1

THE CO-EVOLUTION OF LAND USE AND ROAD NETWORKS

David Levinson, Feng Xie, and Shanjiang Zhu, University of Minnesota, Minneapolis, USA

INTRODUCTION

Transportation and land use are interdependent shapers of urban form. First, changes in land use alter travel demand patterns, which determine traffic flows on transportation infrastructure. Second, changed traffic flows drive the improvement of transportation facilities. Third, new transportation facilities change the accessibility pattern, which drives the re-location of activities and land uses. During this process, both transportation and land use are evolving constantly, leading to salient spatial transformations such as agglomeration and centralization over space and transportation networks. For example, as cities evolved in the first half of the 20th century, we saw a concentration of activities and development at the centers of cities. As freeways were constructed from the 1960s, roads also became more differentiated with regard to their functional designs and running speeds (certainly in the pre-auto era most unpaved streets were equally slow, with paved streets and highways and then freeways, some roads got much faster). Urban agglomeration and differentiated highway networks are referred to as hierarchical systems in this study.

In the context of the co-evolution of land use and road networks, this paper in particular examines the degree to which the dynamics of land use is reinforcing or counteracting hierarchies of road networks. By this we ask will a more hierarchical distribution of activities lead to a more or less hierarchical road network? Observation of historical evidence does not lead to a clear conclusion, as the development of a hierarchy of transit systems during the streetcar/subway era was accompanied with a concentration of development (especially employment) in the center of cities (from an undeveloped state), while the development of a hierarchical road network (from an underdeveloped and largely undifferentiated street system) occurred when those same cities were decentralized from a highly developed state. This paper aims to examine this question in a simulation environment with controlled initial conditions and quantitative measurements of spatial hierarchy.

The remainder of this paper is organized as follows: the next section presents a review of related literature, which is followed by an introduction to the simulation model developed for this study. Then the experiments are outlined, and results are reported, and some sensitivity analyses conducted. The conclusions summarize the findings and suggest future directions for research.

LITERATURE REVIEW

While there have been some investigations of the evolution of transportation infrastructure and that of urban land use separately, few have examined the integrated development of transportation and urban space in an evolutionary way, leaving the co-evolution of transportation and land use still poorly understood.

The investigation of the growth and transformation of transportation infrastructure dates back to 1960s, when a series of studies were conducted by geographers and transportation planners to replicate the changing topology and connectivity of road or rail networks (Garrison and Marble, 1962; Taaffe *et al.*, 1963; Morrill, 1965). The dynamic analysis of transportation networks, however, was based on heuristic and intuitive rules in these studies, due to a lack of understanding on its inherent mechanisms at that time. In recent years, a limited number of attempts have been made to model the dynamics of transportation networks in a more realistic way. Yamins *et al.* (2003) presented a simulation of road growing dynamics on a land use lattice that generates global features observed in urban transportation infrastructure. Van Nes and van der Zijpp (2000) and van Nes (2002) claimed that the emergence of hierarchy in transport networks is a natural phenomenon in maximizing performance while minimizing the resources needed, and also discussed the relation between hierarchy in transport networks and that in spatial structures. Yerra and Levinson (2005) and Levinson and Yerra (2006) incorporated a simplified travel demand model to predict traffic flows on a surface transportation network, and introduced independent agents to invest (disinvest) in individual roads according to the revenue and cost associated with forecasted traffic. They demonstrated that a network could evolve into a hierarchical structure from either a random or a uniform state, even based on completely decentralized decisions of autonomous roads. Previous studies, however, didn't integrate the dynamics of transportation networks with the development of urban space, with land use either ignored or taken as exogenous.

The evolution of urban space has been examined by another steam of studies. The pioneering work by von Thünen (1910) presented a monocentric city surrounded by agricultural land and predicted the rent and land use distribution for competing socio-economic groups. Christaller (1933) introduced central place theory and demonstrated that a hierarchy of central places will emerge on a homogenous plain to serve the surrounding market while minimizing transportation costs. Krugman (1996) explores the phenomenon of self-organization in urban space. He develops an edge city model to demonstrate how interdependent location decisions of businesses within a metropolitan area could lead to a polycentric pattern under the tension between centripetal and centrifugal forces. Based on these theoretical investigations, a host of empirical land use-transport models have been developed to forecast land use development while considering transportation as an important factor. One of the first that gained substantive interest was the Lowry model (Lowry, 1963). Since the 1980s, many integrated land use models have been applied in real cities and some

have been developed into commercial packages. Examples include START (Bates *et al.*, 1991), LILT (Mackett, 1983, 1990, 1991), and URBANSIM (Alberi and Waddell, 2000; Waddell, 2002). A comprehensive review of these integrated land use-transport models has been provided by Timmermans (2003). In most of these models, the dynamics of urban space has been played out as the outcome of the location decisions made by residents and businesses, in which both accessibility to employment and accessibility to population play essential roles (Hansen, 1959; Guttenberg, 1960; Huff, 1963).

Although the concept of accessibility connects transportation with land use development, the change of transportation networks has seldom been considered in previous land use-transport models. A possible explanation is that these models are already complicated enough. They usually involve multiple modeling approaches, incorporate numerous constraints and assumptions, and are estimated from empirical data, unavoidably leading to a comprehensive modeling framework including a wide variety of components. These models are so specific and complex that 1) they are difficult to replicate; 2) the relationships between components are entangled and implicit; 3) the emergent large-scale patterns in space and network are difficult to recognize and analyze. Lee (1973) also has an important critique.

In contrast to those complicated and all-encompassing models that do not provide an explicit perspective, this paper models the integrated dynamics of land use and roads in as simple a way as possible that captures salient properties, enabling us to display and analyze the emergent hierarchy and agglomeration patterns of space and network on a large scale, as well as observe the interactions (reinforcement or counteraction) between the dynamics of roads and the development of land uses. The specific simplifications and assumptions made in our model specifications will be discussed later.

Extending Krugman (1996), Levinson and Yerra (2006), and Yerra and Levinson (2005), this paper models the co-evolution of land use and road network as a bottom-up, rather than a top-down process, by which interdependent location decisions of businesses (equivalently referred to as employment or jobs in this paper) and residents (also called population or workers or housing or resident workers) are incorporated, as well as investment decisions of autonomous roads based on predicted traffic on a network. Planners and engineers would argue that while market-based land use may be constrained by zoning and plans, transportation network investments are decisions that are now driven, or coordinated, by centralized organizations such as state departments of transportation or metropolitan planning organizations that make major investment decisions using a forecasting model and planning process to test and evaluate alternative scenarios. Local jurisdictions, of which there are many in some metropolitan areas, make investments on lower level roads. Certainly these organizations do affect new investment, but the decision to build or expand a link is also constrained by many facts on the ground, actual traffic on the link, competing parallel links, and complementary and upstream and downstream links, the costs of expansion, and limited budgets (Levinson and Karamalaputi 2003a,b). According to Krugman (1996), a self-organizing system of urban space and network will evolve into order and pattern, even based on simple, myopic, decentralized decisions of individual businesses and workers. If we can generate convincing collective representations of land use and network structure without any centralized planning or direction, perhaps planning is not as important in shaping urban areas as it is sometimes credited.

MODEL FRAMEWORK

A Simulator of Integrated Growth of Network Growth and Land-use (SIGNAL) is developed in this study to simulate the co-evolution of land use and road networks. An overview and inter-connection of these models is illustrated in Figure 1. The components of the model include *travel demand*, *road investment*, *accessibility*, and *land use*.

[Insert Figure 1 here]

Travel demand models

The travel demand model converts population and employment data into traffic using the given network topology and determines the link flows by following the traditional planning steps of trip generation, trip distribution, and traffic assignment (for simplicity, a single mode is assumed) (Ortuzar and Willumsen, 2001).

A simplified *trip generation* model estimates the number of vehicle trips that originate from or are destined to a zone as a linear combination of the quantities of employment and population in this zone, without distinguishing trips by purpose:

$$O_i = \xi_1 E_i + \xi_2 P_i \tag{1}$$

$$D_i = \psi_1 E_i + \psi_2 P_i \tag{2}$$

Where O_i and D_i represent the number of trips that originate in or are destined to Zone i respectively, while E_i and P_i are the employment (jobs) and population (resident workers) in this zone.

A doubly constrained gravity-based trip distribution model is adopted to match both trip generation and attraction of locations based on a negative exponential function that assumes the interactions of zones decreases with the travel time between them:

$$T_{ij} = K_i K_j O_i D_j e^{\varepsilon t_{ij}} \tag{3}$$

Where T_{ij} is number of trips from zone i to zone j; K_i, K_j are balancing coefficients; O_i is the production of zone i; D_j is the attraction of zone j. The parameters in this trip distribution model have been calibrated using the empirical data in the Twin Cities, (see Levinson *et al.* (2006) for details). The variable t_{ij} is the generalized travel cost from zone i to zone j calculated as:

$$t_{ij} = \begin{cases} \sum_a (\delta_{i,j}^a t_a) + t_{m,i} + t_{m,j} & i \neq j \\ t_{m,i} & i = j \end{cases} \tag{4}$$

Where $t_{m,i}$ and $t_{m,j}$ represent the generalized intra-zonal travel time in zones i and j, respectively. The generalized intra-zonal travel time captures a variety of costs incurred on trips that rise with land use intensity. It represents things like higher congestion levels, longer elevator waits in taller buildings, greater difficulty of finding parking, and taking longer to engage in parking that add to local travel time and travel cost in both zones. An intrazonal generalized time penalty acts as a surrogate for all of the above. Assuming a simple quadratic relationship between the generalized intra-zonal travel time and land use density in zone i, $t_{m,i}$ is calculated as:

$$t_{m,i} = t_m^0 \left[1 + \left(\frac{G_i}{\bar{G}} \right)^2 \right] \tag{5}$$

Where t^0_m is a specified base intra-zonal travel cost for all zones, G_i is the number of activities in zone i, while $\bar{G}$ represents the average number of activities across all zones. In our case,

$$G_i = E_i + P_i \tag{6}$$

Where E_i and P_i represent the employment and population in zone i, respectively. They will be discussed later in the land use model.

The inter-zonal travel cost between zone i and zone j is computed as a summation of link travel cost along the shortest path from zone i to zone j, where t_a represents the generalized travel time that a vehicle spends on link a, while $\delta^a_{i,j}$ is a dummy variable equal to 1 if link a belongs to the shortest path from zone i to zone j and 0 otherwise. Dijkstra's Algorithm (Chachra *et al.* 1979) finds the shortest path from each node to all other nodes of the network. The generalized cost of travel time on link a is calculated by incorporating adding monetary cost (toll) (with an appropriate conversion factor) to the actual travel time on this link (tolls are charged by the road agent):

$$t_a = \frac{l_a}{v_a} + \frac{R_a / \eta}{f_a} \tag{7}$$

Where l_a, v_a, f_a, and R_a respectively represent the length, average speed, traffic flow, and collected revenue of link a in a given time period. The parameter η represents the average value of time. The calculation of R_a will be discussed later.

A Stochastic User Equilibrium (SUE) is adopted in *traffic assignment* to predict route choices on a network according to perceived travel time, implementing Dial's Algorithm and Method of Successive Average (MSA) (Sheffi, 1985; Davis and Sanderson, 2002). Traffic assignment in a time period starts with the congested travel time resulting from the preceding time period, which makes the convergence in MSA much faster. The convergence rule in MSA specifies a maximal allowable link flow change equal to 0.5 (or a maximum of 100 iterations). A smaller maximal allowable flow change will result in a flow pattern that is closer to the equilibrium, but there is tradeoff between the accuracy and run time. The parameters in the model have also been calibrated by Levinson *et al.* (2006).

Road investment models

Road investment models describe the economic decisions of individual roads as autonomous agents. These decisions in terms of tolling, spending, and investing are abstracted in simple equation forms, also assuming autonomous roads make myopic decisions without considering cooperating with others or saving for the future.

A *revenue* model determines the toll a road collects during a given time period, depending on the traffic that uses this road. To ensure two parallel and opposite one-way links *a* and *b* that connect two nodes are always maintained at the same conditions, we assume that a single agent operates both links as a whole. Let f_a and f_b respectively represent the flow traversing link *a* and link *b* for a given time period, the total revenue collected on both links by the agent can be calculated as:

$$R_{a+b} = \tau l_a \left(f_a + f_b \right) \tag{8}$$

Where τ is the regulated toll rate. A regulated toll rate across all the links simulates a distance based tax, which is the most common practice throughout the United States. Both link *a* and link *b* have the same length: $l_b = l_a$.

The *cost* to maintain links in their present usable conditions depends on link length, flow and capacity. Suppose link *a* and link *b* have the same capacity $C_a = C_b$, the overall spending of the agent operating links *a* and *b* is calculated as:

$$S_{a+b} = l_a C_a^{\sigma_2} \left(f_a^{\sigma_1} + f_b^{\sigma_1} \right) \tag{9}$$

Where the coefficients σ_1 and σ_2 are specified flow and capacity powers in the equation.

An investment model assumes each agent spends all its available revenue at the end of a time period myopically, without saving it for the future. If the revenue exceeds the maintenance cost, remaining revenue will be invested to expand the capacity of subordinate links. In contrast, if the revenue is insufficient to cover the cost, road conditions will deteriorate and link capacity will drop until the link is eventually abandoned. This investment policy adopted by each agent can be expressed in a simplistic form as:

$$C_a^{k+1} = C_a^k \left(\frac{R_{a+b}^k}{S_{a+b}^k} \right)^{\rho} \tag{10}$$

Where $C_a = C_b$ is the capacity of link *a* and *b,* which changes with iteration *(k),* respectively, while ρ is a specified coefficient that affects the speed of convergence. As implied by Equations (8)-(10) and specified parameters (detailed in Table 1), a network equilibrates when the flow on each link equals road capacity in quantity.

[Insert Table 1 here]

Zhang and Levinson (2005) estimated the relationship between the free flow speed of a link and its capacity in a log-linear model based on the empirical data in the Twin Cities. The log-linear relationship is adopted here to update the free flow speed (v_f) of a link after its capacity is changed:

$$v_{f,a} = \omega_1 + \omega_2 Ln(C_a) \qquad (11)$$

where ω_1 and ω_2 are two coefficients in the log linear equation while C_a is the capacity of link a.

The relationship between the free flow speed and congested speed of a link is defined by the BPR function (Bureau of Public Roads, 1964) as:

$$v_{c,a} = v_{f,a}\left[1 + \alpha * \left(\frac{f_a}{C_a}\right)^\beta\right] \qquad (12)$$

where α and β are the coefficients of the function, assumed to equal 0.15 and 4.0, respectively.

Accessibility and land use models

Accessibility reflects the desirability of a place by calculating the opportunities and activities which are available from this place via a road network but are also impeded by the travel cost on the network. Suppose an urban space is divided into J Traffic Analysis Zones (TAZs) or land use cells that contain both employment (jobs) and population (workers). The *accessibility* in each cell (to employment and population) is computed respectively using a negative exponential measure:

$$A_{i,E} = \sum_{j=1}^{J} E_j e^{-\theta t_{ij}} \qquad (13)$$

$$A_{i,P} = \sum_{j=1}^{J} P_j e^{-\theta t_{ij}} \qquad (14)$$

where $A_{i,E}$ is the accessibility to employment (jobs) from zone i while $A_{i,P}$ is the accessibility to population (workers). The coefficient θ indicates how the accessibility of a zone declines with the increase of travel time to the zone. This coefficient basically represents the same idea with ε in Equation (3), indicating the impedance factor in travel that increases with travel time. Thus θ adopts the same value with ε. Though the sensitivity of θ is tested later separately.

A *land use* model is then developed to reflect how the distribution of population and employment respond to the accessibility patterns, while keeping the total population and total employment constant. The land use model is simplified in the sense that accessibility to employment and accessibility to population are the only factors that affect the decision on locations made by businesses and workers. As accessibility is essential in the relationship between transportation and land use, other factors such as land price and administrative policies are excluded to keep this relationship succinct and clear, thus enabling simple accessibility-based rules to which independent location choices can be made. To be

representative, our land use model contains both centripetal and centrifugal forces, that is, a force of attraction (e.g. economies of agglomeration) and a force of repulsion (a desire on the resident workers part for spatial separation, keeping all activities from locating at a single point). We assume people want to live near jobs, but far from other people (to maximize available space and to avoid potential competitors for jobs), while businesses (employment) want to be accessible both to other businesses and to people (who are their suppliers of labor and customers). The following stylized models are developed to track the dynamics of population and employment based on independent decisions of businesses with regard to their locations. The first group of equations describes the dynamics of businesses.

$$U_{i,E} = A_{i,E} + \lambda A_{i,P} \tag{15}$$

$$\overline{U_E} = \frac{\sum_{j=1}^{J}(U_{j,E}E_j)}{\sum_{j=1}^{J}E_j} \tag{16}$$

$$\frac{E_i^{k+1} - E_i^k}{E_i^k} = \gamma(U_{i,E}^k - \overline{U}_E^k) \tag{17}$$

The employment utility (desirability) of a zone is estimated as a linear combination of its accessibility to employment and to population in Equation (15). Note that both accessibility to employment and accessibility to population reinforce the employment desirability, indicating a strong centripetal force exists in shaping the pattern of employment (though intrazonal transportation costs do increase with density). The average utility that each business enjoys is calculated in Equation (16), and the influx of businesses to a zone in the next time period (iteration $k+1$) is proportional to the utility above the average that a business can enjoy in the zone as well as the total number of existing businesses, according to Equation (17). It can be easily proven by adding up Equation (17) for all zones that the total employment is ensured to be constant in these equations. The parameters λ and γ are two coefficients in the linear equations.

$$U_{i,P} = A_{i,E} - \mu A_{i,P} \tag{18}$$

$$\overline{U_P} = \frac{\sum_{j=1}^{n}(U_{j,P}P_j)}{\sum_{j=1}^{n}P_j} \tag{19}$$

$$\frac{P_i^{k+1} - P_i^k}{P_i^k} = \gamma(U_{i,P}^k - \overline{U}_P^k) \tag{20}$$

Similarly, the dynamics of population is described in Equations (18)-(20). The only difference lies in Equation (18), in which the residence disutility is determined by a centripetal force and a centrifugal force. A hedonic analysis of home sale prices in the Minneapolis-St. Paul region conducted by El-Geneidy and Levinson (2006) reveals that μ is near 1.0.

Figure 2 illustrates the feedback relationship between the network and land use variables within our system of co-evolution. An arrow with a plus (+) or minus (-) between two boxes shows a positive or negative relationship between the boxes. As can be seen, road expansion increases capacity, which improves free flow speed; the increased capacity increases cost, then forces the capacity back according to the investment rules. The improvement of travel time increases traffic flow, which increases the revenue and facilitates road expansion. The improvement of travel time also increases both accessibility to jobs and accessibility to houses. Employment density is positively associated with both accessibilities while population density is negatively impacted by accessibility to houses. Increased employment or population density increases intrazonal travel time, which offsets the improvement of travel time due to road investment.

[Insert Figure 2 here]

After investing (or disinvesting) in each link in the network, computing accessibility, and relocating land uses, the time period is incremented and the whole process is repeated. In this study one time period represents a hypothetical year as the day-to-day traffic on the network is predicted and converted to yearly traffic for road investment models.

HYPOTHESES AND SIMULATION EXPERIMENTS

Two sets of experiments are conducted. The first fixes the land use, and explores how the network evolves in response to those fixed land uses. The second allows both the network and the land use to evolve simultaneously.

The research question is the degree to which hierarchies of road networks are reinforced or counteracted by the dynamics of land use. It is posited that this depends on initial land use and network conditions. Initially flat road networks become more concentrated, and initially concentrated networks become less so when land uses are allowed to vary rather than remain constant. That is, they reinforce to a point, and counteract beyond some point.

Simulation experiments were conducted in a hypothetical metropolitan area where both the population and employment are distributed over a two-dimensional grid. For simplicity, the experiments here are conducted over a square planar surface, stretching 20 km in both dimensions, divided into a 20X20 grid lattice of land use cells (400 zones). Each zone occupies one square kilometer of land. A total of 400,000 people are living in this city, which is equivalent to an average of 1,000 residents in each zone. Total employment equals 400,000 as well (and each resident holds a job). Two-way roads connect the centroids of each pair of adjacent zones, thus forming a 19X19 grid of road network as well, comprising 400 nodes and 1,520 links.

Table 1 lists parameters and their values for our experiments. As explained in Table 1, the toll rate and value of time are adopted from empirical estimates; the coefficients that define the log-linear relationship between link capacity and free flow speed are estimated by Zhang and Levinson (2005) using the empirical data in the Twin Cities. Among those parameters that are arbitrarily specified for the models, some of them were tested in the experiments using sensitivity analysis, which will be discussed later.

Each set of experiments was tested under two different sets of initial conditions. Both sets of initial conditions specify a uniform network in which the same initial conditions are specified for all the links except for their locations: each link is 1 km in length with a free flow speed of 35 km/h, and a capacity of 800 veh/h. The first specifies uniform land uses with both population and employment of each zone equal to 1,000; the second assumes a concentrated distribution of road capacity. The experiments are outlined in Table 2.

[Insert Table 2 here]

A series of measures of collective properties are developed to track the patterns in the experiments. The Gini index is adopted in this study to indicate the degree of spatial agglomeration for land use and network infrastructure. The Gini index has been widely adopted as a measure of spatial concentration (Krugman, 1991; Chatterjee, 2002). Chatterjee (2003) elaborates the computation of the Gini index based on the Lorenz Curve.

The Gini index of land use (employment or population) is computed in this study to reflect how evenly land uses are distributed on the hypothetical space. The index is a number from zero to one, which is equal to zero when employment or population is uniformly located across all zones, while close to one when all employment or population is located in one zone. The more unevenly land use is distributed, the higher value the index is.

Similarly, the Gini index of road capacity is computed to reflect how evenly roads are developed. The index equals zero when all roads have the same capacity while it becomes higher when a larger portion of total capacities are occupied by a smaller number of roads.

In analogy with kinematics, measures of the moment of inertia (***I***) and the equivalent radius (***r***) are computed to reflect the spatial clustering patterns of land use and network infrastructure.

The moment of inertia for the spatial distribution of employment is computed as:

$$I = \sum_{j=1}^{n} E_j d_j^2 \tag{21}$$

where E_j represents the employment of Zone j while d_j is the distance between the centroid of this zone and the center of the hypothetical metropolitan area.

The equivalent radius is then computed as:

$$r = \sqrt{I \Big/ \sum_{j=1}^{n} E_j} \tag{22}$$

The equivalent radius ***r*** essentially reflects how far away employment is distributed from the center of a region. A radius of zero indicates all employment clusters in the center of the region while a larger radius indicates employment is located farther away from the center.

Similarly the equivalent radius can also be computed for the spatial distribution of population as well as road capacity.

RESULTS

Experiments 1(a) and1(b) allow roads to invest in their capacities while fixing the land use, these experiments are similar in nature to those presented in Yerra and Levinson (2005) and Levinson and Yerra (2006), though differing in specific parameters, the route assignment model, and initial conditions. Figure 3 illustrates the fluctuations of average link capacity for 1(a) and 1(b) in the first 50 iterations. As can be seen, with fixed land use road dynamics reaches equilibrium quickly. Whether starting from a uniform state with an average link capacity of 800 veh/h or from a concentrated state with an average capacity of 1426 veh/h, the network adjusts itself in response to the fixed land use pattern and converges to an average capacity of about 983 veh/h. The observation that initially flat network becomes more concentrated while the initially concentrated network becomes less so, and they tend to converge on the same level of average capacity suggests a stable hierarchical distribution of road capacity may emerge from different initial conditions.

[Insert Figure 3 here]

Experiments 2(a)-2(b), on the other hand, allow both land use and network to evolve, thus generating different network structures and land use patterns. The evolving spatial patterns of network and land use were analyzed by plotting the measures of Gini index and equivalent radius for link capacity, employment, and population on a time horizon over 1,000 iterations. Since significant changes in networks occurred during the first 50 or so iterations, the horizontal axis is plotted at a log scale. The plots are summarized in Figures 4 (i)-(iv). Each plot displays four fluctuations from uniform and concentrated initial network with and without land use dynamics, that is, Experiments 1(a), 1(b), 2(a), and 2(b).

[Insert Figure 4 here]

Plots 4 (i) and Plot 4(ii) demonstrate how spatial patterns of road capacity distribution evolve over time from the perspectives of agglomeration (reflected by the Gini index) and centralization (reflected by equivalent radius), respectively. As already shown in Figure 3, Experiments 1(a) and 1(b) reached equilibrium with fixed land use within the first 50 iterations and remained unchanged thereafter, both resulting in a Gini index of 0.035 and an equivalent radius of 7.9 km. In Experiments 2(a) and 2(b), on the other hand, the network quickly adjusted its distribution of road capacity to the contemporary traffic pattern from its uniform or concentrated initial state in the first 50 iterations and then gradually changed as the land use evolved. After about 50 iterations, the Gini index in both experiments keeps increasing while the radius dropping, showing a strong trend of agglomeration and centralization of road capacity. More interestingly, whether starting from an uniform or concentrated network, the experiments allowing land use dynamics (2(a) and 2(b)) generate a consistently higher Gini index and lower radius compared to their counterparts with fixed land use, suggesting the evolution of land use distribution reinforces the differentiation of roads.

Plots 4(iii) and 4(iv) illustrate how the spatial patterns of population and employment evolve over time. Starting from a uniform network or a concentrated network, land use

patterns display almost the same fluctuation (despite slight differences in the first 100 iterations). Although the Gini index and equivalent radius for both population and employment keep increasing, the distribution of population display a consistently lower Gini index and higher equivalent radius than that of employment, indicating employment has a stronger tendency of agglomeration and centralization, which is consistent with our assumption that employment wants to locate near to each other while people do not like to live together, but want to be near jobs.

Our findings can be further corroborated by the snapshots of emergent network patterns shown in Figure 5. Figure 5 displays two emergent networks over 1,000 iterations in Experiment 1(a) and Experiment 2(a), respectively. Different levels of capacity are displayed in five different colors in a relative scale. Obviously, the resulting network of Experiment 2(a) with evolving land use is more concentrated than that of 1(a) with fixed land use, suggesting land use dynamics reinforces the hierarchical distribution of road infrastructure in the context of co-evolution of network and land use. Figure 5(i) shows the emergence of beltways that are more important than internal roads, Figure 5(ii) does not have a similar beltway, roads just decline in importance with distance from the center.

SENSITIVITY

The specified capacity power σ_2 in our road cost model affects the pattern of road infrastructure. A range of σ_2 was tested. Higher values σ_2 (say 1.5) impose a high maintenance cost on roads, and generate a shrinking network infrastructure over time (given initial capacities); lower values for σ_2, on the other hand, set the cost so low that the capacity expanded rapidly. For example, a value of 0.5 expands the average link capacities by 10 times in 20 years; finally the value of 1.0 was chosen for it generated a moderate and reasonable growth of network infrastructure with an increase of average road capacity from 800 veh/h to 1,015 veh/h over 1,000 iterations, which allows us to illustrate other salient points in the model. Another parameter ρ, capacity reduction factor in Equation (10), affects the speed of network convergence without changing the final converged pattern. Taking a higher value of 1.0, for example, the network in Experiment 1(a) converges within only 2 iterations.

Changing the specified values of two parameters λ and θ in the land use model may affect the emerging spatial patterns significantly. The coefficient λ in Equation (15) indicates the importance of accessibility to population in the location choices of employment, relative to accessibility to other employment. When λ equals zero, the location of employment only depends on the accessibility to jobs; while a large λ indicates employment more likely pursues a population-rich location. The accessibility reduction factor θ in Equations (13) and (14) determines how fast the accessibility of a place will decline with the increase of (generalized) travel cost to that place, reflecting the extent to which the change of travel time can affect the location of land use. Different values for the two parameters were tested and the results are summarized in Figure 6 (i)-(iv). To be concise, only the Gini index of land use in the uniform scenario is plotted. This analysis is based off of experiment 1(b).

As can be seen in Plots 6(i) and 6(ii), an increased λ magnifies the concentration of both population and employment. When λ equals 10, employment is rapidly attracted to population-rich places, making these places more attractive to population, and thus forming a positive feedback. As shown in Figure 6(iv), the decrease of θ (the accessibility impedance

factor) basically exaggerates and quickens the concentration of employment because it puts more weight on the reinforcement effect associated with road dynamics. When θ equals 0.01, the Gini index of employment peaks within 70 iterations, while when it equals 0.1, the concentrations become very slow. Figure 6(iii) shows that although the concentration of population does not occur as fast as employment, the increase of θ still significantly quickens its concentration process.

CONCLUSIONS

This study models the co-evolution of land use and transportation network as a bottom-up process by which the re-location of activities and expansion of roads are driven by interdependent decisions of individual businesses, workers, and road agents according to simple decision rules. The model was kept simple so that collective spatial patterns of land use distribution can be displayed and analyzed without multiple conflating factors, while the sensitivity of these patterns were also discussed. The Gini index and equivalent radius were adopted to track down the evolution of spatial patterns.

This paper in particular examines the evolution of road networks under the context of the co-evolution of network and land use. Simulation experiments suggest that there may exist an inherently stable hierarchical distribution of road capacity so that flat networks become more concentrated (and concentrated network become less concentrated) given a particular land use pattern. Experimental results also demonstrate that the agglomeration and centralization of road infrastructure is reinforced by the dynamics of employment and population under the tension of pushing and pulling forces. Land use organization and concentration make the road network more concentrated than it otherwise would be. Since it has been replicated in a self-organizing process based on completely decentralized decisions in this study, this reinforcement phenomenon is suggested to be an emergent property of the co-evolution of land use and road network.

As cities have evolved in the 20th century, we have seen a flattening of the density gradient of land use (centers of cities are relatively less important) as more highways are constructed and road networks became more hierarchical (certainly in the pre-auto era most unpaved roads were equally slow, with paved highways and then freeways, some roads got much faster). In a sense the faster roads have enabled decentralization of activities. Our simulation model can be employed in later studies to examine the concentration and flattening of land use that could be reinforced or counteracted by the evolution of road networks.

REFERENCES

Alberti, M. and P. Waddell (2000). An integrated urban development and ecological simulation model. *Integrated Assessment*, **1**, 215-227.

Bates, J., M. Brewer, P. Hanson, D. McDonald, and D.C. Simmonds (1991). Building a strategic model for Edinburgh. *Proceedings of Seminar D, PTRC 19th Summer Annual Meeting.* PTRC, London.

Bureau of Public Roads (1964). *Traffic Assignment Manual.* U.S. Dept. of Commerce, Urban Planning Division, Washington D.C.

Chachra V., P.M. Ghare, and J.M. Moore (1979). *Applications of Graph Theory Algorithms.* North Holland, New York.

Chatterjee, S. (2003). Agglomeration Economies: The Spark That Ignites a City? *Business Review*, **Q4**, 6-13

Chatterjee, S. and G. Carlino (2002). Employment Deconcentration: A New Perspective on America's Postwar Urban Evolution. *Journal of Regional Science*, **42**, 455-475.

Christaller, W. (1933). *Central Places in Southern Germany*. Jena: Gustav Fischer. English translation by C. W. Baskin. Prentice-Hall, London,1966.

Davis, G. and K. Sanderson (2002). Building Our Way Out Of Congestion. *Final Report MN/RC-2002-01*, Minnesota Department of Transportation.

El-Geneidy, A. M. and D. Levinson (2006). Access to Destinations: Development of Accessibility Measures. *Technical Report MN/RC-2006-16*, 31-37, Minnesota Department of Transportation.

Garrison, W.L. and D.F. Marble (1962). The Structure of Transportation Networks. U.S. *Army Transportation Command, Technical Report*, **62-II**, 73-88.

Guttenberg, A.Z. (1960). Urban structure and growth. *Journal of American Inst. Planners*, **26**, 104-110.

Hansen, W.G. (1959). How accessibility shapes land use. *Journal of American Inst. Planners*, **25**, 73-76.

Huff, D.L. (1963). A probabilistic analysis of shopping trade areas. *Land Economics*, **39**, 81-90.

Krugman, P. (1991). *Geography and trade*. MIT Press, Cambridge.

Krugman, P. (1996). *The Self-Organizing Economy*. Malden: Blackwell Publishers Inc., 53-100.

Lee, D., Jr. (1973). Requiem for Large-Scale Models. *Journal of the American Institute of Planners,* **40**, 163-78.

Levinson, D. and R. Karamalaputi (2003). Predicting the Construction of New Highway Links. *Journal of Transportation and Statistics* Vol. 6(2/3) 81–89

Levinson, D and R. Karamalaputi (2003). Induced Supply: A Model of Highway Network Expansion at the Microscopic Level. *Journal of Transport Economics and Policy*, Volume 37, Part 3, September 2003, 297–318

Levinson, D. and B. Yerra (2006). Self Organization of Surface Transportation Networks. *Transportation Science*, **40(2)**, 179-188

Levinson, D., N. Montes de Oca, and F. Xie (2006). Beyond Business as Usual: Ensuring the

Network We Want is the Network We Get. *Technical Report for Minnesota Department of Transportation*. St. Paul, Minnesota.

Lowry, I.S. (1963). Location parameters in the Pittsburgh model, *Papers and proceedings of the Regional Science Association*, **11**, 145-165.

Mackett, R.L. (1983). The Leeds Integrated Transport Model (LILT). *Supplementary Report 805*, Transport and Road Research Laboratory, Crowthorne.

Mackett, R.L. (1990). The systematic application of the LILT model to Dortmund, Leeds and Tokyo, *Transportation Reviews*, **10**, 323-338.

Mackett, R.L. (1991). LILT and MEPLAN: A comparative analysis of land-use and transport policies for Leeds, *Transportation Reviews*, **11**, 131-141.

Morrill, R.L. (1965). Migration and the Growth of Urban Settlement. *Lund Studies in Geography, Series B, Human Geography*, **26**, 65-82.

Ortuzar, Juan de Dios, and L.G.Willumsen (2001). *Modeling Transport*. John Wiley & Songs, LTD, West Sussex.

Sheffi, Y. (1985) *Urban Transportation Networks: equilibrium Analysis with Mathematical Programming Methods*. MIT Press, Cambridge.

Taaffe, E., R.L. Morrill, and P.R. Gould (1963). Transportation Expansion in Underdeveloped Countries: a Comparative Analysis. *Geographical Review,* **53**(4), 503-529.

Timmermans, H. (2003). The Saga of Integrated Land Use-Transport Modeling: How Many More Dreams Before We Wake Up? *Proceeding of 10th International Conference on Travel Behaviour Research*, Lucerne, August 10-15, 2003.

Van Nes, R. (2002). *Design of multimodal transport networks: a hierarchical approach*. Doctoral dissertation Delft University of Technology, published by DUP (Delft University Press) Science, ISBN 90-407-2314-1, 65-79.

Van Nes, R. and N.J. van der Zijpp (2000). Scale-factor 3 for hierarchical road networks: a natural phenomenon? In: *Proceedings TRAIL 6th Annual Congress*, Part 1, 2000, Delft University Press, ISBN 90-407-2135-1, 131-156.

Von Thünen, J. H. (1910). *Isolated State*. Jena: Gustav Fischer. English translation by C. W. Baskin. Pergamon Press, Oxford, New York, 1966.

Yamins, D., S. Rasmussen, and D. Fogel (2003). Growing Urban Roads. *Networks and Spatial Economics*, **3**, 69-85.

Yerra, B. and D. Levinson (2005). The emergence of hierarchy in transportation networks *Annals of Regional Science,* **39(3)**, 541-553

Zhang, L. and D. Levinson (2005). Road Pricing with Autonomous Links. *Journal of the Transportation Research Board #1932*,147-155.

TABLES AND FIGURES

Table 1. Model parameters

Parameter	Description	Citation	Value	Source
$\xi_1,\ \xi_2,$ $\psi_1,\ \psi_2$	Coefficients in trip generation and attraction	Eq.(1)	0.5 trips/person, 1.0 trips/person, 1.0 trips/person, 0.5 trips/person	Specified
ε	Trip distribution coefficient	Eq. (3)	0.05/min	Empirical calibrated
t_m^0	Base intra-zonal travel time	Eq. (5)	10 min	Specified
η	Value of time	Eq. (7)	$10 /h	Empirical estimates
τ	Toll rate	Eq.(8)	$1.0/ veh-km	Specified
$\sigma_1,\ \sigma_2$	Coefficients in cost model	Eq.(9)	0, 1	Specified*
ρ	Capacity reduction factor	Eq.(10)	0.25	Specified*
$\omega_1,\ \omega_2$	Coefficients in the *capacity-freeflow speed* loglinear function	Eq.(11)	-30.6 km/hr, 9.8	Empirical estimates
$\alpha,\ \beta$	Coefficients in BPR function	Eq.(12)	0.15, 4.0	Typical values
θ	Impedance factor in accessibility model	Eq.(13), Eq.(14)	0.05/min	Specified*
λ	Coefficient in employment desirability model	Eq.(15)	1.0	Specified*
μ	Coefficient in population desirability model	Eq.(18)	1.0	Empirical estimate
γ	Coefficient in land use model	Eq.(17), Eq.(20)	1.0×10^{-6}	Specified

Note: Analyses were conducted on the sensitivity of asterisked parameters

Table 2. Specification of experiments

No.	Initial conditions			Dynamics	
	Link capacity	Employment	Population	Roads	Land uses
1a	Uniform	Uniform	Uniform	Evolving	Fixed
1b	Concentrated	Uniform	Uniform	Evolving	Fixed
2a	Uniform	Uniform	Uniform	Evolving	Evolving
2b	Concentrated	Uniform	Uniform	Evolving	Evolving
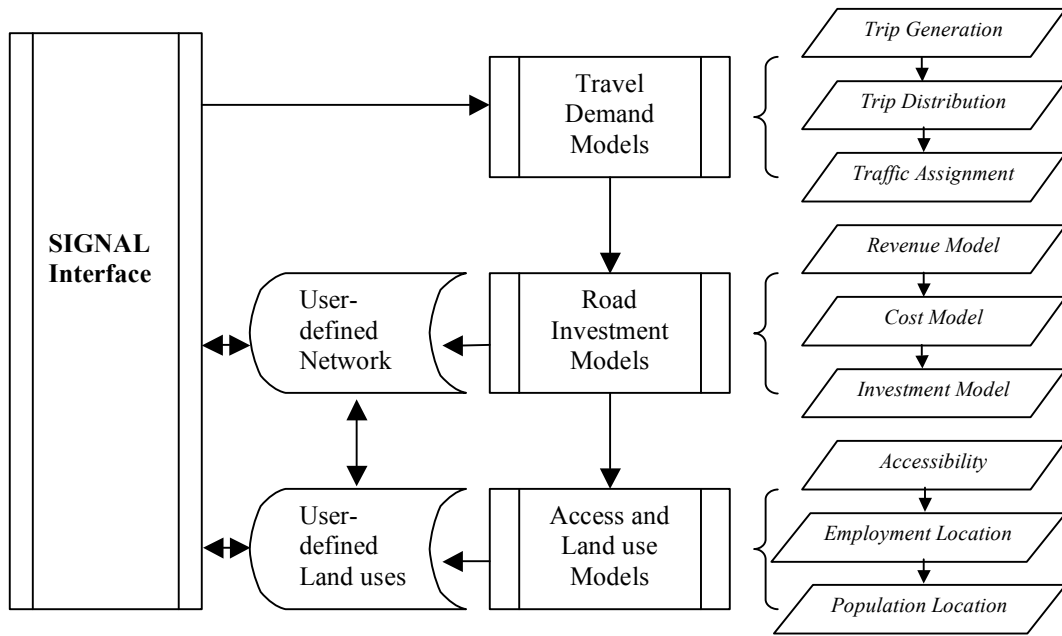
Figure 1. Overview of the SIGNAL model.
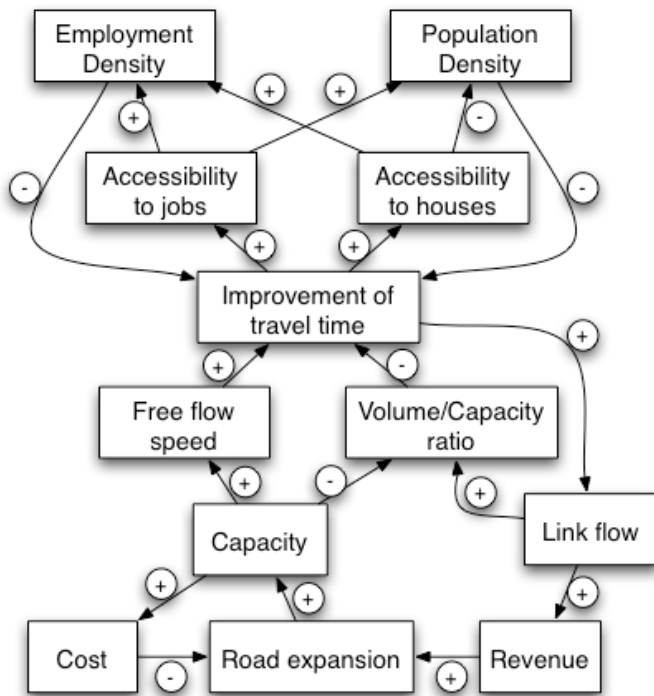
Figure 2. The feedback relationship in the transportation/land use system
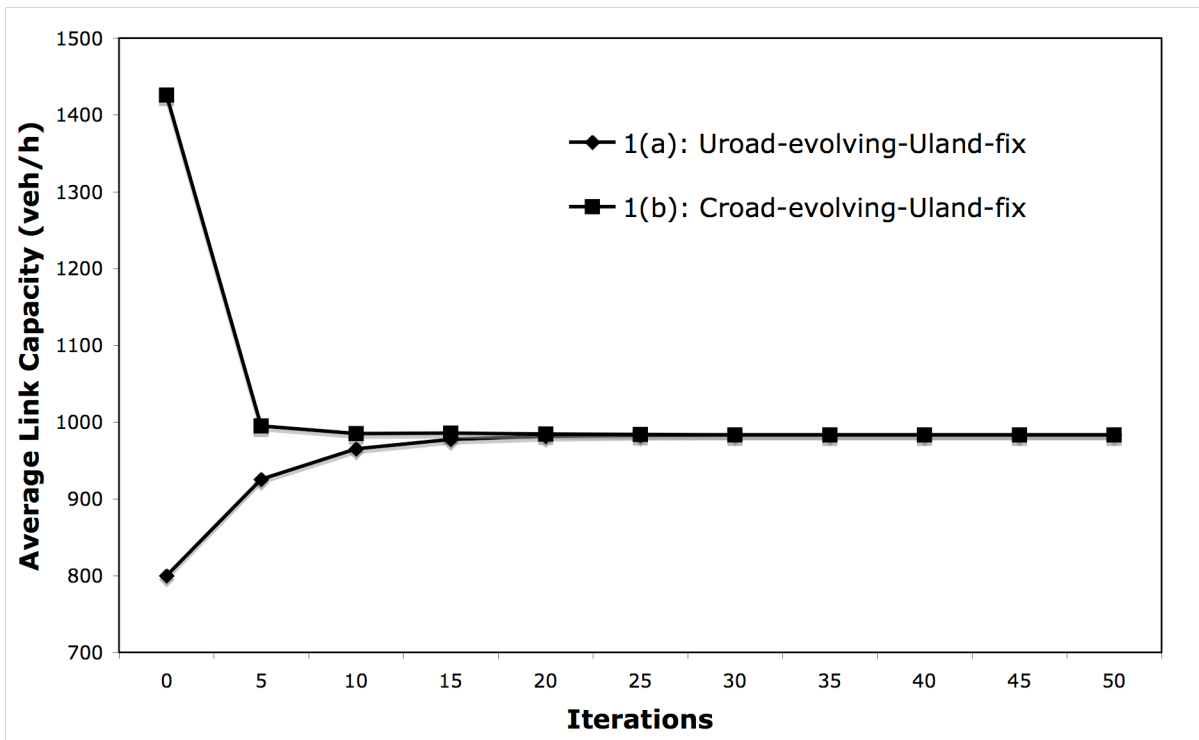
Figure 3. The fluctuations of average capacity with fixed land use
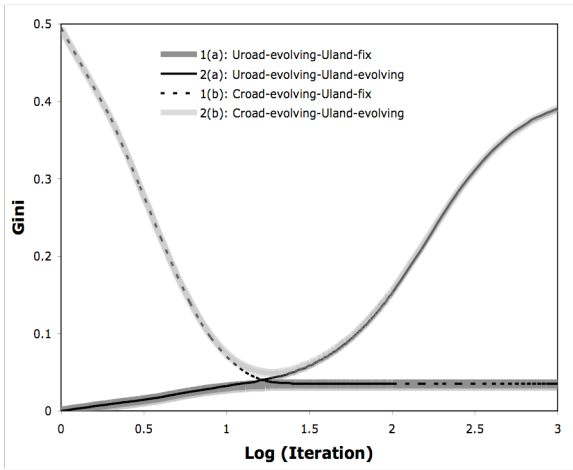
(i) Gini index for road network
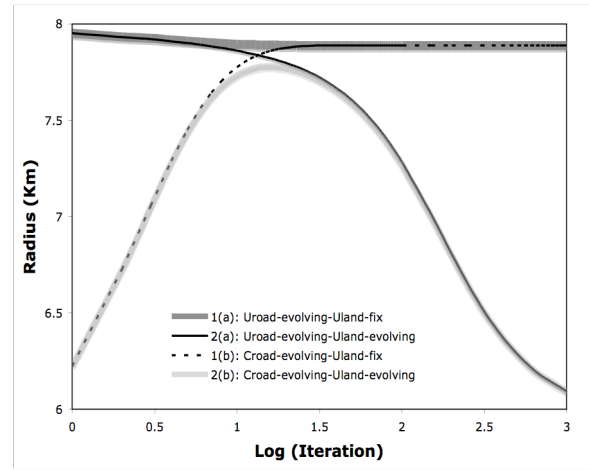
(ii) Equivalent Radius for road network
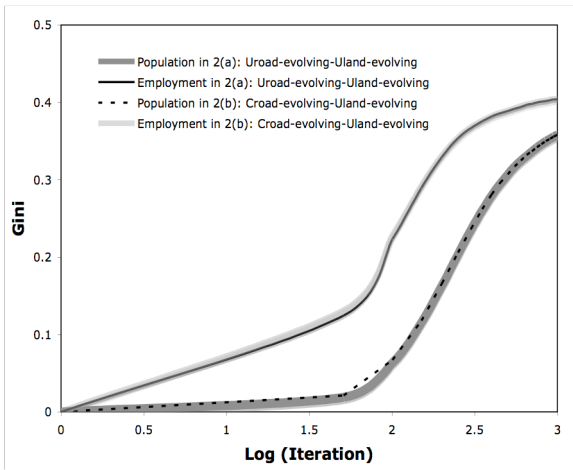
(iii) Gini index for land use
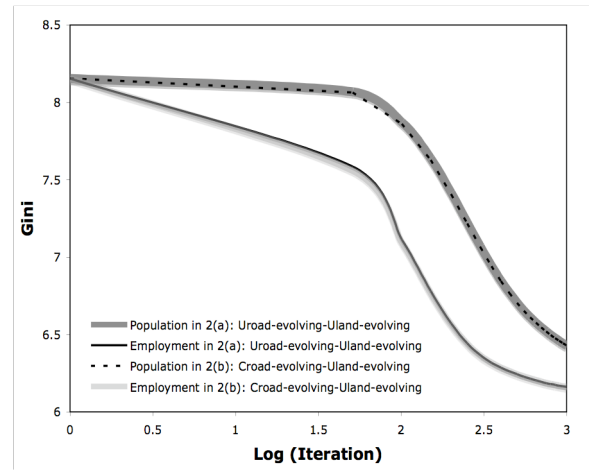
(iv) Equivalent Radius for land use
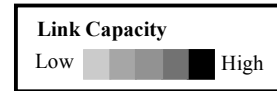
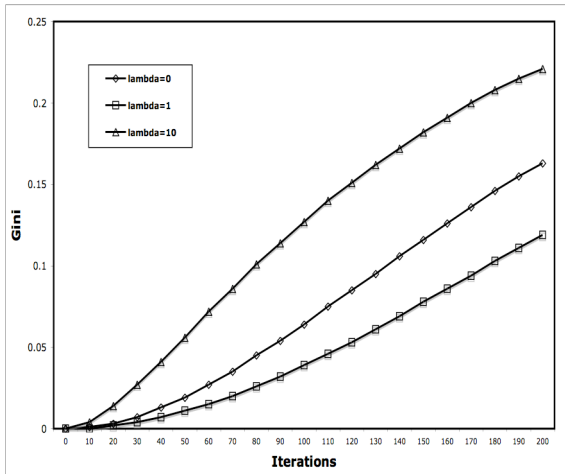Figure 4. Measures of spatial patterns
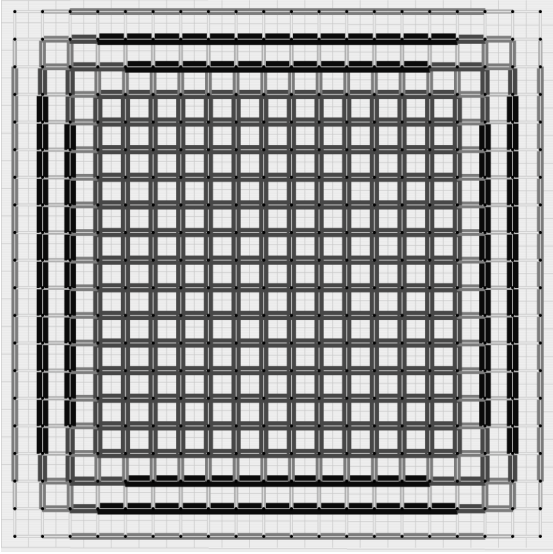
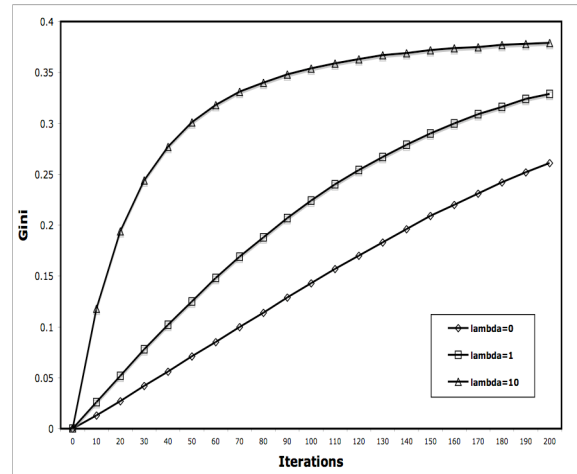**(i) Experiment 1(a) Uniform initial conditions- fixed land use – road evolution (iteration 1000)**
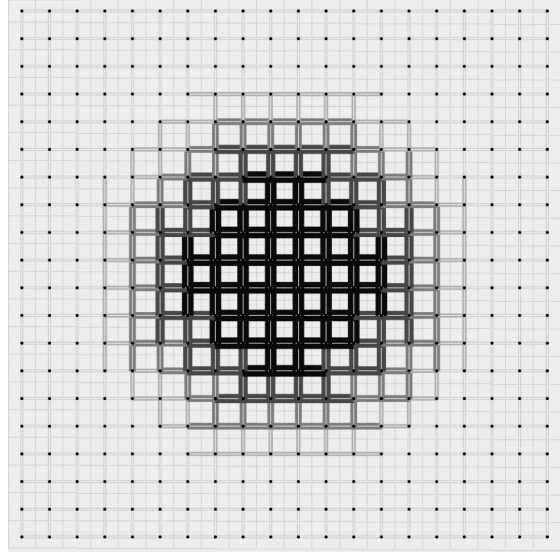
(ii) Experiment 2(a) uniform initial conditions- land use evolution– road evolution (iteration 1000)

Figure 5. Emergent network patterns.

Link Capacity	
Low	High

Link Capacity	
Low	High

Levinson, David, Feng Xie, and Shanjiang Zhu (2007) The Co-Evolution of Land Use and Road Networks.
Published in Transportation and Traffic Theory 2007 (ed. Richard E. Allsop, Michael G. H. Bell, and   Benjamin Heydecker)
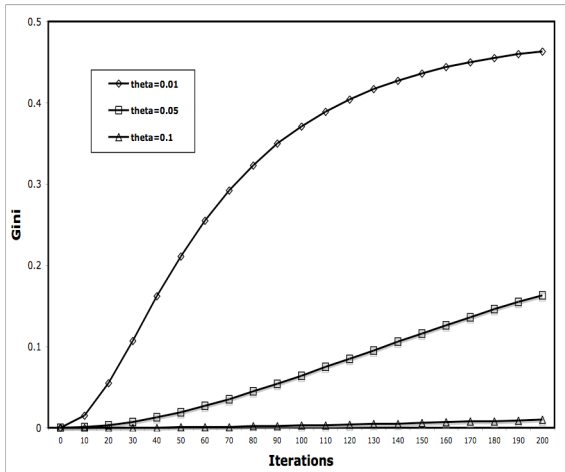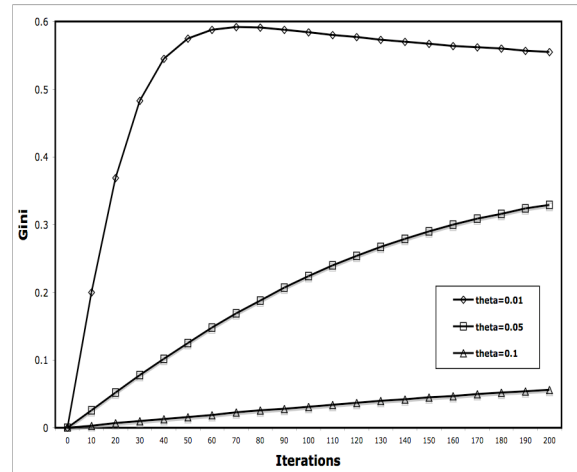Emerald Group Pub Ltd. pp. 839-859.
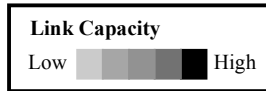
(i) Sensitivity Analysis of lambda:

Gini for population

(ii) Sensitivity Analysis of lambda:

Gini for employment

(iii) Sensitivity Analysis of theta (accessibility impedance factor):

Gini for population

(ii) Sensitivity Analysis of theta (accessibility impedance factor):

Gini for employment

Figure 6. Sensitive analyses for two parameters