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Editorial

Editorial for the Special Issue on Modelling and Simulation of Human-Environment Interactions

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At the core of the Anthropocene lies human influence on the environment. Loss of biodiversity, deforestation, and more frequent extreme events such as flooding or heat waves are just a few of the human-induced environmental changes. Over time, human domination has become more apparent, and its influence on the environment has deepened the complexity of the global system. The scientific community embraced these challenges and responded by developing and applying new transdisciplinary approaches to study complex socio-ecological systems (SES). Computational modeling is now an integral part of systems research.

The use of computational models to study interactions between societies and ecosystems has a rich history. Indeed, using computers to model human and natural systems dates can be traced back to the 1960s. Initially, the modeling efforts were isolated. While statistical modeling was well established, dynamic representations of systems were only emerging [1]. Over time, system dynamics modeling gained popularity, especially in ecology [2,3]. With advances in complexity science [4,5], new approaches arose: individual-based models (ecology) and agent-based models (social science) [6,7]. The popularity of complex system modeling has also increased due to advances in data science, ranging from our ability to continuously acquire data to the growing availability of sophisticated analytical tools (e.g., Geographic Information Systems, Deep Learning for satellite images). Researchers and, to a lesser extent, practitioners recognized the value of system modeling as a tool of knowledge integration and as an instrument for forecasting future system trajectories. At the same time, voices of criticism or outright rejection of social-ecological systems models occurred [8]. Critics pointed to mismatches between the simplicity of models and the complexity of the ever-growing environmental change on a planetary scale. Simply put, the modeling community was not prepared for tackling real-word complex global problems of the Anthropocene. Experts identified insufficient representation of couplings across space, time, scale, and institutions [9].

However, the role of SES modeling should not be underestimated. SES models contribute to understanding and guiding our exploration of system structure. Hidden interrelationships within complex systems are hard to grasp without the formal and explicit conceptualization afforded by models. Developing and employing systems thinking skills does not come naturally to humans [10], who are often agnostic regarding nonlinear causation and primarily think of simple chains of causes-and-effects despite the existence of feedback loops. The limited mental capabilities of humans are felt both on fundamental properties of complex SES (non-linearity, cyclic, delays) and on higher-level properties such as adaptation and emergence. Thanks to SES models, we shift from an attempt at navigating ‘implicit models’ in our mind to a structured approach based on an ‘external model’ that formalizes the system. The external and formal representation of a system provides immense capabilities to identify the hidden unknowns in systems or identify potential interventions. Despite these many advantages, the **educational use** of SES models is still limited.

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One of the flagship characteristics of complex SES is emergence. System-wide properties cannot be explained by examining a system as one big whole or dissecting its components and studying them in isolation. Instead, the macro patterns are indirect results of micro-decisions at a local scale. Climatic change on a global scale is an excellent example of a byproduct of decisions made by individual households, industries, and agriculture. The role of human behavior has long ago been identified as critical at explaining changes at the system level. However, conceptualizing human behavior is not a trivial task. Traditional representations of decision-making rely heavily on formal statistical and econometric models, grounded in well-developed theories. These approaches have many deficiencies, including the assumption of rational decision-making or easy access to relevant information, which can be aggregated into representative system actors. However, the profound changes in the environment result from different human and organizational actions. Thus, SES models are excellent tools to represent **heterogeneous behavior** leading to a large assortment of consequences of human and institutional decision-making.

The recent decade brought about an enormous amount of **data**. This includes the rise of the Internet of Things and the ability at continuously acquiring sensor data. Data from social media has also shown its importance for understanding the arguments formed during debates on pressing socio-ecological issues. The increased scientific attention to data sharing and replicability has led to the development of open-access data repositories in which data is discoverable and reusable. Under the umbrella of 'big data', these heterogeneous data sources have been used to augment applied modeling, to better characterize the relevant factors and inter-dependencies system (i.e., designing a conceptual model), fine-tune a model (i.e., calibration or 'training') or evaluate its quality (i.e., validation or 'testing'). Despite these advances in the availability of data, we are still limited by methods of information extraction. Traditional data collection methods rely on well-structured survey instruments and quantitative data from secondary sources like international databases [11] and spatial data clearinghouses [12]. Such data bodes well for SES modeling, where variables are easily identifiable and quantifiable. While not new to science, in-depth, open-ended interviews are still uncommon in SES model development, often due to a lack of **mixed-methods** that translate qualitative data into quantitative model inputs.

It is now generally accepted that without public trust, SES modeling will largely remain an academic exercise. For SES models to serve as reliable instruments used in solving critical environmental challenges, they need to be embraced by people and communities that 'live and breathe' these problems. Stakeholder engagement in both data collection and model development (from the early steps of design to the final matters of validation and scenario evaluation) enhances model transparency and credibility. SES is inherently spatial, and **participatory modeling** allows researchers to gain insight into the tacit knowledge of local communities, households, and governments. Furthermore, the traditional approach to communicating model outputs, where modelers develop models and produce scenarios presented as the final product to stakeholders, has been vastly criticized. Frequently, stakeholders do not accept these results simply because they do not understand or agree with the underlying assumptions. Instead, they refuse to accept the outcomes because they feel left out of decision-making [13].

The four challenges of SES modeling described above, namely (1) data collection and information extraction, (2) citizen participation in model development, evaluation, and application, (3) exhaustive and inclusive representation of decision making, and (4) the educational role of models in deepening our understanding of complex SES, permeate the papers in this Special Issue.

To set the stage, we start from the philosophical discourse by Shultz and Wildman, who stress the importance of a realistic representation of the social factor in SES systems models—a topic that they call 'human simulation'. After a brief outline of the recent advances in SES modeling, they move on to the glaring gaps in existing simulation endeavors, namely, insufficient representation of the human dimension in model design and application, with limited variety of values and worldviews of system actors. The authors advocate for more active **stakeholder participation** in model development. They also point out the deficiencies in the commonly used decision-making rules and encourage the use of more realistic cognitive architectures when designing and implementing **human decision-making**.

A step towards a more realistic representation of human agency in SES modeling is the information extraction approach proposed by Djenontin, Zulu, and Ligmann-Zielinska. In their study in Malawi, they collected data on farmers' restoration decisions using focus group discussions, role-playing games, and household surveys. They demonstrate a procedure in which these seemingly incompatible data sources are progressively used to identify stakeholders' goals, which in turn shape their **individual and collective decisions**, and result in quantifiable practices and activities that influence both the extent and the magnitude of agricultural land restoration.

In their article, Lenfers et al. report on using **real-time sensor data** to improve the accuracy of simulations in real-time. They describe their framework on the example of agent-based modeling for an adaptive massive urban transportation system in Hamburg, Germany. Finally, they discuss how sensor data can improve the predictive capabilities of models, building public trust in model outcomes to gain political support for Smart City investments.

In another urban study, Jiang and colleagues describe an agent-based model built to investigate shrinking cities, i.e., deteriorating metropolitan areas with an ever-increasing vacant land and population decline. Their study is an excellent real-world example of system emergence. The primary process in the model is a real estate market of buyers and sellers, whose decisions ultimately drive the spatiotemporal change in housing occupancy. Both groups of agents make decisions based on very different goals operating within very different constraints. Hence, the authors point to the importance of explicit operationalization of agent **heterogeneity** within and across system actors.

Next, we turn to the educational and participatory aspects of SES. Guadagno and colleagues developed a unique **educational tool** called STEPP that equips students with critical systemic thinking skills. STEPP is a hybrid model developed to teach students how to formalize systems by defining their structure, identifying the key variables driving the processes, and manipulating them to define system states and the necessary transitions between them. The research team reports on a usability study of the tool done by a group of high school teachers. The tool was met with enthusiasm. The teachers pointed to positive user experience, applicability in STEM-C, and STEPP's practicality in a real-world classroom setting. As such, the tool is one of the pioneering examples of active learning about complex systems by directly manipulating models emulating these systems.

While Guadagno et al. propose a tool that assists in abstract model formulation, Tschimanga and colleagues demonstrate how to integrate and systematically present distinct empirical SES data. They report on a comprehensive, integrated information system to explore the complex climate-water-migration-conflict nexus in the Congo Basin. The system provides tools that assist in data collection, analysis, and synthesis packed into one convenient yet rigorous database easily accessible on the internet and open to anyone interested in the topic. They built the system from quantitative and qualitative data amounting to over 500 variables, grouped into thematic areas from sociodemographic characteristics, through conflict resolution and community resilience, to water transfer. The tool can provide practical knowledge for decision-makers, encourage community engagement in conflict resolution, and support formulation of robust solutions, especially in situations involving migration and conflict. The ultimate goal is to provide a transparent yet extensive source of information that can assist in **participatory decision making** to seek solutions that balance human and community needs, simultaneously minimizing adverse effects of human activities on natural resources.

We conclude with a review paper on the methods and tools of quantitative human-water nexus models by Meijer, Schasfoort, and Bennema. The authors report on a structured literature assessment focusing on modeling human responses to changes in water availability. They identify several typologies, including the theories applied to frame the problem, methods used in the study, its extent (and hence, the generalizability of results), and the relevance for policymaking. The authors stress an **inadequate representation of human agency** in the reported studies. On the one hand, decision-making in dynamic models rarely goes beyond direct water use. On the other hand, statistical analyses, brimming with a wide variety of predictors, lack the behavioral mechanisms underlying human actions. To reconcile these mismatches, the authors propose an eight-step framework for human response quantification of water resource use.

The seven articles of this Special Issue make important contributions through their innovative methods and applications. However, research on modeling and simulation for complex socio-ecological systems must continue to evolve given the complexity of the challenges that we face and the urgency of addressing them. This continuation is already visible as our core themes remain central in the next series of Special Issues [14,15]. While such publications highlighting the ongoing need for the scientific committee to rise to the challenge, we stress the necessity to complement the necessary academic exercise of reporting with a demonstration of tangible impact in solving environmental challenges.

List of Contributions

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