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Using Pattern-oriented Modeling (POM) to Cope with Uncertainty in Multi-scale Agent-based Models of Land Change

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Abstract

Local land-use and -cover changes (LUCCs) are the result of both the decisions and actions of individual land-users, and the larger global and regional economic, political, cultural, and environmental contexts in which land-use systems are embedded. However, the dearth of detailed empirical data and knowledge of the influences of global/regional forces on local land-use decisions is a substantial challenge to formulating multi-scale agent-based models (ABMs) of land change. Pattern-oriented modeling (POM) is a means to cope with such process and parameter uncertainty, and to design process-based land change models despite a lack of detailed process knowledge or empirical data. POM was applied to a simplified agent-based model of LUCC to design and test model relationships linking global market influence to agents' land-use decisions within an example test site. Results demonstrated that evaluating alternative model parameterizations based on their ability to simultaneously reproduce target patterns led to more realistic land-use outcomes. This framework is promising as an agent-based virtual laboratory to test hypotheses of how and under what conditions driving forces of land change differ from a generalized model representation depending on the particular land-use system and location.

1 Introduction

Local land-use and -cover changes (LUCCs) resulting from human-environment interactions cumulatively contribute to global environmental change (DeFries et al. 2004, Ellis and Ramankutty 2008, Foley et al. 2005, Keys and McConnell 2005, Meyer and Turner 1992, Turner et al. 1994, 2007). Similarly, global and regional economic, political, cultural, and environmental forces exert downward influences on local LUCC processes (Adger et al. 2009, Geist et al. 2006, McConnell and Keys 2005). Local LUCCs are the direct result of the decisions and actions of individual land-users, which are concurrently shaped by the larger contexts in which their land-use system is embedded (An et al. 2011, Liverman and Cuesta 2008, Valbuena et al. 2010). Such cross-scale causation presents a substantial challenge for understanding global and local linkages of LUCC. Yet the growing influence of economic globalization on local land-use decisions demands that such linkages be incorporated explicitly into our understanding and models of LUCC (Lambin and Meyfroidt 2011).

Understanding and modeling global and local linkages are challenging in several ways. The inherent complexity of land systems presents substantial conceptual challenges to understanding the causes and consequences of land change. Land-use at the local scale is influenced by a wide array of driving forces often found to be highly dependent on local context, which

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makes generalizations about the forces that drive land-use change at the global scale difficult (Geist and Lambin 2001, Lambin et al. 2001, Parker et al. 2008, Rindfuss et al. 2004, 2007, Turner et al. 1994). Mismatches between the resolution of remote sensing data and spatial and temporal scales of important social and/or biophysical processes, for example, plague land-use change studies (Rindfuss et al. 2004), which inherently must account for a diverse range of causal explanations. The best available data representing global scale drivers of LUCC, such as market influence (Verburg et al. 2011), is too coarse to represent the market-oriented land-use decisions of individual land users. More fundamentally, the impossibility of widespread experimental manipulations of land systems, the multitude of forces influencing land-use system change, and the complexity of their interactions, represent major obstacles to connecting land-use changes with their causes at and between local, regional, and global scales (Rindfuss et al. 2004). Given these challenges, substantial uncertainty exists surrounding the mechanisms through which global and regional drivers influence local land-use decisions, and how such relationships may or may not vary by location.

Arguably the most extensive and widespread driver of local LUCC is economic globalization. Lambin and Meyfroidt (2011, p. 3471) assert that land systems should be understood and modeled as open systems, because they are subject to "long distance flows of commodities, capital, and people that connect local land-use to global scale factors". Similar claims have been made within the development and sustainable livelihoods communities, which cite the importance of access to global and regional market opportunities in shaping local land-use and livelihood choices (Barrett 2008, Barrett et al. 2001, de Janvry et al. 1991, Reardon et al. 2006). However, the empirical data and process knowledge needed to parameterize a model of such linkages are lacking.

Specifically, no systematic measurements of farm-level crop prices, input costs, and wage rates in relation to global market settings exist. International development case studies provide quantitative measures of such local economic conditions, but they tend to be location-specific and expressed broadly in terms of market participation (e.g. Barrett 2008, Barrett et al. 2001). Moreover, such studies do not provide insight into how local economic factors might vary with global market settings, since this is usually beyond their intended scope. However, applicable theory for understanding the local economic conditions that influence consumption and production decisions has developed from the accumulation of fragmented case-study knowledge.

de Janvry et al. (1991) offer a generic explanation for variations in market participation across sites relating to local farm-gate prices, internal costs of production, and food prices. Missing or inefficient markets for agricultural products or input factors are commonly observed in agricultural systems in the developing world (de Janvry et al. 1991, Ellis 1993, Netting 1993). Such market failures occur when transaction costs are higher than potential gains, in which case non-market transactions (e.g. in-kind trade) may take the place of formal market transactions, or transactions might fail to occur at all. According to de Janvry et al. (1991), the potential for successful market transactions varies with particular households as a function of transport costs to and from the market, opportunity and transaction costs, and perceived risks associated with uncertain prices. A 'price band' results in which the sale prices of commodities, such as food and farm inputs, are fractions of their purchase prices (de Janvry et al. 1991). The relationship between internal costs of production and farm-gate prices, which are dependent on local market influence (i.e. both physical access to markets and purchasing power), determine the value of agricultural products (i.e. shadow price) for a given household. The shadow price of agricultural products, relative to the costs of purchasing food on the market, structure the consumption and production decisions of households, and consequently

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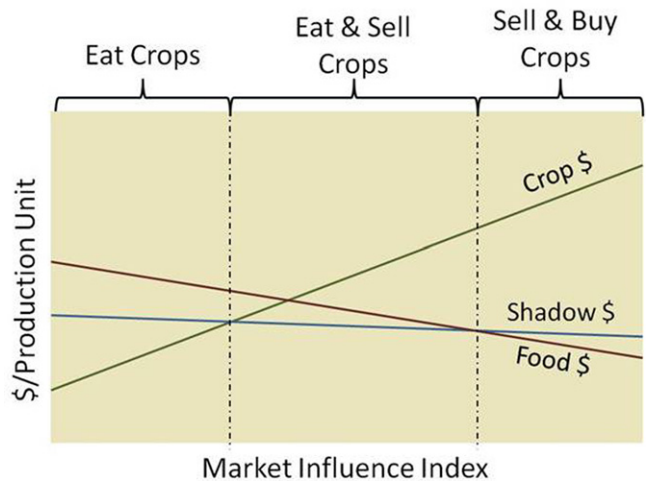

Figure 1 An illustration of the price band described by de Janvry et al. (1991) and its effects on smallholder consumption and production decisions

their degree of market participation. If the shadow price of a given product or factor falls within the price band, it is more costly to acquire or sell it on the market than it is for the household to produce/consume it, thus no market transaction will occur. An illustration of this price band interpreted from de Janvry et al. (1991) is provided in Figure 1.

The same logic applies to the relationship between farm and non-farm wages. Each of these factors is subject to both local labor market conditions and regional access to non-farm wage opportunities (Barrett et al. 2001, de Janvry et al. 1991, Ellis 1993, Netting 1993). Farm wages are influenced by access to the market, farm-gate prices, and the costs of agricultural inputs. Similarly, non-farm wages are influenced by the relative value of non-farm labor and transaction costs associated with locating, securing, and maintaining non-farm wage employment. When non-farm wage rates are above those obtained from on-farm labor, households may shift labor allocation away from the farm to include more non-farm activities. Thus, access to non-farm wage opportunities influences the intensity of land-use, as non-land-based income sources can supplement or fulfill food and income requirements (Barrett 2008, Chowdury 2010, Ellis 1993, Netting 1993, Reardon et al. 2006). Combined, these theoretical strands provide a potential framework for household consumption and production decision rules that explicitly link local economic conditions, household land-use decisions, and regional land-use outcomes. However, the paucity of empirical data describing variations in these factors in relation to global and regional market settings presents a substantial obstacle to endogenizing such relationships as a set of decision rules within multi-scale models. The following section reviews the dominant approaches within LUCC modeling and their potential for representing global to local linkages. In Section 3, the pattern-oriented modeling (POM) approach is presented as a means to design and test agent-based models (ABMs) capable of exploring the effects of economic globalization on local land-use decisions. The POM approach is then illustrated with an example ABM of local LUCC in Section 4. Section 5 reports the results of this modeling exercise, and Section 6 concludes with a discussion of POM's potential for advancing the representation of global influences on local LUCC processes within land change models.

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2 Representing Global to Local Linkages in LUCC Models

The complexity of land-use systems present substantial analytical challenges to understanding the factors and processes that shape their dynamics. Simulation models are thus valuable tools for conceptualizing land-use system structure and testing causal explanations of LUCC (Parker et al. 2001, 2003, Veldkamp and Lambin 2001, Verburg 2006). However, land-use models have yet to fully connect large-scale drivers to land user decision-making. LUCC models typically follow either an inductive, macro-scale or deductive, micro-scale approach (Verburg et al. 2004). Inductive models, such as integrated assessment and hierarchical regression models, are based on the analysis of changes in spatial patterns of land-use, and can link large-scale economic drivers and aggregate resource demands to local landscape changes. These models have dominated land change modeling thus far, for two reasons. First, system-level data, such as classified remote sensing data of land cover change, is typically more widespread and reliable than lower-level data, such as household surveys. Thus, it is easier to build models explaining land-use change at the local level by downscaling relationships between regional-level drivers and landscape-level patterns of land cover change. Second, such models tend to produce more reliable predictions of system-level change (e.g. Verburg et al. 1999), because they can be calibrated to and validated against empirical data at the system-level. However, inductive modeling has two distinct disadvantages. Because these models are designed, calibrated, and verified in reference to patterns of land change in a particular region, modeled relationships might only be valid for the patterns present in and limited time frame of data from that region; they have a small effective domain of applicability and may be 'overfitted' to that particular land system (Latombe et al. 2011). Additionally, inductive models do not model the decision-making processes that produce observed patterns of land change, and thus cannot model the adaptive responses of land-users to changing local and/or global factors (Parker et al. 2001, Verburg 2006).

Deductive models, such as ABMs, explicitly represent the decision-making processes of land users, and can make direct, mechanistic connections between agent behaviors and land-use changes. However, ABMs of LUCC face several obstacles to linking local processes of land change to regional/global drivers. First, the validity of any ABM is only as good as the specification of agents' decision-making rules and interactions (Verburg et al. 2004). The lack of reliable data to parameterize decision-making models can introduce substantial uncertainty and subjectivity into model design. Second, in an effort to make ABMs more realistic, agents' decision-making rules might be parameterized to conform with individual-level empirical data, such as characteristics associated with agent typologies (e.g. Le et al. 2008). The danger in this is encoding an 'imposed response' into agents' decision rules, which reduces the model's effective domain of applicability by 'overfitting' to the particular system (Latombe et al. 2011, Railsback 2001). Finally, due to the complexity of local agent-agent and agent-environment interactions and the high data requirements needed for model parameterization, ABMs of LUCC have generally been limited to place-based and local scale applications (Valbuena et al. 2010). Despite these challenges, ABMs have been implemented successfully for local case studies of LUCC (e.g. An et al. 2005, Brown et al. 2008, Evans et al. 2001, Deadman et al. 2004, Schreinemachers and Berger 2011), and their explanatory power is undeniable. Following the logic presented by Overmars et al. (2007), if an inductive and deductive model of the same land system explain roughly similar amounts of variation in patterns of LUCC, the deductive model provides an intrinsically better explanation because it includes the underlying processes producing system-level patterns.

A major challenge for LUCC modeling, then, is to simultaneously represent both large-scale forces and individual-level decision-making processes driving LUCC. To do this, land

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change models must find the proper balance between the number and types of interactions represented and the simplicity of their representation. Grimm et al. (2005) refer to this as the 'medawar zone' in which model's payoff is maximized with moderate model complexity. Applied to LUCC modeling, a model's payoff would be maximized when realistic land change dynamics can be reproduced without over-specifying the processes involved to fit a particular land-use system. Cross-scale interactions are clearly important processes shaping land-use systems, and thus must be included in LUCC modeling – but at a level of simplicity that can both link large-scale driving forces to individual land-use decisions and offer a means for comparing the effects of economic globalization on different land-use system types.

3 Methods

A simplified ABM of smallholding farmer decision-making and LUCC is applied to an example test site to assess how global market influence interacts with local environmental and demographic conditions to affect local livelihood and land-use decisions. Since little is known about how economic globalization explicitly influences local livelihood and land-use decisions, the pattern-oriented modeling (POM) approach (Grimm et al. 2005) is used to test alternative representations of global to local market connections through a set of cost and price functions. Using a set of three smallholder behavioral patterns as performance criteria, a genetic algorithm is used to search for combinations of cost and price function parameters that meet all performance criteria simultaneously.

The model presented here is highly simplified and lacking in detail, and thus is not intended to make a substantive contribution to the understanding of global market influence on local land-use outcomes. It does, however, illustrate how the POM method can be used to parameterize model relationships for which little empirical data exists, and suggests how, with a fuller model, global to local connections could be explicitly represented within an agent-based framework to link agents' behavioral responses to economic globalization and local LUCC.

3.1 Site Description and Data

The example test site is located near the town of Taoyuan in the hilly regions of northern Hunan Province in south central China (Figure 2). The site is characterized by fairly high population density dispersed within and along the edges of two main valleys. Intensive cultivation of rice is present around settlement areas in fertile valleys, while extensive cultivation occupies areas with moderate slopes on the edges of valleys. Nearly 80% of the land is suitable for agriculture, but some reductions in potential yields exist due to the hilly terrain. Market influence is moderate, but market access is quite low due to the remoteness of the site (GAEZ 2011a, b).

The model environment is parameterized with environmental, population density, and economic variables from the set of publicly available datasets described in Table 1. Each dataset is re-sampled in ArcGIS 10 using mean zonal statistics to a 100 by 100 cell raster with a spatial resolution of 100 m (total area = 100 km^2) in WGS 1984 UTM Zone 49N Projection.

3.2 Model Description

The model landscape is represented on a 100 by 100 cellular grid, which is divided into 10 by 10 cell 'settlement areas' evenly distributed across that landscape. Agents represent a

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Site Name	N. Hunan
Latitude	28°54′27″ N
Longitude	111°12′35″ E
Population Density (ppl km^{-2})	
Min	1.2
Mean	**124.2**
Max	2,777.6
Shannon's Evenness Index for Population Distribution (Equal Dist. = 1.0)	0.8781
Market Influence	
Min	0.51
Mean	**0.59**
Max	0.67
Market Access	
Min	0.06
Mean	**0.17**
Max	0.41
Slope (%)	
Min	0
Median	**11.3**
Max	45.9
Land Suitability	
Class 1 (%)	37.9
Class 2 (%)	**41.2**
Class 3 (%)	19.1
Class 4 (%)	1.8

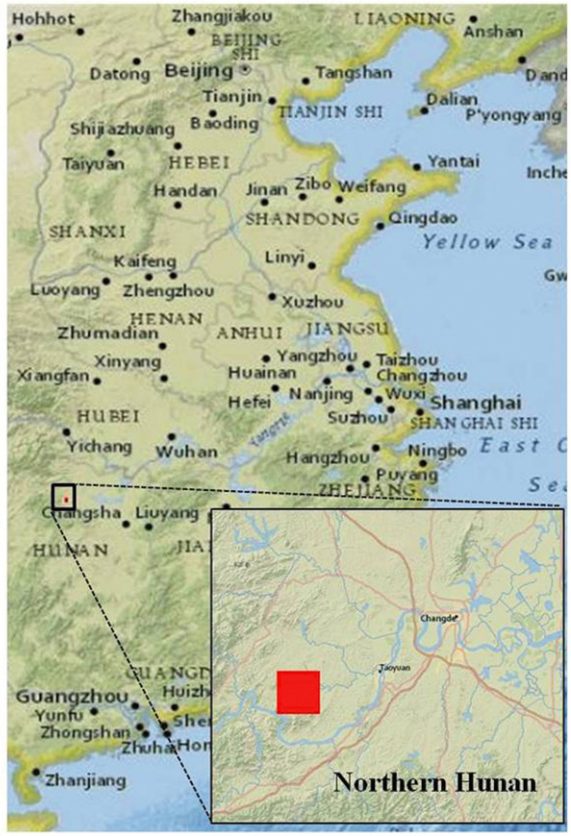

Figure 2 Descriptive statistics and map of the 100 km^2 example test site (indicated by the red box) located in northern Hunan Province in south-central China

settlement of smallholder households – the number of which vary with spatially explicit population density – located in a given settlement area. Each settlement is allocated 100 ha of land, and dwellings are located in a single cell adjacent to the most productive land to minimize transportation costs. Agent characteristics, such as subsistence and income requirements and total labor supply, are the aggregate of individual households, which are assumed homogeneous within settlements and are held constant throughout the simulation. A full ODD Protocol model description is provided in the Appendix.

Though most of the theory drawn upon conceives of the relevant decision-making at the household level, a model of settlement agents is a reasonable approximation of the household context. Assuming: (1) that households in the village are equally endowed with labor, land, and capital; (2) land-use choices are significantly constrained by land suitability; and (3) that there are no significant spatial arrangements within the settlement that affect access to land, a model of household agents would produce identical results in terms of the areas allocated to each land-use activity, though the spatial patterns may be different. The settlement agent simplification does not require detailed knowledge of local land allocation mechanisms, thus maintaining the generality of model outcomes. Although the representation of individual households would more realistically capture spatial patterns and heterogeneity of land-use

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Table 1 Input data used to parameterize the model environment

Input Data	Description	Native Resolution	Source
Population Density	LandScan 2000 population density model	30 m	Dobson et al. (2000)
Market Access and Influence	Based on travel time to large cities and purchasing power parity, respectively	30 m	Verburg et al. (2011)
Potential Agricultural Yields	Climatic potential wheat yields	30 m	Monfreda et al. (2008)
Slope	Percent slope calculated from DEM	15 m	ASTER GDEM (2012)
Land Suitability	Percent reduction in potential agricultural yields due to slope and precipitation constraints	30 m	GAEZ (2011a)
Precipitation Constraints	Related to length of growing season	30 m	GAEZ (2011b)
Land Use/Cover	Classified LandSat images	30 m	Ellis et al. (2009)

decisions, it would also reduce the simplicity, and therefore generality, of the model's structure and is beyond the scope of this article.

Seven different land uses/covers are present in the test landscape and represented in the model. Three are productive uses (intensive agriculture, extensive agriculture, and pasture for grazing livestock), and four are non-productive uses: forest, fallow, dwellings/urban, and non-use (water, barren/rock). Productive land uses are defined by functional group, rather than particular types (i.e. 'intensive' and 'extensive' versus irrigated rice or shifting cultivation based on cassava, for example), which vary in their potential productivity, degradation/regeneration rates, and labor and input costs. The model is initialized with non-productive uses in the same locations as in the real landscape, but all other cells are set to the lowest labor input agricultural use (i.e. extensive).

Land-use outcomes are modeled as the result of each agent's labor allocation process at annual increments over a 20-year period (with a previous 10 years for model spin-up). Agents' behavioral rules are derived from smallholder household economic theories (Boserup 1965, Chayanov 1966, Ellis 1993, Netting 1993), which guide the labor allocation process (Section A1.3.1). An agent's total available labor is allocated to home, farm, or non-farm activities, and farm labor to subsistence or market production, according to the heuristics in Figure 3. Expected returns from possible livelihood activities (i.e. farm versus non-farm wage and agricultural production for subsistence versus market use) are calculated based on expected crop prices and yields and labor costs (Section A1.3.6). Rates of labor re-allocation between livelihood activities depend on the direction and magnitude of changes in food and monetary stocks (e.g. decreasing stocks results in increased 'work' labor). Once farm labor has been allocated, expected marginal return on labor from subsistence production and

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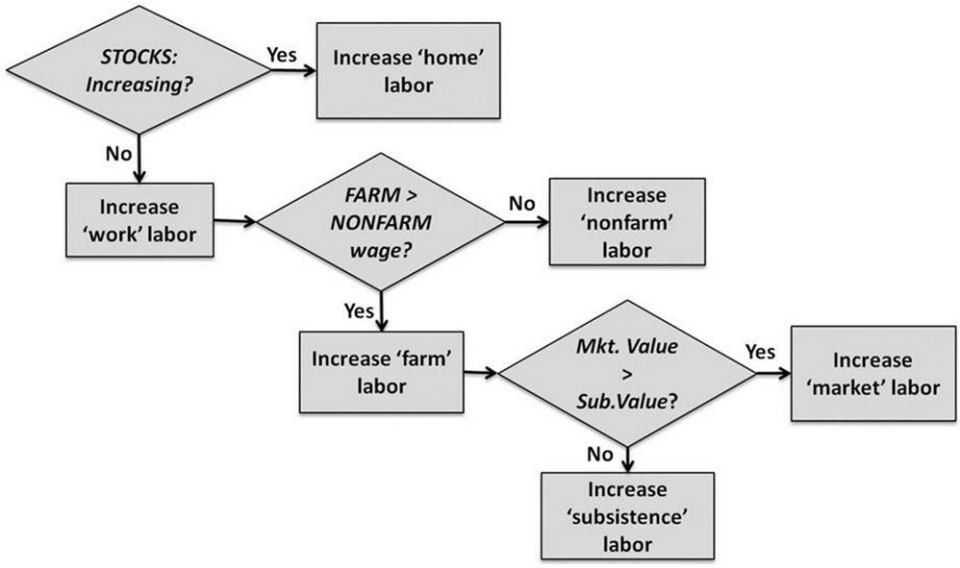

Figure 3 Heuristic decision tree of agents' labor allocation process

expected net marginal return from market production are calculated for all possible land uses in each cell of an agents' settlement area (Section A1.6). Land uses that maximize expected utility in subsistence and market production are chosen for each cell. Agents first allocate on-farm subsistence labor to cells that maximize marginal expected utility from subsistence production until subsistence labor or land constraints are met. Market labor is then allocated to remaining cells that maximize expected marginal utility from market production until market labor or land constraints are met (Section A1.6). Actual returns net own consumption/input costs are calculated. Food and monetary stocks are updated, and price and yield expectations are formed for next period. Landscape cells are updated with new land-uses, and potential yields degrade/regenerate given the time in current land uses (Section A1.2.3).

3.3 Linking Global Market Settings to Local Economic Conditions

The exact relationships between local farm-gate and food prices, farm input costs, and non-farm wages and transaction costs, and how they affect livelihood and land-use decision-making, are difficult or impossible to quantify, because they vary with both global/regional market forces and individual households' access to markets and perceptions of risk (Barrett 2008, de Janvry et al. 1991, Ellis 1993, Netting 1993). The best available quantitative data at the global scale is an index of market influence and access (MII) (based on purchasing power parity and access to large cities; see Verburg et al. 2011 for a more detailed description), while local prices and costs in relation to larger-scale market settings have only been described anecdotally or theoretically (e.g. Barrett 2008, Barrett et al. 2001, de Janvry et al. 1991, Reardon et al. 2006).

A set of cost functions are hypothesized that link global market influence index values (Verburg et al. 2011) to local farm-gate and food prices, farm input costs, and non-farm wages

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and transaction costs. Global commodity prices and the U.S. minimum wage represent agricultural commodity prices and non-farm wages realized by a farmer in locations with a market influence index at or near 1. Local product and factor prices and costs in locations with market influence less than 1 vary according to the cost functions in Section A1.2.4.

3.4 Implementation of POM with an ABVL of LUCC

Pattern-oriented modeling (POM) (Grimm et al. 2005) is a framework for designing and testing ABMs for 'structurally realistic' processes and parameters, and is particularly well-suited for modeling systems for which little process knowledge and/or empirical data exist (Kramer-Schadt et al. 2007). A pattern is defined as "any observation made at any hierarchical level or scale of the real system that displays non-random structure" (Kramer-Schadt et al. 2007, p. 1557). The main principle of POM lies in the reproduction of multiple patterns observed in real systems simultaneously. If a model can accomplish this, one can conclude that the model's process representation and internal structure are reasonably consistent with those of the real system (Grimm et al. 2005, Kramer-Schadt et al. 2007). Target patterns can include those not directly predicted by either micro- or macro-scale data, which makes POM perfectly suited to test alternative representations of global influences on local land-use decision-making.

The POM approach is used to formalize and test the proposed set of cost and price functions. Agents allocate labor to land-use and livelihood activities based on perceived costs and potential gains, which depend on local crop prices, input costs, and farm and non-farm wage rates. Thus, the *process* that is tested using POM is that of smallholding farmer labor allocation in response to local economic conditions. The set of four unknown *parameters* that are tested represent factors relating local crop prices, input costs, and farm and non-farm wage rates to global MII through the set of cost and price functions (Section A1.2.4). The 'non-farm wage factor' determines the relationship between a benchmark non-farm wage and the global MII. Local non-farm wage equals the benchmark non-farm wage when the MII equals one, and varies nonlinearly with declining MII at rates between 0 and 2.5. The 'farm cost factor' is a scalar between 0 and 1 that describes the relative costs of non-labor agricultural inputs given market access. The 'non-farm wage cost factor' is a scalar between 0 and 1 that modifies the transaction costs associated with locating, securing, and maintaining non-farm wage employment and is assumed to vary with market access (Barrett et al. 2001, de Janvry et al. 1991). Finally, the 'crop price factor' specifies farm-gate prices as a relationship between a given location's MII and global commodity price for a given crop. Farm-gate prices are assumed to vary nonlinearly with MII at rates between 0 and 2.5.

Substantial uncertainties exist not only in the functional forms of the cost and price functions, but also in the size of the potential parameter space. Each parameterization of the cost and price functions represents a potential realization of the relationship between a location's global market setting and local economic conditions influencing agents' livelihood and land-use decisions. Therefore, the POM approach is used to test and parameterize the price and cost functions to create a structurally realistic representation of global market influence on local economic conditions based on the model's ability to match individual behavioral and landscape-level land-use patterns arising from agents' decisions.

3.5 Target Patterns

Three target patterns are identified from the economic development and livelihoods case study literatures: (1) the presence of a 'normal surplus' in agricultural production; (2) meeting or

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Table 2 Performance criteria associated with three agent-level behavioral patterns used to implement the genetic algorithm

Criteria	Threshold Value	Description	Source
Normal Surplus	<25% food surplus, at least 90% of time steps	Little or no surplus due to minimizing risk of and labor in agricultural production	*Turner and Ali (1996)*
Minimum Aspiration Level	≥ 90% of agents earn income >= farm costs (subsistence) or farm wage (market)	Income sufficient to support on-farm activities, or subjective income requirement	*Turner and Ali (1996)*
Variance in Consumption	CV of consumption <25%, at least 90% of time steps	Livelihood diversification supports 'consumption smoothing' between harvests	*de Janvry et al. (1991)*

exceeding minimum aspiration levels; and (3) 'consumption smoothing'. These patterns represent 'stylized facts' describing empirical regularities in agent-level behaviors associated with land-use decisions (e.g. de Janvry et al. 1991, Turner and Ali 1996) (Table 2). *Normal surplus* is a level of agricultural production commonly observed in smallholder farming systems. In an 'ideal' subsistence system (i.e. low market influence), production constraints and uncertainty in crop yields lead smallholding farmers to minimize risk of and labor in production by producing only as much as is needed to meet subsistence needs (i.e. little or no surplus, termed 'normal surplus') (Turner and Ali 1996). *Minimum aspiration level*, in this context, is defined as the minimum income needed to support farming activities and/or purchase food on the market. As market influence increases, social structure and aspirations change and transform behavior (Turner and Ali 1996). Consequently, production levels exceed what is necessary to meet subsistence needs, as surplus can be sold on the market, and labor is allocated increasingly to maximize profits from market crops. Thus, income levels are expected to more frequently meet or exceed minimum subsistence needs as global market influence increases. *Consumption smoothing* is frequently observed in smallholder consumption patterns, and is measured here as the coefficient of variation in the difference over time between agricultural production and monetary income levels relative to subsistence needs. In response to uncertainties in agricultural yields and/or markets, smallholders have been observed to diversify their livelihood activities to achieve consistent sources of food and revenue over time (Barrett et al. 2001, de Janvry et al. 1991, Ellis 1993).

3.6 Genetic Algorithm for Cost and Price Function Parameterization

A set of cost and price function parameters can be thought of as a 'market regime' defined by the value of each parameter relative to others. In other words, the combination of parameters within a parameter set represent a particular economic relationship between the global market setting and local economic conditions, and changing one parameter value while holding the

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others constant would represent an alternative, unique, and equally plausible economic reality. This interdependence between parameters renders traditional methods of calibration and sensitivity analysis, involving perturbations of one parameter at a time, ineffective. In addition, the uncertainties inherent in the cost and price functions linking the global market setting to local economic conditions create a large potential parameter space.

A genetic algorithm (GA) is applied to search for model parameterizations that produce model outcomes that satisfy all three target patterns simultaneously. GAs provide a means to test combinations of parameters as a unique unit, and have been used successfully within the POM approach to efficiently search large parameter spaces (e.g. Latombe et al. 2011). Performance criteria for selecting successful solutions are specified as threshold values at which each of the three target patterns are satisfied. Table 2 provides the threshold values used to quantify each of these patterns. The genetic algorithm is initialized with a population of 20 potential parameter sets with each parameter value randomly drawn from their respective uniform distribution. Each set represents a 'chromosome', in the GA terminology, and consists of one value each for the non-farm wage, farm cost, non-farm wage cost, and crop price factors, which are analogous to 'genes'. The model is run with each parameter set in the population and agents' behavioral outcomes are evaluated relative to the performance criteria. The extent to which a parameter set meets the performance criteria determines its 'fitness'. The top 10% of parameter sets, ranked by the number of patterns successfully reproduced, are selected as 'parents' for the next generation's set of 20 test parameters, which are created from the parent set using a combination of chromosomal cross-over and random mutation techniques. Three generations of 20 parameter sets each are tested for a total of 60 model iterations.

4 Results

The GA tested the ability of 60 parameter sets as inputs into the cost and price functions described in Section 4.1 to meet performance criteria (Table 2) associated with three agent-level behavioral patterns described in Section 4.2. The GA narrowed the potential parameter space by selecting parameter sets that reproduced the most patterns. All 60 parameter sets simultaneously reproduced the 'normal surplus' and 'minimum aspiration level' patterns, but only 14 (23.3%) also reproduced 'consumption smoothing' and were thus deemed 'successful'. As illustrated in Figure 4, parameter values for successful sets were most constrained for the non-farm wage factor (parameter 1), farm cost factor (parameter 2), and crop price factor (parameter 4), while a wider variation was observed for the non-farm wage cost factor (parameter 3). This result illustrated the interdependence between parameter values within a set, and the importance of testing them as a unique unit. An unsuccessful set might share up to three parameter values with a successful set, but still fail to reproduce all three target patterns.

Once successful parameterizations were found, the model's ability to reproduce the quantity of land uses and covers present in the example site was assessed. The number of cells in each land use/cover class in the real and modeled landscapes is shown in Figure 5. At the landscape scale, the model reproduced the quantity of landscape cells in intensive cultivation relatively well, but large discrepancies were apparent in extensive (i.e. low labor input) and non-use land cover classes. Disaggregating these results based on land suitability class provided a more nuanced assessment of model performance. Within each of the four land suitability classes (1 = most suitable to 4 = least suitable), the ratio of the number of cells in each land use/cover to the number of cells in the land suitability class was calculated. These ratios were compared to those from the real landscape with a simple multi-dimensional distance measure (D):

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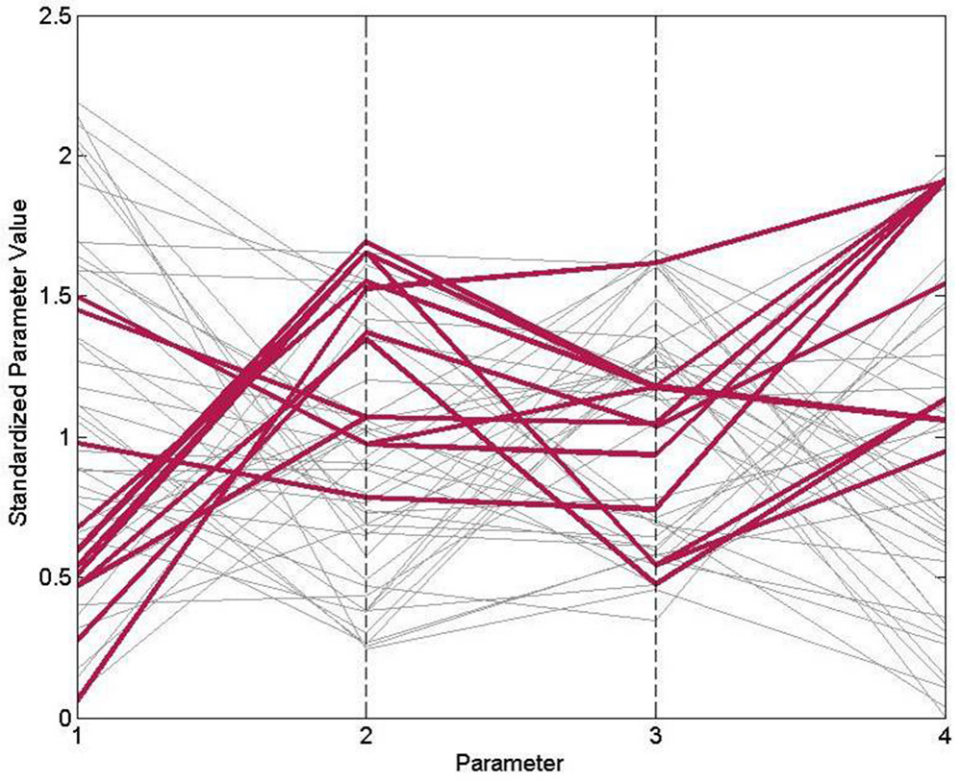

Figure 4 A parallel coordinate plot in which the value of each parameter for a particular set is plotted as a single line intersecting each axis at the parameter's value. 'Successful' parameter sets, which reproduced all three agent-level behavioral patterns are bolded in red, while 'unsuccessful' parameter sets are in gray. The parameters are as follows: non-farm wage factor (1), farm cost factor (2), non-farm wage cost factor (3), and crop price factor (4)

$$D_c = \sum_{i=1}^{7} \sqrt{(R_{ic} - M_{ic})^2} \tag{1}$$

where R_{ic} and M_{ic} were the ratios of land cover cells to land suitability class cells in the real and modeled landscapes, respectively, for land use/cover category i in land suitability c. A comparison of landscape outcomes between successful and unsuccessful parameter sets demonstrated overall better agreement between real and modeled landscapes in model runs with the successful parameter sets (Figure 6). All parameter sets performed similarly for the best land suitability class, but the successful parameter sets were slightly better in the other land suitability classes.

5 Discussion

The use of a GA in combination with POM provided a means to formalize, test, and parameterize functions linking global MII to agents' decision-making processes, and parameter sets

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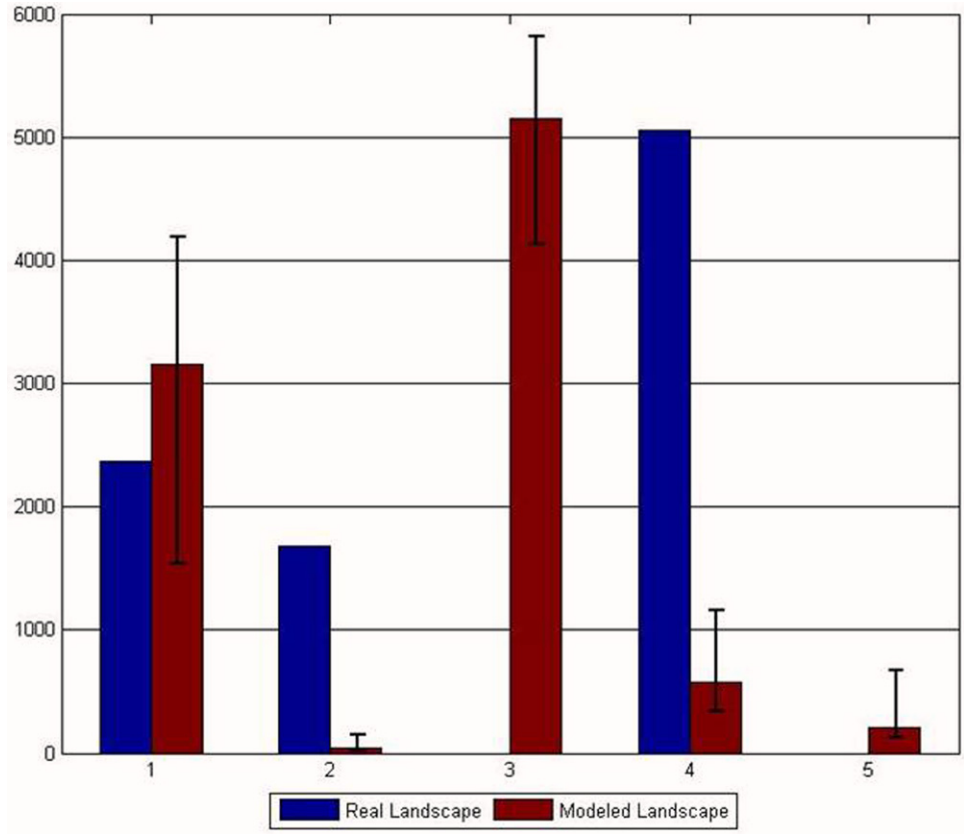

Figure 5 Counts per land cover class in the real and modeled landscapes (with 95% confidence interval bars). Land use/cover classes are as follows: 1 = intensive agriculture; 2 = extensive agriculture; 3 = pasture; 4 = forest; 5 = fallow. Dwellings, barren/rock, and water classes are not shown, since they are initialized in the modeled landscape in equal quantity to the real landscape and held constant through the simulation

that satisfied all three pattern-oriented performance criteria performed better than those that only reproduced two target patterns. This approach had several advantages. First, with an efficient means to search the large potential parameter space, the cost and price functions linking local economic conditions to global MII could be formalized at a generalized level. Second, alternative parameterizations of those relationships were tested against multiple patterns simultaneously to increase the structural realism of the model (Grimm et al. 2005, Kramer-Schadt et al. 2007). Most importantly, following from these points, this approach made possible the design of a model with a broad effective domain of applicability, which can be used to test hypotheses of global to local linkages driving land change across sites – a feature critical to building theories of land change (Parker et al. 2008).

In this modeling exercise, the model failed to accurately reproduce quantities of land use/cover seen in the real landscape, but, more importantly, it did so systematically. In particular, extensive agriculture and forest cover were generally substituted for pasture. Two explanations for this discrepancy are possible and not mutually exclusive. First, this area in Hunan is characterized by narrow fertile valleys surrounded by steep hillsides. With the dense populations in

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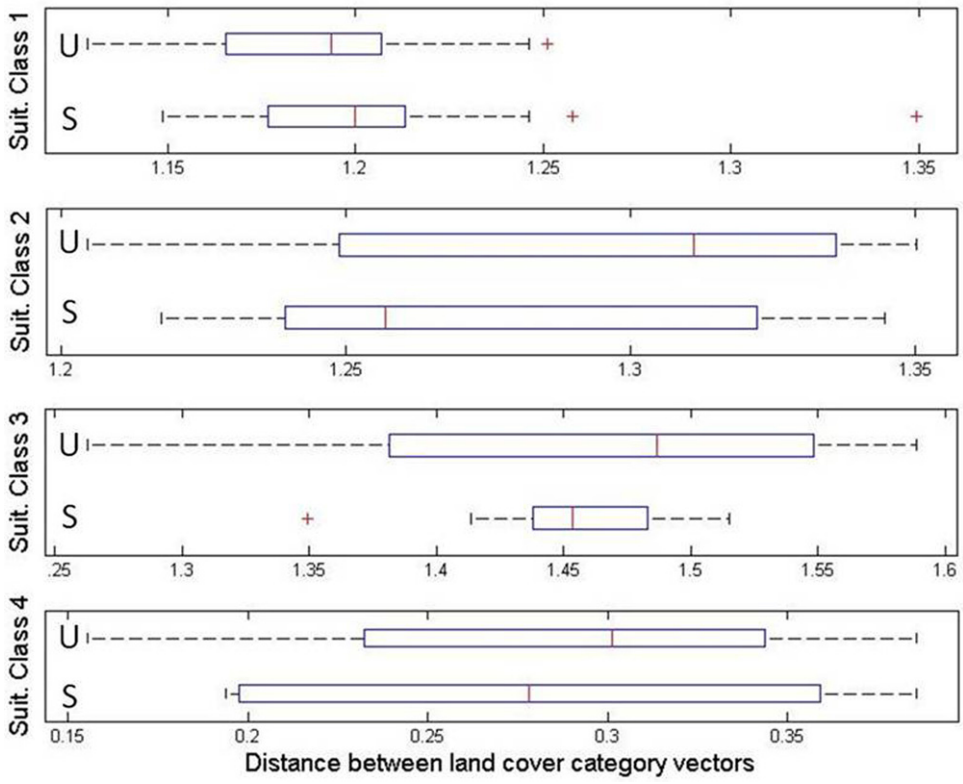

Figure 6 Box plots comparing the error (i.e. distance) between real and modeled landscape cell counts across land-uses/covers within each of the landscape suitability classes with unsuccessful (U) and successful (S) parameter sets. The borders of the boxes represent the quartiles of the distribution, and the middle lines the medians

the area, rice production is the dominant subsistence crop occupying prime agricultural land, which the model predicts well. The remaining land is less suitable for intensive agriculture, and the model predicts pasturing to be the next best option for these locations based on climatic variables, labor costs, and market value for pasture products. Instead of choosing pasturing, which is relatively high yielding in this area with low labor input, tea, bamboo and Chinese fir tree are chosen as cash crops. Currently, cash crops are not explicitly represented in the model, and these results indicate they strongly influence land-use choices in this location. A second plausible explanation for these model failures is the presence of strong land tenure rules. Historically, land was allocated evenly to individual households based on productivity. Consequently, individual holdings could consist of many small, fragmented areas – which would not support large grazing pastures (Buck 1937). Based on this historical context and the model results, land tenure rules are clearly an important influence on the types of land uses chosen, and thus should be included in a more detailed model of this location.

The model presented here was highly simplified and lacking in detail, and a much fuller model would be necessary to create a reliable model of LUCC for this example site. In particular, cost/price functions were represented by simple functions assumed to vary with MII (Section A1.2.4). Without direct measurements of local crop prices, input costs, and farm and

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non-farm wage rates in relation to global market context, we cannot verify the veracity of the cost/price functions implemented here. Thus, future research will attempt to derive generalized empirical relationships between MII and widely available proxies for local economic conditions. Although global to local economic linkages were simplified, this implementation illustrated how the POM method can be used to parameterize model relationships for which little empirical data exists, and suggests how global to local connections can be explicitly represented within an agent-based framework. Designing an ABM is an iterative process in which the modeler must harness the best available process and parameter data and knowledge to build a representation of the real system, and then let the model's failures guide hypotheses about how the real system's structure and dynamics differ from those in the model (Grimm and Railsback 2005, Latombe et al. 2011). Model failures can provide insight into both incorrect representations of real system processes and important processes that were not initially included in the model design.

These insights illustrate the potential of the POM approach to create virtual agent-based laboratories of LUCC. A simple model, designed to be applied across a wide range of land systems globally, provided insights into important local and cross-scale influences on land use and cover patterns. The strength of the POM approach lies in the use of strong inference in testing alternative decision models and/or parameterizations against one another on the basis of their ability to reproduce multiple patterns simultaneously (Grimm et al. 2005, Latombe et al. 2011). Decision models and/or parameterizations that do not reproduce multiple patterns can be rejected, and only the minimum set of processes and parameters needed to reproduce target patterns are included in model design. By gradually introducing additional processes hypothesized to influence land-use patterns, this approach can tease apart the relative importance of global/regional and local factors in driving local land-use changes across different locations and land systems globally. This process maintains parsimony in model design increasing interpretability and minimizing the number of uncertain parameters and potential embedded errors (Oreskes and Belitz 2001). Since little empirical data or general theory exists describing how large-scale forces influence local decision-making, POM provides a means for coping with parameter and process uncertainty to formalize testable models that include large-scale driving forces of LUCC in local ABMs. Only when large-scale driving forces can be represented in the same context as land-users decision-making processes can progress be made towards entirely process-based models of land change.

6 Conclusions

The growing influence of economic globalization on local land-use decisions requires that cross-scale linkages be incorporated explicitly into our understanding and models of LUCC (Lambin and Meyfroidt 2011). Since land systems do not lend themselves to conventional experimentation, agent-based virtual laboratories provide a means to test direct, mechanistic explanations of land change. The dearth of detailed empirical data and knowledge about cross-scale linkages is a substantial challenge to formulating multi-scale land change models, but the POM approach can facilitate the use of local ABMs of land change as virtual laboratories for testing the influence of large-scale drivers of LUCC on local decision-making processes. The POM approach provides a means to cope with structural and process uncertainty, and design realistic models that can be tested against empirical patterns and/or theoretical predictions. Agent-based virtual laboratories can test hypotheses of how and under what conditions driving forces of land change might differ from a more general model representation

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depending on the particular land-use system or location, and how agents' motivations might change as economic globalization restructures local economic opportunities. Thus, the POM approach offers a way forward to design structurally realistic process-based models that can be used as tools to explore ways in which global/regional driving forces interact with local land systems and build towards a general theory of land change.

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Supporting Information

Additional supporting information may be found in the online version of this article:

Figure A1: Components of the hypothetical landscapes: (a) artificial topography and land suitability for agriculture; (b) simulated land uses with agents 7 and 59 indicated (Section A2.5)
Figure A2: Process overview and scheduling presented as pseudo-code
Table A1: Parameter descriptions for settlement agents that apply equally to all households within a village
Table A2: Potential productivity and price parameters
Table A3: Matrix of combined labor input costs, expressed in person-weeks ha^{-1}, for converting from land-use *i* to *j*. Land-use are 'intensive' agriculture (1); 'extensive' agriculture (2); pasture (3); forest (4); fallow (5); and dwellings (6). Land-use conversions that are not possible (e.g. 'intensive' agriculture to forest) are indicated with '-' symbols. Based on Evans et al. (2001)

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