as by application to a case study or by more generic attention to topics. The current state of practice includes bias toward reporting success as well as reporting results (the know-what) rather than practices leading to these outcomes (the know-how). Part of this state of practice stems from the capabilities of modelers, due to poor technical examples of good practice and a lack of shared lexicon for defining and formalizing practices. However, the current state of practice is also a consequence of poor motivation or limited capacity of modelers in terms of resources, to carefully deliberate on choices made during model development, and to prudently analyze uncertainties introduced and propagated through the modeling process.

# 6. A vision for GMP: choices and education matter

The modeling community must however address how to advance modeling so that good practice becomes not just well-known but common practice. We posit several instruments for achieving this around: regulation by journals in terms of standards that they require for relevant papers published; developing incentives for following good practice; building a vibrant institutional/community culture around it; promoting legal requirements or accreditation for GMP; and expanding education and capacity building in modeling that focuses from the start on good practice as being fundamental. We share a vision for the modeling community (see Figure 2), wherein good modeling practice is the norm. This vision includes a roadmap for how this could be achieved, including the role of journals and institutions in creating incentives, and a shift in the modeling community's culture towards knowledge sharing, commitment to good practice as a minimum standard, and recognition and treatment of the social aspects of and choices in modeling.

## 6.1 GMP as a social process with norms

In our vision the scoping phase of modeling is rich and transparent in the rationales given for decisions taken and seen as key for meeting fitness-for-purpose (Hamilton et al., 2022; Wang et al., 2023). Furthermore, the modeling process more broadly is considered a social process that links scientists (including modelers), decision makers and other stakeholders (Hamilton et al., 2019; Badham et al., 2019), wherein technical choices are not neutral and multiple perspectives are vital. Therefore it considers all above participants' backgrounds, habitats and preferences (Babel et al., 2019), the decisive influence of legacy on model selection (Addor & Melsen, 2018), the influence of experienced modelers (Melsen, 2022), negotiated uncertainty (Scoones & Stirling, 2020), etc. With modeling shifting beyond the traditional technical realm, the value of communication, including use of narratives around uncertainty and scaling in the modeling (not just in the model), is embraced (Iwanaga et al., 2021b). Modelers cannot presume more certainty and objectivity than is warranted.

Modeling may also be viewed as a social process of sharing and co-producing knowledge (Hamilton et al., 2019; Zare et al., 2024). Therefore, building trust and changing habits, institutional process and governance in the model or modeling becomes more than just proper application of scientifically robust technical procedures. These processes are critical for generating legitimacy and credibility in the modeling. Equally important is the relationship between (and among) modelers, scientists and other stakeholders. Building trust and GMP therefore encompasses communications and interactions among the people involved in the modeling process (Cash & Belloy, 2020). Acknowledging ignorance or uncertainties is one of the keys to building trustworthy relationships between modelers and stakeholders.

## 6.2 Instrumenting GMP

Here, we outline several instruments we have identified for making GMP common practice (summarized in Figure 2):

- ***Journals have more prescriptive guidelines and publish examples of good modeling practices***. Regulation by scientific journals (for example, certain practices as a submission requirement) could provide a key to motivating modelers to follow good practices (Refsgaard et al., 2005; Crout et al., 2008). Regulation by journals can also help mainstream practices such as sharing codes, methods, data and lessons learned through the modeling process. The former (sharing codes, methods, and data) has been recognized and emphasized by many journals. The latter (sharing lessons learned through the modeling process) still needs more appreciation. Furthermore, journals publishing exemplars of GMP can be an incentive within itself as well as help provide guidance to others on how to apply practices in different contexts.

- ***Collective commitment to good practice as a minimum standard***. Societies and conferences can help build collective commitment to GMP. This includes encouraging a culture that embraces humility and ethics. The Open Modeling Foundation (OMF: https://www.openmodelingfoundation.org/) is an example of a scientific community that is dedicated to promoting good modeling practices. Specifically, OMF aims to identify and develop standards and practices for FAIR (Findable, Accessible, Interoperable and Reusable; Wilkinson et al., 2016) modeling across environmental, social and geophysical sciences, and promote these standards through incentives and education (Barton et al., 2022).

- ***Incentives such as awards for good practice are commonplace.*** While the outcomes of adhering to good practice (e.g., more effective or impactful models) should be a sufficient motivator for modelers, barriers to GMP remain, including insufficient project resources or lack of recognition of its importance. Incentives such as awards can help generate value to modelers through recognition of quality of practice and efforts by peers or others. For example, journals can award an Open Code Badge to publications that apply best practices for accessibility and reuse and make their source code publicly available (see CoMSES network); such badges help recognize and differentiate those papers.

- **Decision makers and the public need to promote legal requirements or accreditation.** Decision makers and the public need to play a role in informing the cultural practices by demanding that good practices are applied in modeling, such as via legal requirements or accreditation. Funding agencies, for example, are increasingly requiring making the publications, data and software produced open access. Requiring certain standards of modeling practice, such as documentation, would be in line with this overall trend, which was partly triggered by the FAIR principles.

- ***Lessons are shared across a wide assemblage of scientific communities***. Increasing the know-how of modelers around GMP is critical to its mainstreaming. Towards this end, the modeling community needs to foster a learning and knowledge sharing culture (Wang & Grant, 2021), wherein reflexive approaches to reporting both successes and failures are encouraged (Iwanaga et al., 2021b), 'proven to work' practices are systematically and more formally documented and shared, and knowledge sharing is promoted through the use of living bodies of knowledge that continuously seek community input and are regularly updated.

- ***An evolving modeling curriculum is collaboratively designed and developed***. One key instrument for mainstreaming GMP is the formalization and consolidation of the collective experience and knowledge about modeling practices. Much of the learning around modeling practices is achieved through experience, with documentation at best done in an ad-hoc manner. This calls for the design and development of a modeling curriculum that distills core requisite knowledge about modeling as well as proven-to-work routines and practices that can be scaled up in different contexts. If made widely accessible, such a curriculum can help to build capacity and expertise in modeling, enabling researchers and practitioners to gain the competencies needed to implement good practice in all their modeling work.

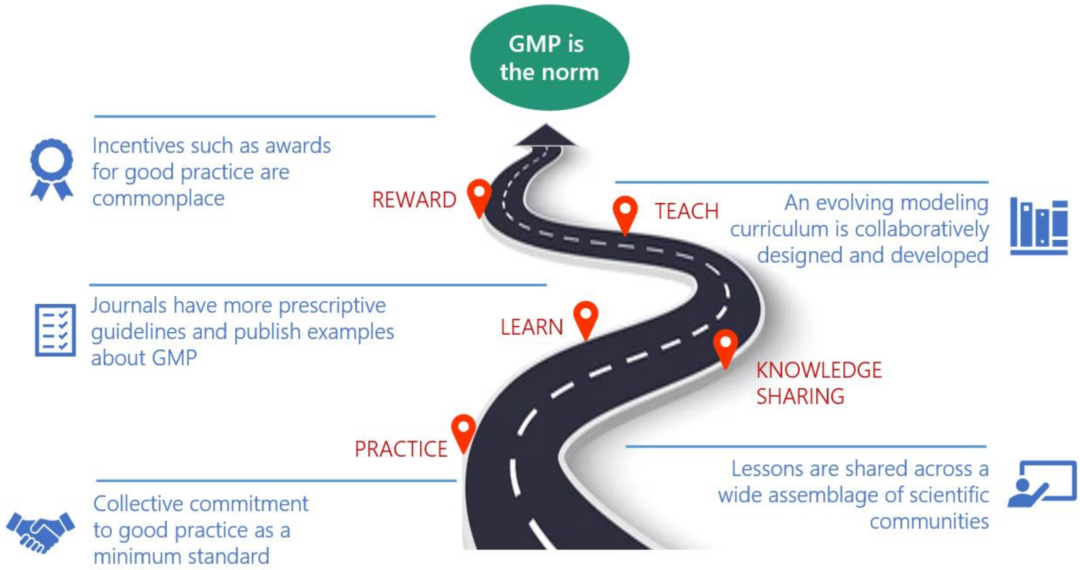


**Figure 2:** A roadmap showing a vision and pathway towards a future wherein Good Modeling Practice is the norm.

## 7. Conclusions

In this introduction paper to the Joint Special Issue (JSI) Collection on GMP, we have attempted to characterize the nature of the many decision choices that are made throughout the modeling process. In addition to the need for more comprehensive documentation of such decisions, a next crucial step is more thorough justification of decisions, wherever possible stating the comparative effect of decision options on the outcomes of the modeling. We have also synthesized some of the existing efforts to provide advice, identified a list of essential topics demanding more attention, and suggested instrumental ways that GMP can become normal practice. Of course, the socio-technical perspectives of GMP undoubtedly differ from one project to another, and the challenge is to embrace most of the perspectives of GMP to a project. Therefore, through many contributors' examples and emphases to this Joint Special Issue, we hope to capture most of them and promote the necessity and normality of GMP.

As a final note, modeling will always be a fundamental tool for addressing complex, grand challenge issues that occur in the earth and socio-environmental sciences. Modeling must be relied upon as a thinking tool to systematically capture and share our understanding and assumptions about how the system of interest operates, and to facilitate how we can analyze it with the data and knowledge we have, for given purposes. Modeling provides "if-then" answers to important questions: if we agree on a certain set of assumptions, we have to accept the corresponding results. Since the assumptions, even for the same system and question, can and will vary at all steps of the modeling process, modeling can only help us solve problems if we see it as part of a discourse. GMP in all its dimensions is essential if we are to maximize the value of modeling, especially its utility in informing decision making. Fortunately, the authors see that the need for progressing GMP is being increasingly appreciated. Witness the interest and contributions in this JSI and the many facets of GMP that it addresses. May we be reaching a turning point in the acceleration of its basic principles and its application.

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