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Multi-scale analysis of a household level agent-based model of landcover change

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Abstract

Scale issues have significant implications for the analysis of social and biophysical processes in complex systems. These same scale implications are likewise considerations for the design and application of models of landcover change. Scale issues have wide-ranging effects from the representativeness of data used to validate models to aggregation errors introduced in the model structure. This paper presents an analysis of how scale issues affect an agent-based model (ABM) of landcover change developed for a research area in the Midwest, USA. The research presented here explores how scale factors affect the design and application of agent-based landcover change models.

The ABM is composed of a series of heterogeneous agents who make landuse decisions on a portfolio of cells in a raster-based programming environment. The model is calibrated using measures of fit derived from both spatial composition and spatial pattern metrics from multi-temporal landcover data interpreted from historical aerial photography. A model calibration process is used to find a best-fit set of parameter weights assigned to agents' preferences for different landuses (agriculture, pasture, timber production, and non-harvested forest). Previous research using this model has shown how a heterogeneous set of agents with differing preferences for a portfolio of landuses produces the best fit to landcover changes observed in the study area.

The scale dependence of the model is explored by varying the resolution of the input data used to calibrate the model (observed landcover), ancillary datasets that affect land suitability (topography), and the resolution of the model landscape on which agents make decisions. To explore the impact of these scale relationships the model is run with input datasets constructed at the following spatial resolutions: 60, 90, 120, 150, 240, 300 and 480 m. The results show that the distribution of landuse-preference weights differs as a function of scale. In addition, with the gradient descent model fitting method used in this analysis the model was not able to converge to an acceptable fit at the 300 and 480 m spatial resolutions. This is a product of the ratio of the input cell resolution to the average parcel size in the landscape. This paper uses these findings to identify scale considerations in the design, development, validation and application of ABMs of landcover change.

Keywords: Scale; Land cover change; Agent-based model; GIS

1. Introduction

Agent-based models (ABMs) of landcover change are effective tools for the exploration of how local level decision-making produces landscape landuse and landcover change outcomes. Agent-based techniques can be used to identify how information diffusion and spatial externalities affect the spatial pattern and composition of landcover over time. As with the empirical study of landcover change processes, scale issues affect the development and testing of ABMs of landcover change. These scale issues enter the modeling process both in the integrity of the data used to calibrate and validate the model as well as in the design of the model structure. Scale dependencies have been observed in the relationship between various social and biophysical variables (Walsh et al., 1999). We explore how similar scaling issues affect the process of the development and application of ABMs of landcover change.

This paper presents a model of landcover change constructed for one township (an area roughly $10 \times 10\ \text{km}^2$) in south-central Indiana using an agent-based

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modeling approach. The purpose of this model is to describe factors contributing to the process of forest regrowth that have occurred in this area over the last 60 years. The main agent in this model is a household that makes decisions about landcover conversions on a yearly basis. Individual simulated agents (households) are allocated spatial partitions of the landscape using historical land ownership records as a basis for cell assignments. A cell is the minimum mapping unit in this ABM and a parcel is a group of cells owned by an individual agent. The performance of the model is evaluated by comparing modeled landscapes to observed data at a series of time points in roughly 10–15 year intervals. By scaling the input datasets, the observed landcover data, and the model structure, we explore how the model results vary as a function of scale. Given the scale dependence observed in social and ecological phenomena, it is reasonable to expect that these scale dependencies are also present in models that incorporate social and biophysical phenomena. We examine this hypothesis and identify under what conditions this ABM with parcel/household agents is sensitive to scale issues.

1.1. Landuse/landcover change in south-central Indiana

The study area used for this research lies in south-central Indiana. This part of the state was primarily forested prior to the arrival of European-based settlers in the early 1800s. These settlers cleared substantial areas of land for agricultural production (crops and pasture) and for forest products used for construction materials. It is estimated that in the early 1800s more than 87% of the state was covered with forest of some type across a wide range of topographic zones (Lindsey et al., 1965; Lindsey, 1997). The process of land clearing continued until the early 1900s at which time areas marginal for agricultural production were gradually abandoned resulting in a pattern of forest regrowth in areas of low agricultural suitability. The combination of agricultural clearing and timber extraction reduced Indiana's forested land to approximately 560,000 ha (~1,390,000 acre), or about 6% of the state by the early 1920s (Nelson, 1998). Since that time, the extent of forest cover has increased to over 1.6 million ha (4 million acres) (Nelson, 1998). Today, Indiana retains only an estimated 0.06% of its old growth forest from its estimated original forest cover at time of European–American settlement (Davis, 1993; Lindsey, 1997). The majority of forest cover in the state is relatively young successional forest covering approximately 18–20% of the state. It is this afforestation process (abandoned agricultural land allowed to recover to a forested state) that is explored with the model presented here.

Indian Creek Township, an area of approximately $10 \times 10\ km^2$ located in southwest Monroe County, Indiana, comprises the spatial extent for this model. Private landholders are the primary actors in the landscape. Indian Creek Township is characterized by a series of rolling hills with bottomland areas suitable for agricultural production

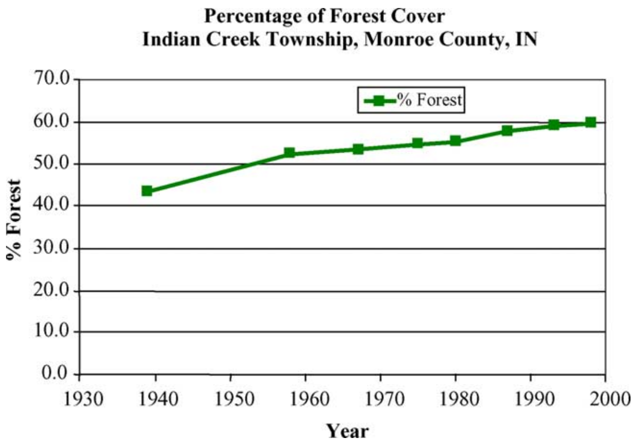

Fig. 1. Forest regrowth in Indian Creek Township, 1939–1998.

interspersed between ridges/hills that are largely forested. Forest cover composed 43% of the landscape in 1939 and 60% by 1998 (Fig. 1). In general, afforestation has occurred in steeply sloped areas while areas with shallow topography remain in some type of agricultural landuse (Tables 1 and 2, Fig. 2). Landowners are a mix of households that derive a portion of their household income from extractavist practices (agriculture, farming, haying, timber harvesting) and other households that derive all their income from non-farm activities (Evans et al., 2001b; Koontz, 2001). It is this mix of household types that we explore with the model presented here. The development of landcover change models is often made in the context of what data are readily available or in the context of new data acquisition efforts in which case the modelers have an opportunity to determine at which scale data are compiled. In both cases the modeler needs to understand the implication of running a model at multiple scales of analysis and the potential for the model results to vary as a function of scale. To explore the sensitivity of the model to scale effects, the ABM was run using input data at 60, 90, 120, 150, 240, 300, 480 m spatial resolutions.

Table 1
Landcover proportions in Indian Creek Township, 1939 (all values are%)

Landcover class	Landcover proportion 1939	Low slopes $S < 4°$	Moderate slopes $4° \leq S \geq 10°$	Steep slopes $S > 10°$
Forest	43.3	17.0	50.4	83.6
Non-forest	56.7	83.0	49.6	16.4

Table 2
Landcover proportions in Indian Creek Township, 1998 (all values are%)

Landcover class	Landcover proportion 1998	Low slopes $S < 4°$	Moderate slopes $4° \leq S \geq 10°$	Steep slopes $S > 10°$
Forest	59.5	30.9	69.0	92.6
Non-forest	40.5	69.1	31.0	7.4

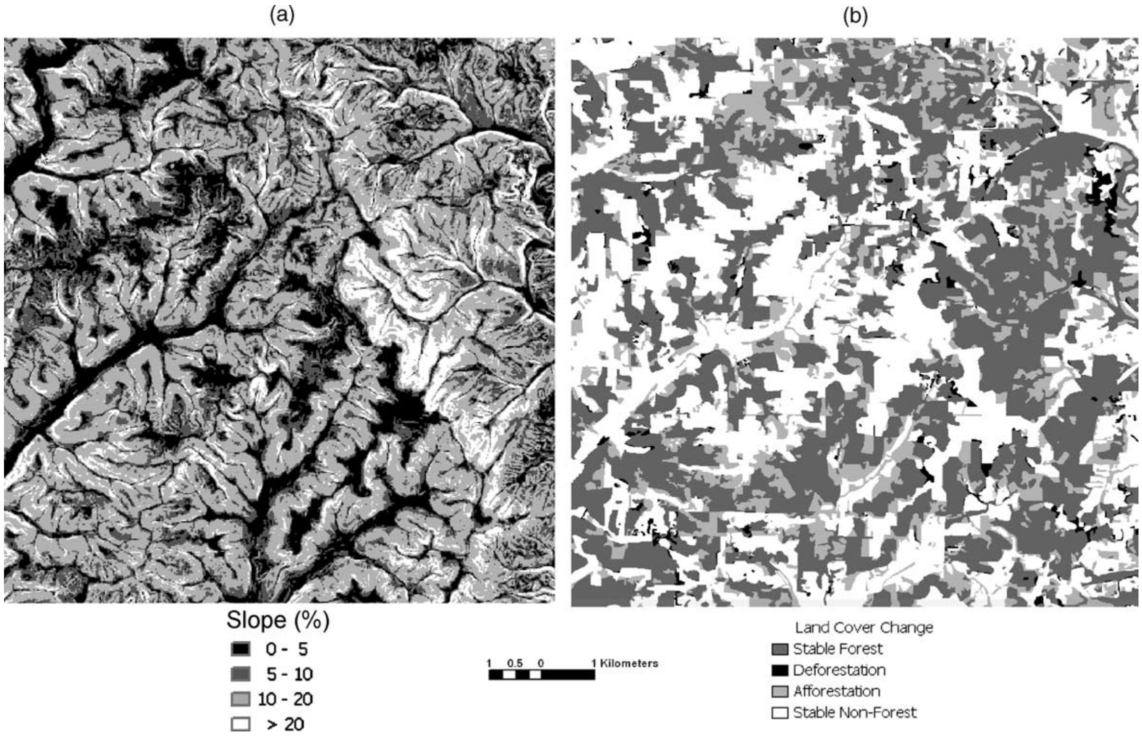

Fig. 2. (a) Surface topography in Indian Creek Township. (b) Landcover change in Indian Creek Township, 1939–1993.

2. Scale and agent-based models of landcover change

The landuse/landcover change (LUCC) community has used a variety of techniques for modeling complex social–ecological systems. Examples include spatial interaction models, cellular automata (Clarke and Gaydos, 1998; Messina and Walsh, 2001) and dynamic systems models (Evans et al., 2001a). In particular agent-based modeling approaches have been used to explore the decision-making processes of land managers in the context of spatial and social interactions. Reviews of applications of agent-based modeling approaches to landcover change scenarios can be found in Berger and Parker (2002) and Parker et al. (2002, 2003). Early ABMs were comparatively abstract representations that explored fundamental aspects of spatially explicit systems, but were not necessarily related to specific real-world applications (Epstein and Axtell, 1996). More recent applications of ABMs have produced comparatively complex representations of social–ecological systems (Berger and Ringler, 2002; Hoffmann et al., 2002; Kelley and Evans, submitted). Berger and Parker (2002) characterize these models in terms of whether environmental and agent model components are empirically grounded or designed, but not substantiated. Recent modeling projects are currently producing research grounded in a rich empirical foundation (Lim et al., 2002; Berger, 2004), including the research presented here.

A fundamental reason why agent-based approaches are an effective tool for exploring the complexities of landcover change processes in south-central Indiana is the spatial pattern and heterogeneous nature of topography in the area. This heterogeneity creates a patchy land suitability environment, which in part results in the complex spatial patterns observed. In concert with these land suitability heterogeneities are the variety of landowner characteristics, histories and experiences. Koontz (2001) found that while the majority of landowners in a 1997 household-level survey noted nonmonetary reasons in their landuse decision-making, the relative importance of nonmonetary factors varied by the size of the parcel owned by the landowner, household income, and educational attainment. Because our goal is to explore the spatial pattern of forest cover change, and in particular the decreasing patchiness of forest over time, these agent heterogeneities are important factors to consider in the context of land suitability and parcel characteristics. Agent-based modeling is an effective approach for exploring these dynamics because ABM's are spatially explicit. They allow for the creation of agents with different characteristics, and agent and landscape heterogeneities can be explored within the spatially explicit agent-based structure.

However, as with any spatial analysis applications, scale issues can affect the relationships observed. Scale issues have been explored in remotely sensed data (Quattrochi and Goodchild, 1997), vegetation and topography (Bian and Walsh, 1993), and in population-environment relationships (Walsh et al., 1999). The importance of scale issues has been expressed within an array of disciplines in the social sciences (Gibson et al., 2000; Evans et al., 2002). These same scale issues should be considered in the design, development, and application of models of LUCC that incorporate complex social–biophysical relationships (Evans et al., 2002). Previous research has indicated the importance of acknowledging scale effects when studying spatial interactions (Peterson, 2002) and many models are explicitly designed to be run at multiple scales of analysis to address these scale dependencies. Examples of these types of multi-scale models include raster-based ecosystem models (Voinov et al., 1999) and spatially explicit regression models such as with the CLUE model (Kok et al., 2001).

Because of the structure of associating agents with landscape partitions in ABMs, scale issues pose particular issues that must be considered in the design of models. Fig. 3 presents a diagram with a general representation of how these scale issues relate to the model design, development and application process. In particular, the linkage between the agent and the landscape must be designed with consideration of data validation and model structure. The model structure determines the smallest sized spatial partition that an agent can change in the landscape, which can be termed a Minimum Change Unit, analogous to a Minimum Mapping Unit in GIS nomenclature. However, even if a model is designed with a very small minimum change unit, data may not exist to validate the model at that spatial scale. Thus, the availability of high resolution landcover, topographic and soil data are considerations in the design and implementation of ABMs.

Another consideration in the design, implementation, and application of ABMs are the computational constraints posed by issues of spatial scale. These computational issues are affected by: (1) the spatial resolution at which the model operates, (2) the spatial extent of the model, (3) the temporal resolution of the model, (4) the temporal extent (duration) of the model, and (5) the number of simulated agents in the model (e.g. number of households or individuals). Few models operate at fine spatial resolutions over large spatial extents with a fine time interval for long time durations (Agarwal et al., 2002; Grove et al., 2002) in part because of the reality of computational constraints. Model developers must balance these various aspects that affect the applicability of a model to a particular scenario or application.

Last, model developers must consider how the model will be applied and who the intended model users are. Issues of spatial and temporal resolution and extent in part determine to which scenarios a model is applicable. Likewise, a model that incorporates aggregated agents (e.g. households or communities) has different policy relevance than a model with individuals as agents. These issues are collectively considered in the process of designing, implementing and applying models.

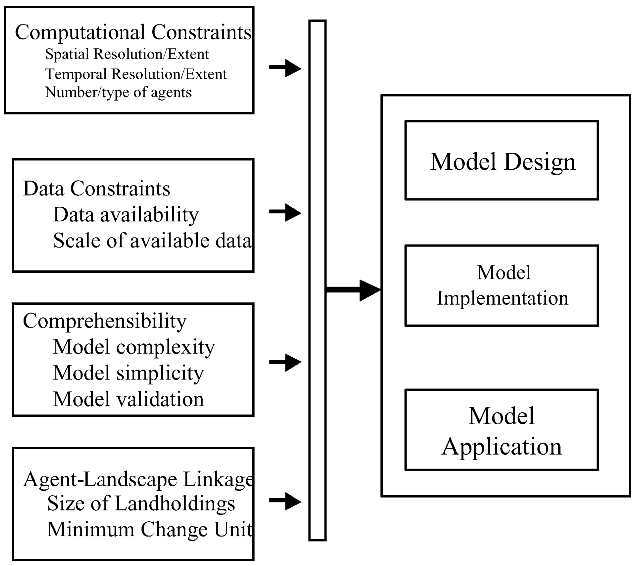

Fig. 3. Considerations in the model development process.

3. Data and methods

A broad array of data sources are used to represent key dynamics in the land use management system. These data sources include economic/price/wage, landcover, demographic, and agricultural census information. Crop price, timber price, and wage labor rate data are considered exogenous and uniform for all agents. Annual crop and timber prices were acquired for the major types of row crops and tree species harvested from 1940 to present. These prices are used to determine the economic benefit from agriculture and timber harvesting landuses in the model. Crop prices for corn and soybeans were aggregated to a single mean price/bushel measure derived from US Agricultural Census data sources. Timber prices for a group of hardwood species were also aggregated to a single index price per board foot for potential timber harvest income. As described below, our landcover data does not allow us to discriminate with a sufficient level of accuracy what crops are being grown in agricultural areas or what tree species compose forested areas over time. Thus, we simplify the model to a single agriculture class and a single timber/forest class in our model runs.

The change in off-farm wage labor rates is represented by the minimum wage between 1940 and the present. While household residents were employed in an array of occupations, many of which had wages higher than the minimum wage, we have used a coefficient term to modify the impact of the wage labor rate assuming that the trend in minimum wage increase is indicative of changes in income levels for occupations requiring more than a minimum wage.

Many of these data inputs are broad scale data and assumed to be homogenous within the study area (e.g. crop prices, wage data). However, there are several datasets that are critical to the scale issues being addressed in this research. These data include landcover, land ownership and surface topography. There is likely to be more local level variability in landcover and topography compared to factors such as crop prices and labor wages and so these data have been compiled at the highest spatial resolution possible.

3.1. Landcover data

Aerial photography was interpreted to produce a time series of landcover data for the following dates: 1939, 1958, 1967, 1975, 1980, 1987, and 1993. The aerial photography products ranged in scale from 1:15,000 to 1:40,000. Individual $9'' \times 9''$ index sheets were digitally scanned and visually interpreted using a combination of heads-up digitizing complemented by the hard copy product. A minimum mapping unit of 30×30 m was used to produce a series of forest/non-forest layers for each date. Sample areas were interpreted by several individuals to assess the consistency of the visual interpretation. An attribute code was used to tag polygons where the analyst had less confidence in the assigned landcover code. A post-processing error assessment was conducted to identify miscoded polygons and imprecise digitizing. From 1939 to 1998 forest cover in Indian Creek increased from approximately 43–60% of the landscape (Fig. 1). Small patches of forest cover loss are also evident during this time period, but the net pattern in the township is one of forest cover increase.

Fig. 2 shows the pattern of land cover and topography in Indian Creek Township. These figures, along with the data presented in Table 1, indicate that there is a relationship showing forest cover to be predominantly located in areas of steep topography and that afforestation in the last 60 years has occurred primarily in areas of steep topography. This is mainly due to the fact that areas of shallow slope are more suitable to agricultural production. However, it should be noted that many of these steeply sloped areas were cleared of forest at one time. It can be seen that (1) forests account for a larger proportion of the landscape in 1998 than in 1939 and (2) the forest regrowth has occurred in both shallow slope areas ($<4°$ surface slope) and steep slope areas ($>10°$ surface slope).

Two metrics generated from the multi-temporal landcover data can each be used for fitting the model. We currently are fitting the model to one individual metric, but have plans to fit the model to both the composition and pattern metrics simultaneously in the future. The first metric used for fitting the model is a measure of landscape composition, which is the proportion of different landscape components within a parcel. In this case, we use the percent of the parcel measured in forest because we have only two landcover classes and this measure thus, directly corresponds to the percent of the parcel in non-forest. The class area (CA) metric is a compositional measure that represents the total land area in a specific cover type on the parcel (i.e. forest)

$$\mathrm{CA} = \sum_{j=1}^{n} a_{ij}\left(\frac{1}{10,000}\right), \quad (1)$$

where a is the area of patches of type ij in hectares (assuming cell area is in square meters).

The other metric used for model fitting is landscape edge (TE), which is a measure of the total length of land cover boundaries in the parcel. For example, for a single patch of forest surrounded by an agricultural field, the amount of edge in the landscape is the perimeter of the forest patch. Total edge is calculated as

$$\mathrm{TE} = \sum_{k=1}^{m} e_{ik}, \quad (2)$$

where e_{ik} represents the total amount of edge of all patches of type i.

From 1939 to 1992, the study area experienced an increase in forest cover (Fig. 4), an increase in mean patch size and a decrease in the amount of edge in the landscape (Fig. 5). The trends in these two metrics are a result of the spatial location of forest regrowth during this period. Forest regrowth is occurring adjacent to pre-existing forest cover

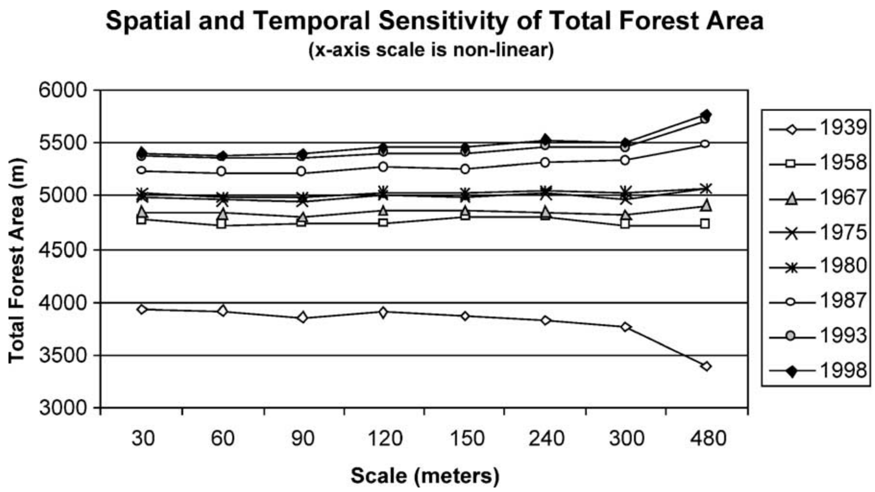

Fig. 4. Spatial and temporal sensitivity of total forest area in Indian Creek Township.

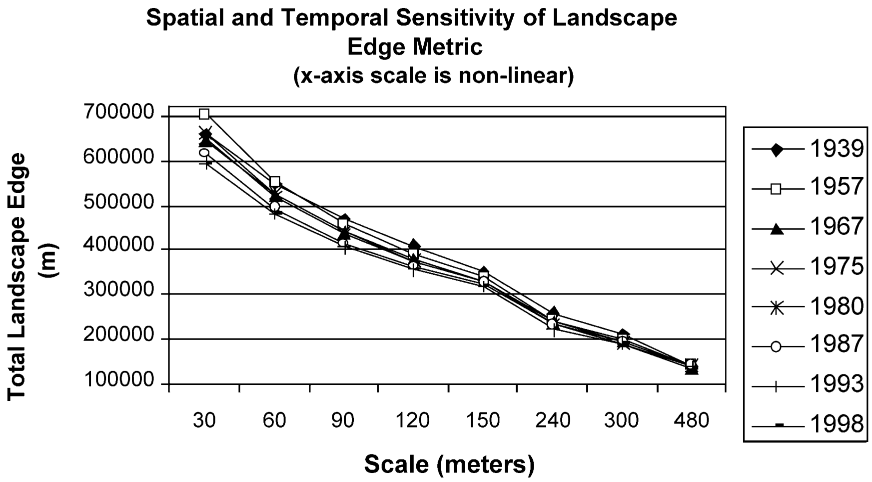

Fig. 5. Spatial and temporal sensitivity of landscape edge in Indian Creek Township.

and in patches of non-forest within large patches of forest cover, filling in these patches to create a more homogenous pattern of forest cover.

3.2. Land ownership

Land ownership boundaries were derived from historical parcel maps from 1928 to 1993 and from a digital GIS dataset provided by the Monroe County Tax Assessors office for 1997. These parcel boundaries provide the mechanism whereby agents are assigned to the landscape over time. Vector datasets of land ownership boundaries were constructed for each time point and converted to a raster representation for input into the main model.

3.3. Topography

Surface topography was generated from a Digital Elevation Model (DEM) with a spatial resolution of 10 m that was constructed from contour lines extracted from 1:24,000 scale topographic base maps. A slope surface dataset was derived from the 10 m DEM dataset using a moving window algorithm that fits a plane to a 3×3 window around the central output cell. Thus, the slope value for each 10 m cell was derived from a $30 \times 30\ \mathrm{m}^2$ area, but produces a slope dataset with a cell resolution of 10 m.

3.4. Scaling data

The observed multi-temporal landcover and agent ownership datasets were converted from vector representations to raster datasets with a spatial resolution of 30 m. These datasets and the topography dataset each were aggregated to produce a series of datasets at the following spatial resolutions: 60, 90, 120, 150, 240, 300, and 480 m. The landcover data and ownership data were scaled using a greatest-proportion rule whereby the landcover class or owner-identifier assignment to cells was made based on which class or owner-identifier composed the greatest proportion of the output cell using the POLYGRID command in the Grid module of Workstation ArcInfo 8.2. The raster slope dataset was scaled from the 10 m cell size to the coarser cell sizes by taking the mean value of the larger scale neighborhood using the AGGREGATE command in the Grid module of Workstation ArcInfo 8.2. The continuous cell values in the input slope dataset were thereby smoothed in the output datasets at each higher scale. All data were then converted to ASCII files for import to Matlab and integration into the model.

4. Model description

4.1. Model framework

The purpose of the research presented here is to demonstrate the scale dependence of the ABM constructed for south-central Indiana and identify what aspects of household-level ABMs with spatial structures similar to this model are sensitive to scale effects. Thus, in describing the model we emphasize those elements of the model that relate to spatial structure of the model. A more complete description of the economic and decision-making structure in our generalized model can be found in Kelley and Evans, submitted. The model is constructed within a spatially explicit framework whereby the landscape is partitioned into discrete land ownership units (parcels) that are associated with individual simulated agents (households). There are no stochastic components to the model structure. Parcels are composed of a set of regular sized cells, which in aggregate form a raster landscape of agent-owned cell groupings. Household agents have characteristics (e.g. wealth, labor supply, preferences, memory) as do cells (surface slope, current landcover).

At each time point, agents evaluate the portfolio of landuses in which their owned cells are occupied. Some landuses deliver an immediate monetary gain to households (farming), while others are investments providing forward-looking benefits. At each time interval, agents can make land conversion decisions on a cell-by-cell basis. Thus, the cell resolution determines the spatial precision with which landscape alterations can be made.

The general model is composed of a set of discrete modules within which system processes are programmed. These modules include: (1) agent decision-making dynamics; (2) household demographics; (3) landuse changes and biophysical processes, and (4) crop price, timber price, and wage labor rate tracking.

4.2. Agent characteristics and landuse decision-making

The agents in our simulation adapt their labor allocation L_i (where i refers to the possible set of activities) over time among the following potential landuses: farming *(farm)*, pasture/grazing *(gr)*, off-farm wage labor *(off-farm)*, aesthetics associated with the benefits of having a forested landscape *(aes)* and timber harvesting *(tree)*. Their utility is composed of pecuniary or profit components and non-pecuniary aspects such as aesthetic enjoyment. This allows the model to represent agents who manage their landscape as their primary source of income and agents who manage their landscape with less regard for financial returns associated with extractivist landuse activities. Each year agents observe the new set of exogenous (e.g. prices) and endogenous (e.g. land suitability) parcel and household features of their environment and they recalculate their myopic optimal allocation of labor.

We assume each household has a time or labor constraint regarding the labor they can supply. The modifier λ is the Lagrange multiplier on this constraint and L is the total available household labor hours. The agent must choose the L_i allocation in order to solve the constrained expected utility ($E(U)$) maximization problem at each time point:

$$\begin{aligned} E_t(U_t) = {} & \alpha_{\text{farm}}(P_{\text{farm}}A_{\text{farm}}L_{\text{farm}}^{\beta 1}M_{\text{farm}}^{\beta 2} - C_{\text{farm}} - Y_{\text{farm}}^2 \text{RA}\sigma_{\text{farm}}^2) \\ & + \alpha_{\text{tree}}(P_{\text{tree}}A_{\text{tree}}L_{\text{tree}}^{\beta 1}M_{\text{tree}}^{\beta 2} - C_{\text{tree}} - Y_{\text{tree}}^2 \text{RA}\sigma_{\text{tree}}^2) \\ & + \alpha_{\text{gr}}(P_{\text{gr}}A_{\text{gr}}L_{\text{gr}}^{\beta 1}M_{\text{gr}}^{\beta 2} - C_{\text{gr}} - Y_{\text{gr}}^2 \text{RA}\sigma_{\text{gr}}^2) \\ & + \alpha_{\text{off-farm}}(P_{\text{off-farm}}A_{\text{off-farm}}L_{\text{of-farm}}^{\beta 1}M_{\text{off-farm}}^{\beta 2} \\ & - C_{\text{off-farm}} - Y_{\text{off-farm}}^2 \text{RA}\sigma_{\text{of-farm}}^2) \\ & + \alpha_{\text{aes}}(P_{\text{aes}}A_{\text{aes}}L_{\text{aes}}^{\beta 1}M_{\text{aes}}^{\beta 2} - C_{\text{aes}} - \text{RA}\sigma_{\text{aes}}^2) \\ & + \lambda(L - L_{\text{farm}} - L_{\text{tree}} - L_{\text{gr}} - L_{\text{off-farm}} - L_{\text{aes}}) \end{aligned} \quad (3)$$

The parameter preference weight (α) is fundamental to the identifying agent heterogeneity, and each landuse component in the expected utility function has an associated preference weight. The model is calibrated to find the preference weights for each agent based on observed landcover changes over time. The farm, tree, grazing, and off-farm terms indicate pecuniary aspects of the decision-making process. The aesthetics term indicates the non-pecuniary 'output' derived from afforestation activities. RA represents the degree of risk aversion, and σ_1^2 represents the variance of income. Here the A_i values are aggregate representations of productivity enhancing inputs, but will be referred to as 'technology' for simplicity. In practice, A_i includes inputs such as physical capital (e.g. tractors, timber harvesting technology), human capital (education), the age of forest cover, the slope of the cell, soil quality, and any local production externality effects. Two forward-looking utility components that consider future alternative uses of the land are included. L represents labor allocation, and M is the number of cells in a particular landuse i. P is the price income for a landuse per unit area (cell). The exponents $\beta_1 = \beta_2 = 0.5$ for all i generate constant returns to scale in production and substitutability with respect to the inputs hours of labor and acres of land. Costs involved with each use (both fixed and transitional) are captured in the C term and Y is the productivity for a particular use.

Agents in the model can undertake four agricultural activities (farming, growing trees, harvesting trees, or fallowing the land); they also have the option of pursuing off-farm employment (Bloomington, the urban center of Monroe County at one time had a substantial number of manufacturing firms). Crop and timber prices are exogenous to the model; production by households does not affect these prices since the total aggregate households comprise a relatively small amount of the total market supply. The goal of each agent is to maximize his/her expected utility by balancing expected pecuniary profits from production and non-pecuniary aesthetic utility derived from the presence of forests.

In each year, the sequence of possible actions is as follows. At the beginning of the year, based on past information and their expectations about the future, each household makes a decision about the utility maximizing labor allocation land usage location bundle. Labor is then allocated to a set of landuse maintenance activities or conversions. The agent decides which cells optimally would be selected for the new landuses used on the ideal portfolio of land use allocations on the parcel. Thus, a key component to the model is the minimum spatial unit as defined by the cell resolution in the model (*minimum change unit*) that can be converted in the context of the overall parcel size. At the end of each turn household income is summed from farm and off-farm sources and cell characteristics (such as the age of forested cells) are updated.

The key aspects of the market setting are the multiple potentially heterogeneous agents who can differ based on the quality and/or quantity of land owned or in their risk and production preferences (including their preference for extractive landuses vs. more aesthetically oriented landuses). Labor inputs can be used for four activities: growing crops, growing trees, harvesting trees, or working off-farm. The model presented here does not incorporate uncertainty or imperfect information, although this is a dynamic we intend to add in the future.

Agents make their decisions by solving the constrained utility maximization problem, allocating labor to each of the four possible landuse activities. Agents make a parcel-level decision when determining the overall household labor allocation decision. This determines how much labor is allocated to each of the possible activities (including off-farm employment). At the parcel level the input biophysical data are averaged parcel characteristics. Given these full-parcel labor allocations, an agent makes a cell-level decision about where to employ the labor allocated to each activity. Consistent with earlier land use literature (Puu, 1997), it is assumed that an agent chooses the number of cells to change that both exhausts their total labor allocation across activities and provides the set of maximal improvements in utility. This requires that an agent be able to rank their cells in terms of suitability for particular uses and to pick the best cells to use each year. This allows the agent to identify the expected change in utility for each cell, and for each feasible use of the cell. The agent then selects the maximal cell-activity pairs until their total available labor allocation L_i for each activity is exhausted. This procedure is then repeated for every agent and every year of our simulation.

The agents' decisions involve first choosing the various labor allocations in order to maximize their income, then selecting the most appropriate cell locations to apply this allocated labor by specific landuse type. Each element of the expected utility expression includes a parameter preference weight (α). These parameter weights are fit for each parcel to adjust for the observed landcover changes that occur on a particular parcel. Thus, the heterogeneity and distribution of these parameter weights reflect the diversity of agent types in the model study area.

4.3. Model fitting and model evaluation

An iterative system is used to run the model sequentially using a set of specific parameters for each agent's utility functions. The modeled landscapes are compared to the observed landscapes constructed from historical aerial photographs. These comparisons are conducted using a series of metrics that describe the spatial pattern and composition of the landscape. These metrics include a composition metric, or measures of the landcover proportion in different classes, and a pattern metric—specifically landscape edge. The parameters are fit for each agent in relation to the landcover changes observed on his/her parcel over time. Thus, the metrics are calculated at the parcel level, and the parameter weights on the preferences are fit at the household level.

After a model run is completed and the measure of fit between the modeled landscape and observed landscape is determined, a gradient descent search method is used (*fminsearch* in Matlab) whereby the parameter weights are modified and the model is re-run to see if the new parameter weights produce an improved fit than the previous run (Kelley and Evans, submitted). This process is continued until there is no improved fit obtained through manipulation of the α values in the preference functions for each parcel/agent.

The model was fit to each of the following parameters:

1. preference for agriculture/farming/pasture (α_{farm}),
2. preference for aesthetics (α_{aes}),
3. a spatial externality measure for agriculture/pasture landuses,
4. a spatial externality measure for forest, and
5. strength of impact of surface slope on agricultural and forest regrowth.

The externality measures are used to allow the model to position land conversions in the context of a spatial neighborhood. The externality is implemented as a parameter in the model by increasing the utility of a landuse activity on a specific cell as a function of the number of adjacent cells that have the same landuse activity. Empirical data indicate that the afforestation that has occurred in Indian Creek Township has been primarily in areas proximal to existing forest (Fig. 2b). The externality parameter weights allow the strength of this spatial effect to be included on a parcel-by-parcel basis. Thus, parcels where afforestation has filled in gaps in existing forest patches will have a higher forest spatial externality parameter weight. Parcels where afforestation occurs far from existing forest patches will have a lower forest spatial externality parameter weight.

Fig. 2 and Tables 1 and 2 indicate the strong relationship between landcover and topography over the entire study area. Table 1 shows that 92.6% of steep slopes were forested and 69% of moderate slopes were non-forested in 1998. This relationship is exhibited graphically in Fig. 2 where the flat/dark areas in Fig. 2a correspond with the non-forested (white) areas in Fig. 2b. However, the landcover/topography correspondence varies from parcel to parcel. Some individual landholdings exhibit afforestation only on steeply sloped areas, which is indicative of the overall trend in the study area. Other areas exhibit afforestation occurring in flat areas (suitable for agricultural production) and deforestation on steep slope areas (marginal for agricultural production). A parameter weight is used to measure the strength of this landcover–topography relationship whereby a lower weight indicates a weaker relationship between landcover and topography on a parcel.

An important test of the logical consistency of a model is whether the modeled landscapes are a better match to the observed landscape at time point t than the initial landscape. The landscapes for each simulated agent are fit to a Null_R^2 value that is a measure of whether the model produces a better prediction than the landscape at

$t = 0$ (1939). The Null_R^2 is calculated as follows

$$\text{Null\_}R^2 = 1 - \frac{\text{SSR}}{\text{SSN}}, \text{ with} \tag{4}$$

$$\text{SSR} = \sum_{t=1}^{n} (\text{L}\hat{\text{C}} - \text{LC})^2 \text{ and} \tag{5}$$

$$\text{SSN} = \sum_{t=1}^{n} (\text{LC}_t - \text{LC}_1)^2, \tag{6}$$

where LC is either the landscape composition metric (percent forest on the parcel) or the landscape edge metric (total edge on the parcel). The SSN term compares the modeled landcover metric at time t to the observed landcover metric at $t = 0$. The SSR term is the residual sum of squares that compares the modeled landcover metric at time t to the observed landcover metric at time t. In other words, the Null_R^2 value is a comparison of the modeled landscape at time t to the initial landscape. It is a measure of whether the modeled landscape at time t is a better fit to the observed landscape at time t than the initial landscape at $t = 0$. This null model uses the landscape metric value at the first time period ($t = 1$) to predict all future dates, and then calculates the resulting null SSE. This is a more robust test of the model than a simple comparison of the modeled landscape at time t to the observed landscape at time t (Pontius and Malanson, 2004). The Null_R^2 is a comparison of the model predictions relative to the sum of squared error that would be obtained in the absence of any model. Null_$R^2 > 0$ indicates the model does better than nothing, Null_$R^2 < 0$ indicates that our model is worse than doing nothing, i.e. relative to using the 1939 cover to predict all future dates.

5. Results

5.1. Model performance

The following section describes how model performance changes as a function of the resolution of the input data and the resolution at which the model is run. Model runs were performed for each agent/parcel that showed landcover change in the 1939–1992 period. Due to aggregation effects, the actual number of agents in the entire landscape changes as a function of scale (Table 3). Thus, the model runs at the coarser cell resolutions included only a subset of the agents that exist at the finest cell resolution. For reasons of salience to the issue of scale in ABMs we focus here on the two parameters indicating the strength of preference for farming and forest aesthetics (α_{farm} and α_{aes}, respectively). While we attempted to fit the model to the 300 and 480 m spatial scales, the gradient descent parameter search method did not converge on a fit at these spatial resolutions. The parameter search method seeks to find optimal parameter values for each parameter. The search method is automatic, between model runs parameters are adjusted and then the model output is evaluated to determine if the new parameters improved the fit of the model. In some cases, the search method did not find a parameter space that would allow iterative runs to find more optimal parameter values and in these cases the iterative model runs did not lead to better model fits. We expect that this inability to fit the model at these resolutions is due to the high level of aggregation in the owner and landcover datasets.

Table 3
Landscape structure/precision at different scales

Cell size (m)	Number of cells in landscape	Number of agents	Number of agents with fewer than four cells
30	102,060	200	0
60	25,596	200	0
90	11,340	200	2
120	6399	200	5
150	4095	198	19
240	1640	192	61
300	1056	184	93
480	420	154	127

Fig. 6 presents the median of the Null_R^2 values for each individual agent demonstrating the ability of the model to fit parameters for each agent/parcel at each spatial scale (for both percent forest and landscape edge). These graphs indicate that the 60 m cell resolution model runs provided the best fits overall (largest proportion of agents with high Null_R^2 values). The 120 m resolution model runs produced fits that were worse than both finer and coarser resolutions. We believe this is a product of the gradient descent search algorithm not being able to find the correct parameter space at this particular resolution. With more iterations it is possible a better fit could have been found, but even with increasing the number of gradient search iterations at this scale we could not improve the fit at this resolution. The coarser cell resolutions do not produce as large a proportion of parcels/agents with good fits as the 60 m cell resolution, but there is not a clear trend of decreasing quality of fits

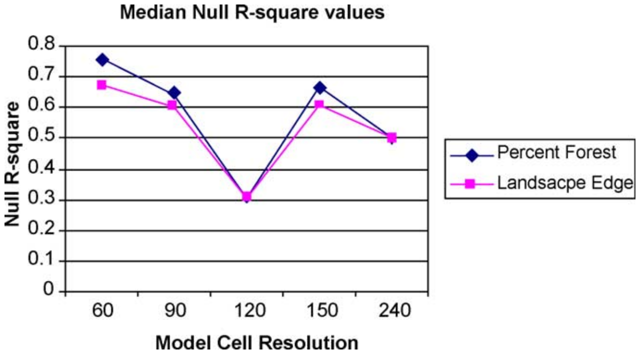

Fig. 6. Median null R^2 values by model cell resolution (for percent forest and landscape edge).

from 90 to 240 m cell resolution (Fig. 6). The median Null_R^2 values of the 150 m model runs are comparable to the 90 m runs both of which produce median agent fits that are higher than the 120 and 240 m runs.

5.2. Agent diversity

Histograms of parameter weights (α values) for model runs at each cell resolution are presented in Figs. 7 and 8.

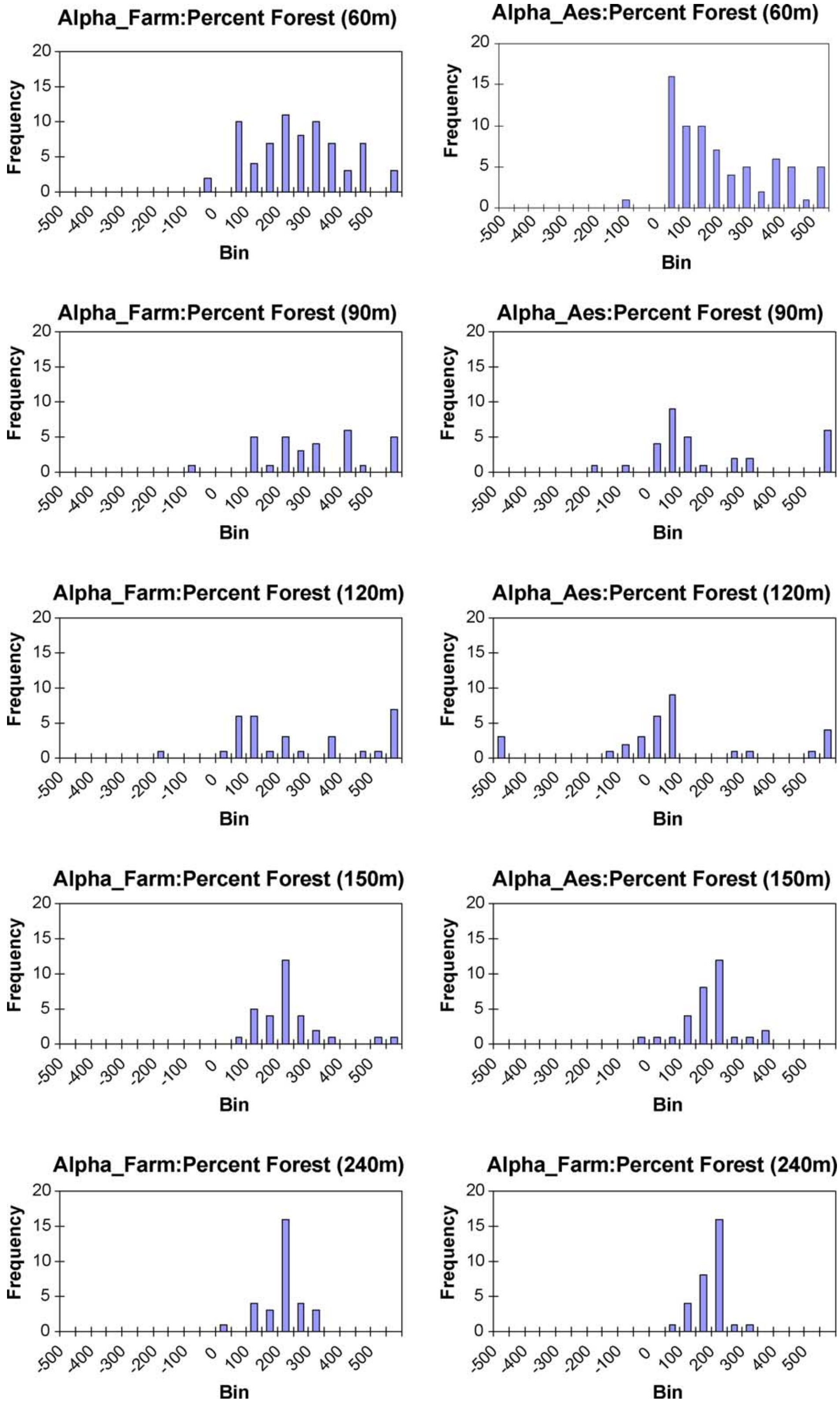

Fig. 7. Parameter fits for farming and aesthetics preferences by scale, fit to percent forest metric.

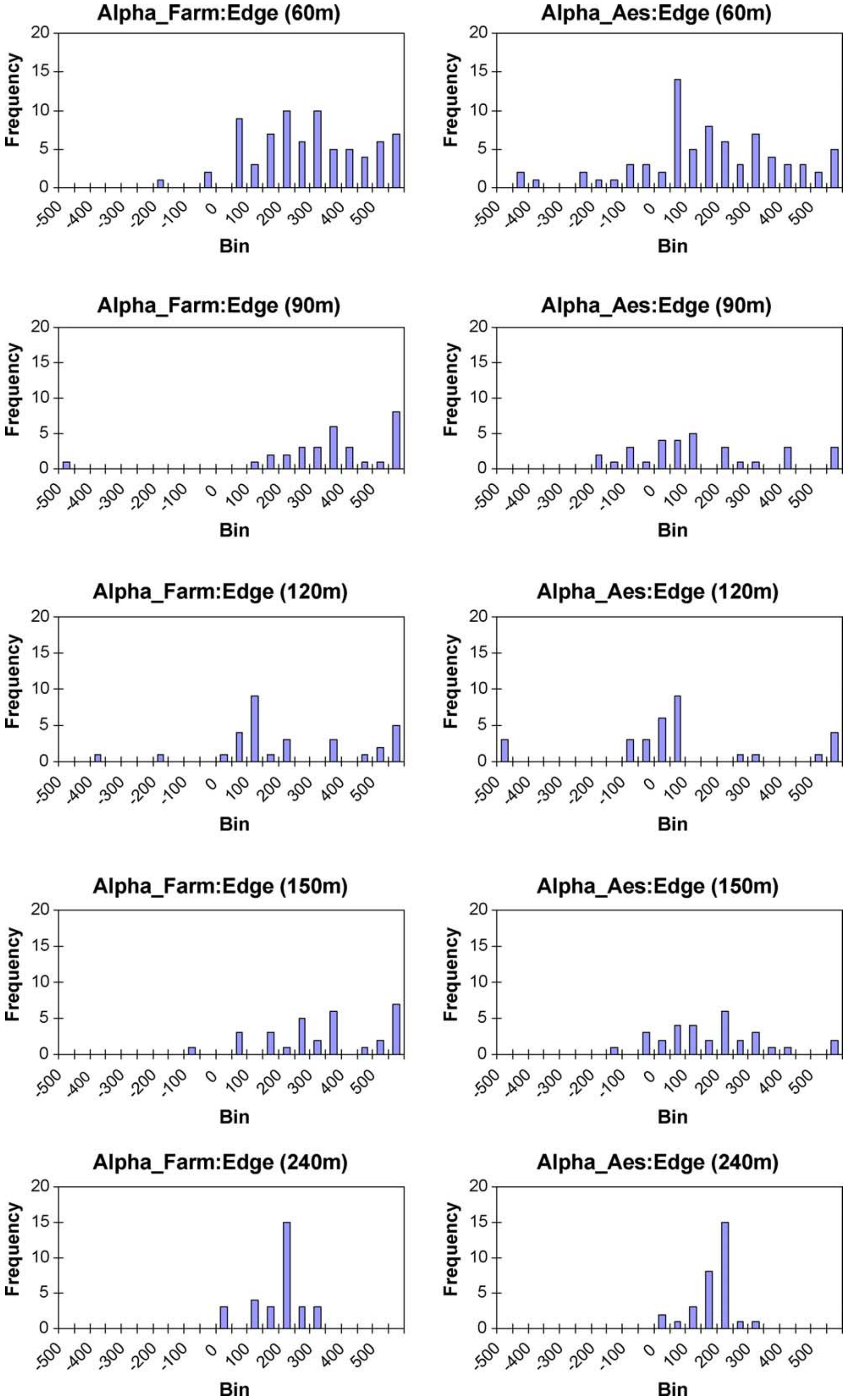

Fig. 8. Parameter fits for farming and aesthetics preferences, fit to landscape edge metric.

The x-axis shows the α values for each model parameter. Higher α values indicate a stronger preference for that landuse activity. The α values for farming and aesthetics represent a balance that is associated with the likelihood and amount (total spatial area) of afforestation occurring on the parcel in the 1939–1992 period. Agents with a higher α_{farm} value have a strong preference for farming (or non-forest) landuses. Agents with a high α_{aes} value have a stronger preference for forest on their parcel, including a preference for converting non-forest areas to forested areas over time. Fig. 7 shows model runs fitting landscape outcomes to the percent forest metric. Fig. 8 shows model runs fitting landscape outcomes to the landscape edge metric. These histograms indicate the number of agents in each parameter weight bin. Overall, the variance in parameter weights for the farming preference and the aesthetics preference decrease as the scale increases. The 240 m runs produced a relatively concentrated set of parameter weights or agent types in terms of total variance of parameter values among all households. In other words, the finest spatial resolution model runs generated a more diverse set of agent types than the coarser resolutions. Agent-type variance was lost at coarse spatial scales because (1) some agents dropped out of the landscape due to aggregation effects and (2) overall, agents have fewer cells in their parcels, simplifying the heterogeneity of landcover in their landscapes. At the 240-m cell size almost one-third of all agents had three or fewer cells in their parcels (61 out of 192, see Table 3).

6. Discussion

The change in cell size resulted in a variety of artifacts that affected how well the model was able to fit agent parameter weights. As the model cell resolution increases, the total number of agents in the model decreases due to agents dropping out if they were assigned to parcels whose spatial configuration results in aggregation loss. This occurred with small parcels or irregularly shaped parcels (e.g. moderate-sized rectangular parcels with a width much longer than the height). Thus, the total number of agents in the landscape declines from 200 at 30 m resolution to 154 at the 480 m resolution (Table 3). This also produces the by-product of erroneously associating territory from one parcel to an adjacent landowner. This can produce varying parameter weights across scales on an agent-by-agent basis.

One fundamental aspect of the coarse scale analysis was that there was less agent diversity (or variance in agent characteristics) produced by model runs at coarser spatial scales. This loss of agent diversity is due in part to the fact that some agents dropped out of the landscape due to aggregation effects. In addition, at coarser resolutions agents have fewer cells in their parcels, simplifying the heterogeneity of landcover in their landscapes. At the 240 m cell size almost one-third of all agents had three or fewer cells in their parcels (61 out of 192, see Table 3). In addition, as the cell resolution increases the number of agents with very few cells within their parcels increases. Aggregation errors of omission and commission affect the precision with which landcover changes are detected on the landscape. Very coarse cell sizes can cause either small patches of change to drop out of the change sequence data or, by errors of commission, create larger areas of change than actually occurred. Because the amount of landcover change detected on an agent's parcel changes as a function of scale, the parameter weights for any individual agent also can vary across scales.

The aggregation of cell units within parcels also impacts the allocation of labor by simulated agents. In the model structure, agents first evaluate what the optimal set of landuses is at each time point in the context of their current landuse allocations. The agents then evaluate where on their parcels they optimally should allocate labor to either maintain or convert landuses. With coarser cell resolutions agents must allocate labor to larger discrete spatial partitions on the landscape. In this way agents lose the ability to more precisely allocate labor to find an optimal distribution of labor given current price conditions and labor constraints.

Lastly, aggregation error also affects the spatial distribution of topography in the landscape. The main mechanism whereby topography influences model results is in the relationship between surface slope and land suitability for agriculture. Small areas of steep topography within large areas of shallow topography may be lost due to aggregation error, modifying the portfolio of land suitabilities on the parcel as a function of scale. The influence of this effect is a function of the spatial variability of topography. Because of the ridge/valley

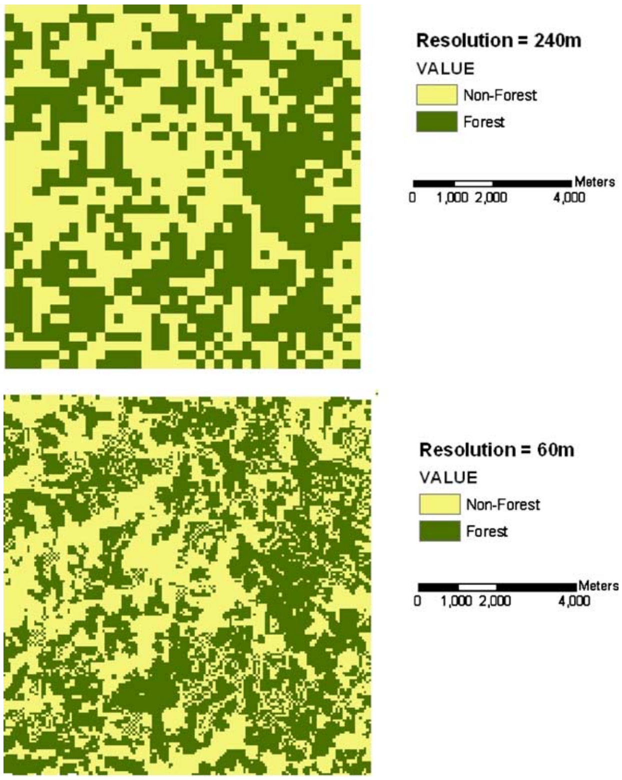

Fig. 9. Landscapes generated from model runs at 240 and 60 m spatial resolutions, fit to percent forest metric.

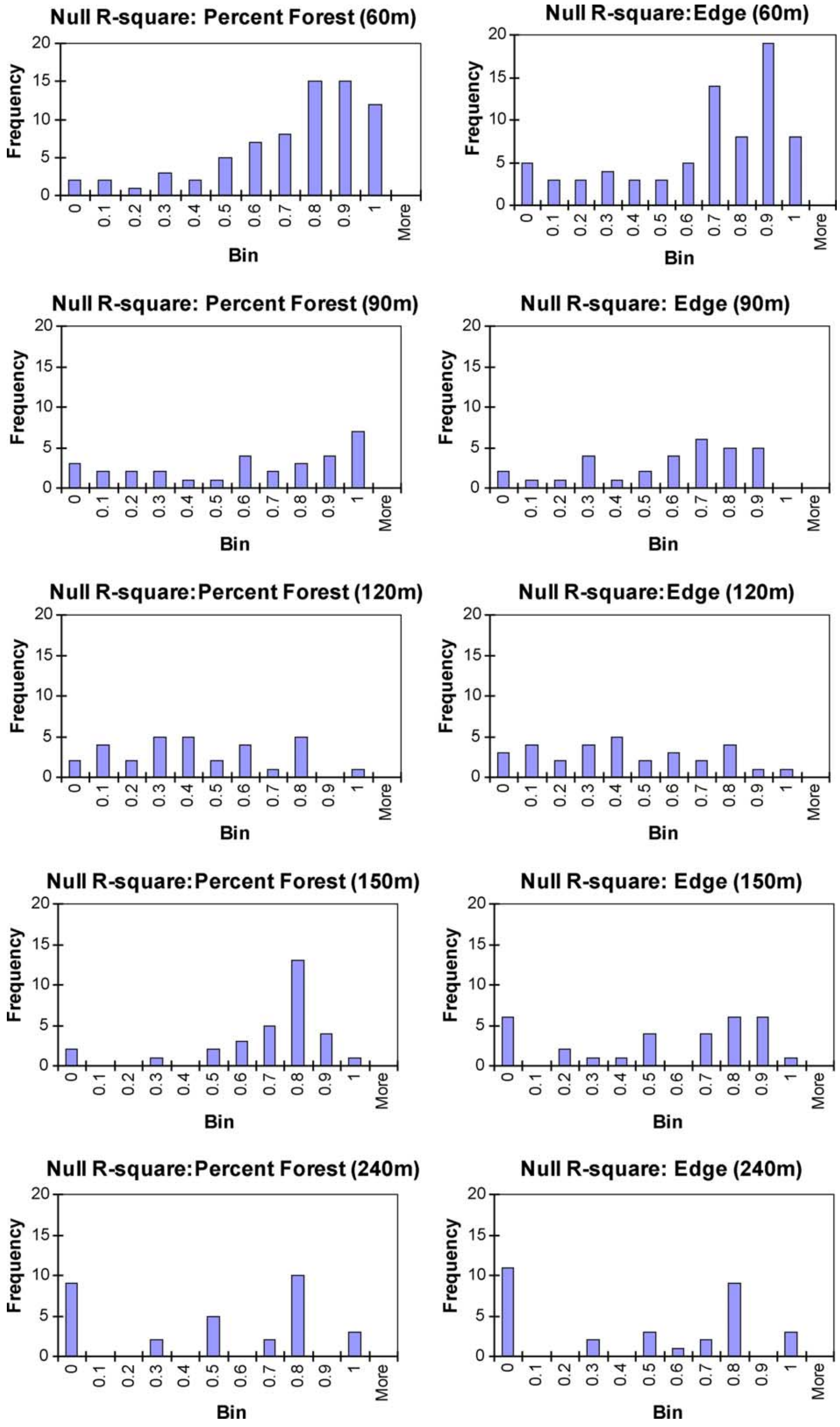

Fig. 10. R^2 values for model runs at 60, 90, 120, 150, and 240 m (fit to percent forest and landscape edge).

nature of topography in Indian Creek Township the error introduced due to spatial aggregation may be more prominent than in areas where topography is less heterogeneous.

The impact of increasing cell resolution on model performance can be summarized as follows:

1. loss of agents due to errors of omission,

2. homogenization of landcover and omission of small patches of landcover change,
3. reduction in precision with which agents can allocate labor,
4. smoothing of topography, homogenization of land suitability.

In aggregate, these factors result in a model that produces a more homogenous set of agent types, which reduces the value of the object oriented nature of the agent-based approach.

6.1. Fitting the model to landscape composition and edge metrics

The median Null_R^2 values do not suggest that either the percent forest or landscape edge metrics produced appreciably better fits (Fig. 6). Both the percent forest fits and the landscape edge fits produced the best results at the 60 m cell resolution and the worst results at the 120 m cell resolution. This was a surprising result , since the edge metric is highly sensitive to spatial resolution and the percent forest metric is much less sensitive to spatial resolution. Fig. 4 shows little variation in the measurement of percent forest in the observed data as a function of scale. The only anomalous values are at the highest level of aggregation (480 m) where the 1939 percent forest value deviates from the value at the finer cell sizes. The variance in percent forest is maintained through all dates allowing the model to establish parameter fits as this metric varies. Fig. 9 shows the different landscapes generated from the model using 60 and 240 m cell resolutions and visually demonstrates the difference in the spatial representations produced at these two spatial resolutions.

In contrast to the percent forest metric, the landscape edge metric decreases in variance as a function of increasing cell resolution. At the coarsest cell size there is almost no variance in landscape edge over time, while the 30 m cell resolution exhibits a range of over 100,000 m. Thus, we would expect the model to perform better at the finer spatial resolutions compared to the coarser resolutions when fitting to the landscape edge metric. This is because the lack of variance at the coarse spatial resolutions does not provide the model with information sufficient to revise parameter values to produce a landscape that more closely matches the observed data. However, Fig. 10 indicates that the model is able to produce positive Null_R^2 values for most agents, and Fig. 6 indicates that the median Null_R^2 values found using the landscape edge metric are comparable to Null_R^2 values found when fitting to the percent forest metric. This lack of variance in the edge metric perhaps explains the inability of the model to fit at the 300 and 480 m cell resolutions with the edge metric, but does not explain why fits were not possible at these resolutions when using the percent forest metric. In future research, we plan to evaluate a wider variety of metrics and produce models that fit to a combination of pattern and compositional metrics.

Because of these various scale related issues we recommend that models be constructed in the context of the spatial configuration issues addressed here and various constraints described in Fig. 3. In particular, models should be run at a range of spatial scales. Modelers can choose the bottom bound resolution by identifying the spatial resolution at which agents have sufficient partitions on their landscapes within which to make decisions (*minimum change unit*) and where the heterogeneity of the landcover and land suitability measures are adequately represented. The coarsest, or upper bound, resolution for model runs can be identified by the resolution at which appreciable data loss occurs. Within this range of resolutions the model results can be compared to examine the overall model fits and the diversity of agent characteristics generated. Both the model fits (in this case, the Null_R^2 values) and the heterogeneity of agent parameters should be examined in evaluating the most suitable spatial resolution for the model. A model with greater agent heterogeneity is not necessarily a more plausible model scenario, but should be considered as one candidate in the portfolio of potential simulations. Because one strength of ABMs is their ability to explore heterogeneity in complex systems, finding model scenarios that generate the greatest agent heterogeneity should be one modeling goal.

7. Conclusion

The model presented here demonstrates a scale dependence in model outcomes within an agent-based model of landcover change. The structure of households associated with discrete landscape partitions (land ownership areas/parcels) results in different model outcomes depending on the spatial scale of the input data and the scale of the model analysis. In this research, the finest resolution produced the most useful results. The overall fit was best at this spatial resolution and the model produced a more diverse set of agent types. A comparison of model results across scales indicated that agent variance was masked at coarser resolutions in part due to aggregation effects. However, this does not indicate that models should necessarily be run at the finest cell resolution possible. Because the model fits here do not decline monotonically as a function of scale, these results do not necessarily indicate that models run at a fine resolution produce better results than models run at coarser resolutions. Modelers must make a choice of cell resolution for modeling, but if the model is only run at a single cell resolution then it is not possible to know where on the monotonic trend the selected spatial resolution lies. Therefore, these results suggest that agent-based models of landcover change with a similar household/parcel framework should be run at a variety of spatial scales to explore the scale dependence of the model outcomes.

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