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From mathematical models to policy design: predicting greywater reuse scheme effectiveness and water reclamation benefits based on individuals' preferences

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ABSTRACT

The residential reuse of greywater has attracted interest in recent years as a strategy to face water security problems. Nowadays, some cities such as Santiago de Chile are seeking to promote new laws that allow residential greywater reuse and make the incorporation of the necessary infrastructure (machinery and a parallel pipe system) mandatory for new buildings. The success of any such schemes, in terms of the amount of mains water that can be saved, is clearly influenced by the decision that individual consumers make on whether or not to use the parallel system, as they will also be the ones to face the potential externalities produced by the system (e.g., odours, noise from technology). Understanding and anticipating the behaviour of individuals is not an easy task, especially in the context of systems not yet widely implemented, but the groundwork has been laid with the application of approaches that allow analysts to determine the heterogeneity in consumer preferences based on the qualities of the product or service. However, there has been a lack of focus on making predictions that quantify the impact of acceptability on the volume of water recovered, driven in part by methods that been applied. This paper presents a way of predicting policy effectiveness and potential greywater reclaim benefits based on individuals' preferences. For this, we use two existing models that allow us to make predictions of greywater reuse for different domestic purposes. In a case study application to the city of Santiago de Chile, we carry out scenario tests to predict the potential uptake under potential future policy settings and show how allowing for an additional permitted use of greywater could save several hundred litres of water per month per household.

Keywords: greywater reuse; water reuse policies; prediction of greywater reclamation; stated preference; choice modelling

1. INTRODUCTION

A sufficient and reliable supply of water is crucial to the health and wellbeing of people. In this context, one such approach receiving increased attention is the reuse of greywater, which involves storage and recycling of water previously used for hand washing, bathing, or laundry. Reusing treated greywater reduces the requirement for high quality treated water from the mains distribution systems for activities such as toilet flushing and garden irrigation. Greywater does not contain faeces, food residues, oil and fats, making it easier to treat (Lambert and Lee, 2018), and there are now technologies to treat greywater for non-consumptive (e.g. through biological treatments) or consumptive activities (e.g. through biological processes combined with solids separation, filtration and disinfection practices) that can be deployed *in-situ* in households (Fountoulakis et al., 2016; Jefferson et al., 2004; Li et al., 2009; Wu, 2019).

The implementation of greywater reuse schemes in Australia, California, India, Singapore, Spain and areas of South Africa, has revealed that treated greywater reuse in cities can provide clear environmental benefits and improve water security (Wilcox, Nasiri, Bell, & Rahaman, 2016). These schemes have shown that the reduction in the demand for water from the mains system can range from 30% to 80%. This wide range is attributed to two factors. First, regulatory restrictions will limit the allowed uses for public health reasons. Second, the amount of water that can be saved depends on consumer preferences (i.e., whether people are actually willing to reuse greywater if allowed). There is evidence that this willingness is heterogeneous among individuals (Ilemobade et al., 2013; Wester et al., 2015), that is, two people may perceive reusing water differently, which directly impacts the potential uptake of greywater reuse and therefore, the success of management measures (Lefebvre, 2018; Muthukumaran et al., 2011; Subramanian et al., 2020; Roshan and Kumar, 2020; Vuppaladadiyam et al., 2019).

Deployment and uptake of greywater reuse must be enabled by appropriate laws and policies, and the above discussion suggests that successful laws and policies need to consider the role of end user preferences. The ideal way of understanding user's uptake of greywater reuse would clearly be to acquire this knowledge from evidence based on real-world policy schemes.

However, in cities that are starting to allow residential water reuse, much time and money would be required for the implementation and monitoring of pilot practices (Wanjiru and Xia, 2018), and this has made basing regulations on the results of practices of other locations an appealing solution. While the implementation and use of greywater reuse systems elsewhere is a key input for cities that want to integrate greywater reuse as part of their supply sources, the direct transfer of policies and regulations could lead to unsuccessful outcomes due to differences between areas (Ormerod et al., 2019). Indeed, as with any innovation, the extent to which practices of greywater reuse is transferable between cities is unclear (Wester and Broad, 2021).

Until now, insights into individuals' responses to water reuse schemes have been based on social and psychological interpretations of the individual (Dolnicar et al., 2011; Fielding et al., 2019; Goodwin, Raffin et al., 2018; Hartley, 2006). Different approaches can be used to understand these public responses towards reuse (Smith et al., 2018), such as methods based on the *theory of planned behaviour* (Ajzen, 1985), *random utility models* (Domencich and McFadden, 1975), statistical analysis, for example using *Statistical Package for the Social Sciences* SPSS (see some aplications in Buyukkamaci and Alkan, 2013; Gu et al., 2015). In addition, there has been interest in approaches that are more focused on guiding and monitoring behaviour change, such as the Focus, Opportunity, Ability, and Motivation (FOAM) that aims to understand who is the target audience and what is the desired behaviour (Coombes and Devine, 2010).

The most valuable cross-disciplinary insights that these methodologies can bring to the field of water reuse is that they have highlighted that consumer preferences, and thus acceptability, a key element in the success of any policy, can be linked to different factors such as mental, physical and/or cultural associations (Hurlimann and Dolnicar, 2016; Mankad and Tapsuwan, 2011; Wester and Broad, 2021;Stithou et al., 2012), and can vary by geographic location (Ormerod et al., 2019; Beveridge et al., 2017; Budziński et al., 2018; Czajkowski et al., 2017). These studies have also provided guidance and allowed to monitor behaviour change (Aldirawi et al., 2019; Coombes and Devine, 2010). However, although the identification of the most promising *target audience* for new schemes is a very important step, many of these studies do not make the transition from the academic field to the real world for policy design. Specifically, there is a gap in using these methods to make forecasts or evaluate the pre-implementation feasibility of measures in terms of designing policies and regulations for cities without widespread current greywater reuse. Importantly, the ability to do so depends not just on the interest of the analyst, but on the analytic approach used for uncovering preferences.

In this paper, we make use of the insights from such past work, but with a particular focus on using the results from consumer preference studies in making predictions of the potential effectiveness of different policy schemes. Our attention is focussed on areas where greywater reuse is not a widely implemented practice, where this study considers the scenario of a city, Santiago de Chile, where the residential reuse of greywater is legally permitted (Law 21,075 of 2018) for two uses, toilet flushing and garden irrigation, but as yet there are no official technical regulations supporting the actual implementation of the law. We propose an integrated framework to build bridges between theory and practice, taking quantitative results from modelling work that measures the impact of both quantitative and qualitative variables on potential uptake, and using them for policy evaluation through scenario testing. This final component is often a key missing step in academic work on consumer behaviour.

The integrated assessment framework suggested in this work focuses on five objectives (described later) that seek to understand individual water reuse preferences based on knowledge of *who* makes decisions about greywater consumption and *why, where* specific decisions are reached, *how much* these are likely to impact on water consumption, and *what* would happen *if* there were a change in policy or a shift in behaviour. Given that the central objective of this paper is to move from mathematical models to policy design, we rely on the outputs of previously estimated models. In particular, two different model structures belonging to the family of Discrete Choice Models (DCM, cf. Train, 2009) were used in the work providing the inputs to this paper. DCM are mathematical structures that seek to explain the role of product and consumer characteristics in decision making. They have been used in different areas such as environmental assessment (Hoyos et al., 2015), flood impact reduction (Veronesi et al., 2014), water collection systems (Lu et al., 2019), technology (Su et al., 2018), health (Minton et al., 2017) and transport (Ortúzar et al., 2014). These models are grounded in micro-economic theory and are suitable for making predictions of future behaviour (Ortúzar and Willumsen, 2011 Chapters 3, 7, 8 and 9, Hess and Daly, 2014), yet also allow for the inclusion of psychological features (Hess et al., 2018).

While the two models used in this paper differ in their structure and approach, they both share the key aim of capturing heterogeneity in preferences across consumers. The first, reported in Amaris et al. (2021a), is a latent class (LC) model used to identify segments in the population with different behaviour/preferences according to their sensitivities to changes in the greywater service. The second, reported in Amaris et al. (2021b), is a hybrid choice (HC) model used to capture the heterogeneity in preferences, based on individual characteristics and psychological constructs towards greywater. It is important to highlight that much of the work in this area makes use of experimental techniques rather than "real world" decisions, especially for choices involving new products and/or services. The same applies when seeking to understand the response to characteristics that are difficult or impossible to measure in real choices, such as risk, or characteristics with insufficient real-world variation to capture changes in behaviour, such as key qualitative attributes like noise and smell.

Alongside the specific geographic setting and application context addressed in this paper, the work presents a general illustration of how results from such studies can be further processed. This can provide insights into the potential impact of changes in sensitivities and attitudes, as well as public policies in urban environments, motivating strategies that integrate social and economic components, as well as technical ones. This work should facilitate the transition of methodological work from academia into real-world practice, aimed at developing approaches to motivate the implementation of residential greywater reuse as a water management strategy. Additionally, we use this analysis to assess the potential effectiveness of the current greywater laws, contrast them with alternative rules, and thus determine the potential of the city to implement a new parallel integrated system of greywater and drinking water.

2. CASE STUDY FOR SANTIAGO DE CHILE

The study area is Santiago (Chile), a large city with no prior experience with residential greywater reuse, but where a new law requires collection, reuse and disposal of greywater in new properties (Law 21,075 of 2018). Santiago is an urban area located in the Metropolitan Region of Chile which covers an area of 641.4 km^2 and is administratively divided into 37 municipalities (Figure 1).

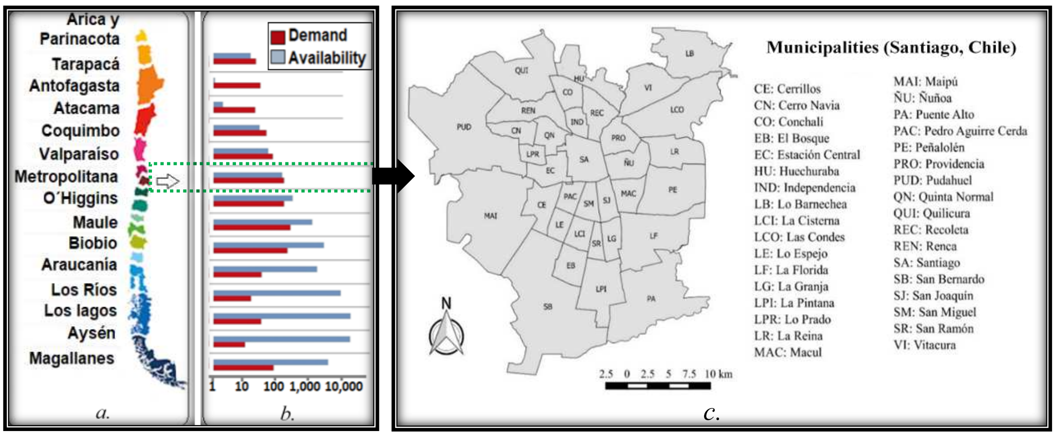


Figure 1. Study area.
a. Chile by Regions; b. Streamflow m^3/s; c. Municipalities

There are three reasons to use Santiago as a case study; it is an area with i) water security risks, ii) a growing and changing population, and iii) residential greywater reuse is allowed by law and mandatory for new buildings. A more detailed description of each one is presented below:

(i) Water security risks.

The potable water supply comes predominantly from the *Maipo River*, supported by the *Mapocho River*, the *Yeso reservoir* and some groundwater wells (Meza et al., 2014). Almost 90% of the population receives its water supply and sewage services from a private company called *Aguas Andinas*. Currently, residential water demand per capita averages 150 l/day, but can be as high as 600 l/day in some neighbourhoods, depending on the presence and size of gardens (Bonelli et al., 2014). Water losses due to pipe leaks in the mains water system are around 30% (Aguas Andinas, 2019).

The *Metropolitan* Region has severe water deficit problems and is predicted to become the area with the highest deficit in Chile by 2025 (Valdés-Pineda et al., 2014), with periods between one to four weeks of very low flows (Vicuña et al., 2018). In 2014, for example, 102 districts across Chile declared a state of water emergency for four consecutive years because of droughts (Fundación Chile - FCH, 2017; Ministerio del Interior y Seguridad Publica, 2014). Despite the efforts of *Aguas Andinas* to strengthen the main drinking water system, it continues to be fragile in the face of significant threats due to climate variability, climate change and population growth (Vicuña et al., 2018).

(ii) A growing and changing population.

Approximately 40.5% of the Chilean population lives in the Metropolitan Region, and the large majority of these people (93%) live inside the urban area. The overall population is growing, although the rate is low (1%), and socio-demographic characteristics such as age and family composition are changing. Furthermore, the growth of private homes between 2002-2017 in the Metropolitan Region was 44.9%, while increaseing population density has led to 8% of households having five or more inhabitants per room, and are considered to be critically overcrowded (INE, 2018).

(iii) Regulation to allow greywater reuse.

Given the extent and severity of the 2014 drought in Chile, Law 21,075 was published in 2018 to allow for the regulation, collection and reuse of greywater in urban and rural areas of the *Metropolitana* Region. The law has three key components.

- It sets out the requirements to request authorization for the operation of a greywater system.
- It determines which urban uses are permitted (sanitary devices and garden irrigation - Article 8), and which are not permitted (human consumption, swimming pools, or any other use that the health authority considers risky for health - Article 9). The permitted uses require prior approval, and depending on this, the authorities are required to establish the quality that the water should have according to the projected use. The owner is required to meet certain quality levels for the requested use and, in turn, is responsible for the operation and maintenance of the technology (Article 12).
- It sets out the mandatory installation of greywater reuse systems for new buildings.

This final point, especially, is a key motivation for research looking at the potential future uptake of treated greywater reuse by consumers, given the anticipated widespread future availability of the technology in dwellings.

3. METHODS AND DATA

3.1.Integrated assessment framework

In this study, we illustrate a multi-component assessment framework to analyse residential greywater reuse preferences and use empirical results to develop policy insights. In particular, we rely on mathematical models that can be used to understand and predict consumer decisions for real-world applications and illustrate how they offer valuable information for policymaking in cities that have no previous experience with greywater reuse.

The integrated assessment framework suggested focuses on five objectives that seek to understand individual water reuse. The first two objectives relate to understanding ***who*** makes specific decisions on greywater reuse, and ***why*** these decisions are reached, by seeking to understand the influence of consumer and service characteristics. The third objective is concerned with understanding ***where*** specific decisions are reached (i.e., studying the influence of geographic differences on preferences). The fourth objective looks at ***how much*** impact greywater reuse could have, that is, seeking to understand the quantitative impact (volume of water) of allowing the greywater reuse for different residential uses, considering users' preferences, and also understanding the potential impact of different policies on behaviour through scenario testing. Finally, the fifth objective looks at ***what*** would happen ***if*** there is behavioural adaptation and/or changes in policies. We hypothesise that once these questions are answered, it should be possible to create insights for policy knowing in advance the possible effectiveness of the measures in terms of highest willingness to use, and thus expected water demand reduction.

The framework comprises:

a) **Step 1**: collect data on end-user uptake, either from existing experiences or hypothetical settings (carefully design and with bases on real experiences);

b) **Step 2:** develop models that allows to quantify the willingness to reuse greywater and heterogeneity therein (*Who and why*);

c) **Step 3:** explore individual preferences and heterogeneity, including geographic differences expand the results from the sample level to the local population level (*Where*); and

d) **Step 4:** use the models to predict behaviour in potential future scenarios, including the effect of policy interventions and various management strategies (*What if*).

While each individual methodological step is not *novel*, their integration is, especially with a view to making the transition from modelling to practice (i.e., step 4 above).

It is important clarify that in many cases, including in the present paper, steps 1 and 2 may draw from previous studies (i.e., using previously collected data and mathematical models that have been estimated before to identify the *who* and *why* of preferences in relation to greywater reuse). The interrelation between objectives in this framework are shown in Figure 2.

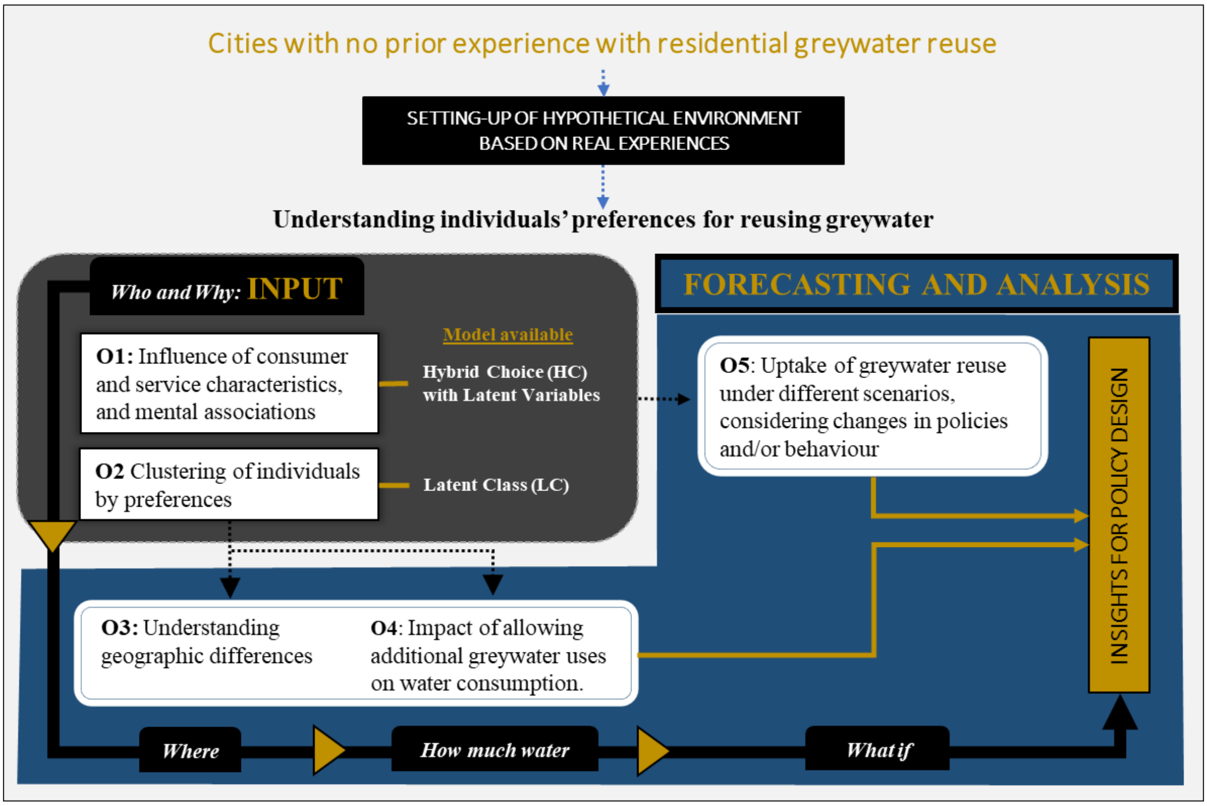


Figure 2. Integrated assessment framework for understanding the potential effectiveness of greywater reuse policies within a city.

3.2. Data

For this study, we are reusing data from a stated choice survey designed to gather information to understand quantitatively how the willingness to reuse residential greywater depends on qualitative (i.e., colour, odour, uses) and quantitative attributes (i.e., water savings) of greywater after treatment. A specific advantage of such data is that it allows us to test how this willingness varies as a function of characteristics of the individuals, their attitudes, and their sensibilities to changes in the greywater appearance and its intended uses (Amaris, et al., 2020). The final data contains information from 510 households covering 29 of the 37 municipalities of Santiago. The key components of the database used in this paper concern:

- **Characterization of dwelling and household:** 15 questions related to the number of household members, their socioeconomic characteristics and their dwelling facilities (e.g., age, gender, house size, presence of garden and coverage percentage, kind of coverage – grass or another kind of vegetation).

- **Greywater reuse:** six questions with predefined possible answers/ratings were asked to gather information related to respondents' attitudes (e.g., reactions to the concept of greywater reuse, confidence in a greywater reuse system).
- **Perceptual indicators:** six attitudinal questions were used to capture differences in attitudes across respondents: "*Water protection will provide a better world for me and for my family*", "*Water and the environment must be protected for the well-being of the entire population*", "*We should be more concerned with protecting water than with economic growth*", "*Everyone can contribute by saving water*", "*The claims that there is a drought are exaggerated*", and "*If the government does not take care of water problems, why should I?*". Responses were captured on a 5 point Likert scale.
- **Stated choice survey:** six different hypothetical choice scenarios, where each participant had to choose between reusing greywater or not reusing greywater, according to the appearance of water, savings and uses.

All this information is fundamental for the analysis of policies. However, the stated choice analysis is at the heart of this study. In what follows, we describe the most relevant information about the experimental design and the variables that were considered.

To understand and quantify the potential demand for greywater reuse in urban settings where that practice is not widely implemented, it is necessary to i) collect information about consumer behaviour with an instrument specifically designed for that purpose and then ii) develop a model to explain users' preferences. As a next stage, that model can be used to predict demand under varying scenarios.

Data on consumer decisions is the basis for modelling, and therefore the design of the data collection tool (usually surveys) must be carried out with utmost care. The information collected by the survey can be obtained either from what decision-makers have been observed to choose in real-world settings (Revealed Preference), or what they say they would do in hypothetical settings (Stated Preference, generally in the form of Stated Choice amongst mutually exclusive options, Louviere et al., 2000). Given that greywater reuse is not a common practice in Santiago, the second technique better fits the objectives of this study.

The Stated Choice (SC) survey starts by showing the respondent a hypothetical environment as a <u>*baseline*</u>, which is later used as the basis for different <u>*choice tasks*</u> (see Figure 3).

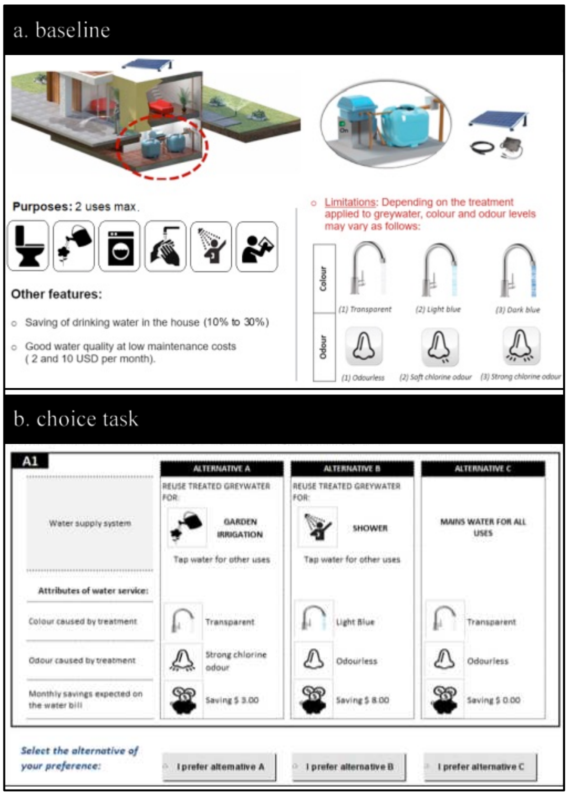


Figure 3. Stated choice example

<u>*Baseline*</u>: The baseline assumption given to the study participants was that the greywater reuse technology would deliver the highest water quality standards (Figure 3a). Hydro4 (see

Appendix A) was used as an indicative technology - it is as easy to use as a domestic appliance (e.g., washing machine), and, as it is solar powered, it does not add to the energy bill. However, and crucially for the hypothetical choice scenarios, the colour and odour of the treated water could vary (and differ from mains water) as a result of the treatment. This is consistent with residential greywater reuse around the world (Domnech and Saurí, 2010; Ilemobade et al., 2013; Wester, et al., 2016).

<u>*Choice tasks:*</u>

The technique used here is known as *stated preference elicitation*, where each respondent faces a set of scenarios (Figure 3b. stated choice example) in which a choice must be made between mutually exclusive alternatives. Participants could see and evaluate the characteristics of greywater after treatment (colour and odour) and the water savings (monetised) that they would obtain if they reused water for a specific residential use. The survey considered six possible uses: garden irrigation, toilet flushing, laundry, washing hands, shower and drinking. Each alternative in the survey considered treated greywater for one use only (with mains water for all other uses). Each of these characteristics were based on real experiences in Spain, South Africa and the USA (Domnech and Saurí, 2010; Ilemobade et al., 2013; Wester et al., 2016), and are described in more detail by Amaris et al. (2020).

As mentioned before, each respondent faced a set of six choice situations, with the alternatives varying between scenarios. The different alternatives presented in the tasks were produced by an experimental design that allows the combination of the different levels of each attribute. Table 1 shows the levels used for this study, where full details on the experimental design and survey can be found in Amaris et al. (2020).

Table 1. Attributes and levels. Source: Amaris et al., (2020)

	Attributes			
	colour	**odour of chlorine**	**Savings***	**Uses**
levels	Transparent	odourless	10%	garden irrigation
	light blue	light	20%	toilet flushing
	dark blue	strong	30%	laundry
	-	-	-	washing hands
	-	-	-	shower
	-	-	-	drinking

*expected savings on water bill

3.3. Behavioural models

3.3.1. *Overview*

The models used in this study belong to the DCM family, which seek to explain how individuals make different choices as a function of changes in the characteristics that describe the product or service they are faced with, in our case through the choice scenarios in the SC survey. We specifically rely on Random Utility Maximisation (RUM) structures, which explain choices under the assumption that consumers maximize the "utility" or benefit they receive by choosing a particular alternative. This utility is based on the characteristics or attributes that define the alternative and the sensitivities of the user towards them (Ortúzar and Willumsen, 2011, Chapters 7–9; Train, 2009; Hess and Daly, 2014). Characteristics that describe the good/service can be desirable or undesirable for the respondent, and according to their perception, they will choose the option that provides the highest utility or benefit. As the process of utility formation is not observed by the analyst, the models incorporate a random component and the choices become probabilistic (Train, 2009).

To better understand the concepts, in simple terms, imagine an individual having two options, where option 1 is to reuse water that is transparent and odourless, in return for a 10% savings in the water bill, while option 2 is to use the mains supply system and not get any savings. If we observe this individual choosing option 1, we can assume that this person feels greater satisfaction or utility by maintaining a reasonable level of service and obtaining an extra monetary benefit. Now imagine that the same individual is asked to choose an alternative a second time, but under different conditions of the greywater service, where the treated water now has dark colour and a strong smell of chlorine but would lead to a saving of 20% in the water bill. If we now observe the person to choose option 2, and reject the greywater option, we can assume that the individual's utility decreases due to their perception of what a good quality of service means, and that the increase in savings was insufficient to motivate greywater reuse. Returning to the earlier point about heterogeneity in preferences, a second individual presented with the same options could choose differently (e.g., always option 2), reflecting their different individual tastes.

A discrete choice model seeks to explain the above process by estimating parameters that explain the impact of the attributes of the available alternatives and the characteristics of the decision maker in the choices observed in a specific sample. In particular, let $x_{n,t}$ be a vector containing the attributes describing the different alternatives as faced by decision maker *n* in choice situation t (for example colour and odour), with $Y_{n,t}$ giving the observed choice for individual *n* in situation t. The model thus takes the broad form of:

$$Y_{n,t} = f(x_{n,t}, \Omega) \tag{1}$$

where Ω is a vector grouping together the parameters estimated for the model, and $f()$ is the functional form of the model, including its error structure. While in regression, $Y_{n,t}$ would be continuous, in a discrete choice context, the dependent variable can take on a few mutually exclusive discrete outcomes (in our case 1, 2 and 3, given the three alternatives in the data). Each of these outcomes has a probability between 0 and 1, and the probabilities sum to 1 across alternatives. As explained above, we make use of the notion of utility maximisation, where each alternative has a given *utility* for an individual that is a function of the attributes of that alternative and the sensitivities of the individual. The individuals choose the option that gives them the greatest utility. Notwithstanding extensions to non-linear specifications, the utility for a given alternative (say i) is typically given as a linear in attributes specification, such that:

$$V_{i,n,t} = \beta_n{}' x_{i,n,t} = \sum_{k=1}^{K} \beta_{n,k} x_{i,n,t,k} \tag{2}$$

In this notation, $x_{i,n,t,k}$ is a specific attribute (the k^{th} attribute out of K) of alternative i, as seen by person n in choice situation t. The parameter $\beta_{n,k}$ captures the marginal utility for person n in response to this attribute. Imagine, for example, that attribute k relates to the savings in the water bill. Then we would expect that $\beta_{n,k}$ is positive (i.e., that, as the level of savings of a greywater alternative increases, so does its utility). The subscript n on $\beta_{n,k}$ reflects the fact that different individuals may have different sensitivities to changes in the attributes, as explained earlier. In practice, it is impossible to estimate separate parameters for each individual, and such heterogeneity is accommodated through estimating interactions between sensitivities and consumer characteristics (for example different parameters for men and women) and through allowing for additional random heterogeneity, as we will see in later sections.

In the simplest type of random utility model, the Multinomial Logit (MNL) model, which serves as the starting point for what follows, the probability of person n choosing option i in task t is given by:

$$P_{n,t}\left(i \mid x_{n,t}, \Omega \right) = \frac{e^{V_{i,n,t}}}{\sum_{j=1}^{J} e^{V_{j,n,t}}}, \tag{3}$$

where Ω groups together the different model parameters. Returning to the above example of the savings in the water bill ($x_{j,n,t,k}$) increasing for alternative i, this would imply that $V_{i,n,t}$ increases too, and as a result, the probability of person n choosing that option (i.e., reusing greywater), becomes larger. It is clear from Equation (3) that this probability is between 0 and 1 for each alternative, and sums to 1 across alternatives.

The optimal values for the vector of parameters Ω are obtained through maximum likelihood estimation, by finding the values that best explain the choices observed in the data, that is those that maximise the log-likelihood function given by:

$$LL(x, z, \Omega) = \sum_{n=1}^{N} log \prod_{t=1}^{T} P_{n,t}(Y_{n,t} \mid x_{n,t}, \Omega) \quad (4)$$

where the vectors x and z now group together the data for all individuals in the sample. In a *perfect* model, the choice of each person would be explained with certainty, such that $P_{n,t}\left(Y_{n,t} \mid x_{n,t}, \Omega \right) = 1, \forall \mathrm{n}, \mathrm{t}$, and the log-likelihood in Equation (4) would be zero. In reality, choices are difficult to explain and data is noisy, thus the analyst seeks only to find the model that *best* explains the data, while retaining a certain level of error.

In this paper, we reuse the results of two distinct models, with a particular focus on explaining differences in preferences across consumers. A brief overview of the aims of each model structure is given below, with more details on the econometric implementation given in Appendices B and C and the above referenced papers. Before describing the two models, it is important to highlight that both of them are complementary in the sense that both determine an individual's willingness to reuse greywater; the results are consistent by virtue of being based on the same data. However, each model studies behaviour from a different perspective, and this is very useful in evaluating policies that motivate the reuse of greywater.

3.3.2. *Latent Class model (LC)*

The latent class (LC) model was estimated previously by (Amaris et al., 2021a) for the city of Santiago. A LC model probabilistically splits decision-makers into classes with distinct preference patterns. This not only provides important insights into preference patterns in the population but is crucial in predicting how distinct consumer segments may behave in future scenarios. The parameter estimates for the LC model are shown in Table 2.

Table 2. Estimation results for latent class model. Source: Amaris et al., (2021a)

	Class 1		Class 2		Class 3		Class 4	
	Estimate	**Robust t- ratio**	**Estimate**	**Robust t-ratio**	**Estimate**	**Robust t-ratio**	**Estimate**	**Robust t-ratio**
(1) ALTERNATIVE SPECIFIC CONSTANT								
Left alternative[†]	-0.367	-6.39	-0.367	-6.39	-0.367	-6.39	-0.367	-6.39
(2) GREY WATER SERVICE APPEARANCE								
Colour								
… Clear (reference)	0	*reference*	0	*reference*	0	*reference*	0	*reference*
… Light blue	0	n.s.	0	n.s.	0	n.s.	-1.301[‡]	-2.05
… Dark blue	-0.313	-3.13	0	n.s.	-0.619	-5.09	-1.301[‡]	-2.05
Odour								
… Odourless (reference)	0	*reference*	0	*reference*	0	*reference*	0	*reference*
… Light chlorine	-0.169	-1.45	0	n.s.	-0.472	-3.53	0	n.s.
… Strong chlorine	-0.816	-6.48	-11.057	-21.08	-1.032	-6.4	0	n.s.
(3) USES								
0. Mains water (reference)	0	*reference*	0	*reference*	0	*reference*	0	*reference*
1. Toilet flushing	3.963[‡]	6.74	-4.959[‡]	-9.79	0.303[‡]	2.14	5.957[‡]	2.1
… shift for female[†]	0.728	4.26	0.728	4.26	0.728	4.26	0.728	4.26
… shift for previous knowledge[†]	0.375	1.35	0.375	1.35	0.375	1.35	0.375	1.35
2. Garden irrigation	3.963[‡]	6.74	-4.959[‡]	-9.79	0.303[‡]	2.14	5.957[‡]	2.1
3. Clothes washing	3.963[‡]	6.74	-4.959[‡]	-9.79	0.303[‡]	2.14	0	n.s.
… shift for female[†]	0.257	1.75	0.257	1.75	0.257	1.75	0.257	1.75
… shift for previous knowledge[†]	0.448	2.22	0.448	2.22	0.448	2.22	0.448	2.22
4. Hands washing	3.71[‡]	5.98	-4.959[‡]	-9.79	0	n.s.	0	n.s.
… shift for female[†]	0.289	2.05	0.289	2.05	0.289	2.05	0.289	2.05
5. Shower/Tub	3.71[‡]	5.98	-15.29[‡]	-18.02	0	n.s.	0	n.s.
6. Drinking	2.397	3.88	-15.29[‡]	-18.02	-0.82	-3.33	0	n.s.
… shift for female[†]	0.448	2.15	0.448	2.15	0.448	2.15	0.448	2.15
(4) SAVINGS ON WATER BILL								
Low water expenditure group[†]	0.089	4.26	0.089	4.26	0.089	4.26	0.089	4.26
High water expenditure group[†]	0.039	3.39	0.039	3.39	0.039	3.39	0.039	3.39
CLASS ALLOCATION MODEL								
Constant	0	*reference*	-1.574	-3.7	-0.595	-2.41	-8.091	-5.52
Low educational level	0	*reference*	0.723	2.75	0.471	1.79	-1.046	-1.95
Garden	0	*reference*	-0.824	-2.49	0	n.s.	6.771	4.34
House	0	*reference*	1.402	2.98	0	n.s.	0	n.s.
Class weight	40%		24%		30%		6%	

†: parameter shared across classes

‡: parameter shared across multiple uses or multiple levels of categorical attribute

n.s.: parameter constrained to zero after initial estimate was not significantly different from zero

According to the model, individuals can be split into four classes, which according to the specific signs of the coefficients of attributes have been labelled as *"enthusiasts"* (class 1), *"greywater sceptics"* (class 2), *"appearance conscious"* (class 3) *and "water expenditure* *conscious"* (class 4). Note that all coefficients have a statistically significant impact on utility or benefit (at or above the 95% level) and, hence, on the probability of choosing a greywater option. Also note that the magnitude of the different coefficients show that the different attributes of the greywater service exert different weight and influence (positive or negative) on the utility or benefit that the user perceives, which directly affects potential uptake. The model highlights that worse appearance of the water reduces the probability of greywater reuse, while increased savings are beneficial. There are also differences as a function of the intended use of the greywater, where these vary as a function of respondent characteristics.

3.3.3. *Hybrid choice (HC) model with latent variables*

The HC model with latent variables used in this paper was estimated previously by (Amaris et al., 2021b) for the city of Santiago. This type of model incorporates a role for additional psychometric constructs, in this case an attitude towards greywater reuse, which was calibrated using the six attitudinal statements described in section 3.2. As with the LC model in Section 3.4.1, there are specific reasons to adopt this model for the present study, given that psychometric factors are likely to play a major role in determining the success of greywater schemes.

The model coefficients most relevant for the present paper are shown in Table 3 (additional parameters for the measurement model associated with the attitudinal indicators are available in Amaris et al., 2021b). Like the LC model, the HC model shows that worse appearance of the water reduces the probability of greywater reuse, while increased savings are beneficial for uptake. There are again differences in the utility of different uses (e.g., toilet flushing vs shower), and these differences again vary as a function of respondent characteristics.

Table 3. Results for choice model component. Source: Amaris et al., (2021b)

Attribute	General description	Estimate	t-ratio
	Constant for left most alternative (δ_1)	-0.697	-5.58
Colour	**Clear or light blue**	**0**	
Colour	Dark blue (β)	-0.651	-5.28
Odour	**Odourless**	**0**	
Odour	Light chlorine (β)	-0.517	-3.74
Odour	Strong chlorine (β)	-1.480	-9.39
	Savings on water bill (β)	**0.189**	**4.70**
	… shift for high-water water expenditure group (Δ)	-0.106	-2.66
Toilet flushing	**Mean for utility β (μ_1)**	**3.172**	**5.75**
Toilet flushing	**Standard deviation for β (σ_1)**	**1.846**	**4.92**
Toilet flushing	… λ_1 (impact of LV)	2.565	7.95
Toilet flushing	… shift for female (Δ)	0.751	1.56
Toilet flushing	… shift for female and high-water expenditure group (Δ)	-0.861	-1.45
Toilet flushing	… shift for low education (Δ)	-1.457	-3.09
Toilet flushing	… shift for low education and high-water expenditure (Δ)	0.707	1.12
Garden irrigation	**Mean for utility β (μ_2)**	**2.615**	**6.31**
Garden irrigation	**Standard deviation for β (σ_2)**	**0.432**	**1.45**
Garden irrigation	… λ_2 (impact of LV)	1.972	6.84
Garden irrigation	… shift for female (Δ)	0.445	1.38
Garden irrigation	… shift for female and high-water expenditure (Δ)	-1.827	-3.86
Garden irrigation	… shift for low education (Δ)	-1.617	-4.65
Garden irrigation	… shift for low education and high-water expenditure (Δ)	1.246	2.76
Washing clothes	**Mean for utility β (μ_3)**	**2.095**	**5.05**
Washing clothes	**Standard deviation for β (σ_3)**	**1.847**	**5.68**
Washing clothes	… λ_3 (impact of LV)	1.872	5.43
Washing clothes	… shift for female and high expenditure (Δ)	-0.758	-1.82
Washing clothes	… shift for age below 55 and high-water expenditure (Δ)	0.521	1.29
Washing clothes	… shift for low education (Δ)	-0.819	-2.36
Washing hands	**Mean for utility β (μ_4)**	**1.092**	**3.18**
Washing hands	**Standard deviation for β (σ_4)**	**0.878**	**3.14**
Washing hands	… λ_4 (impact of LV)	1.572	6.02
Shower/ Tub	**Mean for utility β (μ_5)**	**1.728**	**4.32**
Shower/ Tub	**Standard deviation for β (σ_5)**	**1.530**	**5.57**
Shower/ Tub	… λ_5 (impact of LV)	1.973	6.03
Shower/ Tub	… shift for female and high-water expenditure (Δ)	-1.117	-3.06
Shower/ Tub	… shift for low education (Δ)	-0.478	-1.48
Drinking water	**Mean for utility β (μ_6)**	**-1.066**	**-2.30**
Drinking water	**Standard deviation for β (σ_6)**	**-1.366**	**-3.02**
Drinking water	… λ_6 (impact of LV)	1.152	4.46
Drinking water	… shift for female (Δ)	0.870	1.96
Drinking water	… shift for female and high-water expenditure (Δ)	-2.153	-3.64
Drinking water	… shift for age below 55 and high-water expenditure (Δ)	0.985	2.14
Drinking water	… shift for previous knowledge and high-water expenditure (Δ)	1.928	3.28
	Standard deviation of error component (σ_ξ)	1.945	13.51
	Goodness of fit for model component (ρ^2)	0.280	
	Impact of socio-demographics on underlying attitude α_n (γ parameters)		
	Female	-0.199	-1.75
	Age below 55	-0.323	-3.00
	Low income (less than 200.000 CLP)	0.509	1.75
	Low education	-0.367	-3.20
	Previous knowledge	0.299	2.28

But in contrast with the probabilistic split into four classes in the LC model, the hybrid structure incorporates heterogeneity first through additional continuous random variation in preferences (σ terms), showing extensive differences in the appeal of different greywater uses across individuals. Notwithstanding this finding, for all six uses, the utility (and hence probability of choosing a given use) additionally varies as a function of underlying attitudes towards greywater reuse (λ parameters), where the utility increases/decreases with a more positive/negative attitude. This attitude itself is latent, and has a deterministic as well as a random component, where the former highlights a more negative attitude for female respondents, younger respondents, and those with lower education, and a more positive attitude for lower income respondents and those with past greywater reuse knowledge.

4. RESULTS AND DISCUSSION

4.1. Individual preferences and heterogeneity (Step 3)

4.1.1. *Statistics of predicted uptake*

Once the data is collected (step 1) and the model(s) are estimated (step 2), the next step is to explore individual preferences and heterogeneity therein, including geographic differences. This also involves expanding the results from the sample level to the local population level (*step 3*).

We used the estimated models to predict the expected probability of reusing treated greywater at the level of individual consumers in the estimation sample, looking separately at each of the six types of use. We specifically did this for a case where the treated greywater is odourless and clear in colour, meaning that the greywater fully meets the standards of Law 21,075 for urban and rural areas of Chile.

We use the models to analyse the range of predicted uptake of treated greywater by respondents for different residential uses. Figure 4 contrasts the results for the two models. While the average predictions for the different uses are similar between the two models, the fact that each one measures different sources of heterogeneity (type of consumer in the LC model vs the role of greywater reuse attitudes in the HC model), means that the heterogeneity around the mean predictions (width of the box) is larger in the hybrid model; this is a result of the continuous treatment of random heterogeneity. The notable exception is for "drinking", where the HC model uncovers more heterogeneity across consumers for this use.

Figure 4 shows that the probability of reusing greywater in the surveyed sample exceeds 40% for the vast majority of respondents across uses (except for drinking in the HC model), when treated to mains standards, for a modest 10% cost savings. Furthermore, for over half of the respondents, the predicted probability exceeds 50% for all uses apart from drinking. However, the mean probability decreases for uses with higher skin contact; this is consistent with other studies on water reuse (Aitken *et al*., 2014; Fielding *et al*., 2018; Massoud *et al*., 2018; Oh *et al*., 2018). While the mean probabilities are relatively stable across uses, the amount of inter-consumer heterogeneity differs more across types of use, revealing different levels of heterogeneity in the preferences that individuals have for different uses. Garden irrigation has the greatest variation, perhaps reflecting the range in garden sizes in the sample and the fact that many households do not have a garden (37%).

Therefore, this step of the analysis indicates that a significant proportion of people would accept unconventional sources of greywater reuse for direct and indirect household uses, as long as the water's quality and appearance are similar to that obtained from the mains water supply system. This is consistent with other findings in the literature, from different types of analysis (Oteng-Peprah et al., 2018). However, as shown in the detailed results in Amaris et al. (2020), any reduction in the the quality of the treated greywater reduces predicted uptake.

a. Prediction with latent class model

b. Prediction with hybrid model with latent variable

Greywater conditions:
Appearance: Water without colour and without odour
Water's savings: 10% of water bill

Figure 4. Probability of using treated greywater (with no discolouration or odour) instead of mains water according to use (the whiskers extend up from the top of the box to the largest data element that is less than or equal to 1.5 times the interquartile range (IQR) and down from the bottom of the box to the smallest data element that is larger than 1.5 times the IQR)

4.1.2. *Exploring preferences and heterogeneity, including spatial effects*

Once we have characterized the preferences in statistical terms, we proceed to analyze the relationship between consumer characteristics, geographic location and reuse preferences. For this, we use the LC model as it allows us to segment people into clusters more easily than the continuous approach in the HC model. As described in Section 3.4.1, the latent classes classify the population into four categories reflecting their attitude towards greywater: "*Enthusiasts", "Sceptics", "Appearance Conscious*", and "*Expenditure water conscious"*.

After estimation, the *posterior* probability of belonging to each class (all four probabilities sum to one) was calculated for each respondent on the basis of the individual's demographic characteristics and their observed choices in the hypothetical scenarios. This information allows us to infer the characteristics of individuals in the different classes. Table 4 shows a gender split in the enthusiast and sceptic classes; for example, men show a higher propensity to be in the former and women in the latter. A possible interpretation for this finding could be that women are more risk averse about the use of products that have a household-level health implication (i.e., water use). This is in line with general findings about gender roles and concerns about the well-being of others (Gustafsod, 1998; Kim et al., 2018).

Recognizing the characteristics of each class is fundamental to better understand potential future uptake, and, for instance, to develop the best possible campaigns to promote greywater reuse (Katz et al., 2015). This spatial analysis highlights that by adding one more dimension (geolocation) to the analysis, patterns emerge in the probabilities of class memberships that would not be seen otherwise. In this way, it can be recognized if there are other factors that can influence heterogeneity in preferences for greywater reuse, as is the case of other cities (e.g. the Reno-Sparks community area of northern Nevada, USA), and that can be relevant when establishing strategies to achieve greater uptake according to people's sensitivities (Wester and Broad, 2021).

Table 4. Characterization of individuals in different classes

Socio-economic characteristic	Class 1	Class 2	Class 3	Class 4	Sample average
Gender					
… Male	0.37	0.32	0.34	0.34	0.35
… Female	0.63	0.68	0.66	0.66	0.65
Age					
… Under 30 years old	0.16	0.09	0.06	0.1	0.11
… Between 30 and 60 years old	0.57	0.55	0.62	0.65	0.58
… Over 60 years old	0.28	0.36	0.32	0.25	0.31
Garden					
… Front garden (1)	0.25	0.25	0.27	0.18	0.25
… Rear garden (2)	0.09	0.06	0.1	0.01	0.08
… Front and rear garden (3)	0.51	0.5	0.47	0.81	0.51
… None (4)	0.15	0.19	0.17	0	0.16
Type of garden					
… Front garden with grass	0.28	0.31	0.33	0.43	0.31
… Front garden with another type of vegetation	0.59	0.65	0.55	0.85	0.61
… Rear garden with grass	0.14	0.12	0.13	0.41	0.15
… Front garden with another type of vegetation	0.39	0.36	0.32	0.52	0.37

In particular, our analysis of the results for the estimation sample relates to understanding the spatial element of heterogeneity trough the latent class model. In the model, each individual has a non-zero probability of falling into each class, but these probabilities become more skewed towards the 0-1 bounds when moving to posterior probabilities, as these also consider the individual-level choices. This allows us to make the simplifying assumption of considering that those individuals who have a posterior probability greater than 0.5 for one of the classes fall into that class (which was the case for 508 out of the 510 respondents). We then plotted the geographic location of these individuals, segmented by class. A geographic information system (GIS) was used, with results reported at the municipality level, as shown in Figure 5.

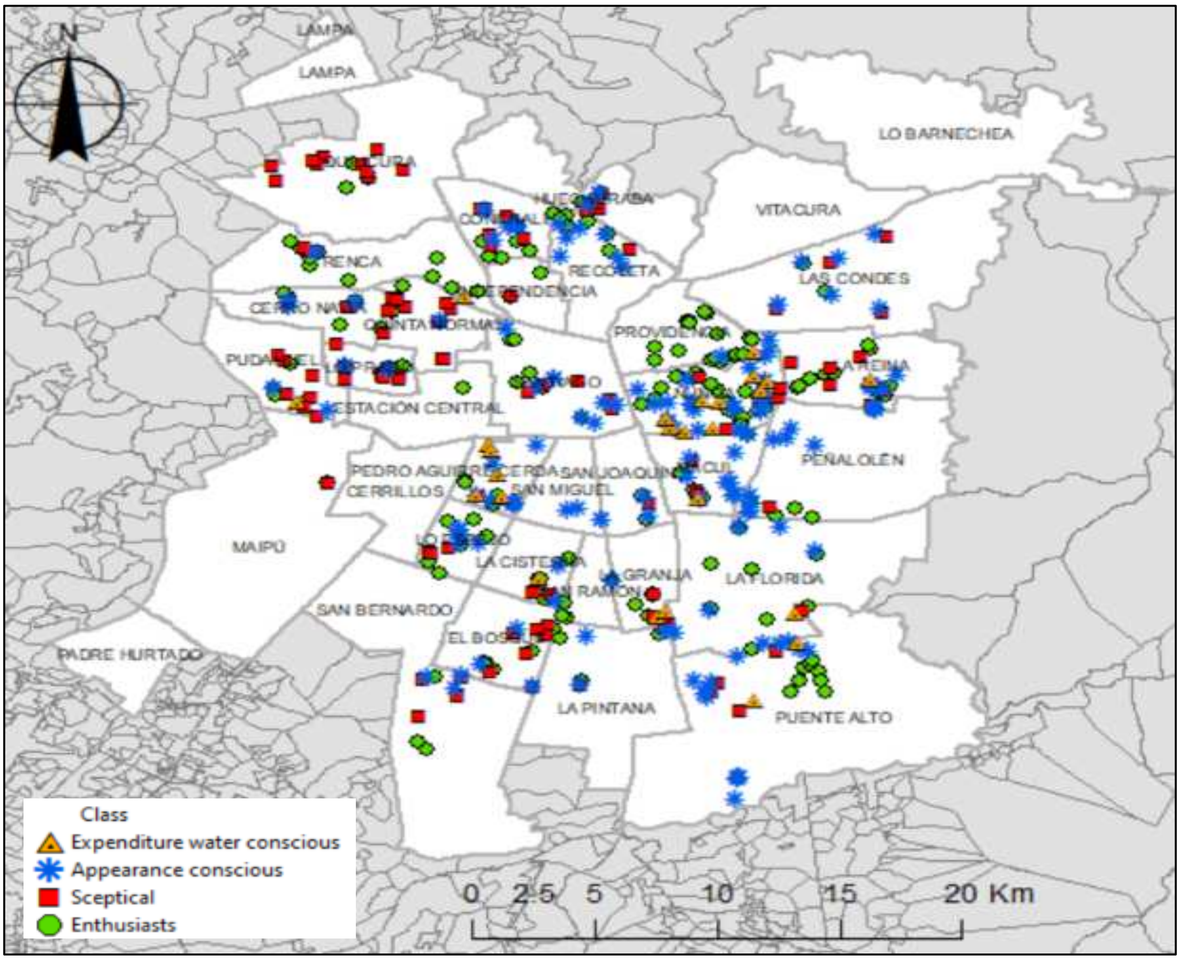


Figure 5 The most likely class membership for each respondent. In all cases the highest probability for the dominant class exceeds 50%.

The forecasts on the map allow us to look for spatial patterns of classes linked to the users' preferences for certain characteristics in the greywater service. For example, in Santiago, people that are more likely to belong to the category who are more positive about reusing greywater for any use (i.e., the "*Enthusiasts*") are more prevalent in the high-income municipalities of *Providencia*, *Ñuñoa, La Reina* and the eastern zone of *Puente Alto*. In the context of *El Gran Santiago*[1], these areas have a denser concentration and also have recent planning approval for buildings of 5 or more storeys (between 2010 and 2017). These areas are characterised by individuals with a total average monthly income per household of over CLP1,360,000 (1,772 USD), and socioeconomic groups that have clustered together because they share certain lifestyle attitudes and conducts (Gfk, 2019). These findings are valuable in urban planning terms since the regulations for residential reuse of greywater in cities have considered new buildings as a starting point (Law 21,075 in Chile). The presence of people that are *enthusiastic* about reusing greywater in areas where new buildings have been planned could be key.

Another pattern is that although the people more likely to belong to the category of *Sceptics* (i.e., people with more negative perceptions about greywater reuse) are spread through the city, they are especially prevalent in zones to the north-west of Santiago, such as*, Quilicura, Quinta normal, Pudahuel, Lo Prado*, where the predominant socioeconomic levels are medium-low (C3), low (D) and very low (E). The link between scepticism and lower socioeconomic levels is consistent with Akter et al. (2017) and Schmuck (2000), who showed the relation between climate change action and low educational attainment, lack of access to information and, perhaps most importantly, increased prevalence of religious beliefs. On the other hand, individuals most likely to belong to the *Appearance conscious* class are spread throughout the

[1]https://www.ciperchile.cl/2020/01/03/contra-el-urbanismo-de-la-desigualdad-propuestas-para-el-futuro-de-nuestras-ciudades/

city with no marked pattern; this is to be expected in areas without previous experience with water reuse.

4.1.3. *Reweighting of results to match CENSUS data*

The datasets used for estimating econometric models are not, in general, fully representative of the population of the study area. By virtue of relying on a limited sample size, some population segments may be under-sampled while others may be over-sampled. Therefore, the direct model results relate to the estimation sample rather than to the area's population. If the way in which preferences vary across consumers relates to the sampling method used, then a correction is required before using the results for policy analysis. Using weights during estimation is a statistically inefficient process, and also implies that the observations for under-sampled respondents are "more important" than those for over-sampled respondents. In addition, such weighting means that the results cannot easily be adapted for predicting future changes in the population. A more flexible approach is to correct for sampling after estimation. This can be done either by using sample enumeration (i.e. applying the models to a larger, more representative, sample), or by reweighting the predictions from the estimation sample using weights that correct for the under/over-sampling of specific segments (Hensher et al., 2015).

The results discussed so far relate to the unweighted estimation data, that, for example, over-samples women (65% of the sample vs. just over 50% from the census). We next used the 2017 Census data (INE, 2018) to create individual-specific weights for each respondent in our sample, correcting by gender and age (with three categories, namely under 54, 55-64, 65 and over). Of course, further reweighting along other socio-demographic dimensions would be possible with more detailed data. Combining the individual-level posterior probabilities for different classes (as used in Section 7.2) with the individual-level weights, we can compute an expected class-membership probability for each of the four classes for each neighbourhood, as shown in Figure 6.

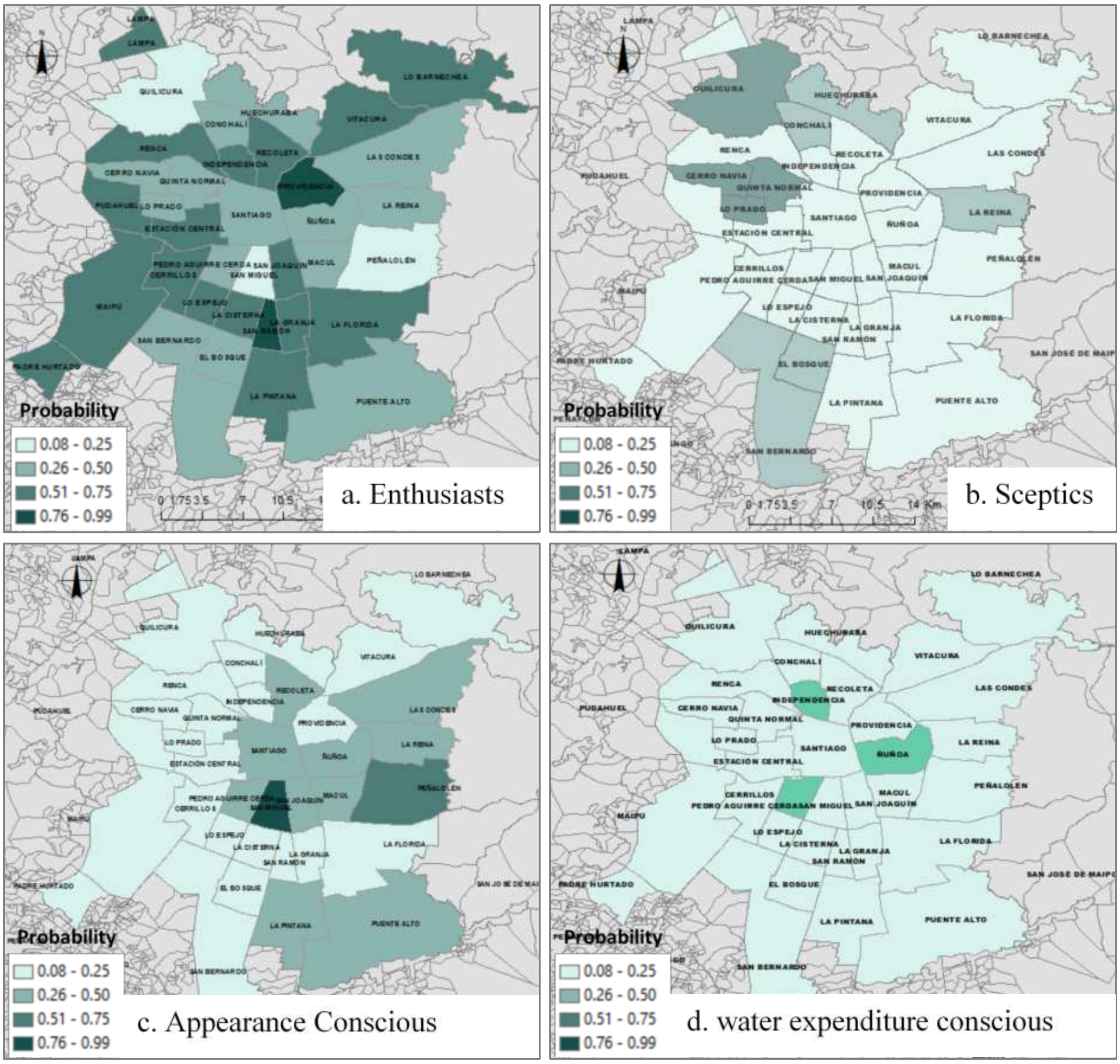


Figure 6a - probability of belonging to Class 1. 6b - probability of belonging to Class 2. 6c -probability of belonging to Class 3. 6d - probability of belonging to Class 4.

The maps shown in Figure 6 provide a preliminary indication of areas in Santiago most likely to be receptive to reusing greywater. By also taking into account the preference structures in the four different classes, we can further understand the type of reuses most likely to be accepted, and then, by implication, what type of information or policy approach could help to improve uptake. These maps also show how mathematical models can be translated into real life applications and can offer valuable information for policymaking in cities that have no previous experience with greywater reuse.

For example, in the case of Santiago, we could say that:

The municipalities of *Providencia and San Ramón* have the highest proportions of **enthusiasts** (Figure 6a), that is, people who would use greywater for the widest range of domestic uses. High proportions are also observed in other areas, with the exception of *Peñalolen, Quilicura* and *San Miguel*. However, since the level of predicted uptake in each zone is not the same, different strategies would be required to increase the confidence of individuals regarding the residential reuse of greywater; these will be discussed later.

Figure 6b shows municipalities with high levels of **scepticism**, including *Quilicura, Cerro Navia, Quinta Normal, and Lo Prado,* where a policy consistent with the needs of these areas would be to design campaigns more oriented on raising awareness about the safety of treated greywater and the economic and environmental benefits that it provides. On the other hand, municipalities such as *Peñalolen and San Miguel* are dominated by **appearance conscious** people (Figure 6c). But it can also be seen that the high concentration of these individuals covers an area that corresponds to those zones with a high socioeconomic level in the *Gran Santiago* area (i.e. municipalities of *Las Condes, La Reina*). Therefore, for these areas it could be useful to promote campaigns focused on showing how technology can achieve optimal water quality and appearance for domestic uses. Finally, **expenditure conscious** people are the smallest group; in fact, only the municipalities of *Ñuñoa, Independencia* and Pedro *Aguirre Cerda* exceed 20% of people in this class. Strategies targeted at this group could be oriented to emphasize the amount of water (and hence also money) that can be saved if they decided to reuse residential grey water.

It is also important to highlight that, although some municipalities are heavily dominated by one class, many – including those with the most expenditure conscious people - are fairly mixed. For example, *Ñuñoa* is a mix of enthusiasts (48%), appearance conscious (27%) and expenditure conscious (18%) individuals. Strategies need to recognise this diversity by using a mixed approach to encourage uptake or focus on a particular group to initiate the process.

4.2. Assessment of policies and changes in behaviour

The final step in the analysis involves scenario testing to predict the potential uptake under different future settings. In the analysis, and according to the type of models used, the impact of two possible types of changes were included: (i) changes to policy in terms of which uses are allowed, and (ii) changes in preferences, for example as a result of education campaigns. In the first case, given the current mix of preferences, as established by the modelling work, an analyst can contrast the impact of different policy decisions, for example looking at the likely success of incentives or the impact of changes in regulation, such as allowing for additional types of uses of treated greywater. In the second case, with models that capture extensive heterogeneity in preferences, the analyst has the ability to predict the impact on potential uptake of changes in preference in the population. For example, one could simulate the success of educational campaigns or other practical demonstrations to reduce scepticism in a population as yet *unfamiliar* with the service.

In what follows, we describe both cases.

4.2.1. *Impact of allowing for additional uses*

Residential water reuse is typically preferred for uses that do not require direct contact with the skin (i.e., toilet flushing and garden irrigation; Mankad and Tapsuwan, 2011; Garcia-Cuerva et al., 2016; Leong, 2016), and this is reflected in the uses allowed by the current law in Santiago. This inevitably leads to a situation where some greywater remains unused and must be discarded (to avoid water stagnation[2]); this is especially the case when many people do not have gardens or do not need to water plants all year round. This section analyses the likely amount of greywater used (and discarded) depending on the permitted uses.

The process starts by making assumptions about consumption levels in each household. This was estimated based on the daily consumption per use and per inhabitant indicated by the Superintendency of Public and Sanitary Services of Chile (SISS; cf. Appendix C) and the characteristics of the households in our sample, after the reweighting explained in Section 4.1.3. The resulting averages are shown in Table 5 under *"average monthly consumption (L)"*, showing clear differences between winter and summer, and whether the household has a garden. We evaluated two possible regulations, namely the current one where only toilet flushing and garden irrigation are permitted uses, and a hypothetical situation where the use of greywater for laundry was also allowed.

The potential amount of treated greywater that can be reused in a household is capped by two factors, *regulation of uses* and *water resource availability*. Firstly, the fact that not all uses are permitted caps the possible amount of greywater that can be reused at the total household consumption of those, as reflected in Table 5 under *"average monthly consumption in GW permitted uses (L)"*. Furthermore, the possible amount that can be reused is also capped by the physical availability of greywater for treatment. Not all greywater produced by a household is suitable for treatment, and available *raw* greywater before treatment is limited to that from handwashing, tooth brushing, taking a shower/bath, and laundry. Consistent with other studies (Lefebvre, 2018; Silva et al., 2019; Vuppaladadiyam et al., 2019) and information from Chile

[2] https://www.waterless.com/blog/six-rules-for-using-grey-water-properly

(Rodríguez et al., 2020), we assumed a 70% recovery rate of water for these uses. This provides the "*average volume of GW available per month (L)*"

Based on these three inputs, and the estimated LC model, we conducted a simulation exercise using the reweighted sample of respondents (i.e., as in Section 4.1.3), where we predicted the monthly consumption of greywater in situations where multiple uses are permitted and could be used simultaneously for each individual. The predictions are then aggregated across households. An iterative process was used, as follows:

1. For each permitted use, we first assign the probability of choosing to reuse greywater as opposed to mains water, separately for each given use, calculated with the LC model, for each individual in the sample, say P_{nk} for person *n* and use *k* (where *k=1,…,6*, with 1=toilet flushing, 2=garden irrigation, 3=laundry, 4=washing hands, 5=shower, and 6=drinking).
2. These probabilities indicate how likely a given individual is to choose a specific use in a binary choice against mains water. In making predictions, we need deterministic outcomes; that is, whether or not a given person *n* will reuse greywater for use k in a specific simulation run. Use *k* should be chosen to person *n* with a probability given by P_{nk}, and to move from probabilities to outcomes, we select as chosen those uses where $P_{nk} > \nu_{nk}$, where ν_{nk} are separate uniformly (U[0,1]) distributed disturbances. The logic in this is easily understood by noting that, with $\nu_{nk} \sim U[0,1]$, there is a probability P_{nk} of the draw ν_{nk} being less than this threshold. For example, if a given use has a probability of being chosen of 0.7 according to the model, then there would be 70% chance of a uniform random variable falling below that value.

3. Three conditions were tested:

    a. If none of the uses is chosen (i.e., $P_{nk} < \nu_{nk}, \forall k$), then no greywater is assumed to be consumed by that individual.

    b. If a single use is chosen (e.g., only $P_{n1} > \nu_{n1}$), then greywater is assumed to be consumed for that use, if allowed by law, and capped by both the available amount of greywater and the household consumption for that use.

    c. If multiple uses are acceptable (i.e., exceed the threshold), they are ranked in decreasing order in terms of by how much P_{nk} exceeds the random draw ν_{nk}. Uses with a higher probability given by the model, will have a higher probability of being ranked first, but the random nature of probabilities is considered. Then the algorithm iteratively assigns greywater for reuse, going through the ranked options, and again considering the regulatory and physical availability constraints mentioned in step b. The amount of greywater actually available to the household is decreased accordingly after each use (with less greywater remaining), and the algorithm moves on to any other uses found acceptable in step 2, until no further uses are allowed, or no more greywater is available.

4. The process in steps 2-3 is repeated a large number of times in a Monte Carlo simulation scheme (in our application, we used 250 iterations to obtain a stable solution), the results are averaged across iterations, and are then reported at the population aggregate as *"average predicted amount of greywater used per month (L)"* in Table 5, and also expressed as a ratio in *"share of available GW used"*. The simulation exercise was conducted under the best conditions of appearance of greywater after treatment (transparent water, without odour). Each time, we looked separately at individuals with and without a garden, and also made separate predictions for winter and summer.

Table 5. Impact of allowing additional greywater uses on water consumption in summer and winter

Description	*No garden*		*Garden*	
	current regulation	a third use allowed	current regulation	a third use allowed
	winter			
average monthly consumption (L)	13,947		17,177	
average monthly consumption in GW permitted uses (L)	1,928	2,766	3,461	4,384
average volume of GW available per month (L)	8,009	8,009	9,138	9,138
average predicted amount of greywater used per month (L)	1,176	1,566	2,026	2,436
share of available GW used	15%	20%	22%	27%
	summer			
average monthly consumption (L)	16,620		29,017	
average monthly consumption in GW permitted uses (L)	2,120	3,127	12,469	13,577
average volume of GW available per month (L)	9,880	9,880	11,275	11,275
average predicted amount of greywater used per month (L)	1,293	1,763	5,865	6,145
share of available GW used	13%	18%	52%	55%

Table 5 first shows that, whether or not a third use is allowed, the amount of greywater available far exceeds the actual demand in allowed uses, except in the summer for houses with a garden (e.g., 1,928L vs 8,009L in the case of houses without a garden in winter and with two permitted uses). This implies that the current law would mean that some greywater would be wasted, even if greywater reuse was universally accepted by consumers. We next turn to the predicted consumption. With or without the additional permitted use, the amount of greywater reused is below the possible maximum (e.g., 1,176L vs 1,928L in the case of houses without a garden in winter and with two permitted uses). This is a result of the heterogeneity in preferences across individuals and the fact that there is not a universal predicted uptake of greywater. The results clearly show that with the current law, the share of greywater that would be discarded is high, especially for those houses without a garden (85% discarded in winter, and 87% in summer), but also for houses with a garden in winter (78% discarded) – although 55% of greywater would be reused for houses with gardens in summer. Allowing for an additional use in the form of laundry can lead to a modest increase in the share of available greywater that is actually used. However, even though this percentage is modest, it would still lead to savings of several hundred l/month/household, which is crucial in an area with serious water security problems.

4.2.2. *Scenario tests with changes in behaviour*

We now use both the LC and HC models in a sensitivity analysis to determine the impact of changes in sensitivities and attitudes on the predicted uptake of greywater reuse. We consider a baseline scenario and five possible future scenarios, as follows:

Baseline - S0: This scenario reflects the current circumstances, that is ideal conditions for the appearance of greywater (no colour and no smell) and savings in mains water associated with less use of the main drinking water system and sanitation (see Figure 7). We compute this baseline forecast separately for the two models. As both models were calibrated on the same data, the results are expected to be very close, albeit with more heterogeneity in the HC model given the additional psychological constructs.

Scenario 1 – S1: This strategy is based on monetary incentives. We use the HC model to look at the situation of ideal greywater appearance after treatment and 30 % of savings in the water bill (associated with 20% less use of the mains system plus 10% as an additional incentive).

Scenario 2 – S2: This strategy is based on increasing educational awareness about greywater reuse and how the system could work inside the home. Using the HC model, we look at the situation of ideal greywater appearance after treatment, 10% savings in the water bill, and all individuals having previous knowledge of greywater reuse.

Scenario 3 – S3: This strategy is based on educational awareness with the objective of removing scepticism from the population; this could be possible if the population is shown how the system works with a real-life example (technology pilot test) and individuals can observe that the appearance of greywater after treatment is as good as that of mains water (Dolnicar et al., 2011; Smith et al., 2018). Additionally, this example considers the situation of ideal greywater appearance after treatment and 10 % of savings in the water bill. The mechanism for this scenario test is to use the LC model, and shift people out of class 2 (sceptics) into the remaining three classes, using allocations proportional to the existing class sizes.

Scenario 4 – S4: This strategy is also based on educational awareness with the objective of removing scepticism from the population but focused on increasing prior knowledge and strengthening the pro-water reuse attitudes of individuals (i.e., using the HC model). This is achieved by giving all individuals the attitudes of the most positive group in the population, for example through campaigns aimed at showing environmental benefits and social benefits with additional information. The scenario uses a mains water consumption reduction (10%) along with the optimal appearance of treated greywater.

Scenario 5 – S5: This strategy is based on combining several others together. It provides ideal greywater appearance after treatment, 30 % water bill savings (20% reduced mains use plus 10% as an additional incentive), educational awareness and a more positive attitude.

Figure 7 summarizes the resulting probabilities for the different scenarios. In particular, the box-plots show the probability (in a binary setting) of people preferring treated greywater reuse over the mains system for toilet flushing, garden irrigation and laundry. Each box corresponds to a management scenario to evaluate the potential uptake in the population. The two base scenarios correspond to the current probability distribution of the surveyed population estimated from the LC and HC models. These provide the point of reference for evaluating the effectiveness of each strategy. Although the distribution of both models is not exactly the same, they maintain the same magnitude for the mean.

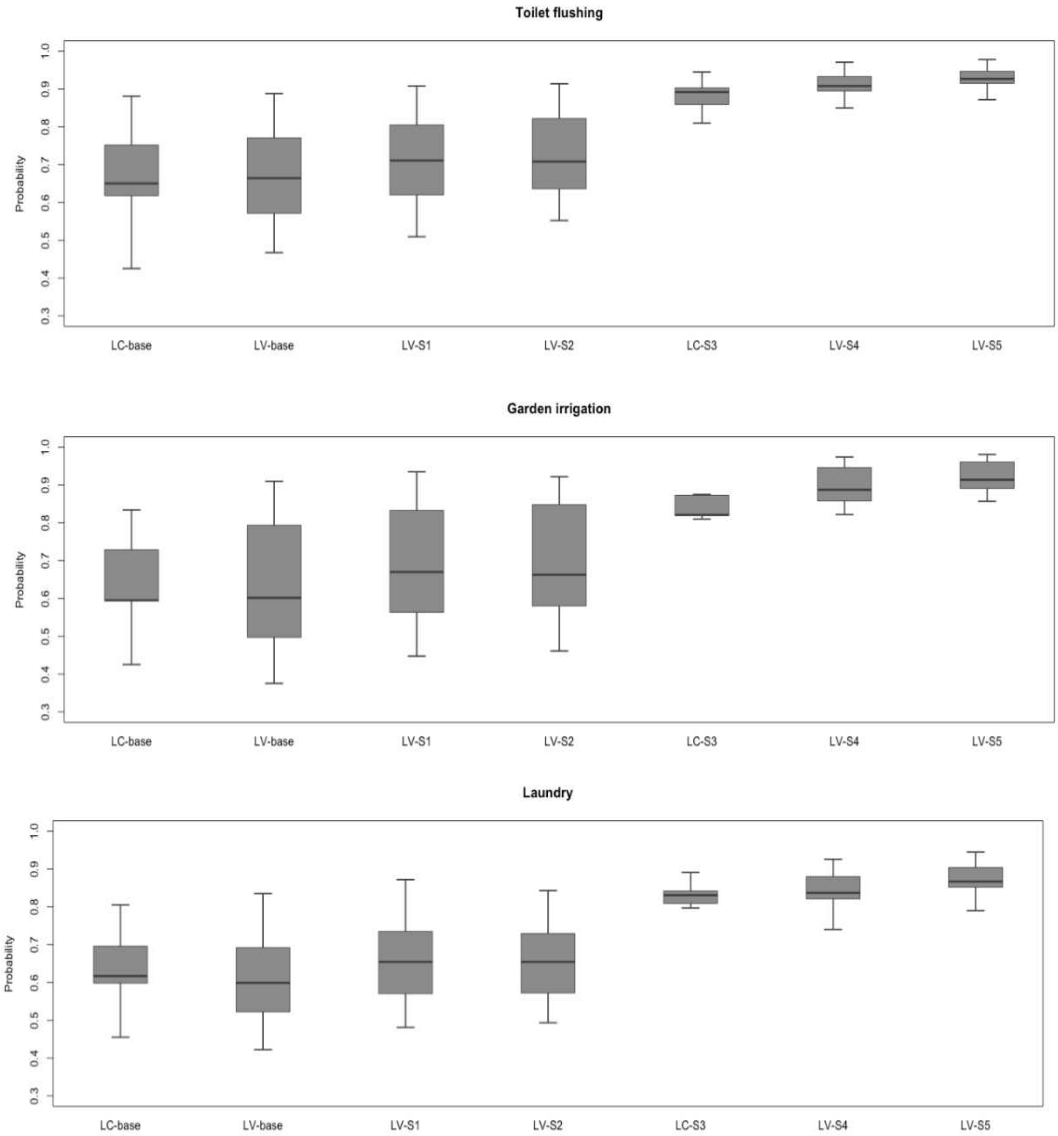
The plots show that there is clear potential for increasing greywater reuse uptake through different means. In the case of reusing greywater for **toilet flushing**, predicted uptake could reach up to 0.9, which in the specific case of the analysed population corresponds to a percentage increase of up to 25% from the base. In the case of reusing water for **garden**

irrigation, predicted uptake can again reach up to 0.9, but the most interesting point in this case is that by establishing strategies to achieve a higher willingness to reuse greywater, the average probability of reusing greywater could reach up to 30% increase with respect to the initial decisions (0.6 to 0.9). Finally, note that here is a high probability in the population to reuse greywater for **laundry**. However, current Chilean regulations do not allow this use. An average predicted uptake of up to 0.9 could be achieved for greywater reuse for laundry if strategies are established to promote this use.

Looking in more detail at each scenario, we note that:

- All the evaluated situations show an increase in predicted uptake, with some of them more effective than others. For the three uses, monetary incentives (S1) have almost the same impact as generating educational awareness in individuals (S2). However, although both strategies separately show an increase in predicted uptake (e.g., going from 0.65 to 0.7 for toilet flushing for both S1 and S2), this does not represent a notable increase compared to the base situation. At this point, it is important to clarify that other studies have shown that disseminating information on water reuse has a positive effect on acceptability (Hou et al., 2020). Although the results of this study support this claim, it also clarifies that the impact of changes in sensitivities/preferences depends on the intended use.

Figure 7 Probability of using greywater according to different scenarios



Description	LC Base	LV Base	Scenario 1 (S1)	Scenario 2 (S2)	Scenario 3 (S3)	Scenario 4 (S4)	Scenario 5 (S5)
Model specification							
Latent class model	*				*		
Latent variable model		*	*	*		*	*
Appearance:							
- Water without colour	All scenarios						
- Water without odour	All scenarios						
Water's savings:							
10% of water bill	*	*		*	*	*	
30% of water bill			*				*
Behaviour							
- higher knowledge GWR.				*		*	*
- individuals with pro-GWR attitudes.						*	*
- change of attitude of sceptical people (class 2)					*		

- Scenarios S3-S4 show that a change in the attitude of sceptical people and a shift towards more pro-greywater reuse attitudes could be more effective in achieving higher uptake than offering monetary incentives or strengthening the general knowledge about water reuse (scenarios S1 and S2). Note that S4 achieves higher predicted greywater reuse without offering extra monetary incentives which could be an important input to create strategies to promote water reuse. This is not addressed as an objective in this paper. Additionally, note the fact that the interquartile range in the box-plots for these scenarios is narrower, meaning that individuals would have similarly high levels of predicted uptake.
- The strategies considered in scenarios S3-S5 show that differences in the effects vary across uses. We observe that removing consumers' scepticism about reusing greywater for **toilet flushing** by generating educational awareness about water or even incorporating monetary incentives would have the same impact on behaviour. Therefore, for this particular use, promoting educational awareness for toilet flushing can achieve greater uptake. In contrast, scenarios S3-S5 show a different impact on potential greywater reuse for **garden irrigation**. Promoting educational campaigns (S4) would be more efficient than trying to remove scepticism from the population (S3) and more economical than assigning extra monetary incentives (S5).
- If we now analyse the option of reusing water for laundry, which is proposed in this study as a suitable alternative to be incorporated into current Chilean regulations, we can see that the optimal strategy to achieve higher uptake would be to promote educational awareness campaigns and monetary incentives (S5). However, if no extra monetary incentives were offered, it could still be effective in increasing potential uptake for reusing greywater for this purpose, with an average probability between 0.8 and 0.9.

The evaluated scenarios take as an input potential changes in sensitivities or attitudes of individuals. These could be realised in practice through communication strategies (Katz et al., 2015; Tortajada and Nambiar, 2019). In particular, the study carried out by Katz et al., (2015) shows that diffusion strategies are a good tool to achieve greater acceptability. However, they highlight two elementary components: i) the need for each place to conduct its own analysis of preferences and ii) get the language right (e.g., speak as briefly and simply as possible, promote two-way communication, using graphics and videos).

5. CONCLUSIONS

The paper has sought to use the results from studies of consumer preferences in evaluating the potential effectiveness of policy schemes aimed at allowing and encouraging residential greywater reuse in areas where this practice is not widely implemented. Our work not only provides important qualitative and quantitative insights specific to the present study, including on the potential amount of mains water that can be saved, but can also serve as a guideline for an integrated approach for other similar studies.

The first aspect that must be considered is that understanding individuals is not an easy task. This paper has used stated preference (SP) techniques in this context, based on the notion that it is possible to obtain a reliable approximation of real-world consumer decision-making (Louviere et al., 2000). In the context of wanting to understand and disentangle the separate influences that different characteristics of a greywater service may have on potential uptake, we suggest that it is important to use advanced mathematical models that bring together economic theory and behavioural foundations from psychology. This study used advanced discrete choice models (DCM), which allowed us to quantify the influence of qualitative and quantitative attributes on potential residential greywater uptake and make a detailed analysis of it based on choice scenarios. Of course, there are other approaches that can be used, for example using the theory of planned behaviour – for a review of possible alternatives, see Smith et al. (2018)

This research has shown how changes in sensitivities or attitudes can improve the potential level of uptake, more so than economic incentives alone. We have created insights that would be useful for developing outreach strategies for residential water reuse, considering the extensive heterogeneity in users' preferences.

An important insight obtained from this paper involves the forecasts (4.2.1) of the volume of water that could be recovered under current regulations *vs* the volume of water that could be recovered under the scenario of allowing an additional use (laundry), which does not require direct contact with the skin or actual water intake. Our results show that this would lead to additional savings of several hundred litres per household, with clear environmental benefits, as well as a more efficient use of the greywater reuse system by reducing the gap between the amount of available treated greywater and that which is actually used. Of course, this analysis was limited to the uses studied in our survey, but the findings could be extrapolated to suggest that if individuals are willing to reuse greywater for residential uses, they could also accept it in other high-consumption urban uses such as washing cars.

By limiting the uses to those that do not require direct contact with the skin (i.e. toilet flushing and garden irrigation), the laws may be acting as a demotivator. For example, many houses do not have gardens and are therefore unable to fully exploit the potential of greywater, reducing the motivation for installing a greywater treatment system in existing dwellings. Furthermore, although toilet flushing is a major component of household water use, efficiency improvements mean that modern toilets use less than half the water of those installed over 10 years ago. This further reduces the absolute benefits from a greywater system limited to a small number of uses. Our analysis shows that increasing the number of uses for greywater could improve system efficiency and effectiveness, which should increase uptake.

The results provide important insights into potential uptake of greywater reuse technologies in Santiago. They allow the development of more effective strategies to increase the acceptability of residential greywater reuse and, thus, the number of users. However, the insights are not limited to Santiago, but should also be an important contribution to other communities that want to start establishing water reuse within cities together with new regulations. The steps outlined in the framework constitute the key components required for applying similar work elsewhere. The key distinction will arise in the data sources, the local regulations, and of course the findings in terms of behavioural patterns, which is the key aim of the modelling work.

As with any study, there are limitations and opportunities for future work. First, the empirical modelling results are based on data from hypothetical choice scenarios. There are good reasons for this, given that the lack of widespread implementation of greywater schemes limits opportunities for studying choices in a real-world setting. Great care was taken to ensure realistic choice behaviour[3] in the data (cf. Louviere et al., 2000), but nevertheless, there is scope for validating the results with real-world data post-scheme implementation, to learn lessons for future studies. Second, some of the insights are potentially specific to the study area, i.e. Santiago. Changes to the type of questions asked in surveys and/or the modelling approach may be needed in other cities, however, the broad framework outline still applies. Also, in Santiago, the work was motivated by the fact that the installation of greywater treatment facilities is going to be mandatory for new buildings – in other cities, different circumstances

[3] See also the discussions in Amaris et al. (2020) and the importance of carefully explaining the notion of new technologies such as greywater treatment to respondents in surveys,

may apply, and the selection of study areas will also depend on whether the quantity of produced greywater would justify the investment in technology. Finally, alongside more quantitative factors such as the role of monetary incentives, our work has focussed on predicting the impact on potential uptake of changes in sensitivities and attitudes. In line with evidence in e.g. Katz et al., (2015), we have posited that these changes could be achieved through information/education campaigns. The actual extent to which this is the case, i.e. the level of impact of these campaigns, needs to be evaluated on a case by case (local) basis, which is another area for future research.

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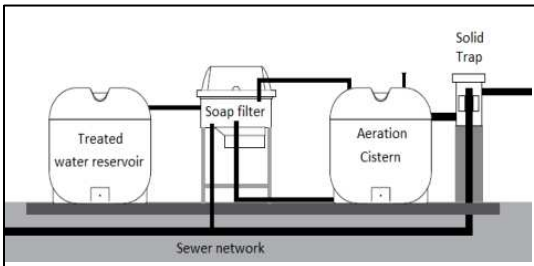
8. APPENDIX

8.1.Appendix A. Technical specifications of water recycling technology (Hydro4)



Equivalent inhabitants	*Daily flow [L/day]*	*Electrical consumption [kWh/day]*
30 max.	3000	22
60 max.	6000	35
120 max.	12000	70

	Guiding Values	
Control in treated water	**Greywater entry**	**Greywater recovered exit**
Turbidity [NTU]	22 - 100 NTU	< 2
E. Coli [CFU / 100 ml]	10-10000 UFC/100 ml	No detected
DBO5 [mg/Lt]	90 - 100	< 20
pH if chlorine is added		7.0 - 8.0

8.2.Appendix B. Specification of latent class model

In a model with S different classes, each class would then be characterised by a different vector of parameters, say Ω_s for class s. This could for example capture the existence of one class of individuals who are particularly sensitive to reductions in water expenditure, while another class is more sensitive to the qualitative appearance of the water. If we knew with certainty that person n falls into class s, then the choice probability would simply be given by $P_{n,t,s}(j \mid x_{n,t}, z_n, \Omega_s)$, where this would be given by Equation (3) when using an underlying MNL model inside each class. However, the actual class allocation is not observed deterministically, and a LC structure consequently uses a class allocation model, where respondent n belongs to class s (out of a total of S classes) with probability $\pi_{n,s}$, where $0 \leq \pi_{n,s} \leq 1$ $\forall k$ and $\sum_{s=1}^{S} \pi_{n,s} = 1, \forall s$. These class allocation probabilities can vary across individual decision-makers as a function of their observed characteristics, i.e. $\pi_{n,s} = h(z_n, \gamma)$, where γ is an additional vector of estimated parameters, and z_n are characteristics of the decision maker. Returning to the above example, this model component might for example explain that lower income respondents are more likely to fall into the class that is more sensitive to reductions in water expenditure, while higher income respondents might be more likely to fall into the class that is more sensitive to qualitative appearance of the water. In contrast with the simple MNL model, the log-likelihood function now uses a weighted average across separate sub-models (one for each class), with the weights given by the class allocation probabilities, such that:

$$LL(x, z, \Omega, \gamma) = \sum_{n=1}^{N} log \sum_{s=1}^{S} \pi_{n,s} \left[\prod_{t=1}^{T} P_{n,t,s}(Y_{n,t} \mid x_{n,t}, \Omega_s)\right] \quad (5)$$

where this is now also a function of the vector of parameters γ used in the class allocation model, and where $\Omega =< \Omega_1, \ldots, \Omega_S >$. The final model specification implemented in this study uses four classes, where the preferences in these classes allowed us to refer to them as *"enthusiasts", "greywater sceptics", "appearance conscious" and "water expenditure conscious"* (cf. Amaris et al 2021a).

In the present paper, the model is *applied*, rather than *estimated*. In estimation, we rely on class allocation probabilities $\pi_{n,s}$ that are independent of the observed choices and thus equal for two individuals with the same socio-demographics. However, two individuals that have the same observable characteristics may still make different choices, and this disparity can help yield further insights into class membership, post estimation. In application of the model, such as prediction, we can then make use of the *conditional* class allocation probabilities, calculated using Bayes rule, thus explaining how likely a specific individual is to fall into a given class *s*, given the sample level model as well as the observed choices for that individual. We have:

$$\widehat{\pi_{n,s}} = \frac{\pi_{n,s} \prod_{t=1}^{T} P_{n,t,s}(Y_{n,t} | x_{n,t}, z_n, \Omega_s)}{\sum_{s=1}^{S} \pi_{n,s} \left[\prod_{t=1}^{T} P_{n,t,s}(Y_{n,t} | x_{n,t}, z_n, \Omega_s)\right]} \quad (6)$$

where all the individual terms have been defined above. These posterior class allocation probabilities $\widehat{\pi_{n,s}}$ can then be used to make predictions of behaviour at the level of individual respondents in the data. For example, imagine making a prediction of a given respondent n accepting the use of a greywater alternative (say alternative 1) in a binary choice against mains water only (alternative 2). This would then be calculated as:

$$P_n(1 \mid x_n, \Omega) = \sum_{s=1}^{S} \pi_{n,s} P_{n,s}(1 \mid x_n, z_n, \Omega_s) \tag{7}$$

In addition, we can use the posterior class allocation probabilities to, after estimation, understand the socio-demographic make-up of individual classes, i.e. producing a membership profile for each class. For example, let $z_{c,n}$ indicate whether individual n has the specific characteristics z_c, with for example $z_{c,n}$=1 if the individual is female, and $z_{c,n} = 0$ otherwise. We can then calculate the share of individuals in class *s* having that characteristic as:

$$\widehat{z_{c,s}} = \frac{\sum_{n=1}^{N} \widehat{\pi_{n,s}} z_{c,n}}{\sum_{n=1}^{N} \widehat{\pi_{n,s}}} \tag{4}$$

where *N* is the number of individuals in our sample. Again, this could highlight how people or households with given characteristics fall into given preference clusters, and this information can be helpful in targeting specific population segments for early implementation of a new scheme, or for further policy measures such as incentives or information campaigns.

8.3.Appendix C. Specification of hybrid choice models

In a HC model, we recognise that the preferences of individuals are driven in part by underlying (but unobserved) psychological constructs such as attitudes and perceptions. Using a single such latent construct, say in our case an attitude towards greywater reuse, we define this as:

$$\alpha_n = \gamma z_n + \eta_n \tag{5}$$

where this latent attitude has a deterministic component, with γ being a vector of parameters capturing the influence of characteristics of the individual, z_n, and a random component, η_n, which is normally distributed across individuals.

We then rewrite the probability of a choice as $P_{n,t}(j \mid x_{n,t}, z_n, \alpha_n, \Omega)$, where Ω now includes parameters that capture the influence of the latent variable α_n on the choices. To allow us to calibrate the role of the latent attitudes in a model, we make use of additional information at the person level, typically in the form of answers to attitudinal questions, with say person *n* answering L different such questions, with $I_n =< I_{n,1}, \dots, I_{n,L} >$. We specify a measurement model to explain these answers on the basis of the latent variable, with say $P_n(I_{n,l} \mid \alpha_n, \Psi)$, where Ψ is a vector of estimated parameters. The specific functional form used for $P_n(I_{n,l} \mid z_n, \Psi)$ depends on the data at hand, e.g. whether the attitudinal questions are categorical or continuous.

Both $P_{n,t}(j \mid x_{n,t}, z_n, \alpha_n, \Omega)$ and $P_n(I_{n,l} \mid \alpha_n, \Psi)$ now depend on α_n, which is unobserved, meaning that the actual likelihood for person *n* is given by an integral over the distribution of the random component in α_n, with $\eta \sim N(0,1)$.

$$L_n(x_{n,t}, z_n, \Omega) = \int_\eta \prod_{t=1}^{T} P_{n,t}\left(i_{n,t}^* \mid x_{n,t}, z_n, \Omega \right) \prod_{l=1}^{L} P_n\left(I_{n,l} \mid \alpha_n, \Psi \right) \phi(\eta) d\eta \qquad (6)$$

8.4. Appendix D. Average per capita consumption of water from the mains (Chile)

		Winter		Summer	
id.	Use	(lt/d)	(m3/month)	(lt/d)	(m3/month)
1	Handwashing	10	0.3	18	0.54
2	Brush your teeth	10	0.3	18	0.54
3	Take a shower	90	2.7	100	3
4	Tub bath	250	7.5	300	9
5	Toilet flushing WC (new)	8	0.24	10	0.3
6	Toilet flushing WC (old)	20	0.6	22	0.66
7	Wash dishes by hand	22.5	0.675	30	0.9
8	kitchen and drink	16	0.48	22	0.66
9	Use the washing machine	75	2.25	90	2.7
10	Water 100 m2 of garden	400	12	400	12