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Approaches and terminology for causal analysis in land systems science

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ABSTRACT
Research into land and social-ecological systems science could benefit from improved clarity in the terminology used for causal analysis and a structured way to make causal inferences. Here I identify two aspects of causality, i.e. causal effects and causal mechanisms, and discuss explanation in historical sciences. I then propose definitions for the major terms used for causal relations, including driver, (spatial) determinant, location and contextual factor, proximate and underlying factors. Finally, I discuss the contribution of various operational approaches, including time series and counterfactual approaches for assessing causal effects and process-tracing approaches for establishing causal mechanisms. Having a coherent concept of causality, agreeing on a precise vocabulary and harnessing our tools with the clear purpose of establishing both causal effects and causal mechanisms should strengthen causal explanations for single cases, for drawing policy-relevant lessons and for theoretical development in relation to land and, more broadly, social-ecological systems processes.

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'*All right, we started out with a laundry list. Yet we were clever enough, inventive enough, to turn a laundry list into poetry.*'
Umberto Eco, *Foucault's Pendulum*[1]

1. Introduction

Land change science, or land systems science (LSS), is the interdisciplinary field that studies the terrestrial component of the Earth system, encompassing the human and natural components of local and global land systems (Rounsevell et al., 2012; Turner, Lambin, & Reenberg, 2007; Verburg et al., in press). LSS contributes to sustainability science, and land systems are a typical example of social-ecological systems (SES). Empirical examples in this paper draw mainly on LSS, but much of its content should be useful for broader research on SES, human-environment interactions and sustainability science.

LSS is explicitly concerned with understanding the causes and consequences of land changes (Geist et al., 2006), which include both changes in land use and management (the purposes and activities for and through which humans influence the land), as well as changes in land cover (the physical properties of the vegetation and land surface). Yet, the terminology used for causal analysis in LSS remains imprecise, and the field is lacking a structured method for establishing causal explanations. Studies often rely on terms like 'drivers', 'driving forces', '(spatial)

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determinants', 'factors' and verbs such as 'influencing' or 'affecting', which hint at causal relations without clearly articulating them. In a recent meta-analysis of the abstracts of 388 articles selected to represent the corpus of the research explaining land change, the word 'cause' did not even appear in the frequently mentioned words, and instead, the general concept of 'driving' was most prevalent (Sonter, Barrett, Moran, & Soares-Filho, 2015).

Two important goals to which this paper might contribute are, first, theoretical developments and, second, the policy relevance of LSS. LSS has been very successful in producing a depth of empirical observations, descriptions and contextual explanations (Lambin & Geist, 2006). However, progress in theoretical generalizations has largely lagged behind (Turner II, 2014). Modeling efforts have been strongly focused on pattern-oriented models that have limited usefulness in the simulation of complex interactions and feedbacks because they lack an understanding of the underlying causal mechanisms. Causal explanation in case studies often bears a resemblance to historical accounts, appearing to provide contextually bound and ad hoc explanations rather than generalizable knowledge. In-depth discussion of theory development and generalizations in LSS is beyond the scope of this paper – though it will refer to it sometimes – but progress in theorization could be bolstered by at least having consistency in the terminology and approaches for discussing causality. Similarly, to provide policy-relevant lessons, LSS must be able to establish causal relations between possible interventions and effects on land systems (Ferraro & Hanauer, 2014a).

In the next section, I discuss how 'causality' and 'causes' can be usefully defined for LSS and SES research. I identify two aspects of causality, i.e. causal effects and causal mechanisms, which are sometimes confused. Following Granger's (1980) call for operational views on causality, I put aside most of the philosophical literature discussing causality and causation, though some epistemological underpinnings will be necessary. In the third section, I build on the second section and return to the terminology in LSS. For the major terms, I propose definitions that should be sufficiently clear to serve as a common language and consistent with the goals of causal analysis. In the fourth section, I discuss operational approaches to assessing causal effects and causal mechanisms. The goal is not an exhaustive methodological review, but a discussion about different ways to explore these two aspects of causality. Throughout, I illustrate the ideas with examples of empirical research in LSS. These examples are not exempt of weaknesses, but they are thought to constitute useful steps forward, considering the methodological challenges of working with empirical data that is sometimes scarce and difficult to collect.

2. Causality and causal explanation

2.1 *What is a cause?*

The concept of cause remains elusive. Most generally, a cause is something which explains an outcome (Elster, 2007).[2] Both the outcome (*explanandum*) and the cause (*explanan*) can be events, facts or variables.

Simple Boolean logic distinguishes necessary and sufficient causes. However, generally, in social and complex systems, causes are neither necessary nor sufficient but are best described as 'contributory' or 'combinatory' causes, within what are called INUS causes (Mackie, 1965; Mahoney, 2008). An INUS cause is an insufficient but necessary part of a combination of causes, which is itself unnecessary but sufficient for the outcome.[3] This approach is compatible with probabilistic reasoning, in that the importance of causes is related to their increasingly necessary or sufficient character: a cause is increasingly necessary when it is present in most combinations leading to the outcome, especially those that are the most likely to occur. A cause is increasingly sufficient when it appears in simple combinations with other variables that have a high likelihood of being present (trivial causes) (Mahoney, 2008). Similarly, in statistical terms, a cause is more necessary when few other factors have a causal effect and those are mostly through interactions with that cause, and more sufficient when its causal effect is stronger.

Equifinality, i.e. the existence of several INUS combinations leading to the same outcome, is ubiquitous (George & Bennett, 2005) and is accepted in most statistical models using additive effects. Therefore, to state that 'X is a cause of Y', or 'Y has been caused by X', does not mean that X is a necessary or sufficient cause for Y, but rather that X is part of a possible combination of factors that suffices to cause Y. Acknowledging this makes it possible to use the vocabulary of 'causes' even when we are unable to identify the full list of causes contributing to a combination (Ferraro & Hanauer, 2014a).

INUS causes are familiar to land systems scientists, for example, in describing combinations or synergies of factors causing tropical deforestation and desertification (also called 'chain-logical causation') (Geist & Lambin, 2002, 2004). In the induced intensification thesis, demand for agricultural products, related to population growth, affluence and market engagement, is generally considered as a necessary cause of intensification (constituting a motivation for intensifying), but not a sufficient one because the actual paths of intensification are moderated and mediated by other technological, institutional and socioeconomic variables (Carr, 2004; Laney, 2002; Turner, Hydén, & Kates, 1993). Combinations of INUS causes organized along a causal chain (see below) also correspond to what are called 'pathways', 'syndromes' or 'archetypes' (e.g., Lambin, Geist, & Lepers, 2003). For example, the combinations of causes of forest transitions have been stylized in several pathways. One pathway combines agricultural intensification with urbanization, market connection and economic development. Another pathway combines a decreasing availability of forest products and services with cultural changes, proactive governments and private actors (Lambin & Meyfroidt, 2010; Meyfroidt & Lambin, 2011; Rudel et al., 2005). Other pathways exist. None of these pathways is necessary, but each may cause a forest transition in certain contexts and they often co-occur in real cases.

2.2 *Causal effects and causal mechanisms*

Causal analysis is too often plagued by the failure to recognize that establishing causality relies on two dimensions: causal effects and causal mechanisms (Elster, 2007; George & Bennett, 2005; see Mahoney, 2008; for a related discussion).

First, an intuitive view of causality, which is well-established in quantitative and statistical research, is that a factor is a cause of an outcome if it has causal effect. A causal effect can be defined in many ways, but essentially it amounts to the change in an outcome Y brought about by the change in a factor X. Granger's widely used definition of causal effect states that if X is a cause of Y then knowing something about X should help to predict something about Y that cannot be provided by another variable (Granger, 1969, 1980). In that sense, the assessment of causal effect has a predictive character. Another very influential model of causal effect is the Rubin Causal Model (RCM), which relies on the notion of potential outcome or counterfactual (Holland, 1986). In this model, the causal effect of a given factor (called the 'treatment') is the difference between the value of a given outcome variable when a unit is affected by this treatment and the value of that outcome when the unit is affected by an alternative control treatment (so that the effect of a cause is always relative to another cause or condition).

However, a complete causal explanation goes beyond this. As acknowledged by Granger (1980), assessing causal effects does not allow for an explanation of *how* the causal process occurred. Statistical evidence was sufficient to establish beyond doubt that smoking has a causal effect on cancer long before research explained how smoking can cause cancer. This is what causal mechanisms are about (Elster, 2007). One definition among many proposes that causal mechanisms are 'ultimately unobservable physical, social or psychological processes through which agents with causal capacities operate, but only in specific contexts or conditions, to transfer energy, information or matter to other entities. In so doing, the causal agent changes the affected entity's characteristics, capacities or propensities in ways that persist until subsequent causal mechanisms act upon it' (George & Bennett, 2005). Plainly said, a causal mechanism explains how the cause or combination of causes produces its effects.

Assessing both causal effects and causal mechanisms improves causal analyses for several reasons. First, their combination enhances trust in the causal inference. A plausible causal mechanism alone, without a corresponding causal effect, is nothing more than a mere conjecture or, at best, a hypothesis to test (Elster, 2007). Conversely, tracing the causal mechanism increases confidence that all relevant third factors are accounted for when identifying a causal effect and, thus, that the link is not spurious and the structure of the relations is properly specified. Granger (1980), from an informal Bayesian perspective, proposed that when one observes both a causal effect and a causal mechanism, one's personal belief or assessment of the likelihood of the causal relation is expected to increase. In one example, an explanation of the causes of reforestation in Vietnam relied on combining statistical analyses of the main hypothesized factors with interpretation of the causal mechanisms drawn from local case studies in various regions of the country (Meyfroidt & Lambin, 2008). Similarly, indirect land use change (iLUC) in Brazil can be explained by combining the identification of a chain of causal mechanisms through which iLUC operates (Richards, 2012) with statistical investigation of the causal effects resulting from that mechanism (Richards, Walker, & Arima, 2014).

Second, identifying causes is generally only an intermediate goal: often we want to understand land change phenomena in order to steer them, design interventions to improve the trajectories, correct failures, modify the tradeoffs and promote sustainable land uses. Understanding the causal mechanism is crucial to attaining these goals because the same cause can produce its effect through different mechanisms, requiring different interventions (e.g. forest scarcity as a cause of forest transitions, see Lambin & Meyfroidt, 2010; Meyfroidt & Lambin, 2011; Rudel et al., 2005) and because different mechanisms may have different consequences (e.g. the impact on livelihood of a forest transition caused by urbanization and rural outmigration is dependent on how these dynamics unfold).

Causal effects and causal mechanisms are thus the two sides of the causal coin. Causal analysis should aim to address both components, although a single study may not always cover both aspects.

2.3 *Causal chains and causal explanation in historical sciences*

When the cause produces its effects in a remote and indirect manner, an explanation has to rely on causal chains, i.e. a continuous chain of causal mechanisms between the *explanans* and the *explanandum*, where each step links a cause or combination of causes with its direct outcome, the latter being a direct cause of the subsequent outcome. As a general rule, the more discretization steps are introduced when analyzing a causal chain, the more convincing a causal explanation will be (Elster, 2007). More direct relations between the cause and outcome at each step are analytically easier to tract, help to control for third factors and can be more easily supported by experimental evidence and general covering laws (see below). Discretization can be realized by hierarchical thinking, i.e. decomposing macrophenomena into causal paths at microlevel, drawing on the principle of methodological or structural individualism ('Coleman's boat', see e.g. Hedström & Ylikoski, 2010). Nevertheless, this is not a necessity as meso-level causal pathways and mechanisms can also be specified (Jepperson & Meyer, 2011). Analyzing the causal chain is thus not an issue of reductionism in the sense of going 'lower' in the chain towards more fundamental physical processes, but rather going 'shorter', in the sense of identifying direct causal links at each step (Mayr, 2004). The level at which these steps can be considered 'short enough' to be convincing is partly intersubjective, as is the case for the level of statistical significance considered sufficient to establish a causal effect. Following the informal Bayesian perspective outlined above, for people already convinced of the validity of a causal relation, a p-value of 0.1 will constitute an additional confirmation, while those that consider the relation to be spurious might not even be convinced by a lower p-value (Granger, 1980). However, this does not constitute a fundamental problem, at least for theory development and testing; a theory never relies on a single study to establish its validity,[4] rather multiple pieces of evidence of causal effects and mechanisms have to be accumulated from various studies to slowly build confidence.

Even with meticulously described causal chains, explanation in LSS will rarely result in the formulation of general, universal covering laws, as is the goal in experimental sciences. Much of the work in LSS and SES in general falls under 'historical sciences', i.e., sciences that focus on explaining social and natural phenomena as they occurred in the real, historical world, as opposed to phenomena described in the laboratory (Cleland, 2002; Passeron, 1991). Typical examples of historical sciences include history, sociology, evolutionary biology, astronomy and geology. Just like experimental sciences, historical sciences aim at explaining reality and developing general knowledge in relation to it. However, in contrast to experimental contexts, historical sciences deal with specific occurrences of the observed phenomena they seek to explain, which are never exactly and entirely reproduced or reproducible, and where single factors cannot be perfectly isolated (Passeron, 1991). Further, the manifestation of new phenomena over time changes the universe being studied. In LSS, for example, fossil fuel agriculture and globalization fundamentally changed the processes of land use. More recently, emerging phenomena such as land grab, biofuels or private-sector led and hybrid forms of land use regulations (Lambin et al., 2014) forced a rethink of the theories and knowledge about land change processes. One crucial contributor, shared with other social sciences, is the agency of humans who, by combining intentionality, forethought, self-reflectiveness and self-reactiveness, change their behavior in reaction to new knowledge (Bandura, 2001; George & Bennett, 2005; Meyfroidt, 2013a; Rudel, 2013).

Therefore, explanations in historical sciences rely on a back and forth between regularities and general mechanisms or laws (as in experimental science) and contextual interpretation of contingencies (Passeron, 1991). Sometimes, a causal mechanism can be identified to explain a phenomenon, but, because that mechanism involves contingent features, it might be impossible to predict what would happen in a subsequent, similar but not identical situation (e.g. see Sloan, 2015 for a discussion on forest transitions). Some parts of the causal chain might be explained, even with experimental evidence, but that is not true of all parts, so we might be unable to explain the causes of a bifurcation at some point. In particular, we might be unable to explain what triggered one causal chain instead of another one (Elster, 2007). From the same initial cause, several mechanisms with counteracting effects may also be triggered. One example is land use intensification triggering both land sparing and rebound effects (Hertel, Ramankutty, & Baldos, 2014). Sometimes it is possible to identify the conditions under which one causal chain will dominate in the net effect. Identifying a 'contextual generalization', i.e. a chain of mechanisms which is valid for explaining a relatively well-bounded range of phenomena, and the conditions or contextual factors which trigger, enable or prevent this causal chain, is akin to elaborating a middle-range theory following Merton (1968), or a typological theory (George & Bennett, 2005).

3. Terminology

We can now return to the terminology used in LSS and discuss definitions that are consistent with the above-described principles (Table 1).

3.1 *Driver and driving force*

'Driver' and 'driving force' are widely used terms in approaches to causality (Bürgi, Hersperger, & Schneeberger, 2004; Geist & Lambin, 2002, 2004; Hersperger, Gennaio, Verburg, & Bürgi, 2010), including in environmental and sustainability sciences (Millennium Ecosystem Assessment [MA], 2003). Their use originated from the interest in Earth system science in having information on the effects of humans on global environmental change through the terrestrial component of the Earth

Table 1. Proposed definitions and uses of the main terms used for causal analysis.

Term	Proposed definition	Comments and selected examples (see Section 3 for more examples and discussion)
Outcome	Any event, fact or variable for which one wants to explain why and how it occurred	Called an '*explanandum*' in philosophy of science. Example: The many dimensions of 'agricultural intensification', typically considered as one type of land use change, highlight the importance of precisely defining an outcome of interest (Keys & McConnell, 2005).
Factor	Any event, fact or variable mobilized in an explanation	Example: Difference in land tenure was put forward as one factor to explain differences in land cover changes along the Kenyan-Tanzanian border in the Serengeti-Mara ecosystem (Homewood et al., 2001).
Cause	A factor that produces a causal effect on an outcome through a chain of mechanisms	Called an '*explanan*' in philosophy of science. Causal effects and causal mechanisms are two sides of the causal coin. Example: Land use policies and smallholder agricultural intensification were two causes of the reforestation in Vietnam (Meyfroidt & Lambin, 2008).
Causal effect	The change in an outcome variable brought about by change in the value of an explanatory variable (the cause)	Relies on regularity of association and congruity of magnitude. Example: Logging concessions had a causal effect of reducing deforestation in Cameroon (Bruggeman et al., 2015).
Causal mechanism	The processes through which a factor produces its effect.	How the cause produces its effect. Examples: (i) In some contexts, urbanization may cause land abandonment (the causal effect) through a reduction of agricultural labor force (the causal mechanism). Yet, in different contexts, other causal mechanisms may occur and the effect of urbanization may differ (Rudel et al., 2005, Meyfroidt & Lambin, 2011); (ii) The main causal mechanism through which protected areas in Costa Rica caused poverty reduction was increased economic opportunities afforded by tourism (Ferraro & Hanauer, 2014b, 2015).
Causal chain	A series of causal mechanisms which links an underlying cause to the final outcome of interest.	The distinction between causal mechanism and causal chain is a matter of discretization in the causal explanation: A mechanism can always be analyzed as a chain of shorter-steps interlinked causal mechanisms. Example: In the forest scarcity path to forest transition, deforestation eventually causes a scarcity of forest products, which causes price rises. Meanwhile, deforestation also causes a decline in environmental services provided by forests, e.g. in terms of protection against soil erosion and regulation of hydrological flows. This, in turn, causes reactions from private actors and governments to protect remaining forests, and restore and plant trees. This chain of causal mechanisms, which can eventually cause a forest transition, is favored or hindered by a series of contextual factors (Hyde, Amacher, & Magrath, 1996, Rudel et al., 2005, Barbier, Burgess, & Grainger, 2010). Sloan (2015) also provides a detailed description of the causal chain explaining forest recovery in Panama.
Causal explanation	To identify the causes of an outcome.	Also 'causal inference'. Ideally requires identifying causal effects and causal mechanisms.

(*Continued*)

Table 1. (Continued).

Term	Proposed definition	Comments and selected examples (see Section 3 for more examples and discussion)
INUS cause and combination of causes	An insufficient but necessary part of a combination of causes which is itself unnecessary but sufficient for the outcome	Example: Agricultural intensification in Africa would cause in an increase in deforestation when combined with global market integration and price-elastic demand, and relatively low yields at onset in the intensifying region (Hertel et al., 2014). Yet, other combinations of causes (e.g. population growth without agricultural intensification) can also cause deforestation in Africa.
Driver/driving force	Factors that are typical or hypothetical causes of land or environmental change and have some evidence of association with the outcome, but for which the evidence or knowledge is not sufficient to firmly establish the causal effects and explain the causal mechanisms.	Also appropriate for variables that are used as inputs into modeling (e.g., Earth system modeling), in contrast to causal relations that are endogenously resolved by the models. Example: Forest and conservation policies, human resettlement and market integration were major drivers for swidden decrease in Southeast Asia, while major drivers in Latin America were market integration and policies that encourage cattle ranching and cash crops through credit or subsidies (van Vliet et al., 2012).
Proximate cause	A factor which constitutes a direct cause of the phenomenon to be explained	Also 'direct cause', or 'proximate source'. In a causal chain, a factor which intervenes close to the end of the causal chain. Typically, the proximate causes of land cover change will be land use or management changes. Example: Soybean expansion was a major proximate cause of deforestation in the Amazon over 2001–2004, but its direct role declined afterwards (Morton et al., 2006, Macedo et al., 2012).
Underlying cause (of land cover change or environmental change)	A factor which causes the proximate causes of land cover or environmental change	Also 'indirect cause'. In a causal chain, a factor which intervenes before the end of the chain, thus being a causally distal factor. Example: Coffee expansion in the 2000s was an underlying or indirect cause of deforestation in the Central Highlands of Vietnam, the main direct cause being shifting cultivation pushed into forest by coffee expansion (Meyfroidt et al., 2013). Further up in the causal chain, global demand for coffee was an even more underlying cause of that deforestation.
(Spatial) Determinant	A factor contributing to statistical explanation of (the location of) an outcome (or other spatial characteristics such as spatial pattern or structure).	Can be proximate cause, underlying cause, pre-disposing factor, or proxy for one of these. Thus, to be used for situations when the causal character of the identified relations is uncertain or cannot be strongly established with the available data or methods (possibly spurious relations). Examples: Accessibility was shown to be a spatial determinant of forest cover change and fragmentation in Honduras, though with complex causal relationships (Nagendra, Southworth, & Tucker, 2003). Several accessibility variables were spatial determinants of cropland abandonment in Albania, while the density of cropland in the neighborhood and inputs intensity were identified in Romania (Müller, Leitão, & Sikor, 2013).

(Continued)

Table 1. (Continued).

Term	Proposed definition	Comments and selected examples (see Section 3 for more examples and discussion)
Contextual factor	A factor which constitutes an element of an INUS cause, typically being a stable or slowly changing factor or a factor that is largely present within a given place, and which explains the location, timing or prevalence of an event.	Also 'predisposing factor'. Contrasted with a 'trigger factor'. May be an important or unimportant cause, depending on the aspect of the *explanandum* on which the study focuses (e.g., occurrence, timing, location, effects of a land change process). Example: Geographic, historical, political or linguistic proximity could predispose countries to have different land use reactions to biofuel policies implemented in a given country (Villoria & Hertel, 2011).
Trigger factor	A factor which constitutes an element of an INUS cause, typically being a rapidly changing, short-lived or stochastic factor, and which explains the precise location or timing of an event.	Contrasted with a pre-disposing factor. May be an important or unimportant cause, as for 'Contextual factor'. Example: Floods were important triggers of forest protection and afforestation policies in 19th century France and Switzerland, and contributed to cause the specific timing of the reforms (Mather, Fairbairn, & Needle, 1999, Mather & Fairbairn, 2000).

system (Turner & Meyer, 1994; Turner, 1989, 2014). Originally, 'driver' was essentially synonymous with 'forcing', corresponding to processes exogenous to the system studied in respect of which there appeared to be some association between the *explanan* and *explanandum*, but for which the rationale and theoretical grounding of the causal mechanism, or the precise causal effect were not sufficiently established. Drivers were thus generally viewed as a black box whose resulting effect on the system studied was principally of interest. These early frameworks avoided referring to 'causes' because the causal mechanisms through which drivers were operating often remained unclear.

Influential frameworks, starting with Turner (1989), distinguished 'proximate sources' on the one hand, and 'human driving forces' (Meyer & Turner, 1992; Turner, 1989; Turner & Meyer, 1994) on the other (or 'proximate causes', 'direct causes' or 'direct actions', versus 'underlying drivers' or 'distal drivers', see Geist and Lambin (2001, 2002), Hersperger et al. (2010)). In Turner (1989), '[t]he proximate sources of change constitute the near-end or end products of human activity whose immediate consequences are alterations and transformations of the environment.' In Geist and Lambin (2001), '[p]roximate causes are human activities (land uses) that directly affect the environment and thus constitute proximate sources of change.' 'Human driving forces of change' are 'the underlying or deeper social forces that drive the proximate sources' (Turner, 1989). The MA recognized the distinction between direct and indirect drivers (Nelson et al., 2006), and defined a driver broadly as 'any natural or human-induced factor that directly or indirectly causes a change in an ecosystem' (MA, 2003, Chapter 4). Here, 'driver' is therefore synonymous with 'cause'. Studies sometimes refer to the 'proximate versus underlying' framework to distinguish 'proximate causes' corresponding essentially to 'spatial determinants' as defined below, as opposed to 'underlying causes' corresponding to the 'real' causes of a phenomenon (Müller, Müller, Schierhorn, Gerold, & Pacheco, 2012; Serneels & Lambin, 2001). However, in order to maintain a coherent definition of a 'cause', the 'proximate and underlying' framework can be more adequately incorporated into the general reasoning in terms of causal chains. Proximate causes, then, are the factors involved in the last steps of the causal chain and underlying causes are those involved in earlier steps in the chain, which are thus distal (in a causal, not geographical sense). This may clarify some confusion. Originally, the distinction between 'proximate' and 'underlying' causes applied to the causes of land cover or environmental change, so that the 'proximate' causes were land use activities. Other studies then used that vocabulary to investigate the 'proximate causes of land use change' (e.g. Serneels & Lambin, 2001), which are generally not land use activities themselves. If land uses are proximate causes of land cover change, then proximate causes of land use change are underlying causes of land cover change.

I suggest using 'cause' rather than 'driver' or 'driving force' when one has sufficient evidence to establish at least the causal effect or causal mechanism of a given phenomenon, or both. First, 'cause' appears more simple and explicit. Second, as acknowledged in the MA (2003), although 'drivers' are widely used in ecology and natural sciences, this term is uncommon in the social sciences that are increasingly mobilized in SES and LSS studies. 'Driver' and 'driving force' remain more appropriate in the discussion of factors which are typical causes of land or environmental change, for which some evidence of causal association with the outcome of interest is presented, but for which the evidence or knowledge is not sufficient to firmly establish the causal effects and explain the causal mechanisms of a specific phenomenon. 'Drivers' is also appropriate when the focus is on the environmental or social change processes being forced by social-ecological or land systems processes.

3.2 *(Spatial) Determinant and location factors*

'Determinant' or 'spatial determinant' are also frequently used (e.g. Müller, Kuemmerle, Rusu, & Griffiths, 2009; Perz & Skole, 2003; Prishchepov, Müller, Dubinin, Baumann, & Radeloff, 2013). These terms have been described as 'variables that are frequently used as location factors in land change models' or as 'a series of biophysical and socio-economic factors [which] can explain the spatial distribution of [land systems]' (Asselen & Verburg, 2012). Spatial determinants in Stolle, Chomitz, Lambin, and Tomich (2003) are landscape attributes that are statistically associated with vegetation fires in Indonesia and used as proxy variables to 'infer the underlying causes of biomass burning'.

'Determinant' is therefore best used for relations that are statistically established ('statistical explanation'), but where causality is not necessarily asserted or assumed. Determinants may actually be proximate causes, underlying causes, predisposing factors (see below) or proxies for one of these. Their association with the outcome may reflect a real causal effect or be spurious. Despite this indeterminacy, identifying determinants can provide some empirical support for causal relations. 'Spatial determinants' or 'location factors' are then determinants that are spatially associated with an outcome, thus providing a statistical explanation of the location or other spatial characteristics (spatial pattern or structure) of an outcome.

3.3 *Contextual factor, predisposing factor, trigger*

Sometimes, the general term 'factor' is used in the sense of 'spatial determinant', e.g. Wassenaar et al. (2007) distinguishes 'local factors' (specific to the precise location) from 'contextual factors' (which qualify the surroundings of a place). However, 'contextual factor' is also used as a synonym for 'predisposing (environmental) factors', i.e. factors which are supposed 'not to drive, but rather – to shape' land cover change (Geist & Lambin, 2001). In addition, the same authors also identified biophysical and social 'triggers' as 'forces or events that often work as catalytic factors leading to sudden shifts in the human–environment condition.'

In the vocabulary of INUS causes, all these factors are causes forming part of an INUS combination. 'Predisposing factors' and 'triggers' contribute to the causal explanation, typically being insufficient and unnecessary causes of a general phenomenon. Various predisposing factors may be part of different INUS combinations with some important cause. For example, deforestation of certain forest plots can be caused by demand for agricultural products (the important cause), combined with different predisposing factors, e.g. favorable soils for cropping, favorable climate or good accessibility to markets, each of which increase the land rents on specific plots. These three predisposing factors are less necessary and thus less important causes than demand for agricultural products, as any of these three may be sufficient to produce an effective INUS combination. Similarly, 'triggers' do not constitute the most structural, important causes of an event. They explain why it happened at that precise moment, but other combinations of the same structural causes with other triggers would likely have led to the same outcome. I therefore suggest using 'predisposing factor' or 'trigger' to refer to causal factors that are relatively unimportant in explaining a class of outcomes, but which may be important causes of the precise location or timing of an event, or in other words, of the actual realization of one specific instance of that class of outcomes.

4. Operational approaches to establishing causality

Here I discuss some operational approaches to establishing causality in LSS and SES research. This is not a substitute for other, more comprehensive discussions of the operational and methodological tools and challenges in LSS (Ferraro & Hanauer, 2014a; Liverman, Moran, Rindfuss, & Stern, 1998; Reenberg, 2009; Rindfuss, Walsh, Turner, Fox, & Mishra, 2004; Rounsevell et al., 2012; Turner et al., 2007; Young et al., 2006). Rather, the goal is to exemplify the distinction and complementarity between causal effects and causal mechanisms and highlight some ways of establishing these two aspects of causality, including emerging or underutilized approaches. While issues of correlation versus causation still bedevil LSS research, I will not focus on this aspect here. First I emphasize that before looking for causal explanation, the precise definition of the outcome to be explained needs to be specified. Second, I discuss approaches to establishing causal effects using time series or counterfactual approaches, which typically rely on the RCM introduced above. Third, I discuss the process-tracing approach to establishing causal mechanisms. Finally, I mention a few complexities of land systems and causal pathways that need to be taken into account in causal explanations.

4.1 *The explanandum: explaining the causes of what?*

A crucial but sometimes neglected aspect of causal analysis is the clear specification of the outcome of interest in a causal analysis, not only the thematic category (e.g. the type of land use/cover change process, such as land abandonment or commodity crop expansion), but also the precise aspects of this process that one wishes to explain. One often-made distinction is that between explaining the amount versus the location of land change (Verburg, Kok, Pontius, & Veldkamp, 2006). This distinction is relative to the scale and extent of the analysis, which also has to be clarified. Explanations could focus on other aspects of a process, such as why the societal or environmental outcomes of the same land change differ spatially and temporally or why a similar outcome occurred through one pathway in one place and another pathway elsewhere. Proper specification of the target and scope of causal explanations would contribute to clarifying long-standing debates and facilitating the comparison and synthesis of findings from case studies through meta-studies (van Vliet et al., 2015).

Here is a classic example: Do roads cause deforestation? Framed in general terms, the question hardly has a meaningful answer. If one wants to explain the amount of deforestation within a large region over a short time period, a single small road will perhaps not have a causal effect. However, if the outcome to be explained is the precise location of deforestation events within that large region, or, alternatively formulated, the amount of deforestation within a small study area close to that road compared to another small area further away, then that road may constitute a cause. In addition, roads may become an important causal factor when considering the long-term development path and land use dynamics of a region. This relates to the discussion of 'predisposing factors' and 'triggers' above, which can be important or unimportant causes depending on the precise aspect to be explained.

4.2 *Approaches to assessing causal effects*

4.2.1 *The RCM and INUS causes*

With different assumptions, the Rubin Causal Model (RCM) can be operationalized in several ways, and it underlies many recent methodological developments for assessing causal effects (Ferraro & Hanauer, 2014a; Imbens & Wooldridge, 2009), including some discussed below. Following this model, (i) causal inferences should focus on assessing the effects of specific causes rather than searching for the causes of a given outcome, (ii) causal effects of a treatment are always defined relative to another cause (the control or counterfactual), and (iii) only variables that can – at least hypothetically – be subject to experimental manipulation in relation to a given unit can be causes, so that, by contrast, attributes cannot be causes. In principle, the RCM is largely compatible with the INUS view of causality, but in practice the RCM focuses on the effect of a given cause rather than on how different causes interact and how a given outcome is produced. Proper assessment of the causal effect of a single factor via the RCM may require sophisticated methodologies, so assessing multiple interactions seems to be beyond the scope of RCM-based approaches so far (Ferraro & Hanauer, 2014a). Furthermore, the INUS view of causality does not prevent attributes to be part of a causal combination. In LSS and related fields, which sometimes rely on scarce data in complex SES and address crucial and dynamic societal challenges, research can hardly rely only on the RCM that focuses on the effect of one cause at a time and avoids looking at the complex relations between multiple variables leading to an outcome. This approach has to be combined with study designs looking at the multiple causes of a given outcome and their interactions.

4.2.2 *Time series*

On the premise that causes must occur before the outcome they produce, time series data are privileged tools in the exploration of causality. Statistical analyses of time series typically rely on Hume's 'constant conjunction' idea, that if X is a cause of Y, then when X occurs, it must be followed by Y. This is often operationalized explicitly or implicitly through Granger's view of causal effect as relying on predictability (see above). For example, Babigumira et al. (2014) explored the factors that influence smallholder decisions to clear forestland by using a 1 year time lag between explanatory factors and area deforestation measure to avoid endogeneity. Panel analyses are typical tools for analyzing time series, such as in cross-country studies (Barbier & Burgess, 2001) and household survey analyses (Bauch, Sills, & Pattanayak, 2014). Recent studies also used time series at intermediate scales: Panel regressions and time series were used to explore the changing relations between soybean expansion and deforestation in northern Argentina (Gasparri, Grau, & Angonese, 2013), to establish links between soybean expansion in southern Brazil and deforestation in the Amazon (a form of iLUC) (Richards et al., 2014) and to assess the socioeconomic determinants of cropland abandonment and recultivation in provinces of Russia, Ukraine and Kazakhstan (Meyfroidt et al., under revision).

Simple approaches to time series analyses may be insufficient in complex dynamic systems with weakly coupled variables, nonlinear relations and feedbacks, so that the same variables are both causes and outcomes of each other. In such cases, convergent cross mapping correlation has been proposed as a tool for distinguishing correlation from causality (Sugihara et al., 2012). This approach has been applied in ecology (Deyle et al., 2013) and climatology (Wang et al., 2014), but to my knowledge not yet to LSS or SES studies. This approach may be too data-demanding for many applications in LSS, as the depth of the time series is a crucial parameter for demonstrating the causal effect, but nevertheless deserves to be explored when feasible.

4.2.3 *Counterfactual thinking in assessing causal effects*

The basic premise of counterfactual thinking is to reverse the causal condition in Hume's view: If X is a necessary cause of Y, then when there is no X, there should be no Y. Thus, counterfactual approaches require the comparison of cases that are identical in all relevant respects, except that one *explanan* differs. A difference in the outcome indicates a causal relation.[5] Counterfactual thinking is fundamental in experimental sciences, but in historical sciences, finding a suitable counterfactual is problematic (Blackman, 2013). In empirical contexts, being aware of all these 'relevant' aspects and measuring them is challenging. Furthermore, the outcome typically occurs only once in the exact same configuration. Even when all the relevant variables are identified, finding a counterfactual whose characteristics are all identical save for one remains challenging. Several approaches are discussed here, ranging from those where a real counterfactual can be identified (natural experiments) to those where plausible counterfactuals for the state of land use without the target factor need to be identified within a population (statistical matching) or constructed (synthetic control methods and simulation models) (see also Ferraro & Hanauer, 2014a; Holland, 1986).

4.2.3.1 ***Natural experiments and case study comparison.*** The rationale of a natural experiment is similar to a laboratory experiment, i.e. to repeat an observation while holding all conditions constant except for one target variable. Natural experiments are possible when a real, suitable counterfactual can be identified, i.e. at least two cases are as similar as possible as regards as many of the causal factors as possible, except for one or a few (Young et al., 2006). The natural experiment can be created by political or administrative borders crossing through a region broadly homogeneous from an environmental point of view (Homewood et al., 2001; Kuemmerle, Hostert, Radeloff, Perzanowski, & Kruhlov, 2007; Kuemmerle et al., 2008), allowing the effects of institutional differences to be captured. Other natural experiments focus on variations in ecological conditions, cultural features or agency within a broadly homogeneous political context (Atran et al., 1999; Meyfroidt, 2013b). Cases need not necessarily be local, but can be constituted by regions, countries or any other units (Boillat et al., 2015; Prishchepov, Radeloff, Baumann, Kuemmerle, & Müller, 2012). The major issues in relation to natural experiments are, first, that there is rarely only one variable that differs among the cases so, although a causal effect can be identified, attributing it to a specific factor is often difficult. Second, the issue of missing variables and the spuriousness of the relations remains. Between two cases, the outcomes as well as the explanatory factor may differ because both are actually caused by a third, unobserved factor. In statistical terms, this constitutes a selection bias (Blackman, 2013). Third, because the cases and their counterfactuals are generally spatially close to each other as a way of maximizing their similarity, the observed differences may actually be caused by spillovers and interactions among them. The before–after design, where the same object or case is observed both before and after a specific change in a potential explanatory variable (e.g. a policy shock or a climatic event), is one particular form of natural experiment (e.g. Oliveira et al., 2007). However, it is fraught with many caveats and sources of uncertainty (Blackman, 2013).

Multiple case studies comparison extends the reasoning of natural experiments to encompass situations where several factors vary among cases so that comparison across more than two cases is used to isolate the effects of the different factors (Meyfroidt et al., 2014). Beyond natural experiments, also called the 'most similar' design, single case studies or case study comparisons can contribute to different forms of causal inference (George & Bennett, 2005). E.g. the 'least similar' design contains cases that are dissimilar in all but one explanatory variable but share a similar outcome, which can provide evidence that the common explanatory variable is part of the explanation of the outcome. The 'most likely' design corresponds to cases where a hypothesized explanatory factor has such a strong value that, if the outcome is not present, it would significantly undermine confidence in the hypothetical causal inference. In contrast, the 'least likely' design is where the explanatory factors are such that there should only be a weak prediction of the outcome. If this outcome is present, nevertheless, it may indicate that the hypothesized relation is strong enough to hold even in unfavorable conditions.

4.2.3.2 *Statistical tools: matching, synthetic control methods, instrumental variables.* To overcome the limitations of simple natural experiments, statistical tools exist that enable the matching of observed cases with appropriate counterfactuals that are similar in relevant observable aspects except on the target factor, avoiding selection biases (Blackman, 2013; Ferraro & Hanauer, 2014a). Matching allows the effects of a 'treatment' variable to be assessed by pairing each treated observation with an untreated observation that is similar in relation to all the control variables and thus constitutes a counterfactual. Matching is increasingly popular in particular for the evaluation of policy effectiveness, e.g. the effects of protected areas and land zoning on deforestation (Andam, Ferraro, Pfaff, Sanchez-Azofeifa, & Robalino, 2008; Bruggeman, Meyfroidt, & Lambin, 2015; Nolte, Agrawal, Silvius, & Soares-Filho, 2013), poverty alleviation (Ferraro & Hanauer, 2014b), or reforestation (Andam, Ferraro, & Hanauer, 2013).

When finding similar observations for matching is impossible, an emerging approach is to construct 'synthetic controls' (Abadie, Diamond, & Hainmueller, 2010). The idea is to combine observations from several untreated observations to construct artifact observations that can be matched with the treated ones. This method is particularly suitable when only a few treated observations exist among a larger number of untreated ones. This approach was used to assess the effects of political transitions on food security (Pieters, Curzi, Olper, & Swinnen, 2014), and of a municipality policy initiative on reducing deforestation in Brazil (Sills et al., 2015). Matching cannot, per se, directly account for unobserved heterogeneity, i.e. unmeasured third factors that may affect the relation between the causal factor and the outcome. However, sensitivity tests can reveal how strong the effects of these omitted variables should be in order to refute the relation (Andam et al., 2008; Imbens & Wooldridge, 2009).

Other approaches such as panel analyses and instrumental variables (IV) provide different ways to address unobserved heterogeneity, depending on assumptions about its characteristics (whether this heterogeneity is time or individual-invariant, for example) (Ferraro & Hanauer, 2014a; Imbens & Wooldridge, 2009). Another limitation is that the matching design is appropriate primarily in assessing the causal effect of a single variable – interactions and complex causal paths or causal chains can hardly be assessed with these approaches. Designs based on IV aims to control for unobserved factors that may create spurious relation between potential causes and the outcomes. An IV is a factor that influences the value of the potential causal variable and can be used to predict it, but does not affect the outcome in any other way. Observing a relation between IV and the outcome should thus indicate that the potential causal variable indeed affects the outcome. Finding a proper IV can be arduous, and this approach is not yet widely used in LSS. One example used the number of ethnicities, the proximity of international borders and extreme weather events as instruments of the presence of conflicts to explain deforestation in the Democratic Republic of Congo (Butsic, Baumann, Shortland, Walker, and Kuemmerle (2015).

4.2.3.3 *Simulation models.* Simulation models are widely used in LSS and SES research, and several reviews discuss their potential and challenges in depth (Brown, Verburg, Pontius, & Lange, 2013; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003; Schlüter et al., 2012). The point here is therefore not to discuss the diversity of such tools, but rather the role of simulation modeling for causal analysis. For that purpose, by enabling 'what-if' questions to be answered, simulation models can contribute to the toolbox of counterfactual approaches for assessing causal effects. For example, several recent studies focused on assessing the effects of land use policies on indirect land use changes or leakage (Henders & Ostwald, 2014). Using a systematic experimental approach varying different parameters and variables of a land use model in a controlled manner allows the effects of different factors to be disentangled (Magliocca, Brown, & Ellis, 2013, Brown et al., 2013). Simple models allow the chain of causal mechanisms responsible for the observed causal effect to be traced (see below), but on reaching a certain level of complexity, models become more akin to a black box. They may enable the causal effect of a given factor to be established, but not the precise pathway or chain of mechanisms through which this causal factor is linked to the outcome.

4.3 *Process-tracing and other approaches for causal mechanisms and causal chains*

Methods for assessing causal effects are typically insufficient in themselves to establish the causal mechanisms that underpin more general theoretical developments (Agrawal, 2014; see also Ferraro & Hanauer, 2014a). Process-tracing is a four-step approach developed in political science to establish the causal mechanisms underlying the relations observed in case studies (George & Bennett, 2005; see also Elster, 2007, Chapter 1).

First, all the steps of the hypothesized causal chain linking initial variables to the observed outcome are identified and decomposed. Second, these steps are analyzed to verify whether they are internally consistent, i.e. logical, and externally consistent, i.e. that each is supported by available empirical evidence of a causal effect. The causal mechanisms at each step can be formulated as a specification of a more general theory (what Elster, 2007 calls 'support from above'), but this is not decisive as 'theories are supported by the successful explanations they generate, not the other way around' (Elster, 2007). Third, for each step of the causal chain, it is necessary to identify and test the additional implications that, although not part of the main causal chain, are expected to be valid if that causal mechanism is valid. The more uncommon or unexpected these verified additional implications are, the more the validity of the hypothesized causal mechanism is supported (what Elster, 2007 calls 'excess explanatory power' or 'support from below'). Fourth, the alternative or counter hypotheses that might explain the same outcomes have to be explored and refuted by showing that their implications are not observed (what Elster calls 'lateral support'). This fourth step relates to the idea of 'strong inference' (Platt, 1964) aimed to reducing the risk of confirmation bias. When all the steps in the causal chain as well as their additional implications are validated, and the counter-hypotheses are invalidated, then the causal mechanism between the initial variable and the outcome can be established.

Process-tracing is a general approach rather than a specific method. The process-tracing approach does not rely on a linear approach of causality, and any kind of systemic view of causal relations with interactions and feedbacks is compatible with that approach: The role of the process-tracing approach is to help analyzing and validating each individual arrow within a possibly complex causal graph. Along each step, various methods and any form of empirical evidence can be mobilized, including quantitative analyses. Abductive causal eventism (Walters & Vayda, 2009; Walters, 2012) is another approach with affinities with process-tracing, in terms of tracing the causal chain backwards from the *explanandum* and assessing the validity of alternative hypotheses rather than only the main hypothesis. Meyfroidt, Vu, and Hoang (2013) used process-tracing to test two main hypotheses to explain the rapid deforestation in the Central Highlands of Vietnam and showed that deforestation was mainly directly caused by shifting cultivation for annual crops, itself partly driven indirectly by the expansion of coffee and other perennial crops over agricultural lands. The causal chain was divided into several steps corresponding to testable sub-hypotheses, which were explored with remote sensing and spatial statistical analyses. The leading alternative hypothesis to explain deforestation in the study area was also tested in a similar way. Likewise, by analyzing both the hypothesized as well as alternative causal chains, another study in a Vietnamese mountain village showed that local smallholders' perceptions of environmental degradation associated with deforestation affected the subsequent reforestation pattern (Meyfroidt, 2013b).

In these studies, process-tracing is supported by eclectic combinations of methods from remote sensing, spatial statistical analyses, household surveys and interviews amongst others. In other cases, single methods are sufficient to reconstruct and test the validity of a causal chain. Simulation models constitute powerful heuristic tools for analyzing causal chains when their level of complexity is such that the chain remains tractable. For example, a simple but robust land use model enabled not only an assessment of the impact of a potential Green Revolution in Africa on cropland expansion and deforestation, but also an understanding of how these outcomes depended on well-identified factors including relative differences between the innovating region and the rest of the world in yields, emissions efficiencies, cropland supply response, and intensification potential (Hertel et al., 2014).

Operationally, the distinction between causal effects and causal mechanisms does not therefore reflect the classic quantitative/qualitative divide. Statistical tools can be mobilized to establish any step in the causal chain, although they are not in themselves sufficient to fully analyze causal chains (Ferraro & Hanauer, 2015). Some statistical approaches are closely related to causal chain analyses, such as structural equation modeling (SEM), path analyses or Bayesian networks (Pearl, 2009). These tools were used for example to assess the links between soil erosion and land use change (Bakker et al., 2005), the role of environmental change and land management in forest disturbances (Seidl, Schelhaas, & Lexer, 2011), and the factors that influenced the decisions of farm households to plant trees on former cropland in China (Frayer, Sun, Müller, Munroe, & Xu, 2014).

4.4 *Issues with complex causal pathways*

Causal mechanisms generally involve more than simple linear chains from causes to effects. Causal chains are often linked into feedback loops, so that events can be both causes and effects, and third-party variables often intervene in the relation between a cause and its effect. This section discusses some of the major issues arising when complex causal pathways are analyzed.

4.4.1 *Temporality and path dependence*

In a narrow sense, path-dependence essentially characterizes 'self-reinforcing sequences' (Pierson, 2000), i.e. 'processes that exhibit increasing returns', or positive feedback loops. A second, broader form of path dependence is what Mahoney (2000) calls 'reactive sequences', i.e. chains of chronologically ordered and causally connected events which exhibit 'inherent sequentiality'. This indicates that the steps in a causal chain linking an initial event to a distal outcome are more tightly connected and less contingent than in typical causal chains. In other words, 'events in a path-dependent reactive sequence are often necessary or sufficient conditions for subsequent events' (Mahoney, 2000). The idea of path dependence helps to bridge the distinction between quantitative and qualitative or incremental and transformative changes. Over time, small incremental differences can cumulate and result in large path-dependent effects that eventually can be considered as transformative (Gordon Walker, 1937; Wallerstein, 1974).[6]

Various self-reinforcing sequences occur in SES, including agglomeration economies (Garrett, Lambin, & Naylor, 2013), lock-ins (Allison & Hobbs, 2004), sunk costs effects (Janssen & Scheffer, 2004) and others. In one fine example of path dependence in land use change, Börjeson (2007) returns the logic of the Boserup theory when analyzing the path-dependent historical chain causing agricultural intensification in the Mbulu Highlands in Tanzania. He concludes that agricultural intensification was not initially caused by land scarcity and population pressure, but instead initial intensification events facilitated an accumulation of landesque capital, which in itself provided further incentives for intensification in a self-reinforcing sequence. Path dependence is also associated with the idea of regime shifts, stemming from complex systems and resilience theory that is gaining traction in LSS (Müller et al., 2014): When some causal forces push the system beyond a certain threshold, the path of change becomes self-reinforcing and difficult to reverse and systems shift to another type of dynamic equilibrium. Path dependence should thus not be confused with monotonous trends. Another temporal effect that complicates causal analysis is inertia (Reenberg, Rasmussen, & Nielsen, 2012). Effects of causal factors can be hampered or delayed by other interacting factors, so that simple correlations between variables observed simultaneously can be misleading.

The feedback loops contained in path dependence and inertia may complicate causal analyses because the same variables are both causes and effects over time (see Sugihara et al., 2012). However, this does not refute the approaches and terminology for analyzing causal effects and causal chains proposed above, as long as the analyst decides on a starting point in the chain of events studied, and a clear *explanandum* (see 4.1).

4.4.2 *Interactions through moderation and mediation*

As mentioned earlier, causal factors in SES rarely function in isolation and multiple forms of interactions between variables exist. One important distinction, best formalized in psychology, is between moderation and mediation (Baron & Kenny, 1986). In the words of Baron and Kenny (1986), 'a moderator is a qualitative (e.g. sex, race, class) or quantitative (e.g. level of reward) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable.' In contrast, a variable B functions as a mediator between a causal factor A and an outcome C when this variable is influenced by A, and itself influences C, and when the causal effect of A on C disappears when these two effects are taken into account in the analysis – i.e. in terms of causal chains, A causes B which causes C. These two terms are too often used loosely, and the assessment of causal chains would be enhanced by proper use of this distinction between moderation and mediation.

4.4.3 *Equifinality and multifinality*

The notion of equifinality was introduced above to refer to different combinations of causes resulting in a similar outcome. However, the symmetric phenomenon also exists: Broadly similar combinations of causal factors can result in substantially different outcomes, if only a few other contextual factors or small contingent events differ. This was called 'non mono-consequentialism' (Agrawal & Chhatre,

2011) or 'multifinality' (George & Bennett, 2005). One example is discussed by Sloan (2008) in relation to an agricultural frontier in Panama. According to the general forest transition theory, off-farm employment and outmigration, resulting in labor scarcity, should have led to land abandonment and spontaneous reforestation. Nevertheless, the economic context pushed farmers to maintain extensive pastures (a 'hollow frontier') rather than leaving land to reforestation, and a small policy shift led timber companies to make massive investments in tree planting in the region.

5. Conclusion

Simple approaches to causality might be insufficient for disentangling causal pathways in complex Restore 'social-ecological systems' in full as per author's request, such as land systems, that are characterized by feedbacks, overdetermination and path dependence. However, establishing a coherent foundation can help to achieve progress in causal analysis. Combining assessments of causal effects and causal mechanisms is required in order to build convincing causal explanations of land system processes. Statistical and other quantitative studies that often identify causal effects, and qualitative and narrative studies that often pay more attention to causal mechanisms, do not provide antagonistic but rather complementary views on SES. But the quantitative–qualitative divide does not directly reflect the causal effect–causal mechanism divide. For example, although the process-tracing approach of causal mechanisms has been often used for case studies, it is not a qualitative approach *per se*. Similarly, a natural experimental study can reveal the causal effect of a given factor even when realized fully with qualitative methods.

Having a coherent conception of causality, agreeing on a precise vocabulary and harnessing our tools with the clear purpose of establishing both causal effects and mechanisms should strengthen causal explanations in relation to single cases, drawing policy-relevant lessons and theoretical generalizations of land and, more broadly, SES processes. This, in turn, should contribute to the broader goals of sustainability science.

Notes

1. Translated by William Weaver.
2. Although in operational approaches, we are often bound to what Elster calls 'second-best' explanatory practice, i.e. explanation of the variance of series or comparisons of facts or events, rather than actual explanation of the event in and of itself (Elster, 2007).
3. Other causes are described as SUIN – a sufficient but unnecessary part of a combination that is insufficient but necessary for the outcome -, but this is rarely helpful (Mahoney, 2008).
4. Although a single, carefully designed study may be sufficient to refute a theory and evidence from a single study supporting a theory under unfavorable conditions (a 'though test') is worth more than evidence under favorable conditions, see George and Bennett (2005).
5. For 'sufficient' variables, the opposite approach is appropriate: Look for a set of cases where in some instances the expected outcome is observed, while in others it is not observed (or different). If the *explanan* variables indeed differ, it shows their causal relation with the *explanandum*.
6. See Wallerstein (1974), p. 98: 'Awareness of this cumulative effect of small differentials provides a bridge to overcoming the somewhat sterile argument about quantity and quality. I agree with P. C. Gordon Walker: "The distinction between changes in quality and changes in quantity is an unreal one. If historians looked for changes in quantity, in degree, they would find that "changes in quality" only in fact result from changes in quantity… [C]hanges of quality are nothing else but a certain stage of intensity reached by preceding changes in quantity"'.

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