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Urban Water Demand Modeling: Review of Concepts, Methods, and Organizing Principles

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[1] In this paper, we use a theoretical framework of coupled human and natural systems to review the methodological advances in urban water demand modeling over the past 3 decades. The goal of this review is to quantify the capacity of increasingly complex modeling techniques to account for complex human and natural processes, uncertainty, and resilience across spatial and temporal scales. This review begins with coupled human and natural systems theory and situates urban water demand within this framework. The second section reviews urban water demand literature and summarizes methodological advances in relation to four central themes: (1) interactions within and across multiple spatial and temporal scales, (2) acknowledgment and quantification of uncertainty, (3) identification of thresholds, nonlinear system response, and the consequences for resilience, and (4) the transition from simple statistical modeling to fully integrated dynamic modeling. This review will show that increasingly effective models have resulted from technological advances in spatial science and innovations in statistical methods. These models provide unbiased, accurate estimates of the determinants of urban water demand at increasingly fine spatial and temporal resolution. Dynamic models capable of incorporating alternative future scenarios and local stochastic analysis are leading a trend away from deterministic prediction.

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1. Introduction

[2] The 21st century marks the first time in history that half of the global human population resides in urban areas [*United Nations Population Fund*, 2007]. Predicting and managing urban water demand is complicated by the tightly coupled relationship that exists between human and natural systems in urban areas. This relationship results from multiple interactions between microscale (individual, household, or parcel level) and macroscale (municipal or regional) processes and patterns. For example, in complex systems, local interactions among individuals cumulate over space and time, generating mesoscale and macroscale variables that in turn feed back to influence or constrain individual choices [*Liu et al.*, 2007; *Irwin et al.*, 2009]. This embedded nature of social and ecological systems in natural resource management poses a significant challenge to water managers. Separate analysis of these systems is not feasible; accounting for the complex and often unpredictable reactions to various shocks, policies, and interventions remains extremely difficult [*Berkes and Folke*, 2001; *Irwin et al.*, 2009].

[3] Analyzing and forecasting urban water demand is a complex yet imperative task, as it is essential that cities meet the water demands of their residents. The ability to estimate water demand under multiple climate, population growth, and conservation scenarios is intimately tied to urban hydrological processes and modeling. Peak water demand forecasts influence infrastructure expansion strategies. Many urban areas face similar stresses and will require expansion of water supply and distribution facilities. Ensuring a least cost and reliable infrastructure expansion strategy requires an accurate estimate of the required size and operation of reservoirs, pumping stations, and pipe capacities. The first step is to develop accurate and reliable water demand forecast models, especially for assessing peak demand. There are two types of demand forecasting. The first are short-term forecasts, which are used for operation and management. The second are the long-term forecasts, which are required for planning and infrastructure design [*Bougadis et al.*, 2005]. Currently, water managers produce demand estimates using long-term climate trends and the principle of stationarity (the idea that natural systems fluctuate within an unchanging envelope of variability) [*Milly et al.*, 2008]. However, climate change introduces uncertainties that may limit the accuracy of this method, as historical trends will no longer be reliable for predicting future climate-sensitive water demand [*Milly et al.*, 2008; *Gober et al.*, 2010].

[4] In coupled human and natural systems, new dynamics can emerge in response to stochastic shocks. Therefore, policy interventions in the future may produce system dynamics that will evolve in fundamentally different ways than in the past [*Irwin et al.*, 2009]. In this context, at the verge of a paradigm shift in water management [*Gober et al.*, 2010] and at a point when the knowledge base is changing rapidly [*Milly et al.*, 2008], a literature review of the progress of demand-

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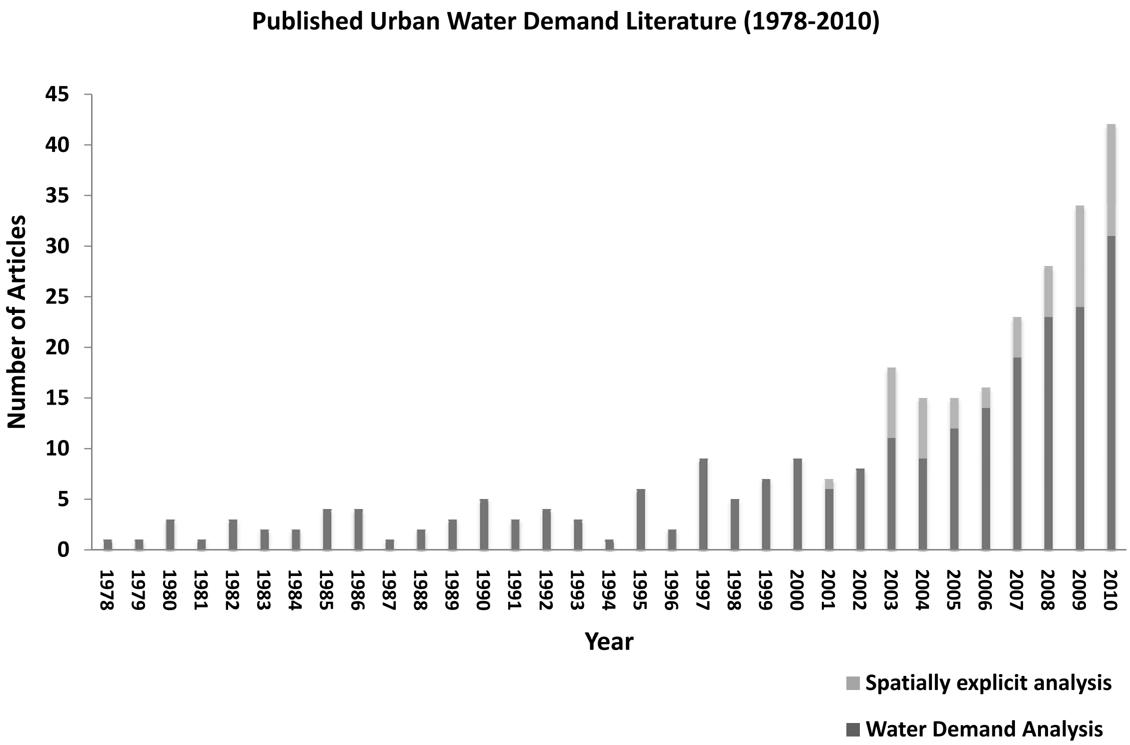

Figure 1. Yearly count of academic papers published on the topic of urban water demand ($n = 304$), 1978–2010. Count is based on publications found through a search of Thomson Reuters (ISI) Web of Knowledge, using the search terms "urban" + "water demand," "municipal" + "water demand," "water use" + "urban," and "water consumption" + "urban." Of the total 304 publications, 46 are based on spatially explicit analysis.

side water management methods is an important contribution. A transition in water demand modeling, forecasting, and management depends first on an understanding of the current and historical methods of acquiring and producing knowledge in the discipline. Also required is an understanding of the origin, structure, and limits of this knowledge. This review focuses specifically on examining urban water demand modeling methodologies. Application of water models to water policy and planning is beyond the scope of this paper; it is discussed in greater depth in the water policy literature [see *Ward*, 2007; *van de Meene and Brown*, 2009; *Gober et al.*, 2010; *van de Meene et al.*, 2010].

[5] The growing threat of anthropogenic climate change has contributed to mounting environmental and social concerns. Coupled with advances in data collection and computer modeling, a rich body of literature focused on urban water management has developed (Figure 1). Comprehensive reviews of the literature assess and synthesize research findings in urban hydrology and water demand modeling. In a seminal review of urban hydrological modeling, *McPherson* [1979] details the advances in urban storm water planning, management, and modeling at the metropolitan scale. McPherson concludes that methodologies appropriate for urban catchments must go beyond traditional approaches and integrate the social, biological, and physical sciences. These new methodologies must account for heterogeneity and the complex interactions and interrelations inherent to the urban environment. Advances in computing power and increasing availability of urban hydrologic and water resource data have led to the development of sophisticated process-based urban hydrologic models. One such model is the storm water management model (SWMM). This and similar models are designed to simulate urban runoff quantity and quality during rainfall events and are considered to be the current state of the art in urban hydrology (U.S. Environmental Protection Agency, storm water management model, http://www.epa.gov/nrmrl/wswrd/wq/models/swmm/). These models, which incorporate landscape structures such as storm pipes, pumps, and storage tanks, are capable of unraveling complex interactions between heterogeneous urban landscape and hydrology at multiple spatial and temporal scales. However, the models do not estimate the effects of human water consumption, heterogeneous urban landscapes, and climate variability on urban water demand.

[6] Many of the previous reviews focus solely on one aspect of urban water demand (i.e., economics or climate) or summarize the results of numerous studies without assessing the methodological advances in the discipline. *Brookshire et al.* [2002] offered a review of water demand literature that focused primarily on methods for determining efficient residential water pricing. For regions where demand outpaces supply, they conclude with a recommendation for the addition of "scarcity value." *Gleick* [2003] reviewed multiple global-scale water forecasts developed during the period 1967–1998 and presented techniques for achieving sustainable levels of water withdrawals by improving large-scale water use efficiency. In three important reviews in the economic literature [*Arbués et al.*, 2003; *Dalhuisen et al.*, 2003; *Worthington and Hoffman*, 2008], econometric water demand functions were evaluated. *Arbués et al.* [2003] examined the combination of time series and cross-section data to form panel data sets and specified functional form by estimating price and income elasticities for residential water

demand. The authors concluded that water price, income, and household composition are crucial determinants of residential consumption. However, water demand is inelastic in terms of water price. In other words, change in price does not affect water demand significantly. Similarly, *Dalhuisen et al.* [2003] presented a metaregression analysis of variation in price and income elasticities of residential water demand and found that the variation in estimated elasticities is associated most significantly with differences in the underlying tariff system. In an updated review, *Worthington and Hoffman* [2008] addressed the empirical problems that arise in the selection and specification of econometric water demand models. They compared the price and income elasticity findings on the basis of tariff metering, price structure, and billing and warned that a continuing fundamental limitation of water demand modeling remains the lack of data concerning households and their demands for water. *Inman and Jeffrey* [2006] and *Hurlimann et al.* [2009] synthesized the social science perspective, focusing on the impact of personal characteristics and behavior on the effectiveness of demand-side water management and conservation tools in the developed world. A current review of the environmental psychology literature by *Russell and Fielding* [2010] assessed the effect of attitudinal factors, beliefs, habits, routines, and personal capabilities on water conservation behavior and demand management. The authors concluded that residents who are committed to water conservation perceive social pressure, see conservation as a moral obligation, believe that conservation is within their control, and have positive attitudes toward water conservation. Recently, *Corbella and Sauri Pujol* [2009] presented a broad review of the significant physical and social determinants of domestic water use, finding four major drivers of water demand: climate, economy, urban design, and demographics.

[7] To the authors' knowledge, no comprehensive, up-to-date review exists that tracks and quantifies the advances in urban water demand modeling methods and analysis. This paper represents a unique contribution to the literature, as it seeks to summarize the advances that have transpired in urban water demand modeling while utilizing the theoretical framework of coupled human and natural (also known as social-ecological) systems [*Gunderson and Holling*, 2001; *Holling*, 2001; *Turner et al.*, 2003; *Walker et al.*, 2004; *Anderies et al.*, 2006; *Cumming et al.*, 2006; *Gunderson et al.*, 2006; *Liu et al.*, 2007; *Turner et al.*, 2007; *Werner and McNamara*, 2007]. In section 2, we begin by introducing the reader to the theoretical underpinnings of coupled human and natural systems. A synthesis and quantification of the progress in urban water demand modeling, estimation, and prediction follows. We explore four themes that are central to coupled human and natural systems theory: (1) interactions within and across multiple spatial and temporal scales, (2) acknowledgment and quantification of uncertainty, (3) identification of thresholds and nonlinear system responses and the consequences for resilience, and (4) the transition from simple statistical modeling to fully integrated dynamic modeling. Finally, section 4 highlights significant methodological advances and remaining limitations.

2. Theoretical Background

2.1. Coupled Human and Natural Systems Theory

[8] A theoretical framework for understanding complex human and natural systems has emerged in response to the increasing scope and intensity of human manipulation and transformation of the natural landscape [*Gunderson and Holling*, 2001; *Holling*, 2001]. What were once primarily local-scale interactions between humans and the biophysical environment have transformed into complex, multiscale interactions. Mismanagement of natural resources may arise because of a mismatch (temporal or spatial) between the scale of management and the scale of the process being managed [*Anderies et al.*, 2006; *Cumming et al.*, 2006]. Short-term, small-scale human activities are linked to and influence long-term, large-scale behaviors of natural systems, resulting in nonlinear system behavior [*Magliocca*, 2008]. Nonlinear responses are characteristic of systems with strong two-way coupling [*Werner and McNamara*, 2007] and are often activated when transition points or thresholds between alternate states are surpassed in either system [*Gunderson and Holling*, 2001; *Holling*, 2001]. Human societies are particularly dynamic because they respond not only to actual changes that occur in the biophysical environment but also to perceived and anticipated changes. Thus, interaction and feedback between the coupled systems become significantly more complex [*Scheffer et al.*, 2001]. In order to remain resilient to internal and external disturbances, these coupled systems change constantly through coevolution and adaptation [*Folke et al.*, 2002]. The disturbances may include climate change, technological advances, or new government policies.

[9] Four themes found in coupled human and natural systems theory are echoed in the urban water demand literature on methodological advancements: (1) scale [*Gunderson and Holling*, 2001; *Holling*, 2001; *Anderies et al.*, 2006; *Cash et al.*, 2006; *Cumming et al.*, 2006; *Walker et al.*, 2006], (2) uncertainty [*Liu et al.*, 2007], (3) nonlinearity [*Gunderson and Holling*, 2001; *Liu et al.*, 2007; *Werner and McNamara*, 2007], and (4) dynamic processes [*Anderies et al.*, 2006; *Walker et al.*, 2006; *Schluter and Pahl-Wostl*, 2007].

2.2. Urban Water Demand as a Coupled Human and Natural System

[10] Human and natural system dynamics are tightly coupled in the urban environment, as human behaviors and resource demands act as both drivers and constraints of natural ecosystem function [*Grimm et al.*, 2000; *Martin et al.*, 2004; *Pickett et al.*, 2008]. Urban water demand represents a coupled human and natural system, characterized by complex interactions between human and natural system variables at multiple spatial and temporal scales. In urban environments, scale mismatches can be particularly pronounced because the scales of social organization and governance structures are often not correctly aligned with the scales of ecological dynamics [*Borgstrom et al.*, 2006]. In the context of water resource management, human and natural scale mismatches can impose substantial unanticipated costs to water utilities if demand is incorrectly estimated [*Billings and Agthe*, 1998]. Stochastic events, such as drought or flood, can have dire consequences for communities if local governance is unprepared or underresourced to respond to larger-scale climate processes. Local-scale processes in both human and natural systems are significant drivers of change, contributing to large-scale patterns of water demand. The amount of water used at the household scale, for example, is influenced by several factors: the norms and values of the individual users, the household's ownership of water-consuming appliances,

individual lawn and garden preferences, and their personal investment in conservation. For example, *Wentz and Gober* [2007] found that a 1 unit increase in the percentage of houses with pools resulted in up to a 1% increase in average yearly water consumption in a Phoenix, Arizona, census tract. Natural processes such as soil types, local rates of evapotranspiration, and types of vegetation will also interact with human preferences to influence demand for water to be used to maintain the health of vegetation. In another case study of Phoenix, *Balling and Gober* [2007] determined that a 10% decrease in annual precipitation would result in a 3.9% increase in per capita annual water demand, while a 1°C increase in annual temperature would cause a 6.6% increase in per capita annual water demand. However, intraurban differences in affluence and vegetation preference also significantly affect residential water consumption. Phoenix, Arizona, and Hillsboro, Oregon, are two cities with diverse climates and urban form. In both cities, neighborhoods are characterized by large housing lots, high proportions of irrigated landscaping, and high incomes. The greater sensitivity of these neighborhoods to weather and climate conditions explains the variations in household water consumption [*Balling et al.*, 2008; *House-Peters et al.*, 2010]. In suburban Hillsboro, Oregon, summer outdoor water consumption is not sensitive to drought conditions citywide. However, some newer neighborhoods with large lot sizes consumed up to 1.85 times more external water during dry summer months compared to climatically normal summers.

[11] Governance structures exist at multiple scales, from the neighborhood to the city to the region, and can influence water consumption decisions. The direction of change, however, depends on the policy and institutional systems [*van de Meene and Brown*, 2009]. For example, at the neighborhood scale, the presence of a homeowner association (HOA) has been positively correlated to an increase in water consumption because of mandatory lawn maintenance policies [*Harlan et al.*, 2009]. However, municipal-scale incentives can be offered to assist in reducing residential and business sector water consumption, for example, to assist in replacing outdated appliances and installing low-flow faucets and showerheads and efficient lawn irrigation technologies [*Hilaire et al.*, 2008]. These small shifts in individual household behavior can cumulate into large changes, either increases or decreases, in city-scale water demand. However, such multiscale analysis of water consumption using a framework of coupled social and ecological systems has not yet been carried out.

3. Methodological Review

[12] In the context of urban water consumption and demand, the complexity of the multiscale interactions between and within the human and natural systems has not yet been elucidated. Nor have the strength of the feedbacks and implications for nonlinear responses been fully revealed. Over the past 3 decades, significant advances in technology and data processing have been made. These advances include the proliferation of geographic information systems (GIS) and the development of integrated dynamic models, such as agent-based models (ABMs). Previous analyses were confined to determining large-scale water demand on the basis of limited climate, water price, and household income variables. These analyses now are transformed to multiscale, accounting for numerous social and natural system variables. In addition, new modeling and analysis methods can integrate policy interventions, individual choices, and climate change uncertainty to explore shifts in water demand under multiple alternative futures. Here we present a review of the methodological developments in urban water demand modeling. The purpose of this review is to quantify model performance and advance knowledge of coupled human and natural systems in four central areas: (1) scale, (2) uncertainty, (3) nonlinearity, and (4) dynamic modeling. We do not intend this review to be a synthesis of the determinants of urban water demand, as such a review has already been comprehensively prepared by *Corbella and Sauri Pujol* [2009].

3.1. Scale

[13] Urban water supply is naturally variable and is also subject to the complex interplay of social and ecological dynamics in the environment. A wide range of researchers and practitioners is therefore interested in achieving a better understanding of the complex spatial and temporal patterns of water usage [*Lee and Wentz*, 2008]. In the 1980s, the primary focus of academic research on urban water demand was the development and utilization of econometric methods, principally multiple regression and time series analysis [*Maidment and Parzen*, 1984]. These methods improved the precision of daily [*Maidment et al.*, 1985; *Maidment and Miaou*, 1986] and monthly [*Agthe and Billings*, 1980; *Maidment and Parzen*, 1984; *Al-Qunaibet and Johnston*, 1985; *Maidment et al.*, 1985; *Miaou*, 1990] demand forecasts. The main purpose of these studies has been to produce an accurate estimate of the amount of water available daily from the supply infrastructure to meet the city's needs. These early statistical analyses, primarily from the economic literature, were fundamentally aspatial, as the data obtained for analysis were either city-scale production data (the amount of water produced to meet all municipal needs) [*Maidment and Parzen*, 1984; *Maidment et al.*, 1985; *Al-Qunaibet and Johnston*, 1985; *Maidment and Miaou*, 1986] or household-level data that lacked spatial coordinates [*Agthe and Billings*, 1980]. Household-level data allowed for increased understanding of how household characteristics, such as income and water price (Table 1), influence overall water consumption. However, because the data are randomly selected across the study area, this approach fails to show the influence of neighborhood characteristics on water consumption. Inherently, the use of aggregate city-scale data in statistical models assumes a lack of a variation in spatial patterns and processes, for example, from the clustering or dispersion of high water users at the neighborhood or census block scale. However, these variations have since been recognized as important determinants of future water consumption [*Wentz and Gober* 2007; *Chang et al.*, 2010]. The role of these variations can be examined further and consciously utilized in urban planning to reduce water demand. "Design-oriented approaches to water conservation" has been coined by *Shandas and Parandvash* [2010] to describe this approach.

3.1.1. Temporal Scale

[14] Although lacking spatial information, large-scale water production data can be obtained at fine temporal scales, often daily. When subjected to time series analysis methods, fine temporal scale data reveal significant temporal trends in water consumption correlated with economic variables, in particular, price, income, and tariff structure, well as weather

Table 1. Common Variables Found Primarily in Temporal or Spatial Water Demand Analyses

Explanatory Variable	Examples From the Literature
Temporal Analysis	
Temperature	*Danielson* [1979], *Maidment and Parzen* [1984], *Al-Qunaibet and Johnston* [1985], *Maidment et al.* [1985], *Miaou* [1990], *Billings and Agthe* [1998], *Zhou et al.* [2000], *Gutzler and Nims* [2005], *Arbués and Villanúa* [2006], *Balling and Gober* [2007], *Franczyk and Chang* [2009], *Harlan et al.* [2009], *Praskievicz and Chang* [2009], *Schleich and Hillenbrand* [2009]
Precipitation	*Howe and Linaweaver* [1967], *Danielson* [1979], *Maidment and Parzen* [1984], *Maidment et al.* [1985], *Thomas and Syme* [1988], *Miaou* [1990], *Billings and Agthe* [1998], *Zhou et al.* [2000], *Campbell et al.* [2004], *Gutzler and Nims* [2005], *Balling and Gober* [2007], *Franczyk and Chang* [2009], *Harlan et al.* [2009], *Schleich and Hillenbrand* [2009]
Wind speed	*Al-Qunaibet and Johnston* [1985], *Ruth et al.* [2007], *Praskievicz and Chang* [2009]
Evapotranspiration	*Howe and Linaweaver* [1967], *Agthe and Billings* [1980], *Maidment and Parzen* [1984], *Agthe et al.* [1986], *Zhou et al.* [2000]
Water price	*Howe and Linaweaver* [1967], *Danielson* [1979], *Agthe and Billings* [1980], *Al-Qunaibet and Johnston* [1985], *Agthe et al.* [1986], *Thomas and Syme* [1988], *Schneider and Whitlach* [1991], *Lyman* [1992], *Billings and Agthe* [1998], *Martinez-Espiñeira* [2002], *Arbués and Villanúa* [2006], *Gaudin* [2006], *Arbués et al.* [2010]
Rate structure	*Agthe et al.* [1986], *Billings and Agthe* [1998]
Population growth	*Morehouse et al.* [2002], *Ruth et al.* [2007]
Income	*Agthe and Billings* [1980], *Al-Qunaibet and Johnston* [1985], *Agthe et al.* [1986], *Thomas and Syme* [1988], *Lyman* [1992], *Billings and Agthe* [1998], *Rock* [2000], *Martinez-Espiñeira* [2002], *Campbell et al.* [2004], *Domene and Saurí* [2006], *Mazzanti and Montini* [2006], *Franczyk and Chang* [2009], *Harlan et al.* [2009], *Schleich and Hillenbrand* [2009]
Spatial Analysis	
Age	*Kenney et al.* [2008], *Schleich and Hillenbrand* [2009]
Family (or household) size	*Howe and Linaweaver* [1967], *Danielson* [1979], *Thomas and Syme* [1988], *Lyman* [1992], *Campbell et al.* [2004], *Arbués and Villanúa* [2006], *Domene and Saurí* [2006], *Mazzanti and Montini* [2006], *Wentz and Gober* [2007], *Schleich and Hillenbrand* [2009], *Arbués et al.* [2010], *House-Peters et al.* [2010]
Education	*Arbués and Villanúa* [2006], *House-Peters et al.* [2010], *Shandas and Parandvash* [2010]
Percent Hispanic	*Balling et al.* [2008]
House square footage	*Tinker et al.* [2005], *Domene and Saurí* [2006], *Wentz and Gober* [2007], *Balling et al.* [2008], *Harlan et al.* [2009], *Chang et al.* [2010]
Number of bedrooms	*Fox et al.* [2009], *Kenney et al.* [2008]
Size of outdoor space	*Campbell et al.* [2004], *Tinker et al.* [2005], *Harlan et al.* [2009], *House-Peters et al.* [2010]
Pool	*Tinker et al.* [2005], *Domene and Saurí* [2006], *Wentz and Gober* [2007], *Balling et al.* [2008]
Garden	*Fox et al.* [2009], *Domene and Saurí* [2006]
Proportion of single-family households	*Schleich and Hillenbrand* [2009], *Shandas and Parandvash* [2010]
Housing typology	*Zhang and Brown* [2005], *Domene and Saurí* [2006], *Fox et al.* [2009]
Normalized difference of vegetation index (NDVI)	*Guhathakurta and Gober* [2007], *Wentz and Gober* [2007], *Balling et al.* [2008]
Urban heat island (UHI)	*Guhathakurta and Gober* [2007]
Conservation policy	*Campbell et al.* [2004], *Kenney et al.* [2008]

and climate factors. Price is a significant mechanism for demand-side management. The effectiveness of pricing policies depends on the accuracy of the estimation of price elasticity of consumption (defined as the ratio of the percentage change in quantity demanded to the percentage change in price) [*Howe and Linaweaver*, 1967; *Arbués et al.*, 2010]. An extensive body of economic literature focuses on methodologies for estimating price and income elasticities under various tariff schemes. Importantly, these include the prevalent use of block rate pricing. This pricing method has serious implications for the estimation of demand elasticities. Because of the nonlinearity and discontinuity of the price structure variable, block rate pricing introduces difficulties in economic demand model specification. Unlike constant unit pricing, block rate pricing is at odds with the standard assumption that price setting is quantity independent [*Dalhuisen et al.*, 2003]. Within water resource economics literature, we see the various methods that have been sought to improve model estimation accuracy and to decrease model specification bias. These challenges exist because of (1) the common use of aggregated data instead of harder to obtain microlevel household data, (2) the inability to assume that consumers are well informed of the water rate schedule, and (3) the problem of simultaneous equations, which violates the ordinary least squares (OLS) assumption of independence between the explanatory variables and the error term [*Agthe et al.*, 1986; *Arbués and Villanúa*, 2006].

[15] Various multiple regression methods have been conceived, utilizing time series and cross-sectional data. The purpose of these models is to determine optimal pricing schemes and to forecast the impact of price and income on residential water demand. However, limitations remain in the econometric methodology. In the context of demand-side methods of water management, price has been shown to be a more cost-effective method to manage demand than implementing nonprice conservation programs [*Olmstead and Stavins*, 2009]. In a seminal paper, *Howe and Linaweaver* [1967] succeeded in determining demand models that differentiated between indoor and outdoor water consumption. These models estimated the impact of price on both morning and evening average peak rates of demand for geographic areas across the western United States. Additional research confirms that determining the differential effect of demand determinants in peak and off-peak periods is an effective way to reduce error in elasticity estimates [*Lyman*, 1992]. Recent research on short-term demand forecasting has demonstrated that univariate time series models based on historical data series are useful and may be combined with other forecasting methods to reduce errors. This is especially helpful when uncertainty exists about which forecasting method will be most appropriate for future prediction [*Caiado*, 2010]. In a case study of water consumption in Spain, *Caiado* [2010] found that the average error rate when using individual forecasting methods to predict a single day was 8.33% higher than when the forecasting methods were combined. When forecasting for 2 and 3 days, the combined forecasts reduced error by 12.77% and 10.64%, respectively.

[16] Following the methodology proposed by *Howe and Linaweaver* [1967], *Danielson* [1979] encountered a problem that commonly occurs when utilizing time series data for demand estimation, that is, the bias that is present because of the existence of serial correlation. Another form of bias affecting elasticity estimates is simultaneous equation bias. This is a type of bias known as endogeneity bias. This bias is a product of the multipart tariffs common to water price. These tariffs result in no unique price during each time period of estimation because the price paid by each consumer depends on the quantity chosen [*Agthe et al.*, 1986]. Empirical research has found that endogeneity bias may produce significantly inflated elasticity estimates. However, *Agthe et al.* [1986] suggest that constructing simultaneous equations for short- and long-run elasticities can help to correct the bias. This method has been supported in more recent research [*Espey et al.*, 1997; *Torregrosa et al.*, 2010]. *Torregrosa et al.* [2010] found that constructing a simultaneous equation model corrected for multicollinearity and serial autocorrelation while allowing the endogenous dependent variables to be simultaneously and jointly determined by a set of exogenous factors. This approach produced an adjusted R^2 value above 0.95. The specification of the independent variable, price, is debated in the economic literature, as econometric demand models under block rate tariff structures use two different approaches. The first type uses average price [*Schneider and Whitlach*, 1991; *Gaudin*, 2006; *Polebitski and Palmer*, 2010]. Others use two price variables, marginal price and a lump-sum payment term representing the fixed charges [*Agthe and Billings*, 1980; *Agthe et al.*, 1986; *Lyman*, 1992]. To overcome the challenge presented by the violation of the assumption that households are perfectly informed of current water price schedules, *Lyman* [1992] suggested the inclusion of a simple lagged price specification in the demand model. This method has become popular in the dynamic panel data approach, which we discuss at the end of this section.

[17] Early research achieved significant gains in determining the relationship between urban water demand and climatic factors, including temperature, precipitation, evapotranspiration, and seasonality. *Agthe and Billings* [1980] designed a dynamic multiple regression model that is capable of explicitly accounting for the strong influence of past water use on current water use by including a time-lagged value of the dependent variable, monthly water consumption, as an independent variable. *Maidment and Parzen* [1984] recognized that the variation in water use over time results from responses to socioeconomic and climatic factors at multiple time scales and presented a time series cascade model that targets these processes. While long-term changes in population and income affect water demand slowly over a period of years, climatic factors produce a seasonal influence on demand, and rainfall and stochastic events (such as a heat wave) produce immediate fluctuations in demand [*Maidment et al.*, 1985; *Miaou*, 1990; *Zhou et al.*, 2000].

[18] Urban water consumption is especially sensitive to seasonal time scales. Peak water demand tends to occur during periods of hot, dry weather because of increases in water use for irrigation of lawn and gardens and because of the need to replace water in pools and other water features, as water is lost to evaporation. Seasonal peak water demand is partly physical and partly psychological [*Zhou et al.*, 2000], as human behavior responds to both actual and perceived changes in the environment. Both considerations go into determining how much water the vegetation will need to survive a dry spell. One widely used and simple methodology accounts for sinusoidal seasonal variability of water demand by separating water use into two components: (1) weather-insensitive, nonseasonal base (winter) use and (2) weather-sensitive, seasonal (summer) use [*Maidment et al.*, 1985; *Maidment and Miaou*, 1986; *Miaou*, 1990; *Rufenacht and Guibentif*, 1997; *Syme et al.*, 2004; *Gutzler and Nims*, 2005; *Gato et al.*, 2007; *Praskievicz and Chang*, 2009; *House-Peters et al.*, 2010; *Polebitski and Palmer*, 2010; *Wong et al.*, 2010].

[19] A more sophisticated method, developed by *Zhou et al.* [2000], recognizes that seasonal variations in water consumption are not completely the result of sinusoidal patterns of air temperature and evaporation, which together will produce smooth increases and decreases in consumption over a year. Sinusoidal patterns can be modeled relatively easily

using a Fourier series. However, seasonal variation is also dependent on stochastic events, such as bursts of precipitation. These types of events garner quick behavioral responses, such as immediate reduction in consumption. Thus, to ensure comprehensive modeling, additional components must be incorporated. This will include the number of days since the last precipitation event (antecedent precipitation index) and an autoregressive function to account for the short-term memory of the system, as water use is dependent on its own past values [*Agthe and Billings*, 1980; *Zhou et al.*, 2000]. *Praskievicz and Chang* [2009] offered a different methodology for modeling temporal autocorrelation in seasonal water consumption, utilizing an autoregressive integrated moving average (ARIMA) model, which includes water use during the previous time period as an independent variable. The ARIMA model has been shown to perform more accurately than time series and multiple regression methods when forecasting demand based on climate variables. This difference in performance is a result of the strong temporal autocorrelation inherent in temperature and precipitation data. Using traditional methodologies, these data can lead to biased demand estimates [*Bougadis et al.*, 2005; *Adamowski*, 2008; *Caiado*, 2010]. In addition to modeling base and seasonal water demand, *Wong et al.* [2010] addressed calendrical use, which accounts for day-of-the-week, preholiday, during-holiday, and postholiday effects, and persistence (the dependence of water use on its own values) in the temporal data series.

[20] An important recent improvement to temporal econometric water demand analysis is the dynamic panel data approach [*Nauges and Thomas*, 2003; *Arbués et al.*, 2004, 2010; *Polebitski and Palmer*, 2010]. Panel data are defined as a data set that contains repeated observations of subjects over multiple time periods. This approach has been found to provide more efficient and consistent estimates of coefficients than OLS methods will provide. This improvement over traditional methods is due to the incorporation of both temporal and subject-based variability into coefficient estimates, which results in more consistent parameter estimates than typical regression analysis will [*Polebitski and Palmer*, 2010]. The use of fine spatial scale household-level consumption data in conjunction with the dynamic panel data approach has shown that consumers respond to a lagged average price specification based on the water bill [*Arbués et al.*, 2004, 2010]. A challenge with earlier estimation techniques that relied on price was the violation of the assumption that water users were knowledgeable of the current bill. In a case study of Seattle, Washington, at the census tract scale, *Polebitski and Palmer* [2010] compare the performance of three regression models to determine how best to account for spatial variability, a fixed effects model (fixed parameters are assigned to each census tract to account for variability), a random effects model (census tract variability is treated as a random variable), and a pooled OLS model (variability between census tracts is ignored). They find that the heterogeneity in the data set is best captured by fixed effects and random effects models, which are characterized by varied intercepts. Furthermore, by omitting the variability between census tracts, the pooled data estimation exhibits bias in the error term. Similar to previous studies [*Nauges and Thomas*, 2003; *Arbués et al.*, 2004, 2010], these authors conclude that panel-based regression methods produce accurate forecasts of per capita residential water demand and represent an improvement over traditional methods.

3.1.2. Spatial Scale

[21] The use of spatially explicit methodologies in urban water demand modeling has improved the ability of analysts to model the influence of significant variables at multiple spatial resolutions. Through these methods, it is possible to determine the scales at which certain processes are most influential and the effect of these processes on the patterns of demand that emerge at larger and smaller scales. GIS and spatial quantitative analysis techniques have become increasingly important and pervasive components of water demand analysis [*Guhathakurta and Gober*, 2007; *Wentz and Gober*, 2007; *Balling et al.*, 2008; *Lee and Wentz*, 2008; *Franczyk and Chang*, 2009; *Praskievicz and Chang*, 2009; *House-Peters et al.*, 2010; *Lee et al.*, 2010; *Polebitski and Palmer*, 2010; *Shandas and Parandvash*, 2010; *Chang et al.*, 2010]. Reliability and availability of spatial data have been steadily increasing. Municipalities across the United States have increased public access to water consumption data containing spatial information, such as household address or census block identification. Also, the accuracy of satellite image classification in urban areas has improved because of the proliferation of high-resolution aerial and satellite imagery. GIS databases, capable of storing and joining myriad types of qualitative and quantitative data on the basis of spatial location, have assisted researchers and managers in compiling rich data sets at fine spatial scales, making possible visualization and quantification of water use patterns across geographic areas [*Lee and Wentz*, 2008]. Enduring challenges associated with using high-resolution spatial data are that (1) the water provider service area is not necessarily the same as the administrative boundary (i.e., census block group or census tract), (2) the individual household level data are often aggregated to a larger spatial scale to protect customer privacy, and (3) different water providers collect water consumption data at different temporal frequencies, introducing uncertainty in comparison across different geographical areas.

[22] The recent increased emphasis on exploring spatially explicit patterns of water demand (Figure 1) is concomitant with a noticeable shift in the variables that are of interest to researchers (Table 1). To understand how local-scale human and natural processes interact to influence water demand, variables beyond water price, household income, and city-scale climate factors must be examined. Investigations of local-scale ecological processes, such as the influence of the presence of a garden and household-level vegetation composition on external water use, have utilized diverse methods, including computer simulation modeling [*McPherson*, 1990], installation of meters on a sample of household irrigation systems [*Sovocool et al.*, 2006], land cover classification to determine irrigated area [*Wentz and Gober*, 2007], and resident surveys [*Syme et al.*, 2004; *Zhang and Brown*, 2005]. Questions regarding the role of urban design and the effect of property characteristics on water consumption have become increasingly popular as city planners and policy makers attempt to integrate land and water planning to accommodate future population growth while halting urban sprawl and reducing per capita water demand. *Fox et al.* [2009] developed a methodology for statistically forecasting the amount of water demand that a new residential development would require on the basis of three property characteristics: number

of bedrooms, architectural type (i.e., detached or semidetached), and presence of a garden. Alternately, *Shandas and Parandvash* [2010] utilized ordinary least squares multiple regression models to determine the influence of urban zoning (i.e., single-family residential or commercial), total building area, and the density of single-family residential developments on water consumption during the period of their research (1999–2005). On the basis of this analysis, Shandas and Parandvash concluded with recommendations regarding the role of land use planning regulations (zoning and density) as a tool for reducing water consumption.

[23] Intraurban analyses of water consumption at the census block group scale [*Chang et al.*, 2010; *House-Peters et al.*, 2010] and at the census tract scale [*Guhathakurta and Gober*, 2007; *Wentz and Gober*, 2007; *Balling et al.*, 2008; *Lee and Wentz*, 2008; *Lee et al.*, 2010] use spatial statistics to elucidate spatial patterns of clustering and dispersion of high and low water users across a municipal area. Identification of neighborhoods that exhibit more or less sensitivity to variations in climate than average [*Guhathakurta and Gober*, 2007; *Balling et al.*, 2008; *House-Peters et al.*, 2010] represents an important step toward pinpointing combinations of social and ecological variables that lead either to increased resilience or to increased vulnerability in the context of future climate uncertainties. Simply, spatial autocorrelation refers to whether adjacent regions exhibit similar or dissimilar patterns. In complex environments where spatial dependence between variables is common, statistical methods that account for spatial autocorrelation, such as spatial regression and geographically weighted regression (GWR), tend to be an improvement over OLS methods [*Chang et al.*, 2010]. Spatial statistical models improve traditional nonspatial models by interpolating spatial phenomena at unknown locations using random variables. For example, *Wentz and Gober* [2007] identified varying degrees of the GWR coefficient for the household size variable, suggesting different sensitivity of water consumption with an increase in household size across different census tracks in the city of Phoenix. If such spatial dependence in explanatory variables is not taken into account, OLS regression model parameters are either overestimated or underestimated, offering limited insights to guide urban water policy and planning. *Chang et al.* [2010] demonstrated that OLS regression models overestimate the influence of building size and age, as these variables show strong positive spatial autocorrelations. Incorporating spatial errors into the regression models explains 11% of additional variations in single-family water consumption. In many cities, the urban heat island (UHI) phenomenon compounds the effects of summertime heat, creating variable temperatures across the urban area based on local-scale land cover characteristics (percent cover of water, trees, grass, impervious surfaces, and buildings). *Guhathakurta and Gober* [2007] include the spatially variable pattern of heating produced by the UHI in their analysis of residential water demand in 287 census tracts throughout Phoenix, Arizona.

3.2. Uncertainty

[24] Uncertainty implies that the particular value a variable will take on is imperfectly known or constantly fluctuates because of a random pattern [*Lund*, 1991]. Uncertainty is inherent in analyses of urban hydrology and water demand because of the spatial and temporal distribution of measured data that contains random fluctuations based on variability across space and time. It is crucial for engineering design that the distinction between variables with imperfectly known values (but values that can be known, or at least estimated, with additional experimentation and experience) be distinguished from variables characterized by randomly fluctuating values [*Lund*, 1991]. Because demand modeling plays a key role in water and wastewater infrastructure planning, design, and development, quantifying the effects of uncertainty on water demand estimates is critically important [*Jenkins and Lund* 2000]. Methods that are capable of visualizing and quantifying spatial and temporal variability allow us to examine the drivers behind the varied responses to stresses through space and time. Data availability across a study area may be limited by legal constraints or nonpublic status of that area. No industry standard exists across water management departments regarding the spatial and temporal scales to which water consumption data are aggregated before becoming available for research. Thus, comparisons of water consumption between geographical areas (e.g., neighboring cities) are limited by data aggregated at conflicting spatial scales (census block versus census tract versus county) or temporal scales (monthly versus quarterly) [*Clarke et al.*, 1997; *Lee and Wentz*, 2008]. Furthermore, the spatial and temporal scale of water use data may not match the scale of explanatory data available, for example, through census estimates and property tax lot data. To overcome these challenges, researchers commonly rely on the methods of interpolation and extrapolation. Interpolation is a method for estimating values for locations within the study area that do not have recorded values. Extrapolation is the process of extending the spatial area of temporal sequence beyond the scope of the observed data. Both approaches build additional uncertainty into space-time analysis [*Lee et al.*, 2010]. *Clarke et al.* [1997] present microsimulation as one method to disaggregate larger-scale water consumption data. This method can effectively estimate microlevel data using chain conditional probabilities, which allow for the incorporation of a wide range of available known data to reconstruct detailed microlevel populations.

[25] Climate change projections present an additional challenge to water demand modeling because of uncertainty regarding the magnitude, timing, and even the direction of the changes that will be experienced in a specific location [*Frederick*, 1997]. Thus, there is a need to assess existing methodologies that are able to recognize, isolate, and quantify sources and magnitudes of uncertainty in water demand analyses. Research within the fields of climate change science, remote sensing and land use change science, and hydrology has led the development and use of methodologies to quantify and incorporate uncertainty into modeling predictions [*Beven*, 2009]. The geostatistical methodology of Bayesian maximum entropy (BME) has recently been used to assimilate data uncertainty into the process of visualizing water consumption data through mapping of extrapolated soft data [*Lee and Wentz*, 2008]. Furthermore, geostatistical methods can cope with nonstationarity properties inherent in environmental data while accounting for spatial autocorrelation [*Lee et al.*, 2010].

[26] The space-time extrapolation technique, which incorporates the BME method, makes an important contribution to water demand research, as it improves data extrapolation. *Lee and Wentz* [2008], for example, found that including soft data uncertainty (such as extrapolation and projection error) in the

model through use of BME allows for a more accurate space-time analysis. Extrapolation based solely on historical data produces inaccurate estimates because the estimates are made outside of the temporal scope of the observed data, violating assumptions of regression analysis. *Lee et al.* [2010] derive statistical moments from the relationship between their dependent variable (water usage) and their independent variable (population density) in the present and apply the statistical moments to projections of the independent variable, thus generating soft data of future water use. When the BME was validated against a space-time kriging technique that uses hard data (historical measurements), the BME approach showed accuracy improvements of 24.1%–26.4% over space-time kriging. One significant drawback of traditional statistical methods is the inability to accurately estimate water demand under future uncertainty. The BME method is able to overcome this challenge. By utilizing knowledge about the relationships between water use, population density, and estimates of future population density, the BME method was successful in creating inferences of future water use in Phoenix over both space and time.

3.3. Nonlinearity

[27] Water demand exhibits sensitivity to both human and natural system stresses, reacting with a nonlinear response once a tipping point value in an independent variable is met. To model the effect of climate thresholds on water use behavior, *Miaou* [1990] devised two functions, $H\tau(T_m)$ and $G\gamma(R_m)$, where $H\tau(T_m)$ represents effective heating based on a threshold temperature and $G\gamma(R_m)$ represents effective rainfall based on a threshold level of precipitation. Piecewise linear regression models are designed to treat structural or temporal regime shift in an OLS regression model. These models create discrete linear segments connected at the empirically or theoretically derived threshold, which is represented by the point of change. The model can estimate the changes in slope that occur once a threshold is passed. Piecewise linear regression models have been used to analyze the effect of temporal variables, such as crossing temperature thresholds [*Maidment and Miaou*, 1986], and spatial variables, such as urban building density, building size, and household income thresholds [*Chang et al.*, 2010]. *Gato et al.* [2007] empirically identify temperature and rainfall thresholds for an urban area in Victoria, Australia, by fitting polynomial functions of daily maximum temperature and daily rainfall to the reciprocal of the corresponding daily water use and then taking the derivative of the function to solve for the threshold when the derivative equals zero. In terms of social system variables, *Polebitski and Palmer* [2010] modeled the nonlinear relationship between affluence, defined as income and property lot value, and seasonal peaking, defined as the ratio of seasonal water use to base use, in Washington State. The authors concluded that a certain threshold of affluence exists above which water consumption increases at a significantly higher rate during the summer season.

[28] Artificial intelligence methods, such as artificial neural networks (ANNs), fuzzy inference systems (FIS), and fuzzy neural networks (FNNs), techniques that were first used in civil engineering and hydrology applications, have proven useful as alternative tools for forecasting demand in complicated water systems [*Adya and Collopy*, 1998; *Adamowski*, 2008; *Ghiassi et al.*, 2008; *Firat et al.*, 2009; *Li and Huicheng*, 2010]. ANNs are statistical models built and maintained through an iterative training process. The ANN accumulates knowledge at each model layer through a self-learning process until a model is created that accurately captures the behavior of the process being modeled and can be used to forecast future values [*Ghiassi and Nangoy*, 2009]. ANNs have been offered as effective alternatives to traditional linear modeling approaches because of their ability to explicitly analyze nonlinear time series events. ANNs have been proposed as an improved method for short-term forecasting of peak daily [*Bougadis et al.*, 2005; *Adamowski*, 2008] and hourly [*Herrera et al.*, 2010] water demand. These improvements have long been pursued in the economic water demand literature but have been beset with bias and accuracy issues because of inherent temporal autocorrelation, the violation of OLS regression assumptions, and the difficulty of correctly specifying the functional form of the regression model. For example, *Ghiassi et al.* [2008] presented a dynamic ANN model for use in urban water demand forecasting that demonstrated an accuracy of 99%, a significant improvement over traditional statistical methods. In a case study of summer water demand in Ottawa, Ontario, Canada, *Bougadis et al.* [2005] and *Adamowski* [2008] concluded that on the basis of statistical measures of goodness of fit and R^2 values, the ANN models outperformed both multiple regression and time series models, minimizing relative error and maximizing robustness. Additionally, ANN models are able to predict outcomes that exceed the bounds on the training set. This capability is particularly useful when predicting the potential impacts of global climate change on water resources, including streamflow [*Gao et al.*, 2010] and sediment flux [*Zhu et al.*, 2008].

[29] FIS is a rule-based system that combines fuzzy rules and produces system results using fuzzy logic to describe human thinking and reasoning within a mathematical framework [*Yurdusev and Firat*, 2009]. In contrast to binary logic, fuzzy logic defines the degree to which a given element belongs to a set and has demonstrated improved forecasting performance over traditional regression methods by minimizing the deviations of the estimates [*Bárdossy et al.*, 2009]. *Bárdossy et al.* [2009] found that the hybrid fuzzy method for water demand estimation produced stable estimate deviations between 5% and 6%, while the traditional regression models produced larger, less stable deviations between 5.5% and 10%. FNNs incorporate fuzzy logic into a neural network and combine these rules with the network's abilities for self-learning and reasoning. Models developed using this framework are able to separate water demand and the factors that influence it into trend and cyclical components that can be analyzed to determine fluctuations over time [*Li and Huicheng*, 2010].

[30] ANN methods vary on the basis of the learning algorithm used. Research involving forecasting of peak weekly water demand in Nicosia, Crete, found that the ANN model utilizing the Levenberg-Marquardt learning algorithm was the most accurate for short-term forecasting when compared to several other ANNs using different learning algorithms [*Adamowski and Karapataki*, 2010]. One ANN, the dynamic architecture for artificial neural networks (DAN2), models nonlinearity through a transfer function of a weighted and normalized sum of the input variables

[*Ghiassi and Nangoy*, 2009]. DAN2 performance was compared to ARIMA for modeling future water demand at multiple temporal scales and was found to perform significantly better than the ARIMA method [*Ghiassi and Nangoy*, 2009]. However, a significant limitation of ANNs is the lack of explanatory power of the results, which makes this methodology unsuitable for some management and planning contexts [*Galán et al.*, 2009]. Forecasting models produced through ANN and FIS methods are sensitive to misspecification error, which occurs when either inappropriate input variables are included or significant variables are missing from the model [*Yurdusev and Firat*, 2009]. Finally, hybrid fuzzy algorithms are highly sensitive to the accuracy of the training data set, as inaccurate training data can lead to inaccuracy in the final water consumption estimation [*Bárdossy et al.*, 2009].

3.4. Dynamic Modeling Approaches

[31] Water demand is generated through dynamic and continually evolving processes on the basis of multiscale interactions between human agents and the natural world. This recognition has led to a recent increase in the development and implementation of dynamic models. Most demand functions are constructed as static; however, research has shown that current water use is strongly influenced by past water use. Thus, the development of a dynamic model that accounts for this relationship between current and past use may improve the accuracy and reliability of parameter traditional estimates over the traditional methods [*Nauges and Thomas*, 2003]. In contrast to conventional static times series and econometric models, dynamic models are developed to capture how water consumption decisions and behaviors, under plausible future scenarios, are affected by urban form and housing [*Galán et al.*, 2009], changes in price [*Athanasiadis et al.*, 2005; *Chu et al.*, 2009], conservation policies [*Chu et al.*, 2009; *Ahmad and Prasha*, 2010], and climate change [*Downing et al.*, 2003]. For example, *Nauges and Thomas* [2003] developed a dynamic model of residential water consumption and found that long-run demand was more elastic than short-run demand. This pattern reflects the slow rate of household behavioral adaptation in response to changes in water price. Two dynamic modeling methods being used to examine urban water demand are ABMs and system dynamics models (SDMs).

[32] ABMs have been used widely in land change science [*Parker et al.*, 2003; *Janssen and Ostrom*, 2006; *Manson and Evans*, 2007; *Parker et al.*, 2008] to examine the drivers and impacts of land use change on sustainability in coupled human and natural systems. ABMs have rapidly gained popularity in complex system analysis because of their ability (1) to incorporate both spatially and temporally explicit data, (2) to model bidirectional relations between individual human agents and the macrobehavior of the social or environmental system being modeled, (3) to capture emerging patterns at higher scales of the system that result from interactions at lower levels, and (4) to blend qualitative and quantitative approaches [*Janssen and Ostrom*, 2006; *Manson and Evans*, 2007; *Galán et al.*, 2009]. ABMs are able to overcome some of the most limiting aspects of traditional econometric methods, for example, when there is a lack of reliable cross-section and time series data or when water consumption is experiencing a period of rapid change [*Chu et al.*, 2009]. In water demand models, water consumers are represented as autonomous agents who make decisions on the basis of set model parameters. Examples include societal attitudes toward water conservation, the availability of information regarding water scarcity [*Chu et al.*, 2009; *Galán et al.*, 2009], the existence of social networks, the speed of diffusion of information about new technology, water reuse availability, and conservation methods [*Athanasiadis et al.*, 2005]. ABMs allow for positive reinforcement and feedbacks to be integrated into the system because changes in agent (water user) behavior happen iteratively over time. These models are able to capture the influence of social networks on agent behavior because not all groups react to policy changes and conservation messages immediately. As early adopters of conservation measures modify their consumption behavior, they also, through social pressure, exert influence on the water demand of other agent groups. These effects are then included in the subsequent iterations of the ABM. *Chu et al.* [2009] demonstrate the unique abilities of ABMs in a case study of water demand in Beijing, China. The authors successfully quantify dynamic patterns of residential water use behavior through the disaggregation of household water usage into specific end uses. The end uses can then be explored in the context of human behavior, attitudes, and choices under diverse policy scenarios.

[33] SDMs are an alternative method that can be used to address dynamically complex problems in water resource management. Dynamic models facilitate the examination of patterns of behaviors within a modeled system and how that system's responses to interventions change over time [*Ford*, 1999]. The foundation of system dynamics is the notion that the behavior exhibited by a system is due to the structure of the system and the relationships, interactions, and feedbacks among the key variables within the system. SDMs also have the ability to link to external systems, such as climate, to examine the impact of climate changes on water demand over long periods of time. SDMs improve on traditional statistical models because of the deeper understanding of the system structure and the relationships and interactions among the variables. Furthermore, SDMs take into account a larger number of components, feedback mechanisms, behavioral responses, and time lags within the system being modeled. For example, *Rosenberg et al.* [2007] demonstrate the usefulness of stochastic systems analysis using geographic, technologic, and behavioral variables affecting water use and conservation actions in Amman, Jordan. Similarly, *Ahmad and Prasha* [2010] demonstrate that the use of a simulation model improves the ability of researchers and practitioners to incorporate diverse variables and multiple submodels and allows for the testing of hypotheses about change under future scenarios that would not be possible using traditional statistical methods. However, unlike ABMs, SDMs cannot simulate the behavior of neighbors and the influence of multiagent behavior on system components over time. SDMs are often conceptualized using stock-and-flow models, which allow for visualization of the effects of different intervention strategies over time. Importantly, in both SDMs and ABMs, modeling and simulation are aimed at providing valuable insights into the behavior of the system over time and are not appropriate for forecasting and point prediction. The SDM methodology has several advantages over traditional methods. These include the ability (1) to use qualitative and quantitative variables, (2) to develop nested models to address a problem at multiple

Table 2. Comparison and Assessment of Methods in Urban Water Demand Modeling

Method	Data	Time Scale	Model Scale	Sources	Characteristics	Limitations
Multiple regression	time series data	daily or monthly	municipal	*Maidment et al.* [1985], *Maidment and Miaou* [1986], *Gato et al.* [2007], *Adamowski* [2008], *Ghiassi et al.* [2008], *Caiado* [2010], *Agthe and Billings* [1980], *Al-Qunaibet and Johnston* [1985], *Maidment et al.* [1985], *Miaou* [1990]	(1) short-term forecasting, (2) identify peak and off-peak daily demand to ensure necessary treatment and distribution capacity to meet demand, (3) estimate price and income elasticities, (4) assess the differential effect of demand determinants during peak versus off-peak periods	(1) lacking or highly aggregated spatial data, (2) aggregated data used instead of microlevel data, (3) OLS assumption of independence in the error term is easily violated, (4) endogeneity bias due to price based on consumed quantity under multipart tariff pricing, (5) serial correlation bias
Multiple regression	time series data	seasonal/sinusoidal	municipal	*Maidment et al.* [1985], *Maidment and Miaou* [1986], *Miaou* [1990], *Zhou et al.* [2000], *Syme et al.* [2004], *Gutzler and Nims* [2005], *Gato et al.* [2007], *Praskievicz and Chang* [2009], *Wong et al.* [2010]	(1) short-term forecasting, (2) separate water use into two components: weather-insensitive base use (winter or indoor) and weather-sensitive seasonal use (summer or outdoor), (3) examine climatic effects on demand	(1) lacking or highly aggregated spatial data, (2) difficult to determine the correct functional form of the model, (3) conventional models may underestimate water use response to climate variables because of the influence of stochastic events on seasonal use
Multiple regression	dynamic panel data	monthly/bimonthly	household level or census tract scale	*Nauges and Thomas* [2003], *Arbués et al.* [2004], *Arbués et al.* [2010], *Polebitski and Palmer* [2010]	(1) incorporates both temporal and subject-based variability into coefficient estimates, (2) more efficient and consistent parameter estimates than OLS, (3) fine spatial scale data, (4) integrate lagged independent variables (e.g., price)	(1) analysis of both disaggregated temporal and spatial data is more time and data intensive than traditional methods, (2) determining the regression method (e.g., fixed effects versus random effects) to account for spatial variability remains uncertain
Piecewise linear regression	time series data; cross-sectional data	daily or monthly	municipal or census block group scale	*Maidment et al.* [1985], *Maidment and Miaou* [1986], *Chang et al.* [2010]	(1) determine structural or temporal regime shift in a regression model, (2) create discrete linear segments connected at a point of change, (3) capture nonlinear responses in slope when thresholds are passed, (4) simple to interpret	(1) difficult to determine a priori the knot (point of change), (2) statistical testing required to ensure that the slopes are statistically significantly different before and after the knot
Spatially explicit ordinary least squares (OLS) regression	cross-sectional data; geotagged data	monthly/bimonthly	census block group scale or census tract scale	*Chang et al.* [2010], *House-Peters et al.* [2010], *Shandas and Parandvash* [2010], *Guhathakurta and Gober* [2007], *Wentz and Gober* [2007], *Balling et al.* [2008], *Lee and Wentz* [2008], *Lee et al.* [2010]	(1) visualize and quantify water use patterns at fine spatial scales, (2) elucidate spatial patterns of clustering and dispersion of high and low water users, (3) model individual household level consumption data, (4) correct for heterogeneity due to spatial autocorrelation, which otherwise causes biased parameter estimation	(1) water provider service areas do not match administrative boundaries (e.g., census block), (2) data usually must be aggregated to protect customer privacy, (3) no consistency between water providers regarding collection of water use data
Geographically weighted regression (GWR)	cross-sectional data; geotagged data	monthly	individual water consumption data aggregated to census tract scale	*Wentz and Gober* [2007]	(1) forecast small-area water consumption, (2) accounts for spatial autocorrelation, (3) calculates a set a unique regression equation for each observation defined by geographic coordinates, (4) improvement over OLS (R^2 = 0.64) versus GWR (mean R^2 = 0.85)	(1) computationally and data intensive, (2) each sample has it own unique regression, difficult to interpret results for a large sample, (3) availability of geotagged data continues is lacking, (4) model demonstrates spatial variation but does not have explanatory power
Simultaneous equation demand model	panel data	monthly	municipal	*Agthe et al.* [1986], *Espey et al.* [1997], *Torregrosa et al.* [2010]	(1) simultaneously and jointly determines the endogenous dependent variables on the basis of exogenous variables, (2) corrects for multicollinearity and serial autocorrelation	(1) data aggregation at large spatial scales, (2) violation of the economic assumption that households are perfectly informed of water price
Autoregressive integrated moving average (ARIMA)	time series data	daily	municipal	*Bougadis et al.* [2005], *Adamowski* [2008], *Praskievicz and Chang* [2009]	(1) accounts for the autocorrelation in the water demand time series, (2) uses the previous day's water use as an independent variable	(1) data aggregation at large spatial scales, (2) difficult to determine a priori correct model form and parameters
State-space forecasting model	time series data	monthly	municipal	*Billings and Agthe* [1998]	(1) Computes forecasts based on the dependence of a variable upon its	(1) The values of the independent variables must be forecasted in order to compute

Table 2. (continued)

Method	Data	Time Scale	Model Scale	Sources	Characteristics	Limitations
					own lags and the cross lags of the independent variable, (2) simpler than ARIMA	a forecast of the dependent variable
Bayesian maximum entropy (BME)	cross-sectional data; soft data	monthly	census tract scale	*Lee and Wentz* [2008], *Lee et al.* [2010]	(1) assimilates data uncertainty into the data extrapolation and mapping process, (2) obtain downscaled estimates from spatially aggregated data, (3) project future water use, (4) inclusion of data uncertainty as soft data	(1) data extrapolation can lead to dubious results because the values are estimated beyond the scope of the known data, (2) computationally intensive, (3) variances can be overestimated if interaction terms are neglected in the models used to build the probabilistic soft data
Artificial neural networks (ANNs)	time series data	daily or hourly	municipal	*Adya and Collopy* [1998], *Bougadis et al.* [2005], *Adamowski* [2008], *Ghiassi et al.* [2008], *Bárdossy et al.* [2009], *Firat et al.* [2009], *Adamowski and Karapataki* [2010], *Herrera et al.* [2010]	(1) highly effective for forecasting short-term demand (99% accuracy), (2) alternative to traditional linear modeling approach, (3) explicitly analyze nonlinear time series events, (4) minimize relative error, (5) maximize robustness	(1) complex, data and computationally intensive training and testing requirements, (2) loss of parsimony, (3) lack of explanatory power of the results, (4) sensitive to misspecification error
System dynamics models (SDMs)	time series data	monthly	regional	*Rosenberg et al.* [2007], *Winz et al.* [2009], *Ahmad and Prasha* [2010]	(1) incorporate diverse variables and submodels, (2) visualize the effects of intervention strategies, (3) continuously test assumptions and system sensitivity under scenarios	(1) unlike ABMs, the behavior of neighbors and the influence of this behavior cannot be simulated, (2) data, software, and computationally intensive

scales, and (3) to continuously test assumptions and system sensitivity under multiple alternative futures [*Winz et al.*, 2009].

4. Conclusions

[34] Urban water demand is part of a complex system, dependent on patterns and processes that emerge through multiscale and cross-scale human-environment interactions. Humans hold a unique role. Our distinctive characteristics of foresight and intentionality give us the ability to build or erode resilience in coupled systems through the management strategies that we choose to implement [*Holling*, 2001]. In this paper, we review advances over the past 30 years that have improved understanding of urban water demand. These advances consist of theoretical and empirical methodologies for representing, modeling, and simulating complex system behavior (Table 2). Increased data availability and advances in technology and computing power have facilitated the development of sophisticated models that can incorporate spatially explicit data and simulate human agency through complex decision-making and social diffusion submodels. Although tangible progress has been made in improving the capabilities of water demand modeling in the four themes investigated in this review, significant limitations remain.

[35] Early methodologies for analyzing urban water demand used relatively simple econometric and time series models based on linear multivariate regression. These approaches required a limited number of data sets and could be performed with modest computing power. The focus of these early methods was narrow, emphasizing development of accurate forecasting methods to optimize water supply infrastructure and reduce costs and risks borne by water suppliers. Moreover, the original water demand models were fundamentally aspatial, ignoring variations in water consumption across the geographic focus area. This limitation to modeling and analysis was due to the lack of available software to process and store large amounts of spatial information. The current availability of both long-term temporal data and fine spatial data allows researchers to carry out a mix of time series analyses and spatially explicit point analyses. The data that can be used in exclusively time series analyses of demand are limited because explanatory variables must have sufficiently long records if they are to be used as independent variables for developing forecasting models. Spatially explicit data currently used in water demand modeling include measures of irrigated vegetation and greenness [*Guhathakurta and Gober*, 2007; *Wentz and Gober*, 2007]. Available social science data focus on measuring human agency, household decision making, water use attitudes, and norms and behaviors through survey and interview methods [*Syme et al.*, 2004; *Miller and Buys*, 2008; *Randolph and Troy*, 2008; *Harlan et al.*, 2009].

[36] The advent of geocoding and GIS allows these varied types of social and ecological data to be linked to household-scale water consumption data, creating rich, spatially explicit data sets available for sophisticated analysis. Analysis of water demand at one point in time across a city or a number of cities does not require that explanatory variables have long temporal records as long as the variables have spatial information. Thus, the types of variables recently included in spatial analyses of water consumption are far more diverse than those found in traditional econometric time series analyses (Table 1). Nonetheless, integrating diverse socioeco-

nomic and ecological variables into a single conventional model remains difficult [*Galán et al.*, 2009]. Increased data richness has led to progress in identifying and quantifying relationships among numerous social, climate, and water consumption variables, but methodologies still need to be developed that will have the ability to incorporate these numerous types of data and to take advantage of this rich information to elucidate relationships at multiple scales. ABMs are one method leading in this direction, but there is also room for improving the transparency of the internal system structure and the variable interactions. A common criticism of both ABMs and SDMs is the trade-off that has occurred between the parsimony of traditional methodologies and the data-hungry, computationally intensive models currently being developed. This necessitates some middle-ground forecasting methods that are not unnecessarily complicated but can take now widely available spatially explicit land information into water demand modeling so that water utility managers can use the methods easily.

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