An agent-based model for domestic water management in Valladolid metropolitan area

José M. Galán,[1] Adolfo López-Paredes,[2] and Ricardo del Olmo[1]

[1] In this work we demonstrate that the combination of agent-based modeling and simulation constitutes a useful methodological approach to dealing with the complexity derived from multiple factors with influence in the domestic water management in emergent metropolitan areas. In particular, we adapt and integrate different social submodels, models of urban dynamics, water consumption, and technological and opinion diffusion, in an agent-based model that is, in turn, linked with a geographic information system. The result is a computational environment that enables simulating and comparing various water demand scenarios. We have parameterized our general model for the metropolitan area of Valladolid (Spain).The model shows the influence of urban dynamics (e.g., intrapopulation movements, residence typology, and changes in the territorial model) and other socio-geographic effects (technological and opinion dynamics) in domestic water demand. The conclusions drawn in this way would have been difficult to obtain using other approaches, such as conventional forecasting methods, given the need to integrate different socioeconomic and geographic aspects in one single model. We illustrate that the described methodology can complement conventional approaches, providing descriptive and formal additional insights into domestic water demand management problems.

1. Introduction

[2] The main challenge in water management has traditionally consisted of ensuring the fulfillment of a certain, preset, demand of water with an often insufficient water supply. As such, domestic water management has been historically focused on supply side policies. This view gradually changed over the 80s and 90s, when the increasing importance of ecological, financial and political constraints led to the realization that the problem of water management is not just an issue of inadequate supply, but it is also possible to make policy from the demand side. Nowadays there is an increasing awareness that a wide range of socioeconomic factors play an influential and important role in urban water use, and also that these factors may be somewhat shaped and harnessed to design and implement better policies.

[3] The perception of water demand as an exogenous uncontrollable variable led to the development and extensive use of a wide range of forecasting methodologies (per capita and per unit approaches, end use models, extrapolation methods and structural models). Most of these forecasting methodologies use statistical evidence to estimate water demand as a function of various factors. The practical value of many of these approaches is beyond doubt, but, on the other hand, their explanatory power is often very limited, since they are based on correlation rather than causality. Thus, assuming structural conditions do not change significantly, forecasting methods may fit the data reasonably well and yield useful predictions, but, given that these methods fail to capture the underlying causal relations that determine water demand, their performance when structural conditions change is at best uncertain.

[4] The need to complement the traditional forecasting methodologies with more descriptive models has created an unprecedented demand for exploratory tools and techniques that explicitly take into account and integrate the whole range of relevant social phenomena and the interactions among them. Here we show that one of the most promising methodologies to do this job is agent-based modeling (ABM) [*Downing et al.*, 2001; *López-Paredes et al.*, 2005; *Moss et al.*, 2001; *Moss*, 2002a].

[5] In this paper we present a hybrid agent-based model designed to analyze the complex causal relations that underlie the formation of aggregated water demand in metropolitan areas. The model developed here is meant to serve mainly as a "tool to think with," i.e., an aid to advance our knowledge about the complex dynamics of the whole water management system, taking into account its most critical subprocesses and the interdependencies between these. This work has also allowed us to assess ABM as an emerging methodology for domestic water management.

[6] We have integrated and adapted different social submodels, models of urban dynamics, water consumption, and technological and opinion diffusion, in an agent-based model that is, in turn, linked with a geographic information system

[1]Department of Civil Engineering, University of Burgos, Burgos, Spain.
[2]Departamento de Organización de Empresas y C.I.M., Valladolid, Valladolid, Spain.

(GIS). To prove that the described methodology can lead to additional insights, different from those obtained with conventional approaches, we have parameterized our general model for the Metropolitan Area of Valladolid (Spain) and analyzed several scenarios.

[7] The structure of the paper is as follows: in the next section we give some background on classical methodologies to forecast water demand, we describe the main features of agent-based modeling, and we briefly explain what scenario analysis is and the reasons why it is particularly useful in this research context. Subsequently we present the general structure of the model and the different submodels that make it up. We also discuss the most relevant issues regarding the implementation, calibration and validation of the model used in this case study. Afterwards we define the set of different scenarios that we analyzed, and discuss the results we obtained. Finally, we present the conclusions in the last section.

2. Background

2.1. Forecasting Water Demand

[8] There are many reasons for forecasting water demand. In fact, most of the decisions in water management are based on estimations, more or less explicit, of future water demand. The classical literature on estimation of urban water demand [*Baumann et al.*, 1998; *Billings and Jones*, 1996] considers four main methodologies: (1) per capita and per unit approaches, (2) end use models, (3) extrapolation methods, and (4) structural or causal models. We can also add to this set the relatively recent use of connexionist methodologies like artificial neural networks for short-term forecasting. The choice of one or another technique is based mainly on the intended use and time frame of the prediction and, of course, on the available data.

[9] Per capita approaches are very simple tools. First they forecast the population to be served, they then estimate the expected water use per capita, and finally, by simply multiplying both forecasts, they provide estimations of future overall water use. An important drawback of these techniques, even in their more sophisticated versions, for example, accounting for different types of customers, is that they ignore the impact of spatial interactions between population groups and how these interactions affect their patterns of water consumption.

[10] End use models consist basically in disaggregating water demand into the different services and uses that people actually make of water [*White et al.*, 2004]. This involves collecting extensive information about consumer behavior and making an inventory of the stock, technical features and patterns of use of all water devices. Even though these techniques have important advantages that can explain demand growth [*Jacobs and Haarhoff*, 2004a, 2004b], they also present two important drawbacks: first, they need a significant amount of disaggregated data that are usually not available, thus making this methodology expensive and often impractical, and second, they are, in principle, static models.

[11] The whole family of extrapolation methods considers time as an explanatory variable. These models can give very good results when the initial assumptions do not change but, as *Herrington* [1996] points out, if structural changes occur in the system, it could be the case that the best models for certain periods are not appropriate for others. Moreover, most of these models are not explanatory, so their suitability to assess the effect of intervention policies is limited.

[12] The search for explanatory power has often led to the use of structural and causal methods, which present very interesting features; for example, they allow us to consider many different explanatory variables (see *Arbués et al.* [2003] for an extensive review) and are based on very strong statistical foundations. However, these methods are not free from weaknesses: they are usually not dynamic, their focus has been mainly on the price of water as the key determinant factor [*Arbués et al.*, 2004; *Bell and Griffin*, 2008; *Bithas and Stoforos*, 2006; *Espey et al.*, 1997; *Montginoul*, 2007; *Taylor et al.*, 2004], they often ignore the endogenous intra-population dynamics, and they sometimes present significant technical problems, for example, those derived from intra-marginal prices [*Arbués et al.*, 2003; *Bachrach and Vaughan*, 1994] or endogeneity with multiblock tariffs [*Martínez-Espiñeira*, 2003; *Reynaud et al.*, 2005].

[13] Artificial neural networks have been used extensively in the past years to forecast water demand, mostly for making short-term predictions [i.e., *Aydinalp et al.*, 2004; *Bougadis et al.*, 2005; *Joo et al.*, 2002]. They can be regarded as a useful tool to approximate complex nonlinear functions, but they also exhibit very important explanatory limitations, just like the extrapolation methods. This lack of explanatory power makes them unsuitable in management and planning contexts.

[14] To conclude this succinct review, we summarize some limitations that are common to most classical methodologies to forecast water demand: (1) They are difficult to abstract and understand the hypotheses embedded in the models, making them suboptimal as explanatory tools. (2) Models do not take into account factors that are generally considered very significant (e.g., geographical features, which are widely recognized to be of critical importance in the domestic water domain). (3) They are difficult to integrate diverse socioeconomic aspects in one single model. Since agent-based modeling has the potential to overcome some of these problems, we consider that models developed using this methodology may assist managers and policy makers to make better decisions. We believe that this approach can complement previous methodologies by providing additional insights and information on the problem of forecasting water demand.

2.2. Agent-Based Modeling

[15] Formally, agent-based modeling can be defined as "a computational method that enables a researcher to create, analyze and experiment with models composed of agents that interact within an environment" [*Gilbert*, 2007]. In essence, the approach consists in creating a computer program in which the entities identified in the target system (and their interactions) are represented by software objects (the agents) interacting among them and within a virtual environment [*Edmonds*, 2001]. The basic idea is to establish a direct correspondence between the actors and the agents in such a way that observing how the program evolves over the course of simulated time in the virtual world can give us some insights over the modeled system.

[16] ABM allows us to position ourselves at an intermediate point between the traditional scientific modeling paradigm in the natural sciences, based on mathematical

equations, and hence formal, and the traditional modeling approach in the social sciences, typically based on natural language. Abstracting individual actors directly as agents avoids the need for simplifying hypothesis about aggregated variables of the system, and facilitates the explicit study of individual influences and interactions. This fact, along with the flexibility of current programming languages, enables us to model agents with greater descriptiveness than when using compact mathematical equations only, without losing the rigor that formal modeling provides. Implementing a model in a computer requires formalizing and making explicit all the assumptions embedded in the model. As a matter of fact, in order to run a model in a computer, this has to be necessarily complete, consistent and unambiguous [*Gilbert*, 2007].

[17] This way of conducting the abstraction process in ABM offers some advantages with respect to other modeling paradigms [see *Epstein*, 1999; *Axtell*, 2000; *Bonabeau*, 2002; *Bousquet and Le Page*, 2004]: (1) It can lead to more natural and transparent descriptions of the target systems. (2) It facilitates relaxing the much-used hypothesis of homogeneity in the population. (3) It allows for incorporating explicit representations of geographical environments with realism. (4) It gives the option of modeling local interactions. (5) It makes possible the modeling of the bidirectional relation between the microdefinition of individuals and the macrobehavior of the system. (6) It can capture emergent behavior, understanding emergence as the appearance of fundamentally new patterns at the higher scales of a system as a result of the interactions at an elementary level [*Holland*, 1998]. (7) The relatively straightforward way in which these models can be interpreted makes it possible to quickly incorporate in the model potential criticisms and suggested modifications made by domain experts and stakeholders. (8) It is possible to include economic, social, territorial, technological, and every influential dimension in one single model, thus generating integrated and interdisciplinary science.

[18] Unfortunately, as one would expect, these benefits often come at a price: most of the models built in this way, and especially when they are developed as support decision tools, are very difficult to be solved analytically, so we are often obliged to resort to computer simulation if we want to deduce the logical implications of our assumptions. Modeling using this approach implies a shift toward the "descriptiveness end" in the trade-off between representational accuracy of a model and the tractability of its analysis.

[19] Thus, ABM seems a suitable methodology to be explored in the context of residential water demand, since in such systems there are a number of heterogeneous interdependent socioeconomic factors of very different nature (such as income and household composition [*Arbués et al.*, 2003], the influence of the territorial model [*Domene and Saurí*, 2006; *Domene et al.*, 2005], or the diffusion of information about the resource [*Edwards et al.*, 2005]) that have proven to be crucial determinants of residential consumption.

[20] It is therefore not surprising that in the past few years there has been an important development of agent-based modeling applications in the domain of water management. In the context of domestic and urban water we can find applications focused on the Thames catchment [*Barthélemy*, 2008; *Moss*, 2002a; *Moss and Edmonds*, 2005], on Barcelona [*López-Paredes et al.*, 2005] and on

Thessaloniki [*Athanasiadis et al.*, 2005; *Athanasiadis and Mitkas*, 2005]. There are also more general models as those developed by *Tillman et al.* [1999] or *Kotz and Hiessl* [2005]. In general, the level of abstraction of these models is high, mainly in what concerns the spatial representation and in the detail and number of agents considered in the simulations. Our article represents a step forward in descriptiveness with respect to these works since the agent-based model developed here is integrated with a detailed geographic information system and includes significantly greater detail on population characteristics.

2.3. Scenario Analysis

[21] Coupled socio-ecosystems in general, and water management systems in particular, are composed of highly adaptive components (e.g., people, businesses, political groups...) that interact in complex ways among them and with their environment. These interactions give rise to dynamics at higher scales that the individual components themselves are able to perceive and react to, potentially modifying their individual behavior and thus affecting the overall dynamics of the whole system once again. The importance of these complex bidirectional loops between individual behavior and global dynamics is particularly acute in water management systems.

[22] Anticipating how a complex system may evolve, even when individual behavior is reasonably well understood, is by no means trivial. Apparently insignificant random incidents can lead to complex chains of events and have important knock-on effects down the road. In short, the complex nature and self-organizing ability of these systems most often implies that it is just impossible to deliver scientifically sound predictions for their overall behavior. Thus, one is often better off recognizing this fact, and trying to gain insights about the dynamics of the whole system by exploring various possible futures that are consistent with the most basic assumptions about how the individual components work and interact. As will be shown later, this is often challenging enough.

[23] Here we openly recognize our inability to deliver sharp predictions and focus on conducting a rigorous scenario analysis instead. A scenario can be described as a possible future. It is not a prediction, but it is considered sufficiently plausible or critical to be worth preparing for. Scenarios are not aiming to predict the future, not even to identify the most likely future. Instead they map out a "possibility space" that provides in-depth insights about the behavior of the system and can be used to inform the decisions of the present.

[24] The use of scenario analysis as a methodology for planning under uncertain conditions is relatively common [*Alcamo*, 2001], not just in the water demand context but also in many other domains. Perhaps the most important function of scenarios is that they can act as a crucial bridge between environmental science and policy making. It is important to emphasize that we do not see scenario analyses and traditional forecasting methodologies as competing approaches; their goals are fundamentally different. Our aim is not to provide short-term predictions, but to gain long-term understanding. In particular, the work presented here demonstrates the importance of various factors such as education campaigns, technological diffusion processes, and social dynamics in domestic water consumption, and

also illustrates the complex feedbacks that may arise in water management systems and the nontrivial consequences that these may have.

3. General Structure of the Model

[25] The model is made up of different subcomponents that capture various influential socioeconomic aspects of water demand in metropolitan areas. Before dealing with the details of each of the submodels, it is important to explain the general structure of the overall model. Two types of entities are represented in the model: the environment and the agents. The environment is a computational entity imported from a vectorial GIS, where every block with dwellings in a geographical area is explicitly represented and characterized by their spatial and economic features. The second layer corresponds to the spatial distribution of the computational agents in the model. Each of the agents represents a family. The location and various other features of the families in the spatial environment are not generated randomly; instead, these data have been retrieved from socioeconomic georeferenced databases of the region (see below, in section 5, details about the different databases used). Once the environment and the agents have been built, the model is considered to be initialized but it still lacks any consumption dynamics.

[26] A key factor in domestic water consumption is the territorial model of the region. The consumption of a family that lives in the compact city, for example, in apartments or flats, is generally different from the consumption of a family living in the suburbs corresponding to the extended city territorial model, for example, in houses with gardens and pools [*Domene and Saurí*, 2006]. In order to capture this effect we have included an urban dynamics submodel to simulate the migratory movement of the families in the metropolitan space on the basis of their socioeconomic factors.

[27] Another important aspect with influence in the water consumption is the social attitude of the population toward the resource. The level of public awareness about water as a scarce resource is known to influence consumption patterns in cities [*Harvie and Jaques*, 2003; *White et al.*, 2003]. In turn, public awareness is affected by social and media pressure, by information on water availability, and by general (cultural) attitudes toward the resource. The dynamics of this factor have been explicitly integrated as a submodel which basically consists in a reversible diffusion process.

[28] Another effect that may be important in the elaboration of demand scenarios is the role of technology. Since the adoption and diffusion of any new technological device is not an immediate process, and it also depends on agents' interactions, we have also incorporated a technological diffusion model for assessing its influence.

[29] The submodels outlined above capture the evolution of several variables that influence individual water demand; however it is still necessary to specify how these variables actually affect the agents' patterns of water consumption. In the present work we have defined this behavior on the basis of statistical models derived from the databases of the supplier company (Aguas de Valladolid S.A.) in the region of study. We characterize the consumption depending on the typology of dwelling, and we attribute different variances to the different social attitudes present in the population.

This use of statistical and econometric models as a mechanism of individual characterization in agent-based models (hybrid approach) has been used in the same domain for residential water demand [*Athanasiadis et al.*, 2005]. From the set of the integrated submodels, and given the parameters defined by a specific scenario, we can compute the individual evolution of consumption and, aggregating the agents' demands, calculate the trajectories of the overall demand in the area (Figure 1).

[30] The classical literature about water demand suggests other explicative factors, mainly the price, which could be included as an influential factor of individual agents' patterns of consumption. However, price has not been considered as a parameter in our case study because water prices (fixed by the water supplier) in the region have been very stable in the past years, and it is therefore very difficult to measure their influence on the basis of the available data. Furthermore, water prices in the study region are very unlikely to change significantly and, in any case, water demand is generally very price inelastic [*Arbués et al.*, 2004]. Anyhow, the methodologies to assess the price effect are well developed, and our interest lies primarily on studying the impact of the dynamics of other social processes, more difficult to be modeled with other approaches. As an example, the effect of variables such as household density, education level or nationality has been considered in the statistical model.

3.1. Urban Dynamics Model

[31] The influence of urban and territorial dynamics on water consumption has been highlighted multiple times [*Arbués et al.*, 2003; *Saurí*, 2003]. Therefore it seems natural that models aimed at forecasting residential water consumption explicitly include subcomponents that model such dynamics.

[32] In spite of the advances in the use of GIS as a base tool in agent-based applications with high level of detail [*Parker et al.*, 2003], this type of exercise is still relatively infrequent, and there is not a wide range of agent-based models of urban dynamics. One of the most relevant applications of urban models (This line of research is strongly influenced by the pioneering work of Michael Batty [*Batty*, 2005]) to real systems is the Yaffo-Tel Aviv model developed by *Benenson et al.* [2002] and *Benenson and Torrens* [2004]. This model is based on the hypothesis of stress resistance as the dynamic engine of urban movement. It represents an interesting example of adaptation of a more abstract metamodel, also proposed by *Benenson* [1998, 1999]. We have followed a similar exercise of adaptation to the metropolitan area of Valladolid.

[33] We assume in the model that agents' selection of residence is based both on intrinsic features of the candidate dwellings and on socioeconomic factors of their neighborhoods. The definition of the urban infrastructure is constructed using GIS information provided by the Center of Geographic Information of the Valladolid City Council (2006) and included in its Urban Development Plan (2003). The social and economic characteristics of the population are retrieved from the 2006 municipal register of the Valladolid City Council.

[34] The rules of Benenson's model are based on the concept of neighborhood of households and buildings. In the original model these are defined using regular cellular
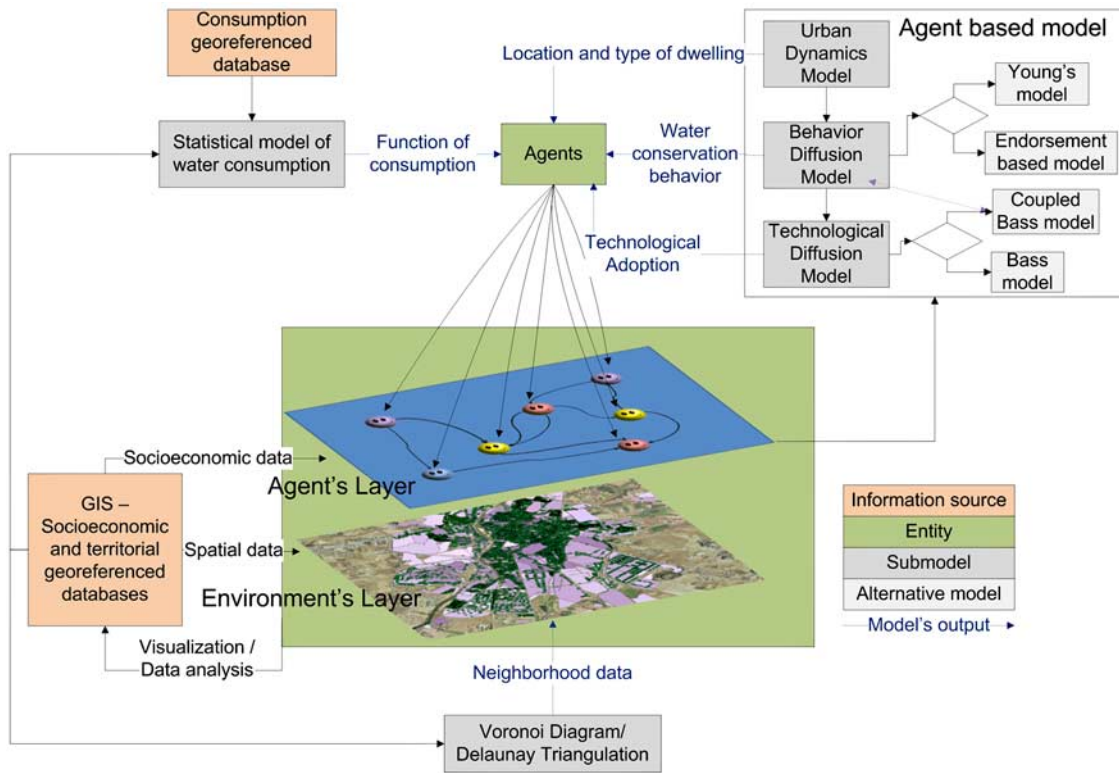
Figure 1.   General structure of the model.

automata rules. In order to generalize that definition to irregular spatial distributions, like the one retrieved from a GIS, we use the concept of adjacency of Voronoi polygons constructed around the centroids of the buildings, following *Benenson et al.* [2002]). We regard two dwellings as neighbors if they are in the same building or if they satisfy the following two conditions: (1) their buildings are adjacent in the Voronoi diagram (or, equivalently, they are joined by a link in the Delaunay triangulation, the dual problem of the Voronoi diagram (see Figure 2)) and (2) the distance between

centroids is less than 300 m (or, equivalently, the link between two centroids in the Delaunay triangulation is lower than 300 m).

[35] In this model the basic assumption is that agents prefer to live among those that are similar to themselves and in dwellings according to their present economic resources. The variable used to quantify the dissimilarity between an agent, its neighborhood and its dwelling is called here "residential dissonance," and it is assumed that the probability of leaving a residence is proportional to this residential
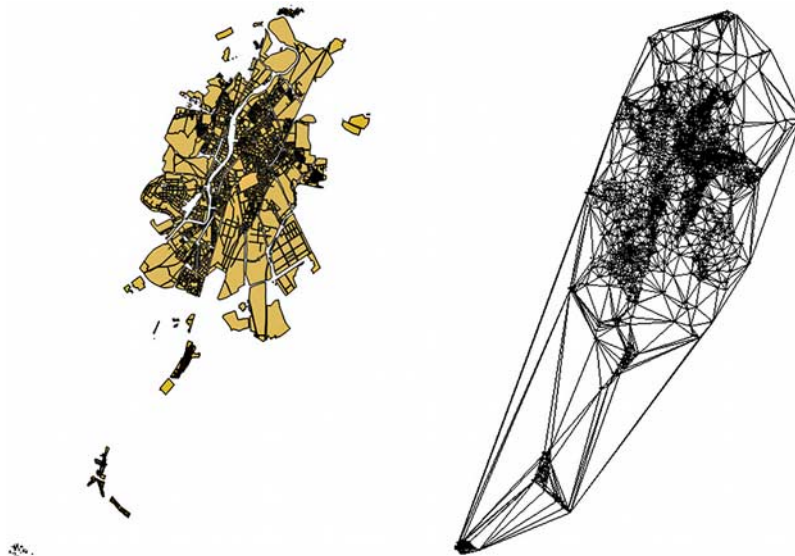

Figure 2.   (left) Valladolid in Spain and (right) its Delaunay triangulation.
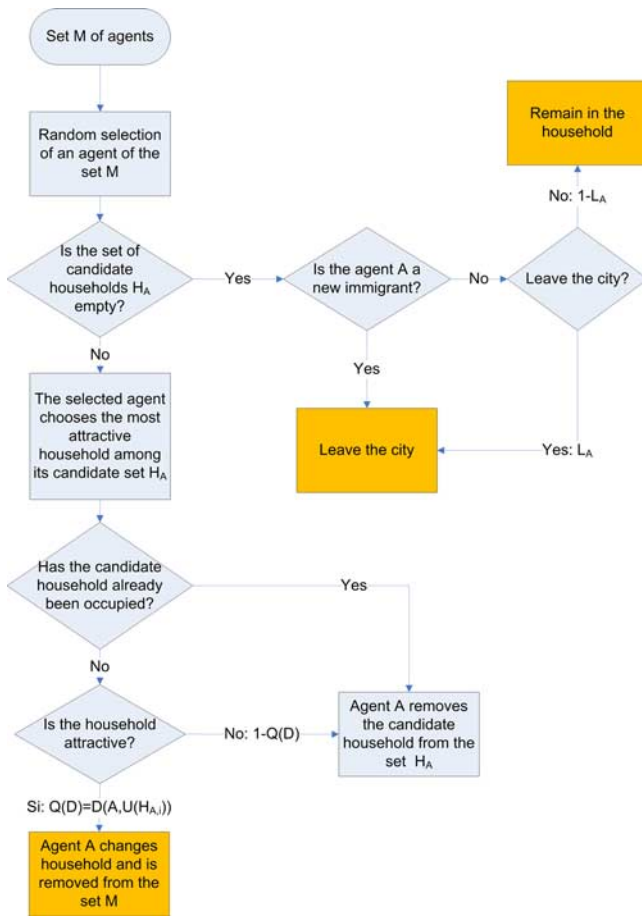
Figure 3. Flow diagram of *Benenson et al.*'s [2002] algorithm for residential selection.

dissonance. Residential dissonance may be caused by differences in terms of nationality or education level, or by imbalances between an agent's wealth and the value of the house where it lives.

[36] Let U(H) denote the neighborhood of an agent *A* that resides in house H. The baseline dissonance between an agent *A* and a homogeneous neighborhood *N* in terms of factor *f* (nationality or education level) is determined by a function $D_f(A, N)$ that takes values between 0 (denoting absence of dissonance) and 1 (maximum dissonance). This function extends naturally for heterogeneous neighborhoods using the following formula:

$$D_f(A, U(H)) = \sum_j D_f(A, U(H)_j) \cdot F_j \qquad (1)$$

where U(H) denotes the (potentially heterogeneous) neighborhood of agent *A* residing in house H, F_j is the proportion of agents in U(H) with factor *f* equal to *j*, and U(H)j is the (hypothetical) homogeneous neighborhood created by assuming that every agent in U(H) displays factor *f* equal to *j*.

[37] With the aim of reflecting possible differences in the population, every factor of the actual dissonance is modeled as a stochastic variable, specifically a normal random variable truncated on [0,1], with mean μ equal to the baseline dissonance as defined above, and standard deviation calculated as $0.05[\mu (1 - \mu)]^{1/2}$, like in *Benenson et al.*'s [2002] model.

[38] The third factor of dissonance depends on the agent's wealth and the value of the dwelling, both considered real numbers between 0 and 4. House values are updated following *Benenson*'s [1998] algorithm (the value of an occupied house is a function of the wealth of the agents that reside in the neighborhood; the value of an empty house decreases over time at a constant rate). Similarly to the other dissonance factors we define a function to quantify the dissonance between the agent's wealth and the dwelling's value. The details of this function, based in a double linear interpolation, are given by *Galán* [2007].

[39] Once every factor that affects dissonance has been calculated, we obtain the overall dissonance of each agent using the following formula:

$$D(A, U(H)) = 1 - \prod_i \left[1 - \alpha_i D_{fi}(A, U(H))\right] \qquad (2)$$

where $\alpha_i \in [0, 1]$ is the weight of f_i in the overall dissonance.

[40] After this, each agent is given the opportunity to change its current residence. The probability of moving depends on the agent's level of dissonance D according to:

$$P(D) = P_0 + (1 - P_0)D \qquad (3)$$

where P_0 is a parameter that represents a minimum value of residential movement in the city. The agents selected for moving are included in a set M of potential internal migrants. Immigrant agents are also appended to this set M. In a second step, every agent A in set M estimates the attractiveness of a number of candidate empty dwellings H_A. This attractiveness is calculated as one minus the dissonance of the agent in that dwelling.

[41] The last step of the residential algorithm that assigns agents in set M to empty dwellings is described in Figure 3. The agents that have not been able to find a suitable house leave the city with probability L_A and remain in his current house with probability $1-L_A$. The immigrant population without dwelling leaves the city too.

3.2. Opinion Diffusion Model

[42] Many social norms and other patterns of behavior are not adopted instantaneously and simultaneously by all members of a society; instead, they are often the result of gradual diffusion processes that take place through various social networks. In many cases, the decision of embracing a certain behavior is strongly influenced by the number of neighboring adopters, hence giving rise to positive reinforcements [*Newman*, 2003].

[43] We model this process using a reversible stochastic diffusion submodel that takes information of water availability as one of its inputs. This component is based on *Edwards et al.*'s [2005] adaptation of *Young*'s [1999] sociologic diffusion model for residential water domains. Our submodel adds extra functionality, including greater heterogeneity in agents' behavior.

[44] This component considers N agents that can choose between two different behaviors over time: E (environmentalist) behavior and NE (non environmentalist) behavior. The model considers an additional percentage of water consumption as consequence of NE behavior. This choice of behavior is determined by a utility function that depends on the agent's current behavior, on the behavior of its social

network and on an exogenous term e_s that measures the pressure toward behavior E. The social network V(A) of an agent A living in house H consists of the set of agents that reside in U(H); therefore different agents may have different number of links. The exogenous term e_s can be considered linked to the water availability or interpreted as pressure in the form of information or public awareness campaigns. Agent A's utilities for adopting behavior E ($v_A(E)$) or behavior NE ($v_A(NE)$) are defined by the following expressions:

$$v_A(E \rightarrow E) = a \cdot V(A, E) + e_S \qquad (4)$$

$$v_A(E \rightarrow NE) = b \cdot V(A, NE) \qquad (5)$$

$$v_A(NE \rightarrow E) = a' \cdot V(A, E) + e_S \qquad (6)$$

$$v_A(NE \rightarrow NE) = b' \cdot V(A, NE) \qquad (7)$$

where $V(A, E)$ and $V(A, NE)$ are the proportion of agent A's neighbors that have adopted behavior E and NE respectively, and a, b, a' and b' are parameters of the model. In order to take into account the individual variability of the response, utilities are transformed into probabilities of adoption according to the following formulas:

$$P(A \text{ chooses } E/E) = \frac{e^{\beta \cdot v_A(E \rightarrow E)}}{e^{\beta \cdot v_A(E \rightarrow E)} + e^{\beta \cdot v_A(E \rightarrow NE)}} \qquad (8)$$

$$P(A \text{ chooses } NE/E) = \frac{e^{\beta \cdot v_A(E \rightarrow NE)}}{e^{\beta \cdot v_A(E \rightarrow E)} + e^{\beta \cdot v_A(E \rightarrow NE)}} \qquad (9)$$

$$P(A \text{ chooses } E/NE) = \frac{e^{\beta \cdot v_A(NE \rightarrow E)}}{e^{\beta \cdot v_A(NE \rightarrow E)} + e^{\beta \cdot v_A(NE \rightarrow NE)}} \qquad (10)$$

$$P(A \text{ chooses } NE/NE) = \frac{e^{\beta \cdot v_A(NE \rightarrow NE)}}{e^{\beta \cdot v_A(NE \rightarrow E)} + e^{\beta \cdot v_A(NE \rightarrow NE)}} \qquad (11)$$

where β is a measure of the randomness of the decision.

[45] The Young-Edwards model makes the implicit assumption that all agents are influenced in the same way, and it is just the context (and a random response function) that determines their behavior. Relaxing this hypothesis by modeling individuals with different motivations has been shown to have an impact on global dynamics [Barthélemy, 2006; Benenson and Torrens, 2004]. For this reason, we have included an individual component of behavior in the agents' utility functions. Thus, in our model it is possible to analyze the impact of assuming agent's homogeneity in the process of diffusion of opinions.

[46] Our adaptation of the model is based on the endorsement mechanism, proposed by Cohen [1985] and occasionally used in social simulation models [Moss, 1998, 2002b;

Pajares et al., 2003, 2004]. Basically, this mechanism gives different weights to each information source in the utility functions, so each agent computes a potentially different value. This effectively allows us to model populations whose opinions are driven mainly by global factors (giving more weight to the exogenous pressure), by local factors (giving more weight to neighborhood behavior), or by individual factors.

3.3. Technological Diffusion Model

[47] It is generally agreed that the most important contribution to innovation diffusion theory was done by Everett M. Rogers in his famous book *Diffusion of Innovations* [Rogers, 1962]; this book constitutes the foundations of the classical approach to the field. According to Rogers, an individual's willingness to adopt an innovation depends on the steps in the purchase process, ranging from awareness to knowledge, evaluation, trial, and adoption. This sequence of stages can be used to classify individuals as innovators, early adopters, early majority, late majority and laggards; each one leading a different phase of the famous S-shaped curve of a product adoption.

[48] Agent-based models that formalize Roger's insights are actually quite uncommon (although there are models focused on agricultural economics [Berger, 2001]). Most technology diffusion models consist of a set of differential equations that slightly depart from Bass' [1969] basic model to include learning, risk aversion, different types of innovation, etc. [Mahajan et al., 1990; Meade and Islam, 2006]. The reason for this is that Bass' model is simple, easily understandable, has meaningful parameters and adjusts remarkably well to the empirically found S-shaped curve of adoption [Ilonen et al., 2006; Meade and Islam, 2006].

[49] Bass' model assumes that the instant rate of adoption of a new product, innovation of technology, depends on two factors: the intrinsic individual tendency to adopt the new technology disregarding the number of previous adopters in the population, and the positive influence generated by the adopters toward the set of potential adopters. The model has two parameters: the innovation coefficient p, and the imitation coefficient q. The formalization of the model is as follows:

$$\frac{dN(t)}{dt} = [m - N(t)]\left[p + \frac{q}{m}N(t)\right], \ t \geq 0 \qquad (12)$$

where N(t) is the accumulated number of adopters, m is the size of the population and t is time.

[50] Since agent-based models are essentially decentralized, as opposed to differential equation models, integrating Bass' model in the complete ABM requires some adaptation. We have undertaken this process following the methodology proposed by Borshchev and Filippov [2004] to convert differential equation models into agent-based models. A second process of discretization was necessary because the time needed by agents to adopt the technology is given by a continuous time function and our model is an event discrete model.

[51] We have also included an extension of Bass model coupled with the behavior diffusion model. In that model

Table 1. Average Consumption and Standard Deviation of Each Type of Residence in Metropolitan Area of Valladolid[a]

Type	Average Consumption (L/person(d))	Standard Deviation (L/person(d))
1	115821.57	156.72
2	642.51	46.81
3–5	158.37	9.69
4	96.3	19.12
Average	190.69	670.95

[a]Type 1 corresponds to houses considered as habitable but that have commercial uses as well as a domestic use. Type 2 corresponds to low buildings of high consumption. Type 3 represents low houses without garden. Type 4 comprises old low houses. Type 5 consists of flats and apartments in the city.

we assume an additional probability of adoption in the population with E behavior if the technology means water consumption savings.

3.4. Statistical Model of Consumption

[52] In order to endow the agents with rules of behavior regarding water consumption, we have resorted to a statistical model. This model is specific to the study area, namely the metropolitan area of Valladolid, and it has been developed integrating spatial data from the water consumption database (water supply Company) and a socioeconomic database (City Council). The consumption of the population has been characterized by a linear regression model using a stepwise method based on F tests for variable selection with $F \leq 0.05$ as inclusion criterion and $F \geq 0.10$ as exclusion criterion. The variables considered are nationality, average age of the family, education level, typology of residences and household density.

[53] We obtained a regression model that includes only three categorical variables (all of them are the different typologies of dwellings) with an adjusted R^2 of 0.837 and maximum p value of 0.001 for the significance of the independent variables and the overall regression. We also considered a multiplicative seasonal study depending on the dwelling type. The residences are classified in 5 typologies (see Table 1): 1, habitable with both commercial and domestic uses; 2, houses with gardens; 3, houses without garden; 4, old houses; and 5, apartments and flats. There is no statistical difference in consumption between types 3 and 5.

4. Implementation, Parameterization, and Validation

4.1. Implementation

[54] The model is implemented in Java using Repast agent-based simulation libraries [*North et al.*, 2006]. We used ArcGIS[TM] to integrate the agent-based model with the simulated environment.

4.2. Initial Parameterization

[55] Up to the middle 1950s, the mainstream paradigm in human decision theory had been strongly based on the concept of optimization. This paradigm, which had been developed almost entirely out of theoretical introspection, was seriously challenged by *Simon*'s [1956] seminal work on the satisficing hypothesis. Since then, the ideas put forward by Simon, which were derived out of empirical psychological

research, have only grown in importance. In the particular field of urban dynamics decision theory, Simon's ideas on satisficing behavior were formalized as the stress resistance hypothesis [*Benenson*, 2004; *Speare*, 1974; *Wolpert*, 1965], which is nowadays one of the best accepted models to explain individuals decisions on residential movement [*Benenson and Torrens*, 2004]. This fact explains our choice of an urban dynamics submodel based on this approach.

[56] As for the specific parameterization of the model, experimental studies of personal residential preferences suggest that no factor is more salient than the others [*van de Vyvere et al.*, 1998], hence all weights α_i in our implementation of *Benenson et al.* [2002] model are initially the same. For parameter P_0, which represents the minimum amount of residential movement due to random causes not directly explained by the residential factor, we have chosen the value 0.05 on the basis of previous applied studies with the same model in other locations [*Benenson et al.*, 2002]. Parameter L_A has been set to 0 to reflect the overall stability of the population in the metropolitan area during the past 20 years Instituto Nacional de Estadística (INE), http://www.ine.es/, 2006). Finally, since future immigration dynamics are quite uncertain in our case study, we have considered a wide range of possibilities by setting up different scenarios.

[57] Given the exploratory nature of this work, we have parameterized the behavior diffusion model looking at models for other European cities in the same context. Young's model has been parameterized following *Edwards et al.*'s [2005] work on the Orb river (Herault, France); these values are a = b' = 0.7, and a' = b = 0.3 (see equations (4)–(7)). We consider that the variance found in water consumption per person within each residence typology is a consequence of behavioral aspects, and hence it is the measure of the reduction or additional amount of water associated to the agent's behavior. Parameter β has been set to 1 to include a certain level of stochasticity in the model [*Edwards et al.*, 2005]. Finally, the values for all the parameters concerning the endorsement mechanism are based on the Thames model implemented by *Barthélemy* [2006] and *Moss and Edmonds* [2005]. The influence of parameter e_s in the behavior diffusion model, and the impact of different adoption profiles in Bass' model are analyzed in detail in the scenario analysis.

4.3. Validation

[58] Model validation is the process of assessing whether a model represents the target system to satisfactory levels of confidence and accuracy, which are determined by the intended application of the model and its application domain [*Brown and Kulasiri*, 1996]. In the case of complex models a validation methodology commonly considered is the so-called validation of the conceptual model (structural validation). This process consists in checking whether the theoretical foundations and underlying assumptions of a model are correct and reasonable within the context of the objectives of the simulation model and its intended use [*López-Paredes et al.*, 2005].

[59] In this model we have followed the basic structure of the FIRMABAR model [*López-Paredes et al.*, 2005], which was validated by a board of stakeholders and domain experts, and we have complemented it with more refined representations of the spatial and social processes. The
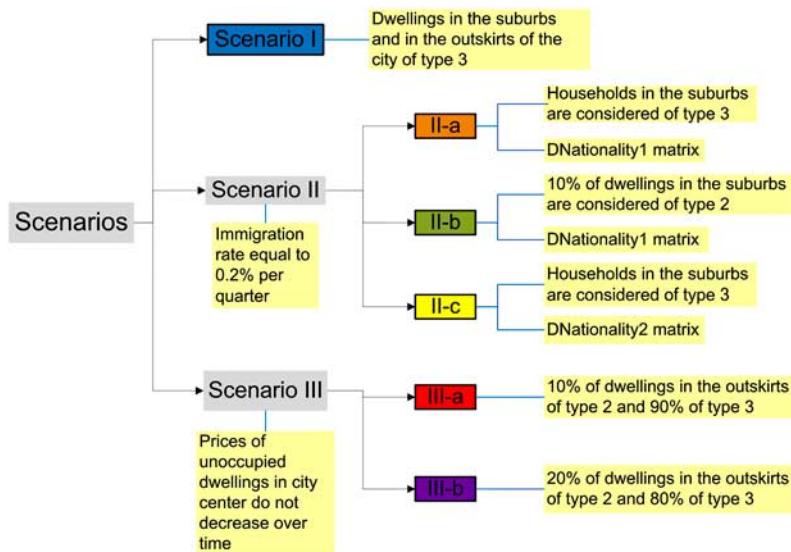
Figure 4. Sketch summarizing the analyzed scenarios. Yellow boxes show the main assumptions considered in each scenario. In each scenario we analyze the effect on the overall consumption and on adoption patterns of the parameter e_S under the alternative hypotheses of Young and the endorsement-based models. We also analyze the effect of water-saving technological diffusion under different adoption profiles in Bass and coupled Bass models considering both behavior diffusion models.

empirical data used to calibrate the model corresponds to the first quarter of 2006; running the model from that point onwards we found that the output of the model is compatible with the empirical data corresponding to the following two quarters.

[60] As an example, consider the following fact: by the end of 2006 a strong national campaign for domestic water savings in Spain led to a reduction in domestic water consumption of approximately 3%, even though our case study region had no scarcity problems. Had we known in advance that this campaign was going to take place, we would have chosen a value for the external information parameter e_S close to 1. The simulation results obtained with such a parameterization on the baseline scenario do show a 3% reduction in water consumption, which is encouraging but, naturally, a single result does not validate the model. More importantly, this whole exercise highlights the importance of conducting scenario analyses rather than aiming for sharp predictions, since one could have hardly hoped to scientifically foresee the implementation of a (in essence political) campaign with a reasonable degree of confidence. In general terms, trying to predict with certainty every possible contingency in such an intricate complex system seems to us a rather futile endeavor. The aim of our model is to develop a tool to explore the nontrivial consequences of the many interrelated complex social processes involved in domestic water consumption under various alternative futures.

5. Scenarios

[61] We have parameterized and analyzed our model for the metropolitan region of Valladolid (Spain). As discussed in the background section, this is a complex model and its complete analysis is not trivial. However, providing an in-depth analysis of the model is not the aim of this modeling exercise. Instead, we analyze specific scenarios that have been considered of greater interest.

[62] The initial setup of the model makes use of the consumption databases of the supplier company of the region (1997–2006), the socioeconomic and georeferenced databases of the Valladolid Council 2006, the 2003 urban development plan of Valladolid City Council, the digital cartography and orthophotographic maps of the JCYL (regional government), and the census of the INE of 2001. Even though the information about the city of Valladolid is very detailed, the rapid growth of the municipalities in the outskirts of the city means that the cartography and the digital information of these suburbs are not completely up to date. Nevertheless, we have decided to include these in our study because the center-periphery urban movements have proved to be very relevant in determining water demand [*Domene and Saurí*, 2006; *López-Paredes et al.*, 2005; *Saurí*, 2003].

[63] Because of computing power limitations, we have had to scale down the simulations. Thus, even though there are about 125,000 families in the metropolitan area of study, our simulations have been run with 12,500 agents. One time step in the simulation represents 3 months because the consumption data is given with this frequency. The time-frame of the simulation is 10 years; it is considered that simulating beyond this period would require updating the infrastructure information of the region. Each parameterization has been run 10 times to reduce the impact of the stochastic elements of the model.

[64] We have analyzed three different scenarios (see Figure 4). Each scenario is defined by a set of assumptions that determine the behavior of the urban submodel. In each scenario we study the effect of the different policies and parameters with the rest of the integrated submodels.

[65] The first scenario is a business-as-usual scenario that provides the benchmark against which the rest of scenarios will be compared. This baseline scenario assumes minimum
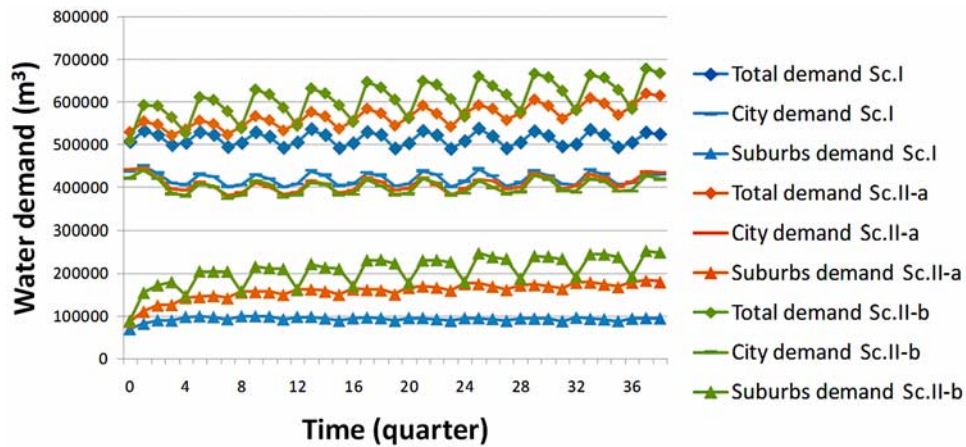
Figure 5. Temporal evolution of water demands in scenarios I and II.

exogenous interference in the diffusion models. It also considers dwellings in the suburbs and in the outskirts of the city to be of type 3.

[66] The second scenario is created to analyze the impact of immigration on water consumption (immigration rate equal to 0.2%). Since we are interested in identifying the greatest possible impact of immigration, we assume foreign immigrant population of low wealth level. This is known to lead to the highest level of dissonance in *Benenson et al.*'s [2002] model. Initially the residences in the suburbs are considered of type 3, although that hypothesis will be relaxed in the simulations.

[67] The third scenario has been created to investigate the impact on water demand of a counterintuitive feature of the Spanish property market that has been empirically observed in many cities in the past few years: prices of unoccupied dwellings in city centers do not decrease over time. In order to reproduce this empirical situation in our model we have relaxed the hypothesis of *Benenson et al.*'s [2002] model that assumes prices of empty residences decrease over time for some of the modeled neighborhoods. We have combined

this assumption with a 10% and a 20% of dwellings in the outskirts of type 2.

6. Results

[68] Figure 5 shows the evolution of the total consumption in the metropolitan area (disaggregating suburbs and city consumption too). The graph indicates in the first scenario a gradual rise of the consumption in the suburbs and a slow drop in the city. This fact can be explained by a slight shift of the population toward the suburbs at the expense of the city until an equilibrium point. This urban movement is consequence of low residential dissonance values generated by nationality and education level, mainly in the second belt of the city. The total consumption in this scenario remains constant because of the hypothesis of the suburb's type of residences, equivalents with regard to water demand.

[69] The model output is significantly different in the second scenario. The arrival of immigrant population generates clusters in some neighborhoods of the second and third belt of the city (Figure 6). These high concentrations cause
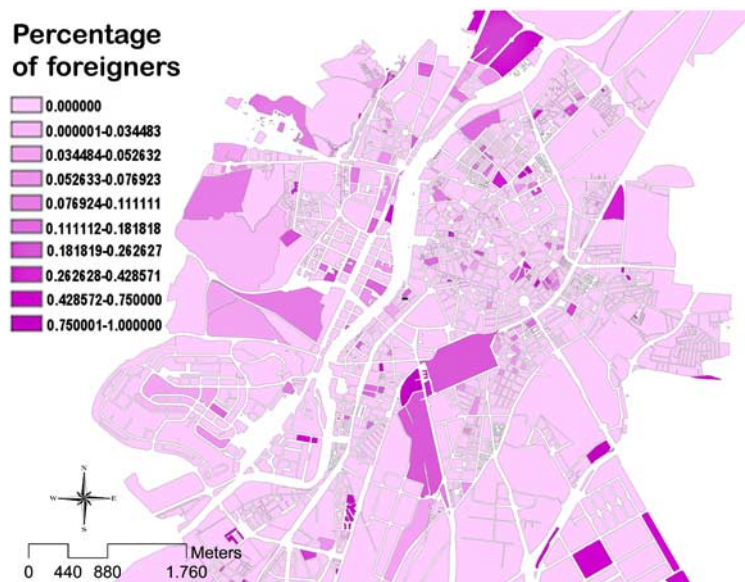

Figure 6. Detail of the immigrant concentration levels at period 40 in scenario II-a.
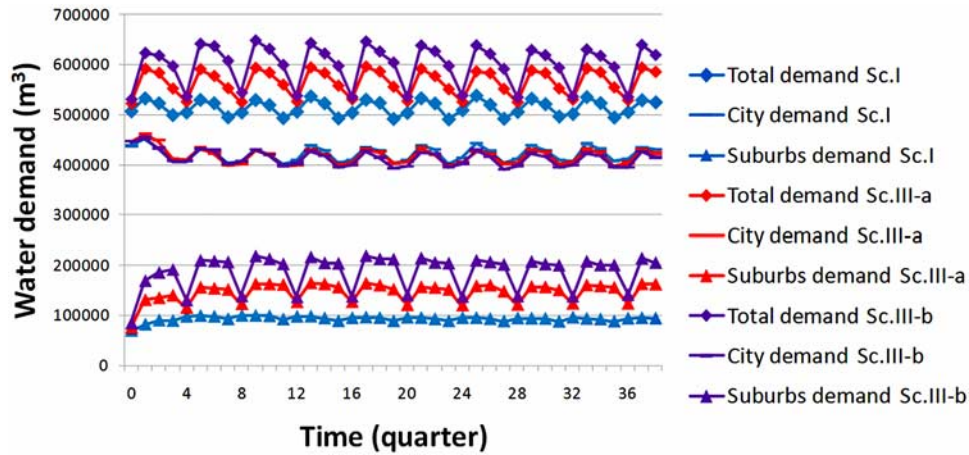
Figure 7. Temporal evolution of water demand in scenarios I and III.

an important increase in the levels of residential dissonance in the adjacent areas which in turn originate an important movement of population toward the suburbs. In scenario II-a, under the hypothesis of identical residence infrastructure in the outskirts and in the city, we can observe a gradual rise in the total consumption, which is a consequence of the population growth. However, when we assume that 10% of dwellings in the suburbs are of type 2 (scenario II-b), there is an exodus of population toward the outlying districts which leads to an important increase in the global consumption. Besides, this modification in the infrastructure amplifies the seasonal variations in the area.

[70] One of the reasons behind this important centrifugal migration effect could potentially be attributed to the extreme nationality residential dissonance matrix considered in our model ($D_{Nationality1}$).

$$D_{Nationality_1} = \begin{pmatrix} & Native & Foreign \\ Native & 0 & 0.95 \\ Foreign & 0.5 & 0 \end{pmatrix}$$

$$D_{Nationality_2} = \begin{pmatrix} & Native & Foreign \\ Native & 0 & 0.5 \\ Foreign & 0.2 & 0 \end{pmatrix}$$

[71] Nevertheless if we change the dissonance matrix $D_{Nationality1}$ for another more tolerant with immigrant people ($D_{Nationality2}$) the results are not considerably altered. The average dissonance falls from 0.083 to 0.064, but this drop is not as significant as one could think. The fall implies a slower movement to the outskirts, but the migration is still important enough. The relatively high values of dissonance are still generated by the incoming immigrate population, but in this latter case dissonance derives from materialistic rather than xenophobic reasons. Since the wealth of the incoming population is low by assumption, and given that the value of the dwellings is influenced by the wealth of the population that lives in the neighborhood, the arrival of immigrant population produces a fall in the values of their nearby residences and consequently an increase of the residential dissonance in the area. Thus, the results in this scenario seem robust to the values in the nationality dissonance matrix.

[72] The third scenario is characterized by the artificial maintenance of the prices of dwellings situated in financially advantaged central areas in the city. In this scenario we do not consider immigration effects to avoid distorting the results. Scenario III-a includes the same hypothesis considered in scenario II-b, i.e., 10% of dwellings of type 2, whereas scenario III-b assumes a higher proportion (20%) of dwellings of high consumption, which is characteristic of the extended territorial model.

[73] The simulations show that the total increase of water use in percentage terms relative to the baseline scenario (scenario I) is very relevant in both scenario III cases (Figure 7). Both scenarios III-a and III-b also feature greater seasonal variability than in the baseline case; this is a consequence of the strong seasonal behavior of the typologies of residences with high water demand. The increase in total consumption is mainly due to the residential movement toward the city outskirts, whose population grows up to ~10% above that in the baseline scenario. This move is driven by the change of residence prices in the city outskirts and center, which generates greater residential dissonance in these areas. The drop of population in the city is approximately of 2%, leading to a reduction in water consumption of ~1.5% in the city. However, all in all, the total consumption is significantly higher than in the baseline scenario, since the population movement is toward the outskirts, where residences are of a greater water demand typology. Consumption in the outskirts can even double for some high-demand quarters.

6.1. Behavioral Dynamics

[74] We have also analyzed the effect of the external information parameter e_S (Figure 8) in the behavior diffusion submodel. Parameter e_S (see equations (4) and (6)) could be interpreted as measuring the success of civic education, environmental or efficiency programs as policy instruments to reduce water demand. The robustness of the model to this parameter e_S has been assessed for 3 widely different scenarios (scenarios I, II-a, and III-a) and considering each of the two alternative behavior submodels (Young's and endorsement-based) within each scenario. In this way, we try to cover a broad area of the uncertain possibility space mentioned in the background section. The analysis has been done for values of the parameter e_S ranging from 0 to 1 in
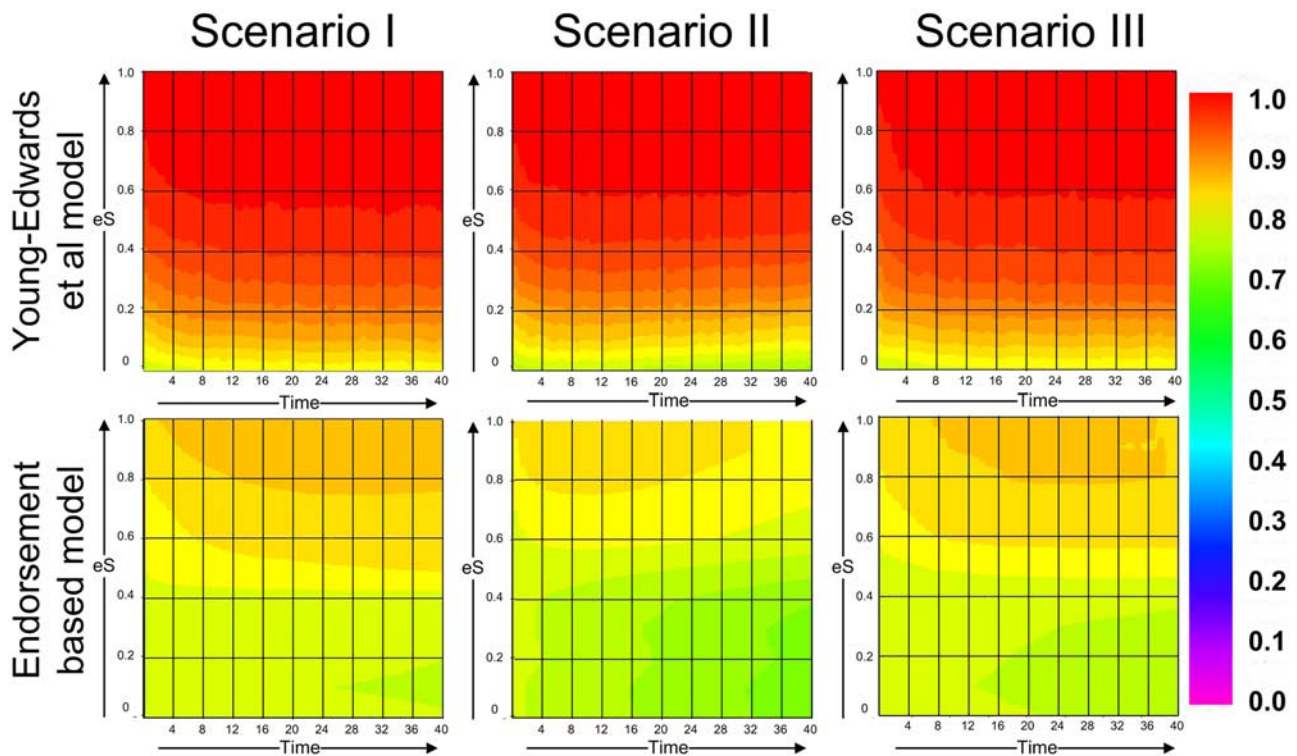
Figure 8. Temporal evolution of the percentage of agents adopting the environmentalist (E) behavior for different scenarios (I, II-a, and III-a), alternative behavior diffusion submodels (Young-Edwards or endorsement-based), and different values of parameter e_S. Higher rates of E behavior adoption in the YE model than in the endorsement-based model are shown.

intervals of 0.1, running 10 simulations for each combination of (scenario, behavior diffusion submodel, parameter value). Figure 8 shows, for each case, the number of agents with environmentalist (E) behavior as time goes by, in percentage terms.

[75] Figure 8 clearly shows that, as expected, higher values of e_S induce greater rates of adoption of environmentalist (E) behavior in all scenarios and for both alternative submodels. In fact, in Young's model with values $e_S \geq 0.6$, practically the whole population adopts the E behavior in the three scenarios. In the case of the endorsement-based model, assuming the same proportion of self, local, and global sourced population, the relation between e_S and E adoption rates is also positive but weaker than in Young's model, and global diffusion is never reached. Note that, while in Young's model every agent is directly influenced by the program in the same way (see equations (4)–(7)), in the endorsement-based model the influence is direct only for those agents mainly driven by global factors, whereas the rest of the agents are influenced indirectly through local interactions; this explains that the relation found is weaker in the endorsement-based submodel. The weakest relation is found in scenario II-a using the endorsement-based submodel. In this case, the formation of clusters of population with NE behavior, which remain relatively unaffected by general campaigns, means that parameter e_S does not impact on behavioral change so much. In any case, the adoption of one or the other behavior by the population has a total effect no greater than ~5% on global water demand.

6.2. Technology Adoption

[76] Finally, we have also studied the effect of adopting environmentally friendly technological devices such as low-flow shower heads. As in the previous section, we conduct this investigation for various "possible futures," by considering different scenarios with different profiles of adoption, two alternative submodels of technology adoption (i.e., the classical Bass model and the Bass model coupled with the diffusion mechanism), and a wide range of parameter values. The Bass model has been analyzed with 3 different profiles of adoption: fast, medium, and slow. The coupled Bass model has been analyzed with fast, medium, and slow profiles, considering the two alternative behavior diffusion mechanisms, and with 3 different values of e_S (0.0, 0.4 and 0.8).

[77] Figure 9 shows the adoption curves for all combinations corresponding to scenario I. With the simple Bass model the results show the classical S-shaped function of adoption; however simulations exhibit a change in the convexity of the adoption curves in the Young and endorsement-based scenarios with the coupled Bass model. The high proportions of population with E behavior have a higher rate of adoption, and this generates a double positive result: on the one hand, a direct effect in the adoption; on the other hand, a second indirect outcome due to the contagion rate. We can also observe that the higher adoption rates are produced with higher values of e_S for each of the behavior submodels. This result suggests that the impact in the adoption of water-saving technological devices, even when
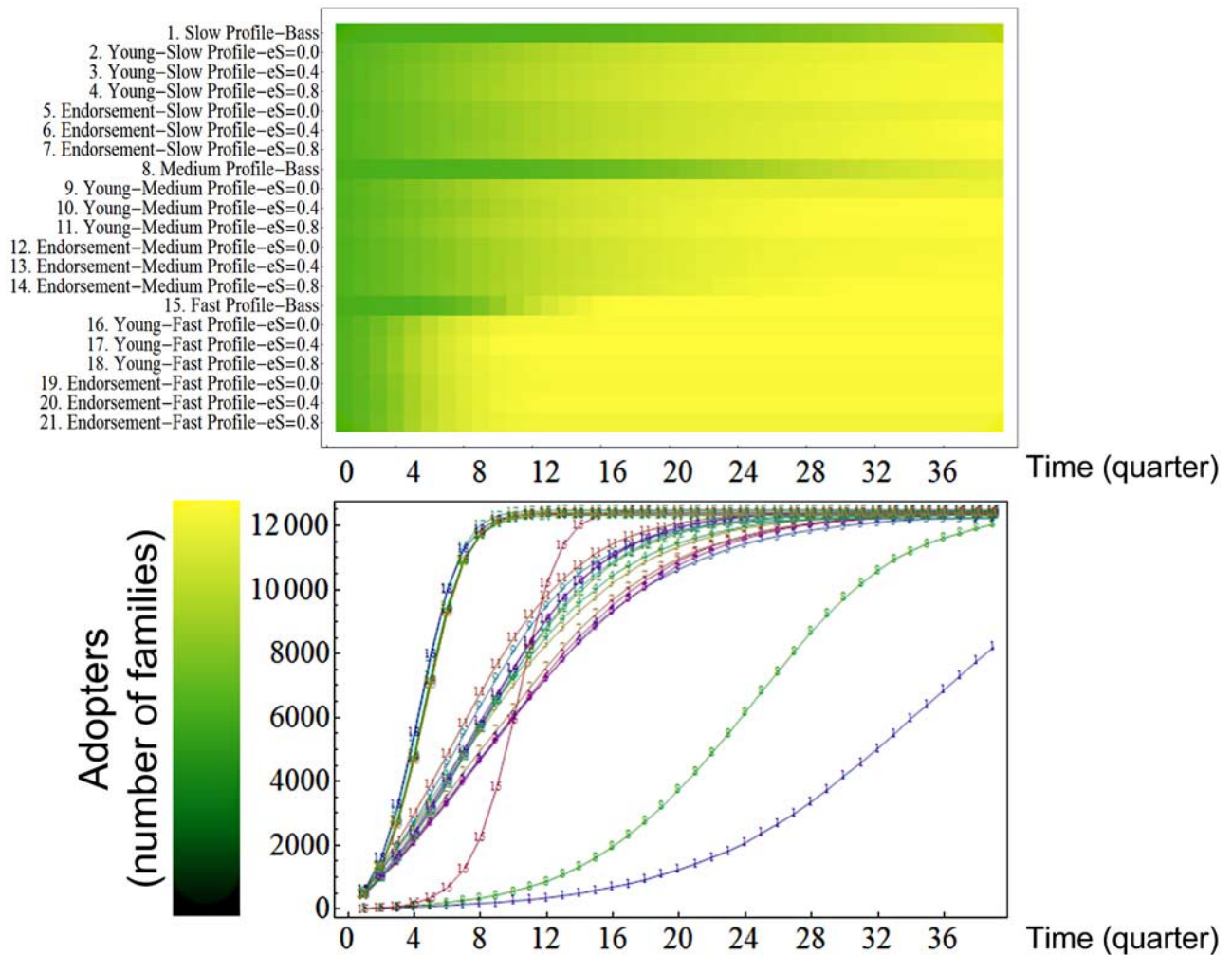
Figure 9. Temporal evolution of the number of adopters of a new technological device. A change in the convexity of the adoption curve with the coupled Bass model is shown.

they have a slow profile of adoption, may be compensated by general information measures.

[78] The impact of this adoption in the different scenarios has a very relevant influence on demand. If we consider the different global consumption in scenario II-a under different profiles of technology adoptions and we compare it with the baseline scenario I we can observe that the impact of the immigration effect and the change of the territorial model can be reduced significantly to just 2–6% of increase in the demand under most of the profile adoptions (Figure 10). In scenario III-a, the generalized adoption can compensate completely the change in the territorial model (Figure 11).

7. Limitations of the Approach

[79] It is important to notice that the conclusions obtained with the different scenario analyses rely on the correct definition of the hypotheses embedded in the model and its correct parameterization. For this reason, at the time of developing the model we have made a substantial effort to implement assumptions that are backed by evidence and are reasonably realistic. To parameterize the model we have used very detailed representations of the region and extensive data from various information sources. We have also analyzed the robustness of our results by exploring alternative diffusion submodels in a systematic and thorough way.

[80] This process has highlighted the various difficulties involved in the empirical validation of interdisciplinary models that integrate different scientific branches and are analyzed considering a variety of possible scenarios. Nonetheless, we do believe that this type of methodology is indeed useful, particularly from a policy analysis point of view. The methodology is relevant since it gives us the opportunity to analyze uncertain situations in a formal, clear and unambiguous way, and to rigorously study the implications of diverse beliefs about how the system works. In this way, the formalization of the problem explicitly reflects the truly complex and adaptive nature of water management systems, where geographical, cultural and socioeconomic phenomena interweave in convoluted ways. From a policy making perspective, this view might avoid naïve effect-cause implications that overlook the undirected relationships of the system.

[81] The combination of GIS and ABM in applied contexts has proved certainly useful, but it is by no means exempt of technical problems, and this may explain its seemingly slow adoption by the scientific community. First of all, ABM applications with real data demand great computational
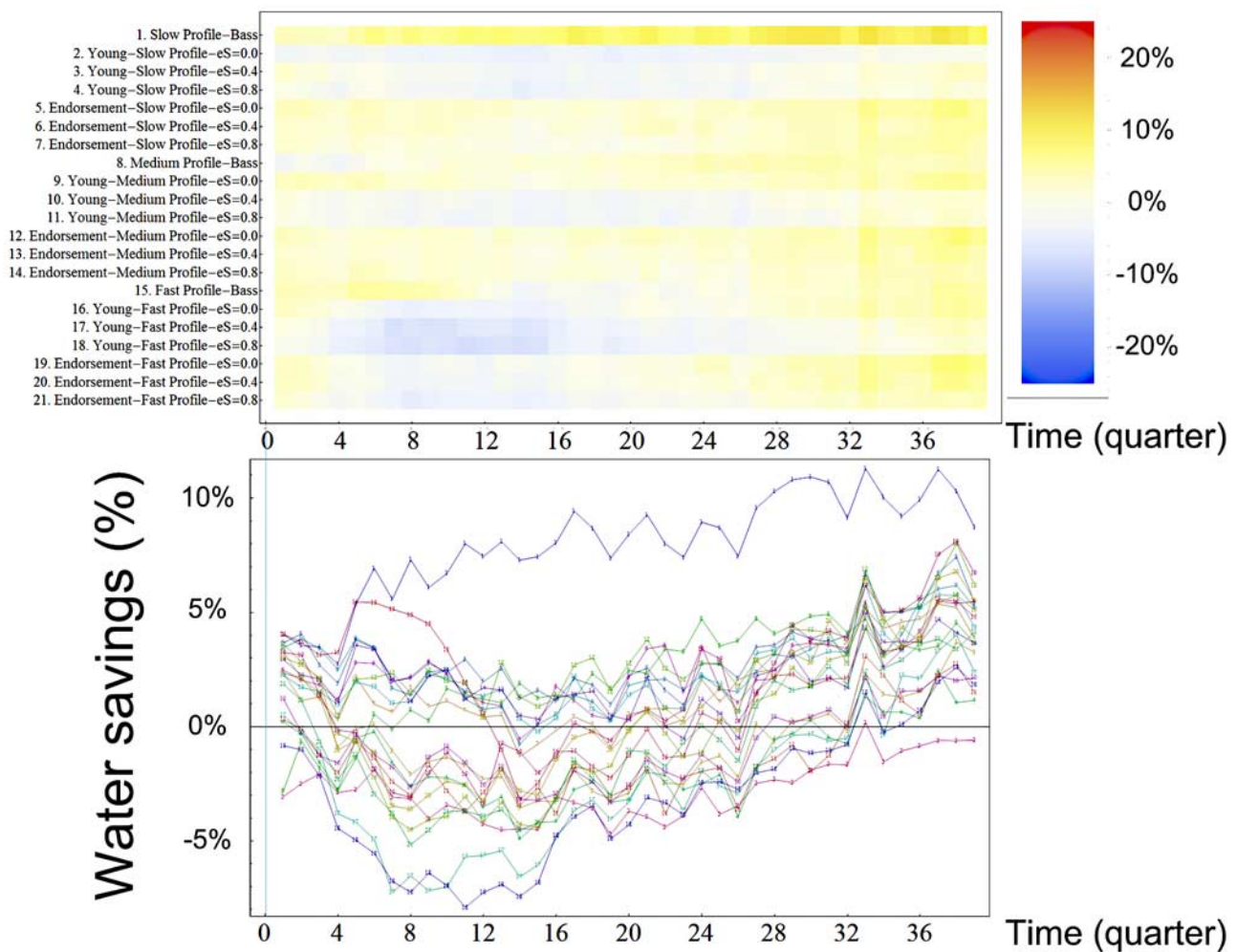
Figure 10. Temporal evolution of the total consumption in scenario II-a under different profiles of technology adoption compared (%) with scenario I.

power; hopefully the development of grid computing will partially ameliorate this problem in the coming years. A second problem is that the development of software that facilitates the integration of the two technologies is still in its infancy. The third problem is the difficulty of obtaining accurate databases with georeferenced information. Even when reliable databases are available the technical problems deriving from their integration are by no means trivial.

8. Conclusions

[82] In this work we have summarized the main problems present in most traditional methodologies used to forecast domestic water demand. Common weaknesses are (1) the difficulty to abstract and to understand the underlying assumptions of the models (and hence their relative lack of explanatory power), (2) the tendency to ignore geographical aspects of the target system (despite the overwhelming evidence for its significance), and (3) the failure to integrate diverse socioeconomic aspects in one single model (even though these are known to influence each other). Since ABM allows overcoming many of these challenges, we consider that the elaboration of refined models with this approach can provide managers with new complementary insights on

the complex issues that characterize water management systems. We do not believe that this methodology should replace the classical demand approaches (especially given that the computational power and the amount of detailed results obtained with complex models somewhat hamper its exhaustive analysis), but we certainly consider that ABM combined with scenario analysis is a useful complement.

[83] In this work we have integrated detailed GIS and socioeconomic information databases on the metropolitan region of Valladolid with a rather general agent-based model to take into account the influence of urban dynamics, behavioral and technological diffusion patterns. By doing this, we have illustrated that ABM, as integrative paradigm, let us incorporate models of disparate nature (even differential equation models).

[84] Focusing now on our application domain, our results show that urban dynamics and the change of the territorial model have a very important influence in the domestic water consumption. Using simulation we have shown that significant variations in water demand need not be caused by changes in population numbers necessarily. People moving from more compact housing (with predominately indoor water use) in the city center to more disbursed
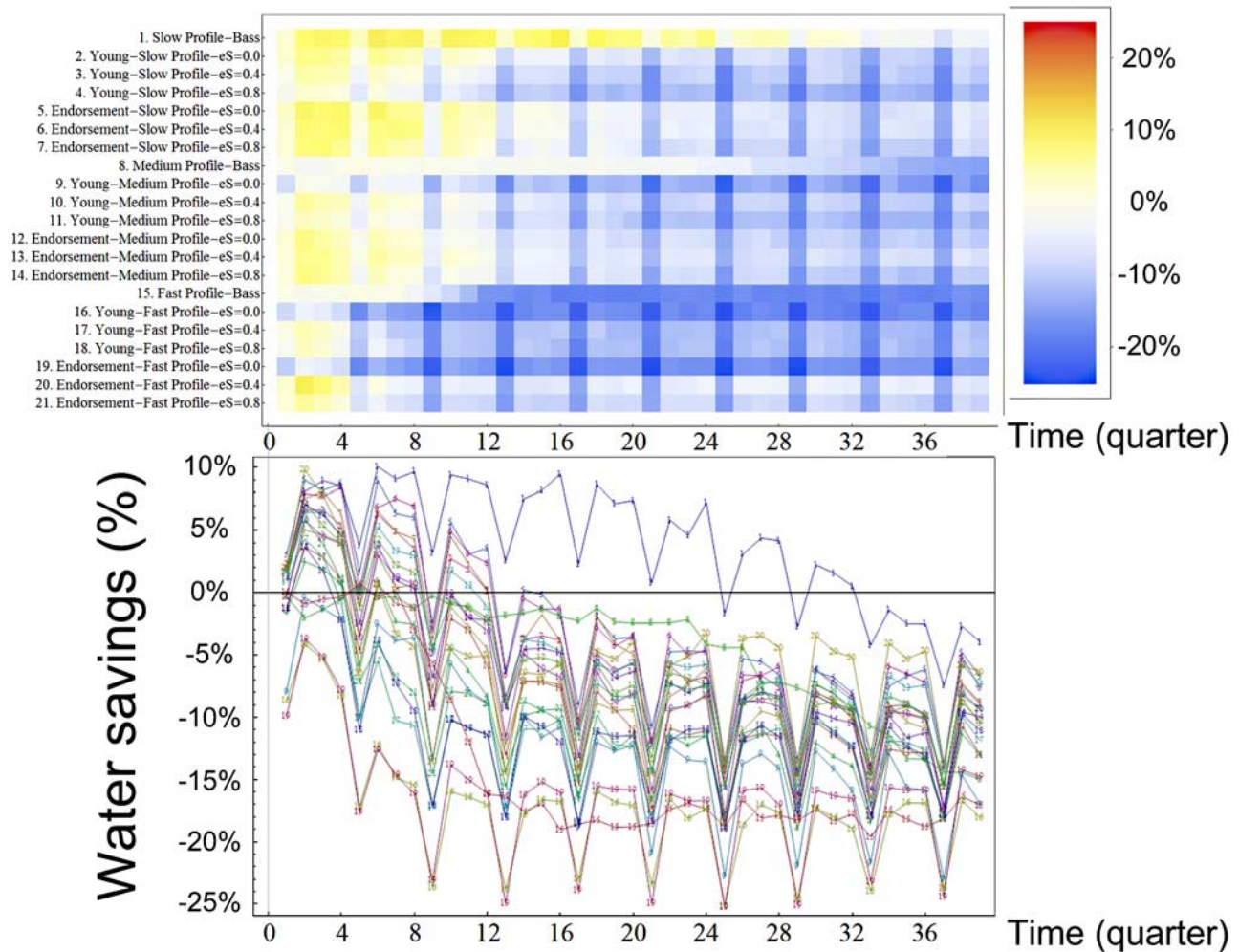
Figure 11. Temporal evolution of the total consumption in scenario III-a under different profiles of technology adoption compared (%) with scenario I.

houses in the suburbs (with significant outdoor water use) can significantly increase city-wide water use.

[85] The simulations show that an increase of population in a city does not necessarily imply a proportional increase in water consumption. Our model, which considers territory and urban dynamics explicitly, indicates that an increase of immigrant population can generate a nonlinear effect on the consumption; this contrasts with the assumptions underlying per capita models. It is certainly true that the arrival of immigrants into the city has a direct effect on domestic water consumption which, among other factors, depends on the typology of the acquired dwellings. However, urban dynamics involving clustering of homogeneous groups and segregation pressures between heterogeneous groups can lead to significant changes in water demand which would be difficult to anticipate without explicit geographical modeling. These phenomena can change the domestic water consumption patterns depending on the alternative typologies of residences.

[86] We have also analyzed the impact of the pressure of external information by considering various behavior diffusion models. We have corroborated that, while this effect is relatively robust to the particular assumptions embedded in the diffusion model, the influence of awareness campaigns seems to be lower in models with heterogeneous behaviors. The results of this effect combined with the technological diffusion model show that water savings can be much higher.

References

Alcamo, J. (2001), Scenarios as tools for international environmental assessments, *Environ. Issue Rep. 24*, Eur. Environ. Agency, Copenhagen.

Arbués, F., M. A. García, and R. Martínez-Espiñeira (2003), Estimation of residential water demand: A state of the art review, *J. Socio Econ.*, *32*, 81–102, doi:10.1016/S1053-5357(03)00005-2.

Arbués, F., R. Barberan, and I. Villanua (2004), Price impact on urban residential water demand: A dynamic panel data approach, *Water Resour. Res.*, *40*, W11402, doi:10.1029/2004WR003092.

Athanasiadis, I. N., and P. A. Mitkas (2005), Social influence and water conservation: An agent-based approach, *Comput. Sci. Eng.*, *7*, 65–70, doi:10.1109/MCSE.2005.21.

Athanasiadis, I. N., A. K. Mentes, P. A. Mitkas, and Y. A. Mylopoulos (2005), A hybrid agent-based model for estimating residential water demand, *Simulation*, *81*, 175–187, doi:10.1177/0037549705053172.

Axtell, R. L. (2000), Why agents? On the varied motivations for agent computing in the social sciences, in *Proceedings of the Workshop on Agent Simulation: Applications, Models, and Tools*, edited by C. M. Macal and D. Sallach, pp. 3–24, Argonne Natl. Lab., Argonne, Ill.

Aydinalp, M., V. I. Ugursal, and A. S. Fung (2004), Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks, *Appl. Energy*, *79*, 159–178, doi:10.1016/j.apenergy.2003.12.006.

Bachrach, M., and M. J. Vaughan (1994), Household water demand estimation, *Working Pap. ENP 106*, Prod. Sect. and Environ. Subdep., Environ. Prot. Div., Inter Am. Dev. Bank, Washington, D. C.

Barthélemy, O. (2006), Untangling scenario components with agent based modelling: An example of social simulations of water demand forecasts, Ph.D. thesis, Manchester Metrop. Univ., Manchester, U. K.

Barthélemy, O. (2008), Water demand Policies, in *Agent-Based Modelling in Natural Resources Management*, edited by A. López-Paredes and C. Hernández, pp. 75–91, Insisoc, Madrid.

Bass, F. M. (1969), A new product growth for model consumer durables, *Manage. Sci.*, *15*, 215–227, doi:10.1287/mnsc.15.5.215.

Batty, M. (2005), *Cities and Complexity: Understanding Cities With Cellular Automata, Agent-Based Models, and Fractals*, MIT Press, London, U. K.

Baumann, D. D., J. J. Boland, and W. M. Hanemann (1998), *Urban Water Demand Management and Planning*, McGraw-Hill, New York.

Bell, D. R., and R. C. Griffin (2008), An annual quasidifference approach to water price elasticity, *Water Resour. Res.*, *44*, W08420, doi:10.1029/2007WR006233.

Benenson, I. (1998), Multi-agent simulations of residential dynamics in the city, *Comput. Environ. Urban Syst.*, *22*, 25–42, doi:10.1016/S0198-9715(98)00017-9.

Benenson, I. (1999), Modeling population dynamics in the city: From a regional to a multi-agent approach, *Discrete Dyn. Nat. Soc.*, *3*, 149–170, doi:10.1155/S1026022699000187.

Benenson, I. (2004), Agent-based modeling: From individual residential choice to urban residential dynamics, in *Spatially Integrated Social Science: Examples in Best Practice*, edited by M. F. Goodchild and D. G. Janelle, pp. 67–95, Oxford Univ. Press, Oxford, U. K.

Benenson, I., and P. M. Torrens (2004), *Geosimulation: Automata-Based Modeling of Urban Phenomena*, John Wiley, Chichester, U. K.

Benenson, I., I. Omer, and E. Hatna (2002), Entity-based modeling of urban residential dynamics: The case of Yaffo, Tel Aviv, *Environ. Plann. B*, *29*, 491–512, doi:10.1068/b1287.

Berger, T. (2001), Agent-based spatial models applied to agriculture: A simulation tool for technology diffusion, resource use changes and policy analysis, *Agric. Econ.*, *25*, 245–260, doi:10.1111/j.1574-0862.2001.tb00205.x.

Billings, R. B., and C. V. Jones (1996), *Forecasting Urban Water Demand*, Am. Water Works Assoc., Denver, Colo.

Bithas, K., and C. Stoforos (2006), Estimating urban residential water demand determinants and forecasting water demand for Athens Metropolitan Area, 2000–2010, *South East. Eur. J. Econ.*, *1*, 47–59.

Bonabeau, E. (2002), Agent-based modeling: Methods and techniques for simulating human systems, *Proc. Natl. Acad. Sci. U. S. A.*, *99*, 7280–7287, doi:10.1073/pnas.082080899.

Borshchev, A., and A. Filippov (2004), From system dynamics and discrete event to practical agent based modeling: Reasons, techniques, tools, in *Proceedings of the 22nd International Conference of the System Dynamics Society*, edited by M. Kennedy et al., 45 pp., Syst. Dyn. Soc., Albany, N. Y.

Bougadis, J., K. Adamowski, and R. Diduch (2005), Short-term municipal water demand forecasting, *Hydrol. Processes*, *19*, 137–148, doi:10.1002/hyp.5763.

Bousquet, F., and C. Le Page (2004), Multi-agent simulations and ecosystem management: A review, *Ecol. Modell.*, *176*, 313–332, doi:10.1016/j.ecolmodel.2004.01.011.

Brown, T. N., and D. Kulasiri (1996), Validating models of complex, stochastic, biological systems, *Ecol. Modell.*, *86*, 129–134, doi:10.1016/0304-3800(95)00039-9.

Cohen, P. R. (1985), *Heuristic Reasoning About Uncertainty: An Artificial Intelligence Approach*, Pitman Adv. Publ. Program, Boston, Mass.

Domene, E., and D. Saurí (2006), Urbanisation and water consumption: Influencing factors in the metropolitan region of Barcelona, *Urban Stud.*, *43*, 1605–1623, doi:10.1080/00420980600749969.

Domene, E., D. Saurí, and M. Parés (2005), Urbanization and sustainable resource use: The case of garden watering in the metropolitan region of Barcelona, *Urban Geogr.*, *26*, 520–535, doi:10.2747/0272-3638.26.6.520.

Downing, T. E., S. Moss, and C. Pahl-Wostl (2001), Understanding climate policy using participatory agent-based social simulation, in *Multi-Agent-Based Simulation*, edited by S. Moss and P. Davidsson, pp. 198–213, Springer, Berlin.

Edmonds, B. (2001), The use of models: Making MABS Actually Work, in *Multi-Agent-Based Simulation*, edited by S. Moss and P. Davidsson, pp. 15–32, Springer, Berlin.

Edwards, M., N. Ferrand, F. Goreaud, and S. Huet (2005), The relevance of aggregating a water consumption model cannot be disconnected from the choice of information available on the resource, *Simul. Model. Pract. Theory*, *13*, 287–307, doi:10.1016/j.simpat.2004.11.008.

Epstein, J. M. (1999), Agent-based computational models and generative social science, *Complexity*, *4*, 41–60, doi:10.1002/(SICI)1099-0526 (199905/06)4:5<41::AID-CPLX9>3.0.CO;2-F.

Espey, M., J. Espey, and W. D. Shaw (1997), Price elasticity of residential demand for water: A meta-analysis, *Water Resour. Res.*, *33*, 1369–1374, doi:10.1029/97WR00571.

Galán, J. M. (2007), Evaluación integradora de políticas de agua: Modelado y simulación con sociedades artificiales de agentes, Ph.D. thesis, Univ. of Burgos, Burgos, Spain.

Gilbert, N. (2007), *Agent Based Models*, Sage, London.

Harvie, M., and P. Jaques (2003), Public awareness and the environment: How do we encourage environmentally responsible behaviour?, *Water Sci. Technol. Water Supply*, *3*, 247–254.

Herrington, P. (1996), *Climate Change and the Demand for Water*, Her Majesty's Stn. Off., London.

Holland, J. H. (1998), *Emergence. From Chaos to Order*, Addison-Wesley, Reading, Mass.

Ilonen, J., J. K. Kamarainen, K. Puumalainen, S. Sundqvist, and H. Kälviäinen (2006), Toward automatic forecasts for diffusion of innovations, *Technol. Forecasting Soc. Change*, *73*, 182–198, doi:10.1016/j.techfore.2004.11.005.

Jacobs, H., and J. Haarhoff (2004a), Application of a residential end-use model for estimating cold and hot water demand, wastewater flow and salinity, *Water SA*, *30*, 305–316.

Jacobs, H., and J. Haarhoff (2004b), Structure and data requirements of an end-use model for residential water demand and return flow, *Water SA*, *30*, 293–304.

Joo, C. N., J. Y. Koo, and M. J. Yu (2002), Application of short-term water demand prediction model to Seoul, *Water Sci. Technol.*, *46*, 255–261.

Kotz, C., and H. Hiessl (2005), Analysis of system innovation in urban water infrastructure systems: An agent-based modelling approach, *Water Sci. Technol. Water Supply*, *5*, 135–144.

López-Paredes, A., D. Saurí, and J. M. Galán (2005), Urban water management with artificial societies of agents: The FIRMABAR simulator, *Simulation*, *81*, 189–199, doi:10.1177/0037549705053167.

Mahajan, V., E. Muller, and F. M. Bass (1990), New product diffusion models in marketing: A review and directions for research, *J. Mark.*, *54*, 1–26, doi:10.2307/1252170.

Martínez-Espiñeira, R. (2003), Estimating water demand under increasing-block tariffs using aggregate data and proportions of users per block, *Environ. Resour. Econ.*, *26*, 5–23, doi:10.1023/A:1025693823235.

Meade, N., and T. Islam (2006), Modelling and forecasting the diffusion of innovation: A 25-year review, *Int. J. Forecast.*, *22*, 519–545, doi:10.1016/j.ijforecast.2006.01.005.

Montginoul, M. (2007), Analysing the diversity of water pricing structures: The case of France, *Water Resour. Manage.*, *21*, 861–871, doi:10.1007/s11269-006-9104-5.

Moss, S. (1998), Critical incident management: An empirically derived computational model, *J. Artif. Soc. Soc. Simul., 1*. (Available at http://jasss.soc.surrey.ac.uk/1/4/1.html)

Moss, S. (2002a), Agent based modelling for integrated assessment, *Integrated Assess.*, *3*, 63–77, doi:10.1076/iaij.3.1.63.7407.

Moss, S. (2002b), Policy analysis from first principles, *Proc. Natl. Acad. Sci. U. S. A.*, *99*, 7267–7274, doi:10.1073/pnas.092080699.

Moss, S., and B. Edmonds (2005), Sociology and simulation: Statistical and qualitative cross-validation, *Am. J. Soc.*, *110*, 1095–1131, doi:10.1086/427320.

Moss, S., C. Pahl-Wostl, and T. E. Downing (2001), Agent-based integrated assessment modelling: The example of climate change, *Integrated Assess.*, *2*, 17–30, doi:10.1023/A:1011527523183.

Newman, M. E. J. (2003), The structure and function of complex networks, *SIAM Rev.*, *45*, 167–256, doi:10.1137/S003614450342480.

North, M. J., N. T. Collier, and J. R. Vos (2006), Experiences creating three implementations of the repast agent modeling toolkit, *ACM Trans. Model. Comput. Simul.*, *16*, 1–25, doi:10.1145/1122012.1122013.

Pajares, J., A. López-Paredes, and C. Hernández (2003), Industry as an organisation of agents: Innovation and R&D management, *J. Artif. Soc. Soc. Simul.*, *6*. (Available at http://jasss.soc.surrey.ac.uk/6/2/7.html)

Pajares, J., C. Hernández, and A. López-Paredes (2004), Modelling learning and r&d in innovative environments: A cognitive multi-agent approach, *J. Artif. Soc. Soc. Simul.*, *7*. (Available at http://jasss.soc.surrey.ac.uk/7/2/7.html)

Parker, D. C., S. M. Manson, M. A. Janssen, M. J. Hoffmann, and P. Deadman (2003), Multi-agent systems for the simulation of land-use and land-cover change: A review, *Ann. Assoc. Am. Geogr.*, *93*, 314–337, doi:10.1111/1467-8306.9302004.

Reynaud, A., S. Renzetti, and M. Villeneuve (2005), Residential water demand with endogenous pricing: The Canadian case, *Water Resour. Res.*, *41*, W11409, doi:10.1029/2005WR004195.

Rogers, E. M. (1962), *Diffusion of Innovation*, Free Press, New York.

Saurí, D. (2003), Lights and shadows of urban water demand management: The case of the metropolitan region of Barcelona, *Eur. Plann. Stud.*, *11*, 233–247.

Simon, H. A. (1956), Rational choice and the structure of the environment, *Psychol. Rev.*, *63*, 129–138.

Speare, A. (1974), Residential satisfaction as an intervening variable in residential mobility, *Demography*, *11*, 173–188, doi:10.2307/2060556.

Taylor, R. G., J. R. Mckean, and R. A. Young (2004), Alternate price specifications for estimating residential water demand with fixed fees, *Land Econ.*, *80*, 463–475, doi:10.2307/3654732.

Tillman, D., T. A. Larsen, C. Pahl-Wostl, and W. Gujer (1999), Modeling the actors in water supply systems, *Water Sci. Technol.*, *39*, 203–211, doi:10.1016/S0273-1223(99)00055-4.

van de Vyvere, Y., H. Oppewal, and H. Timmermans (1998), The validity of hierarchical information integration choice experiments to model residential preference and choice, *Geogr. Anal.*, *30*, 254–272.

White, S., J. Robinson, D. Cordell, M. Jha, and G. Milne (2003), Urban water demand forecasting and demand management: Research needs review and recommendations, *Occas. Pap. 9*, Water Serv. Assoc. Aust., Melbourne, Victoria.

White, S., G. Milne, and C. Riedy (2004), End use analysis: Issues and lessons, *Water Sci. Technol. Water Supply*, *4*, 57–65.

Wolpert, J. (1965), Behavioral aspects of the decision to migrate, *Pap. Proc. Reg. Sci. Assoc.*, *15*, 159–169.

Young, H. P. (1999), Diffusion in social networks, *Work. Pap. 2*, Brookings Inst., Washington, D. C.

————————————

J. M. Galán and R. del Olmo, Department of Civil Engineering, University of Burgos, E-09001 Burgos, Spain. (jmgalan@ubu.es)

A. López-Paredes, Departamento de Organización de Empresas y C.I.M., Valladolid, E-47011 Valladolid, Spain.