ADVANCING PSS WITH COMPLEX URBAN SYSTEMS SCIENCES AND SCALABLE SPATIO-TEMPORAL MODELS

BY

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DISSERTATION

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ABSTRACT

Planning Support System (PSS) with a core of dynamic spatio-temporal model has been developed as analytical and information tools to aid and inform urban planning processes. However, scholarly communities identify that PSS has yet been popularized in planning practices, and not fully capable of meeting the challenge of understanding complex urban environments. I am dedicated to investigate and break through the bottlenecks of PSS with my experiences with University of Illinois Landuse Evolution and Impact Assessment Model (LEAM) PSS, which exemplify a PSS that that aid the process of collaboratively building spatio-temporal scenario models and transferring the knowledge to planning practitioners.

I explore the future applications of PSS including Smart Cities, sentience, resilience, and environmental planning processes and their role in improving PSS usefulness in the practice of planning. PSS improvements will be presented in terms of multi-directional spatio-temporal processes and scenario planning. Moreover, I will address the process of transferring knowledge to users on model validity and 'goodness-of-fit' in real world planning applications.

Beyond the traditional theoretical framework of PSS, the emerging Complex Urban System Sciences (CUS) challenge the core assumptions of spatial models of PSS, and pose opportunities for updating current PSS approaches into scalable spatio-temporal model that adheres to CUS principles. I will analyze this potential infusion by examining next generation PSSs within a framework of current CUS theories and advancement in statistical and computational methods. Case studies involved in my dissertation include LEAM PSS' applications in McHenry County (IL), Peoria (IL), Chicago (IL), and St. Louis (MO).

The final part of this dissertation highlights my contributions to the existing CUS theories. I will demonstrates how evidence from empirical applications can contribute to CUS theory itself. I will show how CUS can challenge the core assumptions of "distance to CBD" models that economists use to characterize urban structure and land-use.

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TABLE OF CONTENTS

CHAPTER ONE: INTRODUCTION…………………………………………………………….1

CHAPTER TWO: PSS APPLICATIONS IN URBAN PLANNING…………………………….8

CHAPTER THREE: THE ROLE OF MULTIDIRECTIONAL TEMPORAL ANALYSIS IN SCENARIO PLANNING EXERCISES AND PLANNING SUPPORT SYSTEMS……..........46

CHAPTER FOUR: KNOWLEDGE FLOW OF PLANNING SUPPORT SYSTEMS (PSSS) INTO PLANNING PRACTICES: A POST-MORTEM CASE STUDY OF LEAM PSS IN MCHENRY COUNTY, IL…………………………………………………………………70

CHAPTER FIVE: MODELING LAND-USE CHANGE IN COMPLEX URBAN ENVIRONMENTS……………………………………………………………………………91

CHAPTER SIX: A REASSESSMENT OF URBAN LAND-USE STRUCTURE AND LAND-USE PATTERNS: CBD OR NETWORK-BASED? — EVIDENCE FROM CHICAGO…….112

CHAPTER SEVEN: CONCLUSIONS, DISCUSSIONS, AND FUTURE WORKS………….136

REFERENCES…………………………………………………………………………140

CHAPTER 1: INTRODUCTION

1.1 OVERVIEW

Planning practitioners are constantly challenged with anticipating the potential consequences of proposed policy and investment choices. This is a difficult task. In fact, examples abound of urban planning problems that have resulted from the unintended consequences of seemingly reasonable urban development policies (Bristol, 1991; Deal & Pallathucheril, 2009; Deal & Schunk, 2004). Some of these problems can partly be addressed with the use of what Batty described as “geo-information-technology based instruments” (Batty, 1995, p574), more commonly referred to as Planning Support Systems or PSSs (Brail & Klostermann, 2001; Geertman & Stillwell, 2004). A PSS brings together base data, analysis engines (models), and information delivery systems (visualization interfaces) to provide planners and communities with critical knowledge of various dynamic systems and provide visual data interfaces in order to facilitate communicative planning approaches (Brail, 2008; Brail & Klostermann, 2001; Deal & Pallathucheril, 2008; S. Geertman & Stillwell, 2003; Geertman et al., 2013).

In typical Planning Support System (PSS) toolboxes, land-use change models and visualization devices are often used to inform planning and decision making by simulating possible future land-use outcomes, such as how land-uses might evolve in a specific place over a specific period of time—and in some cases what impacts these changes might elicit (Sun et al., 2009). The ability to forecast into the future has proven useful in scenario planning and some other planning exercises (Chakraborty et al., 2011; Couclelis, 2005); As the scholarship that surrounds PSS technologies becomes more mature (and computing power continues to advance), the ways in which these tools might be made more useful (i.e., more accessible) and endemic to the planning process has become a more central concern (Saarloos et al., 2008; te Brömmelstroet, 2013; Vonk et al., 2005).

PSS scholars have argued for some time that PSSs need to be “softer”, more flexible, transparent, and capable of addressing a wide range of planning process and practice issues (Batty, 2007; Deal & Pallathucheril, 2009; Klostermann, 1997; te Brömmelstroet, 2010; 2012; Vonk & Geertman, 2008). Because PSS is an immature technology, there has been a necessary but singular focus on geo-information tools and technology development in the past. This resulted in PSSs that were perceived to be too complex, inflexible, and incapable of assisting in practical planning tasks (Vonk & Geertman, 2008; Vonk et al., 2005). Other identified bottlenecks to PSS practicality and usefulness include: a) model-to-user communication deficiencies (Deal & Pallathucheril, 2009; Deal & Pan, 2016; Geertman & Stillwell, 2004; Pelzer et al., 2014; Saarloos et al., 2008; te Brömmelstroet, 2010, 2012, 2013; Vonk & Geertman, 2008; Vonk et al., 2005; Vonk et al., 2006); b) model validity and trustworthiness (Geertman & Stillwell, 2004; Klosterman & Pettit, 2005; Pelizaro et al., 2009; Shiffer et al., 2001; Shiffer, 1995; te Brömmelstroet, 2013); c) collaborative planning (Deal & Pan, 2016; Klosterman & Pettit, 2005; Klostermann, 1997; Pettit, 2005; te Brömmelstroet, 2010), d) encouraging mutual learning (Pelzer et al., 2014; te Brömmelstroet, 2012; Vonk & Geertman, 2008), and e) actively enabling user feedback (Deal & Pallathucheril, 2009; Deal & Pan, 2016; Pelzer et al., 2014; te Brömmelstroet, 2012). Chapter 2 will be focused on refining those bottlenecks based on my research experiences on PSS. Chapter 3 and Chapter 4 will address some of the challenges identified.

Technological challenges also persist. Some concern on how PSSs can help us respond to new planning paradigms such as sustainable planning (Deal & Pan, 2016), smart cities (Deal et al., 2015), resilience and technological sentience (Deal et al., 2017b). Other challenges include the incorporation of geographical agent systems, spatial-temporal database, semi-parametric spatial-temporal models, high-performance statistical learning, and parallelism among others (Deal et al., 2018), the intelligent use of human mobility and social network data (Deal et al., 2018), and the inclusion of new theoretical structures (e.g. Complex Urban Systems).

Randomness, non-linearity, and inconsistency across scales have been found to characterize both inter- and intra- urban-system interactions (Batty, 2012; Bettencourt, 2013; Bettencourt et al., 2007; Bonner, 2011). These and other discoveries have helped define a new science of cities–Complex Urban Systems (CUS) (Batty, 2013). This new approach to analyzing urban structure allows researchers to look at both the macro *and* micro-dynamics within urban systems. It also encourages PSSs to evolve to contribute empirical evidence to the science of CUS, and to the methodologies that can demystify CUS for practical planning applications.

My research concerns the future directions of PSSs (with a core of spatio-temporal models), with a particular interest in the practicality and usefulness in PSS applications including new methodologies and theoretical structures. In the process, I will focus on how emerging CUS science can be seen as both a challenge and an opportunity for spatio-temporal PSS models. My research will also demonstrate how the development and deployment of practical PSSs might contribute to CUS theories and methods.

1.2 DISSERTATION STRUCTURE AND RESEARCH METHODS

I begin this dissertation by defining PSSs and their core models that shape the scope of this research. Next, I explore the existing PSS literature based on my experience with University of Illinois Landuse Evolution and Impact Assessment Model (LEAM) modeling platform. I focus on Smart Cities, sentience, resilience, and environmental planning processes and their role in improving PSS usefulness in planning. I then address PSS improvements in terms of multi-directional spatio-temporal processes and scenario planning. I also address questions of model validity and 'goodness-of-fit' in real world planning applications. I lay out possible PSS evolutions in terms of the emerging CUS sciences and demonstrate how my empirical work on PSS implementation can be used to help solve methodological and theoretical questions posed by CUS theories. I conclude with a short discussion of my findings and contributions to the field of planning.

This dissertation answers the following research questions:

Question 1: How can be PSSs made more useful to planning?

Question 2: How to improve scenario planning practices with multi-directional temporal PSS?

Question 3: How to transfer goodness-of-fit into credibility of PSS model to users? (Paper 3, model and empirical results)

Question4: What evolutions of PSS models are needed to better fit CUS theories and methodologies?

Questions 5: What methodological and theoretical questions of CUS can be answered by empirical research of CUS models?

- *Hypothesis 5.1*: A network-based urban system describes activities in cities better than a "distance to CBD" model of city structure and land-use economics.

1.3 DEFINITIONS AND KEY TERMS

In this section, I define the key terms of my research: 1) Planning Support Systems (PSSs) and 2) its scalable spatio-temporal model that originates from land-use change models.

PSS has a range of definitions. Harris (1989) defines PSS broadly – as computer-based methods and models to support spatial planning. Harris and Batty (1993) define PSS by its function: it records, stores, and presents geographic information. Klostermann (1997) defines PSS as tools that facilitate collective design, with a heart of GIS. Klosterman (1999) created an early prototype of PSS—WhatIf? PSS, that uses GIS data to support community-based collaborative planning processes and decision making, with a range of spatial tools that include land suitability analysis, projecting future land-use demands, and allocating the projected demands. Waddell (2002) describes a PSS (UrbanSim) which is an integration of a spatial aggregation model, an input-output model, and a GIS-based model. Sun et al. (2009) describe a PSS (LEAM) that uses a dynamic spatial modeling engine.

In this research, my case studies and applications use LEAM PSS. Thus, the definition of 'PSS' in my research is tools that aid the process of collaboratively building spatio-temporal scenario models and transferring the knowledge to users (including planners, local stakeholders, and policy makers). Specifically, the PSS model in my research stems from the origin of future land-use change models (White & Engelen, 1994). Inspired by Vonk et al.'s 6 classifications of PSS functions (Vonk et al., 2007), the PSS in my research includes: (1) information visualization (portal.leam.illinois.edu website), (2) information communication (applying PSSs in planning practices), and (3) system modeling (spatio-temporal model). The general scope of PSS and my dissertation structure is shown below (**figure 1)**.

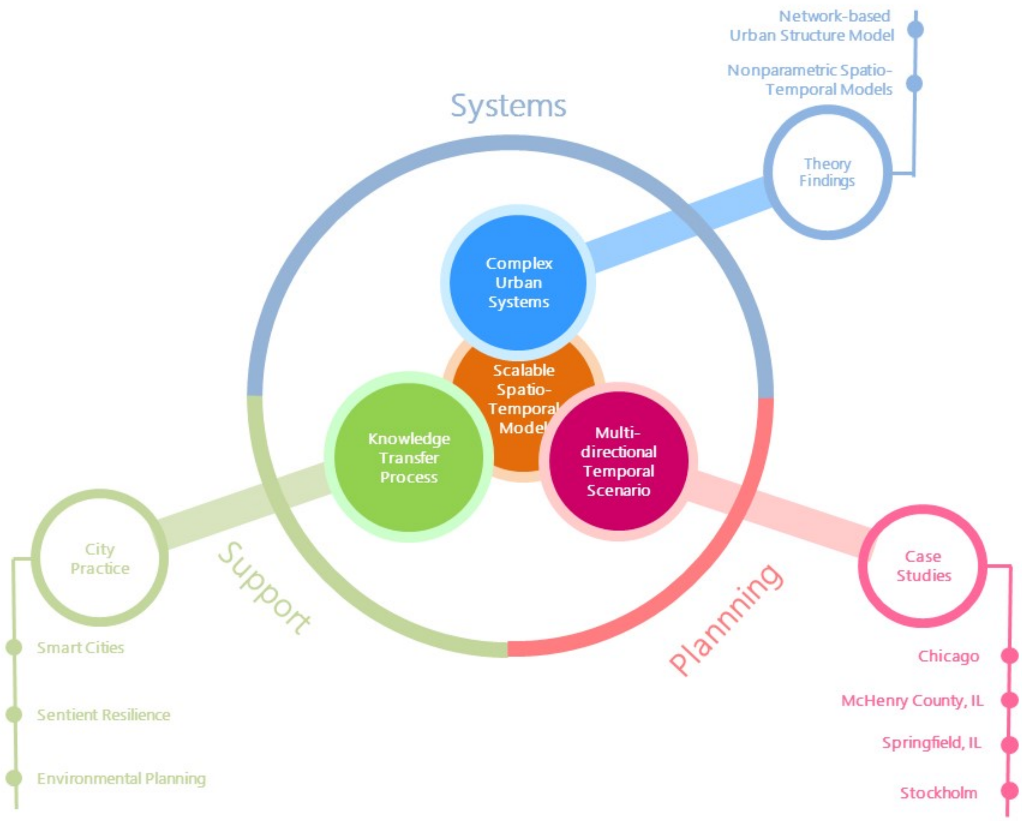

Figure 1 shows the scope of PSS, and how each part relates to my research. The orange circle represents the core of the PSS model that I use in my dissertation - scalable spatial temporal models. The green circle represents the PSS model's connection to urban planning and developmental practices such as knowledge transfer processes, applications in Smart Cities, sentience and resilience planning, and environmental planning processes (my second and fourth chapters). The red circle shows represents the technique to apply spatial model simulations to planning techniques (i.e., scenario planning) with multi-directional temporal analysis (my third chapter). The blue circle represents how the reach of traditional PSS is extended through emerging CUS theories and methods.

The modeling core of PSS in my research stems from land-use or land-cover change models, whose original definition is linking observations at a range of spatial and temporal scales to empirical models for understanding land-use/cover change (Turner et al., 1995). In my research, expansions of this prototype model include modeling a range of events (not just land-use change in urban environments) and enabling multi-dimensional temporal analysis (not just forecasting).

1.4 SUMMARY OF CHAPTERS

Chapter Two focuses on practical applications of PSSs, especially my personal experience with the LEAM PSS. Research on the barriers of PSS in real-world planning applications is well documented. I claim that the wide adoption of PSS also relies on their ability to fit into current and future urban planning and development practices, including "Smart City" projects, sentient systems, urban resilience, and sustainable planning. LEAM and other PSS case studies will be presented and analyzed to consider the direction of needed PSS improvements.

In **Chapter Three** I develop a multi-directional temporal PSS process that improves the salience of PSSs in scenario planning exercises. I apply ideas of *forecasting*, *backcasting*, and *recasting* in a comprehensive planning process that took place in McHenry County, IL in 2006. I consider the model used and the subsequent plan 10 years after the plan is enacted.

Chapter Four proposes a knowledge transfer process for PSS technologies. It attempts to show how modelers can help users of PSS understand the models and their usefulness in practice through a 'goodness-of-fit' analytical process that is easy to perform and understand. I use a *post-mortem* model review process to argue my point.

In **Chapter Five** I introduce emerging CUS science and the challenges and opportunities that it presents to the PSS scholarly community. A number of theoretical and methodological changes will be listed to update current PSS approaches into scalable spatio-temporal models that adhere to CUS principles.

Chapter Six demonstrates how using CUS based PSS techniques in empirical applications can contribute to CUS theory itself. I use the Chicago metropolitan area as a case study. I show how CUS can challenge the core assumptions of "distance to CBD" models that economists use to characterize urban structure and land-use. A stochastic greedy algorithm (SGD) is created to measure network connectivity from places to places in Chicago.

In **Chapter Seven**, I summarize key findings and contributions. I then discuss the future direction of PSS and CUS research, with a particular emphasis on their limitations. This leads to a discussion of my future research.

1.5 PUBLICATIONS FROM THIS DISSERTATION

Chapters Two through **Six** are based on my published or submitted papers co-authored with Prof. Brian Deal, listed as below:

Chapter Two:

- Deal, B., and Pan, H. (corresponding) (2016). Discerning and Addressing Environmental Failures in Policy Scenarios Using Planning Support System (PSS) Technologies. *Sustainability*, 9(1): 13.
- Deal, B., Pan, H., Pallathucheril, V., Fulton, G. (2017).Urban Resilience and Planning Support Systems: The Need for Sentience. *Journal of Urban Technology*, 24(1): 29-45
- Deal, B., Pallathucheril, V., Kim, Y., and Pan, H. (2015). Sentient PSS for Smart Cities in *Planning Support Systems and Smart Cities* eds Geertman, S., Ferreira, Jr. J., Goodspeed, et al.: 281-296

Chapter Three:

- Deal, B., Pan, H., Timm, S. and Pallathucheril, V. (2017). The Role of Multidirectional Temporal Analysis in Scenario Planning Exercises and Planning Support Systems. *Computers, Environment and Urban Systems*, 64: 91-102.

Chapter Four:

- Pan, H. and Deal, B. (Working Paper).Knowledge Flow of Planning Support Systems (PSSs) into Planning Practices: A Post-Mortem Case Study of LEAM PSS in McHenry County, IL.

Chapter Five:

- Deal, B., Pan, H., and Zhuang, Y. (2018) Land-Use Change Models in Complex Urban Systems *in Comprehensive Geographic Information Systems* eds Bareth, G., and Song, Y.

Chapter Six:

- Pan, H., Deal, B, and Chen, Y. (Working Paper). A Reassessment of urban land-use structure and land-use patterns: distance to CBD or network-based? —Evidence from Chicago

CHAPTER 2: PSS APPLICATIONS IN URBAN PLANNING

2.1 OVERVIEW

In this chapter, I focus on applications of PSS in planning practices and their role in future models of urban development. This chapter is based on my experience in developing and using the University of Illinois' LEAM PSS for different places.

In **Section 2.2**, I discuss how future trends of urban development, including smart and resilient cities, need updated PSSs to facilitate information monitoring and collaborative decision-making in developmental processes. **Section 2.3** focuses on the planning process. How can PSS potentially enhance environmental planning processes? In **Section 2.4**, I list key features of PSSs that need to be developed to answer the needs of an updated PSS.

2.2 PSS IN FUTURE TRENDS OF URBAN PLANNING

2.2.1 Smart Cities

Although not new, the term Smart City has evolved over the last decade into a popular and perhaps overused phrase in the urban lexicon (Caragliu et al., 2011). Poole (2014) observes that the term generally implies a manifestation of "the internet of things" at an urban scale, predicated on "ubiquitous wireless broadband and the embedding of computerized sensors into the urban fabric." He also notes that "big technology, engineering and consulting companies" (most notably IBM and Cisco) have been the most energetic in promoting the term in the hope of profiting from big municipal contracts. Many consider the basic vision of a smart city as a *wired* (Kitchin, 2014), *sensor-filled* (Hancke et al., 2013), *tech-heavy* (Lee et al., 2008), "*technolopolis*" (Gibson et al., 1992), that uses sophisticated computing techniques to transform the city into an *intelligent machine* (Hall et al. 2000; Humphries 2013) as fatally flawed. In this world view the *user* does not have a place in the system. This limits its relevance to urban planning and urban management, which privilege consultation and participatory processes. Smart city proponents have not demonstrated if and how citizen voices can be heard in smart ways (Poole, 2014). Greenfield (2013) agrees: "The notion of the smart city in its full contemporary form appears to have originated (without) any party, group or individual recognized for their contributions to the theory or practice of urban planning."

In contrast, other new technologies appear to be paying more rather than less attention to end-users. Smart phones and other hand-held devices with apps directed at the user experience are changing the computing landscape. A majority of all internet traffic is now taking place on mobile devices (Lella & Lipsman, 2014). Hopper (2000) describes this as a movement toward computational environments that are “more responsive and useful with more direct connections to users” within their own physical world. He suggests these systems display a degree of ‘sentience,’ a greater awareness of space, time, context, and user experience. Although sentience is not yet a part of the smart city discourse, an ability to gather information from a particular context in terms of space and time through sensor technologies is a key part of the smart city movement.

The computational basis for smart city approaches has been focused on urban data acquisition techniques, data structures and communication protocols, real-time analysis, and some short-term projection capabilities. This focus ignores the connection to longer time-frame analysis critical to urban planning. Planning support systems can and must help bridge this gap. In this chapter I examine the connection between smart cities, sentience, and the relationship to PSS. I do this by briefly examining the notion of sentience from a computing perspective. I then introduce PSS technologies and describe ways in which a sentient PSS might evolve. To describe the features might be included in such a system, I explore how the current LEAM PSS (Deal and Pallathucheril 2009a; Deal et al., 2017) would need to evolve in order to manifest sentience. We conclude with a discussion on potential drawbacks and paths forward.

Sentient computing systems are described as computational environments that respond to evolving or changing environmental conditions. They are considered one pathway toward ubiquitous or pervasive computing, an advanced concept where computing and computational services are available everywhere, anywhere, all of the time (Saha & Mukherjee, 2003). Hopper (2000) uses the term “sentient computing” to suggest computational environments that are made more responsive and useful by more direct connections to users and to the physical world.

Context Awareness and Adaptability

Schilit of Google Research (the creator of one of the first system infrastructures for location-aware mobile computers while at Xerox PARC) suggests that “context-aware computing applications” do not occur at a single location in a single context, as in desktop computing, but rather span a multitude of situations and locations. He notes that this form of computing is much broader than mobile computing because it concerns mobile people not just mobile computers (Shilit et al., 1994). Harter et al. (1999) add that “a persistent distributed object system” is one of the most important features of a context-aware system and describe an early prototype of an application as ‘sentient’ because it knows the location of users and equipment, the capabilities of the equipment, and the networking infrastructure needed to perform certain tasks. More recently, Henricksen et al. (2006) argue that context-aware computing systems require infrastructure to gather, manage, and disseminate contextual information to applications.

Hewlett-Packard's *nomadic computing* is one early approach to developing a context-aware computing framework (Kindberg & Barton, 2001). In the HP model, every entity has a web representation that includes both static attributes (such as names and locations) and dynamic attributes (in terms of its space and time context). The nomadic framework updates the information associated with the entity and its surroundings as the entity moves through space and time. It is generally intended to support users of wireless, handheld devices interacting with their environment. For example, a user's handheld device automatically displays information about the room into which the user has just entered or the projector in the room projects a presentation file that is on a device carried by the user. In HP's *Cooltown Project*, the nomadic framework has been applied to a virtual city (Kindberg & Barton, 2001) in which entities in the model include people, places and things connected to an urban setting. The computing system "knows" real-time human perceptions of their physical environmental for the whole population (Abdelzaher et al., 2004). All the information is retrievable from a URL associated with the entity.

More common examples include: a tablet computer switching its screen orientation, maps orienting themselves with the user's position or adapting the zoom level in response to the user's speed of travel, and a smart phone adjusting the screen's backlight in response to changing ambient light levels. Although simple, these examples represent strides in context-aware applications. In contrast to traditional approaches, these applications are not designed for a single or a limited set of user contextual experiences; they are designed for a broad range of potential computer-user interactions. It is not just a matter of making sense of data but using the data to predict what a user is likely to want or need and being prepared to satisfy that need.

Interaction with Users

A sentient computing system's ability to sense objects and adapt to change is not limited to its relation to the physical environment. The system is also expected to adjust itself to user behaviors, facilitating smooth user experiences and presenting easily interpreted information through advanced visualization techniques.

Addlesee et al. (2001) point out the importance of user perception in a sentient system: "a sentient computing system doesn't need to be intelligent or capable of forming new concepts about the world—it only needs to act as though its perceptions duplicate the users' [perceptions]." He also notes that one solution involves creating devices and applications that appear to cooperate with users, reacting as though they are aware of the context and manner in which they are being used, and reconfiguring themselves appropriately. Harter et al. (1999) suggest that the ultimate justification and test of sentient computing will be its capacity to deliver benefits to users; enabling them to interface directly with devices and express complex issues in a simple way.

The University of Washington's Portolano project is an early example (Esler et al., 1999). It emphasized invisible, intent-based computing, which infers user intentions via their actions in the environment and their interactions with everyday objects. A user turns on a device (an e-reader) on one network and seamlessly picks up where she left off using another device (a different e-reader) on another network. Project devices are so highly optimized to particular tasks that they blend into the world and require little technical knowledge (Saha & Mukherjee, 2003). The project was part of a DOD DARPA sponsored effort to make computing an integral part of manufacturing.

Another early adopter in sentient user interactions was the AT&T Laboratories Cambridge (AT&T Laboratories Cambridge, 2001). Their stated goal was to "create devices and applications that appear to cooperate with users, reacting as though they are aware of the context and manner in which they are being used, and reconfiguring themselves appropriately."

The AT&T system used sensors to update a model of the real world in terms of object positions, descriptions, and state in a way familiar to the user so that "the model describes the world much as users themselves would." They used the model to write programs that reacted to changes in the environment according to the user's preferences. They referred to this as sentient computing, "because the applications appear to share the user's perception of the environment."

A sentient computer system that interacts with users in a way that understands the social characteristics of users is a step closer to understanding the users' physical environment and real-time emotions. In his description of "social computing," Dourish (2001) calls for an interface design that "recognizes that the systems we use are embedded in systems of social meaning, fluid and negotiated between us and the other people around us."

Ubiquitous or ambient computing are more recent and related terms. They represent a vision for computing that is "everywhere all the time." One example is the Google House project which attempts to integrate ubiquitous sensing/computing networks with handheld user-interfaces (Cabitza et al., 2014). Google apps and technologies in general are moving in this direction. Google Now can exchange data with the Google platform in order to personalize the user experience. The recent purchase of the Nest thermostat system by Google begins to tie these entertainment-oriented systems to building controls and human comfort.

Proponents of smart cities have focused on real-time data acquisition from ever expanding sensor networks and the information and communication (ICT) infrastructure that facilitates use of these data (Giffinger & Gudrun, 2010; Kloeckl et al., 2012; Hancke et al., 2013). The question is: how do we make use of the data available in ways that support planning and decision-making? Kitchin (2014) notes that “the production of sophisticated data analytics for understanding, monitoring, regulating and planning the city,” is critical for realizing smart city goals. Currently however, the value of these data in thinking about future, planning, or using plans to make decisions has been largely overlooked.

Connections to socio-physical systems

Sentient computing system terminology has been adopted into the socio-physical systems lexicon, although at this point in very informal and limited ways. A description of ‘sentient buildings’ is an early example. Wu et al. (2004) describe sentient building systems as context-aware, autonomous, decentralized, proactive, adaptable, and dependable, with real-time guarantees. Mahdavi et al. (2001) describe self-aware buildings (closely related to sentient buildings, as buildings with modular, distributed, flexible, and scalable information collection infrastructure; advanced building information systems; and intuitive, flexible, and organized interface between building operation systems and users (Mahdavi et al., 2001; 2004).

In most descriptions of sentient building systems, sensors (temperature, humidity, CO_2, occupancy, and daylight) are deployed in different areas of the buildings. These sensors act as a continuous monitoring and data collection infrastructure. They typically use building automation and computing systems to identify patterns from past data and simulate future control curves for controlling fans and valves. Like sentient computing systems these systems are context-aware and sensitive to users’ needs: they attend to building user comfort, they turn on lights when users enter a new space, and they regulate fresh air when many people collect in one area. These systems can also be proactive: data from real-time building conditions and user input automatically update future control curves. For example, if users consistently override temperature settings, the system adjusts future settings to reflect the desired change. In many cases, real-time building performance data are sent to a dashboard-type system to present current building system states and to expose control failures for building managers. New dashboard aggregations are also being used to provide some level of building performance feedback to users who lack mechanical system training.

2.2.2 Sentient Resilient Cities

Holling (1973) defined resilience in ecological systems as a capacity to tolerate disturbance without collapsing into a qualitatively different state. Resilient socio–physical systems might also include a capacity for innovation in a major disturbance-fueled response (Folke, 2006). Other descriptions of socio-physical systems resilience include concepts of non-linear dynamics, thresholds, uncertainty, redundancy, diversity, and interdependence, among others (Holling et al., 2001; Berkes et al., 2008). The difficulties inherent in determining some common parameters for urban systems resilience has made its achievement a complex undertaking (Godschalk, 2003; Wilson & Piper, 2010; Davoudi & Porter, 2012). In fact, some research has suggested that the intricacies of urban systems and our limited cognitive ability to understand them, have been the main challenges to achieving urban resilience (Comfort et al., 2001; Fraser et al., 2003; Batty, 2013).

According to Norberg and Cumming (2008), achieving resilient places requires a type of planning that a) continuously monitor the (current and potential future) state of various interdependent systems, b) is prepared to adapt to potential state changes, and c) govern these systems in inclusive ways. I argue that this approach to planning calls for PSSs that: embrace complexity, identify change, understand scale, identify options, and help support critical decisions. In the field of computational sciences these are characteristics of sentient systems, systems that are aware of the world around them and adapt accordingly. Can information systems that facilitate plan-making and city administration be made sentient?

In this section I explore the potential for a new generation of *sentient* PSSs. I consider the ability to collect continuous and diverse data, the ability to iteratively learn from the data, and the ability to transform the data into useful and relevant contextualized information to be critical components in planning for and building more resilient communities. I use the term sentience to represent an ability to collect, process, learn, contextualize, and present locally significant information. However, merely collecting or presenting voluminous amounts of data is not sufficient. Smart information systems are desperately needed to manipulate these big data into information useful to a variety of individuals in a planning process. I PSS to represent the smart information systems needed to translate sentience into a planning framework. I use PSSs as information technologies that help us understand, manage, and plan complex urban systems (Brail & Klostermann, 2001; Geertman & Stillwell, 2003; Brail, 2008; Geertman et al., 2013). These conceptualizations (sentience and planning support) are used to consider how intelligent or sentient planning support systems promote more strategic, context-aware, resilient, and ultimately sustainable communities; what primary design considerations would make such a PSS possible and useful.

I make my case for more sentient PSSs by first briefly examining the concept of urban resilience and its link to urban planning. This helps lead to the notion of sentience. I then frame sentience from a computing perspective and present examples of emerging sentient computing and sensory monitoring applications from socio-ecological and socio-physical perspectives. I then sketch out ways a PSS might acquire sentience. I conclude by considering how this technological advancement might come about by looking at related activities in information delivery and the potential challenges to the development of sentient planning support systems.

Urban Resilience and Planning

Norberg and Cumming (2008) describe “embracing complexity” as one of the important challenges to planning for resilience in a socio-physical (urban) systems context. Liu et al. (2007) cite failures in urban growth management to illustrate that complexities in coupled human and natural systems can trigger counterproductive policy outcomes (e.g., some urban growth policies eventually spur more urban sprawl). Alberti and Marzluff (2004) use complex system properties to illustrate the challenges for urban resilience planning: “many small changes in system patterns at one level can create system instability and unpredictable events at another.” Ernstson (2008) claims that the cultural–political–economic complexities in cities like Phoenix have resulted in emergent, highly dispersed urban patterns that undermine the resilience of the city.

Recent scholarship has proposed various approaches to planning for resilient cities. For example, Fiksel (2006) proposes analyzing multiple models simultaneously to “reflect different system interpretations,” which can be linked to the idea of redundancy and iteration. Folke et al. (2002) argues that in order to counteract the challenge of complexity, “understanding the complex connections between people and nature” is needed for “technological innovations and economic policies aimed at building resilience.” Urban disaster researchers have suggested that urban resilience requires a combination of opposing strictures, including redundancy and efficiency (and in some cases simplicity), diversity and interdependence, strength and flexibility, autonomy and collaboration, and planning and adaptability (Godschalk , 2003; Zimmerman, 2001; Bell, 2002). In this construction, redundancy suggests that future uncertainties can be countered by considering more than one future scenario and corresponding back-up plans, and efficiency refers to the simplification of complex systems interpretations and the avoidance of complex solutions. This commonly requires developing a comprehensive and objective approach for identifying the possible risks and related consequences facing our communities.

According to some, a precautionary approach aimed at reducing vulnerability and enhancing resilience is needed in everyday planning activities (Rozenfield & Kak, 1982; Bulkeley & Betsill, 2005; 2013). There are also many ‘no-regrets actions’ (actions that ignore the costs of preventative action), investments, and regulatory changes that communities can make to reduce their vulnerability and enhance their resilience. These actions, however, require decision making under considerable uncertainty (De Roo & Porter, 2007). Effective adaptation in light of these uncertainties necessitates coordination among diverse stakeholders—including federal, state and local officials—along with private property owners and resource users. Additionally, in many cases adaptation will entail difficult tradeoffs among competing interests (De Roo & Porter, 2007).

To achieve resilience in an increasingly uncertain urban context, we need planning approaches that can forecast into the future and assess the potential impacts that might materialize and how they could influence communal quality of life. The construction of systems models that produce multiple futures and help simplify interpretations of potential outcomes is a necessary component of a planning tool box that can support such an approach. According to Folke et al. (2005), continuously monitoring the state of the system, an ability to adapt to different situations, and a highly diverse approach to governance are also critical components of this toolbox. As I will describe later, these are also critical attributes of sentient systems.

Monitoring

Efforts are being made to monitor and analyze an innumerable array of urban system component parts. This is made possible with the emergence of computational capacity increases and low-cost sensing and monitoring systems. These efforts are being touted as a way to manage and ultimately optimize city operations. Urban management systems of this kind are often connected to the term *smart city*. The smart city concept has been described by global technology firms as “the application of complex information systems to integrate the operation of urban infrastructure and services such as buildings, transportation, electrical and water distribution, and public safety,” and is most popularly connected to a large IBM ad campaign to promote their ICT capabilities (Harrison & Donnelly, 2011; Paroutis et al., 2014). Smart city projects typically make use of sensor networks to monitor, real world, real time systems; provide real-time adjustments and alerts to possible hazards; make use of distributed installations; and use various formats and interfaces for disseminating information.

Environmental monitoring also represents a class of *smart* applications. Instrumenting natural spaces with networked micro-sensors enables long-term data collection at scales and resolutions that are difficult to obtain otherwise. Generally, according to Paroutis et al. (2014), most smart studies and projects can be divided into 2 categories: those that focus on the features of the technology adopted to solve particular problems, and those that consider complex systems that are prone to particular behaviors such as adaptation and self-organization (Portugali, 2000). In each case a large component of the work is the monitoring and sensing of current conditions. Adaptability, in contrast to monitoring, assumes a more dynamic state.

A weakness in the smart monitoring approach is the problem of big data. Enormous volumes of data are generated, only some of which are relevant. Sensing urban infrastructure, for example, produces enormous amounts of data, most of which describe static and stable conditions.

Adaptability

One criticism of the traditional roles of planners is that they lack a good understanding of the upstream or downstream implications of their work. For example, planners have historically failed to recognize the long-term ramifications of planning and building decisions on climate, energy and water supplies, or community wellbeing (Deal & Pallathucheril, 2009a).

Urban planners typically use the term *context* to describe the current, static, conditions, in terms of physical space, social and human variables, and historicism. Good planning however, needs to *contextualize*—to understand and adapt planning principles to the characteristics and demands of specific places at specific points in time, past present, and future. Greater awareness of broader contexts and potential implications enables planning decisions that are more readily adaptable to change and therefore more resilient (Deal & Chakraborty, 2010). For example, planners and communities who make and use plans may not have easy access to the diverse body of information on climate change. The information they do have is generally presented and communicated in ways that are difficult to understand and translate into common planning actions. This gap in understanding of the broader implications and potential effects of climate change limits a community ability to plan for and therefore adapt to climate-related stimulus.

Governance

Folke et al. (2005) emphasizes the importance of "the social dimension of ecosystem management," including organizational and institutional structures for dealing with uncertainty and change. They advocate for a form of dynamic governance involving all citizens as a necessary path toward community resilience. Similar to some participatory planning processes, the concept involves empowering and equipping all community members (equally) with the tools needed to participate in the decision-making process. This in itself is a complex undertaking: it requires ubiquitous access and two-way communication and a deep understanding of individual capabilities. This necessitates communication lines that include traditional and non-traditional approaches. The traditional information push from the system to the users (i.e., information is pushed out from 'expert' sources to decision makers and community members) usually take shape in traditional approaches of report writing or web portal development. Equipping all equally, however, requires that we somehow assess what users know. The traditional push cannot assess this. It requires another line of communication to pull information from the user back to the system to assess understanding and capability.

This type of participatory planning and governance also requires mechanisms whereby individuals can easily interpret information and learn through experiencing and interacting with the data. Berke (2002) stresses that "accumulating experience through collective learning" is key for improving the resilience of socio-physical systems. A user-friendly interface and an individual's ability to understand the data generated by experts and/or their computational systems and mechanisms for feedback are therefore critical to a good decision making processes and PSSs.

2.2.3 PSS in Environmental Planning Processes

It has been suggested that among other attributes, good urban planning might function as a publicly driven counter weight to potential market failures (Klostermann, 1985). Similarly, as a specific planning disciplinary area, environmental planning might be viewed as a tool to counteract market forces that tend to result in environmentally unsustainable developmental patterns. For example, in a self-optimizing free market, no one will pay to avoid environmental externalities, especially those that are difficult to pin down or happen at stochastic spatial or temporal scales—unless there are planning or regulatory frameworks in place. These types of frameworks usually depend on environmental assessment processes and/or tools to uncover the environmental impacts of development or investment decisions and use planning related measures to offset them (Marsh, 2005; Randolph, 2004). In a typical planning process, however, these assessments are usually poorly derived, poorly understood, and poorly applied. This can result from a number of potential issues. For example, there might be a lack of adequate information to correctly assess environmental consequences, or stakeholders might discount the spatial and temporal implications of the impacts. There may also be a failure to understand the dynamic and complex interactions between socio-ecological systems including secondary and tertiary response mechanisms. Finally, it might be that the gravity of the status quo, i.e. blindly following a traditional discourse, is the easiest and most compelling route for an un-informed group of stakeholders.

In this chapter, I argue that if interpretations of environmental impacts are not comprehensively derived and sufficiently exposed to stakeholders, the true costs of development and investment decisions remain masked and will result in massive inefficiencies and ultimately environmental failure. We make this point by looking at environmental market failures within a planning context and the potential for planning support systems to counteract these failures. We do this by first connecting the literature on environmental market failures to planning practices (Section 2) in order to understand how these failures are typically manifested in planning related processes. In Section 3, we suggest three steps that might be incorporated into the planning process to counteract these failures. These steps include: 1) understanding the environmental issue; 2) providing more useful information to stakeholders; and 3) using planning processes to tackle spillover effects. In Section 4, we propose that the use of PSSs can help support these steps. To illustrate the ideas in real-world planning practices, we introduce the implementation of the University of Illinois' LEAM PSS in 3 application and deployment cases: Peoria, IL, St. Louis, MO, and McHenry County, IL. In each case, we demonstrate how the LEAM PSS was used to inform specific planning decisions in response to potential environmental systems degradation. In Section 5, we conclude the paper with a general discussion and conclusions on our ideas and lessons learned, including a brief discussion on the future of PSS technology in environmental assessment.

2.2.3.1 The Realization of Environmental Market Failures in Planning

In the literature on environmental market failures, environmental impacts are often considered undervalued; They are typically described as an externality, or side effect instead of a primary or secondary cost (Jaffe et al., 2005). The consistent undervaluation of environmental costs often results in suboptimal decisions for individuals, organizations, or markets as a whole (Andrew, 2008; Jaffe et al., 2005).The root causes of these environmental market failures are difficult to pin down, although they are typically attributed to information imperfection, global externalities that do not affect local benefits, and/or complicated coordination of technology and ecological innovation. Andrew (2008) points that when market participants have sparse or uneven information, sub-optimal decisions are likely to ensue. This suggests that if information on environmental impacts are not known, market participants in routine development decisions are likely to generate environmental market failures (P.R. Berke, 2002a; Jaffe et al., 2005).

Brueckner (2000) considers planning as a potential remedy to the problem. We agree. However, that if the environmental impacts of development are not sufficiently estimated, trusted, and/or objectively derived, planning will be unable to overcome the negative environmental impacts of market driven forces. We also recognize that environmentally driven planning approaches can lead to undesirable and unintended environmental failures if done in a poor or incomplete way (P.R. Berke, 2002a; He et al., 2011; Naess, 2001). We discuss four potential ways in which urban planning typically fails to realize the true environmental implications of development or investment decisions: 1) a lack of adequate information; 2) stakeholder spatial or temporal discounting; 3) a failure to understand the dynamic interactions between socio-ecological systems; or 4) the gravity of the status quo.

A lack of adequate information to correctly assess environmental consequences

In the literature on market failures, imperfect information or information inefficiency are potential causes of failure. These are usually a product of asymmetric or incomplete information access (Andrew, 2008). This means that certain types of information may be inaccessible to one party but not another, producing an asymmetrical transaction. An often used example is the used car market, where a seller of a used vehicle has much better information on the car's condition than a potential buyer. In this case the failure is due to the asymmetry of the information available to each side of the transaction causing a potential over-valuation of the vehicle's worth by the buyer. In planning and development projects, imperfect information is usually the result of information availability rather than asymmetry. This occurs when a complex development issue is difficult to assess or understand so that decisions are made based on incomplete information. This is especially true in the case of environmental impacts, where the issues may not be well defined, or even understood by the stakeholders or planners involved in the process. This gives rise to suboptimal decision making and ultimately the host of environmental failures we currently see in our urban systems.

He et al. (2011) point out that a persistent failure to deliver environmentally sustainable development solutions is closely linked to the separation of environmental assessment from the typical urban planning process. We suggest that insufficient adoption of environmental assessment is only part of the picture. A more essential problem is that most environmental assessment does not take full account of the environmental impacts of development. So that even when it is considered a part of a planning and development decision process, the delivery of incomplete impacts information can lead to highly probable failure. For example, in a typical environmental assessment, a commercial development that engulfs a patch of agricultural land might associate the implications of the transaction only in terms of the primary impacts produced by the development (site related impacts) or the loss of agricultural lands which can be more regional in scope. If, however, the development is proximal to ecologically sensitive areas, the development could have enormous ecosystem service impacts. This typifies hidden environmental costs that are often neglected by traditional environmental assessments.

A failure to understand the dynamic interactions between socio-ecological systems including secondary and tertiary response mechanisms

Holmberg and Karl-Henrik (2000) propose that the non-linearity of markets often confound plans intended for sustainable development. For example, in the Laguna West master planned community in Sacramento County, CA, new urbanist and sustainable design principles were used as a basis for the development. Despite rigorous planning and analysis when the community began opening, the market for units in the community rose at a startling rate and subsequent phases subverted the planned for economic diversification and sustainability-oriented goals (Katz, Scully, & Bressi, 1994). Such market driven complexities can easily lead to a host of unexpected failures and shortcomings.

The general complexity of urban systems further undermines our ability to evaluate the real environmental costs of planning decisions. Urban planning problems are often referred to as “wicked problems” that are “inherently different from the problems that scientists and engineers deal with.”(Rittel & Webber, 1973). Science and engineering-based approaches, however, often deal with only primary impacts and fall way short of robust outcomes when applied to such wicked complexity. The non-linearity of future urban development patterns, and dependencies among developmental decisions often overwhelm analytical capacities of typical environmental assessments especially those that use static assumptions the most (Barredo et al., 2003). This difficulty in assessing secondary and tertiary (latent) impacts leads to incomplete information and confusion which ultimately leads to environmental failure.

Stakeholder discounting of spatial and temporal environmental impacts

Secondary and tertiary environmental costs typically spill over long spatial distances and trickle into distant futures. These long distances and time lines can lead to the problem of discounting. Discounting occurs when a value is subjectively lowered because it is removed or distant in terms of time, space, or socio-cultural relationships. Discounting is an important concept when discussing environmental sustainability (and climate change). Essentially, the argument is that we should not discount the value of environmental resources (i.e., a healthy climate) for future generations because it will be just as valuable to them in 50 years as it is to us today. However, Fall (2006) argues that we cannot predict how future generations will value environmental resources, and that environmental crisis could alter the discount rates and slow the rate of environmental damage. Weitzman (1998) presents a deductive argument for valuing environmental resources with a low discount rate for long-term planning projects, showing that they are theoretically likely to produce the best return on investment. Hoel and Sterner (2007) take this argument a step further and argue that the rising scarcity of environmental goods will also increase the relative cost and have direct effects on the discount rates. The idea of devaluing costs that are removed from a particular context in terms of space or time is a central problem in planning because it strikes at planning’s very purpose: to adequately account for the costs associated with policy and investment strategies (i.e. plans) made within that context.

Berke and Conroy (2000) argue that although plans are always linked to global concerns, “local plans should acknowledge that communities function within the context of global (and regional) environmental, economic, and social systems.” Empirical data suggest that those links do not always lead to actions; stakeholders tend to overlook and discount the spatial and temporal environmental costs of their plans. They further point out that the high discount rates that undervalue environmental costs with spatial and temporal distance help create plans with severe environmental impact spillovers. We argue that stakeholder discounting plays a large role in this phenomenon.

The gravity of the status quo, i.e., blindly following a traditional, growth-oriented discourse

Some developers, businesses, and even some communities profit by maintaining the historical, developmental pattern status quo. Some argue that these patterns have typically been put in place at a time of ‘unawareness’ of their environmental implications (Andrew, 2008; Naess, 2001). Patterns of sprawl development, for example, were started before their social, health and environmental ramifications were well known. In other words, some historic patterns may no longer be favorable when their associated environmental costs are assigned. Another useful example is energy production. Much of our fossil-based energy infrastructure was developed before the actual costs of carbon emissions were known (Andrew, 2008). Now that we have a better sense of their true costs, some of the infrastructure used in the energy industry is no longer viable. Similarly, urban development patterns continue to follow the sprawling, growth-oriented path initiated during the 1950’s, make it increasingly difficult to make our cities within ecologically sustainable and equitable (Naess, 2001).

In the sustainable design literature, Strategic Sustainable Development (SSD) is a proposed method that might tackle the complexity and uncertainties associated with sustainable developmental policies and thereby challenge the status quo (Brueckner, 2000). SSD incorporates a set of techniques including life cycle analysis, indicator development, natural capital accounting, forecasting, emissions analysis, and backcasting to provide more accurate environmental assessment to current developmental trends and policy scenarios.

In summary, an urban planning context, environmental market failures might be attributed to a lack of knowledge of environmental impacts, a lack of understanding of secondary or tertiary impacts and decision interactions, poor communication between spatially spread stakeholders, and a poor understanding of alternatives from current developmental paths. In the following section, we consider approaches to addressing these shortcomings through spatially explicit PSS. PSSs can help engage environmental decision making in planning by providing more critical and useful information on the environmental implications of development decisions thereby helping stakeholders avoid planning related environmental failures.

2.2.3.2 Improving Planning Decisions with PSSs

The use of PSSs is a relatively new addition to a long-running and persistent discourse on the role of technology in urban planning and policy-making (Deal & Pallathucheril, 2009a; Harris, 1965; Voorhees, 1959). One of the first comprehensive looks at planning PSS was assembled by Brail and Klostermann (2001). Brail (2008) later writes more specifically on large-scale urban modeling systems. Geertman and Stillwell (2004) followed, documenting best practices in PSS technology, with an update on the state of art in 2009 (Geertman & Stillwell, 2009). More recently, the emphasis has shifted to the management of information needs (Power & Sharda, 2009), use-based systems (Power & Sharda, 2009; te Brömmelstroet, 2010), and web-based strategies of information retrieval and delivery (Budthimedhee, Li, & George, 2002; B. Deal & Pallathucheril, 2009a). More recent conceptualizations also include Michael Batty's Smart City (Batty, 2013), described as "a fusion of ideas about how information and communications technologies might improve the functioning of cities" the idea revolves around the need to coordinate and integrate technologies that have synergies in operation but have been developed as separate, much like a modern PSS.

One specific element typical of some spatially explicit PSSs is a land-use change (LUC) modeling core. These models are usually built to help planners and decision makers better understand spatial data, the dynamics and complexity of urban development patterns. In some cases, they can assess the impacts that changing urban patterns have on environmental, economic, and social systems. Although it has been more than 30 years since Cellular Automata (CA) technologies were tested in the development of these spatially explicit modeling cores (White & Engelen, 1994a), and more than 20 years since urban planners begin to adopt and adapt LUC models in first generation PSSs (S. Geertman & Stillwell, 2004a), these models have only recently been adaptable enough to be operationally used in support of planning.

Revealing environmental costs through PSSs

Pioneers have now pushed PSS LUC model prototypes out of research labs and have begun to package the LUC models into operational applications with visual and online user interfaces. The Landuse Evolution and impact Assessment Model (LEAM, 2015), WhatIf (What if? Inc, 2015), and UrbanSim (UrbanSim, 2015) are among three of the best operational examples in the US. These PSSs aim to enable non-experts to input data, operate, localize, and test their PSS LUC models with future potential scenarios, in some instances through web based portals with simple mouse clicks. Some of these models are close to realizing this ideal (LEAM included). In order to fully realize the enormous benefits of PSSs within a structured planning process, a connection to knowledgeable modelers and planners is needed. These experts can: a) facilitate the process and the technology needed to guide communities in applying the tools efficiently and effectively, b) ensure the quality of PSSs inputs and outputs, c) explain the implications of modeled outcomes (to non-technical audiences), and d) suggest implementation strategies in backcasting (Holmberg & Karl-Henrik, 2000) and scenario analysis exercises. More generally, these tools are fundamentally important for countering environmental market failures.

As previously noted, many hidden environmental costs are the result of a weakness in uncovering secondary (or tertiary) environmental impacts. This is compounded by an inability to understand the dynamics and interactions in and between impacts. LUC and PSS technologies are an effective means for addressing these issues. Spatially explicit PSSs bring together LUC models in an information delivery system (visualization interfaces) to provide planners and communities with critical knowledge of various dynamic systems and interactions that can facilitate more effective communicative planning approaches (Brail & Klostermann, 2001a). Infusing critical (environmental) knowledge to stakeholders and making (larger scaled) information available can engage a larger stakeholder group, capable and interested in understanding common environmental spillovers. The ready availability and democratization of information can also encourage communities and individuals to address the environmental externalities of their actions. Environmental impact information infused into public discussion through PSS technologies can also enable a more effective weighing of the trade-offs that might emerge between economic benefits and environmental costs.

Some planning and analysis techniques are greatly improved by PSS technologies (Deal & Pallathucheril, 2003; 2008; 2009a). The ability to easily perform backcasting analysis for example, can help plan-making processes achieve outside-the-norm envisioned, preferred futures rather than depending on a projection from the status quo perspective. These kinds of techniques are important for breaking historic, unsustainable, path-dependent developmental patterns.

Given the potential of PSSs to aid urban planning in uncovering hidden environmental costs, the question becomes how these PSS tools become ubiquitous to real-life planning practices. The University of Illinois and the Landuse Evolution and impact Assessment Modeling Laboratory have had some success in operationalizing and implementing their Planning Support System in a wide variety of regions worldwide, most notably and successfully in the Midwestern US. In the following sections, we describe several examples of the LEAM operationalization process. These examples help to reveal substantive ways in which the LEAM PSS has impacted the planning and policy making and in the process helped to alleviate environmental market failures. First, LEAM PSS has impacted planning and policy making through use-based PSS development and implementation. Next, it has helped to counteract potential market distortions through useful information development and dissemination. Finally, it has impacted planning policy making with its ability to integrate seamlessly and positively affect the process of environmental assessment in plan making. We also propose a future vision in which PSS technologies evolve from user-driven to user-awareness. We suggest this will enable them to be even more effective in practical environmental planning implementation.

The LEAM PSS

The need in planning and policy making to answer both ‘what-if’ and ‘so-what’ questions is fundamental to the LEAM PSS framework. The PSS consists of two major organizational parts: 1) a LUC model, defined by a dynamic set of sub-model drivers that describe the local causality of change and enable an ability to test and play out potential ‘what-if’ scenarios; and 2) impact assessment models that facilitate interpretation and analysis of the modeled future land use changes depending on local interest and applicability. These models help to assess ‘so-what’ questions and explicate the potential implications of a modeled scenario.

The LEAM LUC model utilizes a hybrid Cellular Automata (CA) approach. Like CA, LEAM utilizes a structured lattice surface (cells) with state-change conditions that evolve over time. The lattice is shaped by biophysical factors (such as hydrology, soil, geology and land form), and socioeconomic factors (employment, household structure, administrative boundaries, and planning areas). These factors, when combined, provide a contoured lattice with high and low spots that represent each cell’s probability of potential land use change. Probabilities are predicated on local interactions (e.g. the accessibility of the cell to a given attractor), global interactions (e.g. the state of the regional economy), and other mechanisms of causation (e.g. social forces). Specific rules can be applied and tested. Controlling the constraints in the rule set can be used to produce diverse sets of planning scenarios. Unlike other large-scale efforts, LEAM works at a finely scaled resolution (30 x 30 meters) that includes cell-based micro models. This enables loosely and tightly coupled linking with other models that might operate at a different spatial scale, including regional macro socioeconomic models and transportation infrastructure and demand. The effect is a wider range of potential 'what-if' scenario sets that can be tested and assessed (Deal & Pallathucheril, 2003, 2009a).

LEAM has been both tightly and loosely coupled with other models that operate at various spatial and temporal scales including: economic forecasting models (Deal & Kim, 2013), bi-directional travel demand models (Deal & Kim, 2013), ecosystem service models (Deal & Kim, 2013), water quality models (Choi & Deal, 2008; Wang, Choi, & Deal, 2005); water quantity models (Sun, Deal, & Pallathucheril, 2009) and social cost models (Deal & Schunk, 2004). Coupling these models with LEAM dynamics and making the information useful through a 'use based' implementation process has helped decision makers make sense of the complex interactions between urban change and environmental systems.

2.2.3.3. The LEAM Use-Based PSS Implementation

In the LEAM implementation process, the LUC model evolves as an iterative process of data collection, model building, dialogue, visualization, and general presentation and access. Local planners, policy makers and stakeholders (convened by local planning entities and identified as broadly as possible) provide feedback and input about the local salience and value of any given simulation. This feedback is gathered regularly and begins at project inception. It is used to more effectively capture the local condition, to provide a better local version of the tool, and to inform local stakeholders about the tool and its uses. This form of use-driven modeling and system development, which takes place in very public forums, most distinguishes the LEAM approach (Deal, 2008). The feedback and local dialogue elements are critical in the creation of useful PSS tools especially in terms of overcoming market distortions. Constant internal and external review and interaction are critical to informing both the modeler and the local stakeholders of modeled changes, improvements and scenario outcomes. Presenting this use driven approach in publically accessible PSS visualization portals helps provide another layer of feedback and interaction. Consensus building is performed and achieved using typical planning procedures (Deal and Pallathucheril, 2009a) for a more detailed discussion on use-based modeling and consensus building).

In applying this use-based model process we have found that LEAM can influence decision-making through various pathways (Deal & Pallathucheril, 2009a). In the following, we describe some specific pathways and their effect on the plan-making process in past LEAM applications. The three cases presented below—Peoria, IL, St. Louis, MO, and McHenry County, IL—represent three ways in which the LEAM PSS has made significant impacts on the practice of planning. These include counteracting distortions, facilitating dialogue, and integrated plan making for challenging the status quo.

Counteracting distortions in Peoria, IL

Planning decisions take place over extremely long periods of time – sometimes involving different generations, over large distances. This raises questions of inter-generational and geographic equity. As noted previously, this is compounded by the fact that planning decisions have complicated spatial interactions and environmental impacts that are often secondary, or even tertiary. Environmental costs may accrue in one form, to one generation, or in one part of the geography (community, state, nation, world), while the benefits accrue in a different form, to a different generation, or in another part. Delivering objective, unbiased and apolitical information can help counteract these types of phenomena that can emerge in typical public planning processes (Forester, 1993).

Many of these issues are the result of an under-estimation of environmental impacts that are sometimes the result of information distortions. Information distortions are usually the product of local knowledge that is deeply situated in the web of accepted norms, meanings, and beliefs. If incorrect (distortions of actual causal relationships), their locally embedded nature makes them difficult to overcome with traditional planning communication processes (Stein & Harper, 2012). If left uncorrected, they can lead to problematic conclusions in public discussions. One example can be seen in local and personal discounting discussed above.

In our work, we argue that providing an ability to objectively test and evaluate current and future conditions can be a powerful tool for counteracting potential local distortions and poorly considered discounting that leads to costly future consequences. In an early LEAM application in Peoria, IL, we helped provide those objective arguments for local and regional planners in a simple example.

In the early 2000s, the three counties surrounding Peoria, Illinois (Woodford, Tazwell, and Peoria) were witnessing significant conversion of very fertile and productive agricultural land to residential and commercial land-uses. There was a distinct sense of unease about this trend, although there was no specific analytical proof for its existence. Woodford County in particular, was concerned about its agricultural heritage. The county outlined several strategies for preserving agricultural land. One particular strategy required a change in the county zoning ordinance that would require 40-acre minimum lot size on current agricultural lands. At roughly the same time in a regional planning exercise, a number of simulations of future land-use change for the tri-county region were being run, reviewed, and critiqued in public workshops (Deal & Pallathucheril, 2003). These simulations established the extent and spatial distribution of future growth in a business-as-usual scenario described through maps and depictions of the impacts of this growth. Other scenarios explored included higher and lower growth rates and various public investments and policy ideas, including the proposed ordinance change in Woodford County. **Figure 2** shows expected land-use outcomes in a 'business-as-usual' scenario. After our simulation, we used the land cover data provided by the county's planning board to assess loss of agricultural and ecological lands associated with future growth on 30-by-30-meter resolution.

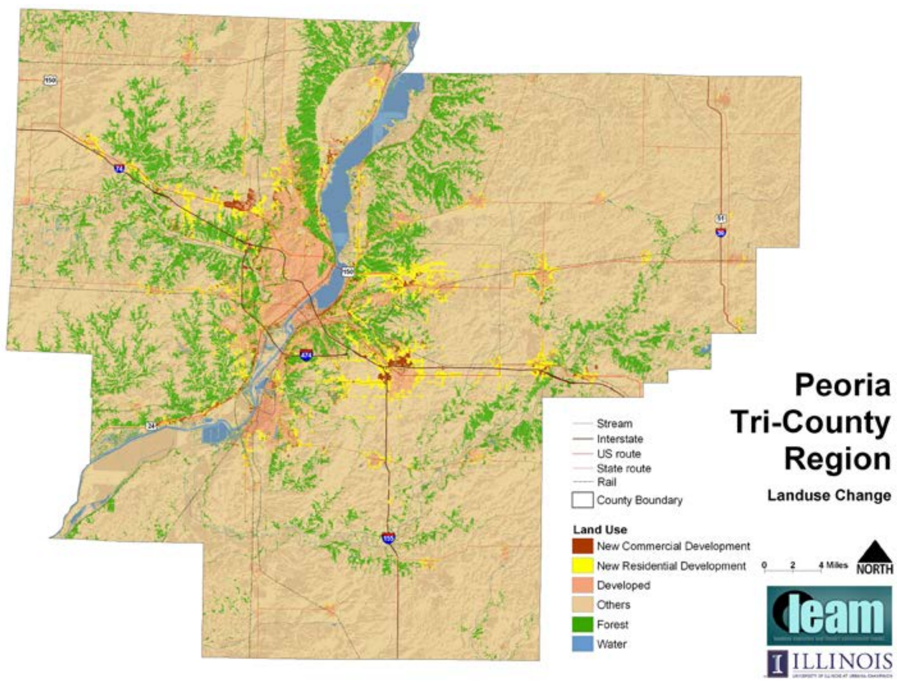

Figure 2. Land use outcomes in the Tri-County Region of Peoria in a 'business-as-usual' scenario. Yellows patches are new residential developments; dark red patches are commercial. The arrow refers to the desirable bluff areas along the river.

To discuss the simulation results, local planners held two big meetings and several smaller focused group meetings. Stakeholders involved in those public discussions included staff from Illinois Department of Natural Resources, citizens, NGO, local planners, and government entities. Public discussions on the 40-acre zoning requirement scenario revealed that the ordinance change would reduce consumption of agricultural land as intended but would also bring with it unexpected regional consequences. Compared to the business-as-usual scenario, the amount of agricultural land lost to development over thirty years with the proposed ordinance change dropped from 10,000 to 7,000 acres, as expected. Unexpectedly, when the proposed ordinance was included in a simulation, new development that would have been located in the agricultural area moved to environmentally sensitive bluffs along the Illinois River, resulting in the loss of 12,500 acres of forestland (**Figure 2**). This revelation changed perceptions of the proposed ordinance, and the ordinance was put on hold until a ravine overlay district focused on protecting the river bluffs was put in place.

Initially, any negative consequences of the proposed ordinance appear to have been discounted. Once people saw the simulations and understood the consequences of the proposed ordinance, this discount rate was substantially decreased to the point that protecting the bluffs became a higher priority.

It appears from the above case that explicating and elaborating on the future consequences of various public policy and investment choices may alter the extent to which these consequences are discounted by stakeholders in public deliberations. When future consequences are vaguely known and ill-defined, they are easily discounted. When potential consequences are represented in tangible and objective ways, however, they make the familiar unfamiliar, they challenge habitual ways of thinking, and they question what appears evident and taken for granted (Fischler, 2000). In short, they can counteract normative distortions.

Facilitating dialogue with the St. Louis Blueprint Model

PSSs can assist planners in convening local stakeholders to discuss and validate environmental assessment results and in the process arouse a regional consciousness of the potential spatial and temporal spillover of environmental impacts. Geertman (2002) points out that PSS tools can enhance participatory planning processes, because "a greater degree of access to relevant information will lead to the consideration of a greater number of alternative scenarios—which in turn will result in a better informed public debate." One project that exemplifies this idea is the application of LEAM to the two-state, eight-county region around St. Louis, Missouri (MO) (Deal & Pallathucheril, 2007; 2008). In this project, we coupled various other models with LEAM to analyze the potential impacts of the land-use change results. Two in particular were a 4 step transportation model that utilized over 2,200 Transportation Analysis Zones (TAZ) to calculate travel time changes for each scenario, and a regional economic input-output model (conducted on a household level) that provided demand for space and assessed economic implications.

In 2003, the East-West Gateway Coordinating Council (the Metropolitan Planning Organization and Council of Governments for the St. Louis region), began to use LEAM (in a version later called the Blueprint Model) as a platform for encouraging a regional dialogue on issues of economic development, social equity and environmental sustainability. Instead of initializing the process with a lengthy model-building exercise, the initial focus was set on quickly producing a set of simulations. This quick-start process served two purposes: to quickly begin the process of engagement and build interest; and to collect information from the local stakeholders on the state of the local condition for adapting the LEAM model to fit local conditions. These early simulations were subjected to public scrutiny in workshops, meetings and other public forums. Participants in these forums provided valuable insights into the dynamics of urban LUC in the region and a direction for future modeling efforts. Conducted on an annual basis, they also provided an excellent platform for dialogue among participants.

One early critique of the preliminary LEAM simulations presented was aimed at the way in which new development was being distributed across the two sides of the Mississippi River—the Illinois on the east, the Missouri on the west. Preliminary simulations showed considerable new developments in Illinois relative to Missouri; at the same time, the central business district (CBD) is in Missouri and has historically seen the bulk of new development. These simulations utilized posted travel speeds and did not take into account the difficulty of crossing the Mississippi River from Illinois into the CBD. When congested speeds were used to measure travel time (taking into account how traffic congestion makes portions of the region more or less attractive), simulated development shifted from Illinois to Missouri. A major factor was the effects of congestion on bridges and the approaches to them (bridges represent severe choke-points with very little opportunity for alternative routing). In the regional dialogue, this outcome highlighted the critical role played by bridges in the distribution of new development across the region.

The construction of a new Mississippi River bridge had been the subject of planning studies, preliminary design and environmental impact analysis for over 20 years in the region. A concerted civic and political effort to secure earmarked federal funding was only partially successful. The resulting funding shortfall called into question the original bridge proposal and how it would be implemented. Alternatives considered included covering the shortfall with a toll and constructing less expensive alternatives such as enhancing the capacity of an existing bridge; there was no regional consensus on the way forward. Facing a stalemate on the issue, the regional planning organization, the East West Gateway Council of Governments (EWGateway) took the lead and sought to inject an analytical basis into the regional debate. In order to do this, however, it became crucial to go beyond traditional cost-benefit analyses and to jointly simulate and analyze future transportation and land-use consequences of the different choices.

Numerous simulations were created by coupling LEAM with the regional econometric input-output model (LEAMecon) and the regional travel demand model (TransEval). The land-use, economic and transportation outcomes in the simulations, and those of a baseline ‘No-Build’ simulation, were the basis for comparisons. Aggregate differences appear to be slight: building the bridge appears to slightly increase development in Illinois (Madison and St. Clair counties), while slightly decreasing development in Missouri (St. Louis and Jefferson counties). Interestingly, imposing a toll increased land development in far northwestern Missouri (St. Charles County). **Figure 3** displays differences in LUC between the Full Build and No Build simulations at a finer resolution; red cells see more growth in the Full Build simulation, green cells see more growth in the No Build simulation. The map presents a more complex set of differences and suggests that aggregating to the county level masks greater change: while building the bridge facilitates greater land development in the Illinois side of the region and takes away from development on the Missouri side of the river, there are significant differences in development at the local level.

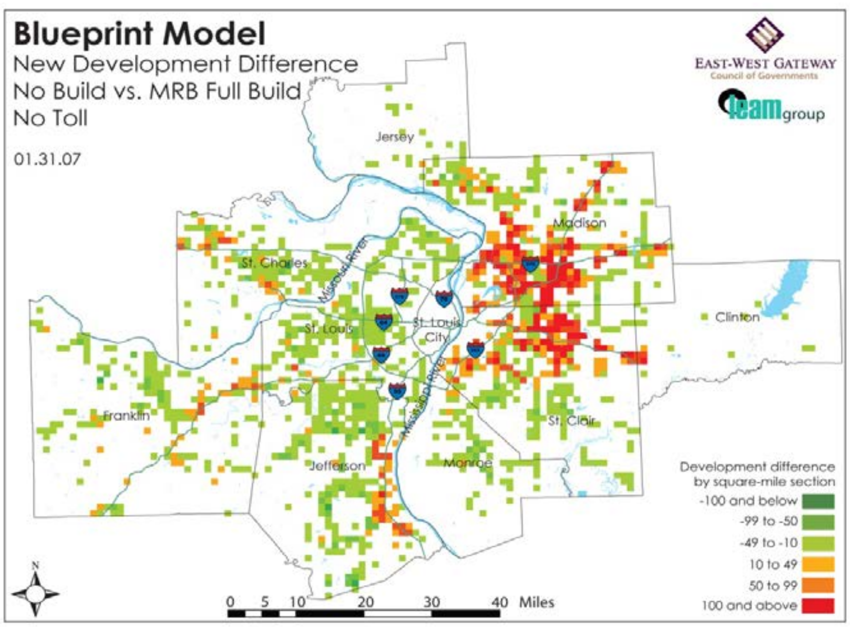

Figure 3. Differences between the Full Build (red) and No Build (green) simulations in the St. Louis Blueprint Model. Yellows are common to both scenarios.

EWGateway convened three big public meetings and dozens of smaller meetings to discuss the simulation results. As might be expected, discussions around these simulations were quite intense. Outcomes appeared counter-intuitive; imposing a toll on the bridge increased total travel times in the region. Working through the complex interactions suggested a striking explanation: the toll was diverting traffic to the other bridges across the river that do not impose a toll, increasing congestion on these bridges, and increasing travel times. This explanation brought into question the wisdom of using a toll to cover the budget shortfall. There were other insights generated: patterns of land use are likely to change if additional river crossings are built. Therefore, cooperative land-use policies and controls must be put in place in these areas to manage these impacts. Ultimately, however, only slight differences were uncovered, even though the magnitude of the investment required for each of the scenarios tested was very different. This suggests that perhaps the lowest cost alternative is preferable. It also suggests that demand-side tactics, such as investing in a better regional jobs-housing balance, might be more cost effective.

In this case, the LEAM PSS assisted planners in convening local stakeholders to discuss and validate each bridge scenario and their potential implications. The user-based process clearly facilitated a regional dialogue and aroused a regional consciousness of the potential spatial and temporal spillover effects. The process also helped challenge conventional thinking about the fundamental needs and benefits of the proposed investment.

Planning for a Deviation from Current Developmental Path in McHenry County, IL

By including environmental assessment in planning processes and decision making, LEAM informed public dialogue. Participants had a better appreciation for the future environmental consequences of their public policy and public investment choices (Deal et al., 2017a). These planning processes however, are essentially forward looking exercises. Many similar processes that don't use PSS technologies rely heavily on projecting existing conditions into the future. They generally fail to capture changing paradigms or emergent behaviors. This often results in the continuation of existing developmental paths.

The use of PSS tools enable a broad range of multi-directional analysis that might be useful in analyzing or planning for structural change – including those needed to address a host of environmental market failures. The idea of backcasting using PSS technologies, for example, has been shown to be effective in sustainable development planning (Deal et al., 2017a). Deal et al., (2017a) propose that backcasting from a desirable future state using PSS tools enables planners to step outside current developmental trends to test ideas and reexamine assumptions. While a forecast projects an image of the future based on a current situation, a backcast starts at a point in time in the future and draws a developmental path back to the current condition. This is useful for plotting a path that responds to “how do we get there” kinds of questions from future states that might not emerge from existing trends.

A LEAM application in McHenry County, IL demonstrates a PSS led backcasting exercise that helped the county understand how a desired deviation from their current developmental path might be achieved.

McHenry County, IL defines the northwest edge of the seven counties that make up the Chicago metropolitan region. It is approximately 60 miles northwest of downtown Chicago. It has a population of 318,000. Its location and unique natural features create a quality-of-life that is attractive to many. Since 1990, the county’s population has grown 40 percent, averaging 2.3 percent growth annually. The previous land-use plan for the county is the McHenry County Land Use Plan 2010, which was compiled in 1993 and updated in 2000. However, McHenry County Regional Planning Commission (RPC) deemed this plan increasingly irrelevant and began to compile the McHenry County 2030 Comprehensive Plan in 2007 (Deal & Pallathucheril, 2009a; McHenry County Regional Planning Commission, 2010a).

In 2007, with the help of the State of Illinois Department of Natural Recourses, the LEAM Laboratory began to build a PSS for the County. The original work was designed to assess the potential future implications that urban land use changes would have on the natural resources in the County. It was soon put to use to inform the discourse and test some of potential distortions emerging from their 2030 process (McHenry County Regional Planning Commission, 2010a). The PSS development process first established a ‘reference’ or ‘business-as-usual’ scenario as a baseline for assessing the impacts of various land use policies being discussed. The reference scenario simulated LUC if current growth pattern trends continue to 2030. Other model scenarios were then compared to the reference scenario to understand the impact that the tested policies might have on various important county assets. LEAM was coupled with other impact models (as described above) to assess land-use, water demand, water quality, wetlands, natural areas, agricultural uses, and groundwater protection (the list was determined by county stakeholders). Of particular interest to the County was the loss of important agricultural and ecological lands associated with future growth. These were evaluated linking LEAM to the Land Evaluation and Site Assessment (LESA) modeling framework from the Illinois Department of Agriculture (Coughlin et al., 1994).

The McHenry County Planning board convened more than 10 public meetings made up of a range of public interests, stakeholder groups, government employees and officials, and planners. The process revealed an early, major concern with the projected population forecast for 2030 that was derived using LEAMecon. This was the bellwether issue that underlay a larger conflict on the future of the County between pro and anti-growth advocates. One group of residents hope to continue the past development trends and environmental groups urged protection of environmentally sensitive and agricultural lands. After lengthy discussions LEAM simulated a range of potential scenarios identified by the County Planning Board (18 prime scenarios) of future land-use patterns. The RPC identified various preferred outcome scenarios (Deal & Pallathucheril, 2009a; Coughlin et al., 1994). One such scenario, the Compact Contiguous Growth (CCG) composite scenario is shown in **Figure 4**. The difference between the reference scenario and the CCG composite scenario is on the left. Areas in blue receive more development in the CCG composite scenario; areas in red receive more development in the Reference scenario. A notable difference is seen in the southwest portion of the County. This is due to a limit that the CCG composite scenario places on the amount of vacant land available in that part of the county. The right shows an urban growth boundary that was also considered as part of the scenario analysis.

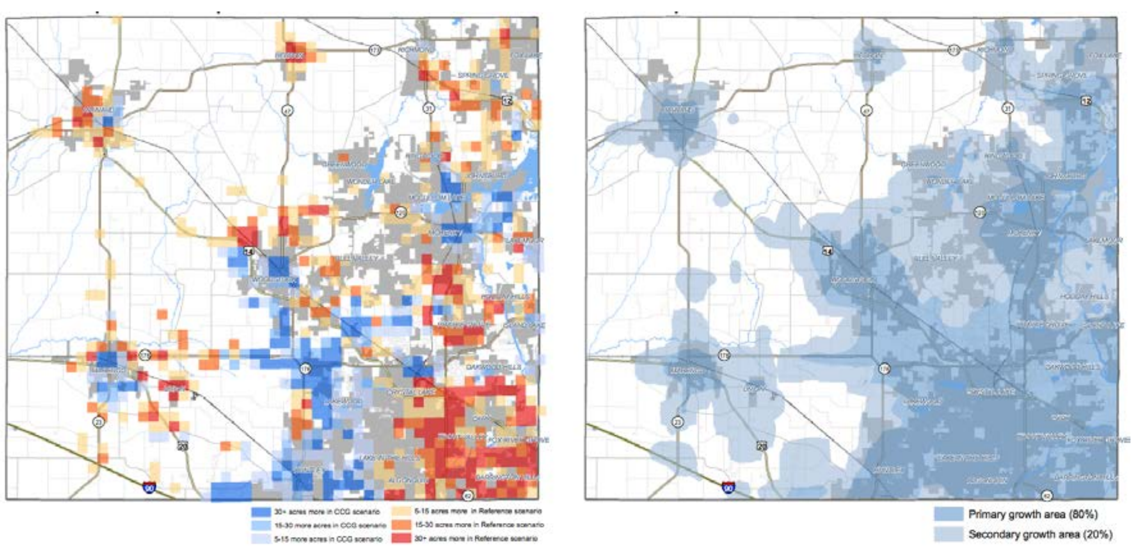

Figure 4. McHenry County CCG scenario growth projection to 2030 compared with a reference scenario (left). Comparison using 1mile x 1mile section scaling. Reds are unique to the reference scenario; blues are changes as a result of the CCG scenario. The right image shows as urban growth boundary that was also a part of the CCG scenario analysis.

The spatially and temporally explicit information generated by the LEAM PSS helped the McHenry County Regional Plan Commission (RPC) objectively assess the impacts of their proposed policies. For example, one scenario identified spatial locations where farmland and ecologically sensitive areas were identified as at risk (McHenry County Farm Bureau, 2008). With LEAM information, the RPC could specify where to set up ecological/agriculture preservation districts to prevent a disruption of the critical areas.

The process represents a typical PSS backcasting exercise. First, a desirable outcome was established—in this case, minimizing agricultural and ecological land losses. Backcasting how to achieve this desirable outcome required an analysis of the complex interactions between a host of variables, so that many multiple model iterations were examined to understand exactly what this preservation meant to county stakeholders. Once these were unraveled, a coherent set of policy levers were developed for how these outcomes for the future might be achieved. In this case agriculture productivity was closely tied to the introduction of a new (and also desired) transportation investment (a new interchange conflicted with highly productive agricultural lands). The LEAM PSS provided useful spatially explicit information on where, when, and how to plan for an alternative, desirable future that was just outside current development patterns.

The LEAM PSS enabled a 'continuous planning' process to take shape in the county. The spatial and aspatial data created for the PSS allows the community to continuously interact with the data and models associated with the plan (an visualized interactive tool is shown in **figure 5**). It is now a living comprehensive plan where critical questions can be examined, progress on critical issues can be updated and communicated, and success or failure can be determined and re-assessed. We suggest this type of tool and process are critical for challenging existing (and unsustainable) growth and development practices and challenging the status quo.

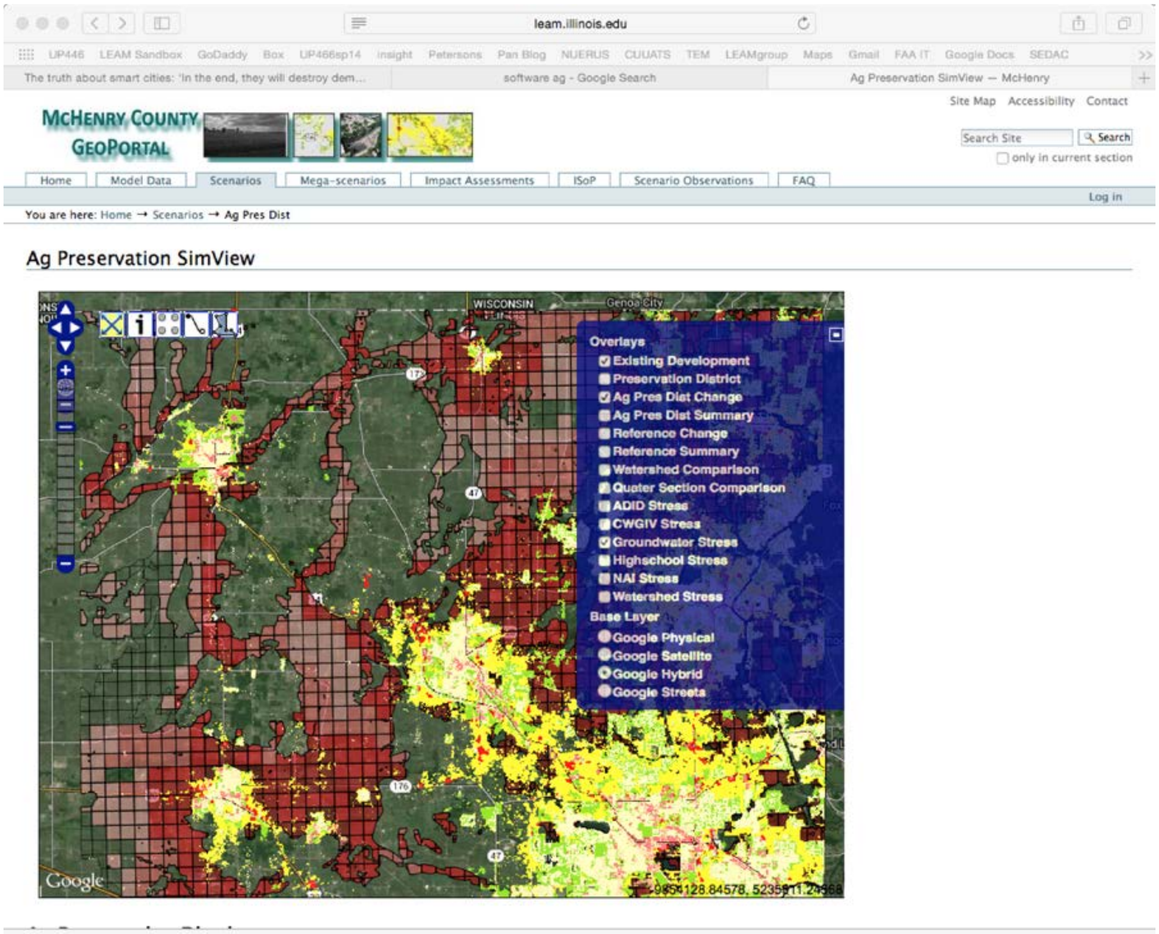

Figure 5. The LEAM PSS ‘GeoPortal’ for McHenry County. The center is the map viewer window with overlay results viewed on an interactive google map. On the right is a legend for the displayed maps. The viewer displays a forecasted agricultural preservation scenario and its associated groundwater stress. Yellow and bright right cells demonstrate the future growth scenario; darker red cells (big cells) represent groundwater stress associated with the growth.

2.2.4 Take-away from PSS applications

After explaining the role of PSS in smart, sentient and resilient cities, as well as its role in environmental planning processes. I summarize a number of features that future PSSs need succeed. This list of features provides some examples outside the PSS realm that have been working towards "sentience."

Dynamic Data

Underlying data sets in most (if not all) contemporary PSSs are relatively static. Sources that can be easily accessed are usually federal repositories with uneven update schedules (e.g., some US Bureau of Labor Statistics are updated monthly, some annually). Some are updated frequently, while others are not (e.g., the US Census is decennial; USGS NLCD data is updated on irregular, 4-8 year intervals). Since data sets tend to be manually accessed, the task can be quite tedious with considerable time passing before data updates are realized. Local government data, which typically are more organizationally proximate to the PSS, are often harder to come by because the data base systems may not be sophisticated or are generally less accessible. For example, many jurisdictions have information systems for tracking building permits, which can be a good indicator of type, intensity and location of urban change. But to date, these data sets typically have not been digitally or readily available, a significant missed opportunity.

A sentient PSS must have the ability to incorporate and automate data-update processes. For our federal data example, these types of repositories typically offer RSS (Real Simple Syndication) feeds that can serve as triggers for data updates. But raw data from these sources usually must be processed before they can be utilized by models contained in a PSS. Sophisticated and automated procedures must be in place in order to preprocess and manipulate the data as it comes into the system. Local data sources represent an even greater challenge. Not only would there need to be greater technical sophistication, but there would have to be changes in the way local organizations are willing to share data.

Some data sources require extraordinary processing procedures. For example, data on future climate conditions produced by a number of global climate models are available from the Earth System Grid Federation. This includes the repository maintained by the Program for Climate Model Diagnosis and Intercomparison and its Coupled Model Intercomparison Project (CMIP5 - available at http://pcmdi-cmip.llnl.gov/). Although understanding climate trends can have important local planning implications, these data sets are resolved at very coarse spatial scales (typically 156 to 313 km). In order to be useful in typical PSS operations, they must be drastically downscaled and preprocessed.

Downscaling using statistical methods (where the resulting spatial patterns are important) or by causal modeling (where system dynamics determine how and when the finer resolution is computed) are currently being utilized for these types of operations, although automation has been limited. CGIAR's Research Program on Climate Change, Agriculture and Food Security (originally Consultative Group or International Agricultural Research) makes data available for any specified geography, spatially downscaled and disaggregated to resolutions ranging from approximately 900m to 18km. Generally, however, CMIP type data updates happen at carefully planned and executed intervals (whereas individual modeling groups produce output at a more frequent and less consistent interval). Here, too, RSS feeds could help trigger automatic data updates rather than waiting for manual processing.

Sensors, RFID and other related technologies present a great opportunity but perhaps an even greater challenge. Vast quantities of data are generated at very fine temporal resolutions. Masucci et al. (2013) recently studied 11 million records taken over a one-week period from Transport for London's (the London tube subway system) electronic ticketing system. This data helped to reveal London as a polycentric system of up to 10 different centers that interlink in complex patterns. Batty (2013) argues that these kinds of data sets can help in planning resilient cities, although he fails to show how this data would be used in the longer time horizons and sometimes larger spatial scales required by most planning processes.

Context. Data contextualization is challenging in large urban systems with multiple layers of interactions. Traditional planning methods struggle to make sense of the varying data contexts across space and time and intuitive understandings can result in over-simplification. Sentient systems may be better suited for contextualizing planning data. They might tackle a complex problem first by analyzing large and diverse quantities of data. Next, they might contextualize the habits of users to make sense of data and places. This process combines systematic (i.e., data collection, user pattern recognition, and quantitative comparison across places) with intuitive interpretations (first-hand experience) by contextual inhabitants.

Sentient Visualization Interfaces

Innovative visualization tools, including 3D representations and temporal displays, have been a focus in recent PSS research. Although the state of the art is changing quickly, a user is still typically presented with a very limited range of data accessibility options in any given PSS. This range is usually one-dimensional – it is uniformly presented regardless of user expertise or knowledge base. Individuals, however, differ in the way they perceive and ingest information. In a study on the speed at which different types of information are recognized, Conati and McLaren (2008) found that perceptual speed varied greatly by individual. This is not surprising, although their work implies that the effectiveness of any given pushed visualization interface depends on the person using the interface. To avoid oversimplification and a loss of critical information, the next generation PSSs must understand both the user and the context from which the user is seeking information. This means they must be aware of who is seeking information and how they need it delivered. To achieve this, many aspects of current PSS visualization approaches must be addressed, including media accessibility, data dynamics, and data manipulation.

Media accessibility. One necessary improvement to accomplish sentience is the accessibility and speed at which various media are delivered and accessed. Accessible media are essential in engaging dialogue and in understanding the potential implications of the analysis (Deal & Schunk, 2004). Effective visualizations catalyze discussion about divergent scenarios and provide a platform from which a set of stories about the future can be generated. There would also need to be a greater variety of media used to deliver content. While most systems use visual representations, there needs to be more effective ways of integrating visual and verbal representations, particularly for those who are not spatially adept and rely more on verbal representations.

Dynamic Scales. The importance of effective visualization devices for dealing with dynamic spatial data sets has long been recognized, especially in the field of natural resource research (Estrom, 1984; Rozenfield & Kak, 1982). Natural resource scientists have been using visualization tools to better understand their science (Onstad, 1988; Cox, 1990) while social scientists have sought to better understand human behaviors vis-à-vis those resources (Malm et al., 1981). While the case for supporting visualization approaches at multiple scales (detailed as well as regional) was made over two decades ago (Orland, 1992), there has not been much progress since.

Data Manipulation. Visualization interfaces should be created with an understanding of the actual use and processing of information by lay people, especially with respect to decision making (Bostrom 2002; 2008). These interfaces should also be informed by an understanding of how communities of people (as opposed to the individuals in communities) think about issues and risks, and how communities acquire knowledge from a variety of sources. Budthimedhee (2002) provides some key insights into the characteristics of visualization devices that can effectively and efficiently support inferences from dynamic spatial data sets. First, because the speed at which inferences can be made is critically important with large data sets, she draws on the idea that we must pay attention to the ease and accuracy with which the pre-attentive visual system can assess relative magnitudes. Second, because of the amount of data needed to make inferences, she draws on the idea that graphic attributes of a visualization device may be the most important feature. Third, she reiterates Wickens' (1992) argument that if bits of information must be proximate mentally in order to support inferences, they must be proximate when visualized.

A sentient PSS, therefore, requires visualization interfaces that are parametric. That is, the system adjusts spatial and material configurations based on new information or individual user differences. There is very little in the literature on system intelligence of this type, but technologies are available for implementing this kind of flexibility. Users can indicate preferences for alternative visualization devices ("Show me these data in a table," or "Show me these data in a different format"). The ability to have user preferences persist over separate sessions is available in many Internet-based information systems and the PSS can learn from and be responsive to individual differences.

System Development

As the link between the system and the user, interfaces must convey valuable information both from the system to the user *and* from the user to the system. This direct learning opportunity is not available in current PSS technology. Many of today's PSSs allow users to leave comments on the information being presented, and such information can help drive system evolution. But can the system learn in less direct ways? Both direct and indirect system interaction and learning will be critical for spatial and temporal specificity and usefulness in a sentient PSS. For instance, an action like searching for the impact of a particular public policy or investment choice in a specific place, might cause the PSS to store that knowledge and remember that there is an interest. If this same search happens repeatedly, the system might generate one or more new scenarios in response. PSS development activity can benefit from this kind of crowd-sourcing. Furthermore, at present, we rely on outside system knowledge to identify data sets to help answer user questions. It would add to the sentience of PSSs if there were ways for the system to learn about and discover new and relevant data repositories that might generate new information and add to an understanding of a problem. In the place-based impact example, the system might uncover data relevant to the stored interest and present it to the user as the new data becomes available.

Additional development is also required in spatial and temporal reasoning within the individual tools that make up a PSS. There must be ways of generating and implementing rule-based procedures and dealing with potential conflicts arising from these rules. This form of sentience could support planners as they attempt to resolve conflicts among different interests.

Plan Making and Sentience

Although PSS visualization interfaces are typically designed to deliver planning related information and knowledge to users, how well do these same interfaces help in the physical act of making plans? Schaeffer and Hopkins (1987) describe plan-making in terms of behaviors (things that people do), tasks (combinations of behaviors that accomplish particular functions), and processes (patterns of tasks that yield plans). Clearly tasks can be supplemented with planning tools (such as GIS systems for making maps). Combinations of tasks might by association also be supplemented by planning tools and PSSs that house these tools. The critical question is how PSSs help to support planning behaviors.

A sentient PSS that is useful for plan making might be most effectively delivered through use-based development rather than solely based on a priori notions of what might work (Deal & Pallathucheril, 2009b). This requires formative rather than summative assessments in system development. It requires working through specific sets of data sources and information with groups of real-world users, building a thorough understanding of the cognitive demands placed on users in a common environment. It also necessitates a computational environment capable of learning from these interactions.

Emphasizing the process of constructing useful PSS models

One important lesson learned is that in order to foster local thought experiments and discussion, it may not be necessary to wait until model results are highly calibrated and fine tuned. In fact, we argue that planning and decision impact can be more important than model accuracy. Preliminary results that can be presented early in the planning process and are easily modified can serve to ignite regional dialogue. For example, the presentation of both favorable and unfavorable scenarios in terms of environmental impacts would be useful in helping a community understand and articulate their preferences. This articulation can help stakeholders and planners communicate with each other as well as steer policy toward achieving important sustainability goals that are sometime difficult to express. This does not absolve planners from providing accurate depictions – especially when challenging accepted norms. At some point in the process reliable and trust worthy information is required. But it does suggest that even ‘quick and dirty’ results can be very useful when planners, stakeholder representatives, and decision makers work cooperatively to interpret them through the lens of expertise and local perspective.

User-driven, use-driven, and user-aware PSS models

User-driven models (such as WhatIf? and UrbanSIM) are packaged into software that can be run with some basic skills sets by planners or policy makers. Use-driven models such as LEAM are created for specific projects at specific instances and sometimes built to answer specific questions. Use-based models involve modelers, contextual experts, and planners to help build, operate, and explain the models in the planning process. Stakeholders and citizens are also critical to their development and deployment. They provide important but difficult to obtain local, historical knowledge, insights about local dynamics, and intimate knowledge of local social constructs. They also provide the specific goals and visions for the future that are so essential to the planning and modeling process.

Use-driven and user-driven PSS models are not mutually exclusive. Component pieces of both are useful. For example user-based interfaces that can allow non-experts to directly modify model factors according to their understanding of their locality, and to generate their own results. Modelers should be on hand to interpret those results and facilitate public discussions based on different model results.

User-aware PSSs are a next-generation process that combines use/user-driven PSS models. User-aware PSS models can adjust their user-interface to different users (modeling experts or layman users) and communicate diverse user-inputs with each other in the system. This can make future PSS operationalization more democratic and interactive.

Post-plan involvement for operationalizing a PSS

Currently, PSS generated information are mainly utilized during the pre-implementation phase of the planning process. Although monitoring can be an important component of plan implementation (that sometimes can determine the success or failure of a plan), due to time constraints it is not often feasible for planners to collect new data, look back and analyze previous plans. A next generation PSS might automate this process so that “actual” emerging developments and real-time environmental impacts can be included in scenario and plan development. And as the time and effort for post-plan monitoring are conserved, planners and modelers can afford additional time with the communities to ensure that implementation can more closely follow the plan intent. This can also be useful in helping stakeholders understand the dynamic interactions between socio-ecological

Examples towards sentience

The evolution of Building Information Modeling (BIM) technology could provide some parallels for the development of a sentient PSSs. Current BIM research has produced models that use a concurrent engineering approach to building design based on dynamic, integrated frameworks. BIM systems are linked to an iterative workflow package, involving a series of design refinements and simulations of environmental and energy impacts, habitability, and social performance measures (Fortner, 2008). Some work is also being done to integrate two- and three-dimensional visualization environments into the BIM suite of tools.

Other attempts at producing semi-sentient information systems go as far back as 1983. In their work on rapid prototyping of linear representations (in AutoCad), Cao and Miyamoto (2003) used models that provided support for verifying consistency across different levels of abstraction. Integrated assessment modeling and reduced-form modeling were topics receiving considerable attention in quantitative policy analysis circles in the 1990s, and like other undertakings before them, these approaches resulted from an attempt to bring different levels of abstraction, spatial, or temporal scales together.

Although currently used at a site planning scale, the concept of *geodesign* offers a methodological reference for future sentient planning support systems. Geodesign aims to enhance traditional environmental planning with technology integrations that include advanced computation, future simulation, remote collaboration, impact analyses, and effective visualization (Flaxman, 2010; Goodchild, 2010; Ervin, 2011). Many of the proposed components of geodesign systems, such as context-based, simulations, dashboards, and time/dynamic manager (Ervin, 2011), aare similar to the components described in our conceptualization of a sentient PSS. The current geodesign literature, however, is still focused on traditional information push processes and does not include dynamic data acquisition, storage and retrieval approaches which are integral to a sentient PSS. Geodesign processes are currently also initiated by planners and designers in a top-down exercise, while a sentient PSS might start an analytical process on its own or from any user of the system.

We can also demonstrate LEAM's cloud based PSS structure as a step towards sentient PSS (**figure 6**). A complicated and LUC model and a large-scale data service sits on the cloud. They can handle demanding computational and storage tasks on high-performance computers. Users for each modeling site have access to one specifically crafted interface for the site. The interfaces understand users' preferences, site-specific data, as well as calibrated parameters for each model. Users can enter inputs into their interface, and then request LUC model run from the cloud.

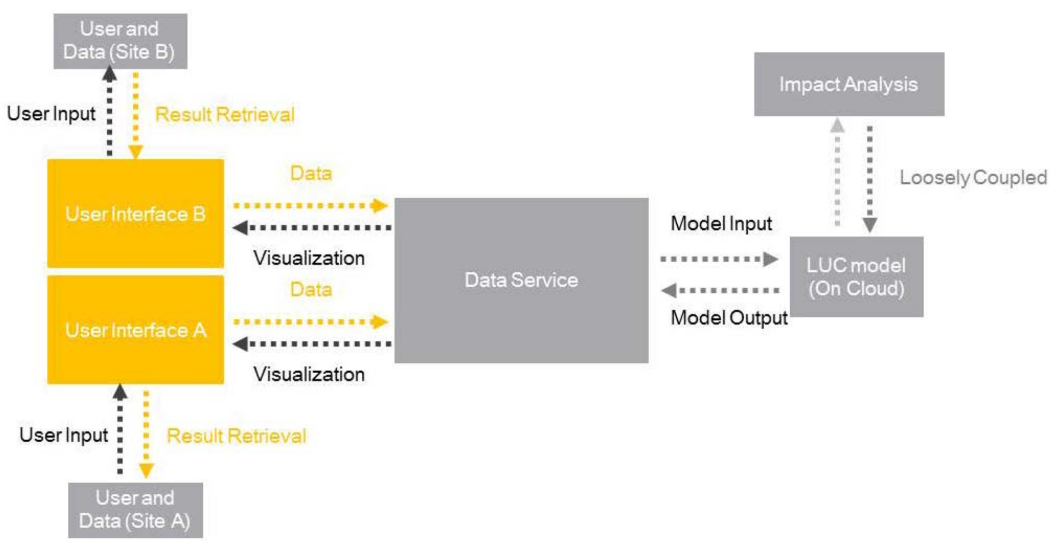

Figure 6. The cloud-based structure of LEAM PSS. Multiple users can assess the model and enter their spatial data through specific interfaces (the 4 boxes on the left). The input data from different cites is stored into one database (data service). A common LUC model (on cloud) can receive the data and start running computation job when request is made from an interface. The results will be pinned back to the interfaces for visualization. The LUC model can be coupled with other impact assessment models.

2.2.5 Conclusions and discussions

In this chapter, I argue that future planning applications require PSS that go beyond the ones we have today. I call for PSSs that possess a greater degree of sentience—a greater awareness of application contexts and user needs. We need information and planning systems that are much more than sensor networks and data acquisition exercises. To make use of big data, we need smart PSS that can supply timely and useful information in support of complex plan-making tasks. Smart PSS cannot be expected to replace planners in practices. Successful implementation and application of PSSs requires a process that involves modelers as well as local planners, decision makers, and stakeholders.

To address both the system and process of PSS for future planning applications, I demonstrate my development on LEAM PSS in the next 2 chapters. **Chapter Three** will focus on PSS systems that better serve scenario-planning exercises—a multidirectional temporal PSS model. **Chapter Four** describes a participatory process that modelers can use to transfer knowledge from technical analyses of PSS and to establish credibility of PSS results.

CHAPTER 3: THE ROLE OF MULTIDIRECTIONAL TEMPORAL ANALYSIS IN SCENARIO PLANNING EXERCISES AND PLANNING SUPPORT SYSTEMS

Planning practitioners are constantly challenged with anticipating the potential consequences of proposed policy and investment choices. This is a difficult task. In fact, examples abound of urban planning problems that have resulted from the unintended consequences of seemingly reasonable urban development policies (Bristol, 1991;Deal & Schunk, 2004; Deal & Pallathucheril, 2009a). Some of these problems can partly be addressed with the use of what Michael Batty described as “geo-information-technology based instruments” (Batty, 1995, p.574). More commonly known as Planning Support Systems (PSSs) (see Brail & Klostermann, 2001; Geertman & Stillwell, 2004). Planning Support Systems have generally been found to be useful in support of scenario planning processes (Pallathucheril & Deal, 2007; Geertman & Stillwell, 2013). To this point in time however, PSSs have primarily utilized future-looking land-use change models to project and compare scenario outcomes. They have not yet widely embraced other temporal directional analysis methods that can enhance and inform additional aspects of scenario planning and help minimize unintended outcomes.

Forecasting PSS urban modeling and simulation techniques have typically focused on expanding external model drivers to a wide(r) range of factors or including a broader range of spatial scales in order to compare scenario outcomes (Monticino et al., 2006). Hubacek and Sun (2001) conduct forward-looking simulations on Chinese land-use scenarios based on changes in economic activity and societal interactions. Packaged PSSs (*WhatIf?* and others) typically embrace a real-world simulation mechanism that creates scenarios through a process of user specification of external drivers, usually represented by a suitability of development designation (Klosterman, 1999; Waddell, 2002; Petit, 2005). Verburg and Overmars (2009) simulate scenarios of a future European land-use under a wide range of local and global conditions. Their work assumes that casting a wider (scenario) net will lead to an improved understanding of the future condition. Couclelis (2005) concurs, arguing that PSSs should interface a broad range of qualitative and quantitative scenario models to help future oriented activities in planning. In general, our review of the literature suggests that when scholars analyze the time sequence constructions of multi-scenario simulation analysis, they commonly run forward-looking models. We contend, however, that PSSs that focus only on future forecasts lose several important opportunities: to learn from the past, to create scenarios that envision major shifts from current established structures, and an ability to understand *how* to attain future goals or outcomes effectively.

We argue that in order to help planners and decision makers avoid the unintended consequence of policy decisions, a PSS should do more than forecast into the future. We suggest that a good PSS should also have the ability to: a) *recast* from a point in time in the past to the current condition; b) *pastcast* from the current condition to a point in time in the past; and c) *backcast* from a point in time in the future back to the current condition (see Figure 1). PSS-based scenario planning processes and outcomes will be improved by including the ability to do these multi-directional temporal analyses.

In this paper, we explore the benefits of multi-directional analysis by analyzing various scenario simulations using the Land-use Evolution and impact Assessment Model (LEAM) as part of a larger PSS that was developed for McHenry County, IL. LEAM simulations were used in a county-wide comprehensive planning process to help determine the spatial and population distributions of future development given various policy investments. The process culminated in the publication of a 2030 comprehensive plan in 2010 (McHenry County RPC, 2010). We use the McHenry example to examine the following questions:

1) What are the potential benefits of multi-directional timeline and scenario analysis compared with traditional forecasting techniques?
2) Can a method for performing multi-directional timelines and scenario analysis be usefully constructed and applied? For example, how do we interpret the comparison between simulated results to actual land-use development patterns?
3) What are some of the potential confounding issues in conducting such analysis and how might they be resolved?

We address these questions first, through a more detailed discussion on multi-directional analysis, its potential benefits, and its connection to the existing literature. We then outline a method for doing this type of analysis within an existing PSS and test its usefulness by applying the methods to a previous planning process and PSS application. We discuss how *backcasting* methods were applied in the scenario development process in the comprehensive planning process in McHenry County Illinois. We also present a *recasting* exercise from past county spatial population and development distributions to what were current conditions (in this case 2010). We compare spatial population distributions simulated in different scenario conditions to actual distributions as reported in block group level census data in 2010. This helps us measure the potential impacts of each scenario on planning decisions made in the county over the recast period. Finally, we conclude our analysis by exploring its strengths and weaknesses and by suggesting improvements and potential future work.

3.1 THEORY: MULTI DIRECTIONAL ANALYSIS FOR SCENARIO PLANNING

The spatial data sets typically used in spatio-temporal planning simulation modeling environments are now available for multiple points in time. This has not always been the case. Until recently, modelers were restricted to just 1 or 2 spatial data points in time from which to construct a coherent model. With dependable, multiple time point data sets, more reliable and in-depth analysis linking the past to the present can now be examined. These examinations can help planners more readily understand scenario plans and scenario planning processes, where they fail(ed) to catch an important causal relationship, or when the plan might fail to achieve its desired effect. In addition, we argue that an ability to make these types of examinations along multiple directions in timeline will also lead to more robust and reliable future forecasts.

We define multi-directional analysis (from an urban planning perspective) as an ability to analyze urban development problems along a temporal timeline in any direction—past or future. This ability enables the analysis of scenario constructions to be made from many different temporal positions (**Figure 7**). The terminologies used in this paper to describe this analytical process include: i) *Forecasting*. Currently the most common approach in scenario planning. A typical forecast starts from a (near) current condition and projects to a future state—this usually refers to the land-use changes that might occur over some specified time period. ii) *Backcasting*. The reverse version of forecasting – the model starts from a future state and draws a developmental path back to the current condition. This is useful for plotting a path that responds to "how do we get there" questions. iii) *Recasting.* Basically, recasting is a reconstruction of the present. It uses forecasting techniques that start from a condition set in the past and project to the current state, usually for comparison purposes (from a projected current state to the actual state). This type of analysis is useful for calibration purposes and understanding a previously unforeseen condition that emerges in the present state. iv) *Pastcasting.* This analysis starts from a current time point (again, not necessarily the current state; it may often be a virtual, more preferred 'current' state) and draws a developmental path back to a previous point in time. This approach is useful for understanding the processes that took place (or should have taken place) in order to arrive at the current or virtual state.

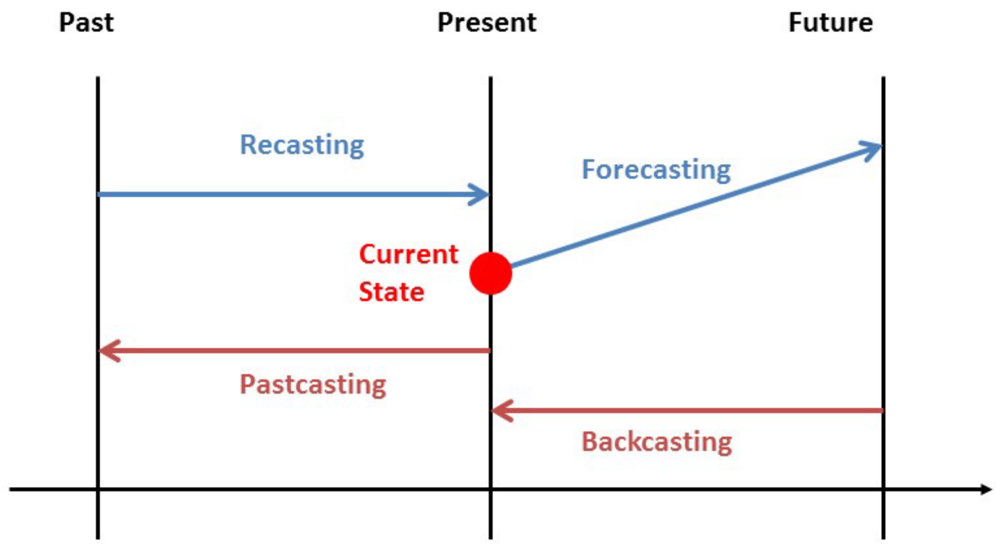

Figure 7. Multi-Directional Analysis using forecasting, backcasting, recasting, and pastcasting to and from the present or current condition. This multidirectional analysis is useful for constructing and understanding robust planning scenarios.

As noted, typical PSSs have primarily utilized future-looking forecasting processes to compare scenario outcomes and the approach is well articulated elsewhere in the literature (Deal, 2011; Batty & Xie, 1994; Geertman & Stillwell, 2009). The following is a more detailed description of other proposed temporal directional analysis methods.

3.1.1 Backcasting from the Future

Although scenario planning process usually utilize forecasts, the analysis, modeling methods, and thought processes do not necessarily have to follow that timeline (going forward in time) in order to construct or explain a scenario in useful ways. Backcasting, the process of starting an analysis from a future state and considering the path required to achieve this state, has been found to be an extremely useful process, especially in the sustainable development realm (Vergragt and Quist, 2011).

Holmberg and Karl-Henrik (2000) define backcasting in planning as a process that starts with a desired (sometimes sustainable) outcome and then explores the strategies needed to achieve it. In other words, “what shall we do today (in order) to get to the desired scenario (outcomes)?” The backcasting process always starts with a preferred future scenario, and then opens up a discussion about how this future can be achieved (Vergragt and Quist, 2011; Kok et al., 2011; Robinson et al., 2011; Dreborg, 1996; Shiftan et al., 2003; Robèrt et al., 2002). Backcasting is methodology that is often applied when planning for complex systems (Dreborg, 1996; Robèrt et al., 2002).

Backcasting from a desirable future state using PSS tools enables planners to step outside of the haze of current realities and trends to test ideas and to reexamine assumptions. **Figure 8** is a schematic illustration of this process. Where a forecast projects an image of the future (blue dashed line to dashed black circle) based on a current situation (red dot on the 'present' line), a backcast starts at a point in time in the future (not always a preferred state, but a state in the future – shown as dashed black circles) and projects back to the present (brown dashed lines to red dot). The brown lines represent the path or the things that need to be done to achieve the future outcome(s).

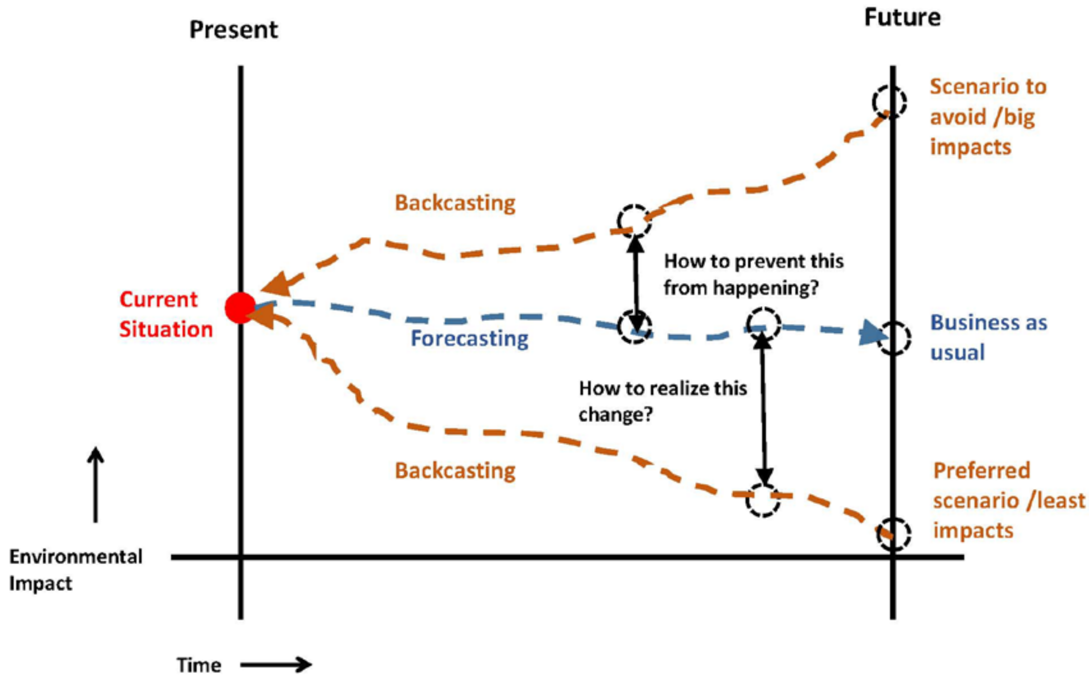

Figure 8. Forecasting and Backcasting.

The process can also be used to avoid undesirable scenarios. In business planning, this type of analysis is referred to as *pre-mortem analysis* (Klein, 2007). First, a team is initially briefed on the idea of a project. Everyone in the team imagines a future scenario in which the project has failed. The group discusses the failures and develops strategies to avoid these future traps. Pre-mortem analysis is described as beneficial in helping the project team to identify potential problems in their projects, to avoid dismissive attitudes of people who are overinvesting, and to give value to those who describe potential weaknesses (Eckert, 2015).

In an urban planning context, backcasting has additional benefits. First, backcasting processes can help community or regional development stakeholders consider potential goals through a different lens, highlight potential problems in reaching the goals, and help create strategies to overcome the identified problems. Traditional forecasting approaches may overlook some crucial developmental factors that are not considered in the forecasted scenario model. Second, backcasting can help communities and planners depart from present unsustainable extrapolations to define new potential future conditions (Holmberg & Karl-Henrik, 2000). Third, backcasting can help planners overcome psychological decision traps in planning and decision-making which include over-estimating future growth, resisting discussions of big investment failures, and under-estimating future risks (Pallathucheril & Deal, 2012). Finally, backcasting can promote systems thinking and inform potential risky outcomes (environmental degradation).

3.1.2 Pastcasting and Recasting to the Past

Along with traditional forecasting and the now more prevalent concept of backcasting, we argue that pastcasting and recasting to past points in time (using similar modeling techniques) can be useful for helping to construct and understand planning scenarios and scenario outcomes. Recasting is relatively similar to standard forecasting-based practices in spatio-temporal land-use change models, but instead of projecting into the future, the simulation recasts from the past to the present. This process of recasting from the past to the present is useful for ground truthing and calibrating the modeled outcomes. It is also useful for understanding emergent properties in a system and how these properties might implicate future conditions. In contrast, pastcasting is closer to scenario planning practices. We move from what planners had envisioned for a current situation to past time points to find out where the developmental pattern deviated from the planned path.

Figure 9 is a schematic illustration of recasting and pastcasting analysis. The dashed blue line indicates the pathway simulated by a land-use change model from a past situation (left red dot) to a recasted current situation (dashed black circle). In all likelihood the recasted situation will not fit the current situation or the actual developmental path (black dot and brown dashed lines). From the deviation of the two pathways, we can compare the actual and hypothesized effects of drivers of change that were included in the simulation. Were all relevant drivers included? Were any omitted? Also, if the actual path of development ends up more or less desirable than the simulated path, what lessons can we learn from the decisions previously made? This process can foster a valuable conversation between planners and local communities, and spur a mutual learning process about the locality.

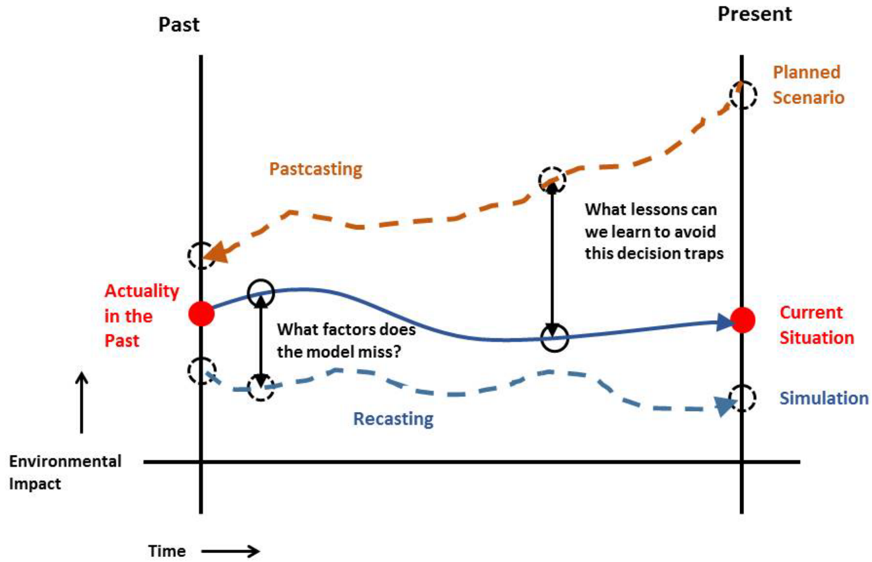

Figure 9. Pastcasting and Recasting.

The idea of using the past to learn from and improve current and future planning processes is not new. Prominent examples of the approach appear in both strategic sustainable development literature and strategic business planning literature. In the sustainability literature, Holmberg and Karl-Henrik (2000) propose a pastcasting equivalent to review past sustainability plans and their outcomes. They use the pastcasting exercise to unravel the evolution of the plans and to explain alternative paths that may have produced more effective results. They point out that non-linear changes in the market often confound sustainable development plans by increasing complexities and the potential for emergent behaviors. They note that this complexity leads to many unexpected failures and shortcomings (Holmberg and Karl-Henrik, 2000). They point out the benefits of utilizing pastcasting analysis in a planning process in a robust PSS. They show how the pastcasting analysis might help planners and the public more broadly come to understand what they failed to see in previous planning exercises, including the specific conditions that may not have been included in the initial planning analysis (or in our case the PSS model). This kind of insight can also enable constructive conversations among stakeholders to facilitate mutual learning and understanding.

In business planning, recasting is typically termed a *post-mortem analysis*, which takes place at the end of a project (summative post-mortem) or while it is still being carried out (formative post-mortem). It requires the project team to engage in a three- or four-day exercise to analyze every problem that occurred during the project (Davies, 1995). Research teams have a natural disincentive to conduct post-mortem analysis because it is a frank analysis of past failures. Thus, it is important to make the process positive and blame-free with no penalizing decisions on future projects (Collier et al., 1996). In a PSS framework, a recasting analysis can promote continuous knowledge management and improvement activities, foster sharing and understanding of perspectives among project team members, integrate individual and team learning, illuminate hidden conflicts, and help document best practices and problems (Birk et al., 2002).

3.2 TESTING A MULTI-DIRECTIONAL APPROACH

Current PSS technologies typically do not address the multi-directional temporal analysis methods described above. We argue, however, that PSS-based scenario planning processes and outcomes would be greatly improved by including them. In this section we test this assertion by examining the McHenry County, IL comprehensive plan and planning process from 2010. The process utilized the LEAM PSS to inform the production of the county's 2030 comprehensive plan. The following describes the PSS application and the construction of scenarios developed. We show how *backcasting* was applied in the process of developing the scenarios and demonstrate how *recasting* might have been usefully employed to challenge the assumptions and outcomes of the simulated scenarios.

3.2.1 The LEAM PSS

The University of Illinois' Land-use Evolution and impact Assessment Model (LEAM) model is a spatially explicit PSS that aims to help communities assess environmental impacts of different land-use scenarios and make better decisions for sustainable development. The LEAM model and PSS have been explained in detail elsewhere (Deal, 2008; Sun et al., 2009; Deal & Pallathucheril, 2007; 2009a; Pallathucheril & Deal, 2012). The LEAM PSS consists of two major parts: (1) a land-use change model defined by multiple drivers that describe the local causal mechanisms and allow easy addition and removal of variables for playing out alternative scenarios, and (2) impact assessment models that support rapid analysis and interpretation of land-use changes depending on local interest and applicability (B. Deal, 2011). LEAM has been integrated with regional economic models (Deal, 2011; Deal and Kim, 2013), transportation models (Deal and Kim, 2013), and hydrology models (Wang et al., 2005; Choi & Deal, 2008). LEAM's user interface facilitates stakeholder participation and learning. The PSS is delivered through a content management system with interactive spatial information portals to enable easy access and modification by users.

In this application, LEAM scenario simulations used 30 x 30 meter data from the USGS National Land Cover Database (NLCD) from 2005-06 (Fry et al., 2011), updated in 2010 using a cell by cell visual comparison process that utilized current satellite imagery from 2010. Simulations were run to the year 2030 to project change in land use (commercial and residential land use) over the 20-year period.

3.2.2 The LEAM PSS in McHenry County, IL

McHenry County is one of seven counties that typically make up the Chicago metropolitan region. It is approximately 35 miles northwest of downtown Chicago and has a population of 318,000. Its location and unique natural features create a quality-of-life that is attractive to many. Since 1990, the county's population has grown 40 percent, averaging 2.3 percent growth annually. The previous land-use plan for the county is the McHenry County Land Use Plan 2010, which was compiled in 1993 and updated in 2000. The County's Regional Planning Commission (RPC) however, found this plan to be increasingly irrelevant and began to compile the *McHenry County 2030 Comprehensive Plan* in 2007 (McHenry County Regional Planning Commission, 2009; Deal and Pallathucheril, 2009a).

The LEAM PSS was adopted by the RPC for use in collecting information, modeling and building scenarios, displaying data, and advising policy decisions as part of their comprehensive planning process. A McHenry County LEAM model was constructed using basic local land use information to establish the base condition (land use, public space, no growth areas, zoning maps, etc.). Travel time calculations were used to establish the relative accessibility of a number of variables to and from any given place in the county including: population centers, employment centers, cultural centers, slope, highway access points, natural attractors (such as water bodies and green space). Input variables are calibrated to the local condition by plotting the spatial distribution of each variable to current land-use patterns and deriving (by specific geography) frequency probabilities in map form. The basic model form also included dynamic CA drivers inherent in the model structure (adjacency, diffusion, and spontaneous characteristics) that affect development probabilities by geography at each time step. We also include the whole Chicago metropolitan region in the land-use model to consider the impacts of neighboring spatial regions on McHenry County, and then clip out McHenry County for further analyses.

In calibrating our model, we include both technical and non-technical approaches.

Technical calibration uses a Kappa statistic to compare an existing condition (2006 NLCD map) to *recasted* development patterns using 2001 data simulated to 2006. Non-technical calibration used a participatory, visual approach to review simulation outcomes. In collaboration with the RPC and other local stakeholders we showed the base case or R*eference Scenario* simulation while asking the question, “Why is this wrong?” in order to help reveal local variable weights and potential new variables to include in the model. This process helped stakeholders synthesize to simulation outputs and afforded a modicum of local trust in the model outcomes, while helping to improve the accuracy of localized version of the model. A more detailed description of the LEAM modeling approach in McHenry County can be found in Sun et al., (2009), Deal and Pallathucheril, (2009a), and McHenry County Regional Planning Commission (2010).

The localized model utilized growth policies (such as restriction areas, fast and slow growth areas), Land Evaluation and Site Assessment (LESA) scores, and other policy drivers as defined by stakeholder generated scenarios (see **Section 3.3** for an example). These policies were used as inputs to the *Reference Scenario* to create new scenarios of simulated future land-use change for a given policy or package of policies. As part of this effort, LEAM synthesized a number of important county characteristics using data gathered from a variety of local, state, and federal sources including: the McHenry County Conservation District, Illinois Department of Natural Resources, Illinois Department of Transportation, Illinois Workforce Development, the US Census, Bureau of Labor Statistics, County Business Patterns, Illinois Department of Agriculture, and the US Geological Survey (Deal and Pallathucheril, 2009a). The LEAM model and modeling process helped the RPC to develop and test a range of scenarios, assess their environmental impacts, and show the projected impacts in dialogue with stakeholders.

A review of meeting minutes published by McHenry County RPC (available on the RPC website) showed much initial conflict about the plan both inside and outside the board. Much of it concerned the population forecast for 2030 (McHenry County Board and Committee, 2007). Disagreements arose between local pro-growth commissioners and residents hoping to continue the trend of sprawling development and anti-growth residents, commissioners, and environmental groups urging protection of agricultural and environmentally sensitive lands. Ultimately, based on the LEAM simulated scenarios, the RPC adopted a developmental path that merged several scenarios (agricultural preservation, compact growth, and development zones) into a plan that tries to preserve the existing land-use and population growth momentum in the county, while materializing the growth in a pattern with the least environmental impacts.

Almost 20 unique scenarios of future land-use patterns for McHenry County were developed as part of a public process with the board and local residents. Scenarios included business as usual, high growth rates, low growth rates, more compact and contiguous developmental patterns, growth controls, agriculture preservation, aquifer recharge zone preservation, green infrastructure focused development, development zones, high density, and scenarios that minimized environmental impacts.

In order to constructively compare the implications of interpreting errors, only two scenarios were selected for review in this study: 1) a **Reference Scenario** (or business as usual), assumed that current development patterns and trends would continue with no modification from 2005 to 2010; and 2) **Agricultural Preservation Scenerio** (agPreserve), agricultural preservation districts are designated as low to no-growth areas to preserve sensitive agricultural and natural lands. Agricultural preservation was an important policy for the county and greatly influenced the decisions outlined in the 2030 Comprehensive Plan. Because of this influence on the final plan, for the purposes of this analysis we refer to this as the ‘preferred scenario’ (even though there were other scenarios that might also be considered ‘preferred’). **Figure 10** shows the starting and ending (simulated) land-use states for the reference scenario. **Figure 11** denotes differences between the Reference and agPreserve scenarios in terms of stress on high quality farmland soils.

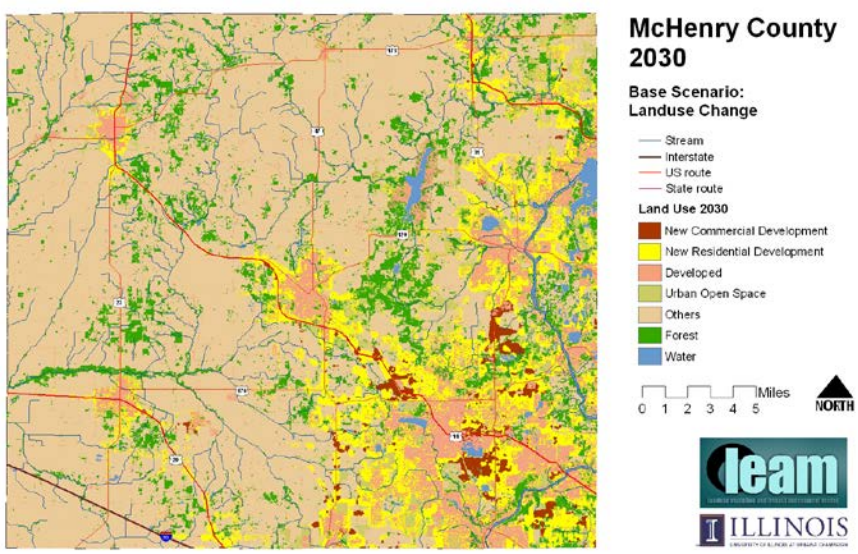

Figure 10. LEAM McHenry County Reference Scenario Simulation. Yellow are new residential cells and red are new commercial cells. Beige are existing development areas.

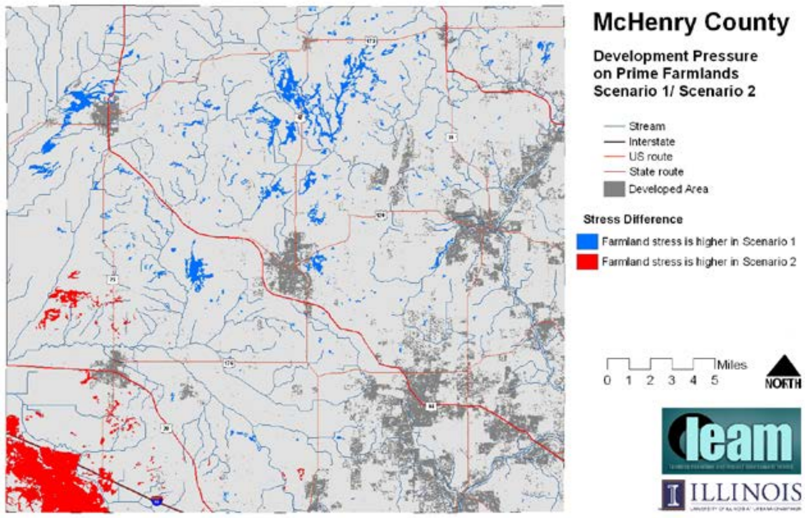

Figure 11. LEAM McHenry County AgPreserve Scenario Simulation difference map. Reds are prime farm areas pressured by development in the reference scenario, but protected in the agPreservation scenario. Blues are prime farm lands affected by an alternate scenario.

Our analysis of the scenarios was undertaken with the following questions in mind: 1) How well did the simulation perform with respect to the way the situation actually evolved? 2) Can the difference tell us anything useful about the way we conducted these scenario simulations? and 3) What inferences can we make about plan implementation?

3.2.3 Backcasting: Constructing Preferred Scenarios

Backcasting techniques were applied to the construction of preferred scenarios. A future preferred land-use pattern was determined by analyzing preferred outcomes relative to the scenario in question. For example, in the agPreserve scenario LESA scores were used to assess agricultural productivity (Illinois Department of Agriculture, 2001). Preferred productivity and LESA outcomes (minimizing impacts on each) dictated the spatial allocation of population and employment at each time step in a linear optimization process presented by **equation (1)**.

$$min \sum_{i=1}^{n} l_i R_i + l_i C_i; \qquad s.t. \sum_{i=1}^{n} e_i C_i = d_e; \quad \text{and} \quad \sum_{i=1}^{n} p_i R_i = d_r \qquad (1)$$

where n is the number of total census blocks; l_i is the estimated average LESA score for land productivity for census block group *i*; variable R_i is the total residential cell developed in census block group *i*; variable C_i is the total commercial cell developed in census block group *i*; e_i is the estimated average employment density for each (30m x 30m) commercial cell for block group *i*; p_i is the estimated average population density on each (30m x 30m) residential cell for block group *i*; d_e is the total estimated employment growth to the target year (2040 in this case); and d_r is the total estimated employment growth to the target year (2040 in this case).

After reviewing several simulation exercises, an agricultural preservation policy was formulated. Critical areas for preservation districts are formed to have very low to no probability of residential and commercial developments. The resulting growth pattern represented the agPreserve scenario.

The agPreserve scenario construction represents a typical backcasting process. First, a desirable outcome is established—in this case, minimized agricultural productivity loss from urban development. This outcome is determined from one perspective without reference to other variables. Backcasting how to achieve this desirable outcome, however, requires an analysis of the complex interactions between a host of variables; many multiple iterations need to be examined. Once these are examined, a coherent set of policy levers can be developed. In the case of McHenry County, agricultural productivity impacts were closely tied to the introduction of a new (and also desired) transportation investment (a new interchange conflicted with highly productive agricultural lands) and any ensuing policy needed to address it.

3.2.4 Recasting: Comparing Expected vs. Observed Land-Use Patterns

In recasting simulations, we used the original (cleaned) 2005 USGS spatial data and reran simulation scenarios from 2005 to 2010. We then compared simulated patterns to the actual patterns existing in 2010. Other economic, demographic, natural resource, and preservation zoning data for 2005 were obtained from ACS 2005 (U.S. Census Bureau, 2012) or were provided by the McHenry County RPC (McHenry County Regional Planning Commission, 2009). Block group level population for 2005 came from ACS, and population for 2010 came from US Census 2010 (U.S. Census Bureau, 2012).

In order to compare simulation results to the 2010 census data we needed to transform spatial simulation outcomes into the relevant census spatial scale—in this case block groups. To translate simulated land-use distributions to population distribution by block group, we have 2 challenges: 1) First, locational variables (longitude and latitude) do not have linear or quadratic relations to the population distribution in the county. However, adjacency of census tracts is likely to indicate a level of development; 2) commercial land-use and residential land-use are obviously correlated and cannot be both used as independent variables in ordinary linear regression. However, it is unreasonable to eliminate any of them in the predictive model as key information from LEAM simulation.

To address the challenges, we applied a ridge regression method to establish the land-use/population relationship. The ridge regression method is considered a better prediction method than ordinary linear regression in our research for two reasons. To address the first challenge, we divided the county into 5 longitudinal zones and 5 latitudinal zones and used binary variables to indicate if the block groups belong to those zones. Unfortunately, this approach adds 10 degrees of freedom to the model, resulting in possible over fitting. Ridge regression has a variable shrinkage function, so it generally reduces the risks of over fitting. To address the second challenge, Ridge regression is very useful in handling correlated input variables by limiting their coefficients to generally small values (to properly account for data outliers).

Ridge regression is a modified version of a least square (LS) regression method. It minimizes the normal criterion for LS, but also adds a penalty term, or shrinkage parameter (γ) that can be multiplied by the sum of norms of coefficients. With a larger λ, the coefficients will shrink – tending to 0. Ridge regression is not unbiased with $\gamma > 0$, although it usually has a smaller variance than LS. By tuning the shrinkage parameter (γ) we can calculate the smallest mean square error (MSE) of the model. Given a response vector *y* and a predictor matrix *X*, a ridge regression attempts to minimize γ for vector β. The optimization function to estimate coefficient $\hat{\beta}$ is presented in **equation (2)**.

$$\hat{\beta} = argmin_{\beta}(y - X\beta)^T(y - X\beta) + \gamma \ \beta^T\beta$$
(2)

where β is the coefficients vector and γ is the shrinkage parameter, and *X* is a matrix of vectors $\{x_{area}, x_{commercial,} \ x_{residential}, x_{longitude}, , x_{latitude} \}$. The details of variables can be found in **Table 1.** (Vogel, 2002).

For variable selection in this study, we define *longitude and latitude* as distance variables, *count of commercial land-use cells* (in the LU raster map) and *count of residential land-use cells* (in the LU raster map) as land-use variables, and *population* as outputs for each census block group. Ridge regression is used to predict the future population in each block group based on applying the coefficients of the initial dataset to predict future population from our simulated future land-use patterns (**Table 1**).

Variable	Mean	Std. Dev.	Min	Max
Input Variables from Training Group (2006 NLCD)				
Block Group Area (square meters)	6,756	11,938	196	57,052
Commercial Land Use (number of raster cells)	220,515	260,416	900	1,945,350
Residential Land Use (number of raster cells)	934,954	536,304	92,250	2,742,750
Longitude (categorical)	5 zones[1]			
Latitude (categorical)	5 zones[2]			
Output Values from Training Group (2005 ACS)				
Population Counts	1,722	836	472	6,325
Input Variables from Test Group (LEAM raster land-use 2010 output)				
Block Group Area (square meters)	6,221	11,183	207	57,055
Commercial Land Use (number of raster cells)	204,116	241,360	900	1,786,950
Residential Land Use (number of raster cells)	872,539	453,892	328,500	1,808,550
Longitude (numerical)	5 zones (see notes below)*			
Latitude (numerical)	5 zones (see notes below)**			
Output Values from Test Group				
Population Counts	1,664	1,893	792	3,650

Table 1. Regression model variables for each census block group.

The comparisons between the average numbers of the 2005 input and the 2010 simulation do not necessarily indicate actual growth of population and land-use categories because

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[1] The county is divided into 5 equally sized zones according to longitude values, and "if the block group is in that zone" is represented by binary variables.

[2] The county is divided into 5 equally sized zones according to latitude values, and "if the block group is in that zone" is represented by binary variables.

the census block groups have been changed over time. The strength of our learning method is that it does not rely on the exact same geographical unit to project past data to simulated data. Rather, it learns useful information from past data, tries to find the pattern, and decides how the simulation data gap should be filled. In this sense, the process handles the potential changing of data in census blocks extremely well. In addition, we tested a range of additional variables that were considered potentially relevant including density (residential and commercial cells) and travel distance to the regional center (downtown Chicago). The inclusion of cell density increased our reference scenario accuracy by just 2.37%. The inclusion of the distance to Chicago center increased the reference scenario accuracy by only 1.65%. Although potentially important when nested with other variables, the additional accuracy was considered insignificant when compared to our original error (27% - see Section 4.1.1).

3.3 RESULTS: IMPACTS ON PLANNING DECISION MAKING

The process described above facilitates the use of a comparative metric (total population for each block group in 2010) for analysis across scenarios. This process enables a comparison of the actual population in 2010 to the simulated and recasted scenarios and a response to the question – How well did simulations perform when compared with actual data? We further analyze this question by presenting the percentage of errors and the spatial distribution of the errors for each of the 2 scenarios studied. We then explore the plan implementation implications of the model results.

3.3.1 The Reference Scenario Assessment

Using our comparative variable, the reference scenario projects a population distribution in McHenry County that is fairly consistent with actual census counts in 2010 (**Figure 12**). Also Moran's I analysis indicates existence of global and local spatial-autocorrelations (on simulation errors), the existing urban center in the southeast of the region does not show significant over or underestimation of population from the model simulation. In **Figure 12**, red indicates block groups with a higher *actual* population (as reported in the census); blue represents block groups with a higher *simulated* population (using the LEAM PSS). Out of 164 census block groups, the calculated error in the reference scenario was less than 10% in 41 of the block groups and less than 20% error in another 29. The average error is about 27%. There appear to be several block groups in the northwest, southwest, and southeast of the county that were calculated to be more than 40 percent underestimated. These are block groups that are included in or very close to three major township development clusters in the county—Harvard (northwest), Marengo (southwest), and a large group of townships in the southeast. An examination of the data shows that actual development patterns are more closely tied to the existing urban infrastructure than the reference (business-as-usual) simulation.

Using this analysis technique, we can adjust the attractiveness of existing infrastructure to align the reference scenario more closely with actual patterns. This is especially important for a reference scenario, since in typical planning processes, scenario alternatives will be compared to the 'business as usual' (or do nothing) *reference* case. In addition, if the reference scenario exhibits high internal validity (i.e., it calibrates closely in a recasted analysis), we can surmise that each scenario will represent a likely outcome given the variables that have been modified to reflect the alternative future tested. Backcasted goals also can be used as an alternative calibration methodology. If for example, we want to use less water in the future, we can calibrate the scenario outcomes based on how much water each scenario might use.

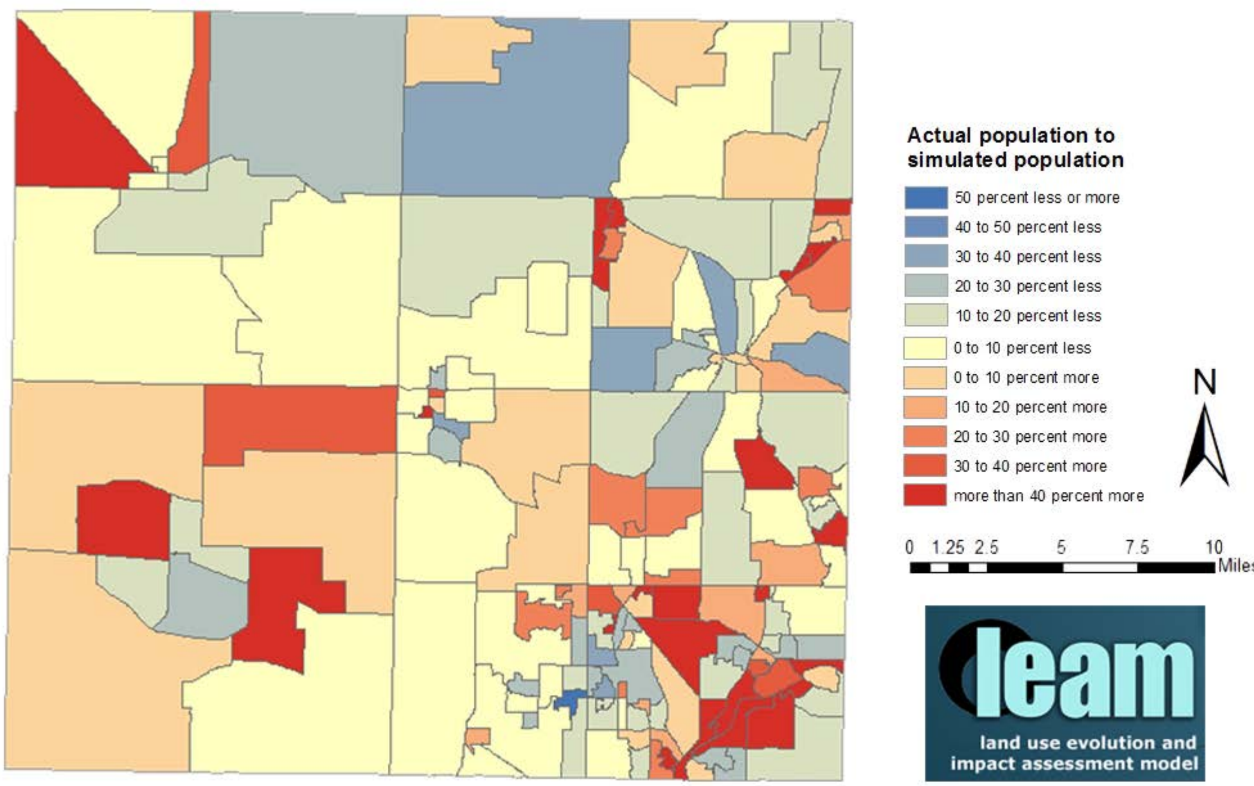


Figure 12. A comparison of the 2010 actual population and the reference scenario simulated population distributions by census block group.

3.3.2 agPreserve Scenario Assessment

The agricultural preservation scenario represents a future with more farmland preserved for agricultural use in the future. Preservation strategies are based on soil conditions, crop productivity assessments, and LESA scores. This scenario shifts areas of urban growth toward existing urbanized parts of the county and away from productive agricultural lands.

A comparison of the actual population to the agPreserve scenario simulation is shown in Figure 5. Predictably, the results are not as favorable, since we adjusted the scenario to represent an alternative to the business as usual trends. Out of the 164 census block groups in the county, the prediction has less than 10% error on 36 of the block groups, and less than 20% error on another 27 block groups. Although the visual analysis is markedly different, the average error is only slightly higher than the reference scenario (just over 28%), since the majority of potential growth remains in already highly urbanized areas.

As noted, compared to the reference scenario, the agPreserve scenario has a much more obvious error pattern. Similar to a growth boundary policy, the scenario removes random rural developments (due to policies that preserve productive agricultural areas) in favor of a more compact pattern of development in already developed areas. The actual population distribution is lower in the existing developed clusters, and it is higher in the fringe area of development. An “underestimation corridor” (red colored block groups in **Figure 13**) is evident from the northeast corner of the county to the mid-southern edge of the county. In comparison, actual growth is more compact than the reference scenario simulation, but less compact than the agPreserve scenario.

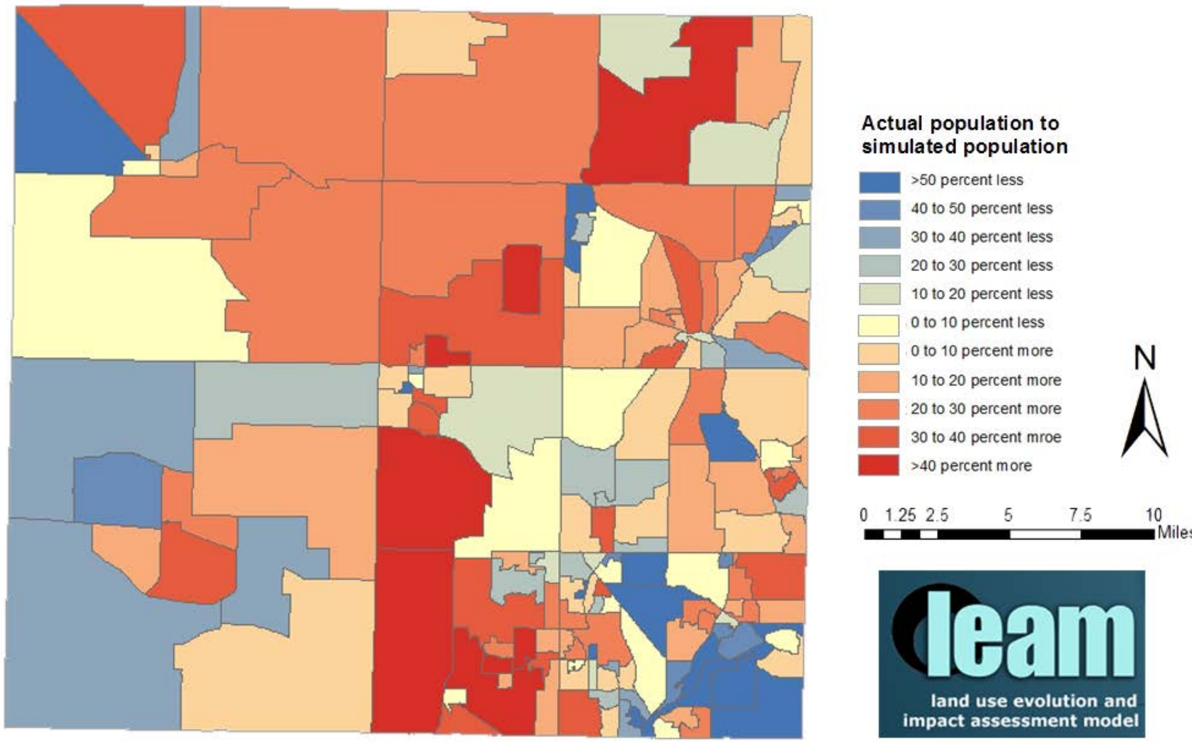


Figure 13. 2010 Actual Population and agPreserve Scenario Simulation Comparison by census block group.

If we overlay the Agriculture Preservation District (green zones in **Figure 14**, which is very close to the established Agriculture Preservation District laid out in the McHenry County 2030 Comprehensive Plan) with the agPreserve scenario outcome, we see that the majority of the fringe growth in the county is moved to the north (black colored block groups). While we expected growth moving out of the preservation zones, we did not expect the rampant fringe growth in other rural, less agriculturally significant areas. This is both expected—growth moving out of the preservation zones, and unexpected—fringe growth still rampant in the county in other rural, but less agriculturally significant areas. The intended consequence of the agPreserve scenario was to improve the compactness of new developments. The unintended consequence might be that instead of compactness, fringe development remains the norm, but moves to other areas that may in fact be equally sensitive from a different perspective (i.e., ecosystem services or green infrastructure services).

The actual growth in McHenry County fails to tightly follow the compact pattern envisioned by the preferred agPreserve scenario, but it does avoid occurring inside the preservation district. The balance of those two forces direct most of the unexpected growth onto the central to northeast corridor of the county, making the shape of the ‘underestimation corridor’ easier to understand.

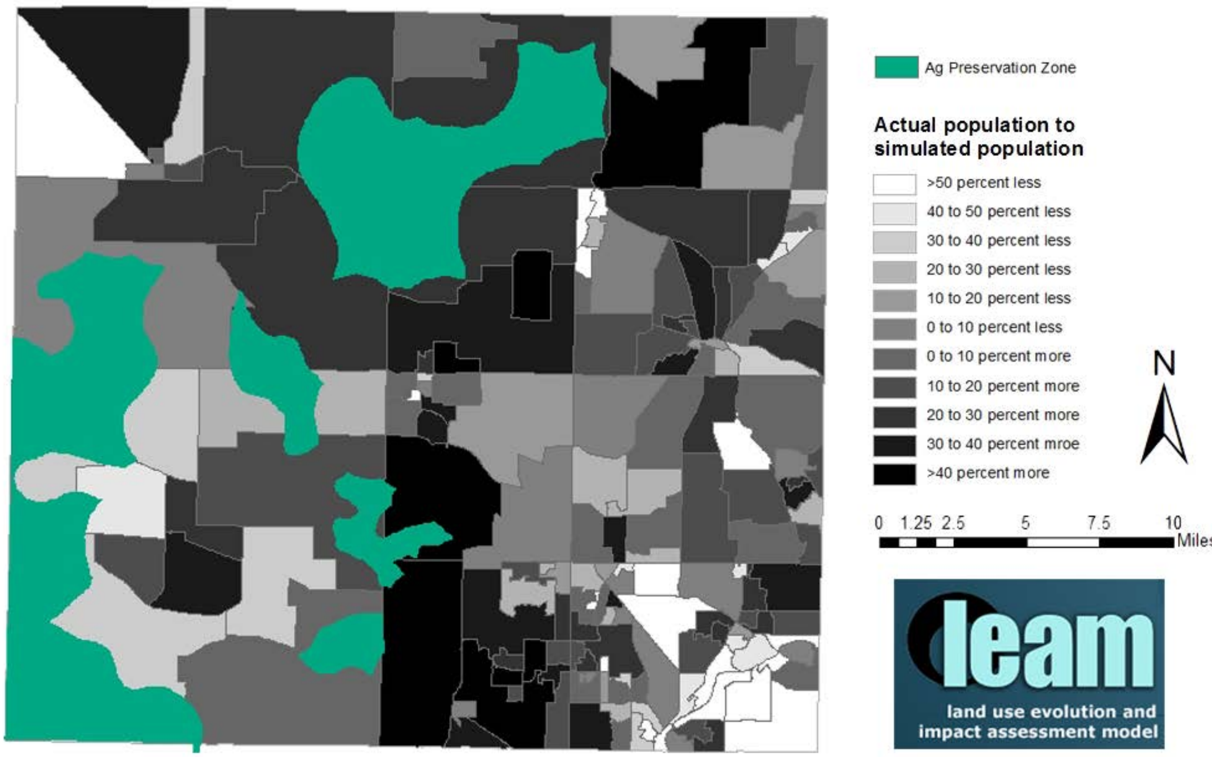


Figure 14. An overlay of agriculture preservation districts (green areas) on the agPreserve scenario outcome (shaded block groups).

3.4 DISCUSSION

3.4.1 Implications of Scenario Comparisons

Like all plan making processes that include some estimation of the future, a population projection is a necessary component when considering potential development scenarios. Using a PSS with multi-directional analytical capabilities, however, can remove some uncertainties surrounding the *time* at which these projections might be realized. It can shift the conversion from “what is our plan for 2030?” to “what is our plan for population X?” The difference is subtle. In the latter, the plan is foreseeing the potential for change and responding to it, not necessarily predicting the change. In McHenry County, it would change the discussion to be more about managing resources in the light of increasing population regardless of when it occurred. In this way, whether or not the population projections are met at the allotted point in time is irrelevant. The county plan acknowledge this concern in a ‘challenges’ section in which they discuss “how to manage and accommodate the anticipated population growth and needed economic development while maintaining the same quality-of-life” (McHenry County RPC, 2010).

As opposed to population growth, the actual county land-use growth patterns exceeded the land-use growth in residential and commercial developments that were simulated for 2010. In fact, in McHenry County the overall population *decreased* by 2% (to 308,000) in 2010 even though land-use area actually increased by more than 30% in some block groups. This implies that there is a general inter-regional movement in the county from more densely populated areas to less densely populated areas. A multidirectional analysis can help understand and capture this phenomenon.

Comparing forecasted and recasted simulation results to actual population distributions helps expose differences. These differences enable diverse interested parties (modelers, planners, community groups) to collaboratively re-examine the assumptions that are made in model parameters. Critical questions that emerge in the process of examining these differences is – how do we attribute the found errors?—to which variable(s)? Furthermore, when analyzing specific scenario interventions, the inconsistencies might be in the difference between the simulated policy and the actual policy implemented.

3.4.2 Usefulness and Goodness of Fit in Multi-Directional Analysis

Below are some tentative evaluation criteria for multi-directional analysis in a ‘useful’ scenario PSS derived from our McHenry County experiences (**Table 2**). In our comparative framework, we suggested 2 critical differences in the interpretation of model results: a) is it accurate?; and b) is it useful? This generally follows the popular aphorism, “all models are wrong, some models are useful” (commonly attributed to Box, 1976). First, do the models succeed or fail in conveying some of the factors affecting future development patterns and subsequent population distributions? Alternatively, even if not particularly accurate, do the model results influence the decision-making, planning, and/or implementation process in the region? We argue here and elsewhere (Deal & Pallathucheril, 2009a) that ‘b’ is generally preferred in the planning and decision making process, although ‘a’ is typically seen as the standard used to assess model validity.

Scenario creation techniques					
		Backcasting	Forecasting	Recasting	Pastcasting
Evaluation Criteria		Is there a structural change?	Is goodness-of-fit important?	Modeling error interpretation	Plan implementation error interpretation
Types of Scenarios	Reference scenario	No.	**No.** We aim for a better developmental pattern	Missing developmental drivers; basic assumptions do not hold for the future	If trend is more sustainable than this scenario, policies are effective; otherwise policies are not better than before.
	Preferred scenario	**Yes.** Change to a more sustainable pattern.	Yes.	Insufficient projection on policy effects	Insufficient policy consideration
	Scenario to avoid	**Yes.** Downward change to unsustainable pattern	**No.** We want to stay away from this scenario happening	This is scenario to be avoided, so it's good to have "errors" for this scenario comparing with the ground truth	

Table 2. Proposed multi-directional evaluation criteria for a *useful* scenario planning PSS.

We contend that in order to be useful, a PSS should inform and improve the planning and decision-making process. Whether or not the model is accurate may be less relevant. For example, in the McHenry County process, it became clear that the protection of agricultural resources was a priority for the County. In another scenario (an investment in a new interstate interchange), growth pressures moved from other parts of the county down to the area of the interchange. The area of the interchange, however, is an area of highly productive agricultural soils. The impetus for the interchange lacks a logical construct (it does not improve travel time for commuters or other travelers) and is more emotional than rational, so that a simple solution – reject the interchange investment in favor of investments that would have less of an impact on agricultural lands – was not feasible. Another strategy is to plan for the interchange, but also implement agriculture protection policies as a hedge against the potential negative consequences on agriculture—which in the end was the preferred path. Whether or not the model accurately depicted the change in growth pressures is not important. The fact that the county wants both an interchange and to protect agricultural resources was made clear by the modeling process and was an important component in policy formation that will help in achieving both desired goals and outcomes.

3.5 CONCLUSIONS

In this paper we argue that multi-directional analyses for scenario planning can bring the planning community additional benefits to the typical PSS forecasting analysis. We contend that in order to help planners and decision makers avoid unintended consequences, a PSS must do more than forecast into the future. We suggest that a good PSS should also have the ability to: *recast* from a point in time in the past to the current condition, *pastcast* from the current condition to a point in time in the past, and *backcast* from a point in time in the future back to the current condition. We show through a real-world scenario planning exercise in developing a county-wide comprehensive plan in McHenry County, Illinois that PSS-based scenario planning processes and outcomes can be improved by including the ability to do these multi-directional temporal analyses.

We conclude that PSSs that are more flexible in navigation through timelines will better serve sustainable planning goals. First, pastcasting and recasting can help planners and communities learn from past experiences and help avoid repeat mistakes. They can also help re-evaluate past goals in terms of performance outcomes in order to prioritize new potential strategies. Second, recasting and pastcasting reveal potential drivers that PSS models might fail to recognize for specific regions, enabling the construction of more nuanced localized models that will increase local model validity. For example, using this recasted analysis we can adjust the attractiveness of existing infrastructure to tune the reference scenario to more closely align with actual patterns.

Finally, recasting and backcasting allow for a departure from present unsustainable extrapolations to help attain new goals and assist in the definition of new potential conditions. If, for example, we want to use less water in the future, we can use backcasting techniques to calibrate the scenario outcomes based on how much water they use. PSS with multi-directional analytical capabilities can also remove some of the uncertainties surrounding the *time* at which projections might be realized. It can shift the conversion from “what is our plan for 20XX?” to “what is our plan for population X?” In the latter, the plan is foreseeing the potential for change and responding to it, not necessarily predicting the change.

In our comparative framework, we suggest 2 critical differences in the interpretation of model results—i.e., is it accurate? vs. is it useful? First, do the models succeed or fail in conveying some of the factors affecting future development patterns and subsequent population distributions? Alternatively, even if not particularly accurate, do the model results influence the decision-making, planning, and/or implementation process in the region? We argue here and elsewhere that usefulness is generally preferred in the planning and decision making process, although accuracy is typically seen as the standard used to assess model validity. There is gap in the existing planning literature on PSS LUC model validation. In our estimation a good validation process should exhibit: objectiveness, reasonableness, understandability, and practicality. This fundamental part of PSS LUC development however, requires much further work.

In this paper we contend that in order to help planners and decision makers avoid the unintended consequence of policy decisions, a PSS should do more than forecast into the future. We suggest that a good PSS should also have the ability to travel in multiple temporal directions in order to more thoroughly inform the planning and decision making process. We argue that PSS-based scenario planning processes and outcomes will be greatly improved by including the ability to do multi-directional temporal analyses and usefully present the results.

CHAPTER 4: KNOWLEDGE FLOW OF PLANNING SUPPORT SYSTEMS (PSSS) INTO PLANNING PRACTICES: A POST-MORTEM CASE STUDY OF LEAM PSS IN MCHENRY COUNTY, IL

It has been almost 25 years since scholars began investigating the use of land-use change models to simulate the evolution of urban land-use patterns (Deal et al., 2017; White and Engelen, 1994). The use of these types of models for understanding urban phenomena has been increasing both in the laboratory and the profession of planning ever since (Geertman and Stillwell, 2003). The models have become a major component part of Planning Support System (PSS) tools. In typical PSS toolboxes, land-use change models and other data, models, and visualization devices are used to inform planning and decision making by simulating possible future land-use outcomes, such as how land -uses might evolve in a specific place over a specific period of time. This has proven especially useful in scenario planning and other practical planning exercises (Chakraborty et al., 2011; Helen Couclelis, 2005). As the scholarship that surrounds PSS technologies becomes more mature, the ways in which these tools might be made more useful (i.e., more accessible) and endemic to the planning process have become more central concerns (Saarloos et al., 2008; te Brömmelstroet, 2013; Vonk et al., 2005).

PSS scholars argue that it is now time for PSS model development to move beyond the technical issues of the models and into "softer" issues that involve social and practical issues (Michael Batty, 2007; B. Deal & Pallathucheril, 2009b; R. E. Klostermann, 1997; Marco te Brömmelstroet, 2012; MT te Brömmelstroet, 2010; Vonk & Geertman, 2008). Overly focusing on geo-information tools result in that PSS is perceived to be too complex, inflexible, and incompatible to planning tasks (Vonk et al., 2005; Vonk and Geertman, 2008). The critical bottleneck now is transparency, understandability, flexibility of PSS and its connection to the planning practices (Marco te Brömmelstroet, 2012; MT te Brömmelstroet, 2010; Vonk & Geertman, 2008). Specific problems of popularizing PSS in practices include model to user communication (B. Deal & Pallathucheril, 2009b; Brian Deal & Pan, 2016; S. Geertman & Stillwell, 2004a; Pelzer et al., 2014; Saarloos et al., 2008; Marco te Brömmelstroet, 2012, 2013; MT te Brömmelstroet, 2010; Vonk & Geertman, 2008; Vonk et al., 2005b; Vonk, Geertman, & Schot, 2006b), assuring users of modeling validity (S. Geertman & Stillwell, 2004a; Richard E Klosterman & Pettit, 2005b; Pelizaro, Arentze, & Timmermans, 2009b; M. Shiffer, Brail, & Klosterman, 2001b; M. J. Shiffer, 1995; Marco te Brömmelstroet, 2013), facilitating collaborative planning (Brian Deal & Pan, 2016; Richard E Klosterman & Pettit, 2005b; R. E. Klostermann, 1997; Pettit, 2005; MT te Brömmelstroet, 2010), encouraging mutual learning (Pelzer et al., 2014; Marco te Brömmelstroet, 2012; Vonk & Geertman, 2008), and actively enabling community feedback (B. Deal & Pallathucheril, 2009b; Brian Deal & Pan, 2016; Pelzer et al., 2014; Marco te Brömmelstroet, 2012).

In this paper, we argue that knowledge transfer from technical analysis to useful and understandable planning practice guidance is the key issue that PSS scholars need to address to improve the social and practical aspects of PSS applications. Technical result such as goodness-of-fit of a simulation model, a simulated future land-use map, parcel-to-parcel based scenario comparison, or sectoral gain/loss in an economic impact analysis, may not make sense to policy-makers directly. Goodness-of-fit of simulation model depends on the measuring spatial units and "null resolution" (Costanza & Maxwell, 1994; Koomen, Rietveld, & de Nijs, 2008; Pontius et al., 2008; Pontius, Huffaker, & Denman, 2004), thus it is difficult for non-spatial modeling expert to make sense of the context associated with a "percentage of accuracy". Another example is about future land-use change maps. A city may only have 5 percent of urban land-use expansion over 10 years. When modelers show a simulated future land-use map with a current land-use map to policy-makers, they might barely see the differences, let alone making any policy implications from it. In sum, most "plain products" from technical analyses of PSS do not fit the practical needs of users, thus their values are limited without a carefully managed knowledge transfer process.

Knowledge transfer of technical terms based on modelers' immersion into and understanding of planning practices can make PSS results influential to policy decisions. Vonk et al. (2006) claim that PSS results are hardly suitable for direct usage by decision makers, because decision making is more a game of politics and power than technical analysis. However, this can be different if knowledge transfer has been applied the technical analysis. Instead of showing stakeholders a simulated "business-as-usual" land-use map that has 5 percent difference to the current land-use situation, if modelers interpret the results as "most development would gravitate towards western parts of the county if the developmental trend is not intervened", this message will be a point that may be frequently cited by certain stakeholders in the decision making process.

We further argue that to identify needs and goals of transferring technical knowledge into practical usage, or even figure out necessary technical analyses, requires PSS scholars to be immersed into planning practices that involve PSS themselves. For example, thousands of patterns may be abstracted from one simulated future land-use map using plain language. However, there might only be one or very few patterns that pinpoint the core of planning debate, such as locations under political struggle or local intuitions that confront the technical results. This requires modelers to be involved into plan-making processes to understand outstanding needs and debates of the plan making process.

In this paper, we aim to use a real-world PSS aided plan making process to substantiate our argument. In **Section 4.1**, we first introduce a use-driven PSS involvement in the plan-making process in McHenry County, IL to show how knowledge transfer occurred mutually between modelers and local stakeholders. Then, we conduct a post-mortem study as around 10 years has passes after the initial model is built. During our experience with other LEAM users and the McHenry County planners after the initial plan, we found out that 2 questions need to be answered: the interpretation of reference scenario model and the "continuous plan" evaluation of the initial McHenry County Plan. To answer those questions, we develop and adapt 2 spatial analytical methods in **Section 4.2** on the goodness-of-fit of model simulations, and try to convey the results to users in an understandable and practically useful way. **Section 4.3** includes our conclusions and future works.

4.1 A POST-MORTEM CASE STUDY OF LEAM PSS IN MCHENRY COUNTY, IL

4.1.1 Project Background

In 2009, LEAM and its PSS was applied to McHenry County, IL as a part of their comprehensive planning process. McHenry County is one of seven counties in the Chicago metropolitan region, approximately 35 miles northwest of the city. It has a population of 318,000. Since 1990, the county's population has grown 40 percent, averaging 2.3 percent growth annually. The previous land-use plan for the county was compiled in 1993 and updated in 2000. By 2007 the McHenry County Regional Planning Commission (RPC) deemed the plan irrelevant and began the McHenry County 2030 Comprehensive Planning (McHenry County Regional Planning Commission, 2010b).

The LEAM model and PSS have been explained elsewhere in detail (Deal and Pallathucheril, 2009). The system consists of two major parts: (1) a land-use change model defined by multiple drivers that describe the local causal mechanisms of potential change for playing out alternative scenarios; and (2) impact assessment models that support rapid analysis and interpretation of land-use changes (Deal et al., 2011). The LEAM PSS is delivered through a content management system with interactive spatial information portals to enable easy access and modification by users with a simple user interface that facilitates stakeholder participation and learning.

In this application, LEAM scenario simulations used 30x30 meter data from the USGS National Land Cover Database (NLCD) (Fry et al., 2011) from 2006. Simulations were run from the year 2010 to the year 2030 to project changes in land-use (commercial and residential) over the 20-year period. The role of the LEAM PSS was to help the RPC to create various scenarios, assess their environmental impacts, and reveal the projected impacts to stakeholders. Data for the simulation effort was gathered from a variety of local, state, and federal sources including: the McHenry County Conservation District, Illinois Department of Natural Resources, Illinois Department of Transportation, Illinois Workforce Development, the US Census, Bureau of Labor Statistics, County Business Patterns, Illinois Department of Agriculture, and the US Geological Survey (Deal & Pallathucheril, 2009). 18 unique scenarios of future land-use patterns for McHenry County were developed as part of a public process with the board and local residents.

4.1.2 A Use-Driven Approach

The particular interesting points of this project is that local planners planned to adopt and adapt one of LEAM's simulated scenarios into the final land-use plan of the County (McHenry County Regional Planning Commission, 2010b), so this is a rare project that PSS results heavily influenced the final results of a plan. The PSS development process first established a "reference" scenario as a baseline for assessing the impacts of various land use policies being discussed. The reference scenario simulated land-use change if current growth pattern trends continue to 2030. Other model scenarios were then compared to the reference scenario in order to understand the impact that the tested policies might have on various important county assets (Brian Deal & Pan, 2016).

In the scenario development phase, modelers conducted the standard use-driven approach of LEAM model (B. Deal & Pallathucheril, 2009b). The preliminary scenario simulation outputs were shown to local stakeholder groups, government employees and officials, and planners. The modelers put up questions, such as: "Do you think this developmental pattern looks reasonable if XX policy were to be enacted?" The local groups were invited to visually check the model outputs and offer their opinion (the visual validation process was used at that time but later improved, which will be described in **Section 4.2**). Various responses and criticisms are collected, including "development not in the right direction", "commercial development not clustered right", and "this existing lot is actually vacant, so it should be redevelopable rather than having no change for 30 years." The LEAM team took these responses and forged a knowledge transfer from "intuitive opinions" to "operational requirement" to programmers of the model, including changing weights of some variables (such as accessibility roads), increasing probability of growth for cells with neighboring development in the dynamic growth process, and manual clean-up some existing commercial areas into "developable lands." Then the modelers bring updated results to local stakeholders again and let them visually check—"is there any improvement?” This process of mutual knowledge transfer was interactively conducted until the model scenario results were deemed reasonable by local stakeholders.

Apart from honing the technical sides of the model, the modelers also paid intensive attention to the heat of political debates revolving the plan. LEAM team participated in than 10 public meetings convened by the McHenry County Planning board with a range of public interests, stakeholder groups, government employees and officials, and planners. The process revealed an early and major concern with the projected development outlook for 2030. This was the bellwether issue that underlay a larger conflict on the future of the County between pro and anti-growth advocates; one group of residents hoping to continue the past development trends and environmental groups urging protection of environmentally sensitive and agricultural lands. With understanding the critical issue, LEAM team proposes the local planners to compose the final land-use map based on Agricultural Preservation Scenario (agPreserve) from the 18 simulated scenarios.

To make stakeholders with different views (pro-development and pro-preservation), LEAM team and the local planners conduct a “backcasting” method to create final land-use map. LEAM results are linked to Land Evaluation and Site Assessment (LESA) modeling framework from the Illinois Department of Agriculture (Coughlin et al., 1994) to form a linear optimization problem that maximizes preserved agricultural land value while meeting the constraint of development goal. This procedure is well documented in Deal et al. (2017). The knowledge transfer was focused on the linear optimization problem. The LEAM team translated math formulae of the linear optimization into 2 simple discourse—“maximizing preserved agricultural land value” (objective of the optimization) and “maintaining developmental goal” (constraints of the optimization) to address stakeholders of different views. This approach was proven successful as LEAM agPreserve scenario was eventually adapted to the enacted 2040 land-use map of McHenry County (McHenry County Regional Planning Commission, 2010b).

4.1.3 Post-Mortem Questions

We are now 8 years after LEAM’s initial application to McHenry County (2009) and 11 years after the start year of the simulation model (2006). LEAM’s experiences with further users when referring back to the McHenry model, as well as post-plan communication with planning staff in McHenry County, IL, raise 2 issues that need clarification.

Interpretation of reference scenario. The reference scenario model of McHenry County sparks particular curiosity from other prospective LEAM users. The questions are: “what does it mean?" and "how well does it fit the actual developmental pattern?" Those 2 questions are actually connected. LEAM's definition of reference scenario is that "simulated land-use change if current growth pattern trends continue to 2030." LEAM's users want to further now how much validity that should be given to this "continuation of growth pattern trends." Is it still the scenario that best forecasts the future land-use change? Or is it no longer relevant since growth patterns will often be alternated by planning efforts? We should be able to give an answer, since ground-truth data are available now to validate the initial reference scenario for McHenry County.

Monitoring of plan implementation. LEAM PSS intended to enable a "continuous planning" process for McHenry County (Brian Deal & Pan, 2016). A visualized online tool is created to allow the community to continuously interact with the data and models associated with the plan. Apart from this tool, McHenry County planners are also interested in how well the land-use development of the county has conformed to the chosen agPreserve scenario. Especially, whether agPreserve or reference scenario better captures the actual developmental pattern, and what inference can be drawn from the conclusion.

We find out new interests from planning practitioners through LEAM team's continued engagement with PSS users. Interpretation of reference scenario and monitoring of plan implementation require updated technical analyses that measure and compare goodness-of-fit of PSS models. More importantly, we need to convey the results of goodness-of-fit under a complicated planning context to users—which requires knowledge transfer. In **Section 3**, we will demonstrate how we apply a new technical methods to measure and compare goodness-of-fit of past LEAM model, and then discuss how the results can be transferred to user and understandable and useful knowledge.

4.2 MEASURING, COMPARING, UNDERSTANDING, AND COMMUNICATING GOODNESS-OF-FIT

In **Section 4.1.3**, we identify that "interpretation of reference scenario" and "monitoring plan implementation" are the two questions we need to explain to LEAM users, and methods of measuring and comparing goodness-fit are needed to extract relevant information from the model results. In this section, we use 2011 NLCD land-cover map as the "ground-truth" (actuality) to measure and compare goodness-of-fit of the first 5-year simulations of reference and agPreserve scenarios. We could present simulated and actual land-use maps to planners and let them perform visual comparison, which is the process adopted by some previous land-use modelers (Al-Ahmadi, See, Heppenstall, & Hogg, 2009a; X. Li & Yeh, 2004; Santé, García, Miranda, & Crecente, 2010). However, it is not suitable for our goal for two reasons. First, the interpretation of reference scenario is meant to be explained to future users that are not from McHenry County. Their lack of understanding of the context of the county is likely to impair the information they can see from the maps. Second, our simulated scenarios and actual development are urban growth occurred within 5 years, thus the vast majority of lands are classified as "persistence" (or unchanged). It is difficult for users to visually distinguish trivial differences for two maps with only 5% of cells changed.

There exists several literature from geographers and land-use modelers on how to "ground-truth" land-use simulations (Al-kheder, Wang, & Shan, 2008; Ballestores Jr & Qiu, 2012; Ligmann-Zielinska & Sun, 2010; Pontius Jr, Peethambaram, & Castella, 2011; F. Wu, 2002). We need to adapt and adopt those methods to fit in our particular cases. Further, practical users are not likely to directly make sense of the goodness-of-fit results generated from those methods, such as Kappa index (Ballestores Jr and Qiu) or a 3 dimensional table and figure of merits (Pontius Jr et al., 2011). Plus, goodness-of-fit of PSS models have little value unless we understand them in practical context. In the following part of this section, we are going to demonstrate how we use technical methods and transfer them into understandable knowledge to answer the question of "interpretation of reference scenario" and "monitoring plan implementation." Then we will discuss how to make use of the "goodness-of-fit" as useful knowledge in planning practices.

4.2.1 Interpretation of Reference Scenario—Continuous Resolution

Reference scenario simulates land-use change of McHenry County if current policy and developmental pattern persists. Measuring its goodness-of-fit against 2011 NLCD actual map require some special considerations. First, 5-year urban growth of Chicago suburb will not be drastic at all. If we measure agreement of all land-use cells for simulated and actual maps, 90% and above goodness-of-fit is easily attainable, which is not a correct message for users to understand the validity of PSS results. For this reason, we decide to only measure the simulated vs. actual land-use change. However, on a 30x30 meter cell-by-cell level measurement, agreement level is very low (only 384 of 10,868 new developed cells overlap, 3.5% goodness-of-fit). The comparison is shown in **Figure 15**.

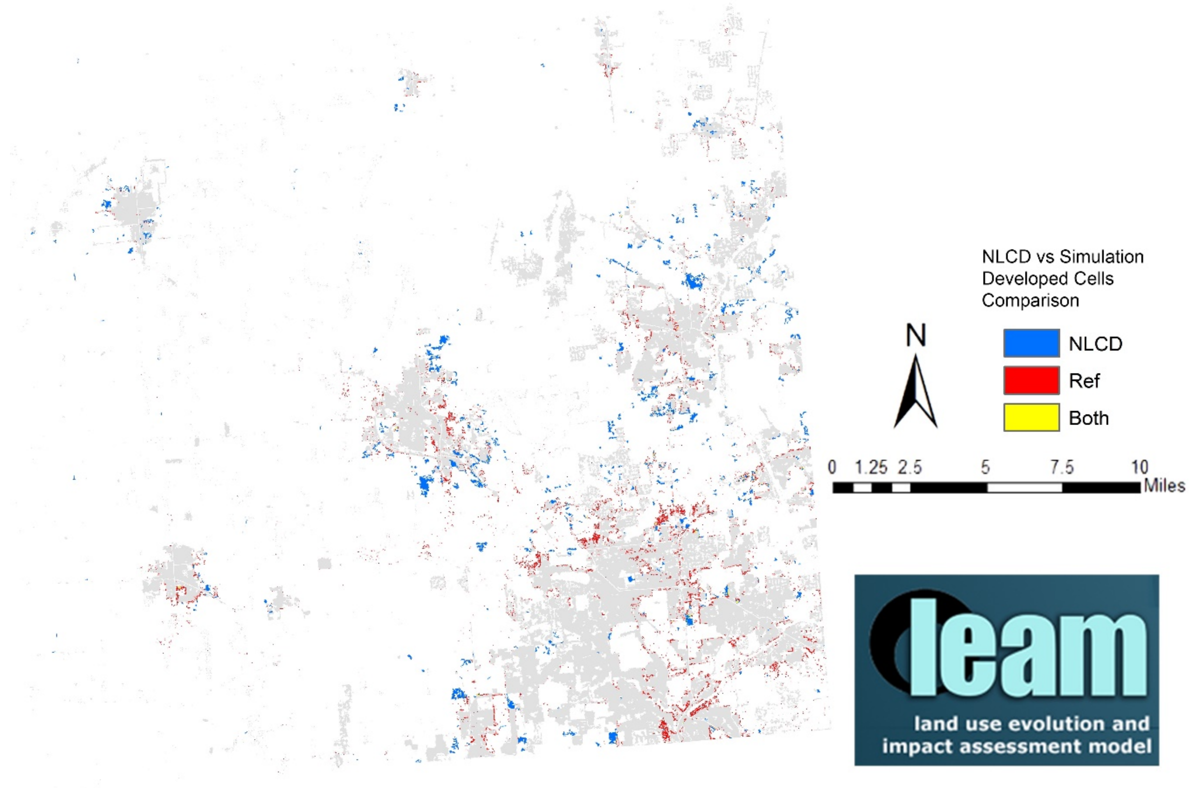


Figure 15. A comparison of the LEAM reference simulation (red) and actual development (blue) in McHenry County, IL from 2006 to 2011; yellow cells represent instances of both actuality and simulation.

A 3.5% goodness-of-fit is neither a reasonable depiction of the validity of the reference scenario. Urban development is a process inherent with uncertainty and randomness, prediction to a 30x30 meter accuracy cannot be reasonably expected.

Wu (2002) points out this problem and proposes a zonal aggregation method to aggregate cells spatially into smaller and more discrete subdivisions. The process applies numeric validation calculations on each zone to determine how many simulation cells are transformed vs. the actual zonal change. The approach is an improvement on aggregate numeric comparisons as the smaller zones improve spatial location concerns. However, the selection of the type, size, and spatial construct of the zone may imply an arbitrariness that can compromise its validity. Pontius Jr et al. (2011) applies a multi-resolution process to mitigate the arbitrariness of selection of zones in zonal aggregation. However, this process is a generic method comparing land-use simulations and considers matching all types of future land-use possibilities (change and persistence). Its results are embedded in a 3-dimensional table and figure of merits. For our case, this method fails to focus on the point we concern (change vs. change) and the results are not understandable and useful knowledge to stakeholders.

For a validation process that fits our case, we take the concept of Wu (2002), Pontius Jr et al. (2011), and the "null-resolution" concept from Costanza and Maxwell (1994), Koomen et al. (2008), and Pontius et al. (2004, 2008). we apply a continuous resolution process to compare the reference to the actual land-use map in 2011. The detailed methodology description and math derivation are available in **Section 4.4 Part 1.** Here, we use plain language to describe the method, and make sense of the results.

First, similar to Wu (2002), we divide the whole maps into several grid-like subdivisions of a certain dimension. We sum up cells that experience change in land-use category in each grid of both simulated and actual maps. Then, we take the squared difference of simulated and actual sum of cells in each subdivision, and sum the squared differences. This is the "residual squared error". Then we imagine a "null-map", which has the same total cell changed as actual map, but evenly distributed in each cell. We take the sum of squared difference between "null-map" and actual map again, and this is the "total squared errors". We use the ratio of "residual squared error" to "total squared errors" to subtract 1, and that is our "zonal R^2" goodness-of-fit.

Understanding R^2 requires basic statistical knowledge, and we should not expect that from all users of PSS models. Moreover, this R^2 measures "the scale of squared errors in each subdivision", rather than the fit-of-line that is defined in regression models. One distinct difference is that this R^2 has value range from minus infinity to 1 (the case for a regression model without intercept) while the R^2 in simple linear regression ranges from 0 to 1. These knowledge are certainly overwhelming to convey, and require us to construct a more understandable deliverable. We varies the subdivision size to get different R^2, and it is intuitive that a larger zone size is likely to result in a larger R^2 (but not exact monotonic). We want to find a zone size beyond which R^2 values are consistently larger than 1, and we name it as the "accuracy resolution" of the scenario—the point that the scenario modeled land-use better than an educated guess with bare information of the future (total number of changes). The outcome of "accuracy resolution" is a size of spatial units, such as "500x500 meters", which is more understandable as it can be interpreted to be "the model provides valid information over 500x500 meter scale."

We apply this continuous resolution process to LEAM's reference scenario of McHenry county and the analysis shows a reasonably scaled 8500x8500m as the point at which our R^2 measure becomes consistently positive, which is the reference scenario's "accuracy resolution" (**Figure 16**).

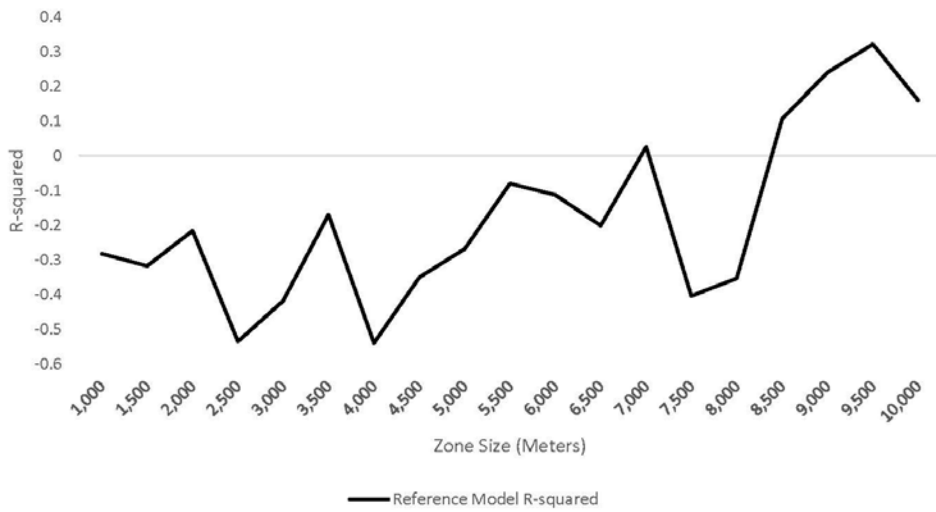


Figure 16. A chart of R^2 accuracy for differing zone sizes

So how do we transfer this knowledge to future LEAM users who want to know the interpretation of the reference scenario model? First, 8500x8500m grids divide McHenry County into 16 equal-sized grids. We interpret this as "the reference scenario can capture the general directions of development (such as towards north, south, or south east)" and "the reference scenario can tell which township is likely to have more growth, and it will usually happen in reality". Those are the two pieces of knowledge that can help users understand the problem, and they are abstracted from our technical analyses above. Also, we need to make clear to users the essence of reference scenario—it is not a scenario that we think will exactly match the future. It is meant to help planners and stakeholders identify problems (such as agricultural and ecological land loss) if no plan intervention is taken to the current developmental pattern, and the planned outcome needs to avoids unwanted development in the reference scenario.

4.2.2 Monitoring Plan Implementation—Boundary Softening

In the McHenry County planning process, the reference scenario assumes business-as-usual development patterns while the agPreserve scenario is a policy-based scenario. It was intended to represent a more environmental and agriculturally favorable outcome and should produce more compact development patterns by discouraging development in agricultural or ecologically sensitive areas. In the county comprehensive planning process, planners argued for the agPreserve scenario and ultimately it was included in the plan. After several years of the enactment and start of implement of the plan, McHenry planners and stakeholders pose the question: “is the county developing as planned (more similar to agPreseve scenario, or sticking to the existing pattern (reference scenario)?”

To answer this question, we seek to compare both agPreserve and reference scenarios’ simulations by the year 2011 to NLCD 2011 ground-truth (actual map), and interpret the conclusions to local planners. A feasible methods is to apply our continuous resolution validation to both scenarios, and find out which has a finer “accuracy resolution”. However, our initial attempt turns out that both scenarios have very similar “accuracy resolution” and we cannot conclude significant difference from the comparison.

We analyze the situation and figure out that the boundary problem is what leads to the perplexing results. For example, in **figure 17(a)** simulated cell and an actual cell fall within the same boundary. In **figure 17(b)**, they fall into different boundaries, reducing the simulation’s overall goodness-of-fit measurement without changing locational or statistical properties. To avoid this inconsistency, we propose modifying hard boundaries into soft boundaries. Our approach is to diffuse individual cells (**figure 17(c)** and **(d)**). The amount of diffusion based on a decay function so that the farther from the actual change site, the lower the spread (see **Section 4.4 Part 2** for technical details). Each simulated cell can be measured in terms of its proximity to an actual cell based on its diffusion score, regardless of boundary location.

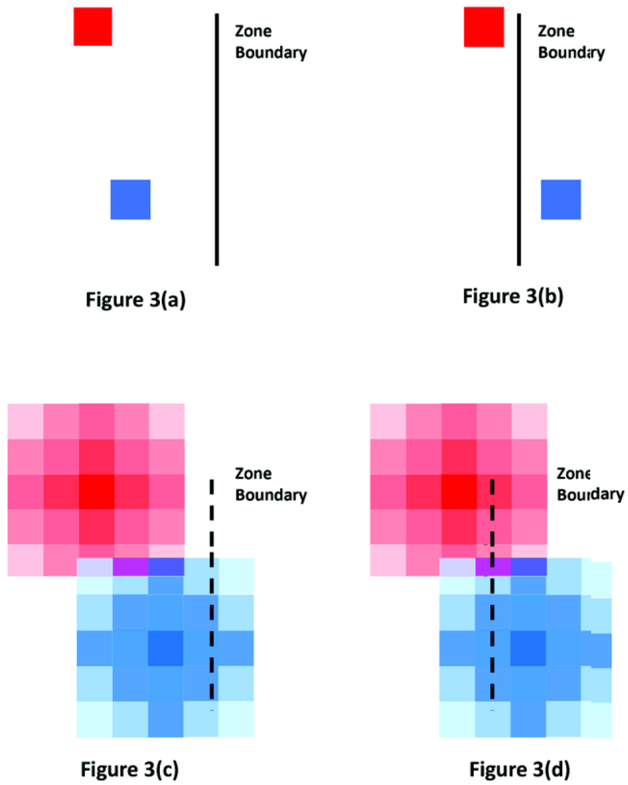


Figure 17. Zonal Boundary and Cell Diffusion. In **(a)**, both simulation (red) and actuality (blue) cells fall within the same zone. In **(b),** the exact same cells fall into 2 separate zones and would score lower on a goodness-of-fit measurement. The white area represents cells that remain unchanged. In **(c)** a color gradient represents a diffusion of values and a less severe change in goodness of fit given **(d)** a different zonal boundary.

Using a softened boundary improvement, we calculate R^2 values for both reference and agPreserve simulations when compared to actually developed cells over a range of zone sizes (100x100m to 300x300m). Results (**figure 18**) show a consistent and constant positive zonal R^2 for each scenario. Our R^2 results fluctuate within 0.06-0.12, and show no discernable increasing or decreasing trends. This suggests that both simulations consistently produce a better understanding of spatial development at a structural level than random cell placements. It's worth noting that the reference scenario consistently out performs the agPreserve scenario within the varying spatial units tested.

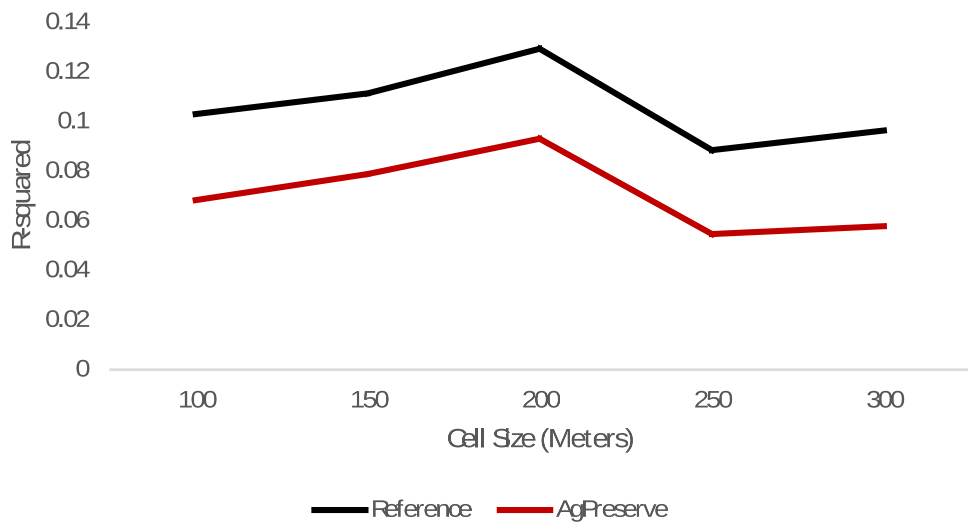


Figure 18. Illustrates boundary softening based R^2 accuracy measures for reference (black) vs. agPreserve (red).

The result shown in **figure 18** indicates that reference scenario over-performs agPreserve on all 5 cell size we tested (from 100 to 300 meters with 50-meter interval). If the 2 scenario has similar goodness-of-fit, the percent of one scenario better than the other on a given cell size should be 50%. If the null hypothesis holds (agPreserve is similar to reference scenario in terms of goodness of fit), reference scenario has a 3.13% chance to over-perform agPreserve scenario on 5-cell-size comparisons. Thus we can reject the null hypothesis on a 5% significance level and conclude that reference scenario over-performs agPreserve scenario. This is very important information for local planners, since the scenario they included in their official plan fails to be closer to the county's development than the scenario that assumes continuation of older path, after few years of plan implementation. The inferior performance of agPreserve scenario may be attributed to policy effectiveness or implementation, data, or model mechanism issues. Our goodness-of-fit process itself does not causal possibilities, but it is a signal for planners and modelers to further investigate their assumptions in policy decisions, plan implementation, and modeling.

In this section, we develop methods of measuring and comparing goodness-of-fit of PSS model scenarios. We transfer the results into understandable and useful knowledge to answer users' most concerned questions in post-planning era of McHenry county 2040 comprehensive plan. As we point out, goodness-of-fit results themselves cannot determine validity of PSS models, and they cannot address causal mechanisms of model fits or misfits. Understanding validity and casual mechanisms of scenarios requires a more complicated collaborative learning process involving planners, modelers, and stakeholders. And this process can certainly make use of information regarding goodness-of-fit. In the section session, we will discuss how goodness-of-fit can be used collaborative learning processes to serve critical planning purposes.

4.2.3 Beyond Goodness-of-fit

Credibility of PSS models. Cellular Automata based PSS model is an example of applying system models to study complex social problems. However, misuse of system approaches in public policy arena draws skeptical views to the model (Andrews, 2000). A quantitative measure of goodness-of-fit, even carefully explained, cannot alone convince users' credibility of the system.

According to Andrews (2000), modeling experts need to spend extra efforts outside technical realm to restore system legitimacy for non-technical users. Some of the approaches include tailoring analysis to context, interact with stakeholders via participatory workshops, and seek both status-based and consent-based sources for building models.

From PSS perspective, what we can learn from Andrews' suggested approaches is to involvement local stakeholders and planners to build PSS models to achieve system credibility, as we demonstrated in the use-driven case in McHenry County, IL (**Section 4.1.2**). However, using a continuous resolution method in addition to visual validation provides additional values. First, we can interpret credibility of our PSS model to users outside McHenry County with common accepted standards. Second, while building the model with local stakeholders, quantitative approach can help modelers to refine model outcomes before showing to stakeholders for collaborative tuning, thus reducing burdens for stakeholders to receive overwhelming information of various qualities.

Multi-directional analysis. Additionally, Deal et al. (2017) argue that PSS-based scenario planning processes and outcomes will be improved by including the ability to do multi-directional temporal analyses, which include "forecasting", "backcasting", "recasting", and "pastcasting". Apart from traditional forecasting model that predicts future scenarios from current situation, the other 3 types of "-casting" can combine collaborative model building and validation processes to improve validity of PSS models, monitoring plan implementations, and even finding out casual mechanisms of some developed patterns.

By recasting, modelers can compare past predictions to current “ground-truth” conditions. This process was demonstrated in **Section 4.1.2** and **4.1.3** with continuous resolution and boundary softening approaches for scenario validation and implementation monitoring. This approach can also be applied to collaborative tuning of the weight of model variables in model development. Modelers can add, remove, tune-up or down the weights of certain model variables (such as accessibility to road or population centers), and check what are the goodness-of-fit scores of those models to recast from past to current land-use map. Then these models and their goodness-of-fit scores can be shown to the local planners and stakeholders to collaboratively understand the casual mechanisms of how variables influence model goodness-of-fit scores. Do those scores make sense? Which developmental drivers are perceived to be much more important for the local context? Are they correctly reflected in our modeling approach? Pastcasting starts from current situation and use a “time-reverse” model to simulate the past land-use, which can be similarly applied to this variable tuning process.

Backcasting means to model from future land-use to current situation with a “time-reverse” model. Backcasting approach was applied in developing McHenry County 2040 plan (**Section 4.1.2**). It was used to find an optimal developmental path from the start of planning year to 2040 to achieve valuable agricultural land conservation. We can further use backcasting to monitor plan implementation by finding out how “far” current situation is to the desired scenario (such as 2040 agPreserve scenario in McHenry case) by checking goodness-of-fit result of backcasting from future. When local planners and stakeholders see this results, a collaborative deliberation can be held to agree on what actions could be done differently in the future than in the initial plan or implementation phase.

4.3 CONCLUSIONS

In this paper, we argue that the knowledge transfer from technical analyses of PSS models to users are the key of addressing “softer” issues of popularizing PSS among plan practitioners. Existing PSS Literature focus on describing either systems and application of PSSs (S. Geertman & Stillwell, 2004a; Richard E Klosterman, 1999; Richard E Klosterman & Pettit, 2005b; Pettit, 2005; Waddell, 2002b), or in general how PSS should be improved for popularization (Pelzer et al., 2014; Marco te Brömmelstroet, 2012; MT te Brömmelstroet, 2010; Vonk & Geertman, 2008; Vonk et al., 2005b, 2006b). We claim that the need of technical analysis and knowledge transfer has to be determined by modelers’ involvement into the plan making and collaborative model building phase.

To fill the gap, we study a real-world case—the application of LEAM PSS in McHenry

County 2040 Comprehensive plan. In the post-mortem study of the plan, we figure out that 2 pieces of critical information are needed to help future users to interpret our reference scenario and McHenry planners to monitor their plan implementation. Based on those needs, we adopt and adapt model validation methods to create our continuous resolution and boundary softening approach. The goodness-of-fit results are transferred into understandable and useful knowledge, such as “the reference scenario can capture the general directions of development (such as towards north, south, or south east)”, “the reference scenario can tell which township is likely to have more growth, and it will usually happen in reality”, and “reference scenario consistently over-performs agPreserve scenario in fitting the first several years of county development”.

We further acknowledge that values of goodness-of-fit are not adequate by themselves to grant credibility to PSS models for users, serve model calibration, monitor of plan implementation, and find casual mechanisms. It involves deliberate processes of modelers, as well as local planners and stakeholders. Methods of obtaining goodness-of-fit scores can certainly be used in the process iteratively to achieve the goals. We frame the collaborative process of using goodness-of-fit scores in multi-directional temporal analyses including forecasting, backcasting, recasting, and pastcasting. The real-world application of those processes is an extremely interesting filed for future study.

One question remaining is: can we conclude that better information leads to better planning? Our case shows a relatively well-informed planning process with the involvement of PSS model pre- and post-planning. However, our post-mortem does not suggest that the original intention of the plan is adequately implemented. My opinion is that better information does not necessarily lead to better planning. There are two reasons. First, PSS technology helps to objectively assess future impacts and possibilities of planned scenarios, but it does not change the objective that the community wants to achieve. With different objectives and local ways of thinking about development, the same assessment result can be interpreted into many different ways, and lead to various planned decisions. Second, PSS can help evaluate plan implementation as I show in this chapter, but PSS does not help implementing a plan itself.

Though not necessarily resulting in a better plan, PSS provides information that enables discussions among various stakeholders based on an objective information and assessment. It can also rectify distortions on future consequences, and can also be viewed as an early warning sign of implementation problems (Deal and Pan, 2016). Thus, better information from PSS enhances the planning process to be more participatory and informed, and better process correlates with better planning outcomes

Other expansions to our research can be further need of technical methods that figured out in the PSS application processes, and modelers' transfer of the analytical results to stakeholders. We hope to see a "dictionary" of practitioners' requirements and questions from PSS models in practical applications, modelers' analytical responses to the requirements and questions, and what information abstracted from the analytical results are proven understandable and useful to the planning processes.

4.4 TECHNICAL DETAILS

4.4.1 Part 1

To illustrate a single-resolution zonal process, we generate two sets of data in a blank data window (with resolution of 0.1x0.1 units on a 5x5 grid or 50x50 total units) to represent "actual growth" and "simulated growth" over a fixed period of time (**figure 19 (a)**). Red cells represent simulated cell change and blue cells represent actual cell transformations. Yellow circles represent the cells that exactly overlay in simulation and actuality (common). Each set of cell sets (simulation and actuality) represent 50 developed cells for 100 total cells allocated within the window. The two sets of cells are allocated around the same 5 centers (represented by **+** in the **figure 19(a)**), using the same rules for allocation, i.e., they each exhibit a similar variance from the (statistical) "+" centers. The physical representation is seen in **figure 19 (a)**, with the following mathematical process of creating it:

The two-dimensional data (X_{ki}, Y_{ki}) in each class k (simulated or actual cells) is generated from the same bivariate Gaussian distributions with uncorrelated components, same variances, and same means, each pair of X_{ki} and Y_{ki} is uncorrelated. The data generation process can be described below:

$$(X_{ki}, Y_{ki}) \sim N(\boldsymbol{m}_l, \Sigma_l)$$
(3)

where, $\boldsymbol{m}_l$ is two-dimensional and each dimension randomly selected from $\{0, 0.1, \dots, 3.9, 4.0\}$, Σ_l is a two dimensional covariance matrix and $\mathrm{diag}(\Sigma_{kl})$ is randomly chosen from $\{0.4, 0.5, \dots, 0.8\}$; 0 for other elements of $\mathrm{diag}(\Sigma_{ki})$; l denotes the 3 shared centers and variances of (X_{ki}, Y_{ki}); $l = 1, 2, 3$ and $\mathrm{p(l = 1)} = \mathrm{p(l = 2)} = \mathrm{p(l = 3)} = 1/3; k = 0,1; p(Y = 1) = p(Y = 2) = 1/2.$

A visual examination of our illustration suggests that the simulation (in red) generally follows the patterns exhibited by the actual developed cells (in blue). From this we might infer that the simulation captures the general causal mechanisms for cell change in the window. And although the simulation is quite good at replicating actual patterns (center and variance of the clusters), only 7 of the 50 simulated cells would be counted as correct in a cell-by-cell overlay (this translates into a 14% goodness-of-fit score). A more reasonable approach would tolerate minor errors of the simulation and focus more on the accuracy of general patterns.

One way to accomplish this is to produce smaller scaled “resolution sub-zones” (Wu, 2002). In our example data window, we might divide our window into sub-zones and aggregate developed cells (both simulated and actual) by these zones (**figure 19(b)**). Simulation goodness-of-fit is evaluated by comparing the numbers of developed cells predicted to the actual development for each sub-zone. This has the advantage of ignoring spatial offsets of simulated cells that are less than the coverage of the sub-zone. In this way, one can better evaluate the quality of the general pattern of spatial simulations without the problem of cell-to-cell inaccuracy. As noted above, however, the arbitrariness of the sub-zones can be problematic.

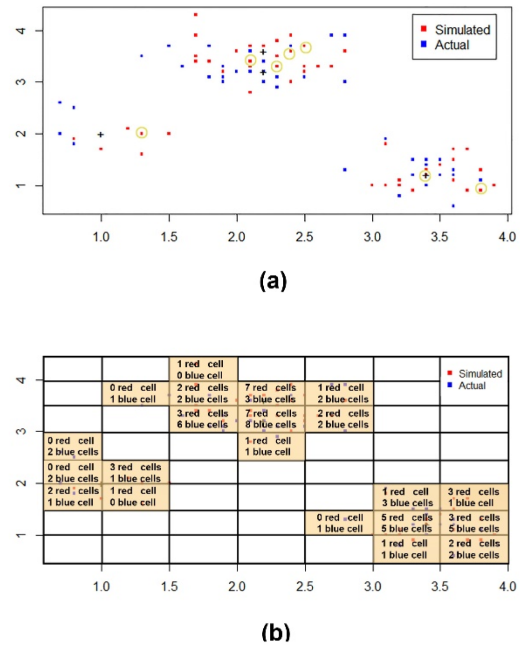


Figure 19. (a) is illustration of simulated (sim) vs. actual (act) developed cells generation window. Red cells represent 50 simulated cells and blue represent 50 actual cells. Yellow circles represent cells that exactly overlay. **(b)** is illustration of zonal aggregation approach. The window has been subdivided into 56 sub zones. The 2 numbers in each zone represent the number of red (sim) and blue (act) cells in each zone. White areas represent cells that remain unchanged in both sim and act scenarios.

Here I will illustrate how to perform a sub-zone based R^2 goodness-of-fit validation. First we merge data cells $X|Y = 1$ and $X|Y = 2$ into "number of cells in each sub-zone (assuming that each travel zone is of size 1 unit by 1 unit)", which is:

$$N_{ijk} = n_{x \in D_{ij}}(X|Y = k)$$

(4)

where D_{ij} is a rectangular region defined by $(\mathrm{i}, -\mathrm{j}), (\mathrm{i}+\mathrm{d}, \mathrm{j}+\mathrm{d}), (\mathrm{i}+\mathrm{d}, \mathrm{j}), (\mathrm{i}, \mathrm{j}+\mathrm{d})$, and $i, j \in \{1,2, \ldots 9,10\}$ represents the x and y coordinate of the centroid of each sub zone; $2\mathrm{d}$ is the size of each sub-zone; of k is a class (actual or simulated growth) label with $k = 0$ or 1, $n_{x \in D_{ij}}(X|Y = k)$ is the number of cells that locate in a zone.

Then we can apply the R^2 function:

$$\mu = \frac{1}{n} \sum_i \sum_j N_{ij1}$$

(5)

$$SS_{tot} = \sum_i \sum_j (N_{ij1} - \mu)^2$$

(6)

$$SS_{res} = \sum_i \sum_j (N_{ij1} - N_{ij2})^2$$

(7)

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

(8)

where *n* is the total number of sub-zones. In our continuous resolution process, we vary d and plot a line graph of R^2 to d (**Figure 20**). In **Figure 20**, the measure becomes positive when zone size is equal to or larger than 0.5x0.5 units, approaching 1 as the zone size approaches 2.25. This suggests that for the simulated to actual relationship in our example window, the resolution of 0.5x0.5-units and higher surpasses a guess of homogenousness. We refer to this as our test simulations “spatial accuracy resolution”—the resolution at which point its goodness-of-fit measure (in this case R^2) is above 0 and at perhaps its optimal place for both spatial accuracy and tuning.

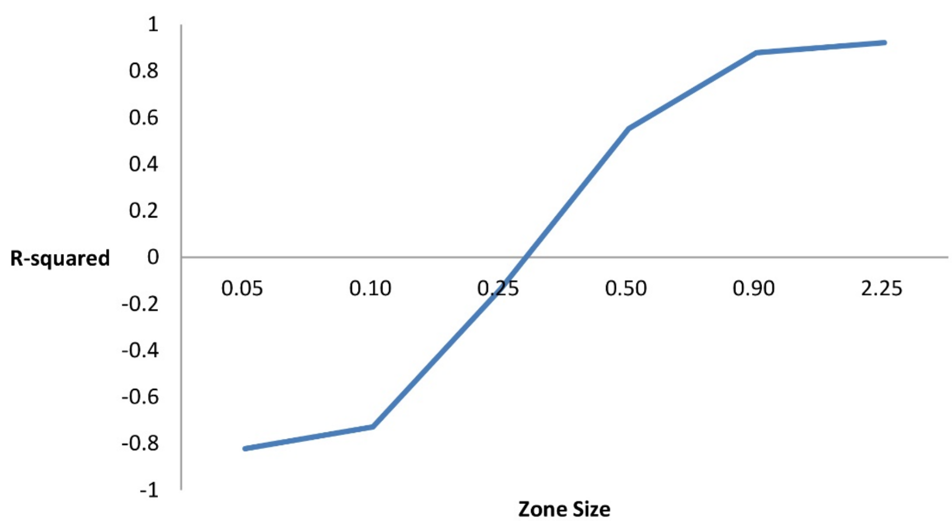


Figure 20. The Zonal R^2 measure for increasing zone sizes in our sim vs act example window. Its spatial accuracy resolution is at $R^2 = 0$.

4.4.2 Part 2

We can introduce a "soft-boundary" model by applying cell diffusion method. Here I use linear kernel of kernel density method (Meyer, 2014). The new values of cells $(X|Y)$ become a "smoothed" value between 0 (undeveloped) and 1 (developed), rather than a binary value of 0 or 1. We can calculate the new values of X by:

$$\widehat{f_h(x)} = \frac{1}{n}\sum_{x'\in N(x)} K\left(\frac{\|x-x'\|}{h(x)}\right)$$

(9)

where $K(\blacksquare|x') = \blacksquare \cdot y|x'$, n is the number of cells in the neighborhood of x (such as a sub-zone centered on x). h is the bandwidth (defined for each x) of the neighborhood ($h_{ij}(x) = \sum_{x'\in D_{ij}}\|x - x'\|$).

Then we can use updated $\widehat{f_h(x)}$ values to calculate new R^2 (similar to the **Part 2** approach).

In our example data set (see **figure 21 (a)** and **(b)** simulated cells (red) are on the left and actual cells (blue) are on the right), both simulated and actual patterns exhibit identifiable clusters in the top of the window and in the lower right, with a less obvious grouping in the lower left. Using our diffusion method, we calculated a zonal R^2 value of 0.97 when comparing the 2 data sets. This is significantly higher than our previous validation measurements.

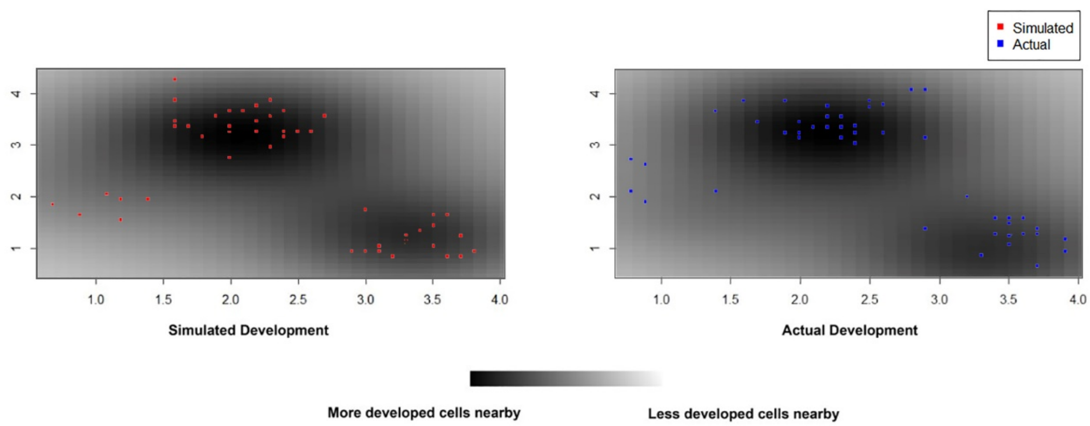


Figure 21(a) and **(b)** are illustration of softened boundaries in our data window example. After diffusion, simulation **(a)** and actuality **(d)** results appear structurally similar.

CHAPTER 5: MODELING LAND-USE CHANGE IN COMPLEX URBAN ENVIRONMENTS

The literature on urban dynamics has recently begun to focus on issues that relate to urban systems complexity. Multiple theories and research approaches (on non-linearity, network connection, and temporal dynamics for example) have been recently introduced. In addition, traditional, well-established modeling assumptions within the urban dynamics realm, such as approximating geographical influences through linear functions of Euclidean distance, are being challenged. For example, in an attempt to improve traditional gravity models to study human mobility patterns, Simini et al. (2012) use a stochastic process that captures discreet local mobility decisions to replace the Euclidean distance measure traditionally utilized.

Theories of complex urban systems are now emerging in response to traditional linear statistical methods. Brockmann et al. (2006) for example, use a power law function to model the distribution of travel distances in an urban setting. Batty (2006) on the other hand, suggests that using only one model to describe multiple scales (as in cities) is problematic. He argues that although power laws are applied for scale distribution of events, “such as cities, firms and internet hubs”, on microscopic scale, we need to be wary of “volatile and often turbulent micro-dynamics”. So that instead of functions of distances and sizes, more complex network interactions should be used to model transportation and social links between people and places in the city. He also points out that microscopic networks in urban systems have complex implications and require the use of “network science, allometric growth, and fractal geometry” in order to adequately depict system interactions (Batty 2008).

Some urban theorists posit that increases in complexity within urban systems interactions will result in greater difficulties in modeling their future evolutions (Song et al., 2010; Gonzalez et al., 2008). Other research however, has shown that complexity theories can help us overcome these difficulties. Song et al. (2010) for example, uses entropy to measures the predictability of human movements in the configuration of urban systems. They conclude that there is “remarkable lack of variability” in these movements and that a large majority are entirely predictable. Gonzalez et al. (2008) analyze human pathways using big mobile datasets. They also find a high degree of temporal and spatial regularity despite an apparent randomness in the data. Song et al. (2010) also showed that although patterns of pedestrian movement usually assimilate to a random walk model, they inherently obey scaling laws. These and other urban systems research are being cited in an attempt to establish a common framing for a new science of complex urban systems (CUS) (Batty, 2005; 2006; 2008; 2013; Bettencourt et al., 2007; Bettencourt, 2013;

Puliafito, 2007)

In this chapter, we argue that Planning Support Systems (PSS), with LUC models at their core, are the most effective means for infusing these new theories of CUS into urban planning practice. In the following, we analyze this potential infusion by examining next generation PSSs within a framework of current CUS theories. In the process we address the following: a) What are some of the new ideas in CUS that might inform LUC models and PSSs?, b) What are the limitations and challenges in current LUC modeling for embracing CUS?, and c) How might the future LUC modeling community address these challenges?

We do this by first introducing (**Section 5.1**) the opportunities that new theories in complex urban systems science pose for urban LUC modeling. In the process, we identify some of the specific CUS computational, statistic, and spatial econometric advancements relevant to current LUC model enhancement. **Section 5.2** we outline CUS temporal component advancements that may be useful in current LUC model and PSS development. In **Section 5.3**, we propose necessary modifications to current LUC models needed to fit within the CUS theoretical frame. And in **Section 5.4**, we present our work at the University of Illinois' LEAM lab on an exploratory PSS for Chicago, IL as a case study example of the proposed modifications. In this example we test parallel network computational algorithms, findings of non-linearity in urban LUC behaviors, as well as interactive user-interface enhancements. **Section 5.5** concludes the chapter.

5.1 COMPLEX URBAN SYSTEMS AND LAND USE CHANGE MODELING

The literature on CUS is replete with theoretical constructs. As with many wickedly complex issues, there are many approaches and viewpoints. In this work, we focus on only a few: a) network connection complexity (Batty 2008) – the important connection between people and places; b) non-linearity (Simini et al., 2012; Brockmann et al., 2006; Batty, 2006) – the complex ways cities evolve; c) spatio-temporal interactions (Simini et al., 2012) the complex relationship between space and time in urban areas; d) multi-oriented driving factors (Walloth et al., 2014)—the variegated fields from which causal relationships must be drawn in urban analysis; e) systems feedbacks (Forrester, 1969)—the complicated feedback systems that affect variable interaction in urban systems; and f) tightly coupled systems models (Clarke and Gaydos, 1998; Deal et al., 2013)—approaches to understanding the above complexities by linking varous systems models. We consider these the most relevant when discussing CUS relative to LUC models and PSSs.

As previously noted, we consider LUC and PSS technologies the most effective means for infusing theories of CUS into urban planning practice. Spatially explicit PSSs bring together base data, analysis engines (models), and information delivery systems (visualization interfaces) to provide planners and communities with critical knowledge of various dynamic urban systems in order to facilitate communicative planning approaches (Brail and Klostermann, 2001; Geertman and Stillwell, 2003; Brail, 2008; Deal and Pallathucheril, 2008; Geertman et al., 2013). Currently, most spatially explicit PSSs use Cellular Automata (CA) (or modified CA) engines in their LUC models to forecast future land-use scenarios (White and Engelen, 1994). CA models are typically used to model complex systems by breaking the system into smaller units in a mathematical model that have simple rules governing their actions. These models become complex when systems interactions and big data sets are introduced. A spatio-temporal CA model uses a grid-based lattice along with temporally specific algorithms to dictate the potential changes in urban system behaviors over space and time.

CA combines elements of many fields of research (Langton, 1986; Epstein and Axtell, 1996; Weisstein, 2016). A CA model is considered both spatially discrete and dynamic. Space is represented as a regular spatial grid or lattice, and posses any one of a finite number of states. The states of the cells in the lattice are updated at each time step according to a local rule or programmed model. The state of a cell at any given time is dependent not only on its local rules for change but also on the states of it's nearby neighbors at the previous time step. All cells on the lattice can be considered interdependent relational entities. They are updated synchronously so that the visual state of the entire lattice advances in discrete time steps.

More specifically, on a 2-dimensional (n x n) lattice plane $\boldsymbol{S}$, a CA model defines a state for each cell on $\boldsymbol{S}$ from the state space Ω (for simplicity, define Ω to be $\{1,0\}$). For any cell (i, j) on lattice $\boldsymbol{S}$, define its state on time-step t ($t \in \boldsymbol{Z}$ and $t \geq 0$) to be k_{ijt} (with the initial state to be k_{ij0}). A "neighborhood" of cells can be defined as (i, j). In CA applications, a 'neighborhood' can be defined in many different ways, Typically, it refers to the 4 adjacent cells to (i,j) (excluding the corner cells), 8 adjacent cells to (i,j) (including the corner cells), or all cells within a distance threshold. For simplicity, the 4 adjacent cells to (i,j) are conserved the neighborhood of (i,j), with a current 'state' set at time t as $\mathbf{N}_{ijt} = \{k_{i-1j0}, k_{i+1j0}, k_{ij+10}, k_{ij-10}\}$. Given the information of all the cell states at time t, cell (i,j)'s transition probability at the next time step p_{ijt+1} can be shown as **equation 10**:

$$p_{ijt+1} = f\left(k_{ijt}, \boldsymbol{N}_{ijt}\right) \tag{10}$$

where f() is the transition function that calculates transition probability for cell (i,j) based on its own state and neighborhood states.

In planning applications, the 'state' of a cell can represent land-use classes (residential, commercial, forests, and other types), buildings, landscape types or other related classifications. The time-step for interaction with these types of classifications can vary from one month to several years. A typical LUC model using CA approaches can help show the potential future evolutions of the classification being studied. These evolutions can be used to evaluate land-use scenarios that can inform policy makers about the possible future implications of their investment or policy decisions.

One challenge for CA techniques in urban LUC models is that some parameters and variables need to be calibrated and tuned to local conditions in order to closely approximate reality and yield reasonable outputs. Other CA modeling challenges that emerge include:

a. A neighborhood ($\mathbf{N}_{ijt}$) is typically defined simply by adjacency or a geo-distance thresholds and not by network connections between cells (such as travel time on road networks, etc.);
b. The function f(.) that determines probabilities of state change are usually more complicated than the linear functions often used. These functions should consider scaling laws (power functions), or even laws without analytical functional types (non-parametric relations);
c. Typically, LUC probabilities in CA applications do not include geo-physical characteristics (slope, elevation, vegetative quality) and usually depend only on a cell's relative relationships within a smooth and flat surfaced grid;
d. LUC dynamics occur at many different spatio-temporal scales (unit of *t* and *i*,*j*); CA models have difficulty with spatio-temporal granularities;
e. LUC processes dynamically interact with other socio-physical processes (economic development, demographic distributions, human mobility, or environmental change), LUC models should be able to integrate and tightly couple with other socio-physical models.

Some additional complex urban systems challenges:

Computational challenges. o enable a finer spatio-temporal resolution, more driving variables, complicated network interactive patterns, and integration of various models, LUC models for CUS will be computationally demanding;

Flexible mathematical forms. CA models typically use differential equations to represent temporal processes in each cell. LUC models in CUS environments require more flexible forms of mathematical representations.

In the flowing we analyze current thinking in the computational, statistics, and spatial econometric sciences that can potentially help address these challenges.

5.1.1 Geographic Automata Systems (GAS) for Complex Interactions

Torrens, Benenson, and Kharbash have defined the main restrictions in CA models as: the static nature of the lattice or an inability of automata cells to move (Torrens and Benenson, 2005), and a limitation to orderly partitioning of spatial units (Benenson & Kharbash, 2005). In response, they propose the use of Geographic Automata Systems (GAS). GAS unites CA and multiple agent systems, allowing spatial units to move freely across space and set up unique relationships with other units or in the case of LUC models - land parcels. Torrens and Benenson (2005) formulated Schelling's popular segregation model (occupancy and relocation model) as a GAS. Torrens then (2007) applied GAS to an urban household occupancy and resident mobility model.

We suggest the use of GAS in lieu of CA for use in LUC models The GAS flexibility allows more complicated modeling structures to accommodate CUS interactions. The established mathematical framework by Torrens and Benenson (2005) facilitates model specifications for more complicated models. **Equation 11** is a simple mathematical description of a GAS framework:

$$\boldsymbol{T_S} = (S_t, L_t, N_t, I_t) \rightarrow S_{t+1}$$

$$\boldsymbol{M_L} = (S_t, L_t, N_t, I_t) \rightarrow L_{t+1} \tag{11}$$

$$\boldsymbol{R_N} = (S_t, L_t, N_t, I_t) \rightarrow N_{t+1}$$

where $\mathbf{T_S}$ is the transition rule for automata at state S; $\mathbf{M_L}$ is the movement rule for automate at location L; $\mathbf{R_N}$ is the neighborhood rule for a cell with neighborhood N; S_t is the cell state at time t; L_t is the agent location at time t; N_t is the agent neighborhood at time t; L_t is the external input at time t.

In the three functions in **equation 11,** $\mathbf{T_S}$ is the rule that dictates the state transition of each agent based on given conditions (current state, location, neighborhood, and external inputs). For example, a $\mathbf{T_S}$ rule might be, "if an agent has 3 or more neighborhood cell with state 1, it will be state 1 in the next time step”. $\mathbf{M_L}$ is the rule that dictates the location movement of each agent based on given conditions. An $\mathbf{M_L}$ rule might be, “if an agent is in state 0 has 3 or more neighborhood cell with state 1, it will move right by 1 cell in the next time step”. An $\mathbf{R_N}$ is the rule that dictates the neighborhood assignment of each agent based on given conditions. A $\mathbf{R_N}$ rule might be, “if an agent’s Y coordinate is larger than 5,00, it will count every other agent within 100-meter distance as neighbors”.

In traditional CA models there is only 1 state transition rule for $\mathbf{T_S}$, so that cells do not move and a neighborhood is invariant. The added flexibility of transition rules for **Ts** and the ability to move cells helps enable GAS model complex interactions in a CUS framework. We will revert to the notations in **equation 11** in later parts of the chapter.

5.1.2 Semi-parametric Spatial Models for Non-linear Pattern Calibration

In **Section 5.1.1** we showed that GAS configurations can evolve given certain rules ($\mathbf{T_S}$, $\mathbf{M_L}$, and $\mathbf{R_N}$). To find a set of rules that properly represent the temporal developmental patterns of a specific spatial region, we need to calibrate the historical developmental patterns of that region. Traditional linear regression modeling approaches might be used. These assume linearity of repressor impacts on the probability of state of location change. As an example we address the following question: How likely is a piece of current agricultural land to change into residential land-use classes? In this example we assume that *n* cells in its one-mile neighborhood are residential land-use. For simplicity, we only consider state change ($\mathbf{T_S}$) in the example, and we use a logistic regression framework. We might such an equation as **equation 12**:

$$L(p) = \beta_0 + \beta_1 \mathrm{n} \qquad (12)$$

where p is the probability for a cell to change from agricultural land-use class to residential land-use class L(.) is the link function that transform the probability by $L(p) = \ln(p/(1-p))$, β_0 and β_1 are scalars that we need to estimate.

Using a linear estimator has two major weakness: 1) it cannot account for non-linear effects; and 2) it does not reflect spatial dependencies with different distance thresholds.

An example of the first weakness might be residential land-use density as it relates to highway accessibility. Residents generally do not want to settle too close to a highway (due to noise and safety concerns), however they want a reasonably easy access to the service the highway provides (quicker travel times to other places). For this reason, instead of a linear representation, this relationship may be best represented by a bell curve. A highway has low attractiveness close to the highway, higher attractiveness some critical distance away (from the negatives) then dropping again as the distance makes it more difficult to access the positive services it provides.

In terms of the second weakness, a good example is the case of inter-county road infrastructure investment spillovers. If county X decides to invest on road infrastructure, it is likely that neighboring county Y is likely to experience improvements in accessibility and travel times – without cost. This effect may also be present to a much lesser extent, in second-order neighboring counties as well. Spatial spillovers however, are difficult to consider in a linear model. Some researchers have proposed using semi-parametric or non-parametric spatial models for spatial data inference to address these limitations (Belitz et al., 2010; Su, 2012). For example, Belitz et al. (2010) the use of non-parametric or semi-parametric regression techniques since nonlinear covariate effects can be estimated and complex interactions between variables can be included. According to (Robinson 2010; 2011) semi-parametric spatial models also fit well with lattice shaped spatial constraints, although lattice shaped spatial data is not very common in the geo-spatial sciences, this configuration fits GAS and LUC models.

Semi-parametric LUC models. In order to use semi-parametric spatial approaches in LUC models, we adapt model specifications from Su (2012). Consider a spatial configuration at time *t* and all cells at state 0 (n cells in total), with p different neighborhood features for all cells of state 0 as matrix $\mathbf{N_{t,np}}$ and q different external input matrix $\mathbf{I_{t,nq}}$. To calculate the transition probability vector $\mathbf{P_{t,n}}$ for cells of state 0, we can write the equation as **equation 13**:

$$L\left(P_{t,n}\right) = m\left(N_{t,np}\right) + \mathrm{v}\left(I_{t,nq}\right) + \mathrm{U}_n \tag{13}$$

where L(.) is the link function introduced in **equation 11**; $\mathbf{U_n}$ is the error vector, m(.) and v(.) are unknown functions. We can use another way to formulate the model by substituting m(.) and $\mathbf{N_{t,np}}$ by spatial weight matrix $\mathbf{W_{nn}}$ and cell state vector at time *t* $\mathbf{Y_{t,n}}$, which more closely assimilates model specifications of spatial econometrics model in **equation 14**:

$$L\left(P_{t,n}\right) = \beta r(W_{nn}Y_{t,n}) + \mathrm{v}\left(I_{t,nq}\right) + \mathrm{U}_n \tag{14}$$

where β is a scalar coefficient for spatial auto-correlation; r(.) is a known function to convert categorical vector $\mathbf{Y_{t,n}}$ into a value (or a vector of values) representing impacts of neighbors. One example of $r(\mathbf{W_{nn}}\ \mathbf{Y_{t,n}})$ can be converting every cell in state 0 to value 1, and cell in other state to value 0 in **equation 15**:

$$r(W_{nn}Y_{t,n}) = \left(\sum_{i=1}^{n} w_{ij}\, g(y_{t,i})\right)_j \tag{15}$$

where:

$$g(x) = \begin{cases} 1 \ \ if \ \ x = 0 \\ 0 \ \ if \ \ x \neq 0 \end{cases} \tag{16}$$

It can be seen from the above that non-linear formed functions such as m(.) and v(.) in **equations 13** and **14** allow spatial inputs or spatial neighbors. This allows more flexibility in calibration and uncovering non-linear impacts. The coefficient estimation process of semi-parametric spatial models can reference existing literature (Robinson 2010; 2011; Su 2012). There is also a statistical package in R available (see McMillen, 2015) that supports semi-parametric spatial analysis.

5.1.3 Statistical Inference Model Optimization

The calibration of spatial models to real world conditions with a large number of cells and a large number of variables is very costly. It is particular difficult when the models run at very fine spatial resolutions, such as a 30-by-30-meter cell (the cell size used in LEAM described in later sections). Computational time (*O*) for a linear regression is approximately proportional to the square number of variables (*c*), multiplied by the number of observations (*n*), so that the computational time for a linear regression can be expressed as $O(c^2n)$. The problem is that when variables are added to the model, the computational cost increases dramatically—by a power of two. When this is then multiplied by the number of observations (or cells, which in a LUC case is usually very large), it will result in a huge computational increase. Unfortunately, adding and testing various variables that potentially influence urban growth is a necessary practice in LUC modeling process and therefore computationally expensive.

One solution is brute force processing – throwing more computational power at the problem. This is not always possible or feasible. Another is using high-performance algorithms. Bach (2013) describes using Stochastic Descent Gradient (SDG) processes to optimize the computational time associated with large scale linear regression, which has a computational time cost of *O(cn)*. An available statistical package Vowpal Wabbit (Langford, 2016), uses the SDG methods to enable different machine learning algorithms such as logistic regression, decision trees and support vector machines. Alternatively, Chen and He (2015) offer a high-performance classification method termed "Extreme Gradient Boosting (XGB)" that has proven to be very powerful. The classification capability of XGB fits well with model requirements in LUC models.

One shortcoming of using these available high-performance statistical packages for LU model calibration is that the packages generally do not explicitly support spatially aware datasets. To overcome this challenge, we either have to develop a high-performance statistical package that is compatible with spatially dependent data, or modify the model structure to approximate spatial data so that it can be run by current packages. For example, in **equation 5**, we can force r($\mathbf{W_{nn}Y_{t,n}}$) to generate a nxp matrix $\mathbf{X_{t,np}}$ (n>p). Then we can form a new formula **equation 17**:

$$L(P_{t,n}) = f(X_{t,np}, I_{t,nq}) + \mathrm{U}_n \tag{17}$$

where f(.) is either a linear and non-linear form of formula that is supported by the current available statistical packages. Actually, the linear form of equation 8 can be approximately viewed as the spatial lag of X (SLX) model (Vega and Elhorst, 2015). A drawback to this method is that only local spatial spillover effects are considered and we assume no spatially related heteroscedasticity in the residuals, which does not model the actual spatial relations very well. Thus, development of a high-performance spatial statistical model is needed if LUC model calibration processes are to embrace both advances in computational statistics and the spatial sciences.

5.1.4 Parallelism in GAS

Computational costs in terms of time and processors are perceivable challenges to models with high spatial resolutions. A promising solution is the use of high- performance computing resources and parallel processing (X. Li, Zhang, Yeh, & Liu, 2010). A host of frameworks for parallel computation in CA systems have been proposed (Shook et al., 2013; Tang and Wang, 2009). Tang and Wang (2009) suggest parallelizing spatial computational processes by *domain* decomposition. The method subdivides the CA spatial lattice into sub-regions and simulates state change actions within each sub-region simultaneously. For example, if computational time for a GAS is approximately proportional to squared total cells *($O(n^2)$)*. For a m by m spatial lattice, the computational time can be calculated as *$O(m^4)$*. If we apply the domain decomposition method to subdivide the region into 4 equally sized sub-regions (m/2-by-m/2), we can simultaneously simulate the 4 regions $O(m^4/16)$ assuming there are no dependencies among those 4 regions.

Dependencies require that when an agent or agent neighborhood cross the border of a sub-region, the system needs to initiate communication between the two processes. This will slow computational time. If the requirement for communication between paralleled processes is high, the computational efficiency of the parallel model may be even worse than the original sequential model. In a GAS configuration, it is difficult to know when and where difficult communication between cores might occur before the simulation process starts.

In urban LUC models, we suggest that process parallelization has advantages over domain decomposition. We consider process parallelization be intrinsically closer to the processes occurring in complex urban systems. Previously GAS parallelization focused on sequentially modeling the events and their correlations at each time step. This is intuitive in the construction and coding of the models. However, we show that those events can be also viewed as different processes occurring in parallel and interacting with each other at specific points in the process. In this way, next generation of GAS may not be constructed in time steps – but in concurrent processes that happen in parallel with interactions that are scheduled to occur based on temporal sequencing.[3]

To illustrate how process parallelization works, we construct a hypothetical integrated LUC model with 4 processes: a) land demand generation, b) land-use change, c) road building, and d) environmental protection district establishment. A prototype of our model is illustrated in **Figure 21**. In this construct, the four above processes interact with each other at various stages. Each process is represented as a sequence of states/actions, which either cycles from end to beginning or spawn its child processes within its lifespan. Each process happens naturally in parallel and could be easily computed in a parallel environment.

[3] It will be a fascinating future research opportunity to see how parallel GAS performs in efficiency compared to previous models, and what are the relationships and differences between different representations of the same phenomena.

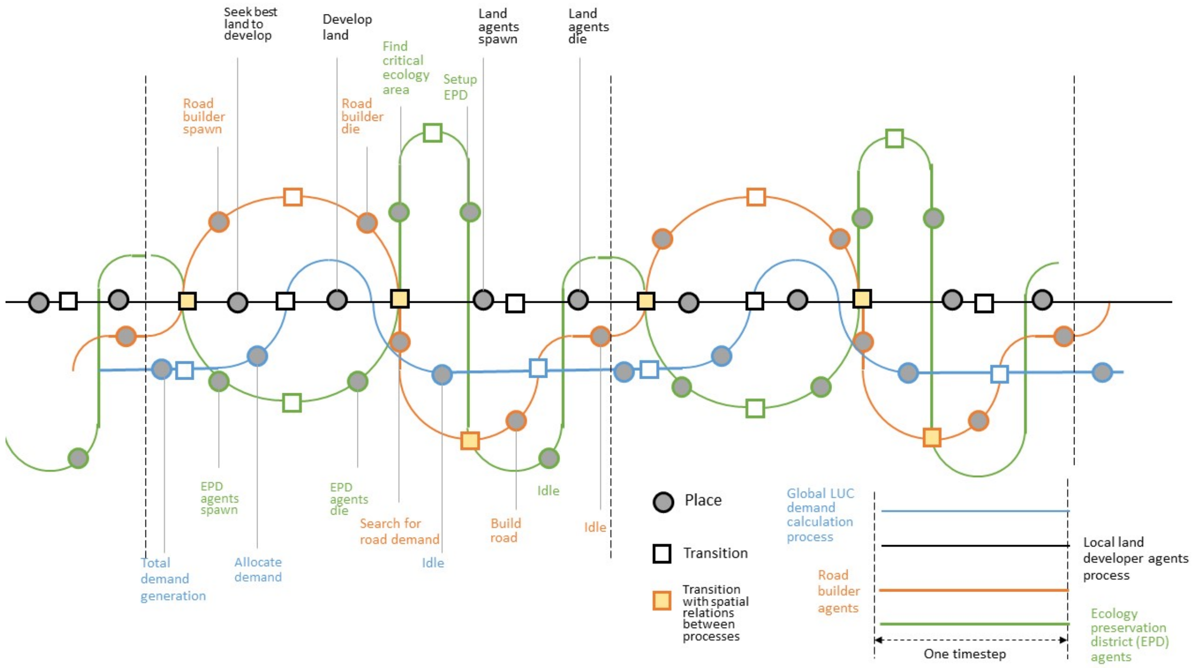


Figure 22. Parallel processing in an urban LUC model

Below is more detail on the 4 processes described in **Figure 22**:

Process 1. Global LUC demand generation. This process generates a general demand for change. It generates demand by macro-socioeconomic area. At each time step, a generated LUC demand initiates a seeking and developing activity with a group of developer agents. The global LUC demand and allocation correlates with the general transportation accessibility of the region, so the demand generation process begins only after road building agents set transportation variables (starting at $time_0$).

Process 2. Town-level LUC developer agents. In the town level LUC process, speculative development opportunities are identified through a process of evaluation. In this process neighborhood developers seek out lands (cells) that have a development attractiveness that exceeds a certain threshold. After the cells are identified, the most attractive cells are converted into the desired land use (residential, multi family, commercial, industrial). The total number of transformed cells depends on the total demand for the specific use. This process also initiates EPD agents (see process 4) to “find critical ecological areas” and road builders to “search for road demand”. These corresponding processes must wait for the results of the LUC. The LUC process, once in place, spawns new developer agents looking for newly developable cells. Old developer agents that have not been active for a certain period of time die away.

Process 3. Road builder agents. In this process, road builder agents seek spatial regions with the highest demand for new roads and then work to satisfy that demand. The road demand seeking node in the process depends on developer agents' land development process (where new developments take place). Road building depends on the EPD (Environmental Preservation District) setup because it needs to know what areas are preserved and cannot be invaded by road building. Road builder agents spawn new road builder agents onto cells with new roads built, and old road builder agents that have not been active for a certain period of time die away.

Process 4. EPD (Environmental Preservation District) agents. In this process, the EPD agents seek undeveloped cells (and some already developed cells – in special cases) that have the most *ecological value* and the most *development stress* associated with new LUC developments. Newly established EPDs exclude any other use on any area. The "find critical ecology area node" in the process depends on the developer agents' demand for development. EDP agents spawn new EDP agents onto cells with new EPDs established, and old EPD agents that have not been active for a certain period of time die away.

Spatial dependencies. Some of the processes noted above are spatially dependent; agents from different processes only interact if they are within a spatial neighborhood that they send/receive information from.

The transition that takes in information from land development, road builder and EPD processes and expels information into "seek land to develop", "EPD agents spawn", and "road builder agents spawn" at the beginning of each time step characterizes an interaction between these 3 processes that has spatial dependencies. Developer agents can only "see" and "go to" places within their defined neighborhoods to look for land to develop based on road builder agents and EPD agents' actions that alter land suitability and attractiveness. Thus, if road builder and EPD developers' actions occur outside of developer agents' neighborhoods in a given time step, their interaction would not happen in that time frame. Similarly, road builder agents and EPD developers' finding places to build roads and set up EPD also depend on the spatial locations of development of land-use by developer agents. The interaction happens only if land-use development is within neighborhood of EPD or road builder agents. Finally, road builder agents' road building action also spatially depends on EPD agents' establishing the EPD districts. If the proposed new road constructions overlap with the previous established EPDs, the road constructions would not occur.

If we define the computational time for the four processes to be *a*, *b*, *c*, and *d*; the total time to be *n*; and process communication time at each step to be *e*; we can calculate that a sequential LUC model would have a computational time of $n(a+b+c+d)$. Conversely, the same model in parallel would have a computational time of $n(\max\{a,b,c,d\}+e)$. Since the process parallel model has defined all the communication nodes and information between different processes, its computational time will be much shorter and more controllable.

5.2 SPATIO-TEMPORAL ANALYSIS

In previous sections we look at refining LUC models to improve spatial resolutions and complex interaction interpretation. There is also potential to enhance LUC models on a temporal axis. In the following we introduce improved spatial and temporal analysis by integrated spatial-temporal statistical models.

Progresses have been made on integrating spatial-temporal components in order to formulate models on higher spatial dimensions that include the influence of both spatial and temporal 'lags'. Research on this issue has involved both data structure to represent and store spatial-temporal data (Erwig et al., 1999) and estimations of integrated spatial-temporal models (B. Li, Genton, & Sherman, 2007). Here, we briefly introduce the data format and estimation process of integrated spatial-temporal models.

Erwig et al. (1999) constructs a method using relational database to contain spatial-temporal data. We can use this method to construct a data input of an agent moving along a spatial line *mroute* from year *a* to year *b* and changes from state 0 to 1, we can represent it as:

agent (id: *agentid*; from: *a*; to: *b*; route: *mroute*, statestart:*0*, stateend:*1*)

With this data format, we can use nonparametric spatial-temporal modeling processes as suggested in Li et al. (2007). In Li et al. (2007), if you want a spatial-temporal covariance estimation for 2 agents at different spatial and temporal point (with same initial state 0), you sample other agents with the same initial state and similar spatial-temporal distances **in equation 18**:

$$\hat{C}(h,u) = \frac{1}{|\boldsymbol{S}(h)|\boldsymbol{T_n}|} \sum_{s\in S(h)} \sum_{t=1}^{n-u} \overline{z(s,t)}\,\overline{z(s+h,t+u)} \tag{18}$$

where *h* is the spatial distance bandwidth considered in the model; *u* is the temporal time step difference considered in the model; $\boldsymbol{S}(h) = \{s: s \in S, S+h \in S\}$; $\boldsymbol{S}$ is the overall spatial area considered; |***S**(h)*| is the number of elements in ***S**(h)*; $|\mathbf{T_n}|$ and *n* is the total time step considered; $z(s,t)$ is the average observed value of agents at location *s* and time *t*. Note that the model assumption is that $z(s,t)$ has to be zero-mean and stationary. While spatial observations generally can be normalized to zero-mean, transform data into stationary spatial-temporal series may be a challenge (we will not expand on this issue further in this chapter).

o connect this with the spatial-temporal data structure by Erwig et al. (1999), we show how to generate a query to fetch all agents pairs within bandwidth distance *h* (with location notation to be *x* and *y*) and time difference *u* (with time notation *t*) from a dataset *AGENTSMAP*:

```
SELECT id

FROM AGENTSMAP as Current_Row

LEFT JOIN AGENTSMAP as Next_Row

WHERE Current_Row.id <> Next_Row.id

AND Current_Row.startstate = 0

AND minvalue(mdistance(Current_Row.route, Next_Row.route)) <= H

AND Next_Row.to <= Current_Row.from + u

AND Next_Row.to > Current_Row.from
```

where *mdistance* is a function defined in Erwig et al. (1999) to calculate minimum distance between two lines.

Next, we show how to use the covariance estimated in **equation 18** to infer land-use state change probability for an agent with initial state 0. First we have the probability estimation model in **equation 19**:

$$L(p_{t,k}) = \sum_{i,j=0}^{i=H,j=U} \rho_{ij}\, z(i,j) + \boldsymbol{x_{t,k}}\beta + \mathrm{u} \tag{19}$$

here L(.) is the link function introduced in **equation 12**; p is the change probability for agent *k* at time *t*; u is the model error vector; H and U are maximum spatial and temporal threshold considered to be neighborhoods; $z(i,j)$ is the observation value with spatial distance *i* and temporal distance *j* to the agent *k*; ρ_{ij} is the coefficient to be estimated for $z(i, j)$ (note that ρ_{ij} has to satisfy causal and identifiable similar to the conditions for time-series model (Box, Jenkins, Reinsel, & Ljung, 2015); $\mathbf{x_{t,k}}$ is the external input variable (without spatial dependencies) vector for agent *k* at time *t*; β is the coefficient vector.

To estimate the model coefficients, first we can view the model (**equation 20**) of a linear model for non-spatial inputs $\mathbf{x_{t,k}}$:

$$L(p_{t,k}) = \boldsymbol{x_{t,k}}\beta + \mathrm{w} \tag{20}$$

where *w* is the error of the model.

After this process, we can ensure that w has expectation of 0. Then we further estimate for ρ_{ij} in **equation 21**:

$$w = \sum_{i,j=0}^{i=H,j=U} \rho_{ij}\, z(i,j) + \mathrm{u} \tag{21}$$

To estimate ρ_{ij} here, we can use the method of moment approach to set up equation systems with sampled covariance $\hat{C}(h, u)$ in **equation 17** and the theoretical autocorrelation calculated from **equation 21** (here $z(0,0)$ can be used to substitute *w*). To avoid clumsy notations, details of this estimation process is omitted in this chapter.

As shown above, integrated spatio-temporal models can simulate 3-dimensional (two space dimensions and one time dimension) or even 4-dimensional spaces. They can also provide a data structure that is flexible and possesses potential for large volume data analysis. Thus it is a promising pathway for the evolution of CUS LUC models.

5.3 MODEL INTEGRATIONS

CUSs are essentially a complex web of interconnecting parts, such as land-use, transportation, water, and economic systems, to name just a few. Future evolutions of Land-use have implications for many of these parts. For example, increasing impervious surface area associated with land urbanization casts a burden on water, sewer and storm water systems – raising the risks of flooding, the potential for polluting freshwater supplies, and a change in ground water recharge systems. Similarly, changes in other systems also induce alterations in the patterns of land-use. Economic development for example, often calls for changes in the spatial demand for commercial land-uses in a region. Therefore, modeling LUC itself is not sufficient in considering its rippling effects and feedbacks. It is necessary to couple LUC models with dynamic models of other (interacting) systems.

The coupling of LUC models has been discussed elsewhere in the literature (Iacono et al., 2008; Couclelis, 2005; Matthews et al., 2007; Deal, 2008; Deal and Kim, 2013). The important issue of model integration however, and its multiplier effect on uncertainty (of coupling multiple systems) is largely overlooked. In this section, we will introduce an integrated LUC, hydrological, and economic framework as an example of a fully integrated CUS model. We then outline how to deal with the uncertainty issues within the modeling frame.

5.3.1 Integrated Model

In this example, we propose an integration of a land-use change model, a hydrometeorological/hydraulic model, a virtual water trade flows model, a catchment water quality model, and an economic and policy analysis model. Integrating models of varying spatial and temporal specification requires careful consideration—both from a top down and from a bottom up perspective. Top down analysis using a cascading models approach from large scale natural systems dynamics to small scale discrete choices of human activities and the related infrastructure needed to support them is important for understanding the implications of a changing climate on human activities. Bottom up feedback is equally important for understanding how human systems and human decision making affect these larger scaled systems and ultimately how they implicate climate changes. Our example proposes the hierarchical incorporation of models to integrate the diverse spatial and temporal scaled models noted. Larger scaled models will provide the constraints from which smaller scaled model results will operate and smaller scaled models will provide the dynamic changes that will feed back up into the larger models. This simple but important concept helps to frame the aggregation of our smaller scaled human interaction and decision models back up to the larger scaled models. **Figure 23** shows the framework for model coupling. In the later part of this section, we will introduce how each part of the model functions in this integration.

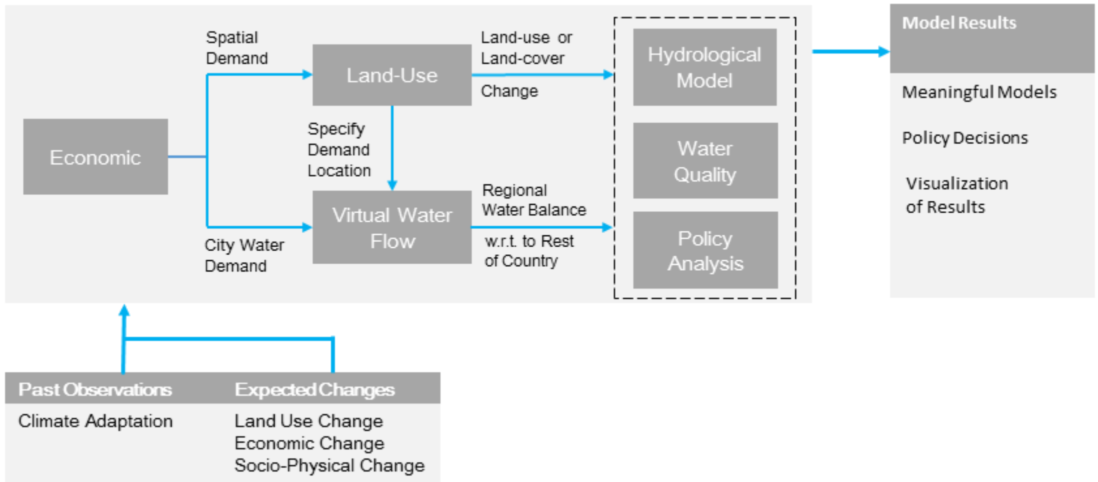


Figure 23. A model integration framework.

5.3.2 Models

In the following we introduce the functionality and dynamics of each model involved in our model integration example. Then we introduce our approach of model integration. The models utilized in this analysis are existing models that have already been usefully applied.

Land-use Modeling. Demographic output and the future demand for space are derived from the econometric model described below. This output is fed into a dynamic spatial LUC model. LUC model simulates future LUC and its consequences using a modified cellular automata approach where cells evolve over a surface defined by biophysical factors such as hydrology, soil, geology and landforms; and socio-economic factors such as administrative boundaries, census districts, and planning areas. Fundamentally the LUC model is defined by two major parts: 1) A dynamic land use change model (at a 30x30 meter resolution) which is driven by a set of sub-models that describe the local causality of land use changes and allows the creation of what-if scenarios. 2) Impact assessment models that use these land use change scenarios in order to analyze the impacts generated by these changes. One example of such model is the University of Illinois Landuse Evolution and Impact Assessment Model (LEAM) The approach enables loose and tightly coupled links with other models that might operate at a different spatial scale (Deal and Schunk, 2004; Pallathucheril and Deal, 2007). LEAM has been loosely coupled with economic forecasting models (CREIM), bi-directional travel demand models in both in Chicago (Deal and Kim, 2013); water quality models (Choi and Deal, 2008); water quantity models (Sun et al., 2009); and social cost models (Deal and Pallathucheril, 2008). LEAM has previously been applied in Chicago, Stockholm, and Washington DC.

Hydrometeorological/Hydraulic Modeling. There are two potential procedures for hydrologic/hydraulic modeling. One is for river channels at the watershed scale using the Variable Infiltration Capacity model (VIC), to calculate river discharge for continuous flow processes and HEC-RAS, analyzing one-dimensional river/channel hydraulics (e.g., flow stage and velocity), each coupled with an event-based model, HEC-HMS (USACE, 1998) that simulates rainfall-runoff processes (Liang et al., 1994; 1996) Cherkauer and Lettenmaier, 2003). Urban water movement (at the sewershed level with sewer overflow and urban floods), will be modeled using SWMM, a 1-D, unsteady hydrology (rainfall-runoff) and hydraulic model of open-channel and closed-conduit systems typically used for single event or continuous simulation across a variety of scales, pervious and impervious surfaces, and engineered drainage infrastructures (EPA, 2013; Cantone and Schmidt, 2011).

For hydrometeorological model, we employ the General Circulation Model (GCM) for climate modeling, which simulates the response of global circulation to large scale forces (synoptic scale systems) and the RCM to account for sub-GCM grid scale forcings (e.g. local circulations, complex topographical features and land cover inhomogeneity), which gives long-term climate prediction. Statistical downscaling or dynamic downscaling approach will be used to produce data more suitable for hydrological models (Bárdossy and Pegram, 2011).

Virtual Water Trade Flows. The concept of virtual water trade flows builds on the idea of (Allan, 1993; 1994; 1998) and the interregional input-output framework developed by (Leontief, 1953; 1956; 1970). In essence, it determines how much virtual water is embodied in the production of goods and services made in a region and traces whether that water (i.e. associated commodities and services) is consumed locally or externally (through export to the rest of its country or the world). The same idea applies to the imports a region makes so that one can determine whether it is a net importer or exporter of virtual water. If found to be a net-exporter, significant changes in water policy would likely be required from the region to ensure that best economic and ecological use is made of this scarce resource.

Catchment Water Quality Modeling. Water quality is a critical issue in water policy. Both point source and non-point source pollution should be accounted for. The

Hydrological Predictions for the Environment (HYPE) model is a spatially semi-distributed model which can be used to explicitly account for the spatially distributed pollution sources including total suspended solids (SS), nitrate, and phosphate. (Donnelly et al., 2016; Lindström et al., 2010). However, it does not consider the social-economic factors. To address this, we will apply the Catchment Land Use for Environmental Sustainability model (CLUES) developed by NIWA, which is a GIS based modeling system capable of assessing the effects of land use change on water quality and socio-economic indicators (Semadeni-Davies and May, 2014). The model has been coupled with OVERSEER, the Soil Plant Atmosphere System Model (SPASMO) and the Spatial Regional Regression on Watershed Attributes model (SPARROW). Land-use scenarios and socio-economic model inputs will be generated by the LEAM model and the economic and policy analysis model, described in sub-section **Model I*ntegration***.

Economic and Policy Analysis Models. We integrate an input-output modeling framework with a demographic component that helps make up a regional econometric model used for impact analysis and forecasting. Examples of details of the system can be found in Israilevich et al. (1997) and its application to Chicago (the Chicago Regional Econometric Input-Output Model—CREIM) in Kim et al. (2015). The model provides information on production, income, and employment for several sectors, population cohorts, migration, and ultimately water demand data for use in subsequent models. This annual model, with a current forecasting horizon is complemented by shorter-term indices that mimic leading indicators and business cycles, thus providing the opportunity to integrate analysis over the shorter and longer-terms. The economic model is be synthesized to include water demand, flood damage assessments, and the costs of water degradation. It also feeds a market-based, dynamic optimization model that derives optimal adaptive flood management and pollution policy.

Synthesized models are estimate the damages associated with simulated flood events where the value of damages depends on how frequent and severe flooding is, and how much economic activity is present in the affected areas. The cost of water pollution is estimated by the treatment/replacement cost of polluted water with clean water. We will use standard benefit transfer methods (Brouwer & Bateman, 2005), applying the results of previous analyses to estimate the values of changes in flood and pollution control regulation.

5.3.3 Uncertainty analysis

Our integrated approach is subject to the limits of data, models and long-term forecasts; therefore, handling uncertainty is critically important (Kabat, Van Vierssen, Veraart, Vellinga, & Aerts, 2005). Uncertainty can be modeled using a global sensitivity analysis (GSA) in order to 1) locate the parameters that have significant effects on the system studied, 2) evaluate their effects on the performance of the entire system, as well as of individual components, and 3) derive the propagation path of various uncertainty sources by mapping the impact from one component to others. Traditional sensitivity analysis tests the impact of uncertainty with one parameter ("one at a time"), which ignores the possible interactions between input parameters and the correlation between the uncertainties, and thereby does not capture the final impact of all uncertainties acting on the system (Vrugt, Diks, Gupta, Bouten, & Verstraten, 2005). Global Sensitivity Analysis (GSA) can be used to determine the contribution to the uncertainty in the output of a system from different sources of uncertainty in the input variables (Saltelli et al., 2008). Quantitative methods for GSA are based on variance decomposition or (Sobol & Petrovskaya, 1993) decomposition .

To address deep uncertainty, we employ a robust decision making framework. Robust decision making employs three key concepts: multiple views of the future, a robustness criterion, and an iterative process based on a vulnerability-and-response-option rather than a predict-then-act decision framework. Utilizing multiple future states of the world rejects the view that a single probability distribution represents the best description of a deeply uncertain future (B. Deal & Pallathucheril, 2007b). In this work, a range of potential futures are assessed using a vulnerability-and-response-option analysis framework. This framework characterizes uncertainty and helps identify and evaluate robust strategies by using combinations of relevant futures. The approach has cognitive benefits for decision making, by uncovering the key assumptions and uncertainties that underlie each alternative future. This differs from traditional predict-then-act approaches that characterize the future and then rank orders the desirability of alternative options using static criteria. The vulnerability-and-response-option considers all potential futures as viable, it's the uncertainty in each that separates them.

5.4 CONCLUSIONS

In this paper, we argue that CUS theories play an important role in the advancement of urban urban LUC models and the planning support systems that house them. CUS theories have helped identify some of the weaknesses in current urban modeling approaches. The ideas have also providing a pathway for improving our general understanding of urban systems, and the fact that they may indeed be predictable to some extent, even in their apparent randomness. We point out that LUC models and CUS are evolving a symbiotic relationship where CUS is helping to improve the models and the models are improving our understanding of CUS by providing real world applications that can be verified and ground truthed.

We propose a future LUC modeling paradigm that contains key breakthroughs in the computational, statistical, and spatial econometric fields. We suggest that for a basic construction of LUC models, GAS provides a more flexible and comprehensive structure than traditional CA model approaches. To address the computational challenge for fine spatial resolution models in large urban areas, high-performance statistical models and parallel computing techniques offer the most promising solutions. To integrate spatial and temporal dependencies into LUC models, semi-parametric spatial econometrics models and recent advancement in spatial-temporal models provide model calibration methods for LUC models.

We also suggest that LUC models would be more capable and useful in the support of planning if they were integrated and coupled with other dynamic urban system models – as suggested by the CUS literature.

CHAPTER 6: A REASSESSMENT OF URBAN LAND-USE STRUCTURE AND LAND-USE PATTERNS: CBD OR NETWORK-BASED? — EVIDENCE FROM CHICAGO

The “distance to central business district(CBD)” based city model has been a core assumption of spatial equilibrium models of urban economic structure since its initial theorization by Alonso (1974), Mills (1967), and Muth (1969). Later modifications by Fujita and Ogawa (1982), Ogawa and Fujita (1989), Lucas (2001), Lucas and Rossi–Hansberg (2002), and McMillen and Smith (2003) have improved, verified and/or expanded on the original concepts, maintaining its “distance to CBD” based city core. The goal of the model is to explain the spatial distribution of a population in a city. Its main mechanism is the relation between commuting costs, housing price, and housing consumption. The model has two core assumptions: that people want to live in areas with the best amenities and the most efficient access to jobs (Y. Chen & Rosenthal, 2008); and that businesses think that spatial agglomeration will help attract labor (Behrens, Mion, Murata, & Südekum, 2017).

The "distance to CBD" model has enabled a practical understanding of the urban condition. Understanding the mechanisms of congestion (Brinkman, 2016; McDonald, 2009; Tsekeris & Geroliminis, 2013), and forecasting future land-use change (Deal et al., 2012) are two examples that have directly informed planners and policy makers on the spatial implications of their decisions. However, proximity to CBD has both (and different) agglomeration and dispersion effects on location preferences of firms and workers (Behrens et al., 2017). Chen and Rosenthal (2008) demonstrate that higher consumer amenity quality typically attract retirees, while better business environments typically repel retirees relative to workers. Brinkman (2016) concluded that jobs are much more clustered than residents, which suggests that different spatial forces work on firms compared to workers.

An alternative to the "distance to CBD" based city assumptions draws from literature on Complex Urban System (CUS). CUS theories surmise that population and businesses are clustered along urban systems networks (depending on functional characteristics) (Walloth et al., 2014), are non-linear (Simini et al., 2012), and display scaling properties (Batty, 2008). Batty argues that instead of distances functions, more complex network interactions should be used to model transportation and social links between people and places in the city. He points out that microscopic networks in urban systems have complex implications and require the use of “network science, allometric growth, and fractal geometry” in order to adequately depict system interactions (Batty, 2008). The hypothesis is that people and businesses agglomerate in relation to transportation network accessibility, rather than Euclidean distances to an urban CBD. This agglomeration pattern is complicated by distance decay functions along networks and temporal factors, such as relocation and the immigration of people and businesses. Another complicating factor against the "distance to CBD" assumption is that non-work trips now dominate urban networks. According to Huang and Levinson (2015), approximately 90% of all trips are now non-work related.

Other studies have updated the "distance to CBD" model of urban structure using square, gridded, road networks (see Dong and Ross, 2015; Tsekeris and Geroliminis, 2013). Barabási (2009) however, argues that human networks are scale-free; that very few nodes in the network are connected to many other nodes. This scale free pattern has been shown to apply to urban road networks (M. Batty, 2008, 2013). Batty (2008) uses population and employment distributions in London, UK to show that the size and density of their frequencies decay according to scaling laws. He also notes that there is a direct relation between connectivity and city size in England and Wales. In a 2013 study, Batty uses economy of scale to explain a scaling/superlinear relation between where humans settle and how they are connected (Batty, 2013). His work suggests that people tend aggregate in the key (well-connected) nodes of scale-free networks.

In this paper we use CUS theories to construct a model for testing the relation between urban transportation networks and urban structure. We construct a Stochastic Greedy Algorithm (SGA) to evaluate how available lands are connected to existing urban amenities using network accessibility and shortest path measures. We quantify the connectivity of all unique cells in a finely scaled (30x30 meters) lattice of the Chicago Metropolitan Statistical Area (hereafter, Chicago) to existing attractive amenities (population and employment centers, points of interests (POIs), points of network accessibility—on ramps, major intersections). We measure the attraction of each relative to the frequency of existing commercial and resident land-uses. We adopt gravity-like functions that consider attractiveness for both firms and residences (i.e. how well an available land is connected to labor forces and to employers and established businesses). We do this in order to examine several hypotheses that offer theoretical departures from current urban structure models. It is important to note that we do not aim or expect to have results that totally reject existing “distance to CBD” models. The traditional urban structure model has many merits in its theoretical constructions and applications to empirical cases. Some of the findings of our research actually do not reject “distance to CBD” model assumptions. But we also show that some of the phenomena will be much better explained if we adopt an alternative model (network based urban structure).

Our first hypothesis is that large urban systems organize around scale-free urban networks. We test this using our SGA method to simulate shortest path finding behaviors to expose underlying urban structures. Our second hypothesis is that proximity to urban attractors has both agglomeration and dispersion effects on location preferences for commercial and residential land-uses. We measure the relation between attraction levels (calculated from connectivity) for land-use cells and their probability to be commercial and residential cells. If simultaneous agglomeration/dispersion effects occur, the resulting relations should differ from the super-linear or scaling increasing curves as posed by Batty (2013, 2008). Our third hypothesis, unexamined in previous literature, is that new urban growth patterns are different than existing agglomeration patterns. We test this, by analyzing SGA patterns in Chicago from 2001 to 2011 and compare the results to newly developed land-uses—post 2011.

This analysis contributes to both the empirical urban economics and the CUS literature. First, our scale free network hypothesis challenges the core assumptions of models of urban economic structure by Alonso (1974), Dong and Ross (2015), Fujita and Ogawa (1982), Lucas (2001), Lucas and Rossi–Hansberg (2002), Mills (1967), Ogawa and Fujita (1989), Tsekeris and Geroliminis (2013). Next, our hypothesis on the simultaneous agglomeration/dispersion effects of proximity to urban centers adds to Batty (2013, 2008), Behrens et al. (2017), Chen and Rosenthal (2008), and Brinkman (2016). Our new perspective on urban structure and land-use also provides an alternative method to the study of urban economics policies with spatially explicit implications, such as congestion (Brinkman, 2016; McDonald, 2009; Tsekeris & Geroliminis, 2013) and geographical knowledge spillover (Agrawal et al., 2015). Finally, our analysis approach offers a new, policy driven, calibration methodology for improving land-use change models (Al-Ahmadi, See, Heppenstall, & Hogg, 2009b; Xia Li, Liu, Liu, Chen, & Ai, 2013; X. Liu, Li, Liu, & Ai, 2008) .

The rest of this paper is organized as follows. In **Section 6.1**, we introduce the data, hypotheses, and analytical methods used in our analysis. We present our results and their implications in **Section 6.2.** And we conclude our findings in **Section 6.3.**

6.1 HYPOTHESES, DATA, AND METHODS

In this research, we aim to 1) measure connectivity and attractions of available urban land cells through transportation networks; 2) quantify agglomeration/dispersion effects of proximity measured by network connectivity; and 3) compare urban land-use growth patterns to existing agglomeration patterns. We use cleaned and reclassified 2011 land-cover data (30x30-meter resolution, around 181 million land-use cells in total) from

NLCD (Fry & et al., 2011c)to identify major land-use types in Chicago. We also detect differences between 2001 and 2011 land-cover data from NLCD to identify land-use changes in this time period. The land-use and land-use change maps are shown in **figure 24(a)** and **(b)** respectively.

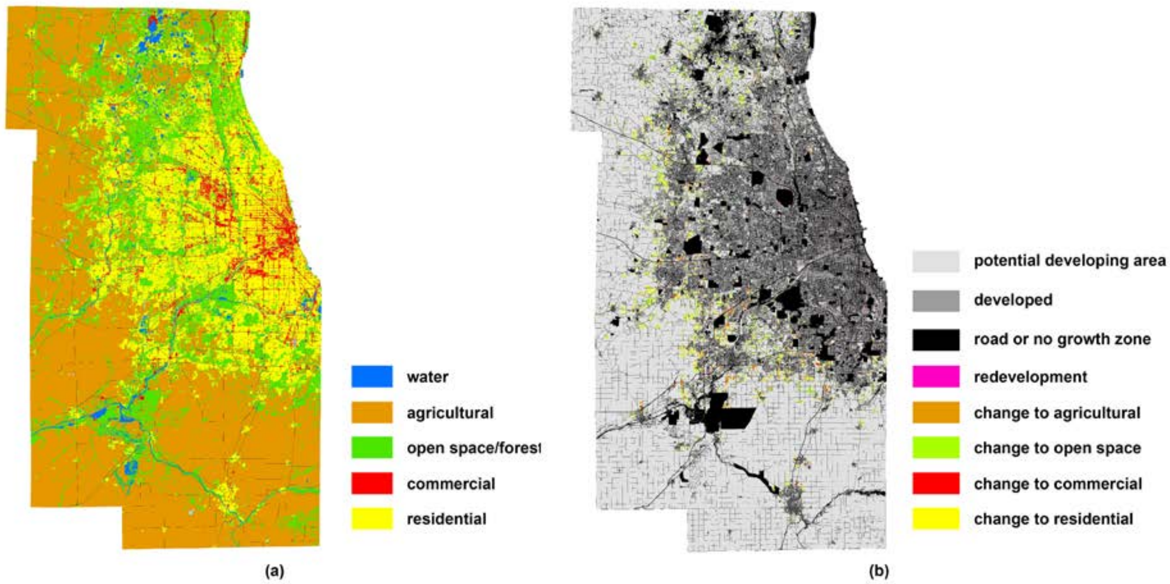


Figure 24(a) Land-use Map of Chicago in 2011**. Figure 24(b)** Land-use Change Map of Chicago from 2001 to 2011

The Chicago regional attractors we use in our analysis include: population centers, highways, major roads, and points of road network access—on ramps, major intersections (from Smith with U.S. Census Bureau, 2012); employment centers from D&B Hoover Industry Directory (Dun & Bradstreet, Inc., 2017); and other Points of Interests (POIs). POIs represent Chen and Rosenthal's (2008) "quality of life amenities". They are gathered using a *Yelp* API (Yelp, 2017) to obtain geotagged reviews for more than 10,000 restaurants, bars, stores, public and private services, hotels, and real estate purchases as of March 2016. Yelp reviews serve as a proxy for usage frequencies, although as a food based recommendation service, the Yelp API may exaggerate restaurant and bar usage relative to other amenities. The data collected is based on the physical numbers of reviews, and does not make any distinction on POI quality. For example a poor or un-preferred restaurant may still elicit a high number of reviews.

6.1.1 Stochastic Greedy Algorithm: measuring networked-based urban structure

Our first hypothesis is that, in large and complex urban systems, urban structure unfolds around network-based systems. We examine this by measuring the network connectivity between every cell in a 30x03meter land use land cover lattice of the Chicago region and our urban attractors. If our hypothesis holds, we expect to see urban attractors distributed with a scaling network form exhibiting a gravity-like decay.

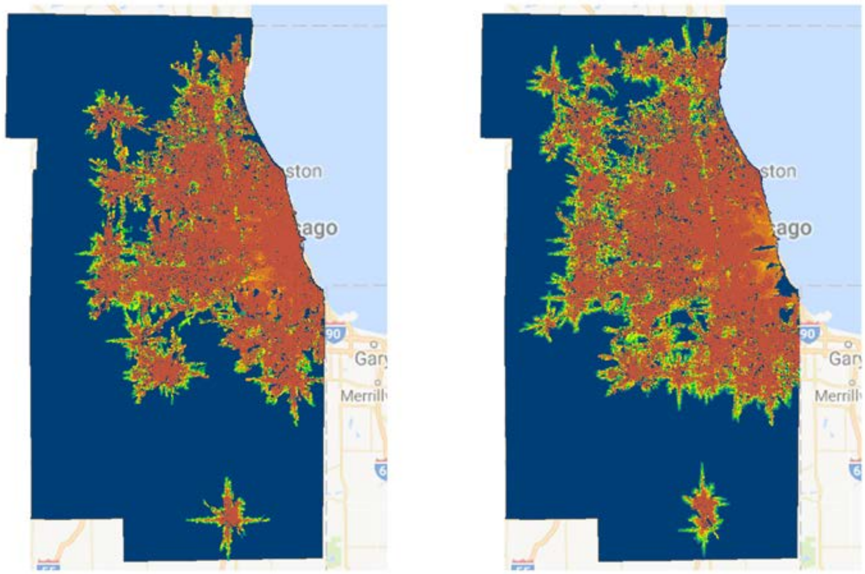
Our proposed network-based urban structure hypothesis differs from the “distance to CBD) based model in two important ways. First, it suggests that city and employment centers cannot be abstracted into one “centroid”. Empirical evidence shows that they are distributed around the city in what Batty describes as ‘scale free’ patterns (M. Batty, 2008b). We attempt to capture this by looking at a distributed set of attractors using data proxies for employment and production centers (actual employment locations and POIs). Second, we eschew the abstract notion of ‘center’. We believe that connections to a center need to be established through actual city networks and not the Euclidian distances and geometric circles used in developing the “distance to CBD” theories (see Alonso, 1974; Fujita and Ogawa, 1982; Lucas, 2001; Lucas and Rossi–Hansberg, 2002; Mills, 1967; Ogawa and Fujita, 1989). We also surmise that homogenized gridded networks (see Dong and Ross, 2015; Tsekeris and Geroliminis, 2013) still fail to capture empirical realities. To test our scale-free hypothesis, the networks used need to be derived from actual urban networks rather than over-simplified models.

As noted, the method we use to identify network connectivity is by simulating human movement to/from urban attractors using a Stochastic Greedy Algorithm (SGA) to establish shortest path routes through existing travel networks. An SGA incorporates learning into generating localized optimal solutions. It learns the characteristics of optimal solutions and then applies them to individualized solution sets (Viswanathan, Sen, & Chakraborty, 2011). We use SGA for its computational efficiency and its resemblance to actual human behavior. We apply the function to finding shortest travel time from all cells in the Chicago region to the top 100 population centers per US census data, the top 100 employment center per D&B Hoover data directory, our collection of POIs (Yelp Data), and points of network accessibility—intersections, ramps, and highways (U.S. Census Tiger/Line Data).

The traditional method for calculating shortest travel costs (in terms of time) derives global optimums using the computationally voracious Dijkstra algorithm. Dijkstra consumes computational time at a rate of $O(n^2)$ for n number of nodes (Goodman et al., 2016). In our case, one cell in our Chicago regional 30m lattice of 181 million cells equals one node. A Dijkstra algorithm calculation of this magnitude would take an inordinate amount of time and/or computational resources to complete. An alternative to Dijkstra is the Greedy Algorithm. At its core a Greedy Algorithm optimizes a system using a simple rule, “what looks best?” at any step. So a greedy *routing* algorithm would start by going to the closest one, then to the next closest, and so on (Cormen et al., 1990). So for the same problem with *n* nodes, the Greedy Algorithm has a much smaller computational complexity *O(n)*. A Greedy Algorithm finds localized optimums, sacrificing globally optimum solutions in the process. For example, a greedy algorithm might help me find my shortest commute path, but it cannot find the shortest or most efficient paths (on average) for all commuters (global optimum). This process captures individual behaviors well (localized optimal decision making), although fundamentally it may sacrifice some performance for computational efficiency.

To achieve a balance between performance and efficiency, we propose a parallel Stochastic Greedy Algorithm (SGA) to find the shortest travel times. The basic idea is to run hundreds of Greedy algorithms together with each assigned a randomized decision rule. This gives the algorithm a chance to “jump” out of a local optimization to reach a globally optimal solution (Viswanathan et al., 2011). An SGA resembles probabilistic path finding processes in the sense that much like human way finding, the algorithm considers both moving along a direct path to the destination *and* moving along the fastest route based on probabilistically outcomes.

In our SGA, we disseminate 1,000 agents from each of population and employment identified attractors the Chicago regional study area using high-performance paralleled computing resources. Each agent has been directed to move as far as it can travel in 1 direction for 1 hour in 1 cell increments. Direction is probabilistic and a continuous variable (see appendix). Time and speed are based on network speeds and land cover impediments. For example it’s harder to cross a forested land cover than an agricultural land use and it is impossible to cross water excepting at network (bridges). After simulating the movement patterns of all 200,000 agents disseminated, we designate each cell in the regional lattice an optimum travel time (shortest travel time) to each attractor (**Figure 25**). Because of the stochastic nature of our SGA, some peripheral cells are unvisited by an agent. These are recorded as having an infinite travel time. To address the possibility that some cells are *missed* by agents, we interpolate their travel times to cells within 5 steps (using straight-line distance) divided by travel barrier values. If a cell is visited multiple times, we consider the shortest time recorded for any visit as the optimal. A summary process and detailed pseudo code of SGA is provided in the attached **Section 6.4**.



(a) (b)

Figure 25(a) is the travel cost map for Chicago employment centers using SGA algorithm. **Figure 25(b)** is the travel cost map for Chicago population centers using SGA algorithm. Warmer color indicates shorter travel time.

The computational complexity for our SGA algorithm can be defined as $O(TN)$, where N is the number of iterations specified, and T is a time-based distance cutoff. In our SGA model, we specify T at 1,000 steps (30,000 meters). We consider the information generated at >30,000 meters from an attractor to be inconsequential. Note that N and T in our SGA are significantly smaller than the total cell number n used in Dijkstra. This results in a much smaller computational cost. Further, our N iterations of randomized agent dispatches have no dependencies and therefore can be processed in parallel. In this case, the computational time will be $O(TN/C)$, where C is the number of threads available for parallelization. One further improvement is that congested speeds can be considered when calculating agent travel times on the road network.

6.1.2 Examining relations between connectivity, attraction and land-use frequency

Our second hypothesis is that proximity to urban attractors has both agglomeration and dispersion effects on location preferences for commercial and residential land-uses. To quantify agglomeration/dispersion effects that result from network connectivity, we examine the relation between existing commercial and residential land-use frequency to our set of urban attractors (population centers, major employers, POIs and points of network accessibility – intersections, ramps, and highways). We are also interested in the temporal aspects of urban structure and land-use—what are the evolutionary mechanisms? We suspect that newly emerging urban development has different mechanisms from existing, historically driven developments, a phenomenon that, to date, has not been addressed in static equilibrium models (see Chen and Rosenthal, 2008; Fujita and Ogawa, 1982; Ogawa and Fujita, 1989).

To test this hypothesis, we use our SGA attractor connectivity scores as a basis for establishing the relative *attractive gravity* of each location using gravity-like functions. Attractive gravity levels are broken into 50 quantiles. The frequency of existing residential and commercial land uses cells that fall within each quantile is calculated by overlaying existing land-use / land cover maps with attractive gravity results. Finally, functional relations between land-use categories and urban attractors are determined using statistical methods and mathematical mapping processes in a 'best mapping relations' exercise.

6.1.2.1 Methodology for H2

In the first step, we calculate an attraction value for each attractor based on their importance (e.g. use, size, population, or number of visitors) and distances to each land-use cell. For attractor type i's attraction to land-use cell k, we calculate its attraction a_{ik} by:

$$a_{ik} = \sum_{j \in S_i} \frac{p_j}{d_{jk}} \qquad \textbf{(22)}$$

where S_i is the set of all attractors that belong to attractor type i; p_j is the level of attraction for jth attractor in S_i; d_{jk} is the distance between jth attractor in S_i and land-use cell k. The inverse distance model is similar to gravity model, and there is an extensive discussion on the proper power coefficient selection for gravity models (Anderson & Van Wincoop, 2003; Bergstrand, 1985; Mátyás, 1997; Pan, Li, & Dang, 2013). We use 1 for the power coefficient since **equation 22** is an additive model of attractions to various places normalized by travel time, so that traditional gravity model coefficients may not be suitable. The gravity model literature also focuses on the use of gravity models to directly model spatial problems, while we use the inverse distance here only to process data for examining other theoretical models. Thus, we tend to preserve the originality of data without using a power coefficient. Whether this turns out to be a limitation will be the focus of future work.

To demonstrate what S_{i} (set of attractors for type i) mean and how we choose p_{j} and d_{jk} for each attractor type, we clarify each attractor type we examine below:

Employment Attraction ($\boldsymbol{S_1}$). p_{j} is the total employment at place j according to the Hoover data directory, and d_{jk} is the shortest network travel time from place j to cell k obtained from SGA.

Population Attraction ($\boldsymbol{S_2}$). p_{j} is the total population at place j according to 2010 US Census, and d_{jk} is the shortest network travel time from place j to cell k obtained from SGA.

Review Attraction ($\boldsymbol{S_3}$). p_{j} is the total reviews received from www.yelp.com at business location j, and d_{jk} is the Euclidean distance from place j to cell k. We did not use travel time for reviews because there are more than 10,000 review locations in Chicago MSA, thus a shortest network travel time algorithm costs too much time. Also, we think that dense distributions of review locations make network travel time calculation not as important as other centers.

Accessibility Attraction ($\boldsymbol{S_4}$). p_{j} is the posted speed at major road j (highway, interstate, or major roads), and d_{jk} is the Euclidean distance from highway j to cell k. We use posted speed and distance decay to represent how close one cells is to major road transport networks. This attraction value map can also be viewed as "density of roads" map of Chicago.

After calculating the attraction values, we break up the values into 50 quantiles (each quantile consist of an equal number of cells) based on their sorted value of attractions. Formally, we give each land-use cell k_{m_i} an index m_i for each attractor type i:

$$m_i = \sum_{j=0}^{49} (j+1) \mathbb{1}_{\mathrm{a}_{\mathrm{i}k_{m_i}} \in (\boldsymbol{v}_{i,[\frac{n}{50}]j}, \boldsymbol{v}_{i,[\frac{n}{50}](j+1)}]} \qquad \textbf{(23)}$$

where $\boldsymbol{V}_i$ is the sorted (increasing) vector of attraction value i; $\boldsymbol{v}_{i,k}$ is the kth element in vector $\boldsymbol{V}_i$; n is the total number of elements in $\boldsymbol{V}_i$; $[\frac{\blacksquare}{\blacksquare}]$ is a mathematical operator for integer division.

We sort attraction values into quantiles because we want to calculate the frequency of land-use cells (commercial or residential) by equal parts as well in order to map their functional relation. To demonstrate this calculation mathematically, we first define some sets of land-use class of concern (note that we have preprocessed NLCD data to excluding existing roads and misclassifications before this analysis):

$\boldsymbol{E}$ **:** set of land-use classes cells belonging to all classes in NLCD 2006 (Fry & et al., 2011c) legend excluding water related classes (excluding classes that are starting with 1-).

$\boldsymbol{R}$: set of land-use cells belonging to low intensity developed lands in NLCD 2006 legend (class 22).

$\boldsymbol{C}$: set of land-use classes including medium to high intensity developed lands in NLCD 2006 legend (class 23 and 24).

Equation 24 and **equation 25** represent how we calculate our target frequency in each quantile for each attractor:

$$f_{i,s,r} = \frac{\sum_{m_i = s} \mathbb{1}_{k_{m_i} \in \boldsymbol{R}}}{\sum_{m_i = s} \mathbb{1}_{k_{m_i} \in \boldsymbol{E}}} \qquad \textbf{(24)}$$

$$f_{i,s,c} = \frac{\sum_{m_i = s} \mathbb{1}_{k_{m_i} \in \boldsymbol{C}}}{\sum_{m_i = s} \mathbb{1}_{k_{m_i} \in \boldsymbol{E}}} \qquad \textbf{(25)}$$

where $f_{i,s,r}$ is existing residential cell frequency for attractor type i, s^{th} quantile ($s \in [1,2,\dots,50]$); $f_{i,s,c}$ is existing commercial cell frequency for attractor type i, s^{th}; $f_{i,s,l}$ is changing into residential cell frequency for attractor type i, sth quantile; $f_{i,s,h}$ is changing into commercial cell frequency for attractor type i, s^{th} quantile.

Finally we can examine the mapping relations between land-use/land-use change frequency and attraction values. We define vectors $F_{i,r} = (f_{i,s,r})$, $F_{i,c} = (f_{i,s,c})$, $F_{i,l} = (f_{i,s,l})$, $F_{i,h} = (f_{i,s,h})$; similarly, we can define attraction values of sets of attraction values divided into 50 quantiles, with $A_i = (\mathrm{a'}_{\mathrm{i}k_{m_i}})$. To make $g_{i,t}(\blacksquare)$ comparable for different i, we normalized all $\mathrm{a}_{\mathrm{i}k_{m_i}}$ into $\mathrm{a'}_{\mathrm{i}k_{m_i}} \in [0,1]$ we define 8 possible mapping relations:

$$A_i = g_{i,t}(F_{i,t}) + w_{i,t} \qquad \textbf{(26)}$$

where $t \in (r, c)$; thus we have mapping relations $g_{i,t}(\blacksquare)$ for 2 different land-use types and 4 different attractor types (employment, population, reviews and accessibility for $i \in$

(1,2,3,4); $w_{i,t}$ is a zero-mean white noise.

Our hypothesis of possible types of $g_{i,t}(\blacksquare)$ include **power functions** and **polynomial functions**. The power form of $g_{i,t}(F_{i,t}) = kF_{i,t}{}^{\xi}$ indicates that a land-use type agglomerates to a certain attractor. The idea of modeling agglomeration by power law was proposed by Bettencourt et al., 2007 and Batty (2008). In Bettencourt et al., 2007 and Batty (2008), empirical data showed that key urban indicators (such as new patents or GDP) in major US, European, and Chinese cities follow a power function relative to the size (population) of the city. More specifically, $\xi > 1, \mathrm{k} > 0$ for wealth and creativity; $\xi < 1, \mathrm{k} > 0$ for the infrastructure needed to sustain the population. Bettencourt et al. (2007) proposed that it is economies of scale that allow this efficient growth of wealth and innovation with increasing population. Polynomial functions suggest the coexistence of agglomeration and dispersion effects. The mechanisms for this can be determined by examining the patterns of first and second order derivatives. It is noteworthy that Batty (2013) empirical finding of superlinear relations between city size and connectivity provides a specific case both for power and polynomial functions**.**

In this study, we fit all possible functional candidates (power and polynomial) for 8 $g_{i,t}(\blacksquare)$ in a relation mapping exercise. Because each function has differing degrees of freedom, and since the data are not of similar scales, normal measurements of fit (such as *R*-squared and AIC) are not applicable. We therefore choose an average sum-of-square error measure in a 'leave-one-out' procedure **(equation27)** to determine goodness-of-fit (Kohavi & others, 1995). In this process, we conduct a data, curve fitting process *n* times (*n* is the number of total data points, 50 for each candidate in this case) to determine a functional curve (for each candidate). We intentionally leave out one randomly selected data point in each attempt. We then try to predict the left-out data point using the resultant functional curve and record the error of its prediction. Finally, we average out the sum of squared errors for all *n* points for each curve candidate to determine a best-fit function. Because the model tries to predict "out-of-sample" points with its original scale preserved, it can avoid the degrees of freedom and mapping scale trap(see Kohavi and others, 1995) for a good discussion of the mapping scale trap). In this case, for attraction with function t we define its leave-one-out error $e_{i,t}$ as:

$$e_{i,t} = \frac{1}{50}\sum_{s=1}^{50}(\widehat{g_{i,t,s}(f_{i,s,t})} - a'_{i,s})^2 \quad \textbf{(27)}$$

where s represents the index of 50 quantiles ($s \in [1,2,\ldots,50]$), $\widehat{g_{i,t,s}(\blacksquare)}$ is the least mean-squared error mapping of $F_{i,t}$ to A_i without the information of data point $f_{i,s,t}$ and $a'_{i,s}$; $\widehat{g_{i,t,s}(f_{i,s,t})}$ is the least mean-squared error prediction of $a'_{i,s}$ without the information of $a'_{i,s}$ itself.

Our leave-one-out validation results are recorded in an attached **Appendix**. There are some instances where different functions of $g_{i,t}(\blacksquare)$ have similar leave-one-out errors ($e_{i,t}$). In those cases, we choose the fitting curve to the function by its relevance to CUS theories and other existing literature. We highlight those instances and provide more detailed explanations in the **Appendix.**

6.1.3 Examining the temporal aspect: land-use change

Our third hypothesis is that new urban growth patterns are different from existing agglomeration patterns. We test this, by analyzing SGA patterns in Chicago from 2001 to 2011 and compare the results to newly developed land-uses – post 2011. To do this we must first define 3 new sets of land-use categories.

N: a set that consists of all land-use classes that are *not* developed lands (urban or rural structures) and not water in NLCD 2001 (excluding class 22, 23, 24, and classes starting with 1- in NLCD 2001).

L: a set that consists of all land-use classes that are *not* developed lands (urban or rural structures) and not water in NLCD 2001 (**N**), *and* cells that changed into low intensity developed lands in 2006 (changed into class 22 in NLCD 2006).

H: a set that consists of all land-use classes that are *not* developed lands (urban or rural structures) and not water in NLCD 2001 (**N**), *and* cells that changed into low intensity developed lands in 2006 (**L**), *an*d changed into class 23 or 24 in NLCD 2006.

Similar to **equation 24** and **equation 25**, we then calculate frequencies of land-use changes to residential and commercial land-use over the 10 years (**equations 28** and **29)**.

$$f_{i,s,l} = \frac{\sum_{m_i = s} \mathbb{1}_{k_{m_i} \in \boldsymbol{L}}}{\sum_{m_i = s} \mathbb{1}_{k_{m_i} \in \boldsymbol{N}}} \qquad \textbf{(28)}$$

$$f_{i,s,h} = \frac{\sum_{m_i = s} \mathbb{1}_{k_{m_i} \in \boldsymbol{H}}}{\sum_{m_i = s} \mathbb{1}_{k_{m_i} \in \boldsymbol{N}}} \qquad \textbf{(29)}$$

Finally, we use the same procedure shown in **equations 26** to find the mapping relations between land-use change frequency and attraction values. If our hypothesis holds, newer urban growth will demonstrate a significantly different pattern than existing agglomeration patterns. In other words, it should be evident in that the relations we find for newer land-use changes are inherently different from the relations we find for older, existing land-uses.

6.2 RESULTS

6.2.1 Network-based urban systems

Figure 26 describes the results of attraction value calculations for employment, population centers, POIs, and accessibility variables in the Chicago metro region. Recall that hypothesis 1 suggests that large and complex urban systems unfold with network accessibility rather than around a single CBD (the "distance to CBD" assumption). Population and accessibility attractors (**Figures 26(b)** and **26(d)** respectively), display significant breaks from the "distance to CBD" assumption. The downtown of Chicago has higher overall attraction, but other high attraction values follow road networks, especially highways and do *not* radially decay from the urban center as surmised in spatial equilibrium models. Employment and POI attraction maps (**Figures 26(a)** and **26(c)** respectively) follow the "distance to CBD" more or less. Highest attraction values cluster around downtown Chicago, in the POI (**3(d**)) we can see an obvious northerly shift in the reviews distribution compared to the employment distribution. We imagine that this shift of center is caused by a retail and tourist magnet north of the city center (the Michigan Avenue 'magnificent mile'), where firms and commercial related factors (employment and POIs) are more spatially concentrated. But is the urban center really providing enough production externality improvements to affect the locational choices and agglomeration characteristics of firms? We consider this question in the later land-use frequency analysis.

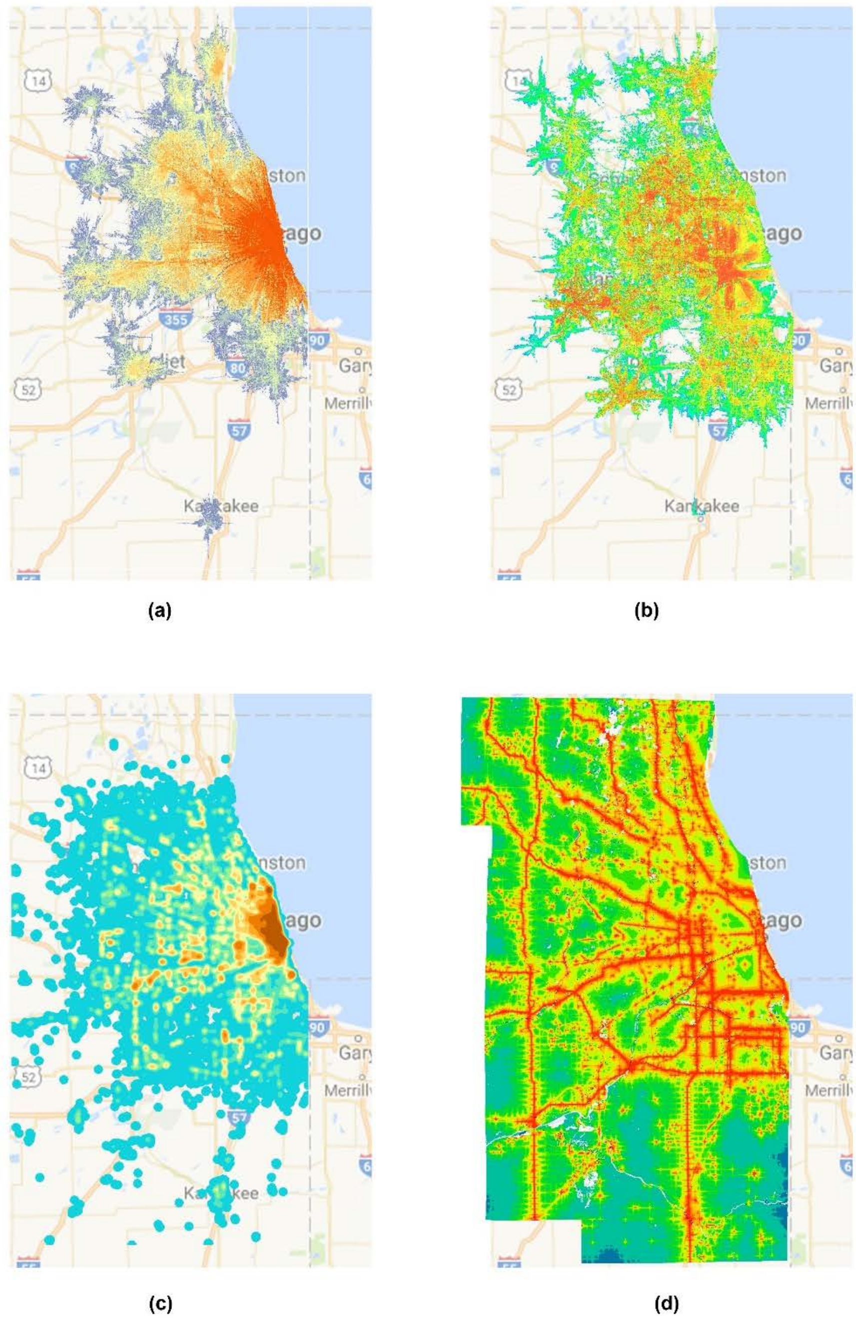


Figure 26 are attractiveness maps for different "attractors" in Chicago to every 30x30 meter land-use cell. Warmer colors indicate higher attractiveness. (a). Employment attraction (b) Population attraction (c) Review attraction (d) Accessibility attraction.

6.2.2 Agglomeration and dispersion to attraction and connectivity

In **figure 27(a)** and **27(b)** we illustrate the relation between land-use frequency and urban attraction values. For commercial land-uses, frequencies are fitted by the power law of employment, population, and review attractions. Considering the above in light of our findings from **Section 6.2.1**, we conclude that commercial land-use structures in Chicago do in fact, aggregate close to downtown Chicago and display agglomeration effects. Residential uses however, can only be fit with a power coefficient curve of <1. We find that population land uses are agglomerated by points of interest to some extent, but not to other attractors. Residential land-uses also demonstrate a decrease in their probability of development as they move closer to employment centers ($\mathrm{A}_{\mathrm{emp}} > 0.6$). Possible explanations to this include that expensive property prices and high level of congestions to the most proximity of employment clusters overweigh a short increase in commuting time (compare, for example, 10 minutes to 20 minutes driving).

The accessibility attractors are best fitted using a polynomial curve and that is found to be generally increasing with an increase of both commercial and residential land-use frequencies. The first derivative of the curve is negative when $A_{access} < 0.06$ for commercial land-use and positive overall for residential land-uses. This logically, means that when commercial lands are far from major roads and highways, accessibility is no longer a concern—they are too far from any attractor and its locational attributes are no longer based on accessibility measures. When accessible places are close to major roads and highways however, they are highly sought after by both residential and commercial developments.

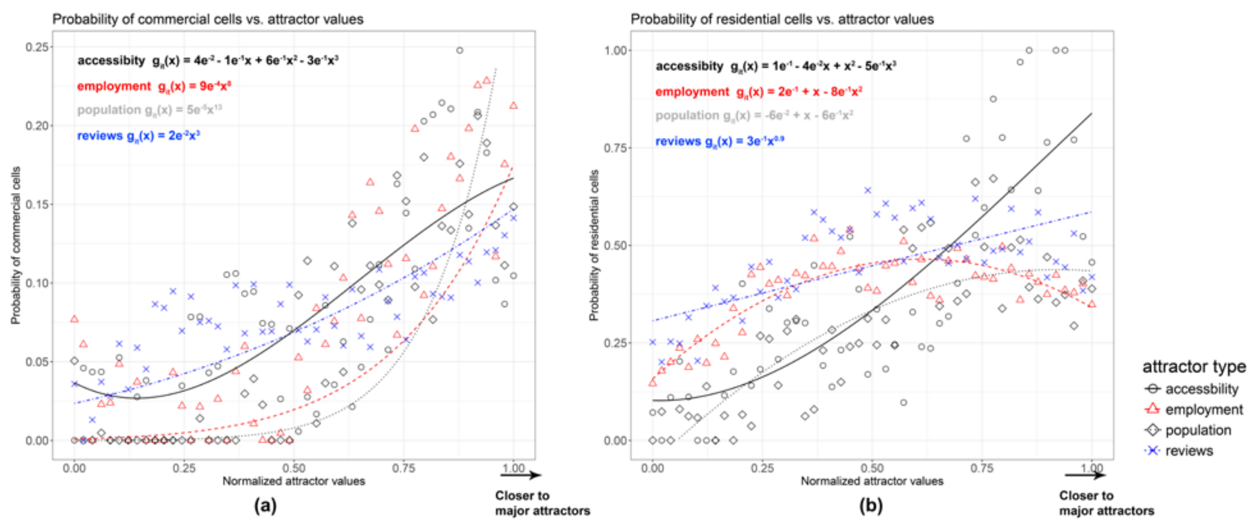


Figure 27(a) and **27(b)** illustrate best mapping relations between probabilities of commercial and residential land-uses' occurrence in available lands vs. connectivity to various attractors in Chicago. The horizontal axis is the attractive level. The vertical axis is probabilities of an available land to be certain land-use within an attractive level range. Probabilities of land-use occurrence of commercial/residential land-use in regard to attractive levels are drawn as points on the graph. A curve (fitted and chosen by "leave-one-out" method") is drawn for each attractor type in regarding to each land-use category.

Our take-away from this result is that the "distance to CBD" and network-based models are both valid for commercial land-uses to some extent. On the other hand, Residential land-uses are located in proximity to higher "quality of life" and accessibility places, which are overlooked factors by "distance to CBD" assumptions. Population centers, employment centers, and POIs have obvious positive production externalities for commercial land-uses, however only POIs attract residential land-uses (better quality of life amenities); proximity to employment even shows dispersion for residential land-uses (higher land-rent outweighs shorter commuting time). Compared to the traditional "distance to CBD" based urban economic models, the result shows that the distances to major road networks (rather than connectivity to employment and population centers) shape the spatial distributions of urban residential and commercial land-uses. Moreover, we suggest that residential land-use allocations are influenced by a plethora of factors rather than just commuting distance and land rents.

6.2.3 Temporal aspect of city structure and land-use

We propose that urban structure and land-use patterns that emerge on the landscape take different form over the course of time. To test this we use SGA and attractiveness mapping approach to compare the static (2011) vs. temporal changing (20061-2011) urban land-use structure in relation to 4 types of attractors. We hypothesized that static and temporal changing urban land-use structure will show significant differences. In this section, we will show that our findings substantiate this hypothesis.

In **figure 28,** we compare the attraction/frequency relation curves for both existing land-uses (2011) and new land-use changes (from 2001 to 2011) in the region. The results intuitively describe how existing and changing land-use patterns differ. In **figure 27(a)**, population and accessibility attractors increase with existing commercial land-use and commercial land-use change. This suggests that jobs and businesses display similar locational preferences relative to population and accessibility measures—i.e. both seek to locate in places that are more accessible to larger pool of potential users. Newer businesses however, may be less inclined to locate in close proximity to existing competitors, preferring new less competitive markets. This can be seen in **figure 28(a)** in the curve of changing commercial land-use frequency in regarding to employment. In **Figure 28(b)** (residential land-use structure—exiting vs. change)**,** only review and accessibility attractions increase with existing residential land-use and residential land-use change. This implies a tendency to search for infrastructure—both life-facilitating (POIs) and transportation infrastructure.

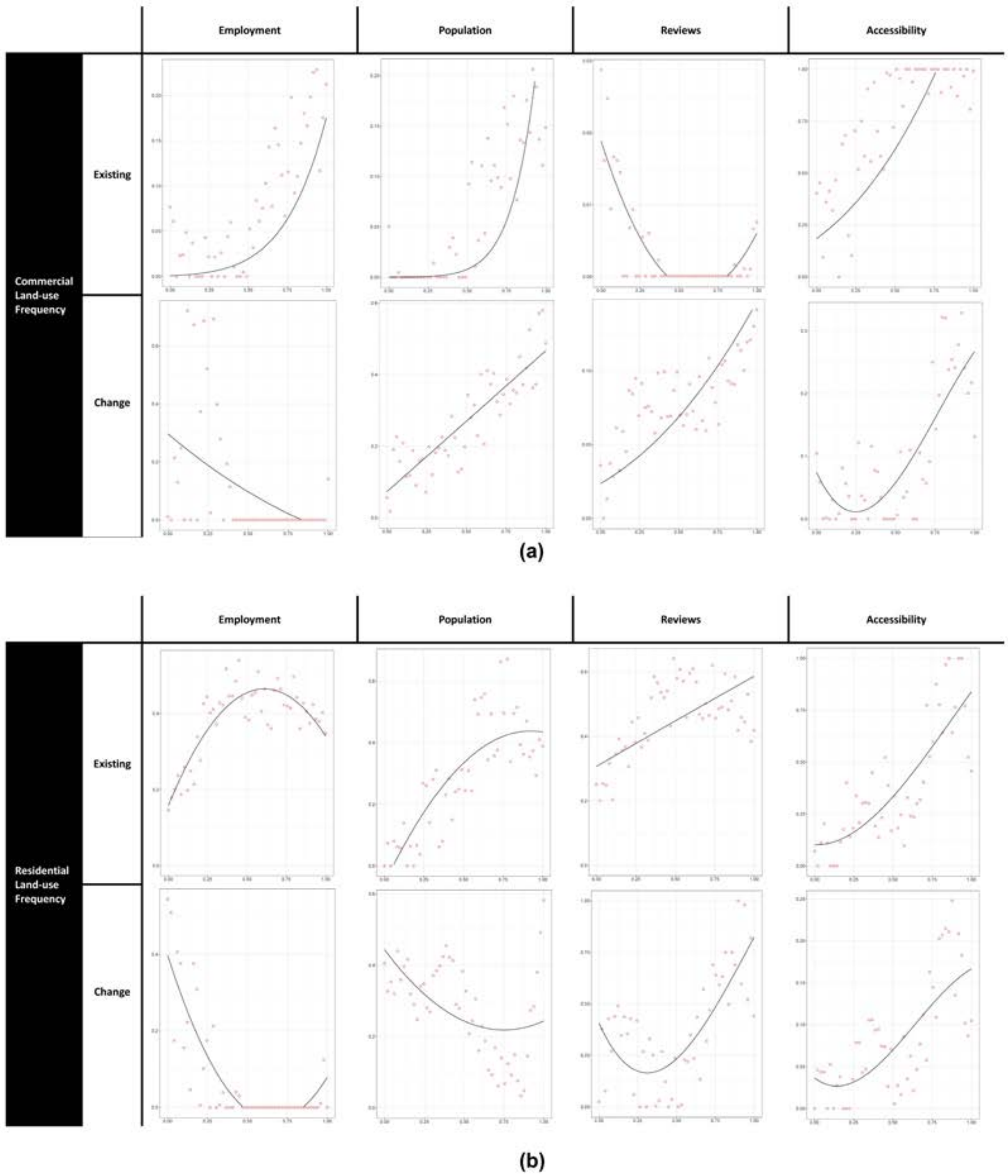


Figure 28(a). Frequency of commercial land-use/land-use change vs. attraction values (b) Frequency of residential land-use/land-use change vs. attraction values. The horizontal axis is normalized attraction values, the vertical axis is the frequency of designated land-use (change) types. The curves and points are shown in detail in **figure 27** and **29**. The comparisons between curves in the upper row (existing) vs. lower row (change) for both residential and commercial land-uses demonstrate the differences between static and changing land-use structures.

To analyze the temporal mechanism of land-use structure change, we demonstrate another mapping relation map (**figure 29**, land-use vs. attractors) similar to **figure 27**. **Figure 29(a)** and **29(b)** illustrate in detail the relations between land-use change frequency and urban attraction values. With sharp contrast to existing commercial land-uses, proximity to employment and POIs become negatively associated with newly developed commercial lands. Competition, higher wage premium, and congestion overshadow production externality for new firm location choices. Only population attraction has linear and positive correlation with new commercial development; this is probably due to labor and consumer supply. Accessibility has similar effects in comparison to existing commercial land-uses (the first order derivative is negative when $A_{access} < 0.38 \ \ and \ \ A_{access} > 0.73$), meaning that new firms do not want to be too close or too far from existing centers.

Newly developed residential lands are highly attracted to major roads and highways (fitted with power functions to accessibility attraction), but generally are repelled by employment and population centers. This further shows that new residents avoid existing urban centers due to higher land rent and congestion. Quality of life amenities—POIs, are still attractive to new development over a certain connectivity cutoff ($A_{reviews} > 0.42$).

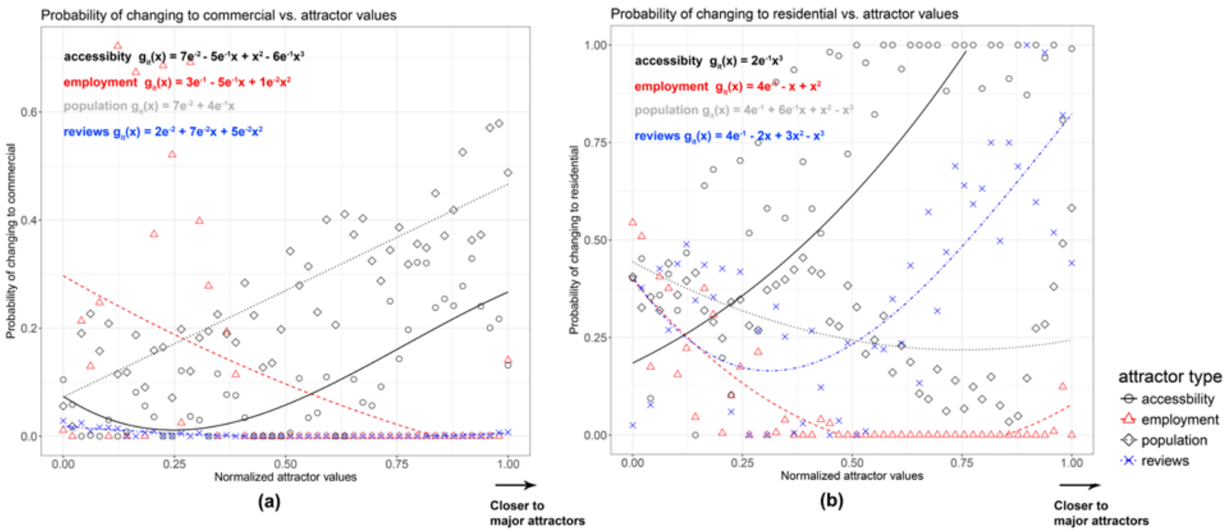


Figure 29(a) and **figure 29(b)** illustrate best mapping relations between probabilities of land-use change and connectivity vs. various attractors in Chicago from 2001 to 2011. The horizontal axis is the attractive level. The vertical axis is probabilities of an available land to be certain land-use within an attractive level range. Probabilities of land-use occurrence of commercial/residential land-use in regard to attractive levels are drawn as points on the graph. A curve (fitted and chosen by "leave-one-out" method") is drawn for each attractor type in regarding to each land-use category.

The above analysis suggests that newer urban development patterns break significantly from previous patterns. That urban structure moves, over time toward more complex, chaotic patterns. More importantly, when we separate new development from current urban structures, the "distance to CBD" model does not explain the new development any longer (dispersion effects of proximity are very strong). New commercial establishments do not locate around existing clusters of employment centers—CBD. New residents or movers also find places far away from existing CBD, but are still attracted to life amenities—POIs. Congestion and higher costs, and land rents are possible causes of these phenomena. On the other hand, the network connectivity/accessibility-centric model better described the urban structure reformation.

6.3 CONCLUSIONS AND DISCUSSIONS

In this paper, we reexamine the monocentric city, a core assumption of urban economic structure models. We propose an alternative, scale-free network model of urban structure based on theories of CUS. We suggest that people and businesses agglomerate in relation to network accessibility factors, rather than Euclidean distances to an urban CBD. We construct a model for testing this relation using an SGA to evaluate how available lands are connected to existing urban amenities. We use network accessibility and shortest path measures to quantify the connectivity of all unique cells the Chicago metro area to population and employment centers, points of interest, and points of network accessibility. We measure the attraction of each relative to the frequency of existing commercial and resident land-uses. We do this in order to examine several hypotheses that offer theoretical departures from current urban structure models.

Our first hypothesis is that large urban systems organize around scale-free urban networks rather than circular rings centered on one CBD. This hypothesis has two major differences from current urban structure models: 1) city and employment centers are distributed all over the cities rather than in one CBD and 2) connections of city center need to be established through actual city networks rather than using Euclidean distances. Previous urban structure models have only one center and uses over-simplified measures for urban spatial connectivity. Using SGA we found out that population distribution in Chicago has multiple centers that are connected by transportation road networks. On the other hand, employment and POI distributions demonstrate more concentration on one CBD, and the distributions diffuse through transportation networks. Checking how existing residential/commercial land-uses are attracted by those attractors, we found that existing commercial land-uses show agglomeration around employment centers, which does not reject “distance to CBD” assumption, while commercial land-uses also tend to grow along major transportation networks, as network-based city assumed. Residential land-use distribution, on the other hand, cannot be described by “distance to CBD” assumption and is better described by network-based city assumption.

Our second hypothesis is that proximity to urban attractors has both agglomeration and dispersion effects on location preferences for commercial and residential land-uses. This assumption has been checked by previous literature, but not put under the lens of a network-based urban system. To answer this question, we use a gravity-like measure the relations between commercial and residential land-use frequency and urban attraction levels. Our initial results demonstrate that commercial land-use structure can be described by the “distance to CBD” based model, but it also shows attachment to major transportation networks. On the other hand, “distance to CBD” model cannot explain residential land-use structure as well as network based model. Especially, quality-of-life measure—proximity to POIs—is not included in the “distance to CBD” model which only focus on work related trips. Our findings suggest that proximity to POIs is the single most attraction for residence location choices, confirming Chen and Rosenthal (2008) findings and supporting network based city assumptions..

Our third hypothesis is that newer urban growth has different patterns from existing agglomeration patterns. This hypothesis implies an intuitive but unexamined dynamic of urban structure formation: driving forces and choices of agglomeration changes with time. Our results suggest that new urban development significantly breaks away from existing patterns. "Distance to CBD" model assumptions cannot be applied to new development because of dispersion effects of established employment (Behrens et al., 2017; Brinkman, 2016; Y. Chen & Rosenthal, 2008) which could outweigh agglomeration effects of production externality and proximity to employment. Network accessibility is the most powerful drivers for both new residential and commercial development. This result suggests that when urban systems grow larger and more complex, scale-free network based urban structure explains new developmental patterns better than "distance to CBD" based structure.

Our research presents empirical evidence of how CUS theories can be applied to reform traditional assumptions of "distance to CBD" urban structure. We do not intend to discard the "distance to CBD" urban structure model, as it is still useful in many aspects, especially on the existing commercial land-use structure. However, when we take into account a plethora of factors (such as non-work related trips) that affect residential land-use choices and temporal dynamics of land-use growth, network based urban model has better explanatory power. An important challenge and future work is to theorize the market and spatial equilibrium of CUS based urban model. This will be a complicated task, because CUS theorize cities have scale free networks which no longer has a definite form compared to a ring-shaped "distance to CBD" city. Another future extension to the empirical work is to include the interactions between different factors in determining land-use distributions. Finding interaction effects can provide additional explanations to the complexities in the function forms we find for individual factors' impact on land-use distributions. We find inclusion of network based urban structure in urban economic models very existing, because this is a great opportunity to unify the findings on fractal properties of city morphology (CUS sciences) with economic and market driving mechanisms that create these morphological properties.

6.4 TECHNICAL DETAILS

Figure 30 is a summary of SGA process for finding shortest path from one population center *k* to other cells. **Figure 31** is a detailed pseudo code for SGA process.

```
Algorithm SGA{
    Initiate every cell on the map with infinity travel time;

    Repeat the following N times{
        Initiate a direction;

        Repeat the following T steps{
            Agent from current cell moves to an adjacent cell, with higher
            probability to the cell with lesser travel barrier and in accordance with
            the original direction #agent from population center k in the first step
        }
    }
    Update the least travel time from population center k for every cell on the map
}
```

Figure 30. Brief Pseudo-code of SGA

```
Algorithm SGA{
    Initiate every cell on the map with infinity travel time;

    Repeat the following 1,000 times{
        Randomly draw a direction d from direction set M = {N, NE, E, SE, S, SW,
        W, NW} with equal chance; # N—North, E—East, S—South, W---West,
        NE—Northeast, etc;

        Repeat the following 1,000 steps{
            Define P as a probability vector with {p_N, p_NE, p_E, p_SE, p_S, p_SW, p_W,
            p_NW}, where every element of P is a continuous number in [0, 1];

            Create set of neighboring direction vector of d as E={e_1, e_2, e_3}; # for
            example, if d is NE, then E={N, E, NE}

            Randomly draw 2 directions from E as vector D={d_1, d_2} with equal
            probability; #in this case, assume NE is the direction d and D={NE,
            N}

            Assign the probability P for cell to move in direction of each of the
            elements of D as 0.35; for the 2 directions adjacent to E but not in E as
            0.1; for the remaining 4 directions as 0.025; In our example, P={p_N,
            p_NE, p_E, p_SE, p_S, p_SW, p_W, p_NW}={0.35 ,0.35 , 0.025, 0.09, 0.025, 0.025,
            0.025, 0.09};

            Assign a L probability vector to each direction based on the travel
            barrier of the land-use type on each cell;

            Calculate the final direction moving probability Q={q_i:i∈N, q_i =
            p_i l_i / ∑_{j∈N} p_j l_j};

            Agent from current cell moves to an adjacent cell with probability
            vector Q to {N, NE, E, SE, S, SW, W, NW};
        }
    }
    Update the least travel time from population center k for every cell on the map
}
```

Figure 31. Detailed Pseudo-code of SGA

CHAPTER 7: CONCLUSIONS, DISCUSSIONS, AND FUTURE WORKS

This chapter synthesizes and discusses the theoretical implications and contributions of this dissertation to the field of planning. I discuss the limitations of my research and the broader limitations of current PSS and CUS approaches. Urban system research and tool development must look beyond urban planning. The reach of this and related work can and should be much broader. For example, it might include city governance, urban economists, transportation engineers, real estate developers, and environmental scientists. Practical applications of CUS sciences need to address its scale and predictive limitations. I conclude the dissertation with a discussion of future research I intend to pursue.

7.1 CONTRIBUTIONS AND THEORETICAL IMPLICATIONS

In my dissertation, I studied multiple aspects of a model driven PSS, and proposed improvement to PSS in almost every aspect—from practicality to methodology and theory. In each of the improvement areas I use both theory and practical application to make my arguments.

Previous PSS research has focused on pinpointing the weakness of current PSS approaches or on technical improvements. In my view technical improvements and practical weaknesses are not connected. My research attempts to bridge this gap. In the above, I have proposed ways to improve PSSs' processes and methods from multiple perspectives, such as environmental planning, sentience, resilience, and smart city-based perspectives. In summary I propose two basic improvements to help make PSSs more useful in the practice of planning. The first is multi-directional temporal analyses for scenario planning. The second is knowledge transfer of PSS in planning processes to promote system credibility.

The CUS science literature inspires both opportunities and challenges for the future of PSSs. My research uses PSSs to operationalize CUS theories into tools that guide city development practices. Drawing from the latest statistical and computational methods, I proposed a better fit for PSSs into the CUS theoretical framework. I then validated those methods using the case of Chicago and the LEAM PSS model calibration. This provides quantitative evidence that network based CUS models better describe land-use structure in Chicago than traditional "distance to CBD" based economic approaches, especially in terms of residential land-use, and the temporal evolution of land-use structure.

Other specific points made in this dissertation in relation to my original research questions include:

- Some of the future application fields of PSS includes but are not limited to Smart City projects, sentient and resilient cities, and environmental planning processes. To better aid those processes and goals, PSSs need to 1) be able to process dynamic data; 2) possess sentient visualization systems; 3) and emphasize the processes of creating PSS models;
- Multi-directional temporal scenario planning processes can improve usefulness of PSS model simulation results.
- A collaborative process of PSS model validation can better transfer practical knowledge embedded in the goodness-of-fit of PSS model simulations using a "multi-resolution fitting process" in a knowledge transfer process.
- Evolutions of PSS models include geographic automata systems, semi(non)-parametric spatio-temporal models, paralleled statistical models and integration of several urban system models.
- CUS network-based urban system theories are useful in describing activities in urban setting more effectively than "distance to CBD" models of urban structure.
- A large-scale and fine-grained spatio-temporal model will better enable spatial reasoning for complex urban development dynamics (see below).

7.2 LIMITATIONS

My work has a number of limitations and they indicate challenges as well as opportunities for future research.

First, it might be a wrongheaded goal to "improve PSS model usefulness in the practice of planning." The failure of a wide adoption of PSSs after more than 30 years of existence may not be a result of PSS problems—it may actually be a problem within the field of planning. Planning education has increasingly focused on dismissing systemic and rational planning approaches. Instead, mainstream planning has moved to grassroots and social movements. Thus, restoring system legitimacy will not be useful if targeted users have no interest in accepting knowledge from systemic approaches. On the other hand, the city development realm as a whole is increasingly open to analytic and data-driven methods, with popular concepts including "smart cities," "big data," and "urban analytics." At the same time, city governance, urban economists, transportation engineers, real estate developers, and environmental scientists are paying more attention to the impacts of urban development. Therefore, a future direction of spatio-temporal urban system models might be to focus on its integration with other disciplinary fields, and making groundbreaking findings by introducing dynamic spatial evolutions into models that traditionally do not include such elements.

Second, CUS sciences have not shown adequate practical value yet. Besides its theoretical complexity, I identify two problems with its operationalization: 1) CUS theories mainly describe large scale urban phenomena which do not fit into practical scales; and 2) CUS theories are primarily descriptive and their predictive capability has yet to be proven. In my research, I use bottom-up forecasting PSS models combined with CUS theories to make practical use of CUS sciences in planning practice. Bottom-up PSS models can forecast and fit into practical resolutions (such as 30 x 30 meters), while CUS sciences can be used to calibrate and validate PSS forecasts. As far as I know, this is the only practical use of CUS sciences. Future research should operationalize the findings and methods of CUS sciences.

7.3 MY NEXT CHAPTER

Acknowledging the limitations of PSS, CUS, as well as my own research, I will continue my researches down the following paths:

1. I plan to develop spatio-temporal model methodology to operationalize CUS-based PSS models with fine spatial and temporal resolutions. I'll explore the Shanghai railway and urban night light levels with monthly nightlight data for the Yangtze Delta River area (including Shanghai) from 2012-2014 on 500x500 meter resolution and annual HSR passenger volume data for each station in the area.
    a) I will analyze and compare nightlight levels for counties with and without HSR, and for time periods pre- and post- HSR operation.
    b) I will perform traditional dif-n-dif model analysis on county level nightlight comparisons for counties with and without HSR and for time period pre- and post- HSR operation.
    c) I will use a Hadoop-based non-parametric spatio-temporal modeling approach to examine differences in HSR operation impact on different urban design and planning levels (500m, 1,000m, 5,000m, and county level).
2. I plan to examine CUS human movement assumptions vs. urban landscape factors using Chicago migration data.

    a. I will access Chicago household address data for 5 years for over 3.4 million households.
    b. I will explore unconditional sampled cumulative distribution of migration

radius, which is hypothesized to follow CUS theory of "Levi flight" pattern.

c. I will investigate how physical and social boundaries (highway and main roads, water, and census tract) in Chicago change the unconditional distribution (using Bayesian inference);
d. I will examine how housing affordability (census tract based data) changes the conditional distribution of household migration radius and direction in Chicago.

3. I will examine how commuting time and quality-of-life amenities (such as Yelp review locations) intervene the conditional distribution of household migration radius and direction in Chicago.Some further extensions will also be explored on existing chapters, which include but are not limited to:

1. combine PSS techniques with technological-aided design approach (such as “geodesign”) in future projects, and conduct exploratory research (extension to Chapter Two);
2. develop a calibration and validation technique that uses CUS theories and methods to improve multidirectional scenario planning techniques (extension to Chapter Three);
3. systemically investigate the knowledge flow from PSS technologies to planning users; theorize and abstract the findings from practices into communicative planning theories (extension to Chapter Four);
4. operationalize a paralleled and coupled complex urban system models on HPC platform (at least involving LEAM and regional input-output model) (extension to Chapter Five);
5. construct a spatial and market equilibrium urban structure model based on network city assumptions (extension to Chapter Six).

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