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Quantitative sustainable design (QSD) for the prioritization of research, development, and deployment of technologies: a tutorial and review†

Yalin Li,[ab] John T. Trimmer,[c] Steven Hand,‡[ad] Xinyi Zhang,[d] Katherine G. Chambers,[e] Hannah A. C. Lohman,[d] Rui Shi,[f] Diana M. Byrne,[g] Sherri M. Cook[e] and Jeremy S. Guest*[abd]

The pursuit of sustainability has catalyzed broad investment in the research, development, and deployment (RD&D) of innovative water, sanitation, and resource recovery technologies, yet the lack of transparent and agile methodologies to navigate the expansive landscape of technology development pathways remains a critical challenge. This challenge is further complicated by the higher levels of uncertainty that are intrinsic to early-stage technologies. In this work, we review and synthesize published literature on the sustainability analyses of water and related technologies to present quantitative sustainable design (QSD) – a methodology to expedite and support technology RD&D. With a shared lexicon and a structured approach, QSD facilitates interdisciplinary communication and research consistency. In introducing QSD, we review existing studies to highlight best practices and discuss them in the context of the specific steps of QSD, which include defining the problem space, establishing simulation algorithms, and characterizing system sustainability across economic, environmental, human health, and social dimensions. Next, we summarize tools for QSD execution and provide recommendations to account for uncertainty in this process. We further discuss applications of QSD in the fields of water/wastewater and beyond (*e.g.*, renewable fuels, circular economy) in combination with uncertainty, sensitivity, and scenario analyses to generate the desired types of insight. Finally, we identify future research needs for sustainability analyses to advance technology RD&D. Ultimately, QSD can be used to elucidate the complex and intertwined connections among design decisions, technology characteristics, contextual factors, and sustainability indicators, thereby supporting transparent, consistent, and agile RD&D.

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Research, development, and deployment (RD&D) of innovative technologies are often impeded by the lack of transparent, systematic, and agile approaches to prioritize investment across the expansive landscape of technologies and design/operational decisions. This tutorial review synthesizes research on sustainability analyses to present quantitative sustainable design (QSD) – a structured methodology to expedite the RD&D of water, sanitation, and resource recovery technologies.

[a] *Institute for Sustainability, Energy, and Environment, University of Illinois Urbana-Champaign, 1101 W. Peabody Drive, Urbana, IL 61801, USA. E-mail: jsguest@illinois.edu; Tel: +1 (217) 244 9247*
[b] *DOE Center for Advanced Bioenergy and Bioproducts Innovation, University of Illinois Urbana-Champaign, 1206 W. Gregory Drive, Urbana, IL 61801, USA*
[c] *The Aquaya Institute, PO Box 21862-00505, Nairobi, Kenya*
[d] *Department of Civil and Environmental Engineering, University of Illinois Urbana-Champaign, 3221 Newmark Civil Engineering Laboratory, 205 N. Mathews Avenue, Urbana, IL 61801, USA*
[e] *Department of Civil, Environmental and Architectural Engineering, University of Colorado Boulder, 1111 Engineering Drive, Boulder, Colorado, 80309, USA*
[f] *Department of Chemical Engineering, The Pennsylvania State University, 121 Chemical and Biomedical Engineering Building, University Park, Pennsylvania, 16802, USA*
[g] *Department of Civil Engineering, University of Kentucky, 354F Raymond Building, Lexington, Kentucky, 40506, USA*

† Electronic supplementary information (ESI) available: Table S1. Additional literature examples illustrating concepts, steps, and applications of QSD. See DOI: **https://doi.org/10.1039/d2ew00431c**

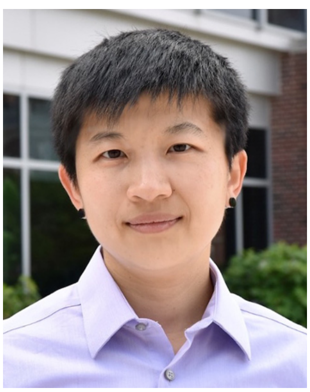
‡ Current address: Carollo Engineers, Inc., 14755 Preston Road, Suite 500, Dallas, Texas 75254, USA.

1. Introduction

With roots in ancient civilizations,[1–4] sustainability has gained public attention in recent decades with a series of landmark reports,[5–8] events,[9] and treaties.[10,11] These efforts recognize the necessity to promote equitable and prosperous communities while simultaneously maintaining the ecosystems that support them.[12–15] This need is particularly relevant for water technologies as they safeguard basic human rights (water and sanitation[16–18]) and are essential components of broader initiatives to re-envision other systems designed to meet societal needs (*e.g.*, resource recovery,[19,20] green chemistry,[21–23] regenerative agriculture[24,25]).[26–29] In line with this need, the field of sustainability science[30–33] and sustainability engineering[34] continue to evolve in support of the society's transition toward sustainability.[35,36]

To apply the concept of sustainability in the research, development, and deployment (RD&D) of technologies, implementable and systematic methodologies are necessary to quantitatively evaluate technologies as they mature.[37,38] To this end, multiple sets of guiding principles (*e.g.*, the Green Chemistry[39] and Green Engineering[21] Principles) and frameworks (*e.g.*, the UN Inclusive Wealth framework[40]) have been proposed. These principles and frameworks often represent aspirational goals for technologies, engineered systems, or national entities, and are not intended to provide structured guidance to inform the prioritization of RD&D for specific technologies. Similarly, methodologies such as Life Cycle Sustainability Assessment have been proposed to address the "whole-picture" of sustainability,[41] but methodologies such as this often lack quantitative, transparent strategies to navigate tradeoffs across dimensions of sustainability and technology-specific indicators of engineering performance (*e.g.*, contaminant removal).[42] More critically, there is a growing recognition of the importance of uncertainty, especially for early-stage technologies associated with higher levels of uncertainty.[43,44] Nonetheless, the results of sustainability analyses are often presented as single values. This "false precision" overlooks aleatory (due to randomness) and epistemic (due to the lack of knowledge) uncertainty that is ubiquitous for early-stage technologies, thereby compromising the veracity of the results.[45] Ultimately, these limitations undermine the accessibility and utility of sustainability analyses to inform decision-making for the RD&D of technologies, which is crucial in the society's pursuit of sustainability.[8]

In this paper, we review and synthesize published literature related to sustainability analyses to present a tutorial review on quantitative sustainable design (QSD). QSD integrates concepts associated with sustainability science and engineering to expedite and support the RD&D of technologies (Fig. 1). Through the lens of QSD, we establish a shared lexicon as the foundation for interdisciplinary communication and to support methodological transparency and consistency (Table 1). In presenting this methodology, we discuss published studies using the shared lexicon to put them in the context of QSD. Specifically, we begin by defining the problem space, which includes specifying the system of interest as well as relevant decision variables, technological parameters, and contextual parameters (section 2). Next, we establish design and process algorithms to generate the system inventory (mass and energy flows that enter and leave the system, section 3). Sustainability indicators can then be quantified using techniques that span economic, environmental, human health, and social dimensions (section 4). By compiling all algorithms used in system simulation and sustainability characterization, a system model can be created to quantify uncertainty and generate the desired types of insight (section 5.1). Through the review of existing tools, we discuss the status of tools for sustainability analyses and how the different steps of QSD can be executed under uncertainty (section 5.2). With literature examples and representative figures, we further illustrate how QSD can be used (i) to characterize sustainability indicators under uncertainty, (ii) to identify sustainability drivers, (iii) to set RD&D targets, (iv) to understand uncertainty drivers, (v) to explore alternative scenarios (*i.e.*, distinct combinations of decision variables, technological parameters, and contextual parameters), and (vi) to inform practical deployment (section 5.3). Ultimately, QSD can be used to elucidate the complex and intertwined connections among design decisions, technology characteristics, contextual factors, and sustainability indicators, thus enabling transparent and agile planning and design processes. Finally, we identify future research needs for the continued development and application of sustainability analyses for technology RD&D, with the goal of supporting society's pursuit of sustainable development (section 6).



Yalin Li

Dr. Li is a Research Scientist in the Institute for Sustainability, Energy, and Environmental at the University of Illinois Urbana-Champaign. With an experimental background on the development of thermochemical and catalytic technologies for resource recovery from wastewater, Yalin is interested in advancing the sustainability of water and energy infrastructure through experimentation and quantitative sustainable design. Recent research projects span across sanitation and resource recovery systems, field-to-market bioeconomy value chain, and the development of open-source platforms for process design, sustainability analyses, as well as decision-making.

2. Define problem space

The first step of QSD is to define the problem space. In essence, this is the process of specifying the technology of interest, what will be included or excluded from the analysis (*i.e.*, the system boundary), and the ranges of assumptions that can be made for QSD inputs. QSD inputs comprise any assumptions that may influence the performance and sustainability of the system, including decisions about the system design or operation of the system (*i.e.*, decision variables), characteristics of the technology or its components (*i.e.*, technological parameters), and the context in which the technology can be deployed (*i.e.*, contextual parameters). The QSD inputs form an N-dimensional "problem space" encompassing all possible combinations of values of the QSD inputs (N is the number of QSD inputs), and the sustainability of the system will be evaluated within this space through QSD. To help familiarize the reader with these terms and their meaning, a summary of terminology definitions can be found in Table 1 and specific examples from the literature can be found in Tables 2 and S1 (ESI†).

2.1. Construct system

Constructing the system (at a conceptual level) requires the specification of the system boundary to identify unit

John Trimmer

Dr. Trimmer is the Deputy Director of Research at the Aquaya Institute, a non-profit research and consulting organization dedicated to safe water and sanitation. Based in Nairobi, Kenya, John develops and oversees Aquaya's research programs, with particular focus on safe and sustainable sanitation in urban and rural contexts. Previously, John studied the sustainability of resource recovery from sanitation as a post-doctoral research associate and doctoral student at the University of Illinois Urbana-Champaign. He also served for three years as a United States Peace Corps Volunteer in Uganda, where he supported the NGO Brick by Brick Uganda and studied Ecological Sanitation.

Diana Byrne

Dr. Byrne is an Assistant Professor in the Department of Civil Engineering at the University of Kentucky. Her research focuses on applying and adapting quantitative sustainable design tools such as life cycle assessment and quantitative microbial risk assessment to guide decision-making for water and sanitation infrastructure. She is interested in applications of sustainable design in various settings, with an emphasis on context-specific objectives and constraints. Within civil engineering, she engages in research and teaching that focus on applying sustainable design and engineering principles to pursue meaningful impacts for people and the environment.

Sherri Cook

Dr. Cook is an Assistant Professor of Environmental Engineering at the University of Colorado Boulder. Her research group has three main research thrusts: charting pathways for sustainable water and waste management systems by applying existing evaluation methodologies, in particular life cycle assessment (LCA), to existing and novel technologies to enable sustainable water treatment technology development and implementation; advancing sustainability-based evaluations and engineering decisions by developing new methods and decision frameworks to promote universal and sustained sanitation; and advancing environmental biotechnology applications by investigating novel biological process capabilities to enable safe water reuse.

Jeremy Guest

Dr. Guest is an Associate Professor and the David S. Crawford Faculty Scholar in the Department of Civil and Environmental Engineering at the University of Illinois Urbana-Champaign (UIUC). His research and teaching centers on the development of technologies for sustainable water, sanitation, biofuels and bioproducts with applications in both high-income and underserved communities. In addition to research and teaching, he also serves as the Associate Director for Research for the Institute for Sustainability, Energy, and Environment (iSEE) and as the Illinois Thrust Lead for Sustainability for the IBM-Illinois Discovery Accelerator Institute, both at UIUC.

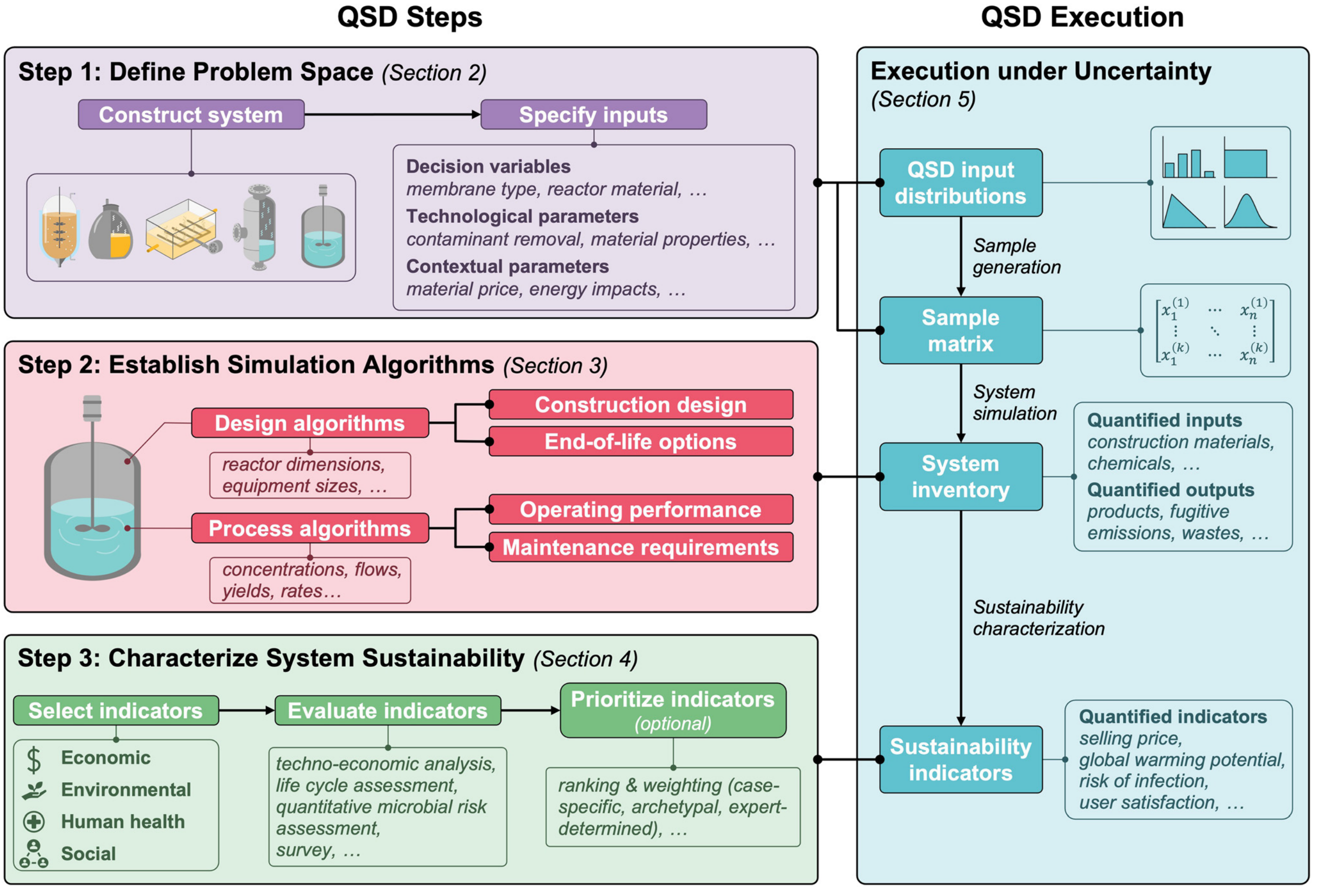


Fig. 1 Overview of the quantitative sustainable design (QSD) methodology, which includes the steps of defining problem space, establishing simulation algorithms, and characterizing system sustainability (left panel); corresponding outputs from each step (and their integration under uncertainty) are included in the right panel.

processes and sources of impact that will be included in or excluded from QSD. This conceptual system should contain the technologies of interest and their interactions with upstream, downstream, and parallel unit processes. Notably, the system does not need to be limited to the boundary of any specific physical system, but it can include any related processes that may be impacted by changes to QSD inputs. In selecting the system boundary, an "all-inclusive" approach would involve all upstream and downstream unit processes that interact directly or indirectly with the technologies. However, this approach may result in the inclusion of unit processes that are inconsequential to system sustainability, add unnecessary layers of complexity, and introduce sources of uncertainty that demand additional resources to evaluate. For example, in comparing capacitive deionization and reverse osmosis (RO) for brackish water desalination, pretreatment and brine disposal were excluded from one study because of their high sensitivities to variables (feedwater composition and geographical location, respectively) that were not relevant to the objectives of the study.[62] Excluding these unit operations allowed the researchers to focus on core comparisons between capacitive deionization and RO without introducing additional unknowns that were expected to be independent of desalination technology choice (*e.g.*, brine disposal method). Moreover, depending on the objectives of the QSD study (*e.g.*, the number of technologies to be evaluated), the scale of the system can vary from a single unit process to a network of multiple subsystems across different disciplines and industries. Similarly, resolution of the design, simulation, and analyses can be tailored to the different unit processes within the system. Therefore, the definition of the conceptual system can be an iterative process to maintain focus on unit processes that are relevant to the sustainability indicators of interest or the targeted insight.

2.2. Specify inputs

2.2.1. Decision variables. Decision variables are independent QSD inputs that can be controlled by the designer or operator. Decision variables may include system configurations, detailed design decisions for individual unit operations, operating conditions, and end-of-life options. They can be continuous, taking on any value within a specified range (*e.g.*, operating temperature, adjusted pH, disinfectant concentration); or discrete, selected from a set of pre-specified values (*e.g.*, aerobic or anaerobic treatment, catalyst type, fate of biosolids). Moreover, decision variables can be fixed or adjustable during operation. For example, when designing a membrane bioreactor, decision variables

Table 1 Summary of QSD terminology[a]

Term	Definition
Sustainability analyses	Evaluation of a system's sustainability which may address one or multiple dimensions, including economic, environmental, human health, and social
Quantitative sustainable design (QSD)	A structured methodology for the sustainability analyses of technologies
Section 2. Define problem space (step 1 of QSD)	
QSD input	Variable or parameter that influences the sustainability of the system, including decision variables, technological parameters, and contextual parameters
Decision variable	Independent variable that can be controlled by the designer or the operator[46]
Technological parameter	Parameter that is intrinsic to a technology (including components of the technology)[46]
Contextual parameter	Non-technological parameters that influence the sustainability of a technology[47]
Problem space	Conceptual N-dimensional space formed by the combination of all possible values of the N QSD inputs, across which the system will be evaluated
Opportunity space	A sub-space of the problem space in which the selected technology outcompetes alternative technologies
Unit process	The smallest element considered in QSD; mass and energy flows of unit processes are considered in the system inventory analysis[48–50]
System boundary	Set of criteria specifying which unit processes and upstream/downstream sources of sustainability impact are included in the system[49,50]
System inventory	Mass and energy flows that enter and leave the system
Section 3. Establish simulation algorithms (step 2 of QSD)	
Life cycle stage	Particular phase of the system, including construction, operation and maintenance, and end-of-life stages
Design algorithm	Set of equations or procedures to generate mass and energy flows during the construction and/or the end-of-life stages of all unit processes within the system
Process algorithm	Set of equations or procedures to generate mass and energy flows during the operation and maintenance stages of all unit processes within the system
Section 4. Characterize system sustainability (step 3 of QSD)	
Goal	Broad, qualitative statements about objectives[12]
Indicator	Quantitative measures selected to assess the progress toward or away from a stated goal[12]
Target	Specific goals with endpoints and timetables to reach desired indicator values[12]
Trend	Change in the value of an indicator over time[12]
Driving force	Process that influences trends and the ability to meet targets[12]
Life cycle costing (LCC)	Technique to estimate the costs associated with the existence of the system[51]
Techno-economic analysis (TEA)	Technique to assess the financial viability of the system when considering all associated costs and revenues through a discounted cash flow analysis[52]
Cost–benefit analysis (CBA)	Technique to compare the projected or estimated costs and benefits (or opportunities) associated with a project to the society[53]
Life cycle assessment (LCA)	Technique to compile and evaluate the inputs, outputs, and potential environmental impacts of the system throughout its life cycle[49,50]
Foreground (unit) processes	Unit processes that can be controlled by designers or operators[54]
Background (unit) processes	Unit processes that designers and operators exercise no direct influence upon, but are relevant to foreground processes[54]
(Foreground) system[b]	Group of foreground processes in specific order (including their inputs and outputs) to conceptually represent the technologies to be studied in QSD[54]
Background system[b]	Group of background processes (including their inputs and outputs)[54]
Life cycle inventory (LCI)	Inventory of mass and energy flows for both foreground and background systems[49,50]
Quantitative risk assessment (QRA)	Technique to quantify the risks associated with an engineering process[55]
Quantitative microbial risk assessment (QMRA)	Technique to assess human health risks that arise from the exposure to pathogens[56]
Social (and social-economic) life cycle assessment (SLCA or S-LCA)	Technique to assess social and socio-economic impacts of the system throughout its life cycle, including how stakeholders (*e.g.*, technology users, regulators, governments) perceive and interact with technologies[57]
Section 5. Execution and applications	
System design	Definition of the problem space and establishment of simulation algorithms (steps 1 and 2 of QSD)
System simulation	Execution of the simulation algorithms to generate the system inventory
System sustainability characterization	Quantification of sustainability indicators using system inventory; certain sustainability characterization techniques (*e.g.*, LCA) may convert system inventory to system life cycle inventory in this process (step 3 of QSD)
System model	Compilation of all algorithms used in system simulation and sustainability characterization
Monte Carlo method	Statistical technique to use stochasticity (*i.e.*, randomness) for problems that are deterministic in nature[58]
Monte Carlo sampling	Sampling technique to generate samples by repeatedly drawing random values from defined distributions (*i.e.*, the problem space) using random number generators (*i.e.*, random sampling)[59]
Latin hypercube sampling	Quasi-random sampling technique that ensures all portions of the problem space are sampled by first dividing the uncertainty range of each QSD input into N strata of equal marginal probability, then sampling once from each stratum[60]

Table 1 *(continued)*

Term	Definition
Uncertainty analyses	Systematic procedure to quantify the uncertainty of QSD results[49,50]
Sensitivity analyses	Systematic procedure to study how the uncertainty in the model outputs can be apportioned to different sources of uncertainties in model inputs[44]
Scenario	Individual set of QSD inputs based on a coherent and internally consistent set of assumptions about key driving forces and their key relationships[61]
Scenario analyses	Systematic procedure to draw conclusions for certain sets of inputs with specific values (*i.e.*, scenarios)[19]

[a] Additional details about each term can be found in their respective sections of this tutorial review. [b] Unless specified with "background", "system" and "unit processes" in QSD refers to the foreground system and unit processes.

may include membrane material (a discrete, fixed decision variable), membrane area (a continuous, fixed decision variable), and membrane flux (a continuous, adjustable decision variable).[46]

Table 2 Literature examples illustrating concepts, steps, and applications of QSD[b]

	Example 1	Example 2
Title	Evaluation of life cycle assessment (LCA) for roadway drainage systems[306]	Quantitative microbial risk assessments for drinking water facilities: evaluation of a range of treatment strategies[143]
QSD objectives	Evaluate the cost and environmental impacts of roadway drainage systems to guide future drainage design and operation	Estimate the risk associated with pathogens for different drinking water treatment processes and their potential failures
Step 1. Define problem space		
System boundary	Roadway drainage system components including basin (detention or retention), linear conveyance element (bioswale, grass swale, storm sewer), culvert, and pipe underdrain	Drinking water treatment facilities
Life cycle stages	Construction, operations, maintenance, end-of-life	Operations, maintenance
Decision variables[a]	Type of linear conveyance element	Treatment processes
Technological parameters[a]	Concrete mix design; removal efficacy of basins and swales	Disinfection volume and flowrates; hydraulic baffling factor
Contextual parameters[a]	Precipitation; initial pollutant concentration in the runoff; interest rate; unit costs of materials; frequency of maintenance activities	Temperature and pH of the raw water
Step 2. Establish simulation algorithms		
Algorithm types and levels of complexity[a]	Theoretical values: calculation of the characterization factor for fugitive CO_2 emissions from degraded biochemical oxygen demand in the stormwater	Theoretical values: illness relationships (*i.e.*, infection rates) for pathogens without literature data
	Existing design & data: design of drainage system components based on design standards	Existing design & data: disinfection log removal
	Design heuristics; empirical models: direct emissions from equipment and flow from road into the drainage system	Design heuristics; empirical models: pathogen dose response curves
		Mechanistic models: hydraulic retention time distribution using the *N*-CSTR approach (*N* is the number of theoretical continuously stirred tank reactors)
Step 3. Characterize system sustainability		
Sustainability dimensions	Economic; environmental	Human health
Characterization techniques	Life cycle costing (LCC); life cycle assessment (LCA)	Quantitative microbial risk assessment (QMRA)
Sustainability indicators	Cost and environmental impacts (ozone depletion, climate change, smog, acidification, eutrophication, carcinogenics, noncarcinogenics, respiratory effects, ecotoxicity, fossil fuel depletion, cumulative energy demand)	Disability-adjusted life years (DALYs)
Execution and applications		
Execution tools[a]	SimaPro; MATLAB	Not reported
Analyses[a]	Uncertainty analyses: Fig. 2 and S2†	Uncertainty analyses: Fig. 1 and 4–6
	Sensitivity analyses: Fig. S8–S10†	
	Scenario analyses: Fig. 5 and S11†	Scenario analyses: Fig. 3

[a] Non-exhaustive list in the example paper. [b] Refer to Table S1 in the ESI† for additional literature examples.

In determining the values and distributions of the decision variables, the maturity of the technology is often considered and can be represented by technology and/or manufacturing readiness level (TRL/MRL). TRL, in particular, is often used when technology development (as opposed to manufacturing) is the focus.[63,64] For example, for established technologies such as RO (TRL of 9[65]), typical ranges of rejections have been established for different applications (*e.g.*, micropollutant treatment[66]), whereas decision variables for emerging technologies such as CO_2 utilization (TRL of 2–4) may be highly uncertain as designers and/or operators characterize the landscape of technical feasibility.[67] Therefore, the latter case may require evaluation across wide ranges of decision variables and robust consideration of uncertainty in QSD execution (section 5.2).

2.2.2. Technological parameters. Technological parameters are parameters intrinsic to a technology's design and operations (*e.g.*, material properties, reaction coefficients). Unlike decision variables, values of technological parameters are subject to the technology rather than the designer or the operator (*e.g.*, maximum specific growth rate when designing a biological treatment process). Notably, if a parameter is not intrinsic and can instead be calculated (*e.g.*, cell growth rates can be calculated using maximum specific growth rates, temperature, and relevant constituent concentrations), this parameter should be modeled through algorithms rather than being included as an independent input. Similar to decision variables, magnitudes of technological parameter uncertainty can be related to TRL/MRL, with early-stage technologies having larger uncertainty due to the lack of knowledge. However, one can leverage theoretical values or technological limitations to constrain parameter uncertainty during QSD execution (section 3.2), and the results of QSD can be used in turn to set targets for technological parameters in research and development (section 5.3).

2.2.3. Contextual parameters. Contextual parameters represent non-technological values that influence the sustainability of technologies, especially at the deployment stage.[36] These parameters are intended to capture the specific circumstances in which the technology would be deployed. They reflect the local and regional nature of primary stressors to humans and the environment,[13] accounting for economic (*e.g.*, tax rates, unit costs), environmental (*e.g.*, ambient temperatures), social (*e.g.*, household size), political (*e.g.*, regulations), and other conditions in which the system exists.[68,69] As one example, outcomes associated with energy-intensive technologies may be especially sensitive to the characteristics of the local electricity grid, which can vary widely across and within countries: for example, the price of the electricity varies from \$0.04 in Oklahoma to \$0.26 in Hawaii,[70] and the greenhouse gas (GHG) emissions from electricity production vary from 0.081 kg CO_2 eq. per kW h^{-1} for the Bonneville Power Administration to 1.0 kg CO_2 eq. per kW h^{-1} for the Ohio Valley Electric Corporation.[71–73] Additionally, although contextual parameters are independent of the technology being evaluated, they may nonetheless directly or indirectly affect the technical performance of the system. For example, solar irradiance could directly impact the efficacy of sunlight-mediated disinfection technologies,[74] while local and national regulations could indirectly affect the performance of waste sludge treatment systems through the set legal limits (*e.g.*, how much sludge can be accepted by a landfill facility).[75]

For contextual parameters, the resolution of the data is also an important consideration. While higher resolution data (*i.e.*, data being more specific to the deployment site) will yield results that more accurately reflect the deployment context, researchers may also be limited by the availability of data or the feasibility of new data collection. Generally, objectives of the QSD study will determine the appropriate resolution of contextual parameters (*e.g.*, locality-specific, regional, nationally, or internationally representative averages), and additional analyses can be performed to assess how uncertainty in these parameters impacts system sustainability.

3. Establish simulation algorithms

After defining the problem space, the next step in QSD is to automate the process of translating QSD inputs into a system inventory (*i.e.*, all mass and energy flows entering and leaving the system), which can be accomplished by establishing mathematical representations of the system across its life cycle. This step in QSD leverages design algorithms and process algorithms, where design algorithms correspond to the construction and end-of-life stages and process algorithms correspond to the operation and maintenance stage. Both design and process algorithms are linked to QSD inputs such that the system performance – including mass and energy balances across the life cycle – responds to changes in decision variables, technological parameters, and contextual parameters (illustrated in the following section).

3.1. Algorithms across system life cycle stages

3.1.1. Design algorithms for construction and end-of-life. Design algorithms are sets of equations for the construction (*e.g.*, equipment sizing, material selection) or end-of-life (*e.g.*, disposal, salvage) stages of unit processes within the system. These algorithms can vary in complexity. For example, a simple design algorithm can scale the dimensions or number of fermenters based on the required volume, but a more complex model may include the specification of fermenter height, wall thickness, and weight, which are calculated using factors such as aspect ratio, fractional weld efficiency, reactor pressure, and material properties.[76] Compared to construction, the relative importance of the end-of-life stage can be minor and is often excluded from the analysis (*e.g.*, for wastewater treatment facilities[77]). However, this should not be considered a general rule, as end-of-life assumptions may be impactful in some systems or particularly relevant to specific analyses (*e.g.*, recycling of demolition waste from residential buildings[78]).

3.1.2. Process algorithms for operations and maintenance. Process algorithms are used to calculate the mass and energy flows throughout the system during the operation and maintenance stage. These flows can be used to gauge the performance of the technology (*e.g.*, calculating contaminant removal) and to determine the relevant inventory items required for sustainability characterization (*e.g.*, raw chemicals consumed, generated products and wastes, electricity consumption, and fugitive emissions such as CH_4, CO_2, and N_2O). Like design algorithms, the complexity of process algorithms can vary widely from assumed performance based on theoretical values to calibrated and validated mechanistic models.

3.2. Algorithm selection

Regardless of their type (*i.e.*, design *vs.* process), the complexity of the algorithms should be tailored to the objectives of the QSD study. Additionally, algorithm complexity can also be constrained by data availability. For technologies with high TRLs/MRLs (7+), data are generally more abundant as these technologies have been applied across more diverse contexts. Consequently, selection of the algorithms is often not data constrained and the algorithms can range from assumed values to more mechanism-driven, complex models. In contrast, emerging technologies with low TRLs/MRLs (1–2) may be limited to simple algorithms or assumed values due to the scarcity of the data (Fig. 2).

In general, more complex algorithms can be more responsive to QSD inputs, but the complexity of an algorithm does not inherently correlate with usefulness or accuracy. As the algorithm becomes more mechanism-driven and complex, it may require additional or larger datasets for calibration, validation, and prediction, which may not be readily available. Its accuracy may also be affected by parameter uncertainty and missing mechanisms that introduce bias and skew results, and the increased complexity will increase demand for computational resources. For example, one study used a complex model for risk evaluation of radioactive waste disposal composed of 286

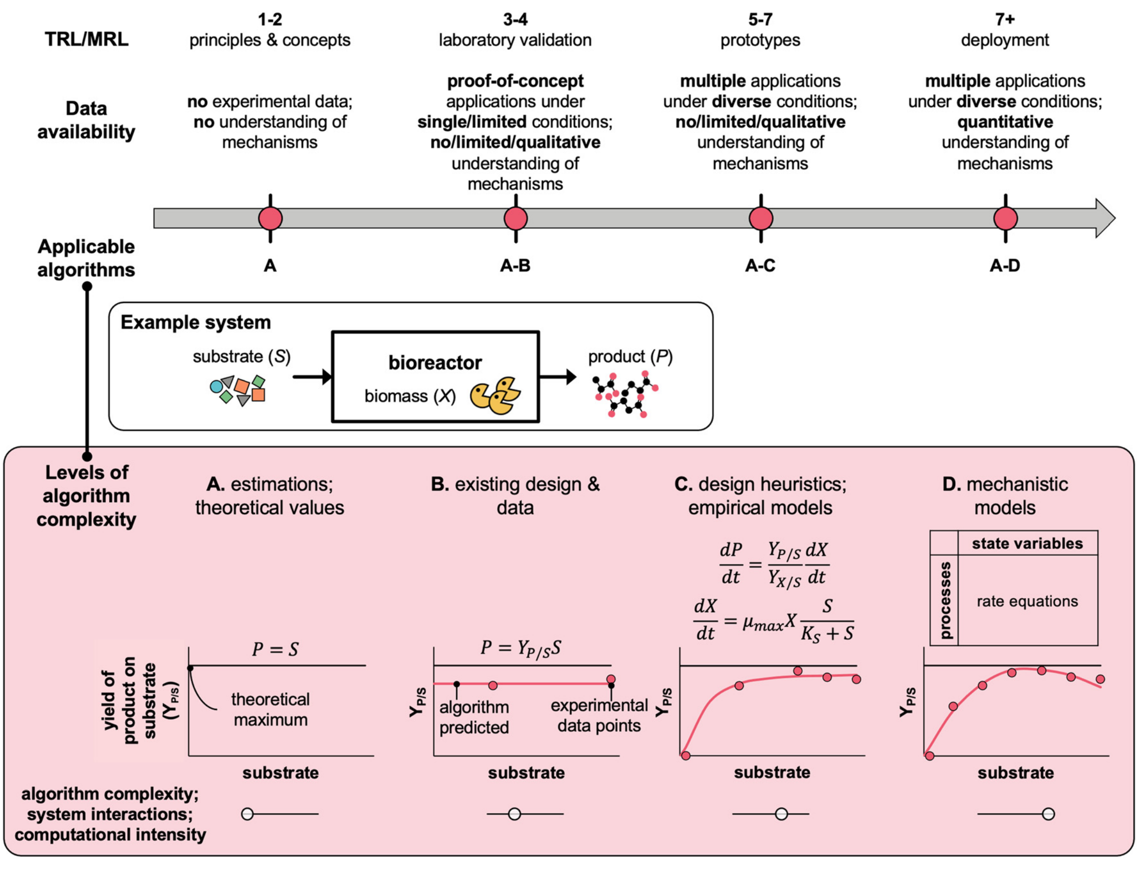


Fig. 2 Illustration of algorithm selection with varying technology/manufacturing readiness levels (TRL/MRL) and data availability. The example system centers on the biological conversion of a substrate (*S*) to a product (*P*). For technologies with a higher TRL/MRL and more robust experimental data sets, algorithms that are more mechanism-driven can be developed to more explicitly represent underlying interactions within the system and elucidate hidden connections between QSD inputs and system sustainability. However, the availability of data should not dictate the choice of algorithms, as mechanism-driven models, which often have higher levels of complexity, can also require more computational resources and may introduce additional sources of uncertainty that are not relevant to the objectives of a QSD study. The illustration of algorithm complexity, system interactions, and computational intensity (bottom of the figure) for each type of the algorithms are solely for comparative purposes. In practical applications, they depend on multiple factors (*e.g.*, the actual mechanisms) and could deviate from the typical ranges shown here.

sub-models and thousands of parameters, but its utility was undermined by the large uncertainty of a single key variable.[79] In contrast, the Arrhenius equation, an empirical equation describing the correlation between a reaction rate constant and temperature, consists of only two reaction-specific parameters, yet it is arguably one of the most widely used models in thermodynamics.

For technologies with a TRL/MRL of only 1–2 (observation of basic principles and formulation of concept), theoretical values or "back-of-the-envelope" estimations can be used. For example, a 100% thermodynamic conversion efficiency could be used for mass flow simulation,[80] and industry averaged capital[81] or utility[82] costs from a similar technology could be used as an early estimate for capital and operating costs. If "proof-of-concept" studies have been conducted (TRL/MRL 3–4), existing designs or experimental data can be used for more realistic design and simulation of the system. When more designs and data become available with prototype implementation (TRL/MRL 5–7), engineering heuristics (*e.g.*, the choice of separation technology, typical reactor aspect ratios[83]) and empirical models can be used to establish more mathematical connections between QSD inputs and the system inventory. For technologies with higher TRL/MRL (7+), these connections may be able to be mathematically represented based on first principles using mechanistic models in design and process algorithms. As examples, electricity consumption of a pump can be calculated using fluid flowrate, total dynamic head, and pump efficiency,[46] and biomass growth can be modeled using metabolic reactions and fluxes.[84] Notably, regardless of the level of complexity of the selected algorithms, uncertainty of the algorithm inputs and parameters should be considered; this uncertainty could be particularly important for early-stage technologies where the algorithms often rely on estimations, theoretical values, or very limited experimental data.

Overall, the complexity of design and process algorithms will dictate the connections (or the lack thereof) among specific QSD inputs and the system inventory, the latter of which directly influences system sustainability and the types of insight that can be generated. Consequently, the objectives of a QSD study can also inform the selection of algorithms. For example, when the objective is to evaluate a technology's site-suitability (*e.g.*, sanitation-based resource recovery systems[19,47,85]), it will be essential to use a model which incorporates geo-spatial data and corresponding contextual parameters, but complex algorithms with many technological parameters may not be necessary. Alternatively, when the objective is to identify and elucidate the sustainability drivers for research prioritization (*e.g.*, electrode specific capacitance and contact resistance in capacitive deionization technologies[86]), mechanistic algorithms can provide more pertinent insight.

4. Characterize system sustainability

After generating the system inventory, the next step in QSD links the mass and energy flows across the system's life cycle with quantitative sustainability indicators, the values of which can be used to track the progress toward or away from the stated project goals.[12] This section discusses techniques to characterize system sustainability with respect to economic, environmental, human health, and social dimensions. These four categories are adapted from the tripartite conception of sustainability (economic, environmental, and social dimensions[87]), explicitly considering human health as its own dimension to highlight its significance in the context of environmental technologies and its distinct characterization techniques. Discussion of these four dimensions will focus on the steps of sustainability characterization including indicator selection, indicator evaluation, and (optionally) indicator prioritization. In the first step, sustainability indicators are selected based on the objectives of the QSD study and availability of the resources (*e.g.*, data). Next, impact of the system inventory on each indicator is quantified. Finally, if desired, the indicators within each dimension can be ranked or aggregated (*e.g.*, through weighted sum) to prioritize critical indicators and reduce the number of indicators from which to draw insight.

4.1. Economic

Economic analysis is an essential component of QSD for systems where costs often govern decision-making. Traditional cost and profitability indicators, such as investment cost, operating and maintenance costs, payback period, return on investment (ROI), and net present value (NPV), are commonly used in the literature.[52,83,88,89] To compare products that are of equivalent utility but that were generated from different technologies,[90] indicators such as levelized cost or minimum selling price (MSP) are often used. Both indicators quantify the average net present cost of a product over a system's entire lifetime, but they are typically used in different contexts: levelized cost is usually used in the context of energy (*e.g.*, electricity)[91] and (more recently) water[92] systems, whereas MSP is often used in the context of biorefineries.[52] The selection (and prioritization) of economic indicators will depend on stakeholder preferences. For instance, technology developers may focus on levelized cost to compare against benchmark technologies (*i.e.*, the conventional technologies against which they are competing)[62,91,93] while technology adopters (*e.g.*, water or wastewater utilities) may focus on payback period.[94,95]

To obtain the values for these indicators, life cycle costing (LCC; *e.g.*, ref. 46, 96 and 97) and techno-economic analysis (TEA; *e.g.*, ref. 98–100) are two of the most commonly used techniques for economic indicator evaluation during technology development. Both techniques rely on the system inventory generated by system simulation. After linking those data to unit prices of cost inventory items, additional costs (*e.g.*, labor, tax, insurance) are included with revenues from co-products (*e.g.*, recovered nutrients) to calculate indicators such as the NPV of the system. During these calculations, costs and revenues in future years are discounted (using an interest rate) to account for the time value of money.[83] In the case of LCC, costs and revenues over the lifetime of the system are converted to a common time (*e.g.*, present value,[101] annual value[102]) based on the preferences of decision-makers.[103–105] LCC generally centers itself on one or more actors (*e.g.*, producer, consumer, waste management operator), which should be chosen based on the objectives of the QSD study.[51] LCC results can be reported for the project as a whole, or they can be normalized to the defined functional unit (a reference unit to quantify the performance of a system[49,50]). In contrast, TEA is typically used to determine the financial viability of the system through selling of the generated product(s), including the potential for acceptable risk and ROI.[83] Specifically, a discounted cash flow rate of return analysis is often used to calculate a product's breakeven point, which is the point where the equivalent value of the sum of all cash flows at the base cost year equals zero (*i.e.*, NPV = 0). At the breakeven point, the product cost or selling price is referred to as the leveraged cost or the MSP, and the discount rate is referred to as the internal (or investor's) rate of return (IRR).[83] Appropriate IRR targets are typically set according to industry-specific standards based on the type of technology, the stage of development, and the level of risk associated with investment. For example, a 10% IRR is commonly used for a mature industry,[98,106,107] but higher IRRs (*e.g.*, 10–20%) may be required for projects with emerging technologies, and IRRs below 10% may be acceptable for lower risk ventures (*e.g.*, infrastructure debt).[108,109]

In addition to LCC and TEA, cost–benefit analysis (CBA) is also a technique used for economic sustainability evaluation, but it is more often used for policy assessment (by considering external costs and benefits that are incurred by parties not directly involved) than technology development. For example, the U.S. Environmental Protection Agency has undertaken thousands of CBA analyses for relevant policies (*e.g.*, the Clean Water Act).[110] Therefore, discussions in this review will focus on LCC or TEA given their relevance to technology RD&D.

4.2. Environmental

To align societal development with the maintenance of resilient and accommodating environmental systems, it is critical to limit the environmental footprints of human activities within the "safe operating space" of planetary boundaries.[111–114] Indicators in the environmental dimension can be generally categorized into ecosystem quality (*e.g.*, eutrophication), resource scarcity (*e.g.*, fossil resources), and human health (*e.g.*, particulate matter). Many techniques, including life cycle assessment (LCA),[49,50] eco-efficiency assessment,[115] and environmental performance evaluation,[116] have been developed for environmental management. Among these techniques, LCA is the most comprehensive and widely used to quantify the environmental impacts of a product (including goods and services)[49,50] system throughout its life cycle.

LCA is comprised of four phases including goal and scope definition, inventory analysis, impact assessment, and interpretation.[49] In the context of QSD, the first phase of goal and scope definition is realized through the definition of the problem space (step 1 of QSD), and the LCA can be tailored to include the life cycle stages of interest (*e.g.*, cradle-to-grave, cradle-to-gate, cradle-to-cradle).[49,50,117] For the last phase of interpretation, results from LCA are often discussed together with those from other dimensions, thereby providing a comprehensive evaluation of the system that considers trade-offs among these dimensions and potential improvements to the analysis (section 5.3).

Particularly relevant to sustainability characterization are the inventory analysis and life cycle impact assessment (LCIA) phases. For inventory analysis, different approaches can be used and LCA can therefore be classified as economic input–output LCA (EIO-LCA), process-based LCA, or hybrid LCA which combines the two.[118–121] In QSD, process-based LCA is typically used as it is capable of characterizing the environmental implications associated with changes in QSD inputs. An additional distinction among LCAs is whether they are attributional or consequential, where attributional LCA focuses on the flows to/from the environment and consequential LCA focuses on how the flows may change in response to decisions.[77,122] Either attributional or consequential LCA may be used in QSD, and the selection of one (over the other) should be based on the desired insight. Furthermore, there are a number of forward-looking LCA approaches focusing on emerging technologies, including prospective (model the technology in a future, more developed phase), *ex ante* (prior to the market introduction of the technology), dynamic (consider the dynamics of QSD inputs over time), anticipatory (engage stakeholders and emphasize on uncertainty), and combinatorial (consider alternative technologies) LCA.[123–127] Despite the differences among these approaches, they can all be used to guide the RD&D decisions of a new technology before it is commercially implemented, with the goal of ensuring it is environmentally competitive or advantageous to the incumbent technology mix. Additionally, all relevant approaches require the system inventory be compiled from the foreground system to execute the inventory analysis, and converting the system inventory to the life cycle inventory (LCI) by considering impacts incurred in the background.[54] For example, in operating a membrane reactor, the system inventory could include a specified number of membrane, while the LCI would include all mass and energy flows associated with these membrane modules across their life cycle.[46]

With regard to the life cycle impact assessment (LCIA) phase, many methods have been developed in recent years (*e.g.*, ReCiPe,[128,129] TRACI[130–132]). These LCIA methods provide characterization factors, which translate every individual emission or raw material requirement in the LCI into normalized, quantitative environmental impacts. These characterization factors can be developed at the midpoint or endpoint of the environmental impact cause-effect chain. While the midpoint characterization factors are developed for a particular impact indicator (*e.g.*, 100-year global warming potential), they can be aggregated into endpoint characterization factors representing different impact categories (*e.g.*, ecosystem quality, human health).[129,133] In this process, varying groups of assumptions (*e.g.*, time horizon) may be adopted to reflect the uncertainties and choices associated with these characterization factors.[129] For example, based on the hierarchist perspective in ReCiPe, methane has a midpoint characterization factor of 34 kg CO_2 eq. per kg^{-1} for 100-year global warming potential, which can be further translated to the human health endpoint using a factor of 9.28×10^{-7} disability-adjusted life years (DALYs) kg CO_2 eq.$^{-1}$.[129]

Finally, three optional elements in LCA – normalization, grouping, and weighting – can be included in the LCIA phase if their application is consistent with the goal and scope of the LCA. Specifically, normalization compares the magnitude of indicator results to reference values, grouping sorts and ranks the impact categories, and weighting converts and aggregates indicator results across impact categories by weighting categories relative to each other.[50] With these elements, one may represent the environmental sustainability of a system with a single score, which can be easily compared across a range of systems in decision-making. However, as the scores are directly affected by subjective choices during normalization, grouping, and weighting, uncertainty and sensitivity analyses should be included to consider the impacts of these subjective decisions on final scores. Additionally, stakeholders should be engaged throughout this process to reflect their priorities in the final indicator values (section 4.4).

4.3. Human health

While global human health-related impacts can be quantified with LCA (*e.g.*, carcinogenics and non-carcinogenics in TRACI[130–132]), LCIA methods often have toxicity models (*e.g.*, USEtox in TRACI[130–132]) and embedded assumptions about the environmental fate of contaminants, human exposure, and human health effects (including dose response relationships).[134] Consequently, the human health category within LCA includes modeled impacts spread over large spaces and time scales, and these "averaged" impacts do not explicitly consider localized effects from chemicals or pathogens that may be particularly relevant to project stakeholders. Therefore, when local health risks from exposure to chemical and microbial hazards are of concern, impact indicators (*e.g.*, benchmark quotient of risk level[135]) should be selected and evaluated with corresponding techniques (*e.g.*, QRA). In the human health dimension, quantified indicators often include probability of infection, probability of illness, or DALYs, all of which can be calculated from one another with certain assumptions. Additionally, there have been methods developed to calculate monetized indicators based on the contribution of pollutants to mortality and the value of a statistical life (VSL; *e.g.*, human health damage from freight transportation[136]). However, this approach has not been widely adopted in the development of environmental technologies due to its shortcomings and controversies (*e.g.*, how VSL is estimated).[137–139]

To quantify human health indicators, QRA can be performed following the steps of hazard identification, exposure assessment, dose response, risk characterization, and risk management.[55,140] More specifically, to assess local human health risk due to pathogens, QSD inputs and process algorithms can be used to simulate pathogen concentrations, after which quantitative microbial risk assessment (QMRA)[141] can be performed to quantify the human health risk. QMRA can be performed with generic (*e.g.*, using generic pathogen concentrations in feces for evaluating water and sanitation systems[142]) or site-specific data (*e.g.*, ref. 143–145 and example 2 (ref. 143) in Table 2). Additionally, there are examples where QMRA is hybridized with LCA[56,146,147] to characterize trade-offs between human health risk and environmental impacts.[148–150] Similarly, when health risk related to chemicals (*e.g.*, contaminants of emerging concern) is the focus, quantitative chemical risk assessment (QCRA)[151] can be applied.[135] To facilitate the risk assessment, quantitative structure models (*e.g.*, quantitative structure–activity relationship, QSAR;[152] quantitative structure property relationship, QSPR[153]) can be used to predictively model the properties (*e.g.*, toxicity, albeit with significant uncertainty[154]) of interest, and certain semi-quantitative techniques (*e.g.*, CHEM21 guide[155] as applied in ref. 156) can be used as a screening strategy to exclude technologies that have significant safety concerns.

4.4. Social

Social sustainability is generally intended to capture how stakeholders (*e.g.*, technology users, regulators, governments) perceive and interact with technologies, which are often critical considerations to enable sustained adoption and long-term success of a project.[9,157] Social sustainability is often neglected in sustainability analyses,[158] partly stemming from the lack of widely used indicators and/or standardized evaluation techniques.[159,160] Social life cycle assessment (SLCA) is one of the most developed techniques with guidelines[161] and methodological sheets[162] providing detailed instructions for indicator selection, data availability and collection methods.[163,164] Nonetheless, the application of SLCA has been limited (in part) due to the challenges associated with data collection and the qualitative nature of social indicators.[165] Though proxies (*e.g.*, transparency, income level[166]) may be used to quantitatively represent qualitative social indicators, these approaches cannot fully capture the unique aspects of social sustainability (*e.g.*, highly site-specific, unequal impacts on different societal groups).

To address these challenges, stakeholders can be engaged throughout the indicator selection, evaluation, and prioritization steps. When, how, and which stakeholders are engaged depends on the objectives of the QSD study and resource availability, and the engagement methods can range from low to high stakeholder input and influence (corresponding to the least to the most resource intensive). In the indicator selection step, indicators can be identified by domain experts (the lowest stakeholder input and influence option),[167,168] selected or supplemented by stakeholders from pre-generated options or "master lists",[169–171] or generated by stakeholders through focus groups, photovoice, and interviews (the highest stakeholder input and influence).[172,173]

Likewise, during the indicator evaluation step, stakeholders can be engaged through data collection methods of varying stakeholder input and influence. For instance, some structured approaches rely on quantitative data from existing census data or with close-ended surveys (*e.g.*, user cost,[174–177] number of annual meetings,[177,178] number of jobs[167,179,180]). These approaches are common in the technology development literature because they are often less resource intensive and enable data collection across multiple contexts with limited incremental cost (*i.e.*, the cost of gathering data from another location or context is low).[181–184] In contrast, approaches such as semi-structured interviews and case studies[185] are more open to stakeholder elaboration, and they are therefore more resource intensive.

Finally, when needed, stakeholders can also be engaged in the indicator prioritization step. This can be performed in conjunction with MCDA to generate a single score or recommendation. When aggregating indicators, their weights can be determined by experts (the lowest stakeholder input and influence option),[186] derived from archetypal schemes representing different societal groups,[187] or developed for the specific study by stakeholders that directly interact with the technology (the highest stakeholder inputs and influence option).[188,189]

Overall, as each stakeholder engagement method has limitations, the selection of stakeholders should be a careful process that balances resource requirements, social dynamics, and stakeholder representation. For example, the focus group approach, while requiring less resources than interviewing each of the individuals, may not reflect individual goals[190] and can suppress marginalized voices,[191] resulting in a lack of comprehensive goals,[172,192] influences,[193] and decision criteria.[194] Ultimately, substantively addressing social sustainability necessitates the engagement of experts from relevant domains (*e.g.*, the social sciences and humanities) and, when explored in a specific deployment context, local stakeholders who will be directly or indirectly impacted by the project.

5. Execution and applications

5.1. Tools for QSD execution

5.1.1. System simulation. To execute QSD, the first step is to simulate the system and generate the system inventory, for which multiple types of tools can be used. On the simpler end of the spectrum, designs from existing literature can be used and system inventories can be scaled from the literature design (*e.g.*, scaled based on key flowrates). In this case, spreadsheets[81] or programming languages (*e.g.*, R,[195,196] Python[76,197]) can be used for inventory scaling, and this process can be automated through spreadsheet built-in functions (*e.g.*, Microsoft Excel Macros[198,199]) or add-in applications (*e.g.*, Crystal Ball®,[200] SimVoi®[201]). Though straightforward, this strategy relies on existing designs with limited capacity to accurately reflect the intrinsic correlations between QSD inputs and system sustainability. Additionally, as mass and energy flows within the system would be scaled using generic algorithms (often linear correlations) rather than being solved analytically or numerically to convergence, the results could be inaccurate as values of the QSD inputs diverge from the existing design. Therefore, this strategy is generally only appropriate for very preliminary evaluations or for the evaluation of relatively mature technologies for which well-tested scaling algorithms are available.

On the opposite end of the spectrum, high-fidelity, commercial process simulators (*e.g.*, GPS-X™,[202] BioWin,[203] Aspen Plus®,[204] SuperPro Designer,[205] AnyLogic[206]) with rigorous design and process algorithms have been widely used for system design and simulation, especially for large-scale, multi-unit process systems (*e.g.*, wastewater treatment trains,[207,208] bio- or chemical refineries[209–211]). Supported by commercial companies, these simulators are well-tested and capable of solving complex algorithms, allowing deeper investigation into the dynamics among the QSD inputs, system inventory, and sustainability. However, because of their proprietary nature, these simulators are often less accessible and transparent. They may have also limited flexibility to evaluate early-stage technologies due to the lack of corresponding unit operations and associated design and process algorithms.[52] Moreover, many of these simulators have no or limited capacity for advanced statistical analyses (*e.g.*, global sensitivity analysis beyond correlation and regression methods). Thus, they often cannot independently fulfil the objectives of QSD studies.

Notably, in recent years, there has been a push to develop open-source tools for design and simulation of various systems in fields such as water and wastewater,[212,213] waste valorization,[214,215] chemical engineering,[197,216–218] green chemistry,[219,220] and transportation.[221] Their open-source nature allows these tools to be freely used and continuously developed by the general community, and some of these tools have integrated (or are built with extendable capacities for) advanced statistical analyses, sustainability characterization, and multi-objective optimization (*e.g.*, ref. 197 and 213). These features are especially beneficial for early-stage technologies which have not been included in commercial simulators and with higher levels of uncertainties due to the lack of data. However, despite their advantages, these open-source tools can be difficult to adopt (*e.g.*, due to the lack of graphic user interfaces) and challenging to maintain without a central supporting organization. Therefore, laying the groundwork for community-led platforms is vital to the long-term success of these tools, which could be realized *via* collaborative platforms (*e.g.*, GitHub,[222] GitLab[223]) and preparation of easy-to-access documentation. Additionally, to support broader community engagement, it is beneficial if the developed open-source packages do not rely on commercial platforms (*e.g.*, the waste-to-energy system simulation model WESyS relies on STELLA,[214] a set of open-source wastewater treatment models rely on MATLAB and Simulink[224]).

5.1.2. Sustainability characterization. Characterization of sustainability can be performed either within or outside the system simulation platform. For economic sustainability, capital and operating expenditures can often be extracted from the commercial simulators, and some of these simulators have functionalities for profitability and cash flow analyses. However, these built-in functionalities often have little or no support for users to adjust parameter values (*e.g.*, equipment and chemical costs). Therefore, additional analyses are often conducted outside these simulators to explore an expanded QSD problem space (*e.g.*, using spreadsheets[210]).

With regard to environmental sustainability, dedicated LCI databases (*e.g.*, ecoinvent[225]) are often used to translate the system inventory into the system LCI, after which different LCIA methods can be used to quantify the environmental sustainability of the system. To streamline this process, environmental sustainability is often characterized using specific tools (*e.g.*, SimaPro,[226] GaBi,[227] openLCA,[228] Brighway2,[229] GREET[230]). These tools generally have embedded LCI databases and/or allow the importing of external LCI databases, and some of them are equipped with built-in functions or mechanisms (*e.g.*, *via* inter-process communication[228]) that allow the user to account for uncertainty.

To characterize human health indicators, relevant system inventory data (*e.g.*, pathogen concentration), exposure assessment algorithms, and dose response models can be compiled using generic computation tools (*e.g.*, spreadsheet, programming languages). Particularly for QMRA, recommendations by the Center for Advancing Microbial Risk Assessment[231] can be followed to select pathogen-specific dose response parameters based on the type of the model (*e.g.*, exponential, approximate beta-Poisson).

For the characterization of social sustainability, no universal tools have yet been developed for its evaluation. Though some LCA tools (*e.g.*, SimaPro, openLCA, SEEbalance®[232,233]) include databases such as the Social Hotspots Database[234] for SLCA, the primary goal of this approach is to evaluate social risks along a supply chain without including stakeholder input.[235] These tools can facilitate indicator evaluation, but engagement methods described in this work should be followed to more holistically integrate social sustainability into QSD by incorporating stakeholder input across the indicator selection, evaluation, and prioritization steps (section 4.4).

As a range of tools may be used for system simulation and sustainability characterization, data organization and transfer between these tools can be challenging due to the heterogeneity in data requirements (*e.g.*, file format), despite the fact that the same system inventory is used.[236] For example, for a wastewater-based microalgal cultivation system that recirculates water internally, Aspen Plus® was used for system simulation, after which the system inventory was exported for TEA in a spreadsheet and LCA using SimaPro.[237,238] Although programming languages can be used to facilitate data formatting and transfer, this nonetheless presents challenges in QSD execution when system simulation and sustainability characterization need to be repeated thousands of times or more to consider uncertainty (section 5.2). Alternatively, there are ongoing efforts in tool development to integrate system simulation and sustainability characterization on a single, open-source platform (*e.g.*, for sanitation and resource recovery systems,[213] biorefineries[197]). Though still at the early stage, these tools offer the opportunity for streamlined QSD execution with much greater flexibility, better consistency, and higher computational efficiency, all of which are critical to QSD and its application.

5.2. Accounting for uncertainty

5.2.1. Sources of uncertainty. At its core, QSD relies on an aggregated, computational system model to represent the behaviors of physical technologies. This system model is compiled by connecting the algorithms used in system simulation and sustainability characterization to predict the quantities of interest across a range of QSD inputs. Prediction uncertainty of this system model can arise from multiple sources: (i) model structure, (ii) system non-deterministic behaviors, (iii) numerical error, and (iv) model inputs and parameters.[239] Among these sources, the uncertainty of model structure can be considered by empirically comparing or aggregating the predictions of multiple viable models; the uncertainty due to a system's non-deterministic behaviors can be characterized by incorporating stochastic elements into a deterministic model; and the numerical error in calculating model results is usually much smaller than other sources of uncertainty.[239]

Consequently, most essential to QSD is the uncertainty from model inputs and parameters (*i.e.*, QSD inputs), which can be aleatory, epistemic, or both. Aleatory uncertainty (also called variability or irreducible uncertainty) arises from randomness or variations due to "hidden" factors that are not included in the model. Epistemic uncertainty (*i.e.*, true uncertainty, reducible uncertainty), on the other hand, derives from a lack of knowledge of the "true" values.[240–244] Uncertainty associated with decision variables are inherently aleatory as their values are subject to the choice of the designer or the operator, and probability distributions can be used to reflect the designer's or operator's preference within the ranges of feasible decisions. In contrast, uncertainties associated with technological parameters and contextual parameters can be caused by randomness (aleatory), lack of knowledge (epistemic), or both. For example, a location's average temperature on a certain date in the future (a contextual parameter) is random to some extent (*i.e.*, aleatory), and at the same time, practitioners may have imperfect knowledge of its "true" range of variability based on historic data (*i.e.*, epistemic). For LCA, uncertainty may also come from the background systems (*e.g.*, the LCI of the stainless steel), and more accurate (or localized) LCI data are needed to reduce the uncertainty.

5.2.2. Monte Carlo methods. To quantitatively characterize the overall uncertainty introduced in QSD results, Monte Carlo methods are usually applied by using stochasticity (*i.e.*, randomness) to solve problems that are deterministic in nature.[58] In the context of QSD, the first step is to select a subset of QSD inputs to be included as input variables in the uncertainty analysis, after which their probability distributions are defined (*e.g.*, through probability density functions) to quantitatively represent their uncertainties. While including more QSD inputs in the Monte Carlo simulation will likely provide more accurate characterization of the overall uncertainty of QSD outputs (*i.e.*, sustainability indicators), it will also increase the required sample size and thus computational time. To address this, sensitivity analysis can be used to identify input variables that are key drivers of system uncertainty (section 5.3). Notably, as the selection of uncertain input variables can affect results of the sensitivity analysis, uncertainty and sensitivity analyses may be performed iteratively to narrow the input variable pool. Similarly, selection of the probability distributions should be based on the available information on the QSD inputs (*e.g.*, the abundance and reliability of the collected data). To maintain consistency and transparency in this process, a workflow or a set of standard criteria is recommended to define which inputs will be included/excluded and the included inputs' associated probability distributions (*e.g.*, as in ref. 245 and 246). Additionally, in LCA, when there are limited life cycle inventory data available, the pedigree matrix approach[247–249] can be used to characterize the background uncertainty based on a semi-quantitative description of the data quality.

Next, a set of samples (*i.e.*, the sample matrix) are generated from the joint probability distribution of all selected input variables to represent the entire problem space. When all input variables are independent of each other, generating samples from their joint probability distribution is equivalent to sampling separately from the probability distribution of each individual model input. Otherwise, correlations between input variables need to be characterized to properly define and generate samples from their joint probability distribution.[250] Different techniques can be used for sample generation, and the selection of technique is often determined by the types of uncertainty and sensitivity analyses of interest (section 5.3). In practice, Monte Carlo sampling (*i.e.*, random sampling) generates samples by repeatedly drawing random values from a defined distribution using random number generators.[59] Alternatively, low-discrepancy, quasi-random sequences (*e.g.*, Latin hypercube sampling,[60] Sobol sequence[251]) can be used to significantly reduce the sample size (and thus the number of model evaluations) required to generate representative empirical distributions of model outputs.

With the generated samples, empirical distributions of sustainability indicators can be obtained by repeatedly simulating the system and characterizing its sustainability at each sample point, and descriptive statistics (*e.g.*, 5th, 25th, 50th, 75th, and 95th percentiles for each indicator) can be calculated from these empirical distributions. With a representative set of samples, these distributions and the descriptive statistics can reflect the expected values and variations of the chosen sustainability indicators due to the uncertainties in QSD inputs, thus avoiding the "false accuracy" from a single simulation that only represents one point in the problem space.

Ideally, aleatory uncertainty and epistemic uncertainty should be propagated through the model separately.[252] However, such separation is costly and not always possible. Nonetheless, this distinction should be reflected in the interpretation of the uncertainty and sensitivity analysis results.[242] For example, when the prediction uncertainty of system performance is largely attributed to a lack of knowledge of the true value of a technological parameter, research should focus on reducing the epistemic uncertainty of this parameter (*e.g.*, through more accurate experimental measurement to narrow the possible range of its true value). On the other hand, if decision variables are found to be the driver of the variation in the predicted system performance, development of the technology should focus on optimizing the design and operation decisions to limit the aleatory uncertainty.

5.3. Representative applications

5.3.1. Uncertainty analysis to prioritize technology targets. Uncertainty analysis is the most straightforward application of the Monte Carlo methods as it involves minimal pre-simulation sample selection and post-simulation statistical computation. With uncertainty analysis, one can characterize sustainability indicators, identify the drivers of system sustainability, and set targets for future research and development.[19,62,99,245,246,253–256]

To summarize the results from Monte Carlo simulation, one can first characterize the sustainability indicators by reviewing their distributions and descriptive statistics of interest, which can help to understand the variability of these indicators and the likelihood of achieving a specific target (*e.g.*, carbon-neutral or negative,[257] Fig. 3A; Fig. 1 of example 2 (ref. 143) in Table 1). Notably, to compare the sustainability of different technologies, joint Monte Carlo simulation (where the difference in indicator values between technologies is calculated for each set of input variables),

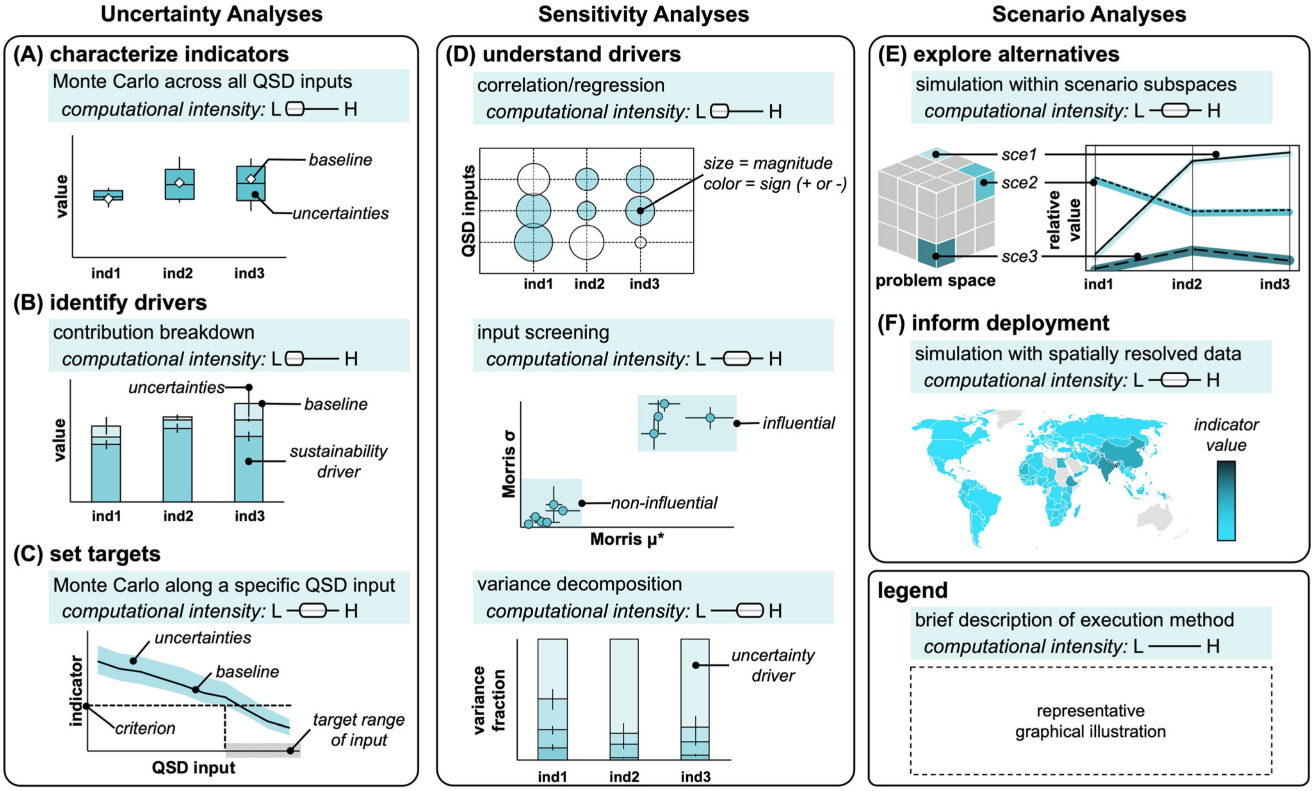


Fig. 3 Representative applications of QSD including (A–C) uncertainty, (D) sensitivity, and (E and F) scenario analyses. Analyses are shown with a brief description of the execution method, the typical computational intensity, and a representative graphical illustration. Note that the computational intensity for each graph herein is solely for comparative purposes. In practical application, it depends on multiple factors (*e.g.*, algorithm complexity, error tolerance, sample size) and could deviate from the typical range shown here.

rather than independent Monte Carlo simulation of each technology, should be performed to avoid the misinterpretation of overlap areas as indistinctive results (refer to Müller *et al.*[80] for illustrative examples).

To identify the drivers of system sustainability, values of key sustainability indicators (*e.g.*, MSP) can be attributed across different sources (*e.g.*, equipment, material, labor) based on their contributions (Fig. 3B). Given that sources with the largest contributions exert the most influence toward indicator values, they may be prioritized in RD&D to advance system sustainability. For example, because feedstock costs can account for roughly half (or more) of the MSP of algal biofuels, strategies to reduce the production cost of algae (*e.g.*, development of high-productivity strains) should be prioritized.[198,199,258,259]

Finally, uncertainty analysis can also be conducted to set targets for parameter values, which are particularly relevant to early-stage technologies (Fig. 3C). This can be achieved by conducting a Monte Carlo simulation at each value (or each step point within the potential range) of the parameter of interest. For instance, when studying the catalytic treatment of spent ion exchange brines for nitrate removal, one key technological parameter could be the number of brine use cycles. Monte Carlo simulation can be executed at different numbers of brine use cycles to explore the minimum number of cycles required for the catalytic technology to be more sustainable than the conventional technology.[253] Technological advancements that lead to a larger use cycle forms the opportunity space for this catalytic treatment technology, where it outcompetes the conventional alternative.

5.3.2. Sensitivity analysis to understand uncertainty drivers. To understand what is driving the observed uncertainty in sustainability indicators for the system, sensitivity analysis is often used to apportion the uncertainty in the model outputs to different sources of uncertainties in the model inputs (*i.e.*, the "effects" of the inputs[49]). The results of sensitivity analyses are represented as input sensitivity indices for each output of interest. In other words, for each model output, all uncertain model inputs will have one or more sensitivity index values to represent their relative importance to that output's uncertainty (Fig. 3D).[260] Sensitivity analysis can be classified as local or global based on whether the effects of input variables are evaluated in the vicinity of a base point (local) or across the entire problem space (global).[261,262] Local methods can be used for quick assessment of parameters' impact on the system's sustainability (*e.g.*, with single-point sensitivity analysis at the minimum/maximum values of a parameter[263,264]), but global methods are recommended when possible because they are more robust and can be more informative (*e.g.*, yielding more generalizable insight across the problem space).[44,265] In QSD, global sensitivity analysis can be applied to facilitate research prioritization (*e.g.*, to achieve sustainability targets), model improvement (*e.g.*, to simplify models and reduce computational intensity), and data collection (*e.g.*, to narrow probability distributions).[46,74,144,266–272]

Specifically, correlation- or regression-based methods (*e.g.*, Spearman ranking;[273] Fig. S8–S10† of example 1[306] in Table 1) are the least computational intensive and sufficient for monotonic models, where "monotonic" indicates that the model output increases or decreases monotonically with individual model inputs over their ranges of uncertainty (*e.g.*, water treatment plant annual material cost always increases with the increasing unit price of an input chemical).[260] These methods are often performed in tandem with uncertainty analysis (*i.e.*, using the results generated from the uncertainty analysis) as they do not require specific sampling techniques, and have been widely used sustainability analyses to highlight the significance of technological advancement or data collection (*e.g.*, ref. 46, 144, 270 and 272).

Screening or variance-based methods are more robust for complex models as they do not rely on assumptions about the model structure (*i.e.*, monotonic or not). Screening methods (*e.g.*, Morris one-at-a-time[274]) are used to identify non-influential inputs that can be fixed at given values within their uncertainty ranges without significantly reducing the output variance.[260] These methods are typically used in a qualitative manner (*i.e.*, values of the sensitivity indices are only for comparative purposes), and smaller sample sizes are typically used to reduce model complexity by fixing non-influential inputs. In one study, for example, the Morris method was used to determine the most important individual and groups of input variables in estimating the yield of urban water supply systems.[275]

Unlike screening methods, variance-based methods (*e.g.*, the Sobol method) decompose the variance in model output as the sum of effects associated with the model inputs.[276,277] Due to their quantitative nature, variance-based methods are more computationally intensive than screening methods, especially when the quantification of interaction effects is desired. Thus, variance-based methods are often conducted for models with relatively small numbers of inputs or after fixing non-influential inputs. As an example, a variance-based sensitivity analysis was performed in one study to determine that 97% of the variance of a location's suitability for a hazardous waste landfill facility was jointly induced by only three variables, thus allowing the original model to be greatly simplified without compromising its accuracy.[266]

5.3.3. Scenario analysis to explore scenarios and inform deployment. For complex systems with a large number of inputs and expansive problem space, scenario analysis can be used to draw conclusions for certain sets of inputs with specific values (*i.e.*, scenarios, Fig. 3E). Each scenario should be based on a coherent and internally consistent set of assumptions about key driving forces (*e.g.*, demographics and socio-economic development) and the relationships among these key driving forces.[61] Scenario analysis is often placed in a future setting,[278] and scenarios based on different sets of assumptions are often compared to inform decision-making. For example, to mitigate GHG emissions, different scenarios, each consisting of varying technologies, have been evaluated for decarbonization.[61] Similar applications of scenario analysis can be found in other topics (*e.g.*, water and wastewater treatment,[46,145,279,280] renewable energy,[199,254,257,281] waste management[215]), or for a certain technique (*e.g.*, using different scenarios of electricity mix in LCA to assess the environmental sustainability of electric vehicles[282]). In essence, scenario analysis divides the entire problem space into discrete, representative sub-spaces. It reduces the dimensionality of the system (fewer or less uncertain inputs) and simulation needs, while providing a detailed understanding of distinct alternatives that may be of particular interest for policymaking or implementation in specific contexts.

When the primary objective of QSD is to inform technology deployment, spatial analysis is often used to account for site-specific parameters that can influence the sustainability of systems (Fig. 3F). At its core, spatial analysis can be considered as a special category of scenario analysis where each deployment site is a scenario, and the implications of deployment site are reflected through the values of contextual parameters that are site-specific. To facilitate spatial analysis, geospatial data that link locality-specific contextual parameters with location information are collected, and they can be further combined with temporal information to reveal the evolution of attributes over time.[283] These geospatial data may include physical information (*e.g.*, geological properties,[266,284,285] distances,[286,287] existing infrastructure[288]), policies,[285] cultural preferences,[272] and any other contextual parameters that could serve as QSD inputs (*e.g.*, energy and water unit impacts,[289,290] costs and impact characterization factors[291]). As contextual parameters can be particularly important for the human health and social dimensions of sustainability that are highly site-specific, measures should be taken to ensure the representativeness of these values (*e.g.*, use high stakeholder input and influence methods discussed in section 4.4). To address spatial considerations, geographic information systems (GIS) is often used to capture, organize, calculate, and integrate multiple layers of spatial information into QSD (*e.g.*, assessing spatial co-location of recoverable nutrients and agricultural demands for deployment of nutrient recovery sanitation systems[292,293]). Further, as uncertainties in these data (*e.g.*, from different resolutions[294]) can directly affect the conclusions of sustainability analyses, uncertainty analysis is often incorporated in spatial analysis and tailored to the data (*e.g.*, based on the data structure[295]).

6. Conclusions to guide the pursuit of more sustainable technologies

As society endeavors to pursue more sustainable water, sanitation, and resource recovery systems, a range of new technologies are required to replace existing infrastructure that was built to accomplish narrowly defined functions without considering externalities.[23,296] To navigate through the vast opportunity space ahead of us, sustainability analyses must be integrated throughout the RD&D of technologies to ensure a trajectory toward sustainability. In support of this integration, we reviewed existing literature on the sustainability analyses of water/wastewater and broader environmental technologies and synthesized our findings into a structured methodology – QSD. We introduced QSD as a methodology that addresses four critical challenges in sustainability analyses that had been largely overlooked in the existing literature: (i) the lack of a shared lexicon to standardize terminology for interdisciplinary communication and research consistency; (ii) the lack of dynamic connections among decisions, parameters, and sustainability indicators that can be leveraged to generate the types of insight needed to advance sustainability; (iii) the lack of robust uncertainty and sensitivity analyses, and (iv) the lack of a guide for the planning and execution of sustainability analyses.

Through the discussion of and with examples from the literature, we illustrated how QSD can be leveraged to guide the RD&D of technologies and inform decision-making. With future development of sustainability characterization techniques, QSD can be enhanced to consider crucial but often overlooked areas (*e.g.*, adding impact categories and indicators for biodiversity in LCA[297,298]). Meanwhile, the development of integrated, agile, open-source tools for sustainability analyses will streamline QSD execution and benefit its adoption across different disciplines.

Finally, the results of QSD can be used to inform decision-making, including in structured methodologies such as MCDA (*e.g.*, quantified sustainability indicators can be used to evaluate, compare, and recommend technologies based on stakeholder priorities as in ref. 290 and 299). Tools and methods developed in the discipline of decision analysis can in turn be used in QSD for indicator selection (*e.g.*, the MCDA Index Tool,[300] the Delphi method[301]) and prioritization (*e.g.*, the analytical hierarchy process [AHP],[302] the preference ranking organization method for enrichment evaluations [PROMETHEE] approach[303]). Moreover, with objective functions established in MCDA, tools developed for sustainability analyses can potentially be expanded to automate the optimization of system design in early-stage research and development,[304] or to support stakeholder engagement in transparent planning and design processes.[305] Overall, QSD offers the potential to reveal the sustainability implications of technology innovations under a given context, thereby enabling stakeholders at all levels to understand and make informed decisions about the multidimensional effects of technologies, ultimately contributing to the society's transition toward sustainability.

Conflicts of 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.

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