Dynamic marginal cost curves to support water resources management

Citation for the original published paper (version of record):

Nicolaidis Lindqvist, A., Carnohan, S., Fornell, R. et al (2024). Dynamic marginal cost curves to support water resources management. Journal of Environmental Management, 368. http://dx.doi.org/10.1016/j.jenvman.2024.122004

(article starts on next page)

Journal of Environmental Management 368 (2024) 122004

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Dynamic marginal cost curves to support water resources management

Andreas Nicolaidis Lindqvist [a,b,c,1,*], Shane Carnohan [a], Rickard Fornell [a], Linda Tufvesson [b], Thomas Prade [b], Andreas Lindhe [d], Karin Sjöstrand [a]

[a] RISE Research Institutes of Sweden, Ideon Beta5, Scheelevägen 17, 22370, Lund, Sweden
[b] Swedish University of Agricultural Sciences, Sweden
[c] Stockholm Resilience Centre, Stockholm University, Sweden
[d] Chalmers University of Technology, Sweden

ARTICLE INFO

Handling Editor: Lixiao Zhang

Keywords:
Marginal cost curve
Water
System dynamics
Simulation
Cost-effectiveness

ABSTRACT

Marginal cost curves (MCCs) are popular decision-support tools for assessing and ranking the cost-effectiveness of different options in environmental policy and management. However, conventional MCC approaches have been criticized for lack of transparency and disregard for complexity; not accounting for interaction effects between measures; ignoring ancillary benefits and costs; and not considering intertemporal dynamics. In this paper, we present an approach to address these challenges using a system dynamics (SD)-based model for producing dynamic MCCs. We describe the approach by applying it to evaluate efforts to address water scarcity in a hypothetical, but representative, Swedish city. Our results show that the approach effectively addresses all four documented limitations of conventional MCC methods. They also show that combining MCCs with behavior-over-time graphs and causal-loop diagrams can lead to new policy insights and support a more inclusive decision-making process.

1. Introduction

Marginal cost curves (MCC), also known as marginal abatement cost curves, are a decision support and communication tool first developed after the oil crisis in the 1970s for analyzing the cost-effectiveness of energy efficiency improvement strategies (Kesicki and Strachan, 2011). The MCC approach has since been widely used for assessing abatement potential and marginal costs of climate change mitigation measures (Kesicki and Ekins, 2012). It is now a standard tool used in environmental policy design (Jiang et al., 2020) for ranking interventions, strategies, and policies based on their cost-effectiveness and potential. MCCs come in different forms and are produced using different methodological approaches (broadly categorized into expert-based and model-based MCCs), but they typically comprise a graph that specifies the potential of a measure on the horizontal axis and the marginal costs associated with the measure on the vertical axis (Kesicki, 2011) (Fig. 1). MCC is a popular tool among policy-makers because of its simplicity, as the cost-effectiveness of different management measures can easily be deduced from the shape of the curve and the format allows users to compare a range of complex measures in an easily digestible way (Sjöstrand et al., 2019).

The literature is rich with examples of MCCs being used as a tool for guiding decision makers when comparing potential measures and strategies for greenhouse gas reduction and energy policy in different sectors. For instance, Peng et al. (2018) applied the MCC methodology in the transport sector, Worrell et al. (2000) used it in the cement industry, and Eory et al. (2018) applied it for agricultural climate policy assessment. Applications beyond climate and energy policy remain relatively rare, but in recent years a handful of studies have developed MCCs to provide decision support in water resources management. For instance, Addams et al. (2009) developed water availability cost curves (WACC) at the national level for China, South Africa, and India to analyze strategies to increase water availability. Chukalla et al. (2017) developed the first model-based MCC to analyze water footprint reduction strategies in agriculture, Xiong et al. (2020) developed MCCs for water ecosystem impact abatement in the Beijing urban water system, and Sjöstrand et al. (2019) developed an expert-based MCC for addressing water scarcity on the island of Gotland, Sweden.

The popularity of MCC as a decision support tool, and its diffusion to domains beyond energy and greenhouse gas abatement, can be

* Corresponding author. RISE Research Institutes of Sweden, Ideon Beta5, Scheelevägen 17, 22370, Lund, Sweden.
E-mail address: andreas.nicolaidis@ri.se (A. Nicolaidis Lindqvist).
[1] Nicolaidis Lindqvist started his position at Stockholm University during the revision process of the paper.

https://doi.org/10.1016/j.jenvman.2024.122004
Received 21 November 2022; Received in revised form 5 July 2024; Accepted 25 July 2024
Available online 14 August 2024

interpreted as an indication of methodological fertility and acceptance among policy makers. However, as with all methods, the conventionally used MCC methodologies have their limitations. Some well-documented limitations are: (i) difficulty in balancing trade-offs between transparency and complexity (Du et al., 2015); (ii) limited capacity to account for interaction effects between measures and between sectors (Jiang et al., 2020; Kesicki and Ekins, 2012); (iii) limited capacity to capture ancillary benefits and costs of policies (Jiang et al., 2020; Kesicki and Ekins, 2012); and (iv) lack of consideration of inter-temporal dynamics (Crépin and Polasky, 2021; Kesicki and Ekins, 2012). These limitations can be significant for the utility of MCCs as a decision support tool for environmental management and policy making (Jiang et al., 2020; Kesicki and Ekins, 2012). This is especially true when the method is applied to new domains, e.g., the water management domain, where the number of previous studies is limited, and the implications of the limitations might not be well-documented. Despite substantial methodological developments (see Huang et al. (2016) for an extensive summary), the need for further research on how to address the above-described limitations is well supported by the MCC literature (Huang et al., 2016; Jiang et al., 2020; Kesicki and Ekins, 2012). Surprisingly, few (if any) attempts to derive MCCs using non-equilibrium/dynamic simulation modeling have been published. A promising approach in this regard that has well-documented suitability for policy analysis of complex, feedback-rich, nonlinear social systems is system dynamics (SD) modeling (Forrester, 1958; Sterman, 2000).

The aim of this study was to determine whether system dynamics modeling can be a valuable tool for addressing the four limitations described above. This aim was pursued by developing a method for producing MCC for addressing water scarcity, based on an integrated multi-sector SD model. The model obtained was explored in a case study of a hypothetical Swedish city (defined in this study, based on previous work by the authors (Nicolaidis Lindqvist et al., 2022; Sjöstrand et al., 2019)), located on the Swedish island of Gotland (57.6°N, 18.3°E) in the Baltic Sea. Simulation experiments were conducted to explore the marginal cost of different water scarcity mitigation measures and combinations of measures. Effects on a number of policy-relevant ancillary benefits and costs were monitored, including how these are distributed across sectors and over time.

The remainder of the paper is structured as follows: Section 2 provides an introduction to SD modeling and its theoretical suitability for addressing the limitations stated above. In section 3, an SD-based model for generating MCCs is described and applied to the study object (i.e., a representative small Swedish city) to compare measures, and combinations of measures, to address water scarcity. In section 4, results from the simulation experiments are presented and examples are used to illustrate whether the suggested approach addresses the limitations stated. Section 5 discusses the significance of the results from a water management perspective and from a broader MCC perspective, as well as limitations of the novel approach. In section 6, key findings are summarized and avenues for further research and development are indicated.

2. Justification for using a system dynamics approach

System dynamics is a methodology for computer simulation modeling commonly used to improve understanding of the causal drivers of dynamic system behavior, and to test and evaluate policies to improve system performance by means of simulation experiments (Forrester, 1958; Sterman, 2000). System dynamics models are created by mapping the causal structure of the system under study and representing this in terms of stocks, flows, and information feedback loops (Radzicki, 2010; Sterman, 2000). Stocks represent the accumulation of material and information in the system, and they are filled and drained by their associated inflows and outflows. Feedback loops are circular chains of causality, where the level of a stock influences the rate of its own flows. This could be a direct influence, or an indirect influence where the causal chain goes through a series of intermediate auxiliary variables in other parts of the system (Duggan, 2016). Close attention to

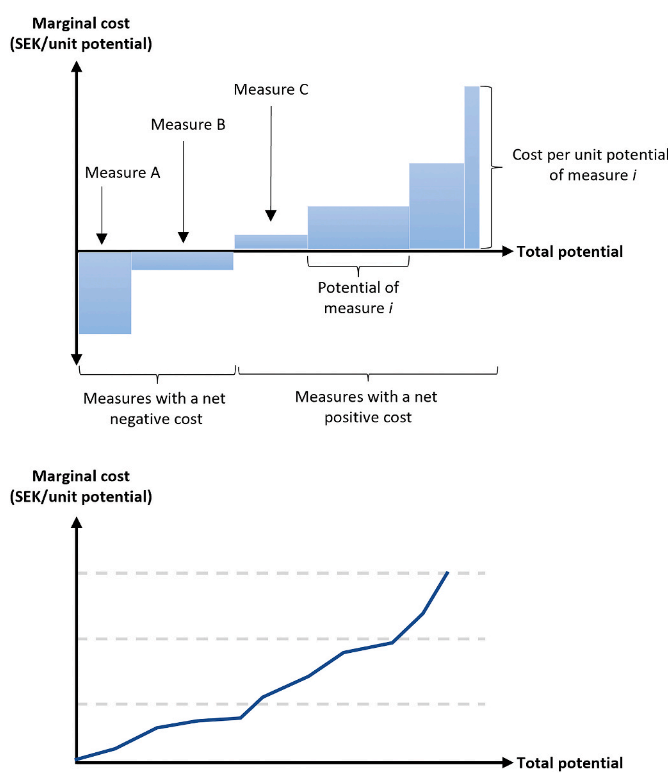

Fig. 1. Schematic description of (upper panel) an expert-based marginal cost curve (MCC) and (lower panel) a model-based MCC. Diagrams adapted from Sjöstrand (2020) and Kesicki (2011).

feedback loops is a defining element of SD modeling (Lane, 2006), as these are key structural features determining system behavior (Meadows, 2009). In mathematical terms, SD models are simulated as differential or difference equations where the net flows of material and information are accumulated by integration in the stocks of the system. The integration process and the feedback loops give rise to the complex, nonlinear dynamics often observed in social, ecological, and economic systems (Radzicki, 2010).

Emphasis on realistic representation of system structure is central to the SD approach, but it also comes with its own set of challenges. For instance, as is always the case when working with generative models (McElreath, 2020), SD-based modeling and simulation relies on the assumption that the true causal structure of the studied system (1) is known with sufficient accuracy to the analyst (or can be elicited from available information sources) and, (2) that the true world structure is accurately represented in the model (Kelly et al., 2013). Furthermore, SD modeling typically focuses on system-level phenomena and feedbacks but pays relatively little attention to the technical details of individual processes or the heterogeneity of individual agents, which are generally represented in aggregated form as stock variables. Finer detail complexity can be represented in SD models by disaggregation but this typically results in less intuitive models and makes analysis and validation more difficult without necessarily contributing to improved system understanding (Lade et al., 2021; Sterman, 2000).

Methodological limitations aside, the utility of qualitative and quantitative SD modeling for understanding and managing complex systems is well-documented in the literature (Kelly et al., 2013; Lade et al., 2021), and there is a strong tradition of using SD for environmental management and policy analysis (e.g., regional water resource management (Naderi et al., 2021; Nicolaidis Lindqvist et al., 2022), rural toilet retrofitting (Li et al., 2021), social-ecological interactions (Berrio-Giraldo et al., 2021) and public policy assessment (Ghaffarzadegan et al., 2011)). With specific regard to water resources, both top-down (expert-driven policy analysis) approaches (e.g., Simonovic (2002)) and bottom-up (stakeholder-driven) approaches (e.g., Carnohan et al. (2021); Gunda et al. (2018)) are common. Additionally, SD has been extensively applied in the field of economics (Forrester, 2003; Radzicki, 2010; Sterman, 1986), where it can complement and improve upon conventional economic modeling methods by incorporating fundamental systems principles that are often absent from classical economic models (Radzicki, 2010).

The work in this study built on this tradition by applying the SD methodology to address some of the challenges in conventional MCC modeling (see Table 1 for justification).

Table 1
Challenges when using marginal cost curves (MCC) and reasons for using a system dynamics (SD)-based approach to address these challenges.

Challenge	Reason	References
(i) Capturing systemic complexity without sacrificing transparency	The SD methodology uses visual modeling methods, primarily stock-and -flow diagrams (SFDs) and causal loop diagrams (CLD), to represent system structure. This differentiates the method from other "black box" modeling approaches by increasing transparency, revealing structural assumptions made by the modeler, and significantly lowering the need for users to have modeling experience.	(Banitz et al., 2022; Lade et al., 2021)
(ii) Accounting for interaction effects between measures and between sectors	Mapping interrelationships and feedback effects between system elements is a defining feature of the SD methodology. The ambition is to derive an endogenous explanation of system behavior. This often requires broad system boundaries and a transdisciplinary approach, involving expertise and information drawn from multiple perspectives and sectors.	(Duggan, 2016; Li et al., 2021; Naderi et al., 2021; Richardson, 2011)
(iii) Capture ancillary benefits and costs of policies	The broad system boundary, and the high level of sectoral integration, typical in SD modeling, allows for multiple costs and benefits to be effectively studied in parallel. Furthermore, SD modeling, combined with simulation experiments, allows unanticipated dynamics, side-effects, of policies to be explored.	(Pedercini et al., 2019; Sterman, 2001)
(iv) Accounting for intertemporal dynamics	The SD method focuses explicitly on the dynamics of systems, i.e., how stocks and flow rates change over time as a function of endogenous feedback and temporal delays making up the system structure.	(Dangerfield, 2014; Sterman, 2000)

3. Material and methods

We developed an integrated SD model to explore the marginal costs of different water scarcity mitigation measures, and combinations of measures, and applied it to a hypothetical Swedish city.

3.1. Case description, indicators, and interventions

The study object was defined as a representative Swedish city with 20,000 households (50,000 people) supplied by a centralized, groundwater-dependent, public water system. The case characteristics were derived primarily from previous empirical studies conducted by the authors in Sweden (Sjöstrand et al., 2019). Average per capita water use was set to 140 L/day (corresponding to 128 m^3 per household and year) (SWWA, 2022). At the start of the 25-year simulation period, including 25 annual time steps, the public system was assumed to operate at its maximum capacity, with water scarcity as an emerging problem due to a growing housing sector and uncertain groundwater availability. The objective in simulations was to increase water availability in a cost-effective way by measures that either increase water supply or improve water use efficiency among existing consumers. More specifically, we aimed to identify the measure (or combination of measures) that has the lowest marginal cost per cubic meter of water added or conserved regardless of where in the system the cost occurred (at the household or utility level). The distribution of costs and benefits in each scenario was not considered, as such an analysis extends beyond the MCC method and the scope of this paper.

In order to test the ability of the developed SD-approach on addressing the four challenges in Table 1, four measures were considered for the case city, namely enhanced public groundwater extraction (GW), rainwater collection and treatment (RWC), greywater recycling (GwR), and vacuum toilets (VacWC) (Table 2). The measures were analyzed both individually and in combinations (see section 3.3). Estimates of construction time delays, technology diffusion rates, interaction effects, decision rules, etc. were obtained from official Swedish sources, the scientific literature, and technical reports (see section 3.2 and Table 4). Outcome indicators are shown in Table 3. It is important to underline that the groundwater withdrawal indicator is useful for considering overall consumption, but also consumption avoided due to e.g., distributed water-saving technologies.

Table 2
Summary of water scarcity mitigation measures included in the study. Technical potential, cost estimates, and technical lifetimes are based on Sjöstrand et al. (2019) unless otherwise stated.

Intervention	Short description	Potential	Costs	Lifetime (years)
Public groundwater extraction (GW)	Increased public water supply through exploitation of a new aquifer, investment in a new water treatment plant, and associated infrastructure.	2,000,000 m^3/year	**CAPEX** New wells: 3 MSEK Water treatment plant: 8,25 MSEK Pipes: 15 MSEK Technical components: 8,25 MSEK **OPEX** Treatment costs: 518 SEK/household/year (Carlsson et al., 2017) Distribution costs: f(consumers, pipes per consumer, pressure control station) See Stahre et al., 2007 for details.	50 25 50 10 – –
Rainwater collection (RWC)	Household level rainwater collection and treatment to potable water quality.	35 m^3/household/year	**CAPEX** Treatment system: 12 KSEK/household Pumps: 5 KSEK/household Installation: 34 KSEK/household **OPEX** 1.74 KSEK/household/year	25 25 – –
Vacuum toilets (VacWC)	Replacement of conventional flush toilets with vacuum toilets.	27 m^3/household/year	**CAPEX** Closet, pipes, etc.: 55 KSEK/toilet Installation: 34 KSEK/toilet **OPEX** 1.75 KSEK/toilet/year	25 – –
Greywater recycling (GwR)	Installation of greywater recycling and treatment systems. Greywater from showers, laundry and dishwashers collected, treated, and recycled for non-potable purposes.	82 m^3/household/year	CAPEX Treatment system: 39 KSEK/household Storage tank: 14 KSEK/household Installation: 10 KSEK/household **OPEX** 400 SEK/household/year	25 25 – –

Table 3
Key outcome indicators monitored in the simulated scenarios.

Outcome indicator	Units	Details
Marginal cost of water	SEK/m^3	Annuitized cost per cubic meter of water added to the system.
Average cost of water utilized	SEK/m^3	Annuitized total cost of water produced in the system divided by the volume of water utilized.
Groundwater use	m^3/year	Volume of groundwater extracted from the municipal aquifer per year.
Service capacity	Households	Number of households served with water per year.
Net water availability	m^3/year	Net change in water availability in the system compared with the start year of the simulation.
Consumer water price	SEK/m^3	Price per cubic meter of water paid by consumers on the municipal grid.

The measures considered in this study are relevant not only in the Swedish context, but also to broader European (Hofman-Caris et al., 2019) and global (Cheng et al., 2018; Wurthmann, 2019) water resources management contexts where cost-effective water supply alternatives have been investigated. Outcome indicators, in particular, were related directly to widely regarded international benchmarks (e.g., UN SDGs).

3.2. The model

The simulation model developed consists of seven interconnected submodules for modeling housing, municipal water production (GW), investments in RWC, GwR, and VacWC, water pricing, and calculating the cost-effectiveness of the combination of one or multiple measures (from here on referred to as a scenario). The GW, RWC, GwR, and VacWC modules are policy modules that can be activated or deactivated depending on which mitigation measures the modeler wants to simulate.

Fig. 2 presents a causal loop diagram that illustrates the cause-and-effect relationships among key model variables. To support understanding of the structural mechanisms and assumptions driving simulation results, the key feedback processes that give rise to endogenous behavior are also visualized.

Overall, the system is goal-seeking and composed of feedback loops, which act to balance each other. The housing expansion loop adds new household connections in response to surplus water supply from the municipal grid. As the number of on-grid households increases, the surplus capacity is depleted, thus limiting additional new connections. The price and fee adjustment loops respond to increasing on-grid households, increasing both expenditure (decreasing cost coverage) and total water municipal groundwater use (which increases the yearly revenues). If cost coverage is reduced, both the desired water price and desired yearly fee will increase, resulting in a corresponding increase in realized cost to consumers.

Distributed technologies are driven by their respective technology innovation loop, technology imitation loop, and spreading the word loop. All households are considered to be potential adopters at the start of the simulation. Adoption from advertising increases the adoption rate, reducing the number of potential adopters as they become adopters of a given technology. Adopters can influence the adoption rate through word of mouth to potential adopters, moderated by the fraction of total potential adopters remaining.

Computations performed in each module are presented in Table 4 and the complete model code is available from the GitHub online

Table 4
Model description.

Module	Computations performed	Description	Equations
Household module	Simulates growth in the housing stock.	Households are modeled as a stock, H, that increases by new constructions, ΔH (Equation (1)). If the service capacity of the municipal water system, SC_{GW}, exceeds total service demand, SD, this triggers new constructions at a maximum rate of 300 houses per year (Unni Karlsson, 2021), ΔH_{max}, according to Equation (2) where α is a construction delay.	$H(t) = H(t-dt) + (\Delta H)dt$ (1) $\Delta H = MIN\left(\Delta H_{max}, \frac{(SC_{GW} - SD)}{\alpha_H}\right)$ (2)
	Calculates yearly total water demand as a function of the number of households.	Yearly water demand, D_T, is calculated as the product of the number of households, H, and the average water use per household and year, HWU.	$D_T = H^*HWU$ (3)
	Calculates yearly groundwater demand.	Groundwater demand, D_{GW}, is calculated as the yearly water demand, D_T, minus water supplied by installed decentralized technologies (S_{RWC}, S_{GwR}, S_{VacWC}).	$D_{GW} = D_T - (S_{RWC} + S_{GwR} + S_{VacWC})$ (4)
GW	Simulates investment and construction of a new municipal groundwater plant.	If the GW module is activated, investment in a new water plant capacity, CI_{GW}, occurs at time t. After a nine-year planning and construction delay (Region Gotland, 2018), α_{GW}, the plant is taken into operation, resulting in a step increase in municipal service capacity, SC_{GW}.	$SC_{GW}(t) = DELAY(CI_{GW}, \alpha_{GW})$ (5)
	Simulates OPEX and CAPEX for the municipal water supply system.	Yearly OPEX and CAPEX are calculated according to specifications provided in Table 2.	See Table 2.
	Calculates yearly groundwater withdrawals from the municipal aquifer.	Yearly groundwater withdrawal, YGW, is calculated as the yearly groundwater demand in the household sector, D_{GW}, multiplied by a leakage fraction representing non-revenue water losses, β.	$YGW = D_{GW}^*\beta$ (6)
	Calculates municipal revenue from water fees and tariffs.	Yearly municipal revenue, YMR, is the sum of revenues from water tariffs (total household water use, *HWU*, multiplied by the consumer water price, WP), RFT, and revenues from service fees (total households on grid, H(t), multiplied by the yearly service fee per unit, SF), RFS.	$YMR = RFT + RFS$ (7) $RFT = HWU^*CWP$ (8) $RFS = H(t) + SF$ (9)
	Calculates the cost-effectiveness of groundwater production and use.	SEK/m^3 water produced and water utilized is calculated using the annuitized present value, PV, method described by Sjöstrand et al. (2019). Discounted capital expenditure, $CAPEX_{GW}$, and operational expenditure, $OPEX_{GW}$, are annuitized over the time horizon of the analysis, T, giving an equivalent annual cost (EAC_{GW}). The EAC is then divided by the technical potential of the measure, TP_{GW}, to give the marginal cost per cubic meter of water added or conserved (MC_{GW}), or by the simulated yearly water demand, D_{GW}, to give the utilized cost per cubic meter (UC_{GW}). A discount rate, r, at 3.5% (Swedish Transport Administration, 2023) was used for the simulations[2].	$PV_{GW}(t) = PV_{GW}(t-dt) + (\Delta PV_{GW})dt$ (10) $\Delta PV_{GW} = \frac{OPEX_{GW} + CAPEX_{GW}}{(1+r)^t}$ (11) $EAC_{GW} = \frac{r(PW_{GW})}{1 - \frac{1}{(1+r)^T}}$ (12) $MC_{GW} = \frac{EAC_{GW}}{TP_{GW}}$ (13) $UC_{GW} = \frac{EAC_{GW}}{D_{GW}}$ (14)
RWC	Simulates RWC technology adoption and calculates total water supply potential of the technology.	Technology adoption is modeled using a standard technology diffusion approach (Bass, 1969) that considers the total stock of households, H(t), consisting of potential adopters, $PA_{RWC}(t)$, and adopters, $A_{RWC}(t)$. The technology adoption rate, TAR_{RWC}, is the sum of potential adopters that adopt the technology through innovation (with a propensity to innovate, *p*) or imitation (with a propensity to imitate, q). At the start of the simulation, $A_{RWC}(t)$ is set to zero and standard values for the innovation and imitation coefficients are used according to studies by Sultan et al. (1990).	$A_{RWC}(t) = A_{RWC}(t-dt) + (TAR_{RWC})dt$ (15) $TAR_{RWC} = pPA_{RWC}(t) + qA_{RWC}(t)\frac{PA(t)}{A(t) + PA(t)}$ (16)
	Calculates total water supply/savings potential from RWC.	Total RWC potential is modeled as the product of RWC adopters, $A_{RWC}(t)$, and the RWC technical potential per household, TP_{RWC}.	$P_{RWC} = A_{RWC}(t)^*TP_{RWC}$ (17)
	Calculates the cost-effectiveness of the RWC.	Cost-effectiveness is calculated using the same approach as described in the GW section.	See Equation (10)–(14)
GwR	Simulates GwR technology adoption and calculates total water supply potential of the technology.	Technology adoption is modeled using the same approach as described above.	See Equation (15) to (16)
	Calculates total water installed and utilized supply/savings potential from GwR.	Total installed GwR potential, P_{PwR}, is modeled as the product of GwR adopters, $A_{GwR}(t)$ and the GwR technical potential per household, TP_{GwR}. Water supplied from GwR is assumed to be only used for non-potable purposes and an interaction effect between GwR and VacWC is assumed. Thus, the total utilized GwR potential, UP_{GwR}, is calculated as the number of GwR adopters, $A_{GwR}(t)$, multiplied by the non-potable water use per household, NPWU. Non-potable water use is set based on estimates by SWWA (2022), minus the technical potential of VacWC, TP_{VacWC}, if that measure is adopted.	$P_{GwR} = A_{GwR}(t)^*TP_{GwR}$ (18) $UP_{GwR} = A_{GwR}(t)^*NPWU$ (19)
	Calculates the cost-effectiveness of GwR.	Cost-effectiveness is calculated using the same approach as described for GW.	See Equation (10)–(14)

(*continued on next page*)

Table 4 (*continued*)

Module	Computations performed	Description	Equations	
VacWC	Simulates VacWC technology adoption and calculates total water supply potential of the technology.	Technology adoption is modeled using the same approach as described above.	See Equation (15) to (16)	
		Total installed VacWC potential, P_{VacWC}, is modeled as the product of VacWC adopters, $A_{VacWC}(t)$, and the VaxWC technical potential per household, TP_{VacWC}.	$P_{VacWC} = A_{VacWC}(t)*TP_{VacWC}$	(20)
	Calculates total water installed and utilized supply/savings potential from VacWC.			
	Calculates the cost-effectiveness of VacWC.	Cost-effectiveness is calculated using the same approach as described for GW.	See Equation (10)–(14)	
Water pricing module	Simulates municipal water price adjustment.	Household costs for public water consist of two parts: a water use tariff, WUT(t), and a yearly service fee, YSF (t). Together these two make up the yearly municipal revenues, MREV.	$MTC = OPEX(t-1) + CAPEX(t-1)$	(21)
		Municipal total costs, MTC, is the sum of municipal OPEX and CAPEX from the previous year. If there is a balance gap, BG, between MREV and MTC, a new target tariff, WUT*, and service fee, YSF*, are set and the actual WUT and YSF are adjusted over a one-year adjustment time, AT, until the gap is closed.	$MREV = (D_{GW}*WUT(t)) + (H(t)*YSF(t))$	(22)
		A price adjustment rule where 65% of the costs are covered by the tariffs and 35% are covered by the service fee (Region Gotland, 2021) was assumed.	$WUT(t) = WUT(t-dt) + (\Delta WUT)dt$	(23)
			$\Delta WUT = \frac{WUT^* - WUT(t)}{AT}$	(24)
			$WUT^* = WUT(t) + \frac{BG*0.65}{D_{GW}}$	(25)
			$YSF(t) = YSF(t-dt) + (\Delta YSF)dt$	(26)
			$\Delta YSF = \frac{YSF^* - YSF(t)}{AT}$	(27)
			$YSF^* = YSF(t) + \frac{BG*0.35}{H(t)}$	(28)
MCC calculation	Calculates the cost-effectiveness of the simulated mitigation scenario.	MC and UC for the mitigation mix, MC_{mix} and UC_{mix}, are calculated as the annuitized sum of the PV of all simulated mitigation measures as described in Equations (10)–(12), divided by the yearly net volume of water added to the system, YNWA, or the yearly water use, YWU, respectively.	$MC_{mix} = \frac{\sum(EAC_i)}{YNWA}$	(29)
			$UC_{mix} = \frac{\sum(EAC_i)}{YWU}$	(30)

repository,[2,3].

3.3. Simulation approach

To address the challenges defined in Table 1, four water scarcity mitigation measures were explored. All possible combinations of these four measures were tested, leading to a total of 15 simulated scenarios. The measure(s) studied were introduced in the year 2020 and simulated for a time horizon of 25 years. For each scenario, the cost-effectiveness (marginal cost and average utilized cost) was analyzed and a cost curve, showing the volume of water provided and average cost per cubic meter for each mitigation measure included, was generated. The changes in groundwater withdrawal, service capacity, net water added, and consumer water price, over time were also generated for each scenario. The different scenarios were then ranked based on their relative performance for each outcome indicator.

4. Results

The results of the case study are presented in relation to each of the four different challenges addressed in this paper. First the dynamic model is presented and resulting impacts on the MCC curve are revealed. Next, different captured interaction effects between measures, and how these result in different values for cost-effectiveness for water added and water used, are shown. Ancillary benefits and costs estimated are then presented, including a rating of the relative performance between different measures on different benefits and costs. Finally, intertemporal dynamics for two different measures are presented.

4.1. Comparative assessment: conventional vs. dynamic MCC

The model structure presented in Fig. 2 was utilized here to support the interpretation of results and explain the novelty of the dynamic approach to MCC. For example, Fig. 3 shows the marginal cost per cubic meter of water added to the system calculated using the conventional static MCC approach as described by Sjöstrand et al. (2019) (top panel) and using the dynamic simulation-based approach developed in this paper (bottom panel). The width of the bars represents the volumetric increase in water availability compared with at the start of the simulation period, and bar height shows the average cost per cubic meter of water added. The two approaches give important differences in results. First, the static MCC consistently suggests higher water availability potential than the dynamic MCC. This difference is caused by the fact that the static approach does not account for material and information time delays associated with implementation of the different measures, e.g., implementation inertia and time for technology adoption. In the dynamic MCC, on the other hand, increase in water availability is modeled as a function of technology adoption over time (left set of loops in Fig. 2), meaning that only installed capacity, not planned capacity, contributes to water availability potential in the calculations.

Fig. 3. (Upper panel) A conventional static marginal cost curve (MCC) and (lower panel) a dynamic MCC curve derived for the four mitigation measures studied (GW = groundwater extraction, RWC = rainwater collection, GwR = greywater recycling, VacWC = vacuum toilets; see Table 2 for details).

The second difference between the two approaches is that although

[2] https://github.com/NLAndreas/Dynamic_MCC.git

[3] To assess the sensitivity of simulation results to the choice of discount rate, simulations were conducted using a low (1.4%), medium (3.5%) and high (5.0%) discount rate. This range reflects the average discount rate used by Stern (2006) and the recommended rate for Swedish infrastructure projects (Swedish Transport Administration, 2023). This analysis revealed that the overall results of the study (the relative cost effectiveness of different combinations of measures) are largely insensitive to the choice of discount rate.

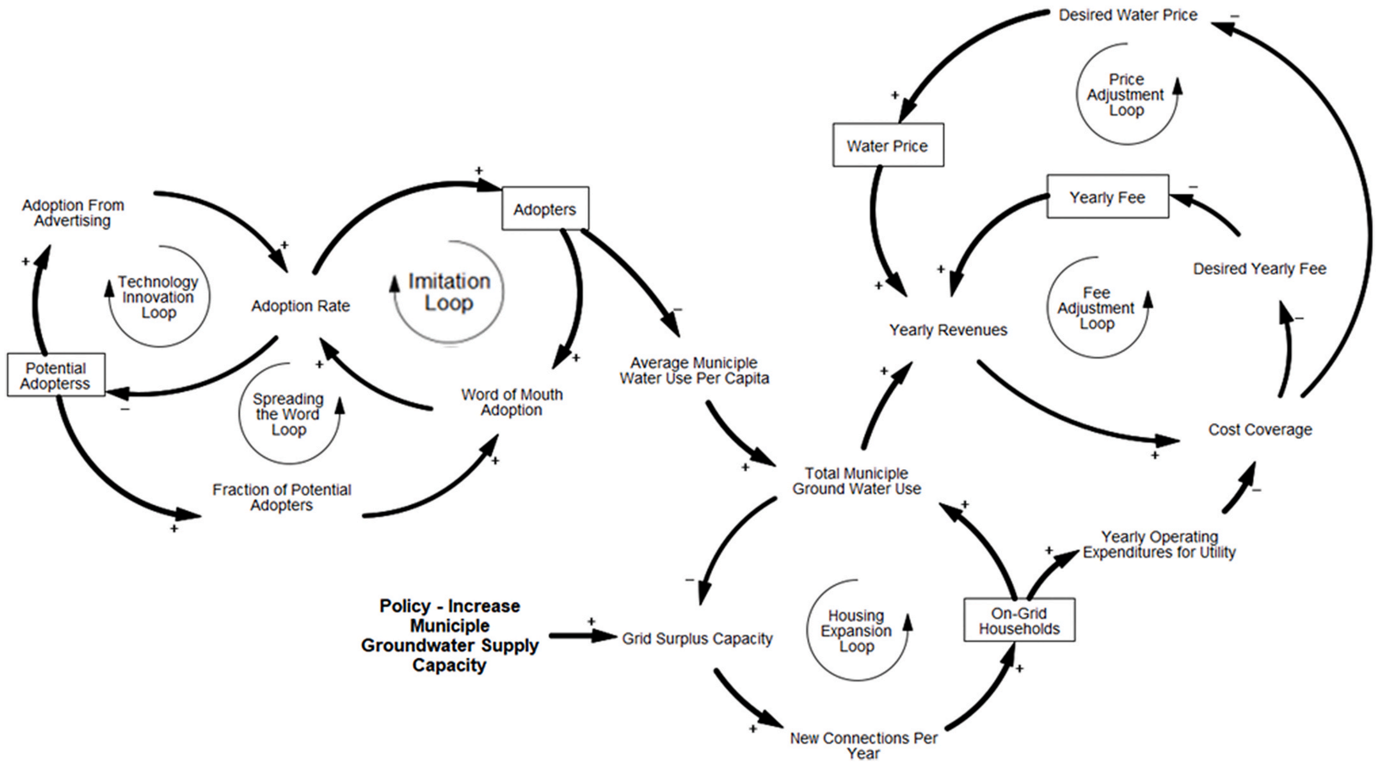

Fig. 2. Causal loop diagram (CLD) illustrating the feedback structure of the constructed model. Boxes represent stock variables and arrows indicate positive (+) or negative (−) polarity causal relationships between variables. Feedback loops in the system are named and indicated by curved arrows in the diagram.

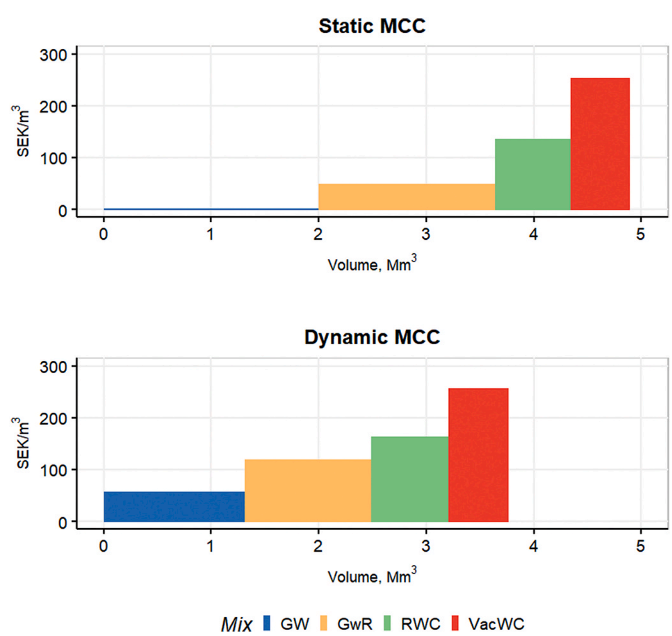

Fig. 3. (Upper panel) A conventional static marginal cost curve (MCC) and (lower panel) a dynamic MCC curve derived for the four mitigation measures studied (GW, RWC, GwR, VacWC; see Table 2 for details).

the static and dynamic MCCs give the same relative order of the mitigation measures, the static approach consistently gives a lower marginal cost than the dynamic one (Fig. 3). In the static MCC, the marginal cost per cubic meter for GW, GwR, RWC, and VacWC is 1.3, 49, 135, and 254 SEK/m^3 respectively. In the dynamic MCC, the corresponding cost estimates are 57, 120, 163, and 256 SEK/m^3. This is partly caused by the lower water availability potential of the latter (the same cost is distributed over a smaller water volume), but interaction effects between measures also contribute. For instance, when one of the distributed measures is introduced, it will compete with the existing municipal water supply system and reduce groundwater use. However, since municipal costs for operation and management of water production and treatment cannot be cut at the same rate as groundwater use, the overall cost-effectiveness of the system declines and the marginal cost of water increases (the left and bottom loops in Fig. 2 will not be perfectly balanced in connection to the upper right loop).

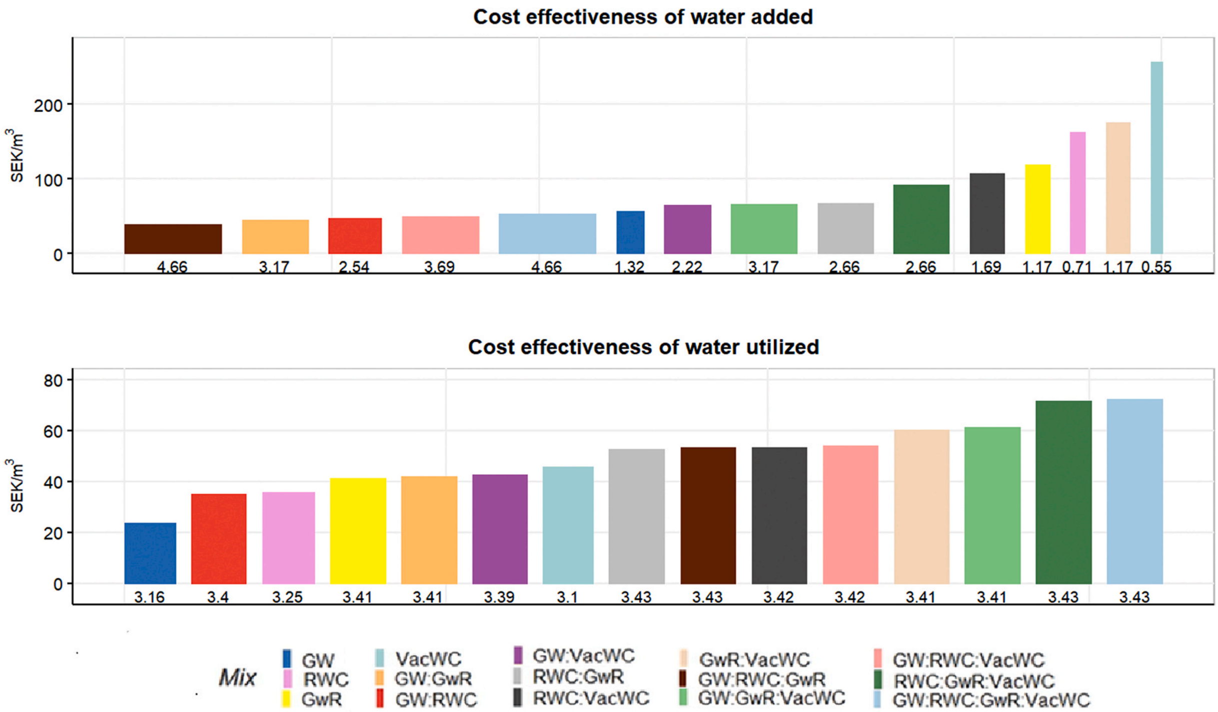

Fig. 4. (Upper panel) Marginal cost per cubic meter of water available and (lower panel) average cost per cubic meter of water utilized for the 15 simulated scenarios. Bar width represents water volume available/utilized in million cubic meters per year (indicated by numbers under each bar). GW = groundwater extraction, RWC = rainwater collection, GwR = greywater recycling, VacWC = vacuum toilets (see Table 2 for details).

The remainder of this section focuses on the dynamic MCC results accompanied by an explanation of how the model structure produces these. Implications of the intertemporal dynamics and interaction effects between mitigation measures, unique to the dynamic MCC, are represented as scenarios in sections 4.2-4.4.

4.2. Interaction effects between measures

The cost-effectiveness of a mitigation measure is influenced by the other measures included in the scenario. For instance, in the GW scenario the cost per cubic meter of groundwater utilized is about 24 SEK. However, when combined with other technologies in the GW:RWC:GwR scenario the cost of groundwater increases to about 47 SEK/m^3. This cost increase is caused by an overall decline in groundwater demand due to improved water use efficiency (caused by installation of greywater recycling systems) and increased use of rainwater. Thus, the GW infrastructure is not fully utilized, which drives up the marginal cost. On the other hand, this overcapacity can have positive impacts as it provides the system with a groundwater buffer (Tsur and Graham-Tomasi, 1991) that can be used during periods of drought. It is evident that the cost-effectiveness of each mitigation measure is conditional on the context in which it is introduced.

Fig. 4 shows the cost-effectiveness of the 15 simulated scenarios. In the top panel, the width of the bars represents the volumetric increase in water availability produced by each scenario mix over the simulation period. Bar height shows the average marginal cost per cubic meter of water added. It should be noted that the volumetric increase in water availability is not the same as the volume of water utilized. For instance, rapid investments in supply capacity can lead to overcapacity, meaning that water availability will be, at least temporarily, greater than water use. This effect can be seen in the bottom panel, where the width of the bars represents the average volume of water utilized over the entire 25-year simulation period, while bar height represents the average cost per cubic meter.

The scenario combining GW, RWC, and GwR has the lowest marginal cost in the ensemble (39 SEK/m^3). Interestingly, this is significantly lower than when GW measure is applied in isolation, suggesting that combining measures can have synergistic effects on cost-effectiveness which are not seen when studying the mitigation measures individually. In terms of average cost of water utilized, on the other hand, the GW scenario is the most cost-effective (24 SEK/m^3) and the GW:RWC:GwR scenario is intermediate (53 SEK/m^3). These diverging results in the marginal cost assessment and the average utilized cost assessment are due to differences in net water availability relative to water demand in the scenarios. This is further explored, together with ancillary benefits and costs, in section 4.3.

4.3. Ancillary benefits and costs

Fig. 5 illustrates the trade-offs between different outcome indicators for all scenarios studied. It is clear that each combination of mitigation measures come with its own ancillary benefits and costs. For instance, the GW mitigation scenario performs best in terms of cost-effectiveness of water utilized and results in the lowest consumer water price of all scenarios. On the other hand, it results in the highest groundwater use and performs poorly with regard to total water availability and service capacity. If optimizing for groundwater conservation is the primary goal, then several of the scenario involving decentralized solutions perform much better. The GW:RWC:GwR scenario is especially interesting, as it not only performs well in terms of groundwater conservation, but also in terms of net water availability and service capacity.

In the example shown in Fig. 5, all six outcome indicators are given equal weight, but in a real-life setting the relative weight of each indicator could be tailored to the specific context and priorities of the decision maker.

4.4. Intertemporal dynamics

The impact of time delays is seen clearly in Fig. 6. In the GW scenario, a top-down policy is put in place, beginning in 2020. However, it takes

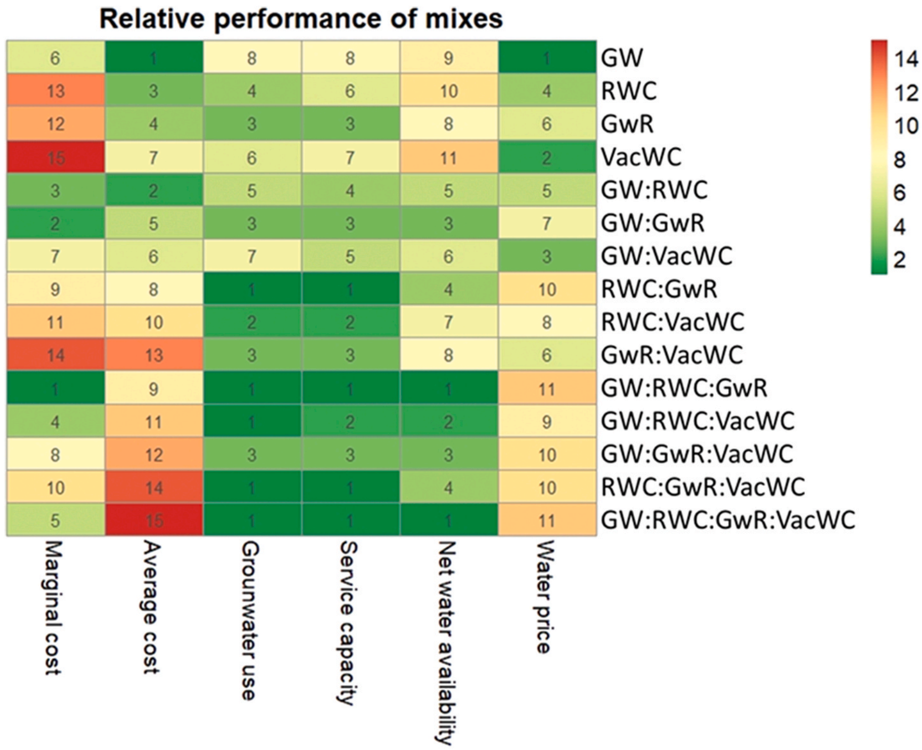

Fig. 5. Heatmap illustrating relative performance of the different scenarios with respect to the six outcome indicators and overall score of each combination of measures. Note that the scale 1–15 does not reflect distance but purely relative rank, so some scenarios show the same rank, e.g. for groundwater withdrawal. GW = groundwater extraction, RWC = rainwater collection, GwR = greywater recycling, VacWC = vacuum toilets (see Table 2 for details).

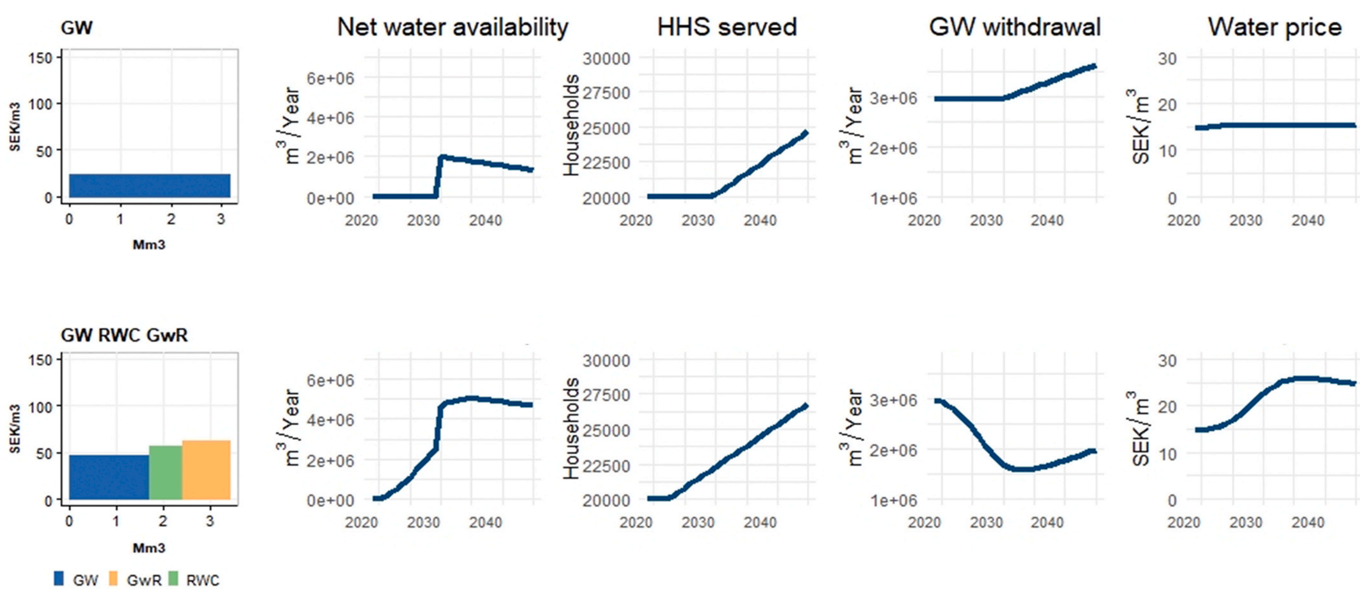

Fig. 6. (Left column) Breakdown of the average cubic meter costs of the GW scenario (top row) and the GW:RWC:GwR scenario (bottom row) into their constituent mitigation measures. The four columns to the right show how net water availability, service capacity, groundwater withdrawal, and consumer water price, change dynamically over the simulation period for the same two scenarios. (For the complete set of time graphs of all scenarios, see supplementary material S1). GW = groundwater extraction, RWC = rainwater collection, GwR = greywater recycling, VacWC = vacuum toilets (see Table 2 for details).

time to identify a suitable withdrawal location and build the pumping infrastructure required to increase supply. Therefore, the net water availability remains at zero until, after a nine-year delay period (Region Gotland, 2018), it increases sharply. During this time, water prices remain relatively constant, but the addition of new households is also stagnant.

Fig. 6. (Left column) Breakdown of the average cubic meter costs of the GW scenario (top row) and the GW RWC GwR scenario (bottom row) into their constituent mitigation measures. The four columns to the right show how net water availability, service capacity, groundwater withdrawal, and consumer water price, change dynamically over the simulation period for the same two scenarios. (For the complete set of time

graphs of all scenarios, see Supplementary material S1).

In contrast to such centralized solutions, where the dynamics are dominated by time delays in the planning and construction process, decentralized technologies typically scale by a nonlinear process of technology diffusion and adoption (Bass, 1969; Meade and Islam, 2006). The GW:RWC:GwR scenario includes investment in a mix of one centralized/top-down measure (GW) and two bottom-up/decentralized measures (RWC and GwR). These technologies result in a sigmoidal curve of net water availability increase, as seen in Fig. 6. Because there are no large planning or construction delays for the RWC and GwR technologies, net water availability starts increasing several years earlier in the GW:RWC:GwR scenario than in the GW scenario. Additionally, the centralized and decentralized measures interact to create complex dynamic behaviors of the overall scenario. Water from rainwater harvesting and recycled greywater can replace municipal groundwater for most everyday uses. Thus, as these technologies spread, they increase net water availability not only by providing additional new water to the system, but also by freeing up groundwater so it can be used for other purposes. This leads to an increase in net water availability, and substantially higher service capacity, in the GW:RWC:GwR scenario compared with the GW scenario, despite substantially lower groundwater use (Fig. 6). These results shed light on an important trade-off: As municipal water use declines, revenues from water sales also decline. To maintain cost coverage for operation and maintenance, the municipality needs to increase water tariffs, resulting in overall increases in consumer water prices.

5. Discussion

In this study, a system dynamics-based approach for producing MCC was developed using water scarcity mitigation as a representative case. The purpose of using this semi-hypothetical case was to explore the potential of the SD-based approach to address limitations of conventional MCC methods and to assess whether new policy insights can be achieved by applying this approach to water resources management and beyond. This section discusses the significance of the results from a specific water management perspective and from a broader MCC perspective. Finally, some limitations are described, along with key avenues for further improvements.

5.1. Insights for water resources management

The presented approach to dynamic MCC analysis reveals several important, novel, and generic insights for water resources management and planning that are not provided by the conventional static MCC. Interaction effects and intertemporal dynamics of the system can change the cost-effectiveness and service delivery of mitigation efforts in ways that cannot be intuitively predicted when considering the measures individually (Sterman, 2010). The dynamic simulation model presented here is based on the cause-effect structure of socio-hydrological systems and captures these important effects. While the interactions included are not exhaustive, a visual representation of the system, a CLD in our case, provides value as it makes structural assumptions explicit in a way typically not seen in contemporary MCC analyses. This transparency can aid practitioners (e.g., decision makers) and researchers in understanding why a certain intervention may give an (potentially) unexpected result. This creates an opportunity for results to be challenged, supporting further improvement of the model during application, where new data and contextual features of the system emerge.

Temporal dynamics can be a critical aspect in regions experiencing acute water scarcity. Our results show how simulation experiments can be useful to identify technology and information delays, and support understanding of the implications. This can assist regions addressing long-term trade-offs. For example, selecting a mitigation strategy that can scale rapidly and add new water to the system early can be of greater value than choosing the most cost-effective strategy.

Ancillary costs and benefits, as described in this study, also have implications for the development and selection of water scarcity mitigation strategies. The performance matrix presented in Fig. 5 demonstrates this, and could be used to broaden the indicators chosen for decision making beyond simple cost-effectiveness. The diverse effects of different mitigation scenarios on groundwater withdrawal is a clear example. Given that groundwater conservation is a high political and ecological priority in many regions (UN-Water, 2021), providing information on groundwater use together with the results of conventional MCC is crucial to balance sustainability and cost-effectiveness in water resources management. Conserving groundwater by using alternative water sources when available has the additional benefit that it adds resilience to the water supply system by maintaining a reserve of groundwater that can be used as an insurance for periods of drought (Langridge and Van Schmidt, 2020; Tsur and Graham-Tomasi, 1991). The value of this benefit is not quantified in the MCC in this paper, but in future studies it could be included as an economic benefit in the PV calculations if the willingness to pay for this 'insurance' is known or can be reliably estimated.

Results from the present study also provide guidance for future MCC assessments beyond water resources management.

- In complex systems the temporal aspect of management interventions, i.e., when to act and the delays associated with those actions, can have a large impact on the results. Therefore, assessments of cost-effectiveness in these systems should study the systems dynamically, not statically.
- When developing MCC for complex systems, interaction effects and feedback loops between measures should be considered. This can be done effectively by means of SD-based models, ideally combined with a CLD, or other visualization aid, to ensure transparency is maintained and to invite further development and improvements of the underlying model.
- Accounting for multiple ancillary benefits and costs in the MCC assessment can add important insights in terms of synergies and benefits between mitigation measures and influence the results of the assessment.
- The presented approach, using SD-based simulation combined with the matrix visualization in Fig. 5, allows decision makers to compare alternative investment or mitigation strategies from multiple perspectives, enabling holistic comparison, dialogue, and communication of investment decisions between different stakeholders.

Even though the potential of the presented SD-based approach is clear, a word of caution is in order. The true value of any model depends how it is applied. Careless application of even the most accurate model is likely to lead to misleading results. Therefore, great care must be taken to ensure quality and scientific rigor is maintained throughout each step of the modeling process. We recommend Sterman (2000) and Martinez-Moyano and Richardson (2013) for in-depth descriptions of best-practice in SD modeling and application.

5.2. Limitations

For the case presented, the model developed only handles a small part of the complexity of the real-world system. Many additional links and feedbacks could be included, which could lead to additional important insights. For instance, pricing strategies could influence future water use, or different household types might respond differently to pricing based on whether they are linked to the municipal grid or have their own well. Another feature missing from the current model is the effect of technology development. For instance, an increased demand for new RWC, GwR, or VacWC technologies could push up prices, and thereby drive faster adoption of these measures (Jain and Rao, 1990).

A thorough sensitivity analysis that evaluates the robustness of conclusions against uncertainties in model structure and parameter assumptions should complement any model-based approach to decision support. In recent studies, Sjöstrand et al. (2019) used Monte-Carlo simulations to evaluate uncertainties in MCC calculations, and in a similar vein, Nicolaidis Lindqvist et al. (2022) used a multivariate Monte Carlo simulations to analyze the sensitivity of simulation results in a SD-based model of a socio-hydrological system on Gotland, Sweden. In Supplementary material S2, we illustrate how the Monte Carlo-based approach can be adopted for dynamic MCC applications. We conclude that the relative performance of different mitigation scenarios is relatively robust to parametric uncertainty in key variables governing system dynamics, e.g., technology diffusion rates and construction time delays. Still, further efforts should be devoted to reducing uncertainty around future water use and service capacity by improving parameter estimates and expanding the sensitivity analysis to include additional parameters in the analysis.

Another limitation in our example is that we only account for households on the demand side of the water supply-demand system. In reality, water users in a city are a heterogeneous mix of households, services, industries, etc. that would respond differently to different mitigation measures and potentially influence one another. We also made the simplifying assumptions that all households are potential adopters of all distributed mitigation measures, and that all mitigation measures have the same diffusion potential. In reality, households would have preferences for certain mitigation measures over others, and the costs and characteristics of different mitigation technologies would influence diffusion speed and potential (Fichter and Clausen, 2021).

Furthermore, the lack of realistic representation of hydrological dynamics is another limitation, and an opportunity for further research, in the presented study. For simplicity, the water supply capacity of the simulated mitigation measures is static and set to be equal to their estimated technological potential, as reported by Sjöstrand et al. (2019). In reality, the potential of each measure varies over time with weather, precipitation, and local hydrology. Adding exogenous time series of data on weather and precipitation, and integrating the MCC model with a hydrological model to capture effects of local conditions on water supply capacity, would improve hydrological realism and allow exploration of how different weather scenarios, uncertainties, supply disruptions, etc. could change the outlook for the different mitigation scenarios.

6. Conclusions and further research

In this study, we attempted to overcome four well-documented limitations of the MCC approach when assessing the cost-effectiveness of investment, management, and policy decisions. We did this by using an SD-based approach to derive MCCs in a hypothetical case on water scarcity mitigation in Sweden. The following conclusions can be drawn.

- Ancillary benefits and costs of different measures can be studied effectively using conceptual and formal system models. In the hypothetical case studied, this was exemplified by including effects on groundwater use and consumer water price as ancillary effects of the simulated mitigation measures.
- Intertemporal dynamics can effectively be captured by using SD-based simulation models to derive the MCC. We recommend that future MCC assessments use this approach to study the dynamic behavior of key policy indicators (e.g., water availability or groundwater use), as this can provide valuable insights into the decision-making process regarding when in time the costs and benefits of different measures occur.
- Interaction effects between measures and systemic feedbacks can have a significant impact on the performance of different measures and combinations of measures. These effects are often difficult to predict intuitively, but we show that even relatively simple SD models allow these interactions to be modeled and tested explicitly.
- Complementing formal simulation models with CLDs, or other system conceptualization tools, can make the logic of the model more accessible for non-modelers, and the underlying structural assumptions of the modeler more transparent. This allows the model to be to questioned, evaluated, and improved, and overall opens the way for a more inclusive assessment of policy options (Maeda et al., 2021).

The last point is a particularly interesting avenue for further research. Inclusive participatory processes have long been recognized as an essential aspect of achieving sustainable management of water resources (De Stefano, 2010). It is widely acknowledged that visual tools play an essential role in supporting these processes, to enhance inclusion of value perspectives and enable boundary-spanning problem solving (Eaton et al., 2021), as is necessary for effective management of coupled human and natural systems (de Vos et al., 2021). The general conclusions from our study are applicable well beyond the water resources management domain and we recommend further application and development of the dynamic MCC approach to other contemporary environmental and natural resource problems (e.g., energy systems management, plastic pollution, and climate change mitigation and adaptation).

CRediT authorship contribution statement

Andreas Nicolaidis Lindqvist: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Shane Carnohan:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization. **Rickard Fornell:** Writing – review & editing, Writing – original draft, Conceptualization. **Linda Tufvesson:** Writing – review & editing. **Thomas Prade:** Writing – review & editing. **Andreas Lindhe:** Writing – review & editing. **Karin Sjöstrand:** Writing – review & editing, Resources.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.122004.

References

Addams, L., Boccaletti, G., Kerlin, M., Stuchtey, M., 2009. Charting Our Water Future: Economic Frameworks to Inform Decision-Making. McKinsey & Company, New York.

Banitz, T., Hertz, T., Johansson, L.-G., Lindkvist, E., Martínez-Peña, R., Radosavljevic, S., Schlüter, M., Wennberg, K., Ylikoski, P., Grimm, V., 2022. Visualization of causation in social-ecological systems. Ecol. Soc. 27 https://doi.org/10.5751/ES-13030-270131.

Bass, F.M., 1969. A new product growth for model consumer durables. Manag. Sci. 15, 215–227. https://doi.org/10.1287/mnsc.15.5.215.

Berrio-Giraldo, L., Villegas-Palacio, C., Arango-Aramburo, S., 2021. Understating complex interactions in socio-ecological systems using system dynamics: a case in the tropical Andes. J. Environ. Manag. 291, 112675 https://doi.org/10.1016/j.jenvman.2021.112675.

Carlsson, H., Haraldsson, M., Kärrman, E., Lidström, V., Lundh, M., Malm, A., Malmström, H., Pendrill, L., Rönnbäck, M., Sjögren, L., Svensson, G., 2017. Investeringsbehov och framtida kostnader för kommunalt vatten och avlopp [Investment needs and future costs in municipal water and sewer systems]. Swedish Water Reports 27, 2017-1.

Carnohan, S.A., Clifford-Holmes, J.K., Retief, H., McKnight, U.S., Pollard, S., 2021. Climate change adaptation in rural South Africa: using stakeholder narratives to build system dynamics models in data-scarce environments. J. Simulat. 15, 5–22. https://doi.org/10.1080/17477778.2020.1762516.
Cheng, S., Li, Z., Uddin, S.M.N., Mang, H.-P., Zhou, X., Zhang, J., Zheng, L., Zhang, L., 2018. Toilet revolution in China. J. Environ. Manag. 216, 347–356.
Chukalla, A.D., Krol, M.S., Hoekstra, A.Y., 2017. Marginal cost curves for water footprint reduction in irrigated agriculture: guiding a cost-effective reduction of crop water consumption to a permit or benchmark level. Hydrol. Earth Syst. Sci. 21, 3507–3524.
Crépin, A.-S., Polasky, S., 2021. Decision analysis based on optimisation. The Routledge Handbook of Research Methods for Social-Ecological Systems. Routledge, pp. 400–411.
Dangerfield, B., 2014. Systems Thinking and System Dynamics. a primer, pp. 29–51.
De Stefano, L., 2010. Facing the water framework directive challenges: a baseline of stakeholder participation in the European Union. J. Environ. Manag. 91, 1332–1340. https://doi.org/10.1016/j.jenvman.2010.02.014.
de Vos, A., Maciejewski, K., Bodin, Ö., Norström, A., Schlüter, M., Tengö, M., 2021. The Practice and Design of Social-Ecological Systems Research, the Routledge Handbook of Research Methods for Social-Ecological Systems. Routledge, pp. 47–63.
Du, L., Hanley, A., Wei, C., 2015. Estimating the marginal abatement cost curve of CO2 emissions in China: provincial panel data analysis. Energy Econ. 48, 217–229. https://doi.org/10.1016/j.eneco.2015.01.007.
Duggan, J., 2016. An Introduction to System Dynamics, System Dynamics Modeling with R. Springer, pp. 1–24.
Eaton, W.M., Brasier, K.J., Burbach, M.E., Whitmer, W., Engle, E.W., Burnham, M., Quimby, B., Kumar Chaudhary, A., Whitley, H., Delozier, J., Fowler, L.B., Wutich, A., Bausch, J.C., Beresford, M., Hinrichs, C.C., Burkhart-Kriesel, C., Preisendanz, H.E., Williams, C., Watson, J., Weigle, J., 2021. A conceptual framework for social, behavioral, and environmental change through stakeholder engagement in water resource management. Soc. Nat. Resour. 34, 1111–1132. https://doi.org/10.1080/08941920.2021.1936717.
Eory, V., Pellerin, S., Garcia, G.C., Lehtonen, H., Licite, I., Mattila, H., Lund-Sorensen, T., Muldowney, J., Popluga, D., Strandmark, L., Schulte, R., 2018. Marginal abatement cost curves for agricultural climate policy: state-of-the art, lessons learnt and future potential. J. Clean. Prod. 182, 705–716. https://doi.org/10.1016/j.jclepro.2018.01.252.
Fichter, K., Clausen, J., 2021. Diffusion of environmental innovations: sector differences and explanation range of factors. Environ. Innov. Soc. Transit. 38, 34–51. https://doi.org/10.1016/j.eist.2020.10.005.
Forrester, J.W., 1958. Industrial dynamics: a major breakthrough for decision makers. Harv. Bus. Rev. 36, 37–66.
Forrester, J.W., 2003. Dynamic models of economic systems and industrial organizations. Syst. Dynam. Rev.: The Journal of the System Dynamics Society 19, 329–345.
Ghaffarzadegan, N., Lyneis, J., Richardson, G.P., 2011. How small system dynamics models can help the public policy process. Syst. Dynam. Rev. 27, 22–44. https://doi.org/10.1002/sdr.442.
Gunda, T., Turner, B.L., Tidwell, V.C., 2018. The influential role of sociocultural feedbacks on community-managed irrigation system behaviors during times of water stress. Water Resour. Res. 54, 2697–2714. https://doi.org/10.1002/2017WR021223.
Hofman-Caris, R., Bertelkamp, C., de Waal, L., van den Brand, T., Hofman, J., van der Aa, R., van der Hoek, J.P., 2019. Rainwater harvesting for drinking water production: a sustainable and cost-effective solution in The Netherlands? Water 11, 511.
Huang, S.K., Kuo, L., Chou, K.-L., 2016. The applicability of marginal abatement cost approach: a comprehensive review. J. Clean. Prod. 127, 59–71. https://doi.org/10.1016/j.jclepro.2016.04.013.
Jain, D.C., Rao, R.C., 1990. Effect of price on the demand for durables: modeling, estimation, and findings. J. Bus. Econ. Stat. 8, 163–170. https://doi.org/10.2307/1391978.
Jiang, H.-D., Dong, K.-Y., Zhang, K., Liang, Q.-M., 2020. The hotspots, reference routes, and research trends of marginal abatement costs: a systematic review. J. Clean. Prod. 252 https://doi.org/10.1016/j.jclepro.2019.119809.
Kelly, R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., van Delden, H., Voinov, A.A., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Software 47, 159–181. https://doi.org/10.1016/j.envsoft.2013.05.005.
Kesicki, F., 2011. Marginal Abatement Cost Curves for Policy Making – Expert-Based vs . Model-Derived Curves.
Kesicki, F., Ekins, P., 2012. Marginal abatement cost curves: a call for caution. Clim. Pol. 12, 219–236. https://doi.org/10.1080/14693062.2011.582347.
Kesicki, F., Strachan, N., 2011. Marginal abatement cost (MAC) curves: confronting theory and practice. Environ. Sci. Pol. 14, 1195–1204. https://doi.org/10.1016/j.envsci.2011.08.004.
Lade, S.J., Anderies, J.M., Currie, P., Rocha, J.C., 2021. Dynamical systems modelling. The Routledge Handbook of Research Methods for Social-Ecological Systems. Routledge, pp. 359–370.
Lane, D.C., 2006. IFORS' operational research Hall of fame jay wright forrester. Int. Trans. Oper. Res. 13, 483–492. https://doi.org/10.1111/j.1475-3995.2006.00559.x.
Langridge, R., Van Schmidt, N.D., 2020. Groundwater and drought resilience in the SGMA era. Soc. Nat. Resour. 33, 1530–1541. https://doi.org/10.1080/08941920.2020.1801923.
Li, Y., Cheng, S., Li, Z., Song, H., Guo, M., Li, Z., Mang, H.-P., Xu, Y., Chen, C., Basandorj, D., Zhang, L., Li, T., 2021. Using system dynamics to assess the complexity of rural toilet retrofitting: case study in eastern China. J. Environ. Manag. 280, 111655 https://doi.org/10.1016/j.jenvman.2020.111655.
Maeda, E.E., Haapasaari, P., Helle, I., Lehikoinen, A., Voinov, A., Kuikka, S., 2021. Black boxes and the role of modeling in environmental policy making. Front. Environ. Sci. 9 https://doi.org/10.3389/fenvs.2021.629336.
Martinez-Moyano, I., Richardson, G., 2013. Best practices in system dynamics modeling. Syst. Dynam. Rev. 29 https://doi.org/10.1002/sdr.1495.
McElreath, R., 2020. Statistical Rethinking: A Bayesian Course with Examples in R and Stan. CRC press.
Meade, N., Islam, T., 2006. Modelling and forecasting the diffusion of innovation – a 25-year review. Int. J. Forecast. 22, 519–545. https://doi.org/10.1016/j.ijforecast.2006.01.005.
Meadows, D.H., 2009. Thinking in Systems : a Primer. Earthscan, London ; Sterling, VA, p. ©2008.
Naderi, M., Mirchi, A., Bavani, A.R., Goharian, E., Madani, K., 2021. System dynamics simulation of regional water supply and demand using a food-energy-water nexus approach: application to Qazvin Plain, Iran. J. Environ. Manag. 280, 111843 https://doi.org/10.1016/j.jenvman.2020.111843.
Nicolaidis Lindqvist, A., Fornell, R., Prade, T., Khalil, S., Tufvesson, L., Kopainsky, B., 2022. Impacts of future climate on local water supply and demand – a socio-hydrological case study in the Nordic region. J. Hydrol.: Reg. Stud. 41, 101066 https://doi.org/10.1016/j.ejrh.2022.101066.
Pedercini, M., Arquitt, S., Collste, D., Herren, H., 2019. Harvesting synergy from sustainable development goal interactions. Proc. Natl. Acad. Sci. USA 116, 23021–23028. https://doi.org/10.1073/pnas.1817276116.
Peng, B.-B., Xu, J.-H., Fan, Y., 2018. Modeling uncertainty in estimation of carbon dioxide abatement costs of energy-saving technologies for passenger cars in China. Energy Pol. 113, 306–319. https://doi.org/10.1016/j.enpol.2017.11.010.
Radzicki, M., 2010. System dynamics and its contribution to economics and. Economic Modeling 727–737.
Region Gotland, 2018. VA-Plan 2018: VA-plan För Region Gotland [Water and Sanitation Plan for Region Gotland 2018.
Region Gotland, 2021. Avgifter för Region Gotlands vatten- och avloppsverksamhet [Tariffs and fees for water utility services in Region Gotland]. In: Environment and Town Planning Committee. Visby, Gotland.
Richardson, G.P., 2011. Reflections on the foundations of system dynamics. Syst. Dynam. Rev. 27, 219–243. https://doi.org/10.1002/sdr.462.
Simonovic, S.P., 2002. World water dynamics: global modeling of water resources. J Environ Manage 66, 249–267. https://doi.org/10.1006/jema.2002.0585.
Sjöstrand, K., 2020. Decision Support for Sustainable Water Security. Chalmers Tekniska Hogskola (Sweden).
Sjöstrand, K., Lindhe, A., Söderqvist, T., Dahlqvist, P., Rosén, L., 2019. Marginal abatement cost curves for water scarcity mitigation under uncertainty. Water Resour. Manag. 33, 4335–4349. https://doi.org/10.1007/s11269-019-02376-8.
Sterman, J., 2000. Business Dynamics: Systems Thinking and Modeling for a Complex World. McGraw-Hill.
Stahre, P., Mellström, G., Adamsson, J., 2007. Värdering av vatten- och avloppsledningsnät [Valuation of water and sewer distribution networks]. Swedish Water Development Reports 2007-13, 49–52.
Sterman, J.D., 1986. The economic long wave: theory and evidence. Syst. Dynam. Rev. 2, 87–125. https://doi.org/10.1002/sdr.4260020202.
Sterman, J.D., 2001. System dynamics modeling: tools for learning in a complex world. Calif. Manag. Rev. 43, 8. https://doi.org/10.2307/41166098.
Sterman, J.D., 2010. Does formal system dynamics training improve people's understanding of accumulation? Syst. Dynam. Rev. 26, 316–334.
Stern, N., 2006. Stern Review: the Economics of Climate Change.
Sultan, F., Farley, J.U., Lehmann, D.R., 1990. A meta-analysis of applications of diffusion models. J. Market. Res. 27, 70–77. https://doi.org/10.2307/3172552.
Swedish Transport Administration, 2023. Analysis Method and Socio-Economic Cost and Benefit Values for the Transport Sector: ASEK 6.1.
SWWA, 2022. Drinking Water Facts (Dricksvattenfakta). Swedish Water and Wastewater Association.
Tsur, Y., Graham-Tomasi, T., 1991. The buffer value of groundwater with stochastic surface water supplies. J. Environ. Econ. Manag. 21, 201–224. https://doi.org/10.1016/0095-0696(91)90027-G.
UN-Water, 2021. Summary Progress Update 2021: SDG 6—water and Sanitation for All.
Unni Karlsson, 2021. Regional Bostadsmarknadsanalys - gotlands län 2021 [Analysis of the regional housing market - Gotland county 2021]. Gotland County Administrative Board.
Worrell, E., Martin, N., Price, L., 2000. Potentials for energy efficiency improvement in the US cement industry. Energy 25, 1189–1214. https://doi.org/10.1016/S0360-5442(00)00042-6.
Wurthmann, K., 2019. Assessing storage requirements, water and energy savings, and costs associated with a residential rainwater harvesting system deployed across two counties in Southeast Florida. J. Environ. Manag. 252, 109673.
Xiong, W., Li, Y., Pfister, S., Zhang, W., Wang, C., Wang, P., 2020. Improving water ecosystem sustainability of urban water system by management strategies optimization. J. Environ. Manag. 254, 109766.