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System dynamics modeling for municipal water demand estimation in an urban region under uncertain economic impacts

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ABSTRACT

Accurate prediction of municipal water demand is critically important to water utilities in fast-growing urban regions for drinking water system planning, design, and water utility asset management. Achieving the desired prediction accuracy is challenging, however, because the forecasting model must simultaneously consider a variety of factors associated with climate changes, economic development, population growth and migration, and even consumer behavioral patterns. Traditional forecasting models such as multivariate regression and time series analysis, as well as advanced modeling techniques (e.g., expert systems and artificial neural networks), are often applied for either short- or long-term water demand projections, yet few can adequately manage the dynamics of a water supply system because of the limitations in modeling structures. Potential challenges also arise from a lack of long and continuous historical records of water demand and its dependent variables. The objectives of this study were to (1) thoroughly review water demand forecasting models over the past five decades, and (2) propose a new system dynamics model to reflect the intrinsic relationship between water demand and macroeconomic environment using out-of-sample estimation for long-term municipal water demand forecasts in a fast-growing urban region. This system dynamics model is based on a coupled modeling structure that takes into account the interactions among economic and social dimensions, offering a realistic platform for practical use. Practical implementation of this water demand forecasting tool was assessed by using a case study under the most recent alternate fluctuations of economic boom and downturn environments.

1. Introduction

Domestic water consumption by households is a principal municipal water demand in urban regions (Kindler and Russell, 1984). Short- and long-term forecasting of the municipal water demand is essential to water utilities for system planning, design, and asset management. Short-term forecasting is useful for operation and management of existing water supply systems within a specific time period, whereas long-term forecasting is important for system planning, design, and asset management. Achieving the desired prediction accuracy is challenging, however, because the forecasting model must simultaneously consider a variety of factors associated with climate changes, economic development, population growth and migration, and even consumer behavioral patterns. Thus, water demand forecasting at different temporal and spatial scales must fully account for varying levels of system complexity.

Because of large economic fluctuations, accurate prediction of domestic water demand in fast-growing urban regions has received a renewed interest. To achieve the desired prediction accuracy, the forecasting model often requires simultaneous consideration of the variables in climate change, economic development, and population dynamics. Influential factors (e.g., independent variables) that can affect water demand may include per capita income, household income, education level, population density, total population, population distribution, commercial activities, industrial activities, ecological conservation of source water environment, water pricing, and conservation. Techniques including traditional regression and time series analysis or relatively newer artificial neural networks (ANN) were proposed for estimation of the water demand based on those independent variables, all of which require long-term, continuous historical records.

This study had two objectives: (1) to thoroughly review water demand forecasting models over the past five decades, and (2) to propose a new system dynamics model to reflect the intrinsic relationship between water demand and macroeconomic environment so that an out-of-sample estimation may be used for long-term municipal water demand forecasts in a fast-growing urban

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region. A case study was carried out based on the annual data from 2003 to 2009 in Manatee County, Florida, but the seven data points provided neither enough information for training the neural network models nor enough degrees of freedom to include all the aforementioned independent variable terms when applying regression and time series analyses, let alone consider the quadratic and interactive terms. If available data are limited, it is difficult to reflect the level of system complexity; however, our system dynamics model can reveal the interactions among essential socioeconomic factors considering the impact of the economic boom and downturn environments in a fast-growing urban region.

2. Literature review

In the past few decades, many approaches have been proposed to forecast short- and long-term municipal water demands. They are grouped into five categories: the regression analysis, the time series analysis, the computational intelligence approach, the hybrid approach, and the Monte Carlo simulation approach.

2.1. Multivariate regression analyses

Traditional regression analyses were normally carried out based on statistical estimation of the relationship between water demand and some explanatory variables (i.e., independent variables), such as socioeconomic factors, and assumed that the relationships will continue in the future. Such a regression analysis approach can then be applied for both short- and long-term analyses when a training dataset is available. In this type of regression practice, independent variables are usually related to the trend of population growth for long-term water demand forecasting, but air temperature and rainfall may be included to address the short-term variability in forecasting. Some nonlinear regression models were formulated with the inclusion of multiplicative terms as an integral part of the econometric analysis applied for residential and nonresidential water demand modeling (Davis, 2003). Four types of models were formulated for econometric analysis with an emphasis on average rate of water usage, disaggregate factors forecast, functional per unit, and functional population models (Table 1a; Davis, 2003).

2.2. Time series analyses

Time series analysis in water demand forecasting is based on a statistical abstraction of the various trends that inherently contribute to the change of water demand over time. A time series model may inevitably include a long-term trend component, a cyclical component, and a short-term variance component. Because of less reliance on mechanistic representation of controlling factors such as income and population at a given municipality, the time series analysis has been extensively used for short-term water demand forecasting (Table 1b).

2.3. The computational intelligence models

The computational intelligence models, including ANN, fuzzy-logic, and agent-based models, are mathematically suited to simulate complex systems. For example, ANN normally consists of at least three modeling layers: input layer, output layer, and the layer in-between or hidden layer that connects the inputs and outputs by a set of highly interconnected nodes, and maps the model inputs to the model outputs. This model is purely data driven, using input data to capture the behavior of a process and forecast output values. Historical data are used to train a valid learning algorithm in which ANN output values are compared with the actual values, and model errors are propagated backward throughout the ANN to refine model parameters under a supervised or an unsupervised training process. This training process continues iteratively until an acceptable error rate can be found. The ANN and other computational intelligence models can be developed for water demand forecasting (Table 1c).

Table 1a
Summary of water demand forecasting methods based on the regression analyses.

Literatures		Remark	Short term	Long term
1960s	Howe and Linaweaver (1967)	Models of residential water demand with parameters estimated from multi-city cross-sectional data by regression analysis. The results indicated that domestic demands were relatively price inelastic.		X
1970s	Cassuto and Ryan (1979)	A regression model to forecast residential elasticity of water demand using long-term water conservation programs, revenue, and cost as independent variables in Oakland urban area, California.		X
	Foster and Beattie (1979)	A generalized model considering the categorical effects of regional and size-of-city difference on urban residential water demand.		X
1980s	Hughes (1980)	The water demand functions were developed with data from systems ranging from very small low-density rural systems to large Salk Lake City's water system. Water price and outdoor use index were the two primary independent variables in short-term demand.	X	
	Maidment et al. (1986)	A regression model developed using daily water consumption data from nine cities in Florida, Pennsylvania and Texas to forecast short-term usage fluctuation to rainfall and air temperature variables. Average coefficient of determination R^2 is 0.96 in Texas, 0.73 in Florida, and 0.61 in Pennsylvania.	X	
1990s	Billings and Agthe (1998)	The regression method and time series state space method, were compared to the simple monthly average approach for short-term water demand forecasting in Tucson, Arizona.	X	
2000s	Davis (2003)	Four types of econometric models were studied to identify the cumulative effect by using the multiplicative functions.	X	
	Babel et al. (2006)	A regression model for domestic water demand forecasting based on a multivariate econometric factors such as socioeconomic characteristics, climate factors and public water policies and strategies.		X

Table 1b
Summary of water demand forecasting methods based on the time series analysis.

Literatures		Remark	Short term	Long term
1980s	Hansen and Narayanan, 1981	A monthly multivariate time series model for forecasting water demand. Independent variables include water pricing, average temperature, total precipitation, and percentage of daylight hours.	X	
	Maidment and Parzen, 1984	A combination of the regression model and time-series analysis for forecasting water use in six Texas cities. In the model, a long-term trend was analyzed by a stepwise regression analysis for variables population, household income and water price, and by applying short-term memory related to climatic variations.	X	
	Maidment et al., 1985	A multivariate time series model of daily municipal water for Austin, Texas. Rainfall and air temperature were the two independent model variables.	X	
	Franklin and Maidment (1987)	A cascade modeling approach for weekly water demand based on the data from Deerfield, Florida. Inclusion of the autocorrelation term in the model improved the forecast accuracy.	X	
	Smith (1988)	A time series model of daily municipal water use developed in which the time series model was formulated as a conditional autoregressive process with randomly varying means to account for water use changes as a result of water pricing, customer income, and some other socioeconomic factors.	X	
	Sastri and Valdes (1989)	An iterative computer algorithm based on a model-switching transfer function to estimate water consumption with rainfall interventions.	X	
1990s	Miaou (1990)	A nonlinear monthly time-series urban water demand model developed for Austin, Texas. The model performance was reported to have the adjusted R^2 of 0.961, and was further compared with conventional linear models.	X	
	Jowitt and Xu (1992)	A time series analysis technique using a combination of exponentially weighted mean and autoregressive structures to predict daily water demand.	X	
	Homwongs et al. (1994)	An adaptive smoothing filtering approach to forecast hourly municipal water usage. The seasonal time-series model and adaptive forecasting algorithm, utilizing Winters' exponential smoothing, recursive least squares, and Kalman filter, can capture both weekday and weekend cycles and produce hourly forecasts in a 24-h period.	X	
	Molino et al. (1996)	A time evolution model of water consumption for prediction of short-term water demand using autoregressive moving average.	X	
2000s	Zhou et al. (2000)	A time-series model developed using an autoregressive procedure for short-term water demand variations. Maximum temperature, precipitation and evaporation were climactic variables in modeling of short-term water consumption. Fourier series was employed to represent long-term seasonal cycle. The model performance R^2 0.896 was reported.	X	X
	Zhou et al. (2002)	A time series model developed for water demand projection in next 24 h. Long-term demand variation was expressed as a Fourier series, and the short-term variability was captured by climatic regression and auto regression. Model performance R^2 0.75 was reported.	X	
	Fullerton and Elias (2004)	An autoregressive moving average linear transfer function model for short-term water consumption dynamics in El Paso, Texas. The model was based on monthly time-series variation of metered water consumption, days with temperature above 90 °F, daily rainfall, number of days with rainfall, average real price, and a proxy of income.	X	
	Aly and Wanakule (2004)	A deterministic smoothing algorithm developed to forecast short-term water usage variability in several municipalities near Tampa, Florida. Daily deviations from the monthly average were forecasted for up to six days using the autocorrelation and weather dependence in six years of daily training data.	X	
	Gato et al. (2007)	Extended the work of Maidment et al. (1986) and Zhou et al. (2000), a method developed to calculate temperature and rainfall threshold that would affect the water baseline use. The model performance R^2 of 0.81 was obtained in field applications.	X	
	Caiado (2007)	The individual and combined univariate time-series models (exponential smoothing, autoregressive integrated moving average, and generalized autoregressive conditional) were compared in the forecast accuracy for baseline urban water demand modeling and for multi-step water demand forecasting.	X	
	Alvisi et al. (2007)	A pattern-based water demand forecasting model developed on the basis of a periodic component in the time-series data to refine daily and hourly demand values generated in model's forecasting module.	X	

Table 1c
Summary of water demand forecasting methods based on computational intelligence techniques.

Literature		Remark	Short term	Long term
Artificial neural networks (ANN)				
2000s	Jain et al., 2001	Two types of ANN models developed to link water demand to physical variables (e.g., weekly average maximum air temperature, total weekly rainfall) in the study; one model has only one hidden layer and the other has two hidden layers. ANN model with two hidden layers offered the best model performance when compared with the conventional regression and time serial analysis methods.	X	
	Liu et al., 2003	A three-layer ANN model designed to process the inputs of water pricing, house income, and household size for water demand forecasting in Weinan City, China. The model evaluation showed correlation coefficients 90% both for the training data and the testing data.	X	X
	Bougadis et al., 2005	ANN models used to forecast short-term peak water demand for rainfall, air temperature, and past water demand as input variables. ANN models outperformed regression models and time series analysis in forecasting accuracy.	X	
	Jain and Kumar, 2006	A hybrid neural network model developed for hydrologic time series forecasting by combining conventional and ANN techniques. The resulting modeling framework is robust and capable of capturing the nonlinear nature of the complex time series for more accurate forecasts.	X	
	Msiza et al., 2007	ANN model investigated for forecasts of both short- and long-term water demands in the Gauteng Province, South Africa. The multi-layer perceptron (MLP) and the radial-basis function (RBF) neural network architectures were compared for the speed of convergence toward a model solution.	X	X
	Ghiassi et al., 2008	A dynamic ANN architecture different from traditional back propagation proposed for urban water demand forecasting. The new method reduced the number of parameters required for model creation and offers better performance than the traditional ANN and autoregressive integrated moving average method across all modeling time frames.	X	X
	Cutore et al., 2008	As a novel application, the Shuffled Complex Evolution Metropolis algorithm (SCEM-UA) calibrated an urban daily water consumption prediction model. The SCEM-UA algorithm for ANN model calibration yielded values of model parameters and prediction uncertainties. Its predictive capability was compared to those of the classic deterministic calibration techniques.	X	
	Yurdusev et al., 2009	Feed-forward and radial-basis ANN investigated for the prediction of monthly water consumption under several socioeconomic and climatic factors.	X	
	Caiado, 2010	Doubled seasonal univariate time series models such as ARIMA and GARCH were applied to track down the trend of water demand.	X	
Fuzzy-logic approach				
2000s	Altunkaynak et al., 2005	A fuzzy forecasting model described as a function of three consecutive antecedent water consumption amounts to predict future monthly water demand in Istanbul City, Turkey. Unlike the regression models and the time series analysis methods, this method requires no assumed linearity, normality, and independence of the prediction residuals.	X	
Agent-based approach				
2000s	Athanasiadis et al., 2005	The method in which water consumers and water-pricing policy makers, as the assigned agents, interacted through an influence diffusion mechanism. The water demand was estimated in the variable of price policies.	X	X

Table 1d
Summary of water demand forecasting methods based on the hybrid approaches.

Literatures		Remark	Short term	Long term
Patten recognition approach				
1990s	Shvartser et al., 1993	A model based on a combination of pattern recognition and time series analysis for orecasting of hourly water demand. Three possible daily demand patterns, 'rising', 'oscillating', and 'falling' were defined as the states of a demand curve of a Markov process. The transition probabilities were learned, and low-order autoregressive integrated moving average models were fitted in the historical data.	X	
Neural-fuzzy approach				
2000s	Pulido-Calvo and Gutierrez-Estrada, 2007	A hybrid methodology combining feed-forward computational neural networks, fuzzy logic, and generic algorithm to forecast next-day daily water demand at irrigation districts. The result showed that the hybrid model performed significantly better than univariate and multivariate autoregressive neural networks.	X	
	Wu and Zhou, 2009	A combination model developed to forecast annual water demand in urban areas. It relied on Hodrick–Prescott filter to calculate the trend and cyclical components and used multiple linear regression method to simulate the trend components. The fuzzy neural network was build based on the cyclical components.		X
	Yurdusev et al., 2009	A generalized regression neural network proposed for municipal water consumption prediction. It combines the regression analysis with ANN techniques, producing accurate and reliable water consumption predictions.	X	
M5 model tree approach				
2000s	Solomatine and Xue, 2004	M5 model tree as a machine learning technique investigated for flood forecasting in the upper reach of the Huai River in China. The M5 model tree offered similar performance as the ANN models, but at faster speed in training, while the hybrid of M5 and ANN models yielded the best prediction result.	X	

2.4. Hybrid approaches

The hybrid approach integrates various models to gain some synergistic advantages. It can be in a form of pattern recognition, neural-fuzzy modeling system, and the so-called M5 model tree (Table 1d). It may be deemed as an extended approach of computational intelligence models.

2.5. Monte Carlo simulations

Advanced water demand forecasting models should be able to detail water demand variation on a per capita basis and simulate the inherent system dynamics in a structure in which the forecasting uncertainties can be quantified in some way, such as the use of Monte Carlo simulations. Two recent studies (Table 1e) are examples of the Monte Carlo-based forecasting practices for future water demand projections.

2.6. System dynamics models

System dynamics modeling is a well-developed systematic tool often used to describe system behaviors with feedback loops for accurate projections. System dynamics, designed similarly to system thinking, is a well-established methodology to quantify complex feedbacks in system interactions (Forrester, 1961, 1968). It requires a construction of the 'causal loop diagrams' or 'stock and flow diagrams' to form a system dynamics context for applications. Within this context, stocks represent the accounting of a system component, either spatially or temporally (i.e., population); flows are the rate at which the component flows in or out of the stock, and converters modify rates of change and unit conversions. All may be intuitively assembled to simulate the dynamic processes of a system. Principles to develop system dynamics models can be found in a series of literature (Forrester, 1961, 1968; Randers, 1980; Richardson and Pugh, 1981; Mohapatra, 1994).

Most computer simulation applications using system dynamics models rely on the use of software packages, such as Vensim® and Stella®, in which the mechanisms of system dynamics can be handled by a user-friendly interface. These model development procedures are designed using a visualization process that allows model builders to conceptualize, document, simulate, and analyze models of dynamic systems (Forrester, 1961, 1968). They offer a flexible way for building a variety of simulation models from causal loops or stock and flow (Forrester, 1961, 1968). The dynamic relationships between the elements (including variables, parameters, and their linkages) can be created onto the interface using user-friendly visual tools. The feedback loops associated with these employed variables can be visualized at every step throughout the modeling process. Such applications can be found for business systems (Sterman, 2000), ecological systems (Grant et al., 1997), social-economic systems (Forrester, 1969, 1971; Meadows and Meadows, 1973), agricultural systems (Qu and Barney, 1998; Saysel et al., 2002), political decision-making systems (Nail et al., 1992), and environmental systems (Vizayakumar and Mohapatra, 1991, 1993; Vezjak et al., 1998; Ford, 1999; Wood and Shelley, 1999; Abbott and Stanley, 1999; Deaton and Winebrake, 2000; Guo et al., 2001). Such a system dynamics modeling approach for water demand estimation and forecasting has not been explored elsewhere; however, we propose a unique water demand estimation method by using a system dynamics model in which Stellar®,

Table 1e
Literature review for water demand forecasting based on the Monte Carlo simulation approach.

Literatures		Remark	Short term	Long term
Per capita based approach with uncertainties in global change				
2000s	Khatri and Vairavamoorthy, 2009	A method using Monte Carlo simulation to predict the total future population with uncertainty, and using the Latin Hypercube Sampling technique to analyze micro-components of water demand and spatiotemporal distribution of per-capita water consumption. Uncertainties related to climate change were incorporated, and climatic variables were assessed using regression models developed from historic records.		X

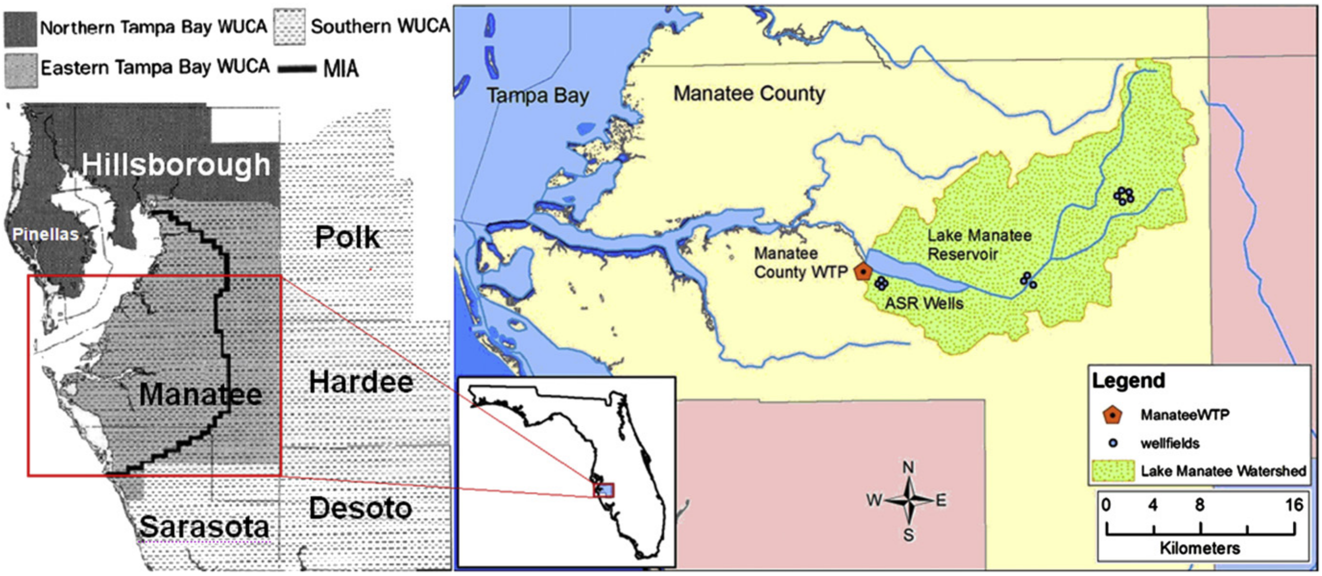

Fig. 1. Location of study area.

an iconographic software using basic building blocks such as stocks, flows, and converters, was employed to build up the essential modeling framework in our study.

3. Study area and methodology

3.1. Water supply and demand

Manatee County is located in the Southern Water Use Caution Area (Southern WUCA) within the depleting Upper Floridian Aquifer (Board of County Commissioner, 2008). The entire western portion of the county is designated as the Most Impacted Area (MIA) within the Eastern Tampa Bay Water Use Caution Area (Eastern Tampa Bay WUCA) relative to the Southern WUCA (Fig. 1). According to the Manatee County 2008 water supply facilities work plan (referred to as the work plan hereafter; Board of County Commissioner, 2008), the county has been experiencing residential and tourist population growth, a trend predicted to continue in the future. This fast-growing urban region was therefore selected for the water demand estimation and forecasting under economic impacts using a system dynamics model.

Principal customers of Manatee County water supply are retail customers, significant users, and wholesale customers. Significant users refer to those customers with water demand >94.635 m^3/day, while retail customers are mostly composed of residential water users. The significant users accounted for approximately 8782.2 m^3/day water consumption in 2006. Wholesale customers include the cities of Bradenton, Palmetto, Longboat Key, and some regions in Sarasota County to the south. The water demand to wholesale customers is predictable because of the prescribed contracts and supply agreements. The current agreements with city of Bradenton and town of Longboat Key will remain effective through 2030, and the water demands for these two customers are relatively stable at 1892.7 m^3/day and 9463.5 m^3/day, respectively (Table 2). In contrast, future water demand by retail customers and significant users is difficult to predict using mathematical forecasting models because water usage is commonly projected on a per capita basis (Table 3).

The county-wide water demand in 2006 was 180,018.4 m^3/day including 114,455.1 m^3/day for domestic water supply and 65,563.3 m^3/day for wholesale customers and significant users. The Board of Country Commissioners (2008) projected that the yearly average portable water demand will increase to an estimated 234,317.0 m^3/day by 2030 based on the projected population increase. Currently the county has an annual average of permitted water supply of 200,059.0 m^3/day, which is sufficient to meet the projected water demand until 2014. Thus, expansion of current water system facilities is required to meet the year-2030 water supply goal as the supply and demand will likely become imbalanced by 2014. The water supply shortage predicted by 2030 is projected to be 34,447.2 m^3/day.

3.2. The unique economic booming and downturn environments

Comparative plots were formed between the historical trend of domestic water demand and previously estimated demand by Manatee County (Fig. 2). The estimated demand by Manatee County (Board of Country Commissioner, 2008), based on the assumption of fixed value of per capita demand, is challenging. In fact, a various number of macroeconomic factors may affect the per capita values such as unemployment rate and average annual income. The Florida unemployment rate reflects the most recent recession cycle from 2003 to 2009 (Fig. 2). When the unemployment rate declined to the lowest level in 2006 and then rose until

Table 2
Water demand projections for wholesale customers in terms of annual average flows (Board of County Commissioner, 2008).

Wholesale customers	2006	2010	2015	2020	2025	2030
City of Bradenton	1.8927	1.8927	1.8927	1.8927	1.8927	1.8927
City of Palmetto	7.5708	7.5708	9.4635	10.4099	11.3562	12.1133
Town of Longboat Key	9.4635	9.4635	9.4635	9.4635	9.4635	9.4635
Sarasota County	37.8541	30.2833	22.7125	18.9271	0.0000	0.0000

Unit: 1000 m^3 per day.

Table 3
Water demand projections for retail and significant users in terms of annual average flows (Board of County Commissioner, 2008).

Customers	2006	2010	2015	2020	2025	2030
Retail customers	115.46	115.31	132.19	149.87	168.30	187.61
Significant customers	8.78	14.35	16.47	18.66	20.93	23.36

Unit: 1000 m^3 per day.

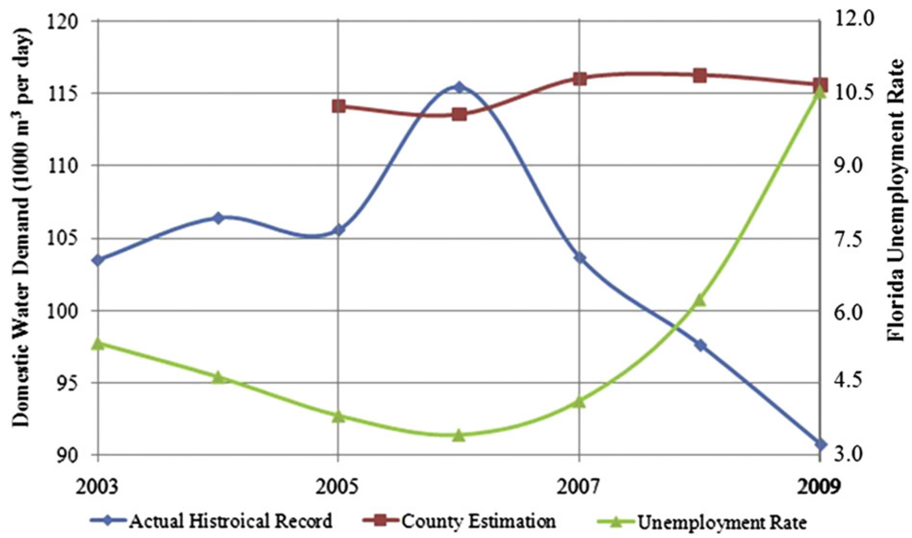

Fig. 2. Historical domestic water demand, county estimation and unemployment rate.

2009 due to the United States subprime mortgage crisis in 2007, water demand dropped sharply. Furthermore, the annual average wage of all occupations in Florida (Fig. 3) exhibits a mild linear increase over the study period and shows a seemingly unrelated association between the sharp increase of water demand after 2004 and the sharp drop of water demand after 2007. The two key questions are (1) will the unemployment rate and average annual income, which are deemed as two principal indicators of the changing macroeconomic environments, interact with other socioeconomic factors, and (2) how they will impact the domestic water demand in Manatee County.

Unemployment rate is a well-known indicator in macroeconomic systems (Nefti, 1984; Sichel, 1989; Rothman, 1991). Unemployment rate is generally believed to have an asymmetric characteristic of rapid increase during recession and slower decline during economic recovery (Fig. 4). In particular, Nefti (1984) found some statistical evidence in support of this observation. Although this significant finding of asymmetry was questioned by Sichel (1989) due to an error in Nefti's calculations, Rothman (1991) further strengthened the belief of such asymmetry by using a modified version of Nefti's test and proved that it is statistically significant. Due to this asymmetric property, unemployment rates are highly persistent in the economic recovery period, and slower recovery from the recession impacts may last for a decade (e.g., from 1982 to 1991 and from 1992 to 2001). In other words, the sharp rise in the unemployment rate in 2008 and 2009 due to the United States sub-prime crisis may take a decade for relief. Thus, a reasonable assumption may be made for the next decade that as the global economic environment enters the recession recovery period, the unemployment rate will slowly decline. Hence, our system dynamics model, particularly in response to the changing correlation between unemployment rate and water demand, can be constructed and validated for this study, and out-of-sample estimation can possibly be carried out for future water demand forecasting under the alternating impact of macroeconomic boom and downturn.

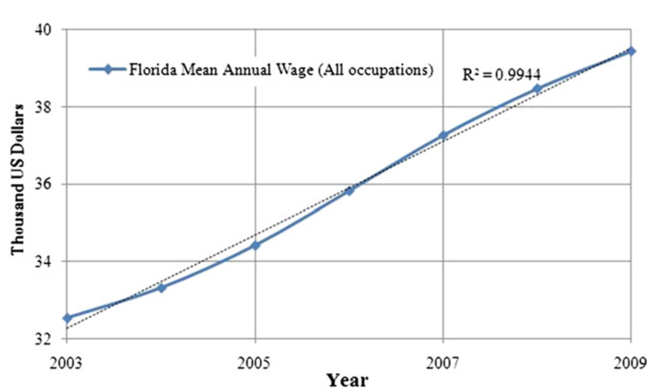

Fig. 3. Historical Florida mean annual wage (all occupations) in which the dotted line is the straight line for comparison purpose (Source: United States Department of Labor, Bureau of Labor Statistics).

3.3. Water demand estimation methodology

In the design philosophy of this system dynamics model (Fig. 5), water demand estimation is driven by two macroeconomic indicators: unemployment rate and average annual income. These information flows were fed into the calculations of per capita water demand affected by some independent socioeconomic factors such as population dynamics, real estate market, and net immigrations. The internal linkages among those socioeconomic factors are implicitly established and supported by historical data from year 2003 to 2009, which may be statistically confirmed by including interactive and quadratic terms in addition to the first order terms. The socioeconomic impact of these interacting factors can be translated to determine their affect on water demand at the county level. Using the projected demographic delineation and per capita water demand under the postulated uncertain socioeconomic impact, the domestic water demand in Manatee County can be estimated by such a system dynamics model.

To validate this system dynamics model, model output of the domestic water demand must be compared with the corresponding historical record. If the goodness of fit criteria are confirmed, the model is deemed valid and may be used for future water demand forecasting in the next decade based on some assumptions. For example, considering the asymmetric property of the long-term unemployment rate in the business recession cycle, we need to assume that the global economy enters a recovery period and the unemployment rate continues to decline over the next decade. Further, because the average annual income exhibits a significant linearly increasing trend over the years in a full business recession cycle from 2003 to 2009, the linear tendency may be assumed to persist in the future. Therefore, with these two assumptions, future

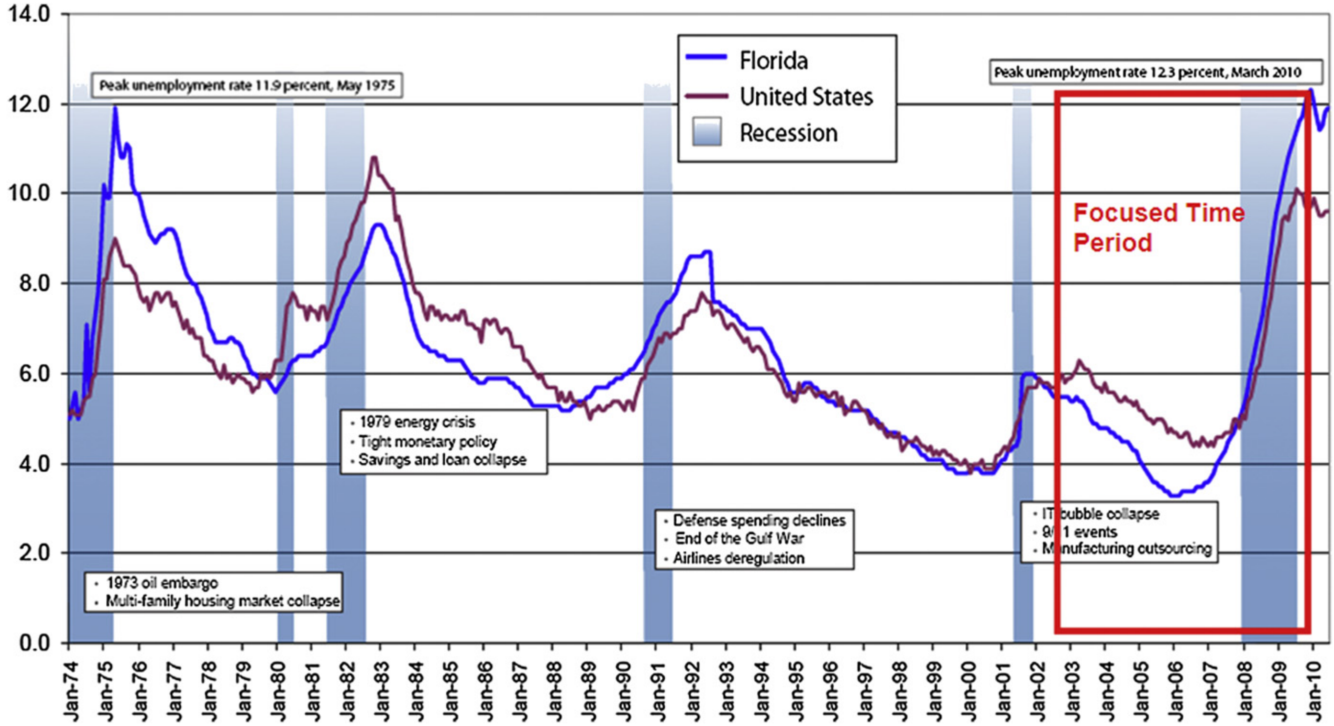

Fig. 4. Florida and United States labor statistics and recessionary periods, and unemployment rates from Jan. 1974 to Sept. 2010 seasonally adjusted. Source: Florida Agency for Workforce Innovation, Labor Market Statistics Center, Local Area Unemployment Statistics Program, in cooperation with the U.S. Department of Labor, Bureau of Labor Statistics. Prepared October 2010 (seasonally adjusted).

domestic water demand under the impact of the current macroeconomic environment may be realistically forecasted.

4. Formulation of the system dynamics model

The system dynamics model used in this study was developed to estimate domestic water demand for Manatee County, Florida during our study period from 2003 to 2009. First, the system diagrams must be created to link all related socioeconomic and managerial components throughout three submodels, including socioeconomic, population dynamics, and water demand forecast. Real-world data relevant to various internal linkages among socioeconomic and managerial factors must be processed to retrieve regression equations that support flows and conditions within and among these three submodels. Real-world water demand data from 2003 to 2009 can then be used for model validation. Once the system dynamics model is created and validated, it becomes applicable for future water demand forecasting and the new input data can be generated by other socioeconomic scientists.

4.1. Modeling the system dynamics

Population dynamics were modeled as a stock delineated by a number of neighboring components, such as the net immigration rate within the submodel (Fig. 6). Outside the submodel, however, birth and death rates as well as economic conditions such as unemployment rate and average income may play a critical role. With this setting, modeling water demand in this study became associated with population dynamics and per capita water demand driven by some major relevant socioeconomic factors, directly and indirectly. Three submodels are therefore interconnected within the modeling framework. The inputs of unemployment rate and average annual income uniquely reflect the changing macroeconomic conditions from 2003 to 2009 that, in turn, affect the real

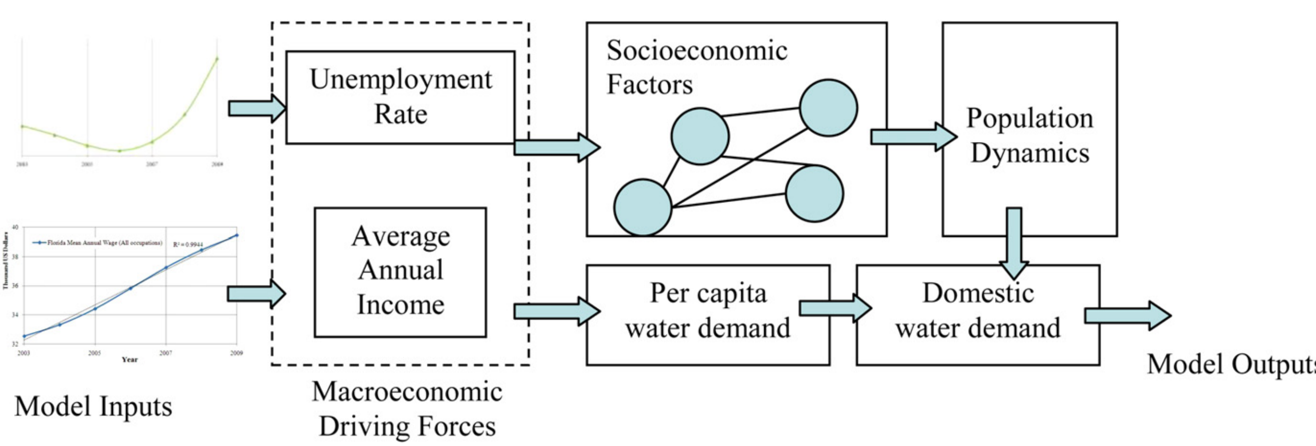

Fig. 5. System diagram of system dynamics modeling approach.

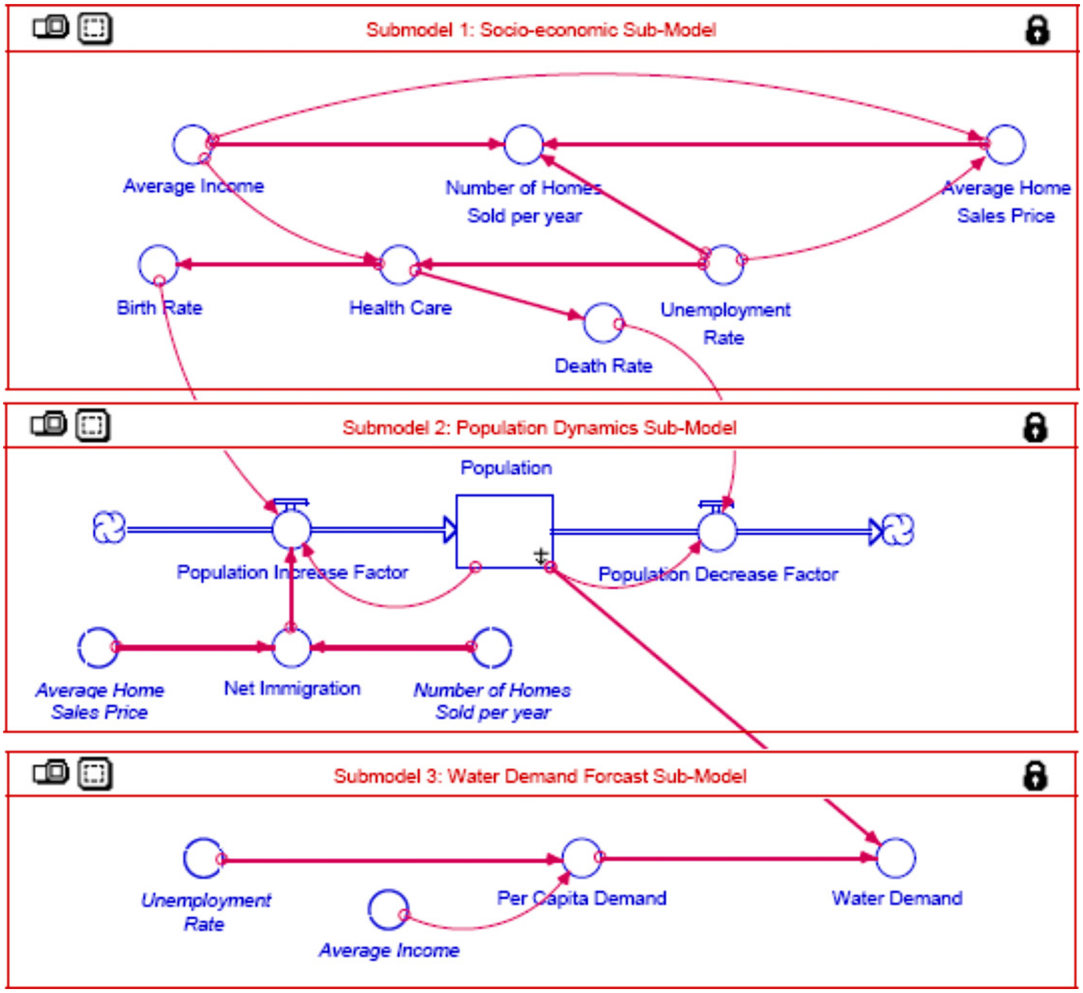

Fig. 6. The system dynamics model for domestic water demand estimation.

estate market and other socioeconomic factors in the socioeconomic submodel. The population dynamics submodel is created by using a component method, in which a component of population change per day due to births, deaths, and net migrations is calculated to update the population over years. The component method has been adopted by the U.S. Census Bureau for population projections. The Bureau particularly employed time series models to estimate the component of population change in many practices. Yet our system dynamics model integrates the intrinsic, interactive relationships of these components (mortality, fertility, and net migration) and socioeconomic factors cohesively to address the component. Given the birth rate, death rate, and net migration under the impact of a changing macroeconomic environment, the population dynamic submodel simulates the population growth, generating and translating the input data for the water demand forecast submodel, where the synthesis of all information from socioeconomic and population submodels can be integrated. The water demand forecast submodel, therefore, was formulated based on a per capita basis with respect to the per capita coefficient, which can be dynamically updated in association with the changing macroeconomic environments.

The next step is to characterize those intertwined internal linkages within and between these submodels. To carry out the

Table 4
Definition of socioeconomic and managerial factors.

Social-economic factor name	Definition
Population increase factor	The amount of population increased each year in Manatee
Population decrease factor	The amount of population decreased each year in Manatee
Net immigration	The amount of population increase due to net immigration in Manatee
Birth rate	The percentage of birth among the population in Manatee
Death rate	The percentage of death among the population in Manatee
Population	The population in Manatee
Health care	The number of uninsured by health insurance in Florida
Number of homes sold per *year*	The average number of houses sold per year in Manatee
Average home sales price	The annual average home sales price in Manatee
Per capita demand	The daily average water demand per capita in Manatee
Unemployment rate	Unemployment rate in Florida
Average income	Average annual income in Florida
Water demand	Domestic water demand per day in Manatee

Table 5
Regression and empirical equations derived in support of the system dynamics model.

Socioeconomic factors	Empirical equations		
Population increase factor	= Population × Birth rate + Net immigration		
Remark	Population increase factor is the sum of new births and net immigration.		
Population decrease factor	= Population × Death rate		
Remark	Population decrease factor is the amount of deaths.		
Water demand	= Per capita demand × Population		
Remark	It is a theoretical equation for water demand that total demand equals the product of population and per capita demand.		
	Regression equations	R^2	*p*-value
Net immigration	= −3030 + 0.783 × Number of homes sold per year − 0.00000011 × Average home sales price × Average home sales price	86.7%	0.002
Remark	There is causal relationship between immigration inflows and real estate market and positive correlation was found according to Saiz (2003, 2007)		
Birth rate	= 0.00813 + 0.000001 × Health care	66.0%	0.026
Remark	Birth rate is statistically related to the health insurance coverage according to Wennberg et al. (1987)		
Death rate	= 0.014 − 0.000001 × Health care	86.7%	0.002
Remark	Death rate is statistically related to the health insurance coverage according to Wennberg et al. (1987)		
Health care	= 4513 − 1061 × Unemployment rate + 0.0237 × Average income × Unemployment rate	95.1%	0.002
Remark	Health insurance is related to the unemployment rate and income (Fronstin, 1998; Kutter, 1999)		
Number of homes sold per year	= 30616 − 0.000046 × Average income × Average income + 0.082 × average home sales price + 0.018 × average home sales price × unemployment rate	95.3%	0.040
Remark	Case (1991) and Case et al. (2000) show the intrinsic relationship between the real estate market and macroeconomy		
Average home sales price	= 368990 − 129770 × Unemployment rate + 2.81 × Unemployment rate × Average income	97.3%	<0.000
Remark	Case (1991) and Case et al. (2000) show the intrinsic relationship between the real estate market and macroeconomy		
Per capita Demand	= 122 − 0.000269 × Unemployment rate × Average income+0.594 × Unemployment rate × Unemployment rate	87.8%	0.015
Remark	Per capita demand is driven by the two macroeconomic indicators.		
Average income	= −2164909 + 1097 × Year number	97.2%	0.000
Remark	Average annual income presents strong linear property over years as shown in Fig. 3.		

modeling practices, the statistical relationships based on all relevant socioeconomic and managerial factors (discussed earlier) are quantified by fitting regression equations stepwise in support of a suite of legitimate internal linkages in our system dynamics model (Table 4).

Observations in the literature show that the intrinsic relationships between these socioeconomic and managerial factors exist either causally or statistically. The intrinsic relationships between the real estate market and macroeconomic fluctuations were well documented in New England, California, Alaska, and Hawaii (Case, 1991; Case et al., 2000). These studies showed that 72% of all bank lending during the boom from 1984 to 1988 was collateralized with real estate, and the real estate loans accounted for more than 90% of Bank of New England's losses in the economic downturn from 1988 to 1992. Rising housing prices in the boom fueled consumer spending and expanded the employment rate; however, in the economic downturn, mortgage default rates and foreclosures rate were high and losses were severe, which in turn affected the real

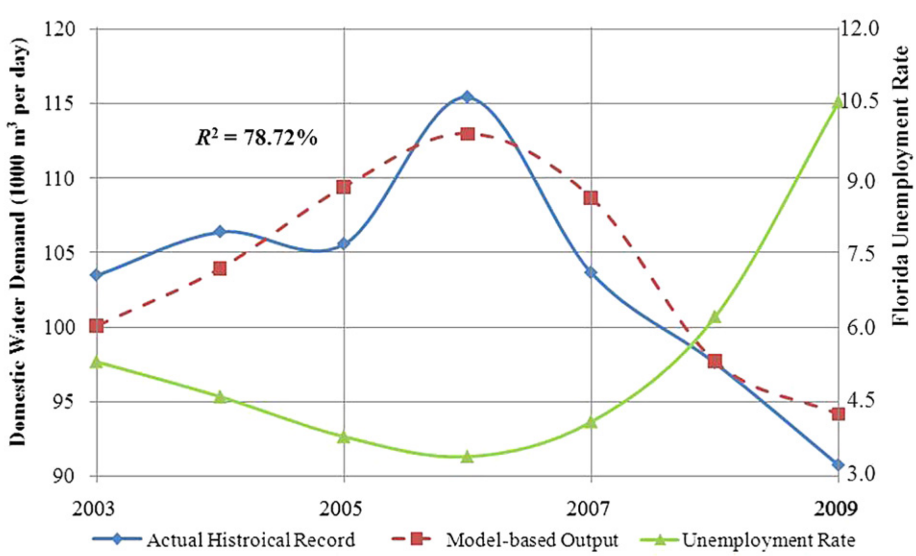

Fig. 7. Model validation.

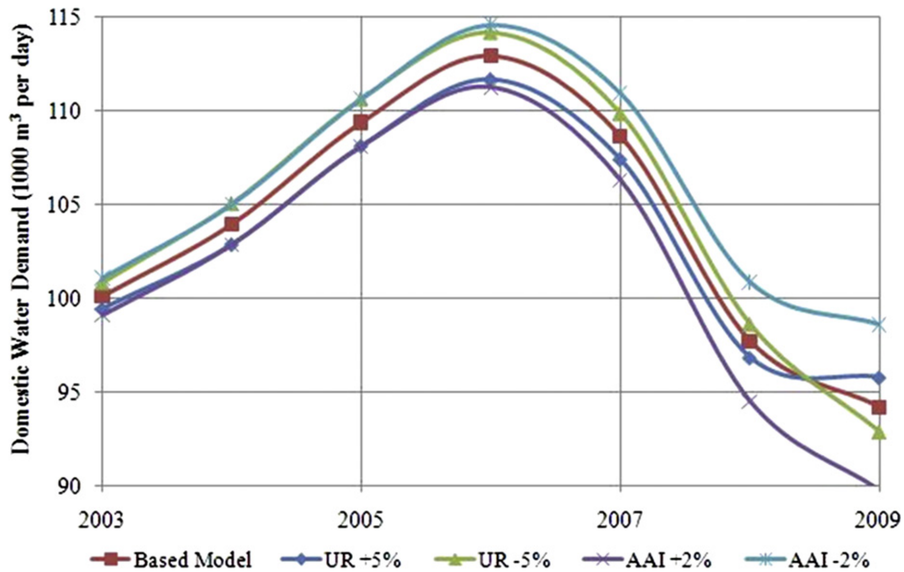

Fig. 8. Model outputs based on the offset unemployment rate and average annual income. The vertical solid lines represent the intervals of water demand, which are caused by the fluctuations or uncertainties, associated with the changing macroeconomic environments. The triangle marks stand for the estimated values of the base model relative to those fluctuated values above and below them.

estate value and turnovers. In our model, the statistical linkages between the real estate market (average home sales price and number of homes sold per year) and the macroeconomic indicators (unemployment rate and average annual income) were established using statistical regression analysis. Based on the local data collected in Florida and Manatee County from 2003 to 2009, the linkages were significant (Table 5).

Our findings indicate that the local real estate market can be further interrelated with the immigration movement. Burnley et al. (1997) reported that immigration was one of the important short- and long-term driving forces of the real estate market, and Saiz (2003, 2007) provided evidence of a causal relationship between immigration inflows and the housing market in American cities. Thus, a quantitative linkage between the net immigration rate and the real estate market (e.g., average home sales price and number of homes sold per year) became available in our system dynamics model. This linkage was also significant based on the local historical data in Manatee County (Table 5).

Furthermore, Kutter (1999) reported that most Americans rely on their employers for health insurance. In 1997, of the 167.5 million nonelderly Americans with private health insurance, 151.7 million belonged to employer-provided health plans (Fronstin, 1998). A strong relationship exists between national expenditures on health care and national income (Parkin et al., 1987), and insurance premiums and income become factors for people not included in employer-sponsored health plans. Health care level (e.g., the number of uninsured) is therefore interrelated to unemployment rate and average annual income. Local data in Manatee County and Florida show that this linkage is significant. Health care level can also indicate fertility and mortality. Wennberg et al.

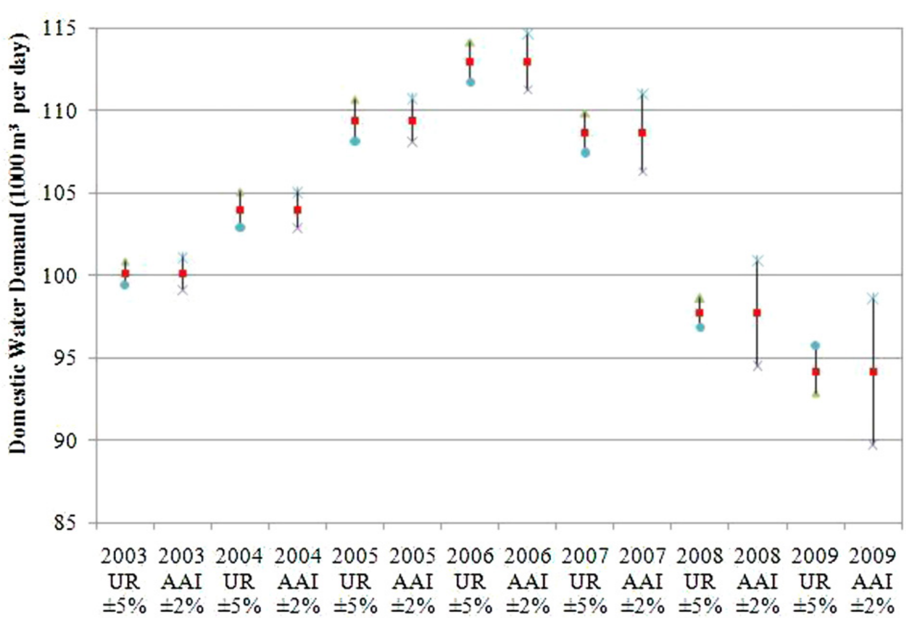

Fig. 9. Sensitivity analysis of domestic water demand in response to offset unemployment rate and average annual income.

(1987) found a statistical relationship between medical insurance claim data and health care outcomes, so that data maintained by medical insurance plans could be used to evaluate the incidence of birth and death. Hence, health care and death rate can be quantitatively linked. The relationship among population increase, birth rate, and net immigration inflows is thus strongly interrelated, as addressed in our system dynamics model.

Finally, the water demand forecast submodel can be defined on the basis of per capita water demand so that it is affected by both unemployment rate and average annual income. Impacts of changing macroeconomic environments may then propagate throughout the system dynamics model, leading to a sound elucidation of water demand trends related to primary socioeconomic factors.

Water price is a well-known factor that may impact per capita water demand. Price was not included in this model, in part because water demand is a fundamental requirement for life, and water resources have no substitute. In addition, water bills are not typically a big proportion of expense in the sense that the elasticity of water demand is not sensitive (Savenije and van der Zaag, 2002). Therefore, domestic water demand was deemed inelastic to water price even though price elasticity may be slightly different from zero in our system dynamics model.

Note that the majority of the historical data used in our study came from the U.S. Census Bureau and U.S. Department of Labor. Statistical regression analyses associated with these internal linkages within and between submodels were then available based on the historical data from 2003 to 2009 (Table 5). These linkages are also supported by the literature (Burnley et al., 1997; Saiz, 2003, 2007; Kutter, 1999; Fronstin, 1998; Parkin et al., 1987; Wennberg et al., 1987).

4.2. Model validation

The proposed system dynamics model was validated by comparing estimated values to historical data from 2003 to 2009. Model simulation runs begin in 2003 with the designated initial data for the stock component (e.g., population). Unemployment rate, one of the macroeconomic driving forces, was replaced by the real historical recorded data. Another macroeconomic driving force, average annual income, was also estimated by using the regression equation (Table 5). Thus, the model-based output for Manatee County domestic water demand (Fig. 7) can be denoted as the base model output in this study. The model-based estimation curve is close to the actual historical curve, confirming the fidelity of the proposed system dynamics model. The prediction accuracy of domestic water demand estimation in Manatee County from 2003 to 2009 can be further validated based on the relatively higher R^2 value (i.e., 78.72%). This validated model indicates the pattern of domestic water demand in Manatee County is clearly driven by the Florida unemployment rate and average annual income, and our system dynamics model is deemed successful.

5. Sensitivity analysis

In the system dynamics model, the uncertainties embedded in parameters or equations being derived associated with the two driving forces should be further explored by sensitivity analysis. This analysis helps us gain a better understanding of the reliability of estimated water demand under uncertain economic impact given that the domestic water demand in the study period is highly nonlinear in response to the changing macroeconomic environments. Therefore, small offsets on the two driving forces were designed to continue the trend, so that the offset demand curved would be in a similar pattern as the base model (Fig. 8). In the sensitivity analysis, unemployment rate (UR) and average annual income (AAI) are offset by $\pm 5\%$ and $\pm 2\%$, respectively. The resultant impact on domestic water demand can be illustrated with respect to the upper and lower bounds of the estimated water demand in response to the offset unemployment rate and annual average income from 2003 to 2009 (Fig. 9).

The sensitivity analysis indicates that the subtle change of unemployment rate results in a greater change, but such a fluctuation does not change the patterns of the estimated water demand curve. Furthermore, the subtle change of average annual income may result in a greater impact to the water demand compared to the impact of unemployment rate fluctuations. This impact on water demand due to the uncertain average annual income becomes obvious when the unemployment rate is high (e.g., 2008 and 2009). The increase in average annual income may positively affect the real estate market and further affect the population growth and migration; yet, the phenomenon of declining estimated water demand in response to increasing average annual income is mainly caused by the total population decrease, which is primary due to the change of net immigration rate. Therefore, we may conclude that the proposed system dynamics model is less sensitive to the uncertainties of unemployment rate than the average annual income.

6. Conclusions

Through a rigorous literature review, we conclude that our system dynamics model carries unique features that support the need for complex interactions among system components for water demand estimation and forecasting. The case study using the system dynamics modeling tool to estimate the domestic water demand from 2003 to 2009 for Manatee Country, Florida, was successful, even with limited historical data of population and water consumption. The success of this limited model leads to a challenge: how do we build a representative model to account for the interactions among those factors under global macroeconomic changes at different temporal scale in an urban region? Such a system dynamics modeling analysis eventually allows us to answer the proposed science questions in regard to whether or not the unemployment rate and average annual income, which are deemed as two principal indicators of the changing macroeconomic environments, can interact with other socioeconomic factors and how they are going to impact the domestic water demand in Manatee County. Overall, socioeconomic factors including underlying economic development, income, real estate status, and health care level were considered by this model to be simultaneously influential factors in relation to the domestic water demand. With proper assumptions associated with these two driving forces, the system dynamics model allows us to estimate and forecast the future water demand under the impact of changing macroeconomic environments. At a practical level, a proper sensitivity analysis aligns the impact from several parameters with the water demand estimations to improve the reliability in modeling analysis.

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