Current Landscape Ecology Reports (2019) 4:125–138
https://doi.org/10.1007/s40823-019-00046-4

INTERFACE OF LANDSCAPE ECOLOGY AND NATURAL RESOURCE MANAGEMENT (Y. WIERSMA AND N. KOPER, SECTION EDITORS)

How Integrated Ecological-Economic Modelling Can Inform Landscape Pattern in Forest Agroecosystems

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Published online: 8 November 2019

Abstract

Purpose of Review The purpose of this review is to analyse recent advances in ecological-economic modelling designed to inform desirable landscape composition and configuration. We explore how models capture the economic and ecological consequences of landscape pattern, and potential feedbacks to the responses by policy or landholders.

Recent Findings Modelling approaches are becoming increasingly interlinked, coupling components of empirical-statistical modelling, spatial and bioeconomic simulation, land-use optimization and agent-based models. We analyse recent methodological advances and find that only few examples capture feedbacks between landscape pattern and decision-making.

Summary We outline how future hybrid models could build on these recent advances by inter alia an improved representation of landscape patterns, refining the theory behind decision-making, incorporating uncertainty and reducing model complexity. We conclude that coupling recent developments in land-use optimization and agent-based models may help bridge gaps between modelling philosophies as well as parsimony vs. complexity. This fruitful field of research could help to improve understanding on the role of landscape pattern in social-ecological systems.

Keywords Bioeconomic modelling · Social-economic models · Portfolio analysis · Landscape metrics · Ecosystem services · Trade-offs

Introduction

Ecosystem management has lately been framed as a “wicked problem” [1], which arises from the interdependence between economic and ecological systems. To tackle this problem, the landscape approach has emerged. It seeks to include interactions between human and natural systems through inter- and transdisciplinary research for different socio-economic and ecological contexts [2]. A key question is how landscape patterns are impacted by human decisions, and how these decisions affect ecological functions with implicit consequences for human welfare. Landscape patterns reflect both the composition and spatial arrangement, or “configuration” of land uses and land covers (LULC) within the landscape structure [3•]. Landscape patterns refer to the heterogeneity of landscapes, which is seen as an important driver of local biodiversity and for maintaining ecosystem functioning [4–7]. Here, we focus on human-dominated landscapes, which usually comprise both, agricultural and forest management, as well as natural ecosystems. To this interface, we refer to with “forest agroecosystems”.

This article is part of the Topical Collection on *Interface of Landscape Ecology and Natural Resource Management*

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Designing sustainable landscape patterns [8] can only be achieved by integrating economics with natural sciences. As these interrelations can hardly be solved with analytical approaches only, modelling approaches now form the backbone of integrated economic-ecological landscape research. Attempts to model ecological-economic interactions started with “bioeconomic” [9] models (Table 1) which focused on investigating optimal, i.e. predictive, management strategies at the farm level or for a social landscape planner at aggregated levels [10]. They have been criticised, to build on simplified assumptions, while lacking predictive power, often demanded by decision-makers [11]. More complex modelling approaches, more lately summarized under the term “social-ecological models” (Table 1) have emerged [11]. Among them are descriptive system dynamics and simulation models, as well as agent-based models [12] (Table 1). Here, we summarize these models under the term “ecological-economic” models. These approaches are no mutually exclusive alternatives, while there is a clear trend to integrate components of different approaches [13•].

This review aims at giving an up-to-date overview on recent advances in ecological-economic modelling designed to inform landscape pattern. We explore how future models could effectively couple model components to contribute to a better understanding of the role of landscape pattern in social-ecological systems. Here, we refer to studies which integrate (landscape) ecology of forest agroecosystems with socio-economic considerations and explicitly analyse landscape composition and/or configuration with a decision and management-oriented perspective. To give an up-to-date review, we focus on recent advances, covering the time span between 2015 to April 2019.

Our review is structured along the following questions:

1. How are economics and landscape ecology (conceptually) interlinked with landscape pattern of forest agroecosystems?
2. How do recent ecological-economic modelling approaches capture these interlinkages?
3. Which steps to take in order to better inform landscape pattern?

Our objective is to provide an overview for colleagues who are familiar with landscape ecology but are new to the field of ecological-economic modelling. But, we also hope that his article may inspire those working with ecological-economic models to more explicitly include landscape patterns in their research questions. In the last section, we outline future fields of research to facilitate an improved coupling of landscape ecology and economics in ecological-economic models.

Conceptualizing the Interlinkages Between Economics, Landscape Ecology and Landscape Pattern

Landscape research commonly links (socio) economics with ecology by viewing economics as driver of land use decisions—illustrated as early as 1845 by Johann Heinrich von Thünen [14] (left solid arrows in Fig. 1). A landscape pattern may be viewed as a consequence of the averaged or aggregated land-use decisions of individuals or communities owning or managing the land to whom we will also refer to as “agents”. Speaking in

Table 1 Brief definitions of the model approaches considered in the article (see also Table 2 for comparison of models)

Socio-ecological systems	Coupled Human-Environment systems [11]
Ecological-economic models	Models integrating environment-economy interactions to analyse dynamic processes, cause-effect relationships and potential solutions for environmental problems. The term may be used as synonym for socio-ecological models, while we emphasize the economic model component in this review.
System dynamics	System dynamics seek to understand non-linear and dynamic behaviour of complex systems through compiling individual causal or observed relationships, transition probabilities and feedbacks into one model. Methods of system dynamics may be qualitative and/or quantitative. (based on [11])
Simulation models	Simulation models operationalize information from system dynamics into computer models which may approximate the defined process or system in order to conduct experiments and understand the system’s behaviour. The simulation model usually consists of a series of mathematical equations which exceed the potential of a purely analytical solution.
Bioeconomic models	Bioeconomics aims at the integration of two disciplines, economics and biology. Bioeconomic models integrate economic and biophysical components, and are seen as extensions of economic models. They therefore usually build on optimization models, where an economic objective function is to be maximized given natural resource and economic constraints (based on [10, 11])
Agent-based models	Structurally-rich models, which “give a computational representation of agents, their properties, and interactions with each other and their environment” [11]. Agent-based models are often spatially explicit and consider the temporal dynamics of model processes.

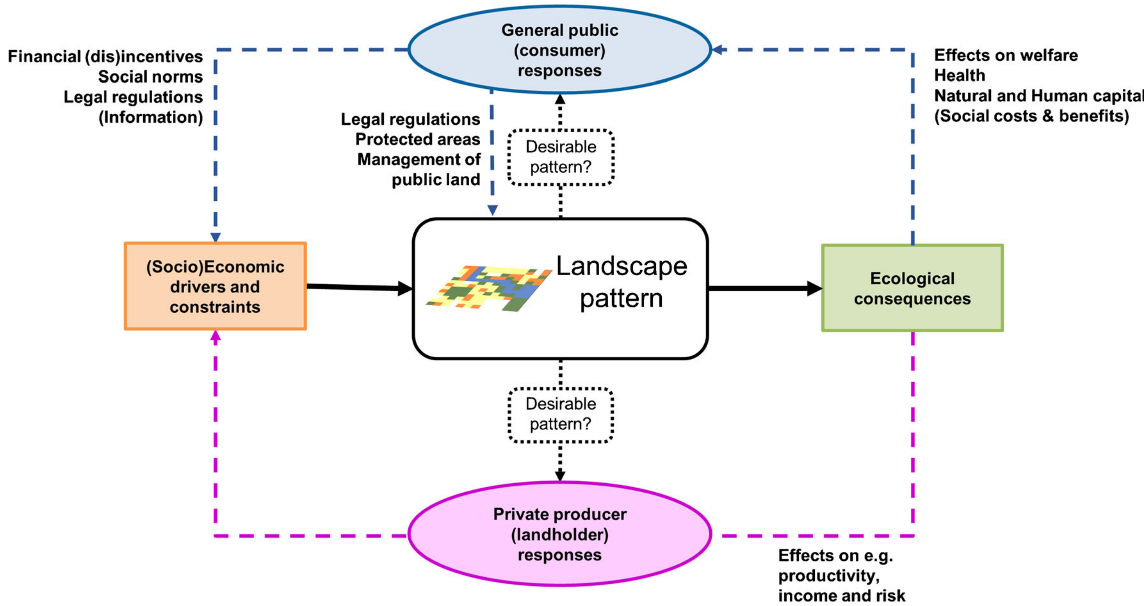

Fig. 1 Conceptual feedbacks between landscape pattern (i.e. landscape composition and configuration), ecological consequences and (socio) economic drivers of decisions analysed in this review. Direct links captured in ecological-economic models are depicted as solid lines, while potential responses and feedback loops are depicted as dashed lines

economic terms, agents allocate scarce land resources to LULC options in a way that maximizes their utility. Utility is an economic unit to express the level of satisfaction, which may be expressed but is not limited to willingness to pay. As we will show later in this review, it is not the only one but still the most common concept for mimicking land-use decisions.

To describe resulting landscape pattern (centre box in Fig. 1), landscape metrics range from measures of compositional diversity or heterogeneity, such as the Shannon Index of Diversity, the Simpson's evenness index or share of natural vegetation, to aspects of configuration or landscape aggregation (see [6]), such as patch density, edge density, Euclidian nearest neighbour distance, contagion index among others [15] and most recently also aspects of the three-dimensional-space (e.g. [16]).

Changes in landscape pattern may have ecological consequences (right solid arrow in Fig. 1). Landscape ecology has linked landscape metrics to species habitat, species distribution patterns or conservation value [17] and more recently also to ecosystem service (ES) provision [6, 7]. Concepts to maintain and enhance ecosystem functioning and related ES emphasize the importance of high compositional and configurational diversity, connectivity of sufficiently large habitats and high shares of native vegetation, while reducing field sizes and input use [5, 18]. In addition, (re-)introducing specific landscape elements, such as flower strips [18, 19], forest patches and agroforestry, are promoted [20].

The link between economic decisions and ecological consequences is not unidirectional. Ecological consequences may feed back into economic decision-making (illustrated by the dashed arrows in Fig. 1). Two main feedbacks have been conceptualized: first, classic bioeconomic farm models (see [10, 21]) follow the premise that a (rational) landholder, here also referred to as "private producer", may adjust land-use decisions, provided that anticipated biophysical and ecological consequences of landscape patterns directly affect the decision criterion, such as utility (see lower pink dashed arrow in Fig. 1). This might be the case when yields of diversified land-use practices are increased due to synergistic growth effects [22] or reduced soil degradation [23].

The second line of feedbacks integrate ecological consequences for the overall society as inter alia operationalized by the ES concept, which are then economically valued using methods of welfare economics [24] (upper, blue dashed line in Fig. 1). This means that public decision-making will be affected by improved knowledge on changes in natural and human capital, but also intrinsic values and/or derived social costs related to changes in landscape patterns. As a response, the general public, represented by policy decisions, may introduce legal regulations or financial incentives/disincentives, such as payments for ecosystem services [25] or may try to influence social norms, e.g. through education.

Figure 1 reveals that socio-economic criteria in an economic-ecological system reflect both, drivers and consequences of landscape pattern. Yet, our understanding of how landscape pattern affect these interactions is still incomplete. In the following section, we will review how current modelling approaches capture these feedback loops.

Brief Summary of Recent Advances in Ecological-Economic Modelling Approaches

We classify recent modelling approaches into four main categories: (i) empirical statistical modelling, (ii) system dynamics and mechanistic simulation, (iii) LULC optimization models and (iv) agent-based models, following earlier reviews [3•, 11, 12] (Table 2).

We used two different review methods: first, we screened for current review articles, which exist for each of the individual approaches. An overview and critical analysis of recent methods more specifically referring to landscape pattern is, however, missing. We therefore refer the reader to up-to-date reviews for each modelling category, while we focus on methodological approaches which have emerged since 2015. In a second approach, we screened the ISI Web of Knowledge using the search algorithm TS = (landscape* AND econ* AND (forest* OR agri*) AND model AND (config* OR compos* OR matrix) AND IC Timespan = 2015–2019). We also replaced the general term "model" by the specific model categories (e.g. "optimization", "agent* OR agent-based" etc.). We only included studies which explicitly incorporate and investigate landscape pattern, i.e. investigate composition, configuration or structural landscape elements or deal with decisions at the farm level, while considering feedbacks at landscape scale or an element of upscaling to the landscape. We excluded the topic of urban development and sprawl, more linked to geographical terrestrial planning than landscape ecology. The list of studies cited here does not claim completeness; our intention is to give insightful examples.

For each modelling approach, we analyse (i) which ecological-economic links and feedbacks are considered and (ii) how methodological aspects are implemented, such as the measure of landscape pattern used, the consideration of aspects of time dynamics and uncertainty, as well as model complexity (see Table 2). (iii) We analyse how each model has been linked to other approaches. From these findings, we will derive six key issues for further research in the last section.

Empirical Statistical Modelling

Empirical statistical models aim at revealing the correlative nature of the links between landscape pattern and ecological and economic drivers/consequences, thus mostly focussing on the solid arrows in Fig. 1 only. But, they have recently also considered the upper feedback loop in Fig. 1, by investigating effects on ES values [26]. Recent studies suggest a generally positive relationship between heterogeneous landscapes and ES values [27, 28]. Zhang and Gao [28] showed that the total ES value was negatively correlated with landscape fragmentation for gas regulation, climate regulation, soil protection and raw materials, but was positively correlated with water supply, waste treatment, biodiversity protection and recreation at the sub-watershed scale. They also showed that patch size is a critical variable affecting the relationship between landscape metrics and economic values, which needs to be accounted for in future research.

While there is growing availability of empirical models describing ecological consequences, the understanding of socio-economic drivers of landscape pattern is still weak (left solid arrow in Fig. 1). Ochoa et al. [29] outline that empirical studies have focused on explaining income diversification, but few studies have actually used land-use diversification at farm levels as a dependent variable. They found for a landscape in the dry forest of Ecuador that land-use diversification was driven by subsistence needs and that financial support and off-farm income may adversely affect landscape heterogeneity. Weigel et al. [30] found that on-farm diversification of crop portfolios showed a weak effect on stability of economic returns in southern Germany. They attribute this finding, which contradicts economic theory (see [31]), to the strong impact of agricultural subsidies. The finding undermines the importance of considering both public and private responses in ecological-economic models.

Hence, empirical-statistical models provide important information, lately also benefitting from advances in spatial statistics to predict landscape changes [32]. Yet, they are less suitable as a stand-alone model to investigate entire systems and feedback loops as depicted in Fig. 1.

System Dynamics and Simulation

System dynamics and simulation models often build on statistical correlations and/or physiological processes, to achieve an improved system understanding of dynamically complex problems [11]. In the context of landscape patterns, the entire feedback-loops depicted in Fig. 1 may theoretically be captured. This model category comprises a wide range of approaches from semi-quantitative models (e.g. causal loop diagram or fuzzy cognitive maps [33]) to quantitative mechanistic simulations, which we will mainly focus on. Approaches which are of particular appeal for spatial landscape simulation are Markov chain models (MCM), state and transition models (STMs) and cellular automata (CAM) [34].

MCMs and STMs describe LULC changes using probabilities of change. STMs in the landscape context are based on the assumption that each, usually discrete, spatial unit of a landscape can exhibit multiple alternative discrete states (i.e. LULCs) in discrete time. Transitions between states take place with a certain probability. Recent developments are for example summarized in [35•]. They suggest a STM, in which the stochastic transition probabilities and transition types may be

Table 2 Summary of literature review

Model category	Subcategory	Modelling philosophy	Feedbacks (responses) considered		Landscape patterns considered		Continuous patterns	Aspects of time dynamics	Integration of uncertainty	Model complexity	Recent reviews	Recent example studies
			Pub	Priv	Comp	Config						
Empirical statistical	Spatial statistics	descriptive/ predictive	(✓)	x	✓	✓	✓	time as covariable	Estimation of prediction error	+	[26, 32]	[27, 28]
	Non-spatial mostly econometric approaches		(✓)	(✓)	✓	(✓)	✓			+	[98]	[29, 30]
System dynamics and process-based simulation	Markov Chain models	descriptive/ predictive	✓	✓	✓	✓	x	Adjustments within time are possible; simulation period is pre-defined	Captured in parts in (predefined) transition probabilities	++	[33, 34]	[40–42]
	State and Transition Models		✓	✓	✓	✓	x				[34]	[35, 36]
	Cellular automata		✓	✓	✓	✓	x		Mostly no, rule based simulation of change		[34]	[38, 40–42]
	Bioeconomic farm simulation		✓	✓	✓	✓	x		Inclusion of stochastic processes, e.g. timber and yield fluctuations		[21]	[22, 43]
Optimization models	Classic bioeconomic model	prescriptive (single goal under constraints)	✓	✓			✓		In recent advances yes (e.g. fuzzy programming)	+	[10]	[92]
	Portfolio-based		✓	✓	✓	(✓)	✓	future is known to decision-maker but dynamic programming emerges	Yes, as driver of decision-making	+(+)	[10, 31, 45]	[47–49, 49, 99]
	Multicriteria optimization	prescriptive (multiple goals)	✓	✓			✓		Possible, but only recently included	+(+)	[10, 52, 53]	[51, 56]
	Pareto optimization	prescriptive (trade-offs between goals)	✓	✓	✓	(✓)	(✓)	Depends on simulation approach used	Usually not	++	[60]	[54, 61–63]
Agent-based models		descriptive/ constructivist	✓	✓	✓	✓	(✓)	temporal dynamics considered, dynamic optimization approaches included	Stochastic processes and effects of uncertainty on decision-making could be included but hardly done	++	[13, 64, 66, 68, 74, 88]	[67, 70–73, 91]

Feedbacks refer to our concept defined in Fig. 1 (Pub = public response, Priv = private producer's response). Ticks refer to studies found, which integrate such aspects (Comp = landscape composition, config = configuration). Grey ticks denote aspects which can theoretically be included but is seldom done so far according to our review. Ticks in parentheses denote aspects which are considered under specific conditions, described in more detail in the text, or which could be developed in the future. The "x" Symbol refers to aspects which cannot be integrated by the respective model category. In the column "model complexity" one "+" denotes high and "++" very high complexity and computational time needed. The intermediate symbol +(+) expresses that for this model category complexity may be reduced, depending on algorithms used. Recent studies refer to example studies within the time span 2015 to April 2019, updated during the simulation process [35•]. Recent STMs also allow for including target areas instead of transition probabilities [35•]. Both are important developments to include changing economic conditions and political scenarios. For example, Costanza et al. [36] simulated the spatial landscape dynamics resulting from different biomass production scenarios to meet bioenergy demands in North Carolina. Exogenous economic demand was incorporated by using the outcomes of an economic timber supply model [37] as target areas for the STM. They found that satisfying bioenergy demands from forestry rather than biomass crops increased forest area but decreased ecological quality (i.e. structural diversity) of remaining forests.

Similar to MCMs and STMs, CAMs are based on simulating changes in the state of grids (or cells), but based on pre-defined rule sets, mostly omitting stochastic processes. Their advantage is that neighbouring cells are defined in relation to a specified cell, which is important for implementing economic feedbacks. For example, Grashof-Bodkdam et al. [38] assume in their model that the more farmers invest into green infrastructure, the reliability of natural pest regulation increases as compared to conventional use of pesticides. They find that high social cohesion and conversion costs were the most important drivers for adoption of landscape elements.

All three simulation approaches have been coupled with spatial statistics to predict LULC change. Among them are CLUE-S [39], CA_MARKOV [40] and DINAMICA EGO [41] (see [34] for detailed descriptions and comparisons). These models have a predominantly predictive character, representing the unidirectional link of economic drivers affecting spatial patterns with consequences for ecological outcomes. Feedback loops focus on the estimation of economic values of ES [40] or analysing differences in policy scenarios implemented through allocation constraints [42] (see upper dashed lines in Fig. 1).

Process-based simulation models furthermore play an important role for capturing effects of heterogeneity at the field and farm level. Such bioeconomic simulations combine biophysical growth models [21] with economic simulations, including stochastic and time dynamic aspects, such as price fluctuations or extreme weather events [22, 43]. The results can also be integrated into optimization approaches (see below) in order to reflect adaptive management of landholders (see lower dashed arrow in Fig. 1).

In sum, we found important advances in accounting for spatial and time dynamics of landscape pattern. Yet, the majority of simulation models reviewed focused on describing ecological consequences from few discrete socio-economic scenarios, rather than a comprehensive modelling of potential feedbacks.

Normative Land-Use Land-Cover Optimization Methods

Instead of asking "what if", LULC optimization models ask "what should be", irrespective of what is. In Fig. 1, this perspective is depicted by boxes, denoted as "desirable pattern", representing the question of what would be the optimal landscape pattern to fulfil public consumer's (upper box) and/or private producer's needs (lower box). Mathematical programming is applied to estimate such "optimal" patterns to satisfy one or multiple goals. This approach has the advantage that a solution is searched for within a continuous set of land-use patterns, rather than pre-defined scenarios as described above. These approaches are predominantly used in farm-based bioeconomic modelling [10]. Recently, this field has contributed to an improved understanding of the risk-reducing effect of land-use diversification [10], by incorporating portfolio theory [31]. This theory builds on the statistical effect that if the fluctuations of the decision criterion (e.g. economic return or yield) for individual LULCs are not perfectly correlated, a higher compositional diversity will reduce the standard deviation of the expected mean of this respective criterion. This risk-reducing effect has been demonstrated for inter alia economic returns when mixing different crop types within agricultural farms [44], tree species or stand types in the forest [45] or combinations of trees and crops within a farm [22, 46, 47] and even for allocation of water resources [48] at a landscape scale. This provides economic arguments for higher degrees of land-use diversification and the integration of structural elements, such as agroforestry at the farm level [22] (lower dashed line in Fig. 1). Yet, such analyses are very data intensive, as the approach is based on the correlations and covariances between the decision criterion of all LULC considered. To overcome this drawback, robust optimization approaches have been suggested [49], which avoid the need for covariances. Analysis of compositional diversity at the farm level have been upscaled to the landscape level by using area weighted estimates of optimized farm portfolios for different farm types [50] or by optimizing spatially explicit farms by using the sum of farmer's utilities [51••].

In order to cover public responses (Fig. 1 upper dashed line), multi-criteria decision analysis has been coupled with mathematical programming [52•, 53]. Two main logics are used to combine multiple objectives into one mathematically solvable objective: they may be considered as sum or linear combination of weighted individual goals [54, 55]. This implies that indicators (e.g. ES) are substitutable. Alternatively, goal programming strives to reduce the distance across each of the multiple goals to the attainable maximum [56••, 57], thus avoiding substitution effects. Recently, uncertainty has also been integrated into multi-objective goal programming following the logic of portfolio theory [56••]. This study demonstrated that a high Shannon Index of land-uses buffered the risks associated with the uncertain provision of multiple ES at a landscape scale.

A drawback of these approaches is that they are usually not spatially explicit, with [58] being one of the few exceptions. Representing spatial dynamics requires hybrid approaches, which either use a set of rules to distribute optimized proportions of LULC types in a real-world landscape [56] or by coupling them with CAMs [59]. For analysing spatially explicit landscape configurations, deriving the Pareto frontier (also called efficiency or production possibility frontier) has become popular. It illustrates the landscape pattern that provides the highest level of one criterion (e.g. ES) for each target level of the other criterion [60]. The underlying logic does not allow one criterion to improve, without compromising the other. It is thus well suited for illustrating trade-offs between ES [61] and for testing effects of policy scenarios [62]. For identifying efficient combinations, evolutionary and genetic algorithms are used [63], and more lately also artificial immune systems and warm intelligence algorithms [52•]. These algorithms require long computation times and cannot offer an exact solution. This makes results hard to reproduce and bears the risk of falsely identifying solutions as optimal, which are actually suboptimal. This may explain why effects of uncertainty on land-use decisions have hardly been incorporated in Pareto frontiers to avoid further complexity.

To summarize, optimization approaches are able to consider a continuous set of landscape pattern and consider important feedback loops between landscape diversification and land-use decisions. Yet, they are usually data intensive and therefore mostly disregard aspects of land-use configuration. LULC optimization models are closely interlinked with other models. They build on simulation approaches while often being a component of ABMs.

Agent-Based Modelling

ABMs have received increased attention since the late 1990s and are considered particularly useful for analysing ecological-economic trade-offs at landscape scale [11, 64•, 65, 66]. This is because they account for heterogeneous decision-makers and interactions between agents, as e.g. diffusion of knowledge, attitudes or beliefs. They also account for temporal dynamics. Given their rule-based structure, ABMs allow for adjustments within each time step. They are thus capable of incorporating complex, non-linear feedback loops as depicted in Fig. 1. Agents may represent farmers, households, communities but could also represent governance forces and institutions [67, 68]. Decisions are usually implemented via rule-based approaches, multivariate regression [69, 70] but may also involve mathematical programming at the individual agent's (farm) level [71••, 72] and Bayesian networks [67, 73].

In terms of landscape patterns, ABMs consider spatial composition but also configuration. Similar to optimization approaches, they can be made spatially explicit by coupling simulation runs with GIS information [67]. Yet, we found only few studies which actually focus on effects on landscape patterns rather than landscape allocation, making its output similar to that of optimization models [72]. Given that ABMs have a strong basis in ecological research (where they are often called individual-based models), they would actually be suitable for representing non-linear ecological feedbacks of landscape patterns, for example related to biodiversity [3•]. Yet, in a review of ABMs focussing on agricultural policy evaluation [74], only 2 out of 30 studies used spatially explicit data, while the majority used random allocation of agents within space, disregarding aspects of autocorrelation. This may be attributed to the high data demand for such models. Gonzalez-Redin et al. [67] use a spatially explicit ABM to show that the Wet Tropics of North-East Queensland may be one of the rare examples, where the current landscape pattern performed better in providing biodiversity, carbon sequestration and sugarcane production compared to scenarios of land sharing or land sparing. This example reveals one of the drawbacks of ABMs. Being a simulation model, ABMs depend on pre-defined scenarios, while the high model complexity and long computational times limit in-depth sensitivity analyses [13•]. While most models include some components of stochasticity, uncertainties are seldom incorporated in decision-making of agents [75].

To reduce the high data needs, recent ABMs build on newly evolving landscape generators [76••], which produce simplified, but realistic representations of landscape patterns. These can help to systematically vary initial landscape configurations to explore differences in the effects of private and public responses. For example, Dislich et al. [71••] use the landscape generator EFForTS-LGraf [77] (based on [78]), for building a virtual landscape, parameterised by data from Sumatra, Indonesia. Using an ABM, they demonstrate how differences in farmer's productivity affect ecological-economic trade-offs and related landscape pattern and how these interact with external price changes.

In sum, ABMs have become a backbone of landscape science [13•] and are well suited to integrate different approaches [13•]. Yet, few of them focus on landscape pattern. To do so, further refinements will be necessary in terms of the landscape metrics and ecological-economic interactions incorporated, as well as an improved consideration of uncertainties in decision-making. A further challenge is the need to develop and apply general guidelines to efficiently manage data needs and model complexity.

Next Steps to Take in Ecological-Economic Models to Better Inform Landscape Pattern

Schlüter et al. [11] state that full feedback loops in social-ecological models are still missing. Our review shows that this is also true for studies investigating feedbacks with landscape pattern. To incorporate such feedbacks, the different modelling approaches should not be viewed as competing alternatives. Instead, the strengths of each approach (summarized in Table 2) should be combined in comprehensive nested, modular and potentially step-wise approaches [12] (Fig. 2). From our review of recent methodological advances and the already existing links between models, we derive six priorities for the design of hybrid ecological-economic models to inform landscape pattern. We structure these aspects along the criteria in Table 2, in which we found that the models differed, and discuss how some of the challenges could be tackled.

1. Coupling the "what if" and the "what should be" perspectives

From our own experience, it is vital for modellers in interdisciplinary research groups to jointly identify the modelling philosophy best suited to support the research question. Not all links are always necessary to include, while often misunderstandings exist concerning the feedback loops that may be captured by either descriptive, prescriptive or predictive models. For example, pure simulation approaches alone are not suitable for identifying "optimal" landscape patterns or management strategies—even though this term is often used in this context—while LULC optimization is usually not designed for deriving predictions on future development, even though some positive approaches exist [79].

The advantage of a deterministic solution, following a prescriptive modelling philosophy is that it is derived from a continuous set of LULC compositions and configurations, thus reducing the probability of the actually best option being left out [80]. LULC optimization may thus form a basis for participatory approaches to develop a common understanding of a desirable landscape development. Yet, using pre-defined scenarios has the advantage that socially or technically inacceptable scenarios and landscape pattern are omitted, without having to define additional constraints. Therefore, Pareto frontiers have become more common to illustrate efficient, but pre-defined landscape configurations within participatory approaches [52•]. A large number of hypothetical scenarios may help to reduce the chances of leaving out more efficient ones [26]. Hence, in situations where rather specific policy scenarios are to be compared, deriving Pareto frontiers from spatial simulation [52•, 61] and ABM models [81] offers a promising hybrid tool to inform landscape pattern.

However, to derive compromise solution, which satisfy multiple needs simultaneously, combining recent advances in multi-objective goal programming [52•, 56, 82] with spatial simulation seems promising. This could also be extended to ABM models, for example by incorporating such multi-criteria algorithms as the agent's decision criterion.

Even if pure LULC optimization may result in infeasible landscape configurations or compositions, the obtained pattern may serve as a benchmark. Exploring the landscape patterns resulting from defining different objectives and/or constraints may improve understanding of interactions. Such "what should be" results could then be coupled with structurally more complex ABMs and spatial simulation models, to investigate which parametrisation and thus policies would be needed to approach the desirable state (Fig. 2).

2. Improved considerations of landscape patterns and related ecological effects

We excluded many articles, which provided some components of LULC patterns as output (particularly aspects of forest cover), but did not incorporate any interlinkage of these patterns with economic-ecological drivers and consequences. The studies which we did include mostly focussed on aspects of land-use composition, rather than configuration. This may be due to the spatial mismatch of advances in landscape ecology at landscape scale with economic variables at the household/field (micro) or the regional/national (macro) economy scale. But how to overcome this mismatch?

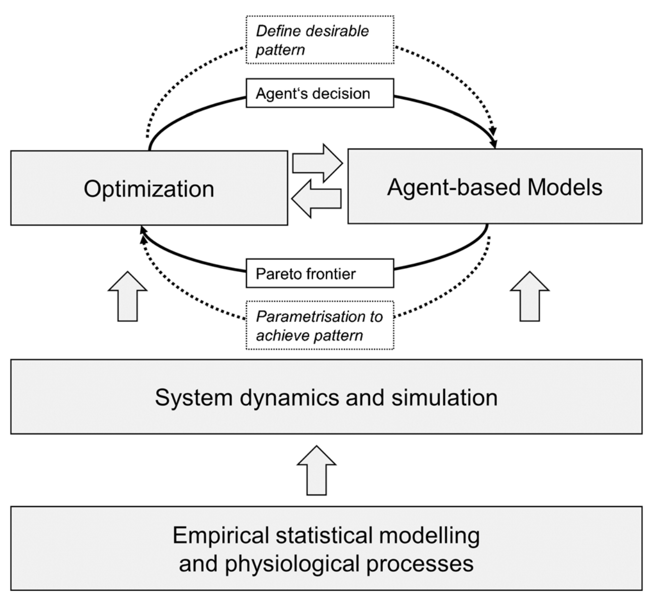

Fig. 2 Conceptual links between models found in this review (grey arrows). Empirical statistical models and system dynamics are often incorporated into LULC optimization and agent-based models. We specifically outline how optimization and agent-based models are strongly interlinked. Solid black arrows denote already existing links, while dashed line respond to our suggestion outlined in the text

Most ecological-economic landscape models implicitly depend on the patch matrix model to represent ecological effects, where the landscape is viewed as a mosaic of discrete patches [15]. More recently graph-based networks and gradient surface models with associated surface metrics have evolved [15]. Even though analytical ecological-economic approaches using graph-based models exist [83] and may offer a fruitful field for future research, we follow the suggestion of Lausch et al. [32] that the patch matrix model provides a helpful grounding to link aspects of landscape ecology with human decision-making. For this purpose, data collection should be designed in a way that can be linked to discrete patches. This means that, for instance, discrete spatial units need to be assigned to specific agents and their household data [71••], while ecological data should ideally be linked to these units.

Building on the idea of discrete landscape units, it is easier and maybe also more reliable to only include those ecological functions/services which are proportional to the number of units allocated to each LULC and do not depend on configurational aspects. Verhagen et al. [7] found that a majority of ES mapping studies (65% in their review), which often provide input for economic-ecological modelling, did not account for aspects of configuration, with the exception of those considering nutrient retention, such as the InVEST model. But which are the services for which configurational aspects should be accounted for? Most obviously, this is the case for biodiversity, which is rarely included in ecological-economic ABMs [3•]. Improved incorporation of biodiversity models into economic-ecological modelling is needed [3•], for example by coupling them with metacommunity models [84, 85].

So far, biodiversity is mostly captured through its indirect effect on ecosystem functions and ES [24]. Verhagen et al. [7] found that there is evidence that landscape configuration affects the ES nutrient retention, pollination, landscape aesthetics and sediment retention, while there are mixed effects for crop production, flood control and pest control and no evidence for carbon sequestration. Likewise Duarte et al. [6] found that landscape aggregation (here fragmentation) only explained provision of the ES, pollination and water quality. But, all ES considered responded to some aspects of landscape composition and compositional diversity. This finding reinforces the importance of even the simpler landscape metrics. The differences between predicting ES based on landscape composition only and accounting for configuration will most likely decline at larger spatial scales [7]. Hence, even if landscape configuration is a desirable aspect to include, more explicitly exploring aspects of landscape composition and compositional diversity will already be an important step forward. Incorporating aspects of configuration might not always be necessary for very large landscapes or if not all functions are of interest.

If configurational aspects are to be investigated, our review shows that spatial simulation models and ABMs may be most suitable to account for spatial autocorrelation in both natural (e.g. effects of fires, desired or undesired species expansion) and socio-economic processes (e.g. diffusion of knowledge and perceptions, distance to urban centres). If the research question calls for LULC optimization models, future studies could account for configuration through offering (discrete) LULCs with differing diversification levels of, e.g. agrobiodiversity and agroforestry to the optimization model. For example, Knoke et al. [45] optimize the allocation of land to different forest stand types of varying species richness. These approaches could be expanded by building on spatial simulation approaches. For example, Yoshimoto et al. [59] use a CAM coupled with integer optimization to estimate ideal control of invasion spread (see also [86]). Such ideas could also be used to estimate ideal investment decision into agroforestry systems. Mixed integer programming could also assist in incorporating patch size and shape (see, e.g. [87] for a problem of land consolidation).

In order to move landscape pattern in the focus of research, refining the integration of spatial autocorrelation and landscape structures is needed to allow for investigating feedbacks with consequences for socio-economic decision-making. We see much potential in the evolving landscape generators [76••] for more directly including landscape pattern not only for ABMs, but also all other simulation, optimization and hybrid approaches. The reduced data needs could allow for important insights before applying them to real landscapes.

3. Refining the theoretic foundations of decision-making

We found that simple profit maximizing is still often assumed as ex- or implicit driver of land-use decisions (e.g. [62, 71••]). Likewise, Groeneveld et al. [88•] state that a theoretic background is often lacking in decision rules of ABMs, while this also applies for other approaches reviewed here. Among those ABM studies backed by theory, the expected utility frameworks clearly dominated the simulated decision-making [88•], followed by theories of "satisficing". This term was originally created by Herbert A. Simon to express the combination of the words "satisfy" and "suffice" [89]. "Satisficing" builds on aspiration levels of the decision-making to be fulfilled and represents one aspect of "bounded rationality". Groeneveld et al. [88•] state that such psychological theories are still underrepresented. Kremmydas et al. [74] suggest to better integrate empirical research on interactions of decision-maker, as well as interactions of institutions (e.g. [68]). Yet, empirical calibration of social decision-making and integration of more complex psychological aspects will be time and resource intensive, while individual decision-making will remain a black box. Hence, improved incorporation of important aspects of learning and interaction may also be represented by established economic theory, such as using appropriate, for example risk-averse utility functions [51••]

and accounting for spatial or temporal autocorrelation among agents [38]. Future approaches may also build on aspects of bounded rationality as compared to the often criticised assumption of the rational decision-maker [88•]. We suggest that instead of aiming at perfectly reproducing behaviour, models may benefit from addressing the inherent and inevitable uncertainty associated with individual decision-making. Yet, this does not undermine the importance of incorporating participatory approaches or experiments like role playing games to involve landowners and stakeholders and to validate, as well as improve the modelling of decision-making processes [69, 90, 91].

4. Incorporating effects of uncertainty

Groeneveld et al. [88•] found that only 17 out of 134 ABMs reviewed incorporated aspects of uncertainty. Of the optimization models reviewed by Castro et al. [10], 15 out of 21 studied considered aspects of uncertainty when focusing on a single objective optimization problem. Hence, uncertainty has more prominently been incorporated in LULC optimization approaches. However, in multi-criteria optimization, accounting for uncertainty is also still an exception [10].

Incorporating aspects of uncertainty for investigating landscape patterns is, however, crucial, firstly, as no model will be able to perfectly reflect human decision-making or the resulting provision of ES. Secondly, as shown in this review, incorporating uncertainty in decision-making may lead to higher landscape diversity, in an attempt to buffer risks through diversification of income (for the private producer) and/or ES provision (from the public consumer's perspective) [56]. We found that portfolio theory is a powerful tool to account for both ecological and economic effects of compositional landscape diversity [31]. Hence, this feedback between landscape pattern and economic or ecological risk could play a more prominent role in future research, for example also in ABMs (see, e.g. [75]). To do so, the challenge will be to incorporate uncertainty into spatial simulation approaches on the one hand (see, e.g. [92]), and on the other hand allowing for more complex spatial interactions in existing portfolio-based LULC optimization. For example, uncertainty is also integrated in STMs, as they express changes as probability distributions. A drawback is that the simplified spatial autocorrelation does usually not allow for deriving covariances between transitions, which would be necessary to account for the portfolio effect on returns/ES. The same problem applies to ABMs. If such information on spatial correlation was available, uncertainty could be integrated into agent's decision-making through risk-averse utility functions. To avoid the need for these data-intensive correlations, future hybrid approaches could benefit from recent developments in robust optimization approaches, which avoid the need for estimating covariance-matrices [49, 56••, 93].

5. Time dynamics

We find that advances have been made in order to depict more complex temporal dynamics, particularly in simulation approaches (e.g. [35•]). Improved incorporation of time dynamics, such as adjustments of transition probabilities, preferences or changing exogenous prices [71••] are important for including economic feedbacks. Such simulation approaches could then be combined with dynamic programming [10]. The drawback of deterministic optimization problems used for agent's decisions provides that the future is known to the decision-maker. This means that dynamic effects over the entire observation period are modelled and included in a one-time decision. Future hybrid models could build on novel computational models and, e.g. recursive utility functions, emerging for solving these problems [94].

6. Reducing complexity and data needs

As De Fries et al. [1] put it, "ecosystem management must avoid two traps: falsely assuming a tame solution and inaction from overwhelming complexity". In this line, applying the principle of parsimony throughout model design and interpretation has been suggested [12, 95, 96]. Hybrid approaches may only gradually add more components or modules to structural rich models. One example could, for example, be to include information on land-use diversification from empirical modelling as constraints into an optimization-based portfolio model [29]. This would avoid the need for capturing complex interactions between individual drivers of landscape diversification in simulation models. We furthermore suggest to couple parsimonious normative models on landscape patterns with low computation time (e.g. [56••]), with structurally complex ABMs informed by landscape generators [71••], through a stepwise hybrid approach. Simpler normative models could help to pre-select the major drivers of land-use decisions and the ecological functions which seem to affect landscape patterns from a private producer's and/or public consumer's perspective. This could help to focus on crucial interrelationships and drivers in structurally more complex ABMs or spatially explicit and dynamic models. LULC optimization could also be used to first derive a theoretically desirable land-use pattern. Secondly, a parametrization could be searched for in the ABM, which approaches this theoretical landscape pattern (Fig. 2).

Conclusions

Our review shows that landscape patterns are pre-dominantly considered as an outcome of economic decisions. The ecological and economic consequences of different landscape pattern are, however, seldom fed back into decision-making (dashed lines in Fig. 1). We have shown that the few examples which actually do so are inter alia found for the risk-reducing effect of compositional diversity, aspects of targeted invasion control or valuation of ES. The resulting call for hybrid approaches is not new [3•, 11, 13•], but the recent methodological advances outlined here may help to improve consideration of spatial and temporal autocorrelations needed for such research endeavours. We would particularly like to underline the fruitful exchange of LULC optimization approaches and ABMs (Fig. 2), which are often viewed as competing modelling approaches. Finally, we would like to motivate authors to provide their model codes and input data in open-access data repositories (e.g. [71••, 97]) to support the development of such interdisciplinary hybrid approaches.

Acknowledgements This work has benefitted from research funded by the Deutsche Forschungsgemeinschaft (PA 3162-1, KN586/9-1) and research in the framework of the collaborative German-Indonesian research project EFForTS (CRC 990, project number 19262686).

Compliance with Ethical Standards

Conflict of Interest Carola Paul, Esther Reith, Jan Salecker and Thomas Knoke declare no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by the author.

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