FORECASTING VACANCY DYNAMICS IN GROWING VERSUS SHRINKING CITIES: A SMART CITY INITIATIVE

A Dissertation

by

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ABSTRACT

Every city seeks to spur economic development, and land, especially vacant land, plays an important role in these endeavors. Although vacant land exists in every city regardless of whether they are growing or shrinking, the causes and effects of changes in vacant land differ. While large scale annexation can increase vacant land in growing cities, depopulation and economic downturn may increase vacant properties in shrinking cities. However, despite these different characteristics, most cities pursue growth-oriented development strategies due, partially, to their inability to accurately predict future urban growth/decline patterns.

Therefore, understanding land use alternation patterns and predicting future possible scenarios is critical when developing more proactive land use policies on urban decline and regeneration. In this study, the city of Chicago, Illinois, was used as a case site to test an urban land use change model predicting future vacant lands in shrinking cities, and the city of Fort Worth, Texas, was selected to forecast vacant land transformation in growing cities. By understanding not only simple decrease or increase of vacant properties but also analyzing historical patterns of vacancy changes and predicting the probability of future transitions with accuracy outputs, this research can be used to improve policies on vacancy. This project employed the Land Transformation Model (LTM) which combines GIS and artificial neural networks to forecast land use change. While this research used causal drivers to predict future vacant land changes in growing and shrinking cities, findings can also be used to simulate land use changes to

suggest suitable alternatives for shrinking and growing cities with high risk of vacancy and future infill development plans.

Study results indicate that housing market conditions and economic factors are the primary variables contributing to land vacancy decline with mobility and physical conditions being stronger predictors of vacant land specifically in growing cities. In terms of plan quality associated with vacancy-related policies, this study found that Fort Worth is more attentive to socially and physically vulnerable areas, working to revitalize the economy and reduce vacant properties, than healthier communities while Chicago may need to improve their policies regarding the transportation accessibility and physical conditions of their structures.

DEDICATION

To my family

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CONTRIBUTORS AND FUNDING SOURCES

Contributors

Part 1, faculty committee recognition

This work was supervised by a dissertation committee consisting of Professor Dr. Galen D. Newman [advisor], Dr. Philip R. Berke and Dr. Jun Hyun Kim of the Department of Landscape Architecture and Urban Planning and Professor Dr. Ann O'M. Bowman of the Department of Public Service and Administration.

Part 2, student/collaborator contributions

The analyses depicted in Chapter 3 were conducted in part by Dr. Galen D. Newman of the Department of Landscape Architecture and Urban Planning and were published in 2016.

All other work conducted for the dissertation was completed by the student independently.

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1. INTRODUCTION

The world is currently undergoing the largest phase of urban growth in history. The global population is projected to increase by 2.3 billion by 2050, with urban populations rising from 3.6 billion to 6.3 billion, nearly 67% of the world's population (The United Nation, 2014). However, this trend is not evenly distributed, as not all cities will absorb this rapid urban population growth. In recent decades, many former manufacturing industrial cities have and will continue to experience serious depopulation (or shrinkage), job loss and economic decline. Relatedly, vacant urban land in different cities is also not evenly distributed. As a process of urban economies' restructuring away from manufacturing to the service industry, there has been spatial and temporal vacant pattern dynamics in both shrinking and growing cities.

In growing cities, a large scale annexation can also increase vacant land at urban skirts for future growth in size and population to improve the economies of scale of existing urban services. Bowman and Pagano (2004) found that growing cities (boundaries increase in size) tended to have more vacant land than did stable (boundaries decrease or stay the same in size), which reported higher levels of structural abandonment. According to the survey by Pagano & Bowman (2000), for example, Phoenix, Arizona reported 43% land vacancy after growing its population by 55% between 1980 and 1995.

In contrast, vacant land can be the most visible byproduct of urban shrinkage and therefore, sometimes it represents the physical manifestation of economic decline.

Collapse of economy and depopulation in post-industrial cities such as Detroit and Baltimore might result in widespread housing vacancy in city centers and the issue of these properties has emerged as a critical theme to measure the effects of urban decline (Hollander et al., 2009; Accordino & Johnson, 2000; Silverman et al., 2013; Pagano & Bowman, 2000; Bowman and Pagano, 2004).

As such, the current urban challenge should not concentrate on simply projecting urban development, but find ways to analyze land use changes and manage the vacant land as a resource that can be beneficial to local communities socially, physically and environmentally (Bowman & Pagano, 2004; Drake & Lawson, 2014). More accurate and proactive land-use planning mechanisms may be more effective than reactive policies in dealing with the vacancy issue (Newman et al., 2016). Relatedly, LTM is a good spatial solution for analyzing historical urban land-use changes, forecasting future possible situations, and simulating policy scenarios (Newman et al., 2016).

This research seeks to analyze the historical vacant land pattern changes of both growing and shrinking city over the past 20 years, to differentiate the causal predictive factors between each type of city in regards to vacant land formation and to verify the analytical and technical capabilities of using a Land Transformation Model (LTM) to predict future vacant land. In most land use prediction studies, there is a lack of explanation of the influences of predictor variables and insufficient testing of the accuracy assessment of the prediction output. To fill this gap and increase model output validity and reliability, this research performs four different accuracy assessment processes: kappa coefficients, percent correct metric (PCM), and agreement/disagreement measures, and the relative operating characteristic (ROC). Moreover, most LUCC models have been developed to predict urban growth patterns, there is no single model specifically targeting vacant land use patterns at a local municipal scale. While this research both develops and uses causal drivers predict future vacant land prediction in both growing and shrinking cities, findings are useful for simulating land use changes more accurately to suggest suitable alternatives for both shrinking and growing cities having high risk of vacancy and future infill development plans.

1.1. Theoretical Justification/Rationale

In the past two centuries, many urban areas in America have experienced capacious expansion both populating and depopulating cities. The pursuit of bigger, faster and more growth-oriented planning policies parallels a situation where municipal decline has been recognized as a global epidemic. Under the circumstance, many post-industrial cities also underwent rapid land use change due to a population explosion and increasing demand for land development during the flourishing of manufacturing industries in the 1970s. Most areas were filled with buildings and infrastructure to support the economy. However, in recent decades, many older-industrial cities have experienced significant depopulation, job loss, economic decline, and massive increases in vacant and abandoned properties due primarily to losses in industry and relocating populations. As employment shifted from a manufacturing to a service economy, and the trend of suburbanization took hold, many people moved to suburbs and the infrastructure and resources built for a large population and economic activity became a white elephant, and a growing number of properties have been neglected and became vacant.

To better understand the geographical dynamics of vacant properties change in shrinking cities, a growing number of recent studies have sought to quantify the extent of their influence. Most of this research has identified the number of vacant properties by cities or by region, but failed to do longitudinal assessments or develop comprehensive factors to predict both spatial and temporal dynamic changes simultaneously. Historically, this was primarily due to insufficient databases and a lack of development in computer technology.

To address the inability to accurately predict future urban growth patterns, a multitude of land use/land cover change models (LUCC) have been developed over the last 50 years in diverse fields including urban planning, geography, statistics and computer science, ranging from statistical and econometric models to GIS-based models. Many researchers and professionals have used diverse land use change models to explore the drivers and patterns of land use change, to make possible future scenarios and to provide appropriate policies affecting the changes by analyzing the causes and consequences of land use changes (Agarwal et al., 2002; Brown & Duh, 2004; Verburg et al., 2011; Herold et al., 2005). Considering influences of diverse socioeconomic and physical characteristics, LUCC models are able to simulate spatial and temporal patterns of land use and provide possible scenarios of future conditions and make more informed decisions. Most existing land use change models, however, have been criticized for not being able to provide reliable accuracy assessment processes of the output effectively

(Conway, 2009; Verburg et al., 2004). Since doubt and questions about the outputs still remain, the models can have difficulties adapting to local circumstances due to reliably and accuracy issues and there has been considerable controversy about the accuracy assessment of observed sample data (Landis et al., 2011; Landis, 1994).

Therefore, this research seeks to develop a model to accurately predict future vacant land transition by analyzing the historical vacant land patterns and differentiate the causal predictive factors between growing versus shrinking cities and verify the analytical and technical capability in using a land transformation model to predict future vacant land. Since the processes of analyses can provide not only statistical results but also visualized results, local governments can understand what factors have accelerated/decelerated urban shrinkage, how the vacant land patterns have changed, and which areas have a possibility of vacancy in the future and which areas are the most at risk for future decline. This research presents a suitable method to predict for future vacant lands in shrinking cities in an effort to project more accurate future land use patterns and suggest better plans and policies to create more sustainable urban conditions.

1.2. Research Purposes

The main purposes of this research are threefold: (1) to determine driving factors influence on a spatial and temporal vacancy dynamics in shrinking cities which have suffered chronic vacancy issues and growing cities having plans for rapid infill development, (2) to develop a methodological framework to simulate vacant land pattern change in the cities which is validated using proving methods of calibration and (3) to quantify the influence of each input factors between growing versus shrinking city. Unlike the traditional land use change models which have developed for regional scale analysis and have been criticized due to the lack of accuracy assessment of the output, the vacant land prediction model developed here explicitly elaborates for targeting vacant land use patterns in local and municipal scaled prediction and accomplishes four different assessment methods for the model accuracy.

As a process of urban economies' restructuring away from manufacturing, there has been spatial and temporal vacant pattern dynamics in both shrinking and growing cities. Vacant land is "both ubiquitous and diverse and both a problem and a resource" (Bowman & Pagano, 2004, p. 1): While vacant land is one of the most important potential resources that can provide ecological, social and cultural opportunities into community, the properties can also cause economic, social and environmental problems influencing not only surrounding neighborhoods, but also a whole city. Therefore, this research explores to understand not only the simple increase or decrease of vacant land for given regions but also the factors influencing land use changes, the location and direction of the changed land, the historical pattern change, and the future transition probability of vacant land. Then, based on the prediction output, existing policies and strategies are evaluated to determine how well they consider the areas having the high risk of vacancy issue. Figure 1 presents the conceptual framework.

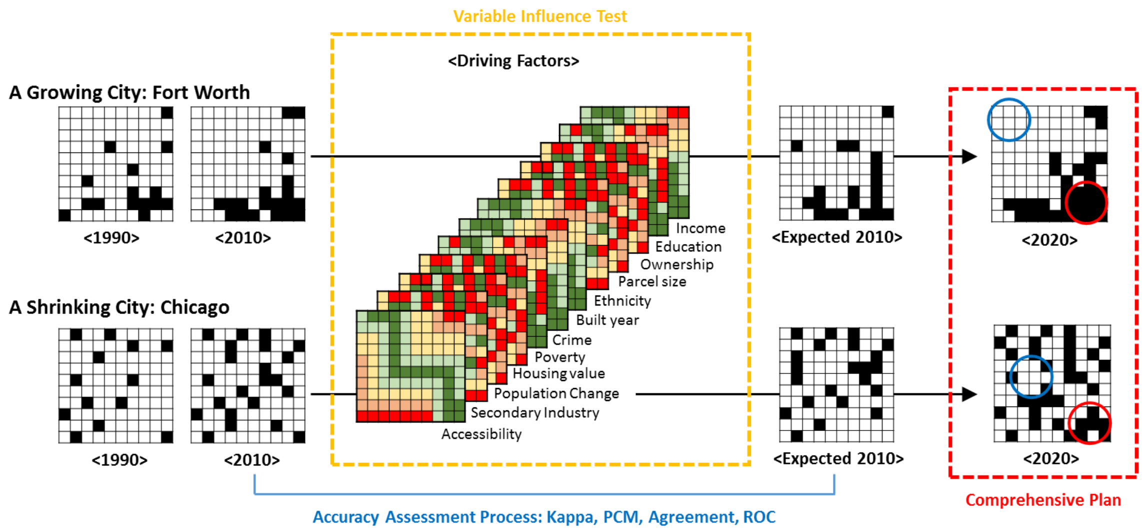


Figure 1. Conceptual Framework

1.3. Research Process

This research consists of three parts: The first part mainly focuses on forecasting future urban vacancy/abandonment based on historical spatial and temporal land use dynamics, and then, I compare influential factors of the vacancy between a growing and shrinking city. In the third part, this research evaluates how well the existing policies and strategies consider the specific areas having the high risk of vacancy issue in both growing and shrinking city by reviewing each city's comprehensive plan.

The study area of this research includes Fort Worth in Tarrant County, Texas as an example of growing city, and Chicago in Cook County, Illinois as a case of shrinking city. For analyzing historical changes, location and direction of the changed vacant land, time-series data from 1990 to 2010 is used. This time span is selected because both North Central Texas Council (for Fort Worth, TX) and Chicago Metropolitan Agency for Planning (for Chicago, IL) provide the land use and vacant land inventory data in GIS format after 1990 in 10-year increments.

Since the variable selection can greatly affect the outcome of vacancy prediction, it is critical to collect appropriate driving factors which have contributed and could potentially contribute to vacant land. Based on the literature, 18 different causal variables linked to a vacancy are selected as input factors, and the data are able to be obtained from U.S. Census Bureau (demographic and economic data) and the cities' Geographic Information Systems (parcels and major streets).

1.4. Research Question

Primary:

The main research question of this study is "<u>What factors determine vacant land formation when comparing shrinking and growing cities?</u>" This main research question consists of the following sub-questions.

Subsidiary:

Sub 1. Is the LTM a feasible and reliable model for vacant land prediction??

Sub 2. How does each factor's effect on vacant land differ between shrinking and growing cities?

Sub 3. How well are the primary factors contributing to vacancy reflected in existing plans in growing and shrinking cities?

2. THEORY & LITERATURE REVIEW

Around 140 articles were reviewed which all related to the dissertation subject to a certain degree, and can be categorized into three segments. The first segment is about the literature to enhance the theoretical background of the dissertation. Second is the literature about urban shrinkage and vacant properties. The studies in the third segments are about land use change models and LTM.

2.1. Theoretical Background

Over the last five decades, chronic depopulation and unemployment of industrial cities have drawn keen attention to a central question about why some regions/cities are shrinking more than others. Many planners and theorists began to recognize the severity of the problem and have struggled to understand the theoretical basis in order to develop future tasks to confront the situation. Since this study seeks to correlate the vacant land use dynamics and its causes, it is important to understand the theoretical framework of urban shrinkage and land use structures, and how the proposed conceptual foundations would be able to provide a set of interrelated concepts and definitions. Throughout an overview of the theoretical literature, three primary theories, the broken window theory, stage theory and fractal theory are useful in establishing theoretical and methodological frameworks and an empirical test will be conducted based on the theoretical foundations.

2.1.1. Broken window theory

“Broken windows” is a community policing approach which attempts to prevent small crimes that would contribute to eliminating more serious crimes and create an atmosphere of order and lawfulness (Lachmann, 1988; Kelling & Wilson, 1982; Bratton & Kelling, 2015). This phenomenon has also been witnessed by many shrinking cities where neighborhood decay and blight happens. A few abandoned and deteriorated properties can move a bad impression forward to a whole neighborhood, and spread throughout an entire city. The neglected properties might be a signal to the communities that no one cares, including the property owners or the city government. These lots can quickly become a nuisance as a hotbed of crime and a lure for children. Obviously, people who live near the structures cannot help but suffer from serious threats to health and safety, and, as a result, the overall quality of life and property values are also negatively affected.

Developing Zimbardo’s psychological viewpoint, Wilson and Kelling (1982) applied the concept to explain the relationships among disordered neighborhood environments, a personal recognition of and attention to the environments, and crimes at a macro level perspective. When residents do not care about the neighborhood environment, the number and seriousness of crimes in the area will increase due to a lack of natural surveillance for crime prevention at abandoned and blighted properties. Meanwhile, a stable neighborhood where people pay attention to their environment and human behavior experiences fewer and less serious crimes. The neighborhood level research was also applied to a city level project in New York. In the early 1990s, the city removed the graffiti from the walls and cleaned the trash-filled spaces of New York subways. As a result, the crime rate decreased significantly in New York City, with murder decreasing by 72 percent and total crime by 51 percent between 1990 and 1998 (Cohen et al., 2000; Bratton, 1994).

This phenomenon has also been witnessed by many shrinking cities where neighborhood decay and blight happens. A few abandoned and deteriorated properties can move a bad impression forward to a whole neighborhood, and spread throughout an entire city. The neglected properties might be a signal to the communities that no one cares, including the property owners or the city government. These lots can quickly become a nuisance as a hotbed of crime and a lure for children. Obviously, people who live near the structures cannot help but suffer from serious threats to health and safety, and, as a result, the overall quality of life and property values are also negatively affected.

Even if many cities try to raze abandoned buildings and clean up trash-filled properties, a lack of municipal resources to clean up and secure the sites makes it difficult to meet the increased demand of new vacant land (Schilling & Logan, 2008). Developers and business owners are reluctant to invest in the neighborhood due to the uncertain revitalization planning guide. Because most vacant properties are still privately owned, code enforcement authorities and abatement powers are limited to the transfer of ownership of such properties and buildings (Schilling & Logan, 2008). Therefore, it is necessary to understand the current crisis accurately and suggest clear and reliable planning standards and guidelines to increase the developers' investments and encourage private owners to maintain or improve their properties.

2.1.2. Stage theory

There are several studies showing cities passing through stages of rising, falling, and recovery, and a common element of the cycle is associated with population change and the economic position of a city (Friedrichs, 1993; Couch et al., 2005). The rise and fall of a core city obviously influence the peripheral areas, and the metro area evolves through four stages with relative population change trends: urbanization, suburbanization, de-suburbanization and re-urbanization (Berg et al., 1982; Champion, 1986; Richardson, 1978; Emery & Flora, 2006). The first two stages (urbanization and suburbanization) are a growth phase, and last two stages (de-suburbanization and re-urbanization) are a decline phase (Klaassen & Paelinck, 1979).

The first urban growth stage is urbanization. Due to rapid industrial development, the population of industrial urban areas grows explosively and the core city and entire urban region are densely populated. As urban concentration continues, the limited resources of a city cannot accommodate all the population and industry. The unprecedented influx of population and lack of public transportation networks and road facilities cause many urban issues such as a shortage of houses, poor residential environments, and limiting the life of residents.

Suburbanization, as a dispersive urbanization, is the second growth stage. This phase indicates that the secondary industry is showing signs of stagnating after about 20 years of tremendous growth and the economy begins a downward spiral. Since the tertiary industry leads the economic growth and the road networks have been expanded, residents move to the suburbs for a safer and better living environment, and economic activities also disperse into the urban fringe. At this stage, the population movement rate from the core city to the periphery surpasses the population growth rate of the city. As the result, the entire urban region enters a phase of absolute decentralization.

De-suburbanization is the third stage in which both population and industry dispersion bring about depopulation of the metro area. As the population and employment opportunities of the region decrease, income inequality becomes serious. While young and skilled laborers are able to migrate to other areas for work, unskilled manual workers age 45 and over cannot help but stay in the shrinking city due to the limited job opportunities (Friedrichs, 1993). Under the circumstances, the selective migration segregates low-income residents into the core and the higher unemployment and crime rate of the area makes the region a slum. However, in spite of declining suburbs, sprawling development patterns such as low density and scattered and/or leapfrog developments are continuing.

The final stage is the re-urbanization phase where city planners and officials draw up planning policies to prevent losing population and maintain employment stability. However, the policies have a minimal effect. While the population of a core city rises slightly, overall population growth of the urban region is stagnant or declines.

In light of the phases of the stage and urban life cycle theory, most shrinking cities in the U.S. are at the second or third urban growth stage, suburbanization or de-suburbanization. While they have experienced serious depopulation and economic downturn in core areas, urban fringes have emerged as new economic centers. In some regions, however, as population outflow to different metro areas surpasses the population inflow to suburban and urban areas, the whole urban region has also decreased in population. Following this stage of development, depopulation and job loss is not a matter only for core cities. It is necessary to establish policies to handle the decline over the whole metropolitan area.

Table 1. The stage of Urban Development Model

Stage of development	**Phase**	**Population change characteristics**			**Growth / Decline**
		Core	**Ring**	**Urban Region**	
Urbanization	1. Absolute centralization	++	-	+	Overall Growth
	2. Relative centralization	++	+	+++	
Suburbanization	3. Relative decentralization	+	++	+++	
	4. Absolute decentralization	-	++	+	
De-suburbanization	5. Absolute decentralization	--	+	-	Overall Decline
	6. Relative decentralization	--	-	---	
Re-urbanization	7. Relative centralization	-	--	---	
	8. Absolute centralization	+	--	-	

(Source: Berg et al., 1982; Champion, 1986; Klaassen & Paelinck, 1979)

2.1.3. Fractal theory

A large number of applications and theories have been launched for the geographical analysis of urban growth. Even if these geographical theories are rational and produce useful results, they tend to regard urban activities as relatively simple locational patterns and a state of static and stable equilibrium. Most studies have focused on identifying functional relationships between land use patterns and driving factors using statistical regression. Consequently, if it is difficult to find the patterns and regularity in real data sets, after much statistical processing, they determined that “this is simply taken as confirmation that world is unfortunately noisy” (White & Engelen, 1993, p. 1175).

In sharp contrast to the premise of the geographical theories, urban activities and geographical phenomena are obviously resulting from complex but functionally interactions of geological, social and physical factors. Since the complexity and irregularity of the fractal structures are inherent and important features of every city, it is important to understand the complexity in some way as an essential quality (White & Engelen, 1993). A city evolves not as a simple functional relationship of certain elements, but as a complex of irregular and countless temporal and spatial elements, and it can be restrictive to analyze and explain urban spatial growth patterns by a singular statistical model. Furthermore, the existing geographical analysis has a limitation in measuring urban activities and geographical patterns which have been influenced by diverse socio-economic, physical, and environmental factors. Unlike simply measuring population density or mapping land use patterns, a fractal dimension is useful parameters able to monitor geographical pattern dynamics reflecting the diverse influences of urban activities and generate reasonable scenarios of actual urban forms (White & Engelen, 1993).

Fractal theory was introduced to interpret the urban activities and spaces that are complex but quantitatively follow regular patterns and forms. Ever since Mandelbrot proposed the concept of 'fractals' in 1983, they have been applied extensively to measure and estimate the complexity of geographical phenomena and urban activities (Benguigui et al., 2000). Fractal geometry shows three distinctive features: self-similarity, randomness, and non-linearity. Even if urban activities and the patterns look random and irregular, all of them have regular rules and order with a lot of information in the complex geometry. Thus, it would be meaningful to explain the intricate mix of spatial and temporal dynamics of urban land use using a fractal dimension that measures and estimates the urban form changes. Different fractal models to measure and estimate the urban form changes have been developed including the box-counting method, the divider method, the spectral analysis method, and the BET method. The diver and BET methods were developed to measure the length of a fractal dimension, and the spectral analysis method provides statistical plots for longitudinal data analysis such as annual river flow changes. Since this research computes and models two-dimensional geographical systems of fractal features by means of cellular automata (CAs), the box-counting method is most suitable.

The basic algorithm of fractal geometry is shown in Figure 2. Unlike classical geometry calculated by a formula, fractal geometry is processed by an algorithm which is a sequence to obtain an output through an iteration process. The assumption of fractals is that this feedback process is infinite, and the development of computer technology enables an endless loop.

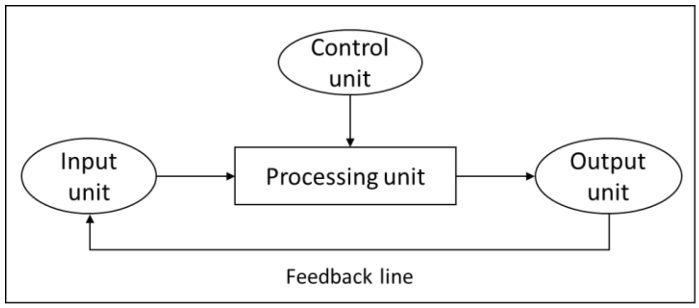


Figure 2. The Basic Algorithm of Fractal Geometry

The box-counting method covers a fractal dimension of objects with a grid, and then calculates how many boxes of the grid are covering the image (Ge & Lin, 2009). As shown in figure 3 and 4, the size of the grid determines the accuracy of the output. By reducing the size of the grid, a more accurate structure of the pattern can be captured. The equation below shows the relationship between the accuracy and the size of the boxes. The fractal dimension (D) is the slope of the line (log-log plot), and has a value between 1 and 2. While a flatter, lower-valued slope means fewer fractals, a steeper slope means more fractals and complexity as the box size decreases.

$$\mathrm{D} = \lim_{r \to 0} \frac{\log N}{\log(\frac{S}{r})}$$

r = the length of the grid, n = the number of boxes which cover the image,

N = total number of boxes, S=the length of whole grid, D = fractal dimension

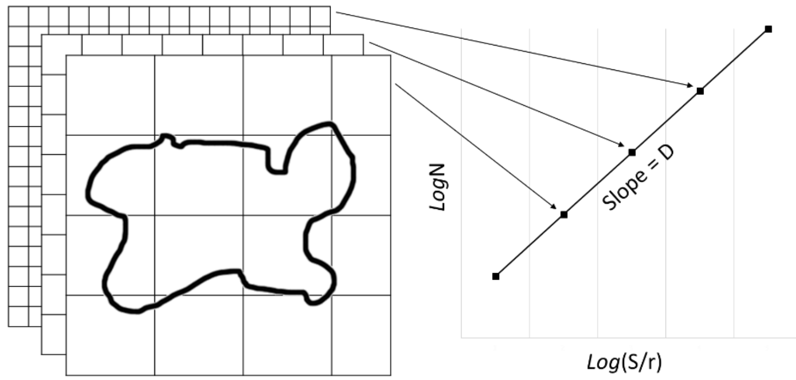


Figure 3. Relationship between Complexity and Box Size

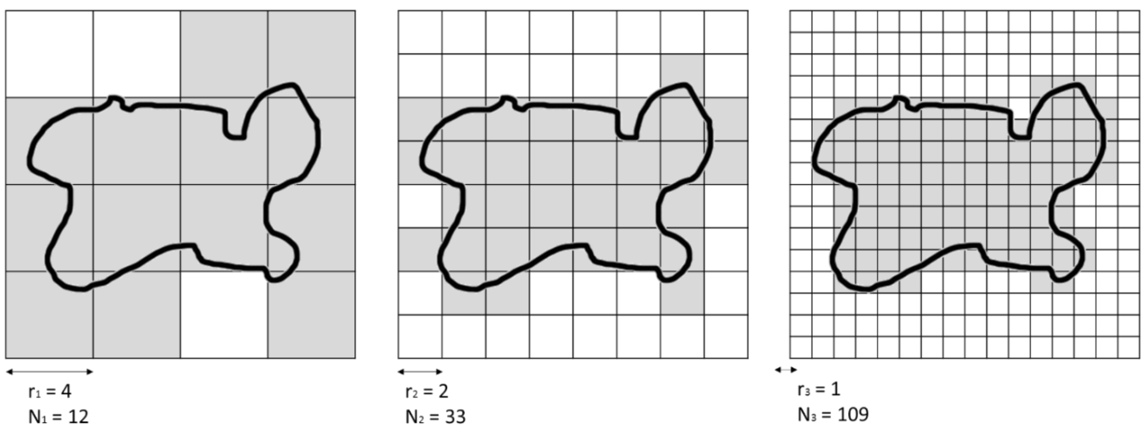


Figure 4. The Outline of Box-Counting Method

Studies have revealed significant correlations of urban spatial structure and its transition with the dimension of fractal mass to grasp the logics and patterns of the phenomena of spatial irregularity, structure, and process. Batty and Longley (1994) measured the irregularity of size, shape, scale and density and simulated fractal geometry of a city's form. They argued fractal rendering would be more useful and plausible solutions to measure complex patterns of a city than using Euclidean geometry which describes the urban form with straight lines or flat planes. Benguigui et al. (2000)

found that the fractal dimension in a metropolitan area increases over time and is associated with the growth of population density, while the structure of a fractal is conserved. Azimzadeh (2008) also analyzed the spatial transition of Gothenburgh in Sweden as an urban development project of over 400 years based on the concept of fractal dimension.

Existing literature on the complexity of urban form using fractal theory explains the geographical pattern changes using a physical index, especially population density and structural distributions (Batt & Longley, 1994; Jun, 2001; Benguigui et al., 2000) or focuses on spatial but not temporal transitions (Ge & Lin, 2009). Since it is difficult to accurately analyze the urban activities and geographical phenomena with only physical characteristics, it is necessary to understand a city as an organism and consider its diverse socioeconomic and environmental characteristics. A lack of consistent database on temporal transitions make it possible to only compare among cities in a single period. Moreover, most studies attempt to find a regular pattern from buildings or block layouts that look irregular and disordered (Azimzadeh, 2008).

Therefore, this research attempts to examine the complex and irregular geographical pattern changes over 20 years and describe how fractal geometry can help analyzing relationships between the vacancy dynamics and integration of the physical and socio-economic factors. A pixel-based raster vacant land layer from the land use dataset of an orthorectified satellite image from 1990 to 2010 is used to compute and model the cellular automata as a fractal dimension. After calculating the direction, amount, and dispersion of historical vacant patterns, fractal geometry is used to predict future possible scenarios. This research on fractal geometry to understand urban activities would be helpful in predicting future geographic phenomena and suggesting guidelines.

2.2. Definition of Key Terms

2.2.1. Growing city

Growing city is often recognized as a city experiencing rapid population and economic growth, and increase in neighborhood quality (Narain, 2009; Giffinger et al., 2010, Weller, 2008). Generally, since growing economies induce with increasing the demand and supply of both works and consumers, the economic growth are strongly associated with population growth. Therefore, most planning and economic literature and media have concentrated on population and employment growth to analyze the patterns of growing city trends.

In 2016, The U.S Census Bureau announced the list of the 10 fastest growing and shrinking cities with populations of at least 50,000 from 2014 to 2015. The Census Bureau noted that the fastest growing cities were predominately in Texas, while the fastest shrinking cities were scattered around the South and Midwest. According to the research, five of the growing cities were in the Texas and top on the list is the Austin suburbs of Georgetown, Texas with its population jump up about 7.8% from a year prior (See Fig.5). Looking at the demographic and economic transition of the growing cities, they are not just physically growing but becoming economic hubs. The Brookings Institution (2016) distinguished growing city based on population and employment growth data of the world's 300 largest metropolitan areas in 2015. The research revealed that cities with the fastest growth rates were concentrated in developing countries.

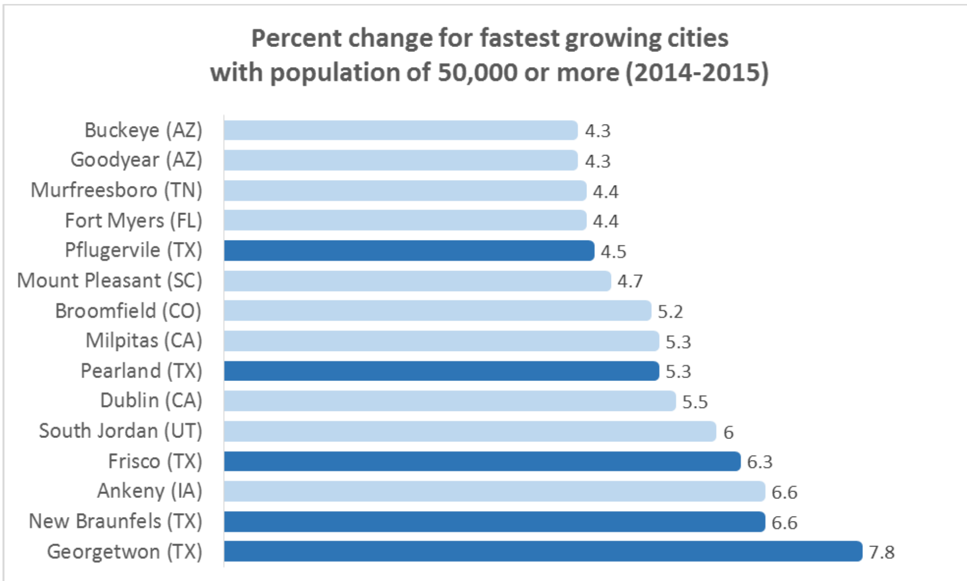


Figure 5. Percent Change for Fastest Growing Cities between 2014 and 2015
(Source: Population division, Vintage 2015 Population Estimates)

2.2.2. Shrinking city

While the term 'shrinking city' has been widely discussed, the definitions, measurements and symptoms of urban decline have been categorized quite differently, depending on the purpose of research. Among the diverse concepts and definitions, the population is one of the most popular tools to identify it. Schilling and Logan (2008) defined a shrinking city as older industrial city losing population more than 25% over the last 40 years. Reckien and Martinez-Fernandez (2011) also concentrated on demographic change and defined shrinking cities as urban areas that have experienced depopulation, employment loss or/and economic downturn over the past 40-50 years. Pallagst (2008) also described shrinking city as a densely populated urban area that is losing population, undergoing negative economic transformations and ultimately changing the characteristics of built environment. In 2004, the Shrinking Cities International Research Network (SCIRN) was launched at the instigation of the University of California, Berkeley. They achieved a consensus definition of a shrinking city as an urban area with more than 10,000 residents that have experienced depopulation for more than two years and the consequential economic crisis (Hollander et al., 2009). To measure urban decline, Downs (1999) used not only population density and geographic size of urban areas but also crime rate, poverty rate, per capita income and percentage of older housing and concluded concentrated poverty is highly associated with urban decline. It is difficult to define "urban shrinkage" with a single general concept because it is relative to both time and space and thus is flexible when applying the definitions to different societies.

Table 2 shows top 10 shrinking cities using population loss as a measure of shrinkage. Among 192 cities with more than 100,000 population in the U.S in 1980, forty-three or 22% have experienced depopulation over three decades (See Appendix A). The top 10 shrinking cities of these forty-one in terms of their population growth and ranked in a hierarchical order (ascending from the greatest loss of population). Except for New Orleans, nine of these cities are in the Rust Belt region. From the 1950 peak year to 2010, Detroit lost over 1,100,000 population and Chicago's population was also down about 925,000 during the same period. However, while shrinkage of Detroit has been recognized as a national issue, the depopulation of Chicago has tended to be underestimated and ignored historically.

In summary, urban shrinkage can be defined as a non-growing city with diluted urban physical, social and environmental functions due to loss of population, a slowdown in economic growth and deterioration of urban infrastructure. Several Northeastern cities such as Detroit, Chicago and Youngstown share similar trends of depopulation and economic downturn. However, we need to keep in mind that the problem of population loss is not about size itself, but about who is leaving and who is staying. As Beauregard mentioned, “just because a city has fewer residents and fewer jobs does not mean that it is experiencing decline; the issue is the composition of those changes, their pace and the resultant distribution of costs and benefits” (Lang, 2005: p 2). In some cases like Pittsburgh, for example, population loss does not of necessity bring economic collapse or decline in living standards. Rather, the municipal decline can sometimes provide a creative re-use opportunity and improve their life qualify in spite of population loss.

Table 2. Top 10 Shrinking Cities with more than 100,000 Population from 1980 to 2010 (Peak year highlighted)

City	State	Belt	1950	1960	1980	2010	Change Rate (%)	Change
Detroit	MI	Rust	1,849,568	1,670,144	1,203,368	713,777	-61.4	- 1,135,791
Chicago	IL	Rust	3,620,962	3,550,404	3,005,072	2,695,598	-25.6	- 925,364
Philadelphia	PA	Rust	2,071,605	2,002,512	2,002,512	1,688,210	-26.3	- 545,599
St. Louis	MO	Rust	856,796	750,026	750,026	452,801	-62.7	- 537,539
Cleveland	OH	Rust	914,808	876,050	876,050	573,822	-56.6	- 517,993
Pittsburgh	PA	Rust	676,806	604,332	604,332	423,959	-54.8	- 371,102
Baltimore	MD	Rust	949,708	939,024	939,024	786,741	-34.6	- 328,747
Buffalo	NY	Rust	580,132	532,759	532,759	357,870	-55.0	- 318,822
New Orleans	LA	Sun	570,445	627,525	627,525	557,927	-45.2	- 283,696
Cincinnati	OH	Rust	503,998	502,550	502,550	385,460	-41.1	- 207,055

2.2.3. Vacant land

Every city makes efforts to promote economic growth using a number of resources. Among those resources, land plays an important role, especially vacant land (Bowman & Pagano, 2004). Since the most visible and demoralizing byproduct of urban shrinkage is vacant and abandoned property, vacant land represents a physical manifestation of economic decline. The issues of these properties have emerged as a critical theme to measure the effect of urban shrinkage (Hollander et al., 2009; Accordino & Johnson, 2000; Silverman et al., 2012; Pagano & Bowman, 2000; Bowman and Pagano, 2004).

So, what is vacant land? When no structure exists in the property and the land is not currently used by humans, can we define the area as vacant land? Even so, how long the area should be empty to say the land is vacant? Like diverse definitions and meanings of the term urban decline, there are a multitude of ways to define vacant land; it can be defined by municipality, situation, duration of vacancy, and/or function of parcel. In some cases, only urban lots deemed unsafe or difficult to develop are designated as vacant land. However, brownfields or abandoned parcels including dilapidated residential, commercial or industrial buildings/sites are also sometimes considered vacant land. Further, in some studies, vacant land has also included open space such as parks, farm sites and properties with particular natural resource value (Pagano & Bowman, 2000).

Vacant land includes not only empty or underperforming areas, but also abandoned and neglected industrial buildings that may pose a threat to a public safety. The National Vacant Properties Campaign (NVPC) defined a property as vacant if one or both of the following characteristics was met: “The site poses a threat to public”, and/or “the owners or managers neglect the fundamental duties of property ownership (e.g., they fail to pay taxes or utility bills, default on mortgages, or carry liens against the property.)” (NVPC, 2005 p.1). Based on this definition, vacant properties include not only under-performing industrial buildings and lots (brownfields) but also residential and commercial properties (greyfields) that have been unoccupied or beyond repair over a year.

In 1964, Hearle and Niedercorn surveyed land use pattern trends in 48 American cities, and defined vacant properties as undeveloped but not submerged lands. They found that the average proportion of vacant land to the total area was approximately

23.3% and the relative amounts decreased to 21.6% between land-use surveys. They also indicated that while the vacant land was fast disappearing and relatively little vacant land remains in the central cities, residential and industrial densities decreased significantly. They indicated that this was because the cities already reached their upper limits of population and industrial and commercial employment.

Northam (1971) classified vacant land in U.S. cities by five different types based on the characteristics of each site and their probability of development: (1) Remnant parcels which are not included in the developmental process because of small size or irregular shape, (2) Unbuildable parcels (slopes in excess of 10-15%, subject to flooding, unstable subsurface materials), (3) Corporate reserve which owned by locally represented business corporations such as utility companies, and remained for expansion or relocation of the business, (4) Parcels held for speculation which owners of the land are waiting to sell them in market place until a profit will be derived, and (5) Institutional reserve: which owned by a public or organization for development as need or funding arises. While remnant parcels and unbuildable parcels are not suitable for development due to the physical barriers and characteristics, other types of vacant land are likely to be developed by stronger market conditions and needs.

Based on the criteria, he found over one-fifth of the area of cities with more than 100,000 population in the U.S is vacant, while small cities with populations less than 5,000 recorded approximately 60 percent of vacancy. Furthermore, as the result of survey of thirty-three cities in the Oregon States and eighty-six cities with populations greater than 100,000, he concluded that the amount of vacant land in the urban centers has decreased as the population becomes greater. Looking at the amount of vacant properties available per capita in the eighty-six cities, all of the cities have over 2,279 square feet of vacant land per capita. While over 5,900 square feet of vacant land per capita are available in the highest decile cities including Corpus Christi, the cities of Beaumont, Houston, Lubbock, Mobile, Newport News, Phoenix, San Diego, and San Jose, only 155 square of the properties are available in the lowest decile including the cities of Chicago, Detroit, Minneapolis, Newark, New York, Paterson, San Francisco, and St. Louis. Moreover, the regression analysis also shows that as the urban population size becomes greater, the amount of vacant land has reduced. In order to see the regional differences of the per capita amounts of vacant land around the U.S cities, those eighty-six cities of over 100,000 population are grouped by 9 different geographic divisions defined by Census Bureau. While the cities in the West South Central division have the largest amount of the mean amount of vacant land per capita over 6,276 square feet of vacant land per capita are available in the highest decile cities including Corpus Christi, the cities of Beaumont, Houston, Lubbock, Mobile, Newport News, Phoenix, San Diego, and San Jose, only 155 square of the properties are available in the lowest decile including the cities of Chicago, Detroit, Minneapolis, Newark, New York, Paterson, San Francisco, and St. Louis.

Pagano and Bowman (2000) surveyed to city officials of 70 cities over 50,000 population to see the amount of usable vacant land in the U.S in the late 1990s. They found that 15.4% of a city’s land was vacant for entire 70 cities including not only contaminated brownfields but also undistributed open space on average. While cities in

South region recorded the highest proportion of vacant land (19.3 percent), Northeast cities only reported 9.6% of the vacant land. They also investigated the relationship between vacancy rate and population growth. Unlike common expectation that cities with positive population growth will have less vacant land, almost one-fourth was vacant in nineteen fast growing cities while cities have experienced depopulation only reported 6.0% vacancy. The number of abandoned structures were also collected in 60 cities, and more than two abandoned structures (2.6 structures on average) per 1,000 inhabitants existed in the 60 cities. While the Northeastern cities reported the least proportion of vacant lot (8.3%), they have the most number of abandoned structures per 1,000 inhabitants (7.5). In contrast, cities in West only reported 0.6 structures per 1,000 inhabitants in spite of 15.7 percent of vacant land. The study concluded that temporary vacancy of the cities may be not an issue, but long-neglected or not large enough/odd shaped parcels are problems.

Recently, the City of Fort Worth (2014) included three land uses: brownfields, vacant structures/housing units, and vacant agricultural as the vacant land. Vacant brownfields are described as underutilized, obsolete, or structurally deteriorated industrial or commercial properties where improvements are hindered by real or perceived contamination. Vacant structures/housing units contain a house, apartment, mobile home or other units, vacant but intended for occupancy as separate living quarters. Vacant agricultural describes areas with one residential unit per structure on a one or more acre lot with no city water or sewer service; or land with no existing buildings, except for those related to mining, crops or grazing

As discussed above, there have been a number of efforts to define and measure vacant land. Based on the literature, vacant land can be defined as “both ubiquitous and diverse and both a problem and a resource” (Bowman & Pagano, 2004, p. 1). Since the characteristics and conditions of a parcel of land are not immutable, a formerly productive and active area can be transformed into unwanted and undesirable sites depending on the usages of the properties.

Due to oversupplies of urban vacant land in some urban areas, property owners in neighborhoods having large amounts of vacant lots oftentimes have difficulty re-selling, and thus lose the market value of their properties. Consequently, decreasing tax revenues from reduced property values can make it difficult for the city to perform public improvements and maintenance on these sites (Accordino & Johnson, 2000).

Vacant or neglected properties are not always a bad thing, and they do not always have to be damaged or derelict (Heckert & Mennis, 2012). All underutilized land does not have to be developed. Some types of vacant land are unused but can be productive. Some may have natural resource value for inhabitants and provide green space such as parks space or green infrastructure. Once a city has too much vacant land, it may reflect a long cycle of depopulation and economic downturn. So, a lot of vacant lots is of a concern in shrinking cities to change them into a valued commodity. In contrast, insufficient vacant land might hinder future growth and development. The primary goal is, therefore, to find the most effective land supply usage (Pagano & Bowman, 2000).

2.3. Trends of Shrinking Cities

Today, the world is undergoing the largest wave of urban growth in history. However, not every city is a part of this process of rapid urban growth. In recent decades, while urban populations are increasing globally, many former manufacturing industrial cities have experienced serious depopulation, job loss, economic decline and massive increases in vacant land due to loss of industry and a fleeing younger population. Consequently, the terminology of “shrinkage” and “perforation” have arisen to depict demographic and spatial changes, particularly depopulation, out-migration and deterioration in the urban regions (Haase, 2008).

Shrinkage is not an uncommon phenomenon for a number of countries anymore, especially for developed countries like the U.S. and western European countries (Van et al., 1982). Among 414 cities with a population of 1,000,000 people or more, 30 cities experienced zero to negative average annual growth (Audirac 2007). Furthermore, in the last 50 years, 370 cities with a population of more than 100,000 have experienced a depopulation of at least 10% worldwide since mid-century, and most of these cities are located in western developed countries, including 59 in the United States, 27 in Britain and 26 in Germany (Oswalt & Rieniets 2007).

Among the fifteen largest cities in the U.S. in 1950, eleven of them experienced depopulation in every subsequent decade, and many of these top fifteen have lost more than one-third of their population (Glaeser & Gyourko, 2005). Furthermore, 80 inner cities in the U.S were shrinking, while only 64 inner cities were growing in 1970 (Rieniets 2009). New York, Boston, Chicago, Minneapolis and Atlanta lost more than

10% of their population during the 1970s. Municipalities judged that the U.S. cities were dying and it would be impossible to get back the population and economy of large U.S. cities (Rappaport 2003).

The 2006 Census estimates also showed that sixteen cities have experienced a predominant population loss among 1950's twenty largest cities. From 1950 to 2008, more than 50% of the population left Cleveland (-59.0%), Youngstown (-56.7%), Pittsburgh (-54.2%) and Detroit (-50.7%), and Philadelphia and Baltimore lost a third of their population (Shetty 2009; Hollander et al., 2009). Moreover, 13 of the 64 inner suburbs also experienced a decline in income level growth from 1980 to 2000 (Audirac 2007).

Beauregard (2009) investigated historical urban population change from 1820 to 2000. He found that only fifteen large cities lost population between 1820 and 1920 while forty-one cities between 1950 and 1980 and eighteen between 1980 and 2000. Looking at the population loss of geographical incidence, the proportion of depopulation cities in Northeast and Midwest regions was higher than South and Midwest until 1980. This can be explained by the rise and fall of Rust Belt where was the manufacturing heartland of the nation in the Midwest and Northeast Census Bureau regions. (Beauregard 2009). Worse, these trends are not limited to post-industrial Rust Belt cities anymore. According to Hollander and Nemeth (2011), Sun Belt cities where people are attracted to the warm and sunny climate in the southern and western regions such as Atlanta, Las Vegas and Phoenix where population exploded in 1990's and early 2000 have also experienced prominent population losses recently. They found that 20 percent of Sun Belt cities with population of more than 100,000 lost housing units between 2006 and 2009.

Since all human activities influence the uses of the land where they live, the primary objective of urban policies and plans is to recognize the problems of current land uses and come up with an effective plan using limited resources. While rapid urbanization and industrial growth require developing more urban areas for new populations and unplanned expansion, development of transportation and the need for better quality of life causes suburbanization and deindustrialization. Under the circumstance, every city makes efforts to promote economic growth using a number of resources, and among those resources, land plays an important role, especially vacant land (Bowman & Pagano, 2004). Vacant land and abandoned properties are becoming a serious problem in both growing and shrinking cities regardless of economic and population growth. Increased commercial, industrial and residential property vacancies have negatively influenced on not only business owners and landlords but also the entire economic climate of a city.

As Beauregard (2009) pointed out, the decline might be a natural phenomenon in a cycle of boom and bust that many U.S cities have experienced over 200 years. However, depopulation and economic downturn by the urban decline cannot be dismissed as a simple stream of times any longer. In the current trend of metropolitan growth pattern, it is critical to analyze the past and current spatial interrelationship and predict prospective movements of different types of land uses for better growth management, infrastructure investment, social justice and environmental preservation.

Once it is possible to not only look at the current situation but also predict the accurate future land use changes, it would be possible to establish much more effective and better planning policies and design guidelines and prevent unplanned or undesirable urban growth/decline. Thus, it is critical to analyze the causes and effects of the shrinkage and understand how the land alteration pattern changes have influenced urban growth or decline to accurately predict transformations in a physical change. More accurate predictions will have profound effects on social, environmental and economic conditions of urban shrinkage and will be more effective than reactive policies in dealing with the vacancy issue (Park & Von Rabenau, 2014).

2.4. Causes and Impacts of Vacant and Abandoned Properties in the Shrinking Cities

Industrialization does not always bring economic and demographic growth; it sometimes causes significant depopulation and an economic downturn in the older deindustrializing cities. The unprecedented economic decline caused by the out-migration of the middle class to the suburbs has accelerated the process of urban shrinkage. Obviously, the older industrial cities have experienced rapid deindustrialization and have suffered from job loss, violent destruction, lack of investment, and maintenance in public infrastructures, and the phenomenon of urban shrinkage spreading to surrounding neighborhoods.

Urban shrinkage is a multi-faceted process created by the interaction of many physical, social, economic and environmental factors. Newly developed neighborhoods in the outer peripheral areas of core cities attract people and urban activities by pull factors of sufficient public infrastructures, well-planned street networks, and pleasant surroundings, while the urban areas suffer from depopulation due to many push factors, such as deterioration of structures, lack of infrastructures, unsatisfactory living in tiny spaces, and a high cost of living. A Fannie Mae survey (1997) apparently showed that over 70% of Americans want to live in a single-family home at a reasonable cost in the suburbs far from cities or rural areas. The desire for better jobs and education, a larger house, and safer neighborhood are the primary reasons for moving to the suburbs (Farris, 2001). Since older built-up areas in the central city do not satisfy these desires, the deterioration of urban environments provides an opportunity for population outflow to suburban areas, and the increased vacant land and abandoned structures have caused a vicious cycle of a city's continuous shrinkage.

The primary contributors to land abandonment are economic causes of land demand and supply. As neighborhoods decline, decreases in property values typically occur. As a result, rental properties do not produce enough income to cover taxes and other related costs, this forced landlords to disinvest in the aging properties. Property owners may wish to sell urban lots which are no longer economically viable, but increased housing supplies on the suburban fringe decreases demand for these properties, consequently, it can become nearly impossible to sell them (Sternlieb et al., 1974; Immergluck & Smith, 2006; Goldstein et al., 2001; Keenan et al., 1999). Since landlords reluctant to maintain or invest in declining properties, the ability to attract new tenants decreases. Theses interrelated consequences make vacant land, the by product or urban decline, a causal factor of itself. Increases in vacancies and abandonment produce deterioration and a waste of housing resources, causing more residents to feel unsafe and leave. These vacant and abandonment properties are recognized as problems to not only the property itself but also entire neighborhoods and local governments in a vicious cycle of decline.

In addition to the house price decline as a financial driver, relatively higher tax rates for urban residents and businesses than for suburban areas is another factor. People who are paying high city taxes including property, sales, and income taxes began to seek a less expensive life in the suburbs (Goldstein et al., 2001; Schilling, 2002). The movement of families and businesses exacerbates the financial issues due to the per capita tax burden of the cities. The loss of economic activity by reduced municipal revenue and population in the urban area leads to a lack of investment and maintenance in public infrastructures. Goldstein et al, (2001) found that more than 70% of new businesses, especially high-technology and service-based industries, have been created outside cities because of lower taxes and property costs, including land assembly and building costs, and less regulation. Farris (2001) discovered that standard suburban residential sites typically have a cost from $0.25 to $4.00 per square foot for site assembly including acquisition, relocation, demolition and site preparation, while it costs around $15 in an urban environment for blighted areas. Since the land assembly costs of blighted land are higher than expected profit and value of the site for the intended reuse, developers and business owners are reluctant to invest in the neighborhood (Farris, 2001).

A decline in output and employment in the manufacturing sector can also be a primary factor contributing to urban shrinkage. The weakened industrial competitiveness of traditional U.S. industries (e.g. steel and iron manufacturing) has led to both reduced demand for unskilled or low-skilled laborers and decreasing income levels of workers dependent upon these industries. Consequently, unstable financial situations due to long-term unemployment and increases in non-regular workers have shaken and destabilized many shrinking communities and created a situation where affluent skilled laborers leave the city and only people who cannot afford to move stay.

The urban decline can be also explained from social and environmental perspectives. When a city becomes obsolete, housing prices and neighborhood quality decreases. Consequently, affluent residents want to leave the city, and the influx of new lower income families begins to accelerate. Since the deteriorated and blighted neighborhoods are occupied by people with a lower socioeconomic status, socio-economic activities also shrink in the core area while suburbs rapidly rise in economic power. Obviously, the polarization of wealth between the suburbs and the core city is growing and the economic segregation leads to racial and social segregation.

Growing amounts of vacant and abandoned properties threaten neighborhood stability. As properties decay further, they can be used for violent crime or be targets of vandalism (Cui & Walsh, 2015; Spelman, 1993; Immergluck & Smith, 2006; Han 2014). Increased vacancy rates and violent crime levels contribute to lower residential satisfaction and result in lower rents or housing prices, and consequently, lead to a growing number of residents' decisions to move out. Spelman (1993) found that 41% of abandoned residential buildings are unsecured and 83% are used for illegal activities in a low-income neighborhood in Austin, Texas. Recently, Cui and Walsh (2015) and Immergluck and Smith (2006) also examined the relationships among foreclosure, vacancy, and crime. They found that many abandoned unsecured residential properties are used for illegal activities. According to the research, once foreclosed properties become vacant, violent crime rate can increase by more than 15% (Han, 2014).

In spite of many attempts of local governments to control these issues, vacant properties have rapidly spread through many cities due to insufficient resources and lack of demand for investment in vacant lots. According to a survey conducted by the U.S. Government Accountability Office in 2011, many shrinking cities spent a majority of their investments on boarding up and cleaning vacant properties. For example, Chicago spent $875,000 on 627 properties, Detroit spent $1.4 million on 6,000 properties, and Baltimore spent over $2 million each year (Han, 2014). In spite of these investments, the research also found that there is an increased financial burden on local governments to maintain public infrastructure; there is an annual increase of $1,427 for each vacant property for police and fire services, on average (Han, 2014).

2.5. Policies, Regulations and Incentives

Planning can play an important role in guiding land use and development in areas having a high risk of vacancy issue. Communities have created and adopted a number of plans to promote economic growth and reduce community vulnerability to multiple urban issues. Since the 1970s, local governments failed to manage their growth effectively and it has been necessary to implement stronger mandating and coordinating growth management policies by state governments. The state planning mandates and comprehensive plans have been designed to guide local governments in coordinating local plans and require them to adopt general state plans that meet state and regional goals (Nelson & Duncan, 1995).

Development management is the deliberated and integrated government program designing to achieve broad public interest goals by controlling the type, quality, scale, rate, sequence or timing of development (Berke et al., 2006; Nelson & Duncan, 1995; Godschalk, 2000). As low density suburban development were spread out around the most cities during the postwar era, uncontrolled and wasteful consumption of land and resources by single-use development became a problem. Meanwhile, the needs of reasonable development management have also arose across communities, regions and states to address the issues directly. Thus, growth management programs were developed to achieve orderly urban growth, preservation of green space and natural resources, and efficient transportation systems (Godschalk, 2000). Ultimately, the purpose of growth managements is to improve urban form more efficiently through preventing urban sprawl and protecting taxpayers (Nelson & Duncan, 1995).

Statewide growth management can be explained by three historical phases. The initial phase, concerning environmental problems, occurred in the 1960s and 1970s. In the second phase, comprehensive planning and growth management were developed to deal with a lag in the provision of infrastructure during the 1980s. In the third phase starting in 1992, increasing environmental degradation and urban sprawl led to a new program, smart growth (Godschalk, 2000). It is true that the basic concept of smart growth is similar to traditional growth management in terms of their goals to achieve orderly urban growth and livable communities. However, smart growth suggests new approaches to deal with the sprawl issues that contribute to central cities' weakening in competitiveness and many environmental and social issues (Nelson & Dawkins, 2004; Godschalk, 2000).

Despite many policies and strategic plans that have been put in place for inner-city revitalization, conventional market-based redevelopment policies aggravate market dysfunction, chronic decay, and disinvestment (Pagano & Bowman, 2004; Schilling & Logan, 2008). Thus, instead of chasing industry with hefty incentives and the other standard economic development tools, some practitioners and scholars have begun to focus on improving the quality of the built and natural environments for those left behind. Against this backdrop of significant social and physical urban declines, there has been a pending paradigm shift from traditional urban growth to "right sizing" (Schilling & Logan, 2008; Hollander & Nemeth, 2011) in shrinking cites. In order to cope with the shrinking population and economy of a city, the development management programs would work to return the deteriorated and blighted properties to productive uses by encouraging private investment and inducing neighborhood participation.

This section examines how the how the traditional development management tools and policies can be developed to address urban sprawl and shrinkage as new strategies and activities: market-based redevelopment vs. governmental or quasi-public land bank programs. Proper and effective planning policies for reinvestment and revitalization of central cities would contribute to slow down sprawl and solve the depopulation and vacancy issues. The methods and concept of plan evaluation I used would provide a strong foundation for this research by quantifying the quality of the planning process and the strength of its implementation.

In this study, in order to contribute to improve local plans in ways that reduce vacant properties and revitalize local economy, I evaluated the comprehensive plan which is a logical process and tool to establish shared goals and guide a community's future land use decisions seeking to balance development pressure with preservation for long-term economic health and quality of life by multiple jurisdictions (Kelly, 2010; Berke et al., 2013). Through the processes, counterproductive efforts will be able to be reduced by more efficiently land uses and better information.

2.5.1. Conventional revitalization strategies

Over the last several years, collapse of the American housing market resulted in massive foreclosures and widespread housing vacancy throughout the country and continues to be a highly visible symptom of the current economic recession. According to Pagano and Bowman (2004), the primary causes of increased vacant land in the 1990s are associated with deindustrialization and the consequential economic downturn.

In order to address this issue, many city governors, consultants, and urban planners have responded to vacant land in abandoned areas, and suggested many alternatives to solve the consistent urban decline. Among many strategies, redevelopment programs such as razing and rebuilding (Audirac, 2007), and raising taxes (Rybczynski & Linneman, 1999) are most popular and direct solutions. Unfortunately, however, the impact of existing alternatives seem to fall short of city planners' expectations.

The lack of understanding of the space and appropriate planning policies have failed to stem population decline and increased vacant and abandoned properties. Typical land use regulations are designed to restrict the development of inside urban areas, resulting in rural areas appearing more attractive (Nelson & Duncan, 1995). Furthermore, since most policies and strategic plans have been put in place for inner-city revitalization, conventional market-based redevelopment policies aggravate market dysfunction, chronic decay, and disinvestment (Pagano & Bowman, 2004; Schilling & Logan, 2008). Furthermore, in most cases, the ability of public redevelopment is limited by deficient public funds (Hollander 2011). Sometimes, it is difficult to find investors for the abandoned areas because of the uncertainty of economic return on investment, a lot of ongoing costs for maintenance and too lower surrounding property values. Additionally, they still have a larger housing supply, transportation and public infrastructures than they can use and pay for maintenance. As the result, the strategies have made the shrinking cities less attractive and productive places to work and live as "a self-destructive response" (Rybczyski & Lineman, 1999).

2.5.1.1. An example of conventional revitalization program: Project 5000 (2002): Baltimore, Maryland

Early in 2000, the vacancy rate of Baltimore was 14.1 percent, the fourth highest in the nation. To solve the problem, the city of Baltimore announced an anti-blight initiative aiming to redevelop 5,000 of 14,000 abandoned houses and 10,000 problem vacant properties in two years in 2002 (Bainum, 2006). In the four years since it began, over 6,000 abandoned properties have been rehabilitated. In terms economics, sales revenues were $ 4.5 million, and over $1.8 million was collected for taxes and fees from 2003 to 2006 (Bainum, 2006). However, according to a survey by Jacobson (2007), the quality of life in Baltimore has deteriorated. The percentage of residents in poverty has been increased, but the property value has been decreased. The study notes that the Project 5000 program demolished 1,399 former public housing properties for reuse. But only 383 of the properties has been reused five years after the project began. In addition, the resale values of the vacant houses after rehabilitation often fall short of the reconstruction costs. Looking at the case of Sandtown-Winchester Project, in order to rehabilitate the abandoned properties, the city government and private organizations spent a cost between $83,000 and $140,000 in homes, but the homes were sold for between $37,000 and $60,000 after redevelopment (Cohen, 2001; Friedman, 2003).

2.5.1.2. An example of conventional revitalization program: Neighborhood Transformation Initiative (2001): Philadelphia, Pennsylvania

Between 1967 and 1987, 160,000 manufacturing workers lost their jobs in Philadelphia, and the city recorded third largest population decline in the U.S. (First: Baltimore, Second: Detroit) (McGovern, 2008). The post-industrial economic decline in Philadelphia has exacerbated the vacant housing crisis, crimes and segregation issues. In April 2001, the city government announced to support $295 million for implementation of the Neighborhood Transformation Initiative (NTI) for blight elimination, assembling land for housing redevelopment, stimulating neighborhood investments. For five years, $160 million funds were used for the demolition of approximately 14,000 vacant houses including larger commercial and industrial buildings among 31,000 vacant lots and 26,000 abandoned buildings. Also, $50 million has been budgeted to attract private investment for large developable vacant properties (Kromer, 2002). NTI anticipated this redevelopment project would stimulate investment by for-profit developers of market-rate housing, and create construction jobs for local residents (McGovern, 2006). However, the outcome of NTI project has not been as satisfactory as expected. During NTI's first year of operation, their first major demolition project in the Strawberry Mansion neighborhood of North Philadelphia was planned to demolish 1,845 abandoned properties during the spring 2002. But this project was postponed for about one year due to a lack of consultation with local residents. Moreover, the average cost of razing residential buildings was estimated at $11,500 at first. One year later, the actual cost of the demolition was about double that cost to $22,000 per unit (McGovern, 2006).

2.5.2. Smart decline

"Small doesn't mean giving up."

Due to the failure of conventional revitalization strategies, instead of chasing industry with hefty incentives and the other standard economic development tools, there has been a pending paradigm shift from traditional urban growth to "right-sizing" (Schilling & Logan, 2008; Hollander & Nemeth, 2011) in shrinking cities against this backdrop of significant social and physical urban declines. Under this widespread demographic disturbance, some practitioners and scholars have begun to reject the growth-based paradigm, and argued that not all cities must grow back to their former glory. The problem of population loss is not about size itself, but about who is leaving and who is staying. In some cases like Pittsburgh, for example, population loss does not of necessity bring economic collapse or decline in living standards. Rather, the municipal decline can sometimes provide a creative re-use opportunity and improve their life qualify in spite of population loss. Thus, the different approaches from the traditional urban growth of "planning for less-fewer people, fewer buildings, fewer land uses (Popper& Popper 2002)", is emerging for improving the quality of life rather than just growing the size of a city (Schilling & Logan 2008; Hollander & Nemeth 2011).

2.5.3. Urban greening & Temporary use

The urban vacant land has diverse potential of ecological, social and environmental benefits to improve the quality of life in the community. According to a recent survey by Nemeth & Langhorst (2013), by using the land as green space, they would provide infrastructural functions such as stormwater infiltration. The study notes that the open space can help form social and environmental justice for the neglected and marginalized communities in hazardous environmental conditions by providing an aesthetic experience. Consequently, the greening of vacant urban land would contribute to reduce violent crimes and improve royalties for the regions, health and safety of a resident in the abandoned area. Not only would access to green space also leads to diabetes and obesity, it would also increase the value of homes by at least 12% (Colin Tetreault, Earth911). However, since there is a lack of similar greening research models of economic return on investment, it is difficult to attract investment and funding into the area. Moreover, the negative image and awareness, lower surrounding property values, and a lot of ongoing costs on the abandoned areas also obstruct the investments. (Nemeth & Langhorst, 2013; Mallach 2011)

The vacant land can also provide short-term access to diverse experimental activities such as pop-up retails, art exhibitions, mobile architecture events, companies' advertising or commercial outdoor recreation, and urban gardens. By creating the unexpected pocket space in the run-down urban fabric, these flexible and incremental reuses can contribute to create safer and more dynamic neighborhoods, and also improve the cities' images, appearances, and the property value. However, there are some issues that need to be considered. First of all, since existing policies and permitting processes are planned for long-term use and permanent tenants, they are not fit to temporary uses. Furthermore, even if a land has been vacant for a while, most landlords do not want to lease the land for short-term frames. High ongoing maintenance expenses would be also an issue.

2.5.3.1. An Example of Urban Greening & Temporary Use: 2010 Citywide Plan (Youngstown, Ohio)

The big eight cities (Akron, Canton, Cincinnati, Cleveland, Columbus, Dayton, Toledo, and Youngstown) that had led Ohio's economy over a hundred years are faced with serious depopulation like many other older industrial cities. Worse, the population loss has also caused increased job loss, poverty and numbers of vacant and abandoned properties. The entire population of the cities is only 41 percent of what it was in 1950, and Cleveland (-55%) and Youngstown (-59%) have fallen by less than half. As the result, the eight cities lost $ 49 million in tax revenue and spent $15 million for city services due to the vacant properties (Schilling & Logan, 2008). To revitalize the economy, the city of Youngstown begun to plan for land reconfiguration in 2005 as the termed 2010 Citywide Plan. Youngstown recognized that there are still too many oversized urban structure and 43 percent vacant properties. Unlike development-oriented ideas in other shrinking cities, they planned downsizing the size of built infrastructures and then, the major part of this plan is recreating the city as a sustainable mid-size city. At first, they readjusted unrealistic population projection and modified to 70,000 or less population in the future, not the 170,000 that recorded the highest in the 1950s, nor the 250,000 that the city once expected (Parris, 2010). Based on their new population projection, the abandoned and blight lots have been cleaned up and changed to productive open space such as community gardens. Of course, this project is also facing some issues. Youngstown received approximately $ 3.8 million from the federal Department of Housing and Urban Development (HUD) in the initial stage. However, they didn't get the funds from 2008 and it made Youngstown demolish buildings as fast as other become vacant. Due to the lack of funding, only 103 structures were razed in 2008, compared to 351 in 2006 and 474 in 2007 (Kutner, 2011; Mallach 2011).

2.5.4. Land Bank Program

Land banks would be one strategy to empower community residents, stabilize dysfunctional markets, and rediscover the value in forgotten urban lands. Different from typical redevelopment authorities, a land bank is a governmental or quasi-public entity created to efficiently convert tax-foreclosed and vacant properties back to productive use (Alexander, 2005; Schilling & Logan, 2008). Since the St. Louis Land Reutilization Authority created the first major land bank program in 1971, many local governments have adopted these land banks to address economic decline issues caused by industrial closings.

Enabled by state legislation and enacted by local ordinances, land banks acquires tax-delinquent properties without the existing owner's consent. After the acquisition process, land banks clear titles and waive back taxes on the property and then, transfer the ownership to responsible nonprofit and private developers at below-market prices. Land bank programs are not simply short-term fiscal tools to increase public revenue, but a long-term planning tool to revitalize entire communities and provide the greatest benefit based on state-wide smart growth goals.

Since governments themselves take the initial risk of preparing land in weak and unstable real estate markets, private development and investment can be prompted for neighborhood revitalization, promoting economic development and tax revenues, removing public nuisances and discoursing criminal activities (Schilling & Logan, 2008). Genesee County Land Bank Authority has been one of the most successful land banking programs.

2.5.4.1. An Example of Land Bank Program: Genesee County Land Bank Program (Genesee County, MI)

Like other manufacturing cities, Flint, Michigan, experienced a serious depopulation and economic downturn due to the shrinkage of the automobile industry in the 1970s. Flint's total population went from 163,143 in 1950 to 112,524 in 2000 (31% decline), and the total employment of the city fell by almost 42% from 1970 to 2006 (Hollander, 2010). Flint implemented 14 redevelopment projects between 1970 and 1992 to reverse the city's continuing economic decline, costing $569 million. These projects largely failed to revitalize the economy (Hollander, 2010). According to the 2000 U.S. Census, over 5,000 residential (or 12%) properties in the city are vacant or abandoned (Griswold & Norris, 2007).

Since the launch of the Genesee County Land Bank (GCLB) in 2002, the land bank authority acquired and cleared the title for of over 3,500 tax-foreclosed properties and more than 650 of the properties were returned to private ownership and property tax rolls. Moreover, 275 of the GCLB properties were sold for $1.00 to adjacent neighborhood homeowners who already owned a property on the same block through the "Side Lot Program" (Griswold & Norris, 2007; Alexander, 2011). Griswold & Norris (2007) estimated that the total positive impacts of the GLCM program during the 2002-2005 period exceeded $112 million, and the net benefit was estimated to be more than $109 million, including $3.5 million spent on demolitions. As a result of the urban revitalization efforts, over $60 million in private investment has been made.

However, while establishing land banks in the communities provides many benefits as a part of a right-sizing initiative, there are two common barriers in implementing and maintaining them. The inherently weak fiscal capacity of shrinking cities is the first challenge. There are costs for demolition and acquiring the properties. Since it is difficult for municipalities to start a land bank operation due to a lack of sufficient acquisition funds, federal and state financial support is needed (Schilling & Logan, 2008; Alexander, 2005; Accordino & Johnson, 2000).

Moreover, it is questionable whether the tax-reverted properties would provide enough economic value and public revenue. In cases where the revenues from the sale of the properties are lower than site preparation costs, it would not be cost-effective and would be another significant financial burden for a city. The cities of Baltimore and Philadelphia illustrate this problem.

2.5.5. Conclusion

Rising concerns over urban shrinkage and a large amount of vacant land have led to an increasing need for new and systematic growth management tools for state and local governments. Since the 1970s, diverse policies and strategies have been implemented to address the problems including the use of zoning, subdivision regulations, and aggressive redevelopments. Despite these efforts, conventional market-based redevelopment policies aggravate market dysfunction, chronic decay and disinvestment, and cities are still lagging in their response to the projected impacts of depopulation and increased vacant properties.

Therefore, instead of chasing industry with hefty incentives and the other standard economic development tools, there has been a pending paradigm shift from traditional urban growth to an allowance of "right-sizing" (Schilling & Logan, 2008; Hollander & Nemeth, 2011) in shrinking cities.

Of course, the new policies and projects alone might not be able to solve the issues directly. Rather, it can be problematic to manage the city by uniformly establishing related plans according to top-down uniform regulations and criteria without considering the local characteristics of different environmental and urban conditions. Though some development management tools have been put into practice successfully in certain social contexts, they may cause adverse effects in different situations. Furthermore, it is not easy to change the common perception "depopulation is always bad". As Hollander et al. states, "*the key obstacle is the notion that a healthy city always grows in population and that only unhealthy ones shrink*" (Hollander et al., 2009: p232).

The term “decline” is conventionally recognized as a “bias toward growth” (Johnson et al. 2014) for not only urban residents but also policy makers. Consequently, most cities blindly chase growth-oriented political agenda and top-down approach despite economic and populating declines (Haase, 2008; Hollander, 2011; Hollander & Nemeth, 2011). Under the circumstance, acceptance of decline is considered as driving the city into pessimistic and unhealthy images. Since admitting decline is recognized as a cultural taboo, most planners and politicians still only focus on a strategy of economic and population growth that rarely leads to success in the declining cities in spite of continuous shrinking (Hollande et al., 2009; Shetty, 2009; Pallagst, 2007).

Thus, more research is needed to explore how these new frameworks and strategies can contribute to the economic growth of shrinking cities and quality of life for neighborhoods. Recently, a new movement to see decline as land use management strategy has begun in some cities because losing population do not always lead to lower quality of life and social value (Johnson et al., 2014). For the declining cities, the question, “Why are they still there are at all”, not “why aren’t they growing” should be the primary consideration (Glaeser & Gyourko, 2005).

2.6. Land Transformation Model

2.6.1. Urban land-use modeling

As computer systems and federal data organizations in the late 1950s and mid-1960s developed, urban growth and land use change models emerged to allocate future growth (Landis et al., 2011). Most land use change models were initially developed to predict the economic and environmental impacts of land-use transportation policies. In 1959, the basic gravity models were employed to investigate the attractiveness and accessibility of cities in metropolitan areas for future development (Ewing & Bartholomew 2009), and Ira Lowry (1964) also applied a transportation model to allocate future residential and service employment zones based on the analysis of travel costs and attractiveness of in the Pittsburgh region (Batty 2013).

There are largely two types of causal-based spatially explicit models: regression models and spatial transition based models (Theobald & Hobbs, 1998). Econometric models are the most common statistical technique, using multiple regression analysis. After Swerdloff and Stowers (1966) developed the early statistical technique, Chapin and Weiss introduced a probabilistic model of residential growth in 1968, and a statistical model has still employed in several related current studies (Briassoulis, 2008). Since the application of the statistical models have been employed to analyze the problems involving economic demand and supply, the application of these statistical techniques are useful to analyze the relationship between the distribution of land use types and other driving factors, and estimate the layout of urban land uses based on principle of economic/market equilibrium (Briassoulis, 2008; Batty 2009; Irwin & Geoghegan, 2001). However, these traditional econometric models were criticized because the modeling processes are too static and aggregated macro-scale data are used due to the limitation of data collection and technology (Sayer, 1979). Since the statistics-based models basically assume the long-linear relationship and temporal stationarity, it is restrictive to apply the models in real. In order to relax this assumption, different empirical models such as non-linear statistical method and artificial neural networks have been used with the advanced computing abilities.

While regression models focus on identifying functional relationships between variables using statistical regression, spatial transition based models produce realistic landscape patterns based on artificial neural networks (ANNs) approaches which calculate the transition probabilities. Especially, the emergent technological development of geographic information system (GIS) has facilitated faster and easier manipulation of spatial data sets. As a result, computer simulation models based on GIS such as UrbanSim (Waddell, 2002), Cellular Automata models (Batty et al., 1999; Batty, 1992, Torrens, 2003) and SLEUTH (Clarke et al., 1997) have remarkably grown in the last 30 years (Newman et al., 2016). Since these models simulate transitions using spatially explicit digital maps, they provide graphical outputs and rely not only on economic theories, but also real situations and historical urban trends. While the past regression modeling tools were based on mathematical equations, the GIS-based models are computer simulation and visualize the output to intuitive maps and diagrams. Therefore, the ability to generate road maps for local policy makers, developers and residents who are not familiar with economic theories and statistics is much easier. Table 3 shows the selected recent GIS-based spatial analytic models with a few key selection criteria.

As computing systems continue to develop since the 1980s, data sources are more organized, accessible and easier to calibrate and several different approaches involving interactions between land use patterns and environmental and socioeconomic elements have been introduced. Especially, the emergent technological development of geographic information system (GIS) has facilitated faster and easier manipulation of spatial data sets. Based on historical land use data (input patterns) and influential drivers (input factors), the models are available to predict both temporal and spatial changes.

Of course, doubt and questions about the models still remain even if diverse land use change models have been developed in many different areas for several decades. They have been criticized for not being able to provide reliable accuracy assessment processes of the output effectively (Conway, 2009). Due to the accuracy issue, it is difficult to calibrate the contribution of these models to policy decisions and the models have difficulties to adapt to local circumstances and communities regularly and reliably (Landis et al., 2011). In order to accept urban growth models widely and improve modeling capability, it is critical to utilize a series of accepted assessment methods which to increase and validate model accuracy.

To address the reliability and validity issue of the LUCC, there are couple methods to calculate the relative percentage success of a model for model accuracy. Among them, a GIS and neural net-based model known as the Land Transformation Model has risen in popularity due to the high level of accuracy and ability to use not only physical factors but also social, political and environmental factors as influential variables to forecast land use changes (Almeida et al., 2008; Pijanowski et al., 2002). Allen and Lu (2007) investigate the reliability and validity of 66 different cases of neural net models for predicting land use change in coastal South Carolina and find that spatial transition based models using the neural net outperform the logistic regression models.

In 55 of 66 cases, on average, the accuracy of neural networks is approximately 10.8% higher than the conventional regression models. The neural networks also record much smaller risks related to prediction errors.

It is true that these land use change models are not perfect and nobody can be convinced 100 percent about the results of prediction due to the characteristics of non-linearity and complexity of diverse physical, social and environmental interactions in reality. However, based on qualified theories and relevant data sources, we have shown how the land pattern in a city can change and will likely change. Then, we can make a desirable decision for cities that have suffered severe depopulation and economic crisis by constructing a rational prediction model for the future. The analysis of causes and consequences of land pattern changes would be useful to construct, support and promote new land use planning policies. In other words, these prediction models will play a role as “a key analytical bridge between envisioning alternative bridge between envisioning alternative urban development patterns and evaluating their impacts” (Landis et al., 2011, p.127).

2.6.2. Land Transformation Model (LTM)

In an effort to assist in solving many of the aforementioned urban issues, planners have slowly moved into spatial and temporal models which are more scientifically and technologically driven. The LTM, one such model, is a Geographic Information Systems (GIS) and artificial neural networks (ANNs) based land use/cover change (LUCC) model which has recently grown in popularity to analyze spatial and temporal land use dynamics, estimate the impacts of urban growth alterations and forecast land use changes (Pijanowski et al., 2001; Newman et al., 2016). GIS tools are used to process and manage spatial data layers while, ANNs learn about input patterns (driving factors) and output data (historical land use change) (Pijanowski et al., 2014). While most computer modeling tools have focused on regional scale analysis, local and municipal scaled predictions using the LTM are rare and testing of the overall accuracy of the model has not been thoroughly conducted. Furthermore, although many other computer-based models are based on similar processes and concepts, one great asset of the LTM is that it displays the accuracy of the model while other models typically simply specify whether inputted drivers or factors have a significant effect on urban growth.

Figure 6 shows four sequential steps of the LTM (Oyebode, 2007; Pijanowski et al., 2002; Newman et al., 2016): 1) Data processing – spatial input layers integrated with GIS are generated, stored and managed. GIS is used to quantify historical temporal changes in spatial pattern and also forecast future possible scenarios. The grid cells of base input layers represent land use as binary (presence = 1 or absence = 0, in this study, vacant land = 1 or occupied land = 0).

2) Spatial rules application – the predictor variables are reclassified from the input layers based on two different transition rules in ANNs: patch size and distance from the location of a predictor cell. Since socioeconomic variables can be obtained by census boundary (e.g., census tracts or block groups), the variable values of all cells within the defined patches are same. The Euclidian distance formula is used to calculate

the values of transportation/street related variables as a tool of the distance spatial transition rule.

3) Grid integration – this step allows an artificial neural networks to learn about input layers (driving factors) and output data (historical land use change pattern). There are three different integration methods: multi-criteria evaluation (MCE), ANNs, and logistic regression (LR). Each method requires a different data normalization process and there are various ways of defining the transition rules and model structures. In this research, all cell sizes and analysis window are set to a fixed base layer by ANNs, deal with the complex relationships of land use conversation and provide a simulation environment using a gridded space (raster).

4) Temporal scaling of prediction output – “principal index driver” (PID) is used to determine the amount of land expected to transition over a given time period. Generally, existing literature assumes that the same number of cells will transition to a land use based on the analysis of historical temporal and spatial land use data (Oyebode, 2007). This study, however, also consider historical population growth statistics and future projection to calculate the PID. By using both land use and population data, it would be possible to obtain more reliable future possible scenarios.

The LTM, artificial neural networks (ANNs) based LUCC model, was originally developed by the Human-Environment Modeling and Analysis Laboratory at Purdue University to simulate future land use change over regions for the purpose of measuring environmental and economic impacts of urbanization and agricultural expansion. Since a variety of input factors including physical, socioeconomic, political and environmental

Table 3. GIS based Spatial Analytic Models

Model	Purpose	Strength	Weakness
California Urban Futures (CUF-1 & CUF-2)	To evaluate the effects of development and growth policies on location, pattern and intensity of urban development based on trend prognosis of economic and population development.	- Preparing and evaluating alternative policy scenarios quickly and showing results as a map forms to understand easily. - Simulating future alternative development in responding to specific policy changes.	- Only providing a method for projecting and allocating residential development, but not including for industrial, commercial and public activities. - Requiring GIS based spatial database of hectare-scale grid cells, not irregularly-shaped polygons. - Requiring detailed knowledge of statistics for model calibration. - Unavailable for "off the shelf" purchase.
The Clarke Urban Growth Model (The SLEUTH Model)	To simulate urban growth for understanding the effects of urban expansion on their surrounding land and local environment.	- Simulating diverse urban growth pattern concurrently: spontaneous, diffusive, organic and road-influenced. - Providing results as a map forms to understand easily and also statistical outputs.	- Overlooking the population, policies and economic impacts on the land use change.
DRAM/EMPAL	To quantify the distributions and interactions of employment and population locations, and transportation facilities that connect them in metropolitan areas.	- The most widely used predicting model to measure the interrelationships among transportation, location and land uses in many metropolitan areas (over 50 metropolitan studies are existed internationally). - Using easily accessible input data sources as required input data. - Easy to calibrate	- Limited number of independent variables: difficult to measure the full impacts and projection. - Simulating only for regional level, but not city level. - Expensive ($30,000-$60,000) and requiring initial consultant involvement and training.

Table 3. Continued.

Model	Purpose	Strength	Weakness
Land Transformation Model (LTM)	To evaluate the impacts of various land use change driving variables and forecast the land use change.	- Providing results as a map forms to understand easily and also statistical outputs. - Various social, political and environmental factors and unlimited number of input variables to measure full impacts on land use change - Providing the degree of statistical reliability of results. - Applying to not only regional level but also city or community level projection depending on available input data.	- Requiring the knowledge of C programs t couple the GIS and ANNs. - Generally requiring to train NN training over 250,000 times: time consuming.
UrbanSim	To simulate future population and employment for cities, incorporating the interactions between land use, transportation and public policy.	- Providing demographic forecasts as well. - Providing diverse visualization components including 2 and 3-dimensional mapping, and charts and graphs to compare model results. - Open source software: flexibility of modification and redistribution of its code.	- Requiring a great deal of disaggregate and high quality data (smaller than 150 meters by 150-meter grid cell). - More complex to prepare, estimate and calibrate than aggregate models. - Requiring huge model runtimes.

variables can be used for predicting future land use change, LTM can provide valuable information about the potential effects of land use change in diverse fields such as forest cover change and urban environments (Pijanowski, 2002; Pijanowski et al., 2014; Tayyebi et al., 2014).

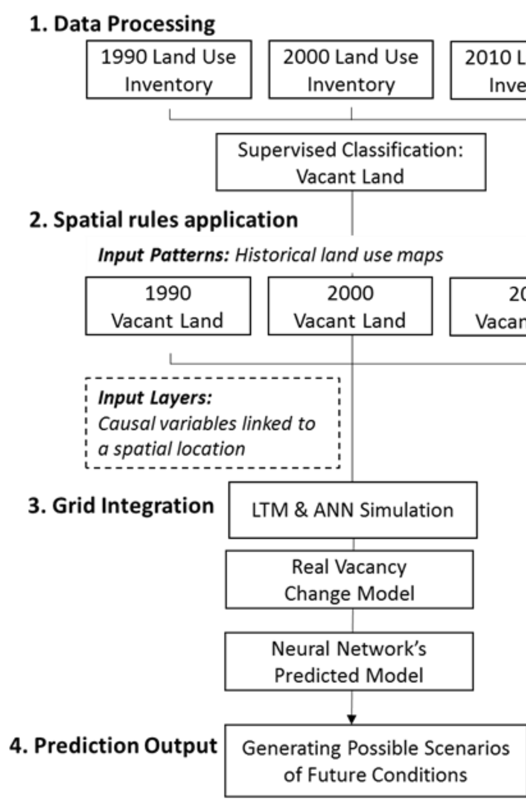


Figure 6. LTM Process Diagram

The LTM's ability to successfully simulate land use changes has increased its utility on a multitude of scales/locations (Almeida et al., 2008). It was developed over 15 years ago and has now been utilized in a variety of places around the world (Pijanowski et al., 2014). The model has been applied not only in the United States but also in areas such as central Europe (Pijanowski et al., 2006), East Africa (Olson et al., 2008; Washington-Ottombre et al., 2010) and Asia (Pijanowski et al., 2009) in different fields and scales. Brown, Pijanowski, and Duh (2000) used the model to predict regional forest-cover changes in the Upper Midwest, USA, using multiple socio-economic human-induced drivers, results showed that land use and land cover were linked and linear functional relationships between the two were established through regression analysis. Tang, Engel, Pijanowski, and Lim (2005) investigated urbanization patterns on a watershed scale and forecasted land use change by 2020 and 2040 using the LTM. As a tool of environmental impact assessment, the research used the model to generate information about future urbanization patterns and estimate potential environmental impacts. Similarly, the LTM was used to examine the impacts of land use morphology on environmental processes by Ray and Pijanowski in 2010. The model has also recently been coupled with mesoscale drivers to project urban growth using multiple city-scaled projections combined and assessed on a national scale (Newman et al., 2016).Tayyebi et al. (2013) forecasted civic boundary expansion in an effort to control for urban growth finding that LTM models performed relatively well using this method and that the introduction of small scaled data into large-scale LTM simulations significantly increased model accuracy.

2.6.3. Artificial Neural Networks (ANNs)

ANNs are self-programming networks that find and resolve complex interactions between input layers and predicted output layers imitating the brain's ability to sort patterns, learn from trial, observe relationships in data, and simulate the structure like human (Vafeidis et al., 2007; Pijanowski et al., 2002; Li & Yeh, 2002). The ANN learns the pattern of urbanization using historical land use data from at least two different time periods (input layers), calculates the change between these periods, and uses this change as an influencing raster dataset alongside the input drivers (Tayyebi et al., 2013; Newman et al., 2016). Different types of variable/drivers can be used ranging from physical, social, economic, cultural and/or environmental factors. ANNs assess probabilities by means of non-parametric approaches (Almeida et al., 2008) and attempt to simulate human reasoning and logic based on input variables (Moore 2000). Non-parametric approaches have been suggested to be better situated to cope with the nonlinearities of changing urban environments, making ANNs more suitable for deciphering issues in complex urban pattern dynamics (Li & Yeh 2002; Yeh & Li 2003; Guan et al., 2005) and have been repeatedly shown as appropriate for modeling land use change, if appropriate spatial data exists (Clarke et al., 1997; Openshaw, 1998, Fischer & Abrahart, 2000).

After Rosenblatt created the first simple neural network (Fig. 7A) performing linear functions with a single node in 1958, Rumelhart, Hinton and Williams (1986) developed the simple neural machine to the multi-layer perceptron (MLP) neural net (Fig. 7B) and this is one of the most widely used ANNs today (Pijanowski et al., 2002). The MLP consists of three layers: input, hidden or exclusionary, and output layers. ANN's consist of input layers, output layers, and optionally hidden or exclusionary layers. Input layers are a series of processing units connected by neurons which are responsible for passing information throughout the network and are characterized by weights based on positive or negative influence on a predictor variable (Bishop, 1995). The input layers are driven by the logic of the modeler and consist of the variables/driver built into the model, which drive the connecting neurons. These connections decipher solutions between inputs (i.e. drivers of change) and outputs (e.g. locations of change occurring between two time periods) using non-linear functions and weights (Pijanowski et al., 2005).

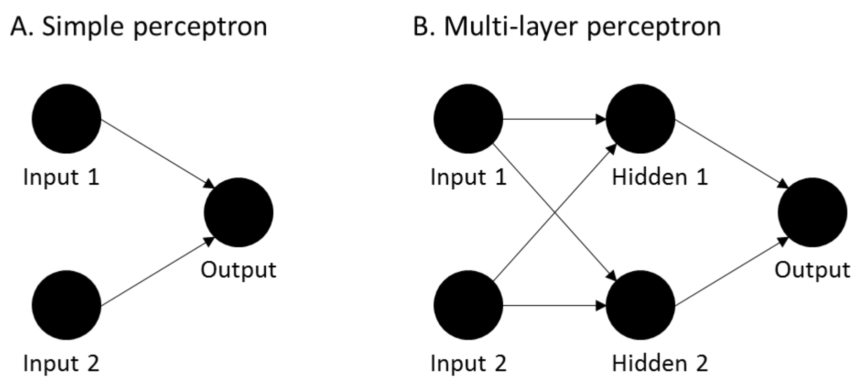


Figure 7. A Simple (A) and Multi-Layer Perception Neural Net (B)

2.7. Evaluation of the Accuracy and Reliability

Although LTM model has risen in popularity, they have been criticized for not always being able to provide highly reliable accuracy outputs due to ineffective assessment processes (Conway, 2009). Due to this issue, it can be difficult to calibrate the contribution of these models, making the models have difficulty in adapting to local circumstances and communities (Landis et al., 2011). In order to have an acceptable model and improve the model's reliability, it is critical to use proven assessment methods for improving model accuracy. There are a few accepted methods to validate a model's performance. For model calibration, four different sets of metrics are used in this research to verify the goodness of fit of the neural network based model: Kappa coefficients, percent correct metric (PCM), agreement/disagreement measures, and the relative operating characteristic, detailing how well the real change and predicted change between the time frames matched one another. Since diverse accuracy assessment procedures have different processes, results and limitation, this section reviews the four model accuracy approaches.

Spatially-explicit LUCC models typically begin with a digital map of an initial time and then simulate transitions in order to produce a prediction map for a subsequent time (Pontius et al., 2008). To stabilize the error level to a minimum value, the ANN is required to be trained over 4000 cycles. For the best output, since over 250,000 cycles of training are recommended, each training session was run up to 250,000 cycles. As a result of the neural network training, the LTM produces two automated statistics, Kappa values and percent correct metric (PCM) every 1000 cycles, thus, the cycle with the highest match rate of a pair of maps from categorical land use datasets (actual change and simulated model) was selected for future prediction purposes and assessment (Pijanowski et al., 2002; Newman et al., 2016; Pijanowski et al., 2014).

The actual and probable transitions toward vacancy between two periods can be compared visually and mathematically by using the Raster Calculator tool in ArcGIS. By juxtaposing actual and predicted maps, four different values can be obtained: 0 = no actual and no predicted transition (true negative), 1 = actual but no predicted (false positive), 2 = no actual but predicted (false negative) and 3 = both real and predicted (true positive). Based on the scores, the accuracy assessment processes will be explained with an example of a nine pixels based map.

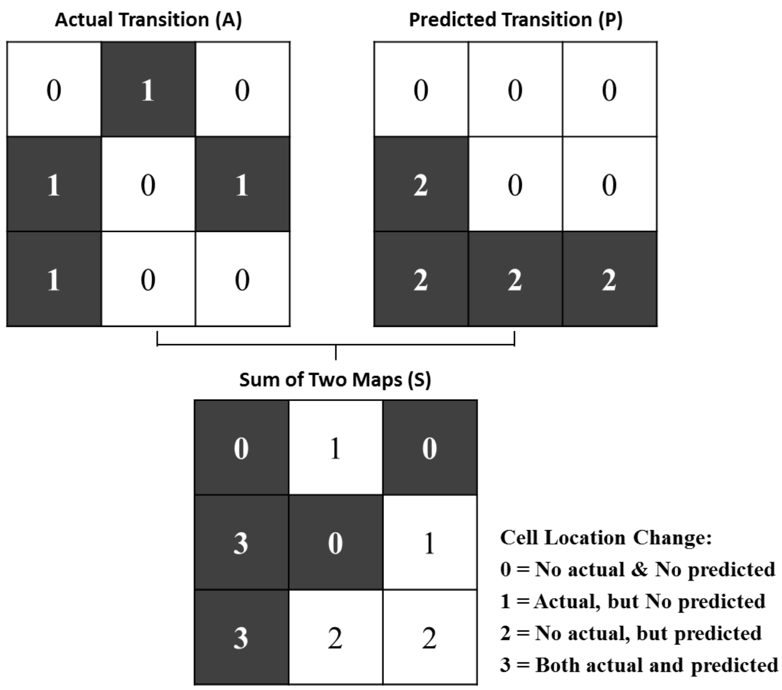


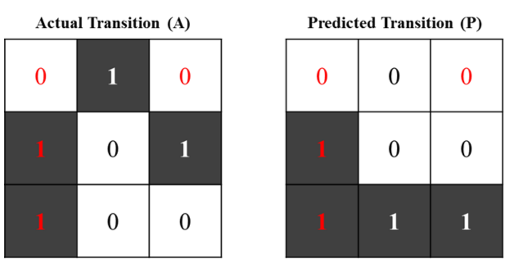
Figure 8. Diagram illustrating Actual Transition, Predicted Transition and Composite Score

2.7.1. Kappa analysis

Among the accuracy assessment processes, Kappa analysis has, for a long period, been a standard component in the conduction of accuracy assessments. (Congalton et al., 1983). As Congalton and Green (1999) stated, “Kappa analysis has become a standard component of most every accuracy assessment and is considered a required component of most image analysis software packages include accuracy assessment procedures

(Pontius & Millones, 2011, p. 4408), this accuracy assessment can be simply computed and easily understood and interpreted.

The Kappa statistic is calculated to measure the agreement between how much agreement is actually present from an actual transition map compared to how much agreement would be expected from a predicted transition map. Since the value is standardized to lie on a 0 to 1 scale showing degree of agreement, the Kappa value can be interpreted the same across multiple studies (McHugh, 2012). A value of 1 implies perfect agreement, exactly what would be expected by chance for 0, less than change agreement would equate to a negative value. Generally, values between 0.01 and 0.20 indicate no or slight agreement, 0.21-0.40 as fair, 0.41-0.60 as moderate, 0.61-0.80 as substantial, and 0.81-1.00 as almost perfect agreement (Almeida et al., 2008; Pijanowski et al., 2006, 2002; Tayyebi et al., 2013).



$$\textbf{Kappa} = \frac{P_o - P_e}{1 - P_e}$$

V: vacant NV: non-vacant		Actual Transition (A) V	Actual Transition (A) NV	Total
Predicted Transition (P)	V	2 (a)	2 (b)	4
	NV	2 (c)	3 (d)	5
Total		4	5	9

P_o = Either vacancy or non-vacancy agreement between A & P

P_v = Vacancy agreement between A & P

P_{nv} = Non-vacancy agreement between A & P

P_e = The expected fraction of agreement $= P_v + P_{nv}$

Figure 9. Diagram illustrating the Use of Kappa Statistic

Figure 9 is a simple example illustrating the process to calculate a Kappa statistic. Using land use maps A and P (A: actual transition, P: predicted transition), four different categorical pixel values (a, b, c, and d) are obtained as shown in the bottom of figure 9. Based on the values, the Kappa coefficient is calculated with the formula below. Based on the formula, the Kappa coefficient of the example is 0.1, meaning that the agreement would be too poor to accept if this was an actual model.

$$\textit{Kappa coefficient} = \frac{\left(\frac{3}{9}+\frac{2}{9}\right)-[\left(\frac{5}{9}*\frac{5}{9}\right)+\left(\frac{4}{9}*\frac{4}{9}\right)]}{1-[\left(\frac{5}{9}*\frac{5}{9}\right)+\left(\frac{4}{9}*\frac{4}{9}\right)]} = 0.10$$

2.7.2. Quantity disagreement & Allocation disagreement

Since land use maps are categorical datasets, Kappa analysis is frequently used to compute the agreement between a pair of maps. Nevertheless, some conceptual problems and methodological flaws of the Kappa index have been revealed. On the surface, the Kappa index seems to be a fairly appropriate approach to assess vacant land predictions, considering that both land use change (including transition to vacant land) and vacant land are both intrinsically stochastic in nature. However, the use of only Kappa can be somewhat limited because the Kappa score is a one-dimensional index which fails to accurately evaluate both quantity and location accuracy in grid cells between the utilized maps (Pontius, 2000). Further, the Kappa index can sometimes muddle information about the quantity of each category on the maps with information about the location of each category on the maps. For these reasons, quantity disagreement and allocation disagreement for general map comparison can also sometimes provide additional insight (Pontius & Millones, 2008; Newman et al., 2016).

Quantity disagreement indicates the amount of difference between the actual transition map (A) and the predicted transition map (P). Allocation disagreement describes the amount of spatial difference between the two maps. Using the same example above, the total number of pixels of quantity disagreement, allocation disagreement, and overall agreement can be calculated (See Fig. 10).

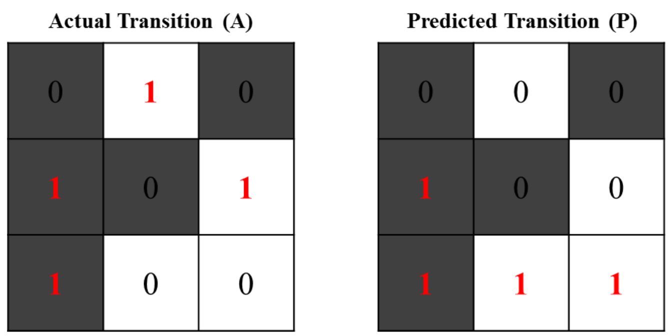


Figure 10. Diagram illustrating the Use of Quantitative and Allocation Disagreement

Both actual and predicted transition maps consists of nine pixels with four pixels having 1 value (change) and five white pixels having 0 value (non-change). Since they have the same number of changed and non-changed pixels, there is zero quantity disagreement. In terms of allocation disagreement, the five black pixels indicate the spatial agreement of A and P, meaning both A and P maps have same values in the same location while four white pixels do not share the same values. Thus, the allocation disagreement is 45% (=$\frac{(9-5)}{9}$)*100. Based on the quantitative disagreement and allocation disagreement, overall agreement is calculated as follows and since more than 85% of overall agreement is generally used as a baseline for an accuracy assessment to be considered as good, this model is not acceptable (Pontius et al., 2011).

Overall Agreement (%) = 100 – (Quantitative Disagreement + Allocation Disagreement) = 100 – (0 + 45) = 55%.

2.7.3. Percent Correct Metric (PCM)

The assessment process of PCM is relatively similar to the process of allocation disagreement. While allocation disagreement shows the overall proportion of misallocated pixels including zero value pixels, PCM focuses on the transited pixels having one or two values. Since the value of PCM indicates the proportion of pixels that transition, it is used to understand the transition of the land-cover category under investigation. Generally, the PCM result is interpreted as follows: values between 60% to 80% accuracy indicate an exceptional model and 40% to 60% are acceptable models (Almeida et al., 2008; Pijanowski et al., 2006, 2002; Tayyebi et al., 2013). For the fictitious example provided below, the PCM is acceptable.

As shown in figure 11, there are four changed pixels. Among them, two pixels are in the same location, the PCM is the proportion of the number of 2's divided by the number of cells that transition. In this example, thus, the PCM is 50%, indicating 50% spatial agreement.

$$PCM = \left(\frac{Cells\ correctly\ predicted\ to\ change}{Cells\ actually\ transitioned}\right) * 100$$

= (2/4)*100 = 50% spatial accuracy.

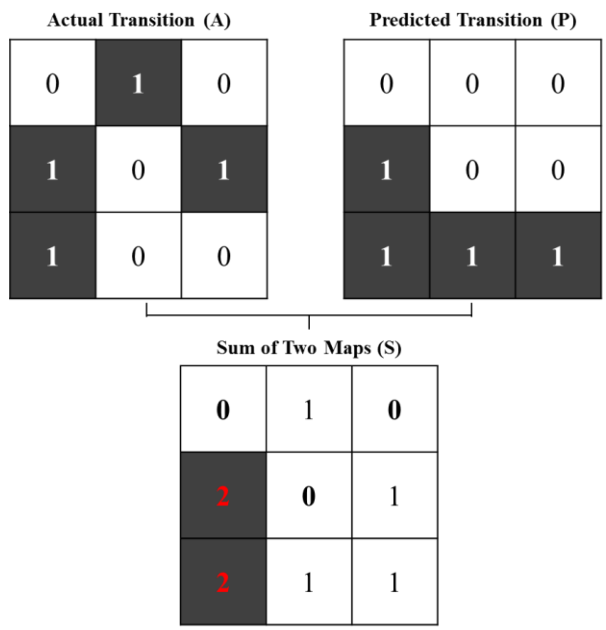


Figure 11. Diagram illustrating the Use of PCM

2.7.4. Receiver Operating Characteristic (ROC)

Finally, the receiver operating characteristic (ROC) curve analysis is a quantitative measurement tool to validate the goodness of fit of the LUCC model (Pontius & Schneider, 2001; Pontius et al., 2014; Pontius & Batchu, 2003). The two-class (binary classification) prediction model has four different outcomes: True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). Using these four values, the sensitivity (true positive rate) and specificity (true negative rate) is calculated using the formula below, based on the overall agreement cell score outputs. Figure 12 describes meaning and number of each value. Then, the ROC curve graphs sensitivity on the x on the y-axis against 1-specificity –axis, and the area under the ROC curve (AUC) graphically displays the overall accuracy as shown in figure 13. For example, the resulting AUC value for the provided fictitious model is 0.45, meaning that this model fails to be acceptable. Typically, values between 0.70 and 0.79 indicate a fair model, 0.80-0.89 substantial, and 0.90-0.99 as excellent (1.0 is perfect) (Osborne et al., 2001; Rutherford et al., 2008).

$$\text{Sensitivity (true positive rate)} = \frac{TP}{(TP+FN)} = 0.5$$

$$\text{Specificity (true negative rate)} = \frac{TP}{(FP+TN)} = 0.6$$

Value	Description	Count
0	No actual change and no predicted change (TN)	3
1	Actual change, but not predicted by the model (FP)	2
2	No actual change, but change predicted by the model (FN)	2
3	Actual change and predicted change (TP)	2
Total		9

	Real change categories		Total
Predicted change categories	TN	FN	SN
	FP	TP	SP
Total	RN	RP	GT

	Real change categories		Total
Predicted change categories	3	2	5
	2	2	4
Total	5	4	9

Figure 12. Diagram illustrating the Use of ROC Curve

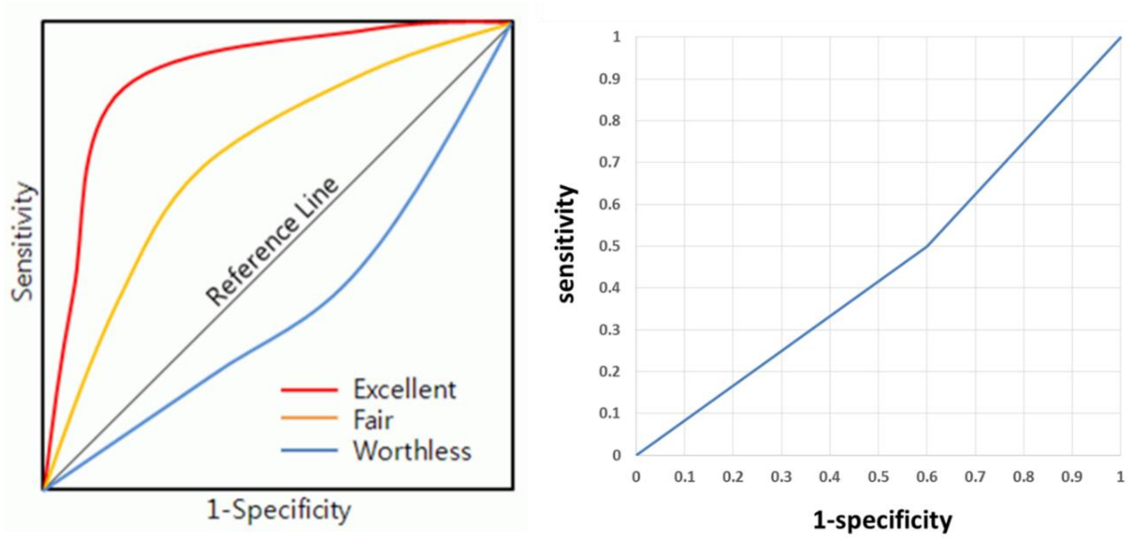


Figure 13. The Example of ROC Curves and AUC Output

2.8. Evaluation of Existing Research

Overall, many studies on urban shrinkage have been conducted over the last fifty years, and a simplified description of urban decline is to perceive it as dense cities that have experienced undesirable deterioration in whole or in part because of any reasons not only physical decay, depopulation and growing employment loss but also social exclusion. However, the existing research has the following limitations:

First, even if there have been many attempts to investigate the relationships between vacant land and its factors, the definition of vacant land is still unclear and varies depending on the purpose of the research and study areas. There are difficulties to find a consensus on the definition of the terminology and reliable approaches to analyze the amount of vacant and abandoned properties due to the different classification whether abandoned buildings or deteriorated structures do not be excluded, and unclear criterion about how long a property stays empty to determine as vacant land. Based on the literature, I define vacant land as not only empty or underperforming areas but also abandoned and neglected industrial buildings that would pose a threat to a public safety for two years or more.

Since differently defining vacant land might over- or underestimate the quantity of vacant land of a city, plans and policies for the areas may fail to address the real problems and achievements. The lack of clear definitions, unclear land use, and land cover categories would make it difficult to establish appropriate planning policies. Thus, it is necessary to review studies defining vacant land, and find the most reliable definition and concept for this research. Once a definition is agreed upon, research into the implications of spatial patterns and vacant land would proceed from a common base.

Second, most studies have focused on physical and economic aspects such as depopulation and unemployment rate as the primary factors for urban shrinkage. As Beauregard mentioned, “just because a city has fewer residents and fewer jobs does not mean that it is experiencing decline; the issue is the composition of those changes, their pace and the resultant distribution of costs and benefits” (Lang, 2005, p. 2). The problem of population loss is not about size itself, but about who is leaving and who is staying. While some research tried to examine how socio-economic status changes in a declining city, it is difficult to find any literature on the relationships between a mix of physical, social, and economic characteristics and vacant land. While most of the studies describe the demographic trends of a region, only a small number of existing studies attempt to assess the statistical significance of those factors. Since every urban activity and geographical phenomena are influenced by diverse elements in combination, it would be useful to analyze how the factors are associated with vacancy land patterns. Based on the literature, 18 different driving factors are identified as the principal causal mechanisms contributing to vacant urban land. These factors can result in an oversupply of vacant land which can then depress land prices, property values, and tax revenues, increase abandonment, decrease employment rates, sales, investments and vitality, and result in losses of residential, commercial and business activities (Schilling & Logan, 2008).

Third, in terms of computer modeling tools, most of them have been developed for regional scaled analyses, local and municipal scaled predictions are rare. Another large segment of limitations with which land use change models struggle is the accuracy assessment process. Most of them do not provide an accuracy assessment of the input data and reliability of the output. Generally, the kappa coefficient is thought to be the most standard method, but it is not always the most appropriate (Foody, 2002). The kappa index has some limitations in regard to remote sensing because the indices are calculated by an observed sample matrix, and are not based on a total population matrix. Frequently, kappa values can become quite complicated to compute leading to less useful interpretations, and the statistical results only show the reliability of the output but it is difficult to explain the influences and relationships among input variables. Thus, four different methods, Kappa, PCM, overall agreement and ROC, would be calculated and compared to address the validity issue.

Last, much of the existing literature on Land Transformation Model (LTM) have also obvious limitations and have been inadequately implemented for targeting vacant land use patterns. While most researches on LTM have concentrated on the impacts of urban development patterns on forestry and natural resources, it is difficult to find a singular model which targets vacant land pattern dynamics. Although Newman et al. (2016) investigated vacancy dynamics using the LTM, they focused on a growing city, not a shrinking city, and hence it might be not easy to understand the main determinants of urban shrinkage and apply them directly to the declining cities.

Despite economic and populating declines, many shrinking cities are still hindered by an inability to accurately predict future urban growth and decline patterns, specifically in regards to vacant land accumulation. It is critical to understand land use alteration patterns to predict transformations of physical change. More accurate predictions will have a profound effect on social, environmental and economic factors in declining cities. While this research both develops and uses causal drivers predict future vacant land prediction in both growing and shrinking cities, findings are useful for simulating land use changes more accurately to suggest suitable alternatives for both shrinking and growing cities having high risk of vacancy and future infill development plans.

3. RESEARCH DESIGN & METHODOLOGIES

3.1. Study Area

For the first part of the research to compare vacant land formation between growing and shrinking cities, the city of Fort Worth, TX and the city of Chicago, IL were selected as study areas. In 2000, 62 cities in the United States had a population of over 250,000 (excluding Honolulu, HI). Among them, Fort Worth recorded the largest population growth, 206,512 (+39%) between 2000 and 2010, while the city of Chicago lost 200,418 people (-7%), the second largest loss after Detroit (-237,493 or -25%) during the same time period (Table 4). The table shows the fastest growing cities are mostly located in the South or West (Sun Belt), while the most shrinking cities are located in the Midwest or Great Lakes regions (Rust Belt). In spite of Chicago's depopulation rate, decline related issues in the city have been relatively overlooked compared to other shrinking cities such as Detroit, Cleveland and Baltimore. Thus, Fort Worth and Chicago are selected as examples of a growing and shrinking cities to compare vacant pattern transition and its driving factors. Figure 14 shows the location, area and population of two cities.

The relationship between population growth and socio-economic status of the 62 cities are shown in figure 15 (See Appendix B: Full list of the 62 cities with population and socio-economic status). As shown in the charts, depopulating cities recorded higher vacancy, poverty, minority and unemployment rate and lower household income than growing cities. However, proportion of manufacturing employment to all industries seems not to be strongly related with population growth.

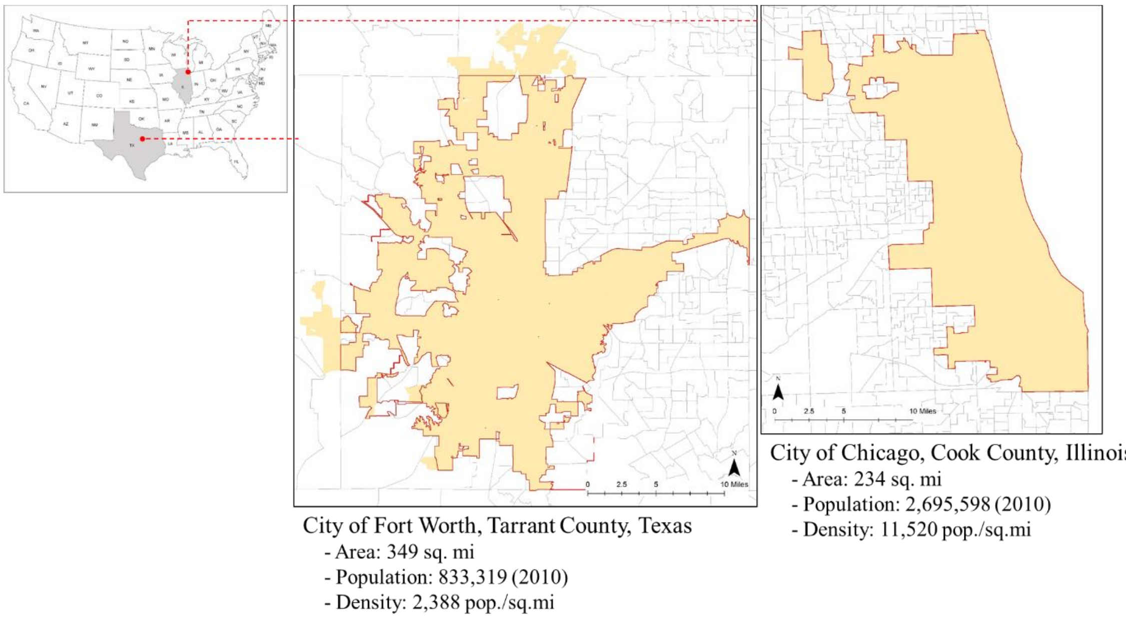


Figure 14. Map of Fort Worth and Chicago with Area, Population and Density

Table 4. The Fastest and Slowest Growing Cities by Population Growth from 2000 to 2010

	City	Population Change	Population Change (%)
Top 10 Fastest Growing Cities	Fort Worth (TX)	206512	39%
	Charlotte (NC)	190596	35%
	San Antonio (TX)	182761	16%
	New York (NY)	166855	2%
	Houston (TX)	145820	7%
	Austin (TX)	133828	20%
	Raleigh (NC)	127799	46%
	Phoenix (AZ)	124587	9%

Table 4. Continued

	City	Population Change	Population Change (%)
Top 10 Fastest Growing Cities	Las Vegas (NV)	105322	22%
	Los Angeles (CA)	97801	3%
Top 10 Most Depopulating Cities	Detroit (MI)	-237,493	-25%
	Chicago (IL)	-200,418	-7%
	New Orleans (LA)*	-140,845	-29%
	Cleveland (OH)	-81,588	-17%
	Cincinnati (OH)	-34,342	-10%
	Buffalo (NY)	-31,338	-11%
	Baltimore (MD)	-30,193	-5%
	St. Louis (MO)	-28,895	-8%
	Pittsburgh (PA)	-28,859	-9%
	Toledo (OH)	-26,411	-8%

*: Since about 29% of population were lost after Hurricane Katrina in New Orleans, the demographic trends of the city might be different from those of cities with a population over 250,000.

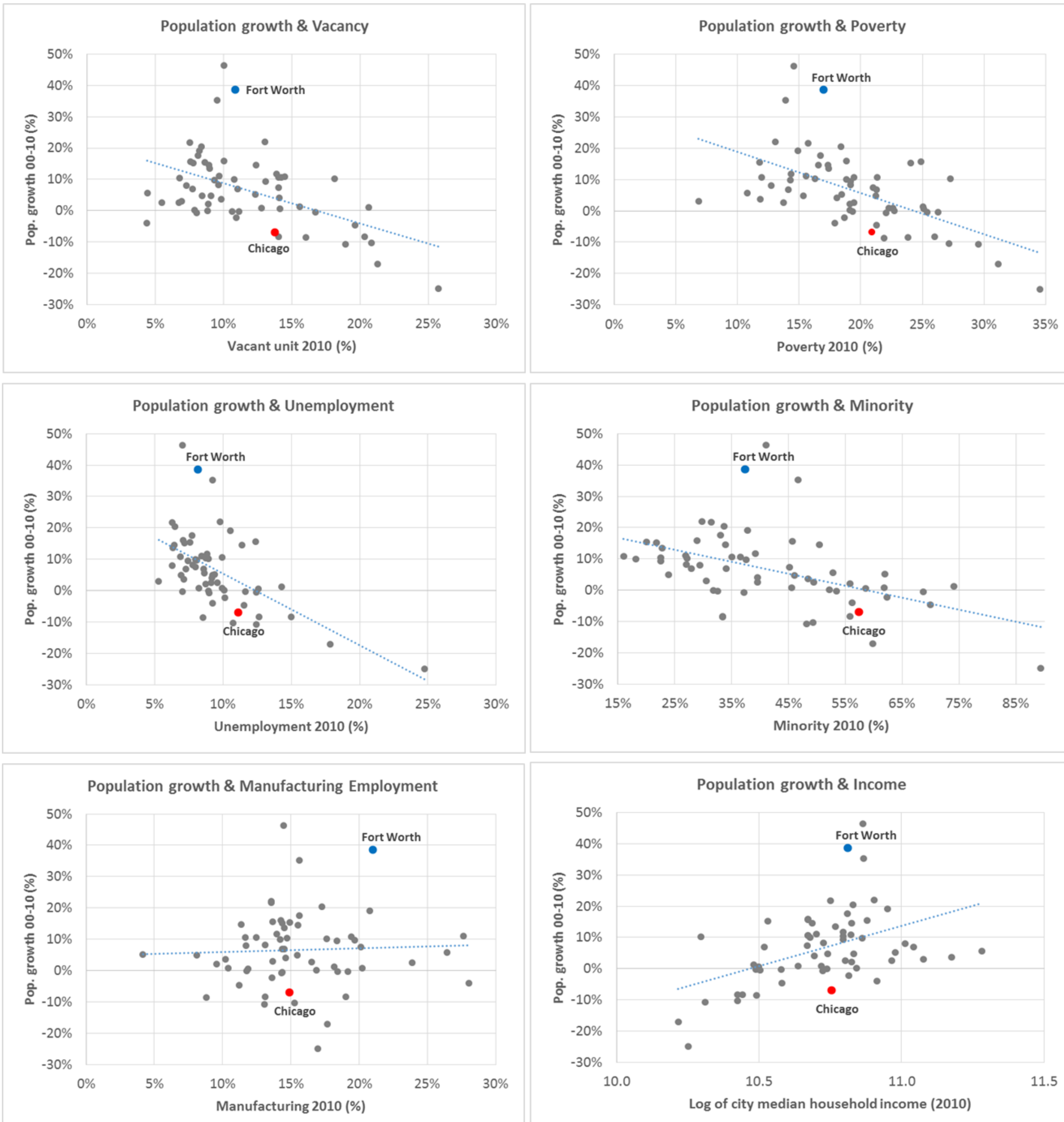


Figure 15. The Relationship between Population Growth from 2000 to 2010 and Socio-economic Status in 2010 of 62 Cities with over 250,000 Population

3.1.1. The City of Fort Worth

The City of Fort Worth in Tarrant County is chosen as an example of growing cities in this research. Tarrant County is the third most populous county in the state of

Texas, and Fort Worth is the 16th-largest city in the U.S and 5th-largest city in Texas (U.S. Census Bureau, 2010). The U.S. Census Bureau also indicated that the population of the city increased by 206,512 persons (+37%) between 2000 and 2010 becoming the fastest growing large city with more than 500,000 population. The rapid population growth is forecasted to continue considering the immigration and domestic migration enhanced by a strong economy. Figure 16 displays population growth from 1950, and North Central Texas Council of Governments (NCTCOG) project city's population will keep growing, exceeding 1 million between 2025 and 2030, and reaching an estimated 1.38 million in 2040 (2016 Comprehensive Plan, the City of Fort Worth). Prince (2014) expected that annexation rights of Fort Worth would contribute to increase the population and size by grabbing unincorporated land on its borders and it could double in physical size and population during this century.

Not only population growth, economic trends of the city also show a strong pace of hiring and low unemployment, and positive economic outlook. A growing number of jobs has been created, forecasting an average annual employment growth of 2.3% and median family income for the Fort Worth-Arlington Metro Area increased from $60,100 to $70,500 between 2001 and 2015, an average annual increase of 1.4% ((2016 Comprehensive Plan, the City of Fort Worth). In the 1990s, the city attempted to diversify its economy through small business development. Consequently, the economy is diversified in many industrial factors today and they contribute to the economic growth in spite of national trends of significant job losses and economic downturn.

Due to the rapid growth, the foreclosure rates in Fort Worth was much lower than cities on the east and west coasts. Of the total 286,526 housing units in 2009, about 11%

units were vacant. While there was only 2.9% vacancy rate among owner-occupied housing units, 14.8% of rental units were vacant. In order to decrease the vacancy rate and revitalize the communities having a large number of vacant units, Fort Worth adopted diverse programs in recent years such as mixed-use development and development outside of designated growth centers and downtowns.

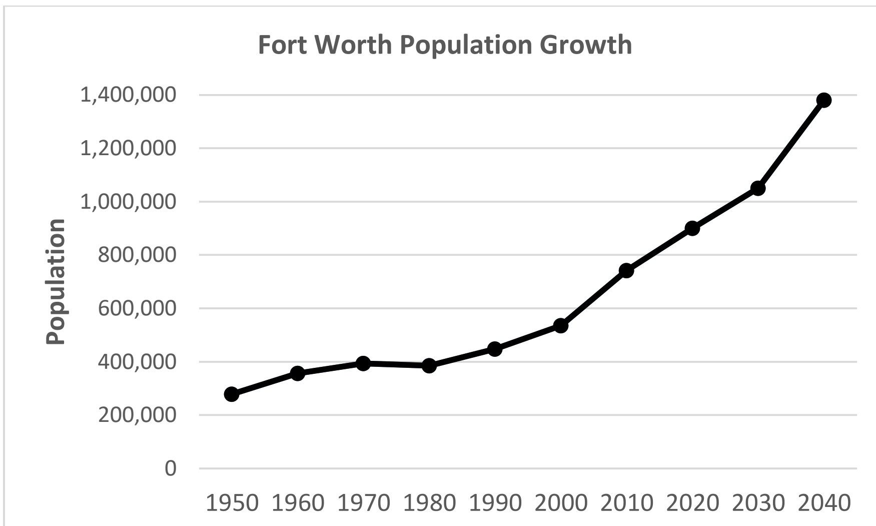


Figure 16. Population Growth of Fort Worth from 1950 to 2040

3.1.2. The City of Chicago

Chicago did experience rapid population growth until the 1950s. As early as 1947, manufacturing factories began to move from the urban area into the suburbs. By 2010, Chicago had lost around 925,000 from the 1950 population peak, reporting a 6.9% decrease between 2000 and 2010, and Englewood, a neighborhood on the southwest side of Chicago, has lost roughly two-thirds of its population from 1950. The U.S. Census Bureau projected Chicago to lose more than 1 million people between 1950 and 2020, which only two municipalities worldwide have experienced: London and Detroit (Cox, 2011).

The city also faced a high unemployment rate during this time (11.2%), ranking 11th among the fifty largest cities in 2010. Further, per capita income in Chicago was significantly lower than the national average ($ 28,000), only 70% of the national average of $40,000. By 1980, the U.S. Census also showed that among the 16 poorest neighborhoods in the country, 10 were located in Chicago (Squires et al., 1989). The more serious problem is racial segregation. While racially mixed and predominantly African American neighborhoods have lost jobs, communities with a higher percentage of the white population have experienced net gains (Squires et al., 1989).

Otherwise, the population in suburban area have steadily increased over the years. The suburbs added more than 460,000 people or grew at a rate of 216% for last six decades (US Census Bureau, 2010; Cox, 2011). As the overall suburban population of this metropolitan area has increased, the trend has a decisive effect on the geospatial dynamics. While only 28.7 percent of the metropolitan area was urban in 1990, it has increased to about 38.9 percent in just twenty years (See Fig.17). In contrast, the city of Chicago lost approximately 89,000 people or -3.2 percent during the same period, and fell to a population of 2.7 million, the lowest count since the 1920 census. Compared to 1950, which recorded the highest population, the population is down from 3,620,962 to 2,695,598, with a growth rate of -25.6 percent.

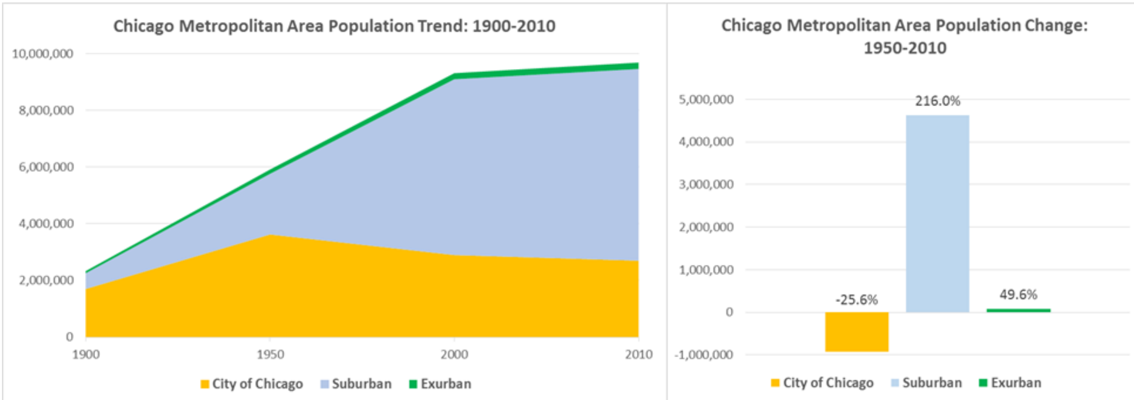


Figure 17. Chicago Metropolitan Area Population Trend by Spatial Boundary

Moreover, like many older industrial cities in the U.S, the city of Chicago has also suffered from a growing number of vacant lots and abandoned lots. This condition was more recently exacerbated due to the national foreclosure crisis in 2008 and other depopulation trends characterizing its surrounding region. Figure 18 shows the trend of vacant properties in Chicago and Collar counties between 2010 and 2013. The U.S. Department of Housing and Urban Development (HUD) reported that there were over 62,000 vacant properties in the areas. Even if south and west side neighborhoods and suburbs have greatly struggled with the vacancy epidemic, this imposes a burden on the entire region with poverty, unemployment, racial segregation, and violence that disgraces Chicago’s image.

The decline of the city of Chicago has also influenced the entire Chicago metropolitan area. There were 69,275 vacant homes for more than two years in 2012 in the Chicago six county region, increasing 55% from the end of 2008 (Butler, 2016). The abandoned and vacant properties decrease the entire neighborhood’s property values, and weaken the tax base, resulting in fiscal stress on the local government.

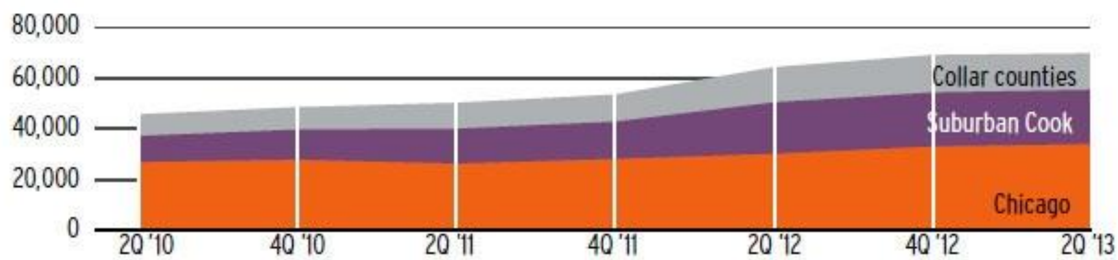


Figure 18. Number of Vacant Properties from 2010 to 2013 of Chicago Metropolitan Area (Source: Cook County Circuit Court)

In order to address the negative impacts of the vacant lots in their neighborhoods, Chicago has implemented various redevelopment projects since the 1970s. As aggressive urban renewal programs, most planning and redevelopment initiatives were concentrated in core Chicago, the Loop, and the near North Lakefront through a variety of investment cooperation projects by private groups who were only interested in downtown-oriented business and large-scale urban renewal. Unfortunately, no concerted planning and redevelopment policies had been implemented outside the central area with any institutional support of public or private resources and the majority of the neighborhoods have hardly been affected by the increased concentration of core activities (Squires et al., 1989).

3.2. Data Sources & Expected Datasets

The spatiotemporal datasets in a geographic format are required in this research. The time span of the analysis is 20 years from 1990 to 2010. North Central Texas Council (for Fort Worth, TX) provided the land use and vacant land inventory data in GIS format in 5-year intervals from 1990 and Chicago Metropolitan Agency for Planning (for Chicago, IL) provides the data from 1990 in 10-year increments. To avoid the data bridging problem caused by the difference, I use the data in 10-year increments. Depending on the data characteristics, different institutes and particular governments provide such datasets. While some of them are open to the general public to easily access, some are classified. Table 5 identifies data sources. As previously mentioned, 19 different causal variables linked to a vacancy are collected from the same data sources.

Table 5. Data Sources and Expected Datasets

City	Institutes	Expected Data
City of Fort Worth	U.S. Census Bureau -Decennial Census Data for 1990 and 2000 - 2006-2010 ACS estimates for 2010	- Population - Race - Poverty - Educational attainment - Household income - House value - Home ownership - Vacancy - Age of buildings - Unemployment - Service industry - Manufacturing industry

Table 5. Continued

City	Institutes	Expected Data
City of Fort Worth	Tarrant Appraisal District (tad.org)	- Land value - Market value - Parcel size
	City of Fort Worth Geographic Information System (GIS) program	- Proximity to highways - Proximity to railroads
		- Land use inventory
City of Chicago	U.S. Census Bureau -Decennial Census Data for 1990 and 2000 - 2006-2010 ACS estimates for 2010	- Population - Race - Poverty - Educational attainment - Household income - House value - Home ownership - Vehicle accessibility - Vacancy - Age of buildings - Mobile homes - Unemployment - Service industry - Manufacturing industry
	City of Chicago Geographic Information System (GIS) program	- Proximity to highways - Proximity to railroads - Crime - Parcel size
	Institute for Housing Studies at DePaul University U.S. Department of Housing and Urban Development	- Long-term vacancy (USPS vacant address data)
	The Chicago Metropolitan Agency for Planning (CMAP)	- Land use inventory

3.3. Variable Selection

Because prediction outcomes are greatly affected by variable selection, identifying which factors determine vacant land formation/accumulation is critical to output accuracy. Several studies have identified principal causal mechanisms contributing to vacant urban land, but studies that quantify the exact influence on vacant land accretion are difficult to find (Newman et al., 2016). The primary causes of vacant land can be categorized by four different, yet overlapping, classifications: (1) deindustrialization or shifts from an industrial to service economy (Buhnik, 2010; Lindsey, 2007; Németh & Langhorst, 2014; Rieniets, 2009), (2) weak market conditions and downturns (Bontje, 2005; Johnson, Hollander, & Hallulli, 2014; Ryan, 2012), (3) decreasing personal wealth (Audirac, 2007; Cunningham-Sabot & Fol, 2009; Rybczynski & Linneman, 1999), and (4) odd physical characteristics/bad location (Cunningham-Sabot & Fol, 2009; Henry et al., 2001; Németh & Langhorst, 2014). Due to these factors, losses in residential, commercial and business activities due to an oversupply of vacant land can, in many cases, result in a decrease in land prices, property values and tax revenues (Schilling & Logan, 2008; Hollander & Nemeth, 2010).

With this in mind, eighteen appropriate input factors that contribute to vacant land were selected as drivers to predict urban vacancy pattern changes which were based on evidence derived from the literature. Depending on the data capability from each time frame assessed, these models used fourteen to eighteen input factors. The driving factors were categorized into five domains: employment trends, socio-economic status, household composition and housing, physical characteristics, and accessibility and transportation. Table 6 shows each input factor by the year it was examined, a description and the previous research which utilized it as a causal driver for vacant land formation.

3.3.1. Employment trend

Employment trends such as unemployment rate and secondary industry quotient are typically noted as primary causes of vacant land (Squires et al., 1989; Clark et al., 2002; Cochrane et al., 2013; Fee & Hartley, 2011). Since 2000, more than five million manufacturing jobs have disappeared in the U.S. While about 24% of American workers were employed in manufacturing in 1960, only about 8% American workers have a job in the sector today (Long, 2016). The devastation of most American manufacturing cities, particularly in the Midwest, is a testament of this decline. Almost all MSAs that have experienced depopulation since the 1970s have a larger share of manufacturing industries than the average MSA. This transformation can be explained by three primary forces: suburbanization, regional population movement, and deindustrialization. Manufacturing employment is down by about 40 percent from 1979 when it was at its peak, while service employment has grown (Mallach, 2012). As a result, only 9 percent of the workforce is currently manufacturing, down from 22 percent from 1979, while the service share jumped from 54 to 69 percent. The two main reasons for this significant loss of manufacturing jobs are 1) introduction of labor-saving technologies and equipment and 2) transportation cost savings and expansion of global trade to low-wage

Table 6a. Years Examined, Description, and Literature on Input Factors Utilized as Drivers for Vacancy Prediction (Fort Worth)

Input Factors	Input Patterns			U.S. Census Definition	References for Input Factors
	90-00	90-10	00-10		
Unemployment Rate	O	O	O	Unemployment rate for civilian population in labor force 16 years and over	Fee & Hartley (2011), Aryeetey-Attoh et.al. (2015), Mallach (2012)
Service Industry	O	O	O	Proportion of service industry to all industries	Glaeser (2013), Fee & Hartley (2011), Mallach (2012), Glaeser & Kahn (2004), Lester et. al (2013), Cochrane et. al (2013)
Secondary Industry	O	O	O	Proportion of Secondary industry to all industries	Glaeser (2013), Fee & Hartley (2011), Mallach (2012), Glaeser & Kahn (2004), Wegener (1982), Dong (2013), Cochrane et. al (2013)
Household Income	O	O	O	Median household income (Inflation adjusted dollars)	Glaeser (2013), Fee & Hartley (2011), Ryan (2012), Aryeetey-Attoh et.al. (2015)
Education	O	O	O	Percent of persons 25 years of age and older, with less than or equal to high school graduate (includes equivalency)	Glaeser (2013), Fee & Hartley (2011), Mallach (2012), Parka & Cioricib (2015)
Poverty	O	O	O	Individual Poverty Rate: Individuals below poverty=”under .50” +“.50 to .74” + “.75 to .99.”)	Glaeser (2013), Fee & Hartley (2011), Ryan (2012), Parka & Cioricib (2015), Mallach & Brachman (2010)
Ethnicity	O	O	O	Non-white Population rate to total population	Ryan (2012), Fee & Hartley (2011), Massey and Denton (1993), Sugrue (1996), Hollander (2010)
Home Ownership	O	O	O	Proportion of owner occupied housing units to all occupied housing units	Bradford (1979), Pond & Yeates (2013), Aryeetey-Attoh et.al. (2015), Parka & Cioricib (2015), Hoyt (1993), Temkin & Rohe (1996)
Land Value	O	O	O	Land value per square meter of each parcel	Glaeser & Gyourko (2001), Capozza & Helsley (1989), Dong (2013), Aryeetey-Attoh et.al. (2015)
Market Value				Land value + improvement value per square meter of each parcel	Glaeser & Gyourko (2001), Glaeser et al., (2006), Anas (1978) Pond & Yeates (2013)
Housing Value	O	O	O	Median house value for all owner-occupied housing units	Glaeser & Gyourko (2001), Capozza & Helsley (1989), Dong (2013), Aryeetey-Attoh et.al. (2015), Hollander (2010)
Vacancy	O	O	O	Vacancy Rate to all housing units (Occupancy Status)	Dong (2013), Mallach (2012)
Population Change	O	O	O	Zero or negative population change between each period	Wegener (1982), Pond & Yeates (2013), Dong (2013)
Parcel Size			O	Parcel size smaller than 5,000 square foot	Colwell & Munneke (1997) Carrion-Flores & Irwin (2004) Pond & Yeates (2013), Lester, et. al (2013), Northam (1971)
Age of Buildings	O	O	O	Built before 1950 (except buildings in historical preservation districts)	Wegener (1982)
Highway	O	O	O	Proximity to highways	Rappaport (2003), Bourne (1996), Dong (2013), Lester, et. al (2013)
Number of Variables	14	14	16	---	---

Table 6b. Years Examined, Description, and Literature on Input Factors Utilized as Drivers for Vacancy Prediction (Chicago)

Input Factors	Input Patterns			U.S. Census Definition	References for Input Factors
	90-00	90-10	00-10		
Unemployment Rate	O	O	O	Unemployment rate for civilian population in labor force 16 years and over	Fee & Hartley (2011), Aryeetey-Attoh et.al. (2015), Mallach (2012)
Service Industry	O	O	O	Proportion of service industry to all industries	Glaeser (2013), Fee & Hartley (2011), Mallach (2012), Glaeser & Kahn (2004), Lester et. al (2013), Cochrane et. al (2013)
Secondary Industry	O	O	O	Proportion of Secondary industry to all industries	Glaeser (2013), Fee & Hartley (2011), Mallach (2012), Glaeser & Kahn (2004), Wegener (1982), Dong (2013), Cochrane et. al (2013)
Household Income	O	O	O	Median household income (Inflation adjusted dollars)	Glaeser (2013), Fee & Hartley (2011), Ryan (2012), Aryeetey-Attoh et.al. (2015)
Education	O	O	O	Percent of persons 25 years of age and older, with less than or equal to high school graduate (includes equivalency)	Glaeser (2013), Fee & Hartley (2011), Mallach (2012), Parka & Cioricib (2015)
Poverty	O	O	O	Individual Poverty Rate: Individuals below poverty="under .50" +".50 to .74" + ".75 to .99.")	Glaeser (2013), Fee & Hartley (2011), Ryan (2012), Parka & Cioricib (2015), Mallach & Brachman (2010)
Ethnicity	O	O	O	Non-white Population rate to total population	Ryan (2012), Fee & Hartley (2011), Massey and Denton (1993), Sugrue (1996), Hollander (2010)
Crime			O	Incidents of crime that occurred in the city	Kuo & Sulivan (2001), Cui & Walsh (2015). Spelman (1993), Jones & Pridemore (2013)
Home Ownership	O	O	O	Proportion of owner occupied housing units to all occupied housing units	Bradford (1979), Pond & Yeates (2013), Aryeetey-Attoh et.al. (2015), Parka & Cioricib (2015), Hoyt (1993), Temkin & Rohe (1996)
Housing Value	O	O	O	Median house value for all owner-occupied housing units	Glaeser & Gyourko (2001), Capozza & Helsley (1989), Dong (2013), Aryeetey-Attoh et.al. (2015), Hollander (2010)
Mobile Homes	O	O	O	Mobile home rates to all housing units	Glaeser & Gyourko (2001), Capozza & Helsley (1989), Dong (2013), Aryeetey-Attoh et.al. (2015), Hollander (2010)
Vacancy	O	O	O	Vacancy Rate to all housing units (Occupancy Status)	Dong (2013), Mallach (2012)
Population Change	O	O	O	Zero or negative population change between each period	Wegener (1982), Pond & Yeates (2013), Dong (2013)
Parcel Size			O	Parcel size smaller than 5,000 square foot	Colwell & Munneke (1997) Carrion-Flores & Irwin (2004) Pond & Yeates (2013), Lester, et. al (2013), Northam (1971)
Age of Buildings	O	O	O	Built before 1950 (except buildings in historical preservation districts)	Wegener (1982)
Railroad	O	O	O	Proximity to railroads	Rappaport (2003), Bourne (1996), Lester, et. al (2013)
Highway	O	O	O	Proximity to highways	Rappaport (2003), Bourne (1996), Dong (2013), Lester, et. al (2013), Kittrell (2012)
Accessibility	O	O	O	Proportion of no vehicle available housing units to all occupied housing units	Rappaport (2003), Bourne (1996), Dong (2013), Lester, et. al (2013), Kittrell (2012)
Number of Variables	16	16	18	---	---

and low-cost regions. Fee and Hartley (2011) found that declining MSAs had a large concentrations of employment in manufacturing industry, an average of 30%, while the manufacturing industry rate in other MSA was less than 20% in the 1980s. As such, MSAs with the heaviest historic concentration of manufacturing jobs have a much higher rate of depopulation and economic decline than the average MSA: simultaneously the growth of service industries tends to attract people cities (Cochrane et al., 2013; Fee & Hartley, 2013).

A strong association has been also found between vacant land and unemployment (Mallach, 2012). Limited job opportunities in a city encourage young and skilled laborers migrate to other areas, and consequently, housing demand sinks, increasing vacant properties. Thus, it was assumed that higher unemployment rates and secondary industry rates and lower service industry rates increase in vacant land in the future.

3.3.2. Socio-economic status

Since human capita is a primary component to the successful growth of a city, factors associated with individual personal wealth and socio-economic statuses such as poverty rate, income level, and the level of educational attainment are also highly associated with increases in vacant land. Some studies have focused on how the level of educational attainment has affected urban growth or decline (Glaeser, 2013; Fee & Hartley, 2013; Mallach, 2011). Glaeser (2013) investigated the relationship between population growth and share of the population with college degrees across metropolitan areas between 1940 and 2000. He found that a higher level of education is a critical growth engine for population and income growth for many cities across the country. While population growth exceeds 70 percent in the top quintile of college graduates between 1970 and 2000 across all MSAs in the U.S, population growth in the bottom quintile of college graduates during the same period was only 30 percent (Glaeser, 2013). Mallach (2011) also indicated that the percentage of adults who hold a bachelor's degree or higher is the most critical tool in measuring a city's social and economic well-being, and that a higher level of education is a critical growth engine for population and income growth for cities.

Variables related to personal wealth such as poverty rate, income level and housing value are also found to be associated with vacant land transformation. As widely known, neighborhoods tend to be more stable as income and housing value increase and as poverty rate decreases. For example, Mallach & Brachman (2010) found that the poverty level of eight shrinking cities in Ohio was about twice as high as the national average (of 13.2 percent). Unstable financial situations due to weakened industrial competitiveness and long-term unemployment destabilized many communities. As such, low-income residents who cannot afford to move to other areas often remain in cities while affluent skilled laborers tend to leave.

Racial segregation has also been found to be associated with an increase in vacant properties. The proportion of African Americans also can also affect urban shrinkage as a result of increased racial disparities produced through social, economic and political marginalization. As industrial cities began to decline in the 1950s, a large percentage of the white population attempted to flee from predominantly black settlements while many African Americans moved into cities seeking industrial jobs in downtown areas (Ryan, 2012). Over time, widespread racial discrimination, seen in hiring and in housing market trends, has systematically limited relocation options for many minority populations (Massey and Denton, 1993; Sugrue, 1996). When a neighborhood loses jobs, minorities have fewer housing choices, further increasing the minority concentration in these areas (Hollander 2010). While the residential population of African Americans near the central business district (CBD) was approximately 30 percent among shrinking MSAs, the fraction in the moderate- and fast-growth MSAs was less than 20 percent from 1980 to 2010. This shows the legacy of African American migration into northeast manufacturing-oriented cities during economic booms and subsequent collapse of the Rust Belt cities over the past three decades. Fee and Hartley (2013) investigated demographic changes within thirty-six MSAs experiencing depopulation between 1980 and 2010 and found that in spite of drops in total population density during the time, the fraction of minority residents increased near the CBD, mostly within ten miles of the CBD (Fee & Hartley, 2013).

Lastly, the higher vacancy rate and violent crime level contribute to lower residential satisfaction and lower rents or housing prices, consequently leading to a growing number of affluent residents' decisions to move out, increasing vacant properties in the city. Recent research (Cui, 2015; Immergluck & Smith, 2006) examined the relationship among foreclosure, vacancy, and crime. They found once foreclosed properties become vacant when the violent crime rate increases by more than 15% (Han, 2014). Therefore, this model assumed that the higher crime rates and lower and lower socioeconomic status would be affected by increases in vacant land in the future.

3.3.3. Household composition & housing

Housing quality and homeownership are also clearly defined as factors contributing to an increase in vacant and abandoned properties. The Census Bureau released the national residential housing vacancies and homeownership report recently. The research found that rental housing vacancy rate (6.9%) in the fourth quarter of 2016 was about four times higher than homeowner housing (1.8%). A survey of the U.S. Department of Housing and Urban Development (2013) also revealed that the city homeownership rate is approximately 50 percent while the rate in suburbs is 73 percent. This is because low-income tenants occupy most multifamily housing stocks in central cities. Farris (2001) explained that eight out of ten American households believe that having their own houses would be better than renting not only in terms of quality of living; they also believe that owning a house would be a good investment. Since the replacement costs of housing may not cover rent in neighborhoods with high rental housing vacancy rates, incentives exist for neither developers nor homeowners to build new houses or to fix up their properties. Consequently, investments and support for these neighborhoods stop, and both unoccupied and occupied structures are often neglected over time. As Hollander (2010) indicated, analysis of occupied housing unit density is an important measure of physical changes in a city. Since neglected properties might be a sign to communities that there is a lack of neighborhood support, high vacancy rates and lower housing value of a neighborhood can increase the vacancy rates in the entire city.

3.3.4. Physical characteristic

Beyond socio-economic variables, physical conditions such as parcel size, depopulation and age of buildings are also associated with vacancy. American Community Survey data in 2009 revealed that 38% of housing structures in the U.S. cities were built before 1970 and may need extensive repairs and maintenance. However, in deteriorated urban environments, landlords are reluctant to maintain or invest in their properties to attract new tenants because repair costs do not produce satisfactory profits. Vacancies and deterioration often mean a waste of housing resources. Parcel size is also a proven factor which can contribute to increase in vacant land. Small/irregularly shaped parcels sometimes are unable to be developed and referred to as leftover/remnant properties (Lester et al., 2013; Newman et al., 2016; Setterfield, 1997). Since it can be difficult to sustain functional use in these lots due to physical constraints, this model assumed that smaller parcel size would contribute to increases in vacant land. Parcels less than 5000ft^2 were selected as remnant parcels which contribute to vacant land accumulation.

3.3.5. Accessibility & transportation

The massive highway and road constructions characterizingmid-20th century drastically enlarged the size of the geographical area in which people could both live and work (Rappaport, 2003). A growing number of people who have left urban areas now commute suburb-to-suburb rather than into the city. Since healthy transportation systems can improve the amenity value of a site by establishing efficient movement of goods and providing options for people to get to various activities, the accessibility to urban services affects development patterns. Thus, it was assumed that sites nearer to existing major transportation lines would result in decreased vacant land.

3.4. LTM Process

Two different types of input drivers were used to forecast vacant land by 2020 using the LTM: (1) raster-based causal variables linked to a spatial location such as socio-economic data, referred to as input factors (i.e., socio-economic variables at block group level, land value and lot size variable at parcel level and crimes and proximity to main streets at point or line level) and (2) raster-based historical vacant land use inventories for two different time frames, referred to as input patterns (Newman et al., 2016). Between 14 and 18 different causal variables were chosen as input factors, each of which has been shown to increase vacant land. Then, 5 different types of land use were omitted from the analysis, referred to exclusionary layers due to their specialized functionality (e.g., military bases, airports, public facilities, parks and open space and existing vacant areas). Using the rasterized input drivers and exclusionary layers, the LTM forecasted three possible vacant land pattern scenarios: Scenario A based on 1990-2000, Scenario B based on 1990-2010 and Scenario C based on 2000-2010 vacancy patterns.

Using the input drivers and exclusionary layers, the LTM follows four sequential steps: (1) analyzing historical vacant land pattern transformation between 3 different time frames, 1990, 2000 and 2010 (2) producing expected vacant pattern changes using 10-year input patterns and sixteen to nineteen input factors (3) measuring the agreement by output statistics between an actual vacancy transition map and a predicted transition map from first and second processes: Kappa, PCM, Overall agreement and AUC (4) predicting future (2020) vacant land patterns

4. RESULT

As described in Section 1, the main research question of this dissertation is to determine the influence of input factors on vacant land formation when comparing shrinking and growing cities, and develop a methodological framework to forecast the possible scenarios of the patterns in the future using Land Transformation Model. Through the raster-based GIS modeling and Artificial Neural Network processes, location and direction of the historical vacant pattern change was analyzed and then, 3 different future transition probability (2020) were computed using 14-18 different driving factors and 3 historical vacancy pattern data (1990, 200 and 2010) in the City of Fort Worth and the City of Chicago.

4.1. The City of Fort Worth

4.1.1. Possible scenarios of vacancy patterns by 2020

The City of Fort Worth (2014) categorized vacant land into three different land uses: brownfields, vacant structures/housing units, and vacant agricultural as the vacant land. Vacant brownfields are described as underutilized, obsolete, or structurally deteriorated industrial or commercial properties where improvements are hindered by real or perceived contamination. Vacant structures/housing units contain a house, apartment, mobile home or other unit, vacant but intended for occupancy as separate living quarters. Vacant agricultural describes areas with one residential unit per structure on a one or more acre lot with no city water or sewer service; or land with no existing buildings, except for those related to mining, crops or grazing.

As shown in figure 19, in the 1990s, a large scale annexation increased the vacant land by 50% in Fort Worth, but the annexed vacant parcels rapidly decreased by about 12% in 2010 due to the new development on the periphery (Newman et al., 2016). The rapid change of vacant land for two decades was also reflected to predict the future vacancy transitions.

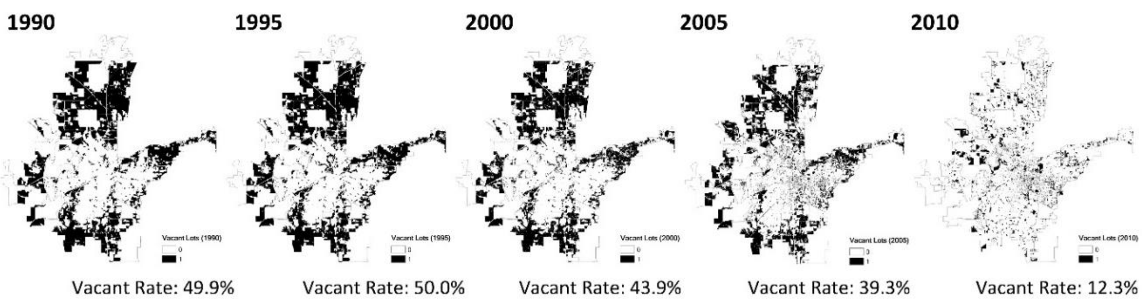


Figure 19. Vacant Land Patterns and Ratios of Vacant Land in Fort Worth, TX, from 1990 to 2010 in 5-year Intervals

*Reprinted with permission from (Newman, Lee, & Berke, 2016).

Figure 20 indicates three different possible scenarios of vacant land in 2020 based on the historical vacant land transformation in three different time frame and 2020 population projection: Scenario A based on 1990-2000, Scenario B based on 1990-2010 and Scenario C based on 2000-2010 vacancy patterns. With two basic assumptions that current contributing factors on vacant land would remain consistent in the future and the trends of vacancy would be occurred at the same rate as it did between two historical time frames, it could be said that these are possible scenarios for vacancy pattern in 2020. For example, the population change between 1990 and 2010 was +295,414 (+21.2%), and the number of vacant cells (100x100ft) that transitioned at that time was 43,338. Since the estimated population in 2020 is 877,450, indicating the change between 1990 and 2020 would be 4.5 times more than 1990-2000, cell change was also estimated to increase at the same rate (4.5).

As shown in figure 20, Scenario A predicts that most of the vacant land would be accumulated on the city's periphery in 2020, while Scenario B and C estimate urban core area has the highest risk of vacancy in 2020.

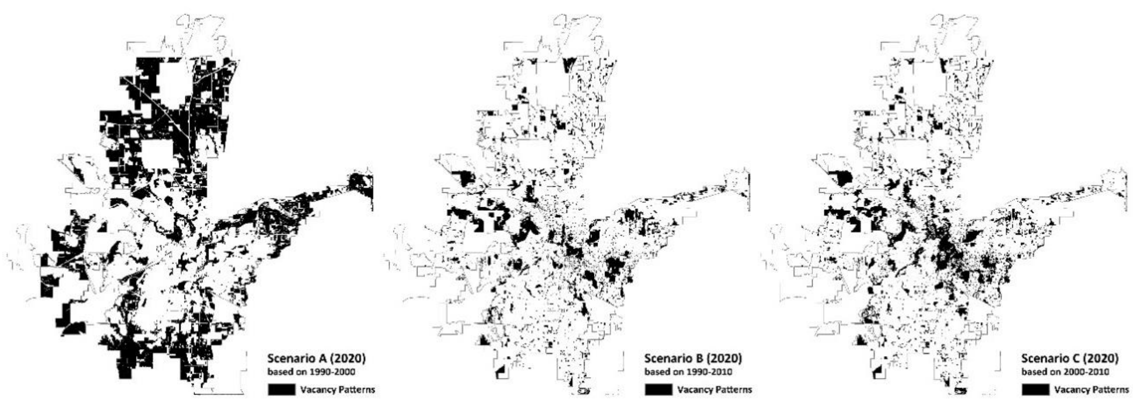


Figure 20. Possible Scenarios of Vacancy Patterns by 2020 based on (A): 1990-2000, (B): 1990-2010, and (C): 2000-2010

*Reprinted with permission from (Newman, Lee, & Berke, 2016).

Table 7 shows the output statistics for all models and scenarios trained. Generally, 60 to 80% accuracy is considered as an exceptional model and 40 to 60% of PCM is said to perform with highly acceptable predictability (Almeida et al., 2008; Pijanowski et al., 2006, 2002; Tayyebi et al., 2013; Newman et al., 2016), and the result shows all scenarios had high enough PCM's to merit acceptability of prediction. However, since different models suggest different prediction scenarios, it would be really useful to create one composite score map by amalgamating all three scenarios of each city to determine which areas have the higher risk of vacancy issue in the future.

Table 7. LTM Statistical Output for All Models and Scenarios Trained

Input patterns	**No. of input factors**	**Highest training probability**	**PCM* (%)**	**Kappa ****	**QD (%)**	**AD (%)**	**OA*** (%)**	**AUC ******
1990-2000	15	70,000th	44.5	0.43	0.0	4.0	96.0	0.75
1990-2010	16	7,000th	44.3	0.37	0.0	12.3	87.7	0.74
2000-2010	16	90,000th	54.7	0.50	0.0	9.6	90.4	0.77

*PCM: 40–60% is acceptable

**Kappa: 0.41-0.60 is moderate,

***OA (Overall agreement): more than 85% is considered good.

****AUC: 0.70-0.80 is fair

Each 2020 scenario was given a score of 1 (vacancy) or 0 (non-vacancy), and a composite score map of all three scenarios was created to find the probability of future vacancy/abandonment. Thus, areas where all three scenarios overlapped had a total score of 3, a score of 2 where two scenarios overlapped, and a score of 1 where only one scenario predicted future vacancy for the parcel (see Fig. 21). This accounts for 6.3% of the city’s total land area, meaning that 6.3% of the city’s land was predicted to become vacant by all three scenarios in identical locations, suggesting a high probability of future vacancy/abandonment in these areas. There was a 13.9% overlap for any two combinations of scenarios, suggesting the relatively high probability of future vacancies in these lots, while nearly 3/4 of the parcels were only predicted by one of the given scenarios (74.9%), suggesting a moderate threat of future vacancy. Further, Scenarios B and C were the only situations where overlaps among predicted vacant parcels were actually larger than non-overlapping parcels. Shared prediction locations from the B and C models constituted 67.3% of the 13.9% total double scenario overlap. These results reinforce the suggestion that the use or more current data with smaller time frames may have less prediction variance and be more beneficial for more accurate output data.

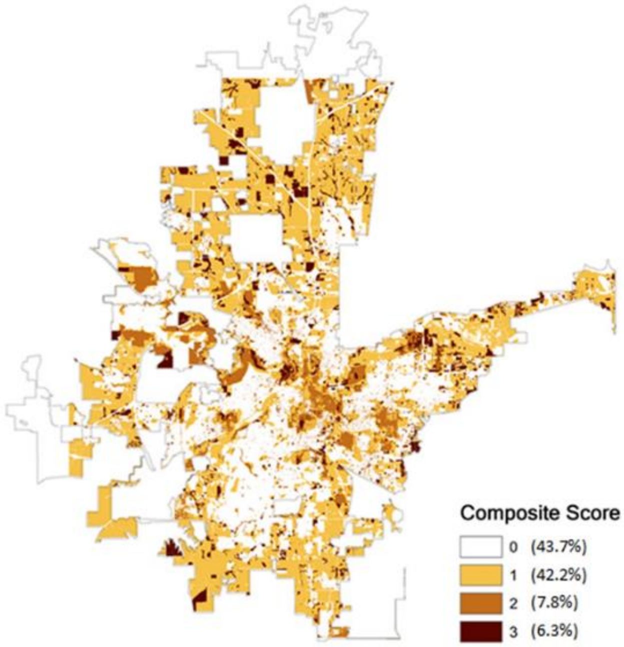


Figure 21. Overlap of All Three Scenarios for 2020 Vacant Land Predictions in Fort Worth, TX

*Reprinted with permission from (Newman, Lee, & Berke, 2016).

4.1.2. Statistical vacant land clustering: pattern density and hot spot analysis

To analyze the statistical clustering of vacant land within the composite score map, pattern density and hot spot analyses were run. Pattern density analysis shows where higher vacant land uses concentrate spatially (Newman et al., 2016). The output from this analysis shows that vacant land will be concentrated near the city center, while the periphery will have relative lower amount of vacant land in 2020 (see Fig. 22). The hot-spot analysis tool in GIS is useful to assess statistically significant spatial clusters of high values (hot spots) and low values (cold spots) based on a z-score and p-value for each feature examined which are used as measures of statistical significance indicating whether the observed spatial clustering is more pronounced than one would expect in a random distribution (Grubesic & Murray, 2001). This type of spatial analysis has been used to study geographic changes such as soil pollution locations (Li et al., 2004), low income housing locations (Wang & Varady, 2005), biodiversity impacts (Cincotta et al., 2000), crime activity (Anselin et al., 2008), and broad land-use changes (Jusuf et al., 2007). The results indicate that Scenarios B and C using 2010 vacancy data as an input pattern are more likely prediction than Scenario A considering most of the vacant land tended to be significantly clustering closer to the urban core area (see Fig. 22). Scenario B and C primarily reflect the increase of many small vacant parcels within urban core between 1990 and 2010, while Scenario A only reflects the change between 1990 and 2000.

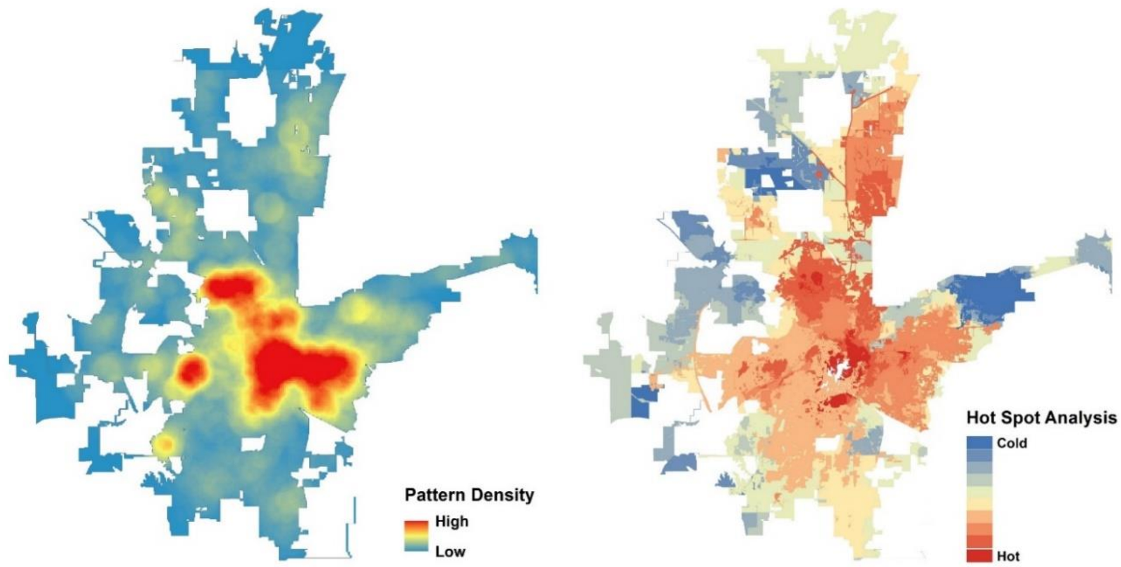


Figure 22. Vacant Land Pattern Map (left) and Hot Spot Analysis showing Statistically Significant Clusters of Vacant Land (Right) in Fort Worth, TX

*Reprinted with permission from (Newman, Lee, & Berke, 2016).

4.1.3. Variable influences

In order to quantify the influence of each variable, the influence test approach developed by Pijanowski, Shellito, Baurer and Sawaya (2001) is used. By dropping one variable per model using 2000-2010 input patterns, 16 alternative versions of the model are created with PCM and Kappa outputs and the influence of each variable is ranked from high to low (1=lowest and 16=highest) (See table 8). Comparing the statistical output to the full model results, when dropping the rate of secondary industry (proportion of secondary industry employees to all industries), the model produces a higher PCM and Kappa than the full model, meaning that the factor may not be an influence to predict the vacant land in the City of Fort Worth. Since existing manufacturing and construction industries in a growing city may not be deindustrialization, this factor may be more powerful and influential in legacy or shrinking cities where have experienced serious depopulation and deindustrialization.

In contrast, market condition and economic variables such as market value and land value seemed to have a stronger influence on the model than most other factors. PCM and Kappa statistics decreased immensely when these variables were removed. Personal wealth variables such as income and employment also showed a strong influence on increasing prediction accuracy. Surprisingly, however, it was expected that population change would be the primary demographic factor in predicting vacant land but, while a necessary input factor, another demographic variable, ethnicity, was actually more influential on improving the model's accuracy. Physical and locational characteristic variables had weak but positive influences. Not surprisingly, proximity to highways proved to be a stronger influence than proximity to railways (Newman et al., 2016)

Table 8. Variable Influence Outputs by Dropping One Variable per Model Using 2000-2010 Input Patterns (Fort Worth)

Domain	Variable	Training	PCM	Kappa	Rank
Employment Trend	Unemployment	25,000th	52.2	0.47	14
	Secondary Industry	10,000th	55.1	0.5	1
	Service Industry	80,000th	54.4	0.49	4
Socio-economic	Income	70,000th	52.6	0.47	12
	Education	80,000th	53.5	0.48	9
	Poverty	8,000th	54.7	0.49	2
	Ethnicity	35,000th	52.6	0.47	13
Household / Housing	Ownership	60,000th	53.5	0.48	7
	Value	90,000th	47.8	0.42	15
	Vacant Rate	70,000th	53.5	0.48	8
Physical	Population Change	50,000th	52.7	0.47	11
	Parcel Size	30,000th	54.3	0.49	5
	Built Year	80,000th	54.5	0.49	3
Accessibility	Railroads	25,000th	53.5	0.48	6
	Highway	3,500th	53.1	0.48	10
	Full Model	90,000th	54.7	0.50	

4.2. The City of Chicago

4.2.1. Possible scenarios of vacancy patterns by 2020

The City of Chicago defines vacant land as "*land in an undeveloped state, with no agricultural activities nor protection as open space*" (CMAP, 2010). Vacant land was categorized into four different classifications: brownfields, vacant structures/housing units, under development/construction and vacant forested, grassland and wetlands. Vacant brownfields are described as underutilized, obsolete, or structurally deteriorated industrial or commercial properties where improvements are hindered by real or perceived contamination. Vacant structures/housing units contain undeveloped land classified as residential, commercial and industrial by county assessor. Under development/construction is described as lands with construction activities in aerial imagery (i.e., roadway begun, partially-completed structures, missing or incomplete landscaping). Vacant forested, grassland and wetlands describes grassland or wetlands with more than 2.5 acres.

Figure 23 shows vacant land patterns and ratios of vacant land in Chicago between 1990 and 2010 in 10-year increments. As population of the city became stable in the 1990s and early 2000, the total amount of vacant land in Chicago slightly dropped 0.4% to about 5.5%. However, like many older industrial cities in the U.S, Chicago has also suffered from a growing number of vacant lots and abandoned lots due to the national foreclosure crisis in 2008 and other depopulation trends characterizing its region for decades. The city lost over 200,000 people from 2000 to 2010; this negative population growth contributed to increases in vacant land. Chicago increased in the vacant land by 2.8% from 2000 to 2010, with a large majority of current vacant parcels residing in the city's core and its surrounding neighborhoods and urban districts. Chicago had 33,902 vacant homes in 2013, an increase of 22% from 2010. Regionally, suburban Cook County had 21,479 vacant homes, up 79% from 2010 and a vacancy rate over 17% in some census tracts in South Side neighborhoods, according to Gallun & Maidenerg (2013).

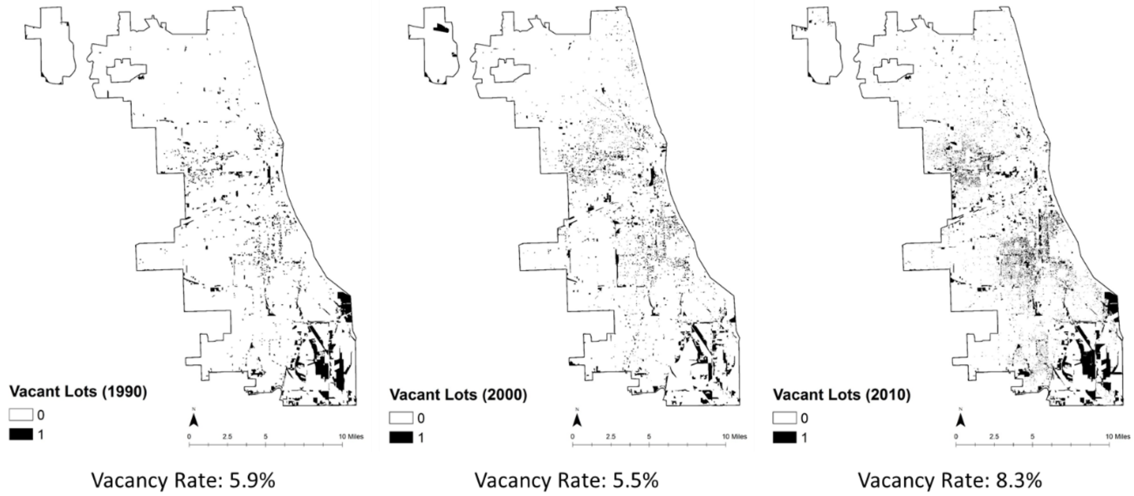


Figure 23. Vacant Land Patterns and Ratios of Vacant Land in Chicago, IL, from 1990 to 2010 in 10-year Intervals

In order to forecast future vacant land patterns, both spatial patterns and population change between each time period were assessed. For example, the population change between 1990 and 2000 was +112,290 (+4.0%), and the number of vacant cell (100x100ft) that transitioned at that time was +2,821 (-0.4%). Since the projected population in 2020 projects to be 2,700,000 (losing 196,016 from 2000), cell change was estimated to change at the same rate. Figure 23 shows three different possible scenarios of vacant land in 2020 based on the historical vacant land transformation in three different time frame and 2020 population projections: Scenario A based on 1990-2000, Scenario B based on 1990-2010 and Scenario C based on 2000-2010 vacancy patterns. As shown in figure 24, all three scenarios represent similar prediction outputs because vacancy dynamics in the city were fairly been stable between 1990 and 2010. The results suggest that most of the vacant land will accumulate in the downtown area and manufacturing/industrial neighborhoods in the southeast by 2020.

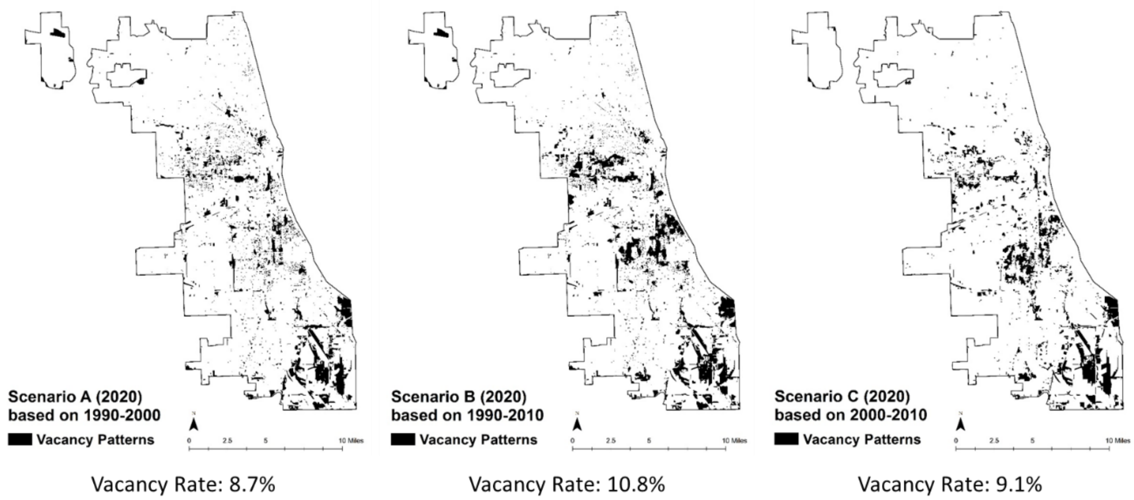


Figure 24. Possible Scenarios of Vacancy Patterns by 2020 based on (A): 1990-2000, (B): 1990-2010, and (C): 2000-2010

The statistical outputs (Kappa, Overall agreement, PCM and AUC), the number of input factors and the highest probability of each training cycles were displayed in table 9. Overall agreement, PCM and AUC. Overall results from the data produced from LTM show that all scenarios had high enough statistical reliability to merit acceptability of prediction when examining all four methods of accuracy assessment.

Table 9. LTM Statistical Output for All Models and Scenarios Trained

Input patterns	No. of input factors	Highest training probability	PCM* (%)	Kappa **	QD (%)	AD (%)	OA*** (%)	AUC ****
1990-2000	16	$15{,}000^{th}$	51.0	0.49	0.0	3.7	96.3	0.70
1990-2010	16	$100{,}000^{th}$	44.6	0.41	0.0	6.2	93.8	0.70
2000-2010	18	40,000th	50.9	0.48	0.0	3.7	96.3	0.75

*PCM: 40–60% is acceptable

**Kappa: 0.41-0.60 is moderate,

***OA (Overall agreement): more than 85% is considered good.

****AUC: 0.70-0.80 is fair

Then, in order to determine which areas have the higher risk of vacancy issue in the future, a composite score map was created by amalgamating all three scenarios in the same way for the City of Fort Worth. Since each 2020 scenario was given a score of 1 (vacancy) or 0 (non-vacancy), areas where all three scenarios overlapped had a total score of 3, a score of 2 where two scenarios overlapped, and a score of 1 where only one scenario predicted future vacancy for the parcel (see Fig. 25). This composite score shows that LTM predicted 4.2% of the city' land becomes vacant in 2020 by all three scenarios, suggesting a high probability of future vacancy/abandonment in these areas. There was 4.7% overlap for any two combinations of scenarios, meaning the relatively high probability of future vacancies in these lots, while 5.5% of the land were only predicted by one of the given scenarios, suggesting a moderate threat of future vacancy. The composite score output also accounts that southeast and surrounding areas of downtown would have a high risk of vacancy in the future.

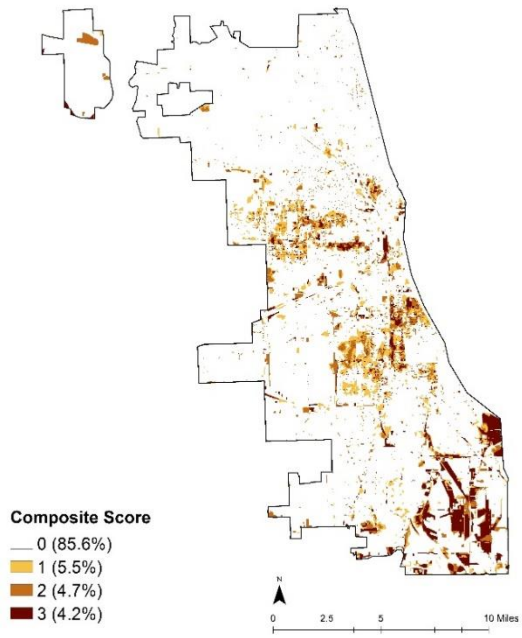


Figure 25. Overlap of All Three Scenarios for 2020 Vacant Land Predictions in Chicago, IL

4.2.2. Statistical vacant land clustering: pattern density and hot spot analysis

Pattern density and hot spot analysis were run to analyze the statistical clustering of vacant land within the composite score map. Pattern density analysis shows where higher vacant land uses are concentrated spatially. The output from these two analyses shows that vacant land will be concentrated near the city center and Southeast, while the periphery on North area have a relatively lower probability of vacancy in 2020 (see Fig. 26).

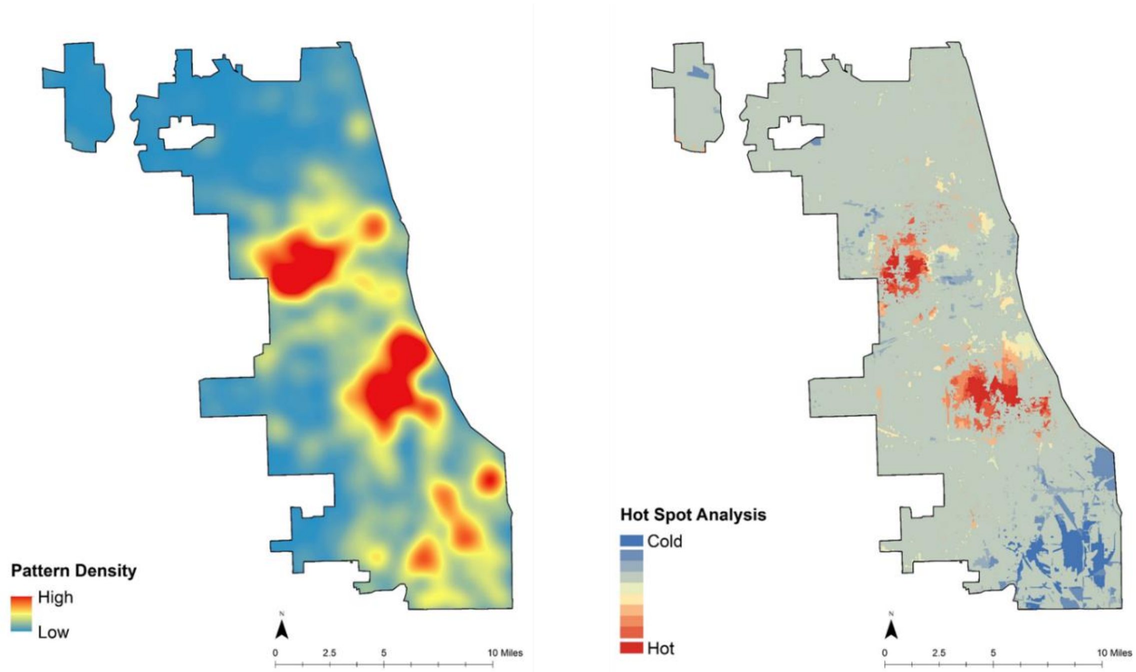


Figure 26. Vacant Land Pattern Map (left) and Hot Spot Analysis showing Statistically Significant Clusters of Vacant Land (Right) in Chicago, IL

4.2.3. Variable influences

The influence of each variable is quantified using the influence test approach developed in 2001. Using 2000-2010 dataset which has the largest number of input factors and relatively higher LTM statistical output, 18 alternative versions of the model are created with PCM and Kappa output by dropping one variable per model. Then, the influence of each variable is ranked from high to low (1=lowest and 18=highest) (See table 10). Comparing the statistical output to full model results, all of 18 factors maybe influence to predict the vacant land in the City of Chicago because every result of the influence test produce lower PCM and Kappa than the full model.

When dropping the proximity to highway and vehicle accessibility (percent of households with no vehicle available), the model produces the lowest PCM and Kappa value, meaning that transportation and accessibility related factors had a stronger influence on the model than most other factors. Since the Chicago metropolitan area is a transportation center passing massive amounts of goods to the rest of the country and leading a number of events, these variables had influences. Furthermore, housing related variables including housing value and mobile home rate also showed a stronger influence on increasing vacant land in the City of Chicago. However, personal wealth variables such as income, unemployment rate and educational attainment seemed to be weak influences to predict the vacant land in the Chicago. Since Chicago have suffered more serious shrinkage issues in the 1960s and 1970s, rapid population changes might be already occurred at that time. Thus, these factors may be more powerful and influential in cities have experienced depopulation and deindustrialization recently or fast growing cities.

Table 10. Variable Influence Outputs by Dropping One Variable per Model Using 2000-2010 Input Patterns (Chicago)

Domain	**Variable**	**Training**	**PCM**	**Kappa**	**Rank**
Employment Trend	Unemployment	200,000th	50.5	0.48	1
	Secondary Industry	45,000th	48.9	0.46	9
	Service Industry	50,000th	49.9	0.47	3
Socio-economic	Income	45,000th	50.1	0.47	2
	Education	40,000th	49.8	0.47	4
	Poverty	25,000th	49.0	0.46	7
	Ethnicity	80,000th	48.6	0.46	11
	Crime	100,000th	48.3	0.46	13

Table 10. Continued

Domain	Variable	Training	PCM	Kappa	Rank
Household / Housing	Ownership	150,000th	49.6	0.47	5
	Value	150,000th	47.9	0.45	14
	Mobile Homes	250,000th	46.0	0.43	16
	Vacant Rate	150,000th	47.8	0.45	15
Physical	Population Change	10,000th	49.3	0.47	6
	Parcel Size	200,000th	48.9	0.46	8
	Built Year	10,000th	48.6	0.46	12
Accessibility	Railroads	15,000th	48.7	0.46	10
	Vehicle Accessibility	15,000th	45.8	0.43	17
	Highway	150,000th	45.5	0.43	18
	Full Model	200,000th	50.9	0.48	

4.3. A Comparison of variable influence between Fort Worth and Chicago

Although the urban land use change analysis of LTM has proven to be a powerful tool to predict vacant land through various accuracy assessment, predictive analysis can have difficulties dealing with multiple qualitative or noisy input variables (Lee et al., 2004; Newman et al., 2016). Sometimes, ANN's provides little insight into the influences of each input factor. An influence test approach developed in 2001 was utilized to determine the influence of each input factor and to quantify the model performance (Pijanowski et al., 2001). Using 2000-2010 input data, two statistical results (PCM and Kappa) were calculated by dropping one variable for each city, Fort Worth and Chicago, and then, the differences in variable influences were compared between those two cities.

Due to different data capabilities of these two cities, different input factors that contribute to vacant land increase were selected. While 18 rasterized variables were utilized for the City of Chicago, Fort Worth used 16 input factors, excluding mobile home rates, crime rates and vehicle availability. Figure 27 and table 11 displays the variable influence (highest to lowest) by city and the difference in the influence between these two cities. This indicates that market condition and accessibility such as housing value and proximity to highway have a stronger influence on both Chicago and Fort Worth than most other factors. Since these factors are related to neighborhood quality, poor economic conditions may decrease housing value. As such, when housing demand sinks to certain threshold levels, neighborhoods can lose portions of their population, increasing vacant or abandoned properties.

Surprisingly, in contrast to literature that suggested that personal wealth indicators have more powerful implications for shrinking cities, unemployment rate, income and ethnicity may not be strongly influential when predicting vacant land in Chicago even though these variables showed a strong influence on Fort Worth, a growing city. This may be partially due to the fact that the City of Chicago has experienced serious depopulation and economic downturn over the past 60 years, with population movement stabilizing only recently. Growing cities, on the other hand, might face a deeper problem of increasing economic segregation and rapid demographic changes, leading to a growing amount of vacancy in vulnerable neighborhoods. In contrast to small parcel size, low home ownership rate seemed to have a weak, negative influence on vacancy.

Not surprisingly, secondary industry (proportion of secondary industry to all industries) appeared to be more influential in Chicago where many existing manufacturing industries have been deindustrializing than in Fort Worth, a growing city, while service industry (proportion of service industry to all industries) proved to be less influential than secondary industry in predicting vacant land in both cities. This may be due to the fact that continuous deindustrialization of manufacturing industries may influence depopulation and increase vacant land in a shrinking city such as Chicago. However, the statistical outputs suggest that secondary industry is influential, though only marginally. Since the mass deindustrialization of Chicago began from the 1960s to 1980s, the secondary industry may be more influential if the variable influence test is conducted using input drivers in 1960s or 70s.

Poverty rate also had a stronger influence in Chicago than Fort Worth. Since depopulating and deindustrializing neighborhoods with a higher poverty rates may result in a loss of potential future economic growth, this factor can contribute to more people to moving out.

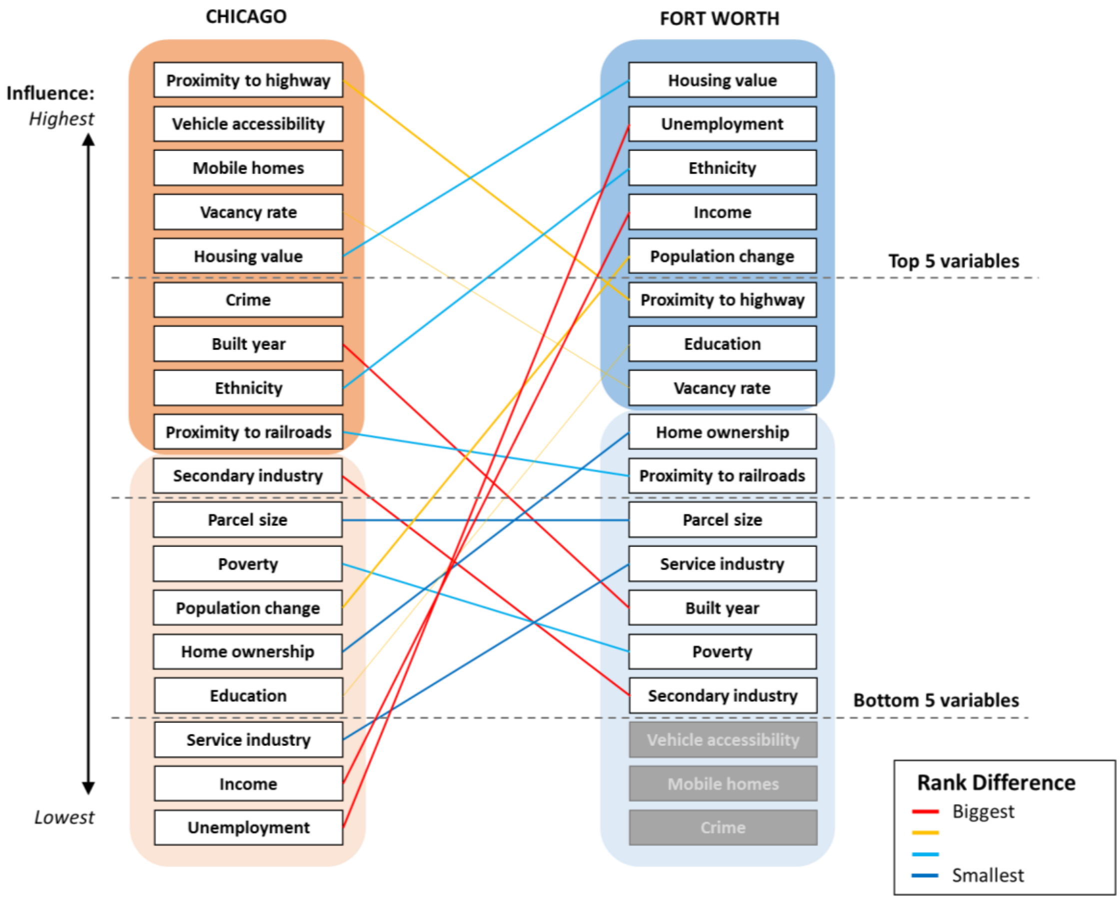


Figure 27. Difference of Variable Influence between Chicago and Fort Worth

Table 11. Difference of Variable Influence between Fort Worth and Chicago

Domain	Variable	City of Chicago			City of Fort Worth			Difference (rank)
		PCM	Kappa	Influence	PCM	Kappa	Influence	
Employment Trend	**Unemployment**	50.5	0.48	0.00	52.2	0.47	0.87	0.87 (15)
	Secondary Industry	48.9	0.46	0.47	55.1	0.5	0.00	0.47 (12)
	Service Industry	49.9	0.47	0.12	54.4	0.49	0.20	0.08 (1)
Socio-economic Status	**Income**	50.1	0.47	0.06	52.6	0.47	0.73	0.67 (14)
	Education	49.8	0.47	0.18	53.5	0.48	0.53	0.36 (9)
	Poverty	49.0	0.46	0.35	54.7	0.49	0.07	0.29 (7)
	Ethnicity	48.6	0.46	0.59	52.6	0.47	0.80	0.21 (6)
	Crime	48.3	0.46	0.71	N/A	N/A	N/A	N/A
Household Composition / Housing	**Ownership**	49.6	0.47	0.24	53.5	0.48	0.40	0.16 (3)
	Value (market/land)	47.9	0.45	0.76	47.8	0.42	0.93	0.17 (4)
	Mobile Homes	46.0	0.43	0.88	N/A	N/A	N/A	N/A
	Vacancy Rate	47.8	0.45	0.82	53.5	0.48	0.47	0.36 (8)
Physical Status	**Population Change**	49.3	0.47	0.29	52.7	0.47	0.67	0.37 (10)
	Parcel Size	48.9	0.46	0.41	54.3	0.49	0.27	0.15 (2)
	Built Year	48.6	0.46	0.65	54.5	0.49	0.13	0.51 (13)
Access / Transportation	**Railroads**	48.7	0.46	0.53	53.5	0.48	0.33	0.20 (5)
	Vehicle Accessibility	45.8	0.43	0.94	N/A	N/A	N/A	N/A
	Highway	45.5	0.43	1.00	53.1	0.48	0.60	0.40 (11)

4.4. Plan Quality: Vacancy related Policies in Local/Regional Comprehensive Plan

In the last section, different influences of each input factor on model performance was quantified. Through this analysis, I found that property value, unemployment rate, ethnicity, income, population change and proximity to highway are influential on increasing vacancy in Fort Worth, while proximity to highway, vehicle accessibility, mobile home, property value and crime showed a strong influence on Chicago. Therefore, this chapter evaluates comprehensive plans to determine how well the primary factors contributing to vacancy are reflected to existing plans in both growing and shrinking city.

A comprehensive plan is a process and tool used to guide communities' future land use decisions, seeking to balance development pressure with preservation for long-term economic health and quality of life (Kelly, 2010; Briassoulis, 2004). Considering a relatively long timeline of about twenty years, a community plan should include all land in its regulatory jurisdiction and also consider all physical developments of the community (Kelly, 2010). This includes the following elements: land use, housing, transportation, utilities, parks and open spaces and other public and institutional activities. Thus, development management regulations must be consistent with the goals and purposes of the comprehensive plan.

Generally, a local comprehensive plan is composed of two parts: 1) analysis of existing conditions and trends and 2) goals, objectives and policies. Since "existing conditions and trends" provides a foundation and basis for the formulation of "goals, objectives and policies" by indicating the current status and problems of the local community, both sections should be reviewed. This section of the study consists of two parts. First, I analyzed which neighborhoods in Chicago and Fort Worth neighborhood are socially vulnerable and possess a high risk of vacancy by planning district. Then, comprehensive plans from each city were reviewed to determine how well their plans take into account current problems by comparing wealthy-occupied and vulnerable-vacant communities of each city.

4.4.1. The City of Fort Worth

The Fort Worth 2016 comprehensive plan contains guidance for making decisions about growth and development relating to twenty-two functional sectors, including land use, housing, transportation, infrastructure, conservation, recreation and open spaces and capital improvement. The comprehensive plan describes future development patterns and population projections for the city and protects natural and cultural resources for present and future generations. Among the twenty-two categories of the plan, I reviewed ten different sections that contribute to vacancy: land use, housing, capital improvements, financial incentives, parks and community services, critical facilities (libraries, police services, fire, and fire and emergency services), economic development and transportation (See Table 12). Since planning districts are delineated in order to coordinate plan policies that influence the social, physical, economic, and natural factors affecting each community, they are appropriate units of analysis to examine each plan’s quality (Berke et al., 2015; Berke et al., 2006).

Since the City of Fort Worth and its extraterritorial jurisdiction have been divided into sixteen sectors for planning purposes, the current socio-economic and vacancy status of each district was identified based on their district boundaries. Using the analytical outputs of physical, social and economic circumstances of the neighborhoods, two districts having the highest and lowest risk of vacancy and showing large differences in socioeconomic status were selected to compare how well the comprehensive plan considers the socially and physically vulnerable district.

Table 12. City of Fort Worth 2016 Comprehensive Plan

Components	Use	Note
I: Building Strong Neighborhoods		
1.1. Land Use	O	
1.2. Housing	O	
1.3. Parks and Community Services	X	
1.4. Libraries	O	Related with critical facilities
1.5. Human Services	X	
1.6. Neighborhood Capacity Building	O	Related with critical facilities
II: Developing A Sound Economy		
2.1. Economic Development	O	
2.2. Transportation	X	
2.3. Education	O	
2.4. Historic Preservation	X	
2.5. Urban Design	X	
2.6. Arts and Culture	X	
III: Providing A Safe Community		
3.1. Police Services	O	Related with critical facilities
3.2. Fire and Emergency Services	O	Related with critical facilities
3.3. Environmental Quality	X	
3.4. Public Health	X	
3.5. Municipal Facilities	O	As a kind of critical facilities

Table 12. Continued

Components	Use	Note
IV: Tools for Implementation		
41. Capital Improvements	O	Related with housing & Economic development
4.2. Development Regulations	X	
4.3. Financial Incentives	O	Related with housing & Economic development
4.4. Annexation Policy	X	
4.5. Intergovernmental Cooperation	X	

2020 forecasted vacancy patterns, long term vacancies and socioeconomic of each district indicate that Southeast is the most physically (vacancy) and socially vulnerable district, while Far North among the healthier communities in the city (See Fig. 28, Table 13 and 14).

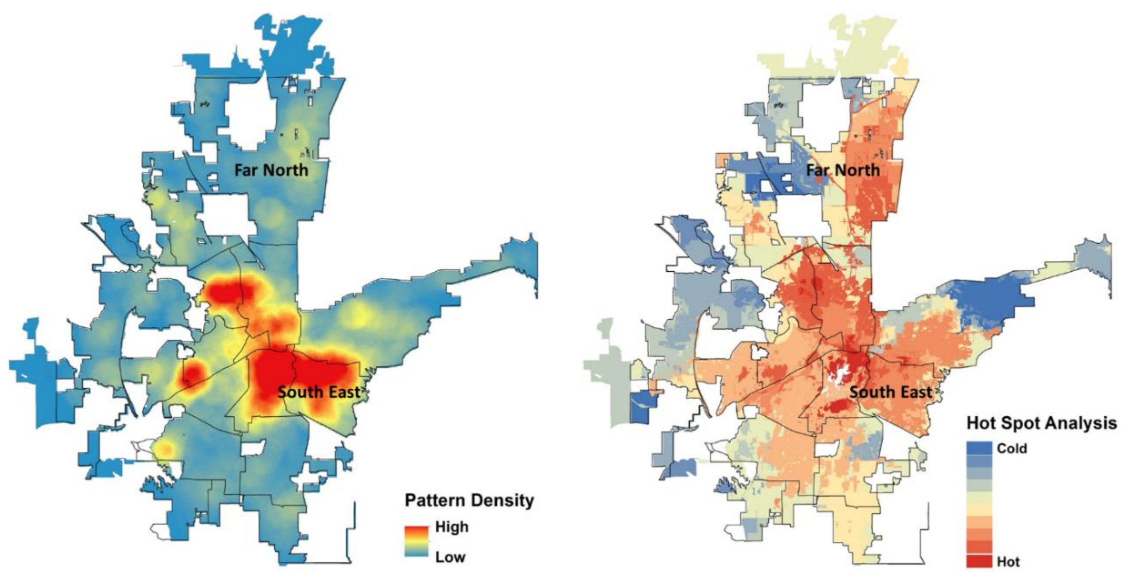


Figure 28. Vacant Land Pattern map by District in Fort Worth, TX

Table 13 indicates long-term vacancies for 2010-2014 (24 months or longer) and the proportion of vacant areas using the 2020 predicted composite score. Since the Southeast is located near downtown, most of the area is already developed and about 56 percent of the area is expected to be vacant in the near future, a proportion lower than the city average (60%). However, there are a lot of small vacant parcels in the district. The Southeast recorded a proportion of long-term vacant property (over 24 months) three times higher than average in 2010, rising steadily every year from 4.1 percent in 2010 to 6.9 percent in 2014. In contrast, the long term vacancy rate of the Far North was only 0.2 percent, which is twenty times lower than the Southeast.

The socioeconomic status in each district also indicates that the Southeast (SE) is the most vulnerable among the 16 planning districts, while the Far North (FN) is one of the most stable and wealthy neighborhoods (See Table 14). The rate of African American residents in the SE (37%) is four times higher than in the FN (9%). The poverty rate (31%) is six times higher (5%), the median household income ($28,374) is three times lower ($83,367), the unemployment rate (14%) is three times higher (5%), and the crime rate per 100,000 people (814) is twice as high (429). Under these circumstances, the Southeast district needs careful and specific planning policies to reduce vacancy rate, improving economic outcomes and developing safe communities. Therefore, this chapter reviews how well the local comprehensive plan reflects these issues of the Southeast and compares the evaluation results with the healthiest community, the Far North.

As noted above, the variable influence outputs indicate marketing conditions and economic variables such as housing value, unemployment rate, ethnicity and income have a greater influence on vacant land transition than most other factors. On the other hand, industry quotient (secondary and service industry), poverty and age of buildings did not seem to be strongly influential when predicting for vacant land in the City of Fort Worth. Thus, the basic policy direction on vacant land in the city should focus on improving economic opportunities/conditions and reducing racial segregation.

Table 13. 2020 Future Vacancy and 2010-2014 Long-term (24+months) Vacancy by Planning District (Fort Worth)

District	2020 Predicted Composite Score				Long-term (24+ months) Vacancy				
	1	2	3	Total	2010	2011	2012	2013	2014
Arlington Heights	18.6%	17.3%	3.7%	39.7%	3.5%	4.7%	6.1%	6.2%	5.6%
Downtown	36.2%	17.5%	2.6%	56.3%	1.4%	1.6%	2.0%	1.8%	2.3%
Eastside	41.8%	7.4%	8.5%	57.7%	1.3%	2.2%	3.4%	3.9%	3.6%
Far North	**65.2%**	**2.4%**	**9.8%**	**77.4%**	**0.2%**	**0.4%**	**0.5%**	**0.4%**	**0.4%**
Far Northwest	60.4%	3.9%	8.3%	72.6%	0.1%	0.1%	0.2%	0.2%	0.2%
Far South	63.3%	5.5%	4.6%	73.4%	0.1%	0.3%	0.4%	0.3%	0.2%
Far Southwest	70.2%	0.4%	7.9%	78.5%	0.0%	0.0%	0.0%	0.1%	0.1%
Far West	36.3%	16.9%	5.8%	59.1%	0.3%	1.4%	2.2%	2.2%	1.8%
Northeast	35.1%	11.1%	6.1%	52.4%	2.8%	3.0%	3.4%	3.5%	3.5%
Northside	27.4%	17.9%	6.8%	52.0%	3.6%	4.8%	5.6%	5.8%	5.4%
South East	**30.4%**	**19.8%**	**6.0%**	**56.2%**	**4.1%**	**5.4%**	**6.8%**	**7.4%**	**6.9%**
Southside	25.4%	19.2%	5.8%	50.4%	4.6%	5.7%	6.9%	6.7%	6.2%
Sycamore	51.3%	4.0%	4.5%	59.9%	0.7%	1.2%	2.1%	2.2%	2.3%
TCU West Cliff	23.0%	7.5%	1.9%	32.4%	0.9%	1.1%	1.7%	1.9%	1.5%
Wedgwood	28.8%	4.8%	4.2%	37.7%	0.6%	0.8%	1.4%	1.3%	0.8%
Western Hills-Ridglea	22.1%	4.2%	3.3%	29.6%	3.6%	5.1%	6.4%	6.4%	6.5%
Fort Worth	44.8%	8.4%	6.7%	60.0%	1.5%	2.4%	3.1%	3.2%	3.0%

Table 14. 2010 Socio-economic Status by Planning District (Fort Worth)

District	Race[1]	Education[2]	Unemploy.	Income[3]	Vacancy	Value[4]	Poverty	Ownership	Mobile home	Crime[5]
Arlington Heights	12.6%	17.6%	6.8%	$ 47,415	12.4%	$ 166,191	16.6%	49.5%	0.1%	1,644
Downtown	24.4%	17.7%	5.3%	$ 51,196	16.7%	$ 236,800	21.0%	13.8%	1.1%	3,774
Eastside	33.8%	18.0%	9.6%	$ 46,268	13.2%	$ 119,948	15.8%	44.6%	1.6%	4,643
Far North	**8.8%**	**6.9%**	**5.2%**	**$ 83,367**	**4.8%**	**$ 164,606**	**4.8%**	**74.2%**	**2.4%**	3,358
Far Northwest	7.8%	10.6%	8.1%	$ 71,811	8.7%	$ 144,348	7.1%	74.8%	1.7%	4,065
Far South	26.9%	10.9%	5.5%	$ 65,559	9.0%	$ 125,163	9.6%	73.4%	3.9%	4,482
Far Southwest	20.6%	6.7%	4.6%	$ 95,884	5.6%	$ 189,249	3.8%	85.8%	0.6%	1,729
Far West	9.6%	14.4%	6.5%	$ 59,124	7.2%	$ 102,276	9.2%	60.9%	1.4%	3,602
Northeast	9.1%	50.7%	9.9%	$ 33,836	10.9%	$ 73,534	25.5%	56.5%	0.5%	5,913
Northside	3.2%	53.7%	9.4%	$ 199,857	14.2%	$ 72,133	27.1%	48.9%	3.8%	6,036
South East	**36.9%**	**42.8%**	**14.0%**	**$ 28,374**	**14.3%**	**$ 52,551**	**31.2%**	**52.0%**	**6.6%**	6,368
Southside	16.8%	44.6%	12.7%	$ 29,268	14.8%	$ 75,547	37.7%	43.9%	0.5%	5,634
Sycamore	28.5%	31.3%	10.6%	$ 40,120	12.0%	$ 82,577	26.4%	53.1%	3.9%	5,566
TCU West Cliff	3.4%	7.0%	5.9%	$ 60,563	9.7%	$ 282,905	14.5%	46.6%	0.6%	1,644
Wedgwood	22.1%	9.6%	6.0%	$ 55,048	9.3%	$ 144,063	10.8%	49.3%	0.2%	3,645
Western Hills-Ridglea	12.5%	18.1%	9.2%	$ 39,795	16.3%	$ 138,401	19.5%	34.0%	0.3%	3,732
Fort Worth	18.7%	21.9%	8.2%	$ 61,436	11.0%	$ 131,854	17.4%	53.2%	1.8%	4,111

Table 15 displays the number of vacancy-related policies by variables and districts in their order of influence from high to low. As noted, housing market condition and economic status are critical variables to control vacant properties of Fort Worth and the city suggests diverse policies and strategies to revitalize vulnerable districts. There are 123 policies/strategies that are related with vacancy. Among them, 63 policies are suggested to revitalize South East where is one of the most vulnerable districts in Fort Worth, and 41 of them are associated with economic growth or quality of life such as reducing unemployment rate, poverty and increasing income.

Fort Worth suggests diverse housing policies and strategies to increase the supply of quality housing and expand homeownership opportunities. To encourage revitalization of the central city and surrounding neighborhoods, various development incentives programs were developed such as tax abatements and fee waivers. Through Neighborhood Empowerment Zones (NEZs) program and Community Development Block Grant (CDBG) funds, local development activities were planned for low to moderate income households such as affordable housing and infrastructure development. Figure 29 shows that the NEZs and CDBG eligible areas are concentrated in the downtown and its surrounding districts including the Southeast, Southside and Northside for revitalization.

Table 15. The Number of Vacancy-related Policies/Strategies of Two Selected Districts (Fort Worth)

Variable	Land Use			Housing			Economic Development			Capital Improvement			Financial Incentives			Critical Facilities			Transit			SUM		
	FN	SE	O	FN	SE	O	FN	FN	SE	O	SE	O	FN	SE	O	FN	SE	O	FN	SE	O	FN	SE	O
Housing value	1	1		1	5	3																2	9	5
Unemployment	2	1		1	3	2					1					1	1					4	14	5
Ethnicity					1	2					1				1							0	2	3
Income	2	1		1	3	2					1				2	1	1					4	12	7
Population change																						0	0	0
Highway								1	1	1									1	1	1	1	1	1
Education																						0	1	2
Vacancy rate		1	1			1					1											0	4	3
Ownership						1																0	0	1
Railroad	4	3	3	1	2	2		1	1										1	1		6	6	5
Parcel size																						0	0	0
Service industry																						0	0	0
Built year					1																	0	1	0
Poverty	2	1		1	3	2					1				2	1	1					4	13	7
Secondary industry																						0	0	0
Total	11	8	4	5	18	15	0	2	2	1	5	0	0	0	5	3	3	0	2	2	1	21	63	39

FN: Far North, SE: South East, O: Overall (entire city)

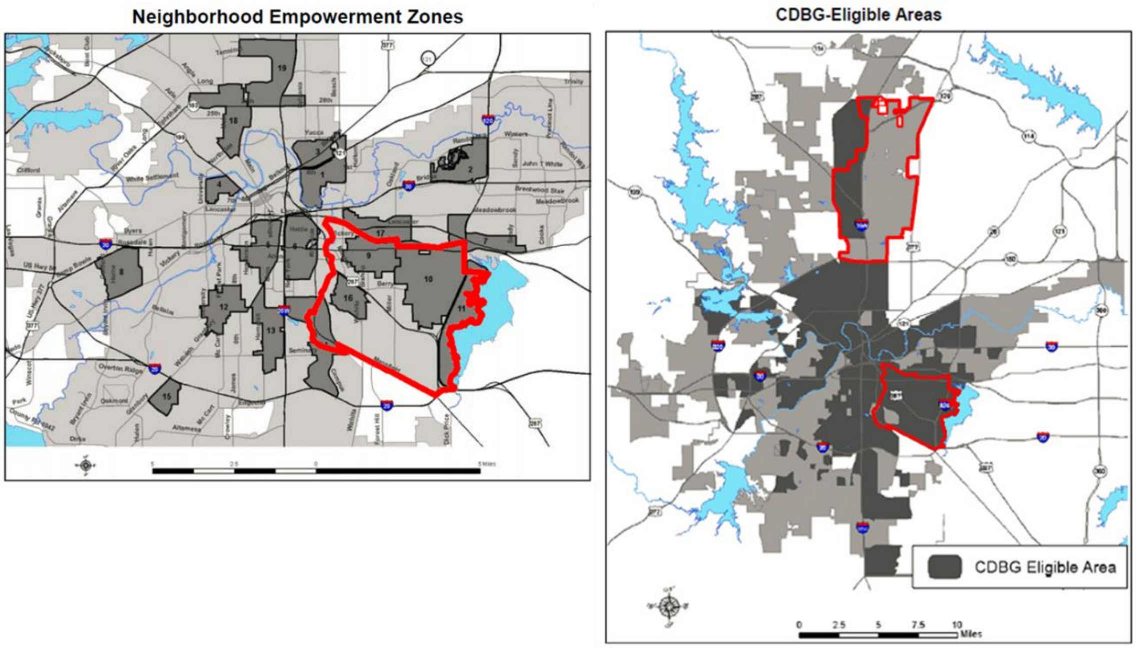


Figure 29. 19 NEZs* and Census Tract-based CDBG-Eligible Areas**

(Source: 2016 Comprehensive Plan, p.226 and p.215)

* Neighborhood Empowerment Zones (NEZs): An area to revitalize the central city through development incentives: promote 1) the development and rehabilitation of affordable housing within the zone; 2) an increase in economic development within the zone; and 3) an increase in the quality of social services, education, or public safety provided to residents of the zone. 20 NEZs have been designated by the City Council ((2016 Comprehensive Plan, p226). ** CDBG Eligible Area: Census tract in which fifty-one percent (51%) or more of the residents in that census tract have low to moderate incomes as defined by the United States Department of Housing and Urban Development (2016 Comprehensive Plan, p214).

In terms of economic growth, the 2016 comprehensive plan provides diverse programs for job creation and an increase in the tax base. Fort Worth designated six significant employment centers with large concentrations of employees (See Fig. 30). Among them, Far North district established the Alliance Foreign Trade Center, including 7,400 single-family homes and 260 companies. The employment center created 28,000 jobs in 2011 and is projected to develop about 2,100 acres of commercial space and employ 92,000 workers in the future. In Southeast district, although no employment center exists in the neighborhood, there are several policies and strategies to stimulate economic development and enhance community validity using $ 15million in federal funds. As a purpose of property acquisition, environmental cleanup, and reconstruction, workforce/opportunity center and redevelopment target center is planned in the area providing job recruitment, job training and placement services for program clients (See Fig. 30). However, while the Far North has more economic growth engines such as three shopping centers becoming an integral part of the economic and social fabric of the communities, it is difficult to find any facility to promote fiscally sustainable growth in the Southeast (See Fig. 31).

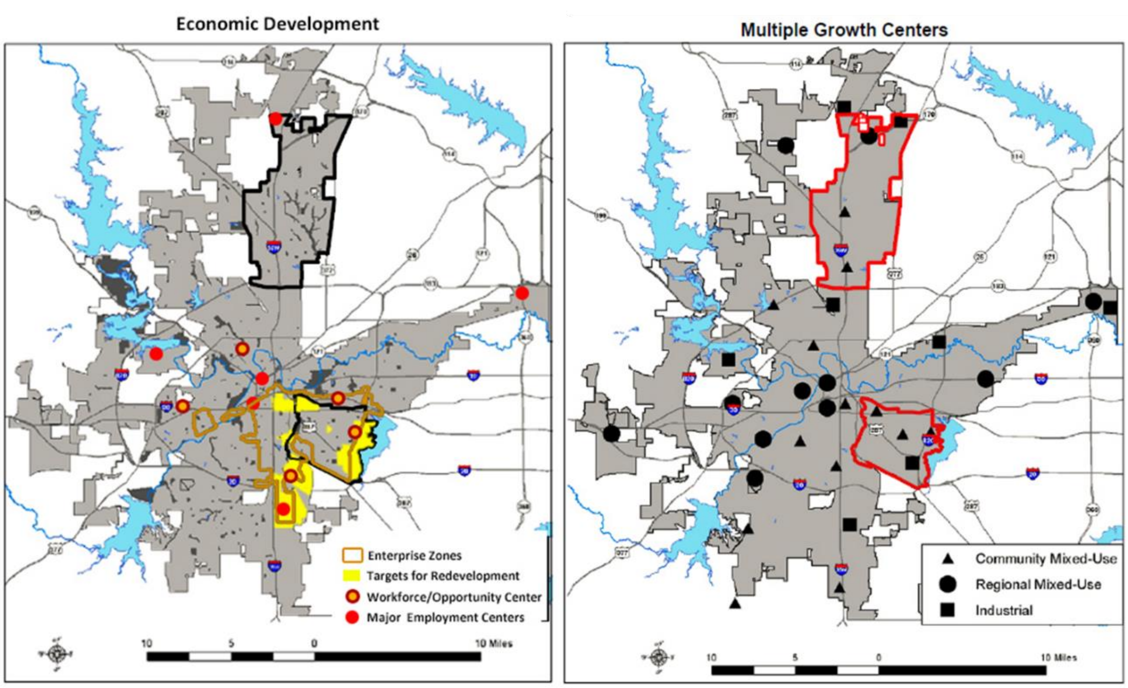


Figure 30. Economic Development Centers (left) and Multiple Growth Centers (right)

(Source: 2016 Comprehensive Plan and Planning & Development Department, 2011)

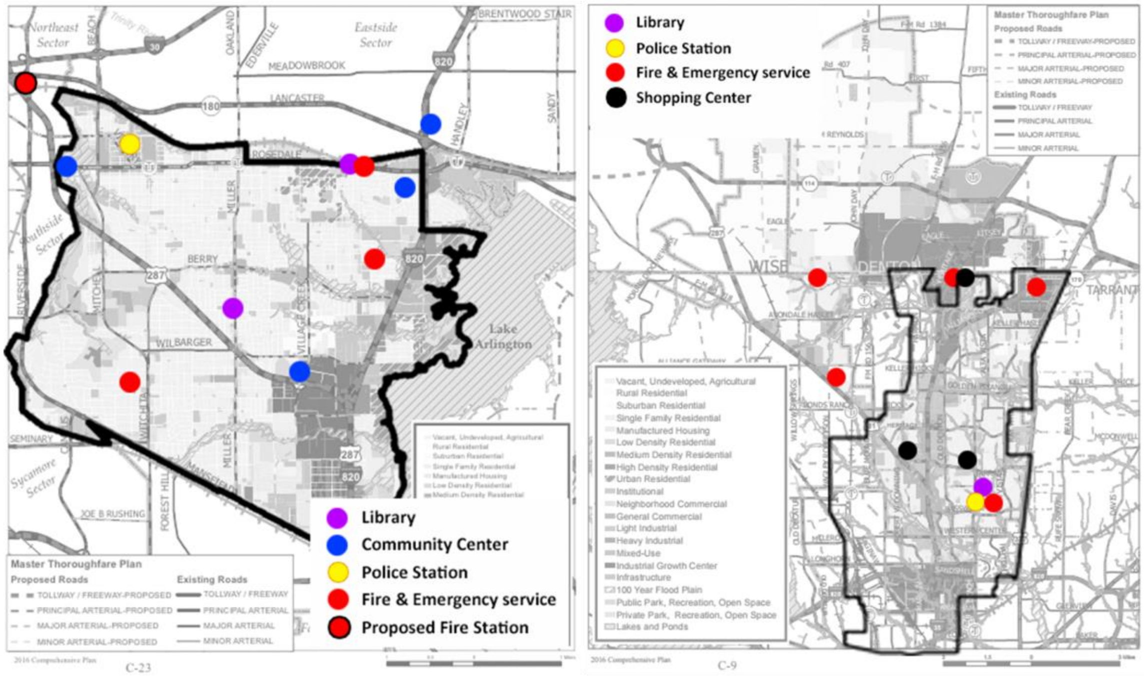


Figure 31. Critical Facilities in Southeast and Far North

Lastly, the city implemented many transportation-related projects to provide better access to work, home, school, shopping and leisure activities. Between 2004 and 2008, three major bond package allocations were approved for the rehabilitation of 206 neighborhood streets ($65 million) ,12 arterial street projects ($57 million), and public transportation improvements ($150 million), and 9% of these bond program projects are currently under construction or in design (2016 Comprehensive Plan). To cover the cost for expansion of the arterial street networks, the City Council designated 27 transportation impact fee service areas in 2008. As a part of revitalization projects in the central city, however, 7 areas are excluded from the transportation impact fee service areas and the entire Southeast district is one of them (See Fig. 32).

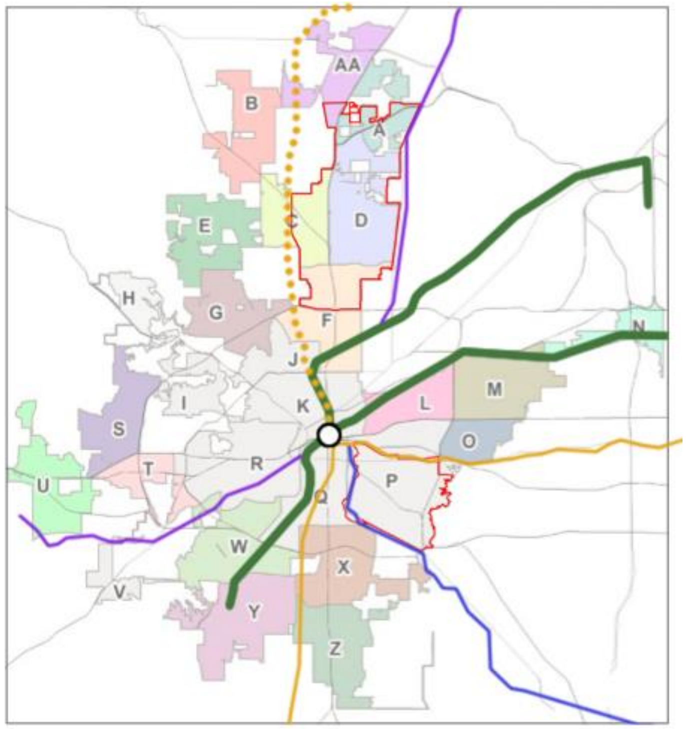


Figure 32. Transportation Impact Fee Service Areas and Commuter Rails

4.4.2. The City of Chicago

GO TO 2040 is the long-range comprehensive regional plan for the Chicago metropolitan region that includes 7 counties and 284 communities by Chicago Metropolitan Agency for Planning (CMAP) which is the official regional planning organization for the northeastern Illinois counties. Based on the region’s existing challenges and opportunists, the comprehensive plan contains 12 functional sectors including land use, housing, parks and open space, sustainable local food, capital improvements, governance, and transportation. Among those 12 high-priority sections, 7 chapters were reviewed which are associated with vacant properties: land use, housing, parks and open space, sustainable local food, education, workforce development and transportation (See Table 16).

Table 16. City of Chicago 2040 Comprehensive Plan (GO TO 2040)

Components	Use	Note
I: Livable Communities		Land Use & Housing Policy
1.1. Achieve Greater Livability through Land Use and Housing	O	
1.2. Manage and Conserve Water and Energy Resources	X	
1.3. Expand and Improve Parks and Open Space	O	
1.4. Promote Sustainable Local Food	O	
II: Human Capital		
2.1. Improve Education and Workforce Development	O	Education & Economic Development
2.2. Support Economic Innovation	O	Related with Service Industry
III: Efficient Governance		
3.1. Reform State and Local Tax Policy	X	
3.2.Improve Access to Information	X	
3.3. Pursue Coordinate Investments	X	
IV: Regional Mobility		
4.1. Invest Strategically in Transportation	O	
4.2. Increase Commitment to Public Transit	O	
4.3. Create More Efficient Freight Network	X	

The City of Chicago has been divided into 77 districts for planning purpose. Among them, four districts (two vulnerable and two healthy) were selected to compare how well the comprehensive plan considers the socially and physically vulnerable districts to reduce vacant properties and improve their neighborhood quality.

Considering a 2020 forecasted vacancy patterns and socioeconomic status by districts, Englewood and Washington Park seemed to be the most physically (vacancy) and socially vulnerable districts, while Lake View and Lincoln Park are healthier communities in the city (See Fig. 33, Table 17 and Table 18).

Table 17 indicates the expected vacancy rate in 2020 based on the composite score of three different scenarios and long-term vacancies for 2010-2014 (24 months or longer). The 2020 scenarios predicted that 69% of Englewood and 41% of Washington Park might have probability of future vacancy, while 3% of Lake View and 4.7% of Lincoln Park were predicted to become vacant in 2020. Moreover, looking at the long-term (over 24 months) vacancy rate by districts, the average long-term vacancy rate between 2010 and 2014 in Englewood (9.2%) and Washington Park (7.1%) were higher than Lake View (1.3%) and Lincoln Park (1.5%).

The analysis of socio-economic status of each district also shows how Englewood and Washington Park are socially and physically vulnerable compared to Lake View and Lincoln Park. Over 98% of the population in Englewood and Washington Park were African American in 2010, while Lake View and Lincoln Park had less than 5%. Both income and housing value of those vulnerable districts are less than 30% of the wealthy neighborhoods. Furthermore, the poverty rate (43%) is about four times higher (11%), the unemployment rate (22%) is four times higher (5%), and the crime rate per 100,000 people (11,662) is twice as high (5151). Under the circumstances, Englewood and Washington Park need careful and specific planning policies for reducing vacancy rate, improving economic outcomes and providing a safe community.

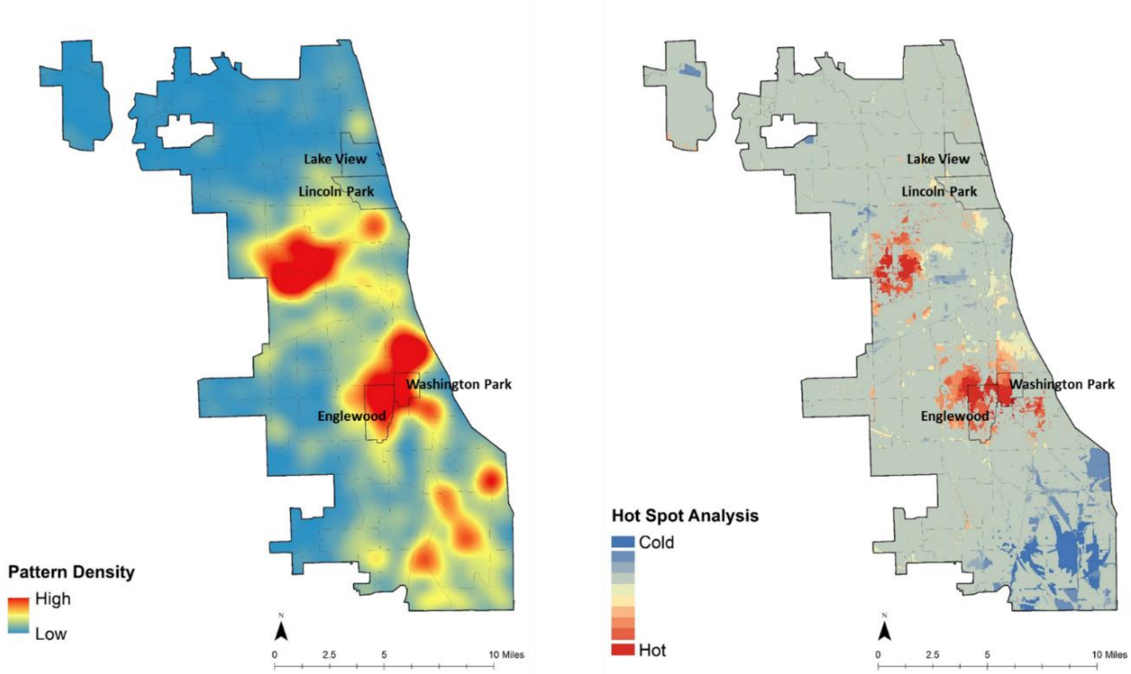


Figure 33. Vacant Land Pattern Map by District in Chicago, IL

However, since the seven county regional plan of Chicago metropolitan area does not provide specific policies for each district of Chicago city, it was not able to evaluate the comprehensive plan at the neighborhood level. Therefore, broad evaluation of entire city was conducted. Table 19 displays the number of policies which are associated with vacancy by plan category.

As noted above, the variable influence test in section 4.3 indicates that mobility and public transportation, housing condition and crime seemed to have a stronger influence on increasing/decreasing vacant land, while some economic variables such as unemployment rate and income are influential, but only marginally when predicting for vacant land of Chicago. Thus, the basic policy direction on the vacant land of the city should be focused on improving transportation networks and promoting the rehabilitation of older housing stock to increase housing values and reduce crimes for Chicago. Due to the recent economic downturn, metropolitan Chicago faces fiscal pressures, damaging quality of life and created various policies and strategies to revitalize the economy. The result of plan evaluation indicates that workforce development is recognized as one of the most important factors to revitalize their economy. Among 65 vacancy-related policies, 27 policies were obtained from "Improve education and workforce development" section which addresses the high-quality labor force and reducing differences between racial groups in terms of income, educational attainment and many other measures. Furthermore, 19 policies are suggested to improve the public transit system and highway systems focusing investments on maintenance and modernization.

Table 17. 2020 Future vacancy and 2010-2014 long-term (24+months) Vacancy by Planning District (Chicago)

District	2020 Predicted Composite Score				Long-term (24+months) Vacancy				
	1	**2**	**3**	**Total**	**2010**	**2011**	**2012**	**2013**	**2014**
Albany Park	0.0%	0.1%	0.0%	0.1%	1.8%	1.3%	1.4%	2.1%	2.6%
Archer Heights	3.7%	0.9%	0.0%	4.6%	0.6%	0.9%	1.4%	1.6%	1.7%
Armour Square	2.8%	6.3%	0.0%	9.1%	0.8%	0.9%	0.6%	0.6%	1.0%
Ashburn	4.0%	5.7%	0.0%	9.6%	0.6%	0.7%	1.1%	1.4%	1.2%
Auburn Gresham	7.2%	5.9%	0.0%	13.1%	2.5%	2.5%	3.2%	3.9%	4.1%
Austin	34.8%	13.3%	3.0%	51.0%	2.6%	2.3%	2.8%	3.2%	3.1%
Avalon Park	1.6%	1.3%	0.0%	2.9%	1.8%	1.8%	2.5%	2.8%	3.3%
Avondale	1.9%	1.5%	0.1%	3.5%	3.2%	2.1%	1.7%	2.3%	2.2%
Belmont Cragin	0.9%	1.7%	0.0%	2.6%	1.2%	1.4%	1.8%	2.0%	1.9%
Beverly	0.3%	1.7%	0.0%	2.0%	0.9%	0.7%	0.8%	1.2%	1.2%
Bridgeport	7.1%	3.2%	0.0%	10.3%	1.1%	1.2%	1.4%	1.5%	1.6%
Brighton Park	4.2%	1.1%	0.0%	5.3%	1.6%	1.5%	1.8%	2.0%	1.7%
Burnside	2.9%	4.4%	0.0%	7.2%	3.9%	4.4%	5.1%	4.9%	5.2%
Calumet Heights	4.4%	4.0%	0.0%	8.4%	2.1%	1.9%	2.5%	3.0%	2.9%
Chatham	9.1%	3.3%	0.0%	12.4%	3.2%	3.3%	4.8%	4.5%	4.8%
Chicago Lawn	4.3%	3.2%	0.0%	7.5%	2.9%	3.5%	4.3%	4.1%	4.3%
Clearing	2.1%	1.7%	0.0%	3.8%	0.8%	0.8%	1.1%	1.3%	1.1%
Douglas	9.0%	6.6%	6.1%	21.7%	1.3%	1.2%	1.2%	0.9%	1.1%
Dunning	3.0%	4.0%	0.0%	7.0%	1.0%	1.0%	0.9%	1.0%	0.8%
East Garfield Park	20.5%	16.1%	0.0%	36.6%	3.9%	3.5%	4.1%	4.4%	5.3%
East Side	5.8%	5.9%	0.0%	11.7%	2.8%	3.1%	3.6%	3.4%	3.1%
Edgewater	0.0%	0.9%	0.0%	0.9%	1.9%	1.1%	1.2%	1.8%	1.7%
Edison Park	0.0%	0.0%	0.0%	0.0%	0.6%	0.6%	0.8%	0.9%	1.3%
Englewood	**55.4%**	**13.6%**	**0.0%**	**69.0%**	**8.6%**	**9.3%**	**9.8%**	**10.1%**	**8.4%**
Forest Glen	0.0%	0.8%	0.0%	0.9%	0.5%	0.3%	0.4%	0.4%	0.4%
Fuller Park	8.4%	2.7%	1.9%	13.0%	10.4%	7.4%	5.0%	6.2%	8.0%
Gage Park	1.6%	2.3%	0.0%	3.9%	1.4%	1.4%	1.7%	2.0%	1.7%
Garfield Ridge	1.9%	8.5%	0.0%	10.4%	0.6%	0.6%	0.8%	0.9%	0.9%
Grand Boulevard	23.2%	25.1%	14.6%	62.9%	5.3%	6.2%	7.2%	5.5%	4.4%
Greater Grand Crossing	12.6%	3.9%	0.0%	16.5%	4.5%	5.0%	6.0%	6.1%	5.8%
Hegewisch	14.3%	27.1%	0.0%	41.4%	1.9%	2.2%	2.4%	2.7%	2.9%
Hermosa	0.0%	0.6%	0.0%	0.6%	2.1%	1.9%	2.4%	2.6%	2.1%
Humboldt Park	23.2%	13.2%	3.2%	39.6%	4.3%	3.8%	4.2%	4.8%	4.3%
Hyde Park	0.5%	0.9%	0.0%	1.4%	2.2%	2.4%	3.2%	2.5%	1.4%
Irving Park	0.0%	0.1%	0.0%	0.1%	2.1%	1.6%	1.6%	1.9%	1.9%
Jefferson Park	0.0%	0.0%	0.2%	0.2%	1.0%	1.0%	1.3%	1.5%	1.3%
Kenwood	6.7%	5.1%	0.7%	12.5%	3.3%	3.0%	3.6%	2.6%	1.9%
Lake View	**2.0%**	**1.0%**	**0.0%**	**3.0%**	**1.4%**	**1.0%**	**1.2%**	**1.7%**	**1.4%**
Lincoln Park	**1.8%**	**2.9%**	**0.0%**	**4.7%**	**2.1%**	**1.6%**	**1.3%**	**1.2%**	**1.5%**

Table 17. Continued

District	2020 Predicted Composite Score				Long-term (24+months) Vacancy				
	1	2	3	Total	2010	2011	2012	2013	2014
Lincoln Square	0.2%	0.2%	0.0%	0.5%	1.3%	1.2%	1.1%	1.2%	1.3%
Logan Square	8.1%	5.4%	0.3%	13.8%	2.8%	2.7%	2.3%	2.3%	2.7%
Loop	3.0%	1.9%	0.0%	4.9%	1.4%	1.8%	3.4%	2.5%	1.1%
Lower West Side	6.6%	8.6%	0.0%	15.2%	2.8%	2.3%	2.4%	2.8%	3.4%
McKinley Park	0.7%	2.4%	0.0%	3.2%	1.8%	1.5%	1.2%	1.5%	2.0%
Montclare	0.4%	0.7%	0.2%	1.3%	0.6%	0.7%	0.9%	1.0%	0.9%
Morgan Park	3.3%	3.4%	0.0%	6.7%	1.9%	1.8%	2.1%	2.5%	2.7%
Mount Greenwood	0.3%	4.4%	0.0%	4.7%	0.4%	0.5%	0.8%	0.8%	1.0%
Near North Side	14.0%	14.7%	0.0%	28.7%	1.6%	1.8%	1.9%	1.6%	1.3%
Near South Side	10.8%	8.8%	0.0%	19.7%	0.6%	1.0%	2.1%	2.5%	1.7%
Near West Side	30.6%	38.7%	0.0%	69.3%	0.9%	0.9%	0.9%	1.0%	1.3%
New City	38.8%	36.1%	0.0%	74.9%	6.0%	4.7%	5.8%	6.7%	8.0%
North Center	1.3%	2.7%	0.0%	4.0%	3.2%	2.2%	2.1%	1.9%	1.7%
North Lawndale	36.0%	16.3%	0.0%	52.3%	3.9%	3.3%	4.0%	4.9%	5.4%
North Park	0.7%	0.9%	0.4%	2.0%	1.4%	1.3%	1.5%	1.6%	1.3%
Norwood Park	0.2%	0.9%	0.0%	1.0%	0.5%	0.5%	0.8%	0.8%	0.7%
Oakland	7.0%	7.8%	3.7%	18.5%	3.7%	4.2%	5.1%	3.3%	1.5%
O'Hare	1.9%	18.7%	0.0%	20.6%	0.8%	0.8%	1.2%	1.3%	1.0%
Portage Park	0.3%	0.2%	0.0%	0.5%	1.5%	1.5%	1.8%	2.1%	1.8%
Pullman	5.5%	7.8%	0.0%	13.3%	4.5%	3.6%	5.5%	5.4%	5.8%
Riverdale	16.2%	11.2%	0.0%	27.4%	28.3%	25.0%	23.0%	23.2%	25.3%
Rogers Park	0.3%	1.6%	0.0%	1.9%	3.2%	2.1%	1.8%	2.3%	2.2%
Roseland	13.6%	1.2%	0.0%	14.9%	4.1%	3.9%	4.4%	4.3%	5.4%
South Chicago	15.7%	7.3%	0.0%	23.0%	7.4%	8.2%	9.3%	9.0%	9.6%
South Deering	28.6%	45.2%	0.0%	73.8%	1.9%	2.0%	3.0%	3.5%	4.0%
South Lawndale	14.4%	15.2%	0.0%	29.7%	1.6%	1.2%	1.5%	2.0%	2.2%
South Shore	4.7%	4.0%	0.0%	8.7%	6.1%	7.5%	6.0%	5.1%	5.5%
Uptown	0.6%	2.7%	0.0%	3.3%	1.2%	1.1%	1.3%	1.8%	1.5%
Washington Heights	3.1%	3.8%	0.0%	6.9%	1.7%	1.8%	2.4%	2.4%	2.7%
Washington Park	**16.5%**	**11.8%**	**13.1%**	**41.3%**	**6.4%**	**6.4%**	**8.6%**	**8.5%**	**5.7%**
West Elsdon	0.0%	1.2%	0.0%	1.2%	0.8%	0.7%	0.8%	1.1%	1.4%
West Englewood	37.7%	22.0%	0.0%	59.7%	5.7%	5.8%	6.9%	7.8%	8.3%
West Garfield Park	21.4%	6.7%	2.1%	30.3%	4.6%	4.1%	4.0%	4.3%	4.6%
West Lawn	3.4%	3.0%	0.0%	6.4%	0.8%	0.9%	1.0%	1.0%	1.1%
West Pullman	15.5%	14.5%	0.0%	30.0%	4.7%	5.1%	5.6%	5.9%	6.6%
West Ridge	0.6%	1.9%	0.3%	2.8%	2.9%	1.9%	1.9%	1.9%	1.5%
West Town	5.1%	10.0%	1.5%	16.6%	2.3%	1.8%	1.9%	2.8%	2.2%
Woodlawn	15.1%	9.9%	3.4%	28.3%	5.1%	5.7%	7.3%	6.8%	6.4%
Chicago	5.5%	4.7%	4.2%	14.4%	2.5%	2.4%	2.7%	2.8%	2.7%

Table 18. 2010 Socio-economic Status by Planning District

District	Race[1]	Education[2]	Unemploy.	Income[3]	Vacancy	Value[4]	Poverty	Ownership	Mobile home	Crime[5]
Albany Park	3.8%	34.9%	9.0%	$ 46,865	8.7%	$ 328,123	19.6%	38.3%	0.2%	2,287
Archer Heights	1.1%	36.4%	14.2%	$ 44,171	12.1%	$ 259,372	12.4%	64.6%	0.7%	4,483
Armour Square	11.2%	37.5%	11.6%	$ 29,430	9.9%	$ 244,607	30.1%	37.1%	1.3%	4,590
Ashburn	50.8%	18.3%	8.8%	$ 62,205	4.2%	$ 203,099	10.8%	88.7%	0.1%	3,070
Auburn Gresham	98.6%	19.5%	24.2%	$ 35,003	14.4%	$ 162,760	27.6%	50.4%	0.0%	6,932
Austin	86.6%	25.0%	21.0%	$ 34,275	15.6%	$ 227,455	27.7%	40.9%	0.1%	7,070
Avalon Park	97%	13.3%	16.6%	$ 44,682	8.3%	$ 170,101	19.4%	70.0%	0.0%	7,439
Avondale	3.4%	25.7%	9.3%	$ 46,982	10.5%	$ 343,544	15.7%	46.3%	0.2%	4,071
Belmont Cragin	5.7%	37.0%	11.5%	$ 43,390	8.4%	$ 302,504	20.5%	50.5%	0.4%	3,899
Beverly	33.4%	5.1%	7.8%	$ 87,173	5.6%	$ 322,293	4.2%	82.2%	0.2%	2,468
Bridgeport	1.4%	26.1%	11.7%	$ 43,054	14.7%	$ 293,381	18.4%	49.6%	0.3%	2,940
Brighton Park	1.0%	48.2%	11.2%	$ 39,726	13.4%	$ 222,120	23.8%	47.1%	0.3%	2,935
Burnside	97.8%	18.6%	23.4%	$ 31,391	8.2%	$ 141,400	31.5%	55.9%	0.7%	4,983
Calumet Heights	96.1%	11.2%	17.2%	$ 55,840	7.2%	$ 194,811	14.6%	75.9%	0.4%	6,814
Chatham	97.7%	13.7%	19.0%	$ 35,059	15.2%	$ 179,384	24.5%	37.1%	0.1%	9,105
Chicago Lawn	55.8%	31.6%	11.9%	$ 39,273	17.7%	$ 178,183	24.7%	47.3%	0.2%	7,163
Clearing	1.5%	18.5%	9.6%	$ 54,622	6.7%	$ 241,552	6.4%	75.2%	0.1%	1,858
Douglas	76.3%	16.9%	16.7%	$ 40,042	19.1%	$ 177,867	27.5%	20.7%	0.0%	5,250
Dunning	1.2%	18.0%	8.6%	$ 61,757	4.8%	$ 298,414	7.7%	78.6%	0.3%	1,782
East Garfield Park	92.2%	26.2%	16.4%	$ 25,010	25.8%	$ 237,982	41.6%	29.2%	0.0%	10,813
East Side	2.5%	35.5%	14.5%	$ 41,596	9.9%	$ 154,254	20.7%	71.4%	0.0%	2,348
Edgewater	14.1%	9.1%	8.9%	$ 47,803	9.3%	$ 311,524	16.4%	39.4%	0.1%	2,917
Edison Park	0.0%	8.4%	7.7%	$ 79,646	5.3%	$ 363,559	4.4%	81.9%	0.3%	679
Englewood	**98.7%**	**29.4%**	**21.3%**	**$ 21,138**	**26.6%**	**$ 135,587**	**45.1%**	**31.8%**	**0.5%**	**11,289**
Forest Glen	1.9%	6.3%	5.5%	$ 90,735	4.3%	$ 462,245	5.8%	86.3%	0.0%	1,505
Fuller Park	94.8%	33.7%	40.0%	$ 16,204	30.4%	$ 120,961	46.6%	34.9%	4.6%	13,628
Gage Park	4.9%	54.1%	14.0%	$ 38,709	11.4%	$ 212,705	20.7%	57.7%	0.5%	3,709
Garfield Ridge	8.9%	19.4%	8.1%	$ 61,664	7.9%	$ 244,987	9.1%	83.4%	0.3%	2,353
Grand Boulevard	94.7%	19.4%	20.6%	$ 32,922	20.3%	$ 301,460	31.0%	28.6%	0.1%	6,842
Greater Grand Crossing	98.0%	17.9%	18.9%	$ 30,033	19.3%	$ 162,509	31.4%	37.6%	0.3%	9,059
Hegewisch	8.7%	17.9%	9.6%	$ 50,292	8.9%	$ 160,088	13.1%	76.0%	6.8%	2,594
Hermosa	1.9%	41.9%	12.9%	$ 42,676	12.2%	$ 316,207	19.9%	46.3%	0.6%	3,441
Humboldt Park	43.6%	36.8%	12.3%	$ 30,142	17.7%	$ 253,712	32.7%	34.3%	0.2%	6,458
Hyde Park	33.9%	5.3%	6.9%	$ 46,918	16.1%	$ 293,951	21.2%	38.5%	0.0%	4,676
Albany Park	3.8%	34.9%	9.0%	$ 46,865	8.7%	$ 328,123	19.6%	38.3%	0.2%	2,287
Archer Heights	1.1%	36.4%	14.2%	$ 44,171	12.1%	$ 259,372	12.4%	64.6%	0.7%	4,483
Armour Square	11.2%	37.5%	11.6%	$ 29,430	9.9%	$ 244,607	30.1%	37.1%	1.3%	4,590
Ashburn	50.8%	18.3%	8.8%	$ 62,205	4.2%	$ 203,099	10.8%	88.7%	0.1%	3,070
Auburn Gresham	98.6%	19.5%	24.2%	$ 35,003	14.4%	$ 162,760	27.6%	50.4%	0.0%	6,932

Table 18. Continued

District	Race[1]	Education[2]	Unemploy.	Income[3]	Vacancy	Value[4]	Poverty	Ownership	Mobile home	Crime[5]
Lincoln Square	4.9%	12.5%	6.8%	$ 58,210	10.2%	$ 375,125	11.5%	41.2%	0.0%	2,887
Logan Square	7.5%	18.5%	7.5%	$ 51,993	10.3%	$ 405,750	21.3%	38.0%	0.2%	5,247
Loop	10.5%	3.4%	4.2%	$ 81,068	22.4%	$ 387,971	12.3%	50.1%	0.2%	22,568
Lower West Side	3.0%	44.3%	13.0%	$ 34,328	18.3%	$ 285,993	29.0%	30.3%	0.0%	3,518
Mckinley Park	1.3%	31.8%	11.9%	$ 42,206	11.5%	$ 256,521	15.5%	58.5%	0.0%	3,821
Montclare	4.7%	28.4%	10.8%	$ 48,463	8.0%	$ 302,504	11.6%	62.4%	0.6%	2,968
Morgan Park	65.5%	10.9%	14.9%	$ 53,805	12.8%	$ 201,701	14.1%	75.4%	0.2%	4,730
Mount Greenwood	5.4%	4.5%	6.9%	$ 82,743	4.8%	$ 253,442	2.5%	88.2%	0.0%	1,335
Near North Side	13.2%	3.8%	5.6%	$ 73,348	17.6%	$ 459,946	15.1%	47.5%	0.1%	9,173
Near South Side	35.5%	7.1%	5.7%	$ 76,205	13.6%	$ 388,066	11.8%	53.8%	0.1%	5,454
Near West Side	35.7%	11.2%	10.7%	$ 61,064	12.2%	$ 352,069	27.5%	41.7%	0.1%	9,788
New City	31.6%	42.4%	17.4%	$ 34,613	23.3%	$ 195,803	33.9%	42.5%	0.5%	5,908
North Center	3.0%	5.4%	4.5%	$ 84,015	11.3%	$ 545,334	7.2%	52.9%	0.0%	3,054
North Lawndale	92.5%	30.4%	18.5%	$ 26,165	26.6%	$ 209,021	42.4%	26.4%	0.4%	9,406
North Park	2.7%	18.2%	7.5%	$ 53,889	6.7%	$ 374,113	11.4%	56.2%	0.8%	2,854
Norwood Park	0.5%	13.6%	7.4%	$ 66,555	3.9%	$ 353,104	5.9%	77.4%	0.2%	1,376
Oakland	93.9%	17.6%	26.6%	$ 21,506	10.2%	$ 366,031	34.1%	22.5%	0.0%	5,776
O’Hare	1.1%	11.4%	4.9%	$ 50,462	9.1%	$ 225,346	9.7%	49.3%	0.1%	4,423
Portage Park	2.2%	18.7%	10.6%	$ 52,277	9.5%	$ 324,694	14.6%	57.1%	0.2%	2,575
Pullman	84.5%	15.6%	21.0%	$ 37,144	12.2%	$ 138,865	23.9%	48.8%	0.0%	5,684
Riverdale	97.7%	24.6%	26.4%	$ 13,795	39.9%	$ 97,709	60%	15.7%	0.0%	6,709
Rogers Park	30.4%	18.4%	7.3%	$ 41,374	15.8%	$ 254,681	26.1%	31.0%	0.1%	3,673
Roseland	98.0%	17.4%	17.8%	$ 40,847	12.9%	$ 148,513	23.4%	59.6%	0.2%	7,915
South Chicago	73.9%	28.2%	17.7%	$ 32,057	21.5%	$ 149,574	31.0%	41.2%	0.0%	7,720
South Deering	59.7%	21.9%	11.8%	$ 38,482	11.2%	$ 120,362	27.0%	68.2%	0.0%	6,280
South Lawndale	14.7%	58.7%	11.5%	$ 34,014	22.3%	$ 223,179	29.5%	37.6%	0.0%	3,117
South Shore	96.9%	14.9%	17.7%	$ 28,783	23.3%	$ 205,114	31.8%	23.1%	0.1%	8,863
Uptown	20.2%	13.9%	7.9%	$ 39,028	9.0%	$ 304,175	26.9%	29.6%	0.0%	3,673
Washington Heights	96.9%	15.6%	18.3%	$ 43,559	9.9%	$ 155,628	19.3%	69.5%	0.2%	5,813
Washington Park	**98.1%**	**28.3%**	**23.2%**	**$ 24,001**	**30.7%**	**$ 176,320**	**41.6%**	**21.6%**	**0.5%**	**12,035**
West Elsdon	2.4%	39.6%	13.5%	$ 50,348	7.7%	$ 232,108	11.8%	77.0%	0.1%	3,122
West Englewood	96.3%	30.3%	34.7%	$ 27,412	24.3%	$ 117,392	41.4%	46.6%	0.1%	10,148
West Garfield Park	97.7%	26.2%	25.2%	$ 24,676	26.5%	$ 229,365	39.9%	27.5%	0.1%	9,051
West Lawn	3.4%	33.4%	7.8%	$ 47,413	6.3%	$ 218,347	18.6%	77.8%	0.4%	3,710
West Pullman	94.8%	22.6%	17.0%	$ 38,399	16.3%	$ 134,032	25.8%	64.5%	0.0%	6,745
West Ridge	10.6%	19.6%	7.9%	$ 49,447	10.8%	$ 285,661	17.5%	52.9%	0.2%	2,638
West Town	9.8%	13.4%	6.0%	$ 63,470	12.2%	$ 422,685	17.6%	40.4%	0.2%	7,019
Woodlawn	89.0%	17.9%	17.3%	$ 28,475	27.6%	$ 228,166	28.8%	27.5%	0.0%	8,797
Chicago	34.3%	20.8%	11.2%	$ 48,648	13.7%	$ 292,604	21.0%	48.1%	0.3%	5,314

Race[1]: African American, Education[2]: Less than high-school graduate, Income[3]: Median household income, Value[4]: Median house value Crime[5]: Crime/100,000 pop.

Table 19. The Number of Vacancy-related Policies/Strategies of Chicago

Variable	Livable Communities	Sustainable Food	Workforce Development	Economic Innovation	Regional Mobility	SUM
Highway	1				2	3
Vehicle Accessibility						
Mobile homes						
Vacancy rate		3				3
Housing value						
Crime						
Built year						
Ethnicity	3					3
Railroad	3				13	16
Secondary industry						
Parcel size						
Poverty	4	1	9			14
Population change						
Ownership						
Education						
Service industry				4		4
Income		1	9			10
Unemployment		1	9	2		12
Total	11	6	27	6	15	65

5. CONCLUSION & LIMITATIONS

The research model in this dissertation is designed to compare factors contributing to vacant land in growing versus shrinking cities and to develop a methodological framework to simulate vacant land changes more accurately. As noted earlier, vacant land is not only associated with shrinking, or massively depopulating, cities but also quickly growing cities. In post-industrial manufacturing cities, deindustrialization and the consequential economic downturn has led to the collapse of the housing market resulting in massive foreclosures and widespread housing vacancies throughout the country. Furthermore, vacant land and abandoned properties are recently becoming a serious problem in growing cities as well regardless of economic and population growth. Existing vacant land could lead to increased vacancies because of decreased property value and increased crime. Consequently, this can lead to an increased financial burden on local governments to maintain these properties. Thus, these conditions require a better understanding of urban vacancy patterns and methods of assessing urban conditions in shrinking as well as growing cities (Newman et al., 2016; Brophy & Vey, 2002; Kozloff, 2007).

Although many studies on urban shrinkage and vacancy conducted over the past twenty years shed light on geographical transformations and quantify its effects, they have failed to conduct longitudinal assessments and predict future spatial and temporal dynamic changes due to limited databases and the absence of modern-day technologies. As such, in order to accurately predict future urban land use patterns, LTM has been utilized to establish more accurate GIS-based land use change model targeting vacant land use patterns on a local scale.

LTM has shown that all scenarios in this study have sufficiently high accuracy outputs to merit the acceptability of predictions. Each model have acceptable Kappa scores and PCM's (40% or more) with fair to good AUC outputs (between 0.70 and 0.80). Overall, all models have high level of agreement. This project found that market conditions and economic status are the most influential variables affecting vacant land transformation when using LTM in Fort Worth while transportation systems and physical conditions such as proximity to highway and year structure was built play a larger role in shrinking cities. Therefore, different policies and strategies on vacancy should be implemented considering the unique conditions of shrinking and growing cities.

Since local housing market and socioeconomic status can significantly affect whether vacant properties can be transformed to productive urban land, policies to stabilize property values and reduce racial segregation should be considered in Fort Worth. In contrast, improving transportation systems and physical conditions should be emphasized when creating policies in Chicago. The plan quality analysis indicates that vacancy-related policies in socially vulnerable districts have a higher risk of vacancy than in non-vulnerable districts in Fort Worth. An analysis of metropolitan Chicago's comprehensive regional plan also indicates that the City of Chicago has recognized the vacancy issue and has suggested the following strategies to solve the problem: addressing the vitality of transportation system and rehabilitation of older housing stock.

Thus, when a community has a growing amount of vacant and abandoned properties that threaten neighborhood stability, planners and decision makers have a high vacancy-risk perception which results in high-quality plans that incorporate more revitalization policies.

5.1. Research Question Assessment

Sub 1. Is the LTM a feasible and reliable model for vacant land prediction?

Yes. Although LTM model has risen in popularity, some have criticized use of the model for not always being able to provide highly reliable outputs due to ineffective assessment processes (Conway, 2009). As a result, it can be difficult to calibrate the contribution of these models, making it difficult to adapt these models to local communities (Landis et al., 2011). To have an acceptable model and improve the model's reliability, it is critical to use proven assessment methods to improve model accuracy. Therefore, four different sets of metrics are considered to verify the goodness of fit of the neural network model in this research for model calibration: Kappa coefficients, percent correct metric (PCM), agreement/disagreement measures, and the relative operating characteristic. To stabilize the error level to a minimum value and get the best output, over 250,000 cycles of training sessions were run for each model and the results of four statistics were used to compare actual vacancy rates and predict vacancy rates using 10-year input patterns and input factors. Results for all comparisons of both cities yielded high enough statistics to merit the acceptability of predictions.

Sub 2. How does each factor's effect on vacant land differ between shrinking and growing cities?

Based on evidence derived from urban decline and vacant land literature, 18 different driving factors which could contribute to vacant land were selected. Each model was then developed using 14 to 18 of these factors, depending on data availability. These driving factors are categorized into five domains: employment trend, socio-economic status, household composition and housing, physical characteristic, and accessibility and transportation.

Using 2000-2010 input factors and pattern data, the influence of each variable was quantified and then the variable influence was compared between City of Chicago and City of Fort Worth. The variable influence test outputs indicate that housing market condition and accessibility such as housing value, land value and proximity to highway more strongly influence both Chicago and Fort Worth than other factors. Surprisingly, in contrast to previous literature which suggest racial and economic segregation as prominent issues in shrinking cities, most socio-economic variables such as unemployment rate, ethnicity, income and educational attainment in Chicago, a declining city, seemed to be less influential as in Fort Worth, a growing city. This may be partially due to Chicago's history of depopulation and economic downturn over the past 60 years and its current stabilization of demographic transformation and vacant land patterns in contrast to growing cities or cities that have recently experienced depopulation as a result of increasing economic, social and racial segregation and rapid demographic changes, leading to increased vacancy in vulnerable neighborhoods.

Therefore, socioeconomic variables may have had a stronger influence if this research had used data from the 1960s or 70s from Chicago. Not surprisingly, secondary industry (proportion of secondary industry to all industries) seemed to be more influential in Chicago where many existing manufacturing and construction industries have been deindustrializing in comparison to growing cities.

Sub 3. How well are the primary factors contributing to vacancy reflected in existing plans in growing and shrinking cities?

From the first subsidiary research question, the effect of each factor on model performance was quantified in both Fort Worth and Chicago. Based on the result, each city's comprehensive plan was evaluated to determine how well the primary factors contributing to vacancy are reflected in policies in vulnerable districts compared to wealthy districts. The results indicate that the cities place a greater emphasis on economy revitalization in vulnerable districts than in healthier communities. Fort Worth has 123 policies/strategies which are associated with vacant properties. Among them, 63 policies covers South East, one of the most vulnerable districts in Fort Worth, that aim to revitalize the economy and reduce vacant properties. Also, 50 of the policies in South East closely correspond to neighborhood market conditions and socioeconomic statuses such as stabilization of property value and job markets which are stronger predictors of vacant land in the City of Fort Worth. Therefore, Fort Worth seems to recognize the vacancy issue in socially and physically vulnerable districts and provide diverse policies and strategies to revitalize these areas and reduce vacant properties.

In contrast, City of Chicago does not have a city-level comprehensive plan. Rather, they have a comprehensive regional plan for the Chicago metropolitan area including 7 counties and 284 communities. Since the plan could not be evaluated at the neighborhood level, I reviewed the plan to determine how well it considers the vacancy issue at city level. The variable influence test suggests that transportation system and physical condition are the most influential variables affecting vacancy transformation in Chicago while most personal wealth related variables have marginal influence predicting vacancy in the city. However, the results show that the city makes a greater effort to improve socioeconomic status than mobility and physical characteristics. Among 65 vacancy-related policies of the regional comprehensive plan, nineteen polices strived to improve the public transit system, highway system and physical condition of structures while thirty-nine policies targeted socioeconomic status, aiming to increase income and educational attainment and decrease the unemployment rate and poverty. Therefore, to overcome the chronic vacancy issue in Chicago, they would need to create more policies to improve mobility and physical conditions of structures.

5.2. Study Limitations and Future Study

5.2.1. Study limitations

Although this study sheds light on land use change models and demonstrates that LTM may be a good resource to forecast future possible vacancy scenarios and quantify the influence of driving factors, there are limitations in this modeling process.

First, this study is focused only on Fort Worth and Chicago and the relatively small sample size may lack enough statistical power to generalize conclusions to all municipalities.

Second, definitions and measurement of vacant land differ between cities. For example, brownfields and vacant structure/housing units are classified as vacant land in both Chicago and Fort Worth. However, while Chicago includes underdevelopment/construction and vacant grassland/wetlands with more than 2.5 acres as a vacant land, Fort Worth includes only vacant agricultural, which are areas with one residential unit per structure on more than 1 acres. Since it is difficult to directly compare the vacancy changes between the cities, models performed on multiple cities can be plagued by these inconsistent classifications of vacant land. Furthermore, vacant properties are not always a negative trait of cities, and since it is impossible to account for the value of vacant properties, outputs could overlook the positive characteristics of the vacant properties such as natural resource worth.

Third, this project conducted a variable influence test to determine how each factor affects vacant land in shrinking cities and growing cities by using Kappa values and PCM. Although the statistical output was useful in ranking each variable's influence, rank differences are not equal in interval. Therefore, it might be necessary to run a statistical regression to quantify the influence degree of each factor.

Fourth, since LTM modeling is a complicated GIS and ANNs-based tool, it requires long training times for reliable outputs. As a result, it may be difficult to apply LTM when planning if one is not familiar with the program's tools and extensions.

Lastly, in terms of evaluating vacancy-related plan quality by districts, while Fort Worth provides a city-level comprehensive plan, Chicago has a regional comprehensive plan for the Chicago metropolitan region that includes 7 counties. Since the regional plan does not provide specific policies or strategies by planning district in the city of Chicago, it is difficult to determine how well the existing policies consider the socially and physically vulnerable neighborhoods.

5.2.2. Future Study

Overall, this study strived to predict future possible vacancy scenarios in a growing city and shrinking city, quantify the influence of each driving factor and provide initial solutions that can be utilized in future projects. This study has not only supported methodological frameworks of land use change models but has also explored theoretical and practical connections between planning and policy implementation.

Through spatial accuracy tests of the models, LTM has proved to be capable in targeting sites at a high risk of vacancy in current and/or potential future vacancy if a clear inventory of vacant land conditions and various types of variables are available. Policymakers can also modify driving factors of vacancy given appropriate circumstances and can interpret the simulation results with not only statistical outputs but also intuitive maps and diagrams. Therefore, it is much easier to generate roadmaps for local policy makers, developers and residents who are not familiar with economic theories and statistics.

However, this is only a starting point to understanding the overall vacant land transformation. Further research is needed to extend study areas, define key terminologies, collect better data and provide more applicable policy implications. First of all, the study area needs to be extended to other communities facing serious depopulation and deindustrialization and/or experiencing rapid growth in size/population. Second, to reduce the uncertainty of model outputs, it is necessary to improve and monitor inventory of vacant land conditions and specific data related to input factors such as parcel value or under-constructed structure data. Furthermore, this study did not examine every plan in each city but concentrated on city or regional comprehensive plans. Since the comprehensive plan is a tool used to guide overall future land use decisions, evaluating only the comprehensive plan may be not be comprehensive enough to understand a city's vacancy-related policies. If cities have small area programs or plans regarding depopulation or vacant properties such as central area revitalization plans, parks and open space plans and transportation plans, it may useful to include these in future studies.

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APPENDIX A

Appendix A. LIST OF ALL SHRINKING CITIES WITH MORE THAN 100,000 POPULATION FROM 1980 TO 2010 AND THE LARGEST POPULATION WITH PEAK YEAR

City	State	Highest Pop. (year)	1980	1990	2000	2010	Pop. Change
St. Louis	MO	856,796 (1950)	453,085	396,685	348,189	318,809	-62.8%
Detroit	MI	1,849,568 (1950)	1,203,339	1,027,974	951,270	759,340	-58.9%
Cleveland	OH	914,808 (1950)	573,822	505,616	478,403	409,221	-55.3%
Pittsburgh	PA	676,806 (1950)	423,938	369,879	334,563	308,003	-54.5%
Buffalo	NY	580,132 (1950)	357,870	328,123	292,648	266,012	-54.1%
New Orleans	LA	627,525 (1960)	557,515	496,938	484,674	295,285	-52.9%
Gary	IN	178,320 (1960)	151,953	116,646	102,746	84,407	-52.7%
Flint	MI	196,940 (1960)	159,611	140,761	124,943	107,807	-45.3%
Dayton	OH	262,332 (1960)	203,371	182,044	166,179	145,609	-44.5%
Cincinnati	OH	503,998 (1950)	385,457	364,040	331,285	300,165	-40.4%
Newark	NJ	442,337 (1930)	329,248	275,221	273,546	274,674	-37.9%
Rochester	NY	332,488 (1950)	241,741	231,636	219,773	211,977	-36.2%
Baltimore	MD	949,708 (1950)	786,775	736,014	651,154	620,538	-34.7%
Syracuse	NY	220,583 (1950)	170,105	163,860	147,306	144,734	-34.4%
Akron	OH	290,351 (1960)	237,177	223,019	217,074	202,814	-30.1%
Hartford	CT	177,397 (1950)	136,392	139,739	121,578	124,760	-29.7%
Albany	NY	134,995 (1950)	101,727	101,082	95,658	97,951	-27.4%
Philadelphia	PA	2,071,605 (1950)	1,688,210	1,585,577	1,517,550	1,504,950	-27.4%
Washington	DC	802,178 (1950)	638,333	606,900	572,059	584,400	-27.1%
Erie	PA	138,440 (1960)	119,123	108,718	103,717	101,635	-26.6%
Chicago	IL	3,620,962 (1950)	3,005,072	2,783,726	2,896,016	2,703,466	-25.3%
Macon	GA	122,423 (1970)	116,896	106,612	97,255	92,284	-24.6%
Warren	MI	179,260 (1970)	161,134	144,864	138,247	135,791	-24.2%
Toledo	OH	383,818 (1970)	354,635	332,943	313,619	291,851	-24.0%
South Bend City	IN	132,445 (1960)	109,727	105,511	107,789	102,073	-22.9%
New Haven	CT	164,443 (1950)	126,109	130,474	123,626	128,885	-21.6%
Norfolk	VA	307,951 (1970)	266,979	261,229	234,403	242,143	-21.4%
Milwaukee	WI	741,324 (1960)	636,212	628,088	596,974	589,697	-20.5%
Richmond	VA	249,621 (1970)	219,214	203,056	197,790	201,828	-19.1%
Evansville	IN	141,543 (1960)	130,496	126,272	121,582	118,186	-16.5%

Appendix A. CONTINUED.

City	State	Highest Pop. (year)	1980	1990	2000	2010	Pop. Change
Atlanta	GA	495,039 (1970)	425,022	394,017	416,474	413,462	-16.5%
Springfield	MA	174,463 (1960)	152,319	156,983	152,082	152,906	-12.4%
Lansing	MI	131,403 (1970)	130,414	127,321	119,128	115,634	-12.0%
Livonia	MI	110,109 (1970)	104,814	100,850	100,545	97,915	-11.1%
Peoria	IL	126,963 (1970)	124,160	113,504	112,936	113,853	-10.3%
Savannah	GA	149,245 (1960)	141,390	137,560	131,510	134,348	-10.0%
Shreveport	LA	206,989 (1980)	205,820	198,525	200,145	198,477	-4.1%
Grand Rapids	MI	197,649 (1970)	181,843	189,126	197,800	190,441	-3.6%
Mobile	AL	202,779 (1960)	200,452	196,278	198,915	195,619	-3.5%
Chattanooga	TN	169,514 (1980)	169,565	152,466	155,554	164,481	-3.0%

APPENDIX B

Appendix B. LIST OF THE 62 CITIES WITH OVER 250,000 POPULATION IN 2000 WITH POPULATION CHANGE AND SOCIO-ECONOMIC STATUS

City	State	Pop. Change	Vacancy (%)	Poverty (%)	Unemploy. (%)	Minority (%)	Manufact. (%)	Income ($)
Raleigh	NC	46.3%	10.0%	14.6%	7.1%	41.0%	14.5%	52,219
Fort Worth	TX	38.6%	10.9%	17.0%	8.1%	37.4%	21.0%	49,530
Charlotte	NC	35.2%	9.6%	13.9%	9.2%	46.7%	15.6%	52,446
Las Vegas	NV	22.0%	13.0%	13.1%	9.8%	29.8%	13.5%	54,334
Albuquerque	NM	21.7%	7.5%	15.7%	6.3%	31.4%	13.6%	46,662
Austin	TX	20.4%	8.4%	18.4%	6.5%	33.6%	17.3%	50,520
Riverside	CA	19.1%	8.3%	14.9%	10.6%	37.9%	20.8%	56,991
Aurora	CO	17.6%	8.1%	16.7%	7.7%	33.1%	15.6%	49,515
San Antonio	TX	16.0%	10.0%	18.9%	7.1%	28.9%	14.3%	43,152
Fresno	CA	15.7%	7.6%	24.9%	12.4%	45.8%	13.7%	43,124
Colorado Springs	CO	15.4%	8.7%	11.8%	7.6%	20.0%	14.9%	53,074
El Paso	TX	15.2%	7.8%	24.1%	7.2%	21.8%	14.4%	37,428
Sacramento	CA	14.6%	8.9%	17.3%	11.4%	50.5%	11.4%	50,267
Oklahoma City	OK	14.6%	12.4%	16.6%	6.4%	33.9%	15.5%	43,798
Lexington-Fayette	KY	13.5%	9.0%	17.4%	6.3%	22.8%	14.5%	47,469
Jacksonville	FL	11.7%	13.9%	14.3%	8.8%	39.2%	14.0%	48,829
Wichita	KS	11.1%	9.7%	15.6%	8.4%	27.0%	27.6%	44,360
Mesa	AZ	10.8%	14.5%	11.9%	6.9%	16.0%	19.4%	50,079
Tampa	FL	10.6%	14.3%	19.5%	9.9%	35.0%	12.5%	43,117
Columbus	OH	10.6%	14.0%	21.4%	8.9%	36.6%	11.7%	43,122
Portland	OR	10.3%	6.8%	16.3%	8.8%	22.5%	14.7%	48,831
Miami	FL	10.2%	18.1%	27.3%	8.9%	27.2%	17.6%	29,621
Corpus Christi	TX	10.0%	10.8%	18.8%	8.0%	18.2%	14.2%	43,457
Arlington	TX	9.8%	9.3%	14.3%	8.1%	37.6%	19.7%	52,094
Phoenix	AZ	9.4%	13.1%	19.1%	7.4%	22.5%	18.4%	48,823
Denver	CO	8.2%	9.6%	19.2%	7.8%	27.1%	13.1%	45,501
Seattle	WA	8.0%	7.3%	12.7%	6.3%	29.5%	11.7%	60,665
Houston	TX	7.5%	14.0%	21.0%	8.0%	45.2%	20.1%	42,962
San Diego	CA	6.9%	7.8%	14.1%	7.3%	34.1%	14.4%	62,480
Tucson	AZ	6.9%	11.0%	21.3%	8.6%	27.9%	14.5%	37,025

Appendix B. CONTINUED.

City	State	Pop. Change	Vacancy (%)	Poverty (%)	Unemploy. (%)	Minority (%)	Manufact. (%)	Income ($)
San Jose	CA	5.7%	4.4%	10.8%	8.7%	52.9%	26.4%	79,405
Washington	DC	5.2%	12.3%	18.5%	9.4%	61.9%	4.2%	58,526
Omaha	NE	4.9%	8.4%	15.3%	6.9%	23.9%	15.5%	46,230
Boston	MA	4.8%	9.1%	21.2%	9.3%	46.1%	8.1%	50,684
Kansas City	MO	4.1%	14.1%	18.1%	9.2%	39.5%	14.6%	44,113
San Francisco	CA	3.7%	9.8%	11.9%	7.1%	48.4%	10.2%	71,304
Virginia Beach	VA	3.0%	7.0%	6.8%	5.3%	30.6%	13.7%	64,618
Los Angeles	CA	2.6%	6.7%	19.5%	9.1%	49.4%	16.5%	49,138
Anaheim	CA	2.5%	5.5%	13.7%	9.6%	39.6%	23.9%	57,807
New York	NY	2.1%	8.9%	19.1%	8.8%	55.8%	9.6%	50,285
Newark	NJ	1.3%	15.6%	25.0%	14.3%	74.1%	18.2%	35,659
Atlanta	GA	0.8%	20.7%	22.6%	9.9%	61.8%	10.4%	45,171
Dallas	TX	0.8%	12.8%	22.3%	8.2%	45.6%	20.2%	41,682
Philadelphia	PA	0.6%	14.1%	25.1%	12.6%	58.6%	11.9%	36,251
Long Beach	CA	0.2%	7.9%	19.1%	10.1%	52.2%	16.9%	51,173
Minneapolis	MN	0.0%	8.8%	22.7%	9.0%	31.8%	11.8%	46,075
Tulsa	OK	-0.3%	11.1%	19.3%	7.0%	32.6%	18.4%	39,289
Milwaukee	WI	-0.4%	10.6%	26.3%	11.6%	53.4%	19.2%	35,921
Memphis	TN	-0.5%	16.7%	25.4%	12.5%	68.7%	14.4%	36,473
St. Paul	MN	-0.7%	8.0%	22.0%	9.0%	37.2%	14.3%	45,439
Oakland	CA	-2.2%	10.9%	18.7%	10.1%	62.3%	13.6%	49,721
Santa Ana	CA	-4.0%	4.4%	17.9%	9.3%	56.2%	28.0%	54,877
Baltimore	MD	-4.6%	19.6%	21.3%	11.5%	70.0%	11.2%	39,386
Chicago	IL	-6.9%	13.8%	20.9%	11.1%	57.3%	14.9%	46,877
St. Louis	MO	-8.3%	20.3%	26.0%	12.7%	55.9%	13.1%	33,652
Toledo	OH	-8.4%	14.0%	23.8%	15.0%	33.5%	19.0%	34,260
Pittsburgh	PA	-8.6%	16.0%	21.9%	8.6%	33.5%	8.8%	36,019
Cincinnati	OH	-10.4%	20.8%	27.2%	10.7%	49.3%	15.2%	33,681
Buffalo	NY	-10.7%	18.9%	29.6%	12.4%	48.2%	13.1%	30,043
Cleveland	OH	-17.1%	21.3%	31.2%	17.8%	59.8%	17.7%	27,349
Detroit	MI	-25.0%	25.8%	34.5%	24.8%	89.4%	17.0%	28,357

Pop. Change: population change from 2000 to 2010, Unemploy.: Unemployment rate, Manufact.: Manufacturing industry rate