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ABSTRACT

This paper explores how meta-studies can support the development of process-based land change models (LCMs) that can be applied across locations and scales. We describe a multi-step framework for model development and provide descriptions and examples of how meta-studies can be used in each step. We conclude that meta-studies best support the conceptualization and experimentation phases of the model development cycle, but cannot typically provide full model parameterizations. Moreover, meta-studies are particularly useful for developing agent-based LCMs that can be applied across a wide range of contexts, locations, and/or scales, because meta-studies provide both quantitative and qualitative data needed to derive agent behaviors more readily than from case study or aggregate data sources alone. Recent land change synthesis studies provide sufficient topical breadth and depth to support the development of broadly applicable process-based LCMs, as well as the potential to accelerate the production of generalized knowledge through model-driven synthesis.

1. Introduction

Human modification of the natural landscape through land use is a complex and multi-dimensional process that requires insights from a wide range of scientific disciplines to understand and predict. Land use is the direct result of human decision-making and as such has a wide variety of causes, ranging from factors at the level of individual land-users to the regional and global settings in which local land-use decisions are embedded (Lambin and Meyfroidt, 2011). The consequences of land use are equally as varied and concern processes such as food production, biodiversity

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preservation, and carbon storage, all with impacts on ecosystems and human well-being (Rindfuss et al., 2008; Verburg et al., 2013a). Given this complexity, the land change science (LCS) community, which encompasses both land-use and land-cover change research, has identified two major challenges: "(1) improving our understanding of the complex feedbacks between the societal and environmental components of the integrated land system, and (2) up-scaling of local and regional process understanding to achieve global process understanding" (GLP, 2005; Rounsevell et al., 2012: 900). Numerous disciplinary approaches and analytical tools have been used to study land-use and land-cover change, but integration between two approaches in particular – synthesis research (e.g., meta-studies) and process-based modeling – has the potential to address both of the above challenges.

Land change models (LCM) are frequently used as tools to improve our understanding of land systems through historic analyses of land-use and land-cover change (referred to as 'land change' from hereafter), or ex-ante assessments of policy options (Brown et al., 2013; NRC, 2013). While some models adopt a pattern-based approach (i.e. aim to describe changes in observed land change patterns using statistical, machine learning, or comparable approaches), an increasing number of models use a process-based approach (i.e. aim to represent the mechanisms through which land change patterns are produced). General classes of process-based LCMs include sector-based (e.g., Hertel et al., 2009) and spatially disaggregated economic models (e.g., Irwin and Bockstael, 2002) and agent-based models, which tend to include more social science data than pattern-based LCM approaches (NRC, 2013). As human decision-making is fundamental to land change, process-based LCMs are critical for developing a causal understanding of the behavior of land-change agents in response to changing environmental, economic, or institutional conditions, and the feedbacks that such behavioral responses may create (NRC, 2013; Rindfuss et al., 2007).

However, empirically-grounded models of human decision-making processes often have high data demands throughout the iterative model development process (Messina et al., 2008; van der Leeuw, 2004; van Vliet et al., 2011), and such data can span biophysical and social realms and multiple spatial and temporal scales in order to adequately capture all the factors that influence decision-making (Janssen and Ostrom, 2006; NRC, 2013; Robinson et al., 2007). Place-based case study research has traditionally been an important source of data and knowledge for process-based LCMs. Case studies consistently integrate biophysical, socioeconomic, cultural, and/or institutional elements and their links to observed land changes, and are thus the standard for causal explanations in land change research (Rindfuss et al., 2007; Rounsevell et al., 2014). Process-based LCMs that leverage the rich empirical traditions of land change case study research (e.g., Houet et al., 2010; Robinson et al., 2007; Valbuena et al., 2010a) are well suited to understand human–environmental interactions and feedbacks, and thus address the first major challenge for the LCS community.

While the deductive nature of process-based models is well suited to the second challenge to the LCS community (Overmars et al., 2007) – to scale-up local and regional to global process understanding – process-based LCM built from case studies are, by definition, location specific. This is due in part to the tendency for case studies to investigate the local contextual conditions that may not be easily generalized and valid at broader scales or coarser resolutions of analysis. Regional or global scale LCMs must then abstract from heterogeneous, local-scale processes, such as land-use decision-making, based on simplistic theoretical concepts such as profit optimization or expert-based decision rules that directly relate land use choices to land or climate suitability (Bamière et al., 2011; Gusdorf and Hallegatte, 2007; Rounsevell et al., 2014). Both approaches lack adequate representation of the huge spatial and temporal diversity of human behavior and decision processes, resulting in biases towards particular land change decision assumptions or contexts (e.g., market-driven), overly focused on variables only available from regional or national-level census products, poorly validated, and/or regarded as highly uncertain (Verburg et al., 2013b). In order to create process-based models that can *also* scale-up local insights to broader scales, such models must be designed, parameterized, and tested with data and causal explanations synthesized from many local observations to ensure broader applicability at regional and global scales.

As a synthesis research method, *meta-studies* have potential to overcome the challenges of scaling-up placed-based insights to regional or global scales when integrated into the model development process. *Synthesis* is a research approach that draws upon and distills many sources of data, ideas, explanations, and methods in order to accelerate knowledge production beyond that of less integrative approaches (see 'synthesis' at http://sesync.org/glossary/). *Meta-studies* are a sub-group of synthesis methods that are distinct from literature reviews, analytical review methods, and fully quantitative synthesis methods because they (a) conduct analyses across prior case studies of a common phenomenon as the observational unit (Rudel, 2008), and (b) possess systematic case selection criteria intended to produce a comprehensive and comparable collection of cases (see Magliocca et al., 2015 for details). Conducting a land change meta-study generally involves the steps of: 1) comprehensive case study search, 2) systematic case selection, 3) synthesis of explanatory frameworks presented by case study authors, 4) statistical analysis of quantitative and/or coded qualitative data reported in case studies, and 5) identification and interpretation of commonalities and differences in the causes and/or consequences of land change. To avoid confusion with the more common parlance of *meta-analysis*, we adopt the distinction presented in Magliocca et al. (2015) which defines *meta-analysis* as a special case of meta-study that utilizes more standardized and explicit methodologies to statistically compare parameter values and their variance within and across systematically selected case studies.

In land change science, meta-studies compare local variations in a particular land change phenomenon and investigate the drivers and/or impacts of that change to discern broader-scale patterns and explanations, and thus contextualize the relative scope and generalizability of the land change under study. Land change meta-studies tend to either analyze the processes that contribute to (i.e., cause) the observed change or the processes that the land change influences (i.e., consequence), although there are exceptions that study both (e.g., Cramb et al., 2009; Kendal et al., 2012). To date, most land change meta-studies have focused on the consequences of land change (Magliocca et al., 2015). A meta-study of synthesis methods in land change science was conducted by Magliocca et al. (2015) and found that out of the 181 studies analyzed only 27 were explicitly used to inform modeling efforts, and of those only five used meta-study techniques. More importantly, all five of these meta-studies analyzed the consequences rather than the causes of land change.

These five meta-studies covered a wide range of land change consequences. Seto et al. (2011) performed a cross-site meta-data-analysis of 326 case studies reporting remotely sensed extents of urban land cover change, which was used to formulate a statistical model to predict future urban expansion based on variables such as GDP and population growth. Schueler et al. (2009) conducted a meta-analysis of 65 studies that reported the effects of impervious surface cover on urban stream degradation, and their findings were used to evaluate the ability of the impervious cover model (ICM) to predict urban stream indicators based on the proportion of a watershed covered by impervious surfaces. Two meta-analyses of effect sizes (Schlossberg and King., 2009; Vanderwel et al., 2007) tested the effects of logging on North American forest and shrubland bird species abundance and habitat use, and were used to develop statistical species abundance models to predict bird responses to future forest habitat alteration. Finally, Van Den Bergh and Rietveld (2004) synthesized 69 studies that provided estimates for the limits of global human population, which produced an overall distribution of all estimates as well as several targeted estimates under different sets of assumptions common across the models they reviewed. Each of these synthesis efforts were explicitly used to develop broadly applicable pattern-based models.

Meta-studies of the causes of land change have seen far less integration with efforts to develop broadly applicable, process-based LCMs (Magliocca et al., 2015; van Vliet et al., submitted for publication). Many meta-studies of the causes of land change have been conducted for a wide range of land change processes, including deforestation (e.g., Rudel, 2007), desertification (Geist and Lambin, 2004), wetland conversion (van Asselen et al., 2013), agricultural intensification in the tropics (Keys and McConnell, 2005; van Vliet et al., 2012), and rural land change and landscape preferences in Europe (van Vliet et al., 2015a; van Zanten et al., 2014). These meta-studies systematically compare patterns of context-specific versus general causes of land change across locations and scales. Such synthetic knowledge has the potential to inform the development and implementation of more broadly applicable process-based LCMs, particularly when it comes to linking micro-level with macro-level modeling endeavors. However, such potential synergies are only beginning to be explored (e.g. Magliocca et al., 2014; Murray-Rust et al., 2014; van Vliet et al., 2015a).

This paper aims to identify and explore potential synergies between land change meta-studies and the design, parameterization, and evaluation of LCMs, in order to advance the development of broadly applicable and process-based LCMs to meet two major research challenges in LCS. We also identify situations where integrating meta-study and modeling is problematic given the model purpose or target of the meta-study. The next section describes the model development cycle and discusses potential synergies between meta-studies and LCMs with example applications in each phase. Two examples of efforts to integrate meta-studies with process-based model development are then described, from which key land change features and variables required for meta-study and model integrating are proposed. Interactions between the motivations for modeling and the specific design of meta-studies are then examined, highlighting opportunities and limitations in integrating the practices.

2. Using meta-studies for model development

2.1. The model development cycle

An extensive and varied literature about the model development process exists (e.g., Crooks et al., 2008; Filatova et al., 2013; Harmel et al., 2014; Jakeman et al., 2006; Robson et al., 2008; van Delden et al., 2011; van der Leeuw, 2004). The model development process we propose here is not new, but rather introduces ways for integrating information and data from meta-studies with current model development practice to develop broadly applicable and process-based LCMs. Thus, the framework we present here is simply a convenient division of the modeling process into four stages to facilitate discussion of the points of entry for using meta-studies. Each stage in the model development process – the problem entity, a conceptual model, a computer model, and a model application – is associated with one or more modeling activities that can be informed by meta-studies (Fig. 1). While stages in model development and the related modeling activities are shown here sequentially, iteration is a key aspect of model development (Jakeman et al., 2006), as findings in later steps might require revisiting earlier stages. Starting from the problem entity, we elaborate on the different modeling activities below, and subsequently indicate the possibilities for meta-studies to support these activities.

2.2. Defining the problem entity

The starting point of a model development project is the *problem entity*; the land change process or phenomenon that is the actual topic of research. This problem entity can involve land-use change in general, but often it is more specific, targeting a particular land change process in a particular region. Selecting the problem entity is typically driven by the research question of interest and the knowledge gap the research aims to address. It is also influenced by the researcher's view of the context in which it operates, including the known range of variation of the problem entity, and the problem scale (both the importance of local context, and the relevance to broader-scale patterns). The initial context description is important in determining the ultimate usefulness and correctness of model outcome interpretation, and may be used to examine how differences in context from one case to another affect outcomes.

2.3. Conceptual modeling and conceptual validation

Analysis of the problem entity yields a *conceptual model*, which is a description of this problem entity, typically in terms of its components and their relations (e.g., candidate agents, variables, processes, and system boundaries) that can be expressed as equations, conceptual maps, and/or textual descriptions. A conceptual model is inherently a simplification, as it represents the modelers' perception of reality and formalization of selected processes, components, and their relationships. Regardless of the process used to perform the conceptual modeling, the goal is the same: to make

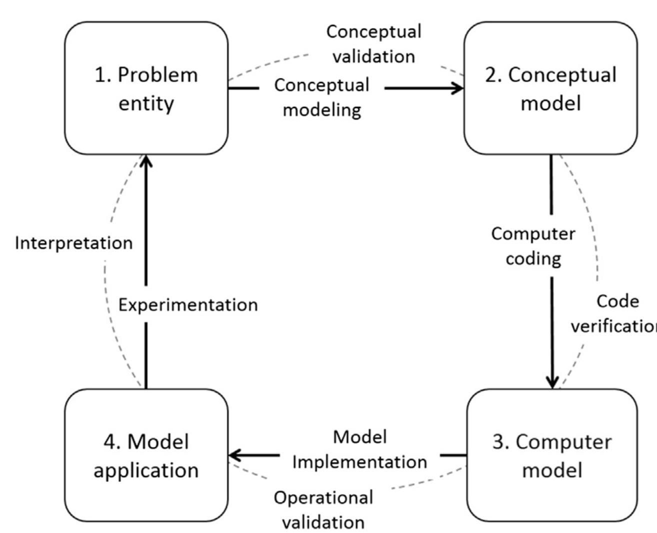

Fig. 1. The series of steps in the development cycle for land-use models and the related modeling and validation processes. Boxes indicate the four stages in the model development process, solid lines indicate modeling activities, and dashed lines indicate the evaluation of these respective modeling activities.

the modeler's implicit thinking about the system explicit, and thus open it to testing, criticism, refinement and improvement. The process of *conceptual validation* then assesses whether the selected theories and assumptions are appropriate and logical in light of available data and the intended purpose of the model.

Meta-studies can play several possible roles during conceptual modeling. Meta-studies can support conceptual modeling by providing a basis for describing the system components a model should include, the range of outcomes the model should produce, defining the scope of the model, and/or supplementing theory or select appropriate elements of theory to inform models (Table 1). For example, one of the first land change meta-studies on deforestation (Geist and Lambin, 2002) synthesized a framework for explaining land change patterns in terms of proximate causes and underlying drivers. Geist and Lambin's framework has since been used to conceptualize numerous land change analyses and modeling efforts.

2.4. Computer coding and code verification

Implementation of a conceptual model in computerized code yields a *computer model*. In the framework presented in Fig. 1, computer coding is essentially a software development task. However, the computer coding phase is not completely independent from other phases, and model verification (checking that model behavior matches its design (North and Macal, 2007)) is an important and often over-looked piece of an iterative model development cycle (Brown, 2006; Crooks et al., 2008). Using meta-studies as a guide for implementing model structure and a constrained set of components (e.g. which spatial layers to include, what agent types to represent) can support the development of more generalized and parsimonious process-based models.

For example, Gaucherel et al. (2014) illustrate how meta-studies focusing on various types of landscapes and their related processes and dynamics can guide the translation of a conceptual model into a generic code (i.e. a modeling platform). The authors propose a computer code (a "landscape language") based on equations grouping elementary attributive and/or geometrical landscape processes (Gaucherel et al., 2012) to implement various types of models for multiple land change applications. The authors reviewed landscape modeling approaches across agricultural, forested, arid, and urban landscapes to identify common landscape transitions, generate a list of representative processes, and map the advantages and drawbacks of various model implementation strategies for each landscape type. The resulting computer code was developed based on the assumption that land change processes may depend on the resolution, extent, and/or landscape type considered, making individual models more or less flexible (i.e. application-specific) depending on their formalization (e.g. Houet et al., 2014). Using meta-studies to formalize a generalized conceptual model of landscape types helps to define the model's scope and applicability and required generality in coding, which can then be combined with a model comparison approach (e.g., Mas et al., 2014; Pontius et al., 2008; Rosa et al., 2014) to assess the appropriateness of a given landscape representation to the concerned application.

2.5. Model implementation and operational validation

Instantiating a computer model for a particular case study by adding data and parameters yields a *model application*. This includes the identification of the relevant instances of model components. For example if a general model applies agent types, the implementation requires the identification of the relevant agent types for the case study region, such as commercial livestock farmers, commercial cropland farmers, and lifestyle farmers (Valbuena et al., 2010b). Model application also includes model calibration, which is by definition site-specific and application-specific, as the values indicating the influence of various drivers can differ from one region to another. Operational validation, or pattern validation, is the assessment of the accuracy of model outcomes and/or structure, and similar to calibration, is also case specific. For a more detailed discussion of the application and validation of LCMs, please see NRC (2013), Pontius et al. (2008), and van Vliet et al. (2011).

Meta-studies can be used at several points during this phase of model development (Table 1). For model implementation, meta-studies can suggest which variables are most uncertain, as indicated by a wide range of outcomes or rates of land change observed across case studies within a meta-study, and should be the focus of calibration and sensitivity analysis. For example, if a meta-study finds the same land change is associated with many different drivers (e.g., deforestation with agricultural and livestock expansion), or a specific driver is found to be important in some cases but not others (e.g., population density with land intensification and abandonment), this might suggest that a particular set of model processes and/or parameters can lead to many possible outcomes and are important targets for analyses of model sensitivity to initial conditions. Similarly, differences among specific cases within a meta-study can provide counterfactuals for model validation. Given a set of cases in which the addition or subtraction of a particular driver led to different outcomes, the realism of a model could be evaluated with an experiment designed to test the model's ability to reproduce divergent outcomes with the omission or modification of a particular parameter.

Meta-studies can also be used to establish empirically-based parameter ranges by translating qualitative system behaviors to quantitative parameter settings or to define the functional forms

Table 1
Summary of opportunities for meta-studies to support land change models (LCMs) through various modeling activities in the model development cycle (Fig. 1).

Modeling Activities	Meta-studies to Models	Example applications
1. Conceptual modeling & validation	Identify key drivers, system components and interactions; define range of applicability, target outcomes	Proximate and underlying causes framework (Geist and Lambin, 2002)
2. Computer coding & code verification	Encoding model structure and requisite components to operationalize conceptual model	Landscape types (Gaucherel et al., 2012, 2014)
3. Model implementation & operational validation	Parameterization, calibration, and evaluation	Regional land-use agent-based model (ABM) (Murray-Rust et al., 2014); Cross-site comparison with ABM (Magliocca et al., 2014)
4. Model experimentation & interpretation	Define experimental space; evidence-based scenario development; contextualize model results	REDD+ (Davis et al., 2009; Phelps et al., 2010; Purnomo et al., 2013), Urban planning (Bartholomew and Ewing, 2008; Waddell, 2002)

of equations to be estimated. Agent-based models (ABMs), which explicitly represent human decision-making, can particularly benefit from this mode of meta-study and model integration. Meta-studies can describe qualitative patterns in the role of actors in mediating land change processes, which cannot be easily derived from spatial data analysis. Meta-studies of case studies based on interviews and questionnaires can provide systematic descriptions of actor characteristics, including perceptions, attitudes and personal characteristics (van Vliet et al., 2015a), which are well suited for model implementation. As an example, a synthesis of case studies that use non-market valuation techniques to derive willingness to pay values for cultural ecosystem services would be a valuable source of information for implementing agent attitudes towards natural landscape features (e.g., Daniel et al., 2012).

Finally, operational validation entails a quantitative and/or qualitative comparison of model outcomes and behaviors with empirical data. The spatial relationships and/or temporal trends revealed in meta-studies can be used to confront model results. In addition to comparing model outcomes to aggregate patterns, meta-studies can be used to evaluate the realism of the model structure, i.e. how well the modeled processes and their structure represent the real-world phenomenon under study. Behavioral patterns described across many cases, such as delayed adoption of new farming technologies (Schreinemachers et al., 2007) or limited participation in incomplete markets (de Janvry et al., 1991), can be used as qualitative validation targets with methods like pattern-oriented modeling to assess a model's structural and process realism (Grimm et al., 2005; Magliocca and Ellis, 2013; Magliocca et al., 2013).

2.6. Experimentation

While *experimentation* is not the goal of every modeling endeavor, it has the potential to be a very fruitful phase for leveraging meta-studies, but such opportunities remain mostly unexplored. A calibrated and validated model application is ready for use in experimentation, which includes scenario explorations, ex-ante assessments, and parameter perturbations. The review and synthesis of many land system state and change observations provides the substrate and bounds for evidence-based scenario analysis by defining a model's range of applicability (in terms of model parameters, settings or contexts) and/or possible outcomes within which experiments can or should occur (Happe et al., 2006). Meta-studies offer a systematic survey of the diversity of outcomes in response to the same driving force (e.g., climate change) across locations, many possible system states along a land change trajectory (e.g., forest transition theory; Grau and Aide, 2008) through space-for-time substitution in the absence of longitudinal data, or alternative policy interventions and/or institutional settings related to land change outcomes.

The growing body of literature exploring the effectiveness of reduced emissions from deforestation and forest degradation (REDD+) implementation and associated deforestation outcomes is a good example of the potential for linking meta-studies and models for scenario analysis. A review by Phelps et al. (2010) outlined the relationships between centralized and decentralized forest governance and implementation of REDD+, and a report from the World Resources Institute (Davis et al., 2009) described 25 alternative mechanisms for building developing country capacity for REDD + activities. On the modeling side, a recent ABM developed by Purnomo et al. (2013) explores REDD + carbon providers' responses to various institutional arrangements for implementing REDD + agreements. These syntheses of REDD + institutional arrangements and capacity-building indicators could provide rich information sources for developing evidence-based scenario analyses in an ABM to explore the most effective REDD + designs and implementations.

Meta-studies can also improve the interpretation of experimental results from any particular model application through an understanding of the wider context (beyond that of an immediate case study) and the extent to which they can be translated to other settings. This applies not only to model results themselves, but also to the generalizability or specificity of modeled processes and outcomes, and so reveals important aspects of uncertainty in results (e.g. Laliberté et al., 2010; Poeplau et al., 2011). For example, simulation models have a long tradition in supporting urban planners, by means of scenario studies and analysis of alternative land use, transportation, and environmental outcomes (Waddell, 2002). However, urban planning case study and modeling research has not been systematically linked to examine how global economic and environmental changes will affect specific regions. A meta-study by Bartholomew and Ewing (2008) compared 85 land use-transportation planning scenarios drawn from 18 different metropolitan areas and found that, on average, a 17 percent reduction in vehicle miles traveled was predicted from regional development plans that adopted compact growth scenarios. The suite of scenarios and findings of this meta-study could be implemented in a simulation model to understand if there are particular mechanisms and/or context-specific conditions influencing land use-transportation scenario planning success across cities.

3. Two examples of direct integration of meta-studies to support model development

The use of meta-studies in various model development activities is still in its infancy. To our knowledge, few examples of direct integration of meta-studies with LCMs exist. This section provides two concrete examples where meta-studies have directly contributed to the development of LCMs. These examples illustrate the potential avenues, as introduced in the previous section, for integrating meta-studies and modeling in a more formalized, systematic way, and provide a starting point for leveraging meta-studies to develop broadly applicable and process-based LCMs.

3.1. Model implementation — representing agent behavior and attitudes

As awareness of the importance of land-use and land-cover within the Earth system has grown, the necessity of incorporating land change dynamics into existing models has become clear. However, the representation of human behavior in existing large scale land change models is generally simplistic, which reduces its applicability for a wide range of scenario applications that critically depend on human decisions, including climate change adaptation (Arneth et al., 2014; Rounsevell et al., 2012). A recent effort to develop an agent-based LCM framework that more realistically represents land-use decision-making and can be applied at national to continental scales is the CRAFTY model (Competition for Resources between Agent Functional Types). The CRAFTY model framework is based on the demand and supply of ecosystem services (ES) that are produced by agents representing land managers. Demands are introduced exogenously, and agents compete to satisfy these on the basis of their productive ability and behavioral characteristics. Agents utilize locational capitals that describe the productive potential of land in order to produce ES according to defined production functions (for a full description of CRAFTY see Murray-Rust et al., 2014 and Brown et al., 2014).

CRAFTY exists as a generic framework, and implementing this framework for a particular case study requires the definition of capitals, agent types and properties, and services (Brown et al., 2014). Capitals are spatial variables that represent the intrinsic characteristics of a location, such as slope, fertility or climate. The implementation of the CRAFTY model for the simulation of land change in Europe was supported by a meta-study of the manifestation and underlying drivers of agricultural land change across Europe (van Vliet et al., 2015a). This meta-study identified accessibility, topography and soil fertility (or agricultural production capacity) as the most commonly important location factors, which can be directly linked to locational variables in the model. Additional locational factors that were found to be important in particular contexts include land use plans, agricultural subsidies (such as less favored areas and environmentally sensitive areas), tenure security, and off-farm employment. Whether these factors are considered spatial depends on the scale of the intended application, and on a European scale, these drivers differ considerably between countries and places, and can therefore be implemented as locational variables.

Agents in CRAFTY are characterized by their agent functional type; i.e., each agent belongs to one of a limited number of classes (Arneth et al., 2014; Murray-Rust et al., 2014). Agents can have characteristics that can influence their behavior, such as age, education, or religion. Both the agent types and the characteristics of agents can be defined per application and were identified in the meta-study for this implementation. The meta-study identified full-time commercial farmers, part-time commercial farmers, lifestyle farmers, retired farmers and subsistence farmers. The most important farmer characteristics included their attitude, which can be characterized as productivism or environmentalism, their age, and whether or not a successor had been identified.

This example illustrates how a meta-study, in this case van Vliet et al. (2015a), can guide the implementation of a generic model framework to a specific model application. Moreover, because the model implementation is based on synthesized empirical findings, rather than more subjective expert knowledge, it has a more credible scientific basis. However, information from the meta-study is not sufficient to implement the model completely. Parameter values indicating the relative importance of specific variables could not be derived from the meta-study, and hence the model could not be parameterized based on this information. Rather, the frequency with which an underlying driver was identified in case studies was indicated, which leaves it to the modeler to determine how to quantify these drivers. In addition, the meta-study identified a number of underlying drivers that are not well represented in the model structure, such as technological drivers. While the CRAFTY model offers several opportunities to implement such effects indirectly, for example through production functions, they cannot be represented straightforwardly as a single variable. Despite these caveats, this example shows that a meta-study can provide useful guidance in the implementation of a generic agent-based LCM to simulate land changes on a European scale.

3.2. Model validation — structural validation for cross-site model comparison

Despite the wealth of insights case study land change research has provided, systematic knowledge of the mechanisms through which land users respond to changing climate conditions or economic globalization and how such responses vary across locations has yet to develop (NRC, 2013). Because of their explicit representation of human decision-making processes, Rindfuss et al. (2008) proposed use of ABMs of land change as a powerful tool for cross-site comparisons and synthesis. Parker and colleagues (2008) made a first attempt at a systematic comparison of ABMs of land change in frontier regions, but their comparison was limited by inconsistencies in how the same processes were represented across models developed for different purposes. The location-specific design requirements of case-based ABMs can provide insights into land change processes for a particular system, but their scope of applicability is limited and not well suited for synthesis across cases to generate general knowledge and build theory. This requires ABMs with generic and flexible design that can be applied across sites to build synthetic knowledge.

Magliocca et al. (2013) and Magliocca and Ellis (2013) developed and implemented the first agent-based virtual laboratory (ABVL) framework explicitly designed for cross-site comparison and synthesis. Rather than attempting to synthesize common or contrasting land change processes across sites through model comparison, the generalized modeling framework is applied across sites as a standardized observational and experimental tool, which eliminates barriers to cross-site comparisons due to variations in model design. The model explains shifts in rural land-uses and livelihoods as the result of adaptive decision-making in response to changing demographic, environmental, and economic conditions at both local and regional to global scales. Agent decision-making rules are grounded in a synthesis of several agricultural household economic theories (e.g., Boserup, 1965; Ellis, 1993; Netting, 1993), which supports a broadly applicable decision framework. Land-use and livelihood decisions are affected by a suite of local and global exogenous factors and constraints, such as environmental suitability and variability, population density, market influence and accessibility, commodity prices, development policies (e.g., land-use subsidies/exclusions), which determine access to and potential payoffs of each activity. Agro-ecological dynamics emerge from land-use choices, which in turn provide feedbacks to agents' subsequent yield and price expectations (see Magliocca et al. (2013) for a full ODD ('Overview, Design concepts, and Details') protocol description).

In its first empirical application, the model was applied to six test sites with widely varying land-use systems, ranging from swidden to commercial agriculture in USA, Laos, and China (Magliocca et al., 2014). In order to investigate the relative importance of generalized versus context-dependent processes across sites, the pattern-oriented modeling (POM; Grimm et al., 2005) approach was used to assess the realism of the model's structure and representation of land-use decision-making processes. Empirical patterns of household agricultural production, assets, market participation, and consumption levels that were consistently observed across a large number of case studies were drawn from a literature review by de Janvry et al. (1991) and two meta-studies of rural household livelihoods (Misselhorn et al., 2005; Winters et al., 2009), and used as validation criteria in the POM approach. These patterns reflected peasant household economic behavior, and were reported at the appropriate level of generality to enable direct comparisons with ABVL output to evaluate which model structure best reproduced a suite of production, consumption, and livelihood strategy choices across test sites. The two meta-studies did not report quantitative information about the distribution of livelihood strategies among study populations, but rather aggregated livelihood information to regional or national scales, which is not uncommon for global scale meta-studies. While distributional livelihood information would have provided a more rigorous standard, model validation based on meta-study results from a large geographic extent enabled the development of a broadly applicable and process-based LCM that could be both deployed across highly heterogenous test sites and evaluated against empirical data.

3.3. Designing meta-studies to support the development of land change models

The two example modeling efforts from the previous section illustrate the potential for integrating meta-studies in two different phases of the model development cycle. The development of CRAFTY took place in parallel with a meta-study on agricultural land change (van Vliet et al., 2015a), and this information was used in conceptual modeling and model implementation. The ABVL example used pre-existing meta-studies to extract patterns in land use and livelihoods to compare against model results for structural model validation. However, the contribution of meta-studies to model development in future modeling efforts could be further increased if the meta-studies were specifically designed to support model development. Toward this end, we propose a list of key land system variables and parameters that could guide effective integration of meta-study information into the development of broadly applicable process-based LCMs (Table 2). This table is based on the lessons learned from developing the CRAFTY and ABVL model frameworks, and could be adjusted to other models or model applications.

Ideally, one would like to obtain both descriptive information about the mechanisms underlying observed land changes as well as parameter values, however most case studies do not typically report all necessary information. In practice, the type of information and corresponding case studies used for conceptual modeling and model implementation are often different than those used for operational validation and model experimentation. Conceptual modeling and model implementation, as described for the CRAFTY model above, tends to use categorical data, such as the drivers that are underlying agricultural land use change, the different types of actors that have a role in these changes and the properties of these actors that influence their decisions. Operational validation and model experimentation, as described for the ABVL application above, tends to use quantitative data describing empirical patterns that can be compared against model output. Consequently, each application required a different type of meta-study: categorical data can be obtained from more open ended questions on the drivers underlying land changes, such as asked in several meta-studies (e.g., Geist and Lambin, 2002, 2004; van Asselen et al., 2013; van Vliet et al., 2015a), while the latter required meta studies that synthesize statistics across case studies (e.g., Misselhorn et al., 2005; Winters et al., 2009).

Additionally, the scale and context of the land change process being modeled may also influence the variables required in a meta-study. For example, fine-scale information about household demographic structure is less important than landscape suitability and agent functional types for simulating the regional-scale land-use patterns represented in CRAFTY. On the other hand, preliminary results from an ABVL application (Magliocca et al., 2014) have already demonstrated that in some contexts market influence is strong enough to override the effects of environmental and agent heterogeneity on livelihood decisions. Thus, due to varying modeling research questions and objectives, it is unlikely that any given meta-study of a particular land change phenomenon can support all applications of LCMs of that phenomenon, and additional data sources (i.e., conventional data sources, such as remote sensing or global mapping products) will likely be needed to facilitate meta-study and model integration.

4. Practical considerations for integrating meta-studies and modeling

4.1. Meta-study methodology

Meta-studies can interact with models in various ways throughout the model development process. While meta-studies can be a powerful tool, limitations inherent in meta-study methodology translate into limitations for their appropriate use with modeling. Understanding these limitations must begin with the individual case studies included in a meta-study. While a fundamental robustness can and must be assumed in most cases, some objective evaluation of each case study's strengths and weaknesses is necessary (Thompson and Pocock, 1991; Lortie and Callaway, 2006; Garg et al., 2008). The process of meta-study might otherwise obscure shortcomings in the methodology, scope or applicability of the component case studies, potentially resulting in unidentified gaps or biases in results (Stanley, 2001). Meta-studies and model-building are both used to reduce the complexity of reality rather than recreate it faithfully, therefore the combination of these approaches risks producing a circular reinforcement of biases or omissions.

Full assessment of these issues is complicated by the diversity and multidisciplinarity of land change science. Many land change meta-studies ask open questions, e.g. what drives a certain land change (e.g., Geist and Lambin, 2002, 2004; van Asselen et al., 2013; van Vliet et al., 2015a). As a consequence, a wide range of theoretical lenses and research methods are used, resulting in inconsistencies in data reporting, outcome measures and conclusions, even between case studies that relate to the same land change process (Guo and Gifford, 2002; Melo et al., 2009; Magliocca et al., 2015). Similarly, meta-studies often define their selection criteria, scope and variables on the basis of methodological requirements that differ from case to case (Lortie and Callaway, 2006), but the effects of differing spatial scales of analysis are not often considered (Kwan, 2012). The spatial scales at which case studies were conducted must be assessed for their suitability in meta-study or modeling synthesis to adequately capture the problem of interest. Potentially harder to account for are biases in case study selection related to language, discipline, accessibility, or geography (Keys and McConnell, 2005; Rudel, 2008; Martin et al., 2012; Schmill et al., 2014), or scale-dependencies that may inadvertently become crystallized in model structure (e.g. Rahbek, 2005). One way of dealing with this issue is by attempting to align biases in analysis and modeling, with the aim of retaining, at least, clear delineations of accuracy of applicability (e.g. Osenberg et al., 1999). Another approach is to seek a range of biases that might interact 'correctively' to some extent, especially where these biases can be robustly identified and defined (Hewitt et al., 2007). In every case, it is crucial to assess the extent to which the case selection in meta-studies represents the problem entity, and whether the studies, data, or variables used allow essential information to be missed (Stanley, 2001; Duval and Tweedie, 2000).

4.2. Meta-study findings

The use of meta-study findings for modeling implies a number of further challenges. First, many meta-studies are unable to produce robust quantitative findings because of a lack of comparable case study evidence (e.g., Guo and Gifford, 2002). Similarly, meta-studies may identify important processes that are not readily modeled, such as personal or social factors (e.g. Seto et al., 2011; van Vliet et al., 2015a). Therefore, it is unlikely that meta-studies can provide *complete* model parameterizations, but are rather better suited to aid in conceptual model design and implementation and model validation.

Second, models and meta-studies may not pursue the same research questions. Research questions ultimately define the choice of system components and boundaries, and therefore any epistemological incompatibilities must be taken into account. For example, most land change meta-studies tend to be correlative and

Table 2
Priority contextual, agent, and interaction variables that would be required in meta-studies designed to support the development of broadly applicable process-based LCMs of agricultural change that incorporate cross-scale influences on local land-use choices. Variables with asterisks in the second and third columns were used in the CRAFTY (Competition for Resources between Agent Functional Types) and ABVL (Agent-Based Virtual Laboratory) applications, respectively.

	For conceptual modeling & implementation	For operational validation & experimentation
Purpose of meta-study	Identification of important land change variables	Description of important land change variables
Type of information	Variable types, interactions, and relative importance (mostly qualitative)	Outcome values, trends, and/or spatial distributions (mostly quantitative)
Example application	CRAFTY (Murray-Rust et al., 2014; Brown et al., 2014)	ABVL (Magliocca et al., 2013, 2014)
Contextual variables		
Environmental conditions	• Land suitability classes* • Potential land uses and products* • Environmental variability	• Land-use/cover composition* • Land-use/cover location* • Land-use/cover conversion rates • Landscape fragmentation
Economic conditions	• Wage and price levels, volatility • External market access/influence* • Household expenditures • Livelihood activities* • Aspiration levels • Land use subsidies	• Diversity of household livelihood activities* • Population-level livelihood participation rates* • Household income share per livelihood activity* • Food insecurity, poverty rates
Social & institutional conditions	• Land exchange mechanisms* • Land tenure rules and security • Size distribution of land holdings • Land-use knowledge*	• Land exchange sizes, rates, and variability • Land holding distribution related to socio-economic status*
Demographic conditions	• Household size* • Labor supply* • In/Out-migration rates • Household life cycle stage • Education level	• Population age structure • In/Out-migration rates*
Agent characteristics		
Preferences & decision-making	• Landscape preferences* • Agent typologies* • Satisficing* • Risk-aversion • Profit-maximization* • Gender roles	• Amount of divergence from profit-maximizing land-use choices • Willingness to pay/stated preference for particular land-uses • Agent land-use and/or livelihood types
Agent interactions		
Agent–environment interactions	• Agro-ecological dynamics • Ecosystem services* • Land conversion pathways	• Cultivation/Grazing intensity* • Yield gap* • Landscape fragmentation
Agent–agent interactions	• Social network influences • Imitation and learning	• Technology adoption rates • Livelihood activity adoption rates

unsuitable for finding generalized causal patterns of the kind required by process-based models. A further complication is that case study evidence is necessarily based on historical changes, while many LCMs are used to explore potential future changes (Sterk et al., 2011). The use of meta-studies to inform such models therefore assumes stationarity in land change processes – an assumption that is effectively untestable and potentially unsafe under climatic or land system change, for example (Kolb et al., 2013; Rounsevell et al., 2014). Nevertheless, some allowances can be made for this through the substitution of spatial for temporal change, so that case studies are selected to approximate site-specific potential future trajectories of a non-stationary process. For example, Grau and Aide's (2008) meta-study of land use transitions in Latin America used case studies from a deforestation-reforestation continuum to capture potential forest transitions caused by temporally dynamic land change processes. Generally, the types of questions posed by meta-studies tend to be more helpful in the development of general LCMs than models intended to predict changes at particular locations.

4.3. The role of established theory

The appropriate phase of model development in which meta-studies are applied depends on the presence of established theory (Fig. 2). In this context, established theory refers to theoretical frameworks that have been proposed and vetted in the literature and used frequently to guide analysis and/or model building, as opposed to frameworks that have been proposed but not widely used or referenced. Multiple complementary (and sometimes conflicting) theoretical frameworks linking individual decision-making to aggregate land-use patterns exist, some of which have been verified against empirical data. For example, Boserup's (1965) agricultural intensification thesis posited a set of hypothesized relationships, such as between population density and food demand, explaining the intensity of cultivation and farmers' decisions to minimize labor and risk in agricultural production. These relationships were later tested and verified by a number of empirical observations (e.g., Ellis, 1993; Turner et al., 1977), and are now at the core of contemporary induced intensification theory (Turner and Ali, 1996).

In the presence of established theory as a basis for modeling, the research process begins with the formalization and encoding of theory in a model and meta-studies can serve as a basis for model validation and experimentation (i.e., Fig. 2, steps 3 through 1, 'Computer Model' through 'Model Application' and back to 'Problem Entity'). Case selection and analysis in meta-studies in this context are oriented towards testing existing theory against a collection of empirical case study observations. With regard to the consequences of land change, numerous meta-studies have investigated the assumed relationship between land change and declining species richness and abundance (e.g., Laliberté et al., 2010; Murphy and Romanuk, 2014). Such meta-studies have assembled empirical data to test specific predictions based on theory, and are thus appropriate for model calibration or quantitative outcome validation (Fig. 2, steps 3–4).

In the absence of established theory as the basis for modeling,

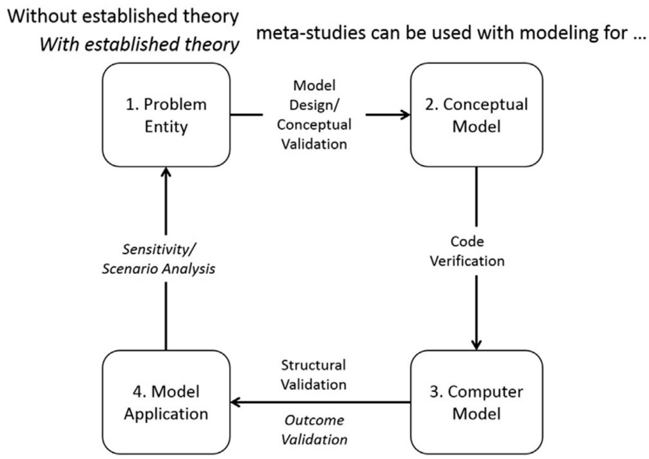

Fig. 2. Opportunities for integrating meta-studies and models throughout different phases of the model development process depending on the presence (italic text) or absence (regular text) of established theory as the basis for modeling. Boxes indicate the four stages in the model development process and solid lines indicate modeling activities.

meta-studies can provide descriptions of the generalized relationships and factor interactions needed for model development. Meta-studies can identify important factors and their interactions that are common across cases, and thus necessary for the design and conceptual validation of broadly applicable, process-based LCMs (steps 1–3, Fig. 2). Meta-studies can also specify which behaviors should be expected from the model based on the range of case study observations, which also provide a basis for structural validation and sensitivity analysis of model outcomes once functional relationships have been encoded into the model (steps 3–4, Fig. 2). Modeling, in turn, offers the ability to formalize meta-study findings and explore interactions between the causes and consequences of land change in ways not possible with current meta-study techniques.[1]

Importantly, these two modes of meta-study and modeling integration – in the presence or absence of established theory – are *mutually exclusive paths*. The same meta-study cannot be used to both design and validate a model in order to maintain independence of model inputs and outputs. Unlike case study data where a dataset can be partitioned into calibration data and validation data components (Peterson et al., 2011, pp. 55), such partitioning is often not possible with meta-studies because it is likely impossible for anyone other than the meta-study author to trace the contribution of each case study to synthesized results. Similarly, the use of meta-studies in the model development process must be consistent with the purposes, goals, and questions of the model. If the meta-study is used to specify the factors to include in the model and their relationships (i.e., in the absence of established theory), the model should not be expected to perform well in comparison with any specific, quantitative case study observations. In this situation, structural validation, rather than outcome validation, is appropriate (i.e., steps 3–4). Conversely, in the presence of established theory, theory will inform model design, while parameter values can be drawn from meta-studies to calibrate models and model outcomes can be validated against specific case study observations. Best practices for integrating meta-studies and models necessitate a clear separation between studies used to conceptualize factors and their interactions underlying land change processes and tests for operational validation.

[1] The authors are speculating here that it may be possible with some land change topics, such as deforestation, to conduct meta-studies that connect whole trajectories of causes, consequences, and feedbacks of land change trajectories. This has not yet been accomplished, although it is the objective of research currently underway by some of the authors.

5. Conclusions

Multiple entry points for meta-studies have been identified to support the development of process-based LCMs capable of investigating land change beyond any particular location. Two recent modeling efforts – the CRAFTY and ABVL frameworks – highlighted the potential for and current shortcomings of integrating meta-studies in the model development process. In addition, a template for conducting meta-studies that would directly support the development of broadly applicable process-based LCMs of agricultural change was proposed based on lessons learned from the CRAFTY and ABVL efforts. The approaches to model development presented here are not new, per se, but are rather prospects for leveraging the structured and systematic empirical-grounding of meta-studies to build and/or validate process-based LCMs capable of being applied and producing insights at regional to global scales.

Developing process-based models that can provide insights at broader scales requires both a large number of empirical case study findings and a synthesis of common trends, categorizations, and explanations across those findings (Boero and Squazzoni, 2005). Further, linking human decision-making processes to broad-scale land-use and biophysical changes requires information about how decisions are made and the factors affecting those decisions. Given the labor-intensive nature of collecting such data, especially at the household level, and the fact that many of the factors influencing land-use decision-making are qualitative, such as the role of agent preferences and behavior, it is much easier to synthesize a collection of case studies containing location-specific observations than to assemble aggregate data describing an entire region of interest (Boero and Squazzoni, 2005). The recent increase in synthesis approaches in land change science (Magliocca et al., 2015; van Vliet et al., submitted for publication) provides sufficient topical breadth and depth to support the development of large scale and generally applicable LCMs. Potential synergies between land change meta-studies and models remain under-utilized, and despite the limitations of each, their integration offers the possibility to accelerate the production of generalized knowledge through model-driven synthesis.

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