A cellular automata model on residential migration in response to neighborhood social dynamics

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A B S T R A C T

Residential migration patterns result from complex processes involving households and their neighborhoods. Simulation models assist in understanding this relationship by contextualizing residential mobility within a theoretical framework. The objective of this study is to model these migration patterns created by the interaction between changes in the social structure of households and the positive or negative social attractors in the neighborhood. Specifically, this study links residential mobility to the dynamic interplay between the micro-environment existing within a household and the meso-environment that structures a neighborhood. The cellular automata model developed in this study incorporates transition rules which govern households in their decision to move. The results represented by a cellular grid demonstrate that residential mobility is significantly influenced by density rates, individual household factors and neighborhood attractors. Three contrasting scenarios are presented in this paper to illustrate the impact of occupancy, density, neighborhood social influence, and the effect of a conglomeration of negative social attractors in a neighborhood. Future iterations of this model will incorporate census and crime data in order to test whether the rules governing this model are an accurate reflection of residential mobility in a mid-sized Canadian city.

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1. Introduction

Residential urban migration is an integral aspect of city and crime control planning. This type of movement does not occur uniformly over time and space, rather there are specific social dynamics occurring within cities that render certain areas more transient and others more stable (see [1–8]). Furthermore, other social problems overlap the transient areas, whereas there are fewer issues in stable neighborhoods (see [9,3–6]). For instance, there is more crime in areas where there is high residential mobility, but less so in established neighborhoods (see [3,4]). While this is a simple illustration of the social problems related to higher residential mobility, the underlying mechanisms of urban migration continue to be of concern to a number of social agencies. The growing availability of data in this area provides researchers with the empirical knowledge to further investigate this urban phenomenon (see [10–16]). In order to effectively study the complex social processes involved in urban migration, a non-linear mathematical method needs to be applied (see [17–22]).

Since the beginning of the 20th century, as American cities began to expand at a rapid speed, criminologists turned their attention to urban migration because they found that it followed the aggregate crime patterns in a city (see [23,5,6]). In 1925, Park and Burgess developed the first concise criminological model to describe the relationship between urban migration and crime. The concentric zone model was derived from data collected in the city of Chicago and as such followed

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the urban development occurring in that city [6]. As an American city grows, the more affluent move to the periphery of the city while poorer residents stay close to the central business district where they have easier access to transit and work [6]. Social disorganization is a centrally important concept emerging from this model [6]. It is a reciprocal social process which accompanies the urban growth of American cities and with disorganization comes reorganization [6].

The increasing availability of data in the 1940s allowed McKay and Shaw (1969) to apply juvenile delinquency rates to the *Concentric Zone Model* in Chicago [5]. They found that these rates followed the zones and delinquency was more concentrated in zones of transition where social disorganization was physically apparent [5]. These results were also reflective of delinquency patterns in other cities. The authors conclude that crime is most prevalent in transitional zones where the majority of delinquents reside [5]. Transitional neighborhoods are defined as inner city areas where population movement is high, where there are more individuals who have lower education and median family income, and where housing is in a deteriorated state [5].

During the 1980s criminologists reviewed the link between crime and urban migration (see [1,2,7]). For instance, Brantingham and Brantingham (1984) study the crime patterns of several cities [2]. They see the Park and Burgess *Concentric Zone Model* as a compelling explanation for crime rates in urban areas from the 1930s to the 1950s [2]. However, the zones are too large a unit to properly analyze and even McKay and Shaw abandoned this model in their later research [2]. The areas of social disorganization are sometimes dispersed throughout the city and the patterns are not concentrically predictable [2]. Rather, smaller urban areas are better suited units with which to investigate urban crime patters [2]. The Brantinghams found that three structural factors determined higher crime rates: residential mobility, low social economic status, and ethnic heterogeneity [2].

The reciprocal process of social disorganization and reorganization is examined by Sampson and Groves (1989). In their study, they build on the determinants of social disorganization developed by McKay and Shaw, however, they also develop a social organization construct which allows them to test the reciprocal nature of these two factors [7]. Regression analysis is used to look at this relationship [7]. There are limitations to this linear statistical approach as it cannot fully describe the non-linear dynamic interplay existing between these two constructs. Indeed, urban migration happens in a non-linear fashion in space and in time and is best studied using non-linear mathematical methods (see [11,20,21,24–27,22]).

More recently, the study of urban migration has gone further than the aggregate studies previously discussed to now include the micro-factors that influence a household's decision to move. More specifically, researchers have looked at the impact of victimization, both direct and indirect, on the decision to move [28]. This variable is also compared to other household specific factors such as unemployment, education and age [28]. The results of these studies show the confluence of influences on this decision (see [29,28,8]). Indeed, a household's decision to move is triggered by internal factors such as a change in income level, but also indirect factors such as neighboring households being victimized by crime.

Additional research has shown that certain neighborhood features such as school catchment areas or questionable establishments also influence the household's decision to move (see [29]). These can be considered as positive or negative social attractors. Positive social attractors are associated with the institutions within the community that further strengthen the social structure of a household. For instance, a school with a good reputation attracts households that value such positive community attributes. On the other hand, negative locations such as bars that are likely to attract crime may be viewed as negative social attractors (see [30]). The decision to move closer to either type of social attractor, be it positive or negative, would resonate with the social structure of the household making such a decision.

The decision to move may be dependent upon multiple factors such as trading up with the aim to save for retirement, a new birth in the family thus generating need for space, or other factors such as loss or gain of employment. However in the decision to move, households will balance the pull of the community with the quality of the house (see [31]). Research findings indicate that households look for both better neighborhoods and better housing when they move. Similarly when neighborhoods begin to decline, household will look to leave in order to secure the asset (see [4]).

In the past decade, mathematical modeling has been applied to the study of crime and urban development (see [11,32,19–21,33,24–27,16]). This type of method is highly applicable because it can model urban dynamics both spatially and temporally [17]. The mathematical approach used in this study is cellular automata (CA) modeling. In CA modeling each cell can be assigned various values which can change over time following transition rules [34]. Cells can represent multiple factors present in the urban domain and they can also model the interaction between these factors [34]. For instance, a cell can be a household and the transition rules for these cells can replicate the social interactions between households. The goal of this study is to present a mathematically structured method to describe the dynamic social interaction of individuals in a community. A CA model of urban migration is developed to show the social relationship between households. This model effectively describes the impact of the social structure in a household in the decision to stay or move.

2. Model development

The project team consisted of members from the fields of Computing Science, Criminology, Environmental Science, Geography and Mathematics. Covering such interdisciplinary breadth proved invaluable in terms of having the expertise to be able to undertake the project. Transforming well-expressed domain knowledge into something computable may appear natural, but in fact hidden inconsistencies and ambiguities may make this problematic [35]. Furthermore, ensuring that all team members are on the same page can be difficult when differences in academic background and terminology are
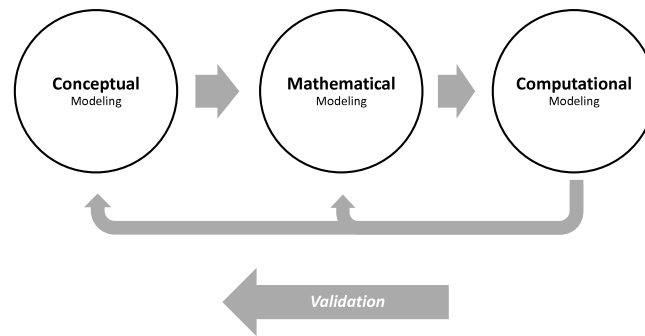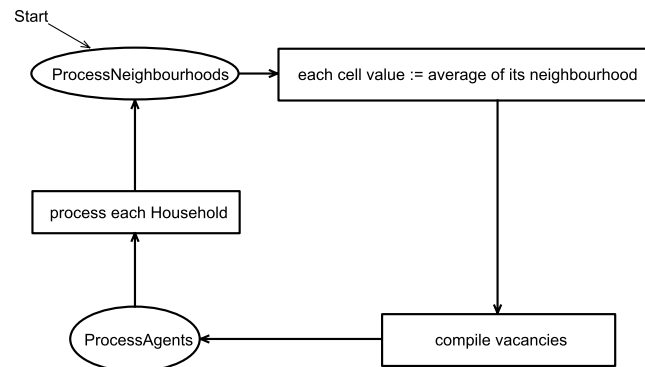
Fig. 1. Three phases of modeling.

Fig. 2. System-wide process model of a single time step.

present. In order to address these challenges, the development methodology presented in *Modeling criminal activity in urban landscapes* was implemented [13]. In this method, model building consists of three phases: *conceptual, mathematical and computational* (see Fig. 1).

In the conceptual modeling phase, the subject and its general behavior are identified using domain knowledge and described in natural language. This description is then formalized in the next phase into an abstract model that is fundamentally mathematical in nature. It is important at this point that the model is both precise in a mathematical sense while still remaining comprehensible to all team members. In other words, technical details or terminology should not obfuscate any defined property of the model. We used *Control State Diagrams*, such as Figs. 2 and 3, as well as mathematical formulae to build the model in this phase [36]. We also maintained written documentation to serve as an auxiliary explanation of these formalizations. These measures ensured that it was straightforward to verify that the mathematical model accurately captured the essence of what had been described in the conceptual modeling phase. This methodology for developing the formal structure of the model was chosen because it is precise and mathematical without being overly technical. As such, it is an appropriate methodology for a small interdisciplinary research team in an academic setting. For a wider-scale distribution or use with a larger group, it would be worthwhile to consider using the Unified Modeling Language (UML) to document the model.

Once a robust mathematical model has been produced, it can be used as the foundation for building an executable computational model that is capable of running experiments. The results of these experiments can be used for both technical and domain-specific purposes. They may answer experimental queries, highlight new issues to investigate, or suggest improvements to the model. The three modeling phases imply a natural order moving from *conceptual to mathematical to computational*, but in practice the entire process is iterative and can involve returning to previous stages when changes or corrections are made. However, the flexibility provided by this development style allowed us to progressively improve and add to our model as our understanding grew. It also helped emphasize the role of the model as a vehicle for knowledge discovery, rather than as a goal in and of itself.

3. Cellular automata model

A cellular automata (CA) is a mathematical method which can effectively analyze the non-linear qualities of dynamic human interaction among the individuals in a community (see [17,37]). A CA model can further assist in describing and understanding urban migration patterns [17]. This analytical method is suitable for this type of research because it can take into account both local interactions and also more distant influences [17].
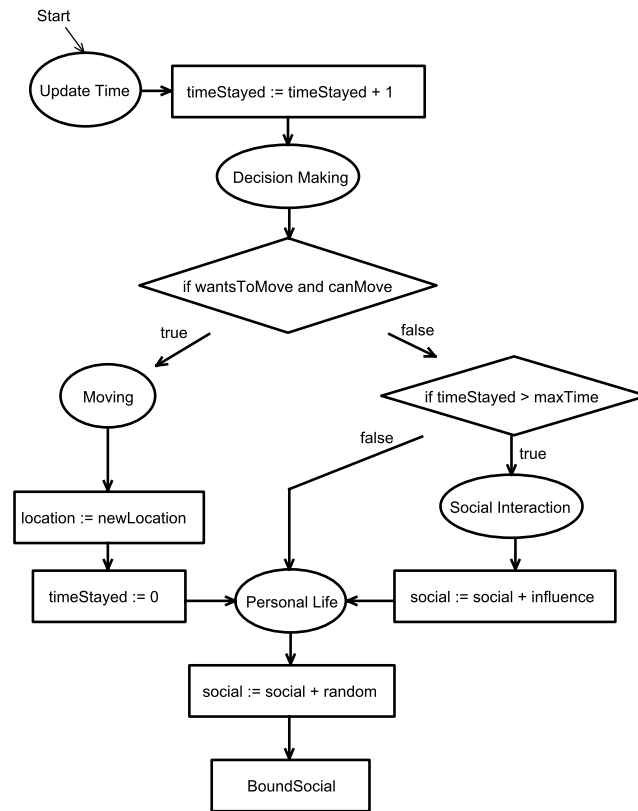
Fig. 3. Decision making process of an individual household.

An urban environment can be represented in a CA model as a two dimensional grid where each cell represents a household in the urban area [17]. The state of each cell can vary depending on pre-determined rules. These rules are derived from an existing theoretical framework describing a particular phenomenon and are used to model what is happening in the real world. In order to simplify the complexity of human behavior, CA modeling must make assumptions which are supported by previous research in this area.

In a CA model, interactions happen over time. Since each cell has the capability of holding the information pertaining to that cell, changes can be recorded. In general, CA models measure time discretely, in other words, progress through time is represented as a series of time steps. The cells capture the information at each time step and have the ability to alter states through successive iterations. The state of the cells is updated simultaneously at each time step following pre-determined transition rules [17].

In this model, the underlying premise is that households are biased and want an appropriate place to live based on their social structure. As well, the social structure of a household is influenced by others in the community. In this model each cell can potentially be influenced by neighbors in its neighborhood.

4. Model description

The objective of this CA model is to simulate the impact of social structure in the household on residential migration in an urban area. The model generates scenarios depicting decisions to move by households and the consequential effect of positive and negative social attractors in the neighborhood. In this study, social structure refers to a combination of household variables such as the average age of residents, average income, number of parental figures, employment status, and criminal propensity of residents within the household. These variables affect the behavior of the people residing in the household. The social structure of each household is represented by a single value that changes over time based on the dynamics of the CA model. The decision to move emerges when there is a significant discrepancy between a household and its neighbors. Once the decision to move is formulated, the household selects a position in the model based on its own social structure and on neighborhood social attractors.

5. Theoretical framework

This cellular automata model is based on four general assumptions. First, households frequently experience minor changes in their social structure due to relatively inconsequential events (see [12,29,38,5]). However, a household will

occasionally experience a significant change due to events such as a job promotion, employment loss, marriage or death in the family (see [1,38,7]). These events either increase or decrease the social structure of the household and can result in a move.

Second, the social structure of a household is influenced by the social structure of neighboring households [1]. In essence there is a social balance between households and when a sharp contrast emerges the balance is offset and this can trigger a move (see [1,5,6]). This assumption is supported by research findings on how community structure can either positively or negatively influence behavior. For example neighborhoods that contain residents with similar social characteristics promote shared supervision of community residents, thereby diminishing the opportunity for unregulated problematic activities [7]. Conversely, socially disordered neighborhoods, such as those dominated by low-income, unemployed or single parent households can impose a negative influence on their residents through a non-cohesive and less trusting community structure that offers minimal community supervision and fewer pro-social adult role models (see [2,8]).

Third, a household's decision to move is influenced by the difference between its social structure and that of its neighbors. This may refer to situations in which social order declines and leads to poor community cohesiveness and increased criminal activity [38]. In addition, a similar discrepancy between the social structure of a household, and that of its neighbors, may be brought on by a new job or a growing family, either encouraging a move into an area with a higher social structure, or necessitating a move to an area with better access to schools. While the converse situation of gentrified neighborhoods leading to displacement of current residents may exist, there appears to be limited evidence to support this process [3]. Regardless, our model generalizes this process and considers both possible types of social change.

The fourth assumption of the model states that a household's decision to move is influenced by neighboring households and the positive or negative social attractors (see [29,13,39,32]). A household will move to the most appropriate position considering both the neighboring households and the proximity of social attractors. The household is not in a position to select the best position, but rather the most appropriate position.

There is no representation of immigration, emigration, births and deaths in the model at this stage. By assuming that these phenomena balance each other out, the model is simplified thus allowing the key concepts to come forward. Any explicit inclusion of such phenomena would introduce additional complexity that is unwarranted at this stage of the project. In future iterations, these variables can be introduced as the influences of social structure become clearer. This model is theoretical in nature, and aims to act as a broad simulation of a complex concept, rather than an empirical model aimed at testing cause and effect. A complex subject is captured using a generalized variable which encompasses a broad range of factors included in the decision to move. This can include a household's decision to move to a larger home, or to a neighborhood with better access to schools, just as it captures the decision to move as a result of increased crime and social disorder occurring in the immediate neighborhood.

6. Model structure

The model is implemented on a grid of cells that replicates an urban area. Each cell represents a land parcel in which one or more households may reside depending on the capacity of the cell. Not all cells are occupied by households in order to facilitate household migration. At each step of the model, the value representing the social structure of a household is subject to change based on a random variable that triggers a change in the household (assumption one from the previous section). Next, the neighborhood of each household is evaluated by calculating the average social threshold of the surrounding cells. Households then make the decision to move when their social structure is different from the average social structure of the neighborhood (assumption three). In order to ensure that households are not moving at every step of the model, a probabilistic function is used to determine when they will migrate. The chance of a move occurring is dependent on the dissatisfaction of the household with their neighborhood, or in other words, the difference between their social structure and the average social structure of their neighbors.

A household with a different social structure from its neighborhood engages in a search of all cells in the urban area in order to find a cell that best matches its social structure (assumption four). The household will remain in its current location if no vacant cells exist. If the household does locate a cell that meets these criteria, it will migrate to the new cell. All households that do not move and have been in their current neighborhood for a minimal time period have their social structure recalculated based on the average social structure of the neighborhood (assumption two). That is, the social structure value of a non-relocated household will move closer towards its neighborhood value. The updating of social structure values concludes a single time step of the model.

At each time step in the model, two processes are performed to update the states of the cells and households. Updating the neighborhoods consists of two parts:

1. Calculating the average value of each cell.
2. Compiling a list of vacancies.

In the case of a single occupancy cell, we consider the social structure of the cell itself along with its occupied neighbors to generate the average value. For a higher capacity cell, the social structure value of the occupants in that cell is used to generate the neighborhood average. Cells that are not completely full are compiled into a list of vacancies, which is organized into groups based on social structure. Fig. 2 is comprised of this process and its two parts, along with the process to update the households.

Fig. 4. Moore neighborhood superimposed on households.

In this process phase, the changes in each household for one time interval are processed. If the household decides to move and a viable location exists, they will relocate. Otherwise, if the household has been at their current location for more time than the threshold value, they will be socially influenced by their neighbors. All households will then have their social structure adjusted by a random value, in order to reflect changes experienced due to personal events in the family. This random value follows a normal distribution, so it will be a very small change in the majority of cases, with the occasional large change in a positive or negative direction. This models the changes that occur in daily activities in the sense that both minute everyday developments and life-changing disruptions of both the positive and negative variety are represented with appropriate intensity and frequency. The final step of this phase is to truncate the social threshold value in the case that it has gone beyond the maximum or minimum value.

At each step, all households undergo varying amounts of change to their social structure. This change in social structure is influenced strictly by internal factors. In other words, an event such as the death of a family member or a promotion at work is responsible for a large alteration of the social structure. External, or neighborhood factors, begin to influence the household when the time stayed in their current location is more than the minimum amount of time a household needs to settle in and start interacting with their neighbors.

Fig. 3 depicts the decision making process undertaken by each household for each time step. This process is driven by the social structure of the said household relative to its neighborhood. Based on this relative difference, the household probabilistically determines whether or not it wants to move. A household which possesses both the willingness and ability to move identifies an appropriate vacant area from the queue and proceeds to move there. Once moved to its new location, the household is assigned a new social structure and a time stayed value of zero. If a household lacks either the willingness or ability to move, it is only subject to the influence of its neighbors as well as changes in its personal life. Households continue to consider the moving options each time step; however, they will not move until the conditions are right.

7. Rules

This CA model attempts to replicate the physical interaction between households within a neighborhood. The cityscape, represented in this model with a grid, can easily be conceptualized using the most popular symmetric CA neighborhoods such as von Neumann or Moore neighborhood (Fig. 4).

The location of cells in the grid is denoted by (i, j) and N_{ij} shows a neighborhood of (i, j). The parameters used in this model are classified into two main classes:

1. household parameters: denoted by H
2. location parameters: specific to each cell in the grid.

This model is scenario based and the parameters with the rules that govern households and the locations in the grid are meant to reflect the social dynamics underlying urban migration.

7.1. Household parameters

Household parameters represent the social characteristics of the households at each time step.

- T: Time to settle into the neighborhood.
- $T_{ij}(t)$: The length of stay in (i, j) at time t. This is a counter and it resets to 0 when the household moves.

- $s(t)$: The social structure of the household H at time t and varies from S^- to S^+. It is randomly set at the beginning of the simulation and varies after that.

There is a lapse time (T) built into the households to allow them to settle into a neighborhood. During this time, they are not influenced by their neighbors. After T has lapsed, the social influence factor is triggered. The social threshold $s(t)$ captures the multiple factors in a household which can influence a household to move or stay. It depicts the social structure of a household and varies over time according to various rules.

$H_{ij}(t)$ shows the state of the household (H) at a given time (t). This is represented by:

$$H_{ij}(t) = [s(t), T_{ij}(t), T].$$

7.2. Location parameters

Location parameters are characteristic parameters of each cell (i, j) at each time step. These parameters depend on the surrounding cells.

- C_{ij}: Represent the capacity of residents at (i, j). In this model the capacity for each cell is one household per cell (low density) or more than one household per cell (high density).
- $C_{ij}(t)$: This represents the capacity at time t. The capacity of the cell is less than or equal to the determined cell capacity. $C_{ij}(t)$ can vary from zero (not occupied) to the maximum capacity (fully occupied) therefore $C_{ij}(t) \leq C_{ij}$.
- $V_{ij}(t)$: Value of the cell (i, j) at time t based on the neighborhood social structure. $V_{ij}(t)$ is the average of the households in the neighborhood.

$S_{ij}(t)$ is the average social structure of the households that live in (i, j) when $C_{ij} > 1$. Clearly, $S_{ij}(t) = s(t)$ in the case when $C_{ij} = 1$. Let

$$V_{ij}(t) = \sum S_{i'j'}(t)$$

which (i', j') varies in the neighborhood N_{ij}. Then

$$\begin{cases} V_{ij}(t) = (1/|N_{ij}|) \sum S_{ij}(t) & \text{if } C_{ij} = 1 \\ V_{ij}(t) = S_{ij}(t) & \text{if } C_{ij} > 1 \end{cases}$$

where (i, j) varies in N_{ij}.

In other words, if a household lives in a cell (i, j) with capacity 1 then the value of social structure of its neighborhood is the average of the social structure of the cells in that neighborhood. This value is the average of social structure of households in the cell (i, j), in the case that it lives in a higher capacity cell.

Since there is no specific definition for the parameter $s(t)$ and its value depends on a given what-if scenario, we call $s(t)$ a scenario parameter. Following that $V_{ij}(t)$ is a scenario parameter. The parameters with specific values are deterministic parameters. In the future, these values can be obtained by collecting data from previous studies. In this model the parameters T, $T_{ij}(t)$, C_{ij} and $C_{ij}(t)$ are deterministic.

7.3. Updating cells

In this model cells will be updated according to the following three rules. The first rule updates the social threshold of a household and the last two rules update cells based on when and where a household moves. At each time step, all cells in the grid will be updated simultaneously.

7.3.1. Update for $s(t)$

The parameter $s(t)$ can change over time and there are rules that govern this change. This is a scenario-based variable that changes gradually. There are two updates for $s(t)$: one is internal to the household and one is external. The internal factors cannot be changed by the household.

Internal influences on $s(t)$

The internal changes in $s(t)$ are meant to illustrate how certain factors or events in a household can change the social structure of the household. Parameter $s(t)$ is dependent on these changes and they cannot be avoided. This includes both minor and major circumstances such as a death in the family, a new birth, the loss of a job or a raise at work. These internal changes affect the social structure of the household, and can alter it enough to put the household in a position to move. At each step the model is updated according to this internal $s(t)$ rule:

$$\begin{cases} s(t) = \min\{s(t-1) + \epsilon, S^+\} & \text{if } s(t-1) + \epsilon > 0 \\ s(t) = \max\{s(t-1) + \epsilon, S^-\} & \text{if } s(t-1) + \epsilon \leq 0. \end{cases}$$

The parameter ϵ is a randomly determined value with a normal distribution centered on zero. In this rule, ϵ represents the change in social structure that a household experiences at each time step. This change varies at every time step for each individual household. The standard distribution of this value is a scenario parameter.

External influences on $s(t)$

After T, the time required to settle into a neighborhood, the household's social structure can be influenced by other households in the neighborhood. If the social structure of the household is less than the average of the neighborhood, then the household will receive a positive influence. However, if the social structure of the household is more than the average of the neighborhood, then the household will receive a negative influence. These changes are described in the following formulae. If $T_{ij}(t) > T$ then

$$\begin{cases} s(t) = s(t-1) + c & \text{if } s(t-1) \le V_{ij}(t) \\ s(t) = s(t-1) - c & \text{if } s(t-1) > V_{ij}(t). \end{cases}$$

The value of c indicates the amount of social influence a neighborhood has on a household. It is a fixed scenario parameter. It can be considered as the incremental effect on the social structure of a household because of the received social interactions from a neighborhood.

7.3.2. Moving from (i, j)

When the social structure of a household is close to the average, the probability of moving is significantly lower. The greater the difference between the household and the average, the greater the likelihood of moving. If $T_{ij}(t) > T$ then it moves with the probability

$$P(t) = |V_{ij}(t) - s(t)|/(S^+ - S^-)$$

where S^+ and S^- are the upper and lower bounds for social thresholds $s(t)$, respectively.

7.3.3. Moving to (i, j)

When a household moves it will select the most appropriate location which is the closest one to its own social structure. This move is dependent upon the capacity of the cells. Therefore we have $s(t) \approx V_{ij}(t)$ and $C_{ij} > Cij(t)$. As soon as H moves to (i, j) the time counter resets and $T_{ij}(t) = 0$.

7.3.4. Attractor influence on the decision to move

When a household is deciding to move it will consider locations which have a social structure closest to theirs. Once these locations are identified, the positive or negative attractors in the model are the final step in the decision making process. These attractors can be considered as tiebreakers: if there are two identical locations that are available, the location closest to the appropriate attractor will be selected. There are currently only positive and negative social attractors. Households that have a positive social structure (>0) are only influenced by positive attractors, whereas households with a negative social structure (<0) are influenced by negative attractors. In the case where a household has a zero value it is influenced by both attractors.

8. Simulation and results

For the simulation of this CA model a two dimensional 50×100 cell array type was used. Each element of the cell array is a vector storing household parameters, location parameters, internal influences and external influences. These vector elements were updated with time following the transition rules. The model was run for 5000 iterations. The time threshold is set at ten iterations by default, indicating the amount of time a household will spend in a cell before being influenced by immediate neighbors. The move threshold refers to the neighborhood social structure for a cell, and simulates the required difference between a household and its neighborhood in order for it to move. Three contrasting household distributions were simulated.

8.1. No attractors versus positive or negative attractors

An initial run of the model, using the default inputs, reveals the spatial patterning displayed in the No Attractors images below. After 5000 iterations, there are distinct clusters of households displaying high social structure values displayed in green cells, and those displaying low social structures are displayed in red cells. There appears to be a transition zone between the areas of high and low social structures, where values average out to near-zero displayed by the light green, to white, to light red cells. There are several individual cells with low social structure amidst a generally high socially structured area and, likewise, several display high social structures in lower social structure areas. These different cells within the clusters are multi-household cells, and as such, are more influenced by neighbors within the same complex than single households around them.

A very different spatial pattern is revealed when features are added to the model to represent a positive and a negative social attractor. Almost immediately, households displaying positive social structures start to cluster around the positive social attractors which are located in the upper left-hand corner. Likewise, households with negative social structures start to cluster around the negative social attractor. These patterns are strengthened throughout further iterations, with a near-equal division between households with positive and negative social structures (see Fig. 5).
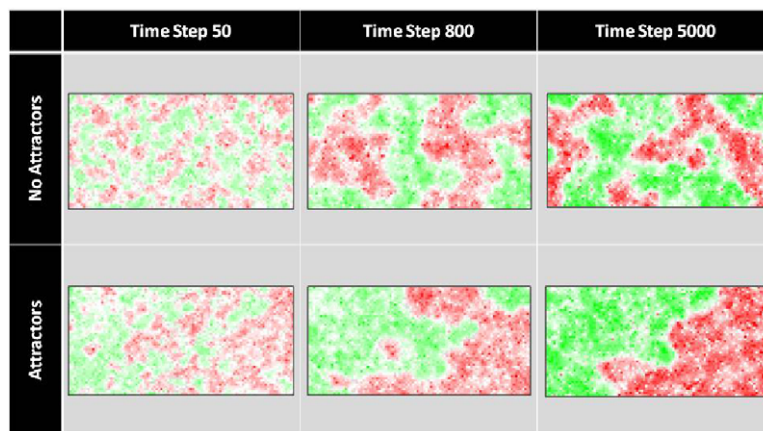
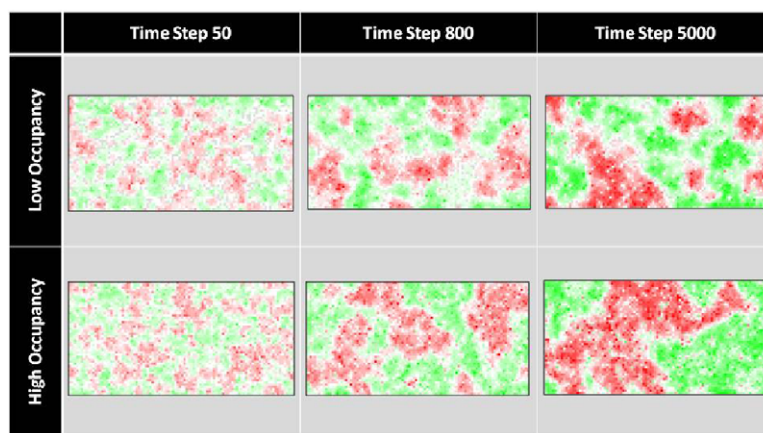**Fig. 5.** No attractors versus positive or negative attractors.

Fig. 6. Low versus high occupancy.

8.2. Low occupancy versus high occupancy

The default input for single occupancy households in this CA model is 90%, therefore the other 10% is multiple occupancy, representing multi-family dwellings such as apartments or condominiums. The default maximum occupancy for multiple household cells is 10 households. The occupancy rate is set at 90%, indicating that ten percent of available spaces are left unoccupied.

The impact of the amount of available space becomes clear when the results from a low occupancy run are compared with a high occupancy run. Households tend to group with similar households if given increased options for locations to move and defined clusters will form where the social structures of the households are similar. The unoccupied cells, defined by the light gray cells, increase in the low occupancy rate scenario. Further, in reducing occupancy levels, the transition zones which separate areas of high and low social structure which are denoted by the light red, white, and light green cells, increase in size. In this scenario the occupancy is set at 0.7.

Households have far fewer available cells to move into when this model is run with a higher occupancy rate of 0.999. As such, the households are increasingly impacted by the social structure of their neighbors. As a result, there are strict divisions between areas of high and low social structures. While smaller clusters of high or low social structure appear in the initial iterations of the model, these small islands quickly disappeared further into the simulation and are replaced by larger zones of either low or high social structure (see Fig. 6).

8.3. Low neighborhood influence versus high influence

The influence factor, or the amount of impact that neighboring households have on one another, is set at a default level of 0.01. The personal factor, or the amount of impact that a random personal event may impact a household's overall social structure, is set at 0.1.
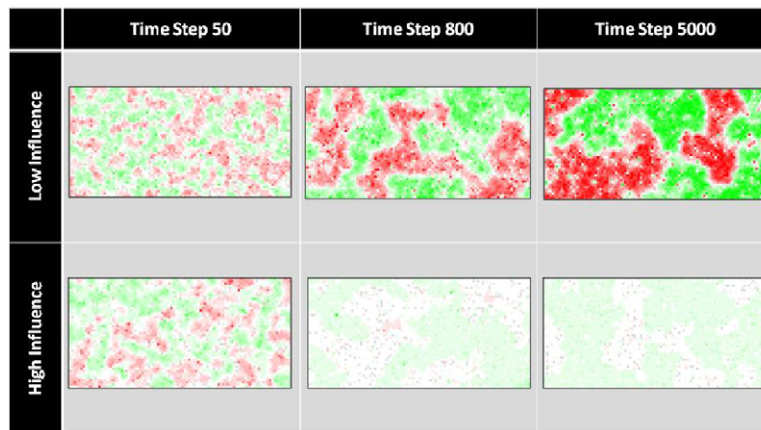
Fig. 7. Low versus high neighborhood influences.

Interesting patterns emerge when the social influence households have on each other is explored. The social influence factor has a larger impact on the model when there are fewer opportunities for movement. Early in the simulation, there is significant clustering of similar social value households, but these areas are quickly washed out as households with very high or very low social structures move closer to a zero value. After multiple simulations, it appears that a low positive social structure value dominates, with much of the display appearing as very light green (Influence = 0.1).

We see an interesting contrast to this simulation when exploring the impact of low social influence. Households tend to move to areas that are close to their personal social structure when they are not influenced by their neighbors. This creates another dramatic division between very high and very low social structured neighborhoods. The results show a near even split, with only a handful of low social structured cells found in the high social structure zone, and vice versa. In this scenario the influence factor is set at 0.001 (see Fig. 7).

9. Future directions

There are limitations apparent in the initial test model of migration patterns in a residential urban area. First, the model design, created to represent an urban neighborhood, is generalized into a series of cells, each capable of containing one or more households with a randomly assigned social structure. This generalization, in its current state, is certainly not representative of a real urban landscape. This model does not take into account all of the features in the built environment that would attract or detract residents because it only includes residential land use. In addition, this model has a number of parameters that are lacking a specific definition. The social structure of a household is an abstract concept containing any number of socio-economic or demographic factors. We hope to expand and elaborate on these concepts in later iterations of this model.

This model simulates aspects of the complex and multi-faceted process associated with urban residential migration. CA modeling provides an ideal methodology at this theoretical modeling stage because it is a valuable visualization of the processes and interrelationships between key variables associated with residential migration. This model expands the current body of knowledge on residential migration and neighborhood structure by exploring the influence of social structure on the decision to move. Once this model is moved from the abstract into the concrete and applied field of urban migration, key variables can be introduced into the model. Census data is a logical starting point for expanding and elaborating on the variables pertaining to the social structure of a household.

The literature emphasizes the importance of socio-economic variables such as income, education level, and housing tenure [40]. Furthermore, the physical characteristics such as housing type or condition, and proximity to educational facilities, influence residential mobility. The measures for these variables can be found in the Canadian census, acquired every 5 years, with the most recent census occurring in May 2006. This data can be scaled to fit this CA model, and at the same time, other data sources can be introduced. Research indicates that neighborhood-level crime and victimization are both relevant factors influencing residential migration (see [28,40]). Individual household-level crime data is available for inclusion in further iterations of this model. Finally, mobility data can be acquired from the Canadian Census, as a method of verifying further iterations of this model.

In the next phase of model development, data from a subset of a Canadian city will be introduced into the model using census, land use and crime data. This model will be run over the course of 25 years in order to study the impact of social structure on the decision to move. Introducing the socio-economic, structural and crime information into the model further contributes to understanding the complex dynamics associated with residential mobility. With these new parameters, this model can assist urban policy planners in determining development projects since current neighborhoods can be entered into the model and future plans can be assessed in terms of migration patterns.

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