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MULTI-AGENT SIMULATIONS OF RESIDENTIAL DYNAMICS IN THE CITY

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ABSTRACT. *This paper considers a multi-agent simulation model of the population dynamics in a city, in which inhabitants can change their residential behavior depending on the properties of their neighborhood, neighbors and the whole city. The autonomous agent in the model is characterized by its economic status and cultural identity and these two properties differ in their nature. The economic status is supposed to be uni-dimensional and quantitative, while the cultural identity is treated as a multidimensional and qualitative feature. Special attention is devoted to the comparison of the consequences of the individuals' interactions according to these features.*

URBAN MODELING: FROM TOP–DOWN TO BOTTOM–UP APPROACHES

The minimal model representation of a city demands two layers, one for the city's infrastructure units, and the other for migrating human individuals (Portugali & Benenson, 1997). The elements of urban infrastructure (land units, network segments, buildings, etc.) are immobile, while human individuals are potentially free to change their location in the city.

The 1970s and 1980s were characterized by intensive development of the regional approach, which considers the dynamics of these two layers conjointly. Regional modeling is based on the presentation of a geographical system by means of "zones" which exchange population, goods, capital, etc. among themselves, with each zone characterized by a vector of socioeconomic indicators. Components of this vector are the numbers/proportions of population groups in a zone according to age, culture, education or employment, as well as the numbers/proportions of jobs in different industries, dwellings of various kinds, services of different types, etc. (Allen, 1982; Allen, Engelen, & Sanglier, 1986; Allen & Sanglier, 1981; Anselin & Madden, 1990; Bertuglia et al., 1994; Engelen, 1988; Putman, 1990; Weidlich & Haag, 1988). The number of parameters of a typical regional model is of an order of hundreds or even thousands. For example, within the

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framework of one of the most elaborate models of Amsterdam's residential dynamics, the city is divided into 20 zones, with each zone distinguished by 11 dwelling types and 24 household types of four different sizes. The intensity of migration and the residential choice of each family are dependent upon the age of the head of household (according to 5-year age categories) and on the number of family members (seven groups; Van Wissen & Rima, 1988). As a result, the model includes about 1,500 variables representing demographic, residential and employment processes with all the problems induced by the lack of the experimental data, inability to study the structural stability of the model, etc.

The regional models utilize a *top–down* approach to complex system studies. Within their frameworks, an urban system is expanded into a predetermined (and very high) number of components. This inherent expansion is maintained throughout and, thus, does not allow characterizing spatial phenomena that are accompanied by changes in the regions' boundaries or emergence of new regions having different properties from those of the existing regions.

The *bottom–up* approach represents the city as a potentially infinite collective of simple elementary units whose interactions define the dynamics of the urban system at large. Applications of ecological models to urban systems (Day, 1981; Dendrinos & Mullally, 1982, 1985; Dendrinos & Sonis, 1990; Zhang, 1989) lie halfway between the top–down and bottom–up approaches. Ecological models continue to work with a few predetermined city components but describe their dynamics according to rules that can be considered as the global consequences of the elementary units' interactions. The most obvious examples of such rules are those describing diffusion, such as the applied study of diffusion in the Chicago black ghetto during 1968–72, in which the population is shown to be growing according to the logistic law (O'Neil, 1981). The model of "predator–prey" relationships between density and the economic status of the population of American cities (Dendrinos & Mullally, 1982, 1985) is another example of such an approach.

The bottom–up approach in its pure form is realized in the framework of cellular automata (CA) theory. In urban applications of CA, the city is represented by a two-dimensional lattice of cells (Couclelis, 1985; Phipps, 1989, 1992). Each cell is found in one of a finite set of states, usually representing land uses — dwellings, commercial, industrial, etc. The cells change their states according to local transition rules, that is, the state of the individual cell and the states of the cell's neighbors at the current time step define the state of the cell at the next time step. In comparison to the diffusion models, the global state of CA is determined by the neighboring cells per se, and not by the global consequences of cells' interactions. "Fractal" models (Batty & Longley, 1994; Frankhauser, 1994; Schweitzer & Steinbrink, 1997) also utilize a bottom–up approach to modeling city infrastructure dynamics on a lattice of interacting cells, but limit themselves to transition rules that generate self-similar urban patterns (Batty & Longley, 1994). It is worth noting that the thermodynamic approach to urban modeling, developed by Haag and Weidlich during the 1980s (Haag & Weidlich, 1982, 1983; Weidlich, 1997), can be considered as the general theoretical foundation for CA modeling.

The available versions of CA models account for neighborhood size and form varying in space and time. The associated transition rules are either deterministic or stochastic and depend on the current state of the cell and its location within the lattice. Recently it was demonstrated that few predetermined states of land parcels are sufficient to obtain likelihood simulation of city growth by means of CA models (Batty & Xie, 1994; Benati, 1997; Itami, 1994; White, Engelen, & Uljee, 1997; Wu, 1996).

In spite of the bottom–up nature of CA and similar models, they still display the inherent restriction of the top–down approach by using a predetermined set of cell states. Human individuals, unlike elementary units of nonliving systems, are themselves open, self-organizing complex systems (Maes, 1995; Portugali, Benenson, & Omer, 1997), and we cannot delimit them by a predetermined classification of their characteristics. The studies of sociocultural segregation in the city has demonstrated, both empirically and theoretically, that new sociocultural groups, whose members have properties absent from the city previously, can emerge in the urban space (Cater, 1989; Grimes, 1992; Omer, 1996; Portugali et al., 1997). Portugali et al. (1997), who have intensively studied the theoretical aspects of the process of sociocultural emergence during recent years, show the emergence of different forms of cultural and economic segregation as a consequence of the interactions between individuals and the city environment at the local and global level.

Their studies are based on the multi-agent (MA) simulation models of urban residential dynamics. In the MA framework, the model city is "populated" by active autonomous agents who interact, change their locations as well as their own properties and imitate accordingly the residential behavior and development of human beings.

The studies of Portugali et al. (1997), are based on the representation of both the economic status and cultural identity of an individual agent by uni-dimensional quantitative variables. In this paper I reject this oversimplification regarding the cultural identity and consider the latter as a multidimensional and qualitative variable.

Two versions of the MA model of spatial residential dynamics in the city are considered. The first, *economic* one is rather simple while the second, *cultural* one is more complicated and implies the crucial process of *recurrent* sociocultural emergence and extinction in the city. A comparison between the models clarifies the differences between discrete and qualitative versus continuous and quantitative features. The possible application of agent-based models for investigating real-world situations are discussed in brief as well.

THE MODEL

The MA model used here operates with a two-layer structure. The first layer — the city's housing infrastructure — represents the properties of urban housing; the second layer — free agents — represents individual citizens and reflects their migratory movements (Portugali & Benenson, 1995). Individual free agents in the MA model have the ability to estimate the state of the city on its two layers and behave in accordance with information regarding three levels of urban organization (Portugali et al., 1997):

(1) the individual;
(2) the local — referring to the characteristics of the neighborhood and the states of the neighbors;
(3) the global — referring to the state of the whole city.

Individual free agents are characterized in the model by their economic status and cultural identity. They migrate into the city, occupy and change residential locations there, and either change themselves or leave the city when conditions are unsatisfactory (Figure 1).

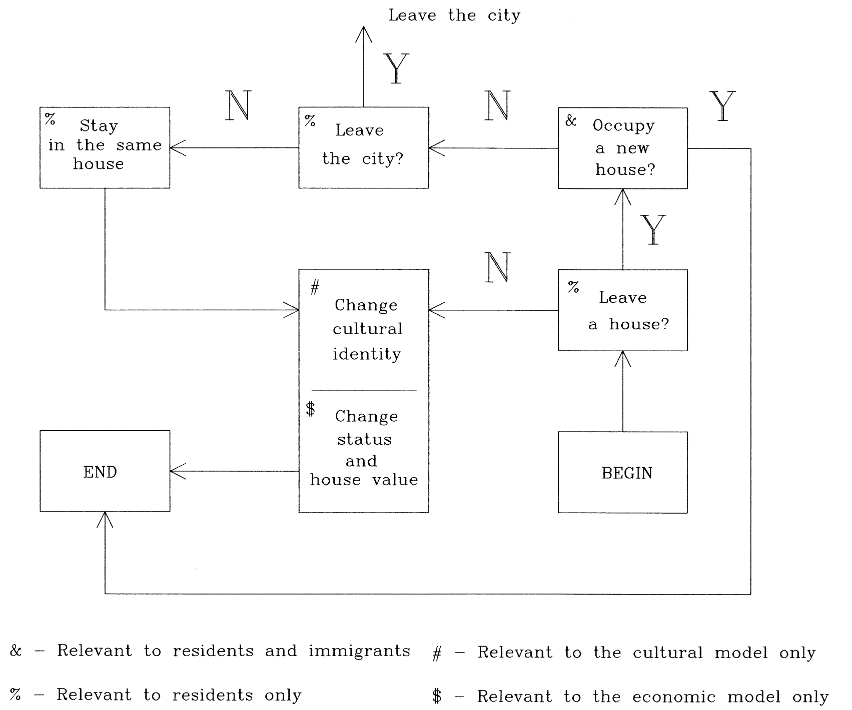

FIGURE 1. Consequence of a model agent's decisions.

The Housing Infrastructure Sub-Model

The infrastructure of the MA model is an $M \times M$ square lattice of cells, which symbolize houses. Each house H_{ij}, $i,j \in [1,M]$, can be either occupied by one individual agent or remain empty. A 5×5 square with H_{ij} in the center is considered as the neighborhood $U(H_{ij})$ of house H_{ij}. Houses differ in their value V_{ij}. For each time step, the value of the house is determined anew. When an agent A occupies house H_{ij}, its value V_{ij} is updated in accordance with A's economic status S_A, (see below) and the average value of the neighboring houses:

$$V_{ij}^{t+1} = S_A^t + (N(U(H_{ij})) - 1) \cdot <V_{ij}^t>_U)/N(U(H_{ij})), \tag{1}$$

where $<V_{ij}^t>_U$ is an average of house values in $U(H_{ij})$ excluding H_{ij}, and $N(U(H_{ij}))$ is the number of houses in $U(H_{ij})$. That is,

$$< V_{ij}^t >_U \equiv \sum_{(i'j')\epsilon\bar{U}_{ij}} V_{i'j'}^t/(N(U(H_{ij}) - 1) \text{ where } \bar{U}_{ij} = U(H_{ij}) - \{H_{ij}\}$$

When an agent leaves house H_{ij} and the latter remains unoccupied, its value V_{ij} decreases at a constant rate, d:

$$V_{ij}^{t+1} = d \cdot V_{ij}^{t} \quad (2)$$

Dynamics of the Agents' Economic Properties

The economic characteristics of an agent A are it's economic status S_A^t and the status growth rate R_A. The dynamics of the economic status of agent A occupying house H are described in a simple logistic way:

$$S_A^{t+1} = (R_A \cdot S_A^t \cdot (1 - S_A^t) - m \cdot V_H^t) / {<}V^t{>}_{\text{city}} \quad (3)$$

where R_A does not depend on t, $m \cdot V_H^t$ is a "mortgage payment" for occupying house H, and

$${<}V^t{>}_{\text{city}} \equiv \frac{1}{M^2} \sum_{ij=1}^{m} V_{ij}^t$$

is the mean value of houses over the city.

The local economic information P_{ij}^t available to agent A, occupying a house H_{ij}, is given by the economic status of A's neighbors and their house values in $U(H_{ij})$. In what follows, P_{ij}^t is a mean of the status of the neighbors occupying the houses within $U(H_{ij})$ and the values of the unoccupied neighboring houses:

$$P_{ij}^t = \Big(\sum_{B_E \bar{U}_{ij}^o} S_b^t + \sum_{(i'j')\epsilon \bar{U}_{ij} - \bar{U}_{ij}^o} V_{i'j'}^t \Big) / \Big(N(U(H_{ij}) - 1) \Big)$$

where B is a neighbor of A and $\bar{U}_{ij}^o$ is the set of houses in the neighborhood of H_{ij} that are occupied.

The migration decision of agent A depends on the absolute value of the difference SD_A between A's status S_A^t and local economic information P^t available to A, namely, on

$$SD_A^t = |S_A^t - P^t| \quad (5)$$

Below, SD_A^t is called a local economic tension of an agent A at location H at time step t.

The average ${<}V^t{>}_{\text{city}}$ of housing values over the city gives the global economic information available to each individual agent at time step t. According to Equation 3, this value provides the influence of the global state of the city on the agent's status dynamics.

Dynamics of the Agents' Cultural Properties

Similar to an inherited genetic code, a "cultural code" of the model individual defines its possibilities for residential behavior and interactions with other agents. In the genetics of qualitative features as well as in studies of artificial life, it is common to represent the individual's genotype by means of a high-dimensional binary vector (Banzhaf, 1994; Kanenko, 1995; Maes, 1995). In this paper, I introduce the cultural code of an individual agent in the same manner. In addition, following Portugali & Benenson (1997), I suggest that the cultural code of an agent and, consequently, its residential behavior can change through its interaction with its neighbors, neighborhood, and the city as a whole.

Formally, the cultural identity of individual A is described by the K-dimensional Boolean cultural code $C_A = (c_{A,1}, \ldots, c_{A,K})$, where $c_{A,k} \varepsilon \{0, 1\}$ and $k = 1, \ldots, K$. As a result, individuals of 2^K different cultural identities might exist in the city. Individuals A and B have different identities when vectors C_A and C_B differ in at least one component. Quantitatively, the difference between A's and B's identities is measured by the fraction of different components among K components of the cultural code:

$$\rho(C_A, C_B) = \Sigma_k |c_{Ak} - c_{Bk}|/K \tag{6}$$

The representation of local cultural information is related to the notion of local spatial cognitive dissonance of free agent A. Applying the general definition (Haken & Portugali, 1995; Portugali & Benenson, 1995) to the multidimensional presentation of cultural identity, the local spatial cognitive dissonance CD_A of agent A, occupying house H_{ij}, can be defined as an average of the differences between A's identity and the identities of its neighbors:

$$CD_A^t = \sum_{B \epsilon \bar{U}_{ij}^o} \rho(C_A^t, C_B^t)/(N^{ot}(U(H_{ij})) - 1) \tag{7}$$

where $N^{ot}(U(H_{ij}))$ is the number of occupied houses in $U(H_{ij})$at time t.

If individuals similar in their cultural codes to A are segregated in the city, then their spatial distribution might affect the behavior of A. The influence of the global structure of the city on an individual's residential behavior increases in the model with a rise in the level of residential segregation. The global cultural information GD_A available to a free agent A is determined in the model by the value of Lieberson's segregation index LS_x, (Lieberson, 1981) expressed as a probability of a member of culturally homogeneous group X located at house H_{ij} meeting a member of its own group within $U(H_{ij})$. Visually, values of LS_x below $0.3-0.4$ correspond to a random distribution of the agents belonging to group X, while values above $0.7-0.8$ correspond to one or several domains occupied almost exclusively by these individuals. Formally, for agents of identity C_A,

$$GD_A^t = \max\{0, (LS_A^t - LS^*)\}/(1 - LS^*), \tag{8}$$

Here, LS^* is the value of the Lieberson index that corresponds to the visually segregated pattern (below LS^* is set equal to 0.4).

Local and global information influence an agent's cultural identity in alternative ways. High local cognitive dissonance $CD^t{}_A$ forces agent A to change its cultural identity. In contrast, a high level of segregation $GD^t{}_A$ of agents having an identity C_A (not necessarily close to A's location) forces A to preserve its current identity. Agent A's sensitivity to local cognitive dissonance L_A and to global segregation G_A, where L_A $G_A \varepsilon [0, 1]$ are properties inherent to A and independent of t.

Model Dynamics: Trade-Off Between Migration and Change in Agent Properties

The conjunction between individual, local, and global factors can lead individual agent A to decide to continue to occupy house H in spite of high economic tension or cultural dissonance. The reason for this behavior might be, for example, a lack of attractive vacant houses in the city. The basic suggestion of the model is that in such a situation, the dissonance is resolved either by leaving the city, or by a change in the properties of the free agent itself.

According to the model's flow chart (Figure 1), at every time step, each free agent A in the city decides whether to move from or to stay at its present location. It is suggested that for agent A located currently at H_{ij}, the probability of leaving its current location increases monotonically with an increase either in an individual's economic tension $P^t{}_{ij}$ or in that individual's local cognitive dissonance $CD^t{}_A$. The probability of occupying an empty house G when it is the only possible choice decreases monotonically with an increase in an individual's estimation of the economic tension or local cognitive dissonance at G and does not depend on the previous location of that individual (Figure 2; Portugali & Benenson, 1997). A vacant house H_{ij} is attractive for agent A, when at least four houses in $U(H_{ij})$ are occupied. For details of the choice between several vacant houses see Portugali et al. (1997).

Trade-off between migration and changes in an individual's economic status. If, in spite of high economic tension, an agent remains at its current location, the tension continues to increase. However, this tension can be occasionally resolved by the agent leaving the city with probability p_U (see Emigration section). An insolvent agent, that is, one whose economic status has dropped below zero, leaves the city eventually.

Trade-off between migration and changes in an individual's cultural identity. If agent A is forced to occupy its current location in spite of high cognitive dissonance, then its cultural identity can be changed. This occurs in the model when the local tendency of an agent to vary exceeds the global tendency to preserve its current identity, that is when $L_A \cdot CD_A{}^t > G_A \cdot GD_A{}^t$. When this condition holds, the probability that the i-th component of A's cultural identity will be changed is proportional to the module of the difference between the fraction of A's neighbors having the i-th component valued one and the value (zero or one) of the i-th component of C^t_A. Additionally, "mutation" of the cultural code is possible, with probability r_m per component.

As a result, for an agent A having identity $C_A = (C_{A,1}, \ldots, C_{A,i}, \ldots, C_{A,K})$, occupying house H_{ij}, the probability of change in the I-th component $C_{A,i}$ of C_A to its negation, i.e., from unity to zero or vice versa, equals:

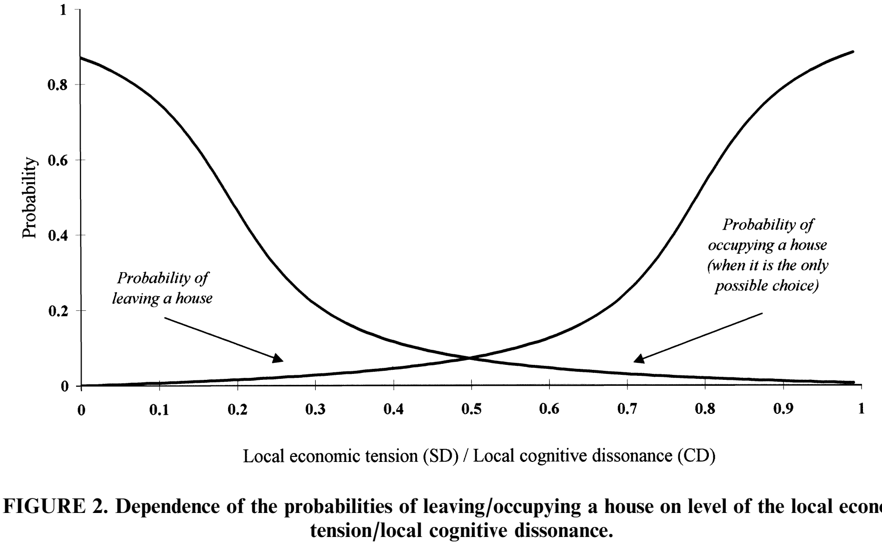

FIGURE 2. Dependence of the probabilities of leaving/occupying a house on level of the local economic tension/local cognitive dissonance.

$$p_{A,i} = \max\{0, (L_A \cdot CD^t_A - G_A \cdot GD^t_A).(|f^t_i - c^t_{A,i}| + r_m)/(\Sigma_k|f^t_k - c^t_{A,k}| + r_m.K)\}, \quad (9)$$

where ${f_k}^t$ is the frequency of $NOT(c_{A,k}{}^t)$ in the cultural identities of A's neighbors at time step t:

$$f^t_k = \sum_{B\epsilon U^o_{ij}} \mu(c^t_{Bk}, c^t_{Ak})/(N^{ot}(U(H_{ij})) - 1) \text{ where } \mu(C^t_{Bk}, c^t_{Ak}) = \begin{cases} 1 \text{ if } c^t_{Bk} = 1 - c^t_{Ak} \\ 0 \text{ if } c^t_{Bk} = c^t_{Ak} \end{cases} \quad (10)$$

It is assumed that only one component of cultural identity can be changed at a time step.

Emigration. A free agent that fails to reside might either leave the city (with probability p_U) or remain at its current location. In the latter case, an economic agent changes its status according to Equation 3 and a cultural agent changes its identity according to Equation 9.

Immigration. At every time step, a constant number of individuals tries to enter the city from without and to occupy a house. In the economic version of the model, the economic status S_I and growth rate R_I of each immigrant I are assigned randomly and independently. The distribution of the immigrants' status is normal, with mean equal to $<V^{t-1}>_{\text{city}}$ and constant CV. The distribution of R_I is also normal and independent of t. In the cultural version of the model, the identity of the immigrants is assigned at random, in proportion to the current fractions of agents having each of the 2^K possible identities.

RESULTS

The aim of the model is to examine and compare the processes of economic and cultural self-organization in the city, the inhabitants of which can vary in their economic status according to one continuous trait or in their cultural identity according to potentially infinite number of discrete traits. More particularly, the questions are: "What are the number and the level of segregation of the emerging groups — if any?" "Are they fixed or do they vanish with time?" "What is their 'life-history'?"

To qualify as a new entity, a group of individuals sharing close economic status or the same cultural identity must fulfill simultaneously these two conditions (Portugali et al., 1997):

(1) At the local level, most of the group members should be located within economic/culturally uniform neighborhoods.
(2) At the global level, the number of group members and their spatial segregation have to be sufficiently high.

The Evolution of a City Populated by the Economic Agents

Regarding economic status, the residential dynamics in the city are relatively simple (Benenson & Portugali, 1995; Portugali & Benenson, 1995). Qualitative suggestions regarding monotonous dependencies of probabilities to leave/occupy a house on economic difference SD imply rapid self-organization of the gradient of all three characteristics of the city's economic state (Figure 3). Irrespective of their initial state, the distribution of housing values, of the agent's status and of the status growth rate all converge to

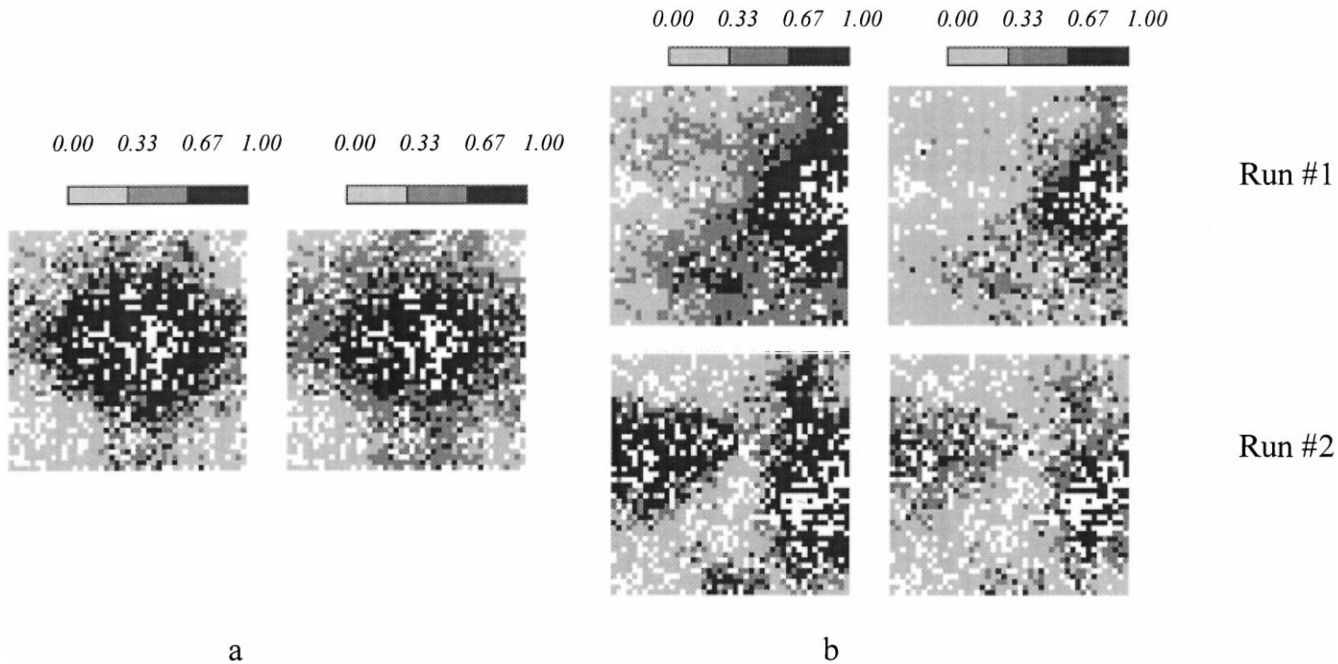

FIGURE 3. Economic MA model: snapshots of population distribution according to economic status and status growth rate.

smooth and correlating patterns during several hundred time steps (Figure 3a). After an initial period of rapid change, these distributions evolve very slowly, with persisting "rich" and "poor" domains that move slowly and stochastically throughout the urban area (Figure 3b). Accordingly, we can argue that from the economic point of view, the city evolves toward the distribution, which is characterized by the segregated location of individuals of different economic capabilities. At one pole is a group of agents who are characterized by low economic status, a low rate of status growth, and occupying houses of low value. At the other pole is a group of agents having high status values and status growth rates and occupying the domain of high-value houses. The distance between the domains, occupied by agents from different economic groups, is proportional to the differences between these groups (Figure 3). Referring to the above question regarding emerging populations, we can say that the only possible outcome of interactions based on economic status is the persistent segregation of low- and high-status groups.

The consequences of cultural interactions of the agents are more complex. Let us consider them in detail.

The Evolution of a City Populated by the Cultural Agents

Our previous studies demonstrate three types of persistent residential dynamics in a city populated by agents, who differ according to an uni-dimensional quantitative cultural identity that varies between zero and one (Benenson & Portugali, 1995). One type can be termed a random city, where individuals of all possible cultural identities exist and no segregation occur. Another is a homogeneous city, in which almost all of the agents belong to the "zero" or "unity" cultural group. Three coexisting, segregated cultural groups characterize the third type. Two of these groups are the polar "zero" and "unity" entities, while the third is newly emerging, its members having cultural identity close to mid value of 0.5 (Benenson & Portugali, 1995; Portugali & Benenson, 1997). With a multi-dimensional cultural code the random, homogeneous and segregated residential dynamics are observed as well. The set of parameters entailing the most interesting "structured" type of residential dynamics is used here to investigate the model in depth. The system behavior is analyzed for the case of up to a five-dimensional cultural code.

Parameters' Value and Initial Conditions

The model runs were executed on a 40×40 lattice, all beginning with a small patch of all-zero agents in the center of a lattice and sharing the following conditions:

(1) Immigration rate of 4 individuals, or 0.0025 of the maximum number of city residents.
(2) Probability p_U of leaving the city, when failing to occupy a new house, equals 0.075.
(3) Distributions of sensitivities L and G are uniform on [0, 1]. They are assigned to the agents independently of each other.
(4) Mutation rate r_m equals 0.02.
(5) Threshold group size sufficient to recognize a group as an "entity" is set to 40 individuals (enabling up to 40 different cultural groups to exist simultaneously in the city). The threshold level of segregation sufficient to recognize a group of more than 40 individuals as a cultural entity is set to $LS^* = 0.4$

The results below are based on five repetitions of each scenario.

An inherent source of the cultural dynamics in the model is a mutation process that prevents it from becoming culturally homogeneous. Unlike the changes in the one-dimensional economic status, the changes of agents' cultural identities do not decrease the cultural diversity of the city. As an example, consider the agents located at the boundary between two segregated groups of individuals (0, 0, 0, …, 0) and (1, 1, 1, …, 1). According to Equation 9, there is a high probability that the identity of, say, the (0, 0, 0, …, 0)-agent will change to a new one (with a unity instead of zero value for one of the components), thus, will differ from the identities of the agents in both groups. This salient consequence of multidimensional representation of C_A determines most of the results here.

At present, our computer allows us to study the system's behavior when the dimension of the cultural identity vector C_A is less or equal to 5. The preliminary investigation currently in progress, demonstrates that the case of $K=5$ is representative of a high-dimension C_A.

Presentation of Urban Cultural Patterns

Certain difficulties exist in presenting the spatial characteristics of a city when a cultural identity is a multidimensional vector. An urban cultural pattern is presented here by means of three kinds of maps (Figure 4). The first represents the distribution of the agents' cultural identities, with each identity marked by its own color. This method of presentation is the most detailed of the three, but inconvenient for $K>2$ in view of the high number and nonlinear ordering of identities. The second type of map is that of the difference $\rho(C_A, C_0)$ between the identity C_A of agent A, occupying house H, and some identity chosen a priori, say, $C_0=(0, 0, 0, \ldots, 0)$. This map shows those effects that do not depend on K; its disadvantage lies in the fact that several different identities C_A can differ equally from the identity selected for comparison. The third map is that of the distribution of the cultural cognitive dissonance of the residents (Portugali, Benenson, & Omer, 1994). It represents the domains of the most intensive changes either in population distribution or in the cultural identity of the model agents. The third map is a surrogate of a stability–instability surface (Portugali et al., 1995) in the sense that the higher the dissonance, the greater the probability that the state of an individual, occupying a given house will change.

Before proceeding to the analysis, let us point out that the dynamics of the distribution of cultural identity depends on the number K of its components. In general, an increase in K increases the "resolution" of identity, but maintains the range of its variability. That is, according to Equation 6 the maximal possible value of $\rho(C_A, C_B)$, i.e. the difference between individual A of identity C_A and individual B of the opposite identity C_B remains equal to one, no matter what K is.

Model Dynamics for Low-Dimensional Cultural Identity: $K=1$ *and* $K=2$

The case of $K=1$ corresponds to our previous analysis of residential segregation between two cultural groups (Portugali et al., 1994). The model city dynamics in that case entailed a fast self-organization of (0)- and (1)-identities within two or several segregated patches. The boundaries between the homogeneous patches remain areas of instability, with intensive exchange of individuals (Figure 4a; cf. Portugali & Benenson, 1994).

When K equals 2, the dynamics of the city still resemble our previous results (Portugali & Benenson, 1997; Portugali et al., 1997). At the beginning of the runs, in accordance with the restriction of mutation by one component per time step, only (0, 1)- and (1, 0)-agents

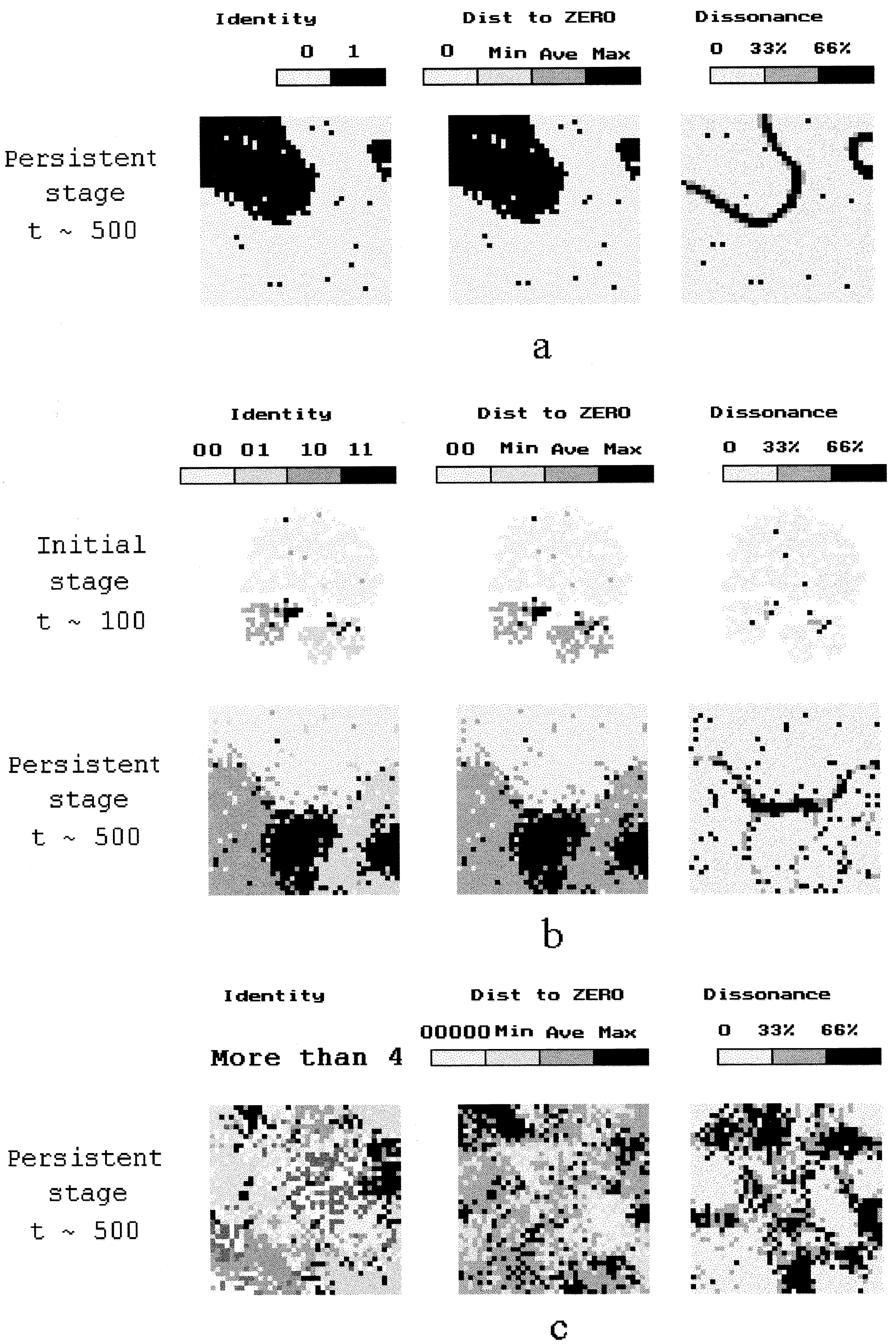

FIGURE 4. Cultural MA model: snapshots of population distribution according to cultural identity for $K = 1$ (a), $K = 2$ (b) and $K = 5$ (c).

emerge. The numbers and level of segregation of the initial (0, 0)- and of the new (0, 1)- and (1, 0)-identities reach levels satisfying the conditions of sociocultural emergence, to $t = 100$, when the fraction of unoccupied locations in the city is at a level of 25%. At this stage those agents having either identity (0, 1) or (1, 0) and changing it to (1, 1) because of mutation or dissonance with their neighbors, still have available to them many vacant houses. As a result, the (1, 1) sociocultural entity emerges in the city (Figure 4b) in all of the model runs to $t = 400$. In parallel, the number of vacant houses tends to approach zero, and strong competition for houses turns out to be the factor that defines the survival of the entities. In general, the position and the size of one or several domains occupied by an entity determine that entity's survival. The high value of the perimeter/area relation, as well as the common boundary with an opposite entity, for example (0, 1) for (1, 0)-agents, decreases the life span of the entity. As a result, in the long term (we stopped the simulations at $t = 2{,}500$), the number of sociocultural entities existing simultaneously in the city for $K = 2$ fluctuates between 3 and 4 and the mean life span of an entity is of an order of 1,000 time steps. Let us skip the intermediate cases of $K = 3$, 4 and proceed to $K = 5$.

Model Dynamics for High-Dimensional Cultural Identity: K = 5

Initial stage of the model dynamics. The number of possible identities for this case is $2^5 = 32$. The initial mutant agents belong to one of five "close-to-zero" identities, which are characterized by one (unity) at one of the components and zero at the others. Compared to $K = 2$, it is not necessary that all of them emerge at the first stage of the development of the model city. In the five runs we performed, their number varied between two and four.

Persistent dynamics of the city. The entities that emerge first determine the further dynamics of the city. In a way similar to the case of $K = 2$, the boundaries between two homogeneous domains (occupied by the entities that emerged at the first stage) and the heterogeneous domains (occupied by the agents of varying identities) are areas of instability. The agents located there either leave their houses or change their identities. None of the properties of the specific cultural identity existing currently can be predicted in the long term, but it is still possible to delineate the following properties of the population distribution as a whole:

(1) The persistent city structure is characterized by a self-organizing mixture of spatially homogeneous and heterogeneous domains. The former, whose populations form cultural entities, cover about half of the city's area for $K = 5$ (Figure 4c). The distribution of cultural differences $\rho(C_A, C_0)$ between the agents with the cultural code C_A and the "basic" cultural identity $C_0 = (0, 0, 0, 0, 0)$ is self-organizing as well (Figure 4c).

(2) A limited number of cultural entities can exist in the city simultaneously (Figures 4c and 5a).

(3) The life span of a sociocultural entity is finite; newly emerging entities replace each other in the city space over time. About 20% of the entities persist in the city for not less than 10 time steps and about 10% exist for not less than 25 time steps (Figure 5b).

The global model dynamics can be explained on the basis of the distribution of cultural differences, presented in the middle column of maps of Figure 4. This distribution has two opposing characteristics. First, the difference $\rho(C_A, C_0)$ increases with the increase in

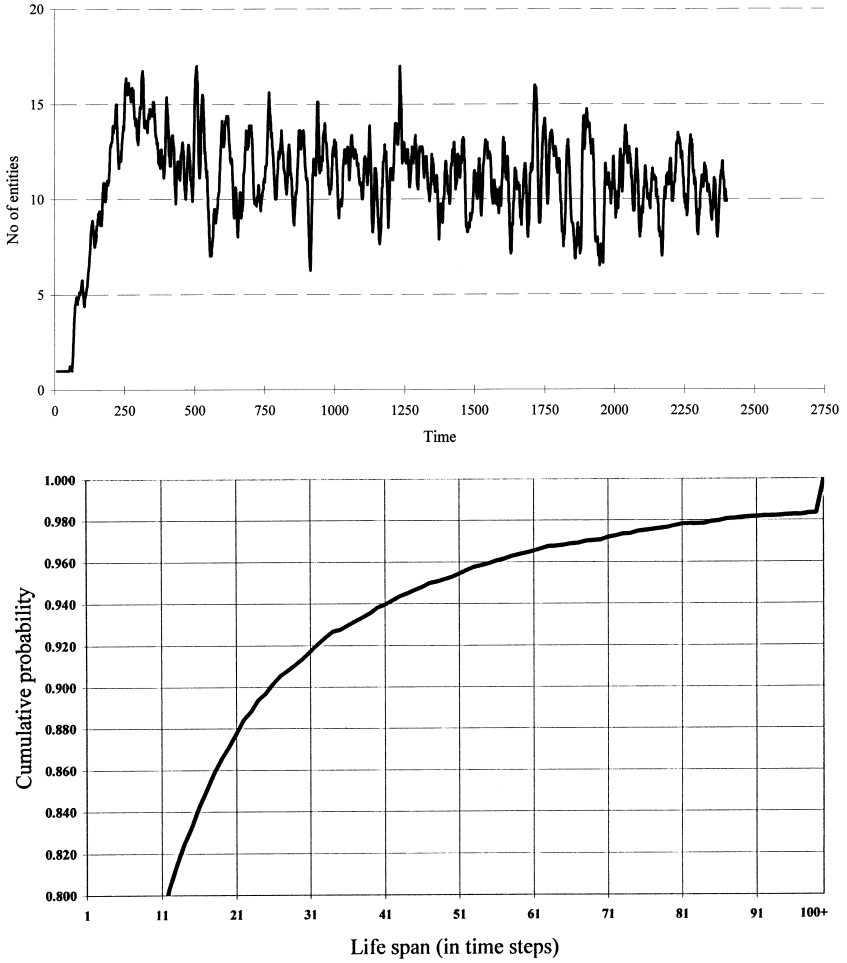

FIGURE 5. Dynamics of the number of cultural entities (a) and entity's life span probability function (b) for five-component cultural identity.

distance of agent A from the location of the agents having cultural code C_0. Second, the multidimensionality and, hence, nonlinear ordering of the identities implies the recurrent emergence of adjacent entities C_A and C_B that differ equally and significantly from C_0 and between themselves ($\rho(C_A, C_0) \sim \rho(C_B, C_0) \sim \rho(C_A, C_B)$). This can be observed, for instance, at the bottom of Figure 4c, where the boundary between the identities represented with dark gray and light gray (first map from the left) is an area of high dissonance between these two identities (last map), while both of them differ from C_0 (middle map). This phenomenon implies non-monotonic dependence of the city's instability, given by the fraction of individuals that want to leave their houses, over the number of entities (Figure 6). According to Figure 6, with an increase in the number of entities, instability first decreases parallel with the increase in the overall area occupied by the cultural entities. With a further increase in the level of segregation, the emerging cultural entities occupy most of the city's territory, while the heterogeneous areas vanish. In such circumstances,

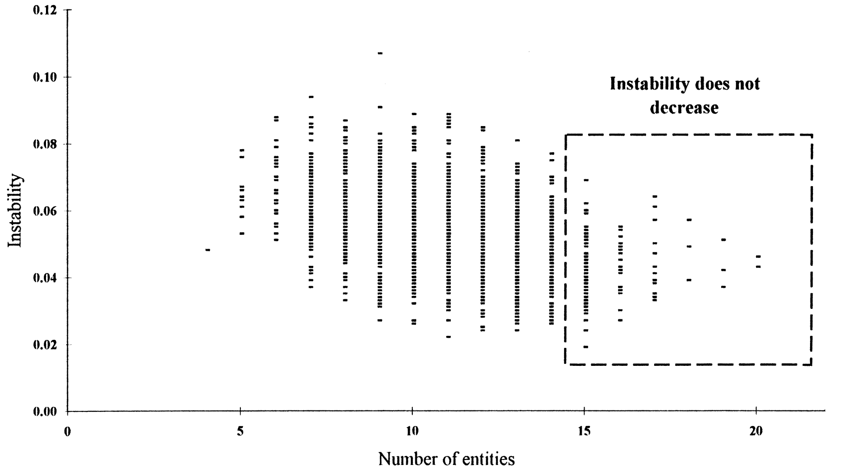

FIGURE 6. Dependence of city's instability on the number of cultural entities.

adjacency between contrasting entities is inevitable. The boundaries between them sharpen and expand, and the city's instability increases once more (Figure 6). As a result, we can say that the city's instability is limited from below while the city itself is self-organizing and evolving toward a critical structure that preserves its internal capacity to change.

DISCUSSION AND CONCLUSIONS

The paper is based on the recently developed idea that an individual human agent is able to change him/herself depending on information available at different levels of city structure (Portugali & Benenson, 1997; Portugali et al., 1997). The consequences of the interactions of the individuals, as well as the ability of individuals to vary according to two antithetic characteristics, are studied and compared. The residential distribution based on uni-dimensional and quantitative economic status converges towards a smooth, slowly varying spatial pattern. The city population preserves the overall range of economic variation, and the location of the domains, occupied by individuals of low and high status, can be foreseen in the short and medium term, although not in the long term.

The notion of "cultural code", introduced in this paper, describes the individual as a multidimensional and qualitative unit. Three qualitative phenomena related to the multidimensional cultural identity are revealed: first, the recurrent emergence and extinction of the cultural groups in the city; second, only a limited number of cultural entities (from a large number of possible ones) can exist simultaneously in the city space; and third, the city as a whole preserves cultural instability. The persistent cultural landscape of a city is a mixture of a few homogeneous domains, each occupied by individuals of a certain cultural identity as well as areas of heterogeneous population. The evolution of the existing cultural entities depends on the emerging situation and can be predicted in the short term only.

Two important questions should be considered in relation to the results presented. The first concerns the consequences of the interrelations between urban residential distribution and its infrastructure, which includes a number of important non-residential components (transportation networks, industrial regions, public areas, etc.). The encouraging results from the simulations of the infrastructure dynamics of several real-world cities obtained by means of CA and fractal models (Batty & Longley, 1994; Batty & Xie, 1994; Sanders, Pumain, Mathian, Guerin-Pace, & Bura, 1997; White et al., 1997; Wu, 1996) make them serious nominees for inclusion among the infrastructure-modeling tools. The spatial resolution of CA models is at the level of land parcels, which change their states over the years. The MA approach described deals with the decisions posed to people more frequently and considers the residential dynamics at the level of houses and families. Thus, the CA and MA approaches work with different but "adjacent" space and time resolutions. If we interlace the two, we can argue that the "fast" residential dynamics of the MA model should account for the outcomes of the "slower" CA model of land use dynamics as the external parameters that define the location of residential areas, number of available dwellings, etc. An MA model then feeds back information regarding the qualitative changes undergone by the urban population to the infrastructure level and influences thereby the laws of transition between land uses. It is an open question as to whether other levels of the urban hierarchy — in addition to those defined by land use and individual residential behavior — should be considered separately.

The second question concerns our ability to apply an MA approach to real-world situations. The breakthrough here can be the implementation of the agent-based models in the framework of a geographic information system (GIS). Many high-resolution GIS-based sources of spatial and attributive information have recently become available. The GIS framework makes it possible to substitute the abstract cellular space background of the MA model by the housing structure of an actual city. The initial version of the GIS-based MA simulation model has already been implemented and has clearly demonstrated the role of housing heterogeneity and varying neighborhood structure in urban dynamics (Benenson & Portugali, 1997). It is worth noting that the hybrid computer environment consisting of PC-based GIS and high-performance computer should make it possible to simulate residential dynamics for areas containing up to 10,000 houses and some 10,000 families. The GIS would serve as the tool for data storage, display and spatial analysis, while a high-performance computer would be the engine for the simulations. This hybrid version of a MA model of urban residential dynamics is currently under development.

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