Assessing multiagent parcelization performance in the MABEL simulation model using Monte Carlo replication experiments

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Abstract. In this paper we present and test the functionality of a parcelization algorithm, implemented in our spatially explicit, agent-based land-use-change model which we call the Multi Agent-based Behavioral Economic Landscape (MABEL) model. In order to test the best possible spatial configuration of the algorithm and its efficiency compared with historically observed land-use changes, we employed a Monte Carlo simulation approach with a series of replication experiments across time, and compared observed changes between 1970 and 1990, and across two different landscapes in Michigan, USA. We compare the simulated parcel shapes with historically observed land-use changes using the landscape-ecology metric program, FRAGSTATS.

1 Introduction
Understanding the nature of the proximate and underlying driving forces of change in land use is challenging and often requires analysis of decisions at the individual, farm, or community levels, and of how they are influenced by policy and other factors at local, state, national, and international scales. Previous efforts to simulate land-use change have focused on a grid-cell modeling environment approach (for example, Gimblett, 2001; Parker and Meretsky, 2004; Pijanowski et al, 2005; Pontius, 2002). In such a modeling environment cells within a grid are assigned values related to their probabilities of undergoing transitions, which are often derived from the spatial relationships of a cell’s location in the grid compared with the location of ‘driver cells’ such as a road. Few attempts (for example, Brown et al, 2001), however, have been made to simulate land-use change of ownership parcels over space and time. Challenges of modeling in this environment include the need to determine how parcels subdivide after land transactions, how cells can be accounted for during transactions, and how boundaries for new ownership parcels are modified during land transactions.

The main research question that we are addressing in this paper is whether we can represent the spatial nature of parcelization during land-use change using geographic information systems (GIS) and the Swarm agent-based modeling (Minar et al, 1996; Swarm Development Group, 2000) environment. We report here the results of our Multi Agent-based Behavioral Economic Landscape (MABEL) model simulations of agents who are selected to participate in a simple stochastic land-bidding model. We use a historical parcel database, developed for Michigan, USA, to execute a series of Monte Carlo simulations. We compare simulated parcel patterns with observed parcel patterns by quantifying parcel shapes with the use of the landscape-ecology metric software FRAGSTATS (McGarigal et al, 2002).

The structure of the paper is as follows. First, we provide a brief overview of the MABEL model, and describe the agents and the process of introducing the agents in...
our simple land-bidding model. Second, we present the parcelization algorithm that we have developed. Third, we then describe the simulations that we conducted that test the applicability of the parcelization algorithm. Fourth, a description of the results of our simulations is presented, with a comparison of the results with historical parcel data. Fifth, we discuss the results of our study and highlight some of the important aspects of the results.

2 Overview of the MABEL model
A more complete description of MABEL can be found in Lei et al (2005), Alexandridis and Pijanowski (2002), and Alexandridis and Pijanowski (in review), respectively. We briefly describe the model components relevant to this study.

We recognize two different types of agents in MABEL. The first type are base agents, which are agents that own land and are placed into classes according to how they use the land. The other type are nonbase agents, which do not necessarily own land, but represent policymakers and local and regional planners, among others. Land-use-based attributes are the main drivers of the simulation, and land-use-driven acquisition of land in a land-bidding model represents the basic framework for determining base agents’ actions.

Each agent also contains a variety of attributes, which are either assigned to individual agents (socioeconomic), or are geographic (distance to a road) or biophysical (soil type, elevation, or slope). Agents can also interact within the Swarm development environment as they are able to draw (on the screen) and update themselves in the simulated world, and respond to users’ inquiries to view an agent’s attributes (see, Lei et al, 2005). Currently, an agent’s behavioral model is configured using a Bayesian belief network (BBN) model (see Alexandridis and Pijanowski, in review). For the purposes of this paper the BBN component is replaced with a stochastic simulator (see section 4.3) in order to examine the performance of the presented parcelization routine.

Our MABEL model contains a simple land-bidding model. Here, agents whose intention is to buy or sell are sent to the area ‘market’ (that is, simulation area), where they ‘bid’ for portions of existing parcels. Agents attempt to determine which land transaction represents the most desirable outcome. The land-bidding principle helps a potential agent who intends to ‘buy’ (for convenience we call these buyer agents, but they have not changed agent type—only announced their intentions to buy) make the most desirable transactions with any corresponding agent who desires to ‘sell’. The degree of the desirability of a transaction depends on how close the transaction quantity of the buyer agent meets that of the seller agent.

The land-bidding model first classifies all participating agents in different transaction groups by action type (that is, buy or sell), and sorts the agents in each group by the transaction quantity. Then, a buyer agent, which we call the premium buyer agent, possessing the largest transaction quantity in the buyer-agent list, checks the seller-agent list for a matched premium seller agent. If a match is successful a transaction is made between the premium buyer agent and the premium seller agent. If the premium seller agent does not sell all its land to the premium buyer agent, a new agent is created within the transaction area. The new agent inherits the attributes from the original seller agent, and adopts the land-use type of the buyer agent. The original premium buyer agent and premium seller agent update themselves, and are inserted back to the seller–buyer agent list, so long as they still satisfy the policy or rule requirement, such as minimum parcel size, of the transaction. The matching of premium buyer and premium seller agents for transactions continues until the buyer or seller lists are empty.
3 The parcelization algorithm in MABEL

3.1 Agent partitioning algorithm details

In the creation of the new agent a seller agent has to determine how to partition the original area into two blocks with a corresponding shape and position for the new agent (that is, the buyer agent) and seller agent after the land transaction. There are many ways to partition land to achieve multiple objectives of maintaining accessibility to a road, achieving width/length ratios that are allowable by local government, etc. To address this challenge we created several partition algorithms. To illustrate, assume that the following square area of sixteen cells (figure 1) is occupied by a seller agent, and each cell is indexed by a number (1 – 16). Furthermore, let five alternative shapes (labeled as A – E in figure 1) indicate the configuration (that is, extent) of land owned by the seller agent. These configurations are meant to show different parcel shapes, although these five are not exhaustive.

When the seller agent begins to sell its land, it scans and allocates land from its parcel in a specific order (or pathway), and ‘give’ (or allocates) the cells to the new agent until the required area of the new agent is reached. We consider sixteen different ‘scan and allocate pathways’ (see figure 2). The scanning algorithms (listed in the upper left corner of figure 2) are defined by the search pattern describing two scanning directions, namely the left-right and the top-down scanning directions. The scanning sequence of the algorithms always starts from one of the four corners of the closest confined rectangle that encloses the agent’s parcel. In all cases in figure 2 the buyer is attempting to acquire five cells (shown in dark gray). The original parcel from the seller not being considered in the acquisition is in light gray and areas outside the original parcel are white.

![Figure 1](image-url) Five selected hypothetical parcel shapes for the MABEL parcelization-algorithm experiment. The shape complexity indices are shown in the lower-right-corner graph. The area index is divided by a factor of 10 to enhance visualization. Shapes C and E display identical complexity index values, but they yield different parcelization-algorithm values.
Scan-and-allocate pathways: priority and order of scan algorithm
1 Vertical, top-left (VTL)
2 Horizontal, top-left (HTL)
3 Vertical, top-right (VTR)
4 Horizontal, top-right (HTR)
5 Vertical, bottom-left (VBL)
6 Horizontal, bottom-left (HBL)
7 Vertical, bottom-right (VBR)
8 Horizontal, bottom-right (HBR)
9 Square, top-left (STL)
10 Square, left-top (SLT)
11 Square, top-right (STR)
12 Square, right-top (SRT)
13 Square, bottom-left (SBL)
14 Square, left-bottom (SLB)
15 Square, bottom-right (SBR)
16 Square, right-bottom (SRB)

**Figure 2.** The sixteen scanning algorithms for shapes A–E in the MABEL parcelization routine. Cells shown in dark gray are those the buyer is attempting to purchase; cells in light gray are those in the original parcel which are not being considered in the purchase, and white cells are those outside the original parcel.
Because any scan-and-allocate order may produce different area or size allocation effects in different agent shapes, seller and buyer agents must select the partition algorithm that yields the best possible shape for the ownership parcel after the partition. We currently use three metrics for our assessment of the best possible parcel shape: occupancy/area ratio \( (O) \), width/height ratio \( (W) \), and landscape shape index \( (L) \). Each of these represents a different dimension of a parcel’s spatial configuration. The occupancy–area ratio describes how fully an agent occupies the contiguous scanned rectangle compared with its land transaction amount. The latter closely confined rectangle can be considered in landscape terms as the smallest possible patch. Forman (1995, page 116) describes it as “the dimensions of the narrowest rectangle that inscribes or just encloses a patch.” It resembles the patch-occupancy concept used often in landscape-ecology studies of animal populations (Fortin et al, 2003; Rutledge, 2003). The width/height ratio describes how much the confined rectangle departs from a square. Last, the landscape shape index accounts for the ‘clumpiness’ properties of an agent’s parcel, taking into account both the area and the perimeter of the parcel. We quantify this index by using a minor modification of McGarigal and Marks’s (1994) landscape-shape-index metric computed by FRAGSTATS (McGarigal et al, 2002). An inverse landscape shape index is used here to normalize it consistently with the other two metrics. Note that we can allow for other metrics to be considered especially when a simulation-specific policy or rule is needed.

3.2 An example of the parcelization algorithm functionality

Figure 3 illustrates how \( O \), \( W \), and \( L \) are calculated. For each distinct shape (original shape, buyer shape, remaining seller shape), we can define a minimum confined rectangle containing the entire parcel. As shown in the figure, the seller agent originally occupies the dark-shaded area; areas not shaded are not owned by the seller. The original seller area (we refer to this as the original area, to distinguish this from the area of the parcel after the parcel is divided following the land transaction) is mostly confined to rectangle A, the smallest confined rectangle. In this example, the seller agent begins a scan starting in the upper left corner of the smallest confined rectangle and then counts, in one of sixteen possible pathways (summarized in figure 1), the number of cells that is owned by the seller until the area to be acquired is reached. All of the cells within this area scanned by the seller are then allocated into a rectangle, B.

**Figure 3.** An example of quantity measurements of the best possible shape for a hypothetical MABEL agent: rectangle A, the smallest confined rectangle for the agent \( i \), is denoted by the thick-bordered rectangle, and contains the entire area of the agent \( i \); rectangle B denotes the scanned area for agent \( i \) (buyer agent’s smallest confined rectangle); and rectangle C denotes the unscanned area for agent \( i \).
as shown in figure 3. The unscanned area representing the remaining shaded agent area is confined in rectangle C, and is left to the seller agent.

If we consider only the original agent, the occupancy-area ratio for each agent type, \( i \), is:

\[
O_i = \frac{A_{i}}{A_{\text{A}}} = \frac{A_{\text{shaded}} - A_{\text{nonshaded}}}{A_{\text{rectangle A}}},
\]

(1)

where \( A \) represents area. The width/height ratio is

\[
W_i = \min \left\{ \frac{x_A}{y_A}, \frac{y_A}{x_A} \right\},
\]

(2)

where \( x_A \) and \( y_A \) represent the width and height of rectangle A respectively. And the landscape shape index is:

\[
L_i = \frac{\min(e_i)}{e_i},
\]

(3)

where \( e_i \) and \( \min(e_i) \) denote the length and the minimum length of the landscape patch perimeter, respectively. The derivation of \( L \) is provided in appendix A.

To select the best partition algorithm we consider the three parcel metrics above for the new agent (that is, the buyer, designated as b), and the seller agent, s. For a certain partition algorithm \( j \), let the agents select the algorithm with the largest value, \( B_j \):

\[
B_j = \frac{A_s}{A_i} (w_1 O_s + w_2 W_s + w_3 L_s) + \frac{A_b}{A_i} (w_1 O_b + w_2 W_b + w_3 L_b),
\]

(4)

where \( w_1 + w_2 + w_3 = 1 \), and \( w_1, w_2, \) and \( w_3 \) are defined as the weight configurations for \( O, W, \) and \( L \) of the best parcel shape, respectively.

4 Monte Carlo simulation analysis in MABEL

4.1 Simulation methodology

We used a Monte Carlo simulation approach to test the applicability of the parcelization algorithm in MABEL. Briefly, the Monte Carlo procedure we employed follows a five-step process described by Mooney (1997) in which we (a) defined the artificial pseudopopulation to reflect the ‘real’ observed population; (b) generated a pseudosample from that pseudopopulation; (c) estimated the statistics of interest, and stored it as a vector element; (d) repeated (b) and (c) \( t \) times, where \( t \) is the number of the replications; and (e) constructed a relative frequency distribution of all the estimated statistics across all \( t \) replications. An important consideration for all Monte Carlo experiments is the necessary size of the replications required to provide a sufficiently adequate confidence level on the observed behavior of the statistic of interest. We follow Kleijnen (2004), who suggested using the \( cn \) rule, where \( n \) is the number of attributes of interest, and \( c \) is a constant that is around 10 or more. Our goal is to examine attributes of parcelization across different landscapes (\( n = 2 \)—one county dominated by urban use and another county dominated by agriculture use) and different land-use types (\( n = 3 \); urban, agriculture, and forest). Thus, combining the landscape level and land uses, we get \( n = 2 \times 3 = 6 \). Therefore, a Monte Carlo simulation of sixty or more runs is necessary to analyze two landscape and three land uses.

4.2 Study areas

Our study area focused on two counties (Grand Traverse County and Mecosta County) located in Michigan, USA. Ownership parcels were digitized from plat maps\(^{(1)}\)

\(^{(1)}\) Paper parcel-boundary maps provided by the local townships' planning and zoning committee.
for eight 3 mile × 3 mile blocks and land uses were assigned to classes on the basis of aerial-photography interpretation. Data represent land uses in 1970, 1980, and 1990. A more detailed description of these data can be found in Brown et al. (2001). It was our aim to examine the effects and accuracy of simulation results across these two diverse landscapes which are common in the Midwest region. Grand Traverse County (hereafter GTC) blocks represent a dynamically changing urban–suburban landscape with several lakes that influence land use. In 1990 (table 1) the number of parcels observed in the 720 square miles of GTC was more than double the number observed in 1970. In 1970 the GTC study area had 9.4% of its parcels in urban use and the remainder were nearly equally divided between agricultural and forest use. In contrast, Mecosta County (hereafter MC) represents a more static landscape, with nearly two thirds of the area remaining agricultural through the twenty years. The number of parcels in urban use increased, however, nearly threefold, representing a greater proportional increase in urban parcels than that of GTC during the same period.

Table 1. Historical land-use parcel changes in eight 3 mile × 3 mile sampling frames in two Michigan counties (1970–90).

<table>
<thead>
<tr>
<th>Time scale</th>
<th>Number of parcels</th>
<th>Number changed</th>
<th>Percentage changed (2 way)</th>
<th>Percentage changed (3 way)</th>
<th>Urban parcels (%)</th>
<th>Agricultural parcels (%)</th>
<th>Forest parcels (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grand Traverse County</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1970</td>
<td>711</td>
<td>-</td>
<td></td>
<td></td>
<td>9.4</td>
<td>41.8</td>
<td>45.6</td>
</tr>
<tr>
<td>1980</td>
<td>1074</td>
<td>363</td>
<td>51.06</td>
<td>-</td>
<td>12.1</td>
<td>36.5</td>
<td>48.1</td>
</tr>
<tr>
<td>1990</td>
<td>1432</td>
<td>358</td>
<td>33.33</td>
<td>101.41</td>
<td>15.8</td>
<td>29.9</td>
<td>50.3</td>
</tr>
<tr>
<td>Mecosta County</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1970</td>
<td>651</td>
<td>-</td>
<td></td>
<td></td>
<td>3.6</td>
<td>66.8</td>
<td>26.3</td>
</tr>
<tr>
<td>1980</td>
<td>913</td>
<td>262</td>
<td>40.25</td>
<td>-</td>
<td>6.6</td>
<td>71.7</td>
<td>18.2</td>
</tr>
<tr>
<td>1990</td>
<td>1089</td>
<td>176</td>
<td>19.28</td>
<td>67.28</td>
<td>9.1</td>
<td>66.2</td>
<td>21.1</td>
</tr>
</tbody>
</table>

For each of the time periods the GIS data gridded to 30 m were provided as ASCII (American Standard Code for Information Interchange) raster cells of two layers—land-use and unique parcel (agent) ID—as inputs in the MABEL model. For each case we ran one hundred Monte Carlo simulations according to the initial simulation assumptions and configurations outlined in the next section. Three temporal categories of Monte Carlo simulations were generated:
(a) MABEL Monte Carlo simulations \((n = 100)\), from 1970 to 1980;
(b) MABEL Monte Carlo simulations \((n = 100)\), from 1980 to 1990;
(c) two-step MABEL Markov-Chain Monte Carlo simulations \((n = 100)\), starting from 1970, intermediate at 1980 (step 1), and continuing to 1990 (step 2), with the random seed reset between decadal runs. In practical terms this means that a simulation tournament similar to (a) was performed, but, in addition, the output of the simulation runs for 1970–1980 were fed back to a second set of simulations, similar to (b).

4.3 Simulation assumptions
Time steps in MABEL simulations were fixed such that the number of the transactions in the simulation equaled the number of transactions in the historical database for each county (see table 1). We conducted six sets of Monte Carlo replication experiments, two sets of the three temporal decadal simulations, for a total of 600 simulations. These experiments were repeated for each of the potential best algorithm-weight configurations [see assumption (g) below], which resulted in a total of 3000 different simulations for this study. We introduced the following stochastic conditions for the simulations.
(a) For each simulation there are fifty potential buyers and fifty potential sellers participating in the land-bidding procedure, which were chosen randomly from existing agents through the use of a random-number generator, with a different random seed for each run. This does not mean, however, that there are fifty transactions occurring in each replication—because the latter is dynamically determined by the model dynamics—but rather introduces an adequate level of stochasticity to detrend potential spatial dependencies that may exist in the initial landscapes.

(b) The basic agent classes are designed to represent a level-1 land-use classification—that is, urban (resident-type agents), agricultural (farmer-type agents), and forest—wetlands (forest-type agents) classes—and a set of allowable transactions were imposed as follows:

1. **sell action function:**
   - forest and wetlands → agriculture → urban; or
   - forest and wetlands → urban;

2. **buy action function:**
   - urban → agriculture → forest and wetlands; or
   - urban → forest and wetlands.

In practical terms this means that a forest-type agent can allocate his or her land to any of the three agent classes (that is, he or she can sell to another forest-type agent, or to either a farmer-type agent or a resident-type agent); a farmer-type agent can allocate his or her land to either another farmer-type agent or a resident-type agent; and a resident-type agent can only allocate his or her land to another resident-type agent. Similarly, in terms of the acquire action function (which is defined only for new agents created in the simulation), a new resident-type agent can acquire land from any of the three agent classes, a new farmer-type agent can acquire land from another farmer-type agent or a forest-type agent, and a new forest-type agent can only acquire land from another forest-type agent.

(c) Areas covered by water or previous urban use were excluded from the simulation.

(d) There are not restrictions imposed on the repeatability of agent actions throughout the Monte Carlo simulation replications. Thus, an agent already transitioned in a previous time step can freely participate in subsequent time steps of the simulation.

(e) Though the amount of land to be acquired was fixed at 50% of the seller's area, no restrictions were imposed on the location at which parcels could be acquired. Certainly, one can impose such a restriction, especially in cases in which one might want to test spatially dependent drivers of change (for example, the application of an ordinance that restricts development within a riparian corridor). However, to assess the parcelization algorithm we chose not to introduce a more complex bidding routine that included variable bidding amounts.

(f) We fixed the minimum transaction area and excluded from consideration parcels for which the width/height ratio exceeded certain values. Both of these factors are contained in MABEL because in the future we will introduce land-use zoning ordinances that encompass these two factors. In our Monte Carlo simulations we fixed the minimum transaction areas to sixty-four cells: the resolution of our land-use maps is 30 m$^2$ which amounts to approximately 0.5 acre, a minimum area that can be transitioned at any time. We also limited the range of dimensions that such a parcel can have to the following:

$$\frac{1}{4} \leq \frac{x}{y} \leq 4,$$

where $x$ and $y$ are the parcel's vertical and horizontal length dimensions respectively, as measured by the length of the line connecting the longest path in each direction.
We also compared five different parcelization-algorithm weight configurations (table 2) as described in equation (4). We tested whether the weight configurations have significant effects on the parcelization outcomes, given the shape properties of the three metrics of the $B_j$ algorithm. We introduced weight configurations both to test the importance of alternative geometrical and shape characteristics of a parcel, and to examine the sensitivity of the parcelization algorithm over a variable array of shapes. To address this, we altered the relative significance of each of the three components (configurations 1, 4, and 5), and compared them with relatively equally balanced weight configurations (configurations 2 and 3).

### Table 2. Parcelization-algorithm weight configurations ($w_1$, $w_2$, and $w_3$) for MABEL Monte Carlo simulation runs. $O$, $W$, and $L$ represent the occupancy-area ratio, width/height ratio, and landscape shape index, respectively.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>$w_1$ ($O$)</th>
<th>$w_2$ ($W$)</th>
<th>$w_3$ ($L$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3/5</td>
<td>1/5</td>
<td>1/5</td>
</tr>
<tr>
<td>2</td>
<td>2/4</td>
<td>1/4</td>
<td>1/4</td>
</tr>
<tr>
<td>3</td>
<td>1/3</td>
<td>1/3</td>
<td>1/3</td>
</tr>
<tr>
<td>4</td>
<td>3/6</td>
<td>1/6</td>
<td>2/6</td>
</tr>
<tr>
<td>5</td>
<td>3/7</td>
<td>1/7</td>
<td>3/7</td>
</tr>
</tbody>
</table>

#### 4.4 Monte Carlo analysis

Output from the simulations were introduced to FRAGSTATS (McGarigal et al, 2002) and a series of landscape-ecology spatial pattern metrics were computed for each of the 3000 replications of the experiment. The use of landscape-ecology spatial pattern metrics to assess spatial accuracy has been adopted by Pijanowski et al (2005) to test the ability of the artificial-neural-network-based landscape transformation model to simulate land-use changes in two large metropolitan areas in the upper Midwest area of the United States. FRAGSTATS computes spatial pattern metrics for three different levels of spatial patterns: patch, class, and landscape. We employ the latter two here for this study and focus on those spatial pattern metrics that quantify shape. FRAGSTATS calculates summary statistics for a class pattern metric (for example, means, standard errors) for cells in patches (that is, parcels) belonging to the same class—land use in our case. Landscape shape metrics calculate summary statistics for entire landscapes without regard to classes contained in the landscape. We report on class shape metrics whenever we compare land uses between locations and between temporal simulations. Landscape shape metrics are used to compare shape metrics between locations and/or years.

Analyses of shape-metric data were accomplished through the use of the SPSS statistical package (SPSS Inc., 2003). Class shape metrics used are: shape index, clumpiness index, fractal-dimension index, and landscape division index. Landscape shape metrics used are: shape index, fractal-dimension index, related circumscribing circle, landscape shape index, contiguity index, perimeter–area fractal dimension, and landscape division index. The shape-metric equations and descriptions can be found in McGarigal et al (2002), Larg (2003), or in Forman (1995).

We also conducted partial correlation analysis to examine how the shape metrics correlated with one another. This analysis, following Sokal and Rholf (1995), and Sprott (2000), accounted for differences in location (county), year, and the weight configurations.

We used the Kolmogorov–Smirnov test (KS) (D'Agostino and Stephens, 1986; Massey, 1951) to examine the null hypothesis that the spatial patterns generated by the parcelization routine do not significantly differ from a random distribution of
spatial patterns. The KS test utilizes an empirical cumulative distribution function (CDF), \( \hat{F}(x) \),

\[
\hat{F}(x) = \begin{cases}
0, & -\infty < x_i < x_1, \\
\frac{i}{N}, & x_i \leq x_i < x_{i+1}, \quad \forall i = 1, 2, ..., N - 1, \\
1, & x_N \leq x_i < \infty,
\end{cases}
\]

where \( x_i \) is the \( i \)th observation in the sample, ranging from 1 to \( N - 1 \) (\( N \) is the total number of observations in the sample, in ascending order). The KS tests the underlying empirical CDF against a normal distribution, with mean \( \mu \) and standard deviation \( \sigma \),

\[
\mu = \frac{\sum_{i=1}^{N} x_i}{N}, \quad \text{and} \quad \sigma = \frac{\sum_{i=1}^{N} \frac{x_i}{N} \sum_{i=1}^{N} x_i}{N - 1},
\]

by calculating the theoretical cumulative distribution function, \( F_0(x_i) = F_{0,i}[(x_i - \mu)/\sigma] \), and computing the differences as such,

\[
D_i = \hat{F}(x_{i+1}) - \hat{F}(x_i), \quad \text{and} \quad \bar{D}_i = \hat{F}_0(x_i) - F_0(x_i).
\]

The KS statistic is \( Z_{KS} = N^{1/2} \max_i(|D_i|, |\bar{D}_i|) \), and the two-tailed probability level is

\[
p = 1, \quad \text{if} \quad 0 \leq Z_{KS} < 0.27;
\]

\[
p = 1 - \frac{2.506628(Q + Q^9 + Q^{25})}{Z_{KS}}, \quad \text{if} \quad 0.27 \leq Z_{KS} < 1,
\]

where \( Q = \exp(-1.2337Z_{KS}^2) \);

\[
p = 2Q - Q^4 + Q^9 - Q^{16}, \quad \text{if} \quad 1 \leq Z_{KS} < 3.1,
\]

where \( Q = \exp(-2Z_{KS}^2) \); and

\[
p = 0, \quad \text{if} \quad Z_{KS} \geq 3.1.
\]

Also, we used reliability analysis to assess how reliable our stochastic simulation methods were in capturing the variability present in our real-world observed changes. We used Cronbach’s alpha as a measurement of reliability (Nunnaly, 1978). It is the lower bound of the true reliability of the sample. We can define it as the part of

\begin{table}[h]
\centering
\caption{Partial correlation coefficients for landscape shape metrics. The correlation analysis accounts for differences in the area (county), simulation year (through replication experiment), and simulation configuration (through algorithm calibration weights). Figures in parentheses are corresponding two-tailed significance levels (\( p \)).}
\begin{tabular}{|l|c|c|c|}
\hline
 & shape index & fractal-dimension index & related circumscribing circle \\
\hline
Shape index & 1.000 & 0.999 (<0.001) & 0.984 (<0.001) \\
Fractal-dimension index & 0.999 (<0.001) & 1.000 & 0.987 (<0.001) \\
Related circumscribing circle & 0.984 (<0.001) & 0.987 (<0.001) & 1.000 \\
Landscape shape index & 0.810 (<0.001) & 0.812 (<0.001) & 0.801 (<0.001) \\
Contiguity index & -0.525 (<0.001) & -0.548 (<0.001) & -0.570 (<0.001) \\
Perimeter–area fractal dimension & 0.202 (<0.001) & 0.180 (<0.001) & 0.116 (<0.001) \\
Landscape-division index & -0.009 (0.632) & -0.001 (0.937) & 0.008 (0.647) \\
\hline
\end{tabular}
\end{table}
the variability in our sample results that can be accounted for by differences in the parcels (spatial items). That is, we expect that the Monte Carlo simulation results will vary across land uses owing to the size, shape, and individual spatial characteristics of the initial (original) land parcels, and not owing to the stochastic nature of the simulation. The mathematical form of Cronbach’s alpha is,

$$\alpha = k \left( \frac{\text{Cov} / \text{Var}}{1 + (k - 1) \left( \frac{\text{Cov} / \text{Var}}{\text{eq. } V} \right)} \right) \approx \frac{n \bar{r}}{1 + (n - 1) \bar{r}}$$,

(13)

where \( \alpha \) is Cronbach’s coefficient, or alpha, \( k (= n) \) is the number of items in the sample, and \( \bar{r} (= \text{Cov} / \text{Var}) \) is the ratio of the average interitem covariance to the average item variance, but under the assumption of equal variances of the sample items (right side of \( \approx \), where \( \text{eq. } V \) denotes equal variance), it denotes the interitem correlation coefficient. When \( r \) is used, the ratio is also known as \textit{standardized item alpha}, or the \textit{Spearman–Brown stepped-up reliability coefficient}. Cronbach’s alpha values range from 0.0 to 1.0, with greater values reflecting greater reliability. Nunnaly (1978) has argued that alpha values > 0.7 are best, although values between 0.5 and 0.7 could cautiously be considered as reliable (Limnios and Nikulin, 2000).

5 Assessment of the Monte Carlo results

Table 3 summarizes the results of a partial correlation analysis of class and landscape shape metrics computed for the six sets of Monte Carlo simulations. This analysis accounts for the differences in location, year, and weight configuration. We can see from this table that there are four different groups of shape metrics. The first group contains the shape index, fractal-dimension index, related circumscribing circle, and landscape shape index. All are highly correlated with one another, with \( p < 0.001 \); all correlation coefficients are greater than 0.800. The contiguity index, on the other hand, is inversely correlated with the first four groups and has correlation coefficients around 0.5 with the metrics in the first group. The perimeter–area fractal-dimension index has small correlation coefficients with the first four shape metrics, which are not significant. The landscape division index differs from the other three groups of metrics, with correlation coefficients near 0.0 and low significance levels.

The KS test was computed across configuration weights for the two locations and for the three temporal simulation sets for each of the five landscape metrics. The results (table 4) indicate that, in the overwhelming majority of the Monte Carlo simulations, we can reject the null hypothesis that the landscape metrics of the sample replications

<table>
<thead>
<tr>
<th>landscape shape index</th>
<th>contiguity index</th>
<th>perimeter–area fractal dimension</th>
<th>landscape-division index</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.810 (&lt;0.001)</td>
<td>−0.525 (&lt;0.001)</td>
<td>0.202 (&lt;0.001)</td>
<td>−0.009 (&lt;−0.632)</td>
</tr>
<tr>
<td>0.812 (&lt;0.001)</td>
<td>−0.548 (&lt;0.001)</td>
<td>0.180 (&lt;0.001)</td>
<td>−0.001 (&lt;−0.937)</td>
</tr>
<tr>
<td>0.801 (&lt;0.001)</td>
<td>−0.570 (&lt;0.001)</td>
<td>0.116 (&lt;0.001)</td>
<td>0.008 (&lt;−0.647)</td>
</tr>
<tr>
<td>1.000</td>
<td>−0.422 (&lt;0.001)</td>
<td>0.517 (&lt;0.001)</td>
<td>0.348 (&lt;0.001)</td>
</tr>
<tr>
<td>−0.422 (&lt;0.001)</td>
<td>1.000</td>
<td>0.281 (&lt;0.001)</td>
<td>−0.088 (&lt;0.001)</td>
</tr>
<tr>
<td>0.517 (&lt;0.001)</td>
<td>0.281 (&lt;0.001)</td>
<td>1.000</td>
<td>0.155 (&lt;0.001)</td>
</tr>
<tr>
<td>0.348 (&lt;0.001)</td>
<td>−0.088 (&lt;0.001)</td>
<td>0.155 (&lt;0.001)</td>
<td>1.000</td>
</tr>
</tbody>
</table>
observe a random normal distribution. The findings support the fact that the parcelization algorithm provides a nonrandom distribution of parcels across the landscape.

Figure 4 (over) summarizes the mean perimeter–area fractal-dimension index across a hundred simulations organized by location and across the three temporal simulation groups. We use an illustration of simulation iterations, graphed through the use of a line following a well-known approach in iterative agent-based modeling presented by Deadman and Schlager (2002), in order to visualize the dynamics of the simulation. The entire simulation mean and 95% confidence interval are also plotted here with solid and dashed lines, respectively. Three observations can be made from this figure: (1) the variation across the iterations is evenly distributed around the mean—in other words, there is no obvious increasing or decreasing trend; (2) in a comparison of the two areas (estimated and observed), the amount of variation observed seems to be very similar; and (3) the perimeter–area fractal dimensions in GTC and MC, compared with both ten-year periods (that is, 1970–80; 1980–90), are slightly larger for the 1970–90 simulation sets.

If the different landscape shape metrics (for example, fractal-dimension index) for the 1970–1980 simulations are compared (figure 5), for both locations, MC produces few large deviations from the mean and more consistency between values within simulations for the fractal-dimension index. This is probably due to the fact that the MC landscape contains few very large agricultural parcels, compared with the GTC landscape, which occasionally result in larger deviations from the mean when these parcels subdivide.

Mean shape-index values—according to land use, location, and year—plotted across simulation runs, are shown in figure 6. The values for shape index are greater than or

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Grand Traverse County</th>
<th>shape-index mean</th>
<th>fractal-dimension index</th>
<th>related circumscribing circle index</th>
<th>contiguity index</th>
<th>landscape-division index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970 – 1980</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (3-1-1)</td>
<td>3.678 (&lt;0.001)</td>
<td>2.418 (&lt;0.001)</td>
<td>1.249 (0.088)</td>
<td>7.197 (&lt;0.001)</td>
<td>16.734 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>2 (2-1-1)</td>
<td>4.043 (&lt;0.001)</td>
<td>2.104 (&lt;0.001)</td>
<td>1.036 (0.234)</td>
<td>7.483 (&lt;0.001)</td>
<td>16.807 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>3 (1-1-1)</td>
<td>4.379 (0.000)</td>
<td>1.476 (0.026)</td>
<td>1.488 (0.024)</td>
<td>7.868 (0.000)</td>
<td>16.837 (0.000)</td>
<td></td>
</tr>
<tr>
<td>4 (3-1-2)</td>
<td>3.601 (&lt;0.001)</td>
<td>2.258 (&lt;0.001)</td>
<td>1.463 (0.028)</td>
<td>7.626 (&lt;0.001)</td>
<td>16.704 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>5 (3-1-3)</td>
<td>3.589 (0.000)</td>
<td>2.333 (0.000)</td>
<td>1.150 (0.142)</td>
<td>7.714 (0.000)</td>
<td>16.762 (0.000)</td>
<td></td>
</tr>
<tr>
<td>1980 – 1990</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (3-1-1)</td>
<td>3.832 (&lt;0.001)</td>
<td>2.421 (&lt;0.001)</td>
<td>1.116 (0.166)</td>
<td>7.423 (&lt;0.001)</td>
<td>16.740 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>2 (2-1-1)</td>
<td>4.210 (&lt;0.001)</td>
<td>2.335 (&lt;0.001)</td>
<td>1.333 (0.057)</td>
<td>7.285 (&lt;0.001)</td>
<td>16.633 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>3 (1-1-1)</td>
<td>4.074 (&lt;0.001)</td>
<td>1.612 (0.011)</td>
<td>1.175 (0.127)</td>
<td>8.154 (&lt;0.001)</td>
<td>16.734 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>4 (3-1-2)</td>
<td>3.581 (&lt;0.001)</td>
<td>2.685 (&lt;0.001)</td>
<td>1.391 (0.042)</td>
<td>7.698 (&lt;0.001)</td>
<td>16.663 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>5 (3-1-3)</td>
<td>3.862 (&lt;0.001)</td>
<td>2.517 (&lt;0.001)</td>
<td>1.332 (0.058)</td>
<td>7.348 (&lt;0.001)</td>
<td>16.733 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>1970 – 1990</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (3-1-1)</td>
<td>5.017 (&lt;0.001)</td>
<td>3.454 (&lt;0.001)</td>
<td>1.061 (0.210)</td>
<td>6.862 (&lt;0.001)</td>
<td>15.825 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>2 (2-1-1)</td>
<td>4.749 (&lt;0.001)</td>
<td>3.290 (&lt;0.001)</td>
<td>0.567 (0.905)</td>
<td>7.292 (&lt;0.001)</td>
<td>15.886 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>3 (1-1-1)</td>
<td>4.487 (&lt;0.001)</td>
<td>0.841 (0.479)</td>
<td>1.502 (0.022)</td>
<td>6.680 (&lt;0.001)</td>
<td>16.148 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>4 (3-1-2)</td>
<td>4.964 (&lt;0.001)</td>
<td>2.999 (&lt;0.001)</td>
<td>0.973 (0.300)</td>
<td>7.583 (&lt;0.001)</td>
<td>15.779 (&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>5 (3-1-3)</td>
<td>4.552 (&lt;0.001)</td>
<td>2.966 (&lt;0.001)</td>
<td>1.185 (0.121)</td>
<td>7.298 (&lt;0.001)</td>
<td>15.924 (&lt;0.001)</td>
<td></td>
</tr>
</tbody>
</table>

a Empirical cumulative distribution function values for calculation of the KS statistic were calculated from the sample data.

b To test the null hypothesis: the sample distribution is normal.
equal to 1.0; larger values reflect patches that depart in shape from a perfect square of the same size. In most of the six simulation sets forest use has the largest mean shape index, followed by agricultural and then urban use. The differences in mean shape-index values between the two decadal simulations (1970–80 and 1980–90) are not great. However, of significance are the 1970–90 simulations in MC; here, the mean shape index fluctuated greatly between simulations and contained values greater than 1.40 in approximately 20% of the simulation runs. Such values were not observed in the two decadal simulations or any of the three temporal simulations in GTC. Given that there are few large patches of agriculture in this landscape, some simulations may have resulted in highly irregular shapes, especially during the early portion of the simulation.

The land-use-class shape metrics (figure 7) are shown for the sequential decades 1970–80, 1980–90, and 1970–90 across the two counties, GTC [figures 7(a)–7(c)], and MC [figures 7(d)–7(f)], for the Monte Carlo simulation replications. The lines represent the mean shape-index values for each of the three land uses, for 1970–80 (solid) and 1980–90 (dotted), for the two counties observed. Thus, each of the lines represents the observed data, by which we can compare the effects of the weight configurations on our simulations. Each of the data points represents the mean of the hundred-step iterations for a given year, a given configuration, and a given county. Error bars represent the range of the 95% confidence intervals from the means. Five important observations can be made of this graph. First, in a majority of cases (four out of six graphs) the simulations produced shape indexes smaller than observed. Second, even weight configurations produce shape values that are larger than those of uneven configurations in three out of the six cases. Third, some simulation replications yield

Table 4 (continued).

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Mecosta County</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>shape-index mean</td>
</tr>
<tr>
<td>1970–1980</td>
<td></td>
</tr>
<tr>
<td>1 (3-1-1)</td>
<td>5.161 (&lt;0.001)</td>
</tr>
<tr>
<td>2 (2-1-1)</td>
<td>6.996 (&lt;0.001)</td>
</tr>
<tr>
<td>3 (1-1-1)</td>
<td>7.314 (0.000)</td>
</tr>
<tr>
<td>4 (3-1-2)</td>
<td>5.294 (&lt;0.001)</td>
</tr>
<tr>
<td>5 (3-1-3)</td>
<td>5.897 (0.000)</td>
</tr>
<tr>
<td>1980–1990</td>
<td></td>
</tr>
<tr>
<td>1 (3-1-1)</td>
<td>5.907 (&lt;0.001)</td>
</tr>
<tr>
<td>2 (2-1-1)</td>
<td>6.705 (&lt;0.001)</td>
</tr>
<tr>
<td>3 (1-1-1)</td>
<td>7.010 (&lt;0.001)</td>
</tr>
<tr>
<td>4 (3-1-2)</td>
<td>6.161 (&lt;0.001)</td>
</tr>
<tr>
<td>5 (3-1-3)</td>
<td>5.873 (&lt;0.001)</td>
</tr>
<tr>
<td>1970–1990</td>
<td></td>
</tr>
<tr>
<td>1 (3-1-1)</td>
<td>6.453 (&lt;0.001)</td>
</tr>
<tr>
<td>2 (2-1-1)</td>
<td>8.164 (&lt;0.001)</td>
</tr>
<tr>
<td>3 (1-1-1)</td>
<td>7.318 (&lt;0.001)</td>
</tr>
<tr>
<td>4 (3-1-2)</td>
<td>7.318 (&lt;0.001)</td>
</tr>
<tr>
<td>5 (3-1-3)</td>
<td>6.397 (&lt;0.001)</td>
</tr>
</tbody>
</table>
insignificantly different shape indexes [for example, figure 7(b)], or very significant shape configurations [for example, figures 7(a), 7(e), and 7(f)] between weight configurations. Fourth, some of the simulations yield results that do not differ significantly from observed results. This is true more often in MC than in GTC. In GTC all the weight configurations produced mean shape indexes significantly smaller than the observed values. Fifth, mean shape indexes for the 20-year time step are generally significantly smaller than each of the two 10-year simulations.

Figure 8 presents a similar illustration of a different shape metric (fractal-dimension index) which shows the effects of weight configuration on alternative land-use patch shapes for the two counties across the three time periods. As in figure 7, weight configurations seem to influence model performance across different time periods, different land uses, and different types of landscapes (MC versus GTC).

In our analysis we used seven basic shape metrics, and computed Cronbach’s alpha using the covariance matrix calculated for the simulation data. Figure 9 shows the results of an analysis to test whether the metrics used to quantify the results of the stochastic simulation capture the significant variability that exists in the shape characteristics we are measuring within our landscapes. In other words these graphs illustrate how well the Monte Carlo simulation process captures the parcelization process in each of the
two counties, across years and land uses. These results indicate clearly that the majority of the calculated simulation runs and metrics display a relative low level of reliability, with most values below 0.5. The most reliable simulations correspond to forest uses in MC. Though the Cronbach’s alpha values are more appropriate measures of reliability in our analysis, mainly owing to the use of the covariance matrix used in the analysis (thus, the assumption of equal variances cannot be easily made), we reported also the standardized version of the index, as an indicator of the relative importance of the values computed. Here, the urban class appears to give reliable values close to and in some cases exceeding 0.5. In most cases, however, the results cannot capture accurately the process that has been observed in the simulation replications. We also note that there are observable differences of reliability between the two spatial regions of the simulation, possibly owing to the nature and type of land-use changes present in each area. The relative heterogeneity of the urban landscape in terms of its landscape shape

![Figure 5. Three patterns of mean landscape metrics for the Monte Carlo replication experiments, 1970–80.](image)

(a) Grand Traverse County (GTC) fractal-dimension index; (b) GTC, contiguity index; (c) GTC, landscape division index; (d) Mecosta County (MC) fractal-dimension index; (e) MC, contiguity index; (f) MC, landscape-division index. Solid and dotted lines denote replication-run mean values and 95% confidence interval limits, respectively.
composition, and the relative homogeneity of the agricultural landscapes, respectively, are the reasons for the observed differences across land-use types.

6 Discussion and conclusions

In this paper we presented and tested a parcelization algorithm used in our spatially explicit, agent-based, land-use-change model, called the Multi Agent-based Behavioral Economic Landscape (MABEL) model. We employed a Monte Carlo simulation approach with a series of replication experiments across time, and compared observed changes between the years 1970, 1980, and 1990 and across two groups of landscapes that present different kinds of land-use changes. We compare the simulated parcel shapes with historically observed land-use changes using several landscape-ecology spatial pattern metrics generated by FRAGSTATS.

We examined seven different landscape-level shape metrics using a partial correlation analysis, accounting for differences in location, simulation year, and simulation
configuration, and found that four of these (shape index, fractal dimension, related circumscribing circle, and landscape-shape index) were highly correlated. Three others (contiguity, perimeter–area fractal dimension, and the landscape division index) provided different results from one another and from the four highly correlated shape metrics. This underscores the importance of examining a variety of shape metrics for these types of studies, and how they are correlated. A diverse set of shape metrics are likely to provide a more thorough assessment of model performance for any parcelization routine.

Figure 7. Mean values and error bars for a 95% confidence interval of the mean shape index in the MABEL Monte Carlo simulations, plotted as a function of parcelization-algorithm weight configurations (see table 2). (a) Grand Traverse County (GTC) urban land use; (b) GTC, agricultural land use; (c) GTC, forest land use; (d) Mecosta County (MC) urban land use; (e) MC, agricultural land use; (f) MC, forest land use. Solid and dotted lines denote the mean shape index of the observed landscapes for the 1970–80 and 1980–90 periods, respectively.
We were also able to show that the parcelization routine produced shapes across locations that departed significantly from a random distribution of shapes and that nearly all shape metrics provided us with the ability to detect these differences from a normal distribution, except the related circumscribing-circle metric. A reliability analysis showed that the shape metrics that we used were best suited for urban patterns, followed by forest patterns and then agricultural patterns. A standardized Cronbach's alpha met or exceeded adequate levels (greater than 0.5) for only urban patterns in three of the six sets of simulation years.

**Figure 8.** Mean values and error bars for a 95% confidence interval of the mean fractal-dimension index in the MABEL Monte Carlo simulations, plotted as a function of parcelization-algorithm weight configurations (see table 2). (a) Grand Traverse County (GTC) urban land use; (b) GTC, agricultural land use; (c) GTC, forest land use; (d) Mecosta County (MC) urban land use; (e) MC, agricultural land use; (f) MC, forest land use. Solid and dotted lines denote the mean shape index of the observed landscapes for the 1970–80 and 1980–90 periods, respectively.
and for both locations. The standardized Cronbach's alphas for the other years and uses were less than 0.4 and in some cases were less than 0.15. Thus, the parcelization routine produced results that departed from random but did not adequately match exactly observed data for all sites, years, and land uses.

A comparison of the performance of the parcelization routine across different locations (GTC and MC) and different time periods (1970–80, 1980–90, and 1970–90) suggests that the weight configurations in the parcelization routine have a high degree of influence on model performance. We were able to show that the weight configurations need to be adjusted across different time periods, and across different types of landscapes.

The parcelization routine will require additional components that we believe are important to the parcelization process in the real world. First, parcelization is greatly influenced by accessibility to roads. Parcels need to be subdivided in a way that provides access to roads for all new parcels. Second, proximity to natural resources such as rivers, lakes, and views or vantage points (for example, placing homes on hilltops) as well as infrastructure amenities such as utilities, need to be considered as well. Third, parcels are likely to be split, and possibly to be split in large aggregations, via subdivision development, on the basis of neighborhood characteristics. We forced the agents to divide their parcel after a land transaction into halves (that is, we employed a 50% parcel-split rule) that should be relaxed in future simulations. Fourth, many parcelization decisions are made on the basis of complex planning and management rules which are designed for economic or environmental goals at local to international scales (Bousquet et al, 2002; Burgi et al, 2004). These need to be examined and incorporated into the parcelization rules as well. Finally, all of these behaviors have economic and psychological determinants (Irwin and Bockstael, 2002; Parker and Meretsky, 2004), which need to be incorporated into the parcelization process. Efforts to do this are underway using Bayesian belief networks (Alexandridis et al, in review; Marcot et al, 2001) and role-playing simulation (Barreteau et al, 2001; Bousquet et al, 2002).
Acknowledgements. We wish to acknowledge funding from a grant from NASA’s Land-Cover and Land-Use Change Program (NAG5-6042) and a cooperative agreement with the USDA Forest Service North Central Forest Experiment Station (#23-95-50), grants from the National Science Foundation BE/CNH 0308420 and WCR 0233648, and a grant from the Great Lakes Fisheries Trust. We also thank Dan Brown for assistance with the parcel database used in this study. Snehal Pithadia provided technical assistance. We also thank three anonymous peer reviewers for comments that improved the quality of this paper.

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Appendix A
Calculation of the landscape shape metric for the MABEL parcelization algorithm computational

In computing the MABEL landscape shape metric, $L$, for the parcelization algorithm, we can consider the agent area as shown in the example of figure 3. Such an area can be expressed as the product of the vertical and horizontal dimensions of the smallest confined rectangle. It is similar to the patch elongation measure that can be encountered in the literature (Forman, 1995). In the specific example, $i = \{A, B, C\}$, where $A$, $B$, and $C$ are the closest confined rectangles of the original agent $i$, the buyer-agent, and the seller-agent, respectively,

$$a_i = x_i y_i,$$  \hspace{1cm} (A1)

where $a_i$ is the area of the minimum confined rectangle of the agent $i$. We can also define as $n$ the closest integral of the square root of the area $a$, and $m$ as the difference between the area $a$ and the $n^2$ (McGarigal and Marks, 1994),

$$n_i = \int(a_i)^{1/2},$$  \hspace{1cm} (A2)

$$m_i = a_i - n_i^2.$$  \hspace{1cm} (A3)

By substituting (A1) into (A2), we have

$$n_i = \int(x_i y_i)^{1/2}.$$  \hspace{1cm} (A4)

And by substituting (A1) and (A2) and (A3) we have

$$m_i = x_i y_i - \left[\int(x_i y_i)^{1/2}\right]^2.$$  \hspace{1cm} (A5)

The conditions for the $e_i$ calculations are (Bogaert et al, 2000; McGarigal and Marks, 1994):

$$e_i = \begin{cases} 4n_i, & \text{if } m_i = 0; \\ 4n_i + 2, & \text{if } n_i^2 < a_i \leq n_i(1 + n_i); \\ 4n_i + 4, & \text{if } a_i > n_i(1 + n_i). \end{cases}$$  \hspace{1cm} (A6)

By substituting (A1), (A2), (A3), (A4), and (A5) into (A6) we have:

$$e_i = \begin{cases} 4\int(x_i y_i)^{1/2}, & \text{if } x_i y_i - \left[\int(x_i y_i)^{1/2}\right]^2 = 0; \\ 4\int(x_i y_i)^{1/2} + 2, & \text{if } \left[\int(x_i y_i)^{1/2}\right]^2 < x_i y_i \leq \left[\int(x_i y_i)^{1/2}\right]^2[1 + \int(x_i y_i)^{1/2}]; \\ 4\int(x_i y_i)^{1/2} + 4, & \text{if } x_i y_i > \left[\int(x_i y_i)^{1/2}\right]^2[1 + \int(x_i y_i)^{1/2}]. \end{cases}$$  \hspace{1cm} (A7)

Also, we can define,

$$\min(e_i) = \min\{e_i\}_{i=1}^k.$$  \hspace{1cm} (A8)

$L$ can be calculated by,

$$L_i = \frac{\min(e_i)}{e_i}.$$  \hspace{1cm} (A9)

Or, by substituting (A8) into (A9), we have,

$$L_i = \frac{\min(e_i)}{e_i}.$$  \hspace{1cm} (A10)

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