



Synthesis, part of a Special Feature on [Archetype Analysis in Sustainability Research](#)

Archetype analysis in sustainability research: methodological portfolio and analytical frontiers

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ABSTRACT. In sustainability research, archetype analysis reveals patterns of factors and processes that repeatedly shape social-ecological systems. These patterns help improve our understanding of global concerns, including vulnerability, land management, food security, and governance. During the last decade, the portfolio of methods used to investigate archetypes has been growing rapidly. However, these methods differ widely in their epistemological and normative underpinnings, data requirements, and suitability to address particular research purposes. Therefore, guidance is needed for systematically choosing methods in archetype analysis. We synthesize strengths and weaknesses of key methods used to identify archetypes. Demonstrating that there is no “one-size-fits-all” approach, we discuss advantages and shortcomings of a range of methods for archetype analysis in sustainability research along gradients that capture the treatment of causality, normativity, spatial variations, and temporal dynamics. Based on this discussion, we highlight seven analytical frontiers that bear particular potential for tackling methodological limitations. As a milestone in archetype analysis, our synthesis supports researchers in reflecting on methodological implications, including opportunities and limitations related to causality, normativity, space, and time considerations in view of specific purposes and research questions. This enables innovative research designs in future archetype analysis, thereby contributing to the advancement of sustainability research and decision-making.

Key Words: *archetypal; global change; knowledge transfer; land system; pattern; review; socio-ecological system; up-scaling*

INTRODUCTION

Harmonization between economic, socio-cultural, and biophysical aspects of development is a prerequisite to achieve sustainable development. The concept of sustainability is a paradigm for thinking about a world in which basic human needs and aspirations are met without degrading the natural environment, now and in the future (United Nations 2015). By recognizing problematic development pathways related to the (over)use, unequal access to, and (mis)management of land, water, species, and other natural resources, the concept essentially links earth system dynamics with normative assumptions, values, and power relations (Reid et al. 2010, Schmiege et al. 2018). This link facilitates reasoning about what kind of development is considered as more desirable and the ways to achieve such development, thereby providing the foundation for the Agenda 2030 and its Sustainable Development Goals (United Nations 2015). Sustainable development calls for targeted efforts at local, regional, and global scales toward promoting harmonized ways in which human and nonhuman entities interact and coevolve with their environment. Coupled human and natural systems have been framed as social-ecological systems, also called socio-ecological systems; i.e., complex, integrated systems in which humans are intrinsically linked with nature (Berkes and Folke 1998). Specific interactions between societies and nature locally result from complex causes with diverse background conditions and dynamics. However, distinct interactions recur within the multitude of social-ecological systems, inspiring extensive research on archetypes.

In sustainability research, archetypes depict representative patterns of human–nature interactions. Archetype analysis in this field of research has been used to understand factors and processes that repeatedly determine the (un)sustainability of social-ecological systems. This includes development drivers and outcomes related to livelihood vulnerability, land use, economic development, food security, and climate adaptation, among others (e.g., Jäger et al. 2007, Oberlack et al. 2016, Frey 2017, Sietz et al. 2017, Vidal Merino et al. 2019). Archetype approaches have also contributed to scenario analysis whereby recurrent development trajectories that social-ecological systems may take in the future were classified in archetypal scenarios (e.g., Bina and Ricci 2016, Wardropper et al. 2016). For a comprehensive overview of core features and diverse meanings of archetype analysis in sustainability research, see Oberlack et al. (2019).

Archetype analysis in sustainability research offers the opportunity to assess recurrent causes and effects of human–nature interactions as an integrated set of processes rather than as isolated factors, considering specific spatio-temporal contexts in which they evolve. This allows generalizations about key interlinkages and dynamics of coevolving processes that are relevant for sustainability research (Kates et al. 2001, Chapin et al. 2011). This generalization is useful to understand functional similarities and differences in a broader perspective and inform decisions that need to be made across diverse spatial scales (Miller et al. 2014, Verburg et al. 2015), linking local realities with global change processes. Importantly, recognizing similarities can enhance learning and inform the scaling-up of sustainability

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solutions. Yet, the ways in which factors, processes, and feedbacks that shape (un)sustainability can best be generalized remains a critical methodological question.

As an emerging research field, there is not yet a universally accepted set of analytical methods for archetype analysis. The methods used to assess and evaluate archetypes of social-ecological systems have evolved rapidly over the last decade and range from meta-analyses and artificial neural networks to qualitative dynamic modeling. However, these methods differ in their specific analytical purposes, data requirements, and epistemological and normative foundations, which challenges the choice of methods in archetype analysis. We aim to facilitate the choice of methods in future archetype analysis based on a sound understanding of methodological implications and potentials of using and combining methods suited for pattern recognition. We review an evolving set of methods, drawing from a broad range of studies and fields of application, discuss the advantages and limitations of archetype methods, and highlight analytical frontiers that can advance the design of future archetype studies.

METHODS

This paper emerged from two international research workshops held in 2017 and 2018, a series of follow-up meetings, and a literature search conducted by the authors of this study. The workshop participants involved 46 multidisciplinary experts in archetype analysis (ecology, geography, environmental sciences, applied mathematics, sociology, economics, climatology, and agricultural sciences) from Europe, Asia, and North and South America. They were selected based on (i) their engagement in advancing the conceptual foundation of archetype analysis, and (ii) their methodological experience.

To select studies, we followed a two-step approach. First, we identified key publications that all authors considered central to the archetype literature, including references collected in the Preparatory Survey for the 1st International Research Workshop (Oberlack et al. 2017). Second, to complement the initial set of archetype studies, we conducted a literature search on Web of Science and Scopus databases (last accessed 30 November 2017) using the following keywords: (“archetyp*” OR “typical pattern*”) AND (“sustainab*” OR “global change” OR “land” OR “resilien*” OR “vulnerab*” OR “adaptation” OR “socio-ecologic*” OR “socio-environm*” OR “human-natur*” OR “human-environm*”). Acknowledging alternatively used terms, we also included studies that referred to “typical pattern” analysis. Moreover, we aimed at capturing the “syndrome” approach (Petschel-Held et al. 1999, Lüdeke et al. 2004) as the precursor of archetype analysis using the following keywords: syndromes AND (sustainab* OR “global change”), excluding the subject area “medicine”. These searches yielded 994 articles. We selected studies that met the following inclusion criteria: peer-reviewed, provision of comprehensive information on the frameworks, data, and methods used, sound methodologies for identifying archetypes, and rigorous interpretation of results. Through this selection process, we identified 84 studies.

From the selected studies, we gathered the methods and discussed their strengths and weaknesses, epistemological background, normative substantiation, data prerequisites, and applicability to particular research objectives. We structured the discussion of identified methods according to four gradients that capture key

aspects of archetype analysis in sustainability research. We selected these gradients for two reasons. First, they were agreed upon by the participants of the two international workshops and other researchers who were familiar with archetype analysis and were involved in follow-up discussions. Second, the aspects captured in the gradients were identified independently as key for archetype analysis during the literature review, and every method that we reviewed could be assigned to one or several parts of each of the four gradients. We used these gradients to present the methodological portfolio and assess the suitability of each method to address key aspects of archetype analysis in sustainability research.

- 1. Gradient I: Treatment of causality** (ranging from description, thick description, causal factor configuration to causal mechanism), motivated by the need to understand the properties and causality of (un)sustainable development patterns;
- 2. Gradient II: Treatment of normativity** (ranging from nonevaluative to normative purpose), motivated by the need to entail standards of judgment and behavior to improve human well-being while maintaining ecosystems' health;
- 3. Gradient III: Treatment of space** (ranging from methods with no spatial reference to spatially implicit and explicit approaches) motivated by the necessity to know where social-ecological processes unfold and how they interact spatially; and
- 4. Gradient IV: Treatment of time** (ranging from methods with no time consideration to methods with implicit and specific time considerations), motivated by the need to understand how social-ecological conditions change over time.

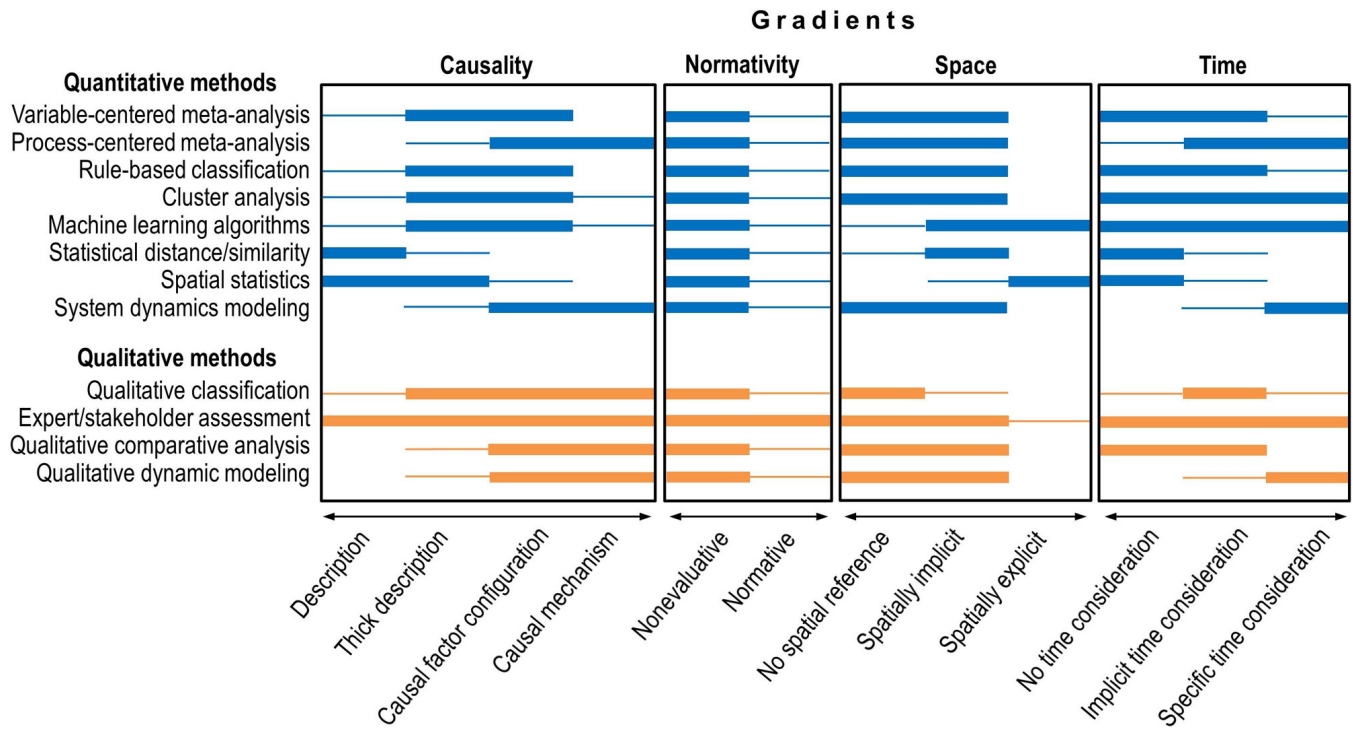
In addition, we turned our attention to the main analytical frontiers that have advanced or hold promise to advance archetype analysis considering causality, normativity, space, and time aspects. These frontiers highlight methodological directions that can inspire novel approaches in future archetype analysis.

RESULTS AND DISCUSSION

Overview of methods used for archetype analysis

This section provides an overview of the methods used to analyze archetypes in sustainability research. We explicitly focus on methods suited to identifying recurrent features or patterns in a set of entities or units of analysis. Units of analysis may range from social-ecological properties over causal factors to causal mechanisms (e.g., observed or modeled), and are associated with a particular functional or spatial scale (e.g., household or grid cell) and temporal scale (e.g., point in time or time series). Information about various stakeholders' perspectives on these entities may also be available. Table 1 summarizes the quantitative and qualitative methods, together with their key features, advantages, and limitations. Most of these are quantitative methods that process data; i.e., measurable or countable features, based on statistical analyses, rule-based classification, machine learning algorithms, and system dynamics modeling. In contrast, qualitative methods analyze non-numeric information using qualitative classification, expert and stakeholder assessments, qualitative comparative analysis, and qualitative simulation models. Information collection and preparation procedures

Fig. 1. Overview of the methods discussed in this paper along four gradients depicting core aspects of archetype analysis in sustainability research: causality, normativity, space, and time considerations. The lines that span the gradients represent the level of a method’s suitability for the respective part of the gradient: thick line = high suitability; thin line = suitable but less targeted; no line = out of scope.



preceding archetype analysis depend on a study’s purpose and research questions, and involve a vast variety of methods (for further details, we refer the reader to specific methodological literature).

The methods described in Table 1 differ in their treatment of causality, normativity, space, and time in archetype analysis, whereby each method covers all gradients at least partially (Fig. 1). Among all the methods we reviewed, most quantitative methods are best-suited for a thick description of patterns and identification of causal factor configurations (see causality gradient in Fig. 1). In contrast, all the qualitative methods enable the identification of both causal mechanisms and causal factor configurations. Qualitative assessments by experts and stakeholders can be used to assess archetypes in both nonevaluative and normative ways (see normativity gradient in Fig. 1). Spatially explicit archetype analysis relies mainly on quantitative methods (see space gradient in Fig. 1), while time can be captured implicitly or explicitly by most methods (see time gradient in Fig. 1). More specific details of the methods’ suitability are discussed in the following subsections along the causality, normativity, space, and time gradients. For each gradient, we discuss example methods that are suited to illustrate specific parts of a gradient. In this discussion, we emphasize the most important features of a method for archetype analysis and pay particular attention to the gradients’ center and end points as they matter most for sustainability research. Table 1 and Fig. 1 contain more detailed information than the following discussion and serve as complementary resources.

Gradient I: Treatment of causality

Description – Thick description – Causal factor configuration – Causal mechanism

The treatment of causality in archetype analysis ranges from pure description of archetypical features of social-ecological systems, such as vulnerability, adaptation, or land management, to analysis of causal mechanisms that link archetypical features and outcomes. At one extreme of this gradient, a description characterizes a social-ecological system’s archetypical features. This characterization provides structured knowledge about the nature of recurrent features without addressing the reasons why those features may occur. Going beyond characterization, a thick description delivers more quantitative insights into, or a detailed qualitative narrative of, recurrent features and context. A causal factor configuration adds insights into patterns of archetype determinants. It represents a set and arrangement of causal factors that lead to a specific outcome (e.g., high drought sensitivity together with inefficient policy implementation and lack of livelihood alternatives causing a farming system’s vulnerability). At the other extreme of this gradient, causal mechanisms explain and explicitly refer to the processes that link causal factors and (un)sustainability outcomes (Meyfroidt 2016, Magliocca et al. 2018).

Both quantitative and qualitative methods (Table 1, Fig. 1) have served to describe archetypical features and to analyze causal patterns in social-ecological systems. For example, cluster analysis has been widely used for thick archetype description and assessment of archetypical causal factor configurations.

Table 1. Overview of methods used to identify archetypes in sustainability research

Method	Key features for archetype analysis	Advantages	Limitations	Example applications
1) Quantitative methods				
Variable-centered meta-analysis of case studies	Reappearing causal factors assessed using frequency analysis Large <i>N</i> sample size	Trends easily quantified across many locations Characterize range of applicability Enhances comparability	Uncertain robustness of cause-effect relationships reported in case studies Structure of causal relationships lost during generalization Scarcity of comparable case study methods and evidence	Geist and Lambin (2004), Keys and McConnell (2005), Sietz and van Dijk (2015)
Process-centered meta-analysis of case studies	Reappearing causal mechanisms and causal factor configurations identified by frequency analysis Informed by causal models in case studies Small <i>N</i> sample size	Capable of analyzing causal factor configurations and mechanisms across multiple locations	Robustness of cause-effect relationships reported in case studies Coding often requires simplification of cause-effect relationships Intercoder reliability Often limited by the absence of “no change” cases More demanding validation due to more complex coding of causal mechanisms Scarcity of comparable case study methods and evidence	Rudel et al. (2009), Oberlack and Eisenack (2014), Messerli et al. (2015), Oberlack et al. (2016), Oberlack 2017)
Rule-based classification	Links diagnostic information on drivers and causes to categorization of effects Allows independent rules instead of one general model	Combination of rules often effective Rules can be effectively defined using artificial neural networks (see <i>Machine learning algorithms</i>)	Conflicts in data set are hard to parse Rules often require hand-crafting or supervision (expert knowledge)	Hill et al. (2008), Weissteiner et al. (2011), Stellmes et al. (2013)
Cluster analysis	Categorization using hierarchical and partitioning algorithms	Applicable at any spatial and temporal scale	Requires estimation of optimal number of clusters (e.g., based on cluster stability)	Ellis and Ramankutty (2008), Sietz et al. (2011), van Vliet et al. (2012), Kok et al. (2016), Lim-Camacho et al. (2017), Locatelli et al. (2017), Sietz et al. (2017), Vidal Merino et al. (2019)
Machine learning algorithms	Clusters depict typical indicator combinations Reveals nonlinear patterns	Accommodates high-dimensional data spaces	Sensitive to outliers and distance measure	
a) Self-organizing maps	Unsupervised algorithm for clustering observations based on similarity Preserves topology of data space	Pattern detection in high-dimensional data sets Allows pattern comparison based on topological properties of data space	Requires estimation of optimal number of clusters Requires appropriate data standardization	Václavík et al. (2013), van der Zanden et al. (2016), Dittrich et al. (2017), Levers et al. (2018)
b) Artificial neural networks	Detect nonlinear patterns Have been further developed to deep learning (convolutional networks)	High explanatory power of models depending on the informativeness of the training sample and network complexity Capture spatial interactions	Special algorithms necessary to extract information; if not, remains black box Normally large <i>N</i> data required	Frey and Rusch (2013), Frey and Rusch (2014)
Statistical distance/similarity analysis	Reveals patterns based on distance measure Different types of distance measures in multidimensional space of variables available (e. g., Euclidean, Manhattan, Canberra)	Continue to be developed at very high pace Supports transfer of sustainability solutions based on similarities across locations Allows comparison based on high-dimensional data	Sensitive to distance measures and outliers	Ellis (2012), Václavík et al. (2016)

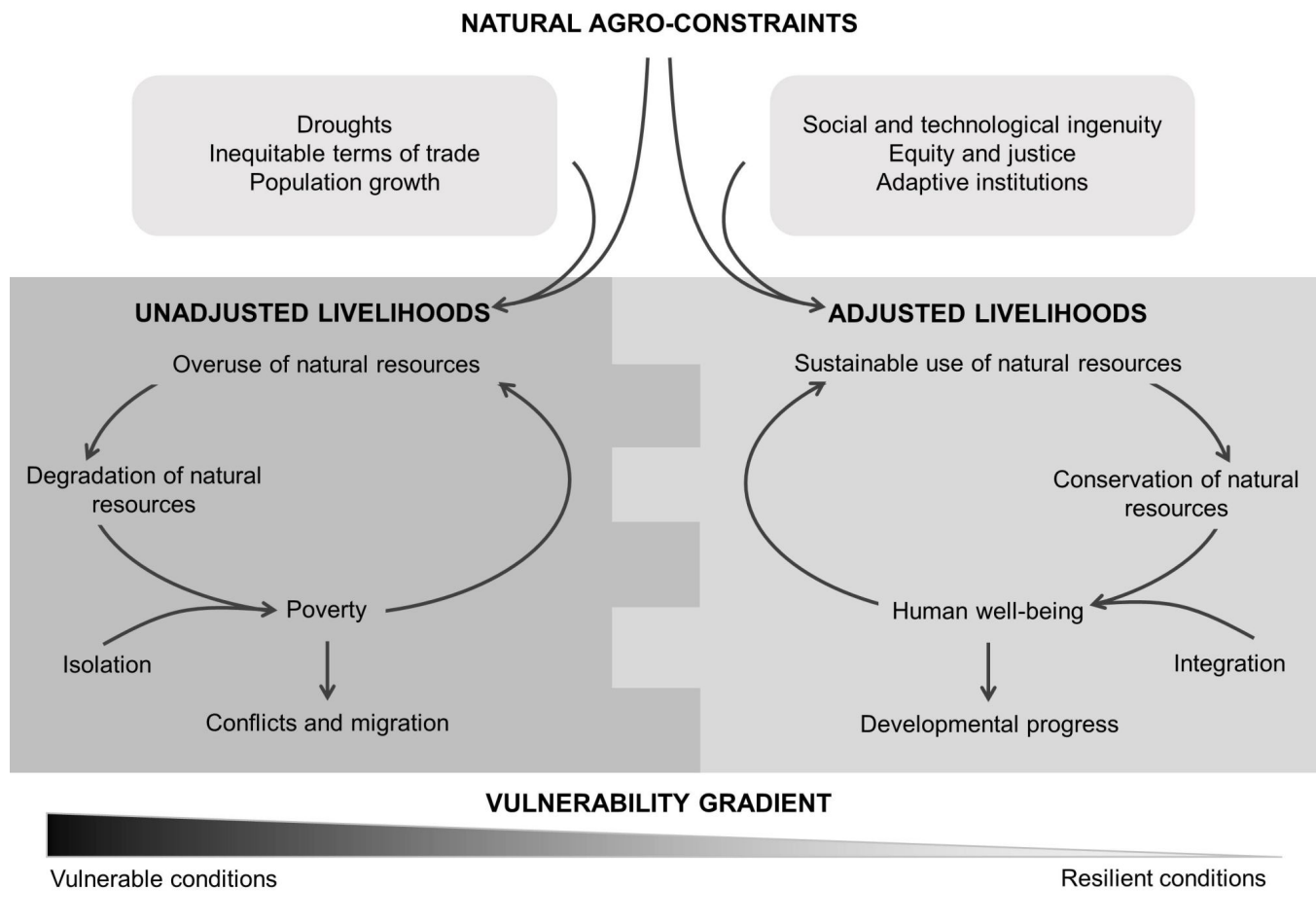
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Spatial statistics; e.g., local indicator of spatial association	Reveal recurrent variable combinations Provide insights into geographic interactions between a study location and its neighborhood	Account for spatial dependence Indicate if patterns are statistically significant or occur by chance	Statistical significance determined by computationally intensive Monte Carlo analysis Sensitive to different definitions of neighborhood	Kehoe et al. (2015), Delzeit et al. (2017)
System dynamics modeling	Captures generic structures of system behavior using reinforcing and balancing feedback loops Simulates behavioral patterns of interacting subsystems	Simulates system dynamics especially when behavior of whole system cannot be explained by behavior of its components Reveals nonlinear dynamics supporting reasoning about causal mechanisms	Difficult to predict long-term system behavior due to system inertia and because even small variations can cause large differences in future outcomes Time consuming and demanding model validation	Mokhtar and Aram (2017), Turner et al. (2017)
2) Qualitative methods				
Qualitative classification	Observations grouped according to similarities Iterative process aimed at saturation of classification	Combination of deductive and inductive coding Emerging themes in a given research field captured	Intercoder reliability and handling of conflicting entries Achieving mutually exclusive categorization Reflective, unable to support social-ecological transformation in radically new ways (i.e., method is prone to false negatives)	Manuel-Navarrete et al. (2007), Eisenack (2012), Bocken et al. (2014)
Expert and stakeholder assessment	Narratives, scenario analysis, causal loop diagrams and (fuzzy) multicriteria evaluation of common human–nature interactions Reveals observed and hypothesized causal mechanisms	Supports normative assessment through differentiation of perceptions about (un)sustainability processes Solution-oriented bridging science–policy gap	Requires consistent archetype understanding among experts and stakeholders Degree of abstraction need to be defined based on sustainability challenges and opportunities and response options	Schellnhuber et al. (1997), Lüdeke et al. (2004), Jäger et al. (2007), Wardropper et al. (2016), Brzezina et al. (2017), Moraine et al. (2017)
Qualitative comparative analysis	Groups cases into sets with similar causal factor configurations Configurational analysis of multiple conditions determining a given outcome Based on set relations and Boolean algebra	Allows inclusion of under-researched sustainability aspects and perceptions Distinguishes two causality dimensions: equifinality and causal asymmetry Prominent role of conjoint causation Differentiates between necessary and sufficient conditions typically leading to an outcome Deviant cases reported	Problem of limited diversity Case knowledge necessary Difficult interpretation of complex solutions Geared toward counterfactual analysis	Rudel (2008), Fiss (2011), Meurer (2014)
Qualitative dynamic modeling	Qualitative differential equations capture relationships between variables Based on monotony assumptions Resulting qualitative trajectories highlight typical trend combinations of variables and their temporal evolution	Reveals nonlinear dynamics facilitating reasoning about causal mechanisms Less data-demanding than parameterizing full numerical models Relevant trend combinations can be indicated in a spatially explicit way	Velocity of modeled dynamics and distance to critical thresholds unknown Large number of variables constrain aspired reduction of complexity and generalization of underlying processes	Petschel-Held et al. (1999), Sietz et al. (2006)

Applications include classifications of archetypes of people's risk perception and climate adaptation behavior (Lim-Camacho et al. 2017), anthropogenic biomes depicting recurrent human–nature interactions (Ellis and Ramankutty 2008), and archetypical patterns of vulnerability (Kok et al. 2016, Sietz et al. 2017, Vidal Merino et al. 2019). In particular, the establishment of hypotheses about causal mechanisms, such as low primary productivity and

socio-political remoteness that limit well-being of dryland people (Fig. 2), provides a bridge to causal analysis (Sietz 2011). In clustering, decisions on the optimal number of clusters, treatment of outlying indicator values, and use of specific cluster algorithms and distance measures (e.g., Euclidean distance) (Janssen et al. 2012) determine the level of detail and meaningfulness that cluster results can deliver for thick archetype description and

Fig. 2. Example of cause–effect hypotheses used to assess archetypes of vulnerability in drylands. Causal factors affecting dryland vulnerability include agro-ecological constraints and the level of adjustment of livelihoods to these constraints. An important causal mechanism depicts unadjusted livelihoods which enforce vulnerable conditions resulting from the degradation of marginal natural resources, which induces poverty, conflicts, and migration. Selected external and endogenous drivers of unadjusted or adjusted livelihoods are shown at the top (adapted from Sietz et al. 2011).



identification of causal factor configurations. Clustering supports the identification of complex causal factor configurations as it can accommodate high-dimensional data spaces and is applicable at any spatial or temporal scale (Table 1; see also Gradients III and IV). In other research fields, clustering is referred to as unsupervised learning in pattern recognition, typology construction in social sciences, and numerical taxonomy development in biology (Theodoridis and Koutroubas 1999).

Among machine learning algorithms available for pattern recognition, self-organizing maps have been used among others to identify land system archetypes and archetypical trajectories of land use changes without directly capturing causal mechanisms (Václavík et al. 2013, van der Zanden et al. 2016, Levers et al. 2018). Self-organizing maps are competitive learning algorithms especially suited for clustering high-dimensional data spaces (Table 1), supporting thick archetype description and identification of multivariate causal factor configurations. While some clustering methods require decisions on parameter

thresholds that help discriminate between clusters, self-organizing maps have the advantage of being unsupervised learning algorithms that do not depend on these decisions and therefore are less prone to potential biases. These features make self-organizing maps suitable for more data-driven archetype analysis, although without revealing causal relationships. However, studies have used the outcomes of self-organizing maps to generate at least testable hypotheses about the studied phenomena; e.g., the underlying drivers of land system archetypes and their temporal dynamics (Václavík et al. 2013, Levers et al. 2018).

Artificial neural networks, another set of machine learning algorithms, have seen major advances in the last years and continue to leap ahead in the field of machine learning. Challenges that have been overcome and contribute to analysis of causal factor configurations include adding hidden layers for solving complex problems without overfitting, establishing large memory storage, and reducing execution time for large data sets. Yet, special algorithms are needed to extract relevant information

(Table 1). First attempts have been made in social-ecological systems research to turn the implicit (black box) relationships between variables and sustainability outcomes into explicit patterns (Frey and Rusch 2013). This possibility makes artificial neural networks suitable for moving their application in archetype analysis toward assessing causal models. Other studies have generated hypotheses about causal relationships by overlaying archetypes (i) with possible explanatory factors to discuss reasons for land use change (Levers et al. 2018), and (ii) with armed conflicts to investigate consequences of vulnerability (Sterzel et al. 2014).

Meta-analysis of case studies uses frequency analysis to assess reappearing causal variables or processes as the means for archetype identification. Variable-centered meta-analyses tend to consider large sample sizes (e.g., > 30 case studies) (Geist and Lambin 2004, Keys and McConnell 2005, Sietz and van Dijk 2015) but do not explicitly capture interactions of variables (Table 1). This limits causal inference to causal factor configurations at best. In contrast, process-centered approaches consider configurations of variables to retain causal relationships or models during the synthesis of case study information (Rudel et al. 2009, Meyfroidt et al. 2014, Oberlack et al. 2016). Process-centered meta-analyses are typically limited to small sample sizes to manage the required level of analytical accuracy (Table 1), narrowing the observation space from which generalized causal inferences can be drawn. The scarcity of comparable case studies limits both types of meta-analysis, while coding of causal mechanisms and validation of patterns are particularly demanding in process-centered approaches (Table 1).

Qualitative classification also offers the opportunity to reveal causal patterns. For example, this method has served to identify recurrent causal mechanisms that generate vulnerability to hydro-meteorological disasters in Central America and the Caribbean, potentially constituting a syndrome of vulnerability (Manuel-Navarette et al. 2007). In this classification, reported causal relations were categorized in an iterative process that moved toward saturation of cause-effect relations, highlighting emerging knowledge in the field of vulnerability assessment (Table 1). However, the severity of vulnerability in relation to specific causal mechanisms remains to be investigated in a spatially explicit way to gain an understanding of which mechanism(s) may trigger or reinforce the syndrome in a given region.

More sophisticated causality analysis in archetype research benefits from consideration of two dimensions: equifinality and causal asymmetry (Rihoux 2006, Wagemann and Schneider 2010). These can be captured by qualitative comparative analysis (QCA) (Rudel 2008, Fiss 2011, Meurer 2014), a qualitative method that groups cases into sets of similar causal factors and examines the configurations of multiple conditions that determine a certain outcome. Equifinality implies that different combinations of archetypical features may lead to the same outcome; e.g., different business archetypes achieving high performance (Fiss 2011). Causal asymmetry entails that causal mechanisms that explain the presence of an outcome differ from those mechanisms that cause the absence of that outcome. For example, particular business archetypes consistently achieved high performance, whereas no configuration of archetypical business features consistently led to low performance (Fiss 2011).

Qualitative comparative analysis offers analytic benefits through (i) depicting conjoint causal effects, and (ii) reporting deviant cases (Table 1). Yet, QCA analysts need to agree on the case selection and the coding of causal factors, processes, and related outcomes to ensure archetype reliability. Several QCA studies used for archetype analysis do not comply with the standards of good QCA practice (Schneider and Wagemann 2010); e.g., suffering from an imbalance between few cases and too many variables.

Gradient II: Treatment of normativity

Nonevaluative purpose – Normative purpose

Archetype analyses also differ in their treatment of normativity, ranging from nonevaluative to normative approaches. Nonevaluative archetype studies describe archetypical patterns without any judgment on the desirability of these patterns or on how the causal mechanisms may or should be adjusted to result in more desirable patterns. Studies positioned more toward the normative end of this gradient often apply a problem-oriented approach and tend to start from normative measures that should be taken or from premises with inherent normative content.

Given the normative nature of sustainability, archetype studies applied in this research field are often located toward the normative end of the gradient, although most methods typical for archetype analysis can be applied without evaluating whether certain archetypical patterns are more desirable than others (Fig. 1). For example, meta-analytical approaches are suitable to describe archetypical patterns or analyze their causal mechanisms, but they can also help better understand how to move toward more sustainable outcomes. As a specific example, archetypical drivers of dryland development derived from meta-analysis of case studies provided a basis for designing policy interventions to achieve more sustainable development (Geist and Lambin 2004). In another example, meta-analysis was used to classify archetypes of livelihood vulnerability and sustainability potentials (Oberlack et al. 2016), whereby the framework of sustainable livelihoods provided the normative foundation for evaluating livelihood outcomes. Another meta-analysis of case studies grouped well-being outcomes in relation to water scarcity into six archetypical classes entitled “syndromes” (Srinivasan et al. 2012). The authors discussed these syndromes with respect to resource (un)sustainability, vulnerability, and water scarcity.

Expert and stakeholder assessments are the most suitable approaches for normative archetype analysis (Fig. 1), as they support normative assessment through differentiation of perceptions about sustainability processes. For example, experts and stakeholders were involved in evaluating common human–nature interactions across the world (Schellnhuber et al. 1997, Lüdeke et al. 2004, Jäger et al. 2007). Among others, the interactions of water scarcity, soil degradation, remoteness, and weak governance were identified as archetypical triggers of dryland vulnerability (Jäger et al. 2007). The participatory process started with building a consistent archetype understanding among experts and stakeholders and defining an appropriate level of abstraction considering the aim to overcome sustainability challenges while seizing opportunities at broader scales (Table 1). Moreover, interdisciplinary expert discussions provided the basis for a qualitative classification and evaluation of symptoms of agricultural land use (Manuel-Navarette et al. 2009). In another

example, stakeholder discussions enabled refinements in proposed archetypal mechanisms underlying crop and livestock management according to specific perceptions of land use options and constraints (Moraine et al. 2017). In addition, business model archetypes identified by qualitative categorization were discussed with industry partners to foster firm innovation (Bocken et al. 2014). By providing a common language, this approach can support participatory innovation but is unable to stimulate entirely new business designs given its reliance on historical innovation evidence (Table 1).

Gradient III: Treatment of space

No spatial reference – Spatially implicit assessment – Spatially explicit assessment

The way in which space is considered in archetype analysis ranges from nonspatial to spatially implicit and spatially explicit methods. In the simplest way, archetypal patterns of social-ecological phenomena can be characterized without a reference to the geographic location in which they occur. Such approaches can be based on examinations of nonspatial data but can also be purely conceptual. For example, Fischer et al. (2017) proposed a qualitative conceptual framework for the food–biodiversity challenge that described four archetypes of social-ecological system states. This framework related social-ecological systems to archetypal extremes, and provided opportunities to test whether drivers and feedbacks associated with each archetype held true across a range of cases, irrespective of their geographical location. In contrast, quantitative analyses of nonspatial data, such as meta-analyses of case studies, may demonstrate regional variations of studied phenomena (Oberlack and Eisenack 2014, Messerli et al. 2015, Sietz and van Dijk 2015). However, these studies either have not accounted for spatial aspects or did so only implicitly by acknowledging the location of cases studies, sometimes with specific consideration in the results.

Most methods applied in archetype analysis can use spatially structured variables (Fig. 1) referenced with their geographic location (sensu Peters and Herrick 2004), thereby enabling spatially implicit archetype analysis and visualization with maps (Ellis and Ramankutty 2008, Stellmes et al. 2013). One such method is rule-based classification where the application of certain rules (e.g., derived from classifying the results of regression analyses, projecting them onto maps, and associating them with general land change processes) led to spatial insights (Stellmes et al. 2013). Self-organizing maps stand out among machine learning and clustering methods because they preserve the topology of data points when assigning them to clusters so that similar clusters occur closer to each other (Table 1). This allows for the comparison of typical variable combinations both in terms of similarity and, if spatial data are used, geographic proximity. This approach has been used for various purposes; e.g., analyzing bundles of ecosystem services at a national level (Dittrich et al. 2017) and developing typologies of agricultural landscapes in Europe (van der Zanden et al. 2016). Moreover, archetype analyses performed at multiple scales can support regionally differentiated discussion of sustainable development strategies. For example, global dryland archetypes have been refined considering regional farming specificities in northeast Brazil using mixed methods that combine qualitative dynamic modeling and cluster analysis (Sietz 2014). Moreover, nested vulnerability

archetypes in African drylands were derived from cluster analysis performed at both continental and regional scales (Sietz et al. 2017).

Although simple archetype mapping may sometimes be referred to as a spatially explicit endeavor, true spatially explicit approaches consider spatial dependence or neighborhood effects (Peters and Herrick 2004). Accounting for spatial aspects explicitly is challenging but important because it can provide insights into geographic interactions between a study location and the surrounding area. Spatial statistics are promising for archetype analysis because they can show not only where typical variable combinations recur but also indicate whether these combinations are statistically significant or occur merely by chance. Yet, very few archetype applications are based on spatial statistics. For example, local indicator of spatial association (LISA) (Anselin 1995) was applied to understand global archetypal combinations of biodiversity and agricultural production potential (Fig. 3) (Delzeit et al. 2017). The study identified statistically significant spatial hot spots where biodiversity could be threatened by potential cropland expansion in the future. Incorporation of neighborhood effects when comparing spatial variables on a grid cell-to-grid cell basis is important because simple map overlays may be affected by differences in spatial resolution, misregistration, or data noise (Fotheringham and Rogerson 2013).

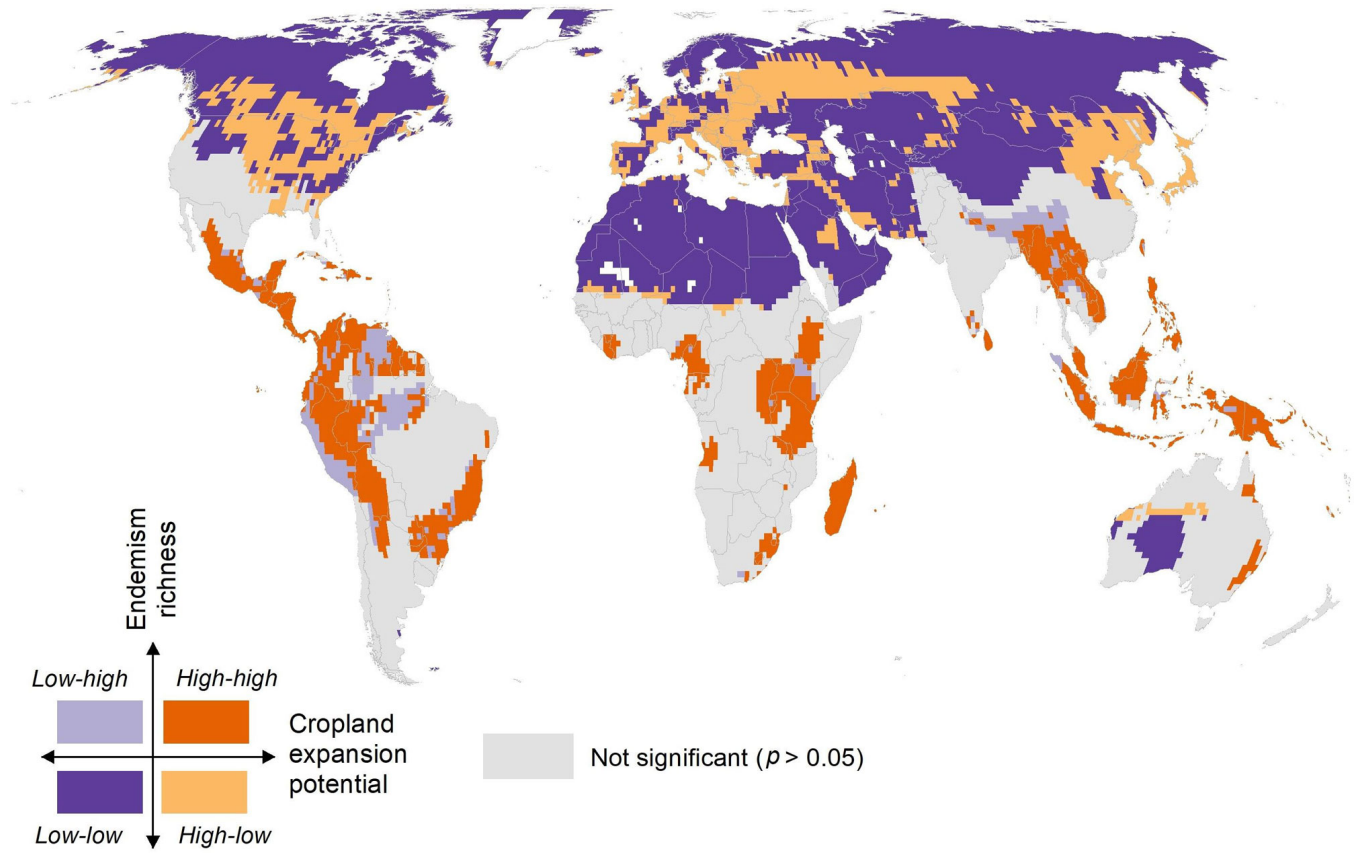
Gradient IV: Treatment of time

No time consideration – Implicit time consideration – Specific time consideration

This gradient differentiates the treatment of time in archetype analysis ranging from methods without a time reference over temporally implicit methods to time-specific ones (Fig. 1). At one extreme of this gradient, archetype analysis disregards temporal change. For example, construction of archetypes has been proposed as a formal concept to qualitatively analyze society–nature interactions (Eisenack et al. 2006). Using this conceptual approach, archetypal barriers to climate change (e.g., moral hazard, poverty traps) have been discussed based on a qualitative classification without specific time reference (Eisenack 2012). Moreover, cluster analysis has been used to identify time-independent business models of private land conservation based on financial productivity, owner objectives, and other characteristics (Clements et al. 2016).

Archetype analysis with implicit time consideration focuses on processes as the unit of analysis. Instead of single events, this type of archetype analysis captures chains of events, activities, and outcomes over time. For example, process-centered meta-analysis is especially suited to analyze processes over time as it allows quantifying trends and changes in causal factors (Table 1). This type of meta-analysis of case studies has served to depict typical interactions and trends in the drivers of deforestation and biodiversity decline in the tropics, including state-enabled smallholder farmers and enterprises as deforestation drivers (Rudel et al. 2009). Moreover, several aspects of QCA can be tailored in order to include time in the analysis, particularly in terms of the sequencing of events (Caren and Panofsky 2005, Ragin and Strand 2008). However, at the time of writing, no time-related QCA application to archetype analysis was available.

Fig. 3. Example of spatially explicit archetype analysis modified from Delzeit et al. (2017). Local indicator of spatial association was applied to understand four archetypal combinations of global biodiversity (represented by endemism richness of birds) and future food production (represented by an area's potential for cropland expansion). The analysis highlighted global hot spots where biodiversity could be negatively affected by future cropland expansion (high–low archetype), but also areas where additional expansion of cropland may pose lower threats to biodiversity (high–high archetype), thus representing opportunities to sustainably support food security. The method identifies significant spatial associations between two variables by accounting for contributions of each observation (e.g., a grid cell) and for the spatial clustering of similar values in the neighborhood of that observation.



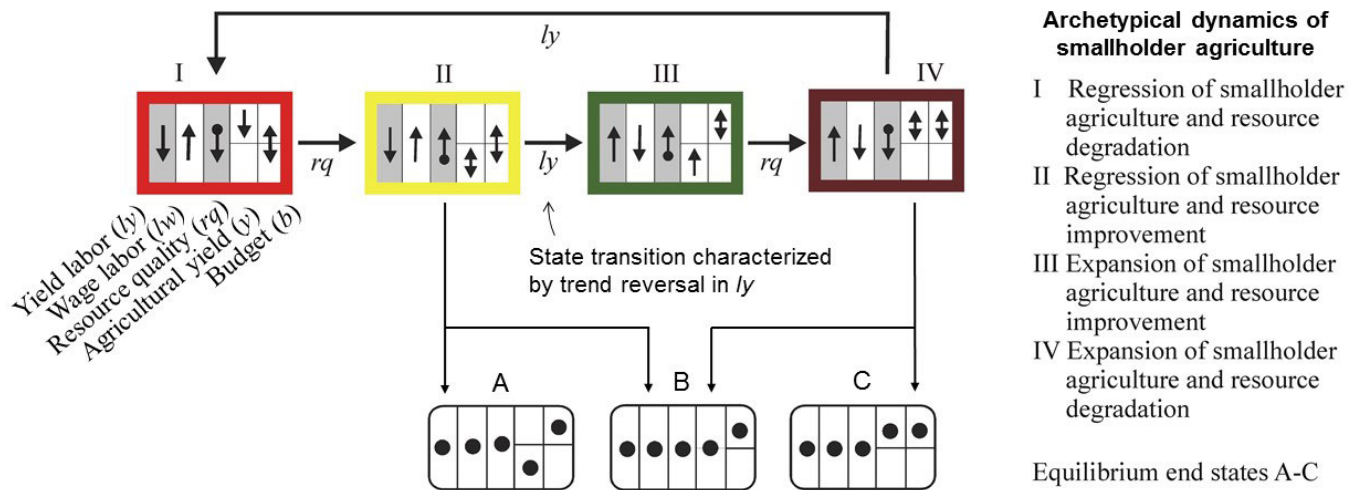
At the other extreme of this gradient, studies investigate temporal dynamics of key archetypal patterns (Fig. 1). These approaches use time-series data and information that reflects a phase or several points in time to investigate development trajectories of social-ecological systems. For example, self-organizing maps have been used to identify archetypal changes in land systems in Europe (Levers et al. 2018). Moreover, clustering served to reveal dynamics in archetypes of dryland vulnerability between 1970 and 2050 (Lüdeke et al. 2014), distinct trajectories of ecosystems services depending on land use intensity (Locatelli et al. 2017), and typical land use dynamics (van Vliet et al. 2012).

System dynamics modeling and qualitative dynamic modeling are among the methods especially suited to capture time-specific aspects in archetype analysis (Fig. 1). In particular, they can reveal nonlinear dynamics that enable reasoning about causal mechanisms of archetypal patterns (see also Gradient I). For example, system dynamics modeling has been used to forecast changes in agricultural land use and related soil impacts in the United States considering system archetypes associated with agricultural land transformation (Turner et al. 2017). System

dynamics modeling is suited to understand the dynamic behavior of complex systems by representing a system's structure and the coupled, sometimes time-delayed relationships among its components. It is especially suited to quantitatively simulate a system's dynamics when the behavior of the whole system cannot be explained by the behavior of its components. System dynamics approaches also offer valuable qualitative tools to support trend identification and provide insights into interlinked causes of (un)sustainable development enabling the identification of targeted leverage points for sustainability solutions; e.g., sustainable water management (Mirchi et al. 2014). Yet, these have remained underutilized in archetype analysis. As for all types of models, sensitivity analysis is important to test which components exert the greatest influence on the outcomes, which feedback loops are dominant at particular times and in particular situations, and how a system reacts to variations in components and feedback loops.

Moreover, an integrative, mixed-methods approach combining qualitative dynamic modeling, fuzzy logic, and expert evaluations has been used to evaluate “syndromes of global change” (Schellnhuber et al. 1997, Petschel-Held et al. 1999, Lüdeke et al.

Fig. 4. Example of a time-specific archetype analysis using a qualitative dynamic model to assess smallholder agriculture in northeast Brazil. The model results in archetypical trend combinations of the relevant variables (states) and the time evolution of the states (trajectories). To highlight the main characteristic of the development trajectory, closely related substates that are connected bidirectionally are summarized in the four archetypical states I to IV (indicated as boxes). The trajectory shows the time evolution—trends and magnitudes—of five key variables. Archetypical trend combinations of “ly” and “rq” are shaded in grey. The choice of colors reflects the criticality of smallholder conditions. Arrows symbolize temporal trends. The position of the yield (y) and budget (b) variables refers to thresholds indicating their magnitude. Dots indicate that the variable is constant over time. The model results include final equilibrium states (A to C) (adapted from Sietz et al. 2006).



2004). In these studies, syndromes of global change represented typical subdynamics of worldwide environmental and developmental processes capturing complex cause-effect relationships often including strong feedback mechanisms. Dynamics in these syndromes have been assessed through qualitative dynamic modeling (Petschel-Held et al. 1999, Sietz et al. 2006). This is possible because qualitative differential equations capture the relations between variables subsuming a multitude of quantitative differential equations for which many parameters remain unknown with the necessary resolution and coverage (Table 1). This modeling revealed nonlinearity in trajectories of typical trend combinations of variables and their relation to critical thresholds (Fig. 4). Yet, qualitative dynamic modeling does not provide insights into the urgency of interventions, since it does not reflect the velocity with which the dynamics unfold or the distance to critical thresholds.

Analytical frontiers

Taking up the methodological challenges and potentials for archetype analysis discussed in the previous section, this section outlines the most important analytical frontiers that we identified in our workshops, follow-up meetings, and reviewed literature. Here, analytical frontiers represent the furthestmost limits of understanding and achievements in the field of archetype analysis. Therefore, we highlight existing studies that are at the forefront of the research field and show several promising directions for pushing further the boundaries of archetype analysis in the future. Regarding the causality, normativity, space, and time gradients, four of the frontiers relate to particular gradients, while three cross-cutting frontiers capture overarching perspectives. In particular, advances in capturing the strength of causal relationships (Frontier I) are useful to identify archetypical

factors and processes leading to (un)sustainability outcomes and to directly improve our understanding of causality. In addition, concrete approaches to overcoming biases (Frontier II) are discussed as critical topics in relation to causality and normativity. Moreover, exploring archetypes at multiple spatial scales (Frontier III) reveals different manifestations and the nestedness of archetypical factors and processes enhancing spatially implicit and explicit insights. Furthermore, embracing rapidly growing high-resolution data (Frontier IV) enables improved analysis of causal mechanisms at high spatial and temporal resolutions. Finally, cross-cutting frontiers highlight the role of representing uncertainty for more nuanced decision-making (Frontier V), validation (Frontier VI), and up-scaling of sustainability solutions (Frontier VII). The following subsections detail the seven analytical frontiers.

Frontier I: Capturing the strength of causal relationships

Although causal analysis is critical in sustainability research, it is only beginning to receive the necessary attention (Meyfroidt 2016). Most of the methods we reviewed that are best suited to identifying archetypical causal mechanisms are qualitative (see causality gradient in Fig. 1). While these methods reveal the recurrence of positive or negative causal relationships (e.g., based on QCA or meta-analysis) (Rudel 2008, Fiss 2011) or assess their consequences (e.g., qualitative dynamic modeling) (Sietz et al. 2006), they do not provide quantitative measures of the strength of these relationships. This also applies to frequency-based meta-analysis of case studies that focuses on causal mechanisms. In contrast, statistical analyses provide insights into the strength of associations between causal factors as a basis to discuss causal relationships. To strengthen conclusions derived from multivariate statistical analysis, well-defined hypotheses about

cause–effect relationships—i.e., grounded ideas about underlying mechanisms— are important (van Asselen and Verburg 2012, Kok et al. 2016, Vidal Merino et al. 2019). Precise definition of hypotheses is not only essential to appropriately quantify underlying processes but also to consistently interpret and validate the patterns identified. For example, Sietz et al. (2012) interpreted and validated archetypical patterns of farmers' vulnerability in the light of cause–effect hypotheses used to define and quantify the relevant processes. This study showed that the vulnerability-creating mechanisms implied by the patterns were consistent with stakeholder reports about archetype-specific damages caused by weather extremes. This combination of qualitative and quantitative approaches highlights the value of using mixed methods in archetype analysis (Vidal Merino et al. 2019).

Adapting causal analysis techniques from other disciplines is another way forward to support causal inference from multivariate statistical analyses in archetype research. Quasi-experimental designs, which match control and treatment observations using covariate similarity or propensity scores to test for an average treatment effect, have been applied to evaluate sustainability policies, such as the establishment of protected areas to halt deforestation (e.g., Blackman et al. 2015). Other methods that rely on time series analysis, such as Granger causality testing (e.g., Seto and Kaufmann 2003) or survival analysis (e.g., Irwin and Geoghegan 2001, An and Brown 2008), have been successfully applied in land use change research to establish causal explanations of land use transitions. The main obstacle for applying these methods more widely in sustainability research is data availability. Both quasi-experimental and time series approaches require extensive spatial and/or temporal data for matching observations and detecting meaningful signals. Such data requirements are exacerbated when having to consider both social and ecological dimensions of sustainability. Mixed methods can again help in this regard. For example, Magliocca et al. (2019) combined spatio-temporal statistics (e.g., survival analysis and propensity score matching) and QCA of case studies to construct archetypical pathways of the commodity crops, social impacts, and timing and extent of (in)direct land use changes caused by economic land concessions in Cambodia. This study demonstrated that no single method could completely explain observed spatio-temporal patterns of social impacts and land conversion due to data limitations. Yet, synergies among the combined methods were exploited to identify recurrent causal relationships that formed the basis of archetypical development pathways triggered by land concessions. This example shows that mixed methods clearly have the potential to bridge data gaps and support causal inference in archetype analysis.

Frontier II: Overcoming biases

Biases in archetype analysis can be introduced from methodological and data limitations. For example, meta-analytical procedures using case studies can be strongly biased since case studies tend to reveal primarily variables with significant coefficients (Sietz and van Dijk 2015), potentially leading to biases in inference. Meta-analytical archetype analysis would become more robust by controlling for nonsignificant factors and processes. Qualitative comparative analysis may serve as an example in which standards of good practice require a distinction between positive cases leading to a given outcome and negative cases not leading to this outcome (Rihoux 2006,

Schneider and Wagemann 2010). Moreover, statistical archetype analysis is sensitive to outliers. Outliers skew the overall data distribution and may distort the pattern recognition, particularly when using clustering and machine learning algorithms that are based on distance measures. This is particularly relevant for small data sets. Winsorization—i.e., replacing the outlying values with the next available, less extreme value (Barnett and Lewis 1994)— is a way to des skew data sets and more adequately focus on most cases investigated (Sietz et al. 2012).

Moreover, machine learning methods enable data treatment by reducing the dimensionality of high-dimensional data spaces. For example, t-distributed stochastic neighbor embedding (t-SNE) has been used for exploring patterns in high-dimensional data spaces to generate new hypotheses on complex data (van der Maaten and Hinton 2008). It is an algorithm that provides a more unbiased way to analyze and compare data spaces independent of previous knowledge. By clearly separating groups and introducing less bias, it compares favorably to other dimensionality reducing methods. Yet, the interpretation of results is often demanding since the algorithm adapts to the data analyzed and transforms the data during the analysis. Moreover, t-SNE results can be strongly influenced by the selected parameterization. For example, “perplexity” is an important parameter that estimates the number of neighbors each data point has (van der Maaten and Hinton 2008). Misinterpretation can be avoided through carefully studying how t-SNE behaves with simple data sets, and different parameters should be tested to get insights into the robustness of results. Conclusions derived from statistical analysis can also be strengthened by applying different methods of analysis within the same sample to detect variations in the significance of specific variables (Kazianga and Masters 2002).

Expert and stakeholder assessments offer the opportunity to more closely engage relevant societal actors and assess potentially contrasting perspectives in archetype analysis. For example, local stakeholders in northern America perceived social values more frequently as an archetypical driver of future change than did global scenario developers (Wardropper et al. 2016). Capturing various stakeholders' perspectives on environmental or livelihood risks, potential damage, and their own adaptive capacity is important to overcome biases.

Frontier III: Exploring archetypes at multiple spatial scales

Social-ecological systems are shaped by a variety of ecological and anthropogenic processes operating at and across multiple spatial scales. However, archetype analyses have focused primarily on single scales, including local (e.g., Vidal Merino et al. 2019), regional (e.g., Cullum et al. 2017, Levers et al. 2018), or global scales (e.g., Crona et al. 2015, Kok et al. 2016). Multiscale approaches may strengthen archetype analysis because (i) archetypical patterns observed at one scale may manifest differently at another scale, and (ii) up-scaling is feasible when relationships between archetypical patterns and processes are constant across scales. This is important especially for designing policies at an intermediate level tailored to particular contexts (Campbell et al. 2006, Andersen et al. 2007, Vetter 2013); e.g., reflecting particular social groups or exposure to specific stresses.

One way to operationalize a multiscale approach is to focus archetype analysis on various spatial scale extents. Working at two spatial scale extents, Sietz et al. (2017) identified nested

archetypes of vulnerability in the drylands in Sub-Saharan Africa. This allowed a more differentiated discussion of opportunities for sustainable intensification at a regional scale. Another option is to use finer grained information on factors of interest (Sietz 2014, Václavík et al. 2016). Multiscale archetype analyses demonstrate how findings derived at various spatial scales can complement each other, instead of any one scale being considered the most important (see also Eisenack et al. 2019). Providing a feedback to case study research, archetypical mechanisms identified at multiple scales may inspire further investigations in specific settings.

Frontier IV: Embracing rapidly growing high-resolution data

Recent improvements in high-resolution spatial and temporal data from conventional (e.g., remote sensing) and newly emerging sources (e.g., Twitter, Flickr, mobile phone traces) present opportunities to overcome limitations arising from scattered empirical evidence. Using newly available “big data”, rapid regional changes that may not be observable in coarsely resolved data and infrequent standardized measurements (e.g., census data) are now possible targets for archetype analysis. For example, the opening up of the Landsat archive paired with multisensor fusion efforts have made time series analysis of archetypical land use patterns possible, even in consistently cloudy locations (Hansen et al. 2013) or for particularly difficult-to-detect land surface changes (e.g., tree plantations) (Hurni et al. 2017). These new data sources can help push the boundaries of causal archetype analysis by enabling cause–effect analysis at high temporal and spatial resolutions and more precisely evaluate archetypical pathways of change. However, new data sources come with their own unique challenges, including uncertain motivations of users/contributors, incomplete or ambiguous geospatial information, and difficulties in assessing the veracity of content (Jackson et al. 2013, See et al. 2016). These limitations can be addressed; e.g., by validating crowdsourced data against conventional sources (Mislove et al. 2011, Edwards et al. 2013, Sloan et al. 2013).

Machine learning algorithms such as artificial neural networks are well-suited to finding patterns in such large and often noisy data sets. Besides the potentially high explanatory power, further development, including deep learning and reinforcement learning, show particular promise to enhance artificial neural network application in archetype studies. Yet, there are still few machine learning applications in the field of archetype analysis. The use of fully or semiautomated (i.e., unsupervised or partially supervised) machine learning techniques for data collection, management, and analysis also poses challenges. In general, as the data increase in volume and heterogeneity, the more comprehensive and robust the training data set needs to be to produce reliable algorithms for data filtering, classification, and analysis. A potential solution is the triangulation of multiple methods and data sources to fill in spatial and temporal gaps in validated training data (Mertens and Hesse-Biber 2012), thereby enabling thorough examination of algorithms before applying to full data sets.

Frontier V: Representing uncertainty for more nuanced decision-making

Social-ecological conditions and decision-making are inherently associated with uncertainties resulting from conceptual

ambiguity, incomplete knowledge, absence of sharp spatial boundaries, measurement errors, and inherent variability. Such uncertainties challenge archetype analysis in support of developing sustainability policies. Fuzzy set theory (Zadeh 1965) is a promising tool for future archetype analysis to reconcile the persistent imprecision of real-world phenomena. In fuzzy set theory, units of analysis have a degree of membership in two or more classes. For example, fuzzy clustering (Zadeh 1977) offers the opportunity to investigate the degree to which an object (e.g., region or household) is characterized by two or more archetypical mechanisms that influence vulnerability, land management, or other sustainability aspects (Rao and Srinivas 2006). Moreover, fuzzy set QCA allows the representation of gradients of archetypical conditions ranging from high to low values rather than just the presence or absence of conditions. For example, fuzzy set QCA has been applied to study recurrent configurations of factors differentiating the ability of governance systems to respond to climate change challenges (Pahl-Wostl and Knieper 2014) and the emergence and persistence of local autonomy among institutions that govern biodiversity conservation (Basurto 2013). In addition, fuzzy classification has been used to overcome the challenges of mapping continuous ecological conditions that lack well-defined spatial boundaries (Cullum et al. 2017). An important difference of fuzzy set QCA and fuzzy classification compared with fuzzy clustering is that they prescribe the structuring characteristics for categorization via the membership functions (calibration) pertaining to a specific classification problem. Fuzzy set methods that reflect the uncertainty in available knowledge and data offer a valuable opportunity to bridge quantitative and qualitative approaches for archetype analysis and contribute to more nuanced decision-making and design of appropriate intervention options.

Frontier VI: Validation

Validation is key for providing credible archetype analysis that would be taken up in decision-making on sustainable development. However, validation has rarely been applied in archetype studies. Both empirical and application validity (Bossel 1994) are important to illustrate archetypes’ relevance and credibility. Archetypes are considered to be empirically valid if they correspond to reported (un)sustainability outcomes, and if the mechanisms causing these outcomes are consistent and plausible. For example, a local study in the Peruvian Andes demonstrated that the identified archetypes of vulnerability were consistent with independently reported causal mechanisms and damage smallholder farmers experienced due to weather extremes (Sietz et al. 2012). This empirical validation confirmed the relevance of findings for decision-making. Working at a local level provides a clear advantage since limitations in regional or global observational data often constrain such a validation on broader scales. As alternative, though less rigorous approaches, expert evaluation (Levers et al. 2018) and comparison of results with independent case study knowledge (Sietz et al. 2017) have served to test the empirical validity of archetypes in continental and global studies. More systematic use of independent data sets and multiple methods for validation purposes represents a promising avenue for future archetype analysis. Some of the methods addressed in this study can provide examples in these respects, for instance with reference to the use of case studies that explore QCA results (Schneider and Rohlfing 2016) and recent contributions

that link QCA and process tracing (Schneider and Rohlfing 2013), and embedding these in mixed-method research (Rohlfing and Schneider 2018).

Moreover, archetypes show application validity if the transferability of strategies to enhance sustainable development can be shown within a given archetypal pattern. For example, independent case studies served to demonstrate the application validity of archetypes in global drylands (Sietz et al. 2011, Kok et al. 2016). These case studies reported that soil and water conservation measures that had successfully reduced vulnerability in western Africa were later up-scaled to other locations categorized in the same archetype. This reported transfer confirmed the hypothesis that suitable interventions are similar within comparable social-ecological conditions. A more systematic collection of evidence, including high-resolution data (see Frontier IV), is important to demonstrate empirical and application validity in future archetype assessments (see also Eisenack et al. 2019) as a prerequisite for scaling sustainability solutions (see Frontier VII).

Frontier VII: Scaling of sustainability solutions

Archetype analysis supports the scaling and transfer of knowledge from one place to another in a systematic way. The assumption that similarities in social-ecological conditions link to similarities in interventions directly contributes to the debate about the scalability of sustainability solutions. When assessed in a spatially implicit or explicit way, archetypes help identify potential scaling domains (Coe et al. 2014); i.e., locations to which successful interventions may be out- and up-scaled. One approach is to quantify the transferability potential of sustainable development strategies. For example, Václavík et al. (2016) calculated the statistical similarity of locations to a relevant project archetype to estimate the potential to up-scale or transfer insights derived from place-based research on sustainable land management. These authors used archetypes of land use intensity and environmental and socioeconomic conditions (Václavík et al. 2013) to assess transferability and provide hints on the scalability of insights from large place-based research programs. The scaling of best practices can also be informed by spatial insights into similarities among social-ecological systems. For example, vulnerability profiles derived from cluster analysis depict locations of similar problem structure, suggesting a similar response to interventions such as water harvesting and soil fertility improvement (Kok et al. 2016, Sietz et al. 2017). Both clustering and statistical similarity methods can be applied at any scale, enabling the identification of nested archetypes, and are thus well-suited to inform decisions made at local, regional, or global scales.

Insights derived from archetype analysis enable decision-makers to evaluate a region's potential for scaling successful interventions within its broader context (see also Oberlack et al. 2019). This is a fundamental step since decisions—for example, to provide advisory, financial, or material support to farmers—are made mainly above the local level. The evaluation provides broad entry points whose implementation requires detailed local knowledge about the social-ecological conditions, synergies, and trade-offs that shape the interactions between societies and ecosystems.

CONCLUSION

Using results from two international research workshops, a series of follow-up discussions, and a literature review, we demonstrated the diversity of methods available to analyze archetypes of social-ecological systems and the great variety of sustainability domains in which these methods have been applied. We synthesized these methods to provide a basis for better understanding the causal mechanisms underlying particular archetypes and their (un)desirability at appropriate spatial and temporal scales. Quantitative methods included meta-analysis of case studies, rule-based classification, cluster analysis, machine learning algorithms, statistical distance/similarity analysis, spatial statistics, and system dynamics modeling. Qualitative methods covered qualitative classification, expert and stakeholder assessment, qualitative comparative analysis, and qualitative dynamic modeling. This synthesis reveals major strengths and weaknesses in gaining a more complete perspective of sustainability opportunities and challenges helping to achieve Agenda 2030.

The overview of archetype methods we provided facilitates the reflection on specific methodological implications, enabling researchers to evaluate a method's suitability for archetype analysis depending on their research purpose and specific research questions. For example, if quantitative data were available to cover a large range of (un)sustainability drivers and associated outcomes, and if the aim was to identify complex patterns, machine learning would offer a suitable methodological approach. Yet, if few case studies were to be assessed with respect to causal factor configurations leading to a (un)sustainability outcome, qualitative comparative analysis would be a suitable candidate. Different methods can be adapted to varying interdisciplinary and transdisciplinary requirements based on conceptual specificities and data availability.

Our synthesis provides impetus regarding three major realms for future archetype analysis. First, causal analysis techniques should be explored more intensively to demonstrate in which ways recurrent biophysical and socioeconomic (un)sustainability drivers and consequences coevolve and interact across local, regional, and global scales. This will help overcome the scarcity of causal analysis in sustainability research. Second, temporal dynamics in archetypes need to be analyzed in greater detail. We discussed a range of quantitative and qualitative methods that explicitly capture changes over time in order to stimulate their use in the future. Third, archetypes need to be rigorously validated considering relevant stakeholders' perceptions, expectations, and demands. This will enhance the credibility of archetype findings as a prerequisite to be taken up in decision-making as regards the design of sustainability solutions and the systematic up-scaling of sustainability interventions across locations. Overall, this synthesis will support the sustainability research community to effectively combine methods for designing innovative research approaches that advance comparison and generalization at an intermediate level in between the particularities of single cases and panacea perspectives.

Responses to this article can be read online at:

<http://www.ecologyandsociety.org/issues/responses.php/11103>

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