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Understanding the Residential Water Demand Response to Price Changes: Measuring Price Elasticity with Social Simulations

Pol Vidal-Lamolla [1,2,*], María Molinos-Senante [3,4] and Manel Poch [1]

[1] LEQUIA, Institute of the Environment, University of Girona, 17004 Girona, Spain; manuel.poch@udg.edu
[2] Aigües de Barcelona, Empresa Metropolitana de Gestió del Cicle Integral de l'Aigua, General Batet 1-7, 08028 Barcelona, Spain
[3] Institute of Sustainable Processes, University of Valladolid, C/Mergelina 4, 47011 Valladolid, Spain; maria.molinos@uva.es
[4] Departamento de Ingeniería Química y Tecnología del Medio Ambiente, Universidad de Valladolid, C/Mergelina 4, 47011 Valladolid, Spain
* Correspondence: pol.vidal@udg.edu

Abstract: Water pricing is an economic instrument traditionally used to reduce water demand. However, its effective implementation requires knowledge of the extent to which users reduce water consumption with increasing water prices. The price elasticity of water demand has been estimated using econometric regression, which relies on cross-sectional and time-series water data. As an alternative, we propose the use of agent-based modelling, which does not require reliable historical data on water prices and consumption and enables the simulation of multiple scenarios with different consumer profiles, behaviour profiles and water price changes, thereby allowing comprehensive understanding of price elasticity estimates. To illustrate the potential use of agent-based modelling for the estimation of water demand price elasticity, we performed an empirical application to a residential area in Chile. Price elasticity estimates ranged from −0.0159 to −0.1036 (mean −0.0250), indicating that residential water consumption is inelastic to price changes. This result is consistent with previous findings. Agent-based modelling is an alternative for the ex-ante assessment of the potential effectiveness of water pricing policies intended to reduce residential water demand.

Keywords: agent-based modelling; price elasticity; residential water demand; consumer profile

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1. Introduction

Growing water scarcity is a leading challenge for sustainable development [1]. According to the United Nations' estimates, about 2.3 billion people live in water-stressed countries and about 4 billion people, representing two-thirds of the global population, experience severe water scarcity during at least 1 month of the year [2,3]. As the global population grows, living standards increase and the effects of climate change intensify, many countries' water resources and infrastructure are failing to meet accelerating water demands [4]. Although the residential water demand represents less than 10% of the total water consumption worldwide [5], access to sufficient, safe, acceptable, physically accessible and affordable water for personal and domestic use is a human right [6].

Residential water demand analysis is not new for scholars or water utilities [7,8]. Researchers have examined the influences of factors such as income, age, household size, weather variables and water price on this demand (e.g., [9–12]), and water utilities have analysed the demand to predict future residential water consumption, a key input for decision making, including that about investments [13,14]. As the availability of water is expected to decline in the near future, economic instruments for water management may be relevant in efforts to guarantee efficient and sustainable domestic water use [15,16]. Water pricing is the main economic incentive used to charge for residential water and discourage its wasteful use [17]. Its use to manage increasing water demand over time, however, requires a better understanding of the sensitivity of this demand to changes in price [18]. In other words, the use of water pricing to reduce the residential water demand requires the estimation of the demand price elasticity, i.e., measurement of the degree of responsiveness of water consumption to a change in water price, ceteris paribus [19].

The price elasticity of the residential water demand has been estimated in numerous studies (for a review, see [8,20,21]). Econometric regression has traditionally been applied in efforts to establish quantitative relationship between the water price (and other relative variables) and aggregate cross-sectional or time-series water use data [22]. This approach requires the selection of an appropriate functional form, e.g., linear, log-log, semi-log or Stone–Geary, which may affect the resulting estimates [23,24]. Moreover, the procedure used to estimate the function, e.g., ordinary least squares, instrumental variables or discrete continuous choice, may influence price elasticity results [16]. Alternatively, contingent valuation has been employed to assess responses to hypothetical water price changes [25–27]. Econometric analysis and contingent valuation have been useful to a certain extent for estimating the price elasticity of residential water demand, but are significantly limited when reliable cross-sectional and time-series data are lacking and when water use is experiencing a period of rapid change [22].

To overcome these limitations, one must look beyond these approaches. Agent-based simulations have been applied successfully in the evaluation of diverse aspects of water systems and policies (for a review, see [28]). Agents are autonomous software programmes that exhibit human-like behaviours, such as goal-directed, reactive and social capabilities [29]. Agent-based modelling is performed with artificial agents, computational entities programmed with artificial intelligence to act independently and according to pre-set interests [30]. Each agent can mimic the behaviour of an individual element (e.g., a household) in a system [31]. Agent-based models (ABMs) have been used to test water demand–side management strategies [32,33].

The agent-based modelling approach has the following positive features for the estimation of the price elasticity of water demand: (i) it allows ex-ante assessment, as it does not require past data on changes in the water price and its impact on water use; (ii) it captures the diversity of consumption profiles and human behaviour in estimations; and (iii) it enables the simulation of multiple water price variation scenarios to assess changes in water consumption in different contexts. To our knowledge, however, an ABM has been used for this purpose in only one study, with the application of water-related historical data from 15 years previously [22]. This situation raises the question of whether ABMs can provide feasible price-demand elasticity values when historical data are limited or scarce.

Against this background, the main objective of this study was to develop and apply an ABM to estimate the price elasticity of residential water demand under different water-price variation scenarios with limited historical water-price data. Beyond the case study developed, this study provides new empirical evidence of the usefulness of the agent-based modelling approach for this purpose. Water utilities and regulators can further develop and use this novel approach to better understand the behavioural and social factors that influence the price elasticity of water demand and to improve their water consumption forecasts.

The rest of this paper is organised as follows. In the fisrt part of Section 2, the ABM designed is described following the 'overview, design concepts and details' (ODD) protocol of Grimm et al. [34,35,36]. In second part of Section 2, the calibration of the model using real data from the case study and the simulation experiments performed with consideration of multiple tariff variation scenarios are described. The main results are presented and discussed in Section 3, and conclusions are provided in Section 4.

2. Materials and Methods

2.1. Model Description

The application of the ODD protocol [34–36] makes ABMs easier to replicate and thus less easily dismissed as unscientific [35]. We apply it to our case study is as follows.

2.1.1. Purpose

The proposed ABM aims to quantify the price elasticity of residential water demand under different water-tariff variation scenarios. Thus, it must capture differences in factors that affect customers' behaviour, such as consumption profiles, housing types and socio-economic characteristics.

2.1.2. Entities, State Variables and Scales

Each agent in the ABM represents a household whose drinking water is provided by Aguas Cordillera, a water company that operates in three communes of the Metropolitan Region of Santiago, Chile (Lo Barnechea, Las Condes and Vitacura; Figure 1). State variables characterising the households depend on the commune in which they are located, and comprise the consumption profile, housing type, house size, number of household members, number of bathrooms, income and behavioural profile (Table 1).

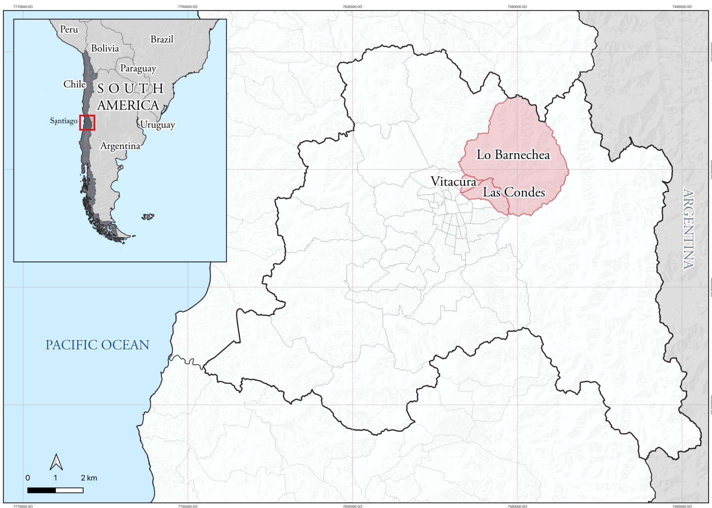

Figure 1. Location in Chile of the three communes studied.

Table 1. State variables of households and their possible values.

Parameter	Range of Values
Commune	Lo Barnechea, Las Condes, Vitacura
Consumption Profile (m^3/month)	Low (<6), Medium (6–15), High (15–40), Very high (>40)
Housing Type	Flat, Terraced house, Single house
House Size (m^2)	40–100, 100–150, >150
Members	1 to 10
Number of Bathrooms	1 to 6
Monthly Household Income (in CLP *)	309,000 to 26,391,666
Behavioural Profile	1, 2, 3 or 4

Note: * On 14 April 2023, the conversion rate was 802 CLP ≅ 1 US$ and 883 CLP ≅ 1 €.

The three communes assessed contain three types of housing: flats, terraced houses and single houses. All households have indoor water use for functions such as toilet flushing, personal hygiene in the sink, dish washing, showering and clothes washing. The occupants of terraced and single houses, those with sizes of 100–150 m^2 and >150 m^2, may also have outdoor water use (for gardens). The households perform actions to save water and reduce their spending based on their water bill costs [37]. This is a consideration that is also used in econometric approaches, where income can be found as one of the variables considered [38]. The types of action that they can perform are defined according to their behavioural profiles, and consist of: (i) device replacement, (ii) changes in practices, (iii) device replacement and changes in practice and (iv) no action. Simulations run from the model take place in daily time steps for 1 year.

2.1.3. Process Overview and Scheduling

The proposed model represents days in discrete steps, in which consumption is defined and enacted and billing and saving decisions are made (Figure 2). At the beginning of each week, the weekly distribution of household water use is set. On the last day of each month, the households receive water bills. In deciding whether to act to reduce their water consumption, the households take into account the amounts that their water bills represent as percentages of their incomes [39,40].

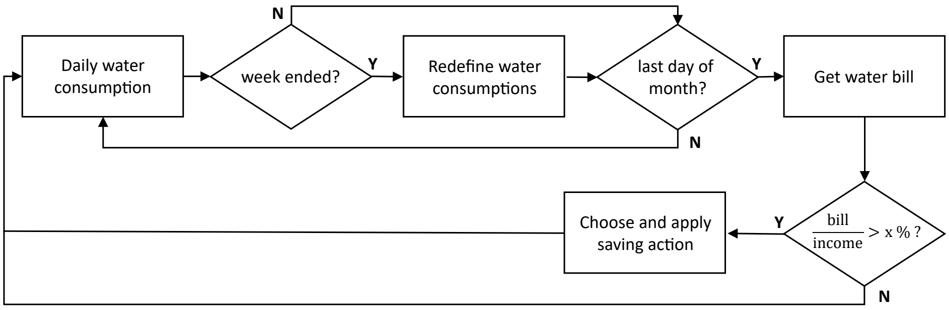

Figure 2. Water consumption and billing cycle of agents in the proposed ABM.

2.1.4. Design Concepts

Basic principles. The proposed ABM relies on the price-demand elasticity phenomenon, measured as the relationship between changes in water pricing and the demand response [Equation (1)] and thus entailing multiple phenomena and complex human decision-making and other behaviours [41].

$$E_p = \frac{\Delta demand_{in\%}}{\Delta price_{in\%}} = \frac{\Delta Q/Q_t}{\Delta P/P_t} = \frac{(Q_{t+1} - Q_t)/Q_t}{(P_{t+1} - P_t)/P_t} \quad (1)$$

where E_p is the price elasticiy of demand, Q_t is the volume of drinking water consumed during time t and P_t is the price of drinking water during time t.

Emergence. The aggregated variation in domestic water consumption emerges from the modelled individual household decision-making processes. These processes interrelate agent state variables entailed in consumption patterns and decision criteria.

Adaptation. The adaptative behaviours of households (including none) vary according to their profiles. In general, however, households' water consumption patterns are not adaptable. For example, agents can take shorter showers or use more efficient devices, but they are not expected to stop showering.

Objectives. The objective guiding households' water consumption–reducing behaviours is defined by the relationship between their water bills and monthly incomes. When the water bill represents less than 3% of its total income, the threshold for water affordability according to United Nations [40], a household's behaviour does not change. A larger percentage triggers households to take action to reduce their water consumption.

Prediction. In the proposed model, the agents do not make explicit predictions. However, when a household is triggered to consider replacing a device, its members inherently make a prediction. The water bill increase required to trigger a household to consider changing a device is not the full price of the device. In making such decisions, households conceptually take into account their bill increase and the amount that they will be paying in subsequent months. In this way, the households predict how much more they will be paying in assessing whether device replacement is worthwhile.

Sensing. Households are aware of their water consumption, billing and incomes when making decisions. The water consumption and income are related strongly to other state variables, such as the housing type and number of household members, but these variables do not directly influence decision making. The relevance of such variables in a household's water consumption is shared with econometric approaches, where income or household members, for example, are variables used in estimations [8,38].

Stochasticity. The state variables are assigned following random, exponential and Poisson distributions (Despite the potential for state variables to follow various distributions, the modelling environment used permitted only exponential, gamma, normal and Poisson distributions. The Kolmogorov–Smirnov test was applied to each data group to select the best-fitting distribution, with a confidence interval ≥ 0.05. When no distribution fit the model, the state variable was distributed randomly.). The behavioural profiles are assigned randomly. Some water uses, e.g., doing laundry or a member's lack of showering on a given day, are also chosen randomly. Actions related to decision making (changes of practice and/or device) are chosen with fitness-proportionate selection [42], which makes some actions more likely to be chosen (e.g., due to their lower cost) but lets other options to be chosen, assuming that not all households follow the same reasoning scheme.

Observation. The data generated by the model consist of monthly household consumption and billing data and state variables, facilitating the analysis of variation in consumption according to criteria such as the consumption profile, housing type, number of members and income.

2.1.5. Initialisation

The model starts on 1 January with a user-defined number of agents. The agents' state variables are defined based on real data gathered by the Chilean water regulator [Superintendencia de Servicios Sanitarios (SISS)] and the National Socio-economic Characterisation (CASEN) survey performed by the Chilean authorities [43], except the behavioural profile variable, which was based on SISS (Superintendencia de Servicios Sanitarios) [44].

2.1.6. Input

The proposed ABM uses five data inputs to define the households' state variables. First, a geographic information system dataset provides the locations and consumption profiles of households in the three communes. This input was produced from the 2019 (These data may not be the most recent, but the data from 2020 and 2021 were affected by the consequences of the COVID-19 pandemic and could not be considered to represent regular consumption.) meter-reading and billing data of Aguas Cordillera, provided by the SISS.

As more than 50,000 points from which agents could be generated remained after data cleansing and filtering, a second input was included to scale the model down to the user-defined number of agents while maintaining the proportions of customers and consumption profiles in each commune (Figure 3).

Then, a third input database was used to assign the housing type, house size and number of members to the households (Table 2).

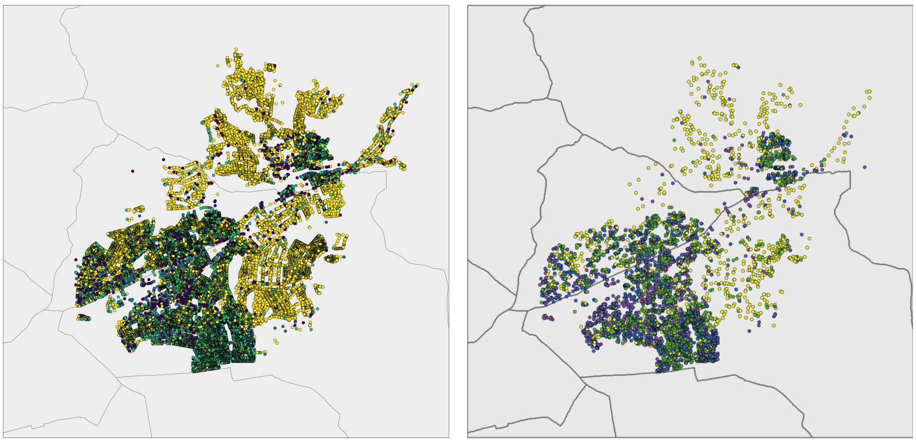

Figure 3. Comparison between the total amount of points obtained before data cleansing (generated in RStudio), and 5000 points in the model initialization (in NetLogo) after scaling down.

Table 2. State variables included in the input database used to characterize households.

Consumption Profile	Consumption Range (m^3/Month/Household)	Housing Type	Size (m^2)
Low	<6	Flat	40 to 100
Medium	6 to 15	Flat	100 to 150
		Terraced House Single House	40 to 100
High	15 to 40	Flat	>150
		Terraced House Single House	100 to 150
Very High	>40	Terraced House Single House	>150

Based on the previous input data, fourth and fifth database inputs were used to define the remaining state variables: the number of bathrooms and monthly income, respectively. The microdata used to define all variables were obtained from CASEN (2020).

2.1.7. Submodels

Agent Scale Down

First, the 2019 meter-reading and billing data obtained from the SISS were cleaned and filtered to identify matching customers (households) according to: (i) house type, (ii) monthly consumption $\leq$1000 m^3, (iii) 6 $\leq$ months with 0 m^3 consumption and (iv) receipt of 12 bills in 1 year. This procedure resulted in the identification of 127,982 households. As households can share geographical locations (i.e., in the case of apartment buildings), we simplified each such point to ease visual interpretation by selecting the household with the majority consumption profile in that location. This step reduced the sample to 42,286 households (Tables S1 and S2).

The location-based filtering also altered the consumption profile proportions, necessitating rescaling to match the original consumption profile distribution and make simulation feasible with our computational capabilities. We chose a reduction factor of 0.04 and applied Equation (2) to ensure representative consumption profiling, which led to the inclusion of 5000 agents in the model:

$$P_{delete} = n - N \cdot f_C \cdot f_{P'} \tag{2}$$

where P_{delete} is the number of households to be deleted, n is the initial number of households in a commune with a certain consumer profile, N is the requested number of total households in the model, f_C is the percentage of households in the commune and $f_{P'}$ is the percentage of the consumer profile in that commune.

State Variables Definition

The number of household members, number of bathrooms and income were distributed in two steps. First, household members were distributed according to the commune, housing type and house size, using the distribution method chosen for each group. Then, the number of bathrooms and monthly income were assigned using a specifically selected distribution with the commune, housing type, house size and number of members as grouping criteria. For households with numbers of members and no matching number of bathrooms or income data available for the distribution, a new number of members was assigned according to the previously set state variables (commune, housing type and house size). In this way, the filtered microdata were assigned to 159 groups.

Water Consumption Definition

Base water consumption was assigned to households with consideration of the number of members, number of bathrooms and, in the case of garden watering, the housing type and house size (Table 3). This consumption was used to create a weekly consumption distribution, with variation among households of the days on which non-daily water uses (e.g., washing machine use or one member not showering) are performed. At week's end, the consumption values are saved in a monthly counter; likewise, monthly consumption values are saved in a yearly counter at month's end.

Table 3. Water consumption possibilities included in the model.

Water Use	Consumption (L per Use)	Frequency	Variations
Toilet discharge	8 ± 4	5 per day and member	−5% (if 1 bathroom) +5% (per bathroom, if bathrooms > 2)
Sink (washing hands or brushing teeth)	6 ± 2	8 per day and member	−5% (if 1 bathroom) +5% (per bathroom, if bathrooms > 2)
Washing dishes	45 ± 15 (by hand) 10 (dishwasher)	1 per day (1 member) 2 per day (2 or 3 members) 3 per day (4 or 5 members) ...	
Showering	40 ± 10	5 per week and member	−15% (if 1 bathroom) +15% (per bathroom, if bathrooms > 2)
Washing machine	240 ± 45	1 per week (1 member) 2 per week (2 or 3 members) 3 per week (4 or 5 members) ...	
Garden watering	400 (terraced house, 100 to 150 m^2) 600 (terraced house, <150 m^2) 2750 ± 250 (single house, 100 to 150 m^2) 3000 ± 500 (single house, < 150 m^2)	7 per week (December to March) 6 per week (April and November) 5 per week (May and October) 4 per week (June and September) 3 per week (July and August)	

Billing

Water bills were created following the tariff scheme of Aguas Cordillera, which sets peak (December–March) and non-peak (April–November) prices (Table S3). In addition, households consuming less than 40 m^3 water/month and having above-average water consumption during the previous non-peak period pay an overconsumption charge during peak months [45]. At the end of each month, household water charges were calculated using the data stored in the monthly counter, resembling the function of a water meter.

To define overconsumption for households with very high consumption profiles from January to March 2019, a gamma distribution was applied to real consumption data for the previous (2018) non-peak period. When December 2019 was simulated, the average non-peak water consumption for 2019 was calculated for each household in the model.

Action Choices

Three behavioural profiles were defined (Table 1). Profile 1 consists of device replacement with more efficient products, profile 2 is characterised by the changing of practices to reduce consumption and profile 3 entails both, but with a 70% probability of changing practices before devices. At the end of each month, each household receives a water bill and decides to save water when the total water cost represents more than 3% of the total household monthly income (Figure 4).

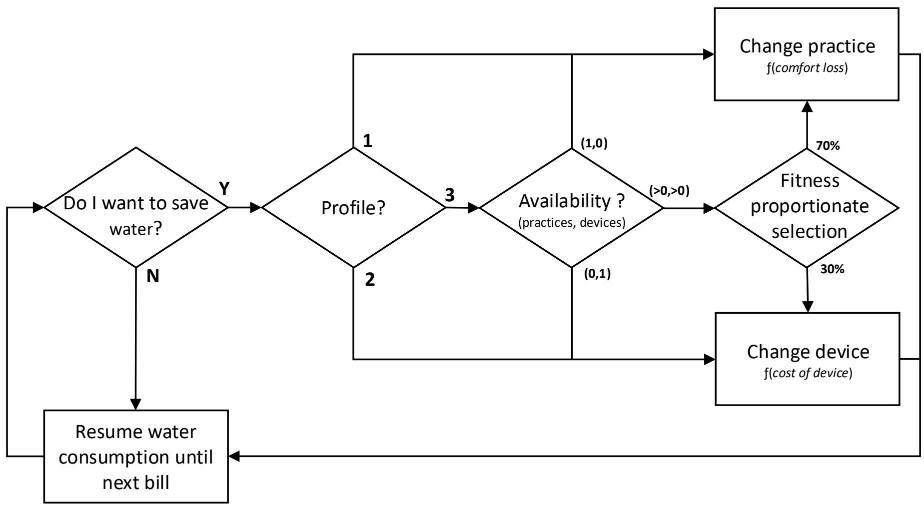

Figure 4. Reasoning scheme of households behind acting to decide whether to save water or not.

Different devices are available as replacement options, but only under certain conditions (Table 4). Households select the devices to be changed based on the difference in monthly water cost. A household's decision to replace multiple devices is based on the inverse of the bill increment required to consider that replacement. Households are more likely to change to first select cheaper replacement devices. For practice changes, a non-monetary criterion was used (Table 5). The probability of choice depends on the perceived loss of comfort associated with the habit change; for example, households are three times more likely to select better washing machine loading than shorter showers and twice as likely to select night-time garden watering than stopping to take care of the surroundings of larger houses.

Table 4. Device replacement available options for households.

Water Consumption	Consumption Change	Savings Attributed to	ΔBill to Consider the Change (CLP/Month)
Sink	−10%	faucet aerator	10,000
Washing dishes	10 L/day	installing dishwasher [1]	35,000
Shower	−10%	showerhead aerator	15,000
Garden watering [2]	−30% −15%	replacing watering devices replacing turf species	65,000 85,000

Notes: [1] Only households which previously didn't have a dishwasher can install one. [2] Replacement option only available for households owning a garden.

2.2. Model Adjustment and Use

2.2.1. Calibration

Two main aspects of the proposed ABM were tested and calibrated: water consumption and billing. The availability of real data eased calibration to ensure that the model reproduced the behaviour of households in the case study accurately.

Estimates of water consumption for different uses in Chile [44] (Table S4) were entered into the model, and calibration simulations were run to test whether the output consumption patterns matched the real consumption data. A heuristic approach was used, with consumption values and daily/weekly consumption frequencies adjusted iteratively until the desired consumption and billing outputs were achieved (Figure 5). This process yielded the water consumption values defined in Table 3.

Table 5. Practice changes available options for households.

Water Consumption	Consumption Change	Savings Attributed to	Weight Assigned for Probability
Sink	−10%	more efficient use	1/1
Washing dishes	−10%	better loading of the machine	3/1
Shower	−10%	more efficient use	1/1
Washing machine	−33% (2/3)	better loading of the machine [1]	3/1
Garden watering [2]	−10% −15%	watering at night stop watering surroundings of the house [3]	2/1 1/1

Notes: [1] Not available to low consumption profiles, they are considered to be already using their washing machine as efficiently as possible. [2] Practice only available for households owning a garden. [3] Only possible for houses with >150 m^2.

For all consumer profiles, actual water consumption was slightly less than that estimated using the ABM (Figure 5a). Two main factors caused this divergence. First, in Chile, as in other many countries, water meters are analogue devices, with water consumption recorded manually. As water meters are not always read on the same day of the month, monthly water consumption is approximated and may represent, for example, consumption over 28 instead of 30 days. Second, some buildings have common water heaters shared by all households. The water meters for these devices are independent from those for the flats (households). Thus, consumption recorded by the household water meters omits heated water consumption. The ABM integrates both of these sources, yielding an output that is slightly greater than real water consumption (Figure 5a). This phenomenon affects mainly the low and medium consumer profiles, which cover most households living in flats. These two reasons that explain the difference between real and estimated water consumption also apply to the difference between real and estimated water bills. In addition, real water bills may include other items, such as re-billing from previous months due to non-payment or billing errors.

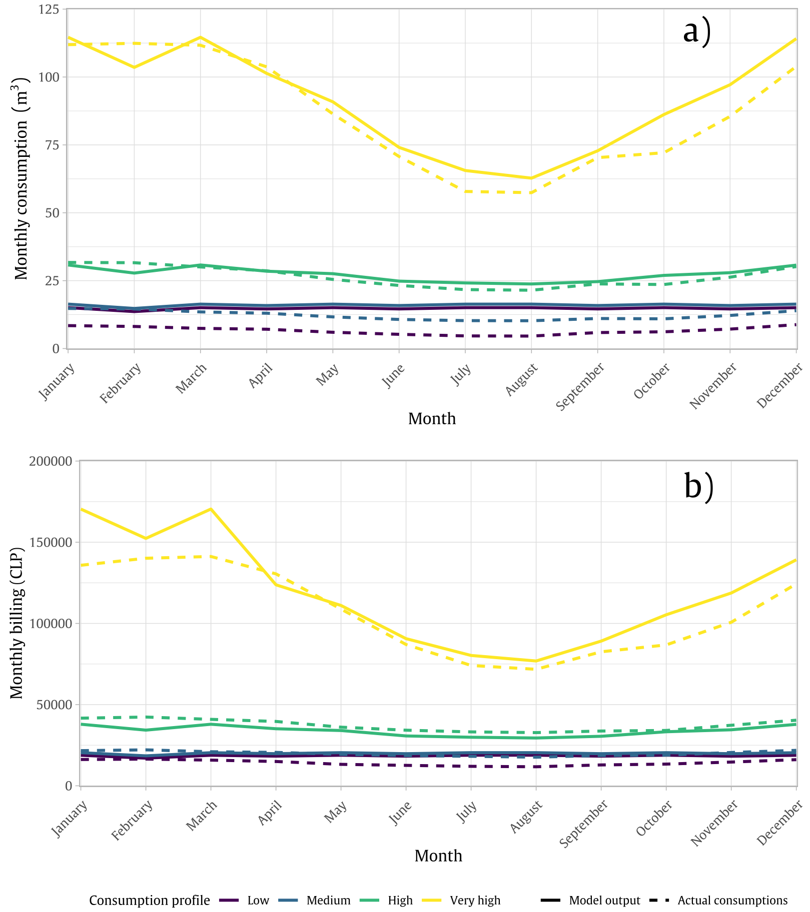

Figure 5. Average real and simulated water consumption (**a**) and water billing (**b**) per consumer profile.

The water bill–monthly income relationship triggering households water conservation was then defined. A full-year simulation was run and output data on all households' monthly incomes and mean water costs. The percentages of total household income represented by water costs are shown for the four water consumption profiles in Figure 6. For 4763 (95.26%) of 5000 households analysed, water costs represented less than 3% of the total income. This threshold was exceeded to a greater extent by very high water consumers (19.6% of these households). These results indicated that water affordability was not a major issue in the case study.

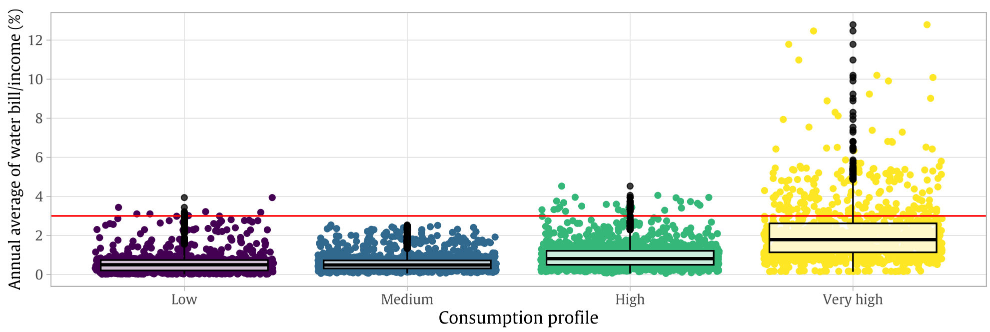

Figure 6. Boxplot and point dispersion graph representing the distribution of the yearly mean bill and income relationship in %. The red line is the 3% chosen as the value which triggers households to save water.

2.2.2. Scenarios

Water price increases were taken into account in the scenarios, with preservation of the current tariff structure. These increases (as percentages) affected peak, non-peak and overconsumption prices equally. Fixed charges and wastewater collection and treatment costs remained constant, as the focus of the study was the evaluation of the price elasticity of water demand. Water price increases ranged from 5% to 100% in 5% increments. No other policy was implemented in the scenarios.

2.2.3. Simulation Scenarios

Twenty-one simulations were run with the model in NetLogo [46]. The base scenario was run with the base water price, and this price was increased incrementally until it had been increased by 100%. The data, output in comma-separated values format, included the household identifier, commune, consumption profile, behaviour profile, income and monthly consumption and bill. The data files were combined to obtain results using the tidyverse R package [47] with R Statistical Software ([48]; v4.2.2) in RStudio ([49]; v2022.7.2.576).

3. Results and Discussion

Water consumption in the 21 simulated scenarios for the four household profiles is shown in Figure 7. Overall, the number of days per month affected the average water consumption; this effect was more pronounced for low and medium consumers and in February. For the high and very high consumption profiles, monthly water consumption differed notably between the peak and non-peak periods due to significant outdoor water use. For example, the average monthly water consumption for very high consumers in the base scenario during the peak and non-peak periods was 115.0 and 84.7 m^3, respectively. This pattern was not observed for the low and medium consumption profiles, for whom most water uses are indoor. Whereas water consumption decreased with increasing water price, the consumption pattern throughout the year remained constant for the four household profiles (Figure 7). Hence, the price elasticity for water demand was estimated based on annual estimates (Table 6).

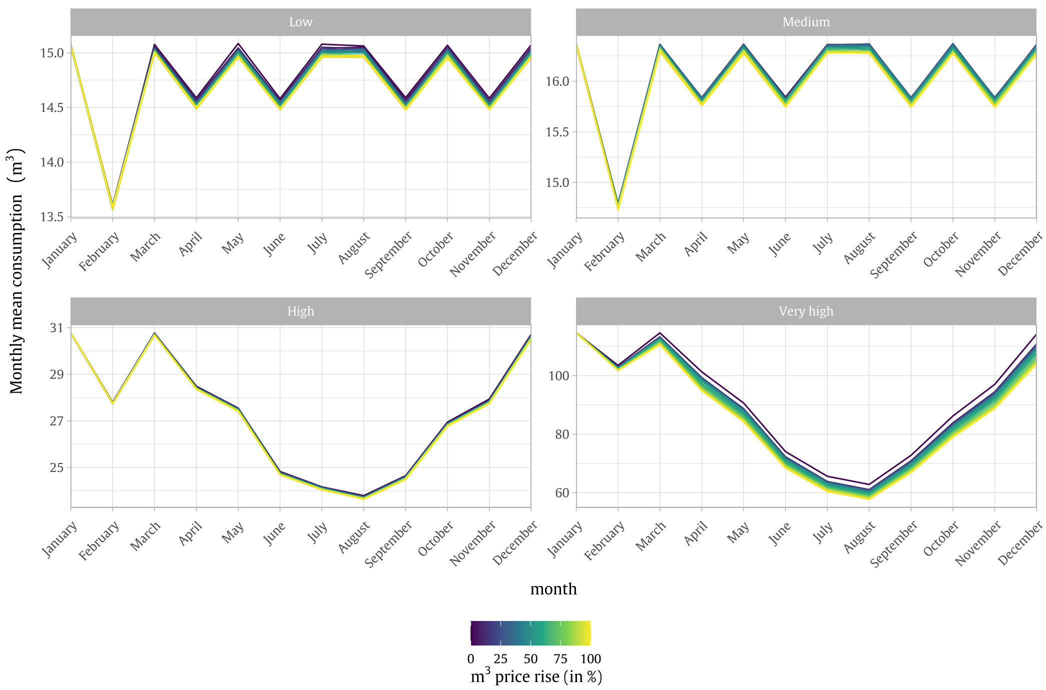

Figure 7. Monthly average water consumption for each consumer profile and 5% price rise. Note the difference in the *Y* axis scale.

The price elasticity for domestic water demand was estimated for each water consumption profile and for the 20 simulated scenarios with water price increases using Equation (1), with computation of the average yearly water consumption. The use of the agent-based modelling approach allowed us to estimate this price elasticity by consumer profile (Table 6 and Figure 8) and behaviour profile (Table 7) (Price elasticity estimates for each individual agent are shown in the Supplemental Material). Average elasticity values from the 20 scenarios ranged from −0.0016 for medium consumers to −0.1007 for very high consumers. The finding of the least elasticity for medium consumers may seem unexpected but can be attributed to the singularity of the bill–income relationship value distribution for this profile; all values, even outliers, are below 3% (Figure 6). This factor, combined with the mostly indoor nature of water consumption, leads this group to have the most inelasticity. Nevertheless, the estimated price elasticity for low, medium and high water consumers was quite similar, whereas that for very high consumers was an order of magnitude greater. The very high consumer profile was defined by the consumption of more than 40 m^3 water/month, but the average consumption for this profile ranged from 60 to 115 m^3 water/month (Figure 7). Thus, this group of consumers has the greatest potential to save water and therefore the greatest price elasticity.

Table 6. Price elasticity for water demand for each consumer profile and its weighted average.

Price Rise	Consumer Profiles				Weighted Average
	Low	Medium	High	Very High	
5	−0.0262	−0.0042	−0.0262	−0.4289	−**0.1036**
10	−0.0105	0.0009	−0.0114	−0.2168	−**0.0504**
15	−0.0118	−0.0007	−0.0111	−0.1460	−**0.0363**
20	−0.0091	−0.0003	−0.0080	−0.1144	−**0.0281**
25	−0.0067	−0.0005	−0.0085	−0.1010	−**0.0251**
30	−0.0066	0.0010	−0.0068	−0.0846	−**0.0207**
35	−0.0057	−0.0013	−0.0063	−0.0779	−**0.0197**
40	−0.0050	−0.0010	−0.0062	−0.0699	−**0.0177**
45	−0.0040	−0.0010	−0.0055	−0.0648	−**0.0163**
50	−0.0044	−0.0019	−0.0059	−0.0612	−**0.0160**
55	−0.0046	−0.0021	−0.0056	−0.0613	−**0.0160**
60	−0.0047	−0.0020	−0.0053	−0.0632	−**0.0163**
65	−0.0051	−0.0021	−0.0055	−0.0661	−**0.0170**
70	−0.0044	−0.0024	−0.0055	−0.0686	−**0.0175**
75	−0.0041	−0.0025	−0.0052	−0.0654	−**0.0167**
80	−0.0042	−0.0028	−0.0047	−0.0678	−**0.0172**
85	−0.0040	−0.0022	−0.0049	−0.0647	−**0.0164**
90	−0.0041	−0.0024	−0.0049	−0.0648	−**0.0165**
95	−0.0044	−0.0023	−0.0052	−0.0638	−**0.0164**
100	−0.0037	−0.0025	−0.0048	−0.0625	−**0.0159**
Average	−**0.0067**	−**0.0016**	−**0.0074**	−**0.1007**	−**0.0250**

The weighted average price elasticity for the four consumption profiles ranged from −0.0159 to −0.1036 (mean, −0.0250; Table 6). As all values have an absolute value between 0 and 1, the water demand was inelastic. This issue was observed for all water consumers and the 20 simulated price increases. These results indicate that water affordability was not a major issue in this case study, which is in agreement with only 4.6% of customers in the Metropolitan Region of Santiago needing subsidy to pay for drinking water [50] (p. 64). Figure 8 shows the variation in the estimated price elasticity for water demand with increasing price. For low, medium and high water consumers, the price elasticity was so low that the price increases had very little influence. For very high water consumers, in contrast, price increases of up to approximately 60% influenced elasticity, with no change observed for larger increases. The aggregation of the four water consumption profiles revealed that price elasticity remained constant from a water price increase of approximately 40%

onward. The price elasticity trends shown in Figure 8 are very relevant from a policy perspective, as they indicate that water price increases exceeding 40% have no additional effect on the reduction of water consumption. Thus, water companies requiring additional reductions in water demand need to implement other measures. Moreover, our results show that the greatest changes in water consumption occur with price increases of 5–25%; increases beyond this range lead consumers to pay more and more with smaller variations in consumption (Figure 8).

Among behaviour profiles, households that changed devices and habits had the greatest price elasticity (mean, −0.0450; Table 7), as expected from a theoretical perspective. The elasticity estimates indicated that habit changes played a more essential role in reducing water consumption than did device replacement. As expected theoretically, price elasticity estimates for the 'no-change' group were close to zero and associated with the random conditions imposed in the ABM. The average price elasticity for the four behaviour profiles ranged from −0.0159 for a 100% price increase to −0.1036 for a 5% increase. The influence of price increases on the estimated elasticity followed the same trend as that represented in Figure 8.

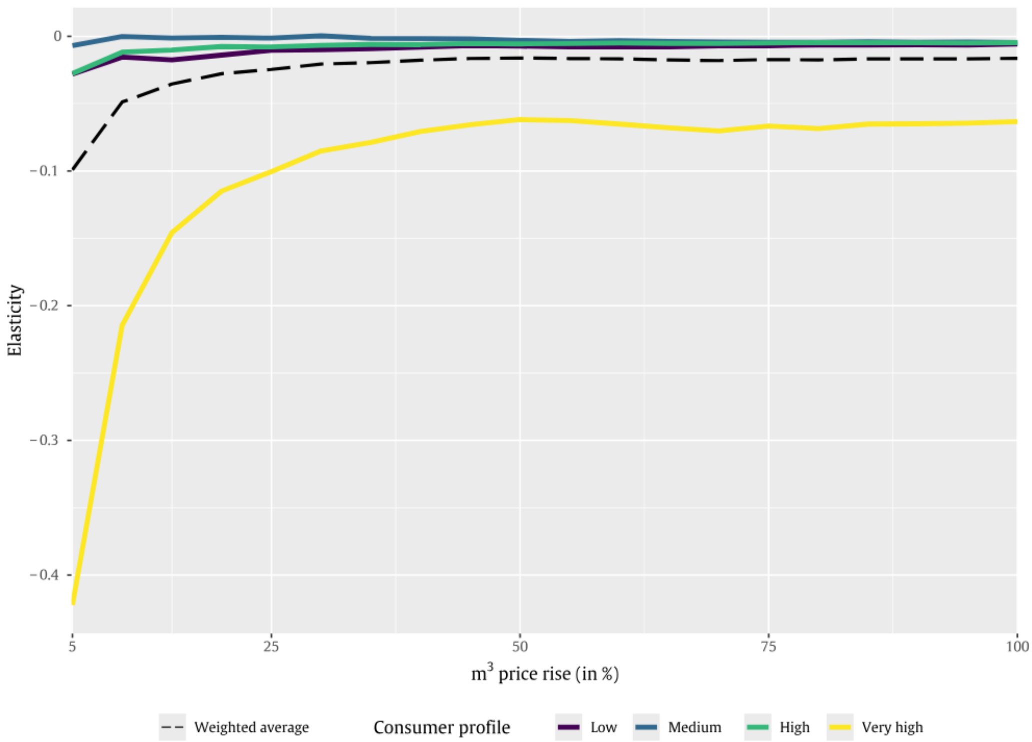

Figure 8. Elasticity variation in all different price rise simulated.

Regardless of the consumption profile, behaviour profile and water price increase, all estimated price elasticity values have an absolute value between 0 and 1, indicating that the residential water demand was inelastic to price changes in the case study. In other words, the percentage change in water demand is smaller than that in price. The estimated price elasticity ranged from −0.0159 to −0.1036 (mean −0.0250), meaning that a 1% water price increase reduced demand by 0.0250%. The price elasticity estimates obtained with the ABM are consistent with previously reported estimates for residential water demand obtained using traditional methodological approaches, such as econometric regression. A review of scientific articles published internationally from 1974 to 2023 yielded average price elasticity values of −0.030 to −1.160 and showed that the price elasticity for residential water demand depended mainly on local water use and socio-economic conditions [8]. In two studies conducted in Chile, estimated price elasticity values for residential water demand were determined to be –0.080 using a log-log functional form in a regression analysis [51] and between −0.069 and −0.542 for the city of Concepción using different aggregation levels [41].

Table 7. Elasticity value for behavioural profile and its average.

Price Rise	Behaviour Profiles				Average
	1: Devices Change	**2: Habits Change**	**3: Devices and Habits Change**	**4: No Changes**	
5	−0.0043	−0.1894	−0.2255	0.0046	**−0.1036**
10	−0.0015	−0.0944	−0.1084	0.0025	**−0.0504**
15	−0.0052	−0.0681	−0.0702	−0.0015	**−0.0363**
20	−0.0033	−0.0544	−0.0549	0.0002	**−0.0281**
25	−0.0051	−0.0486	−0.0466	−0.0001	**−0.0251**
30	−0.0029	−0.0408	−0.0385	−0.0005	**−0.0207**
35	−0.0057	−0.0360	−0.0364	−0.0005	**−0.0197**
40	−0.0071	−0.0322	−0.0315	−0.0001	**−0.0177**
45	−0.0063	−0.0311	−0.0282	0.0005	**−0.0163**
50	−0.0070	−0.0298	−0.0269	−0.0002	**−0.0160**
55	−0.0084	−0.0293	−0.0267	0.0004	**−0.0160**
60	−0.0135	−0.0261	−0.0253	−0.0002	**−0.0163**
65	−0.0161	−0.0269	−0.0249	−0.0001	**−0.0170**
70	−0.0209	−0.0250	−0.0244	0.0001	**−0.0175**
75	−0.0206	−0.0236	−0.0226	−0.0002	**−0.0167**
80	−0.0215	−0.0238	−0.0235	0.0000	**−0.0172**
85	−0.0223	−0.0232	−0.0205	0.0002	**−0.0164**
90	−0.0220	−0.0224	−0.0216	−0.0000	**−0.0165**
95	−0.0222	−0.0219	−0.0216	0.0000	**−0.0164**
100	−0.0221	−0.0209	−0.0208	−0.0000	**−0.0159**
Average	**−0.0119**	**−0.0434**	**−0.0450**	**0.0003**	**−0.0250**

In this context, we emphasise that agent-based modelling should not be viewed as a method of obtaining exact results or conducting precise forecasting. Rather, its strength lies in the ease of obtaining a better understanding of the studied phenomena [32,52]. It would be also needed to account with complementary methodologies addressing other important sources of water consumption, namely industry [53] and agriculture [54], shich suppose 20% and 70%, respectively, of the overall consumption in the world [55]. In the present study, the expected price-demand elasticity with increasing water price and the various interactions and relationships among different household profiles were explored. More robust results and understanding of how and why consumers act could be obtained with better definitions of consumer profiles and behaviours. The use of value-driven agents, for example, could increase the diversity of consumer representation, with more goals, actions and triggers guiding their behaviour [56,57]. The data needed to achieve these improvements could be gathered through surveys; the case specificity could be increased without requiring historical data, although such approaches increase ABM complexity. Thus, modellers need to conduct cost–benefit analyses to assess whether greater complexity is compensated by significantly better results.

4. Conclusions

Climate change, population growth and urbanisation are imposing new challenges in the management of water resources, including the decreased availability of water for human consumption. Water pricing is an economic incentive traditionally used to reduce domestic water demand, but its effective modulation requires an understanding of the extent to which water demand decreases with increasing prices (i.e., price elasticity). This topic has been examined in econometric analyses, in which price elasticity estimation is based on statistical data on water prices, consumption and other variables. Thus, in the absence of reliable cross-sectional and time-series data, this methodological approach has notable limitations.

As an alternative approach, we propose the use of ABMs to estimate price elasticity for residential water demand. Positive features of this approach include: (i) the lack of need for long-range historical data on water prices and consumption, and the ability to estimate price elasticity (ii) for different consumer and behaviour profiles and (iii) under multiple price change scenarios. In other words, a detailed understanding of the obtained price elasticity estimates can be gained. Nevertheless, ABMs do not provide exact values. The deepening of user behavioural profile definition, distribution and relationships with other variables would be needed to obtain more trustworthy results. In this sense, fully developed ABMs are very case specific.

To demonstrate the potential use of agent-based modelling for the estimation of the price elasticity of water demand, we performed an empirical application of the model to a residential area in Chile. Households were categorised using several consumer and behaviour profiles, and water price increases from 5% to 100% of the actual residential water price were simulated. The price elasticity estimates ranged from −0.0159 to −0.1036 (mean −0.0250), consistent with previous findings. Thus, water regulators can use ABM-derived price elasticity estimates to support decision making on strategic water-pricing policies, such as price increases to reduce water demand or changes from a volumetric uniform water tariff to an increasing block tariff. To assess the effectiveness of water pricing policies ex ante, estimates of the price elasticity of water demand are needed and ABMs are useful tools for obtaining them.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w16172501/s1, Table S1: Total number of household types distributed by communes; Table S2: Number of households types not sharing the same location in each commune; Table S3: *Aguas Cordillera* water tariff scheme; Table S4: Water consumption for different water uses in Chile, SISS (Superintendencia de Servicios Sanitarios) [44]; Figure S1: Dot chart representing each individual household (specifying their consumption and behaviour profiles) calculated elasticity for every simulated price rise. With the aim to ease graph interpretation some random noise has been added on the x-axis values.

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Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent-Based Model
ODD Protocol	Overview, Design concepts and Details Protocol
SISS	*Superintendencia de Servicios Sanitarios*
CASEN	*Caracterización Socioeconómica Nacional*

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