Development of a Prototype Land Use Model for Statewide Transportation Planning Activities

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Disclaimer

Metric Conversion Table

Approximate conversions to SI (Modern Metric) units

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
AREA				
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2

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16. Abstract

Future land use forecasting is an important input to transportation planning modeling. Traditionally, land use is allocated to individual traffic analysis zones (TAZ) based on variables such as the amount of vacant land, zoning restriction, land use planning and policy limitations, and accessibility, under an externally estimated control number in population and employment growth at the county level. This land use allocation approach does not consider agglomeration factors, the market equilibrium of supply and demand, and is not sensitive to different land use and transportation policy changes. To overcome the limitations of this conventional approach, this research project uses a new analytical approach, i.e., a combination of cellular automata (CA) and agent-based modeling methods to estimate future land use allocation.

CA models have been used extensively in modeling and simulating complicated spatio-temporal processes like land use change. It can model the changes of land use patterns over time and can simulate a variety of spatial processes and influences relevant for land use changes. Agent-based models represent the interactions of different decision-making entities. The agent-based model provides a flexible representation of heterogeneous decision makers or agents, whose behaviors are potentially influenced by interactions with other agents and with their natural and built environment.

This study uses CA to capture the spatial relationships (e.g., clustering) of land development, as well as agglomeration factors. CA represents complicated systems well and is thus a good method to show changes of land use patterns. However, the CA model alone cannot sufficiently explain the changes, because CA model is not sensitive to policy variables. Thus, the study also uses agent-based models to capture the behavior of each agent, which makes it sensitive to policy changes. Agent-based models, unlike CA, can model individual decision-making entities' behavior as well as their interactions. In addition, this study applies multinomial logit (MNL) model to formulate the CA transition rule for different land types, which estimates the probability of future land use for each cell. Therefore, the model this study developed is an MNL-CA-Agent land use model, which is called LandSys.

In the developed LandSys model, land use changes are performed by the CA model, with external drivers as agents. These agents include: employer, household, developer and government. The model is estimated and validated using a cell-based representation of land (50m x 50m). Then the estimated land use changes can be plugged into Florida Standard Urban Transportation Modeling Structure (FSUTMS) models as updated inputs. In response, FSUTMS models update their demand modeling of the transportation system. The updated traffic information (e.g., accessibility) is then fed back to the LandSys to capture the interaction between land use and transportation and generate more accurate simulation results. LandSys simulates land use change at multiple spatial and temporal scales, as well as representing decision making behaviors of households, employment, developers, and government policies. Future land use patterns and socioeconomic data can be produced to update those inputs of the transportation model. Policy scenarios, such as mixed land use growth management policies, can be simulated and analyzed for decision makers.

The major advantage of this modeling approach is its integration with FSUTMS models. The feedback cycle between land use and transportation models can simulate the interactions between the two. This study employs three indicators to compare the simulation accuracy between the integrated framework and standalone FSUTMS models, including link saturation in the transportation network, overall vehicle miles traveled (VMT), and vehicle hours traveled (VHT). The results show that the inclusion of the land use and transportation feedback in the integrated modeling framework produces better results than the land use or transportation model alone, can help modelers better simulate land use-transportation system, and help decision makers better understand the consequences of different scenarios of the land use and transportation planning.

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Executive Summary

Land use information is essential for transportation demand modeling, and land use modeling is critical for producing future land use information. In 2009, the Florida Department of Transportation (FDOT) Central Office surveyed FDOT and MPO modelers asking for input on the current state of modeling. Land use modeling and integrated land use and transportation modeling are identified as the top priority for future modeling development in the state of Florida.

Traditional land use models, like Lowry and Lowry-type models, allocate land use based on the amount of vacant land, zoning, accessibility, land use policies and constraints (e.g., urban growth boundaries, land conservation) at individual traffic analysis zones (TAZ), and population and employment growth at the county level. Agglomeration factors and market equilibrium of land supply and demand, which are important in integrated land use and transportation modeling [1], are not adequately considered. To address these issues, this study presents a prototype land use model based on an integrated Cellular Automata (CA) and Agent-based Model to simulate the temporal and spatial dynamics of interactions of land use and transportation. Data from Orange County, Florida, is used as a case study.

The land use model is based on the 50m x50m cell grid, using CA model to capture the influence of land characteristics (e.g., slopes and neighboring land use types) and accessibility (e.g., travel time or distance to major transportation facilities) on land use changes, and agent-based models to model behaviors of individual decision maker or agent. The market equilibrium of land demand and supply is based on the bid-rent theory.

Land use change is related to several factors. In this study, the spatial factors are handled by the CA model, while other external drivers are treated as agents. The land development equilibrium is formulated as two integer linear problems to combine CA and Agents results to generate the land use change at cell level for next year. The bid-rent based land use supply-demand market equilibrium is used to produce the household and employment results at TAZ level. The use of agent-based model (e.g., household, employment, and developer agent） in CA models is beneficial. CA analyzes the spatial suitability of land use change, while the agent models represent policy making and cumulative effects of many micro decision-making entities on land use dynamics.

The CA Model is used in spatial suitability analysis of land change. The spatial properties include: (1) the physical attributes of land cell, including soil quality and slope; (2) the number of developed cells in Moore neighborhoods; and (3) the local spatial attributes, including transportation accessibility, and distance to specific areas (e.g. Central Business District (CBD), shopping centers, education institutes and other main public facilities). The regression results of the CA model offer several valuable empirical findings. For example, for vacant cells, the closer to CBD, the more likely to be changed to commercial land. In the case of neighborhood attributes, the positive coefficient suggests that if a cell is surrounded by more residential cells in the Moore neighborhoods, it will be more likely to be developed into residential land, reflecting the clustering development phenomenon.

CA models have limited ability to reflect socioeconomic representations and decision making processes, since the models focus on simulating the change in the state of individual cells based mainly on the characteristics of neighboring cells [2]. It is difficult to incorporate human decision making into these models. Torrens argues that these drawbacks provide motivation to integrate agent simulation [3]. Agent-based models can model individual decision-making entities' behavior as well as their interactions. Therefore, when modeling land use change, the Multi-Agent method is used to capture the behavior of households, employers, developers, and other factors of governmental policies and economics. In our model, the agents include government, transportation, household, employment, and developer.

It is assumed that the urban land market functions by an auction mechanism where the real estate/land parcel is assigned to the highest bidder. In the land market, the behaviors of developers constitute the market supply, whereas the household and employment agents form the market demand. Under equilibrium conditions, the land price is generated with the bid-rent theory. From the interactions between market demand and supply, land use prices are updated and provide feedback to the land use forecasting model for the next time period.

Take the household agent for example. From the calibrated results of the household mobility model, the probability of the household's willingness to moving decreases with the increase of household size and with the presence of school-age children and people older than 50. Increases in the number of workers in the household, income, and vacant dwelling units enhance household mobility. In the household location choice model, the willingness-to-pay function was calibrated with both 1990 and 2000 data. The calibration results show that the number of commercial, institutional, residential cells in neighborhoods had a positive effect on household location choice. Total travel time for all purposes has a negative impact, which means that, when evaluating the potential future land use of a vacant cell, long travel times to the location would reduce the possibility of developing into commercial and residential land uses.

To capture the interaction between land use and transportation, a feedback loop is introduced in the LandSys program. The output of land use forecasting and allocation models provides the input to the trip generation step of the travel forecasting model, and the accessibility and travel time resulting from the transportation demand forecasting model are then fed back to and become the input of the land use model.

The introduction of the feedback loop has increased the accuracy of the land use model. This research experimented with two approaches to the CA model: one using the multinomial logit (MNL) model (or MNL-CA-Agents model), the other using artificial neural networks (or the ANN-CA-Agents model). The results are very similar, as shown by an accuracy of 87.6% for the MNL-CA-Agents model and that of the ANN-CA-Agents model of 87.7%. Because the ANN models employ a "black box" technique, which makes it difficult to test the effects of policy intervention, the MNL-CA-Agent land use model provides a more clear relationship between spatial variables and land use change, allowing for a better interaction with Florida Standard Urban Transportation Model Structure (FSUTMS). For the MNL-CA-Agent land use model, most allocation errors fell within a range of [-50, 50] for households (~52% of cells) and employment (~37% of cells). At the TAZ level, the model predicts changes in household and employment with accuracies of 75.7% and 69.9%, respectively, considering the error ranges within ±200.

To evaluate the performance of the integrated land use and transportation model, three indicators -- link saturation in the transportation network, overall vehicle miles traveled (VMT), and vehicle hours traveled (VHT)-- are used to compare the results of the integrated model and the traditional transportation demand modeling alone. Four scenarios were examined for Orange County in 2000, 2012, and 2025: business-as-usual, land use integration model, urban growth boundary options, and mixed land use. The results show that in the integrated model, the values of the three indicators are lower than those predicted by standalone FSUTMS models, that indicates the transportation model alone without the land use model produces higher VMT and VHT. In addition, this also shows that the standalone land use model without the accessibility feedback produces fewer households and employments in the center of the study area and more at the edge of the city than that estimated by the integrated model.

This study shows that the LandSys is capable of producing accurate land use change results, is able to capture the decision makers' behavior, and is sensitive to policy changes and transportation accessibility and travel time changes. The next step is to create a user-friendly graphical interface to integrate the LandSys model into the transportation demand modeling (e.g., FSUTMS model), and to automate the land use-transportation feedback loop. The ultimate vision is to create a new function inside

the FSUTMS using Cube Voyage so that transportation modelers can model the land use changes and integrate the land use model results into the transportation model, and the results of the transportation demand modeling results can be automatically fed back into the land use model, to achieve a fully automatic and seamless process.

Key words： integrated land use and transportation modeling, cellular automata, agents model, land use modeling, GIS

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1. Introduction

1.1 Background

In 2009, the FDOT Central Office conducted a survey of Florida Standard Urban Transportation Model Structure (FSUTMS) users, including 26 metropolitan planning organizations (MPO), FDOT districts, and other planning agencies in Florida. From this survey, the most important need was identified to be integrating land use models into FSUTMS. Improving integrated land use and transportation models is highly recommended by the State agencies and MPOs to model the interaction of land use and transportation and facilitate what-if analysis in land use and transportation policies.

All traffic demands result from different land use formation. Analyzing land use changes is essential to traffic demand modeling. In particular, the land-use patterns (e.g., types, intensity, and changes) are necessary for understanding travel demand and traffic congestion. To effectively capture land use in transportation demand analysis, the traditional four-step transportation demand model takes land use information as given and reflects it in its first step --a trip generation model. The results of trip generation are heavily influenced by land use patterns, because different land use patterns lead to different travel demands (trip generation and attraction).

Land use change is a dynamic process that involves complex interactions between many factors (e.g., land suitability, zoning and land use policies) and decision makers (e.g., developers, government agencies, residents and employers) at various spatial scales (e.g., neighborhoods, cities, counties and metropolitan areas). The complexity of this dynamic process makes the creation of a comprehensive land use model very challenging.

1.2 Goal and Objective

The objective of this study is to explore the feasibility of developing a land use model based on readily available data to serve the needs of the Florida Standard Urban Transportation Model Structure (FSUTMS), a transportation model primarily developed to forecast travel demand for long-term transportation planning in Florida [4]. The goal is to develop a prototype of such model.

Ideally, the model should be able to

- Provide land use data as input to FSUTMS models;
- Accurately reflect land use changes in the past (accurate validation);
- Be sensitive to policy changes;
- Reflect behavior changes of different players in the supply and demand of land use market;
- Conduct what-if scenario analysis;
- Have strong theoretic basis;
- Use existing readily available data;
- Be seamlessly integrated with GIS and FSUTMS model.

1.3 Methodology Design and Modeling Framework

Land use change is a complicated and dynamic process over both spatial and temporal dimensions with many impetus factors, including changes in demand, economic factors, land suitability, and the complicated decision-making processes of households, firms, developers, land owners and governmental policies. Ideally, all of these factors must be considered when modeling land use changes. However, in reality, due to the limitations of data availability, only some of the factors are included in the land use modeling process. Nevertheless, land use models should at least reflect three important categories of factors (or processes) that shape land use changes: characteristics of the location and the nature of the land use, the market demand and supply, and the behavior of different decision makers who make decisions on the purchase and construction of different land developments, as well as government policies.

This research uses cellular automata (CA) and agent-based models for modeling land use changes and the bid-rent theory to represent the equilibrium of the market demand and supply of land uses. Cellular automata models have been extensively used in modeling and simulating complicated spatio-temporal processes. CA can model the changes of land use patterns over time and simulate a variety of spatial processes and influences relevant to land use based on the location and the characteristics of the land as well as the influence of the neighboring land use. The agent-based model presents a flexible representation of heterogeneous decision makers, or agents, whose behaviors are potentially influenced by interactions with other agents and with their natural and built environment, including employment agent, household agent, developer agent and government agent. Each agent is composed of dynamic models and elements. Dynamic models depict the agent state change (e.g., change from vacant to residential, or from residential to commercial) from one base year to the next. The input data of these dynamic models is generated from the elements of the agent itself and other agents. By using a cell-based representation of land, and transition rules defined for each cell considering the agents' behavior and impacts, the land use changes over time can be well modeled and simulated.

A major advantage of this modeling approach is the integration of the CA and agent-based models, which can not only capture the changes of land use patterns, but also model the behavior of individual decision-making entities and the interactions between them. This method incorporates social processes and non-monetary influences on land use change, such as agglomeration, consumer preferences, and government policies in transportation, land use and growth management. The proposed approach can also reveal important factors that affect land use patterns over time and over space. Therefore, it could produce better results for modeling land use changes and forecasting future land use development patterns. Detailed framework of the model is shown in Figure 1-1 and Figure 1-2. Figure 1-1 describes the model structure while Figure 1-2 depicts the relationship between different modeling components and relationship with the transportation demand models.

The CA model analyzes the spatio-temporal land use changes using the multinomial logit model based on the characteristics of land (such as accessibility, slope and distance to certain attractions like airport, central business district and transportation hubs) and the nature of the neighboring land use types. The transitional rule is estimated as the probability of the changes of land use from one state in one year (i.e., land use types) to another in the following year (e.g., from vacant land in year *t* to commercial development in year t+1). The output of the CA model is the amount of land use by type in different geographic locations at certain time period. The model is validated by measuring its accuracy in replicating land use changes in the past. The CA model can capture the spatial and temporal characteristics of complex urban processes, and has earned a positive reputation for its use in simulating land use change [5 6].

Though cellular modeling techniques offer greater flexibility than TAZ-based models when representing spatial and temporal dynamics, CA models have limited ability to reflect socioeconomic representations and decision-making processes, since the models focus on simulating the change in the state of individual cells[2]. These models are difficult to incorporate human decision making into the process. Torrens[3] argues that these drawbacks provide motivation to integrate agent simulation into CA models agent simulation. Agent-based models can model individual decision-making entities' behavior as well as their interactions. Therefore, as shown in Figures 1-1 and 1-2, when modeling land use change, the Multi-Agent method is used to capture the behavior of households, employers, developers, land owners, and government policies.

In the Multi-Agent Model, the first step is to use the bid-rent function to calculate households' and employment's location choice. This assumes that the urban land market is operated by an auction mechanism where the real estate/land parcel is assigned to the highest bidder. CA land use model will produce a land use allocation strategy, and then the bid-rent model will generate new developed residential/employment cells as well as the number of households/employment allocated in these cells. After that, the Land Owner Agent captures land owners' willingness to develop the vacant land, using the Monte Carlo method to simulate the probability of this happening. Then, a Government Policy Agent is used to estimate government policies on land use. This includes decisions regarding conservation land parcels, zoning and land use planning. Finally, a Land Price Agent is used to capture land price changes.

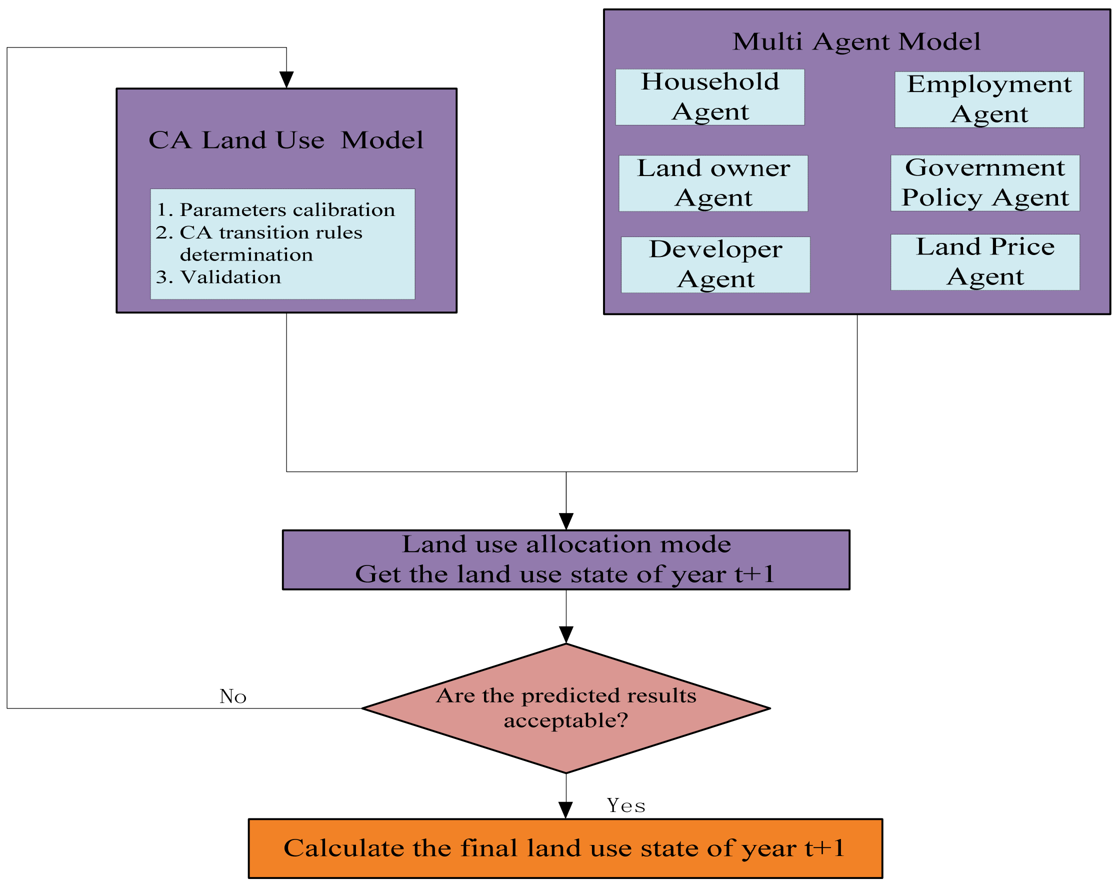


Figure 1-1. Model Structure

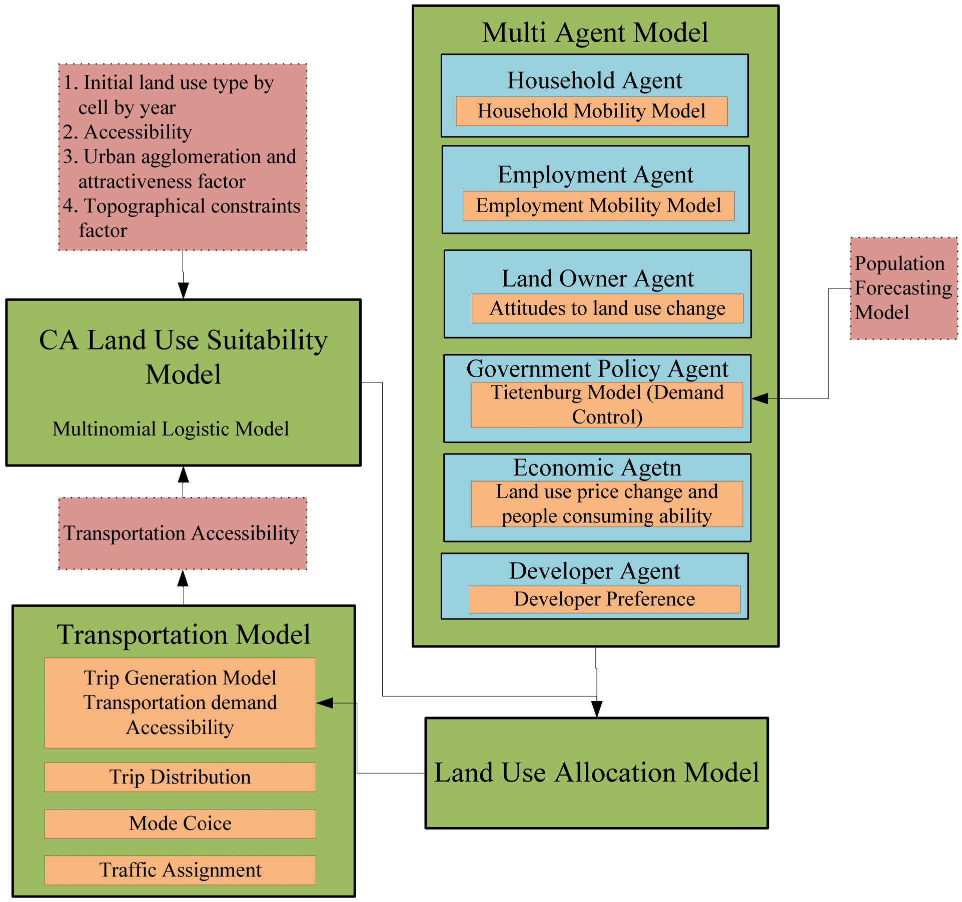


Figure 1-2. Input and Output Relationship between Models

1.4 Geographic Scale

Land use models can be estimated in different geographic scales. Most existing land use models are estimated at the traffic analysis zone (TAZ) level, which makes it difficult for the models to identify the changes of land use and transportation facilities at the micro level, which makes the analysis of some microscopic policy changes difficult, such as mixed land use, or transit-oriented development. The simulation of land use change at a smaller grid cell level is one way to address this concern.

Therefore, this research uses a small cell (50m X 50m) as the basic unit of modeling analysis (more discussion will be given later in the document). The cells also allow for the integration of raster-based geospatial datasets in Geographic Information System (GIS). We realize, however, there are some problems with the use of cells in land use modeling, such as the modeling results may be sensitive to the size and layout of the cells [7 8]. Nevertheless, compared to TAZ-based models, the cell-based land use models provide greater simplicity and a clearer representation of the dynamics of land use change [9].

2. Model Specifications and Literature Review

2.1 Integrated Land Use and Transportation Modeling Review

The integration of land use development with transportation planning has been regarded as an important facet of smart growth and sustainable development [10 11]. Transportation demand results from the spatial distribution of various land use patterns. Investigating the spatial interactions between land use and transportation is essential for transportation policy-making and long-term planning. Forecasting future land use change is the first step for transportation demand modeling as future land use generates socioeconomic and demographic data for transportation models [12]. Based on forecasts of future land use development patterns, transportation planners can simulate what measures should be taken to enhance positive impacts and avoid certain negatives effects. Thus, the accuracy of land use forecasting is crucial for transportation planning modeling.

Land use change is related to the interactions among social, ecological, and geophysical processes [13]. The consequences of land use change can include a loss of biodiversity, climate changes, increased pollution, urban sprawl, and traffic congestion. The demand for industry and residential land contribute to many of these changes, as do transportation developments, which have transformed large areas of agricultural land to residential and industrial land along highways [14]. When choosing suitable land, the nearby transportation system is an important factor, especially in respect to accessibility and travel cost. While conversely, haphazard land use development may induce increase in travel demand, which is a result of different spatial pattern of activities resulted from various land use patterns. Due to the complex relationship between land use and transportation, for the sake of future transportation planning and policy, it is important to understand how land use change interacts with transportation [1 11 15]. Based on simulations of future land use situations, planners and decision makers can take measures to plan well for future growth.

2.1.1 TAZ-based Integrated Model

Modeling land use change is complex and challenging, because it involves dynamic and complex activities, including the interactions between multiple land use attributes (e.g., suitability, zoning, policy) and decision makers (e.g., developers, government agencies, households, employers). Examples of land use models include Lowry and Lowry-type models, Land Use Model for Santiago City (MUSSA), Production Exchange and Consumption Allocation System (PECAS), Integrated Land Use Transport model (TRANUS), and Transportation Analysis and Simulation System (TRANSIMS) [16 17 18 19 20]. In traditional models, households and firms are allocated to traffic analysis zones (TAZ), based on vacant land zoning, accessibility, growth management policies, and land use zoning policies.

In TAZ-based land use models, especially when the TAZ is large, TAZ-level data provides insufficient information for the detailed land use and transportation analysis. Land use change is difficult to track at the TAZ level. In addition, the forecasting transportation results show only the allocated results in aggregate (e.g., number of household and firms), rather than the detailed geographical location inside each TAZ. This makes it difficult to analyze the interactions between land use and transportation within a TAZ; therefore, forecasting land use change at a cell level (e.g., 50m × 50m) has the potential to generate land use change more accurately. There are, however, several problems when using cells in land use modeling, such as the modeling results may be sensitive to the size and layout of the cells [7 8]. Nevertheless, compared to TAZ-based models, the cell-based land use models provide greater simplicity and a clearer representation of the dynamics of land use change [9].

2.1.2 Cell-based Integrated Model

The cell-based model, when compared with TAZ-based models, is able to calculate the change in land usages. The discrete cell not only represents these changes more accurately, but also enables the integration of raster-based geospatial datasets in GIS (see Figure 2-1).

Figure 2-1. Cell-based Land Use Map. (An illustration of the cell concept, not the 50m X 50m cell)

2.2 CA Model

CA is used to simulate complicated spatial-temporal processes [21]. In the 1940s, Ulam suggested that the notion of a self-replicating machine would be amenable to rigorous treatment if it could be described in a “cell space” format – a geometrical grid or tessellation, regular in all dimensions [22]. Since then,, CA has been used to investigate the logical nature of self-reproducible systems [21] and extensive experiments [23], simulate phenomena in the geo-spatial domain, and dynamically simulate the land use change [24 25 26].

CA represents the dynamic behaviors in both temporal and spatial dimensions. However, it is limited in its ability to reflect socioeconomic characteristics and decision-making processes. This is the inherent drawback of CA motivated agent-based models, which otherwise flexibly represents individual decision-making entities’ behavior and interactions [3]. Integrating the CA and agent-based models provides a way to capture spatial drivers, human behaviors, and socioeconomic characteristics of land use change.

In the CA model, the space is composed of individual cell which can take one of several states. The states of each cell may represent any spatial variable, e.g., the various types of land use with different intensity. The CA will evolve over a sequence of discrete time steps. Transition rules are the heart of a CA, as they guide its dynamic evolution. A transition rule normally specifies the states of cell before and after updating based on its neighborhood conditions. In CA, the state of a cell can change only based on the transition rules, which are defined in terms of neighborhood functions.

Recent advances in CA and agent-based models make them viable to dynamically simulate land use change [27 28]. The CA models represent space as a grid (raster) with a set of rules that govern the state of a cell based on the configuration of its adjacent cells [28 29]. The discrete cells in CA models accurately represent the spatial and temporal characteristics of complex urban processes and enable the use of integrating raster-based geospatial datasets into GIS. Therefore, when compared to TAZ-based land use models, CA models better simulate land use cover changes. However, when reflecting socioeconomic representations and decision-making processes, they have limited ability since they only focus on the changes in the state of individual cells and are unable to incorporate human decision making [2]. To solve this problem, Torrens [3] recommends an integration of agents into CA models.

2.3 Agent Model

Development of cellular automata (CA) and agent-based models provide a powerful and flexible tool for the dynamic modeling of land use change [30].

Agent-based models have many of the characteristics of cellular automata modeling. They can be used to model the behaviors of mobile agents within a geographic area. Agents can be considered as a special case of an automaton, having all features of the general automation, but there is a distinction in that these agents are mobile and can represent the external drivers responsible for processes (e.g. socio-economic, population, etc)[31]. Thus, agent-based models are mobile geographical automata with transition rules. While cellular models are focused on landscapes and transitions, agent-based models focus on human actions.

An agent in the agent-based modeling is considered to be a self-contained program that has its own behavior and makes its own decision to achieve its own goals and objectives, based on its perception of its environment and relationship to other agents. Several characteristics define the agents. For example, they are autonomous, share an environment through agent communication and interaction, and make decisions that tie their behavior to the environment [32] . Agent-based models capture the behavior and decision-making process that each individual decision maker (agent) performs, as well as related interactions. The agent-based model provides for an extremely flexible representation of heterogeneous decision makers, who are potentially influenced by interactions with other agents and with their natural environment. Agent-based modeling has become popular in the land use modeling community in recent years, because it can capture the behavior and decision-making process of each individual decision maker (agent) and their interactions by considering social interaction, adaptation, and decision making at different levels.

Under certain social interactions, adaptation, and decision making choices, agent-based models capture the behavior and decision-making processes of each individual decision maker (agent) and their interactions[33]. For example, in the UrbanSim model, agents are used to reflect the key choices of households, businesses, developers, and government bodies and their interactions in the real estate market [12]. By focusing on certain principal agents in urban markets and their choices relating to location and development, the UrbanSim model deals directly with behaviors that are readily understood and analyzed by planners, policy makers, and the public. To achieve market equilibrium, Zhou and Kockelman (2010) developed an agent-based approach at the parcel level to forecast land use change by relying on behavioral foundations for market agents (households, firms, and land developers/owners) and their interactions.

Multi-agent system land use change (MAS/LUCC) models are particularly well suited for representing complex spatial interactions under heterogeneous conditions and for modeling decentralized, autonomous decision making. MAS/LUCC combines two key components into an integrated system[30 31]. First, a cellular mode that represents the landscape over which decision makers making decisions, which is consistent with the discrete cells in the ANN based CA model. The second component is an agent-based model that describes the decision making architecture [34].

Sudhira (2004) developed a framework for the integration of agent-based and CA models for geospatial simulations. Here, all processes are modeled as agent-automata in the agent-based modeling process, which effectively helps visualize ‘what if’ scenarios. The integration of CA models with the agent-based model are also adopted in UrbanSim (Waddell, 2002 and 2003). In the design of the UrbanSim system, several of the preceding modeling approaches have been assimilated. In UrbanSim, a cell-based representation of land, and a probability of change in development type from one year to the next that is influenced by the state of neighboring cells, and the real estate development model component is modeled using cellular automata

This project extends this line of research by integrating the CA model and multi-agent-based model in the forecasting of land use. It differs from previous research in two aspects. First, it specifically focuses on land use forecasting at the travel analysis zone level for the purpose of serving transportation demand modeling. This is unlike the previous studies, which have focused on explanations of current land use patterns. Second, transportation and land use are integrated by feeding the transportation modeling results back into the land use models. By using a cell-based representation of land, and a transition rules defined for each cell considering the agents impacts, the land use forecasting can be well implemented.

2.4 Bid-Rent Theory

Bid-rent theory is a geographic economic theory that refers to how the price and demand of real estate change with distance, as it increases towards some point in the market, usually the Central Business District (CBD) [35 36]. Because travel costs rise with distance from the market (typically the CBD), rents of real estate generally tend to fall correspondingly. Generally, retail establishments wish to maximize their profitability, so they are more willing to pay higher rents for land close to the CBD [37].

In an integrated land use and transportation model, the market-based supply-demand relationship tends to dominate aggregate behavior, with prices being endogenously determined in determining the outcome of these supply-demand interactions. If these major supply demands are not considered, the model cannot capture the dynamic evolution of urban system over time [1]. To describe the interactions of agents' behavior in the integrated land use and transportation models, bid-rent theory has gained increasing interest in capturing the market equilibrium [18 38 39 40]. The bid-rent theory describes how the price and demand of real estate vary over distance. For example, the price of the land typically but not always increases as the land is closer towards some point in the market, usually the Central Business District (CBD), and decreases as the land is away from the CBD [35 36]. The MEPLAN model directly represents land market dynamics with location-choice processes of different industries and households and their interactions [41]. The MUSSA model [18 42] employs a bid-rent theory to simulate the competitive urban land market, where land rents are endogenous and consistent under equilibrium conditions (e.g., land availability and the developers' behavior). In the UrbanSim model, a hedonic regression is used to reflect the effects of site, neighborhood, accessibility, and policy on land prices [12].

Bid-rent theory has become increasingly popular among the integrated land use and transportation models [18 38]. The MUSSA model developed by Martínez — a land use equilibrium model — focuses on the bid-choice of competitive urban land market [18]. In a four-stage transportation model, the interactions between land use and transportation can be captured in a static equilibrium. Briceño (2008) proposed a global system equilibrium model which integrates land use bidding, land use supply, and Markovian traffic in a hyper-network [39]. The integrated equilibrium model assures the convergence of solutions under certain conditions; however, it is based on static rather than dynamic land use changes. To capture the relationship between transportation and residential location, Chang and Mackett (2006) proposed a bi-level model which explores the bid-rent network equilibrium by accounting for the decision making process of households which is similar to an *n*-player non-cooperative game following the Nash equilibrium [43].

In land use and transportation models based on bid-rent theory, the changes in travel cost and transportation accessibility result in the households' relocation choice through a bidding location process, which affects the transportation demand in transportation networks [44]. Like Briceño's integrated model [39] and Martínez's bidding model [45], the bid-rent model in this study is integrated with a dynamic land use change-based CA model to explore the effect of land use allocation on transportation.

In bid-rent theory, the urban land market is assumed to follow an auction mechanism where the land will be developed by the highest bidder. In bid-rent, households' residential location choice model and the bidders (i.e., the households) are categorized into different types (h = 1, 2, …, and $\bar{h}$), according to socioeconomic characteristics. The bids are represented by the consumer's willingness to pay function for an available residential location, which is in turn related to the household income, the spatial attributes of a location, and potential transportation effects.

For household of type h and cell i available for residential location, the willingness to pay function B_{hi} is postulated as follows [39]:

$$B_{hi} = -b_h + z_{hi}(\tau_{i1}) - \sum_p M_h^p \varphi_{hi}^p(t) \tag{2-1}$$

where b_h is a monetary disutility bid for household agent of type h and is proportional to household's income. z_{hi} is a function of τ_{i1} and captures how a household of type h values the spatial attributes of cell i. The last term indicates the total transportation utility under different trip purposes p, which chooses cell i as a residential location. M_h^p is the number of trips with purpose p for household of type h. $\varphi_{hi}^p(t)$ is the total cost to reach purpose p, when the household of type h chooses cell i as the residential location. $\varphi_{hi}^p(t)$ is obtained from the logit-based trip distribution model.

The bid function $\tilde{B}_{hi}$ is assumed to be a random variable. This accounts for the behavior produced by idiosyncratic differences among consumers within a cluster [20]. The bid function can be represented by $\tilde{B}_{hi} = B_{hi} + \varepsilon_{hi}$, where the random item ε_{hi} is assumed to follow IID Gumbel distribution with dispersion parameter θ. The bid probability, $\Pr_{h/i}$, probability that the household type h is the highest bidder for location *i*, is given as follows:

$$\Pr_{h/i} = \Pr(B_{hi} \geq B_{h'i}) = \frac{\exp(\theta B_{hi})}{\sum_{h'} \exp(\theta B_{h'i})}, \quad (\forall h' = 1, 2, ..., \overline{\mathrm{h}}) \tag{2-2}$$

In the supply side, a residential location is assumed to be offered to the household with highest payment. As a result, the rent of location r_i is determined by the expected highest bid and could be given as follows:

$$r_i = E[\underset{h}{Max}\, \tilde{B}_{hi}(i)] = \frac{1}{\theta} \ln\left(\sum_h \exp(\theta B_{hi})\right) + \frac{\gamma}{\theta} \tag{2-3}$$

where γ is a constant.

The household agents' optimal choice for a residential location is supposed to maximize the surplus between bidding price and rent, which results in the following problem: $Max_{\forall i}(B_{hi} - r_{hi})$ where $\{i \mid i \in \Omega_0, x_{i1} = 1\}$ denotes the available residential cells. The rent is taken as a deterministic variable. The choice probability $\Pr_{i/h}$, probability that an alternative residential location $i \in \Omega_1$ yields the highest utility to household agent of type h given by:

$$\Pr_{i/h} = \frac{\exp(\theta(B_{hi} - r_i))}{\sum_{i \in \Omega_0} x_{i1} \exp(\theta(B_{hi} - r_i))} \quad (2\text{-}4)$$

$\Pr_{i/h}$ is the probability that the household of type h chooses residential location i when location i is developed for residential land use.

2.5 Artificial Neural Network (ANN) Model

Simulating land use change is a complex and challenging process, since it is a dynamic spatial-temporal activity that involves complex interactions between multiple land use attributes (e.g., suitability, zoning, and policy) and multiple human decision making behaviors (e.g., developers, households, firms, government agencies) [46 47]. Moreover, modeling land use change for transportation demand analysis involves modeling many land use types. Depending on their contribution to trip generation, Meyer and Miller [48] divide land use into five general types: residential, industrial, commercial and services, institutional (education), and transportation. Modeling changes among multiple land use types is complicated and more difficult than modeling urban growth, which is normally done on a binary basis: land is either developed or undeveloped [28].

In the last decade, along with the rapid development of artificial intelligence (AI), symbolic approaches [e.g., artificial neural network (ANN), evolutionary programming, and fuzzy logic] are becoming integrated into modeling land use change [28 46 49 50 51 52]. Neural network technology helps geographers address issues previously poorly handled by traditional statistical techniques, such as scale, space–time dependencies, nonlinear relationships, and data outliers [52]. There has been an explosion of interest in ANN models, which have been successfully applied in geographic and spatial research, including remote sensing, image recognition, climate change, ecological and environmental sciences, and land use change [53 54].

Neural networks are silicon analogs of neural structure that are trained to associate outcomes with stimuli. ANNs therefore use a learning approach to quantify and model complex behaviors and patterns. The relationship between spatial factors and land use change is most often non-linear, irregular, and highly complex. An advantage of ANNs is their ability to handle non-linear functions. They can capture the complex non-linear relationships between input and output layers through an adaptable learning process. ANNs provide highly flexible function approximates for any data and, once trained, are extremely efficient with computations [54].

The temporal and spatial complexities of land use change in urban systems can be well modeled by properly defining transition rules in CA models [28 29 55]. A transition rule specifies the state of cell before and after updating. In a CA land use model, varying transition rules are deployed to satisfy multiple objectives and specifications, or they can be coupled by setting a series of constraints, all of which work towards generating an idealized urban form [21 28 46 56]. Conventional methods used to define transition rules include statistical regression models, logit models, fuzzy logic, neural networks, support vector machines, and multi-criteria evaluation techniques [57]. When defining parameters, neural networks have the ability to reduce the tedious work, while also relaxing the condition of independence between spatial variables, as opposed to many other conventional methods used when defining transition rules.

3. Data Processing

3.1 Data Source

To implement the model, the required raw data includes parcel level data, including land use, planning and zoning data; and data from both parcel and traffic analysis zones (TAZ), including household, employment, and other socio-economic data. The model database includes digital elevation model (DEM) files from U.S. Geological Survey [58], soil information, land use/cover data, parcel data, and zoning boundaries information from Florida Geographic Data Library [59], census information from the Census Bureau, and the transportation network skim file from FSUTMS.

Travel time data provided by FSUTMS, was generated by the Central Florida Regional Planning Model (CFRPM), and implemented in Cube Voyager. After the distribution, model split and assignment steps, the zone to zone travel time for Orange County was extracted from the output of CFRPM after distribution, model split and assignment steps. In the agents' model, the index of agents' total travel time is used as an index for decision making. This ensures reliable data are provided for further land use change modeling.

3.2 Data Processing

Figure 3-1 shows the procedures of data processing that employs a set of tools built from both Matlab and ArcGIS to read, analyze, and process the original GIS data. In the case of the CA model, all data were converted into grid cells (50m X 50m). In the case of the agent models, the household information from polygon-based census data are allocated into residential cells according to different residential density, while the employment information are assigned correspondingly into employment land cells. The individual household and employment information are linked with land cells in the database.

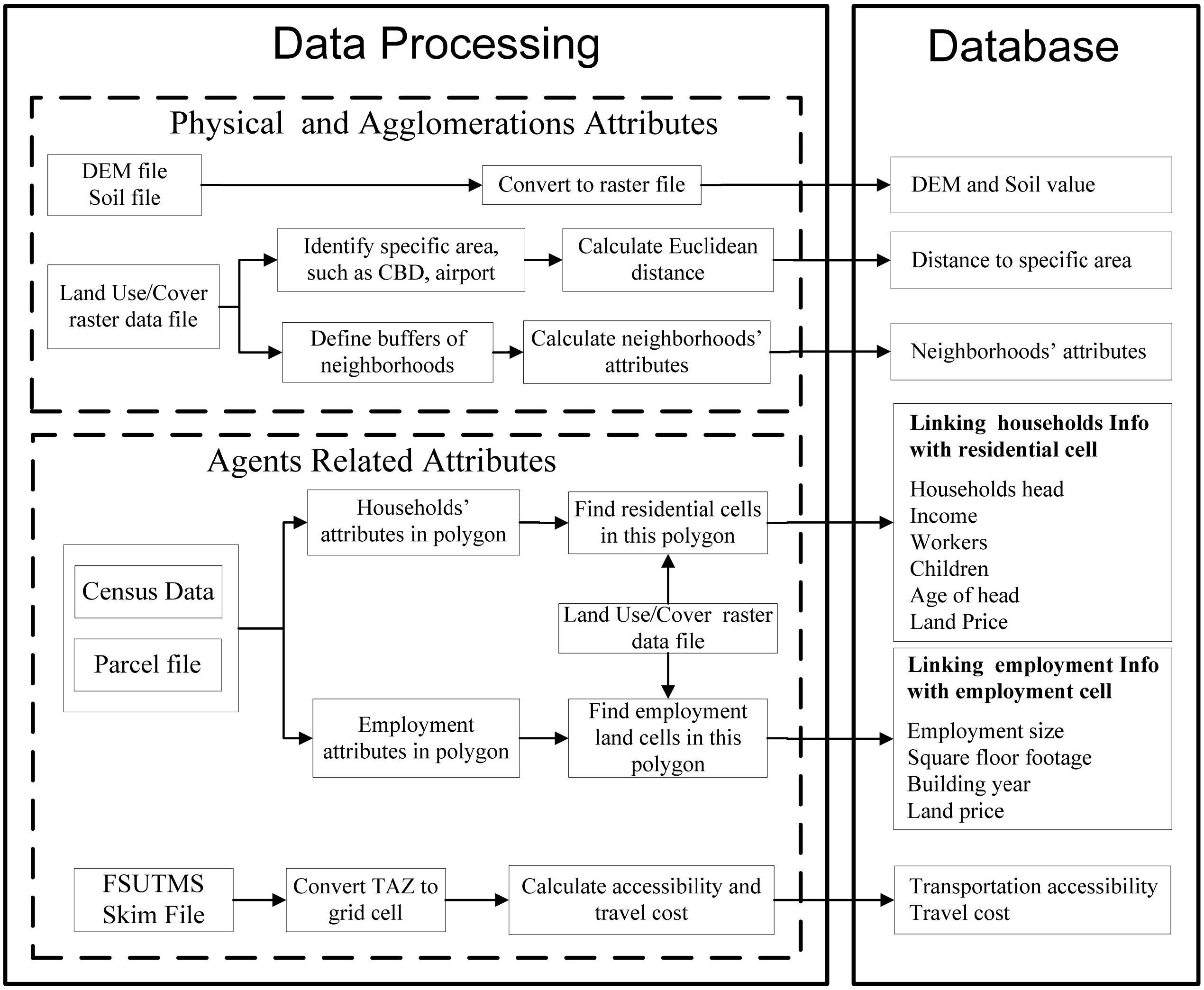


Figure 3-1. Schematic Diagram of Data Processing

In order to read, analyze, and process the raw data, a set of tools were constructed using both Matlab and ArcGIS. When using ArcGIS, all data were converted into raster format, with each cell representing an area of 50m X 50m. For the data in the agent model, the household information from polygon-based census data was assigned to residential cells based on residential density, and the employment information are assigned correspondingly into employment lands. The individual household and employment information were linked with land cells in the database.

3.3 Land Use Classification

Based on their contributions to trip generation, Meyer and Miller [48] divide land into five land use types: residential, industrial, commercial and services, institutional (education), and transportation. The first four are related to travel demand and the last is related to travel supply.

This study focuses only on changes of travel-demand related land uses, and therefore travel-supply related lands (e.g., roads, airport, railway station) are not considered. There are more than 40 land types in land use/cover data of Orange County, FL. To satisfy the requirements of the proposed land use model, all land types are reclassified into four land use types: A, B, C, and D (see Table 3-1). Related to travel demand, land use Type C is further classified into residential, industrial, commercial and services, and institutional (education).

Table 3-1. Reclassification of Land Use Types

New Land Types	**Features**	**Original Land Types in land use/cover data**
A	Unchanged over time	Rivers, lakes, water, reservoirs, bays and estuaries
B	Related with travel supply	Transportation, communication and utilities, airport
C	Related with travel demand	Residential, commercial services, institutional, industrial
D	Vacant	Open land, agriculture, range land, special classification land, wetlands, tree plantation area, upland forests

The reclassification of land use types, based on transportation demand, has been completed using data from Orange County. A quantitative method was developed to discover what land types are subject to change in relation to with trip generations.

3.3.1 Land Classification in Orange County

Orange County land use data was provided by the Florida Geographic Data Library (FGDL) to the researchers. There were four years for which data was available, 1979, 1990, 2000, and 2004. Two of these, 1990 and 2000, were chosen for this study, and the land use types reclassified.

The Orange County land use/cover data attribution table for both 1990 and 2000 distinguishes land use types into three levels. The first level includes eight classifications, which are mainly used to distinguish between urban and nonurban areas. The second level is related to land types involving trip generation, such as residential, industrial, commercial and services, and institutions. There are 40 of these divisions in 1990, and 38 for 2000. The third level of the data includes 123 types with more detailed land use information.

For the purposes of this study, one level needed to be chosen as the base. The first level is too broad; and the third level would produce a data process unnecessarily complicated for this work, therefore, the middle level is chosen.

Table 3-2. Original Land Use Classifications (Level 1 and Level 2)

LEVEL ONE	**LEVEL TWO**		
Land use type	Land use type	1990 index	2000 index
Water	Bays and Estuaries	28	37
	Lakes	23	10
	Reservoirs	20	7
	Streams and waterways	27	26
	Water	7	33 (beach)
Wetlands	Non-vegetated wetlands	40	35
	Vegetated non-forested wetlands	3	13
	Wetland coniferous forests	15	16
	Wetland forested mixed	18	8
	Wetland hardwood forests	9	9
Upland forests	Tree plantations	26	24
	Upland coniferous forests	6	11
	Upland forests	37	2 (con.)
	Upland hardwood forests	16	5
Agriculture	Cropland and pastureland	8	22
	Feeding operations	29	36
	Nurseries and vineyards	31	29
	Other open lands (rural)	33	31
	Specialty farms	35	32
	Tree crops	12	19
Barren Land	Disturbed land	28	14
	Sand other than beaches	38	34

LEVEL ONE	**LEVEL TWO**		
Land use type	Land use type	1990 index	2000 index
Rangeland	Herbaceous (dry prairie)	17	18
	Mixed rangeland	24	27
	Shrub and brushland	2	12
Special Classifications	Special classifications	4	38
	Vegetation	5	N/A
Urban and Built-up	Extractive	21	4
	Open land	10	20
	Commercial and Services	1	3
	Recreational	11	25
	Industrial	32	17
	Institutional	25	28
	Residential, high density (> 6)	13	6
	Residential, low density (< 2)	14	23
	Residential, medium density (2-5)	22	21
	Communications	36	30
	Transportation	30	1
	Transportation, communication & utilities	34	N/A
	Utilities	19	15

3.3.2 Land Use Types in Orange County

Using the level two land classification, the land use types were reclassified to allow for further analysis. The data was reclassified into five A/B/C/D/E levels. Certain spatial land use types, such as rivers and most forest and conservation areas, do not change over time. These land types as classified as A. In addition, those land types which contain only an extremely small number of cells, so much so that they can be neglected in the data analysis, are labeled type A. Type B is defined by land types that are not related with trip generation. These areas may change from one land usage to another, but they are not suitable for construction. Examples include certain wetlands and forests. These would never be land types related with trip generation. Thus, A and B lands are not included in the integrated land use and transportation model. After they are removed, the remaining land that will be used in the model is further divided.

All land related to trip generation is classified as Type C. This is further divided into residential, industrial, commercial and services, and institutional land, depending on trip purposes. Transportation network and facilities are also included in Type C, which will be expanded according to increasing traffic demand. Classifications for type C are shown in Table 3-3.Those areas that could possibly be changed into C are classified as type D. The land use forecasting model for transportation demand will focus on this category when examining changed traffic demands.

Table 3-3. Land Uses in Level 2 that Contribute to Transportation Planning Purposes

Major LU for Transportation		Land uses in LEVEL 2 (with the corresponding 1990 index)
C	**Commercial and Services**	Commercial and Services (1)
		Recreational (11)
	Industrial	Industrial (32)
	Institutional	Institutional (25)
	Residential	Residential, high density (13)
		Residential, low density (14)
		Residential, medium density (22) Communications (36)
	Transportation	Transportation (30)
		Transportation, communication and utilities (34)
		Utilities (19)

3.3.3 Quantitative Definition

Next, we will introduce the method used to categorize land into either A, B or D, as mentioned above.

First, each land use change for type i in Level Two will be further classified into two sets: change out $\{i_{\rightarrow}\}$ and change in $\{_{\rightarrow}i\}$. Set $\{i_{\rightarrow}\}$ includes all the land types that current land type i will change to, namely the future land use type set. Set $\{_{\rightarrow}i\}$ includes all the land types that current land type i are from, the past land use type set. Based on the land use change between 1990 and 2000, set $\{i_{\rightarrow}\}$ will be generated using 1990 data as the base year data for land use change analysis. Set $\{_{\rightarrow}i\}$ will use 2000 data as base year data. Detailed notations for data reclassification are shown as following:

N_i : Total number of cells in type i .

$N_{i_{\rightarrow}}(j)$: Number of cells that change from type i to type j

$N_{i_{\rightarrow}}(j)$: Number of cells that change from type i to type j

$P_{i\rightarrow}(j)$: Proportion of the cells (raster) number in type i that are changed into

type j ; $\sum_j P_{i\rightarrow}(j) = 1$ and $P_{i\rightarrow}(j) = N_{i\rightarrow}(j) / N_i$.

$P_{\rightarrow i}(j)$: Proportion of type i cells that are changed from type j ;

$\sum_j P_{\rightarrow i}(j) = 1$, $P_{\rightarrow i}(j) = N_{\rightarrow i}(j) / N_i$

Permitting for a certain range of allowed error, according to the definition, type A, B, and D can be formulated as follows:

$$A = \{P_{\rightarrow i}(i) > 90\%\} \cup \{i \mid N_i \leq 100\}$$

$$B = \{i \mid P_{i\rightarrow}(j) < 0.03 \text{ and } P_{\rightarrow i}(j) < 0.03, \forall j \in C\}$$

$$D = \{i \mid P_{i\rightarrow}(j) \geq 0.03 \text{ or } P_{\rightarrow i}(j) \geq 0.03, \forall j \in C\}$$

3.3.4 Results of Reclassification

Using the spatial data analysis tool in ArcGIS for the LEVEL ONE water data, 91.2% of cells show no land use change. The five corresponding subsections in Level Two are reclassified as type A. According to the definitions of B and D, by calculating the change-in set and change-out set of categories, C, B and D will be separated.

Table 3-4 shows the main results of change-out data, based on the change between 1990 and 2000 data, according to the definitions of B and D. Using the change-out proportion $P_{i\rightarrow}(j)$, over 70% of land in Category C will remain unchanged. What did changes were mostly internal, such as a shift from low-density residential land to medium density (0.17) or medium-density land shifting to high-density (0.16) or industrial land converting to commercial land.

Table 3-4. Change-Out and Change-In Results from 1990 to 2000

Type C		Change out $\{i_{\rightarrow}\}$			Change in $\{_{\rightarrow}i\}$				
	i	$N_i\,90$	$P_{i\rightarrow}(j)$		$N_i\,00$	$P_{\rightarrow i}(j)$	j	$P_{\rightarrow i}(j)$	j
Commercial and Services	Commercial and Services 1	7161	0.66	1	10059	0.52	1	0.04	30
			0.09	32		0.08	32	0.09	2
			0.08	30		0.08	6	0.03	10
						0.05	9	0.03	22
								0.04	8
	Recreational 11	3273	0.53	11	3695	0.04	22	0.03	8
			0.04	25		0.11	12	0.07	16
			0.06	22		0.05	10	0.04	2
			0.03	10		0.03	9		
			0.03	6					
Industrial	Industrial 32	3011	0.25	1	2899	0.53	32	0.04	2
			0.51	32		0.03	10	0.23	1
						0.03	11		
Institutional (Education)	Institutional 25	2399	0.03	10	5056	0.11	9	0.03	1
			0.04	28		0.04	8	0.33	
			0.03	11		0.15	6	0.05	24
			0.06	22		0.04	2	0.03	15
			0.70	25					
Residential	Residential high 13	4364	0.79	13	12650	0.27	13	0.08	12
			0.07	22		0.08	10	0.07	6

Type C		Change out $\{i_{\rightarrow}\}$	Change in $\{_{\rightarrow}i\}$	Type C		Change out $\{i_{\rightarrow}\}$	Change in $\{_{\rightarrow}i\}$	Type C	
	i	N_i 90	$P_{i_{\rightarrow}}(j)$		i	N_i 90	$P_{i_{\rightarrow}}(j)$		i
Residential	Residential, low density 14	7933	0.04	16	7532	0.03	6		
			0.51	14		0.72	22		
			0.17	22		0.05	14		
			0.05	8		0.04	12		
			0.03	6		0.03	10		
	Residential, medium density 22	24038	0.16	13	23973	0.13	22	0.07	12
			0.72	22		0.04	8	0.05	10
			0.04	14		0.54	14		

Using the results from Table 3-3 and the definition of types B and D, a detailed reclassification is shown in Table 3-5.

Table 3-5. Land Use Type Reclassification for the Integrated Land Use and Transportation Model

Land use type	Land use type		
Water	Bays and Estuaries	28	A
	Lakes	23	
	Reservoirs	20	
	Streams and waterways	27	
	Water	7	
Wetlands	Non-vegetated wetlands	40	D
	Vegetated non-forested wetlands	3	D
	Wetland coniferous forests	15	D
	Wetland forested mixed	18	D
	Wetland hardwood forests	9	D
Upland forests	Tree plantations	26	D
	Upland coniferous forests	6	D
	Upland forests	37	D
	Upland hardwood forests	16	D
Agriculture	Cropland and pastureland	8	D
	Feeding operations	29	A
	Nurseries and vineyards	31	D
	Other open lands (rural)	33	D
	Specialty farms	35	D
	Tree crops	12	D
Barren Land	Disturbed land	28	D
	Sand other than beaches	38	D
Rangeland	Herbaceous (dry prairie)	17	D

Land use type	Land use type		
Rangeland	Mixed rangeland	24	D
	Shrub and brushland	2	D
Special Classifications	Special classifications	4	D
	Vegetation	5	D
Urban and Built-up	Extractive	21	D
	Open land	10	D
	Commercial and Services	1	C
	Recreational	11	C
	Industrial	32	C
	Institutional	25	C
	Residential, high density (> 6)	13	C
	Residential, low density (< 2)	14	C
	Residential, medium density (2-5)	22	C
	Communications	36	C
	Transportation	30	B
	Transportation, communication and utilities	34	B
	Utilities	19	C

The land use/cover data of Orange County includes more than 40 land types. Figure 3-2 shows the reclassification results of the land use/cover data for Orange County, FL.

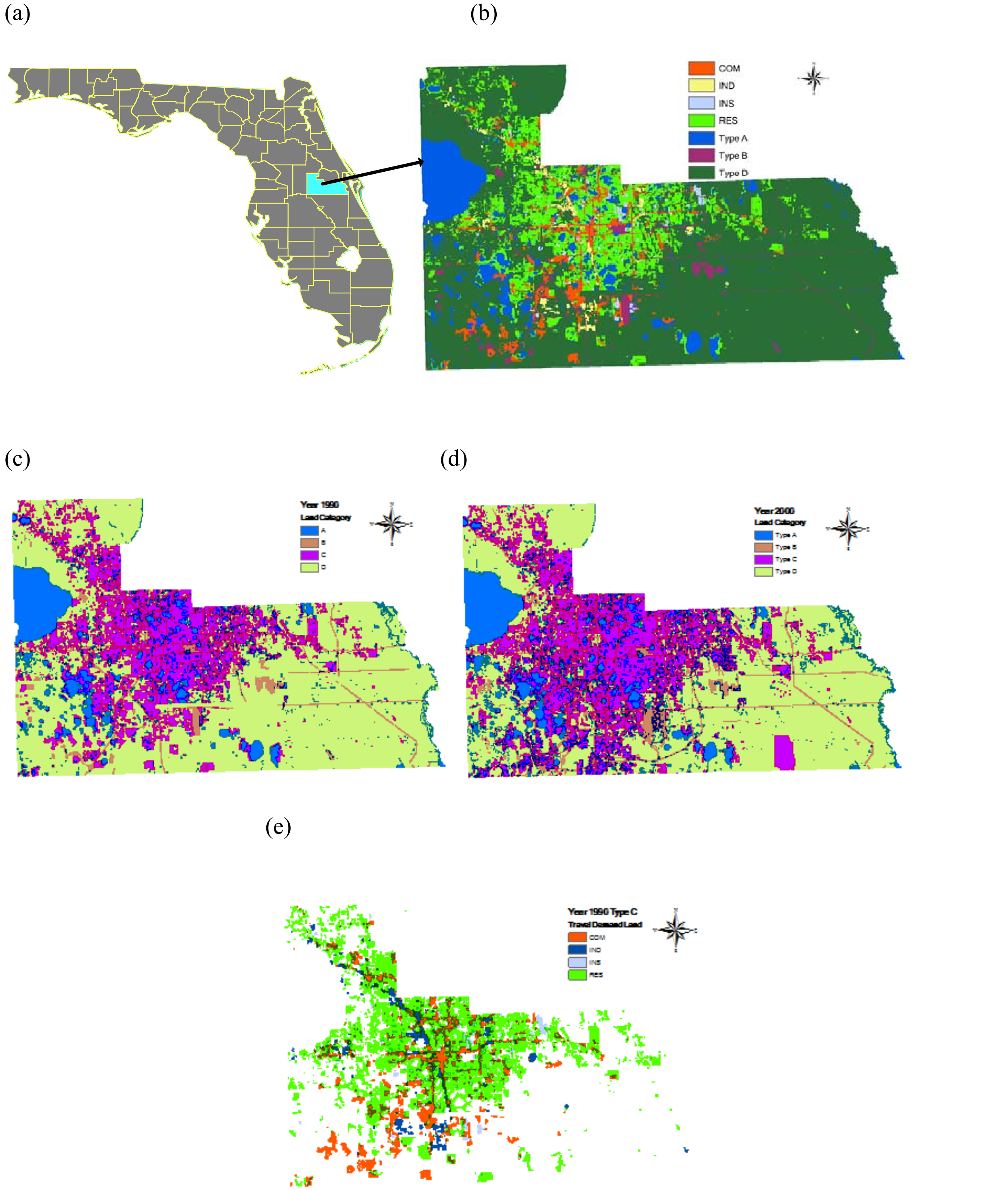


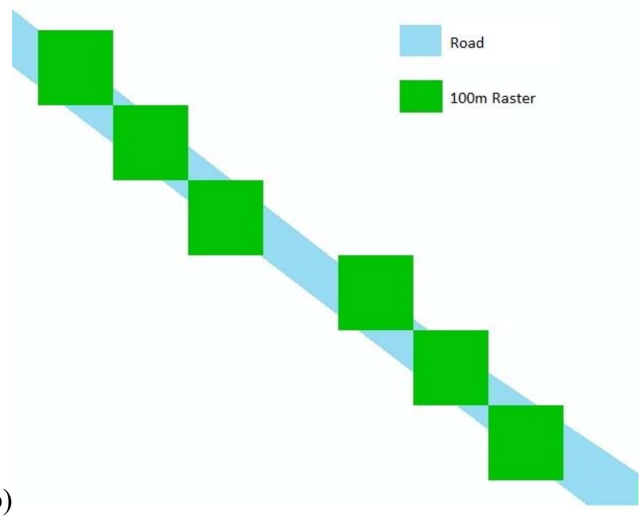
Figure 3-2. Reclassification of Land Use in Orange County, FL. (a) Study area, Orange County, Florida; (b) Reclassification of land use types in 1990; (c) All Land use types in 1990; (d) All Land use types in 2000; (e) Type C Land use in 1990.

3.4 Determination of Cell Size

According to the requirements of the square shape used in the CA model, the land use/cover feature data for each year is converted into raster data based on Level Two values. The cell size is 50m x 50m. We experimented with four different cell sizes. By comparing situations with 30 meters, 50 meters, 100 meters and 300 meters, only the total raster count at 50 meters was deemed appropriate, as it can represent the trip related lands well, and it is large enough for efficient analysis [60].

Figure 3-3(a) shows the raster image of 100m, demonstrating that selected segments of roads in feature based land use data are not included. Figure 3-3(b) shows the raster image at 50 meters, which covers most of the road. Depending on the purpose of analysis, this must be considered.

(a)



(b)

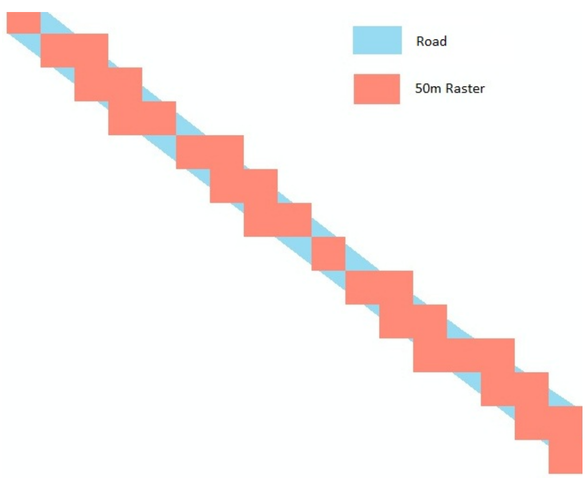


Figure 3-3. (a) Transportation Network Converted into Raster, (100*100m); (b) Transportation Network Converted into Raster (50m x 50m)

4. Multinomial Logit and Artificial Neutral Network based Cellular Automata Model

A multinomial logit (MNL) model is also known as multinomial logistic regression. As its names indicates, MNL model is a regression model predicting the probabilities of the different possible outcomes. MNL is integrated into land use models to generalize the probabilities when a certain land use is transferred to other types. Artificial Neutral Network (ANN) is also employed in land use modeling because it generally can generate more accurate validation results of land use changes. ANN considers its inputs and outputs as a set of interconnected artificial neurons, using a connectionist approach to process data and made prediction. It is an adaptive system that changes its structure based on the information flows through the network during the training phase. But due to its "black box" nature, the ANN approach is not useful for conduct what-if policy analysis. We employ the ANN model as a way to validate the accuracy of the MNL model.

4.1 Multinomial Logit (MNL) Based CA model

In the CA model, each cell has a state representing the land use type. Based on the transition rules, the land use type is updated at each time step by its spatial properties. In a conventional CA-based land use model, the cell states are described as developed or undeveloped only, regardless of development types (e.g., residential, industrial, commercial). In this study, to track land use change from Type D to transportation related land use types (*LUT)*, the MNL model formulates the CA transition function for multiple land types, which estimates the probability of future land use for each cell in Type D.

The CA model is used to capture the spatial properties of land use change from Type D to *LUT*. The spatial properties of the cell include: (1) the physical attributes of land cell, $\boldsymbol{\upsilon}_{ik}$, including soil quality and slope; (2) the number of developed cells in Moore neighborhoods, $\boldsymbol{\eta}_{ik}$; and (3) the local spatial attributes, $\boldsymbol{\tau}_{ik}$, including transportation accessibility, and distance to special trip generators such as CBD, shopping centers, education institutes and other main public facilities.

For each cell in Type D, its land use status will either change to four *LUT* or remain unchanged. The suitability of land Type D changing into land Type k (k=1, 2, 3, 4 and 5) in cell i can be depicted as

$$u_{ik}^{\mathrm{CA}} = \mathbf{w}_{k1,\mathrm{CA}} \boldsymbol{\upsilon}_{ik} + \mathbf{w}_{k2,\mathrm{CA}} \boldsymbol{\eta}_{ik} + \mathbf{w}_{k3,\mathrm{CA}} \boldsymbol{\tau}_{ik} \tag{4-1}$$

where $\mathbf{w}_{k1,\mathrm{CA}}$, $\mathbf{w}_{k2,\mathrm{CA}}$, and $\mathbf{w}_{k3,\mathrm{CA}}$ are the corresponding linear coefficients. Since most spatial attributes are measured at varying scales, the variables are normalized before further calibration. The mean utility function u_{ik}^{CA} is associated with a stochastic item ε_{ik} , which is assumed that errors follow the IID Gumbel distribution. In the CA model, the probability of land use change in cell i from vacant land to a new land use Type k can be formulated as

$$\mathrm{Pr}_{i,k}^{\mathrm{CA}} = \frac{\exp(\beta u_{ik}^{\mathrm{CA}})}{\sum_{k} \exp(\beta u_{ik}^{\mathrm{CA}})} \quad (k = 1, 2, 3, 4) \tag{4-2}$$

The vacant cells with higher values of P_{ik}^{CA} are more likely to be developed into type k land use.

4.2 ANN CA model

The model proposed in this work employs a neural network to define the transition rules in the CA model to simulate spatial land use changes. Generally speaking, ANN models simulate land use change via four subsequent steps [47]: (1) design the network, inputs, and outputs, based on historical data; (2) choose a subset of the inputs and perform neutral network training; (3) validate ANN with the full data set of the inputs; and (4) employ ANN to simulate changes in future years.

4.2.1 Principles of ANN

The multi-layer perceptron (MLP) network used in this study is one of the most popular ANN architectures [54 61 62]. MLP is a feed-forward network framework and represents non-linear functional mappings between a set of input and output variables. It includes an input, hidden, and output layers. As shown in Figure 4-1, circles represent neurons and lines indicate unidirectional interconnections between neurons in the corresponding layer [61].

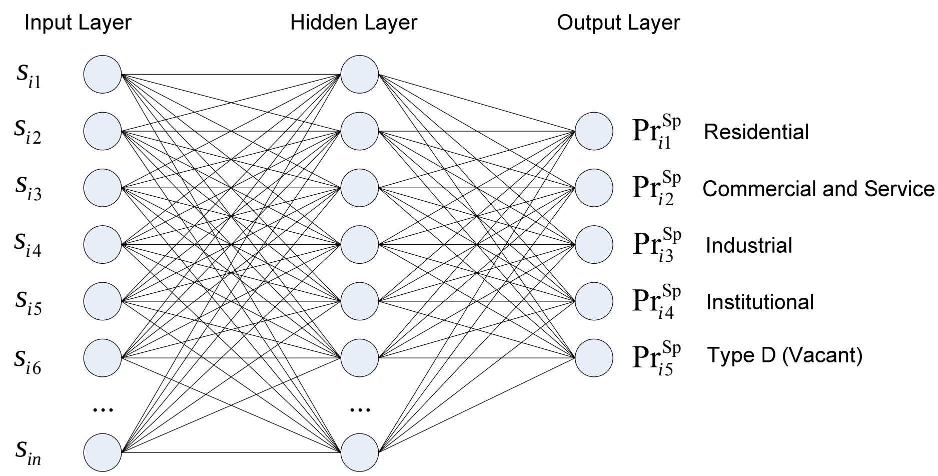


Figure 4-1. Neural network structure for land use change from Type D to *LUT.*

To simulate the effect of spatial attributes on land use change from Type D to *LUT*, the input layer has $\overline{n}$ neurons with regard to spatial attributes s_{in}. There are 16 spatial attributes considered in the input layer: the physical attributes of land cell, including soil quality and slope; six Moore neighborhood attributes, including the number of industrial, commercial, institutional, residential, Type A and Type D land; and the local spatial attributes, including distance to railway station, airport, CBD, bus hubs, major roads, commercial center, industrial center and residential center. All inputs are normalized into the range of [0, 1], according to the following method:

$$s_{in} = (s_{in}^0 - \min_i s_{in}^0) / (\max_i s_{in}^0 - \min_i s_{in}^0) \tag{4-3}$$

where s_{in}^0 denotes the initial value of attribute *n* in cell *i*.

In Kolmogorov's theorem, the use of $2\bar{n}+1$ hidden neurons (with $\bar{n}$ the number of input neurons) in a hidden layer guarantee the goodness of fit [61]. Previous studies shows that $2\bar{n}+1$ hidden neurons may be too many in applications and that $2\bar{n}/3$ hidden neurons can achieve almost similar accuracy while requiring less training time [28 54 63] . To ensure a balance between accuracy and simulation speed, 15 ($\bar{m}$) hidden neurons were used in this study's ANN.

The topology of network structure can be translated into the corresponding mapping function. The output of *m*th hidden neuron is obtained by a weighted linear combination of the $\bar{n}$ input variables. Activation functions are used to represent the non-linear mapping function. In the one hidden layer MLP, the activation of hidden neuron *m* is then obtained through the logistic sigmoid activation function. The output of *m*th hidden neuron can be formulated as:

$$v_m = \frac{1}{1+\exp(-\sum_n w_{mn} x_n)} \tag{4-4}$$

The output layer has five neurons which calculate the land change probability ($\mathrm{Pr}_{ik}^{\mathrm{Sp}}$) from current vacant land cell *i* (Type D) to residential, commercial, industrial, institutional, and unchanged lands, respectively. It can be calculated as follows:

$$\mathrm{Pr}_{ik}^{SP} = \sum_m w_{mk} v_m \tag{4-5}$$

where w_{mn} in Eq.(4-4) and w_{mk} in Eq.(4-5) are the weights from input to hidden layer, and from hidden to output layer, respectively. Weights are obtained through neural network training. Using the neural network toolbox available in Matlab, the training process is automatically implemented by a back-propagation algorithm. The algorithm iteratively minimizes error between the network outputs (predictions) and desired outputs (observations) by adjusting the weights based on the training data set. Essentially, the network 'learns' the mapping relationship in the training data.

To evaluate the effect of hidden layers on the ANN performance, this study compares one and three hidden layers to each other. In the ANN with three hidden layers, the number of neurons and activation that function are 15 (logistic sigmoid), 10 (pure linear), and 15 (logistic sigmoid). Similarly, the mapping functions can be deduced from Eqs. (4-4) and (4-5).

The selected Type D data from base year 1990 and observation year 2000 are used to train the ANN. After training, the neutral network was validated by using the whole Type D land cells in 1990, and produced Pr_{ik}^{Sp} $(k=1, 2, 3, \text{and } 4)$ for each cell i. The land cells with high transition probability are more likely to be developed into type k land. According to maximizing the development probability, and constrained by the total development cells from type D to *LUT*, the predicted land use development can be generated for year 2000.

4.2.2 Model Evaluation Method

To evaluate the model goodness of fit goodness, two methods have been employed in this study. The first method was evaluated by comparing predicted with actual land use change, as denoted by the following formula [47]:

$$R_k = \frac{N_k^{\mathrm{SameC}}}{N_k^{\mathrm{ActualC}}} \tag{4-6}$$

where N_k^{SameC} denotes number of cells that predicted to change to Type k land and is the same as the observed results. N_k^{ActualC} denotes the total number of cells that change to type k land from observation. The latter method is to employ confusion matrix to compare the predicted and actual value cell-by-cell [28], which is detailed in the Results and Discussion chapter

.

5. Bid-rent-based Agents models

Cellular Automata (CA) models are based on stationary grid cells. Although integrating with MNL and ANN models can greatly improve the simulation accuracy, CA models still cannot fully capture the dynamics of land use changes. This is largely caused by the fact that people who decide land uses are mobile in nature. To bridge this gap, this research weaves agent-based models into land use models and integrates them with CA models to better understand land use dynamics.

5.1 CA-Agent Model Framework

To generate comprehensive inputs for transportation models (e.g., FSUTMS), a desired land use model should consider the following factors: population change; the spatial suitability of land use development, such as topographic, slope, and neighborhoods attribute; and the decision making behavior of stakeholders (e.g., households, employers, developers).In the CA-Agents model framework, Table 5-1 shows the specific sub-models used to simulate the land use change.

Table 5-1. Individual Models Employed to Simulate the Land Use Change for Specific Land

	Land Use Change		**Models**										
	Initial type	Final type	CA	Agents									
				Household agent		Employment agent							
				HH LCM	HH MM	IND LCM	IND MM	COM LCM	COM MM	SER LCM	SER MM	CON	DEM
Z2	Type D	RESL	√	√								√	
	Type D	INDL	√			√						√	
	Type D	COML	√					√		√		√	
	Type D	INSL	√									√	
Z1	RES	Non-RESL			√								√
	IND	Non-INDL					√						√
	COM	Non-COML							√		√		√

RESL = residential land; INDL = industrial land; COML = commercial and service land; INSL= Institutional land; Non-RESL= Nonresidential land; Non-INDL=Non industrial land; Non-COML=land type other than commercial and service land

HH=household agent, COM=commercial employment agent, SER=retail service agent; IND=industrial employment agent, LCM=location choice model, MM=mobility model, CON=construction model; DEM=demolition model

Figure 5-1 shows the proposed land use model that integrates the CA model, Agents model, and bid-rent market equilibrium mechanisms. The land use model is able to interact with FSUTMS. The land use development is forecasted in agent-based CA models. When the interactions between the agents are described by the bid-rent theory, both the specific household characteristics (e.g., population, residential type, car ownership) in residential cells and the number of firms by sector in the non-residential cells are produced at cell level, aggregated to TAZ level thereafter to update the required inputs of FSUTMS. The new travel cost and accessibility are calculated from FSUTMS and then fed back into the data store, updating the inputs for land use model in the next time period.

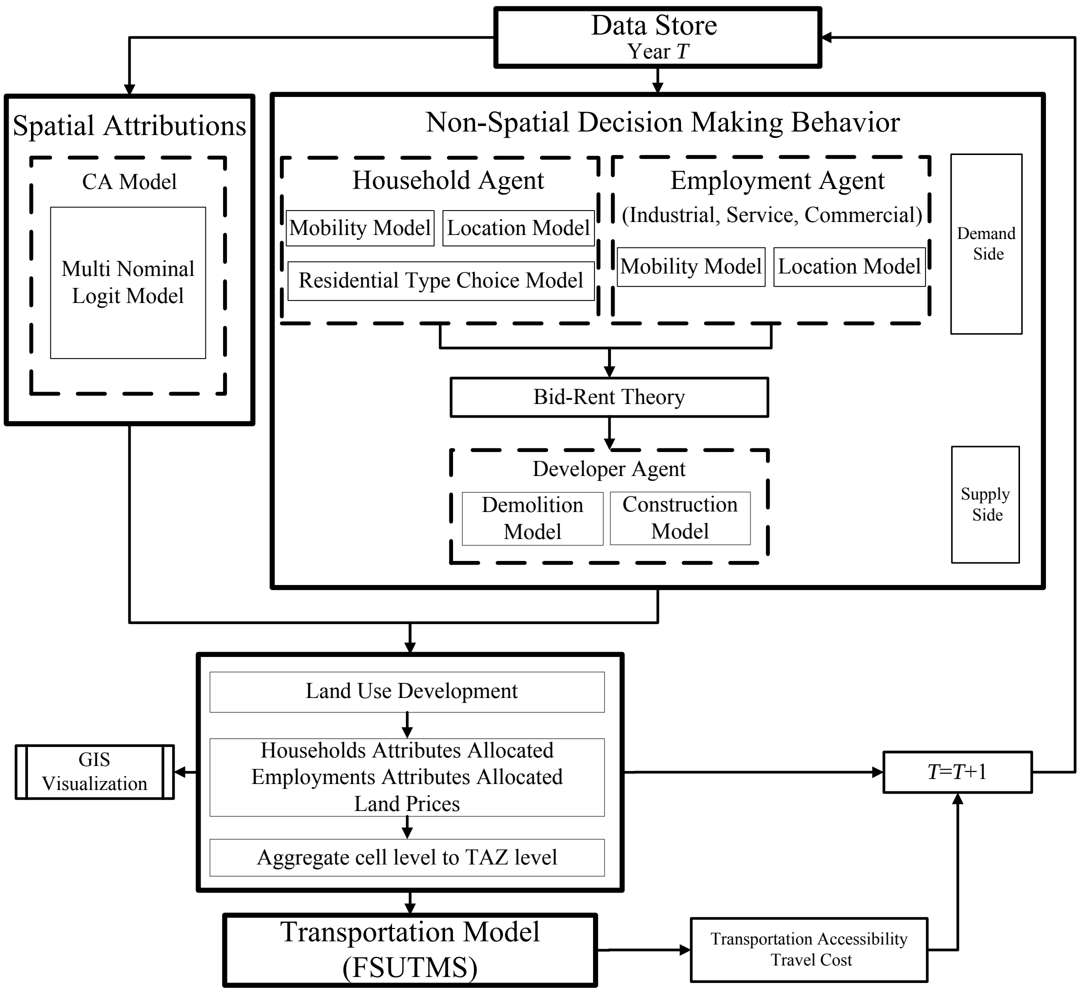


Figure 5-1. Framework of the Land Use Model.

The multinomial logit (MNL) based CA model captures the spatial attributes of land use change. In the CA model employed here, MNL is employed to process the transition rules of multiple land use change. The MNL-based CA model determines the probability of each vacant land cell to be converted to the land use type related with travel demand (*LUT*, including residential, industry, commercial and services, and institutions). The spatial properties of each land cell include physical attributes (e.g., soil quality, slope, and topographic), neighborhood characteristics, accessibility, and distance to other special trip generators (e.g., CBD, shopping centers, education institutes, and other main public facilities).

Three agents are investigated: household agents, capturing the residential mobility, location choice, and housing type choices for the households; employment agents, to generate uniform input data for FSUTMS, employment is categorized into three sectors: industrial, commercial, and retail service employment, and each employment sector then uses two sub-models: employment mobility and location choice; and developer agents, developers and land owners decide whether to demolish or construct houses, apartments, or buildings of each employment sector on a specific land cell.

In the land market, the behaviors of developers constitute the market supply, whereas the household and employment agents form the market demand. Under the equilibrium condition, the land price is generated with the bid-rent theory. From the interactions between market demand and supply, land use prices are updated and provide feedback to the land use forecasting model for the next time period.

5.2 Agents Model

Each agent contains two parts: dynamic models and elements. Dynamic models are used to depict the agent's behavior in Year T+1 based on data from Year T. The elements are the basic variables. The input data of these dynamic models can be generated from the elements of the agent itself or from other agents. Combined with the ANN model, the output of the agent models will be used to refine transition rules for land use change.

The relationship between the household, employment and developer agents is shown in Figure 5-2. The relationship among these agents is based on bid-rent theory, using endogenous land prices. In the land market, the behaviors of developers constitute the market supply, whereas the household and employment agent form the market demand [64]. Bid-rent theory is able to represent the interactions between the demand and supply sides.

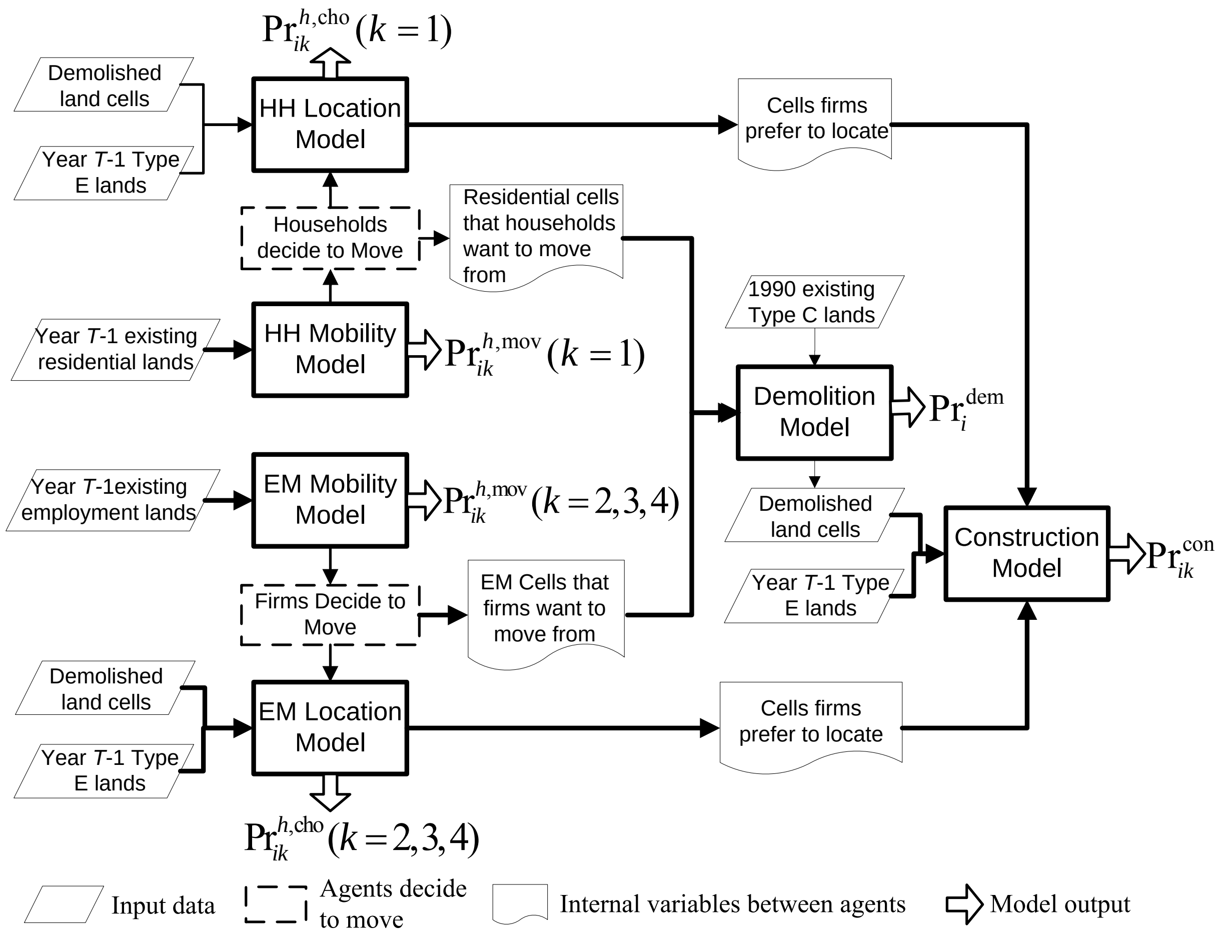


Figure 5-2. Interrelationships between Household, Employment, and Developer agent.

5.2.1 External Agents

The government agent is considered external, as it uses external inputs to account for policies (e.g., zoning preference, urban growth boundary, and conservations). The government agent includes a policy quantification model, which interprets land polices into the constraints or preference and integrates them into the predicted land use change for next time period. For example, polices on protection areas will be interpreted as a constraint, as no development will occur in this area. The zoning preferences are interpreted by assigning a different preference score to each zone.

5.2.2 Household and Employment Agent Model

In the household agents, according to their size, income and car ownership, households are clustered into $\overline{h}$ categories and will be subsequently allocated into available residential cells. In the employment agents, firms are categorized into industrial, commercial, and retail service. Industrial firms are allocated to industrial land cells, while commercial and retail service firms are allocated to commercial and services land cells. Households are assumed to be only in residential cells.

Both mobility and location choice behavior are captured in the household and employment agents. In the mobility model, the existing agents (households/firms) decide whether to move from its current location or not. If a household/firm has chosen to move, it is added to the set of new households/firms that have no current location, and will be located in the location choice model.

In the location choice model, a household/firm that is either new (from exogenous immigration) or has decided to move within the study area (from household/employment mobility model) will choose a particular residential/employment location cell. Based on the bid-rent theory, households of different types bid for residential location based on income and other household characteristics (e.g. household composition, number of children). Similarly, the firms at different sectors places a bidding price for a particular cell based on firms' attributes.

5.2.2.1 Household Mobility Model

In the Household Mobility Model, Binary Logit is employed to estimate the probability of existing households moving out from current residential cell i or staying during a particular time period, denoted by $\mathrm{Pr}_{ik}^{h,\mathrm{mov}}$. The utility of mobility $u_i^{h,\mathrm{mov}}$ that represents the behavior of household h are related with household's characteristics $\mathbf{I}_{h,\mathrm{mov}}$ (e.g. household size, age, income), the attributes of current residential cell i , $\mathbf{O}_i$ (e.g. vacant dwelling units, owner occupancy) and accessibility $\mathbf{A}_i$

$$u_{ik}^{h,\text{mov}} = \mathbf{w}_{1,\text{mov}} \mathbf{I}_{h,\text{mov}} + \mathbf{w}_{2,\text{mov}} \mathbf{O}_i + \mathbf{w}_{3,\text{mov}} \mathbf{A}_i \tag{5-1}$$

where $\mathbf{w}$ are coefficients. $u_{ik}^{h,\text{mov}}$ is assumed to follow IID Gumbel distribution with dispersion parameter ξ .The mobility probability $\Pr_{ik}^{h,\text{mov}}$, can be denoted as

$$\Pr_{ik}^{h,\text{mov}} = \frac{\exp(\xi u_{ik}^{h,\text{mov}})}{1+\exp(\xi u_{ik}^{h,\text{mov}})} . \tag{5-2}$$

Similar to the household agent model, the independent variables in employment mobility model include individual firm's characteristics, attributes of current cells, including transportation accessibility, neighborhood attribute, and land price.

5.2.2.2 Location Choice Model

In bid-auction processes, the location choice is determined by the willingness to pay function. In the classical urban economic theory, it is widely accepted that the urban land market behaves like an auction [65]. Goods are taken by the highest bidder and bids are represented by a function of the consumer's willingness to pay. Households' willingness to pay for an available residential location is related to household income, the spatial attributes of a desired location, accessibility and transportation cost. For the type h household, when cell i is available for residential location, the willingness-to-pay function of household h is postulated as [65]:

$$B_{i1}^{h} = -b_h + z_{hi} - \sum_p N_h^p \varphi_{hi}^p(t) \tag{5-3}$$

where b_h is a monetary disutility bid for household agent of type h based on the income. z_{hi} captures how a household of type h values the spatial neighborhoods' attributes of cell i. The final component represents the transportation utility under different trip purposes p if the cell i is chosen as the residential location. N_h^p translates to the number of trips with purpose p for household agent of type h, where the destination cell $j \in s$. $\varphi_{hi}^{p}(t)$ represents the cost to reach purpose p when the household of h type chooses cell i as the residential location.

The bid function $\tilde{B}_{ik}^{h}$ is also assumed to be random and accounts for the behavior produced by idiosyncratic differences among consumers within a cluster [45]. The bid can be represented by $\tilde{B}_{ik}^{h} = B_{ik}^{h} + \varepsilon_{k}^{h}$, where the random item ε_{k}^{h} is assumed to follow IID Gumbel distribution with dispersion parameter θ . The bid probability, $\mathrm{Pr}_{ik}^{h,\mathrm{bid}}$ ($k = 1$ residential land), probability that the household type h is the highest bidder for residential location *i*, is given as follows:

$$\mathrm{Pr}_{ik}^{h,\mathrm{bid}} = \frac{\exp(\theta B_{ik}^{h})}{\sum_{h}\exp(\theta B_{ik}^{h})}, \quad (\forall h = 1, 2, ..., \bar{h}; k = 1) \tag{5-4}$$

It is assumed that a residential location in the supply side is offered to the household with the highest payment; therefore, the rent of location r_{ik} (k =1 for residential) is determined by the expected highest bid and could be given as follows

$$r_{ik} = E[\underset{h}{Max}\, \tilde{B}_{hi}^{k}(i)] = \frac{1}{\theta}\ln\left(\sum_{h}\exp(\theta B_{hi}^{k})\right) + \frac{\gamma}{\theta} \tag{5-5}$$

where γ is a constant. r_{i1} denotes the rent in residential cell *i*. Eq. (5-5) shows that the location rents are endogenously built from locators' willingness to pay as a result of the bid-auction process. The household agents' optimal choice for a residential location is supposed to maximize the surplus between bidding price and rent, which results in the following problem: $Max_{\forall i}(B_{hi} - r_{hi})$ where $\{i \mid x_{i1} = 1\}$ denotes the available residential cells. The rent is taken as a deterministic variable. The choice probability $\mathrm{Pr}_{ik}^{h,\mathrm{cho}}$, ($k$=1 for residential) that an alternative residential location yields the highest utility to household agent of type h given by:

$$\Pr_{ik}^{h,\text{cho}} = \frac{\exp(\theta(B_{hi}^{k} - r_{ik}))}{\sum_{i} x_{i1} \exp(\theta(B_{hi}^{1} - r_{ik}))} \tag{5-6}$$

$\Pr_{i1}^{h,\text{cho}}$ is the probability that the household of type h chooses residential location i when location i is developed for residential land use.

The bid-auction theory is deployed in the employment location choice model. Based on urban economics and available data, the attributes considered in the willingness to pay function for each employment sector include characteristics of employment/firms and agglomeration economies. The attributes of agglomeration economies include total commuting time, neighborhoods attributes, and distance and travel time from employment centers.

5.2.3 Developer Agent Model

To maximize profit and satisfy the needs of households and employments, developers study both location and type of development. In the developer agent, two sub-models are deployed, a demolition and a construction model. In the demolition model, the developers' decision towards existing buildings in Type C land cells is considered to either be demolished or keep unchanged. In the construction model, both the redevelopment for demolished cells, and development for Type D cells are taken into consideration.

For demolition behavior in Type C land cells, the profit of demolition is formulated as

$$u_{i}^{\text{dem}} = \sum_{k} \delta_{ik} (w_{1,\text{dem}} m_{ik} + w_{2,\text{dem}} v_{ik}) - w_{3,\text{dem}} c_{i}^{\text{dem}} \tag{5-7}$$

where δ_{ik} is the characteristic variable of land type in cell i, and $\delta_{i1} = 1$ if the developed cell i is residential cell. c_{i}^{dem} denotes the demolished cost, and v_{ik} denotes maintenance cost. m_{ik} is the expected utility of existing locator's (household or employment sector) mobility. m_{ik} can be deduced by

$$m_{ik} = \frac{1}{\xi} \ln[\sum_{h} \exp(\xi u_{ik}^{h,\text{mov}})] + \frac{\gamma}{\xi} \tag{5-8}$$

where $u_{ik}^{h,\text{mov}}$ denotes the mobility utility of type *h* consumer in cell *i* with land type *k*, which follows IDD Gumbel distribution with dispersion parameter ξ. The demolition model of developer agent is implemented following a Binary Logit model, and the probability of demolition for existing developed cell i can be represented as follows:

$$\Pr_i^{\text{dem}} = \frac{\exp(\sigma_{\text{dem}} u_i^{\text{dem}})}{1+\exp(\sigma_{\text{dem}} u_i^{\text{dem}})} \tag{5-9}$$

For the construction behavior in Type D land cells, the profit function of developers is defined as the difference between the rent r_{ik} [from Eq.(5-5)] that will be obtained from a supply option and its production cost, including land l_{ik}, construction c_{ik}^{con}, and maintenance cost items v_{ik}. The profit of a vacant land (Type D) or currently demolished as vacant land (from Type C) to be constructed into type *k* land can be formulated as

$$u_{ik}^{\text{con}} = w_{1,\text{con}} r_{ik} - w_{2,\text{con}} l_{ik} - w_{3,\text{con}} c_{ik}^{\text{con}} - w_{4,\text{con}} v_{ik} \tag{5-10}$$

Additionally, profits are assumed to be stochastic, IID, which leads to an optimum supply probability with the MNL form. For each cell location *i*, the probability of the developer would like to develop it into type *k* development, which can be represented as:

$$\Pr_{ik}^{\text{con}} = \frac{\exp(\sigma_{\text{con}} u_{ik}^{\text{con}})}{\sum_k \exp(\sigma_{\text{con}} u_{ik}^{\text{con}})} \tag{5-11}$$

5.3 MNL-CA-Agent and ANN-CA-Agent Land Use Model

Based on the framework of MAS/LUCC, this study employs a MNL/ANN-CA-Agents land use change model that combines the spatial factors and the affect of decision makers' behavior on land use change. Coupled with the transition rules from the MNL/ANN based CA model that deploy spatial factors on land use change, the output of the agent models will be used to refine transition rules of land use change at discrete cell level, taking decision makers behavior into consideration. The proposed model was implemented using data from Orange County, which has experienced much population growth, and will continue to do so.

The actual land use change model, which links spatial attributes and the agents' micro-scale decisions to macro-scale phenomena, is shown in Figure 5-3. With certain policy making, government agent captures the change of Type A land over time. The water area is supposed not change over time, and the parks and protection areas are updated through policy changes. Type B land is updated from FSUTMS based on future transportation facilities. Type C land, representing existing developed land, remains mostly unchanged, though some lands are demolished or changed to other land use types, as seen in FIGURE 2-1. When capturing land use change involving existing developed Type C land uses, only the agents' behavior is considered, including household and employment mobility model, and developers' demolition model.

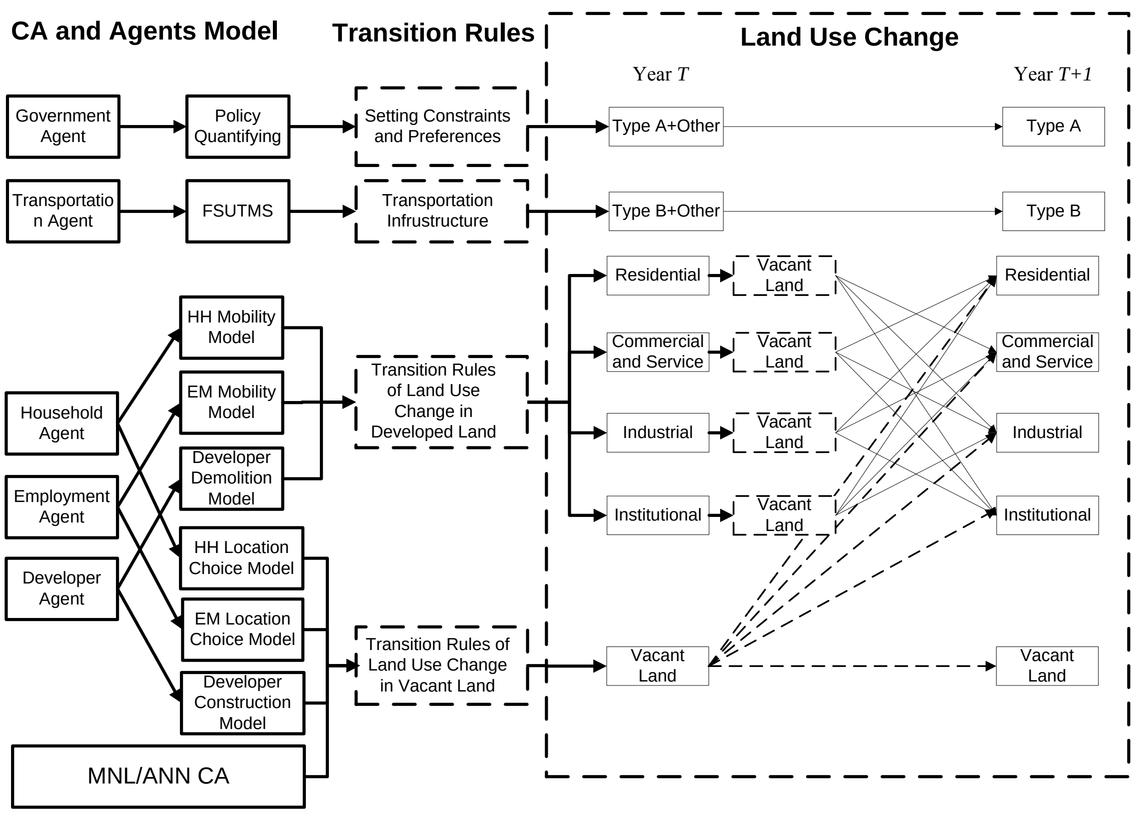


Figure 5-3. Schematic of the Interactions between the Micro-models, Transition Rules, and Land Use Change

Vacant lands especially experience changes. With increasing population, vacant lands will be developed if the current land cannot meet the increasing land demands. To capture land use change from Type D land to *LUT*, the ANN-based CA model is employed to deploy the spatial attributes, and household and employment location choice model. The developer's construction model is used to capture the agents' preference on land development. Transition rules of land use change from vacant land to *LUT* are defined from interacted results of both spatial attributes and micro agents' preference.

5.4 Land Market Equilibrium Model

In the land use market, both supply and demand are assumed to be in equilibrium, at least in the long. Therefore, certain vacant land cells will be developed, while some existing developed properties will be demolished and redeveloped to satisfy land demand at the cellular level. Under the supply-demand market equilibrium, each household and firm will find a location, which simultaneously satisfies the conditions to achieve the maximum utility for each location and maximum bid for each consumer.

5.4.1 Land Development Equilibrium

The land development equilibrium can be formulated as two integer linear problems: optimization problem Z1 and Z2. Z1 captures land use change in existing land Type C that is related with travel demand, to be demolished or unchanged. Optimization problem *Z*2 describes the land use development of vacant cells in land Type D and demolished cells from Z1, to satisfy the location needs of households and firms. To describe the land use change in Type C land, Z1 employs the household and employment agents mobility model and demolition model. In the case of land use change in Type D and demolition cells in Type C, Z2 uses the CA, location choice, and developer's construction models. To maximize the demolition probability, the optimization problem *Z*1 represents land use change in existing travel-demand related land Type C is determined by the mobility preference of households and firms agents, and demolition behavior of developer agent.

$$Z1 = \max_{y_{ik}} \sum_{i \in \Omega_C} (w_k^1 y_{ik} N_{ik} \Pr_i^{\text{dem}} + w_k^2 \sum_h \Pr_{ik}^{h,\text{mov}}) \tag{5-12}$$

$$\text{s.t.} \qquad y_{ik} = 1 \text{ or } 0 \tag{5-13}$$

$$\sum_i y_{ik} N_{ik} \le M_k, \qquad i \in \Omega_C \tag{5-14}$$

where y_{ik} is a characteristics variable denoting whether cell i in Type k will be changed. If y_{ik} equals to 1, cell i will be reset as vacant land, and all consumers N_{ik} in cell i must find a new location, which is simulated in location choice model. w_k^1 and w_k^2 denote the weights. M_k denotes the total amount of constraint of households or firms that decide to move, which can be generated from historical data through move ratio.

The problem Z2 is formulated as follows:

$$Z2 = \max_{(x_{ik}, S_{ik})} \sum_{i \in \Omega_D + \{i | y_{ik} = 1\}} \sum_k x_{ik} (w_k^3 \Pr_{ik}^{\text{CA}} + w_k^4 \Pr_{ik}^{\text{con}} + w_k^5 \sum_h \Pr_{ik}^{h,\text{cho}}) \tag{5-15}$$

$$\text{s.t.} \qquad \sum_k x_{ik} \le 1 \text{ and } x_{ik} = 1 \text{ or } 0 \tag{5-16}$$

$$\sum_i x_{ik} \le Q_k^T \tag{5-17}$$

where the three terms in Eq. (5-15) aim to maximize the spatial suitability of total land development, the developer's profit, and agents' location choice probability, respectively. w_k^3, w_k^4 and w_k^5 denote weights, respectively. The characteristic variable x_{ik} indicates whether the vacant cell i will be developed into land type k. Q_k^T is the bound of new developed land area of land type *k* at year *T*, denoted by the number of cells with the same area (50m x 50m). This value can be generated from historical data.

The constraint Eq. (5-16) indicates that each land cell can only be developed into one land use type. Eq.

(5-17) ensures the new developed land area in each land type falls within the maximum bounded supply Q_k^T. The outputs of Z1 and Z2, (**x, y**), are the results of land use change at cell level, in which the programming problem Z1 and Z2 can be defined as the transition rules of the land use change of each cell.

5.4.2 Equilibrium between Land Supply and Demand

The land use supply-demand market reaches equilibrium when all agents are located in the developed land cells. On the supply side, according to the maximizing developer's profit in Eq. (5-12), the optimal number of building supply of land type *k* in cell *i* is:

$$S_{ik} = S_k \frac{x_{ik} \exp(\sigma_{\text{con}} u_{ik}^{CON})}{\sum_i x_{ik} \exp(\sigma_{\text{con}} u_{ik}^{CON})} \tag{5-18}$$

where x_{ik} ensures the supply of type *k* building only exists in the new type *k* cells. S_k denotes the total building supply of type *k*. For example, if $x_{ik} = 1$, the cell i will be developed into type *k* development, and the developer will construct buildings with the dwelling supply S_{ik}.

For residential lands, the building type is divided into single family and multiple families, which are further determined by those households located in this cell using the residential type choice model. For each location in land type *k*, the developer chooses the highest bidder among all $\bar{h}$ consumers and the consumer will be allocated in this cell. According to Eq. (5-4), the number of agents allocated in each developed cell *i* for land use type *k* is created as follows:

$$N_{ik}^h = S_{ik} \frac{x_{ik} \exp(\theta B_{ik}^h)}{\sum_h x_{ik} \exp(\theta B_{ik}^h)} \tag{5-19}$$

Eq. (5-19) simulates an auction-type process with stochastic bids at each location *i*. By combining Eq. (5-18) and (5-19), the land supply-demand equilibrium can be easily generated as follows.

$$\sum_{h} N_{ik}^{h} = S_{ik} \tag{5-20}$$

$$S_k = \sum_{i} S_{ik} \tag{5-21}$$

$$\sum_{i}\sum_{h} N_{ik}^{h} = \sum_{i} S_{ik} \tag{5-22}$$

Eq. (5-20) represents the equilibrium between the land supply and demand at each location *i*. Eq. (5-21) means the total supply of type *k* development equals the sum of supply of type *k* development in each location. From Eqs. (5-20) and (5-21), the equilibrium between supply and demand for the whole study area can be deduced as Eq.(5-22). The results of land use development and the inputs for FSUTMS can be generated from the above three equilibrium problems.

5.5 Transition Rules of Land Use Change

5.5.1 Transition Rules between the Government Agent and Transportation Model

Government policies are organized into two categories, G1 and G2. *G*1 are the lands that must be strictly preserved, such as conservation areas and parks. Second, there are *G*2 areas, which are the zoning preferences. These dictate what types of development that will occur, but recognizing there may be zoning variances. The transportation network facilities are an output from the transportation (e.g. FSUTMS) model, which contains development of future transportation facilities for specific years. The transition rules are described as if-then rules, as follows:

$$\text{If } i \in G1(T+1)\text{, then } i \rightarrow \text{Type A } (T+1) \tag{5-23}$$

$$\text{If } i \in G2(T+1)\text{, then } \Pr_{ik}^{G2} = 1\text{, otherwise , } \Pr_{ik}^{G2} = 0 \tag{5-24}$$

$$\text{If } i \in \text{Tr}(T+1)\text{, then } i \rightarrow \text{Type B } (T+1) \tag{5-25}$$

The zoning preference $\Pr_{ik}^{G2}$ vacant cell, are integrated into the transition rules in Section 5.3.

5.5.2 Transition Rules for Land use change on Already-Developed Land

The transition rules governing land use change on developed land cells are described as the optimization problem $Z1$, where the results y_{ik} is a characteristics variable denoting whether cell i in type k will be changed or not, representing the results of land use change (or transition) in the cell.

5.5.3 Transition Rules of Land Use Change in Vacant and Demolished Land

The optimization problem $Z2$ is used to describe the land use development of vacant cells (Type D lands) and demolished cells from $Z1$. Land development is deployed by the ANN model, the construction model of developer agent, the agents' location choice model, and the government policy (G2).

6. LandSys-FSUTMS Integration

6.1 LandSys Design

LandSys is a land use simulation program based on MNL-CA-Agent (multinomial logic cellular automata and agent). The program is built upon Matlab 2009 platform, which has powerful image processing and matrix manipulation capabilities. LandSys calls for a .m file to establish graphical user interface (GUI) and generates an executable file to improve the performance of user interface. The executable file will be called by FSUTMS transportation program to integrate land use with transportation modeling.

As shown in Figure 6-1, LandSys includes three modules: the basic module, a parameter adjustment module, and an application module. Of the three modules, the basic module is for early-stage preparations. The parameter module is used for system learning and the determination of model parameters. Finally, after plugging in the parameters, the LandSys program can simulate land use changes and generate input data for FSUTMS transportation models.

The basic module contains three sub-modules: land use categorization, data processing and storage. Land use categorization classifies initial land use types via Quantitative Change In-out method. The input data are the land use/cover data of case study areas in the past two periods (to avoid misclassification, the selected two periods are always 10 years apart). The output data includes the reclassification of land use types in account of land use and transportation integration of the case study area.

The input data in the data processing and storage module consists of three groups: spatial data, such as DEM and land use (data i1), output data from transportation modeling (FSUTMS) concerning travel time and accessibility (data i2), and statistics like population and employment (data i3). According to data processing flow chart, the data processing and storage can be divided into three steps:

(1) Convert data *i1* to 50m x 50m raster data by ArcGIS Spatial Analysis tools; then use Matlab to read the raster data and save them as matrix.

(2) Establish a module converting TAZ data to raster data. More specifically, convert data i2, which is based on TAZs, to raster data, then record and store the travel cost and accessibility information that connects one cell to each of other cells.

(3) Based on statistics and land use classification, assign household information to associated residential automata; assign employment information to non-residential automata; and save this information as matrix.

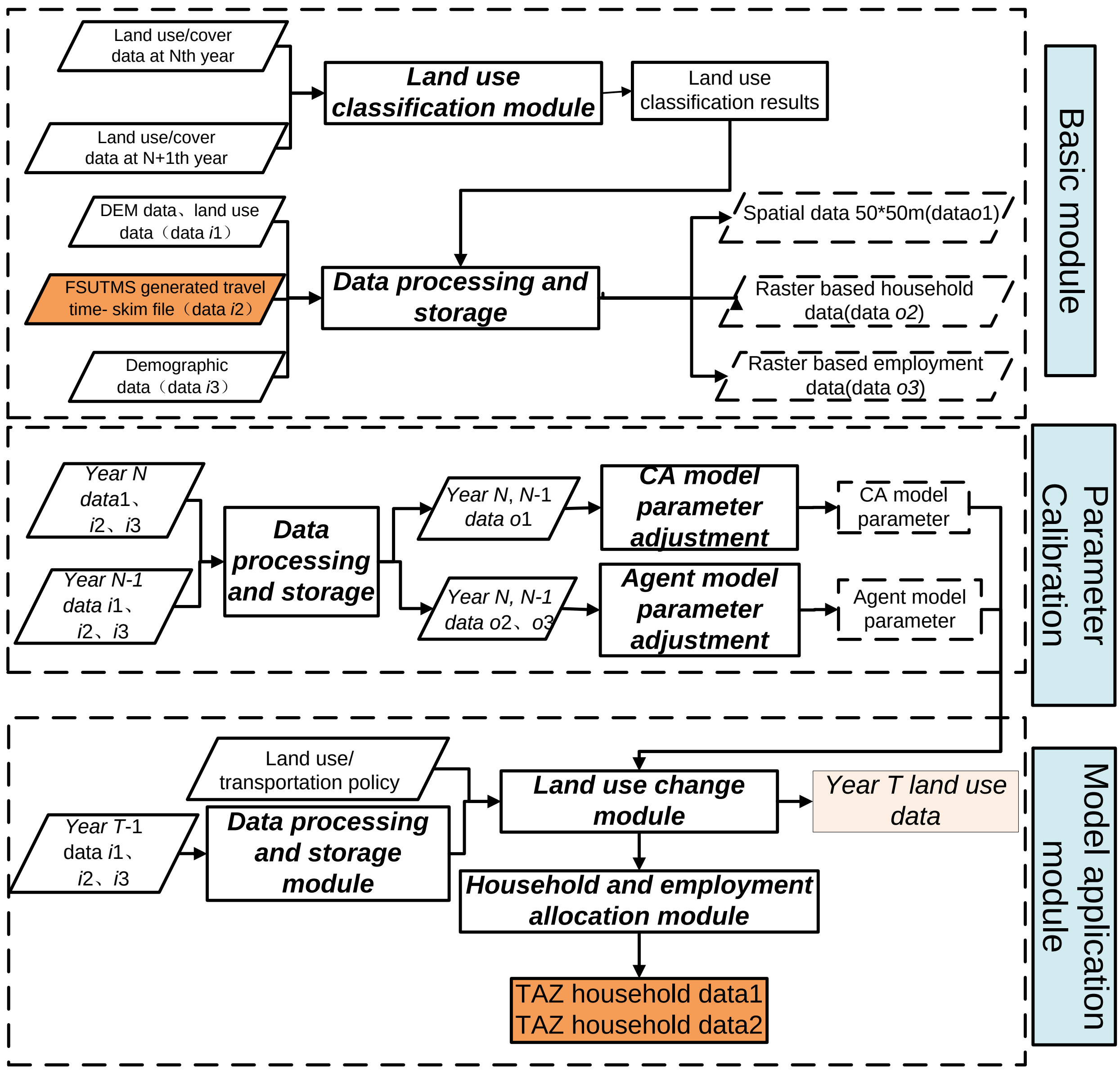


Figure 6-1. Model Framework

The parameter adjustment module includes two sub-modules: parameter adjustment sub module of CA models and parameter adjustment sub module of Agent models. The input in the data processing and storage sub-module includes data i1, data i2 and data i3 of year N and year N+1. The output data are o1, o2, and o3. Then data o1 and land use data of year N and year N+1 are plugged into parameter adjustment module of Cellular Automata modeling, which calculates the accuracy of the model by standardizing the MNL model parameter and process randomly selected samples. Similarly, data o2 and o3 are plugged into the parameter adjustment module of the Agent model adjusted to the model parameters. The adjusted parameters are major inputs of model application module.

The model application module includes a land use change sub-module, as well as an information assignment module based on land use, household and employment. The land use change sub-module includes two parts: conversion rules based on external factors, such as government and transportation policies; and the estimated land use of next year based on the solutions of optimization model Z1 and Z2 according to land development balance. The assignment module generates TAZ-based household and employment data for the next year, based on the solutions of land biding theory and the balance model of the supply and demand of the land market.

6.2 FSUTMS Introduction [66]

The FSUTMS model structure consists of standardized computer software programs, urban area data formats, and operating procedures. These standards are common to all urban transportation models in Florida, and were developed for the primary purpose of reducing the time and effort required to produce long-range travel demand forecasts for the Metropolitan Planning Organizations (MPOs) Long Range Transportation Plans. Under such standardization, the FDOT Central Office is able to efficiently provide software updates, procedural manuals, and technical support to both the FDOT districts and MPOs.

The primary objective of travel demand forecasting is to predict the effects of various policies, programs, and projects on highway and transit facilities [67]. These impacts are commonly quantified by representing the projected travel demand in terms of forecasted traffic volumes and transit ridership. Forecasting travel demand is an integral part of an area’s MPO Long Range Transportation Plan.

Travel demand forecasting consists of four primary steps: trip generation, trip distribution, mode choice, and assignment. However, to create the necessary input files for each of the four primary steps the FDOT has expanded these steps to a total of 12 steps in the FSUTMS software. The twelve steps in the FSUTMS software are the:

- External Travel Model
- Trip Generation Model
- Highway Network Model
- Highway Pathbuilding Model
- Trip Distribution Model
- Transit Network Model
- Transit Pathbuilding Model
- Mode Choice Model
- Highway Assignment Model
- Highway Evaluation Model
- Transit Assignment Model
- Transit Evaluation Model

In Florida, as of 2003, there were 25 MPO planning models, eight non-MPO planning models, eight regional models, and one statewide model. The urban area MPO and the regional models are maintained jointly by the MPO and FDOT District Planning staffs. The non-MPO models are maintained by the counties and FDOT Planning Districts.

6.3 Integration Framework

The integrated land use and transportation platform for Orange County, FL is a combination of the LandSys land use model and FSUTMS transportation model. Its framework is shown in Figure 6-2.

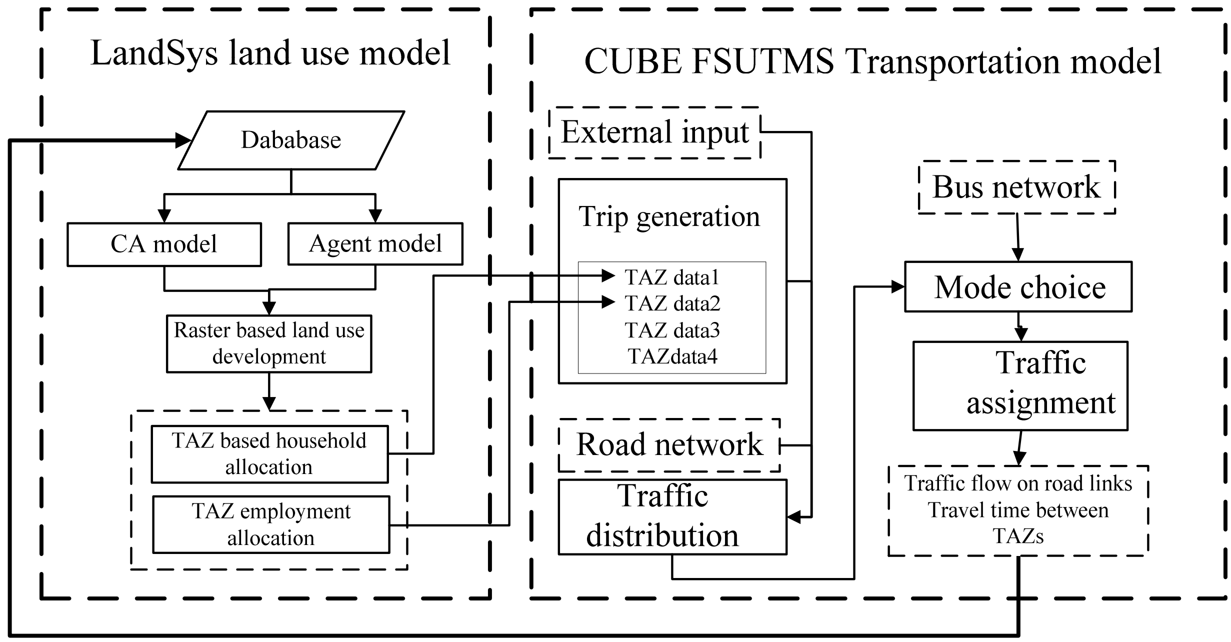


Figure 6-2. Model Framework of Integrated LandSys-FSUTMS Model

The results of the LandSys model include household and employment information based on TAZs. These results are connected to the FSUTMS models by updating their TAZ data 1 and 2 of the trip generation module. With these updated data, the trip flows and accessibility of TAZs generated by transportation model will be used as inputs of land use models. The described connections between land use and transportation models explain the relationship between land use and transportation: the spatial distribution of different land uses causes the variation of trip generation; the travel cost and accessibility of each TAZ directly impact land uses.

Figure 6-3 displays the analysis framework. The variation of transportation policies, such as the construction of new networks and new alternative transportation modes, are weaved into FSUTMS transportation models as updated inputs to get new network information. The inputs of integrated modeling are taken into consideration of demographic statistics, regional economic statistics, land use, government policy, and community planning. The modeling result can help analyzing planning policies. Different land use strategies, transportation policies, transportation planning and other planning strategies can be included into the models by updating transportation and land use inputs. The impacts of news policies on transportation and land use can be captured by the models. In addition, the regional environmental assessment, cost-benefit analysis, and air quality, etc can also be analyzed by the integrated land use and transportation models.

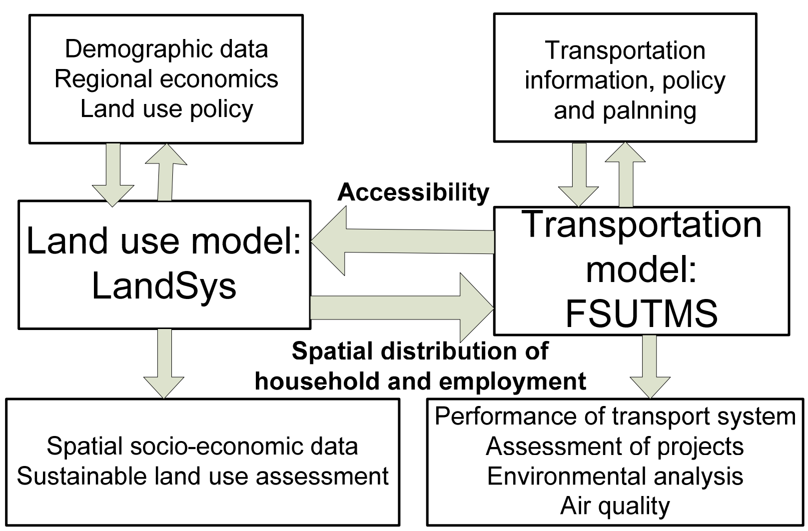


Figure 6-3. The Policy Analysis Framework of the Integrated LandSys-FSUTMUS Models

6.4 Software Design

Table 6-1 shows the comparison between the integrated LandSys-FSUTMS models and other mainstream models in terms of model structure, composition of sub-models, real estate development, policy analysis. Etc.

Table 6-1. Comparison between the Integrated LandSys-FSUTMS Models and Other Mainstream Models

Characteristics	DRAM/EMPAL	MEPLAN	PECAS	UrbanSim	CUF-1/CUF-2	LandSys-FSUTMS
Structure	The Lowry Model	Spatial input-output model	Spatial input-output model	Discrete choice model	Discrete choice model	Discrete choice model
Behavior of household location choice	yes	yes	yes	yes	No	yes
Behavior of business location choice	yes	yes	yes	yes	No	yes
Real estate	yes	yes	yes	yes	Yes	yes
Spatial unit	Statistical community	TAZ	TAZ	Cell, parcel or TAZ	cell	cell and TAZ
Sensitivity of policies	no	Congestion pricing	Land use policy	Congestion pricing, land use policy and regional planning	Land use policy	Land use policy, congestion pricing, regional planning, environmental impact
Temporal scale	year	year	year	year	year	Year or customized scale
Interaction with transportation models	yes	yes	yes	yes	No	yes
Software ownership	Commercial software	Commercial software	Open source	Open source	N/A	TBD

As opposed to other models, LandSys-FSUTMS takes into account the behavior of household and employment based agent, and includes land use and transportation policies. It also mimics the land market equilibrium by employing land bid-rent theory. When describing the change of land use, accuracy is guaranteed by using 50m x 50m raster data. The raster data can be converted to TAZ format when they are used as inputs of transportation models,.

Another important characteristic of LandSys-FSUTMS is that LandSys can adjust its parameters by self-learning the historical data of the case study area. Therefore, the portability of the models makes uncomplicated to adjust model parameters and apply the models in different cities. Furthermore, the models of LandSys can be coupled with transportation models other than FSUTMS if the types of input data match with each other. This means that LandSys models can also be integrated with many models other than FSUTMUS.

7. Results and Discussions

7.1 CA Results

7.1.1 MNL-CA Results

Fifty percent of Type D land cells in 1990 land use/cover data were selected to calibrate MNL-based CA model. In 1990, the total number of cells in Type D was 566,093, with 70,261 cells that changed to trip generated land types in 2000. The cells of Type D in 1990 were grouped into five categories based on the final land use types in 2000: commercial land (17,765 cells); industrial land (2,012 cells); institutional land (8,790 cells); residential land (41,694 cells); and unchanged (495,832 cells). By using a Monte Carlo sampling process, fifty percent of the cells in each category were chosen for calibration, and the category 'remain unchanged' is considered to be the baseline category.

Table 7-1 shows the calibrated results of MNL (Eq. 4-1). The regression results of the CA model offer several valuable empirical findings. For example, in the interpretation of the coefficients of distance attributes, 'distance to airport' has a positive coefficient, which indicates the farther the cell from the airport, the more easily it will be developed into the corresponding land types. The possibility of land cell change to *LUT* increases with its distance to airport increases, whereas the cells near major roads and the CBD are more likely to be developed at a closer distance. For vacant cells, as the distance to CBD decreases, its possibility of changing to commercial land increases. In the case of neighborhood attributes, under 'Number of Residential,' the positive coefficient of 1.3391 means that if a cell is surrounded by more residential cells in Moore neighborhood, then it will be more likely to be developed into residential lands. Land cells with more industrial cells in neighborhood are more possible to be developed into industrial land and less possible to be developed into residential land. This is partly a result of zoning and partly a result of the agglomeration effect.

Table 7-1. Calibrated Coefficients of Multinomial-logit Model

	Attributes Description	Parameters for each land use type							
		Commercial		Industrial		Institutional		Residential	
		Coef	T-stat	Coef	T-stat	Coef	T-stat	Coef	T-stat
Physical attributes	Cell soil	0.350	12.85	0.121	4.28	0.136	4.85	0.365	14.05
	Cell slope	0.057	1.36	0.111	2.57	0.214	5.03	0.436	11.10
Spatial accessibility	Distance to railway station	-0.191	-1.49	-0.716	-5.50	-0.026	-0.20	-2.697	-23.70
	Distance to bus station	0.244	3.47	0.322	4.47	0.563	8.15	1.139	17.04
	Distance to airport	0.648	8.57	0.500	6.52	0.066	0.88	1.786	25.13
	Distance to major roads	-0.118	-3.12	-0.173	-4.44	-0.109	-2.84	-0.592	-16.83
	Distance to CBD	-0.843	-16.65	-0.282	-5.39	-0.455	-8.84	-0.644	-13.55
	Distance to commercial center	-0.221	-3.03	0.044	0.59	0.657	9.24	-0.099	-1.41
	Distance to industrial	-0.009	-0.21	-0.036	-0.78	-0.289	-6.48	-0.038	-0.90
	Distance to residential	0.271	7.85	0.067	1.86	0.145	4.16	-0.093	-2.66
Moore neighborhood	Number of commercial	1.414	5.95	0.675	2.68	0.917	3.60	0.300	1.26
	Number of industrial	0.294	0.98	1.344	4.81	0.486	1.59	-0.466	-1.60
	Number of institutes	0.630	1.83	0.645	1.84	2.797	9.27	0.094	0.28
	Number of residential	0.453	1.81	0.426	1.66	0.887	3.44	1.339	5.56
	Number of Type A	-0.042	-0.17	-0.094	-0.37	0.257	1.02	-0.352	-1.47
	Number of Type D	0.079	0.33	-0.029	-0.12	0.187	0.76	-0.097	-0.42
Constant	Constant	-1.687	-7.03	-1.448	-5.89	-1.852	-7.47	-1.084	-4.62
Dependent Variable	$\Pr_{i,k}^{CA}$, the probability of land use change in cell i from the current vacant land to new type k land from CA model.								

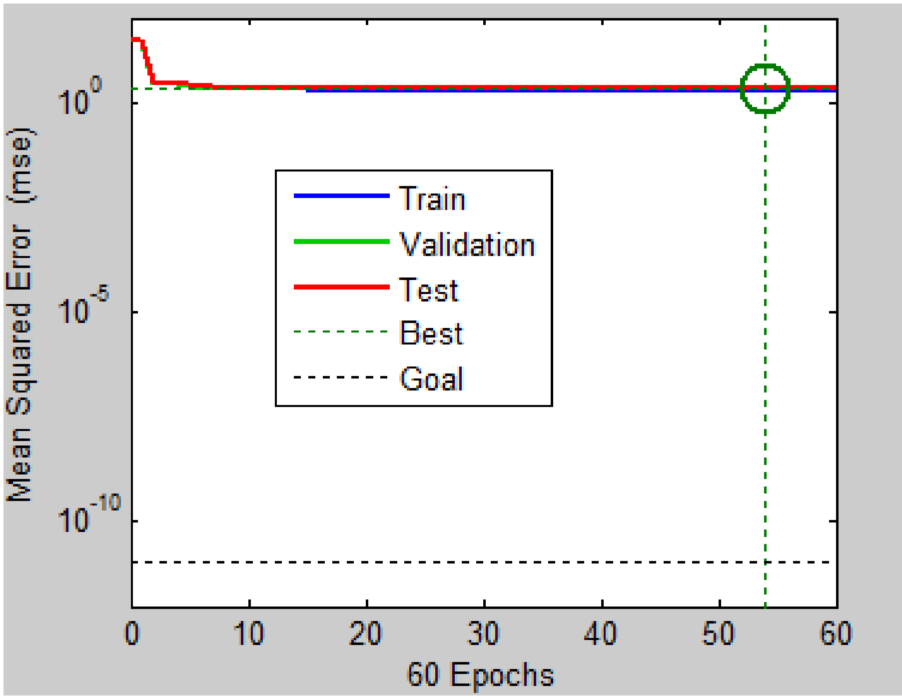
RESL = residential land; INDL = industrial land; COML = commercial and service land; INSL= Institutional land; Coef= Coefficients; T-statistics=T-stat

7.1.2 ANN-CA Results

7.1.2.1 Training the ANN

For each selected training cell *i*, the input value corresponding to input layer of neural network in are the spatial attributes of cell *i*. The output neuron was assigned with the desired value of 1 when the vacant cell in 1990 changes to the associated target land use in 2000. For example, if in 2000 the cell was residential, then the value for each neural in the output layer is (1, 0, 0, 0, 0). When comparing the land use data, the total number of Type D cells in 1990 was 566093, where 70261 cells were changed into *LUT* in 2000: to commercial land, 17765 cells; to industrial land, 2012 cells; to institutional land, 8790 cells; to residential land, 41694 cells; and remain unchanged, 495832 cells. By using a random sampling process, 25 percent of the cells in each category are chosen for training the neural network.

(a)



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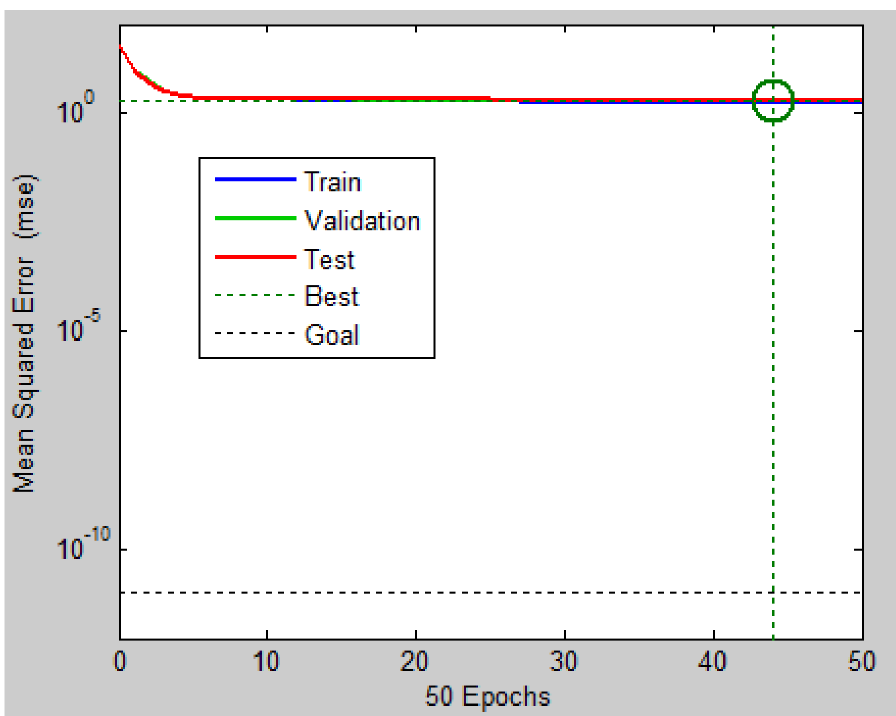


Figure 7-1. Training Performances of ANN. (a) Network with One Hidden Layer; (b) Network with Three Hidden Layer.

Figure 7-1 shows the training performance of ANN with one- and three-hidden layers. During the training, prediction errors decreased rapidly in a short time, followed by a steady reduction. In the one hidden layer neural network, the convergence reached at 54th epochs, (3 minutes 36 seconds), whereas in three hidden layers, it reached at 44th epochs (7 minutes and 14 seconds).

7.1.2.2 Validation of the ANN

To predict land use change based on all of the Type D cells in 1990, Table 7-2 compares the prediction performance of training the ANN with one and three hidden layers. According to the goodness of fit presented by Eq. (4-6), the total accuracy for all *LUT* can reach 69.7% and 74.6% for ANN with one and three hidden layers, respectively. With the increase in hidden layers employed in a multilayer neural network of ANN, the ANN could reach higher precision. The training time, however, is longer with the increase of hidden layers.

Table 7-2. Validation of the ANN with Different Hidden Layers

Land Type		One hidden layer			Three hidden layers	
1990	2000	N_k^{ActualC}	N_k^{SameC}	Accuracy R_k	N_k^{SameC}	Accuracy R_k
Type D	Commercial	17765	10983	0.618	11934	0.672
Type D	Industrial	2012	53	0.026	118	0.059
Type D	Institutional	8790	6671	0.759	6600	0.751
Type D	Residential	41694	31221	0.749	33792	0.810
Total Accuracy				0.696		0.746

7.2 Calibration Results of Agent Models

The calibration results of the household mobility model are shown in Table 7-3. From the calibrated coefficients, the probability of household mobility decreases with the increase of household size, and with the presence of school-age children and people older than 50. Increases in workers, income, and vacant dwelling units enhance the likelihood of households' mobility.

Table 7-3. Calibration Results of Household Mobility Decision Model

	Attributes Description	Coefficients	T-statistics
Household's characteristics	Constant	1.432	30.18
	Household size	-0.139	-9.15
	Workers	0.213	10.11
	Presence of children between 5 and 17 years of age	-0.040	-2.30
	Presence of persons above 50 years of age	-0.909	-11.97
	Average Income per person (/1000)	0.017	4.37
Attributes of current cells	Vacant dwelling units	0.156	5.09
	Owner occupy	-0.088	-9.80
Dependent variable	$\Pr_{ik}^{h,\text{mov}}$, the probability of existing households moving from current residential cell i.		

Note: LLC stands for log-likelihood at convergence; *n* is sample size.

In the location choice model, the willingness-to-pay function was calibrated with both 1990 and 2000 data. The calibration results are shown in Table 7-4. The number of commercial, institutional, residential cells in neighborhoods had a positive effect on household location choice. Total travel time for all purposes has a negative impact, which means that long travel time in vacant cell *i* reduces the possibility that this cell is converted for the residential land uses.

Table 7-4. Coefficients of Household Location Choice Model

	Attributes Description	Coefficients	T-statistics
	Constant	-1.730	-52.41
Household characteristics ($-b_h$)	Income	0.004	5.01
	Household size	0.277	40.06
Neighborhood attributes (z_{hi})	Number of commercial cells in Moore neighborhood	0.087	15.64
	Number of institutional cells in Moore neighborhood	0.046	5.58
	Number of residential cells in Moore neighborhood	0.533	197.62
Travel time (T_{hi})	Household's total travel time under three trip purposes	-0.405	-13.07
Dependent variable	$\Pr_{i1}^{h,\text{cho}}$, the probability that the household of type h chooses residential location i.		

The detailed calibrated model results of the willingness-to-pay function for each employment sector are shown in Table 7-5. The total travel time to the existing commercial center had a negative effect on location choice of the commercial and service employment sectors, which indicates both firms prefer cluster together. In Economic Geography, it is well known that clustering firms together can significantly decrease production costs, and therefore attract more suppliers and customers. The benefits of clustering were also recognized in neighborhoods within 500 and 2000 meters. Locations with more residential cells in a neighborhood are more attractive to commercial and service firms, since they are more likely to reach potential customers. In contrast, with respect to the location choice results of the industrial sector, there are negative coefficients in respect to the number of residential cells in neighborhoods, indicating that the industrial activities prefer those cells that are surrounded by less residential lands, partly as a result of zoning. Higher land price has a negative effect on employment location choice, which means the higher land price will lead to less likelihood of firm location choice. Locations with high accessibility to airport and major roads are preferred by all kinds of employers

Table 7-5. Calibration Results of Employment Sectors Location Choice Model

	Attributes Description	Commercial		Service		Industrial	
		Coefficients	**T-statistics**	**Coefficients**	**T-statistics**	**Coefficients**	**T-statistics**
	Constant	0.5251	7.45	-1.0987	-22.13	-1.5236	-29.97
Employment Characteristics	Employment size	0.0316	14.54	0.0314	49.87	0.3793	58.49
Neighborhood Attributes	Number of commercial cells within 500 meters	0.0009	31.60	0.0013	55.69	N/A	N/A
	Number of Industrial cells within 500 meters	N/A	N/A	N/A	N/A	0.0002	3.53
	Number of residential cells within 2000 meters	0.0025	15.32	0.0039	29.17	-0.0004	-2.14
Agglomeration economies	Total travel time to commercial center	-1.8278	-30.48	-1.3165	-37.55	-0.2731	-8.54
	Total travel time to industrial center	1.7944	30.02	1.2971	37.25	0.2613	8.38
	Distance to major roads	-4.10E-06	-0.94	-3.08E-06	-0.09	0.0000	-0.69
	Distance to CBD	-0.0033	-11.05	0.0007	3.17	-0.0014	-6.60
	Distance to commercial center	-0.0099	-19.64	-0.0031	-12.02	N/A	N/A
	Distance to industrial center	N/A	N/A	N/A	N/A	0.0013	5.29
	Land price	-0.0018	-8.30	-0.0021	-10.42	-0.0015	-6.22
Dependent variable	$\Pr_{ik}^{h,\text{cho}}$, the probability that the firm of type h chooses location i in land type k.						

N/A = Not Applicable.

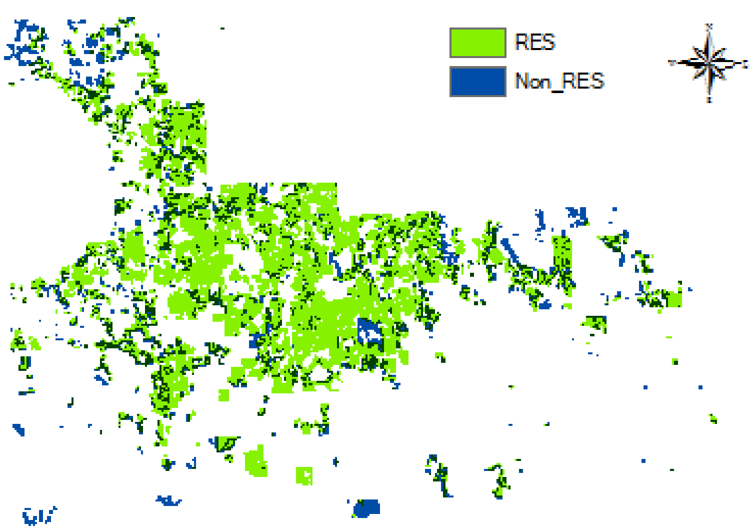
7.3 CA-Agent Results

7.3.1 MNL-CA-Agent Model

7.3.1.1 Forecasting Land Use Change in Land Type C

The model is validated using GIS data from Orange County, employing a three-step process. First, data from 1990 is calibrated. Second, land use development for 2000 is predicted. Third, the real data from 2000 are compared to the predictions. According to the first optimization problem of land development equilibrium (Z1), the land use change in existing Land Type C can be simulated through the results (y_{ik}). The demolition results of existing residential lands and the corresponding redevelopment (to other land types or keep demolished) of those demolished cells are shown in Figure 7-2. From Figure 7-2 (a), residential cells, especially those that are far from the CBD, are demolished (Non_Res in Figure 7-2 (a)), some are redeveloped into other land types. The model correctly estimated the demolished lands 75.10, 65.03, and 53.95% for residential, commercial, and industrial land, respectively.

(a)



(b)

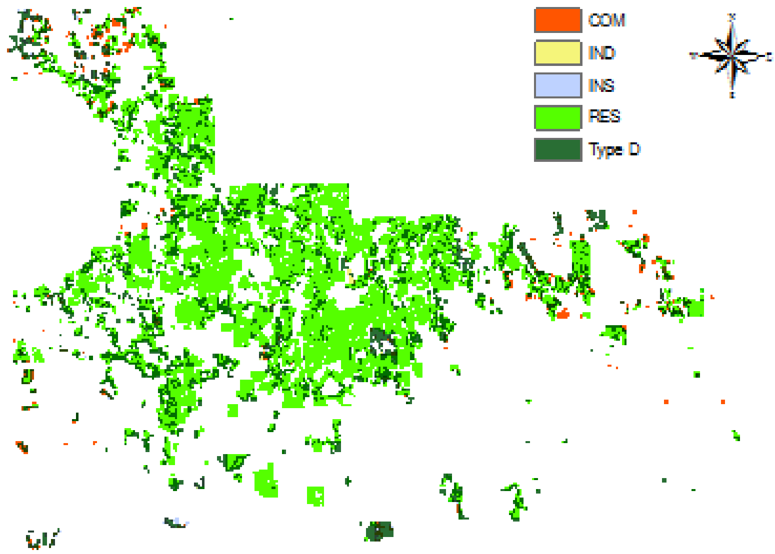


Figure 7-2. The Simulation of Land Use Change for Type C. (a) Demolition Results of Existing Residential lands. (b) Land Redevelopment of the Demolished Cells.

7.3.1.2 Model Prediction Performance

To evaluate simulation accuracy, a confusion matrix is used to compare the predicted and actual value cell-by-cell [67]. Table 7-6 shows a cell-by-cell comparison using the confusion matrix. In the case of *LUT*, the simulation accuracy of CA model only was 60.7%. When combined with Agent models, the integrated CA-Agents model improves the prediction estimation to 85.4%, which is a significant improvement (~25%) from the CA model only. In the case of all land types, the combined CA-Agents model has a high prediction accuracy of 89.9%.

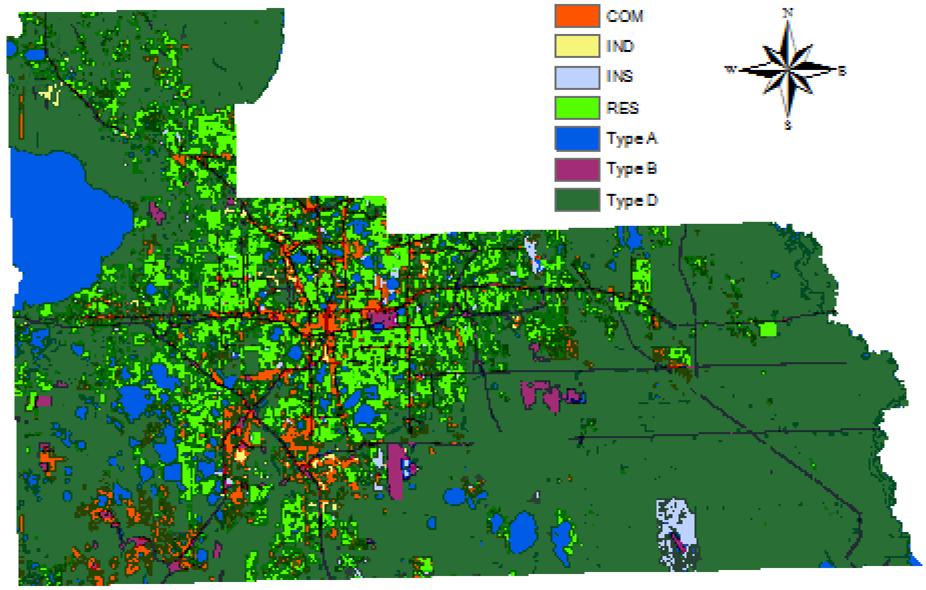
Table 7-6. Cell-by-Cell Comparison of the Results of the CA and Agents Model Predictions and Actual Land Changes [a]

Cell-by-cell Comparison (By Land use types)			Simulation results: Type A	Type B	Type C: RESL	COML	INDL	INSL	Type D	Accuracy (%)
Actual results	Type A		89261	518	424	378	262	321	19675	80.5
	Type B		309	19160	492	656	634	642	16888	49.4
	Type C	RESL	1651	659	163465	2889	223	1701	5995	92.6
		COML	524	1673	1495	43255	2130	1506	3964	79.3
		INDL	91	216	502	3460	5926	90	1383	50.8
		INSL	565	330	1468	2110	245	12931	2635	63.7
	Type D		4748	3670	1083	3752	2318	1627	609145	97.3
Overall Accuracy (%)										87.6
Accuracy of LUT										85.7

[a] RESL = residential land; INDL = industrial land; COML = commercial and service land; INSL= Institutional land; Non-RESL= Nonresidential land; Non-INDL=Non industrial land;

High prediction accuracy indicates that the proposed Agents-based CA model is sufficiently accurate to simulate land use change. The precision of residential, commercial, industrial and institutional land is 92.6%, 79.3%, 50.8%, and 63.7%, respectively. The visual map of predicted land pattern and actual land in 2000 is shown in Figure 7-3. The map demonstrates that the land use change predicted by the Agent-based CA Model is similar with the actual map of development.

(a)



(b)

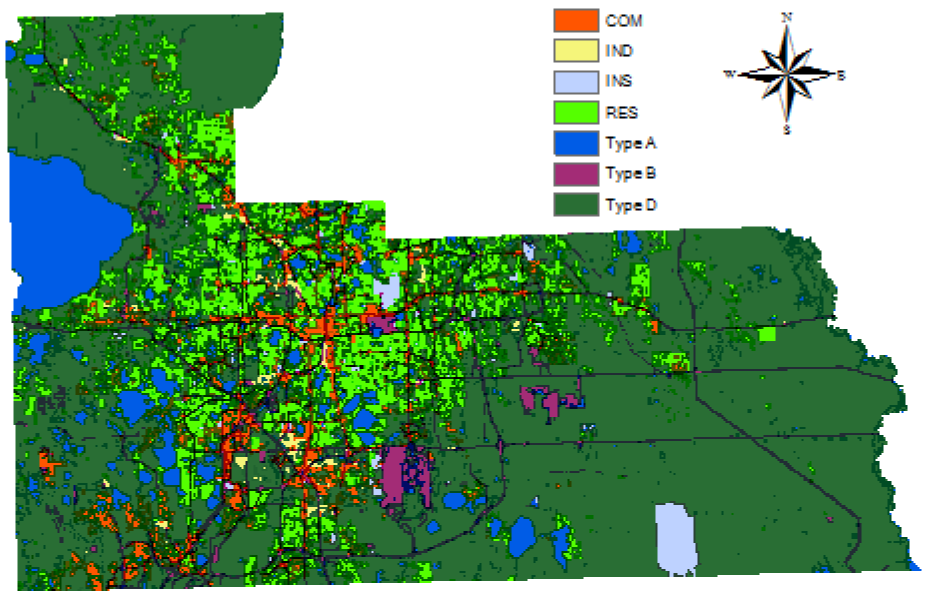


Figure 7-3. Comparison of Predicted and Real Land Use Development. (a) Land Use Development Results of Combined CA and Agents Model, Year 2000. (b) Actual Land Use Developments in 2000

7.3.2 ANN-CA-Agent Model

To simulate land use development for the year 2000, based on 1990 data, the ANN part of the model ran for 26 minutes. When integrated with the agent models, the model ran for four hours and 32 minutes, which includes data processing, calibrating the ANN and Agents model, and simulating land use change based on the optimization problems Z1 and Z2.

To simulate land use change with the ANN-CA-Agents model, four scenarios are considered: (1) ANN with one hidden layer, (2) ANN with three hidden layers, (3) integrated agent models with ANN (one hidden layer), and (4) integrated agent models with ANN (three hidden layers).

Each of the above scenarios is subjected to a goodness of fit measure, using Eq. (4-6), as shown in Figure 7-4. In the combined ANN and Agent-based model (scenario 3 in Figure 7-4), the precision of the *LUT* land in 2000 that changed from Type D land in 1990 can achieve 86%, which is quite acceptable. Figure 7-4 demonstrates that the combination of the ANN and agent-based models provides higher precision than using solely ANN. This is particularly true in industrial land. The results of the scenarios show that though ANN can reach a high precision of land use simulation for land types with large size, however the simulation robustness for lands with small size land use change is extremely poor (2.6% in scenario 1 and 5.8% in scenario 2). In our agent-based models, industrial firm agent in employment agent is considered as an important contribution to industrial land development, can help significantly improve the precision when combined with neural network.

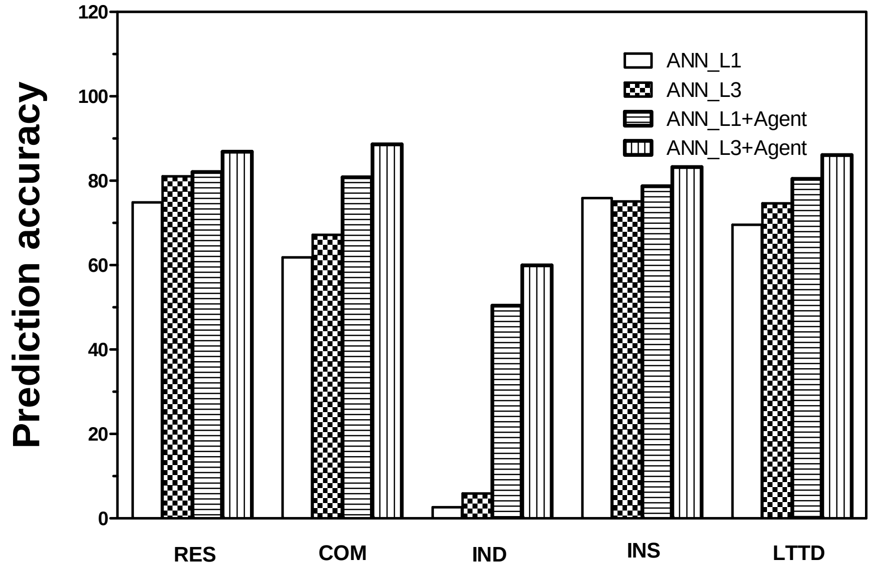


Figure 7-4. Comparison of goodness of fit of four scenarios. (Scenario 1:ANN_L1, Scenario 2:ANN_L3, Scenario 3:ANN_L1+Agent, Scenario 4:ANN_L1+Agent)

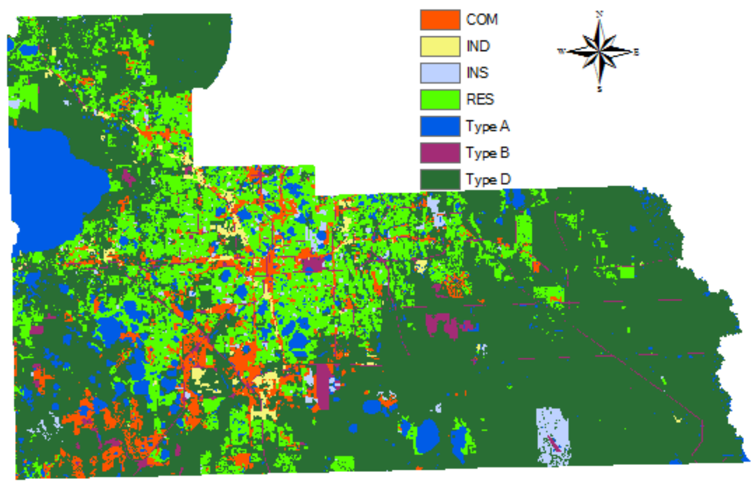
Table 7-7. Confusion Matrix Comparison of the Results of the ANN-CA-Agents Model Predictions and Actual Land Changes [a]

Cell-by-cell Comparison (By Land use types)			**Simulation results**							Accuracy (%)
			Type A	Type B	Type C				Type D	
					RESL	COML	INDL	INSL		
Actual results	Type A		89261	518	2074	1334	191	129	17332	80.5
	Type B		309	19160	1342	2386	462	523	14599	49.4
	Type C	RESL	1651	659	165819	3553	525	1180	3196	93.9
		COML	524	1673	3106	44336	3057	964	887	81.2
		INDL	91	216	255	2884	7140	30	1052	61.2
		INSL	565	330	2561	1497	227	13525	1579	66.7
	Type D		4748	3670	1083	15165	4230	2507	1957	94.8
Total Accuracy (%)										89.8
Accuracy of *LUT* Land										87.7

[a] RESL = residential land; INDL = industrial land; COML = commercial and service land; INSL= Institutional land; Non-RESL= Nonresidential land; Non-INDL=Non industrial land;

Table 7-7 shows the detailed results of the confusion matrix comparing of the actual data in 2000 and the results of Scenario 4 (combined three hidden layer neural network and Agent-based model). The accuracy of the simulation of land use developments for all land types and *LUT* were 89.8% and 87.7%, respectively. This shows that the integrated ANN-CA-Agents model is sufficiently accurate to simulate land use change. The prediction precision of residential, commercial, industrial and institutional land is 93.9%, 81.2%, 61.2%, and 66.7%, respectively. The actual and predicted land use patterns are shown in Figure 7-5. Residential and commercial lands are mainly distributed around the urban centers and spread along roads in the later years. The map demonstrates that the land use change predicted by the Agent-based CA Model looks similar with the actual map of development.

(a)



(b)

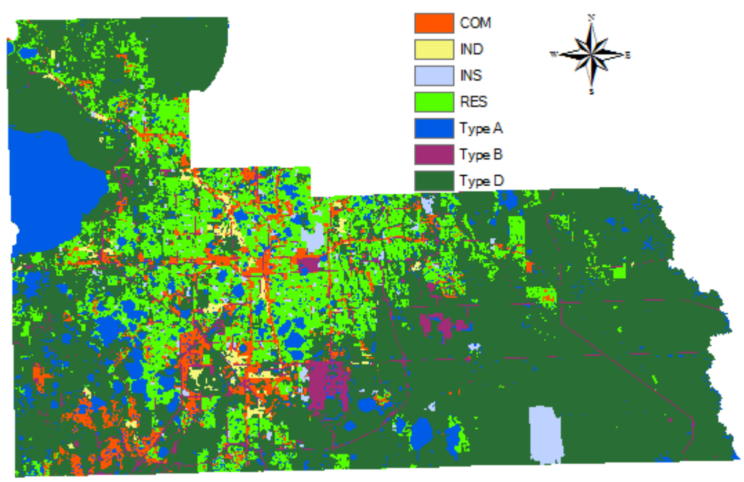


Figure 7-5. Visual Maps of Predicted Land Pattern and Actual Land in 2000. (a) Predicted Land Use Development of ANN-CA-Agents model (b) Actual Land Use Development in Year 2000

7.4 Forecasting the Allocation of Household and Employment

Under bid-rent equilibrium, households and employment (firms) are allocated at the cell level. To generate inputs for transportation models (such as FSUTMS), the allocation results of households and employment at the cell level, N_{ik}^{h}, are further aggregated into TAZs. In the FSUTMS model, 662 TAZs are assigned for Orange County, Florida. Based on the difference between the predicted and actual households/employment from 1990 to 2000, the allocation of households/employment at TAZ level can be divided into seven ranges: <-500, [-500, -200], [-200, -50], [-50, 50], [50, 200], [200, 500], and >500 zones. Under the example of [200,500], the results for the predicted number of households/employment subtracting the actual one are within the interval of [200, 500]. Figure 7-6 correlates the percentage of TAZs (number of TAZs/total number of TAZ) with the above seven allocation ranges. The figure shows that the predictions of the proposed CA-agent based model match well with the observed data in 2000 because most allocation errors fall within plus or minus 50 ([-50, 50]) range in the case of households (~52%) and employment (~37%). It further shows that household and employment change was corrected predicted for 75.7% and 69.9% of the zones when the difference range is within 200 ([-200,200]).

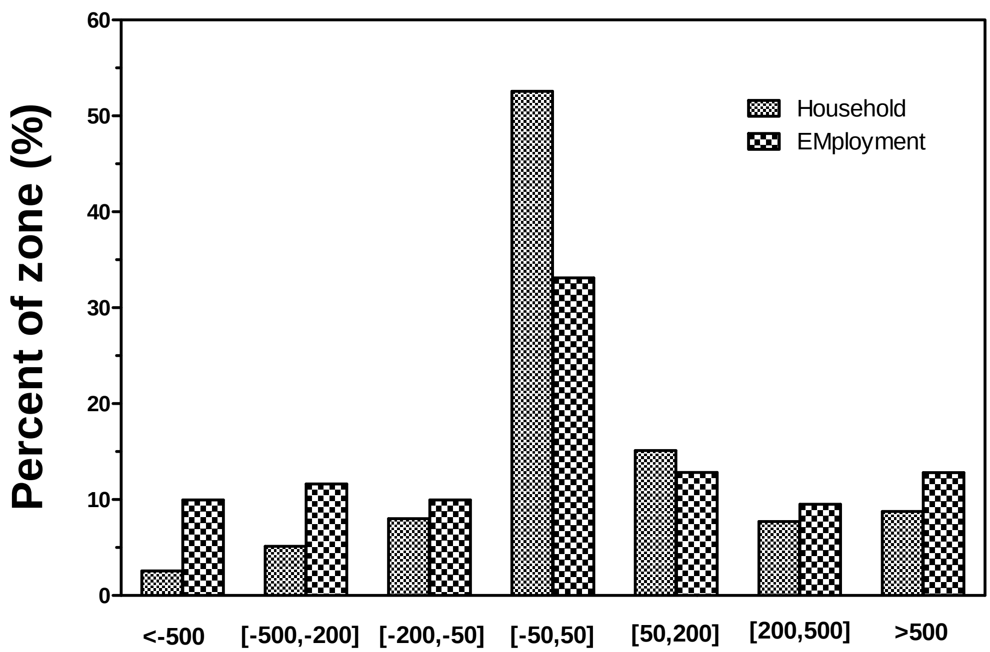
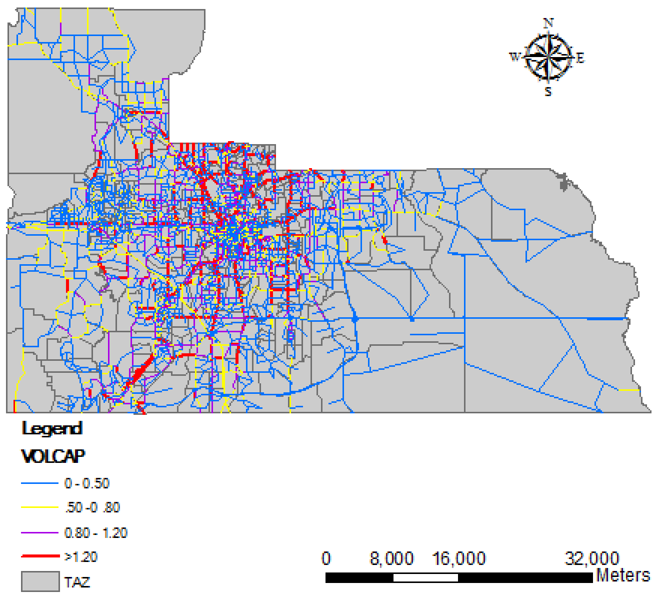


Figure 7-6. Difference between the Simulated and Observed Household/Employment from 1990 to 2000.

7.5 Transportation Network Results

Figure 7-7 displays the degree of saturation of network traffic flows in Orange County, for the year 2000. The results are produced by mono-transportation model and integrated model. The degree of saturation is categorized into four groups: 0-0.5 (blue), 0.5-0.8 (yellow), 0.8-1 (purple), and bigger than 1.2 (red).

(a) The distribution of degree of saturation in Orange County generated by FSUTMS



(b) The distribution of degree of saturation in Orange County generated by LandSys-FSUTMS

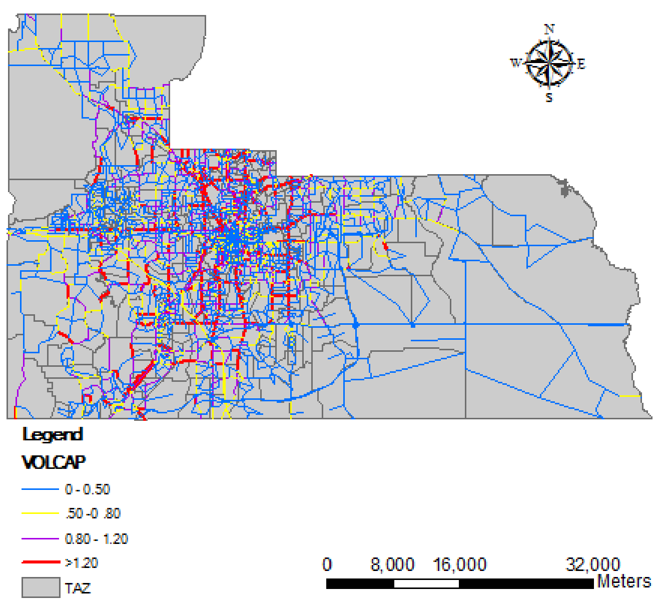


Figure 7-7. The Distribution of Degree of Saturation of FSUTMS and LandSys-FSUTMS

According to the above figure, the road paths with high saturation (shown in purple and red) concentrate in the center of study area. This is because the urban center tends to have intense land development and dense transportation networks. On the edge of the study area, saturation is lower, as these places have less travel demand.

In 7-1(a), as opposed to 7-1(b), there are more paths with high saturation. This indicates that FSUTMS models alone without considering land use feedback predict more links with high saturation than LandSys-FSUTMS models.

Table 7-8 lists the saturation distribution across different intervals of both FSUTMS models and LandSys-FSUTMS models in 2000, 2012 and 2025. This suggests that with population growth, the transportation network expands to meet increasing travel demand. The links of transportation network increase from year 2000 to year 2025. Among the simulation results of the year 2000, 2012 and 2025, FSUTMS models produce more road links with lower saturation (degree of saturation less than 0.8). LandSys-FSUTMS models generate less road links with higher saturation (degree of saturation bigger than 0.8). This means that by considering land use and transportation feedback loop, the LandSys-FSUTMS models produce less road saturation than the transportation model alone.

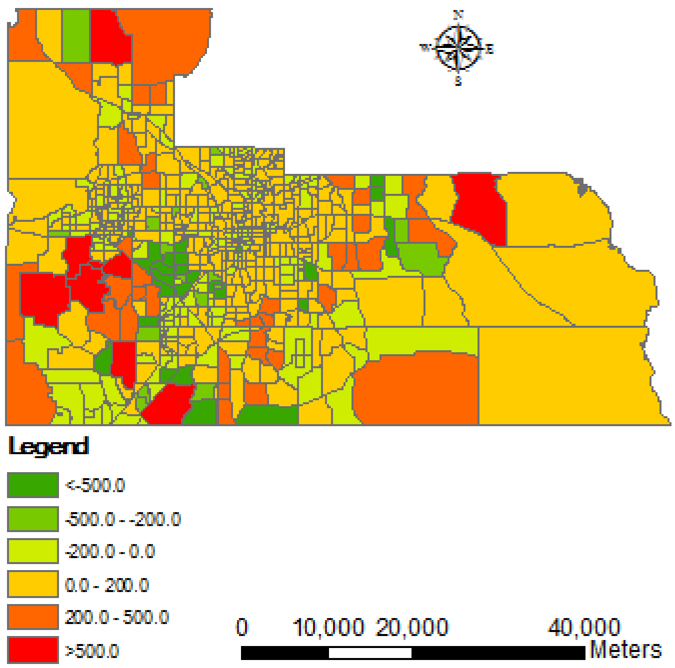
Table 7-8. The distribution of saturation under different intervals

	Year 2000		Year 2012		Year 2025	
Total links	13862		14816		15372	
Saturation	FSUTMS	LandSys-FSUTMS	FSUTMS	LandSys-FSUTMS	FSUTMS	LandSys-FSUTMS
[0,0.5）	6797	6910	6909	7015	5847	6029
[0.5,0.8）	2306	2394	2134	2514	1909	2101
[0.8,1.2）	3075	2943	3466	3392	3655	3815
>1.2	1684	1615	2310	1895	3961	3427

7.6 Land Spatial Distribution Results

Figure 7-8 illustrates the spatial distribution of households and employments generated by FSUTMS and LandSys-FSUTMS models in 2012. The numbers shown in the figure are the result that the allocation of households and employments generated by LandSys-FSUTMS models in each TAZ minus their counterparts generated by LandSys models.

(a) The difference value of household quantum



(b) The difference value of employment quantum

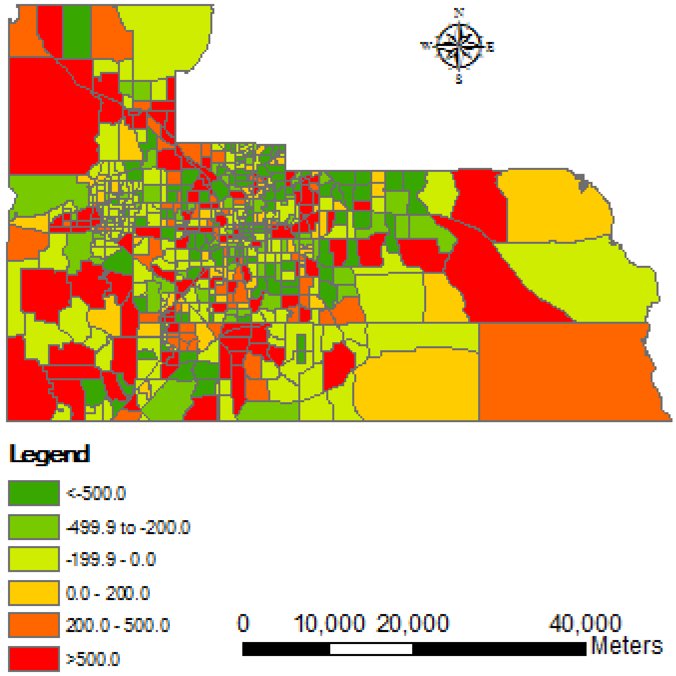


Figure 7-8 Difference between LandSys-FSUTMS Models and LandSys Models in 2000

Above figure shows that the LandSys-FSUTMS models generate higher household allocation than the FSUTMS models in the center of study area. This is because the LandSys-FSUTMS models consider updated travel costs and accessibility as input data. With the updated transportation information, LandSys-FSUTMS models divert traffic from central congested area and, therefore, lower travel cost. Generally speaking, The difference between LandSys and LandSys-FSUTMS is even larger in the year 2025.

Figure 7-8(b) illustrates that the allocation of employment shows similar characteristics to the allocation of household. Generally, LandSys-FSUTMS models allocate greater employment on the edge of the study area than FSUTMS models, and less employment in the center. This means that the integrated models assign less employment to the already congested areas. This is so because travel costs and accessibility are updated and plugged back into the land use models. Therefore, LandSys-FSUTMS models can adjust the spatial distribution of households and employments to estimate travel demand.

8. Conclusions

In this project, by integrating CA and agents models, GIS, and current transportation models (e.g., the Florida Standard Urban Transportation Model Structure, FSUTMS), we have developed a new modeling framework – LandSys -- to provide a more comprehensive approach for simulating the dynamic process of land use and transportation changes in space and over time. Data from Orange County, Florida, is used as a case study for model estimation and validation.

This project finds that, when simulating lands with small size, the robustness of ANN-based CA model may appear very low, and the accuracy is poor for these lands. The Agents mode that represent policy and micro human decision making can better simulate land use changes and improve the predicting accuracy when integrated with the ANN based CA model, and can overcome this low robustness.

A well-known limitation of ANN is the "black box" used to descript the mapping relationship between input and output variables. Compared with using the multinomial logit model (MNL) based CA and Agents models, ANN can achieve greater accuracy, requires less input data, and reduces the complexity of checking parameters. However, MNL provides detailed information of model parameters and is therefore more convenient when evaluating the contribution of each factor in the interactions between land use and transportation. A comparison of the ANN and MNL results show that two models generates very similar results, which confirm the MNL model is adequate in modeling the transition rule of the CA model and is also transparent to policy changes.

By representing land use types at the cell level, the MNL-CA model simulates the changes of land use patterns over time and space. The agent-based model provides a flexible representation of heterogeneous decision makers (agents), whose behaviors are influenced by interactions with other agents and the natural and built environments. LandSys is therefore developed from the integrated multinomial logit (MNL) based CA-Agents land use model. To facilitate the travel demand analysis, the LandSys simulates land use change at spatial and temporal dimensions, as well as represents decision making behaviors of households, employment, and developers. Future land use patterns and socioeconomic data (e.g., household, firms, and population) can be produced to update those inputs of transportation model (e.g., FSUTMS).

When compared to conventional land use models, LandSys has several unique features, including: (1) data processing using a land use classification based on its relationship with transportation, (2) agent models for each agent (e.g., households, firms, and developers), using bid-rent theory to represent the agents' relationships; and (3) allocation of household and firms at the cell level, as well as capturing land use change. Under the land development equilibrium, the model deploys two optimization sub-models to forecast land use change (e.g., demolition of existing developed land cells and development of new cells) at a manageable cell level (50m x 50m followed by employing bid-rent theory to allocate households and firms under the land supply-demand equilibrium.

The performance of land use forecasting using LandSys was evaluated by comparing predicted and observed data. For travel demand-related land development, the model predicts the land use change at 85.4% accuracy. At the cell level, the allocation of households and firms is aggregated at the TAZ level, which matches well with the observed data.

To evaluate how land use change affects the transportation system, this project compares the performance of FSUTMS model with and without integrating with LandSys model. Three major indicators of transportation networks were used for comparison purpose using data from Orange County, FL as case studies in 2000, 2012 and 2025. These three indicators include link saturation in the transportation network, overall vehicle miles traveled (VMT), and vehicle hours traveled (VHT). To understand the effects of the existing and future transportation system on land use development, the TAZ-based household/employment allocation results from LandSys are also compared with and without integration with FSUTMS. The results show that the transportation model alone overestimates the VMT, VHT.

This study shows the LandSys is capable of producing accurate land use change results, is able to capture the decision makers' behavior, and is sensitive to policy changes and transportation accessibility and travel time changes. The next step is to create a user-friendly graphical interface to integrate the LandSys model inside the transportation demand modeling (e.g., FSUTMS model) process, and to automate the land use-transportation feedback loop. The ultimate vision is to create a new function inside the FSUTMS using Cube Voyage so that transportation modelers can model the land use changes and integrate the land use model results into the transportation model, and the results of the transportation demand modeling results can be automatically fed back into the land use model, to achieve a fully automatic and seamless process.

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