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Foreword

In 2018, the Intergovernmental Panel on Climate Change (IPCC) issued a report that fundamentally reshaped the climate conversation. Its Special Report on Global Warming of 1.5 °C (SR15) concluded that limiting warming to 1.5 °C would require not only rapid and deep reductions in greenhouse gas emissions, but also the deployment of carbon dioxide removal (CDR) methods to offset residual emissions and potentially achieve net-negative emissions.

Of course, just because we need CDR doesn't mean it's easy. The fundamental challenge is that CO_2 is, energetically speaking, quite happy to hide as a mere part-per-million in the immensity of the sky. Extracting it from that diffuse state takes serious effort—whether through biology (like photosynthesis), physical methods (like membranes or liquid injections), or chemistry (such as reacting it with alkaline substances). Each approach comes with a price. There's the direct financial cost, and then there's the environmental footprint—sometimes simple, like energy, water, or land use; sometimes more complex, like impacts on ecosystems, toxicity, or human health. In short, pulling CO_2 from the air means pushing against the grain of physics and chemistry—and there will always be trade-offs. Recognizing those trade-offs early is essential if we want to invest in CDR solutions that are not just possible, but genuinely worth pursuing.

Around the time of the SR15 report, I was advising several philanthropic foundations on how they could help jump-start CDR research and development – and specifically, on whether the ocean could play a role. The reason was simple: the ocean is vast (covering 70% of Earth's surface) and is already the planet's biggest active carbon reservoir. It continuously exchanges gases with the atmosphere. This means if you remove CO_2 from seawater, the ocean will draw in CO_2 from the air until a new equilibrium is reached. Among various ocean-based CDR approaches, I was particularly drawn to ocean alkalinity enhancement (OAE): When seawater's alkalinity is increased, dissolved CO_2 is chemically transformed into bicarbonate and carbonate, which are stable forms of carbon lasting tens of thousands of years. This reaction creates a concentration gradient that pulls more CO_2 from the atmosphere into the ocean to restore balance.

Back in 2018, OAE was still mostly theoretical, with only a handful of papers exploring its potential. But one stood out. Phil Renforth—who had already been thinking deeply about this for years—teamed up with Gideon Henderson to publish a 2017 paper that compiled the first credible estimates of OAE's cost and capacity. Using literature values for mineral dissolution, shipping logistics, and global deployment scenarios, they showed that, under the right conditions, OAE could be cost-competitive with other carbon removal methods. This work put OAE on the map. It showed that geochemical CDR pathways like OAE might be done cost-effectively and with a manageable life-cycle impact – if the engineering and logistics can be worked out. It was enough to convince me that OAE deserved a closer look. The big question was: Can this concept deliver in practice what was promised in theory?

To find out, we launched the Carbon to Sea Initiative with a simple but ambitious goal: to systematically assess whether OAE could truly help solve climate change. We anchored our work around three questions: Does it work? Is it safe? Can it scale? Since then, we've committed over $30 million to research teams around the world—supporting everything from lab experiments to open-ocean trials to global modelling efforts.

But beneath all of this lies a deeper question—one that every serious climate solution must answer: even if it works, is it worth it? Answering that means grappling with trade-offs and doing the math: weighing climate benefit against financial, environmental, and logistical costs.

Techno-economic assessment (TEA) and life-cycle assessment (LCA) are the best tools we have for this. TEA tells us how much energy and material a process requires, how efficiently it removes CO_2, and what it costs per ton. LCA captures the broader picture—emissions from mining and shipping, marine impacts, resource use—and asks whether the net outcome still helps the climate and whether it causes other harm. But here's the problem: these tools only work if we're all using the same playbook. Until now, there's been no standardized approach to applying TEA and LCA to OAE. Different assumptions, boundaries, and metrics have made results difficult to compare—and easy to misinterpret.

That's what makes this work such a breakthrough. Some of the world's foremost experts on industrial TEA and LCA (including Renforth's group at Heriot-Watt) have now created a harmonized framework for applying TEA and LCA to OAE, one that brings consistency, transparency, and comparability to a field that urgently needs it. By standardizing everything from CO_2 uptake chemistry to how we handle uncertainty and time lags, this framework enables true apples-to-apples comparisons across different OAE approaches—and a much clearer view of what's actually viable.

Just as importantly, it integrates forward-looking analysis – recognizing that OAE technologies are at an early stage, the framework incorporates methods to project how performance and costs might improve with scaling and learning, rather than looking only at present-day data. This is a critical innovation, since we care about where these technologies could get to in 5, 10, or 20 years if successful, not just where they are today.

To put the framework to the test, the authors applied it to one of the most promising OAE pathways: electrodialysis—an electrochemical method that uses electricity to generate alkalinity from ordinary seawater. It could offer major efficiency gains over classical electrolysis, though it's still early in its development. I strongly encourage a close read of this case study—it's a standout example of what rigorous, holistic evaluation of a CDR technology should look like. The analysis goes well beyond surface metrics, unpacking cost per ton, energy use, full life-cycle impacts, and key sensitivities like membrane performance and electricity sources. It's a powerful demonstration of how this framework can identify what really matters—and where innovation will make the biggest difference.

I cannot overstate the importance of this framework for the broader OAE community. By providing a common yardstick for techno-economic and environmental performance, it allows researchers, investors, NGOs, and policymakers to all speak the same language when discussing different pathways. An investor weighing a portfolio of carbon removal projects can now compare an OAE project's potential on equal footing with, say, a direct air capture project. A policymaker considering regulations or incentives for CDR can base decisions on harmonized assessments rather than one-off claims.

As someone who has spent many years exploring climate solutions, I am heartened by this advancement. The harmonized TEA/LCA framework presented here is much more than just an academic exercise – it's the foundation for action. It will guide researchers on where to focus their efforts, help technology developers attract funding by transparently demonstrating their performance, and inform stakeholders at all levels about the realities of OAE's potential.

Moreover, I believe the framework will not only help unlock OAE's potential, but will also serve as a model for evaluating other pioneering climate interventions. Our window for achieving climate stability is narrow, but with efforts like these – grounded in data, transparency, and collaboration – we can accelerate the development of safe, scalable solutions. I am excited to see how this guidance will be put to use, and I am optimistic that, armed with knowledge and frameworks like this, we can indeed harness the best of science and innovation to help secure a liveable climate for future generations.

Dr Antonius Gagern, Executive Director at the Carbon to Sea Initiative

Berlin, May 2025

Executive Summary

Ocean alkalinity enhancement (OAE) includes a range of approaches that propose to remove carbon dioxide from the atmosphere, i.e., carbon dioxide removal (CDR), and convert it into stable ocean bicarbonate ions through its reaction with alkaline rocks or liquids. Interest in OAE has expanded in recent years given the imperative to address climate change and given that the geophysical potential of the technology (e.g., alkaline rocks, brines, ocean storage capacity) appear to be far greater than what might be needed.

However, there are substantial technical, environmental, governance, social, and financial challenges associated with scaling up OAE approaches, which will limit their CDR rate and maximum deployment potential. Fundamental to all of these challenges is the need for a comprehensive understanding of how OAE technologies perform. Yet this knowledge in isolation is insufficient for robust decisions on future OAE deployments and should be supplemented with diverse assessment criteria that include the social, ethical, political, regulatory, and wider economic implications.

The aim of this document is to provide a framework for assessing the technical potential of OAE by harmonising robust tools for environmental and economic performance, specifically life-cycle assessment (LCA) with techno-economic assessment (TEA). This framework provides comprehensive guidance for conducting technical, economic, and environmental assessments of OAE technologies for CDR. The development of this guidance document is crucial as OAE emerges as a potential large-scale CDR solution. With increasing interest in OAE deployment, there is an urgent need for standardised assessment methodologies to ensure consistent evaluation across different technologies and implementation scenarios.

The framework integrates three primary assessment tools: LCA, TEA, and integrated assessment models (IAMs). While traditional assessments focus on current technology performance, the novel contribution of this framework lies in its structured approach to prospective analysis. This forward-looking methodology is particularly critical for emerging technologies like OAE, where current pilot-scale operations must be evaluated for their potential at climate-relevant scales.

OAE technologies face unique challenges that necessitate specialised assessment approaches. These include the delayed response in CO_2 removal following alkalinity addition, spatial variability in removal efficiency, and complex MRV requirements. For electrochemical methods specifically, the management of acid by-products could present additional technical and environmental considerations. This framework addresses several of these challenges directly, since the delayed CO_2 removal is captured through 'time-adjusted warming potential' calculations incorporating radiative forcing effects, while spatial variability is addressed through integration with ocean modelling.

Several critical areas require further development. These include: i) the development of specific impact categories for OAE environmental assessment, ii) the quantification of 'additionality' effects in different deployment scenarios, iii) the refinement of MRV protocols and associated cost estimates, and iv) management strategies for acid by-products from electrochemical processes.

By providing a structured approach for both traditional and prospective analyses, while explicitly acknowledging areas needing further development, this framework enables more robust assessment of technology performance and viability across various possible futures. The document outlines how to integrate data from IAMs to inform both background systems analysis and technology deployment scenarios. The early establishment of these assessment guidelines can help accelerate technology development while ensuring environmental safeguards are properly considered.

A key innovation in this framework is its detailed guidance on prospective analysis methods, moving beyond static analyses and traditional 'what if' scenarios to include 'what will' projections, based on historical analogies and consistently formulated future scenarios. This includes methods for projecting technology performance from laboratory to commercial scale, and for analysing how changes in the operating environment may affect technology viability. The framework provides specific guidance on handling technology upscaling challenges, recognising that performance may improve, deteriorate, or remain constant depending on the specific technology and context.

For OAE technologies in particular, the framework emphasises several unique considerations. These include the delayed response in CO_2 removal following alkalinity addition, the importance of ocean modelling in site selection and efficiency estimation, and the need to consider both local and global environmental impacts. The framework also addresses the challenges of scaling OAE technologies to gigatonne (Gt) levels, including raw material availability, infrastructure requirements, and environmental monitoring needs.

By providing standardised methodologies for technical, environmental, and socioeconomic assessments, the framework enables consistent and transparent evaluation of OAE technologies at various scales. The integration of prospective analysis, alongside traditional approaches, ensures that both current performance and future potential are rigorously examined.

As interest in OAE continues to grow, this framework equips stakeholders with the tools needed to address key challenges, accelerate innovation, and guide responsible deployment that aligns with climate and environmental objectives.

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1.0 Introduction

1.1 Background and context

To avoid the most severe consequences of climate change, humanity will need to prevent the buildup of greenhouse gas (GHG) emissions in the atmosphere. Drastically reducing emissions in the coming decades is essential to achieving climate targets, but this will need to be supplemented with removing carbon dioxide (CO_2) from the atmosphere ('carbon dioxide removal', CDR, Smith et al., 2024), to offset residual and unavoidable emissions and to remove historical emissions. CDR methods include those that manage terrestrial biomass stocks (e.g., afforestation, soil carbon sequestration) and/or use biomass for carbon removal and storage or directly remove CO_2 from the atmosphere using physical or chemical sorbents, i.e., direct air capture (DAC). Ocean alkalinity enhancement (OAE) is an emerging method of CDR that involves increasing the alkalinity of surface seawater (typically up to 100 m depth), which can enhance the ocean's ability to absorb atmospheric CO_2 and convert it into stable bicarbonate, and to a lesser extent carbonate ions, thereby reducing the GHG concentrations in the atmosphere. When distributed globally, large amounts of carbon removal and durable storage (at least 10,000 years) can be achieved with small changes in ocean chemistry (Renforth and Henderson, 2017).

The ocean is the largest active carbon sink on Earth, absorbing approximately 29% of anthropogenic CO_2 emissions annually (Friedlingstein et al., 2023). The natural process of oceanic carbon sequestration is facilitated by the ocean's alkalinity, which determines its capacity to neutralise atmospheric CO_2 and store it in the form of dissolved inorganic carbon. However, the increasing levels of atmospheric CO_2, primarily due to fossil fuel combustion and land-use change, are outpacing the ocean's natural buffering capacity, leading also to ocean acidification (Sabine et al., 2004).

OAE works by adding alkaline substances, such as crushed silicate, carbonate or hydroxide minerals or liquids, to seawater. These substances dissolve and react with CO_2 to form bicarbonate and carbonate ions, increasing the total alkalinity of seawater and thereby enhancing its capacity to absorb additional CO_2 from the atmosphere. The reactions (Eqs. 1.1-1.3) underpinning CO_2 removal and storage can be summarised as follows:

$$Mg_2SiO_4 + 4CO_2 + 4H_2O \rightarrow 2Mg^{2+} + 4HCO_3^- + H_4SiO_4 \quad \text{(Eq. 1.1)}$$

$$CaCO_3 + CO_2 + H_2O \rightarrow Ca^{2+} + 2HCO_3^- \quad \text{(Eq. 1.2)}$$

$$Ca(OH)_2 + 2CO_2 \rightarrow Ca^{2+} + 2HCO_3^- \quad \text{(Eq. 1.3)}$$

As such, the primary benefit of OAE is its ability to increase the ocean's uptake of atmospheric CO_2, thereby helping to mitigate climate change. Some OAE approaches also temporarily increase seawater pH at the point of addition, which could be used to counteract ocean acidification in localised environments – a phenomenon that poses significant threats to marine ecosystems, particularly calcifying organisms such as corals and shellfish (Doney et al., 2009). This effect would be temporary, and frequent additions, at least until the economy is decarbonised, would be required to sustainably address this problem.

1.2 Considerations in assessing the potential of OAE technologies

Despite its potential, OAE faces several challenges. The logistics of mining, grinding, and distributing or dissolving large quantities of minerals pose a significant technical and economic challenge. Similarly, when OAE technologies are deployed at scale, they will consume substantial amounts of materials and energy, whose environmental and cost footprint depend on supply abundance and sustainability. This may change with time and location, e.g., as the world moves to decarbonised (and otherwise more sustainable) supply chains.

Furthermore, the effectiveness of OAE depends on the specific chemistry of the local marine environment, including temperature, salinity, and existing alkalinity levels. Therefore, site-specific studies and pilot projects are essential to assess the feasibility and optimise the implementation of OAE strategies (Eisaman et al., 2023). Moreover, the ecological impacts of introducing these substances into marine environments are not fully understood and warrant careful investigation (Bach et al., 2019).

The following list highlights the key challenges for OAE technology assessment along three interrelated dimensions. We list them here, as they will serve as a thread through this document and the guidelines proposed:

Time. The temporal dimension affects the net carbon removal potential (and wider environmental footprint) of OAE approaches in two ways. First, the CO_2 drawdown for some OAE approaches is distributed over time, rather than being immediate. This temporal delay is caused in the following circumstances:

i) When fast-dissolving (e.g., hydroxide-rich) solid minerals or liquids ('unequilibrated alkalinity') are added to the ocean, they will rapidly increase alkalinity but the full equilibration of the alkalinity with CO_2 may take several years or even decades (Zhou et al., 2024).

ii) When slow-dissolving solid minerals are added to coastal/shelf environments, the change in alkalinity is gradual, as is their CDR potential, which can span decades to centuries (Foteinis et al., 2023).

iii) When unequilibrated alkalinity is either added intentionally to, or mixes with, deeper water that is isolated from the atmosphere, i.e., when alkalinity is lost to deep waters, this alkalinity may eventually remove atmospheric CO_2 (or prevent the emission of CO_2 from the ocean) when the water returns to the surface, depending on location (Butenschön et al., 2021; Harvey, 2008).

Other CDR technologies like enhanced rock weathering, afforestation/reforestation, and bioenergy with CO_2 storage can also have temporal lags in removal or storage (Kanzaki et al., 2024). Conversely, CDR technologies such as DAC with geological storage remove and store atmospheric CO_2 virtually instantly. This time discrepancy will need to be accounted for in calculating the true climate change potential of OAE, as discussed in Section 5.5.

Second, the net CO_2 removal potential requires full accounting of GHGs emitted to enable the OAE process, e.g., accounting for both direct and indirect emissions from energy and materials supply chains. As such, these technologies could be associated with a carbon penalty. However, it is expected that energy and materials supply will decarbonise and become more sustainable as the world transitions to meet agreed climate targets, and this makes it imperative to assess OAE pathways using consistent and robust temporal 'lenses' and assumptions on how the techno-economic, environmental, and social context may change over time.

Location. The spatial dimension to OAE deployment is another highly influential factor when assessing the technical potential. The reason again is twofold.

First, the CDR efficiency by alkalinity addition strongly depends on local seawater conditions. For instance, if alkaline material is added to an ocean current that is downwelling, the alkalinity may not have sufficient time to equilibrate with CO_2 in the air, and the CO_2 drawdown efficiency will be limited. Furthermore, higher seawater temperatures imply lower CO_2 solubility than lower temperatures. This means that the CO_2 efficiency of alkalinity addition is different for each location in the world.

Second, location determines the cost and environmental sustainability of supply chains. The cost of construction and labour varies by country, and even sub-nationally. Likewise, the environmental footprints of energy and materials supply chains vary spatially, depending on the local energy mix and practices. These have a direct effect on the economic and environmental viability of OAE projects and imply there is no single global 'performance' for an OAE pathway.

Environmental uncertainties. Finally, the nascent state of OAE means that the science of the environmental effects of alkalinity addition is still developing. Three key areas need deeper understanding to underpin sound quantification of OAE performance. First, there are already natural cycles of alkalinity addition and removal in the ocean, and the impact of OAE on these is not fully quantified (termed 'additionality' (Bach, 2024)). Second, the understanding of the ecosystem effects at the point of addition, and beyond as the alkalinity spreads globally, is still developing (Goldenberg et al., 2024; Paul et al., 2024). Third, there is limited representation of the ocean impacts of OAE in current life-cycle assessment (LCA) impact categories, and additional work is required to interpret emerging environmental impacts research into the LCA framework, which may require the development of new indicators.

1.3 Scope and boundaries of the framework

There has been growing interest in OAE, which has attracted $200 million in public and private investment. Most of this investment has occurred in the last five years, and half has been directed to early-stage commercial operators. However, there are only a handful of publicly available studies, published over the last 30 years, that consider the technical potential of OAE pathways. Given that these studies do not typically consider the breadth of OAE approaches, are inconsistent in their scope and assumptions, and do not account for the features discussed above, it is not possible to prioritise investment in specific OAE pathways or understand how the technical performance compares to other CDR approaches, let alone varies with time and location.

The evaluation of technology encompasses a broad set of scientific, engineering, and philosophical traditions. At its heart is technology's fundamental relationship with society, both for technology's intended utility and its unintended consequences (Grunwald, 2009). Understanding the technical performance of technology provides the foundation for a wider assessment of its implications, and it helps to guide policy, investment, and research. However, these tools are insufficient in isolation to evaluate OAE as a legitimate response to climate change. A broader set of methodologies that attempt to understand and address the social consequences of OAE will also be essential; however, they fall beyond the scope of this framework.

We review technical appraisals of OAE pathways (Section 2.1) and the current state of the art for TEA and LCA (Sections 2.2 and 2.3). The framework is divided into seven parts, as a means of taking readers through the sequential stages of preparing and undertaking technology assessment:

Part A: Technology conceptualisation and flowsheet development. This section describes the initial step in defining the technology as a technical system.

Part B: Scenario development for scalable deployment. Here, the techno-economic context in which the technology will be assessed is chosen and described. This part also describes procedures for defining deployment scenarios.

Part C: Data collection, mass and energy balance assessment, and technology performance indicators. This section considers how data is sourced, and how the flows of mass and energy through the system are accounted for. It also considers the key technical performance indicators for a technology.

Part D: Classical life-cycle assessment. This section describes the steps for undertaking a conventional cradle-to-grave LCA for OAE approaches.

Part E: Classical economic analysis. Here, the steps for undertaking a bottom-up economic analysis to derive the costs of a first-of-a-kind OAE project are described.

Part F: Prospective analysis. The steps required to robustly assess how the economic and environmental performance of OAE may change over time are considered in this section.

Part G: Uncertainty analysis. Best practices for assessing the uncertainty of OAE approaches are presented.

This framework does not consider the following:

Detailed bottom-up costs or environmental implications of monitoring systems. While monitoring and modelling will be essential in the safe and accountable deployment of OAE, there is no widely agreed protocol for all archetypes. Once monitoring protocols are well established, it is possible to use this framework to make a bottom-up assessment of their costs. Furthermore, existing methods are specific to given projects and are not meant to monitor wider system changes that are essential for informed decisions on CDR scaling-up (Butnar et al., (2024)). As such, it may also be appropriate to make a distinction between monitoring of a specific project (attributable to the foreground for a technology) and wider/global monitoring across all OAE projects and approaches (attributable to the background system of a technology).

LCAs are parameterised with known data on the environmental impact of technologies. Supply chains for OAE are well covered by existing LCA databases, since most OAE component technologies such as mining, processing (comminution), and transportation of alkaline material are mature technologies that already operate at scale. However, possible impacts (both co-benefits and drawbacks) of specific OAE approaches on the ocean through alkalinity increase are unknown and are not currently included within LCAs. As such, the LCA described in this framework is 'cradle-to-deployment plus carbon removal'. Ongoing research will eventually supply this type of data. Life-cycle inventories can be updated to suit, and this framework would then be used to undertake full 'cradle-to-ocean' LCAs for OAE.

2.0 Techno-economic and life-cycle assessment

2.1 Ocean alkalinity enhancement technologies

Ocean alkalinity enhancement (OAE) is defined as the conversion of atmospheric CO_2 into bicarbonate and carbonate ions for long-term storage in the ocean. This is a feature all OAE technologies share; however, the pathway to achieving this varies considerably across the technology space. Here we define a functional classification of OAE using i) the source of mineral alkalinity, ii) the transformation processes, and iii) the pathway to the ocean. Each of these influences the technical performance of the OAE approach and has specific implications for regulation and policymaking. Even with simplified demarcation of alkalinity sources, processes, and pathways, Table 2.1 illustrates that 54 variations are possible. For ease of communication, these have been subdivided into four taxonomic families.

A comprehensive introduction to the many OAE approaches can be found in the *Guide to Best Practices in Ocean Alkalinity Enhancement Research* (Eisaman et al., 2023; Oschlies et al., 2023). We have included a short summary below.

2.1.1 Enhanced weathering

Approximately ~1 $GtCO_2\ yr^{-1}$ is removed by natural terrestrial weathering of silicate rocks globally (Hartmann, 2009). The dissolved products (for example, Na^+, Ca^{2+}, HCO_3^-, silicic acid (H_4SiO_4)) are transported by rivers and reach the ocean, where they uptake more atmospheric CO_2.

Here we use the term 'enhanced weathering' as a taxonomic family of technologies that add minerals directly to the environment with minimal transformation. This approach involves first mining and grinding rocks such as peridotite or basalt which contain alkaline minerals such as olivine, plagioclase feldspar, and pyroxene, and then spreading these onto environments where their weathering is accelerated by corrosive (elevated CO_2) chemistry of soils or sediments, or in the case of addition to the marine environment, the action of waves and tidal currents (Hangx and Spiers, 2009; Kheshgi, 1995; Montserrat et al., 2017; Rau, 2008; Renforth et al., 2022, 2013; Renforth and Kruger, 2013). The method is potentially highly scalable, and cost effective, with the added potential of integration into beach nourishment schemes (Foteinis et al., 2023). However, the monitoring, reporting, and verification (MRV) is challenging, and uncertainties remain regarding secondary mineral formation which can reduce the CO_2 removal efficiency (Flipkens et al., 2023).

Limestone ($CaCO_3$), which is abundant and inexpensive, can be used as a feedstock for a variety of OAE pathways. However, surface ocean waters are already supersaturated with $CaCO_3$, so limestone will not practically dissolve (Renforth and Henderson, 2017). However, crushed limestone could be added to specific CO_2-rich upwelling regions, i.e., areas of the ocean where deep, nutrient-rich waters rise to the surface (Harvey, 2008).

2.1.2 Ocean liming

Limestone could be calcined (and slaked) to produce highly reactive lime (CaO), which can be easily dissolved in seawater to increase its ability to absorb CO_2 in a process known as ocean liming (Kheshgi, 1995). Here we use 'ocean liming' to refer to approaches that transform minerals through heat. In these technologies, limestone is mined, crushed, transported to kilns for calcination, and slaked to produce slaked lime ($Ca(OH)_2$) before being transported to the ocean and spread by ships. Ocean liming could make use of the spare capacity of the lime and cement kiln industries, thus alleviating the need for new reactors and supply chains (Renforth et al., 2013). However, logistical challenges, such as the distribution of lime in the open ocean and the energy requirements for calcination, remain significant hurdles, particularly given the requirement for carbon capture and storage infrastructure (Foteinis et al., 2022). $Mg(OH)_2$ can be used as an alternative to $Ca(OH)_2$, but it must be produced from the carbonation of magnesium-rich silicate rocks such as olivine (Renforth and Kruger, 2013). As a further option, limestone could also be converted into a more soluble form by hydration, so-called hydrated carbonate minerals. One promising candidate is $CaCO_3 \cdot 6H_2O$, which is created first by dissolving limestone in a pressurised vessel with high concentrations of CO_2, followed by precipitating the hydrated form at low temperature under vacuum and regenerating the CO_2 for re-use in a closed loop (Renforth et al., 2022). This technology has potentially lower cost and environmental footprint than other OAE technologies, but is currently at low technology readiness level (TRL) and may only be applicable to cooler regions (<15°C) where ikaite can be stably transported to the ocean.

2.1.3 Electrochemical

Electrochemical ocean CDR technologies, particularly electrochemical salt splitting, involve the use of electricity to modify ocean chemistry in ways that promote CDR (Eisaman, 2024). One of the central approaches is electrochemical alkalinity enhancement. This approach involves splitting brines (or seawater), which are rich in salts such as sodium chloride (NaCl), to produce NaOH, which can react with dissolved CO_2 to form HCO_3^-. There are two primary approaches: electrolysis and electrodialysis. Electrolysis passes a high-voltage current through the brine, causing salt (NaCl) and water splitting, producing NaOH and by-product gases Cl_2 and H_2, and some O_2 (Du et al., 2018). The electrolysis step is energy intensive, and the pretreatment stages may require barium salts, which could have a high environmental footprint. However, electrolysis is a mature technology owing to its use in the chlor-alkali process and produces high concentrations of NaOH which can be easily transported. Electrodialysis, on the other hand, uses electricity to promote ion diffusion through a series of stacked membranes, creating NaOH, and primarily HCl as a by-product from the dissociation of NaCl (de Lannoy et al., 2018; Eisaman et al., 2018). Electrodialysis is potentially far more energy efficient than electrolysis and can operate using abundant seawater rather than requiring highly saline brines. However, it has low TRL, and produces lower concentrations of NaOH than electrolysis. Innovations in membrane technology as well as process optimisation could make electrodialysis a very promising route for OAE.

2.1.4 *Chemical extraction and transformation*

Chemical extraction and transformation approaches use other chemical molecules to extract cations or transform minerals into a form in which they can be used for OAE.

Accelerated weathering of limestone works by contacting limestone with high partial pressures of CO_2 in engineered reactors; the resulting $Ca(HCO_3)_2$ solution can be released into the ocean for storage (Rau et al., 2007). Innovations in this area include buffered accelerated limestone weathering, which uses additional $Ca(OH)_2$ to buffer any unreacted CO_2 and reduce the risk of CO_2 degassing upon release (Caserini et al., 2021). The primary benefit of these approaches is that the monitoring is straightforward, since the captured CO_2 is a directly measured quantity. However, this approach requires high concentration CO_2 (and would only be a CDR approach if the CO_2 is derived from DAC or biomass combustion for CDR).

Renforth et al. (2022) proposed the transformation of calcite (contained in limestone) into hydrated carbonates, which would dissolve in the surface ocean. Hydrated calcium carbonate, such as the mineral ikaite, occurs naturally but is ephemeral and will spontaneously transform into more stable anhydrous minerals. It may be possible to manufacture hydrated minerals and add them to the surface ocean such that they will dissolve and increase alkalinity

Table 2.1 A taxonomic framework for OAE				
Taxonomic family (*n* is the number of subclasses)	**Mineral source of alkalinity/acid sink**	**Transformation process**	**Pathway to the ocean**	**Example studies**
'Enhanced weathering' *(Direct addition of minerals to the environment)* *n = 19*	Bsc, Ult, Lmst, MH, Wst	Grinding	Direct mineral addition to land and transport via river water	Bsc (Beerling et al., 2020)
			Direct mineral addition to drainage waters/rivers or wastewaters	
			Direct mineral addition to the open ocean, including upwelling regions	Ult (Köhler et al., 2013) Lmst (Harvey, 2008)
	Bsc, Ult, MH, Wst		Direct mineral addition to coastal/shelf environments	Ult (Montserrat et al., 2017)
'Ocean liming' *(Heat transformation of minerals)* *n = 4*	Lmst	Calcination	Addition of hydroxides to the open ocean via ships	(Caserini et al., 2021; Renforth et al., 2013)
	Ult	Carbonation + calcination	Addition of hydroxides to waste waters	(Renforth and Kruger, 2013)
'Electrochemistry' *(Electrochemical transformation of brines for indirect transformation of minerals)* *n = 20*	Bsc, Ult, Wst	Electrolysis conversion of brine/seawater Disposal of acid in mineral	Addition of sodium hydroxide to rivers and coastal environments through outfalls Addition of hydroxides to the open ocean via ships	
		Electrodialysis conversion of brine/seawater Disposal of acid in minerals (e.g., Bsc/Ult)		Mineral non-specific – electrodialysis technology (Eisaman et al., 2018)
'Chemical' *(Chemical extraction and transformation of minerals)*	Lmst	Digestion under elevated CO_2 derived from biomass	Within waste-water treatment systems and co-eluted with the outfall On-board ships using biomass-based fuel into the ocean	(Rau, 2011)

n = 11		Digestion under elevated CO_2 derived from DAC.	Terrestrial-based systems alkalinity eluted through outfall. On-board ships added to the ocean	
		Conversion of Lmst into hydrated carbonates	Hydrated carbonates added to outfalls of wastewater. Hydrated carbonates transported via ships and added directly to the ocean	(Renforth et al., 2022)
	Ult	Conversion of Ult into MH through alkaline digestion	Addition of sodium hydroxide to rivers and coastal environments through outfalls Addition of hydroxides to the open ocean via ships	Conversion technology - (Madeddu et al., 2015)
	Ult, Wst	Conversion of serpentine into MH via ammonium sulphate roasting	Addition of MH to the environment as in enhanced weathering pathways	Conversion technology - (Nduagu et al., 2012)

Mineral code:
Bsc – Naturally occurring basic igneous rocks (e.g., basalt)
Ult – Naturally occurring ultrabasic igneous rocks (e.g., olivine-rich dunite), and hydrothermal alteration (e.g., serpentinite)
MH – Magnesium hydroxide, existing as a natural/artificially created product of hydrothermal alteration of magnesium carbonate deposits.
Wst – Waste alkaline materials (e.g., steel slag, cement waste, mine waste, brines)
Lmst – Naturally occurring carbonate rocks (primarily limestone, but potentially dolomite)

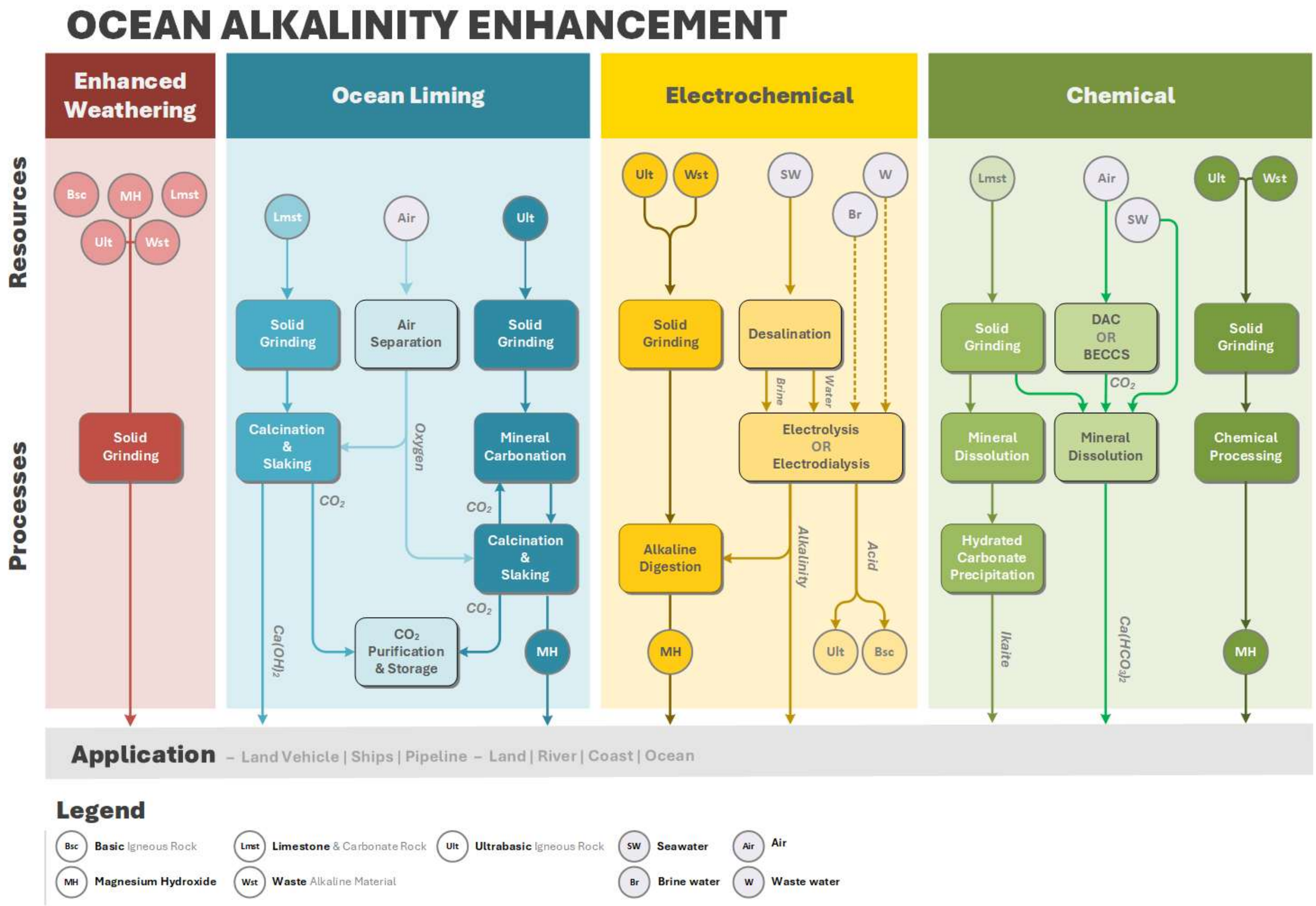

Figure 2.1 Overview of OAE pathways. Key material inputs shown for each pathway. Utility inputs (electricity, fuel, etc.) omitted for clarity.

2.2 Overview of approaches for techno-economic assessment

2.2.1 Introduction

Engineering economics is vital for evaluating the potential value and feasibility of engineering projects. Conventionally, it is used to assess the profitability, cost benefits, and risks of a technology in commercial or industrial settings. For research and development of novel technologies, such analysis is used to guide future research directions and applications, contribute to technology design, and inform policymaking.

In-depth guidelines for defining and performing a TEA have been developed for CO_2 management approaches both by academia (e.g., (Arno W Zimmermann et al., 2020)) and by different organisations, such as SINTEF (Alstom, 2011; DOE/NETL, 2021; EPRI, 2021; GCCSI, 2011; Global CO2 Initiative, 2022; IEAGHG, 2021)CO_2(Alstom, 2011; DOE/NETL, 2021; EPRI, 2021; GCCSI, 2011; Global CO2 Initiative, 2022; IEAGHG, 2021). Across these organisations, varying terminologies are used to quantify different cost elements in an examined plant. (Rubin et al., 2013) have aggregated different nomenclatures into a consistent glossary for capital and operating expenditures; we have readapted this nomenclature for OAE projects, as shown in Table 7.1, and adhering to this terminology going forward is recommended.

A TEA can be broken down into several phases. The goals and scope of the TEA will form the basis of the study (McCord et al., 2020). Summarily, goals describe the application of the technology, the context, and the audience of the TEA study, whereas the scope defines boundaries, system elements, plant capacities, and assessment indicators (see Section 3.6.1 for examples). Clear goals and scope allow an appropriate plant inventory to be defined, which includes the inputs, outputs, systems, and assumptions of the techno-economic model. These definitions are necessary for calculating mass and energy balances, which form the basis for plant cost estimations and key TEA indicators.

Plant costing aims to account for all expenses and revenues associated with a production system before, during, and after the plant's lifetime. The general approach to obtaining these costs is to estimate the capital requirement and operating expenses for a plant design. Together with mass and energy balances of the plant, these costs are used to determine the results of key performance indicators (KPIs) such as the total life-cycle cost, product cost, payback period, break-even point, and internal rate of return. Different forms of analysis are used in TEA studies to evaluate changes in KPIs with respect to key variables (sensitivity analysis), locations (geospatial analysis), and scenarios (case studies). In this section, methods used to reach these outputs are reviewed.

2.2.2 Capital cost estimation

Fundamentally, capital expenses are linked to the costs of materials, instrumentation, and labour required to install the equipment (i.e., 'bare erected costs', BEC) (Rubin et al., 2013). Ideally, BEC would be estimated through third parties with experience in costing the technology (IEAGHG, 2021). If this option is not feasible, then other cost estimation methods can be used, such as equipment cost correlations provided in literature (Sinnott and Towler, 2020a; Smith, 2005; Woods, 2007), cost estimation software (AspenTech, 2023), or vendor quotes from plant costing studies (Hughes et al., 2023). For the latter methods, there can be differences in BEC estimates for the same equipment type (Symister, 2016; van der Spek et al., 2019). Therefore, where possible, the specifications of the costed equipment should be verified (e.g., operating conditions of equipment used in study versus vendor quote).

Capital cost estimates tend to be inaccurate. Therefore, contingency values are applied to obtain costs within range of their true values. A project contingency value is used to estimate the uncertainty resulting from the choice of cost estimation method (AACE, 2020), and a process contingency value is used to estimate uncertainties resulting from the TRL of the process (e.g., underestimating individual components or the balance of plant, or assumptions around economies of scale) (AACE, 2020; Greig et al., 2014). Guidelines for selecting appropriate contingency values are described further in Section 7.2.1.

Engineering and procurement costs, total overnight costs, and total capital requirements are typically estimated as a function of the total BEC, such as in guidelines summarised in Section 7.2.1. These capital expenses include items such as engineering services, owner's costs, contingencies, and interests incurred from loans during plant construction.

2.2.3 Operating cost estimation

Operating (or manufacturing) costs are typically divided into variable and fixed operating costs. Variable operating costs fluctuate with production output (e.g., fuel, electricity, raw materials, chemicals, catalysts). Historical price data for variable cost items are frequently available through market reports and industry databases, while utility costs can be calculated from plant mass and energy balances. Fixed operating costs are relatively constant regardless of output (e.g., labour required for plant operation maintenance, administration). Fixed labour costs can be estimated using national labour statistics, with other fixed costs typically estimated as percentages of total plant costs or related cost categories according to industry guidelines (DOE/NETL, 2023; EPRI, 2021; GCCSI, 2011). For CDR projects, additional considerations may include MRV requirements. Operating costs must also account for regional variations and capacity factors.

2.2.4 Cash flow analysis

The total life-cycle cost of a plant is determined through cash flow analysis, which depicts capital and operating expenses over the course of the project's projected lifespan. For TEAs, discounted cash flows should be used to express the net present values (NPVs) of a project since the value of expenses and revenues change with time. A company's discount rate or weighted average cost of capital is applied to calculate the present value of future cash flows. These rates approximate how the project will be financed but are also an indicator of the minimum rate of return for investors. Note that discounted cash flows can be reported on a 'constant' or 'current' monetary (typically US dollars) basis, which either excludes or includes effects of inflation. It is generally recommended to report costs on a 'constant' dollar basis since the inclusion of inflation can distort costs when comparing technologies (Global CCS Institute, 2013), particularly because inflation affects higher-cost technologies more significantly in absolute terms, potentially exaggerating cost differences over time.

2.2.5 Key performance indicators

Indicators for TEA typically assess quantitative aspects such as metrics related to mass, energy, and cost or qualitative aspects such as the TRL or scalability of a process. In the context of CDR technologies, commonly used quantitative metrics are the CO_2 removal rate, specific energy consumption for CO_2 removal, and the levelised cost of CO_2 removal. These metrics are calculated based on the net or gross CO_2-eq removed, and can include or exclude indirect emissions (e.g., due to upstream use of materials, chemicals, feedstocks, or utilities) (Terlouw et al., 2021). Assessments are not limited to these metrics and can include other aspects such as resource usage and availability (e.g., water), or CO_2 removal efficiencies.

When assessing the economic viability of CDR technologies, different KPIs can be used, depending on whether product costs are known. If revenue from products is known, metrics such as payback periods or internal rates of return can be determined. At present, CDR markets are still developing, and future prices are uncertain, so it is preferable to determine product costs. The levelised cost of a product is a standard method used to evaluate projects related to electricity generation, carbon capture and storage, and other chemical industries (e.g., hydrogen and ammonia). Levelised costs generate a constant price value for a process and represent a minimum cost required to meet all expenses over a plant's lifetime (i.e., total life-cycle cost of a plant). For CDR technologies, the levelised cost of carbon removed (typically \$/tonne CO_2) is defined as the cost to remove a tonne of CO_2 if it were constant over the plant's lifetime. Other KPIs for a TEA may include heat or electricity use, raw material consumption, or waste/by-product production.

2.2.6 Analysis methods

Different forms of analysis have been developed to improve the interpretation of key performance indicators and provide meaningful results. These methods can be applied to various scales of analysis to evaluate the impact of materials, unit operations, processes, supply chains, and/or geospatial effects. For example, geospatial factors could be incorporated into the techno-economic model to reveal how location-specific variables (e.g., resource availability, transportation costs, local regulations) impact the economic viability of a project. Typically, uncertainty and sensitivity analysis are used to evaluate variances in KPIs when changes in inputs or assumptions are made to the techno-economic model. Local sensitivity analysis is common in TEA studies (i.e., varying one parameter at a time). However, recent research has demonstrated that more comprehensive methods based on global sensitivity analysis methods can provide more meaningful conclusions (Strunge et al., 2023; van der Spek et al., 2020a). Uncertainty analysis methods are described further in Section 9.

These evaluations can provide different insights. However, to weigh the importance of these different lenses and evaluate trade-offs, multi-criteria decision analysis can be used. This method is a structured approach for evaluating multiple, often conflicting, criteria in decision-making. In the specific context of TEA, multi-criteria decision analysis can be used to balance economic considerations with other important factors such as environmental impact, social acceptance, and technical feasibility. This method allows decision-makers to systematically compare alternatives based on a set of weighted criteria, providing a more holistic evaluation that goes beyond purely economic metrics.

2.3 Overview of approaches for life-cycle assessment

2.3.1 Historical context

Sustainable consumption and production are enshrined in goal number 12 of the United Nations (UN) Sustainable Development Goals (SDGs) (United Nations Department of Economic and Social Affairs, 2023), providing that responsible use and production patterns should be introduced and adopted for the benefit of future generations. This is also consistent with the concept of 'circular economy', where production systems should focus on reducing, reusing, and recycling to promote sustainable consumption and production. This implies that the use of natural resources, materials, and energy as well as relevant emissions, wastes, and environmental impacts over the whole life-cycle of the service, system, or products should be minimised, or avoided altogether. However, their estimation and quantification are not straightforward and require robust tools. The first comprehensive attempt to quantify the raw materials and energy (fuels) use within a production system and to translate this into environmental impacts occurred in 1969, when the Midwest Research Institute undertook research for the Coca-Cola Company. This project explored natural resources supply and the environmental impacts of beverage containers (Hunt et al., 1996). Industries have since worked towards integrating a range of environmental considerations into product design and development processes. Yet this is a difficult exercise given complex and globally distributed mass production and consumption. Furthermore, the identification and quantification of environmental impacts is also a difficult exercise, as multiple impacts can be imposed from a single activity and those impacts can affect aquatic ecosystems (e.g., marine and freshwater eutrophication), soils (e.g., land use change), and air (e.g., particulate matter airborne emissions), while having broader consequences such as climate change. Those environmental impacts are typically attributed across production stages and the lifespan of the product, service, system, or process, requiring comprehensive analyses across all life-cycle stages, including end-of-life emissions (e.g., decommission and landfilling/recycling/reuse). This implies the need for a complete list of the (raw) materials, energy flows, and transportation distances as well as relevant emissions and wastes, i.e., a detailed 'life-cycle inventory' (LCI), along with accurate methods that can quantify key environmental impacts, i.e., 'life-cycle impact assessment' (LCIA). This need gave rise to LCA, which is a comprehensive methodology that can be used to assess different environmental impacts throughout the life-cycle of a product, service, or (sub)process. In 1990, the term LCA was defined during the SETAC (Society of Environmental Toxicology and Chemistry) congress in Smuggler Notch (Vermont - USA). LCA has been applied across sectors of the economy, and more recently its use to evaluate CDR approaches has been reviewed (Butnar et al., (2024).

2.3.2 Introduction to life-cycle assessment

LCA is a well-established methodology that can be used to evaluate different environmental impacts associated with a material, product, process, service, or technology, typically throughout its entire life-cycle (cradle-to-grave assessment or full LCA), i.e., starting at raw materials extraction and processing; moving to manufacturing, transportation, distribution, use, and maintenance; and encompassing the end-of-life phase (disposal/recycling) (Loiseau et al., 2012; van der Giesen et al., 2020). In LCA, the subjects of study are typically physical products, and the term 'product system' indicates that a life-cycle perspective is adopted, meaning that all processes necessary to provide the product's function are taken into account. The main reason for applying a life-cycle perspective is that it helps identify and prevent burden shifting between different life-cycle stages or processes. This occurs if efforts to reduce environmental impacts in one stage unintentionally lead to (potentially greater) impacts in others (Bjørn et al., 2018b). While LCA has been primarily applied to product systems, it can also be used to analyse more complex man-made entities, including companies, energy systems, transportation, waste management systems, and even infrastructure and cities. The assessment in all applications adopts a life-cycle perspective, with the function of the studied entity as the focal point. However, different approaches, also known as LCA variants, can be adopted depending on the goal of the LCA study. These include:

Cradle-to-grave. The cradle-to-grave, or the full LCA, covers every step of the life-cycle of the production system under study. This typically includes breaking the analysis into three different stages: a) resource extraction and production stage, such as extraction, processing, and distribution of raw materials, as well as manufacturing of the product; b) distribution stage, such as transportation, warehousing, wholesale and retail distribution and sale; and c) consumption or use and disposal stage, such as use and maintenance, as well as its waste management, i.e., its recycling, reuse, or disposal. Since the full life-cycle is examined, the 'cradle-to-grave' analysis is typically referred to as 'full LCA' (Lee et al., 2004).

Cradle-to-gate. This type of analysis is restricted up to the manufacturing stage, i.e., the use and disposal stage is not considered. As such, this type of analysis is also referred to as partial LCA. Similar to cradle-to-grave, the analysis starts at the very beginning, e.g., raw materials (resource) extraction, but it stops at the factory gates, i.e., before reaching end users (customers). As such, cradle-to-gate analyses examine environmental impacts up to the point where a product leaves the production facility. This approach is beneficial for conveying information down the value chain (Collado-Ruiz, 2024).

Gate-to-gate. This is also a partial LCA, but in this case it only focuses on specific (sub)processes within a production chain, typically to identify hotspots and improve their environmental performance. The gate-to-gate results can later be linked to or incorporated into more complete analyses such as in cradle-to-gate or even cradle-to-grave LCAs. As such, this approach is also used to simplify complexity by assessing only one value-added process in the production chain, which can later be linked to create a more comprehensive analysis assessment (Bjørn et al., 2018a). Both cradle-to-grave and gate-to-gate approaches are mainly applied to business-to-business products, encompassing all companies that develop goods and services for other businesses.

Cradle-to-cradle. This approach is similar to classical cradle-to-grave, but in this case no wastes are generated during the end-of-life disposal stage, since the 'wastes' of this LCA approach are raw materials (resources) for the same or other production systems. This type of analysis is also known as 'new products closed-loop LCA' (Bjørn et al., 2018a). As such, the cradle-to-cradle LCA is directly connected to the circular economy.

Furthermore, LCA results not only provide information about specific environmental impacts, such as (eco)toxicity and eutrophication, but can also provide comprehensive coverage of environmental issues. Specifically, at midpoint level, single environmental issues are tackled and examined, with existing multi-issue LCIA methods typically covering between a handful to 18 (e.g., ReCiPe 2016 Midpoint) impact categories. These issues include, global warming (climate change), water use, land occupation and transformation, eutrophication, depletion of non-renewable resources, and (eco)toxicity impacts from metals and synthetic organic chemicals (see Section 6). The core reason for considering multiple environmental issues is to prevent burden shifting, which is also the rationale for adopting a life-cycle perspective. Burden shifting occurs when efforts to reduce one type of environmental impact inadvertently lead to increases in other types of impacts (Hauschild et al., 2018; Lee et al., 2004). These issues can be then translated to environmental damages, which are more relevant to decision- and policy-makers, and which reflect the environmental impact on three higher areas of protection, i.e., human health, biodiversity, and resource scarcity.

The International Organisation for Standardisation (ISO) provides a standardised methodology for conducting LCA, namely ISO 14040:2006 and ISO 14044:2006 and their amendments. ISO identifies four phases when conducting an LCA study: i) goal and scope definition, ii) LCI analysis, iii) LCIA, and iv) results interpretation (International Organization for Standardization, 2006). Methodological framework, stages of LCA, and its application are illustrated in Figure 2.2.

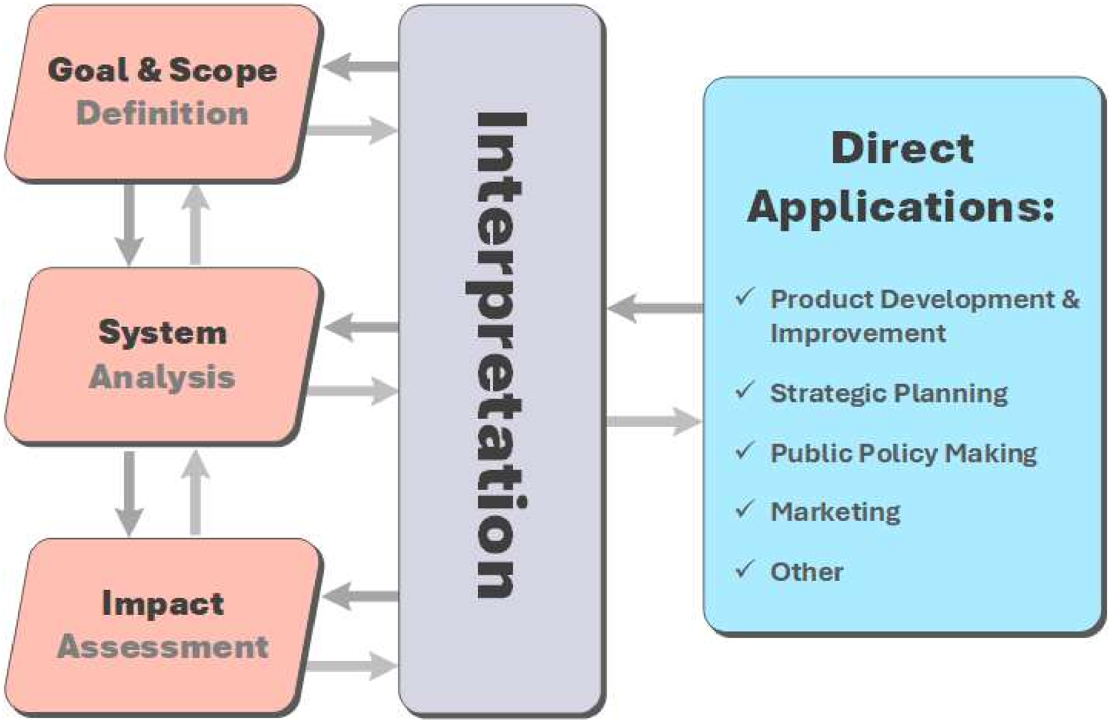

Figure 2.2 The framework of an LCA modified from the ISO 14040 standard (International Organization for Standardization, 2006).

The main focus of this framework is using traditional environmental LCA methodologies (Section 5) for OAE approaches. Other methods of LCA that may eventually be applied to OAE as it matures as a technology, including sustainability assessment, input-output LCA, footprint analysis, and consequential LCA.

2.3.3 Goal and scope definition

Defining goal: An LCA begins with a careful consideration and a deliberate definition of the study's goal. Several key questions should be included, such as, 'Why is this study being conducted? What specific question(s) does it aim to answer, and who is the intended audience?' (Lee et al., 2004). (See Section 6).

Scope definition: Defining the goal for the LCA study serves as the foundation for the scope definition. Among other things, the scope outlines and frames the assessment in alignment with the defined goal, primarily in terms of defining the functional unit, delimiting the system boundary, scoping the product system, selecting assessment parameters, and establishing geographical and temporal boundaries (Bjørn et al., 2018a). Details and terminology relevant to scope definition are given in Section 6, while the main components of the goal and scope phase are briefly discussed below.

Defining the functional unit: This involves providing a quantitative description of the function or service being assessed, which serves as the basis for determining the reference flow of the product. This reference flow guides the data collection in the next phase of the LCA (inventory analysis).

Scoping the product system: This step entails identifying which activities and processes are included in the life-cycle of the production system under study.

Selecting LCIA parameters: This refers to choosing the specific environmental impacts and/or damages that will be evaluated in the study.

Establishing geographical and temporal boundaries: This includes defining the spatial and time-related coverage of the LCA study, as well as determining the relevant technological level for the processes within the product system.

Choosing the appropriate type of analysis: This involves deciding whether the LCA study will be consequential, i.e., assess how flows from and to the environment to the system under study change as a result of examined intervention, or attributional, i.e., evaluating the impacts associated with the specific product system being studied (Butnar et al., (2024).

2.3.4 Life-cycle inventory analysis

LCI analysis involves data collection and calculations to quantify the inputs and outputs (flows) of materials and energy related to the product system. The data collection process involves physical flows, such as details of the inputs of resources, materials, and final products, as well as energy flows and the outputs of emissions to air, soil, and water, along with wastes and possible valuable (co/by)products within the product system. The LCI analysis examines all processes identified as part of the product system, with flows scaled according to the reference flow of the product determined by the functional unit (Hauschild et al., 2018; Lee et al., 2004).

The inventory analysis frequently depends on generic data for various processes sourced from databases containing unit processes or cradle-to-gate information, which outline the input and output flows for a specific unit process, such as material production, heat or electricity generation, transportation, or waste management.

The outcome of the inventory analysis is the LCI of the production system under study, which consists of a list of quantified physical elementary flows linked to the product system that provides the service or function specified by the functional unit.

2.3.5 Life-cycle impact assessment

In the LCIA stage, the collected LCI is converted into different environmental impacts by using knowledge and models from environmental science. The impact assessment contains five components, with the first three being mandatory according to the ISO 14040 standard (International Organization for Standardization, 2006):

Selection of impact categories: This step involves identifying impact categories that are relevant to the system under study and better represent the assessment parameters established during the scope definition. A corresponding quantifiable indicator is used to represent each impact category (e.g., the impact category 'climate change' has as a category indicator the infrared radiative forcing, representing the global warming potential of all identified and quantified GHG emissions). A characterisation factor derived from a characterisation model allows for the conversion of the LCI data to the common unit of each category indicator.

Classification of elementary flows: This process assigns the elementary flows (smallest measurable interactions between the product system and the environment) of the LCI by assigning them to impact categories based on their potential to affect each selected category indicator.

Characterisation: This step utilises characterisation factors derived from a characterisation model for each impact category to quantify how each assigned emissions to air, water or soil, affects each category indicator. The resulting characterised impact scores are presented in a common metric for each category, enabling the aggregation of all contributions into a single score that reflects the total impact of the product system within that category. The combined scores across different impact categories (each in its own respective metric) create the characterised impact profile of the product system.

Normalisation: This process provides insight into the relative importance of each indicator result across the various impact categories by relating them to reference information. The background impact from society (e.g., a European citizen) is often used as the reference information. The outcome of normalisation is the normalised impact profile of the product system, where all category indicator scores are standardised to the same metric.

Grouping and weighting: This process converts and potentially aggregates indicator results of different impact categories by using weighted factors based on value-choices (e.g., monetary values). Weighting enables the aggregation of all weighted indicator results into a single overall environmental impact score for the product system, called a weighted index. Both weighted and unweighted results can be helpful when integrating the LCA results into decision-making alongside other summarised information, such as the economic costs associated with different alternatives.

2.3.6 Results interpretation

The final step of an LCA study is to interpret the results and address the questions outlined in the goal definition from the initial stage. It is essential that the interpretation aligns with the goal and scope definitions, while also considering the limitations imposed by scoping choices, such as geographical, temporal, or technological assumptions, to ensure a meaningful understanding of the results. In addition, the first three stages in LCA are linked to the interpretation (Figure 2.2), which indicates that at each step of the LCA, it is possible to review and revise each step based on the results of the interpretation. For example, the results of the LCA should align with the goal and scope of the study, and the interpretation should be consistent with the data collection or the LCI stage.

Sensitivity analysis and uncertainty analysis can be employed as part of the interpretation phase to help draw conclusions from the results, evaluate the robustness of those conclusions and the influence on the results of assumptions and methodological choices made, and identify areas that require further investigation to verify and reinforce the findings.

LCA provides a deep understanding of the overall interdependence of environmental impacts from both human activities and industries. LCA results can be used to support recommendations for improving design and lowering the impact of a product or process and to formulate an environmental declaration/environmental-based labelling

(Muralikrishna and Manickam, 2017). The availability of required LCI data directly affects the accuracy of LCA results. The data gathering process is the main challenge when carrying out LCA studies. As a result, a clear understanding of the assumptions and uncertainties of LCA data is important.

2.4 Overview of prospective life-cycle and techno-economic assessment

2.4.1 Introduction to prospective analysis

Ex-ante and prospective analysis, in its nature, attempts to analyse the performance and potential feasibility of technologies and systems that have yet to reach maturity. This means that commercial-scale performance in a real operating environment is unknown, as the technology is currently at a lower level of technology development. The reality is that performance of some technologies, systems, or processes may improve when moving up the TRL ladder, while the performance of others may deteriorate or remain constant. This implies that performance upscaling should be dealt with on a case-by-case basis, ideally by practitioners with deep understanding of the process (Piccinno et al., 2016). See the box below for terminology.

This creates a challenge in assessing feasibility, because the current TRL, e.g., laboratory, bench, or pilot scale, may not reflect how it will perform at commercial scale (Roussanaly et al., 2021; Rubin, 2019). The box below defines relevant terms. Many technology characteristics will evolve as the technology progresses from the laboratory and bench scales to small pilot and commercial scales. These changes may include the technology and process design, the design of the balance of plant or reactor performance as a function of scale-up, the integration of process synergies to reduce the final waste stream through material and energy recovery and recycling, the knowledge and experience gained from industrial-scale production, and the influence of future developments in external systems on the production of the studied technology (Roussanaly et al., 2021; van der Hulst et al., 2020). Additionally, many things can change in a technology's (or system's) operating environment (Sacchi et al., 2022), as discussed in Section 1.2, for example:

Physical and/or climatic conditions - the concentration of CO_2 in the air and oceans, air and ocean temperatures and flow patterns, as well as solar irradiation.

Production and supply chains - energy and materials availability and environmental footprints.

Economic conditions - market demands, energy and materials prices, interest rates, and carbon price.

To date, systems analysts have mostly dealt with this by using current technology and systems analysis approaches, like classical TEA and LCA (Fernández-Dacosta et al., 2017), which were originally developed to study the performance of existing or 'close-to-commercial' technologies and systems (Roussanaly et al., 2021). Often, 'what if' type case studies and scenarios and/or sensitivity analyses are added to investigate how a technology may perform under varying conditions (Rubin, 2019). For example, how does a technology perform under varying electricity prices and feedstock costs? What if the reactor yield, or membrane permeance, or carbonation rate improves by a certain percentage? While relevant and insightful, such analyses are not truly prospective in nature, because they cannot answer more prognostic (what will?) type of questions. Questions on how technologies *will* likely develop (e.g., based on historical analogies) and how the operating environment *may* develop given certain (consistently formulated) scenarios are most often left out.

Recently, more prospective analysis has been considered, particularly for LCA ('prospective LCA' or prLCA), taking into account technology development from laboratory to commercial scale, and changes in the operating environment of a technology/system (Müller et al., 2024; Sacchi et al., 2022). In more detail, prLCA is defined as an LCA that 'models the product system at a future point in time (relative to the time at which the study is conducted)' (Arvidsson et al., 2024). It aims to assess the future environmental impacts of the product system under study by anticipating changes in the 'foreground' as well as 'background' system in which a technology operates (Cucurachi et al., 2018; van der Giesen et al., 2020). prLCA uses the same four steps as classical LCA, which were discussed above (Cucurachi et al., 2021; Saavedra del Oso et al., 2023), although iterative adaptations are recommended (Langkau et al., 2023). The literature on projecting technology performance from laboratory to commercial suggests mostly improvements in technology performance, but this depends on the type of technology/system under investigation. For example, van der Hulst et al. (2020) suggest the GHG footprint of the production of a new type of photovoltaic solar cell will decrease by 75% between the pilot and first commercial scales. Also, Thonemann and Schulte (2019) assume improvements in technology performance between the laboratory scale and commercial scale for the electrochemical production of formic acid. They examined four different upscaled processes and compared them with the performance of a laboratory-scale process, where all the scaled processes show a lower mean global warming impact. However, especially with processing plants (chemical processes) the opposite can often be true (Rubin, 2019). Frequently processes operate at lower material and energy efficiency at scale compared to the laboratory, because mixing and mass and heat transfer become much less effective at larger length scales. Here, the LCA community can potentially learn from process engineering and the field of techno-economics, where the challenges with upscaling are better understood (Roussanaly et al., 2021).

The literature on future projections for the operating environment – 'background system' in LCA terminology – suggests the use of adjusted background LCI databases (e.g., ecoinvent), updated with information retrieved from consistently formulated integrated assessment modelling (IAM) scenarios (Section 2.4.1). This means that the environmental performance of a technology can be investigated for a range of intrinsically consistent future scenarios, usually combinations of the so-called shared socioeconomic pathways and climate change pathways (Sacchi et al., 2022). For example, Arvidsson et al. (2018) reviewed several case studies of prLCA in relation to different technologies, such as biomaterials and energy, and provided various guidelines for prLCA studies. Sacchi et al. (2022) introduced '*premise*', a tool to streamline the generation of prospective LCI databases for prLCA, where scenarios from multiple IAMs were used to adjust the ecoinvent LCI database. Focus was placed on the electricity generation sector, cement and steel sector, road transportation sector, and supply of conventional and alternative fuels, while necessarily neglecting other value chains. It was found that the adjustments of LCI databases can greatly improve the utility of prLCA studies, since they now align with consistently formulated views of possible futures.

The thinking on prospective TEAs is perhaps less developed, especially when it comes to including future background systems, or operational environments. For foreground technology systems, Rubin et al. (2017) have explored the projection of technology costs from laboratory or pilot scale to FOAK commercial scale using appropriate (project and) process and system integration contingencies. (Greig et al., 2014) have explored cost escalations from lab/pilot to first commercial applications using historical analogies and expert interviews and have independently proposed appropriate process and estimate (project) contingencies for FOAK and early-mover projects. Van der Spek et al. (2020b) then propose using technological learning (learning or experience curves/rates) to project the cost from FOAK to NOAK, based on a certain deployed scale achieved.

Terminology for future-oriented analysis

Future-oriented analysis considers the assessment of early-stage technologies and how performance may change over time. The following outlines common terms used in future-oriented analysis (adapted from Arvidsson et al., 2024) and how they are integrated (Figure 2.3).

'Ex-ante': 'Before the event', used in this context to refer to the assessment of a technology before it is commercially operating, but at relatively high TRL.

'Prospective': Used in this context to refer to the assessment of a technology before it is commercially operating.

Foreground technology: Systems and processes for transforming raw materials and energy into a product or service. Typically, the boundaries of a classical TEA or LCA.

Background system: The socioeconomic and environmental context in which the foreground technology operates. This includes the supply chain for raw materials and the market for products and services.

First-of-a-kind (FOAK): The first large-scale deployment of a technology in which both the foreground and background are tested in real operating conditions. Typically, larger than a bench-scale or pilot prototype, most often TRL9 (see Section 6).

Nth-of-a-kind (NOAK): The technology following iterative learning through increased deployment. To avoid ambiguity, the assessor should state the cumulative capacity of a NOAK but preferably show the relationship between cumulative capacity and KPIs (see Section 8).

Learning rates: Learning rates in technology development describe how quickly the cost or efficiency of a technology improves with increased production or experience. Typically, for every doubling of cumulative output, costs decrease by a consistent percentage due to factors like process optimisation, mass/repeat production and learning how to operate a system.

Deployment scenarios: These describe how the technology might scale from contemporary FOAK to prospective NOAK. These scenarios might be constrained by raw material supply, previous rates of deployment for similar technologies, geophysical limits, access to finance or markets, or regulation (see Section 4).

Background scenarios: These describe how the background system might change during the transition of a technology from contemporary FOAK to prospective NOAK. These scenarios might include changes to the cost of raw materials and energy, their CO_2 intensity, and a possible market price of CO_2 removal.

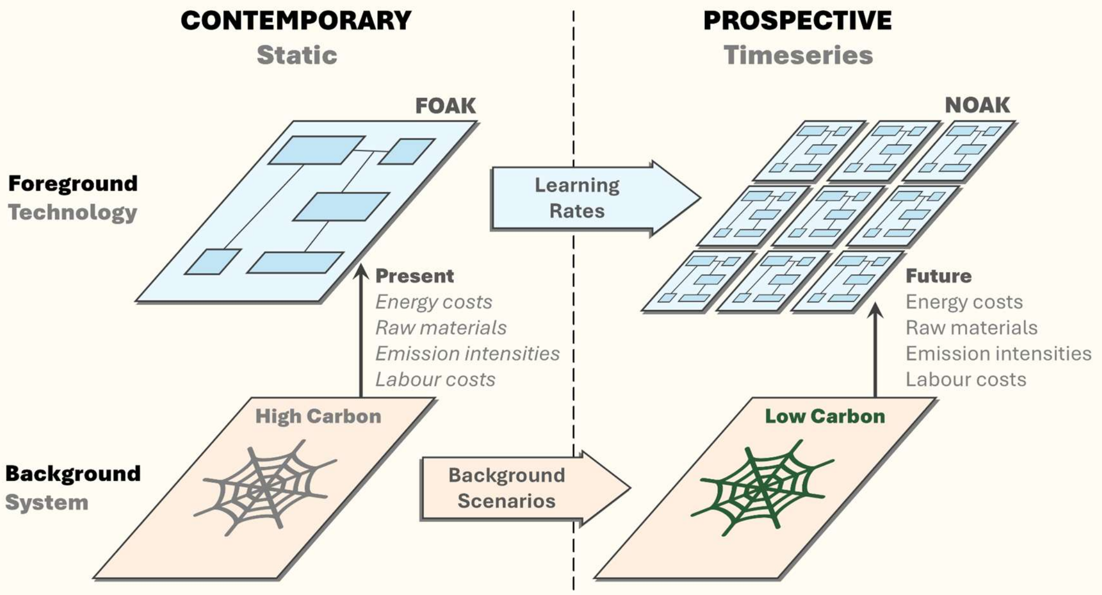

Figure 2.3 A diagrammatic overview of how static/contemporary technology assessment relates to prospective analysis through the application of learning rates and scenarios.

Meanwhile, changing the 'background' for TEA, in a manner similar to changing the background for LCA, has been explored (Renforth et al., 2024). Cost and energy/materials CO_2 intensity information were sourced from IAM pathways and were used to explore the performance of steel decarbonisation in several future scenarios. This is analogous to how the *premise* Python library updates the ecoinvent database to future IAM scenarios.

2.4.2 Overview of integrated assessment models

IAMs are sophisticated computational tools used to analyse the interplay between human activity, environmental impacts, and economic responses within the context of climate change. These models are designed to integrate knowledge from multiple disciplines – such as economics, energy systems, environmental science, and social policy – to provide policymakers with quantitative frameworks for assessing potential climate policy outcomes. IAMs have become crucial in international climate negotiations, most notably in assessments by the Intergovernmental Panel on Climate Change (IPCC), as they allow the simulation of complex scenarios over extended periods, predicting long-term impacts and enabling informed policy decisions.

IAMs support scenario analysis, a technique that explores various hypothetical futures. For example, the Global Change Assessment Model (GCAM) evaluates energy, water, and agricultural systems to predict emissions pathways under various socioeconomic and policy scenarios (Calvin et al., 2019). Scenario analysis helps policymakers visualise the potential outcomes of different emissions reduction targets, such as limiting global warming to 1.5°C or 2°C above pre-industrial levels.

Example: REMIND integrated assessment model

The REMIND (Regional Model of Investment and Development) model is a numerical framework used to simulate and analyse the complex correlations between global economic development, energy production, and climate change (Luderer et al., 2020). The primary aim of REMIND is to identify the optimal allocation of investments across economic and energy sectors in various regions, considering factors such as population trends, technological advancements, policy measures, and climate constraints. REMIND was developed by Potsdam Institute for Climate Impact Research. Key features include a) determining the best allocation of investments between economic and energy sectors across different regions and energy sector development, b) projecting the evolution of the energy sector, including shifts towards renewable energy and advanced technologies, and c) assessing climate mitigation pathways for reducing GHG emissions to meet international climate goals.

Use of IAMs in feasibility assessment. IAMs assess the costs and benefits associated with climate policies by quantifying economic damages from climate change impacts, like global mean sea level rise and agricultural productivity losses. For example, the Dynamic Integrated Climate-Economy model estimates the social cost of carbon – a measure of the economic cost of emitting one additional tonne of CO_2. These estimates provide a benchmark for policymakers to set carbon pricing and other economic instruments, creating financial incentives to reduce emissions (Nordhaus, 1992). IAMs help evaluate policy feasibility by simulating the implementation of various policy instruments, such as carbon taxes, cap-and-trade systems, and renewable energy subsidies. The Regional Dynamic General-Equilibrium Model has been instrumental in analysing how different regions might adopt cost-effective policies that align with both local and global objectives, balancing equity and effectiveness (Nordhaus, 2017).

Limitations and criticisms of IAMs. While IAMs are instrumental in policymaking, they face criticism regarding their assumptions, simplifications, and ethical implications (Keen, 2021). Some argue that IAMs oversimplify natural and social systems, potentially overlooking critical feedback mechanisms (Pindyck, 2017). Additionally, IAMs often underestimate the complexities of marine biogeochemistry, making them less reliable for evaluating marine-based climate solutions. IAMs typically apply a discount rate, which reflects the present value of future costs and benefits. Critics argue that high discount rates undervalue future generations, affecting long-term sustainability (Stern, 2007). Damage functions, which estimate climate change impacts, are based on limited data, and their accuracy has been questioned (Weitzman, 2009). Despite these limitations, IAMs remain central to climate policy development, especially as data and methodologies improve over time.

Technology parameterisation into IAMs. In IAMs, technologies are parametrised through detailed variables and equations that quantify their characteristics, costs, efficiencies, and potential emissions impacts. Each technology type is represented through specific parameters that IAMs use to simulate how changes in technology can impact overall climate scenarios.

Outcomes of IAMs. One of the primary outcomes of IAMs is the projection of temperature trajectories and emissions pathways, helping policymakers to better understand the levels of emissions reduction needed to meet different climate change policy targets. IAMs also assess economic costs, providing estimates like the cost of carbon, supporting decisions on carbon pricing and other financial incentives for interventions.

IAMs further help evaluate optimal policy combinations – such as carbon taxes or renewable energy subsidies – that balance effectiveness and feasibility across different regions. These models also outline energy system transitions, offering pathways for reducing reliance on fossil fuels while scaling up renewable energy sources. Additionally, IAMs project the impacts of climate policies on land use and agriculture, including potential trade-offs between bioenergy, food production, and carbon sequestration.

IAM outputs thus provide a comprehensive foundation for strategic climate planning, enabling policymakers to weigh costs, manage risks, and promote equitable, sustainable development aligned with global climate goals.

3.0 Framework Part A: Technology conceptualisation and flowsheet development

Key recommendations:

- We recommend the following as generic goals for OAE technology assessment, to be adapted as required:

LCA: To evaluate the wider environmental consequences of OAE as a CDR approach to guide technology development.

TEA: To evaluate the technical and economic performance of a CDR approach for a specified situation' or 'to compare the technical and economic performance of perturbations of a CDR approach, and/or to other CDR approaches.

- A description of the technology should delineate what parts represent the foreground and what is considered background.

Foreground technology: Systems and processes for transforming raw materials and energy into a product or service. Typically, the process under investigation in a classical TEA or LCA.

Background system: The socioeconomic context in which the foreground technology operates. This includes the supply chain for raw materials and the market for products and services.

- The functional unit should be specified. For TEA a net tonne of CO_2 removed is appropriate, and for LCA a gross tonne of atmospheric CO_2 drawdown is more typically be used. It can also be useful to specify secondary functional units for additional analysis (e.g., a tonne of alkaline material, such as sodium hydroxide).
- The assessment should specify one or more locations. Location-specific data should be used where possible (e.g., energy prices, embodied emissions of raw materials) and local ocean OAE efficiencies should be used unless transport to alternative deployment sites is specified.
- The reference year in which the data is derived should be highlighted.

3.1 Define the goal and scope

The reasons for conducting the LCA or TEA should be clearly articulated early in the assessment. The goal determines the overall purpose of a study and is the first step of an LCA and a TEA. The primary goal for many LCAs on CDR approaches is to evaluate their net-negativity, i.e., their total capacity for removing atmospheric CO_2 when accounting for their life-cycle carbon emissions, although the holistic aim of LCA is to assess and evaluate the wider environmental consequences (e.g., potential impacts on human toxicity, terrestrial acidification, and resource depletion) of a CDR approach, typically using as a functional unit the removal of 1 tonne of CO_2. For TEA, the goal is to evaluate the technical and economic performance of a CDR approach. A clear goal will guide the entire LCA or TEA process. Also, it should be stated whether the goal is to do a diagnostic ('what if') or a prognostic ('what will') type of study as these require the adoption of different approaches.

While not prescriptive, the following are suggested goal statements:

> LCA: To evaluate multiple environmental impacts of OAE as a CDR approach to guide technology development.
>
> TEA: To evaluate the technical and economic performance of a CDR approach for a specified situation' or 'to compare the technical and economic performance of perturbations of a CDR approach, and/or to other CDR approaches.

The assessment should also clearly state its purpose, outlining its context, intended applications, target audience, and how the findings will be used, including whether they involve comparative assertions (International Organization for Standardization, 2006). The outcomes of a TEA or LCA can identify processes that contribute most to its overall impacts or costs (referred to as 'hotspots' in LCA). This information can support technology development and scaling. Based on the recommendation of Delval et al. (2024b), research questions for an OAE-specific assessment should focus on pinpointing these hotspots and examining key drivers of CDR capacity.

The scope defines the system boundaries, functional unit, methodology, and data requirements for the assessment, ensuring alignment with its goals (Hauschild et al., 2018). Section 5 provides details on development of the data requirements, and Sections 6 and 7 consider the LCA and TEA methodologies, respectively.

3.2 System boundaries

The system boundary of the analysis must be identified at the first stage of both LCA and TEA. This involves specifying what processes and sub-systems of the CDR approach under study will be included in the analysis and what will be excluded (external to the system boundary). Setting the system boundary also determines how an LCA or a TEA should take place and helps to determine its comprehensiveness. For OAE approaches, in which the intention is to scale to global >GtCO_2, the system boundary must include raw material extraction/supply, manufacturing or key processing steps, transportation, product use if appropriate (e.g., dispersion to seawater), and end-of-life emissions, if any. It is not appropriate for studies to assume that anthropogenic materials (e.g., strong acids, strong bases, pure water, refined brines, high purity CO_2) will be available in sufficient quantities to allow for a process to scale.

Both foreground and background systems should be clearly identified and included within the system boundary. The foreground system includes the primary process steps and related infrastructure processes, such as the manufacturing of the cation and anion exchange membrane in the case of bipolar membrane electrodialysis (BPMED). This foreground system is supported by the background system, which consists of material and energy inputs into the foreground system, and the economic context in which it operates.

The foreground and background for a generic OAE approach are indicated in Figure 3.1. In this generic OAE system, the foreground includes every process that contributes to the production of the final product. Figure 3.1 illustrates the flows of all relevant resources (e.g., chemical, materials) and energy supplied (e.g., electricity A, gas B) as well as the OAE technology (foreground process). Currently, only the CDR effect of OAE is included within the system LCA system boundary. Other potential impacts on the ocean environment such as ecological or biogeochemical changes are not considered, as methodologies to assess and parameterise these impacts are still under development. As these methodologies evolve, it is expected that broader ocean-related environmental impacts will be incorporated into future system boundaries.

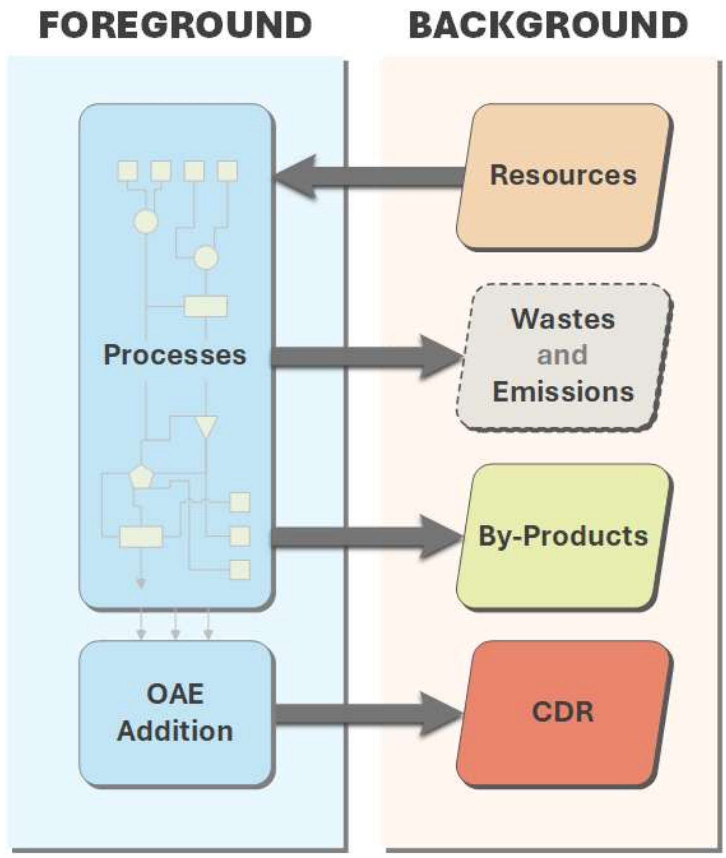

Figure 3.1 System boundaries of generic OAE technologies.

3.3 Conceptual design and flowsheet development

Articulating the nature of the OAE approach is fundamental to any assessment. The process description should contain a set of chemical reactions that describe how the raw materials react with CO_2 and result in an increase in ocean alkalinity. An initial conceptual design of the system should indicate how the raw materials interact with the primary process, and how the resulting products remove CO_2 from the atmosphere. For example, Figure 3.2 shows a conceptual design of a BPMED process, from which the sodium hydroxide produced can be used for OAE. Many of the ancillary processes are missing from this initial conceptual design. For instance, the BPMED produces hydrochloric acid as a by-product, which needs to be managed or utilised in subsequent processes. In addition, the raw materials for BPMED (brine, desalinated water) are derived from reverse osmosis.

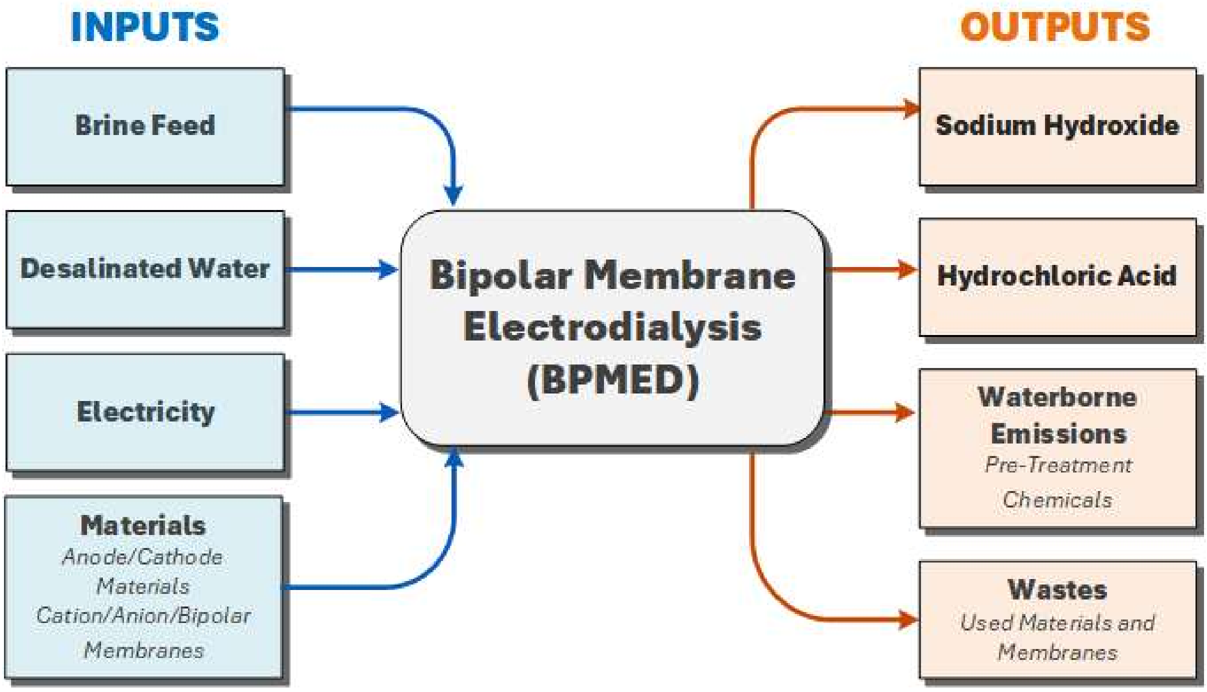

Figure 3.2 Stylised unit processes of BPMED with input and output flows.

For both TEA and LCA, this initial conceptual design must be described with a flowsheet to include key mass and energy balances (see Figure 3.4). A comprehensive flowsheet (i.e., process flow diagram) should clearly illustrate all major unit operations, material and energy flows, and key process parameters that define the system under study. For OAE processes, the flowsheet must capture raw material preparation, alkalinity generation processes, product separation steps, ocean discharge systems and, where possible, by-product/waste handling systems.

Proper documentation and analysis of these flows are key to tracking OAE's resource efficiency and emissions. Understanding these flows helps identify areas for process optimisation and impact reduction, ensuring minimal environmental impact and maximum cost efficiency during operation.

3.4 Functional unit

The functional unit is the reference unit that the analysis will use for comparison. Choosing an appropriate functional unit is essential for meaningful comparisons between assessments.

For TEA a net tonne of CO_2 removed should be used.

For LCA a tonne of CO_2 removed should be used.

For OAE, application of alkaline material does not initially lead to immediate and complete CO_2 removal. This delayed response in the global warming potential, and consequently the equivalent amount of CO_2 removed when calculated in present-day terms, is lower compared to technologies which remove CO_2 at the start of a system's lifetime (see Section 5.5). This is why for OAE, a unit of alkaline material added can also be a helpful functional unit.

3.5 Specification of base case spatial and temporal context

The contemporary temporal context would normally constitute the base case scenario, from which future performance can be projected using scenarios and prospective TEA and LCA (see Section 4). A base case spatial context needs to be articulated carefully, considering attributes enabling or restricting siting an OAE project (this could be the availability of land, energy, raw materials, and/or attributes of the ocean, regional currents, wildlife). For exploratory research for technology feasibility, investigating several locations is preferred to allow the assessment of OAE across a broad range of geographies.

A noteworthy restriction with OAE projects is that the addition of alkaline material has varying CO_2 removal rates across different locations and through time. Ocean models have been developed to forecast this effect, and based on the efficiencies of such models, ideal locations can be identified. In addition, locations should also consider the labour and infrastructure requirements (skilled workforce, access to utilities, port facilities), proximity to suitable points for OAE, and proximity to raw materials. If urban centres (>100k population) are used as a proxy for access to labour and infrastructure, and if raw materials and alkaline material addition is limited to <150 km, it is possible to identify promising locations for the deployment of OAE (Figure 3.3).

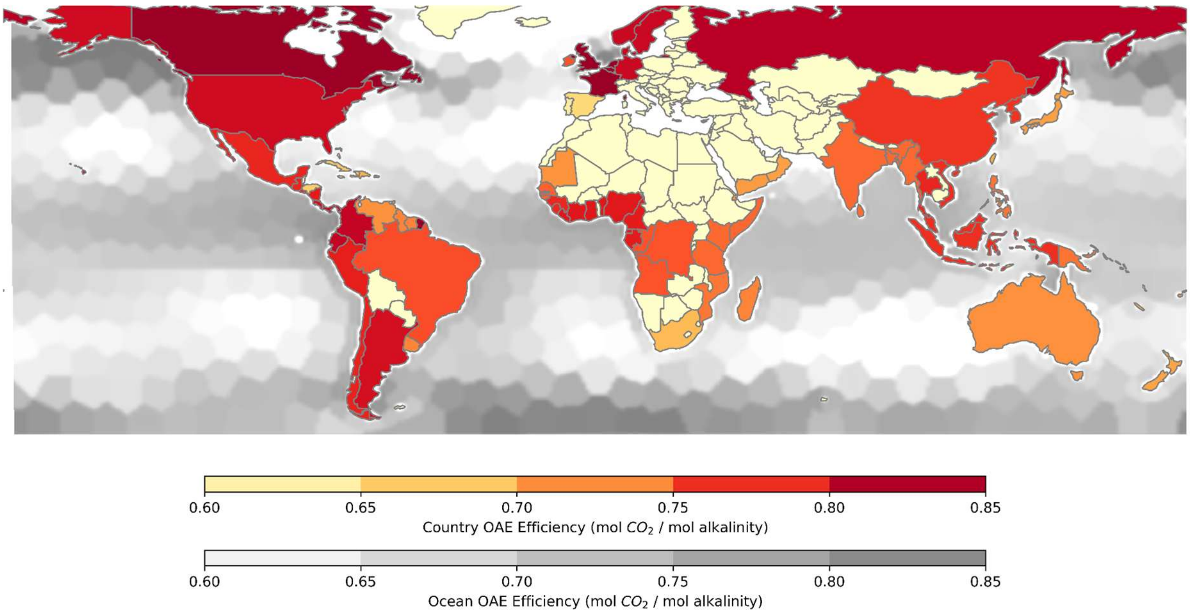

Figure 3.3 The spatial distribution of OAE efficiencies derived from Zhou et al. (2024) and averaged for national efficiencies.

3.6 Assumptions, limitations, and attribution

Assumptions about the durability of CO_2 storage, marine biogeochemical effects, and scalability of OAE must be clearly stated. These assumptions should be based on current scientific understanding and highlight any uncertainties or knowledge gaps. For example, assumptions about the permanence of CO_2 storage in marine environments should consider potential biogeochemical cycles that could release stored CO_2. The scope of work should also define the allocation method (if necessary, since allocation should be preferably avoided).

3.7 Integration between LCA and TEA

The potential of a technology can and should be assessed across a diverse set of criteria to endow decision-makers with the richest understanding. The *TEA and LCA Guidelines for CO_2 Utilisation* (Arno W. Zimmermann et al., 2020) provides recommendations for the integration of TEA and LCA. They outline three methods for integration which we summarise below:

Qualitative: A discursive integration is adopted in which the TEA and LCA results are considered together, but not necessarily produced from identical input parameters. This may be most appropriately applied when scope and boundaries of the TEA and LCA are sufficiently similar, but not completely aligned.

Quantitative: Quantitative or 'combined indicator-based', integration is undertaken for TEA and LCA studies that have aligned boundary conditions, scopes, and input processes. The indicators most likely to be shared between assessments are the global warming potential manifest in LCA and levelised cost of carbon removal produced from a TEA.

Preference-based: This methodology proposes to integrate a decision-maker's preferences into a multi-criteria analysis of the technology. Such analysis should be undertaken in addition to qualitative or quantitative assessment, as guidelines do not typically recommend weighting or aggregating outcomes.

If both a TEA and an LCA are intended to be undertaken concurrently, we recommend a quantitative integrated approach, which provides the most comprehensive outcomes for decision-makers.

3.8 Case study: Conceptualisation and flowsheeting

3.8.1 Goals

- Quantify and evaluate the wider environmental and economic impacts from employing BPMED for OAE.
- Exemplify an integrated techno-economic and environmental framework.
- Define and set benchmarks for OAE approaches.

3.8.2 System boundaries

The conceptual design involves converting raw seawater into alkaline and acid products. The alkaline products are re-introduced to the ocean while the acid product is disposed of (e.g., through reaction with silicate rocks). This defines the boundaries of the system for the analysis and is akin to a cradle-to-grave boundary. The foreground process starts from the seawater extraction and pretreatment stage, followed by the precipitation softening, ion exchange, reverse osmosis, bipolar electrodialysis for generation of products, and application of alkaline materials to the ocean (Figure 3.4). The background process includes energy utilities (electricity), materials (e.g., membranes), and chemicals for running the process.

The end of life of HCl generated from the BPMED process (by-product) is excluded from the system boundaries. While at small scale, produced HCl may be sold commercially, when operating at scale this material flow may saturate, or substantially contribute to, the volume of existing markets. Therefore, large volumes of dilute HCl will need to be disposed of through the reaction with silicate minerals (either at the surface or injected underground). The complexity in the variant technologies in acid disposal, its potential utility, and the relatively small contribution this material flow is likely to make warrant its exclusion from this LCA. In the sensitivity analysis we consider the application of BPMED-OAE to desalination waste brines (Section 6.7.6).

The technology uses seawater as the brine feedstock, which requires considerable treatment to meet the needs of BPMED. Some have suggested that this requirement could be reduced if the technology were applied to desalination waste brines (Committee on A Research Strategy for Ocean-based Carbon Dioxide Removal and Sequestration et al., 2022). The desalination industry applies a range of treatments to seawater prior to reverse osmosis (Poirier et al., 2023), including screening, disinfection, flocculation, floatation, and filtration. These remove suspended solids from the seawater and prevent biofouling within the process. Scaling is problematic in some processes, which is reduced by the addition of acid to the influent seawater, chemical softening, or nanofiltration. However, scaling is primarily an issue for reverse osmosis plants that use brackish water and used for seawater when recovery operates above 35% (DuPont Water Solutions, 2021). We have separately considered the application of BPMED to desalination waste brines through a series of 'variant configurations' in case-study sections of this framework (Sections 5.6, 6.7.6, 7.5.4).

These variants include:

1. Base - The original electrodialysis (ED) Case with softening (using precipitation).
2. No Soft - ED Case without softening.
3. Soft NF - ED Case with softening (using nanofiltration).
4. Reject - ED Case without reverse osmosis and softening. The raw material water and salt were derived from reject/waste sources (e.g., seawater desalination plant + wastewater plant effluent).

3.8.3 Key performance indicators

Technical

- Net and gross CO_2-eq removed.
- Specific energy consumption per unit of alkaline material generated.
- Specific energy consumption per unit of net CO_2-eq removed.
- Energy efficiency

Economic

- Levelised cost of CO_2 removal.

Environmental

- Eighteen midpoint categories will be used (see Table 6.3)

3.8.4 Functional units

Assessment will be made relative to the amount of gross atmospheric CO_2 drawdown by the system and the amount of alkaline material generated by the system.

3.8.5 Base case spatial and temporal context

The base case will be evaluated starting from the present year, and will include the construction period, plant operation period, and an additional number of years past the plant's operation to account for CO_2 drawdowns from OAE.

- *Year of construction: 2023*
- *Construction period: 3 years*
- *Plant life: 25 years.*
- *Post-plant life: 25 years*

Locations ideal for OAE (from Figure 3.4) were selected in the following regions:

***North America**: USA (Washington, Alaska), Canada (Vancouver)*
***Europe**: Netherlands (Groningen), Germany (Bremerhaven), Denmark (Esbjerg), Norway (Kristiansand), United Kingdom (Hull)*
***South America**: Ecuador (Guayaquil)*
***Asia**: China (Dalian), Thailand (Bangkok)*
***Africa**: Nigeria (Lagos)*
***Oceania**: Australia (Darwin)*

3.8.6 Flowsheet development

BPMED can be used to produce acid and base products from desalinated water, salt, and electricity. Sodium hydroxide produced from the reaction can be used for OAE, which aids in sequestration of CO_2. The foreground system will have a FOAK capacity of 10 kt per year of sodium hydroxide.

$$Bipolar\ membrane\ electrodialysis:$$

$$NaCl_{(aq)} + H_2O_{(l)} \rightarrow HCl_{(aq)} + NaOH_{(aq)} \qquad \text{(Eq. 3.1)}$$

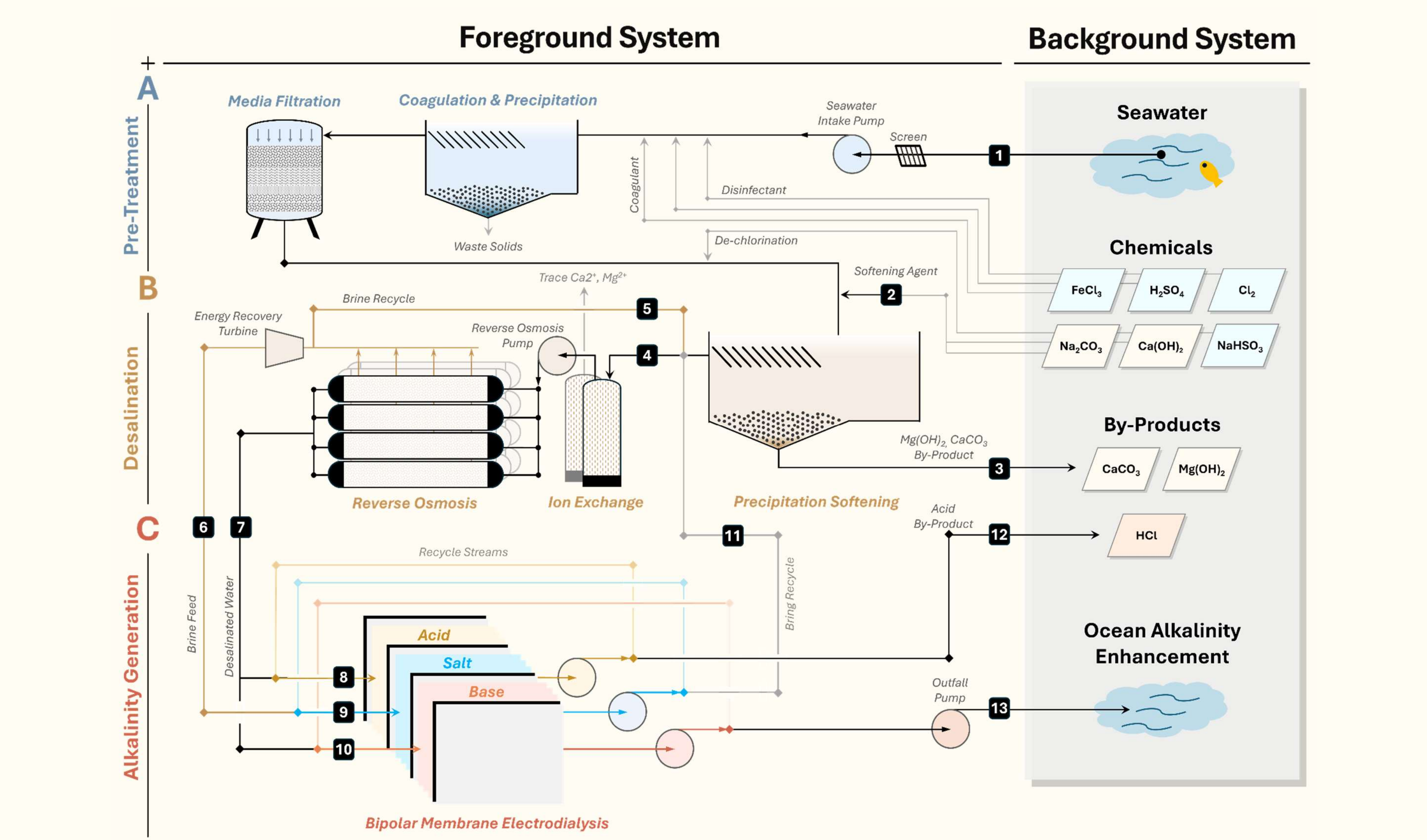

Figure 3.4 Process flow diagram of the BPMED case study. The base case includes seawater pretreatment and desalination via precipitation softening and reverse osmosis processes.

Brine and water feed for the reaction can be supplied from seawater. However, this requires seawater pretreatment followed by desalination to condition the feed. Pretreatment of seawater may follow conventional processes (e.g., screening, disinfection, removal of organics and solids), though there may be slight adjustments to account for differences in operational requirements for BPMED.

The desalination process used here aims to produce desalinated water and brine feed for the BPMED unit. Conventional water desalination is achieved using reverse osmosis, and brine from the unit is normally rejected to the ocean. Bivalent ions such as Mg and Ca may cause scaling in the electrodialysis unit depending on the seawater composition (DuPont Water Solutions, 2021). Avoiding these issues would require additional softening prior to performing reverse osmosis. Relatively large amounts of Mg and Ca ions are present in seawater, so the softening process should be able to process the specified quantity and concentration. Furthermore, monovalent ions such as sodium are desirable, so selective separation processes are required. Precipitation softening in combination with a cation exchange was considered for the base case.

In the precipitation softener, Na_2CO_3 and $Ca(OH)_2$ are added in stoichiometric quantities (see Eqs. 3.2 to 3.5) to remove non-carbonate salts of magnesium and calcium (consisting of most bivalent salts in seawater). A pH of 10 – 11 is required to precipitate the ions as magnesium hydroxide and calcium carbonate salts. NaOH from the BPMED unit is used to control the pH in the precipitator, and HCl from the BPMED unit is used to neutralise the alkalinity of the softened water from the precipitator. A cation exchange resin is used to remove trace quantities of bivalent ions remaining in the stream before introducing the softened brine to the reverse osmosis unit.

Removal of non-carbonate magnesium hardness:

$$MgSO_{4(aq)} + Ca(OH)_{2(aq)} \rightarrow Mg(OH)_{2(s)} + CaSO_{4(aq)} \quad \text{(Eq. 3.2)}$$

$$MgCl_{2(aq)} + Ca(OH)_{2(aq)} \rightarrow Mg(OH)_{2(s)} + CaCl_{2(aq)} \quad \text{(Eq. 3.3)}$$

Removal of non-carbonate calcium hardness:

$$CaSO_{4(aq)} + Na_2CO_{3(aq)} \rightarrow CaCO_{3(s)} + Na_2SO_{4(aq)} \quad \text{(Eq. 3.4)}$$

$$CaCl_{2(aq)} + Na_2CO_{3(aq)} \rightarrow CaCO_{3(s)} + 2NaCl_{(aq)} \quad \text{(Eq. 3.5)}$$

The reverse osmosis unit separates the softened brine into desalinated water and brine feeds for the BPMED unit. Reverse osmosis requires high pressures (55 to 85 bar) for separation and generates desalinated water in the permeate stream, and high-pressure brine in the reject stream. Typically, about 35 – 45% of the feed's volume is recovered as desalinated water. The high-pressure reject stream is passed to an energy recovery device which reduces the energy requirements of the reverse osmosis booster pump.

The BPMED unit uses stacked cells with three compartments (acid, base, and salt) separated by a series of bipolar, anion exchange, and cation exchange membranes (see Figure 3.5). The acid and base compartments are used to generate HCl and NaOH, respectively, whereas the salt compartment is used to separate NaCl and provide ions to the acid and base compartments. A fraction of the brine feed from the reverse osmosis unit is passed through the salt compartment to drive the reaction (Eq. 3.1) in the BPMED unit, and the remainder is returned to the ocean. The desalinated water from the reverse osmosis unit is used to dilute the acid and base streams to maintain their feed concentrations at 2 wt.% in the BPMED unit. Desalinated water is also required as feed for the reaction (Eq. 3.1), and to form diluted acid and base products with 2.5 wt.% concentrations. Brine from the reverse osmosis unit is used to concentrate the recycled brine from the BPMED unit and maintain a feed concentration of 4 wt.%.

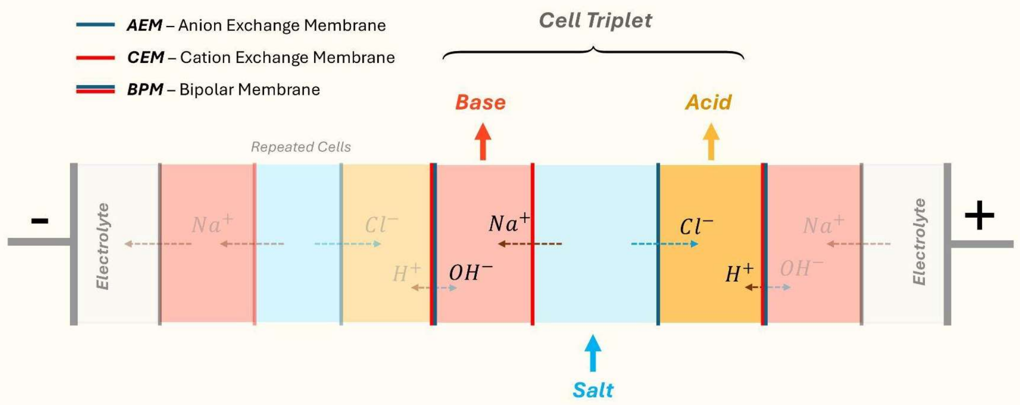

Figure 3.5 Simplified schematic of a BPMED stack. A cell triplet and a single repeated cell are shown for representative purposes.

The BPMED unit produces a concentrated base, concentrated acid, and partially converted brine with 2.5, 2.5, and 3.2 wt.% concentrations, respectively. The acid is mainly a by-product from the system and is either disposed of or sold for revenue. The base product and converted brine are mixed with the remaining brine reject (from the reverse osmosis unit), and this mixture is returned to the ocean for alkalinity enhancement.

3.8.7 Variants and flowsheet development

No Softening Case (Figure 3.6). Technical uncertainties regarding electrodialysis unit performance in the presence of bivalent ions led to the development of this variant. This case study evaluates the potential benefit of eliminating softening processes while maintaining efficient electrodialysis operation. In this configuration, unreacted brine is recycled to minimise seawater consumption. However, scaling remains a significant challenge in these systems, with scalants potentially accumulating in the recycled loop (stream no. 8). The Stiff and Davis Stability Index (SDSI) was calculated at the most concentrated points in the process to ensure minimal scaling potential (SDSI = 0).

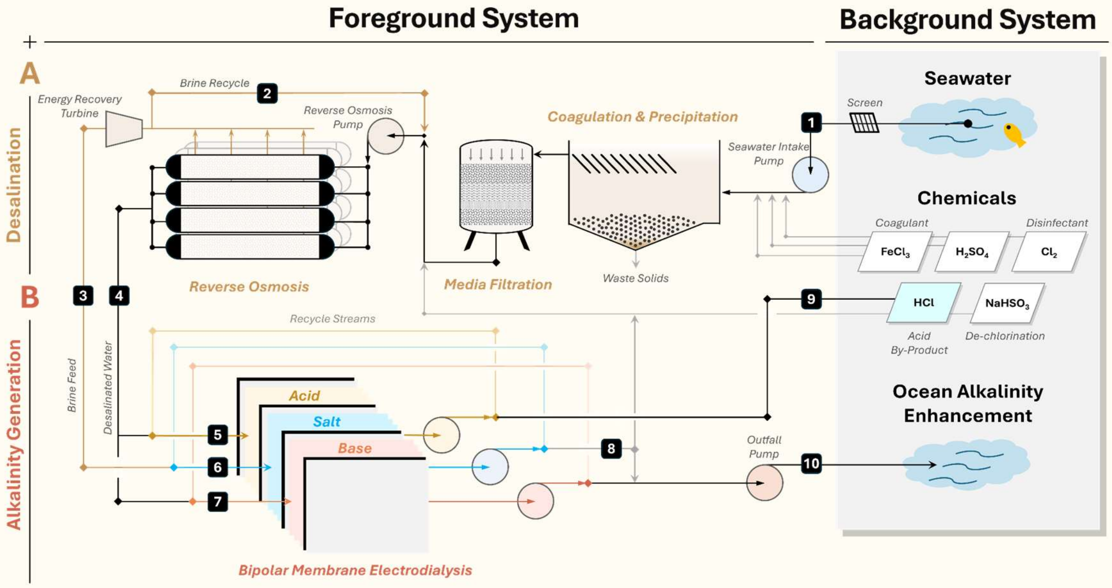

Figure 3.6 Process flow diagram of the case study variant without softening processes. Unlike the base case, bivalent ions are not removed. Note that bivalent ions can accumulate in the electrodialysis loop; therefore, the SDSI was determined to limit the accumulation in the recycled stream.

Softening via Nanofiltration Case (Figure 3.7)**.** Compared to precipitation softening processes, nanofiltration requires no chemical agents for operation. Additionally, the large CO_2 footprints associated with sodium carbonate and lime production make precipitation softening less desirable from both economic and environmental perspectives. The nanofiltration process should employ membranes that selectively remove bivalent ions while maintaining low rejection values for sodium ions. Such membranes have previously been utilised for seawater nanofiltration, but not all commercial membranes possess the required specifications for this application. Based on the seawater composition and electrodialysis feed requirements, membranes with sodium rejection below 30% are necessary. We have identified suitable membranes from (Abdelkader et al., 2018)). Since bivalent ions are not completely removed by nanofiltration, a smaller precipitation softening unit was still included in this configuration.

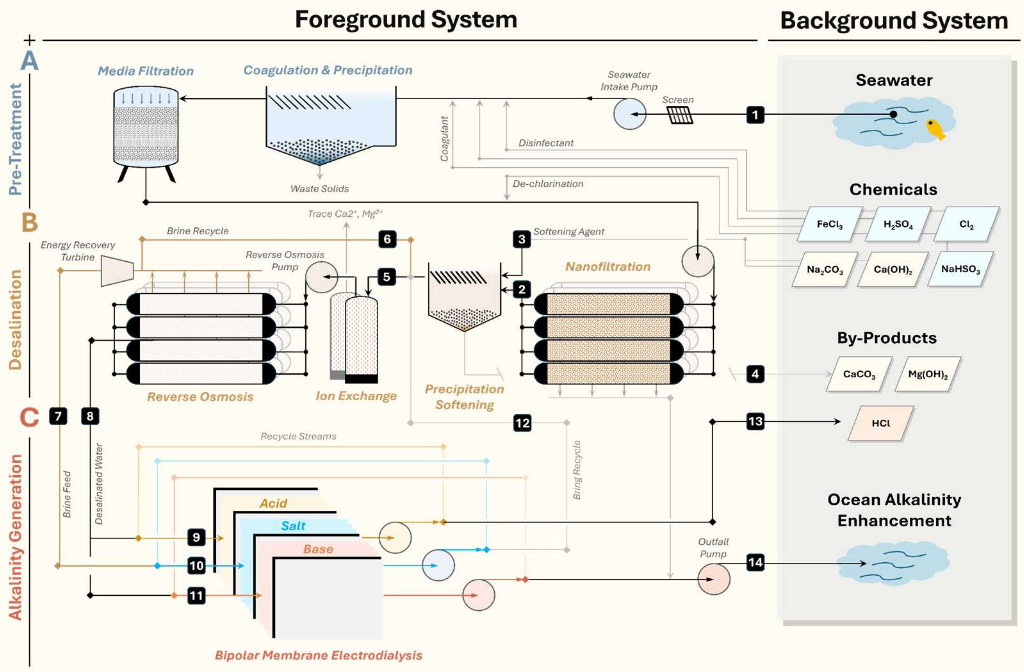

Figure 3.7 Process flow diagram of the case study variant using nanofiltration for softening. Compared to the base case, bivalent ions are primarily removed using nanofiltration membranes, with residual amounts in the permeate subsequently removed through precipitation softening.

Reject/Waste Stream Case (Figure 3.8). This case examines an electrodialysis unit co-located with a waste brine source (e.g., from an existing seawater reverse osmosis plant) and a low-salinity wastewater source (e.g., wastewater treatment plant effluent). This configuration benefits from utilising existing infrastructure rather than developing a greenfield site. Furthermore, these streams typically undergo pretreatment and, in some cases, softening processes, potentially eliminating the need for additional treatment before entering the electrodialysis unit. Although this case is constrained by the availability of suitable locations, it represents the most optimistic scenario for this technology's deployment.

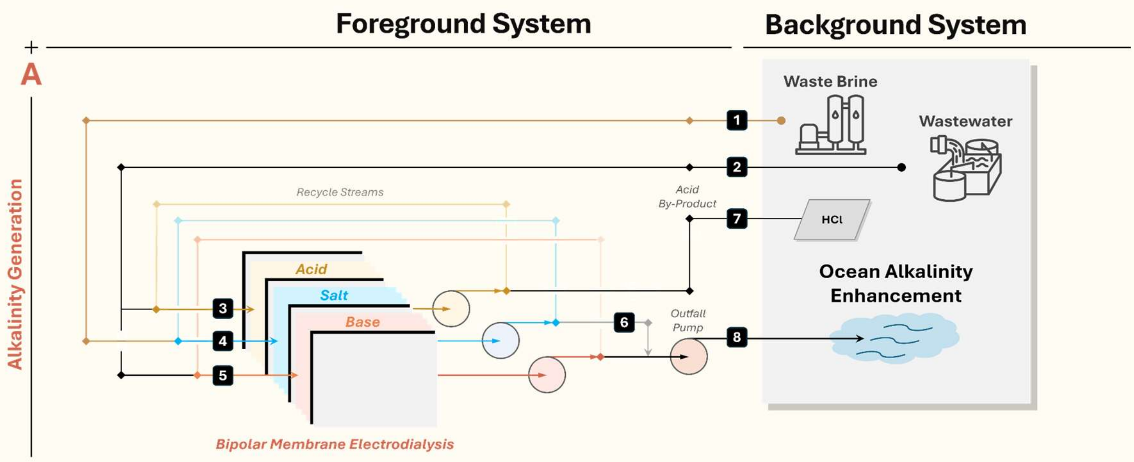

Figure 3.8 Process flow diagram of the case study variant utilising rejected/waste brine and water streams as feeds to the electrodialysis unit.

4.0 Framework Part B: Scenario development for scalable deployment

Key recommendations:

- It may take many years or decades for early-stage technologies to operate at scale. At this point, both the foreground processes and background systems may have changed considerably. Scenarios should be used to provide a consistent description of these changes.
- Results from integrated assessment models (IAMs) may be used as scenarios for changes in the background system. Here, we recommend the shared socioeconomic pathway #2 in combination with representative concentration pathways 1.9 or 2.6 as appropriate general base case scenarios. While additional scenarios could be tested, one of these reference scenarios should be assessed for comparison.
- Scenarios should also be used to communicate the potential of the technology to operate at scale. We recommend using a logistic function to provide a stylised pathway over time (t):

$$f(t) = P_0 \cdot e^{m(1-e^{-kt})}$$

$$m = ln\frac{L}{P_0}$$

Where P_0 is the initial 'first-of-a-kind' deployment scale, L is the maximum deployment scale, and k is the scale-up rate.

4.1 Introduction

Scenarios play a crucial role in climate change research by describing plausible future development paths based on key assumptions. Scenarios are used to describe changes to both foreground technologies and background systems and could be driven by one or more key socioeconomic (demographics, economics, governance), technology (industries, energy, agriculture, carbon removal), and/or climate drivers (emissions, aerosols, land-use, ocean, volcanos). This section describes a method for identifying scenarios that can explore changes to the background system of a prospective analysis (see Section 8). It also considers how to develop deployment scenarios for technology upscaling, which influences the development of the foreground technology in a prospective analysis (see Section 8). The feedback or interdependency between technology development and the wider socioeconomic systems in which they operate is not incorporated into this framework.

4.2 Background system scenarios

Describing future climates is essential for understanding the impacts of climate change and identifying targets to mitigate risks and negative outcomes. The social, economic, and technical context that underpins these futures has also been widely explored (Houghton et al., 1990; Pörtner et al., 2022).

'Scenarios of different rates and magnitudes of climate change provide a basis for assessing the risk of crossing identifiable thresholds in both physical change and impacts on biological and human systems'. Source: *Towards New Scenarios for Analysis of Emissions, Climate Change, Impacts, and Response Strategies* (Moss et al., 2008).

These scenarios form the foundation for IAMs, which combine various economic and environmental system models to explore the impact of policy change on climate targets.

The definition and application of scenarios can vary depending on the research question. Scenarios are not predictions or forecasts, but rather tools for exploring possible futures. Different IAMs have been developed with varying underlying system models and assumptions, each with its own set of defined scenarios. As such, there is no fixed method for defining scenarios; instead, they are broadly categorised based on their socioeconomic assumptions and climate mitigation outcome (Guivarch et al., 2022).

Scenarios used in climate change research are categorised based on a set of socioeconomic assumptions paired with specific climate outcomes. The shared socioeconomic pathways (SSP) framework is used to represent baseline narratives for future socioeconomic development. These narratives describe projections of GDP, population, urbanisation, economic collaboration, and human and technological development in the absence of climate change and additional climate policies. Five distinct pathways are commonly used to broadly describe possible futures (O'Neill et al., 2017). Given that the SSP framework is extensively used within IAMs, it is a good basis on which to undertake prospective technology analysis.

Climate outcomes are currently defined using representative concentration pathways (RCPs), which describe how GHG concentrations evolve over time. These RCPs represent nominal radiative forcing levels in the year 2100. The IPCC AR6 has introduced eight scenarios (labelled C1 to C8) to categorise scenarios and IAM outputs (Table 4.1). While combinations of SSP-RCP pathways have been associated with each category, climate outcomes can differ for the same SSP-RCP pathway depending on the underlying IAM used.

For the purposes of prospective TEA and LCA, data produced from IAMs can be used to explore the evolution of background systems. Background system data is necessary when performing TEA's or LCA's, and due to the time-variant nature of this data, it allows for prospective TEA or LCA analysis to be performed. Defining multiple plausible and relevant scenarios is necessary to capture uncertainties in how climate change drivers could develop. Scenarios should be selected with consideration for their plausibility with the deployment of OAE. The most extreme emission scenarios (e.g., SSP5-RCP8.5) already appear unlikely given recent progress in climate change policy, and some argue that they no longer represent 'business as usual' (Hausfather and Peters, 2020).

Table 4.1 Categorisation of scenarios by climate outcome (Adapted from Riahi et al., 2022).

	Category	Description	WGI SSP
C1	Limit warming to 1.5°C (>50%) with no or limited overshoot	Limits warming to 1.5°C in 2100 with a likelihood of greater than 50% with no or limited overshoot*.	SSP1-RCP1.9
C2	Return warming to 1.5°C (>50%) after a high overshoot	Exceed warming of 1.5°C during the 21st century with a likelihood of >67%, and limit warming to 1.5°C in 2100 with a likelihood of >50%. High overshoot refers to temporarily exceeding 1.5°C global warming by 0.1°C–0.3°C for up to several decades.	
C3	Limit warming to 2°C (>67%)	Limit peak warming to 2°C throughout the 21st century with a likelihood of >67%.	SSP1-RCP2.6
C4	Limit warming to 2°C (>50%)	Limit peak warming to 2°C throughout the 21st century with a likelihood of >50%.	
C5	Limit warming to 2.5°C (>50%)	Limit peak warming to 2.5°C throughout the 21st century with a likelihood of >50%.	
C6	Limit warming to 3°C (>50%)	Limit peak warming to 3°C throughout the 21st century with a likelihood of >50%.	SSP2-RCP4.5
C7	Limit warming to 4°C (>50%)	Limit peak warming to 4°C throughout the 21st century with a likelihood of >50%	SSP3-RCP-7.0
C8	Exceed warming of 4°C (≥50%)	Exceed warming of 4°C during the 21st century with a likelihood of ≥50%.	SSP5-RCP8.5

Current socioeconomic environments resemble SSP2, which is therefore an appropriate baseline narrative for evaluating climate mitigation technologies (Strefler et al., 2021). Furthermore, it includes emissions removal to reach the pathway, which is relevant for OAE technologies. However, future socioeconomic trends may change to more sustainable pathways (SSP1) or worsen (SSP 3, 4, or 5). Selected scenarios should consider CDR technologies, and in terms of climate outcomes this would include RCP 1.9 to 2.6, which aim to limit warming to 2°C or below, and would thus require carbon removal in addition to other emissions reduction approaches.

Pathways such as SSP1-RCP1.9 appear ambitious today based on recent projections by Climate Action Tracker (CAT, 2024). Global warming is happening at a rate of close to 0.3°C per decade. This rate suggests an 'optimistic scenario' of 1.9°C by 2100 may be more reliable with higher levels of transparency. Without a major, unexpected technological breakthrough, we will exceed the 1.5°C target (Ritchie, 2024).

4.3 Technology deployment scenarios

For a technology to make a meaningful impact on climate change, it will need to be sustainably scaled up. Assessing the scalability of disruptive technologies is complex given that there can be rapid and unanticipated technology development, unpredictable policy or regulatory shifts, and/or changes in market dynamics. Nemet et al. (2023) use historical scale-up rates to constrain the possible deployment of CDR. They argue that technology adoption can be broadly characterised by a logistic function (Eq. 4.1).

$$f(t) = \frac{L}{e^{-k(t-t_i)}} \quad \text{(Eq. 4.1)}$$

Where L is the asymptote of the function, k is the growth rate (1-14% for historical technologies, median of 6%), and t_i is the time of inflection. Many global technologies require decades to pass the inflection point. For deployment scenarios, a more helpful logistic relationship may be the Zweifel and Lasker (1976) re-parameterisation of a Gompertz function (Tjørve and Tjørve, 2017) in Equations 4.2 and 4.3.

$$f(t) = P_0 \cdot e^{m(1-e^{-kt})} \quad \text{(Eq. 4.2)}$$

$$m = \ln \frac{L}{P_0} \quad \text{(Eq. 4.3)}$$

$$\mathrm{S}_{\mathrm{NOAK}} = \mathrm{S}_{\mathrm{FOAK}} \cdot e^{m(1-e^{-kt})} \quad \text{(Eq. 4.4)}$$

Where P_0 and S_{FOAK} are the initial scale (attributable here to the FOAK) and S_{NOAK} is the Nth-of-a-kind scale. A range of outcomes of this equation are shown in Figure 4.1. This parameterisation is useful, as it can be directly related to the scale of a FOAK system (Eq. 4.4), which can be estimated for an early-stage technology, and it does not require an estimate of the time for inflection, which is difficult to predict.

For the deployment of OAE, it may be possible to constrain maximum deployment scenarios against geophysical limits, the use of the most-scarce/limiting resource, or reasonable technology scale-up rates (Table 4.2). Beyond geophysical or thermodynamic limits, the selection of appropriate parameters is uncertain. Some have suggested growth rates of CDR technologies on the order of 25% with multi-gigatonne maximum potential (equating to doubling gas use and a 50% increase in electricity use for the deployment of DAC, Hanna et al., 2021) may be possible if emergency 'wartime-like' deployment is needed. Large growth rates similar to what has been possible during wars could possibly be sustained for years, or even decades, but as more of society's resources are directed towards the scale-up effort, there will be trade-offs with other parts of the economy. For this and other reasons, some have noted the problems of framing climate change as an 'emergency' (HODDER and MARTIN, 2009), while others highlight some utility (Patterson et al., 2021). Given this, we suggest large growth rates should be avoided for base-case scenarios, but they could be reasonably included in sensitivity analysis.

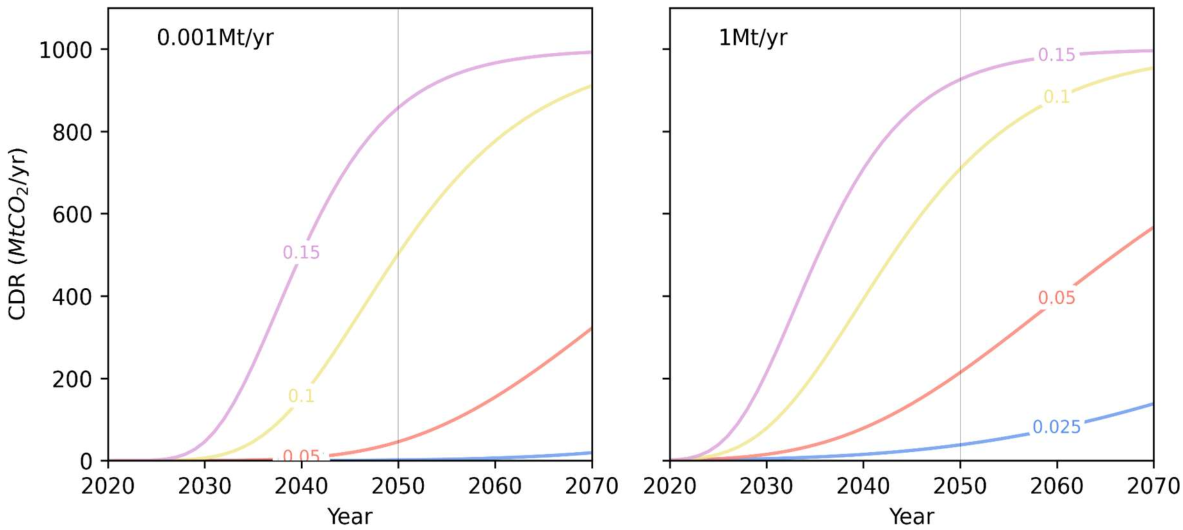

Figure 4.1 The general solution to the modified Gompertz function showing the deployment of a CDR approach in which the asymptote is 1 $GtCO_2$/yr, for initial FOAK of 1 kt/yr and 1 Mt/yr for different growth rates (2.5% - 15%).

The impact of scale-up challenges is dynamic, varying across temporal and spatial dimensions. Certain constraints are more pronounced in FOAK projects due to the absence of established processes or infrastructure. However, these challenges can be mitigated or even eliminated over time through learning-by-doing, innovation, and technological breakthroughs. Conversely, as deployment scales increase over the long term, other constraints may emerge or intensify, driven by growing resource demands and operational complexities.

In the near term, scale-up rates can both drive and be driven by technological advancements. Recognising and accounting for this feedback loop is necessary when designing deployment strategies, particularly for technologies at lower technology readiness levels, where significant improvements are possible during the scale-up. The aim of this exercise is to produce a plausible range of future operating capacity based on technical limitations. Environmental or ecological limits and regulatory and financial constraints are not considered here but may be more limiting for some OAE approaches.

Table 4.2 Summary of upscaling challenges of OAE that could be used to constrain deployment scenarios.

OAE technologies	Possible size of FOAK[a] process	Growth rate (k)	Potential limits to maximum scale (L)
Coastal enhanced weathering	The size of a dedicated spreading vessel (100's kt ultrabasic rock/yr in split hopper barge)	Upscaling spreading operations or ultrabasic rock supply (2-10%/yr)	Availability of coastal/shelf locations for spreading
Limestone to upwelling regions	The size of a dedicated spreading vessel (10-100's kt limestone/yr in barge)	Upscaling spreading operations or limestone rock supply (2-10%/yr)	Ocean circulation (~1 $GtCO_2$/yr)
Ocean liming*	The size of an industrial kiln fit with carbon capture and storage (100's kt to Mt lime/yr)	Zero-emission calcination, and potentially the conversion of spare capacity within the cement production sector (10-20%/yr)[b]	Acceptable use of future energy resources
Mineral carbonation with ocean liming*	The size of an industrial high-pressure/temperature reactor (kt to 10's kt/yr)	Scaling the high-pressure/temperature production process	
Accelerated weathering of limestone/buffered accelerated limestone weathering*	The size of an industrial accelerated weathering of limestone reactor (kt to 10's kt/yr)	Scaling up the size of the reactor system + the supply of zero-emission lime + the supply of CO_2 from DAC or biogenic sources	
Electrolysis*	The size of an industrial electrochemical system (~MW power draw)	Scale-up of the electrochemical system (2-4%/yr); the supply of low-carbon electricity	Acceptable use of low-carbon electricity
Electrodialysis*			
Hydrated minerals*	The size of an industrial precipitation/crystalliser reactor	The size of an industrial precipitation/crystalliser reactor +	Geographic-constrained to cold water environments

* These technologies could potentially be deployed at wastewater treatment/power station/desalination outflows. The scalability of this deployment pathway could be limited by the flow of water in the outflow.
a-'First of a kind' refers to the scale at which the whole process is demonstrated.
b- The International Energy Agency's scenarios consider growth rate in calcination carbon capture and storage to be 13-20%/yr.

4.4 Case study: Scenario development data

4.4.1 Background scenario

We used data from the REMIND IAM, specifically focusing on the SSP2EU-PkBudg500 scenario. This scenario follows the SSP2 narrative, representing a 'middle-of-the-road' future with moderate challenges to mitigation and adaptation. The scenario includes a cumulative carbon budget of 1,150 Gt CO_2, which aligns with efforts to limit global warming to 2.0°C. Two key parameters for selected regions were extracted from the model: the evolution of electricity grid costs and corresponding grid-related emissions over time. These parameters are presented in Figure 4.2 and Table 4.3.

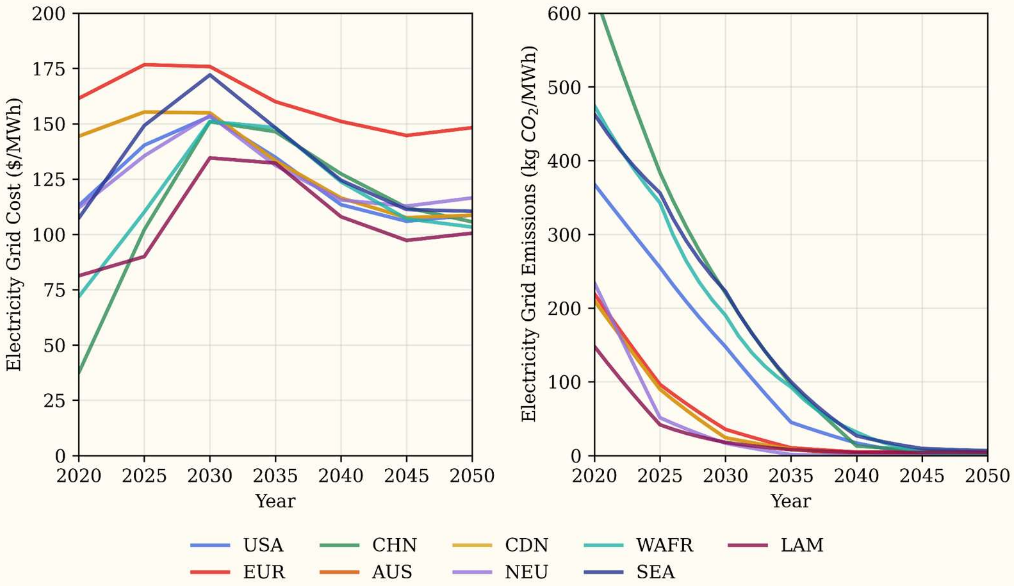

Figure 4.2 Prospective TEA data obtained from the REMIND model for SSP2EU-PkgBudg1150. The legend shows regional codes used in the model, where USA = United States of America, EUR = Europe, CHN = China, AUS = Australia, CDN = Canada, NEU = Northern Europe, WAFR = West Africa, SEA = Southeast Asia, and LAM = Latin America.

There are inherent uncertainties in IAM projections, particularly regarding future electricity prices. Historically, these models have demonstrated limitations in accurately predicting significant cost reductions in renewable technologies such as wind and photovoltaic solar energy (Gambhir et al., 2019; Jaxa-Rozen and Trutnevyte, 2021). This conservative tendency in IAMs has been well-documented in the literature, with models consistently underestimating the pace and scale of cost decreases for renewable technologies. Consequently, the electricity price projections used in our analysis should be interpreted with appropriate caution, recognising that actual future costs—especially for renewable energy—may decrease more rapidly than the models suggest.

Table 4.3 An example of prospective data used in Section 8.

Countries / regions	2020	2030	2040	2050	2060	2070	2080	2090	2100
	Electricity grid costs (US$2023/MWh)								
Australia	144	155	116	109	108	109	108	103	99
UK	161	176	151	148	151	150	151	145	135
USA	113	153	113	109	103	96	92	90	86
Canada	144	155	116	109	108	109	108	103	99
China	37	151	127	106	121	122	122	116	103
Germany	161	176	151	148	151	150	151	145	135
Netherlands	161	176	151	148	151	150	151	145	135
Denmark	161	176	151	148	151	150	151	145	135
Non-EU European states	112	154	116	116	129	125	121	117	110
Western Africa	72	151	124	103	115	115	120	123	117
Southeast Asia	107	172	124	110	118	118	117	112	105
South America	81	135	108	101	114	110	107	102	94
	Electricity grid intensity (kg CO_2/MWh)								
Australia	234.4	16.8	0.4	0.0	0.0	0.0	0.0	0.0	0.0
UK	219.4	35.6	4.8	4.5	2.6	0.9	0.1	0.0	0.0
USA	368.0	147.6	17.0	0.2	0.0	0.0	0.0	0.0	0.0
Canada	234.4	16.8	0.4	0.0	0.0	0.0	0.0	0.0	0.0
China	210.1	24.2	0.9	0.0	0.0	0.0	0.0	0.0	0.0
Germany	219.4	35.6	4.8	4.5	2.6	0.9	0.1	0.0	0.0
Netherlands	219.4	35.6	4.8	4.5	2.6	0.9	0.1	0.0	0.0
Denmark	219.4	35.6	4.8	4.5	2.6	0.9	0.1	0.0	0.0
Non-EU European states	463.0	222.8	26.8	6.7	3.2	1.3	0.3	0.0	0.0
Western Africa	234.4	16.8	0.4	0.0	0.0	0.0	0.0	0.0	0.0
Southeast Asia	474.6	190.1	31.8	0.1	0.0	0.0	0.0	0.0	0.0
South America	403.6	199.0	62.6	9.5	0.7	0.0	0.0	0.0	0.0

4.4.2 Capacity upscale scenario

The capacity upscale scenario models the potential deployment trajectory of OAE technologies from initial small-scale plants to significant commercial deployment by 2050 and beyond. The scenario development is based on three key parameters: initial capacity, maximum deployment potential (asymptote), and growth rate. For the base case, we established the following parameters:

- **Initial FOAK capacity** of 50 kt/yr (*representing multiple smaller installations of approximately 10 kt/yr each*).
- **Target deployment endpoint** of 200 $MtCO_2$/yr, which yields >100 $MtCO_2$/yr deployment by 2050 under our base growth rate.
- **Growth rate** of 10%, derived from analysis of CDR industry deployment data when modelled using a logistic curve.

To account for uncertainty in technology adoption, we developed two additional scenarios:

- **Optimistic (fast growth) scenario:** Assumes a higher asymptote of 1,000 $MtCO_2$/yr with an accelerated growth rate of 20%.
- **Pessimistic (slow growth) scenario:** Assumes a lower asymptote of 100 $MtCO_2$/yr with a reduced growth rate of 5%.

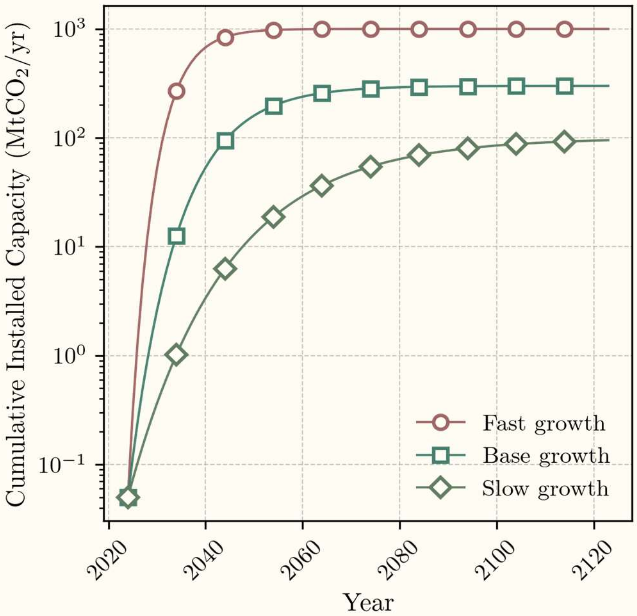

Figure 4.3 Projected deployment capacities for OAE under three scenarios: base case (10% growth rate, 200 $MtCO_2$/yr asymptote), fast growth case (20% growth rate, 1,000 $MtCO_2$/yr asymptote), and slow growth case (5% growth rate, 100 $MtCO_2$/yr asymptote). All scenarios start from an initial 50 kt/yr capacity in 2025.

5.0 Framework Part C: Data collection, mass and energy balance assessment, and technical performance indicators

Key recommendations:

- The sources of data must be transparently reported. The most up-to-date data from reputable databases should be used where possible.
- For early-stage technologies, real plant process data may not always be available. Mass and energy balances can be generated through process simulation software (e.g., Aspen Plus) and/or with in-house models (e.g., built on Excel or Python). The form and function of these models should be described sufficiently to allow for reproduction.
- The gross CDR attained by the OAE approach should be reported.
- Projects must report the OAE efficiency (moles CO_2 removed per equivalent of alkalinity added), specific to the deployment location.
- For approaches that add unequilibrated alkalinity, the time evolution of the OAE efficiency should be considered.
- We recommend that projects also calculate a time-adjusted warming potential of 100 years to highlight the additional radiative forcing of delayed removals. These should be presented alongside the base-case non-adjusted result.

5.1 Technology performance data

Technology performance data details specifications, assumptions, and operating conditions used to simulate a process and calculate results/parameters for techno-economic or environmental assessments. The preferred methods for data collection begin with operational data from industries, followed by pilot plant studies, laboratory experiments, and finally simulations. When collecting this data, it is essential to consider its consistency with the technology in question and whether chosen values are representative of current standards. Values with significant variability should be specified as ranges of values; such parameters are worth considering in sensitivity or uncertainty analyses.

5.2 Life-cycle inventory

The life-cycle inventory (LCI) is a critical step in a life-cycle assessment (LCA), involving the collection and quantification of data on all material, energy, waste, and emission flows within the system boundary of a product or service. Accurate and transparent LCI data are essential for modelling the environmental performance of a system, as they provide quantitative information on flows entering (e.g., raw materials, energy) and leaving the system (e.g., emissions, waste).

These flows, referred to as elementary flows, capture the interactions between the product system and the environment, such as resources extracted from nature or emissions released into the environment. The LCI step typically relies on a combination of primary sources (e.g., process simulation results, manufacturer specifications) and secondary sources (e.g., LCI databases, literature). To support these efforts, dedicated LCA software is often used to model the system based on its life-cycle stages, which are organised into interconnected processes depending on the system boundary. For example, in a cradle-to-grave approach, the analysis spans from raw material extraction to end-of-life disposal. The ecoinvent database is frequently used for this purpose due to its comprehensive coverage of over 20,000 processes and 3,500 distinct products across various economic sectors and geographies. This database provides reliable information about energy, material, water flows, and emissions for typical materials and processes used in industrial and agricultural applications. For OAE specifically, the LCI step involves data collection for each unit process within the system boundary. This typically includes upstream processes for generating alkaline materials and downstream processes for atmospheric CO_2 removal via alkalinity enhancement. In the foreground process, relevant material, energy, waste, and emission flows are identified for both upstream and downstream activities.

These data flows are supported by background systems that provide additional context for the foreground processes. The particular challenge for OAE technologies lies in their developmental stage. Many technologies rely on data derived from laboratory experiments, stoichiometric reactions, mass and energy balances, or process modelling rather than established industrial-scale operations. Secondary data from literature and reliable databases like ecoinvent in SimaPro are also frequently employed to supplement these efforts. According to Goglio et al. (2018), clear and transparent LCA planning is essential for informing science-based policy on CDR technologies and should rely on the best available data. However, the issue for OAE technologies is that most technologies are being developed.

Comprehensive data collection during the LCI step ensures that environmental impacts of OAE technologies are accurately reflected, supporting sustainable development and robust policymaking. More details about ecoinvent can be found through Introduction to the Database.

5.3 Plant cost data

Techno-economic assessment requires data for cost estimates of foreground and background systems, factors for capital and operating cost estimation (where necessary), and learning rates of technologies for prospective analysis. Cost estimates include items such as equipment costs, labour (direct and indirect), materials, feedstocks, utilities, and products or by-products (if applicable). Pricing for these items, in this preferred order, can be obtained from vendor quotes, reports from reputable organisations, market reports, industry databases, cost estimation software, or other literature. Note that pricing data sources should be consistent with the spatial and temporal context of the study (e.g., for plant location in Europe in 2020, electricity prices for Europe in 2020 should be obtained from sources such as Eurostat), and that for equipment cost estimates this can be adjusted using equipment cost indices and location factors. When sources for other capital or operating costs elements cannot be found, these can instead be estimated using factors whose methods of application are described in Section 7.2. Data for technology learning rates can be found in online literature or from fitting data from industry (technology costs versus deployment scale); alternatively, these values can be estimated using guidelines from (Roussanaly et al., 2021).

5.4 Mass and energy balances

Mass and energy balances are fundamental to understanding the process flows, resource requirements, and overall efficiency of the technology. These balances are necessary for both techno-economic and environmental assessments. Mass and energy balances are calculated through systematic analysis of process inputs, outputs, and transformations. System boundaries should be identified first, and specifications for the composition and conditions of the inputs (e.g., raw material, seawater, primary energy sources) and outputs (e.g., alkaline material) of the system should be defined. Compositions and conditions of process flows can be obtained from real plant data or be generated through process simulation software (e.g., Aspen Plus) and/or with in-house models (e.g., built on Excel or Python).

5.5 Technical performance indicators

5.5.1 CO_2-eq removed

OAE is a CDR process, so quantifying the amount of CO_2 removed is critical to understand its technical performance, and subsequently life-cycle environmental and economic performance. This quantification is essential for calculating the levelised cost of CO_2 removal and for accurately determining emissions in LCAs. There are three peculiarities in calculating the amount of CO_2 or CO_2-eqs removed. These have to do with gross versus net removed (relevant to any carbon management strategy), with OAE efficiencies (a result of mineral dissolution kinetics and ocean mixing processes), and with the timing of CO_2 removal (only relevant to these strategies where the CO_2 capture and the CO_2 emitted happen in different years).

Gross versus net removed. CO_2-eq removed is typically reported as a net removal rate. It accounts for the gross CO_2 drawdown reduced by the direct and indirect GHG (or CO_2-eq) emissions (scopes 1, 2, and 3). Direct emissions (in carbon accounting called scope 1) include the emissions from within the fence (foreground) of a project, e.g., the combustion of fuels for heat generation. Indirect emissions include scope 2 (emissions from the generation of purchased utilities and electricity) and scope 3 (indirect emissions from the upstream value chain, e.g., feedstock mining and downstream value chain, e.g., biochar oxidation to CO_2). Only by taking the sum of all GHGs removed and of all the GHGs emitted do we obtain the true CO_2-eq balance of a carbon management project. A project that emits more CO_2-eq to the atmosphere than it removes by definition is not net negative, but net positive.

Ocean alkalinity enhancement efficiency. The efficiency of OAE, defined as the amount of CO_2 removed per unit of alkaline material added, is complex due to both temporal and spatial factors. Unlike DAC with geological storage where CO_2 removal is immediate, OAE involves a gradual uptake of CO_2 that continues for years after the initial alkalinity addition, with complete removal typically taking over five years. This delayed removal reduces the climate benefit, as CO_2 remains in the atmosphere longer compared to immediate removal. Additionally, the maximum achievable efficiency varies significantly by location due to differences in ocean chemistry, circulation patterns, and mixing rates, which affect both the rate and ultimate extent of CO_2 removal (see Figure 5.1) (Zhou et al., 2024). In addition, the efficiency may be further reduced due to carbonate precipitation within the ocean (Hartmann et al., 2023), although this effect depends on how the alkalinity is increased and is not currently parameterised in modelling studies. Experimental work also suggests that elevated alkalinity may suppress natural alkalinity generation in the ocean (Bach, 2024), but the implications for OAE efficiency have not been well constrained. This spatio-temporal variability creates unique challenges for quantifying climate benefits, as the warming impact of GHGs depends on both their quantity and residence time in the atmosphere.

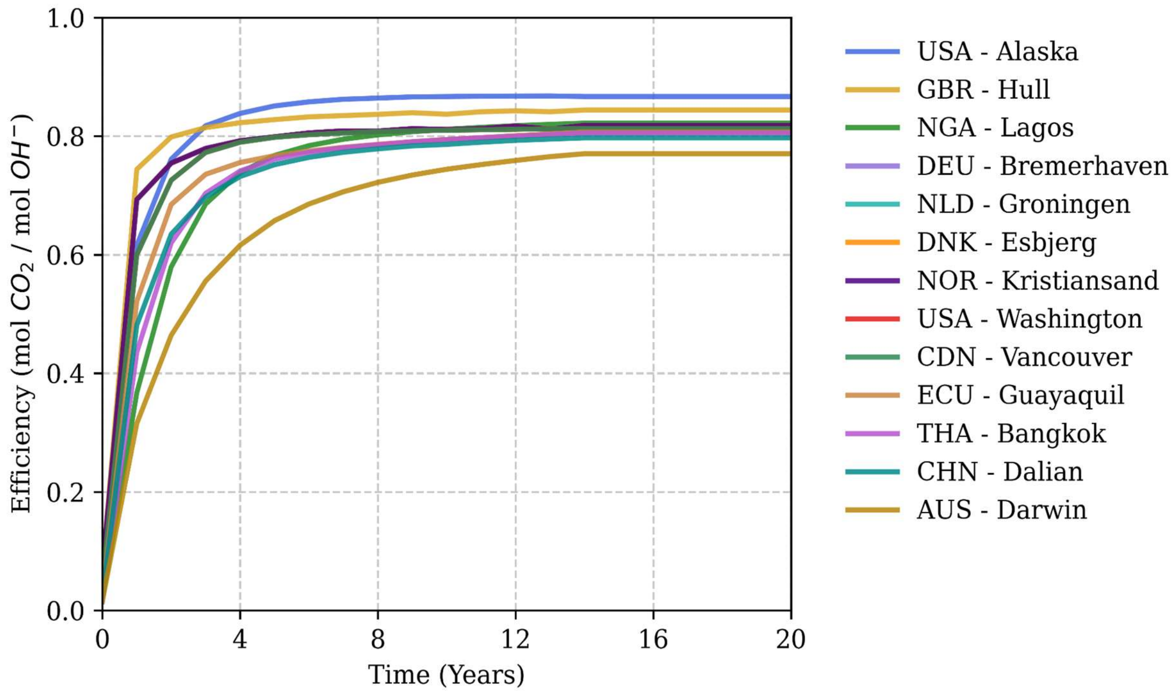

Figure 5.1 OAE efficiency for a single addition of alkaline material (OH^-) over selected locations for the case studies. These locations represent areas with the highest efficiency, but they require a minimum of five years to reach a complete drawdown (Zhou et al., 2024).

The timing of GHG emissions. Delayed CO_2 drawdown leads to smaller reductions in near-term warming potential compared to immediate removal. Figure 5.2 (a) demonstrates this effect by comparing the radiative forcing reduction from 1 tonne of CO_2 removed immediately (at year 0) versus the same quantity removed gradually through OAE addition. To account for this, time-adjusted warming potentials (TAWP) can be used to determine CO_2-eq emissions in present-day terms (similarly proposed by Tyka, 2024). TAWP accounts for emissions timing by varying the period considered for the cumulative radiative forcing effect of the GHG. Detailed use of this method is provided in (Kendall, 2012). For OAE, only the gross CO_2 removed due to alkalinity enhancement should be considered in this calculation, with the temporal distribution of removal properly weighted. Time horizons (*T*) for this calculation are arbitrary but should be consistent with climate policy (Environmental Protection Agency, 2024). This effect can be calculated as shown in Equations 5.1 and 5.2, where RF_i is the radiative forcing of species i (here, CO_2), *T* is 20 or 100 years, and *y* is the year of the emission. RF_i can, e.g., be calculated using Python libraries from (Schivley, 2023).

$$\mathrm{TAWP}_i(y) = \frac{\int_0^{T-y} \mathrm{RF}_i(t)dt}{\int_0^{T} \mathrm{RF}_{\mathrm{CO_2}}(t)dt} \quad \text{(Eq. 5.1)}$$

$$\mathrm{CO}_{2,\mathrm{eq}}(y) = m_i(y) \cdot \mathrm{TAWP}_i(y) \quad \text{(Eq. 5.2)}$$

The result of this approach is demonstrated in Figure 5.2 (b), which shows the cumulative CO_2 removal over time from a single addition of alkaline material in USA - Washington. Here, TAWP values for a 20- and 100-year time horizon were applied to obtain cumulative amounts of CO_2-eq removed. The final equilibrated value can be used to convert units of alkaline material added to total CO_2-eq removed. The final CO_2-eq removed per unit of alkaline material added for locations specified in this framework are summarised in Table 5.1. The method presented in this document does not account for potential feedback mechanisms such as changes in natural carbon cycling due to atmospheric CO_2 removal, or broader ocean chemistry impacts from alkalinity enhancement beyond the immediate CDR. This method is valid when the marginal change in atmospheric carbon is small.

Table 5.1 Total CO_2 removed per unit of alkaline material addition (i.e., NaOH or OH^-) for selected locations in this framework. Real CO_2 drawdown values obtained are yearly averages (Zhou et al., 2024) and CO_2-eq values were calculated using the TAWP method for 20- and 100-year time horizons.

Region	Country - City	Real Drawdown	TAWP-20	TAWP-100
		(mol CO_2/mol OH^-)	(mol CO_2-eq/mol OH^-)	(mol CO_2-eq/mol OH^-)
N. America	USA - Alaska	0.867	0.809	0.857
	USA - Washington	0.813	0.760	0.804
	Canada - Vancouver	0.813	0.760	0.804
Europe	United Kingdom - Hull	0.844	0.798	0.836
	Germany - Bremerhaven	0.818	0.770	0.810
	Netherlands - Groningen	0.818	0.770	0.810
	Denmark - Esbjerg	0.818	0.770	0.810

	Norway - Kristiansand	0.818	0.770	0.810
S. America	Ecuador - Guayaquil	0.807	0.740	0.795
Asia	China - Dalian	0.797	0.726	0.785
S.E. Asia	Thailand - Bangkok	0.805	0.730	0.792
Africa	Nigeria - Lagos	0.822	0.736	0.807
Oceania	Australia - Darwin	0.770	0.666	0.752

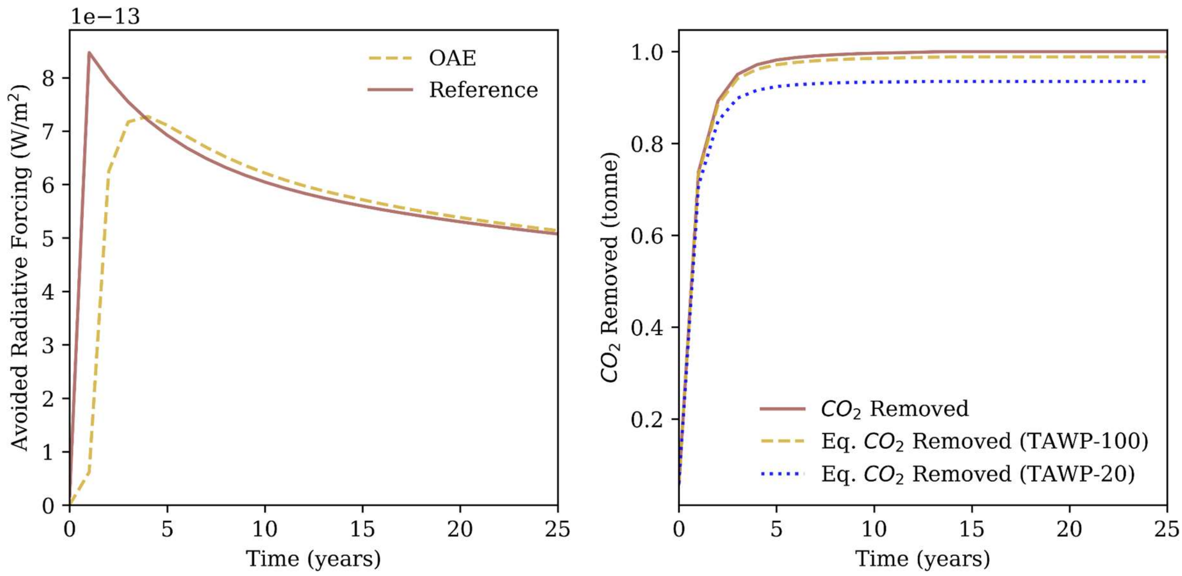

Figure 5.2 OAE efficiency for a single addition of alkaline material in USA - Washington (1.12 tonne of NaOH to remove 1 tonne of CO_2). (a) compares the radiative forcing reduction between immediate CO_2 removal and gradual OAE-based removal for 1 tonne of CO_2, while (b) shows the temporal evolution of cumulative CO_2 removal and the resulting CO_2-eq removal when accounting for the timing effects over 100- and 20-year time horizons. Panel (b) shows that the time-adjusted CO_2-eq removal is 1.15% and 6.45% lower with TAWP-100 and -20 than the absolute removal.

While the disparity is relatively modest when using TAWP-100 metrics, the divergence becomes more pronounced with TAWP-20. These findings have important implications for climate change mitigation strategies. As shown in Figure 5.3, which presents calculations across all possible coordinates in the global ocean dataset provided by (Zhou et al., 2024), the distribution of error for TAWP-100 remains relatively concentrated around smaller values, while TAWP-20 shows a broader spread of discrepancies between actual CO_2 and CO_2-eq removal values. This quantitative evidence underscores the importance of temporal considerations in carbon accounting methodologies. This temporal variation in equivalence is particularly relevant for standards organisations, carbon removal marketplaces, and policymakers who should incorporate these considerations into their CO_2 removal accounting frameworks and credit verification processes. The application of this to LCA and TEA is described in

Sections 6 and 7, respectively. We recommend using a 100-year TAWP to be consistent with established hierarchist impact assessment approaches.

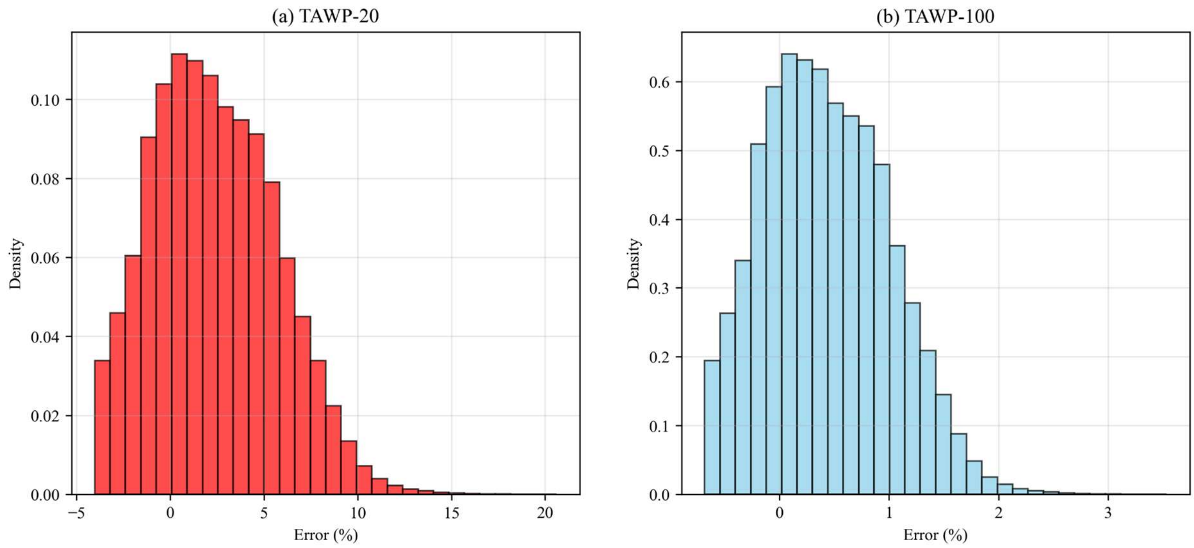

Figure 5.3 Distribution of error between CO_2 and CO_2-eq removal values. The plot shows the difference between actual CO_2 removal and calculated CO_2-eq removal using TAWP-100 (blue) and TAWP-20 (red) adjustment factors. The greater spread in the TAWP-20 distribution indicates increased divergence in shorter time horizons, highlighting the temporal sensitivity of carbon equivalence calculations.

From a climate science perspective, the long-term global temperature change depends on cumulative emissions and removals, and not on their timing (Allen et al., 2009). Climate policy is also focused on what is achievable within the coming decades (United Nations Framework Convention on Climate Change (UNFCCC), 2023). Uniquely for delayed removals, in which the near-term emission from deployment is more certain than the eventual long-term removal, we may even place more value on the activity that happens within a decade. In all cases, it is important to select appropriate time horizons which encompass the complete carbon removal cycle, including potential re-equilibration with the atmosphere. If our time-frame of concern is hundreds of years, then as (Brander and Broekhoff, 2023) note, there is no need to consider the TAWP, and unadjusted cumulative carbon accounting is appropriate. This approach is more consistent with our prospective approach (Section 8). In practice, technology assessment will attempt to collapse complex analysis into a set of simplified KPIs, and that practitioners should undertake this with care such that important nuances are not lost within the simplification.

5.5.2 Specific energy consumption

This metric quantifies the energy demand per unit of CO_2-eq removed via the process. It is calculated based on the net energy demand (i.e., consumption and generation) of the project. This demand typically comes in the form of fuel, electricity, heat (e.g., steam), and cooling. These forms of energy are not equivalent to one another, and if they were summed without converting to an equivalent value, it might skew results when assessing different technologies.

Two approaches are recommended for standardising energy consumption:

Specific primary energy consumption (SPEC): This approach converts all energy forms to their primary energy equivalent. Primary energy consists of products extracted or captured directly from natural resources (e.g., fossil fuel, biomass, wind, hydro). While this method provides a clear link to resource utilisation, it's worth noting that some primary energy sources (like wind) are already in power form, while others (like oil) require conversion processes.

Specific work equivalent consumption (SWEC): This approach converts all energy forms to their work equivalent, which may provide a more practical comparison when evaluating different technologies, particularly when comparing processes using different primary energy sources.

For both approaches, secondary energy sources should be converted based on their conversion efficiency from the primary source and specified process (e.g., thermal efficiency of a boiler for steam, electric efficiency of fossil fuel conversion, coefficient of performance for heat pumps or refrigeration units). The choice of energy conversion process is dependent on the process design and choice of primary energy used to produce the secondary form. Engineering textbooks such as (Sinnott and Towler, 2020a; Smith, 2005) are useful for determining conversion efficiencies.

The general equation for both metrics is:

$$SPEC = \sum_{n} \frac{E_{primary,n} + \frac{E_{secondary,n}}{\eta_{secondary}}}{m_{CO_{2,net,n}}} \quad \text{(Eq. 5.3)}$$

$$SWEC = \sum_{n} \frac{\left(\frac{E_{primary,n}}{\eta_{primary}} + \frac{E_{secondary,n}}{\eta_{secondary}}\right)}{m_{CO_{2,net,n}}} \quad \text{(Eq. 5.4)}$$

Where $E_{primary}$ and $E_{secondary}$ are primary and secondary energy sources, and $\eta_{primary}$ is the efficiency of converting primary energy to work, and $\eta_{secondary}$ is the process efficiency for primary to secondary energy conversion.

5.5.3 Energy efficiency

Various definitions for energy efficiency can be employed, and appropriate definitions can vary depending on the context and purpose of the study. When assessing energy efficiency, it is essential to consider the system boundaries and reference energy input used to quantify this metric, which could be the gross fuel input, gross electrical input, thermodynamic minimum energy consumption, or other relevant reference. For carbon removal technologies, establishing a common reference across all system archetypes, such as the thermodynamic minimum energy requirement for CO_2 removal and storage, is particularly useful.

However, the complexity of different carbon removal technologies presents challenges in establishing a universal efficiency metric. For instance, when comparing DAC with geological storage to OAE, the thermodynamic minimum energy requirements differ due to their distinct final thermodynamic states. In such cases, alternative efficiency metrics may be more appropriate, such as electrical efficiency, thermal efficiency, or total efficiency. It's important to note that for processes with different system boundaries and dominant energy sources (e.g., biomass combustion with geological storage versus OAE), efficiency metrics may not be directly comparable and are thus unsuitable. For such cases, other key performance indicators such as specific primary energy or work equivalent consumption are more appropriate for technology comparison and evaluation. Despite these limitations, efficiency metrics remain a valuable tool for evaluating individual technologies. They provide good benchmarks for process improvement and can highlight specific areas requiring further development.

5.6 Case study: Data collection and mass and energy balances

5.6.1 Technology performance data

For the BPMED case study, performance data has been summarised in Table 5.2. This data is used for process simulation in Aspen Plus, from which key mass and energy flows were determined.

5.6.2 Environmental performance data

For the BPMED case study, this data has been presented per key unit operation of the process (i.e., stages). The LCI data of each stage have been normalised per functional unit, i.e., into the amount of material (e.g., chemical) or energy (e.g., electricity) needed per 1 tonne of gross CO_2 drawdown in a year to enhance alkalinity for seawater (Table 5.3). Note that an OAE efficiency of 0.9 $tCO_2/tNaOH$ is applied in Table 5.3. For a specific location this efficiency must be changed based on values shown in Table 5.1. Pretreatment (stage 1) and reverse osmosis (stage 4) data are mainly adopted from a literature review of LCA of seawater desalination using reverse osmosis with the similar assumption of percentage of water recovery and characteristic of water output to our case study. Precipitation softening (stage 2) data is derived from mass balance and process simulation results, while ion exchange (stage 3) data is estimated from mass balance and the literature review focus on removing Ca^{2+} and Mg^{2+} hardness by ion exchange resins for seawater pretreatment. LCI data of the final stage of bipolar electrodialysis is mainly obtained from (Eisaman et al., 2018).

Most of the wastes generated from stage 1 through stage 5 are residual chemicals, materials, and membranes used in reverse osmosis and BPMED processes. Landfill is suitable for the waste management in this study. As a result of increased risk of leachate contamination of waste into water bodies, a landfill site should be suitably managed to be hydrologically isolated from local water bodies.

Table 5.2 Technology performance assumptions for the BPMED case study.

Parameter/Assumption	Value	Unit	Description	References
Pretreatment				
Seawater intake pump pressure	1.7	bar	Online calculation for 7 m depth, 2 km length, 2 m diameter pipe	(BBA Pumps BV, 2023)
Seawater intake pump efficiency	75	%	Calculated in Aspen Plus	
Desalination				
Reverse osmosis membrane lifetime	8	yrs		(DuPont Water Solutions, 2021)
Reverse osmosis water recovery	45	%	From reported range (35 - 45%)	(Lenntech B.V., 2025a)
Booster pump pressure	60	bar	From online calculator	(Lenntech B.V., 2025b)
Booster pump efficiency	90	%		(Danfoss A/S, 2025a)
ERD outlet pressure	1	bar	Assumed	
ERD efficiency	95	%		(Danfoss A/S, 2025b)
Nanofiltration membrane lifetime	8	yrs		(Lejarazu-Larrañaga et al., 2022)
Nanofiltration pump Pressure	30	bar	Dow Filmtec NF90-2540	(Abdelkader et al., 2018)
Nanofiltration rejection Na+, Mg2+, Ca2+	15, 95, 95	%		
Ion exchange resin lifetime	7	yrs		(Aldex Chemical Company, Ltd., y, 2022)
Alkaline Material Generation				
Recirculation pump pressure increase	0.1	bar	Assumed	
Recirculation pump efficiency	75	%	Calculated in Aspen Plus	
Alkaline material/brine outfall pump pressure	1.7	bar	Online calculation for 7m depth, 2km length, 2m diameter pipe	(BBA Pumps BV, 2023)
Alkaline material/brine outfall pump efficiency	75	%	Calculated in Aspen Plus	
Number of BPMED stacks	4	-		(Eisaman et al., 2018)
Total area per BPMED stack	250	m^2	Includes CEM, AEM, BPM	(de Lannoy et al., 2018)
Area of cell triplet in BPMED	1	m^2		Own estimate
Cell triplets per BPMED stack	333	-	Calculated from total area and area of a cell triplet	Own calculation
Acid, base, salt feed concentrations	2, 2, 4	wt. %		(de Lannoy et al., 2018)
Acid, base, salt product concentrations	2.5, 2.5, 3.2	wt. %		

Table 5.3 Life-cycle inventory data for the bipolar membrane electrodialysis case study (base case). Values are normalised per 1 tonne of gross CO_2 drawdown. This is based on an assumed OAE efficiency of 0.9 $tCO_2/tNaOH$. For specific locations, this conversion factor would need to be adjusted according to values shown in Table 5.1.

Input, output and waste	Type	Value	Unit	Performance assumptions	References
Stage 1: Pretreatment					
Seawater	Input	85.3	tonne	Resource extracted from nature at 88.6 m^3/hr	Process model output
Chlorine	Input	251.2	g	Disinfectant	(Fritzmann et al., 2007; Skuse et al., 2023)
Sulphuric acid	Input	2,092.9	g	pH adjustment	
Ferric chloride	Input	251.2	g	Coagulant/flocculant	
Sodium bisulphite	Input	502.3	g	De-chlorination agent	
Electricity for pretreatment	Input	14.45	kWh	Typical electricity consumption seawater pretreatment process	Process model output
Electricity for sea water intake pump	Input	2.17	kWh	Electricity for pump to intake seawater	Process model output
Ferric chloride	Waste	251.2	g	Waste to landfill	Process model output
Sodium bisulphite	Waste	502.3	g	Waterborne emissions	Process model output
Stage 2: Precipitation softening					
Pretreated water	Input	86.2	tonne	Output from pretreatment	Process model output
Sodium carbonate	Input	572.5	kg	Used to precipitate non-carbonate hardness	Process model output
Calcium hydroxide	Input	335.1	kg	Used to precipitate non-carbonate magnesium hardness	Process model output
Magnesium hydroxide	By-product	263.8	kg	Waterborne emissions	Process model output
Calcium carbonate	By-product	540.7	kg	Waste to landfill	Process model output
Stage 3: Ion exchange					
Softened water	Input	85.91	tonne	Output from precipitation softening	Process model output

Cation exchange resin	Input	23.7	g	Lewatit®MonoPlus S100. Assumed Lifetime of 7 years. Capacity equal to 2 bed volumes/hr.	(Aldex Chemical Company, Ltd., 2022; Lanxess, 2025)
Softened water	Output	85.91	tonne	Output from ion exchange	Process model output
Cation exchange resin	Waste	23.7	g	Waste to landfill	Process model output
Stage 4: Reverse osmosis					
Softened water	Input	85.91	tonne	Output from the ion exchange process	Process model output
Reverse osmosis membrane module	Input	767.5	cm^2	Dow chemical 8 inch spiral wound modules SW30XLE-440i Membrane type: Polyamide Thin-Film Composite Assumed lifetime of 8 years	(Abdelkader et al., 2018; Lejarazu-Larrañaga et al., 2022; Lenntech, 2024)
Sodium tripolyphosphate	Input	87.1	g	Antiscalant	(Fritzmann et al., 2007; Skuse et al., 2023)
Electricity for pump (Booster pump)	Input	362.3	kWh	Pump energy required to pressurise feed from 1 to 65 bar.	Process model output
Electricity (Energy recovery device)	Input	-143.1	kWh	Energy recovery device de-pressurises down to 1 bar.	Process model output
Net electricity for reverse osmosis process	Input	219.3	kWh	Assumes a yearly increase of 12.5%, which accounts for membrane fouling	(Skuse et al., 2023; Voutchkov, 2018)
Desalinated water	Output	82.87	tonne	Permeate from the reverse osmosis. System assumes a 45% recovery of water by volume	Process model output
Brine feed to BPMED	Output	3.04	tonne	Retentate from the reverse osmosis system	Process model output
Membrane	Waste	767.5	cm^2	Waste to landfill	Process model output
Stage 5: Bipolar membrane electrodialysis					
Desalinated water	Input	82.87	tonne	Output from reverse osmosis	Process model output
Brine water	Input	3.04	tonne	Output from reverse osmosis	Process model output

Anion exchange membrane	Input	1.0	g	Lifetime of 5 years Membrane: Selemion AAV, Supplier: Asahi Glass	(de Lannoy et al., 2018)
Cation exchange membrane	Input	1.7	g	Lifetime of 5 years, Membrane : Neosepta, Supplier: Astom	(de Lannoy et al., 2018)
Bipolar exchange membrane	Input	4.6	g	Lifetime of 3 years, Membrane : Neosepta, Supplier: Astom	(de Lannoy et al., 2018)
Cathode	Input	0.2	g	Lifetime of 5 years, Material: V4A stainless steel	(Reig et al., 2016)
Anode	Input	0.1	g	Lifetime of 5 years, Material: Pt/Ir-coated titanium	(Reig et al., 2016; Ehisen Insoluble Anode, 2024)
Electricity for operating BPMED	Input	2,036.2	kWh		(de Lannoy et al., 2018)
Electricity for recirculating stream	Input	2.4	kWh	Electricity for pumps used to recirculate NaOH, HCl, and brine	Process model output
Electricity for outfall pump to release alkaline material/brine	Input	1.0	kWh	Electricity for pump that release brine and NaOH to ocean	Process model output
Net electricity in BPMED	Input	2,039.6	kWh	Total electricity consumption for BPMED	Process model output
Hydrochloric acid	By-product	40.51	tonne	Net acid by-product from the BPMED	Process model output
Anion exchange, cation exchange, and bipolar membranes	Waste	7.3	g	Waste to landfill	Process model output
Sodium tripolyphosphate	Waste	87.1	g	Waterborne emissions	Process model output

5.6.3 Project costing data

The collection method for plant cost data of the BPMED case study is described in Table 5.4. Values for the foreground system's costing data is shown in Tables 5.5 and 5.6, and data for the background system in Table 5.7.

Table 5.4 Summary of data collection methodology for foreground (F) and background (B) systems.

Capital cost data		**Collection method**
Equipment costs	F	Equipment cost of BPMED, clarifier, and ion exchange systems were obtained from Eisaman et al. (2018). These costs are vendor quotations for a production capacity of 9,763 tonne NaOH per year. Bare erected costs for the seawater desalination plant were obtained from Caldera and Breyer (2017), and include costs for seawater reverse osmosis and pretreatment.
Scaling factors	F	Equipment cost scaling factors were assumed based on suggestions in Section 7.2.1.
Material factors	F	No material factors were necessary for this case study.
Installation factors	F	Installation factors were determined using the method from Aromada et al. (2021).
Equipment cost indices	B	CEPCI values were chosen for this case study.
Location factors	B	Location factors were obtained from the 'COMPASS Construction Yearbook' (2023).
Contingencies	F	Process and project contingencies were selected based on guidelines in Section 7.2.1.
Operating cost data		
Chemical operator salary	B	Data for chemical plant operator salaries were collected from national labour statistics, and alternatively from websites/databases showing salaries in different countries.
Productivity factors	B	Productivity factors were obtained from the 'COMPASS Construction Yearbook' (2023).
Electricity prices	B	Wholesale industrial or non-domestic prices were obtained. Local values from the supplier can be obtained; otherwise, national values can be obtained. Furthermore, if supply curves were available, price values for an annual energy consumption band of 2,000 to 20,000 MWh/year were used (e.g., available for Europe, Eurostat, n.d..).
Consumable prices	B	Bulk chemical prices were obtained from databases such as (Business Analytiq Pte Ltd, 2024; ICIS, 2007), or chemical suppliers.
Economic analysis data		
Discount rates	B	Rather than presuming values for each location, ranges have been specified based on whether a country is developed or developing. Similar ranges have been used in (IEA, 2023).
Learning rates	F	Rates for the BPMED and its membrane costs were taken from (Böhm et al., 2019). For equipment related to seawater desalination, learning rates were obtained from (Caldera and Breyer, 2017).

Table 5.5 Foreground system capital and operating cost data for the BPMED case study. Capital costs obtained from Eisaman et al. (2018) are for a plant capacity of 9763 tNaOH/yr, these costs are rescaled for a capacity of 10 ktNaOH/yr using appropriate equipment cost scaling factors (see Section 7.).

Process/Equipment	Cost	Unit	Year	Reference
Pretreatment				
Operating costs				
Ferric chloride	110	*$/kg*	2007	(ICIS, 2007)
Chlorine	358.25	*$/tonne*	2024	(Business Analytiq Pte Ltd, 2024)
Sodium bisulphite	716.5	*$/tonne*	2007	(ICIS, 2007)
Sulphuric acid	140	*$/tonne*	2024	(Business Analytiq Pte Ltd, 2024)
Desalination				
Capital costs				
Clarifier	69,200	*$*	2018	
Ion exchange	120,700	*$*	2018	(Eisaman et al., 2018)
Nanofiltration	506,600	*$*	2018	
Reverse osmosis plant	2070	*$/(m³/day)*	2015	(Caldera and Breyer, 2017)
Operating costs				
Sodium carbonate	210	*$/tonne*	2024	(Business Analytiq Pte Ltd, 2024)
Calcium hydroxide	120	*$/tonne*	2024	(Business Analytiq Pte Ltd, 2024)
Nanofiltration membranes	20	*$/tonne*	2024	(Alibaba Seller, 2025)
Ion exchange resin	5	*$/kg*	2024	(Delving Blue, 2025; Sunresin New Materials Co.Ltd, 2024)
Reverse osmosis membranes	20	*$/m²*	2020	(DuPont FilmTec, 2024)
Alkaline material generation				
Capital costs				
Electrodialysis unit (excl. membranes)	422,700	*$*	2018	
Electrodialysis membranes	115,000	*$*	2018	(Eisaman et al., 2018)
Operating costs				
Electrodialysis membranes	460	*$/m²*	2018	

Table 5.6 Foreground system equipment cost estimation parameters. based on the methodology provided in Section 7.2.1.

Equipment	Cost Type	Quant.	Scaling Factor	Installation Factor	EPC Factor	Process Contingency	Project Contingency	Learning Rate
Clarifier	Uninstalled	1	0.6	5.0	38%	30%	40%	1%
Ion exchange	Uninstalled	1	0.6	3.9	37%	10%	40%	1%
Nanofiltration	Uninstalled	1	0.6	3.0	26%	30%	40%	1%
Reverse osmosis plant	BEC	1	1.0	-	-	10%	40%	1%
Electrodialysis unit (excl. membranes)	Uninstalled	4	0.9	2.2	25%	50%	40%	18%
Electrodialysis membranes	BEC	4	1.0	-	-	50%	40%	18%

Table 5.7 Background system cost data for the BPMED case study.

Country - ***Location***	**Discount Rates**	**Productivity Factor**	**Location Factor**	**EPC Location Factor**	**Operator Salary**	**Sources***
	%	-	-	-	$/year	-
Australia	5 - 10	1.10	1.05	0.75	95400	(Labour Market Insights Australia, 2023)
UK	5 - 10	1.20	1.07	0.74	35500	(Office for National Statistics, 2023)
USA - *Alaska*	5 - 10	1.13	1.25	1	79390	(U.S. Bureau of Labor Statistics, 2023)
USA - *Washington*	5 - 10	1.05	0.97	1	79390	(U.S. Bureau of Labor Statistics, 2023)
Canada	5 - 10	1.15	1.02	0.64	33580	(Job Bank Canada, 2023)
China	5 - 10	1.30	0.96	0.31	26600	(World Salaries, 2023)
Germany	5 - 10	1.15	1.05	0.83	69800	(Economic Research Institute, 2023)
Netherlands	5 - 10	1.15	1.05	0.75	66400	(Economic Research Institute, 2023)
Denmark	5 - 10	1.20	1.06	0.83	79300	(Economic Research Institute, 2023)
Norway	5 - 10	1.35	1.13	0.81	61500	(Economic Research Institute, 2023)
Nigeria	10 - 20	2.20	0.93	0.71	2100	(World Salaries, 2023)
Thailand	5 - 10	1.70	0.94	0.83	1200	(Economic Research Institute, 2023)
Ecuador	10 - 20	1.50	0.95	0.62	12100	(World Salaries, 2023)

*Sources corresponding to operator salaries.

5.6.4 Mass and energy balances

A detailed composition of seawater is provided in Table 5.8. Based on the technology performance data in Table 5.9, the process (Figure 5.4) was simulated in Aspen Plus to obtain key material and energy streams. Note that not all components in seawater were simulated here since they have negligible impacts on the overall assessment. Only the key components present in the product and by-products are shown in Table 5.10.

Table 5.8 Standard seawater composition. (Millero et al., 1993).

	Mass Composition		Mol Composition	
	g/kg	%	mol/kg	%
H_2O	964.83	96.49	53.54	97.95
Cl^-	19.35	1.94	0.55	1.00
Na^+	10.78	1.08	0.47	0.86
SO_4^{2-}	2.71	0.27	0.03	0.05
Mg^{2+}	1.28	0.13	0.05	0.10
Ca^{2+}	0.41	0.04	0.01	0.02
K^+	0.40	0.04	0.01	0.02
HCO_3^-	0.10	0.01	0.002	0.003
Total	**1000**	**100**	**-**	**100**

Components with weight fractions lower than bicarbonate were not considered, and potassium was replaced with sodium on a 1:1 molar basis.

Table 5.9 Energy balance of the ED case study and its variants.

Item	Units	Base	No Soft	Soft NF	Reject
Seawater Intake Pump	kW_{el}	2.3	3.2	4.6	-
Pretreatment	kW_{el}	15.3	15.3	30.7	-
Nanofiltration Pump	kW_{el}	-	-	186.9	-
Reverse Osmosis Pump	kW_{el}	383.7	382.9	268.2	-
Energy Recovery Device	kW_{el}	-151.5	-132.6	-151.8	-
Bipolar Membrane Electrodialysis	kW_{el}	2156.0	2156.0	2156.0	2156.0
Re-Circulating Pumps	kW_{el}	2.5	2.5	2.5	2.5
Alkaline material/Brine Outfall Pump	kW_{el}	1.0	1.1	3.0	3.3
Net Electricity Consumption	**kW_{el}**	**2409.4**	**2428.5**	**2500.2**	**2161.8**

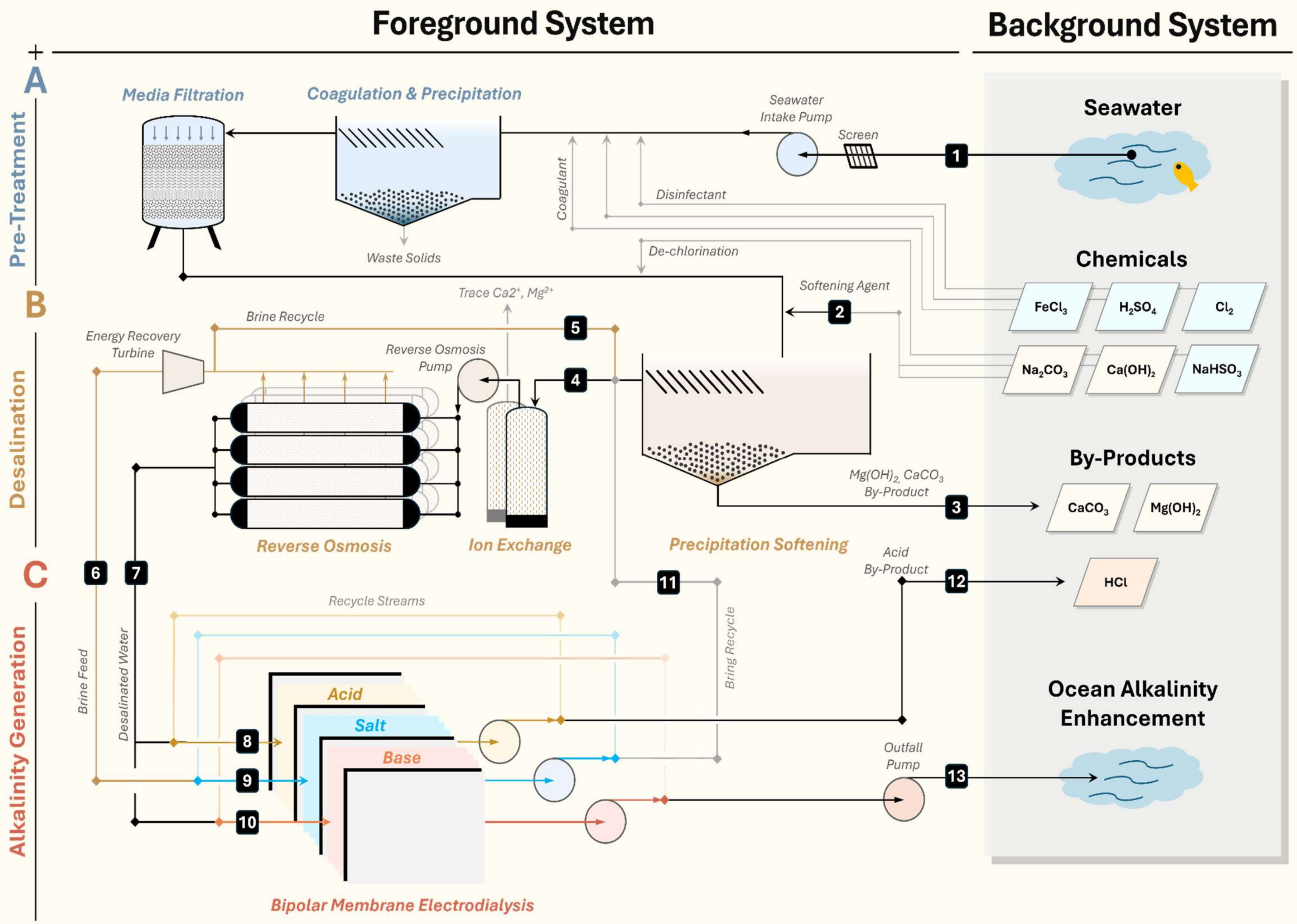

Figure 5.4 Process flow diagram of the BPMED case study with stream numbers. See Table 5.9 and 5.10 for the corresponding mass and energy balances of this diagram.

Table 5.10 Mass balance of the BPMED case study obtained from Aspen Plus Simulations. Process flow diagram with the corresponding stream numbers are shown on Figure 5.3.

Stream no.	Mass flowrate (tonne/hr)	Volumetric flowrate (m³/hr)	Mass fractions (wt.%)							
			H_2O	NaCl	NaOH	HCl	Na_2CO_3	$Ca(OH)_2$	$Mg(OH)_2$	$CaCO_3$
1	90.3	88.6	97.2	2.8						
2	1.0						63.1	36.9		
3	0.9								32.8	67.2
4	216.2	210.5	96.3	3.7						
5	20.8	19.9	93.5	6.5						
6	101.6	97.5	93.5	6.5						
7	93.7	94.1	100.0							
8	244.4	239.0	98.0		2.0					
9	229.5	223.5	96.0	4.0						
10	224.2	224.4	98.0			2.0				
11	104.4	102.2	96.8	3.2						
12	42.9	42.9	97.5			2.5				
13	47.1	45.8	97.5		2.5					

Table 5.11 Mass balance of the BPMED case study (No Softening Variant) obtained from Aspen Plus Simulations. Process flow diagram with the corresponding stream numbers are shown on Figure 3.6.

Stream no.	Mass flowrate (tonne/hr)	Volumetric flowrate (m³/hr)	Mass fractions (wt.%)			
			H_2O	NaCl	NaOH	HCl
1	193.3	189.8	97.2	2.8		
2	21.6	20.8	94.5	5.5		
3	99.6	96.2	94.5	5.5		
4	93.7	94.1	100.0			
5	244.4	239.1	98.0		2.0	
6	229.5	223.5	96.0	4.0		
7	224.2	224.4	98.0			2.0
8	106.3	104.1	96.8	3.2		
9	42.9	42.9	97.5			2.5
10	153.4	149.9	97.0	2.2	0.8	

Table 5.12 Mass balance of the BPMED case study (Softening via Nanofiltration Variant) obtained from Aspen Plus Simulations. Process flow diagram with the corresponding stream numbers are shown on Figure 3.7.

Stream no.	Mass flowrate	Volumetric flowrate	Mass fractions (wt.%)							
	(tonne/hr)	(m^3/hr)	H_2O	NaCl	NaOH	HCl	Na_2CO_3	$Ca(OH)_2$	$Mg(OH)_2$	$CaCO_3$
1	181.7	178.4	97.2	2.8						
2	90.5	89.1	97.6	2.4						
3	4.8×10^{-2}						63.1	36.9		
4	4.3×10^{-2}								32.8	67.2
5	214.9	210.1	96.9	3.1						
6	20.0	19.3	94.5	5.5						
7	101.1	97.7	94.5	5.5						
8	93.7	94.1	100.0							
9	244.4	239.0	98.0			2.0				
10	229.5	223.5	96.0	4.0						
11	224.2	224.4	98.0		2.0					
12	104.4	102.2	96.8	3.2						
13	42.9	42.9	97.5			2.5				
14	138.3	135.1	97.0	2.1	0.9					

Table 5.13 Mass balance of the BPMED case study (Reject/Waste Variant) obtained from Aspen Plus Simulations. Process flow diagram with the corresponding stream numbers are shown on Figure 3.8.

Stream no.	Mass flowrate	Volumetric flowrate	Mass fractions (wt.%)			
	(tonne/hr)	(m^3/hr)	H_2O	NaCl	NaOH	HCl
1	100.9	97.8	95.0	5.0		
2	93.7	94.1	100.0			
3	244.5	239.1	98.0		2.0	
4	229.5	223.5	96.0	4.0		
5	224.2	224.4	98.0			2.0
6	104.4	102.2	96.8	3.2		
7	42.9	42.9	97.5			2.5
8	151.5	149.0	97.5	2.2	0.8	

5.6.5 Technical performance indicators

Net CO_2-eq removal

For reference, the cumulative radiative forcing effect over 100 years for 1 kg of CO_2 emitted in year 1 is:

$$\int_0^T \mathrm{RF}_{\mathrm{CO_2}}(t), dt = 4.60 \times 10^{-11}\ \mathrm{W} \cdot \mathrm{m}^{-2}$$

Compare this effect to the effect of 1 kg of CO_2 when released at a later year and over the same time period considered. The ratio of cumulative forcing between year 1 and subsequent years is used to obtain the TAWP of emissions at a later year and over the same time horizon (here, 100 years) (see Table 5.11). In Table 5.14 the CO_2 removed each year (m_{CO2}) from the addition of 1.12 tonnes of NaOH is shown in column 3 (this amount results in a total removal of 1 tonne of CO_2). Applying the TAWP to these values yields the CO_2-eq removal from this addition (m_{CO2eq}), and the sum of these values can be used to obtain a simple conversion factor for the total amount of CO_2-eq removed per tonne of alkaline material.

Table 5.14 Time-adjusted warming potential (TAWP) and CO_2 removal calculations for OAE.

Year	Cumulative radiative forcing effect $\int_0^{T-y} RF_i(t)dt$ (W.m^{-2})[a]	Total averaged warming potential $TAWP_i$ -	Actual CO_2 removed m_{CO_2} (kg)[b]	CO_2-eq removed accounting for TAWP-100 $m_{CO_2,eq}$ (kg)[c]
1	4.60 ×10^{-11}	1	59	59
:	:	:	:	:
3	4.53 ×10^{-14}	0.984	155	152
:	:	:	:	:
5	4.45 ×10^{-11}	0.968	21	20
:	:	:	:	:
10	4.27 ×10^{-11}	0.928	1.9	1.7
:	:	:	:	:
15	4.08 ×10^{-11}	0.887	0.59	0.53
Total			**1,000**	**989**

a. Cumulative radiative forcing avoided of 1 kg of CO_2.
b. Annual CO_2 removal
c. CO_2-eq removal over a 100-year time horizon for a single addition of alkaline material resulting in 1 tonne of total CO_2 removal

For an annual production rate of 10 kt of NaOH per year, the BPMED process would remove 8.85 kt of CO_2-eq, and total 221 kt of CO_2-eq over the plant lifetime (25 years).

Specific primary energy consumption (SPEC)

Energy consumption in this case study is primarily in the form of electricity, and no fuel, cooling, or heating is required for the proposed design. The energy balance shown in Table 5.10 was consulted to obtain the SPEC relative to net CO_2-eq removal rates.

$$SPEC = \sum_n \frac{E_{el,n}}{m_{CO2,eq,net,n}}$$

$$SPEC = \frac{511,296,250 \text{ kWh}_{el}}{214424 \text{ tonnes}}$$

$$SPEC = 2385 \text{ kWh} \cdot \text{tonne}^{-1} \text{ CO}_2\text{,eq}$$

$$SPEC = 8.59 \text{ MJ} \cdot \text{kg}^{-1} \text{ CO}_2\text{,eq}$$

6.0 Framework Part D: Classical life-cycle assessment

Key recommendations:

- Established methodologies exist for conducting life-cycle assessment (LCA). We recommend using those that consider a range of impact categories that include, but also go beyond, global warming potential.
- The mandatory steps in the life-cycle impact assessment (LCIA) for generic OAE include selecting impact categories, classifying life-cycle inventory (LCI) results, and characterisation. Normalisation, grouping, and weighting are optional steps in LCIA.
- A midpoint and endpoint analysis of LCA results should be conducted to understand the range of environmental impacts and their weighted aggregation into damages.
- Normalisation in the LCIA phase supports interpreting the impact profile generated during characterisation. It involves scaling environmental impacts relative to a reference value, enabling comparison of impacts between different inputs, and identifying the most significant environmental impacts.
- The use of impact weighting is optional and should be undertaken and presented with care. It consolidates LCA results into a single score, making it easier to compare the environmental impacts of different products or scenarios of generic OAE. If used, we recommend also reporting the unweighted results.

LCA is an established methodology for identifying and quantifying environmental impacts throughout the entire life-cycle of a product system. When used to assess different CDR approaches, including OAE, its strength lies in the provision of information about a wide array of environmental impacts, far beyond an initial carbon balance. LCA variants such as cradle-to-grave and the gate-to-gate can be used, as described in detail in Section 2.3.1. Thus far, LCA has focused on land-based CDR approaches, including DAC, which are more mature than OAE approaches, while the number of LCAs for ocean-based CDR remains limited.

This section sets out a framework for LCA for a generic OAE approach. It integrates aspects of the LCA guidelines for ocean-based CDR approaches from Delval et. al. (2024b). This section also includes the example of LCA for using BPMED for OAE. The approach and case study presented here are for a 'classical LCA', in which it is parameterised with contemporary information from value chains, flows, and infrastructure.

6.1 Nomenclature

For ease of the reader, commonly used LCA nomenclature is summarised in Table 6.1.

Table 6.1 Summary of nomenclature used in life-cycle assessment.

Term	Description
Goal and scope	Goal and scope define the study's purpose, boundaries, functional unit, and key assumptions to ensure clarity and relevance of the assessment. (see Section 3.)
Life-cycle inventory (LCI)	LCI involves a comprehensive accounting of all inputs and outputs within the system boundaries and with reference to the functional unit. This includes detailed documentation of raw materials, energy use categorised by type, water consumption, and emissions to air, water, and land, specified by substance. (see Section 5.)
Life-cycle impact assessment (LCIA)	LCIA focuses on translating LCI data and is linked to specific environmental impacts and damages. This phase involves identifying and evaluating the magnitude and significance of potential environmental impacts associated with the studied system. The impact assessment phase consists of mandatory steps (classification and characterisation) and optional steps (normalisation, grouping, and weighting).
Midpoint indicator	Midpoint indicates impacts somewhere between the emission and the endpoint.
Endpoint indicator	Defined at the level of the areas of protection (natural environment, human health, and natural resources).
Ecoinvent	LCA database developed by the Swiss Centre for Life Cycle Inventories.
Classification	Mandatory step in LCIA: the step where the elementary flow is assigned to the selected impact categories.
Characterisation	Mandatory step in LCIA: LCI data are modelled and expressed into the environmental impact category by using characterisation factor or equivalency factors.
Normalisation	Optional step of LCIA: the results are divided into reference values to identify the potential impacts relative to a specific spatio-temporal reference system.
Grouping	Optional step of LCIA: the impact indicators are ranked into one or more groups.
Weighting	Optional step of LCIA: the impact categories are multiplied by specific weighting factors to obtain the weight impacts.
Impact category	Class representing environmental issues of concern to which LCIA results may be assigned.
Interpretation	Analysing results to draw meaningful conclusions, identify significant impacts, and provide actionable recommendations aligned with the study's goals.

6.2 Phases of an LCA in OAE

ISO 14040:2006 and ISO 14044:2006 recognise four stages in LCA (see Section 2.3.1): i) the goal and scope definition, ii) the creation of a life-cycle inventory (LCI), iii) the life-cycle impact assessment (LCIA), and iv) the interpretation. The goal and scope for an OAE LCA are discussed in Section 3, and the LCI development is considered in Section 5. This section specifically details the methodology for undertaking and interpreting an LCIA for OAE.

6.3 Methodology selection

Choosing an appropriate LCA methodology depends on the study's goal, scope, and regional context. Table 6.2 provides a summary of common LCA methodologies. The selection typically balances methodological comprehensiveness, relevance to the subject matter, and ease of application. This should be undertaken when defining the goal and scope (Section 3), as this will determine what data is collected (Section 5). Geographic and regulatory factors also influence the choice of methodology. For example, TRACI is tailored to North American environmental conditions, while LIME incorporates Japan-specific cultural and ecological values. ILCD aligns with European Union sustainability priorities, offering harmonised guidance for regional assessments.

Table 6.2. Summary of methodology choices for life-cycle assessment.

Methodology	Description	Scope* (impact categories)	Source
ReCiPe	Integrates midpoint and endpoint approaches to evaluate environmental impacts across categories like climate change, eutrophication, and human health.	M (18), E (3)	(Huijbregts et al., 2017)
IMPACT 2002+	Combines midpoint and endpoint approaches, addressing environmental impacts like climate change, human health, and resource use.	M (15), E (4)	(Jolliet et al., 2003)
CML	Focuses on midpoint indicators such as acidification, eutrophication, and global warming potentials, developed by the CML at Leiden University.	M (10)	(Guinee, 2002)
TRACI	Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts, used primarily in North America.	M (10)	(Bare, 2011)
Eco-indicator 99	Endpoint methodology that aggregates impacts into damage categories like human health, ecosystem quality, and resource depletion.	E (3)	(GOEDKOOP , 2007)
LIME-3	International Reference Life Cycle Data System methodology, providing harmonised guidelines for LCA practitioners.	E (4)	(Inaba and Itsubo, 2018)
ILCD	International Reference Life Cycle Data System methodology, providing harmonised guidelines for LCA practitioners.	M (13)	(European Commission 2010)
EDIP	Environmental Design of Industrial Products, with a focus on Danish environmental standards and normalisation methods.	M (10)	(Wenzel et al., 1997)
GWP (Global Warming Potential)	Specific to GHG impacts, expressing climate change effects over time horizons such as 20, 100, or 500 years.	M (1)	

*M - Midpoint indicators, E - Endpoint indicators

This framework recommends choosing a general methodology with diverse impact categories, such as ReCiPe 2016 (Goedkoop et al., 2009; Huijbregts et al., 2017). This method includes both midpoint indicators that consider the impacts associated with specific impacts and endpoint indicators that combine the contribution of midpoint impacts to provide a broader perspective on damage to human health, ecosystem quality, and resources available (Huijbregts et al., 2017). Using an LCIA method like ReCiPe provides a diverse assessment (beyond the climate impacts, which are largely defined with the functional unit), and provides summary outcomes that are useful for communicating the environmental performance to non-expert stakeholders.

6.4 Impact category selection and analysis

The LCIA stage in generic OAE also comprises three mandatory steps: i) selection of impact categories, ii) classification of LCI results, and iii) characterisation. In addition, normalisation, grouping, and weighting are optional steps in LCIA, which can be employed for improved results interpretation. Popular software tools like SimaPro, GaBi, and OpenLCA are widely used for their robust databases, advanced modelling capabilities, and integration with industry standards. SimaPro is noted for its flexibility in defining complex systems, while GaBi excels in industry-specific applications with an extensive proprietary database. OpenLCA is an open-source option with a wide range of plug-ins and databases.

6.4.1 Selection of impact categories

As its name implies, the first step of LCIA involves selecting the impact categories that are relevant to the goal and scope of the study, considering the specific geographical, technological, and temporal context. Since OAE technologies are novel and have not been applied at scale yet, it is suggested that as many environmental impact categories as possible should be selected to avoid environmental burden shifting. However, this may not always be needed or justified. When the key contributors to a midpoint indicator cannot be quantified, it can be better to omit the indicator from the results. The practitioner can also choose to limit the number of indicators for clarity. Table 6.3 describes the midpoint indicators for ReCiPe. Midpoint indicators are then translated through damage pathways into endpoint indicators, for which ReCiPe has three:

Damage to human health: This indicator considers long-term health impacts caused by environmental factors such as air pollution, toxic emissions, and radiation exposure. It is typically expressed in disability-adjusted life years, capturing the burden of diseases, premature deaths, and diminished quality of life due to environmental degradation.

Damage to ecosystems: This indicator evaluates the negative effects of environmental stressors like habitat destruction, pollution, and climate change on biodiversity and ecosystem services. It is often measured in terms of species lost or ecosystem quality reduction, highlighting the long-term impacts on ecological health and sustainability.

Damage to resource availability: This indicator assesses the depletion of natural resources, including minerals, fossil fuels, and freshwater, due to human activities. It measures the long-term implications for future generations, often expressed in terms of increased energy or economic costs required to access scarce resources.

Table 6.3 Summary of the midpoint indicators for ReCiPe (Huijbregts et al., 2017).

Indicator	Description	Unit *equivalent	Environmental Concern
Climate Change	The impact of GHGs on global warming.	kg CO_2*	Global warming
Ozone Depletion	The effect of substances that deplete the ozone layer.	kg CFC-11*	Stratospheric ozone depletion
Terrestrial Acidification	Acidifying emissions that affect soil and terrestrial ecosystems.	kg SO_2*	Acid rain
Freshwater Eutrophication	Nutrient enrichment of freshwater ecosystems, resulting in algal blooms and oxygen depletion.	kg P*	Water quality degradation
Marine Eutrophication	Nutrient enrichment in marine ecosystems.	kg N*	Marine water quality degradation
Human Toxicity	Toxic emissions affecting human health.	kg 1,4-DCB*	Human exposure to toxins
Photochemical Oxidant Formation	Smog formation caused by volatile organic compounds (VOCs) and other pollutants.	kg NMVOC*	Air quality degradation
Particulate Matter Formation	Health impacts of fine particulate matter (PM2.5) emissions.	kg PM10*	Respiratory health impacts
Terrestrial Ecotoxicity	The impact of toxic emissions on terrestrial ecosystems.	kg 1,4-DCB*	Ecosystem toxicity
Freshwater Ecotoxicity	The impact of toxic emissions on freshwater ecosystems.	kg 1,4-DCB*	Aquatic ecosystem toxicity
Marine Ecotoxicity	Toxic effects on marine ecosystems.	kg 1,4-DCB*	Marine ecosystem toxicity
Ionising Radiation	Health impacts of exposure to radioactive substances.	kBq U235*	Radiation exposure
Agricultural Land Occupation	Land-use impacts related to agriculture.	$m^2 \cdot$year	Land availability for biodiversity
Urban Land Occupation	The impact of urban land use on ecosystems.	m^2 year	Ecosystem disturbance
Natural Land Transformation	Converting natural habitats for human use.	m^2	Loss of natural habitats
Water Depletion	Freshwater consumption.	m^3	Water scarcity
Metal Depletion	The depletion of metal resources.	kg Fe*	Resource scarcity
Fossil Depletion	The depletion of fossil fuel resources.	kg oil*	Energy resource availability

6.4.2 Classification

In classification, the elementary flows from the collected LCI are assigned to the selected impact categories, and their contribution is quantitatively estimated based on the effect that each flow/substance has on the environment (midpoint or endpoint level). For example, through classification, the substances that have the potential to deplete the ozone layer will be assigned to the ozone depletion midpoint impact category, while at endpoint level their effect on human health (e.g., skin cancer) can be assigned.

6.4.3 Characterisation

Characterisation substance-specific factors ('characterisation factors') are used to quantitatively estimate the potential environmental impact or damage of each substance that has been ascribed to each specific impact category. By doing so, the information for each individual substance that is included in the same impact (damage) category is converted to the same unit of measurement, by multiplying it with the specific characterisation factor. Therefore, the environmental impact/damage can be quantitatively estimated by simply aggregating the results within the same impact/damage category.

6.4.4 Optional: normalisation, grouping, and weighting

Normalisation of the magnitude of the calculated environmental impact/damage is estimated by normalising the results with a reference situation (such as per geographic area (or global) and/or per person for a reference year). For this reason, normalisation factors are used, with popular choice being the global normalisation factors for the reference year 2010, which cover a large collection of data for emissions and extracted resources for this year and at a global scale (Sala et al., 2018).

The characterised or normalised results can also be grouped (i.e., sorted or ranked) based on defined but subjective criteria that were set out in the goal and scope of the LCA study. Due to its subjectivity, grouping might be of little use for OAE LCAs.

Finally, weighting is a useful tool, particularly given that weighted results can be expressed into a single damage category. This is useful for comparative analyses but is also associated with high uncertainties, so ISO 14044 advocates for its careful use and suggests that it should not be employed in studies intended for non-specialist audiences. As such, weighting can be a useful tool for OAE, since it provides a common reference for comparison. If used, it should be acknowledged, and non-weighted results should be presented (Hauschild et al., 2017).

6.5 Interpretation

Robust conclusions and recommendations are formulated based on the study's goals and scope. The interpretation should cover the main three areas: a) identification of significant issues (i.e., the key findings, including all impact categories examined; parameters should be included), b) evaluation of the results through completeness, sensitivity, consistency, and uncertainty checks; and c) drawing conclusions, limitations, and recommendations from the LCA study.

For OAE, it is recommended to conduct sensitivity analysis to evaluate the impact of different parameters on the overall outcome of the LCA study (Delval et al., 2024a). This is done by altering one variable at a time within a realistic range and reporting the resulting changes in the outcome (Arvidsson et al., 2024). For example, an LCA for coastal enhanced weathering explored the sensitivity of the mineral particle size and the effect of its nickel content (Foteinis et al., 2023). However, most OAE technologies will be sensitive to the carbon intensity of energy and transportation means and distance.

Furthermore, it is advised to include a description of the knowledge gaps in the OAE technology and their potential implications for the technology's environmental performance. The known environmental benefits and possible side effects of the technology should also be highlighted.

Furthermore, marine ecosystems are a primary focus of environmental protection and a key target of the UN Sustainable Development Goal 14 (SDG 14). As a result, the preservation of marine ecosystems has become a central objective of environmental protection. Ocean pollution directly impacts marine organisms and their food chains, while indirectly affecting humans (Landrigan et al., 2020). Activities that release toxic compounds and other hazardous substances into the ocean, such as effluent discharge, are major contributors to ecotoxicological damage to marine environments. The marine ecotoxicity impact category in LCIA is used to assess the potential effects of toxic chemical discharges on marine ecosystems. The available characterisation models generally evaluate impacts by considering environmental mechanisms such as transport, destination, exposure, and effect. These models can measure the level of ecosystem damage in endpoint modelling (Rosenbaum, 2015).

6.6 Limitations and further work

The impact of elevated alkalinity on the ocean is not parameterised in LCIA. A substantial amount of research is needed to create robust classification and characterisation models that are relevant to OAE. For projects that release non-equilibrated alkalinity into the ocean, it is possible that impacts could be attributable under the 'ocean acidification' midpoint indicator. Research for identifying relevant characterisation factors for ocean acidification impacts on marine biodiversity (Scherer et al., 2022) should be prioritised.

For non-alkalinity OAE impacts, LCA classification and characterisation models are robust enough to capture, at midpoint level, the impacts associated with ecotoxicity and eutrophication of marine environments (marine eutrophication and marine ecotoxicity impact categories). For impact categories in LCIA methods, marine eutrophication is defined as the response of a marine ecosystem to an excessive availability of a limiting nutrient. In this case, nitrogen is considered the limiting nutrient in marine water and phosphorus in freshwater ecosystems. The availability of the limiting nutrients stimulates primary production in the ecosystem and creates adverse effects on species in water, including accumulation of algal toxins and odour problems (Smith, 2003). For OAE, focus should be placed on more accurately capturing the effect of co-dissolved metals (e.g., the N equivalence of dissolved iron) when released at the scale that each OAE intervention proposes. Candidate materials for OAE can contain impurities in their matrix which could impose (eco)toxicity pressures when used at scale, and existing classification and characterisation models should be supplemented with impacts when known. For example, nickel contained in olivine-rich rock used for coastal enhanced weathering could cause (eco)toxicity pressures in marine ecosystems. However, it may take years to decades or even centuries to be fully released, while a large part of the released nickel might end up in sediments. Therefore, research should focus on answering specific questions about the nature and fate of these releases to inform more robust classification and characterisation models for OAE.

Trade-offs and positive impacts (co-benefits) should also be explored. For example, in ocean iron fertilisation, the spreading of dissolved iron in seawater is proposed as a means of improving primary production, thus boosting the carbon export efficiency to deep waters. Therefore, in this case, iron releases might reflect a negative effect on eutrophication, but the improved carbon export efficiency, which to the best of our knowledge is not captured in existing LCIA methods, might counteract the eutrophication pressures and lead to several other co-benefits.

6.7 Case Study: Classical LCA implementation for bipolar membrane electrodialysis (BPMED)

Here, the classical LCA method is exemplified for the BPMED case study. For convenience, the below partially repeats goal and scope definitions from Section 3.

Goal: "Quantify and evaluate the wider environmental impacts from employing bipolar membrane electrodialysis (BPMED) for OAE"

***Target audience*:** the target audience for this case study includes technology innovators, R&D managers, industries, decision makers and policy makers, local, regional, and central government.

***Benchmark*:** The results will be compared to a benchmark coastal enhanced weathering (CEW) pathway.

6.7.1 Scope and system boundaries

The system boundary of the case study is cradle-to-gate including CO_2 drawdown, i.e., from raw materials production, energy generation, and seawater intake until the production of NaOH and release into the ocean for CDR. The system boundary is illustrated in Figure 6.1.

Foreground processes of pretreatment, precipitation softening, ion exchange, reverse osmosis, and bipolar membrane electrodialysis are included in the scope boundaries. The end of life of HCl generated from the BPMED process (by-product) is excluded from the system boundaries (see Section 3.8.2). In the sensitivity analysis we consider the application of BPMED-OAE to desalination waste brines (Section 6.7.6).

The functional unit is selected as 1 tonne of alkalinity (here, NaOH) added to the ocean. However, to compare the performance of BPMED with other OAE approaches (e.g. coastal enhanced weathering, ocean liming), 1 tonne gross atmospheric CO_2 drawdown was chosen as a secondary functional unit. The temporal context is 2023, the location is assumed to be the UK. Further assumptions for the case study are provided in Section 3.6.5.

6.7.2 Life-cycle inventory

The LCI is described in Section 5.6.2, Table 5.3. Foreground data was obtained from process simulations and literature studies. Background data was obtained from ecoinvent version 3.10 and the LCI was implemented in SimaPro version 9.6.0.1. The input and output are normalised to the functional units of 1 tonne gross CO_2 captured and 1 tonne of alkaline material produced (NaOH for the BPMED case).

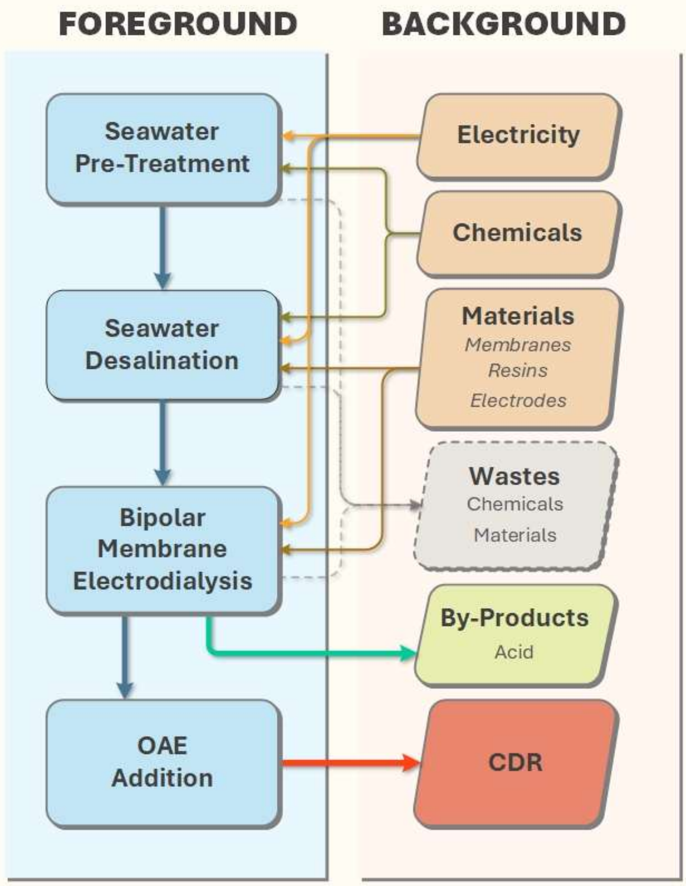

Figure 6.1 System boundaries for the BPMED system.

6.7.3 Life-cycle impact assessment

The three main LCIA steps for the case study are:

i) Selection of impact categories: This case study employed ReCiPe 2016 (version 1.14, hierarchist perspective), which is a robust and harmonised multi-issue LCIA method for translating LCI into life-cycle impact scores at both midpoint and endpoint levels (Huijbregts et al., 2017). Here, we present all 18 ReCiPe midpoint indicators. For the midpoint level of ReCiPe 2016 (H) all 18 impact categories are shown in Table 6.3. At the endpoint level, the ReCiPe 2016 (H) method only covers the following environmental impact categories: damage to human health, damage to ecosystems, and damage to resource availability.

ii) Classification: This involves assigning material/energy inputs and outputs in LCI to the relevant impact categories. For example, during the classification phase, all inputs and outputs that contribute to GHG emissions (e.g., CO_2, methane) are assigned to the climate change impact category. This classification process is specified in SimaPro.

iii) Characterisation: The classified LCI data are modelled and expressed into impact category indicators, using conversion factors known as characterisation or equivalency factors.

6.7.4 Results and discussion

Midpoint indicators

The potential environmental impacts (ReCiPe's 2016 midpoint scores) from each stage included in the BPMED case study are presented in Table 6.4. The dendrogram of the major contributors to the life-cycle GHG emissions of BPMED to capture 1 tonne of atmospheric CO_2, is shown in Figure 6.2. The percentage contributions of midpoint 18 impact categories are given in Figure 6.3 to provide a better understanding of each environmental impact.

BPMED and precipitation softening processes dominate the score of most environmental impact categories compared to other processes. Both processes have a high contribution to global warming, ionising radiation, terrestrial ecotoxicity and human non-carcinogenic toxicity; however, the BPMED process contributes the most to midpoint impact category scores such as fossil resource recovery due to its large electricity consumption (Table 6.4).

The total life-cycle GHG emissions from operating the BPMED system are generated during the pretreatment, precipitation softening, ion exchange, reverse osmosis, and BPMED stages. According to the dendrogram from SimaPro, the BPMED-OAE process produced 196 kg CO_2-eq per tonne of atmospheric CO_2 drawdown into the ocean (equivalent to 1.087 tonnes of alkaline material added to the ocean).

The BPMED stage is the largest contributor to total life-cycle GHG emissions, emitting 555 kg CO_2-eq when operated with the current UK electricity grid (grid intensity of 0.27 kg CO_2-eq/kWh in 2021 from ecoinvent-database version 3.10). The carbon footprint of the BPMED stage accounted for 46.4% of the total life-cycle GHG emissions, with electricity at medium voltage being the primary hotspot, releasing 520 kg CO_2-eq (Figure 6.2). Due to the high amount of electricity consumption in the BPMED phase (2,040 kWh), electricity is the key driver influencing the system's carbon footprint.

Additionally, precipitation softening plays a vital role in the system's GHG emissions, accounting for 44% of total emissions (Figure 6.3). Specifically, the use of soda ash (sodium carbonate) and hydrated lime (calcium hydroxide) resulted in 203 kg CO_2-eq and 313 kg CO_2-eq of total GHG emissions, respectively. The extensive dosage of both soda ash and hydrated lime contributed to the high carbon footprint of the BPMED system.

Tracing back to the emissions factors for both the production and use phases of soda ash and hydrated lime, the UN Framework Convention on Climate Change (2015) reports that the emissions factor for soda ash production is 0.097 tCO_2 per tonne of trona (sodium sesquicarbonate, $Na_2CO_3 \cdot NaHCO_3 \cdot 2H_2O$), while the emissions factor for the use of soda ash is 415 kg CO_2 per tonne of Na_2CO_3. Using these emissions factors to estimate GHG emissions, using 572 kg of Na_2CO_3 for precipitation softening results in approximately 237 kg CO_2-eq, which closely aligns with the emissions estimated by SimaPro (203 kg CO_2-eq). In terms of global warming potential, the average emissions factor for hydrated lime production in Europe is 0.94 kg CO_2-eq per kg of hydrated lime produced (Laveglia et al., 2022). In the BPMED case study, the addition of 335 kg hydrated lime in the precipitation softening process generated approximately 315 kg CO_2-eq, closely aligning with the carbon footprint estimation from SimaPro (313 kg CO_2-eq).

Table 6.4 ReCiPe's 2016 Midpoint (H) of 18 impact categories per functional unit of 1 tonne gross CO_2 captured on five examined stages in BPMED.

Impact category	Unit (eq)	Pretreat-ment	Precipita-tion softening	Ion exchange	RO	BPMED	Total impact
Global warming (GW)	kg CO_2*	5.22	548.25	26.33	61.24	554.73	195.77[a]
Stratospheric ozone depletion (SOD)	kg CFC_{11}*	2.93×10^{-6}	9.59×10^{-4}	2.67×10^{-5}	7.46×10^{-4}	3.47×10^{-4}	1.22×10^{-3}
Ionising radiation (IR)	kBq Co-60*	3.19	27.54	12.17	32.03	379.25	454.18
Ozone formation, human health (OF_{HH})	kg NOx*	0.01	0.85	0.05	0.10	1.00	2.01
Fine particulate matter formation (FP_{MF})	kg PM2.5*	0.01	0.62	0.04	0.06	0.39	1.11
Ozone formation, terrestrial ecosystems (OF_{TE})	kg NOx*	0.01	0.90	0.05	0.10	1.03	2.10
Terrestrial acidification (TA)	kg SO_2*	0.03	2.17	0.09	0.14	1.12	3.55
Freshwater eutrophication (FE)	kg P*	1.06×10^{-3}	0.17	0.02	0.03	0.08	0.30
Marine eutrophication (ME)	kg N*	2.18×10^{-4}	0.02	1.79×10^{-3}	2.88×10^{-3}	0.02	0.05
Terrestrial ecotoxicity (TE)	kg 1,4-DCB	53.90	3,898.09	293.24	449.84	3,307.91	8,002.98
Freshwater ecotoxicity (FET)	kg 1,4-DCB	0.25	29.97	1.71	2.69	19.57	54.19
Marine ecotoxicity (MET)	kg 1,4-DCB	0.37	41.72	2.51	3.89	27.94	76.43
Human carcinogenic toxicity (HT_C)	kg 1,4-DCB	0.78	92.34	8.62	12.40	69.98	184.12
Human non-carcinogenic toxicity (HT_{NC})	kg 1,4-DCB	4.81	562.34	38.60	55.65	351.82	1,013.22
Land-use (LU)	m^2a crop*	0.60	23.96	1.07	4.82	69.64	100.09
Mineral resource scarcity (MRS)	kg Cu*	0.02	2.27	0.14	0.21	1.44	4.08
Fossil resource scarcity (FRS)	kg oil*	1.77	85.55	7.11	16.87	191.07	302.38
Water consumption (WC)	m^3	0.07	96.66	87.35	85.52	88.70	358.32

[a] *The total score for the global warming category includes 1 tonne of CO_2 captured from the atmosphere which results in a total positive score*

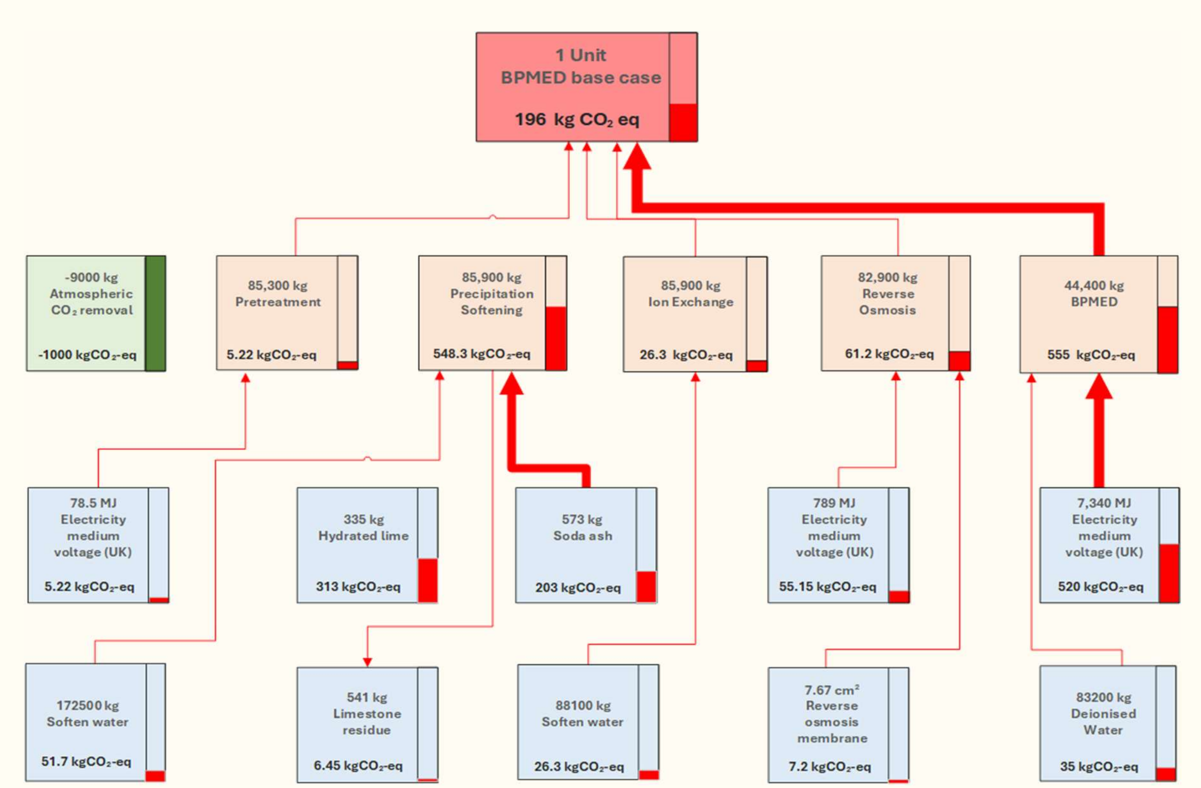

Figure 6.2 Dendrogram (with 0.5 % cut-off) illustrating the BPMED carbon footprint with a seawater input of 85.3 tonne per 1 tonne of CO_2 captured from the atmosphere. Red arrow: GHG emissions; green arrow: atmospheric CO_2 captured.

Reverse osmosis accounted for 62.6 kg CO_2-eq of the BPMEDs total carbon footprint, of which 55.15 kg CO_2-eq was attributed to UK grid electricity. The remaining emissions were generated by the reverse osmosis membrane and softened water (Figure 6.2). From the percentage contribution, CO_2 emissions from reverse osmosis accounted for 5.1% of the total GHG emissions. Moreover, pretreatment and ion exchange had a relatively small impact on climate change, emitting 5.22 kg CO_2-eq, and 26.3 kgCO_2-eq, respectively (Figure 6.3).

Furthermore, the carbon penalty of the BPMED-OAE system is approximately 195.77 kg CO_2-eq, or around 20%, implying that a significant portion of atmospheric CO_2 drawdown from the atmosphere is offset by emissions produced during the process. Several factors contribute to this carbon penalty. First, the system's energy-intensive operation relies on electricity, and since the power grid in the UK predominantly uses fossil fuels, particularly natural gas, the emissions generated during electricity production significantly offset the atmospheric CO_2 removal achieved by the system. Alternatively, BPMED-based OAE systems can consider operating off-grid, using purpose-built renewable electricity to fulfil their energy demand. In that case, the intermittency of renewable electricity supply will need to be addressed by adding sufficient electricity storage, or by operating the OAE process flexibly, which may reduce the capacity factor, the amortisation, and thus levelised cost of removal.

Also, operational inefficiencies within the BPMED process, such as membrane resistance and energy losses, increase the system's energy demand, leading to higher emissions (Iizuka et al., 2012). Another factor contributing to the large carbon penalty could be related to the system's design and operating conditions. A well-designed electrochemical process is crucial for the system's performance. For example, the configuration of membrane stacking in BPMED and the type of cation exchange membrane and anion exchange membrane influence the efficiency of NaOH (alkaline material) generation (de Lannoy et al., 2018). If the design of BPMED is not fully optimised, an increase in CO_2 emissions may result. As previously discussed, high GHG emissions in the precipitation softening process is mainly attributed to the use of soda ash and calcium hydroxide (softening agents), so reconsidering the design configuration of the BPMED-OAE process is essential to reduce its carbon footprint as well as its carbon penalty. Possible improvements include using alternative softening agents with lower emissions, replacing precipitation softening with nanofiltration, or integrating alternative processes alongside precipitation softening to enhance hardness removal of Ca^{2+} and Mg^{2+} from seawater (see Section 6.7.6).

Under the assumptions of the BPMED case study, there is potential for improvement to make this technology achieve net-negative emissions. The strategies include: a) using renewable energy to reduce reliance on fossil fuels by incorporating sufficient electricity storage, b) optimising the process by reducing membrane resistance and improving membrane stacking in BPMED, c) substituting high-emission softening agents in the precipitation softening process with lower-emissions alternatives, and d) redesigning the BPMED-OAE configuration by integrating nanofiltration process, either as a replacement for precipitation softening or in combination with it. A lower emissions energy supply is considered in the prospective analysis (see Section 8.7)

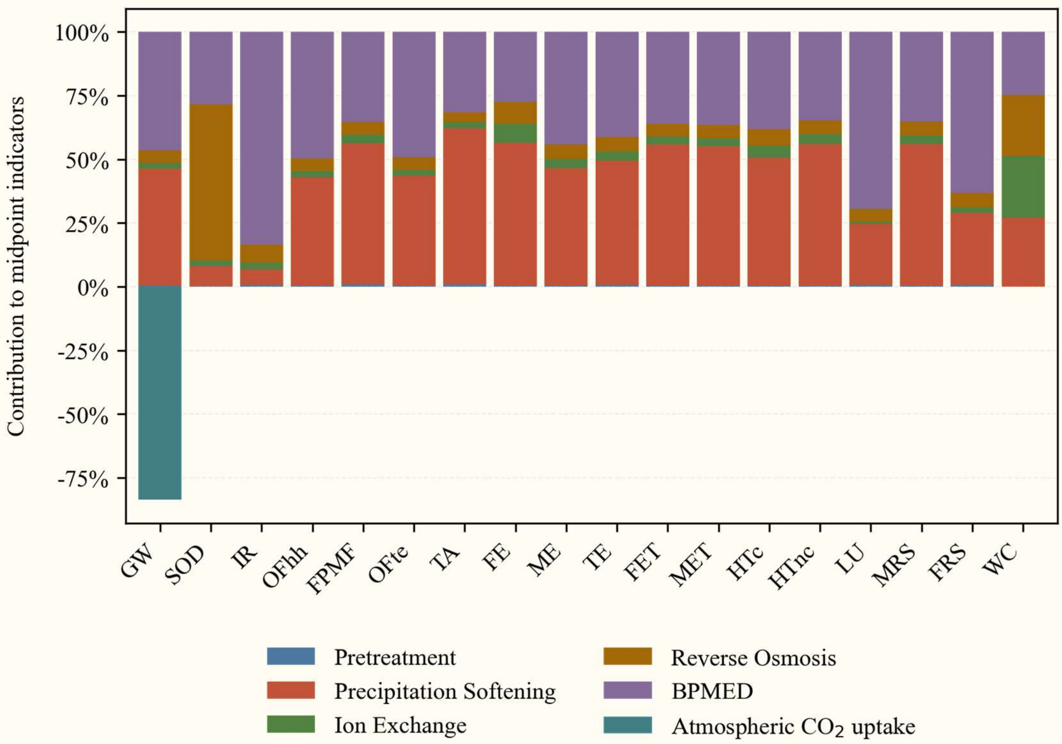

Figure 6.3 The percentage contribution of five examined stages in the BPMED system per 1 tonne of gross CO_2 captured on ReCiPe's 18 midpoint (H) impact categories.

The total percentage contribution to global warming impact from the five examined stages in the system is 1,196 kg CO_2-eq. However, with the design capturing 1 tonne of gross atmospheric CO_2, the total net CO_2 emissions generated by the BPMED-OAE system are 196 kg CO_2 eq. This represents an 84% reduction in atmospheric CO_2 uptake efficiency.

Aside from the global warming impact, precipitation softening has a large contribution on most environmental categories, particularly fine particulate matter formation (FPMF), terrestrial acidification (TA), freshwater eutrophication (FE), terrestrial ecotoxicity (TE), freshwater ecotoxicity (FET), marine ecotoxicity (MET), and mineral resource scarcity (MRS) (Figure 6.3). Since the production of soda ash and hydrated lime involves mineral extraction, the use of both significantly contributes to mineral resource scarcity, accounting for 56% of the total impact on mineral resources scarcity. The application of these two substances has a detrimental effect on terrestrial organisms, the environment, and soil pH, contributing to 49% of total terrestrial ecotoxicity and 61% of total terrestrial acidification.

The electricity consumed by the BPMED process also affected other environmental impact categories. For example, the high percentage of land use (70%) is linked to the land required for the construction and operation of natural gas power plants and electricity transmission, while the reliance on fossil fuels for electricity generation contributes to a large percentage of fossil resource scarcity (63%). Fossil fuel itself also had a high impact on human carcinogenic toxicity and non-carcinogenic toxicity, further discussed in the next section of endpoint.

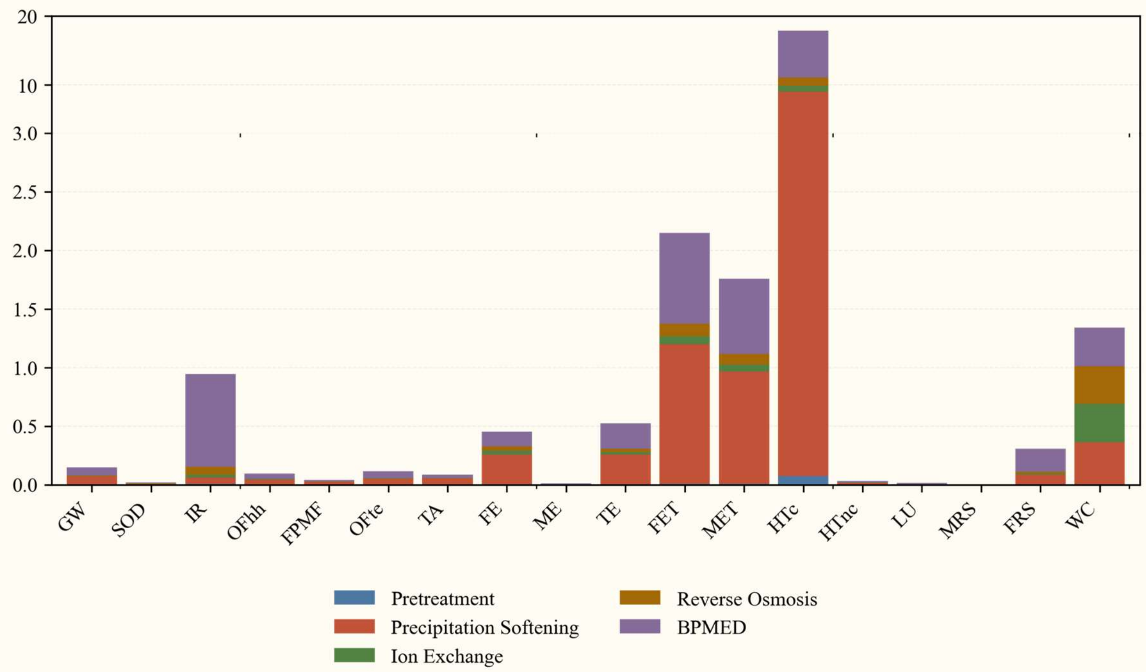

Figure 6.4 Normalisation of 18 impact categories, expressed per 1 tonne of gross CO_2 drawdown on ReCiPe's midpoint.

Furthermore, reverse osmosis membrane modules contributed to the high percentage of stratospheric ozone depletion (61%), while softened water fed to the reverse osmosis system contributed to around 24% of total water consumption.

Normalisation was carried out with the aim of equalising the overall impact category value. It helps prioritise which inputs have the most significant environmental consequences. Figure 6.4 shows normalisation value of the five analysed stages in the BPMED system assessed per 1 tonne gross carbon captured on ReCiPe's 2016 midpoint.

Human carcinogenic toxicity (HTc) is the most impacted midpoint category, followed by freshwater ecotoxicity (FET) and marine ecotoxicity (MET), all of which were significantly influenced by the precipitation softening and BPMED processes. Results show that the normalisation score for human carcinogenic toxicity was 8.97 for precipitation softening and 6.80 for BPMED, making them the primary contributors to this impact category.

The production of soda ash (sodium carbonate) and hydrated lime (calcium hydroxide) is not classified as carcinogenic by the Mine Safety and Health Administration (MSHA), the Occupational Safety and Health Administration (OSHA), or the International Agency for Research on Cancer (IARC). However, the production of hydrated lime can be associated with crystalline silica exposure (if the limestone used contains impurities), and crystalline silica has been classified by IARC as a Group 1 carcinogen-carcinogenic to humans when inhaled (Rey-Brandariz et al., 2023; *Safety Data Sheet - Hydrated Lime*, 2015). Moreover, normalisation results from the ecoinvent database indicate electric arc furnace slag and oxygen furnace slag (by-products of steel production) are major contributors to human carcinogenic toxicity. These slags are generated during the manufacture of BPMED cathodes and anodes. While the material demand of both cathode and anode is relatively low, steel production inherently produces by-products that may pose carcinogenic risks.

As previously discussed, the softening agents used in the precipitation softening process also contributed to freshwater ecotoxicity and marine ecotoxicity in the ReCiPe midpoint score, which aligns with the normalisation value shown in Figure 6.4. In addition, the pretreatment process has a slight effect on these three distinct normalisation scores, likely due to the input chemicals for pH adjustment, disinfection, coagulation, and dechlorination in the first stage, which contributed to HTc, FET, and MET.

Endpoint indicators

The endpoint indicator results were analysed to reflect the damage to human health, damage to ecosystems, and depletion of resources. As mentioned in Section 2.3.5, weighting is the fourth (optional) step in LCIA. This step is used to assign relative importance or significance to different impact categories (e.g., climate change, human health, ecotoxicity) based on their perceived environmental, social, or economic significance.

The weighted results are expressed in a consistent unit that can be aggregated into a single score, reflecting the overall environmental impact of a product or scenario. The SimaPro 9.6.0.1 software utilises Point (Pt) units to represent the resulting impact. In the environmental indicator method, the Pt unit is dimensionless, with a value of 1 Pt corresponding to one-thousandth of the average environmental burden of the European population over the course of a year (Morsali, 2017).

Weighting results of three damage categories of five stages examined in the BPMED-OAE system is given in Figure 6.5. The unit of weighting results are expressed in Pt (points), where the total score for an impact category in the BPMED system is presented as a value in points.

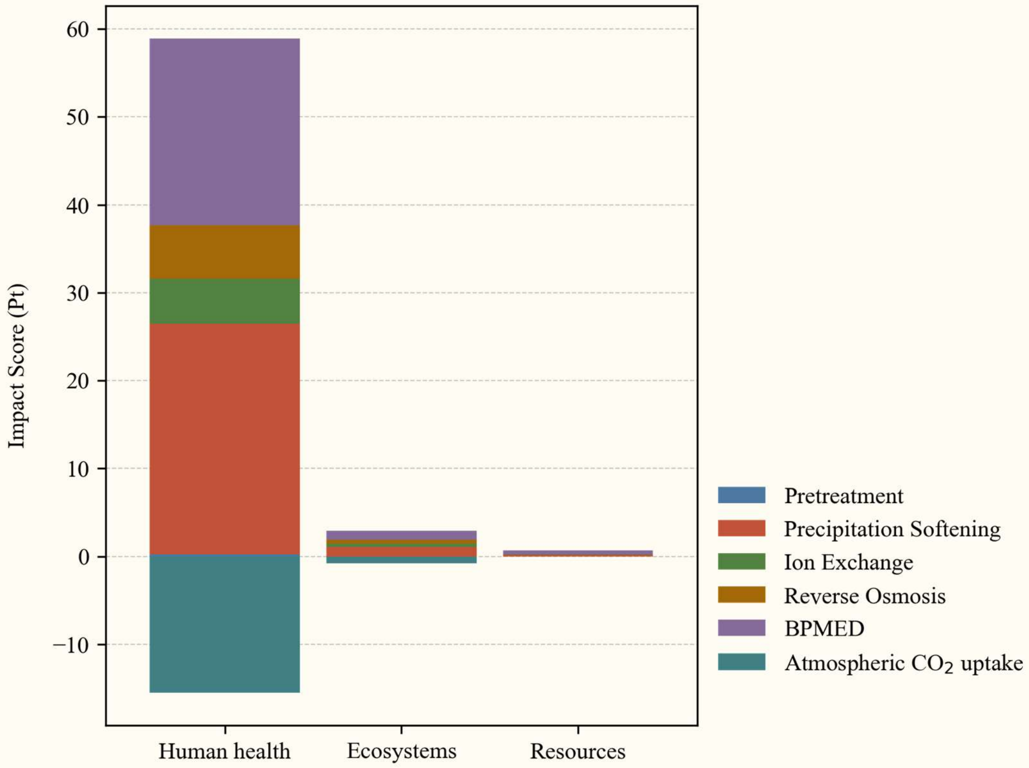

Figure 6.5 Weighting results of three damage categories per 1 tonne of gross CO_2 drawdown at ReCiPe's 2016 endpoint.

At the endpoint level, the effect of CO_2 uptake from the atmosphere is included in the analysis. The weighting results reveal that total human health received the highest score of 43.42 Pt, followed by ecosystems with 2.18 Pt, and resources with 0.71 Pt. Precipitation softening stage affected human health with the highest score of 26.21 Pt, followed by BPMED (21.24 Pt), reverse osmosis (6.06 Pt), ion exchange (5.14 Pt), and pretreatment (0.26 Pt).

The findings are also consistent with the previous normalisation value at midpoint level, where the BPMED and precipitation softening stages mainly contributed to human carcinogenic toxicity. This suggests that the GHG emissions from grid electricity and softening agents (soda ash and hydrated lime) have a significant impact on human health, while having comparatively smaller impacts on both ecosystem and resource damage categories.

6.7.5 Interpretation

The key findings of the LCA study on the BPMED case study are as follows:

- The midpoint scores of 18 environmental impact categories are largely driven by the BPMED and precipitation softening processes.

- The BPMED-OAE system needs to generate 1.087 tonnes of NaOH to uptake 1 tonne of atmospheric CO_2 emissions.

- To capture 1 tonne of atmospheric CO_2, the BPMED-OAE system emits 196 kg CO_2-eq per year. This estimate is based on the assumption of treating 90.3 tonnes of UK seawater through pretreatment, precipitation softening, ion exchange, reverse osmosis, and BPMED processes with 8,500 hours of operation in a year.

- The base case has a carbon penalty 19.6% when considering the system's uptake of 1 tonne of gross atmospheric CO_2 captured., meaning that the base case is not negative CO_2 technology.

- Fossil-fuel based electricity used in the BPMED process is the main hotspot influencing global warming impact (555 kg CO_2-eq), while softening agents (soda ash and hydrated lime) used in the precipitation softening are the second-largest source contributing to climate change impact (548 kg CO_2-eq).

- Precipitation softening significantly impacts multiple environmental categories, particularly fine particulate matter formation (FPMF), terrestrial acidification (TA), freshwater eutrophication (FE), terrestrial ecotoxicity (TE), freshwater ecotoxicity (FET), marine ecotoxicity (MET), and mineral resource scarcity (MRS).

- Grid electricity consumption in BPMED has a significant impact on land use and resource scarcity due to the land required for power plant construction and operation, as well as the reliance on fossil fuels for electricity generation.

- Based on normalisation results, the most significant environmental impact is human carcinogenic ecotoxicity, followed by freshwater ecotoxicity and marine ecotoxicity.

- Both precipitation softening and BPMED are the main hotspot contributors to high normalisation values of these three environmental impacts, which align with the midpoint score.

- At endpoint level, the BPMED-OAE system has the greatest impact on human health, compared to its effects on ecosystems and resources.

The recommendation is to reduce the carbon footprint from BPMED-OAE under this case study including the following strategies:

a) Operating the system off-grid using low-carbon sources of electricity.

b) Optimising the BPMED operation conditions, such as reducing membrane resistance, enhancing membrane stacking, and selecting appropriate cation and anion exchange membranes.

c) Replacing high-emissions softening agents with lower-emissions alternatives in the precipitation softening process.

d) Redesigning the BPMED-OAE process configuration by either removing the precipitation softening process or integrating nanofiltration with the precipitation softening process.

Future scenarios where different types of electricity sources are integrated will be evaluated using a prospective LCA approach (see Section 8.7), which is beneficial for forecasting how OAE technologies will evolve in the future (e.g., electricity grid with increasing shares of low-carbon energy sources, decarbonisation of softening agent production, or replacement of materials to minimise environmental impacts in certain OEA technologies). Prospective LCA incorporates future scenarios derived from IAMs, considering anticipated changes in key energy-intensive sectors. This approach generates future LCI databases, built on the ecoinvent LCI database (Sacchi et al., 2022).

6.7.6 Sensitivity analysis - technology variants

The boundary of this LCA case study uses seawater as the raw material brine. For seawater to be used, it requires softening to remove calcium and magnesium prior to reverse osmosis to increase the salt concentration. To avoid some of these processes, it may be possible to use brine water from desalination plants.

Pretreatment requirements for seawater desalination depend on the quality of the intake water, but conventional systems include disinfection, screening, flocculation, flotation, sedimentation, filtration, and anti-scaling (Poirier et al., 2023). Anti-scaling typically involves acidifying the influent seawater to prevent the formation of $CaCO_3$. Acidification does not remove calcium ions but helps to prevent precipitation at the chemical gradients experienced at a reverse osmosis membrane. It is not clear if this would be sufficient to prevent scaling at the chemical gradients experienced at a BPMED membrane. Some desalination facilities use processes that decrease the concentration of calcium ions (including water softening and nanofiltration), in which case the desalination brine may be more appropriate for BPMED input.

For this reason, we include a reanalysis of the results for variants of the BPMED case studies. These variants include a) case without precipitation softening process, (b) case with precipitation softening and nanofiltration, and (c) a case which uses reject/waste streams which require no softening or desalination processes (Table 6.5). Process flow diagrams of the variant of case studies are given in Section 3, Figures 3.6, 3.7, and 3.8.

Table 6.5 Impacts of BPMED OAE variant case studies, including the base case, the case without softening process, the case with nanofiltration and softening processes, and the case of BPMED using waste brine.

Selected impact	Base	No softening	Softening NF	Using waste brine
Global warming potential (kg CO_2-eq)	195.77	−313.10	-197.36	-442.88
Human carcinogenic toxicity (kg 1,4-DBC)	184.12	97.65	127.30	70.83
Human health (Pt)	43.42	19.36	35.07	6.14
Ecosystems (Pt)	2.18	1.23	2.38	0.30
Resources (Pt)	0.71	0.54	0.60	0.46

The comparison of sensitivity analysis of the BPMED variant case studies included 1 tonne CO_2 atmospheric uptake in the analysis. The results for total life-cycle GHG emissions reveal that the reject stream case had the highest negative GHG emissions (-442.88 kg CO_2-eq), followed by the BPMED variant without precipitation softening (-313.10 kg CO_2-eq) and the BPMED with nanofiltration (-197.36 kg CO_2-eq). The large amount of negative GHG emissions in the variant BPMED case confirm the effect of GHG emissions from the use of softening agents (Na_2CO_3 and $Ca(OH)_2$) in the softening process. The scenarios of BPMED without softening yield the lower total GHG emissions compared to softening NF case (softening via nanofiltration), while the reject stream case examines the effect of waste brine from BPMED that could be integrated with pretreatment. Switching BPMED to waste feedstock provides the most climate benefit, likely due to avoided raw material processing and fewer pretreatment needed. While Softening via NF is an improvement over the base, it introduces additional energy-intensive steps that partly offset the benefits.

The reason behind the large contribution in BPMED base case to the global warming or carbon footprint is twofold: i) currently, electricity consumption in the UK is associated with a relatively large carbon footprint (i.e., 0.207 kg CO_2 per kWh) (Department for Energy Security and Net Zero, 2023), and ii) the BPMED stage, which is the main electricity consumer of the overall process, has not yet matured and electricity consumption is not near the theoretical potential, i.e., here it was assumed that around 1.8 kWh are consumed in the electrolyser to produce one kg of NaOH, while theoretically this value should stand between 0.65 to 0.81 kWh/kg. We explore changes in energy consumption of BPMED further in the prospective analysis Section 8.7.

As discussed previously, precipitation softening and BPMED processes were the main contributors to human carcinogenic toxicity. Hydrated lime production (one of softening agent) can introduce crystalline silica, which pose a lung cancer risk, while by-products from steel-making (electric arc furnace slag and oxygen furnace slag) used in the production of cathode and anode also contribute to carcinogenic toxicity. A comparison of the sensitivity analysis results reveals that BPMED variants without precipitation softening (waste brine and no softening) had lower human carcinogenic toxicity scores compared to those with precipitation softening. BPMED with a softening process via nanofiltration requires a smaller amount of precipitation softening agents to completely remove bivalent ions than the amount needed in the base case. As a result, the BPMED base case contributed the highest to human carcinogenic toxicity impacts.

The results at the endpoint indicators for the other three scenarios show a similar trend with the base case. Human health gained the highest score, followed by ecosystems and resources. Endpoint indicators are derived from the aggregation of midpoint indicators, e.g. how each midpoint impact affects areas such as human health, ecosystems and resources. Despite the negative score of global warming at the midpoint of both BPMED with softening via nanofiltration and without softening precipitation, human health at endpoint scores for these two scenarios are 35.07 Pt and 19.36 Pt, respectively (Table 6.5). This suggests that deploying both BPMED variants significantly reduced CO_2 emissions while affecting a slight decline in human health. When tracing back to the normalisation step, human carcinogenic toxicity had the highest magnitude among the other midpoint indicators, surpassing global warming. Consequently, the endpoint indicator followed the same trend of midpoint, indicating that in the long-term, human health was the most significantly damaged category resulting from employing BPMED base case and its three variants.

6.7.7 Comparison of LCA of CEW and BPMED

LCA offers the most insight as a comparison tool between technologies. As such, we present the results of a previous LCA on an OAE approach for illustration. Environmental considerations represent only a single axis on which to base a decision on the feasibility of a technology, as such this comparison should not be used in isolation. Coastal enhanced weathering (CEW) is a CDR strategy that involves spreading crushed silicate minerals across coastal regions, where they are gradually weathered by the action of waves and tidal currents, releasing alkaline material and sequestering atmospheric CO_2 (Foteinis et al., 2023). Details of this OEA approach including its feedstock, technology readiness level, and energy penalty are in Table 2.1. Foteinis et al. (2023) conducted an LCA of CEW to evaluate its carbon and environmental footprint, as well as its potential for CDR. Olivine with a 0.3% nickel (Ni) concentration of silt-size (10 μm) and spread in Europe's waters are considered in the base scenario of this study. The scope of this study is cradle-to-grave, consisting of three main stages: quarrying, comminution, and coastal spreading (the process diagram is explained in Section 2, Figure 2.1).

The geographical location of LCA study of CEW is in Europe and the functional unit is 1 tonne of net CO_2 removal (1 tonne uptake of CO_2 from the atmosphere). SimaPro (version 9.4.0.2) was employed in the LCA of CEW study, and the ReCiPe 2016 with the hierarchist perspective was chosen for the LCIA. For BPMED-OAE process, as mentioned prior in 6.7.1, the geographical location is in United Kingdom, the temporal context is 2023 and the functional unit is 1 tonne of CO_2 drawdown. Both LCAs on OEA aim to assess the wider environmental impacts of the technology, with the cradle-to-grave system boundaries.

These two OAE approaches differ in their mechanisms and timeframe for one tone atmospheric CO_2 uptake. For CEW, the weathering and alkalinity release depend on wave and tidal action reacting with crushed olivine, a silicate mineral. In contrast, alkalinity (NaOH) generation in the BPMED process results from splitting seawater into acidic and alkaline streams through a chemical reaction. Olivine with 0.3% Ni silt size 10 µm in CEW case require a decade or more than decade for olivine fully dissolved and uptake atmospheric CO_2 whereas, BPMED operates for one year to generate alkalinity 10 kiloton for drawdown CO_2 emissions. Additionally, several factors in the LCA studies of the two cases are not aligned, including the temporal context (year) and geographical location. Temporal context of CEW and geographical location was 2022 and Europe, while the year of LCA study of BPMED and location was 2023, and the United Kingdom.

Though the contexts of the two OAE approaches are not fully aligned, the LCA comparison aims to provide insight into their environmental impacts and assess which approach—CEW or BPMED—is environmentally superior under the current assumptions.

A comparison of the classical LCA study for BPMED variants and CEW is presented in this section to illustrate two different OAE technologies that could contribute to different environmental impacts. The total score of ReCiPe 2016 midpoints across 18 impact categories and total weighting score at endpoint of BPMED (base case), BPMED without softening, and BPMED with softening via nanofiltration and CEW are discussed in the session.

Midpoint indicator

Total ReCiPe's 2016 midpoint score of 18 impact categories per functional unit of 1 tonne gross CO_2 captured from CEW and BPMED variants (BPMED base case, No softening case, and Softening via Nanofiltration Case) are given in Table 6.6.

Results clearly show that BPMED base case and its variants contributed to higher midpoint scores of most environmental impacts compared to scores from the CEW excluding global warming (BPMED without softening and softening via NF variants), stratospheric ozone depletion and marine ecotoxicity. BPMED base case and CEW emitted 196 kg CO_2-eq, and 50.7 kg CO_2-eq, respectively, for its total life-cycle GHG emissions when taking account of 1 ton atmospheric CO_2 emissions drawdown. BPMED variants of no softening and softening via nanofiltration show a better performance with the negative GHG emissions of -313.10 and -197.36 kg CO_2-eq (Table 6.6). This indicates that these two BPMED variants are negative technologies (when considering 1 ton CO_2 atmospheric drawdown), and the variant without precipitation softening has better efficiency to capture CO_2 emissions.

Table 6.6 ReCiPe's 2016 midpoint (H) of 18 impact categories per functional unit of 1 tonne gross CO_2 captured from CEW and three technology variants of the BPMED case study.

		Total impact			
Impact category	**Unit**	**BPMED Base Case**	**BPMED No Softening**	**BPMED NF-Softening**	**CEW**
Global warming (GW)[a]	kg CO_2 eq	195.77	-313.10	-197.36	50.07
Stratospheric ozone depletion (SOD)	kg CFC_{11} eq	0.0012	0.0012	0.0013	0.05
Ionising radiation (IR)	kBq Co-60 eq	454.18	452.13	449.42	19.84
Ozone formation, human health (OFHH)	kg NOx eq	2.01	1.23	1.43	0.29
Fine particulate matter formation (FP_{MF})	kg PM2.5 eq	1.11	0.54	0.68	0.11
Ozone formation, terrestrial ecosystems (OF_{TE})	kg NO_x eq	2.10	1.27	1.48	0.29
Terrestrial acidification (TA)	kg SO_2 eq	3.55	1.49	1.86	0.29
Freshwater eutrophication (FE)	kg P eq	0.30	0.14	0.21	0.04
Marine eutrophication (ME)	kg N eq	0.05	0.03	0.04	6.12
Terrestrial ecotoxicity (TE)	kg 1,4-DCB	8,002.98	4,385.91	5,458.96	179.90
Freshwater ecotoxicity (FE)	kg 1,4-DCB	54.19	25.80	32.44	2.10
Marine ecotoxicity (ME)	kg 1,4-DCB	76.43	36.99	46.58	1,768.30
Human carcinogenic toxicity (HT_C)	kg 1,4-DCB	184.12	97.65	127.30	23.20
Human non-carcinogenic toxicity (HT_{NC})	kg 1,4-DCB	1,013.22	480.70	622.06	77.50
Land use (LU)	m^2a crop eq	100.09	80.68	87.07	9.00
Mineral resource scarcity (MRS)	kg Cu eq	4.08	1.93	2.46	0.11
Fossil resource scarcity (FRS)	kg oil eq	302.38	230.05	259.53	14.32
Water consumption (WC)	m^3	358.32	278.55	519.86	0.87

[a] The total score for the global warming category includes 1 tonne of CO_2 captured from the atmosphere which results in a total positive score in BPMED (base case) and CEW.

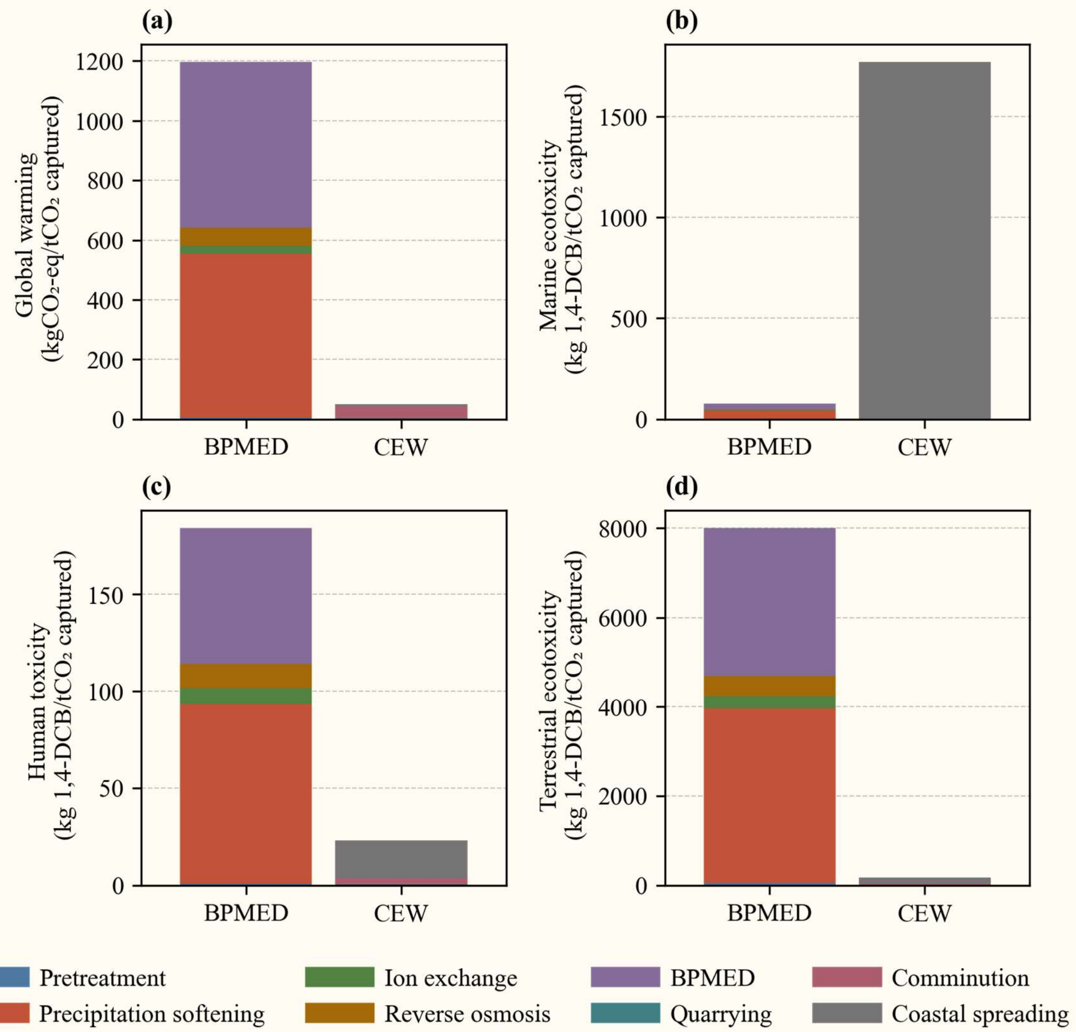

Figure 6.6 ReCiPe's 2016 midpoint environmental impact metrics per 1 tonne gross atmospheric CO_2 captured in each examined stage of CEW and BPMED base case: (a) life-cycle GHG emissions in kg CO_2 eq, (b) life-cycle marine ecotoxicity in kg 1,4-DBC, (c) human carcinogen toxicity in kg 1,4-DBC, and (d) life-cycle terrestrial ecotoxicity in kg 1,4-DBC.

The comparison of four important environmental impacts at midpoint score of each stage in BPMED base case and CEW are illustrated in Figure 6.6. Softening precipitation and BPMED stages influenced the global warming (Figure 6.6 (a)), marine ecotoxicity (Figure 6.6 (b)), terrestrial ecotoxicity (Figure 6.6 (c)) and human carcinogenic toxicity (Figure 6.6 (d)), while coastal spreading phase in CEW base case represents the main stage affecting this impact, particularly on marine ecotoxicity.

For climate impact, both systems are not considered as net-negative emissions technologies; however, the BPMED base case emits GHGs at a rate ten times higher than the CEW system (Figure 6.6 (a)). In BPMED-OAE, the precipitation softening and BPMED stages are the primary contributors to life-cycle GHG emissions, while in CEW, the comminution is the leading process of the system's carbon footprint. As discussed in the previous section, the reliance on the UK's fossil-fuel-based electricity and the high emissions from the softening agents were main reason behind carbon penalty of BMPED base case. In contrast, Europe's average electricity mix was the main hotspot of the comminution process in .

Terrestrial ecotoxicity and marine ecotoxicity impact from both BPMED and CEW followed the same trend of climate impact. However, BPMED base case affected terrestrial ecotoxicity impact (8,002.98 kg 1,4-DCB) more than forty times compared to the same impact of CEW (179.9 kg 1,4-DCB). This is due to the use of softening agents (soda ash and hydrated lime) in the precipitation softening process, which cause a substantial increase in the impact.

The coastal spreading process resulted in a higher marine ecotoxicity impact (1,768.30 kg 1,4-DCB) from the CEW process. The coastal spreading stage, where nickel emissions from olivine dissolution in seawater, contributed to marine ecotoxicity. These emissions can pose risks to marine organisms, leading to toxicological effects when nickel concentrations in organisms exceed certain threshold levels (Flipkens et al., 2023).

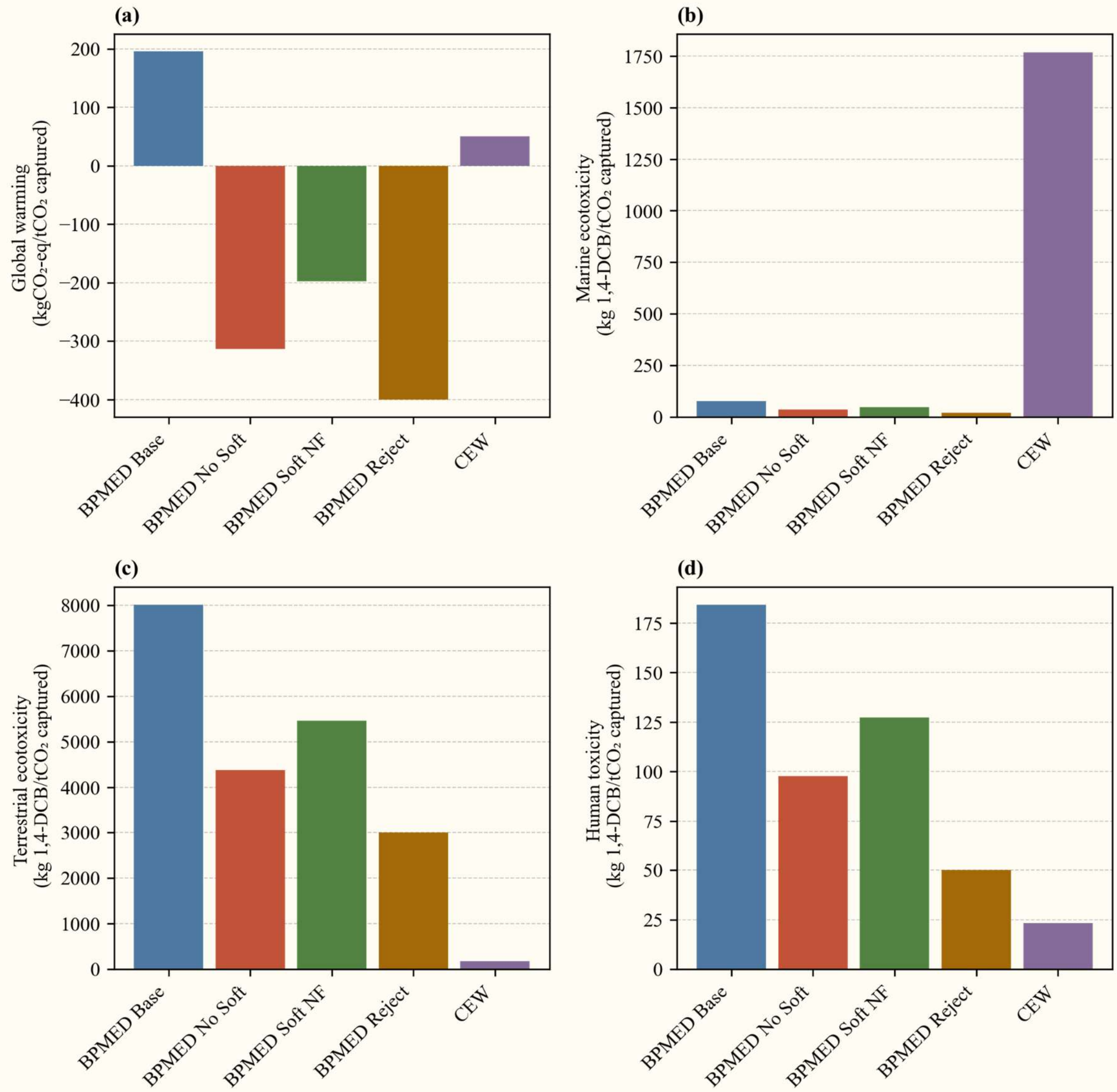

Figure 6.7 ReCiPe's 2016 total midpoint environmental impact metrics per 1 tonne gross atmospheric CO_2 captured for different system configurations when

considering 1 tonne of atmospheric drawdown (CEW, BPMED base case, BPMED No Soft, BPMED NF Soft, BPMED Reject): (a) life-cycle GHG emissions in kg CO_2 eq, (b) life-cycle marine ecotoxicity in kg 1,4-DBC, (c) life-cycle terrestrial ecotoxicity in kg 1,4-DBC, and (d) human carcinogen toxicity in kg 1,4-DBC. The comparison of various BPMED variants and CEW at midpoint score of ReCiPe 2016 (H) with different impacts are given in Figure 6.7.

In addition, terrestrial ecotoxicity and human carcinogenic toxicity impacts followed the same trend as the climate impact. The BPMED base case had the highest impact, followed by BPMED with softening via nanofiltration, BPMED without softening, BPMED with waste rejection, and finally CEW. On the other hand, CEW showed the greatest impact on marine ecotoxicity compared to the BPMED base case and its three variants. This is primarily due to the coastal spreading of olivine, which can release nickel emissions and potentially contaminate marine ecosystems and coastal environments.

Endpoint indicators

To simplify comparisons and facilitate interpretation of these two different OAE approaches, a weighting stage at endpoint by ReCiPe's 2016 (H) is implemented.

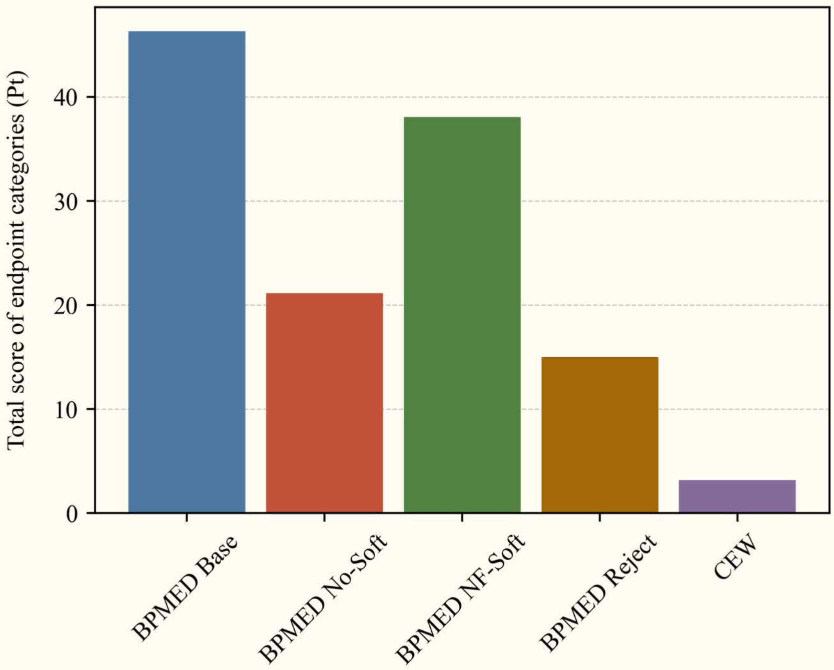

Figure 6.8 Weighting results of total score of CEW, BPMED base case, BPMED No Soft, BPMED NF Soft, and BPMED Reject cases per 1 tonne gross atmospheric CO_2 captured at ReCiPe's 2016 endpoint.

The cumulative score for all examined stages in BPMED based case, BPEMD without softening, BPMED with softening via nanofiltration, BPMED with reject waste its three variants, and CEW was 46.32 Pt, 21.14 Pt, 38.06 Pt, and 3.2 Pt, respectively.

The total weighting score of the BPMED base case and BPMED NF-Soft are approximately more than 10 times higher than that of the CEW process. On the other hand, the total endpoint score of both BPMED without softening process and BPMED with reject scenarios are substantially lower than the base case and softening via nanofiltration.

Based on previous deep analysis of endpoint score, the precipitation softening process in BPMED base case is the key driver contributing to the total score of 27.47 Pt, followed by the BPMED stage with a score of 22.73 Pt, and reverse osmosis with 6.53 Pt. This implies that BPMED variants without precipitation softening would contribute to a lower total impact. According to sensitivity analysis (Section 6.7.6), human health damage represents the most significant damage categories followed by ecosystems and resources for BPMED base case and its three variants.

The comminution stage in CEW is the dominant contributor, accounting for a total endpoint score of 1.73 Pt, while the quarrying and coastal spreading phases each had total weighted scores of less than 1 Pt. According to Foteinis et al. (2023), human health is the most significantly affected damage category, followed by ecosystems and resources. In addition, the comminution stage affected human health impacts with the approximately 1.6 Pt.

The comparison results clearly indicate that each analysed stage in the BPMED base case and its three variants contributes higher weighting points than all stages in CEW, suggesting that the BPMED-OAE approach has a significantly larger impact at the endpoint compared to the CEW approaches.

Summary

LCA comparison results of BPMED base case and three variants (no softening, softening via nanofiltration and reject stream) and CEW under current assumptions are summarised as follows:

- The BPMED base case and its three variants contribute a larger environmental impact across most categories compared to CEW technologies, except for marine ecotoxicity, stratospheric ozone depletion, and global warming (only BPMED base case).

- Neither BPMED base case nor CEW qualifies as a net-negative emissions technology, as both generate more emissions than the amount of atmospheric CO_2 drawdown.

- BPEMD without softening and softening via NF variants are CO_2 negative technologies when considering 1 tonne atmospheric CO_2 drawdown and these two performed better than CEW in terms of climate impact.

- The comminution stage in CEW acts as the main environmental hotspot, followed by the coastal spreading and quarrying.

- The key driver of CEW's environmental footprint is its reliance on fossil fuel-based electricity for olivine comminution, accounting for 50.6% of total impact. Nickel

(Ni) release during olivine weathering is the second-largest contributor, making up to 20.9% of the total impacts.

- Nickel emissions released during the coastal spreading stage significantly contribute to marine ecotoxicity impact.
- The use of softening agents in the precipitation process stage is a major contributor to emissions; removing this step or reducing the amount of softening agents in BPMED significantly reduces CO_2 emissions.
- Fossil fuel-based electricity consumption for BPMED operation and softening agents in softening precipitation are two main hotspots of environmental burden in the BPMED and its three variants, particularly GHG emissions, terrestrial ecotoxicity impacts, and human non-carcinogenic toxicity.
- At endpoint level, BPMED base case contributed the largest total score, followed by BPMED with softening via nanofiltration, BPEMD without softening, BPMED with waste rejection, and CEW.
- In BPMED base case, the precipitation softening process and BPMED are the two largest contributors to the total endpoint score, whereas the comminution is the main contributor stage in CEW.
- Human health represents the most significant long-term damage category associated with the deployment of CEW, BPMED base case and its three variants.
- BPMED-OAE approach, including the base case and its three variants, has a significantly larger impact at the endpoint indicator compared to the CEW approach. However, this comparison is based on specific assumptions for both case studies.
- According to the recommendations from the LCA study on CEW, employing multi-issue LCIA methods to assess a broad range of environmental impacts from CDR/OEA approaches is a preferable approach compared to selecting an LCIA method focused solely on carbon footprint impact.

7.0 Framework Part E: Classical economic analysis

Key recommendations:

- Where commercial sensitivities allow, all cost data should be transparently reported. If it is not possible to openly report underpinning cost assumptions, the techno-economic assessment must be independently verified.
- All input factors (e.g., engineering and procurement, maintenance, owner's costs, weighted cost of capital) must be transparently reported.
- Bottom-up costing for capital expenditure estimation should consider i) bare erected costs, ii) engineering, procurement, and construction costs, iii) contingencies appropriate for the technology readiness level (TRL) and project definition level, iv) start-up and owner's costs, and v) anticipated cost escalations during construction.
- Early-stage OAE approaches require the inclusion of substantial contingencies. Depending on the stage of the project and the level of design, these will likely be on the order of 50-100% of the engineering, procurement, and contractor costs.
- Cost analysis should be location specific. The timing of the CO_2 drawdown may also be accounted for via discounting methods.
- Capital costs should be amortised together with discounted future cash flows to calculate their net present value, and the levelised cost of net carbon removed.

In this section, recommended practices for performing a classic techno-economic assessment are provided and exemplified through the proposed case study. This methodology represents the conventional approach used to assess FOAK project costs across various industries (see definition in Section 2.4). Using this method, a consistent approach to cost estimation and techno-economic assessment can be made, which is essential for benchmarking and comparing emerging technologies. Special emphasis is given to elements of specific importance to OAE. Part F discusses how to derive N^{th}-of-a-kind project costs from the FOAK cost estimated in this section.

7.1 Nomenclature

Using shared nomenclature when evaluating project economics is essential when comparing and benchmarking different projects. Different nomenclatures proposed by DOE/NETL, IEAGHG, and EPRI have previously been unified by (Rubin et al., 2013) for CO_2 capture and storage projects, and this standard is recommended in this work, too. Definitions for cost elements have been adapted from (Rubin et al., 2013) and (DOE/NETL, 2021) and are shown in Table 7.1 below. Note that this nomenclature was harmonised for industrial and power sector CO_2 capture, utilisation, and storage, and may differ from nomenclature typically used in, e.g., the mining sector.

Table 7.1 Capital cost elements for projects and facilities.

Capital cost elements	Description
Bare erected cost (BEC)	Cost of process equipment, on-site facilities, and infrastructure that supports the plant, and labour required for construction and installation
Process equipment	Includes all materials and sales tax (if applicable)
Supporting facilities	On-site facilities needed for the project
Labour (direct and indirect)	Costs associated with personnel for equipment installation and construction (direct), and required supervisory, engineering, administrative, and support staff activities (indirect)
Engineering, procurement, and construction cost (EPC)	Comprises the BEC plus the cost of services provided by the EPC contractor
Engineering services	These services include detailed design, contractor permitting, and project/construction management
Total plant cost (TPC)	Comprises the EPC costs and project and process contingencies
Process contingencies	Contingency which accounts for the uncertainties of technology development status (e.g., technology readiness level)
Project contingencies	Contingency which accounts for the level of detail applied when estimating project costs
Total overnight cost (TOC)	Comprises the TPC, overnight costs, and owner's costs; 'overnight' costs assumes that additional costs during construction are ignored
Feasibility studies	Initial studies to assess project viability, including technical and economic analyses
Surveys	Site surveys, geological studies, and environmental assessments
Land	Cost of land acquisition
Insurance	Project insurance costs during construction
Permitting	Costs associated with obtaining necessary permits and licences
Finance transaction costs	Fees related to securing project financing
Pre-paid royalties	Advance payments for technology licences or intellectual property rights
Initial catalyst and chemicals	Start-up chemicals and catalysts required for first fill
Inventory capital	Working capital for spare parts and initial inventories
Pre-production (start-up)	Costs associated with plant commissioning and initial start-up
Other site-specific items unique to the project	They may include items sometimes referred to as 'outside the battery limits'; examples include site improvements, transmission interconnects, and economic development incentives
Total capital requirement (TCR)	Sum of all capital expenditures incurred during the capital expenditure period
Interest during construction	Financing costs accrued during the construction period
Cost escalations during construction	Increases in costs due to inflation and market changes during the construction period

Table 7.2 Operating cost elements for projects and facilities.

Operating cost elements	Description
Fixed operating costs (FOC)	Costs assumed to be independent of the project's output
Operating labour	Staff directly involved in project operations
Maintenance labour	Personnel costs for routine and preventive maintenance activities
Administrative and support labour	Office staff, management, and support personnel costs
Maintenance materials	Spare parts, tools, and materials used for equipment maintenance and repairs
Property taxes	Local and state taxes based on facility value
Insurance	Property and liability insurance premiums
Variable operating costs (VOC)	Costs assumed to be dependent on the project's output
Energy and utilities	Energy and utility source costs (e.g., coal, natural gas, biomass, electricity)
Feedstocks	Raw materials that serve as the primary inputs for the production process (e.g., minerals)
Consumables: *Catalysts* *Membranes* *Chemicals* *Auxiliary fuels* *Water*	Includes all materials used in proportion to the plant capacity (itemised for each project)
Waste disposal*	Costs for handling, treating, and disposing of waste materials
Transportation*	Costs for moving materials to/from facility; for OAE, this could include ship-based delivery and spreading of alkaline solids or pipeline costs for alkaline liquid delivery
Storage*	Costs for maintaining inventory of materials and products
Monitoring, reporting, and verification**	Costs associated with environmental compliance, emissions monitoring, data collection, reporting, and third-party verification
By-product sales (credit)	Revenue from selling secondary products or waste materials
Emissions tax (or credit)	Charges for emissions or credits for emissions reduction

**Transport, storage, and waste disposal may also be capital cost items, depending on project scope*
***May also be treated as a fixed operating cost, or capital cost item, depending on project scope*

7.2 Cost estimation methodology

7.2.1 Capital cost estimation

Capital cost estimation aims to identify and quantify all capital expenses needed to develop, construct, and commission/start up a project. The most inclusive capital expense category following the nomenclature used here is the total capital requirement (TCR). The different costs adding up to the TCR are discussed below. This departs from an estimate of the bare erected cost (BEC), that is, the bare costs of purchasing and installing equipment/hardware. There are different ways to quantify equipment costs, bare erected costs, and other cost categories, also discussed below. It is understood that not all OAE projects are of the process engineering kind, and some capital expenses may be in the form of ships or mining equipment. Where needed, specific capital cost categories not relevant to the OAE project can be omitted, while others not listed here may need to be added. We highlight again that the capital costing methodology presented here is a classical TEA, which, by definition, estimates the cost for the next project (not for aspirational projects further in the future) (Roussanaly et al., 2021; Rubin, 2019). In the case of emerging technologies, this normally means the first demonstration or commercial project, i.e., the FOAK plant.

Step 1: Bare erected costs (BEC)

The following methods, listed in order of decreasing accuracy, can be used to estimate costs associated with materials, labour (both direct and indirect), and supporting facilities required for plant construction and installation for feasibility or budget studies. Out of scope here are the very detailed cost estimates used for (final) investment decisions that usually specify every single item to be included (up to the smallest detail) plus firm offtake quotes with vendors:

1. **Vendor quotes:** Cost estimates are obtained directly from vendors for the specific application and equipment specifications (e.g., sizing, operating conditions). These costs may include installation requirements.
2. **Reference cost values from high-quality reports:** Organisations such as the DOE and NREL publish comprehensive reports with benchmark cost values (BECs) for various equipment and processes (e.g., (Hughes et al., 2023; Zoelle and Kuehn, 2019).
3. **Cost estimation software:** Specialised software packages supported by extensive databases (e.g., Aspen Capital Cost Estimator, (AspenTech, 2023)) can provide relevant, first-tier estimates for equipment purchase costs and installation requirements (labour and supporting facilities). Cost estimation software adjusts costs per equipment type and is based on large surveys across the chemical and process engineering industry. Additionally, cost estimation through software is a consistent and comparable method, aiding interpreting and comparison.
4. **Correlation-based methods:** Equipment costs can be estimated either using correlations from literature or by scaling from a single reference cost for specific equipment size. When using correlations, cost scaling (Eq. 7.1) or parametric equations (Eq. 7.2) can be employed, although they are generally more uncertain. Equipment cost correlations are available in literature sources such as (Sinnott and Towler, 2020b; Woods, 2007). For cost scaling, C_{eq} is the cost of the equipment, S_{eq} the size of the equipment, C_{ref} the cost of the reference equipment, and S_{ref} the sizing of the reference equipment.

$$C_{eq} = C_{ref} \cdot \left(\frac{S_{eq}}{S_{ref}} \right)^{n} \quad \text{(Eq. 7.1)}$$

For parametric equations, C_{eq} is a function of equipment parameters/sizing (S_m) and parameters used to fit the cost correlation (A_m and n_m).

$$C_{eq} = f\left(S_1, \ldots S_m, A_0, \ldots A_m, n_1, \ldots n_m \right) \quad \text{(Eq. 7.2)}$$

$$Example:\ C_{eq} = A_0 + A_1 S_1^{n_1} + A_2 S_2^{n_2} \quad \text{(Eq. 7.3)}$$

When scaling from a single reference cost (using Equation 7.1), differences in equipment sizing specifications should be adjusted using an appropriate scaling factor (n). A value of 0.6 can be assumed for n. However, for modular technologies which scale linearly (e.g., membranes), a value of 0.9 or greater should be applied. If the equipment sizing is multiple orders of magnitude larger than the reference scale (S_{ref}), a different cost estimation source should be used.

Material adjustments: Differences in material specifications should be adjusted using appropriate material cost factors. This factor accounts for changes in material costs and labour costs associated with the material used for equipment construction. More recent material factors from (Aromada et al., 2021) are recommended. Here, f_m refers to the material factor of material A or B.

$$C_{\mathrm{eq,B}} = \frac{f_{\mathrm{m,B}}}{f_{\mathrm{m,A}}} \cdot C_{\mathrm{eq,A}} \tag{Eq. 7.4}$$

Installation costs: BECs comprise equipment construction and installation costs. If the latter is not included in the cost value obtained (i.e., only the cost of equipment as delivered to the site is included), it can be estimated using installation cost factors. Well-known installation factors such as Lang factors, Hand factors, or factors available in (Sinnott and Towler, 2020b; Smith, 2005; Woods, 2007) are outdated, lack better considerations for variations in installation requirements and value/scale of the equipment, and are thus unrecommended.

In this framework, it is recommended to use the method in (Aromada et al., 2021) for estimating installation costs. The method provides a set of detailed factors (f_i) which account for the costs of labour, piping, instrumentation, electricals, buildings, site development, and ancillary buildings (which form the sum of direct installation costs). To obtain BEC of the equipment, detailed installation factors (f_i) are summed and multiplied by the equipment costs (C_{eq}).

$$BEC_{eq} = C_{eq} \cdot \sum_i f_i \tag{Eq. 7.5}$$

$$BEC_{eq} = f_I \cdot C_{eq} \tag{Eq. 7.6}$$

Time and location adjustments. The cost estimate obtained seldom aligns with the geographic and temporal scope of the TEA study. For instance, costs may be obtained for a particular country or region, while the studied project may be located in another region. Likewise, equipment costs may be obtained for a different base year. In these cases, costs need to be adjusted using location factors and/or cost indices.

1. <u>Cost escalation:</u> Cost estimates provided for a past year should be adjusted (escalated) to the base cost year selected for a study since equipment costs are subject to inflation and other price changes over time. This adjustment is performed using cost indices such as the chemical engineering plant cost index (CEPCI). Note that the CEPCI is valid for the USA and that for other countries or regions, a different cost index ideally should be applied, such as WEBCI (Netherlands), Chemie Technik (Germany), UCCI (Global), or Intratec plant cost index (ca. 33 different countries). It is noted these indices may be difficult to access

in the public domain/free of charge, in which case a fallback option is to use the CEPCI. Here, CI refers to the cost index at time A or B.

$$BEC_{eq,B} = \frac{CI_B}{CI_A} \cdot BEC_{eq,A} \tag{Eq. 7.7}$$

2. Location factors: Equipment construction and installation costs have geographical differences due to varying labour and material costs. Many EPC contractors have their own database with location factors. Location factors can also be sourced from specialist construction resources, e.g., here, factors are used from the 'COMPASS Construction Yearbook' (2023). Here, f_{loc} refers to the location factor of location A or B.

$$BEC_{eq,B} = \frac{f_{loc,B}}{f_{loc,A}} \cdot BEC_{eq,A} \tag{Eq. 7.8}$$

Step 2: Engineering procurement and construction costs (EPC)

Fees for engineering design, procurement, and construction costs for a project are included in the EPC cost. If contractor quotes are unavailable, these costs can be estimated. Often this is costed as a percentage of the total BEC (typically 7 to 15% of BEC costs, (Rubin et al., 2013)):

$$EPC = (1 + f_{EPC}) \cdot BEC \tag{Eq. 7.9}$$

However, such estimates lack consideration of the size of the investment and/or plant scale, and location of the study. It is instead recommended to follow the approach in (Aromada et al., 2021) for estimating EPC costs, which applies specific EPC factors to individual equipment costs:

$$EPC = \sum_i (1 + f_{EPC,i}) \cdot BEC_{eq,i} \tag{Eq. 7.10}$$

Step 3: Total plant costs (TPC)

Total plant costs include the EPC costs plus required contingencies. Contingencies account for the expected capital cost increases that occur as the project develops. Two types of contingencies are normally considered. The process contingency accounts for the state of development of a process (e.g., indicated as TRL), and it quantifies the additional capital costs required as a technology matures, to cover costs still unforeseen at the pre-commercial level and/or costs associated with engineering out the problems that inevitably arise during upscaling. Think, for instance, about severe equipment fouling when operating in a real seawater environment. Additional capital items may need to be included in the design to ensure reliable continuous operation without plant trips due to fouling issues.

The project contingency, on the other hand, accounts for additional capital costs due to specific site requirements and level of detail of the engineering design (often low for feasibility or concept studies). These contingencies are included in the total plant costs.

While project contingencies are applied to the project as a whole, process contingencies can be applied with different values to individual equipment costs, depending on the equipment or unit's TRL. Works by (Roussanaly et al., 2021; Rubin, 2019; Rubin, 2012) give helpful explanations of what process and project contingencies include, and why they need to be added. Recommended values for both are presented in Tables 7.3 and 7.4.

Table 7.3 Recommendations for process contingency values.

Description	**TRL**	**Process contingency** (% of EPC cost)
New concept with limited data	~3	40+
Concept with bench-scale data	~4	30 – 70
Small pilot plant data	5 – 6	20 – 35
Full-sized modules have been operated	7 – 8	5 – 20
Process is used commercially	9	0 – 10

Table 7.4 Recommendations for project contingency values.

Class	**Design effort**	**Project contingency** (% of EPC plus process contingencies)
AACE 5	Conceptual	30 – 50
AACE 4	Simplified	20 – 30
AACE 3	Preliminary	15 – 30
AACE 2	Detailed	5 – 15
AACE 1	Finalised	5 – 10

Process contingencies can be applied to the BEC of equipment, whereas the project contingency is applied to the total of EPC and BEC.

$$TPC = (1 + f_{project}) \cdot (1 + f_{process}) \cdot EPC \qquad \text{(Eq. 7.11)}$$

Process contingencies, if varied for individual pieces of equipment or by plant section, can be applied in the following way:

$$TPC = (1 + f_{project}) \cdot \sum_i (1 + f_{process,i}) \cdot EPC_{eq,i} \qquad \text{(Eq. 7.12)}$$

Note that some sources suggest applying the process contingency to the BEC instead of the EPC. This approach is also correct and will drive proportionally higher engineering and construction management fees, as these services are typically calculated as percentages of the total installed equipment cost.

Step 4: Total overnight costs (TOC):

Various owner costs associated with the project such as those listed in Table 7.1 are included in the TOC. Variable and fixed operating costs should be estimated before calculating the TOC, since start-up costs are estimated as a function of some operating cost. Currently, the methodology shown in (DOE/NETL, 2021) provides the most comprehensive estimate for owner's costs, spares, and start-up costs.

$$C_{start-up} = f_{st,cap} \cdot TPC + f_{st,lab} \cdot FOC_{Labor} + f_{st,chem} \cdot VOC_{Chem} + f_{st,E\&F} \cdot VOC_{E\&} \quad \text{(Eq. 7.13)}$$

$$TOC = TPC \cdot (1 + f_{Own} + f_{spares}) + C_{start-up} \quad \text{(Eq. 7.14)}$$

Step 5: Total capital requirement (TCR)

Finally, additional costs and financing required during the period of plant construction (i.e., cost escalation) are included in the TCR. The financing cost can be calculated as shown below based on the discount rate or weighted average cost of capital (r), total construction period (T), and capital distribution (D_n) in each year (n). DOE/NETL recommend construction periods of three or five years and with a 10/60/30 or 10/30/25/20/15 distribution over these years, respectively ((DOE/NETL, 2021). However, early-mover technologies with demo-scale capacities may consider a shorter construction period.

$$f_{TCR} = \sum_{n=1}^{N} D_n \cdot (1 + r)^{T-n+1} \quad \text{(Eq. 7.15)}$$

$$TCR = TOC \cdot f_{TCR} \quad \text{(Eq. 7.16)}$$

7.2.2 *Operating cost estimation*

Operating costs include sources of expenses required to maintain and operate a process (also known as operations and maintenance costs, or O&M). Expenditures are typically sub-divided into variable operating costs (VOC) and fixed operating costs (FOC), which describe costs which are assumed to be dependent (variable) or independent (fixed) on the production rate of the system.

VOC's include costs for feedstocks, utilities, consumables, waste disposal, transportation, by-product revenues, carbon taxes and credits, and monitoring, reporting, and verification (MRV) (depending on the MRV process). Variable operating costs can be calculated from the quantity used per annum (Q) of item i, and its price per unit (P), as shown:

$$VOC = \sum_{i} Q_i \cdot P_i \quad \text{(Eq. 7.17)}$$

Note that revenues from key products or by-products are also often added to variable costs.

FOC's include direct (e.g., operators, maintenance) and indirect (e.g., administration) labour costs, maintenance material costs, insurance costs, and taxes. These costs can be estimated as a function of other capital or operating cost elements. However, for OAE projects, especially those involving offshore operations or novel technologies, it may be necessary to adjust these standard estimation methods. Consider consulting with industry experts to refine these estimates for OAE-specific applications. Below, we have provided a standard guide to estimate operating costs:

Table 7.5 Operating cost estimation methods.

<table>
<tr><th>Operating cost components</th><th>Estimation method and considerations</th></tr>
<tr><td colspan="2">Variable operating costs</td></tr>
<tr><td>Feedstocks</td><td>From the required consumption rate (Q) and market price (P) of the feedstock, costs are calculated using Eq. 7.17.</td></tr>
<tr><td>Utilities</td><td>Costs for fuel, heating, cooling, electricity, water, instrument air, and purge gas (nitrogen) required for the process. Based on the net consumption rate (Q) utility costs are calculated using Eq. 7.17. When estimating utility costs, consider the following for each utility:
● Cooling: Consider the coefficient of performance (COP) for cooling systems or sources for cooling water costs, including both capital and operating expenses.
● Fuel: Use the mass flow rate of fuel, considering the fuel heating value and conversion efficiency in process simulations.
● Heating: Consider the source of heat (electricity or steam). For heat pumps, include reasonable COP values; for imported steam, use appropriate pricing (see Sinnott and Towler, 2020a).
● Water: Consider the source and treatment requirements (e.g., seawater, river water, tap water, pre-treated water, softened water, desalinated water, or higher-purity water).</td></tr>
<tr><td>Consumables</td><td>Lifetimes of consumables should be determined, and the quantity required per year (Q) is calculated from the lifespan (Life) and total quantity for a single fill (Q_L) (Eq. 7.18). Lifetimes of materials are normally described online or in product specification sheets. The quantity per year and price of the consumable can then be inputted to Eq. 7.17.
$$Q = \frac{Q_L}{Life}$$ (Eq. 7.18</td></tr>
<tr><td>Waste disposal</td><td>Waste disposal methods and costs vary by type of waste and local regulations. If prices and quantities are known, waste disposal costs can be determined using Eq. 7.17.</td></tr>
<tr><td>Transportation</td><td>Based on the transportation method (e.g., truck, pipeline, ship), transportation distance (Q), and cost per unit distance of the method (P), the transportation cost of material (e.g., feedstock, equipment, product) can be determined using Eq. 7.17.</td></tr>
<tr><td>Monitoring, reporting, and verification (MRV)</td><td>MRV costs for OAE should be estimated with caution, considering the significant uncertainties in measurement techniques and verification protocols. While Mercer et al., (2024) suggests a baseline cost of $28/tonne CO_2, this figure should be treated as preliminary given the nascent state of OAE technology and limited field deployment experience. A comprehensive uncertainty analysis is recommended.</td></tr>
<tr><td colspan="2">Fixed operating costs</td></tr>
</table>

Operating labour	The number of operators (NOp) required in a chemical plant can be estimated using a correlation by Alkhayat and Gerrard, (1984). Here, *P* is the number of process steps involving solids handling (incl. transport, grinding, separation), Nnp is the number of process steps not involving solid handling (incl. compression, heating, cooling, mixing, separation, reactors), Sh_{Total} is the total shifts per year, and Sh_{Op} is the shifts per operator per year. $$N_{Op} = \frac{Sh_{Total}}{Sh_{Op}} \cdot \sqrt{6.29 + 31.7 \cdot P^2 + 0.23 \cdot N_{np}} \quad \text{(Eq. 7.19)}$$ Alternatively, Webb et al., (2023) provide estimates for megatonne-scale DAC facilities, and suggest one full-time operator per 500 tonne/day CO_2 removal capacity. The costs per operator (wOp) is based on annual wages for chemical plant operators. $$C_{Op} = w_{Op} \cdot N_{Op} \quad \text{(Eq. 7.20)}$$ Of note, staffing requirements are different for larger 24/7 scale operations compared to pilot plants due to safety regulations and operational needs. While pilot plants might operate remotely and/or with reduced personnel during limited operating hours, commercial-scale plants requiring continuous operation must maintain minimum staffing levels across all shifts as mandated by workplace safety laws. These requirements cannot be circumvented by automation or remote operation systems alone.
Maintenance labour	Labour costs for maintaining plant equipment and facilities can be estimated as a fraction ($f_{Maint,Labour}$) of the TPC (calculated using Eq. 7.11). The total maintenance costs (labour and materials) of the plant can be estimated as 1.5 – 3% of the TPC (but can vary with process type), and 40% of this value can be estimated as the maintenance labour cost ($C_{Maint,Labour}$). Therefore, $f_{Maint,Labour}$ is typically estimated as 0.6 – 1.2% of the TPC. $$C_{Maint,Labour} = f_{Maint,Labour} \cdot TPC \quad \text{(Eq. 7.21)}$$
Maintenance materials	Materials required for maintenance are estimated as 60% of the total maintenance costs (which is 1.5 – 3% of the TPC). The total maintenance costs (labour and materials) of the plant can be estimated as 1.5 – 3% of the TPC (but can vary with the process type), and 60% of this value can be estimated as the maintenance labour cost ($C_{Maint,Mat}$). Therefore, $f_{Maint,Mat}$ is typically estimated as 0.9 – 1.8% of the TPC (calculated using Eq. 7.11). $$C_{Maint,Mat} = f_{Maint,Mat} \cdot TPC \quad \text{(Eq. 7.22)}$$
Administrative and support labour	Usually estimated as 20 – 30% of the total operating (C_{Op}, calculated using Eq. 7.20) and maintenance labour cost ($C_{Maint,Labour}$, calculated using Eq. 7.21) of the plant. $$C_{Admin} = f_{Admin} \cdot (C_{Op} + C_{Maint,Labor}) \quad \text{(Eq. 7.23)}$$
Insurance and property taxes	Usually estimated as a fraction ($f_{Ins,Tax}$) equal to 1 – 2% of TPC costs (calculated using Eq. 7.11). $$C_{Ins,Tax} = f_{Ins,Tax} \cdot TPC \quad \text{(Eq. 7.24)}$$

7.3 Economic analysis

The objective of economic analysis is to understand how the costs of a project balance the revenues, what return can be expected on an investment, and/or what the break-even cost of a product should be, given a desired return. At the root of all such evaluations is the time value of money. This means that a unit of money is worth more today than it will be next year. The reason for this is twofold: first, we normally see some inflation in an economy, meaning that money loses value over time – a revenue of \$100 in five years is worth less than a revenue of \$100 now. Second, and perhaps more importantly, an investor (bank, business, private person) will always invest their money to make a return. They can make safe investments (e.g., state loans or obligations) rendering modest returns (e.g., 1 – 3%), or more risky investments (e.g., in start-up companies), requiring a high return to justify the risk taken. Any investment will always be evaluated against the option to invest in a comparatively safe way, justifying a return of 7 – 8%. This return is the interest or discount rate against which cash flows (expenditures and revenues) are 'discounted'. It is often also called the cost of capital, or the weighted average cost of capital.

7.3.1 Weighted average cost of capital

The weighted average cost of capital (WACC) or discount rate represents the minimum rate of return that a company must earn on its investments to satisfy its investors and creditors. The WACC accounts for the cost of equity (r_e) and debt (r_d) financing, weighted by their respective proportions in a company's capital structure. This rate is significant because it serves as a hurdle rate for evaluating new projects and investments, helping companies determine whether a potential investment will generate sufficient returns to justify the use of capital.

$$WACC = \left(\frac{E}{E+D}\right) \cdot r_e + \left(\frac{D}{E+D} \cdot r_d \cdot (1 - f_{tax})\right) \qquad \text{(Eq. 7.25)}$$

Whether real (includes inflation) or nominal discount rates are used should be stated in the analysis. The choice of discount rate depends on the purpose of the study. While nominal discount rates can provide a fair comparison of technologies by abstracting impacts of inflation, real discount rates would provide more accurate assessments for locations with significant inflation.

The WACC varies significantly based on technology maturity, risk profiles, policy environments, and regional contexts. Novel technologies typically face higher rates (up to 20% for early-stage ventures) due to technological and market uncertainties (Donovan and Corbishley, 2016). However, government interventions can dramatically reduce financing costs through mechanisms like contract for difference schemes and regulated asset Base models (reducing rates to 4-7%) or state-backed financing (lowering rates to 1-5%) (Young et al., 2023). Geographic location creates substantial variations, with developing economies facing higher rates (>10%) compared to developed nations (<10%) due to differences in perceived country risk, policy stability, and capital market development (IEA, 2023; International Energy Agency, 2021; Polzin et al., 2021). For emerging technologies like OAE, the combination of technological novelty and underdeveloped market structures suggests higher discount rates are appropriate initially, though these may decrease as technologies mature and dedicated policy frameworks emerge, improving economic viability.

7.3.2 Discounted cash flow

In techno-economic assessment, cash flow analysis is used to determine the net present value (NPV) of the project by accounting for all sources of expenses and revenues over the project's lifetime. With a discounted cash flow, the value of future cash flows is discounted using the WACC to determine its present value. By discounting future cash flows to their present value, this DCF analysis accounts for the time value of money and provides a more accurate representation of a project's true worth. Additionally, it incorporates the concept of risk by using a discount rate that reflects the project's risk profile and the expected return on investment. Yearly cash flows (CF) are determined from the sum of net annual expenses such as capital, variable operating cost (VOC), fixed operating cost (FOC), and revenue. Net cash flows are then discounted by a rate (r) which is the WACC or discount rate of the project. The sum of discounted cash flows represents the total life-cycle cost of the plant. Any techno-economic study should use discounted cash flows instead of absolute cash flows to allow inter-project or inter-investment comparison for a selected base year.

$$CF_n = CAPEX_n + VOC_n + FOC_n - Revenue_n \quad \text{(Eq. 7.26)}$$

$$DCF_n = \frac{CF_n}{(1+r)^n} \quad \text{(Eq. 7.27)}$$

$$NPV = \sum_n DCF_n \quad \text{(Eq. 7.28)}$$

While capital recovery factors offer a simplified approach to calculating discounted cash flows, their use is not recommended for OAE projects or similar complex evaluations. Capital recovery factor methods assume uniform annual costs and revenues, which is particularly problematic for OAE projects where multiple cost elements (such as raw materials, energy, and carbon prices) can vary significantly over time. These temporal variations lead to different discounting effects that cannot be captured by the capital recovery factor approach. Therefore, a full discounted cash flow analysis, though more complex, provides a more accurate economic assessment by properly accounting for the time-varying nature of individual cost and revenue streams.

7.3.3 Real versus nominal

Discount rates (and WACC) should explicitly state whether they are in real (constant) or nominal (current) terms. This distinction affects how inflation is included in the economic analysis. Nominal or current terms represent actual prices in the year they occur, including the effects of inflation. Nominal cash flows reflect the actual monetary amounts expected to be received or paid out at future dates. Real or constant terms, on the other hand, remove the effects of inflation and express all values in constant dollars relative to a chosen base year. Real cash flows show the purchasing power of money, allowing for more meaningful comparisons across different time periods. While real or constant terms are generally recommended, the choice between real and nominal analysis should align with the goals and intended audience of the assessment. Whichever approach is chosen, it should be clearly stated and consistently applied throughout the analysis to ensure meaningful and accurate results.

7.4 Economic performance indicators

Unlike chemical plants designed to generate constant outputs, OAE technologies have time-variant CO_2 removal rates which are dependent on ocean conditions. Ocean and climate models that model the CO_2 drawdown versus time are available, and this time-series can be reflected in the indicator's calculation where possible or desired. Specifically, indicators such as the CO_2 removal rate and levelised cost of CO_2 removal must be well defined to appropriately quantify OAE processes.

Given these time-variant characteristics, the CO_2 accounting in cash flows can be approached in two ways: either as constant total values for the year (based on total efficiency of the alkalinity enhancement), or as a time series showing accumulations across different years. The choice between these methods largely depends on future regulatory frameworks, carbon pricing mechanisms, and MRV processes. Given this uncertainty in implementation, economic analyses may consider both accounting methods to provide comprehensive results. The cost impacts of this characteristic are demonstrated in Section 7.5.3.

The choice of economic indicator depends on whether product costs are known. If the revenues from product sales are known or can be specified, metrics such as payback periods or internal rates of return can be determined. Markets for CO_2 removal are still developing, and future prices of CO_2 are uncertain, so product costs (here, the cost of CO_2 removed) are more suitable KPIs for comparing economic performance of OAE projects.

7.4.1 Levelised cost of CO_2 removal

One helpful indicator for indicating the economic viability of a CDR technology is the levelised cost of CO_2 removal. Levelised costs generate a constant price value for a process (but under the strict assumption that expenses and revenues remain constant over the project lifetime) and represent the minimum cost required to meet all expenses over a plant's lifetime (i.e., total life-cycle cost of a plant). For CDR processes, the levelised cost of CO_2 removal (LCCR, \$/tonne CO_2 net removed) quantifies the costs per tonne of net CO_2-eq net removed. The LCCR is obtained from the project cash flow by determining the price value required to match the net present value of the project (at the end of the plant's lifetime). The derivation below represents this operation, and the final equation is the most commonly represented form of this calculation in literature:

$$LCCR = \frac{NPV}{\sum_n \frac{m_{CO_{2,n}}}{(1+r)^n}} \quad \text{(Eq. 7.29)}$$

Other definitions of levelised costs have been proposed. However, the definition shown in Equation 7.29 is widely used by the IEA, DOE/NETL, and department for business, energy & industrial strategy (UK), and is the recommended method for project's that need to account for varying costs over their lifetime (e.g., wind/solar plants or biochar) (Aldersey-Williams and Rubert, 2019).

7.4.2 Payback period

The payback period (*pp*) indicates the time at which the NPV of the plant is zero (i.e., when the project recovers its initial investment). It can be determined from the discounted cash flow analysis by identifying the year or period at which the cumulative NPV of the plant is negative (which in this case implies that the revenue is greater than expenses) (Eq. 7.31). The cost of CDR would need to be assumed to determine the payback period, and this value could be based on future tax values or projections from other economic models. The payback period (*pp*) is found when the NPV becomes positive when summed from year 1 to *pp*; for example, in a 25-year cash flow, *pp* would lie between years 1 and 25 (Eq. 7.33).

$$0 < NPV \tag{Eq. 7.30}$$

$$0 < \sum_{n=1}^{pp} \frac{CF_n}{(1+r)^n} \tag{Eq. 7.31}$$

$$0 < \sum_{n=1}^{pp} \frac{CAPEX_n + VOC_n + FOC_n - Revenue}{(1+r)^n} \tag{Eq. 7.32}$$

$$Example : 0 < \frac{CF_1}{(1+r)^1} + \frac{CF_2}{(1+r)^2} + ... + \frac{CF_{pp}}{(1+r)^{pp}} \tag{Eq. 7.33}$$

7.4.3 Internal rate of return

The internal rate of return indicates the minimum return to investors required to achieve a NPV of zero at the end of the project's lifetime. It can be determined from the discounted cash flows by equating the project's discount rate to the internal rate of return and adjusting it until the NPV of the project is zero. Similar to the payback period, a cost of CO_2 removal would be assumed. An example of a 25-year-long cash flow is shown in Equation 7.37; in this case, the internal rate of return would need to be guessed until an NPV of zero is obtained at year 25 (e.g., through Excel's solver or goal seek, or root finders in Python).

$$0 = NPV \tag{Eq. 7.34}$$

$$0 = \sum_{n} \frac{CF_n}{(1+IRR)^n} \tag{Eq. 7.35}$$

$$0 = \sum_{n} \frac{CAPEX_n + VOC_n + FOC_n - Revenue}{(1+IRR)^n} \tag{Eq. 7.36}$$

$$Example : 0 = \frac{CAPEX_1 + VOC_1 + FOC_1 - Revenue}{(1+IRR)^1} + \ldots$$
$$+ \frac{CAPEX_{13} + VOC_{13} + FOC_{13} - Revenue}{(1+IRR)^{13}} + \ldots + \frac{CAPEX_{25} + VOC_{25} + FOC_{25} - Re}{(1+IRR)^{25}} \tag{Eq. 7.37}$$

7.5 Case study: Classical TEA implementation

This example demonstrates the application of the classical TEA methodology to the BPMED case study for a FOAK deployment. The technology uses seawater as the brine feedstock, which requires considerable treatment to meet the needs of BPMED. We have separately considered the application of BPMED to desalination waste brines by analysing alternative variants of the technology (Section 7.5.4). The calculations are based on data for the year 2023 and SSP2EU-PkBudg500 scenario from the REMIND model, initially focusing on a facility located in Washington, USA, as the reference case. While the primary demonstration uses Washington as the reference location, comparative results are also presented for multiple geographical locations to illustrate the framework's adaptability and highlight regional economic variations.

7.5.1 Cost estimation

Capital costs

Equipment cost estimates from Table 5.5 (obtained from Eisaman et al., (2018)) were adjusted following the guidelines in Section 7.2.1. Table 7.6 shows the cost values after each adjustment step. The sum of the final adjusted item costs (last column) represents the total BEC of the plant. Capital cost elements (EPC, TPC, TOC, and TCR) were estimated from the total BEC (Table 7.7).

Table 7.6 BEC estimation showing sequential adjustments for equipment sizing, material selection, installation requirements, time escalation, and location factors for the BPMED case study.

Equipment list	Quant.	Bare erected cost estimates (US$$_{2023}$)					
		Ref.	Size (Eq. 7.1)	Material (Eq. 7.4)	Installation (Eq. 7.5)	Time (Eq. 7.7)	Location (Eq. 7.8)
Electrodialysis	4	1,690,800	1,727,696	N/A	4,509,286	5,966,523	5.787,528
Electrodialysis membranes	4	460,000	471,167	N/A	N/A	623,431	604,728
Reverse osmosis	1	5,782,752	N/A	N/A	N/A	8,287,780	8,039,147
Ion exchange	1	120,700	122,450	N/A	408,982	541,150	524,915
Clarifier	1	69,200	70,203	N/A	244,307	323,258	313,560
						BEC SUM	**15,269,877**

Operating costs

Operating cost items were calculated based on the methodology presented in Section 7.2.2. The summation of these costs represents the total annual operating expenditure for the plant, with first-year costs detailed in Table 7.8.

Table 7.7 Summary of FOAK capital cost elements for the BPMED case study. Cost additions leading to each value are shown as preceding items.

Capital cost element	Cost (US$$_{2023}$)
Bare erected costs (BEC)	**15,269,877**
Engineering/procurement/construction fees	+673,198
Engineering, procurement, and construction costs (EPC)	**15,943,075**
Process contingency	+4,167,737
Project contingency	+8,044,325
Total plant costs (TPC)	**28,155,138**
Owner/start-up/spare costs	+3,155,198
Total overnight costs (TOC)	**31,310,335**
Additional financing	+5,920,784
Total capital requirement (TCR)	**37,231,120**

Table 7.8 First-year operating cost breakdown for the BPMED case study.

Operating cost element	***Cost (US$$_{2023}$ year^{-1})***
Variable operating costs	
Electricity	2,607,576
Chemicals	991,707
Membranes	178,333
Fixed operating costs	
Operating Labour	1,032,070
Maintenance Labour	337,862
Administrative and Support Labour	410,979
Maintenance Materials	506,792
Taxes and Insurance	281,551
Total Operating Costs	6,346,872

7.5.2 Economic analysis

<u>*Discounted cash flow and net present value:*</u>

Total capital requirement (TCR), variable operating costs (VOC), and fixed operating costs (FOC) were calculated following Section 7.2. This case study focuses on determining product costs; therefore, the cash flow analysis considers only plant expenses (revenue from non-carbon benefits = 0). Table 7.9 presents the full discounted cash flow, with representative years 4, 13, and 28 shown for illustration. The project's NPV is calculated at -105.5 $M.

Table 7.9 Discounted cash flow analysis showing capital expenditure, operating costs, net cash flow, discount factors, and cumulative NPV for the BPMED case study. Costs are in US$ 2023.

End of Year	*Capital Expenses ($)*	*Variable Operating Costs ($)*	*Fixed Operating Costs ($)*	*Cash Flow ($)*	*Discount Factor*	*Discounted Cash Flow ($)*	*Net Present Value ($)*
Plant Construction							
1	*3,443,423*	-	-	*-3,443,423*	*0.95*	*-3,263,908*	*-3,443,423*
2	*21,004,881*	-	-	*-21,004,881*	*0.90*	*-18,871,886*	*-22,135,795*
3	*12,775,100*	-	-	*-12,775,100*	*0.85*	*-10,879,450*	*-33,015,244*
Plant Operation							
4	-	*3,777,617*	*2,569,255*	-6,346,872	*0.81*	*-5,123,302*	*-38,138,546*
:	:	:	:	:	:	:	:
13	-	*3,777,617*	*2,569,255*	-6,346,872	*0.50*	*-3,164,301*	*-73,756,739*
:	:	:	:	:	:	:	:
28	-	*3,777,617*	*2,569,255*	-6,346,872	*0.22*	*-1,417,395*	-105,518,666

7.5.3 Economic performance indicators

<u>*Levelised cost of net CO_2 removal*</u>

The levelised cost of CO_2 removal (LCCR) represents the break-even price of CO_2 removal that makes the project's NPV equal to zero. While the equation for LCCR appears to discount the physical quantity of CO_2 removed, it actually discounts the expected revenue stream from the CO_2 removal service. The net CO_2-eq removed is determined using the methodology presented in Section 5.5.1. The discounted revenue from the CO_2 removal is shown in Table 7.10. Two methods used to account for the CO_2 removal each year were considered to demonstrate their impact on the levelised cost of CO_2 removal. The first method quantifies the CO_2 removed as the CO_2 efficiency fully applied to the year of alkaline material addition (a more 'conventional' approach). The second method quantifies the real CO_2 drawdown over time following the drawdown curves obtained from (Zhou et al., 2024)).

The FOAK LCCR is calculated by dividing the project's total discounted costs (NPV) by the sum of discounted revenues from CO_2 removal over the project lifetime. When this calculated LCCR is used as the CO_2 removal price, the project's NPV equals zero, representing the minimum price needed for economic viability. As shown below, the method in which carbon is accounted for in the cash flow creates a significant difference in costs (+32%).

Table 7.10 Annual net CO_2-eq removal quantities and corresponding discounted revenue streams used in LCCR calculation. Two methods for accounting CO_2 in the cash flows are shown. Method 1 quantifies the total expected CO_2 removed in the year at which alkaline material is added. Method 2 quantifies the real CO_2 drawdown each year.

Year	$m_{CO_{2_{net,eq}}}$ **(tonne)**		***Discount Factor***	$\sum_n \frac{m_{CO_{2,n}}}{(1+r)^n}$ **(tonne)**	
	Method 1	*Method 2*		*Method 1*	*Method 2*
Plant Construction*					
1	0	0	0.95	0	0
2	0	0	0.90	0	0
3	0	0	0.85	0	0
Plant Operation					
4	2538	-5526	0.81	2049	-4461
:	:	:	:	:	:
13	2538	2500	0.50	1265	1247
:	:	:	:	:	:
28	2538	2538	0.22	567	567
Post-Operation					
29	0	8064	0.22	0	1707
:	:	:	:	:	:
42	0	5	0.11	0	0.5
Total	**63,444**	**63,444**	**-**	**28,990**	**21,937**

* No removal occurs during years of plant construction

Levelised cost of net CO_2 removed (net LCCR):

$$Method1 : LCCR = \frac{NPV}{\sum_n \frac{m_{CO_{2,n}}}{(1+r)^n}} = \frac{105,518,666}{28,990} = 3640 \text{ \$ per tonne } CO_{2,eq}$$

$$Method2 : LCCR = \frac{NPV}{\sum_n \frac{m_{CO_{2,n}}}{(1+r)^n}} = \frac{105,518,666}{21,937} = 4810 \text{ \$ per tonne } CO_{2,eq}$$

The notably high-cost values are primarily driven by process-related emissions that effectively penalise the net CO_2 removal cost calculation. To better understand the underlying economics without this emission penalty, it is more appropriate to consider the gross levelised cost of CO_2 removal. When recalculated using both methods, the cost difference between the two methods remains significant although smaller at 8% (compared to the 32% difference in net costs).

Levelised cost of gross CO_2 removed (gross LCCR):

$$Method1 : LCCR = \frac{NPV}{\sum_n \frac{m_{CO_{2,n}}}{(1+r)^n}} = \frac{105,518,666}{97,979} = 1077 \text{ \$ per tonne } CO_{2,eq}$$

$$Method2: LCCR = \frac{NPV}{\sum_n \frac{m_{CO_{2,n}}}{(1+r)^n}} = \frac{105,518,666}{90,926} = 1160 \text{ \$ per tonne } CO_{2,eq}$$

7.5.4 Comparison of electrodialysis case study variants

Our comparison of four electrodialysis process designs (Base with precipitation softening, No Soft, Soft NF with nanofiltration, and Reject using waste resources) reveals that the Base case in fact emits more CO_2 than it removes when applying standard TEA and LCA methods. This counterintuitive result stems from the high carbon intensity of precipitation chemicals (soda ash, lime), which creates substantial carbon penalties. The Reject case shows the most promising economics, at approximately $1,200 per tonne CO_2 removed.

For greenfield installations, avoiding softening entirely would be optimal, but when softening is necessary, nanofiltration (Soft NF) proves significantly more sustainable than precipitation methods under current conditions. When emission penalties are excluded – simulating a decarbonised future – both the No Soft and Soft NF cases demonstrate comparable economics, with costs of approximately $900 and $1,000 per tonne CO_2, respectively.

The analysis clearly demonstrates that background system emissions (upstream materials and energy) contribute most significantly to overall costs. As these background systems become increasingly decarbonised, electrodialysis will become more economically viable, and the technical constraint of softening would not substantially impact economic feasibility. The cost breakdown analyses of both capital expenditure (CAPEX) and operating expenditure (OPEX) items further support these conclusions, highlighting specific components that could be targeted for cost reduction strategies.

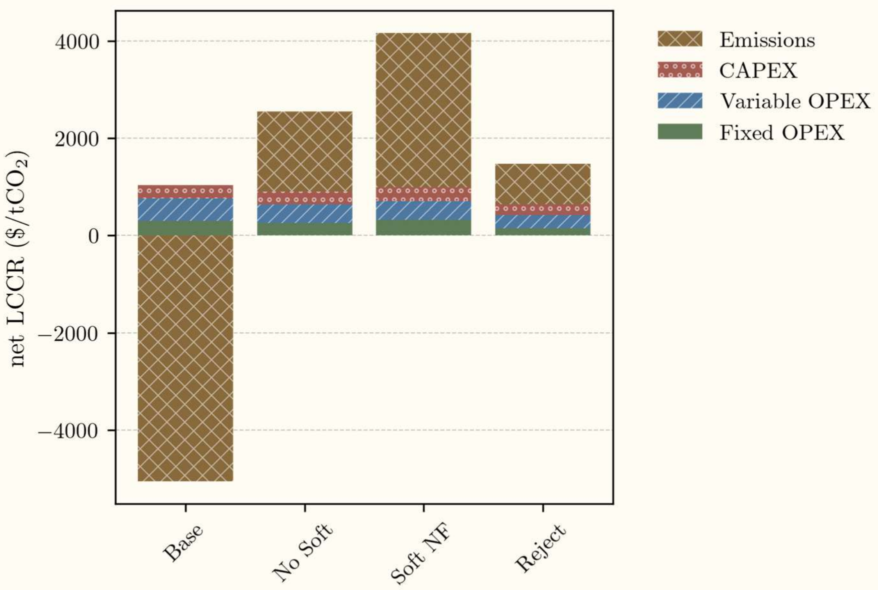

Figure 7.1 Levelised cost of net carbon removed (net LCCR) for four process variants: electrodialysis without softening (ED), with precipitation-based softening (ED-Prcp), with nanofiltration-based softening (ED-NF), and using waste streams only (ED-

Reject). Each bar shows the cost breakdown between CAPEX, variable OPEX, fixed OPEX, and carbon emission penalty.

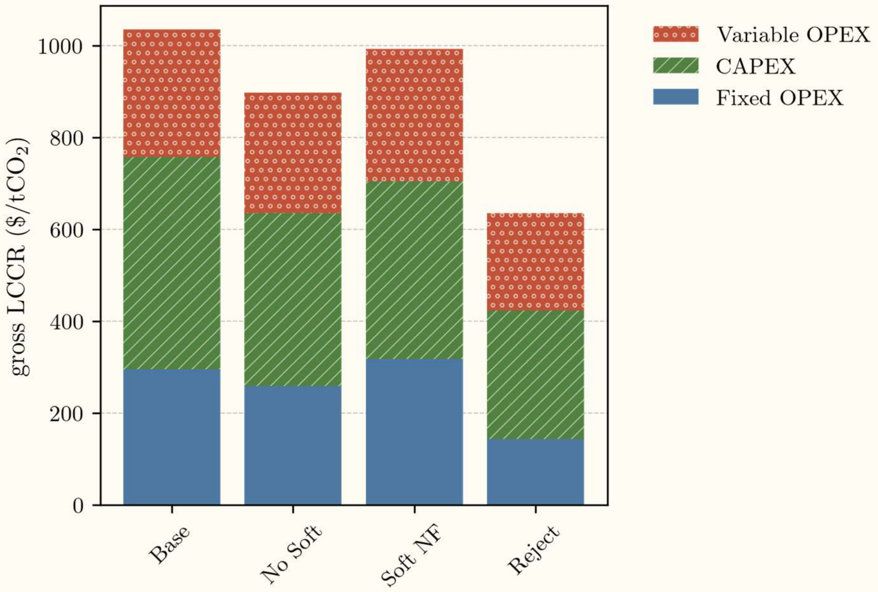

Figure 7.2 Levelised cost of gross carbon removed (gross LCCR) for the four case study variants of the electrodialysis process. The bars indicate the relative contributions of CAPEX and OPEX to the total cost for each process configuration.

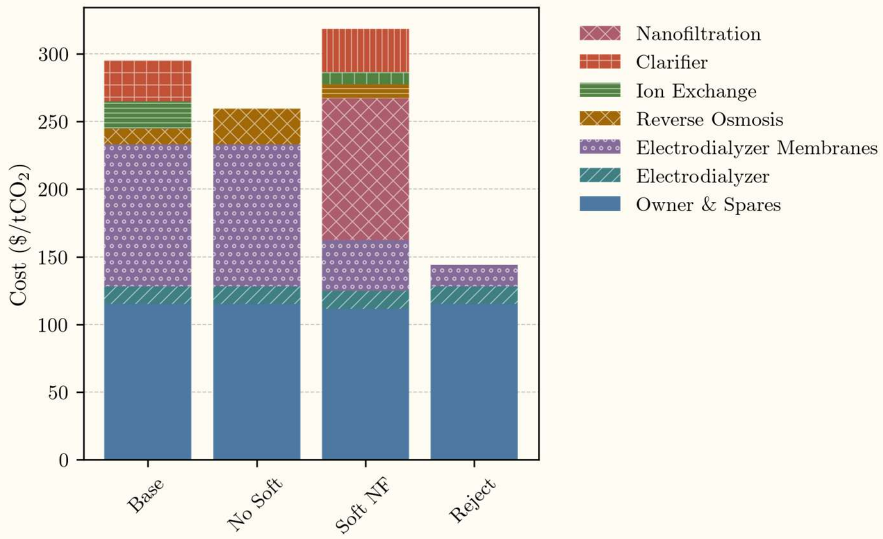

Figure 7.3 Detailed breakdown of CAPEX components contributing to the levelised cost across the four electrodialysis process variants. The figure illustrates the relative contribution of specific CAPEX items for each case study configuration.

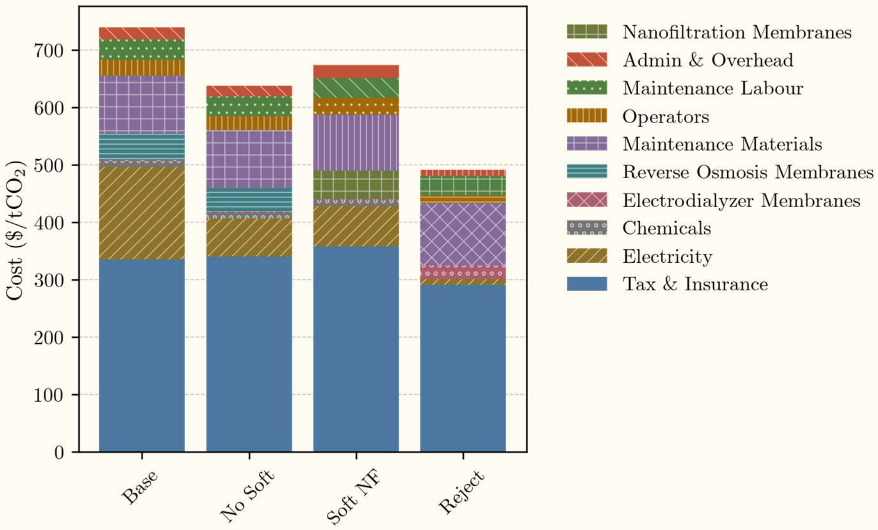

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Figure 7.4 Detailed breakdown of OPEX components contributing to the levelised cost across the four electrodialysis process variants. The figure shows the relative contribution of specific OPEX items for each case study configuration.

7.5.5 Location analysis

A spatial analysis of costs was conducted across multiple potential deployment locations specified in this framework (see Section 3.6.5). For each location, we calculated the levelised cost of both net and gross CO_2 removal (Figures 7.1 and 7.2), along with detailed breakdowns of capital (Figure 7.3) and operating costs (Figure 7.4) using the methodology described above. This analysis allows us to understand how geographic variations in factors such as renewable energy availability, logistics, and local operating conditions influence the economic viability of OAE projects. Note that for Ecuador, a negative LCCR was found since the emissions resulting from the background system (grid electricity usage) exceed the amount of CO_2 removed.

This FOAK plant cost analysis uses 2023 data from the REMIND model as its baseline. As countries transition towards cleaner energy infrastructure, the emissions-related cost penalties will gradually decrease, causing net LCCR values to converge towards gross LCCR values. While the net LCCR provides insight into suitable locations based on current background systems and infrastructure, the gross LCCR offers a clearer picture of location suitability based solely on the foreground technology's requirements.

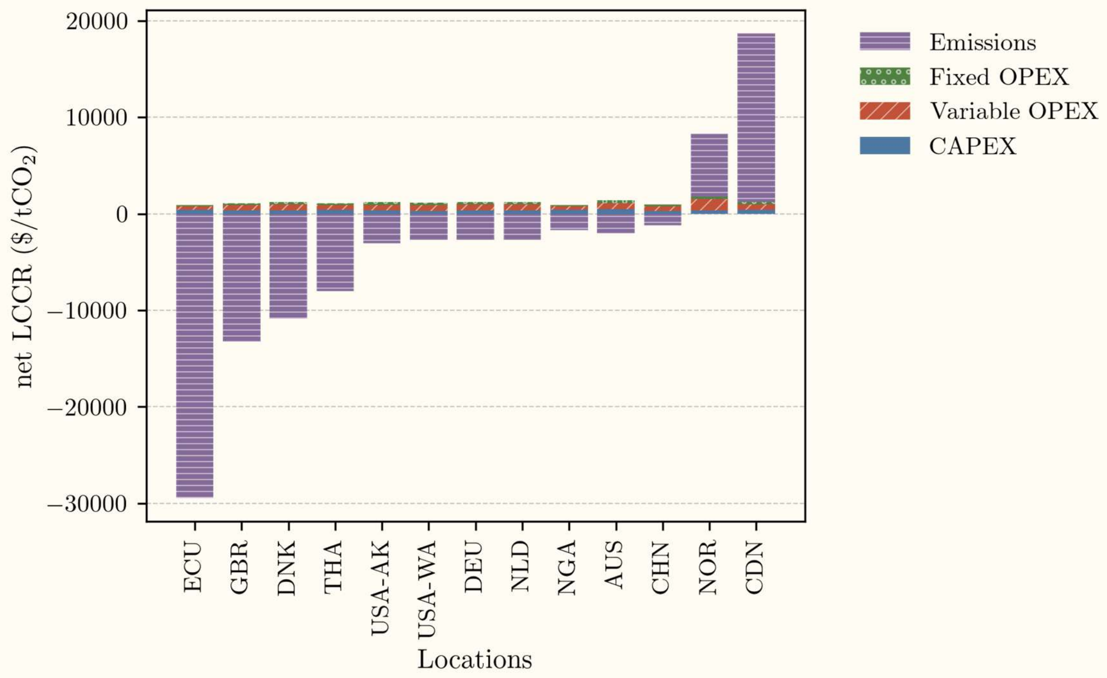

Figure 7.5 Regional variation in levelised cost of net CO_2 removal (LCCR) for a FOAK project across specified locations, with cost components broken down into CAPEX, OPEX (variable and fixed), revenue, and emissions. Data from the year 2023 and SSP2EU-PkBudg500 scenario from the REMIND model was used here. LCCR calculated using Method 1. Locations are ranked from the most negative to positive total net LCCR. Emissions which have negative values indicate that more carbon is emitted than removed; this is true for all cases except Norway and Canada.

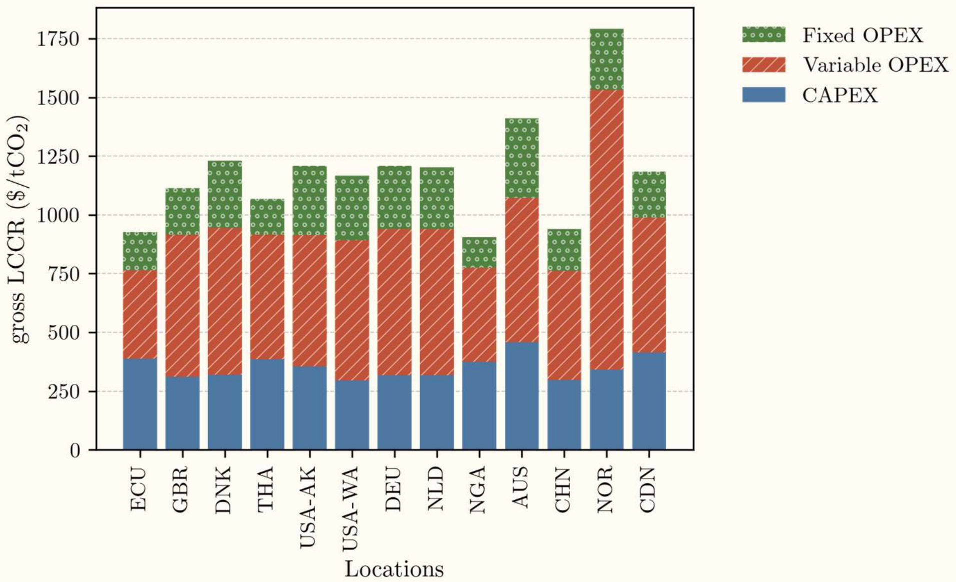

Figure 7.6 Regional variation in levelised cost of gross CO_2 removal (LCCR) for a FOAK project across specified locations, with cost components broken down into CAPEX, OPEX (variable and fixed), revenue, and emissions. Data from the year 2023 and SSP2EU-PkBudg500 scenario from the REMIND model was used here. LCCR calculated using Method 1.

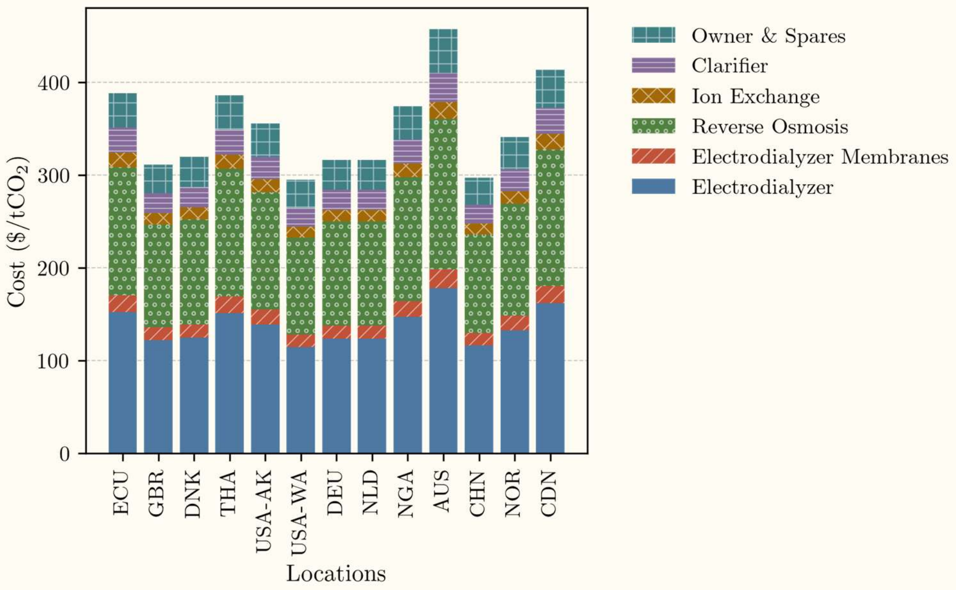

Figure 7.7 Contribution analysis of major equipment items to total CAPEX, highlighting key cost drivers in the FOAK BPMED system.

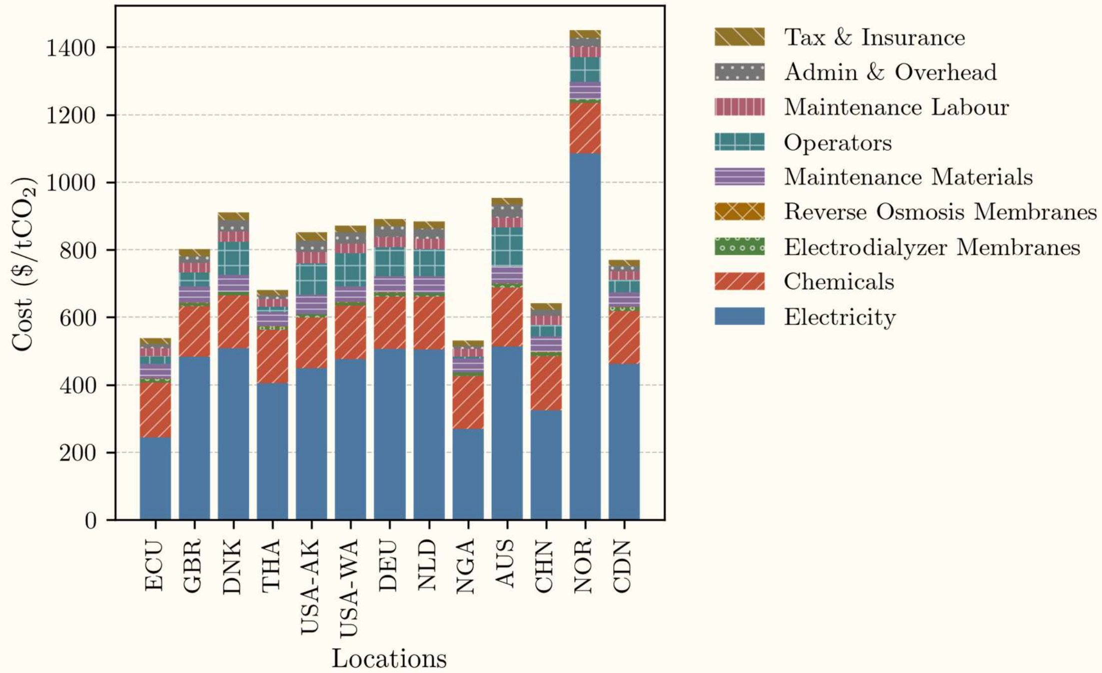

Figure 7.8 Breakdown of operating cost components showing relative contribution of each element to total OPEX for the FOAK BPMED system.

8.0 Framework Part F: Prospective analysis

Key recommendations:

- Future cost and environmental estimates should align with relevant published decarbonisation scenarios, for instance, from the IPCC 6th assessment report databases.
- Future cost and environmental estimates should include i) changes in technology performance resulting from repeated deployment, and ii) changes in the operating environment, e.g., electricity and feedstock prices and carbon intensities.
- Because future deployment rates are unknown, it is recommended to explore a wide, yet plausible, scale-up rate envelope commensurate with the selected decarbonisation scenarios.
- The selection of learning (or experience) rates for prospective performance trajectories should follow established theory or analogies. Base case values have been provided but may be adapted to suit specific assessments.

The deployment of novel climate technologies like OAE follows distinct stages that influence how we conduct techno-economic and environmental analyses. While classical analysis methods (Sections D and E) are well suited for evaluating current and near-term implementations for mostly existing technology, prospective analysis becomes essential when projecting future deployment scenarios. The transition point between these approaches typically occurs after the FOAK commercial deployment, where significant uncertainty remains about future scaling patterns.

This section presents recommended practices for deriving nth-of-a-kind (NOAK) project performance (along with relevant KPIs) from FOAK project performance, discussed in Sections D and E. We illustrate the critical factors such as learning rate, deployment scale, and growth rate using the BPMED case study. These approaches demonstrate the application of prospective analysis to OAE and similar climate technologies and show how FOAK costs, typically characterised by high CAPEX and OPEX, can evolve into more predictable and often lower NOAK costs over time.

8.1 Nomenclature

Table 8.1 Prospective analysis definitions.

Item	Description
First-of-a-kind (FOAK)	The first commercial demonstration or deployment of a system or technology at scale. It is typically associated with TRL 9 and serves as a key transition point in the deployment curve, enabling real-world experience learning for further scaling and optimisation.

Nth-of-a-kind (NOAK)	A stage in the development and deployment lifecycle where a technology or system is widely deployed with proven reliability, scalability, and cost-effectiveness.
Hybrid-costing model	A cost estimation method that combines both engineering-economic ('bottom-up') methods and the experience curve method to forecast the NOAK costs of advanced technologies for purposes of preliminary assessments.
Learning rate	Learning rates in technology development describe how quickly the cost or efficiency of a technology improves with increased production or experience from the FOAK onward. Typically, for every doubling of cumulative output, costs decrease by a consistent percentage due to factors like process optimisation, mass production, learning by doing, and economies of scale.
Deployment scale	The capacity at which a technology is deployed, influencing its cost and scalability.
Deployment rate	Or scale-up rate, as applied in the logistic function to estimate the deployment trajectory of a technology over time. It controls the rate at which the technology adoption progresses towards its asymptote.

8.2 Technology deployment scenario

The deployment trajectory is influenced by both foreground and background factors. Foreground factors relate directly to the technology itself, including learning rates, scale-up potential, and technical improvements. Background factors encompass broader system changes like energy costs and GHG intensity, infrastructure development, and policy frameworks. For OAE specifically, current expectations suggest deployment could scale to 0.1 to 1 Gt/year by 2050 (Committee on A Research Strategy for Ocean-based Carbon Dioxide Removal and Sequestration et al., 2022), though these projections carry significant uncertainty ranges in both the ultimate deployment capacity and the growth rate (see Section 4).

The deployment pathway spans from FOAK installations to mature, large-scale implementation at the asymptotic limit (see Figure 8.1). Throughout this deployment, multiple iterations of the technology would occur, leading to successive generations of installations with progressively reduced economic and environmental impacts through technological learning, economies of scale, and supply chain development.

While some researchers have proposed more granular approaches to characterising technology deployment stages (Nemet et al., 2023), we adopt/suggest a logistic function approach, as it effectively captures the essential dynamics of technology deployment using just three parameters – initial deployment size, growth rate, and an asymptote. This parsimony is particularly valuable given that OAE is a novel technology with significant uncertainties around its precise scaling pathway. To account for this uncertainty, we consider a wide range of growth rates and asymptotic values based on historical data from other technologies, ensuring our analysis encompasses various possible deployment scenarios.

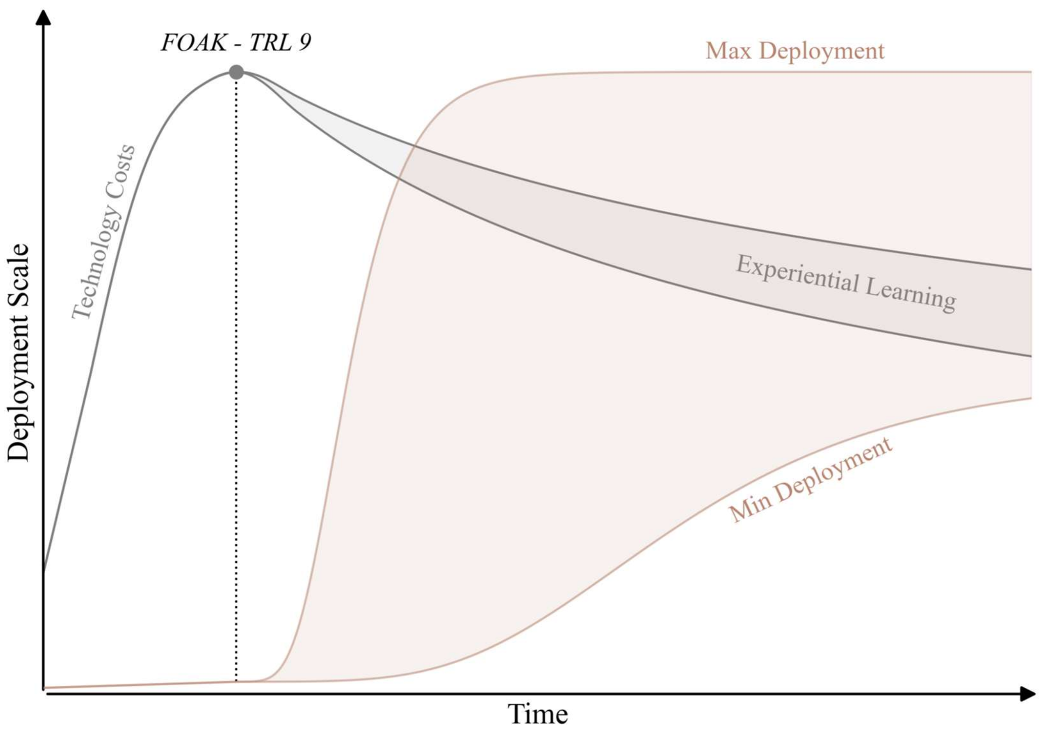

Figure 8.1 Schematic representation of technology deployment (brown) and cost (grey) trajectories over time. The initial phase shows increasing unit costs during technology maturation stages, reaching a peak at FOAK commercial scale. Subsequently, deployment accelerates while costs decline due to learning effects and economies of scale.

8.3 Application to techno-economic analysis

As novel climate technologies like OAE move from initial to commercial deployment, TEA must evolve to capture both current costs and future cost reduction potential. This section presents frameworks and methodologies for projecting how technology costs change with deployment scale.

Effectively integrating foreground and background data is fundamental to prospective techno-economic assessment (prTEA), particularly for emerging CDR technologies. These data types inherently vary across temporal and spatial dimensions and should align with the well-defined development scenarios as detailed in Section 4. Such integration facilitates a comprehensive and dynamic evaluation of the technology's performance, environmental impacts, and economic viability, capturing the critical interplay of evolving temporal and regional conditions essential for robust and informed decision-making.

8.3.1 Progression from first-of-a-kind to nth-of-a-kind

The evolution from FOAK to NOAK installations represents a critical phase in technology deployment where foreground system costs typically decrease due to learning effects and economies of scale. This work seeks to adhere as closely as possible to the current best practices for estimating the future NOAK cost of advanced technologies. At present, NOAK costs can be determined using a 'hybrid costing method', which combines bottom-up engineering estimates (see Section 7) with learning curve approaches that mathematically describe cost reductions as cumulative production increases (Roussanaly et al., 2021). The basic principle of learning curves is that each time cumulative production doubles, costs decrease by a consistent percentage, known as the learning rate (LR). This relationship is typically expressed as shown in Eqs. 8.1 and 8.2.

$$b = \frac{\ln(1 - LR)}{\ln(2)} \quad \text{(Eq. 8.1)}$$

$$C_{NOAK} = C_{FOAK} \cdot \left(\frac{S_{NOAK}}{S_{FOAK}}\right)^{-b} \quad \text{(Eq. 8.2)}$$

where:

- C_{FOAK} is the cost at the FOAK deployment scale.
- C_{NOAK} is the cost at the Nth-of-a-kind deployment scale.
- S_{FOAK} is the deployment scale at the FOAK instalment.
- S_{NOAK} is the deployment scale at the Nth-of-a-kind instalment.
- b is the learning exponent

Although learning rates have often been applied to the overall plant, it is recommended to apply them in a more granular manner where each subprocess (or unit operation) has a specific learning rate (Sievert et al., 2024). This allows more detailed modelling of cost reductions specific to each component. The NOAK plant cost is then determined by summing the costs of all subprocesses.

While this learning curve model directly relates cost reductions to cumulative production, it does not inherently specify the timing of deployment. To adapt this framework for prospective analysis, we incorporate deployment curves that describe how cumulative capacity grows over time (see Section 4 for further details):

$$\mathrm{S_{NOAK}}(t) = \mathrm{S_{FOAK}} \cdot e^{m(1-e^{-kt})} \quad \text{(Eq. 8.3)}$$

This time-explicit hybrid costing model allows us to project both the magnitude and timing of cost reductions as technology deployment progresses. We have developed a systematic methodology to apply this novel method specifically to OAE technologies, as detailed in the following steps and illustrated in Figure 8.2.

8.3.2 Step 1 prospective TEA: decomposing the overall plant into major technology sub-processes:

The decomposition of complex industrial facilities into major technological sub-processes is a fundamental approach to understanding and analysing cost reduction potential through learning effects. This step is particularly crucial because different components of a system often exhibit varying learning rates and historical deployment scales, which directly influence their potential for cost reduction. For instance, while some components may be well established with decades of industrial application, others might be novel technologies with limited deployment history.

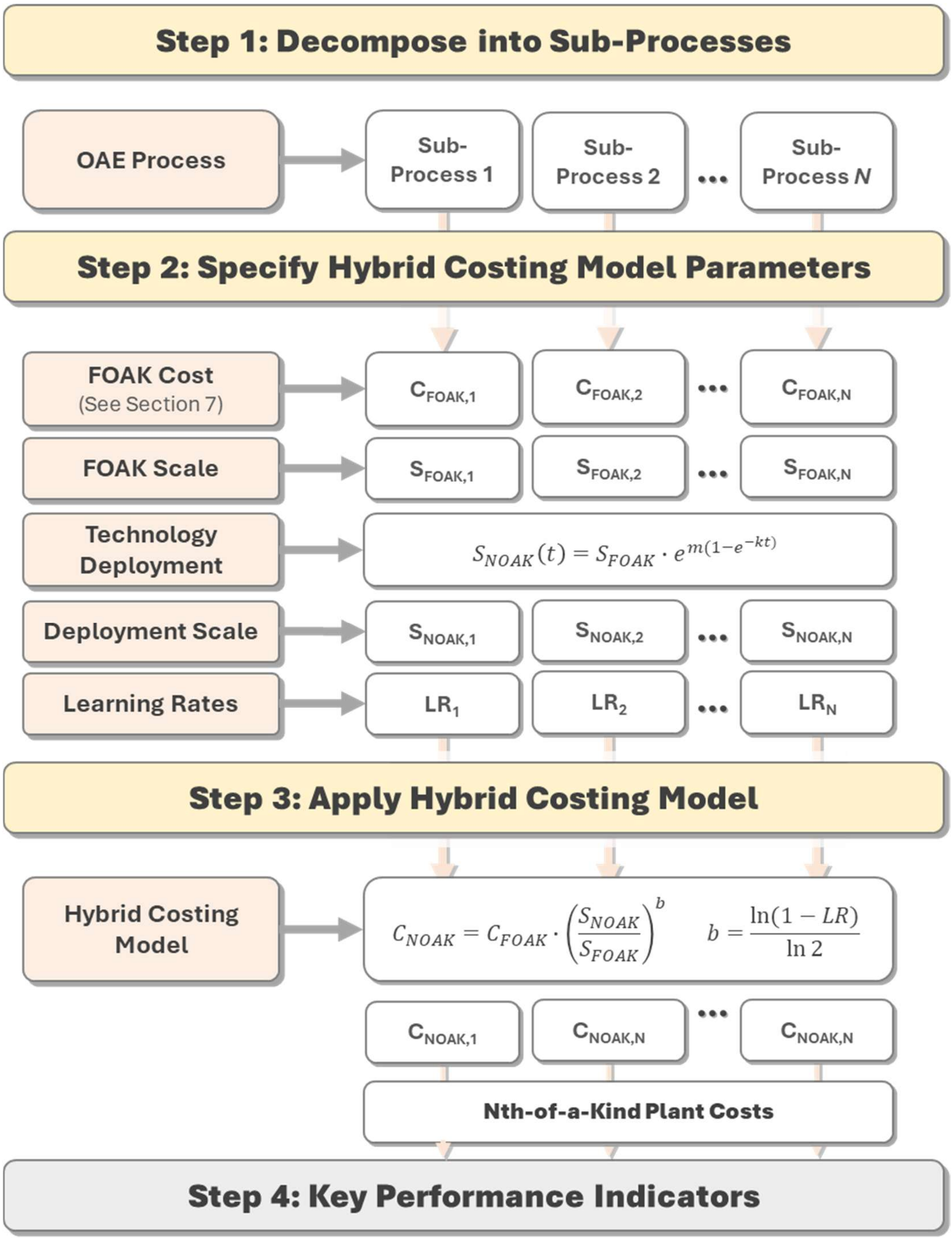

Figure 8.2 Methodological framework for time-explicit cost estimation of NOAK plants. The flowchart illustrates the systematic approach from initial process decomposition through to final performance indicators, incorporating hybrid costing methods and technology deployment curves. Left column indicates key inputs and methods utilised at each stage of analysis.

When breaking down a plant design into sub-processes, we focus on grouping equipment and processes that collectively perform specific functions (Roussanaly et al., 2021;

Zimmermann et al., 2020). For OAE, these sub-processes might include seawater pretreatment systems, electrodialysis units, ocean discharge infrastructure, DAC components, and sorbent regeneration processes. Each of these sub-processes represents a distinct technological cluster with its own learning trajectory and cost reduction potential.

8.3.3 Step 2 prospective TEA: specifying hybrid-costing model parameters:

Plausible cost modelling of OAE technologies requires careful consideration of both FOAK and NOAK scales, along with representative learning rates for each technological sub-process. These parameters vary significantly between novel technologies and existing commercial solutions, necessitating different approaches for their estimation and implementation in cost models.

Novel technology. For novel processes such as electrodialysis and DAC, the FOAK scale typically equals the initial plant scale. However, early cost estimates often underestimate actual commercialisation costs due to operational challenges and unforeseen complications. Following the conservative approach in (Roussanaly et al., 2021), several commercial plants must be successfully operated before achieving estimated FOAK costs. For example, if the first plant scale is 10 kt/yr, a recommended FOAK scale would range from 10 to 100 kt/yr to account for early-stage uncertainties. The NOAK scale would then follow the deployment curve outlined in the broader analysis.

While traditional learning curves often specify learning rates for a range of deployment scales, this approach may not suit all technologies, particularly those experiencing continued learning beyond conventional deployment scales, such as solar and wind energy. Although some studies propose multiple learning rates for different NOAK scales (Roussanaly et al., 2021), the high uncertainty in predicting transition points makes such detailed segmentation challenging to justify for early-stage technologies. Historical evidence suggests that some technologies maintain high learning rates even at substantial global deployment scales, indicating that learning can potentially continue throughout the entire deployment trajectory e.g., renewable energy markets like solar PVs (Haas et al., 2023; Parker and Sedoglavich, 2023). Given the limited information available specifically for OAE and CDR industry learning rates, we use learning rates from analogous technologies as proxies, considering a range of possible rates as detailed in our analysis (see Table 8.2). For example, BPMED systems may share some learning characteristics with fuel cells and electrolysers.

When direct analogues for learning rates cannot be found for novel technologies, alternative methods can be used. (Sievert et al., 2024) propose structured expert elicitations to estimate learning rates based on technological characteristics rather than historical data. Through expert interviews, mean learning rates are established for each archetype (typically ranging from 5% to 20%), with more standardised technologies showing higher potential for cost reduction. However, it's important to note that significant uncertainty remains inherent. Therefore, rather than relying on single point estimates, a range of possible learning rates should be considered through comprehensive uncertainty analysis (detailed in Section 8.5.3) to better understand the potential variability in cost projections.

Established technology. For established technologies with significant market penetration, such as air separation and seawater desalination, the FOAK scale should reflect current installed capacity, while the NOAK scale should account for both conventional growth trajectory and additional deployment for OAE applications. For instance, air separation units have a documented learning rate of 10% with current installed capacity of 563 Mt of oxygen per year. Since this market dwarfs the capacity potentially added by OAE, reaching even a 10% cost reduction would require doubling the installed capacity to 1,126 Mt of oxygen per year.

Table 8.2 Recommended learning rates for OAE components. Learning rates in this table should be applied to the deployment scale for OAE. Learning rates for novel and established technologies are applied to the capital cost of the sub-process.

Technology	Recommended Learning Rate (range)	Analogues	Data Source
Novel Technologies			
CO_2 Conditioning	10 (5 – 15)%	CCS	(Roussanaly et al., 2021)
Mineral Spreading	7 (5 – 15)%	Coastal erosion defence	(Breyer et al., 2019; Faber et al., 2022; McQueen et al., 2021; Sievert, Schmidt, and Steffen, 2024; Young et al., 2023)
Mineral Carbonation	7 (5 – 15)%	Calciner, process engineering	
Mineral Precipitation Alkaline Digestion	10 (5 – 15)%	Process engineering	
Electrolysis/Electrodialysis	18 (15 – 25)%	Fuel cells, electrolysis	(IRENA, 2020)
Direct Air Capture	12 (5 – 19)%	-	(Sievert et al., 2024; Young et al., 2023)
MRV	-	Ships, sensors, buoys, satellites	-
Established Technologies			
Air Separation	Recommended learning rate of 0 - 5% for established technologies. Note that this learning rate is applied using the scale of OAE deployment.		(Roussanaly et al., 2021)
Solid Grinding			
Seawater Pretreatment and Desalination			
Calcination and Slaking			
Operating Costs			
Fixed Operating Costs*	5 - 10%	-	(Sievert et al., 2024)
Variable Operating Costs	0 - 5%	-	

*Fixed operating costs vary with CAPEX and would decrease with CAPEX. This rate should be applied to fixed operating costs, which are independent of capital cost items (e.g., labour costs).

When applying learning rates from literature, it is critical to consider current installed capacity. However, these values are not always readily available and may have minimal impact if the technology is already widely deployed. For such cases, we recommend a simpler approach: applying a conservative learning rate of 0-5%, with 1% serving as a reasonable baseline. The FOAK and NOAK scale would correspond to the OAE technology's deployment scale as described in Section 8.3.2. This approach is supported by Sievert et al. (2024) and aligns with established patterns where mature technologies tend to have lower learning rates. As Roussanaly et al. (2021) note, mature plant sub-sections often show negligible cost changes with small capacity additions, potentially obviating the need for detailed experience curve analysis. This conservative approach is also consistent with the environmental investigation agency's methodology, which typically assumes learning rates of approximately 1% for mature technologies at large deployment scales. Note that negative learning rates have also been observed, as with nuclear power plants, where increased safety regulations have led to cost increases instead of reductions (Roussanaly et al., 2021).

Learning rates for operating costs: Learning rates for fixed operating costs (FOC) and variable operating costs (VOC) typically differ from those of capital costs. FOC (except labour costs), when estimated as a function of capital costs (e.g., maintenance costs, as shown in Section 7.2.2), follow the same learning rate as that applied to capital costs. There is limited data for how operating labour costs change, though for conventional chemical plants there are legal minimum requirements for staffing the plant which would not change due to learning effects. However, for processes with higher labour requirements (e.g., mineral spreading, MRV, mining) this assumption may not hold true and a conservative learning rate of 0 - 5% may be applied with appropriate uncertainty analysis (Sievert et al., 2024).

VOCs demonstrate learning through improved operational efficiency and optimisation of resource usage. Recommended learning rates between 0-5% (Sievert et al., 2024) can be applied to the total of the VOCs. Importantly, learning rates for VOCs must respect physical constraints such as minimum mass requirements for stoichiometric conversions and thermodynamic limits for energy consumption.

8.3.4 Step 3 prospective TEA: applying the hybrid-costing model:

The calculation of NOAK costs from FOAK costs requires careful consideration of learning rates and their application across different cost components. This methodology outlines the process of converting FOAK costs to NOAK costs for various sub-processes of a project. Before applying learning rates, it is crucial to understand their context and source. The application depends on whether the learning rate data was derived from total plant cost (TPC), bare erected cost (BEC), or total capital requirement (TCR) values. Additionally, consideration must be given to the cumulative capacities from which these learning rates were obtained, including their suitable upper- and lower-bound ranges.

Typically, learning rates should be applied to the TPC of the sub-process and to the annual OPEX unless specified otherwise. It is important to note that applying learning rates directly to unit cost contributions (i.e., $/t$CO_2$) of CAPEX/OPEX items is not recommended, as this may overlook learning effects on dependent costs, such as maintenance costs, which are typically calculated as a percentage of TPC.

The process begins with calculating specific FOAK costs (C_{FOAK}) for each sub-process using the classical cost estimation method presented in Section 7. These FOAK costs are then converted to NOAK costs using the experience curves (Eq. 8.2). Once NOAK costs are determined, the process requires:

1. Adjustment of other operating expenses or capital expenses that are functions of the updated NOAK costs (e.g., maintenance costs, which can be a function of total plant costs).

2. Recalculation of cash flows using the new NOAK costs.

3. Re-evaluation of key performance indicators using the revised NOAK costs and cash flows, following the methodology outlined in Section 7.

8.3.5 Integrating background systems and scenarios

The previous section discussed how to project the costs of the foreground system from FOAK to NOAK scale. Building on this, we now integrate background system variables into future scenarios – refining the hybrid costing model inputs in Steps 2 and 3 in Figure 8.3. The overall process is outlined in the diagram below.

The integration process is built upon clear definitions of the foreground and background system of OAE approaches of interest. Sourcing data for background systems could utilise IAMs like IMAGE, REMIND, and GCAM. However, several constraints exist on the availability and applicability of background data, necessitating careful consideration of additional sources and methodologies.

Data availability constraints. Not all necessary background system inputs are readily available from IAMs, as these models focus on high-level economic and climate scenarios rather than sector-specific cost breakdowns. Some background data variables may also have limited temporal granularity or time frame, making it difficult to capture year-by-year cost variations. To address this:

i) Industry reports, engineering indices, historical trends or market-based forecasts, and literature values can be incorporated to complement IAM-derived background trajectories.

ii) A mathematical trend matching approach, including linear interpolation, polynomial fitting, and exponential growth modelling, can be applied to seamlessly extend and refine IAM projections, ensuring both continuity and enhanced granularity for specific parameters.

Heterogeneous data sources. Data from IAMs are often harmonised across socioeconomic and climate pathways (e.g., RCPs). While parameters sourced outside of IAMs have uncertainties in the long-term, they are independent or less dependent on the specified mitigation pathways (e.g., labour cost). To address this:

i) Multiple scenarios (e.g., baseline, optimistic, and conservative cases) can be developed and evaluated to cover the most possible future trends.

ii) Sensitivity analyses can assess how variations in background costs affect the KPIs' evolution in the deployment scales.

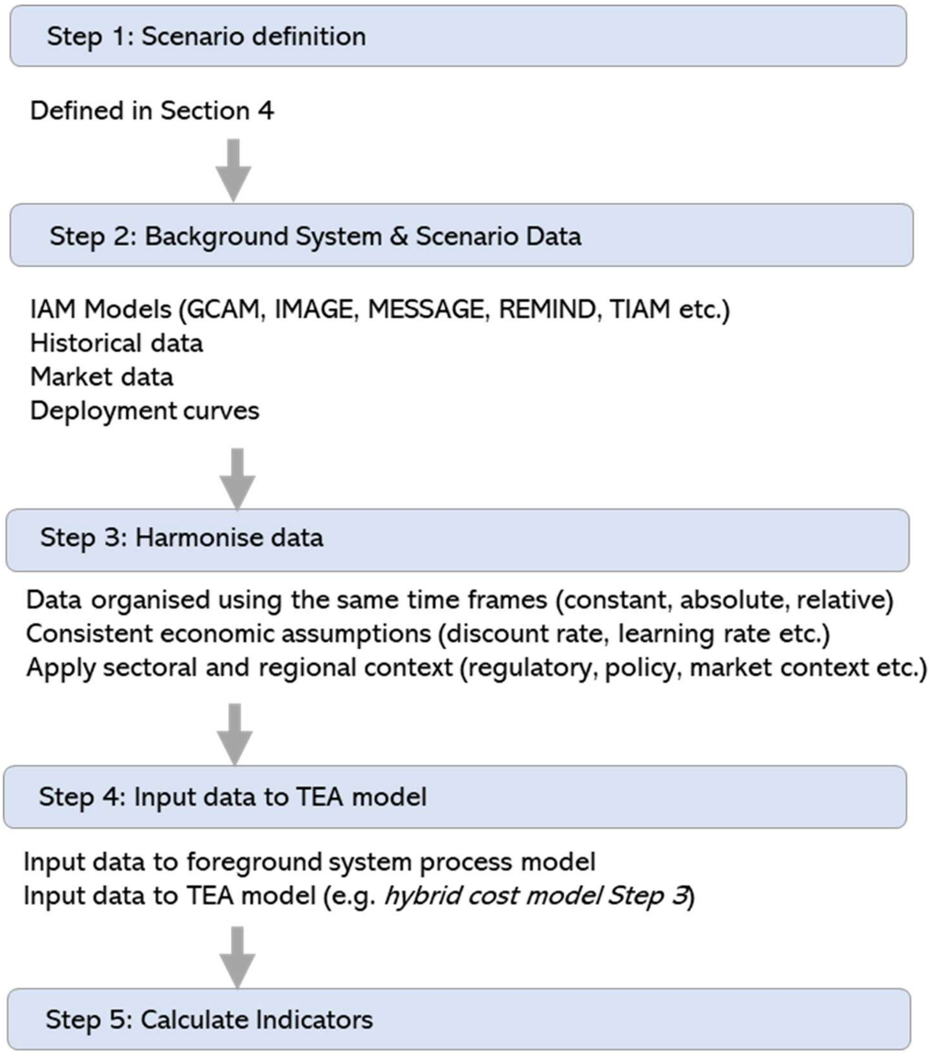

Figure 8.3 Process flow diagram for integrating background systems and scenarios.

Static vs. dynamic background inputs. Some background elements are time explicit or exhibit stepwise changes over time (e.g., projected carbon intensity of electricity over decades). Others, such as regulatory compliance or theoretical deployment asymptotes (e.g., land availability limits), tend to remain relatively constant over time.

i) Static background data is acceptable if the parameter is stable and does not significantly impact long-term cost trends.

ii) For OAE approaches, dynamic background inputs across different sub-processes may vary in their time frames. Careful harmonisation of these variables is necessary to ensure a coherent and consistent background system.

When integrating foreground and background data into the assessment model, it is crucial to ensure that background projections – whether derived from IAM-based models or non-IAM sources – are harmonised with foreground data in terms of time frames and economic assumptions. Proper alignment of these variables is essential for producing accurate and coherent future cost projections. The projected background data relevant to OAE are summarised in Table 8.3.

Table 8.3 Variables from background systems relevant for techno-economic assessment of OAE.

Variable	Description	Source
Energy Price	Costs of electricity, natural gas, and fuels ($/kWh, $/GJ).	IAM (Dynamic) IEA IRENA
Construction Material Price	Market costs for construction materials (e.g., steel, cement).	COMPASS
Materials Price	Market costs of materials (minerals, polymers, metal, chemicals) used in the process.	Market reports
Water Price	Cost of cooling or process water ($/m^3).	Market reports
Carbon Price	Market price for CO_2 emissions (e.g., $/tonne CO_2).	Market reports (ETS, VCM)
Land Price	Cost of land acquisition or leasing for development projects ($/acre or $/hectare).	Market reports, local land registry, authorities
Labour Costs	Wages, benefits, and other personnel expenses for chemical operators or other relevant workforce ($/hour or annual).	National statistics
Equipment Cost Index	Measure that tracks changes in cost of equipment over time resulting from price fluctuations and inflation.	CEPCI Intratec
Carbon Intensity of Energy Source	Emissions per kWh for fuel or electricity use (e.g., gCO_2/kWh).	IAM, IPCC
Carbon Intensity of Materials	Emissions per unit of material used (mineral, polymer, metal, chemical).	IAM Reports
Discount Rate	Rate used for net present value (NPV) calculations (%).	Literature reports

8.5 Case study: Prospective techno-economic assessment implementation

8.5.1 Steps for prospective *TEA*

In this case study, the prospective TEA methodology from Section 8.3 is applied to a case study that explores the costs of BPMED for OAE. The methodology is applied in three steps to demonstrate progressive changes (Figure 8.4):

(1) Step 1: Conventional hybrid costing model with no time series to determine the change in costs of the foreground system versus the total deployment scale.

(2) Step 2: Hybrid costing model with technology deployment rate to determine the change in costs of the foreground system versus time.

(3) Step 3: Inclusion of background system data to evaluate changes in costs resulting from changes in the foreground and background system versus time.

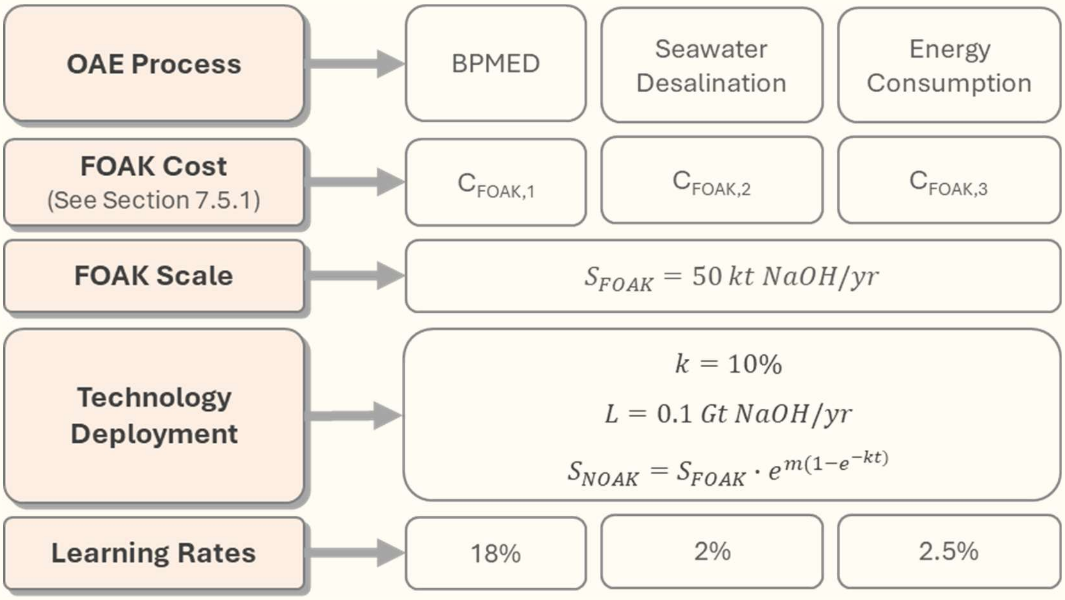

Figure 8.4 Summary of specifications used to determine the NOAK plant costs.

Step 1: Conventional hybrid-costing model. The electrodialysis process is decomposed into the BPMED unit (Part C in Figure 3.4) and the seawater pretreatment/desalination (Parts A and B in Figure 3.4). Learning was applied to equipment in these sub-processes, and to the energy consumption of the electrodialysis process. The cost of these elements was previously calculated using the classical TEA framework (Section 7) for a plant scale of 10 kt NaOH/yr. For the FOAK deployment scale (S_{FOAK}), five plants with a total installed capacity of 50 kt NaOH/yr were assumed. Values of learning rates for all sub-processes are applicable to the plant's alkaline material or CO_2 removal capacities, so the FOAK and NOAK scale would be the same for all sub-processes.

NOAK scales up to 0.1 Gt/yr were evaluated (S_{NOAK}). Learning rates (LR) from Table 8.2 were used, and for the electrodialysis energy consumption, a 2.5% learning rate was applied as suggested in Section 8.3.3, while maintaining a minimum energy requirement of 0.81 MWh/tNaOH for the process (Kumar et al., 2019). The calculations are based on those for Washington, USA, for the initial year 2023 and data for the background system is taken from the SSP2EU-PkBudg500 scenario from the REMIND model (electricity prices and electricity carbon intensity). Parameters summarised in Figure 8.3 were used as inputs for the hybrid costing model. The costs of the sub-sections at 50 kt/yr (FOAK), 1 Mt/yr, and 100 Mt/yr are shown in Table 8.4 to demonstrate selected cost reductions resulting from learning effects. The NOAK costs below are used to calculate cash flows and key performance indicators for the NOAK plant (at the specified deployment scale).

Table 8.4 Progression from FOAK to NOAK plant costs for the BPMED case study. Capital costs of sub-processes are shown as total plant costs (TPC) (see Table 7.1 for definition).

Sub-process cost (\$/tCO$_2$)	***FOAK Plant (at 50 kt/yr)***	***NOAK Plant (at 1 Mt/yr)***	***NOAK Plant (at 100 Mt/yr)***
Bipolar Membrane Electrodialysis	*155.1*	*65.9*	*17.6*
Seawater Pretreatment and Desalination	165.0	154.3	139.5
Electricity Costs	317.4	288.4	249.4

The analysis reveals that NOAK installations could achieve up to 30% lower carbon removal costs compared to FOAK plants, considering both net and gross metrics (Figure 8.5). The 30% cost reduction occurs at a CO_2 removal capacity of 0.1 GtCO_2/year. Drawing insights from Roussanaly et al., (2021), it is estimated that with 20 replications (or four to five doublings) of the FOAK scale, the NOAK cost for our case study could decrease to approximately \$3,000/tCO_2 at a capacity of 1 Mt CO_2/year, representing a cost reduction of roughly 14%. This suggests that most cost reductions are achieved during the deployment of the initial few dozen replications, with (expected) diminishing returns from learning and cost reductions as cumulative capacity increases over time.

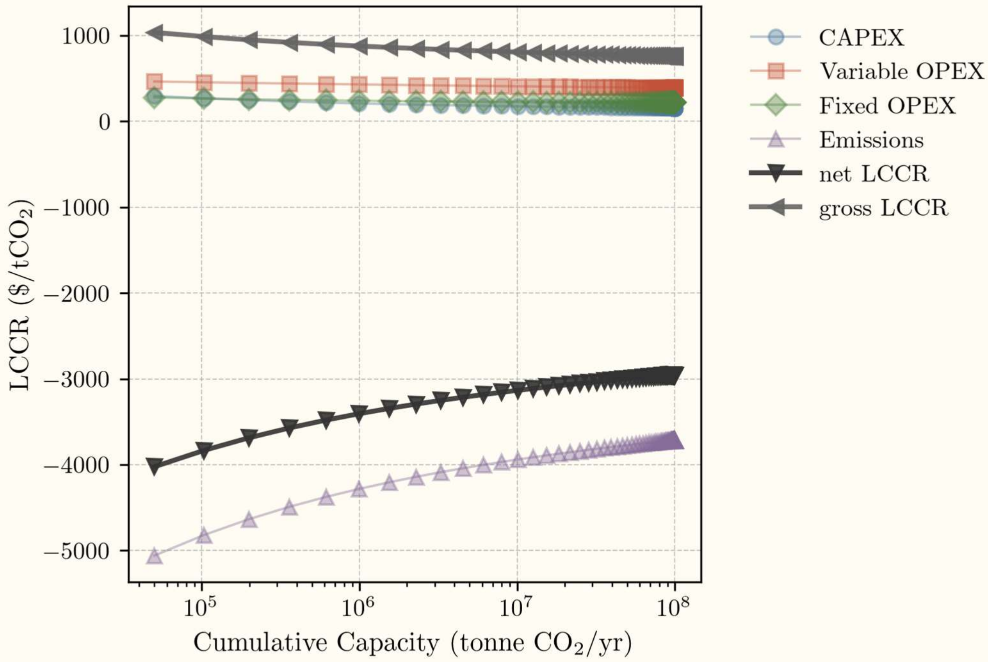

Figure 8.5 Carbon removal costs versus cumulative installed capacity for the BPMED case study in USA-WA. The progression from FOAK to NOAK shows cost reductions driven by technological learning, with the net cost considering cost penalty from emissions and the gross cost representing total system expenses.

Step 2: Dynamic foreground and static background. The conventional hybrid costing model does not yield values with specific time markers, so technology deployment rates obtained using Equation 4.2 were used to determine the cumulative capacity versus time. A growth rate of k = 10% and asymptote L = 0.3 Gt NaOH/yr were specified. Shown in Figure 8.6 is the levelised cost of CO_2 removal versus time. By 2050, a deployment scale of 100 Mt/yr is reached and most cost reductions resulting from learning are met. Although the foreground system's costs improve over time, costs due to carbon emissions from electricity use remain high, as these are part of the background system and are kept constant here.

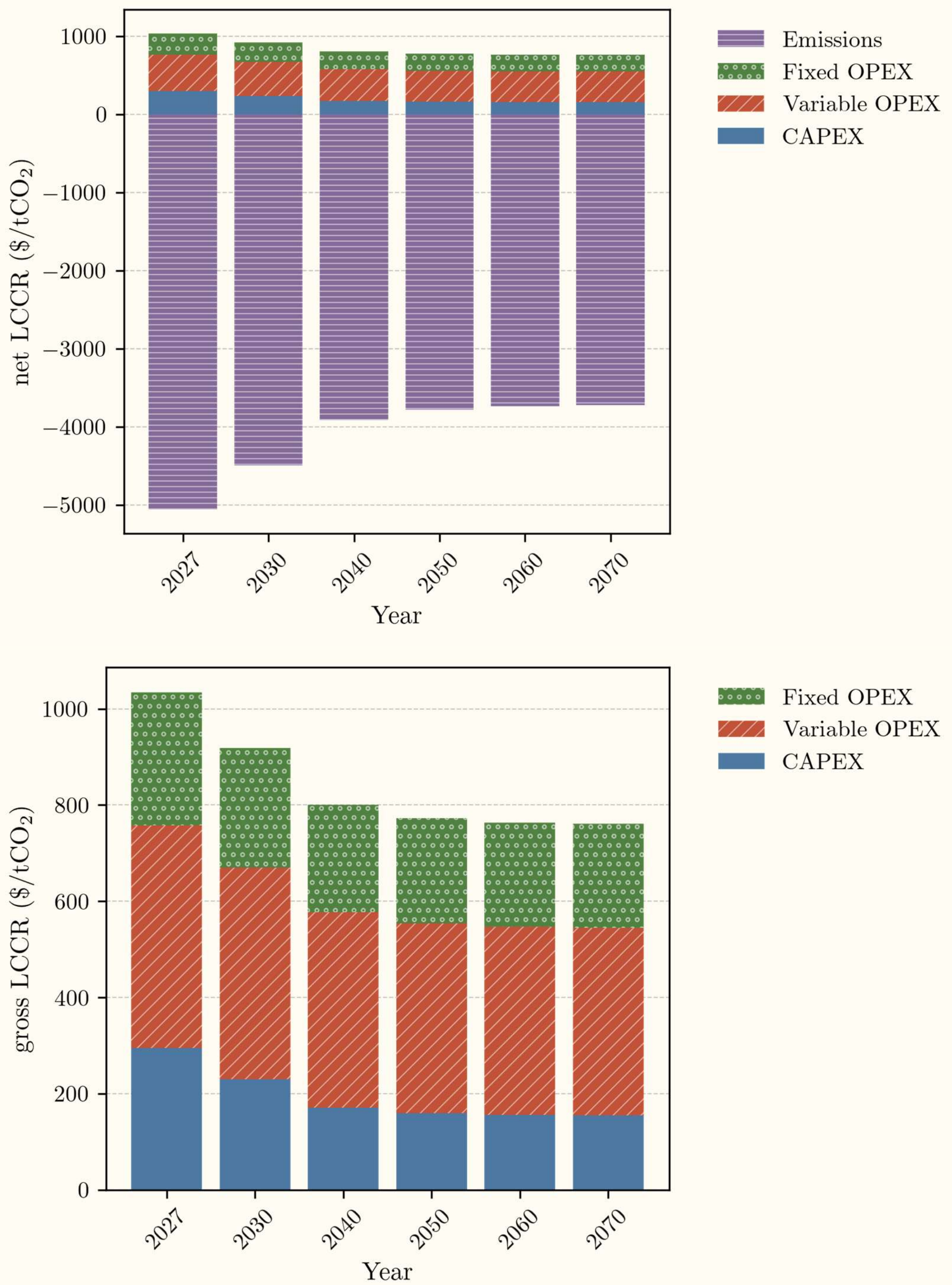

Figure 8.6 Net and gross carbon removal costs versus time for the BPMED case study, using dynamic foreground system values obtained through hybrid-costing and technology deployment curve analysis. Results are based on static background data from 2023 using the REMIND model's SSP2EU-PkBudg500 scenario for USA-WA. Operational cost learning only applied to the BPMED.

Step 3: Dynamic foreground and background. In step 3, inputs from the background system are treated as a time series. Due to future reductions in grid electricity carbon intensities, the cost penalty resulting from these emissions decreases (compare Figures 8.6 and 8.7). Including the background system as a time-series has a significant effect on cost, particularly for cases where emissions from process inputs are high (electricity for the electrodialysis case). Emissions associated with material inputs (e.g., soda ash, lime) decrease only marginally, and account for the majority of cost penalties.

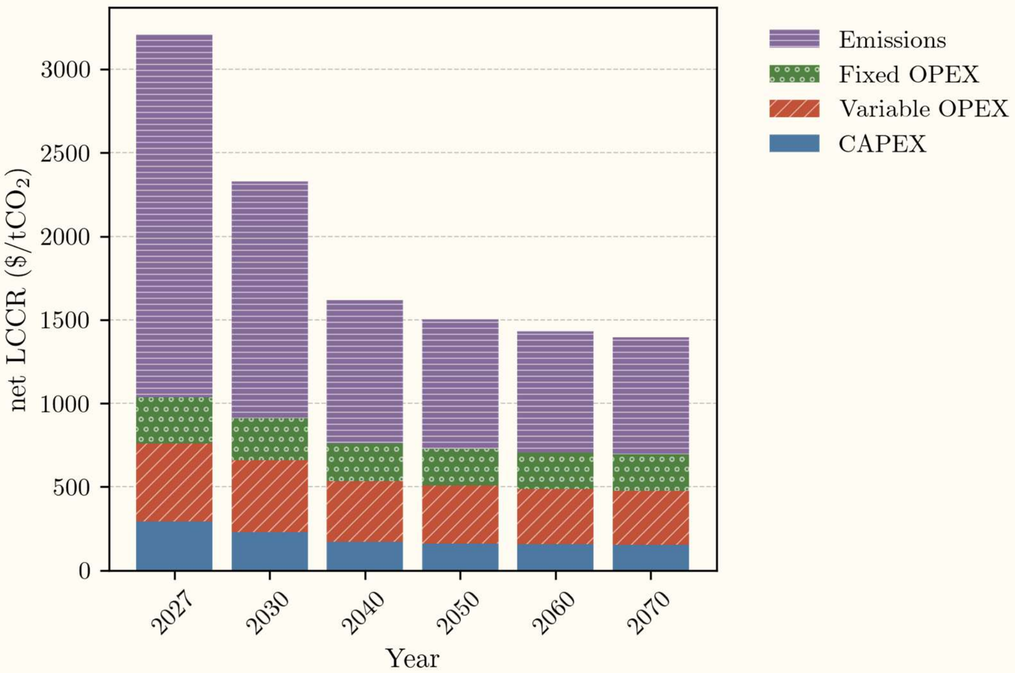

Figure 8.7 Net carbon removal costs versus time for the BPMED case study, using dynamic foreground and background system values. Results are based on dynamic (time-series) background data from the REMIND model's SSP2EU-PkBudg500 scenario for USA-WA.

This stepwise refinement enables a more accurate representation of cost evolution across different deployment scales and temporal scenarios, enhancing the predictive capability of the TEA methodology for large-scale implementation. Naturally, it is recommended to develop similar results for different future scenarios that need substantial CDR utilisation to reach their climate targets.

8.5.2 Comparison of classical vs prospective TEA results

In Figure 8.7, costs of each location specified for the BPMED case study were ranked. A comparison of rankings is made for (1) classical analysis with static foreground and background systems, and prospective analysis where (2) one or (3) both systems are dynamic. Incorporating a dynamic background leads to drastic changes in cost rankings, particularly for countries such as the UK, Norway, and Australia. Although a dynamic foreground system does not appear to change cost rankings for the net LCCR (since costs are largely due to emissions from background systems), it does have some impact on the gross LCCR.

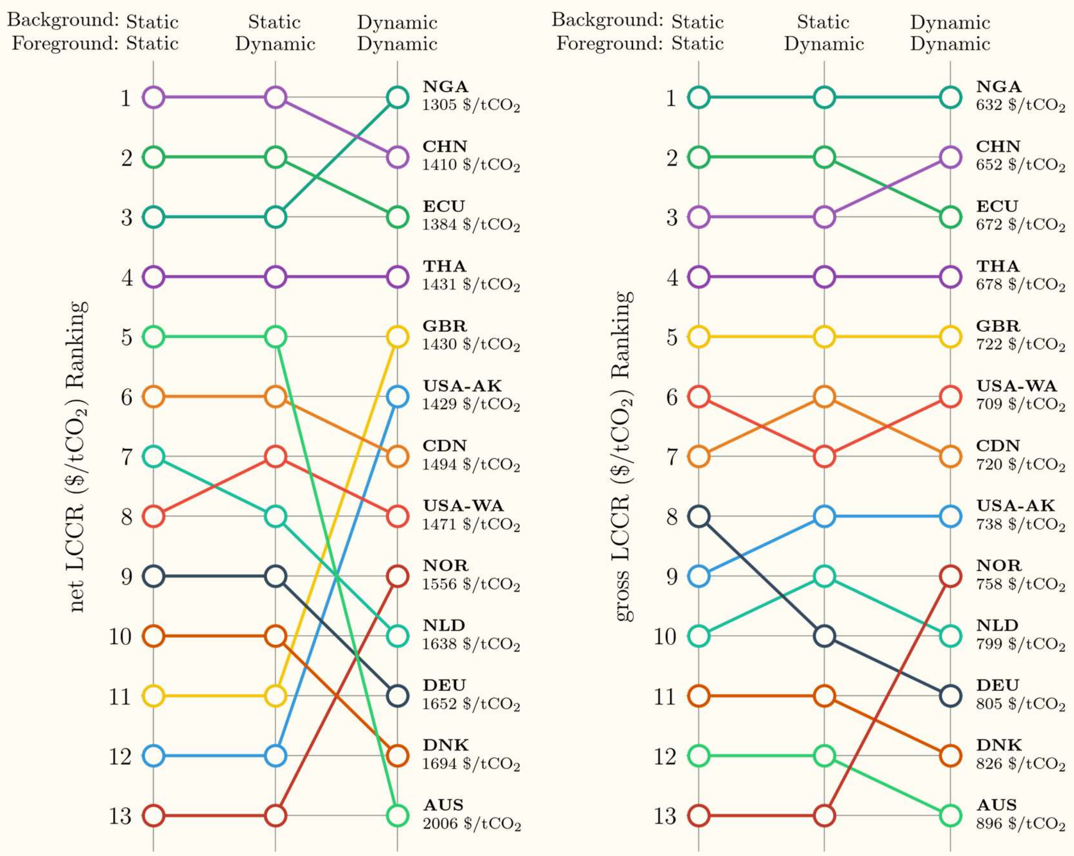

Figure 8.8 Location rankings based on net and gross levelised carbon removal costs for the BPMED case study under three analytical approaches: (1) classical TEA analysis with static foreground and background systems, (2) dynamic foreground analysis using time-explicit hybrid-costing model with static background, and (3) fully dynamic analysis incorporating both dynamic foreground and REMIND model-based dynamic background data. Results for the year 2050 are shown for approaches with dynamic systems.

8.5.3 Comparison of electrodialysis case study variants

In Figure 8.9, the net levelised cost of CO_2 removal is shown for the four technology variants of the BPMED case study as defined in Section 5.6. Their costs versus time when applying both dynamic foreground and background systems (REMIND Model SSP2-RCP1.9) show consistent decreases over time. The base case does not fully decarbonise since emissions resulting from chemical use in the precipitation softening unit do not vary with time. In the other variants, no softening or softening via nanofiltration yields far lower cost penalties from CO_2 emissions. When the variants are compared (as seen in Figure 8.10), it is evident that nanofiltration softening has better economic viability than precipitation softening, and if softening were necessary, it would not require a significant cost to implement. Of note is that the reject case (which uses waste streams as feed), has the lowest cost and by 2050 the cost is around 350 $/tCO_2$, although waste sources are limited, it would provide competitive costs and be the best option for deploying and scaling the technology in the early years (where its costs start at 710 $/tCO_2$.

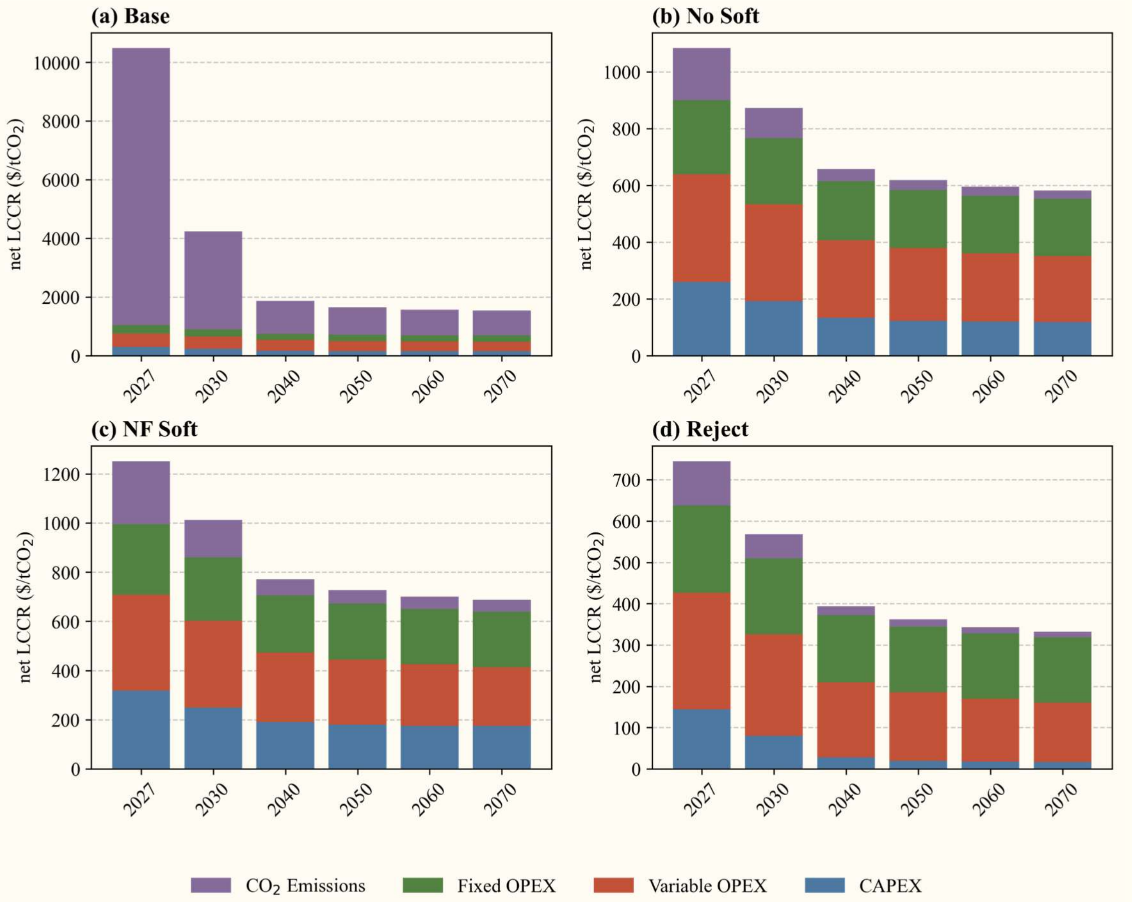

Figure 8.9 Net carbon removal costs versus time for the technology variants of the BPMED case study. Variants include: (a) base case, (b) no softening case, (c) nanofiltration softening case, and (d) reject brine and water feed case. Results are based on background data from the REMIND model's SSP2EU-PkBudg500 scenario for USA-WA.

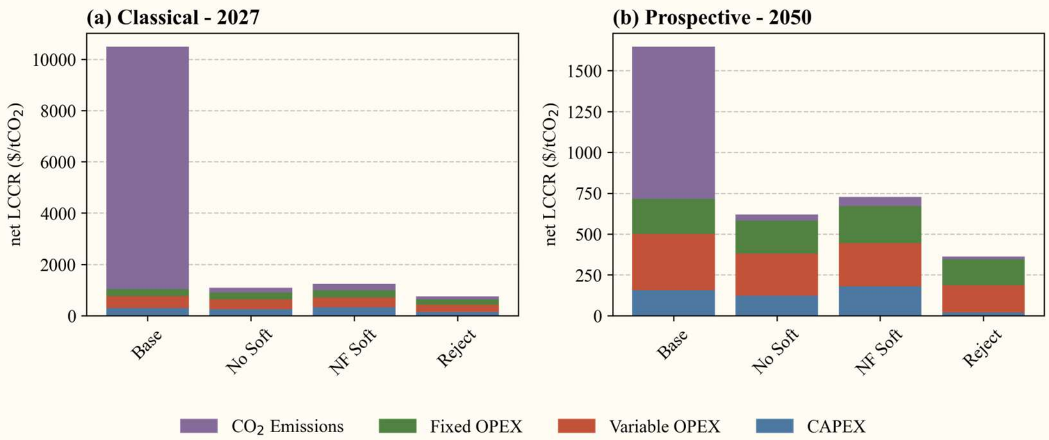

Figure 8.10 Comparison of net carbon removal costs versus time for the technology variants of the BPMED case study. Results are compared for the year 2027 and for the year 2050. Results are based on dynamic (time-series) background data from the REMIND model's SSP2EU-PkBudg500 scenario for USA-WA.

8.5.4 *Impacts of learning rates and technology deployment rates*

Learning rates from FOAK to NOAK are not yet known for carbon removal technologies and could vary from the base case, so considering a high or low learning rate, as shown in Figure 8.11, is necessary to capture the range of possibilities sensitive to realistic changes.

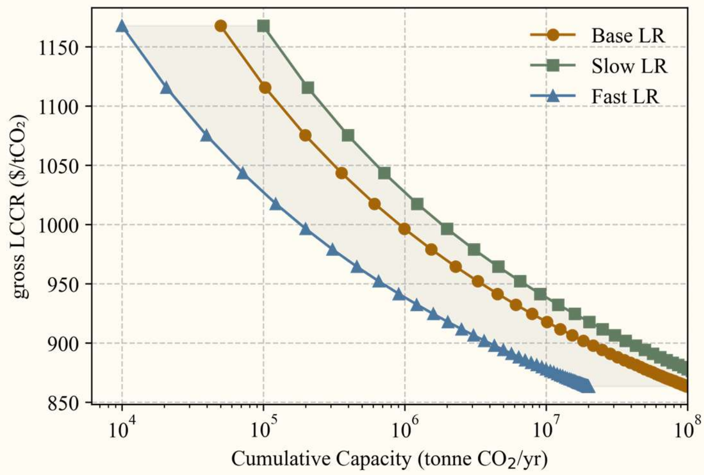

Figure 8.11 Sensitivity of gross carbon removal costs to different learning rates for the BPMED system (only). Higher learning rates lead to more rapid cost reductions with increasing cumulative capacity, highlighting the importance of technological advancement and industry experience. A slow LR corresponds to a 10% learning rate for equipment and 1% learning rate for electricity costs. A fast LR corresponds to a 25% learning rate for equipment and 5% learning rate for electricity costs.

Likewise, the deployment rate for CDR technologies can only be estimated with significant uncertainty, and a range of deployment rates and asymptotes should be considered. Using the deployment function, the impact of deployment rates and total deployment scale of a technology are shown in Figure 8.12. Cost variations are larger in the short term but trend towards similar values in the long term.

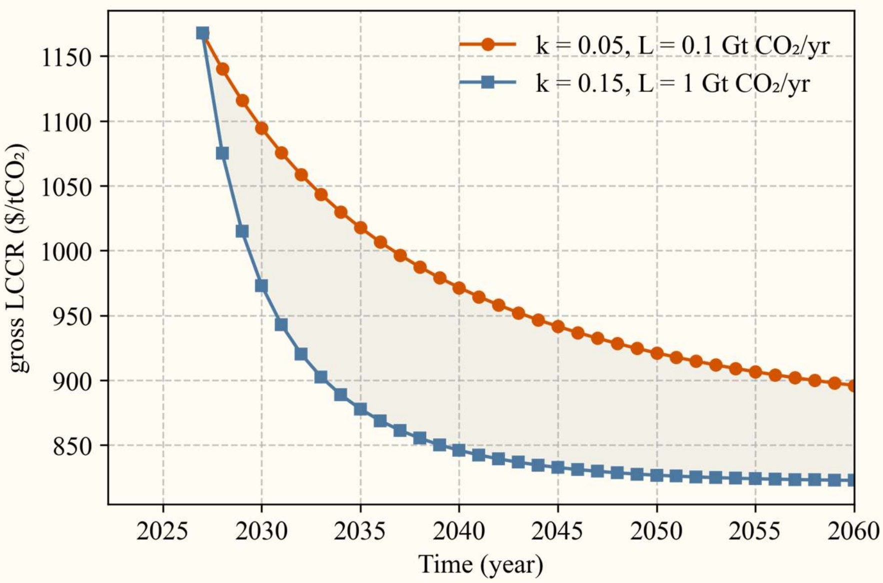

Figure 8.12 Impact of varying growth rates (k) and asymptotic capacity (L) on the NOAK gross carbon removal costs over time. Higher asymptotic capacities (L) lead to greater overall cost reductions due to larger cumulative production volumes, enabling more extensive learning effects. Growth rates (k) primarily influence near-term cost trajectories by affecting how quickly initial capacity is deployed, though their long-term impact is less significant than the asymptotic capacity.

8.6 Application to life cycle assessment

Classical LCA methods, as detailed in Section 6.0, evaluate systems and process designs based on current state of technology, making them potentially less suitable for assessing emerging technologies like OAE approaches. Conversely, prospective LCA (prLCA) models a product system at a future time relative to when the assessment is conducted (Arvidsson et al., 2024). The overall framework for prLCA allows a similar structure to classical LCA, as described in Section 2.3, with the same fundamental steps. However, prLCA requires the integration of additional elements within these steps to account for future technological and environmental changes, ensuring that assessments better reflect the technological and infrastructural developments anticipated over time.

LCA consists of four key phases: (i) goal and scope definition, (ii) life-cycle inventory analysis, (iii) life-cycle impact assessment (LCIA), and (iv) interpretation. For prLCA, the first two stages, which are detailed in Sections 3 and 5 for classical LCA, require modifications to incorporate future-oriented aspects. The third step, LCIA, will not change a lot unless one might want to include prospective characterisation factors in their assessment. The interpretation phase may evolve in prospective LCA, as shifts in time and location can lead to adjustments in the goal and scope, thereby influencing how results are analysed, and conclusions are drawn.

8.6.1 Step 1 prospective LCA: goal and scope definition

Temporal boundaries in LCA must be clearly defined and consistently applied to all parameters in the assessment. In prLCA, these boundaries extend into the future and should align with established scenario methodologies. This means selecting a specific future year or period as the temporal scope.

Choosing an appropriate temporal scope ensures that the emerging technology has reached a sufficient level of market penetration and maturity, making its environmental impacts more representative of a commercial product. In prospective LCA, selecting the temporal scope allows for assessing the expected technological maturity at a given future time point. This enables estimation of the process-level mass and energy balances, which can then be aligned with projected future scenarios to construct consistent background databases.

In prLCA, both foreground and background system developments must be considered to draw the most insightful conclusions, while it can still be beneficial to assess only the future state along one of these two axes. The foreground system, representing the technology under study, should incorporate technological development trajectories, upscaling potential, and respective market evolution. Meanwhile, the background system, which encompasses surrounding technological and economic systems (i.e., the total value chain), must account for broader economic developments and the long-term trajectory of the energy transition. The projected changes in process efficiency and value chain relations must be integrated into both foreground and background databases, ensuring internal consistency and coherence with the chosen scenario storyline (Sections 4 and 8.2).

8.6.2 Step 2 prospective LCA: life-cycle inventory analysis

Prospective life-cycle inventories (prLCIs) are one of the key factors which differentiates classical from future-oriented environmental assessments. Unlike conventional LCIs, which capture the current state of the economy, industrial activities, and trade, prLCIs project these elements into the future based on specific scenarios. To develop such scenarios, researchers mostly rely on IAMs, which are computational frameworks designed to analyse the complex interactions between human and natural systems. These models incorporate stylised representations of energy systems, land use, climate science, and economies to project how different variables evolve over time. Their outputs include key indicators such as temperature change, energy access, and resource use.

Two fundamental scenario concepts used in prLCA are shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs), both of which describe potential future developments while focusing on different elements. SSPs outline different socioeconomic trajectories based on factors such as population growth, energy consumption, and technological progress, ranging from sustainability-driven development (SSP1) to fossil-fuel-intensive growth (SSP5). RCPs, on the other hand, define greenhouse gas concentration trajectories and their associated radiative forcing by 2100, with pathways varying from high emissions (RCP8.5, commensurate with 4.3°C temperature change) to aggressive mitigation (RCP1.9, commensurate with 1.5°C temperature change). By combining SSPs and RCPs, researchers can explore the feasibility of climate targets and assess the impacts of policies under varying economic and environmental conditions.

The background LCI databases for prLCA are usually created by using the open-access tool *premise* (Sacchi et al., 2022). This tool integrates process-based LCI datasets from the ecoinvent database and adjusts these with scenario outputs from IAMs. It modifies ecoinvent activities according to the selected scenario and exports new prLCI databases in various formats. *premise* applies a series of key transformations to ensure that LCI datasets align with the future technological and economic developments selected. These include adjusting power plant efficiencies, establishing regional electricity markets, and introducing new fuel production pathways such as synthetic fuels. Additionally, it refines emissions to reflect projected regulatory and technological advancements, updates market structures for passenger and freight transport, and improves process efficiencies in cement and steel production. Where applicable, carbon capture and storage is also integrated into the dataset. On the other hand, IAMs which inform future scenarios, often provide data at a coarse regional scale and focus primarily on energy, transport, and land use systems, offering limited resolution for industrial processes. As a result, databases derived from IAMs—such as those generated using the *premise* tool—tend to have limited coverage of sectors like the chemical industry or mining activities, which are highly relevant in emerging technologies like OAE. These gaps can lead to underrepresentation or oversimplification of key environmental burdens, highlighting the need for careful interpretation and targeted data improvements in sector-specific assessments.

Beyond background system changes, the prLCI accounts for advancements in the foreground technology itself. When coupled with prospective TEA, learning rates applied to items such as the energy consumption of the BPMED, can be used to describe the foreground technology's advancements, as discussed in Section 8.3.1. These learning rates directly affect the energy consumption of emerging technologies over time, while acknowledging that other approaches may be needed to capture the effects of other technological advancements. By integrating these dynamic changes, prLCA provides a more realistic evaluation of future sustainability pathways, making it a valuable tool for long-term decision-making.

8.6.3 Steps 3 and 4 prospective LCA: impact assessment and interpretation

Steps 3 and 4 of a prLCA remain largely unchanged from classical LCA (see Sections 6.4 and 6.5). But similar to the TEA, it is useful to model and interpret a dynamic foreground including improvements in technology efficiency with a static background (steps 3 and 4A), in addition to a dynamic foreground and background (steps 3 and 4B).

8.7 Case study: prospective life-cycle assessment implementation

Here, the prospective LCA methodology from Section 8.6 is applied to assess the environmental impacts of BPMED for OAE. The LCA is exemplified following a similar approach to capture prospective changes as in the TEA example:

8.7.1 Step 1: Goal and scope definition

The system boundary for the electrodialysis process is shown in Figure 3.4. The emissions of subprocesses are previously calculated using the classical LCA framework (Section 6). The results of classical LCA for current time using ecoinvent v.3.10 is reported in Figure 8.10. The total net CO_2-eq emissions per tonne of gross CO_2-eq drawdown is 235.01 kg. A detailed breakdown of these results is available in Section 6.7. As in the TEA example, we select the SSP2-RCP2.6 (pkBudg1150) scenario combination from the REMIND model for our illustration.

- Location: United Kingdom
- Year: up to 2050
- System boundary: Cradle-to-gate specified in Section 3.2
- Functional unit: One tonne of gross CO_2-eq drawdown

8.7.2 Step 2: Life-cycle inventory analysis

The life-cycle inventory analysis involves collecting all relevant input and output data, including material and energy flows, emissions, and waste streams. The details of mass and energy balance for the system are provided in Section 5.6.2, Table 5.3. The only element that differs in the foreground database of prLCA in this specific case study is that we applied learning rates to the energy consumption of BPMED, and we can see that the energy consumption decreases over years due to technology development. The changes in energy consumption of BPMED are reported in Table 8.5.

Table 8.5 Life-cycle inventory for electricity consumption of the BPMED over the upcoming years in the BPMED case study. Values are normalised to 1 tonne of gross CO_2-eq drawdown.

Stage 5: Bipolar membrane electrodialysis				
Time (year)	Current	2030	2040	2050
Net electricity in BPMED (kWh)	2,039.6	1,897.9	1,666.6	1,588.8

8.7.3 Steps 3/4.A: Dynamic foreground with static background

Technology learning rates from Section 8.3 are applied to model prospective changes. Over time, BPMEDs electricity consumption is expected to decrease due to technological learning, replication, and mass production. The corresponding reduction in CO_2-eq emissions, as shown in Figure 8.10, is attributed solely to lower energy consumption in the BPMED. The improved energy efficiency of the electrodialysis cell lowers BPMED CO_2-eq emissions from 555 in the current state to

519 by 2030, and further to 440 by 2050. This represents a 6.5% reduction by 2030 and a maximum reduction of 20.7% by 2050 compared to the current scenario's climate change impact, highlighting the significant potential for future technological improvements (Figure 8.13). Note that these improvements appear moderate, and stem from the conservative energy learning rates assumed (Section 8.3.3).

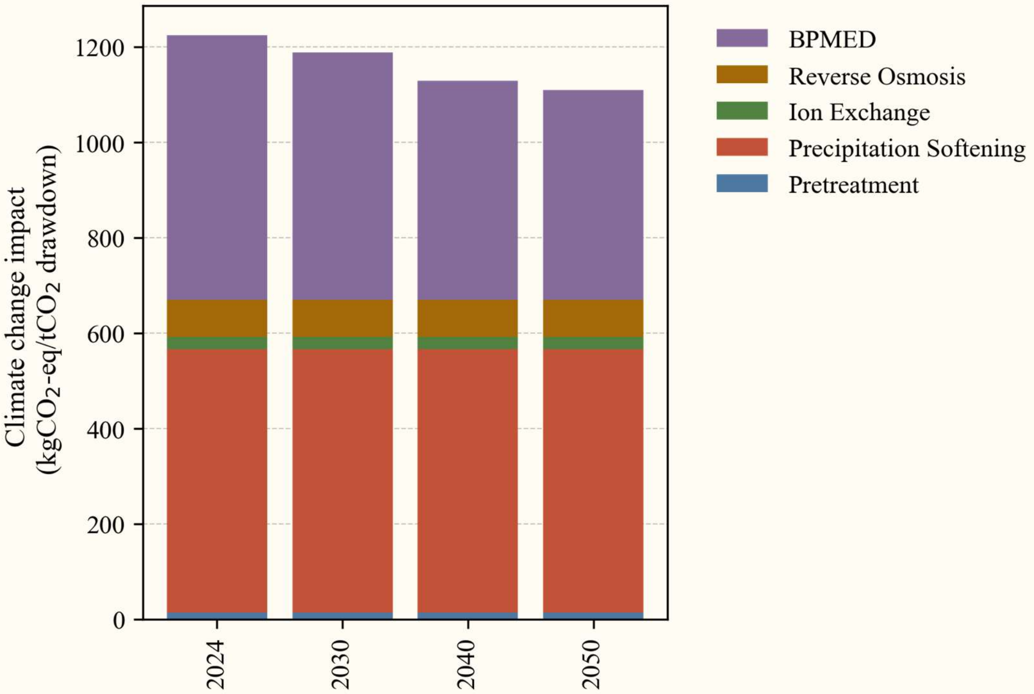

Figure 8.13 Contribution analysis of each subprocess per 1 tonne of gross CO_2-eq drawdown for the climate change impact category. Contribution analysis of the process shows decreasing emissions from the BPMED when specifying a static background database (ecoinvent v.3.10) and foreground database with learning rates applied to the energy consumption of the BPMED.

8.7.4 Steps 3/4.B: Dynamic foreground and background

In this step, background databases are generated using *premise* for each year for the selected scenario, as outlined in Section 8.4. For this analysis, we used the REMIND SSP2-RCP2.6 scenario. Incorporating a dynamic background alongside changes in the foreground system has a substantial impact on GHG emissions. This effect is particularly notable in subprocesses where emissions are primarily driven by electricity consumption rather than raw chemical inputs. The results are shown in Figure 8.14. The main reduction of emissions comes from decarbonisation of the electricity grid in the UK. In this scenario, the carbon intensity of the electricity grid decreases from 0.087 kg CO_{2eq}/kWh in 2030 to 0.019 CO_{2eq}/kWh in 2040, reaching 0.015 CO_{2eq}/kWh by 2050. This decrease in grid carbon intensity, combined with reduced electricity consumption driven by technology learning rates, results in an overall climate change impact reduction of 58%.

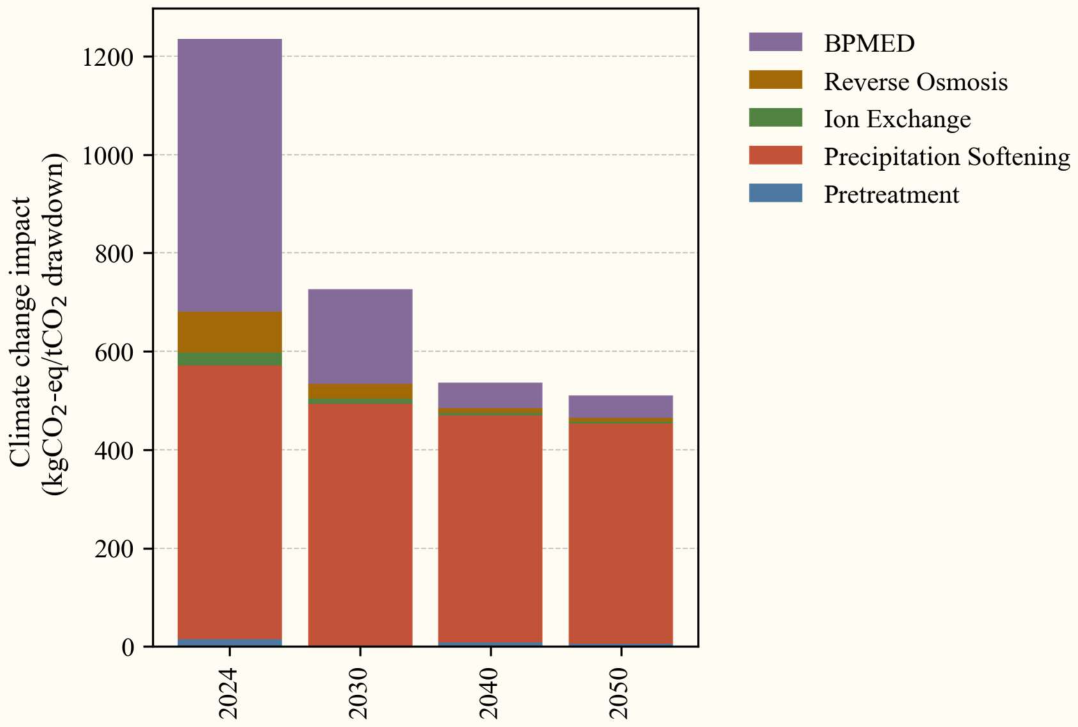

Figure 8.14 GHG emissions contribution of each subprocess per tonne of gross CO_2-eq removed. The prospective analysis indicates that in the coming years, the share of BPMED will decline due to reductions in energy consumption driven by technology advancement, as well as the decarbonisation of the electricity grid in future scenarios.

8.7.5 Steps 3/4.C: Non-climate change environmental impact categories

While climate change is a critical environmental concern, focusing solely on it may overlook other significant impacts. Evaluating multiple impact categories is the core principle of LCA and ensures that improvements in one area (like reduced GHG emissions) do not inadvertently cause negative effects elsewhere. This comprehensive approach helps pointing out burden shifting and supports the development of solutions that are genuinely sustainable across all environmental dimensions.

Here, we selected nine environmental impact categories (discussed further in Section 6.4) based on the data available in foreground LCIs. the values for each environmental impact category are normalized based on the maximum value of that impact category through all the studied scenarios (2024, SSP2-RCP2.6 (2030), SSP2-RCP2.6 (2040), SSP2-RCP2.6 (2050)). The overall results show that many impact categories (e.g., Terrestrial Eutrophication, Marine Eutrophication Potential, Terrestrial Acidification, and Ozone Depletion) decreases over time. This improvement typically reflects decarbonisation efforts, cleaner energy mixes, and better pollution controls projected in the SSP2-RCP2.6 pathway. Some categories show consistent improvement across the entire period from 2024 to 2050, like material and energy resources scarcity. Other categories may exhibit a slower decline (e.g., marine ecotoxicity) or temporary plateaus, indicating that certain impacts respond more gradually to technological and policy changes. The general trend shows lower impacts for most categories than in 2024, reflecting the cumulative effects of decarbonisation and technological progress by 2050.

Figure 8.15 illustrates that under the SSP2-RCP2.6 scenario, most non-climate environmental impacts tend to decrease over time, driven by cleaner energy, improved technologies, and policy interventions. However, the degree of improvement varies by category, highlighting both the progress made and the ongoing need to address potential trade-offs.

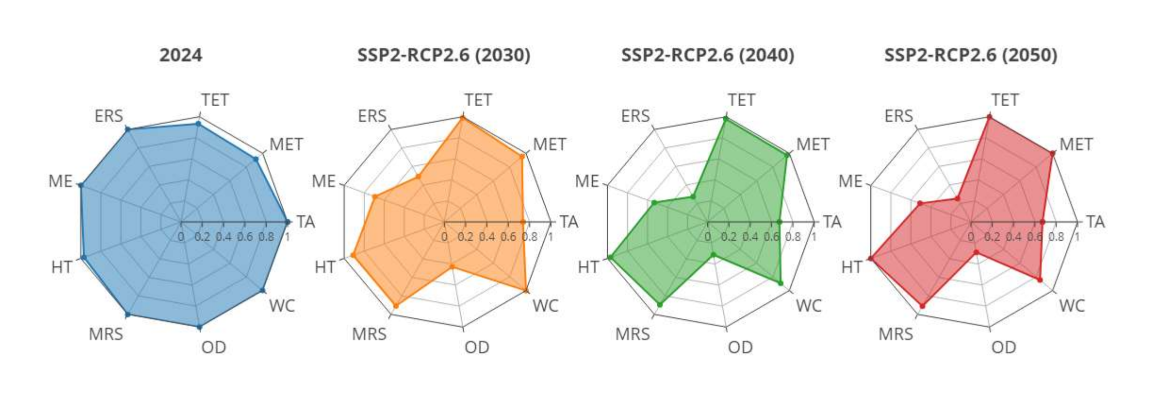

Figure 8.15 Comparison of non-climate change environmental impact categories over time. SSP2-RCP2.6 is the IAM scenario used for generating the background database for different years. Most impact categories improve as time progresses. The assessed categories include Terrestrial Ecotoxicity (TE), Marine Eutrophication Potential (MEP), Terrestrial Acidification (TA), Water Consumption (WC), Ozone Depletion (OD), Material Resource Scarcity (MRS), Human Toxicity (HT), Marine Ecotoxicity (MET), and Energy Resource Scarcity (ERS).

9.0 Framework Part G: Uncertainty analysis

Key Recommendations:

- Employ local sensitivity analysis methods only when computational resources are severely constrained. Global sensitivity analyses methods should be prioritised.
- Avoid using global sensitivity analyses for making strictly prognostic predictions of OAE deployment outcomes.
- Assess parameter interactions beforehand and use Sobol indices when significant interactions are present or expected.
- Otherwise, prioritise SRCC or Borgonovo (or similarly computationally efficient) indices to minimise resource demands.

Effective research, development, and investment in CO_2 mitigation strategies, such as OAE, rely on data-driven decision-making to support the transition to net-zero GHG emissions. However, many of these approaches face significant challenges: (i) they remain at low levels of technological maturity, (ii) their underlying physicochemical mechanisms are not yet fully understood, (iii) process and system designs are still in early development stages, and (iv) future environmental, financial, policy, and societal conditions remain uncertain. As a result, large-scale deployment of OAE is hindered by these uncertainties, making it crucial to assess its feasibility and impacts rigorously.

9.1 Nomenclature

To navigate this uncertainty, the application of uncertainty analysis methods is strongly recommended to enhance the transparency and reliability of LCA and TEA studies. TEAs and LCAs evolve throughout the technology development process, ranging from simplified assessments based on mass and energy balances to detailed evaluations using high-fidelity modelling, plant data, and bottom-up costing approaches. The choice of uncertainty analysis method should align with the complexity and purpose of the model. However, selecting suitable uncertainty analysis methods is not always straightforward. Some methods are computationally intensive and require extensive data, while others are more accessible but may oversimplify the analysis. Most commonly we can distinguish between 'local' and 'global' sensitivity analysis methods. In the following section we discuss how to use those methods, explain their advantages and shortcomings, and recommend when to use which method for the development of OAE technologies. An overview of the methods discussed here is shown in Table 9.1.

Table 9.1 Uncertainty analysis definitions. Adapted from Strunge et al. (2023).

Item	Description
Local sensitivity analysis	Only one or a few inputs are varied at a time around a reference parameter. The sensitivity of the outcome is tested against small perturbations of the inputs.
Global sensitivity analysis	Feasible variation of uncertain inputs within the operating space of the model.
One-at a time	Local sensitivity analysis that changes one input at a time using two extremes (Mishra and Datta-Gupta, 2017).
One-way	Local sensitivity analysis that changes one input at a time over an interval. (Mishra and Datta-Gupta, 2017). Unlike one at a time, nonlinearities can be detected.
Multiple-way	Local sensitivity analysis that changes multiple inputs at a time over an interval(van der Spek et al., 2020b). Simple interaction effects between parameters can be detected.
Scatterplot-analysis	A global sensitivity analysis that results in the visual analysis of a Monte Carlo simulation in input-output scatter plots(Mishra and Datta-Gupta, 2017). Visual interpretation possible to identify sensitive parameters.
Spearman rank correlation	A global sensitivity analysis in which regression analysis is used for ranked input-output pairs (Marelli et al., 2024).
Sobol (variance-based)	A global sensitivity analysis that measures how much an output variance could be reduced if inputs were fixed (Saltelli et al., 2008). Interaction and total effects can be analysed in-depth.
Borgonovo (density-based)	A global sensitivity analysis that measures the distance between the output density when no inputs are fixed and the density where one input is fixed (Borgonovo and Plischke, 2016). This method is moment independent.

9.2 Local sensitivity analysis

Local sensitivity analyses (LSA) are among the most commonly applied methods in *ex ante* technology assessments. These methods involve varying one or multiple input parameters around a base value to assess their influence on key model outputs. The simplest form of LSA is the one-at a time (OAT) sensitivity analysis, where individual input variables x_i are changed using two realisations (e.g., ±10%, ±50%, or predefined minimum and maximum values) around a base value (van der Spek et al., 2020b). The OAT sensitivity can then be calculated as follows, where $y^+_{i,j}$, $y^-_{i,j}$ are the values of model output y_j when replacing one input i with the extremes of x^+_i and x^-_i and y^0_j is the value of the output without changing x_i (Eq. 9.1).

$$OAT[y_{i,j}] = \frac{|y^+_{i,j} - y^-_{i,j}|}{y^0_j} \quad \text{(Eq. 9.1)}$$

To visualise the results, output responses for each varied input can be presented in a tornado diagram, where variables are ranked based on their OAT indicator, with the most influential variable appearing at the top.

An extension of this approach is the one-way local sensitivity analysis, in which input variables are varied across a predefined range (e.g., ten steps within ±10%) rather than just two realisations. While this method provides a more detailed understanding of sensitivity, it also requires higher computational effort. Spider plots are commonly used to visualise the results of one-way sensitivity analyses, allowing for an assessment of the strength, direction, and nature of the local input-output relationships based on slope comparisons (Mishra and Datta-Gupta, 2017). In some cases, it can also be beneficial to alter multiple variables at the same time, which is commonly referred to as multiple-way sensitivity analysis.

9.3 Global sensitivity analysis

Although LSAs are computationally efficient, they lack probabilistic considerations, making parameter variations (e.g., ±15%) somewhat arbitrary (Saltelli et al., 2008). To address this, global sensitivity analyses (GSA) are often recommended for ex ante technology assessments (Mishra et al., 2009; Van der Spek et al., 2021; van der Spek et al., 2020b). Unlike LSA, GSA evaluates how probabilistic variations in input parameters influence model outputs (Mishra et al., 2009). Given the complexity of LCA and TEA models, especially in later stages of technology development of OAE technologies, GSA typically relies on statistical techniques and probabilistic sampling.

Key steps include characterising uncertainty by defining probability density functions (PDFs) for input variables. Uncertainty is propagated in the model by drawing samples using Monte Carlo or advanced techniques like Latin hypercube or Sobol sampling. Finally, the importance of uncertainty is evaluated by analysing input-output relationships to identify critical parameters (Mishra and Datta-Gupta, 2017). These methods improve robustness by capturing interdependencies and avoiding biases in the input space.

9.3.1 Uncertainty characterisation

Defining PDFs for input parameters is a critical step in GSA, requiring a balance between real uncertainty and potential biases. Poor data quality or unrealistic assumptions can lead to misleading results, so PDFs must reflect physically possible ranges (e.g., non-negative values). Several methods help assign PDFs effectively:

1. **Decision tree method** (Hawer et al., 2018) – This approach recommends PDFs based on data quality and nature (e.g., discrete or continuous). It allows for subjective assumptions or objective estimations using statistical methods. However, it requires detailed data, which may not always be available for emerging technologies.
2. **Maximum entropy principle** (Harr, 1987) – This method selects from five PDF types (uniform, triangular, normal, beta, and Poisson) based on known constraints like bounds and mean. It avoids unnecessary assumptions while maintaining flexibility.
3. **Uniform distribution** – This is the simplest approach, assuming equal probability for all values within a defined range. This method requires minimal prior knowledge but may oversimplify uncertainty.

Despite these strategies, modeler bias remains a challenge. Expert input can help refine distributions, but access to specialists is often limited. Ultimately, even well-defined PDFs are approximations of reality and should be interpreted with caution. In (Strunge et al., 2023), the three common methods for PDF determination were compared, showing that it is always recommended to follow the most comprehensive decision tree method when possible. Since the uncertainty characterisation method can have a significant impact on the results, it is imperative to i) use all available data and ii) for multiple comparative analyses (i.e., comparing multiple OAE technologies or deployment options) to rely on the same PDF determination method.

9.3.2 Uncertainty evaluation

Various methods have been developed to assess the uncertainty importance of the output space. This document briefly describes several common approaches, including scatterplot analysis, rank correlation, variance-based methods, and density-based methods. The primary distinction among these methods lies in their underlying assumptions, making them more suitable for different applications. A key differentiation is whether a method is parametric (i.e., it assumes a specific distribution for the inputs when ranking them) or non-parametric (i.e., it does not assume a specific input distribution when ranking). Generally, parametric methods offer higher accuracy but impose stricter application requirements. In this study, rank correlation and density-based measures (i.e., Borgonovo method) are non-parametric; variance-based measures (i.e., Sobol method) are parametric; and scatterplot analysis is qualitative. To compute these methods, open-source software is available such as UQLab, which enables easy application of the methods discussed here (https://www.uqlab.com/). In the following, the methods are briefly described. More detailed guidance and comparison can be found in Strunge et al. (2023).

Scatterplot analysis. Scatterplots illustrate bivariate relationships and allow visual assessment of input-output dependencies. The output sample generated by Monte Carlo simulations is plotted against the realisations of each input variable. A strong relationship appears as a smaller variance in the sample (Mishra and Datta-Gupta, 2018). Scatterplot analysis requires significant computational resources.

Spearman rank correlation. The Spearman rank correlation coefficient (SRCC) evaluates how well the relationship between an input sample and an output sample follows a monotonic function (Helton et al., 1991). Unlike linear correlation measures, SRCC does not assume a specific relationship form, making it widely applicable, including in TEAs and LCAs where various input-output relationships exist. SRCC is computed by ranking the inputs and outputs from the Monte Carlo sample. Each input-output pair is assigned a rank transformation and, where values are ranked from 1 to *n* (where *n* is the number of variables). The SRCC is then calculated using Equation 9.2:

$$SRCC[x_i, y_j] = \frac{\left(\Sigma_l\left(x_{i,l}^{trans} - \bar{x}_i\right)\left(y_{j,l}^{trans} - \bar{y}_j\right)\right)}{\left[\Sigma_l\left(x_{i,l}^{trans} - \bar{x}_i\right)^2 * \Sigma_l\left(y_{j,l}^{trans} - \bar{y}_j\right)^2\right]^{\frac{1}{2}}} \qquad \text{(Eq. 9.2)}$$

This method assumes a monotonic relationship, which must be verified through visual inspection. If the relationship is non-monotonic, SRCC may yield unreliable results.

Sobol indices. Variance-based methods assess how the expected variance of the output model changes when an input realisation is known with certainty. The Sobol indices (Sobol', 2001) are widely used for this purpose. They provide a quantitative measure of the strength, direction, and nature of input-output relationships. Sobol indices include:

- **First-order indices:** Measure the effect of one input variable alone on the output.
- **Total-order indices:** Capture interactions between multiple input variables.

These indices help identify interaction effects that other methods cannot detect (Mishra et al., 2009). However, because Sobol indices depend on variance, they may produce misleading results if inputs influence the entire output distribution without significantly affecting variance (Borgonovo and Tarantola, 2008). Because calculating Sobol indices requires the calculation of all partial variances, which quickly leads to thousands or millions of calculations to be computed, multiple shortcut methods have been proposed. A useful method is the Janon estimator (Janon et al., 2014) (Eq. 9.3), which allows quick calculation of first-order and total-order effects. We considered two independent Monte Carlo samples $x=(x_1,\dots,x_n)$ and $x=(x'_1,\dots,x'_n)$, resulting in $y=g(x)$ and $y_v=g(x'_1,\dots,x'_{v-1},x_v,x'_{v+1},\dots,x'_n)$, which are then computed using Equation 9.3:

$$S_v = \frac{\frac{1}{N}\sum y_i\, y_i^v - \left(\frac{1}{N}\sum\left(\frac{y_i + y_i^v}{2}\right)\right)^2}{\frac{1}{N}\sum\frac{y_i^2 + y_i^{v\,2}}{2} - \left(\frac{1}{N}\sum\frac{y_i + y_i^v}{2}\right)^2} \qquad \text{(Eq. 9.3)}$$

Borgonovo indices. Since Sobol indices rely on variance (a second-moment measure), they may not fully capture sensitivities when input PDFs have long tails (Borgonovo, 2007). Density-based approaches like Borgonovo's method address this limitation by comparing the shapes of input and output distributions. Borgonovo indices are computed using conditional and unconditional probability density functions (Eq. 9.4).

$$\partial_i = \frac{1}{2} * Ex_i\left[\int \left|f_{y_j}(y_j) - f_{(y_j|x_i)}(y_j|x_i)\right| dy\right] \qquad \text{(Eq. 9.4)}$$

9.3 Case study: Uncertainty analysis

Here, all described methods from Section 9.2 have been applied to a CO_2 mineralisation (Strunge et al., 2023), but derived recommendations can be transferred to assessing uncertainty of LCAs and TEAs of OAE technologies. For decision-making processes, meaningful results and their illustration can be crucial. Application of local sensitivity analyses methods is shown in Figure 9.1 and Figure 9.2. OAT analyses should commonly be illustrated using tornado plots (see Figure 9.1). Here, values with the largest induced changes will be displayed at the top of the graph. For one-way analyses, spider plots commonly are used to illustrate if non-linearities are present. In two-way analyses (Figure 9.2), contour plots can be used to illustrate the results.

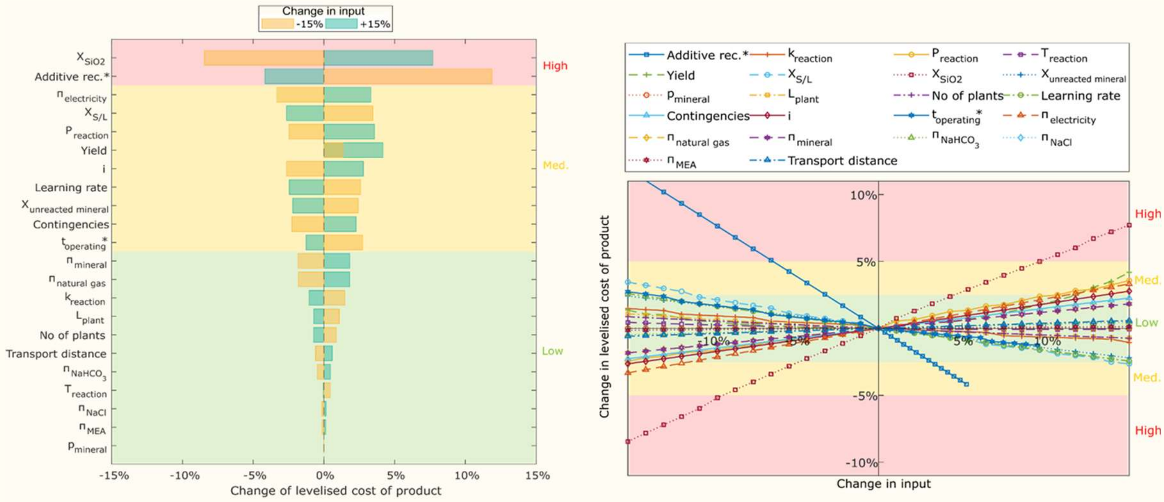

Figure 9.1 Exemplification of OAT local sensitivity analysis using a tornado diagram (left) and one-way local sensitivity analysis using a spider plot (right), taken from Strunge et al. (2023).

To identify variables with high impacts on the output, we recommend clustering results in predefined ranges. This can help the analysis and guide decision-makers to extract meaningful results. The applied local method can give a first indication of which variables or variable pairs will have the biggest impact on results, but to finally identify the impact of uncertainty on the output, GSA methods should be used.

Applying GSA methods is shown in Figure 9.3 and Figure 9.4. The results illustrate that scatterplot analysis, while showing a nice illustration, can make it difficult to determine variables with high impacts. Additionally, Sobol indices allow investigating both first-order and total-order sensitivity (meaning the impact comes primarily from the variable itself or in combination with other variables), and Borgonovo indices can additionally be beneficial for input PDFs with long tails. The case study shows that for some models, the choice of uncertainty evaluation method might not change the outcomes much, while for some it can significantly alter the derived results. For example, in this case, studying quantitative GSA methods (i.e., SRCC, Sobol, Borgonovo) produced consistent ranking orders due to limited interaction effects being present. Nevertheless, in many cases LSA methods can be insufficient in identifying all critical input parameters, sometimes misclassifying their importance. As a result, we recommend a broader application of GSA methods to enhance the robustness of uncertainty analysis, ultimately improving their value for policy and decision-making in the OAE sector.

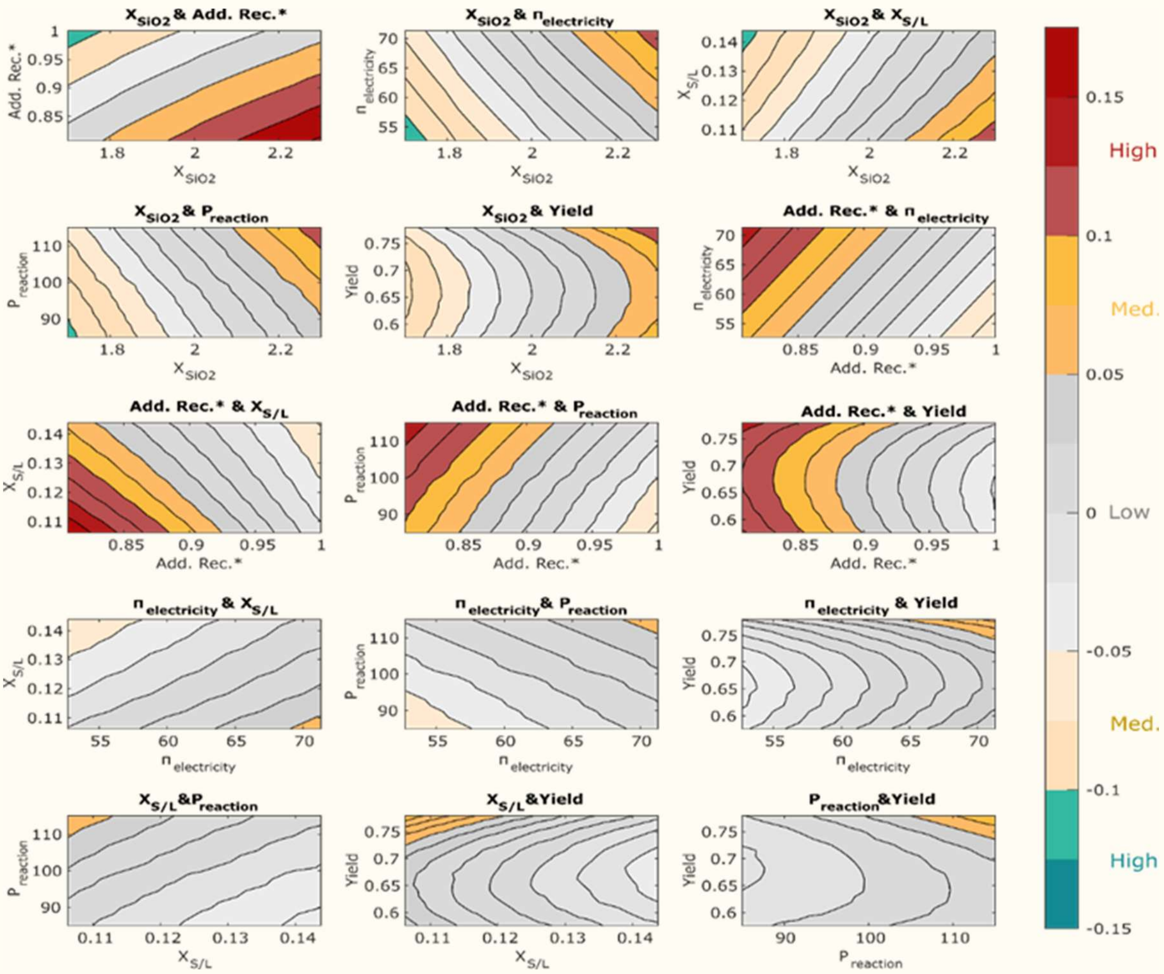

Figure 9.2 Exemplification of illustration of two-way sensitivity analysis using contour plots, taken from Strunge et al. (2023).

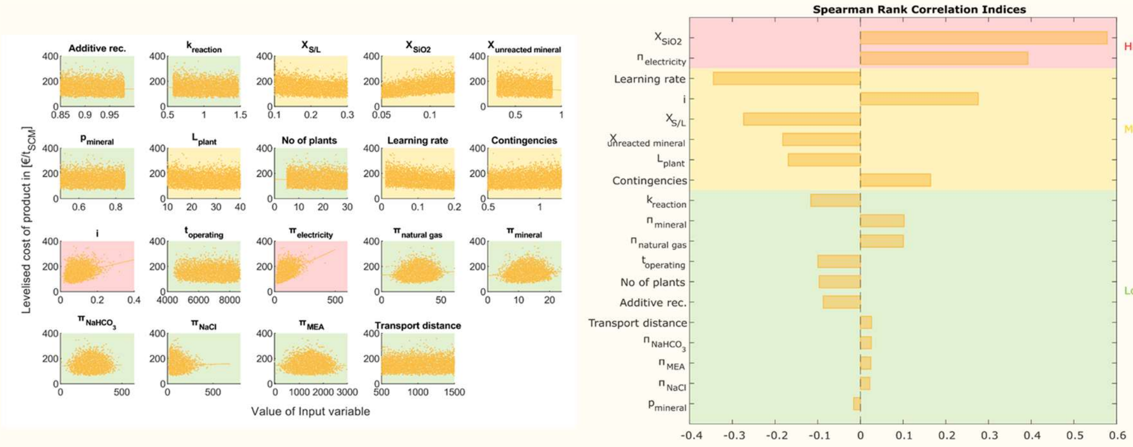

Figure 9.3 Exemplification of scatterplot analysis (left) and Spearman rank correlation analysis (right), taken from Strunge et al. (2023).

To choose the uncertainty evaluation method, both accuracy and computational requirements should be considered. Since Sobol analysis requires significantly higher computational effort, it may often be sufficient to use SRCC or Borgonovo indices. However, we recommend first assessing the presence and magnitude of interaction effects – either by conducting a reduced-variable Sobol analysis or through multiple-way LSA – since strong interactions can lead to discrepancies in parameter rankings across methods. If interaction effects are minimal or negligible, SRCC or Borgonovo indices should be preferred due to their lower computational cost. This consideration is particularly crucial when dealing with complex and nonlinear OAE models.

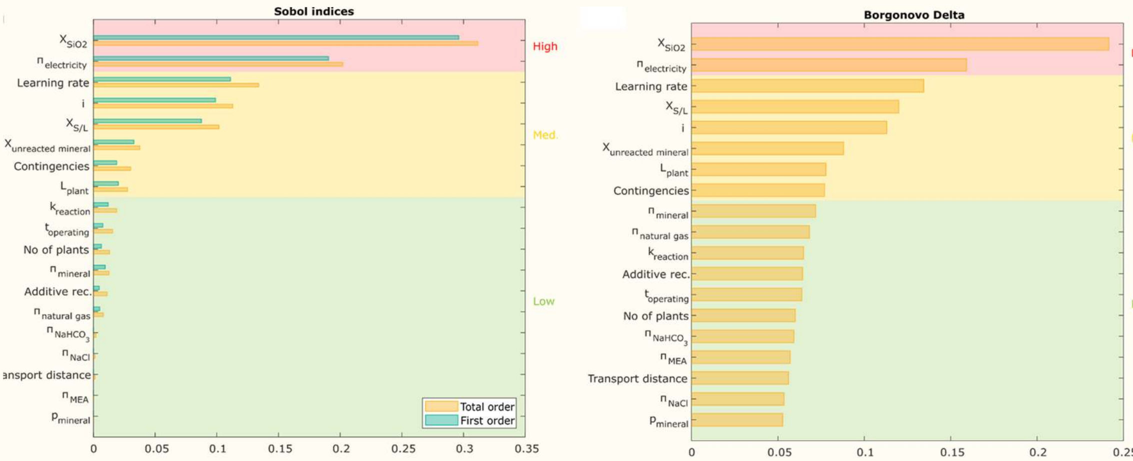

Figure 9.4 Exemplification of illustration of Sobol and Borgonovo indices using sorted bar plots, taken from Strunge et al., (2023).

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Version history		
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1.0	9th May 2025	Initial version, drafted 2024 and 2025.