Relationship between Single-family Residential Water Use and Its Determinants

A Spatio-Temporal Study of Phoenix, Arizona

by

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ABSTRACT

The dynamics of urban water use are characterized by spatial and temporal variability that is influenced by associated factors at different scales. Thus it is important to capture the relationship between urban water use and its determinants in a spatio-temporal framework in order to enhance understanding and management of urban water demand. This dissertation aims to contribute to understanding the spatio-temporal relationships between single-family residential (SFR) water use and its determinants in a desert city. The dissertation has three distinct papers to support this goal. In the first paper, I demonstrate that aggregated scale data can be reliably used to study the relationship between SFR water use and its determinants without leading to significant ecological fallacy. The usability of aggregated scale data facilitates scientific inquiry about SFR water use with more available aggregated scale data. The second paper advances understanding of the relationship between SFR water use and its associated factors by accounting for the spatial and temporal dependence in a panel data setting. The third paper of this dissertation studies the historical contingency, spatial heterogeneity, and spatial connectivity in the relationship of SFR water use and its determinants by comparing three different regression models.

This dissertation demonstrates the importance and necessity of incorporating spatio-temporal components, such as scale, dependence, and heterogeneity, into SFR water use research. Spatial statistical models should be used to understand the effects of associated factors on water use and test the effectiveness of certain management policies since spatial effects probably will significantly influence the estimates if only non-spatial statistical models are used. Urban water demand management should pay attention to the spatial

heterogeneity in predicting the future water demand to achieve more accurate estimates, and spatial statistical models provide a promising method to do this job.

Dedicated to my family,
for all their love and support

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TABLE OF CONTENTS

CHAPTER Page

CHAPTER Page

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

Chapter 1

INTRODUCTION

1.1 Problem Statement

Although urban water use represents a relatively small part of overall water withdrawal around the world, its great importance is highlighted by the fact that more than half of the global population lives in urban areas. Maintaining a sustainable water supply to meet different categories of urban water demand, including residential, commercial, industrial, and institutional, is key to achieving urban sustainability, especially in hot, dry cities (Gober, 2010). However, the sufficiency and quality of future urban water supply is still in question, largely due to urban population growth, economic development, and urban expansion in the face of climate change and variability under deep uncertainty (Milly et al., 2008; Gober and Kirkwood, 2010; Stakhiv, 2011). In the 20th century, the traditional approach to resolving water scarcity has been to seek and explore new water resources. Large water projects, such as the Central Arizona Project (CAP) that transfers water from the Colorado River into central and southern Arizona via a 336-miles long canal, have been developed in many places around the world. However, such supply side management has been called into question since limited freshwater resources have been extensively used globally. In such a context, water demand management has been increasingly recognized as an important way to maximize the benefits of urban water use while minimizing the demand for new water resource development (Gleick, 2000; Sharma and Variavamoorthy, 2009).

Urban water demand involves complex human-environment interactions, and thus is a typical representation of coupled human and natural systems (CHANS) (House-Peters and Chang, 2011). A better understanding of the dynamics of urban water demand necessitates capturing the complex interactions between urban water demand and associated socio-economic and environmental factors. Earlier studies are primarily focused on the economic aspect. Brookshire et al. (2002) reviewed previous studies that focused on impacts of water pricing on urban residential water demand, and recommended adding a scarcity value in the water price structure in order to improve the efficiency of water pricing. Arbués et al. (2003) also reviewed residential water demand studies that focused on water price, as well as relevant econometric models. They concluded that water price, income and household composition are the main determinants of residential water demand, and that residential water demand is generally found to be price inelastic. Worthington and Hoffman (2008) reviewed the estimation methods of econometric models as well as price elasticity and income elasticity in previous urban residential water demand studies. They also found that price elasticity and income elasticity are generally low.

There are also studies from other perspectives. Inman and Jeffrey (2006) reviewed five categories of tools of residential water conservation—financial, technological, educational, operation and maintenance, and legislative, and identified influences on their effectiveness and influences on the adoption of these tools. Corbella and Pujol (2009) reviewed main findings about the relationship of urban residential water use with population, territorial, social, and cultural factors. They concluded that these variables are important to be included in models, and help assess what determines the temporally and spatially uneven residential water use. Russell and Fielding (2010) reviewed psychological research on residential water management, and emphasized the practical importance of understanding the key psychological drivers of residential water conservation behaviors. House-Peters and Chang (2011) provided a review on advances in urban water demand modeling in terms of four themes of CHANS theory including scale, uncertainty, nonlinearity, and dynamic modeling.

The dynamics of urban water demand are characterized by spatial and temporal variability that is influenced by associated factors at different scales. Thus it is important to capture the relationship between urban water use and its determinants in a spatio-temporal framework if we are to enhance our understanding and management of urban water demand. A large number of previous studies have focused on the spatial and/or temporal patterns of urban water use since a seminal paper by Howe and Linaweaver published in 1967. Spatial scale in these studies ranges from household, census block, census block group, census tract, to city; and temporal scale ranges from Hourly, daily, weekly, monthly, seasonal, to annual (Table 1.1). These studies contribute to our understanding of urban water demand in general and provide insights into relevant management efforts.

Table 1.1 Common spatial and temporal scales found in urban water use research

Dimension of scale	Scale	Examples from the literature
Spatial scale	Household	Gibbs, 1978; Danielson, 1979; Jones and Morris, 1984; Agthe and Billings, 1987; Nieswiadomy and Molina, 1988; Nieswiadomy and Molina, 1989; Lyman, 1992; Hewitt and Hanemann, 1995; Dandy et al., 1997; Billings and Agthe, 1998; Renwick and Archibald, 1998; Pint, 1999; Gunatilake et al., 2001; Hajispyrou et al., 2002; Arbués et al., 2004; Mylopoulos et al., 2004; García-valiñas, 2005; Zhang and Brown, 2005; Arbués and Villanúa, 2006; Jansen and Schulz, 2006; Domene and Sauri, 2006; Haley et al., 2007; Kenney et al., 2008; Harlan et al., 2009; Arbués et al., 2010a; Rosenberg, 2010
	Census block	House-Peters et al., 2010
	Census block group	Chang et al., 2010; Breyer et al., 2012
	Census tract	Guhathakurta and Gober, 2007; Wentz and Gober, 2007; Balling et al., 2008; Balling and Cubaque, 2009; Guhathakurta and Gober, 2010; Lee et al., 2010; Polebitski and Palmer, 2010; Aggarwal et al., 2012

	Municipality	Wong, 1972; Young, 1973; Berry and Bonem, 1974; Billings and Agthe, 1980; Maidment and Parzen, 1984a; Maidment and Parzen, 1984b; Maidment and Miaou, 1985; Cochran and Cotton, 1985; William and Suh, 1986; Maidment and Miaou, 1986; Griffin and Chang, 1990; Miaou, 1990; Nieswiadomy, 1992; Homwongs et al., 1994; Hansen, 1996; Höglund, 1999; Malla and Gopalakrishnan, 1999; Nauges and Thomas, 2000; Zhou et al., 2000; Jain and Ormsbee, 2002; Joo et al., 2002; Martínez-Espiñeira, 2002; Garcia and Reynaud, 2004; Martínez-Espiñeira, 2003; Liu et al., 2003; Nauges and Thomas, 2003; Martínez-Espiñeira and Nauges, 2004; Bougadis et al., 2005; Gutzler and Nims, 2005; Hoffmann et al., 2006; Mazzantia and Montini, 2006; Balling and Gober, 2007; Gato et al., 2007; Martínez-Espiñeira, 2007; Martins and Fortunato, 2007; Musolesi and Nosvelli, 2007; Chu et al., 2009; Praskievicz and Chang, 2009; Schleich and Hillenbrand, 2009; Adamowski and Karapataki, 2010; Arbués et al., 2010b; Herrera et al., 2010; March and Sauri, 2010; Wong et al., 2010; Shandas and Parandvash, 2010; Zhang et al., 2010; Nasseri et al., 2011
	Utility/local water agency	Shvartser et al., 1993; Renwick and Green, 2000; Alvisi et al., 2007; Ghiassi et al., 2008; Dharmaratna and Harris, 2012
	Metropolitan area	Howe and Linaweaver, 1967; Smith, 1988; Kostas and Chrysostomos, 2006
	County	Hartley et al., 1994; Franczyk and Chang, 2008
	State	Gottlieb, 1963
	Region	Foster and Beattie, 1979
Temporal scale	Hourly	Homwongs et al., 1994; Alvisi et al., 2007; Ghiassi et al., 2008; Herrera et al., 2010
	Daily	Zhou et al., 2000; Jain and Ormsbee, 2002; Joo et al., 2002; Arbués et al., 2004; Arbués and Villanúa, 2006; Gato et al., 2007; Ghiassi et al., 2008; Wong et al., 2010; Arbués et al., 2010b
	Weekly	Bougadis et al., 2005; Ghiassi et al., 2008; Adamowski and Karapataki, 2010
	Monthly/bi-monthly/quarterly (seasonal)	Gibbs, 1978; Danielson, 1979; Billings and Agthe, 1980; Maidment and Parzen, 1984a; Maidment and Parzen, 1984b; Agthe and Billings, 1987; Nieswiadomy and Molina, 1988; Nieswiadomy and Molina, 1989; Griffin and Chang, 1990; Miaou, 1990; Lyman, 1992; Hewitt and Hanemann, 1995; Renwick and Archibald, 1998; Billings and Agthe, 1998; Malla and Gopalakrishnan, 1999; Pint, 1999; Renwick and Green, 2000; Gunatilake et al., 2001; Martínez-Espiñeira, 2002; Martínez-Espiñeira, 2003; Martínez-Espiñeira and Nauges, 2004; Mylopoulos et al., 2004; García-valiñas, 2005; Hoffmann et al., 2006; Jansen and Schulz, 2006; Haley et al., 2007; Martínez-Espiñeira, 2007; Martins and Fortunato, 2007

		uhathakurta and Gober, 2007; Ghiassi et al., 2008; Kenney et al., 2008; Balling et al., 2008; Balling and Cubaque, 2009; Praskievicz and Chang, 2009; Arbués et al., 2010a; Chang et al., 2010; Galán et al., 2009; Guhathakurta and Gober, 2010; House-Peters et al., 2010; Nasseri et al., 2011, Aggarwal et al., 2012; Dharmaratna and Harris, 2012
	Annual/biennial	Gottlieb, 1963; Howe and Linaweaver, 1967; Wong, 1972; Young, 1973; Berry and Bonem, 1974; Foster and Beattie, 1979; Jones and Morris, 1984; Cochran and Cotton, 1985; William and Suh, 1986; Nieswiadomy, 1992; Hartley et al., 1994; Hansen, 1996; Dandy et al., 1997; Höglund, 1999; Nauges and Thomas, 2000; Hajispyrou et al., 2002; Liu et al., 2003; Nauges and Thomas, 2003; Garcia and Reynaud, 2004; Gutzler and Nims, 2005; Zhang and Brown, 2005; Domene and Sauri, 2006; Kostas and Chrysostomos, 2006; Mazzantia and Montini, 2006; Wentz and Gober, 2007; Balling and Gober, 2007; Musolesi and Nosvelli, 2007; Franczyk and Chang, 2008; Lee and Wentz, 2008; Chu et al., 2009; Harlan et al., 2009; Schleich and Hillenbrand, 2009; Lee et al., 2010; Shandas and Parandvash, 2010; Zhang et al., 2010; Rosenberg, 2010; March and Sauri, 2010; Qi and Chang, 2011

Despite of the large body of literature on urban water use at different spatial and temporal scales, many issues still remain. This dissertation focuses on two of them. First, these studies generally focus on one single spatial and temporal scale. There is little knowledge of whether scale influences the relationship between urban water use and its associated factors. Second, these studies do not incorporate spatial and temporal dependence in the relationship between urban water use and its associated factors. The goal of this dissertation is to further our understanding of urban water use by exploring the scale effect and spatial-temporal dependence. Residential water demand is a top priority in urban water supply, and can be a large proportion of the total urban water demand although it varies from region to region. This dissertation is focused on single-family residential water use because it is often a great part of residential water demand in large metropolitan areas where the urban lifestyle is heavily oriented towards single-family homes.

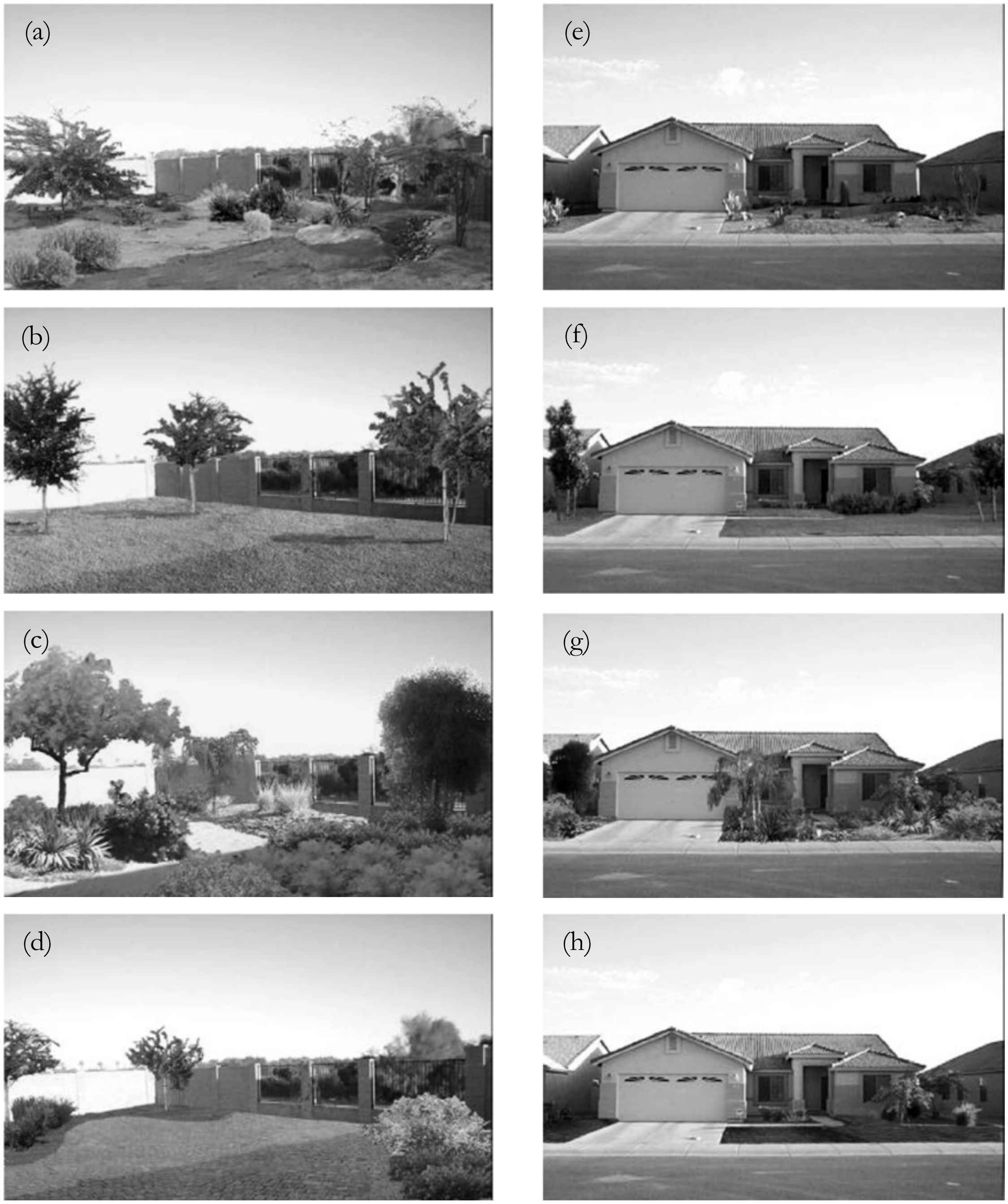

Figure 1.1 Common residential landscape typologies in Phoenix, Arizona: (a) backyard—desert; (b) backyard—lawn; (c) backyard—oasis; (d) backyard—courtyard; (e) front yard—desert; (f) front yard—lawn; (g) front yard—oasis; (h) front yard—courtyard (Larsen and Harlan, 2006)

1.2 Research context

To address the issues outlined above, this study focuses on the Phoenix metropolitan area centered on the city of Phoenix, the sixth most populous city in the United States. Over the last 100 years, this area has been developed from an agricultural center to a major urban area that is home to some 4 million residents. In particular, the city of Phoenix has a population of 1.4 million according to US Census 2010. The desert climate in this area results in an average annual precipitation of 8 inches (200 mm) and an annual average temperature of 73°F. Urbanization of this area led to significant urban heat island (UHI) effects. The summer nighttime temperature increased by about 10°F between 1948 and 2000 (Brazel et al., 2000). The implication of this climate on single-family residential water use is generally higher summertime water use for irrigation and pools.

A long-standing oasis life-style dominates this area as illustrated by the prevalent lush green landscapes (Figure 1.1) and backyard swimming pools. Single-family residential (SFR) water use almost accounts for half of the municipal water supply. After decades of demand side management efforts, SFR water use still maintains a high per-capita level despite of a 20% decrease in gallons per capita per day (gpcd) from 2000 (224 gpcd) to 2010 (177 gpcd) (City of Phoenix, 2011).

Water supplied for municipal use in the Phoenix area comes from three sources: local surface water from the Salt and Verde rivers, local groundwater, and water transferred from Colorado river via Central Arizona Project (CAP). To date, available surface water, local and transferred, has been almost fully allocated to various uses, and groundwater pumping is limited by the Groundwater Management Act of 1980 due to the overdraft problem. New single-family residential development, population growth, and climate uncertainty put a big question mark against the water sustainability as well as urban sustainability in this area. The importance of SFR water demand in municipal supply and the urgency of water management make this area a suitable platform for us to study the relationship of SFR water use and its determinants in a spatio-temporal framework. Although this dissertation focuses on the Phoenix metropolitan area, the implications of this research represent a much broader scientific context especially arid cities.

1.3 Organization of the Dissertation

The objectives of this dissertation are three-fold:

(1) To examine whether spatial scale may lead to ecological fallacy in the relationship between SFR water use and its determinants.

(2) To develop spatial panel data models for SFR water use research.

(3) To explore the historically contingent effects of associated factors on SFR water use as well as the spatial heterogeneity and spatial connectivity in these effects.

Chapter 2 addresses the first objective. Studies that evaluate determinants of residential water demand typically use data from a single spatial scale. Although household-scale data are preferred, especially when econometric models are used, researchers may be limited to aggregate data such as census tract and city levels. There is little, if any, empirical analysis to assess whether spatial scale may lead to ecological fallacy problems in residential water use research. Using linear mixed-effects models, I evaluate the results for the relationship of single-family water use with its determinants using data from household, census tract, and city/town scales.

Chapter 3 addresses the second objective. Panel data models used in SFR water use generally do not account for the spatial dependence that may cause biased estimates and thus can potentially lead to erroneous conclusions. The recently developed spatial panel data models not only can capture both the spatial and temporal variations of water use, but also can provide estimation of spatially interaction effects including both the spatial dependence of water use itself and the effects of associated factors on water use in neighboring spatial units. This chapter presents an empirical study that applies spatial panel data models to a dataset of single-family residential water use at the census tract scale in the city of Phoenix, AZ.

Chapter 4 addresses the third objective. Previous studies quantifying the spatial patterns do not consider how spatial dependence at one time manifest into future patterns of water use. The historical development of a city describes the current state of high water use rates in Phoenix. But there is lack of study that quantitatively examines the spatial effects of historical change in associated factors on current residential water use. This chapter presents a study in the city of Phoenix at the census tract scale that explores the historical contingency, spatial heterogeneity, and spatial connectivity in the relationship of SFR water use and its associated housing, household, and climate factors by using ordinary least squares (OLS) regression, spatial error model, and geographically weighted regression (GWR).

Chapter 5 is the conclusion. In this chapter, I summarize the major research finding, discuss contributions and limitations of this dissertation, and put forward directions for future research.

Chapter 2

A MULTI-SCALE ANALYSIS OF SINGLE-FAMILY RESIDENTIAL WATER USE IN THE PHOENIX METROPOLITAN AREA

This chapter is an article that has been accepted for publication in *Journal of the American Water Resources Association*, and the authors are Yun Ouyang, Elizabeth A. Wentz, Benjamin L. Ruddell, and Sharon L. Harlan.

2.1 Introduction

Single-family residential water use often accounts for the largest part of residential water demand in large metropolitan areas such as Phoenix, Arizona, where the urban lifestyle here is heavily oriented towards single-family homes (Balling et al. 2008; Wentz et al. 2013). To effectively manage residential water demand, it is imperative to understand what factors may influence individual household water use. However, single-family residential water use research is often limited to using aggregated water data due to, for example, confidentiality restrictions on household-scale data. Water use data that are accessible to researchers may be aggregated to areal units, such as census blocks, census block groups, census tracts, and cities. To match the water use data, similarly aggregated data for the factors considered to influence water use should also be used. This may lead to an ecological fallacy problem, which can occur when the statistical analysis and conclusions based on aggregated data are not applicable at the individual scale (Openshaw, 1984). Although many previous studies have used aggregated data to draw conclusions about single-family water use (Worthington and Hoffman 2008), there is little, if any, empirical analysis that assesses whether spatial scale may cause an ecological fallacy problem in residential water use research. The goal of this study is to address this issue by using the Phoenix area, Arizona as a case study.

The structure of this paper is as follows. In the next section, we provide a literature review on spatial scale in single-family residential water use research and introduce five groups of factors considered in this study. Then we present a case study of Phoenix, including data, models, results, and discussion. Finally we evaluate the limitations of our study and discuss future research priorities.

2.2 Literature Review

2.2.1 Scale Issues

Scale, either temporal or spatial, is an important issue for studies on urban water use as well as residential water use (House-Peters and Chang 2011). Although some variables, such as water price and climate factors, can reveal significant temporal trends with finer temporal scale data, we focus on spatial scale in this study. Although spatial scale may have different meanings in the literature (Ruddell and Wentz 2009), here we mean the spatial unit of observation rather than spatial extent. In single-family residential water use research, spatial scale can be defined at the individual household level or can be constructed following an administrative boundary or geographic area. Most studies on single-family residential water consumption consider one single spatial scale. Some typical spatial scales appearing in literature include household (Gibbs 1978; Jones and Morris 1984; Agthe and Billings 1987; Nieswiadomy and Molina 1989; Renwick and Archibald 1998; Arbués and Villanúa 2006; Harlan et al. 2009), census block (House-Peters et al. 2010), census block group (Chang et al. 2010; Turner and Ibes 2011), census tract (Guhathakurta and Gober 2007; Wentz and Gober 2007; Aggarwal et al. 2012), and city (Nieswiadomy 1992; Martinez-Espiñeira 2002). There are also some city-scale studies that include water use for other residential types, such as apartments, condominiums, and mobile homes, or the commercial, industrial, and public sectors. Examples of the former category are Billings and Agthe (1980), Höglund (1999), Nauges and Thomas (2003), Mazzanti and Montini (2006), Martins and Fortunato (2007), Musolesi and Nosvelli (2007), Schleich and Hillenbrand (2009), and March and Sauri (2010). Eexamples of aggregated urban water use research include Wong (1972), Young (1973), Berry and Bonem (1974), Cochran and Cotton (1985), Griffin and Chang (1990), and Praskievicz and Chang (2009).

Variability in household water consumption is due to different individual household water use behaviors and, in theory, estimation of residential water use using household-scale data is preferred over aggregated data, especially when econometric models are employed to relate water use with characteristics of households and properties, water price, weather, and other factors (Renzetti 2002; Arbués et al. 2003; Worthington and Hoffman 2008). This is because in the analysis of water demand decisions, household-scale data "better reflect the heterogeneity of references, avoid aggregation biases and produce robust estimation of parameters" (Arbués et al. 2010). However, as House-Peters and Chang (2011) point out, because household-scale data are randomly selected across the study area, models based on household-scale data fail to show the influence of neighborhood characteristics on water use. The inter-household interactions or social norms that influence individual water use behaviors (Edwards et al. 2005) cannot be directly captured by econometric models. In addition, in many cases, the unavailability of household-scale data, or the high costs of obtaining such data, often makes researchers fall back on aggregated data that overlook variations across households (Worthington and Hoffman 2008).

Aggregated scale research has its own unique advantages. First, we can include factors about urban form and spatial patterns of land use and land cover in the models, which are seldom considered in other studies (Stevens et al. 1992; March and Sauri 2010).

Second, when the spatial pattern of residential water use is the research focus, it is more effective to use aggregated data rather than a sample of water records from single-family homes. This is because all the aggregated scale spatial area can cover the study area in a seamless way, while a sample of water records probably cannot. Studies using aggregated data can also identify spatial dependence in residential water use patterns, which means that neighboring census blocks, census block groups, or census tracts may exhibit similar water use behaviors (Wentz and Gober 2007; Chang et al. 2010; House-Peters et al. 2010).

The choice of scale is closely related to two important but different methodological problems: one is the modifiable areal unit problem (MAUP), and the other is the uncertain geographic context problem (UGCoP). The MAUP problem has been extensively examined in geography literature (Dark and Bram, 2007). It arises from the different shapes or/and sizes of the areal units that may lead to different statistical results. Scale effect is one of the two important issues associated with MAUP, while the other is zonal effect (Openshaw and Taylor, 1979). The scale effect is attributed to the number of areal units used for aggregation, and the zonal effect is attributed to the manner in which areal units of the same number are aggregated. The UGCoP problem is relatively new, and it is considered in studies that examine the effects of factors measured at an aggregated scale on individual outcomes. The UGCoP "arises because of the spatial uncertainty in the actual areas that exert the contextual influences under study and the temporal uncertainty in the timing and duration in which individuals experienced these contextual influences" (Kwan, 2012).

Neither MAUP nor UGCoP has been considered in studying the relationship of water use and its determinants. In this study we partly address the MAUP by constructing panel data models for three different spatial scales and comparing their results. We do not consider the UGCoP, however, because in the household-scale model, we do not include any contextual factor at a higher scale. The UGCoP is a topic for future residential water use research because spatial dependence as well as temporal variability in water use patterns has been found in previous studies (Wentz and Gober 2007; Aggarwal et al. 2012) and thus contextual factors at aggregated scales could be included in household-scale studies.

2.2.2 Determinants of single-family residential water demand

A large number of studies have analyzed what factors determine residential water use. However, one seldom sees two studies that use the same set of factors, possibly because these studies have different objectives or the researchers are using such data as availability. Here we do not plan to present an exhaustive list of factors that have been examined in previous studies. We only review the five groups of factors we will use in the case study, including household characteristics, housing characteristics, climate factors, water price, and urban structure. There are other potentially important factors not included in our study, such as non-pricing policies and conservation programs (Kenney et al. 2008; Worthington and Hoffman 2008; Michelsen et al. 1999), behavioral characteristics (Fielding et al. 2012), technological characteristics of end uses as to water fixtures and appliances (Chu et al. 2009; Endter-Wada et al. 2008), and attitudinal factors (Syme et al. 2004; Wilis et al. 2011; Grafton et al. 2011). However, data on most of these factors will not be readily available to the typical water use modeler of a current U.S. city, so the omission is justified given our primary goal of examining the effects of scale on a typical water use modeling exercise.

Household characteristics include socio-economic and demographic attributes of households that may imply habits and tendencies of household members to use water facilities for different purposes. Three often-used variables are household income (Nieswiadomy and Molina 1989; Guhathakurta and Gober 2007; Schleich and Hillenbrand

2009), household size (Martinez-Espiñeira 2002; Domene and Sauri 2006; Arbués et al. 2010), and age distribution of household members (Nauges and Thomas 2000; Martínez-Espiñeira 2003; Schleich and Hillenbrand 2009). Income reflects the budgetary restriction of households. Residential water demand has been generally found to increase with income (Syme et al. 2004; Guhathakurta and Gober 2007; Schleich and Hillenbrand 2009), but income elasticity is almost unanimously found to be low (less than 1) (Wong 1972; Arbués et al. 2004; Harlan et al. 2009; Aggarwal et al. 2012). It is interesting that two effects of high-income households on water use offset each other: on the one hand, high-income households tend to use more efficient water-using appliances, and are likely to be highly educated so that they may be more environmentally sensitive; and on the other hand, high-income households use more water to support their relatively high living standards (Harlan et al. 2009). Property value can be used as a proxy for household income when relevant income data are not available (Nieswiadomy and Molina, 1988; Arbués et al. 2004). Household water demand also increases with household size since more people use more water. However, water use increases more slowly than household size due to economies of scale. Arbués et al. (2010) find that smaller households in Zaragoza, Spain are more sensitive to price changes.

In addition to household size, age distribution of residents also affects household water demand, since people of different ages tend to demonstrate different water-related behaviors at home. There are conflicting results about the effects of age distribution in previous studies. Some, such as Nauges and Thomas (2000), Martínez-Espiñeira (2003), Martins and Fortunato (2007), and Musolesi and Nosvelli (2007), find a negative relationship between per capita water use and the share of elderly people living in households, while other studies, such as Fox et al. (2009) and Schleich and Hillenbrand (2009) find that older people use more water. Households with children may have higher water demand since children are more likely to use lawns for play and recreation (Hurd 2006; Balling et al. 2008), although children may use less water than adults for washing and hygiene (Schleich and Hillenbrand 2009).

Housing characteristics are the physical features of properties that influence water use efficiency and water needs for the daily life of households, net of influences of household characteristics. Many different housing features have been used, such as type of dwelling (Mylopoulos, Mentes et al. 2004; Domene and Sauri 2006; Hoffmann, Worthington et al. 2006), age of dwelling (Howe and Linaweaver 1967; Nieswiadomy and Molina 1988; Nauges and Thomas 2003; Harlan et al. 2009; Chang et al. 2010), indoor and outdoor water facilities (Renwick and Archibald 1998; Arbués et al. 2004; Endter-Wada et al. 2008; Harlan et al. 2009), number of bedrooms (Kenney et al. 2008; Fox et al. 2009; Chang et al. 2010), lot size (Pint 1999; Renwick and Green 2000; Wentz and Gober 2007), dwelling size (Nieswiadomy and Molina 1989; Domene and Sauri 2006; House-Peters et al. 2010), yard size (Nieswiadomy and Molina 1989; Lyman 1992; House-Peters et al. 2010), landscaping type (Wentz and Gober 2007; Balling et al. 2008; Harlan et al. 2009), presence of pool or pool size (Agthe and Billings 1987; Guhathakurta and Gober 2007; Harlan et al. 2009), and property value (Howe and Linaweaver 1967; Danielson 1979; Arbués et al. 2004). Dwellings can be classified as rented or owned. Hoffmann et al. (2006) find that residents of owner-occupied dwellings have higher price and income elasticity of water demand than those living in rented dwellings. Age of the dwelling matters mainly because more recently built homes have more efficient water fixtures in order to comply with increasingly strict standards (Harlan et al. 2009). Water fixtures with advanced technology improve water efficiency. Variables that measure physical size, such as number of bedrooms, lot size, dwelling size, yard size, and pool size, are generally positively related to residential water use.

Residential water use is impacted by short-term weather change and climate variability, but the impact of long-term climate change is seldom considered. Three climate factors generally considered are precipitation (Howe and Linaweaver 1967; Kenney et al. 2008; Harlan et al. 2009), temperature (Danielson 1979; Guhathakurta and Gober 2007; Arbués et al. 2010), and evapotranspiration (Howe and Linaweaver 1967; Billings and Agthe 1980; Farag et al. 2011). Precipitation has a direct effect on outdoor water use such as irrigation. Temperature significantly influences both indoor and outdoor water use. On hot days, for example, irrigation, swimming pools, and personal hygiene typically require more water (Hoffmann et al. 2006). Temperature variables have been used in many ways in previous studies, and they include maximum temperature (Martínez-Espiñeira 2007), minimum temperature (Praskievicz and Chang 2009), average temperature (Nieswiadomy 1992), and temperature difference (Guhathakurta and Gober 2010). Evapotranspiration, which includes both evaporation and plant transpiration, is an indicator of environmental water demand. Evapotranspiration increases with higher temperatures, which may lead to more outdoor water use for, e.g., irrigation and swimming pools. Residential (and urban) water use exhibits seasonal change, but the relationship of climate factors and water use may not be linear. Using the concept of partitioning the daily urban water use into base use (weather insensitive) and seasonal use (weather sensitive) from Maidment et al. (1985), Gato et al. (2007) identify the temperature threshold, below which temperature would not influence daily urban water use, and the rainfall threshold, above which more rainfall would not reduce water use, in East Doncaster, Victoria, Australia.

Pricing has been a key component of demand side water management with an essential logic that higher water prices lead to lower water demand, but the price elasticity of residential water demand has been found to be generally low (Arbués et al. 2003). Four water price structures have been investigated in the literature: uniform marginal price (Olmstead et al. 2007), increasing block (Martínez-Espiñeira 2003), decreasing block (Nieswiadomy and Molina 1989), and flat rate (Howe and Linaweaver 1967). In a uniform marginal price structure, a household's water bill is based on a single marginal price; in an increasing block rate (IBR) structure, marginal price increases with water use; in a decreasing block rate structure, marginal price decreases with water use; and a flat rate structure has a fixed fee regardless of the amount of water use. A pressure or potential of water scarcity usually leads to the adoption of an IBR structure based on a notion that water users respond to marginal price. However, such a notion is relatively simplistic. Water users, especially households, often do not have a clear understanding of the rate structure. Moreover, they rarely know their real-time water use (Foster and Beattie 1979; Carter and Milon 2005; Kenney et al. 2008). Although economists generally accept that pricing is a way of reducing water demand, previous empirical studies have demonstrated that water demand is price inelastic and therefore has limited effects on regulating water use (Arbués et al. 2003). In addition to conservation, water utilities are often more concerned with two other objectives: (1) to generate revenues to recover costs, and (2) to achieve equity among customers in terms of affordability (Griffin 2001).

Due to the different price structures, economic studies linking water demand and price have used different specifications of water price. Two notable definitions are average price and marginal price. In a uniform marginal price structure, average price and marginal price have the same value, while in an increasing or decreasing block rate structure, the marginal price varies with the amount of water used. Economists Howe and Linaweaver (1967) argue that marginal price rather than average price should be used to explain water use. Previous empirical results show that price elasticity tends to be overestimated using average price instead of marginal price (Gibbs 1978; Dalhuisen et al. 2003; Schleich and Hillenbrand 2009). The use of marginal price is based on a notion that water users are perfectly informed of the price information. However, most water users do not devote much effort to understanding the pricing, especially when the pricing structure is complex (Arbués and Villanúa 2006). A second problem with the use of marginal price is the endogeneity caused by a loop causality between water use and marginal price: marginal price influences and is influenced by water use. Another problem is that the same marginal price may be associated with different water use when the sample includes households from communities with different water price structures. To reflect the pricing structure that a water user faces, a variable has been introduced by Nordin (1976) to account for the difference between a household's water bill and what it would have been if charged at the marginal price. This variable is used together with marginal price (Billings and Agthe 1980; Hewitt and Hanemann 1995; Martínez-Espiñeira 2003; Arbués et al. 2004). Despite the intuitive appeal of the difference variable, Renzetti (2002) finds that the effects of including it have been mixed at best.

The urban structure factors associated with water use are rarely examined. In fact when aggregated scales are studied, the average statistics of housing characteristics can also be considered as urban structure factors, but here we still have housing characteristics at aggregated scales as a separate group. In a study in Portland, Oregon, Chang et al. (2010) use building density as an urban structure factor, and find that single-family homes in census block groups with higher building density tend to use less water on average, but there is a threshold above which the effect of building density appears to be more moderate. Houses with larger lot sizes in the affluent neighborhoods typically use more water for yard irrigation. Houses with smaller lot sizes in areas of higher density do not have lawns, and thus further increasing building density does not significantly reduces water consumption.

2.3 Study Area: Phoenix, Arizona

Our case study focuses on the Phoenix metropolitan area, which is centered on the city of Phoenix, the capital of Arizona and the sixth most populous city in the United States. The modern development of this area in central Arizona during the late nineteenth and twentieth centuries was based on irrigated agriculture. The Salt River Project, which uses local surface water from the Salt River and the Verde River and local groundwater, and the Central Arizona Project, which transfers water from the Colorado River to central Arizona via a 336-mile long aqueduct, were developed to provide water for agriculture in central Arizona. With population growth and urbanization, municipal water use has increased significantly while water used for irrigated agriculture has simultaneously decreased. Going forward, there are few options for provisioning municipalities with more water because available surface water sources have been almost fully allocated to different uses and groundwater pumping is limited by the Groundwater Management Act of 1980. Prior preservation of water rights by other users, for example, agriculture and Native American tribal communities, makes it highly costly to seek new water resources for municipal use. Currently, two-thirds of municipal water use in the city of Phoenix is residential, and single-family houses account for about 75% of residential use. The economic development of Phoenix has depended upon the availability of water and especially marketing its image as an oasis (Hirt et al. 2008). Water-intensive residential lifestyles in this area are illustrated by the prevalent lush green landscapes and swimming pools in many residential backyards in middle- and upper-income neighborhoods.

In recent years, single-family residential water use in Phoenix, AZ has received more attention as shown by a growing number of journal articles on this topic. A large number of these publications are on the relationship between residential water use and climate factors. Balling and his colleagues published three papers that examine the relationship of residential water use and climate variability in Phoenix. Balling and Gober (2007) find that at the city scale, climate factors, such as temperature, precipitation, and drought conditions, all have impact on residential water use, but annual water use responds to climate variability relatively slowly in Phoenix where a sizable majority of residential water use is for outdoor purposes. In a census tract scale study, Balling et al. (2008) find that the census tracts with larges lots, more pools, higher proportions of mesic landscaping, and higher proportions of high-income residents are more sensitive to year-to-year climate variability, whereas census tracts with larger families and more Hispanics have lower climatic sensitivity. Downscaling the climate scenarios from the IPCC model results, Balling and Cubaque (2009) estimate that mean residential water use in Phoenix will increase by an average of 3% by 2050 due to climate change, but the change in residential water use varies across census tracts significantly. The rapid urbanization in Phoenix has resulted in substantial urban heat island effects (urban area is warmer than the surrounding rural areas during nighttime). Several articles address the effect of urban heat island on residential water use in Phoenix. Guhathakurta and Gober (2007) identify a significant and positive effect of daily temperature on monthly water use of a typical single-family household in Phoenix. Using a different modeling approach, Guhathakurta and Gober (2010) confirm the urban heat island effect on residential water use in Phoenix, but also find that impervious surface and larger lots with pools and mesic landscaping increase residential water use. A further study by Aggarwal et al. (2012) shows that the effect of nighttime temperature on water use varies significantly with lot size and pool size.

There are also some other interesting findings. Wentz and Gober (2007) use a geographically weighted regression model and census tract scale data, and find that there exists spatial dependence in the relationship of water use and its determinants in Phoenix. Harlan et al. (2009) use a panel data model and household-scale data, and find that household income, irrigable lot size, and landscape type has significant effects on residential water use, but attitudes towards community and the environment do not. Turner and Ibes (2012) find no significant correlation between residential water use and present or absence of homeowner associations at the census block group scale. Two other studies are also noteworthy. In a census block group level study, Breyer et al. (2012) compare Phoenix and Portland, and find that temperature sensitivity of single-family residential water use decreases with tree canopy coverage in Phoenix, while the opposite relationship holds in Portland. Vegetation patterns explain the most variation in temperature sensitivity in Phoenix. Gober et al. (2013) use a survey dataset from Phoenix and Portland, and show that although both water managers and land planners are aware of importance of each other's issues, the two groups have different priorities in their work and there is little cross-sector involvement. These studies provide important insights for our variable selection in this study, although the purpose of our study is on the scale issues as we discussed above.

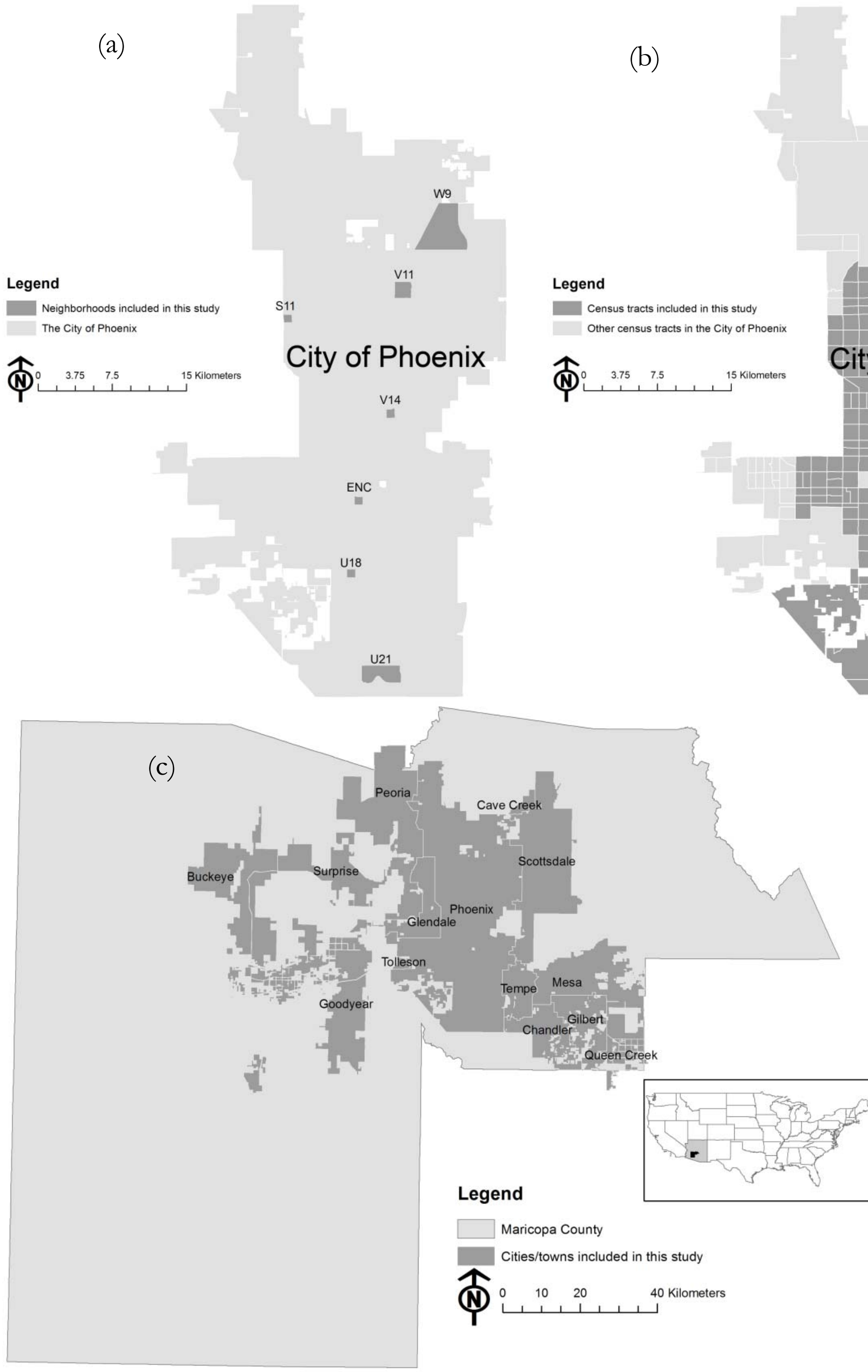

Figure 2.1 Study area: (a) 7 neighborhoods from which 207 households were selected for the household scale study; (b) 252 census tracts were selected for the census tract scale study; (c) 10 cities (Chandler, Glendale, Goodyear, Mesa, Peoria, Phoenix, Scottsdale, Surprise, Tempe, and Tolleson) and 4 towns (Buckeye, Cave Creek, Gilbert, and Queen Creek) in Maricopa County, Arizona were selected for the city/town scale study.

Table 2.1 Definition of variables used for three different spatial scales and their data sources

Variable	Household scale		Census tract scale		City/town scale		Unit
	Definition	Data source	Definition	Data source	Definition	Data source	
W	Household monthly water use	City of Phoenix	Average household monthly water use	City of Phoenix	Average household monthly water use	Arizona Department of Water Resources	gallon
Household characteristics							
HHS	Household size	Phoenix Area Social Survey	Average household size	US Census 2000	Average household size	US Census 2000	person
HHI	Annual household income	Phoenix Area Social Survey	Median annual household income	US Census 2000	Median annual household income	US Census 2000	$
RA	Respondent age	Phoenix Area Social Survey					year
MA			Median Age	US Census 2000	Median Age	US Census 2000	year
Housing characteristics							
HA	House age in 2001	Maricopa County Assessor Database	Average house age in 2001	Maricopa County Assessor Database	Average house age in 2001	Maricopa County Assessor Database	year
PS	Pool size	Maricopa County Assessor Database	Average pool size	Maricopa County Assessor Database	Average pool size	Maricopa County Assessor Database	m^2
LA	Livable area	Maricopa County Assessor Database	Average livable area	Maricopa County Assessor Database	Average livable area	Maricopa County Assessor Database	m^2
ILS	Irrigable lot size	Maricopa County Assessor Database	Average irrigable lot size	Maricopa County Assessor Database	Average irrigable lot size	Maricopa County Assessor Database	m^2
FYD	Indicator variable, equal to 1 when front yard is desert	Phoenix Area Social Survey					0-1
FYML	Indicator variable, equal to 1 when front yard is mostly lawn	Phoenix Area Social Survey					0-1
FYSL	Indicator variable, equal to 1 when front yard has some lawn	Phoenix Area Social Survey					0-1

FYP	Indicator variable, equal to 1 when front yard is patio	Phoenix Area Social Survey					0-1
BYD	Indicator variable, equal to 1 when backyard is desert	Phoenix Area Social Survey					0-1
BYML	Indicator variable, equal to 1 when backyard is mostly lawn	Phoenix Area Social Survey					0-1
BYSL	Indicator variable, equal to 1 when backyard has some lawn	Phoenix Area Social Survey					0-1
BYP	Indicator variable, equal to 1 when backyard is patio	Phoenix Area Social Survey					0-1
Climate factors							
R	Monthly precipitation	AZMET, MCFCD	Average monthly precipitation	AZMET, NOAA, MCFCD	Average monthly precipitation	AZMET, NOAA, MCFCD	inch
R*R	Square of monthly precipitation	AZMET, MCFCD	Square of average monthly precipitation	AZMET, NOAA, MCFCD	Square of average monthly precipitation	AZMET, NOAA, MCFCD	$(\text{inch})^2$
TEMP	Monthly average maximum temperature	AZMET, MCFCD, PRISMS	Mean monthly average maximum temperature	AZMET, NOAA, MCFCD, PRISMS	Mean monthly average maximum temperature	AZMET, NOAA, MCFCD, PRISMS	Fahrenheit
Water price							
MP					Marginal water price corresponding to average household monthly water use for each city and town	14 cities and towns	$/1000 gallons
Urban structure							
BD			Single-family house density	Maricopa County Assessor Database	Single-family house density	Maricopa County Assessor Database	house unit/km^2
%MR			Percentage of mesic residential area	CAP LTER, SRP			percentage
Other							
S	Indicator variable, equal to 1 if the month is June, July, August, or September		Indicator variable, equal to 1 if the month is June, July, August, or September		Indicator variable, equal to 1 if the month is June, July, August, or September		0-1
T	Time trend		Time trend		Time trend		month

2.4 Data

Three panel datasets with different spatial scales are used in this study (Figure 2.1). On the household scale, we use a sample of 207 single-family homes in seven neighborhoods (defined by census block group boundaries) in the city of Phoenix. A resident in each of these households responded to the Phoenix Area Social Survey (PASS) conducted in 2001 and 2002 (Harlan et al. 2003). In total there were 302 survey respondents including residents who lived in apartments and other multi-family dwelling. Only 207 single-family homes can be matched to metered water data used in this study, so this is the number of households modeled at this scale. The neighborhoods were chosen to represent diverse locations, housing ages, and household incomes. On the census tract scale, we have a sample of 252 (out of 303) census tracts in the City of Phoenix (excluding those with fewer than 50 household water use records and those without other relevant data to match). On the city/town scale, we include 10 cities (Chandler, Glendale, Goodyear, Mesa, Peoria, Phoenix, Scottsdale, Surprise, Tempe, and Tolleson) and 4 towns (Buckeye, Cave Creek, Gilbert, and Queen Creek) in the Phoenix metropolitan area. Public water companies supply these cities and towns with municipal water, with the exception of a small part of Buckeye. We exclude the residences that are supplied by private wells and private water companies and only consider those supplied by public water companies.

For all three spatial scales, we have monthly records of single-family residential water use in 2001 and 2002. Water use records on the household and census tract scales are from the Water Services Department, City of Phoenix, and water use data on the city/town scale are extracted from the imaged records of the Arizona Department of Water Resources' Schedule F. Measurement error on the household scale was introduced by differing dates of meter reading, which resulted in a household billing cycle that differs from a calendar month.

In addition, at the household scale, some irregular zero household water use records (possibly because the houses are not occupied in these months) are removed, and therefore the household-scale data are unbalanced with missing data for some households in certain months (99.5% of monthly water records have non-zero values).

In this study, we consider five categories of factors that may influence single-family residential water use: (1) household characteristics, which represent the socio-economic and demographic attributes of the households; (2) housing characteristics, which are features of the housing units; (3) climate; (4) water price; and (5) urban structure. Urban structure is only included for the aggregated scales, i.e. census tract and city/town. Data on these factors were obtained to match the monthly water use records of the 24 months in 2001 and 2002. It should be noted that, even in the same category, the data of some factors are not available for all three scales. Variable definitions and data source information are provided in Table 2.1.

For the household-scale analysis, household characteristics are obtained from the PASS database, including household size, annual household income, and respondent's age. For the census tract and city/town scales, household characteristics data are acquired from the US Census 2000 database, including average household size, median annual household income, and median age per census tract or per city/town.

Data on four factors of housing characteristics are acquired from the Maricopa County Assessor database for three spatial scales, including house age, livable area, pool size, and irrigable lot size. The calculation of irrigable lot size follows Harlan et al. (2009):

$$ILS = LS - \frac{LA}{S} - PS \tag{2.1}$$

where *ILS* is the irrigable lot size; *LS* is the lot size; *LA* is the livable area; *S* is the number of stories; and *PS* is the pool size. On the aggregated scales, we use the average values for all the single-family houses in a census tract or city/town. We also consider the effect of landscaping types on water use, although we use different measures at the household and census tract scales due to data availability. On the household scale, we use the data of front yard and back yard landscaping types collected in PASS. PASS recorded five differing types of landscaping: (1) mostly lawn; (2) some lawn and plants with some crushed stone; (3) no lawn with only desert plants and crushed stone; (4) courtyard, predominantly patios; and (5) no landscaping. On the census tract scale, we extract the data of percentage of mesic residential area from a land use and land cover database classified from a 2000 ASTER image using an expert system approach (Stefanov et al. 2001). Similar to the method of Wentz and Gober (2007), we remove the residences that used flood irrigation water from the Salt River Project (SRP) for irrigation because such water was not supplied by the city of Phoenix and therefore not recorded in the monthly water bills. Therefore, the calculation of the percentage of mesic residential area for each census tract is based on the following formula:

$$\%MR = \frac{AREA_{MR} - AREA_{SRP}}{AREA_{MR} + AREA_{XR}} \cdot 100 \tag{2.2}$$

where $\%MR$ is the percentage of mesic residential area; $AREA_{MR}$ is the area classified as mesic residential; $AREA_{SRP}$ is the mesic residential area that uses flood water from SRP; and $AREA_{XR}$ is the area classified as xeric residential. Unfortunately, the land use and land cover image does not cover all the 14 cities and towns, and we do not have data on landscaping types for the city/town scale. The adoption of water fixtures and appliances may also influence water use because of different water efficiency, but we do not have such data in this study.

Climate factors include monthly precipitation and monthly average maximum temperature. We tried to acquire relevant data from as many weather stations as possible to cover our study area. Some of them regularly record both precipitation and temperature, but others only have reliable precipitation or temperature data. We obtained the precipitation data from 142 weather stations operated by 3 networks—Arizona Meteorological Network (AZMET), National Oceanic and Atmospheric Administration (NOAA), and Maricopa County Flood Control District (MCFCD). The near surface (2 m) temperature data from 39 weather stations operated by AZMET, NOAA, MCFCD, and Phoenix Real-time Instrumentation for Surface Meteorological Studies (PRISMS) are used to represent temperature. On the household scale, we use the data observed by the closest weather station located in the area of the same land use type to represent the precipitation and temperature of each neighborhood. On the two aggregated scales, we adopt a different strategy. After extracting the monthly precipitation and monthly average daily maximum temperature data of these point observations, we use ArcGIS 10 software to map them and implement interpolation by using the ordinary kriging method for each month of 2001 and 2002. Then the interpolation images are joined to the census tract and city/town boundaries, and average values are calculated for each census tract and each city/town.

Although previous studies such as Stevens et al. (1992) and March and Sauri (2010) use population density as a proxy for urban structure, here we use single-family house density to represent urban structure on the aggregated scales because of our focus on single-family residential water use. The house density only takes into account those single-family houses served by public water companies, and is calculated by dividing the number of these single-family houses in each census tract (city/town) by the area of the census tract (city/town).

The 14 cities and towns provided water rate and sewer rate schedules for 2001 and 2002. Typically the sewer charge was combined with the potable water charge in the same monthly bills. However, sewer charge calculation in some cities, e.g. Phoenix and Mesa, was not based on water use of the same month as water charge calculation, but in terms of the average monthly water use in certain months of the previous year. This causes difficulty in reconstructing the sewer prices. Therefore, we only consider water charges excluding sewer charges. As we said above, there exists an ongoing debate on whether marginal price or average price should be used as the correct specification of water price (Renzetti 2002). In this study, we use the marginal price of average household water use as the water price factor on the city/town scale.

2.5 Statistical Models

We use a linear mixed-effects model for panel data (i.e. longitudinal data) (Frees 2004) to study how the factors influence single-family residential water use on the three spatial scales. A linear mixed-effects model has an advantage over a pooled cross-sectional ordinary linear regression model because the former includes a subject-specific random variable as the intercept for controlling the heterogeneity of individuals. It also has an advantage over a fixed-effects model because it can include time-constant variables for which coefficients are inestimable in a fixed-effects model. The linear mixed-effects model is also known as the error-components model or random-intercepts model. Mixed-effects models have been used in residential water demand studies such as Höglund (1999), Martinez-Espiñeira (2002), Martins and Fortunato (2007), Kenney et al. (2008), and Harlan et al. (2009). The panel data models that have been used in residential water use research as well as the model we use in this study do not consider spatial autocorrelation that would potentially cause bias in coefficient estimates or standard errors. It is relatively easier to consider spatial autocorrelation in cross-sectional regression models, but relatively complex in using panel data models. Recent development on spatial panel data models (Anselin et al. 2008; Elhorst 2010) provides possible methodological options for future research in residential water use. The reason we do not use the spatial panel data model is that our focus is not to develop a better model, but to compare how the same variables at different spatial scales predict water use.

The general equation of a linear mixed-effects model is:

$$Y_{it} = \beta_0 + \beta_1 X_{it,1} + \cdots + \beta_m X_{it,m} + \beta_{m+1} X_{i,1} + \cdots + \beta_{m+n} X_{i,n} + \mu_i + \varepsilon_{it} \qquad (2.3)$$

where i is the index to identify each subject, or unit of observation; t is the time period; Y_{it} is the response of the i-th subject in the t-th time period; $X_{it,1},\ldots, X_{it,m}$ are a set of time-related explanatory variables; $X_{i,1},\ldots, X_{i,n}$ are a set of time-constant explanatory variables; β_0, $\beta_1,\ldots,$ β_{m+n} are parameters that represent the fixed effects of the explanatory variables on Y_{it}; $\mu_i \sim N(0,\ \sigma_\mu^2)$ is a subject specific portion of the error term that represents unobserved time-constant random effects on Y_{it}; $\varepsilon_{it} \sim N(0,\ \sigma^2)$ is the other portion of the error term to represent the remaining non-explained variation of Y_{it} that is both subject specific and time-related.

The MIXED procedure in SAS 9.2 provides three methods for parameter estimation of this model—maximum likelihood estimation (ML), residual maximum likelihood estimation (REML), and minimum variance quadratic unbiased estimation (MIVQUE0) (SAS Institute Inc., 2009). We run our models by using all the three estimation methods.

Since their results are very close to one another in our study, we only present the results of ML estimation.

The mixed-effects model is applied to all three spatial scales. We use the natural logarithm of monthly water use as the dependent variable. On the household scale, the explanatory variables include household size (HHS), natural logarithm of annual household income (*ln*HHI), respondent age (RA), house age in 2001 (HA), pool size (PS), irrigable lot size (ILS), monthly precipitation (R), (monthly precipitation)^2 (R*R), monthly average maximum temperature (TEMP), summer (S), and time trend (T). Variables that are only for the household scale include respondent age (RA) and eight dummy variables of which four are for five front yard landscaping types and the other four represent five back yard landscaping types: front yard most lawn (FYML), front yard some lawn (FYSL), front yard desert (FYD), front yard patio (FYP), back yard most lawn (BYML), back yard some lawn (BYSL), back yard desert (BYD), and back yard patio (BYP). The use of logarithmic form for both water use and household income is essential to meet the assumption that the households have a constant income elasticity, which is the parameter of *ln*HHI (Nieswiadomy 1992). We do not include the marginal price in the household-scale model. The vast majority of households in our sample on the household scale use water over the base volume included in the monthly basic charge, and in the city of Phoenix, there was only one constant marginal price for any single-family residential water use over base volume in each month. Therefore, the inclusion of marginal price does not explain cross-sectional variability. On the other hand, there were seasonal changes of water price—the lowest prices in the winters, higher prices in the springs and falls, and the highest prices in the summers. Hence marginal price is significantly and highly correlated with TEMP. Livable area is also not used in the household-scale model because it is significantly and highly correlated with *ln*HHI, and inclusion of livable area would cause significant multi-collinearity.

On the census tract scale, the explanatory variables include average household size (HHS), natural logarithm of median annual household income (*ln*HHI), median age (MA), average house age in 2001 (HA), average pool size (PS), average irrigable lot size (ILS), monthly precipitation (R), (monthly precipitation)^2 (R*R), monthly average maximum temperature (TEMP), building density (BD), percent of mesic residential area (%MR), summer (S), and time trend (T). Although it is arguable that average or median values of some variables on the aggregated scales may have different meanings from these variables on the household scale, we contend they consistently represent the same types of influences on single-family residential water use. Therefore, we use the same acronyms for both household and the other two aggregated scales. Since the water rate schedules are the same in these census tracts (all of them are in the city of Phoenix), we do not use marginal price in the census tract model (for the same reason it is not used for the household scale). All the factors used for the census tract scale are included for the city scale except %MR. An additional variable in the city/town model is the logarithm of marginal price (*ln*MP), which corresponds to the average single-family household water use of a city/town. As in the household-scale model, we do not include livable area in the census tract scale and city/town scale models because of significant multi-collinearity problems.

2.6 Results and Discussion

2.6.1 Models with common variables

Since some variables only have data for one spatial scale, to compare the model results of the household and census tract scales, both sampled from the city of Phoenix, we first examine the results of models with only variables they have in common as shown in Table 2.2. Based on the significance test and the signs of parameter estimates, the household and census tract scale models produce similar results. The coefficients of common variables are all statistically significant at the 0.05 level. The coefficients of the same variable have the same sign, which indicates that the coefficients of common variables in the household-scale and census tract scale models reflect the same direction in influences of these factors on single-family residential water use. For each of the common variables except pool size and time trend, the 95% confidence intervals of the coefficients on these two spatial scales intersect. Although there is some scalar difference in the coefficients of these common variables, we recognize that the meanings of the "same" variable on the two scales are not exactly the same due to the logarithmic form of water use and HHI and the adoption of median or average values on the census tract scale. It should also be noted that the spatial effects on water use cannot be captured in the mixed-effects models. On the household scale, spatial effects may include inter-household relationships. For example, the change of water use behaviors and the adoption of new technologies and methods do not only depend on personal interest but also are influenced by social pressures, especially from neighboring households (Edwards et al. 2005). Wentz and Gober (2007) also find spatial effects on the census tract scale—neighboring census tracts exhibit similar water use behaviors.

The results on the household and census tract scales show, as expected, that household size has a positive effect on water use (Table 2.2). It is not surprising since more people in the same household use more water, and it is consistent with previous studies such as Gibbs (1978), Agthe and Billings (1987), Renwick and Archibald (1998), and Arbués and Villanúa (2006). Household income also has a positive effect on water use, which is consistent with the finding of Harlan et al. (2009) and other studies (Gibbs 1978;

Nieswiadomy and Molina 1989; Renwick and Archibald 1998). Harlan et al. (2009) point out that the positive effect of household income on water consumption may mean that large house sizes and numbers of water use facilities and water-intensive activities in more affluent households outweigh the water-saving effects of adopting new technologies of higher water efficiency in those households. Since household income is also highly correlated with livable area and livable area is not included in the model, we expect livable area should also have a positive effect on water use. House age positively influences water use because the building regulations mandate newer houses to use more efficient water fixtures. The positive coefficients of pool size and irrigable lot size reflect their influence on increasing outdoor water use.

The negative coefficient of monthly precipitation and the positive coefficient of squared monthly precipitation indicate that there is a threshold beyond which more precipitation does not further decrease but starts to increase household water use. Rainwater can be used for irrigation, but when the irrigation need is met, more rain may result in more indoor water use for activities such as personal hygiene and washing. The use of panel data models has an advantage over time series and cross-sectional models in capturing the spatial and seasonal variability of rainfall in Phoenix. There are two distinct rainfall seasons in Phoenix, one in winter and the other in summer, and the spring and fall months are generally dry. Even in winter, there can be a month or more with no precipitation. During the monsoon season (usually July and August, but it can start in June and end in late September), Phoenix is subject to thunderstorms with heavy downpours. The nonlinear relationship of precipitation and water use has also been found by Gato et al. (2007) although they use a different model and consider the daily temporal scale. Temperature has a positive impact on water use because higher temperature leads to more water for irrigation and pool use, and also more indoor activities and washing take place when temperatures are higher. From the standardized estimates of R, R*R, and TEMP, we find that climate factors have stronger influences on single-family residential water use on the census tract scale than on the household scale. It might be because the household-scale data are sampled only in a limited number (seven) of neighborhoods, and the climate factors exhibits similar patterns in the same neighborhood. Thus the data on climate factors do not show so much variation at the household scale as they do on the census tract scale in explaining the residential water use. Although temperature is typically higher in summer than in other seasons, we still include the binary variable of summer because it does not cause a significant multi-collinearity problem. The positive effect of summer reflects more water-use activities in the summer. The positive coefficient of the time trend indicates that there is an increasing trend of single family water use over time, after controlling for all other factors. Since our dataset only includes water records of twenty-four months, we cannot make an inference about the long-term trend. It deserves further study in the future with data that cover a longer time period (such as ten years).

The model results on the city/town scale are different from those on the other two scales (Table 2.2). Of all the common variables, only household size, pool size, temperature, and time trend have statistically significant coefficients. Although the coefficient of each of these four significant variables on the city/town scale has the same sign (all positive) as those on the other two scales, their confidence intervals of household size or pool size do not intersect. Household size and temperature seem to have greater positive influences on SFR water use on the city/town scale than on the other two finer scales. The spatial extent of the city/town scale is much larger than those of the other two scales that are only in the city of Phoenix. Since a mixed-effect model assumes constant parameters for the factors that influence water use, the big difference on the city/town scale should be due to spatial heterogeneity in the relationship of water use with its determinants in the different cities and towns in Phoenix metropolitan area.

2.6.2 Models with all variables with available data

In addition to the common variables, there are also some other variables with available data specific to a scale or two scales. On the household scale, we also have RA, FYML, FYSL, FYD, FYP, BYML, BYSL, BYD, and BYP; on the census tract scale, we have MA, BD, and %MR; and on the city/town scale, we have MA, *ln*MP, and BD. Including these additional variables does not cause significant multi-collinearity problems, and, therefore, we are able to examine the influence of these additional scale-unique variables on water use, albeit without the ability to draw conclusions about the comparison among scales as in Section 3.1 above. We have confidence that the scale-unique variable coefficients are valid and that there is no significant multi-collinearity problem because the coefficients of those common variables as shown in Table 2.3 are comparable with the results obtained in Section 2.3.1.

In the household-scale model, respondent's age has a positive impact on water use, but it is not statistically significant at the 0.05 level. Respondent's age does not measure the age distribution of all members in a household except in the case when the household has only one member so it is a bit unclear how this finding relates to the mixed findings on age in the literature. Harlan et al.'s (2009) study only includes backyard landscaping categories and finds that backyard desert has a significant negative effect on water use. However, of all the parameter estimates of the landscaping variables (including front yard and backyard) in our study, only front yard desert (FYD) is statistically significant. The negative impact of

FYD on water use indicates that households that have desert landscaping in their front yards tend to use less water. Many homeowner associations restrict front yard vegetation to desert plants rather than a lawn or oasis design (Martin et al. 2003). Our result may suggest that such regulation helps reduce household water use in single-family homes.

On the census tract scale, median age and percent of mesic residential area do not show significant effects on water use, but building density has a significant negative effect on water use. Census tracts with higher single-family house density tend to use less water per household. This finding provides evidence that single-family residential development may influence single-family water use patterns. We echo Chang et al. (2010) and Gober et al. (2013), and argue that municipal water managers and land use planners should consider better coordination of their respective efforts to ensure urban water sustainability. There are two things that should be noted with respect to this result. One is that we do not include other housing units, e.g. the multi-family apartments, into the house density calculation. The other is that higher house density may result in a stronger urban heat island effect (Oke 2006) that is found to be associated with more water use per single-family house in Phoenix (Guhathakurta and Gober 2007; Aggarwal et al. 2012). In this study, we do not capture these complicated relationships. The absence of a significant effect of percent mesic residential area is consistent with the finding of Wentz and Gober (2007). They also point out important reasons for that finding that the spatially clustered mesic residential area in the central part of Phoenix is not included in their study (as well as our study) because of the SRP flood water delivery for irrigation, and remaining mesic landscaping parcels are spatially diverse.

Table 2.2 Parameter estimates, 95% confidence intervals, standardized coefficients, and test statistics for three linear mixed-effects models of different spatial scales with only common variables

	Household scale				**Census tract scale**				**City/town scale**			
	Parameter Estimate	95% Confidence Interval		Standardized Coefficient	Parameter Estimate	95% Confidence Interval		Standardized Coefficient	Parameter Estimate	95% Confidence Interval		Standardized Coefficient
		Lower Limit	Upper Limit			Lower Limit	Upper Limit			Lower Limit	Upper Limit	
HHS	0.0774*** (3.88)	0.0382	0.1165	0.169	0.0906*** (7.59)	0.0672	0.1140	0.167	0.2525*** (4.01)	0.1287	0.3763	0.245
ln(HHI)	0.339*** (6.85)	0.242	0.436	0.338	0.200*** (5.79)	0.133	0.268	0.240	-0.098 (-0.41)	-0.5656	0.3691	-0.050
HA	0.00784*** (5.47)	0.00503	0.01065	0.242	0.00704*** (11.03)	0.00579	0.00829	0.313	0.00673 (1.61)	-0.00148	0.01494	0.158
PS	0.0046** (2.73)	0.0013	0.0079	0.131	0.0183*** (12.98)	0.0156	0.0211	0.482	0.0369*** (6.31)	0.0254	0.0483	0.541
ILS	0.000071* (2.35)	0.000012	0.000131	0.102	0.000111*** (4.62)	0.000064	0.000158	0.102	-0.000010 (-1.19)	-0.000030	0.000007	-0.058
R	-0.1045*** (-3.50)	-0.1630	-0.0460	-0.074	-0.1076*** (-12.55)	-0.1244	-0.0908	-0.152	-0.0343 (-0.63)	-0.1415	0.0729	-0.045
R*R	0.0729*** (5.11)	0.0450	0.1009	0.104	0.0701*** (15.01)	0.0609	0.0792	0.177	0.0284 (0.97)	-0.0291	0.0859	0.066
TEMP	0.0120*** (16.02)	0.0105	0.0135	0.238	0.0125*** (61.40)	0.0121	0.0129	0.530	0.0145*** (11.00)	0.0119	0.0171	0.590
S	0.0889*** (3.76)	0.04248	0.1352	0.055	0.1051*** (15.96)	0.0922	0.1180	0.136	0.0612 (1.42)	-0.0235	0.1460	0.075
T	0.00986*** (10.73)	0.00805	0.01166	0.090	0.00655*** (25.39)	0.00604	0.00705	0.125	0.00803*** (4.64)	0.00462	0.01144	0.144
N	4941				6048				336			

Notes: *t*-Statistics in parentheses

*p<0.05; **p<0.01; ***p<0.001

Table 2.3 Parameter estimates, 95% confidence intervals, standardized coefficients, and test statistics for three linear mixed-effects models of different spatial scales with all variables with available data

	Household scale				**Census trace scale**				**City/town scale**			
	Parameter Estimate	95% Confidence Interval		Standardized Coefficient	Parameter Estimate	95% Confidence Interval		Standardized Coefficient	Parameter Estimate	95% Confidence Interval		Standardized Coefficient
		Lower Limit	Upper Limit			Lower Limit	Upper Limit			Lower Limit	Upper Limit	
Household characteristics												
HHS	0.0896*** (4.37)	0.0494	0.1297	0.195	0.1207*** (6.89)	0.0864	0.1550	0.222	0.2355*** (3.60)	0.1067	0.3643	0.229
ln(HHI)	0.273*** (5.63)	0.178	0.368	0.272	0.191*** (4.93)	0.115	0.267	0.228	0.051 (0.30)	-0.2892	0.3921	0.026
RA	0.00559 (1.89)	-0.00020	0.01138	0.089								
MA					0.00462 (1.85)	-0.00027	0.00950	0.078	0.00198 (0.33)	-0.00992	0.01388	0.029
Housing characteristics												
HA	0.00351 (1.96)	-0.000007	0.00702	0.108	0.00629*** (8.06)	0.00476	0.00782	0.280	0.00940* (2.54)	0.00212	0.01668	0.221
PS	0.0046** (2.92)	0.0015	0.0077	0.132	0.0172*** (11.54)	0.0143	0.0202	0.453	0.0303*** (7.12)	0.0219	0.0386	0.444
ILS	0.000075** (2.66)	0.000020	0.000131	0.107	0.000067* (2.44)	0.000013	0.000121	0.062	-0.0000027 (-0.34)	-0.00002	0.000013	-0.015
FYD	-0.333* (-2.19)	-0.630	-0.035	-0.218								
FYML	-0.175 (-1.12)	-0.482	0.132	-0.101								
FYSL	0.049 (0.32)	-0.255	0.353	0.026								
FYP	-0.046 (-0.22)	-0.470	0.377	-0.011								
BYD	-0.045 (-0.34)	-0.303	0.2142	-0.023								
BYML	0.144 (1.13)	-0.106	0.394	0.083								
BYSL	0.139 (1.10)	-0.110	0.387	0.082								

BYP	0.171 (1.26)	-0.095	0.436	0.088								
Climate factors												
R	-0.1046*** (-3.50)	-0.1631	-0.0461	-0.074	-0.1076*** (-12.56)	-0.1244	-0.0908	-0.152	-0.0333 (-0.61)	-0.1410	0.0745	-0.044
R*R	0.0731*** (5.12)	0.0451	0.1010	0.104	0.0701*** (15.02)	0.0610	0.0793	0.177	0.0286 (0.97)	-0.0292	0.0864	0.067
TEMP	0.0120*** (16.03)	0.0105	0.01347	0.238	0.0125*** (61.43)	0.0121	0.0129	0.530	0.0147*** (11.02)	0.0120	0.0173	0.595
Water price												
ln(MP)									-0.0382* (-2.13)	-0.0735	-0.0030	-0.084
Urban structure												
BD					-0.000110** (-3.11)	-0.00017	-0.00004	-0.070	0.000245 (1.48)	-0.00008	0.00057	0.078
%MR					0.000933 (0.98)	-0.00093	0.002794	0.029				
Other												
S	0.0886*** (3.75)	0.0422	0.1350	0.055	0.1051*** (15.96)	0.0922	0.1180	0.136	0.0615 (1.42)	-0.0237	0.1467	0.075
T	0.00986*** (10.73)	0.00806	0.01660	0.090	0.00656** (25.46)	0.00606	0.00707	0.125	0.00808*** (4.63)	0.00465	0.01151	0.145
N	4941				6048				336			

Notes: *t*-Statistics in parentheses

*p<0.05; **p<0.01; ***p<0.001

Median age and building density are only used in the models for the census tract and city/town scales, and marginal price is only in the city/town scale model. The effect of median age on water use is not statistically significant on either the census tract scale or the city/town scale. Neither is the effect of building density on water use statistically significant for the city/town scale, which is different from the result on the census tract scale. Considering the spatial extent difference of the two aggregated scales, there should be spatial heterogeneity in the effect of building density on single-family water use among these cities and towns. The marginal price has a negative and significant impact on water use, but the price elasticity (=-0.0382) is lower in absolute value compared with the results of Strong and Smith (2010) for this area.

2.7 Concluding Remarks

In this study, we find that the census tract scale data produce similar results compared to the household-scale data when we use the econometric models to studying the relationship of single-family residential water use and its determinants in Phoenix, Arizona. No significant ecological fallacy problem was identified by this comparative statistical analysis that is based on the signs, magnitude, and confidence intervals of the parameter estimates.

There are several limitations of our study. First, in the household-scale model and the census tract scale model, we only include factors that depict features for the same spatial scale, disregarding contextual factors defined at a larger scale. Adding contextual factors to reflect the influence at a larger scale on household-scale residential water use could confound our results due to the UGCoP (uncertain geographic context problem) as we discussed earlier (Kwan 2012). Second, our results are based on a limited list of variables and only on data from Phoenix. The conclusion regarding the similarity of household and census tract scale results can be also tested by using other factors of interest, and more geographically distributed studies are needed to further validate our finding. Third, we do not fully address the MAUP (modifiable areal unit problem) since we do not compare results from data of different aggregated scales with the same geographic extent. It would be more desirable to have data on other aggregated scales, such as census block and census block group, for the city of Phoenix, and compare their results with the household-scale and census tract scale results. We should also note that studies at different spatial scale all provide important insights, of which some can be easily compared across scales while others are not easily scalable either because some factors are uniquely meaningful on certain spatial scales or because the corresponding data may not be available on other spatial scales.

In addition to the household and census tract scale data, we also use a sample of aggregated city/town scale data from fourteen municipalities in the Phoenix metropolitan area to fit the linear mixed effects model, and find that the model results on the city/town scale are significantly different from the two smaller scale model results. Considering the difference in the spatial extent, there is probably spatial heterogeneity in the relationship of single-family water use with its determinants among the cities and towns in this metropolitan area. Municipal water management policies are relatively independent in each jurisdiction. Water use regulations, water pricing, the age and stage of development, and cultural practices may differ significantly from municipality to municipality. Therefore, assuming fixed parameters of water use determinants for different cities and towns as we do in the city/town scale model would appear to be unjustified. If we are to provide insightful policy advice for municipal water management, it is necessary to explicitly consider such differences among cities and towns. We may consider using random coefficients in the linear mixed-effects models to fix this problem in future research.

Chapter 3

SPATIAL PANEL DATA MODELS FOR SINGLE-FAMILY RESIDENTIAL WATER USE: A CASE STUDY IN PHOENIX, AZ

This chapter has been co-authored with Elizabeth A. Wentz and Benjamin L. Ruddell.

3.1. Introduction

Previous studies have extensively used panel data for residential water use research (Table 3.1). A panel dataset in this context refers to multiple observations of water use on a cross-section of subjects over several time periods. The subjects can be defined by spatial units such as households, census tracts, and cities, etc.; and the temporal scale of collected data can be daily, monthly, seasonal, and annual, etc. Panel data have an advantage over cross-sectional data and time series data because panel data incorporate both temporal and subject-based variability, contain more degrees of freedom and less multicollinearity, improve the efficiency of parameter estimates, and control for the effects of omitted or unobserved variables (Mylopoulos et al., 2004; Arbués and Villanúa, 2006; Polebitski and Palmer, 2010; Dharmaratna and Harris, 2012). However, in a geographic setting, there may exist spatial dependence between neighboring subjects that show similar water use patterns (Wentz and Gober, 2007; Chang et al., 2010; Janmaat, 2013). This spatial dependence is generally ignored in panel data models for residential water use research, which may invalidate the independence assumption of these models. Thus, panel data models may produce biased coefficient estimates that can potentially lead to erroneous conclusions.

The recent development of spatial panel data models (Anselin et al., 2008; Elhorst, 2010) provides a great opportunity for researchers to more accurately model the relationship between residential water use and its associated factors with spatial panel data. Not only can such spatial panel data models capture both the spatial and temporal variations of water use, they also provide estimation of spatially interaction effects including both the spatial dependence of water use itself and the effects of associated factors on water use in neighboring spatial units. Therefore, spatial panel data models are a promising tool to study the spatio-temporal dynamics of residential water use. In this paper, we present an empirical study that applies spatial panel data models to a dataset of single-family residential water use at the census tract scale in the city of Phoenix, AZ.

Table 3.1 Residential water use studies using panel data

Author(s) (year)	**Study area**	**Spatial scale**	**Temporal scale**
Danielson (1979)	Raleigh, NC, USA	household	monthly
Moncur (1987)	Honolulu, HI, USA	household	bimonthly
Nieswiadomy and Molina (1988)	Denton, TX, USA	household	monthly
Nieswiadomy and Molina (1989)	Denton, TX, USA	household	monthly
Lyman (1992)	Moscow, ID, USA	household	monthly
Hewitt and Hanemann (1995)	Denton, TX, USA	household	monthly
Dandy et al. (1997)	Adelaide, Australia	household	annual and seasonal
Renwick and Archibald (1998)	Goleta and Santa Barbara, CA, USA	household	monthly
Höglund (1999)	Sweden	city/town	annual
Pint (1999)	Alameda county, CA, USA	household	bimonthly
Nauges and Thomas (2000)	Eastern France	city/town	annual
Martínez-Espiñeira (2002)	Northwest of Spain	city/town	monthly
Nauges and Thomas (2003)	Eastern France	city/town	annual
Martínez-Espiñeira (2003)	Northwest of Spain	city/town	monthly
Mylopoulos et al. (2004)	Thessaloniki, Greece	household	four-month
Arbués et al. (2004)	Zaragoza, Spain	household	2 years/10 times
Mazzanti and Montini (2006)	Emilia-Romagna, Italy	city/town	annual

Arbués and Villanúa (2006)	Zaragoza, Spain	household	2 years/10 times
Musolesi and Nosvelli (2007)	Cremona Province, Italy	city/town	annual
Martins and Fortunato (2007)	centre region of Portugal	city/town	monthly
Olmstead et al. (2007)	11 urban areas in USA and Canada	household	daily
Kenney et al. (2008)	Aurora, CO, USA	household	monthly
Worthington et al. (2009)	Queensland, Australia	city/town	monthly
Harlan et al. (2009)	Phoenix, AZ, USA	household	monthly
Halich and Stephenson (2009)	Virginia, USA	city/town	monthly
Arbués et al. (2010a)	Zaragoza, Spain	household	2 years/10 times
Polebitski and Palmer (2010)	Seattle, WA, USA	census tract	bimonthly
Miyawaki et al. (2011)	Tokyo and Chiba, Japan	household	monthly
Mieno and Braden (2011)	Chicago, IL, USA	city/town	monthly
Abrams et al. (2012)	Sydney, Australia	household	quarterly
March (2012)	Barcelona metropolitan area, Spain	city/town	annual
Dharmaratna and Harris (2012)	Sri Lanka	NWSDB district	monthly
Aggarwal et al. (2012)	Phoenix, AZ, USA	census tract	monthly

3.2 Study Area

Our study is focused on the city of Phoenix, the capital of Arizona and the sixth largest city in the United States. Phoenix is home to more than 1.4 million residents according to the 2010 US Census. Phoenix has a subtropical desert climate since it is located on the upper edge of the Sonoran Desert, and thus summers are extremely hot and winters are warm here. Phoenix has two distinct rainfall seasons: one in winter and the other in summer. Spring and fall months are generally dry. During the monsoon season (usually July and August, but it can start in June and end in late September), there can come heavy downpours with thunderstorms in Phoenix. Water supply for Phoenix comes from two sources. One is the local rivers (Salt River and Verde River) and groundwater; and the other is from Colorado River transferred by the aqueduct of the Central Arizona Project. With the urban development and increasing population, we expect the city of Phoenix will be faced with gradual pressure to supply water for local demands because (1) available surface water resources have been almost fully allocated, and (2) groundwater has been over-exploited. Currently, two-thirds of municipal water use in the city of Phoenix is for residential purposes. Single-family homes account for 75% of residential water use. Therefore, it is important to understand single-family residential water use, which can provide insights into relevant urban water management.

Recently, an increasing number of studies on residential water use, primarily in the single-family residential sector, in Phoenix, AZ have been published in peer-reviewed journals. Most of these studies are focused on the relationship between water use and climate factors, especially temperature, due to the significant urban heat island effect found in this site (Guhathakurta and Gober, 2007, 2010; Balling and Gober, 2007; Balling et al., 2008; Aggarwal et al., 2012). Single-family residential water use is generally found to increase with temperature, which indicates that the urban heat island, as well as its evolution, in this area has a strong impact on residential water use patterns. Other relevant studies on single-family residential water use in Phoenix include Wentz and Gober (2007), Harlan et al. (2009), Turner and Ibes (2011), and Breyer et al. (2012). These studies used a wide spectrum of factors that may influence single-family residential water use, including housing and household characteristics, yard landscaping, homeowner associations, and attitudinal factors. These studies provide important insights for us to select relevant factors in this study.

3.3 Methods

3.3.1 Data

The dependent variable is natural logarithm of the monthly average single-family household water use (*ln*Water) on the census tract scale (Table 3.2). We have a sample of 252 (out of 303) census tracts in the city of Phoenix (excluding those with fewer than 50 household water use records and those without other relevant data to match). We obtained overall water use records of these census tracts for each month of 2001 and 2002 from Water Services Department, City of Phoenix and calculated monthly average household water use.

Table 3.2 Definition of variables and their data sources

Variable	Definition	Data source	Unit
Water	Average household monthly water use	City of Phoenix	gallon
HHS	Average household size	US Census 2000	person
HHI	Median annual household income	US Census 2000	$
MA	Median Age	US Census 2000	year
HA	Average house age in 2001	Maricopa County Assessor Database	year
PS	Average pool size	Maricopa County Assessor Database	m^2
LA	Average livable area	Maricopa County Assessor Database	m^2
%MR	Percent mesic residential area	CAP LTER, SRP	percent
R	Monthly precipitation	AZMET, NOAA, MCFCD	inch
R*R	Square of monthly precipitation	AZMET, NOAA, MCFCD	$(inch)^2$
TEMP	Monthly average maximum temperature	AZMET, NOAA, MCFCD, PRISMS	Fahrenheit
HD	Single-family house density	Maricopa County Assessor Database	house unit/km^2

There are many previous studies that analyze the determinants of residential water use. However, we seldom see two studies use the same set of factors, probably because of different research questions under study or difficulty in data collection. We do not try to provide an exhaustive set of factors that potentially have effects on residential water use. Given our purpose of water use modeling exercise, we select the factors based on previous residential water use studies in this area and data availability as well.

Since our water use data do not distinguish between indoor and outdoor water uses, we select factors that may influence indoor and/or outdoor water uses. We include ten factors that may influence single-family residential water use for this study (Table 3.2), and they are used to represent household characteristics, housing characteristics, climate, and urban structure. Household characteristics indicate the socio-economic and demographic attributes of households. We include two relevant variables: natural logarithm of media annual household income (*ln*HHI) and median age (MA). These data were acquired from US Census 2000 database. Housing characteristics show the features of physical property, and we have three relevant factors: average house age in 2001 (HA), average pool size (PS), and average livable area (LA). We first extracted these data from Maricopa County Assessor Database and then aggregated them to the census tract level. We also include a variable to represent the landscaping—percent mesic residential area (%MR), which is calculated following Wentz and Gober (2007):

$$\%MR = \frac{AREA_{MR} - AREA_{SRP}}{AREA_{MR} + AREA_{XR}} \cdot 100 \tag{3.1}$$

where $\%MR$ denotes percent mesic residential area; $AREA_{MR}$ denotes the area classified as mesic residential; $AREA_{SRP}$ denotes the mesic residential area that uses flood water from the Salt River Project for irrigation; and $AREA_{XR}$ denotes the area classified as xeric residential.

Two climate factors considered are monthly precipitation (R) and monthly average daily maximum temperature (TEMP). We obtained the precipitation data from 142 weather stations operated by three networks –Arizona Meteorological Network (AZMET), National Oceanic and Atmospheric Administration (NOAA), and Maricopa County Flood Control District (MCFCD), and the near surface (2m) temperature data from 39 weather stations operated by AZMET, NOAA, MCFCD, and Phoenix Real-time Instrumentation for Surface Meteorological Studies (PRISMS). We map both datasets of precipitation and temperature in ArcGIS 10, implement interpolation using the ordinary kriging method, and calculate average values for each census tract in each month in 2001 and 2002. Both the first order term (R) and the second order term (R*R) of monthly precipitation are used to test possible non-linear relationship between single-family residential water use and precipitation. Similar to Aggarwal et al. (2012), we expect that the effects of climate factors on single-family residential water use are also conditional on the parcel structure (vice versa), and therefore we consider the interactions of them and housing characteristics. Since the interactions of R (R*R) and housing characteristics do not show statistically significant results (at the 0.05 level), we exclude these terms in our models and only include the interactions of temperature and housing characteristics. A last variable that represents urban structure is single-family house density (HD), which is calculated by dividing the number of single-family houses by the total area for each census tract.

There are other important factors that we do not include such as behavioral characteristics (Fielding et al., 2012), technological characteristics of end uses as to water fixtures and appliances (Chu et al., 2009), attitudinal factors (Syme et al., 2004; Wilis et al., 2011; Grafton et al., 2011), and water price (Martínez-Espiñeira, 2003). Data on the first three types of variables are not available. Although we have water price data, we still do not include any water price variable because the City of Phoenix has a relatively simple water use structure with a basic charge to cover a base volume and a constant marginal price for further water use above it. The vast majority of households use more water than the base volume. Thus the monthly average single-family household water use on the census tract scale typically corresponds to the same marginal price in each month, and does not present cross-sectional variability. Although there is seasonal change in water price, but the marginal water price is highly correlated to temperature.

3.3.2 Spatial panel data models

A spatial panel data model can be specified in different ways, such as spatial error model, spatial lag model (Anselin et al., 2008), and spatial Durbin model (LeSage and Pace, 2009). A spatial lag model includes weighted spatially lagged dependent variables, and can be formulated as:

$$Y_{it} = \lambda \sum_{j=1}^{N} w_{ij} Y_{jt} + \beta_0 + \mathbf{X}_{it}{}' \boldsymbol{\beta} + c_i + \alpha_t + \varepsilon_{it} \tag{3.2}$$

where Y_{it} is the dependent variable for spatial unit *i* at time *t* (*i* = 1, …, *N*; *t* = 1, …, *T*); $\sum_{j=1}^{N} w_{ij} Y_{jt}$ denotes the effect that the dependent variables of neighboring spatial units have on Y_{it}; $W = [w_{ij}]_{N \times N}$ is the spatial weight matrix that defines the arrangement of the spatial units; λ is the spatial autoregressive coefficient; β_0 is the intercept, $\boldsymbol{\beta}$ is the vector of coefficients, $\mathbf{X}_{it}$ is the vector of independent variables for spatial unit *i* at time *t*; c_i is the spatial effect; α_t is the time-period effect; and $\varepsilon_{it} \sim N(0, {\sigma_\varepsilon}^2)$ is the error term that is independently and identically distributed for all *i* (= 1, …, *N*) and *t* (= 1, …, *T*). In contrast to the spatial lag model, a spatial error model takes a different form that includes a spatially autocorrelated error term, and can be described as:

$$\begin{cases} Y_{it} = \beta_0 + \mathbf{X}_{it}' \boldsymbol{\beta} + c_i + \alpha_t + u_{it} \\ \quad u_{it} = \rho \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \end{cases} \tag{3.3}$$

where u_{it} is the error term for Y_{it}, is autocorrelated with the error terms of neighboring spatial units; and ρ is the spatial autocorrelation coefficient. A spatial Durbin model is a more general form that includes both weighted spatially lagged dependent variables and weighted spatially lagged independent variables:

$$Y_{it} = \lambda \sum_{j=1}^{N} w_{ij} Y_{jt} + \beta_0 + \mathbf{X}_{it}' \boldsymbol{\beta} + \sum_{j=1}^{N} w_{ij} \mathbf{X}_{jt}{}' \boldsymbol{\theta} + c_i + \alpha_t + \varepsilon_{it} \tag{3.4}$$

where $\boldsymbol{\theta}$ is a vector of parameters similar to $\boldsymbol{\beta}$. The spatial Durbin model is simplified to the spatial lag model if $\boldsymbol{\theta} = 0$, and to the spatial error model if $\boldsymbol{\theta} + \lambda\boldsymbol{\beta} = 0$. We construct the spatial weight matrix for all the three types of models based on Rook continuity, which means that census tracts sharing a common border are considered as neighbors. If census tracts *i* and *j* are neighbors, we set the weights $w_{ij} = w_{ji} = 1$; otherwise $w_{ij} = w_{ji} = 0$. By convention, we set the diagonal elements to be zeros. Before being input to the model, the spatial weight matrix is standardized to make the elements of each row sum to 1 (Anselin et al., 2008).

The parameters of a spatial lag model, spatial error model, and spatial Durbin model can be estimated using the maximum likelihood method that extends the version for spatial cross-sectional data. The three models can be implemented using the MATLAB routines developed by Elhorst (2012b), and these routines use maximum likelihood estimation. For all the three models, the spatial effect c_i may be treated as fixed or random effect, while we restrict the time-period effect α_t to be fixed. Since we include all the 24 months that are not selected from a larger sample, it would make no sense if we consider time-period effects as random. We use spatial random effects in this study for two reasons. First, we do not include all census tracts located in the city of Phoenix. If the results are to be extended to all the census tracts, then mixed effects are more appropriate. Second, the number of census tracts included in our study is relatively large, and we have some time-invariant (household) or slow changing (housing) characteristics. The random spatial effects model can avoid the loss of degrees of freedom and the problem that the effects of time-invariant and slow changing variables cannot be (accurately) estimated (Elhorst, 2010; Aggarwal et al., 2012).

We employ a two-step approach to find the most appropriate spatial panel data model. In the first step, we use the model without spatial interaction effects to test spatial lag and spatial error using Lagrange multiplier (LM) tests and robust LM tests. The LM tests were proposed by Burridge (1980) and Anselin (1988) and the robust LM tests were proposed by Anselin et al. (1996) for cross-sectional spatial data. Both types of tests were generalized by Elhorst (2010) to spatial panel data. We also use relevant statistical tests to check whether time-period fixed effects and spatial random effects should be included in the model. A likelihood ratio (LR) test is performed to investigate the null hypothesis that the time-period fixed effects are jointly insignificant (Elhorst, 2012b), and another LM test is performed to investigate the null hypothesis of no spatial random effects (Breusch and Pagan, 1980). If the LM test and robust LM test support either spatial lag model or spatial error model, we move to the next step. In the second step, we estimate the spatial Durbin model with spatial random effects and time-period fixed effects, and test whether it can be simplified to the spatial lag or spatial error models using the Wald tests (H_0: $\boldsymbol{\theta} = 0$ for the spatial lag model and H_0: $\boldsymbol{\theta} + \lambda\boldsymbol{\beta} = 0$ for the spatial error model; Elhorst, 2012b).

A common way to explain the effect of an explanatory variable on the dependent variable is to use its corresponding coefficient estimate in a non-spatial or spatial regression model. However, this may lead to erroneous conclusions for a spatial lag model or spatial Durbin model owing to the loop feedback effects among neighboring spatial units. The feedback effects can be due to the spatially lagged dependent variable or/and due to the spatially lagged terms of the independent variable itself (Elhorst, 2012b). To solve this problem, we consider the direct effects and indirect effects that are derived by LeSage and Pace (2009) for a cross-sectional setting and extended by Elhorst (2012b) for spatial panel models. The direct effect refers to the average effect of changing an explanatory variable on the dependent variable of the same spatial unit (including the feedback effect that passing through neighboring spatial units and back to the original spatial unit); and the indirect effect, also known as spatial spillover effect, is the average effect of changing an explanatory variable in one spatial unit on the dependent variable of its neighboring spatial units. For example, in our case, the direct effect of HHS means the average change of *ln*Water in response to one unit increase of HHS of the same census tract, whereas the indirect effect of HHS means the average change of *ln*Water of a neighboring census tract.

3.4 Results and discussion

3.4.1 Model search

Before searching for the most appropriate spatial panel data model, we test the spatial autocorrelation of average household monthly water use (Water) using the Moran's I statistics for each of the 24 months. The Moran's I statistic is statistically significant at the 0.01 level for each month (Table 3.3), which indicates the general presence of spatial autocorrelation in Water in our dataset.

We test whether the spatial lag model or the spatial error model is more appropriate than a model without spatial interaction effects. The results of the LM test (1006.20, $p<0.001$) and the robust LM test (17.98, $p<0.001$) support the use of spatially lagged dependent variable. Similarly, the results of the LM test (1695.63, $p<0.001$) and the robust LM test

(707.41, p<0.001) also support the use of spatially autocorrelated error term. Thus either the spatial lag model or the spatial error model is a better options than its corresponding non-spatial panel data model.

Table 3.3 Global Moran's I statistics of average household monthly water use (Water) for the 24 months in 2001 and 2002

Month	Global Moran's I	*Z* Score	Month	Global Moran's I	*Z* Score
Jan 2001	0.210	9.01*	Jan 2002	0.203	8.70*
Feb 2001	0.207	8.90*	Feb 2002	0.189	8.09*
Mar 2001	0.210	9.01*	Mar 2002	0.204	8.73*
Apr 2001	0.202	8.59*	Apr 2002	0.194	8.25*
May 2001	0.227	9.55*	May 2002	0.201	8.53*
Jun 2001	0.182	7.78*	Jun 2002	0.207	8.80*
Jul 2001	0.200	8.53*	Jul 2002	0.194	8.30*
Aug 2001	0.189	8.10*	Aug 2002	0.179	7.69*
Sep 2001	0.175	7.52*	Sep 2002	0.203	8.70*
Oct 2001	0.217	9.23*	Oct 2002	0.221	9.39*
Nov 2001	0.210	9.04*	Nov 2002	0.211	9.09*
Dec 2001	0.243	10.45*	Dec 2002	0.240	10.35*

Note: * denotes that p-value is below the 0.0001 level.

We also test the time-period fixed effects and the spatial random effects. The LR test (803.56, df = 24, p < 0.001) indicates the time-period fixed effects are jointly statistically significant, and should be included. The LM test (6869.55, p < 0.001) also indicates statistically significant spatial random effects. Thus in the first step of model search, we find that the spatial lag model and the spatial error model both with spatial random effects and time-period fixed effects are appropriate models.

In the second step, we estimate a spatial Durbin model with spatial random effects and time-period fixed effects. The Wald tests show that the null hypothesis that the spatial Durbin model can be simplified to the spatial error model (163.36, $p < 0.001$) or spatial lag model (491.82, $p < 0.001$) should be rejected, and thus the spatial Durbin model with spatial random effects and time-period fixed effects is found to be the most appropriate model in this model search process.

Table 3.4 Results of models without spatial interaction effects

	Model 1: Pooled OLS regression model	Model 2: Panel data model with spatial random effects	Model 3: Panel data model with time-period fixed effects	Model 4: Panel data model with spatial random effects and time-period fixed effects
HHS	0.1328*** (24.09)	0.1434*** (6.51)	0.1334*** (30.67)	0.1507*** (6.70)
*ln*HHI	0.1548*** (11.73)	0.4107*** (8.48)	0.1560*** (15.01)	0.4696*** (9.58)
MA	0.00520*** (6.37)	0.01473*** (4.55)	0.00521** (8.10)	0.01644)*** (4.93
HA	0.00660*** (25.79)	0.00571*** (5.84)	0.00667*** (33.00)	0.00532*** (5.44)
R	-0.0961*** (-8.44)	-0.0945*** (-10.44)	-0.0420 (-1.35)	-0.0243 (-1.30)
R*R	0.0603*** (9.51)	0.0593*** (11.74)	0.0182 (1.48)	0.0080 (1.08)
T	0.01001*** (38.84)	0.01716*** (33.03)	0.00077 (0.53)	0.00424*** (4.44)
T*LA	0.000026*** (14.66)***	-0.00003*** (-5.43)	0.000026*** (18.66)	-0.00004*** (-11.95)
T*PS	0.000122*** (17.39)	0.000123*** (5.92)	0.000120*** (21.76)	0.000137*** (9.09)
T*%MR	0.000012*** (3.59)	0.000031*** (3.41)	0.000012*** (4.49)	0.000041*** (6.51)
HD	-0.000075*** (-6.89)	-0.00022*** (-5.12)	-0.000074*** (-8.62)	-0.00030*** (-6.74)
Log-likelihood	1798	2783	2032	3869

Notes:

1. *t*-values in parentheses.
2. *: $p<0.05$; **: $p<0.01$; ***: $p<0.001$.

3.4.2 Model Results

Table 3.4 presents the results of four models without spatial interaction effects: (1) pooled OLS regression; (2) panel data model with spatial random effects; (3) panel data model with time-period fixed effects; and (4) panel data model with both spatial random effects and time-period fixed effects. Based on the log-likelihood, Model 4 performs better than the other three in fitting to our dataset. The results of Model 4 show that household size, household income, median age, house age, temperature, the interactions between temperature and livable area, pool size, and percent mesic residential area, and housing density have statistically significant effects (*p*-values are all below the 0.001 level) on residential water use. However, it is unexpected that the relation between the water use and the interaction of temperature and livable area (T*LA) is shown to be negative. Neither precipitation nor squared precipitation has a statistically significant effect (at the 0.05 level) on residential water use, which is also contrary to our expectation. Since Models 1-4 does not capture the spatial interaction effects, the parameter estimates of non-spatial panel data models are probably biased.

Table 3.5 Results of spatial panel data models with spatial random effects and time-period fixed effects

	Model 5: Spatial error model	Model 6: Spatial lag model	Model 7: Spatial Durbin model
Parameter estimate			
w**ln*Water		0.496960*** (43.40)	0.601998*** (49.03)
HHS	0.094633*** (12.49)	0.054331*** (11.18)	0.113838*** (12.31)

*ln*HHI	0.247950***	0.125064***		0.252157***	
	(15.87)	(11.96)		(13.39)	
MA	0.005797***	0.002056***		0.008048***	
	(6.05)	(3.29)		(6.85)	
HA	0.004219***	0.003815***		0.002501***	
	(9.21)	(13.71)		(4.20)	
R	-0.141196***	-0.155584***		-0.152919***	
	(-16.37)	(-17.19)		(-17.57)	
R*R	0.062013***	0.069457***		0.068251***	
	(13.04)	(13.61)		(13.93)	
T	0.001431**	0.001927***		0.001594**	
	(2.79)	(4.09)		(2.96)	
T*LA	0.000014***	0.000016***		0.000009***	
	(6.75)	(11.41)		(3.56)	
T*PS	0.000107***	0.000074***		0.000092***	
	(11.37)	(12.38)		(7.78)	
T*%MR	0.000022***	0.000008**		0.000034***	
	(5.20)	(3.06)		(6.42)	
HD	-0.000102***	-0.000031***		-0.000129***	
	(-7.29)	(-3.48)		(-7.49)	
w*HHS				-0.095271***	
				(-8.47)	
w**ln*HHI				-0.184235***	
				(-7.98)	
w*MA				-0.008953***	
				(-6.07)	
w*HA				0.000862	
				(1.23)	
w*R				-0.010879	
				(-0.64)	
w*R*R				0.005780	
				(0.57)	
w*T				-0.000664	
				(-0.66)	
w*T*LA				0.000004	
				(1.18)	
w*T*PS				-0.000026	
				(-1.83)	
w*T*%MR				-0.000036***	
				(-5.69)	
w*HD				0.000127***	
				(6.11)	
		Direct effect	**Indirect effect**	**Direct effect**	**Indirect effect**
HHS		0.058609***	0.049872***	0.108490***	-0.061664***
		(11.14)	(10.52)	(12.98)	(-3.90)
*ln*HHI		0.133656***	0.113714***	0.245247***	-0.074642*
		(12.14)	(11.56)	(14.28)	(-2.27)
MA		0.002220**	0.001888**	0.007251***	-0.009485***
		(3.28)	(3.27)	(6.76)	(-4.45)

HA	0.004076*** (13.17)	0.003469*** (12.00)	0.003005*** (5.57)	0.005437*** (5.83)
R	-0.166671*** (-16.99)	-0.141882*** (-13.81)	-0.173221*** (-17.81)	-0.236569*** (-6.07)
R*R	0.074329*** (13.42)	0.063274*** (11.64)	0.077520*** (13.59)	0.108001*** (4.50)
T	0.002064*** (3.83)	0.001760*** (3.71)	0.001675** (3.08)	0.000748 (0.35)
T*LA	0.000017*** (11.24)	0.000014*** (10.56)	0.000011*** (4.87)	0.000022*** (4.89)
T*PS	0.000080*** (12.46)	0.000068*** (11.80)	0.000098*** (9.07)	0.000068*** (3.59)
T*%MR	0.000008** (2.99)	0.000007** (2.97)	0.000031*** (6.26)	-0.000037*** (-4.09)
HD	-0.000033*** (-3.46)	-0.000028*** (-3.46)	-0.000119*** (-7.52)	0.000115*** (3.75)
Log-likelihood	3868	3731	3961	

Notes:

1. *t*-values in parentheses.

2. *: p<0.05; **: p<0.01; ***: p<0.001.

The results of three spatial panel data models with spatial random effects and time-period fixed effects are shown in Table 3.5: (5) spatial error model; (6) spatial lag model; and (7) spatial Durbin model. LeSage and Pace (2009) point out that the interpretation of estimated parameters in spatial lag models and spatial Durbin model is more complicated, and their coefficients cannot simply be interpreted as the partial derivatives of the dependent variable with respect to explanatory variables. The direct and indirect effects of explanatory variables for Model 6 and Model 7 are also presented in Table 3.5. The significant and positive coefficient of the spatially lagged dependent variable (w**ln*Water) in Model 7 (as well as in Model 6) indicate that the average single-family residential water use in one census tract increases (decreases) in response to the increase (decrease) of the average single-family residential water use in neighboring census tracts. This confirms what has been found in cross-sectional settings by Wentz and Gober (2007) and Chang et al. (2010). From the results of spatial Durbin model, we can see that the parameter estimates of independent variables are somewhat similar to the corresponding direct effects in terms of signs, sizes, and statistical significance. In comparison, the parameter estimates of the spatially lagged independent variables are more different from their corresponding indirect effects. The estimated coefficients of spatially lagged independent variables, including house age, precipitation, squared precipitation, interaction of temperature and livable area, and interaction of temperature and pool size, are not statistically significant at the 0.05 level, while their corresponding indirect effects are all statistically significant at the 0.001 level. This indicates that interpretation based on the coefficients of spatially lagged independent variables is biased and misleading, and thus we should use the derived estimates of direct and indirect effects for interpretation.

We find quite some differences when comparing the results of Model 4, a non-spatial panel, and the results of Model 7, a spatial Durbin model, both with spatial random effects and time-period fixed effects. For a non-spatial panel data model, we generally interpret parameter estimates as the average effects of independent variables on the dependent variable of the same census tract, which corresponds to the direct effects in a spatial panel data model. For eight variables including household size, log household income, median age, house age, temperature, interactions of temperature and pool size, interaction of temperature and percent mesic residential area, and housing density, the coefficient of each of them in Model 4 and its corresponding direct effect in Model 7 are both statistically significant at the 0.01 level and have the same sign. However, compared to the direct effects in Model 7, the coefficients of these eight explanatory variables are all overestimated in absolute value (by a rate ranging from 30% to 150%) in Model 4. The coefficient of neither precipitation nor squared precipitation is statistically significant at the 0.05 level in Model 4, whereas their corresponding direct effects are both statistically significant at the 0.001 level in Model 7. Although the coefficient of interaction of temperature and livable area in Model 4 and its direct effect in Model 7 are both statistically significant at the 0.001 level, the latter shows a positive sign that is opposite to the former. These differences indicate the importance of incorporating spatial interaction effects into panel data models.

A major advantage of the spatial Durbin model is its ability to quantify both the direct and spillover effects. Not only does each of the estimates of direct effects show statistical significance at the 0.01 level, but also all the estimated indirect effects except that of temperature are statistically significant (at least at the 0.05 level; Table 3.5). All these explanatory variables have direct effects as we expected. Among them, house age, squared precipitation, interaction of temperature and livable area, and interaction of temperature and pool size have positive direct and indirect effects, and precipitation has both negative direct and indirect effects. However, household size, household income, median age, interaction of temperature and percent mesic residential, and house density have direct and indirect effects in opposite directions.

3.5 Conclusion

This chapter explores the spatial effects that influence our understanding of the relationship single-family residential water use and its determinants. We exploit a set of panel data obtained from a variety of sources for the census tracts in Phoenix. Through a series of statistical tests, we find the spatial Durbin model with spatial random effects and time-period fixed effects is the most appropriate model to fit our dataset. The model results confirm the previous finding that the average single-family residential water use of neighboring census tracts is strongly positively related in Phoenix. The direct effects of these factors from this model generally correspond to our expectation. The distinct difference between the direct effects from our spatial Durbin model and the effects found in non-spatial panel data models indicates that ignoring spatial effects in the analysis may cause misleading inference owing to biased coefficient estimation. The estimation of indirect effects provides a valuable way for us to better understand the spillover effects of these associated factors on residential water use in neighboring census tracts.

There are also some limitations that deserve further study. First, our dataset is relatively limited to a subset of factors that may have significant effects on single-family residential water use. The method we employ here can be used for future studies that may include more policy relevant factors. The calculation of indirect effects provides a valuable way to check the policy effectiveness in managing single-family residential water use. Second, the spatial panel data model we use does not include temporally lagged effects. We notice that dynamic spatial panel data models are being developed although (Anselin et al., 2008; Parent and LeSage, 2012; Elhorst, 2012a). Such methodological development may facilitate our water use modeling in future study. Third, we still do not have an explicit mechanism to explain how neighboring census tracts (single-family homes or cities) influence the residential water use pattern of each other. For example, our definition of neighboring census tracts based on common border (Rook continuity) is relatively simple. In addition, interpreting the opposite directions of direct and spillovers effects of some factors, such as household size, household income, median age, interaction of temperature and percent mesic residential area, and house density, still need further study on theory and framework formulation. Social connectivity, social networking, and shared attitudes can possibly influence water consumption behavior, and thus may be explored in future studies. We hope that this study will raise more discussion on this part.

Chapter 4

UNDERSTANDING SINGLE-FAMILY RESIDENTIAL WATER USE IN PHOENIX, AZ: HISTORICAL CONTINGENCY, SPATIAL CONNECTIVITY, AND SPATIAL HETEROGENEITY

This chapter has been co-authored with Benjamin L. Ruddell and Elizabeth A. Wentz.

4.1. Introduction

Cities are increasingly recognized as complex systems where socio-economic and environmental factors interact over space and time (Grimm et al., 2000, 2013). These socio-economic and environmental factors drive fundamental flows of water, material, energy, nutrients, and human behavior that have known and quantifiable spatial and temporal dependence (Wolman, 1965; Kennedy et al., 2007). Quantifying the spatio-structural and temporal dependence to address urban complexity helps assess how spatial units of a city are arranged, how these pieces interact, and how the historical change of associated factors produces the current state of system. The goal of this research is to analyze the spatio-structural and temporal dimensions of residential water use in the city of Phoenix, Arizona.

We select to analyze the residential water use because it involves complex human-environmental interaction and it is an essential element to urban sustainability. We specifically focus on single-family residential (SFR) water use in Phoenix as our dependent variable and several socio-economic and environmental variables including housing characteristics, household characteristics, and climate factors as determinants. Although these three types of factors do not constitute a complete set of factors that may influence SFR water use, we select them because past studies identified them as important variables and our consideration for the spatial and temporal dimensions override the need to include all possible variables (Guhathakurta and Gober, 2007; Wentz and Gober, 2007; Harlan et al., 2009; Chang et al., 2010).

These variables reflect the dependencies of residential water use as a coupled human-environment system (House-Peters and Chang, 2011), yet historical contingency and spatial heterogeneity and connections are also important dimensions for us to understand this complex system (Chang et al., 2010; House-Peters et al., 2010). Wentz and Gober (2007) use a geographically weighted regression (GWR) model to study the relationship between SFR water use and four associated factors in the city of Phoenix. Findings show spatial heterogeneity across the census tracts in Phoenix, and neighboring census tracts exhibit similar water use patterns. The studies quantifying the spatial patterns do not consider how spatial dependence at one time manifest into future patterns of water use. The historical development of a city and its social and political environments describe the current state of high water use rates in Phoenix (Hirt et al., 2008; Larson et al., 2009). But there is lack of study that quantitatively examines the spatial effects of historical change in associated factors on current residential water use. Our objective is to study spatial heterogeneity and connections in the historically contingent effects of associated factors on SFR water use.

In order to address the objective, we can classify a system of residential water use into three types (Types I, II, and III) according to the historically contingent effects of associated factors on residential water use. In a Type I system, the historical states of associated factors X's are more important than their temporal change (referred to as ΔX's) in influencing current residential water use. A Type II system goes in the opposite way so that the effects of ΔX's are more important than that of the historical X's. In a Type III system, these two kinds of effects are relatively of the same importance. Such a classification may help assess the effectiveness of changing associated factors in systematically influencing residential water use. In this study we use statistical models to assess what type of system the SFR water use in Phoenix is.

Census units, such as census blocks, census block groups, and census tracts, are well-designed geographic units to show the spatial and temporal complexity of demographics of an urban system. Census tract is a spatial scale that has been used quite often in recent SFR water use studies probably because of the availability of relevant data to match the obtained water use records at this scale (Guhathakurta and Gober, 2007, 2010; Wentz and Gober, 2007; Balling et al., 2008; Polebitski and Palmer, 2010; Aggarwal et al., 2012). Aggarwal et al. (2012) argue that census tract is an appropriate scale to capture the impact of temperature variations due to urban heat islands on SFR water use. We also argue that census tract is an appropriate scale to reflect neighborhood demographic characteristics and housing development of a city in a spatially explicit way. In this study, we follow these previous studies, and focus on the census tract scale. At the census tract scale, housing characteristics, household characteristics, and annual average climate factors generally change relatively slow. A too short period may not provide significant temporal variability of these factors to produce convincing results. We consider a time period from 2000 to 2009, in which the total water use maintained a relatively stable level while the per-capita water use declined in Phoenix.

In this paper, we present a study in the city of Phoenix at the census tract scale that explores the historical contingency and its spatial heterogeneity and connectivity in the relationship of SFR water use and its associated housing, household, and climate factors. Although these concepts can be broadly defined so that they match different disciplinary realms just as Cadenasso et al. (2006) did, we define them in a relatively narrow sense to fit our research objectives. Specifically, we address the following research questions: (1)

(Historical contingency) How do the household, housing, and climate factors in 2000 and their change during 2000-2009 influence the SFR water use in 2009 at the census tract scale in Phoenix, Arizona? (2) (Spatial heterogeneity) does the association between the SFR water use and these factors demonstrate spatial variability? If yes, what spatial patterns do they show? (3) (Spatial connectivity) does the relationship between the SFR water use and these factors show spatial dependence?

4.2. Methods

4.2.1 Study area

Our study area is the City of Phoenix, the capital of Arizona, US, and one of the fourteen municipalities in the greater Phoenix metropolitan area. Phoenix is located on the upper edge of the Sonoran Desert resulting in warm winters (average January temperature is 56°F) and hot summers (average July temperature is 95°F)[1]. In the past 60 years, this region has experienced extensive urbanization growing from an agricultural center to a major metropolis with a population of near four million in the total metro area and more than 1.4 million in Phoenix alone. Phoenix is supplied by both local sources of surface water and groundwater and external water from Colorado River conveyed by Central Arizona Project. There are few options for further increasing water supply to meet the local demands because (1) available surface water sources have been almost fully allocated, and (2) severe groundwater overdraft in earlier years has led to the Groundwater Management Act (GMA), which limits the groundwater pumping. Approximately two-thirds of water used in Phoenix is in the residential sector, and half is supplied for single-family homes.

[1] Average temperature is calculated based on temperature records from Phoenix Sky Harbor International Airport weather station for the years from 1981 to 2010.

4.2.2 Data

We use the US census tracts in 2000 and 2010 cover the boundary for the City of Phoenix as the basic spatial units of analysis. Thus, we have 303 census tracts in 2000 and 359 census tracts in 2010. However, we encountered a problem of boundary mismatch for the census tracts from 2000 to 2010, which is common for longitudinal studies using census tract data. Although the boundaries of a majority of census tracts (n = 241) remain the same from US Census 2000 to US Census 2010, some merge into larger ones, some split into smaller ones, and others change in an irregular way. We adopt different strategies for the three conditions with an overall strategy to retain the larger geographic area. If two or more census tracts merge into a larger one (n = 4), we use the boundary in US Census 2010. If a census tract is split into several smaller ones (n = 29), we use the boundary in US Census 2000. If boundaries of a subset of census tracts change irregularly but the overall boundary of this subset does not change (n = 3), we choose this overall boundary. We still use "census tract" to call the spatial scale in spite of such strategies adopted. This process resulted in n = 277 census tracts in total for our analysis.

The data on the dependent variable and explanatory variables used in this study were obtained from several sources (Table 4.1). We acquired data on average household water use in 2009 for single-family homes at the census tract scale from the Water Services Department, the City of Phoenix for our dependent variable. To calculate the temporal change of associated factors, we first obtained the data of these factors for 2000 and 2009. Data on average household size and median household income in 2000 and 2009 were extracted from US Census 2000 and 2010, respectively. The median household income in 2009 was deflated by consumer price index to 2000 dollars. The Maricopa County Assessor's Database provides detailed data of property characteristics for each parcel. We extract house age, pool size, and livable area, lot size, and number of stories, and also calculate the irrigable lot size following Harlan et al. (2009):

$$ILS = LS - \frac{LA}{S} - PS \tag{4.1}$$

where *ILS* is the irrigable lot size; *LS* is the lot size; *LA* is the livable area; *S* is the number of stories; and *PS* is the pool size. The parcel level data on house age, livable area, pool size, and irrigable lot size are aggregated to the census tract scale by calculating mean values. Before computing the temporal change in average house age, we adjusted the average house age in 2000 to the year of 2009 by increasing it by nine units for each census tract so that its temporal change really reflects new housing development. Average livable area is not included in our model because it is significantly and highly correlated with median household income (0.925, p<0.001), and inclusion of average livable area would cause significant multi-collinearity.

Our climate factors are average annual precipitation and average daily maximum temperature in 2000 and their temporal change during 2000-2009. We tried to acquire climate data from as many weather stations as possible to cover the metropolitan area. Some of them have both records of precipitation and temperature, but others only have precipitation or temperature data. We obtained the precipitation data from 142 weather stations operated by 3 networks—Arizona Meteorological Network (AZMET), National Oceanic and Atmospheric Administration (NOAA), and Maricopa County Flood Control District (MCFCD). The near surface (2m) temperature data were obtained from 39 weather stations operated by AZMET, NOAA, MCFCD, and Phoenix Real-time Instrumentation for Surface Meteorological Studies (PRISMS). Point data representing annual precipitation and average daily maximum temperature were interpolated using ordinary kriging method. We then calculated the average annual precipitation and average daily maximum temperature in 2000 as well as their temporal change during 2000-2009 for each census tract in our study (n = 277).

The last two factors we considered are housing density in 2000 and the change of housing density between 2000 and 2009. Housing density in 2000 is calculated by dividing the number of these single-family houses in each census tract in 2000 by the area of the census tract. Similarly the temporal change of housing density is calculated by dividing the temporal change of single-family houses in each census tract by the area of the census tract.

Table 4.1 Definition of variables and data sources

Variable	Definition	Data Source	Unit
W09	Average household water use in 2009	Water Services Department, City of Phoenix	Gallon
HHS00	Average household size in 2000	US Census 2000	Person
HHI00	Median household income in 2000	US Census 2000	$
HA00	Average house age in 2000	Maricopa County Assessor Database	Year
PS00	Average pool size in 2000	Maricopa County Assessor Database	m^2
ILS00	Average irrigable lot size in 2000	Maricopa County Assessor Database	m^2
P00	Average annual precipitation in 2000	AZMET, NOAA, MCFCD	Inch
T00	Average daily maximum temperature in 2000	AZMET, NOAA, MCFCD, PRISMS	Fahrenheit
HD00	Housing density in 2000	Maricopa County Assessor Database	house unit/km^2
ΔHHS	Average household size in 2010 - Average household size in 2000	US Census 2000, US Census 2010	Person

ΔHHI	Median household income in 2010 - Median household income in 2000	US Census 2000, US Census 2010	$
ΔHA	Average house age in 2009 - Average house age in 2000	Maricopa County Assessor Database	Year
ΔPctP	Percent single-family houses with pools in 2009 - Percent of single-family houses with pools in 2000	Maricopa County Assessor Database	%
ΔILS	Average irrigable lot size in 2009 - Average irrigable lot size in 2000	Maricopa County Assessor Database	m^2
ΔP	Average annual precipitation in 2009 - Average annual precipitation in 2000	AZMET, NOAA, MCFCD	Inch
ΔT	Average daily maximum temperature in 2009 - Average daily maximum temperature in 2000	AZMET, NOAA, MCFCD, PRISMS	Fahrenheit
ΔHD	Housing density in 2009 - Housing density in 2000	Maricopa County Assessor Database	house unit/km^2

Note:

1. Median annual household income in 2010 is deflated by consumer price index to 2000 dollars before ΔHHI is calculated.

2. We adjust the average house age in 2000 to the year of 2009 by increasing it by nine units for each census tract before calculating ΔHA.

4.2.3 Regression analysis

We use ordinary least squares (OLS) regression, spatial error model, and geographically weighted regression (GWR) to study the relationship between average single-family household water use in 2009 (W09) and sixteen associated factors (Table 1). These factors include average household size in 2000 (HHS00), median household income in 2000 (HHI00), average house age in 2000 (HA00), average pool size in 2000 (PS00), average irrigable lot size in 2000 (ILS00), average annual precipitation in 2000 (P00), average daily maximum temperature in 2000 (T00), housing density in 2000 (HD00), and the other eight factors of temporal change each corresponding to one of the above eight (ΔHHS, ΔHHI, ΔHA, ΔPS, ΔILS, ΔPctP, ΔT, and ΔHD). The change in percentage of single-family houses with pools (ΔPctP) is used instead of the change in average pool size because we think the former can be more intuitively understandable than the latter.

The OLS regression assumes a global relationship between the dependent variable and independent variables across the study area (spatial stationarity), and does not account for possible spatial autocorrelation that violates the independence assumption of the model. An OLS regression model is defined here as:

$$Y_i = \beta_0 + \boldsymbol{X_i}'\boldsymbol{\beta} + \varepsilon_i \tag{4.2}$$

where Y_i is the average household water use in census tract *i*, $\boldsymbol{X_i}$ is the vector of observations of independent variables in census tract *i*, β_0 is the intercept, $\boldsymbol{\beta}$ is the vector of global coefficients for independent variables, and ε_i is the error term. We use GeoDa 1.4.1 to implement the OLS regression.

To account for spatial autocorrelation in the residuals of the OLS regression, we also used spatial regression models (Ward and Gleditsch, 2008; Chang et al., 2010) and GWR (Fotheringham et al., 2002; Wentz and Gober, 2007). The spatial regression and GWR are developed based on two different perspectives. Like the OLS regression, spatial regression models assume a global relationship between the dependent variable and the associated factors (i.e. spatial stationarity), while the GWR assumes spatial non-stationarity in the relationship. Thus a spatial regression model calculates global parameter estimates for all spatial units, whereas a GWR model produces local parameter estimates for each spatial unit. A spatial regression model can be considered to explore the average relationship between the response variable and explanatory variables as an OLS regression model does, whereas a GWR model is to show the spatial heterogeneity in the relationship.

There are two types of spatial regression models. One is the spatial lag model, which includes weighted spatially lagged dependent variables, and the other is the spatial error model, which includes a spatially autocorrelated error term. Two test statistics—Lagrange Multiplier (LM) statistic and Robust LM statistic can be used to test whether the spatial error or spatial lag model should be used. We found that the LM statistic only supports the spatial error model, and thus we only use the spatial error model. The spatial error model is defined as:

$$\begin{cases} Y_i = \beta_0 + \boldsymbol{X_i}'\boldsymbol{\beta} + u_i \\ u_i = \rho \sum_j w_{ij} u_j + \varepsilon_i \end{cases} \tag{4.3}$$

where u_i is the error term for Y_i, which is correlated with the error terms of neighboring census tracts; and ρ is the spatial autocorrelation coefficient. $W = [w_{ij}]_{N \times N}$ is the spatial weight matrix that defines the arrangement of the spatial units. Thus the local relationship is incorporated in the spatial error model through the covariance structure of the error terms. We construct the spatial weight matrix based on Rook continuity, which means that census tracts sharing a common border are considered as neighbors. If census tracts *i* and *j* are neighbors, we set the weights $w_{ij} = w_{ji} = 1$; otherwise $w_{ij} = w_{ji} = 0$. By convention, we set the diagonal elements to be zeros. Before being input to the model, the spatial weight matrix is standardized to make the elements of each row sum to one. The spatial error model is implemented in the GeoDa software.

GWR also attempts to overcome the spatial autocorrelation limitation of OLS regression by accounting for the spatial heterogeneity in a statistical relationship. A local GWR model for spatial unit *i* is defined as:

$$Y_i = \beta_0(u_i, v_i) + \boldsymbol{X_i}'\boldsymbol{\beta}(u_i, v_i) + \varepsilon_i \tag{4.4}$$

where the coefficients $\beta_0(u_i, v_i)$ and $\boldsymbol{\beta}(u_i, v_i)$ are dependent on the geographic coordinates (u_i, v_i) of census tract *i*. For each census tract that has an observation in the sample dataset, GWR runs a local regression model by weighting neighboring observations based on distance. Different weighting schemes have been proposed, but they are based on the same principle that closer spatial units have more influence on the parameter estimation of a local model. The weight matrix of GWR is different from the spatial weight matrix used in spatial regression models that has the diagonal elements to be zeros. Several methods have been proposed to determine the weight matrix (Fotheringham et al., 2002). We use the bi-square weighting function as defined as:

$$w_{ij} = \begin{cases} [1 - \left(\frac{d_{ij}}{b}\right)^2]^2 & d_{ij} < d_{max} \\ 0 & \text{otherwise} \end{cases} \tag{4.5}$$

where d_{ij} is the distance between two census tracts, and d_{max} is the maximum distance from census tract *i*. We adopt the adaptive kernel technique to determine d_{max} for each census tract assuring that each census tract has the same number of neighbors. The number of neighbors (bandwidth) is determined using a cross-validation approach based on the Akaike Information Criterion (AIC). That is, the selected bandwidth minimizes the AIC. We used GWR 4.0 in this study. The spatial variation of the parameter estimate for each independent variable provides a convenient way to examine the spatial pattern as to the effect of each independent variable on water use in 2009. It should also be noted that the local coefficients of the same independent variable may not be uniformly statistically significant. We do not think it is reasonable to consider and compare all the local coefficients of an independent variable in addressing spatial variability if some of them are not statistically significant at a certain level (e.g. 0.05 in this study). Thus, we remove those parameter estimates that are not statistically significant at the 0.05 level based on the *t*-test and only focus on those statistically significant local coefficients.

4.3. Results

4.3.1 Exploratory Analysis

Table 4.2 presents a series of descriptive statistics at the census tract scale for average household water use in 2009 (W09) and the explanatory variables included in regression analysis. W09 ranges from a minimum of 71617 to a maximum of 470214 gallons, but 90% of the values fall below 183382 gallons. The global Moran's *I* score for W09 is 0.164 ($p <$ 0.001), which indicates that W09 has spatial autocorrelation across the census tracts. The census tracts with higher values of W09 are mostly located in the central and eastern part of the city as well as along the southern periphery (Figure 1). These areas are also associated with higher household income. In comparison, we also see that the census tracts with lower values of W09 are located in the upper part around the Phoenix-Deer Valley Municipal Airport, the lower east part around the Phoenix Sky Harbor International Airport, and a small part in the west between N. 67th and 71st Avenues and W. Thomas and Indian Roads (Figure 4.1). These census tracts are homes to mostly low income households. We do not provide discussion on spatial variation of explanatory variables here, and such information will be provided when we present and discuss the GWR results.

Table 4.2 Descriptive statistics on variables at the census tract scale

Variable	Minimum	Maximum	Mean	Standard deviation
W09	71616.983	470213.977	127601.088	47168.440
HHS00	2.27	4.66	3.433	0.537
HHI00	15687	207493	60377.610	30848.445
HA00	3	84	31.740	16.817

PS00	0	40.497	10.656	8.922
ILS00	333	4845	775.830	469.934
P00	5.562	8.417	6.674	0.587
T00	83.853	87.66	85.947	0.595
HD00	7	1143	439.433	252.091
ΔHHS	-0.74	0.6	0.000296	0.221
ΔHHI	-50872	50378	-3156.101	10626.172
ΔHA	-28	2	-2.563	4.725
ΔPctP	-23.37	12.45	1.748	2.920
ΔILS	-3182	475	-52.552	298.897
ΔP	-4.619	-2.263	-3.177	0.489
ΔT	-0.896	1.074	0.296	0.377
ΔHD	-66	440	22.058	50.209

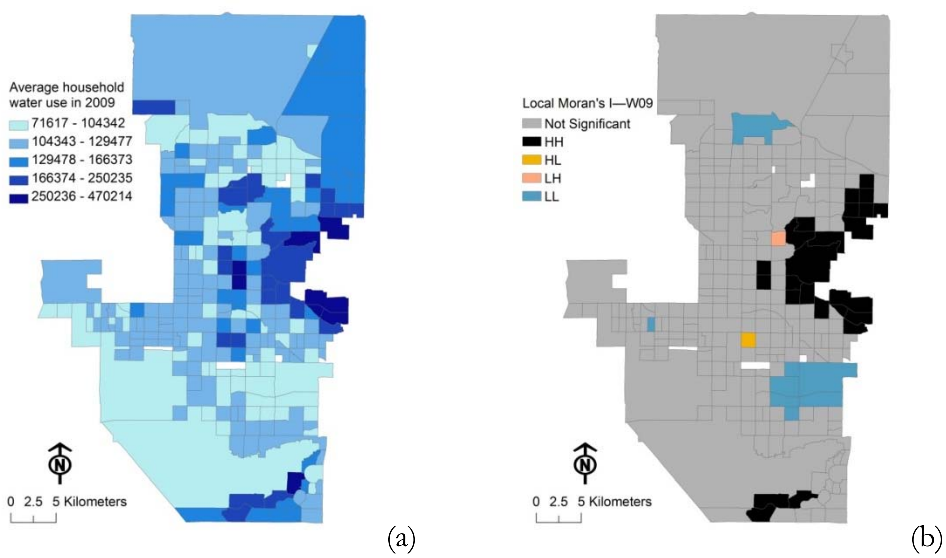

Figure 4.1 Spatial distribution of average household water use in 2009 (W09): (a) map of W09 (b) map of local Moran's I of W09, where HH denotes cluster of high values, LL denotes cluster of low values, HL denotes where a high value is surrounded primarily by low values, and LH denotes where a low value is surrounded primarily by high values.

4.3.2 Results of Global Models

The OLS regression model explains 90% of the variance in W09. The coefficient estimates are presented in Table 4.3. The housing and household variables in 2000, including HHS00, HHI00, HA00, PS00 and ILS00, and T00, show statistically significant effects on W09 (at the 0.05 level; the same hereafter unless stated otherwise). Only two variables of change—ΔHHI and ΔILS have statistically significant results. The standardized coefficients of ΔHHI (0.087) and ΔILS (0.215) are lower than those of HHI00 (0.766) and ILS00 (0.287), respectively, which indicates that the temporal change of HHI and ILS are more important to influence W09 than their corresponding values in 2000. The Moran's *I* score (0.032, p = 0.017) indicates significant spatial autocorrelation of the residuals, which invalidate the use of OLS regression for our case. The LM test for spatial lag is not statistically significant (p = 0.16), which indicates the spatial lag model is not appropriate[2]. The LM test statistic for spatial error is statistically significant (p < 0.001), which sets the stage for the spatial error model.

Compared with the OLS regression model, the spatial error model yields a better fit to the data because of its higher log-likelihood and lower AIC and BIC (Table 4.3). The coefficients in the spatial error model show the same statistical significance results as the corresponding terms in the OLS regression model, but their magnitudes are somewhat different (Table 4.3). The coefficient of the spatially lagged error (0.362) is highly significant (p < 0.001), and the likelihood ratio test also shows significant result (16.926, p < 0.001). In addition, the Moran's *I* score (-0.027, p = 0.431) indicates no significant spatial autocorrelation in the residuals. These results confirm the effectiveness of the spatial error term in controlling spatial autocorrelation.

[2] The Robust LM test should only be considered when the both LM test statistics are significant.

Table 4.3 Results of the OLS regression model and spatial error model (SEM)

Variable	Coefficient		Standard Error		Standardized Coefficients
	OLS	SEM	OLS	SEM	OLS
ΔHHS	-1004.469 (-0.177)	-2781.714 (-0.470)	5663.346	5912.38	-0.005
ΔHHI	0.386 (3.976)***	0.425 (4.685)***	0.097	0.091	0.087
ΔHA	87.292 (0.227)	124.122(0.338)	385.103	367.325	0.009
ΔPctP	7802.84 (0.18)	52946.84 (1.365)	43399.097	38781.97	0.005
ΔILS	33.947 (4.923)***	37.966 (5.732)***	6.896	6.623	0.215
ΔP	-4253.215 (-0.883)	-3367.098 (-0.539)	4817.784	6245.468	-0.044
ΔT	7932.88 (1.301)	10671.97(-0.539)	6096.272	7442.021	0.063
ΔHD	4.076 (0.145)	0.839 (0.031)	28.024	26.721	0.004
HHS00	10931.56 (3.65)***	12526.23 (3.868)***	2995.018	3238.394	0.124
HHI00	1.172 (17.198)***	1.045 (14.917)***	0.068	0.070	0.766
HA00	785.464 (7.158)***	679.918 (5.355)***	109.731	126.969	0.280
PS00	1433.660 (6.143)***	1849.137 (7.813)***	233.384	236.670	0.271
ILS00	28.817 (6.254)***	29.832 (6.624)***	4.608	4.504	0.287
P00	-5637.386 (-1.192)	-5268.937 (-0.851)	4728.071	6194.916	-0.070
T00	11150.87 (2.964)**	12929.08 (2.717)**	3762.181	4759.45	0.141
HD00	3.657 (0.766)	-0.125 (-0.027)	4.775	4.686	0.020

R^2: R^2(OLS) = 0.901; R^2(SEM) = 0.910
Log-likelihood (LL): LL(OLS) = -3053; LL(SEM) = -3045
Akaike information criterion (AIC): AIC(OLS) = 6140; AIC(SEM) = 6123
Bayesian information criterion (BIC): BIC(OLS) = 6202; BIC(SEM) = 6185

Note:

1. *t*-values in parentheses for the OLS regression model.

2. *Z*-value in parentheses for the spatial error model

3. The R^2 of the spatial error model is not directly comparable with the R^2 given for OLS regression. The proper measures of fit to compare the two models are the log-likelihood, AIC, and BIC.

4. *: p<0.05; **: p<0.01; ***: p<0.001.

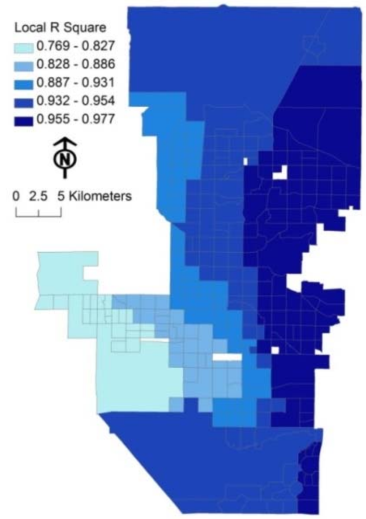

Figure 4.2 Spatial distribution of local R^2 of the GWR model

4.3.3 GWR Model Results

The GWR model on average explains about 96% of the variance in W09. The AIC score of the GWR model (6001) is much lower than those of the OLS regression and spatial error model (6140 and 6123, respectively), indicating that the GWR model is a better fit to the data than both the OLS regression and the spatial error model. The analysis of variance tests the null hypothesis that the GWR model has no improvement over the OLS regression model. The result ($F = 3.94$, $p < 0.001$) allows rejecting the null hypothesis, and indicates that the GWR model has a significant improvement over the OLS regression model. The Moran's *I* score (-0.021, $p = 0.243$) indicates there is no significant spatial autocorrelation in the residuals of the GWR model, and thus the GWR model does account for the spatial effects. Figure 4.2 shows the spatial distribution of the local R^2 for each census tract, with values ranging from 0.77 to 0.98. Overall, the local models do very well in explaining the variance in W09, but the local R^2 shows a clear trend of western low values and eastern high values.

One advantage of the GWR model is its capability to produce the local coefficients and examine their spatial variations. The variation in the local coefficients illustrates the spatial non-stationarity in the relationship between residential water use and its predictors. The geographical variability tests of local coefficients reveal that ΔILS, ΔP, HHS00, HHI00, HA00, ILS00, P00, and T00 exhibited significant spatial variation. However, these results are obtained using all the estimates of local coefficients. Taking a closer look at the local results, we find that none of these factors except HHI00 consistently has statistically significant local coefficients in all the census tracts. Thus, we will focus on those local coefficient estimates that are statistically significant and analyze their spatial variation. Overall, among the variables of 2000, median household income and other housing characteristics, including house age, pool size, and irrigable lot size, are important predictors of residential water uses since they largely have significant effects on W09. The variables of temporal change do not generally reveal significant effects on residential water use, but show clusters with significant local coefficients. We summarize the spatial pattern of significant local coefficients of each explanatory variable in Table 4.4 (also see Figures A1-A8 in Appendix A).

Table 4.4 Spatial patterns of local effects of explanatory variables on average single-family household water use in 2009 (W09)

Variable	Spatial pattern of local coefficients of the GWR model
HHS00	The census tracts where HHS00 has a positive and significant effect on W09 form a large cluster in the central and eastern part, covering some census tracts with higher values of the local coefficients of HHS00 near Paradise Valley, and some with lower values around Phoenix Sky Harbor International Airport (Figure A1).
ΔHHS	ΔHHS does not have a significant effect on W09 at large. The census tracts where ΔHHS shows a significant effect on W09 generally have negative values of ΔHHS. That is, the average household size decreased from 2000 to 2009 in these census tracts. Of them, there are a few census tracts lying to the northeast of Phoenix Mountains Preserve where ΔHHS shows a positive and significant effect. These census tracts have an average household size to be around three. There are also a couple of tracts in the southeast where ΔHHS shows a negative effect

	(Figure A1)
HHI00	HHI00 consistently has a positive and significant effect on W09. The highest coefficients occur in the eastern part near Paradise Valley, and the lowest coefficients cluster in the southwest. HHI00 has a larger effect on W09 than ΔHHI in general (Figure A2).
ΔHHI	The local coefficients of ΔHHI are consistently positive and significant in the central and southern part, but not significant in the north. Some census tracts with the highest values of the local coefficients of ΔHHI cluster in the eastern part to the west of Paradise Valley (Figure A2).
HA00	The local coefficients of HA00 are positive and significant in most of the census tracts. Census tracts with the highest values also cluster to the west of Paradise Valley (Figure A3).
ΔHA	ΔHA only has a positive and significant effect on W09 in a few census tract in the central part, and the largest effect occurs in some census tracts with an average house age ranging from thirty to fifty years. In addition, in those census tracts where both HA00 and ΔHA have significant local coefficients, the local coefficients of ΔHA are generally larger than those of HA00, which indicates that new single-family housing development has a larger effect on W09 than average house age in 2000 (Figure A3).
PS00	PS00 has a positive and significant effect on W09 in all the census tracts except for a couple in the southwest. High values of the local coefficients of PS00 cluster in the southern part, and low values of the local coefficients of PS00 cluster in the west and east (Figure A4).
ΔPctP	The local coefficients of ΔPctP are significant in a few census tracts that lie in the northern and central part where ΔPctP and the effect of ΔPctP on W09 are both positive (Figure A4).
ILS00	ILS00 consistently has a positive and significant effect on W09 in the north, east, and south, but not in most of the western part. High values of its local coefficients cluster to the north and south of Phoenix Sky Harbor International Airport (Figure A5).
ΔILS	The census tracts with significant local coefficients of ΔILS cluster in several places in the central and southern part of Phoenix. Two of the clusters exhibit positive effects while the other two show negative effects. The census tracts where ΔILS has a negative and significant effect on W09 are generally with the ILS00 between 1000 and 2000 square meters (Figure A5).
P00	P00 does not have a significant effect on W09 at large except for three small clusters of census tracts. Two clusters are with a negative effect of P00 on W09: one lies in the northeast where urbanization occurs most recently, and the other is in the central part where the oldest neighborhoods are located. Another cluster with positive effects of P00 on W09 lies to the west of Paradise valley where the average house age is between those of the first two clusters (Figure A6).
ΔP	ΔP does not generally have a significant effect on W09. Two small clusters of census tracts with significant local coefficients of ΔP are formed, of which one is located to the west of Paradise Valley with a positive effect of ΔP on W09, and the other is in the northern part with a negative effect of ΔP on W09. The cluster with a positive effect of ΔP almost coincides with the cluster with a positive effect of P00, and those two effects are similar to each other in these census tracts (Figure A6).
T00	The census tracts with positive and significant local coefficients of T00 form two clusters: one to the west of Paradise Valley, and the other in the west neighboring to the two cities of Glendale and Tolleson (Figure A7).
ΔT	ΔT shows significant effects on W09 in a few census tracts forming three clusters: two clusters with a negative effect on W09 in the eastern part (to the west of Paradise Valley) and in the South Mountain area, respectively; and one cluster with a positive effect on W09 in the west, which almost coincides with the western cluster of T00. In the western cluster, ΔT in general has a larger effect on W09 than T00 (Figure A7).
HD00	HD00 show two small clusters of census tracts with significant local coefficients. One with a positive effect on W09 is in the eastern part to the northeast of Phoenix Mountains Preserve,

	and the other with a negative effect on W09 is in the central part to the west of Phoenix Mountains Preserve (Figure A8).
ΔHD	ΔHD does not show significant local coefficients in any of the census tracts.

Note: By "significant" we mean statistically significant at the 0.05 level.

4.4. Discussion

4.4.1 Historical Contingency

The results of OLS regression and spatial error models suggest that housing, household, and climate factors in 2000 are more important than their temporal change during 2000-2009 in predicting the SFR water use in 2009. This suggests that residential water use in Phoenix belongs to a Type I system as we discuss above. In particular, the housing and household characteristics in 2000 are the major determinants. Although we do not include any behavior and policy factors in this analysis, the much greater importance of housing and household characteristics in 2000 than their temporal change in influencing SFR water use in 2009 indicates the persistence of the lifestyle of high-rate water use because housing and household characteristics to some extent reflect lifestyle of households. Average household water use declined almost systematically in census tracts from 2000 to 2009, with an average rate of decrease of 20%. However, the SFR water use still maintains a relatively high level. Our result seems consistent with the findings of Hirt et al. (2008) and Larson et al. (2009) that the high rates of water consumption persist today are due to the long-standing oasis lifestyle as well as the relatively conservative political environment. In addition, the built environments related to water use changed relatively slowly between the nine years, which is a possible explanation for the more importance of housing characteristics in 2000 than their temporal change in influencing water use in 2009 as well as the persistence of high-rate water use.

Although the effects of the temporal change in housing and household characteristics at large are relatively minor compared to their values in 2000, we still find that the temporal variations of median household income and average irrigable lot size influences SFR water use in 2009 from the results of spatial error model. Increasing median household income by 1000 dollars (in 2000 dollar) during 2000-2009 is associated with 425 gallons more water used by a typical single-family home in 2009. The temporal change in housing characteristics mainly reflects the single-family residential development because few old buildings for single-family residential use were turned down in the period. The effect of temporal change in average irrigable lot size indicates that developing single-family homes with smaller yards can decrease water use. Contrary to our expectation, neither of the housing density factors were statistically significant unlike the findings of Chang et al. (2010). The reason our results are different from Chang et al. (2010) may be that our calculation of SFR housing density was based on the total area of each census tract whereas Chang et al. (2010) used the area zoned as SFR. The inclusion of area zoned for categories other than SFR may confound the results.

Compared to 2000, the year 2009 was generally drier and warmer in Phoenix. However, such climatic difference between 2000 and 2009 does not significantly influence SFR water use in 2009. The GWR model results also indicate that the temperature and precipitation in 2000 do not generally significantly influence the SFR water use in 2009. In fact, when we replace the climate factors in 2000 and their change between 2000 and 2009 with the climate factors in 2009 in the GWR model, we find similar results. Climate factors may have more immediate effects on water use rather than show lag effects over a long period such as nine years as we consider. This may be the reason why concurrent climate factors show statistically significant results in many other cross-sectional and panel studies.

In addition, climate factors are more likely to have effects on SFR water use at smaller temporal scales such as daily, monthly, and seasonal scales (Guhathakurta et al., 2007; Polebitski and Palmer, 2010; Slavíková et al., 2013).

4.4.2 Spatial Connectivity and Spatial Heterogeneity

Our analysis shows several aspects of spatial connectivity in SFR water use and its relationship with associated factors. First, SFR water use shows a significant spatial dependence between neighboring census tracts in Phoenix. Especially high and low SFR water use exhibit clustered patterns. Second, the local effects of the housing, household, and climate factors on SFR water use as represented by the statistically significant local coefficients in the GWR model also show strong clustering patterns. Third, beyond the effects of those factors we have considered in the model, the statistically significant autocorrelation coefficient in the spatial error model indicates that SFR water use is also affected by some other omitted factors locally and between neighboring census tracts.

Spatial heterogeneity is also found in the relationship between SFR water use and the associated factors. The housing, household, and climate factors better explain the variability of SFR water use in the eastern tracts than in the western tracts as indicated by the local R^2 of the GWR model. If we consider all local coefficients of each explanatory variable no matter whether they not statistically significant or not, most of the 2000 variables (except average pools size and housing density) as well as changes in average irrigable lot size average precipitation exhibit significant spatial variation. The clustering patterns of statistically significant local coefficients described in the Results section also demonstrate the spatial heterogeneity in the relationship between SFR water use and each of these factors except change in housing density.

4.5. Conclusion

SFR water use in Phoenix is a complex system involving spatial connectivity, spatial heterogeneity, and historical contingency. Our study illustrates the importance of the spatial effects in residential water use modeling especially at aggregated geographic scales. The GWR model performs the best in fitting the data among the three models, and the spatial error model also outperforms the OLS regression model. The logic of a spatial error model is that the model assumes that spatial autocorrelation originates from the omitted variables that follows a spatial pattern, and uses the spatially lagged error terms to account for the effects of these omitted variables. Thus the relationship of SFR water use and its associated factors in a spatial error model cannot be presented in a spatially explicit way. In comparison, the GWR model provides local coefficients to show the spatial heterogeneity and connections in the relationship between SFR water use and its associated factors.

In addition to addressing the spatial dimensions in the complex system of SFR water use, our study probably is the first to consider the historically contingent effects of associated factors on SFR water use. We find that during the period between 2000 and 2009, housing, household, and climate factors in 2000 exhibit more important effects on the SFR water use in 2009 than their temporal change. However, we think the reasons for such results may be different for housing and household characteristics and climate factors. For housing and household characteristics, we think they reflect high-rate water use behavior that did not experience a radical change probably due to a long-established oasis lifestyle, although the average household water use generally declined in this period. However, it will need more relevant variables of lifestyle to test this hypothesis and make a solid conclusion. As to the climate factors, we think precipitation and temperature may be more influential at a smaller temporal scale (seasonal or monthly) than their annual statistics, and they probably have more immediate effects on SFR water use.

Chapter 5

CONCLUSION

5.1 Summary of findings

This dissertation offers three main contributions to understanding the relationship between SFR water use and associated factors. First, I demonstrate that aggregated scale data can reliably be used to study the relationship between SFR water use and its determinants without leading to significant ecological fallacy (Chapter 2). The usability of aggregated scale data can help researchers carry out scientific inquiry about SFR water use with more available aggregated scale data. Second, this dissertation advances our understanding of spatial and temporal dependence in the relationship between SFR water use and its associated factors (Chapters 3 and 4). Spatial and temporal dependence are both important in that they may bias the estimation of the effects of associated factors on SFR water use. In a more practical sense, spatial and temporal dependence can be used in water demand management to develop stepwise strategies to improve efficiency. From a long-term perspective, the temporal dependence as reflected by historical contingency can help assess whether and how water use level changes or maintains over time. Third, this dissertation also contributes to SFR water use modeling by introducing spatial panel data models (Chapter 3) and evaluating different regression models (Chapter 4). The following discussion summarizes the major findings of the three research chapters.

In Chapter 2, using linear mixed-effects models, I compare the results for the relationship of single-family water use with its determinants using data from the household and census tract scales in the city of Phoenix. Model results between the household and census tract scale are similar suggesting the ecological fallacy may not be significant. I also use city/town scale data from the Phoenix metropolitan area to parameterize the linear mixed-effects model. The difference in the parameter estimates of common variables compared to the first two spatial scales indicates there is spatial heterogeneity in the relationship between single-family water use and its determinants among cities and towns. The positive relationship between single-family house density and residential water use suggests that residential water consumption could be reduced through coordination of land use planning and water demand management.

In Chapter 3, I introduce spatial panel data models to study the spatial effects of associated factors on SFR water use while accounting for temporal dependence in SFR water use as well. I use a search procedure that includes a series of statistical tests, and find the most appropriate spatial panel data model—Spatial Durbin model with spatial random effects and time-period fixed effects to fit the dataset. Results show that non-spatial panel data models produce biased estimates compared with the spatial panel data models. The findings indicate the importance of capturing spatial effects in modeling panel data for residential water use research.

Chapter 4 also addresses the spatial and temporal dependence in the relationship of SFR water use with associated housing, household, and climate factors, but in a different way. In this chapter, I study the historical contingency, spatial heterogeneity, and spatial connectivity in the relationship of SFR water use and its determinants by using three regression models including ordinary least squares (OLS) regression, spatial error model, and geographically weighted regression (GWR). The results show that housing, household, and climate factors in 2000 are generally more important than their temporal change during 2000-2009 in explaining SFR water use in 2009. Especially, housing and household characteristics are the main determinants of SFR water use, which indicates the high-level average SFR water use in Phoenix is possibly due to the long-standing oasis lifestyle as reflected by housing and household characteristics. Compared to those effects of housing and household characteristics, the historical and contingent effects of climate factors are relatively minor, which may be because they have more immediate effects on SFR water use at smaller temporal scales. Spatial dependence and spatial heterogeneity are also found in SFR water use as well as its relationship with these associated factors. Model results also show that GWR performs better than the OLS regression and spatial error model in fitting to the data due to its ability to account for spatial effects and to present local relationship between SFR water use and its associated factors.

5.2 Broader Implication

Beyond these specific contributions to understanding the relationship between SFR water use and associated factors, this dissertation also provides a much broader contribution to better understanding urban water use as a coupled human and natural system (CHANS). Achieving urban water sustainability does not only depend upon exploring new water resources, but also lies in understanding water use patterns and implementing demand management. Water use patterns can be determined or influenced by a range of socio-economic and environmental factors, but including associated factors alone is not enough for us to learn water use patterns. Understanding urban water use as a CHANS necessitates capturing the interactive effects of spatio-temporal components such as scale, dependence, and heterogeneity. In this dissertation, the three research chapters exemplify the importance of these components in explaining water use patterns. The dynamics of an urban water use system may be a relatively slow process, and predicting and managing urban water demand should take into account these spatio-temporal components in order to achieve expected results. Specifically, this research at least contributes to urban water demand management in three ways. First, single-family house density is found to consistently have negative impact on the water use from both the non-spatial and spatial panel data models, which confirms that land use and water use should be managed in a more coordinated way in order to achieve urban sustainability (Gober et al., 2013). Second, although there is no policy-based variables in this research, spatial statistical models should be used to test the effectiveness of certain management policies since spatial effects probably will significantly influence our estimates if only non-spatial statistical models are used. Third, urban water demand management should pay attention to the spatial heterogeneity in predicting the future water demand to achieve more accurate estimates, and spatial statistical models provide a promising method to do this job.

5.3 Limitations and Future Directions

It is important to note the limitations of studies involved in this dissertation, which can help make future improvements. The limitations of this dissertation come from data, methods, and explanation of results. The study in Chapter 2 to examine the model results across spatial scales is limited by the data. First, the data sets on household and census tract scales are limited in the city of Phoenix, whereas the city/town scale data cover fourteen cities and towns in the metropolitan area. I obtained the household and census tract scale data thanks to the previous data collection efforts by two NSF-supported projects (Central Arizona-Phoenix Long-term Ecological Research and Decision Center for a Desert City). However, it would not be possible to obtain data on these two scales from cities and towns other than Phoenix in this metropolitan area only for a dissertation project. Thus, results of these two spatial scales are not completely comparable to the result on the city/town scales due to the difference of spatial extent. Second, comparison of model results is based on a limited list of variables. More factors of interest can be tested by obtaining additional relevant data. Third, even in the city of Phoenix, I only consider household and census tract scales. To really address the MAUP (modifiable areal unit problem), other spatial scales, such as census block and census block group, can be also tested by using the same model in future study.

In addition to similar limitations of data and variables as in Chapter 2, there are two other limitations in Chapter 3. First, although the spatial panel models used in this study account for spatial and temporal dependence, these models are still static without capturing the potential effects of temporally lagged SFR water use and associated factors. Dynamic spatial panel data models are still in the initial stage of development, and these is no readily available software for these models. But the application of these dynamic spatial panel data models in SFR water use can be expected in the near future. Second, there is still no explicit mechanism to explain how neighboring census tracts (single-family homes or cities) influence the residential water use pattern of each other. The definition of neighboring census tracts is relatively simple. Different distance-based neighbor definitions can be tested in future study. It is also expected that this empirical study can encourage further discussion on the spillover effects of SFR water use that can potentially help enhance water demand management.

The study of historical contingency of SFR water use in a spatially explicit way in Chapter 4 is probably the first paper of this kind. Although one decade is considered a relatively long period to reflect the change or continuation of lifestyle of high-rate water use, it would be more desirable to obtain data from multiple time periods to produce more reliable results.

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APPENDIX A

SPATIAL PATTERN OF LOCAL COEFFICIENTS OF THE GEOGRAPHICALLY WEIGHTED REGRESSION MODEL

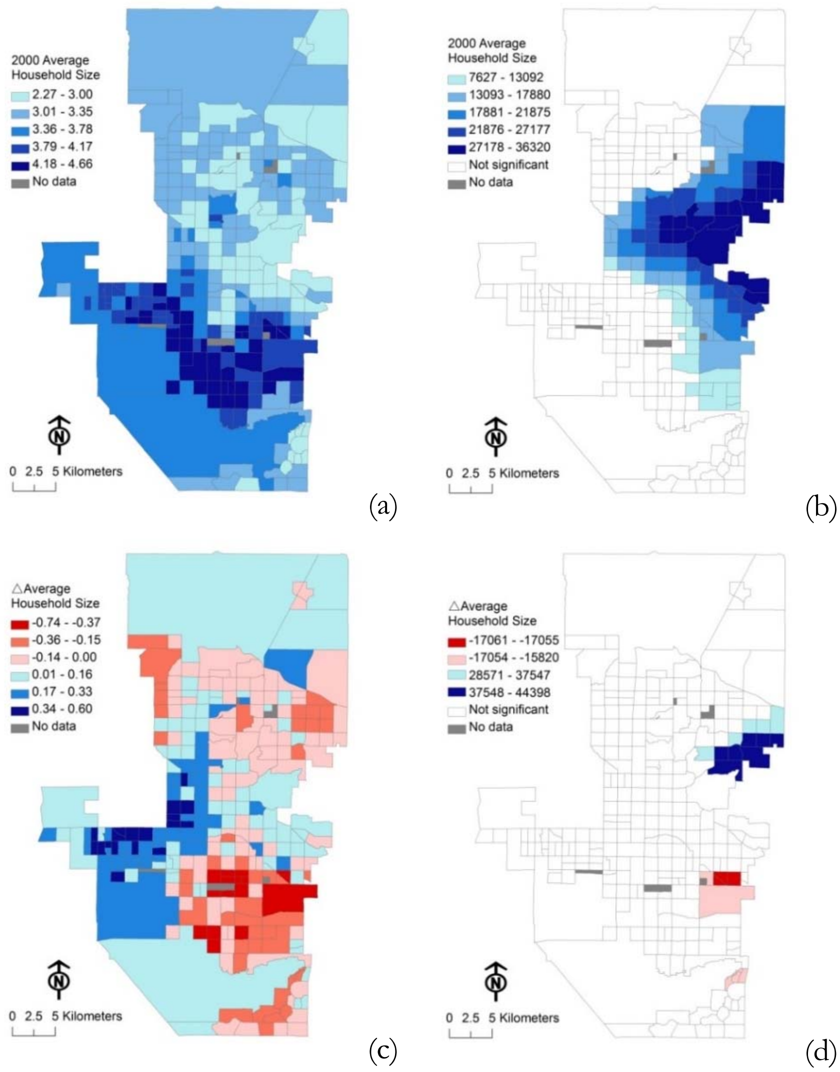

Figure A1. Household size: (a) Spatial distribution of average household size in 2000; (b) Spatial distribution of local coefficients of average household size in 2000; (c) Spatial distribution of change in average household size during 2000-2009; (d) Spatial distribution of local coefficients of change in average household size during 2000-2009.

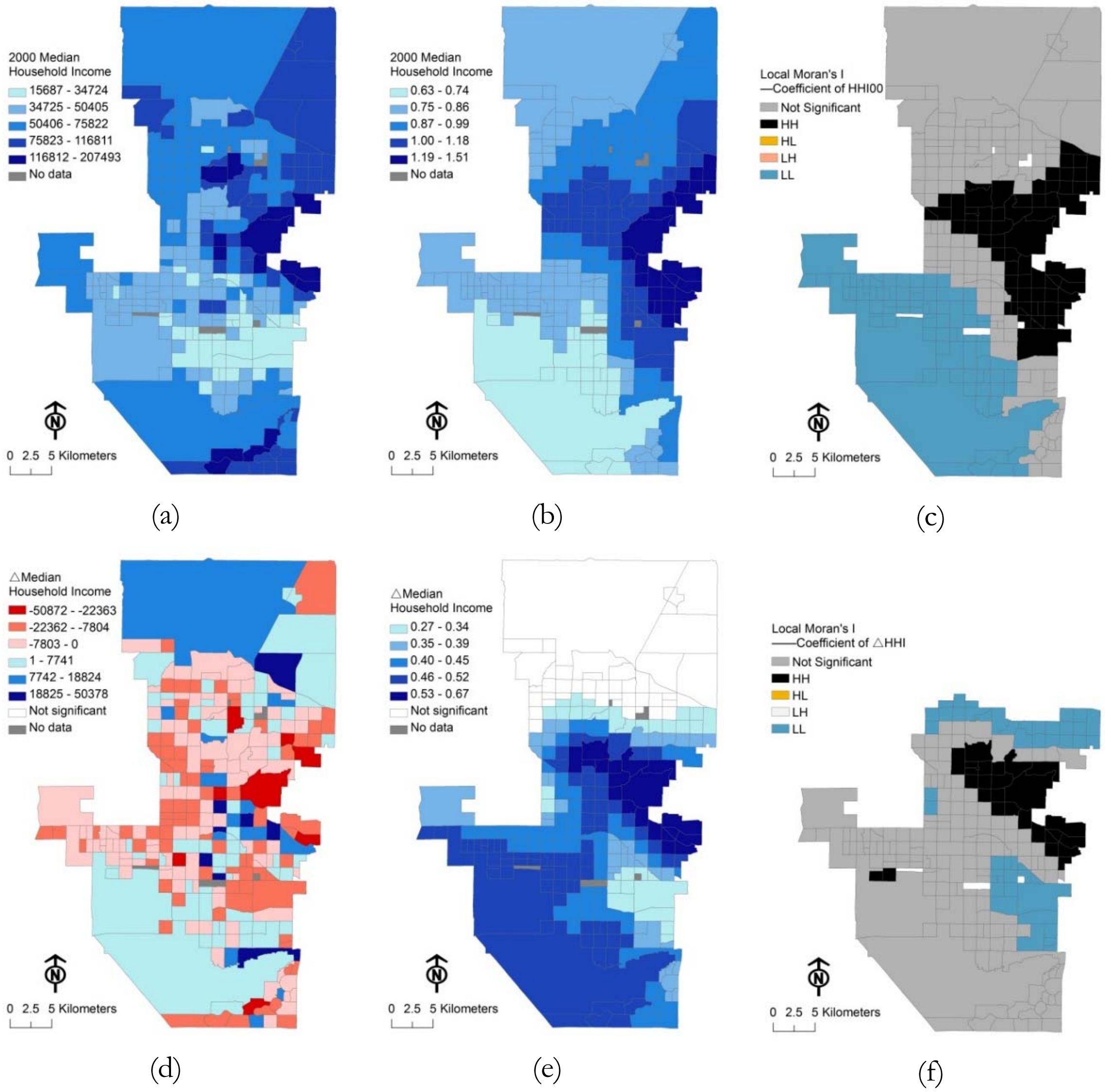

Figure A2. Household income: (a) Spatial distribution of median household income in 2000; (b) Spatial distribution of local coefficients of median household income in 2000; (c) Map of local Moran's I of local coefficients of median household income in 2000; (d) Spatial distribution of change in median household income during 2000-2009; (e) Spatial distribution of local coefficients of change in median household income during 2000-2009; (f) Map of local Moran's I of local coefficients of change in median household income during 2000-2009.

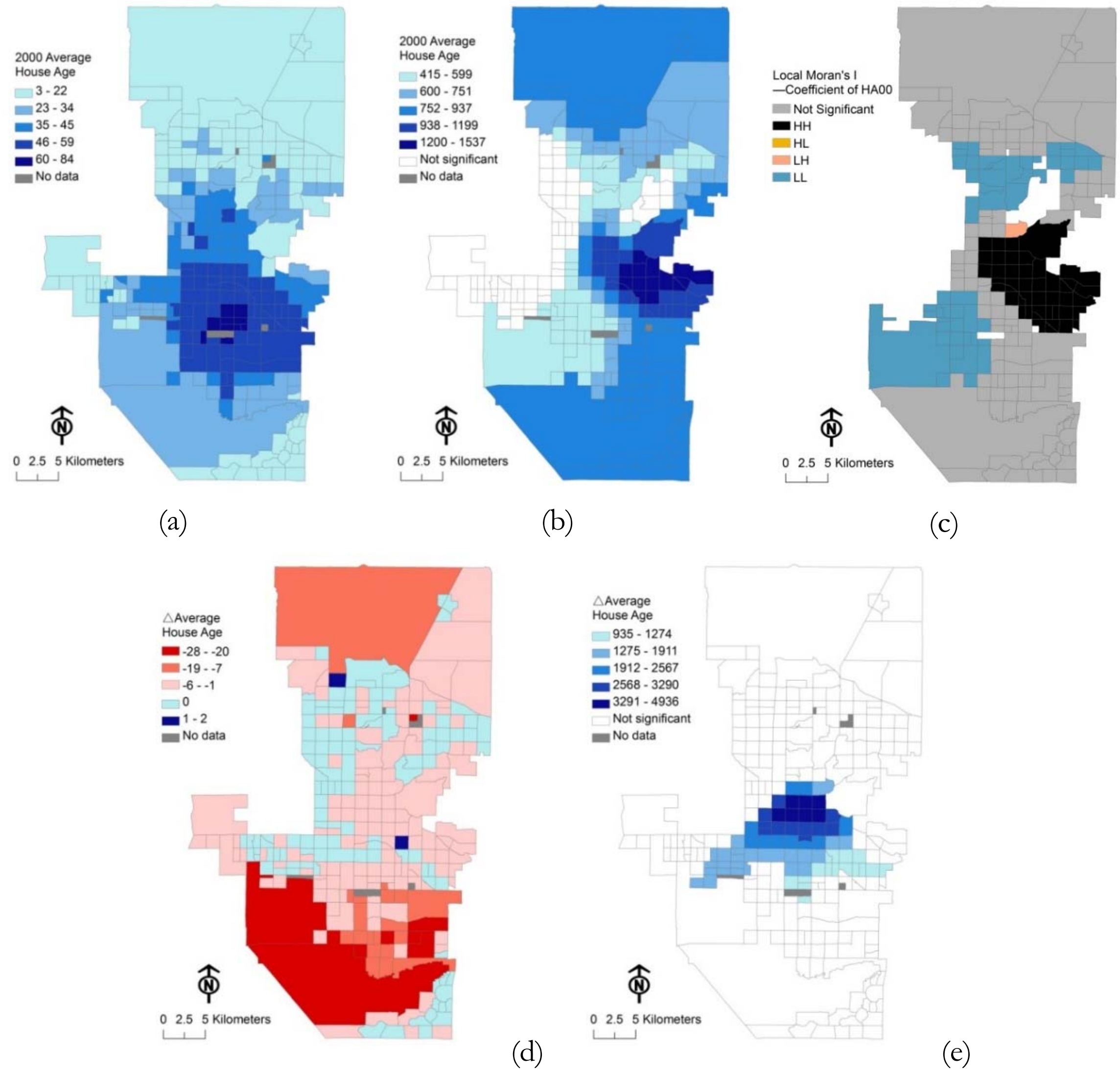

Figure A3. House age: (a) Spatial distribution of average house age in 2000; (b) Spatial distribution of local coefficients of average house age in 2000; (c) Map of local Moran's I of local coefficients of average house age in 2000; (d) Spatial distribution of change in average house age during 2000-2009; (e) Spatial distribution of local coefficients of change in average house age during 2000-2009.

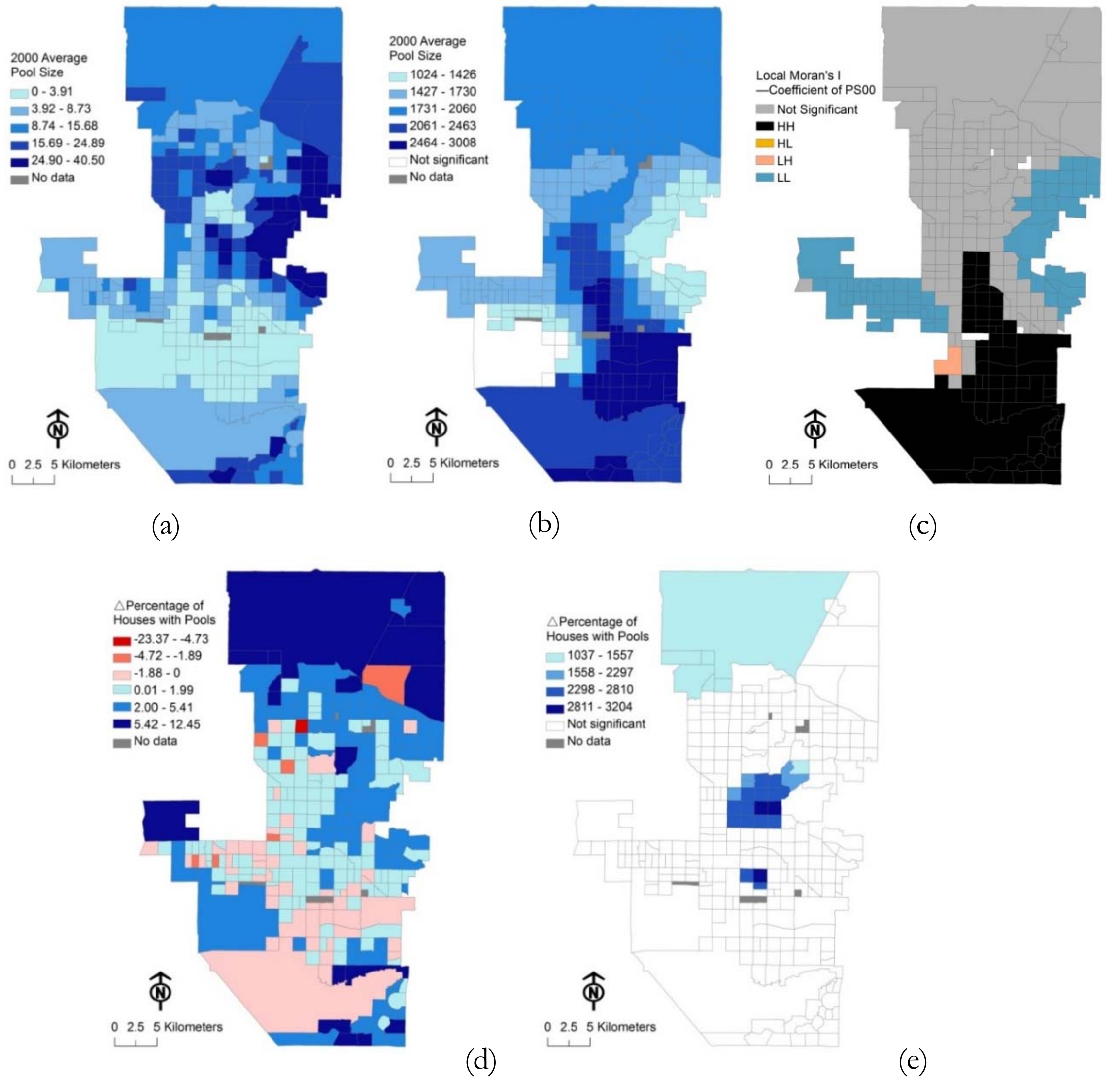

Figure A4. Pool: (a) Spatial distribution of average pool size in 2000; (b) Spatial distribution of local coefficients of average pool size in 2000; (c) Map of local Moran's I of local coefficients of average pool size in 2000; (d) Spatial distribution of change in percent single-family residences with pools during 2000-2009; (e) Spatial distribution of local coefficients of change in percent single-family residences with pools during 2000-2009.

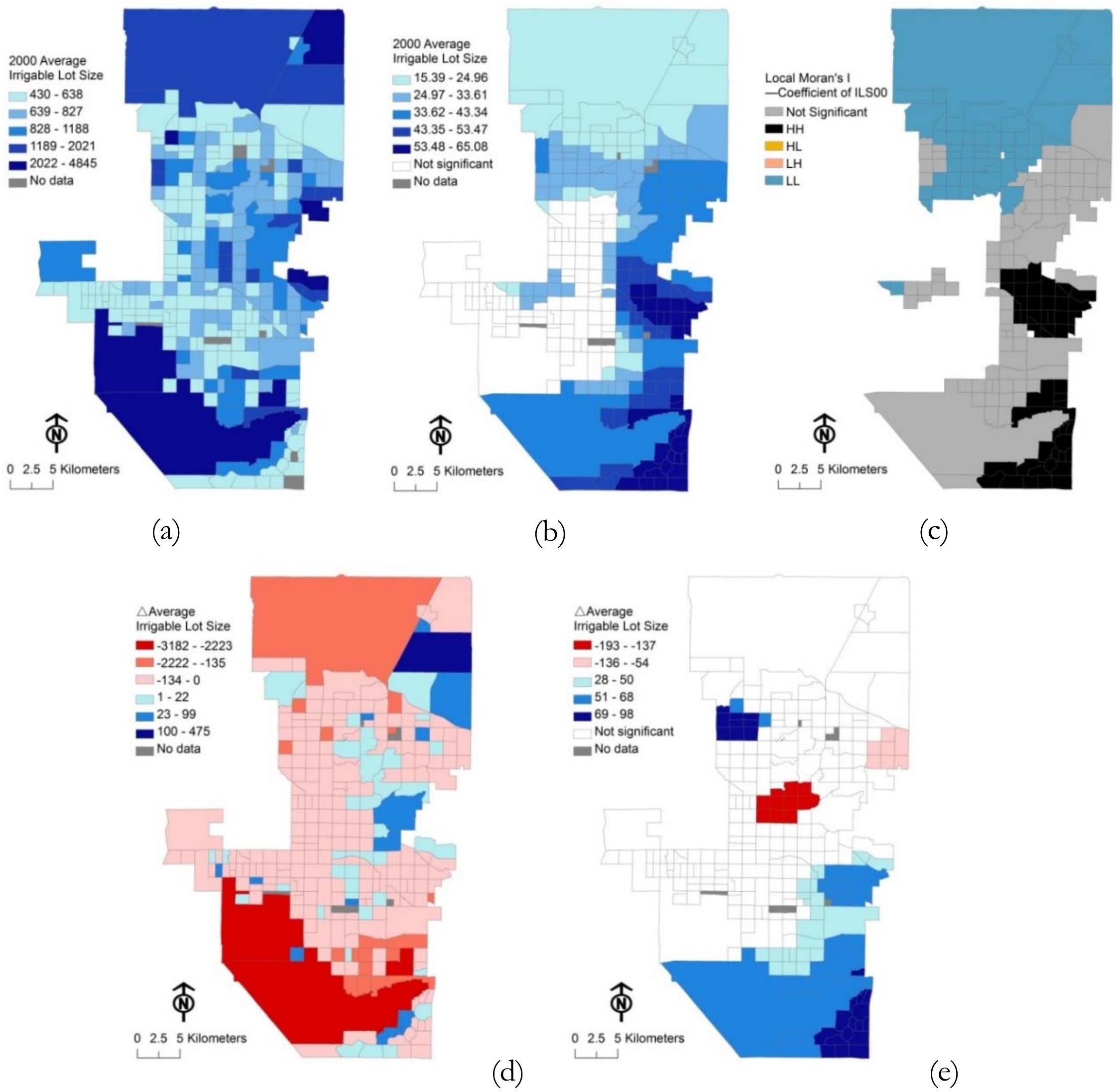

Figure A5. Irrigable lot size: (a) Spatial distribution of average irrigable lot size in 2000; (b) Spatial distribution of local coefficients of average irrigable lot size in 2000; (c) Map of local Moran's I of local coefficients of average irrigable lot size in 2000; (d) Spatial distribution of change in average irrigable lot size during 2000-2009; (e) Spatial distribution of local coefficients of change in average irrigable lot size during 2000-2009.

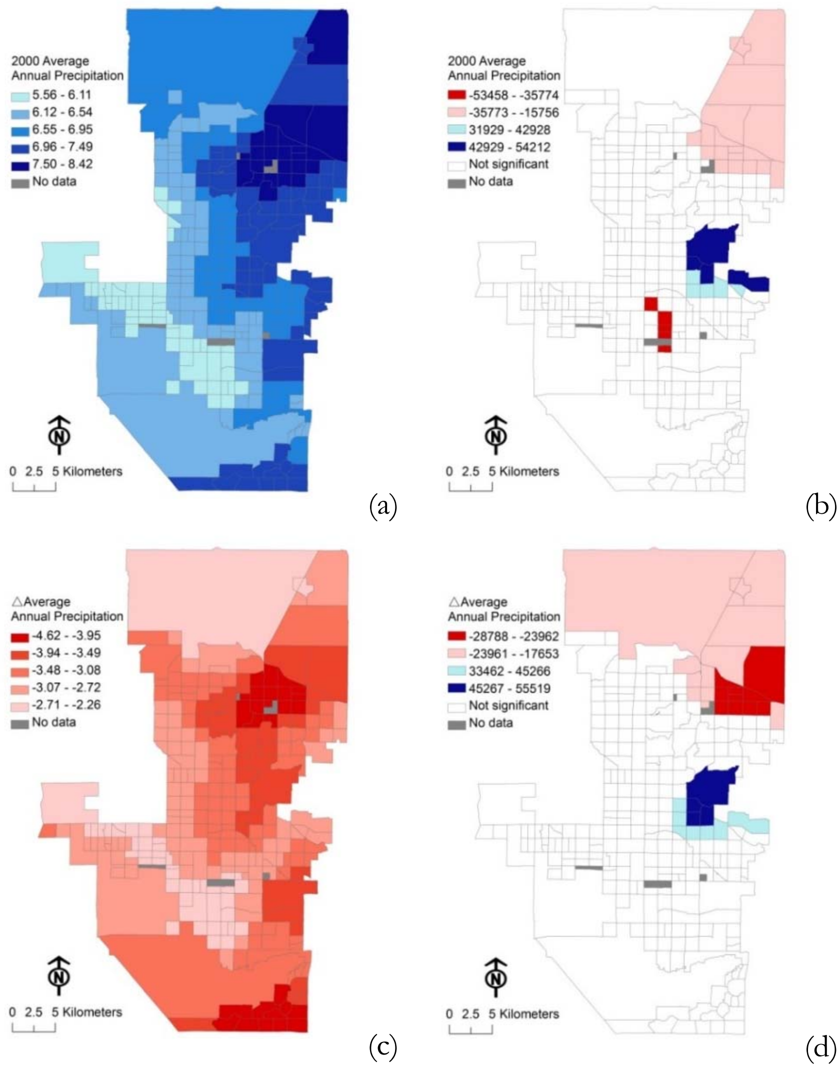

Figure A6. Annual precipitation: (a) Spatial distribution of average annual precipitation in 2000; (b) Spatial distribution of local coefficients of average annual precipitation in 2000; (c) Spatial distribution of change in average annual precipitation during 2000-2009; (d) Spatial distribution of local coefficients of change in average annual precipitation during 2000-2009.

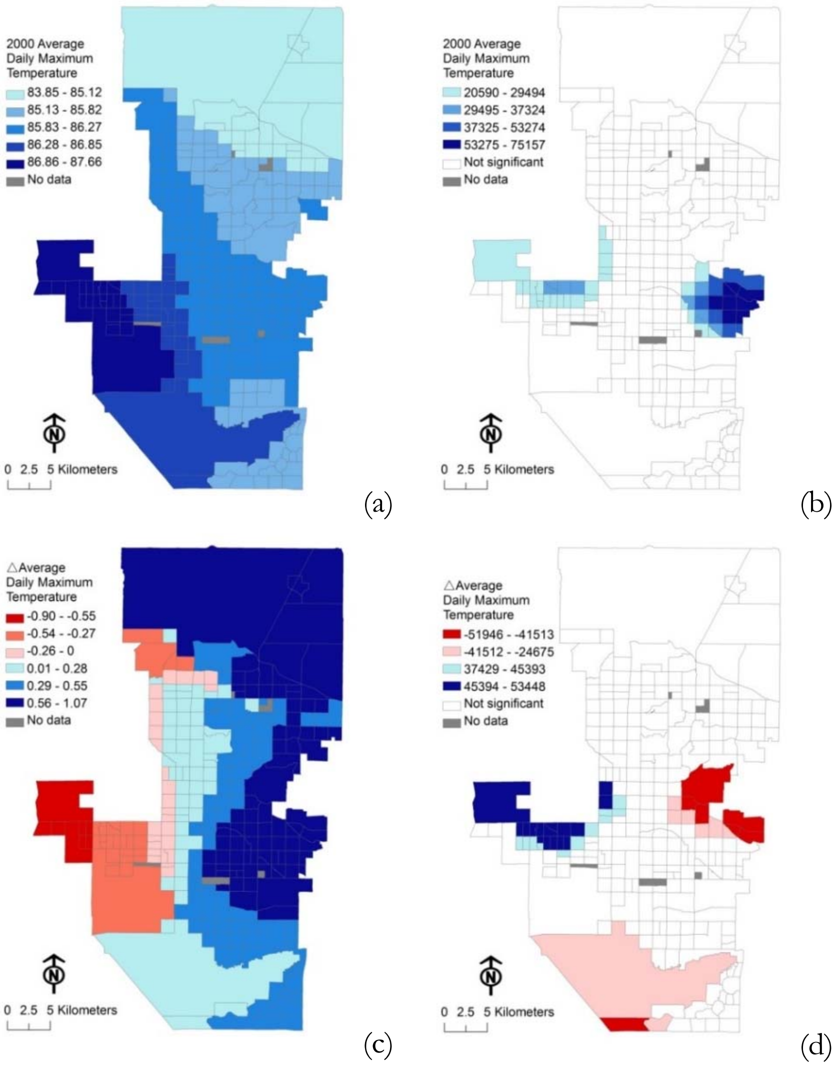

Figure A7. Average daily maximum temperature: (a) Spatial distribution of average daily maximum temperature in 2000; (b) Spatial distribution of local coefficients of average daily maximum temperature in 2000; (c) Spatial distribution of change in average daily maximum temperature during 2000-2009; (d) Spatial distribution of local coefficients of change in average daily maximum temperature during 2000-2009.

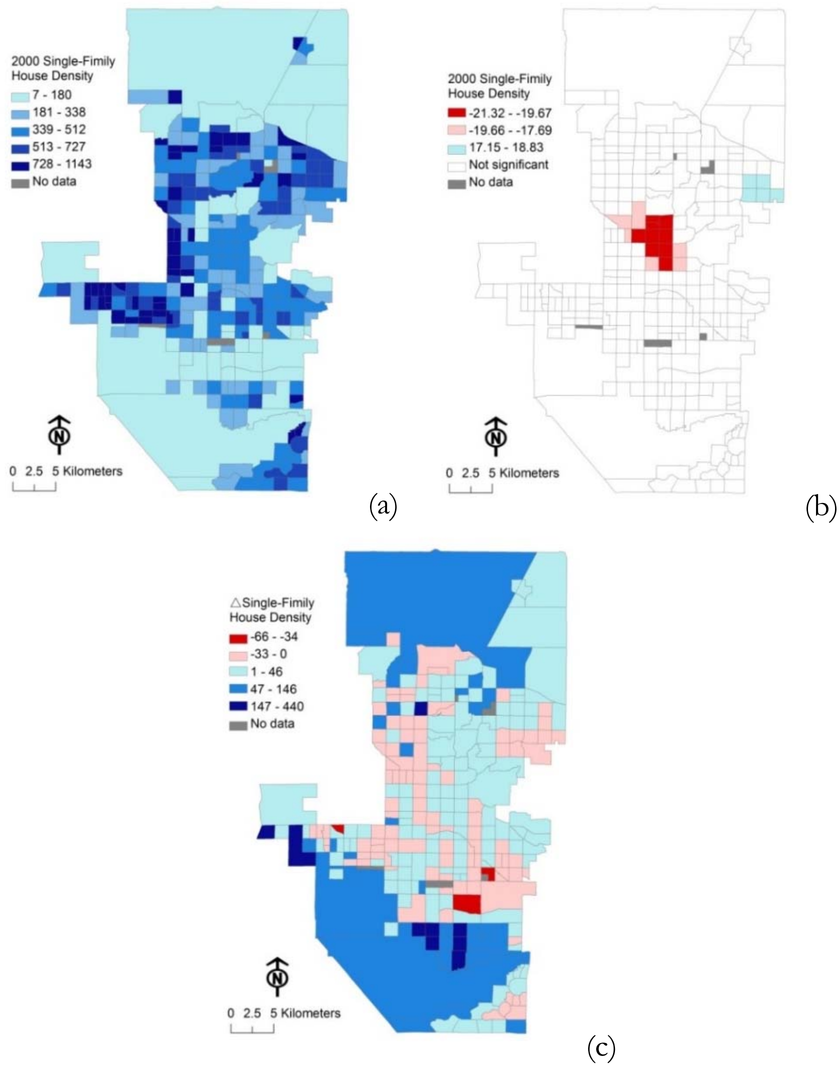

Figure A8. Single-family house density: (a) Spatial distribution of house density in 2000; (b) Spatial distribution of local coefficients of house density in 2000; (c) Spatial distribution of change in house density during 2000-2009.

APPENDIX B

STATEMENT OF PERMISSION

I declare that I have obtained permission from the relevant co-authors for including three manuscripts as chapters in this dissertation. They are:

Elizabeth A. Wentz (Chapters 2, 3, and 4)

Benjamin L. Ruddell (Chapters 2, 3, and 4)

Sharon L. Harlan (Chapter 2)