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# Geographic similarity analysis for Land System Science: opportunities and tools to facilitate knowledge integration and transfer

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**ABSTRACT**

Advances in Land System Science (LSS) rely on the evidence generated by different types of research activities, including place-based case studies, landscape/land-system mapping and synthesis research. However, these activities are usually conducted in parallel, with a lack of integration often leading to important knowledge gaps and limitations. In this article, we provide tools for the application of geographic similarity analysis (GSA), a collection of spatially-explicit methods assessing the degree of similarity between geographic locations, and thereby help to address these limitations. We identify opportunities for employing GSA to support: 1) selecting geographically representative sets of case studies; 2) integrating empirical evidence generated at different scales and levels of abstraction; and 3) facilitating context-sensitive knowledge transfer. The resulting toolbox provides approaches for facilitating researchers to get an enhanced understanding of multi-scale land change processes, as well as supporting land governance in scaling up the knowledge and solutions generated by LSS research.

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## 1. Introduction

Advances in Land System Science (LSS) rely on the interplay between the generation and interpretation of context-specific empirical evidence at different geographic and temporal scales, and the generalisation of cumulative evidence into context-sensitive concepts, theories and applications. Place-based case studies, for example, enable in-depth investigation of the processes leading to land-system change, and the assessment of the resulting trade-offs (Potschin & Haines-Young, 2013). Conducting and comparing multiple case studies using a common analytical framework allows synthesising evidence about how particular decision-making strategies are shaped by their specific contexts and drivers, and identifying potential commonalities and differences across places (Sunderland et al., 2017). Case studies thus provide one of the main foundations for producing empirical evidence in LSS research (Verburg et al., 2015). Remote sensing and spatial data analysis

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provide complementary empirical evidence for mapping and analysing large-scale land-system changes in terms of land use and cover (Song et al., 2018), as well as developments in landscape management, structure, and composition in more detailed case studies (Helfenstein, Diogo, et al., 2022; Kolecka et al., 2018). Synthesis research is then a crucial step to contextualise findings from individual studies and integrate them towards generalised knowledge and theories of land-system change (Magliocca et al., 2018; Meyfroidt et al., 2018). Synthesis research is typically conducted by drawing upon available empirical evidence generated from multiple sources, using methods such as meta-analysis and systematic literature review (Magliocca et al., 2015).

These research activities are, however, often conducted in parallel across different research projects or work packages with limited integration (Rindfuss et al., 2004). Conducting them separately often leads to incomplete explanations on the linkages between local contexts and global change processes (Balvanera et al., 2017). For example, landscape/land-system mapping enables identifying land-change trajectories, and quantifying the effects of the spatial drivers influencing them (Levers et al., 2016, 2018). Yet, these methods alone do not allow inference on the motivations and decision-making leading to these processes. In contrast, place-based case studies allow inference of relevant human behavioural aspects and their consequences at the local scale (Potschin & Haines-Young, 2013). However, the number of case studies that is carried out in a single research project is usually not large enough for making broader generalisations (Magliocca et al., 2018). If not systematically contextualised within a representative sample of other studies, the insights and solutions derived from case studies thus risk falling into idiographic traps, i.e. over-particularisation of case study findings in relation to their historical and social-ecological contexts (Castree, 2005; Flyvbjerg, 2006; Oberlack et al., 2019). This may, in turn, jeopardise the transferability of knowledge and solutions to places and scales beyond the study area (Wuelser et al., 2021).

Conversely, synthesis research may fail to account for important social-ecological features and processes, for instance, during the coding process in meta-studies, given that the appropriate degree of abstraction is unknown *a priori*. Consequently, synthesis may risk falling into nomothetic traps, i.e. overly generalised explanations of land-system change (Oberlack et al., 2019). Furthermore, systematic biases can be introduced by the selection of geographic locations for conducting case studies. In fact, LSS place-based research is often prioritised in relatively accessible locations where salient change occurs, and in areas where nature is protected or perceived as pristine (e.g. Martin et al., 2012; Wohner et al., 2021). Such selection biases potentially limit the scalability or applicability of LSS theory derived from case study synthesis.

In this article, we argue that the targeted application of methods based on geographic similarity analysis (GSA) can help to address the knowledge gaps and limitations in LSS research outlined above, towards an improved articulation between different research activities and their respective scopes and scales of analysis. We first give an overview of concepts, methods, and current applications of GSA in LSS research (Section 2). Then, we identify additional opportunities for advancing LSS research by applying GSA (Section 3). In particular, we devise novel methodological approaches based on GSA to help:

- selecting geographically representative sets of case studies in a project (Section 3.1);
- integrating empirical evidence generated at different geographic scales and levels of abstraction, for contextualising case-study findings (Section 3.2.1) and making context-sensitive generalisations (Section 3.2.2);
- transferring context-sensitive knowledge (Section 3.3).

These approaches aim at supporting both the identification of comprehensive multi-scale explanations of land-system change, and the scalability of knowledge and solutions generated by LSS research (Figure 1). Based on these, in Section 4 we summarise the challenges and approaches presented here by proposing a toolbox for applying GSA, and thereby helping address current knowledge gaps and limitations in LSS research. More specifically, for each of the identified pitfalls,

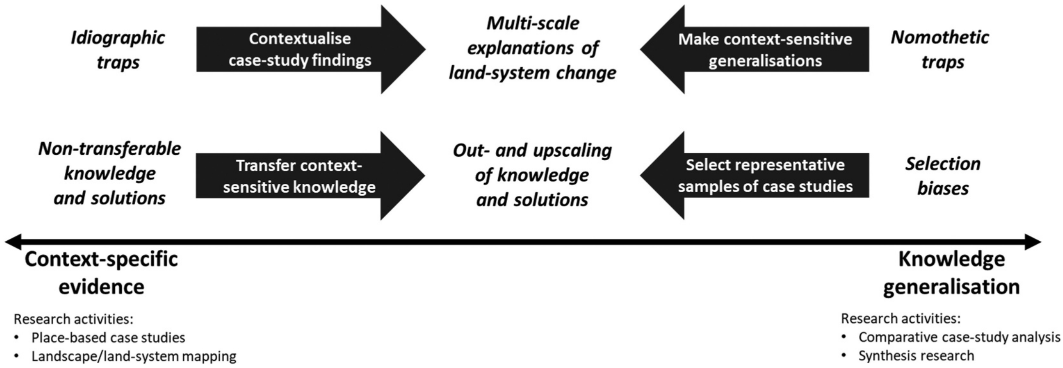



**Figure 1.** GSA-based approaches proposed in this article (black arrows) for articulating different research activities contributing to the generation of context-specific evidence and knowledge generalisation, and thereby addressing current knowledge gaps and limitations in LSS research.

we describe what GSA can do to bridge the gaps between the generation of context-specific evidence and knowledge generalisation, and propose a targeted set of methodological tools for addressing them. When available, we provide illustrative examples based on the 'Operationalizing sustainable intensification pathways in Europe' (SIPATH) project, which uses multiple case studies to gain an understanding of agricultural change patterns (a common approach in LSS). Finally, we discuss remaining challenges in the application of GSA in the support of LSS research and potential ways forward for addressing them.

## 2. Geographic similarity analysis: concepts, purposes and current applications in Land System Science research

We use GSA as an umbrella term that encompasses a collection of spatially-explicit methods for assessing the statistical similarity between land systems across different geographic locations, according to sets of spatial data representing relevant biophysical and socio-economic characteristics of land systems. These may include, for example territorial features such as land use, climate, topography, economic activity, population, and accessibility, but also relevant incoming and outgoing flows across (distant) locations such as agricultural inputs and commodities, migrant workers, and related monetary flows in so-called telecoupled systems (Hull & Liu, 2018; Liu et al., 2013). GSA is rooted on the assumption that comparable land change processes and outcomes can be expected in locations with similar social-ecological configurations (Sietz et al., 2019; Václavík et al., 2016; Zhu & Turner, 2022). Variations in the degree of similarity among locations can thus be used as a criterion to examine the validity of the generalisations made about land change phenomena, for example; which combinations of conditions explain the recurrent occurrence of certain processes and outcomes; which factors contribute to the occurrence of divergent outcomes in similar locations; or conversely, which drivers lead to similar outcomes in locations with distinct socio-ecological features. Hence, GSA can be utilized as a tool for guiding and structuring the interpretation, comparison and synthesis of the empirical evidence gathered across various locations.

GSA belongs to the wider portfolio of methods for configurational comparative analysis applied in archetype analysis, a methodological approach for identifying and understanding recurrent configurations of variables and processes shaping the (un)sustainability of social-ecological systems and land governance (Magliocca et al., 2018; Oberlack et al., 2019). Archetype analysis has, however, a broader scope of analysis and application in terms of the social-ecological attributes, processes and causal mechanisms considered. In particular, depending on the topic of investigation, archetype analysis may use GSA to investigate recurrent combinations of spatially-explicit location factors and land (change) patterns (i.e. large-scale land-system archetypes), but also other quantitative and qualitative methods examining the configuration of social-ecological attributes and processes that do not necessarily have a spatial representation (Sietz et al., 2019). These include, for example, actors and action situation networks (e.g. degree of power asymmetry), governance structures (e.g. degree of law enforcement), and socio-political processes and outcomes (e.g. polarisation of development discourses; see Oberlack et al., 2016).

So far, GSA has been applied in LSS research mainly for four main purposes: mapping landscape/ land-system typologies and archetypes; identifying counterfactual land systems for assessing (causal) impacts of land interventions; assessing the geographic representativeness of collections of case studies; and exploring the transferability potential of place-based research. In Table 1, we provide for each of these purposes a summary of GSA applications and methods currently employed, and respective examples from the literature; in Appendix A, we describe these in more detail.

## 3. Opportunities for advancing Land System Science with geographic similarity analysis

In this section, we propose novel methodological approaches combining GSA methods with other established methods in LSS research, to address the knowledge gaps and limitations identified in Section 1 (Figure 2).

### *3.1. Selecting geographically representative sets of case studies in a project*

Many LSS research projects are composed of multiple place-based case studies in different locations, as a means to generate empirical evidence and investigate how decision-making strategies, land-use interventions and their respective outcomes are shaped by local contexts and drivers (Meyfroidt, 2016). Often, such a project design comes along with the goals of synthesising similarities and differences between case studies, generalising research findings and scaling up solutions to geographic contexts beyond the specific case study areas. For this type of project, the location of the case study sites should, therefore, ideally be selected so that they cover a representative range of the observed variation in characteristics of interest within the geographic universe for which the project results are intended to be generalised and scaled up (Angelstam et al., 2013).

Case study representativeness is, however, rarely assessed during the design phase of a research project. In fact, case study selection is largely determined by pragmatic considerations, such as the existence of long-standing collaboration networks and field teams in focal regions, where previously collected information and data is readily available and connections with local experts, authorities and stakeholders are already established (Sunderland et al., 2017; Van der Zanden, Cord, et al., 2016).

While these considerations constitute critical factors for the success of a project, we argue that LSS researchers should always assess the geographic representativeness of available case study sites during the project design phase. This can offer two main advantages. Firstly, representativeness analysis can support the selection of locations for case study sites. In particular, computing and visualising spatial similarity indices (see Appendix A.3) allows identifying regions of interest that may be under- or over-represented in relation to the topic of investigation and targeted geographic context. Such insights can, in turn, contribute to an iterative refinement and optimisation of the selection of case study sites, in relation to available resources and existing collaboration networks. For example, it can support the identification of regions for which the potential inclusion of additional case studies would be of added value to the project in terms of expanding its geographic representativeness. It can also support decisions for dropping case study sites deemed redundant, given the set of available options and their geographic representativeness.

Secondly, representativeness analysis provides an early evaluation of potential selection biases and defining more specifically the geographic scope for which the research findings may be valid. This can, in turn, be transparently communicated to relevant stakeholders, from the very beginning

**Table 1.** Purposes, methods and current application of geographic similarity analysis in Land System Science research.

| Purpose | Useful for | Methods | Examples |
|---|---|---|---|
| Mapping landscape/land-system typologies and archetypes | Identifying large areas sharing land-system (change) patterns and processes with similar characteristics. | Machine/deep learning algorithms based on spatial data clustering. Expert-based hierarchical classification procedures. | Feizizadeh et al (2021, 2023). Václavík et al. (2013) Van der Zanden, Levers, et al. (2016) Sietz et al. (2017) Levers et al. (2018) Zarbá et al. (2022) Ellis and Ramankutty (2008) Van Asselen and Verburg (2012) Malek and Verburg (2017) Dou et al. (2021) |
| Identifying counterfactual land systems for assessing (causal) impacts of land interventions | Matching a "treated" observation (i.e. a location affected by a given land intervention) to a "control" observation that has a similar socio-environmental context but was not affected by the intervention. | Spatial similarity indices, used to inform statistical inference. | Ferraro and Hanauer (2014) Baumann et al. (2015) Davis et al. (2020) T.A.P. West et al. (2020) Williams et al. (2021) |
| Assessing the geographic representativeness of collections of case studies | Evaluating the extent to which a collection of case studies is representative of the range of variation observed within a given geographic universe. | Statistical hypothesis and Monte Carlo tests. Spatial similarity indices. | Schmill et al. (2014) Meyfroidt et al. (2014) Malek et al. (2019) Wohner et al. (2021) Schmill et al. (2014) Van der Zanden, Cord, et al. (2016) |
| Exploring the transferability potential of place-based research | Identifying locations where the methods, results and/or conclusions generated in a project/case study are potentially applicable. | Spatial similarity indices. Machine learning algorithms based on spatial data clustering. | Václavík et al. (2016) Piemontese et al. (2020) |

of the project. Even in projects for which geographic representativeness is not necessarily important, evaluating the similarity of the case study sites with other regions of interest may provide useful insights or topics for discussion. This includes, for example, projects composed of a single case study and for which the topic of interest is relevant due to its uniqueness or urgency (e.g. technology front-runners, vulnerable indigenous communities, advancing land-use change frontiers), and therefore

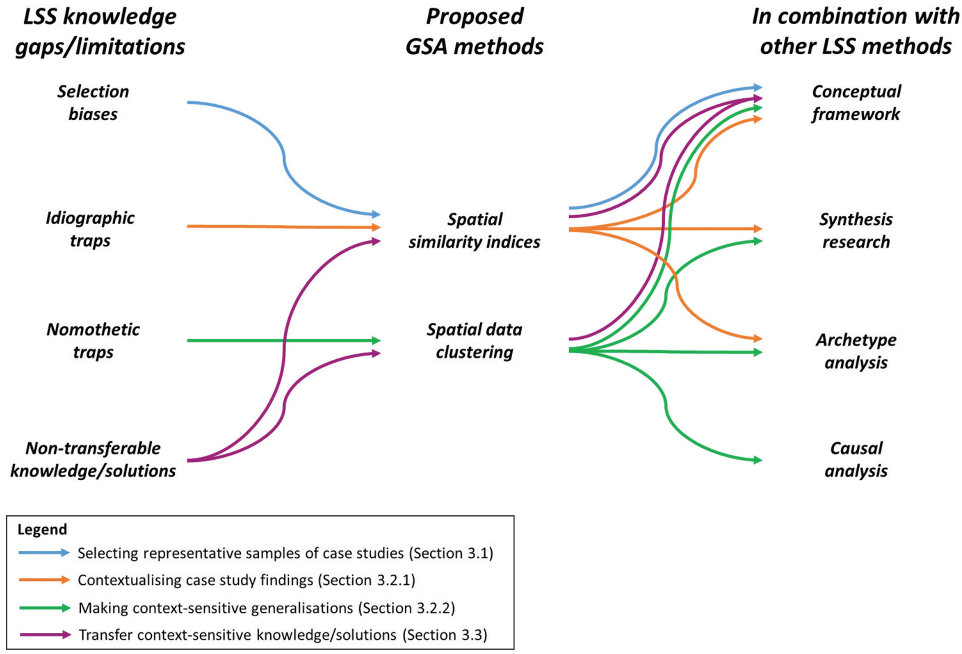



**Figure 2.** Overview of combinations of GSA methods with other established LSS research methods proposed for addressing current knowledge gaps and limitations in LSS.

generalisation is not necessarily a goal. For this type of project, spatial similarity visualisations may enable researchers to identify regions with similar conditions where other research teams may be active, and with which potential opportunities for collaborating and co-learning could be explored (e.g. providing matching cases for counterfactual analysis, anticipating opportunities/risks in regions where the investigated processes have not yet been observed).

The choice of spatial variables for assessing geographic representativeness should, however, not be based purely on data availability, but rather address the question: 'representative for what purpose?' In particular, we recommend using the conceptual framework underlying the project's research questions as a guiding principle for structuring the representativeness analysis. In LSS research, concepts and analytical categories are often arranged in 'box-and-arrow' conceptual framework diagrams, which describe the assumed structural relations and interactions between large sets of variables and components that are considered relevant in a system (Meyfroidt et al., 2018; Oberlack et al., 2019). Conceptual frameworks thus provide a structured approach for formulating and addressing research questions. In this regard, conceptual frameworks can also be used as a basis to define social-ecological dimensions for which representativeness should be evaluated, and to guide the selection of spatial variables employed in the analysis for each of these dimensions.

We illustrate this approach by briefly describing the representativeness analysis conducted to evaluate the selection of case study sites in the context of the SIPATH project. In this project, a number of case studies were conducted in different landscapes across Europe, in order to build a historical perspective on the changes and diversity in agricultural production intensity. The case studies were intended to represent a broad range of biophysical and socioeconomic contexts that are relevant for European agriculture. A conceptual framework was developed in the beginning of the project, providing a structural way to analyse context-specific intensification trajectories and sustainability outcomes. The conceptual framework defines sustainable intensification as a pathway, by considering conceptual linkages from megatrends and contextual drivers affecting decisions on management intensity and landscape structure, all the way to the assessment of sustainability

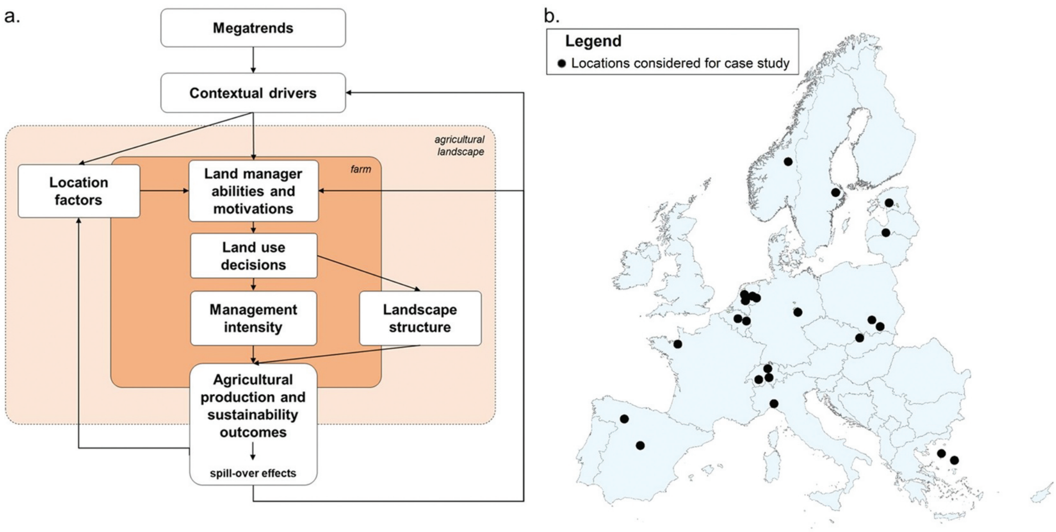



Figure 3. a. SIPATH conceptual framework (adapted from Helfenstein et al., 2020). b. Locations in Europe considered as potential case study sites for the SIPATH project, based on existing collaboration networks.

outcomes (Helfenstein et al., 2020; see also Figure 3a). A first list of potential case study sites was compiled (Figure 3b), by identifying locations where contacts with local teams had already been established in the context of previous/ongoing research projects investigating agricultural development in Europe.

The geographic representativeness of each individual site in relation to the European context was then assessed separately for different social-ecological dimensions considered in the conceptual framework, specifically: contextual drivers, land manager abilities and motivations, management intensity and landscape structure. For each of these dimensions, we selected a set of spatial variables for representing them (see Appendix B), based on a review of studies identifying appropriate variables and proxies for capturing agricultural land-system characteristics in Europe (e.g. Diogo et al., 2022; Perpiña-Castillo et al., 2021; Van der Zanden, Levers, et al., 2016; Verburg et al., 2011). Geographic representativeness was then evaluated by computing similarity indices as specified in Eq. A.1 in Appendix A, using these socio-ecological variables. Figure 4 shows an example of the representativeness analysis on the four conceptual dimensions in one of considered case study sites.

For each of the social-ecological dimensions, and combinations thereof, we then assessed and compared the geographic representativeness of the considered sites (see Fig. C.1 in Appendix C, for an example comparing four case study sites). This type of analysis allowed assessing the degree of complementarity of the considered case study sites in relation to particular dimensions of the agricultural land system in Europe. Finally, we evaluated the overall representativeness achieved by different combinations of complementary case study sites, in order to inform the final selection. This was done by identifying, for each social-ecological dimension, the grid-cells that had high similarity to, at least, one of the case study sites (i.e. similarity index $\geq 0.75$). Fig. C.2 in Appendix C shows the overall representativeness of the final selection of case study sites for each individual social-ecological dimension, and Figure 5 the number of dimensions in each location for which the selected set of case study sites is representative in Europe.

This type of analysis allowed identifying the extent to which the selection of case studies was able to cover a representative range of variation for different dimensions of the land system, and the locations in which these dimensions may be underrepresented. For example, all considered categories appeared to be relatively well covered by the final selection of case study sites, except for the dimension on land manager abilities and motivations. For this particular dimension, locations with

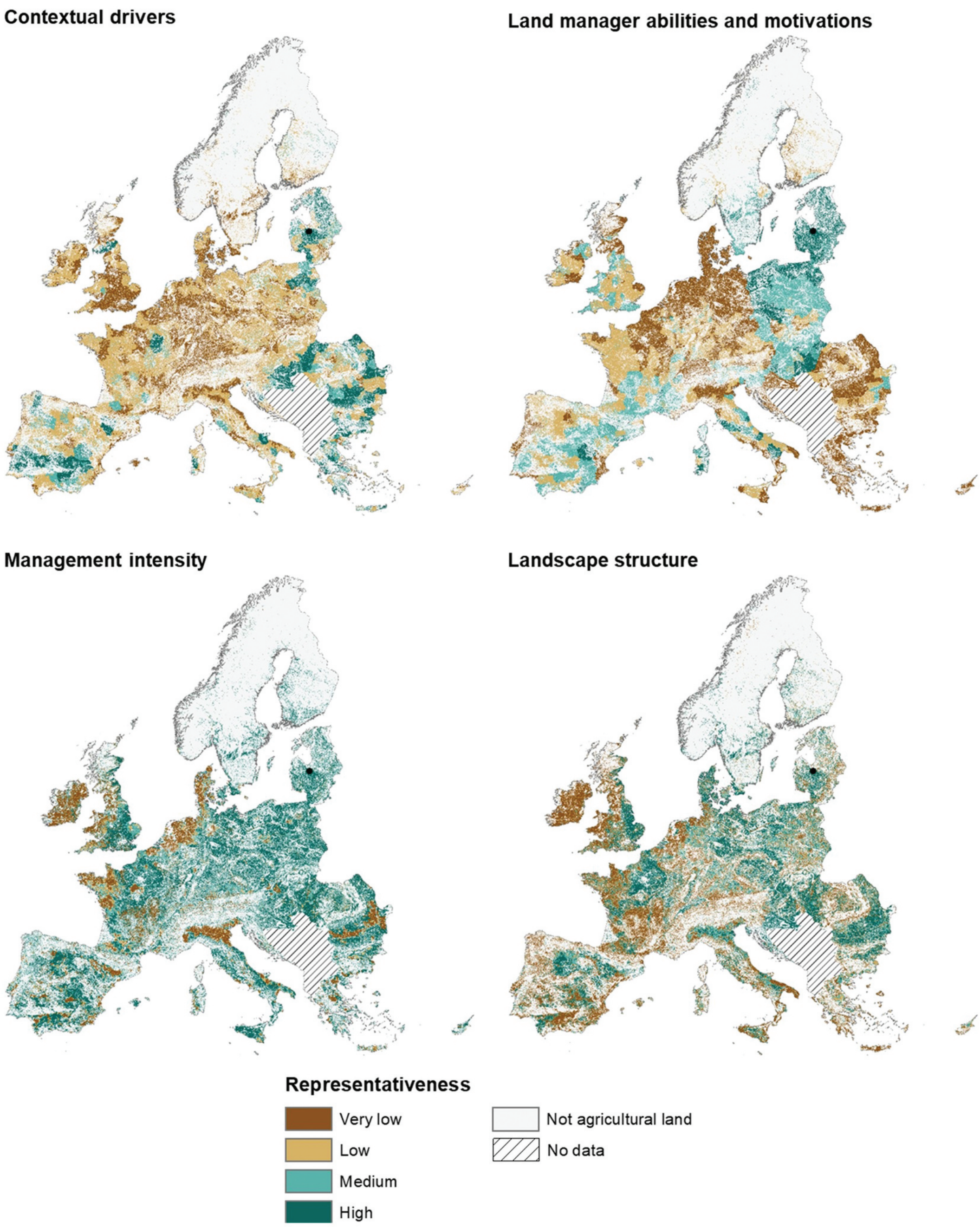



**Figure 4.** Representativeness analysis on the four social-ecological dimensions considered in the SIPATH project for the case study site in Lielvircava, Latvia. The similarity indices range from 0 to 1, with 1 indicating that a location is fully identical to the case study site in terms of considered social-ecological variables. The representativeness categories were defined as follows: Very low representativeness: 0–0.25; Low representativeness: 0.25–0.50; Moderate representativeness: 0.50–0.75; High representativeness: 0.75–1.

high share of farmers older than 65 years and/or high land rental prices appeared to be under-represented. This may indicate that the project's case studies may not provide insights into processes related to, for instance, ageing rural population and farm succession, and high competition for land

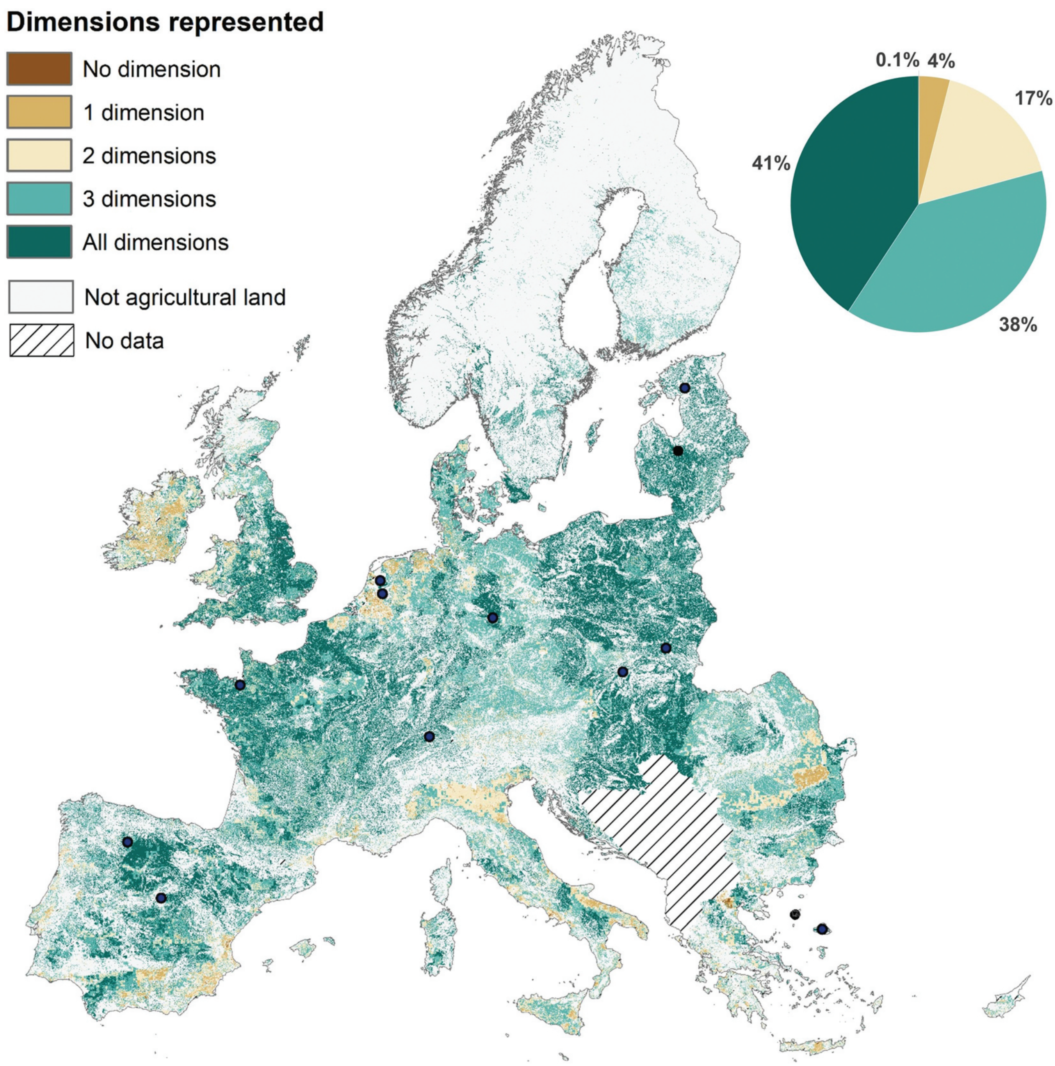



**Figure 5.** Number of considered social-ecological dimensions for which the selection of SIPATH case studies is highly representative in Europe, and the share of each category in terms of the total agricultural land area in Europe.

with other uses, respectively. In terms of management intensity and landscape structure, we could also identify a number of agricultural systems that appeared to be underrepresented by the selected set of case studies (see Figure 5, and also Fig. C.2 in Appendix C), for example: i) areas with both intensive arable farming and industrial landless livestock systems (e.g. in North Italy, Netherlands, Denmark and Romania); ii) open grassland systems with low livestock density (e.g. in Ireland and United Kingdom); iii) large-scale permanent crop systems (e.g. in Mediterranean regions). These aspects of geographic representativeness can then be explicitly taken into account while interpreting, synthesising and communicating the case study results throughout the project. Alternatively, Figs. 5 and C.2 could also have been applied to explore potential locations for additional case studies that could fill the identified 'representativeness gaps' (i.e. the areas depicted in brown in these figures).

The example described above shows that for evaluating the geographic representativeness of a collection of project case studies, two important aspects need to be defined, which in turn depend very much on the specific topic of investigation: 1) the geographic universe for which the project findings are intended to be potentially relevant; and 2) the thematic resolution of socio-ecological dimensions for which representativeness should be assessed. For instance, as the SIPATH project ambition was to provide an overview of intensification trajectories in different contexts across Europe, representativeness was evaluated against all agricultural land in Europe, taking into account relatively generic socio-ecological dimensions and variables relevant for different types of agricultural production systems, including arable farming, livestock production, permanent crops and mixed farming. Had the project been focused, for example, on grassland management in mountainous regions across the world, then representativeness would have to be assessed globally, but only in mountain areas and taking into account dimensions and variables more specific to grassland systems (for example, distinguishing specific types of grassland vegetation and grazing livestock species). Such aspects should be given careful consideration when interpreting the results of a representativeness analysis, particularly when appraising the overall geographic representativeness achieved by a collection of case studies and the share of the geographic universe for which the considered socio-ecological dimensions are considered to be represented (see Figure 5).

## *3.2. Integrating empirical evidence generated at different geographic scales and levels of abstraction*

### *3.2.1. Contextualising case-study findings with synthesis research*

Irrespective of their geographic representativeness, the number of case studies carried out in a single research project usually does not provide enough observations for identifying broader patterns or supporting generalisations with strong evidence (*sensu* Magliocca et al., 2018). To address this limitation, case study research could benefit from being combined with synthesis research, for the contextualisation and systematic comparison of the results generated in a project with other existing studies. GSA methods can support understanding how the evidence generated can be articulated together.

For example, after conducting the place-based case studies in a particular project, synthesis methods such as meta-analysis and systematic literature review could be applied to survey existing literature on the topic investigated in the case studies. The literature search should be guided by the same research questions investigated in the project case studies. In particular, the conceptual framework could be applied to structure the literature review, so that the results from the review are aligned with those obtained in the project case studies. Depending on the sample size and research questions, different methods can be used to analyse existing literature (see Magliocca et al. (2015) and Sietz et al. (2019) for an overview of methods for synthesis research). At the same time, the results from the case studies can inform the literature analysis on the appropriate degree of abstraction (e.g. during the development of the codebook), by providing an indication on the factors and processes that appear to be relevant to be analysed.

Based on the literature analysis, local archetypes of land system patterns and change trajectories can then be defined, based on the identification of similar patterns and phenomena occurring across different locations and contexts (Oberlack et al., 2019). Such archetypes may represent, for instance, recurrent configurations of drivers and land-use change processes (Plieninger et al., 2016), decision-makers (Malek et al., 2019), and land-use outcomes (Oberlack et al., 2016). In addition, the locations of the case studies reviewed in the literature should be geocoded, if possible (Margulies et al., 2016).

The similarity patterns generated with the representativeness analysis of case study sites (see the example in Section 3.1) could then be used to guide the contextualisation, interpretation and comparison of the project case studies with the results of the literature review. In particular, the detailed results from the case studies allow identifying a large range of conditions under which the validity of the local archetype generalisations can be assessed (Møller & Skaaning, 2017). Systematically comparing case study results against the available empirical evidence allows going beyond the kinds of *ad-hoc* comparisons that are usually made within the discussion section of scientific publications. For example, the following questions can be investigated: To what extent are the project case study results comparable to the recurrent patterns identified in the literature, when taking into account their degree of social-ecological similarity? Are the same processes observed in regions with similar socioeconomic and/or biophysical characteristics? What factors appear to explain the similarities/differences? Answering these questions allows testing hypotheses on the assumed relationships between local drivers, processes and outcomes of land change in places with similar characteristics, identifying the potential emergence and/or co-existence of different archetypes in similar locations, and based on that, refining the definition of local archetypes.

#### *3.2.2. Generating context-sensitive generalisations by integrating case studies and synthesis research with large-scale land-system mapping*

GSA can also be employed to support the contextualisation and integration of evidence generated at different geographic scales. In particular, local archetypes identified through synthesis of case studies (either in the context of comparative case study research, or through formal synthesis methodology) can be analysed, contextualised and interpreted in relation to broader structural processes of land-system change identified through large-scale land-system mapping, as a means to identify multi-scale processes and explanations of land-system change.

For example, large-scale land-system observations can be assembled through remote sensing, collection of existing spatial datasets and official statistical records (e.g. on land cover change patterns, production and trade of commodities, use of agricultural inputs, accessibility, population and migration flows) to analyse and identify relevant large-scale patterns, drivers and outcomes of land-system change. Clustering techniques based on statistical similarity can then allow the identification of large-scale archetypes of land system patterns. Alternatively, existing large-scale land-system archetype maps can also be used, if the purpose for which those maps were generated fits the topic of investigation (see the examples in Table 1 and Appendix A.1). Both local and large-scale land-system archetypes present each a synthesis of recurrent configurations of drivers, patterns and/or processes in land systems. By assessing the degree of spatial overlay between local and large-scale land-system archetypes, it would be possible to identify (recurrent) combinations of archetype structures revealing multi-scale interactions and processes of land-system change. Similarly to the application of representativeness analysis described in Section 3.1, the categories of the conceptual framework could be used to guide the definition of such archetypical structures.

We illustrate this approach by showing how the results of the SIPATH case studies (Helfenstein et al., 2023) can be combined with an existing pan-European analysis of archetypical land-system change trajectories (Levers et al., 2018) to reveal multi-scale change trajectories in European agriculture. The SIPATH case studies consisted of interviews with farmers and interpretation of aerial photos to quantify indicators regarding changes on farm management intensity and landscape structure between 2000 and 2020 (Helfenstein, Bürgi, et al., 2022). These surveys were conducted in selected locations representing different contexts and types of agricultural systems in Europe (as described in the example in Section 3.1). The indicators were then used to identify the degree of alignment of the measured changes with three archetypical agricultural development pathways, defined as follows:

- Productivist pathways, characterised by an overall increase in farm management intensity, specialisation, and simplification of landscape structure;
- Post-productivist pathways, characterised by changes towards less intensive and more diverse farms and landscapes;
- Marginalisation pathways, characterised by an overall abandonment of agricultural activities.

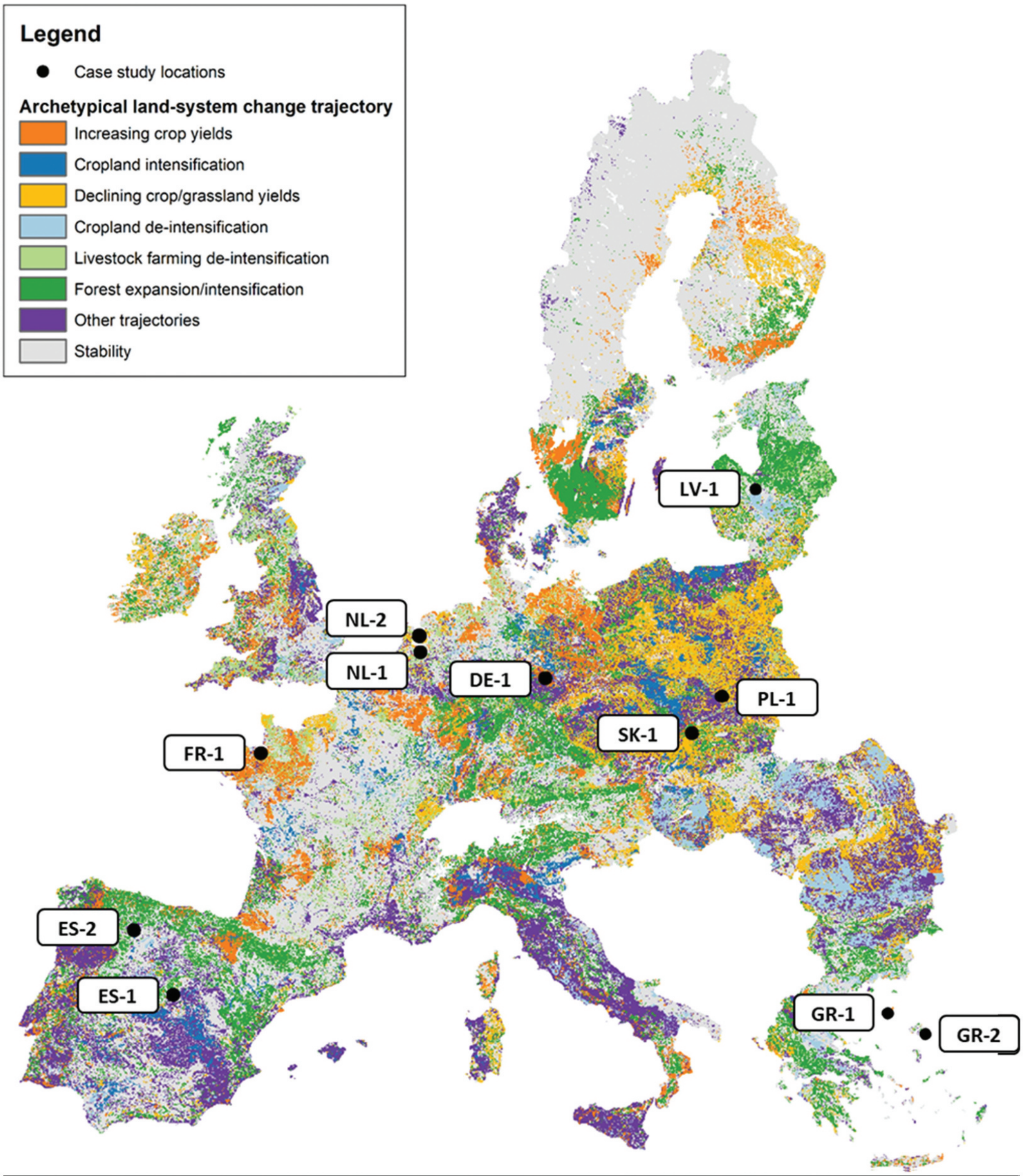
Each observation unit (i.e. a farm or a landscape) was considered to align with a particular pathway when combinations of indicators changed in the direction assumed to be characteristic of that pathway. To illustrate context-sensitive generalizations for the SIPATH case studies, we then overlaid the case-study locations with a pan-European map representing archetypical land-system change trajectories between 1990 and 2006 (Levers et al., 2018). This map was generated by applying an automated clustering approach using a self-organising maps algorithm to identify and group observations with recurrent combinations of similar magnitude changes in land cover and land-use intensity indicators (e.g. harvested biomass, nitrogen input, livestock density). For each case study, we identified the most predominant land-system change trajectories in the case-study area and surroundings. The contextualisation of the case-study results within large-scale land-system change analysis allowed identifying multi-scale trajectories of agricultural change characterized by archetypical developments at the farm, landscape, and land system level (Figure 6). Although the time-period covered by the large-scale archetype analysis only partially overlaps with that of the case studies, we can expect most of the identified large-scale trajectories to remain valid over a longer period (e.g. due to lock-in effects and time-lags in the outcomes of policy reforms).

This type of analysis reveals the nuanced diversity that seemingly similar archetypical trajectories can have when evaluating their developments at different scales. For example, post-productivist development pathways could be identified at both farm and landscape scales in the case studies DE-1, NL-1 and NL-2. The large-land system analysis revealed that while this occurred in the context of ongoing livestock farming de-intensification and declining yields in the area surrounding NL-1 and NL-2, respectively, in DE-1 these developments took place following a period of increasing yields.

Marginalisation pathways can also develop differently at distinct scales, as shown by the multi-scale trajectories in SK-1 and GR-2. For example, while forest expansion over agricultural areas could be identified at the land system and landscape levels in SK-1, the marginalisation pathways observed in GR-2 occurred following a period of stability. This difference may come as a result of the predominance of olive groves in GR-2, a type of agricultural system that typically presents relatively lower input use and slower dynamics in terms of land-use conversion and vegetation succession. Interestingly, we found that most of the case-study sites characterized by productivist farm-scale pathways had stable land-system change trajectories, irrespective of their landscape development pathway. In addition to the temporal mismatch between the two analyses, a number of reasons may also explain this finding. For example, one issue with large-scale land-system analysis is that changes in landscape structure may go unnoticed due to the requirements for detailed spatial data to accurately map fine-scale alterations in field boundaries and landscape elements (Bürgi et al., 2022; Verburg et al., 2013). In addition, farms pursuing divergent development pathways often co-exist within the same area (Malek et al., 2019; Wilson, 2002). This polarization of developments at the local level may somewhat mask out the outcomes of changes in farm management intensity when evaluating them at the more aggregated land system level. These findings highlight the importance of contextualising large-scale land-system analysis with more detailed empirical evidence from place-based case studies for an improved understanding of land change trajectories.

The number of case studies conducted in the context of the SIPATH project was too small (and their socio-ecological characteristics too diverse, see Appendix D) to allow drawing broader generalisations of multi-scale trajectories of agricultural change for the whole of Europe. The multi-scale archetype analysis hereby illustrated should, therefore, ideally be complemented with synthesis research, to firstly contextualise the case study results (as proposed in Section 3.2.1), and then integrate this larger sample of observations with land system analysis (in a similar way as exemplified in Figure 6) in order to identify recurrent combinations of multi-scale trajectories.

When combined with causal analysis methods such as qualitative comparative analysis (QCA) or process tracing (Ragin, 1999; Rohlfing & Schneider, 2018), this type of multi-scale archetype analysis could also provide a basis for identifying archetypical multi-scale causal pathways. Magliocca et al. (2019), for example, applied QCA to identify archetypical pathways of direct and indirect land-use change, and resulting socio-economic outcomes, caused by the establishment of economic land concessions in Cambodia. In this respect, the multi-scale archetype structures could help in guiding the search for cases with (partially) similar configurations of drivers, processes and/or outcomes (Schneider & Rohlfing, 2013), thus supporting causal analysis on identifying combinations of




| id | Site name | Country | Farm pathway | Landscape pathway | Land system change trajectory |
|---|---|---|---|---|---|
| DE-1 | Querfurter Platte | Germany | Post-productivist | Post-productivist | Increasing crop yields |
| ES-1 | Colmenar Viejo | Spain | Productivist | Post-productivist | Stability |
| ES-2 | St. Maria del Paramo | Spain | Productivist | Productivist | Stability |
| FR-1 | Ille-et-Vilaine | France | Productivist | Post-productivist | Increasing crop yields |
| GR-1 | Limnos | Greece | Productivist | Post-productivist | Stability |
| GR-2 | Lesvos | Greece | Marginalisation | Marginalisation | Stability |
| LV-1 | Lielvircava | Latvia | Productivist | Productivist | Stability |
| NL-1 | Scherpenzeel | Netherlands | Post-productivist | Post-productivist | Livestock farming de-intensification |
| NL-2 | Flevopolder | Netherlands | Post-productivist | Post-productivist | Declining crop yields |
| PL-1 | Powiat Miechowski | Poland | Productivist | Post-productivist | Cropland intensification |
| SK-1 | Turzovka | Slovakia | Marginalisation | Marginalisation | Forest expansion/intensification |

**Figure 6.** Archetypical development pathways at the farm and landscape levels identified in the SIPATH case studies (adapted from Helfenstein et al., 2023), and respective large-scale archetypical land system change trajectories (adapted from Levers et al., 2018).

sufficient and/or necessary conditions leading to the emergence of specific land change processes (Gerrits & Pagliarin, 2020).

### 3.3. Facilitating context-sensitive knowledge transfer

Scaling up place-based knowledge can help the design of land governance strategies in support of sustainability transformations (Ehrensperger et al., 2019). However, transferring solutions that proved effective in one place to other places is challenging, because such strategies and outcomes are usually contingent on the social-ecological conditions of the specific geographic context in which they were generated (Wuelser et al., 2021). Such solutions may include not only technology deployment and direct interventions on land, but also innovative institutional arrangements and strategies for empowering networks of actors and strengthening local governance (Sears et al., 2021; Thomas et al., 2018).

GSA can support investigating the potential transferability of place-based research, by identifying regions with characteristics similar to the places where knowledge and solutions are generated (Václavík et al., 2016). However, similarly to the representativeness analysis approach proposed in Section 3.1, we argue that this should not be conducted only in a data-driven fashion, but rather be guided and structured by a conceptual framework. Multi-scale archetype analysis, in particular, can support contextually-explicit generalisations of results from collections of case studies and large scale analysis, and accordingly facilitate the transfer of knowledge by identifying the different contextual and normative conditions operating at multiple scales under which particular strategies effectively support land interventions.

In such a setting, context-sensitive knowledge transfer can help support the envisioning of local- and regional-specific pathways that together contribute to global sustainability transitions (Bennett et al., 2021; Caron et al., 2018). Depending on the type of knowledge and solutions generated in one location and the way they are intended to support pathway envisioning in other locations, four distinct modes of knowledge transfer could be adopted (as defined by Bennett et al., 2021): learning, aggregation, compensation, and contagion (Figure 7). For example, the transfer of solutions through learning could be directly explored in locations that are contextually similar to the case studies where the solutions were generated. This can be particularly relevant in the context of the up- and out-scaling of interventions enabling transformative change as identified in so-called 'bright spots', i.e. places that are performing substantially better than expected given their social-ecological conditions (Bennett et al., 2016; Frei et al., 2018).

In addition, knowledge transfer through aggregation enables to quantify the cumulative effect of upscaling such solutions, by assuming that the solution is adopted across larger regions with a high degree of similarity to the original case study. Piemontese et al. (2020), for example, estimated the global potential for increasing crop production through water harvesting by mapping the regions that were contextually similar to the collections of case studies where water-harvesting technologies were successfully adopted, and then aggregating the potential yield increase that could be achieved if water-harvesting technologies were adopted in those regions.

Land-use interventions usually entail trade-offs unequally affecting different actors and inadvertently leading to new or different challenges, potentially also in distant locations through leakage and spillover effects (Meyfroidt et al., 2020). In particular, the existence of diverse stakeholder groups, and their potentially conflicting interests, can undermine the effectiveness of interventions if not incorporated into the decision-making process. Hence, knowledge transfer should not be pursued with the aim of disseminating 'context-sensitive silver bullets', i.e. solutions that are well suited for particular contexts and supposedly capable of successfully addressing comparable issues across places with similar contextual characteristics. Instead, GSA should be used to guide the identification of locations and larger regions to which place-based knowledge from other locations could potentially inform societal debates and foster further knowledge co-production. In fact, the co-creation and operationalisation of successful sustainability transformations relies to a large extent on the engagement of local

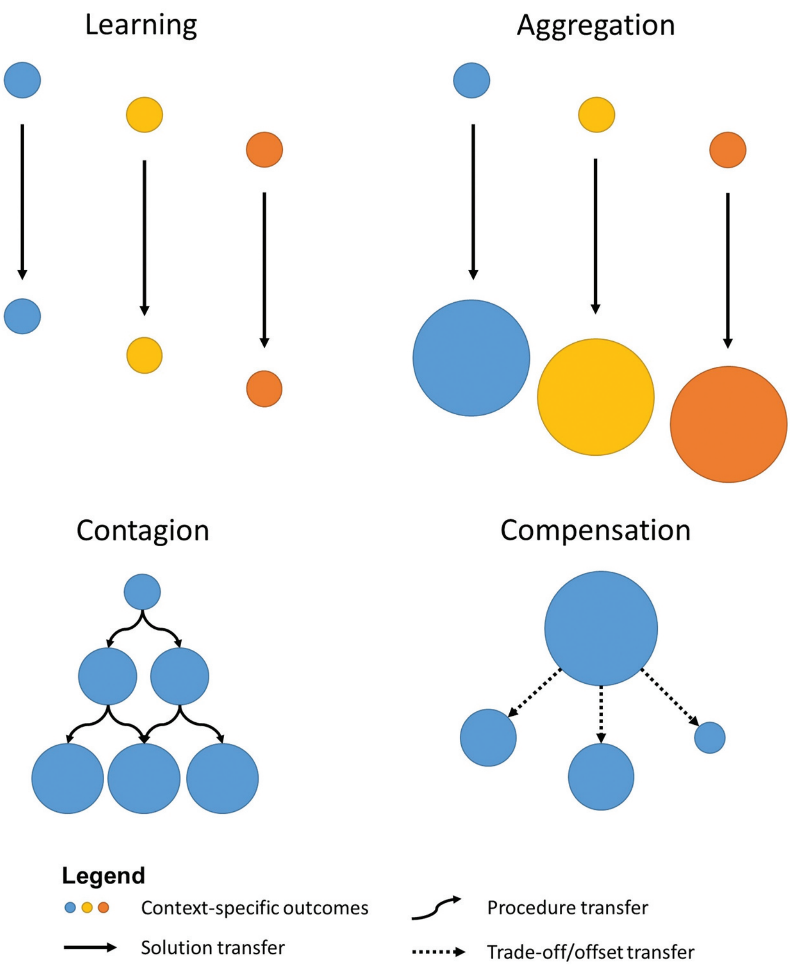



**Figure 7.** Modes for context-sensitive knowledge transfer in LSS research (adapted from Bennett et al., 2021). The colours of the circles represent (distant) locations with high degree of similarity in terms of social-ecological features, the size of the circles the magnitude impact of the knowledge transfer (e.g. in terms of geographical area or option space), and the different arrows the knowledge element that is transferred between locations. Learning: transferring solutions from locations that are contextually similar to the case studies where the solutions were generated. Aggregation: quantifying the cumulative effect of upscaling a solution, assuming that the solution is adopted across regions with a high degree of similarity to the original case study where the solution was generated. Contagion: transferring the procedures used to generate solutions in participatory processes across locations that are contextually similar; new solutions and procedures may iteratively emerge every time such participatory processes take place. Compensation: identifying similar locations where trade-offs from interventions in one location could be potentially offset by interventions in the other location(s).

stakeholders (Hölting et al., 2022). Therefore, not only the solutions but also the procedures that were applied to generated them (Wuelser et al., 2021) could be part of the knowledge transfer to locations with similar social-ecological conditions. Through such transfer modes (i.e. contagion, see Figure 7), new solutions and procedures may iteratively emerge every time such participatory processes take place, building upon the cumulative knowledge previously produced in similar contexts, thus contributing to increasing the option space over time in a context-sensitive way.

The compensation mode of knowledge transfer (Figure 7) is relevant when evaluating land interventions that may lead to significant trade-offs, both locally and in distant locations. For example, expanding agriculture may increase food availability and income locally, but potentially also come at the cost of (semi-)natural vegetation removal, leading to ecosystem service degradation and carbon emissions contributing to global climate change. GSA can help identify locations with similar characteristics where such trade-offs could be potentially offset, for instance, through afforestation measures. This type of knowledge transfer can support, for example, the so-called like-for-like principle for devising interventions achieving land degradation neutrality (Orr et al., 2017). GSA can also help identify where an offset of a desirable outcome may occur through leakage effects from one region to another. This includes, for instance, situations in which policies promoting de-intensification of agricultural production or banning deforestation are implemented in a context of unchanged domestic demand for the respective commodities, leading to land change somewhere else to fulfil this demand (Fuchs et al., 2020; Jonsson et al., 2012). For these cases, GSA can help anticipating the regions where such commodities (or their substitutes) may end up being produced and the potential magnitude of the resulting trade-offs.

## 4. Discussion and conclusions

Following the challenges and approaches described in Section 3, we propose a toolbox based on the application of GSA to help addressing current knowledge gaps and limitations in LSS research (Figure 8). These tools may, in turn, facilitate researchers to integrate knowledge towards an improved understanding of multi-scale processes and outcomes of land-system change, as well as support land governance practitioners and stakeholders in out- and upscaling the knowledge and solutions generated by LSS research.

The approaches proposed in Sections 3.1, 3.2 and 3.3 can be useful in the design, analysis and implementation phases of archetype analysis, respectively, and thereby contribute to improve archetype validity, following the framework for archetype validation proposed in Piemontese et al. (2022). They also demonstrate that being explicit about the conceptual framework underlying a research problem not only increases transparency and reproducibility across knowledge producers (Magliocca et al., 2018), but also provides a boundary object for coherently linking and structuring different analytical methods and applying them at multiple scales.

We acknowledge that the operationalisation of the tools presented in Figure 8 as a whole may be challenging within the context of a single research project, given that many of the tools require a great deal of specialised knowledge and an extensive array of methodological and analytical skills, but project resources are often limited. They would also require parallel and sequential tasks carrying a large degree of interdependencies, which would be difficult to plan and coordinate within the regular time frame of a research project. Nevertheless, we believe this toolbox can provide a useful blueprint to help researchers identifying gaps in current practices, and guidance for defining long-term research agenda goals and for establishing and coordinating inter- and transdisciplinary collaborative efforts that may spawn across several projects.

The underlying assumption behind GSA is that a high degree of contextual similarity between different locations is a pre-condition for identifying common processes and explanations of land-system change, and for transferring knowledge and upscaling interventions to locations with similar characteristics. The approaches presented hereby are, therefore, inherently limited by the availability and quality of spatially-explicit input data to represent social-ecological characteristics. For example, information on land-use intensity is often lacking or in inadequate quality for many regions (Kuemmerle et al., 2013) and capturing information on culture and governance in spatially-explicit datasets is not straightforward (Otto et al., 2015).

Finally, we have only explored aspects of similarity related to territorial characteristics or socio-ecological flows that are spatially associated to particular locations (e.g. trade flows, migration, etc.). However, relational aspects such as long-distance actor networks are also increasingly important in land systems (Liu et al., 2015; S. West et al., 2020). Particularly, farmer organisations, distant land-owners, (foreign) investors, government institutions and global value chains are becoming increasingly influential on local land-use decision-making (Ceddia, 2020; Debonne et al., 2021; Zelaya et al., 2016). Recent advances in network analysis for studying social-ecological systems (Bodin et al., 2019)

| LSS knowledge gaps and limitations | What can GSA do to address these gaps? | How can GSA be applied to address these gaps? |
|---|---|---|
| • Geographic representativeness of the set of case studies in a research project is unknown.<br>• Potential selection biases. | • Supports/optimises the selection of case study sites during the project's design phase.<br>• Evaluates the geographic variation on relevant social-ecological dimensions represented by sets of case study sites. | 1. Compute spatial similarity indices of potential case study sites.<br>2. Use a conceptual framework to structure the analysis.<br>3. Assess representativeness over multiple social-ecological dimensions with different combinations of case-study sites.<br>4. Use that as a basis for iteratively refining the selection of sites |
| • Number of case studies carried out in a research project is too small for making generalisations.<br>• Over-particularisation of case study findings (i.e. idiographic traps). | • Supports the contextualisation, interpretation and comparison of case-study results with knowledge generalised from synthesis research. | 1. Compute spatial similarity indices of the project case study sites.<br>2. Use this as a basis to compare case-study results with local archetypes derived from synthesis research in locations with high geographic similarity.<br>3. Conversely, compare results where socio-ecological conditions are different but observed processes and/or outcomes are similar. |
| • Linkages between land-change patterns and processes at different geographic scales are poorly understood.<br>• Incomplete or overly-generalised explanations of land-system change (i.e. nomothetic traps). | • Identifies recurrent multi-scale archetype structures revealing drivers, processes and/or outcomes of land-system change.<br>• Supports the identification of archetypical multi-scale causal pathways. | 1. Identify and map land-system (change) archetypes.<br>2. Assess their spatial overlay with local archetypes derived from synthesis research.<br>3. Use that as a basis to define multi-scale land-system (change) archetypes.<br>4. Use the multi-scale archetype structures to guide causal analysis. |
| • Social-ecological conditions leading to successful land interventions are poorly understood.<br>• Limited transferability of knowledge generated by case studies. | • Identifies the social-ecological conditions under which particular land interventions are successful.<br>• Identifies regions in which these (partial) sets of conditions are observed. | 1. Compute spatial similarity indices.<br>2. Use that as a basis exploring potential transferability of case-study research.<br>3. Alternatively, map and use multi-scale land-system archetypes, for the same purpose. |

**Figure 8.** Toolbox of GSA-based approaches for addressing current knowledge gaps and limitations in LSS research.

may provide complementary avenues for enhancing the characterisation of similarity across locations and understand the ways in which distant drivers and actors affect local land-use decisions (Bürgi et al., 2022). The approaches hereby proposed thus provide a first step towards better alignment of different LSS research activities and thereby improved understanding of land-system change.

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