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Editorial

Warning! The scale of land-use CA is changing!

1. What kind of panacea are cellular automata?

Geographic modeling is a cool issue today, and Cellular Automata (CA) is a cool issue in geographic modeling. Several reasons of this popularity can be suggested: the idea of CA is clear and can be implemented with minimal programming expertise; much high-resolution spatial data has recently become available; public interest in environmental and land-use forecasting is on the upturn. The last few years have seen a burst of publications in the field, with many applications demonstrating apparent correspondences between the model and recent real world data. On the basis of such fits, models are applied for scenario investigation and prediction.

But why, in reality, does this fit always occur? Does it mean that one or more CA models – such as, for example, the popular constrained CA of White and Engelen (White & Engelen, 1997; White & Engelen, 2000) – are universal tools, sufficient for adequate representation of every city's or region's land-use dynamics?

A possible avenue of explanation for the correspondence between model and reality are immediately obvious: (1) the dynamics of land-use patterns – or at least of the characteristics that we use to describe them – are not, apparently, very complicated; (2) the CA models possess sufficient degrees of freedom with respect to the model's spatial and temporal resolution, neighborhood size and form, parameters of the transition rules and the form of their analytical presentation; and (3) whether done analytically or by trial and error, one can always tune the model to fit a case study.

This is reassuring yet worrying. An analogy with multiple non-linear regression comes to mind and raises reservations regarding the *extrapolation* we seek when modeling system dynamics. 'Nothing new under the sun', might be the response of those who recall Douglas Lee's "Requiem for Large Scale Modeling" (Lee, 1973).

This in turn begs the question, will the contemporary boom come to a similar unseemly end and share the fate of comprehensive modeling? I do not think so.

2. Even simple CA are complex and should be treated with care

The unfortunate experience of comprehensive modeling should encourage us to simplify our models in every respect possible. Yet the prevailing feeling regarding land-use

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CA models is that we have already reached simplification's bottom line with regard to: (1) the distinctions between several states of each land unit; (2) consideration not only of immediate, but also further neighbors' influences; and (3) accounting for factors at the intermediate scale – such as distance to roads or water streams. Consideration of all of these factors seems mandatory.

If, nonetheless, we seek to substitute popular yet complex CA models with simpler representations, would we reach our goal? We would not. Contrary to linear regression, CA models were devised to demonstrate how simple local assumptions can nevertheless result in complex global dynamics. This complexity causes problems for urban modelers no matter how apparently simple the land-use CA are.

Let us illustrate the constraints of complexity with respect to issues of the spatial resolution of CA on the well-known Game of Life (<www.math.com/students/wonders/life/life.html>). Let us set up the "glider's" initial conditions, present the glider cycle (Fig. 1a) and try to repeat the glider's dynamics with CA of half the spatial but the same initial temporal resolution, that is, transform GOL_1 into GOL_2 defined on a superimposed grid of cells twice the size.

First, we need to characterize the states of the GOL_2.cell, which is a 2×2 square, in terms of the GOL_1.cell. This is straightforward – each of 4 GOL_1.cell units within a GOL_2.cell can be in either of two Dead/Alive states, that is, a GOL_2.cell is characterized by a four-component vector, which has $2^4 = 16$ states.

Next, we have to translate the rules of GOL_1 into the rules of GOL_2. Essentially, this should also pose no problem – each *n*-state CA in which the cell's neighborhood consists of K cells can be represented by table *R*, which has (K + 1) columns, and rows that contain all possible configurations of the neighborhood states at t and the cell's next state at $(t + 1)$. The number of rows in *R* is equal to n^K–the maximum number of rules necessary to describe the CA dynamics. In the case of the GOL_1, this results in R_{GOL1}, with $2^9 = 512$ rows. The beauty of the Game of Life is its ability to express a 512-row table using three simple sentences. Applying this (easily automated) step to GOL_2 with its 16 cell-states, one obtains R_{GOL2} with $16^9 \approx 6.7 \times 10^{10}$ rules (rows). Of course, the number of GOL_2 "meaningful" rules is much less, but the simplicity of GOL_1 is definitely lost when we consider it at half the resolution, both with respect to the number of states and the expression of transition rules.

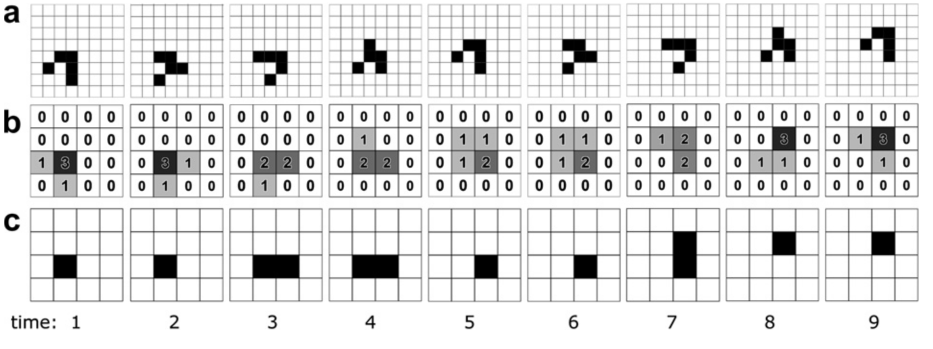

Fig. 1. (a) Glider dynamics in the Game of Life, GOL_1 CA; (b) dynamics of the GOL_{2total}, whose cell's state is given by the number of Alive cells of GOL_1 within; (c) dynamics of the $GOL_{2,2}$, whose cell is Alive if the number of Alive cells of the GOL_1 within is two or more.

One can try approximating GOL_2 with GOL_{2total}, whose cells are characterized by the number of Alive cells of GOL_1 within the larger cell of superimposed GOL_2 (Fig. 1b). The number of the cell states for GOL_{2total} is 5; hence, $R_{GOL2total}$ has $5^9 \approx 1.9 \times 10^6$ rows. The problem, however, is that the set of rules of the GOL_{2total} cannot be expressed by dependence of cell state at $t+1$ on the states of the cell and its neighbors at t: identical configurations at $t=5$ and $t=6$ result in different outcomes at $t+1$. One can further demonstrate that the state of the cell of GOL_{2total} at $t+1$ depends on its state and the states of its neighbors at t and $t-1$.

Can we approximate GOL_2 with 2-state CA? Let us employ the majority rule, just as we often do when deciphering urban RS images. Namely, let us decode a GOL_2 cell as Dead if the number of Alive GOL_1.cells within the GOL_2.cell is below threshold Th_A and Alive otherwise. The possible values of Th_A are 1, 2, 3 and 4; let us denote the resulting CA as $GOL_{2,1} - GOL_{2,4}$.

It is clear from Fig. 1b that $GOL_{2,4}$ and $GOL_{2,3}$ degenerate either immediately or at $t=3$, respectively. The case of $Th_A = 2$ (Fig. 1c) is more interesting. The founder Alive cell stays still for two time steps, then gives birth to the cell at its right, survives two more steps and then dies. The child survives five time steps, gives birth to a cell above it and dies; the founder's grandchild then proceeds to generate a new cycle. As is case of the GOL_{2total}, the set of rules should account for the delay: the state of the $GOL_{2,2}$.cell at $t+1$ depends on states of the cell and its neighbors at t, $t-1$ and $t-2$. What is the $GOL_{2,2}$ set of rules for arbitrarily initial conditions? I leave this question, as well as the problems of $Th_{Alive} = 1$, to the reader.

One can turn this exercise upside down and try representing the Game of Life at double resolution of $1/2 \times 1/2$. Skipping the details, there is no need for more than two cell states {Alive, Dead} in $GOL_{1/2}$ but one cannot describe the $GOL_{1/2}$ dynamics with rules based on a Moore 3×3 neighborhood – identical 3×3 neighborhood configurations might result in different outcomes. The 5×5 Moore neighborhood is sufficient for $GOL_{1/2}$, and this results in $2^{25} \approx 3.3 \times 10^7$ rules.

Game of Life CA are structurally quite distant from land-use CA models but this illustration is sufficient to illustrate my main idea: that the three main components of CA – states, neighborhood and rules – are all interdependent and related to CA temporal and spatial resolutions. We cannot change one of the components yet keep the others constant: this would create *another model* whose similarity to – or difference from – the initial model is not at all evident. When modeling land-use dynamics, we must be clear as to how to perform this scaling no matter how complicated the task; otherwise, we will be unable to understand our own models.

3. If only we knew the real process...

There are two standard ways to avoid incorrect model modifications; both are based on a view of the model as a reflection of the unobserved "real process". If a real process is continuous in space and time, as is the diffusion of a chemical pollutant in the atmosphere, then the basic model should be also continuous, just as the diffusion transport equation is. Diffusion or other continuous models can be investigated analytically in simple cases only; to find solutions numerically, they are translated into a system of difference equations defined on the spatial grid – that is, into the CA model. One can rely on well-established theory to implement such transformations. This theory includes a list of approaches to discretization and formulae that define the states of the grid cell, the necessary size and form of the neighborhood, and the rules for calculating cell states at $(t + 1)$, depending on the states of the cell and its neighbors at t (i.e. CA states, neighborhood and rules). Also important is the fact that the theory provides the cell size and time step, guaranteeing that the numeric solution will remain sufficiently close to the "real" dynamics (i.e. those supplied by the original continuous model) given the interval of extrapolation.

If the background land-use dynamics are viewed as discrete, the model should rely on real lots and parcels – the elementary units that planners and developers consider when making decisions (Benenson & Torrens, 2004; Blaschke, 2006; Samat, 2006; Schmit, Rounsevell, & La Jeunesse, 2006), as demonstrated above with the Game of Life; or, failing this, at least on cells, the size of which are close to that of typical elementary units (Kok, Farrowb, Veldkamp, & Verburg, 2001; Samat, 2006). In this way we are able to play the Land-Use Game at a "natural" resolution while avoiding the side-effects of aggregating or disaggregating (Schmit et al., 2006). This view presumes that only some of the resolutions are adequate for observing the "real" dynamics while the others obscure them from our view. One can only hope that the spectrum of adequate scales is not as narrow as in the Game of Life – and that our noisy urban systems in which land-use changes follow the caprice of landowners, planners, developers and others are structurally more stable.

4. Meanwhile, we can feel good with the CA that approximate only

It is hard to follow the rosy path described above. 30×30 m Landsat images and their derived 60×60 m, 90×90 m, or 120×120 m resolutions will stay with us for a long time, simply because we need historical data for studying land-use dynamics, irrespective of whether we believe that this rigid framework fits natural processes all over the globe. Even though we may be very unsure that the available documented land-use dynamics can be attributed to common background processes, flexible model frameworks with a parsimonious number of parameters can nonetheless be sufficient for our goals.

Two of the most popular land-use CA have actually been developed in this milieu. Clarke's self-modifying land-use CA SLEUTH (Clarke, Hoppen, & Gaydos, 1997) declares its approximation goal explicitly. It distinguishes four kinds of elementary land-use events – spontaneous urbanization, the generation of new centers, diffusion on the edges and road-influenced diffusion. Four corresponding sets of CA rules entail a total of 5 main plus several auxiliary parameters for tuning purposes. The calibration software is supplied together with the model.

Numerous applications of the model (e.g. Goldstein, Candau, & Clarke, 2004) have demonstrated that the trajectories calibrated using part of the available series of the land-use patterns remain close to the real dynamics for the next 5–10 years; and, as such, the length of this period can thus be considered a measure of model fitness. As might be expected, the mandatory calibration of the entire SLEUTH parameter set makes the model quite insensitive to changes in scale (Goldstein et al., 2004; Jantz & Goetz, 2005; Syphard, Clarke, & Franklin, 2005; Dietzel & Clarke, 2006) – since the calibration results in automatic adjustment of the rules. Yet, is this a CA model analog of approximating regression or does it reflect real world processes? Intuitively, I would place the Clarke model closer to the approximation rather than the "real" pole, resting on essential differences between the sets of best-fitting parameters obtained in different cases.

The constrained CA of White and Engelen (White & Engelen, 2000) follow the classic CA idea – that cell state is updated in parallel at every time step with respect to the states of cell neighbors. The neighbors are retrieved from the wide neighborhood of cells located within a spanning distance six times greater than the cell's length. In the model's most recent version, the cell states depend on factors at an intermediate scale such as, for example, distances to the road network, rivers and lakes. The basic (and sometimes forgotten) feature of the model is the predetermined amount of overall land-use change at each time step. The CA model is "constrained" by this amount and focuses on the spatial distribution of these externally defined changes. A tuning algorithm for the constrained CA is also proposed (Straatman, White, & Engelen, 2004), but not supplied as part of the package. The number of parameters for tuning is high – more than 50, and the sets obtained for different cases are more similar to each other than in the case of SLEUTH sets. This lower variation cannot, however, be considered as an argument in favor of constrained CA as a good absorber of "real" dynamics. Just as statistics teaches us, we still have to compare the variance of the parameters' estimates to the variance of the real-world trajectories. This has not yet been done either for SLEUTH or for constrained CA.

Contrary to SLEUTH, it would be difficult to say that recent studies of constrained CA scale-sensitivity (Menard & Marceau, 2005; Kocabas & Dragicevic, 2006; Samat, 2006) successfully account for the inherent relationships holding between model scales and transition rules. Only Samat Samat (2006) mentions qualitative consequences of the scale changes, yet does not relate changes in scale to the changes in parameters of transition rules. One thus cannot say whether the comparison is made between the outcomes of the same model with two different sets of parameters, or in fact is between two different models.

5. Let us test the universality of our CA models on the basis of their terms

Discounting my intuition, can I *investigate* whether my CA land-use model represents reality? Putting philosophy aside, to do this I need a sufficient variety of "realities" in order to ascertain whether my model is adequate for application to every aspect of interest. Yes, this might still be an approximation, but who cares if it always works and I can explain how it works?

Where could one obtain such a collection of "realities"?

I propose that we test the models on the basis of artificial dynamics generated by the models themselves – the *synthetic land-use dynamics*. Should we be interested in applying constrained CA to describe land-use dynamics in China, let us take a variety of Chinese land-patterns in, say, the year 1980, establish the scale that seems representative and the "natural" values of all 50 parameters and their interrelations, and generate all possible dynamics for 20 or 40 years. Contrary to the real data, we now know the scale of the processes, simply because we generate them ourselves.

Let us treat each of these dynamics as if it was real and investigate:

1. How we should modify the CA in order to preserve the same process in its aggregated and disaggregated representations? Can we retain the same set of the cell states or should we turn to a multi-dimensional description? How should the transition rules be modified?

2. As to the calibration algorithm, does it produce the same parameters as those employed for generating the process? What are the variance/confidence intervals of the parameter estimates given the parameters of the synthetic land-use dynamics?

And so on.

And this is only the beginning. We can then proceed in various directions. For example, we might reformulate the transition rules of the CA in a way appropriate for an irregular grid, generate synthetic land-use dynamics based on realistic irregular land partitions, and study the resulting representation by means of the regular grid of the Landsat or SPOT resolution. Or we might introduce human-induced obstacles into the land-pattern generator, say, that owners of some parcels prefer not to sell and some Dwelling → Office transitions are delayed for several years. Can a model that does not account for this information approximate these egoistic dynamics?

Going even further, let us generate land-use patterns with one CA model and simulate them with another. Might several models appear to be equally good?

The tools for investigations of this kind have been recently published in the abovementioned and other papers on land-use modeling (Bolliger, 2005; Herold, Couclelis, & Clarke, 2005; Parker & Meretsky, 2004; Tyrea, Tenhumbergb, & Bull, 2006; Verzelen, Picard, & Gourlet-Fleury, 2006). The applications, however, all aim at finer tuning of the model to real-world dynamics.

I believe that investigation of synthetic land-use dynamics could substitute for the barely realizable analytical study of land-use CA and enable us to understand the predictive power of our working tools, and thus suggest ways of applying them properly and deliberately.

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