LEAM Technical Document

Overview of the LEAM Approach

February, 2005

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OVERVIEW OF THE LEAM APPROACH

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1 INTRODUCTION TO THE LAND-USE EVOLUTION AND IMPACT ASSESSMENT MODEL (LEAM)

1.1 Overview

The Land-Use Evolution and impact Assessment Model (LEAM) utilizes the STELLA/SME/GIS collaborative environment for the purpose of developing a Planning Support System (PSS) to generate and evaluate human development patterns. Developed at the University of Illinois with funding from the National Science Foundation, LEAM describes land-use changes across a landscape that result from the spatial and dynamic interaction among economic, ecological, and social systems in the region. In the LEAM approach, groups or individuals who have substantive knowledge relating to a particular system develop and test separate models of that system. These contextual sub-models are linked and run simultaneously in each grid cell of a set of raster-based GIS map(s) to form the main framework of the dynamic spatial model (LEAM).

The SME collaborative approach enables the model to be created in an open and distributed manner that brings different expertise to bear on the problem. Inputs to the model utilize national land-use data sets (at 30 x 30 meter resolution), census and economic data (readily available and transportable for application to multiple sites) along with variables relating to impact assessment sub-models (e.g., habitat, ecoregional inputs, water and energy inputs) to set model parameters. The products of LEAM model runs are analyses of a series of policy scenarios, presented as GIS maps or movies that show the transformation of the subject landscape as a product of policy related inputs. These dynamic visual outputs are beneficial for testing policy scenarios and raising concerns regarding the impacts of development, environmental degradation, or conflicting land-use policies (George 1997). The final PSS tool will include a simple user interface and transportable data sets for application to multiple sites.

Figure 1-1 describes the fundamental LEAM approach to capturing land-use transformation dynamics. It begins with land-use transformation drivers. These drivers capture the forces (typically human) that contribute to urban land-use transformation decisions. The model drivers describe land-use transformation probabilities. The simulation visually displays the landscape transformation realized at each time-step using scenario based planning exercises. The resulting visual images are then analyzed for environmental impacts during the impact assessment phase. Sustainable indices based on the derived impacts are then developed to feed back into the model drivers.

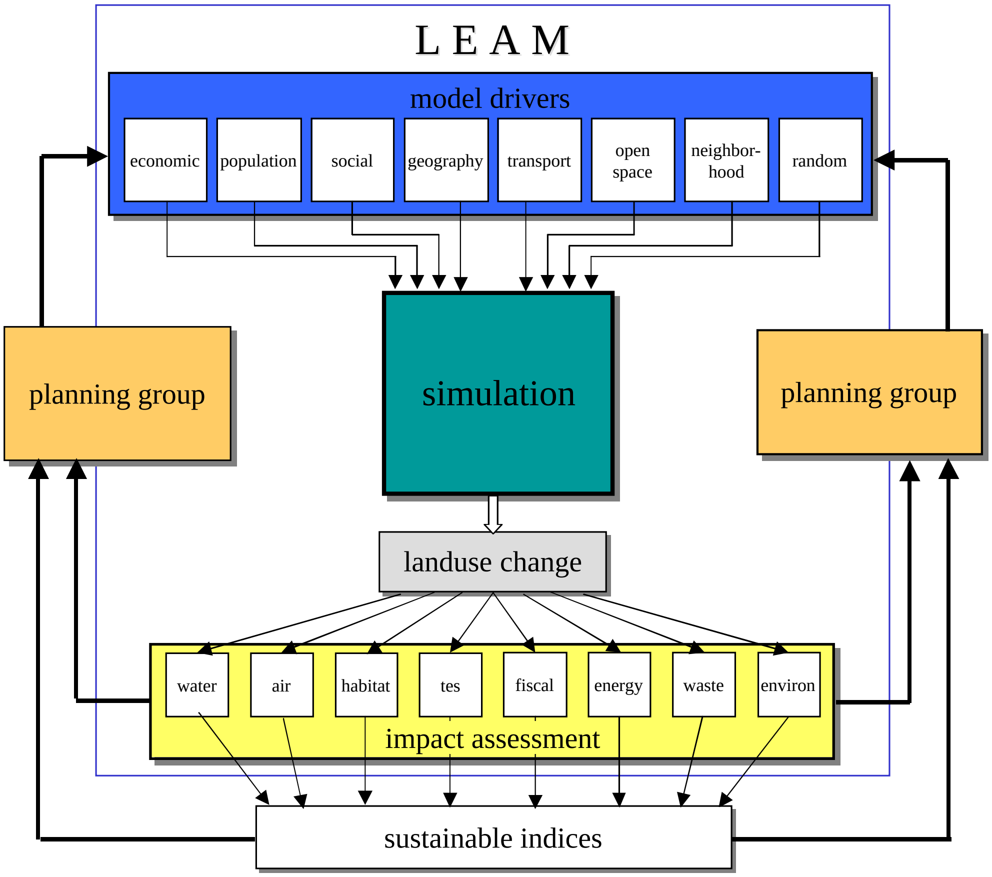

Figure 1-1. The LEAM spatial modeling environment.

1.2 Land-Use Transformation Drivers

A simple illustration of the simulation engine can be viewed in Figure 1-2. The LEAM model uses a 30 m x 30 m raster-based GIS land-use map based on the USGS National Land use Classification System (NLCD MAP). The NLCD maps are used to set the existing land-use conditions; the model uses a 30 x 30 m resolution to simulate socio-economic parcel-by-parcel decision making that influence urban growth patterns. A STELLA model then calculates the development probability (DEV PROBABILITY) for each cell, at each time step. The probability of a cell changing from its existing condition (LU A) to an alternate land use (LU B) is dependent on the CHANGE variable and its associated probability of change (DEV PROBABILITY) that has been calculated at each time step. Whether or not a cell transforms depends on how the conditions for change in the immediate (as well as global) area of study have been calculated using a Markov chain approach.

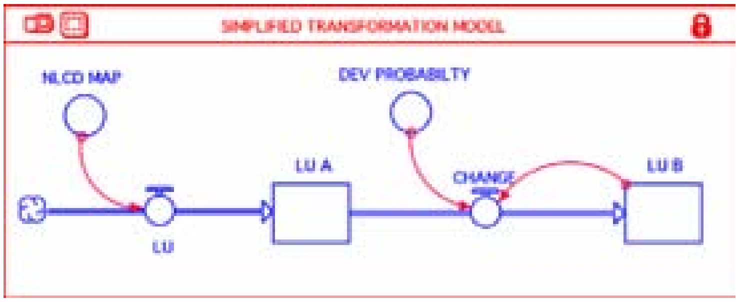

Figure 1-2. **A simplified STELLA transformation model. The stock variable LU A is initialized by USGS data layers (NLCD MAP) the change of stock LU A to stock LU B is dependent on the CHANGE variable and its associated probability of change (DEV PROBABILITY) calculated at each time step.**

A Markov chain is a collection of variables having the property that, given the present, the future is conditionally independent of the past. A simple random walk, or a sequence of steps of fixed length is a good analogy. It is used here to describe the behavior of transition probabilities among a system's states. The process considers the different states that any particular cell in the modeled landscape can assume and the statistical probabilities that govern the transition of the phenomenon from one state to another. In the LEAM approach, any developable cell in the landscape has a probability of land-use change. The calculation of the cell's probability is based on a set of criteria that is evaluated by the model at each time step (see *probability indices* below). Each variable considered in the chain affects the final transformation probability (P at time t) of land-use change dependent upon the sub model indice probabilities (p_i) present and their weighting coefficients (w_i).

The summation of indices and their coefficients provides:

$$P_t = \sum_{i=1}^{n} w_i p_i \,,$$

where $0 \le p_i \le 1$ and $\sum_{i=1}^{n} w_i = 1$.

This approach is conceptually simple and proportional influences can be easily distributed among drivers. This makes for easy access and discussions with stakeholders. A major weakness with this approach however, is that transformation cannot be forbidden (e.g. if slopes are significantly high, or soil particularly unsuitable, development cannot occur). A logical statement that can accommodate an on/off characteristic is needed to simulate cells that cannot develop. So that if a characteristic is true set $P = 0$, otherwise use the original equation. This might be expressed as:

$$\text{IF } \forall \bigcup_{j=1}^{m} q_j \text{ ; THEN } P = 0\text{; ELSE } P_t = k_t \sum_{i=1}^{n} w_i p_i$$

Here: $q_i = TRUE$ in exclusive areas — steep slopes, protected areas, lakes/rivers etc.; k_t is a growth function introduced to determine how well the model is conforming to the household population projection curve generated by an economic model (explained below).

During each time step of the simulation, projected results are compared with simulated activity. If there is a surplus of households in the simulation, the model corrects by reducing the growth function, slowing the construction of new units. If there is a shortfall of units, the model increases the growth function to correct the shortfall. This self-modification function keeps the projected households in line with projections and is a global variable that doesn't vary from cell to cell, but will vary with each time step.

The current LEAM probability indices (p_i) include:

n_i – neighboring land-use characteristics index
ut_i – utility resource availability index
rc_i – random chance of land-use change (spontaneity) index
dem_i – geographic constraints index
lp_i – price considerations index
ec_i – economic considerations index
tr_i – transportation related influences index
sc_i – social systems influences index
gt_i – sub regional growth trends index

This can be described (for any time *t*) as:

$$P_t = k_t(\alpha n_t + \beta ut_t + \chi rc_t + \delta dem_t + \varepsilon lp_t + \phi ec_t + \varphi tr_t + \gamma sc_t + \eta gt_t ...)$$

At each time step the P_t is calculated for each cell in the study area for each of three distinct categorical possibilities: residential land uses ($R_j P_t$), commercial/industrial land uses ($CI_j P_t$), or set aside open space ($OP_j P_t$) (Figure 1-3 is a simple illustration of transformation model Figure1-4 is an example of a probability map based on the equation above). Categorical probabilities are compared to determine the land use with the highest probability for success in that cell ($Cg_i P_t$) so that:

$$Cg_i P_t = R_j P_t; CI_j P_t; OP_j P_t$$

The selected Cg_i is then compared with the probability that no change will occur ($Ex_j P_t$):

$$Cg_i P_t; Ex_j P_t.$$

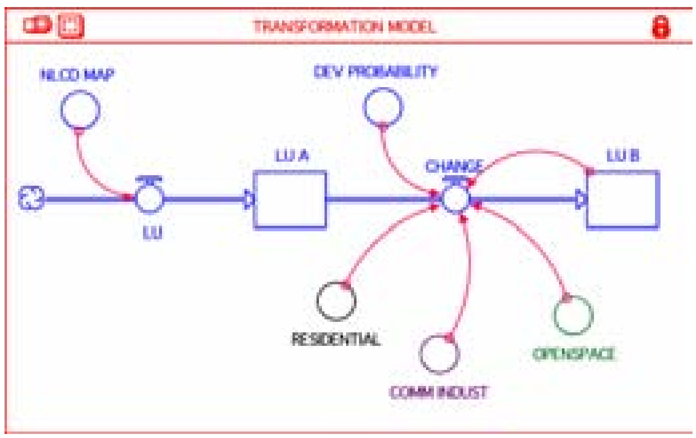

Figure 1-3. The simplified STELLA transformation model with land-use change category determination (RESIDENTIAL, COMM INDUST, or OPENSPACE).

This determines the final outcome for each cell. If $Cg_i P_t < Ex_j P_t$, then the cell in question remains as existing. If $Cg_i P_t > Ex_j P_t$, then the cell in question transforms into the selected categorical land use ($Cg_i P_t$) (residential land uses; commercial/industrial land uses; or open space).

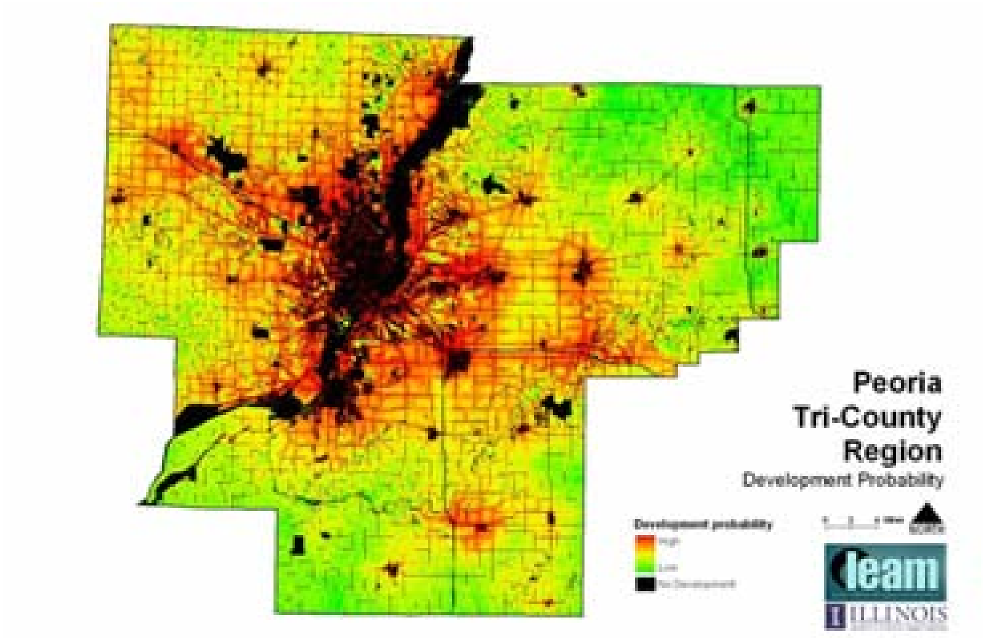

Figure 1-4. Example of a Probability Map. This shows the probability of residential development in year 1 of a simulation for the Peoria metropolitan region. Red indicates areas with a high probability of development, green areas have a low probability, black areas represents areas that have already developed or will not develop (water bodies, protected areas).

Each driver (or index - p_i) is developed as a sub-model; definitions are completed and run independently of the larger LEAM organization (Figure 1-5). Variables of interest can be scaled and plotted in formats that help visualize sub-model behavior and contextual experts can calibrate and test sub-model behavior before it becomes integrated into the larger model. Using iconographic modeling techniques for sub-model development greatly decreases the learning curve for enabling contextual experts; it also increases the ease with which the model can be changed and calibrated. The effects of changes made can be viewed immediately; allowing the user to concentrate on modeling instead of computational details (Maxwell, Villa et al. 1999).

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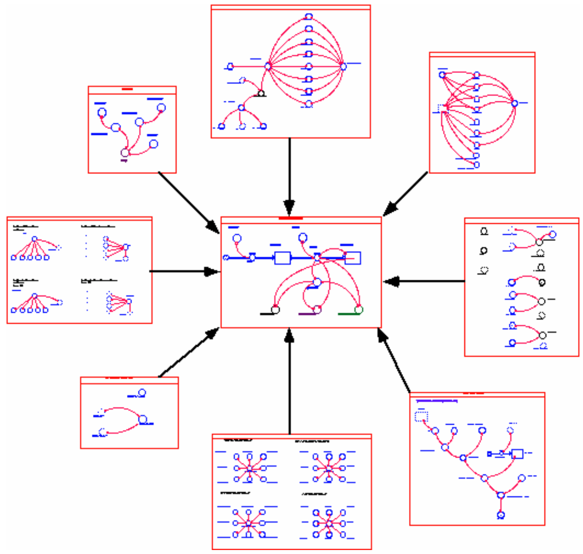

Figure 1-5. The LEAM distributed design approach. Each sub-model is developed independently by subject matter experts, and then incorporated into the larger LEAM framework.

LEAM is a complex system of interrelated sub-models that requires a wide range of expertise to create. Although contextual experts need not agree on all things, all sub-models must conform to some fundamental characteristics: they must ultimately relate to and produce a probability of land-use change, and they must be contextually valid. The contextual expert responsible for sub-model development completes calibration and verification before it is included into the LEAM framework. This first pass at verification insures each sub-model is accurately based on published and recognized literature. For example, the economist must verify and calibrate the economic sub-model using uncertainty analysis typically applied to economics modeling systems or incorporate a published econometric model that is recognizable in its new environment. This is a processed-based approach that does not address variable-to-variable interaction, but it can be an effective means of controlling interoperable and external validity. For more detail on LEAM sub-model drivers see Appendix A.

1.3 Alternative What-If Scenarios

LEAM drivers represent the dynamic interactions between the urban system and the surrounding landscape, and scenario maps visually represent the resulting land-use changes. Altering input parameters (policies) changes the spatial outcome of the scenario being studied.[1] This functionality enables what-if planning scenarios that can be visually examined and interpreted for each simulation exercise. Results of a preliminary LEAM simulation can be seen on the landscape sample in Figure 1-6. The landscape shown is in digital elevation format and the cell transformations are shown in the cell colors as the cells develop over time (darker purple represents a waterway). The newly developed cells represent one of three driver types: spontaneous growth, diffusive growth, and organic growth.

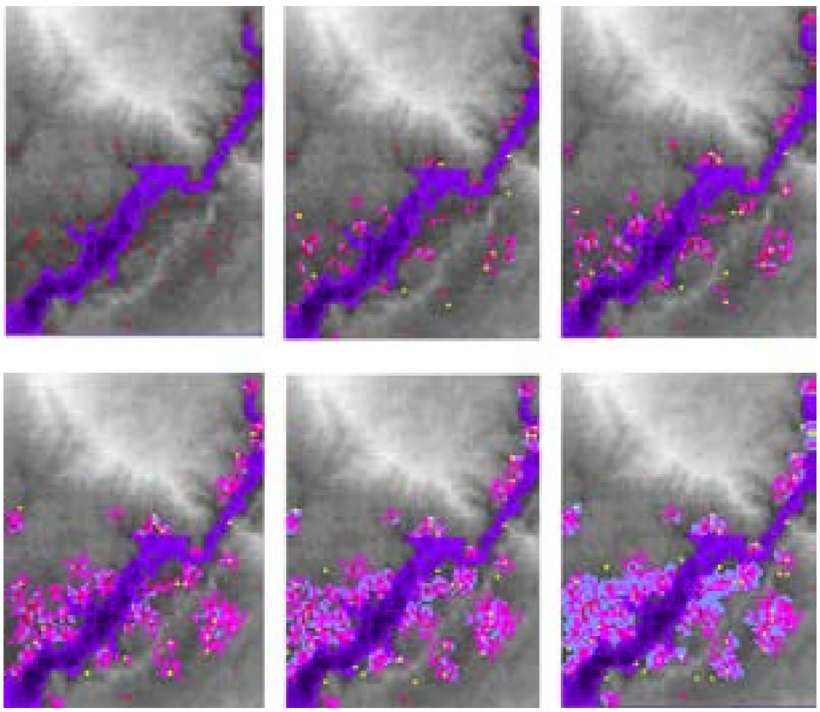

Figure 1-6. A preliminary LEAM scenario of four sample growth characteristics — initial urban land uses, spontaneous growth, diffusive growth, and organic growth.

An alternative scenario may include the construction of a new road in the area being studied. Results of the preliminary LEAM output with a new road system added (**Error! Reference source not found.**7) show how the land-use transformation patterns may vary with the road system added. In this case the planning decision to revise the transportation network in the area has dramatically changed the way the region has developed over a similar time period.

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[1] Similar what-if inputs generate similar output, although not identical due to stochastic influences in the model.

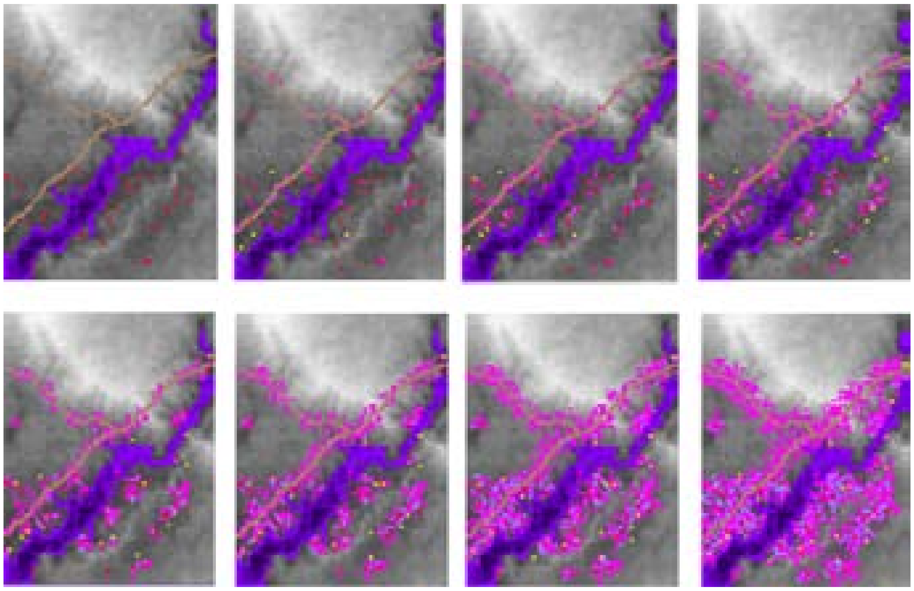


Figure 1-7. An alternative LEAM scenario that incorporates a new road network. In contrast to Figure 1-6, note the increase in development and the changing patterns of development due to addition of roads.

LEAM projects in Kane County, the Peoria Tri-County region, the St. Louis MO-IL region, and several other regions have led to variety of different scenarios being run in LEAM – most scenarios are focused on public policy or large public investments. Examples of scenarios include: transportation investments, agriculture and forest preservation, development or redevelopment incentives for specific areas of a region, closure of major manufacturing or military base, and implementation of a comprehensive plan. .

1.4 LEAM Modeling Utility

The approach taken in developing LEAM has attempted to address at least four limitations of current urban transformation modeling:

- Lack of substantive theoretical explanations for the sustainability of complex urban systems.
- Weakness inherent in the single-programmer approach and the related difficulties in assessing underlying model logic.
- Difficulties associated with scaling-up models to large regions.
- Lack of feedback and support for ‘so-what’ questions associated with changes in urban patterns.

The approach to addressing these shortcomings includes the following. First, its theoretical foundations are derived from the ideas and theories posited by scholars in the Urban Ecology movement. Urban Ecologists emphasize that methods utilized in the study of ecology may be 'profitably applied' to the analysis of the human community (Park, Burgess et al. 1925). In this view, ecological theories provide clues to the way in which urban systems function and provide methodological characterizations for modeling urban systems. This implies that new theories of ecology – hierarchical patch dynamics, incorporation, equilibrium, and diversity theory can help to inform urban transformation models by providing the underlying logic for establishing causal linkages, dynamic driver interactions, spatial resolution and uncertainty analysis, impact assessment measures, and sustainability criteria. Unlike existing transformation models that rarely incorporate substantive theoretical explanations for the urban systems patterns they describe, sub-models developed within LEAM are based on theoretical or empirical explanations for the phenomenon being modeled.

Next, the model logic underlying LEAM is explicitly stated and easy to assess. In the LEAM approach, groups or individuals who have substantive knowledge relating to a particular system develop and test separate models of that system. These systems are explicitly and separately modeled in an open and distributed manner that is easily assessed. The contextual sub-models are then linked within the main framework of a dynamic model, and these relationships are also open to inspection and critique. The LEAM approach enables a broad-based, multi-disciplinary approach to problem solving.

Third, the LEAM approach can be implemented in massively parallel computing environments and is very amenable to scaling up to large regions. In such computing environments, a large study area is split into smaller, distinct and computationally more manageable regions. The model is computed on a separate processor for each of these smaller regions for each time step, and these results are then stitched together to form the aggregate output for the large area. Thus, LEAM simulations can be run on a single platform, a heterogeneous distributed network of platforms, or on massively parallel supercomputers. LEAM simulations have been run in reasonable time (20 minute duration) for an eight-county region consisting of 10 million 30 x 30 m cells using a massively parallel supercomputer.

Finally, and perhaps most importantly, the products of LEAM modeling runs can help to answer the critical 'so-what' questions associated with changes in urban patterns. Impact assessment models, developed in the same way drivers are modeled – using STELLA/SME, can explicate the environmental, economic, and social ramifications for each scenario. This enables policy related decisions to be simulated and assessed with feedback on the (positive or negative) consequences of these decisions. Various commentators have attributed both negative and positive impacts to human development patterns. The long-standing debate on the types, magnitudes and incidence of development costs weighs down the prospects for reaching consensus. Without substantive impact assessments, models of urban systems dynamics offer limited insight to decision makers on issues of community stability, sustainability and the sustainability of community planning practices.

2 LEAM SUB-MODEL DRIVERS

When developing the overall developmental probability (P_t), some factors are multiplicative and some additive. The relational developmental probability of each model driver is calculated independently and is based on regionally specific data sets. A sector-by-sector description follows.

Neighboring Cell Index

The Neighboring Cell Sector works on the principle of adjacency. Cells that are adjacent to developed cells have an increased p_t. Existing urbanized cells embody access to utility infrastructure and are easier and cheaper to develop. The more neighboring cells developed the greater the probabilistic influence (Figure 2-1).

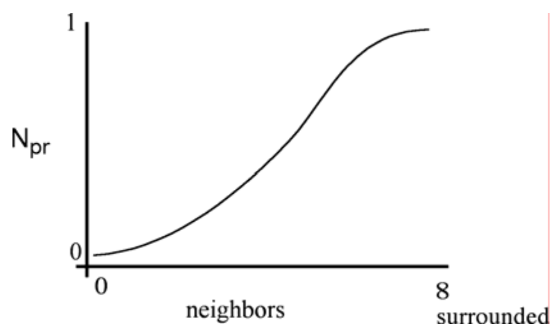


Figure 2 - 1. N_{pr} **as a function of neighboring development.**

The determination of the N_{pr} at any given time step (d_t) for any given cell (j) requires a summation of the neighboring cell characteristics with a spread coefficient (σ_j) over the total surrounding cells. The inclusion of the spread coefficient enables regionally specific data to be used within the model parameters that will more closely resemble regional spread and pattern structure.

$$N_{prj} d_t = \frac{\sum_{8}^{1} (N_{pr} + \sigma_j)}{8}$$

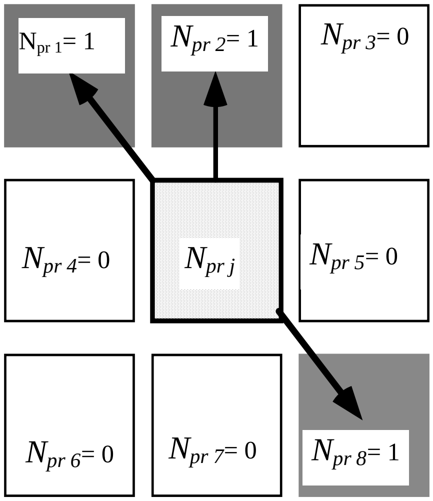


Figure 2 - 2. N_{pr} as a function of neighborhood cell characteristics. Developed neighboring cells influence the neighborhood index value used to determine the overall P_t for each cell.

Neighboring cell characteristics are also important for determining categorical probabilities (Cg_iP_t). Neighboring categorical relationships can be positive - residential development adjacent to open space (R_j;OP_j); negative - residential development adjacent to commercial/industrial development (R_j;CI_j); or neutral - commercial/industrial development adjacent to open space (CI_j;OP_j).

Although currently somewhat simplistic, the conceptual basis for this sub-model can be enhanced to provide more detailed information about each neighbor to improve the reliability of the simulation. For example, a highly priced residential cell can influence the price of subsequent cell development. Adjacent cells may be more attractive for highly priced residential development, but less attractive for more moderately priced developments.

Another important consideration is the scale in which fringe development usually occurs. Typical developments are larger tracts that are subdivided and built up as the markets permit. These tracts are not always contiguous, and the patterns may ‘leap-frog’ from tract to tract (Figure 2-3).

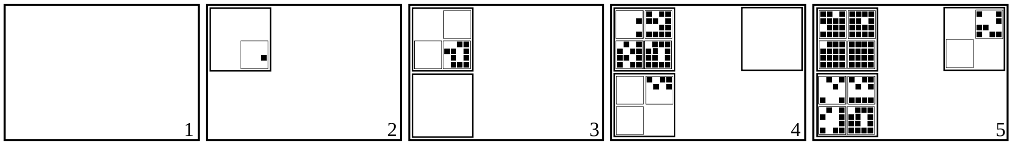


Figure 2 - 3. Typical urban fringe development patterning (left-right). Open space (1) becomes developed into large tracts with the beginnings of smaller sub-tracts and model structures (2). Structure slowly builds into the new development as new home buyers become aware of the region (3), which prompts new sub-tracts to open. Rapid development soon begins and new large tracts appear that are not necessarily contiguous (4). As the initial development fills, adjacent development begins and the process continues.

The hierarchical and fractal nature of fringe urban patterns is difficult to replicate without intensive data collection efforts to determine ownership boundaries. Ownership data are not yet common in geospatial formats and are generally unavailable (although some county assessors are now beginning the process of geo-coding data sets). If the data are available, the cost is very high both from a fiscal and computational perspective. In the LEAM approach clustering and leapfrogging patterns are simulated using attractiveness coefficients (in the utilities resource (ut_i) model and random assignments (rc_i) (see Figure 2-5 and Figure 2-8).

Utilities Index

The Utilities Sector is based on proximity and access to utilities and infrastructure as a means to determine the likelihood of land-use transformation. The presence (or absence) of utilities at or near a site influences its probability of development by altering the effective development costs (Granger and Blomquist 1999). A probabilistic modeling technique has been developed to expose non-adjacent cells to the presence of available utilities and resources at a site. The closer an undeveloped cell is to resource utilities the greater the influence on the probability of development (Granger and Blomquist 1999) (Figure 2-4). This enables non-adjacent cells to urbanize, simulating a skipping ‘sprawl’ type pattern. This pattern is most notably found in geographic regions with little geographic constraints (rivers, mountains, elevation change) to growth and that have favorable resources available in the community to facilitate growth (economic strength).

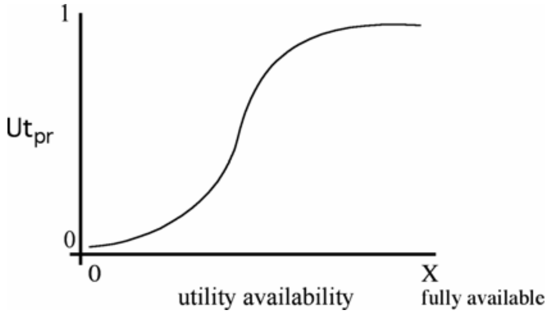


Figure 2 - 4. The relationship between utilities availability and utilities (Ut_i).

All urbanized patches diffuse resource utilities (potable water, sewer, electricity, etc.) and other goods and services available to the community. Existing urbanized cells diffuse resource attractiveness because they embody access to utility infrastructure; cells closer to existing utilities are easier and cheaper to develop (Figure 2-5).

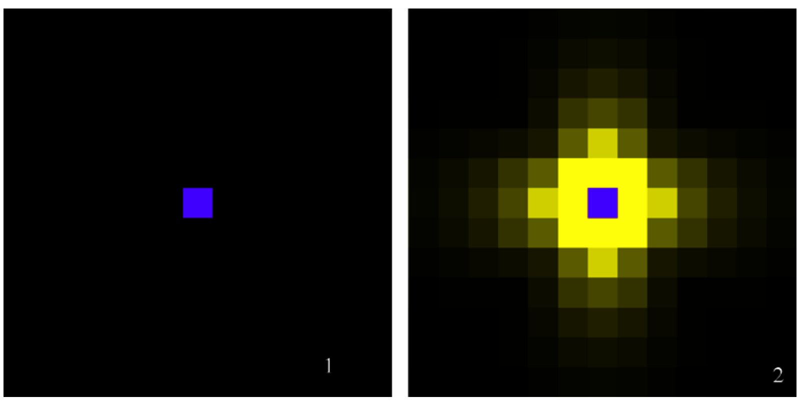


Figure 2 - 5. Diffusion of resource availability information over geographic space. For any developed cell (1) resource availability is pronounced to adjacent cells through the diffusion of information (2). The information (or attractiveness of developing nearby) is diffused over space (light to dark yellow), because infrastructure available from this cell is more costly as distance from the cell is increased.

Roads as the means for transporting large amounts of resources (goods, services and information) attract development by diffusing or displaying those resources as well (Figure 2-6).

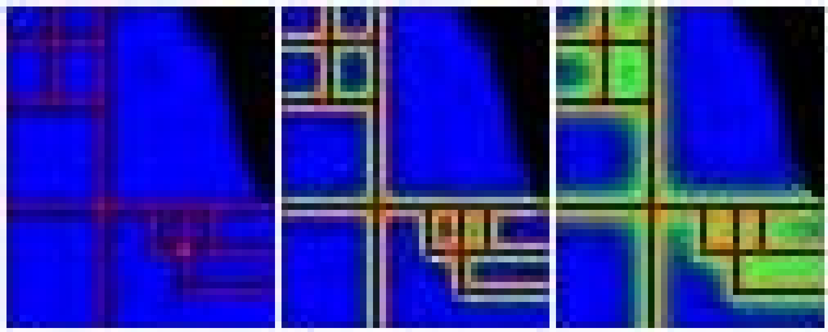


Figure 2 - 6. The diffusion of resources from roadways to attract development. Note the increased attractiveness at road intersections.

Cells closest to the road are the most impacted; the attractiveness weakens as distance from the road increases (Figure 2-7). The attraction coefficient is additive, making roadway intersections highly desirable for development.

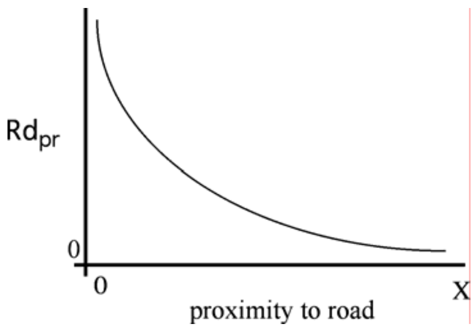


Figure 2 - 7. The relationship between road attractiveness and development probability. As the cell distance form the road increases (proximity to road), the roads influence on development probability (Rd_{pr}) decreases.

It should be noted that some road systems are unattractive to development. Interstate highways, for example, transport enormous amounts of goods, services, and information, but adjacent properties do not have access to them, making adjacent properties neutral in terms of road proximity. This means that cells adjacent to interstate might be unattractive to development due to the noise and lighting associated with interstate highways. It also means that areas that have access to off-ramps and the roads proximal to the ramps are extremely attractive for development because they become conduits to the transported goods and services.

Spontaneous Development Index

This sector represents the chaotic variables found in any social system model. It attempts to quantify the random chance of development occurring in any given cell at any given time (Figure 2-8). This randomness can help describe development patterns that otherwise may not be economically or socially prudent, yet take place anyway.

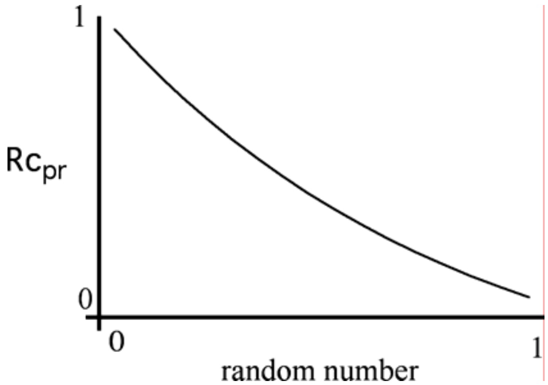


Figure 2 - 8. The random chance that any given cell will develop at any given time.

A simple model was constructed in a simple commercial CA modeling language (StarLogo) to test ability of the utilities (ut_i), neighborhood (n_i) and spontaneous (rc_i) models to replicate existing 'cluster' and 'leapfrog' development patterns. Sub-model rules for reach sector were input to a 40 x 40 grid and run. Output was captured in three segments labeled time 1, 2, and 3 (Figure 2-9). Although not a direct replication, the output patterns reveal a similarity in form to the development patterns noted in Figure 2-3.

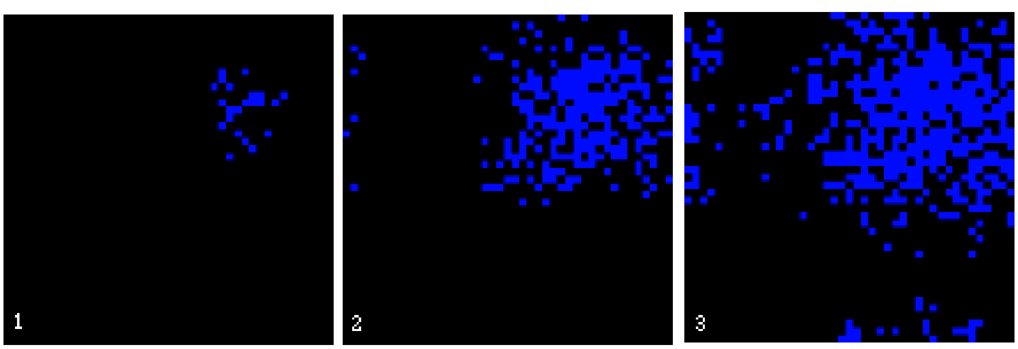


Figure 2 - 9. Output patterns from a sample model built in StarLogo to replicate the ut_i, n_i, and rc_i sub-model structure.

DEM Index

The Digital Elevation Map (DEM_i) sub-model (Figure 2-10) calculates the DEM_{pr} at any time (d_t) based on the geographic features present in the landscape and their affect on development patterns. Inputs include GIS coverages of slope, flood areas, and soils types aggregated into one calculation. Cell slope influence – as cell area slope increases developmental probabilities decrease (Figure 2-11) – is based on regionally specific statistical data. In some parts of the US slopes attract development (especially when views are favorable), in others it repels. In either case, the DEM_{pr} declines as it moves toward code-restricted or economic viability. The probability of development occurring in a flood zone is dependent on the type of zone (flood frequency) based on Federal Emergency Assistance (FEMA) maps and local jurisdictional information. Soils types are used to determine the structural stability of the soil and its capability to handle building construction requirements.

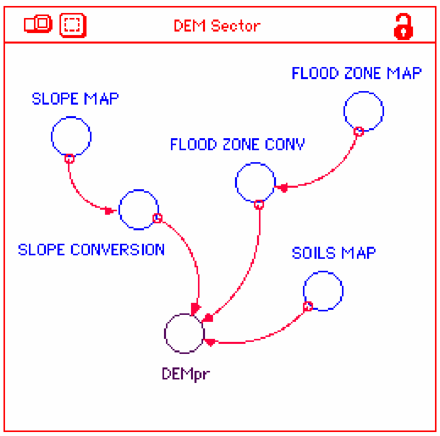


Figure 2 - 10. DEM index model describing the relationship between slope, flood zones, and soil types.

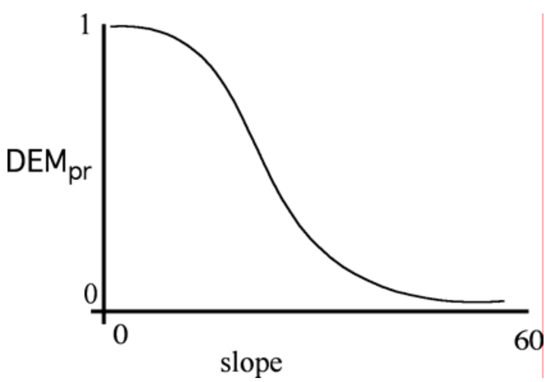


Figure 2 - 11. The DEM_{pr} as it relates to regionally specific slope factors.

Feedback to the DEM_i index model will be made from overland drainage assessment models. Soil erosion coefficients used to calculate suspended solids in streams will be affected by a development that takes place on steep slopes. Policies aimed at reducing suspended solids should include code restrictions on steep slope developments.

Regional Economic Driver

The economic model in LEAM (LEAMecon) forecasts changes in output, employment and income over time based on changes in the market, technology, productivity and other exogenous factors. The resulting economic trend is used as an input to a dynamic housing market simulation that then feeds into LEAM as residential land-use change. The agent-based housing model predicts actual houses built in a given year based on trends in the economy and anticipated demand by specific population cohorts. The combined economic and housing model serves as a prime driver of land-use change. Through LEAM, this work connects knowledge in regional science, housing markets, and spatial land-use analysis.

Using LEAM, alternative investment decisions can be modeled as different scenarios to see their impact on the regional economy and land-use. Scenarios are also a way to model shocks to the system. Shocks include local events such as closing a military base, as well as local responses to external policy changes, such as changes in the tax on gasoline. Shocks can be induced at a point in time or spread out over a period like investment in highway construction over several years. Consistent demographic and economic forecasts under different scenarios enable LEAMecon to model alternative demands on residential and commercial / industrial growth over time in the region. This strengthens LEAM's capacity to provide answers to a wide range of 'what-if' policy questions.

Coupled Input – Output Econometric models provide a wide array of impact analysis and forecasting abilities. When a model is run for a period of 30 years, many structural changes are expected to occur in the economy including changes in production structure, consumption behavior, etc. To capture such dynamics, I-O models are integrated into wider dynamic modeling frameworks. In a computable general equilibrium framework, the coupled model accounts for equating supply and demand sides of each commodity in the market. This is true for matching labor demand and supply through migration patterns, changes in unemployment levels, labor force participation rate, etc.

The core model consists of nine economic sectors and nine components of final demand. The output from each sector is consumed by other sectors (inter industry flows) and by components of final demand (which characterizes value added in the economy). The model consists of five modules of equations for each industrial sector and an additional module for demographics variables. The first module is the input output module that captures flow of goods and services inside the region, their destination to final demand and exports outside the region. To overcome the static nature of Input Output model, it is coupled with an econometric framework, where output, employment and income corrections due to changes in technology, productivity, etc., are made in three different modules. The fifth module endogenizes the dynamics of final demand and provides feedback into the production cycle. The final or sixth module is the demographic model that balances labor force demand and supply mechanisms. All the modules are solved simultaneously to completely forecast regional economic indicators that are used as input to other sub-models in LEAM.

Table 2-1: LEAMecon Variables forecasted

Economic Variables	Demographic Variables
Gross Regional Product	Population by age cohorts
Consumption by households	0-4 School age
Private Investment	5-14
Federal government	15-14
Non defense purchases	15-24 Active labor force and
Defense purchases	25-44 population in driving age
Investment	45-64
State and local government	65+ Retired population
Education	Components of population change
Non education	Births
Investment	Deaths
Personal Income	Net migration
Residential adjustment of income	Labor Force
Contribution to social security	Percent of resident workers
Income from dividends, rent, etc	Percent of non resident workers
Transfer Payments	Unemployment rate
Per capita personal income	Average wage and by industry
Output, employment and earnings: Total and disaggregated by industry	

Table 2-2: List of LEAMecon Economic Sectors

Economic Sectors
Extractive (agriculture and mining sector)
Construction
Manufacturing
Transportation, Communications and Public Utilities
State and Local Government Enterprise
Retail Trade
Wholesale Trade
Finance, Insurance and Real Estate
Federal Government Enterprise

The model described above provides consistent economic and demographic variables for the region (Table 2-1). Various shocks like investments to specific sectors (listed in Table 2-2), increase in public spending or consumption from households, etc., can be applied to the regional economic system. The employment model shows changes in productivity over time to determine regional employment levels. The percentage of workers living outside the region and commuting to work on daily basis is used as a policy variable to model effects of income leakages from the region. The income module models regional average wages in response to interaction between labor demand and labor supply. The average wages are converted into industry specific wages and total regional income is computed. Personal income is derived from wages and salary income after accounting for other components such as contributions to social security, transfer payments, etc. The income leakage due to daily commuting is modeled in this block. Finally, differences in labor demand and supply affects net migration. If the employment demand increases relative to labor supply from households, the regional unemployment rate decreases until people migrate into the region and equilibrium is reached. These dynamics occur with different time lags in different parts of the model. Population change is modeled on births, deaths and net migration. The total population is sub divided into different age-cohorts, each of which has a specific role to play in regional land use change, evolution and impact assessment in the region.

The economic driver model used in LEAM captures causal mechanisms and not just patterns of changes and impacts. The forecasts generated are consistent with local conditions and all coefficients are region specific. It also provides an opportunity to model economy related shocks to the region and evaluate alternative 'what-if' possibilities. In addition to predicting consistent interdependent economic and demographic variables, its transparent structure helps to trace the propagation of shock through the system and present a clear picture of the regional dynamics providing useful information to Land-use Evolution and Impact Assessment Model.

Housing Demand Model

The economic driver sub-model connects economic trends and population pressures into land-use transformation drivers by creating a demand for new housing. The model is based on empirical studies that show a significant correlation between housing transaction volumes and the percentage of deviation from the Gross Area Product (GAP) trend (Ortalo-Magne and Rady 1998) (Figure 2-12). The significant difference between what appears to be a simple concept – when the economy is good housing demand is high – is how a good economy is determined. Ortalo-Magne and Rady have determined that a perception of positive economic activity, usually in the form of an upturn in the GAP, produces and increase in confidence and a subsequent increase in housing demand (after the usual financial and institutional lags).

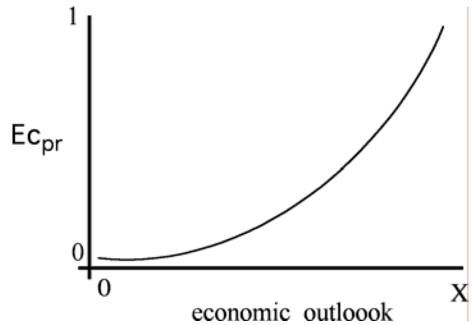


Figure 2 - 12. The connection between economic output and development probabilities Ec_{pr}**.**

Although economic trends determine a favorable economic outlook, transformation will not take place with housing demand. Housing demand in the Ec_i sub-model is developed through population pressure, household income, size and average housing prices (Figure 2-13). New housing demand is modeled as a 'push' of first time buyer rather than a pull from move-up owners. The push is determined by the relative income of first-time homebuyers (typically in the 23 – 30 year old population cohort), and their ability to afford the starter homes in the region.

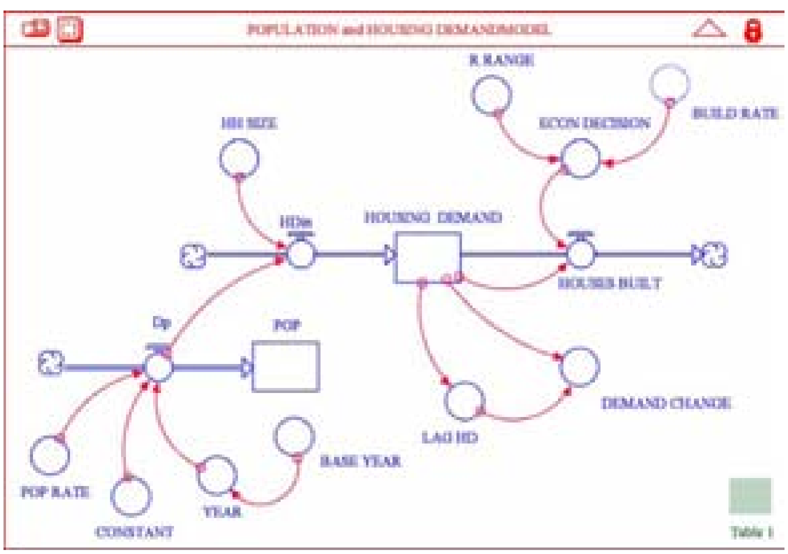


Figure 2 - 13. Population and housing demand model sector.

The population and housing demand sector provides the pressure to build new housing in order to satisfy demand. However, it is not required that all the annual demand be met in one year. Typically boom and bust cycles cause cyclical waves in construction starts causing homebuilders over-build or under-build market areas. Demand also can become pent up during low economic periods (a negative GAP trend), spiking in times when the GAP moves to a positive positions. It was found that the most significant correlations between GAP and housing starts occur when the trend in the GAP rises. Even a low GAP output position that begins to upturn has a positive impact on housing starts. An increased demand also influences housing prices, rising over time in response to the demand.

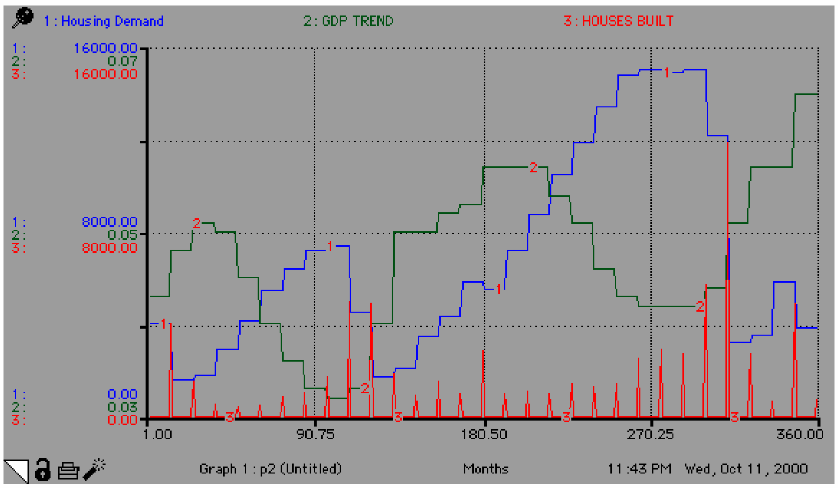


Figure 2 - 14. Stella output of the Economic Index showing the relationship between Housing Demand (blue), GAP trends (green), and housing starts (red).

This index also determines how many housing units will be required for any given year to satisfy final demand. The spatial allocation of these units is determined through the development probability calculations. The current LEAM environment does not attempt to allocate specific numbers of housing units, but it does use feedback control strategies that speed up or slow down the actual number of new units constructed depending upon how well the model conforms to households projected (Figure 2-15).

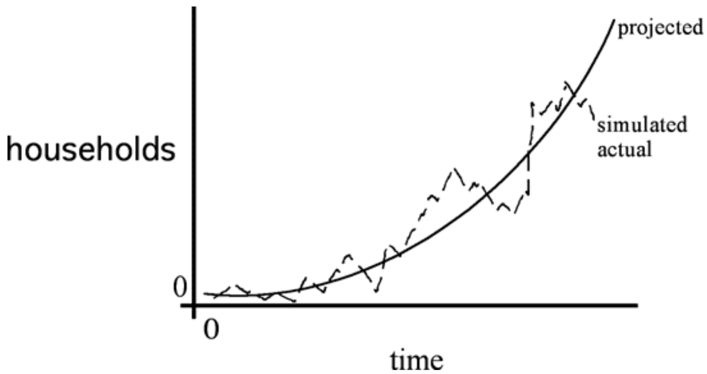


Figure 2 - 15. The adjustment of demand (projected) vs. simulated output of households.

Annual projected household demand (hh_{proj}) is compared with simulated output totals (hh_{sim}) to determine the rate of growth (k_t) for the following year.

$$k_t = hh_{proj} / hh_{sim}$$

If there is a surplus of households in the simulated results ($k_t < 1$), demand for the following year is reduced (by multiplying by k_t) and actual growth will slow, reducing the construction of new units. If the there is a shortfall of units ($k_t > 1$), the growth function increases demand for the following year to correct the shortfall. This self-modification function keeps the simulated households in line with projections.

The economic index is a regionally scaled model that works across the study area in annual time steps. This model is indicative of the need for a hierarchical approach. Economic forecasts occur over large geographic areas and do not impact near-term development or growth related decisions, although they do have a large influence over annualized processes. In the LEAM framework the economic index is an important factor that "decides" if the existing demand can be realized or if the economic constraints are too limiting.

Transportation Index

The transportation sector uses simulation and dynamic modeling techniques to advance an understanding of the connection between transportation systems and the development process. The sub-model generates a transportation based development probability for each cell, at each time step (t_j), based on three major components: road access (ut_i), road carrying capacity (ca_i), and road congestion (cc_i).

Road access considers the probability for developmental transformation based on cell proximity to roadway networks (see ut_i section 0).

Road Capacity and Congestion

Impediments or attractors of land-use transformation can at times relate solely to transportation networks. Population and employment growth increase vehicle numbers; low-density land-use patterns increase vehicle miles driven, and commute times are affected by employers that increasingly move toward the fringe. These factors (among others) are causing an unprecedented increase in local peak-hour congestion that is fast becoming the central issue facing local government agencies (Langdon 1994). Connecting congestion to land-use transformation is difficult, although recent studies (Thorsnes 1994), suggest that in some instances (other variables equalized), development will follow paths of low commute times. This sub-model promotes one strategy to determine probable areas of congestion and their impacts on developmental probabilities.

$$tr_t = ca_t / cc_t$$

The congestion sector (Figure 2-16) is based on road capacity and intensity of use at peak hour times to determine a localized congestion coefficient; as congestion increases development probabilities in that local area decrease. Capacity is influenced by type, width, and speed limits. Wider roads, an increase in lanes, and faster speeds can sustain higher peak loadings than their narrower slower counterparts. Based on Department of Transportation classification standards, regional road networks are classified by type (federal, state, county) and grouped by capacity (low, medium, high). In LEAM these variables are defined and aggregated into a GIS layer for model input.

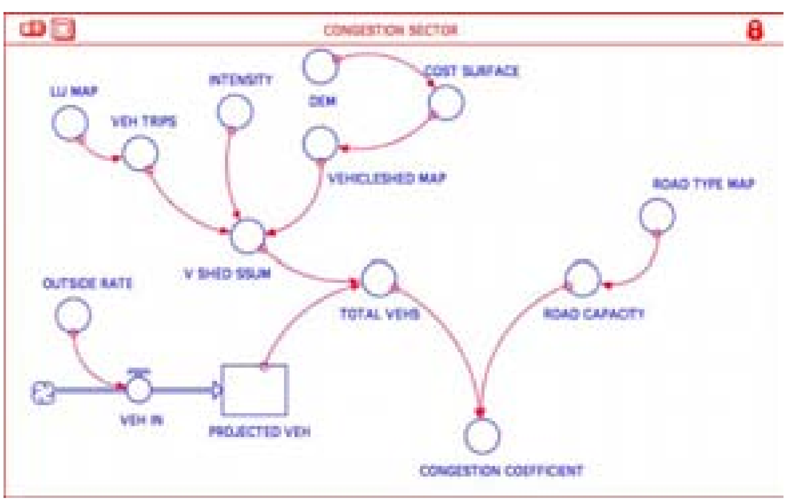


Figure 2 - 16. Congestion sector cell model determining vehicle trips generated by land-use transformation and its impact on road congestion.

The determination of congestion requires an estimate of peak load conditions to compare with road capacity. Once capacity is reached, the road can be classified as congested. Peak loads are simulated by creating vehicle ‘drainage’ areas so that cars can be drained toward the areas of greatest gravitational pull (typical regional commute directions). Like watersheds, vehicle-sheds are hierarchical in nature; gravitational pull is provided by larger roadways networks (arterials, highways, interstates) that are organized around a more central pull (e.g., a regional metropolis or metro center connectors). Vehicle ‘topography’ is developed by the creation of a 'cost surface’ map.

A cost surface is the determination of the relative ease of passage over particular land uses from the perspective of a particular cell ‘origin’. The cost surface shows the relative time costs of going from the origin cell to any other destination cell within the study area. Relative distances and landscape surface features influence the cost (in time) of moving from the original cell to the destination cell (any other cell in the study area). Longer distances are more time consuming as are more difficult surfaces (e.g., woodlands, water, etc.). Close distances and easy migration surfaces (e.g., roads. flat agricultural surfaces, etc.) require less time to traverse. Relative surface land-use travel times (based on the NLCD land-use map) are indexed and expressed in the relative amount of difficulty in crossing a cell of a particular land-use type (Table 2-3).

Table 2 - 3. The Relative Time Index Values for a Given Land-use Type.

No.	NLCD Land-use Type	Time Index
1	21 Low Intensity Residential	10
2	22 High Intensity Residential	10
3	23 Commercial/Industrial/Transportation	10
4	31 Bare Rock/Sand/Clay	.05
5	32 Quarries/Strip Mines/Gravel Pits	.05
6	33 Transitional	,05
7	41 Deciduous Forest	2
8	42 Evergreen Forest	2
9	43 Mixed Forest	2
10	51 Shrubland	5
11	61 Orchards/Vineyards/Other	5
12	71 Grasslands/Herbaceous	5

13	81 Pasture/Hay	5
14	82 Row Crops	5
15	83 Small Grains	5
16	84 Fallow	5
17	85 Urban/Recreational Grasses	5
18	91 Woody Wetlands	.05
19	92 Emergent Herbaceous Wetlands	.05
20	Water	.001

Digital elevation also plays a role in the determination of a cost surface map (Figure 2-17). Steeper slopes or ravines are more difficult while flatter slopes are easier to traverse. Much like a topographical map, the cost surface map can be used to divide the region into hierarchical vehicle sheds based on road networks (instead of waterways), that drain cars (instead of water) to a gravitational roadway system of the next higher order. Vehicle sheds (Figure 2-18) help to interpret the likely movement of vehicle direction at peak times so that an aggregation of loads can be summarized (at determined outfall areas) and compared to capacity.

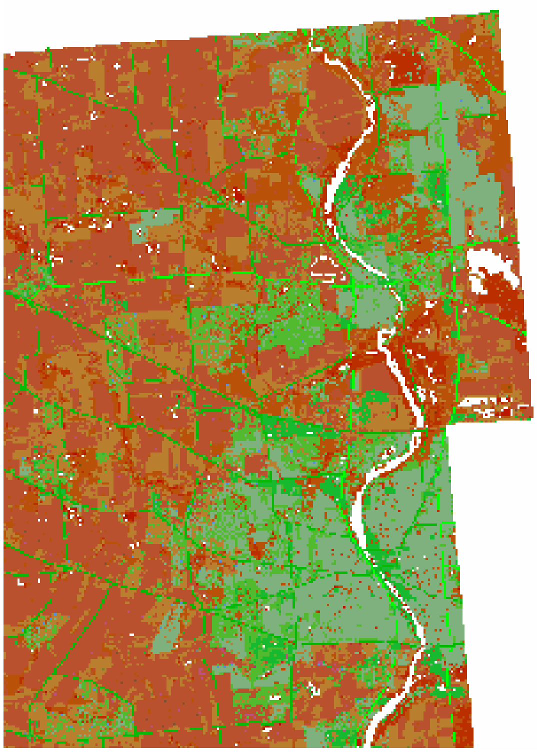


Figure 2 - 17. A portion of the cost surface map for Kane County Illinois. White is water (no passage), green is easily traversed, brown is more difficult.

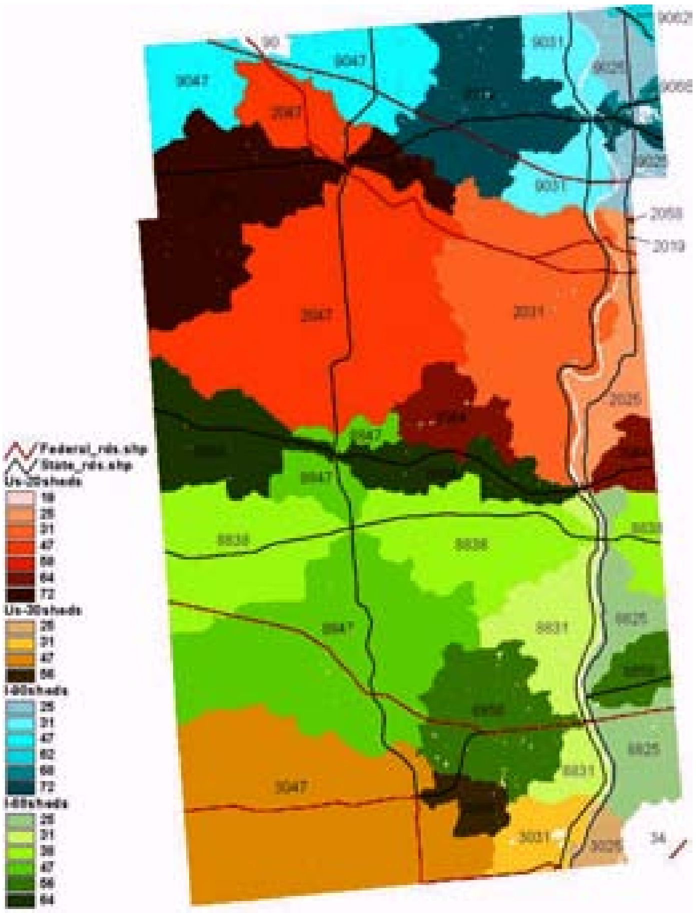


Figure 2 - 18. Vehicle shed delineation of Kane County Illinois. Blue, orange, green and yellow, designate federal systems, shades of color within those ranges delineate state highway systems.

The aggregation of vehicle trips within a particular vehicle shed reveals only one part of the total vehicle number equation. Vehicles that are expected to come from outside the shed area must also be considered when aggregating the total expected. This is accomplished using historic traffic counts. Historic counts (Figure 2-19) are taken from 1960-1990 DOT paper maps and annual average 24-hour traffic volumes determined by the US DOT. A regression analysis is used to develop algorithms for probable ‘outside’ influences on aggregate traffic counts.

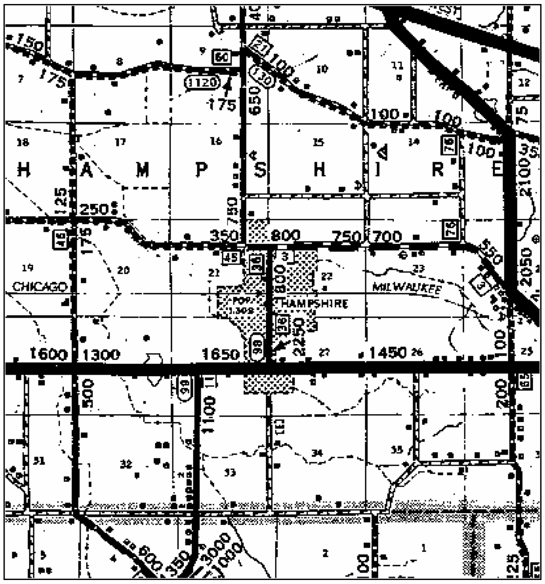


Figure 2 - 19. **Historic traffic count maps used to determine 'outside' influences on total vehicle shed calculations.**

Assumptions made within the congestion sector include: (1) the fact that morning traffic will generally flow toward the nearest metro center while evening traffic will reverse flow and (2) commuters will generally choose routes based on 'least' time averages (although this model excludes stop lights and other considerations).

Cells within each vehicle shed are assigned cc_t for time (*t*), influencing the p_t for that area; as congestion increases, development probabilities in that area decrease (Figure 2-20).

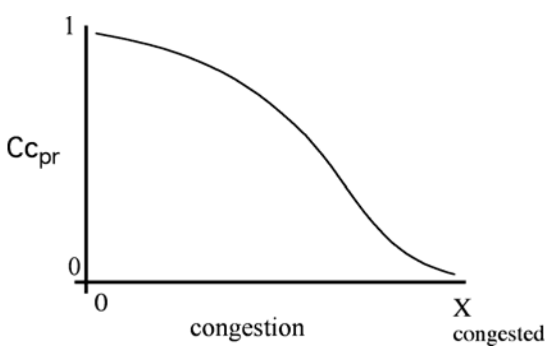


Figure 2 - 20. **The relationship between road congestion (*Cc_{pr}*) and development. probability.**

Example: Transportation as a Driver of Land Use Change in the St. Louis Region

Traffic-flows close to the design-capacity for a road cause the travel-speed on such a road to drop below the design-speed or the free-flow speed, thus, increasing the travel-time over such a road. An increase in travel-time over a road makes it less attractive for people traveling on them. People tend to choose alternative routes, which might not be the shortest path for reaching their destination. To enable perception of this change in behavior, the employment attractors for the region are changed based on the improved travel-times over the roads. These employment attractor maps are then made available for the rest of the LEAM model to generate updated land-use for the region. Thus, the impact on transportation is translated into a driver for land-use change through this mechanism. This approach enables LEAMtrans to run parallel with the LEAM model.

Congestion Calculation Results

LEAMtrans was developed and applied to the St. Louis Metro region. The road network in the analysis was limited to US highways and Interstates in the region. The analysis produced peak hour (evening) traffic on this road network.

Preliminary results from one scenario indicate, as might be expected, that the bridges will become heavily congested over the years. Congestion is also likely on I-270, I-70 between I-270 and the bridge, I-64, I-44 & I-55 between I-270 and the bridge. US-40 connecting I-70 and I-64 is also likely to get congested. Almost all of the roads outside of the St Louis city and on the Illinois side seem to have an un-congested flow in the year 2025.

The congestion is reflected in the reduced travel-speeds and thus reduced travel-times on these roads. This reduction in travel-times causes a significant variation in the employment attractor in the region. The attractiveness of inner city areas declines while that of the outlying areas increases, thereby increasing sprawl (Figure 2-21).

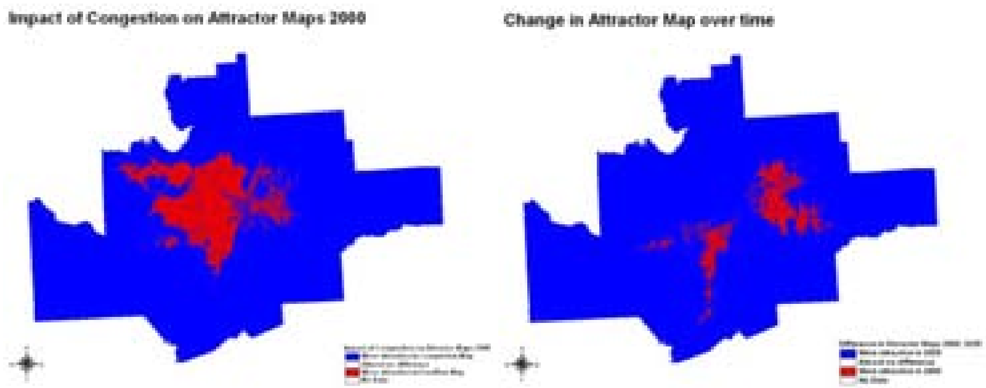


Figure 2-21. The changing attractiveness of outlying areas due to traffic congestion in 2000 (left) and 2025 (right). Red areas represent areas of increased congestion and reduced attractiveness. The congestion is reflected in the reduced travel-speeds and thus reduced travel-times on these roads. This reduction in travel-times, cause a significant variation in the employment attractor in the region. The attractiveness of inner city areas declines while that of the outlying areas increases, thereby increasing the possibility of sprawl.

Growth Trends

The growth trends function (gt_i) is an enumeration of the regional growth aggressiveness (positive or negative) of local municipalities. Historic municipal growth trends are analyzed using statistical regression models. Regional scores are then normalized (from 0-1) from least aggressive to most aggressive. Cells with equalized (P_t) scores are attracted to more aggressive (higher gt_i) communities (Figure 2-22). Community influence buffer areas (Figure 2-23) are calculated using a gravity model to simulate the sphere of influence according the size of the municipal land area. Some states, including Illinois, require a metropolitan planning area that includes a 1.5-mile perimeter buffer. This variable captures regional differences in growth policies (cells within the influence of more aggressive communities are easier and cheaper to develop) and can be modified during the course of a model run to simulate policy shifts.

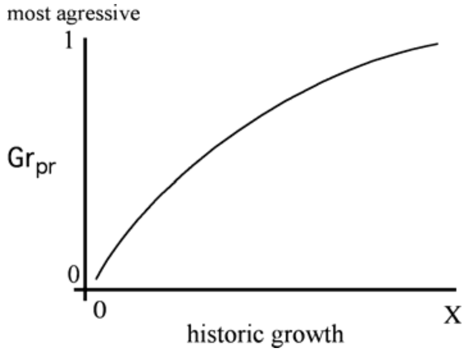


Figure 2-22. Historic growth patterns and the establishment of regional growth aggressiveness rates (gt_i).

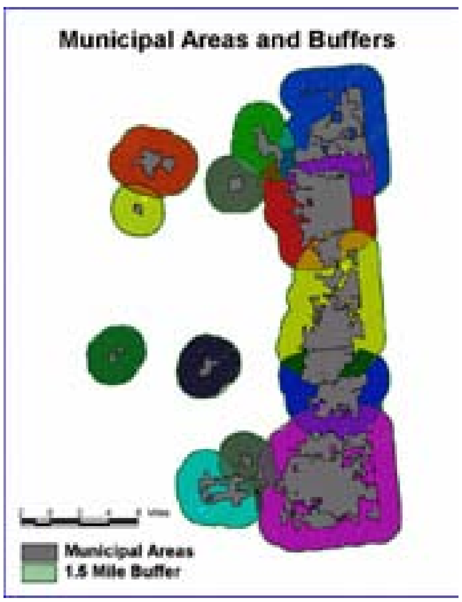


Figure 2-23. Growth area buffers in Kane County, Ill. (differences in buffer values by color).

Social Driver

The Land-use Evolution and impact Assessment Model (LEAM) simulates land-use change generated from new development based on projected population growth and proximity to attractors such as roads and city centers. The weighting of attractors is such that if a vacant cell exists close to city centers in the form of developable land, it has a high probability of development. However, high vacancy may signify areas that are unattractive for development due to demographic or housing conditions. The LEAM Social Model was developed to address this gap – to capture the social or demographic factors affecting patterns of migration and new development in a region. Particular emphasis has been placed on areas of exodus or abandonment, to better understand the dynamics of depopulation that occur in parts of the region.

In addition to their importance to the region, social factors related to metropolitan development have been investigated by a number of scholars. Temkin and Rohe (1998) examine factors influencing the strength of social capital in neighborhoods and thereby their resilience to urban ecological change. Downs (2000) investigates the relations between sprawl and decline across American cities, postulating conditions associated with poverty that may cause migration to the suburbs. Further examination is warranted within metropolitan areas, as described for the case of St. Louis below.

Although development of social theory would be helpful for addressing the social dynamics at play in metropolitan areas, a data-based approach was deemed most immediately useful to inform LEAM. Three empirical analyses were employed at with tract-level census data to examine the social factors embedded in the dynamics of land-use change in the St. Louis region: a spatial analysis of poverty rates in 1990 and 2000; a historical analysis of housing change from 1970 to 2000; and identification of development indicators to inform land-use change.

The analysis began with poverty rate to capture elements of social distress. As used here, poverty rate is the fraction of individuals with incomes below a specified threshold, based on the cost of living to meet the most basic needs. An exploratory analysis revealed the presence of poverty in high concentrations in the center city and East St. Louis areas. Analysis of spatial clustering (autocorrelation) of poverty using a variety of measures for tract neighborhood revealed substantial isolation of poverty, and an increase in this isolation from 1990 to 2000.

With the acquisition of a dataset that extended back to 1970, and using 2000 tract boundaries (as such boundaries change frequently), a thorough historical analysis examined correlates of housing and population change. Housing change (percent change during a decade relative to the base year at the start of the decade) was used as the critical dependent variable, as it ties most directly to land-use change. A variety of regression techniques were used to assess the approximate level of significance of demographic attributes in a base year on housing change in the subsequent decade. Although significance levels varied with decade and with method, certain factors surfaced as significant across the analyses.

Based on the results of the historical analysis, indicator maps were prepared for each of four factors: vacancy rate, average household income, rental rate, and proportion of residents without vehicles. To inform the land-use change drivers of LEAM, a development likelihood function was created based on the frequency of housing unit increases as they correspond with variable levels at the start of the most recent decade (1990-2000).

The spatial and temporal analysis of census data highlights first that poverty is clustered in and around the central city, while affluence is clustered around the fringes; spatial disparity between rich and poor is increasing. Figure 2-24 shows how clusters of poverty (red) become increasingly isolated from clusters of affluence (blue) from 1990 to 2000, indicating growing economic disparity in the region.

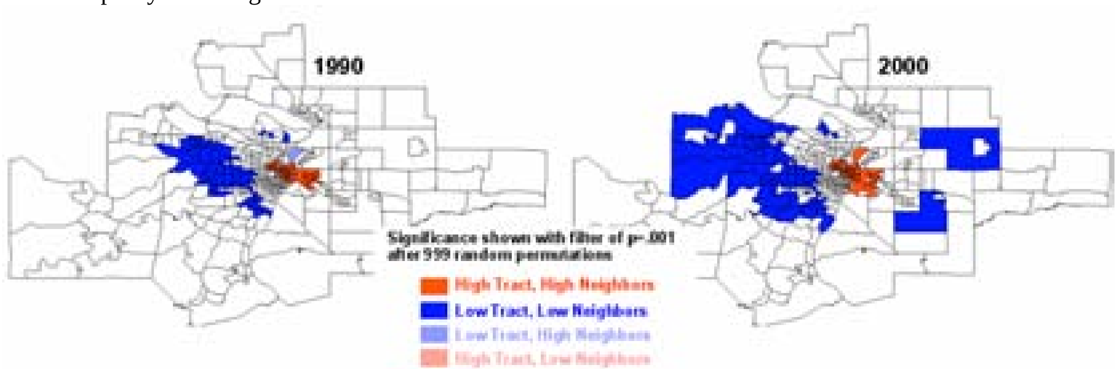


Figure 2-24. The spatial auto-correlation of poverty

Historical analysis of housing change reveals that significant social drivers of land-use change in the region are vacancy rate, income, rental rate, and proportion of residents without vehicles. These demographic factors will be combined with the other drivers of land-use change in LEAM. These factors will be used to assign scores to cells in particular Census tracts, which in turned altered the likelihood of development in those cells. As an example, Figure 2 indicates vacancy rate in the year 2000; dark shades indicate greater likelihood of residential vacancies and a lower likelihood of new residential development.

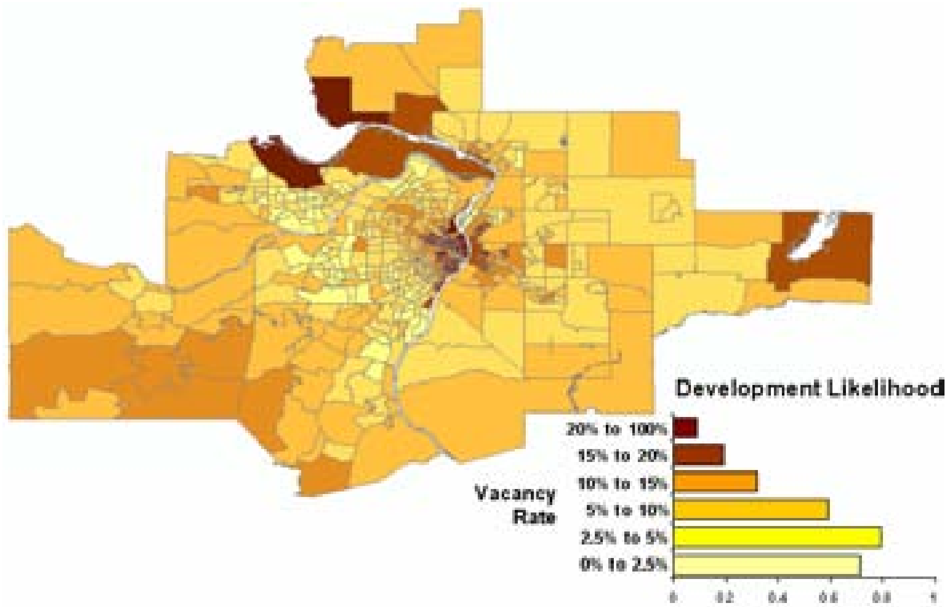


Figure 2-25. Example Vacancy Indicator Map for 2000, St. Louis Region.

Proximity Drivers

The generic LEAM simulations used proximity to city centers as a driver of land-use change. Public review of these simulations suggested that land-use change in this region is likely to be driven by proximity to other centers such as employment, shopping, health, and cultural amenities. Data for these centers have been acquired, processed, and the effects of these drivers are being investigated through LEAM simulations.   Proximity maps are developed using local data sets that identify important local features. A gravity model is then applied to the features map to create a map of approximate travel times to the feature. The map produced gives each a cell a value based on its ‘proximity’ to the feature. A few examples of developed proximity measures are given below.

Employment Centers

Because cities encompass a variety of activities that are not necessarily sympathetic uses, it was determined that employment activity and there spatial location will be an important component in determining model outcomes. For example, to develop a proximity map for employment in the St. Louis metropolitan region, the top 114 employment centers (based on total employment) in the St. Louis region were identified and mapped. The centers were divided into three distinct categories: large employers, medium, and small employers. Travel times to the nearest employment centers were calculated for each cell. Each group was calculated independently and the data combined for 1 employment center proximity map (Figure 2-26).

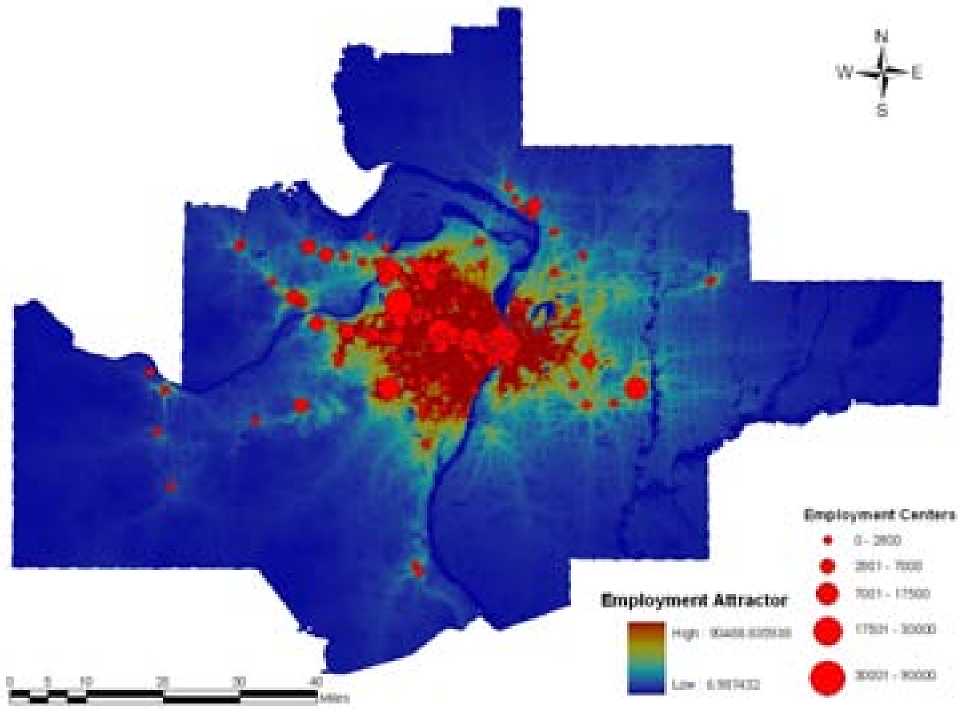


Figure 2-26. An employment proximity map for the St Louis metro area representing the top 114 employers in the region and a cell-by-cell proximity calculation to each.

Healthcare Centers

Although access to jobs is important cities also provide numerous other features that may influence land use change. Access to healthcare may be one. To develop a proximity map for Healthcare, hospitals in a region must be identified and mapped. Travel times to the nearest healthcare centers are calculated for each cell to produce a healthcare center proximity map such as the one developed for the St. Louis region in Figure 2-27.

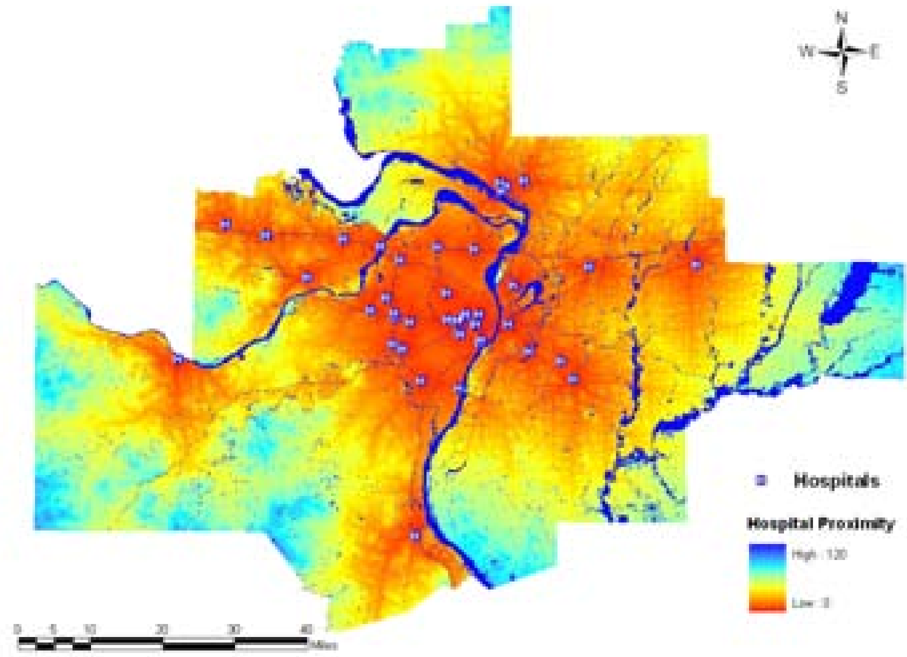


Figure 2-27. Healthcare centers proximity map for the St Louis metro area representing the major healthcare facilities in the region and a cell-by-cell proximity calculation to each. Red areas have easier access to healthcare in the region.

Surface Water Resources

Access and proximity to surface water resources can be an important component for certain types of development. Recreational type developments and open space gravitate toward major water features in the landscape. To develop a proximity map for water resources, major bodies of water in a region are identified and mapped. Travel times to the nearest water feature were then calculated for each cell to produce a water resources proximity map, such as the one developed for the St. Louis region in Figure 2-28.

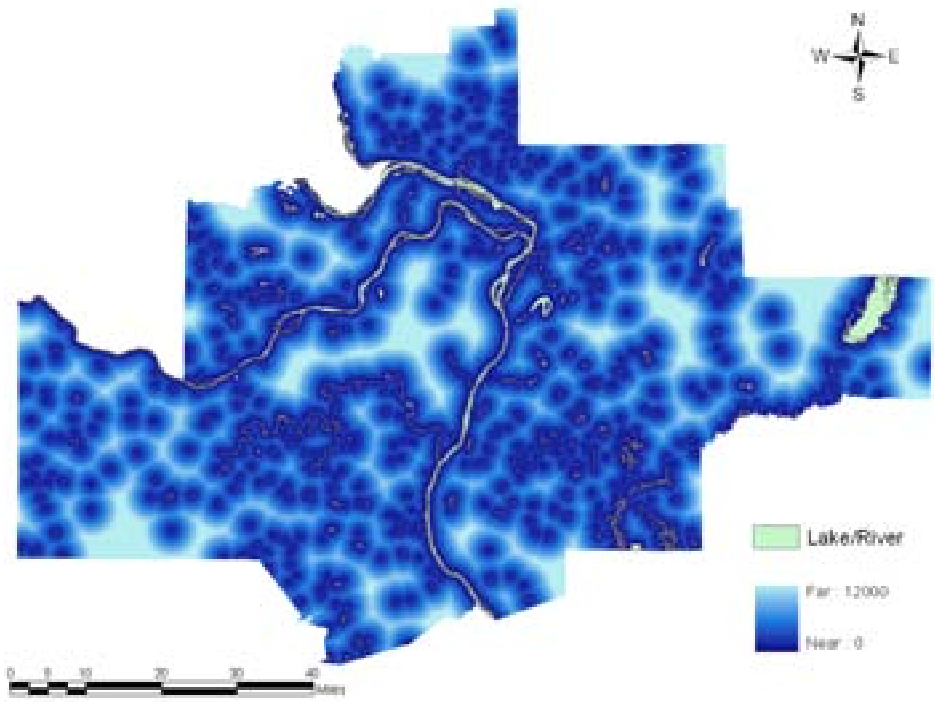


Figure 2-28. Surface water resources proximity map for the St Louis metro area representing the major water features in the region and a cell-by-cell proximity calculation to each. Darker areas have easier access to surface water resources.

Besides the drivers described above, there are several other proximity drivers, which might be used in LEAM, including forest proximity, transportation proximity (accessibility of ramps, major highways, major road intersections), mass transit stations proximity, cultural center proximity, etc. All these drivers are quite similar in terms of how they are created and used.

Spatial Frequency Analysis (SFA)

All LEAM drivers or sub-models eventually will be combined to estimate the land-use transformation probability as described earlier. It also means all the driver (proximity) maps have to be transformed into index probabilities (also called scores). The spatial frequency analysis approach is adapted in LEAM to project a value (travel minutes, slope degree etc.) on a driver map to a score. It has been a critical link in the LEAM model framework.

This analysis is to extract a profile (we also call this profile "graph") of land use distribution on a feature map. Here the feature map means LEAM driver map, like slope map, travel time map to ramps etc. It answers questions like: how many residential cells on land use map are within 5 minutes to interstate highway ramps, and how many are within 10, 20...minutes? Based on this profile information, we can reasonably estimate how likely a certain land use type will happen at certain feature value. In the above example, it tells us what is the residential development possibility (or, more precisely, score) of a cell within certain minutes to highway ramps in the perspective of highway accessibility.

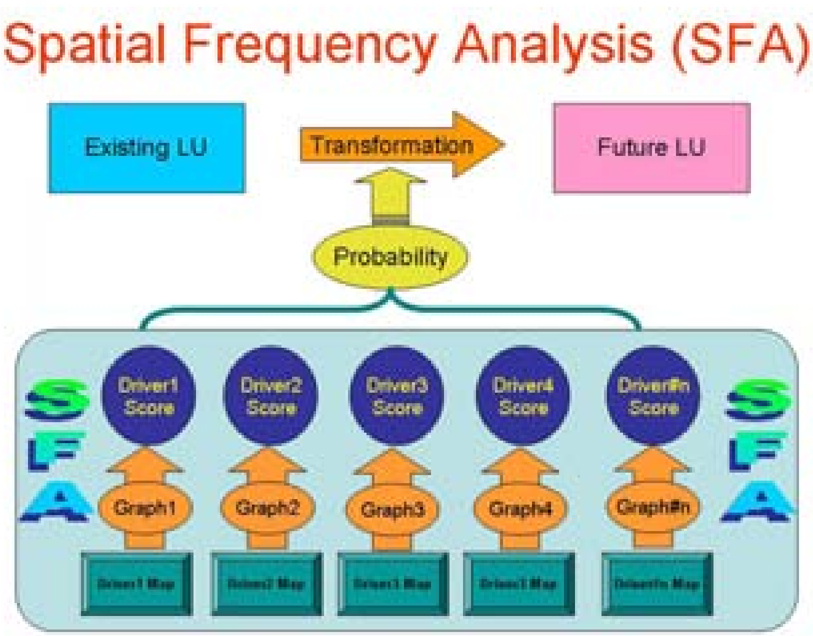
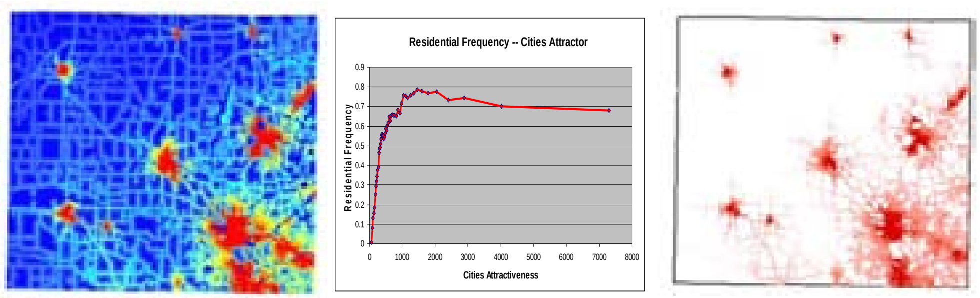


FIGURE 2-29 Spatial Frequency Analysis

Analysis is conducted on the following drivers in generic LEAM:

Driver Name	Description	Units	Comment
Slope	average slope of a cell	degree	data range: 0-90
County Road Proximity	travel time to a nearest county road	15-second	The unit is used to be minutes; 2 hours is the cut-off point

State highway Proximity	travel time to a nearest state highway	15-second	same as above
Ramp Proximity	travel time to a nearest ramp	15-second	same as above
Road Intersection Proximity	travel time to a nearest major intersection	15-second	same as above; we just consider major road intersections
Forest Proximity	distance to a nearest forest patch	meters	small forest patches are removed
Water Proximity	distance to a nearest water	meters	small water patches are not considered; census water data is adapted
City Attractor	it is gravity model to measure a cell's proximity to cities	population/(TravelTime^2)	it is not a simple distance or travel time



(a) Cities Attractor Map (b) Residential Frequency Analysis (c) Residential Score Map

FIGURE 2-30 Frequency Analysis Example

3 WEIGHTING, CALIBRATION, AND VALIDATION ISSUES

How well do LEAM simulations project meaningful information? One way to assess the validity of modeled land-use transformation is to reconstruct historic conditions and then project the resulting model 'forward' to the present. This approach to validation utilizes our inherent knowledge of current conditions as the basis for revealing similarities between the model and actual measured transformation. The approach is limited, however, by the availability of applicable historic data as well as the chaotic nature of economic and social systems. For this reason, models are not capable of *predicting* the future. However, by using carefully selected proxies and assumptions, they may be capable of *projecting* the outcome of a given scenario, and these projections can help to explain discrete pieces of larger realities that we observe.

This distinction between prediction and projection is important:

> The purpose of a spatial transformation model is not to 'predict the future', but to develop credible, defensible projections of the likely consequences arising from a stated set of assumptions, rules, and constraints as applied to a specified set of resources and reported in relation to indicators accepted as valid by the professional planners in that region (Malczewski 1999).

Projections are *not* predictions, but they can be invaluable for planning when based on solid expertise and data sets. A region's thought leaders and prominent decision makers are more capable of producing land-use 'predictions' than a computer model. Comprehensive 10- and 20-year regional plans reveal communal land-use aspirations that can be seen as predictors of the communal vision. But these plans about land-use transformation contribute nothing to sustainability unless they are the end result of analyses that address issues such as:

- the economic, social, and environmental consequences of the transformation plan
- whether the consequences provide long-term benefits to the overall community
- competing alternatives that may promote more sustainable development.

Even if realistically achievable predictions about future land-use change were feasible in a technical sense, they could be considered valid only if the community involved decided not to periodically reevaluate its direction or consider other directions as new possibilities emerged (unlikely given our political and economic structure). On the other hand, the science and art of projecting land-use change and its impacts is premised on idea that human settlements are diverse and subject to chaotic change and that these things should be considered fully and tested periodically.

3.1 Weighting

The ability to weight sub-model drivers in order to reflect (in a reasonably accurate manner) regionally specific land-use change phenomena is an important step toward realizing external validation and transportability goals. The processes of weighting and model calibration are not mutually exclusive – factor weightings can have a large impact on modeled outcomes. Analyzing modeled outcomes can help in determining variable weights. Factor weightings can also affect the reliability and validity of the model, two important components for undertaking a calibration effort. Similar approaches to determine weighting coefficients and the calibration of the modeled output can be affective.

The expressed weightings of model variables can be approached in two ways. The first might be described as a self-weighting process in which model variables are articulated from within the user interface so that affected model output would reflect user-induced preferences. This process removes objectivity from the modeled output and could make it difficult to assess the variability within same regional models runs (if run with different weighting criteria). These negatives, however, may be offset by the attractiveness of user control and self-ascribed reliability. Users who are required to interact and become involved in the modeling process are more likely to believe the outcomes presented.

A second approach is the development of regionally specific variable weightings that are expressed within the model structure and constant for each user in that region. It is important that the model development process include an initialization of the model for a particular region, so that relevant policies and scenarios are pointed at regionally significant factors, drivers, and impacts. This more objective approach requires valid and available historic data sets, but such data sets are difficult to produce. The process analyzes modeled output against the historic data to determine the model(s) explanatory power.

3.2 The GLUC model and Weights

The LEAM Generic Land Use Change (GLUC) model attempts to allocate new residential, commercial, and urban open space land uses. The quantity of new cells is controlled by an external model therefore the GLUC model is only concerned with the spatial location of the land use change.

The GLUC model generates a probability map for each new land use classification based on land use change drivers. The GLUC model currently has 12 drivers but localized versions of the model may have many more. The probability calculation requires a weight be assigned to each driver based on a driver's importance in the land use change process. Initially these weights were estimated using feedback provided by professional planners. Because of the subjective nature of this process and difficulty in optimizing 100 or more weights a more robust calibration process was required.

One of the key advantages of the GLUC model is the use of small (30x30 meters) cells that have a single land use classification instead of mixed use classifications. This advantage of using fine resolution cells is the ability to aggregate results in arbitrary shaped regions such as such as political boundaries, census blocks, transportation analysis zones, watersheds, or school districts without requiring the complex processes of assigning fractions of mixed-use areas to other boundaries.

3.3 Calibration Requirements

The GLUC model calibration had several requirements.

1) the weights should be continuous variables (floating-point values)
2) the weights should be allowed to vary over independent ranges
3) the calibration process should be able to simultaneously deal with a large number of weight

An evaluation of the model run times showed that a simple Monte Carlo approach to calibration would require excessive amounts of computing time even with the availability of a national supercomputing center. After initial attempts using a spatial statistics approach, a genetic algorithm approach was selected.

3.4 Genetic Algorithm Approach

Genetic algorithms (GA) have been successfully used to find approximate solutions to difficult-to-solve problems through application of the principles of evolutionary biology to computer science. Genetic algorithms use biologically-derived techniques such as inheritance, mutation, natural selection, and recombination (or crossover).

Genetic algorithms are typically implemented as a computer simulation in which a population of abstract representations (called chromosomes) of candidate solutions (called individuals) to an optimization problem evolves toward better solutions. The evolution starts from a population of completely random individuals and happens in generations. In each generation, multiple individuals are stochastically selected from the current population, modified (crossover and mutation) to form a new population, which becomes current in the next iteration of the algorithm.

In the case of the GLUC model, the driver weights would be the chromosomes and a specific set of weights would represent an individual. Individuals would be selected for propagation of their chromosomes based on their fitness. The fitness would be the ability of the model to accurately simulate the land use change for a region for a known historical period (typical historic comparison is based on 1993 and 2000 land cover data).

The GA approach begins by creating a population of the individuals each with unique trial weights. Initially the weights are chosen at random based on allowed variance for each weight. For each individual, a model is run and a fitness score calculated. To develop new trial weights, an evolutionary strategy involving selection, crossover, and mutation is used.

During selection two individuals are chosen from the population. The selection process is based on probability; individuals that are evaluated with higher fitness score will most likely be selected for crossover. Those with low fitness values probably will not. The key point is that this phase has an element of randomness just like the survival of organisms in nature.

The probability for selection is based on the individual’s fitness value relative to the rest of the population. Selection begins by determining an individual’s relative fitness by dividing its fitness value by the sum of all fitness values. Then a random number generator is used to select individuals for the crossover phase. The odds of an individual being chosen during each roll of the random number generator are equal to the individual's relative fitness. The number of individuals selected is equal to population size, therefore, keeping the size constant for every generation. Some individuals will be selected more than once in which case multiple copies of the individual will be in the set used by the crossover operation.

3.4.1 Crossover

Crossover is the process of combining the genes (weights) of one individual with those of another to create offspring that inherit traits of both parents. The crossover rate is the odds of an individual being selected for the crossover operation. The individuals that are not selected will not have their genes changed before proceeding to the mutation phase. Those that are chosen will be paired with a mate which is another individual that was also selected for crossover. From each pair, two offspring will be created that will replace their parents. To determine which genes are inherited from the father and which genes will come from the mother, a random number between one and the total number of genes minus one will be created. For the first offspring, the genes numbered between one and the random number will be inherited from the father. The genes numbered between the random number plus one and the maximum number of genes will come from the mother. The genes for the second offspring will be inherited just like those of the first offspring except that the genes that came from the father in the first offspring will come from the mother and those inherited from the mother will come from the father.

3.4.2 Mutation

Just as in nature, some individuals will have random mutations occur in their genes. The mutation rate specifies the odds that a given gene will be mutated. If a gene is selected for mutation then its value will be changed. In our approach the mutation uses the same variance as used when choosing initial weights for the population.

One again a fitness score is produced for every individual within the population. The iteration continues until the minimum fitness function (sum of the error squared) fails to change by 0.01%.

3.4.3 Fitness Function

Generating a fitness function represented a unique challenge for the GLUC model. Ideally the model would start from an initial condition and be configured to progress to another known state. The fitness function would return a value based on deviation of the model results from the observed ending state.

In the case of the GLUC model, final land use data would be compared to an observed land use. Unfortunately, collection of consistent historical maps has proven to be a challenge. The USGS has provided a nation-wide data set of land cover / land use data classified from satellite images collected between 1989 and 1992. The original intent was to provide a similar collection of data sets for 2000. These new data sets would provide an ideal starting and ending states for the model but it seems less likely these 2000 data sets will be available.

An additional complication is caused because a cell-by-cell comparison between the modeled land use data and the observed land use data would flag errors when corresponding cells do not match. In the cases of two neighboring cells, if one cells transitions in the observed data but not in the modeled results and the other cell behave just the opposite manner then cell-by-cell comparison would show both cells being in error. From a practical stand point, spatial placement within two or three cells is accuracy is most likely acceptable. The ideal fitness function would contain a “fuzzy match” mechanism that over came the cell-by-cell comparison.

To overcome these problems the GLUC model has been calibrated by starting with the USGS land use data (circa 1992) and modeling through the year 2000. The resulting model data is aggregated on census block boundaries and results compared to population changes in census blocks from 1990 to 2000. The sum of the error squared for all census blocks is computing and becomes the fitness score for the model run.

The aggregation step provides a “fuzzy match” requirement by allowing any cell development within the census block to correspond to population change in the census block. While some concern exists about comparing the model land use change data to census population data, location of the housing and hence population is one of the primary uses the GLUC model. Therefore calibration based on this feature seems appropriate.

3.4.4 Infrastructure

To manage the large number of runs required by the GA approach, a client/server system was developed. A master server manages the population of individuals, handles selection, crossover, and mutation. Based on new individuals within the population, the server generates a configuration file for the model containing the necessary weights.

The model was modified to download configuration files using the standard HTTP protocol. Following the model run the fitness score is calculated and the fitness score is returned to the server again using the HTTP protocol.

The advantage of this distributed approach is that given access to the large computing facilities, hundreds of models can be run in parallel. This allows convergence to the global minimum in a much smaller amount of time.

4 LEAM Land Use Change Results

Once the data has been collected, a base map has been created (landcover map of region being modeled for base year), drivers have been developed, and the model has been calibrated, a model run can be conducted. Upon completion of the run, landcover maps are generated for each year of the run (runs typically are typically 30 to 50 years). From these results other maps are created that summarize the results of a LEAM run, comparison maps are created that compares the results of two different scenarios, movies are created that show how land use change occurs over time, and databases are created that indicate what land use change is projected to occur for each year of a run.

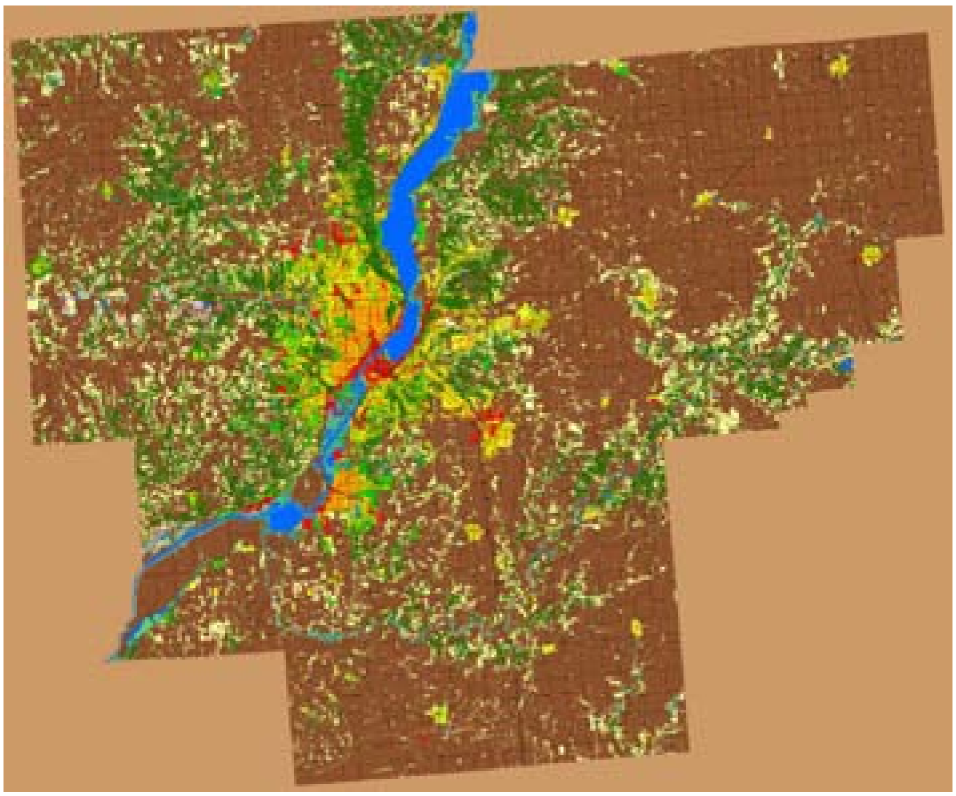


Figure 4-1: 2030 Land cover map of the Peoria, Illinois Tri-County Region based on LEAM "business as usual" scenario run

Figure 4-1 is an example of the output maps that result from a scenario run. This map is the land cover map of 2030, the last year of the model run. A land cover map is produced for each year of the model run period (typically 2000-2030 or 2050), allowing land use change analysis, and corresponding impact analysis to be conducted for any particular year of the run.

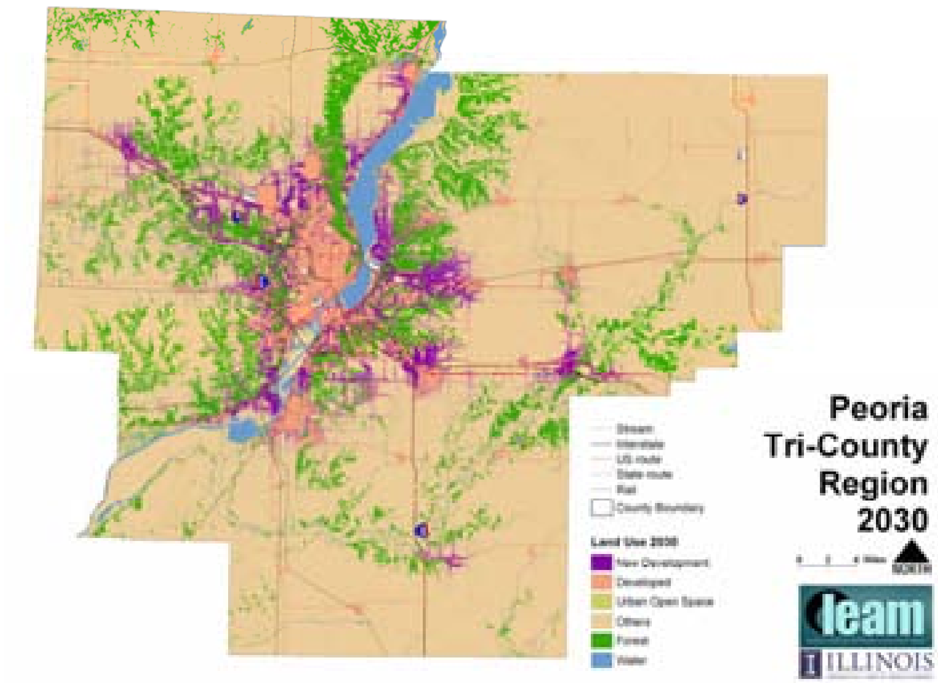


Figure 4-2: Summary Map of Simulation of Land Use Change for the Peoria, Illinois Tri-County Region. Purple cells indicate where new development is projected to occur in the region.

Typically, the results of the 30-50 year run are evaluated with a summary map (Figure 4-2, Peoria region and 4-3, St. Louis region) that indicates where new development is projected to occur in a region during this time period. Summary maps can also be developed that zoom in on a particular part of a region, such as in Figure 4-4, to assist in local planning efforts. Results are also summarized in spreadsheets and graphs that indicate where growth occurred overtime in the region (Figure 4-5) and what land uses declined as urbanization increased (Table 4-1). Figure 4-5 for example, shows that some counties will have significant increases in development over the next few years, but growth will slowly decline over time, and other counties will see more development occur 20 to 30 years from now. Table 1 indicates that forest and agricultural land will decline significantly as a result of urbanization. These results give local stakeholders a perspective on what the model projects the future will hold for a region in terms of where it will occur and how it will impact other land uses.

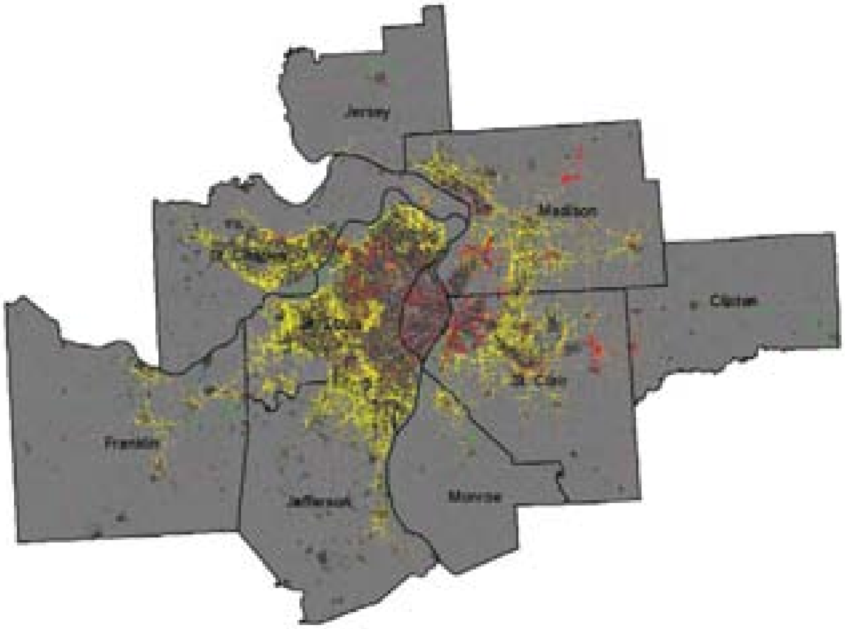


Figure 4-3: Summary Map of “business as usual” Scenario for the St. Louis Region. Red cells represent new commercial development, yellow cells represent new residential development and dark gray cells are existing developing.

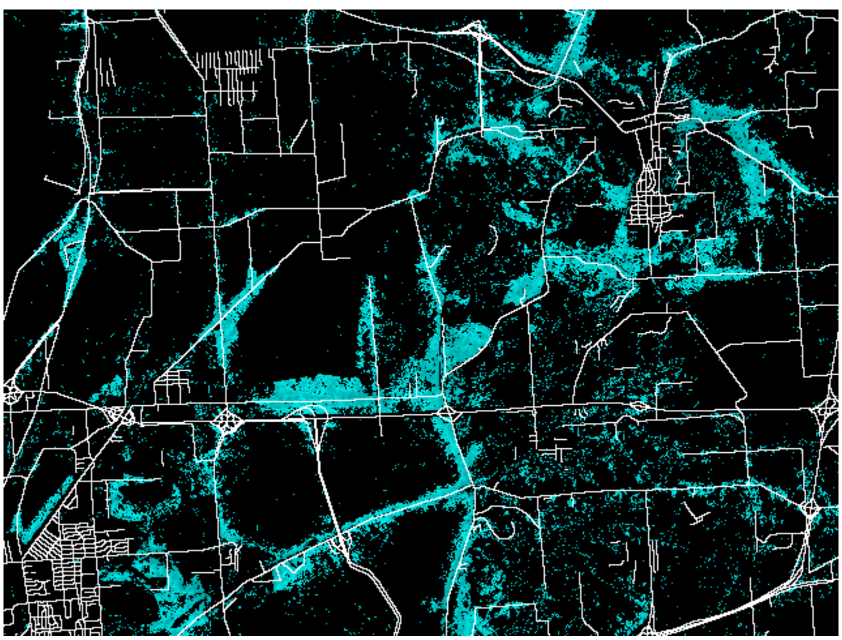


Figure 4-4: Summary Map of New Development for a small area within the St. Louis Region

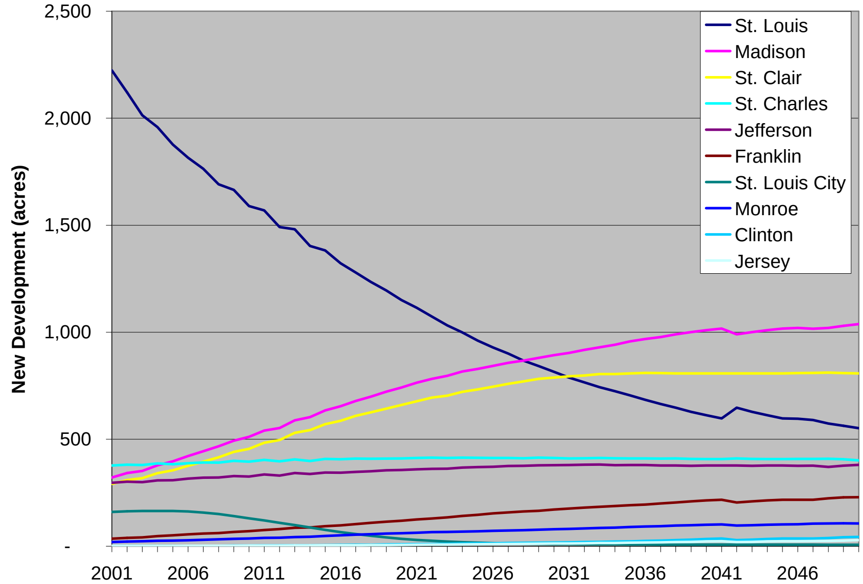


Figure 4-5: Projected New Development in Various St. Louis Region Counties.

Landcover Classification	1993 Landcover	2025 High Growth	2025 Average Growth	2025 Low Growth
Residential	183,408	226,230	218,187	213,641
Commercial/Industrial	232,747	241,615	239,717	238,901
Agriculture	1,677,371	1,644,462	1,650,485	1,653,606
Urban Open Space	164,252	181,133	181,539	181,750
Forest	963,332	930,195	933,314	935,110
Grasslands	37,969	36,684	36,828	36,905
Others	142,001	140,262	140,513	140,669

Table 4-1: Summary of Landcover Change Results from Business as Usual Scenario for the St. Louis Region

Comparing Scenarios

One of the key benefits of LEAM is the ability to conduct scenarios and compare the outcomes. This allows one to see how a specific public policy or public investment will impact development patterns of a region and the potential impacts of these different patterns. For example,

Figure 4-6 compares a “Business as Usual” scenario with a scenario that assumes implementation of the region’s transportation plan. Consequently, this allows policy-makers to see the affect new road projects could have on how the region grows. In this particular case, the map indicates that the addition of these new roads, in particular a new bridge crossing the Mississippi River, will shift more growth to the Illinois counties (Monroe, St. Clair, and Madison) and to the outskirts of Jefferson Franklin, and St. Charles Counties. The question then is how this change in land use patterns will impact road congestion, economic growth, fiscal needs, and watersheds differently than the business as usual scenario.

Figure 4-7 is another example of comparing two scenarios. This map of McHenry County, Illinois reveals development patterns differences caused by the addition of a new interchange at the interstate in the southwestern corner of the county.

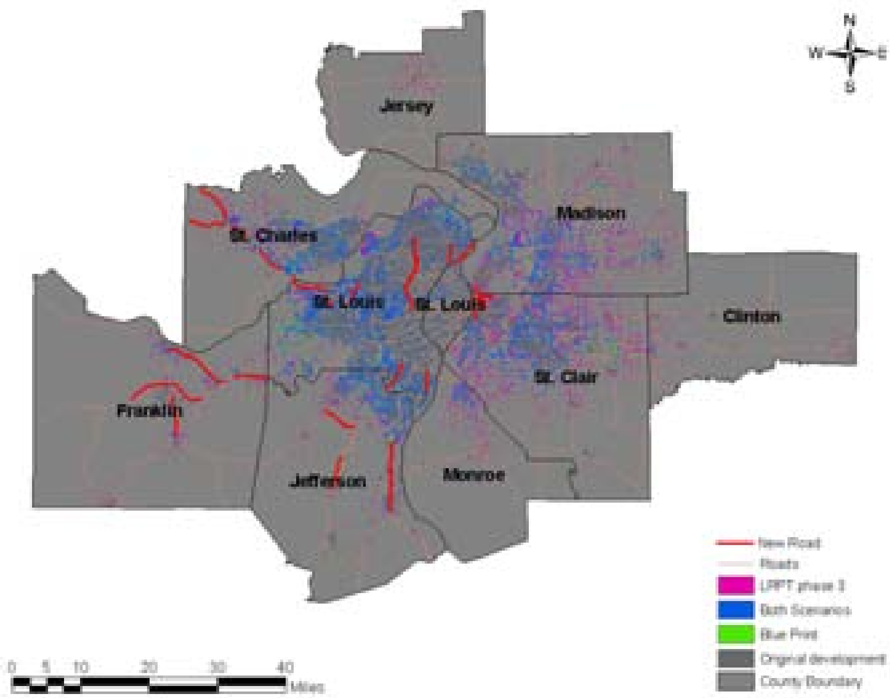


Figure 4-6: Comparison Map for St. Louis Region - Comparing “business as usual” (BUA) scenario with “Implementing Long Range Transportation Plan” scenario. Blue cells represent growth that occurs under both scenarios, pink cells represents growth that only occurs in the “Transportation Plan” scenario, and green represents growth that only occurs in BUA scenario.

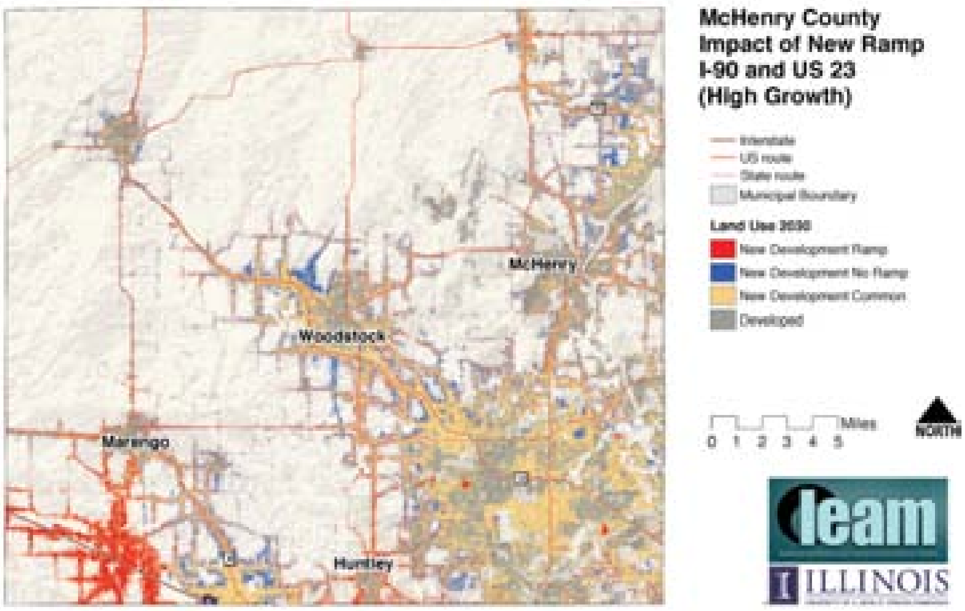


Figure 4-7: Comparison Map for McHenry County, Illinois - Comparing a “business as usual” scenario with a “New Ramp at I-90 and US 23” scenario. The blue cells represent growth that only occurs in BUA scenario and the red cells represent where new growth only occurs in the “New Ramp” scenario. This map shows that growth shifts towards the southwestern corner of the county (the new ramp would be just south of the red cells in the county just south of McHenry).

Spatialization of Data

Intriguing analysis can also be done by examining the scenario results under various spatial extents. This “spatialization” of the land use change results can provide insights on several direct impacts of urban growth; types of impacts that can be estimated include change in impervious surface by watershed, demographics by transportation analysis zone, infrastructure needs such as water and sanitary facilities, and school facilities.

Watershed

As urbanization occurs in a watershed, impervious surface areas increases, leading to increased runoff volume and discharge rates that cause physical changes to streams and rivers. Even at relatively low levels of watershed imperviousness water quality can be impacted. As the imperviousness increases from 10% to 25% stream quality decreases – increased storm flows and higher pollution levels lead to physical change to the streams and reduce biodiversity. At above 25% watershed imperviousness stream quality is severely degraded - making restoration very expensive, if it can be done at all. In a project for the Peoria region, a spatial analysis was conducted to project how much future development (and impervious surface) in the watersheds of the Peoria region will increase under various scenarios. Results in Table 4-2 indicated that over the next thirty years impervious surface will pass 20% for two watersheds and pass 30% for another watershed, suggesting that this watershed is becoming severely degraded.

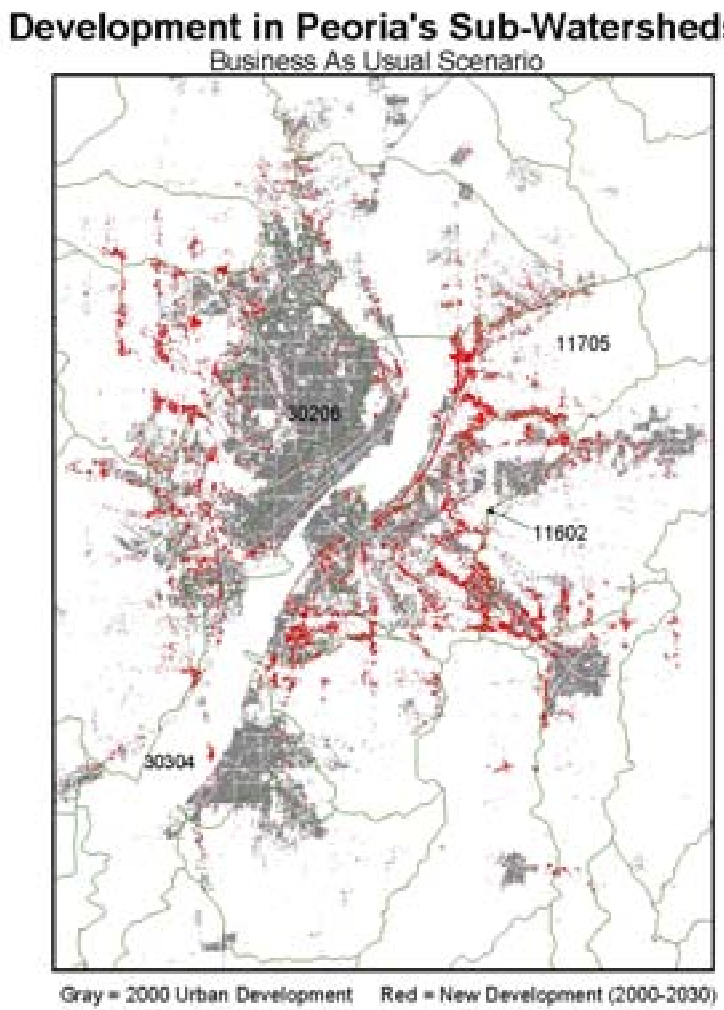


Figure 4-8: Development by Watershed in Peoria, Illinois Region.

Sub-Watersheds Where Imperviousness May Impact Biodiversity

(% of Sub-watershed impervious)

		2030			
Sub-Watershed	Base Year - 2000	Business as Usual	Ag Preservation	Bluff Preservation	Bio-Collaborative
071300011602	15.6%	21.7%	21.3%	21.4%	27.2%
071300011704	6.7%	8.2%	8.2%	8.2%	10%
071300011705	12%	15.9%	16%	15.6%	18.3%
071300030205	10.3%	13.3%	13.2%	13.3%	16.6%
071300030206	29.1%	33%	33.4%	32.5%	34.5%
071300030304	17.9%	20.2%	20.4%	20.1%	21.5%
071300040801	7.9%	9.2%	8.8%	9.4%	10.5%

Table 4-2: Impervious Surface Projections by Sub-Watershed in Peoria Region under Various Scenarios.

School Districts

Another example of spatialization is examining how school districts can be affected by future growth. In Peoria, projected population increases based on LEAM results were calculated for each school district in the region (Figure 4-9). Based on these population projections and information on the number of school-age children per household, student population projections were determined for each school district. These student populations can then be compared to school facilities capacity to estimate when new facilities would need to be provided. Figure 4-11 indicates that new facilities for one school district will be needed between 2021-2026 for elementary, middle, and high schools.

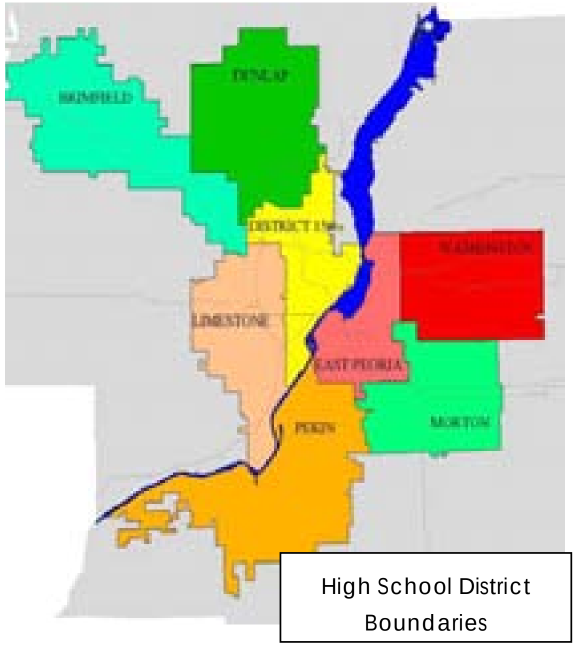


Figure 4-9. School District Boundaries in the Peoria Tri-County Region

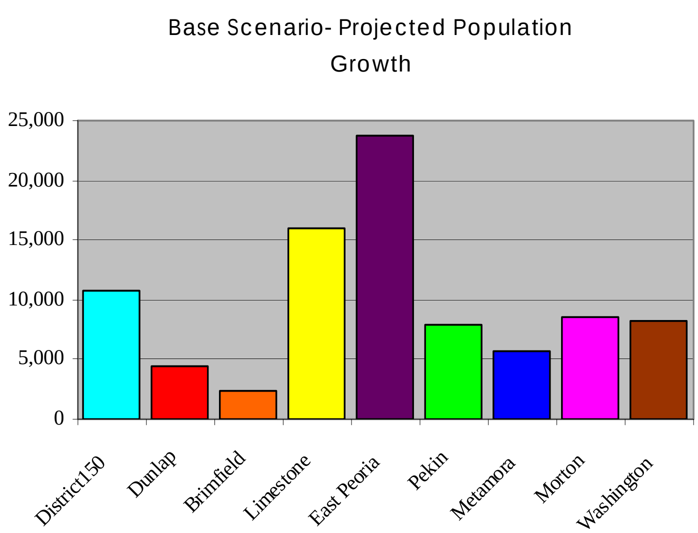


Figure 4-10. Projected Population Increased by School District

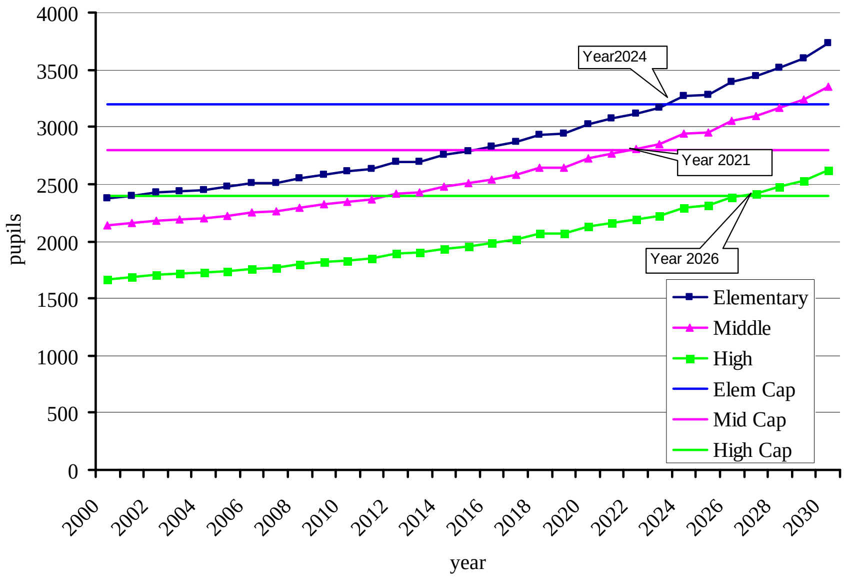


Figure 4-11. Comparison of School Age Population Growth and School District Facility Capacity.

Population Allocation Model

The LEAM population allocation model establishes the relationship between cells and people. It uses LEAM cell location information, census data and demographic information to determine a more accurate assessment of population and households in the region. The key to the approach is determining an estimate of people per residential cell (30m * 30m), i.e. population density. A proper estimation of population density based on the density of housing in any spatial location is critical for spatially distributing regional population growth. Population densities are also critical for land use change impact assessments that use household information extracted from a land use map to determine per capital impacts. In the generic LEAM approach, the spatial variation of housing densities were not calculated, which resulted in uniform densities across different districts within the region. This deficiency led to other, related problems. When calculating the impacts of residential growth on school districts for example, uniform densities, result in uniform economic impacts. The effort required to solve this problem is not trivial due to technology limitations and data availability. The following can be considered a ‘first order approximation’ approach to solving this dilemma.

Methods

According to the 2000 Census data, household size in metropolitan regions varies widely. We also found that lot size appears be less of a factor in this variation, which might be better explained by the density residential units. Using a Census block group as the unit of analysis, we compute:

Population Density = Average Housing Unit Density * Household Size

Where:

- Population Density : average people per residential cell (people/cell);
- Household Size : average household size in a Census block group (People/Household);
- Average Housing Unit Density = High Intensity Residential % * High Intensity Residential Density + Low Intensity Residential % * Low Intensity Residential Density;
- Residential Density : housing units per residential cell (units/cell);

Average household size can be determined from the 2000 long-form dataset. This data will also help in determining housing unit types and numbers for each block group. From this information we can deduce the proportion of high- and low-density residential units. This enables the LEAM population allocation model to calculate population characteristics of any region easily and efficiently. One drawback to this approach is the static nature of the model and the fact that current trends are used in the analysis. This makes it difficult to infer future trends and projections.

To address this weakness we conducted an analysis of historic household size using a logistic decay model (see Figure 1) to help project the household size calculations. In this analysis: *H* is Household size; *H0* is the initial household size; *K* is a constant error calculation; *r* is a decay rate; and *t* is time.

$$H = \frac{K}{1-(1-\frac{K}{H_0})*e^{-rt}}$$

Based on the household size projection, we can then estimate the population density for future projections.

Results for St. Louis Region

The population density of each block group in the St. Louis region was calculated using this approach. Table 4.3 shows a typical calculation. Figure 4-6 is a map of the region with each block group calculation delineated. Figure 4-7 is a projection of future population density to the year 2050 using the logistic decline model noted in figure 4-5.

The LEAM population allocation model establishes the relationship between cells and people. It uses LEAM cell location information, census data and demographic information to determine a more accurate assessment of population and households in the region.

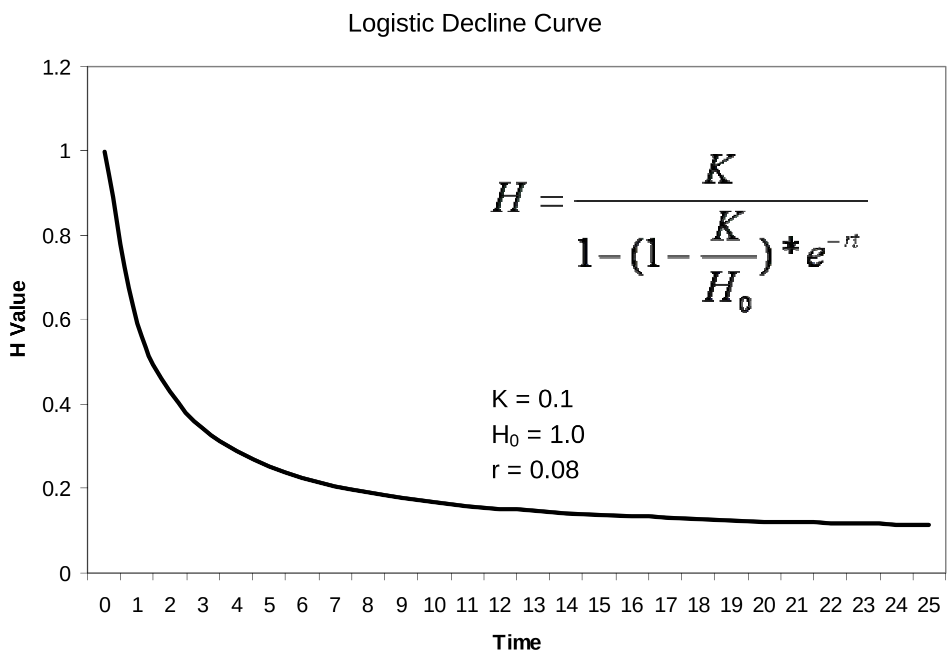


Figure **4-5** Logistic Decline Curve

Table **4-3.** Population Density Information of St. Louis Metro Region

Statistic Information	Value
Number of Block Groups	1915
Minimum Value	0.00
Maximum Value	4.76
Mean	2.16
Standard Deviation	0.49

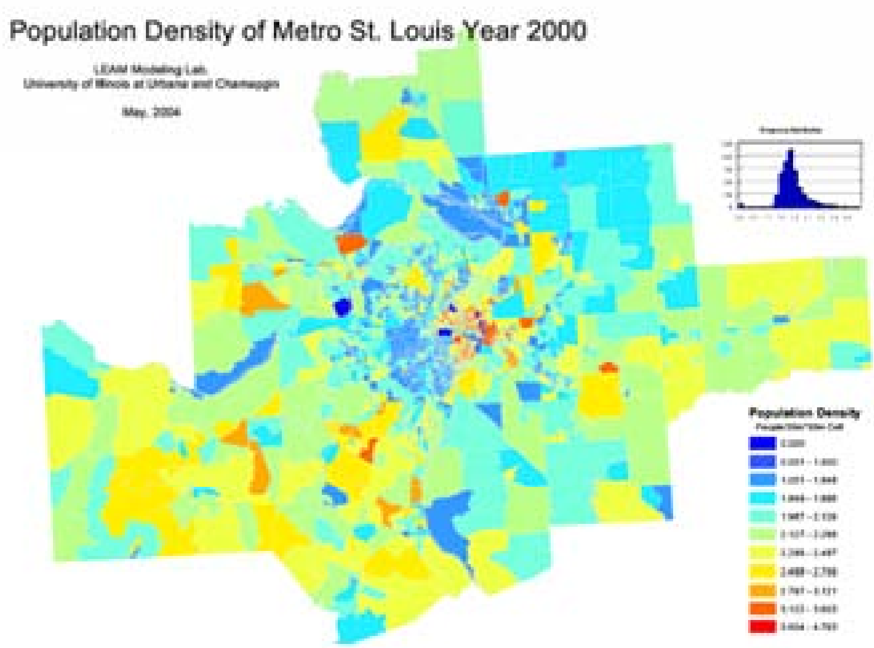


Figure 4-6. Population Density Map of Metro St.Louis Year 2000

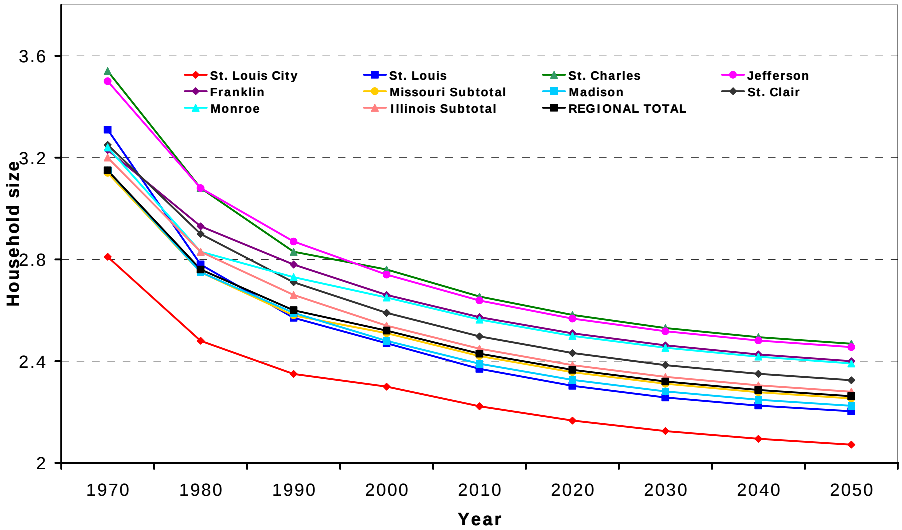


Figure 4-7. Household size of St. Louis Region Year 1970 - 2050

5 LEAM Impact Models

The result of LEAM run is maps that show the land use change for a given scenario – providing an answer to “what if this happens.” However, this information is not that useful unless you can answer the follow up question – “so what?” In other words, the results of LEAM must be used to look at particular impacts of growth beyond the land use change. LEAM has developed several models that estimate some key impacts of land use change – transportation congestion, fiscal impacts, and water quality. Economic impacts, such as employment and income, are discussed in the Economic Driver section in chapter 1 of this report. Several others are currently in development including air emissions,

Transportation Impacts

Highway Congestion

The impact of land-use change on transportation infrastructure and vice versa is of key importance. LEAMtrans helps in assessing the changes in travel demand in the region due to growth in region, relocation of people or introduction of new roads. The impact is measured in terms of an index ‘volume-to-capacity’ (V/C) ratio derived from the traffic volume and capacity of the roads. As this ratio approaches a threshold value of 0.80, we assume that the road is getting congested. This congestion then further drives a change in land-use through changed attractiveness of the affected areas.

Congestion Methodology

To determining the impacts of land-use change on transportation systems, LEAMtrans uses an approach similar to the conventional four-step Travel Demand Modeling approach. In this method, ‘rampsheds’, as shown in figure 13, are utilized in lieu of ‘Traffic Analysis Zones (TAZ)’. Rampsheds are areas around a chosen ramp, to which people are more likely to go than any other chosen ramp. It is developed based on travel-time friction through cells (cost-allocation method). Rampsheds, like watersheds, represent a ‘draining’ of vehicles onto the main highway system. These ramps form the nodes, and the roads connecting two adjacent nodes form the links in the road network. For the analysis, only US and Interstate highways in the region were chosen.

The road network is used in the pre-processing stage to obtain the routes in the road network between all pairs of origin and destination nodes. The inputs for the LEAMtrans are:

- Land-use map
- Road network
- Rampshed map
- Trip Generation rates

These maps are processed using a programming code designed to emulate the four-steps of Travel Demand Modeling and produce traffic counts for the evening (PM) peak hour on the roads. The volumes on the roads are divided with the respective traffic capacity to obtain the V/C ratio for the road. The V/C ratio thus represents the level of utilization of the road and indicates whether the road is running congested or approaching congestion or has un-congested flow. Thus an impact due to land-use change on transportation is measured (Figure 4-1).

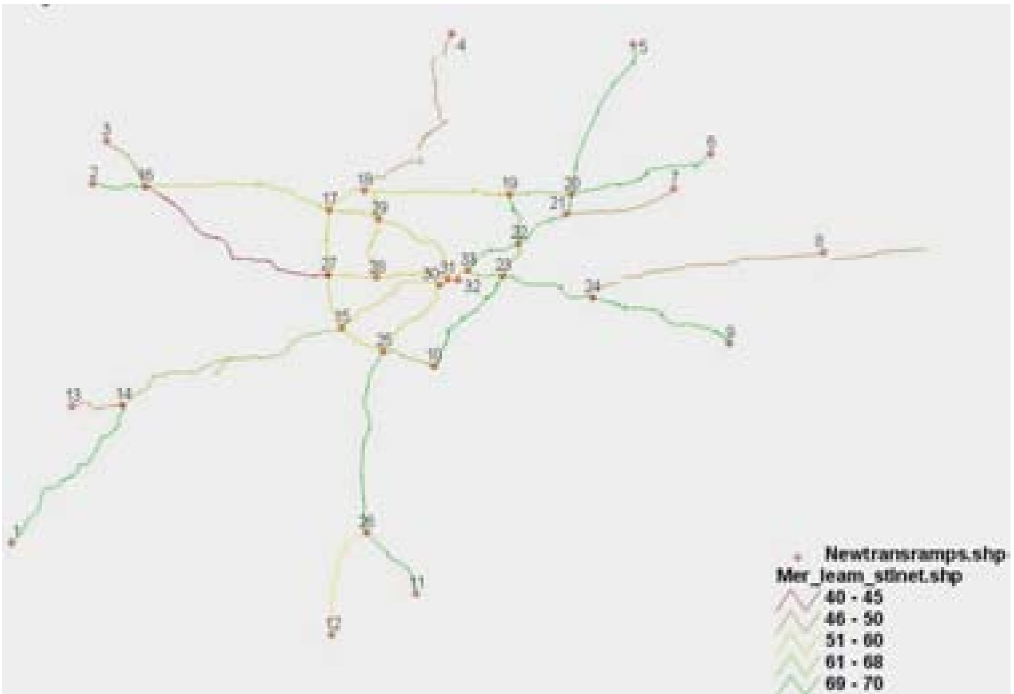


Figure 4-1. A diagram of the St Louis regional road network with calculated congested speeds over road capacity in the year 2030. Red networks are considered congested and green networks un-congested.

Fiscal Impact

After considering various approaches already attempted by others, we tested a regression model based on per-capita expenditure in the year 2000 using a sample of 73 jurisdictions in the Illinois portion of the St. Louis metropolitan area. Our analysis suggests that there are not economies of scale: per-capita expenditure increases as the number of households increase. At the same time, jurisdictions with greater population densities have lower per-capita expenditures, and jurisdictions with greater economic activity (as measured by per-capita sales tax collection) have higher per-capita expenditures.

Table 4-1: Fiscal impact scenarios for Belleville. The results of three scenarios: population density increases 50%; households increased by 50% (with population density remaining constant); and per-capita sales taxes increased by 50% (households and population density remaining constant).

	Change			Per-Capita Expenditure			Total
What If?	**From**	**To**		**Change**	**%**	**Amount**	**Expenditure**
50% increase in population density	848	1272	People/Sq.Km	($113)	-17.3%	$542	($6,521,868)
50% increase in number of households	17,603	26,405	Units	$27	4.1%	$682	$1,122,625
50% increase in per-capita sales tax collected	$154	$231	$/Person	$46	7.0%	$701	$1,911,900

Table 4-1 illustrates the results of three scenarios for Belleville, IL (pop. 41,410). First, what if the population density were to be increased by 50% (along with a proportional decrease in land area to keep population at its present level)? Second, what if the number of households were increased by 50% (with a proportional increase in the land area to keep population density at its present level)? Third, what if per-capita sales tax were to be increased by 50% (keeping number of households and population density constant)?

This model was also used to assess the fiscal impact of land-use change around Belleville in a generic LEAM simulation of conditions in the year 2015. Table 4-2 compares two future scenarios with and without annexation to capture adjacent growth; the annexed area is indicated in Figure 4-2 shows Belleville's existing municipal boundary laid over land-use in the year 2015. The hatched area southwest of the city represents an area that might be annexed by the city to capture development, especially commercial growth.

Development of the fiscal impact model is continuing; the LEAM group is currently developing methods to look at the revenue side of the government budget. This analysis combined with the change in expenditures from increased residential development will allow for the calculation of a break-even home value – the home value necessary to provide enough property tax (given that other revenue sources remain the same per capita) so that revenues equal expenditures for a specific jurisdiction (municipality, school district).

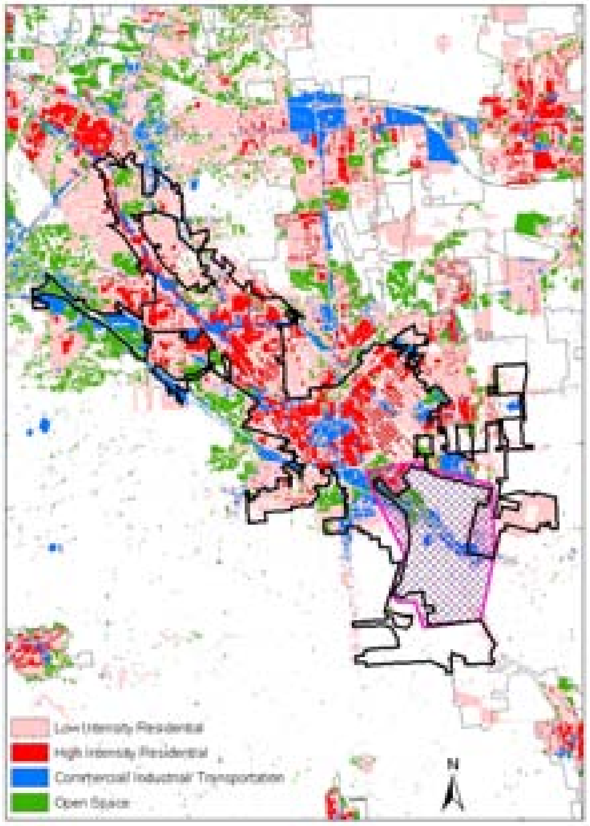


Figure 4-2. Belleville municipal boundaries and a randomly chosen area of potential annexation that occurs in 2015).

Table 4-2: The fiscal impacts of the Belleville growth and annexation (2015) scenario depicted above.

	Without Annexation	With Annexation	Difference
Population	59,861	64,963	5,102
Households	24,640	26,550	1,910
Per Capita Sales Tax	$142	$156	$14
Per Capita Expenditure	$562	$605	$43
Total Expenditure	$33,641,882	$39,302,615	$5,660,733

Water Quality

Urban land use transformation is having a dramatic impact on our local streams and rivers. Urbanization increases imperviousness, which in turn increases surface runoff. Urbanized surface runoff contains a large amount of pollutants such as nutrients and sediments. These increases in non-point source (NPS) pollutants are having a negative affect on surface water quality. LEAMwq represents a method for quickly assessing the impacts of urbanization on surface runoff and NPS pollutant loading. Preliminary assessment with a simple model can provide quick screening of the impacts of urbanization and identify the need for more advanced modeling (Bhaduri and others, 2000).

Water Quality Analysis

A simple export coefficient modeling approach can predict pollutant loading as a function of the export of pollutants from each source in the study area (Johnes, 1996). LEAMwq integrates LEAM with L-THIA, the Long-Term Hydrologic Impact Assessment. L-THIA is a GIS-based export coefficient model developed at Purdue University with support of US Environmental Protection Agency. L-THIA calculates mean surface runoff and NPS pollutant loading for a given region and a period using daily precipitation series, a land use map and a hydrological soil group map. The pollutants selected for this study are total nitrogen (TN), total suspended particles (TSP), and total phosphorous (TP).

The model was tested with land use maps simulated by LEAM from 2005 to 2030 for the St. Louis region with five-year intervals and 1961-1990 daily precipitation series. LEAM was run with three economic scenarios: base, high and low growth. The L-THIA simulation was conducted with each scenario set of land use map series provided by LEAM. TN results are described hereafter.

Results of Water Quality Analysis

The TN output with changing land use in units of tons is shown in Figure 4-3. Under base and low economic growth scenarios, TN increased steadily at decreasing rates. The low growth scenario started at a lower point than the base scenario, and slightly exceeded the base scenario in the year 2030. The TN loading under the high growth scenario kept decreasing until year 2015, and then it began to increase substantially up to year 2020, and eventually settled down between years 2020 and 2030. This can be understood by examining land use change trends between 2005 and 2030. The trend of major land use change under different scenarios. Agriculture, Grass/Pasture, and Forest decreased steadily and dramatically, whereas the area of Low Density Residential land steadily increased. By contrast, changes in Commercial/Industrial/Impervious were very irregular under the high scenario. The area first decreased steadily to year 2015 and then increased abruptly to year 2020. After 2020, it kept increasing but at a lower rate.

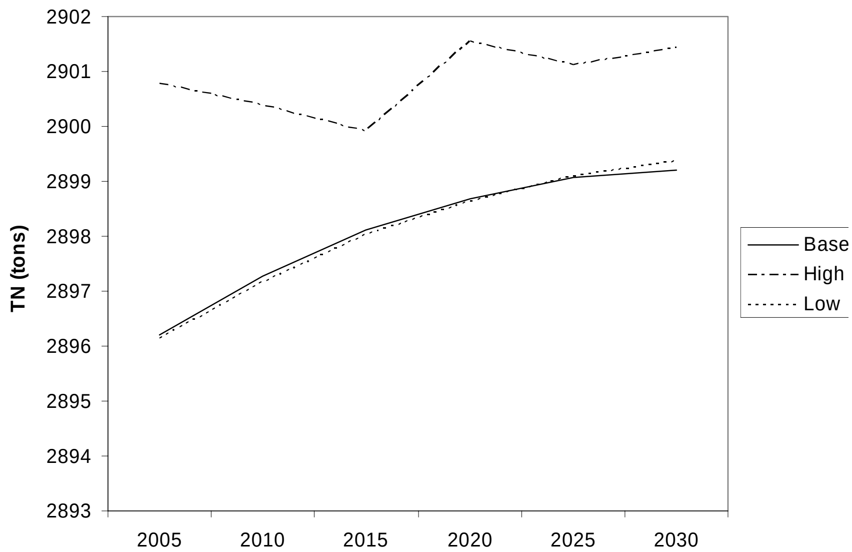


Figure 4-3. Predicted total nitrogen (TN) under base, high, and low economic growth scenarios from year 2005 through year 2030

The decrease-increase trend of pollutant loading under the high scenario reflected the complicated interactions between the land use specific pollutant loading and the land use transformations. In the first half of the period, the pollutant loading decreased due to loss of Agriculture, a type of land associated with the highest pollutant loading. On the other hand, when the effects of increased urban land cover dominated in the second half, the pollutant loading would increase. The runoff pattern is presented in Figure 4-4. Again, the high scenario had a different trend from low and base scenarios. Under the high economic growth scenarios, even though the runoff was increasing throughout the simulation period, there was an abrupt increase between year 2015 and year 2020, as indicated by a steeper slope. It shows the sensitivity of runoff to changes in imperviousness from Commercial/Industrial land uses.

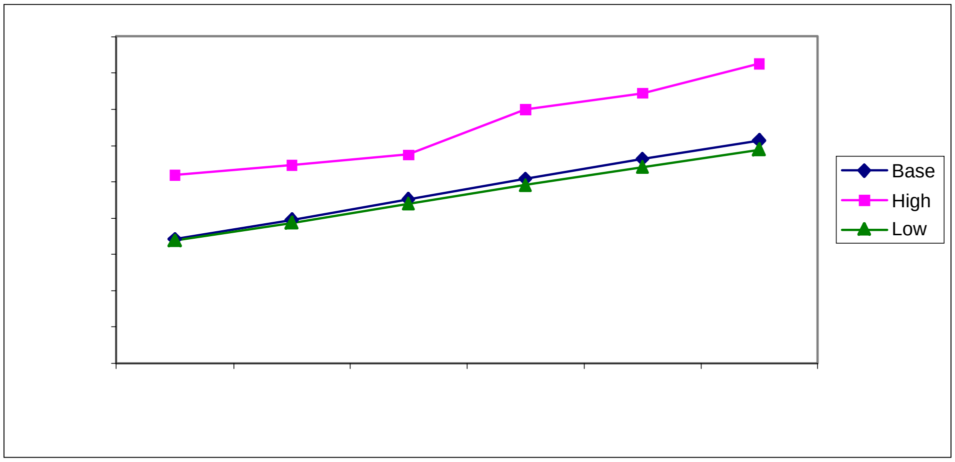


Figure 4-4. The water quality impacts of three LEAM land use scenarios in the metro St Louis region. High growth scenarios increase total nitrogen levels in the study watershed.

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Appendix

Developing a Base Map

Land Cover Data Clean-up Analysis

Several techniques have been developed to verify the base year land cover maps used to run the model for the St. Louis region. Combining several data sets produced the final LEAM Illinois base-map. The 1993 USGS NLCD data was first merged to the 2000 Illinois data to update urban land uses and reclassify errant cells. The USGS NLCD classification coding system was adopted as the final coding system. Road networks are then overlaid onto the map with a new classification designation. A methodical manual process of localizing and verifying the resulting map was then undertaken. This work was completed by regional planners using aerial photos, available local maps, and personal knowledge about the region. The final steps toward base-map production include the calibration of the now updated map to available 2000 census data.

To help verify the 2000 base data map. Census data was compared mapped data at the block level. In Illinois large amounts of random development (noise) initially existed in the map. Census data reveals from 1993 to 2000, just over 9,000 people were added to the region. Our base-map shows 16,000 new residential cells over the same time period. In Missouri, large amounts of densely developed tracts, have consumed all developable areas. In the region from 1993 to 2000, 500,000 new residential cells were found with only 60,000 new people. Although some of this can attributed to migration out from the city center, by comparing populations and households in each census block with the number of cells present in 2000, we can asses how many developed cells should be present to satisfy census calculations.

- Compare LU data to census data,
  - Remove any residential cells from the 1993-2000 difference map in census blocks where 2000 census population growth is negative or zero. (267,000 cells removed - 76,000 in IL (Figure A-1) - almost 200,000 cells in MO).
  - Ignore small or sparsely populated census blocks where the cell to population ratio is less than 2.0
  - For all other census blocks, compare the remaining 2000 LU residential cell counts with 2000 census population data.

- Increase or decrease the number of cells required to satisfy census counts.
- Use LEAM probability maps to place the required cells within the census block.
- Highest development probabilities receiving the required cells

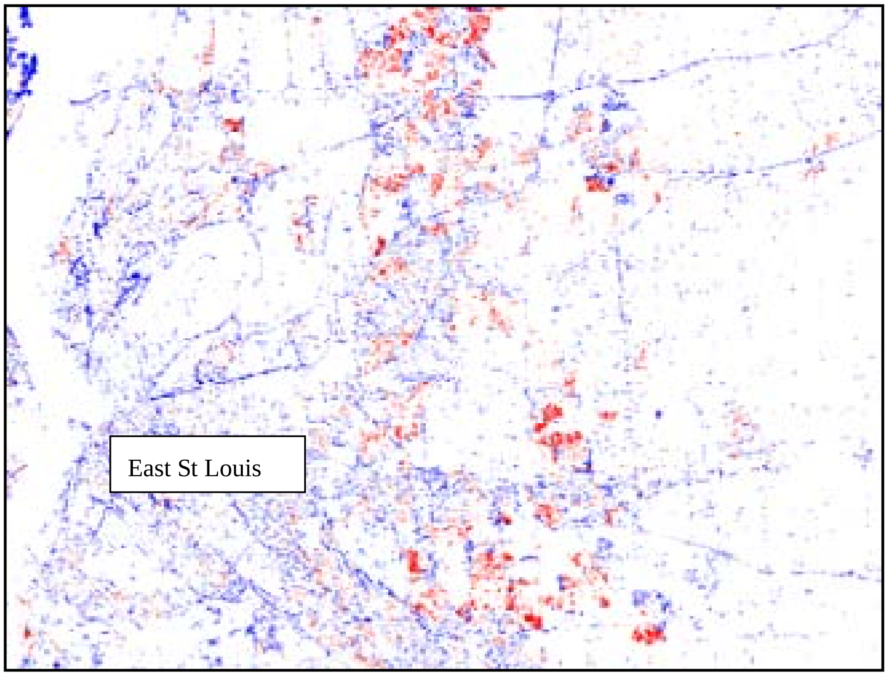

Figure A-1: A sample map depicting changes in the IL base map when noisy satellite data is cleaned

Figure A-1 is a sample map depicting changes in the IL base map when noisy satellite data is cleaned using a 2 mile municipal buffers as an exception and removing all other rural development that shows up in the 2000 data that is not present in the 1993 data. Blue Cells are 2000 data representing development. Red cells have been removed.