EVALUATING ACCESSIBILITY AND TRAVEL COST AS SUITABILITY COMPONENTS IN THE ALLOCATION OF LAND USE, A CASE STUDY OF IDENTIFYING LAND FOR AFFORDABLE HOUSING IN THREE COUNTIES IN FLORIDA

By

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To my wife and children

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LIST OF ABBREVIATIONS

AHP	Analytical Hierarchy Process
AHS	Affordable Housing Suitability Model
AMI	Area Median Income
AR	Access-Rent Opportunity Surface
ARD	Access-Rent-Driving Opportunity Surface
ARDT	Access-Rent-Driving-Transit Opportunity Surface
ART	Access-Rent-Transit Opportunity Surface
CBD	Central Business District
CNT	Center of Neighborhood Technology
CRA	Community Redevelopment Act
CTPP	Census Transportation Planning Package
ESRI	Environmental Systems Research Institute
FGDL	Florida Geographic Data Library
GIS	Geographic Information Systems
GWR	Geographically Weighted Regression
HBO	Home-based Other Trips
HBS	Home-based Shopping Trips
HBSR	Home-based Social and Recreational Trips
HBW	Home-based Work Trips
HT	Housing Transportation Index
HUD	United States Department of Housing and Urban Development
IDW	Inverse Distance Weighted
LUCIS	Land Use Conflict Identification Strategies
LUCI2	Land Use of Central Indiana

MAUP	Modifiable Areal Unit Problem
MCDA	Multi Criteria Decision Analysis
MCDM	Multi Criteria Decision Making
MUA	Multiple Utility Assignment
NHB	Non Home-Based Trips
NHTS	National Household Travel Survey
OLS	Ordinary Least Squares
OWA	Ordered Weighted Averaging
QCT	Qualified Census Tracts
STD	Standard Deviation
SUA	Single Utility Assignment
TAZ	Traffic Analysis Zones
TCRP	Transit Cooperative Research Program
VBA	Visual Basic for Applications
VBEditor	Visual Basic Editor
VLI	Very Low Income Group
VMT	Vehicle Miles of Travel
WLC	Weighted Linear Combination
5Ds	Density, Diversity, Design, Destination and Distance

Abstract of Dissertation Presented to the Graduate School
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The allocation of suitable land for future growth is based on either stochastic or deterministic land use modeling. The stochastic approach uses land use change data samples to predict the future land use in a process to extend the past trend into the future. The deterministic land use modeling uses the data for the whole population to provide a vision for the future. The stochastic approach lacks the flexibility available in deterministic models to include planning expertise and community preferences. Deterministic methods include Multi-Criteria Decision Analysis (MCDA) and the Land Use Conflict Identification Strategy (LUCIS). In these methods, suitability is determined by criteria evaluations using MCDA or by the relative usefulness towards goals and objectives using LUCIS. The allocation of future land use can be conflicting depending on the goals and objectives of the planner or stakeholders. These goals and objectives are presented as suitability surfaces and are combined to generate one suitability surface using the Analytical Hierarchy Process (AHP). LUCIS adds the ability to identify the land use conflict between the sets of goals and objectives. The conflict identification

strategies introduced by LUCIS can, for example, identify the conflict between three main land uses: agriculture, conservation and urban.

The allocation of suitable land for affordable housing differs from the allocation of land for residential locations performed by land use suitability models. Housing affordability is evaluated by estimating the housing cost as a percentage of income. The Center of Neighborhood Technology (CNT) redefined the affordability evaluation to include housing and transportation cost. The affordable housing model in this research is a suitability model that is sensitive to multimodal transportation systems. The research evaluates the use of accessibility and travel cost as components in the allocation of affordable housing. Furthermore, the research introduces a set of new Geographic Information System (GIS) tools for the automation of the affordable housing allocation process.

This research applies LUCIS conflict and allocation methodologies for the allocation and preservation of land for affordable housing in three counties in Florida. For that purpose, LUCIS models have been restructured by updating the goals and objectives in the suitability structure to allow the inclusion of housing cost, travel cost and transit accessibility in the affordable housing suitability model.

CHAPTER 1
INTRODUCTION

Research Purpose

The coordination between land-use and transportation has been the focus of several research studies. Giuliano (2004) identifies the relationship between land-use and transportation as being bi-directional; the impact of transportation on land-use is captured via an accessibility measure (Hanson, 2004; Giuliano, 2004), and the impact of land-use on transportation is captured via land-use descriptors such as diversity, density, design, destinations and distance (Ewing & Cervero, 2001).

With reference to location and residential location theories, the choice of a place of residence depends on the combination of housing cost, transportation cost and other location attributes such as the distance to central business centers (CBD) (Steiner, 1996). Affordable housing is one of the most sensitive types of housing to transportation variables. Chapter 2 reviews the literature related to land use modeling, land use - transportation coordination as well as the literature relating the affordable housing allocation to land use and transportation variables. According to CNT (2007), the relationship between housing cost and transportation cost is a crucial element in deciding the location of affordable housing. Accessibility, mobility and proximity to public transportation and employment centers are also important. Furthermore, the choice of affordable housing locations depends on demographic and site characteristics, and the demand for affordable housing in addition to transportation variables. The CNT (2007) report on affordability focused on housing and transportation cost (HT) and emphasized the importance of the HT index, which is mainly travel cost and housing cost relative to income. The CNT model was the first model to predict travel cost spatially. However, their index was based on a regression model with a coarse spatial resolution (Census blocks 2000) and focuses on national data more than the data from local sources.

Studies on affordable housing location such as the HT model estimate travel cost based on statistical models. This is done by taking the travel cost as a dependent variable and the land use, transportation and socio-economic variables as independent variables in ordinary least square regression models. However, in estimating travel cost and evaluating its burden on suitability, the following should be taken into consideration when using statistical models:

1) They should be applied to small data samples and not on whole populations;
2) They traditionally ignore spatial location;
3) The lack the intervention of planning expertise in deciding suitable locations;
4) They underestimate or overestimate the cost for locations that are under-represented in the sample; and
5) They traditionally applied to political and natural areal units such as traffic analysis zones (TAZ) and Census block groups.

Chapter 4 in this dissertation explains that using natural and political areal units to capture urban form characteristics may lead to inconsistencies in the results. The Modifiable Areal Unit Problem (MAUP) suggests that scale and zoning affect the aggregated values captured by the area unit. Chapter 4 also introduces a method to reduce the scale and zoning problems by using a floating neighborhood that has an optimized size and shape.

Modeling and predicting travel cost spatially can be performed using a spatially discriminated approach based on the latest Florida geo-coded trip-ends data from the National Household Travel Survey (NHTS) 2009. The travel cost estimation in this research is explained in Chapter 5 and follows two main methods; an interpolation approach and a statistical approach. In the interpolation approach, the travel cost is directly estimated from the spatial interpolation of the geo-coded trip location data of the NHTS 2009. The statistical approach uses the trip data in a regression model that relates the travel cost as a dependent variable to land use and urban form variables as independent variables. These independent variables are cross-sectional data sets that include residential density, retail density, connectivity, diversity of land uses in the form of entropy, and an accessibility estimation that represents access to major employment destinations.

Two regression methods are used in the statistical approach; the first method uses a regression analysis by ordinary least squares (OLS) which gives a global regression equation for a regional or county-wide area. The second method uses a geographically weighted regression with different equations representing different geographic locations and different goodness of fit for each location. Both methods result in a predictive model that can be applied to calculate the travel cost depending on land use and urban form characteristics. The regression models can be also used longitudinally by applying them to a different year using different independent variable values due to the future land use change.

Land-use suitability surfaces are used in hierarchal structures that include constructing single utility and multiple utility surfaces in which the composition of these utilities are performed using preferences and community values (Carr & Zwick, 2007). In these utility compositions, accessibility is simplified as the proximity to facilities such as proximity to highways and transit stations without taking other definitions of accessibility into account. Chapter 5 also investigates and compares mathematical models that are used to estimate accessibility in the transportation and land use planning literature.

Gravity, opportunity and distance models are used in statistical and stochastic models (Waddell, 2002; Handy, 2004; Hanson 2004), however, they are applied on either a random data sample or on aggregate and zonal level such as TAZs. This research uses a parcel-level suitability evaluation that captures a combination of access by opportunity and access by distance in a multiple utility assignment. Furthermore, the distance estimation component can be currently performed by network or Manhattan distance as alternatives to using Euclidean distance. The network distance is, the distance travelled between two locations using the road network. The Manhattan distance is the distance travel between two locations following a grid network while the Euclidean distance is the straight line distance between two locations. The aforementioned distance estimation methods are used to evaluate the suitability in the proximity component, and in creating the capture area for the opportunity suitability component.

LUCIS includes a land-use modeling methodology that replaces the traditional multi-criterion methodology. The LUCIS methodology depends on community preferences, suitability surfaces and pair-wise comparisons to build conflict surfaces that are used to identify conflict between different land-uses in the process of allocating lands for future growth. This suitability approach is usually taken by composing multiple utility surfaces (MUA) (Carr & Zwick, 2005). These MUA surfaces are generated from a combination of different suitability surfaces that are weighted by community decision-makers using Delphi or pair-wise comparisons to assess community preferences using automated tools as explained in Chapter 6. Applying these methods in the choice of affordable housing locations can identify suitable places but it does not emphasize the reason that makes these locations suitable for affordable housing. This is because affordable housing locations are associated with a low travel cost, or because they are associated with better amenities. This tradeoff may lead to undesirable results in terms of allocation or preservation of land for affordable housing because of the conflicting nature of elements that generate the suitability surfaces. Chapter 7 explains the allocation of affordable housing by LUCIS models which take conflict into account (Carr & Zwick, 2007) and allow the allocation or selection of suitable lands more flexibility using the LUCIS automated allocation tools. The research conclusions are explained in Chapter 8. In Chapter 8, the results of the affordable housing allocation model are related to the literature on affordable housing, compact development and sprawl. Chapter 8 also explains the research limitations, recommendations and the future research.

Dissertation Objectives

The main objective of this dissertation is to identify the transportation variables that impact the location choice of affordable housing and use these variables in a land-use conflict identification model for the allocation or preservation of affordable housing site. The main objective includes the following sub objectives:

1) Capture the physical relationship between residential locations and services by the use of destination accessibility as suitability surfaces instead of the traditional proximity surfaces used in land use models. This includes the creating these surfaces using different accessibility definitions such as proximity, opportunity and distance;

2) Investigate the use of network distance and network service areas in calculating accessibility and compare the results with Euclidean distance-based accessibility;

3) Enrich the land use suitability model with the use of travel cost as suitability surfaces. This includes creating these surfaces directly from travel surveys or other data sources;

4) Investigate methods for estimating or predicting future travel cost based on travel surveys and the relationship between land use and urban form characteristics; and

5) Introduce an updated conflict identification procedure with an automation tool that helps planners to choose locations for affordable housing in a more flexible and automated process than traditional suitability models.

Research Questions

The research is about creating a deterministic suitability model for the allocation or preservation of land for affordable housing. The research answers the following questions:

1) What are the feasible methods to create and include accessibility and travel cost as suitability surfaces in an affordable housing suitability model?

2) What is the impact of travel cost and transit accessibility on the allocation and preservation of affordable housing sites? and

3) How to incorporate multi-modal transportation and metrics for conceptualizing sprawl in allocating land for affordable housing?

What is The Contribution of This Research?

This research adds to the body of knowledge of transportation land-use coordination in general and specifically to the literature on location choice for affordable housing. Traditionally, suitability models consider proximity to services as a utility function. This research incorporates accessibility and travel cost as suitability surfaces in addition to of proximity. Chapters 7 and 8 show that using these transportation variables impacts the allocation of affordable housing and provides multimodal transportation options. The research also shows that the use of transit accessibility and travel cost can identify locations for compact development instead of sprawl.

Euclidean distance is often the method used in deterministic suitability models. The literature review in Chapter 2 shows that network distance is a better estimation of travel distance than the Euclidean or Manhattan distance. This research investigates and compares accessibility estimations based on network distance versus estimations based on Euclidean distance. In transportation research however, networks are used to estimate distances and travel times. Building network distance suitability surfaces, estimating and creating accessibility surfaces using network distance, or creating opportunity suitability surfaces based on network service areas are not yet covered by the literature of land use and transportation, and is introduced in this research.

The literature identifies the impact of mobility on accessibility, which increases at the regional level or with the use of other transportation modes such as transit. This research takes that into consideration by incorporating a multi-scale accessibility estimation that is sensitive to multimodal transportation systems such as walking, biking, driving and transit. Accessibility is considered on the local scale by estimating neighborhood accessibility to transit stops and other local services. On the regional scale, accessibility is considered in the estimation of travel cost burden and/or the estimation of transit accessibility to employment when transit is a strong competitor.

The CNT (2007) has used travel and housing cost to build an index that is also dependent on income. The HT index created by the CNT aims to estimate the affordability of housing site locations while considering transportation costs for the people that live in those places. This research however, aims to allocate affordable housing land for low income population. Similar to the HT index, travel and housing costs are important factors in deciding residential location. The location in the HT index combines housing and transportation cost. This combination applies a tradeoff between housing cost and transportation cost. Chapter 7 of this dissertation builds conflict surfaces that identify the conflict between travel cost, housing cost and transit accessibility and the urban residential suitability. The research also introduces scenario building to refine the output of the Affordable Housing Suitability (AHS) model and to allocate the most suitable land for affordable housing according to scenario conditions.

The travel cost estimation in CNT's research is performed by ordinary least squares regression. This research also uses ordinary least squares regression to create a travel cost estimation model. Chapter 5 of this dissertation shows that the residuals for the ordinary least squares regression are clustered and introduces using spatial interpolation and geographically weighted regression to estimate travel cost. This research also introduces geographically weighted regression as a method to study the relationship between land use and transportation variables, as it can capture the relationship on a local scale and identifies the local anomalies that the least square analysis ignores.

Chapter 4 explains the research conducted to choose the areal unit and introduces a new method to reduce the effect of the modifiable areal unit problem using an optimized size and shape floating neighborhood instead of using political zoning and natural neighborhood boundaries. The research applies the optimized neighborhood in estimating the aggregated values for the metrics that capture the urban-form characteristics. Metrics such as density, diversity and connectivity are used as variables in the travel cost regression and the affordable housing allocation scenarios.

CHAPTER 2
LITERATURE REVIEW

Housing is considered to be affordable if its burden does not exceed 30% of household income (US Department of Housing and Urban Development [HUD], 2011a). Other evaluations for affordable housing include a housing and transportation burden of 45% of household income (Center of Neighborhood Technology [CNT], 2011). Therefore, the definition of affordable housing in general contains all the income groups. This research focuses on affordable housing for very low income (VLI) groups which is defined as income groups below 50% of the area median income (AMI) (HUD, 2011b). Regardless of their income category, people generally look for the best location available that they can afford within their budget. As such, the location choice for affordable housing can be performed by the same methodology as residential location choice models. The residential location choice depends on transportation cost, housing cost and proximity to CBD (Steiner, 1996). Accessibility, environmental quality and space are also important for deciding where to live (Yamada, 1972). The affordable housing choice imposes additional constraints on the transportation and housing costs and can be seen as a special case of the residential location choice model.

Evaluation of Location Choice Models

The choice of residential location depends on attributes that are derived from location theories. Attributes such as housing cost, transportation cost, distance to CBD, accessibility, space, leisure and environmental quality are frequently used in location choice models (Yamada, 1972). Historically people left the inner city to live in suburban locations that allows them to have more spacious and luxurious homes they can afford. This trend is known as “drive till you qualify”. Housing policies and incentives made suburban residential locations available for people. These suburban locations are promoted by low pricing, low interest rates on mortgages.

As a result of living far away from jobs, the use of cars increased. The use of cars is also encouraged by low gas prices and the increasing mobility due to the construction of highways and freeways. This car-dependent suburban housing has caused sprawl, larger commuting distances and higher transportation costs associated with the rise in gas prices. In terms of affordability, suburban housing has become a heavy burden for householders and less affordable due to increasing transportation cost (Lipman, 2006).

CNT (2007) worked on evaluating the affordability of housing by estimating the housing and transportation cost with respect to income. Housing is considered affordable if the combined housing and transportation cost does not exceed 45% of income. However, the actual spending on combined transportation and housing nationally exceeds 50% of household income. CNT (2007) showed that increasing the commuting distance by living away from work reduces the housing cost but the total housing and transportation cost increases which suggest that the “drive till you qualify” added an extra burden on people and reduced the affordability of residential location.

Transit research on the national level shows an increase in transit ridership in metropolitan areas and CBD’s (TCRP, 1998). Transit studies also show that the transit ridership trends increases for low income and older populations (TCRP, 1998). However, this also depends on the urban form and the level of service of the transit system. Commuting to work by car or by transit for low income populations is a controversial and complex issue. Grengs (2009) shows that transit in a city like Detroit is not advantageous for low income populations where using cars may increase the employment rate and increase accessibility to jobs. Research analysis shows the complexity of the relationship between accessibility, driving and transit especially for low income populations. This suggests that choosing between driving and transit for the trip to work is not a sole choice of the traveler but depends on the accessibility to work and the transit level of service. For Detroit, transit is inferior compared with cars. Car usage adds flexibility especially when the trip chaining for daycare or shopping is needed. Furthermore, transit is inferior in Detroit because the accessibility to employment by transit is very small (Grengs, 2009).

The research on land use transportation coordination suggest the importance of accessibility and urban form characteristics in reducing the cost of driving associated with residential location and increasing the use of other modes of transportation such as walking and transit (Cervero & Kockelman, 1997). This suggests locating residential land uses in places that have high accessibility to services and employment to reduce the travel cost when using cars and at the same time encourage the use of other transportation modes such as walking, biking and transit.

Location choice modeling follows methodologies that are derived from location theories such as the residential location theory. Generally there two main modeling approaches; a deterministic approach such as the Land Use Conflict LUCIS (Carr & Zwick, 2007) and a statistical approach like that used by Waddell et al. (2003) in the statistical components of their UrbanSim models. The deterministic approach assumes that the modeler understands the relationship between model variables and can apply his experience to predict the future. The statistical approach relies on data samples to capture the relationship between variables via regression or other statistically robust methods of analysis.

In location choice models, accessibility to services and amenities is important. Accessibility is taken as a typological proximity estimation in deterministic models while many mathematical forms of typological and opportunity estimations are used in statistical and stochastic approaches. Also, statistical approaches usually do not deal with visual representation using GIS as is often the case with deterministic suitability approaches. Statistical approaches also are applied on data samples unlike deterministic approaches which are typically applied on the general population

The prediction of land-use change does not depend only on accessibility but also on land-use and economic variables. LUCIS models depend on Euclidian distance proximity measurements to include the suitability of locations. Additionally, LUCIS models include community preferences using pair wise comparisons in deciding the potential of land use change on a small scale, ultimately constructing a conflict raster that can be used in the allocation of projected population in different locations. The allocation of population follows the rules that are set by the urban planner. For example, for areas around transit, the allocation is performed using a circular buffer. These are the places that have transit accessibility which is used as a shed in the allocation.

Other economic, spatial and temporal variables are also used indirectly in the generation of suitability surfaces or in the land allocation process depending on the conflict raster surfaces being used (Carr & Zwick, 2007). In other land-use prediction models, cells that represent parcels are also used to construct probability functions that capture the existing land-use pattern and project that to predict the future using Markov-

Chain probability transformation (Levinson & Chen, 2004). The later method ignores the planners and community preferences included in LUCIS models and also it assumes that the same relation between variables in the past will apply to the future which is only estimates for future growth trend. Waddell (2002) used transportation and economic models to feed UrbanSim's land-use parcel models by incorporating travel times and other variables from networks using the trip-based four-step transportation modeling. However, the UbanSim's model does not directly incorporate the visual representation provided by GIS modeling. Furthermore, using four -step transportation modeling does not include the land-use impact on transportation nor the representation of space time relationships that are found in activity based and trip chaining transportation models. This raises the need of activity simulators and the discrete choice models in location choice. It is very difficult therefore to decide which model gives more appropriate results for land-use change due to the lack of comparative scholarly research on different types of models.

Location preferences and choices are also modeled in different ways. In LUCIS models it depends on the community values and participatory sessions while in other land-use models it is mostly probabilistic logit models such as Land Use in Central Indiana Model (LUCI2) (Ottensman, 2004). Location preference and choice decisions can also be facilitated by probability matrices to capture the growth from two different years in the past and using a transformation matrix to calculate the probability of change in the future (Levinson & Chen, 2004).

Waddell et al. (2003) uses more sophisticated statistical methods such as discrete choice models to construct utility and nested utility logit functions. The discrete choice model is an important approach to model location choice (Waddell et al., 2003). The parcel level analysis and discrete choice models have been used effectively in the building of the UrbanSim models. An example application of this methodology was performed on the Spring Field Metropolitan Area and Lane County in Oregon using a disaggregate database (Waddell, 1998). The UrbanSim models are also used for growth management such as studying sprawl, congestion and affordable housing through the integration between transportation and land-use models that can feed each other (Waddell, 2002). Land-use affects transportation systems and transportation systems affect land-use. Therefore computer models like UrbanSim can help the urban planner in running different scenarios through the use of different UrbanSim components.

UrbanSim is a model that simulates land-use and transportation and has many components such as economic elements, and transportation and utilized choice models integrated within other models (Borning & Waddell, 2004). However, several disadvantages of UrbanSim are its lack of the visual and GIS interfaces like those that exist in other land use models. Also, its intensive use of disaggregated travel data precludes its use in states where that level of data may not be available such as in Florida.

There are many models that deal with the effect of transportation on land-use. The traditional way is to use economic factors embedded in an accessibility index. A review of common frameworks can be found in the work of Iacono and Levinson (2008). Iacono and Levinson also compared a new regression approach using additional variables for transportation and compared that to a model that does not include transportation variables. They found that transportation variables exert some influence on land change and land-use patterns.

The use of deterministic or stochastic approaches to model the effect of transportation on land-use depends mainly on the available data and the need of planning intervention in the prediction or visioning process. This research relies on the deterministic approach and investigates the role of transportation in deciding location choice. Statistical methods are also used in this research to understand and capture relationships that might be difficult to obtain using deterministic models. The research will incorporate more transportation variables than what is currently used in suitability modeling. Suitability raster surfaces will be built out of accessibility estimations. However, because of the interdependency between accessibility and mobility, which increases when capturing regional accessibility or when using other modes such as transit (Salomon et al., 1998; Handy, 2004; Hanson, 2004), this research adds the ability to spatially modify the accessibility value according to mobility measurements in a suitability environment. Generally, the mathematical forms of accessibility other than proximity have been used in statistical and stochastic land-use modeling and not in land use suitability analysis. This research will introduce these variables such as accessibility and travel cost as suitability raster surfaces in a land-use suitability model structure for affordable housing location choice.

Suitability Models

Land use suitability analysis is an analytical process that combines inventory information to determine whether the requirements of particular land uses are adequately met by the characteristics of the land. The result is either tabular data or a single map or series of composite maps that display the relative suitability, or appropriateness, for a specific land use, useful for example in location choice studies, or for a number of land uses such as in comprehensive planning (Randolph, 2004, p. 591). As landscape architects in the late 1800s, Charles Eliot and Warren Manning used suitability analysis in their environmental planning pursuits to measure the relative degree lands in Boston were fit for integration into the Boston Metropolitan Park System. Central to this process was the development of a systematic approach to the inventory of site resources and, through the use of overlay mapping, the analysis of the natural fitness of the land (Carr, 2008, p. 5).

Suitability techniques have evolved quickly during the twentieth century. In the 1960s Ian McHarg included an ecological inventory process into suitability analysis. During the late 1960s and early 1970s the advent and use of computers in land use suitability marked the beginning of a revolution expanding the capabilities of suitability analysis. With computers large amounts of information could be combined and overlays became more accurate. The most significant technological advance was the use of the computer to make simple grid maps. The grid cell allowed more precise analysis of map factors between multiple maps. In the 1980s map algebra was developed which allowed mathematical computation among several grid maps. In the early 1990s, GIS became a formal technology. According to Collins et al. (2001) GIS is used to used to manage spatial and none spatial data (storing, analyzing and presenting). GIS also used to create new datasets by overlays and spatial operations.

LUCIS illustrates the next era of suitability modeling. LUCIS is organized in a hierarchical structure of goals, objectives, and sub-objectives, for each respective objective and/or sub-objective, a GIS model is developed. Each model is a sequence of spatial data and geo-processing tools that first assign an estimate of utility and then assigns a suitability value for that utility. In the higher orders of the hierarchy, suitability assignments are made for the development of land uses (i.e., agriculture, conservation, and urban) which are then combined in a single raster to identify the conflict between the land use preferences (Carr & Zwick, 2007).

The suitability index is a value that represents the relative usefulness for a particular land use. In the LUCIS model values ranging from one to nine are assigned, where one represents the lowest suitability and nine the highest suitability value (Carr & Zwick, 2007). Classification into these value ranges occur using various methods depending upon the nature of the criteria to be evaluated or according to the utility to be classified as a suitability surface. Some of the procedures are simple (binary methods) and some of them have higher complexities. Regardless of whether the model measures a qualitative or quantitative process, the output of the LUCIS model employs at least two values, 1 and 9.

GIS layer overlay is the core of suitability analysis. Even suitability analysis undertaken at the time of hand drawn maps was dependent on map overlay (Collins et al., 2001; McHarg, 1969). The overlay procedure in GIS raster analysis depends upon three logical spatial overlay rules: enumeration, dominance, contributory and interaction. According to Carr and Zwick (2007, p. 50-57):

> Enumeration preserves all attribute values from multiple input layers. Enumeration creates an output layer that combines all attributes from the spatial input layers to provide a clear and distinct set of unique attribute combinations from the input. The dominance rule depends on the selection of a single value that is preferred over all other values found at the same spatial location. The selection is defined or governed by external rules, not simply the combination of values. The contributory rule is applied by performing a group of operations [which are] values from one input

> contributing to the results without regard for the values from other inputs. Lastly, the interaction rule, unlike the contributory rule, considers the interaction between factors. However, to consider interactions between factors, the factors must be translated into the same standard intervals.

These rules represent logical operations that can be translated into equivalent functions in land use modeling such as layer weighting and the combination of different utility surfaces into a suitability layer.

The dynamic relationship between land characteristics and land use illustrates the complexity of land use suitability analysis (Driessen & Konijn, 1992). Through interaction, utility is combined to create suitability. Single utility assignments (SUA), which are the assignment of utility values within an individual raster layer, are combined using weights to create multiple utility assignments (Carr & Zwick, 2007). However, utility is a measurement of human satisfaction and thus if applied to land use could represent how much a person can be satisfied by the land characteristics. Utility can be easily connected to people characteristics while suitability is usually connected to the location characteristics. This explains why utility is usually used in statistical choice models while suitability is used in criterion evaluation models or land suitability models. The various approaches to suitability analysis provide alternative ways to understand the interactions between human and nature in ecological planning (Ndubisi, 2002). Therefore, the conflict between planning for urban expansion and ecological systems can be studied and identified by innovative methods in suitability modeling.

The GIS overlay techniques for the Multi Criteria Decision Making (MCDM) method, which is another method for land use modeling that use the hierarchal structure, can be divided into two main methods: the multi-objective method and the multi-attribute method. The multi-objective method depends on two or more objectives to be combined using a set of constraints. This is always solved by standard linear programming methods. The problem in this method is that adding constraints will help the planner in decision making but will add computational complexity making it difficult to apply in a GIS environment. The multi-attribute method is applied using GIS map algebra techniques. It uses weighted linear combination (WLC) and the Boolean operations "AND" and "OR" in the overlay process. This process, however, gives the same weight despite the geographic location, as the WLC is based on the concept of a weighted average. In this method relatively more importance is given to the attributes because it is assumed that the importance of location is taken into account in generating each layer to be combined by the Boolean operator.

Ordered weighted averaging (OWA) has also been used in the MCDM method to overcome the disadvantages of WLC. The OWA method involves two sets of weights; one is the criterion importance weight which is constant for the criterion at all locations, and the other is the order weight which is associated with the criterion on a location by location weight (geographic or spatial weights). Additionally, AHP is a method used in MCDM that incorporates the generation of the linear combination weights by aggregating the priority for each level in the hierarchy process. AHP is also used as a consensus building tool in situations involving group decision making (Malczewski, 2004).

Programmed and automated procedures as well as community participation using Delphi or pair-wise comparison methods (i.e., AHP), are used in ranking and ordering procedures to assess the importance of weights (Carr & Zwick, 2007; Malczewski, 1999, 2004). The pair-wise comparison technique developed by Thomas Saaty in the

1970s and 1980s in the context of AHP multiple criteria evaluation methods, represents the relative importance of criteria. According to Nyerges and Jankowski (2010, p. 140-141):

> Weights are not assigned directly but represent a 'best fit' set of weights derived from the eigenvector of the square reciprocal matrix used to compare all possible pairs of criteria. The advantage of this technique is that information can be used from handbooks, regression output, or decision modelers/experts can be asked to rank order individual factors.

Malczewski defines weight as a value assigned to the output of criterion evaluation. The weight represents the relative important of that output. The criterion is more important if the weight is higher and less important if the weight is lower (Malczewski, 1999).

Both MCDM and LUCIS integrate weights into their methods. MCDM provides four methods for assessing criterion weights: ranking, rating, pair-wise comparison, and trade-off analysis. Malczewski (1999) included the choice of method depends in the trade-offs the modeler is willing to perform, the availability of software, and the method of incorporating GIS based criteria evaluation.

Carr and Zwick (2007) calculate community preference using the more advanced pair-wise comparison method of AHP. In the AHP procedure, a model is created and a project goal is stated. The goal for pair-wise comparison is a statement defining pair comparisons. The objectives and sub-objectives are treated as components of the overall goal. Then, each unique pair is compared for their usefulness in supporting the goal. All components are compared using Saaty's -one to nine scales, ranging from equally important/useful to extremely more important/useful (Table 2-1). Next, the pair-wise comparisons are evaluated within a matrix for all pairs of values to produce final pair-wise utility values (Figure 2-1). Lastly, the final pair-wise utility values are transformed into single utility assignment values ranging from one to nine (Carr & Zwick, 2007). After completing the pair-wise comparisons, the weight for each layer is calculated according to an eigenvalue / eigenvector procedure.

LUCIS (Carr & Zwick, 2007) uses software packages external to the Geographic Information System Software ArcMap environment to calculate the AHP layer combining weights. ArcMap is GIS software created by the Environmental Systems Research Institute (ESRI). The software provides tools that are vector and raster based to spatial analysis and to manage geographic data. Multi Criteria Decision Analysis MCDA uses layer combinations according to the outcomes of AHP and the consensus of Delphi panels. The combination is mainly layer weighting using an interaction rule. However some of the weighting is done in the suitability assignment level in the hierarchy structure. A similar technique is utilized in the LUCIS model. The primary and most important difference is that MCDA uses alternative scenarios and the weights generated by AHP to evaluate the suitability for each scenario while LUCIS uses a conflict surface, which is a matrix that preserves the original preference values. This matrix consists of three or four digits, according to the number of preference surfaces combined to create the conflict surface.

Preference applies community values to the cumulative suitability of land fitness. The aggregation of relative suitability surfaces for a goal can be seen as an opportunity surface even if it has some conflicting aspects. For example, an opportunity surface for urban suitability may contain the complex MUA grids for commercial, industrial, multi-family and single family land uses. The generated opportunity raster surface identifies the conflict between the components of an urban environment yet maintains the original suitability for each individual component. The interaction between sets of goals within each land use, illustrated at the highest level of the hierarchy, demonstrates conflict while preserving the suitability of the generating surfaces (Carr & Zwick, 2005).

The purpose of the conflict surface is to generate a suitability matrix. Individually, suitability is determined and weights are assigned to suitability raster grids from AHP values exercises to create a complex MUA for each respective land use. Next, these land use raster surfaces are transformed from suitability into preference, which places each land use raster surface on the same scale – from one (low preference) to three (high preference) (Table 2-2). Using map algebra, each respective preference surface is combined to create a single conflict surface which is a suitability matrix that identifies the conflict between the preferences.

The generation of the conflict surface is performed by multiplying the first preference by one hundred, the second preference by ten, and the third preference by one (Table 2-3). The surfaces are then combined using additive sum. Multiplication is not performed according to the importance as a weight but only to generate a two decimal index for identifying the conflict.

There are three conflict classifications in LUCIS. No conflict is when a single land use type has the highest preference value and the other land uses in the conflict score have lower values. Minor conflict is when two goals have the same preference value and no other land use type has a higher value. Major conflict is when all land use types have the same preference values. For example, if a conflict surface for three land use types (i.e., agriculture, conservation, and urban) is created and the conflict values were arranged in the conflict matrix as the first, second and third digit respectively then for a given conflict value of 113 the specified location would be highly preferred for urban land uses. Whereas, a given conflict value of 221 would indicate a minor conflict between agriculture and conservation land uses as they both have the same preference for the specified location and urban preference for the land has a lower value.

The value of LUCIS is two-tiered. The first tier consists of the process to determine land use conflict. As described above, the process includes 1) determining land use suitability based upon the pre-determined goals and objectives; 2) determining land use preference; and 3) identifying conflict. The second tier illustrates alternative futures through the allocation of population and/or employment. As stated earlier, the conflict surface is a suitability matrix using the cumulative suitability of the goals within each land use. Early applications of LUCIS allocated people and employment according to a general “urban” category. The development of a conflict surface does not manipulate the original preference values; thus a conflict surface can also be generated between goals for a more detailed analysis of land use preference. Therefore, allocation of urban uses has evolved from areas generally classified as urban to allocating projected residential populations into areas with high multi-family and single family preference.

The MCDA scenario building approach takes different alternatives and calculates the suitability for the model alternatives, which inherits a selection of the more appropriate scenario. However, in the LUCIS structure and the LUCIS allocation procedure, scenario building is performed on multiple levels. The first opportunity is when changing the weights upon combining suitability surfaces for each hierarchical level, which is the same analysis used in MCDA. The second opportunity is in the flexible allocation scenario where the conflict and suitability assignment are used in a combined grid and the population allocation is performed according to priorities specified according to different scenarios. The combine grids join conflict and suitability values and preserve the attributes for these grids in the overlay. The tool is also useful for scenario building and testing of policies.

In the allocation process, Carr & Zwick (2007, p. 167) identifies six general steps to visualize future land use which are:

1. Allocation starts in the area that does not include conflict and where urban preference dominates.
2. Allocation continues if needed in moderate conflict and major conflict, if necessary, where the normal values for urban are highest.
3. Creating a “remaining lands” mask to account for the cells allocated in steps 1 and 2.
4. Allocate remaining cells for future agricultural land where it is not in conflict and the preference is greater than conservation or urban.
5. Allocate remaining cells for future conservation land where it is not in conflict and the preference is greater than agricultural or urban.
6. Allocate remaining cells that are in conflict between agriculture and conservation according to the greater preference.

Incorporating Transportation Variables in Suitability Modeling

Generally, the LUCIS method provides solutions for many of the shortcomings in a traditional MCDM method. For the processes for which MCDM is best known, LUCIS provides a decision analysis framework for land use planners and modelers with knowledge of GIS technologies. Although the role of land use planners is shifting to include more physical and spatial planning analysis skills, LUCIS can facilitate this role-change by automating key procedures in the identification of land use conflicts and the process of allocating future population

The LUCIS model structure is flexible. It may include any goal and objective the planner determines as important in the allocation process. However, transportation variables are not yet fully incorporated in the current LUCIS model. Incorporating such variables would be useful in the allocation of future land uses especially if the model is to be used to allocate locations that are sensitive to travel cost such as in the locating affordable housing units.

The main elements in research on the connection between transportation and affordable housing are accessibility and travel cost. These elements are used in statistical models on Census Block-level data (CNT, 2007). Incorporating these elements as suitability surfaces based on parcels-level data for allocating and preserving affordable housing is not yet in the literature. The bi-directional land-use transportation research does however relate travel behavior indicators such as vehicle miles of travel (VMT) and trip generation to accessibility and other urban form characteristics. Investigation of these bi-directional relationships has on the one hand shown the impact of transportation systems on land-use change. This has included using transportation descriptors in the prediction of the future land-use. However, this can be described as a direct approach for the purpose of modeling location choices. On the other hand, the impact of land use change on transportation systems and travel behavior can be considered as a direct impact when evaluating transportation systems. It also can be seen as an indirect effect on the choice of locations in terms of land-use policies, land-use modeling and the design of new development or urban forms.

Considering the transportation impact on land-use and following applications on the economic theories such as the location theory, central place theory, hedonic pricing models and residential location theory (Steiner, 1996), it could be said that housing cost, transportation cost and the spatial location are important factors for the decision of where to live and work and that the growth pattern and the choice of location follows a utility maximization pattern for community individuals. This may be simple when talking about household rent or housing cost but get complicated if we introduce transportation cost. Taking accessibility and travel cost as the two main elements in the relationship between land use and transportation can lead to a better understanding of this complex relationship. On the first hand we have accessibility and mobility and their impact on land-use and location choice (direct impact). On the other hand, travel cost is the other way around (indirect impact). Different land-uses affect our travel behavior which mainly increase or decrease the VMT or travel cost (Steiner et al., 2010). Travel cost in turn affects our choices for housing and other land-uses. Most of the research addresses an accessibility type of measure which is originally derived from growth theories (i.e. aggregated choice models such as gravity models).

Generally, the research on the effect of transportation on land-use captures micro-level relations with macro level methodologies. For example, the affordability index created by CNT (2007) is based on coarse spatial resolution such as Census blocks rather than parcels. It is usually difficult to capture the impact of transportation on land-use in terms of the complexity of the indicators that can capture the change in the urban forms. Therefore, in most cases, the research studies that deal with the effect of transportation on land-use estimate accessibility and use it along with other variables to predict land-use change, growth patterns and future land-uses.

Evaluating Methods of Estimating Accessibility

This section of the literature review evaluates the research on the direct impact of transportation on the choice of location as well as evaluating the methods of estimating accessibility and proximity which are considered as the most significant variables of this impact. The impact of transportation is captured via a simplified accessibility measurement. The measurement of accessibility varies in existing research, ranging from linear distance to network distance, travel time and the number of activities within a distance from an attraction or a certain residential location.

Accessibility is defined as the potential to interact. To differentiate between the accessibility and mobility, we can say that mobility is the potential to move. In these terms, accessibility is connected to destinations and the mobility is connected to the networks and vehicles. Accessibility for example, measures the number of jobs in a certain area or the number of destinations in a specified area or the availability of choices between modes, while mobility deals with traffic delay and level of service (Handy, 2004). However, this explains that accessibility could be different between modes, but does not take congestion into consideration because it is a mobility measure according to the definition. The same approach for accessibility is taken by Hanson (2004). According to Hanson, accessibly is the number of opportunities within a distance or travel time while mobility refers to the ability to move between different sites. Furthermore, Hanson explains that because of the distance between activities become larger as density decreases, accessibility becomes dependent on mobility (Hanson, 2004). This adds interdependency between density, accessibility and mobility. It is clear that there is a relationship between accessibility and mobility and that this relationship is stronger for regional destinations other than neighborhood destinations particularly when different modes of transportation are taken into consideration (Hanson, 2004; Salomon et al., 1998). In regional destinations, using highways and freeways increases the dependency of accessibility on mobility. Accordingly, when transit is involved accessibility may depend on the level of service and thus on mobility. In this research accessibility and travel cost are estimated on both the local level and regional level using multi modal transportation. Therefore mobility can be incorporated within accessibility and travel cost.

Accessibility can be also defined as the ease with which a destination can be reached and it is one of the important factors in location decision choices. This definition clearly connects accessibility as a function of land-use and transportation patterns. Accessibility also can be defined as the ease with which people can participate in activities. Such a definition acknowledges that the destination activities and location properties are important factors in accessibility (Primerano & Tylor, 2004).

Accessibility measurements can also be divided into personal accessibility and place accessibility. Personal accessibility can be measured by counting the number of activities within a certain distance of a person's home. The measurement can also include the magnitude of the distance for each location in a gravity cumulative approach. The accessibility for a place investigates the number of activities at a certain distance from a place. These are simple methods for calculating accessibility. More advance methods of time- space analysis are needed to address the effect of time on accessibility (Hanson, 2004). However doing time-space analysis on a disaggregate level of data at a dependable accuracy is not always possible in places with poor travel activity diaries.

To simplify, choosing to use personal accessibility or place accessibility depends on whether personal characteristics are included in the estimation of accessibility. For example, it is possible to use personal characteristics to estimate accessibility for existing urban development but it is more complicated to predict personal characteristics for new development. Generally, the estimation for accessibility can be a topological or opportunity measurement or both. The topological estimations are an estimation of physical proximity from origins to destinations which includes the measurement of distance such as the distance to the nearest location. The opportunity models measure a density or attraction of accessible places. Incorporating both gives the relative accessibility which can be clearly shown in gravity models. This relative accessibility if accumulated for a large scale will result in a measure of an absolute accessibility (Levinson & Krizek, 2008).

Land-use change and land-use prediction models use accessibility estimations to model the change of land-use over time. Topological accessibility using proximity is used generally in the suitability models of locations (Carr & Zwick, 2007). Gravity models, which can be based on the available opportunities and their travel distances to the location, are used in the modeling of location using statistical methods (e.g., modeling the employment opportunities for residential location, Waddell et al., 2003). Opportunity and combined opportunity distance accessibility indicators using either Euclidian or network distances are not yet used in land-use suitability analysis. Usually the simple accessibility estimation, as defined as the proximity or the Euclidian distance measurement is used in LUCIS models (Carr & Zwick, 2005).

Many mathematical forms are used to estimate accessibility. Bhat et al. (2002), summarized accessibility measurements into different equations for cumulative opportunity and gravity. However, they are applied on either a random data sample or on aggregate and zonal level such as TAZ level. These estimations are classified as

Gaussian, composite impedance, activity distance and in-vehicle travel time. Table 2-4 compares the variables used for accessibility estimation while Table 2-5 compares the merits and limitations in accessibility estimation using different methods. This research initiates the use of these accessibility estimations in land use modeling as explained in the Chapter 3.

Evaluating Distance Measurement Methodologies

In the absence of measured travel times, the accuracy of topological accessibility estimations depend on the method used to estimate the distance. Generally, distance measurement methods in land use research are one of three methods; Euclidean distance, rectilinear distance (Manhattan)and network distance. Network distance can be obtained from a network property approach by measuring the length of street segments as a percentage of the whole street network (O'nell, 2004), or by measuring the actual distance travelled (Zhao et al., 2003). The use of travel time may be more sophisticated and take additional variables into consideration. However, in measuring network distance barriers can be included to give a more accurate indication of travel distance. Arafat, Steiner and Bejleri (2008) compared network distance to Euclidean and Manhattan distance in research on school sitting. Their research found that the use of network distance gives a better estimation for walking distance than Euclidean or Manhattan distances. Additionally they found that the catchment area for population, which is an accessibility indicator, is exaggerated when using an Euclidean buffer. The network distance is used in transportation research to build accessibility indices in Texas (Bhat et al., 2002), where, the travel distance had been obtained from travel surveys which may not be available on a disaggregate level. An alternative methodology can be used to generate the network distance at a parcel level using

ArcGIS network analyst which is software that can calculate distance from origins to destination following the road networks. In this methodology, the shortest network distance can be measured from each origin to each destination (Arafat et al., 2008).

It is difficult to compare the results of Euclidian or network distances in generating proximity surfaces for two main reasons: The first is that a network proximity surface is not yet used and proximity models use Euclidean distance. On the other hand, these measures of accessibility used in land-use models are normalized using a base cost, that is, for example, a suitable base time for walking or a certain Euclidian or network distance is regarded as the base distance. This makes the comparison more complicated and increases the difficulty of decision-making about the method that gives a better estimation. This base distance or travel time is different from one place to another and from year to year, but if the general trend is assessed it can be seen to be increasing over time. Furthermore, travel time is related to human behavior and motivation which is in turn related to social and technological changes (Janelle, 2004). It is clear, however, that the impact of networks and mobility increases as distances increase. Therefore, it is more useful to use network distance in capturing regional accessibility or travel cost.

Evaluating Literature on the Impact of Land Use on Transportation

The impact of land-use on transportation is captured by research and used indirectly by planners and decision-makers who are concerned about location choice. and land-use modeling. It allows planners to solve transportation network problems and to make improvements on the transportation networks as well as calculating impact fees. Urban form and land-use generally impact the cost of travel which in turn affects choices of where to live. The land-use impact on transportation and travel behavior is covered extensively in the literature. Most of the research focuses on measuring the urban form and its relationship to the travel behavior.

Steiner (1994) reviewed the literature on the effect of residential density on travel behavior and mentioned that most of the research is done on aggregate data in which there is difficulty in separating the economic from the land-use effect on travel behavior. The research typically used the effect of income and density on travel behavior without separating them and their typical conclusion will be that members of lower income households travel less than other types of household (Steiner, 1994).

One of the most important outcomes of research on the impact of land use on transportation is the what is called the 3Ds (5Ds in later work), which refer to density, diversity and design indicators and their effect on travel behavior. Cervero and Kockelman (1997) used 1990 travel diary and land-use records for the San Francisco Bay area and worked on non-work trips to show that built environment affects the miles travelled per household as well as modal choice. Their research showed that the density, land-use diversity or land-use mix in addition to pedestrian-oriented design reduces the trip rate and encourages walking and transit use. They also emphasized that compact development affects modal choice. For the design element, their study showed that a grid network and restricted parking reduced the use of autos and increased the level of transit and walking (Cervero & Kockelman, 1997).

An empirical study to test the impact of land-use on transportation tested the effects of land-use mix, population density and employment density on the use of single- occupant vehicles, transit use and walking in addition to modal choice. In that study, however, the land-use mix was measured at the trip ends and it was shown that walking and transit use increased when density and land-use mix increased while the use of the single- occupancy vehicles decreased (Frank & Pivo, 1994).. The research also shows that measuring land-use mix at the trip ends gives a greater ability to predict modal choices. In addition to that, land-use mix at the trip end also increases walking and transit use and reduces the use of the single-occupancy vehicles (Frank & Pivo, 1994). Ross and Dunning (1997) also found that increasing population density will decrease person-trip and mileage. Steiner et al. (2010) used the land-use variables at trip ends to create a model for calculating trip length induced by new developments. Cervero and Radisch (1996) studied pedestrian activity and learned that modal choice for biking and walking increases in transit-oriented neighborhoods. Handy (1996) also concluded that urban form affects modal choice and increasing local accessibility will increase the people's choices of where to go locally by walking, biking or transit, and in turn that leads to increases in people's modal choices (Handy, 1996).

Zhang (2005) tested measuring urban-form and non-urban forms quantitatively on transit-oriented development. In his research he used regression analysis and calculates the entropy value which is a test of land-use heterogeneity. Ewing and Cervero (2001) summarized most of the literature on the effect of land-use on transportation by assessing the research performed on the 4Ds and 5Ds in later works. The 3D's are density, diversity and design. The fourth and fifth Ds are destinations and distance to major transit stations such as rail stations. The destinations are measured by regional accessibility indices or the accessibility to major destinations, such as activity centers and central business districts. Accessibility and distance are new variables considered to affect land-use in addition to the 3Ds. Ewing and Cervero

(2001) summarized the research done in nearly 50 papers in that domain. Their summary culminated in the creation of elasticity values based on 5Ds. Elasticity is an estimator that is used to quantify the extent to which choice probabilities will change in response to changes in land-use values. Alternatively, it can be defined as the percentage change in the model response (i.e. VMT) with respect to a change in the model input (i.e. 5Ds) (Bhat & Koppelman, 1993). In general, in Ewing and Cervero's summary of the research, elasticity is mainly used to predict how much trip generation or trip length would increase if, for example, density was doubled. Elasticity values of this kind are useful in land-use modeling such as the smart growth index and future land-use prediction and thus represent a feedback for the transportation model that is used for land-use modeling (Ewing & Cervero, 2001).

The same land-use variables included in the 5Ds in Cervero's research are used to study modal split. Litman (2008) summarizes the impact of density, accessibility, land-use mix; roadway connectivity to test how they affect none-motorized travel behavior. Litman's summary showed that feasible use of growth management strategies can affect the land-use variables such as density, diversity, design and etc., which in turn can reduce automobile travel by 20 to 40%. In his analysis Litman shows that the VMT per capita is reduced when density is increased. Furthermore, using cars as a mode is decreased when increasing the land-use mix. Connectivity of the street network also affects VMT which is reduced for higher connectivity networks. For example, choosing walking as a mode is increased when the pedestrian network is highly connected. Furthermore, the mode choice of walking is also affected by the attractiveness and completeness of the street network which supports the design aspects of urban form. Handy et al. (2005) mentions that the research performed in studying the land-use effect on travel behavior showed that increasing density and diversity of land-use did make people drive less but these studies miss the causal relationship. Therefore, neighborhood characteristics, travel preference and residence preference are used in a quasi-longitudinal design study to show the relationship between them and how neighborhood characteristics have a significant causal relation with travel behavior (Handy et al., 2005).

Urban form estimators other than the 5Ds are also used in researching the relationship between land use and transportation. Disaggregate approaches are used to measure built environment indices that help in planning for future land-use change. Rodriguez et al. (2006) used the variety and spatial co-variation and their relation with non-automobile travel to build and generate the Built Environment Index (BEI). A method for calculating the circuity index ratio (El-Geneidy & Levinston, 2007) which is also known as Portland Pedestrian Ratio is adopted by Arafat et al. (2008) to measure the connectivity of networks and the efficiency of using network distance to build a walkability index to be used for school sitting based on a parcel level-GIS and network analysis. These indices help also in predicting the travel behavior in addition to predicting location choice. Bejleri et al. (2008) used urban form indices to capture the urban form effect on student opportunity to walk or bike to school. Furthermore, Frank et al. (2006) used a walkability index developed using density, connectivity, land-use mix and retail floor area and applied that in King County, Washington to find out that a 5% increase in the walkability index decreased the VMT by 6.5% as well as similar reduction in air pollution. Similarly, Pendall and Chen (2002) used a sprawl index based on land-use density, land-use mix, street connectivity and commercial clustering to find that there is a high correlation between these factors and travel behavior, as an increase of the sprawl index decreases the use of alternative modes. Galster et al. (2001) conceptualized sprawl metrics that also can be used in suitability models to avoid sprawl.

Many researchers of the impact of land-use on travel behavior encounter similar issues regarding the research undertaken in this area thus far. Firstly, using aggregated data and macro-scale of analysis where the unit of analysis might be larger than a county-level. Secondly, the mix of economic variables with land-use variables without controlling any of them makes it difficult to identify the land-use effect on travel behavior in a manner independent of the characteristics of the traveler. Thirdly, the research effort to build indices using disaggregate approaches can be spatially represented as surfaces but these indices describe an existing condition and do not predict future trends.

There is also some interdependency between urban form variables. For example, increasing the commercial density may increase the accessibility for shopping as the opportunity increases. Furthermore, the 5Ds concluded from Ewing and Cervero show that increasing density will also increase transportation options but at the same time decrease travel speed and increase travel congestion (Litman, 2008).

The 5Ds research shows that diversity and land-use mix affect travel behavior. However, the literature shows differences between researchers in how they are measured. Cervero and Kockelman (1997) used entropy and dissimilarity to capture the land-use mix of a neighborhood, in addition to the density and design variables used in a regression analysis to find the impact on transportation through modal choice and VMT. Entropy and dissimilarity are indices that are calculated on a neighborhood scale to capture land-use mix. The entropy measure in general takes the percentages of land-use mixes in a neighborhood to build an index. The entropy index developed by Frank and Pivo (1994) describes the evenness of the distribution of built square footage among seven land-use categories.

The aforementioned dissimilarity index was developed by Cervero and Kockelman (1997). This index was based on the dissimilarity of a hectare use from the adjacent eight hectares that surround that specific hectare. The average of hectare accumulations across all active hectares in a tract is the dissimilarity which is an indication of the land-use mix in that tract. The reason for using the dissimilarity is that using entropy lacks the ability of capturing the distribution of land-use mixes spatially, while dissimilarity captures the variety of different land-uses that surround a certain land-use and thus captures the spatial pattern for different land-uses. A Transit Cooperative Research Program [TCRP] (2003) report showed that increasing density increases modes of transportation other than cars. An entropy index, accessibility and dissimilarity indices were also studied, with the accessibility and entropy indices being the most efficient in capturing the travel behavior.

Steiner et al. (2010) studied the effect of land-use mix at trip end to come up with an equation to predict trip length for new development. They found that the entropy measurement proposed by Frank and Pivo (1994) was insignificant for their study in south-east Florida and they suggested a model for calculating the land-use mix as a percentage between residential and non-residential uses.

The literature indicates the importance of the impact of the 5Ds on vehicle trips and on the VMT. CNT (2007) used similar indicators in a regression model for travel cost. Steiner et al. (2010) also used similar variables to model trip length. However, it is not difficult to conclude from the literature that the 5Ds have an impact on travel cost. Generally, from the literature on the indirect effect several conclusions can be drawn. Firstly, the frequently-used 5Ds, density, diversity, design, destinations and distance are the most important variables impacting transportation. Secondly, urban form indices other than the 5Ds can used to capture the impact of urban form on travel cost. Thirdly, many of the existing research has been performed using statistical approaches and performed on aggregate level data and analysis. Fourthly, it is clear that these variables affect the travel cost and VMT and therefore can be considered important variables in a housing location choice model and in deciding the relationship between housing and jobs. This research will use statistical methods on parcel-level and local data to show which variables impact travel cost and use them in the prediction of future travel cost values that can be modeled spatially.

Low transportation cost and connectivity to transit are important factors in determining affordable housing locations, however, at the same time these may conflict with other location costs such as the cost of housing. Therefore building index surfaces for these variables is important because it can work together effectively in the allocation of affordable housing. This research will use spatial interpolation and regression methods to build travel cost surfaces based on travel surveys for a certain year and will modify the cost for a projected year according to the land-use variables at the trip ends such as density, diversity represented by entropy values, design represented by connectivity, destinations represented by the regional accessibility to employment and the distance which represent the distance to major transit stations.

Advanced Methods of Capturing Travel Behavior

The research trend for the coordination between land use and transportation aims to the highest integration of transportation and land use models at the highest possible disaggregation level. This can be seen from the trend to apply parcel-level analysis and the use of activity-based models. Many efforts can be seen in research approaches that try to use activity-based models (Ben-Akiva & Bowman, 1998). Activity-based modeling is a new trend in transportation modeling research even though it has existed since the 1980s. These models process activities with their relevant times and thus allow more consideration for air quality and congestion problems through the space-temporal dimension. If activity-based models are integrated with disaggregate land-use models the result will be a land-use and travel model that corresponds to the behavioral integration of the choices across their relevant times.

Recent trends in transportation research also have seen a growing focus on multi-modal transportation systems including interaction between all modes of transportation, such as driving, transit, bicycling and walking. Traditionally, transportation modeling is represented using a four-step transportation model. The first step is trip generation where trips are divided into home-based and non-home-based trips produced from a place and attracted to another place. In the second step, trip distribution, the trips are distributed between production zones and attraction zones or the number of trips interchangeable between zones. The third step, modal choice, involves the choice between driving, transit, bicycling and walking. The final step, network assignment, concentrates on routes and the transportation network (Kutz, 2003).

Researchers disagree about trip generation in transportation models such as the four step model. Generating the production of trips generally depends on household characteristics such as income, sex, number of people in the household, number of cars etc. and depends on household surveys for the number of trips. A statistical regression model can be generated. The regression equation is used to forecast the number trips. However, this regression model is not sensitive to land-use variables. Iacono and Levinson (2008) investigated the land-use and transportation network elements in generating trips and showed that the transportation network characteristics play a role in generating trips and the transportation network affect the location choice.

The four step model is trip-based and does not include trip-chaining; therefore, the time of day is not scheduled and thus ignored. The use of time in the four step model is limited to certain uses in deciding (i.e. the peak count of trips). The four step model also does not take into account the interdependence between trips and it divides trip into home and non-home-based trips and thus does not distinguish between a single stop home-based journey and a multiple stop journey (Bhat & Koppelman, 1999). Ben-Akiva and Bowman (1998) studied the behavior realism in urban transportation models. Their research gave a more realistic representation of travel patterns. Their paper also followed the evolution of transportation models from models that represent the day schedule as isolated trips which is generally the original trip modeling of four step models, to modified models that combine trips explicitly in tours or chains of trips, and finally to more sophisticated models that combine the tours or chains to their respective times in a day schedule. In the trip-based models, the trips are scheduled as independent one-way trips, with no relationship between trips. In the tour-based model trips are connected in tours with spatial constraints and direction of movement. For the chains or tours attached to a day schedule, the model links the sequence and timing of activities across the chain. The development of such models also led to the inclusion of behavioral variables in the model (Ben Akiva & Bowman, 1998). The trip chaining and the time of day is important for studying congestion and to estimate travel cost that do not depend only on free flow conditions. However, the applications of trip chaining and activity models are not always possible in terms of data availability.

Land-use characteristics do not only affect travel distance as shown in VMT research. It also affects the number of generated trips (Ewing & Cervero, 2001). In the four step model, the trip attraction, which is a function of land-use, is calculated by an empirical equation generated using research results in each Metropolitan Transportation and Planning Organization (MTPO). In land-use models like UrbanSim, a modified five step model is used to replace the four step model. This five step model accounts for the interaction between the transportation modeler and the land-use. This fifth step uses density and transit accessibility measures as a feedback loop between distribution and assignment. The model also uses a nested logit model for home-based work (Franklin et al., 2002). The modification of the four step models indicates the problems facing the MTPOs in using the four step model and the need for more advance and comprehensive transportation models.

Pozsgay and Bhat (2001) used demographic characteristics as well as spatial indicators to identify the impact of spatial location on travel behavior using destination choice models. Destination choice models are also used by Arafat, Srinivasan and

Steiner (2009) to relate the choice of destination to the urban form variables such density, accessibility and distance.

Bhat and Lawton (1999) also addressed the importance of travel forecasting and the importance of integrating land-use and transportation models, especially the movement from trip based modeling to activity based modeling. This move includes treatment and scheduling of tours as a series of linked trips that the traveler performs as a series of activities from the moment he leaves home to the moment he returns to home (Bhat & Lawton 1999).

Waddell et al. (2003) commented that the advancement in research on modeling the location of urban developments, real-state and the analysis of travel behavior is to use the activity based approach. A major development in the UrbanSim model for San Francisco was the shift in paradigm to use a tour-based travel model instead of a trip-based or four step model, originally integrated with UrbanSim. The activity-based integration for the short and long term is to be performed in broader future research projects (Waddell et al., 2003).

The literature shows clearly the new trend in transportation research as focusing on activity-based modeling for transportation and the use of discrete choice modeling to relate the transportation variables to land-use. Unfortunately, the use of activity-based modeling will not always be possible in this type of research due to the data needed for the model. However, trip chaining is still needed because people may use more than one mode of transportation in their daily travel activities. In the absence of the data needed to run activity models and the poor handling of the four step model in prediction at the parcel-level, this research uses a longitudinal approach involving regression to relate travel survey data to urban form variables. It uses the relationship of these variables for future years by assuming that that the relationship between travel cost and urban form characteristics will remain constant. The next section will explain the literature for estimating and predicting travel cost.

Evaluating Methods for Predicting Travel Cost

The interdependency between urban form variables and their relationship to trip length has been also the focus of VMT and travel cost research. Different methods have been used to generate trip miles or VMT using statistical approaches. One method used the Delphi panel consensus for elasticity values linked to the 4Ds (Lee & Cervero, 2007). According to the 5Ds research, the increase of any of the Ds values will decrease VMT, reduce the number of auto-trips generated and increase the share of transit and walking modes (Ewing & Cervero, 2001).

Lee and Cervero (2007) summarized the value of elasticity for VMT. These values can be applied in a post-processing procedure to update the predicted trip according to the change in land-use at the trip ends. Table 2-6 shows the elasticity values for the purpose of updating VMT.

The other method to estimate and predict trip length is using regression, taking the trip length as the dependent variable and the land-use on trip end as independent variables. Steiner et al. (2010) applied this methodology on South East Florida travel diary data which included the positional coordinates at the origin and destination of each trip. Table 2-7 shows the result of the regression model to estimate the trip length of the home-based work and non- work trips and non- home based trips. Back-calculating of the trip length according to the previous model can generate a spatially discriminated prediction surface for the trip length on a parcel or neighborhood level.

Based also on the statistical models, CNT (2007) research developed the HT index, which is an equation for the combined location cost for housing and transportation with respect to income for the house-hold. The variables included in generating this cost are housing cost, travel system characteristics which include road and transit connectivity and density, and the distance from employment. However, they used the Census 2000, Census Transportation Planning Package CTPP 2001 and local data to statistically generate the travel cost which mainly includes travel miles, car ownership cost and transit rides. Furthermore they use general categories such as low, medium, and high to describe the access or transit frequency. The level of analysis can be described as aggregate. Table 2-8 compares the variables used for the travel cost estimation between different methods while Table 2-9 compares the merits and limitations for each method.

The application of discrete choice or geographically weighted models is data dependable. This research will not focus on using discrete choice models in predicting trip cost or generating a cost suitability surface. Instead, this research will use ordinary least squares and geographically weighted regression to predict travel cost and to generate a travel cost suitability and preference surfaces.

Using Conflict Identification Strategies to Identify the Conflict between Transportation and Land Use

The conflict identification strategy (Carr & Zwick, 2005), can be applied on any set of conflicting objectives and goals. It was used in LUCIS to identify the conflict in land use but the same methodology can be used to identify the conflict between transportation planning goals and environmental goals or between affordable housing goals and transportation goals.

In the affordable housing suitability structure, four main objectives may conflict with each other. These objectives are:

(1) Planning for housing sites in terms of land physical characteristics as well as neighborhood socio-economic characteristics;

(2) The objective to relieve the housing burden for low income families;

(3) The transportation planning objectives to increase access and reduce VMT and travel cost; and

(4) The objective to increase transportation options like increasing transit access and walkability.

The process of conflict identification should consider the planning for each objective in isolation of the other objectives. That means when planning for housing preference the planner works on the site characteristics and socio economic characteristic. Therefore the planner will not take into consideration the cost of traveling to work from residential locations. The planner concerned with housing over-burden will work to identify places that are of low housing burden. The transportation planner will plan to reduce VMT and travel cost as well as increasing accessibility without taking into consideration the site preference for affordable housing or the work of the first planner. The same applies to the fourth objective, planning for increasing transit accessibility without taking the other objectives into account. The main criterion for using conflict identification strategies exists in the affordable housing structure.

Building Allocation Scenarios

LUCIS works to identify potential future land use conflict. This conflict can be used in various applications, one of which is future land use allocation scenarios (Carr & Zwick, 2007). The future allocation process based on LUCIS outputs can be seen as identifying the land for future growth and the allocation of people to residential, retail, and industrial land uses, based on densities and/or any other factors that a planner might wish to use in the allocation process.

The allocation procedures in the LUCIS model can be automated by introducing a set of GIS tools for future allocation, scenario building and testing of policies. For example, the automatic allocation of urban land using the LUCIS procedure can be easily understood according to the category it fits in. Three main categories can be identified for the allocation process. The first is an infill category where some of the vacant land should be allocated for use before using other land categories. The second is a redevelopment category where allocation is performed on existing uses that are convenient to redevelop; and the third will be the use of agricultural land in a green field category which is based on the urban, conservation and agricultural conflict.

Using GIS facilitates the allocation process where the identification of land and the allocation process will be performed according to priorities. These priorities may depend on growth patterns, proposed densities, transportation masks, etc. The complex procedure, the accuracy and the time spent in the allocation process generates the need for an automated procedure that can perform the allocation in a more feasible and flexible fashion. Similarly, the automatic allocation process can be performed using the affordable housing conflict surface, in addition to any other conditions and priorities in preparing scenarios for the allocation of affordable housing.

The literature review summarizes the literature on the creating and evaluating the suitability components that are used in the affordable housing suitability models such as neighborhood access to services, transit accessibility and travel cost. The literature review also summarized the literature on location choice and suitability models. The review highlights the importance of urban form characteristics in reducing travel cost and the importance of accessibility in land use modeling. It can be concluded that these variables should be used in modeling land use. However, using transportation variables such as accessibility and travel cost as suitability surfaces has not been implemented yet in the literature of land use modeling. The literature review also summarizes the trend in capturing travel behavior through the use of activity models. Even though this dissertation does not focus on capturing travel cost using activity simulators, the suitability model structure adopted in this research is flexible and can be updated to take activity models into account when the activity diaries data for these models becomes available in Florida.

Table 2-1. Scale for pair-wise comparison (Saaty, 1980).

Definition	Intensity or Importance
Extremely more important	9
Very strongly to extremely more important	8
Very strongly more important	7
Strongly to very strongly more important	6
Strongly more important	5
Moderately to strongly more important	4
Moderately more important	3
Equally to moderately more important	2
Equally important	1

Table 2-2. Preference value descriptions.

Cells with a value of:	Indicate
1	low preference
2	medium preference
3	high preference

Table 2-3. Conflict score matrix (AHS goal 1 and travel cost).

Goal 1 Preference	Travel Cost Low Preference 1	Travel Cost Medium Preference 2	Travel Cost High Preference 3
Low Preference 1	1 *10 + 1 = 11	12	13
Medium Preference 2	2* 10 + 1 = 21	22	23
High Preference 3	31	32	33

Table 2-4. Variables used in accessibility equations.

Article	Distance	Network Distance	Opportunity	Gravity General	Gravity Hanson	Remarks
Carr and Zwick (2007).	D					D- Distance
Levinson and Krizek (2008).	D or TM		O	O, TM, α		TM- Travel Miles α- Decay Factor
Arafat, Steiner and Bejliri, (2008).		ND				ND- Network Distance
Bhat et al. (2002).		TM, TT	O	O, TM, α	O, TT, α	TT- Travel Time
Handy (2004).			O			
Hanson (2004).			O			
Waddell et al. (2003).				O, TM, α		
Grengs (2009).					O, TT, α	
Srour et al. (2002).	D		O- (Driving time buffer)			
Bhat and Guo (2004).	TT			O,TM, α		

Table 2-5. Accessibility matrix (Merits and limitations for different accessibility estimation methods)

	Distance	Network Distance	Opportunity	Gravity General	Gravity Hansen
Merits	Easy to calculate. Spatial surface can be generated directly by raster analysis. Good access estimation for highly connected locations.	Precise measurement of proximity distance. Easy to estimate on zonal level.	Used by many articles as accessibility estimation. Easy to estimate.	Easy to estimate on zonal level. Value the attraction and distance in the model. Considered more precise estimation of accessibility.	Easy to apply on zonal level. Applies on travel time from travel survey or forecasts.
Limitations	Poor estimator for poorly connected places and neighborhood s with higher block sizes. Estimate only distance and does not include attraction in the estimation.	Complex and time consuming to generate accessibility surfaces by this method. Estimate only distance and does not include attraction in the estimation.	The equation will estimate that large attractions are more accessible even though they might be far away.	Applied on zonal level and complicated to be applied on parcel level.	Applied on zonal level if the travel time for each zonal pairs is estimated. Complicated to apply on parcel level.

Table 2-6. Elasticity values for VMT (Lee & Cervero, 2007)

Variable	Elasticity
Density	-0.05
Diversity	-0.04
Design	-0.20
Access	-0.05

Table 2-7. Trip length associated with residential parcels (Steiner & Srinivasan, 2009)

Explanatory Variable	Home-based non-work t stat.	Home-based work t stat.	Non home based t stat.
Constant	7.621	12.592	11.099
Developed area as a % of total neighborhood area	-2.395	-4.426	
Residential area as % of developed area	1.682		
Building square feet (retail commercial)	-2.527		-4.408
Building square feet (office/service)	-2.527	-2.445	-4.408
Building square feet (industrial)		-2.776	
Road miles per developed area	-3.015	-3.793	
Number of intersections per road mile	-2.722		
Distance to nearest regional residential center		-3.925	-1.908
Distance of nearest regional activity center	2.968	5.528	
Range of distances to regional activity centers		-1.330	2.175

Table 2-8. Travel cost matrix (Variables)

Variable	Steiner and Srinivasan (2009)	Lee and Cervero (2007)	CNT (2007)
Density	Ratio of developed area. Residential area per developed area.	Residential Density Dwelling per square mile. Retail and commercial density is taken as floor area ratio.	Net density Gross density
Diversity	Retail SQF Office SQF Industrial SQF	Entropy value: Residential/ retail/ commercial/ services.	Job density.
Design	Road miles per developed area. Number of intersection per road miles.	Street grid density.	Average block size.
Destination	Distance to nearest regional activity center. Distance to regional residential center. Range of distance to major activity centers.	Regional access to major destination-zonal gravity model.	Distance to employment centers.
Other Variables	None	None	Neighborhood access to amenities, household income, household size, Transit connectivity.

Table 2-9. Travel cost matrix (Merits and limitations).

Variable	Steiner and Srinivasan (2009)	Lee and Cervero (2007)	CNT (2007)
Merits	Includes aggregate and disaggregate data. Use overlapping neighborhood definition to limit the effect of the modifiable unit area problem.	Can be replicated nationwide. Can use the output of the four step model in case of no travel survey is available.	Calculates the monetary cost Calculates the affordability index directly.
Limitations	Calculate the trip length for work and non-work trips without calculating the monetary cost The model depends on the travel surveys of South East Florida and is not tested for it is prediction accuracy in other regions.	Course spatial resolution Does not include local access. Does not estimate travel cost directly but via post processors.	Coarse spatial resolution neighborhood level data. Few land use descriptors. Datasets are on the aggregate level of neighborhood and TAZ. Very rough connectivity measurements for roads and transit.

	Goal 1	Goal 2	Goal 3	Goal 4	Goal 5
Goal 1					
Goal 2					
Goal 3					
Goal 4					
Goal 5					

Figure 2-1. Pair-wise comparison matrix.

CHAPTER 3
RESEARCH METHODOLOGY

Study Design:

This research builds GIS simulation tools that integrate transportation variables within a land use suitability model. The suitability model is used for the identification and preservation of land suitable for affordable housing in three counties in Florida. The study design is mainly composed of five parts:

1) Evaluation of methods to create suitability based on neighborhood accessibility to services;
2) Empirical analysis to establish models to create or predict travel cost based on travel surveys;
3) Preparing and validating GIS and simulation tools that use accessibility and travel cost in the allocation of affordable housing;
4) Using the allocation model to test the impact of accessibility and travel cost on the affordable housing location choice: and
5) Evaluating the automation tools to allocate affordable housing in the three case study areas.

The simulation tools are prepared to work within a ArcGIS interface using both an interactive user interface and an integrated model building interface supported by ArcGIS model builder. Generally tools and automated models are prepared to work under the GIS environment.

LUCIS suitability models typically use proximity to services as suitability indicators for residential parcels. The nearer the parcel is to services, the more suitable the parcel will be for a residential location. This research, however, uses neighborhood accessibility to services suitability model. The selection of a neighborhood accessibility estimation method is based on comparing the estimation results between different methods of accessibility estimation. Generally accessibility estimation in this research is based on parcel level data and replaces the traditional proximity tool in LUCIS models. ArcGIS Model Builder is used to create an automated accessibility model which also includes new tools for building and reclassifying the final suitability surface for accessibility. These new tools are programmed using Python programming language and prepared to be used as tools in Model Builder or the ArcGIS interface.

Estimating travel cost is also an important component in the Affordable Housing Suitability model. Two methods are used in the estimation of travel cost spatially. The first is a spatial interpolation method. The interpolation works for geographically mapped trips taken from the NHTS (2009) dataset. The second method involves the generation of a model that relates the travel cost to land use and urban form characteristics. This model uses ordinary least squares and geographically weighted regression to estimate the travel cost based on the NHTS and parcel data for the year 2009.

LUCIS suitability models depend on visual simulation using ArcGIS and are based on a deterministic approach. A program for weighting utility surfaces based on pair-wise comparison and Delphi panel scoring is prepared. This model is associated with ArcGIS Model Builder through the use of a special layer weighting tool prepared using Python programming. This program helps in scenario building where different scenarios can be run interactively during expert or community meetings. However, a tool to help planners in the selection process for affordable housing locations is also prepared by Python programming. This tool works on the final conflict surfaces that are generated using LUCIS. The goals that are used in the conflict surface may include site characteristics, neighborhood characteristics, travel cost, housing cost and transit access. Using additional conditions such as incentives and priorities, the tool can help the planner interactively in the selection of new affordable housing locations or in the analysis to preserve existing affordable housing sites.

Model Structure

The affordable housing suitability model is an automated GIS based suitability model that aims to help local communities in Florida plan for sustainable affordable housing.

> The AHS research project is intended to build The Affordable Housing Suitability model (AHS) which is designed to help Florida's communities plan for attractive, equitable, and sustainable affordable housing. The project goal is to evaluate and identify lands in Florida's communities that are suitable for the development and/or preservation of affordable housing based on local preferences and planning expertise (AHS, 2009, p. 3).

To achieve the goal, the model uses LUCIS conflict identification strategy and the population allocation procedure using combined grids (Carr & Zwick, 2007). The LUCIS layer overlay methodology uses local community preferences and includes identifying lands that are suitable for residential development. However, additional overlay layers are used in the AHS models that are specific to affordable housing residential locations. The conflict surface is the second step in the process which again uses the LUCIS methodology to find places that are suitable for affordable housing based on travel cost, housing burden and transit accessibility. The population allocation procedure refines those locations further by adding more affordable housing suitability and cost indicators such as socio-economic conditions, policies and incentives. This research will focus on objectives that are linked to lowering the transportation burden such as compact development and/or Transit Oriented Developments (TOD). This includes the use of transit accessibility and location specific cost which includes the travel and housing costs. Figure 3-1 shows the structure for the suitability model and allocation procedure.

The suitability model generates an opportunity surface by combining four affordable housing goals. The opportunity surface is then combined with surfaces that represent policy incentives and allocation conditions to generate the combine grid used in the allocation process. The allocation tool in Figure 3-1 is a new ArcGIS tool created using Python scripting language. This tool allocates the affordable housing land based on instructions given in a scenario table.

Computer Requirement and Data Sources

The computer requirements can be divided into two categories; computer requirements for development, and computer requirements for model application. In the model development, the analysis and model preparation include running network analysis to calculate distances on a parcel-level and needs extensive computer computation for millions of records. Therefore the computer used for the model preparation is a quad- pro Intel core computer Q9600. This computer has a processor speed of 2.5 GHZ for each of the four processors and has a memory is 8GB and 1TB of disk space. However, the model application does not need a high specification computer. The models and tools are tested to run on a DUO-core II computer with a 2GB of memory. Running the tool on a lower efficiency computer is not tested and may have some limitations.

In terms of data, the research used the most recent data sources from the Florida Geographic Data Library FGDL, data at d geographic levels from the U.S. Census Bureau, National Household Travel Survey 2009, data from local transit agencies and other local data sources. Table 3-1 shows some of the primary data sources used in the research.

Level of Analysis and Selection of Research Areal Units

Many of the urban-form characteristics are measured on an aggregate scale (Hess et al., 2003). However, the new trend in transportation planning is to perform disaggregate analysis in time and space (Wegener, 2005; Johnston 2004). The characteristics of a predefined areal unit affect the values of an urban form measurement. This problem is known as the Modifiable Areal Unit Problem (MAUP) (Guo & Bhat, 2004; Kwan & Weber, 2008).

The focus of this section is to explain the methodology on the use of an optimized zoning procedure to reduce the effect of the MAUP on the estimation of urban form patterns. To do that, an extensive GIS iterative analysis will be performed on three counties in Florida. To minimize the zonal boundary impact, every parcel will be taken as a center of a zone that will capture the urban form characteristic surrounding that parcel, and then the analysis will be repeated for different zone sizes and shapes to find an optimal size for the zones. The research shows that the use of natural neighborhood boundaries as an areal unit may lead to undesirable results because of differences in size and shape, and suggests the use of GIS tools that use the optimal neighborhood in measuring urban form characteristics.

Urban forms have impacts on transportation and the transportation systems have impacts on urban form and land use. The impact of transportation on land use is captured via a simplified accessibility measurement while the impact of urban form on transportation is captured by many urban form measurements such as density, land use mix, connectivity and accessibility. Some of these variables are better used on parcel-level data while other variables are better used on an aggregate scale.

Density, diversity (land use mix), design (connectivity), destination (accessibility) and distance (5Ds) are used to study the interaction between land use and transportation, especially with regard to the impact of land use on transportation in terms of vehicle trips and VMT (Ewing & Cervero, 2001; Ewing et al., 2007; Lee & Cervero, 2007). The five Ds in general represent some of the measurements for the urban form characteristics. Therefore, their impact is not isolated from scale and zoning problems.

The new trend in transportation planning is to perform disaggregate analysis in both time and space. Disaggregate measurements can be performed on urban form measurements such as accessibility. Urban-form characteristics such as density, diversity and connectivity are usually measured on an aggregate scale (Hess et al., 2003; Dill, 2004). In the MAUP, the scale and zoning of the areal unit affect the value and variation of the aggregated entity. The MUAP is a recognized problem that has faced researchers in the modeling and calculation of entities that have a spatial representation. The scale and zoning in this research are represented by the areal unit characteristics which include but are not limited to the size, shape and location of the areal unit.

GIS can be used to reduce scale and zoning issues and offers solutions to reduce the MAUP. GIS Spatial Analyst offers the tools for defining the areal unit and running iterative analysis on different sizes and shapes. This research presents the impact of size and shape of the areal unit on the urban form characteristics and presents a method to optimize the neighborhood size and shape. For the location of the areal unit, the research presents a floating areal unit method to reduce the effect of the zoning and adjacent neighborhoods limitation.

A first step to obtain the optimal neighborhood for capturing land use and transportation characteristics is researching the effect of size and shape as well as the boundaries of neighborhoods used for the data aggregation. To do that, preliminary research is performed using variable neighborhood size around each parcel to study the effect of neighborhood size and shape on the land use mix entropy value. The same method is applied on other urban form characteristics such as connectivity and density. This methodology accounts for the scale component of the MAUP by taking a variable size neighborhood. The methodology also accounts for the zoning component by using a floating areal unit as well as different unit shapes.

The land use mix in this research is captured by the entropy index. Cervero and Kockelman (1997) used entropy on a neighborhood scale to capture the land use mix. In general, entropy measures the percentages of the land use mixes in the neighborhood to build an index. The entropy index developed by Frank and Pivo (1994) describes the evenness of the distribution of built square footage among seven land use categories. The following equation shows how entropy is calculated for several land uses.

$$Entropy = \left\{ \sum_{k} \left[(p_i)(\ln p_i) \right] \right\} / (\ln k)$$

Where,

p_i is the proportion of specific land use to all land uses in each catchment area.

k the total number of land use categories.

The other two variables studied here are connectivity and density. For neighborhood connectivity, a simple measurement of road density is used as a connectivity indicator. This measurement is primarily miles of roads per unit of area (square miles). Other connectivity measurements can be used too, such as the number of links divided by the number of intersections in the neighborhood (Dill, 2004). Arc Map's Spatial Analyst extension is used to create a raster representing connectivity for a certain defined areal unit. For the density, this research uses a unit per acre variable from the property appraisal data. These density values are aggregated and averaged to the defined areal unit. The value of the average density is assigned to the center point of the areal unit. To eliminate the zoning boundary problem, a floating areal unit is used where each point in the map is a center of a defined neighborhood. In summary, a multi- level analysis for land use mix, density and connectivity is performed using a neighborhood size that is increased incrementally,

Because of the zoning component of the MAUP, each parcel will be taken as a center of this neighborhood and the analysis will be replicated for all parcels. The result surfaces will be compared by ArcGIS statistics by calculating the mean and standard deviation for the change in value and standard deviation due to the incremental change in size. Figure 3-2 shows the scale component by displaying the variable size unit area around the parcel. The smallest size is a 0.5 mile and the increment is taken as 0.5 mile. To study the effect of the areal unit shape, three different unit shapes are studied. These shapes are a square, a circle and a diamond. The square shape represents aggregated parcel blocks in a grid pattern system. The circle represents the Euclidian travel distance, and the diamond shape represents the Manhattan travel distance. The results of the three shapes are overlaid with the street network to obtain the optimal areal unit shape.

ArcGIS Model Builder models and customized Python scripts are used to calculate and create surfaces for the land use mix (entropy), density and connectivity using floating areal units. Multiple shapes and sizes are used in the analysis. The models and scripts calculate the value for each parcel assuming that it is at the center of the areal unit. After generating the surfaces, descriptive statistical methods are used to obtain the optimal neighborhood size and shape.

Introducing Transportation Variables as Suitability Surfaces:

Transportation land-use coordination impacts on each other are identified by literature and were categorized in the literature review in terms of the impact on location choice as direct and indirect effects of transportation. Accessibility is identified as the direct impact of transportation on location choice and specifically on the choice of land for affordable housing. There are many definitions for accessibility in the literature. Many of these definitions are operationalized and used in the estimation of the urban accessibility index (Bhat et al., 2002).

This research uses and compares different accessibility measurements on local and regional levels. For the indirect impact direction in the land-use transportation coordination, the variables are mainly characteristics of the urban form that can be seen to be of importance because they affect transportation which in turn affects the choice of location. These variables are density, diversity, design, destination and distance. There are three approaches that are taken in this research which are as follows:

1) Using travel trip data in spatial interpolation to generate a spatial distribution of travel cost;

2) Using urban form measurements and trip data in a global statistical model and use that statistical model to predict travel cost; and

3) Perform a geographically weighted regression to relate the travel cost to the urban form characteristics.

Investigating Neighborhood Accessibility as a Suitability Surface:

Traditionally, proximity as straight line distance has been used as an accessibility measurement in deterministic land-use model (Zwick & Carr, 2007) while gravity models have been used in statistical and stochastic models (Waddell, 2002). There are also other measurements of accessibility used in statistical models such as opportunity access (Handy, 2004; Hanson 2004). However, using gravity models on a parcel-level scale requires generating huge origin-destination matrices that contain billions of records for the study areas. These origin-destination matrices exceed the capacity of hardware and software used in the analysis. Therefore, a combination between estimating access by opportunity and distance is used in the research. The distance estimation component can be performed by network or Euclidian distance. These distance estimation methods can be also used to generate the capture area for opportunity estimation which has historically taken Euclidean distances. Arafat, Steiner and Bejliri (2008) discussed the differences between capture areas based on network and Euclidean distances in terms of the number of students for within a walking distance to schools and recommended the use of network distance to generate the capture area. However, the use of network distance is time consuming and may not be practical for all planners in terms of hardware and software limitations. Therefore, this research agrees that the network distance-based estimation is better than other estimation methods and, in terms of accessibility, both proximity and opportunity are used as estimators as shown in the literature review. However, multiple utility assignments give a method to combine the suitability based on proximity and the suitability based on opportunity in a multiple utility surface. Therefore, in terms of suitability assignment and based on accessibility measurement methods, it is not difficult to conclude that the network-based combined opportunity-distance estimation can be regarded the best possible suitability assignment for accessibility to services on a parcel level. However, there is no right or wrong method for estimating suitability based on accessibility to services. This research investigates and compares the result of neighborhood accessibility estimation methods that the planner may decide to use.

Generating Neighborhood Accessibility as a Suitability Surface

Distance proximity surface

This is the simplest model to measure accessibility. The Euclidean distance is reclassified according to standard deviation of the normalized distance by the mean distance away from the multifamily parcels which is regarded as the base for suitability reclassification. The ArcGIS model in Figure 3-3 generates this suitability surface. In the model, an ArcGIS customized tool (A4 Suitability) is prepared using Python programming to reclassify the Euclidean distance raster and assign the suitability values based on their distance to services referenced to the average Euclidean distance to multifamily parcels. However the shown model measures and reclassifies the Euclidean distance. A network distances suitability surface is also generated using the Nearest Neighborhood tool (Arafat et al., 2008) which is an ArcGIS customized tool that measures the distances from all parcels to their nearer destinations and generates a network distance raster instead of a Euclidean distance raster. The same reclassification procedure is used for the network distance. This research generates and compares both Euclidean and network distance proximity surfaces.

Opportunity surfaces

The opportunity access can be defined as the number of opportunities within a defined area. It is also can be weighted to include the floor area of services according to the following equation:

$$A_i = \sum_i O_i C_i$$

Where:

O_i = the weight or the attraction for a facility

C_i = 1 for Di < buffer distance and zero else where

Therefore, the opportunity is calculated by accumulating the attraction value of the service which depends on the type of service. This attraction could be the square feet for retail services, the number of beds for hospitals or any other criteria that can be used to discriminate our preference of one service to another. The model captures all the opportunities that lie within the buffer which here is used as the walking and biking distances. The two output surfaces are combined to get a multiple utility assignment (MUA) surface that includes suitability based on opportunity within walking and biking distances. The model in Figure 3-4 is prepared to generate that surface.

However, the model in Figure 3-4 uses a Euclidean buffer which is an exagerated buffer to be used as a capturing area for oppurtunities. The model is modified to take the cummulative oppurtunity inside a dynamic network buffer for both walking and biking and use the opportunity value to generate the suitabilty raster.

Gravity and opportunity distance surfaces

According to Bhat et al. (2002), the accessibility measure is summarized into different equations for cumulative opportunity and gravity measures that are classified as Gaussian, composite impedance, activity-distance and in-vehicle travel time measures. The equation for calculating access from gravity is:

$$A_i = \sum_J \frac{O_j}{d_{ij}^{\alpha}}$$

Where,

O_j is the weight or the attraction for the facility

dij is the distance from each to each destination

J is the number of destinations connected to each origin

α is the distance decay factor

The distance as impedance estimation is a gravity estimation. However, the gravity model is a simple model for use on a zonal level such as TAZs. On a parcel level, the model will generate an origin-destination matrix that contains hundreds of millions of trip combinations for one county. Applying the gravity mathematical equation at that level is impractical in terms of hardware and software limitations. However, in this research the gravity approach is used to capture the regional accessibility to major destinations used to estimate the travel cost in this research. This is because the limited number of destinations will dramatically reduce the number of trip combinations. This will be further explained under the travel cost estimation section.

The combined opportunity-distance surface can be regarded as a modified gravity approach and is generated as an MUA surface that combines the aforementioned distance and opportunity surfaces. The surface will have the same gravity elements which are the retail density and distance but each generated as suitability surfaces and combined deterministically to generate the final suitability surface. This surface can be generated based on network distance using ArcGIS network distance estimation method. However, because estimating the network distance is time consuming, planners may avoid using the network base and prefer to generate a Euclidean distance based opportunity distance access estimation.

Investigating Travel Cost

Travel survey data

Travel cost is important in deciding residential location. CNT (2007) have used travel and housing costs to build a HT index for each income group. The HT index is used by CNT to determine the affordability of housing site locations. In this research travel cost will be used as a suitability surface in a model to find the suitable places for affordable housing. Many research approaches can be taken that include travel cost as shown in the literature review. The first method used in this research is to estimate the travel cost spatially is a spatial interpolation method based on the geo-coded data for trips in the NHTS 2009 trip diary. Figure 3-5 shows sample trip end points for Duval county. These trip ends are geo-coded trip end locations for the trips included in the travel diary for that County. In addition to the geo-coded location, The trip diary includes the purpose, mode and the reported trip miles for each trip.

Investigating NHTS 2009 trip frequency data shown in Table 3-2 in terms of trip length, we can find that nearly 95% of the trips are less than sixty miles long. Figure 3-6 shows the distribution of those trips according to the trip purpose while Figure 3-7 shows percentages of trips classified according to their length and type. From Figure 3-7 we can conclude that more than 95% of the trips are of lengths less than 60 miles, except for work trips and non-home based trips where 95% of the trips are of lengths less than 70 miles. This threshold value for trip length is used to remove the outliers from the travel survey. Additional outlier analysis is performed to identify the local outliers using AcrGIS. An ArcGIS tool to identify the local spatial data outliers (Anselin Local Moran I) (ESRI, 2011) is used. This method depends on the clustering within a certain neighborhood size to find the local outliers. Figure 3-8 shows the interface for the tool while Figure 3-9 shows an example for the outliers identified by tools for Orange County.

Spatial interpolation

This research focuses on the impact of location on travel cost. Therefore, variables considering individual travel characteristics will not be taken into consideration in the research. All the analysis and results are generated for an assumed household of size that is equal to the average house hold size. Other household characteristics, if used, are taken from the average surrounding area characteristics. Generally, after removing the outlier from the data, the trips are classified into five categories as follows:

1. Home-based work (HBW)
2. Home-based shopping (HBS)
3. Home-based social and recreation (HBSR)
4. Home-based other (HBO)
5. Non-home-based trips (NHB)

For generating values for travel cost by spatial interpolation we assume that the spatial location is the most important discriminator in calculating the travel cost. Because the analysis is not performed for a certain neighborhood, the state of Florida NHTS 2009 summary statistics was used in estimating the combination between all trip categories. However, for a certain traveler at the travel survey day, the household may not have certain types of trip. Therefore spatial interpolation is used to estimate values for the missing trips using the nearest surrounding trip data. The combination between the trips is performed when all the missing trips are estimated.

Different interpolation methods were investigated to estimate the missing trips in each category. These methods include deterministic models such as inverse distance weighted (IDW) and stochastic methods such as kriging interpolation. Figure 3-10 shows an example of the IDW cross validation estimation for the interpolation of work trips in Orange County. The interpolation procedure is used in an iterative ArcGIS Model Builder Model environment to create continuous prediction surfaces for all the trip categories as shown in Figure 3-11. Figure 3-12 shows the ArcGIS model used to establish the trip mile and the trip cost out of the trip length data for each category. The trip length is transferred to a dollar value using a per-mile cost of driving. This per-mile car driving cost is posted by the American Automobile Association [AAA] (2011) and includes ownership and maintenance costs. The final values of travel cost are represented into two different ways: The first taken is the parcel location travel as a direct output of the model. The second output is to assume that within a walking distance from a parcel, travel costs should be similar and therefore the output will average the travel cost within the walking distance and assign that value to the parcel in the center. The walking distance is taken as 0.25 mile using a Manhattan buffer. Figure 3-13 shows an example daily travel cost surface for Orange County.

Statistical approach

This approach relates the travel cost as a dependant variable with the land-use and urban form characteristics as independent variables. These independent variables are timely datasets that include but not limited to residential density, retail density, connectivity measurement, a diversity measurement such as entropy and a regional accessibility measurement that represents the regional employment destination. The regression analysis for such a model can be performed by OLS which gives a global regression equation for the whole county or can be performed using geographically weighted regression which will have different equations representing different geographic regions with different intercept and goodness of fit. However both methods give a predictive model that can be applied to find travel cost depending on land use and urban form characteristics, or longitudinally by applying the model to a different year using different independent variable values for the specified year. The aforementioned methods are used and compared to each other.

Global regression. In the global regression approach, urban form and land used characteristics were used as independent variables and the travel cost as a dependent variable. The data set is generated by taken three thousand random points in each county and creates a table of the estimated travel cost and the corresponding urban form characteristics. This table is used for the OLS regression and was prepared for the three counties. The final set of independent variables may vary from one county to another because of statistical tests and the significance of variables. Generally, the following variables were tested in the global regression model:

1. Density
2. Land use mix
3. Connectivity
4. Network accessibility to employment
5. Transit connectivity
6. Income
7. Household size

Density is defined as the number of residential units in one acre. However, there are two different density variables tested in the regression model. The first is the parcel density which represents the number of residential units in an acre area of each parcel. The second is the average surrounding density which is taken as the average parcel density within a 1.25 mile Manhattan distance from the center parcel.   This value was estimated for each parcel assuming that it is the center of the surrounding area. The value of 1.25 mile is chosen because it is the optimal size that reduces the effect of modifiable areal unit problem as shown in Chapter 4.

The land use mix variable is captured by the land use entropy estimation. Land uses are re-categorized into five categories; residential, retail, services, industrial and other. The entropy equation shown earlier is then applied to all parcels in the defined neighborhood. However, because the entropy is an aggregate estimation method, the neighborhood size, shape and location followed the results of the optimal size neighborhood and therefore uses a 1.25 Manhattan distance from the parcel, which is taken in the center of the floating or roving neighborhood. The measurement is then replicated for all the parcels in the county of study.

The connectivity measurement captures the design elements of the street network. Three connectivity variables are tested and the variable of the strongest correlation with the travel cost are used. These three connectivity variables are street density, intersection density and the links/intersection connectivity measurement which is defined as the number of links divided by the number of intersections in the neighborhood. The larger this ratio is, the larger the network connectivity. The neighborhood size for connectivity is taken the same as for density and entropy to reduce the effect of the modifiable areal unit problem.

Network accessibility is taken as a gravity measurement as explained in the accessibility section. In this variable estimation, the major activities are identified, which are the major activities in retail and services. Then the resultant activities are integrated within walking distances to reduce the number of major activities. However, the value of attractions is accumulated in the integrated points. The major activities are then selected, which are the points that have aggregated activities of one million or more square feet. To reduce the size of the origin-destination matrix, the random points taken in the generation of the data set for regression are used as origin points and the major activities are taken as destination points. The resultant origin-destination matrix that contained the network distances generated by ArcGIS Network Analyst is joined to major activities to calculate the attraction for each trip. The trips of each parcel to all activities are used to estimate the accessibility of the parcels to major activities using the gravity access mathematical equation explained earlier.

The transit connectivity score is a simple measurement to indicate how connected a parcel is to transit stops. The estimation is performed using a distance weighted density variable taken by the ArcGIS Kernel Density tool to estimate the transit stop density surrounding the residential unit. For consistency with the density and connectivity variables the same neighborhood size is taken and the density of transit stop is calculated per square mile.

The income and household size variables are based on the Census block group level. The Census block group data is intersected with the random points dataset to establish values for the income and household size in that dataset

Because the urban form characteristics are different from one county to another, additional independent and binary variables are tested for each county separately. For example, the land value taken from the property appraisal data on the parcel level is used in the regression model for Duval County. This variable is initiated as the dollar amount per acre with a local interpolation from the surrounding for missing data. More variables can be also used on a case by case situation. These variables aimed to increase the goodness of the regression model by adding some local variable that can be significant in a county and not significant in another county.

Geographically weighted regression. The variables that proved to be statistically significant in the global regression are used in the geographically weighted regression (GWR). The dataset that relates the travel cost to urban form characteristics can be also geo-coded as points distributed spatially in each county. The geographically weighted regression can be based on a fixed or on adaptable neighborhood. The choice between these two alternatives depends on the distribution of data spatially. Because the distribution of the data is random, taking a fixed neighborhood kernel failed because the kernel may have a large number of points in one place and less points or even no points in another place. The number of needed points for regression is related to the number of variables which makes the regression fail when using a fixed kernel. In this research an adaptable kernel with a fixed number of points is used. To be consistent between the three study areas, the number of points is taken as the minimum number of points of which the regression succeeds in the three study areas, which is 700 points. The geographically weighted regression creates an equation for each point in the map. Each location (point) equation is generated using the surrounding 700 points. This is a sufficient number to perform regression even if one is to use global regression on that location.

Research Automation Tools

The research automation tool box is composed of four tools for use in the LUCIS model environment. However, these tools can be adapted for any spatial analysis method performed within a GIS environment. These tools have been developed to automate standard processes imperative to developing a LUCIS conflict surface and in the allocation process. The first, the A4 Suitability tool, is a utility reclassification tool that reclassifies a utility surface according to a reclassification table or according to statistics based on geographic zones (i.e., zonal statistics). The second tool, the A4 Community Values Calculator integrates pair-wise comparison calculations into the ArcMap environment as a Visual Basic for Applications (VBA) program. The third automation tool is the A4 Layer Weighting tool. This tool uses the output table generated by the A4 Community Values Calculator to execute a map overlay. The fourth and final toolset, the A4 Allocation tools, is a set of three tools. This toolset automatically allocates land, population and employment based on different scenarios. However this section will focus on the first three automation tools. The allocation tool methodology will be explained in a separate section.

The A4 Suitability Tool

Proximity based indicators of change are probably the most important in land use analysis as they integrate transaction costs in determining land use opportunity. Prior to the introduction of the A4 Suitability Tool the planner would take the mean (MEAN), standard deviation (STD), and minimum (MIN) or maximum (MAX) statistics generated from Zonal Statistics to manually calculate the suitability intervals for non-binary classifications. Once the values for each interval were determined these values would be manually input into the Reclassify tool. This method proved to be time consuming, cumbersome, and prone to error.

The A4 Suitability tool functions as a standalone tool available within a custom ArcToolbox or can be seamlessly integrated into a model facilitating a continuous automation procedure. Additionally, the A4 Suitability tool automatically generates the reclassification table and output raster. The reclassification table is a listing of the LUCIS suitability index assignments and the ranges of values to which the tool assigns the specific utility value. To determine this utility value, either the average of the mean values for all zones acts as the baseline for suitability and one-quarter standard deviation ranges; or data from a table introduced by the user is used to determine the remap ranges. The user can manually modify the remap table produced by the A4 Suitability tool and use the modified table for subsequent model analysis. The A4 Suitability tool output raster is based upon the suitability index values listed within the reclassification table.

LUCIS employs two possible suitability index classification value ranges, increasing suitability (ranging from one to nine) or decreasing suitability (ranging from nine to one). Increasing suitability is best described as the further away a feature (i.e. noise sources) is from its objective (i.e. residential development) the more suitable the land. Decreasing suitability is best described as the closer a feature (i.e. roads) is to its objective (i.e. residential development) the more suitable the land. The A4 Suitability tool allows the user to indicate the suitability index as decreasing or increasing within the A4 Suitability tool interface. If the user chooses the decreasing suitability option, the tool will use the mean and a one-quarter standard deviation to compose ranges that correspond to the suitability index values from nine to one, starting with a suitability index of nine for all values up to the MEAN value and decreasing by one-quarter standard deviation increments for eight intervals between the MEAN and MAX value (Figure 3-14). Since the suitability index one is the last value calculated, this value range may be larger or smaller than the other eight suitability index ranges. If the one-quarter standard deviation value is less than the cell size then the suitability index values will be divided into equal intervals between the MEAN and MAX value.

Increasing suitability is calculated in a similar manner. If the user chooses the increasing suitability option, the tool will prepare suitability index values from one to nine, starting with a suitability index of nine for all values above the MEAN and decreasing by one-quarter standard deviation increments for eight intervals between the MEAN and MIN (Figure 3-15). Since a suitability index of one is the last value calculated this value range may be larger or smaller than the other eight suitability index ranges. If the one-quarter standard deviation value is less than the cell size then the suitability index values will be divided into equal intervals between the MEAN and MIN.

The A4 Community Values Program

Once the suitability of each objective and/or sub-objective is determined, they are combined according to their hierarchical level using utility values (i.e. weights) that equal 1.0 (100%). The weights at the objective and sub-objective levels are citizen driven; meaning the weights obtained at this level reflect localized knowledge of community values. These weights are obtained from existing plans, community meetings, or focus groups. Often surveys are used to gauge community values.

To determine the numeric weight, particularly between goals, the A4 Community Values Calculator is developed. The A4 Community Values Calculator is initiated by installing the program as an ArcMap macro in the Visual Basic Editor (VBEditor). Based upon pair-wise comparison methods, this program blurs the line between planner and land use modeler. A planner with minimal experience in modeling can easily use this program within a GIS environment to complete a values survey among stakeholders.

When evaluating the importance between objectives/alternatives the A4 Community Values Calculator integrates any number of objective and/or sub-objective raster suitability surfaces as inputs. The A4 Community Values Calculator interface prompts the user to specify the usefulness of each pair of raster surfaces and dynamically compares the raster pair. As the user indicates values for each pair, the A4 Community Values Calculator automatically populates a pair-wise comparison matrix. The calculator then outputs a parameter table of the raster names and their corresponding relative weights.

As a way to reflect community participation, the tool also uses an algorithm to update the weights based on the different pair-wise comparison assignments for a group of people or a panel meeting. The result is a table of weights reflecting group values which is then used as an input for the A4 Layer Weighting Tool, the tool used to create complex MUAs. Although there are many multi-criteria decision support tools available, having this tool available within the GIS saves time, eliminates the expense of purchasing a third-party software package, and reduces error when inputting values from a standalone software package. The tool is used to determine the weights to combine the suitability in the affordable housing model depending on expert values for the three counties in the study area. Once the expert values are completed, the A4 Community Values Calculator generates a table of weights used by the A4 Layer Weighting Tool to combine the suitability layers.

The A4 Layer Weighting Tool

When determining the final suitability for each land use, the degree of interaction between each goal MUA is measured by the weights generated from the A4 Community Values program. The A4 Layer Weighting Tool is similar to the Weighted Sum tool available in the Spatial Analyst toolbox. Both tools can multiply multiple raster surfaces by a specified weight then sum the surfaces together. Instead of manually entering the weights for each goal surface, the A4 Layer Weighting Tool uses the parameter table generated from the A4 Community Values program or a table of similar structure generated outside the A4 Community Values program as an input to the A4 Layer Weighting tool.

Affordable Housing Opportunity Surfaces

The automation tools help in the automation of the suitability structure which are divided into goals, objectives and sub-objectives. In LUCIS the conflict Identification strategies are used to identify the conflict between the agricultural, conservation and urban goals. The conflict is a suitability matrix that combines the preference of the three goals. The preference number is a number between one and three. The number three represent the highest preference. Two represent moderate preference, and one is the lowest preference. The combination number of 333 means that the area that has the mentioned preference is identified with a major conflict because it is preferred for agriculture, conservation and urban use at the same time. 113 mean that the area has a high preference for urban and low for agriculture and conservation. LUCIS Conflict Identification Strategies are used to generate the conflict surface to identify the conflict between the affordable housing objectives, which are accessibility and neighborhood characteristics, housing burden, transportation burden, and transit access.

Introducing Housing Cost as a Preference Surface

CNT (2007) have used travel and housing cost to build an index that is also dependent on income. The HT index created by CNT aims to estimate the affordability of housing site locations to the people that live in that place, while the case studies in this research aim to allocate affordable housing land for very low income population. Similar to the HT index, travel and housing costs are important factors in deciding the residential location in the model. Generally, housing costs are incorporated as a preference surface in the generation of the final conflict and opportunity surfaces which are the surfaces used in the allocation of affordable housing sites.

There are three ways to incorporate the housing cost in the affordable housing model. The housing cost could be a rent cost or a mortgage cost and depends on the objective of the affordability studies surfaces that can be generated for mortgage or rent. These surfaces could be weighted according to the number of rent or owned units in the Census data to get an estimation or proxy for the housing cost. However, the research uses the rent data for the year 2009 prepared by the Shimberg Center for Housing Studies to estimate the location cost.

Introducing Transit Access as a Preference Surface

The transit accessibility adds a very important transportation option for low income and very low income populations especially when the driving cost gets higher. This research creates a parcel-level transit accessibility score for residential location based on transit stops routes and employment. These transit scores are used to create a preference surface that is used in the generation of the affordable housing conflict/opportunity surfaces. Therefore, if the driving preference is low and the transit accessibility is high this indicates that the place is also eligible to be allocated for affordable housing. The choice of preference number depends on the allocation scenario.

The methodology for creating the transit scores can be divided into three categories:

1. Downstream stop score estimation based on employment opportunities;
2. The network distance or time estimation including time spent in transfers or delays; and
3. The upstream transit opportunities and their distances from residential parcels.

Downstream stations score

The creation of the downstream stop score starts by identifying the activities within the walking distance between each stop and assigns the distance weighted employment to the transit stop. The walking distance buffer is taken as a 0.25 mile Manhattan distance taken from the transit stop at the center of the Manhattan buffer. Two tools were created using ArcGIS customized Python programming for that purpose. The first tool, The Manhattan buffer, created a diamond-shaped Manhattan buffer around point feature classes. Figure 3-16 shows an example of Manhattan buffer features created around transit stops. The second tool measures the Manhattan distance to point features and creates a raster similar to the Euclidean distance raster tool in ArcGIS. Figure 3-17 shows an example Manhattan distance raster created around transit stops. The downstream transit stops could also be upstream transit stops for different transit trips. The transit accessibility measurement depends on creating stop-to-stop, origin-destination matrices which may have some size limitations depending on the computer and the size of the study area. However, some of the downstream stops could be ignored in the analysis if they are not significant in serving employment.

Estimating network distance/time

Depending on the data for bus routes and stop, the distance or time for a transit trip can be calculated using ArcGIS Network Analyst. However, transfer stops should be taking into consideration if the distance is calculated. If time is calculated, the trip time should also include delays at the bus stops and during the transfer. ArcGIS origin destination matrix time or distance estimation using network analysis are used to generate all the alternative trips using transit from each upstream stop. These alternative distance measurements or time measurements are used in addition to the downstream score based on employment in the gravity accessibility estimation equation. This accessibility estimation will generate an accessibility score for each upstream stop.

Creating transit accessibility suitability surface:

The transit access tool is an ArcGIS tool that calculates the gravity access for each trip using the downstream score as an attraction, the trip distance and the route frequencies and aggregates the calculated values of all the trips connected to each upstream station. The tool also uses these upstream transit scores to create the final transit accessibility multiple utility assignment surfaces. First a Manhattan raster is created around each upstream stop. This surface is reclassified according to the distance from residential parcels and represents the walkability to transit stops based on the distance. The second surface aggregates the upstream transit scores that are within the walking distance from residential parcels. This surface is also reclassified according to the mean and standard deviation to create the suitability surface. The final transit access surface is generated by combining the two mentioned suitability surfaces. Figure 3-18 shows an example transit access suitability surface generated for Orange County.

Automatic Allocation for Affordable Housing

The A4 Allocation Tool

The new allocation procedures in LUCIS models adopt automation tools for the future allocation of population and employment, scenario building, and testing of policies. This tool can be also used to build scenarios for the allocation of affordable housing based on prioritizing allocation conditions and policy initiatives. This is done by the A4 Allocation toolbox which consists of three allocation tools

The first tool in the allocation toolset is the Trend Allocation Tool. The A4 Allocation toolset provides tools for an automated allocation of new urban populations and accommodates for spatial constraints and variable density allocations. The foundation of the allocation tools are combine grids. The combine grid is prepared by an enumeration rule that combines all of the grids needed in the allocation process while maintaining their attribute values. The Allocation by Table tool can also be seen as a planning table or a scenario builder where the planner enters the conditions for an allocation depending on each conflict score or on multiple sets of score. Using this tool the planner can perform the allocation using different conditions and priorities as iterations simultaneously. Figure 3-19 shows a sample planning table used for an allocation process, as well as the Planning by Table Tool interface. However, the previous tools work for eight masks and/or conditions for an allocation. A detailed tool can be also used in the allocation process. This detailed allocation can work on twelve different masks and/or additional conditions for an allocation procedure and can also be incorporated into a model that has iterative procedures.

Building Affordable Housing Scenario

The output of the affordable housing model is the conflict/opportunity surface that contains neighborhoods characteristics, rent burden, travel cost and transit accessibility. This combine grid combine the opportunity grid to additional grids that represent walkability, underutilized density, policy incentives areas and other grids that are necessary for the allocation process. The A4 Allocation tools are used to run different scenarios for the allocation of land for affordable housing. These scenarios are based on the affordable housing combine grid which helps the planner to run automated queries for allocation based on a specific scenario. This research will utilize under-utilized density values in a compact development scenario to find places that have location efficiency and at the same time have densities much lower than its surrounding area. The basic element of the allocation will be the conflict surface which will include the four objectives in a 4-digit conflict matrix. This conflict surface will be combined with the under-utilized density raster in addition to other masks and conditions to allocate the land for affordable housing. The full list of conditions utilized in the allocation is shown in Chapter 7.

Model Validation Methods

The validation of the models is included in detail in Chapter 7. In general there are different levels of model validation. The first level is the validation of the automation tools. This is performed by using the ArcGIS user interface in a step by step procedure to validate the tools' internal steps. The second level of validation is on the model output level by doing sensitivity analysis. This is performed by creating the output affordable housing opportunity surface using travel cost and transit accessibility and the other opportunity surface without travel cost and transit accessibility. The output opportunity surfaces are compared using descriptive statistical indicators derived from the 5Ds (Ewing & Cervero, 2001) and the sprawl conceptualization metrics (Galster et al., 2001). The third level of validation is performed by comparing the allocation sites and overlaying them with the Assisted Housing Inventory data (AHI) to analyze the surrounding locations.

Table 3-1. Data sources

No.	Description	Source	Year
1	Parcel data	FGDL	2009
2	Census Blocks, Block Groups and Tracts	Census	2000
3	Hosing Cost	Shimberg Center	2009
4	Trip Data	NHTS	2009
5	Transit Data	Transit Agencies	Varied

Table 3-2. Percentage Trips by purpose (National Household Travel Survey, 2009)

Trip Distance	Home Based Other	Home Based Shop	Home Based Social	Home Based Work	Non-Home Based	Total
Less than 10 miles	16.44	18.37	11.25	5.70	22.06	73.82
10 and 20 miles	3.22	2.31	1.78	2.87	3.64	13.82
20 and 30 miles	1.02	0.58	0.75	1.16	1.25	4.77
30 and 40 miles	0.37	0.21	0.37	0.49	0.55	1.99
40 and 50 miles	0.18	0.16	0.15	0.20	0.24	0.92
50 and 60 miles	0.12	0.04	0.06	0.09	0.17	0.48
60 and 70 miles	0.04	0.04	0.08	0.04	0.09	0.29
70 and 80 miles	0.02	0.02	0.03	0.03	0.07	0.16
80 and 90 miles	0.03	0.01	0.03	0.01	0.08	0.17
90 and 100 miles	0.03	0.03	0.03	0.01	0.04	0.13
100 and 110 miles	0.02	0.02	0.02	0.00	0.03	0.08
110 and 120 miles	0.01	0.01	0.01	0.00	0.03	0.05
120 and 130 miles	0.01	0.01	0.01	0.00	0.03	0.06
130 and 140 miles	0.00	0.01	0.01	0.00	0.03	0.05
140 and 150 miles	0.01	0.00	0.01	0.00	0.02	0.04
150 and 160 miles	0.01	0.00	0.00	0.00	0.01	0.02
160 and 170 miles	0.00	0.00	0.00	0.00	0.01	0.02
170 and 180 miles	0.00	0.00	0.02	0.00	0.01	0.03
180 and 190 miles	0.00	0.00	0.01	0.00	0.01	0.02
190 and 200 miles	0.00	0.00	0.00	0.00	0.01	0.01
More than 200 Miles	0.02	0.02	0.04	0.00	0.16	0.24
Missing	0.80	0.53	0.33	0.38	0.78	2.82

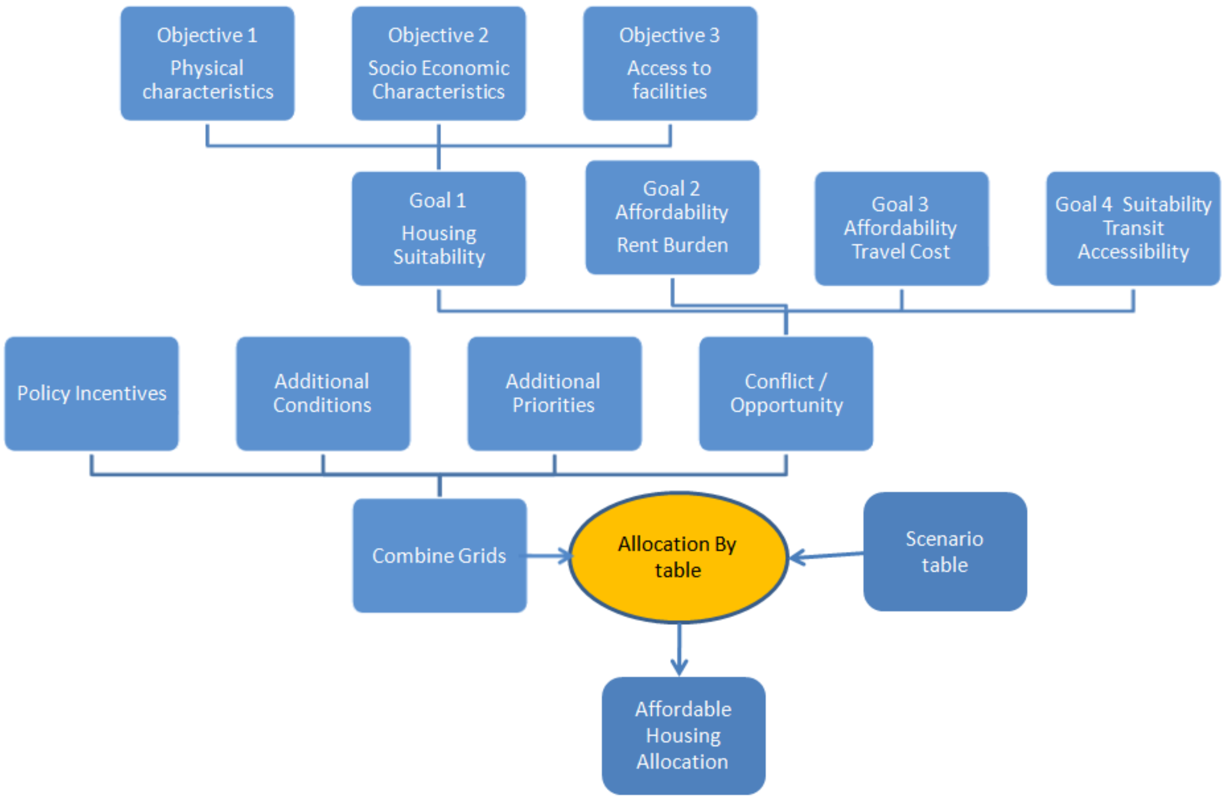


Figure 3-1. Structure for the conflict / opportunity process

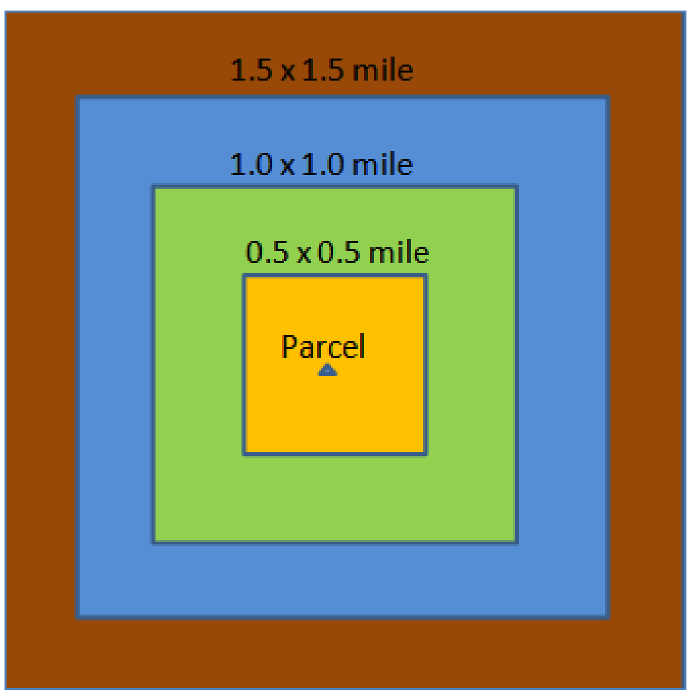


Figure 3-2. Variable size neighborhoods around the parcel

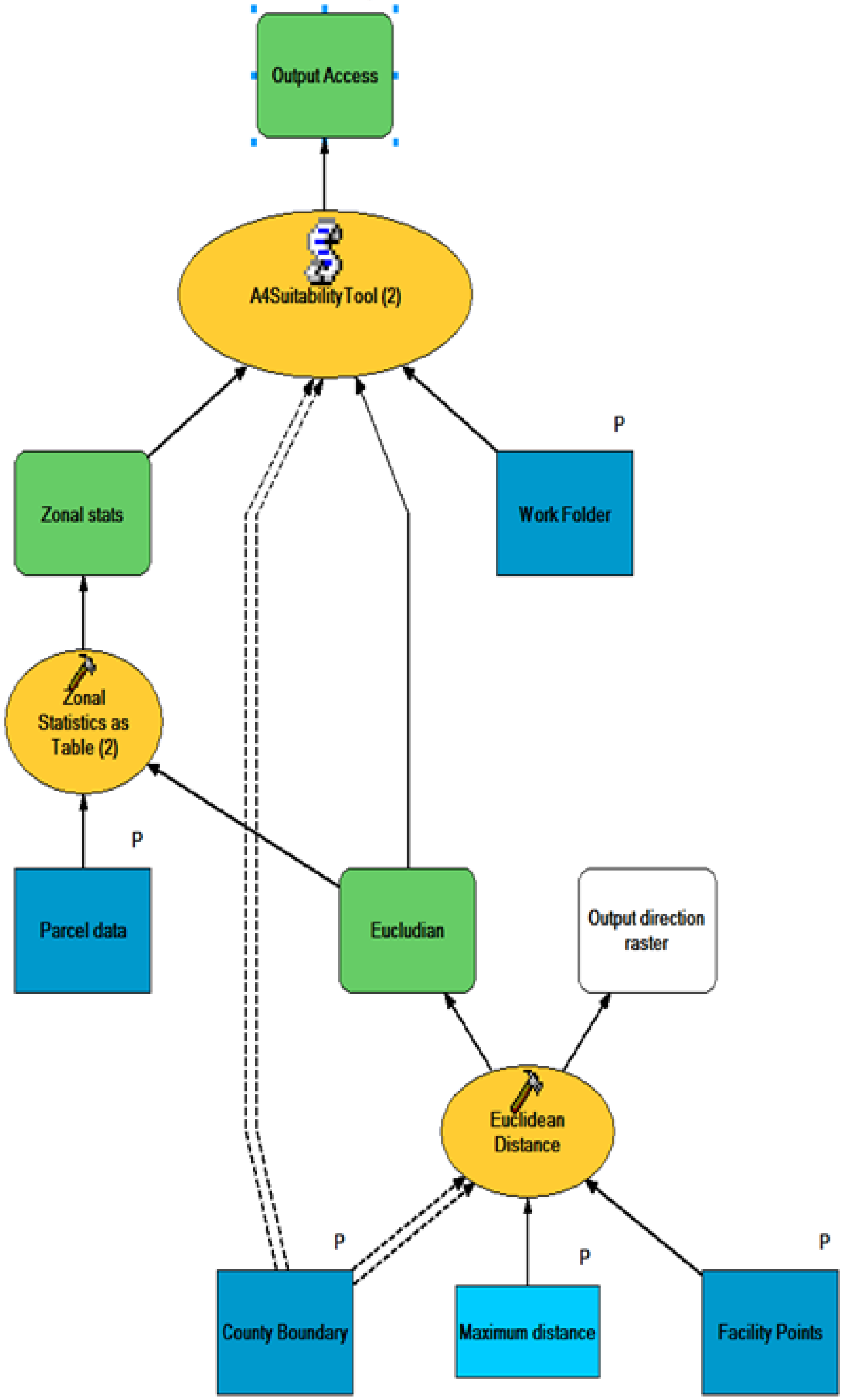


Figure 3-3. Euclidean proximity model

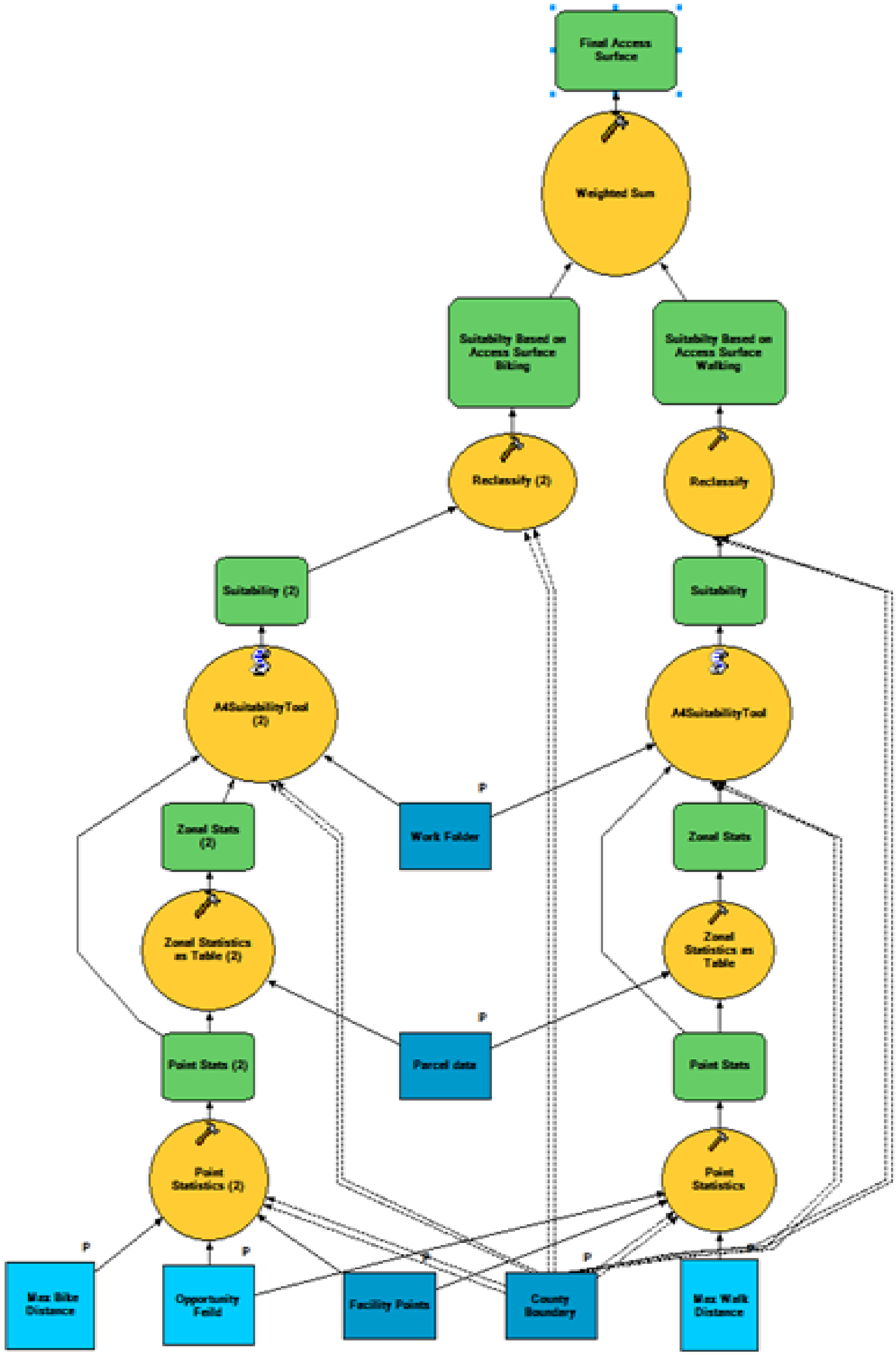


Figure 3-4. Opportunity model

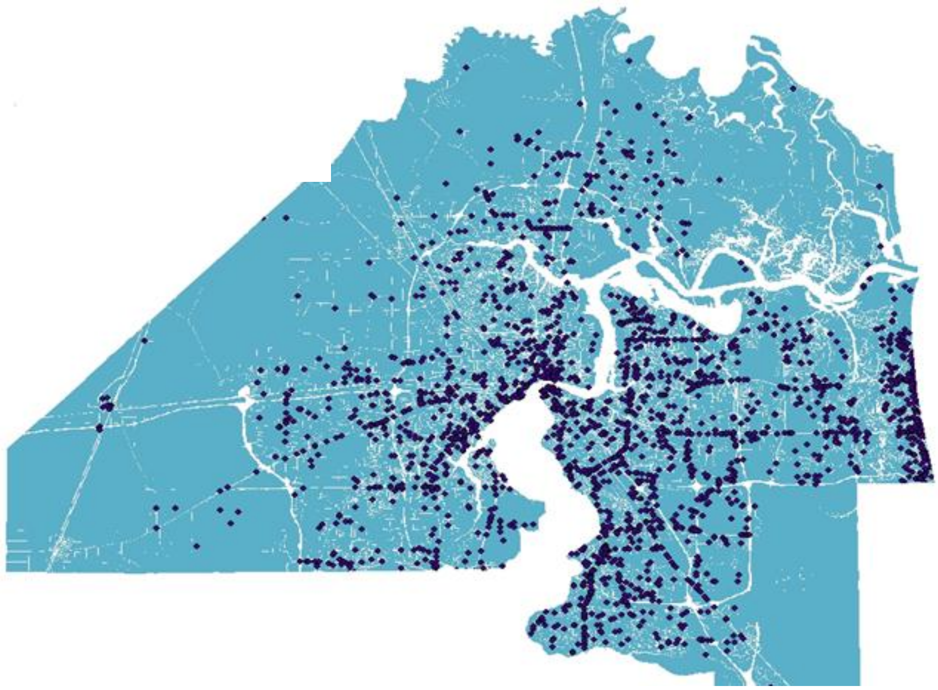


Figure 3-5. Trip end points in Duval County

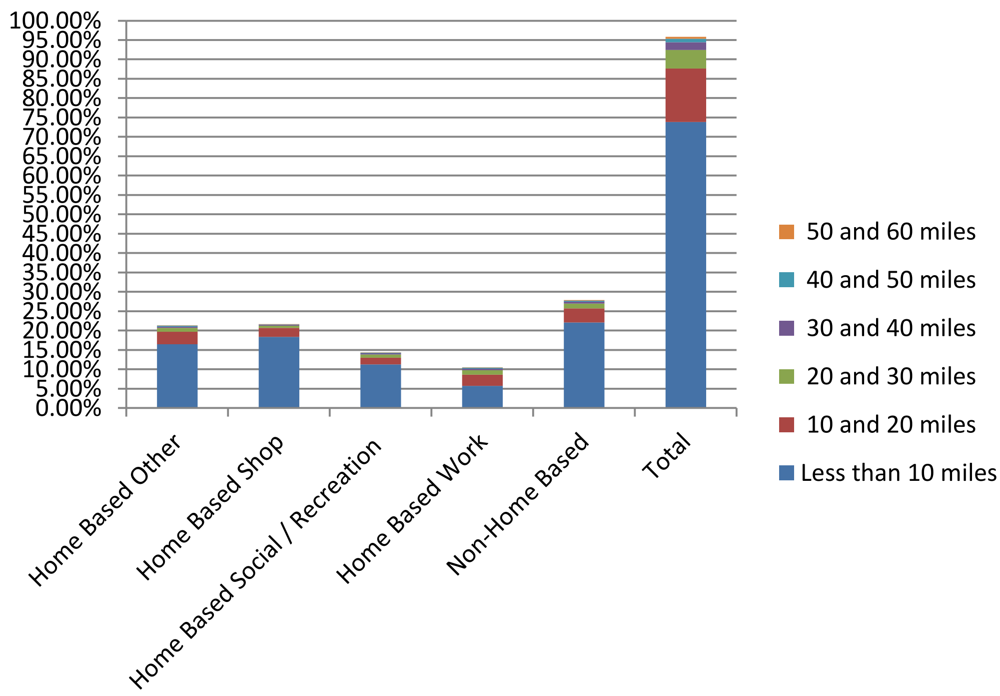


Figure 3-6. Trips by purpose

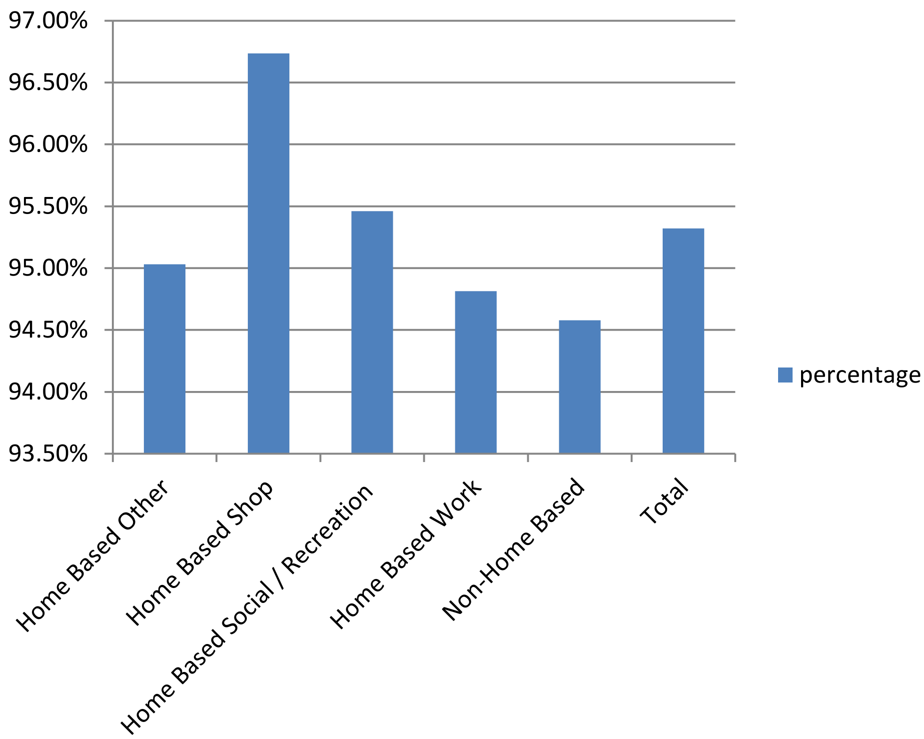


Figure 3-7. Percentage of trips categorized by purpose and trip length

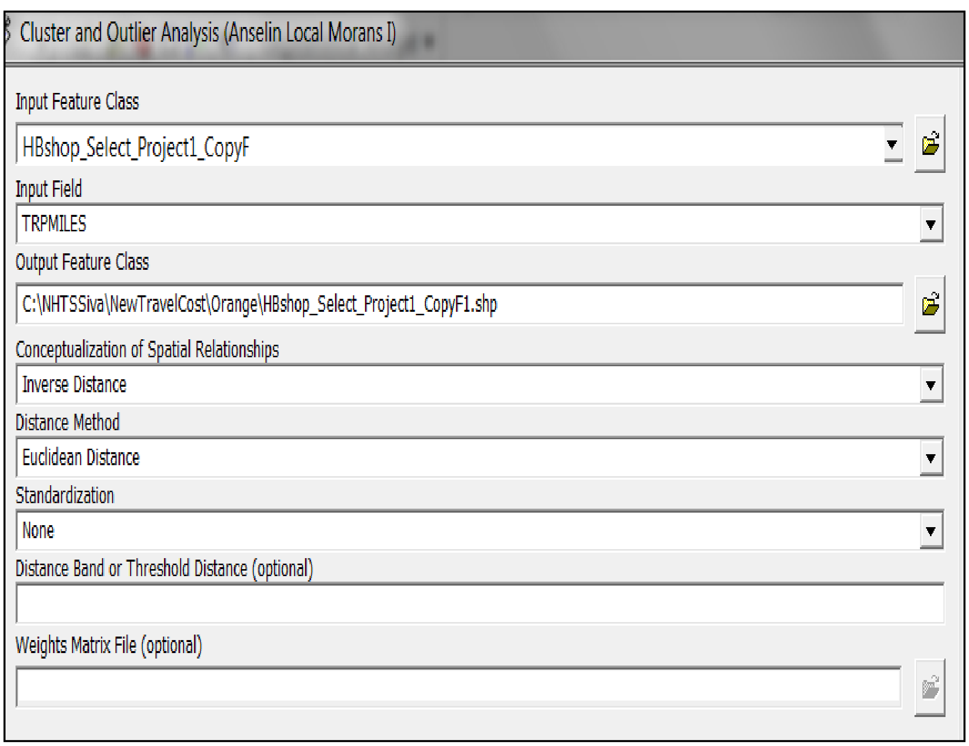


Figure 3-8. Local outlier identification tool

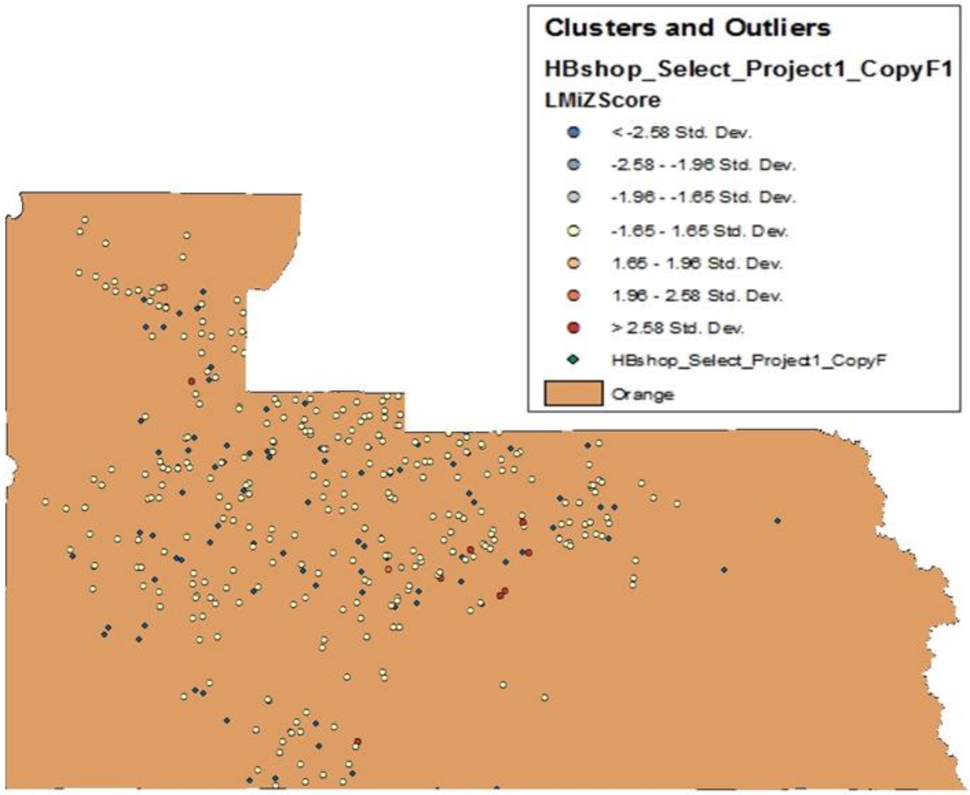


Figure 3-9. Example local outlier identification for Orange County

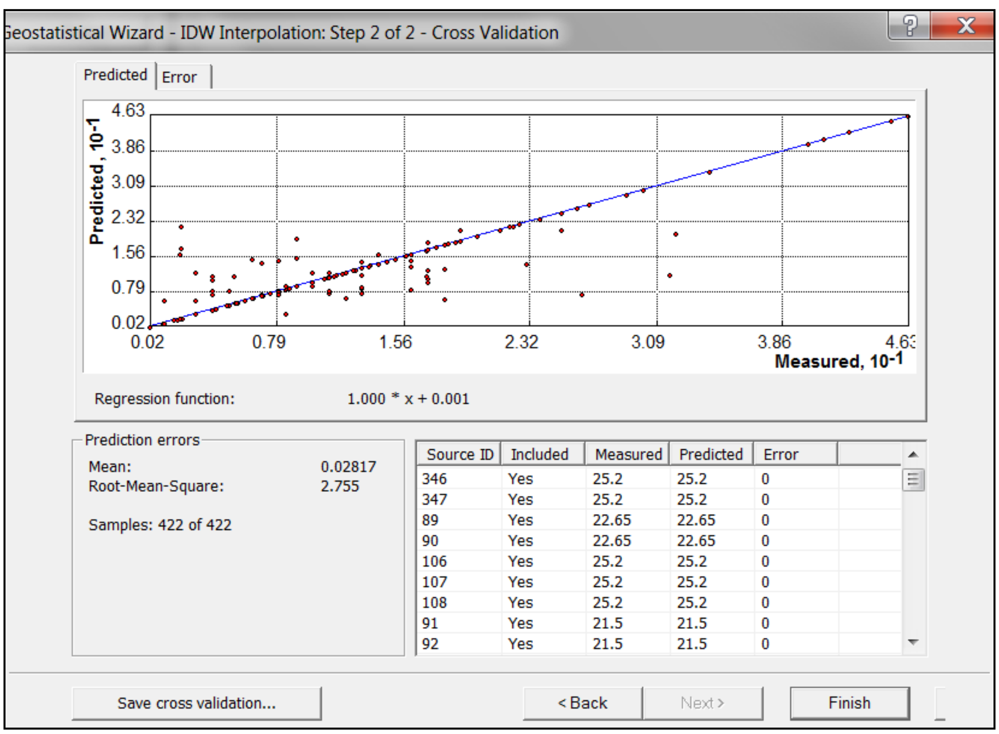


Figure 3-10. Cross validation of errors for interpolating work trips in Orange County.

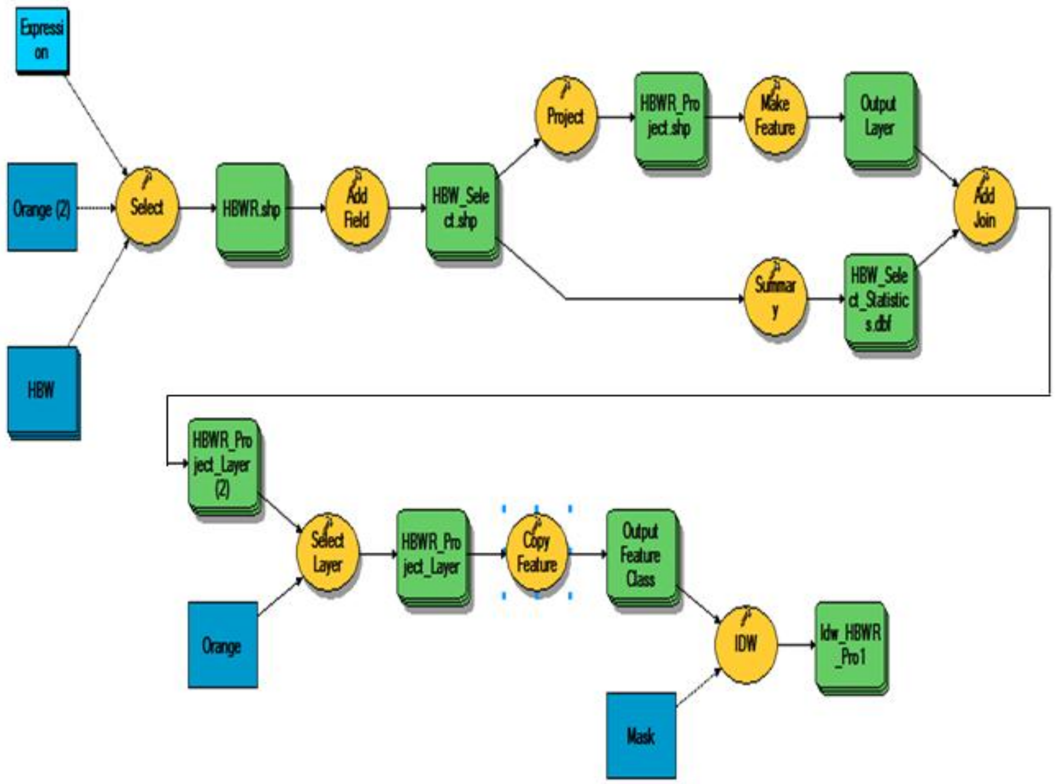


Figure 3-11. Iterative model used to generate travel miles surfaces

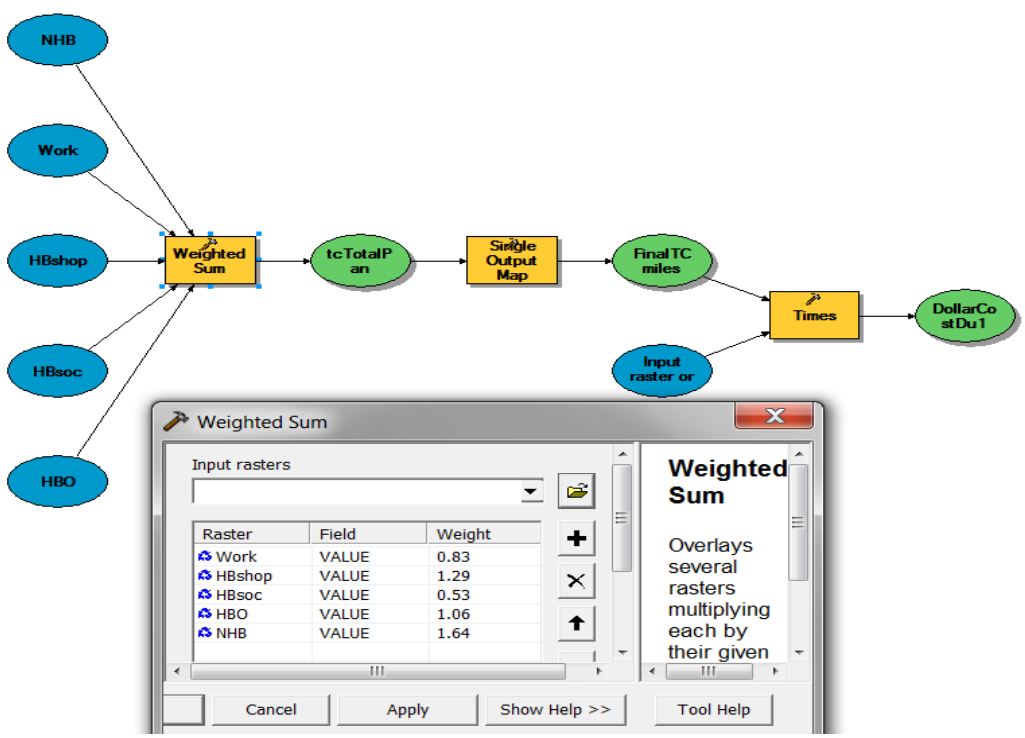


Figure 3-12. Estimation of travel miles and travel cost

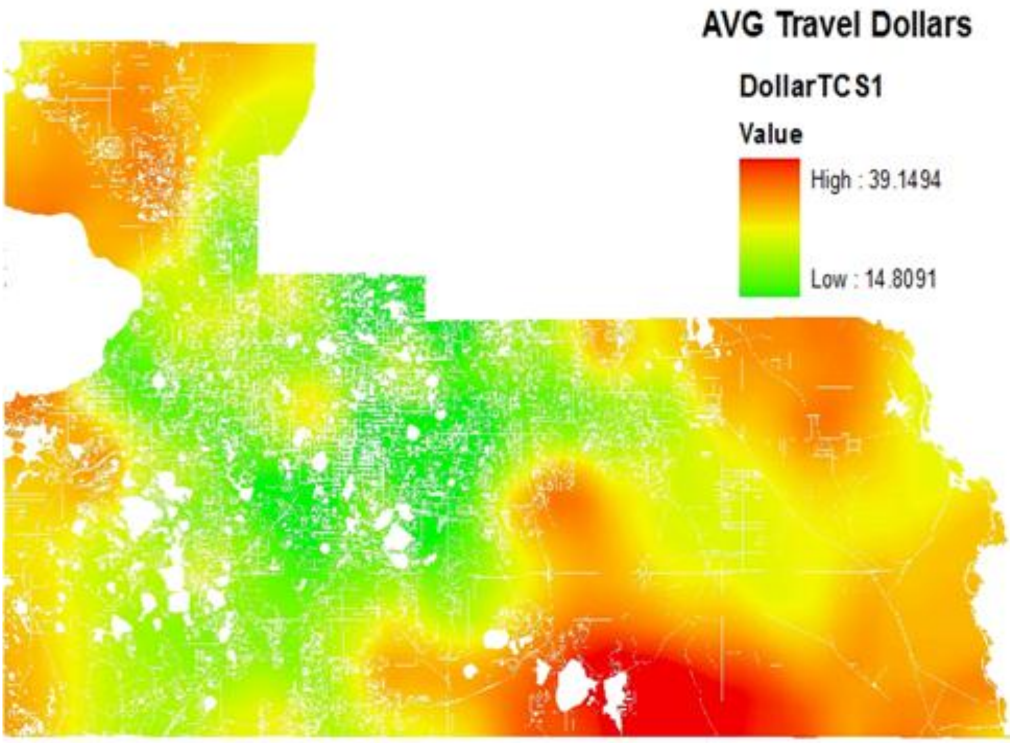


Figure 3-13. Daily travel miles surface for Orange County

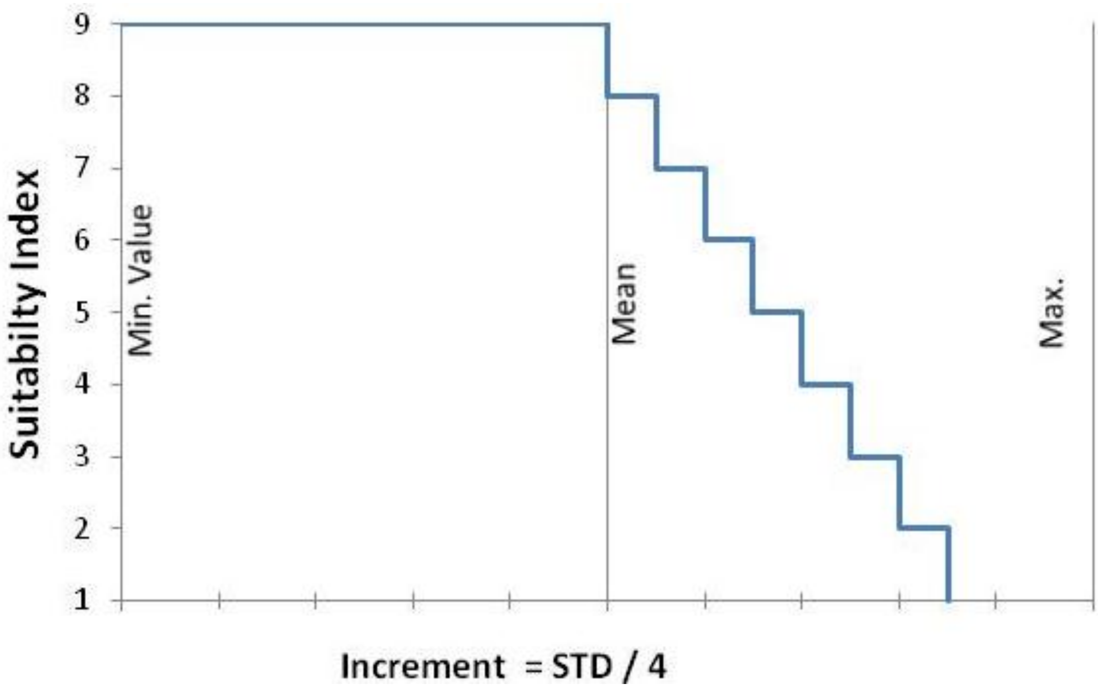


Figure 3-14. Decreasing suitability indexing.

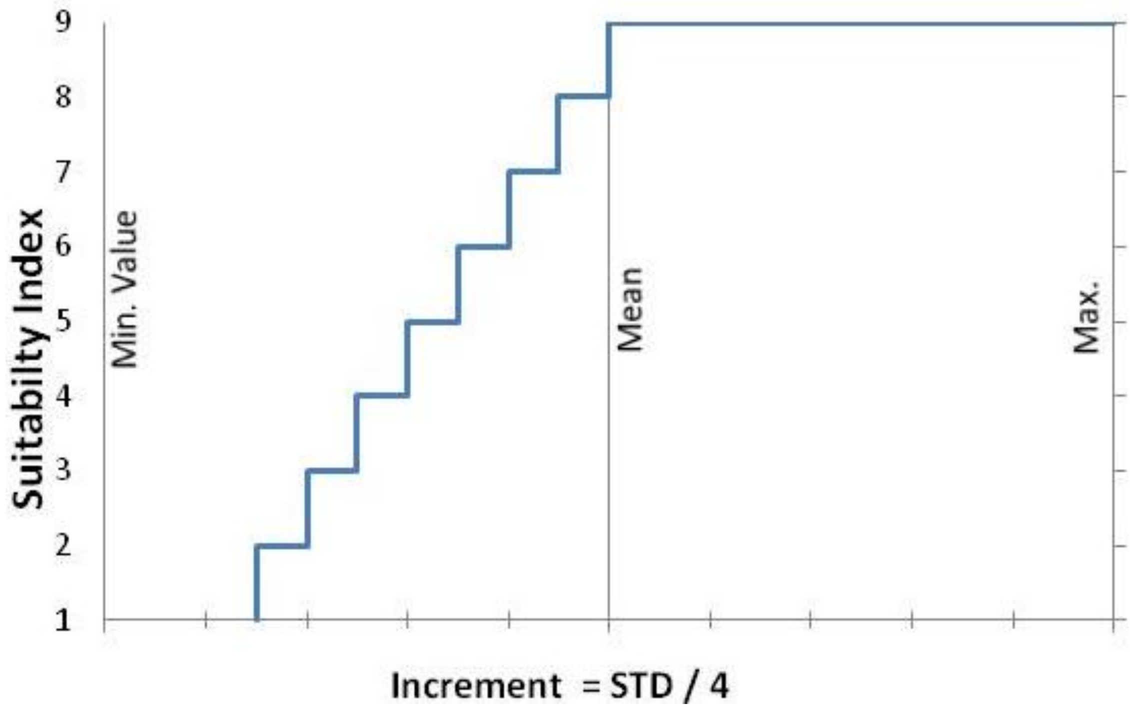


Figure 3-15. Increasing suitability indexing.

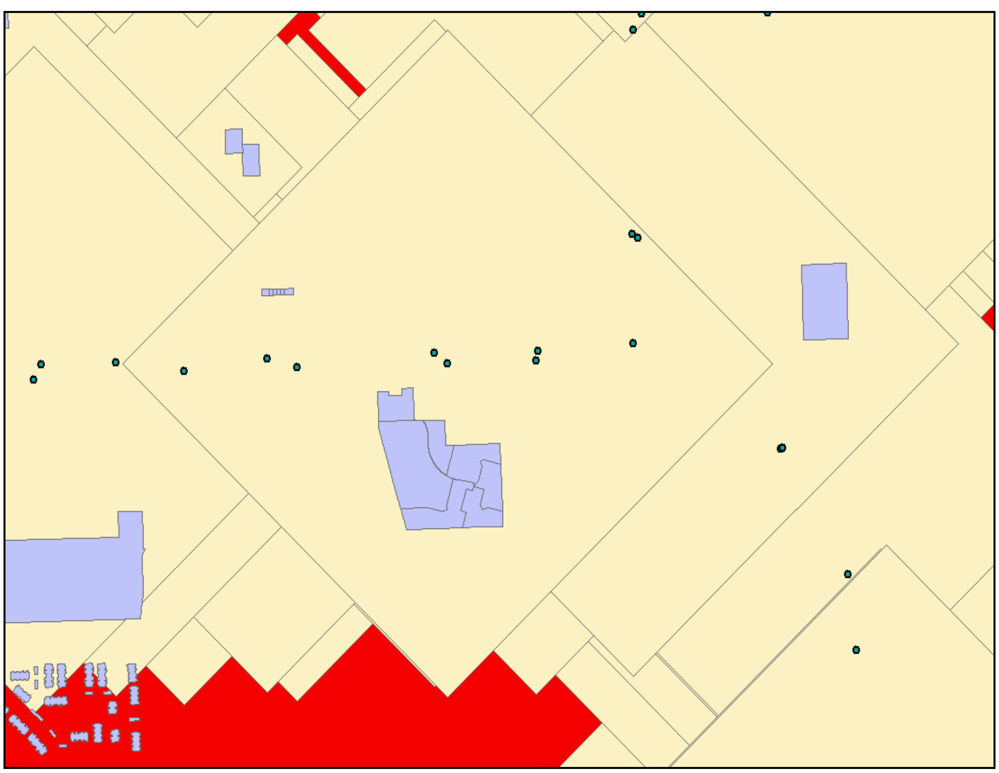


Figure 3-16. Manhattan buffers arround transit stops

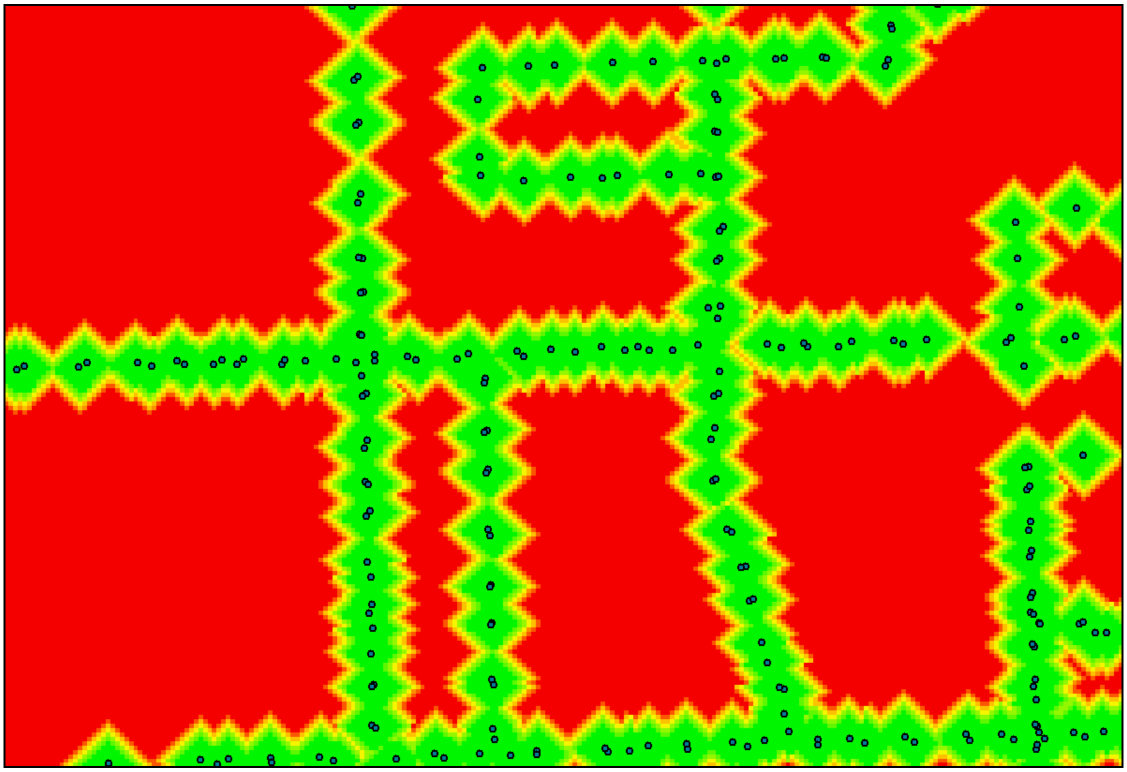


Figure 3-17. Manhattan distance raster to transit stops

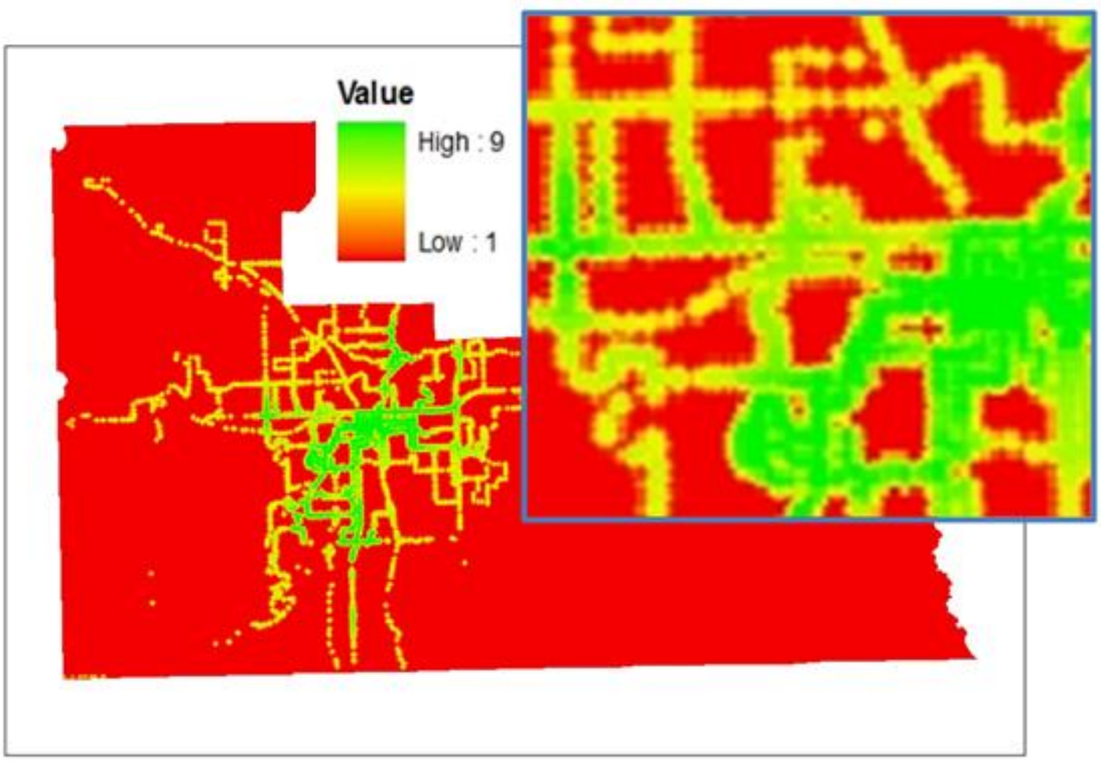
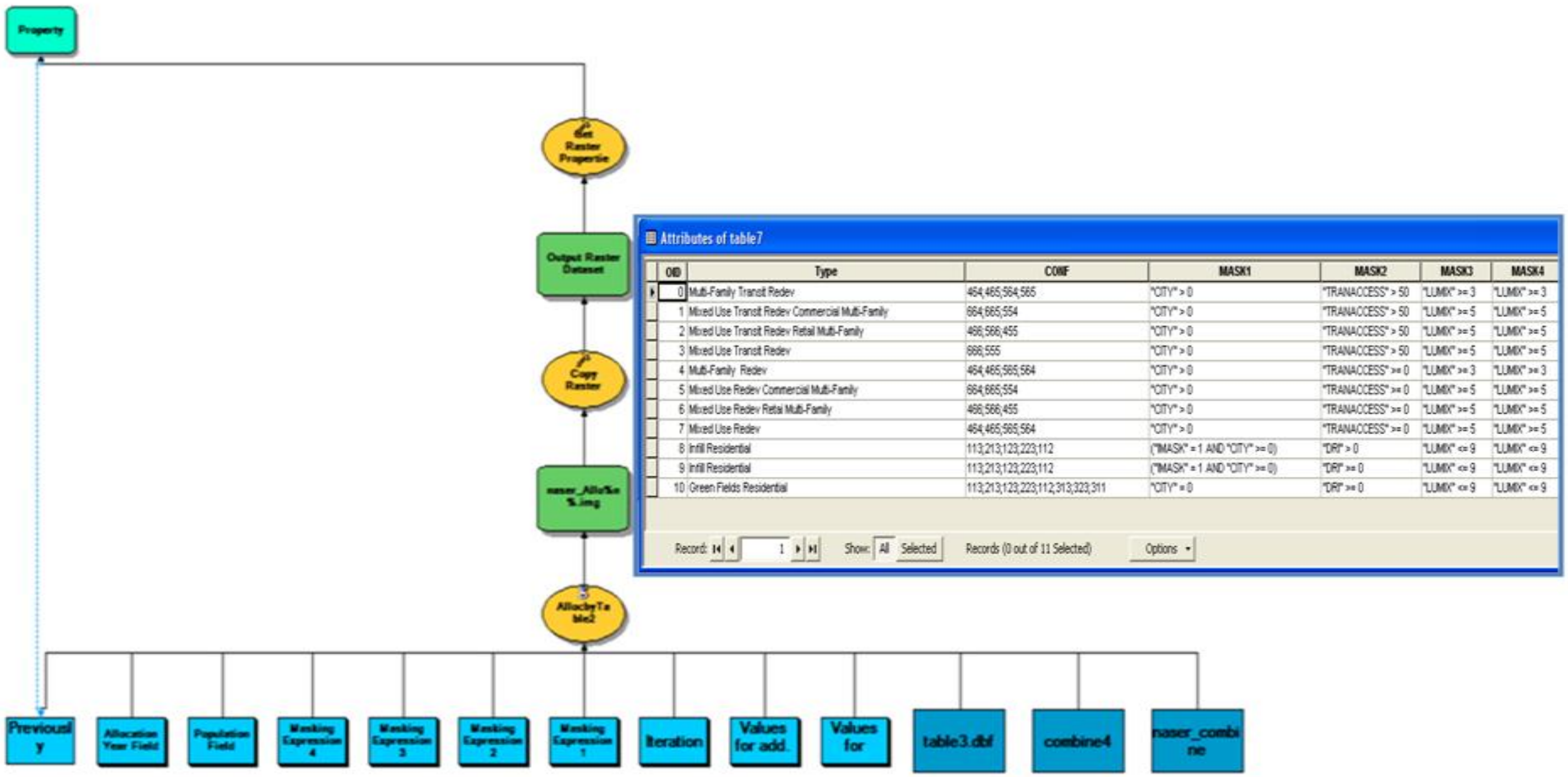


Figure 3-18. Transit access suitabilty surface



OID	Type	CONF	MASK1	MASK2	MASK3	MASK4
0	Multi-Family Transit Redev	464;465;564;565	"CITY" > 0	"TRANACCESS" > 50	"LUMIX" >= 3	"LUMIX" >= 3
1	Mixed Use Transit Redev Commercial Multi-Family	664;665;554	"CITY" > 0	"TRANACCESS" > 50	"LUMIX" >= 5	"LUMIX" >= 5
2	Mixed Use Transit Redev Retail Multi-Family	466;566;455	"CITY" > 0	"TRANACCESS" > 50	"LUMIX" >= 5	"LUMIX" >= 5
3	Mixed Use Transit Redev	666;555	"CITY" > 0	"TRANACCESS" > 50	"LUMIX" >= 5	"LUMIX" >= 5
4	Multi-Family Redev	464;465;565;564	"CITY" > 0	"TRANACCESS" >= 0	"LUMIX" >= 3	"LUMIX" >= 3
5	Mixed Use Redev Commercial Multi-Family	664;665;554	"CITY" > 0	"TRANACCESS" >= 0	"LUMIX" >= 5	"LUMIX" >= 5
6	Mixed Use Redev Retail Multi-Family	466;566;455	"CITY" > 0	"TRANACCESS" >= 0	"LUMIX" >= 5	"LUMIX" >= 5
7	Mixed Use Redev	464;465;565;564	"CITY" > 0	"TRANACCESS" >= 0	"LUMIX" >= 5	"LUMIX" >= 5
8	Infill Residential	113;213;123;223;112	("IMASK" = 1 AND "CITY" >= 0)	"DRI" > 0	"LUMIX" <= 9	"LUMIX" <= 9
9	Infill Residential	113;213;123;223;112	("IMASK" = 1 AND "CITY" >= 0)	"DRI" >= 0	"LUMIX" <= 9	"LUMIX" <= 9
10	Green Fields Residential	113;213;123;223;112;313;323;311	"CITY" = 0	"DRI" >= 0	"LUMIX" <= 9	"LUMIX" <= 9

Figure 3-19. Planning by Table tool

CHAPTER 4
CHOICE OF ANALYSIS UNITS

The choice of the areal unit in this research focuses for the research on land use and transportation coordination. Many urban form indices can be calculated on a disaggregate level, such as at a parcel-level analysis, but results are usually aggregated to a neighborhood or any other aggregate scale such as TAZs. This research studies the effect of scale and zoning of the areal unit by investigating the impact of size, shape and location of the areal unit on the most commonly used urban form characteristics. These urban form characteristics are diversity, density and connectivity. The areal unit in this research is chosen after carrying out areal unit optimization research. This optimization is conducted by calculating the urban form metrics on different scales and studying the effect of scale on these metrics.

The Importance of Defining the Areal Unit

The 5Ds (Lee & Cervero, 2007) are generally urban form measurements. Usually, these measurements are obtained after defining the areal unit of analysis such as the neighborhood or any type of gridding. However, not all urban form characteristics should be aggregated to a defined areal unit. Sometimes it is better to understand the characteristic values on a more disaggregate level, such as at the parcel level.

Accessibility and distance estimations are recommended by many researchers to be performed on a disaggregated and parcel level. Common methods of capturing accessibility are based on aggregate analysis zones such as TAZs (Levinson & Krizek, 2008). However, it is more helpful and more accurate to undertake estimations at the parcel level. Disaggregate and parcel level research can reduce the shortcomings of traditional models by capturing the fine land-use effect on transportation or vice versa (Lee, 2004).

Primarily there are two approaches in the level of analysis used to delineate or determine the connection between land-use and transportation. One of them is an aggregate approach that uses zones such as TAZs and calculates accessibility indices based on the analysis zones. The other approach uses parcel-level analysis. Johnston (2004) mentioned that future land-use and transportation modeling should be discrete in both time and location, and should be based on GIS tracts or street addresses. This shows the common ground for future land-use and transportation modeling.

The same GIS approach has been recommended by Wegner (2005) to deal with disaggregate data in activity-based models, which is fundamental in the latest trend in transportation modeling. However, discrete analysis may not always be possible due to lack of data. Therefore, TAZ and neighborhood urban form aggregation is used to conduct land-use and transportation analysis. Nevertheless, if TAZs are used, the effect of the MAUP should be taken into account for calculating aggregate accessibility values as well as its spatial variation. In practice, most of the mathematical forms for accessibility are used on aggregate levels such as TAZ. The same equations can be applied on a parcel-level to give more accurate accessibility measurements and eliminate the effect of the MAUP for accessibility estimation. Sometimes accessibility is applied in an equation on a parcel-level and the resultant accessibility index is aggregated to a neighborhood level. In this case the areal unit problem should also be taken into account.

Several land use and transportation coordination variables are urban form characteristics that are gross measures by definition, and thus measured on a neighborhood scale or other defined analysis unit areas. The neighborhood scale primarily will affect the value of measurement. Ewing et al. (2008) found the impact of the 5Ds on VMT is less for small areas, thus the elasticity values should different. The differences between values of land use and transportation characteristics aggregated to the neighborhood level are caused by the MAUP. According to Jelinski and Wu (1996) the MAUP has two problem components which are scale and zoning problems. In the scale problem, the value and the statistical variation of the aggregated smaller units will be different depending on the size of the areal unit. The zoning problem, however, deals with the location of the areal unit and the choice of zoning which also affects the value and the variation of the aggregated entities. Due to the zoning problem, the same sized aggregated units may give different results due to differences in location. Researchers frequently suggest grid based approaches to do spatial aggregation. However, little attention is paid to the size of the grid cells and the method of aggregation to reduce the MAUP.

Reynolds (1998) mentioned the MAUP as a problem in spatial research as early as the 1930s but indicated it could be reduced by the use of GIS. He also mentioned that many of the data are collected on a disaggregate level and aggregated to coarser resolution for different reasons such as privacy. However, most time data is measured at a disaggregate level but mapped spatially on an aggregate level. Therefore, the aggregation process will be necessary to map the data. Reynolds also explained the two sides of the areal unit problem which are scale and zoning.

Tomoki (1999) explained the dependence of the map interpretation on the areal unit and emphasized that currently there are only a few criteria on the choice on the areal units. Tomoki explained the effect of the areal unit size on mortality indicators where the variation in the value decreases for larger units. Therefore, taking larger units will be more statistically stable but at the same time the results will be more ambiguous.

In summary, the size, shape and boundaries of neighborhoods affect the value of any aggregate measurement based on these neighborhoods. General gridding procedures and naturally defined neighborhoods are used in the land use and transportation research to define unit areas. If one is to research the land use mix variations using an entropy value on a parcel adjacent to the boundary in a naturally defined neighborhood, this parcel may have, for example, retail and service opportunities surrounding it and the entropy value for that neighborhood will not capture that land use mix. This is mainly a form of the zoning effect induced by the MAUP. Steiner and Srinivasan (2009) proposed a solution for this problem by using overlapping 2 by 2 mile square neighborhoods for calculating the land use and transportation characteristics for their trip length model. To reduce the edge effect of the MAUP, a methodology to overlap neighborhoods is used where the neighborhoods were duplicated and shifted one mile east and the resultant duplicated neighborhood are duplicated again and shifted one mile north. Therefore, a parcel at the edge of a neighborhood will be at the center of an overlapping neighborhood. Figure 4-1 shows the neighborhood overlay according to their methodology (Steiner & Srinivasan, 2009).

Taking into consideration the scale and zoning components of the MAUP, it is clear that the size, location and shape of the areal unit are the main components that may affect the value and the variation of the urban form measurements aggregated to that area. Many of the urban form measurements such as accessibility are recommended to be performed on a parcel-level and therefore there is no need to consider the modifiable area problem. However, other urban form measurements such as density, land use mix and connectivity are needed on an aggregate scale. Therefore, the effect of the modifiable areal unit should be taken into account when dealing with those variables.

Entropy Test

The first experiment is performed on a land use mix index represented by entropy values based on different areal unit sizes. The same experiment is then applied for density and connectivity metrics. Generally, the analysis follows an iterative procedure taking unit sizes of (0.5 x 0.5 mile – 5 x 5 mile) using a 0.5 mile incremental increase. The optimal neighborhood is taken as the minimum size where increasing the neighborhood no longer has a significant effect on the entropy value. Table 4-1 and Figure 4-2 show the change in entropy value that corresponds to an increase of 0.5 mile in the unit size for Orange County. Figure 4-2 shows clearly that the mean entropy values for neighborhoods sizes of 2.5 mile x 2.5 mile are not significantly different from the values for a 3 mile x 3 mile neighborhood. The 2.5 mile unit size is the smallest size that can be chosen as an optimized unit. Figure 4-3 shows that the standard deviation of the entropy value change is very small for unit areas of 2.5 mile or more.

Table 4-1 demonstrates a minimum change in mean and standard deviation for a 2.5 mile x 2.5 mile neighborhood and thus concludes that the optimal neighborhood size for the entropy value is 2.5 x 2.5 miles. The conclusion is also supported by the mean change chart (Figure 4-2) and the standard deviation change chart (Figure 4-3). The analysis is applied to three counties of urban context in the state of Florida. The results of analysis were comparable. Table 4-2 shows the effect of changing neighborhood size on the entropy value for the three counties. Figure 4-4 shows clearly that the minimal change in the entropy mean value occurs when the neighborhood sizes are set to 2.5 mile x 2.5 mile or more. Figure 4-5 shows that the standard deviation of the change in value is generally decreasing when increasing the neighborhood size and the curve is more flat for the size value of 2.5 mile or more.

The result shows also that the variation in entropy values are less for larger neighborhoods which agrees with the literature on the scale component of the MAUP. Figure 4-6 shows the entropy surface based on a 2.5 x 2.5 mile neighborhood for Orange County. Conducting the analysis on a roving unit where the calculated cell value is always in the center of the neighborhood minimizes the zoning problem and creates a surface of a finer resolution.

Density and Connectivity Tests

Density is usually calculated on multiple scales depending on it is use. However, in land use and transportation research the neighborhood density is used to identify the impact of density on travel cost or VMT. In this research, a simple density measurement is used which is the gross population density per acre averaged for each the areal units and assigned to the point at the center of the neighborhood. The same method is conducted for connectivity where a simple connectivity measurement of street density is taken to study the effect of unit size on urban form measurements. Table 4-3 shows the mean value and the standard deviation of the change in density values resulting from a gradual increase of 0.5 miles in each areal unit size. Figures 4-7 and 4-8 show that the minimal changes in density mean corresponds to the unit size of 2.5 x 2.5 mile or more.

The analysis has been performed on three different counties and the result was that the neighborhood size of 2.5 mile x 2.5 mile can be used as an optimal neighborhood size for density calculations for the three counties. Figure 4-9 shows a density surface based on 2.5 mile unit.

For the connectivity measurement, the street density is another urban form measurement to be tested. Table 4-4 shows the mean value and the standard deviation of the change in road density values resulting from a gradual increase of 0.5 miles in unit size. Figures 4-10 and 4-11 show that the minimal change in road density means values correspond to a unit size of 2.5 x 2.5 miles or more.

The analysis is replicated on three urban counties and it was found that the neighborhood size of 2.5 mile x 2.5 mile can be used as an optimal neighborhood size for connectivity calculations for the three counties. Figure 4-12 shows the connectivity surface for Duval County based on a 2.5 mile areal unit.

Shape of Neighborhood Test

The optimal neighborhood size for the three counties is tested for a change in shape. A circle and diamond shaped boundary instead of a square shaped boundary for the neighborhood analysis are used to test the impact of the neighborhood shape on entropy values. Figure 4-13 shows the different areal unit shapes used in the analysis. Figure 4-14 shows a land use mix entropy surface based on a 2.5 mile corner to corner diamond areal unit.

Figure 4-14 is the output entropy surface using a 2.5 mile of a diamond shaped unit which represents a driving / biking distance of 1.25 miles. To understand the results of changing the neighborhood shape, the entropy layer is overlaid with other layers such as street networks, as shown in Figure 4-15. It was found that the land use mix layer resulting from the shape analysis using the Manhattan diamond shape is more subjectively justified than the result surfaces using square and circle neighborhoods. This is because the diamond shaped neighborhood gives more mixed use density in areas that have more street networks, while the other surfaces do not distinguish these areas from others.

Reducing the Modifiable Areal Unit Problem

In conclusion, the analysis in this research proved that changing the areal unit size of a neighborhood changes the aggregated value of the variable being measured. The generated surfaces also show that the variation in aggregated value increases for smaller zones and decreases for larger zones. Therefore, the results show that larger areal units are more stable but the values could be more ambiguous, which is corroborated by the literature on the MAUP. The results also show that the neighborhood size could be optimized for the tested urban form variables which are land use mix, density and connectivity. The graphs for the change in aggregated values corresponds to the change in neighborhood size and shows that the curve is nearly flat for neighborhoods sized 2.5 mile and more, and the standard deviations for the change are very low. This means that the optimal size of the neighborhood is the minimum unit size where the curves began to be flat, which is 2.5 mile x 2.5 mile.

For the scale issue of the MAUP, the results also show that the change in aggregated urban form value is very large for small neighborhood sizes, which means that using small unit sizes as area units may lead to undesirable results. On the local level, the entropy value change is large and unpredictable as shown in Figure 4-1. Therefore, changing from a 0.5 mile to a 1 mile size could positively or negatively change the aggregated values. It is true that the variation is less for larger neighborhood, but from the results, it is not difficult to conclude that the change in aggregated values due to changing neighborhood sizes in small neighborhood is not predictable. However, this will raise the question of how applicable the natural neighborhood will be as an area unit where the unit sizes are always different between zones.

From the results of the analysis we can conclude that it is better to use the same size of area unit for the whole spatial environment and changing the unit size may lead to undesirable results. Taking entropy as an example, the magnitude and direction of change in entropy values for small neighborhoods gives us a hint that the use of an entropy value, in a naturally defined neighborhood may have inconsistencies due to the MAUP. These inconsistencies maybe reduced if the same neighborhood size for the entire model is used. These inconsistencies are also reduced if the optimized neighborhood size is used as well as the floating area methodology.

For the zoning issue in the MAUP, the results show that changing the boundary shape leads to different aggregated results, which confirm the MAUP zoning problem. The results show that the shape can be optimized by analyzing the urban form and the spatial distribution of activities. However, analyzing the land use mix relationship with the street network, we can see that the diamond shape, which represents a Manhattan grid driving or biking distance, gives better aggregate results than the Euclidean distance (circle) or the square neighborhood.

The zoning problem in this research is also reduced by the use of the floating neighborhood where each point in the map is taken as the center of the aggregated zone. However, this unit area definition works for the purpose of tested variables in this research and may not be valid for other types of neighborhood aggregation processes.

The selection of the areal unit research has limitations that can be summarized as follows. Firstly, the research is limited to counties that have similar urban context. The tested counties may have different spatial patterns but the three counties have large cities and CBDs. The research is not applied to rural counties, which will be left for future research. Secondly, the change in aggregated value is compared by the mean and the standard deviation of change. More statistical indicators could be used in the optimization process. This also will be performed in future research. Thirdly, the research is limited to the tested variables for land use mix, density and connectivity. Therefore the results should not be generalized. Finally, the research is limited to the aggregation of urban form measurements that can be used to test the impact of urban form on VMT or travel cost. The optimized unit should not be used for the aggregation of values that depend on small neighborhood sizes by definition, such as walking or transit zones.

Table 4-1. Change in entropy mean and standard deviation

Change in Neighborhood Size in Miles	Entropy Minimum Change	Entropy Maximum Change	Entropy Mean Change	Entropy STD of Change
0.5 - 1	-0.2296	0.5921	0.0784	0.0911
1.0 – 1.5	-0.1684	0.4024	0.0199	0.0484
1.5 – 2.0	-0.2979	0.1776	-0.1126	0.0924
2.0 – 2.5	-0.0764	0.1537	0.0038	0.0204
2.5 – 3.0	-0.0645	0.1205	0.0035	0.0165
3.0 – 3.5	-0.0458	0.0947	0.0031	0.0139
3.5 – 4.0	-0.0395	0.1016	0.0028	0.0124
4.0 – 4.5	-0.0309	0.1115	0.0026	0.0110
4.5 – 5.0	-0.0273	0.0752	0.0025	0.0097

Table 4-2. Change in entropy mean and standard deviation for three counties

Size From	Size To	Mean Change Orange	Mean Change Duval	Mean Change Hillsborough	STD Change Orange	STD Change Duval	STD Change Hillsborough
0.5	1	0.0784	0.0484	-0.0309	0.0911	0.0832	0.0685
1	1.5	0.0199	0.0267	0.0006	0.0484	0.0558	0.0387
1.5	2	-0.1126	0.0177	0.0051	0.0924	0.0406	0.0281
2	2.5	0.0038	0.0126	0.0036	0.0204	0.0315	0.0221
2.5	3	0.0035	0.0097	0.0028	0.0165	0.0257	0.0181
3	3.5	0.0031	0.0077	0.0027	0.0139	0.0213	0.015
3.5	4	0.0028	0.0064	0.0022	0.0124	0.0182	0.0112
4	4.5	0.0026	0.0054	0.0032	0.0110	0.0158	0.0132
4.5	5.0	0.0025	0.0046	0.0023	0.0097	0.0138	0.0102

Table 4-3. Change in density mean and standard deviation

Size From	Size To	Mean Change Orange	STD Change Orange
0.5	1	-0.337	1.286
1	1.5	0.012	0.502
1.5	2	0.003	0.349
2	2.5	0.002	0.259
2.5	3	0.001	0.203
3	3.5	0.001	0.168
3.5	4	0.001	0.145
4	4.5	0.001	0.130
4.5	5.0	0.001	0.116

Table 4-4. Change in connectivity mean and standard deviation

Size From	Size To	Mean Change Duval	STD Change Duval
0.5	1	-4.437	3.529
1	1.5	-4.384	1.197
1.5	2	-0.043	1.351
2	2.5	-0.043	1.027
2.5	3	-0.042	0.820
3	3.5	-0.041	0.671
3.5	4	-0.040	0.572
4	4.5	-0.039	0.491
4.5	5.0	-0.038	0.429

Figure 4-1. Neighborhood definition according to the Steiner and Srinivasan (2009) model

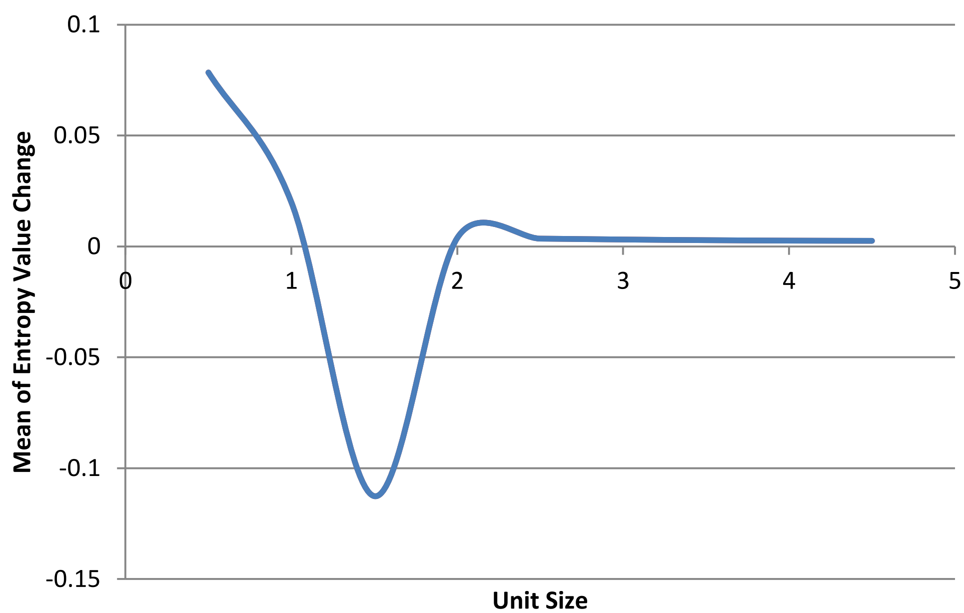


Figure 4-2. Mean of entropy value change that corresponds to 0.5 mile change in unit size for Orange County

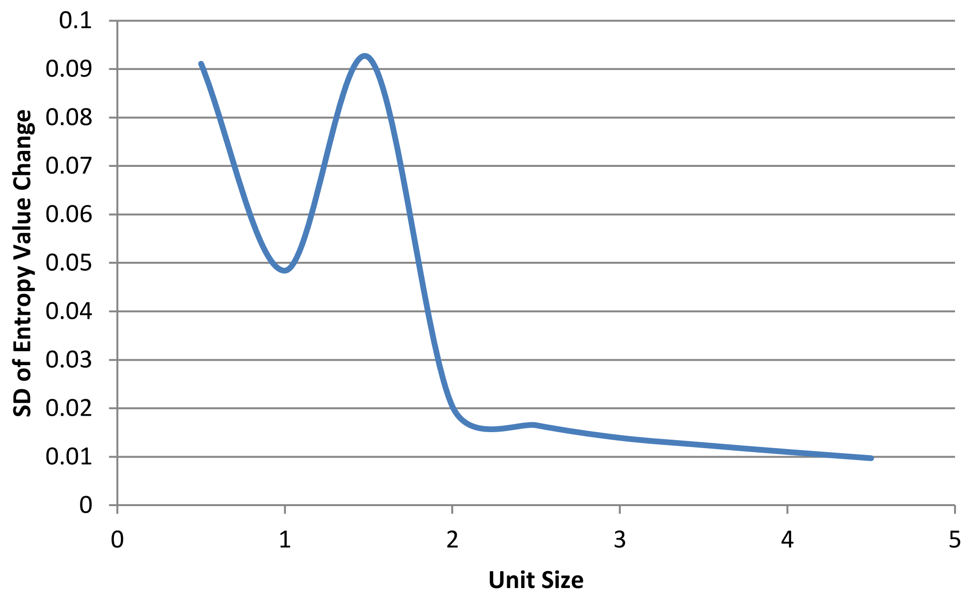


Figure 4-3. Standard deviation of entropy value change that corresponds to 0.5 mile change in unit size for Orange County

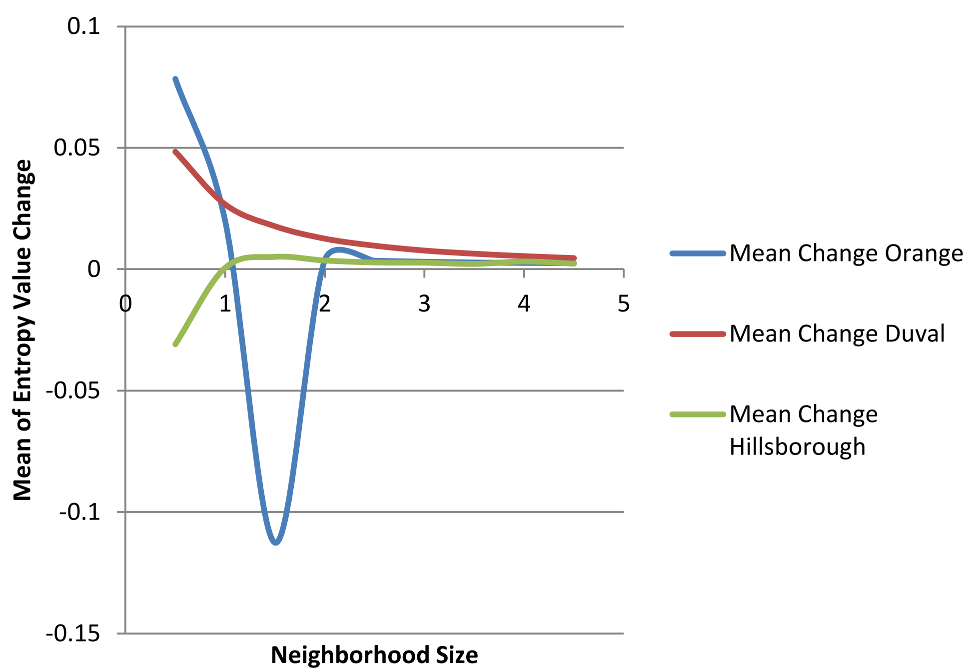


Figure 4-4. Mean of entropy value change that corresponds to 0.5 mile change in unit size for three counties

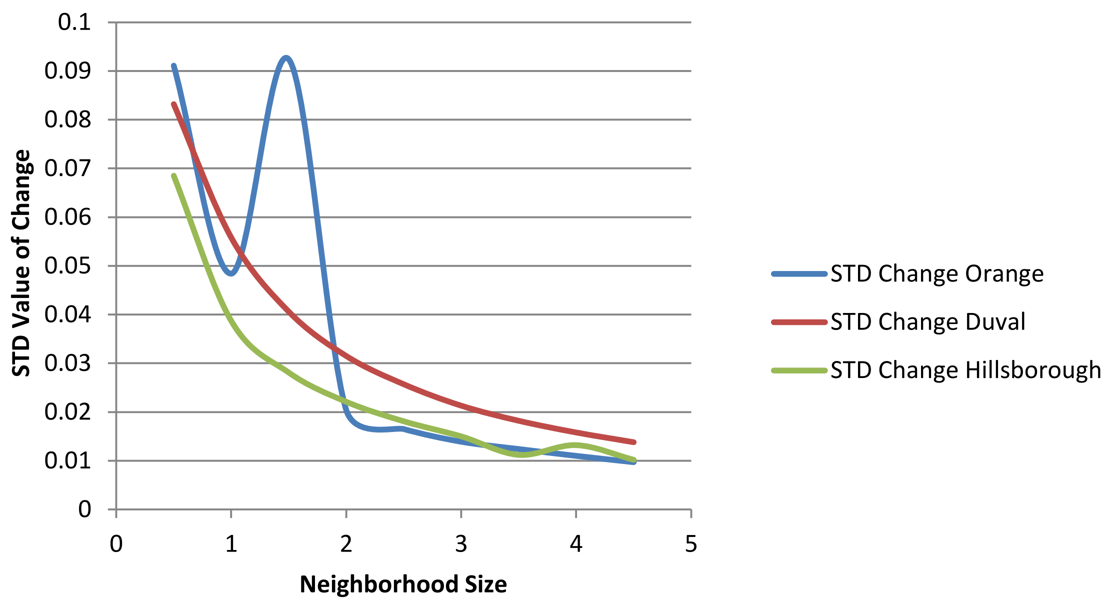


Figure 4-5. Standard deviation of entropy value change that corresponds to 0.5 mile change in unit size for three counties

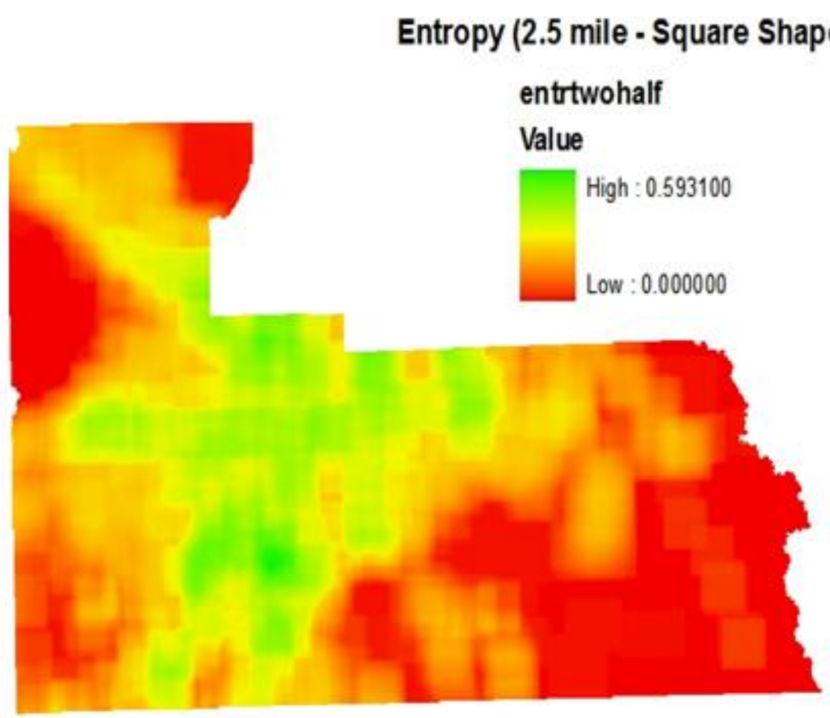


Figure 4-6. Land use mix entropy based on 2.5x2.5 mile areal unit for Orange County

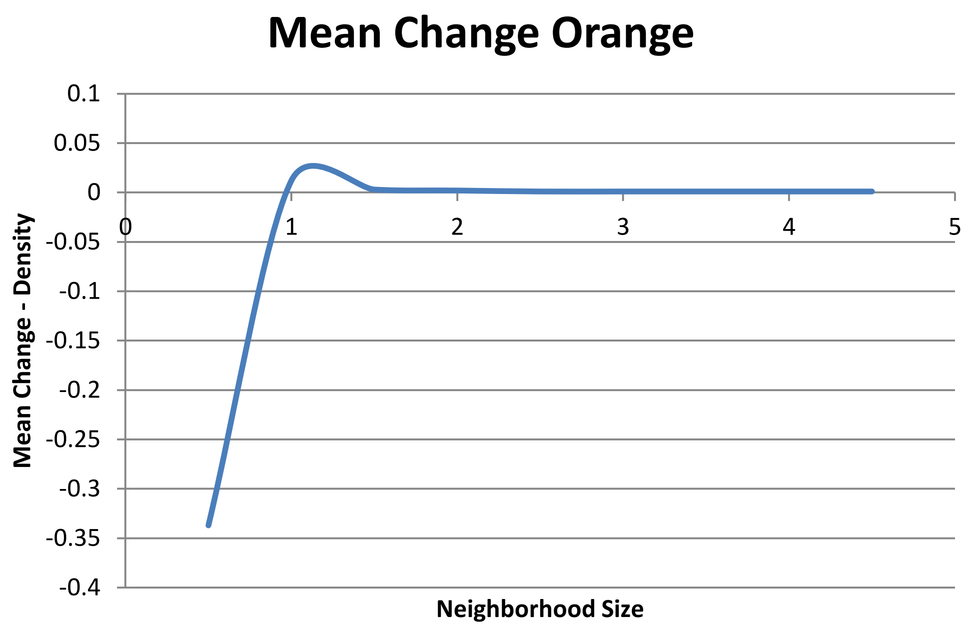


Figure 4-7. Mean of density value change that corresponds to 0.5 mile change in unit size.

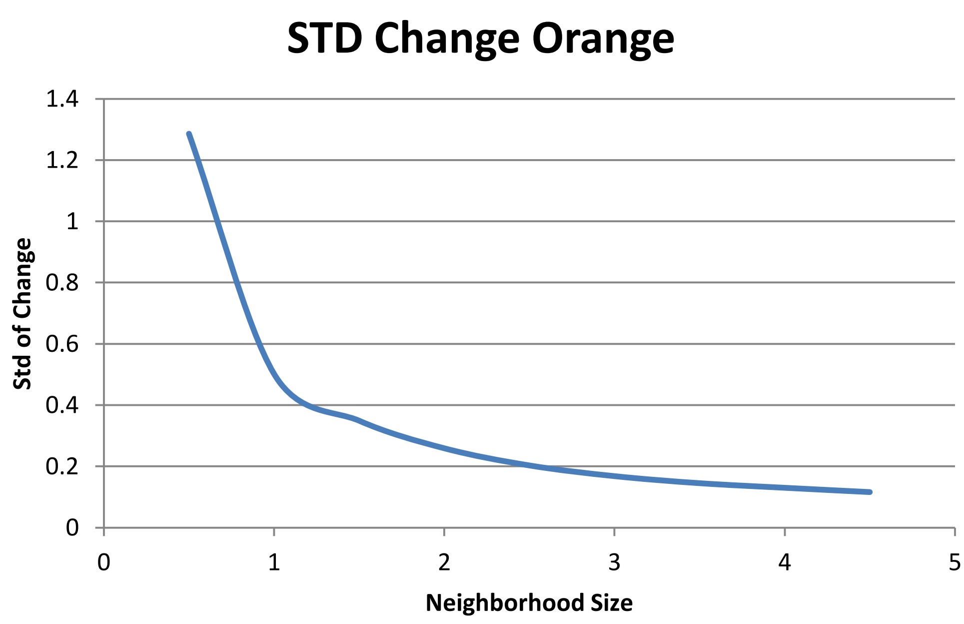


Figure 4-8. Standard deviation of density value change that corresponds to 0.5 mile change in unit size

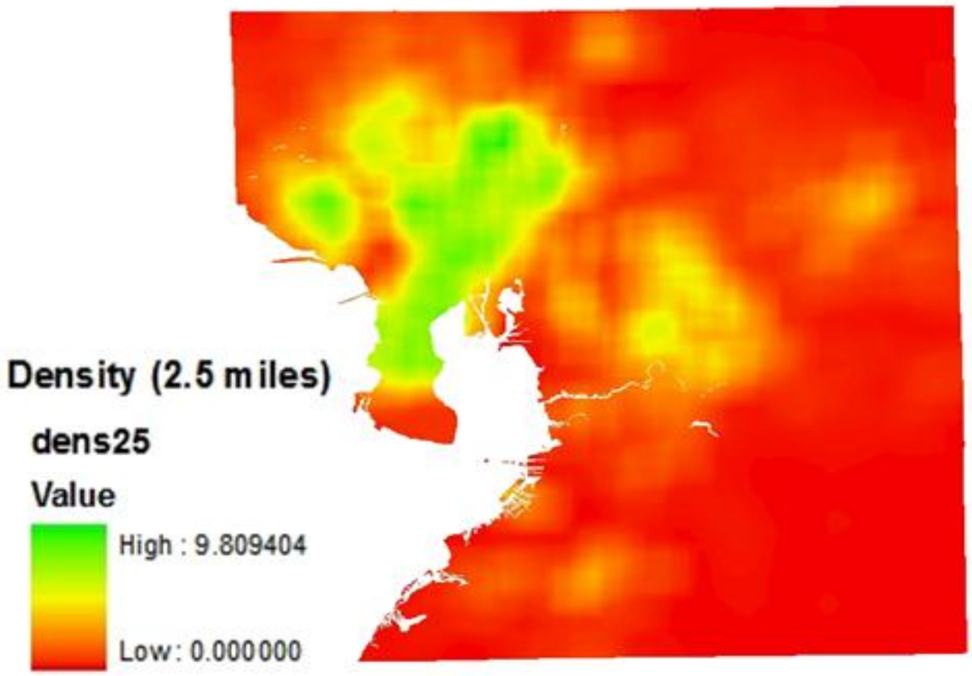


Figure 4-9. Density surface for Hillsborough County based on 2.5x2.5 mile areal unit

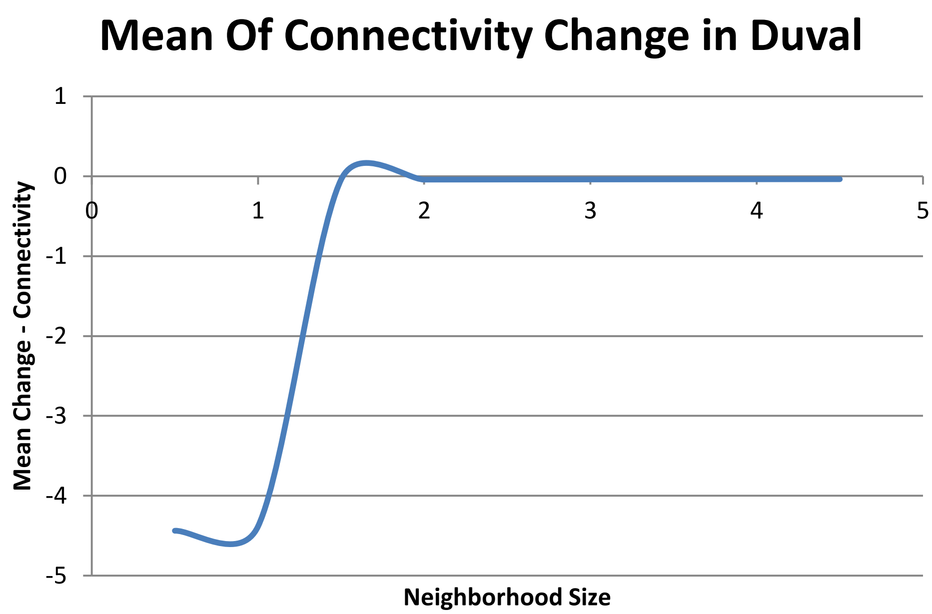


Figure 4-10. Mean of connectivity value change that corresponds to 0.5 mile change in unit size

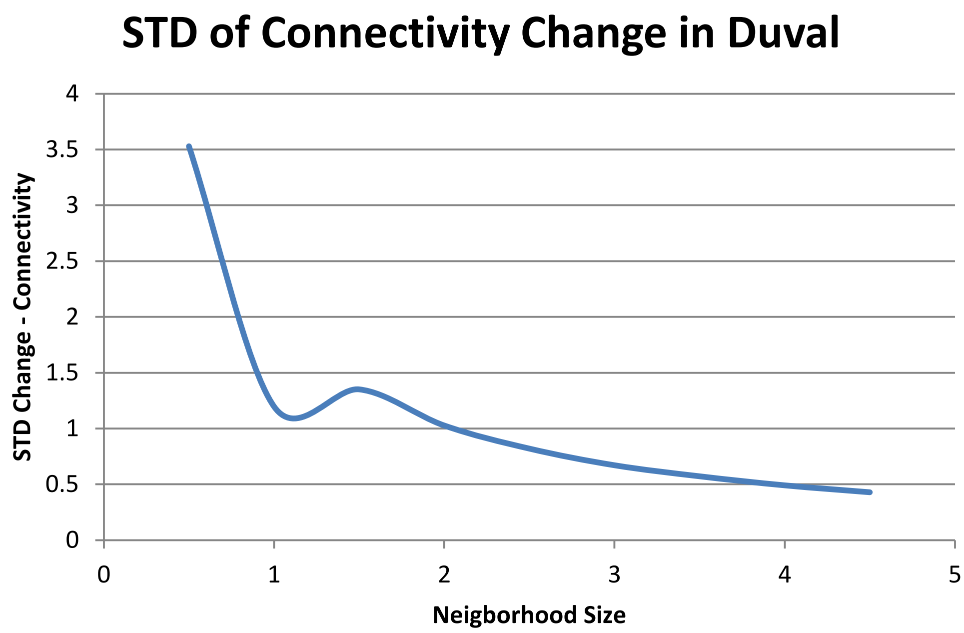


Figure 4-11. Standard deviation of connectivity value change that corresponds to 0.5 mile change in unit size

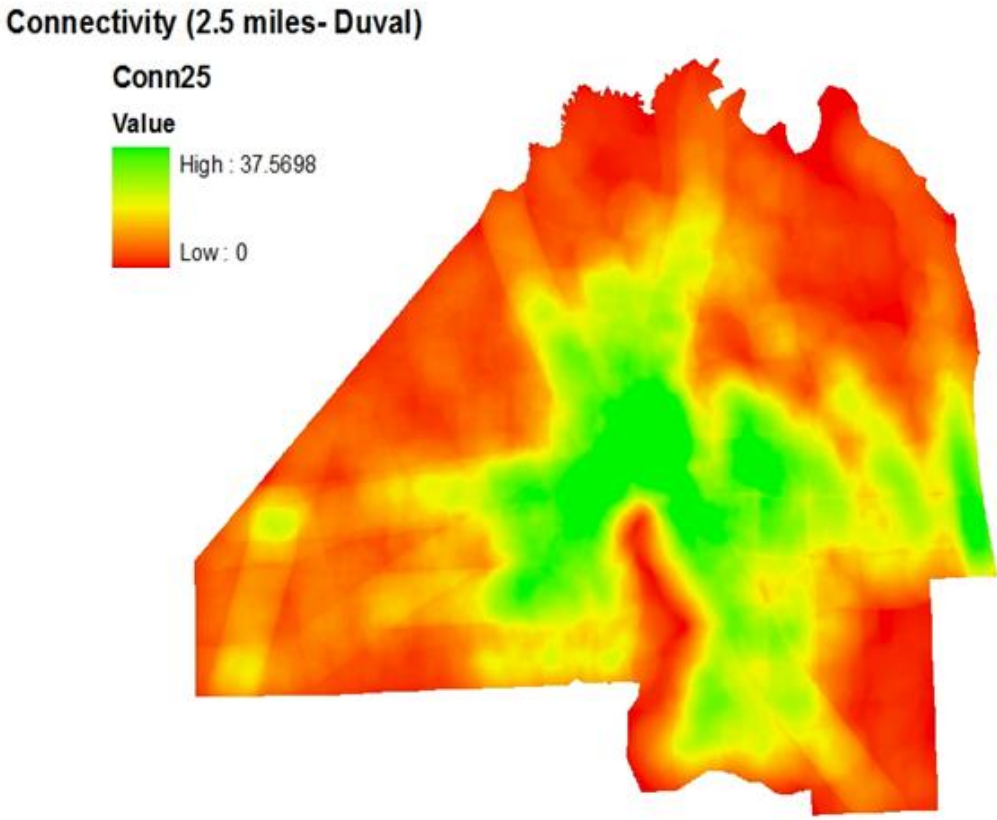


Figure 4-12. Connectivity surface for Duval County based on a 2.5 x 2.5 mile areal unit

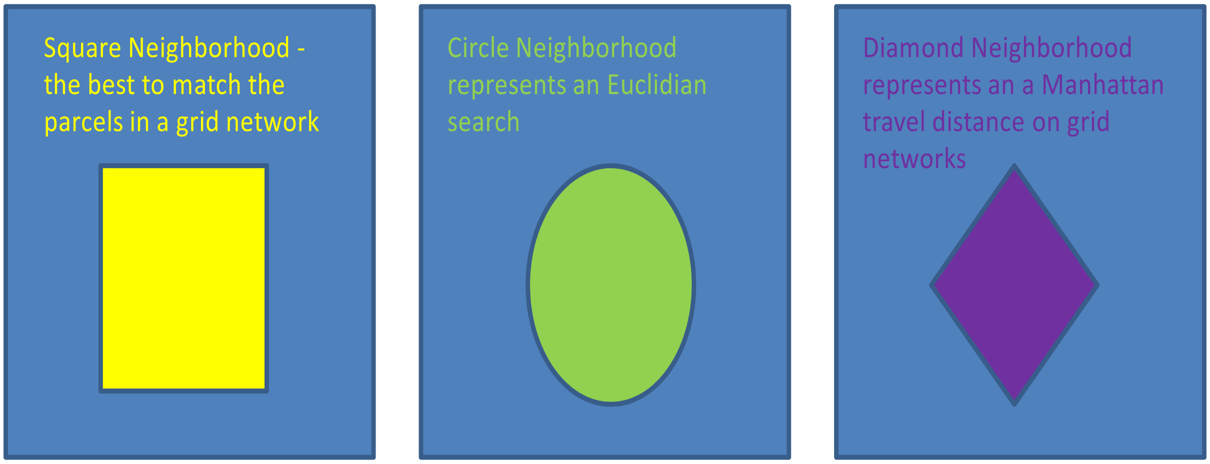


Figure 4-13. Shapes for the tested areal units

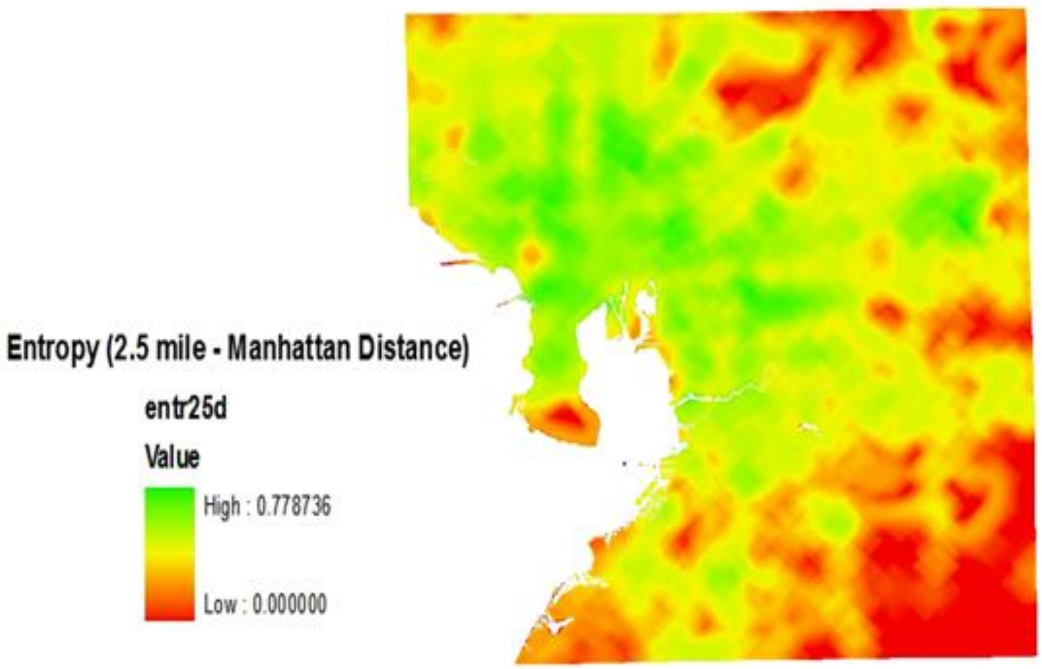


Figure 4-14. Land use mix entropy surface for Hillsborough County based on 2.5 mile diamond shaped areal unit

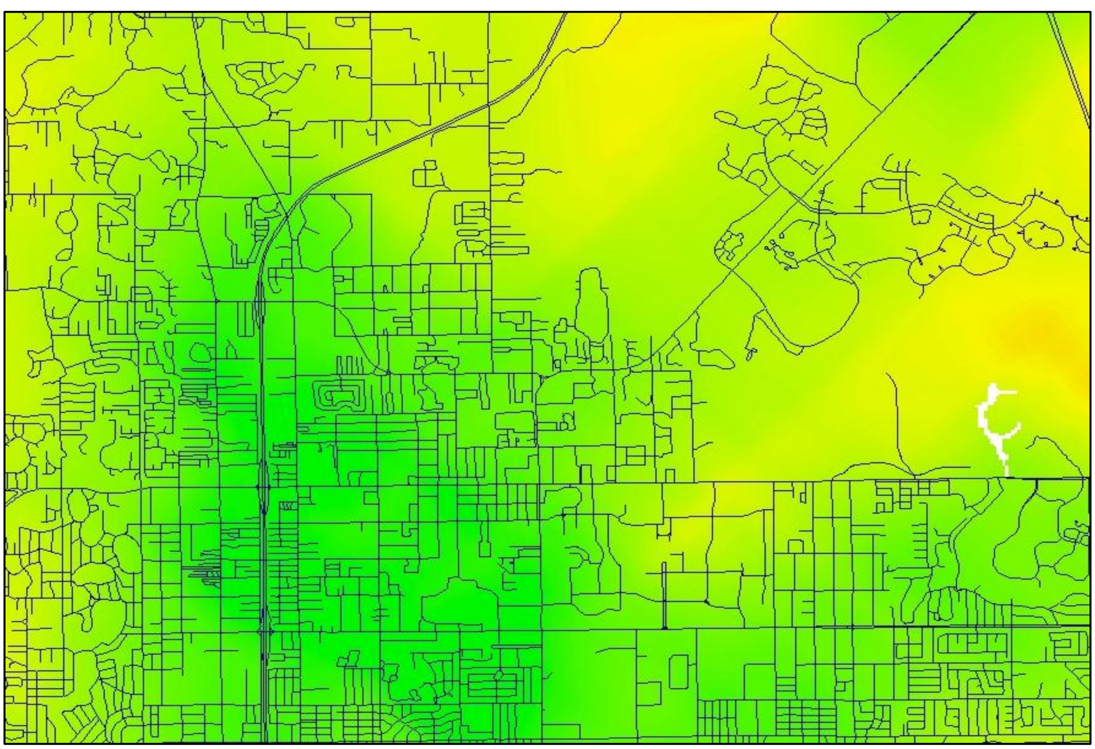


Figure 4-15. Streets and land use mix entropy overlay surface for Hillsborough County based on 2.5 mile diamond shaped areal unit.

CHAPTER 5
ESTIMATING ACCESSIBILTY AND TRAVEL COST

Neighborhood Accessibility

Neighborhood accessibility is estimated using different methods. The first and simplest method to estimate accessibility to services is to use proximity by estimating the Euclidian distance from an origin to a destination. In raster land use modeling the Euclidean raster is used by many researchers. Land use modelers, however, usually use the term proximity and not accessibility when they are using Euclidean distance. It should be noted that the Euclidean raster estimates the distance between any cell in the raster to the nearest facility or destination feature (ESRI, 2011). In suitability analysis, the distance value is transformed into a suitability score. This score will be an increasing suitability score or decreasing suitability score depending on the type of feature. Facilities like schools and hospitals are usually favorable locations in terms of proximity while facilities like prisons and noise sources are regarded as a disadvantage in terms of proximity. For example, distances to amenities will generally have decreasing suitability meaning that if the distance away from the amenity increases, the suitability of a location decreases. Conversely, for facilities that are less desirable to be located near, suitability will increase as the distance away from the facility increases.

The reclassification to decreasing and increasing suitability usually follows a sequential process including descriptive statistics. An example of descriptive statistics used in the process is the zonal statistics of the Euclidean distances for all the residential parcels. From the zonal statistics, the mean and standard deviation is calculated and their values are used to assign the suitability values. It should be noted, however, that proximity does not represent the actual travel distance from an origin to a destination. It also does not discriminate between destinations according to their size or attractiveness. The proximity suitability surface for distances away from shopping centers (Figure 5-1) is reclassified using decreasing suitability based on the mean and the standard deviation of the distance away from multifamily parcels.

Proximity can be also estimated by estimating the network distance from any cell in a raster to the nearest facility or destination feature. However, the estimation process is not a direct output from ArcGIS tools. Network analyst can be used to locate the nearest network points for each origin and its nearest destination. Using the shortest path method, the network distance is also calculated. Then the values for the distance of the whole trip is summed and assigned as a score for the origin in the raster, allowing the user to create a network distance raster. This procedure is automated using a customized Python tool created for this research. The network distance raster (Figure 5-2) is created by the tool. It should be also noted that the raster may be a better estimation of travel distance to services but it does not discriminate between destinations according to their size or attraction. The raster only estimates the distance to the nearest facility. Furthermore, the method is used for destinations that can be reached by walking or driving using street networks. Therefore, it is not used to estimate the proximity to noise generators or sources of pollution. The distance to shopping centers (Figure 5-2) is reclassified to a suitability surface using a decreasing suitability based on the mean and standard deviation of the network distance summarized by zonal statistics using the multifamily parcels as zones.

Opportunity Access Measures

As mentioned before, proximity does not discriminate between services that a person may choose as a destination. It only estimates the distance to the nearest facility. However, a person may travel more for shopping if the destinations have more shopping options (Arafat et al., 2010). The opportunity accessibility measurement captures how many services are within a specified distance. The score for services can be different depending on the type of service such as the area of a retail store or the number of beds for a hospital. The neighborhood or the surrounding distance can be Euclidean distance, Manhattan distance or network distance. The cumulative opportunity score within the specified distance from a parcel is assign as an opportunity score for that parcel (or cell in the raster). A suitability surface is created by the reclassified opportunity surface. Figure 5-3 shows a suitability surface depending on the opportunity access score. The surface is composed by combining two suitability surfaces that represent the opportunity in walking and biking distances. The surface is generated using a Euclidean buffer distance. Figure 5-4 shows the suitability based on the opportunity using a network buffer instead of a Euclidean buffer. The generation of the raster using a network buffer is a sophisticated iterative procedure that needs programming in addition to the use of ArcGIS Network Analyst. A customized GIS tool model was created to estimate the opportunity within the network service areas and to construct the output raster.

Combined Opportunity Distance Access Measures

The opportunity raster does not discriminate between opportunities according to their distance from a parcel. Therefore, the opportunity suitability estimate is combined with the distance suitability estimate to generate an opportunity distance MUA. Figure 5-5 shows the MUA surface based on combined opportunity and distance using a Euclidean distance estimation and buffer while Figure 5-6 shows the combine opportunity and distance MUA based on network distance and network service area.

However, the combined distance opportunity measurement is different from gravity access. Gravity access can be estimated by generating origin- destination matrices for the entire area either by using network or Euclidean distances. The estimation proves efficient for small areas or using zonal level analysis such as with TAZs. On a parcel level analysis the resultant origin-destination matrix could be more than a billion records for a single county which imposes a limitation on the use of gravity access at that level. The gravity estimation in this research is used to estimate transit accessibility. The gravity estimation also is used to estimate accessibility for a limited number of origins picked randomly. This estimation is used to calculate the accessibility to major activity agglomerations which is important in estimating travel cost.

Estimating and Predicting Travel Cost

Travel cost estimation is complex in its nature. The vehicles miles of travel are dependent on urban form characteristic as indicated in many studies (Ewing & Cervero, 2001; Ewing et al., 2007; Lee & Cervero, 2007). However, travel behavior depends also on traveler characteristics. Land use models usually focus on allocating future population in places that are suitable for housing. These models usually do not focus on the household characteristics for the people who will reside in these locations. Neighborhood aggregated values such as income and poverty may be used, however, in the modeling procedure, the use of these aggregated values helps the modeler take into account neighborhood change and social justice issues and to plan for more sustainable communities.

This research is concerned about a spatial discrimination of travel cost. Therefore, it focuses on spatial location more than traveler characteristics. However, aggregated surrounding values such as income and household size are used in the research.

Taking the location and neighborhood characteristics into account, the travel cost can be estimated depending on the National Household Travel Survey 2009. The travel cost can be estimated by the spatial interpolation of the geo-coded trip data or by relating the travel cost to the urban form and neighborhood characteristics and use the output relation to estimate the cost. However, this assumes that there is a travel cost estimate in the data. The NHTS data does not have a travel cost field in its trip diary and it should be estimated indirectly using other fields in the survey. Therefore, trip length is used to generate a travel cost depending on a per-mile travel cost and the household locations provided in the travel survey. Spatial interpolation provides a method of estimating values for missing trip length values for trip categories not reported in the survey. These values are estimated depending on the nearest neighboring values as explained in Chapter 3. The following sections show the results of the travel cost estimations as well as the validation process for the estimation.

Estimating Travel Cost by Spatial Interpolation

Spatial interpolation is used to estimate values for the trip length of a certain category depending on the neighboring values in the travel survey. In the travel survey, a person may have reported a work trip but did not report shopping trips. The proxy of travel cost estimation assumes that each household does all the trip categories each month depending on summary statistics from the travel survey. Therefore, missing trip categories are estimated for each location by spatial interpolation of each trip category independently.

Different interpolation methods were investigated to come up with the method with least errors in the cross validation procedure. In investigating interpolation methods, it should be noted that there are two main categories for spatial interpolators; these are deterministic interpolators and stochastic interpolators. For estimating trip length based on reported values for neighboring points, deterministic methods of interpolation such as inverse distance weighting is more preferable than stochastic methods of interpolation such as kriging. The reason is that deterministic interpolation does not change the reported values during the interpolation. However, these reported values could be changed during the stochastic interpolation procedure. This research tested interpolation methods using both deterministic and stochastic methods such as kriging and inverse distance weighting and it was found that inverse distance weighting gives the lowest estimated cross validation errors (Figure 5-7).

The trips in the travel diary were categorized into home-based and non-home-based trips. The home-based trips are categorized as work, shopping, social and entertainment and other. The non-home-based trips are represented as one category. Spatial interpolation is performed on each category independently and the result is combined to give the final travel cost using the method explained in Chapter 3. The output surface shown in Figure 5- 8 is an estimation of travel cost for Orange County. The surface shows, however, that the variation of travel cost in some locations is high. To reduce the variation, an average surrounding travel cost surface can be generated by taking the mean surrounding travel cost within a walking distance. This value is assigned to the center of the neighborhood as the average surrounding travel cost (Figure 5-9). The average surrounding travel cost surface is generated by focal statistics tool (ESRI, 2011) using a Manhattan neighborhood size of eight hundred meters, which represents the walking distance in Transit Oriented Development (TOD) research. The resulting surface is smoother due to the averaging procedure performed by focal statistics.

Predicting Travel Cost from Location and Urban Form Characteristics

The spatial interpolation method works for places that are highly represented in the geo-coded trip ends data of the NHTS 2009. The spatial estimation also assumes cross sectional data, which means that the spatial interpolation output works for the year 2009. However, any future change in land use will have an effect on increasing VMT as well as travel cost as shown in Chapter 2. Therefore, a future travel cost prediction procedure has to include urban form characteristics. This includes capturing a longitudinal relationship by regression. In the longitudinal relationship, travel cost is sensitive to land use change and not limited to spatial location.

The travel cost estimation resulting from the spatial interpolation using the NHTS 2009 trip data is used in the regression model to capture the relationship between travel cost and urban form characteristics as well as aggregated neighborhood characteristics.

A random data set is generated for each county in the study area that includes approximatly three thousands points. The number of points, however, is reduced due to missing data at certain locations. The data includes the estimated travel cost at each of the random location as well as the following metrics that are taken from the land use transportation coordination litrature.

1. Density
2. Land use mix (Entropy)
3. Connectivity
4. Accessibilty to major retail and service activity agglomerations
5. Transit connectivity
6. Household size
7. Income

The estimation methods of these metrics are explained in Chapter 3. Other variables that are specific to the county location are also used for each county.

Predicting travel cost by ordinary least squares

The first method used in the regression is the OLS method. This regression is a global regression that does not take into account the spatial location of the points used in the regression table. However, spatially differing variables can be used in the regression table. OLS regression is the most common regression method used in relating transportation and land use variables (Ewing & Cervero, 2001; CNT; 2007). It uses a global regression function and may not capture the local variation which usually leads to lower goodness of fit of the regression model. OLS regression is performed on the random data sets generated for Duval, Orange and Pinellas counties.

The results of OLS models for the three counties show that different counties have different relationships between travel cost and urban form charactaristics. The OLS model result for Orange County has an R^2 value of 0.640 while Duval County has a value of 0.450 and Pinellas County a value of 0.388 (Table 5-1). This means that the urban form charactaristics relationship to travel cost is strongest in Orange County and the weakest in Pinellas County. The result shows that the residuals have a normal distibutions. However, the spatial autocorrolation check proved that the regression models for the three counties have cluster residuals. This raises questions about the validity of the global regression for these counties and the need for other regression methods. Furthermore, the OLS regression model proved that the same urban form variables are important in Orange and Duval counties but most of the variables where insignificant for Pinellas County which also suggests that the geographic location and local variables are important in finding the relationship between travel cost and urban form (Table 5-1).

A traditional method of increasing the goodness of a model and reducing residual clustering is to use spatial discriminator such as binary variables. This was tested in Duval County. The new OLS model for Duval County includes additional variables such as land use category and land value. Using additional variables slightly increased the goodness of the model and slightly reduces the residual clustering. The additional variables were not significant in Orange or Pinellas counties which again suggests that the global regression using OLS is differet from one geographic region to another.

The coefficient of the OLS indicates that increasing the surrounding density will decrease the travel cost. The travel cost also decreases if the land use mix, connectivity, accessibilty to major actvity agglomerations and transit connectivity increase. This result matches the literature on compact development. This is not true, however, for Pinellas County where the result indicates that increasing density and accessibilty will decrease travel cost. The other variables such as land use mix, connectivity and transit connectivity however, are not significant.

The clustered residuals indicate that the clustering is not random meaning that there are missing variables in the model. Due to the complex nature of the relationship between urban form and travel cost, it is extremely difficult to identify these missing variables. To validate the goodness of the global model, the percentage prediction error is calculated and mapped for the counties. Figure 5-10 shows the spatial distribution of the prediction error and that it is always less than 10% of the estimated travel cost. The distribution of the prediction error is low in rural areas which have have high travel cost, and higher in the places that have low travel cost such as the CBD area. This can be an indication that some people are living in downtown areas but have large travel costs due to anomalies in the location such as bridges or avoiding congested roads. The prediction error mapping shows that even though the residuals are clustered, the prediction error is low and the model can still be used for the prediction of the travel cost.

The OLS model explains the global relationship between travel cost and urban form charactaristics. For example, increasing density will decrease travel cost and increasing connectivity will decrease travel cost. However, in areas that have geographic anomalies such as bridges that are used for travel, increasing density may increase congestion and as a result increase travel cost. Also, adding street links to the network will increase connectivity but eventually cars will need to travel through the bottle-neck of the bridge. The global regression lacks the ability to capture these anomalies and other local spatial charactaristics. Therefore, this research suggests the use of geographically weighted regression in the estimation of the travel cost.

Predicting travel cost by geographically weighted regression

The same dependent variable and the significant independent variables used in the OLS model are used in the GWR model. The dataset for the GWR model is also the same dataset used for the OLS regression model. However, the GWR model depends on the other data points that spatially surround each of the point in the dataset. This generates a neigborhood or a kernel around each point in the data set.

There are two types of neigborhoods that can be used in geographically weighted regression. The first is the fixed neighborhood in which a distance is set around each point and the points that are inside the neigborhood are used in the regression. The second type is the adaptive neigborhood, where the user can decide the number of point that will be used in the regression. The number of points needed for the regression in GWR depends on the number of explanatory variables. GWR regression fails if that minimum numbr of point is not satisfied, which places a restriction on the use of the fixed kernel in the travel cost regression model. Therefore, the adaptive kernel is used. The choice of numbers of points was performed on a trial and error basis to identify the minimum number of points at which the regression will not fail in any of the three counties. This number was found to be 700 points.

GWR models are tested for the three counties. For Orange County, the GWR model has nearly the same R^2 as the OLS model, which is an indication that the global model of regression is a good model in that county. However, the explanitory variable coefficients are spatially distributed and their values are not constant indicating differences between the GWR and OLS regression models. The results for Duval County were different. The GWR increased R^2 from 0.45 to 0.95 indicating that the GWR model has less prediction error than the OLS model. Table 5-2 shows the difference between the OLS and GWR regression models in terms of their R^2 values for the three counties.

Comparison Between GWR and OLS Results

The regression results using both methods show clearly that GWR models generally have larger R^2 than OLS models (Table 5-2), indicating that the relationship is stronger and the prediction errors are much less. The GWR model also solved the problem of the clustered residual and the need to find more explanatory variables, as explained in the aforementioned OLS section. Therefore, one can say that the GWR model is a better predictor of travel cost. Even though this research focuses on methods of predicting travel cost, explaining the meaning of the explanatory variables is also important to the research of coordinating land use and transportation.

OLS regression for Duval County gives a coefficient of the density explanatory variable -0.062. However, the coefficient for density using GWR for Duval County is not constant and varies spatially. The mean value of the density coefficient is -0.052. The mean coefficients have the same direction and means that, on average, increasing density will decrease the travel cost. However, some areas have the opposite direction of the relationship (Figure 5-11) meaning that increasing the density in the positive relationship area will increase the travel cost. The logical explanation of that can be understood relating the variables in the regression together. Land use variables are complex in nature. The autocorrelation test shows that the variables are independent. On a local scale, these variables may not be absolutely independent. Figure 5-11 shows that the positive density relationship occurred in undeveloped areas with low connectivity and low land use mix. This means that in areas at the fringe of the county, increasing density without increasing land use mix and connectivity will not reduce the travel cost.

The explanatory variable for connectivity also has a spatially discriminated distribution. The negative direction means that increasing connectivity means decreasing travel cost, which matches the results of research relating connectivity to VMT (Ewing & Cervero, 2001). However, there are also areas that have positive directions (Figure 5-12). The positive relationship occurs in two different places. The first is a place of low land use mix and low accessibility at the fringes of the county. The results show that increasing connectivity without increasing land use mix and accessibility to destinations will not help to reduce travel cost. It is reasonable therefore to conclude that reducing travel cost requires adding retail and employment opportunities in these areas, in addition to increasing connectivity. That will increase connectivity, accessibility to destinations and land use and at the same time decrease travel cost.

The second place that has a positive direction in the relationship between connectivity and travel cost is in downtown Jacksonville, at the heartland of Duval County. The result shows an important relationship captured by the GWR model that is not captured by the OLS model. This area has a bridge and increasing the connectivity by adding road links to the network without increasing the bridge capacity will not reduce travel cost. The GWR model captured the anomaly of the bridge that the OLS model could not capture.

In conclusion, both the OLS and GWR models are good models for prediction. The importance of OLS is that it can explain what happens globally if the urban form characteristics or the land use is changed. The results were in agreement with the research with the land use and transportation research mentioned in the literature review. Therefore it can be used for policy makers at the county, state or even national scale. However, it does not capture what happens locally. The urban form has many anomalies that cannot be generalized. GWR can capture some of these anomalies. It can also predict values with less prediction errors. However, it is a local tool and it can be only used for the area for which the model is generated. This conclusion is not different for OLS. The result for OLS for the three counties also proved that the significant explanatory variables are different from one county to another. The explanatory coefficients are different too, meaning that the OLS model also cannot be generalized and used in different geographic locations.

Table 5-1. Explanatory variable coefficients and their significance using OLS

County Variable	Duval Coefficient	Duval t- stat	Orange Coefficient	Orange t- stat	Pinellas Coefficient	Pinellas t- stat
Density	-0.062	-11.82	-0.051	-17.42	-0.099	-33.54
Land Use mix (Entropy)	-0.400	-13.07	-0.179	-16.94	-------	Not Significant
Connectivity (links/Nodes)	-0.121	-2.71	-0.017	-4.68	--------	Not Significant
Accessibility To Major Destination	-0.012	-7.82	-0.043	-5.79	-0.005	-2.51
Transit Connectivity	-0.001	-2.04	-0.004	-10.74	---------	Not Significant
Household size	0.026	3.34	0.049	4.47	----------	Not Significant
Income	-0.002	-10.34	0.001	2.54	0.001	6.56
R2		0.452		0.640		0.388

Table 5-2. R^2 values for OLS and GWR

County	OLS R^2	GWR R^2
Orange	0.640	0.645
Duval	0.452	0.952
Pinellas	0.388	0.757

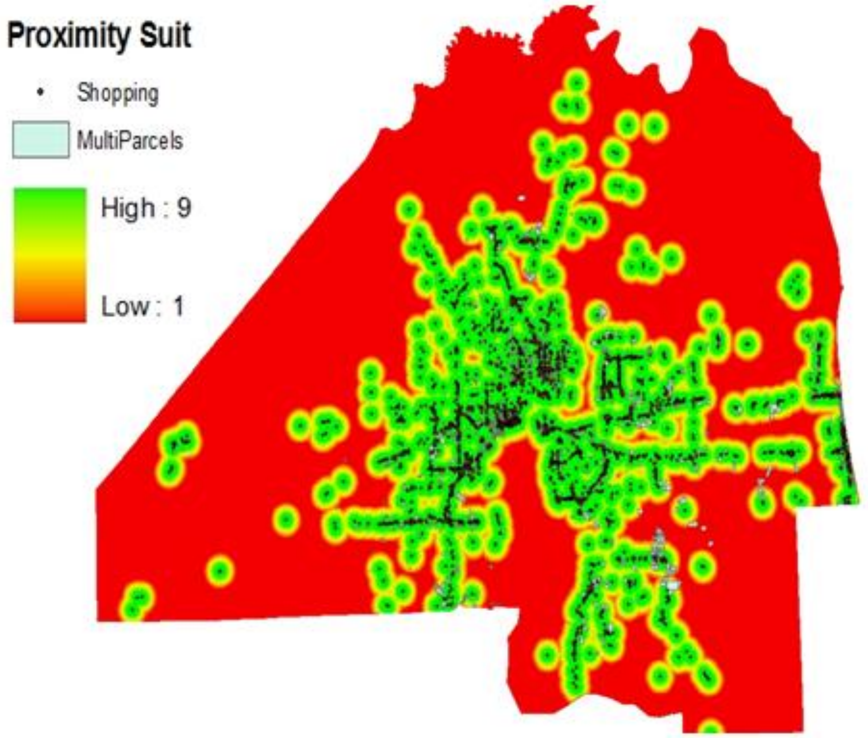


Figure 5-1. Proximity access measures- Euclidean distance

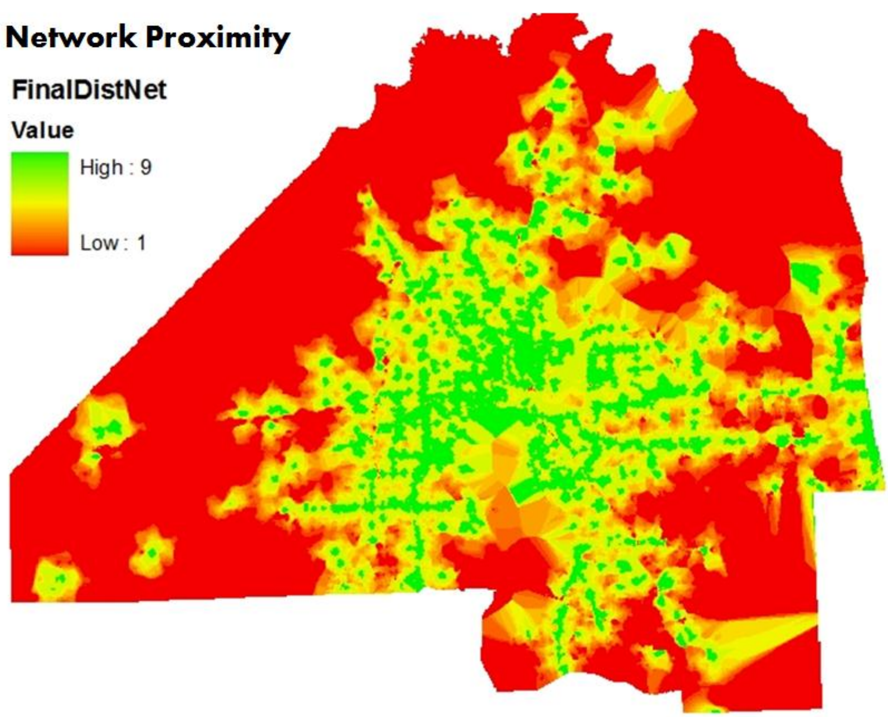


Figure 5-2. Proximity access measures- network distance

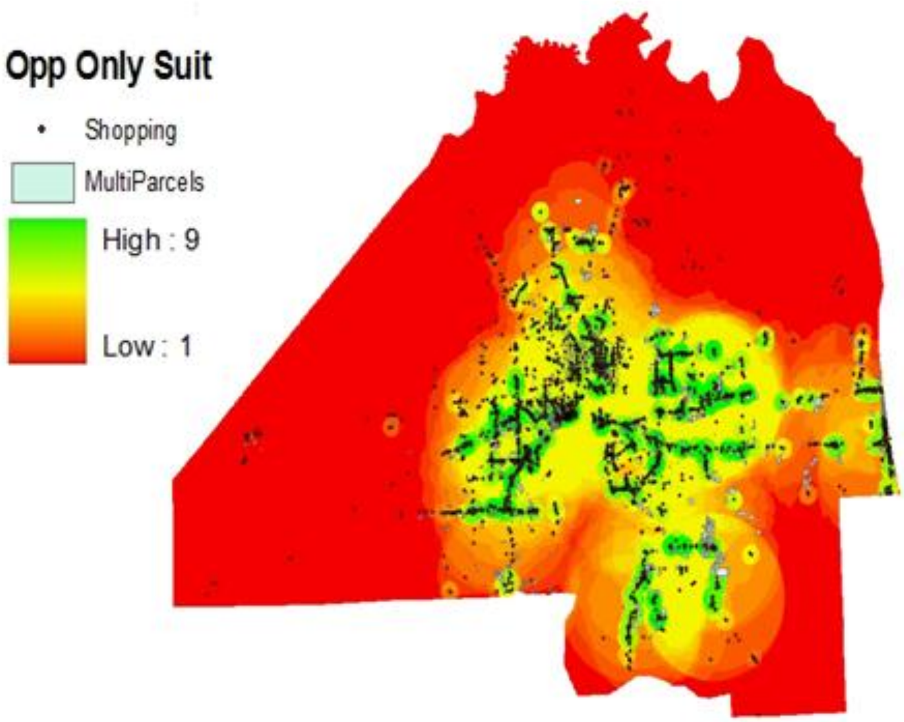


Figure 5-3. Euclidean buffer opportunity access

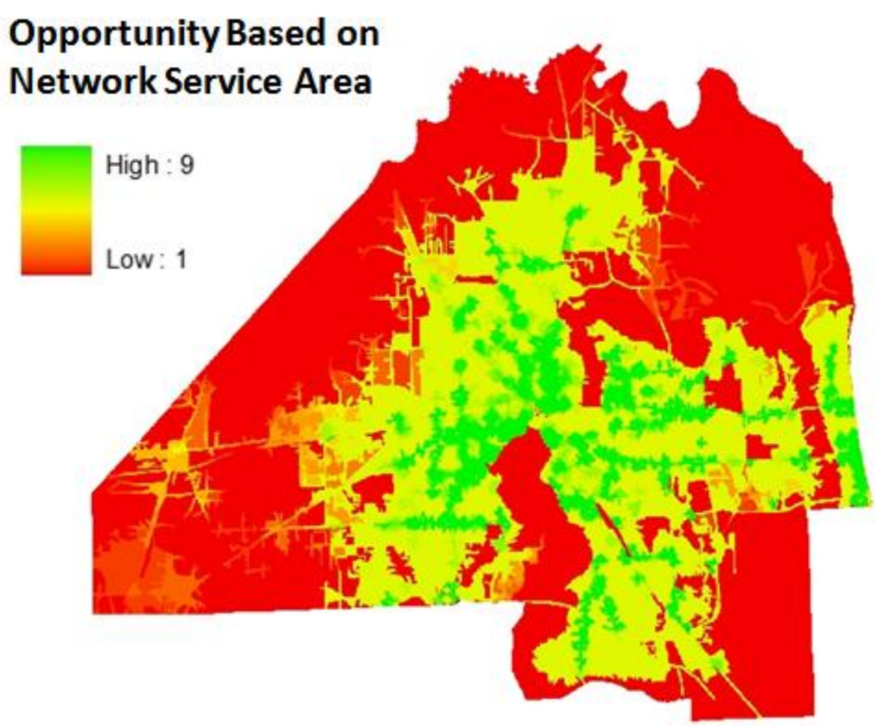


Figure 5-4. Network service area opportunity access

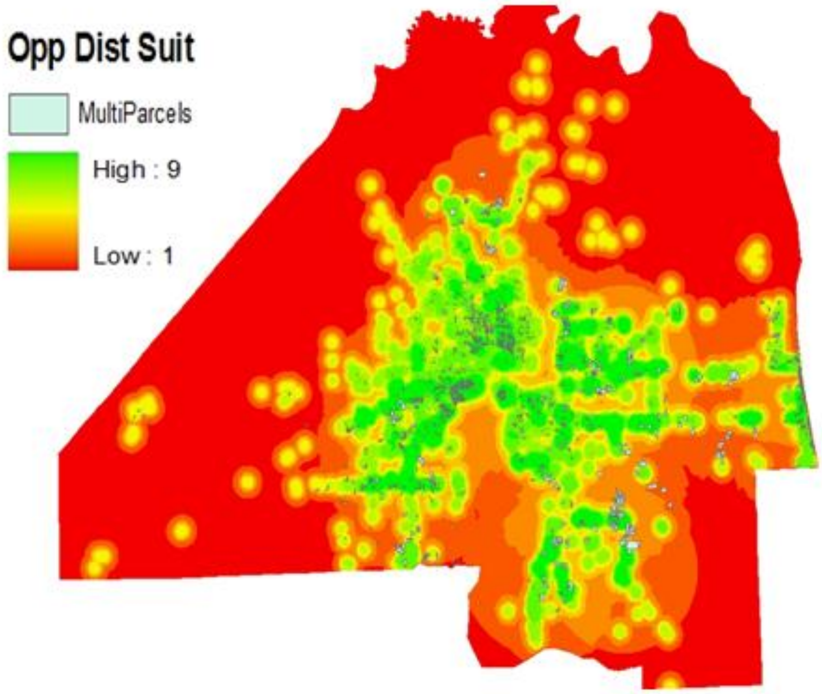


Figure 5-5. Combine opportunity-distance access based on Euclidean distance

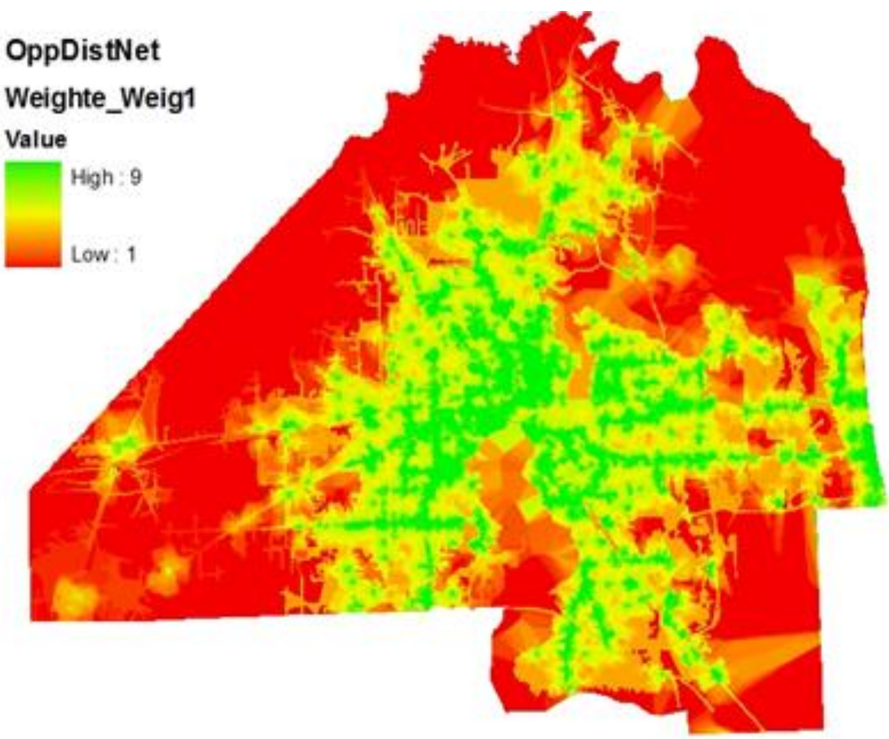


Figure 5-6. Combine opportunity-distance access based on network distance

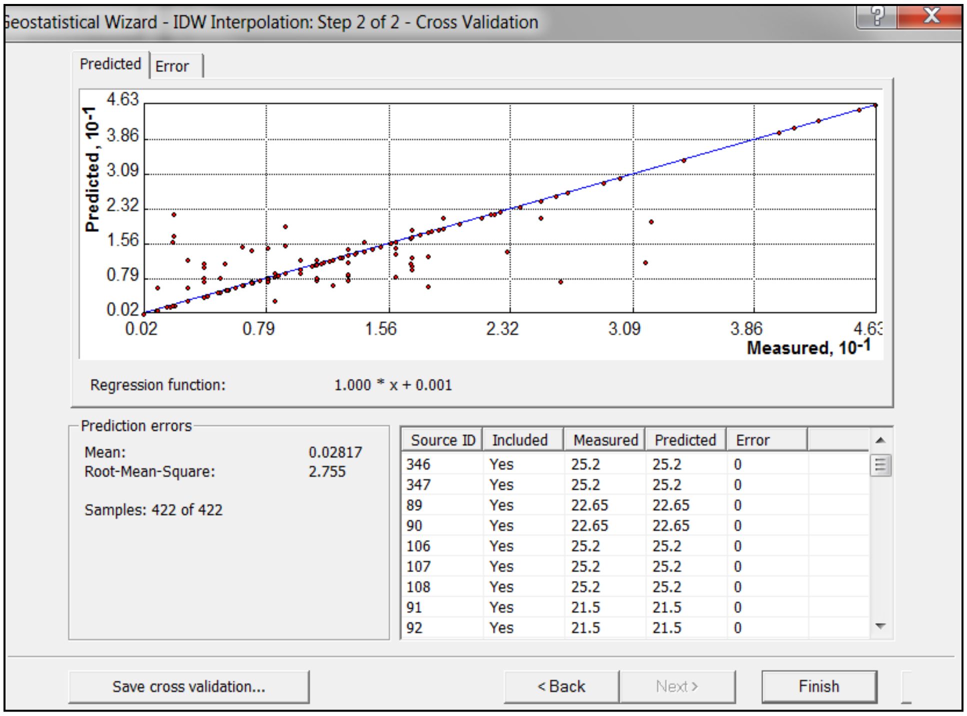


Figure 5-7. ArcGIS cross validation chart for inverse distance weighted interpolation using work trip length as the interpolation field

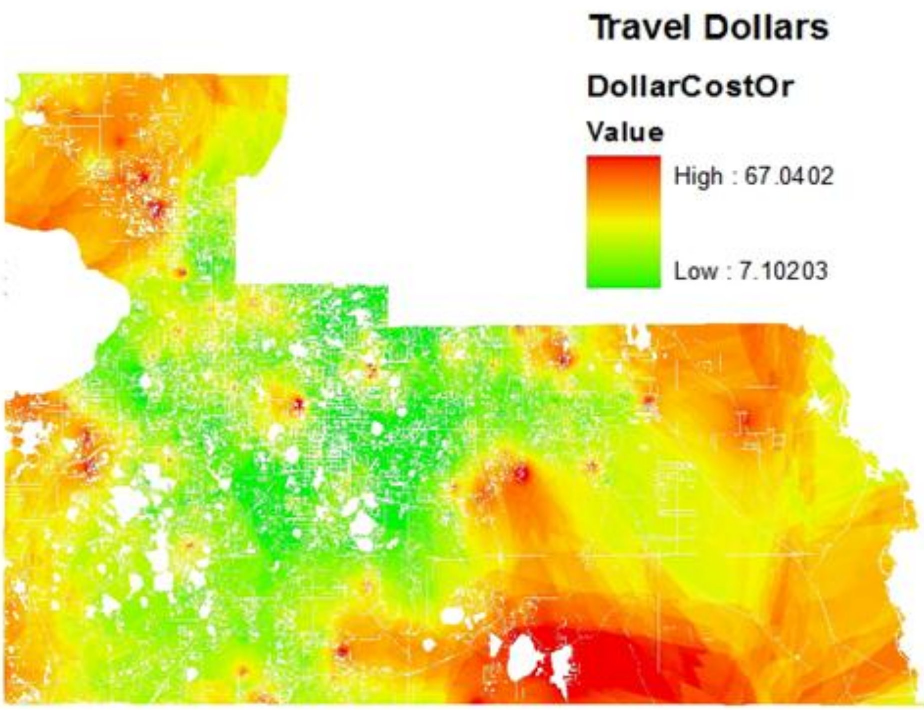


Figure 5-8. Travel cost generated by spatial interpolation

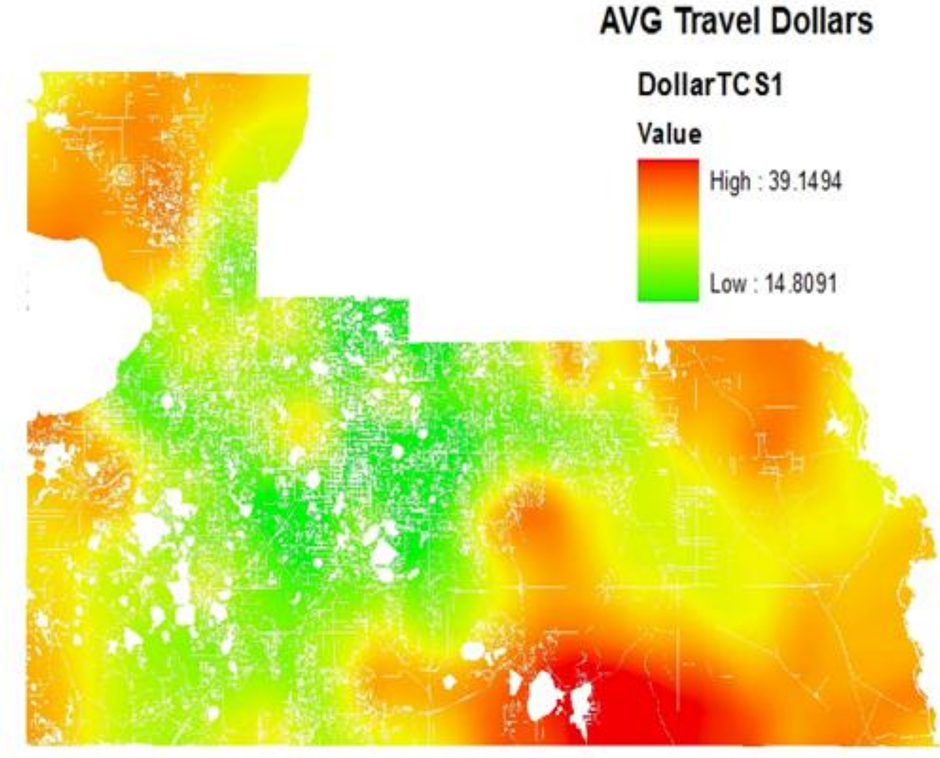


Figure 5-9. Travel cost smoothened within walking distance

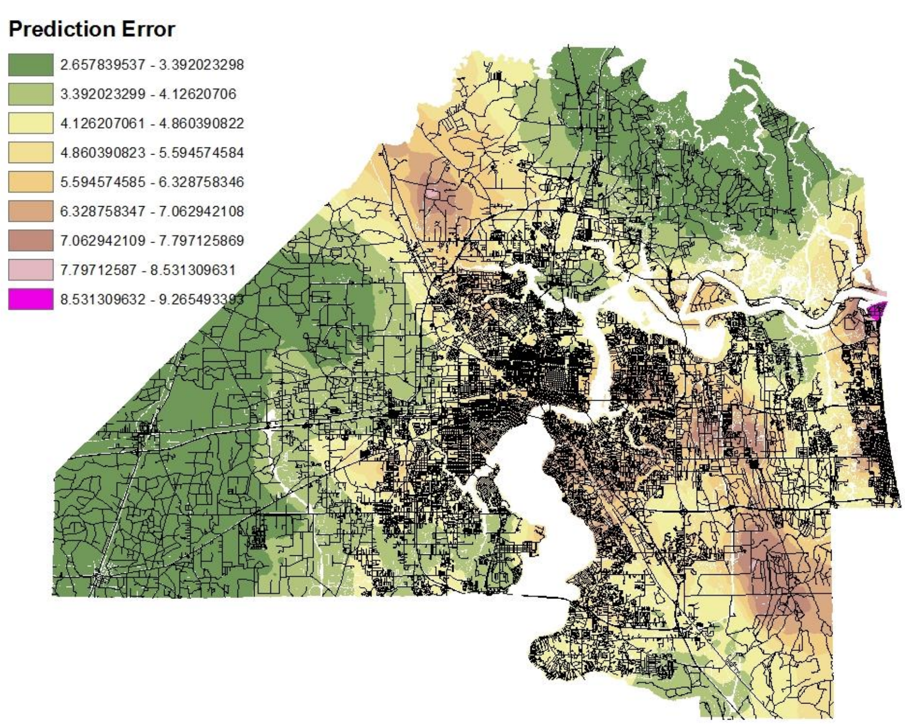


Figure 5-10. Prediction error as a percentage of travel cost

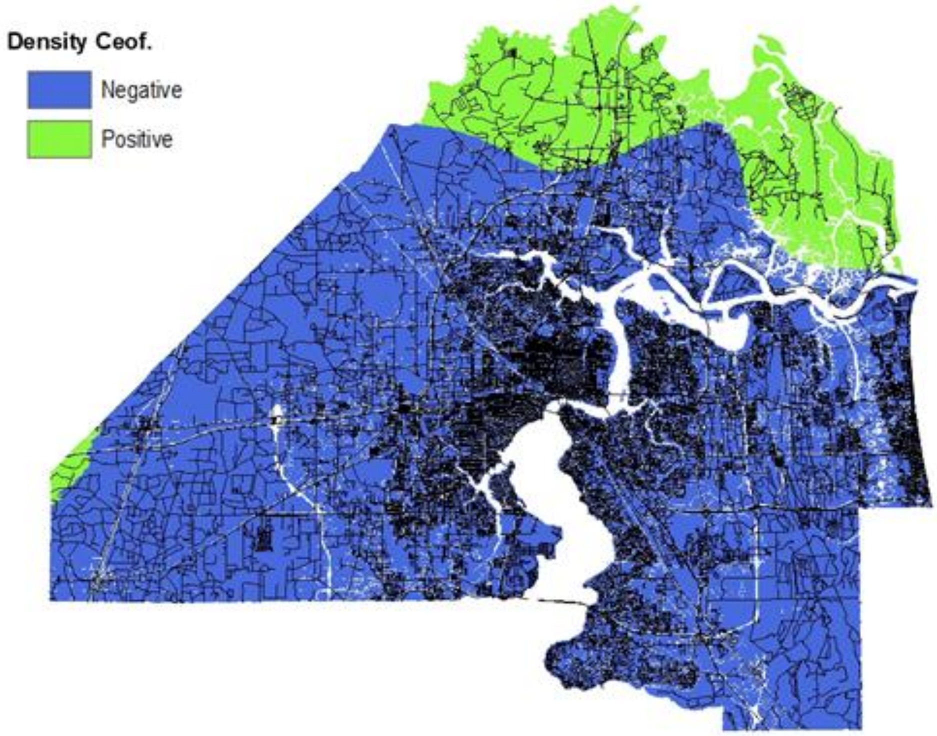


Figure 5-11. Reclassification of the GWR density coefficient.

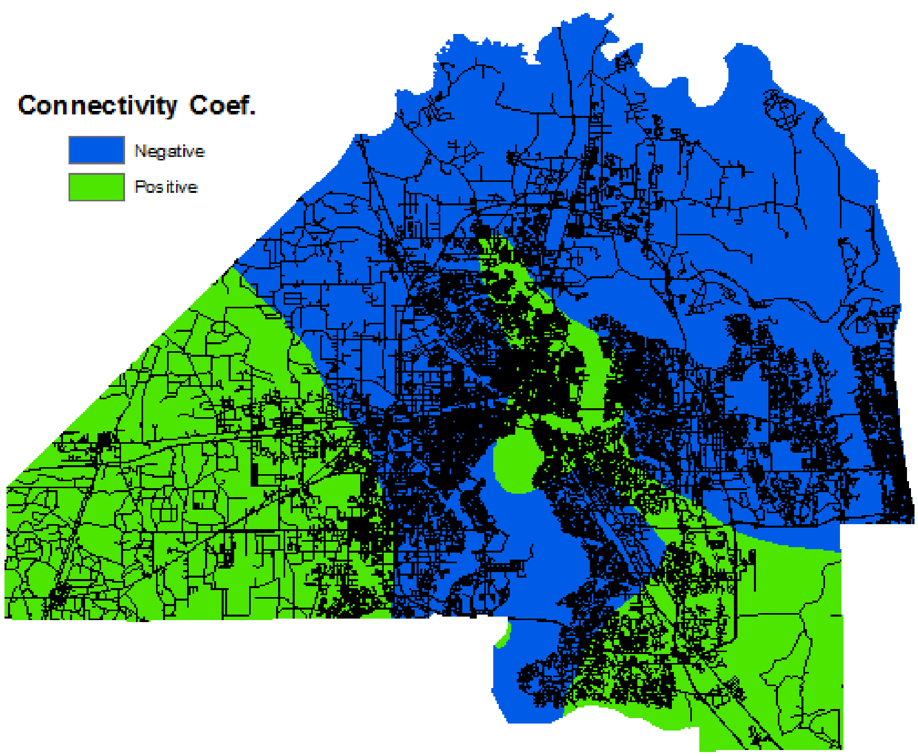


Figure 5-12. Reclassification of the GWR connectivity coefficient

CHAPTER 6
INTRODUCING SUITABILTY AUTOMATION TOOLS

Land use planning has become more complex as the incorporation of sustainable development goals has increasingly taken place. Therefore, the modern planning process involves conflicting and contradicting interests between conservation and economic development. In this new situation, planners face challenges as they attempt to design their projects while taking into account the balance between ecological equilibrium and the project's contribution to economic development at the same time. This adds to the complexity of how planners handle suitability analysis. This complexity has been reduced by the development of GIS analysis, as well as the development of procedures that help to plan for several land use alternatives before making a decision.

ArcGIS software is equipped with analysis tools that can help planners in land use modeling and in making decisions concerning land use. Typically these tools have been designed to be used in many ways. One way to use the tools is interactively, where the user uses icons and menus to initiate the tool. Another way is through the use of toolboxes, organized in a tree structure that classifies the tools into different categories. However, land use modeling is a sequential procedure (Carr & Zwick, 2007). This sequential procedure requires the user to use the GIS tools one after the other, which also allows the process to be automated. The automation process is supported in ArcGIS. The software allows the user to use programming to prepare their customized tools or to incorporate the software built-in tool in a batch process. The programming in ArcGIS is supported by many programming languages such as, Python, Visual Basic and C. It is also supported with graphical programming software called Model Builder, where graphical symbols like circles, ovals, squares and rectangles, represent the input and output data sets as well as the tools. The processes are usually represented by arrows or connectors that join the shapes to generate the process sequence. Model Builder therefore can do programming in a flowchart graphic pattern (ESRI, 2011).

ArcGIS tools and programming methods are used intensively in this research. The aim of using programming is to create customized automated tools that can run complex procedures that are difficult to run using the built in interactive tool. Model Builder, Python and VBA are used to automate suitability modeling as well as in estimating urban form metrics and other procedures. This research will introduce the tools that are used in suitability modeling. The testing of these tools was performed in land use modeling. However, these tools are used also to allocate land that is suitable for affordable housing as shown in Chapter 7.

There are three types of automation tools used in this research, they are: automation tools for suitability assignment, automation tools for suitability overlay and automation tools for the population allocation based on the combined grids. The use of automation tools in the research exceeds the three mentioned categories. However, the tool discussion only focus on the tools that can be used in most of the LUCIS land use models and the AHS model. The tool that works for the suitability assignment (A4 Suitability) is a raster reclassification tool that reduces the manual calculation needed outside the GIS environment.

The second category of tools is the suitability overlay toolbox which contains two tools. The first tool is for calculating suitability overlay weights according to community values (A4 Community Values). The second tool is used to perform the overlay between suitability assignments (A4 LUCIS Weights).

The third tool category is the allocation toolbox which contains three tools, the trend allocation, the allocation by table tool and the detailed allocation tool (A4 Allocation tools).

Suitability Assignment Tool

The suitability index is a value that represents the relative usefulness for a land use. These values are assigned from one to nine in the LUCIS model where one represents the lowest suitability and nine is the highest suitability value (Carr & Zwick, 2007). The utility values are classified from one to nine using different methods according to the nature of the criteria to be evaluated or according to the utility to be classified as a suitability surface. This classification procedure can be performed using interval, ratio, nominal and ordinal data (Carr & Zwick, 2007). Some of the procedures are simple and some of them have higher complexities.

The evolution of suitability analysis has required that current methods be “more accurate, legally defensible, technically valid, ecologically sound, and open to scrutiny by the public” (Ndubisi 2002, 102). Prior to the introduction of the A4 Suitability Tool the planner would take the MEAN, STD, and MIN or MAX statistics generated from Zonal Statistics as Table tool to manually calculate the suitability intervals for non-binary classifications. Once the values for each interval are determined these values would be manually input into the reclassify tool. This method proved to be time consuming, cumbersome, and prone to error. This research introduces the A4 Suitability tool that performs these calculations for the planner and creates nine intervals between the MEAN and MIN or MAX values, depending upon whether the suitability is increasing or decreasing, from the input distance surface. The interface for that tool (Figure 6-1) shows that the tool is prepared to work in the GIS environment as a stand-alone tool.

The tool can be also inserted as a customized tool using ArcGIS Model builder. Zonal statistics as Table and Euclidean Distance (Figure 6-2) are typical tools that are used in LUCIS suitability models. The A4 Suitability tool is inserted within these models in Model Builder to automate the reclassification process (Figure 6-3).

The output of the Zonal Statistics as Table can be easily inserted into the A4 Suitability tool. The tool uses the values from that table and does all the required calculations to generate the suitability table ranges between the minimum and maximum values. The tool will also generate the reclassification table for the raster. Figure 6-4 shows an example zonal statistics table for distance to shopping centers for Duval County, while Figure 6-5 shows the output reclassification table that is internally generated by the tool. This table is automatically used to reclassify the input raster. However, it should be noted that the zonal statistics table does not necessary contain one row. In case of a multiple rows, the zonal statistics table's additional calculation is performed automatically by the tool. The tool can also accept a user generated reclassification table. The user can create any database format DBF table containing the reclassification ranges and the suitability score in the same format that is used to create the output table (Figure 6-5). This table can be generated using Microsoft Excel or Access software.

The A4 Suitability tool has been verified many times by comparing the results of using the A4 Suitability tool with the results of the same raster reclassified by doing careful and time consuming manual calculations and using the ArcGIS raster reclassification tools. The result is that the output reclassified raster layers are always identical and the A4 Suitability tool works only on the automation of the process within the ArcGIS environment. It reduces the chance of the errors that may be caused by the user in the manual calculations. The tool also significantly reduces the time of the process execution. Figure 6-6 shows an example verification raster for Central Florida generated by the two mentioned methods. The tool code was programmed using Python programming language. Appendix (A) contains the full listing of Python code for the tool.

Overlay and Weighting Tools

This research also introduces another new GIS tool, the A4 Community Values Calculator. This tool integrates pair-wise calculations into the ArcMap environment as a VBA program to be used to support land use and affordable housing suitability models. The A4 Community Values Calculator is initiated by installing the program as an ArcMap macro in VBEditor (Appendix B).

When evaluating the importance between goal, objectives or alternatives the A4 Community Values Calculator integrates any number of objective and/or sub-objective raster suitability surfaces as inputs. The A4 Community Values Calculator interface prompts the user to specify the usefulness of each pair of raster surfaces and dynamically compares the raster pair (Figure 6-7). As the user indicates values for each pair, the A4 Community Values Calculator automatically populates an internal pair-wise comparison matrix. When the user enters the values for all pair wise comparisons, the calculator then outputs a parameter table of the raster names and their corresponding relative weights (Figure 6-8).

As a way to reflect community participation, the tool can accept participation from many participants at the same time in a community participation field (Figure 6-7) and use their votes to generate weights. The tool uses the geometric mean to calculate the pair-wise comparison scores generated from the votes of all participants.

There are also methods to update existing weight tables. The first is to input the table of weights into the tool under the base table box. Then the user can either run the pair-wise comparisons again and update the table using the update table button instead of the generate table button (Figure 6-7). The other way is to manually enter the new weights in the table provided by the tool interface and then select the update table button. This manual procedure fits if the tool is used to update the weights according to expert or decision maker values (Figure 6-7).

The weights generated by the A4 Community Values Calculator are automatically used by a new weighting tool (A4 Weighting Tool). This tool is used in the LUCIS model and the AHS models within the Model Builder environment. The weighting tool depends on the DBF output table that is generated by the Community Values program (Figure 6-8). Therefore, updating this table at any time updates the weights associated in the suitability model which allows the user to perform weighting scenarios and run the models according to the new weights within a community meeting. Figure 6-9 shows the weighting tool in the Model Builder environment.

The input layers to the tool (Figure 6-10) should be in a raster dataset format. The tool uses map algebra to combine the input raster grids and to generate the output raster according to the weights in the input table (Figure 6-11). The output raster is placed in the workspace directory specified in the input box for the workspace of that tool. The model (Figure 6-9) shows the input weighting table as a variable added in Model Builder. The tool is prepared to be used to automate models in the Model Builder environment (Appendix B). However, the tool also can be used as a stand-alone tool and it has a user interface which allows the tool to be run interactively and in an ArcGIS user-friendly environment. It is also worth mentioning that the output of the tool was also verified by generating the weights manually using the AHP procedure and combing the layer using the weighted sum tool provide in the ArcGIS environment and the results were identical.

Allocation Tools

The A4 Allocation toolbox contains tools that allocate future population in land use models such as LUCIS. The tools are also used to allocate land for affordable housing as shown in Chapter 7. The new allocation toolbox contains three tools which are the Trend Allocation tool, the Allocation by Tables tool, and the Detailed Allocation tool. The idea of the allocation tools is to generate an iterative environment that runs and display queries used to find the most suitable land for the allocation of future population and populate them by proposed population values. The tool runs on combine grids which act like an enumeration container made up of values of many participating grids that the combine grid is composed of. The tools read the raster attribute table and use that table as a database where the queries can be applied. However, because the combine grid usually is a large file that may contain millions of records, the allocation process may take several days to be completed. Therefore, programming methods were used to reduce the size of the combine and increase the queries processing speed. Appendix (C) shows the source code for the three allocation scripts in Python.

The Trend Allocation tool (Figure 6-12) works on the conflict surface as well as other masks and/or constraints to prioritize the allocation process using combined grids. The combine grid is prepared by an enumeration rule that combines many grids and keeps their attribute values. The Trend Allocation tool works on an iterative procedure to allocate all the available spaces specified by the conditions or constraints, which could be the suitability values and the conflict scores.

The Trend Allocation tool works on two conditions and six masks. The condition is mainly a query that can hold any number while the mask query only hold ones or zeros. The total query is generally composed by an “And” operator between the two conditions and the first three masks and an “OR” operator between the next three masks. If the user leaves a field empty it will be considered optional and removed from the query.

Understanding, the concept of generating the query is a first step to using the tool. However, the next important step is to understand the internal iteration provided by the trend tool. The input of the conditions can be a multivariate separated by semicolons (Figure 6-12). The tool takes the value of the first number of the first condition and generates queries that iterate through all the numbers in the condition generating iteration query statements that are used to allocate population. The tool will also loop to all the values of the first condition which acts like an external or an outside iteration loop. The output of the tool can be taken by two different ways. The first is that the tool generates an output population raster and the second is that the tool populates year and population fields in the combine. If the output is to be extracted from the combine, the combine can be used in different reclassifications or summary methods that allow the display of allocation results.

The detailed allocation tool has the same function as the trend tool but with more conditions added. The previous trend tool worked for six masks and two conditions for an allocation. The detailed allocation can work on six different masks and six additional conditions for an allocation procedure. These added conditions act like inner loops for the iteration. Therefore, careful use of this tool can allocate the population in a region in one step using the power of iterations provided by the tool. However, the detailed tool has a user-friendly interface. It is a complex tool and the user should understand exactly how the iteration is performed in the tool before using it. The simplicity of the Allocation Trend tool and the details in the detailed tool have been compromised to create a cross-tool (The Allocation by Table Tool) that allow the user to perform simpler iteration inside the tool and other external iterations in the Model Builder environment.

The Allocation by Table tool is more sophisticated than the Trend Allocation tool and simpler than the detailed tool. The tool can work with up to eight conditions of which two are iterative inside the tool. Larger iterations external iterations are performed in the model builder environment and are directed by the scenario table which adds more flexibility to the process. The conditions used by the tool vary in complexity depend on the user and what they are trying to do in their scenario. The model iteration in Model Builder is performed by a list (Figure 6-13). These iteration lists are taken from a scenario table (Figure 6-14). Therefore the tool uses the values of the iteration table row by row to allocate the population using the conditions specified by the fields of the table. The tool also populates a field in the scenario table containing the summary of population allocated in each of the iterations (rows). The row of the scenario table is an external iteration performed by model builder. The internal iterations are performed by the values of condition separated by semicolons, as explained in the Trend Allocation tool.

The most important development in the tool is to use conditions instead of masks. Masks are a one or zero value raster while the condition can be any query (Figure 6-14). The allocation by table can also be seen as a planning table or a scenario builder where the planner enters the conditions for an allocation depending on each conflict score or on multiple sets of score. Using this tool the planner can perform the allocation for a specified year or for many year increments at the same time.

This tool is tested and used to allocate the future population in a transit scenario for Orange County using a transit accessibility grid, land use mix and other proximity conditions. The layers (Figure 6-15 and Figure 6-16) show that the allocation is compacted around transit lines and mixed used areas, which was expected from the scenario. The tool was checked and verified by using the query statements generated by the tool against manually generated queries depending on the same allocation conditions. Both the automatically generated and the manually generated queries are used to allocate population. Identical results were obtained in the validation procedure.

Using combine grids facilitates the automation procedure of the allocation process. However, the tools give a raster output file and at the same time update the input combine grid. The combine grid can be also used to present output results by doing different reclassifications or summaries. Additional fields that are not used as allocation conditions are placed in the combine. Examples on these grids are TAZ, Census tracts and Census block groups. The idea of using these grids in the scenario is to summarize the output of the allocation to their zones. Figure 6-17 summarizes the scenario population to the corresponding block groups while Figure 6-18 summarizes the output to different land uses

The A4 Allocation tools are used also to run scenarios for affordable housing as explained later in Chapter 7. LUCIS conflict strategies and the use of combine grids are used for the allocation of affordable housing. All the tools explain earlier are adopted in the allocation procedure of affordable housing.

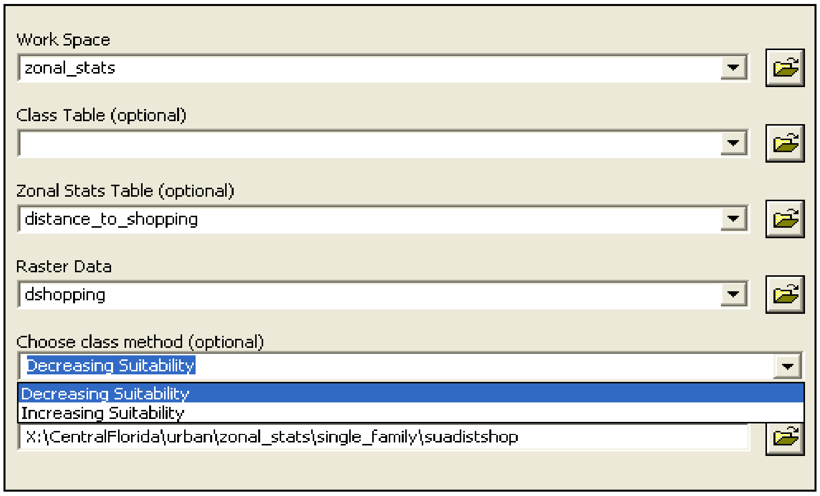


Figure 6-1. A4 Suitability tool interface

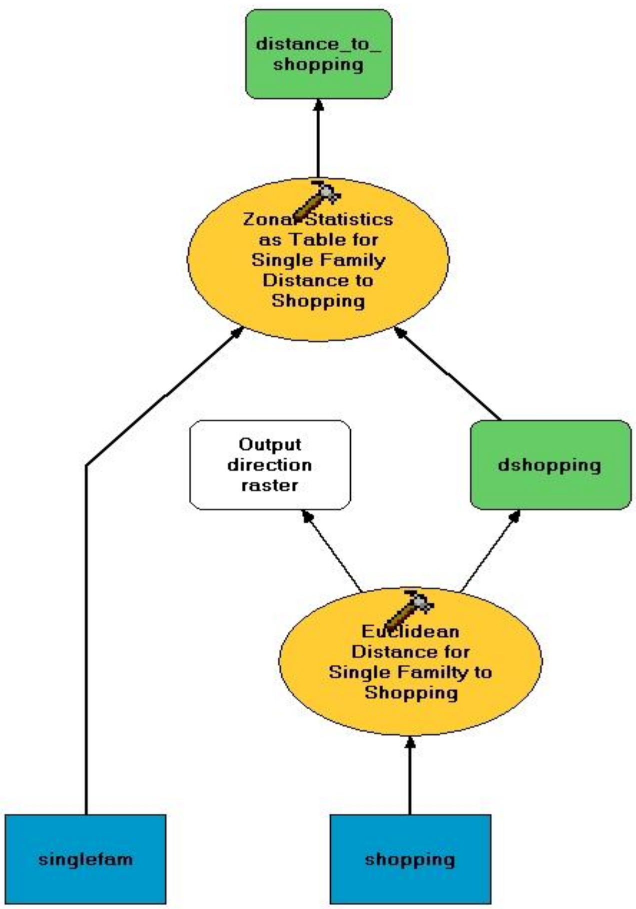


Figure 6-2. LUCIS model illustrating the economic suitability of single family residential land use to retail and shopping opportunities

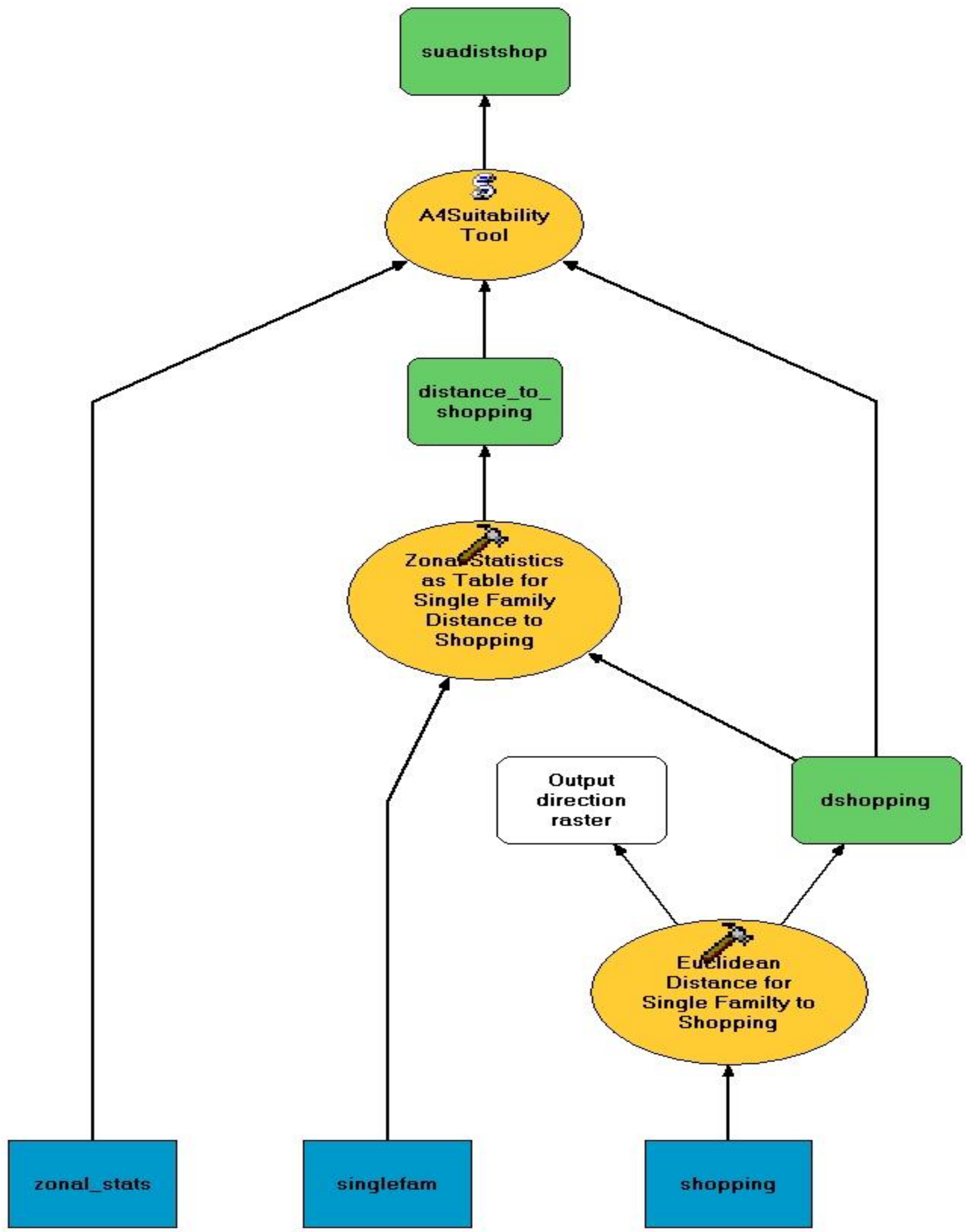


Figure 6-3. Integration of the A4 Suitability tool in a LUCIS model

Rowid	VALUE	COUNT	AREA	MIN	MAX	RANGE	MEAN	STD	SUM
1	1	340752	327462660	0	452824.5	452824.5	48434.613	91164.938	16504191000

Record: 1 Show: All Selected Records (0 out of 1 Selected)

Figure 6-4. Sample zonal statistics attribute table

Rowid	FROM1	TO	OUT	MAPPING
1	0	48434.613281	9	ValueToValue
2	48434.613281	71225.847656	8	ValueToValue
3	71225.847656	94017.082031	7	ValueToValue
4	94017.082031	116808.316406	6	ValueToValue
5	116808.316406	139599.550781	5	ValueToValue
6	139599.550781	162390.785156	4	ValueToValue
7	162390.785156	185182.019531	3	ValueToValue
8	185182.019531	207973.253906	2	ValueToValue
9	207973.253906	10000000	1	ValueToValue

Record: 1 Show: All Selected

Figure 6-5. Output table of A4 Suitability tool

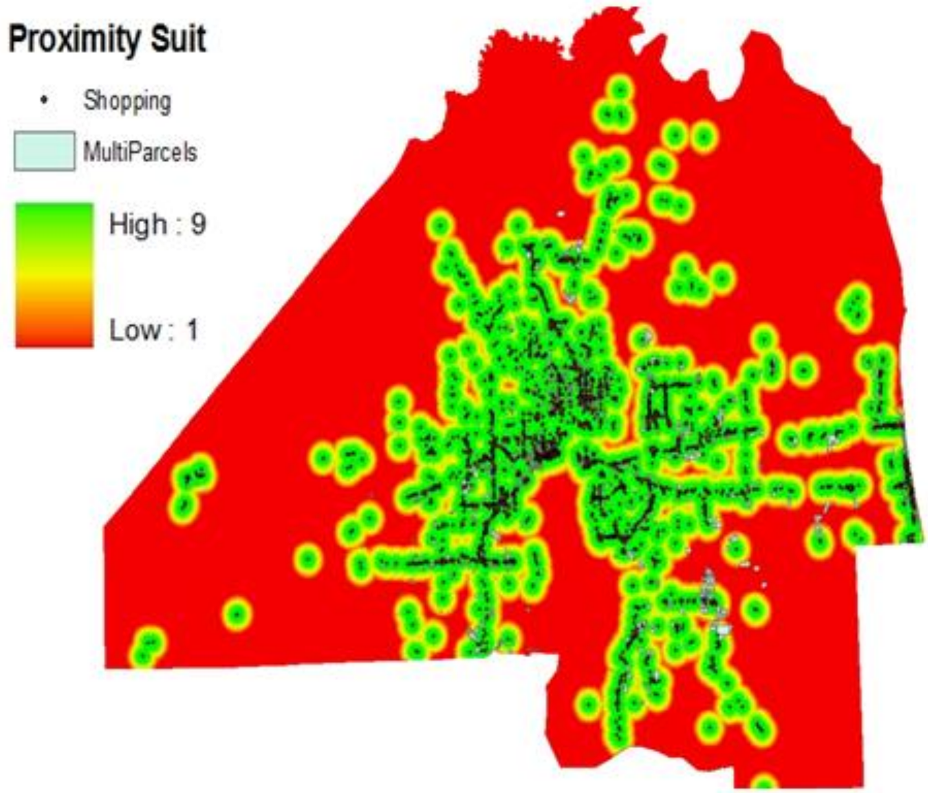


Figure 6-6. Proximity to shopping centers in Duval County reclassified according to the average and standard deviation of the distance to multifamily residential parcels

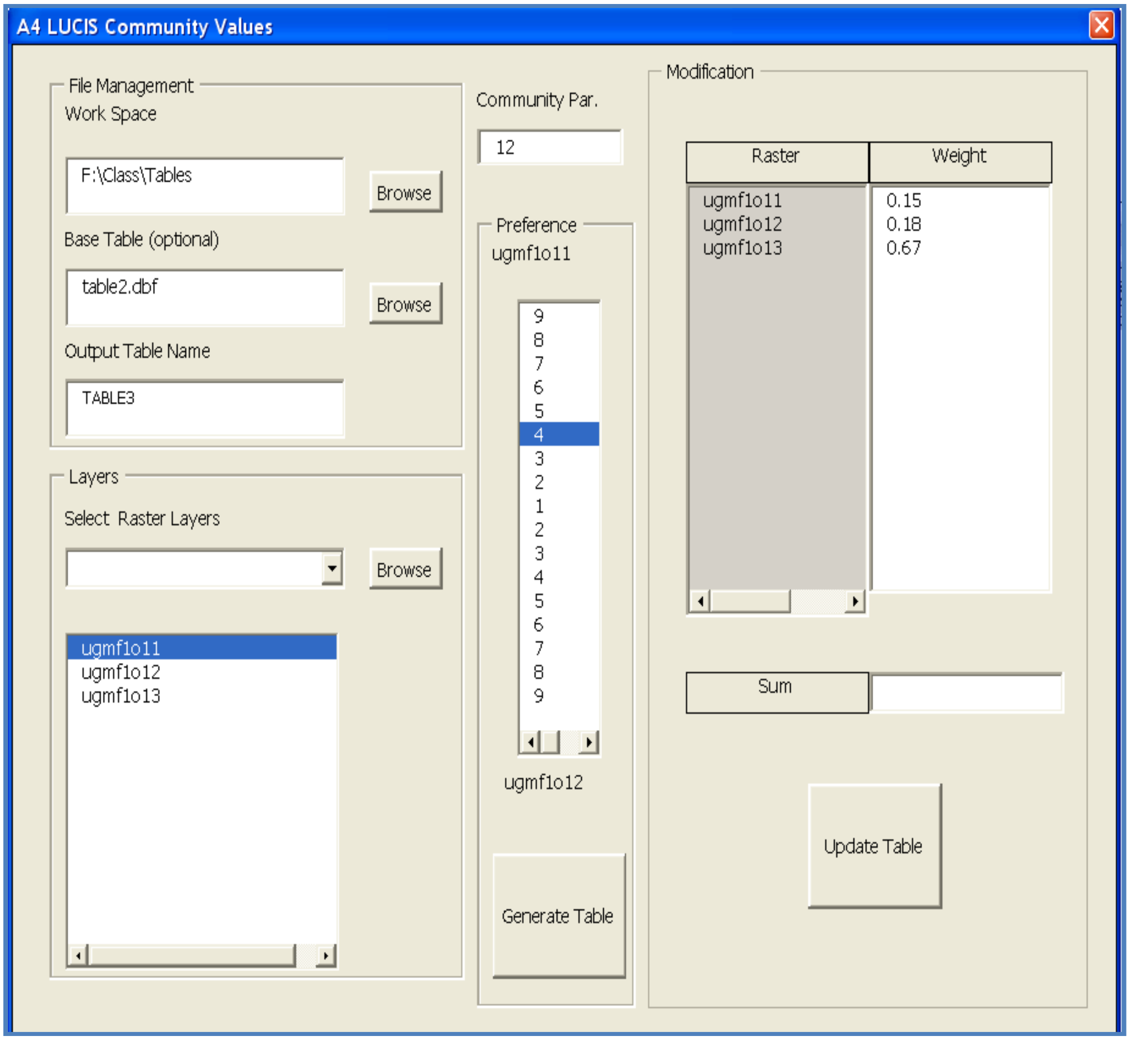


Figure 6-7. The interface of the A4 Community Values program

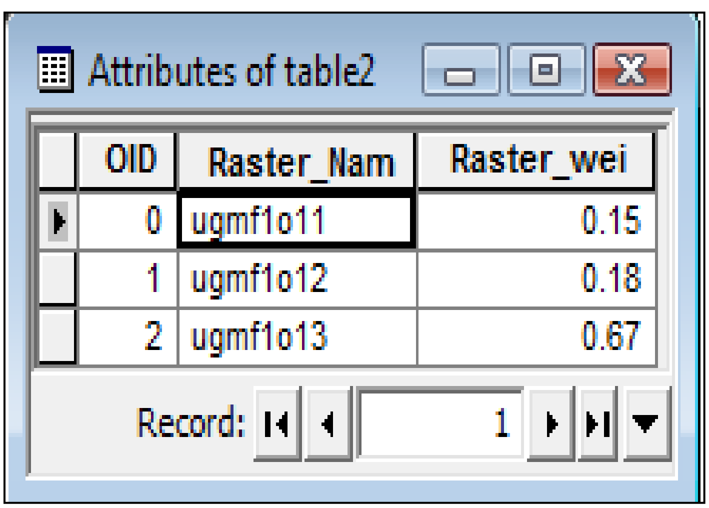


Figure 6-8. Output weights table

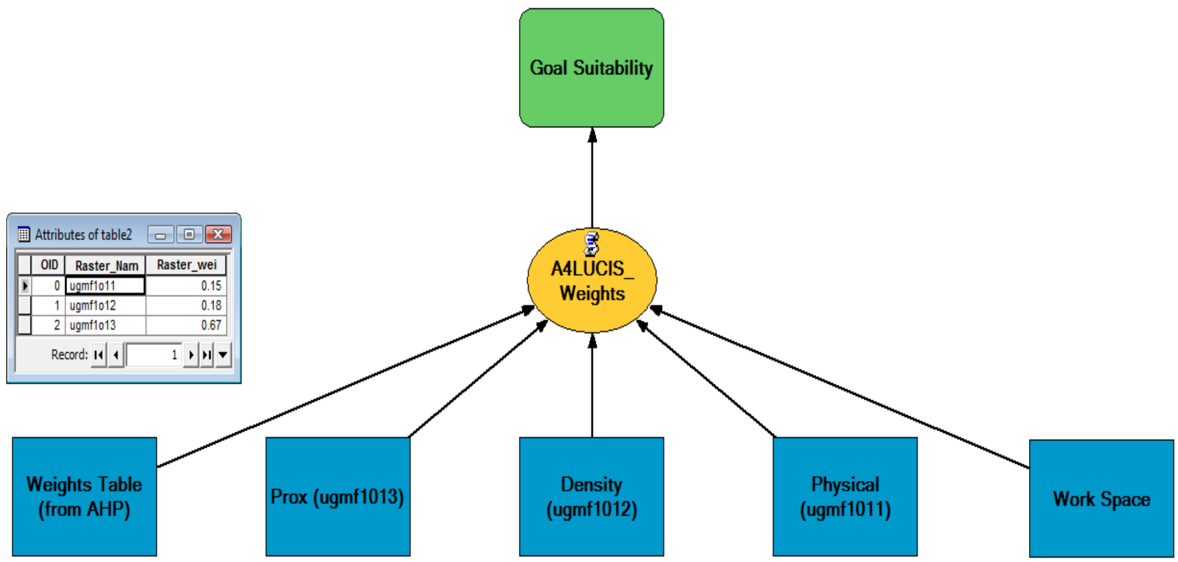


Figure 6-9. The A4 Weighting tool

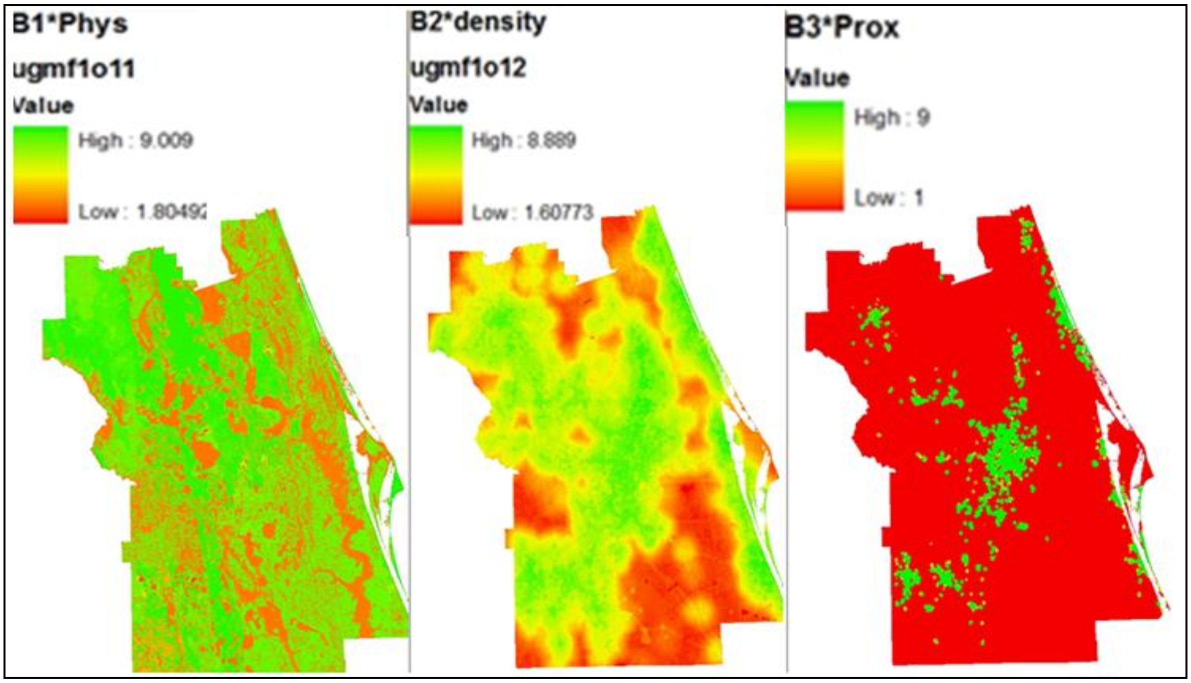


Figure 6-10. Input layers for the Weighing Tool

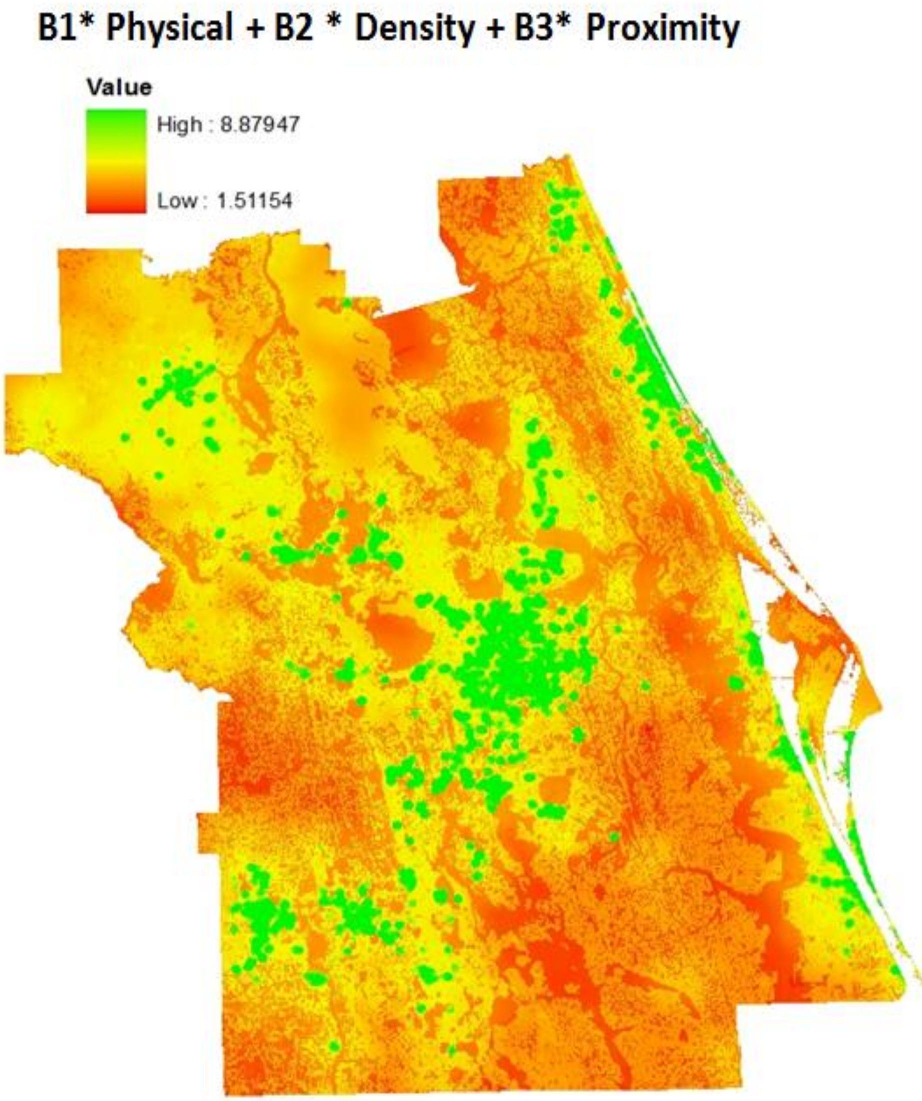


Figure 6-11. Output layer from the Weighing Tool

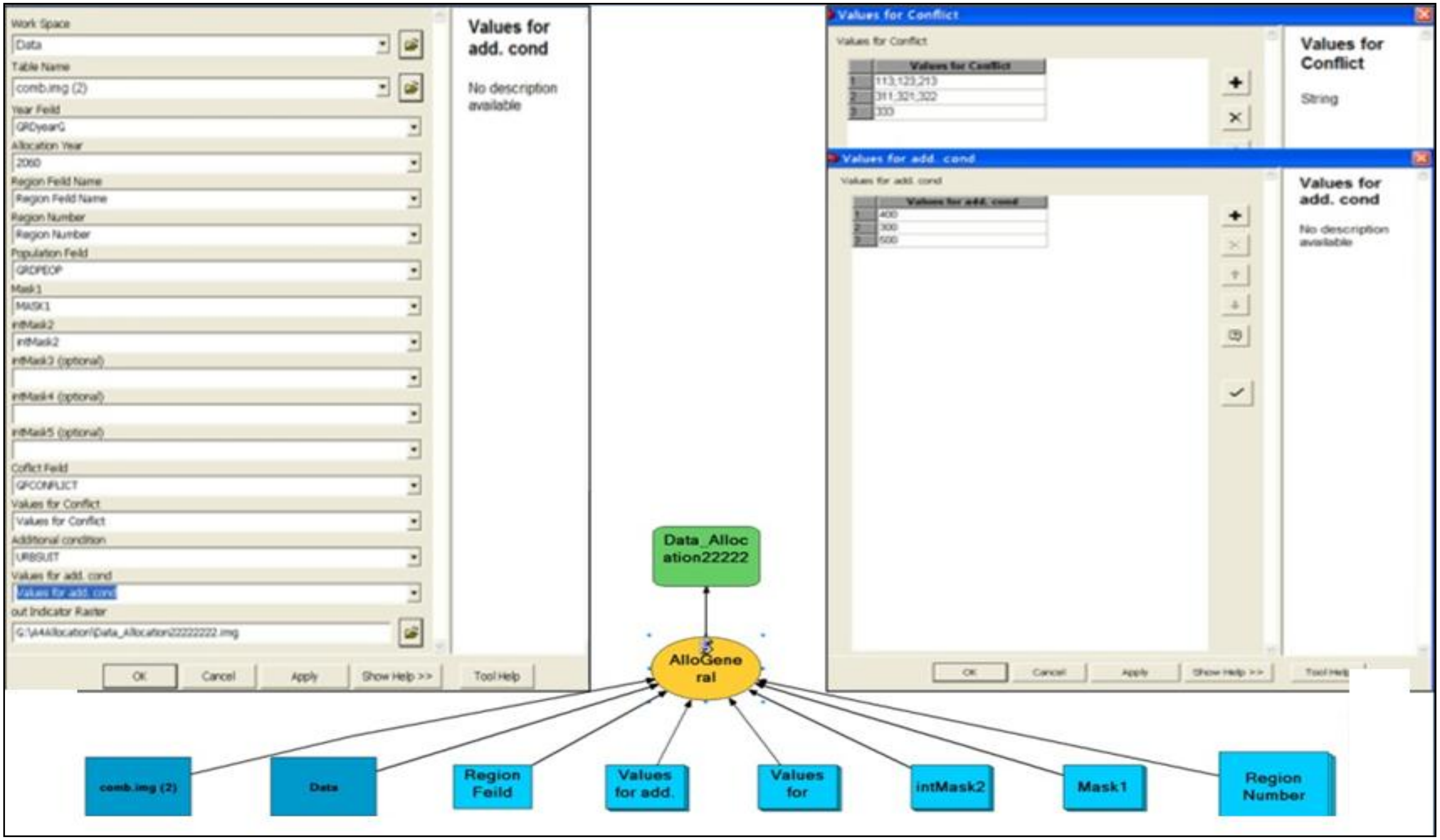


Figure 6-12. Trend Allocation tool

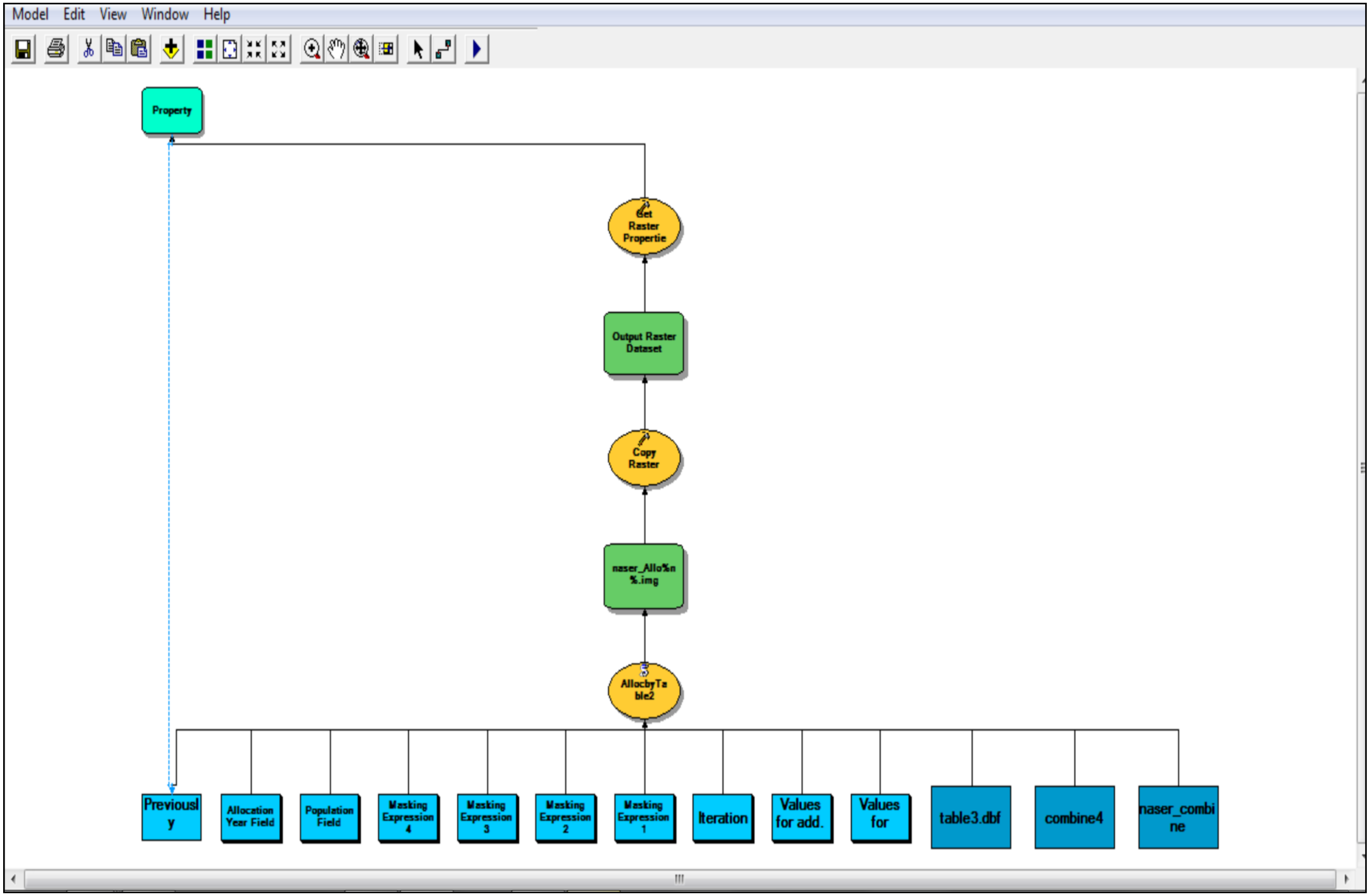


Figure 6-13. Planning by Table tool

Attributes of table7

OID	Type	CONF	MASK1	MASK2	MASK3	MASK4
0	Multi-Family Transit Redev	464;465;564;565	"CITY" > 0	"TRANACCESS" > 50	"LUMIX" >= 3	"LUMIX" >= 3
1	Mixed Use Transit Redev Commercial Multi-Family	664;665;554	"CITY" > 0	"TRANACCESS" > 50	"LUMIX" >= 5	"LUMIX" >= 5
2	Mixed Use Transit Redev Retail Multi-Family	466;566;455	"CITY" > 0	"TRANACCESS" > 50	"LUMIX" >= 5	"LUMIX" >= 5
3	Mixed Use Transit Redev	666;555	"CITY" > 0	"TRANACCESS" > 50	"LUMIX" >= 5	"LUMIX" >= 5
4	Multi-Family Redev	464;465;565;564	"CITY" > 0	"TRANACCESS" >= 0	"LUMIX" >= 3	"LUMIX" >= 3
5	Mixed Use Redev Commercial Multi-Family	664;665;554	"CITY" > 0	"TRANACCESS" >= 0	"LUMIX" >= 5	"LUMIX" >= 5
6	Mixed Use Redev Retai Multi-Family	466;566;455	"CITY" > 0	"TRANACCESS" >= 0	"LUMIX" >= 5	"LUMIX" >= 5
7	Mixed Use Redev	464;465;565;564	"CITY" > 0	"TRANACCESS" >= 0	"LUMIX" >= 5	"LUMIX" >= 5
8	Infill Residential	113;213;123;223;112	("MASK" = 1 AND "CITY" >= 0)	"DRI" > 0	"LUMIX" <= 9	"LUMIX" <= 9
9	Infill Residential	113;213;123;223;112	("MASK" = 1 AND "CITY" >= 0)	"DRI" >= 0	"LUMIX" <= 9	"LUMIX" <= 9
10	Green Fields Residential	113;213;123;223;112;313;323;311	"CITY" = 0	"DRI" >= 0	"LUMIX" <= 9	"LUMIX" <= 9

Record: 1 Show: All Selected Records (0 out of 11 Selected) Options

Figure 6-14. Planning table

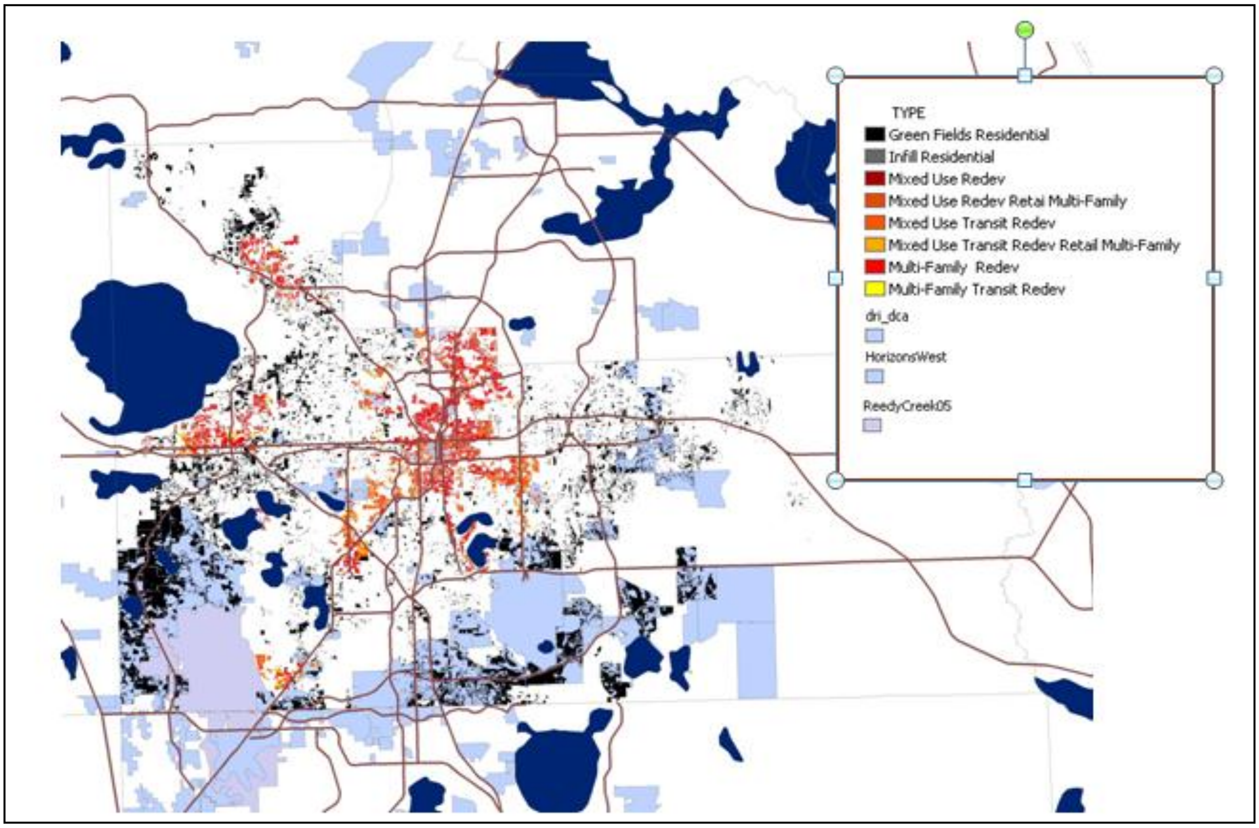


Figure 6-15. Population allocation map for Orange County transit scenario

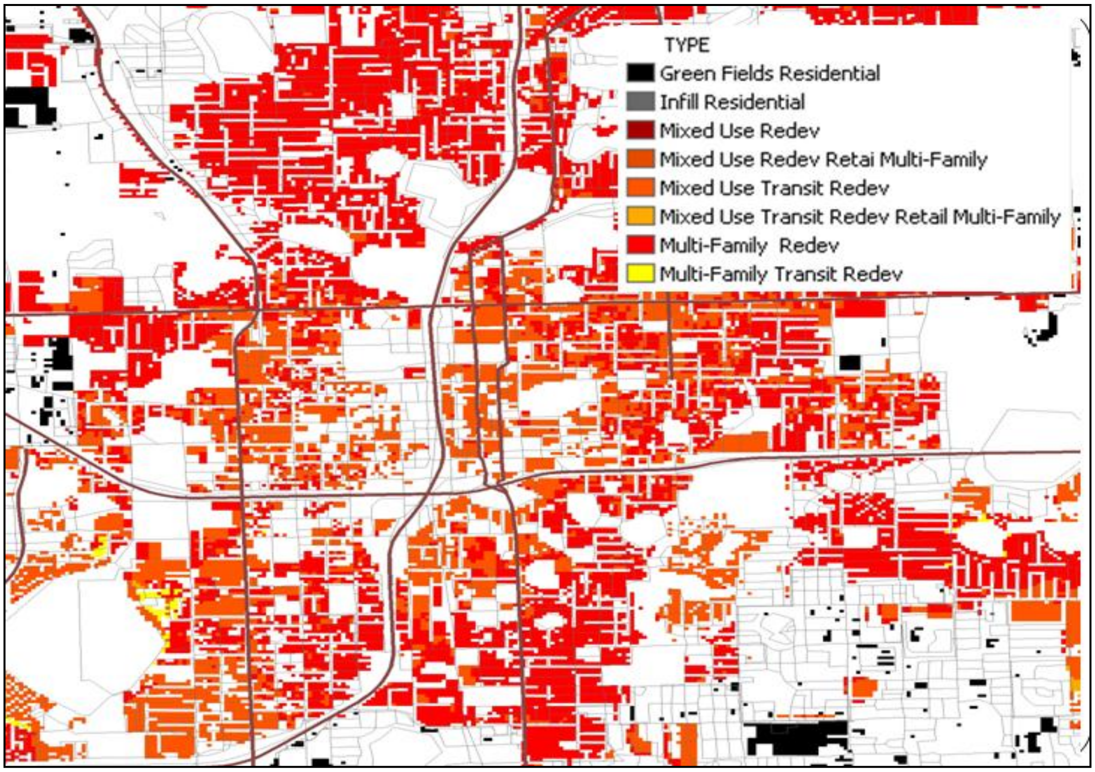


Figure 6-16. Population allocation around transit stops

Attributes of Statistics_blkgrp

OID	BLKGRP	TYPE	FREQUENCY	SUM_GFPOP	SUM_REDPOP	SUM_ACRES	totpop
0	463	Green Fields Residential	17	138	0	11.393616	138
1	464	Green Fields Residential	58	289	0	53.882309	289
2	465	Green Fields Residential	29	107	0	14.716754	107
3	465	Infill Residential	1	2	0	0.237367	2
4	466	Green Fields Residential	30	688	0	71.447467	688
5	467	Green Fields Residential	71	3346	0	303.355026	3346
6	468	Green Fields Residential	84	2320	0	173.040543	2320
7	469	Green Fields Residential	82	2257	0	136.011291	2257
8	469	Infill Residential	4	20	0	0.949468	20
9	470	Green Fields Residential	147	28437	0	2429.451245	28437
10	470	Infill Residential	2	86	0	8.545212	86
11	471	Green Fields Residential	51	703	0	65.988026	703
12	471	Infill Residential	1	2	0	0.237367	2
13	472	Green Fields Residential	4	94	0	18.98936	94
14	473	Green Fields Residential	6	74	0	5.934175	74
15	474	Green Fields Residential	38	185	0	20.413562	185
16	474	Mixed Use Transit Redev	4	0	8	0.949468	8
17	474	Multi-Family Redev	8	0	58	6.171542	58
18	475	Green Fields Residential	1	1	0	0.237367	1
19	476	Green Fields Residential	23	132	0	11.393616	132
20	478	Green Fields Residential	23	4582	0	437.704748	4582
21	478	Infill Residential	1	19	0	1.661569	19
22	479	Green Fields Residential	7	47	0	3.560505	47
23	479	Mixed Use Transit Redev	6	0	48	4.035239	48
24	480	Mixed Use Transit Redev	16	0	636	59.816484	636
25	480	Multi-Family Redev	1	0	3	0.237367	3
26	481	Green Fields Residential	49	935	0	93.285231	935
27	482	Mixed Use Transit Redev	24	0	986	91.861029	986
28	482	Mixed Use Transit Redev Retail Multi-Family	6	0	216	19.938828	216
29	482	Multi-Family Redev	3	0	69	6.408909	69
30	483	Mixed Use Transit Redev	52	0	2115	185.858361	2115
31	483	Mixed Use Transit Redev Retail Multi-Family	7	0	91	7.595744	91
32	483	Multi-Family Redev	2	0	55	5.696808	55

Record: 0 Show: All Selected Records (0 out of 803 Selected) Options

Figure 6-17. Summarizing results to block groups

Attributes of Statistics_landuse

OID	TYPE	FREQUENCY	SUM_GFPOP	SUM_REDPOP	SUM_ACRES
0	Green Fields Residential	8202	390581	0	46217.965937
1	Infill Residential	86	1540	0	203.898253
2	Mixed Use Redev	3	0	43	8.782579
3	Mixed Use Redev Retai Multi-Family	2	0	86	17.090424
4	Mixed Use Transit Redev	2649	0	72330	7611.172855
5	Mixed Use Transit Redev Retail Multi-Family	255	0	4262	554.251945
6	Multi-Family Redev	3753	0	112528	12057.056765
7	Multi-Family Transit Redev	225	0	3435	331.364332

Record: 0 Show: All Selected Records (0 out of 8 Selected) Options

Figure 6-18. Summarizing results to land use

CHAPTER 7
AFFORDABLE HOUSING ALLOCATION

Generating the Affordable Housing Opportunity Surface

The affordable housing opportunity surface is composed of four goals. The first goal is to evaluate suitability of land parcels for affordable housing based on physical and neighborhood characteristics using the LUCIS suitability (Carr & Zwick, 2007). The second goal is to evaluate travel cost in terms of it is burden on low income population. The third goal is to evaluate household rent and it is burden on low income populations. The last goal is to evaluate land parcels in terms of their transit accessibility. This opportunity surface represents a combination of these goals. Taking into account that the general objective is to allocate suitable land for affordable housing, the preference for affordable housing is set as high if the suitability of the first goal, which is based on physical and neighborhood characteristics, is high. When the cost of travel is low the travel cost preference, i.e. the second goal, is set as high. The same is applied to the third goal, household rent, where the preference is set to high when the rent is low. The fourth goal preference is set to high where the transit accessibility is high. The opportunity surface is thus a preference matrix that is a combination of the objectives using LUCIS conflict strategies (Carr & Zwick, 2007).

LUCIS methods are used to evaluate the opportunity of a location for affordable housing. For example, a combination of low travel cost and low rent associated with good physical and neighborhood characteristics could be identified as affordable and at the same time another location of higher travel cost and high transit accessibility could be regarded also as affordable. The use of the conflict strategies adds flexibility to the location choice of affordable housing without the tradeoff between goals that is usually performed in suitability models.

Physical and Neighborhood Characteristic Preference Surface

One of the goals of the AHS model is to generate suitability according to physical and neighborhood characteristic and then find suitable locations for allocating residential housing in general (Figure 7-1). The structure of the suitability model contains many SUA and MUA surfaces that are weighted according to community preferences. During the AHS project execution, many webinars were held that included planners from the case study areas, which were Duval, Orange and Pinellas counties. These webinars had two aims; firstly to include the local planners in the weighting process of the suitability model; and secondly to generate weights that were then used to update the model table of weights and to generate the final AHS suitability surface. Figure 7-1 shows an example of an AHS Goal 1 surface for Duval County. The output surface of the affordable housing Goal 1 is reclassified based on the mean and standard deviations to three preferences high, medium and low (Figure 7-2). The high preference areas are mainly areas those that are preferred for residential development based on parcel and neighborhood characteristics as well as parcel accessibility to services. Many of these places, however, may not be affordable for very low income families.

Rent Preference Surface

The updated 2009 Census Mortgage and Rental data taken from the Shimberg Center for Affordable Housing at the University of Florida is used to create surfaces that represent rent, mortgage or a weighted combination of both rent and mortgage to obtain the housing cost. In the case of very low income populations that are investigated in the affordable housing scenario, however, rent alone is used to create the housing cost preference surface. This surface is a spatial model representing housing rent prices across all of the individual counties, reclassified according to the threshold used in affordable housing research. According to HUD (2011a), the affordability threshold is 30% of VLI, which is approximately 50% of the AMI. The housing cost preference surface is created directly from the rent surfaces by reclassifying the rent burden values. High preference is assigned to areas where the rent is lower that 30% of the VLI. Moderate preference is assigned to areas that have rent lower than 40% of VLI. Areas with a rent burden of more than 40% VLI are considered low preference surfaces. Figure 7-3 shows the rent surface for Orange County and Figure 7-4 shows the rent preference surface obtained by reclassifying the rent surface.

Travel Cost Preference Surface

The travel cost surfaces were created, as explained in Chapter 4, by either spatial interpolation or regression using urban form and land use characteristics taken from the 5Ds research (Ewing & Cervero,2001; Ewing et al., 2008; Lee & Cervero, 2007). However, these surfaces are transformed to monthly values to match the rent surface which is estimated based on monthly rent burden (Figure 7-5). The travel cost surface is also reclassified according to transportation cost thresholds used for affordable housing research. CNT (2011) used the combined percentage of 45% as the combined transportation and housing burden out of income. This means that the transportation cost should be less than 15% of income with regard to location affordability. Therefore, the travel cost surface is reclassified to give a high preference for areas of transportation cost that do not exceed 15% of VLI. The second preference of 25% VLI is used to decide the moderate preference. Any location of transportation cost more than

25% VLI is considered to be a low preference location. Figure 7-5 shows an example travel cost surface for Duval County and Figure 7-6 shows the travel cost preference surface for that county using the mentioned threshold values.

Transit Access Preference Surface

The transit access methodology explained in Chapter 3 is used to create transit access surfaces for the three counties based on the actual transit stop-route-frequency combination in addition to the parcel data from which the employment opportunities were derived. The estimated transit accessibility scores for residential parcels are reclassified to create the transit access surface based on the mean and standard deviations obtained from the zonal statistics for residential parcels (Figure 7-7). The suitability surface for transit accessibility is then reclassified using the mean and standard deviations into three preferences that are high medium and low (Figure 7-8). Figure 7-7 shows an example transit access surface for Pinellas County while Figure 7-8 shows the preference surface obtained from the transit access surfaces for the same county.

Access-Rent-Driving-Transit Opportunity Surface (ARDT)

The four preference surfaces are combined in a conflict surface using LUCIS conflict strategies (Carr & Zwick, 2007). The first surface is the preference based on physical characteristics and neighborhood accessibility, and relates to the letter A in the ARDT opportunity surface. The second surface is the rent preference, and corresponds to the letter R. The third is the driving travel cost, D, and the final surface is the transit access, T. The LUCIS methodology as applied in this research deals with conflict between these four components, accessibility, rent, driving cost and transit access. This research investigates the opportunity by having the components preference combination as an opportunity for affordable housing. The generated ARDT opportunity surface is shown by Figures 7-9, 7-10 and 7-11, which correspond to Orange, Duval and Pinellas counties respectively. The opportunity surfaces can identify areas that have high preferences in location and transportation cost and also identifies places that may not have low driving cost but have alternative transportation options like high transit accessibility.

Refined ARDT Opportunity Surface

In the case of affordable housing, the opportunity surface is easier to understand compared with the conflict surface. The opportunity components A, R, D and T have the same preference direction when investigating affordable housing opportunity. Having the number 3333 in the opportunity surface means that the location is highly preferred for affordable housing based on the evaluation of the four A, R, D and T components. The first digit refer to location and indicates in this example that the location is highly preferable in terms of physical characteristics and neighborhood accessibility to services. The second digit indicates that the location is highly preferred for affordable housing based on rent values. The third digit shows that the location is highly preferred for affordable housing based on driving cost, and the fourth digit shows that the location is highly preferred for affordable housing based on transit accessibility. A digit of 2 in the combination indicates that a location has a moderate preference in the component that corresponds with the 2 digit. For example, 3223 indicates moderate preference based on the rent value and also based on the driving cost. A digit of 1 in the combination shows a low preference in the corresponding component. However, for affordable housing allocation values 2 and 3 are considered places of opportunity while a value of 1 in any of the categories collapses the opportunity for affordable housing. High or moderate transit accessibility does not trade off the need for good neighborhood characteristics. Therefore, for affordable housing scenarios, the opportunity surface can be refined by masking out locations that have low preference in one of the four components. Respectively, the Figures 7-12 through 7-14 show the refined opportunity surface for Duval, Orange and Pinellas counties. All of these surfaces have moderate and high preferences and do not contain the low preference categories.

Impact of Travel Cost and Transit Accessibility on Affordable Housing Opportunity

The ARDT opportunity surface is combined from preferences of the affordable housing preference components based on physical and neighborhood characteristics, rent burden, travel cost and transit accessibility. Another opportunity surface can be generated from the affordable housing preference based on the physical and neighborhood characteristics (A) and rent burden (R) without taking into account the driving cost or the transit accessibility (the AR opportunity surface). Respectively, the Figures 7-15 through 7-17 show the AR opportunity surfaces for Duval, Orange and Pinellas counties. A comparison between locations that is preferred for affordable housing based on the two opportunity surfaces has been conducted. The first comparison is performed by mapping the areas in each opportunity combination. To do that the ARDT categories are collapsed and summarized into AR categories (Table 7-1). The ARDT surface is then reclassified using the collapsed category. The result is two surfaces that have the same opportunity combination. However, these surfaces are different because one of them includes the goals of travel cost and transit accessibility.

The total number of opportunity acres in each surface had been compared. Table 7-2 shows that in Duval County, the total number of preferred acres for affordable housing is reduced by 76.7% if we include the transit accessibility and travel cost. Many of the preferred locations based on the AR opportunity surface are less preferred or even not suitable when travel cost and transit accessibility are included in the ARDT surface. However, this percentage is varied among different categories as we can see that the impact of travel cost and transit accessibility is lower for the most preferred land depending on physical characteristics and neighborhood accessibility such as 33 and 32. This is because these areas have good proximity to neighborhood amenities such as shopping centers which in turn reduces travel cost and eventually results in many of these places already have good transit access. The same result is obtained for Orange County. However, the impact of travel cost and transit access is much stronger in Orange County (Table 7-2) where the preferred land for affordable housing is reduced by 89.5% due to incorporating transit accessibility and travel cost. Pinellas County has the least impact of the three counties, where including travel cost and transit access decreases the preferred land for affordable housing by only 59.2%.

Metrics that are derived from conceptualizing the sprawl and compact development research (Galster et al., 2001; Ewing & Cervero, 2001) have been used to compare the two surfaces. Distance to CBD's is compared between AR and ARDT (Table 7-3). The distance to CBD is also one of the metrics derived from conceptualizing sprawl that captures the centrality of the allocations. The results show that including transit access and travel cost reduces the distance to CBD. This means that the ARDT opportunity surface produces a more central allocation of affordable housing than does the AR opportunity surface, which results more sprawl. However, the degree of change in centrality is different among the three counties. Table 7-3 shows the impact of transportation cost and transit access on centrality is the highest in Orange County and the lowest in Pinellas County. This matches the result of surrounding density as will be shown later and is a sign that the impact of transportation and transit access is indicative of a more compact development pattern that has access to the high employment densities. Furthermore, the impact of travel cost and transit access is lower in the high suitability areas depending on proximity, such as 33 and 32.

The distance to activity center agglomerations is compared between AR and ARDT surfaces (Table 7-4). This is a metric that also captures the poly-nuclear pattern of development and can be used as a metric for sprawl conceptualization and/or compact development patterns. The mean distance to activity centers is also lower in the ARDT surface which also indicates that the allocation of affordable housing using ARDT is less sprawling and tends to be a more compact development pattern.

Density is tested on the areas surrounding locations identified in the opportunity surface as being suitable for affordable housing, using a walking distance neighborhood of 0.5 miles. A compact development trend should, in theory, increase the surrounding density. The effect of existing density depends on how many green-field, low density parcels are in the surrounding neighborhood and theoretically should have the effect of increasing density, indicating the tendency toward compact development (Table 7-5). The results of surrounding density show that in general the preferred lands have higher surrounding densities if we take transit access and travel cost into account. The result also shows that the change in the mean density is the highest in Orange County and the lowest in Pinellas County which again matches the same result taken from the allocated acres. The result also shows that the least change in the mean density occurs for the preferred categories based on physical and neighborhood characteristics, which indicates that the areas that have good proximity to amenities usually have higher densities.

Surrounding land-use mix, represented in entropy values, is also compared between AR and ARDT surfaces. The results in the Table 7-6 show that the ARDT surface has larger land use mix values than the AR surface. Land use mix and density have been used in the literature for land use-transportation coordination and Transit Oriented Development TOD, as shown in the literature review. The impact of land use mix and density have been proved by different research to lower VMT and increase transportation options other than driving (Ewing & Cervero, 2001; Ewing et al., 2008; Lee & Cervero, 2007). From the result in Table 7-6 we can conclude that the ARDT leads to less travel miles and more use of transportation options, which also corresponds with the compact development literature. Tables 7-7 through 7- 9 summarize the comparison results for the three counties and shows the mean and standard deviation for all the tests performed to compare the AR and the ARDT tests. The tables also compare the AR, ARDT surfaces to the Assisted Housing Inventory (AHI). The AHI is 2009 data is taken from FGDL. The results show that comparing AR and ARDT surfaces to the AHI in terms of density, land use mix, distance to CBD and distance to activities suggests that the ARDT surface is more comparable to AHI than the AR surface. However, the results show that in many instances, the model gives less distances to CBD and activity centers when compared to the AHI data. The results also show that transit access and travel cost impact the allocation of affordable housing and that including these transportation variables results in a more compact development pattern.

The use of ARDT surfaces may have some political issues. The refined ARDT surface identifies the opportunity for low and moderate driving cost. This surface also identifies high to moderate transit accessibility. This suggests that both driving cost and transit accessibility are important for the affordable housing allocation. Historically, housing affordability was connected to the driving cost and not transit in what is known as “drive till you qualify”. Figure 7-19 shows the ARD surface where neighborhood accessibility and physical characteristics corresponds to the letter A, rent preference corresponds to the letter R, and travel cost preference corresponds to the letter D .This surface includes the low and moderate travel cost and does not contain the transit accessibility. Figure 7-18 shows locations that are suitable for affordable housing and does not have any transit accessibility. People living in these areas depend on cars for commuting to work as well as other household trips. Figure 7-19 shows the ART surface where neighborhood accessibility and physical characteristics corresponds to the letter A, rent preference corresponds to the letter R, and transit accessibility preference corresponds to the letter T. This surface includes high and moderate transit accessibility but does not include driving cost. In the ART surface, all of the affordable housing sites are within a walking distance from transit stops. However, because the driving cost is not included, the allocation of places that have high transit accessibility and high driving cost is expected. The allocation of these places assumes that people are using transit in their daily commute.

The ARDT surface has both transit accessibility and driving cost in an opportunity surface which suggests that people have the opportunity to decide on the transportation mode they want to use. The traveler may consider using transit if it is more affordable for the work commute. However, the traveler may also prefer to use the driving mode in situations such as where trip chaining is required or driving is more affordable. The aforementioned comparison between ARD and ART surfaces suggests the importance of both driving cost and transit accessibility in the opportunity surface. Therefore, using the ARDT surface is better than using the ARD or ART surface for allocating affordable housing. The allocation of affordable housing using the ARDT surface has also more steps and includes the use of more variables and constraints other than the transit access and travel cost. The process of allocation of affordable housing is performed using the allocation scenarios and will be explained in the next section.

Affordable Housing Allocation

The results in the aforementioned sections suggest that the travel cost and transit accessibility have an impact on the affordable housing opportunity surface. Therefore, this research uses the ARDT opportunity surface for the allocation process for affordable housing. The ARDT opportunity surface includes the land that is moderately or highly preferred for affordable housing based on the four goals that generate the opportunity surface. However, more conditions are needed in the selection of land for affordable housing. These additional conditions may address a certain policy or priorities based on a certain scenario.

An affordable housing final preference score can be assigned using the allocation tools created for the allocation of land and people in land used models such as LUCIS. Acres for affordable housing are used as the allocation field using the A4 Allocation tools presented in Chapter 5. This allocation process is based on iterations. The first iteration targets locations with the highest preference while the last iteration the lowest preference. Parcels and locations that do not meet the criteria set in the conditions are left unranked which means that their preference is lower than the lowest preference in the ranking ladder. However, these unranked parcels are still suitable for affordable housing but they did not satisfy the ranking conditions used in the specified scenario.

The allocation tools work on a combine grid. The combine grid is composed of several grids that represent the opportunity surface as well other grids that can work on refining the places for affordable housing or adding restrictions or constraints on the process. The grids can also represent a change in policy that need to be tested such as new transit lines. The scenario set in the research mainly investigates the opportunity for allocating affordable housing based on the ARDT and additional compact development constraints. The scenario looks at livability indicators such as walkabilty and refines these places according to their density and other variables that are important for compact development. Here, the scenario will target areas that are underutilized when compared to their surroundings. Other variables such as Enterprise Zones, Qualified Census Tracts and places qualified for Community Reinvestment Act funding (CRA) can be used in the allocation process. The scenario in this research, however, focuses on compact development and reducing travel cost and does not address areas of distress or other policy incentive areas.

The compact development scenario may differ from one county to another depending on the availability of data. For example, the livability index includes walkabilty and crime for Orange County while no data for walkability exists for Duval or

Pinellas counties. The following section will explain the grids used for allocation in addition to the ARDT opportunity grid.

Creating the Combine Grid for the Allocation

The combine grid tool (ESRI, 2011) is used to create the base combine grid for each county. The combine grid basically is a grid enumeration tool that can hold multiple grid values for each cell. The grids that are used to create the combine may be different from one scenario to another and will also depend on the political region and boundary. This research used a standardized format for the layers included in the grid. Tables 7-10 through 7-12 show the allocation scenario conditions for Duval, Orange and Pinellas counties. Differences in the grid used for allocation may occur only on the livability grid which will be a walkability-bikability grid for Orange County and a crime density suitability surface for Duval and Pinellas counties. The generated raster will have no significant meaning for the value field. However every grid in the combine is represented as a field in the attribute table for that combine (Figure 7-20). The following sections will explain the grids used in the combine grid in addition to the ARDT opportunity grid.

Underutilized density grid

The underutilized value for land in this research is a number that compares the cell density for a location to the surrounding area density in residential units. The surrounding neighborhood is taken as a quarter mile Manhattan distance that surrounds each cell. The underutilized density is the defined as the number of residential units that could be added to the cell to match its average surrounding density value. Cells that have a density value more than its surrounding neighborhood is assigned as a zero underutilized density. The importance of this surface is to capture the parcels that might be preferable for redevelopment. Figure 7-21 shows an example underutilized density surface for Duval County.

Livability grids

The livability term here is a general term for a category of grids that represent walkability and safety. This grid, however, may be different from one county to another depending on the availability of data. The grid is a utility assignment grid. Therefore it could contain one grid as a single utility assignment, such as a crime avoidance suitability grid (an SUA), and it may contain another grid to estimate a walkability or a bikability MUAs. The crime suitability assignment uses the local crime incidents for the year 2006 in a kernel density estimation (ESRI, 2011) using a 0.25 mile radius which is the walking distance to create a crime density raster. The raster is then transformed to a suitability surface based on the mean and standard deviation values for the residential parcel zonal values. The reclassification uses a decreasing suitability reclassification using the A4 Suitability tool. The walkability and bikability surfaces are a multiple utility surface that incorporates other walkability and bikability indicators such as sidewalks, bike lanes, transit stops and crime densities within the walking and biking distances to generate a multiple utility assignment (Figure 7-22).

Land characteristics

The land characteristics are any parcel characteristics grids that are important in the allocation of affordable housing. For example, a reasonable step is to allocate into vacant parcels, which is regarded as an infill process (Figure 7-23). However, not all of the allocations are looking for vacant parcels. There are also parcels that are good for redevelopment and may have a priority in the allocation process based on the conditions set in the scenario. Therefore other parcel variables are also used in the allocation. This includes land values. Land values are based on the Just Value per acre calculated from county property appraisal data for the year 2009. The grid is generated after cleaning the data which includes removing outliers. The grid is then reclassified into user defined categories according the price ranges (Figure 7-24).

Proximity grids

The distance to the CBD has been used in studies either as an indication of compact development or as a measure of sprawl. The distance to CBD is a metric of mono-nuclear urban pattern and represents the centrality of the mono-nuclear urban areas (Galster et al., 2001). However, the distance to CBD will not work independently and lead to compact development. It should be combined with a density or concentration and other compact development variables for that purpose. In this research a distance to CBD raster is generated for the allocation of affordable housing in the compact development scenario. The surface is generated by getting the central district feature data sets from the FGDL and finding the central feature of that dataset. The distance to CBD is mainly the distance to that central feature. The raster is a Euclidean distance raster that is reclassified into equal intervals of two miles and used in the scenario (Figure 7-25). The allocation prioritization depending on this raster is that the scenario will look in the first two miles away from the CBD in the first iteration and then increase the distance by two miles for other iterations in the same conflict/opportunity category.

The other proximity raster used in building the scenario is the distance from activity agglomeration centers. The inclusion of this surface also corresponds with the compact development or the Transit Oriented Development patterns. This also, if combined with clustering or density, leads to a poly-nuclear pattern of development

(Galster et al., 2001). The proximity grid is created by identifying the larger agglomeration of activities as major activities. This is done by the agglomeration of the activity values within a walking distance. By using spatial overlay, the values of the activity square footage are aggregated and the larger values are selected. In this research a value of one million square feet or more is selected as a major activity. The proximity grid is created by taking the Euclidean distance away from these major activity centers and then reclassifying the grid into equal intervals of half miles (Figure 7-26). During the scenario iterations, the allocation prioritization, depending on this grid, is that the scenario will look in the first half mile away from the major activities in the first iteration and then increase the distance by half mile for subsequent iterations in the same conflict/opportunity category.

Policy grids

The policy grids are prepared to test a certain policy in the scenario. For example, testing a proposed bus route on the allocation will include preparing a new transit access surface and use it as a policy grid. In this research, incentive zones such Enterprise Zones, Qualified Census Tracts (QCT), and Community Reinvestment Act (CRA) areas are regarded as policy grids. These areas are mainly distressed areas that people will avoid if there are no incentives. The generation of grids for these areas is done by assigning a constant value of one for areas outside the zones and a zero for inside the distressed areas (Figure 7-27). The grids can be used by allocating away from distressed areas in a poverty de-concentration scenario by allocating in the areas that have a value of one or by allocating inside of these areas in a policy incentive scenario.

Zoning grids

Census Tracts and TAZ are grids that are used for summary purposes. This research does not use Census Tracts or TAZs in the allocation of affordable housing in general. However, that does not mean they are not useful in the allocation for certain scenarios. In this research, these zones are used for summary purposes only. The generation of these grids is by transforming the zonal feature data into a raster grid data (Figure 7-28).

Compact Development Scenarios

The compact development scenario is based on using the allocation tools on combine grids. Therefore, a combine grid is generated for each county in the study area, namely, Duval, Orange and Pinellas counties. The combine grid is a raster grid that has a large attribute table showing the values of each of the combine grids for a cell or a group of cells (Figure 7-20). Other than the livability field difference between counties mentioned earlier in this section, the fields used in the combine are the same. These fields include underutilized density, opportunity/ conflict, land values, proximity grids, vacant lands and other zoning grids. The affordable housing allocation model (Figure 7-29) uses the Allocation by Table tool that was explained in Chapter 6. Generally, the scenario table used for the allocation (Table 7-10) is replicated for the three counties. However, the priorities may differ slightly from county to county. The scenario table summarizes the conditions set for the scenario. The first two digits in the ARDT conflict/ opportunity are used to prioritize the process. The zonal statistics table for existing density, distance to CBD, and distance to activity center agglomerations are used to set the general direction of priorities which was 33; 23; 32; 22 for Duval and

Pinellas and 33; 32; 23; 22 for Orange. Tables 7-10 through 7-12 are the scenario tables for Duval, Orange and Pinellas counties respectively.

Using the allocation tool and the scenario table, allocation maps that show the allocation of affordable housing are generated for Duval, Orange, Pinellas counties (Figure 7-30), (Figure 7-31), (Figure 7-32). The maps have the ranking scores of 1 to 16 where one is the most preferred land and 16 is the lowest preferred land. The maps also show a 4 digit opportunity number for the areas that do not meet the ranking criteria in the table. However, the opportunity digit is assigned to these areas in case the planner wants to investigate the opportunity for affordable housing in these areas knowing that these areas are of a lower rank than the ranked areas depending on the scenario table. The maps also show line feature classes for the transit lines which suggests that most of the allocations are in areas that have strong transit opportunity.

The resulting allocations for affordable housing based on the compact development scenario are tabulated according their original land uses (Table 7-13), (Table 7-14) and the acres allocated associated with each land use. Table 7-13 shows the major land uses while Table 7-14 shows the minor land uses. The allocation results show that a large percentage of single family residential areas are qualified for affordable housing in addition to multi-family residential areas and other categories like commercial uses. The single family residential areas are in locations that have high densities in their surrounding neighborhoods and they are close to transit and employment opportunities which make them suitable for affordable housing. For further analysis of affordable housing on a parcel-level, the output of the model can be tabulated to the parcels according to the parcel identification number. The output of the tabulation is then joined back to the parcels and more analysis can be performed on the parcel-level to decide on the final suitability of a specific parcel for affordable housing. Chapter 8 will emphasize the use of parcel analysis for housing affordability as part of the research conclusions and recommendations.

Table 7-1. AR and ARDT equivalent categories

ARDT category	Equivalent AR category
3333	33
3332	33
3323	33
3322	33
3233	32
3232	32
3223	32
3222	32
2333	23
2332	23
2323	23
2322	23
2233	22
2232	22
2223	22
2222	22

Table 7-2. Tabulated total acre in each AR category

Equivalent AR category	Acres in AR	Acres in ARDT
Duval County		
33	31034.73	18681.87
32	26274.20	9145.85
23	78198.31	15017.97
22	64430.14	3861.95
Total	199937.38	46707.64
Orange County		
33	3725.17	1701.46
32	17733.89	4824.88
23	28803.24	1242.20
22	78942.30	5731.06
Total	129204.60	13499.60
Pinellas County		
33	4258.99	2744.18
32	10360.98	4632.06
23	12461.62	5424.25
22	22657.09	7449.38
Total	49738.68	20249.87

Table 7-3. Zonal statistics for distance to CBD

Equivalent AR category	AR Mean Distance	AR STD Distance	ARDT Mean Distance	ARDT STD Distance
Duval County				
33	3.100302	2.578092	2.802506	2.390863
32	7.785642	3.404559	6.849874	3.769736
23	4.959660	3.863394	2.212663	2.656914
22	10.856486	3.369811	7.964609	3.718822
Mean	6.942815		3.832192	
Orange County				
33	2.014736	1.489937	1.359414	1.205063
32	5.121713	3.417311	2.987531	1.834654
23	13.98262	5.341965	3.365938	2.892298
22	10.980860	5.357544	5.299049	2.069534
Mean	10.587320		3.798471	
Pinellas County				
33	2.964458	2.780636	2.321152	1.973747
32	5.303665	2.377305	4.524874	2.106511
23	5.035321	3.275428	3.371814	2.046297
22	5.971839	2.910384	4.665094	1.937563
Mean	5.341206		3.968888	

Table 7-4. Zonal statistics for distance to major activity centers

Equivalent AR category	AR Mean Distance	AR STD Distance	ARDT Mean Distance	ARDT STD Distance
Duval County				
33	2.078394	1.489471	1.950296	1.441228
32	2.862418	2.225353	3.052764	2.623640
23	4.990358	3.604055	2.744263	1.872097
22	3.522871	2.073929	4.653375	2.932191
Mean	3.785822		2.644955	
Orange County				
33	1.511171	0.659610	1.296026	0.673130
32	1.956474	1.358564	1.182909	0.682695
23	8.738854	4.378703	2.047809	0.862708
22	4.761751	4.130088	1.328445	0.878023
Mean	5.169607		1.338536	
Pinellas County				
33	0.840397	0.532670	0.787475	0.501397
32	1.259383	0.731996	1.141977	0.688911
23	1.006272	0.590087	0.991877	0.595499
22	1.305712	0.837280	1.020384	0.588548
Mean	1.181200		1.008991	

Table 7-5. Zonal statistics for density of surrounding

Equivalent AR category	AR Mean Density	AR STD Density	ARDT Mean Density	ARDT STD Density
Duval County				
33	3.2239	2.0765	3.3695	2.2164
32	2.7130	2.0152	2.8720	2.1883
23	1.7555	1.7605	2.6443	1.9207
22	1.2838	1.6493	2.7215	2.3418
mean	1.9573		2.9853	
Orange County				
33	13.2905	17.9955	17.5090	22.9969
32	7.7478	6.7021	10.2031	7.8328
23	3.0430	2.9497	6.4122	2.4358
22	5.4815	7.0586	10.4427	7.6341
mean	5.4741		10.8769	
Pinellas County				
33	3.5393	2.3712	3.6140	2.4247
32	2.5754	1.3452	2.6282	1.3762
23	2.6566	2.0439	3.3789	1.9898
22	2.0865	1.5662	2.3728	1.6562
mean	2.4552		2.8690	

Table 7-6. Zonal statistics for entropy of surrounding

Equivalent AR category	AR Mean Entropy	AR STD Entropy	ARDT Mean Entropy	ARDT STD Entropy
Duval County				
33	0.5282	0.1294	0.5486	0.1229
32	0.4770	0.1450	0.5227	0.1486
23	0.3860	0.1796	0.5090	0.1216
22	0.2558	0.2033	0.4722	0.1586
mean	0.3781		0.5244	
Orange County				
33	0.4412	0.1184	0.4462	0.0987
32	0.3337	0.1781	0.4514	0.1123
23	0.2693	0.1346	0.4663	0.1117
22	0.2616	0.1714	0.4609	0.1180
mean	0.2783		0.4562	
Pinellas County				
33	0.2169	0.0213	0.2196	0.0197
32	0.2137	0.0223	0.2168	0.0199
23	0.2033	0.0314	0.2127	0.0250
22	0.2063	0.0360	0.2157	0.0263
mean	0.2079		0.2157	

Table 7-7. Collective measurements for Duval County

Measurement	Statistic	AR	ARDT	AHI
Acres	Mean	199937.38	46707.64	
Distance to CBD	Mean	6.9428	3.8321	3.9282
	STD	3.4445	2.8562	3.7573
Distance to Major	Mean	3.7858	2.6449	2.5935
Activity centers	STD	2.6016	1.9345	2.4658
Surrounding Entropy	Mean	0.3781	0.5244	0.5362
	STD	0.1749	0.1304	0.1097
Surrounding Density	Mean	1.9572	2.9853	4.3606
	STD	1.8071	2.1262	1.9391

Table 7-8. Collective measurements for Orange County

Measurement	Statistic	AR	ARDT	AHI
Acres	Mean	129204.60	13499.60	
Distance to CBD	Mean	10.5873	3.7984	5.7077
	STD	4.9762	1.9523	3.4198
Distance to Major	Mean	5.1696	1.3385	1.5121
Activity centers	STD	3.7050	0.7809	1.6474
Surrounding Entropy	Mean	0.2783	0.4561	0.4249
	STD	0.1626	0.1129	0.1026
Surrounding Density	Mean	5.4740	10.8768	16.7166
	STD	6.4089	9.1630	12.0403

Table 7-9. Collective measurements for Pinellas County

Measurement	Statistic	AR	ARDT	AHI
Acres	Mean	49738.68	20249.87	
Distance to CBD	Mean	5.3412	3.9689	3.4538
	STD	2.8802	2.0102	2.9329
Distance to Major	Mean	1.1812	1.0090	1.0432
Activity centers	STD	0.7273	0.6016	0.9143
Surrounding Entropy	Mean	0.2079	0.2156	0.2148
	STD	0.0308	0.0236	0.0155
Surrounding Density	Mean	2.4551	2.8689	3.2606
	STD	1.7088	1.7856	1.9697

Table 7-10. Duval scenario table

Conflict	Mask1	Mask2	Mask3	Mask4	Mask5	Region
3333	“ACT_1_TENTH” <= 16	“CBD_1_TENTH” <= 30	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3333	“ACT_1_TENTH” <= 32	“CBD_1_TENTH” <= 60	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3333	“ACT_1_TENTH” <= 48	“CBD_1_TENTH” <= 90	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3333	“ACT_1_TENTH” <= 64	“CBD_1_TENTH” <= 120	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3332;3323;2332; 2323;2322;22 32;2223	“ACT_1_TENTH” <= 16	“CBD_1_TENTH” <= 30	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3332;3323;2332; 2323;2322;22 32;2223	“ACT_1_TENTH” <= 32	“CBD_1_TENTH” <= 60	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3332;3323;2332; 2323;2322;22 32;2223	“ACT_1_TENTH” <= 48	“CBD_1_TENTH” <= 90	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3332;3323;2332; 2323;2322;2232; 2223	“ACT_1_TENTH” <= 64	“CBD_1_TENTH” <= 120	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3322;3232;3223; 3222	“ACT_1_TENTH” <= 16	“CBD_1_TENTH” <= 30	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3322;3232;3223; 3222	“ACT_1_TENTH” <= 32	“CBD_1_TENTH” <= 60	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3322;3232;3223; 3222	“ACT_1_TENTH” <= 48	“CBD_1_TENTH” <= 90	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
3322;3232;3223; 3222	“ACT_1_TENTH” <= 64	“CBD_1_TENTH” <= 120	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
2222	“ACT_1_TENTH” <= 16	“CBD_1_TENTH” <= 30	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
2222	“ACT_1_TENTH” <= 32	“CBD_1_TENTH” <= 60	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
2222	“ACT_1_TENTH” <= 48	“CBD_1_TENTH” <= 90	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1
2222	“ACT_1_TENTH” <= 64	“CBD_1_TENTH” <= 120	“UNDERUTIL1” >= 3	“DUVAL_VACANT 1” = 1	“DUVAL_VACANT 1” = 1	“CONREGION” >= 1

Table 7-11. Orange scenario table

Conflict	Mask1	Mask2	Mask3	Mask4	Mask5	Region
3323	"ACT_1_TENTH" <= 16	"CBD_1_TENTH" <= 30	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 50
3323	"ACT_1_TENTH" <= 32	"CBD_1_TENTH" <= 60	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 40
3323	"ACT_1_TENTH" <= 48	"CBD_1_TENTH" <= 90	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 30
3323	"ACT_1_TENTH" <= 64	"CBD_1_TENTH" <= 120	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 20
3322;3223;3222	"ACT_1_TENTH" <= 16	"CBD_1_TENTH" <= 30	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 50
3322;3223;3222	"ACT_1_TENTH" <= 32	"CBD_1_TENTH" <= 60	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 40
3322;3223;3222	"ACT_1_TENTH" <= 48	"CBD_1_TENTH" <= 90	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 30
3322;3223;3222	"ACT_1_TENTH" <= 64	"CBD_1_TENTH" <= 120	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 20
2323;2322;2223	"ACT_1_TENTH" <= 16	"CBD_1_TENTH" <= 30	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 50
2323;2322;2223	"ACT_1_TENTH" <= 32	"CBD_1_TENTH" <= 60	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 40
2323;2322;2223	"ACT_1_TENTH" <= 48	"CBD_1_TENTH" <= 90	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 30
2323;2322;2223	"ACT_1_TENTH" <= 64	"CBD_1_TENTH" <= 120	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 20
2222	"ACT_1_TENTH" <= 16	"CBD_1_TENTH" <= 30	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 50
2222	"ACT_1_TENTH" <= 32	"CBD_1_TENTH" <= 60	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 40
2222	"ACT_1_TENTH" <= 48	"CBD_1_TENTH" <= 90	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 30
2222	"ACT_1_TENTH" <= 64	"CBD_1_TENTH" <= 120	"UDENSITY" >= 3	"ORANGE_VACANT" = 1	"ORANGE_VACANT" = 1	"WALK_BIK" >= 20

Table 7-12. Pinellas scenario table

Conflict	Mask1	Mask2	Mask3	Mask4	Mask5	Region
3323	"ACT_1_TENTH" <= 16	"CBD_1_TENTH" <= 30	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
3323	"ACT_1_TENTH" <= 32	"CBD_1_TENTH" <= 60	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
3323	"ACT_1_TENTH" <= 48	"CBD_1_TENTH" <= 90	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
3323	"ACT_1_TENTH" <= 64	"CBD_1_TENTH" <= 120	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
2323;2322;2223	"ACT_1_TENTH" <= 16	"CBD_1_TENTH" <= 30	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
2323;2322;2223	"ACT_1_TENTH" <= 32	"CBD_1_TENTH" <= 60	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
2323;2322;2223	"ACT_1_TENTH" <= 48	"CBD_1_TENTH" <= 90	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
2323;2322;2223	"ACT_1_TENTH" <= 64	"CBD_1_TENTH" <= 120	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
3322;3223;3222	"ACT_1_TENTH" <= 16	"CBD_1_TENTH" <= 30	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
3322;3223;3222	"ACT_1_TENTH" <= 32	"CBD_1_TENTH" <= 60	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
3322;3223;3222	"ACT_1_TENTH" <= 48	"CBD_1_TENTH" <= 90	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
3322;3223;3222	"ACT_1_TENTH" <= 64	"CBD_1_TENTH" <= 120	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
2222	"ACT_1_TENTH" <= 16	"CBD_1_TENTH" <= 30	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
2222	"ACT_1_TENTH" <= 32	"CBD_1_TENTH" <= 60	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
2222	"ACT_1_TENTH" <= 48	"CBD_1_TENTH" <= 90	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1
2222	"ACT_1_TENTH" <= 64	"CBD_1_TENTH" <= 120	"UDENSITY" >= 3	"PINELLAS_VACANT1" = 1	"PINELLAS_VACANT1" = 1	"CONREGION" >= 1

Table 7-13. Frequently used land uses that are suitable for affordable housing

Description	Duval Ranked	Duval Suitable	Orange Ranked	Orange Suitable	Pinellas Ranked	Pinellas Suitable
Single Family	3287.74	7748.14	640.63	1529.04	1340.63	2332.87
Vacant Commercial	666.76	449.70	308.40	181.69	527.95	582.06
Other Municipal	2.57	56.58	379.07	148.94	417.70	466.66
Condominium	25.21	61.77	478.37	44.09	370.84	391.52
Golf Courses	32.62	7.77	14.66	0.15	331.59	336.60
Vacant Residential	737.99	425.47	173.50	44.51	309.99	341.03
Public Schools	416.61	293.88	188.78	223.11	254.57	354.23
Vacant Industrial.	335.42	39.53	51.04	11.37	213.30	220.54
Churches	476.72	580.40	152.94	175.41	207.12	322.17
Parking Lots	178.87	264.48	89.67	92.91	182.45	190.04
Utilities	133.39	43.68	16.21	6.80	175.66	196.22
Automotive Repair	334.13	366.54	37.84	104.99	170.51	261.42
Parcels With No Value	910.46	375.02	29.41	10.95	156.77	170.49
Mortuaries	104.10	16.29	32.90	3.98	153.36	159.66
Other Counties	727.31	365.92	156.10	81.51	152.52	160.78
Light Manufacture	218.07	165.50	27.11	36.21	152.50	269.58
Multi-Family	149.41	413.83	46.07	100.22	138.93	217.70
Warehouses	705.39	971.26	166.73	305.78	134.48	184.70
Mobile Homes	136.38	122.70	4.79	2.84	118.31	124.82
One-Story	189.72	865.91	60.33	362.04	103.51	132.38
Multi-Family	338.11	1217.63	104.30	744.19	85.84	153.61
Outdoor Recreation	6.25	0.03	0.15	0.17	77.78	80.77
Sewage Disposal	203.53	57.74	6.55	0.84	75.56	110.60
Forest and Park	314.68	91.48	10.48	0.47	66.96	69.13
Stores One-Story	83.81	322.83	51.33	399.60	59.99	99.41
Acreage Not Zoned	31.09	16.37	53.21	30.13	49.75	54.40
Vacant Institutional	250.77	86.94	15.57	4.10	38.68	42.02
Community Shopping	226.99	1260.61	61.52	425.58	38.43	83.98
Clubs and Lodges.	52.92	56.98	14.56	3.81	38.38	51.88
Heavy Manufacture	24.35	12.91	17.80	18.69	34.95	80.50
Rights-Of-Way	29.49	21.34	1.78	3.02	30.87	32.30
Rivers and Lakes.	4.60	1.66	7.56	0.12	29.24	29.78
Improved Agriculture	0.00	0.00	0.00	0.00	25.04	30.97
Supermarket	33.76	206.14	2.77	21.11	23.11	64.95
Mineral Processing	24.15	2.50	3.19	0.00	22.84	26.92
Restaurants	26.05	173.17	1.26	35.99	20.71	31.39
Homes For Aged	17.55	78.92	1.51	20.54	19.15	34.18
Industrial Storage	188.21	68.19	16.04	22.02	19.03	20.71

Table 7-14. Not frequently used land uses that are suitable for affordable housing

Description	Duval Ranked	Duval Suitable	Orange Ranked	Orange Suitable	Pinellas Ranked	Pinellas Suitable
Professional Service	59.66	259.01	5.29	89.52	15.79	43.99
Financial Intuitional	7.96	156.13	1.61	47.58	12.93	28.40
Other State	62.61	178.49	38.90	25.06	11.44	14.85
Private Schools	101.06	142.83	2.97	50.00	10.16	25.83
Other Food Production	20.17	9.00	3.36	3.21	9.89	10.41
Boarding Homes	2.13	0.37	0.00	0.00	9.12	10.01
Orphanages	57.34	37.29	7.02	19.25	7.76	8.82
Sanitariums	0.00	0.00	0.00	0.00	5.44	12.51
Hotels and Motels	23.33	204.33	5.29	141.62	5.14	7.98
Florist and Green houses	3.09	2.97	0.00	0.00	4.84	7.74
Private Hospital	17.40	148.57	0.00	0.00	4.60	5.24
Bowling Alleys	14.21	8.18	5.09	10.33	4.37	18.14
Multi-Story	13.37	540.07	1.68	97.48	3.93	23.06
Drive-In Rest.	8.77	153.81	3.98	94.07	3.16	7.74
Mixed Use	85.49	82.35	24.74	63.22	2.25	3.56
Lumber Yards	11.86	2.50	0.00	1.75	2.00	2.00
Night Clubs and Bars	14.80	23.19	1.41	7.61	1.78	2.25
Cultural Organization	1.58	3.71	0.00	1.04	1.36	7.37
Service Stations	13.27	37.32	0.00	1.04	1.14	1.26
Centrally Assessed	0.00	0.00	4.18	1.31	1.11	1.48
Canneries	44.07	16.52	0.02	0.47	0.82	0.82
Cooperatives	0.17	2.10	0.10	0.00	0.77	0.96
Airports and Marina	4.37	2.99	0.00	0.00	0.74	0.74
Insurance Companies	0.00	0.00	0.00	0.00	0.59	0.91
Repair Services	3.81	10.88	19.55	88.78	0.59	0.67
Other Federal	14.76	106.21	0.00	7.39	0.57	42.39
Regional Shopping	0.25	94.19	0.67	126.42	0.54	0.94
Fruit and Vegetable	0.00	0.00	0.37	28.50	0.44	0.44
Wholesale	0.00	0.00	0.00	0.15	0.22	0.22
Colleges	56.67	249.42	57.71	6.97	0.10	0.10
Cropland Soil	18.04	0.00	3.06	0.30	0.00	0.00
Dairies	0.00	0.00	0.00	3.61	0.00	0.00
Department Stores	26.25	411.10	0.02	80.50	0.00	0.00
Drive-In Theater	0.20	6.15	0.00	0.00	0.00	0.00
Enclosed Theater	0.89	24.25	0.00	8.85	0.00	0.00
Government Owned Lease	46.02	19.07	93.45	67.80	0.00	0.00
Grazing Land	21.87	9.69	24.57	11.00	0.00	0.00
Military	4.87	149.80	4.87	3.48	0.00	0.00
Orchard and Groves	0.00	0.00	5.93	18.12	0.00	0.00

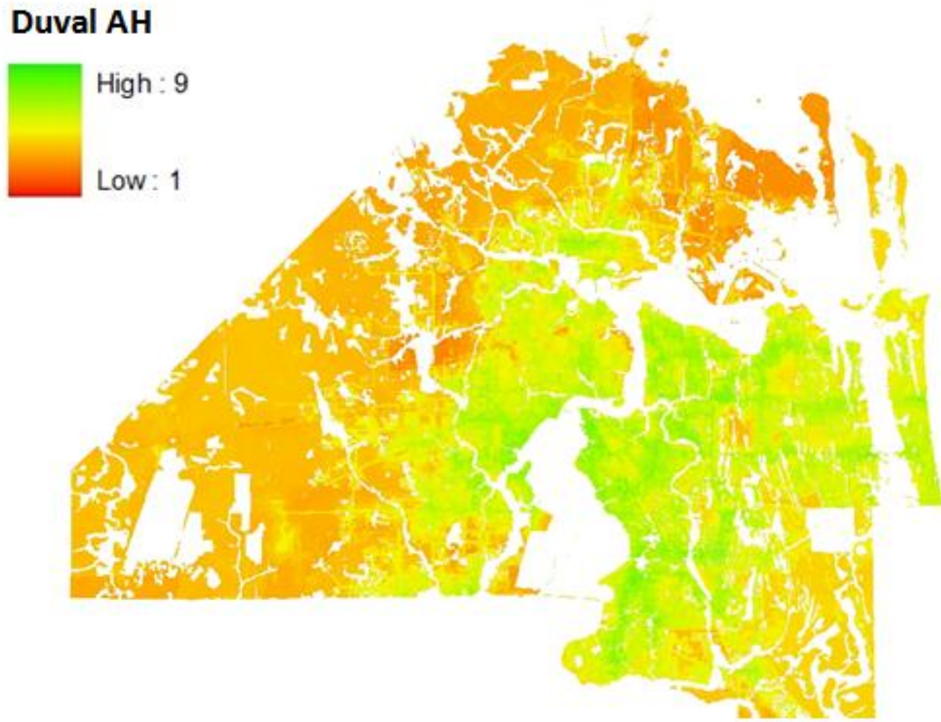


Figure 7-1. Suitability based on AHS goal 1

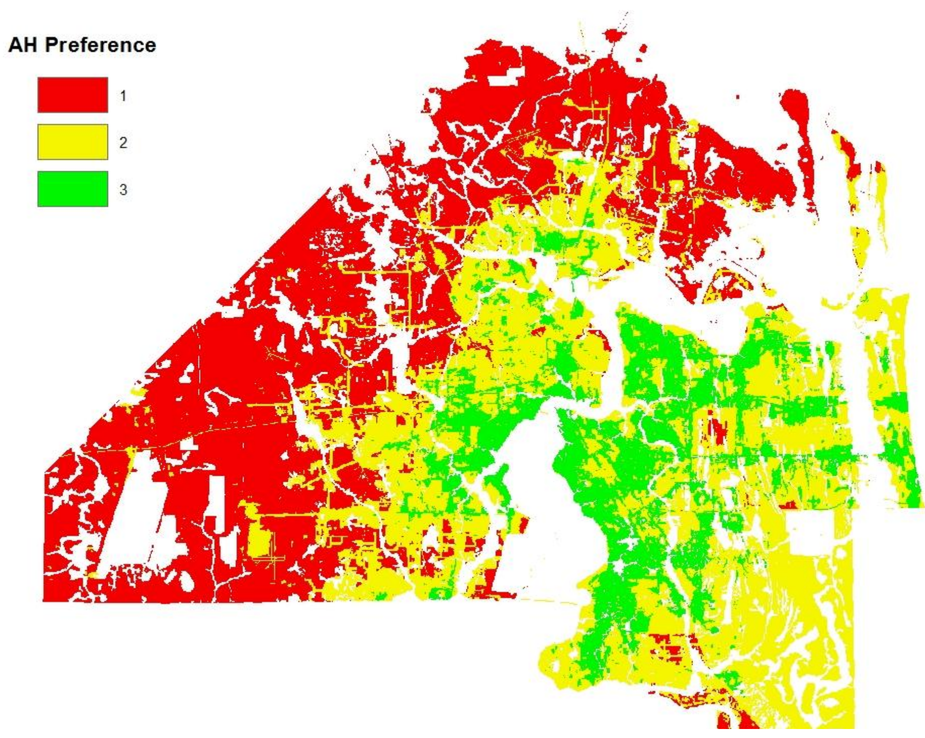


Figure 7-2. Preference based on AHS goal 1

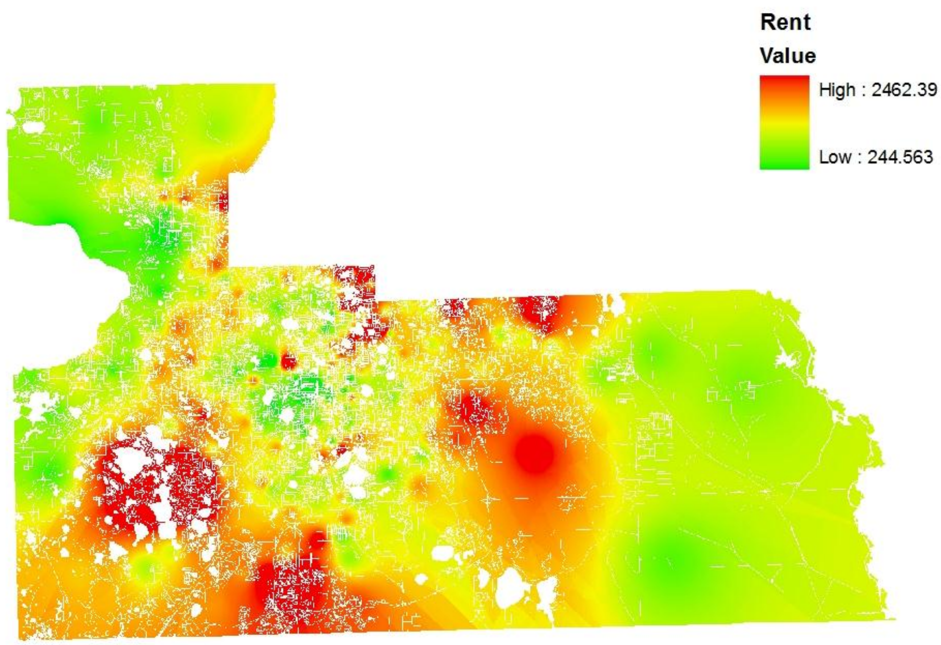


Figure 7-3. Rent monthly estimation for Orange County

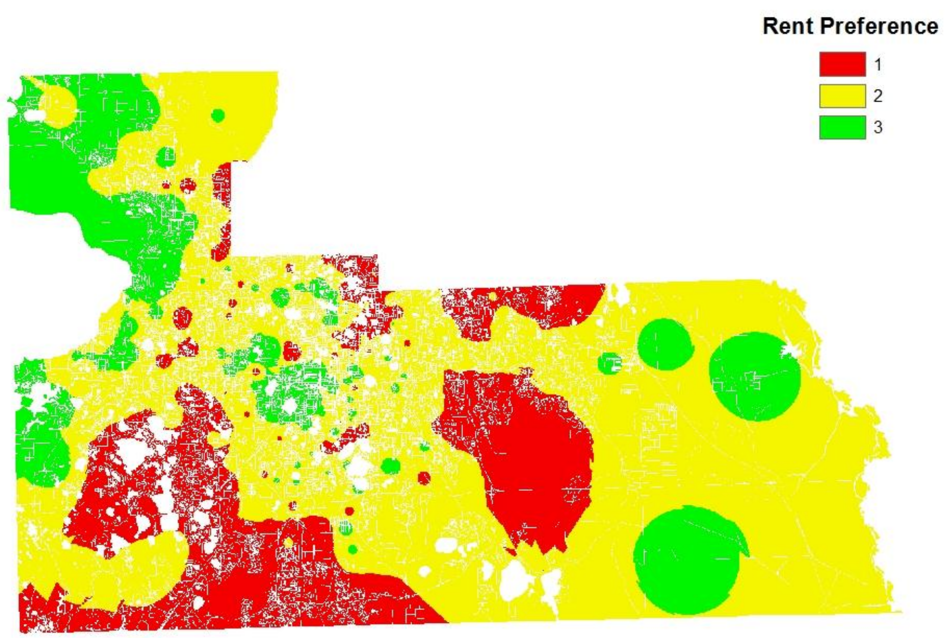


Figure 7-4. Rent preference surface for Orange County

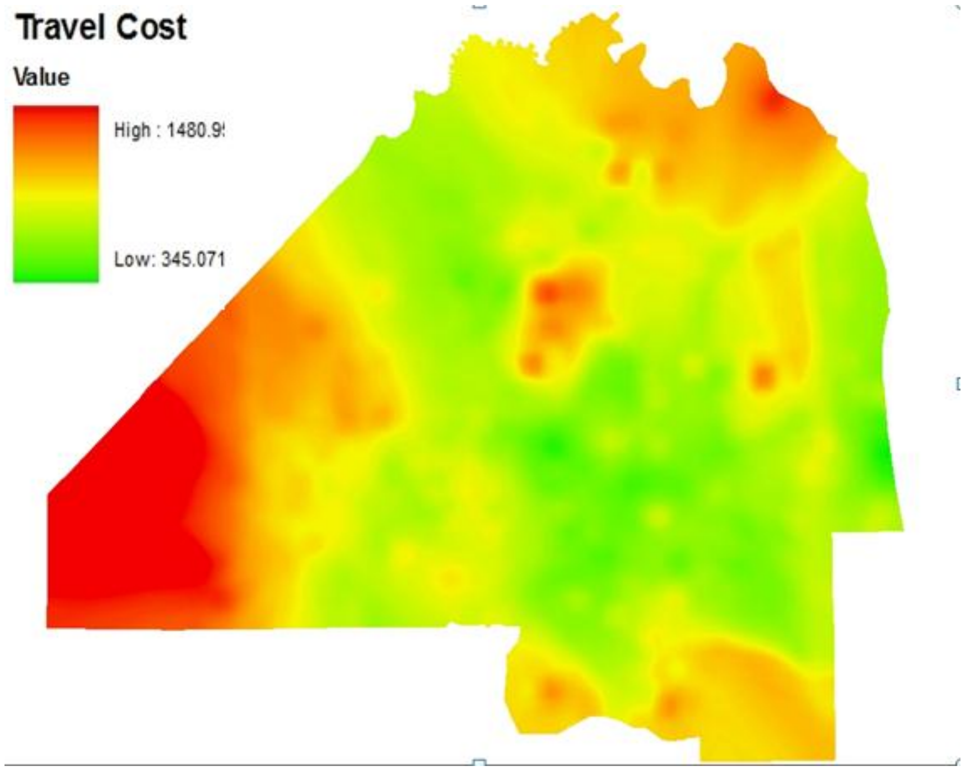


Figure 7-5. Travel cost monthly estimation for Duval County

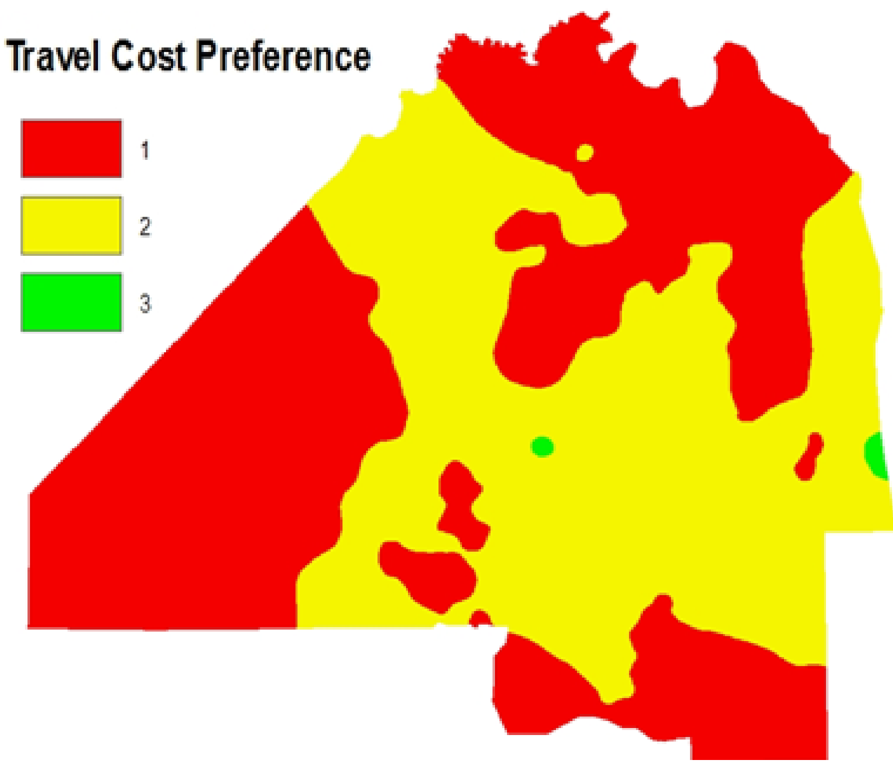


Figure 7-6. Travel cost preference surface for Duval County

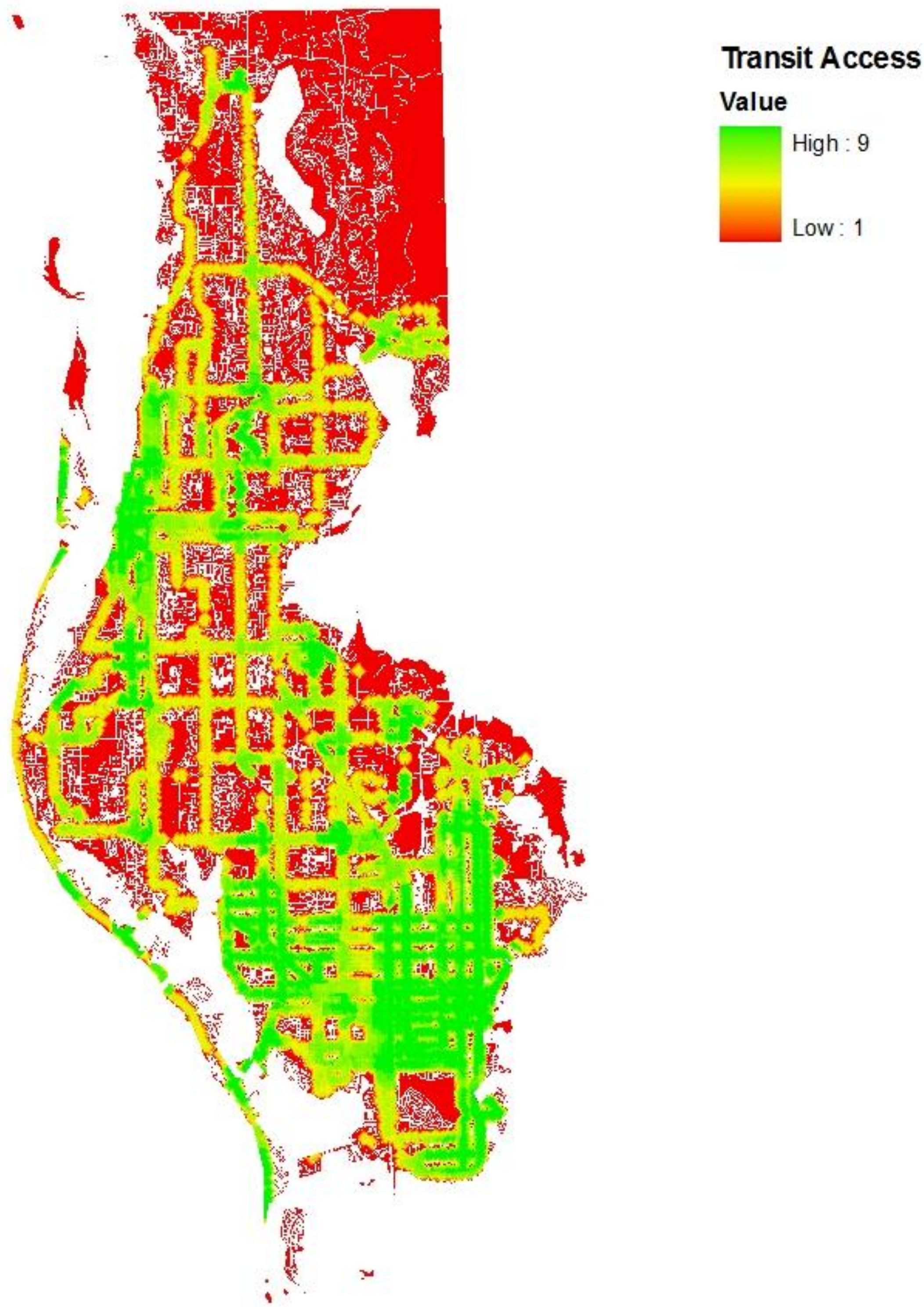


Figure 7-7. Transit access suitability surface for Pinellas County

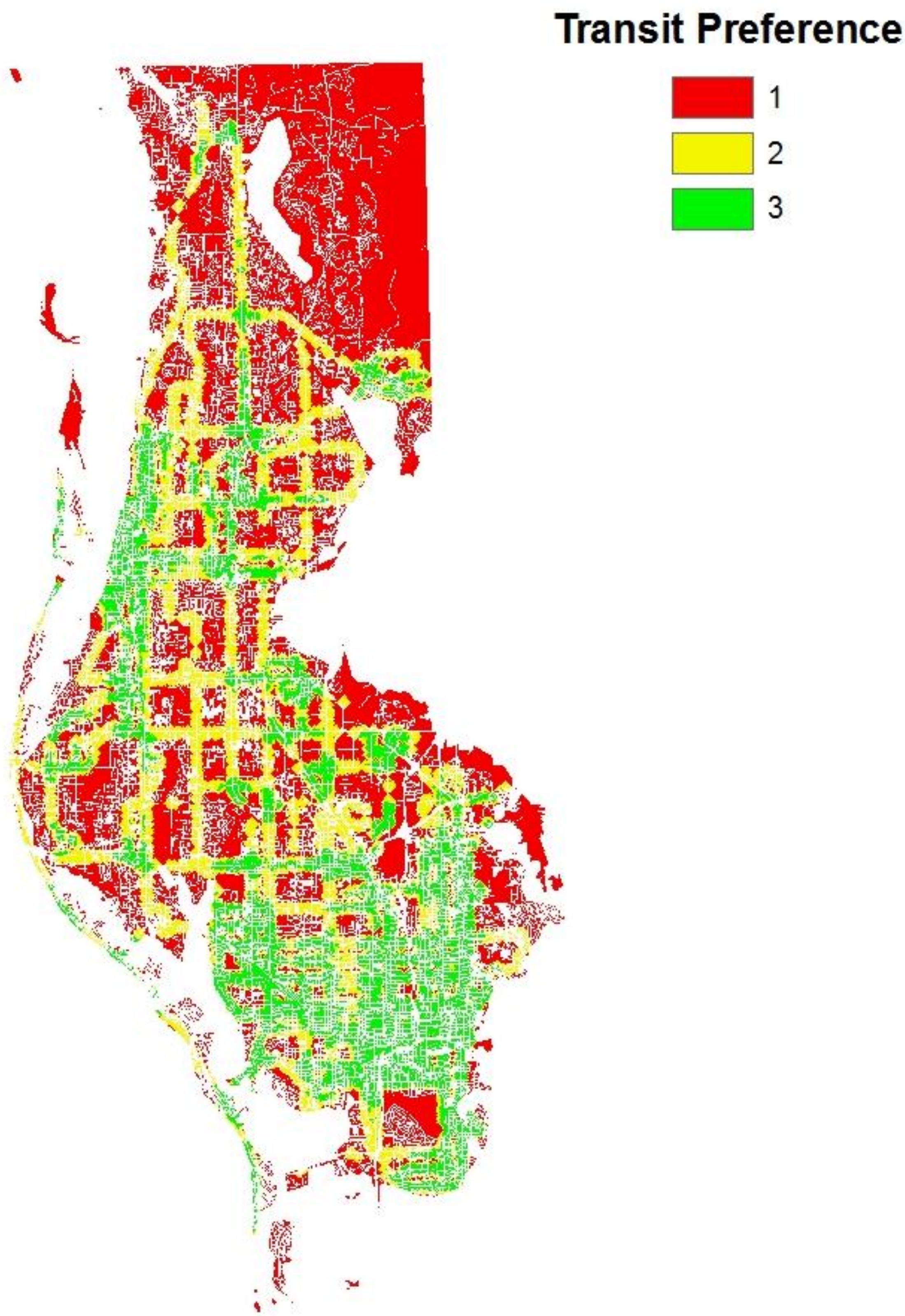


Figure 7-8. Transit access preference surface for Pinellas County

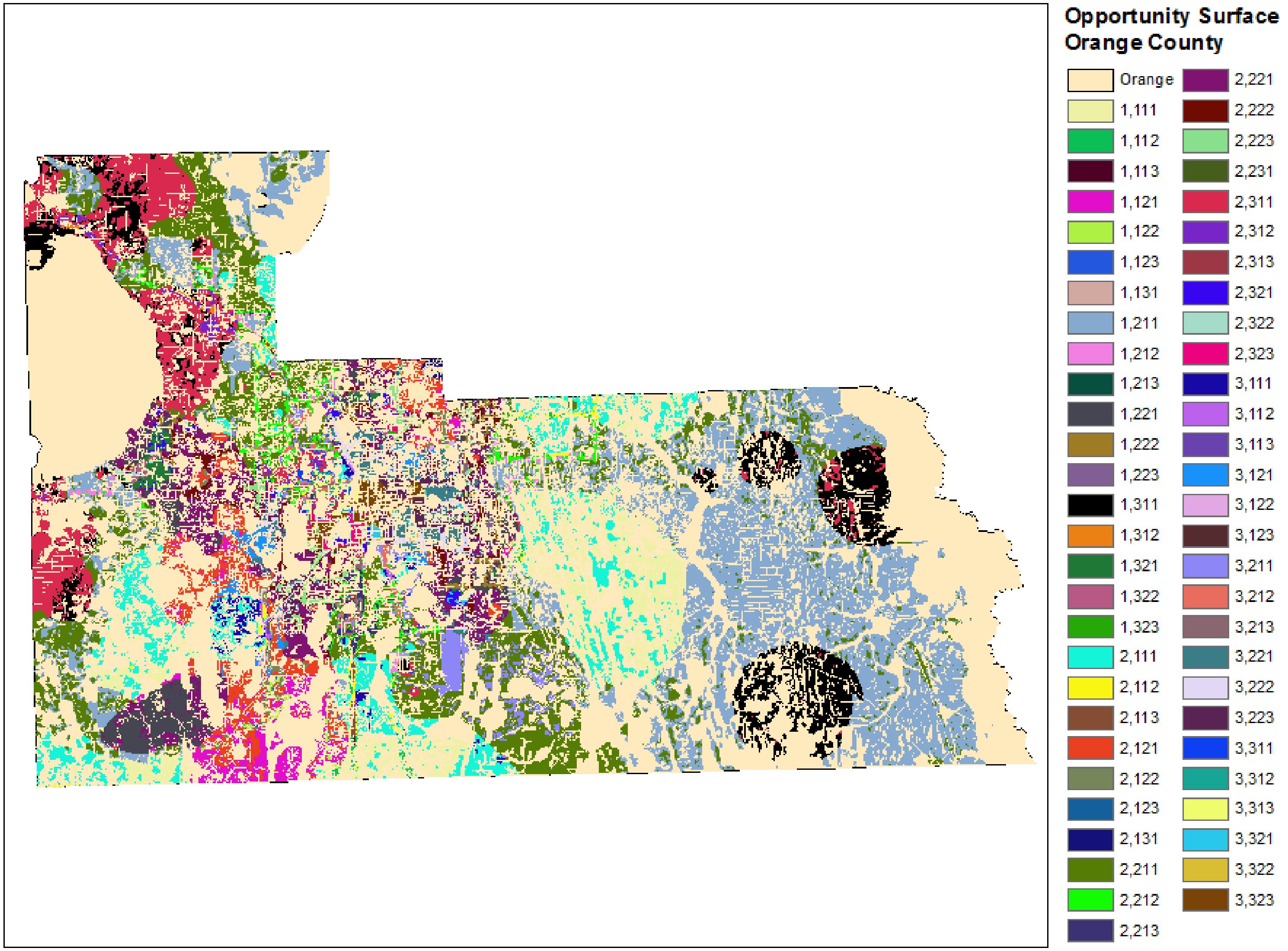


Figure 7-9. ARDT opportunity surface for Orange County

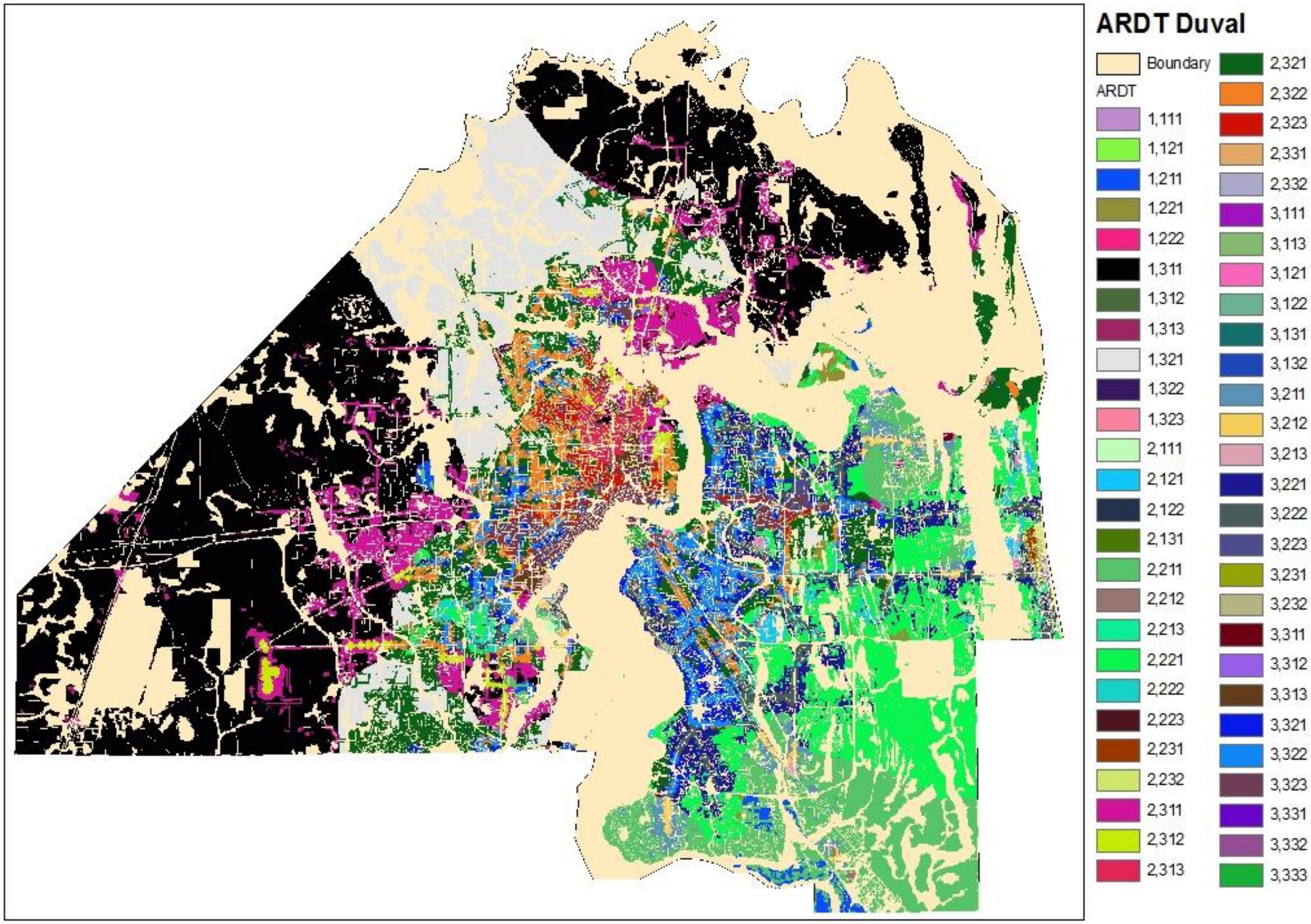


Figure 7-10. ARDT opportunity surface for Duval County

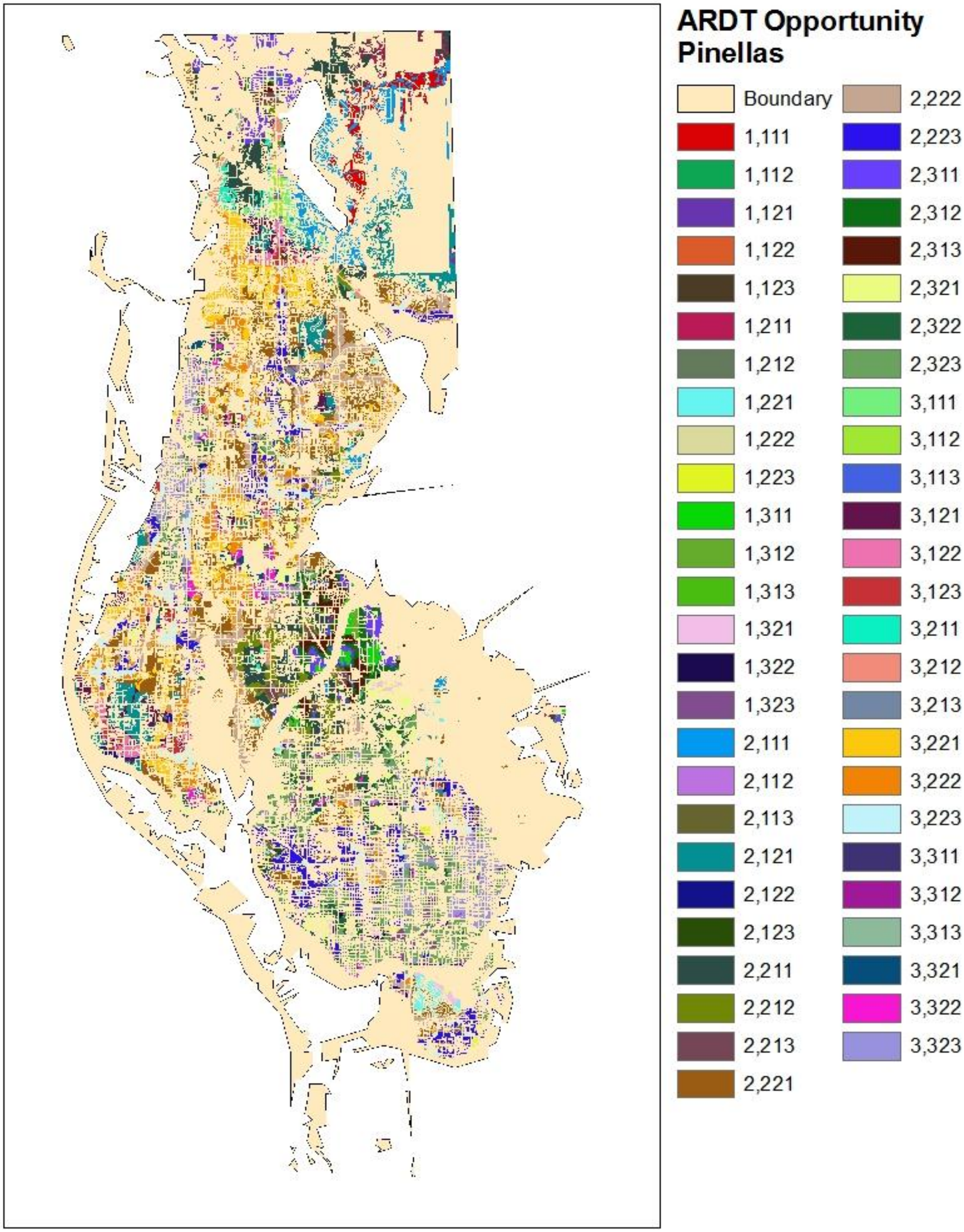


Figure 7-11. ARDT opportunity surface for Pinellas County

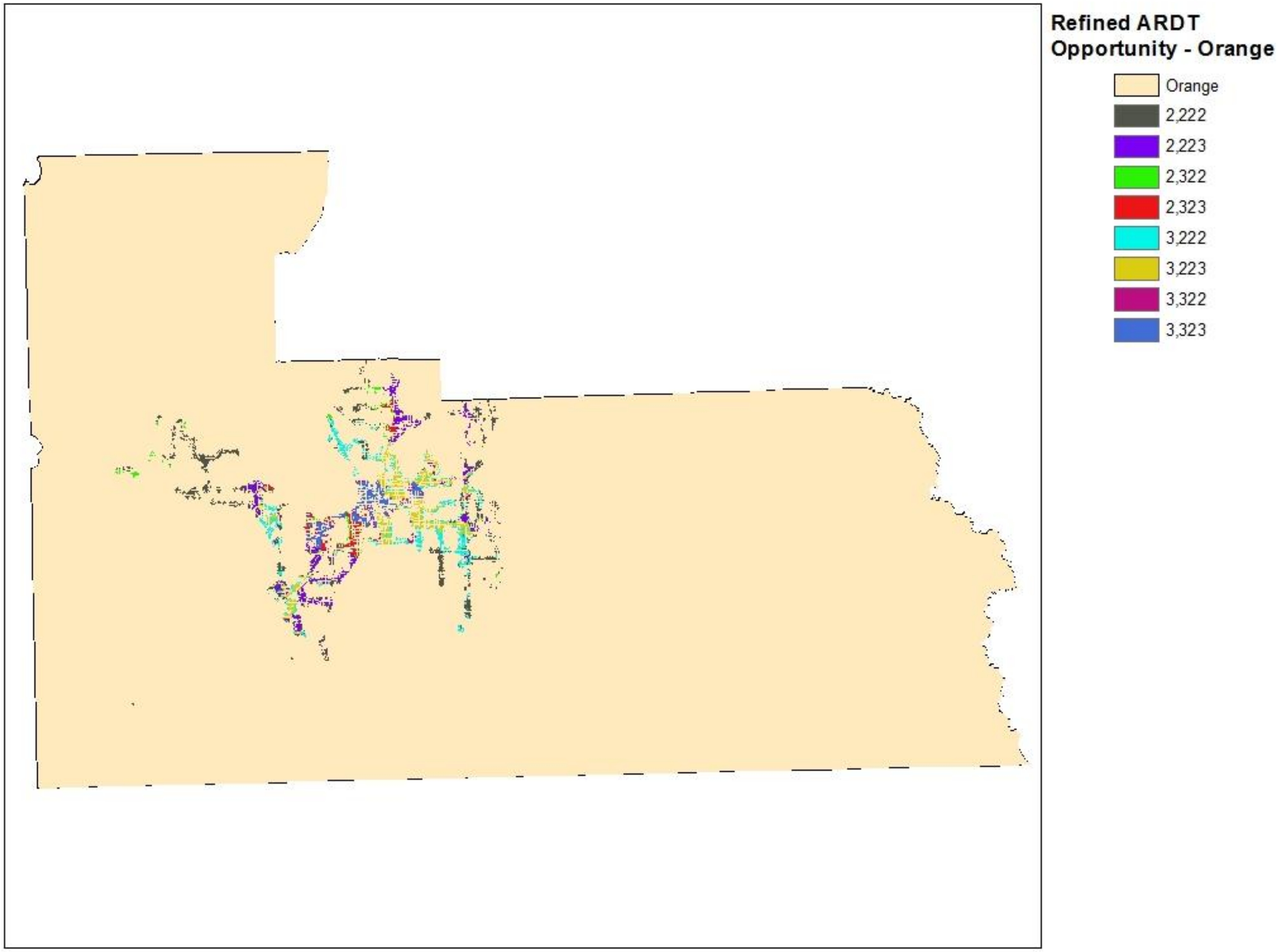


Figure 7-12. Refined ARDT opportunity surface for Orange County

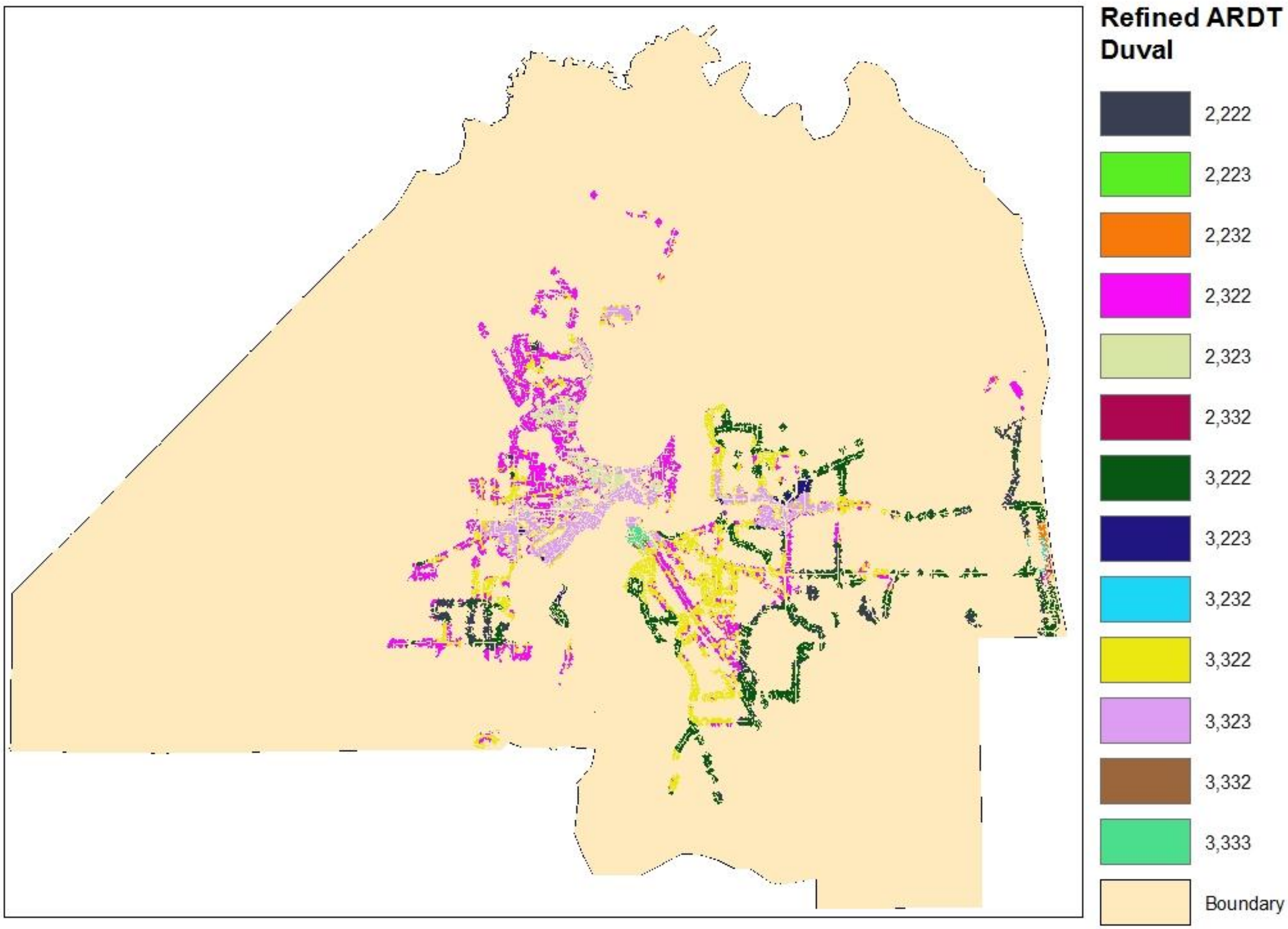


Figure 7-13. Refined ARDT opportunity surface for Duval County

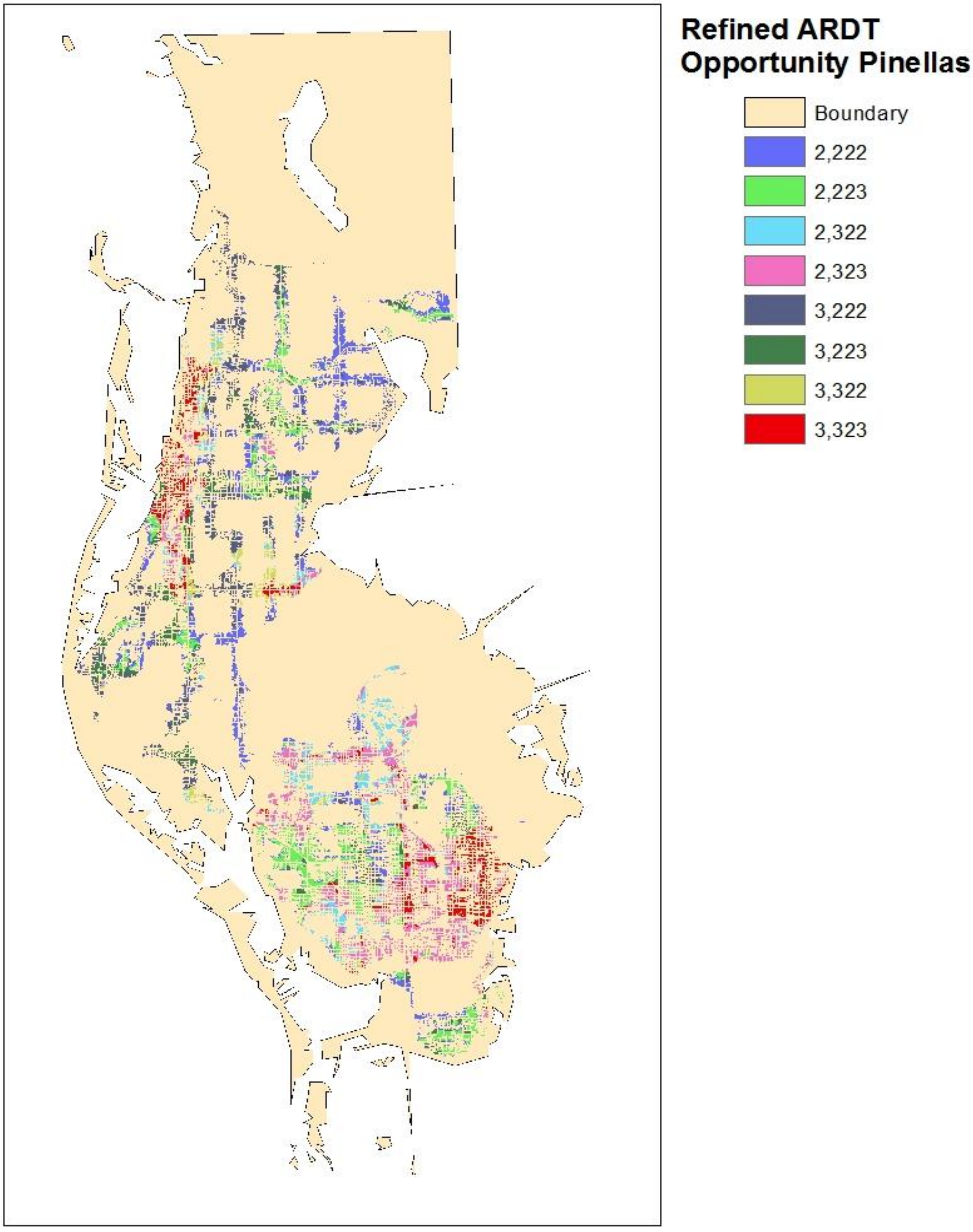


Figure 7-14. Refined ARDT opportunity surface for Pinellas County

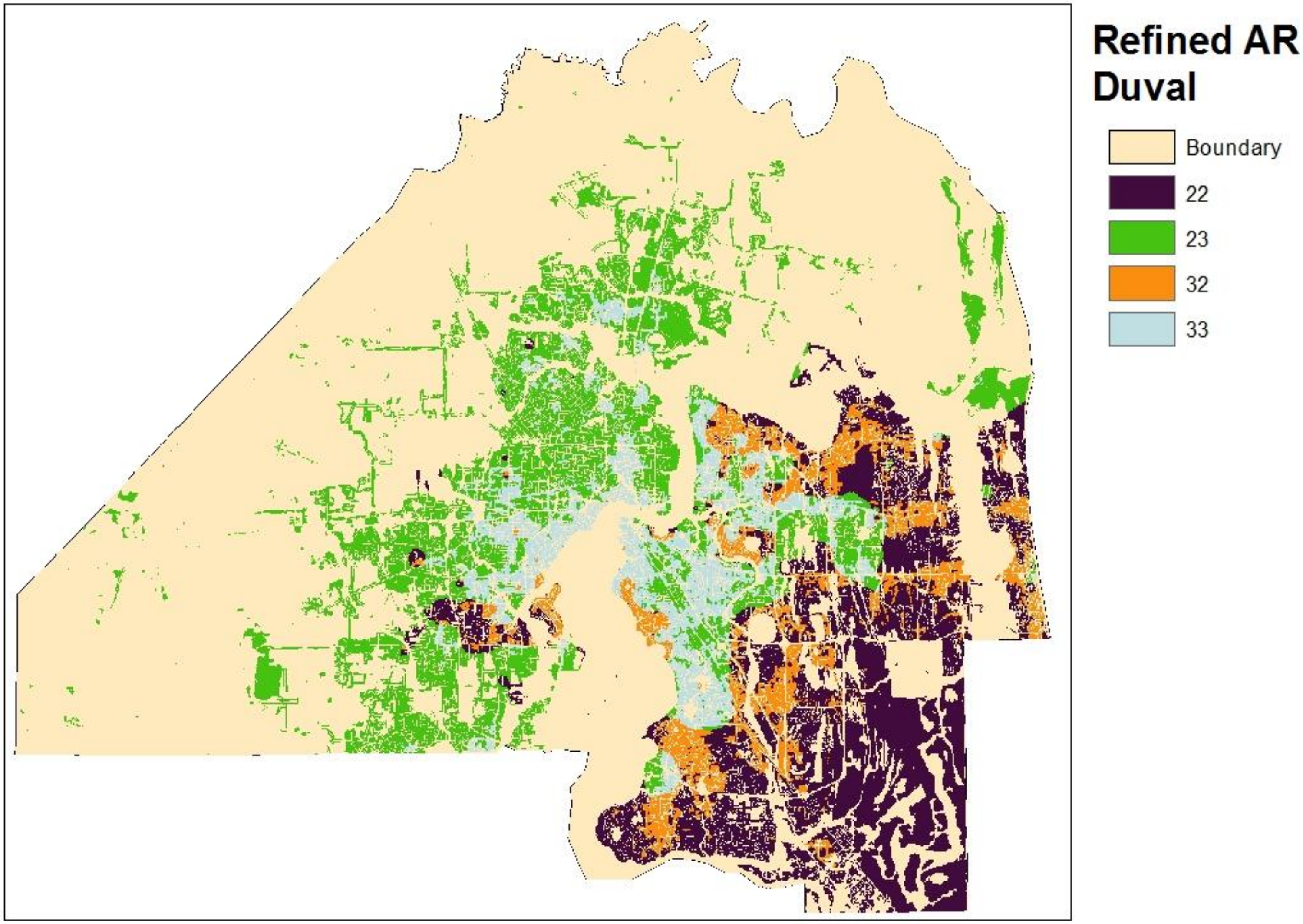


Figure 7-15. Refined AR opportunity surface for Duval County

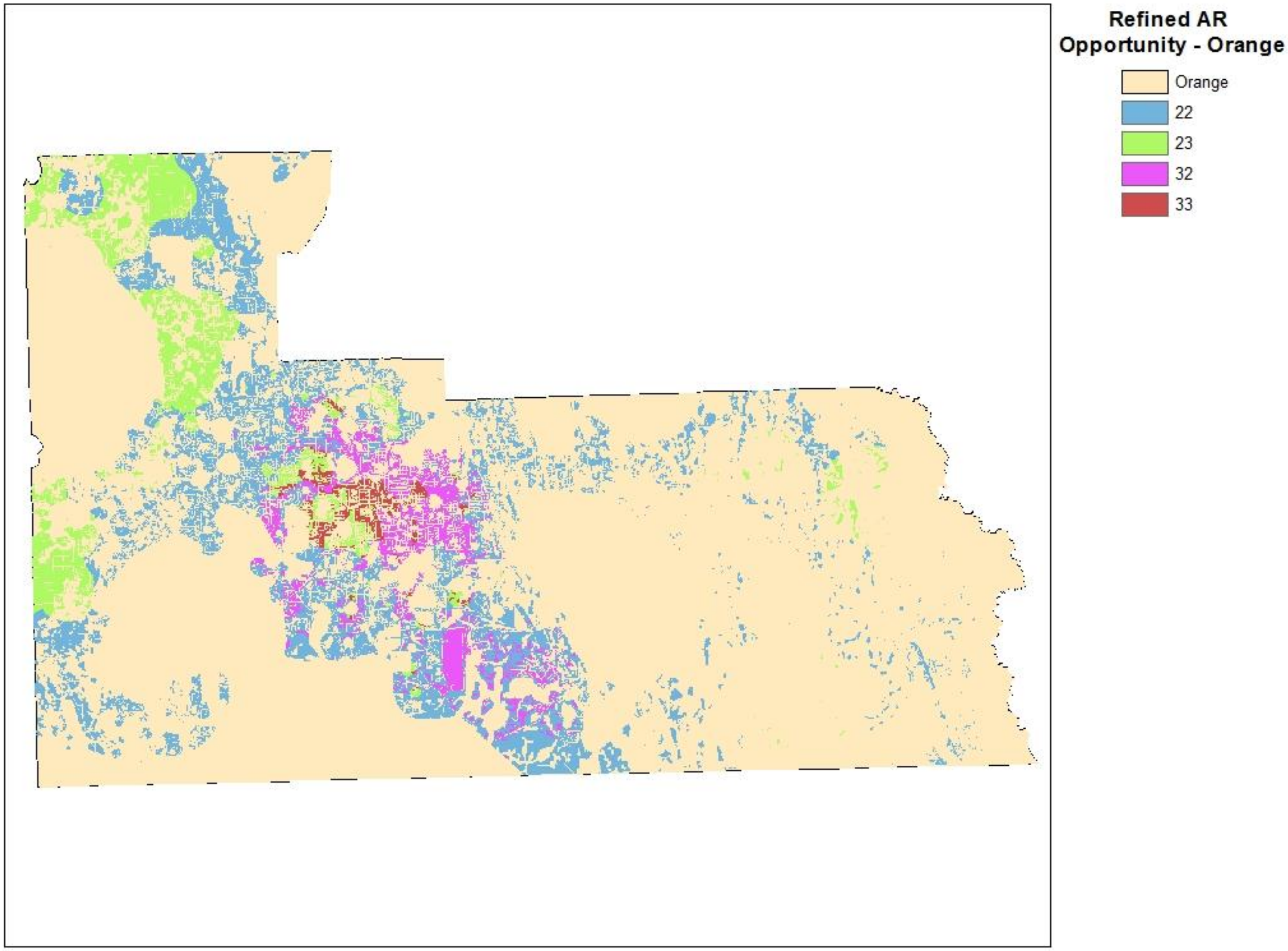


Figure 7-16. Refined AR opportunity surface for Orange County

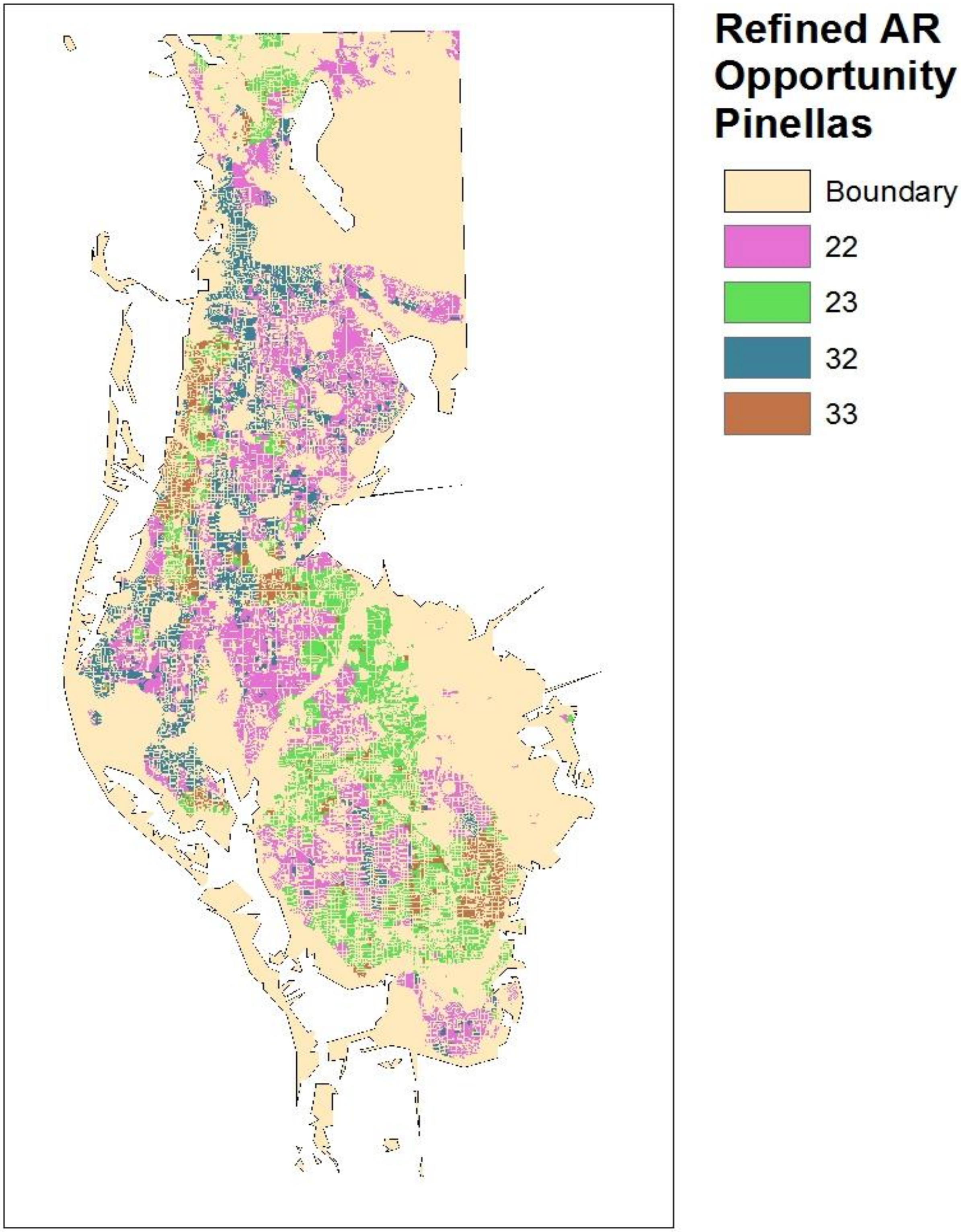


Figure 7-17. Refined AR Opportunity Surface for Pinellas County

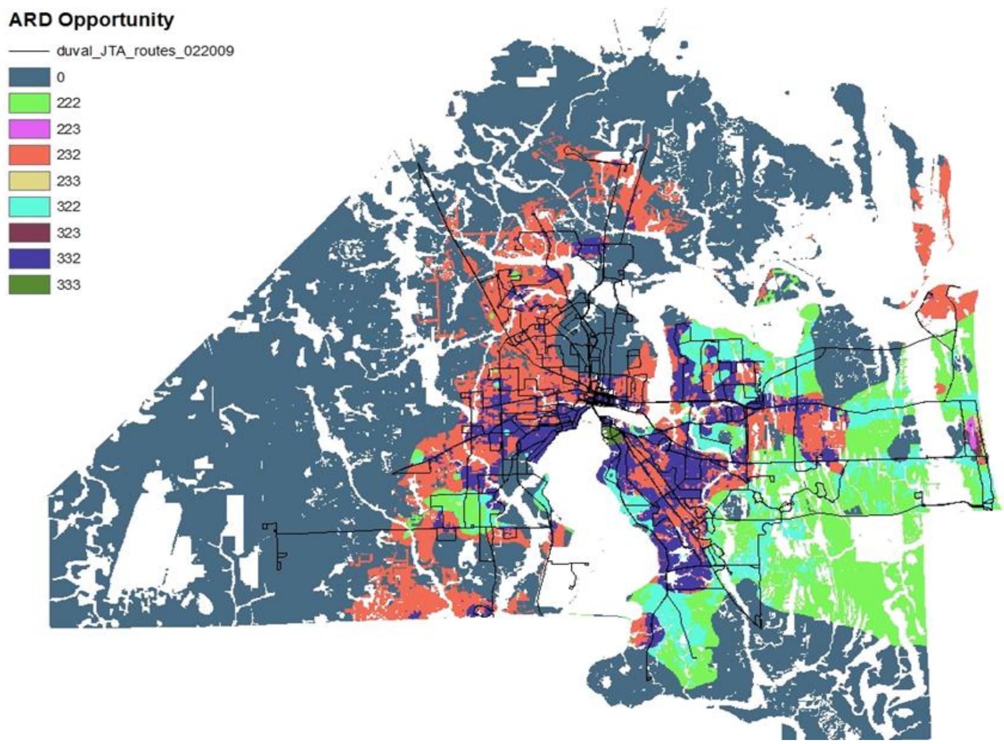


Figure 7-18. Refined ARD Opportunity Surface for Duval County

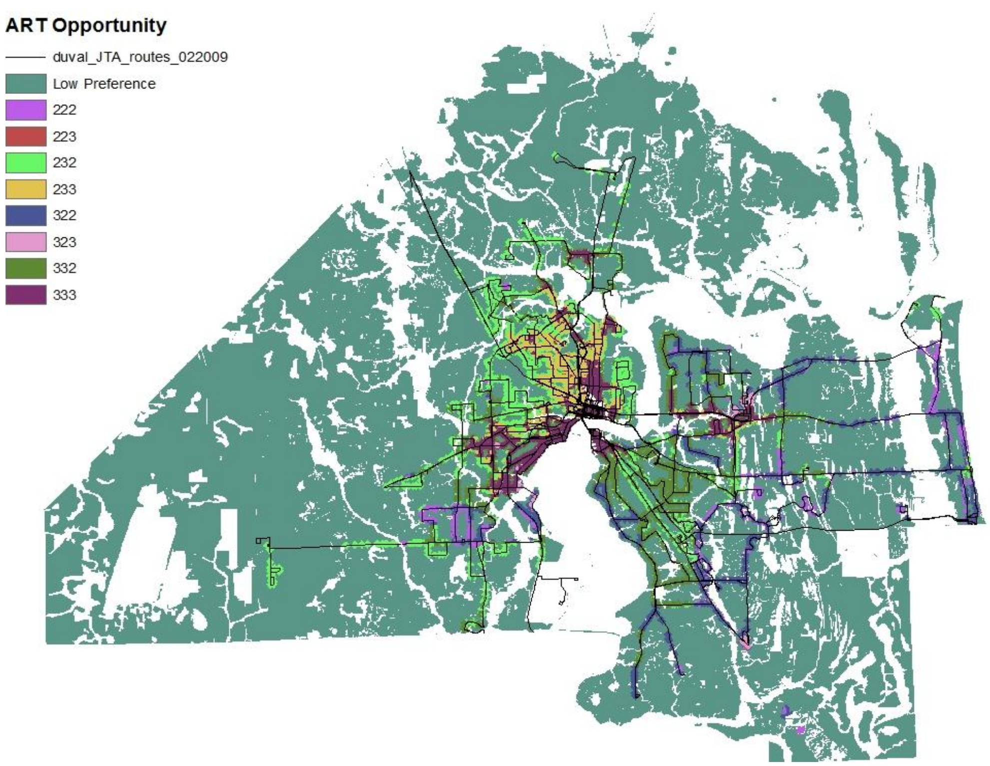
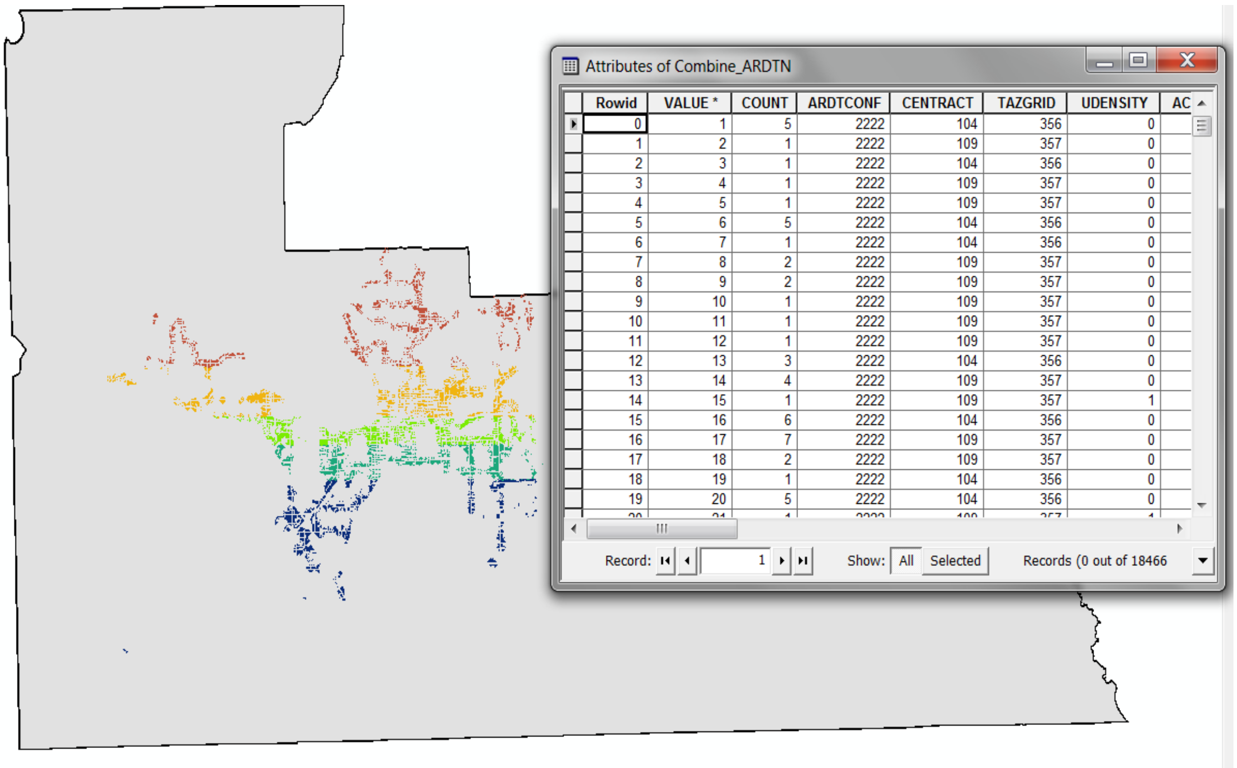


Figure 7-19. Refined ART Opportunity Surface for Duval County



Rowid	VALUE *	COUNT	ARDTCONF	CENTRACT	TAZGRID	UDENSITY	AC
0	1	5	2222	104	356	0	
1	2	1	2222	109	357	0	
2	3	1	2222	104	356	0	
3	4	1	2222	109	357	0	
4	5	1	2222	109	357	0	
5	6	5	2222	104	356	0	
6	7	1	2222	104	356	0	
7	8	2	2222	109	357	0	
8	9	2	2222	109	357	0	
9	10	1	2222	109	357	0	
10	11	1	2222	109	357	0	
11	12	1	2222	109	357	0	
12	13	3	2222	104	356	0	
13	14	4	2222	109	357	0	
14	15	1	2222	109	357	1	
15	16	6	2222	104	356	0	
16	17	7	2222	109	357	0	
17	18	2	2222	109	357	0	
18	19	1	2222	104	356	0	
19	20	5	2222	104	356	0	

Figure 7-20. Example combine grid for Orange County

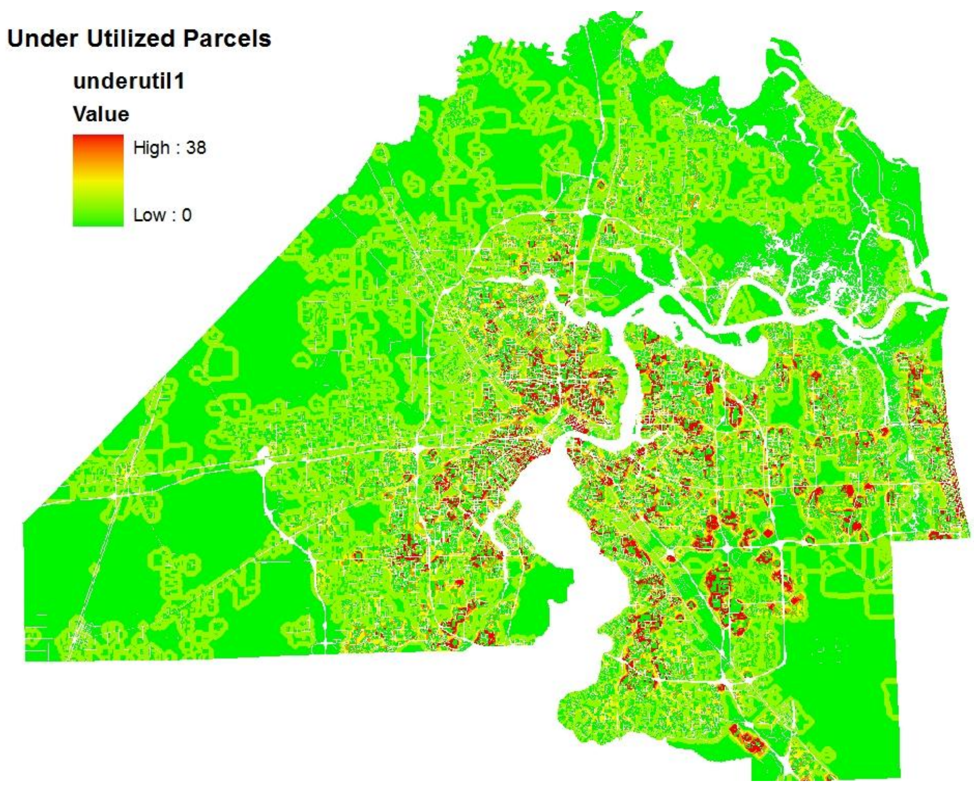


Figure 7-21. Example underutilized grid for Duval County

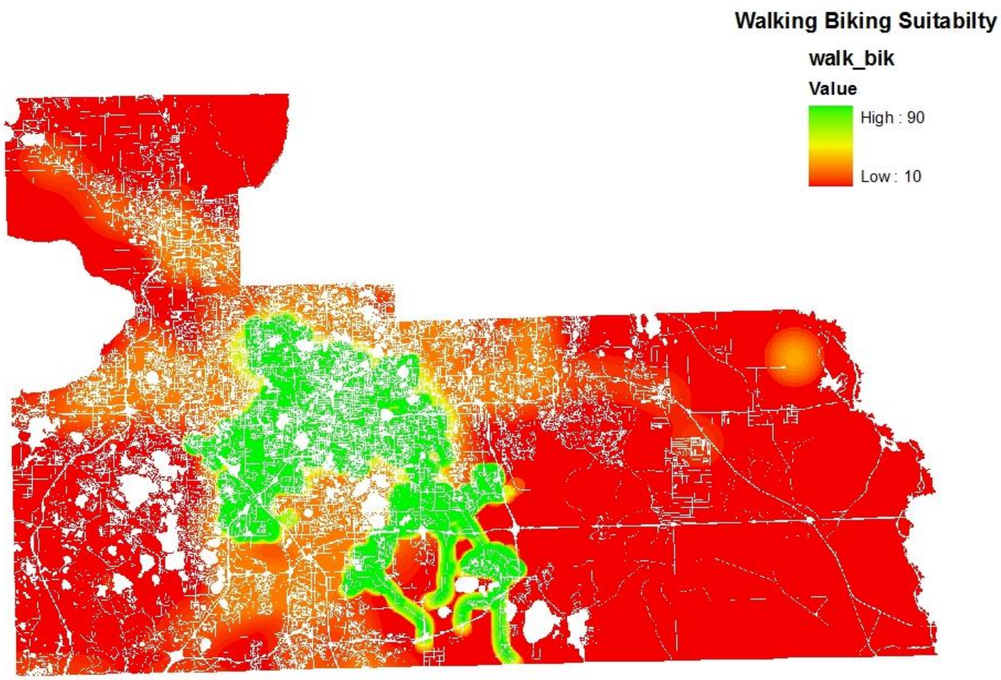


Figure 7-22. Example walkabilty-bikabilty grid for Orange County

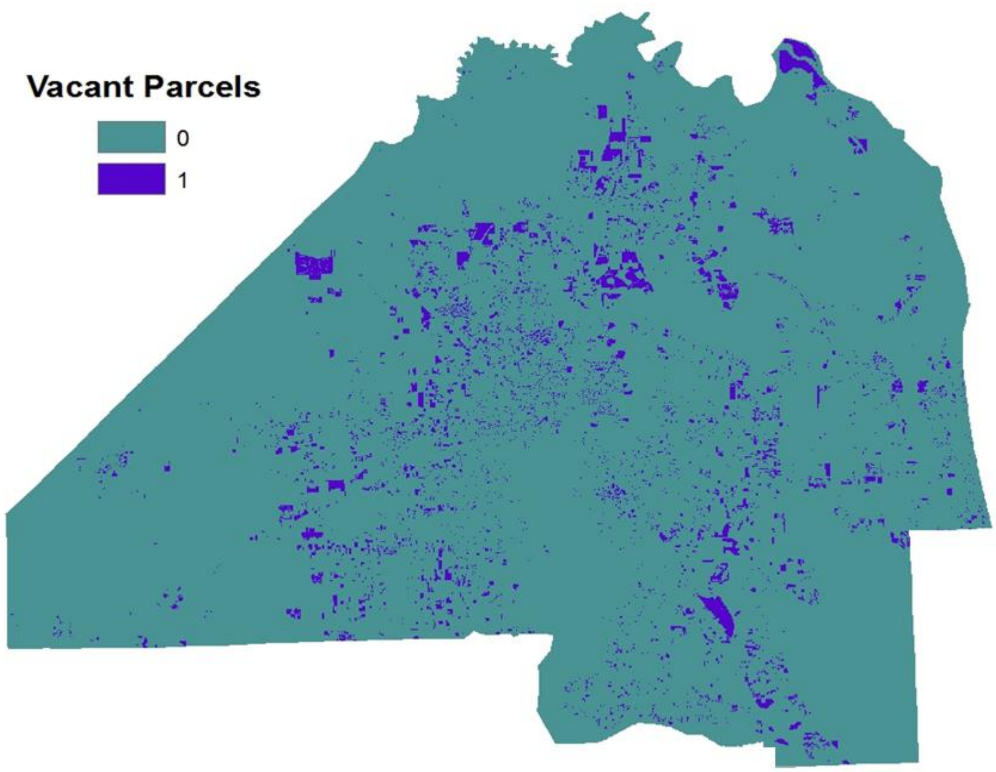


Figure 7-23. Example of vacant parcel grid for Duval County

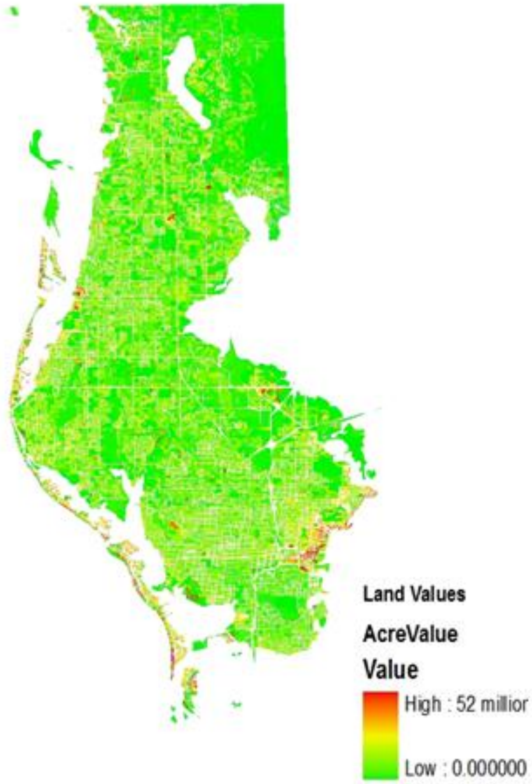


Figure 7-24. Example land value grid for Pinellas County

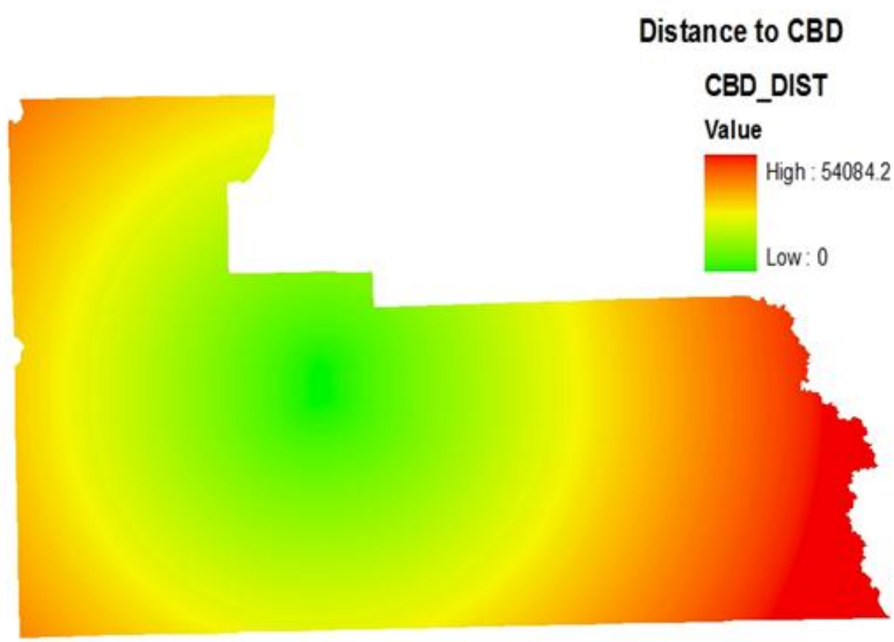


Figure 7-25. Example distance to CBD for Orange County

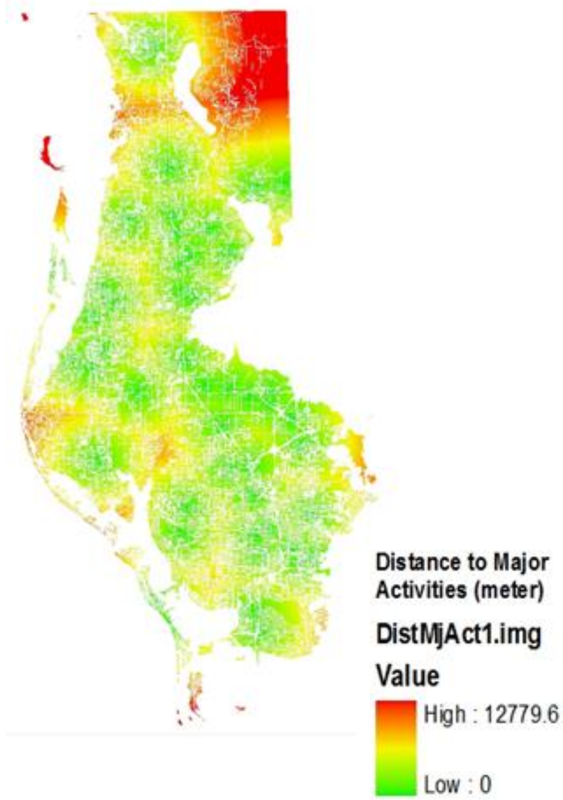


Figure 7-26. Example distance to major activity centers for Pinellas County

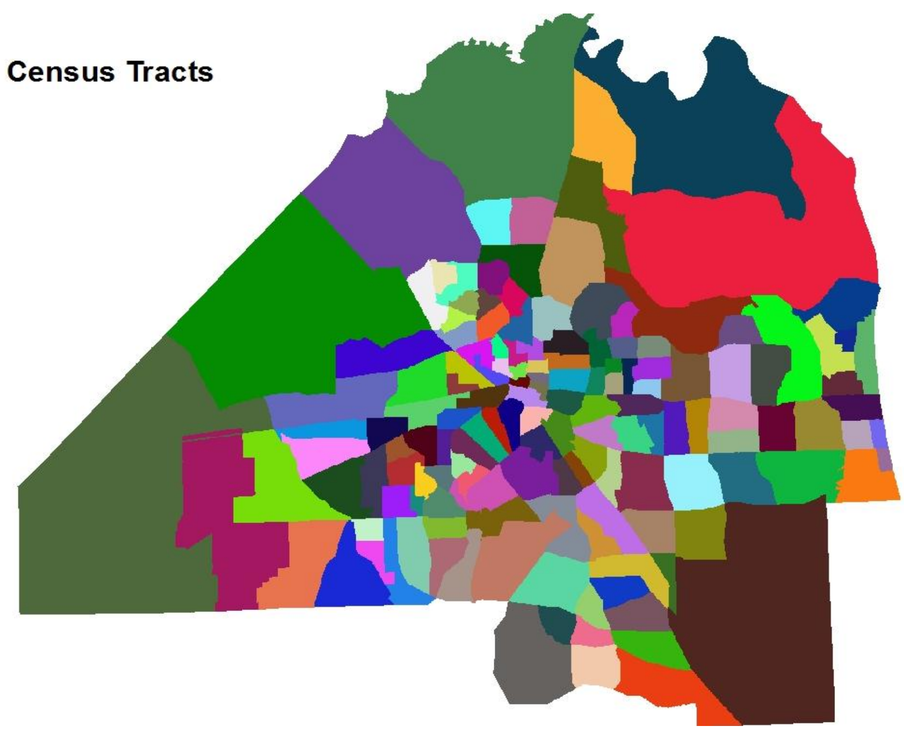


Figure 7-27. Qualified Census tracts grid For Duval County.

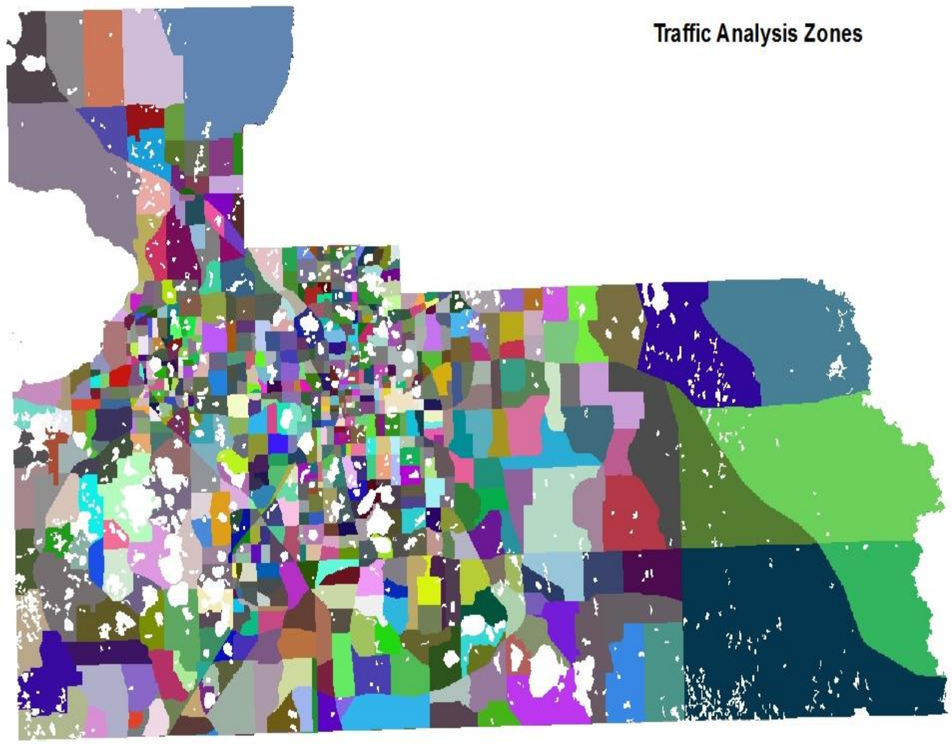


Figure 7-28. Transportation analysis zones for Orange County

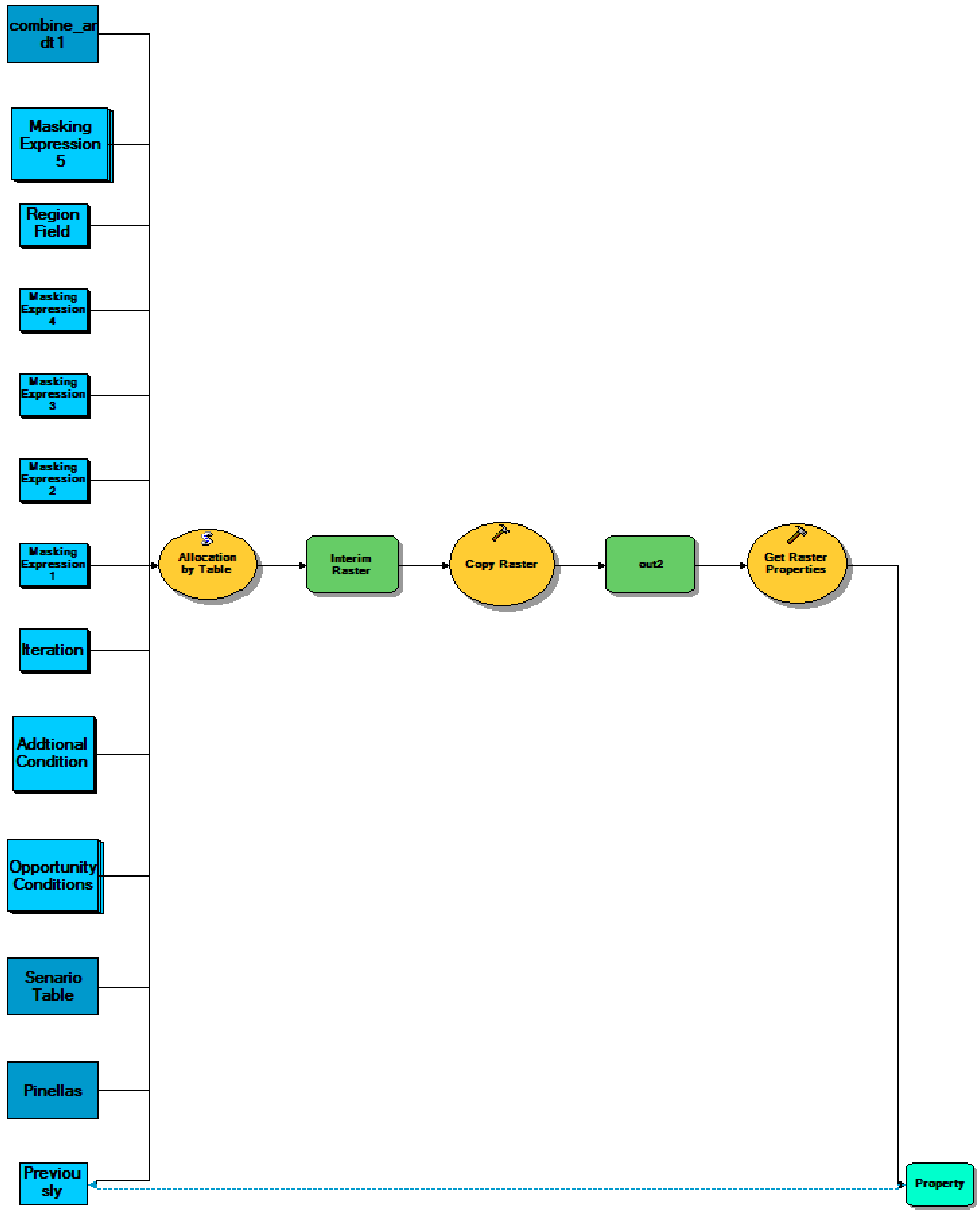


Figure 7-29. Affordable housing allocation model

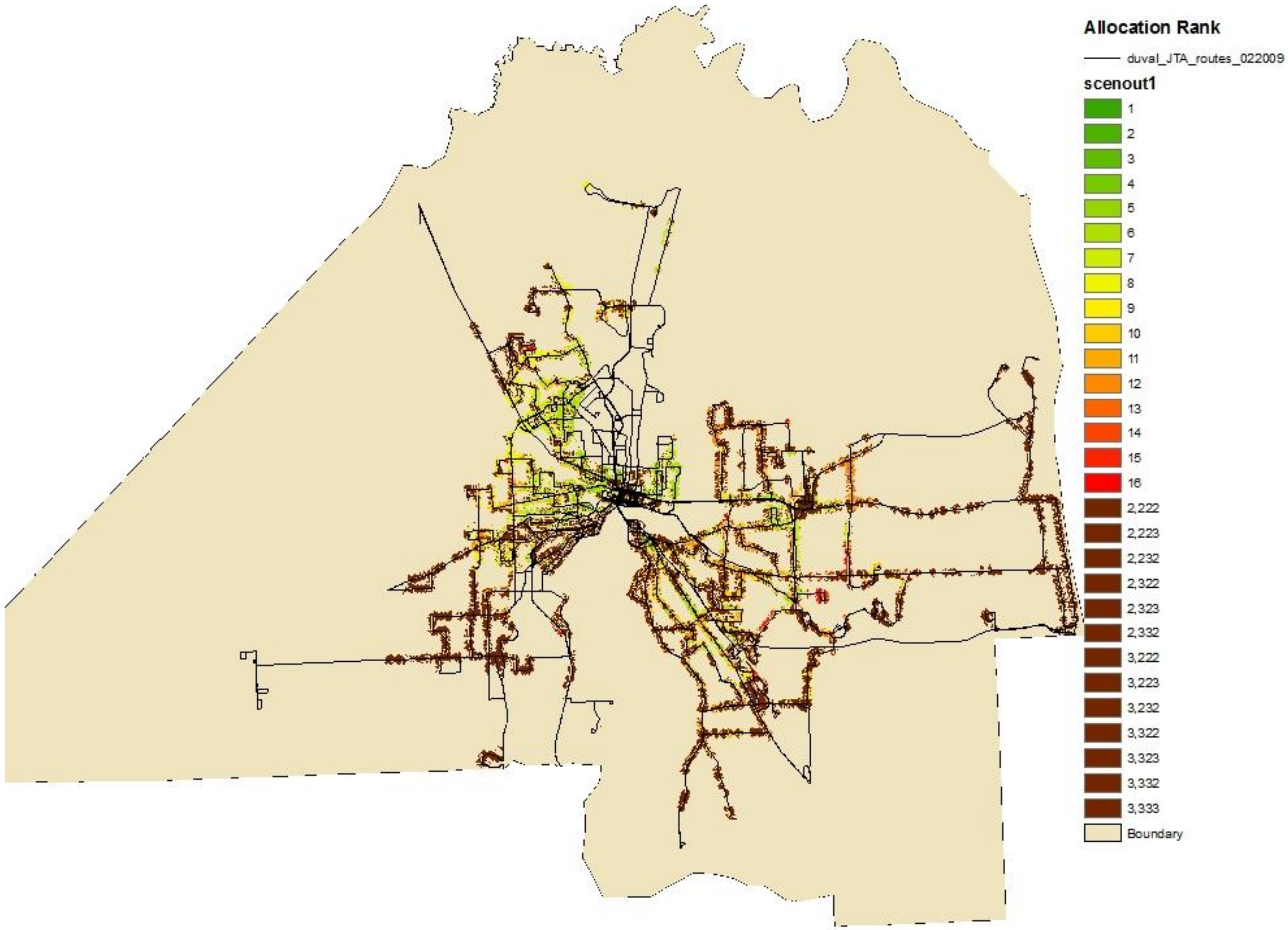


Figure 7-30. Duval County allocation

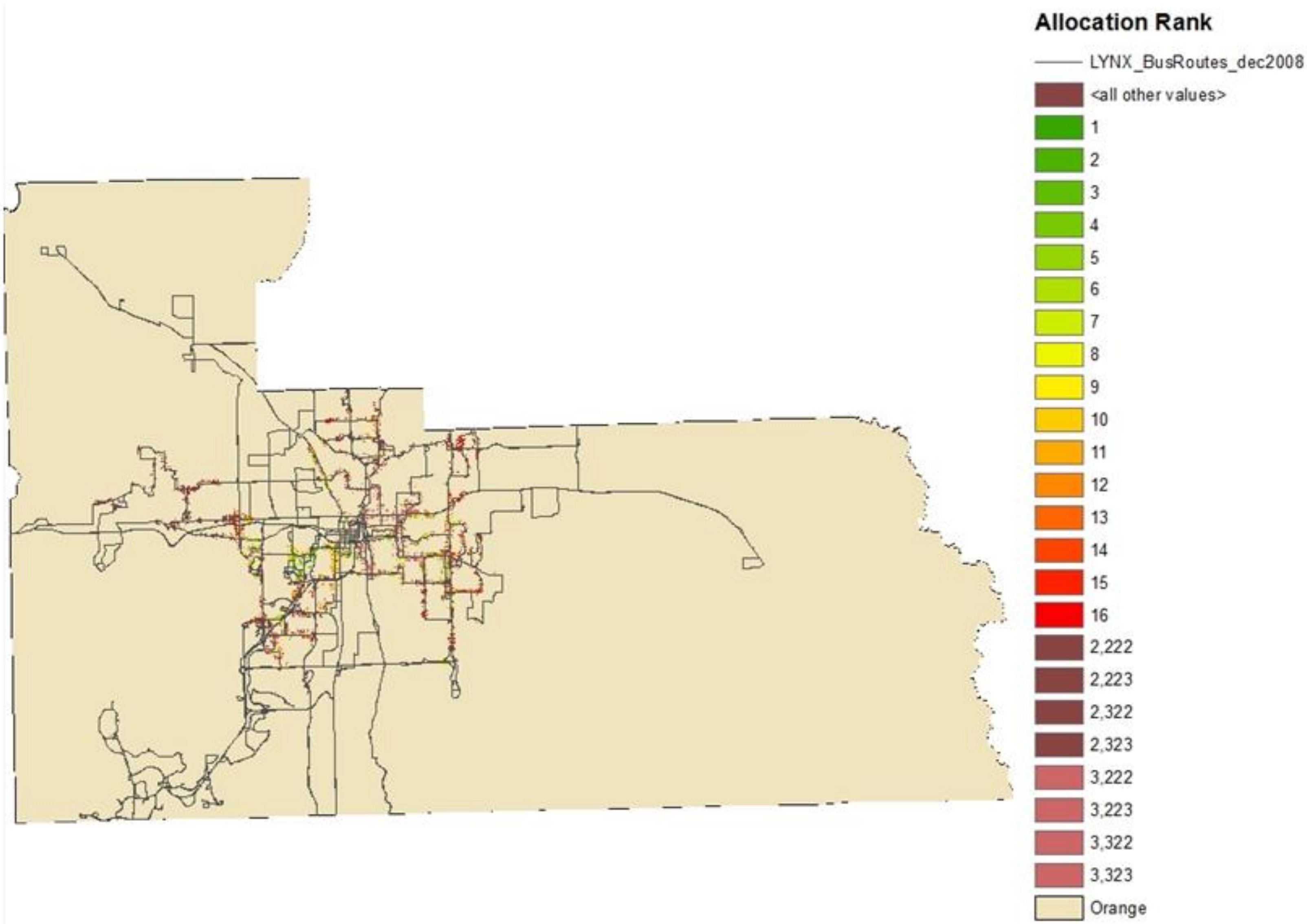


Figure 7-31. Orange County allocation

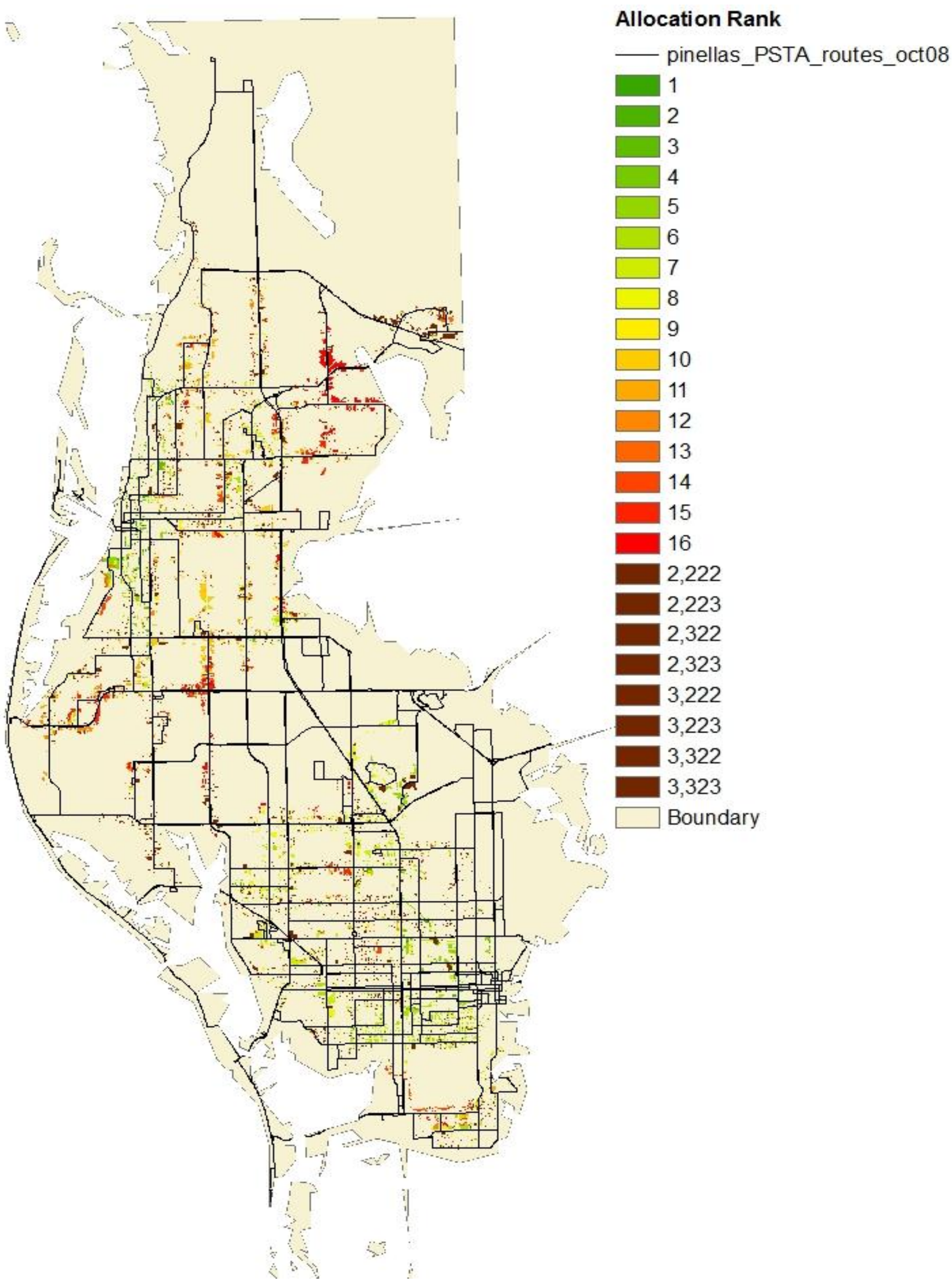


Figure 7-32. Pinellas County allocation

CHAPTER 8
CONCLUSION, RECOMMENDATIONS AND LIMITATIONS

The research developed a hierarchical automated suitability for the allocation of affordable housing that takes into account transportation variables such as accessibility and travel cost. During the process of developing the model, the research answered the following research questions:

1) What are the feasible methods to create and include accessibility and travel cost as suitability surfaces in an affordable housing suitability model;

2) What is the impact of travel cost and transit accessibility on the allocation and preservation of affordable housing sites; and

3) How to incorporate multi-modal transportation systems sprawl conceptualization metrics in allocating land for affordable housing?

The following sections will discuss the extent to which the research answered these questions and will discuss the study's limitations, as well as make recommendations, for future research.

Accessibility and Travel Cost as Suitability Surfaces in an Affordable Housing Suitability Model

The research established methodologies for creating accessibility and travel cost surfaces to be incorporated as suitability components in a hierarchical suitability model for the allocation of affordable housing. In terms of accessibility the research investigated different methods that in the literature are used to estimate accessibility (Handy, 2004; Levinson & Krizek, 2008; Bhat et al., 2002). However, none of the mentioned methods in the literature, other than the simple proximity metric, had been used in a suitability model. This research introduced these accessibility metrics to be used as suitability surfaces that represent accessibility. Chapter 3 established the methodology with which these suitability surfaces were generated and Chapter 5 established automation tools that were used to create these suitability surfaces.

The research discussed the methods and formulas to be used in estimating accessibility. The choice of suitable accessibility estimation depends on many variables. For example, the best estimation method might be to use a gravity accessibility measurement at a parcel level. However, such an approach needs the creation of an origin-destination matrix that would contain billions of records, making it an unrealistic method considering the capabilities of a personal computer. The research compared other methods that can be operated on a personal computer. The comparison served to explain the merits and limitations of each method and allow the planner to choose a suitable model to estimate accessibility in terms of accuracy, limitations and model running time.

In terms of travel cost, the research established statistical models to generate travel cost from travel survey data. Suitability models are deterministic models. Therefore, the combination of different utilities that compose a multiple utility assignment is usually done by a weighting process. This research generated some of these weights using statistical models showing that suitability can be generated by regression. However, the only deterministic steps in generating the travel cost were performed by transforming trip miles to cost and in reclassifying the final raster according to preference thresholds that were informed by other research as shown in the literature review (HUD, 2011a; CNT, 2011). Chapter 4 shows the statistical models that were used to generate the travel cost suitability surfaces.

The research showed that travel cost can be generated by spatial interpolation. However, this method only works to generate the present travel cost. Future visioning of travel cost or predicting travel miles requires travel cost to be related to urban form characteristics, such as the 5Ds (Ewing & Cervero, 2001). These land-use and urban form characteristics change in the future and lead to a change in travel cost. For that, two statistical models were estimated and compared in Chapter 4. These models were the OLS and GWR models. The comparison concluded that the GWR model had the least residual errors and a higher goodness of fit than the OLS model.

The comparison of the two statistical models also showed that the residuals for the OLS model were spatially clustered. The model, however, is still useful because the residuals are small. The OLS model gives constant parameters that can help us to understand global variables, for example, how increasing density reduces travel cost. However, the GWR model shows that this is not always the case and increasing density in some areas may not decrease travel cost because of local anomalies that changed the relationship and the OLS model couldn't capture the new spatially discriminated relationship. There are also limitations of using GWR such as the minimum number of points and distance variables that could lead to the failure of GWR estimations.

The travel cost generated by any of the three mentioned methods can be reclassified and transformed to suitability and preference surfaces and be included in the conflict/ opportunity surface. However, it should be noted that the travel cost surface does not take personal characteristics of the driver into account. Household characteristics other than household size and income by Census block were not included in this research and will be left for future research. Additionally, the output travel cost was generated on a cell-level scale, an area of approximately a quarter of an acre. For future research however, it is recommended that a travel cost value be assigned according to the average cost within a surrounding neighborhood comprised of the cells within a walking distance. The cell at the center of each neighborhood would be assigned a value for the average travel cost for its surrounding neighborhood.

The Impact of Travel Cost and Transit Accessibility on the Allocation and Preservation of Affordable Housing Sites

The research compared the opportunity surface that contained transit accessibility and travel cost to an opportunity surface without transit accessibility or travel cost. Chapter 7 showed clearly that in the affordable housing opportunity surfaces, travel cost and transit accessibility reduced the mean distance to activities, reduced the mean distance to CBD, increased the surrounding density and increased the land use mix. Chapter 7 also compared these values to those generated for properties in the Assisted Housing Inventory (AHI) and showed that the results of the ARDT surface were more comparable to the AHI than the AR surface. The results also showed that the ARDT surface generally had lower distances to the CBD and activity centers while the AHI were generally in slightly denser places.

In summary, it can be concluded that using transit accessibility and travel cost as suitability components leads to a more compact development pattern and that sprawl is reduced in the allocation of affordable housing development. Furthermore, the comparison of the AHI with the ARDT surface is useful in efforts aimed at the preservation of existing affordable housing, where more analysis could be performed on the AHI properties that included categorizing them according to the year built and the type of assistance they are receiving. Categorizing AHI by year can help the preservation efforts according the age of the buildings. However, the year can be also important to study the change in affordable housing allocation policies especially if the location and proximity to services had been considered in funding these sites. In terms of affordable housing program types, there are many funding categories, such as public housing, assisted housing and housing vouchers. There are also programs that support the production of affordable housing such as capital financing, rental subsidies and tax credits (Ray et al., 2009). The potential outcome from categorizing the AHI units according to funding or program type and comparing them to the affordable housing suitability sites is evaluate the efficiency of the program and preservation effort feasibility. Using AHI in preserving affordable housing units and in evaluating affordable housing programs will be investigated in the future research.

Creating the opportunity surface was performed by an automated sequential process facilitated by the suitability tools introduced in Chapter 6. These automation tools included raster reclassification, raster weighting and the analytical hierarchy tools. The research showed how programming languages can be employed to automate the land use suitability models. In earlier LUCIS models, the user had to do some of the analysis outside of the GIS environment. The tools introduced by this research made the process automatic and can be done entirely in the GIS environment. The appendices of this dissertation show the source code of these tools. The tools that were generated in this research were also employed by LUCIS to produce a new version of LUCIS called LUCISplus, where the word "plus" stands for "processing of land use scenarios". However, the use of the tools has the limitation that they can only be used on raster suitability models. Creating tools that work in a vector GIS environment is outside the scope of this research and is left for future research.

The research also measured the collective impact of transit accessibility and travel cost on the opportunity for affordable housing. Measuring the impact of each of the variables independently requires further sensitivity analysis that is not covered by this research and will be addressed in future research.

The application of the models was also performed on three urban counties. Despite the differences between these counties, all of them have urban cores of a large city and each has significant transit routes. The application of the model on rural areas may present some challenges especially in transportation modeling. Rural areas may not have established broad transportation network and transit accessibility. Therefore, some of the affordable housing transportation models and methodologies should be change to apply in rural counties. Applying the models on rural counties will be performed in future research.

Incorporating Multi-modal Transportation and Sprawl Conceptualization Metrics in Allocating Land for Affordable Housing?

A further step in the allocation of affordable housing was the ranking of the affordable housing sites using extra conditions and restraints. The Allocation by Table tool was used in Chapter 7. The table represented a scenario that contained the extra conditions for the ranking procedure. The ranks started at 1 and ended at 16. All the locations that had an opportunity for affordable housing according to the opportunity surface and were not ranked were assigned the values of the four-digit opportunity number. These lands did not satisfy the conditions set in the allocation table. However, they might have been useful for affordable housing under a different scenario. The ranking process took into account the continuity of the affordable housing allocation in the assigned opportunity sites and the areas that were not ranked were only the areas that did not match the scenario. This research suggested a compact development scenario that also had a certain degree of underutilization in the land use. Displaying scenarios other than the compact development scenario will be performed in future research.

The allocation procedure, which included the LUCIS suitability structure to create an opportunity surface and the use of a scenario table to rank the land for affordable housing, incorporated a multimodal transportation system in the process. The multi-modal modal transportation system included walking, biking, transit and driving. The suitability structure had the neighborhood access explained in Chapter 5. The suitability models suggested that access promotes more walking and biking and reduces the use of driving. This effect is explained in the literature review of this research and also explained in the research covered by Handy (2004). The use of a network-based accessibility estimation, however is more effective than the use of Euclidean distance based access measurements but has hardware and software limitations (Arafat et al., 2008). This research recommended the use of a combine opportunity distance metric for accessibility estimation. The use of a network based accessibility estimation needs very intensive computation that is time consuming and was only used within the scope of this research for testing purpose. Applying the network-based accessibility models in the affordable housing suitability model will be dependent on whether the feasibility of their use can be increased by the use of more powerful computers or by development of software packages that can accelerate the process.

Another outcome of incorporating a multi-modal transportation system into the allocation process was achieved by using the travel cost and transit accessibility in the opportunity surface. The transit accessibility surface was generated using the methodology explained in Chapter 3, while Chapter 5 compared the methods of generating the travel cost surface. The ARDT surface explained in Chapter 7 included transit accessibility and travel cost as preference surfaces in the final affordable housing opportunity, based on very low income population thresholds. The preference was set to discourage driving and increase the use of transit as a mode of transportation. This does not mean that people under the VLI income limit would not use a car but the model promotes affordable housing opportunities in areas that have high transit access and lower travel cost. The traveler may finally decide that the use of cars is more convenient. This selection of travel mode may depend on the surrounding households and the characteristics of the traveler. This research did not focus on self-selection, which is an important factor to be investigated in future research. The models do, however, incorporate travel cost and transit accessibility and as such they promote the use of transit and the reduction of driving travel miles.

The use of multi-modal transportation continued at the allocation level by the use of a walking-biking suitability surface in Orange County. The scenario for compact development in the three counties promoted a greater use of walking, biking and transit and lower driving miles. The scenario tables may also include more refined conditions by using the transit accessibility and travel cost suitability surfaces in addition to the preference surfaces included in the opportunity grid. This allows the use of a 1-9 suitability range instead of a 1-3 preference range. This also allows more detailed allocation in the scenario.

The suitability structure is a deterministic procedure. The miles of travel or the trip length are generated by robust statistics. Some deterministic steps are used to generate the travel cost out of the trip miles and to transfer the travel cost into a preference surface. Using a stochastic location choice model is outside the scope of this research. However, this research recommends the use of robust statistics in generating the suitability surface as explained in Chapter 5.

Introducing Parcel Level Analysis for Affordable Housing Sites

The level of analysis was emphasized in Chapter 4 which also utilized the choice of an areal unit. The literature review explained that the level of analysis is dependent on the variable that is analyzed. For accessibility parcel-level analysis is recommended (Johnston, 2004); Wegner, 2005). However, many of the variables used in this research are collective measurements that are recommended to be performed on a neighborhood scale. For these variables, Chapter 4 introduced the floating neighborhood, or the surrounding area characteristics, to reduce the impact of the modifiable areal unit on the metrics used in the analysis. The analysis results in Chapter 4 also recommends the Manhattan distance of 1.25 miles as the optimal surrounding distance for collective measurements such as density, connectivity and land use mix metrics. This distance generated a diamond-shaped neighborhood that is used to estimate the aggregated value of the metric. However, the 1.25 mile Manhattan distance is suggested for studying the impact of urban form on trip miles and mode choice, and does not change the TOD distance of 0.25 mile for buses and 0.50 mile for rail. This research recommended the use of network or Manhattan sheds for such an analysis.

The suitability model is based on raster analysis using a 31 meter x 31 meter cell size, which is a quarter of an acre in size, and can be assumed as being equivalent to a parcel-level in terms of spatial location. The output of the AHS model is in raster cells however and not in parcels. Because parcel characteristics are important in the allocation process, the output allocation grids were transformed to a 10 meter x 10 meter cell size. The values of these cells were also summarized for each parcel and then joined back to the parcel attribute table so that additional analysis queries could be performed using the vector parcel data. This allows the planner to select suitable parcels for affordable housing and investigates their specific land-use characteristics (Figure 8-1).

It should be noted, however, that a shift may occur in the raster analysis which is estimated at half a cell, or in this research, is shift in location of 15.5 meters. This shift may have a significant effect on the allocation into specific parcels. This research focused on the raster analysis and did not focus on the accuracy of the parcel-level vector analysis. Testing the accuracy of such parcel allocation is beyond the scope of this research and will be left for future research.

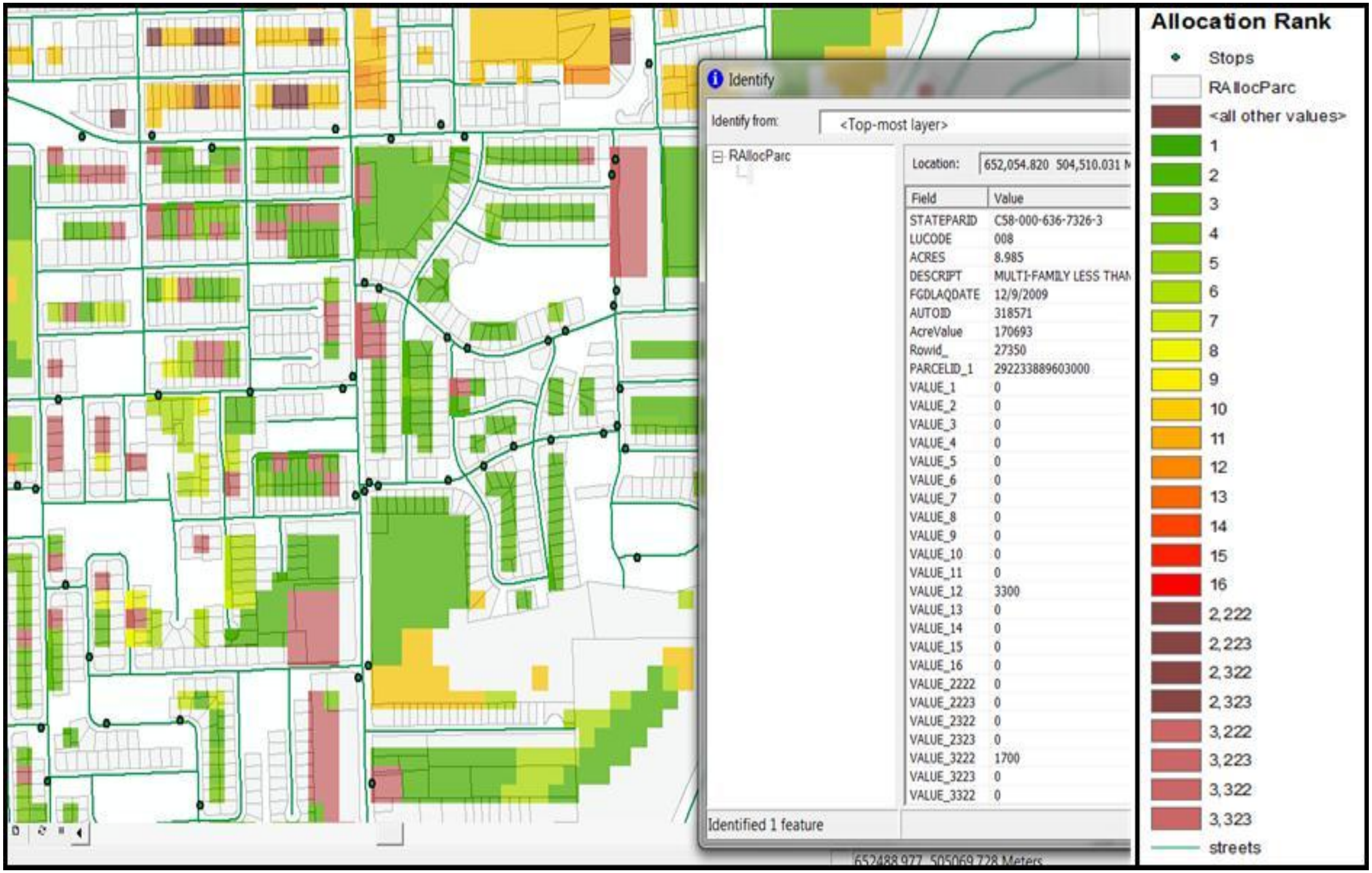


Figure 8-1. Example of parcel level allocation for affordable housing

APPENDIX A

THE A4 SUITABILITY TOOL SOURCE CODE

```
import sys, string, os, arcgisscripting, shutil
# Create the Geoprocessor object
gp = arcgisscripting.create()
gp.SetProduct("ArcView")
gp.CheckOutExtension("spatial")
# Work space
gp.workspace = sys.argv[1]
gp.OverwriteOutput = 1
# Load required toolboxes...
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Analysis Tools.tbx")
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Data Management Tools.tbx")
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")
classTable = sys.argv[2]
infeature = sys.argv[3]
# Set the Geoprocessing environment...
inraster = sys.argv[4]
inClass = sys.argv[5]
reclass = sys.argv[6]
gp.compression = "LZ77"
gp.rasterStatistics = "STATISTICS 1 1"
gp.cartographicCoordinateSystem = ""
gp.tileSize = "128 128"
gp.pyramid = "PYRAMIDS -1 NEAREST"
gp.cellSize = "MAXOF"
distsupfund = inraster
if classTable == '#':
   cur = gp.SearchCursor(infeature)
   row = cur.Next()
   StdSum = 0.
   MeanSum = 0.
   MinValue = row.MIN
   MaxValue = row.MAX
   i = 0
   x = 1
   while row:
```

```
            StdValue = row.STD
            MeanValue = row.MEAN
            StdSum = StdSum + StdValue
            MeanSum = MeanSum + MeanValue
            if (row.MIN < MinValue):
                MinValue = row.MIN
            if (row.MAX > MaxValue):
                MaxValue = row.MAX
            i = i + 1
            row =cur.Next()
        StdQuart = StdSum / (i * 4)
        MeanAvarage = MeanSum / i
        WorkRange1 = MinValue
        WorkRange2= MeanAvarage
        WorkRangeD1= MeanAvarage
        del row, cur
        if (inClass == "Decreasing Suitability"):
            # Local variables...
            URP = gp.workspace
            table2 = URP + "\\tablef
            #Process: Create Table...
            gp.CreateTable_management(URP, "tablef1", "", "")
            Range1 = "FROM1"
            # Process: Add Field...
            gp.AddField_management(table2, Range1, "DOUBLE", "", "2", "8", "FROM1", "NULLABLE",
"NON_REQUIRED", "")
            gp.AddField_management(table2, "TO", "DOUBLE", "", "2", "8", "", "NULLABLE",
"NON_REQUIRED", "")
            gp.AddField_management(table2, "OUT", "LONG", "9", "", "9", "", "NULLABLE",
"NON_REQUIRED", "")
            gp.AddField_management(table2, "MAPPING", "TEXT", "", "", "15", "", "NULLABLE",
"NON_REQUIRED", "")
            gp.deletefield_management(table2, "field1")
            gp.deletefield_management(table2, "OBJECTID")
            # check the number of intervals
            RangeValue = MaxValue - MeanAvarage
            intNum = RangeValue / StdQuart
```

```
    if (intNum < 8):
        StdQuart = RangeValue / 8
    #check first Value
    RangeMinOne = StdQuart * 7
    checkCell = RangeValue - RangeMinOne
    if (checkCell < 30):
        StdQuart = RangeValue / 8
    rows = gp.InsertCursor(table2)
    i = 0
    while i < 9:
        Rank = 9 - i
        if (i == 0):
            FromValue = 0.
            ToValue = WorkRange2
        else:
            FromValue = WorkRange1
            ToValue = WorkRange2
        if (i == 8):
            ToValue = 10000000
        row = rows.NewRow()
        row.FROM1 = FromValue
        row.TO = ToValue
        row.OUT = Rank
        row.MAPPING = "ValueToValue"
        rows.InsertRow(row)
        WorkRange1 = WorkRange2
        WorkRange2 = WorkRange1 + StdQuart
        i = i + 1
    del rows, row
    # Local variables...
    tablef = table2
    # Process: Reclass by Table...
    gp.ReclassByTable_sa(distsupfund, tablef, "FROM1", "TO", "OUT", reclass, "NODATA")
elif (inClass == "Increasing Suitability"):
    # Local variables...
    URP = gp.workspace
    table3 = URP + "\\tableb1"
```

```
#Process: Create Table...
gp.CreateTable_management(URP, "tableb1", "", "")
Range1 = "FROM1"
# Process: Add Field...
gp.AddField_management(table3, Range1, "DOUBLE", "", "2", "8", "FROM1", "NULLABLE",
"NON_REQUIRED", "")
gp.AddField_management(table3, "TO", "DOUBLE", "", "2", "8", "", "NULLABLE",
"NON_REQUIRED", "")
gp.AddField_management(table3, "OUT", "LONG", "9", "", "9", "", "NULLABLE",
"NON_REQUIRED", "")
gp.AddField_management(table3, "MAPPING", "TEXT", "", "", "15", "", "NULLABLE",
"NON_REQUIRED", "")
gp.deletefield_management(table3, "field1")
gp.deletefield_management(table3, "OBJECTID")
# check the number of intervals
RangeValue = MeanAvarage - MinValue
intNum = RangeValue / StdQuart
if (intNum < 8):
   StdQuart = RangeValue / 8
#check first Value
RangeMinOne = StdQuart * 7
checkCell = RangeValue - RangeMinOne
if (checkCell < 30):
   StdQuart = RangeValue / 8
i = 1
while i < 9:
   WorkRangeD2 = WorkRangeD1 - StdQuart
   FromValue = MinValue
   if (WorkRangeD1 < MinValue):
      ToValue = WorkRangeD2
      j = i + 1
   if (i == 8):
      ToValue = WorkRangeD2
      j = 9
   WorkRangeD1 = WorkRangeD2
   i = i + 1
rows = gp.InsertCursor(table3)
```

```
    WorkRangeD2 = ToValue + StdQuart
    WorkRangeD1 = FromValue
    i = 0
    while i < j:
      Rank = i + 1
      if (i == 0):
        FromValue = 0.
        ToValue = WorkRangeD2
      else:
        FromValue = WorkRangeD1
        ToValue = WorkRangeD2
      if (i == 8):
        ToValue = 10000000
      row = rows.NewRow()
      row.FROM1 = FromValue
      row.TO = ToValue
      row.OUT = Rank
      row.MAPPING = "ValueToValue"
      rows.InsertRow(row)
      WorkRangeD2 = WorkRangeD2 + StdQuart
      WorkRangeD1 = WorkRangeD2 - StdQuart
      i = i + 1
    del rows, row
    # Local variables...
    tableb = table3
    # Process: Reclass by Table...
    gp.ReclassByTable_sa(distsupfund, tableb, "FROM1", "TO", "OUT", reclass, "NODATA")
else:
  gp.ReclassByTable_sa(distsupfund, classTable, "FROM1", "TO", "OUT", reclass, "NODATA")
```

APPENDIX B:
WEIGHTING TOOLS

The Community Value Calculator Source Code

```
Option Explicit
Dim GetIndex As Integer
Dim intCounter1 As Integer
Dim intCounter2 As Integer
Dim RankArr(25, 25) As Integer
Dim AhpArr(25, 25) As Double
Dim columnSumArr(25) As Double
Dim normArr(25, 25) As Double
Dim rowSumArr(25) As Double
Dim wtArr(25)
Dim counter As Integer
Private Sub cboChooseLayers_Change()
End Sub
Private Sub cboChooseLayers_Click()
    populateLstBox
End Sub
Private Sub CommandButton1_Click()
End Sub
Private Sub cmdAdd_Click()
   Dim pGxDialog As IGxDialog
   Set pGxDialog = New GxDialog
   pGxDialog.Title = "Add Layers"
   pGxDialog.ButtonCaption = "Add"
   pGxDialog.AllowMultiSelect = False
   pGxDialog.StartingLocation = _
      "c:\"
   Dim pGxFilter As IGxObjectFilter
   Set pGxFilter = New GxFilterRasterDatasets
   Set pGxDialog.ObjectFilter = pGxFilter
   Dim pLayerFiles As IEnumGxObject
   pGxDialog.DoModalOpen 0, pLayerFiles
   Dim pLayerFile As IGxObject
   Set pLayerFile = pLayerFiles.Next
```

```
  MsgBox pLayerFile.Name
  If pLayerFile Is Nothing Then
     Exit Sub
  End If
  MsgBox pLayerFile.Name
  Dim pGxLayer As IGxObject
  Set pGxLayer = pLayerFile
  MsgBox pGxLayer.FullName
  cboChooseLayers.AddItem (pLayerFile.Name)
  LstLayerBox.AddItem (pLayerFile.Name)
End Sub
Private Sub AddShapeFile(folder As String, ShapeName As String)
   Dim pWorkspaceFactory As IWorkspaceFactory
   Dim pFeatureWorkspace As IFeatureWorkspace
   Dim pFeatureLayer As IFeatureLayer
   Dim pFeatureClass As IFeatureClass
   Dim pMxDoc As IMxDocument
   Dim pMap As IMap
   Dim pLayer As ILayer
   Dim pEnumLayer As IEnumLayer
   Set pMxDoc = Application.Document
   Set pMap = pMxDoc.FocusMap
   'Create a new ShapefileWorkspaceFactory object and open a shapefile folder
   Set pWorkspaceFactory = New ShapefileWorkspaceFactory
   Set pFeatureWorkspace = pWorkspaceFactory.OpenFromFile(folder, 0)
   'Create a new FeatureLayer and assign a shapefile to it
   Set pFeatureLayer = New FeatureLayer
   Set pFeatureLayer.FeatureClass = pFeatureWorkspace.OpenFeatureClass(ShapeName)
   pFeatureLayer.Name = pFeatureLayer.FeatureClass.AliasName
   pMap.AddLayer pFeatureLayer
   pMxDoc.ActiveView.Refresh
   pMxDoc.UpdateContents
End Sub
Private Sub CommandButton2_Click()
tableBuild
End Sub
Private Sub CommandButton3_Click()
```

```
  Dim pGxDialog As IGxDialog
  Set pGxDialog = New GxDialog
  pGxDialog.Title = "Load Table"
  pGxDialog.ButtonCaption = "Add"
  pGxDialog.AllowMultiSelect = False
  pGxDialog.StartingLocation = _
    txtWorkSpace.Text
  Dim pGxFilter As IGxObjectFilter
  Set pGxFilter = New GxFilterTables
  Set pGxDialog.ObjectFilter = pGxFilter
  Dim pLayerFiles As IEnumGxObject
  pGxDialog.DoModalOpen 0, pLayerFiles
  Dim pTableFile As IGxObject
  Set pTableFile = pLayerFiles.Next
  MsgBox pTableFile.Name
  If pTableFile Is Nothing Then
     Exit Sub
  End If
  MsgBox pTableFile.Name
  txtFileName.Text = pTableFile.Name
  tableRet
End Sub
Private Sub CommandButton5_Click()
Dim icounter As Integer
   Dim pOIDField
   Dim pWorkspaceFactory As IWorkspaceFactory
   Dim pFeatureWorkspace As IFeatureWorkspace
   Dim workSpace As String
   workSpace = txtWorkSpace.Text
   Dim tableName As String
   If Trim(TextBox5.Text) = "" Then
      tableName = txtFileName.Text
   Else
      tableName = TextBox5.Text
   End If
   Set pWorkspaceFactory = New ShapefileWorkspaceFactory
   Set pFeatureWorkspace = pWorkspaceFactory.OpenFromFile(workSpace, 0)
```

```
    Dim pTable As ITable
    Set pTable = pFeatureWorkspace.OpenTable(tableName)
    Dim pQueryFilter As IQueryFilter
    Set pQueryFilter = New QueryFilter
    Dim pCursor As ICursor
    Set pCursor = pTable.Update(pQueryFilter, False)
  'we need to get the featureClass of the layer
    Dim iCount As Integer
    Dim pRow As IRow
    Set pRow = pCursor.NextRow
    iCount = 0
Do While Not pRow Is Nothing
    pRow.Value(2) = wtArr(iCount)
    pRow.Store
    iCount = iCount + 1
    Set pRow = pCursor.NextRow
Loop
End Sub
Private Sub Frame2_Click()

End Sub
Private Sub Frame3_Click()
End Sub
Private Sub Frame4_Click()
End Sub
Private Sub Label1_Click()
End Sub
Private Sub Label4_Click()
End Sub
Private Sub ListBox2_Click()
End Sub
Private Sub ListBox2_DblClick(ByVal Cancel As MSForms.ReturnBoolean)
Dim newIndex As Integer
newIndex = ListBox2.ListIndex
Dim I As Integer
Dim Num As Integer
Dim sum As Double
```

```
Num = ListBox2.ListCount - 1
For I = 0 To Num
wtArr(I) = ListBox2.List(I)
Next I
wtArr(newIndex) = InputBox("Enter New Weight", "New Weight")
ListBox2.Clear
sum = 0
For I = 0 To Num
ListBox2.AddItem wtArr(I)
sum = sum + wtArr(I)
Next I
TextBox2.Text = sum
End Sub
Private Sub LstBoxRank_Change()
  End Sub
Private Sub LstBoxRank_Click()
End Sub
Private Sub LstBoxRank_DblClick(ByVal Cancel As MSForms.ReturnBoolean)
 Dim strLabel3 As String
   Dim strLabel2 As String
   Dim PeopleLim As Integer
   counter = counter + 1
   RankArr(intCounter1, intCounter2) = Val(LstBoxRank.Text)
   If LstBoxRank.ListIndex < 9 Then
      AhpArr(intCounter1, intCounter2) = AhpArr(intCounter1, intCounter2) + RankArr(intCounter1,
intCounter2)
   Else
      AhpArr(intCounter1, intCounter2) = AhpArr(intCounter1, intCounter2) + 1 /
RankArr(intCounter1, intCounter2)
   End If
   MsgBox "Your total Community Value = " & AhpArr(intCounter1, intCounter2) & " person count =
" & counter
   PeopleLim = TextBox6.Value
   If counter < PeopleLim Then
   Exit Sub
   Else
   AhpArr(intCounter1, intCounter2) = AhpArr(intCounter1, intCounter2) / counter
```

```
            MsgBox "You Final avarage Community Value = " & AhpArr(intCounter1, intCounter2) & " for " & 
counter & " persons "
            counter = 0
            End If
            If intCounter2 = LstLayerBox.ListCount - 1 Then
            Exit Sub
            End If
            If intCounter2 < LstLayerBox.ListCount - 1 Then
            intCounter2 = intCounter2 + 1
            strLabel2 = LstLayerBox.List(intCounter2)
            Label2.Caption = strLabel2
            End If
        End Sub
        Private Sub LstFrame_Click()
        End Sub
        Public Sub LstLayerBox_Change()
            Dim pMxDocument As IMxDocument
            Set pMxDocument = ThisDocument
            Dim pMap As IMap
            Set pMap = pMxDocument.FocusMap
            intCounter1 = LstLayerBox.ListIndex
            intCounter2 = intCounter1 + 1
            Dim strLabel3 As String
            Dim strLabel2 As String
            Dim counter As Integer
            If intCounter1 = LstLayerBox.ListCount - 1 Then Exit Sub
            strLabel3 = LstLayerBox.List(intCounter1)
            strLabel2 = LstLayerBox.List(intCounter2)
            Label3.Caption = strLabel3
            Label2.Caption = strLabel2
            'initializeRankBox
        End Sub
        Private Sub LstLayerBox_Click()
             'initializeRankBox
        End Sub
        Private Sub lstTableBox_Click()
        End Sub
```

```
Private Sub TextBox1_Change()
tableRet
End Sub
Private Sub TextBox2_Change()
End Sub
Private Sub TextBox6_Change()
End Sub
Private Sub UserForm_Click()
   'initializeRankBox
End Sub
Sub initializeRankBox()
Dim itemValue As Integer
Dim intCounter As Integer
LstBoxRank.Clear
For intCounter = 1 To 9
   itemValue = 10 - intCounter
   LstBoxRank.AddItem (itemValue)
Next intCounter
For intCounter = 2 To 9
   itemValue = intCounter
   LstBoxRank.AddItem (itemValue)
Next intCounter
End Sub
Private Sub UserForm_Initialize()
   intializeLayerMenu
   initializeRankBox
   TextBox6.Text = 1
End Sub
Private Sub intializeLayerMenu()
   ' initialize the list box
   Dim pMxDocument As IMxDocument
   Set pMxDocument = ThisDocument
   Dim pMap As IMap
   Set pMap = pMxDocument.FocusMap
   Dim pLayer As ILayer
   If pMap.LayerCount > 0 Then
      Dim intIndex As Integer
```

```
        For intIndex = 0 To (pMap.LayerCount - 1)
            Set pLayer = pMap.Layer(intIndex)
            cboChooseLayers.AddItem pLayer.Name
        Next intIndex
    End If
    ' select the first as default
End Sub
Private Sub populateLstBox()
    GetIndex = cboChooseLayers.ListIndex
     ' initialize the list box
    Dim pMxDocument As IMxDocument
    Set pMxDocument = ThisDocument
        ' define layers
    Dim pMap As IMap
    Set pMap = pMxDocument.FocusMap
    Dim pLayer As ILayer
    Set pLayer = pMap.Layer(GetIndex)
    LstLayerBox.AddItem pLayer.Name
End Sub
Private Sub calculateAhp()
    Dim icounter As Integer
    Dim jCounter As Integer
    For icounter = 0 To LstLayerBox.ListCount - 2
          For jCounter = icounter + 1 To LstLayerBox.ListCount - 1
              AhpArr(jCounter, icounter) = 1 / AhpArr(icounter, jCounter)
          Next jCounter
    Next icounter
    Dim n As Integer
    n = LstLayerBox.ListCount - 1
    For icounter = 0 To n
            AhpArr(icounter, icounter) = 1
    Next icounter
    For jCounter = 0 To n
      columnSumArr(jCounter) = 0
       For icounter = 0 To n
           columnSumArr(jCounter) = columnSumArr(jCounter) + AhpArr(icounter, jCounter)
       Next icounter
```

```
      'normalize
      For icounter = 0 To n
         normArr(icounter, jCounter) = AhpArr(icounter, jCounter) / columnSumArr(jCounter)
      Next icounter
    Next jCounter
      ' find weights
    For icounter = 0 To n
       rowSumArr(icounter) = 0
      For jCounter = 0 To n
          rowSumArr(icounter) = rowSumArr(icounter) + normArr(icounter, jCounter)
      Next jCounter
          wtArr(icounter) = rowSumArr(icounter) / (n + 1)
    Next icounter
    Dim sum As Double
    sum = 0
    For icounter = 0 To n
     sum = sum + wtArr(icounter)
    Next icounter
    TextBox2.Text = sum
End Sub
Private Sub tableBuild()
    calculateAhp
    Dim icounter As Integer
    Dim pOIDField
    Dim pWorkspaceFactory As IWorkspaceFactory
    Dim pFeatureWorkspace As IFeatureWorkspace
    Dim workSpace As String
    workSpace = txtWorkSpace.Text
    Dim tableName As String
    tableName = TextBox5.Text
    Set pWorkspaceFactory = New ShapefileWorkspaceFactory
    Set pFeatureWorkspace = pWorkspaceFactory.OpenFromFile(workSpace, 0)
    Dim pFieldEdit_nameRas As IFieldEdit
    Set pFieldEdit_nameRas = New Field
    Dim pFieldEdit_wtRas As IFieldEdit
    Set pFieldEdit_wtRas = New Field
    Dim nameRas
```

```
    Dim wtRas
    With pFieldEdit_nameRas
        .Type = esriFieldTypeString
        .Name = "Raster_Name"
        .Length = 30
    End With
    With pFieldEdit_wtRas
        .Type = esriFieldTypeDouble
        .Name = "Raster_weight"
        .Length = 15
    End With
    Dim pFieldsEdit As IFieldsEdit
    Set pFieldsEdit = New Fields
    pFieldsEdit.AddField pFieldEdit_nameRas
    pFieldsEdit.AddField pFieldEdit_wtRas
Dim pFields As IFields
Set pFields = pFieldsEdit
    Dim pTable As ITable
    Set pTable = pFeatureWorkspace.CreateTable(tableName, pFields, Nothing, Nothing, "")
    Dim pRow As IRow
    Dim n As Integer
    n = LstLayerBox.ListCount - 1
    ListBox2.Clear
For icounter = 0 To n
    Set pRow = pTable.CreateRow
    pRow.Value(1) = LstLayerBox.List(icounter)
    pRow.Value(2) = wtArr(icounter)
    ListBox2.AddItem wtArr(icounter)
    pRow.Store
Next icounter
Dim pStandaloneTable As IStandaloneTable
Set pStandaloneTable = New StandaloneTable
'assign the table from disk to the standalone table object
Set pStandaloneTable.Table = pTable
Dim pMxDocument As IMxDocument
    Set pMxDocument = ThisDocument
    Dim pMap As IMap
```

```
    Set pMap = pMxDocument.FocusMap
'initialize the tables collection to point to the map
Dim pStandaloneTableCollection As IStandaloneTableCollection
Set pStandaloneTableCollection = pMap
'add the standalone table to the collection of tables
pStandaloneTableCollection.AddStandaloneTable pStandaloneTable
'Refresh the TOC for the table to show up
pMxDocument.UpdateContents
End Sub
Private Sub cmdWorkSpace_Click()
   Dim pGxDialog As IGxDialog
   Set pGxDialog = New GxDialog
   pGxDialog.Title = "Work Space"
   pGxDialog.ButtonCaption = "Add"
   pGxDialog.AllowMultiSelect = False
   pGxDialog.StartingLocation = _
      "c:\"
   Dim pGxFilter As IGxObjectFilter
   Set pGxFilter = New GxFilterContainers
   Set pGxDialog.ObjectFilter = pGxFilter
   Dim pFolders As IEnumGxObject
   pGxDialog.DoModalOpen 0, pFolders
   Dim pLayerFolder As IGxObject
   Set pLayerFolder = pFolders.Next
   If pLayerFolder Is Nothing Then
       Exit Sub
   End If
   Dim pGxFolder As IGxObject
   Set pGxFolder = pLayerFolder
   txtWorkSpace.Text = pGxFolder.FullName
End Sub
Private Sub tableRet()
    Dim icounter As Integer
    Dim pOIDField
    Dim pWorkspaceFactory As IWorkspaceFactory
    Dim pFeatureWorkspace As IFeatureWorkspace
    Dim workSpace As String
```

```
    workSpace = txtWorkSpace.Text
    Dim tableName As String
    tableName = txtFileName.Text
    Set pWorkspaceFactory = New ShapefileWorkspaceFactory
    Set pFeatureWorkspace = pWorkspaceFactory.OpenFromFile(workSpace, 0)
    ‘Q filter
    Dim pTable As ITable
    Set pTable = pFeatureWorkspace.OpenTable(tableName)
    Dim pQueryFilter As IQueryFilter
    Set pQueryFilter = New QueryFilter
    Dim pCursor As ICursor
    Set pCursor = pTable.Search(pQueryFilter, False)
  'we need to get the featureClass of the layer
    Dim iCount As Integer
    Dim pRow As IRow
    Set pRow = pCursor.NextRow
    iCount = 0
Do While Not pRow Is Nothing
    'Set pRow = pTable.GetRow(iCount)
  'create a cursor to point to the selection
    LstLayerBox.AddItem pRow.Value(1)
    Dim xvalue1 As String
    Dim xvalue2 As Double
    xvalue1 = pRow.Value(1)
    xvalue2 = pRow.Value(2)
    'iCount = iCount + 1
    'counter1 = 0
    ListBox1.AddItem xvalue1
    ListBox2.AddItem xvalue2
    Set pRow = pCursor.NextRow
Loop
  ' now find the min, and max values and mean
End Sub
Sub initializeTempBoxes()
  Dim pMxDoc As IMxDocument
  Dim pMap As IMap
  Dim pFeatureLayer As IFeatureLayer
```

```
  Set pMxDoc = ThisDocument 'Application.Document
  Set pMap = pMxDoc.FocusMap
  'let's use the States layer that is the second layer in the map
  'the test below makes sure that the layer is a feature layer (vs image or grid)
  'If Not TypeOf pMap.Layer(3) Is IFeatureLayer Then Exit Sub
  Set pFeatureLayer = pMap.Layer(0)
  'Create the query filter
  Dim pQueryFilter As IQueryFilter
  Set pQueryFilter = New QueryFilter
  'pQueryFilter.WhereClause = "STATE_ABBR = 'FL'" ' OR STATE_ABBR = 'GA'"
  'pQueryFilter.WhereClause = "POP1990 > 5000000"
  'we need to get the featureClass of the layer
  Dim pFeatureClass As IFeatureClass
  Set pFeatureClass = pFeatureLayer.FeatureClass
  'create a cursor to point to the selection
  Dim pCursor As ICursor
  Set pCursor = ptable .Search(pQueryFilter, False)
  Dim lngCounter As Long
  lngCounter = 0
  Dim pFeature As IFeature
  Set pFeature = pFeatureCursor.NextFeature
  Do While Not pFeature Is Nothing
    lngCounter = lngCounter + 1
      cboMinTemp.AddItem pFeature.Value(lngFldIndex)
      cboMaxTemp.AddItem pFeature.Value(lngFldIndex)
    Set pFeature = pFeatureCursor.NextFeature
  Loop
cboMinTemp.ListIndex = 0
cboMaxTemp.ListIndex = 0
End Sub
```

The A4 Weighting Tool Source Code

```
import sys, os
import string, arcgisscripting
# Create the Geoprocessor object
gp = arcgisscripting.create()
gp.SetProduct("ArcView")
gp.CheckOutExtension("spatial")
```

```
# Work space
gp.workspace = sys.argv[1]
#gp.workspace = "X:\\CentralFlorida\\Intermediate"
gp.scratchWorkspace = sys.argv[1]
gp.overwriteoutput = 1
# Load required toolboxes...
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Analysis Tools.tbx")
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Data Management Tools.tbx")
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")
### Argument 1 is the list of tables to be converted
inRasters = sys.argv[2]
print inRasters
gp.compression = "LZ77"
gp.rasterStatistics = "STATISTICS 1 1"
gp.cartographicCoordinateSystem = ""
gp.tileSize = "128 128"
gp.pyramid = "PYRAMIDS -1 NEAREST"
gp.cellSize = "MAXOF"
### get the parameter table
wtTable = sys.argv[3]
### The list is split by semcolons ";"
inRasters = string.split(inRasters, ";")
print inRasters
### The output workspace where the shapefiles are created
oRas = sys.argv[4]
print oRas
count = 0
for inRaster in inRasters:
   print inRaster
   count = count + 1
i = 0
paraM = ""
for inRaster in inRasters:
   print inRaster
   i = i + 1
   print i
   # To start, make sure the input exists
```

```
    cur = gp.SearchCursor(wtTable)
    row = cur.Next()
    while not row.RASTER_NAM in inRaster:
        row =cur.Next()
    RasterName = row.RASTER_NAM
    WtValue = row.RASTER_WEI
    print RasterName, WtValue
    para1 = RasterName + " VALUE " + str(WtValue) + ";"
    if i == count:
        para1 = RasterName + " VALUE " + str(WtValue)
    row =cur.Next()
    print para1
    del row, cur
    paraM = paraM + para1
    print paraM
gp.WeightedSum_sa(paraM, oRas)
```

APPENDIX C
ALLOCATION TOOLS

Trend Allocation Tool Source Code

```
# Import system modules
import sys, string, os, arcgisscripting
# Create the Geoprocessor object
gp = arcgisscripting.create()
# Set the necessary product code
gp.SetProduct("ArcInfo")
# Check out any necessary licenses
gp.CheckOutExtension("spatial")
gp.CheckOutExtension("3D")
# Work space
WorkSpace = sys.argv[1]
gp.workspace = WorkSpace
# Load required toolboxes...
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Conversion Tools.tbx")
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Data Management
Tools.tbx")
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/3D Analyst Tools.tbx")
gp. overwriteoutput = 1
Table = sys.argv[2]
CalcFeild2 = sys.argv[3]
yearP = sys.argv[4]
Feild0 = sys.argv[5]
RegionNum = sys.argv[6]
CalcFeild1 = sys.argv[7]
Mask1 = sys.argv[8]
Mask2 = sys.argv[9]
Mask3 = sys.argv[10]
Mask4 = sys.argv[11]
Mask5 = sys.argv[12]
Feild1 = sys.argv[13]
inCodes1 = sys.argv[14]
Feild2 = sys.argv[15]
```

```
inCodes2 = sys.argv[16]
outTable = sys.argv[17]
inCode0 = RegionNum
Table_View = Table + "_View"
Express1 = "\"" + CalcFeild2 + "\"" + " = 0" + " AND " + "\"" + CalcFeild1 + "\"" + " > 0 "
Express2 = " AND " + "\"" + str(Feild0) + "\"" + " "
Express3 = "= " + inCode0 + " "
Express = "(" + Express1 + Express2 + Express3 + ")"
print Express
exp = ""
expR = ""
if Mask1 == '#':
  expR = ""
else:
  expR = expR + "\"" + Mask1 + "\"" + " = 1 "
if Mask2 == '#':
  exp = exp + ""
else:
  exp = exp + "\"" + Mask2 + "\"" + " = 1 "
if Mask3 == '#':
  exp = exp + ""
else:
  exp = exp + "OR " + "\"" + Mask3 + "\"" + " = 1 "
if Mask4 == '#':
  exp = exp + ""
else:
  exp = exp + "OR " + "\"" + Mask4 + "\"" + " = 1 "
if Mask5 == '#':
  exp = exp + ""
else:
  exp = exp + "OR " + "\"" + Mask5 + "\"" + " = 1 "
exp = expR + " AND " + "(" + exp + ")"
print exp
inCodes1 = string.split(inCodes1, ";")
inCodes2 = string.split(inCodes2, ";")
Count = 0
try:
```

```
  for inCode1 in inCodes1:
    print inCode1
    exp2 = "\"" + Feild1 + "\"" + " = " + inCode1
    for inCode2 in inCodes2:
      print inCode2
      Count = Count + 1
      print Feild2
      exp3 = "\"" + Feild2 + "\"" + " >= " + inCode2
      totExp = Express + " AND " + exp + " AND " + exp2 + " AND " + exp3
      print exp3
      print totExp
      Table_View2 = Table + "_View" + str(Count)
      print Table_View2
      gp.MakeTableView_management(Table, Table_View2, totExp, "")
      print "progress"
      gp.CalculateField_management(Table_View2, CalcFeild2, yearP, "VB")
  outValue = 1
  gp.CreateConstantRaster_sa(outTable, outValue, "INTEGER", "1", "0 0 250 250")
except Exception, ErrorDesc:
     msgStr = gp.GetMessages(2)
     sys.exit(1)
```

Allocation by Table Source Code

```
import sys, string, os, arcgisscripting
# Create the Geoprocessor object
gp = arcgisscripting.create()
# Set the necessary product code
gp.SetProduct("ArcInfo")
# Check out any necessary licenses
gp.CheckOutExtension("spatial")
gp.CheckOutExtension("3D")
# Work space
WorkSpace = sys.argv[1]
gp.workspace = WorkSpace
# Load required toolboxes...
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Conversion Tools.tbx")
```

```
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Data Management Tools.tbx")
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/3D Analyst Tools.tbx")
gp. overwriteoutput = 1
Table = sys.argv[2]
CalcFeild2 = sys.argv[3]
yearP = sys.argv[4]
Feild0 = sys.argv[5]
CalcFeild1 = sys.argv[6]
MaskExp1 = sys.argv[7]
MaskExp2 = sys.argv[8]
MaskExp3 = sys.argv[9]
MaskExp4 = sys.argv[10]
MaskExp5 = sys.argv[11]
Feild1 = sys.argv[12]
inCodes1 = sys.argv[13]
Feild2 = sys.argv[14]
inCodes2 = sys.argv[15]
outTable = sys.argv[16]
IterNum = sys.argv[17]
PeopleLim = sys.argv[18]
PrevAlloc = sys.argv[19]
PlanTable = sys.argv[20]
print PrevAlloc
print CalcFeild2
Table_View = Table + "_View"
Express1 = "\"" + CalcFeild2 + "\"" + " = 0" + " AND " + "\"" + CalcFeild1 + "\"" + " > 0 "
Express2 = " AND " + Feild0
Express = "(" + Express1 + Express2 + ")"
print Express
exp = ""
expR = ""
if MaskExp1 == '#':
  expR = expR + ""
else:
  expR = expR + MaskExp1
if MaskExp2 == '#':
```

```
  exp = exp + ""
else:
  exp = exp + MaskExp2
if MaskExp3 == '#':
  exp = exp + ""
else:
  exp = exp + " OR " + MaskExp3
if MaskExp4 == '#':
  exp = exp + ""
else:
  exp = exp + " OR " + MaskExp4
if MaskExp5 == '#':
  exp = exp + ""
else:
  exp = exp + " OR " + MaskExp5
exp = expR + " AND " + "(" + exp + ")"
print exp
inCodes1 = string.split(inCodes1, ";")
inCodes2 = string.split(inCodes2, ";")
Count = 0
try:
  for inCode1 in inCodes1:
    print inCode1
    exp2 = "\"" + Feild1 + "\"" + " = " + inCode1
    for inCode2 in inCodes2:
      print inCode2
      Count = Count + 1
      print Feild2
      exp3 = "\"" + Feild2 + "\"" + " >= " + inCode2
      totExp = Express + " AND " + exp + " AND " + exp2 + " AND " + exp3
      print exp3
      print totExp
      Table_View2 = Table + "_View" + str(Count)
      print Table_View2
      Phase = 'Iteration'
      PhaseV = int(IterNum)
      print PhaseV
```

```
        gp.MakeTableView_management(Table, Table_View2, totExp, "")
        print "progress"
        gp.CalculateField_management(Table_View2, Phase, PhaseV, "VB")
        print "progress"
        gp.CalculateField_management(Table_View2, CalcFeild2, yearP, "VB")
Express10 = "\"" + CalcFeild2 + "\"" + " = " + yearP + " AND " + "\"" + "Iteration" + "\" = " + IterNum
print Express10
sump = 0
cur = gp.SearchCursor(Table, Express10)
row = cur.Next()
while row:
    y = row.GetValue (CalcFeild1)
    sump = sump + y
    #print sump
    row = cur.Next()
del row, cur
print PrevAlloc
print sump
allocP = int(PrevAlloc) + int(sump)
print allocP
climit = int(PeopleLim) + 100
print climit
AllNeed = int(climit) - int(PrevAlloc)
print AllNeed
if climit < allocP:
    yearP1 = 0
    Table_View2 = Table + "_ViewX"
    print Table_View2
    gp.MakeTableView_management(Table, Table_View2, Express10, "")
    print "table view completed"
    gp.CalculateField_management(Table_View2, CalcFeild2, yearP1, "VB")
    print "pop field updated"
    expr = "\"" + "Iteration" + "\" = " + IterNum
    print expr
    cur = gp.UpdateCursor(Table, expr)
    print "progress"
    row = cur.Next()
```

```
    sump = 0
    yearP = sys.argv[4]
    while row:
      if AllNeed >= sump:
        row.SetValue (CalcFeild2, yearP)
        cur.updateRow (row)
        sump = sump + y
        #print sump
      row = cur.Next()
    del row, cur
  allocP = int(PrevAlloc) + int(sump)
  print allocP
  outValue = allocP
  print outValue
  cur = gp.UpdateCursor(PlanTable)
  print "Updating Table"
  row = cur.Next()
  FieldIter = "Iter"
  Popu = "Pop"
  Prev = "PrevPop"
  Iter1 = int(IterNum) + 1
  print IterNum, Iter1
  while row:
    con = row.GetValue (FieldIter)
    print "condition printed"
    print con
    print IterNum
    if con == int(IterNum):
      print "allocated pop condition granted"
      row.SetValue (Popu, outValue)
      cur.updateRow (row)
      row = cur.Next()
    elif con == int(Iter1):
      print "previous pop condition granted"
      row.SetValue (Prev, outValue)
      cur.updateRow (row)
      row = cur.Next()
```

```
        else:
            print "exception condition granted"
            row = cur.Next()
    del row, cur
    yearP1 = 0
    print yearP1
    Ex = "\"" + CalcFeild2 + "\"" + " = 0" + " AND " + "\"" + "Iteration" + "\" = " + IterNum
    #Ex = "\"" + CalcFeild2 + "\"" + " = " + str(yearP1)
    print "progress"
    print Ex
    Table_View3 = Table + "_ViewZ"
    print Table_View3
    gp.MakeTableView_management(Table, Table_View3, Ex, "")
    print "table view completed"
    gp.CalculateField_management(Table_View3, "Iteration", yearP1, "VB")
    print "Iter field updated"
    print "Generating Raster"
    print outValue
    gp.CreateConstantRaster_sa(outTable, outValue, "INTEGER", "1", "0 0 250 250")
except Exception, ErrorDesc:
        msgStr = gp.GetMessages(2)
        sys.exit(1)
```

Detailed Allocation Tool Source Code

```
# Import system modules
import sys, string, os, arcgisscripting
# Create the Geoprocessor object
gp = arcgisscripting.create()
# Set the necessary product code
gp.SetProduct("ArcInfo")
# Check out any necessary licenses
gp.CheckOutExtension("spatial")
gp.CheckOutExtension("3D")
# Work space
WorkSpace = sys.argv[1]
gp.workspace = WorkSpace
# Necessary tools
# Load required toolboxes...
```

```
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Conversion Tools.tbx")
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/Data Management Tools.tbx")
gp.AddToolbox("C:/Program Files (x86)/ArcGIS/ArcToolbox/Toolboxes/3D Analyst Tools.tbx")
# overwrite output
gp. overwriteoutput = 1
Table = sys.argv[2]
CalcFeild2 = sys.argv[3]
yearP = sys.argv[4]
Feild0 = sys.argv[5]
RegionNum = sys.argv[6]
CalcFeild1 = sys.argv[7]
DenFeild = sys.argv[8]
PeopleLim = sys.argv[9]
Mask1 = sys.argv[10]
Mask2 = sys.argv[11]
Mask3 = sys.argv[12]
Mask4 = sys.argv[13]
Mask5 = sys.argv[14]
Feild1 = sys.argv[15]
inCodes1 = sys.argv[16]
Feild2 = sys.argv[17]
inCodes2 = sys.argv[18]
Feild3 = sys.argv[19]
inCodes3 = sys.argv[20]
Feild4 = sys.argv[21]
inCodes4 = sys.argv[22]
Feild5 = sys.argv[23]
inCodes5 = sys.argv[24]
Prop = sys.argv[25]
outRaster = sys.argv[26]
inCode0 = RegionNum
Table_View = Table + "_View"
# gapredn = "gapredn"
Express1 = "\"" + CalcFeild2 + "\"" + " = 0"
Express2 = " AND " + "\"" + str(Feild0) + "\"" + " "
```

```
Express3 = "= " + inCode0 + " "
if DenFeild == '#':
  Express4 = ""
else:
  Express4 = "AND " + "\"" + DenFeild + "\"" + " >= 1"
Express = "(" + Express1 + Express2 + Express3 + Express4 + ")"
print Express
# Generating expression
exp = ""
expR = ""
if Mask1 == '#':
  expR = ""
else:
  expR = expR + "\"" + Mask1 + "\"" + " = 1 "
if Mask2 == '#':
  exp = exp + ""
else:
  exp = exp + "\"" + Mask2 + "\"" + " = 1 "
if Mask3 == '#':
  exp = exp + ""
else:
  exp = exp + "OR " + "\"" + Mask3 + "\"" + " = 1 "
if Mask4 == '#':
  exp = exp + ""
else:
  exp = exp + "OR " + "\"" + Mask4 + "\"" + " = 1 "
if Mask5 == '#':
  exp = exp + ""
else:
  exp = exp + "OR " + "\"" + Mask5 + "\"" + " = 1 "
exp = expR + " AND " + "(" + exp + ")"
print exp
Table_View1 = Table + "_View1"
# Process: Make Table View...
# gp.MakeTableView_management(Table, Table_View, Express, "")
#searchCursor1 = gp.searchCursor(Table, Express)
if inCodes5 == '#' :
```

```
  inCodes5 = "100000"
if inCodes4 == '#' :
  inCodes4 = "100000"
if inCodes3 == '#' :
  inCodes3 = "100000"
##inCodes1 = "3333;2121;2131;3131"
inCodes1 = string.split(inCodes1, ";")
##inCodes2 = "100;99;98;97"
inCodes2 = string.split(inCodes2, ";")
##inCodes3 = "2;9;1;3"
inCodes3 = string.split(inCodes3, ";")
##inCodes4 = "-1"
inCodes4 = string.split(inCodes4, ";")
##print inCodes4
##inCodes5 = "-1"
inCodes5 = string.split(inCodes5, ";")
sump = 0
Count = 1
try:
  for inCode1 in inCodes1:
    print inCode1
    Count = Count + 1
    exp2 = "\"" + Feild1 + "\"" + " = " + inCode1
    totExp = Express + " AND " + exp + " AND " + exp2
    print exp2
    print totExp
    Table_View2 = Table + "_View" + str(Count)
    print Table_View2
    #gp.MakeTableView_management(Table_View1, Table_View2, exp2, "")
    for inCode2 in inCodes2:
      print inCode2
      for inCode3 in inCodes3:
        print inCode3
        for inCode4 in inCodes4:
          print inCode4
          for inCode5 in inCodes5:
            print inCode5
```

```
#combine_10 = Table_View2
#combine_10 = Search1
#cur = gp.updateCursor(combine_10)
#x = 10
#y = 2015
i = 1
#print y
#row = cur.Next()
print "Done 2"
cur = gp.updateCursor(Table, totExp)
row = cur.Next()
print "done "
while row:
    Var3 = row.GetValue (Feild2)
    print Var3
    if Var3 >= int(inCode2):
        print "Second Condition Satisfied"
        if not Feild3 == '#':
            Var4 = row.GetValue (Feild3)
            print Var4
        if Feild3 == '#':
            Var4 = 100000
        if Var4 >= int(inCode3):
            print "third condition Satisfied"
            if not Feild4 == '#':
                Var5 = row.GetValue (Feild4)
                print Var5
            if Feild4 == '#':
                 Var5 = 100000
            if Var5 >= int(inCode4):
                print "fourth condition satisfied"
                if not Feild5 == '#':
                    Var6 = row.GetValue (Feild5)
                    print Var6
                if Feild5 == '#':
                     Var6 = 100000
                if Var6 >= int(inCode5):
```

```
        print "Fifth cond"
        #print "Allocation"
        if DenFeild == '#':
            peop = row.GetValue (CalcFeild1)
            print peop
        else:
            cnt = row.CELLCOUNT
            den = row.GetValue (DenFeild)
            peop = cnt * den
            if den == 0:
                year1 = 0
            else:
                year1 = yearP
        if Prop == '#':
            Prop1 = 1
        else:
            Prop1 = row.GetValue (Prop)
        row.GetValue (CalcFeild2)
        year1 = yearP
        print year1
        row.SetValue (CalcFeild2, year1)
        y1 = Prop1 * peop
        y = int(y1)
        print y
        row.GetValue (CalcFeild1)
        row.SetValue (CalcFeild1, y)
        cur.updaterow (row)
        sump = sump + y
        print sump,PeopleLim
        if sump >= int(PeopleLim) :
            Express10 = "\"" + CalcFeild2 + "\"" + " = " + yearP
            gp.ExtractByAttributes_sa(Table, Express10, outRaster)
            sys.exit(0)
        row = cur.Next()
    else:
        row = cur.Next()
else:
```

```
                        row = cur.Next()
                    else:
                        row = cur.Next()
                else:
                    row = cur.Next()
            del row, cur
  Express10 = "\"" + CalcFeild2 + "\"" + " = " + yearP
  gp.ExtractByAttributes_sa(Table, Express10, outRaster)
except Exception, ErrorDesc:
    msgStr = gp.GetMessages(2)
    sys.exit(1)
```

LIST OF REFERENCES

American Automobile Association (2011). *Your driving cost 2010 edition.* Retrieved January 5, 2011, from http://www.aaaexchange.com/Assets/Files/201048935480.Driving%20Costs%202010.pdf

Arafat A., Srinivasan, S., & Steiner, R.L. (2010). The impacts of land use and urban form on travel behavior: A parcel level destination choice model applied on south-east Florida. *Proceeding of the 12th World Conference on Transport Research Conference.* Retrieved November 1, 2010, from http://www.civil.ist.utl.pt/wctr12_lisboa/proceedings.htm

Arafat, A., Steiner, R.L., & Bejleri, I. (2008, July). *A method for measuring network distance using network shortest distance and spatial interpolation*. Paper presented at ACSP-AESOP 4th Joint Congress, Chicago, IL.

Bejleri I., Steiner R.L.,Wheelock, J., Perez, B., & Fischman A. (2008, July*). Measuring walkability around elementary schools: A comparison of urban form indices in four Florida counties*. Paper presented at ACSP-AESOP 4th Joint Congress, Chicago, IL.

Ben-Akiva, M. & Bowman, J.L. (1998). Activity based travel demand model systems. In P. Marcotte & S. Nguyen (Eds.), *Equilibrium and Advanced Transportation Modeling* (pp. 27-46). Boston, MA: Kluwer Academic Publishers.

Bhat, C.R., & Guo, J.Y. (2004). A mixed spatially correlated logit model: Formulation and application to residential choice modeling. *Transportation Research Part B: Methodological, 38*(2), 147-168.

Bhat C.R., Handy, S., Kockelman, K., Mahmassani, H., Gopal, A., Srour, I., & Weston, L. (2002). *Development of an urban accessibility index. formulations, aggregation and application* (Report No. FHWA/TX-02-4938-4). Austin, TX: University of Texas at Austin.

Bhat, C. R., & Koppelman, F. S. (1999). A retrospective and prospective survey of time-use research*. Transportation, 26*(2)*,* 119-139.

Bhat, C. R., & Koppelman, F. S. (1993). An endogenous switching simultaneous equation system of employment, income, and car ownership. *Transportation Research Part A: Policy and Practice, 27*(6), 447-459.

Bhat, C.R., & Lawton, T.K. (1999). *Passenger travel demand forecasting*. Transportation Research Board Committee on Passenger Travel Demand Forecasting. Retrieved December 15, 2009, from http://onlinepubs.trb.org/onlinepubs/millennium/00083.pdf

Carr, M. (2008). *Key components of environmental planning*. Gainesville, FL: University of Florida.

Carr M., & Zwick P. (2005). Using GIS suitability analysis to identifying future land-use conflicts in north central Florida. *Journal of Conservation Planning, 1*(1). Retrieved March 15, 2009, from http://www.journalconsplanning.org/2005/index.html

Carr M., & Zwick. P. (2007). *Smart land-use analysis: The LUCIS model*. Redlands, CA: ESRI press.

Center for Neigborhood Technology CNT (2007). Uncovering the hidden assets of established communities, *Housing + Transportation Affordability Report*. Retrieved January 20, 2010, from http://www.oak-forest.org/UserFiles/File/Planning_&_Zoning/Research_&_Studies/H-T-Oak-Forest.pdf

Center for Neigborhood Technology CNT (2010). *True affordability and location efficiency*. Retrieved January 30, 2011, from http://htaindex.cnt.org/

Cervero, R., & Kockelman K. (1997). Travel demand and the 3Ds: density, diversity, and NT design. *Transportation Research D*, *2*, 199-219.

Cervero, R., & Radisch C. (1996). Travel choices in pedestrian versus automobile oriented neighborhoods. *Transport Policy*, *3*, 127-141.

Collins M., Steiner F, & Rushman M. (2001). Land-use suitability analysis in the United States: historical development and promising technological achievements. *Environmental Management, 28*(5)*,* 611–621.

Dill J. (2004). *Measuring network connectivity for bicycling and walking*. Paper presented at the 83th Annual Meeting of the Transportation Research Board (CD-ROM), Washington, DC.

Driessen, P. M., & Konijn, N. T. (1992) *Land-use systems analysis*. Wageningen Agricultural University: Department of Soil Science and Geology.

El-Geneidy, A., & Levinson D. (2007, January). *Network circuity and the journey to work*. Paper presented at the University Transport Study Group Conference, Harrowgate, England. Retrieved February 15, 2008, from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.145.1196

Environmental Systems Research Institute (2011). *ArcGIS 9.3 desktop help*. Retrieved February 18,2011,from http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?TopicName=welcome

Ewing, R., Bartholomew, K., Winkelman, S., Walters, J. & Chen, D. (2008). *Growing cooler: The evidence on urban development and climate change*. Washington, D.C.: Urban Land Institute.Ewing, R., & Cervero, R. (2001). Travel and the built environment: A synthesis. *Transportation Research Record: Journal of the Transportation Research Board, 1780*, 87-114.

Florida Affordable Housing Model (2009). *Affordable housing model methodology*. University of Florida: Department of Urban and Regional Planning.

Frank, L., & Pivo G. (1994). Impacts of mixed use and density on utilization of three modes of travel: Single-occupant vehicle, transit, and walking. *Transportation Research Record*, *1466*, 44-52.

Frank L., Sallis J., Conway T., Chapman J., Saelens B., & Bachman W. (2006). Many pathways from land use to health: Associations between neighborhood walkability and active transportation, body mass index, and air quality. *Journal of the American Planning Association, 72*, 75–87.

Franklin, J.P., Waddell, P., & Britting, J. (2002). *Sensitivity analysis approach for an integrated land development & travel demand modeling system.* Retrieved January 5, 2010, from http://www.urbansim.org/pub/Research/ResearchPapers/ACSP02.doc

Galster, G., Hanson, R. , Ratcliffe, M.R. , Wolman, H. , Coleman, S., & Freihage, J. (2001). Wrestling sprawl to the ground: Defining and measuring an elusive concept. *Housing Policy Debate, 12*(4), 68 -717.

Giuliano, G. (2004). Land use impacts of transportation investments: Highway and transit. In S. S. Hanson and G. Giuliano (Eds.), *The Geography of Urban Transportation* (3rd ed., pp. 237-273). New York: The Guildford Press.

Grengs, J. (2009). Job accessibility and modal mismatch in Detroit. *Journal of Transport Geography*, 18(1), 42-54. doi:10.1016/j.jtrangeo.2009.0.01.012

Guo, J.Y., & Bhat, C.R. (2004). Modifiable areal units: A problem or matter of perception in the context of residential location choice modeling? *Transportation Research Record*, *1898*, 138-147.

Handy, S. (1996). Urban form and pedestrian choices: Study of Austin neighborhoods. *Transportation Research Board: Journal of the Transportation Research Board, 1552*, 135-144. doi:10.3141/1552-19

Handy, S. (2004). Planning for accessibility: In theory and practice. *Proceeding from the Access to Destination Conference.* Minneapolis, MN: University of Minnesota.

Handy, S., Cao, X., Buehler, T. J., & Mokhtarian, P. L. (2005). *The link between the built environment and travel behavior: Correlation or causality?* Paper presented at the 84th Annual Meeting of the Transportation Research Board (CD-ROM), Washington, D.C.

Hanson, S. (2004). The context of urban travel: Concepts and recent trends. In S. Hanson G. Giuliano(Eds.), *The Geography of Urban Transportation* (3rd ed., pp. 3-29). New York: The Guildford Press.

Hess, P., Moudon, A., & Logsdon, M.(2003). Measuring land use patterns for transportation research. *Transportation Research Record, 1780*, 17-24.

Iacono, M., & Levinson, D. (2008). *Predicting land use change: How much does transportation matter?* University of Minnesota: Nexus Research Group.

Iacono, M., Levinson, D., & El-Geneidy, A. (2008). Models of transportation and land-use change. *Journal of Planning Literature*, *22*, 323-340.

Janelle, D. (2004). Impact of information technologies. In S. Hansonand G. Giuliano (Eds.), *The Geography of Urban Transportation* (3rd ed., pp. 86-112). New York: The Guildford Press.

Jelinski, D., & Wu, J. (1996). The modifiable areal unit problem and implications for landscape ecology*. Landscape Ecology, 11*(3), 129-140.

Johnston, R. A. (2004). The urban transportation planning process. In S. Hanson and G. Giuliano (Eds.), *The Geography of Urban Transportation* (3rd ed., pp. 115-140). New York: The Guildford Press.

Kutz, M. (2003). *Handbook of transportation engineering*. New York: McGraw-Hill.

Kwan, M., & Weber, J. (2008). Scale and accessibility: Implications for the analysis of land use-travel interaction. *Applied Geography*, *28*(2), 110-123.

Lee, B. (2004). Parcel-level measure of public transit accessibility to destinations*. Proceeding from the Access to Destination Conference.* Minneapolis, MN: University of Minnesota.

Lee, R.W., & Cervero, R. (2007). *The effect of housing near transit stations on vehicle trip rates and transit trip generation: A summary review of available evidence.* Retrieved April 15, 2009, from http://www.reconnectingamerica.org/assets/Uploads/hcd_tod_resource_paper_2008_09_20.pdf

Leslie, E, Coffee, N., Frank, L., Owen, N., Bauman, A., & Hugo, G. (2007). Walkability of local communities: Using geographic information systems to objectively assess relevant environmental attributes. *Health Place, 13*, 111–122.

Levinson, D., & Chen, W. (2004). Paving new ground: A Markov chain model of the change in transportation networks and land-use. *Proceeding from the Access to Destination Conference.* Minneapolis, MN: University of Minnesota.

Levinson, D., & Krizek, K.(2008). *Planning for place and plexus: Metropolitan land use and transport*. New York: Routledge.

Levinson, D., & Kumar, A. (1994). Integrating feedback into the transportation planning model. *Transportation Research Record: Journal of the Transportation Research Board, 1413*, 70-77.

Lipman, B. (2006). *A heavy load: The combined housing and transportation burdens of working families*. Washington, DC: Center for Housing Policy.

Litman T. (2008). *Land use impact on transport: How land use affect travel behavior*. Victoria Transport Policy Institute. Retrieved February 3, 2009, from www.vtpi.org

Malczewski, J. (1999).*GIS and multicriteria decision analysis*. New York: John Wiley and Sons.

Malczewski, J. (2004). GIS-based land-use suitability analysis: a critical overview. *Progress in Planning, 62*, 3-65.

McHarg, I. L. (1969). *Design with nature*. Garden City, N.Y.: Natural History Press

Ndubisi, F. (2002). *Ecological planning: a historical and comparative synthesis*. Baltimore: Johns Hopkins University Press.

Nyerges, T. L., & Jankowski P. (2010). *Regional and urban GIS: a decision support approach.* New York: Guilford Press.

O'Neill, R., & Chou, J. (1992). Analysis of transit service areas using geographic information systems. *Transportation Research Record ,1364*, 131-138.

Ottensmann, J. (2004). Accessibility in the LUCI2 urban simulation model and the importance of accessibility for urban development. *Proceeding from the Access to Destination Conference.* Minneapolis, MN: University of Minnesota.

Pozsgay, M. A., & Bhat, C. R. (2001). Destination choice modeling for home-based recreational trips. *Transportation Research Record, 1777*, 47-54.

Primerano, F., & Taylor, M. (2004). An accessibility framework for evaluating transport policies*. Proceeding from the Access to Destination Conference.* Minneapolis, MN: University of Minnesota.

Randolph, J. (2004). *Environmental land use planning and management*. Washington: Island Press.

Ray, A., Nguyen, D., O'Dell, W., Roset-Zuppa, P., & White, D. (2009). *The state of Florida's assisted rental housing*. University of Florida: Shimberg Center for Affordable Housing.

Regional Economic Model Inc REMI (2008). *Explore the model*. Retrieved October 10, 2008, from http://www.remi.com/

Reynolds, H. (1998). *The modifiable area unit problem: Empirical analysis by statistical simulation*. University of Toronto: Graduate Department of Geography.

Rodriguez, D., Young, H., & Shneider, R. (2006). *An easy method to compute index for identifying built environment that supports walking*. Paper presented at the 85th Annual Meeting of the Transportation Research Board (CD-ROM), Washington, DC.

Ross, C.L., & Dunning, A.E. (1997). *Land use transportation interaction: An examination of the 1995 NPTS data. Atlanta*. U.S. Department of Transportation: Federal Highway Administration.

Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*. New York: McGraw-Hill.

Salomon, I., & Mokhtarian, P. L. (1998). What happens when mobility-inclined market segments face accessibility-enhancing policies? *Transportation Research Part D: Transport and Environment, 3*(3), 129-140.

Srour, I., Kockelman, K., & Dunn, T. (2002, Janury). *Accessibility indices: A connection to residential land prices and location choices.* Paper presented at the 81st Annual Meeting of the Transportation Research Board (CD-ROM), Washington, DC.

Steiner, R.L. (1996). *Traditional neighborhood shopping districts: patterns of use and modes of access* (Ph.D. dissertation). Berkeley: University of California.

Steiner, R.L. (1994). Residential density and travel patterns: Review of the literature. *Transportation Research Record, 1466*, 37-43.

Steiner, R.L., & Srinivasan, S. (2009). *Vehicles miles of travel based traffic impact assessment empirical analysis* (Unpublished manuscript). Gainesville, FL: University of Florida.

Steiner , R.L., Srinivasan, S., Arafat, A., Provost, R., Anderson, N., & Delarco, L. (2010). *VMT-based traffic impact assessment: Development of a trip length model* (Report No. 2008-007). University of Florida: Center for Multimodal Solutions for Congestion Mitigation.

Tomoki, N. (1999). *An information statistical approach to the modifiable areal unit problem in incidence rate maps*, Kita-ku, Kyoto, Japan: Ritsumeikan University

Transit Cooperative Research Program (1998). *Transit Markets of the Future: The Challenge of Change* (TCRP Report 28). Washington, D.C.: National Academy Press.

Transit Cooperative Research Program (2003). *Traveler response to transportation system changes chapter 15-land-use and site design* (TCRP Report 95). Transportation Research Board 82nd Annual Meeting (CD-ROM), Washington, D.C.

United States Department of Housing and Urban Development (2011a). *Affordable housing*. Community Development Program. Retrieved January 30, 2011, from http://www.hud.gov/offices/cpd/affordablehousing/

United States Department of Housing and Urban Development (2011b). *FY income limits 2009*. Retrieved February 15, 2011, from http://www.huduser.org/portal/datasets/il/il09/index.html

Waddell P. (1998, May). The Oregon prototype metropolitan land use model. *Proceeding of the ACSE Conference on Transportation, Land Use, and Air Quality.* Retrieved November 5, 2010, from http://www.urbansim.org/pub/Research/ResearchPapers/ASCE_Model.pdf

Waddell, P. (2002). UrbanSim: Modeling urban development for land-use, transportation and environmental planning. *Journal of the American Planning Association, 68* (3)*,* 297-314.

Waddell, P., Bhat, C.R., Eluru, N., Wang, L., & Pendyala, R.M. (2003) Modeling the interdependene in household residence and workplace choices. *Transportation Research Record, 2003,* 84-92.

Waddell, P., Bhat, C.R., Ruiter, E., Bekhor, S., Outwater, M., & Schroer, E. (2001). *Land-use and travel demand forecasting models: Review of the literature and operational models*. Seattle, WA: Puget Sound Regional Council.

Waddell, P., Borning, A., Noth, M., Freier, N., Becke, M., & Ulfarsson, G. (2003). UrbanSim: A simulation system for land-use and transportation. *Networks and Spatial Economics, 3*, 43-67.

Wegener, M. (2005). Urban land-use transportation models. In D.J. Macquire, M. Batty, & M.F. Goodchild (Eds.), *GIS, Spatial Analysis, and Modeling* (1st ed., pp. 203-220). Redlands, CA: ESRI Press.

Yamada, H. (1972). On the theory of residential location: Accessibility, space, leisure, and environmental quality. *Papers in Regional Science, 29*, 125–135. doi: 10.1111/j.1435-5597.1972.tb01537.x

Zhang S. (2005). Feasibility study on transit-oriented development, using urban-form and non-urban-form variables*. Proceedings of the Twenty-Fifth Annual ESRI User Conference*. Retrieved November 13, 2009, from http://proceedings.esri.com/library/userconf/proc05/papers/pap1150.pdf

Zhao F., Chow, L., Gan, A., & Ubaka, I. (2003). Forecasting transit walk accessibility: regression model alternative to buffer method. *Transportation Research Record, 1835*(8), 34-41.

BIOGRAPHICAL SKETCH

Mr. Arafat received his Ph.D. in Design, Construction and Planning from the University of Florida in the summer of 2011. He has an educational and research background in civil engineering, land use and transportation planning. Mr. Arafat's research interest is in the coordination of land use and transportation. His research generally focuses on understanding the relationship between urban form and multimodal transportation systems to reduce the vehicle-miles of travel and to improve air quality. His research uses disaggregated and fine spatial resolution approaches using customized GIS automation tools. He has research work in both land use modeling and multimodal transportation systems and has presented his work at many local and international conferences.

Mr. Arafat taught Geographic Information Systems (GIS) in Birzeit University in Palestine before receiving a scholarship from the Palestinian Faculty Development Program to continue his study towards a Ph.D. Upon his completion of his Ph.D. he is interested in continuing research work with the University of Florida and teaching in Birzeit University in his country.