Upscaling in socio-environmental systems modelling: Current challenges, promising strategies and insights from ecology

Gunnar Dressler*[1], Jürgen Groeneveld[1], Jessica Hetzer[1], Anja Janischewski[2], Henning Nolzen[1], Edna Rödig[1], Nina Schwarz[3], Franziska Taubert[1,4], Jule Thober[5], Meike Will[1], Tim Williams[6,7], Stephen Björn Wirth[8,9], and Birgit Müller[1,10]

[1] Helmholtz Centre for Environmental Research – UFZ, Department of Ecological Modelling, Leipzig, Germany
[2] Department of Economics and Business Administration, Chemnitz University of Technology, Germany
[3] Department of Urban and Regional Planning and Geo-Information Management, University of Twente, The Netherlands
[4] German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Germany
[5] Helmholtz Centre for Environmental Research – UFZ, Department of Computational Landscape Ecology, Leipzig, Germany
[6] Department of Industrial and Operations Engineering, University of Michigan, USA.
[7] Environmental Geography Group, Institute for Environmental Studies, VU University, Amsterdam, The Netherlands
[8] Potsdam Institute for Climate Impact Research (PIK), Department Climate Resilience, Potsdam, Germany.
[9] Institute of Crop Science and Plant Breeding, Grass and Forage Science/Organic Agriculture, Kiel University, Kiel, Germany
[10] Brandenburg University of Technology Cottbus-Senftenberg, Cottbus, Germany

Abstract

Sustainability challenges in socio-environmental systems (SES) are inherently multiscale, with global-level changes emerging from socio-environmental processes that operate across different spatial, temporal, and organisational scales. Models of SES therefore need to incorporate multiple scales, which requires sound methodologies for transferring information between scales. Due to the increasing global connectivity of SES, upscaling – increasing the extent or decreasing the resolution of a modelling study – is becoming progressively more important. However, upscaling in SES models has received less attention than in other fields (e.g., ecology or hydrology) and therefore remains a pressing challenge. To advance the understanding of upscaling in SES, we take three steps. First, we review existing upscaling approaches in SES as well as other disciplines. Second, we identify four main challenges that are particularly relevant to upscaling in SES: 1) heterogeneity, 2) interactions, 3) learning and adaptation, and 4) emergent phenomena. Third, we present an approach that facilitates the transfer of existing upscaling methods to SES, using two good practice examples from ecology. To describe and compare these methods, we propose a scheme of five general upscaling strategies. This scheme builds upon and unifies existing schemes and provides a standardised way to classify and represent existing as well as new upscaling methods. We demonstrate how the scheme can help to transparently present upscaling methods and uncover scaling assumptions, as well as to identify limits for the transfer of upscaling methods. We finish by pointing out research avenues on upscaling in SES to address the identified upscaling challenges.

Keywords

1. Introduction

Sustainability challenges in socio-environmental systems (SES) are inherently multiscale (Adger et al., 2005; Elsawah et al., 2020). For example, global change emerges from local socio-environmental processes and subsequently feeds back to affect local realities themselves (Rounsevell et al., 2012; Schill et al., 2019; Verburg et al., 2016). Additionally, there is often a mismatch between the scales at which decisions are made and at which environmental processes operate (Cumming et al., 2006; Davis, 2006; van Delden et al., 2011; Verburg et al., 2016). These cross-scale interactions therefore necessitate a multiscale perspective if scientists are to adequately understand SES and generate generalisable knowledge relevant for decision-makers (Cumming & Peterson, 2017; Magliocca et al., 2018).

Modelling is a useful tool to support system understanding and explore strategies for enhancing sustainability in SES. However, to address the challenges mentioned above, models need to incorporate multiple scales (Cash et al., 2006; Manson, 2008), which requires the representation of relevant processes at different scales and methodologies for transferring information (data and models) between scales. Transferring information can mean both scaling up and scaling down information between different levels on a scale. In this paper, we focus our attention on *upscaling*, i.e., increasing model extent and/or decreasing model resolution (see Box 1 for a list of definitions of terms used throughout the text). Generally, one can distinguish between upscaling along three dimensions: spatial, temporal and organisational (see Figure 1A). These dimensions often correspond with each other, for instance, when upscaling in space (e.g., from m to km) it can also be beneficial to upscale the organisational level (e.g., from households to villages). Such scale transfers are necessary, for example, when available input data are on a different scale than the modelled processes (Elsawah et al., 2020; Parker et al., 2003), when coupling models that operate at different scales (Evans et al., 2013; Filatova et al., 2013), or when making approximations for computational feasibility (Verburg et al., 2016). Overall, progress in this regard in SES has been limited.

Box 1: Definition of terms

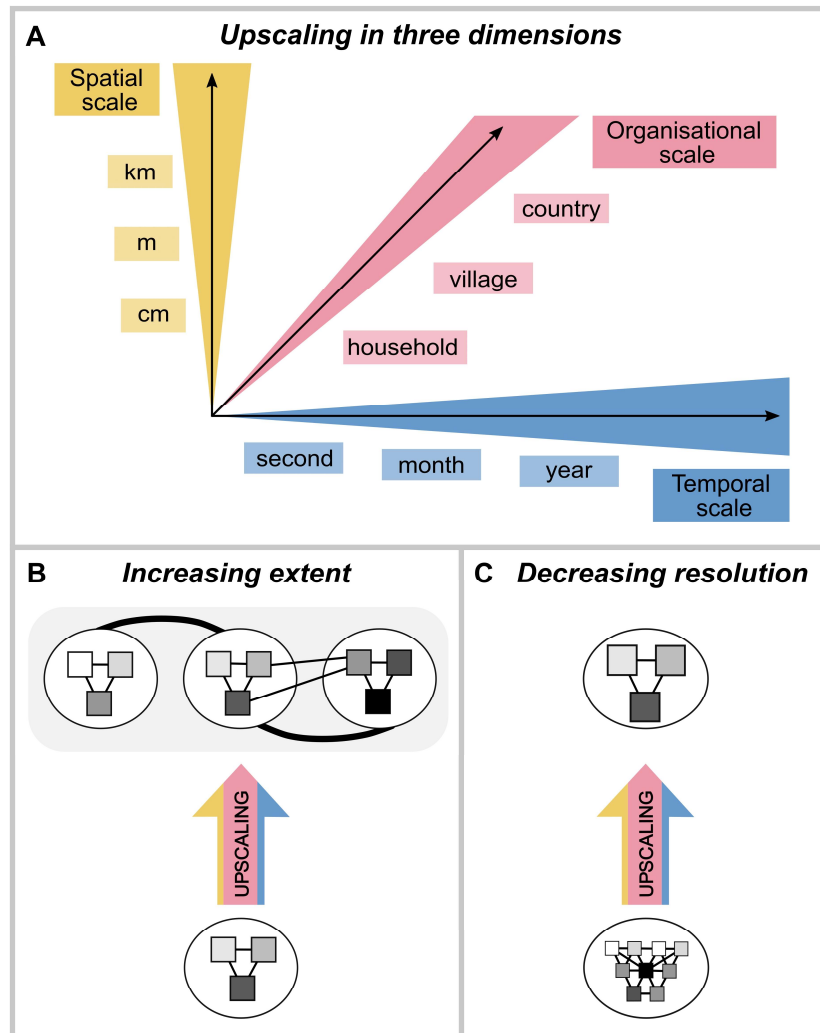|	
Dimension	"The unstructured aspects of reality or phenomena to which scales are applied, such as time, space, power, etc." (Vervoort et al. 2012)
Scale	"The spatial, temporal, quantitative, or analytical dimensions used to measure and study any phenomenon" (Gibson et al., 2000, p. 218). An example of a relevant analytical dimension could be organisational level. For a given scale (e.g., space), information on resolution (e.g., square metres) and extent (e.g., 400 hectares) is needed (Turner et al., 1989).
Levels	"The units of analysis that are located at the same position on a scale." (Gibson et al., 2000, p. 218)
Resolution	The first level of spatial, temporal, quantitative, or analytical grain size (sensu Turner et al., 1989).
Extent	"The size of the spatial, temporal, quantitative, or analytical dimensions of a scale" (sensu Gibson et al., 2000, p. 218).
Upscaling	Decreasing the resolution and/or increasing the extent of the study.
Downscaling	Increasing the resolution and/or decreasing the extent of the study.
Transfer procedure	A quantitative relation to changing grain size (i.e., resolution) and/or extent of data or model processes. One possible transfer procedure to upscale is averaging.
Extrapolation	Transferring information from smaller to larger extents (Wu & Li, 2006a). Extrapolation has also been termed "scaling out" (Rounsevell et al., 2012) and might require additional data and/or resampling of data to cover the larger extent, as well as the implementation of new rules or processes.
Interpolation	Filling gaps between observations or model results.
Generalisation	The selection and simplified representation of detail appropriate to the scale and/or the purpose of a study (adapted from Weibel & Dutton, 1999).
Aggregation	Grouping data, models or model structures at a level of detail or resolution that is coarser than the level at which the data and/or model were collected/modelled (expanded from the definition of Scott, 2008, for aggregation of data)

Figure 1: Conceptualisation of upscaling along three dimensions (adapted from Wu & Li, 2006a, King, 1991). **A:** Upscaling methods typically refer to spatial scale (yellow), temporal scale (blue) or organisational scale (red), enabling the transition from smaller to larger levels along the respective axis (exemplary units are displayed alongside). The aims of upscaling can be separated into two main objectives: increasing the extent (**B**), and decreasing the resolution (**C**). In either case, the starting point is a system (represented by the lower circle) that includes entities (shown in squares) that represent the social and environmental components of the system (e.g., people, plants, water, institutions). These entities can be heterogeneous (reflected by different shades of grey) and interact within the system (lines between entities). By increasing the extent (**B**), additional entities may be added to the system, resulting in higher heterogeneity. Furthermore, interactions can also go beyond the original system extent (shown by lines between squares, respectively circles). When a system is upscaled to decrease the resolution (**C**), the resulting system includes a smaller set of different entities, a reduced number of interactions, and decreased heterogeneity.

Model upscaling is increasingly necessary to represent the cross-scale nature of SES. However, upscaling is not just a simple exercise of extending or averaging results and is difficult for several reasons. First, different social and environmental processes gain and lose importance as scales change, meaning that large-scale patterns cannot necessarily be predicted even when local mechanisms are well characterised (Raffa et al., 2008). For example, when increasing the spatial extent of a model of agricultural production, market dynamics may become important endogenous processes, which were treated exogenously at the smaller scale. Representing these additional processes increases system complexity, which also necessitates a more complex model. Second, representative data are often not available over larger spatial or temporal extents (Elsawah et al., 2020; Rounsevell et al., 2014). Hence model calibration and validation is much more difficult. Due to increasing global connectivity in SES and the heterogeneity and adaptive capacity of actors across scales, these difficulties are especially pertinent to SES. However, upscaling in SES models has received less attention than in other fields (e.g., ecology) and remains a pressing challenge (Elsawah et al., 2020).

With this paper, we aim to contribute to an advancement of upscaling in SES in three ways:

1. Highlight the specifics and the resulting challenges of upscaling in SES, in comparison to purely environmental systems.
2. Present an upscaling scheme to classify existing as well as new upscaling methods, and thereby facilitate the transfer of upscaling methods from other disciplines to SES.
3. Foster cross-fertilisation by providing specific examples for transferring upscaling methods from other disciplines to SES using our scheme.

We recognise that the interdisciplinarity necessary to study SES—whether at a single scale or across scales—can raise epistemological conflicts between the social and natural sciences. For instance, the positivist stance generally present in modelling research can struggle to represent alternative worldviews (Pretty, 1995; Leach et al., 2010). Although bridging different ways of knowing is an important goal in SES modelling (Williams et al., 2022), in this article we focus more closely on the technical challenges that arise when upscaling in SES, relative to the associated meta-level philosophical considerations (Manson, 2008).

The paper is organised as follows. First, we review existing upscaling approaches in SES as well as other disciplines (Section 2). Second, we identify four main challenges that are particularly relevant to upscaling in SES and elaborate why existing upscaling methods might fall short in addressing them (Section 3). Third, we present our upscaling scheme and demonstrate how existing upscaling methods can be transferred to SES, using two good practice examples from ecology (Sections 4 & 5). Finally, we discuss how the identified upscaling challenges could be better addressed and point out shortcomings that warrant future research (Section 6).

2.   Upscaling methods in different disciplines

While the relevance of upscaling for modelling studies is frequently discussed, there remain few concrete examples that realise upscaling in SES. This is due to obstacles related to scaling of processes and data in two principal domains: (a) *conceptual* features of systems in general and (b) *technical* specificities for modelling. In this section, we first summarise the existing approaches within the SES literature in these two domains. We then examine how other disciplines with more mature upscaling histories (economics, ecology and hydrology) have approached such conceptual and technical barriers.

With respect to (a), determining the appropriate scale for the management and assessment of interlinked systems is a challenge (Cash et al., 2006; Cumming et al., 2006; Davis, 2006; Evans et al., 2013; Kok & Veldkamp, 2011; Scholes et al., 2013; Veldkamp et al., 2011). For instance, there is frequently a mismatch between the scale at which environmental processes operate (termed 'process scale' by Bierkens et al., 2000; or 'intrinsic scale' by Wu & Li, 2006a), the scale at which the process is observed ('observation scale') and modelled ('modelling scale') and the scale at which decisions are made ('policy scale', see Bierkens et al., 2000; Cumming et al., 2006; Davis, 2006; Wu & Li, 2006a). For a detailed overview on how these scales are related, see, e.g., Wu & Li (2006a, Figure 1.2) or Bierkens et. al. (2000, Section 1.1) and for an empirical example see Kininmonth et al. (2015). In addition, scholars even emphasise that scales "are part of the socio-political processes, including science, in which they are constructed, reproduced or altered over time" (Buizer et al., 2011, p. 2). However, approaching the systems from multiple scales (Davis, 2006; Scholes et al., 2013) and including cross-scale dynamics (Cash et al., 2006) is recommended as an appropriate means to manage SES.

With respect to (b) (i.e., modelling-specific challenges), representing human behaviour and institutional organisation at large scales is challenging. Rounsevell et al. (2014) emphasise the importance of including human decision processes in global-scale land use models, but at the same time point out that the representation is so far highly simplistic in comparison to the physical processes. Human behaviour is often integrated into models as an external driver or designed through very simplistic assumptions that do not represent decision-making processes (e.g., by shared socioeconomic pathways (SSP) scenarios in integrated assessment models, cf. O'Neill et al., 2014; Riahi et al., 2017). Schlummer et al. (2014) discuss upscaling in SES with a focus on archaeological data. They point out the particular challenges (e.g., integration of social and environmental data) and provide some guiding steps in tackling upscaling in interdisciplinary research endeavours, such as identifying relevant scales at which socio-environmental interactions operate and defining appropriate parameters to describe these scale-specific interactions. With respect to temporal scales, Levin et al. (2013) propose to differentiate between

slow and fast processes, giving the example of herbicide resistance, evolutionary processes and the development of sensible policies. Preston et al. (2015) summarise the current methods for modelling agroecosystems with a focus on scale and human agency. They criticise that most models of agroecological systems only depict spatial and temporal scales but not the organisational scales that represent social institutions or social networks (see Figure 1a for an overview on these three dimensions of scale). Furthermore, similar to Rounsevell et al. (2014), Preston et al. (2015) point out that in regional and global models only aggregated human behaviour is incorporated, e.g., lacking the appropriate representation of actor heterogeneity. A concrete application example can be found in Ewert et al. (2011), where in two test cases the importance of scale changes and their effects on uncertainty is demonstrated by using a model that allows the assessment of agricultural and agri-environmental policies and technologies in Europe.

Economic models also frequently deal with issues of scale. In this discipline, upscaling is often discussed in relation to "aggregation". Aggregation is done over economic sectors and/or regions (i.e., spatial scale, cf. Dietrich et al., 2013). How to avoid aggregation bias is a key question of interest; for example see Britz & van der Mensbrugghe (2016) and Brockmeier & Bektasoglu (2014) who investigate the role of model structure and data aggregation level on model results for the Global Trade Analysis Project (GTAP) general equilibrium model. For a representation of scale in economic theory and its limits see also van der Veen & Otter (2003) and Gräbner & Kapeller (2017). Dynamical systems can show the property of self-organised criticality where some patterns become scale invariant and the distribution of the observable can be described by a power law. One example is the distribution of a financial index (Mantegna & Stanley, 1995). A review on "Power laws in Economics and Finance" is given by Gabaix (2009) including examples of firm sizes, city sizes and income and wealth.

Upscaling methods in ecology have been developed and applied for decades (Denny & Benedetti-Cecchi, 2012; Fritsch et al., 2020; Levin, 1992; Urban, 2005). In the following, we will present ecological modelling examples where methods of upscaling have been used in the widest sense. For further examples, see also Section 4 where we give a systematic overview of upscaling strategies. An example of temporal upscaling is the theory of the separation of time scales (Fahse et al., 1998), where results of one temporal scale (e.g., hours in a behavioural model) can be aggregated and used at a coarser time scale (e.g., years in a demographic model). A similar approach has been applied in the metapopulation theory, where the dynamics of many local populations that may go extinct and be recolonised are summarised in the behaviour of a metapopulation changing much more slowly in time (Hanski, 1998). A set of theories have been introduced to aggregate spatial interactions in continuous space with so-called moment closure methods (Law et al., 2003) and in discrete space with pair approximation methods (Calabrese et al., 2010). Non-linear averaging to account for variability in space and time has been successfully introduced in scale transition theory (Melbourne & Chesson, 2006). Aggregating mechanistic simulation models with statistical meta-models, including machine learning techniques, is also commonly used to extrapolate the findings of the underlying model (see Pietzsch et al., 2020 for an overview). If problems are scale-free, i.e., the same patterns can be observed on all relevant scales, then methods are well established, e.g., scale-free networks (Barabási & Albert, 1999) or allometric scaling (Enquist et al., 1998). Implicitly, most spatially discrete and temporally discrete ecological simulation models assume that derived response functions have homogenous responses on the lowest spatial and temporal resolution. The generation of procedures for aggregating agents can benefit, e.g., from the knowledge of creating plant functional types in ecological models (Fischer et al., 2018; Haxeltine & Prentice, 1996). If the number of actors is getting too large, individuals can be aggregated into so-called super individuals (Scheffer et al., 1995). However, different scales of actors and resources can cause fundamental problems and extrapolation is limited to regions with similar constraints, e.g., biomes of environmental conditions in ecological models or the governmental structures in SES models. To define such regions with similar constraints is not trivial. However, there is a rich toolbox available from the discipline of habitat modelling that may help modellers to do so, e.g., maximum entropy modelling (Baldwin, 2009; Merow et al., 2013).

Scaling has also been a focus of interest in hydrological science. Hydrological processes take place on a variety of spatial and temporal scales. For example, they range "[...] from unsaturated flow in a 1 m soil profile to floods in river systems of a million square kilometres; from flash floods of several minutes duration to flow in aquifers over hundreds of years." (Blöschl & Sivapalan, 1995, p. 253). This heterogeneity of observed and modelled parameters and variables in hydrology poses a great challenge and has led to the exploration of numerous upscaling methods and approaches in recent years. One recent example is the multiscale parameter regionalisation technique (Samaniego et al., 2010; Schweppe et al., 2022) that enables upscaling of high-resolution model parameters to any desired spatial resolution at which the model should be applied using

specific upscaling operators (e.g., arithmetic or geometric mean). Other examples include, e.g., determining representative parameters (Bierkens et al., 2000, Chapter 2.3) or averaging of model equations (Bierkens et al., 2000, Chapter 2.4). For a more detailed overview of scaling issues and approaches in (soil) hydrology see, e.g., Bierkens et al. (2000), Samaniego et al. (2017) or Vogel (2019). However, also in hydrological science the awareness to consider the interactions of time scales of hydrological processes and social development is rising (Sivapalan & Blöschl, 2015).

3.   Upscaling challenges in socio-environmental systems

We identified four challenges related to upscaling of SES models, namely, how to account for 1) heterogeneity, 2) interactions, 3) learning and adaptation and 4) emergent phenomena. These characteristics are not unique to SES and are indeed foundational concepts within complexity science and the study of complex systems in general (cf. Manson, 2001 for a broader overview on complexity research). Modelling of SES is based very much on previous fundamental work in complex adaptive systems (Holland, 1998, 2006) and complex networks (Newman, 2003). For instance, Parker et al. (2003) summarised work by Holland (1998) and others stating that complex systems are "...characterised by interdependencies, heterogeneity and nested hierarchies" (Parker et al., 2003, p. 321).

However, as we detail below, these characteristics within SES can pose specific challenges for model upscaling, for instance because these models represent human behaviour and social structures (Otto et al., 2020). Using the same distinction as in the previous section, the challenges within these four themes are both *conceptual*, i.e., relating to the qualitative representation of processes at different scales, and *technical*, i.e., relating to formalising such processes in models.

The four challenges discussed in this section each relate to system properties that arise from the collection of the modelled SES entities and their dynamics. The entities represent the modelled social and environmental components, for instance, people, plants, water or institutions. These entities are characterised at and act within specific organisational, spatial, and temporal scales (Figure 1A). Upscaling can aim at increasing the extent of at least one of these three scales (Figure 1B) and/or at decreasing their resolution (Figure 1C). In the following, we discuss the challenges produced by these two aims.

3.1   Heterogeneity

The heterogeneity of a collection of entities in an SES can manifest itself, for example, in ecological processes, through variability in growth parameters among different tree species in a forest; or, in social processes, in variable propensity to adopt new technologies among people in a social network. When modelling social systems, it is important to consider the ethical considerations that may arise when modelling heterogeneity (Shults and Wildman, 2019) (e.g., if using race as an independent variable), as these may be distinct to those for non-human entities. At the interface of social and environmental systems, heterogeneity can have important and potentially divergent implications for emergent dynamics (Cumming & Peterson, 2017; Giller et al., 2011). For instance, if households with lower wealth have less capacity to harvest resources, actor heterogeneity can lead to polarisation (Dressler et al., 2019). Yet, diversity in behavioural responses can also foster resilience in SES (Grêt-Regamey et al., 2019). This context-dependence in how heterogeneity affects SES outcomes therefore poses a challenge when attempting to upscale the extent or resolution of an SES model.

Decreasing the resolution of an SES model requires aggregating the heterogeneity of system entities (Figure 1C). Aggregation, thus, might risk losing relevant system properties driving the dynamics in the SES. For instance, upscaling a household-level model to the community-level might require averaging the households' wealth levels, thereby compromising the representation of the mechanisms that drive inequality in the household-level model.

Extrapolating a model often requires an increase in heterogeneity among the entities of the SES (Figure 1B). SES can pose unique challenges beyond purely social or environmental systems in this regard. For example, when extrapolating a model of one region to other regions or countries, a wider range of decision rules (Malek & Verburg, 2020) or environmental governance institutions (Duit, 2016) can make it difficult to simply apply the

original model to the other regions. In the extrapolated model, parameter ranges might need to be extended, or even entirely new rules or processes implemented.

3.2   Interaction

Interaction among entities can be direct or indirect. Examples of direct interaction are land use agreements among pastoralists (McAllister et al., 2006), influence and support through social networks or simple predator-prey interactions among two species in ecological systems. Indirect interaction happens through a third entity of the SES, for example a common resource for which individuals are competing, such as trees competing for light or producers competing for market shares. While in ecological systems, interaction is often constrained by spatial distances, in social systems and SES the possibility for exchange depends on how the interacting agents are connected. This allows for interaction over longer (spatial) distances (i.e., "telecoupling") and in a faster and more connected way than ecological systems, for example through digital global information exchange or global trade (Hull & Liu, 2018). Our conceptual understanding of such complex interaction processes is still very much in development, making its representation in models difficult.

When decreasing model resolution, interactions may need to be aggregated (Figure 1C). Depending on the empirical context, such aggregation could take different forms. In the simplest case, if micro-interactions are dominated by larger-scale features at the aggregated scale, it may be feasible to exclude them (e.g., Magliocca et al., 2013). However, in some cases the nature or outcomes of an interaction can change across scales. For instance, support through social networks can be different when considering individual people or households as a whole (Will et al., 2020). Another example is competition: when aggregating competing individuals to a single entity, the outcome of the competition (such as mutual coexistence or extinction/monopoly) has to be translated to the aggregated level. Upscaling may therefore require representing interactions through new, macroscopic model rules that either model the larger-scale interaction or proxy the outcomes of the smaller-scale interaction.

When extrapolating a model, new interactions might need to be considered (Figure 1B). For example, when increasing the number of human agents, new coordination structures such as regional governance or international trade agreements might become relevant (Veldkamp et al., 2011). Furthermore, external factors might be simplified on a lower level, but are then explicitly modelled on the higher level.

3.3   Learning and adaptation

Learning and adaptation both relate to changes in the decision-making and behaviour of agents. In the literature, diverging definitions of learning and adaptation are used (e.g., Reed et al., 2010; Rounsevell et al., 2014; Smit & Wandel, 2006). Müller et al. (2013) refer to adaptation as when changes in the input for the decision-making rules (e.g., changes in the environment or the behaviour of others) lead to different decisions, while learning refers to changes in the decision rules themselves. In resource management, learning may take place on different organisational levels (from individual resource users to continental or global institutions) and create feedback loops if institutional frameworks are reinterpreted or modified (Pahl-Wostl, 2009). Agents adapting and learning within an SES can create feedback that "can lead to complex dynamics such as threshold effects, multiple equilibria and path dependency." (Rounsevell et al., 2014, p. 126; see also Sivapalan & Blöschl, 2015 for examples related to flood control and water management).

Aggregating the temporal scale can imply that path-dependent learning and adaptation processes need to be considered during the upscaling; what appears as a gradual process at a high temporal resolution, such as the evolution of norms over the course of years, can turn into a sudden change at a coarser temporal resolution, such as decades or centuries.

Extrapolating the temporal scale means that long-term processes of adaptation and learning might have to be added to the modelled SES. This depends on the entities that are incorporated, since different types of organisations require variable amounts of time to change (Otto et al., 2020). For example, whereas technological development (e.g., regarding renewable energy production) may occur rapidly within a few years, the adaptation of policies and regulations regarding the adoption of such new technologies may only take place over long time spans of several decades.

3.4 Detecting emergent phenomena

In complex systems, heterogeneity, interactions and learning / adaptation can lead to emergent phenomena on the macro level (Chave & Levin, 2003). Such emergent phenomena can include regime shifts and tipping points (Reyers et al., 2018). For example, the interaction of water users adapting to water supply in a socio-hydrological system was shown in a modelling study to lead to distinct regimes such as collapse due to drought (Homayounfar & Muneepeerakul, 2021). Detecting regime shifts or tipping points might require analysing model output at a specific spatial or temporal scale (Filatova et al., 2016). Upscaling a model to a different scale could render the model less useful for detecting these regime shifts or tipping points. In addition, the appropriate temporal scale to represent a process can change over time (Lippe et al., 2019). For example, fast-acting fluctuations (in milliseconds) in financial markets can massively affect large-scale dynamics (hundred days), particularly at times near tipping points or collapse, which cannot necessarily be specified *a priori* (Preis et al., 2011). This might require running models multiple times on various scales (Lippe et al., 2019). Aggregating on the organisational scale can imply losing agent heterogeneity with its impact on collective behaviour and preferences, possibly affecting any resultant tipping points (Otto et al., 2020). This makes it difficult to identify well-defined hierarchical systems of analysis (Rotmans, 2002).

Polhill et al. (2016) pose the question of whether – contrary to aggregation – models should operate on finer resolution when modelling transition periods and shocks to properly account for path dependency in the SES. In such an approach, the emergent phenomena to be modelled can help to identify the relevant state variables, processes and appropriate resolution in the sense of pattern-oriented modelling (Grimm, 2005; Grimm & Railsback, 2012).

Extrapolating the temporal scale, i.e., considering a longer time horizon, poses a challenge for detecting regime shifts in SES (Filatova et al., 2016; Polhill et al., 2016), since the detection of such changes depends upon the time horizon that is investigated. A systemic change detected within a short time span might be followed by dynamics leading the system back to its previous state in the long term, and also the magnitude of change might be regarded as substantial in one specific time period but within bounds in another time period (Polhill et al., 2016). As the time horizon increases, so too can the importance of considering outcomes such as intergenerational equity or the potential for shifting societal values (Orlov et al., 2018). In this regard, also the occurrence of 'cascading thresholds' across ecological, social, and economic domains and across scales of space, time, and social organisation might be of high relevance (Kinzig et al., 2006).

4. Upscaling scheme

Modelling SES often requires scaling of data or models as well as integrating processes running at different scales in one model. Despite their ubiquity, these scaling efforts are often done *ad-hoc* without explicitly describing the involved scales and the methods used to link those (Ewert et al., 2011). Several classification schemes of scaling methods already exist (e.g., Bierkens et al., 2000; Dalgaard et al., 2003; Ewert et al., 2011; Fritsch et al., 2020; Harvey, 2000; King, 1991; van Oijen et al., 2009; Wu & Li, 2006b), which have different degrees of generality and complexity. In this section, we present a comprehensive scheme of upscaling strategies that builds upon these existing schemes.

Our scheme is a tool for describing and visualising different scaling strategies that is accessible and comprehensible to a broad audience of SES modellers. Specifically, we synthesise two encompassing schemes provided by Bierkens et al. (2000) and Ewert et al. (2011). Of the schemes we reviewed, we found these two to be the most descriptive, practical and encompassing. Bierkens et al. (2000) developed an extensive framework for scaling methods in environmental science. For upscaling methods, they distinguish four broad classes: averaging of observations or model outputs, finding representative parameters, averaging of model equations and model simplification. Ewert et al. (2011) focus on up- and downscaling methods specifically in the context of agri-environmental systems. They propose a set of 8 scaling methods, which they distinguish into manipulation of data and manipulation of models.

To arrive at our scheme, we combined the strengths of these two schemes, in particular (a) the distinction between upscaling of data and upscaling of models, (b) concepts for five upscaling strategies and (c) the visualisation ideas provided by Bierkens et al. (2000). Despite the strong advantages of the existing schemes,

some ambiguities remained that we clarified in our scheme. For example, the diagrams provided by Ewert et al. (2011) were missing some details on what is being scaled up and how it is done. A lot of these details are provided by Bierkens et al. (2000) in a very technical and mathematical manner, which might hamper the understandability of the scheme. In our scheme, we tried to be more explicit about the object of upscaling (i.e., extent, resolution), by differentiating between transfer procedures that relate to data and models and by providing clear and distinctive diagrams for the different upscaling strategies. Furthermore, we integrated special cases of upscaling discussed by other schemes (Dalgaard et al., 2003; Fritsch et al., 2020; Harvey, 2000; van Oijen et al., 2009).

Our scheme comprises five broad upscaling strategies that encompass all upscaling methods discussed by the classification schemes mentioned above. They are described in Table 1 along with examples for each strategy. The strategies include: 1) Upscaling of model output, 2) Upscaling of input data and/or model parameters, 3) Simplification of model structure, 4) Derivation of meta-model and 5) Nested model. Each strategy consists of three main elements:

  i) the scale S of data and/or models, which comprises the resolution r and extent e. To distinguish different levels on the scales for each component, subscripts are used, e.g. (r_1,e_1).
  ii) the objects that are being scaled, i.e., input data and model parameters, the model itself or model output.
  iii) transfer procedures that are used to scale models and/or data between scales.

Within the five strategies, we distinguish between scaling of data (strategies 1 & 2) and models (strategies 3, 4 & 5), as both are structurally different regarding input and output of the upscaling process. Correspondingly, we differentiate two types of transfer procedures: transfer procedure α for upscaling of data (e.g., input data, model parameters or model output) and transfer procedure β for upscaling of models. Additionally, we note that upscaling does not require changes in both r and e (e.g., it is possible that $r_1=r_2$). The transfer procedures (α and β) can take different functional forms, namely linear, non-linear or hierarchical (cf. Dalgaard et al., 2003). *Linear* and *non-linear* scaling involve parametric transfer functions between the two scales, whereas *hierarchical scaling* means that newly emerging properties are included when system boundaries are extended (e.g., from field to farm level). Some examples for transfer function α include extrapolation or generalisation to change the extent of the data (see Box 1) and interpolation, aggregation or generalisation to change the resolution of the data. Examples for the transfer procedure β for the scaling of models are integration, regression, artificial intelligence techniques or theory-based approaches. Here, the inputs to and outputs of the transfer function are functional relationships, e.g., model rules or equations.

Two types of the strategies in our scheme are most common in existing upscaling applications: the upscaling of model output without changing the underlying model (Strategy 1) and strategies that involve the development of a new model, either through the derivation of an analytical or conceptual model at the larger scale (Strategy 3) or the derivation of a meta-model (Strategy 4). A special case for an analytical approximation to upscale a local population model to a regional scale is the scale transition theory (Melbourne & Chesson, 2006). In this theory, the local model is extended by additional terms (e.g., the variance of the input data) and averages of the input data are used in the submodel. In our taxonomy we would group the scale transition theory under Strategy 3. Harvey (2000) discusses several approaches to derive a new model, such as parameterizing interactions between distinct patches, and van Oijen et al. (2009) propose the creation of deterministic meta-models or stochastic emulators. Furthermore, van Oijen et al. (2009) discuss several approaches for scaling model output, such as running the model for selected points and interpolating the results. Another special case is sometimes referred to as "brute force" upscaling that involves the application of the unchanged small-scale model to a larger extent (Fritsch et al., 2020). However, we see this approach as part of our Strategy 2 in the sense that resolution $r_1 = r_2$ and the model is applied to the same input data and model parameters without prior scaling (i.e., transfer procedure α = *identity*).

In the field of agent-based modelling, which represents a prominent model type in SES modelling, two of our proposed strategies are of particular importance as they are implicitly used in most agent-based models (ABMs): Strategy 1 and 5. Strategy 1, upscaling of model outputs, is used in almost all ABMs when aggregating individual-level model output to the population level, thereby decreasing the resolution of the model output. This reflects the general approach of ABMs tracking population-level outcomes that emerge from individual-level dynamics

Table 1: Upscaling scheme consisting of five general upscaling strategies. Boxes represent the objects that are being scaled, *r* and *e* respectively refer to resolution and extent in data and/or models, and arrows represent links between objects, respectively transfer procedure α and β.

Strategy	1) Upscaling of model output	2) Upscaling of input data / model parameters
Scheme		
Description	Model runs at scale (r_1,e_1) for different parameters; only model output is scaled up using a transfer procedure α that relates model output to the model parameters.	Input data and/or model parameters are transferred from scale (r_1,e_1) to scale (r_2,e_2) using transfer procedure α and the model is applied at scale (r_2,e_2) for all combinations of input data/and or model parameters that occur at larger scale.
Examples	**Averaging of individual-level decisions** (Niamir et al., 2020): Individual household decisions about energy use and investment from an ABM are aggregated to the regional level. **Extrapolating of crop yields** (Morell et al., 2016): Crop yield is simulated for representative weather stations and upscaled to climate zones, based on total harvested area in each climate zone.	**Regionalisation of model parameters** (Rödig et al., 2017, 2018): FORMIND forest model parameterisations from inventory data are correlated with local environmental variables (soil, climate). Based on that, a regression model is derived to extrapolate parameterisations to the whole Amazon and FORMIND is applied to the enlarged extent (see Section 5.2 for a detailed description). (Samaniego et al., 2010): Application of transfer functions (e.g., regression model) to high resolution geophysical datasets to estimate high resolution model parameters. These are upscaled by appropriate upscaling operators (e.g., arithmetic mean, harmonic mean, geometric mean) to the resolution at which the model is applied. **Meta-studies** (Magliocca et al., 2015): Synthesis of information from multiple case studies to inform large-scale process-based land change models by generating parameter bounds, specifying model process design, validating outcomes across sites, and guiding sensitivity analysis. **Agent typology** (Valbuena et al., 2008, 2010): Use farmer survey data to derive agent typology based on expert knowledge, cluster analysis and classification trees. **Brute force upscaling:** General strategy, where the original model (at resolution r_1) is applied to data from a larger extent (i.e., e_2), such as running copies of the model in each grid cell of a larger landscape. Examples are, e.g., forest gap models (Peters, 2002; Shugart et al., 1998).

Strategy	3) Simplification of model structure		4) Derivation of meta-model	5) Nested model
Scheme				
Description	Analytical derivation of model at scale (r_2,e_2) from model at scale (r_1,e_1) using transfer procedure β. Input data & model parameters do not necessarily have to be scaled up.	Development of conceptual model at scale (r_2,e_2) based on model at scale (r_1,e_1). Both model structure and output at scale (r_1,e_1) may influence transfer procedure β.	Meta-model at scale (r_2,e_2) is derived by relating input and output of model at scale (r_1,e_1). This might require upscaling of input / output from (r_1,e_1) to (r_2,e_2) first.	Coupling of models that operate at different scales (r_i,e_i). Models interact and/or exchange data between scales.
Examples	**Mathematical integral** (Thornley & France, 2007): Calculation of annual photosynthetic production of a forest canopy based on gross production of a single leaf by integrating over the leaf area of a tree crown and linear extrapolation in time (year) and space (crown area). **Moment method** (Bolker et al., 2000): Spatially-explicit and individual-based model is approximated by an analytical model based on first two spatial moments. **Analytical approximations**, e.g., moment closure and pair approximation methods to aggregate spatial heterogeneities (Law et al., 2003; Matsuda et al., 1992). **Scale transition theory** provides a theory for non-linear averaging to upscale local scale interactions in potentially nonlinear systems (Melbourne & Chesson, 2006).	**Describing individual-based models by differential equation models** (Tietjen & Huth, 2006): Use of a differential equation (DE) version of an individual-based forest model (IBM) to determine tree growth. Parameters of the DE are fitted to forest dynamics gained from the IBM (transfer function α). DE model dynamics are adjusted to those of the IBM (transfer function β). (Rahmandad & Sterman, 2008): Contrasting dynamics of an ABM and DE model of a contagious disease. Parameters in the DE are calibrated by nonlinear least squares in a large set of ABM realisations (transfer function α).	**Non-parametric transition matrices** (Cipriotti et al., 2016): Upscaling of individual-based rangeland model from patch scale to the landscape scale, where the simulation model is replaced by a transition matrix. State variables & environmental conditions are tallied into discrete states where the transition probabilities are extracted from the simulations of the detailed model (see Section 5.1 for a detailed description). **Aggregating land use at plot scale to regional or country level** (Pütz et al., 2014): FORMIND forest model is used to simulate forest dynamics of forest fragments. Model output is used to parameterise a function that relates biomass loss to fragment size and shape, and the function is applied to estimate biomass loss across whole biogeographic regions. **Power law** (Dressler et al., 2016): Identification of a power law relationship in an ABM on disaster management to relate the number of disaster management organisations (i.e. the agents) and the total time needed to cope with a certain disaster event.	**Land use example** (Thomson et al., 2014): Nesting of a high-resolution agricultural model (field scale) for the US Midwest within a global integrated assessment model, operating at sub-region level. **LPJ model** (Schaphoff et al., 2018): Simulation of processes on different scales, specifically at the level of individuals (average plant functional type) and the population level (grid cell). Scaling of simulated variables between these two levels using the number of individuals per population or population density.

(i.e., emergence). Another highly common strategy in agent-based modelling is nesting sub-models that operate at different spatial, temporal or organisational scales into one model (Strategy 5), for instance in rangeland models where grazing takes place at a finer temporal resolution than vegetation dynamics (Moritz et al., 2015) or in ABMs of environmental migration where migration decisions are made on a coarser temporal resolution than other household decisions such as natural resource use decisions or demographic processes (Thober et al., 2018).

We envision that our proposed scheme will assist modellers during the design stage of models by (a) encouraging consideration of what processes are relevant at what scales, (b) facilitating scaling formalisation by being explicit about the objects and methods of scaling and (c) providing examples to derive inspiration and support.

5. Upscaling examples

In this section, we present two existing upscaling examples. We specifically chose examples from ecology that already use upscaling methods for two main reasons: Firstly, we are not aware of any good practice modelling examples of upscaling in SES. Secondly, upscaling is more advanced in ecological modelling so that we can learn more readily from these examples for SES and describe how their scaling approach might be transferred to a hypothetical socio-environmental example. In a first example, we present how Cipriotti et al. (2016) upscale a stochastic individual-based model of grass steppe dynamics from patch to landscape scale using transition matrices and explain how this approach could help with modelling the adoption of irrigation technology. The second example deals with the regionalisation of model parameters that is used by Rödig et al. (2017) to extrapolate local forest dynamics of the forest model FORMIND to a biome-wide extent. We elaborate on how this technique could be helpful in modelling livestock numbers in Sub-Saharan Africa. For both examples, we explain how the specific method might be able to address the upscaling challenges laid out in Section 2 and their added value.

5.1 Upscaling from patch to landscape scale using transition matrices (Strategy 4)

Cipriotti et al. (2016) use a stochastic individual-based model, COIRON, that simulates grass steppe dynamics on the level of individual grass tussocks, including growth & mortality, colonisation, water dynamics and grazing. The model is used to simulate vegetation cover and above-ground primary productivity, based on rainfall, local stocking rate and vegetation composition. To upscale the individual-based model from local (resolution r_1 = 30 x 30 cm; extent e_1 = 0.15 ha) to landscape scale (r_2 = 38.4 x 38.4 m; e_2 = 4180 ha), the authors develop and use a nonparametric approach using transition matrices. Hence, the method both decreases the resolution and increases the spatial extent. They first define combinations of states of the main external model drivers (precipitation and stocking rate) and target outcome variables (vegetation cover, primary production and cover of large bare gaps). Using a process-based simulation model on the local scale, they then derive transition matrices for each combination of the external drivers (see Figure 2). These matrices describe the probability of the local model transitioning from one state of the target variable to another and are then allocated to the cells of the regional model. Additionally, in the upscaled regional model, spatial interactions between cells are incorporated by defining spatially heterogeneous stocking rates, which are influenced by conditions (such as grazing attractiveness) of the cells in the neighbourhood. This method can be classified as our fourth upscaling strategy, i.e., derivation of a meta-model.

We conceptually translate the upscaling method presented by Cipriotti et al. (2016) to a socio-environmental context using a hypothetical example of irrigation technology adoption (see Supplementary Material A for a detailed comparison of both examples). On the local scale, one village consists of several households. Each household decides whether to adopt an irrigation technology based on its number of neighbours using irrigation, the village-level knowledge of the technology and the precipitation. Transition matrices could then be derived for each combination of mean number of neighbours in a village, village knowledge level and precipitation to give the transition probability of the share of households adopting the technology within a village. Analogous to the stocking rates in the rangeland model of Cipriotti et al. (2016) the knowledge of neighbouring villages could influence the information level within a village. This mechanism would therefore allow for considerations of spatial interaction on the regional scale.
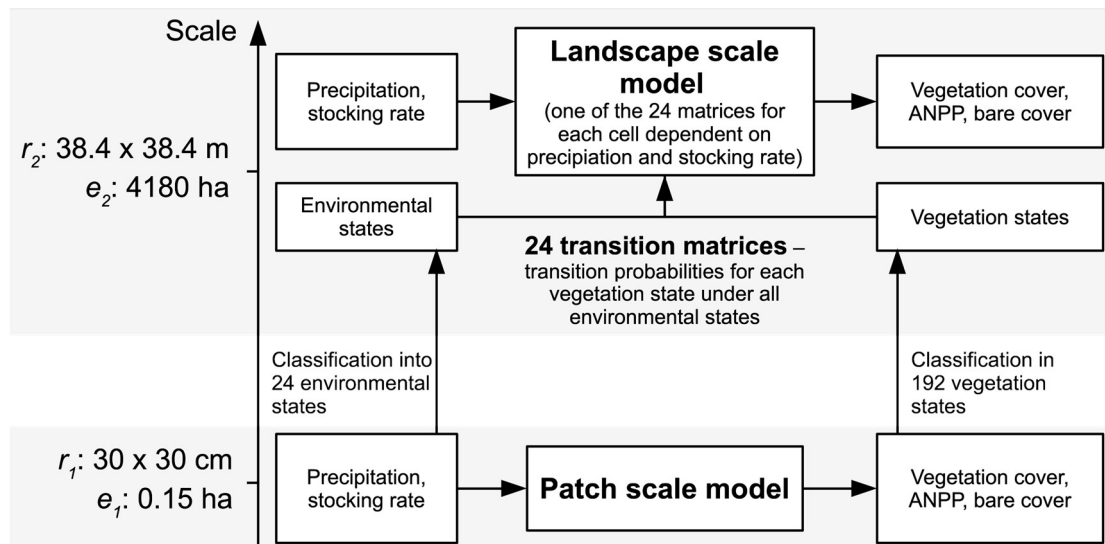
Figure 2: Application of Strategy 4 – Derivation of a meta-model – of the upscaling scheme to the example of Cipriotti et al., (2016).

In this irrigation technology example, however, the challenges specific to SES elaborated in Section 3 become apparent. Heterogeneity with respect to precipitation, mean number of neighbours and information level could be accounted for by creating transition matrices for each combination of these factors. Interaction on the larger scale could be represented by incorporating an effect of neighbouring villages on a village's information level, which could be accommodated through the choice of the respective transition matrix. However, by decreasing the resolution from households to villages, interactions between households are only represented by the *mean* number of neighbours. Thereby, we would lose information about the *distribution* of the number of neighbours (i.e., degree distribution) and thus other aspects of agency, such as power relationships between households, could not be depicted. Furthermore, this aggregation via the mean number of neighbours ignores possible path dependencies that may result from initial household distributions, such as the interconnectedness of early adopters. This information is lost by averaging over all possible initial conditions while creating the transition matrices. Finally, additional processes might become relevant at larger scales, particularly related to governance and policy, which may be heterogeneous across time and space. The development of regional or national policies on water extraction or irrigation may depend on local governance systems and patterns of water usage as well as the geographical context of the region (e.g., the relative positions of the villages within a water catchment may cause additional dependencies between villages). Such cross-scale dynamics are particularly relevant in SES and may be hard to capture with this approach, or at least require a large number of variables for describing the system's state at the smaller scale.

In our view, the use of matrix models in the sense of Cipriotti et al. (2016) to upscale dynamics of SES of a lower spatial scale to a higher scale is a promising and flexible approach, with a potential that has not been tapped. We illustrate, for instance, that it allows for incorporating social interactions (at least up to a certain extent). In land use modelling (and particularly when using cellular automata), matrix models have been used to describe land use changes. However, in these models, social interactions have been very rarely integrated. For exceptions, see Satake et al. (2007), who simulate foresters' harvesting decisions taking into account information flow with neighbours, and Mandemaker et al. (2014) who include in a land use transition model variable levels of farmers' rationality and influence of cooperation. Despite these features, to the best of our knowledge, these models have not been used to upscale insights gained by a process-based model at the lower scale to the higher scale. In this regard, we want to highlight that the Cipriotti et al. (2016) approach is quite unique in the way the Markov transition matrix is calculated, namely based on process-based simulations at the micro scale.

However, we see specific limits of this approach: To derive an appropriate set of transition matrices and select the right matrix from this set, one needs to know both the key model drivers and the corresponding target variables that sufficiently describe the plausible system states. SES models that explicitly represent changes in system states or regime shifts at local scales might be appropriate for this scaling approach, if the same key drivers are still relevant for the same target variables at the larger scale. Nevertheless, key drivers and target variables can change in importance from smaller to greater spatial extents, which may require dedicated

modelling methods in the future (e.g., by structural equation modelling or principal component analysis). For the definition and choice of model drivers and target variables, computational demands may need to be considered; if many drivers have to be included, this increases the computational effort in creating the transition matrices, as the model at the lower scale has to be run for all combinations of driving variables. However, a larger number of transition matrices does not necessarily increase the computational effort at the large scale, as the matrices are usually sparsely populated (most values 0 besides the main diagonal). Finally, to be able to apply the matrix models in general, certain assumptions of the system processes must hold, e.g., that the current state only depends on the previous system state (i.e., the Markov property, also called *memorylessness*, see Geoghegan et al., 1998). In our example, this principle would be violated if (non-linear) memory effects in household behaviour or path dependencies due to initial state, such as the distribution of neighbours discussed above, play a large role. Alternative methods, such as deep neural networks, may be more suitable and flexible when many driving variables influence model dynamics (Rammer & Seidl, 2019 for upscaling of forest dynamics).

5.2 Regionalisation of model parameters (Strategy 2)

FORMIND is an individual-based and process-based forest growth model that has been developed to simulate forest dynamics in species-rich tropical forests, with recent applications in temperate forests and grasslands (Fischer et al., 2016).

The forest model is usually applied to the local scale and, thus, is site-specific and its parameterisation requires sufficient inventory data. Nevertheless, it was possible to extrapolate local forest dynamics of FORMIND to a biome-wide extent by deriving appropriate proxy variables. In this approach, here called *regionalisation* (Rödig et al., 2017, 2018, 2019), FORMIND was first applied to four local forest stands in the Central Amazon where detailed forest inventory data at multiple scales were available. Second, extensive model testing was conducted, which has shown that, when changing solely the tree mortality rate of shade tolerant trees, the forest model can reproduce spatial variability of 114 forest inventories across the Amazon (Rödig et al., 2017). It was also found that tree mortality correlated with local environmental characteristics. As environmental variables are available globally, the tree mortality rate could be extrapolated to the whole area of the Amazon rainforest as a function of precipitation and clay content of soil (see Figure 3). Using these proxy variables, the regionalised forest model FORMIND can thereby simulate forest dynamics at the scale of an individual tree for the entire biome (7.8 million km^2). This method can be classified as our second upscaling strategy, i.e., upscaling of input data, using the transfer function derived from the regression.
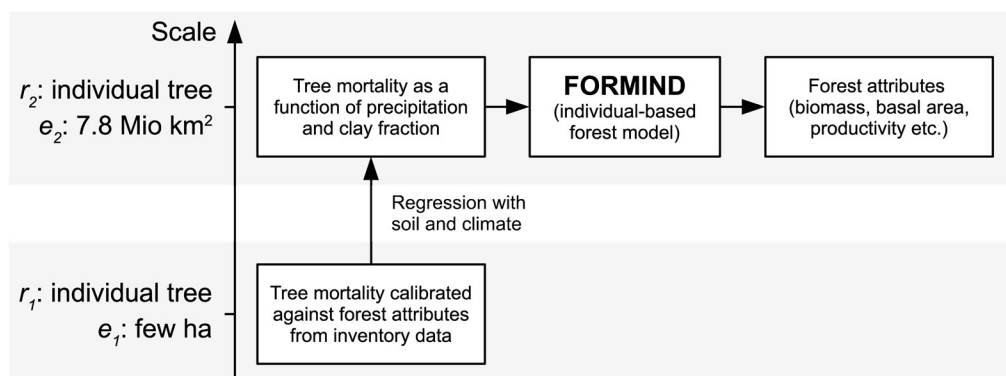

Figure 3: Application of Strategy 2 – Upscaling of input data / model parameters – of the upscaling scheme to the example of FORMIND (Rödig et al., 2017).

In a socio-environmental context, the method of deriving proxy variables to upscale a local model could be applied, for example, to estimate spatial patterns of livestock numbers for areas such as Sub-Saharan Africa. Deriving estimates across such large extents is difficult, as input data are collected with different methods and at different resolutions. Furthermore, livestock numbers depend on farmers' decisions such as where and when to graze, how many animals to stock or sell or whether to provide supplementary feeding. Such decisions could be modelled using an ABM that simulates rangeland dynamics on a local scale (e.g., village level), taking into account the individual and collective decisions of households with respect to livestock and grazing. These decisions depend on different factors, and extensive case-study work would be required to observe them in

detail across large extents. However, similar to the regionalisation approach applied in FORMIND, identifying a set of proxy variables that explain decision-making in local studies would allow for estimating livestock numbers at large scales. Data for such proxy variables need to cover the extent of the region of interest, therefore environmental variables such as primary productivity, vegetation indices (e.g., NDVI), land cover types and climate are suitable candidates. Furthermore, economic, social and cultural data at regional or country level, such as GDP, population density, poverty measures, or indices for market access (e.g., FAOSTAT), might be appropriate.

This conceptual example again reveals challenges that are specific to SES. While heterogeneity can theoretically be represented via the environmental, economic and social proxy variables, these data may not be available at sufficient resolution (e.g., economic or social data may only be available at country level, such as GDP). As the regionalised model is run across a larger extent but still at a fine resolution (i.e., $r_1 = r_2$), aspects of human agency may be well represented by the approach. However, human decision-making unquestionably depends on a larger or more complex set of factors than tree mortality in the ecological example, which might make deriving a suitable set of variables that are available across the extent of the region of interest more difficult. This highlights the inherent differences between upscaling in systems that are ultimately governed by universal physical laws and those that are governed by context-specific and evolving social institutions. Furthermore, across large extents new aspects that are not included in the model at the local scale might become relevant, such as long-distance trade or telecoupling effects. Therefore, even if appropriate proxy variables are available for specific sites, estimates of livestock numbers at the large scale might still deviate from empirical observations if not all aspects of decision-making relevant for livestock management can be mapped in the model.

Nonetheless, the approach of deriving proxy variables is promising for transferring local case study knowledge to larger extents where empirical observations are lacking. Existing maps such as the Gridded Livestock of the World (FAO, 2007; Robinson et al., 2014) offer the possibility of cross-comparison of results and could also be used to guide new research in areas where projected livestock numbers and actual data do not match: these areas could be focal areas to investigate relationships or mechanisms that explain livestock numbers that are not represented in the model.

6. Discussion

6.1 Improving the transferability of upscaling strategies

We advanced our understanding of upscaling in socio-environmental systems (SES) by identifying current challenges related to upscaling in SES models and presenting a scheme of upscaling strategies that enables a better description and comparison of upscaling methods and thereby facilitates the transfer of existing upscaling methods to SES. We have identified four characteristics of SES that pose specific challenges for upscaling: 1) heterogeneity, 2) interactions, 3) learning and adaptation, and 4) emergent phenomena (Section 3). We demonstrated how SES modellers could be guided by examples from ecology that deal with the challenge of heterogeneity, by presenting a regionalisation example of the Amazon Forest and its potential transfer to livestock estimations (Section 5.2). Similarly, we provided an ecological example for the challenge of interaction that uses a matrix model (5.1). While limits to this transfer have been identified, learning from methods in ecology is a useful approach for advancing upscaling in SES.

Our upscaling scheme expands existing schemes (in particular Bierkens et al., 2000; Ewert et al., 2011) and aims to foster cross-fertilisation between disciplines and exploit the full potential of existing upscaling strategies. Specifically, our scheme provides a number of improvements, namely: a) a clearer distinction of what is being scaled up (i.e., data, models or both) and how this is done (e.g., what class of transfer procedures are used); b) removing a number of ambiguities in previous schemes; and c) an easy-to-grasp visualisation through simple diagrams for the different upscaling strategies. We provide examples for each of the upscaling strategies within the scheme (see Section 4 and Table 1) and demonstrate the scheme's usefulness by showing how upscaling strategies from ecology can be transferred to SES (see Section 5). Here, the scheme allowed us to obtain a clearer understanding of the upscaling methods used, in contrast to many modelling endeavours, where scaling is done implicitly without stating, e.g., what is scaled, which scaling dimensions are involved, or which methods are used. Our scheme helps to uncover these implicit scaling assumptions that are taken throughout the modelling

process, and to present them in a transparent manner. This increased transparency helps to improve both the understanding of upscaling itself and the transferability of upscaling methods.

In the following, we discuss challenges remaining for upscaling in SES models (6.2), reflect on limits of our upscaling scheme (6.3) and propose several next steps (6.4).

6.2   Open issues and limits regarding upscaling in SES

The upscaling examples presented in Section 5 do not address the challenge of learning and adaptation. This does not come as a surprise since learning (understood here as changes in the decision rules themselves) is mostly considered a part of human decision-making and not at the core of environmental models. Furthermore, the representation of learning and adaptation in SES models is still a challenge in itself and is further constrained by the difficulty of representing heterogeneity and interaction at larger extents. Thus, we see addressing the challenges of heterogeneity and interactions as a prerequisite before we can develop upscaling methods for learning and adaptation. However, there might be approaches in disciplines such as behavioural ecology where SES models can draw insights for upscaling of learning and adaptation (Mangel & Clark, 1989; Railsback & Harvey, 2020). In these cases, our scheme could be used to position these approaches in a systematic manner (e.g., a meta-model that approximates finer-scale changes in decision rules sits within Strategy 3).

Our upscaling examples also do not address the challenge of detecting emergent phenomena when upscaling. Socio-environmental interactions may lead to emergence in distinct ways than in purely ecological systems (Schlüter et al., 2019). For example, in telecoupled SES, aggregate forms of behaviour link two (or more) spatially disparate regions. Emergent phenomena can appear as a result of these interactions (e.g., demand for soybeans in China can lead to deforestation in Brazil, Liu et al., 2013). Here, there is a need for cross-scale upscaling methods to approximate behaviour in each region and dynamically bridge the spatial divide. Such methods most likely resemble nested models, thus fitting within Strategy 5 in our scheme. Some work in this area is beginning to emerge (e.g., Dou et al., 2019), yet more research is needed to upscale other unique types of socio-environmental emergence.

Regarding upscaling in general, modellers should keep in mind the limits of upscaling and the risk of transferring upscaling methods, such as the scale domain limits over which a particular scaling law is valid (Scholes, 2017). Thus, if an upscaling method exceeds a particular (spatial, temporal or organisational) scale domain, then upscaling might not be appropriate and a more detailed local or regional model is more suitable (see e.g., Azaele et al., 2015; Pausas & Dantas, 2017). Advancements in computational methods and the vast increase in computing power in recent years enable the brute-force integration of small temporal and large spatial scales or vice versa (e.g., plate tectonics, Osei Tutu et al., 2018), rendering alternative upscaling methods unnecessary in some cases.

However, in SES, events that occur in regions larger than the original system extent can raise additional challenges that cannot be summed up in fixed boundary conditions as, due to their rapid changes, they can still have a large influence on behaviour. Such influences (e.g., from global markets and supply chains, telecoupling, or digitalisation) may introduce interactions and complexity that are not easily captured by upscaling techniques established in ecology, where such externalities can often be assumed to be constant or slow to adapt compared to the temporal resolution of crucial processes of ecological dynamics. Furthermore, we currently focus on upscaling only and acknowledge that such a unidirectional view has limitations, particularly when cross-scale interactions are important (Cash et al., 2006; Scholes et al., 2013).

6.3   Limitations of the presented upscaling scheme

The main purpose of our proposed upscaling scheme is to provide a standardised method for classifying and describing upscaling methods, thus facilitating the comparison as well as the transfer of upscaling methods to a new context. Therefore, it does not provide direct solutions to address the specific upscaling challenges mentioned above. While the scheme is well suited to map a particular upscaling method and to uncover its technical constraints, it currently does not aim to assess the suitability of that upscaling method for a given case or to determine which scaling challenges can be addressed by that method. Thus, the scheme does not address some of the conceptual challenges of scaling in SES, in particular those arising from different epistemological perspectives on scale (Manson, 2008). Whereas modelling in general and upscaling in particular requires a clear

specification of resolution, extent, and levels to define scale, this is often not straightforward from a human-environment perspective, where scale may be subjective and socially constructed (Manson, 2008; Marston, 2000). This may pose an additional challenge for the transferability of upscaling methods to SES.

In addition to these more conceptual limitations, the scheme currently lacks a clear representation of the properties of the elements to be scaled, especially those properties that must be preserved at the target scale, for example, heterogeneity or interactions. Finally, there is so far no classification of transfer procedures that provides information about which procedures preserve these properties of the elements as well as preserves general scale properties such as resolution or extent.

6.4   A way forward

We propose three tasks to further advance upscaling in SES, namely a) encouraging the use of standardised descriptions of upscaling methods, b) advancing our proposed upscaling scheme and c) improving the availability of and access to data necessary for upscaling:

- To make upscaling methods more accessible to other users and modellers, we encourage authors to provide a standardised and transparent description of upscaling steps and strategies used, as well as to store well-documented scaling examples in an online repository (e.g., CoMSES Net). For studies that have a research objective that involves upscaling, adding our scheme to the description of a model, e.g., by including it in the ODD/ODD+D protocol (Grimm et al., 2006, 2020; Müller et al., 2013), would be one option to enhance the transparency of model descriptions.

- To advance our upscaling scheme, we propose a number of steps: i) including a clearer depiction of the properties of the elements that are being scaled, specifically of those properties that need to be maintained at the destination scale, (e.g., heterogeneity), ii) creating a classification of transfer procedures that provides information on which procedures preserve those properties of the elements, as well as general scale properties (i.e., resolution and extent), and iii) developing guidelines for selecting suitable upscaling methods in SES. The assessment of the suitability of particular upscaling methods for a specific research question is important to consider but was beyond the scope of our work (see, e.g., Fritsch et al., 2020 for an overview on upscaling methods for different purposes). In this regard the comparison of different upscaling methods for a specific research problem is also of value (e.g., Zimmermann et al., 2015).

- To enhance progress in the applicability and further development of upscaling methods it is important to discuss the current availability and future need of measurements at the different scales. Where is data missing? How can information gaps be closed? New technologies and approaches such as remote sensing, citizen science or (improved) survey methods can help to fill these gaps. For example, recent efforts to establish large-scale datasets of the diversity in land use decision-making (Malek & Verburg, 2020) could, in conjunction with remote sensing data, inform the upscaling of regional SES models to global scales. Such efforts could be integrated with dynamic models of behavioural change (e.g., Magliocca et al., 2013) to generate global, dynamic typologies of land use decision-making under alternative exogenous conditions. To achieve this, an increased sharing of models and datasets will be necessary.

Advancing upscaling strategies and improving their transferability – e.g., by using our proposed scheme – presents one step toward the development of a new generation of large-scale behaviourally-rich socio-environmental models. However, to achieve this, we see the need to a) foster interdisciplinary exchange on suitable upscaling methods and b) further develop theories for SES to improve our conceptual understanding of key processes of socio-environmental systems.

Acknowledgements

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