UMCES (CBL) Ref. No. 07-187

Review of Land Use Change Models

Applicability to Projections of Future Energy Demand in the Southeast United States

Southeast Energy Futures Project
March 28, 2007

Prepared by:
Lisa A. Wainger, Jillian Rayburn, and Elizabeth W. Price
University of Maryland Center for Environmental Science
Chesapeake Biological Laboratory
P.O. Box 38
Solomons, MD 20688

Acknowledgement

Funding for this project was provided by EPA Regional Vulnerability Analysis Program; Betsy Smith, Program Director.

Table of Contents

Executive Summary

Goals of this report

Our focus with this review of land use change models was to identify a model or models appropriate for examining the relationship between land use change and future energy use at detailed spatial scales (e.g., sub-county) and across a multi-state area. We were asked to identify models that would be appropriate for an eight-state area of the Southeast United States (U.S.), requiring that we consider models with an intermediate level of complexity and that would be able to handle a variety of land use types and land conversions. Much of the focus of our evaluation is on models that characterize the conversions from agricultural or forested lands to developed uses such as residential, commercial and industrial uses. However, to include models that might be useful for a wide range of policy analyses, we also consider models that characterize land use decisions in agriculture and commercial forestry. Our final consideration in selecting models for review was that the model or models would be used to project land use change 25 to 30 years in the future and be responsive to different policy scenarios or options. Therefore, models needed to have the capacity to respond to changes in drivers and styles of development and allow alternative futures to be considered.

Key questions asked of models reviewed

1. Is the form of the land use change output appropriate for estimating future energy demand?
2. Are the spatial scales of output and analyses appropriate?
3. Are data needs reasonable?
4. How much work would be required to tailor the model to the Southeast US?
5. Are model equations, behavior rules, coefficients, or parameters developed from appropriate data sources?
6. Can the model represent the scope of changes expected over a 25-30 year time frame?
7. Is the model responsive to conditions reflected in policy scenarios?

Conclusions

We were not able to identify an ideal model that could be readily transferred to the task at hand: providing inputs to analyzing future spatially-explicit energy consumption for an 8-state region of the Southeast US. Rather, we have discussed the strengths and weaknesses of the various modeling options and suggested the lessons drawn from the experiences of various modelers be applied towards developing a strategy for a new model. We have developed the following take-home points:

- In general, there seems to be limited payoff from pursuing the more complex cellular automata models because of the time-consuming nature of such endeavors and the inability to ensure that any unexpected behavior is generated from the desirable "emergent properties" of dynamic agent-based models rather than error.

- Only models that include economic and other behavioral drivers can directly model policy options. Methods to "pre-process" scenarios so that they can be implemented in spatial allocation models that lack behavioral drivers are less desirable since they prevent policy analysts from determining when people are likely to game the system rather than do what is expected.

- Many of the recently published models use multinomial logit (statistical models) to create a transition probability matrix to predict land use conversions. This includes all model types: spatially-explicit econometric models, spatial allocation, and cellular automata models. Therefore, it appears that the land use change modeling field is converging on this technique as the most promising.

- Statistical models offer the advantages that they are quantitatively derived from observations, making their predictive ability and error readily assessable.

- Where time or data constraints create the need to use best professional judgment, formal methods of eliciting judgment (e.g., multi-criteria analysis techniques) are available to reveal assumptions and allow input by a wide group of participants.

- The only truly transferable models are those with limited realism and precision, which are not likely to be useful for policy analysis. Similarly, the transferability of any model aiming for precision (i.e., all statistical models and most calibrated models) is about the same. In other words, the perceived lack of transferability of statistical models is true of any model that embeds one or more equations developed from observing one location through time.

Proposed modeling approaches:

The difficulty of developing a model that can be applied across an 8-state region should not be underestimated. Although modelers appear to be moving towards using multinomial logit models to develop land use change transition probabilities, resources may not be available to develop such models for the region. Alternative approaches might include:

- Statistical models might be developed from regional data sets to provide regional statistical models. However, a limitation of such models might be the inability to find significant relationships between land use change and the variables that drive policy scenarios (e.g., regulation) since land use policies will be heterogeneous across large regions.

- Detailed models might be applied selectively to case study areas and the results applied across the region by matching case study areas to sub-sets of counties or locales within the region. Essentially counties could be classified into groups and a case study area selected to represent each group. Variables such as population size, density and growth rates might be used to classify areas.

- Model results from ongoing or existing national studies (SERGoM, FASOM) might be used and systematically altered to evaluate policy scenarios intended to generate such results. For example, growth could be increased in cities by 10% to test the effect of a general category of policy scenarios designed to achieve that effect. The ability to test actual policies will be limited, but additional models could be developed to inform the scenarios.

1. Introduction

Human-induced land use change is widely considered the most important driver of changes in natural resources and ecosystems (Daily et al. 1997). As a result, interest in understanding the patterns of and processes behind land use change is strong. That interest has generated research in a range of disciplines aimed at modeling land use change decisions and projecting change and related impacts. Because land use change is predominantly driven by human actions, those actions can be affected through the creation of regulations and incentives. In this report, we explore a wide range of types of land use change models geared towards projecting changes in response to policy options.

1.1 Goals of this report

Our focus with this review of land use change models was to identify a model or models appropriate for examining the relationship between land use change and future energy use at detailed spatial scales (e.g., sub-county) and across a multi-state area. We were asked to identify models that would be appropriate for an eight-state area of the Southeast United States (U.S.), requiring that we consider models with an intermediate level of complexity and that would be able to handle a variety of land use types and land conversions. Much of the focus of our evaluation is on models that characterize the conversions from agricultural or forested lands to developed uses such as residential, commercial and industrial uses. However, to include models that might be useful for a wide range of policy analyses, we also consider models that characterize land use decisions in agriculture and commercial forestry. Our final consideration in selecting models for review was that the model or models would be used to project land use change 25 to 30 years in the future and be responsive to different policy scenarios or options. Therefore, models needed to have the capacity to respond to changes in drivers and styles of development and allow alternative futures to be considered.

1.2 Relationship between land use change and energy use

Land use change affects energy consumption directly and indirectly through several pathways that are somewhat distinct for residential vs. commercial / industrial development. Changes in these intensively used urban lands are the primary drivers of changes in energy use although choices made in managing other lands such as working forests and agricultural lands can also influence energy consumption. For any given residence, the pathways are: 1) energy demand depends directly on choices of housing characteristics such as size and type (detached or multi-family dwelling), 2) energy use can be indirectly affected by "urban heat island" or other climatic effects that can be mediated by the pattern of development (density, location, arrangement, and neighborhood vegetation characteristics)[1] (Pielke 2005) and 3) vehicle miles traveled by residents depends in part on house location and surrounding land use. In addition to these effects on the per household rates of energy consumption, the magnitude of growth in an area will also determine total demand.

---

[1] The "urban heat island" is the well-documented effect that air and surface temperatures tend to be warmer in highly developed metropolitan areas relative to less developed surrounding areas. This effect is created by several mechanisms such as the thermal properties of concrete and asphalt that cause these surfaces to retain and radiate heat. The sparseness of vegetation and other factors contribute to relative urban warming. The implications of the heat island effect for energy consumption are that energy use for cooling will typically be higher and energy use for heating will typically be lower in urban locations relative to less urban locations, all else equal.

For commercial and industrial development, similar pathways drive energy demands for any given business: 1) building size, employees per square foot, and energy-intensity of the industry or business will directly contribute to energy demand, 2) the urban heat island effect is more likely to affect businesses since they are more likely to be situated in areas of high impervious surfaces and require energy for cooling during the hottest parts of the day. However, heat island effects can also reduce energy demands for heating. As with housing, total industrial/commercial activity, measured in terms of number of businesses, value of output or other measure of overall activity will determine overall energy use once the consumption rate is determined.

Having identified the pathways by which land use change affects changes in energy consumption, we seek a model or models that can provide inputs needed to project energy consumption. The inputs into energy models are the outputs of the land use change models that provide projections of magnitudes of growth and factors that affect consumption rates per unit of growth. Desirable outputs of the land use change models include: total magnitude of residence and business growth, location of residences and businesses by specific type of industry (e.g., retail, manufacturing, etc.); density of residential or economic activity; and amount of physical separation between residences and jobs or services. Some outputs that are desirable but unlikely from regional models include: characteristics of households such as size, income level and number of residents, and size of commercial buildings. Part of being able to determine vehicle miles traveled depends on transportation routes, available modes of transportation, and congestion. Such outputs are typically only available from transportation demand models and are not typically produced by land use change models. Land use change models may produce only a limited number of the desired inputs, but their outputs can be used as inputs to transportation demand models and can further be used to distribute regional estimates of variables to finer-scale locations.

1.3 Key questions to ask of models used for projecting Southeast energy futures

1. Is the form of the land use change output appropriate for estimating future energy demand?
2. Are the spatial scales of output and analyses appropriate?
3. Are data needs reasonable?
4. How much work would be required to tailor the model to the Southeast US?
5. Are model equations, behavior rules, coefficients, or parameters developed from appropriate data sources?
6. Can the model represent the scope of changes expected over a 25-30 year time frame?
7. Is the model responsive to conditions reflected in policy scenarios?

1.4 How models were chosen for review

Models were identified using several recent reviews, literature searches, web searches, and references from researchers. A comprehensive bibliography had been compiled in May of 2000 (Agarwal et al. 2002), and this effort updates that review and incorporates a wider range of model types for in-depth review. We narrowed the set of identified models to 22 models, based on relevance using the questions listed above. We primarily examined models that used fine scales of spatial resolution (sub-county or finer). In a few cases, we included models that had coarse spatial resolution but whose results could be distributed to finer spatial resolution using observed site characteristics. In selecting models for inclusion in this review, we screened out models that were developed for very specific and narrow applications (e.g., tropical deforestation models), that were not likely to be relevant to the southeast U.S., and that did not offer novel methodologies. We further excluded models aimed primarily at evaluating ecological impacts of land use change rather than predicting land use change based on human decisions or activities. All models examined are listed in the Bibliography.

1.5 Approach to presenting information

The land use change review consists of three components. The main component is an summary describing methods and general findings. To supplement the summary, a detailed matrix is used to compare models based on numerous attributes (Appendix A). And, finally a bibliography lists all models identified, including those not reviewed (Section 4). Models are referred to in the text based on the acronym used by the model developers or by the author(s) and year of the published reference. Readers should refer to the table in Appendix A (Table A-1) or the Bibliography for the full name and citation.

2. Land Use Change Modeling Overview

Various modeling techniques have been developed to project likely future land use change and to evaluate changes in land use or land use pattern that might result from different growth and policy scenarios. Many models are developed and used at the local scale to address specific questions of planners and policy-makers such as estimating transportation needs or planning new sewer and water lines. For this review, we sought models that would be able to project land use change over large areas for a variety of policy scenarios. The types of land use conversions we considered were: conversions to residential, commercial and industrial uses and conversions between forestry and other types of agriculture such as row crops.

The policies that might be explored through the models include a variety of planning options related to transportation, economic development and taxes, zoning or other incentives that might be used to target growth to particular areas or encourage certain behaviors such as the use of public transportation. The broader goals of such model applications might also be to inform policy analysis by linking projections of land use change to models that produce effects on: air emissions, water use, water quality, energy use, deforestation, climate change, or habitat/ecosystem condition. To fully develop the necessary model projections, the land use change models might be linked to transportation models.

2.1 Where is growth vs. How much growth

A major distinction between models is whether they tackle the question of how much growth or land conversion is likely to occur within a region or whether the models are limited to specifying the location and pattern of growth or conversion. Most models we review are geared only towards specifying the expected pattern of urban land use change using external projections of population or employment growth as control totals.

Another set of models we include examines where deforestation for commercial forestry or conversion to other agricultural uses is likely to occur based on expected market demand. Most of those models use projections of population and commodity demands as inputs but do not generate those projections internally. However, a couple of models (FASOM, and REM, See Appendix A for full names and citations) estimate total land conversions through the use of optimization models. These projections still depend on external projections or scenarios of price of commodities or other factors that drive the amount of conversion. Other models use optimization techniques to distribute growth projections to broad regions before allocating growth to a fine scale (White and Engelen 2000).

Determining how much population growth will occur within an area falls under the purview of demographers, planners and economists. Population growth can be modeled as a function of births, deaths and net migration, given a specified population and associated demographic characteristics. Economic or environmental conditions can determine migration patterns and influence population demographics requiring that growth projections consider potential economic growth/decline and changing environmental conditions. Evidence suggests that economic growth is increasingly disconnected from population growth within a given county since workers are willing to commute long distances (Renkow 2004). However, a common practice is to apply a ratio of population growth to employment growth to estimate one from the other. Most economic and population projection models tend to rely on past trends to suggest future growth usually with some adjustments for expected changes to local economies.

A variety of sources are available for population and economic projections. Commonly used sources are projections by the US Bureau of Census and a private firm, Woods and Poole. In addition, states and counties will often develop their own population and economic projections, and economic consulting firms also generate projections. We do not review models that predict only population change or economic growth, but do evaluate a few models that examine changes in the economic sectors of agriculture and commercial forestry since they are responsible for significant land use change. We review the sources of growth projections more thoroughly in another report in preparation.

2.2 Three types of models reviewed

To meet the needs of natural resource managers, researchers and policy-makers, we examined three main types of models that largely reflect different disciplinary approaches to land use change modeling. Models may employ a combination of methods to make land use projections, but most can be characterized in terms of three methodological endpoints: spatially-explicit econometric models, spatial allocation (GIS neighborhood rules) and agent-based modeling (Figure 1). While many models combine elements of two or all of these endpoints, the endpoints are useful because they represent the dominant approaches of different groups of modelers.

2.2.1 Spatially-explicit econometric model

The first type of model considered, the spatially-explicit econometric model, has been developed by economists to characterize the decisions of agents converting land between uses. Structural models are developed by identifying the actors, conceptualizing the drivers of their economic decision process, hypothesizing variables that reflect those drivers, and developing statistical approaches to test hypotheses. Fitted models may then be used to make projections of land use change for the area for which they were developed.

The models used in estimation typically generate probabilities of land use conversion by fitting data on observed land conversions to explanatory variables of value in the converted use. These variables are measured as spatially heterogeneous site and location characteristics.

Models may be estimated in two stages where selling prices are used as an independent variable to characterize desirable parcel characteristics, and then probability of conversion is modeled as a function of selling price in the converted (developed use), costs of conversion, and value of the land in its undeveloped use, such as agriculture or forestry (Bockstael 1996). These models can be made dynamic, in which case they become a type of agent-based model. See review by Irwin and Geoghegan (2001) for further explanation. As an alternative to an agent-based model, survival or hazard model methods may be used to consider the time period in which a parcel is most likely to convert (in addition to conversion probability) without the added complexity of a dynamic model.

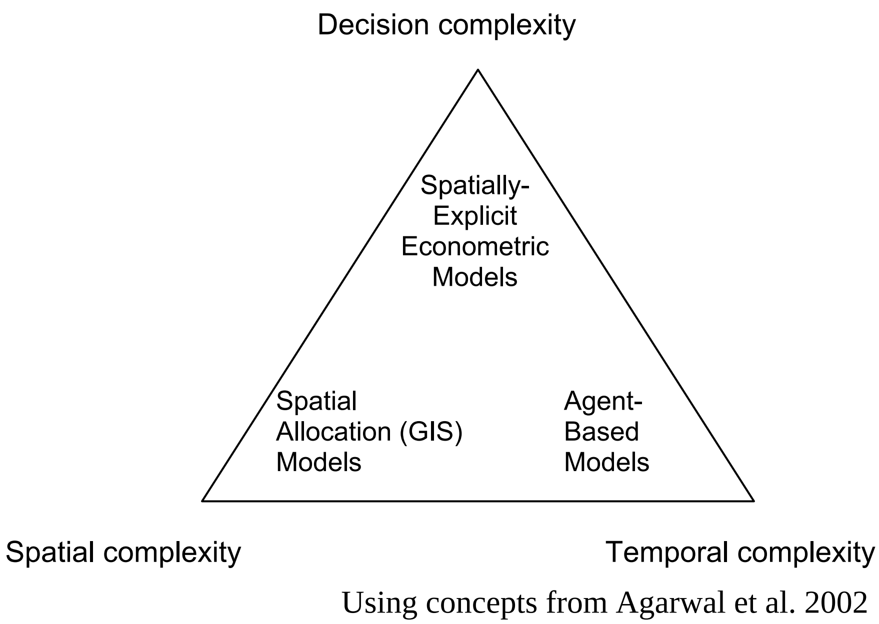

Figure 1. Model classification framework based on structure.

2.2.1.1 Probabilistic representation of land conversion

To represent probabilities of conversion, many models use Markov transition probabilities between states of land use or land cover. Since most land use transitions are from agricultural or forested to residential or commercial, many models focus on these particular transitions. Probability of conversion is modeled based on the expected returns from selling a parcel in its developed use minus the costs of conversion.

prob(developed) = prob((Value of land in current use + Costs to develop) < Returns developed)

The returns from development are estimated probabilistically based on an examination of buyer preferences and market conditions. Typical variables included are distance or travel time to employment centers, proximity to various types of infrastructure (roads, schools), proximity to built and natural amenities (recreational centers, parks, waterfront, scenic views), and proximity to undesirable features (landfills, airports, high crime areas, low performing schools). Tax rates have been proposed as an important variable, but evidence is mixed (Gabe and Bell 2004, Ladd 1998). Costs of conversion are modeled as a function of availability of utilities (esp. water and sewer), slope, presence of forest (vs. agriculture), and presence of problem soils. Undevelopable land (e.g., parks, publicly-owned land) is excluded from consideration.

The statistical model used is typically a *discrete choice model* (Ben-Akiva and Lerman 1985), a type of generalized linear model designed to handle non-continuous dependent variables, since, in this case, the dependent variable is one of a finite set of land use classes. The model assigns relative probabilities of conversion to specific parcels or pixels on the landscape as a function of observable attributes.

Results from discrete choice models can be used to generate predictions of future land development in several ways. A common method is to employ separate estimates of population growth as a "budget constraint" on how many parcels will convert. In some cases, parcels are chosen for conversion based on their high probability of conversion, and then the total amount of growth within the parcel is assigned based on the maximum zoned density or other parcel criteria. The parcels with the highest probabilities of conversion are selected until the projected population growth is accommodated. Alternatively, a probability can be interpreted as the proportion of land within that probability class that will be converted. In other words, 25% of land with a probability of 0.25 will convert given constant growth pressure.

The spatially explicit econometric models are distinguished by their conceptualization of the conversion decision as an economic transaction where expected payoff must exceed costs. The use of an economic framework to structure the model enhances the ability of the model to reflect behavioral responses to policy changes. In practice, these models share many explanatory variables with the other types of models developed by other disciplines. However, these types of models are formulated to consider correlation between variables so that estimated parameters can be correctly interpreted.

A major limitation of such models is that they often require detailed data that are not available in regionally consistent formats. For example, detailed information on home sale prices and housing or lot characteristics may not be easy to obtain. These statistical models promote an approach that uses parcel-based information since this is the unit that is typically purchased or converted, which can add to data gathering complexity. However, an alternative approach may use the pixel as the unit of observation to take advantage of remotely sensed imagery. Remotely-sensed imagery is available for multiple time steps and is regionally consistent. However, such data introduce potential errors such as difficulty of interpreting land use categories, particularly in the identification of exurban (very low density) residential land conversion.

These models may also lack the ability to model conditions that deviate from historic norms, although this problem is common to most models used for making projections. Another criticism of the Markov model is that spatial contagion or spatial repelling properties (described in Irwin and Bockstael 2002) may not be captured. In other words, the choice of building in one area affects the probability of conversion of neighboring parcels in ways that are not captured in the conversion model.

2.3 Spatial allocation models

Spatial allocation models have typically been developed by geographers or planners who identify neighborhood conditions that tend to be correlated with certain types of land conversion, usually residential and commercial development. A predicted amount of residential or commercial growth is allocated to specific locations (e.g., grid cells) to generate future land use. Some type of transition rule is needed that determines the new land use at the end of the time period being modeled. Such transition models may be developed statistically, as described next in the agent-based models, but may also be developed starting with a hypothetical relationship between observed characteristics and final state and calibrating that relationship using data on land cover at several points in time. The parameters that describe the hypothesized relationships are adjusting until the model output matches the observed pattern. Both conversion potential or conversion amount per cell may be estimated in this fashion. The conversion probabilities are based on characteristics of the location and neighborhood that make the site more or less attractive for development such as proximity to existing development, proximity to roads, soil type, and slope.

These models are a natural outgrowth of the types of models that planners typically develop using qualitative techniques and best professional judgment of where new development is likely to occur. The models codify relationships understood by planners and create rules and quantitative relationships to predict change. These models have the advantage of being easy to understand and relatively easy to use. The major limitation is that they may not be able to respond directly to certain types of policy changes, such as implementation of taxes. Therefore, many types of policy scenarios must be translated into spatial growth limitations using additional models or ad hoc relationships.

These models tend to generate a diffusion of growth around existing urban centers unless the growth rules are sufficient to generate new urban centers or recognize feedbacks that might tend to limit diffusion. This limitation can be overcome through selection of landscape variables that recognize land use patterns. The static nature of the estimation usually prevents feedbacks between new growth and old growth from being incorporated. In other words, new growth does not have the ability to influence later growth. In addition, because the models are based on historical observation of behavior, they may not be able to reflect major alterations in behavior or threshold effects.

2.4 Agent-based models

Agent-based models include a large and diverse class of simulation models that characterize systems in terms of autonomous but interconnected "agents" that have the ability to make "decisions" based on changing conditions. These models are shown in Figure 1 as having a high level of temporal complexity but not necessarily spatial complexity. This characterization is accurate for many types of agent-based models, but not necessarily for those used in land use change modeling. In many agent-based models, the model space may not correspond to locations in the real world, but in land use change version of such models, the agent is a fixed location (e.g., a grid cell) on the landscape. The majority of these models are referred to as *cellular automata models*.

Cellular automata models of land use change have most commonly been developed by landscape ecologists and geographers as a set of processes or rules that determine land use change based on a great deal of spatially-explicit information. The spatially explicit versions of such models use heterogeneous landscapes, divided into a lattice of cells, which are described by a list of attributes generated from spatial data. These models are quite similar to the spatial allocation models just described, but are distinguished by their use of dynamic simulation. These models characterize patterns of growth based on historical data and then project those patterns into the future.

These dynamic models allow landscape conditions to change through time and create feedbacks between landscape condition and changes that occur in the next time step. Simulations are run in which agents (cells) respond to changing conditions within the cell, neighborhood, and sometimes entire landscape. One or more sets of rules may be used to identify the state (e.g., land use type) of a cell at a given time step. Changes in state are determined by transition rules that depend on the state of the cell in the previous time step and the state of cells in the surrounding neighborhood. The models are run using discrete time-steps (e.g., one day, one year) and cells are typically updated simultaneously at each time step. This allows feedbacks between environmental variables and neighboring cells to factor into cell transition "decisions" dynamically.

The transition rules used to determine the land use type chosen by the agent may be either probabilistic or deterministic. The probabilistic models will often use Markov models, as described under the spatially-explicit econometric models, to generate probabilities of land use transitions. Bayesian approaches may also be used to estimate probabilities of land conversion (de Almeida et al. 2003). Therefore, when looking only at the transition rules, the cellular automata and spatially-explicit econometric models can appear the same. However, these types of models usually differ greatly in the functional form of the statistical model used and the underlying concepts driving the selection of variables.

Deterministic transition rules are typically developed through quantitative or qualitative comparisons between real world data and model outputs. Multivariate statistical approaches are used as is multiple regression and discrete choice models to determine which characteristics are associated with which land use classes. In one approach (Wu and Webster 1998), the researchers used a formal multi-criteria evaluation and the analytical hierarchy process to determine transition rules.

These models are similar to the spatial allocation models in that they use a system of rules to generate spatial patterns of land use change. However, these models are distinguished by their ability to include temporal dynamics, feedbacks between decisions and environmental variables, and to manifest *emergent behavior* (Bonabeau 2002). Emergent behavior is a model response that could not be predicted from model form. In other words, simple rules can lead to complex behavior. Cellular automata models are most likely to be able to represent a major change in state since they are developed from behavioral rules that can respond to new conditions. Although they may be calibrated to historic land use change, they can be designed so that the model responds to conditions that deviate greatly from historical conditions. However, this property is difficult to achieve in models that aim for high precision, as was the case for many we reviewed.

The highly desirable temporal dynamics of these models typically come at a significant cost in terms of time to implement. These models can be difficult to understand, and they often include multiple sources of error that are difficult to quantify, thereby making their results less acceptable to stakeholders. Even though simulation models are designed to be moved between locations, the process of implementing a model in a new case study area can be quite time-consuming. Calibration to a new area will usually require developing large input data sets for multiple points in time. The process of recalibration involves an iterative process of running the model, comparing data with model output, adjusting parameters to improve model fit, and repeating as many times as necessary. Such calibration of model equations can be highly time-consuming although some models use optimization routines to calibrate models which would eliminate, or at least reduce, the need to make multiple model runs during calibration. In addition, the cellular automata models may involve both a refitting of a statistical model used to estimate transition probabilities as well as recalibration of other functions.

2.5 Summary of model types

Because many models are hybrids of methods, the distinctions we present are not always clear-cut. For example, the statistical methods presented for one model type may apply in the case of another model type. The models are similar in that they all include measures of environmental variables that drive land use decisions. However, they differ dramatically in how they conceptualize the relationship between input and outputs and in the number of variables used. A couple of variables are common to almost all models: relationships among existing land uses and proximity to roads. The use of suitability criteria or screening criteria to limit or exclude development in some areas is also common to many models, although the level of detail used to limit growth using zoning, proximity to undesirable land uses, or characteristics that make an area more expensive to convert (e.g., steep slopes, trees, wetlands) varies substantially.

For our purposes, any model applied across multiple states is likely to be hindered by lack of consistent data sets for local variables such as zoning, therefore, some modelers avoid such variables because of known data limitations. Many models that do not incorporate such data could readily do so if data were available (e.g., SERGoM). The unit of observation used in the model (pixel or parcel) will also affect the ability to include certain variables. Models that use pixels can often rely on readily available regional data sets while models that use parcel boundaries tend to require data available only from state or county agencies.

In summary, the models have a common ability to handle spatial and temporal patterns of land use change but differ in terms of the economic drivers they include, the unit of observation (parcel, grid cell, other), and in the degree of temporal and spatial complexity applied. In our model comparison at the end of this document, we go into further detail of how methods determine the applicability of results.

2.6 Model comparison matrix

We compared the models according to a variety of criteria shown in Table 2-1. These attributes were chosen to compare the ability of models to meet the specified modeling needs for estimating future energy use across a 15-state area in the southeastern US. The first category, model type, identifies where the model falls in model classification framework outlined in the previous section. The remaining categories are aimed at revealing model methods, ease of use and applicability to policy questions.

Note that we did not include certain characteristics common to all models. For example, except where indicated under the column "How much growth?" all models require external projections of population growth. A few of the models incorporate economic projections in addition to population projections, and this detail is covered under "Model strengths." Almost all models require Geographic Information System (GIS) software directly or indirectly, and developers typically used ESRI products within the ArcGIS suite, unless otherwise noted. Most models do not link directly to GIS and therefore can use spatial data produced by any GIS software package. Outputs of models are usually georeferenced maps (GIS layers) which we refer to only as "maps" under "Output."

Under the categories of "Land Uses Predicted," a land use that is shown as "predicted" may be either directly modeled or indirectly modeled as the remainder of land use after other land uses are calculated. In general, only the models labeled as agricultural or forestry models predict changes in agricultural land or forestry directly. Some land uses are only modeled as inputs (e.g., protected area) and are almost never actively modeled.

Table 2-1. Criteria Used in Model Comparison

Variable	Description
Model Type	Where the methodology falls within the model classification framework
Outputs	How is output of land use change represented?
How much growth / conversion?	Does the model generate predictions of total land conversion or population growth?
Where is growth/ conversion?	Does the model allocate growth at fine spatial detail (sub county or finer)
Land Uses Predicted: Residential Commercial Industrial Agricultural Forests Protected Other	Which land uses are considered in future predictions?
Intended User (if specified)	Is the model intended for a specific audience such as a land use planner? Resource Manager? Researcher?
Case Study Area	Previous case study areas identify where the model has been successfully applied and show one measure of the extent of use.
Appropriateness to SE	Has the model ever been applied to the southeast or are there model factors that would limit its application to the southeast US.?
Temporal Duration of Case Study	Over what time period was the model run in the case study or studies? Although the duration may be adjustable, this shows what the model builders intended as a reasonable use.
Time Step	How frequently are results generated and fed back into model estimation?
Spatial Extent	What size area could be appropriately modeled with this method?
Spatial Resolution	What is the cell size or unit of observation?
Uncertainty Quantified?	Is the uncertainty in predictions quantified through a statistical error term, by using Monte Carlo techniques or by using other methods.
Major Strengths (ease of use, ability to model policies)	What are the major advantages of using this model in terms of ease of use or ability to model policy options? Ease of use is measured in terms of three metrics: Data requirements, Transferability to the SE, Technical expertise required to model system.
Major Limitations (ease of use, ability to model policies)	What are the major limitations of using this model in terms of ease of use or ability to model policy options? Ease of use is measured in terms of three metrics: Data requirements, Transferability to the SE, Technical expertise required to model system.
Required Data Inputs	This list includes basic required data inputs, but GIS manipulation or other pre-processing may be required. Optional data inputs are labeled as such. This list gives the reader a sense of model complexity and data demands.
Method of Adapting Model (statistical fit / calibration / BPJ)	What methods are required to adapt model to a new region? Statistical fit - model must be re-fit to a new area using statistical software. Calibration - model parameters are adjusted by user using training data sets so that model replicates land use at 2 or more points in time. Best Professional Judgment (BPJ) Model is adapted to new area by gathering local expertise to weight parameters or select variables of interest.

Table 2-1. Criteria Used in Model Comparison (cont.)

<table>
<tr><th colspan="2">Variable</th><th>Description</th></tr>
<tr><td colspan="2">Technical Expertise</td><td>Expertise required to run model and examine results (after model is installed).</td></tr>
<tr><td rowspan="3">Ease of Use</td><td>Data Requirements (1 low – 5 high)</td><td>1 – Low data demands - Data are publicly available and regionally consistent
3- Medium - Data needs are intermediate because they use a large variety of publicly available data or include some data that must be purchased or data are not available as regionally consistent data sets (i.e., must be collected from local agencies)
5- High – Requires data that are only available by contacting multiple agencies, through site visits, or aerial photo interpretation</td></tr>
<tr><td>Transferability (1 low – 5 high)</td><td>1 – Low difficulty – Model has already been applied to the SE US or a region sufficiently similar that little adjustment will be required.
3 – Medium difficulty – Model must be recalibrated, re-fit, or adjusted using BPJ, but data needs are modest and number of adjustable parameters is limited
5 – High difficulty – Model structure must be altered to fit SE US.</td></tr>
<tr><td>Technical Expertise (1 low – 5 high)</td><td>1 – Low – Model is understandable by educated lay-person, model runs in a desktop computer environment, and no specialized expertise is needed to run model or interpret results.
3 – Medium – Model requires some level of specialized expertise (e.g., statistical modeling experience) but model could be run by person with a modest level of training.
5 – High – Model requires a great deal of specialized expertise or familiarity with model structure in order to understand, configure, run model or to interpret results</td></tr>
<tr><td colspan="2">Infrastructure inputs?</td><td>Does the model require external inputs of infrastructure such as roads or water and sewer lines? This question was added to show whether these models use outputs being produced under other tasks.</td></tr>
<tr><td colspan="2">Energy Consumption</td><td>Is energy consumption explicitly modeled?
Could changes in energy policy be reflected in model?</td></tr>
<tr><td colspan="2">Availability</td><td>How is the model made available to users?</td></tr>
<tr><td colspan="2">Cost</td><td>What is the cost of acquiring model software?</td></tr>
<tr><td colspan="2">Notes</td><td>Other points about the model</td></tr>
<tr><td colspan="2">Sources</td><td>Literature sources that were used to describe model.</td></tr>
</table>

3. Model Recommendations

3.1 Concepts for comparing models

Modeling involves making trade-offs between realism, precision and generality (Levins 1966). Realism implies that the model aims to accurately represent underlying processes rather than precisely matching quantitative outcomes. Precision implies high correspondence between the data and the model output. And generality implies that the model can be transferred to different types of systems or different locations with ease because the model applies basic principles that hold under different conditions. The more precisely a model captures a particular system, the less likely it can be applied to another area (generality). Similarly, models aiming for realism may be most concerned with capturing processes within a particular system rather than being widely applicable. Generalizable models will tend to be simpler, with fewer variables, than models aiming for realism or precision, and will use general concepts that are widely applicable, even if some heterogeneity between systems or locations is not captured.

There is no one "right" answer to how models should be developed, rather models must be selected to best match the needs of the intended application and meet the constraints of the developer's budget. All future projections generated by models are likely to be imprecise when compared to actual outcomes due to the nature of forecasts. Therefore, the investment in developing precise models must be weighed against the value of expected returns. One reason why projections are always less than perfect is that models created from historical observation are unlikely to capture novel behavior.

Both spatial allocation and econometric models are developed from historical observations and therefore have limited ability to generate novel or emergent behavior. Agent-based models may be best positioned to generate unexpected or novel future behavior because these models incorporate rules that allow complex behavior to emerge from simple rules. In addition, some types of agent-based models have among the highest generalizability of all model types (Grimm et al. 2005). However, the agent-based models reviewed here (cellular automata models) are typically aimed for a level of spatial detail that shifted them towards realism and precision, and away from generality. This focus on precision also created significant time demands for model creation.

The application of land use change models to projecting energy consumption requires that the model have a reasonable amount of precision. In other words, the predictions should generally be able to match observations. On the other hand, the model can be fit too closely to existing data and lose realism and generality. A simple example is the statistical model. Model fit generally increases with an increasing number of explanatory variables. However, the more variables used, the more likely that the model will not be reliable (i.e., all variables significant, good model fit) when evaluated for a different data set. Statistical modelers generally aim for an intermediate level of model complexity to capture the major components of variability but to avoid "overfitting" the model. In the case of spatial allocation or simulation models, a similar principal applies. Too much model complexity not only leads to a lack of generalizability, but also creates the tendency to propagate errors in model outcomes due to dependent relationships among model equations.

3.1.1 Error and uncertainty

Model error rates vary dramatically by type of model, more so than the error varies within a specific type of published model. Spatial allocation models are generally considered to have low to moderate accuracy, although the ability to measure accuracy is limited, and moderate generalizability. The error of spatial allocation models depends on how closely the model is calibrated to local conditions which also means the increasing calibration effort will reduce model generalizability. On the other hand, spatially-explicit econometric models are considered to have relatively high accuracy, which can be readily quantified through model fit statistics, but low generalizability. Spatial allocation models typically judge error in terms of the model's ability to replicate a historic set of land transitions after model calibration. Maps of observations and maps of model predictions are compared through various metrics such as the Kappa Index of Agreement.

The prediction error of cellular automata models may be quantified in the same way as spatial allocation models, but model error cannot truly be quantified. Instead, the uncertainty of results may be evaluated using sensitivity analysis where the change in output is evaluated as a function of the variability of model parameters. In the Monte Carlo version of this technique, the model parameters are drawn randomly from a distribution of values, such as a normal distribution with a specified mean and standard deviation, and the change in the range of outputs is used to characterize uncertainty. Such models are known to have the potential for high error rates since error may be compounded by the interdependencies of the many model equations.

In the model comparison matrix (Table A-1), we indicate whether modelers report on error or uncertainty assessments, but due to the difficulties of comparison, we do not include specific reported error rates since they would not serve to usefully compare models. Also, the accuracy statistics cannot be meaningfully related to the ability of the model to make accurate projections 25-30 years into the future. Few model developers would claim that their models are accurate for such long-range projections. More important to evaluating error and uncertainty is developing an understanding of the relative error rates of different types of models and deciding how precision and accuracy might be traded off when making determinations of methods.

3.2 Model types converge in the land use transition matrix

The models we reviewed here share, at their core, a common element critical to the prediction of land use change: the land use transition matrix. The transition matrix is the set of statistical equations or pre-determined relationships (e.g., lookup tables) that determine the likelihood of one land use converting to another as a function of site and neighborhood conditions. Regardless of the type of model constructed, all models depend on some type of transition matrix to create output. Some models use formal statistical methods to develop a *transition probability matrix.* Other models determine likelihood and/or density of growth (or, more generally, amount of conversion) through fixed (deterministic) relationships between observed characteristics and allocated growth.

The methods used to construct the transition matrix determine many aspects of the model's transferability and ability to model policies. The methods differ by: 1) the types of land use transitions they include, 2) the number of variables used to make the prediction, 3) the hypotheses used to develop the equations or relationships, and 4) the use of statistical or non-statistical methods. The last characteristic also tends to determine if the transition rules are probabilistic or deterministic, although not in all cases (e.g., SLEUTH does not use statistical models but still develops probabilistic predictions). Most models use relatively few variables to predict change while the minority uses a relatively long list of variables (UrbanSim, CUF2, DELTA, Bockstael 1996, Irwin et al. 2003).

Although a variety of techniques are used to create the transition matrix, a large number of the models use a particular statistical technique. A few models rely on qualitative best professional judgment (What If? Yankee 2005), quantitative best professional judgment in the form of multi-criteria analysis (Wu and Webster 1998), or calibration to historical datasets (SLEUTH, SERGoM). However, a large proportion of models (9 of the 22 we reviewed) use a type of discrete choice modeling (multinomial logit, a generalized linear model) or other multiple regression statistical methods (See Table A-1).

Judging from our review of the recent literature, it appears that multinomial logit, or similar discrete-choice model, is an increasingly common method used across academic disciplines for constructing the transition matrix. The multinomial logit is the standard method used in econometric models (REM, Bockstael 1996, Irwin et al. 2003). More revolutionary is the adoption of the technique by recently-developed cellular automata models (e.g., Jenrette and Wu 2001, DINIMICA). As another example, the use of multinomial logit was a major enhancement made between the CUF and the CUF2 (spatial allocation) models, and the developers clearly believe this strengthens the model. By basing transition rules on statistically fit relationships, model error can be quantified and tested. One group of model developers (Wear et al. 1999), who did find appropriate spatial data for developing such a model, elicited expert judgment to create data for the dependent variable so they could fit a logit model. Their extra effort to assess commercial forest suitability showed that using the logit is viewed as desirable even when appropriate data inputs are not readily available.

A key question about multinomial logit models is whether the form of the model would hold under different circumstances and over long time periods. Most developers of such models are reluctant to re-use the models in different regions or make long-term predictions with the models. The nature of such models is that they are thought to hold only for conditions very close to the conditions for which the model was estimated. Turner et al. (1996) explicitly addressed this question by conducting tests on whether the models parameters held through time. Not surprisingly, they found that transition probabilities were not stable through time and most likely responded to changing social and economic conditions. Most economists would agree that a great many variables can change the types and rates of land use transitions. Therefore, such models are not readily transferable, and it is generally understood that error increases the farther out in time they are applied.

3.3 Models able to directly model policy scenarios

A few models we examine aim to replicate the economic conditions that change demand for various land use types. Most notably, FASOM (Forest and Agriculture Sector Optimization Model) calculates demand for agricultural and forest land as a function of prices and other economic variables. This model is not spatially explicit and is not easily transferred, however, the developers have created projections for the southeast US that might be used directly when modeling the southeast. Also, collaborations with the developers would offer the opportunity to directly model policies affecting transitions between these two land uses. Other non-spatial econometric models are available to inform land use change models, however this model includes variables that might allow projections to be associated with particular sites such as site condition. This model is useful because it provides predictions of the total conversion of agriculture and forest land in response to policy using standard and well-accepted economic modeling techniques.

Several models that focus on projecting urban land transitions incorporate economic growth or other relevant economic variables. The CUF-2 model offers some of the best use of variables affected by different policies. In addition, the UrbanSim and DELTA models include economic growth projections in their predictions of land use development. However, the level of detail in these models probably makes them unsuitable for use across broad regions. The Yankee 2005 model incorporates economic growth scenarios and an aspect of land value that allows redevelopment rates to be recalculated. This model includes a much lower level of detail than the DELTA, UrbanSim or CUF-2 model making it more tractable for implementation across broad regions. However, as with other growth allocation models, policy scenarios can not be directly modeled but must be translated into simple constraints for the model. The White and Engelen (2000) model seems to offer a similar ability to incorporate economic growth projections, although the limited documentation available did not allow us to fully evaluate the potential of this model.

The REM model is geared towards modeling agricultural land use change, but also incorporates urban land use drivers. This model offers the ability to model agricultural policies directly but has several drawbacks for our purposes because it is not spatially explicit below the county scale (due to data requirements) and does not distinguish between different types or densities of urban growth. This model offers some novel variables compared to other models that would allow certain policy scenarios to be modeled.

The spatially-explicit econometric models (Bockstael 1996, Irwin et al. 2003) offer the ability to directly model a range of policy scenarios with a high level of confidence. These models include behavioral and economic drivers and therefore can directly model many scenarios. Because they do not rely on best professional judgment of the effect of policies, they are more likely to demonstrate unexpected (sometimes undesirable) responses to land use policies. For example, model results have shown the tendency of some types of growth restrictions to increase the likelihood of sprawl (Irwin and Bockstael 2002). However, these models have limited transferability and high data demands.

All models are likely to show a decline in accuracy through time, therefore this issue does not really distinguish any of the modeling methods. The models without direct links to economic drivers are most likely to miss important trends in behavior such as population decline due to a downturn in economies. Patterns of growth over such a wide area as the Southeast US are likely to vary greatly in many respects such as density with distance to city centers. Therefore, it is unlikely that any of the models that require calibration using such relationships (SLEUTH and SERGoM) would capture regional differences without multiple versions of the model being created.

3.4 Models that are easy to understand

Understanding error and sources of error is important for gaining acceptance of model results by planners and local officials. The structure of simulation models are generally more difficult to understand than statistical or spatial allocation models. Their ability to generate novel behavior, while useful, is also an impediment to interpreting results. Unexpected results may not be clearly interpretable since the results may be due to error (undesirable) or emergent behavior of the complex system (desirable). Understanding the sensitivity of the model to input data or parameters of equations can be used to detect error, but this is rarely done in a thorough way with complex cellular automata models. Therefore, the complex cellular automata models are not readily transferred between regions because a lot of time must be invested in order to understand their behavior.

The simple spatial allocation models are clearly the easiest to understand (SERGoM, WhatIf? and Yankee 2005). The rules for making transitions are relatively simple and best professional judgment of planners can be incorporated when the models are applied to a single region at a time. However, the way that policy change enters into the model is not easy to understand. For models, such as these, that lack most behavioral or economic drivers, policies must first be interpreted as land use restrictions or changes in total growth using other models or best professional judgment. When best professional judgment is used, the uncertainty of such estimates cannot be evaluated and unexpected behavior such as methods of "gaming" the system, are not likely to emerge. Therefore, such models only reflect a consensus of current beliefs.

The implementation of policies into spatial allocation models might be improved in several ways. For one, the use of multi-criteria analysis to formalize the elicitation of best professional judgment makes the judgments explicit and available for scrutiny. Sensitivity analysis may also be used to test the effect of relaxing certain assumptions to provide a means of uncertainty analysis.

The spatially-explicit econometric models are developed using methods that may be hard for some to understand, but the results can be readily explained by the model developers. The effect of each variable on the predicted outcome is quantitatively tested and reported. Problems with correlations between variables or non-independence of variables (endogeneity) can complicate the interpretation of variables, but modelers try to minimize such problems.

3.5 Which models provide appropriate inputs for energy consumption modeling?

In order to meet the needs of predicting multiple types of land use transitions, more than one model may be needed. Most models focused on particular land transitions and therefore, to capture all potentially important land use transitions, multiple models would be needed. Alternatively, the transitions deemed to be the most important for determining energy use or other environmental impacts could be selected and other transitions ignored. Models that could be linked to transportation models would offer an advantage in understanding vehicle miles traveled as a result of land use change, but only two models were designed for that purpose (DELTA and UrbanSim), and they are unlikely to be appropriate for regional application.

The most likely focus for understanding energy use change from land use change would be evaluating models that predict urban, suburban and exurban growth. Such a focus would not provide all inputs needed for a comprehensive evaluation of environmental impacts, but would go a long way towards informing energy predictions. Only a few models included the location of commercial activity and only a few provided details on urban density that we have deemed important to predicting residential energy use and that would be important for transportation models. Table 3-2 shows models that provide one or more of these elements.

3.6 Which models are easy to use?

Since we do not know the level of resources available (person-hours and budget) to build the land use change model that will eventually be used, we summarize the information on ease of use in Table 3-3. Three components of ease of use were rated: Data requirements, Transferability and Technical expertise. Transferability was based on the effort needed to move the model to a new case study area. Technical expertise was the expertise required to re-implement the model in a new location and to run the model and examine results. Few models provide a graphical user interface (GUI), therefore even the lowest level of expertise required would be more difficult than using any commercially available software. See Table 2-1 for the specific criteria used to rate each model for ease of use category.

As with most endeavors, the relationship between effort and improvements in outcome is a non-linear one where larger increases in effort are needed to produce the same incremental change in improved outcomes. This is the case here where the resources needed to apply the most complex model greatly exceed the resources needed to create the simplest model, although the benefits of the complex model are primarily in terms of increased flexibility for policy analysis and not improved prediction.

None of the models is particularly easy to use since even the ones with limited data inputs and simple model structure require involved pre-processing of data. The "simple" models may require making many decisions about how the model will operate that may need to be elicited from groups of planners or others, which can require time-consuming meetings to develop consensus. The more complex models rely less on making such ad hoc determinations thereby simplifying that aspect of the forecasting process.

3.7 Conclusions

We were not able to identify an ideal model that could be readily transferred to the task at hand: providing inputs to analyzing future spatially-explicit energy consumption for an 8-state region of the Southeast US. Rather, we have discussed the strengths and weaknesses of the various modeling options and suggested the lessons drawn from the experiences of various modelers be applied towards developing a strategy for a new model. We have developed the following take-home points:

- In general, there seems to be limited payoff from pursuing the more complex cellular automata models because of the time-consuming nature of such endeavors and the inability to ensure that any unexpected behavior is generated from the desirable "emergent properties" of dynamic agent-based models rather than error.

- Only models that include economic and other behavioral drivers can directly model policy options. Methods to "pre-process" scenarios so that they can be implemented in spatial allocation models that lack behavioral drivers are less desirable since they prevent policy analysts from determining when people are likely to game the system rather than do what is expected.

- Many of the recently published models use multinomial logit (statistical models) to create a transition probability matrix to predict land use conversions. This includes all model types: spatially-explicit econometric models, spatial allocation, and cellular automata models. Therefore, it appears that the land use change modeling field is converging on this technique as the most promising.

- Statistical models offer the advantages that they are quantitatively derived from observations, making their predictive ability and error readily assessable.

- Where time or data constraints create the need to use best professional judgment, formal methods of eliciting judgment (e.g., multi-criteria analysis techniques) are available to reveal assumptions and allow input by a wide group of participants.

- The only truly transferable models are those with limited realism and precision, which are not likely to be useful for policy analysis. Similarly, the transferability of any model aiming for precision (i.e., all statistical models and most calibrated models) is about the same. In other words, the perceived lack of transferability of statistical models is true of any model that embeds one or more equations developed from observing one location through time.

3.7.1 Proposed modeling approaches:

The difficulty of developing a model that can be applied across an 8-state region should not be underestimated. Although modelers appear to be moving towards using multinomial logit models to develop land use change transition probabilities, resources may not be available to develop such models for the region. Alternative approaches might include:

- Statistical models might be developed from regional data sets to provide regional statistical models. However, a limitation of such models might be the inability to find significant relationships between land use change and the variables that drive policy scenarios (e.g., regulation) since land use policies will be heterogeneous across large regions.

- Detailed models might be applied selectively to case study areas and the results applied across the region by matching case study areas to sub-sets of counties or locales within the region. Essentially counties could be classified into groups and a case study area selected to represent each group. Variables such as population size, density and growth rates might be used to classify areas.

- Model results from ongoing or existing national studies (SERGoM, FASOM) might be used and systematically altered to evaluate policy scenarios intended to generate such results. For example, growth could be increased in cities by 10% to test the effect of a general category of policy scenarios designed to achieve that effect. The ability to test actual policies will be limited, but additional models could be developed to inform the scenarios.

Table 3-2. Characteristics of Urban Land Use Change Models and Ability to Provide Inputs to Energy Forecast Models

	Appropriate for Regional Implementation	Predicts Residential Density	Predicts location of Commercial and / or Industrial	Uses Roads	Ability to Directly Model Policy Scenarios
SLEUTH (Slope, Land use, Exclusion, Urban, Transportation, Hillshading) (Clark 1997)	no	yes	yes	yes	very limited
Jenerette and Wu 2001	no	no	no	no	limited
Batty, Zie and Sun 1999	no	yes	yes	yes	no
DINAMICA (de Almeida et al. 2003)	no	yes	yes	yes	no
DELTA Model (Simmonds, 1999)	no	yes	yes	yes	limited
UrbanSim	no	yes	yes	yes	yes
SERGoM (Spatially Explicit Regional Growth Model)/ **WFM** (Western Futures Model) (Theobold)	yes	yes	no	yes	no
CUF2 (CA Urban Futures) aka CURBA (Landis et al. 1998)	no	yes	yes	yes	yes
Land Transformation Model	yes	no	yes		no
What If? (Klosterman)	no	yes	yes	yes	no
Yankee, D. 2005	no	yes	yes	no	limited
REM (Resource Economics Model) (Hardie, Parks et al. 2000)	yes	no	yes	no	some
Bockstael 1996	no	yes	no	yes	yes
Irwin, Bell, Geoghegan 2003	no	yes	no	yes	yes

Table 3-3. Ease of Model Use

Model Name	Ease of Use		
	Data Requirements (1-5)	**Transferability (1-5)**	**Technical Expertise (1-5)**
SLEUTH (Slope, Land use, Exclusion, Urban, Transportation, Hillshading) (Clark 1997)	1	5 (3 for uncalibrated case, 5 for calibrated case)	4
Jenerette and Wu 2001	1	3	5
White and Engelen 2000	1	N/A	N/A
Batty, Zie and Sun 1999	1	1	1
DINIMACA (de Almeida et al. 2003)	3	5	5
DELTA Model (Simmonds, 1999)	5	5	5 to develop, 3 to run scenarios
UrbanSim (Waddell, 2002)	5	1	1 (if no structural changes in model required)
SERGoM (Spatially Explicit Regional Growth Model)/ **WFM** (Western Futures Model) (Theobold)	1	1	2
CUF 1 (CA Urban Futures)	3	3	3
CUF-2 (CA Urban Futures) aka CURBA (Landis et al. 1998)	3	3	3
CLUE (Conversion of Land Use and its Effects) **CLUE-S** (Conversion of Land Use and its Effects at Small regional extent) (Verburg) CLUE-CR (Veldkamp and Fresco 1996?? According to Agarwal)	3	3	3
Land Transformation Model	3	3	5
Yankee, D. 2005	3	1	3

Table 3-3. Ease of Model Use (Cont.)

Model Name	Ease of Use		
	Data Requirements (1-5)	Transferability (1-5)	Technical Expertise (1-5)
What If? (Klosterman)	3	1	3
GEOMOD2 (Pontius Jr. et al. 2001)	1	1	1
LUCAS (Land-Use Change Analysis System, Land use change modules only) (Berry et al. 1996, Pearson et al. 1996)	3	1	3
REM (Resource Economics Model) (Hardie, Parks et al. 2000)	1	1	3
Bockstael 1996	5	5	3
Irwin, Bell, Geoghegan 2003	5	5	3
Wear and Balstad 1998	3 (authors techniques were time-consuming but alternative data sources might be used)	3	3
Wear et al. 1999	2 (1 for inputs, 3 for dependent variable)	3	3
FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)	3	5	5

Table 3-4. Scoring criteria for Ease of Use

Data Requirements (1 low – 5 high)	1 – Low data demands - Data are publicly available and regionally consistent 3- Medium - Data needs are intermediate because they use a large variety of publicly available data or include some data that must be purchased or data are not available as regionally consistent data sets (i.e., must be collected from local agencies) 5- High – Requires data that are only available by contacting multiple agencies, through site visits, or aerial photo interpretation
Transferability (1 low – 5 high)	1 – Low difficulty – Model has already been applied to the SE US or a region sufficiently similar that little adjustment will be required. 3 – Medium difficulty – Model must be recalibrated, re-fit, or adjusted using BPJ, but data needs are modest and number of adjustable parameters is limited 5 – High difficulty – Model structure must be altered to fit SE US.
Technical Expertise (1 low – 5 high)	1 – Low – Model is understandable by educated lay-person, model runs in a desktop computer environment, and no specialized expertise is needed to run model or interpret results. 3 – Medium – Model requires some level of specialized expertise (e.g., statistical modeling experience) but model could be run by person with a modest level of training. 5 – High – Model requires a great deal of specialized expertise or familiarity with model structure in order to understand, configure, run model or to interpret results

4. Bibliography

Adams, D.M., R.J. Alig, J.M. Callaway, B.A. McCarl, and S.M. Winnett, 1996. The forest and agricultural sector optimization model (FASOM): model structure and policy applications. Research Paper PNW-RP-495. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Agarwal, C., G.M. Green, J.M. Grove, T.P. Evans, and C.M. Schweik, 2002. *A review and assessment of land-use change models: dynamics of space, time and human choice*. USDA Forest Service, Northeastern Research Station General Technical Report NE-297 and Indiana University Center for the Study of Institutions, Population, and Environmental Change.

Batty, M., Y. Xie, and Z. Sun, 1999. Modeling urban dynamics through GIS-based cellular automata. *Computers, Environment, and Urban Systems* 23(3): 205–33.

Ben-Akiva. M.E. and S. R. Lerman, 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. Cambridge: MIT Press.

Berry, M.W., B.C. Hazen, R.L. MacIntyre, and R.O. Flamm, 1996. LUCAS: A System for Modeling Land-Use Change. *IEEE Computational Science and Engineering* 3(1): 24.

Bockstael, N., 1996. Modeling economics and ecology: the importance of a spatial perspective. *American Journal of Agricultural Economics* 78(5):1168-1180.

Bonabeau, E. 2002. Agent-based modeling: Methods and techniques for simulating human systems. Proc. Nat. Acad. Sci. 99(10):7280-7287.

Carrion-Flores, C. and E.G. Irwin, 2004. Determinants of residential land-use conversion and sprawl at the rural-urban fringe. *American Journal of Agricultural Economics* 86(4): 889-904.

Chomitz, K.M., and D.A. Gray, 1996. Roads, land use and deforestation: a spatial model applied to Belize. *The World Bank Economic Review* 10(3): 487-512.

Claggett, P.R., C.A. Jantz, S.J. Goetz, and C. Bisland, 2004. Assessing development pressure in the Chesapeake Bay Watershed: an evaluation of two land-use change models. *Environmental Monitoring and Assessment* 94: 129-146.

Clark, K.C., L. Gaydos, and S. Hoppen, 1997. A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B: Planning and Design* 24: 247-261.

Daily, Gretchen C., Susan Alexander, Paul R. Ehrlich, Larry Goulder, Jane Lubchenco, Pamela A. Matson, Harold A. Mooney, Sandra Postel, Stephen H. Schneider, David Tilman, George M. Woodwell. 1997. Ecosystem Services: Benefits Supplied to Human Societies by Natural Ecosystems. *Issues in Ecology*, Issue 2. Ecological Society of America.

de Almeida, C.M., M. Batty, A.M.V. Monteiro, G. C’amara, B.S. Soares-Filho, G.C. Cerqueira, and C.L. Pennachin, 2003. Stochastic cellular automata modelling of urban land use dynamics: empirical development and estimation. *Computers, Environment and Urban Systems* 27(5): 481–509.

Feldman, O., D. Ballas, G. Clarke, P. Gibson, J. Jin, D. Simmonds and J. Stillwell, 1999. A spatial microsimulation approach to land-use modelling. Paper for presentation to CUPUM 2005, London.

Gabe, T.M. and K.P. Bell, 2004. Tradeoffs between Local Taxes and Government Spending as Determinants of Business Location. *Journal of Regional Science* 44(1):21-41.

Geoghegan, J., S.C. Villar, P. Klepeis, P.M. Mendoza, Y. Ogneva-Himmelberger, R.R. Chowdhury, B.L. Turner II, and C. Vance, 2001. Modeling tropical deforestation in the southern Yucatan peninsular region: comparing survey and satellite data. *Agriculture, Ecosystems and Environment* 1765: 1-22.

Geoghegan, J., L. Wainger and N. Bockstael. 1997. Spatial landscape indices in a hedonic framework: An ecological economics analysis using GIS. *Ecological Economics* 23(3): 251-264.

Grimm, Volker, Eloy Revilla, Uta Berger, Florian Jeltsch,Wolf M. Mooij, Steven F. Railsback, Hans-Hermann Thulke, Jacob Weiner, Thorsten Wiegand, and Donald L. DeAngelis. Pattern-oriented modeling of agent-based complex systems: Lessons from Ecology. *Science* 30:987-991Hardie, I., P. Parks, P. Gottleib, and D. Wear, 2000. Responsiveness of rural and urban land uses to land rent determinants in the U.S. South. *Land Economics* 76: 659-673.

He, C., N. Okada, Q. Zhang, P. Shi, and J. Zhang, 2006. Modeling urban expansion scenarios by coupling cellular automata model and system dynamic model in Beijing, China. *Applied Geography* 26: 323-345.

Iovanna, R. and C. Vance, 2005. Paying attention to the finer things: a high-resolution model of urban growth. Manuscript available from author.

Irwin, E. G. and N. E. Bockstael, 2002. Interacting agents, spatial externalities and the evolution of residential land use pattern. *Journal of Economic Geography* 2:31-54.

Irwin, E.G., and J. Geoghegan, 2001. Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture, Ecosystems and Environment* 1764: 1-18.

Irwin, E.G., K.P. Bell, and J. Geoghegan, 2003. Modeling and managing urban growth at the rural-urban fringe: A parcel-level model of residential change. *Agricultural and Resource Economics Review* 32(1):83-102.

Irwin, E.G., and J. Geoghegan, 2001. Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture, Ecosystems and Environment* 85: 7-23.

Jackson, L.E., S.L. Bird, R.W. Matheny, R.V. O'Neill, D. White, K.C. Boesch, and J.L. Koviach, 2004. A regional approach to projecting land-use change and resulting ecological vulnerability. *Environmental Monitoring and Assessment* 94: 231-248.

Jenerette, G.D. and J. Wu, 2001. Analysis and simulation of land-use change in the central Arizona – Phoenix region, USA. *Landscape Ecology* 16(7): 611-626.

Klosterman, R.E., 1998. The What If? Collaborative Planning Support System. Draft of Klosterman, R.E., 1999. The What If? Collaborative Planning Support System. *Environment and Planning, B: Planning and Design* 26: 393-408.

Ladd. H.F. (1998). *Local Government Tax and Land Use Policies in the United States: Understanding the Links*. Edward Elgar: Northampton, MA.

Landis, J.D., 1994. The California Urban Futures Model: a new generation of metropolitan simulation models. *Environment and Planning B: Planning and Design* 21: 399-420.

Landis, J.D., 1995. Imagining Land Use Futures: Applying the California Futures Model. *Journal of the American Planning Association* 61: 438-457.

Landis, J.D. and M. Zhang, 1998. The second generation of the California urban futures model. Part 1: Model logic and theory. *Environment and Planning B: Planning and Design* 25: 657-666.

Levins, R. 1966. The strategy of model building in population biology. *Am. Sci.* 54: 421-431.

Littman, T., 1999. Land use impact costs of transportation. BC, Canada: Victoria Transport Policy Institute.

Mertens, B. and E.F. Lambin, 1997. Spatial modeling of deforestation in southern Cameroon: spatial disaggregation of diverse deforestation processes. *Applied Geography* 17(2): 143-162.

Nagendra, H., D.K. Munroe and J. Southworth, 2004. From pattern to process: landscape fragmentation and the analysis of land use/land cover change. *Agriculture, Ecosystems and Environment* 101: 111-115.

O'Callaghan, J.R., 1995. NELUP: an introduction. *Journal of Environmental Planning and Management* 38(1): 5-20.

Oglethorpe, D.R. and J.R. O'Callaghan. Farm-level economic modelling within a river catchment decision support system. *Journal of Environmental Planning and Management* 38(1): 93-106.

Parker, D.C., S.M. Manson, M.A. Janssen, M.J. Hoffman, and P. Deadman, 2003 Multi-agent systems for the simulation of land-use and land-cover change: a review. *Annals of the American Institute of Geographers* 93: 314-337.

Pielke, R.A., 2005. Land Use and Climate Change. *Science Magazine* 310: 1625-1626.

Pijanowski, B.C., D.G. Brown, B.A. Shellito, and G.A. Manik, 2002. Using neural networks and GIS to forecast land use changes: a land transformation model. *Computers, Environment and Urban Systems* 26: 553-575.

Pontius, Jr. R.G., J.D. Cornell, and C.A.S. Hall, 2001. Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. *Agriculture, Ecosystems and Environment* 1775: 1-13. Accessible at https://prism.clarku.edu/~rpontius/pontius_etal_2001_aee.pdf.

Rajan, K.S. and R. Shibasaki, 2001. A GIS based integrated land use/cover change model to study agricultural and urban land use changes. 22nd Asian Conference on Remote Sensing. Singapore, November 5-9.

Renkow, M. 2004. Population, Employment and Mobility in the Rural South. SRDC Policy Series, Rural-Urban Interface Issue number 3. Southern Rural Development Center, Mississippi State University.

Simmonds, D.C., 1999. The design of the DELTA land-use modelling package. *Environment and Planning B: Planning and Design* 26(5): 665-684.

Simmonds, D.C. and O. Feldman, 2005. Land-use modelling with DELTA: update and experience. Presented at Ninth International Conference on Computers in Urban Planning and Urban Management, University College London, June 29 – July 21.

Soares-Filho, B.S., G.C. Cerqueira, and C.L. Pennachin, 2002. DINAMICA—a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. *Ecological Modelling* 154: 217–235.

Theobald, D.M., 2005. Landscape patterns of exurban growth in the USA from 1980 to 2020. *Ecology and Society* 10: 32.

Turner, M.G., D.N. Wear, and R.O. Flamm, 1996. Land ownership and land-cover change in the southern Appalachian Highlands and the Olympic Peninsula. *Ecological Applications* 6(4): 1150-1172.

USEPA, 2000. Projecting land use change: a summary of models assessing the effects of community growth and change on land-use patterns. Washington, DC: National Exposure Research Lab.

USGS, 2006. Project Gigalopolis: urban and land covering modeling. http://www.ncgia.ucsb.edu/projects/gig/ (last accessed January 10, 2007). Santa Barbara, CA.

Verburg, P.H., G.H.J. de Koning, K. Kok, A. Veldkamp, and J. Bouma, 1999. A spatial explicit allocation procedure for modeling the pattern of land use change based upon actual land use. *Ecological Modeling* 116:45-61.

Verburg, P.H, W. Soepboer, A. Veldkamp, R. Limpiada, V. Espaldon, and S.S.A. Mastura, 2002. Modeling the spatial dynamics of regional land use: the CLUE-S Model. *Environmental Management* 30: 391-405.

Verberg, P.H., C.J.E. Schulp, N. Witte, and A. Veldkamp, 2006. Downscaling of land use change scenarios to assess the dynamics of European landscapes. *Agriculture, Ecosystems and Environment* 114: 39-56.

Voinov, A. A., R. Costanza, L. Wainger, R. Boumans, F. Villa, T. Maxwell and H. Voinov. 1999. Patuxent landscape model: integrated ecological economic modeling of a watershed. *Environmental Modelling & Software* 14(5): 473-491.

Waddell, P., 2002. UrbanSim: modeling urban development for land use, transportation and environmental planning. Preprint of an article that appeared in the *Journal of the American Planning Association* 68(3): 297-314.

Wear, D.N., M. Turner and R.O. Flamm, 1996. Ecosystem management with multiple owners: landscape dynamics in a southern Appalachian watershed. *Ecological Applications* 6(4): 1173-1188.

Wear, D.N., R. Liu, J.M. Foreman, and R.M. Sheffield, 1999. The effects of population growth on timber management and inventories in Virginia. *Forest Ecology and Management* 118: 107-115.

Wear D.N. and P. Bolstad, 1998. Land-use changes in Southern Appalachian landscapes: spatial analysis and forecast evaluation. *Ecosystems* 1: 575–594.

What If, Inc. What if? pricing. http://www.what-if-pss.com/purchase.html (last accessed January 12, 2007). Hudson, OH.

White, R. and G. Engelen, 1997. Cellular automata as the basis of integrated dynamic regional modeling. *Environment and Planning B: Planning and Design* 24: 235-46.

White, R. and G. Engelen, 2000. High-resolution integrated modeling of spatial dynamics of urban and regional systems. *Computers, Environment, and Urban Systems* 24:383-400.

White, R., G. Engelen, and I. Uljee, 1997. The use of constrained CA for high-resolution modeling of urban land-use dynamics. *Environment and Planning B: Planning and Design* 24: 323-343.

Wilson, E.H., J.D. Hurd, D.L. Civco, M.P. Prisloe, and C. Arnold, 2003. Development of a geospatial model to quantify, describe and map urban growth. *Remote Sensing of Environment* 86: 275-285.

Woods Hole Research Center, 2006. Overview of the SLEUTH model. http://www.whrc.org/midatlantic/modeling_change/SLEUTH/sleuth_overview.htm (last accessed January 5, 2007). Falmouth, MA.

Wu, F. and C.J. Webster, 1998. Simulation of land development through the integration of cellular automata and multicriteria evaluation. *Environment and Planning B: Planning and Design* 25: 103-126.

Yankee, D., 2007. Tennessee Valley Authority. Personal communication.

Zhou, B. and K.M. Kockelman, 2006. Neighborhood impacts on land use change: a multinomial logit model of spatial relationships. Presented at the 52nd Annual North American Meeting of the Regional Science Association International, Las Vegas.

Appendix A

Table A-1. Model Comparison Matrix

Note

Information in this table was developed largely from publications. Therefore, some information may be out of date or may not represent unpublished implementations of models.

Table A-1. Model Comparison Matrix

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Model Name**	**Model Type**	**Outputs**	**How much**	**Where is**	**Land uses predicted**						
2			**[all maps are GIS (georeferenced data) unless specified]**	**growth / conversion**	**growth/ conversion**	**Residential**	**Commercial**	**Industrial**	**Agricultural**	**Forests**	**Protected**	**Other**
3	**SLEUTH** (Slope, Land use, Exclusion, Urban, Transportation, Hillshading) (Clark 1997)	Cellular automata (simulation) model	GIS maps of probability (continuous) of urbanization in a given year by pixel	no	yes	predicted as 'urban'	predicted as 'urban'	predicted as 'urban'	predicted indirectly	predicted indirectly	input	May be user defined
4	**Jenerette and Wu 2001**	Cellular automata model (with logit transition probability matrix)	probability of transition of desert to urban land use; Maps of 3 land use classes by pixel	no	yes				predicted			land use is classified into three categories: urban, agricultural and undeveloped
5	**White and Engelen 2000**	Cellular automata and multi-agent model	Maps of land use change by pixel for 16 categories of land use	no	yes	predicted						sixteen different land use / land cover in three classifications: active (have targeted levels of growth), passive calculated as remainders from changes in active land uses), and fixed (e.g., water, airports)
6	**Batty, Zie and Sun 1999**	cellular automata	Idealized land use change for 3-5 categories (developed land uses and transportation corridors) by pixel		yes	predicted	predicted	predicted	predicted as 'vacant'	predicted as 'vacant'	no	other land use types possible (e.g., streets)
7	**DINIMACA (de Almeida et al. 2003)**	cellular automata (with logit transition probability matrix)	land use maps by pixel at multiple points in time; spatial transition probability maps		yes	predicted	predicted	predicted	predicted	predicted		all land uses can potentially be predicted

Table A-1. Model Comparison Matrix (continued)

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Model Name**	**Model Type**	**Outputs** **[all maps are GIS (georeferenced data) unless specified]**	**How much growth / conversion**	**Where is growth/ conversion**	**Land uses predicted**						
2						**Residential**	**Commercial**	**Industrial**	**Agricultural**	**Forests**	**Protected**	**Other**
8	**DELTA Model (Simmonds, 1999)**	hybrid of: individual based model (type of agent-based model) and optimization model (simulated annealing)	Maps of households and jobs by fine scale polygons (zones); Economic growth by sector; Travel mode, travel time, congestion;	no; model predictions are not independent of external projections	yes	predicted						
9	**UrbanSim**	Cellular automata and individual based model	Spatial maps of housing units by pixel, non residential square footage per cell and other economic and demographic characteristics	yes	yes	predicted	predicted	predicted	predicted	predicted	predicted	land uses are user defined with up to 10 land use categories
10	**SERGoM** (Spatially Explicit Regional Growth Model)/ **WFM** (Western Futures Model) (Theobold)	Spatial allocation	Maps of new housing density by pixel	no	yes	predicted			predicted indirectly	predicted indirectly	input	
11	**CUF 1 (CA Urban Futures)**	Spatial allocation	Maps of residential land use classes and population density by parcel	yes	yes	predicted			predicted	predicted		

Table A-1. Model Comparison Matrix (continued)

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Model Name**	**Model Type**	**Outputs**	**How much growth / conversion**	**Where is growth/ conversion**	**Land uses predicted**						
2			**[all maps are GIS (georeferenced data) unless specified]**			**Residential**	**Commercial**	**Industrial**	**Agricultural**	**Forests**	**Protected**	**Other**
12	**CUF-2** (CA Urban Futures) aka CURBA (Landis et al. 1998)	Spatial allocation; with population and economic forecasts (with logit transition probability matrix)	Maps of multiple land use classes (residential, industrial, commercial and public) and population density by pixel	yes	yes	predicted	predicted	predicted	predicted	predicted		
13	**CLUE** (Conversion of Land Use and its Effects) **CLUE-S** (Conversion of Land Use and its Effects at Small regional extent) (Verburg) CLUE-CR (Veldkamp and Fresco 1996?? According to Agarwal)	Spatial allocation (using multiple regression equations)	Map of 5 land use/land cover classes by pixel (multiple resolutions) and economic projections of agricultural demand	yes	yes	predicted	predicted	predicted	predicted	predicted		
14	**Land Transformation Model**	Spatial allocation	Map of likelihood of transition to urban development		yes	predicted	predicted		predicted	predicted		
15	**Yankee, D. 2005**	Spatial allocation	Maps of developed land use by relatively fine-scale polygons (transportation analysis zone) and by 5 density classes	no	yes	predicted	predicted as jobs	predicted as jobs				
16	**What If? (Klosterman)**	Spatial allocation	Projected demand for each land use in each output year and input variables used to derive demand (e.g.,) by relatively fine-scale polygons (Uniform Analysis Zones)		yes	predicted	predicted	predicted	predicted	predicted	predicted	

Table A-1. Model Comparison Matrix (continued)

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Model Name**	**Model Type**	**Outputs**	**How much growth / conversion**	**Where is growth/ conversion**	**Land uses predicted**						
2			**[all maps are GIS (georeferenced data) unless specified]**			**Residential**	**Commercial**	**Industrial**	**Agricultural**	**Forests**	**Protected**	**Other**
17	**GEOMOD2 (Pontius Jr. et al. 2001)**	Spatial allocation	map of disturbed land(<80% forest cover) versus non-disturbed land (>80% forest cover) by pixel	no	yes	no	no	no	no	predicted	optional	prediction of disturbed forests
18	**LUCAS (Land-Use Change Analysis System, Land use change modules only) (Berry et al. 1996, Pearson et al. 1996)**	Spatial allocation model (with logit transition probability matrix)	- Probability of change in land cover by pixel - Land cover type by pixel (3-6 classes)	no	yes	predicted as 'unvegetated'				predicted as 'conifer' and 'Deciduous/mixed'		also grassy/brushy, water and snow/ice; additional classes can be user defined
19	**REM** (Resource Economics Model) (Hardie, Parks et al. 2000)	Econometric model (not spatially-explicit) (multinomial logit)	Predicts proportions of five categories of land use by county	no	only by county	predicted as 'urban'	predicted as 'urban'	predicted as 'urban'	predicted	predicted		"all other"
20	**Bockstael 1996**	Spatially-explicit econometric model	generates maps by parcel of: 1) residential land value and 2) probabilities of land conversion to residential land use	no	yes	predicted			predicted	predicted		

Table A-1. Model Comparison Matrix (continued)

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Model Name**	**Model Type**	**Outputs**	**How much growth / conversion**	**Where is growth/ conversion**	**Land uses predicted**						
2			**[all maps are GIS (georeferenced data) unless specified]**			**Residential**	**Commercial**	**Industrial**	**Agricultural**	**Forests**	**Protected**	**Other**
21	**Irwin, Bell, Geoghegan 2003**	spatially-explicit econometric model (empirical hazard model)	probability maps by parcel of the subdivision of an undeveloped parcel in a given period of time	no	no	predicted						Agricultural, Forests and Protected land use is all considered undeveloped in this model. Since land uses are classified as either developed or undeveloped, all of these land uses are predicted
22	**Wear and Balstad 1998**	spatially-explicit econometric model (logit)	probability maps of land use (3 classes) and building density (4 classes) by pixel		yes	predicted	predicted			predicted		forest with buildings, forest without buildings, non-forest
23	**Wear et al. 1999**	spatially-explicit econometric model (logit)	probability of commercial forestry by pixel		yes					predicted		urban commercial forestry
24	**FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)**	dynamic non-linear programming (optimization)	-Allocation of forest and agricultural land where the two compete; -Carbon sequestration resulting from different policies. Predictions by multi-state regions.	yes	no (only regional)				predicted	predicted		

Table A-1. Model Comparison Matrix (continued)

	A	M	N	O	P	Q	R	S	T
1 2	**Model Name**	**Intended User (if specified)**	**Case Study Area**	**Appropriateness to SE**	**Temporal duration of case study**	**Time step**	**Spatial Extent**	**Spatial Resolution**	**Uncertainty/ error quantified?**
3	**SLEUTH** (Slope, Land use, Exclusion, Urban, Transportation, Hillshading) (Clark 1997)	researchers and resource managers	Baltimore/DC area Mid-Atlantic (EPA R3) San Francisco, CA Santa Barbara, CA Atlanta, GA Lisbon and Porto Portugal	Has been applied to one large city in SE (Atlanta). Recalibrated model would be appropriate to other SE urban areas.	15 years	4-7 years (most recent implementation)	cities to region	variable; pixel size from 45 m - 2.6 km	Results presented as probabilities based on Monte Carlo analysis. Sensitivity of results to multiple parameters has not been done.
4	**Jenerette and Wu 2001**		Phoenix, Arizona	no application to SE	20 years using empirical parameters; 40 years using optimized parameters	1 year	cities	varies (analysis of spatial resolution was done in this study)	Monte Carlo simulation used to describe uncertainty
5	**White and Engelen 2000**	policy makers and planners	Netherlands	no application to SE	40 years (from 1989 to 2029)	1 year	national	500 m x 500 m cells	Kappa Index used to compare output to data (ratio of percent success to the expected percent success due to chance alone)
6	**Batty, Zie and Sun 1999**					user defined	user defined	user defined; up to 3000x3000 pixel grid	No
7	**DINIMACA (de Almeida et al. 2003)**		Amazonian colonization frontier	Limited applicability to the SE	8 years	1 year	Region	100 m pixels	Stochastic structure of model allows tests of uncertainty

Table A-1. Model Comparison Matrix (continued)

	A	M	N	O	P	Q	R	S	T
1 2	**Model Name**	**Intended User (if specified)**	**Case Study Area**	**Appropriateness to SE**	**Temporal duration of case study**	**Time step**	**Spatial Extent**	**Spatial Resolution**	**Uncertainty/ error quantified?**
8	**DELTA Model (Simmonds, 1999)**	transportation planner or researcher	Various Cities in Great Britain: West and South Yorkshire, East Midlands, others	primarily applied in urban landscapes so would have limited applicability to rural areas of SE	10 years	not available	city or multiple cities within a region	fine scale transportation analysis zone	No
9	**UrbanSim**	planners and policymakers	Eugene-Springfield, Oregon		15 years	1 year	metropolitan regions and surrounding areas	150 m x 150 m; cell size can be altered	No
10	**SERGoM** (Spatially Explicit Regional Growth Model)/ **WFM** (Western Futures Model) (Theobold)	planners and policymakers	Baltimore/DC Area Continental US	Has been applied to SE	40 years (from 1980 to 2020)	10 years	cities to nation	Various levels of census geography: blocks, block groups, or tracts	No uncertainty analysis available; accuracy has been reported for multiple resolutions (window sizes) combined (Theobold 2005).
11	**CUF 1 (CA Urban Futures)**	planners and policymakers	North California Bay Region	-Model is designed for an urban area in the United States -No direct application to SE		5 year	county to region	parcels	

Table A-1. Model Comparison Matrix (continued)

	A	M	N	O	P	Q	R	S	T
1 2	**Model Name**	**Intended User (if specified)**	**Case Study Area**	**Appropriateness to SE**	**Temporal duration of case study**	**Time step**	**Spatial Extent**	**Spatial Resolution**	**Uncertainty/ error quantified?**
12	**CUF-2** (CA Urban Futures) aka CURBA (Landis et al. 1998)	planners and policymakers	North California Bay Region	-Model is designed for an urban area in the United States -No direct application to SE		5 year	sub-area level (e.g. cities) to larger units (e.g. counties)	1 ha grid cells	
13	**CLUE** (Conversion of Land Use and its Effects) **CLUE-S** (Conversion of Land Use and its Effects at Small regional extent) (Verburg) CLUE-CR (Veldkamp and Fresco 1996?? According to Agarwal)	planner in developing country	-Costa Rica -Honduras -Ecuador -China -Java (Indonesia) -Sibuyan Island (Philippines) -Malaysia -Vietnam -Venezuela	Not readily applied to SE		1 year	country; region (CLUE-S)	balances national demand with local planning/constraints	
14	**Land Transformation Model**		Michigan's Grand Traverse Bay Watershed	possible adaptability	40 years	decades	county	100m x 100m cells	quantified proportion that correctly transitioned
15	**Yankee, D. 2005**	government managers and researchers	Applied to 15-county region surrounding Charlotte, NC	Has been applied to several counties in SE	25 years	25 years	15 county region	transportation analysis zone; or user specified	No
16	**What If? (Klosterman)**	community planner		Has been applied to one or more counties in South Carolina		10 year	cities	"uniform analysis zones" similar to transportation analysis zones	No

Table A-1. Model Comparison Matrix (continued)

	A	M	N	O	P	Q	R	S	T
1 2	**Model Name**	**Intended User (if specified)**	**Case Study Area**	**Appropriateness to SE**	**Temporal duration of case study**	**Time step**	**Spatial Extent**	**Spatial Resolution**	**Uncertainty/ error quantified?**
17	**GEOMOD2 (Pontius Jr. et al. 2001)**		Costa Rica	Not readily applied to SE	30 - 40 years	annual	sub-regional to regional	pixel size of 2 km	Error quantified in terms of Kappa index
18	**LUCAS (Land-Use Change Analysis System, Land use change modules only) (Berry et al. 1996, Pearson et al. 1996)**	researchers	Forested landscapes in - Southern Appalachian Highlands (focus on Little Tennessee River Basin, NC) and - Olympic Peninsula, WA	applied to forested highland areas of the SE, not appropriate for urban areas	16 years	5 years	multiple watersheds	90 x 90 m cells	Error term available from statistical model component
19	**REM** (Resource Economics Model) (Hardie, Parks et al. 2000)	researchers	U.S. South, Mid-Atlantic region	Has been applied to southeast	18 years	na	county to region	county	Error term and fit statistics available from statistical model
20	**Bockstael 1996**		Patuxent River Watershed, Maryland	Model designed specifically for the Patuxent River Watershed; no application to SE			watershed	parcel	Error term and fit statistics available from statistical model

Table A-1. Model Comparison Matrix (continued)

	A	M	N	O	P	Q	R	S	T
1 2	**Model Name**	**Intended User (if specified)**	**Case Study Area**	**Appropriateness to SE**	**Temporal duration of case study**	**Time step**	**Spatial Extent**	**Spatial Resolution**	**Uncertainty/ error quantified?**
21	**Irwin, Bell, Geoghegan 2003**	Local & State governments	Calvert County, Maryland		7 years	flexible, but multi-year	county	parcel	Error term and fit statistics available from statistical model; multiple statistical techniques compared
22	**Wear and Balstad 1998**	resource managers, planners	Southern Appalachian Highlands	Has been applied to highland areas of the southeast; may not be appropriate for lowlands	40 years	na	local to regional	Finest resolution of data inputs was 30 m cell and 1:20,000	Evaluated by comparing to null model and estimating information gain; Error term and fit statistics available from statistical model
23	**Wear et al. 1999**	forestry managers and policy-makers	Virginia, US	Has been applied to rural areas of the southeast	not specified	na	local to multi-county	1:24,000	Error term and fit statistics available from statistical model
24	**FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)**	forestry and agricultural policymakers; focus is on carbon sequestration; benefits measured as consumer and producer surpluses (welfare)	Continental US, divided into 11 supply regions with one national demand	Has been applied to SE region	100 years for demand projections; 50 years for policy scenario supply results.	decade	national and regional	11 regions of the continental US; could be spatially allocated based on forest stand age and condition	No

Table A-1. Model Comparison Matrix (continued)

	A	U	V	W	X
1 2	**Model Name**	**Major Strengths (e.g., ease of use, ability to model policies)**	**Major Limitations (ease of use, ability to model policies)**	**Required Data Inputs (spatial data unless otherwise specified)**	**Method of adapting model (statistical fit / calibration / BPJ)**
3	**SLEUTH** (Slope, Land use, Exclusion, Urban, Transportation, Hillshading) (Clark 1997)	- Relatively easy to transfer among regions if model is not recalibrated (as done by Clagett et al. 2004) - Can incorporate many different land use classifications systems, because classifications are user-defined - Use of probabilistic estimation allows model to generate continuous measure of density of development (if interpreted as such) - Can respond to new conditions because model includes a means to generate new growth areas as a function of roads, or randomly, in addition to growth based on historic pattern - Has active group of users from which to draw support	- Designed for urban settings; does not perform well in low-density areas - Data demands may be high for areas requiring new model calibrations; Input data of continuous measure of development at multiple time periods may not be readily available - Uncalibrated model would produce more error than than recalibrated model - Somewhat difficult to use: users need familiarity with UNIX and optimization methods for calibration; outputs can be difficult to interpret (e.g., explanations for unexpected behavior) - Most policy scenarios cannot be directly modeled due to lack of economic drivers	- Land use (multiple time periods) - Continuous measure of development such as impervious surface cover (optional but helpful) - Road networks (multiple time periods) - Slope (%) - Undevelopable land (e.g., from zoning, or inferred from slopes, protected land, water, wetlands, etc.) - Other data needs depend on case study	Calibration to time series of land use data and roads (script available to automate process)
4	**Jenerette and Wu 2001**	- Minimal data requirements; data readily availble - Simple framework worked well in desert landscape - Inputs are updated frequently within the simulation (annual time step) allowing feedbacks to be modeled.	- Limited transferability to landscapes where multiple types of users compete for land (ag, forestry, residential, commercial). - Limited number of policies can be evaluated (primarily handles land protection policies)	Elevation and slope Land use/Land cover data Census data (Population records)	statistical fit and calibration
5	**White and Engelen 2000**	-Able to examine the effects of economic and other policy changes on land use change (uses economic projections directly) - Minimal data demands - Incorporates spatial interactions	- Developed for densely populated area, may not be suitable for rural areas - Limited documentation available	-land use maps - slope, -soil quality, -zoning regulations - roads -others (unspecified)	Unknown. Transition rules not described.
6	**Batty, Zie and Sun 1999**	- Software is simple to use - General model can be easily transfered among regions. A wide range of model types can be defined to simulate different types of urban land use (commercial retail and services, residential, industry, transportation) - GUI displays results	- Model framework is highly simplified and aggregated, limiting its realism - Limited ability to model policy scenarios due to aggregated model structure	proportions and densities of land uses (required) other data needed depending on optional configurations	transition rules between land use types are user-defined
7	**DINIMACA (de Almeida et al. 2003)**	- Data are all readily accessible - Able to model conditions that diverge from historical norms - Sophisticated techniques used to model transition probabilities - spatial interactions captured	- Moderately difficult to use and transfer among regions - Has only been used in developing countries - Limited ability to model policies due to lack of conceptual model behind statistical model of transition probabilities	land-use/land cover map (multiple time periods) soil vegetation altitude slope rivers roads city centers	Refit logistic (statistical) transition model

Table A-1. Model Comparison Matrix (continued)

	A	U	V	W	X
1 2	**Model Name**	**Major Strengths (e.g., ease of use, ability to model policies)**	**Major Limitations (ease of use, ability to model policies)**	**Required Data Inputs (spatial data unless otherwise specified)**	**Method of adapting model (statistical fit / calibration / BPJ)**
8	**DELTA Model (Simmonds, 1999)**	- High degree of precision in terms of incorporating relevant variables - Although model is complex, the modular structure may allow components to be separated for individual use -Model structure allows some policy scenarios to be directly modeled -Employment modeled by location -Designed to provide inputs to transportation demand model	-High data demands; data not readily available -Designed for metropolitan and surrounding areas only -Structure difficult for users to understand and manipulate -Model complexity limits ability of planners to understand results	Inputs needed for urban location model only: job locations roads public sector development projects microdata on: housing and household demographic characteristics	Re-estimation needed for components of model, calibration may also be necessary.
9	**UrbanSim**	-Structure allows multiple types of policies to be explored because household and real estate development decisions are directly modeled - High degree of precision - Employment locations modeled -Designed to provide inputs to transportation demand model	-High data demands; data not readily available -Designed for metropolitan and surrounding areas only -Structure difficult for users to understand and manipulate - Rigid model structure, not adaptable to conditions outside those used in model creation -Model complexity limits ability of planners to understand results - Output must be imported into GIS for viewing	-Parcel files (from tax assessor offices) -business establishment files -census micro-data (PUMS) -Environmental, political, and planning boundaries -location grid -control totals from economic regional forecasts -travel access indicators from external transportation model -scenario policy assumptions	Calibration; statistical refit of more than one equation
10	**SERGoM** (Spatially Explicit Regional Growth Model)/ **WFM** (Western Futures Model) (Theobold)	- Easy to transfer among regions - Minimal data requirements, data readily accessible - Moderately easy to run - Easy to understand model and interpret results - Generates continuous measure of density of development - Models both urban and rural areas - Growth rules able to generate new urban cores	- Only residential density has been predicted - Does not provide for redevelopment and may underestimate infill - Most policy scenarios cannot be directly modeled due to lack of economic drivers	- Housing density (at least 2 time periods) - Undevelopable land based on: - slopes - protected land - water and wetlands - Roads - City centers	Calibration (manual)
11	**CUF 1 (CA Urban Futures)**	-Outputs are easy to read -Relatively easy to model environmental policy scenarios	-Limited land uses; -Does not address effects from changes in infrastructure or fiscal policies; -Does not allow for urban infill -Technical expertise (knowledge of UNIX and programming language) is necessary for calibration of the model	-Boundary lines of counties and local governments -Bodies of water -Rail Transit -Slope -Marsh and Wetlands -Non-urbanized land -Sewers and Water system -TIGER maps of roads -Historical population growth -Locations of currently undeveloped sites	Calibration

Table A-1. Model Comparison Matrix (continued)

	A	U	V	W	X
1 2	**Model Name**	**Major Strengths (e.g., ease of use, ability to model policies)**	**Major Limitations (ease of use, ability to model policies)**	**Required Data Inputs (spatial data unless otherwise specified)**	**Method of adapting model (statistical fit / calibration / BPJ)**
12	**CUF-2** (CA Urban Futures) aka CURBA (Landis et al. 1998)	-Easy to run once installed and calibrated -Models several types of urban growth (residential, commercial, and industrial), incorporates changes in infrastructure, and allows for re-development -Uses econometric models to project future employment	-Significant data requirements -Somewhat difficult to calibrate (requires advanced statistics) -Designed for metropolitan areas only	-Urban land uses (for 2 time periods) -Slope -Publicly owned lands -Wetlands -City boundaries -Spheres of influence (User defined) -Urbanization and agricultural land quality -General plan designations -Roads -Rail transit	calibration
13	**CLUE** (Conversion of Land Use and its Effects) **CLUE-S** (Conversion of Land Use and its Effects at Small regional extent) (Verburg) CLUE-CR (Veldkamp and Fresco 1996?? According to Agarwal)	- Incorporates numerous economic drivers into model agricultural land use change -CLUE-S economic demand module is flexible and can incorporate complex economic models that allow various policies to be evaluated	-Data demands can be high but flexible Data intputs allowed -Primarily designed for national use in developing countries	-land use represented as % coverage within grid cell (e.g., cell is 40% forest, 20% residential, 40% ag) -maps containing biophysical data such as soil conditions, relief and climate -CLUE-S uses finer scale raster data -- each cell has the value of the dominant lu type within the cell;	Refit of statistical model (3 time steps)
14	**Land Transformation Model**	- Minimal data requirements, data readily accessible - Moderately easy to adapt to different regions - Designed to forecast over large regions	-Predicts growth as a lumped 'urban' category -Most policy scenarios cannot be directly modeled due to lack of economic drivers -Requires training and technical experience with land use modeling to calibrate and run; -Data preprocessing steps are extensive, but data inputs are readily available for the most part	-land use types -roads, - rivers, - shorelines - locations of recreational sites -Elevation □	Refit statistical relationships and recalibrate neural network
15	**Yankee, D. 2005**	- relatively easy to transfer to new regions - modest data needs - easy to understand - allows for land redevelopment based on economic criteria	- Most policy scenarios cannot be directly modeled due to lack of most economic drivers	initial land use and density available land area (from parcel data) parcel land values	Best professional judgement used to alter some parameters
16	**What If? (Klosterman)**	- Easy to run; highly automated software - Model structure easy to understand - Has the ability to incorporate detailed economic information but up to the user to provide this information and develop relationships to land suitability for developed uses; - Incorporates both population growth and economic growth	-Depends on best professional judgment rather than data fitting - Lacks a theoretical basis for combining variables to predict growth - Does not directly incorporate spatial interactions such as accessibility to employment -Designed primarily for single municipalities not broad regions - Most policy scenarios cannot be directly modeled due to lack of most economic drivers	-Many data inputs are optional but are likely to include: - Land use - Slopes - Soils - Natural features (water bodies, views) - Zoning - Planned development - Existing and planned Infrastructure (sewer, water) - Administrative boundaries - Undevelopable areas - Vacancy rates - Other data	BPJ

Table A-1. Model Comparison Matrix (continued)

	A	U	V	W	X
1 2	**Model Name**	**Major Strengths (e.g., ease of use, ability to model policies)**	**Major Limitations (ease of use, ability to model policies)**	**Required Data Inputs (spatial data unless otherwise specified)**	**Method of adapting model (statistical fit / calibration / BPJ)**
17	**GEOMOD2 (Pontius Jr. et al. 2001)**	- Minimal data needs - Adaptable to any geography depending on data availability - Simple to run	-Land use change is only binary change (disturbed vs. undisturbed forest) - Oriented towards deforestation disturbance not necessarily urban growth or specific activities (developing country case study) - limited ability to directly model policy scenarios	- Climate zone / vegetation type - Elevation - Soil type - precipitation - Potential land-use other inputs are optional	no method required
18	**LUCAS (Land-Use Change Analysis System, Land use change modules only) (Berry et al. 1996, Pearson et al. 1996)**	-Modest data needs - Simple model to understand -Already adapted to part of the SE region	- Intended use is forested areas; not appropriate for urban areas - Not all data readily available (vegetation classes were interpreted from satellite imagery) ownership may be difficult to obtain regionally - Limited ability to directly evaluate policy scenarios due to limited number of behavioral or economic drivers	-Land cover type (vegetation) -Slope -Elevation -Roads -Market centers -Population Density -Land ownership (land value optional) -Age of trees	Statistical refitting of transition probability relationships
19	**REM** (Resource Economics Model) (Hardie, Parks et al. 2000)	-Relatively simple to use given adequate statistical software; -Can easily be adapted to any region using regional datasets -Appropriate for modeling policies related to changes in agricultural policies	-Model is not spatially explicit below the county scale -All urban land use categories are lumped -No urban densities are generated -Assumes no land redevelopment -Limited ability to model policies aimed at changing urban development patterns	-Population density -Personal income -Per acre crop revenues -Per acre market value of livestock -Proportion of land in each of two condition classes -Per acre cost of crop production -Average age of farm operator -Percent of farm operators listing farming as their principal occupation	Re-fit of statistical model; potential re-specification of model
20	**Bockstael 1996**	- Many policy options can be directly modeled - Relationships between explanatory and dependent variables are explicitly tested - Explanatory power easily understood	-Residential conversions only - Significant data demands, data not all readily available - Difficult to transfer to new areas because of data demands and need to redefine and refit model	- housing density - land use - census demographic variables - availability of public services (sewer, water) - growth management policies - enrollment in agricultural preservation program - prime farmland - soil types - property tax rates - slope - town center and major business districts - zoning - protected land - Priority funding areas	statistical fit

Table A-1. Model Comparison Matrix (continued)

	A	U	V	W	X
1 2	**Model Name**	**Major Strengths (e.g., ease of use, ability to model policies)**	**Major Limitations (ease of use, ability to model policies)**	**Required Data Inputs (spatial data unless otherwise specified)**	**Method of adapting model (statistical fit / calibration / BPJ)**
21	**Irwin, Bell, Geoghegan 2003**	- Many policy options can be directly modeled - Relationships between explanatory and dependent variables are explicitly tested	- Only residential subdivisions modeled - Significant data demands, data not all readily available - Difficult to transfer to new areas because of data demands and need to redefine and refit model	- housing density - land use - census demographic variables - availability of public services - growth management policies - enrollment in agricultural preservation program - prime farmland - soil types - property tax rates - Critical Area (restricted zoning area) - slope - town center and major business districts - zoning - protected land - Priority funding areas	statistical fit and BPJ
22	**Wear and Balstad 1998**	- Complements models of urban development by considering land use in rural forested areas	- May not produce a consistent model that can be applied regionally - Limited number of land use classes were tested because intended for heavily forested areas - Methods depend on time-consuming data development unless substitute data are used	-land cover at two time periods -roads -building locations (manually digitized by authors); building density is alternative -city centers -elevation and slope	Statistical refit using two time periods of land cover data
23	**Wear et al. 1999**	- Relatively simple model for predicting commercial forestry - Evaluates effect of population growth on viability of commercial operations	- Limited to one specific land use in specific landscape settings - Policy scenarios could only be imposed as a limit on total commercial forestry or by excluding land from consideration	-Maps of commercial forestry likelihood (developed from expert opinion) -Population per square mile -Site index (forest condition from USDA Forest Inventory) -Slope -Two dummy variables defining ease of access to a site	Statistical refit
24	**FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)**	- Uses economic drivers of land demand: agricultural prices and marginal profitability of land in alternative forest and agricultural uses. -Supply and demand are dynamically calculated based on changing conditions; allows the model to analyze conditions that fall outside the range of historical observations. -Able to directly model policy scenarios such as: limits on harvest age, effects of bio-energy production displacing fossil fuel consumption, changes in paper recycling	- Not spatially explicit, but results can be distributed spatially using site information - Economic model will be difficult for some to understand - Data are not regionally available at fine scale - Model not intended to be run by those untrained in economic optimization	-Timber age structure -Management regime -Site condition -Ownership -Suitability for agriculture	Results have been generated for SE

Table A-1. Model Comparison Matrix (continued)

	A	AA	AB	AC	AE
1 2	**Model Name**	**Infrastructure inputs?**	**Availability**	**Cost**	**Sources**
3	**SLEUTH** (Slope, Land use, Exclusion, Urban, Transportation, Hillshading) (Clark 1997)	roads	online -- http://www.ncgia.ucsb.edu/projects/gig/download.htm	free	http://www.ncgia.ucsb.edu/projects/gig/; http://www.whrc.org/midatlantic/modeling_change/SLEUTH/sleuth_overview.htm; - Clark, K.C., L. Gaydos, S. Hoppen, 1997. A self-modifying cellular automaton model of historicla urbanization in the San Francisco Bay area. Envrion. Plann. B 24:247-261 - USEPA. 2000. Projecting Land Use Change: A Summary of Models Assessing the Effects of Community Growth and Change on Land-Use Patterns. National Exposure Research Lab, Washington, DC. (E:\ReVA_R4\Task2LitReview\EPA_reviews\EPA_LULC_Model_Review.pdf) - Claggett, P.R., C.A. Jantz, S.J. Goetz, and C. Bisland. 2004. Assessing development pressure in the Chesapeake Bay Watershed: an evaluation of two land-use change models. Environmental Monitoring and Assessment 94: 129-146.
4	**Jenerette and Wu 2001**	no			Jenerette, G.D. and J. Wu 2001. Analysis and simulation of land-use change in the central Arizona – Phoenix region, USA. Landscape Ecology 16(7):611-626
5	**White and Engelen 2000**				- White, R. and G. Engelen 2000. High-resolution integrated modeling of spatial dynamics of urban and regional systems. Computers, Environment, and Urban Systems 24:383-400. - White, R. and G. Engelen 1997. Cellular automata as the basis of integrated dynamic regional modeling. Env. Plann. B 24:235-46 - White, R., G. Engelen, I Uljee, 1997. The use of constrained CA for high-resolution modeling of urban land-use dynamics. Environ. Plann. B 24:323-343. - Irwin and Geoghegan, 2001. - Parker, et al., 2003.
6	**Batty, Zie and Sun 1999**		Software available		Parker et al. 2003 -Batty, M., Y. Xie, and Z. Sun. 1999. Modeling urban dynamics through GIS-based cellular automata. Computers, Environment, and Urban Systems 23 (3): 205–33.
7	**DINIMACA (de Almeida et al. 2003)**	roads	online -- http://www.csr.ufmg.br/dinamica/	Contact developer	-Soares-Filho, B. S., Cerqueira, G. C., & Pennachin, C. L. (2002). DINAMICA—a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. Ecological Modelling, 154, 217–235. -Almeida, C. M., Batty, M., Monteiro, A. M. V., C^amara, G., Soares-Filho, B. S., Cerqueira, G. C., & Pennachin, C. L. (2003). Stochastic cellular automata modelling of urban land use dynamics: empirical development and estimation. Computers, Environment and Urban Systems, 27(5), 481–509.

Table A-1. Model Comparison Matrix (continued)

	A	AA	AB	AC	AE
1 / 2	**Model Name**	**Infrastructure inputs?**	**Availability**	**Cost**	**Sources**
8	**DELTA Model (Simmonds, 1999)**		Not available for off the shelf purchase -- contact developer	Contact deve	-Simmonds, DC, 1999, "The Design of the DELTA land-use modelling package" Environment and Planning B: Planning and Design. 26(5): 665-684 -Simmonds, David and Olga Feldman, 1999. Land-Use Modelling with DELTA: Update and Experience. Environment and Planning B: Planning and Design. 665-684 -Feldman, Olga, Dimitris Ballas, Graham Clarke, Phil Gibson, Jianhui Jin, David Simmonds, John Stillwell, 1999. A Spatial Microsimulation Approach to Land-Use Modelling. Paper for presentation to CUPUM 2005, London.
9	**UrbanSim**	Roads	http://www.urbansim.org	free	-Waddell, Paul. 2002. UrbanSim: Modeling Urban Development for Land Use, Transportation and Environmental Planning. Preprint of an article that appeared in the Journal of the American Planning Association. 68(3):297-314
10	**SERGoM** (Spatially Explicit Regional Growth Model)/ **WFM** (Western Futures Model) (Theobold)	roads	Methods are published; contact developer for additional information	free	- Theobald, D.M., 2005. Landscape patterns of exurban growth in the USA from 1980 to 2020. Ecology and Society 10: 32. - Claggett, P.R., C.A. Jantz, S.J. Goetz, and C. Bisland. 2004. Assessing development pressure in the Chesapeake Bay Watershed: an evaluation of two land-use change models. Environmental Monitoring and Assessment 94: 129-146.
11	**CUF 1 (CA Urban Futures)**	roads, sewer and water systems	Not available for off the shelf purchase -- contact developer	Contact developer	-Landis, J.D. 1994. The California Urban Futures Model: a new generation of metropolitan simulation models. Environment and Planning B: Planning and Design 21:399-420. -Landis, J.D. 1995. Imagining Land Use Futures: Applying the California Futures Model. Journal of the American Planning Association 61:438-457. - Agarwal et al. 2000 -USEPA. 2000. Projecting Land Use Change: A Summary of Models Assessing the Effects of Community Growth and Change on Land-Use Patterns. National Exposure Research Lab, Washington, DC.

Table A-1. Model Comparison Matrix (continued)

	A	AA	AB	AC	AE
1 2	**Model Name**	**Infrastructure inputs?**	**Availability**	**Cost**	**Sources**
12	**CUF-2** (CA Urban Futures) aka CURBA (Landis et al. 1998)		Not available for off the shelf purchase -- contact developer	Contact developer	-Landis, J. and M. Zhang. 1998. The second generation of the California urban futures model. Part 1: Model logic and theory. Environment and Planning B: Planning and Design 25:657-666. -USEPA. 2000. Projecting Land Use Change: A Summary of Models Assessing the Effects of Community Growth and Change on Land-Use Patterns. National Exposure Research Lab, Washington, DC. (E:\ReVA_R4\Task2LitReview\EPA_reviews\EPA_LULC_Model_Review.pdf) - Agarwal et al. 2000
13	**CLUE** (Conversion of Land Use and its Effects) **CLUE-S** (Conversion of Land Use and its Effects at Small regional extent) (Verburg) CLUE-CR (Veldkamp and Fresco 1996?? According to Agarwal)	No	Not available for off the shelf purchase -- contact developer		- Verburg, P.H., G.H.J. de Koning, K. Kok, A. Veldkamp, and J. Bouma. 1999. A spatial explicit allocation procedure for modeling the pattern of land use change based upon actual land use. Ecological Modeling 116:45-61. - Verburg, P.H, W. Soepboer, A. Veldkamp, R. Limpiada, V. Espaldon, and S.S.A. Mastura. 2002. Modeling the spatial dynamics of regional land use: the CLUE-S Model. Environmental Management 30:391-405. - Agarwal et al. 2002
14	**Land Transformation Model**		Contact developer http://www.ltm.msu.edu	free	-Pijanowski, Bryan C., David G. Brown, Bradley A. Shellito, Gaurav A. Manik, 2002. Using neural networks and GIS to forecast land use changes: a Land Transformation Model. Computers, Environment and Urban Systems 26: 553-575.
15	**Yankee, D. 2005**	No	Contact developer		-Yankee, Dennis, 2007. Tennessee Valley Authority. Personal communication.
16	**What If? (Klosterman)**	new/planned roads new/planned sewer and water	Available through What if?, Inc (http://www.what-if-pss.com)	Professional -- $2,950 for single user, $1,500 for additional user, or $6,000 for 5 users, $10,000 for 10 users; Free demo CD available	http://www.what-if-pss.com/purchase.html - Klosterman, R.E., 1998. The What If? Collaborative Planning Support System. (draft of Klosterman, R.E., 1999. The What If? Collaborative Planning Support System. Environment and Planning, B: Planning and Design 26:393-408.) - USEPA. 2000. Projecting Land Use Change: A Summary of Models Assessing the Effects of Community Growth and Change on Land-Use Patterns. National Exposure Research Lab, Washington, DC. (E:\ReVA_R4\Task2LitReview\EPA_reviews\EPA_LULC_Model_Review.pdf)

Table A-1. Model Comparison Matrix (continued)

	A	AA	AB	AC	AE
1	**Model Name**	**Infrastructure inputs?**	**Availability**	**Cost**	**Sources**
2					
17	**GEOMOD2 (Pontius Jr. et al. 2001)**	roads	Methods published		Pontius, Jr. R. Gilmore, Cornell, Joseph D., Hall, Charles A.S. Modeling the Spatial Pattern of Land-use Change with GEOMOD2: Application and Validation for Costa Rica. 2001. Agriculture, Ecosystems and Environment. 1775:1-13. https://prism.clarku.edu/~rpontius/pontius_etal_2001_aee.pdf
18	**LUCAS (Land-Use Change Analysis System, Land use change modules only) (Berry et al. 1996, Pearson et al. 1996)**	roads	Contact developer	free	- Berry, Michael W., Brett C. Hazen, R. L. MacIntyre, and Richard O. Flamm. 1996. LUCAS: A System for Modeling Land-Use Change. *IEEE Computational Science and Engineering* 3(1):24. - Agarwal et al. 2002 - Turner, Monica G., David N. Wear, and Richard O. Flamm, 1996. Land Ownership and Land-Cover Change in the Southern Appalachian Highlands and the Olympic Peninsula. *Ecological Applications* 6(4):1150-1172
19	**REM** (Resource Economics Model) (Hardie, Parks et al. 2000)		Methods published	free	- Hardie, I., P. Parks, P. Gottleib, and D. Wear. 2000. Responsiveness of rural and urban land uses to land rent determinants in the U.S. South. Land Economics 76: 659-673. - Jackson, L.E., S.L. Bird, R.W. Matheny, R.V. O'Neill, D. White, K.C. Boesch, and J.L. Koviach. 2004. A regional approach to projecting land-use change and resulting ecological vulnerability. Environmental Monitoring and Assessment 94: 231-248.
20	**Bockstael 1996**	roads, sewer systems	Methods published		Bockstael, Nancy. 1996. Modeling Economics and Ecology: The Importance of a Spatial Perspective. American Journal of Agricultural Economics 78(5):1168-1180.

Table A-1. Model Comparison Matrix (continued)

	A	AA	AB	AC	AE
1 / 2	**Model Name**	**Infrastructure inputs?**	**Availability**	**Cost**	**Sources**
21	**Irwin, Bell, Geoghegan 2003**	roads, sewer systems	Methods published	Free	Irwin, E.G., K.P. Bell, and J. Geoghegan, 2003. Modeling and managing urban growth at the rural-urban fringe: A parcel-level model of residential change.Ag and Res Econ Review 32(1):83-102
22	**Wear and Balstad 1998**	roads	Methods published	Free	Wear and Bolstad
23	**Wear et al. 1999**	no	Methods published	Free	Wear et al. 1999
24	**FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)**	no	Results available for SE		Agarwal et al. 2002 Adams, Darius M.; Alig, Ralph J.; Callaway, J.M.; McCarl, Bruce A.; Winnett, Steven M. 1996. The forest and agricultural sector optimization model (FASOM): model structure and policy applications Res. Pap. PNW-RP-495. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 60 p..