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PROBABILISTIC LAND COVER TRANSITION MODELING USING DELTATRONS

Abstract: Our research on the impact of human induced change upon the natural landscape has produced a cellular automaton "deltatron" model of land cover transition. The deltatron model is tightly coupled to and driven by the Clarke Urban Growth Model, a cellular automaton model that simulates urban spread based on initial spatial conditions derived by digital map data and rules governing the behavior of a cellular automaton. The land use change model uses the number of new urban pixels at each time step in the simulation as the driver for further land use change. The deltatrons act as independent agents of change that rely upon historically measured land cover transition probabilities, local topography and the previous time period's changes as a control for enforcing new change within a neighborhood. Using modeled urban growth as a driver, land cover change, classified at Anderson Level 1, has been simulated for the EPA's Mid-Atlantic Integrated Assessment (MAIA) study area at a resolution of 1km. The result is a simulated land use forecast for the area that uses Monte Carlo simulation to estimate both the most likely future land covers class, and the associated uncertainty of the prediction. We introduce the deltatron model in detail, using the MAIA application as a specific data set. We propose that the simplistic spatial assumptions of the deltatron nevertheless are quite powerful in emulating the effect of land use dynamics.

COMPLEX SYSTEM MODELING WITH CELLULAR AUTOMATA

Evolving from previous work, a model of land cover change has been developed and applied to a regional dataset. The cellular automaton (CA) Clarke Urban Growth Model (UGM) simulated the affect of topography, adjacency and transportation networks on the patterns of urbanization though time (Clarke, Gaydos and Hoppen, 1996). This model was calibrated using historical data for a region compiled in a geographic information system (GIS) (Clarke, Hoppen and Gaydos, 1996). These results were then used to forecast the development of the regional urban system into the future (Clarke and Gaydos, 1997). The land cover change Deltatron model, introduced here, is tightly coupled with the UGM, and also utilizes historical, digital data maps to calibrate model performance. The models together are referred to as SLEUTH by reference to the models' input data requirements: *S*lope, *L*and cover, *E*xclusion, *U*rban, *T*ransportation, *H*illshade. Using only the clues given by known data input, SLEUTH seeks to predict the emerging form in a dynamic landscape by modeling the processes of change.

The evolution of land cover patterns is a process governed by a large number of forces both natural to the environment and imposed by human disruption. The state of the system at any given time is the result of the interplay of its many components. Trying to identify the intricate relationship of these many drivers may quickly lead to frustration since the problem is underdetermined. Nevertheless, an emerging body of theory suggests the multitude of interactions that take place on a large scale, at the individual level, forms the basis of system-wide aggregate behavior.

A first application of complexity theory was offered from the discipline of computer science. Von Neuman (1966) presented the idea that a type of computing machine could not only reproduce itself, but could generate a machine of greater complexity than the original. This concept was expressed in the form of a CA. Perhaps one of the most well known examples of a CA is the *Game of Life* developed by Conway (Gardener, 1972). The game is executed upon a regular tessellation of cells, in this case a grid of uniform, square pixels. The cells may exist in one of two states: alive or dead. Configuring the grid so some of the pixels are alive, while others are dead, establishes an initial set of conditions. A simple set of behavior rules determines if a cell changes states: less than three or greater than four live neighbors indicates an area unsuitable for life due to overcrowding. Three to four live neighbors indicate a good opportunity for growth, and new life. Searching each cell’s four or eight cell neighbors, these behavior rules are applied across the game space simultaneously. In this decision process, each cell acts within the system as an independent agent. Its condition is dictated not through outside determinants, but rather, as a result of the spatial and temporal changes dependant upon the current state of a cell and the state of its neighbors. Depending on the configuration of the initial conditions, complex spatial patterns emerge though repeatedly applying the behavior rules to the grid. In recent years CA has been applied in many and various fields, and has now been applied to modeling urban form (White and Engelen, 1992; Papini and Rabino, 1997; Batty and Xie, 1994; Clarke, Hoppen, and Gaydos, 1996).

We have extended the scope of our earlier research from modeling urban development to include how this expansion in turn affects subsequent land transitions. As Clarke pointed out (1997), these land transitions may be characterized in several ways. The first is indicated by a *state change*. A transition occurs when an area changes from one defined land class to another. A parcel’s conversion from forest to agriculture is an example. We assume that urbanization drives this change, and within the model, urban land is an invariant class. Once a pixel is urbanized it will remain so for the duration of that model run. Urban is therefore considered an “absorbing class.” Secondly, the *local context* of transitions must be considered. Transitions are affected by neighborhood dynamics. If many of an area’s neighboring parcels are experiencing a conversion to agriculture, a transition in that area, especially to agriculture, is more likely than in an area that is not experiencing land cover change. Lastly, a transition can take place at a *discrete location.* This can be defined as a point, an area, or in our case a pixel. Although the neighborhood and driving forces do affect the likelihood of change, each transition is made on the spatial level of the individual.

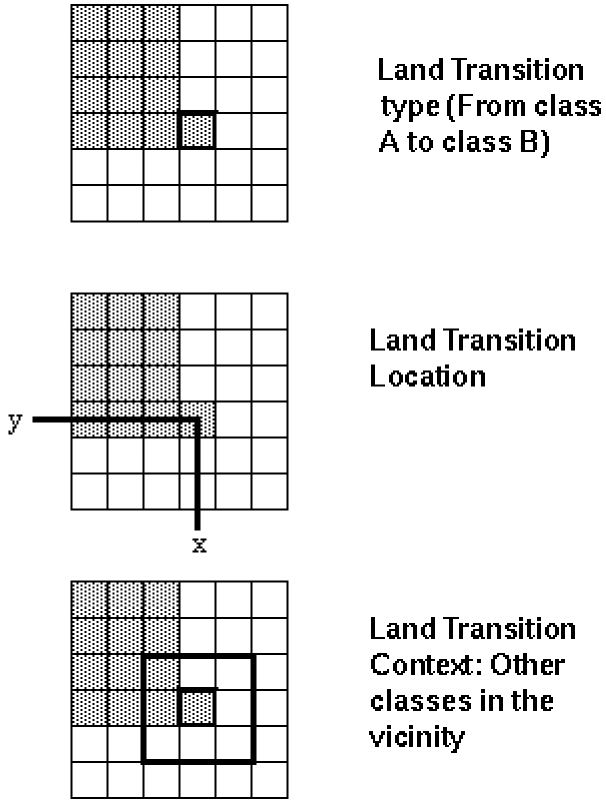


FIGURE 1: THREE CHARACTERISTICS OF LAND TRANSITIONS

Physical patterns of land cover change may be shown three ways. The first is the tendency of one land class to expand into another where the two meet. This is the most common type, and may be seen as the expression of a land type “growing” into its neighbors as topography and neighborhood resistance allows. The second is a less predictable occurrence of a new land cover type being introduced into an otherwise homogenous area. Both of these trends, though they begin at a discrete point and time, may trigger similar transition events in their neighborhood. This third occurrence, a perpetuation of change, enables transition forces to be propagated across a landscape. The deltatron model seeks to build upon and exploit these concepts of how and where land cover dynamics take place.

LAND TRANSITION MODELING

Probability of change

Creating a two-dimensional matrix ***T*** (table 1) of identical land cover maps at different time periods (figure 2) initializes a framework for land transition (Clarke, 1997). This matrix is normalized by the numbers of years between land cover data, and so represents an annual, or single step, probability of class transition. The transition matrix enforces the shift of regional land patterns over time. This design is obviously rudimentary and offers no opportunity to test statistical robustness. Use of three or more land cover maps, and a model of transitional probability change would allow a greater understanding of change dynamics and allow an estimation of variance.

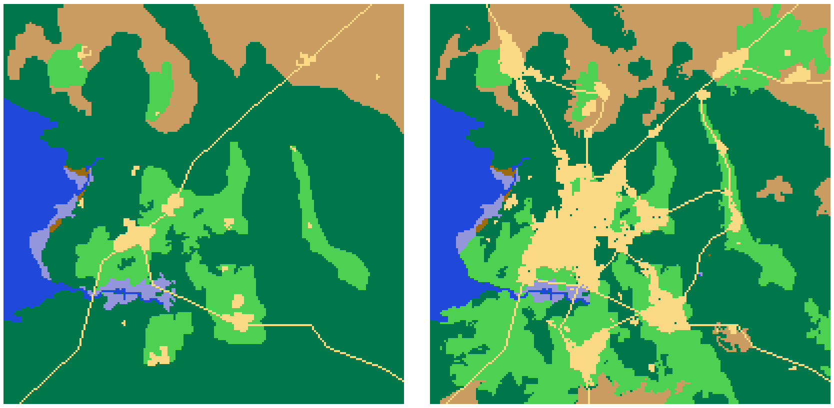


FIGURE 2: LAND COVER MAPS AT DIFFERENT TIME PERIODS FOR FICTIONAL REGION "DEMO_CITY"

	Urban	Agric	Range	Forest	Water	Wetland	Barren
Urban	100.0[924]	0.0[0]	0.0[0]	0.0[0]	0.0[0]	0.0[0]	0.0 [0]
Agric	0.6[1793]	99.3[2777]	0.0[17]	0.0[48]	0.0[0]	0.0[0]	0.0 [0]
Range	0.1[405]	0.3[1193]	99.5[4230]	0.1[229]	0.0[0]	0.0[0]	0.0 [0]
Forest	0.1[1319]	0.3[4513]	0.1[1529]	99.5[17754]	0.0[1]	0.0[3]	0.0 [1]
Water	0.0[1]	0.0[0]	0.0[0]	0.0[0]	100.0[2580]	0.0[0]	0.0 [0]
Wetland	0.2[61]	0.4[159]	0.0[0]	0.0[0]	0.0[0]	99.4[405]	0.0 [0]
Barren	0.0[0]	0.0[0]	0.0[0]	0.0[0]	0.0[0]	0.0[0]	100.0[58]

TABLE 1: TRANSITION MATRIX **T** FOR DEMO_CITY

Influence of Topography

In regions of even moderate topography, the average slope associated with each class may differentiate land cover types. Urbanization will often occupy the flattest land available, coastal plains and flat valley bottoms for instance, until these areas are all occupied. Steeply sloped forestlands are unlikely candidates for agriculture. However, rolling foothills might easily be cleared for orchards or grazing. The practical consideration of how topography affects land cover patterns is implemented in the model by giving preference to those classes whose slope is most similar to that of the pixel being looked at.

Urban driver

While there are many possible influences for any one class to transition to another, it is assumed, on a regional scale, that the most significant force shaping land cover change is consumption of undeveloped land by urbanization. The amount of change introduced to the system is driven by urban growth output from UGM. All other land cover transitions are secondary, and predependent on the level of urban growth.

DELTATRON IMPLEMENTATION

Previous work by Clarke (1997) outlined the deltatron approach and the assumptions it is based upon:

1. That land transitions be considered to take place on a uniform spacing grid.

2. That transition is between and among a finite set of states, where the number of states is small.
3. That the transition matrix accurately estimates land use state transition probabilities from observed counts.
4. That an external model be used to change the state of the dominant or driving class.
5. That there should exist considerable spatial autocorrelation in land transitions.
6. That there exists temporal correlation between land transitions.
7. That specific land transitions are influenced by context.
8. That land transitions happen to some degree at random, i.e. independent from the driving force.

Deltatrons act as “bringers of change” within the land class space. They are created by successful forces of change, and persist through time with their own life cycle. When change occurs, a deltatron is “born.” In the subsequent cycle, while the likelihood of similar conversion is still high, a young deltatron has the power to affect and encourage similar land transitions in its neighborhood. However, once a new land cover type has been established, an immediate adjustment to yet another class is relatively low. Here the deltatrons are also at work. After the initial period of change, a deltatron acts as a placeholder and prevents subsequent transition of the land class for the duration of its lifetime. How many cycles, or years, a deltatron lives may be able to be used as a modifiable parameter to fine-tune the model per application. Due to their sensitivity to local influences, and ability to modify behavior over time, deltatrons are critical to the spatio-temporal autocorrelation of the land transitions.

The process of simulating evolving patterns on a landscape takes place in two phases. The first initiates change in the environment. A disturbance is created, much like a stone dropped in a pool of water. After the stone is dropped, its effect continues to be felt as the energy of the disturbance is carried across the pool over time. How the ripples of change are facilitated for land transitions occurs in the second phase, and is the real work of deltatrons.

Phase I: Create Change

Phase I (figure 3) is driven by the number of pixels that were newly urbanized from UGM in the current time cycle. The cycle begins with a pixel being chosen at a random location *(i,j).* The location is tested for transition suitability. A pixel is not allowed to transition if its land class value is flagged as a) urban b) NODATA c) excluded (water, for example, might be part of this class), or if a deltatron is already at that location. When a suitable pixel is found, two land classes are chosen at random. Of these two, the class whose average slope is most similar to pixel *(i,j)* is selected. This process allows regional topography and land cover to further inform the transition process. The probability of transitioning from the current pixel class to the new class is then accessed. If a randomly drawn number is greater than the transition probability, that pixel fails, and a new random location is selected. However, if the number is less than the transition probability, the modification is implemented in the land class map. This single change is then encouraged to randomly spread to its neighbors in order to form a cluster.

When the phase I selections are completed, several clusters of new land transitions have been formed. At this time, deltaspace is updated with the locations of phase I change, and deltatrons are “born.” Deltaspace holds the deltatrons, and exists separately from the land class grids, though it mirrors the data dimensions exactly. When a deltatron is created it has a value, of one. This indicates its lifecycle age.

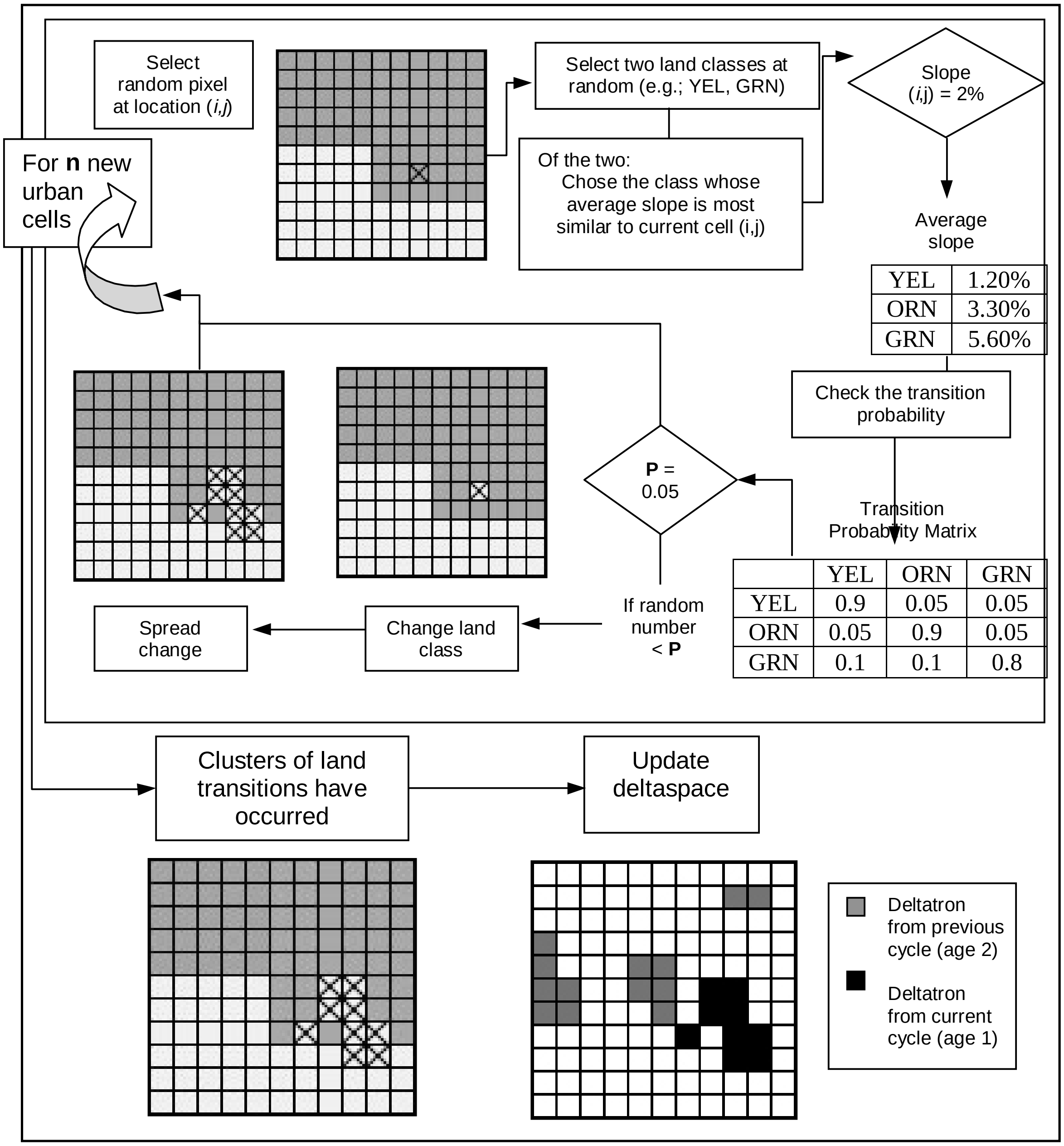
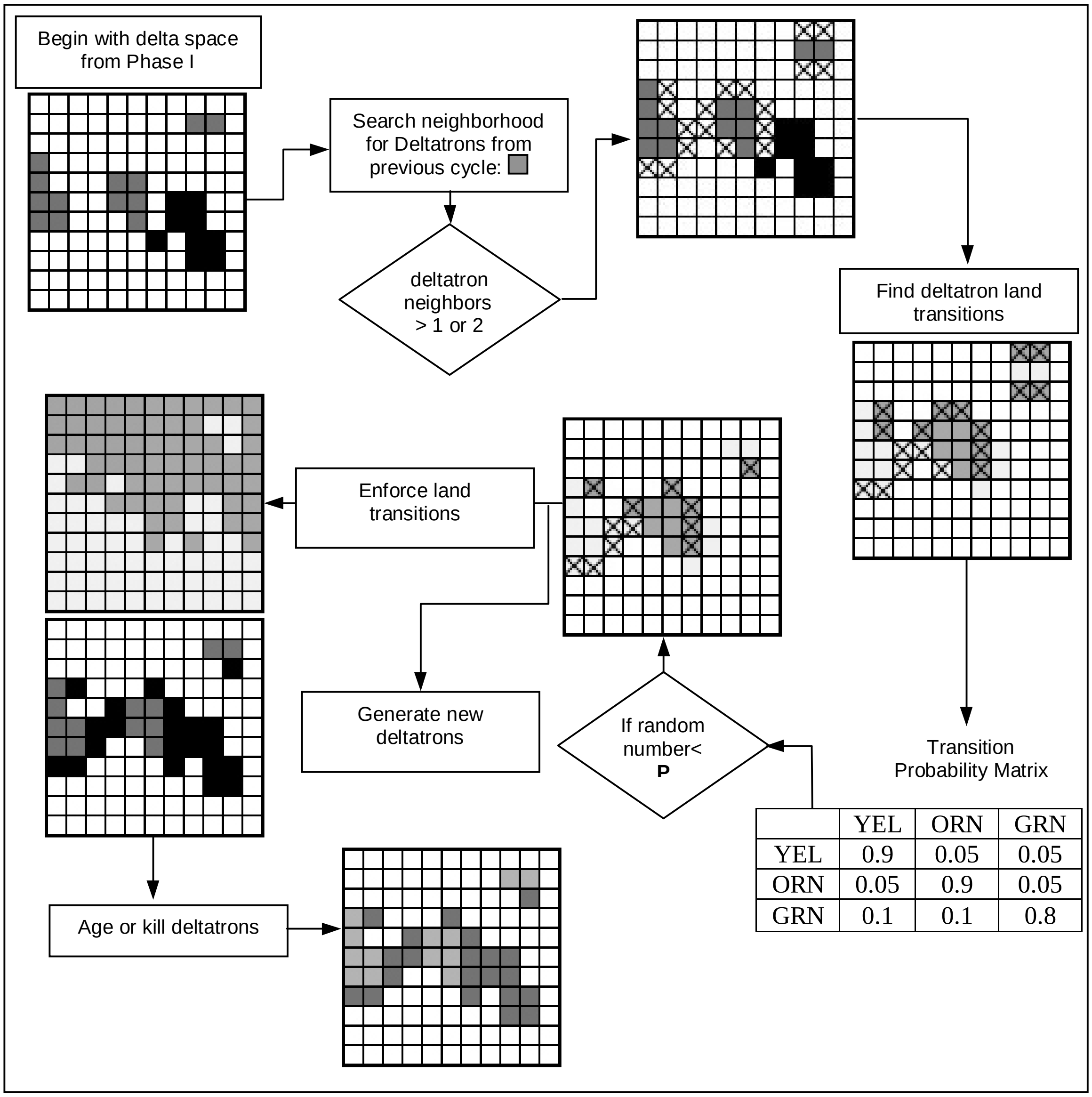


FIGURE 3: PHASE I DELTATRON CYCLE

Phase II: Propagation of Change

In Phase II the deltatrons for the previous cycle (age = two) try to initiate change into available neighborhood land. The search process in phase II is based upon standard CA rules. If a cell is suitable for conversion, is not a deltatron itself, but has two or three deltatron neighbors created in the previous time step, a land change will be attempted at that cell. Whether two or three neighbors are required is randomly set, and adds variation to how the propagating edge is formed. If a cell is selected for transition, its neighborhood deltatrons are searched to discover what type of new land type is being introduced. The probability of converting from the pixel's current class to the new land type is then tested. If a random number test against the transition probability fails, no transition occurs. If successful, the change is enforced onto the land class map, and a new deltatron is generated.

At the end of this process new land class transitions will have occurred due to the previous time step's deltatrons, and deltaspace is again updated with new, age = 1, deltatrons. The final stage of phase II is the aging of the deltatrons. All will be incremented by one. Over time (figure 4) the deltatrons decay and eventually, after their death, the location again becomes available for additional transitions.



	YEL	ORN	GRN
YEL	0.9	0.05	0.05
ORN	0.05	0.9	0.05
GRN	0.1	0.1	0.8

FIGURE 3: PHASE II DELTATRON CYCLE

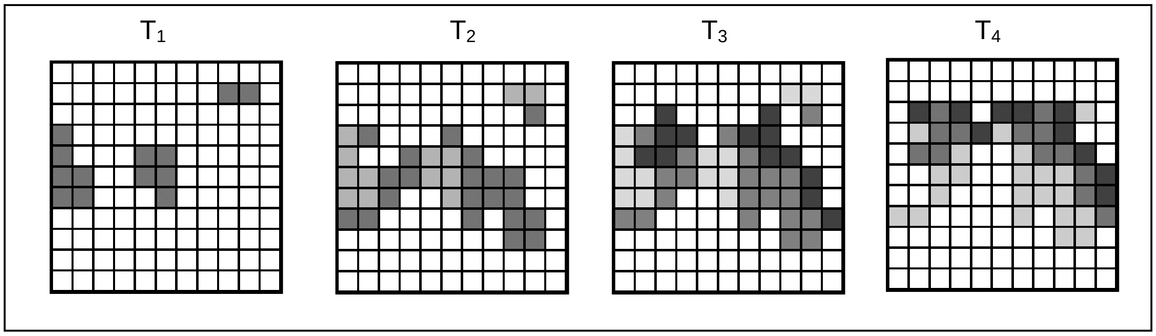


FIGURE 4: AGING DELTATRONS PROPAGATE THOUGH SPACE, OVER TIME

MAIA

The Mid-Atlantic Integrated Assessment (MAIA) study area is an EPA designated region for the implementation of research, monitoring, and assessment of ecological conditions (http://www.epa.gov/maia/html/about.html). It includes eight states on the eastern U.S. coast:

- Delaware
- Maryland
- Pennsylvania
- Virginia
- West Virginia
- New York
- North Carolina
- District of Columbia

The United States Geologic Survey, in cooperation with the University of California, Santa Barbara, applied SLEUTH v2.1 to the MAIA region with a data resolution of 1 km. An extensive calibration of the model (Clarke, Hoppen, Gaydos, 1997) using historic data (table 2) was performed for the region. Two Anderson Level I classified land cover maps (figures 5, 6) were used to set up the transition matrix. For calibration, the earliest land cover map provided initial conditions for the deltatron model. The most recent land cover map was used to measure how well the spatial patterns of land cover evolution were modeled for that year. In the final year a map of modeled land cover is produced and compared on a per pixel basis with the known data. This new comparison metric was added to the calibration process so that deltatron might influence the calibration process.

Data	Year	Data	Year	Data	Year	Data	Year	Data	Year
Urban	1950	Roads	1950	Land Cover		Slope	constant	Excluded	constant
	1970		1970		1975				
	1980		1980						
	1990				1992				

TABLE 2: CONTENTS OF MAIA TEMPORAL GIS DATABASE

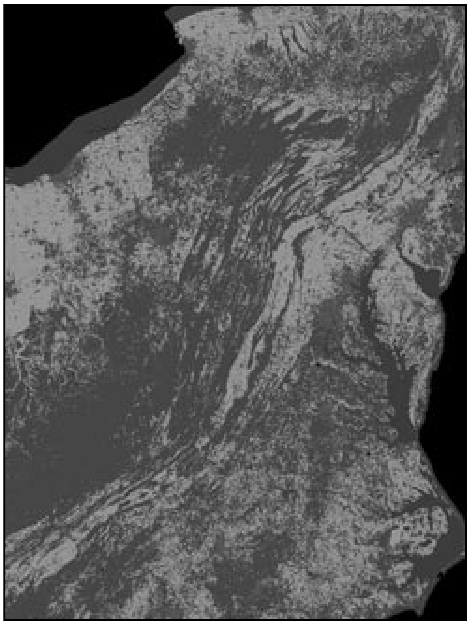


FIGURE 5: MAIA 1975 LAND COVER

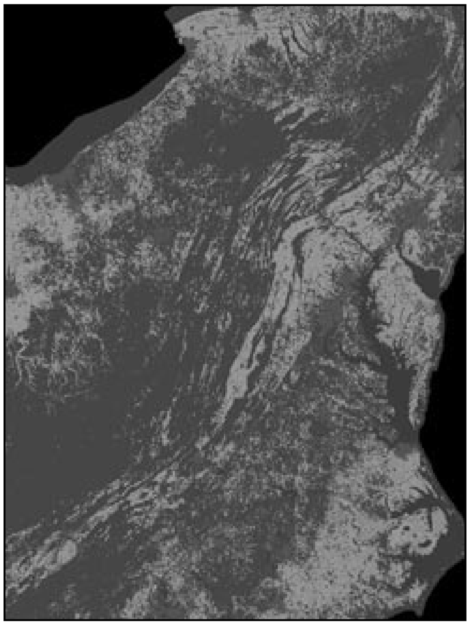


FIGURE 6: MAIA 1992 LAND COVER

PROBABILISTIC FORECASTING

Once model calibration for the MAIA region was complete, urban growth and land cover change was simulated into the future. Beginning in the data year 1992, the model was run over 50 Monte Carlo iterations to the year 2050. From this process, two prediction maps were produced that describe the likelihood and character of land cover change.

The first (figure 7) is a map of the most probable forecasted land class for the year 2050. Each location is classified by its “winning” land cover type. That is, by the land class present most often over the 50 Monte Carlo iterations. Figure 8 shows the pixels that changed class from 1992 to 2050. They are color classified by the class they changed to. The urban growth around already established urban areas is clear.

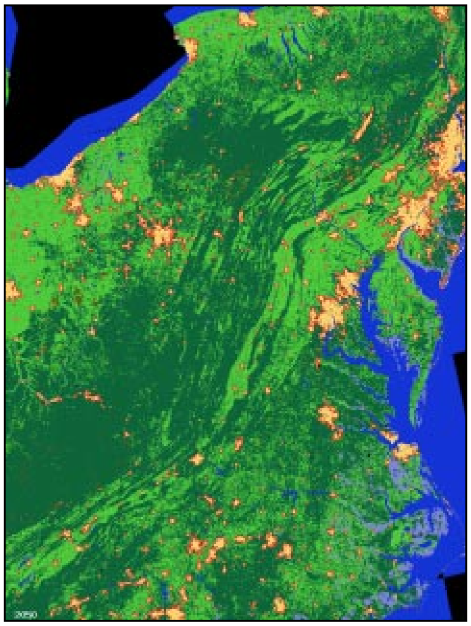


FIGURE 7: MAIA 2050 PREDICTED LAND COVER FROM 1992

FIGURE 8: PREDICTED CHANGE

A second image produced by deltatron (figure 9) is a map of uncertainty that is associated with the land cover forecasts. It is calculated by counting the number of times each class was at a given location over all Monte Carlo iterations. If a location is found to always have the same land cover when the year 2050 is reached, its uncertainty value is zero. However, if one land class is equally likely as another of being present, there is a high degree of uncertainty related to modeled class transition. The higher a pixel's value in the uncertainty map, the less confidant we are in the model's prediction at that location. In the case of pixels that are classified as "NODATA", nothing is known about their state, and their associated uncertainty is also at a maximum.

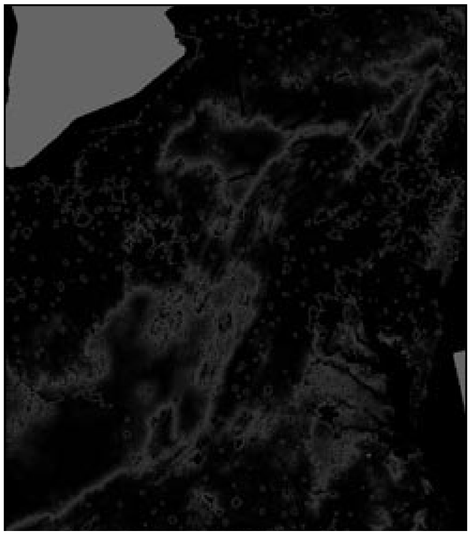


FIGURE 9: MAIA UNCERTAINTY MAP

CONCLUSIONS

The deltatron model is a valuable tool to forecast how the spread of urbanization could shape future land cover patterns. Though still in the early phases of development, the modified CA produced believable results for a large region of the United States. The cumulative land cover and uncertainty maps clearly show the spatial and temporal relation of land transitions. Together, these maps provide a valuable tool to describe predicted land cover change. By bringing the maps back into a GIS database, spatial context can be given to land class forecasts and the amount of confidence associated with it.

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