Agent-based modeling of deforestation in southern Yucatán, Mexico, and reforestation in the Midwest United States

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We combine mixed-methods research with integrated agent-based modeling to understand land change and economic decision making in the United States and Mexico. This work demonstrates how sustainability science benefits from combining integrated agent-based modeling (which blends methods from the social, ecological, and information sciences) and mixed-methods research (which interleaves multiple approaches ranging from qualitative field research to quantitative laboratory experiments and interpretation of remotely sensed imagery). We test assumptions of utility-maximizing behavior in household-level landscape management in south-central Indiana, linking parcel data, land cover derived from aerial photography, and findings from laboratory experiments. We examine the role of uncertainty and limited information, preferences, differential demographic attributes, and past experience and future time horizons. We also use evolutionary programming to represent bounded rationality in agriculturalist households in the southern Yucatán of Mexico. This approach captures realistic rule of thumb strategies while identifying social and environmental factors in a manner similar to econometric models. These case studies highlight the role of computational models of decision making in land-change contexts and advance our understanding of decision making in general.

agent-based model | bounded rationality | decision making | land change | landscape management

Land-change science (LCS) is critical to research on sustainability in coupled human–environment systems (1, 2). Land change results from interactions among social systems, ecological dynamics, and actors, such as households or firms whose behavior is the proximate cause of land change. LCS therefore relies on social science studies, field-based studies of the environment, and remote sensing of land change. The LCS community stresses the importance of developing integrated computer models that combine empirical data with theories of actor behavior to explore land-change processes. These models give insight into the drivers of land-change processes and offer a mechanism to study plausible future trajectories of change and their social and environmental implications.

Unmet challenges in developing integrated models of land change suggest the need for a greater emphasis on individual or household-level decision making. Methodologies that aggregate microlevel behaviors may not capture important aspects of individual decision making (3, 4). Models must work with sufficiently fine-scale data, such as the combination of remote sensing and household interviews, to describe actor practices on the ground, but capture regional land change (5). Few modeling methods effectively represent interactions among actors, society, and the environment at multiple spatial and temporal scales (6). Similarly, many models do not easily bridge the gap between quantitative and qualitative aspects of individual decision making. In sum, land-change models face challenges in micro–macro integration, handling spatiotemporally explicit data, capturing human–environment relationships, and bridging the qualitative–quantitative divide.

Beyond these immediate needs, a greater challenge lies in integrating differing perspectives on individual decision making to enhance our ability to model land change (7, 8). In particular, rational choice theory, expressed as perfect rationality, is being extended through alternatives, bounded rationality in particular. Perfect rationality offers elegance and analytical tractability by assuming decision makers are utility maximizers who use perfect computation and possess complete information on alternatives (9). Bounded rationality weakens these assumptions to better model individuals who face limits on information and computation (10). Boundedly rational agents satisfice, or make suboptimal yet acceptable decisions, or maximize under limits (11–13). These limits imply that agents use decision strategies of limited complexity, such as "rules of thumb" (14, 15) and learn from experience by extending current strategies to new situations (16, 17). A key challenge in comparing theories of perfect rationality and bounded rationality against empirical data is developing testable models. Perfect rationality is typically mapped by econometric research onto statistical approaches (18, 19). Less attention has been given to developing testable models for bounded rationality given its relatively recent emergence, but various viable approaches exist (11, 13, 16, 20, 21). A final challenge is reconciling models of bounded rationality and perfect rationality in a way that recognizes that each approach captures different facets of the same decision-making process.

We examine how agent-based modeling provides a framework for combining modeling and mixed-methods research to represent different forms of rationality, integrate micro–macro processes, use spatiotemporal data, represent human–environment interactions, and blend qualitative and quantitative approaches. An agent-based model simulates adaptive, autonomous entities (or agents) that draw information from their surroundings and apply it to decisions and behavior. Agent-based models of land change are used in contexts ranging from urban growth to deforestation (22, 23). In contrast to modeling approaches that aggregate decisions of many actors, agent-based models examine the decision making of separate actors, such as individuals or households, as locally interacting, autonomous, and heterogeneous entities (24).

Here, we describe the results of using mixed methods and integrated modeling to examine household decision making in

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Abbreviations: LCS, land-change science; SYPR, southern Yucatán peninsular region; LUCIM, land-use changes in the Midwest; HELIA, human–environment integrated land assessment.

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land change. In a reforesting landscape in Indiana, we examine the effects of uncertainty, limits to information, preferences, and future time horizons. For a deforesting landscape in Mexico, we explore the use of agent-based modeling to shuttle between representing decision making as individual rules of thumb versus examining broad social and environmental factors. We discuss the implications of these findings, trace future research directions, and complement the discussion of methods and materials developed throughout this article.

Results

We examined the benefits of combining integrated modeling and mixed-methods research to examine decision making by analyzing forest and agricultural dynamics in two regions that share the same time zone, but are largely dissimilar. First, we explored household-level land-management decisions in south-central Indiana, an area that experienced large-scale deforestation following initial settlement in the 19th century, but then experienced net reforestation from ≈1900 onward. Second, we examine the southern Yucatán peninsular region (SYPR) in Mexico, home to semihumid tropical forests undergoing "slash-and-burn" or extensive agriculture against a background of globalization, neoliberal national transformation, and locally conflicting goals of conservation and development.

There is a substantial amount of research regarding land use in both foresting and deforesting systems. Common proximate causes of deforestation have been identified for tropical regions, typically characterized as the economics of resource extraction coupled with mixed market and subsistence agriculture (4, 25). Alternatively, reforestation has been linked to the abandonment of marginal agricultural areas and increases in prices for timber products (26) along with changes in landowner preferences (27). In both study areas, we find evidence of reforestation and deforestation for specific forest types and, using mixed methods within an agent-based model framework, we demonstrate that, while bounded rationality is a key form of decision making for individuals, we can also usefully make assumptions that fall under the aegis of perfect rationality. In the Indiana case, we started with the assumption that each household maximizes utility and explored how households vary in boundedly rational ways. In the Mexico case, we found that models of bounded rationality and perfect rationality produce similar results in aggregate, whereas the former can also disaggregate the rules of thumb used by individuals.

Actors who were represented as satisficing and possessing imperfect information and cognition produced good model fits against actual multitemporal land-cover data in each study area. While researchers have long known that actor heterogeneity produces complex local landscapes and that household decision making modeled as perfectly rational will ignore aspects of individual decision making (13), it is a challenge to capture these features of decision making in a computer model. Agent-based modeling represents features of bounded rationality, such as heterogeneity, learning, and limited information and computational capacity (28, 29). Agent-based models of land change can extend LCS by explaining and replicating real-world land-change dynamics at the level of individuals while also dealing with the challenges of scalar integration, spatiotemporal data, human–environment interaction, and the qualitative–quantitative divide. Agent-based modeling provides an explicit basis for the comparison of results gleaned from multiple methods and sources, such as contrasting the results of laboratory experiments with historical land use or linking rules of thumb, econometric modeling, and computational intelligence. This integrated approach allows us to understand how individual decision making exists at the interface of individual traits and broader environmental and human contexts. This work also demonstrates the importance of linking data and theory via empirically specified, theoretically driven models of human decision making.

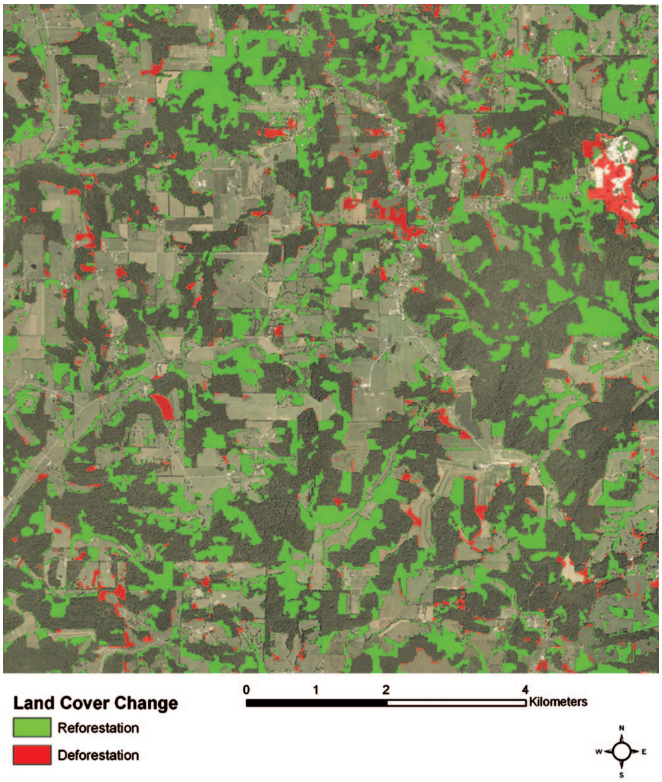

Fig. 1. Reforestation and deforestation in Indian Creek Township, Monroe County, Indiana: 1939–1997.

Reforestation in South-Central Indiana. South-central Indiana has seen net reforestation, but, importantly and in contrast to literature focused on linkages between population and deforestation, this reforestation occurred during a period of increasing population density (see also ref. 30). Analysis of aerial photography (used in lieu of satellite imagery to go further back in the historical record) for Monroe County shows that forest cover increased from 39% to 60% from 1939 to 1997 (Fig. 1). Our analysis of the drivers of reforestation included economic, biophysical, and institutional dynamics, but particularly focused on the land-management decisions of households that reside on parcels ranging from 1 or 2 hectares to hundreds of hectares. Our analysis is motivated by the considerable heterogeneity among land-change processes during this period. Two parcels with nearly identical biophysical properties may exhibit vastly different land-change trajectories. Agent-based approaches are effective means of exploring these heterogeneities and the interactions between actors and the environment that produce this aggregate pattern of reforestation.

As in the research described below on deforestation in Mexico, we integrated findings from multiple methods. We used laboratory-based decision-making experiments and household surveys to complement the agent-based model (3, 31). Individually, each of these methods is valuable, but when used together, they provide a particularly rich understanding of land-change processes. We collected empirical data from contemporary land managers through household surveys, explored the spatial patterns that emerge from diverse decision makers by using laboratory-based experimental research, and simulated the behaviors of decision makers drawing on the basis of these empirical approaches with agent-based models.

Land-use changes in the Midwest (LUCIM). The LUCIM model uses a utility-maximization approach whereby a set of household level land-use preference parameters are fitted to the land-change record derived from historical aerial photography. When we calibrated the model to fit land-change data from 1939 to 1997, we found that it produced agents with a diversity of land-use preference parameters. This finding demonstrates that two land managers faced with the same land portfolio (parcel size, accessibility, land suitability) may make dramatically different land-management decisions. In the south-central Indiana study area, this actor heterogeneity causes both deforestation and reforestation, although the net land-change trajectory is one of reforestation.

Similarly, the fitted parameters demonstrate that no single set of parameter values applied to all actors produces the best fit to the observed data, indicating that different households use different land-management strategies. Even agents with similar land attributes exhibited this diversity in parameter values, emphasizing the importance of household contextual factors, such as household size, wealth, and experience, in the decision-making process. A key finding of the research is that models that focus solely on biophysical factors, such as topography or soil fertility, underemphasize the importance of social factors in local-level patterns of land change.

Another key difference is the distinction between agents who converted forest area to crops/pasture and agents who did not. Despite the economic potential of timber and agricultural production, a substantial subset of agents did not choose this land use. In fact, the number of agents who allowed forest to regrow on their parcels exceeded the number of agents who removed forest. We interpret this result as an indication of a change in the labor market (greater off-farm labor opportunities) and landowner preferences. Although landowners working off-farm could benefit economically from agricultural activities on their parcels (either by using household labor or through leasing), land cover in the area shifted from agriculture to forest. Qualitative data suggest that selective timber harvesting was practiced by many landowners early in the study period, but contemporary household survey data indicate that a majority of residents do not harvest timber within their forested land.

Integration of surveys and laboratory experiments. Surveys are valuable tools for identifying relationships between household attributes and land-management decisions, and data from these surveys can be linked to land-cover data via parcel boundaries (32). The household data showed a weak positive correlation between income and likelihood of reforestation, but also indicated that numerous cases of reforestation occurred on parcels owned by low-income households. In aggregate, household/parcel attributes commonly used in LCS, such as demographic characteristics, distance to markets, and wealth, explain only a small amount of variation in land-change trajectories (e.g., refs. 33 and 34). Household attributes that are more difficult to measure with standard survey approaches, such as learning, information/knowledge, risk aversion, and social networks, are hypothesized to play an important role in the heterogeneity of land-management decisions.

The ability of surveys to provide insight into land-change processes from several decades ago is limited because of the fallibility of memory and the incidence of out-migration and mortality in households. In addition, household surveys have greater reliability when questions are focused on discrete events (tree planting) or metrics (household size) rather than more intangible characteristics, such as risk aversion or learning. Thus, alternative methodological approaches are needed to bridge the gap between decision science and LCS.

Laboratory experiments are a valuable tool for exploring fundamental aspects of natural resource management decision-making in a spatial context (3, 27). We used a spatial experiment to assess the diversity of resource allocation decisions. In the baseline experiment, subjects allocated land to one of two resources and received revenue according to a monotonically increasing price trend for the first resource and a monotonically decreasing price trend for the second. Despite the apparent predictability of the revenue trend, considerable heterogeneity existed in the resource allocation decisions made by subjects. A "perfect" decision maker should simultaneously change his or her entire land portfolio from one resource to another as the prices change. At the nexus where this land change should have occurred, however, the majority of subjects took many rounds to complete the reallocation of their land portfolio, and some persisted in allocating land to the disadvantaged resource through the rest of the experiment.

Next, we extended the baseline experimental design so that each subject had a land portfolio in which some cells were more suitable for one resource than another and revenue was a product of the resource price and the cell suitability. In this experiment, we also saw considerable heterogeneity among subjects' abilities to predict the revenue trend and learn the land suitability patterns. One indicator of landscape complexity is the spatial heterogeneity of the landscape. Landscape edge measures spatial heterogeneity as the sum of the perimeter of all contiguous land-cover patches. For example, in a landscape composed of equal proportions of forest and agricultural area, a checkerboard-type mosaic would have greater edge than a landscape where all forest area was in a single contiguous patch. In the laboratory experiments, the landscapes produced by subjects, for example, had more landscape edge than those that would be produced by utility-maximizing decision-makers with complete information.

This finding is supported by empirical data from both household surveys and laboratory experiments. We find evidence of actor heterogeneity corresponding to diverse land-change trajectories and importantly find theoretical support from laboratory experiments for landscapes with greater land-cover heterogeneity than a utility-maximizing decision maker would produce. Overall, these results suggest the importance of acknowledging that diversity among local-level actors is responsible for diverse land-cover change trajectories.

Deforestation in the Southern Yucatán Peninsular Region.

Like LUCIM, the human–environment integrated land assessment (HELIA) model uses agents to represent real-world actors, namely agriculturalist households in the southern Yucatán (35–38). HELIA combines several methods: multicriteria evaluation, symbolic regression, and evolutionary programming. This work is part of the SYPR Project (39).

Multicriteria evaluation and symbolic regression. Along with many other land-change models, HELIA uses multicriteria evaluation, or the process of assigning the suitability of or likelihood that a given location will undergo land change as a function of spatial factors, such as soil quality or rainfall (40). Households in the southern Yucatán choose locations for agriculture as a function of environmental factors, such as soil quality or precipitation, and social factors, such as land ownership or distance to market. The SYPR Project identified factors relevant to these households via field interviews and in accordance with various land-change theories (41–44). In general terms, theories of relative space consider the importance of distance to key markets and infrastructure (e.g., Alonso, Von Thünen, Christaller, and Lösch models), whereas theories of absolute space see decision making as a function of heterogeneous *in situ* landscape characteristics (e.g., the Ricardian view) or as economies of scale and agglomeration (19, 36, 44).

HELIA represents real-world households and their land-use strategies as virtual agents equipped with multicriteria evaluation strategies. Multicriteria evaluation determines a function

$f(x)$ that assesses the likelihood or suitability in a given location for land change (represented by response variable $\mathbf{Y}$) as a function of spatial predictor variables $\mathbf{X} = \{X_1, \ldots X_n\}$. The form of $f(x)$ varies from statistical equations to more complex approaches, such as neural networks or cellular models (7, 24, 45). HELIA uses land use derived from remotely sensed imagery for the response variable and predictor variables based on data for soils, elevation, slope, aspect, precipitation, surface hydrology, distance to roads and markets, and socioeconomic, political, and demographic factors (see specifics in *Materials and Methods*).

Symbolic regression and decision making. Many land-change models use symbolic regression to estimate the form of the multicriteria evaluation function $f(x)$. Symbolic regression inductively estimates the ideal function $f(x)$ as an approximate function $\hat{f}(x)$ by treating $\mathbf{Y}$ and $\mathbf{X}$ as random variables given by observations at discrete locations. Symbolic regression minimizes error between observed $\mathbf{Y}$ and the value predicted by $\hat{f}(\mathbf{X})$ (38). In land-change models, the locations of these observations often correspond to land parcels or pixels in a remotely sensed image. HELIA agents sample discrete points in a virtual landscape based on the real spatial data noted above.

Land-change models can use many different symbolic regression approaches to approximate $\hat{f}(x)$, but, ideally, the method should satisfy theoretical imperatives. One strong argument for the use of econometric models is that they represent perfect rationality with statistical forms of symbolic regression, such as ordinary least-squares or maximum-likelihood estimation, that are directly derived from the mathematical expressions of these theories (18, 19). Correspondingly, HELIA agents solve their multicriteria evaluation problem with a symbolic regression method termed evolutionary programming that represents features of bounded rationality (46, 47). Evolutionary programming is a computational analog to natural selection that creates software programs that solve specific problems. In particular, it acts as a symbolic regression method when programs evolve to estimate function $\hat{f}(x)$ (48). In essence, programs compete to create offspring programs and parent programs are selected in proportion to their fitness in solving $\hat{f}(x)$.

More broadly, evolutionary programming can represent bounded rationality. Agents possess a set of programs that approximate real-life multicriteria evaluation strategies. An agent uses its fittest strategy to make land-use decisions, but also possesses alternatives for different circumstances (49). Agent computational abilities are restricted by limiting the number and complexity of programs (38, 50). Information is limited by the extent to which offspring carry portions of their parent programs (46, 51). Boundedly rational learning is modeled in how offspring exploit existing strategies (by copying all or most of their parental programming) and create better strategies (by combining parts of different parent programs) (52, 53). Finally, agents also learn by imitating and communicating with other agents by sharing well performing programs (54).

Comparison and complementarity of approach. In addition to representing bounded rationality, evolutionary programming allows agents in aggregate to replicate some characteristics of statistical models of perfect rationality while also individually deriving strategies that are typically identified through household interviews and qualitative research. In particular, evolutionary programs embody realistic rules of thumb while identifying the direction and magnitude of relationships between land change and social and environmental factors in a manner similar to that of an econometric model. The ability to shuttle between models of bounded rationality and perfect rationality illustrates that these models are not necessarily antagonistic because they simplify complicated real phenomena (i.e., human decision making in coupled human–environment systems), and, as such, each approach captures different facets of the same decision-making process.

Table 1. HELIA evolutionary program frequency and directionality analysis (*U*-score) vs. econometric sign and coefficient (*Z*-score)

Factor	HELIA (*U*)	Econometric (*Z*)
Soils	−6.683	−64.146
Elevation	−3.410	−87.615
Slope	0.000	14.799
Road distance	−7.728	−102.072
Market proximity	8.486	4.218
Village proximity	10.259	16.553
Population density (1985)	5.758	44.716
Population change (1980–1990)	8.168	18.249
Lowland forest	−7.137	−39.519
Upland forest	7.001	−8.580
Succession	8.410	13.333
Distance to past agriculture	−10.289	−79.685
Diversity	16.669	8.740

We compared evolutionary programs with an econometric model of land change and example rules of thumb. We sampled the fittest program of 3,200 randomly selected agents over 100 runs of HELIA. Each program represents a multicriteria evaluation strategy for agricultural land use as a function of the environmental and social predictor variables noted above. We compared these programs with example rules of thumb described by other SYPR Project studies (41–43) and with the results of an econometric model developed by the SYPR Project and applied to the same variables (described in ref. 44). Further econometric research by the project is described elsewhere (55, 56).

In terms of rules of thumb, some evolutionary programs are long and complex, but many are quite short (38). These short rules correspond to rules of thumb used by actual households, simple and effective real-world strategies like "clear secondary forest when primary forest is too far from my current location" or "plant new fields adjacent to current fields." While these rules are generated inductively in HELIA via evolutionary programming, they are based on real land change and spatial factors and therefore reflect real household strategies that reduce travel time between fields, minimize walking time to the nearest road or village, and keep fields in locations that have served well in the past (41–43).

In terms of the econometric model, HELIA largely agrees on the importance and effect of factors predicted under theories of relative space. Table 1 compares the evolutionary programs with econometric model results by using a measure of frequency and directionality (U) that is analogous to the sign and coefficient of a Z-score in statistical models (36). The likelihood of deforestation decreases with distance from roads, markets, or settlements. The probability of agents cultivating land is negatively related to distance to existing cultivation, which is explained by the fallow-cycle dynamics of extensive swidden agriculture (fields are replanted for several years and then left fallow) and the fact that land is assigned to a household for years. Diversity is important for both models, likely because mixed land uses give easy access to the forest interior (important for expanding fields and hunting game) and may also indicate agglomeration efficiencies in agricultural production (57).

In terms of absolute space, agriculture is sited on secondary succession and upland forest. This siting is related again to fallow-cycle dynamics and the need to move onto new land. Linkages between population and land use are seldom simple, but population variables control for local agricultural product demand (44). Both models find agriculture is positively related to population and population density. Prevalence of extensive agriculture and relatively abundant land likely account for this relationship. Agricultural land use is less likely with increased elevation because higher areas tend to be more rugged and have thinner, rockier, and drier soils. Agriculture is negatively related to the soil's dummy variable because it reflects generally poor soils, such as rocky soils (lithosols) and clays (gleysols and vertisols) (58). The models differ in two respects. HELIA agents preferred, in aggregate, to site agriculture on upland forest, whereas the econometric model found a weak negative relationship. Agents also uniformly ignored slope, whereas the econometric model found a positive relationship between slope and the probability of deforestation. These differences are the subject of ongoing inquiry.

Discussion

The research findings from Mexico and the United States point to the importance of household factors in landscape outcomes and the potential drawbacks of methodological approaches that aggregate these local processes. In particular, an explicitly household-level approach captures complexity and heterogeneity that is lost at higher levels of aggregation. Similarly, much LCS research focuses on identifying descriptive proximate variables that explain predominant land-use trajectories, such as population density or distance to roads. Our research emphasizes the role of using multiple approaches to understand decision making and, critically, the variability of decision strategies used in both abstract and real-world contexts. The research presented here found that actor heterogeneity produces complex landscape patterns at the local level. Critically, we found evidence of households in both study areas that do not fit the homo-economicus model of the decision maker who has perfect information and makes decisions that yield the greatest economic benefit. Just as importantly, methods that omit household factors and focus on physical attributes, such as soils, topography, and accessibility, underemphasize the role of household characteristics, such as demographics, experience, and access to information, that clearly influence land-management decisions. Together, the combination of complexity and heterogeneity in decision making suggests that single-policy prescriptions designed to target landowners are unlikely to effect broad-scale changes in land-management practices without reference to specific landowners and their circumstances. To effect the greatest change, a diversity of policies (or policies targeting households with different socioeconomic contexts) is more likely to achieve desired environmental outcomes.

In the Indiana case, each method gave insight into the decision-making processes of actors and supported the notion that households are boundedly rational decision makers whose choices are affected by diverse preferences, strategies, or attributes. Although the household surveys found general associations between household attributes and land-use decisions, the correlations were far from perfect. The laboratory-based experiments clearly found considerable heterogeneity among subject decisions despite a relatively simple decision-making context. The agent-based model found that two households with parcels of identical biophysical context may pursue vastly different land-use strategies. The results from each of these methods highlight the connection between actor heterogeneity and landscape heterogeneity and the important role this heterogeneity played in producing the pattern and trajectory of land cover in the south-central Indiana study area.

In the southern Yucatán, comparison of rules of thumb, HELIA, and econometric modeling demonstrates the utility of using evolutionary programming and agent-based modeling to represent a key feature of bounded rationality, the use of rules of thumb, and capture other aspects, such as limits to information and learning over time (36, 38). The evolutionary programming approach is also in keeping with the econometric model by identifying the importance and direction of theoretically important predictor variables for land change. More broadly, evolutionary programming complements and confirms features of econometric modeling and qualitative research. Although evolutionary programming cannot match these other approaches in many respects, such as the analytical power and history of econometric approaches or the depth and nuance of qualitative methods, it does offer a useful alternative.

More broadly, this research points to areas of further exploration. Agent-based modeling has evolved from very abstract formulations to being more closely tied to empirical data, but with this evolution comes research challenges and a greater need for rich, real-world data. Although agent-based models help address the challenge of micro-macro integration, for example, they require data at multiple organizational scales, ranging from individuals through households, communities, and nations. Two particular areas that require attention are the roles of social networks and institutions in individual decision making. Agent-based models ably handle spatiotemporally explicit data, but these data must first exist. For example, the LUCIM modeling effort is one of very few that can lay claim to such a long-term, spatially explicit, time series data (59). Similarly, although agent-based models are in many respects ideal for capturing human–environment relationships, they are built on a broad foundation of research on individual human and environmental systems and the interconnections among them. HELIA, for example, could not exist outside of the large and interdisciplinary SYPR Project (39). Additionally, although these models can link qualitative and quantitative approaches, further research is necessary to match the elegance offered by quantitative approaches, such as mathematics or statistics, while also capturing more of the nuance and sophistication of qualitative approaches.

Conclusion

LCS joins social, ecological, and information sciences. One important medium for this integration is the use of spatially explicit agent-based models of land change. These models give insight into decision making that defines the well-being of individual households and their communities. Agent-based models illustrate local-level dynamics, but importantly, also complement other methods. The value of modeling in general is heightened when used in an integrative manner, bringing together theories of decision making instantiated via different models and combining them with empirical data gleaned through approaches ranging from personal interviews and laboratory experiments to interpretation of remotely sensed imagery. Fortunately, land change is an ideal venue for exploring a mix of theory, method, and data given the larger LCS focus on using multiple approaches to understand land change, the very tangible and therefore measurable effects of land-change processes, and the fact that land change directly or indirectly affects people around the world.

Materials and Methods

Indiana. LUCIM fits household land-use preference parameters to the land-change record derived from historical aerial photography [full model specification available elsewhere (27, 31)]. Seven time points of aerial photography were interpreted to produce a multitemporal data set of digital land-cover data (1939, 1958, 1967, 1975, 1980, 1987, and 1993). Parcel-level land ownership boundaries were derived from hard-copy cadastral maps and integrated with the land-cover data with a geographic information system. Household characteristics were derived from household surveys conducted in 1998 and 2003. The historical time series of crop and timber prices were created by a combination of state and federal economic data sources. The household survey included a series of questions related to past land-use decisions, demographic structure, sources of information related to land-use practices (e.g., media, neighbors, relatives), and awareness of incentive programs targeting conservation. The laboratory experiments included five replications of two experimental designs (nine subjects per session for a total of 45 subjects per experimental design). The experimental research used a custom experimental software platform developed in ArcGIS. All research activities were approved by the Human Subjects Committee at Indiana University.

Southern Mexico. General characteristics of HELIA are given where pertinent for discussions of results but the data, structure, and parameterization of HELIA are described in full elsewhere (35–38). Further information is also available from the SYPR Project (http://earth.clarku.edu), which provided most of the data for the model, including land-use/cover maps from Thematic Mapper imagery for 1987, 1992, and 1995; elevation, aspect, and slope from a 1:50,000 digital elevation model; soil types from a 1:250,000 map (provided by the Mexican National Institute for Statistics, Geography, and Information; *Instituto Nacional de Estadística, Geografía e Informática*); a road network and surface hydrology from 1:50,000 topographic maps; precipitation from 21 federal weather stations; and federal censuses of demographic and socioeconomic data.

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