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# Assessing urban water demand-side management policies before their implementation: An agent-based model approach

Pol Vidal-Lamolla [a,b,*], María Molinos-Senante [c], Luis Oliva-Felipe [d], Sergio Alvarez-Napagao [d,e], Ulises Cortés [d,e], Eduardo Martínez-Gomariz [b,f], Pablo Noriega [g], Gustaf Olsson [h], Manel Poch [a]

[a] LEQUIA, Institute of the Environment, University of Girona, Campus Montilivi, Carrer Maria Aurèlia Capmany 69, E-17004, Girona, Catalonia, Spain
[b] Aigües de Barcelona, Empresa Metropolitana de Gestió del Cicle Integral de l'Aigua, General Batet 1-7, 08028, Barcelona, Spain
[c] Institute of Sustainable Processes, University of Valladolid, C/ Mergelina 4, 47011, Valladolid, Spain
[d] Knowledge Engineering and Machine Learning Group (KEMLG), Department of Computer Science (CS), Universitat Politècnica de Catalunya—BarcelonaTECH (UPC), c/ Jordi Girona 31, 08034, Barcelona, Spain
[e] Barcelona Supercomputing Center (BSC), 08034, Barcelona, Spain
[f] Flumen Research Institute, Universitat Politècnica de Catalunya - Centre Internacional de Mètodes Numèrics en Enginyeria, Barcelona, Spain
[g] CSIC-IIIA, 08193, Bellaterra, Spain
[h] Division of Industrial Electrical Engineering and Automation (IEA), Department of Biomedical Engineering, Lund University, 17004, Lund, Sweden

A R T I C L E I N F O

*Keywords:*
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A B S T R A C T

In the context of climate change and increasing water scarcity, adopting water demand-side management (DSM) policies has become necessary. This study advocates for utilizing agent-based modelling (ABM) as a robust simulation tool to assess the impact of nonprice (nudges) and price (changes in increasing block tariff) measures on urban water use. Overcoming challenges posed by insufficient high-quality data, the research integrates four sociocognitive profiles and diverse household income levels to reflect the variability in DSM policy effectiveness based on socioeconomic characteristics. Through 125 simulated scenarios combining various increasing block tariffs with nonpricing measures, the study reveals an average monthly demand reduction ranging from 8.1% to 15.6%. Significantly, nonprice measures prove more effective in curbing water use than pricing measures, attributed to the prioritization of environmental concerns in conservation efforts. Higher-income households exhibit less-pronounced reductions in water consumption. Emphasizing the reliability of ABM for ex ante evaluations of DSM policies, this research underscores the importance of a balanced approach, incorporating both nonprice and price-based measures, to effectively address water scarcity challenges.

## 1. Introduction

The human right to safe drinking water is officially recognized by the United Nations (UN) General Assembly and the Human Rights Council; it became a binding part of international law in 2010 (UN, 2010). Furthermore, Sustainable Development Goal 6 suggests that we should, "by 2030, achieve universal and equitable access to safe and affordable drinking water for all" (target 6.1) (UN, 2015b). Population growth and climate change hinder universal access to water services (He et al., 2021). The global population is projected to exceed nine billion by 2050 and 10–11 billion by 2100 (Liu et al., 2018), which will increase the demand for water resources by 50%–80% over the next three decades (Flörke et al., 2018). In parallel, climate change will affect the spatial distribution and timing of water availability (Greve et al., 2018), thereby exacerbating water scarcity problems. Currently, 733 million people live in high-elevation and critically water-stressed countries (UN-Water, 2021). However, the situation will be worse in 2050, as it is projected that the urban population facing water scarcity will reach 2.065 billion people (He et al., 2021). Thus, urban water security is one of the major challenges faced by current societies (Michalak et al., 2023).

* Corresponding author at: LEQUIA, Institute of the Environment, University of Girona, Campus Montilivi, Carrer Maria Aurèlia Capmany 69, E-17004, Girona, Catalonia, Spain.

*E-mail addresses:* pol.vidal@udg.edu (P. Vidal-Lamolla), maria.molinos@uva.es (M. Molinos-Senante), loliva@cs.upc.edu (L. Oliva-Felipe), sergio.alvarez@bsc.es (S. Alvarez-Napagao), ulises.cortes@bsc.es (U. Cortés), eduardo.martinez@aiguesdebarcelona.cat (E. Martínez-Gomariz), pablo@iiia.csic.es (P. Noriega), gustaf.olsson@iea.lth.se (G. Olsson), manuel.poch@udg.edu (M. Poch).

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In addressing the critical issue of water scarcity, caused by multiple factors, such as the aforementioned climate change and population growth, but also urbanization, industrialization and agriculture developments (Halli et al., 2022), policy-makers can turn to so-called demand-side management (DSM) policies. According to the review conducted by Abu-Bakar et al. (2021), unlike efforts focused on expanding water abstraction capabilities, these policies aim to enhance the efficiency and conservation of existing water resources through a variety of measures. DSM policies can be categorized into two main types: price-related and nonprice-related approaches. The first type of policy encompasses aspects such as rates, billing systems and tariff structures. The second type, non-pricing policies, includes a vast range of heterogeneous measures, such as public education, efficiency technology, metering, and command and control policies. Illustrating the possibilities of nonprice policies, Poch et al. (2023) proposed the use of nudges (Thaler & Sunstein, 2008) for different scales and for different groups of stakeholders to increase urban water cycle resilience. For instance, nudges have been proved to work effectively in reducing urban water consumption in Costa Rica, with ranges between 4.8% to 4.9% after two months (Miranda et al., 2019), or in South Africa, with reductions of 0.6% to 1.3% after six months (Brick et al., 2023). An illustrative example of price policies was presented by Olsson (2022), who exposed how price structures of water-increasing block tariffs (IBTs) aiming to encourage efficient use of water differ among countries. A joint application of both price and nonprice policies was reported by Tortajada et al. (2019), who analysed decreases in water demand in five Spanish cities over time. Notably, in interviews held with professionals from the utilities in these cities, the interviewees unanimously agreed that nonpricing measures have proven more effective than pricing strategies in reducing water consumption.

An ex ante assessment of the effectiveness of price DSM policies such as water tariffs, i.e., quantifying water use reduction due to the implementation of a specific water tariff structure, can be intricate due to the multitude of factors influencing household water usage, including sociodemographic, socioeconomic housing features or seasonal variables (Cominola et al., 2023; Garrone et al., 2019). To address this complexity, a valuable metric that inherently considers these factors is price-demand elasticity, which examines how changes in price impact household consumption patterns (García-Valiñas & Suárez-Fernández, 2022). Econometric analysis and contingent valuation have provided some insights into the estimation of the price elasticity of domestic water demand. However, these methods fall short when robust cross-sectional and time-series data are absent, especially during times of swift change in water use (Chu et al., 2009). Price-demand elasticity allows the ex ante assessment of price DSM policies, but the effects of nonprice DSM policies cannot be assessed. On the other hand, other approaches based on household water-use patterns also need to account for detailed data (Renwick & Archibald, 1998), which are similarly limited when a data source with those conditions is lacking. Therefore, data availability and quality are usual limiting factors for conducting a detailed ex ante assessment of the effectiveness of implementing DSM policies (Cauberghe et al., 2021; Noga & Wolbring, 2013).

ABM (Agent-based Models) are modelling tools designed to simulate the actions and interactions of artificial autonomous entities, known as agents, within a specified environment. Each agent is programmed to act based on received inputs and its current state, influenced by other components within the model. These agents interact within a predetermined environment, leading to emergent behaviours that arise from the collective dynamics of agents interacting with each other and their environment. The simulation outcomes reflect the aggregated behaviour of the system, which is subsequently analysed (Sattler et al., 2023). Thus, in this study, agents represent the behaviour of individuals or groups characterized by human consumption and household in urban environments.

Given the previously mentioned data-related restrictions and considering the effectiveness of ABMs in simulating water demand under different scenarios (Sattler et al., 2023), we propose a methodological approach that relies on ABMs to assist the ex ante assessment of DSM policy implementation, which is especially convenient when the available data are of poor quality. Numerous authors have harnessed ABMs as effective policy simulators within the domain of water management. Notable examples include ABMs that have been employed in integrated urban water management (Bakhtiari et al., 2020; López-Paredes et al., 2005), conflict resolution (Darbandsari et al., 2020), the estimation of residential water demand (Athanasiadis et al., 2005; Zhang et al., 2023), drought risk assessment (Wens et al., 2019), and the development of new water tariff structures (Vidal Lamolla et al., 2022). ABMs rooted in artificial agents are useful because they enable the representation of the collective behaviours of multiple individuals (namely, domestic water users) coexisting within a shared environment (the water supply) while considering client segmentation. Furthermore, these models can account for divergent behaviours defined not only by sociodemographic factors but also by sociocognitive profiles (Perello-Moragues et al., 2021). Thus, they can easily address urban water supply sustainability from a proper multidimensional view, including aspects such as social, environmental, economic, governance, and asset factors (Cunha Marques et al., 2015).

To the best of our knowledge, no previous studies have explored the use of ABMs in combination with nonpricing policies to assist water tariff design. With the aim of filling this gap in the literature, the primary objective of the current study is to assess ex ante the effectiveness of jointly implementing price and nonprice DSM policies employing the ABM approach. Specifically, the aim is to gauge how variations in domestic water demand respond to the introduction of nudges as a nonprice policy and to modifications to the IBT structure as a price-related policy.

This article is structured into three additional sections to address the implementation of the proposed approach. In Section 2, the ABM used in this study is introduced, and the tariff and nudge design and the scenarios selected for simulation are outlined. Section 3 is dedicated to presenting and discussing the outcomes, utilizing various data grouping criteria derived from the simulated experiments. The paper concludes in Section 4, which offers final remarks and considerations for future research.

## 2. Materials and methods

The ABM utilized in the experimental section of this article is built upon the framework introduced by Vidal Lamolla et al. (2022). This represents the sole prior research that has employed ABM within the context of water tariff design. The model represents a city with a population of 12,000 inhabitants and an average per capita daily consumption of 168 litres/person/day (L/p/d). This tool was developed in accordance with limitations regarding the low quality of available data. The data available used for calibration consist of the city's aggregate consumption over a five-year period (2011 to 2015), during which no price adjustments occurred.[1] Consequently, evaluating the introduction of a new water tariff structure in a city through an elasticity-based approach is infeasible, as is evaluating the introduction of a nonpricing DSM measure.

The model faithfully replicates the sociodemographic characteristics of the same case study city. Individual agents represent entire households whose behaviour is influenced by sociocognitive value profiles, including client, techno-solutionist, committed, and environmentalist

[1] Despite having made some time-scale modifications in the original ABM proposed by Vidal Lamolla et al. (2022), aspects regarding on households' consumption remained unchanged. Therefore, it has not been necessary to recalibrate the model, as it still responds to the calibration performed by Vidal Lamolla et al. (2022) to adjust model overall consumption to the available data.

perspectives (Perello-Moragues et al., 2021). As the main demographic variables, households are assigned variables such as size, quantity of members and monthly income per capita.[2] Each household engages in a set of water-related activities, such as showering, dishwashing, laundering, toilet usage, sink use, and, for households equipped with water, garden watering and swimming pool use, each of which are consumed through calibration with the available data. To align the model with the requirements of the current study, it now operates on a day-to-day basis, encompassing an entire year. Additionally, according to GWI (Global Water Intelligence) (2023), monthly billing is a standard practice for households; therefore, water bills are estimated monthly. The decision of whether to conserve water and the chosen method of conservation, whether through changing habits or adopting more efficient devices, is contingent upon their respective value profiles (see Table 1).

The decision-making of agents can be distinguished between that influenced by pricing policies and that influenced by nonpricing measures. First, an income-based threshold percentage is defined (1.50% for low income, 1.25% for medium income, and 0.75% for high income households) by comparing households' water bills to their net monthly income.[3] Households motivated to save water due to economic considerations are prompted to take action if their water bills fall above their respective income-based threshold percentages. For instance, for a middle-income household with one member, with the exact mean average earnings in this income group (€1720), the threshold corresponds to a €21.5 bill.[4] Second, the household-level motivation to save water for environmental reasons is not influenced by tariff shifts to engage in water-saving practices. As noted by Vidal Lamolla et al. (2022), this poses a limitation to tariffs when used as the only measure to save water.

A full explanation of the model, including which and how household variables are assigned (income, garden, swimming pool...) and the major changes to the original model by Vidal Lamolla et al. (2022), following the overview, design concepts and details (ODD) protocol (Grimm et al., 2006, 2010, 2020) can be found in Appendix A.

### *2.1. Setting nonpricing measures in the ABM*

A hypothetical nonpricing DSM policy is introduced through a nudge (Thaler & Sunstein, 2008). The specific nudge model consists of including informatively the average daily per capita water consumption for each housing type (high, medium or low density) on the water bill received by each household, in addition to its own water consumption.

According to Brick et al. (2023) nudges can operate under various causal mechanisms such as information provision, price saliency, financial incentives, social comparison, intrinsic altruistic motivation, social recognition, and the promotion of public goods. Because the study focuses on assessing the effectiveness of implementing price and non-price DSM policies, the selected nudge leverages on social norms and environmental concerns as main motivations for behaviour change. Thus, the modelled nudge can be categorized as a green nudge aimed at conspicuous consumption using social recognition as a lever (Brick et al., 2023). This approach focused on environmental motivations of people also minimizes the potential rebound effect associated with originally using less water than neighbours.

[2] The number of members in each household varies from 1 to 4. The size ranges are 61 to 90 m$^2$, 91 to 120 m$^2$ and greater than 121 m$^2$, which are distributed in 52%, 30% and 18% proportions, respectively. Income levels in the model are defined as low (up to €938/person/month), middle (between €938 and €2502/person/month) or high (more than €2502/person/month).

[3] The income-bill relationship is determined through data obtained by simulating the tariff of the case study city.

[4] These values come from the following calculations. Average earnings for middle income: 938 + 2502/2 = €1720. Threshold for a middle-income household is 1.25%, therefore: 1720 ∗ 0.0125 = €21.5.

**Table 1**
Different behaviour profiles' action drivers and possibilities.

| Sociocognitive profile | Actions to save water | Reasons to savewater |
|---|---|---|
| Client | Device replacement more than changing habits | Economic savings |
| Techno-solutionist | Only device replacement | |
| Committed | Both device replacement and changing habits | Water conservation |
| Environmentalist | Only changing habits | |

### *2.2. Setting pricing measures in the ABM*

To illustrate the ability of ABM to assess how changes through price DMS policies influence water consumption, we model four alternative IBT structures (see Fig. 1 and Table 2) in addition to the existing baseline scenario, Tariff 0. These alternative structures are reflective of water tariff systems in place globally (GWI, 2023) where IBT represent the 60% of existing tariffs, and are distinct in their number of pricing blocks, as well as the volume and price ranges for each block, allowing for a clear observation of how the structure of water tariffs might affect usage. The key characteristics of each water tariff structure are as follows:

- Tariff 0: Base case tariff replicates the original tariff from the case study in the original model.
- Tariff 1: One-block-per-section tariff is built with 5 blocks, each of which is tailored to a relevant group of households in a consumption section. The first 3 blocks maintain the prices of those from the original tariff, while the final block prices are computed by adding the prices of the first and third blocks (0.299 + 0.575 €/m$^3$) and two times the first block price plus the third block price (2 · 0.299 + 0.575 €/m$^3$).
- Tariff 2: Just-rise-the-price tariff is the most similar to the original case study, retaining the same block volumes but increasing the prices. It starts with a price equivalent to the first block, followed by a direct increase to the price of the third block and the addition of both preceding prices.
- Tariff 3: Free-block-for-the-vulnerable tariff is the only one that sets different prices depending on users' income. The first and second blocks from the original tariff are combined in volume while retaining the second block's price. The third block's pricing remains unchanged. Notably, the first 3 m$^3$, corresponding to the essential 100 L/day for basic needs (UN, 2015a), are offered free of charge for low-income households.
- Tariff 4: Raise-less-for-low-consumers tariff makes the original tariff blocks narrower and adds an extra one. Featuring an initial block of 1 m$^3$, the shortest one among all tariffs is proposed, followed by two equally sized blocks designed for two different consumption groups. Those first 3 blocks have the same price as in the original case study. The final block covers two primary consumption groups, with a pricing structure derived from the addition of the first and last blocks in the original tariff. Compared to the just-rise-the-price tariff, it keeps lower prices for the less consuming households, but not as low as in the base case tariff.

Notably, these IBT structures are proposed with the primary goal of lowering overall water consumption. This objective is achieved by implementing price increases across different water consumption blocks either by reducing their volume or introducing additional blocks. However, alternative approaches, e.g., pursuing more equitable water tariffs by reducing initial block prices and increasing prices for the highest usage tiers, could be similarly evaluated within the framework of the current approach.

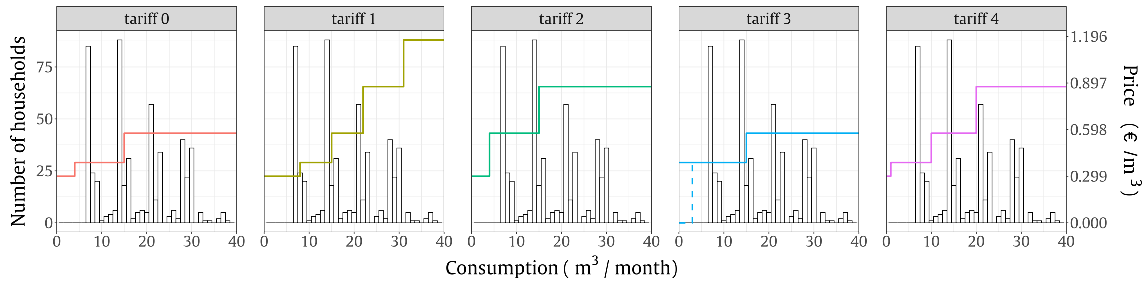


**Fig. 1.** Different water IBTs are introduced in the model.

**Table 2**
IBT from Fig. 1 explained.

| Tariff | Number of blocks | Volumes in blocks (m$^3$/month) | Price of each block (€/m$^3$) | Observations |
|---|---|---|---|---|
| T0 | 3 | 0–4, 4–15, >15 | 0.299, 0.387, 0.575 | Case study tariff from Vidal Lamolla et al. (2022) |
| T1 | 5 | 0–8, 8–15, 15–22, 22–31, >40 | 0.299, 0.387, 0.575, 0.874, 1.173 | |
| T2 | 3 | 0–4, 4–15, >15 | 0.387, 0.575, 0.874 | |
| T3 | 2 | 0–3*, 0–15, >15 | 0*, 0.387, 0.575 | *First 3 m$^3$ are free for low-income households |
| T4 | 4 | 0–1, 1–10, 10–20, >20 | 0.299, 0.387, 0.575, 0.874 | |

### 2.3. Scenarios and simulations

To explore more radical modifications to the current water tariff structure (T0), we introduce a series of alterations to each predefined tariff structure combined with the nudge measure (the latter remaining unchanged). Specifically, scenarios are defined by decreasing the width of water consumption and increasing the price of the water for each volumetric block defined in the original scenario (Table 2). These adjustments entail reducing the consumption bracket width and escalating the price per volumetric block as per the initial scenario. These modifications span from 0 to 80% in increments of 20%, resulting in 125 simulations. A simulation of each possible combination is run for all tariffs using the integrated development environment NetLogo (Wilensky, 1999).

## 3. Results and discussion

The data obtained from the simulations were processed and analysed using RStudio (R Core Team, 2023), shedding light on how different water IBT structures, in combination with the nonpricing measure, influence consumption patterns (all the annual consumption data plots are available in the Appendix B). Specific validation for the results of the effects of the proposed policies could not be performed, as the modelled changes have not taken place in the case study. An alternative approach was to seek for similarities in other case studies where policies were applied. This validation procedure is known as "pattern-oriented validation" and involves make comparisons to general patterns observed in the modelled system and characteristic for its behaviour (Grimm et al., 2005). In our case study, the presented results align with those observed by Tortajada et al. (2019) in different cities in Spain where both kind of DMS policies were applied.

### 3.1. Overall consumptions

Fig. 2 illustrates the mean overall variations in water consumption across various scenarios in comparison to the baseline consumption (Tariff 0, with no alterations in block prices or volumes and without the nudge being implemented).

A general insight into the results allows us to check how the changes in the IBT structure and the introduction of a nudge involve a reduction in water consumption between 8.1% and 15.6%. To clarify, these variations correspond to a 13.7 to 26.2 L/p/d reduction in the average per capita daily consumption. These results appear to align with findings reported by Tortajada et al. (2019), who reported water reductions ranging from 14.0% to 26.4% when water tariffs increased between 52% and 114% and when several education and public awareness campaigns (nonprice measures) were applied in five Spanish cities. The current demand reductions would be situated at the lower end of the spectrum presented in that study; this is likely attributable to the simulation encompassing only one year and introducing a single nonpricing DSM policy.

Fig. 2 also reveals differences in water consumption reduction among households motivated by environmental concerns (clear section) and those motivated by economic reasons (dark section). Households driven by environmental concerns played a primary role in reducing water demand in most instances, achieving reductions spanning from 8.1% to 9.4%. Conversely, economically motivated households displayed lower responsiveness, although in cases where IBT underwent significant changes in block prices and volumes, their responsiveness increased, leading to reductions ranging from 0.0%[5] to 6.2%. In some scenarios, it is evident that the nudging, through establishing a relationship of all households' consumption with environmentally driven households, facilitated greater demand reductions for the latter group, as the savings by economically driven households increased. Essentially, a more substantial demand reduction by client and technosolutionist households lowers the average per capita daily consumption and encourages more committed and environmentally conscious households to make greater reductions in demand.

Despite achieving demand reductions through the combination of IBT and nonprice measures, the results are consistent with the tendency of water demand to be inelastic (Tanishita & Sunaga, 2021), as all savings are proportionally smaller than price increases. This elasticity is considered inelastic and ranges between −1 and 0. This inelasticity is also considered to agree with the original case study city conditions. Approximately half of the households in the case study city do not have outdoor water consumption or reach the mean consumption in the city, although the consumption rate is higher than the national average of 111 L/p/d in Spain (Instituto Nacional de Estadística, 2020). Similarly, these findings closely align with those of other European countries, such as France (with 150 L/p/d in Bordeaux and 156 L/p/d in Lyon) and Portugal (with 148 L/p/d in Lisbon and 130 L/p/d in Porto); however, they still remain notably lower than those of countries such as Canada, with cities such as Vancouver consuming 434 L/p/d

[5] Despite the existence of some scenarios in which demand variations ranged from −0.2% to 0.1, those variations were considered to be caused randomly by model stochasticity and were therefore considered negligible.


**Fig. 2.** Overall consumption variation in all the different scenarios. Lighter sections of the bar correspond to variations by environmentally driven households, and darker sections correspond to those that are economically driven.

and Winnipeg consuming 213 L/p/d (IWA Statistics & Economics, 2020), where much more room for water savings exists. Therefore, in cities with per capita consumptions similar to those in the case study moderated consumption reductions could be achieved following this framework, while greater savings should be feasible for those cases where inhabitants' consumptions are way higher. Prior to these, however, proper ex ante assessment should be carried by adapting the proposed measures to the specific cases where it had to be applied.

Among the water tariff structures tested, Tariff 2 (just-rise-the-price tariff) proved to be the most effective at reducing water consumption, achieving a maximum reduction of 15.6% compared to the baseline when subjected to 80%–80% variations. Therefore, this tariff would be advisable when the aim is to save as much water as possible. Examining water consumption variations in scenarios with one variation set at 80% (as shown in the bottom row and right column of Fig. 2), it becomes evident that an 80% increase in block prices had more pronounced effects than an 80% reduction in block volumes in most cases. Tariff 1 (one-block-per-section tariff), however, deviated from this pattern, exhibiting a stronger response to an 80% reduction in block volume when price increases are equal to or less than 40%. This outcome can be attributed to Tariff 1's distinctive characteristic of having more blocks (5), which results in narrower steps within the IBT structure.

To better understand changes in water use due to water tariff structure modifications, Fig. 3 illustrates the variations in average monthly household consumption for each tariff in scenarios with 0%–0% and 80%–80% changes. Notably, the figure demonstrates a reduction in the number of households in the most common consumption categories, i.e., shifting to the left and flattening peaks, indicating a decrease in consumption. It is worth highlighting that despite a slight reduction, the majority of households with higher consumption levels (those exceeding 32 $m^3$/month) hardly transitioned to lower consumption groups. This phenomenon can be attributed to the correlation between high incomes, larger household sizes and elevated consumption. In this context, Jegnie et al. (2023) emphasized how household-size elasticity (i.e., the variation in water consumption with household dimensions) is positively associated with household income. Thus, households with greater incomes and larger sizes tend to exhibit greater water consumption, thereby limiting the extent to which these households are willing to curtail their water usage, even when facing variations.

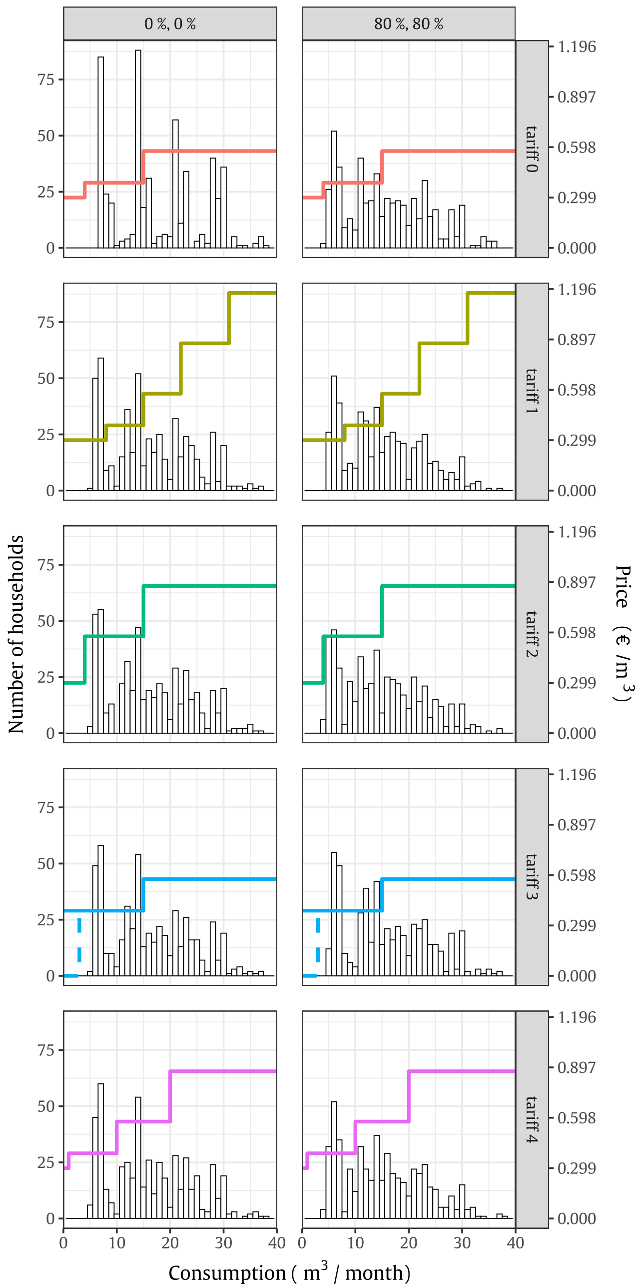


**Fig. 3.** Baseline and 80%–80% scenario comparisons of average monthly consumption distributions by tariff.

### 3.2. Consumption by household groups

This approach effectively mitigates an issue previously emphasized in Vidal Lamolla et al. (2022), namely, the limitation of relying solely on tariff adjustments. A more comprehensive exploration of this situation can be found in Fig. 4, illustrating consumption variations for each behaviour profile. Table 3 illustrates that reductions in water consumption for committed and environmentalist profiles are, in most cases, between two or three times those for client and techno-solutionist profiles. It is also notable in the aforementioned table that demand reductions by environmentally driven households are much more stable. In addition, the highest reductions in these profiles align with the greater reductions in economically driven households. However, those greater values from committed and environmentalist households are not notably different than lower values. This is attributed to the fact that households with these profiles had already reached inelastic situations where most behavioural changes took place and thus had a limited margin in which to act, even if the demand reductions by client and techno-solutionist households increased. The overlapping shown in the graphs for environmentally driven households supports this idea.

**Table 3**
Water consumption variation of households by behaviour (in %).

| | Consumer groups based on behaviour | | | |
|---|---|---|---|---|
| | Client | Committed | Environmentalist | Techno-solutionist |
| T0 | −7.1 | −19.9 | −15.2 | −5.1 |
| T1 | −10.2 | −21.0 | −16.1 | −9.4 |
| T2 | −13.4 | −22.6 | −16.0 | −11.6 |
| T3 | −5.6 | −19.8 | −15.2 | −2.5 |
| T4 | −11.3 | −21.7 | −15.9 | −9.6 |

Since changes in water consumption result in variations in monthly water bills, the data were further scrutinized and categorized to assess the impact of each tariff on household water expenditures across various income levels. Fig. 5 displays the outcomes in four distinct scenarios, which correspond to the extreme quadrants of the raised scenarios (all 125 scenarios are available in the Appendix C). Regarding bill variations, Tariff 3 with 0%–0% increases is the one better at ensuring access to water to households with lower income. Across all the examined scenarios and water tariffs, households with higher incomes experienced the greatest increase in their water bills. This outcome corroborates earlier assertions regarding the low income-demand elasticity for water, suggesting that high-income households tend to not markedly decrease their water consumption in response to price hikes, thereby incurring higher monthly water bills. This finding once more supports the need to adopt both pricing and nonpricing measures to reduce the urban water demand.

Interestingly, when the volume of blocks remained unchanged, with both the 0% and 80% block price increases, Tariff 2 (just-rise-the-price tariff) resulted in higher bill increments. However, when volume reductions occurred, with both the 0% and 80% block price increases, Tariff 1 (one-block-per-section tariff) became the driver of more significant bill increases. This effect is attributed to the distinctive characteristics of both tariffs. On the one hand, Tariff 1 features the highest-priced block (>31 $m^3$ at 1.173 €/$m^3$). On the other hand, Tariff 2 has the costliest 2nd block (4–15 $m^3$ at 0.575 €/$m^3$). Therefore, when prices rise but volumes are kept constant, Tariff 2 prices are the most expensive, even for households with monthly consumption levels of less than 15 $m^3$/month. However, when blocks are reduced (with or without price increases), for Tariff 1, a larger number of households fall into the final tariff block. This makes prices for many households even more expensive than those from Tariff 2 when no volume variations occur.

Additionally, it is noteworthy that, in most cases, some households had negative bill increments, meaning that they managed to reduce their bills even in the 80%–80% scenario. This occurred to a greater extent among high-income and middle-income households, given their tendency to have higher consumption rates. Consequently, they had more room to reduce their water usage, unlike low-income households, which were primarily engaged in indoor activities. It is important to note that some of these reductions were achieved at the expense of acquiring new, water-efficient devices, which is a cost that was not factored into the bill increment calculation.

### 3.3. Implications on policy making

The results of this study suggest several policy implications that should be taken into consideration by urban water regulators and water managers. First, when data availability is limited, ABM has been shown to be a dependable method for evaluating the effectiveness of implementing both price and nonprice DSM policies. The water-use reductions predicted by ABM align with those reported in real

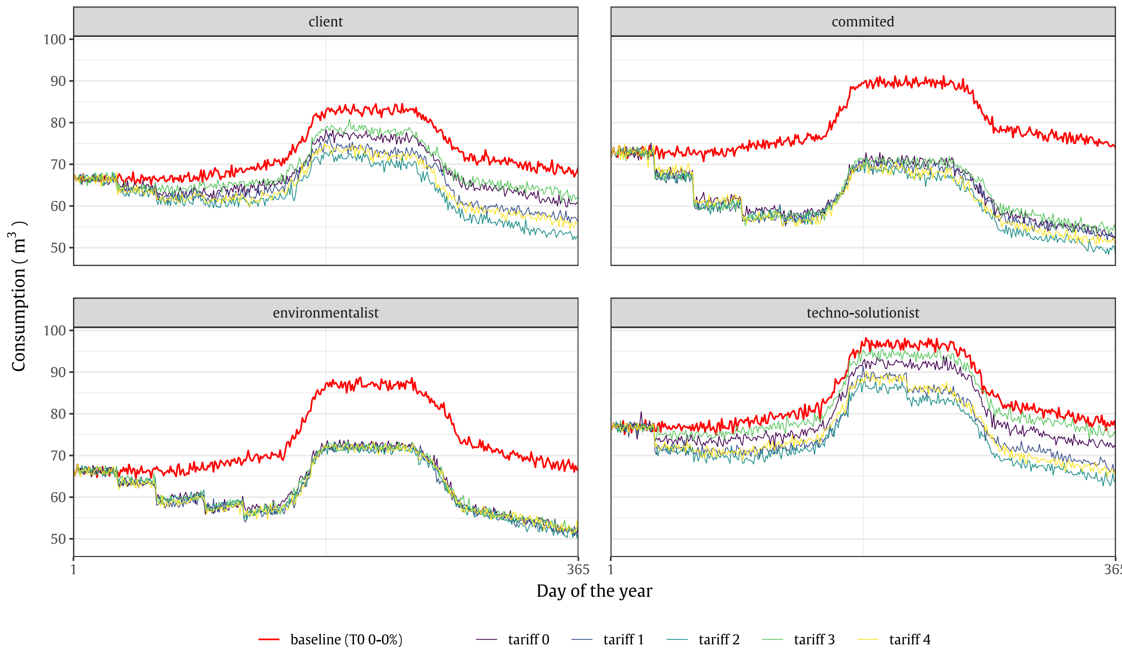


**Fig. 4.** Comparison of aggregated household daily consumption throughout the year in the 80%–80% situation grouped by behavioural profiles.

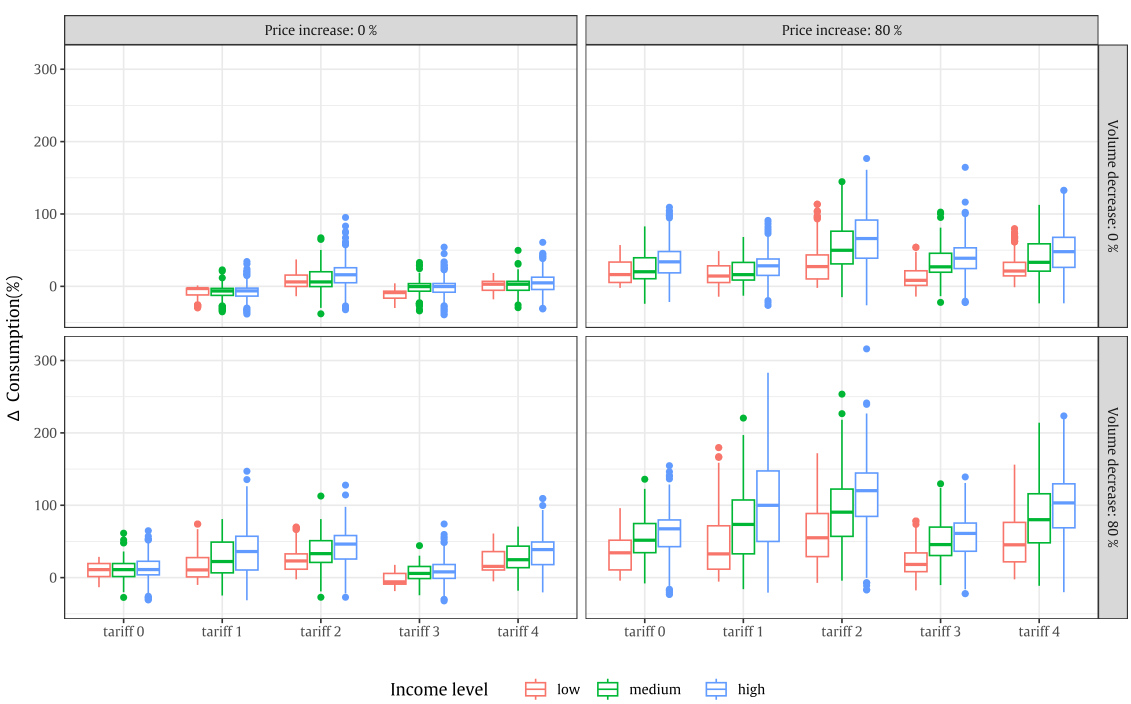


**Fig. 5.** Distribution of bill variations in the baseline and 80%–80% scenarios for each tariff and income group of households.

case studies (Tortajada et al., 2019), which enhances the credibility of this approach. Second, combined DSM policies should not be limited solely to households. For example, when only pricing incentives for reducing water leakage are given to utilities, they are likely to fall short (Molinos-Senante et al., 2019). Third, it is important to acknowledge that the potential water-use reductions achievable through the implementation of DSM policies have limitations. The study has shown that the maximum reduction estimated was 15.6%, even with the introduction of a nudge and an 80% increase in water tariffs. In areas facing high water-scarcity conditions (see, for instance Forero-Ortiz et al., 2020), it becomes essential to supplement DSM policies with measures aimed at augmenting water availability. These measures can encompass conventional water resources or alternative sources such as wastewater reuse, desalination, or rainfall harvesting. Fourth, the study's results indicate that nonprice measures, such as nudges, tend to be more effective at reducing water use than price measures, such as increasing water tariffs. This is primarily because environmental concerns serve as the main motivation for reducing water consumption. This finding is consistent with situations that have been observed in Spain (Tortajada et al., 2019) and Israel (Kim & Morphis, 2021). Moreover, it should be noted that the timescales of both types of measures (price and nonprice) differ. While water-pricing policies can be swiftly adopted to address short-term water shortages, nonprice policies require a longer-term outlook, as they rely on behavioural motivations and are better suited for addressing structural imbalances between water supply and demand. Fifth, the current study highlights that household income plays a pivotal role in determining households' response to water consumption reduction under DSM policies. Specifically, households with higher income levels are less inclined to significantly reduce their water use in response to water tariff increases. This underscores the importance of adopting a combination of price and nonprice DSM policies to effectively curtail water use. Finally, it is crucial for households to comprehend the structure of water tariffs so that they can make informed decisions about their water consumption and manage their water bills effectively. An increase in water tariffs does not necessarily translate into higher water bills for households, as the relationship between tariff structure and actual payments can be complex. Thus, information and communication technologies (ICTs) can play a valuable role in strengthening users' participation and improving governance (Mukhtarov et al., 2018). These findings offer valuable insights for policy-makers and water managers as they navigate the complexities of urban water management and the implementation of DSM policies.

## 4. Conclusions

Demographic trends and climate change pose challenges in the upcoming decades with regard to ensuring water availability. In this context, both price and nonprice DSM policies can provide some solutions for reducing per capita consumption of water and increasing availability of this resource. However, evaluating ex ante the effectiveness of implementing these measures is a difficult task. Sometimes additional obstacles such as the poor quality of available data are present. To address this challenge, the present work proposes an ABM approach to assessing the reduction in water use resulting from implementing a nonprice policy (a nudge) and changing the IBT for different profiles and household incomes.

After testing 4 alternative IBTs involving 125 scenarios in combination with a nudge, the estimated water demand reductions ranged from 8.1% to 15.6%. The greater contributions of those reductions (between 8.1% and 9.4%) came from agents representing households with environmental motivations to save water; i.e., they were due to the implementation of a nudge. For economic reasons, less water was saved (between 0.00% and 6.19%), illustrating the limitations of applying price measures in isolation. These results are in agreement with both the inelastic tendency of water price demand and the fact that combinations of pricing and nonpricing policies are more effective than solely switching tariffs.

The proposed methodology based on the ABM approach has been shown to be adequate for the ex ante assessment of expectable water demand variations as a result of applying pricing and nonpricing DSM policies together. Nevertheless, further research should include interactions between a greater diversity of implemented measures, such as multiple nonpricing measures applied at the same time in combination with different water tariff schemes other than IBT. More precise models and more robust results could also be achieved through conducting experiments in case studies where more detailed of household features are available. In this context, users can be directly asked about their motivations trough surveys where measures are actually implemented, thereby facilitating the validation of models.

## CRediT authorship contribution statement

**Pol Vidal-Lamolla:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Conceptualization. **María Molinos-Senante:** Writing – original draft, Conceptualization. **Luis Oliva-Felipe:** Software, Methodology, Investigation, Conceptualization. **Sergio Alvarez-Napagao:** Supervision, Software, Methodology, Conceptualization. **Ulises Cortés:** Supervision, Conceptualization. **Eduardo Martínez-Gomariz:** Writing – review & editing, Supervision. **Pablo Noriega:** Supervision, Conceptualization. **Gustaf Olsson:** Writing – review & editing. **Manel Poch:** Supervision, Methodology, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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## Appendix A. ODD protocol

The supplementary ODD protocol associated with this article can be found in the online version.

## Appendix B

See Fig. B.1.

## Appendix C

See Fig. C.1.

## Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.scs.2024.105435.

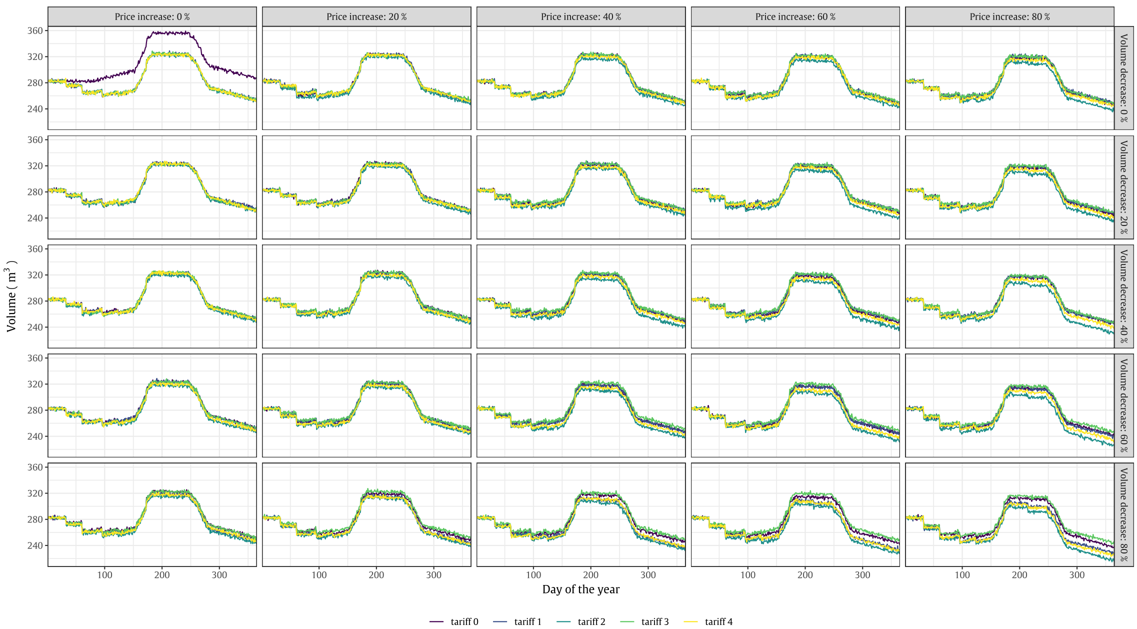


**Fig. B.1.** Overall daily consumption evolution during the year for all tariffs and scenarios simulated.

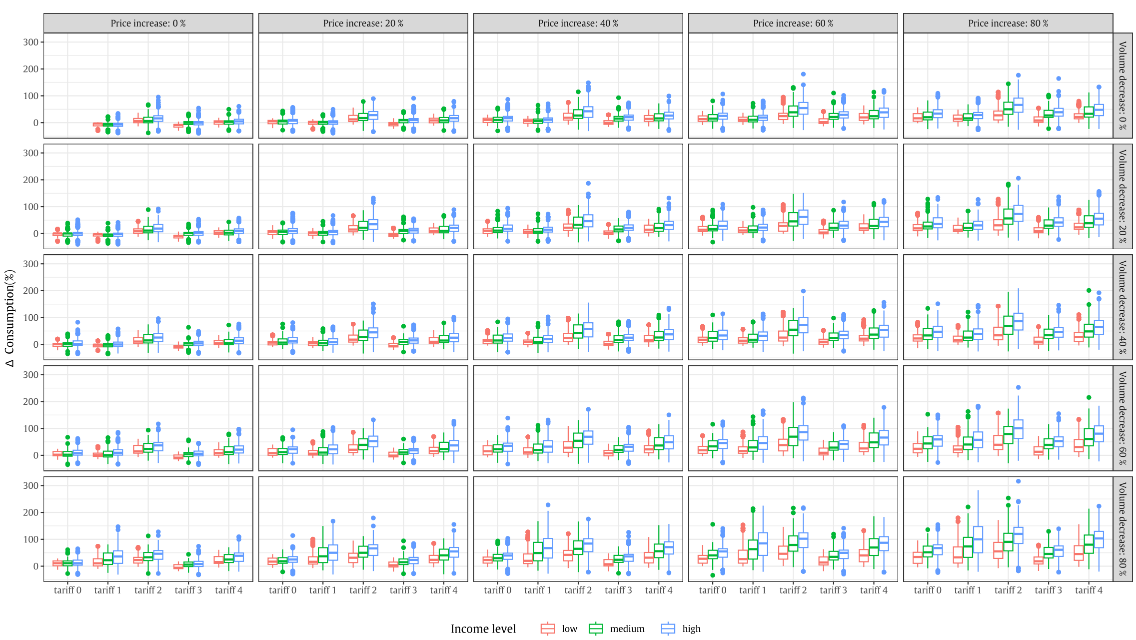


**Fig. C.1.** Billing variations grouped by income levels for all tariffs and scenarios simulated.

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