Spring 5-10-2014

Understanding The Influence Of Participants' Preferences On The Affiliation Network Of Churches Using Agent-based Modeling

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UNDERSTANDING THE INFLUENCE OF PARTICIPANTS' PREFERENCES ON THE AFFILIATION NETWORK OF CHURCHES USING AGENT BASED MODELING

by

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Under the Direction of Dajun Dai

ABSTRACT

As the affiliation network of churches may potentially benefit public health, the impact of participants' preferences on the affiliation network bears further study. This paper attempts to use agent-based modeling techniques associated with geographic information to study the affiliation network between churches and participants. Using churches in ZIP Code 30318 in Atlanta in Georgia, this study specifies the preferences of participants as personal radii and choice patterns. Results suggest (1) personal radii of participants are positively related to the size of affiliation network and the centralities of churches; (2) the change of choice pattern of participants can lead to a sharp reduction in size of the affiliation network of churches; (3) The centralities of churches among the affiliation network are corresponding to population density of census tracts. Findings can be used to understand the formulation of affiliation network of churches and their relationship with participants' preferences.

INDEX WORDS: Agent-based model, Affiliation network, GIS

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

Master of Arts

in the College of Arts and Sciences

Georgia State University

2014

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May 2014

DEDICATION

This thesis is dedicated to my family and whoever gave me help. They have been a great support to me.

ACKNOWLEDGEMENTS

I’d like to thank my advisor Dr. Dai who has spent a lot of time on guiding, advising, and supporting me in developing this thesis. I’d also like to thank my committee members Dr. Rothenberg and Dr. Diem for their help and support in developing this thesis.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

1.1 Background

Understanding the influential factors and the formation process of the affiliation network of churches is important, as this type of social network might contribute to public health prevention (Klovdahl, Graviss and Yaganehdoost 2001, Newman 2003, Pan et al. 2006, Crooks, Castle and Batty 2008). Since religious life has been suggested to play a role in preventing the transmission of sexual diseases and controlling drug use (Cook, Goddard and Westall 1997, Shapiro et al. 1999, Corwyn and Benda 2000, Arnold et al. 2002, Elifson, Klein and Sterk 2003, Flynn et al. 2003), the formation of affiliation relationships between churches bears further study. It is known that the formation of social networks is influenced by people's behaviors (Levine 1972, Allen 1982, Schweizer 1991, Schweizer 1996, Klovdahl et al. 2001, Eubank, Guclu and Kumar 2004). In the case of affiliation network of churches, participants' preferences, e.g. range of activities (Burt 1943, Dixon and Chapman 1980, Worton 1987) and choice patterns (Cliff, Martin and Ord 1974, Sprague 2001, Blank et al. 2002), are critical influential factors. Using an agent-based model, this study attempts to study how participants' preferences influence the affiliation network of churches.

Affiliation network as one type of social networks describes the linkages between actors (e.g., individuals or institutions) and events (Breiger 1974, McPherson 1982, Faust 1997, Skvoretz and Faust 1999, Strogatz 2001, Ramasco, Dorogovtsev and Pastor-Satorras 2004, Lattanzi and Sivakumar 2009, Zheleva, Sharara and Getoor 2009). An event refers to any clearly defined collectivity, like membership in a club, guests at a party, or activities provided by a church (Skvoretz and Faust 1999). Distinct from the usual social networks which represent the linkages between actors (individuals or institutions), affiliation networks record the relationships between actors through the ties of actors to events (Breiger 1974, McPherson 1982, Faust 1997). For instance, if both person A and person B are members of a club, they are considered related in an affiliation network. In this case, the relationship between persons A and B is built up through the event “membership in the same club”.

The principle of affiliation networks, recording the relationships from “actor and event” to “actor and actor”, makes it an efficient approach to study the network of relationships between individuals and organizations / locations (Levine 1972, Bernard, Killworth and Lee 1980, Allen 1982, McPherson 1982, Freeman and Romney 1987, Schweizer 1991). Affiliation networks have been widely used in the studies of interlocking boards of directors (Levine 1972, Allen 1982), voluntary organization (Bonacich 1978, McPherson 1982), informal social gatherings (Bernard et al. 1980, Freeman and Romney 1987), common political activities (Schweizer 1991, Schweizer 1996), ceremonial events (Foster and Seidman 1984), and disease outbreak and transmission (Klovdahl et al. 2001, McElroy, Rothenberg and Varghese 2003, Eubank et al. 2004). In recent years, efforts were made to apply affiliation networks to study the effect of churches’ activities on reducing or preventing the transmission of sexual diseases (Rothenberg 2009). In Rothenberg’s study, information about residents’ behaviors and their using of local churches were combined in an affiliation network to investigate the underlying relationships between churches.

Human immunodeficiency virus (HIV) has become one of the top ten fatal causes in US, and the transmissions of HIV, sexually transmitted infections (STIs), and blood-borne infections (BBIs) present a locally clustered pattern (CDC 2007). According to a life lost report from the U.S. Centers for Disease Control and Prevention (2001-2010), HIV has already caused the death of 2,318,456 Americans in ten years. In local areas, given Atlanta, Georgia as an example, the cases of HIV, STIs, and BBIs concentrate upon the communities with relatively low socioeconomic statuses (US Census Bureau 2000). National data of CDC (2007) shows Atlanta was ranked respectively third and fifth among metropolitan areas in cases of Syphilis and Gonorrhea (both STIs) at 2007; in accumulated cases of HIV, it was ranked 17th at the same year. Moreover, geographic clusters indicated that 40% of the reported 2,254 Syphilis cases in Georgia (2007) concentrated on 6 ZIP Codes in the central Atlanta area.

Previous researches (Williams et al. 1991, Cook et al. 1997, Shapiro et al. 1999, Corwyn and Benda 2000, Ellison et al. 2001, Arnold et al. 2002, Elifson et al. 2003, Flynn et al. 2003) suggested that religious life might play a role in benefiting mental health, controlling drug use, and preventing the risk of sexual diseases. Religious affiliation and attendance may have a salutary effect on participants' senses of well-being and alleviate the negative effects of stress on mental health (Williams et al. 1991, Ellison et al. 2001). Additionally, religious life may positively affect individual behaviors. Literature indicated that solid religiosity led to less involvement in high-risk sexual behaviors and less-permissive sexual attitudes (Shapiro et al. 1999). Individuals with deep religious beliefs often have greater senses of self-discipline, leading them to spontaneously use condoms and to refuse unsafe sexes, thus reducing the risk of HIV (Begue 2001, Elifson et al. 2003, McCree et al. 2003). Because of this fact, church activities might have a direct effect on preventing the transmission of HIV by reducing drug use, as literature also indicated, a possibly positive association between church attendance, religiosity, and drug avoidance (Rothenberg 1993, Cook et al. 1997, Arnold et al. 2002, Flynn et al. 2003, Corwyn and Benda 2000). Although the direct correlation between church activities and preventing the transmission of HIV has not been identified fully, faith-based HIV programs have functioned to educate and provide mental support to communities' participants (Begue 2001, McCree et al. 2003).

Affiliation networks provide a way to map the connections between the churches that have the same character, serving the same group of participants, which indicates their potential values in studying the effectiveness of churches' activities on the prevention of transmission of sexual diseases. In Rothenberg's study (2009), an affiliation network of churches was derived to detail the connections between multiple churches based on empirical data. These connections between churches were built up via the attendances of participants. Thus, if two churches were visited by the same group of participants, these two churches were considered connected. However, the empirical affiliation network of churches highly depends on the available empirical data of churches and participants, which takes time and is expensive to collect. As this study focuses on the impact of influential factors on the affiliation network of churches, it developed a series of experimental affiliation networks to examine the sensitivity of affiliation network of churches to these factors (participants' preferences). The experimental affiliation networks of churches studied in this research is constructed in a virtual environment using agent-based modeling techniques based on the principles of affiliation network.

Agent-based modeling is an efficient approach to combine geographic information and computational modeling to tackle the dynamics of a system (Bonabeau 2002, Tang and Ren 2008, Augustijn-Beckers, Johannes and Bas 2010, Gao et al. 2012, Manley and Kim 2012). Computational modeling is one of the most commonly used approaches in reproduction of systems and prediction of their development (Klovdahl 1985, French, Anderson and Catchpole 1990, Clarke, Brass and Riggan 1994, Helbing, Farkas and Vicsek 2000, Encinas et al. 2007). Traditional computational models are mathematical models, which compute the process and predict the outcome of or a system via a variety of mathematical equations (Albini, FA and Chase 1980, Burgan and Rothermel 1984, Helbing and Molnar 1995, Himoto and Tanaka 2008). For those systems with clear relationships between involved factors, mathematical models could give an accurate reproduction and prediction of the system behaviors (Albini 1985, Pan et al. 2006). However, for some systems which are subject to non-linear relationships, such as fire spread (Trunfio 2004, Encinas et al. 2007, Zhao 2010), emergent evacuation (Lo et al. 2006, Augustijn-Beckers et al. 2010, Zheng and Cheng 2011), or a self-organizing affiliation network (Eubank et al. 2004, Ramasco et al. 2004), their development is highly uncertain. Intelligent models provide a solution for simulating the development of such uncertain processes (Macy and Willer 2002, Zhang, Zhao and Liu 2009, Auchincloss et al. 2011, Ha and Lykotrafitis 2012). An intelligent model usually consists of a collection of intelligent particles, which could represent individual behaviors and perform movement independently. A featured example of intelligent model is agent-based model.

Agent-based modeling is a modeling method that uses intelligent entities and virtual environment to reproduce phenomena (Bonabeau 2002, Crooks et al. 2008, Shi, Ren and Chen 2009). A remarkable distinct of agent-based simulations from other simulation models is that it explores the behaviors and mechanisms behind phenomena, and then reconstructs them by defining various types of agents (Shi et al. 2009, Augustijn-Beckers et al. 2010, Auchincloss et al. 2011). Agent-based models are widely used in studying various problems: urban management (Semboloni et al. 2004, Hanley and Hopkins 2007, Gao et al. 2012), crime reduction (Malleson, Heppenstall and See 2010), land use dynamics (Matthews et al. 2007, Mialhea, Becuc and Gunnelld 2012), building evacuation (Tang and Ren 2008, Zhang et al. 2009, Augustijn-Beckers et al. 2010, Ha and Lykotrafitis 2012), social network (Macy and Willer 2002), and inequalities of diet (Auchincloss et al. 2011).

1.2 Problem statement

The goal of this study was to investigate the impact of participants' preference on the affiliation relationship between churches. To achieve this goal, the objectives of this study were threefold. First, it attempted to simulate the formation process of the affiliation network of churches coupled with the influences of participants' activity ranges using an agent-based model. This study derived a variable called personal radius to explore how participants' activity ranges could affect the formation of the affiliation network of churches. Second, this study aimed to quantify the weight of each church in the affiliation network. Based on the concepts of centralities in social networks, this study derived a variable called importance index, to measure the weight of churches. By comparing the importance indices of churches, this study could evaluate the relative importance of churches among the affiliation network. Third, this study attempted to examine and compare the influences of participants' activity ranges (personal radii), choice patterns, and population on the size of affiliation networks of churches and churches' centralities. This study selected three potential choice patterns to represent the preferences of participants, including randomly choosing, choosing the nearest, and choosing the favorite. The impacts of personal radii, choice patterns, and population of participants on the affiliation network of churches would be examined through a series of scenarios.

1.3 Significances of this study

This study increases the understanding of the relations between behavioral preferences of individuals and the formation of the affiliation network of churches. Considering the locations of actors or the distances between actors in the social networks as measurements provides insights into the impact of these geographic factors on the formation of affiliation networks. Besides, this study reveals the variation in centralities of the affiliation network of churches under the influences of participants' activity ranges, choice patterns, and population. In addition, the increased understanding on the formation process of the affiliation network of churches and the variation in centralities of churches may generate valuable information to improve the local affiliation networks of churches and enhance their role in public health advancement.

2 LITERATURE REVIEW

2.1 The potential factors to affiliation network

One unique feature of affiliation networks compared to other social networks is incorporating geographic locations. Locations' influence usually is not taken into account to the social network studies, because the usual social networks are constructed by the direct relationships (e.g. kinship, friendship) between actors (Wasserman and Faust 1994, Skvoretz and Faust 1999, Strogatz 2001, Newman 2003). However, in constructing the affiliation networks, previous studies (Freeman 1979, Klovdahl 1985, Rothenberg et al. 1998, Klovdahl et al. 2001, Blank et al. 2002) suggested that the consideration of locations was very important. For instance, in communication networks, identifying the locations of actors allows to investigate their influence on information flows (Freeman 1979); embedding the consideration of locations (places) is useful to analyze the outbreak network of infectious diseases (Klovdahl 1985, Rothenberg et al. 1998).

In the affiliation network of churches, it is important to consider the distance between a church and a participant. A previous study (Hampton and Wellman 2001) suggested that the increase in distance may lead to a decrease in number of contacts (connections). To the contrary, the proximity in distance might promote the collaboration between actors (Letaifa and Rabeau 2013). In addition, the distance allows the measurement of the linkages in the affiliation network in a spatial setting. Distance can be used to quantify the linkages of social networks (Dekker 2005) or used to derive a spatial weight on the linkages (Scellato et al. 2010).

Besides locations and distances, the range of personal activity (also called home range) might play an important role in the formation of affiliation network of churches. The home range of an individual refers to a geographic area that an individual might reach in his/her routine activities (Burt 1943, Dixon and Chapman 1980, Worton 1987). It usually uses the location of home as the center (Burt 1943). Therefore, the locations within the home ranges of individuals will have higher frequency to be visited (Dixon and Chapman 1980). In the case of attending a church, participants rather choose a church within their home ranges than those out of it. This study derived a variable, the radius of personal activities (personal radius), to simulate the home ranges of participants.

In addition to the spatial factors mentioned above, the choice preferences of individuals on churches might also affect the formation of the affiliation network of churches. Individuals have different preferences in choosing services (Hu et al. 1991), although choosing the nearest one might be one of the most convincing patterns (Zipf 1950, Cliff et al. 1974, Sprague 2001, Blank et al. 2002). The preference of choosing the nearest location can be supported by the principle of least effort. The core of the principle of least effort is efficiency: it states that human naturally attempt to spend the least effort to gain the most achievement (Zipf 1950). Later, the principle of least effort was extended to spatial level:

individuals tend to perform activities at the nearby locations (Sprague 2001), or with the shortest movement (Cliff et al. 1974). However, the choice preferences of people are various (Pescosolido 1992). Individuals might make choices based on their experience or what they are familiar with (Blank et al. 2002). This study derived three possible choice patterns: randomly choosing, choosing the nearest and choosing the favorite.

2.2 The modeling of affiliation networks

Affiliation networks share the same principles and methods of modeling with other social networks, so they have the same fundamental principle: graph theory. Graph theory is the mathematical and computational scientific studies of graphs. A graph is an organization of vertices and edges, which could be used to describe the relationships among a series of actors. In the case of social science, a graph, also called a network, could be derived to describe a social event (McElroy et al. 2003, Ramasco et al. 2004, Zheleva et al. 2009). A graph has several basic variables: order, degree, size, component, and giant component (Chartrand, Lesniak and Zhang 2010). Order refers to the number of vertices in a graph, while degree refers to the total number of edges connected to a vertex. In addition, size refers to the number of edges in a graph. A component of graph refers to a sub-set of vertices which are connected through edges. A giant component is the component with the largest order (number of vertices) in a graph. A few variables of graphs, degree, order, size, and the size of giant component, are frequently used to quantify the characters of networks (Wasserman and Faust 1994, Newman 2003, Lattanzi and Sivakumar 2009). A bipartite graph refers to the graph with such characters: the vertices in a graph could be divided into two categories and each vertex only connects to the vertices in the other category (Faust 1997, Lattanzi and Sivakumar 2009). The structure of an affiliation network could be presented as a bipartite graph (Wilson 1982, Faust 1997).

Another fundamental principle of affiliation networks is topology. Topology describes the relationships between vertices and edges, which is similar to graph theory, but topology includes the geometric and spatial information (Bilke and Peterson 2001, Guelzim et al. 2002, Ramasco et al. 2004). As a result, topology is applied to describe the structure of the complex systems, where vertices represent the elements of systems and edges represent the interactions between elements (Barabási and Albert 1999, Vázquez, Pastor-Satorras and Vespignani 2002). For instance, with topology, internet could be described as an organization of huge amount of HTML pages, where the HTML pages were represented as vertices, and the links between them were represented as edges (Faloutsos, Faloutsos and Faloutsos 1999).

As graph theory and topology provide the fundamental concepts to affiliation networks, two approaches, random graph and small-world network, provide the basic principles to construct an experimental affiliation network. Random graph is a method to generate networks via random processes (Bollobás et al. 2001, Bollobás and Riordan 2004). The construction of a random graph usually starts with a graph with no edge but only vertices. In this graph, several pairs of vertices will be chosen randomly and then their relationships (connected or not) will be determined by probability (Solomonoff and Rapoport 1951, Erdős and Rényi 1959). The purpose of constructing a random graph is to capture a particular property of a graph and so as to determine at what stage this property arises (Bollobás 1985, Lattanzi and Sivakumar 2009). It may take a lot of times for random graph to reproduce the desired property as the reproduction depends on probability (Skvoretz and Faust 1999). Another approach, small-world network, provides a more efficient way to reproduce the social structure (Milgram 1967, Watts and Strogatz 1998, Abramson and Kuperman 2001). The small-world network was derived from an experiment dated back to 1960s which found the average distance between two randomly chosen people in the social network of US was only six steps (Milgram 1967, Dodds and Watts 2003). Later, the small-world network was applied to study the relationship network, and results found that friendship was the most transitive way to connect people (Kleinberg 2000). The basic principle of small-world network is: if *a* is connected with *b* and *b* is connected with *c*, it will have a high chance that *a* and *c* is connected (Watts and Strogatz 1998, Robins, Pattison and Woolcock 2005). In this study, the methods used to construct the experimental affiliation network were based on random graph and small-world network.

An important property of affiliation networks is the centrality of actors (Freeman 1979, Knoke and Burt 1983, Friedkin 1991, Faust and Wasserman 1992, Wasserman and Faust 1994). The centrality of an actor indicates its relative importance in the affiliation network (Wasserman and Faust 1994, Newman 2003). Literature summarized four major types of centralities: degree, betweenness, closeness, and eigenvector (Freeman 1979, Knoke and Burt 1983, Faust 1997). The degree centrality of an actor measures the number of linkages incident on this actor. Thus, degree centrality evaluates actors by their degree. The closeness centrality of an actor is derived by the sum of length of the shortest paths to all other actors. The greater the total distance of an actor to other actors, the smaller the centrality would be. The betweenness centrality of an actor means the times of this actor as one of the vertices along the shortest path of two other actors. Therefore, betweenness centrality concerns the shortest path between actors (Freeman 1977). The eigenvector centrality assigns proportional score to each actor based on their ties to other actors in the network. The principle of eigenvector centrality is, an actor will have a relatively high score if it connects to other high-score actors (Faust 1997).

These four types of centralities of actors have been widely used in studying social networks. First, degree centrality was used in studying people's observed behavioral interactions (Bernard et al. 1980) and corporate interlock networks (Mariolis and Jones 1982). However, some critiques rested on that degree centrality of an actor did not consider the centrality of its adjacent actors (Faust 1997). Second, with consideration of distance, closeness centrality was employed in the studies of harmonic mean length of paths (Stephenson and Zelen 1989) and network vulnerability (Dangalchev 2006), but its applications in affiliation networks was few. Third, betweenness centrality was used to study the control of a human in the communication network (Freeman 1977), yet its application in affiliation networks was as few as closeness centrality. Eigenvector centrality was commonly applied to study the interlocking corporate boards of directors, due to its advantages in providing proportional importance for actors in the affiliation networks (Mariolis 1975, Mintz and Schwartz 1981, Mizruchi and Bunting 1981, Roy 1983). This study combined the concepts of degree centrality and closeness centrality to derive a variable "importance index" to measure the relative importance of churches in the affiliation network of churches.

2.3 Agent-based modeling

Previous studies suggested that agent-based modeling techniques were very useful in studying social networks and reproducing sociological phenomena (Schelling 1971, Epstein and Axtell 1996, Axelrod 1997, Resnick 1994, Lomi and Larsen 1998). It is noticed that agent-based modeling is not trying to model every entity of the social network but to model the interactions among these entities (Macy and Willer 2002). Besides, agent-based modeling provide a better understanding of the fundamental processes of a phenomenon rather than an empirical prediction to it (Axelrod 1997). Agent-based modeling reproduces the sociological phenomena from the bottom up, especially for those processes that lack in the central coordination (Macy and Willer 2002). The major applications of agent-based models in studying social networks consist in the self-organization of social structures (Reynolds 1987, Resnick 1994) and the emergence of social orders (Schelling 1971, Epstein and Axtell 1996, Lomi and Larsen 1998).

An agent-based model consists of two parts: agents and cells (Bonabeau 2002, Augustijn-Beckers et al. 2010). Agents refer to a collection of intelligent entities, which could perform movement independently based on a series of defined rules. Cells refer to the grid space that simulation model builds on. The scale of model could be determined by the size of cells (Axelrod 1997, Macy and Willer 2002, Ha and Lykotrafitis 2012).

The virtual environment is one of the vital parts of agent-based modeling, because it defines the prescribed circumstances for simulation models which should correspond to researched problem (Pan et al. 2006, Sargent 2010). A virtual environment is usually represented in cells space and each cell has a fixed location. The roles of cells vary based on the research objectives. For instance, in a study (Ha and Lykotrafitis 2012) which simulated emergent evacuation in a study area of multiple rooms and multiple floors, cells were divided into two categories: representing available spaces and representing obstacles. In another study of investigating inequalities of diet (Auchincloss et al. 2011), some cells were assigned for the locations of grocery stores, while some others were assigned for the locations of households.

Agents are the major roles of an agent-based model. They represent the particles of a system. There may be multiple types of agents in a model. Each type of agents would make their movement based on a series of defined rules. In other words, heterogeneous rules could be performed by different types of agents. For instance, Augustijn-Beckers used three types of agents to simulate the behaviors of independent evacuees, non-independent evacuees, and stuffs respectively in studying emergent evacuation in a school building (Augustijn-Beckers et al. 2010). The rules for agent are derived from quantification of behavior and mechanisms as well as empirical studies (Helbing et al. 2000, Berjak and Hearne 2002, Macy and Willer 2002, Pan et al. 2006). Taking Helbing et al.'s study as an example, Helbing et al. used a serious of force-driven equations to quantify evacuees' behaviors and integrated into a cellular automata (2000). Based on the defined rules, each agent individually assesses the environment and performs movement. The simulation of agent-based models is conducted through the interaction between various types of agents as well as the virtual environment (Bonabeau 2002, Zhang et al. 2009, Auchincloss et al. 2011).

Besides agent-based models, another commonly used intelligent model is cellular automata. The concepts of both agent-based models and cellular automata were developed from the Von Neumann machine (Von Neumann 1966), which is a theoretical machine studying reproduction. A cellular automata model consists of an array of cells (Clarke et al. 1994, Encinas et al. 2007). These cells could individually make decisions about their states based on some defined rules, except that their locations are fixed (Batty 1998, Helbing et al. 2000, Yang et al. 2002, Varas et al. 2007).

Agent-based models and cellular automata have several aspects in common, but there are differences between them in the type of agents. The similarities between agent-based models and cellular automata are threefold. First, simulations of both agent-based models and cellular automata are built on grid space (Karafyllidis and Thanailakis 1997, Trunfio 2004, Varas et al. 2007, Zhang et al. 2009). Second, both of these two models consist of discrete intelligent entities, which make decisions independently (Berjak and Hearne 2002, Kirchner and Schadschneider 2002, Ha and Lykotrafitis 2012). Third, behaviors or mechanisms could be quantified or described as rules for the intelligent entities in both of two models (Yang et al. 2002, Encinas et al. 2007, Augustijn-Beckers et al. 2010). However, agent-based models are different from cellular automata. Cellular automata could be seen as a single agent model, in which agents are the cells only (Sudhira 2004). Agent-based models are also called multiple-agents model (Zhang et al. 2009, Ha and Lykotrafitis 2012). It allows multiple agents to be defined and move over the cells. The advantage of defining multiple agents is that various behaviors or mechanisms could be represented by different types of agents, so it allows to investigate the interaction between these behaviors or mechanisms (Augustijn-Beckers et al. 2010). In a cellular automata model, the locations of cells (agents) are fixed, so the development of a phenomenon is simulated by the changes of cells' statuses (Batty 1998, Li and Yeh 2000, Berjak and Hearne 2002). While in an agent-based model, besides using cells' statuses, various types of agents could be used to simulate the movement of individuals. Therefore, an agent-based model provides a more effective and efficient way to simulate a complex system.

The advantages of agent-based models are threefold. First, an agent-based model could capture emergent phenomena. The interaction between individuals or between individuals and environment might cause unexpected emergent phenomena. Since agent-based models allow agents to simulate individual behaviors and make movements independently, these interactions are able to be reproduced, which allow the emergent phenomena to occur (Bonabeau 2002). This advantage encourages the applications of agent-based models in studying human's collective behaviors (Axelrod 1997, Macy and Willer 2002, Zhang et al. 2009, Ha and Lykotrafitis 2012) and complex systems with non-linear factors (Prietula, Gasser and Carley 1998, Sterman 2000). Second, an agent-based model could give a natural description of a system. It means agent-based modeling let the simulation of a system seem close to reality by describing the internal behaviors or mechanisms of the system (Bonabeau 2002). This advantage let agent-based models become an efficient approach to explore the formation process of a system or a phenomenon (Macy and Willer 2002, Augustijn-Beckers et al. 2010). Third, an agent-based model is flexible (Railsback, Lytinen and Jackson 2006). In agent-based models, variables could be easily adjusted to meet the requirement of experiments.

Validation is one of the most challenging and uncertain parts of agent-based modeling. The definitions of validation of simulation models were given from different aspects: (a) a process determining if the model possesses a satisfactory range of accuracy consistent with modeling purpose (Sargent 2003); (b) a process determining if the model represents reality at an acceptable level (Giannanasi, Lovett and Godwin 2001); (c) a process determining the usefulness of a model. Two arguments have been put forwarded to discuss the feasibility of model validation (Coyle 1977). On the one hand, scholars argued the credibility of simulation models can only be demonstrated via tests of validation (Sterman 1984, Kleijnen 1999, Ijeoma, Andersson and Wall 2001, Law and McComas 2001). Simulation models should be proved to be approximate to the actual systems, otherwise, the results or conclusions derived from this simulation are not reliable (Ijeoma et al. 2001). Some studies (Sterman 1984, Kleijnen 1999) suggested statistical techniques might be good to validate simulation models, except that the problem of data availability (e.g. sparse data) in the real systems could become a bottleneck to applying these techniques. One the other hand, scholars pointed out that there is no absolutely valid simulation model, and validation as well as verification are not possible (DMSO 1996, Sterman 2000). The confidence of a simulation model should be built up by evaluating if this model is appropriate for its purpose (Sterman 2000). Likewise, the intended use and prescribed conditions of a simulation model should be stated clearly to let users know where the credibility is (DMSO 1996).

Techniques which could be used to validate simulation models were introduced in previous studies (Martis 2006, Sargent 2010). Three of them are animation, model comparison, and event validity. Animation allows the simulated behaviors of a model exhibits graphically and it directly demonstrates the movement of agents (Balci and Sargent 1984). In some cases, if the simulated system or phenomenon was once studied by other models, model comparison would be an ideal technique for validation (Martis 2006). Results of the testing simulation models could be used to compare with the results of other models to see if they are consistent to each other. Besides, for some systems expecting the occurrence of some specific "event" during its process, event validity could be employed for model validation (Sargent 2010). Event validity means comparing the process of simulation with reality to examine if the expected event occurs.

Other validation techniques include degenerate test, extreme condition test, face validity, historical data validation, predictive validation, Schellenberger's Criteria, and Black-box validation.

- Degenerate test: using appropriately selecting values of parameters to test the degeneracy of model's behaviors (Ijeoma et al. 2001);
- Extreme condition test: testing model with combination of unlikely values of inputs (Sargent 2003);
- Face validity: validating models by consulting knowledgeable people (Forrester 1961);
- Historical data validation: comparing experimental data with historical data (Balci and Sargent 1982);

- Predictive validation: using the testing model to predict the development of a system and then comparing the result with the development of this system in reality (Sargent 2003);
- Schellenberger's Criteria: examining the differences between the assumption of model and perceived reality as well as the validity of data used (Ijeoma et al. 2001);
- Black-box validation: evaluating the accuracy of model representing the real world (Ijeoma et al. 2001).

Among the major software platforms for agent-based model, Netlogo is considered the highest-level (Railsback et al. 2006). Steven Railsback compared and reviewed five major agent-based modeling platforms, including Netlogo, MASON, Swan, Java Swan, and Repast, in his study. The reviewed platforms were compared from various aspects: modeling framework, programming experience, and execution speed. The benefits of using Netlogo could be summarized in three aspects. First, Netlogo provides the most integrated modeling framework for agent-based models. Comprehensive documentation and the programming-friendly language of Netlogo make design of agent easy. Second, Netlogo is compatible with the geographic data provided by ArcGIS, which makes it possible for simulation model to work with real locations. Third, Netlogo has a built-in graphical interface. The process of simulation is able to be reviewed instantly as the model runs.

3 THE STUDY AREA

The study area for this project was ZIP Code 30318 in metropolitan Atlanta, an area in Fulton County, Georgia (Figure 3.1). This particular ZIP Code was chosen for several reasons. First, national data (CDC 2007) showed ZIP Code 30318 as one of the areas in central Atlanta with a high risk for HIV, STIs, and BBIs. Second, the ZIP Code was suitable to investigate the relationship between population density and the formation of an affiliation network of churches, as its population density was as much as thirty-two times higher than the national average. Additionally, the population density in the southern portion of the sample area was much higher than that of the northern portion (Figure 3.1a), indicating an imbalance in population distribution. Lastly, within ZIP Code 30318, the impact of various personal radii could be examined. For instance, the median household income in this area ($29,083) was much lower than the national average ($41,994), providing an environment in which participants' behaviors might be affected by the socioeconomic status. Because a portion of households in this area might not be able to afford a vehicle, the transportation method might make participants' personal radii and church visitation heavily varied.

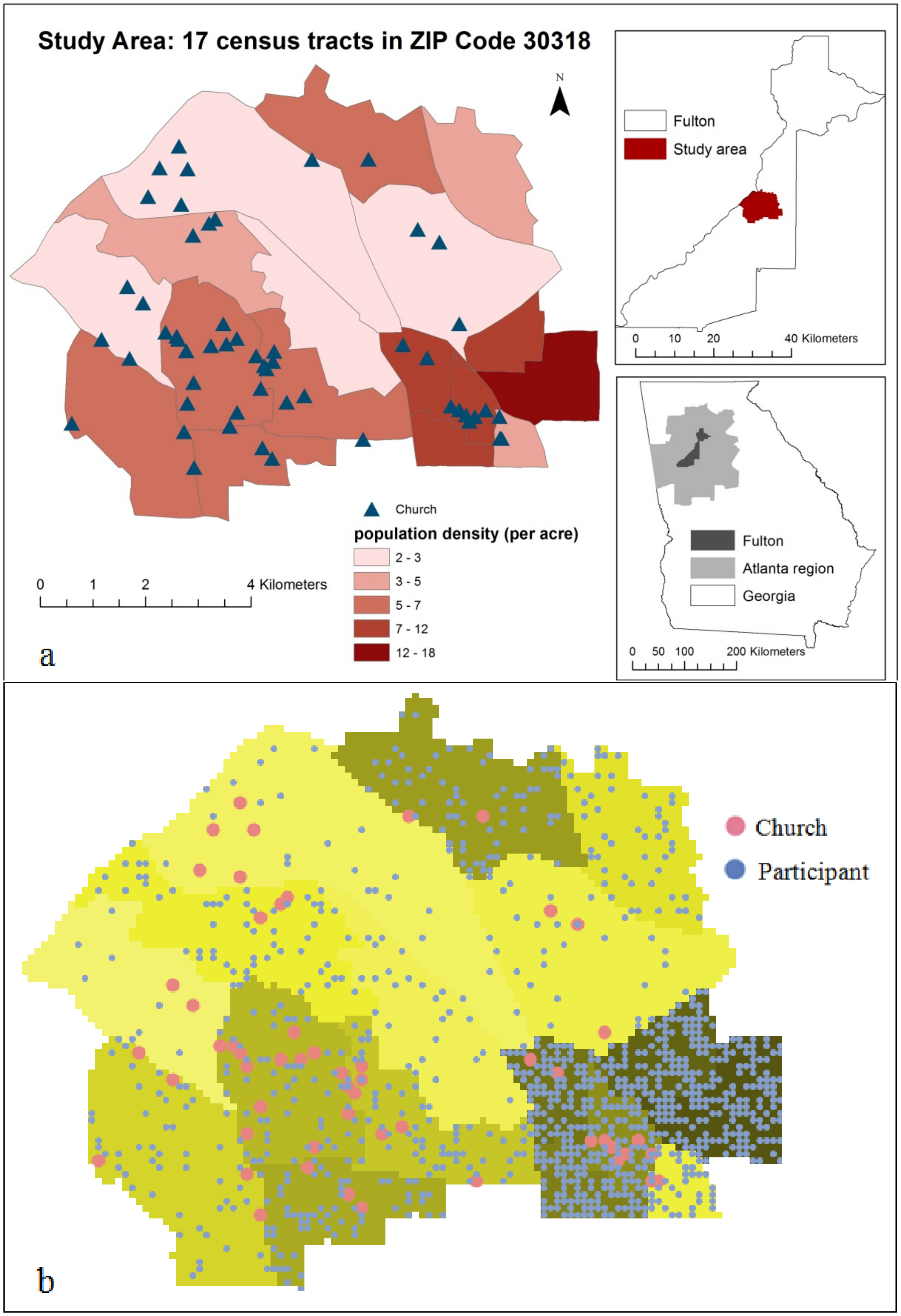


Figure 3.1 Study Area: ZIP Code 30318

Note: (a) location of the study area in Georgia; (b) the digitized study area in Netlogo with randomly allocated participants

In this simulation model, ZIP Code 30318 was represented by 17 census tracts, where the data was obtained from the Atlanta Regional Committee (ARC; www.atlantaregional.org). Census data (2009) of this ZIP Code was employed to describe the distribution of population and to derive the locations of agents in agent-based modeling. There were in total 54 churches identified in the study area. The locations of these 54 churches were obtained from Google Maps. Notably, most of the churches in the ZIP Code were Baptist. This similarity of religious doctrines made it reasonable to assume that churches in the study area were willing to collaborate with one another for the communities they served.

The ARC provided specific data on population and density of population. In the study area, the distribution of churches was consistent with the census tracts' population density (Figure 3.1a). The southern census tracts have higher population density than the northern census tracts, and the greatest number of churches is concentrated on the south side of the study area. The study area was converted into Netlogo (Figure 3.1b). In Netlogo, cells denoted the study area (11.2km× 8.7km, 97.44km^2), with each representing an area of 100 meters ×100 meters (0.01km^2). The shading of the study area in Netlogo was based on the population density provided by the ARC. Pink spots stand for churches, and blue spots stand for participants in communities.

4 AGENT-BASED MODELING

4.1 Agent design

This model designed two types of agents: churches and participants. Each church agent represented one church, while each participant agent represented one participant in religious activities in ZIP Code 30318. The time step in the model was one week, which meant that interaction between church agents and participant agents was recorded weekly. The church agents' attribute was "activity". If a church had no activity, the value equaled 0; if it had an activity, the value equaled 1. The church agents, themselves, determined whether or not to host an activity every week. Therefore, the probability of having an activity and not having an activity were both 0.5 for each church agent. One assumption of this study is that each church welcomes every participant in ZIP Code 30318.

This model used different methods to initialize the locations for church agents and participant agents. Church agents were assigned to actual locations of churches in ZIP Code 30318, while participant agents were allocated according to the population proportions within census tracts. The population proportion was calculated by dividing the population of each census tract by the total population in ZIP Code 30318. For instance, if the population proportion is 0.3, and the total number of participant agents is 100, then this census tract will have 30 participant agents. The participant agents were randomly distributed in each census tract.

4.2 Personal radius

The participant agents' attribute was "personal radius", thus the radius of personal activity range, describing the longest distance that a participant agent was willing to travel for attending a church activity. The personal radii of participants were influenced by both participants' preferences and socioeconomic statuses. The preference refers to an individual's subjective tendency toward long travel or short. Because the socioeconomic status could determine whether a household was able to afford a vehicle, this factor, in turn, could influence the travel to church activities. When a vehicle was present, participants might be willing to travel to distant churches, thus reflecting a large value of personal radius. Alternately, personal radii might be small if walking or public transport was the option. In this study, a normal distribution, an exponential distribution, and a log-normal distribution were used to simulate the diversity of participants' personal radii. The values of personal radii were derived from probability distributions via randomly generated probabilities (Park and Bera 2009). Successful methods of deriving values from probability distributions had been demonstrated by previous studies (Viskov 1986, Wichura 1988, Peterson 1998). One of the most using methods was the transformation of the equation of probability distribution, which was conducted by using *f(x)* to derive the solution of *x*.

Normal distribution was defined by equation (1) (Viskov 1986),

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}}\ e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

where *x* is the variable, *f(x)* is the corresponding probability, *e* is the natural logarithm, *μ* is the mean value of the variable, and *σ* is the standard deviation. Equation (1) could be transformed to equation (2) by using *f(x)* to derive the solution of *x*,

$$f(x) = (-1)^i\sqrt{2\sigma^2 \cdot |\ln\ x \cdot \sigma\sqrt{2\pi})|} + \mu,\ \ \left(0 < x \le \frac{1}{\sigma\sqrt{2\pi}},\ i = 0\ or\ 1\right) \tag{2}$$

where *x* is the probability of the distribution of personal radii, *f(x)* is the corresponding personal radius, and $(-1)^i$ is used to defined whether the personal radius is greater or smaller than the mean. The value of *i* is randomly either 0 or 1. Via equation (2), the values of personal radii could be derived from a normal distribution by substituting a randomly generated *x* (probabilities). In equation (2), *x* was randomly generated from a uniform distribution (Park and Bera 2009). The range of this uniform distribution is [0, $\frac{1}{\sigma\sqrt{2\pi}}$], which is derived from equation (1). In equation (1), the range of *f(x)* is [0, $\frac{1}{\sigma\sqrt{2\pi}}$] (*f(x)* becomes maximum when *x* = *μ*). Since the *x* of equation (2) is the same variable to the *f(x)* of equation (1), they share the same range.

Exponential distribution was defined by equation (3) (Reynolds 1988),

$$f(x) = \lambda e^{-\lambda x},\ \ (x \ge 0) \tag{3}$$

where *x* is the variable, *f(x)* is the corresponding probability, *e* is the natural logarithm, and *λ* is the reciprocal of the mean (*λ* = 1 / *μ*). Equation (3) can be transformed to equation (4) by using *f(x)* to derive the solution of *x*,

$$f(x) = \frac{|\ln\frac{x}{\lambda}|}{\lambda},\ \ (0 < x \le \lambda) \tag{4}$$

where *x* is the probability and *f(x)* is the corresponding value of the variable. Since *λ* = 1 / *μ*, equation (4) can be transformed to equation (5).

$$f(x) = \mu \cdot |\ln \mu x|, \quad \left(0 < x \leq \frac{1}{\mu}\right) \tag{5}$$

The values of personal radii could be derived from exponential distribution by substituting randomly generated probability (variable *x*) in equation (5). The value of *x* was randomly generated from a uniform distribution and the range of this uniform distribution is [0, $\frac{1}{\mu}$]. This range was derived from equation (3). In equation (3), the range of *f(x)* is [0, $\frac{1}{\mu}$] (*f(x)* is maximized when *x* = 0). As the *x* of equation (5) and the *f(x)* of equation (3) are the same variable, they share the same range.

Log-normal distribution was defined by equation (6),

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}}\, e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}, \quad (x > 0) \tag{6}$$

where *x* is the variable, *f(x)* is the corresponding probability, *e* is the natural logarithm, μ and σ are, respectively, the mean and the standard deviation of variables' nature logarithms. In this paper, the mean and standard deviation of variables of equation (6) were denoted as *m* and *s*. The values of μ and σ can be derived by equation (7) and (8).

$$\mu = \ln\left(\frac{m^2}{\sqrt{s^2 + m^2}}\right) \tag{7}$$

$$\sigma = \sqrt{\ln(1 + \frac{s^2}{m^2})} \tag{8}$$

Equation (6) could be transformed to equation (9) by using *f(x)* to derive the solution of *x*,

$$f(x) = e^{(-1)^i\sqrt{\sigma^4 - 2\sigma^2 \cdot (\ln x \cdot \sigma\sqrt{2\pi} + \mu)} + \mu - \sigma^2}, \quad \left(0 < x \leq \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{\sigma^2}{2} - \mu},\ i = 0\ or\ 1\right) \tag{9}$$

The values of personal radii could be derived from log-normal distribution by substituting randomly generated probability (variable *x*) in equation (9). The value of *x* was randomly generated from a uniform distribution and the range of this uniform distribution is [0, $\frac{1}{\sigma\sqrt{2\pi}} e^{\frac{\sigma^2}{2} - \mu}$].

In normal distribution, μ (mean value) reflects the centralization of the data, while standard deviation reflects the variation of data. In equation (2), the mean value (μ) was used to control the centralization of the derived personal radii. When μ was a small value, the derived personal radii were centralized to small values, which meant that the distance that participants were willing to travel to attend church activities was small. On the contrary, when μ was a large value, the derived personal radii were centralized to large values, meaning that participants were willing to travel to distant churches. The standard deviation (σ) of equation (2) was used to adjust the diversity of personal radii among participants. When σ was small, the derived personal radii would be more centralized to the mean and less varied. When σ was large, the derived personal radii would be less centralized to the mean but more dispersed.

In contrast to normal distribution, the mean and standard deviation in log-normal distribution also reflect the concentration or variation of data despite of the distribution of data is different in log-normal. In log-normal distribution, the mean is larger than the mode (the value that appears most often in a set of data), which means the majority of data is smaller than the mean. In equation (9), as the mean increases, the derived personal radii would relatively increase with the majority of derived values concentrated on smaller values than the mean. Besides, in log-normal distribution, the variation of standard deviation would reflect on both of the concentration and diversity of data. In equation (9), as the standard deviation decreases, the diversity of derived personal radii reduces while the probability curve of log-normal becomes more and more proximate to which of normal distribution (the mode tend to equal to the mean). Alternatively, as the standard deviation increases, the derived personal radii become more and more dispersed and the mode becomes smaller and smaller than the mean.

In exponential distribution, λ (reciprocal of μ) was used to adjust both the centralization and variation of the derived personal radii. The probability curve of exponential distribution is descending (Reynolds 1988). When μ was small (λ was thus large), the slope of probability curve would be relatively steep, and most data would be smaller than the mean. However, when μ was large (λ was thus small), the slope of probability curve would be relatively gentle, and the distribution of data would be relatively balanced at both sides of the mean value. In equation (5), as μ decreased, the derived personal radii would be increasingly concentrated on small values, and their variation would tend to be small. As μ increased, though, the derived personal radii would be more dispersed, and their centralization would tend to disappear. Both large value of μ in exponential distribution and large value of σ in normal distribution as well as log-normal distribution could result in diversified personal radii, but the difference between these three is that the former one is one tail while the latter two are two tails. This study derived personal radii using different probability distributions to investigate the influence of participants' activity ranges on the affiliation network of churches.

4.3 Participants' choice patterns

This model selected and developed three choice patterns for participants: randomly choosing, choosing the nearest, and choosing the favorite. An assumption in this study was that participants can obtain all of the churches' information about scheduled activities. At each time step, each participant agent searched for the churches that had activities within the personal radius. If participant agents could not find any church with an activity within their personal radii, they would do nothing. In another case, if more than one church with an activity were found within their personal radii, the assumption was that the participants would select only one church to attend at each time step based on the choice pattern set by the model. When the choice pattern was choosing randomly, the participants would randomly select one church among the churches with activities within their personal radii. When the choice pattern is choosing the nearest, participants would select the church within the shortest Euclidian distance. When the choice pattern is choosing the favorite, the model would predefine a church as the favorite church for each participant agent before the start of simulations, and this predefined church would be selected randomly from the churches within participant agents' personal radii. As the simulation started, the participant agents would definitely choose their favorite church to attend once these churches had activities. Otherwise, if the favorite church did not have an activity, the participant agents would randomly choose a church with an activity within their personal radii to attend.

4.4 The affiliation network of churches

In this model, the construction of the affiliation network of churches would be accomplished in three steps. First, the model would establish a set of linkages, called choice linkages, between participant agents and the churches they chose. This step might be iterated multiples times until the end of simulations. In this step, the model would calculate a weight, called choice weight, denoted as CW_{ij}, for each choice linkage. Second, the model would then establish another set of linkages, called affiliation linkages, between the churches which were attended by the same participant. In step two, the model would compute another type of weight, called affiliation weight, denoted as AW_{ij}, for each affiliation linkage. Third, the model would calculate the centrality of churches, called importance indices, denoted as I_i in this study.

This model used choice weights to quantify the relationships between participants and the churches they chose. The choice weight combined the distance of a church from a participant and the frequency of attendances of a participant. The model computed choice weights (*CW*) by equation (10):

$$CW_{ij} = \frac{D_{max} - D_{ij}}{D_{max}} \times n \tag{10}$$

where n is the number of times a participant agent selects the same church to attend, *i* stands for a participant, and *j* stands for a church. *Dij* is the distance between the participant agent and the selected church. *Dmax* is defined as the length of the diagonal of the study area, which is the longest distance in the study area. On the one hand, the longer the distance between a participant agent and a church agent, the smaller the choice weight would be. On the other hand, the higher the frequency of attendances, the larger the choice weight would be.

To test the sensitivity of the choice weight (combined distance and frequency), this study used two other methods to derive the value of choice weight. These methods were, using the distance between participants and churches as well as the frequency of attendance to separately calculate the choice weight. Thus, the equation to calculate the choice weight would be $\mathrm{CW_{ij}} = \frac{\mathrm{D_{max}} - \mathrm{D_{ij}}}{\mathrm{D_{max}}}$ for using distance only, or $\mathrm{CW_{ij}} = \mathrm{n}$ for using frequency only.

After calculating the choice weights for choice linkages, the model used these results to derive the affiliation weights. As stated in introduction, the affiliation network of churches was used to describe the relations between those churches that had the same group of participants, so the affiliation linkages could be seen as the summaries of the choice linkages. The model used affiliation weights to quantify the affiliation linkages. To clarify, suppose the church agents, which were all linked to the same participant agent, were called a “church group” of this participant. In a “church group”, affiliation linkages were established between any two churches. In Figure 4.1a, the three churches, then, become a “church group” of the participant agent. The calculation of the affiliation weight would be elaborated by the following instance. Figure 4.1a presented a simple affiliation network of churches: the green lines representing the choice linkages and the blue lines representing the affiliation linkages. The weights of affiliation linkages were calculated by dividing the sum of the choice weights by the number of choice linkages, so the affiliation weights of affiliation linkages between church1, church2, and church3 were $\mathrm{AW}_{1,2} = \mathrm{AW}_{1,3} = \mathrm{AW}_{2,3} = \frac{CW_{1,a} + CW_{2,a} + CW_{3,a}}{3}$. Thus, in a “church group”, the weights of affiliation linkages between any two churches were the same. By using the average of choice weights, the affiliation weights summarized the relations between this participant and the chosen churches, smoothing the influence of long distance or high frequency of attendances of particular churches. Besides, to each participant agent, its “church group” was seen as a whole, so using the average weight could describe the relation between a participant agent and its “church group”.

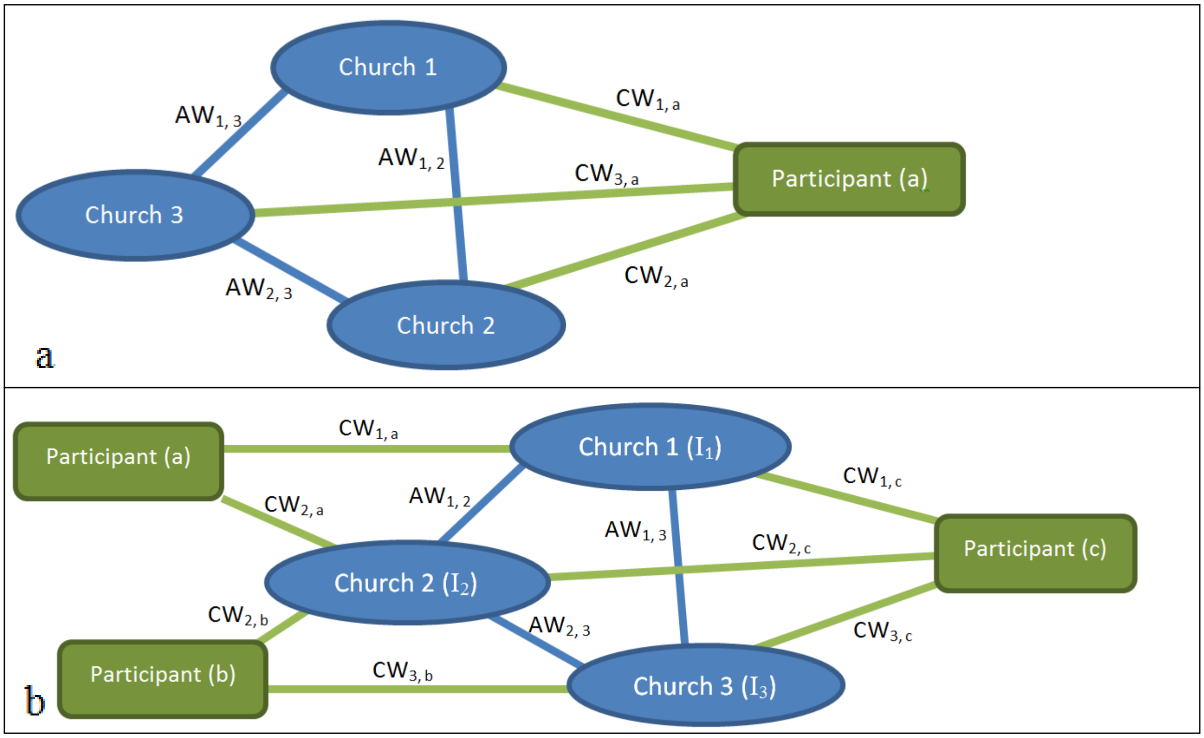


Figure 4.1 Two Examples of the Affiliation Network of Churches
Note: (a) a scenario with one participant; (b) a scenario with three participants

In most cases, a church agent was linked by multiple participant agents. Thus, a church agent might belong to multiple "church groups". When two church agents were linked to the same group of participant agents, and, therefore, belonged to the same "church groups" of participants, the final affiliation weight of the affiliation linkage between these two churches was the sum of the weights gained from all the "church groups". For instance, Figure 4.1b presented a complex affiliation network of churches where both church 1 and church 2 belonged to the "church groups" of participant (a) and participant (c). The average weight of participant (a)'s "church group" was $\frac{CW_{1,a}+CW_{2,a}}{2}$, and the average weight of participant (c)'s "church group" was $\frac{CW_{1,c}+CW_{2,c}+CW_{3,c}}{3}$, so the final weight of the affiliation linkage between church 1 and church 2 equaled to $\frac{CW_{1,a}+CW_{2,a}}{2}+\frac{CW_{1,c}+CW_{2,c}+CW_{3,c}}{3}$. Church 2 and church 3 belonged to both participant (b)'s and participant (c)'s "church groups". The average weight of participant (b)'s "church group" was $\frac{CW_{2,b}+CW_{3,b}}{2}$, and the average weight of participant (c)'s "church group" was $\frac{CW_{1,c}+CW_{2,c}+CW_{3,c}}{3}$, so the final weight of the affiliation linkage between church 2 and church 3 was $\frac{CW_{2,b}+CW_{3,b}}{2}+\frac{CW_{1,c}+CW_{2,c}+CW_{3,c}}{3}$. In contrast, church 1 and church 3 belonged to only participant (c)'s "church groups", so the affiliation weight between church 1 and church 3 equaled to $\frac{CW_{1,c}+CW_{2,c}+CW_{3,c}}{3}$.

To reveal the relative importance of the churches among the affiliation network, this model calculated the importance indices based on the affiliation weights. A church might link to multiple other churches in the affiliation network, thus, having multiple affiliation linkages. The importance index for each church was derived by summing the affiliation weights of all of its affiliation linkages up. For instance, as in Figure 4.1b, the importance index of church 1 $I_1 = AW_{1,2} + AW_{1,3} = \frac{CW_{1,a}+CW_{2,a}}{2}+\frac{2(CW_{1,c}+CW_{2,c}+CW_{3,c})}{3}$; the importance index of church 2 $I_2 = AW_{1,2} + AW_{2,3} = \frac{CW_{1,a}+CW_{2,a}}{2}+\frac{CW_{2,b}+CW_{3,b}}{2}+\frac{2(CW_{1,c}+CW_{2,c}+CW_{3,c})}{3}$; the importance index of church 3 $I_3 = AW_{1,3} + AW_{2,3} = \frac{CW_{2,b}+CW_{3,b}}{2}+\frac{2(CW_{1,c}+CW_{2,c}+CW_{3,c})}{3}$.

5 SCENARIOS

5.1 Overview

This section proposed a series of scenarios to examine how personal radii of participants and participants' choice patterns as well as the population of participants affect the affiliation networks of churches. The scenario analysis consisted of two sections. Scenarios section 1 was proposed to examine how personal radii affected the formation of affiliation networks of churches when controlling the population of participants and the choice patterns. Scenarios section 2 was proposed to examine how the population of participants, personal radii, and choice patterns affected the centralities of churches among the affiliation network. For each scenario, the time step of simulation was one week. However, the simulation cycle for scenarios section 1 was 6 months (26 weeks), while in scenarios section 2, the simulation cycle was 12 months (52 weeks). Scenarios section 1 has a shorter simulation cycle because this research attempted to focus on the initial stages of affiliation networks of churches and investigate their formation processes. For scenarios section 2, the simulation cycle was longer because the centralities of churches required a relatively longer time to evaluate and compare. The 6-month-simulation-cycle for scenarios section 1 was derived from a series of preliminary experiments, which indicated that, in this model, the period from the beginning until the complete formation of the affiliation network of churches would not exceed 6 months (26 weeks). Referring to this result, the simulation cycles for scenarios section 2 were twice as this period (52 weeks).

5.2 Scenarios section 1

Scenarios section 1 had 20 scenarios which were divided into five categories with 300 participant agents each. Each category contained four scenarios. Table 5.1 showed the first 12 scenarios. Category 1 (scenarios 1- 4) was used to examine, if the personal radii had a normal distribution, how the affiliation network of churches would be affected by the mean personal radius. The four scenarios of category 1 were set with different mean personal radii (μ = 0.3, 0.5, 0.7, and 0.9 km, respectively) with the same standard deviation of 0.2 km. Category 2 (scenarios 5-8) was used to examine, if the personal radii had a normal distribution, how the affiliation network would be affected by the change of standard deviations. The four scenarios of category 2 were set with different standard deviations (σ = 0.2, 0.4, 0.6, and 0.8 km, respectively), but with the same mean personal radius (0.5 km), for the normal distribution. Category 3 (scenarios 9-12) was used to examine, if the personal radii had an exponential distribution, how the affiliation network of churches would be affected by the mean personal radius. The four scenarios in category 3 were set with different mean personal radii (μ = 0.3, 0.5, 0.7, and 0.9 km, respectively).

Table 5.1 Parameters Setting of Scenarios Section 1 (normal and exponential distribution)

Scenario	Category	Distribution	μ [1]	σ [2]
1	1	Normal	0.3	0.2
2	1	Normal	0.5	0.2
3	1	Normal	0.7	0.2
4	1	Normal	0.9	0.2
5	2	Normal	0.5	0.2
6	2	Normal	0.5	0.4
7	2	Normal	0.5	0.6
8	2	Normal	0.5	0.8
9	3	Exponential	0.3	NA
10	3	Exponential	0.5	NA
11	3	Exponential	0.7	NA
12	3	Exponential	0.9	NA

Note: [1] mean value of personal radii (km); [2] standard deviation of personal radii (km); for scenarios 1-12, the population of participants is 300 and the choice pattern is randomly choosing.

The last eight scenarios in scenarios section 1 were proposed to study how the affiliation network of churches would be affected if personal radii of participants had a log-normal distribution. Table 5.2 showed the parameters setting of the last eight scenarios in scenarios section 1. The personal radii in scenarios 13 to 20 had a log-normal distribution. To clarify, Table 5.2 used *m* and *s* to represent the mean and standard deviation of personal radii, while μ and σ represented the mean and standard deviation of personal radii's natural logarithms. This study used category 4 of scenarios (13 - 16) to examine how the mean personal radius of participants affect the resulting affiliation network of churches. Scenarios 13 to 16 had a mean personal radius of 0.3, 0.5, 0.7, and 0.9 km, respectively, while their standard deviations of personal radii equaled to 0.2 km. In contrast, this study used category 5 of scenarios (17 - 20) to investigate how standard deviation of personal radii affect the resulting affiliation network of churches when the personal radii had a log-normal distribution. Scenarios 17 to 20 had a standard deviation of personal radii of 0.2, 0.4, 0.6, and 0.8 km, respectively, while their mean personal radius equaled to 0.5 km. In scenarios 13 to 20, the values of μ and σ were derived from equations (7) and (8) based on the values of *m* and *s*.

Table 5.2 Parameters Setting of Scenarios Section 1 (log-normal distribution)

Scenario	Category	Distribution	m [1]	s [2]	μ [3]	σ [4]
13	4	Log-normal	0.3	0.2	0.91475	0.606403
14	4	Log-normal	0.5	0.2	1.535228	0.385253
15	4	Log-normal	0.7	0.2	1.906674	0.280128
16	4	Log-normal	0.9	0.2	2.173124	0.21955
17	5	Log-normal	0.5	0.2	1.535228	0.385253
18	5	Log-normal	0.5	0.4	1.36209	0.703346
19	5	Log-normal	0.5	0.6	1.163439	0.944456
20	5	Log-normal	0.5	0.8	0.974558	1.126837

Note: [1] mean value of personal radii (km); [2] standard deviation of personal radii (km); [3] mean value of personal radii's natural logarithms (km); [4] standard deviation of personal radii's natural logarithms (km); for scenarios 13-20, the population of participants is 300 and the choice pattern is randomly choosing.

This study described and compared the results of scenarios section 1 in three aspects: the resulting affiliation network of churches, the order (number of connected churches) of giant component, and the size (number of connections) of the affiliation network. Figure 5.1 through 5.5 showed and compared the resulting affiliation networks of churches of the 20 scenarios in scenarios section 1. The comparison of results suggested that the personal radii were highly related to the formation of the affiliation network of churches. First, results suggested that the increase of mean value of the derived personal radii boost the affiliation network of churches to expand and thus connect additional churches (Figure 5.1, scenarios 1 – 4). Besides, it was found, when the standard deviation of the derived personal radii was comparatively small, the resulting affiliation networks of the scenarios were relatively simple (had small quantity of connections). Second, results showed that the raise of standard deviation of the derived personal radii led to extension and densification of the resulting affiliation networks (Figure 5.2, scenarios 5 – 8). Comparison of Figures 5.1 and 5.2 suggested that diversified values instead of concentrated values of personal radii (given the mean personal radius was controlled) increased the density of the affiliation network of churches. Third, it was found that when personal radii had an exponential distribution, which meant the derived values of personal radii were relatively diverse, the resulting affiliation networks of churches were comparatively dense (Figure 5.3, scenarios 9 – 12). Forth, results suggested that when personal radii had a log-normal distribution, the resulting affiliation networks of churches become relatively denser (Figure 5.4 and 5.5, scenarios 13 - 20) compared to the scenarios that had a normal distribution but under the same parameters setting. Comparison of Figures 5.1 through 5.5 supported that the influence of diversified values of personal radii on the density of affiliation networks of churches was more obvious than which of concentrated values of personal radii.

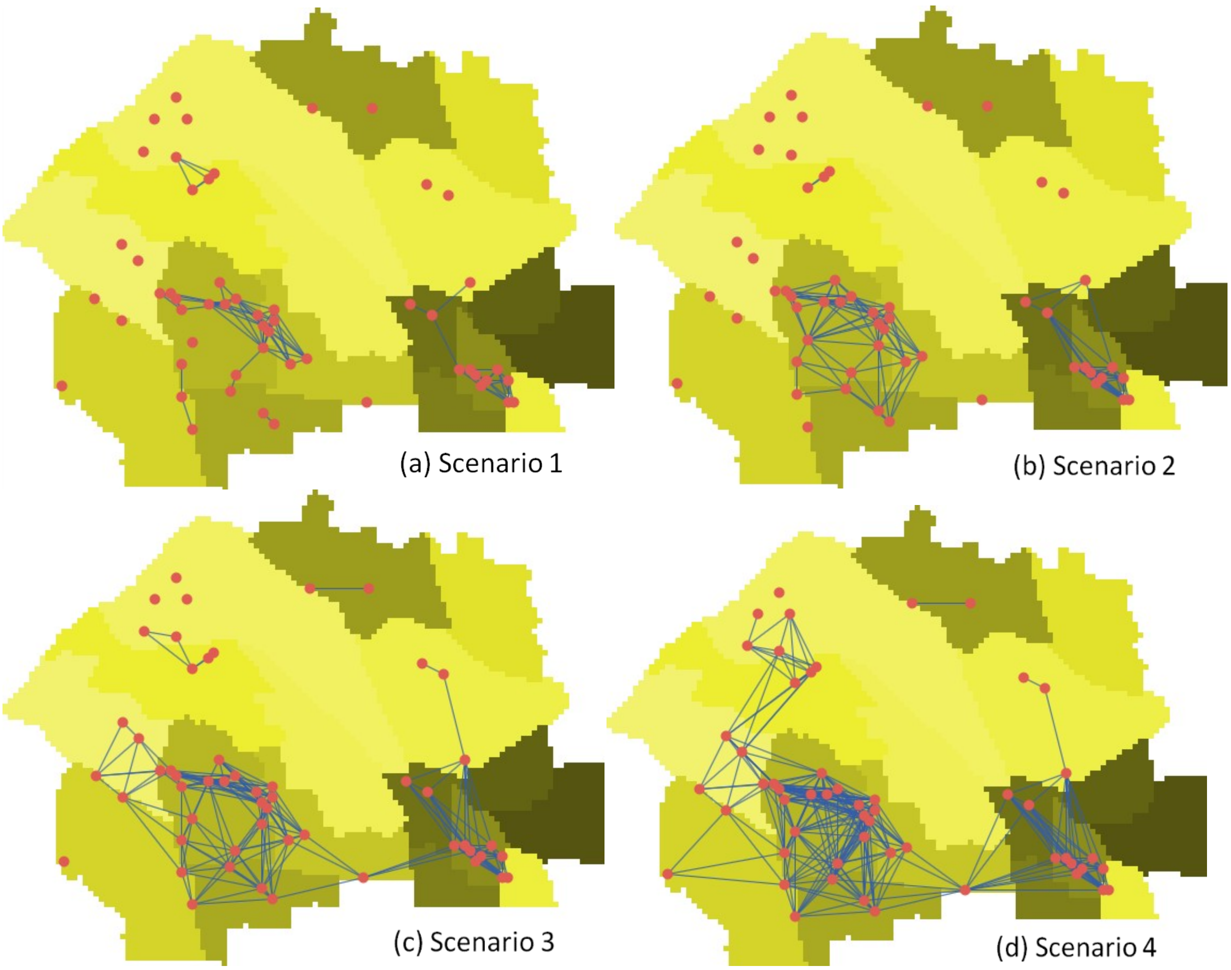


Figure 5.1 Impact of Mean Value (μ) of Normal Distribution of Personal Radii on the Affiliation Network
Note: scenarios 1 to 4 with μ value of 0.3 (a), 0.5 (b), 0.7 (c), and 0.9 (d)

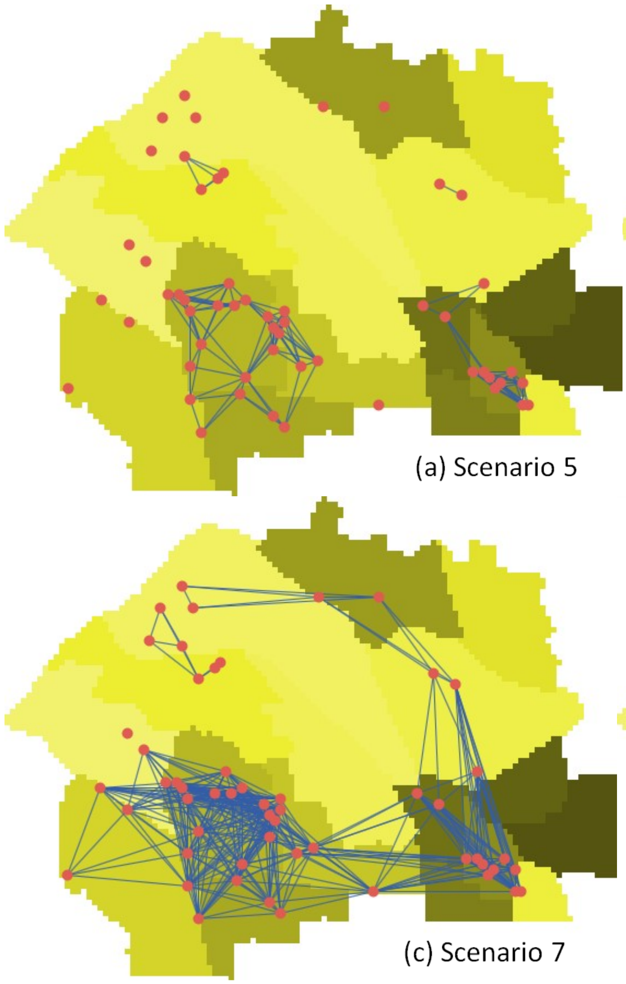


Figure 5.2 Impact of Standard Deviation (σ) of Normal Distribution of Personal Radii on the Affiliation Network

Note: scenarios 5 to 8 with μ of 0.5 and σ of 0.2 (a), 0.4 (b), 0.6 (c), and 0.8 (d), respectively

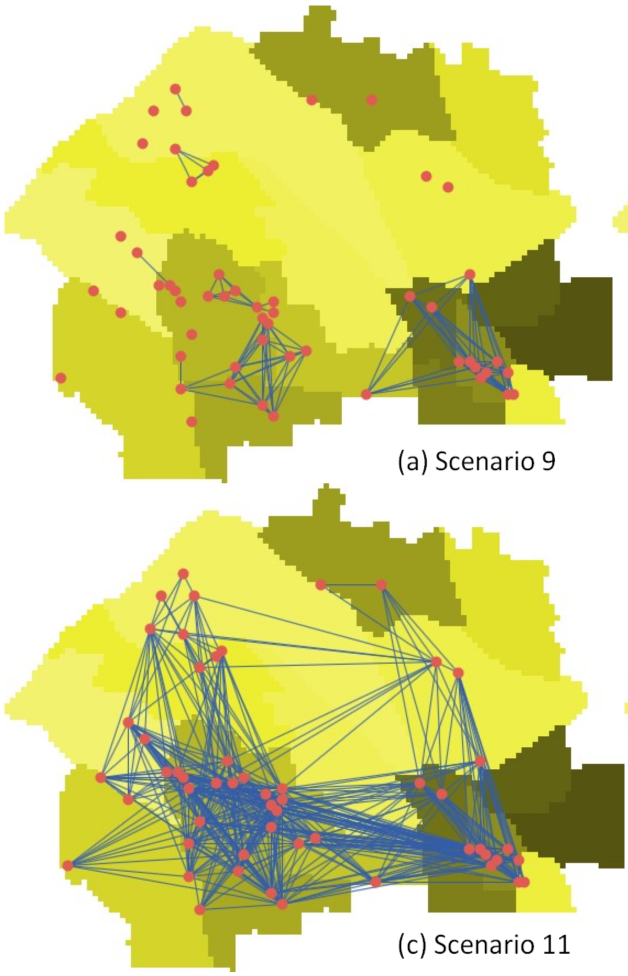


Figure 5.3 Impact of Mean Value (μ) of Exponential Distribution of Personal Radii on the Affiliation Network

Note: scenarios 9 to 12 with μ value of 0.3 (a), 0.5 (b), 0.7 (c) 0.9 (d)

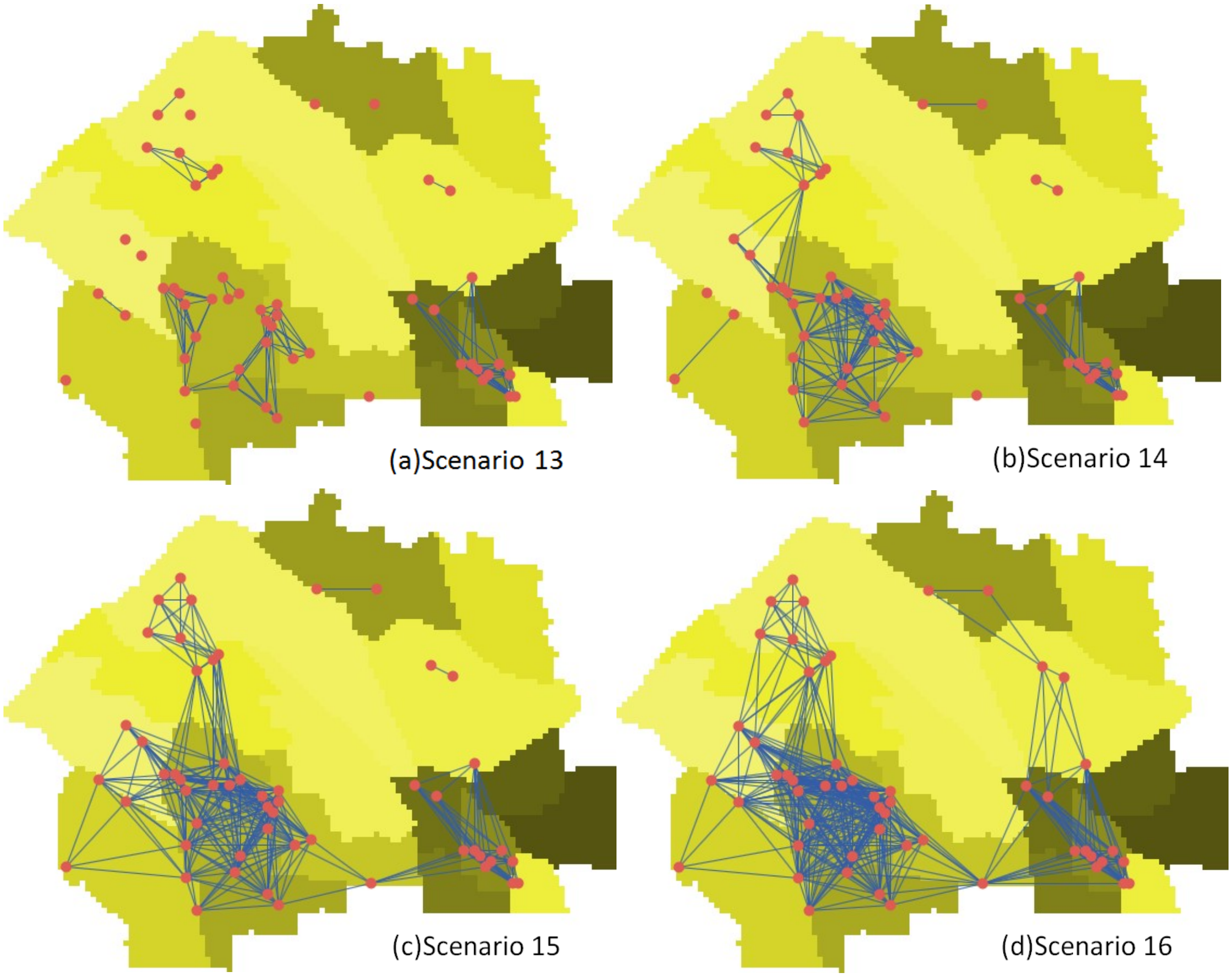
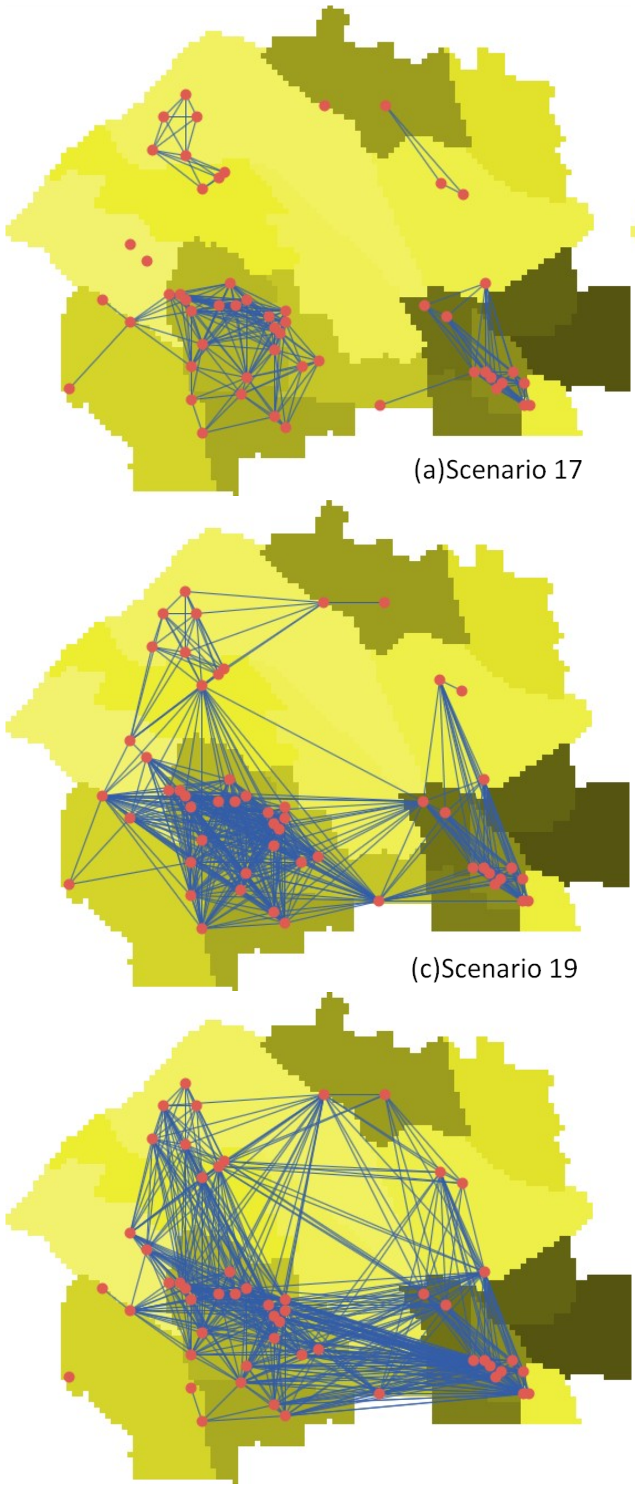


Figure 5.4 Impact of Mean Value (*m*) of Log-normal Distribution of Personal Radii on the Affiliation Network

Note: scenarios 13 to 16 with *m* of 0.3 (a), 0.5 (b), 0.7 (c) 0.9 (d)



(a)Scenario 17

(b)Scenario 18

(c)Scenario 19

(d)Scenario 20

Figure 5.5 Impact of Standard Deviation (*s*) of Log-normal Distribution of Personal Radii on the Affiliation Network

Note: scenarios 17 to 20 with *m* of 0.5 and *s* of 0.2 (a), 0.4 (b), 0.6 (c), and 0.8 (d), respectively

The results of comparing the order of giant components from scenarios 1 to 20 suggested that personal radii of participants were highly related to the growth of the giant components. Figure 5.6 through 5.10 showed the comparison of the resulting giant components from scenarios 1 to 20 in category. The results indicated that the increase of personal radii (increase of mean personal radius) promoted the giant components to grow. Figure 5.6 (scenarios 1 – 4) and Figure 5.9 (scenarios 13 - 16) suggested, when the values of personal radii were relatively concentrated, which is represented by a small standard deviation, order of the final giant components were positively correlated with the mean value of personal radii. In contrast, Figure 5.7 (scenarios 5 – 8), Figure 5.8 (scenarios 9 – 12) associated with Figure 5.10 (scenarios 17 - 20) showed that, when the values of personal radii were relatively diversified, represented by a greater standard deviation in scenarios 5 – 8 and scenarios 17 – 20 or a larger mean value of personal radii in scenarios 9 – 12, the giant components grew more rapidly and the orders of final giant components were relatively larger. In all scenarios, the affiliation network became stable after 11 or 12 weeks. Besides, it was found that the giant component could have a sharp increase in size (refer to the lines of scenario 13 in Figure 5.9 and scenario 18 in Figure 5.10,), which might be stemmed from additional connections between two or more large components in the affiliation network.

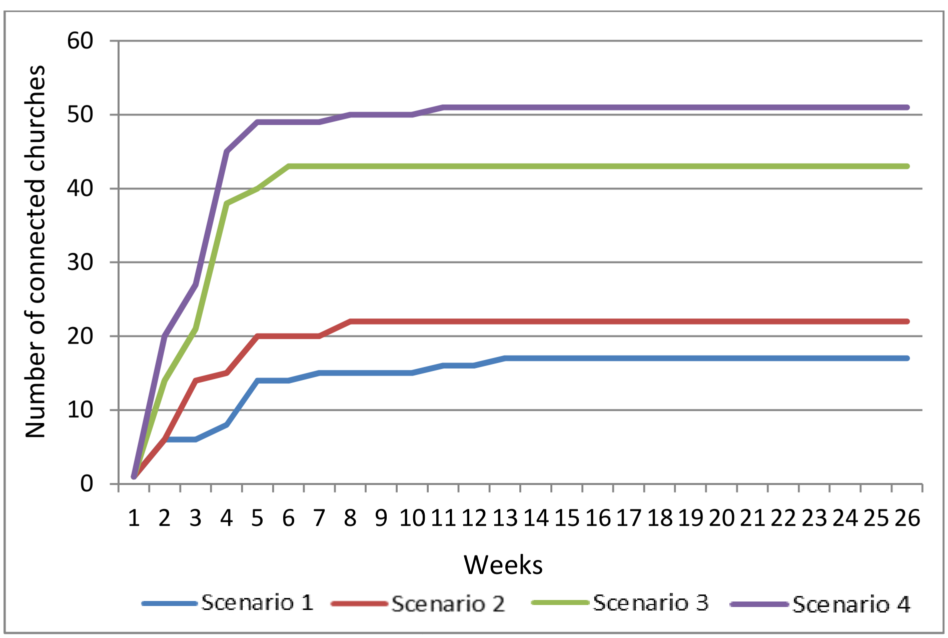


Figure 5.6 Comparison of the Order of Giant Components of Scenarios 1 to 4
Note: scenarios 1 to 4 with μ of 0.3 (Scenario 1), 0.5 (Scenario 2), 0.7 (Scenario 3), and 0.9 (Scenario 4)

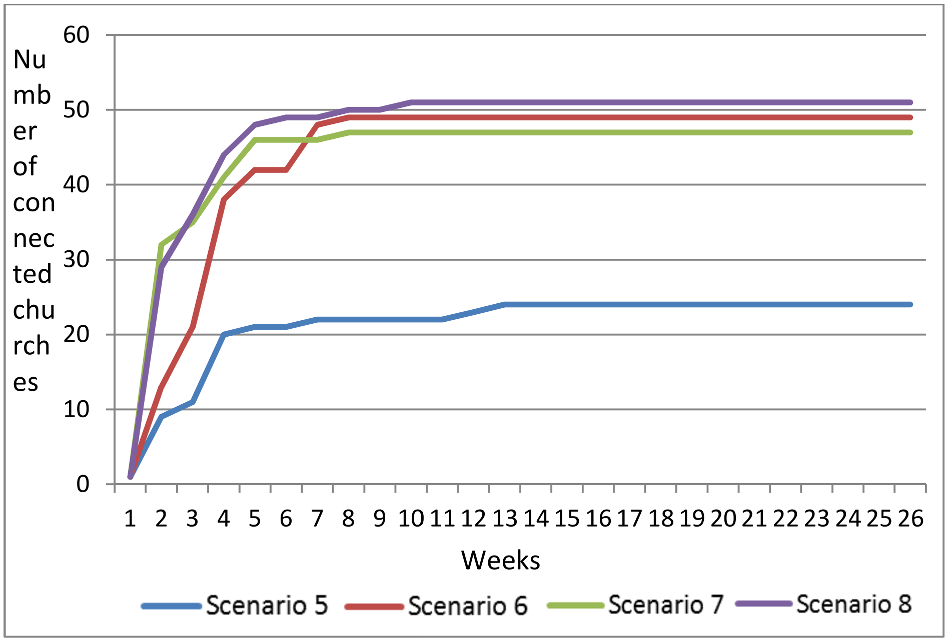


Figure 5.7 Comparison of the Order of Giant Components of Scenarios 5 to 8
Note: scenarios 5 to 8 with σ of 0.2 (Scenario 5), 0.4 (Scenario 6), 0.6 (Scenario 7), and 0.8 (Scenario 8)

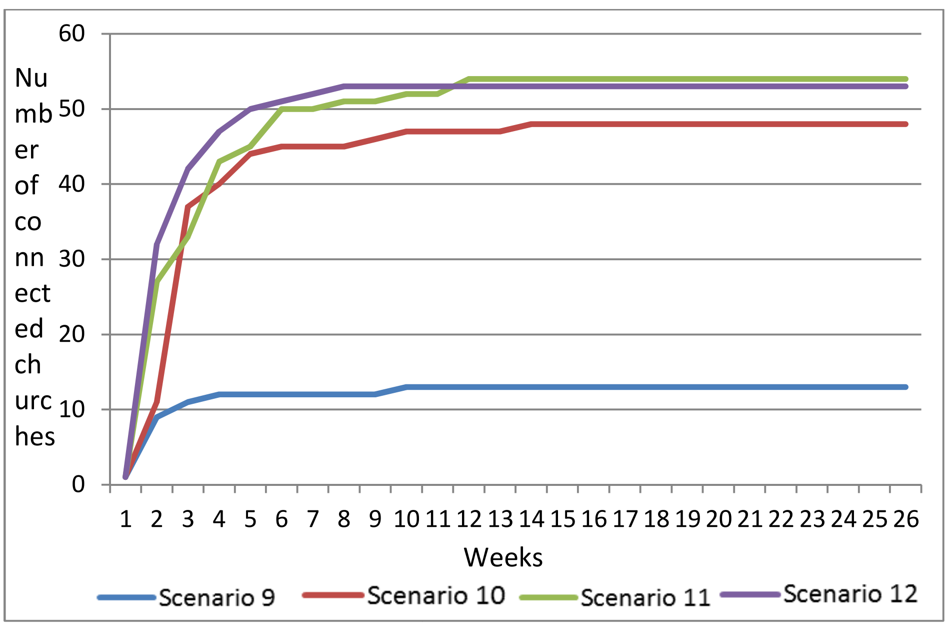


Figure 5.8 Comparison of the Order of Giant Components of Scenarios 9 to 12
Note: scenarios 9 to 12 with μ of 0.3 (Scenario 9), 0.5 (Scenario 10), 0.7 (Scenario 11), and 0.9 (Scenario 12)

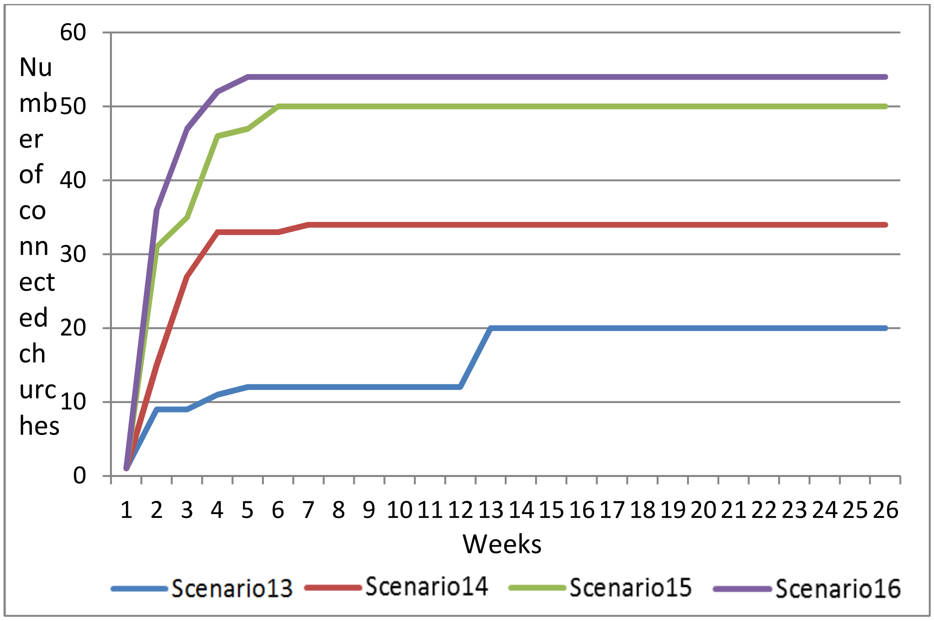


Figure 5.9 Comparison of the Order of Giant Components of Scenarios 13 to 16
Note: scenarios 13 to 16 with *m* of 0.3 (Scenario 13), 0.5 (Scenario 14), 0.7 (Scenario 15), and 0.9 (Scenario 16)

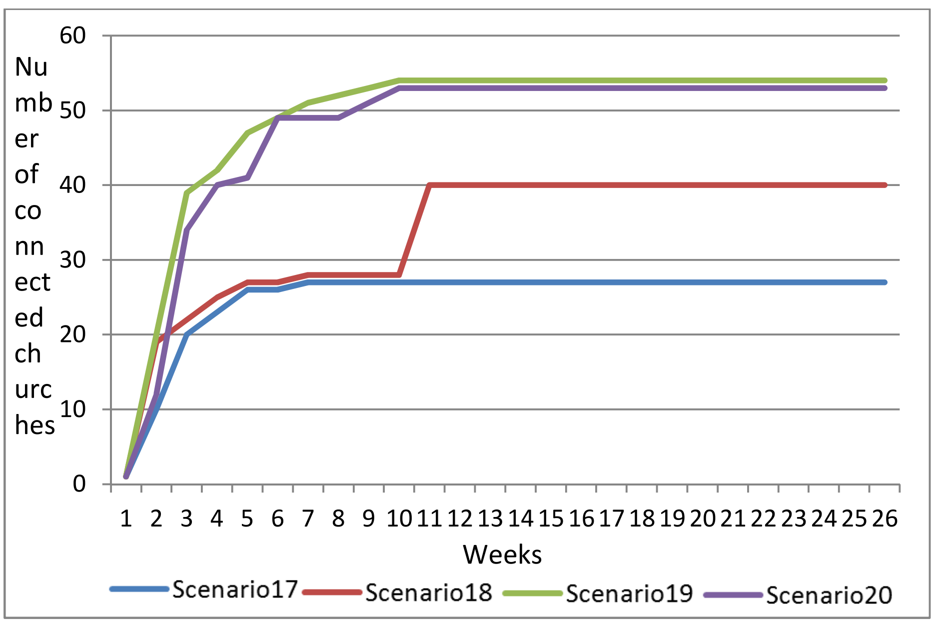


Figure 5.10 Comparison of the Order of Giant Components of Scenarios 17 to 20
Note: scenarios 17 to 20 with *s* of 0.2 (Scenario 17), 0.4 (Scenario 18), 0.6 (Scenario 19), and 0.8 (Scenario 20)

Figure 5.11 showed the comparison of resulting affiliation networks of churches in size (number of connections) of scenarios 1 – 20. Generally, the sizes of affiliation networks of churches grew with the increasing of personal radii. To notice, when the personal radii of participants were relatively diversified— an exponential distribution, a normal or log-normal distribution with a large standard deviation, the sizes of affiliation networks tended to be larger. On the contrary, the sizes of affiliation networks were relatively small when the personal radii of participants were relatively concentrated.

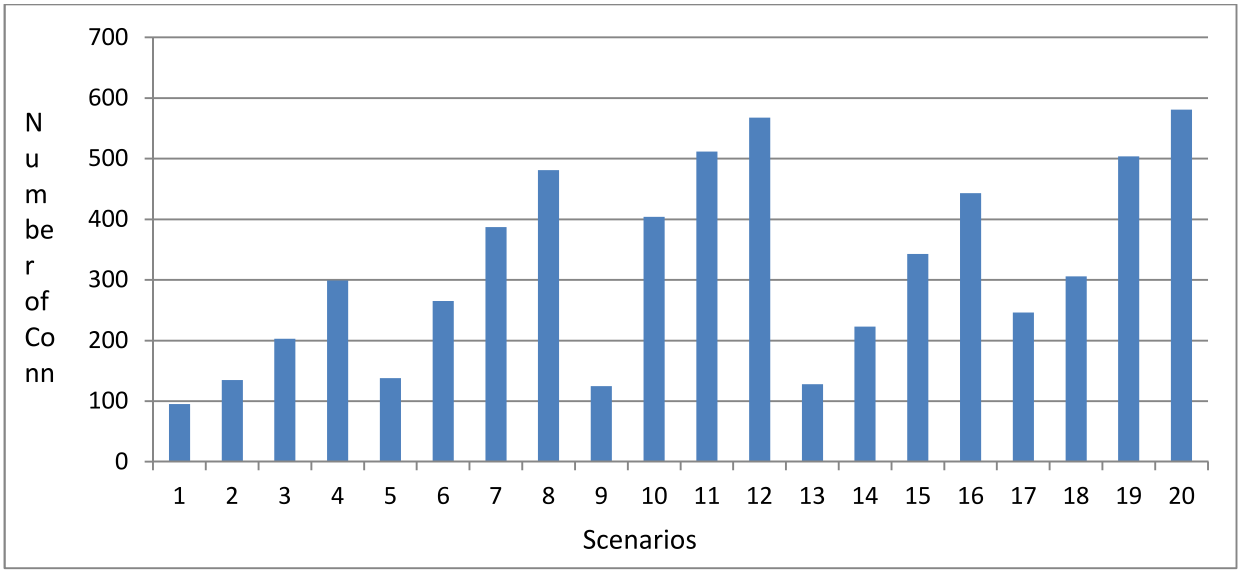


Figure 5.11 Comparison of Size of the Affiliation Network of Churches of Scenarios 1 to 20

5.3 Scenarios section 2

Scenarios section 2 was proposed to investigate the influence of personal radii, choice patterns, and population of participants on the centralities, thus importance indices, of the churches among the affiliation network. This scenarios section included 25 scenarios. Table 5.3 showed the parameters setting of the first 16 scenarios in scenarios section 2, in which the personal radii had a normal or exponential distribution. In contrast, Table 5.4 showed the parameters setting of the last 9 scenarios, in which the personal radii had a log-normal distribution. Scenarios 21 – 25, 30 – 32, as well as 37 - 41 were used to study how the personal radii influence the importance of churches. In scenarios 21 - 23, in which the derived personal radii were assumed to have a normal distribution, the standard deviation (σ = 0.2 km) was relatively small, so the experiment could investigate how the concentrated values of personal radii (μ = 0.5, 1, and 1.5 km, respectively) affected the importance indices of churches. By comparison, scenarios 24 and 25 were set with different standard deviations (σ = 0.5 and 0.8 km, respectively) of normal distribution and used to illustrate how the diversified values of personal radii affected the importance indices of churches. Besides, scenarios 30 – 32 were proposed to examine how the diversified values of personal radii (μ= 0.5, 1, and 1.5 km, respectively) impacted the importance indices of churches, but the personal radii were assumed to have an exponential distribution. In scenarios 37 – 39, the personal radii were assumed to have a log-normal distribution with the purpose to investigate how the importance indices of churches would be affected when personal radii of most participants had a smaller value than the mean personal radius (*m* = 0.5, 1, 1.5 km, respectively). By contrast, this study used scenarios 40 and 41 to examine how the importance indices of churches would be affected when personal radii of participants had diversified values as well as a log-normal distribution, so the standard deviation of these two scenarios were set with relatively large values (s = 0.5 and 0.8, respectively). Scenarios 26, 27, 33, 34, 42, and 43 were proposed to investigate how the choice patterns affect the importance of churches. In scenarios 26, 33, and 42, the choice pattern of participant agents was choosing the nearest church, while in scenarios 27, 34, and 43, the choice pattern is choosing the favorite churches. Scenarios 28, 29, 35, 36, 44, and 45 were used to examine the influence of population of participants on the importance indices of churches, and they were set with 500 participants (Scenarios 28, 35, and 44) and 1500 participants (Scenarios 29, 36, and 45), respectively.

Table 5.3 Parameters Setting of Scenarios Section 2 (normal and exponential distribution)

Scenario (N)[1]	Scenario (E)[2]	Population	μ [3]	σ [4]	Choice [5]
21	30	1000	0.5	0.2	Random
22	31	1000	1	0.2	Random
23	32	1000	1.5	0.2	Random
24		1000	1	0.5	Random
25		1000	1	0.8	Random
26	33	1000	1	0.2	Nearest
27	34	1000	1	0.2	Favorite
28	35	500	1	0.2	Random
29	36	1500	1	0.2	Random

Note: [1] the personal radii in these scenarios had a normal distribution; [2] the personal radii in these scenarios had an exponential distribution; [3] mean value of personal radii (km); [4] standard deviation of personal radii (km), only for the scenarios with normal distribution; [5] the choice pattern of agents

Table 5.4 Parameters Setting of Scenarios Section 2 (log-normal distribution)

Scenario (N)[1]	Population	m [2]	s [3]	μ [4]	σ [5]	Choice [6]
37	1000	0.5	0.2	1.535228	0.385253	Random
38	1000	1	0.2	2.282975	0.198042	Random
39	1000	1.5	0.2	2.699239	0.132746	Random
40	1000	1	0.5	2.191013	0.472381	Random
41	1000	1	0.8	2.055237	0.703346	Random
42	1000	1	0.2	2.282975	0.198042	Nearest
43	1000	1	0.2	2.282975	0.198042	Favorite
44	500	1	0.2	2.282975	0.198042	Random
45	1500	1	0.2	2.282975	0.198042	Random

Note: [1] the personal radii in these scenarios had a log-normal distribution; [2] mean value of personal radii (km); [3] standard deviation of personal radii (km); [4] mean value of personal radii's natural logarithms (km); [5] standard deviation of personal radii's natural logarithms (km); [6] the choice pattern of agents

In order to examine the influence of using different methods to calculate choice weights on the importance indices of churches, this study derived a scatter plot to compare the rank orders of churches in ZIP Code 30318. Figure 5.12 showed the comparison of rank orders of churches using different methods to calculate choice weight. The simulation was based on the parameters setting of scenario 22. In the scatter plot of Figure 5.12, x-axis stands for the rank orders of churches using combined choice weight, while y-axis represents the rank orders of churches using distance choice weight, and frequency choice weight, respectively. The green line represents a 45° diagonal which is used as a reference for other scatter plots: when both of x-axis and y-axis stand for the rank orders of churches using combined choice weight, the plots would locate at a 45° diagonal. Refer to the green line, the scatter plot chart shows the difference of rank order of churches between different choice weight methods. The result suggested that the rank orders of churches generated from three different methods were generally proximate to each other. For the churches with high rank (1st to 10th), their rank orders bore very little change among different methods of calculating choice weight. However, rank orders show relatively large difference between the three types of choice weights among mediate ranks (11th – 45th).

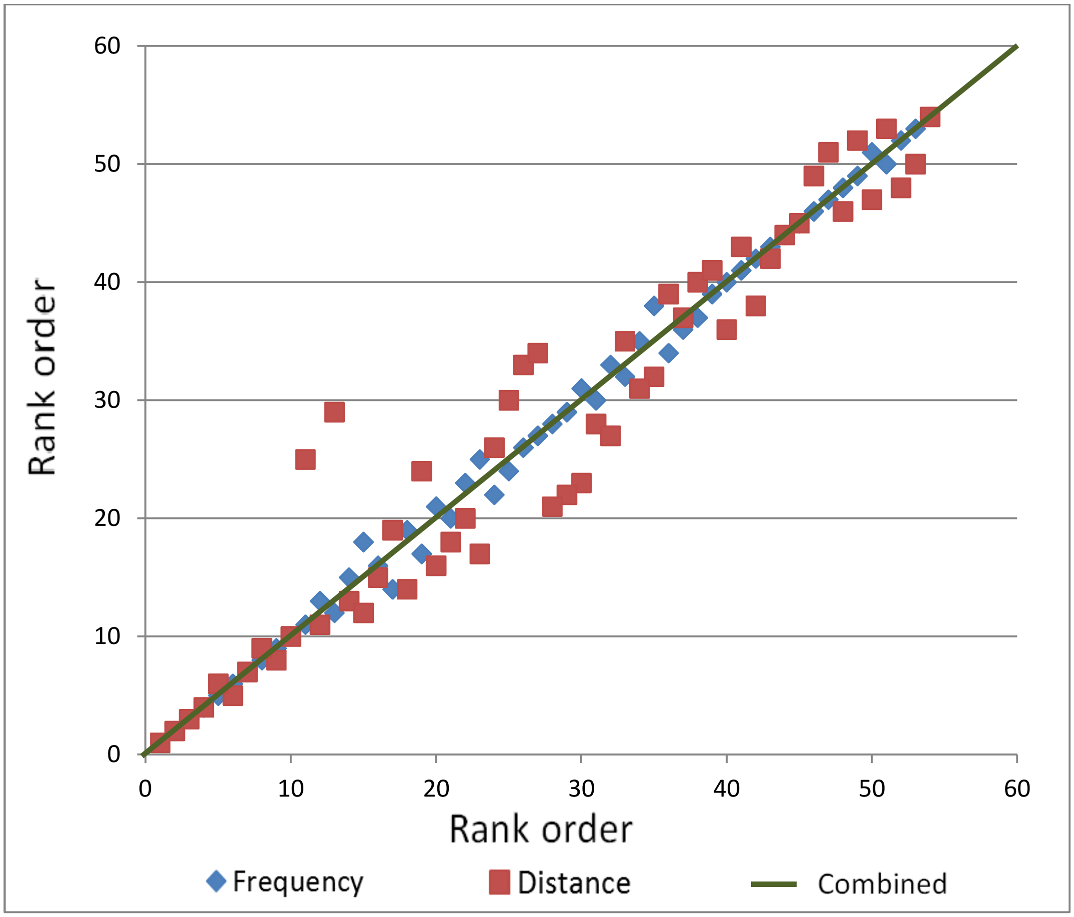


Figure 5.12 Comparison of Rank Orders of Churches Using Three Methods

Figure 5.13 (scenarios 21-23 and 30-32), Figure 5.14 (scenarios 37-39), and Figure 5.15 (scenarios 24, 25, 40, and 41) showed that in general, the importance indices of churches in the affiliation network depended on where they are, which corresponds to the population density very well. In addition, personal radii of participants were one of the major factors that impacted the relative importance of churches among the affiliation network. The results indicated that, generally, the increases of personal radii raised most churches' importance indices in the affiliation network. Figures 5.13a, 5.13c, and 5.13e (scenarios 21 – 23) showed that concentrated values of personal radii (normal distribution) produced relatively simple (small quantity of connections) affiliation networks of churches as suggested in scenarios section 1. In contrast, Figures 5.13b, 5.13d, and 5.13f (scenarios 30 – 32) associated with Figure 5.15 (scenarios 24, 25, 40, and 41) showed that the affiliation networks produced with diverse values of personal radii (exponential distribution, or normal, log-normal distribution with large value of standard deviation) were much denser. It was noticed that the degree of increase in importance indices of churches were different. The churches in the southeast area had higher importance indices than the other churches. Two observations can be made from the comparison of Figure 5.13e and 5.13f (scenarios 23 and 32) which were set with the highest mean value of personal radii among all scenarios). First, when the values of personal radii were relatively concentrated (Figure 5.13e, normal distribution), churches in the southeastern area had a sharp difference in importance compared with other churches in the affiliation network. Second, when the values of personal radii were relatively diversified (Figure 5.13f, exponential distribution), the importance indices between churches were gradually changed.

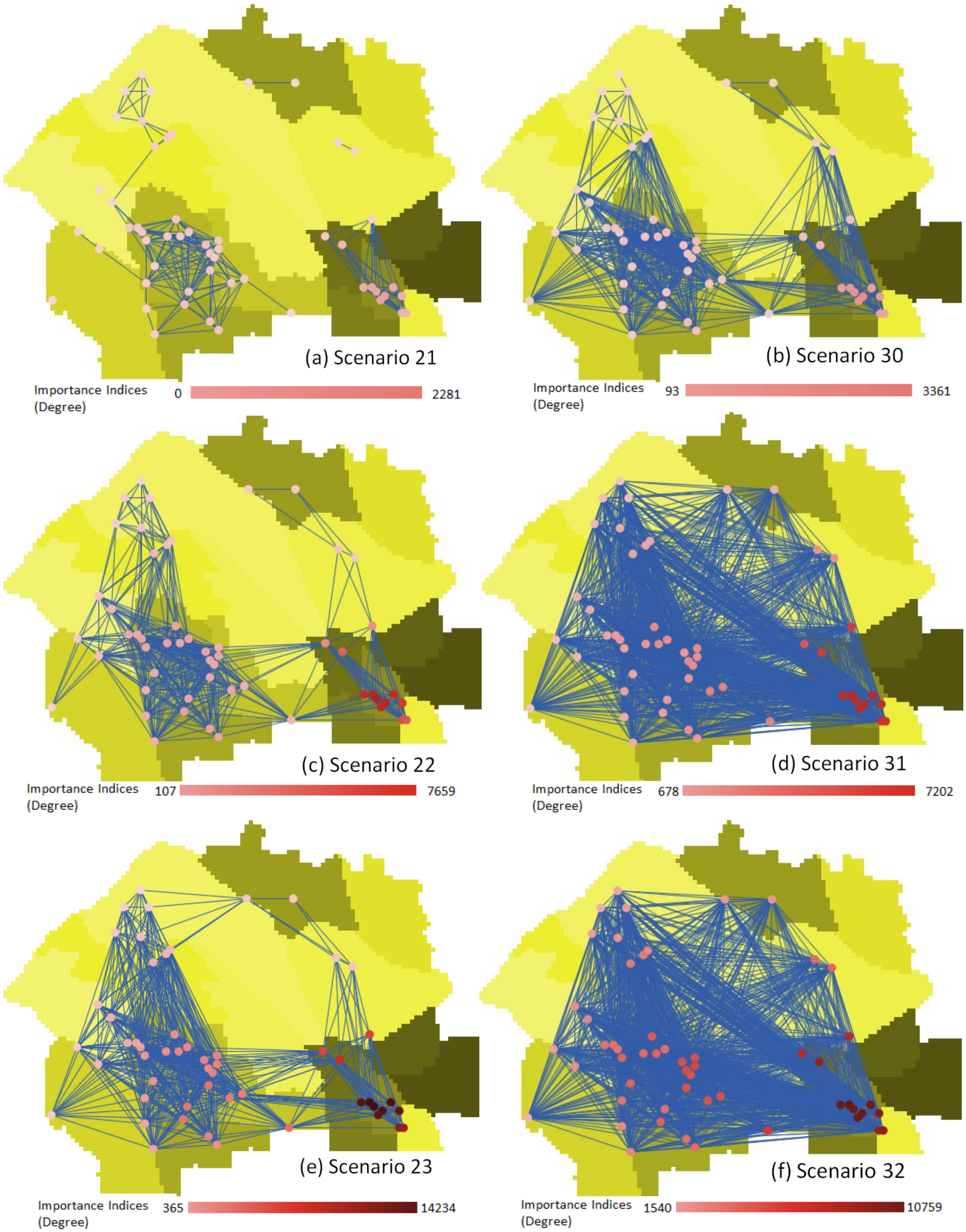


Figure 5.13 Impact of Mean Value (μ) of Personal Radii on the Importance Indices of Churches
Note: normal distribution (scenarios 21-23) and exponential distribution (scenarios 30-32) with μ value of 0.5 (a, b), 1 (c, d), and 1.5 (e, f)

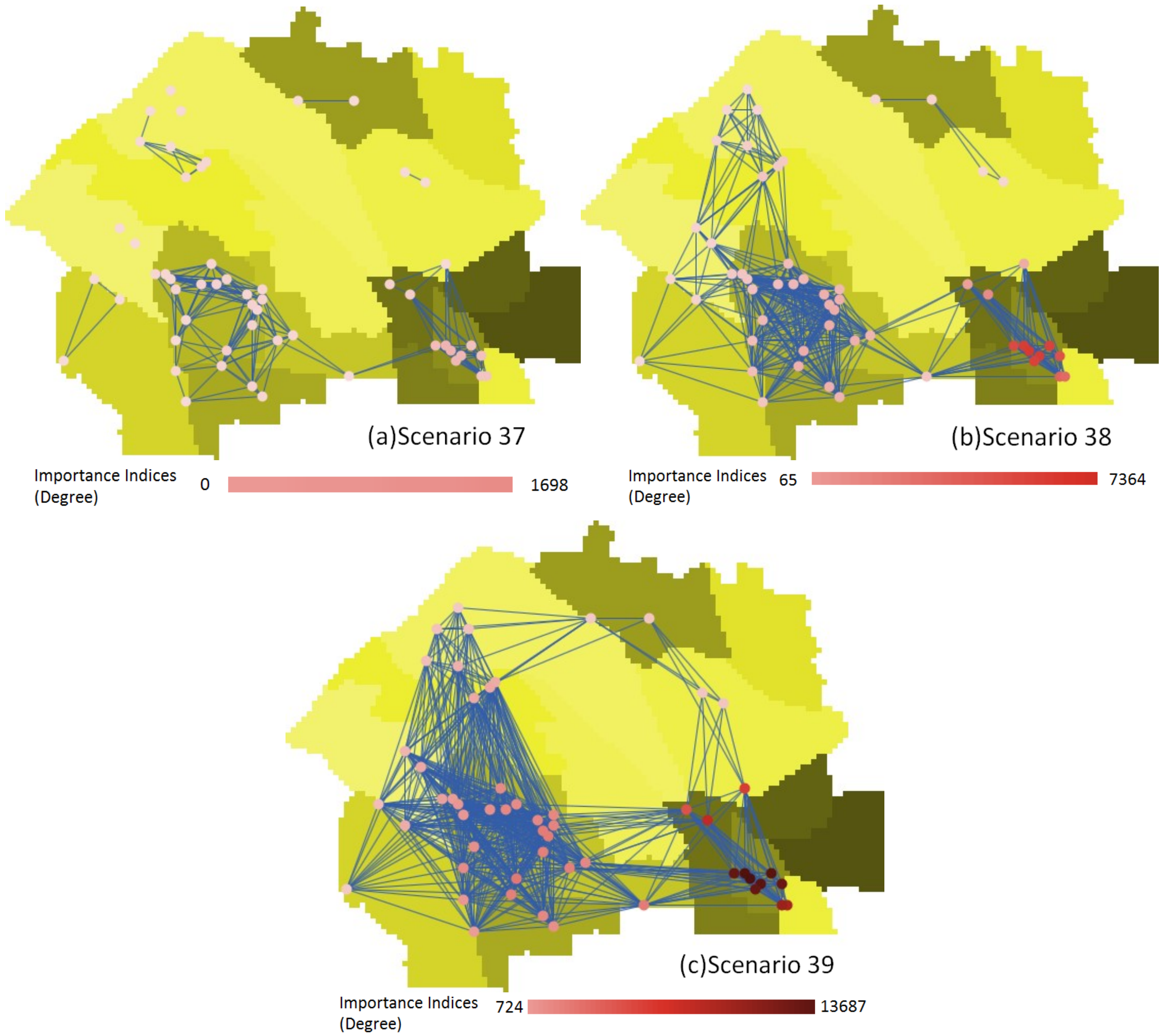
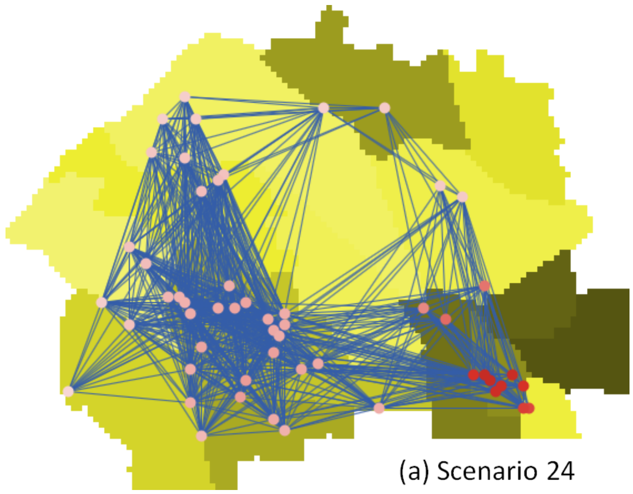
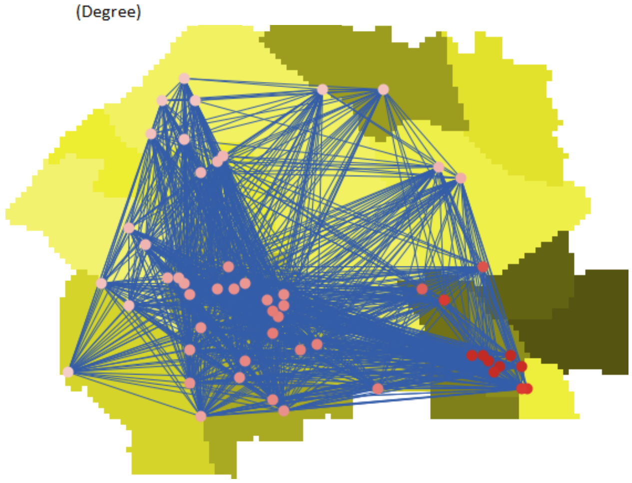


Figure 5.14 Impact of Mean Value (m) of Personal Radii on the Importance Indices of Churches
Note: scenarios 37-39 with m of 0.5 (a), 1 (b), and 1.5 (c)



(a) Scenario 24

Importance Indices (Degree) 350 8760



(b) Scenario 25

Importance Indices (Degree) 667 8924

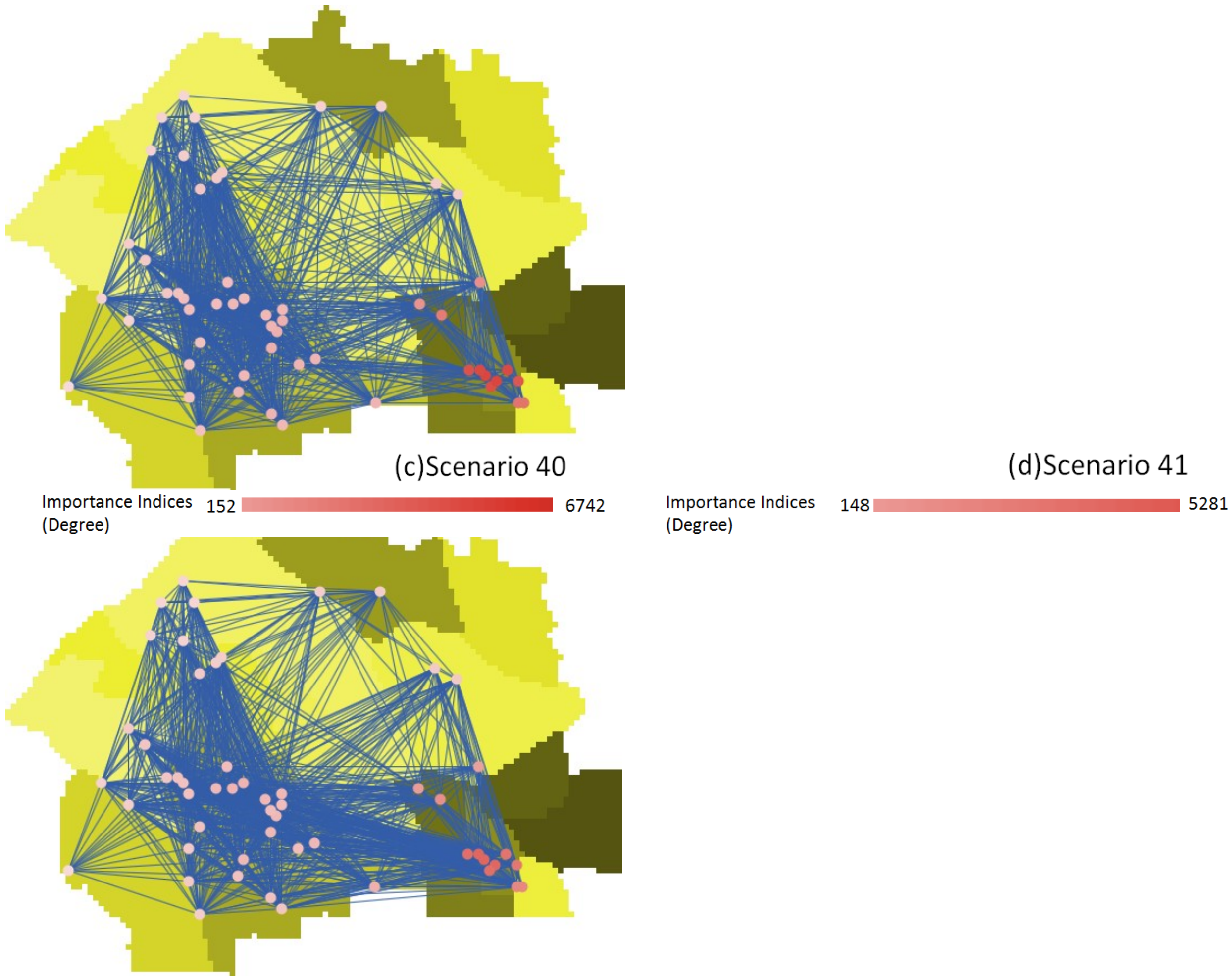


Figure 5.15 Impact of Standard Deviation (σ or s) of Personal Radii on the Importance Indices of Church-es
Note: scenarios 24, 25, 40, and 41 with σ or s of 0.5 (a and c) and 0.8 (b and d)

Figure 5.16 (scenarios 26, 27, 33, 34, 42, and 43) also supported the observation that churches in the densely populated areas are generally more important than the rest churches regardless of the choice patterns of participants. However, some difference in the importance values as well as the size of affiliation network arose when the choice patterns of participants changed. Figure 5.16a, 5.16c and 5.16e (scenarios 26, 33, and 42) revealed that, when the choice pattern of participants was changed to choosing the nearest church, the sizes of the resulting affiliation networks largely reduced, regardless of the values of personal radii were concentrated or diversified. Under this condition, although the importance indices of churches were generally low, the churches with high importance indices shown in

Figure 5.13 still had relatively high importance indices in Figure 5.16a, 5.16c, and 5.16e. In contrast, Figure 5.16b, 5.16d, and 5.16f (scenarios 27, 34, and 43) showed that when the choice pattern of participants was changed to the favorite church, the reduction in size of the resulting affiliation networks, if any, was minor, regardless of concentrated or diversified personal radii. Under this condition, the importance indices of churches were slightly lower than that under the choice pattern of randomly choosing (referred to Figure 5.13c, 5.13d, and 5.14b, respectively, where the mean personal radii were the same).

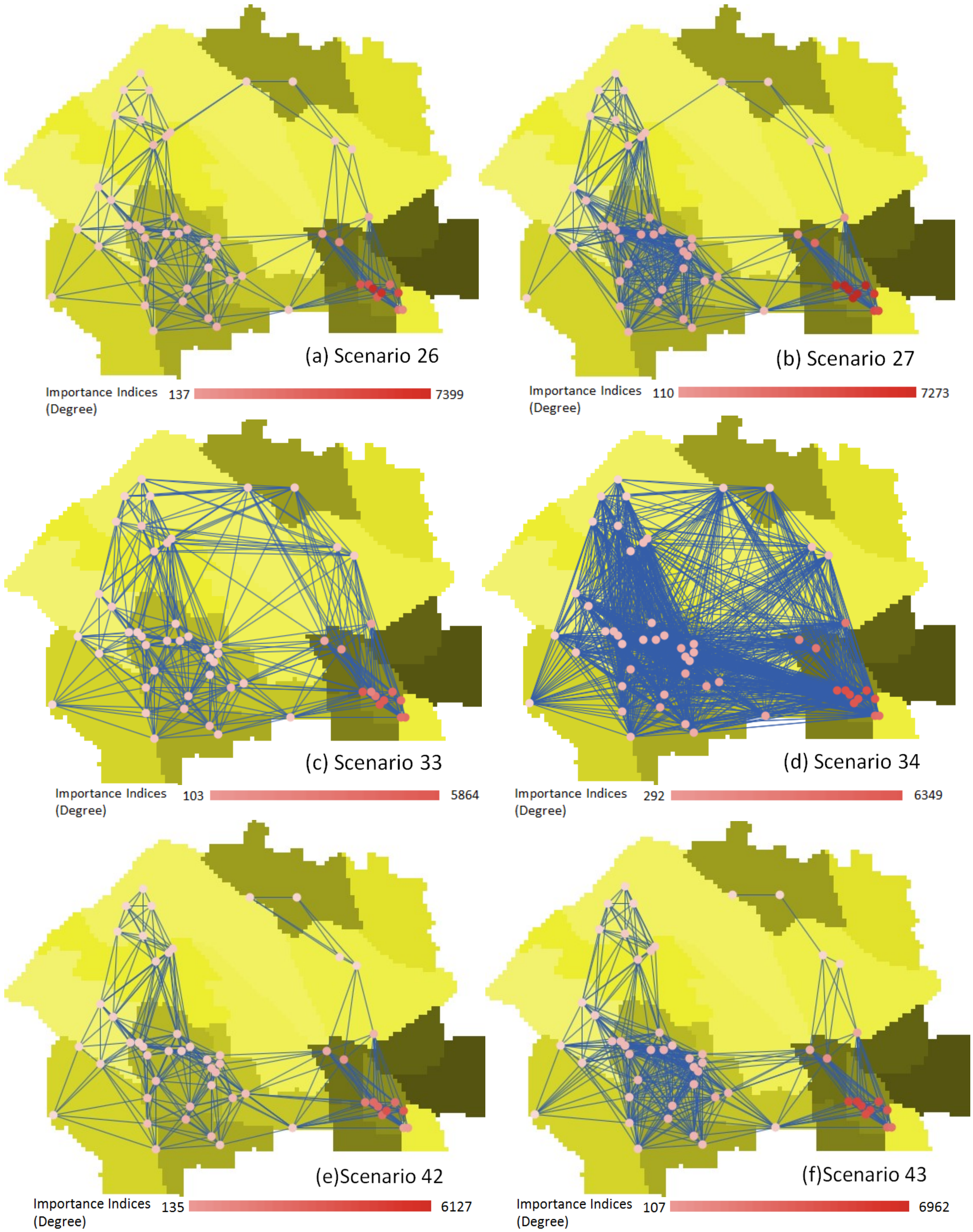


Figure 5.16 Impact of Choice Patterns on the Importance Indices of Churches
Note: scenarios 26, 27, 33, 34, 42, and 43 with choice patterns of choosing the nearest (a, c, e) and choosing the favorite (b, d, f)

Figure 5.17 (scenarios 28, 29, 35, 36, 44, and 45) showed that the population of participants had a notable influence on the importance indices of churches. Figure 5.13c and 5.13d could be used as reference for the four results in Figure 5.17, because they had the same value for the mean personal radius. The comparison of Figure 5.13c, 5.13d, and 5.17 suggested that, larger population sizes would increase importance indices of churches. Besides total population, the importance indices of churches were highly corresponding with the density of population as revealed earlier. This finding was evidenced in Figures 5.13, 5.14, 5.15, 5.16, and 5.17 that, among an affiliation network, the churches with relatively high values of importance indices locating in or nearby the census tracts had comparatively high density of participants.

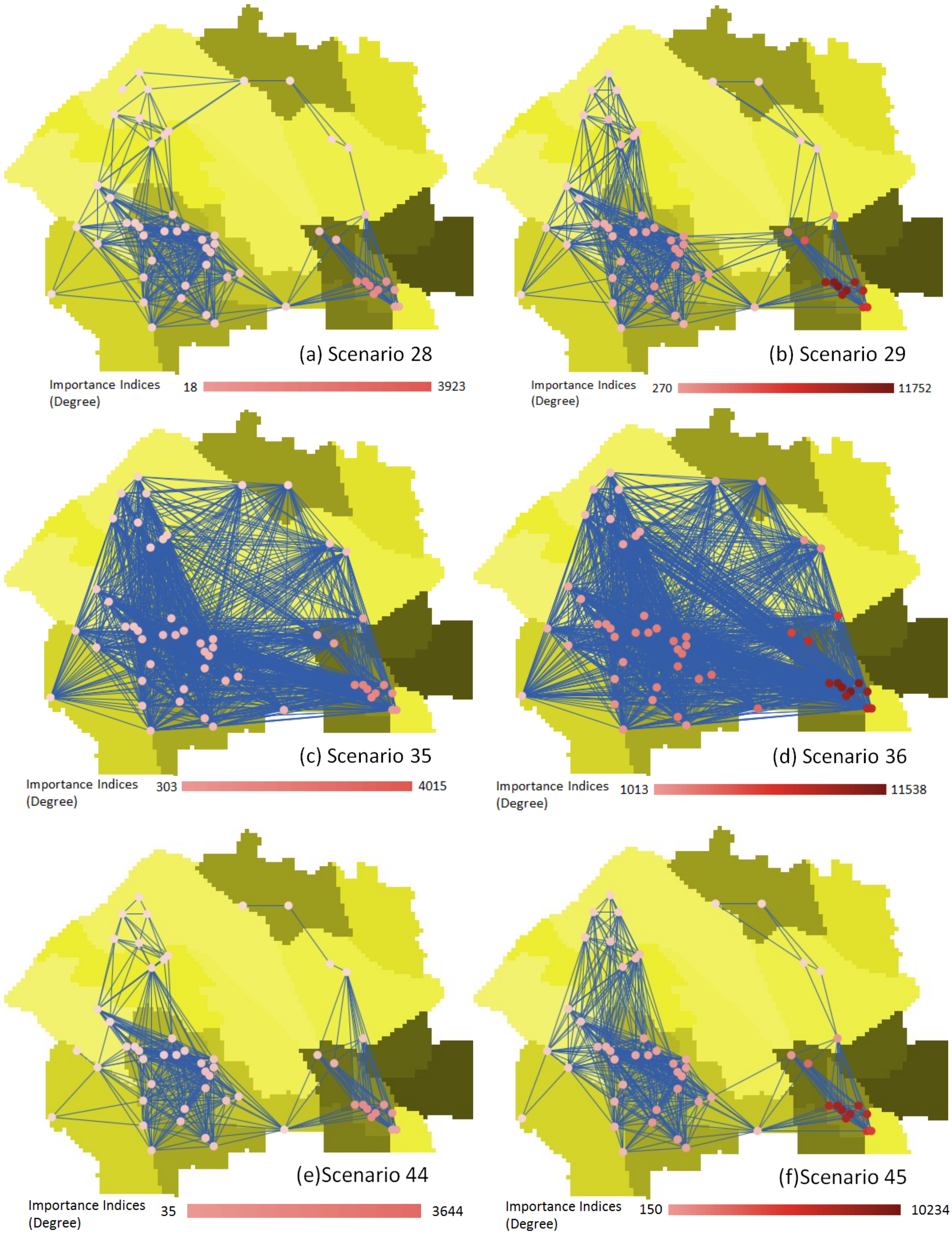


Figure 5.17 Impact of Population of Participants on the Importance Indices of Churches
Note: scenarios 28, 29, 35, 36, 44, and 45 with population of 500 (a, c, e) and 1500 (b, d, f)

Figure 5.18 showed the comparison in size of resulting affiliation networks of scenarios 21 - 45. The comparison indicated that the sizes of affiliation networks were higher when the values of personal radii were diverse (given an exponential distribution), comparing to the affiliation networks under the same condition but with relatively concentrated values of personal radii (given a normal distribution or log-normal distribution with a small value of standard deviation). As the personal radii (the mean personal radius) increased, the size of affiliation network grew. Besides, the comparison also suggested that the change of choice pattern, especially changing to choosing the nearest church, led to notable reduction in the size of affiliation network. Moreover, the comparison revealed that the change of total population of participants had a positive relation to the size of affiliation network.

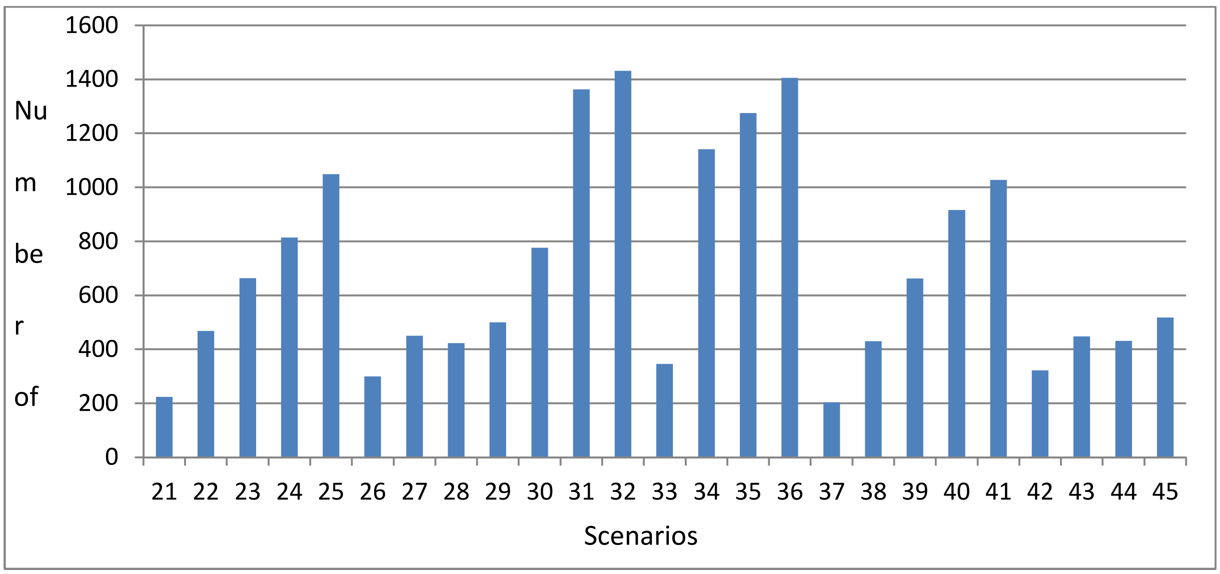


Figure 5.18 Comparison of Sizes of the Affiliation Network of Churches of Scenarios 21 to 45

6 Discussion and conclusion

As religious life has been linked to people's mental health and responsible behaviors (Begue 2001, Ellison et al. 2001, Arnold et al. 2002, McCree et al. 2003), church activities might be helpful in preventing local public health issues such as HIV or STDs and drug abuse (Cook et al. 1997, Corwyn and Benda 2000). Understanding the local affiliation networks of churches is helpful in promoting cooperation between churches, thereby enhancing their larger community influence. This study employs an agent-based model to simulate the formation of affiliation networks of churches and examine the impact of participants' preferences on the size of affiliation network as well as the importance indices of churches. It demonstrates that agent-based modeling is an efficient and productive approach in studying social networks and shed lights on the factors for the formulation of affiliation networks between churches.

In the ZIP Codes like 30318 that are challenged with STDs or HIVs, the affiliation network of churches might have practical meanings. On the one hand, the size of affiliation network of churches might implicate the potential of these affiliated churches in the prevention of diseases transmission. An affiliation network with large size (large quantity of connections) may imply the churches in this area are frequently visited by participants and the participants are willing to attend the activities from different churches. Under this condition, the churches may consider cooperation for providing meaningful and influential activities to the community. On the other hand, the importance indices of churches reveal the respective position of churches among the affiliation network. The churches with high scores of importance indices imply that these churches might serve a great number of participants, be visited frequently, or both. Therefore, the activities provided by these churches are most influential and beneficial to the community. This study investigates the potential factors to the affiliation network of churches, so as to provide usable information about how to achieve affiliation for churches and how to apply the affiliation network of churches for communities.

This study finds that the personal radii of participants are highly related to the affiliation networks of churches. Generally, an overall increase of personal radii is able to promote the affiliation network of churches to grow. As the personal radii of participants are diversified, the size of affiliation network tends to be large. In addition, the overall increase of personal radii could also lead to a general raise in importance indices of churches. Thus, as the general radii of participants' activity ranges in a community are large, it is most likely that the churches within this neighbor are affiliated to each other, and their underlying positions among the network are high. The results with personal radii implicate that the expanding the radii of participants' activity ranges could promote the churches to affiliate. Therefore, for a community with lower car ownership and limited mobility, increasing public transit access or providing services to where highly demands is may help to encourage participation to church activities.

This study also finds that participants' choice patterns might influence the size of affiliation network of churches as well as the importance indices of churches. As the participants tend to choose their favorite church, the resulting affiliation networks show little difference to the results under random choice. However, when participants tend to choose the closest church, the resulting affiliation networks of churches are largely reduced in size and the importance indices of churches decrease generally. This result could stem from the limited church choices for participants. When participants tend to choose the nearest church, those churches not close enough would have a very low chance to be selected. This low frequency of being selected leads to the reduction in the size of affiliation network and the importance indices of churches. As suggested by literature (Hu et al. 1991, Blank et al. 2002), the choice patterns among participants could vary. Therefore, conducting surveys may be a necessary mean for understanding the choice patterns of participants in the neighborhood.

This study finds that the population of neighborhood has relations to the affiliation network of churches. First, a greater population in an area could result in a larger size of affiliation network of churches and a higher value of the importance indices of churches. Second, the relative importance of churches is corresponding to the density of population. As clarified in section 4 of this study, the importance indices of churches are derived from the distance between churches and participants as well as the frequency of attendances. Therefore, the importance indices are relatively high for the churches located in the areas with high density of population, because the churches in these areas are relatively close to a large portion of participants and they may have a high frequency to be visited. This finding highlights the importance of churches in the neighborhoods with high population density when an affiliation network is formulated.

This study demonstrates that agent-based modeling is an efficient technique to study social networks by using agents to simulate social behaviors. Furthermore, agent-based modeling has greater potential to examine the effect of a factor on the social network by controlling other factors (Axelrod 1997, Macy and Willer 2002). The simulation in this research, coupled with empirical surveys on understanding how participants choose churches, gains insights into the affiliation networks formulated between churches. Findings can be used to leverage collaborations between churches within the same affiliation networks, so that programs in some churches could have broader influence on distant participants and benefit others churches and communities. Such collaborations will be a key for reaching out larger audiences with programs and forming greater cooperative networks for the good of those they serve.

The simulation of study subjects to several limitations. First, the change in participants’ need as well as the content of churches’ activities shall be considered in examining the formation of affiliation network. Participants’ need may change over time and thus affect their choice pattern. When the participants need food, for example, they might go to churches that provide food support, instead of those provided HIV education. As a result, the content of churches’ activities might be a potential factor that deserves further study. Second, this study did not consider the denomination of churches. The denomination of churches could be a significant factor affecting the affiliation relationship between churches. Besides, participants seldom go to churches with different religious beliefs or doctrines (Hu et al. 1991, Blank et al. 2002). This research assumed that the denomination of churches has little impact on the choice pattern of participants given that most churches in the study area are Christian. Yet more studies are necessary to evaluate the influence of diverse denominations on the affiliation networks of churches. Third, this research did not incorporate the real road network to the simulations, so the actual network distances between participants and churches may influence the affiliation as well. Future studies may incorporate the traffic network into the agent-based models as various travel means of the participants are involved. Fourth, this study did not consider the population of the adjacent census tracts of the study area, which then, might results in edge effects. It is possible that the actual affiliation network of churches in the study area is much denser than the results in this study, when the population of the adjacent census tracts is generally high. Finally, the agent-based model in this study lacks in cross-validation. Animation validation is the major validation method in this study. The formation of affiliation networks of churches in ZIP Code 30318 was presented graphically by the interface of Netlogo. However, the cross-examinations with other models designed for simulating the same problems (Martis 2006, Sargent 2007), or historical data (Balci and Sargent 1982, Sargent 2007) may help to further validate the model.

In summary, this study drew a conclusion that the formation of affiliation networks of churches was highly related to participants' activity ranges (personal radii), while the centralities of churches were affected by the personal radii, choice patterns, and population. Generally, an increase of the average of participants' personal radii would lead to an exaltation of the size of affiliation network of churches. Additionally, when the values of personal radii were diversified, the size of affiliation network of churches was relatively large, and vice versa. Besides, this study revealed that when participants prefer to choose the nearest church, the size of the affiliation network of churches would have a sharply decrease. Moreover, this study found that the centralities of churches among the affiliation network were highly related to the density of participants in census tracts. High density of participants promoted high centralities of churches. In future, effort could be made on collecting empirical data about experience of attending churches activities, and cross-validating with the results of this study.

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