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A causal analysis framework for land-use change and the potential role of bioenergy policy☆

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ABSTRACT

We propose a causal analysis framework to increase understanding of land-use change (LUC) and the reliability of LUC models. This health-sciences-inspired framework can be applied to determine probable causes of LUC in the context of bioenergy. Calculations of net greenhouse gas (GHG) emissions for LUC associated with biofuel production are critical in determining whether a fuel qualifies as a biofuel or advanced biofuel category under regional (EU), national (US, UK), and state (California) regulations. Biofuel policymakers and scientists continue to discuss to what extent presumed indirect land-use change (ILUC) estimates should be included in GHG accounting for biofuel pathways. Current estimates of ILUC for bioenergy rely largely on economic simulation models that focus on causal pathways involving global commodity trade and use coarse land-cover data with simple land classification systems. This paper challenges the application of such models to estimate global areas of LUC in the absence of causal analysis. The proposed causal analysis framework begins with a definition of the change that has occurred and proceeds to a strength-of-evidence approach that includes plausibility of relationship, completeness of causal pathway, spatial co-occurrence, time order, analogous agents, simulation model results, and quantitative agent–response relationships. We discuss how LUC may be allocated among probable causes for policy purposes and how the application of the framework has the potential to increase the validity of LUC models and resolve controversies about ILUC, such as deforestation, and biofuels.

1. Introduction

Causes of land-use change (LUC) need to be better understood, and models of LUC should reflect evidence about causation. One application of these models is for renewable energy policies that require accounting of greenhouse gas (GHG) emissions from biofuel-induced LUC to determine whether a fuel meets the minimum targets for emissions reductions. For example, to contribute to a renewable energy mandate in the European Union (EU), biofuels must result in at least 35% lower emissions than fossil fuels. The requirement escalates to 50% in 2017 (EU, 2010). Uncertainties surrounding projections of LUC have led to a debate about whether policy targets for reducing emissions are met by particular biofuel production systems (Hertel and Tyner, 2013).

Calculating direct life-cycle GHG emissions reductions from crop-based biofuel production and use is complicated, requiring knowledge and assumptions about baseline landscapes, carbon stocks, and land management, and how fossil fuel and biofuel production interact and influence these and other variables. Uncertainty in emissions estimates increases when poorly defined indirect LUC (ILUC) attributed to biofuel policy is projected in places distant from biofuel production (Liska and Perrin, 2009; Plevin et al.,

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2010; Di Lucia et al., 2012; Sanchez et al., 2012; Warner et al., 2014). Yet ILUC estimates are mandated by some biofuel regulatory systems (USEPA, 2010; ARB, 2010) and may be required by the EU or others in the future.

LUC induced by a biofuel policy is generally estimated using simulation models with distinct assumptions about causal pathways. Most estimates of ILUC have relied on economic models developed for other sectors, such as global trade in agricultural commodities (Hertel et al., 2010; Britz and Hertel, 2011). Typically, a computable general equilibrium model is "shocked" with higher demand for the commodities associated with a biofuel policy, and the distribution of agricultural production under new conditions is compared to a baseline simulation (Banse et al., 2009; Britz and Hertel, 2011).

The model structure and parameters are often based on the assumption that the production and use of a feedstock commodity for biofuels increases demands for food crops, thereby increasing crop prices and expanding total agricultural land area at the expense of natural vegetation, particularly forests. An analysis by Searchinger et al. (2008) was the first to suggest that this series of contingencies was not only plausible but would necessarily be triggered as "farmers around the world respond by clearing more forest and grassland to replace crops for feed and food." However, this analysis has been criticized for these specific causal pathway assumptions that do not reflect policies, social factors, potential trade effects and potential changes in yield (Kline and Dale, 2008; Mathews and Tan, 2009). In contrast, LUC is known to involve interactions among many context-specific factors (Wear and Bolstad, 1998; Geist and Lambin, 2002; Van Asselen et al., 2013). Lapola et al. (2010) note that their ILUC projections for biodiesel in Brazil are a hypothesis, because the causal relationships have not been established.

Many drivers of LUC and deforestation, as well as feedbacks from land management and land manager motivations are omitted from ILUC models. For example, land appreciation (Richards et al., 2014) and causal factors for LUC that vary spatially, such as national land policies (Warner et al., 2014), enforcement of laws, migration, and accessibility via roads, are not represented at the highly aggregated level of most models used for biofuel policy (Kline et al., 2011). Land management and crop production practices (Langeveld et al., 2013) and feedbacks that reinforce or mitigate LUC (Verburg, 2006) are usually ignored. Some land managers may respond only partially to market prices by maximizing rent per acre, as they have other values (Piorr et al., 2009), they may be capital- or labor-constrained (Angelsen and Kaimowitz, 2001) or they may be interested primarily in asserting tenure claims (Lapola et al., 2010; Fearnside, 2008). Insecure tenure is an important driver of deforestation in some regions of the world (Rudel et al., 2009), and tenure regimes can affect deforestation in manners independent of and counter to simple land-rent maximization predictions (Godoy et al., 1998).

If mechanistic LUC models omit important causal factors or steps in a causal pathway, the outputs become dubious. Uncertainties are difficult to quantify, especially when formal validation is lacking (Baldos and Hertel, 2013; Brown et al., 2013).

The few studies that have attempted to examine the potential causal relationships between LUC and U.S. biofuel policy during the period of increasing corn ethanol production since 2001 have found little empirical evidence to support prevailing ILUC conceptual models (Kim and Dale, 2011; Oladosu et al., 2011; Wallington et al., 2012; Langeveld et al., 2013; Babcock and Iqbal, 2014). Empirical studies have been difficult to undertake because of the complexities of potential drivers, lack of consistent definitions of LUC, and limited land-cover and spatially explicit land-management data, especially for quantifying historic trends and background LUC.

Place-based studies of key influences on land changes must accompany global economic models to improve our understanding of causal relationships underlying LUC (Meyfroidt et al., 2013; Richards et al., 2014). More empirical evidence is needed to test linkages between bioenergy and distant land change.

We propose a causal analysis framework to identify when and where biofuel policy is a probable driver of LUC, using deforestation as an example. The framework employs an analysis of multiple lines of evidence and builds on a standard epidemiological approach (Hill, 1965). Without the use of causal analysis, models of policy-induced LUC only produce plausible rather than probable outcomes.

2. Causal analysis

Causal analysis is a formal process that uses evidence to infer causal relations or to link effects and causes. Analyses begin with an association and ask if the most likely interpretation is causation (Hill, 1965). Potential causal pathways and complex webs of influence are evaluated. The concept of a web of causation is prevalent in epidemiology (Krieger, 1994), referring to the characteristics of the host, agent, and environment that cause, prevent, or otherwise affect the rate of spread of a disease.

Unlike definitions of ILUC for biofuels that presume a causal pathway, a more general definition of an indirect effect is used in causal analysis, i.e., a greater relative distance of an event from a cause compared to other variables in a causal pathway diagram (Shipley, 2002). Indirect effects are more uncertain than direct effects, and the number of the former is potentially very large. They often have weak causal linkages, have a delayed effect, act at a distance from the cause, and are mediated by factors not in the direct causal pathway (Njakou Djomo and Ceulemans, 2012). Even where a causal pathway has just two steps [e.g., greenhouse gas emissions leading to regional climate change, and warming temperatures leading to changes in natural systems such as species ranges (Rosenzweig et al., 2008)], this "joint attribution" has reduced statistical confidence compared to attribution of each of the two steps.

Strength-of-evidence approaches can be applied to causal analysis for which causes are not easily diagnosed (Hill, 1965; Morton et al., 2006a,b; Suter et al., 2010). Such analyses consider multiple types of evidence from the case and from related cases, as well as their consistency and coherence.

Some causal relationships are general, whereas others are highly specific. For example, the use of causal analysis frameworks developed by the Surgeon General's advisory committee in the United States (USDHEW, 1964) and Hill (1965) in Great Britain established the general causal relationship between smoking and lung cancer. In a more location-specific example of causal analysis, petroleum production was investigated as a potential factor contributing to regional subsidence and wetland loss along the Gulf Coast of the U.S. (Morton et al., 2006a,b). Ecological applications of causal analysis are typically specific to a location and clearly defined effects (USEPA, 2013).

3. Framework for attributing LUC to bioenergy

We develop a causal analysis framework for determining the probable causes of LUC (and ILUC), with an emphasis on bioenergy (Fig. 1). The framework begins with a clear statement of the problem and definition of the LUC, followed by the generation of hypotheses to explain changes and causal pathway diagrams. Along the way, historic trends and baselines are characterized, and sufficiency of data is considered (Fig. 1). The core of the framework is a strength-of-evidence approach derived from epidemiology that incorporates multiple categories of evidence. Deforestation is used as an example of an important effect. Finally, alternative

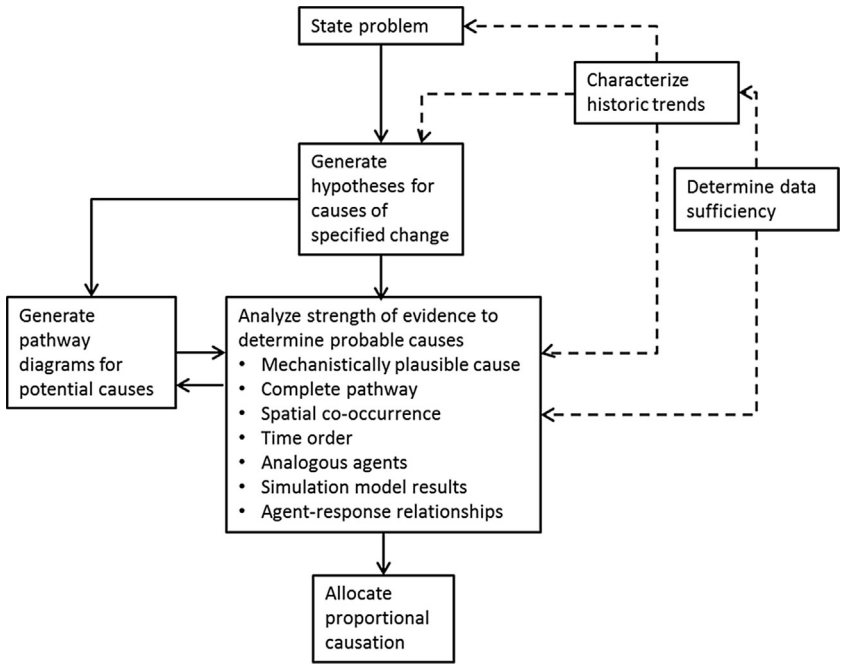

Fig. 1. Causal analysis framework for land-use change. Solid arrows link steps in the process. Dotted lines indicate that steps related to characterizing historic trends and determining data sufficiency are required to inform multiple steps in the process.

approaches for allocating portions of an observed LUC attributable to particular causes are discussed.

3.1. State problem

This first step of the causal analysis framework is to describe the objectives and scope of analysis, but, even before that, to characterize explicitly an observed change. Causal analysis of any change is futile if the change itself is not specified and documented. Because an objective of this framework is to provide evidence of drivers to inform models, clear definitions supporting consistent identification of the change are required.

Applications of causal analysis in a health context begin with a clearly defined change, e.g., a disease occurring in an individual or a trend in mortality. Vaguely defined effects such as "mental state" (Susser, 1986) or "cardiovascular disease" (Rothman and Greenland, 2005) or "climate change" diminish the strength of an association with a potential cause. For example, broadening the definition of Gulf War illness reduced the power to detect the gene-environment interaction (Haley, 2013). When a condition has a variety of symptoms and outcomes and the symptoms of different diseases overlap, it can be unclear who suffers from the same disease. In these situations (e.g., Gulf War illness (Iversen et al., 2007)), Myalgic Encephalopathy/Chronic Fatigue Syndrome (CFS) (Fukuda et al., 1994; Carruthers et al., 2011), it is important to define the condition as specifically as possible before attempting to determine probable causes and to identify effective treatments.

Deforestation (or an increased rate of deforestation) is one LUC manifestation of high concern. Deforestation is quantified differently, depending on the definition of forest, especially whether the definition relates to forest management or forest cover (Coulston et al., 2014). More precise definitions lead to more certainty in causal analysis. Reliable measures of changes over discrete time steps for relevant forest attributes such as forest cover, structure, age class distribution, density, harvested products, disturbance, and ownership facilitate the analysis of causes.

The timeframe and spatial extent of analysis are specified in this step. An example causal analysis objective is to determine whether the policies that incentivized biofuel production had an effect on forest area. To assess potential effects of U.S. policy, an analysis could consider the years prior to and since the rapid growth of ethanol for biofuel beginning in 2001, when policies promoted ethanol initially to replace methyl tert-butyl ether in gasoline and later to fulfill mandates under the Renewable Fuel Standard-1 (2005) and Renewable Fuel Standard-2 (2007). Periods prior to, following, and pertinent to non-biofuel-related, candidate causes (e.g., changes in agriculture and forestry laws, tax incentives, and enforcement, as well as management and disturbance regimes) may also be relevant to the timeframe for an analysis of deforestation.

3.2. Characterize historic trends

Understanding historical LUC trends is essential for defining the baseline dynamics prior to implementation of a bioenergy policy, characterizing the effect of concern, and evaluating types of evidence (Sect. 3.6), such as time order and simulation model results. This step consists of describing past land transitions including types, timing, rates, reversibility, and confidence.

Classifications selected to describe land cover and change trends have important implications. Land management, land cover, and land use must be classified consistently through time (Turner and Meyer, 1994; Letourneau et al., 2012), and classifications must be appropriate for the problem being addressed. Simplified classification systems are often a result of limited data available to distinguish among multiple land uses, management practices and cover types (Verburg et al., 2011b).

Definitions of forest land type are sensitive to thresholds of change. For example, forest lands may go through decades of incremental degradation as timber is selectively removed, roads are constructed, and understory fires burn, prior to a reported change in cover classification (e.g., from forest to agriculture). A land unit 0.5 ha or larger that changes from 100% to 11% canopy cover could have lost over 95% of total aboveground carbon, but remains classified as forest based on guidelines from the Forest and Agriculture Organization (FAO) of the United Nations. When this same unit of

land shifts from canopy cover of 11% to below 10%, then it becomes non-forest (FAO, 2010). In such cases, a majority of change in relevant characteristics such as carbon stocks would occur at earlier times and be related to earlier drivers that may not be obvious when the change in land-cover class occurs.

Characterizing reversibility is also important; a given land unit may change to or from a forest classification multiple times. Long time periods between the actual LUC and when data become available can increase the probability that additional, unrecorded transitions occurred in the meantime. Net changes should be distinguished from gross changes (Langeveld et al., 2013; Fuchs et al., 2015). The debate over disparate figures of deforestation provided by FAO (2010) and Hansen et al. (2013) is also illustrative of the critical role of precise definitions.

3.3. Generate hypotheses for causes of specified change

In this step, hypotheses for causes of change (for example, deforestation) are generated based on prior research and a basic understanding of regional drivers of change. A useful starting point for developing hypotheses is meta-analytic syntheses of land-change processes across case studies (Kaimowitz and Angelsen, 1998; Geist and Lambin, 2004; Rudel, 2008; Seto et al., 2011; van Vliet et al., 2012; Van Asselen et al., 2013). Parsimonious groups of causes of deforestation in particular regions that have been identified through qualitative comparative analysis (QCA) methods (Rudel and Roper, 1996; Scouvart et al., 2007), for example, are reasonable hypotheses for other locations in the region.

Candidate causes of LUC must be appropriate to the scale of analysis and location and may include land tenure policies, social factors, and economic factors such as ease of credit, farm gate crop prices and subsidies (Dale et al., 1993; Pfaff, 1999; Perz and Skole, 2003; Köthke et al., 2013). Energy development and related policy incentives are often drivers (Viña et al., 2004; Drohan et al., 2012). LUC such as deforestation is strongly influenced by accessibility via roads and rivers (Dale et al., 1993; Kaimowitz and Angelsen, 1998; Scouvart et al., 2007; Verburg et al., 2011a), local zoning, and regulations (Robinson et al., 2014). LUC may be constrained by geological and soil characteristics (Dale et al., 1993; Kaimowitz and Angelsen, 1998; Frimpong et al., 2006), other environmental conditions such as climate (Mendelsohn and Dinar, 1999), land ownership, resource rights and zoning, and effective governance and law enforcement mechanisms (Sikor et al., 2013).

Where a policy demands the quantification of bioenergy-induced effects, it is tempting to test exclusively hypotheses that involve bioenergy as a potential cause. However, evidence collection for the purpose of supporting or refuting a single hypothesis about causation increases the risk of a type of cognitive error termed “confirmation bias” (Loehl, 1987) or “hypothesis dependence,” whereby the hypothesis guides the types of data collected (Norton et al., 2003). All reasonable causal hypotheses should be considered during data collection.

3.4. Generate pathway diagrams for potential causes

In this step of the framework, causal pathway diagrams are generated. LUC involves webs of causation that are analogous to the etiology of disease. A web-of-causation diagram begins with potential causal pathways from the literature or field that include links to the effect defined in the first step. If the objective is to influence the development of a new (conceptual) LUC model, then the pathways can take many forms, while potentially being constrained by the theory employed in model design. If the objective is to influence pathways in an existing model, then the causal pathways are more constrained. For example, choices about whether causality is expressed in a hierarchical way with underlying drivers and proximate causes (Kaimowitz and Angelsen, 1998; Geist and Lambin, 2002), or how environmental contributing factors (such as soil type) are considered, or what spatial scale the pathways should take may depend on the structure and purpose of the model.

Causal diagrams should illustrate the pathways prevalent in baseline trends, as well as where and under what circumstances a bioenergy policy was implemented. Major economic, environmental, and social factors, as well as agents, contributing factors and feedbacks, should be included. Pathways vary depending on context (time, place and scale) and should include those suggested by regional empirical analyses, as well as by informed researchers, government agencies, and other stakeholders. Starting points for deforestation pathways could include minimum sets of causes of forest decline identified by researchers for particular regions (Fig. 2).

Models commonly assume a general pathway whereby biofuel policies lead to direct LUC for production of biomass, a corresponding reduction in crop availability for non-biofuels markets such as food or feed, an increase in global crop prices, and an indirect expansion of agricultural lands, resulting in increased deforestation in the U.S. and abroad (Tyner et al., 2010; Warner et al., 2014). While the role of higher demand through global trade is an increasingly important determinant of global LUC (Rudel et al., 2009; Meyfroidt et al., 2013), it is not the only driver, and its influence can reduce deforestation in some places as it increases pressures in others (Meyfroidt et al., 2010; Barretto et al., 2013).

An alternative conceptual model assumes that higher crop prices lead to rapid responses on lands already in production and land near the points of demand or export (see Peters et al., 2009). The potential profitability of higher commodity prices tends to be short-lived, and only those who can quickly and efficiently respond to such market signals are likely to benefit. In tropical forest nations, this conceptual pathway reflects historic trends showing that economic growth and job opportunities in developed areas tend to reduce demographic pressure to settle and clear more forest land on distant frontiers (Kline et al., 2009).

3.5. Determine data sufficiency

The framework requires an evaluation of the data available to support each step, from characterizing the effects and their historic trends to gathering evidence for and against each hypothesized causal pathway. Classifications and spatial and temporal scales of existing data must be compatible with the problem statement. Adequate historical data must be available to allow the change (e.g., deforestation) to be quantified over the period of analysis. Although uncertainties about the extent of forest transitions to other land uses may be high (Grainger, 2008), reported changes in the grassland-pasture-cropland margin have even greater uncertainty (Verburg et al., 2011b; Kline et al., 2013; Johnston, 2013). Land-cover data alone are insufficient to answer questions about how land is managed, which lands are used for biomass production (and how they are used), what is the actual cause of a disturbance, and whether forest change is a temporary condition in a management cycle or reflects a permanent transition (Kuemmerle et al., 2013; Coulston et al., 2014). Data gaps may be filled by additional field studies or expert consultations which involve time and costs – one reason why modeling based on causal assumptions is more common than formal causal analysis.

3.6. Analyze strength of evidence to determine probable causes

The core of the framework is a strength-of-evidence approach to identify probable causes of a specified LUC. Because of the complexity of drivers of LUC such as deforestation, there is “a need for a synthesis of the results gathered from a variety of

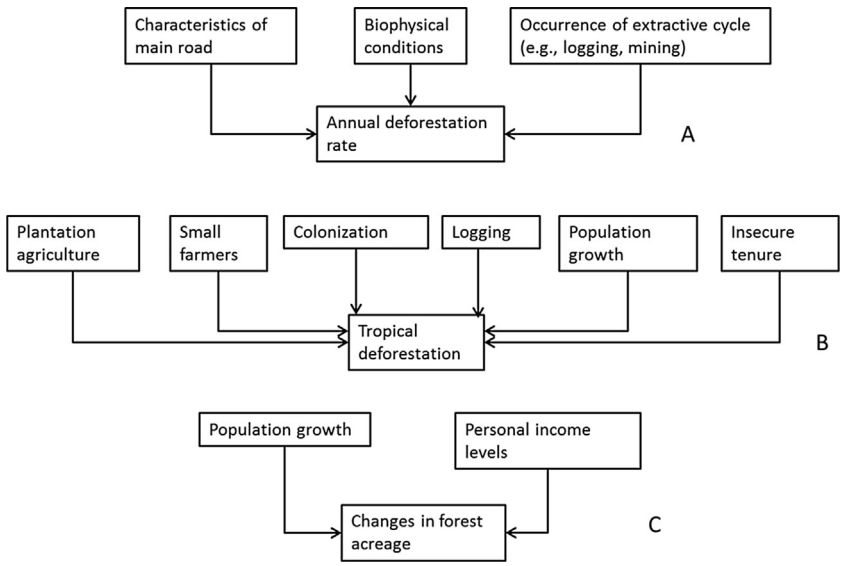

Fig. 2. Example starting points for developing causal pathways and webs for deforestation. Depicted are minimum sets of causes of forest change identified by researchers for particular regions. Arrows represent causal relationships. Some boxes are more appropriately termed catalysts (roads) or constraints (biophysical conditions) than causes, and some are agents, but all could be influenced by bioenergy. A. Brazilian Amazon (Scouvart et al., 2007). B. Southeast Asia (Rudel et al., 2009). C. Southeastern U.S. (Alig, 1986).

investigation methods" (Lambin, 1997). The major lines of evidence adapted from Suter et al. (2010), as well as Hill (1965), Lewis (1973), and Susser (1986), are mechanistic plausibility, complete causal pathway, spatial co-occurrence, time order, analogous agents, and agent-response relationships, each of which is discussed below and summarized in Table 1. We also discuss simulation model results, which rely on many types of evidence. A simulation model can be used as a virtual laboratory (Matthews et al., 2007) and is especially useful for LUC, because field and economic manipulations are not undertaken at regional scales, and complex causal webs are difficult to manipulate (Suter et al., 2010). The taxonomy of evidence (i.e., the names of categories of evidence used in the analysis) is less important than ensuring that sufficient evidence is available and that no relevant evidence is omitted from the analysis.

3.6.1. *Plausibility*

A review of the following questions by experts determines whether the relationships portrayed in a hypothesized causal pathway are plausible, or whether the pathway may be eliminated. Is there a reasonable mechanism to explain the relationship between candidate causes and an observed effect, as well as all proposed steps in the causal pathway? Is each hypothesized mechanism consistent with known theories describing the effect, and basic economics, social sciences, and environmental sciences?

Processes and events that are consistent with mechanisms of deforestation in the literature may be plausible causes. For example, Mather (1992, 2007), Grainger (1995, 1998) and others document how deforestation and afforestation follow a persistent temporal pattern according to the "forest transition curve," moving from high forest cover to deforestation at the forest frontier to afforestation in forest-agricultural mosaics. Factors determining the rate of forest transition and key deforestation mechanisms are described in the context of programs that aim to reduce forest degradation and loss (Angelsen and Rudel, 2013).

Bioenergy policy can be a plausible cause of higher rates of deforestation or reduced rates of deforestation and afforestation. For example, "sound economic reasons" (Malins, 2013) support the hypothesis that if biofuel mandates cause higher demand for commodities in one location, higher prices will follow and drive increased deforestation for agriculture in another region. However, it may not be plausible for such deforestation to be caused by biofuel mandates in cases where the links assumed by the causal pathway do not exist, for example in a forest frontier physically isolated from market information or within a relatively closed economy (Villoria and Hertel, 2011), in regions where deforestation trends show a lack of consistent response to changes in food commodity prices (Scouvart et al., 2007), or in cases where surplus capacity permits higher bioenergy feedstock production without causing higher prices or reduced exports.

Bioenergy can also be a plausible cause of forest regeneration if it leads to intensified production (Barretto et al., 2013) through improved systems efficiency and total factor productivity

Table 1
Types of evidence in strength-of-analysis approach to causal analysis for land-use change (LUC). Bioenergy policy and deforestation are illustrated, but other potential causes and LUCs would need to be considered.

Evidence	Question
Plausibility	Is there a science-based mechanism to describe the relationship between bioenergy policy and the specified deforestation?
Complete pathway	Is there a complete causal pathway from bioenergy policy to the specified deforestation, or is part of pathway blocked?
Spatial co-occurrence	Is the deforestation occurring where a bioenergy policy was implemented or biofuel crops were grown or where effects in a documented causal pathway occur?
Time order	When did deforestation (or change in rate) occur, relative to bioenergy policy?
Analogous agents	Is the hypothesized relationship similar to other cases involving bioenergy or related drivers?
Simulation model results	Do simulation model results support or contradict the hypothesized relationship between the specified deforestation and bioenergy policy? Was the model validated for the effect (e.g., deforestation), or were particular results verified?
Agent-response relationship	Is there a quantitative relationship between bioenergy policy or an agent in the causal chain and deforestation?

(Ianchovichina et al., 2001) or higher returns to forest management and related industries (Raison, 2006), or if bioenergy-induced economic development provides more off-farm employment opportunities, allowing old fields to transition back to forest (Rudel et al., 2005). Bioenergy policy may also plausibly reduce deforestation if it promotes more sustainable land management or if expanding bioenergy-related opportunities allows previously cleared land to come into production and thereby reduces social and demographic pressures to expand into distant forest frontiers (Kline et al., 2009, 2016; Souza et al., 2015). While endorsing the use of plausibility as a type of evidence from which to infer causation, Hill (1965) cautions that plausibility should *not* be required, because this type of evidence "depends upon the. . knowledge of the day."

3.6.2. Complete pathway

A related type of evidence is whether a complete pathway exists from the candidate cause to the effect. In-depth case study results can be used to determine whether hypothesized pathways are consistent with observations. A basic principle of logic that is helpful in causal analysis is that if factor A causes effect C only through intermediate B, and intermediate B is not responsive to A in a particular case, then the pathway from A to C is blocked (Shipley, 2002). This simple principle can prove useful in eliminating potential causal pathways.

Economic modeling for bioenergy often assumes that using crops for biofuel production (A) leads to displacements for non-bioenergy crops (B), and this, in turn, necessitates increased deforestation to expand agricultural production (C). However, an examination of market data in the US and an index decomposition analysis of corn used for ethanol production did not provide support for the modeling assumptions regarding displacement of crop exports (i.e., no B) (Oladosu et al., 2011). Additional analyses show little evidence of commodity price increases resulting from US biofuel production (Ajanovic, 2011; Babcock, 2011; Mueller et al., 2011), while other explanations for price increases seem more likely (Baffes and Dennis, 2013). Indeed, by providing advance notification of a secure and growing demand, biofuel policies appear to have given farmers confidence for added investment leading to record production, a near tripling of US agricultural exports since the early 2000s (USDA, 2014), and increased use of double-crops and other approaches that improve land-use efficiency (Langeveld et al., 2013).

3.6.3. Spatial co-occurrence

With this type of evidence, the analyst asks whether a change is occurring in the same location as the candidate cause. Is there spatial co-occurrence between competing potential causal factors and the effect?

More specifically, is deforestation occurring or enhanced where a bioenergy policy or incentive has been implemented, bioenergy crops are grown, or other stages of the production pathway occur? Is the effect absent where the policy is absent? Do LUC and a proximate cause from the causal pathway co-occur spatially?

Spatial analyses can sometimes inform causal analyses for deforestation, though not conclusively. For example, logging concessions, oil palm plantations, and government-allocated leases have been associated with the deforestation of peat forests in Indonesia (Koh et al., 2011; Carlson et al., 2012). A government-sponsored road construction program and associated oil exploration and production were largely responsible for the pattern of deforestation in a region of Ecuador (Viña et al., 2004). Most land clearing for agricultural expansion in Brazil in the past decades has been occurring on land with no tenure rights (MDA, 2010), suggesting a possible causal link whereby deforestation is driven by the traditionally recognized land rights attained through clearing (Kline et al., 2009; Lapola et al., 2010). Paired comparisons of protected areas and unprotected land showed an association between protected area status and apparent inhibition of deforestation (Soares-Filho et al., 2010).

In a grassland example, private land tenure facilitated land-cover change and wildebeest decline (Homewood et al., 2001). The natural experiment compared effects in regions of the Serengeti-Mara ecosystem where many other potential ecological, microeconomic, and cultural drivers were similar, but different systems of land tenure existed across the Kenya-Tanzania border. Similarly, divergent policies for colonization and road infrastructure led to deforestation patterns that closely followed political boundaries such as the northwestern border of Guatemala with Mexico (Sever, 1998).

Spatial co-occurrence evidence has limitations with regard to LUC analyses. Exact locations of corn and sugarcane production for ethanol and palm oil and canola for biodiesel can be difficult to pinpoint, because these major industrial commodities are produced for multiple uses and markets, with biofuel being a minority share. The distribution and use of commodities among food, livestock feed, fuel, fiber, cosmetics, pharmaceuticals, and other products are determined by speculative investments, varying exchange rates, national policies, and other factors (Gillon, 2010). Thus, it is reasonable to focus first on where effects of concern (e.g., deforestation) occur and analyze spatial co-occurrence of possible drivers.

The spatial-co-occurrence line of evidence is not easily applied to the hypothesis that global market forces mediate effects from the point of policy implementation to distant lands. However, for global market forces to be a plausible mechanism by which LUC from biofuels occurs, there must be spatial co-occurrence of the effect (e.g. deforestation) and a specific change in market forces. Validation of these linkages for LUC model assumptions has been lacking (Kline et al., 2011). Arima et al. (2011) claim to link soy expansion in Brazil to locations of distal deforestation, but others do not find evidence for a connection (Macedo et al., 2012) or sufficient data to analyze these displacement effects (Sparovek et al., 2009). If changes in global prices are a hypothesized cause of LUC, then the causal analysis will likely draw on other types of evidence (e.g., time order, simulation models, analogous agents).

3.6.4. Time order

Time order is a factor that can suggest causation, but it is not emphasized enough (Susser, 1986). Analysts ask when the defined effect (or intermediate effect) occurred, relative to hypothesized drivers or intermediate steps in the hypothesized causal pathway. If biofuel policy is a causal agent, this type of evidence should show that the policy preceded the observed effect, e.g., a change in the rate of deforestation. Because policies are implemented at a defined time, this evidence is more useful than for situations where many potential causes have uncertain beginnings.

Time order is the most decisive type of evidence for eliminating causation (Susser, 1986). A causal process can be confirmed by examining its "correlational shadow" (Shipley, 2002); if there is no temporal correlation, there is no causation.

Feedbacks in causal pathways can be important (Verburg, 2006), but they should not be treated as bidirectional causal pathways. Instead, these pathways represent different directions in causation at different times (Shipley, 2002).

An example of time-order-based analysis is the evaluation by Mueller et al. (2011) of the effect of biofuel production on grain price increases. Growth in biofuel production did not cause the significant grain price increases in 2007–2008, they argue, given the subsequent reduction in food prices as biofuel production continued to grow. An examination of trends in deforestation and soy production in Brazil did, however, show a temporal correlation

between reduced forest clearing and specific policy and economic factors (Macedo et al., 2012).

Potential time lags are important to consider when evaluating evidence related to the time order of events. Time lags are commonly observed after policies are announced and implemented or after crop prices change. For example, farmers have learned that it is risky to rely on a recent price increase to justify capital expenditures for an alternative crop (Rounsevell et al., 2003).

When evaluating evidence of change in a region, it should not be assumed that a current land-cover category (e.g., pasture) is the cause for a prior change in land cover (e.g., forest clearing) (Dale and Kline, 2013). The drivers that interact to determine that a given land area will be deforested are typically distinct from the drivers that subsequently determine how that land is managed each year. For example, a national colonization policy, a road building program, traditional land claiming rights, and timber or mineral concessions may be important causes for initial forest clearing and can operate independently from factors that influence how the land appears or is managed in the years that follow.

3.6.5. Analogous agents

Another line of evidence for causal analysis relates to whether the hypothesized relationship between an agent and the effect is analogous to other, well-established causal relationships. Is the hypothesized relationship between an agent in the causal chain (e.g., bioenergy policy or commodity price increases) and the land-use effect similar to other established cases?

QCA is a Boolean algebra-based meta-analysis tool that is used to compare explanatory models across case studies and has been used in causal analyses of deforestation in the tropics (Rudel and Roper, 1996; Scouvart et al., 2007; Porter-Bolland et al., 2012). The method begins with a multivariate binary data set, and the output is minimum combinations of causes or scenarios that contribute to deforestation in a place (Rudel and Roper, 1996).

Reducing Emissions from Deforestation and forest Degradation (REDD+) is an analogous context to the bioenergy ILUC concern in that analysts seek to quantify and prevent distant emissions caused by forest conservation policies or projects. A major concern in REDD+ is the potential for displaced emissions or leakage (higher emissions outside project boundaries). Leakages may be market-mediated, and these are sometimes modeled using general equilibrium models and are therefore analogous to hypothesized ILUC pathways for bioenergy (Gan and McCarl, 2007; Henders and Ostwald, 2012). In one REDD+ study, broad causes of deforestation in countries without deforestation data were assumed based on causes in other countries on the same continent and at the same forest transition stage (Hosonuma et al., 2012). However, it is important to note that empirical studies that relate LUC in one location to a cause in another are still rare (Meyfroidt et al., 2013; Liu et al., 2013), thus limiting the utility of this type of evidence. Moreover, the fact that drivers of deforestation and reduced deforestation change over time (Rudel et al., 2009; Lapola et al., 2014) must be taken into account when using analogous evidence.

3.6.6. Simulation model results

Simulation model results may support or contradict the hypothesized relationship between the observed effect (e.g., deforestation) and the cause (e.g., biofuel policy). This type of evidence relies upon models that are calibrated based on historic data for the effect and potential drivers. The analyst asks whether a counterfactual simulation supports a hypothesis regarding a driver of change. Counterfactual approaches to causal analysis ask what would have happened if the proposed cause had not occurred (Lewis, 1973).

Models can help identify relationships between land cover and agricultural policies. For example, Plantinga (1996) used a model to show that transitions of marginal agricultural lands to forest in Wisconsin were accelerated by reducing price supports for milk. Econometric models were used to estimate the effect of U.S. agricultural payments on cropland acreage (Gardner et al., 2010).

Counterfactual analysis can be used to generate real or hypothetical scenarios to examine the effect of small changes in (Mathers, 1999) or complete elimination of (Nusselder et al., 1996) a potential cause such as biofuel production. A no-trade counterfactual was used to investigate the effect of trade on global cropland demand (Kastner et al., 2014). Counterfactual simulation was used to suggest that development policies in Brazil during 1970–1985, namely new road building and subsidized credit, were responsible for close to 9.6 million hectares of deforestation (Andersen and Reis, 1997). Golub et al. (2013) used counterfactual simulation (by modeling hypothetical incentives) to investigate climate change outcomes from livestock producers. Determining which factors to leave out in a biofuel-centered counterfactual simulation is challenging, given that some omitted variables may be linked to biofuel production.

If modeling is based on proper techniques for calibration and validation (Baldos and Hertel, 2013), then it can provide useful evidence for attributing LUC to a particular cause. An example is provided by Malins (2013), who describes aspects of the MIRAGE (Modeling International Relationships in Applied General Equilibrium) model that have been calibrated, e.g., yield and area responses to price. So far, however, most models used to estimate LUC resulting from bioenergy policy have not been developed, calibrated, or validated using historical data for regional deforestation and bioenergy (Kline et al., 2011).

3.6.7. Agent-response relationships

A hypothesis about causation is supported when a quantitative relationship exists between potential drivers and the proposed magnitude and probability of LUC or when, based on a previous relationship, the magnitude or frequency of the cause is sufficient to generate the observed effect. A quantitative relationship between an intermediary agent in the causal chain, such as a change in global price of a food commodity, and the effect is pertinent evidence.

A quantitative agent-response relationship (often termed an exposure-response relationship) is one type of evidence commonly used for assessing risk to humans or ecological populations from pathogens or chemical contaminants (Suter et al., 2000). Such a relationship is typically developed where experimental manipulation is possible and the effect is defined consistently among experiments. In contrast, opportunistic data might support an empirical relationship between biomass production and well-defined LUC.

Statistical associations between potential drivers and deforestation can be developed by regression analysis (e.g., Hersperger et al., 2010). Köthke et al. (2013) conducted national scale analyses showing that deforestation trends strongly correlate with changes in population growth and, to a lesser degree, with changes in agricultural yields and suitability index of arable land (production potential), relative to remaining forest endowments. However, because of the complex interactions among the factors affecting land changes, a family of regressions should often be used (Jones et al., 1995). Statistical approaches such as regression analyses tend not to incorporate distant variables and often do not apply outside the subject region (Lambin, 1997). More critically, regressions showing a statistical association (correlation) do not imply probable causation unless accompanied by other evidence. A lack of statistical association, however, suggests that a causal relationship is unlikely.

Relationships between biofuel policies and forest area reductions are occasionally quantified, and predictions range widely (Searchinger et al., 2008; Banse et al., 2009; Bouët et al., 2010; Al-Riffai et al., 2010; Havlík et al., 2011; Bird et al., 2013).

Comparing deforested areas to those predicted by various models for US or EU biofuel policies is not useful for verifying or eliminating bioenergy as a potential cause because relationships are so variable and deforestation is multi-causal. Also, agent-response relationships are more robust for direct than for indirect causal linkages; thus, one should look for evidence of agent-response relationships for each potential intermediate step in the causal chain.

Excluding spurious correlations by examining potentially confounding variables is important (Pearl, 1998; Singleton and Straits, 2009). For example, accessibility variables such as distance to roads and slope could confound hypothesis testing (Gaveau et al., 2009) related to bioenergy policy or social or economic candidate causes. The price of crude oil and relative exchange rates influence commodity prices (Harri et al., 2009) and could therefore confound observed relationships between biofuel policies, commodity prices, exports, and LUC.

3.6.8. Synthesis of lines of evidence

The final step of the strength-of-evidence analysis is the synthesis of evidence for and against each hypothesized cause and causal pathway, leading to the revision of the probable web of causation. Factors that should be considered with respect to the seven types of evidence above are the wealth of types and pieces of evidence, quality and quantity of data, confidence in quantitative relationships, depth of analysis, known model or parameterization biases, relevance of the data from other locations to the subject region, and distribution of evidence across candidate drivers (Norton et al., 2003).

If particular types of evidence are more compelling than others, for example, because of their quality or relevance, then they may be weighted more than others, as long as the weighting scheme is transparent. In addition, results of studies with sectoral bias, i.e., those that examine a particular subset of potential causes, may be weighted less than results from more inclusive studies.

For each hypothesized cause, the consistency and coherence of evidence are considered (Hill, 1965; Cormier et al., 2010; Suter et al., 2010). A convergence of evidence on particular causal factors increases confidence in results; inconsistent evidence indicates that more research is needed (Young et al., 2006) or alternative hypotheses must be considered.

3.7. Allocate proportional causation

The final step of the framework is to allocate proportional causation to multiple probable drivers once they have been identified using the methods above. The allocation of documented increases in deforestation among all probable causes for policy or legal purposes is a challenge. While decision makers may choose to attribute a specific area of LUC to bioenergy if it is shown to be a probable cause of that LUC, the scientific basis for fractional allocation of LUC to multiple probable causes is stronger.

Precedents for attributing multi-causal events to a single dominant cause are found in epidemiology and law. A single dominant disease or injury contributing to a health outcome can be identified through categorical attribution, i.e., assigning all outcomes to a single cause among a set of "mutually exclusive and collectively exhaustive categories and a set of rules" for selecting the dominant cause (Murray et al., 2000). Motor vehicle accidents are often fully attributed to alcohol use (Ezzati et al., 2006) even if other causes were operating. Parties to a lawsuit might have to demonstrate that a single agent or event "more likely than not" caused an adverse health effect. For example, criteria (pack-years of cigarettes) were developed to legally attribute cases of lung cancer in Quebec to smoking (Siemiatycki et al., 2014). Using this "more likely than not" criterion, a specific deforestation event could be fully attributed to biofuel policy if it was identified as a predominant cause, even if other probable causes were identified as well.

Table 2
Proportional allocation of a land-use change to one or more probable causes. Types of causes in gray are generally included in the allocation; causes in white are sometimes included, depending on the objectives of analysis.

Included in most allocation decisions	Included in some allocation decisions
Single dominant cause	Additional causes
Anthropogenic causes	Natural causes
Proximate causes	Distal variables in causal pathway
Causes that determine outcome	Causes that affect timing of outcome
Causes but for which effect would not occur	Other factors contributing to effect
Primary products	Co-products

Many researchers find single-factor causation for complex effects like tropical deforestation to be unsatisfactory (Geist and Lambin, 2002). Others think it is not fair or useful to assign the entirety of a projected ILUC effect to a single cause, given the multiple drivers of change (Kim et al., 2012). Geist and Lambin (2002) examined five categories of underlying driving forces in tropical deforestation (economic, institutional (policy-related), technological, cultural, and demographic) in 152 subnational case studies. In Latin America, for example, only 21 percent of 78 cases of LUC were attributed to just one of these broad causal categories. In 37% of Latin American cases, LUC was attributable to all five categories (Geist and Lambin, 2002). Similarly, a meta-analysis of swidden agriculture showed that particular combinations of drivers were better at explaining changes than single drivers (van Vliet et al., 2012). Going through the exercise of identifying multiple probable causes and then reducing the list to a single cause leads to a loss of information.

Allocation of proportional causation for LUC to multiple drivers can be informed by empirical techniques and models to identify a hierarchy of causation if sufficient data are available (Eglington and Pearce-Higgins, 2012). However, in most cases of recent tropical deforestation, a lack of data results in the need for subjective decisions (Table 2). One choice is whether to divide 'blame' for deforestation among all probable causes or only among probable anthropogenic causes. Allocation procedures could place more weight on direct, proximate causes than on more distant variables or contributing factors in the causal pathway, or more weight on factors that affect eventual outcomes rather than timing or rates of change. In epidemiology, a distinction is made between 'excess' cases that would not have occurred without the cause and 'etiologic' cases that have a link to the cause but merely accelerate the incidence time (Greenland and Robins, 1988).

Allocation methods may consider whether the outcome depends on a particular driver. In US tort law (related to negligence), the "but for" test asks whether an outcome, such as deforestation, required the presence of the putative cause, such as biofuel policy. Decision makers may choose only to include causes that pass the "but for" test. Necessary elements of a jointly sufficient set of conditions (Honoré, 2010) might all be treated as equally important causes.

Additional decisions are made over how to allocate bioenergy LUC effects among co-products—whether effects should be apportioned based on mass flow, relative energy value, or relative revenue (Huo et al., 2009; Acquaye et al., 2011). Early versions of economic models used to evaluate biofuel policies did not include co-products, and the extent of co-production may still be underestimated (Langeveld et al., 2013). While calculations related to co-products are within the purview of science, selecting the units for apportionment is essentially a policy or management decision. Clearly specifying the problem statement can guide decisions about which allocation approach is most appropriate.

4. Discussion and conclusions

A causal analysis framework has been developed that can be used to identify probable drivers of clearly specified LUC. This multidisciplinary approach provides a framework for systematic learning and can stand alone as a tool for LUC analysis as well as be applied to inform the design of LUC simulation models. Causal analysis can strengthen the scientific basis of modeling assumptions and help investigators calibrate models to historic events to produce probable rather than plausible outcomes. Nonetheless, some investigators have suggested that ILUC effects are too diffuse and are based on too many assumptions to be certain enough for policy (Mathews and Tan, 2009). Even with the evidence from causal analysis, decision makers need to decide whether the uncertainty of model-derived LUC estimates is acceptable for their needs.

Causal analysis has been valuable for resolving contentious questions about causal relationships in epidemiology, ecology, climate change, and other fields. There is an urgent need to apply science-based causal analysis to LUC; "...no facet of land change research has been more contested than cause" (Turner et al., 2007).

Our application of the causal analysis framework focuses on bioenergy. International, national, and US state policies require knowledge of the quantity and type of LUC attributable to biofuels so that net GHG emissions can be estimated and compared to performance standards for renewable fuels. Changes in historic LUC trends that follow the implementation of a major biofuel policy, along with a formal analysis of causation, are relevant to projecting changes attributable to biofuels.

For LUC, single lines of evidence, such as relationships between remotely sensed observations and social agents (dos Santos Silva et al., 2008), correlations between LUC and crop prices (Morton et al., 2006a,b), or simulations of global trade-related drivers (Golub and Hertel, 2012), considered individually, are insufficient to demonstrate probable cause. Multiple types of evidence lead to greater confidence in a causal relationship. The framework provides a foundation for systematic learning based on the strength of evidence, as with epidemiological approaches. Causal analysis unites plausibility with spatial and temporal associations and other evidence to ascribe effects to probable causes.

The initial problem statement step of causal analysis describes the scope of analysis and defines the effect. In studies of human-environment interactions, dependent variables are often hard to define and measure in ways that are consistent and agreed upon by research communities (Young et al., 2006). The concept of ILUC has been inconsistently applied in the context of projected effects of biofuel policy. The proper attribution of LUC and net GHG emissions to bioenergy and other potential causes cannot occur until the change of concern is clearly defined. The lack of clear and consistent definitions for LUC and ILUC is a major reason why the bioenergy LUC debate remains contentious. We discuss deforestation as an example of LUC that can be well-defined and quantified.

The causal analysis framework has several benefits: encouraging the use of specific definitions of LUC and better characterizing observed changes: revealing plausible and implausible mechanisms for bioenergy-induced LUC; generating evidence for or against alternative hypotheses; informing more spatially explicit LUC models (Hellmann and Verburg, 2011); and illuminating key data gaps and research priorities. For example, our discussion of the complete-pathway line of evidence suggests that several relationships assumed by economic models should be tested based on empirical data over recent decades. The framework approach also explains why models that use single lines of evidence and omit known social and policy drivers of deforestation would not simulate actual deforestation induced by biofuels.

Limitations to this causal analysis approach include costs, data, and inconsistencies in classifications and definitions, as well as complexity of the relationships. For example, most deforestation data are limited and carry large uncertainty (Grainger, 2008; Fritz et al., 2011). However, these limitations are not unique to quantifying bioenergy-induced LUC. Vague definitions, inconsistent land-cover data, a paucity of empirical research, complexity in attribution, and policy pressure to estimate displacement effects all characterize attempts to implement REDD+ policies as well (Atmadja and Verchot, 2012).

Defining a focal effect such as deforestation is meant to facilitate causal analysis, but it can also constrain the analysis and lead to neglect of other effects that help determine GHG emissions. For example, Wallington et al. (2012) describe the need for assessing the contribution of increased biofuel production to increased agricultural yields. Langeveld et al. (2013) demonstrate that implementation of biofuel policies after 2005 coincides with a strong increase in double cropping and loss of agricultural land. Biofuel policy interactions with changes in total factor productivity and the efficiency of food production systems are important determinants of bioenergy-induced changes in GHG emissions.

Improvements to global models can be supported by the growing accumulation of evidence at regional scales, and models might be disaggregated to incorporate regional differences (Kaimowitz and Angelsen, 1998). Sometimes the failure to find a causal relationship between economic or policy variables and deforestation in a meta-analysis may be due to the breadth of the contexts considered (Kaimowitz and Angelsen, 1998; Magliocca et al., 2014) or because the most influential drivers were not considered.

Applying the causal analysis framework for LUC can provide rigor and transparency in analyses and thereby help resolve controversies surrounding probable drivers. When observed changes rather than assumed changes are considered, the causal analysis framework can generate replicable results.

The human mind is wired to build models of causation despite a paucity of evidence (Tenenbaum et al., 2011). Intuition and expert judgments on causality are often biased (Cox, 2013), so a formal causal analysis framework is needed. Getting causal relationships and model assumptions wrong could lead to poor investment decisions and delay the effective development of alternatives to today's fossil-fueled economy.

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