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# Optimal Deployment of Engineered Carbon Dioxide Removal (BECCS & DACCS) in the North Sea Region

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**Abstract**

Achieving the 1.5°C climate target outlined by the IPCC requires the large-scale deployment of Carbon Dioxide Removal (CDR) technologies. This study focuses on two engineered options: Bioenergy with Carbon Capture and Storage (BECCS) and Direct Air Carbon Capture and Storage (DACCS), to determine least-cost deployment strategies across nine European countries bordering the North Sea from 2025 to 2050. A dynamic, spatially explicit optimization model is developed to minimize the discounted cost per ton of net $CO_2$ removed, delivering 100 $MtCO_2$/yr of engineered removals by 2050. Results show that BECCS is deployed earlier, leveraging biomass availability and existing infrastructure, while DACCS investments become dominant after 2040 as biomass becomes scarcer, technological costs decline, and clean electricity expands. Overall, BECCS represents around 78% of total net negative emissions. The average removal cost reach 231 €/$tCO_2$, but significant disparities emerge across countries. The United Kingdom and Sweden deploy the largest CDR fleets, while the order changes for costs: France bears higher costs than the UK due to a comparatively larger share of DACCS investments. Smaller countries such as Denmark and the Benelux region contribute less. Additional concerns arise from the electricity demand generated by such projects. The study reveals a feasible but costly objective that requires European coordination for fair burden sharing and robust actions on biomass governance, clean energy policies, and $CO_2$ transport and storage infrastructures.

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# 1 Introduction

The recent IPCC report presented that carbon dioxide removal (CDR) will have a critical role to play in meeting the 1.5°C objective. This objective can hardly be attained without a large-scale deployment of CDR methods, such as Bioenergy with Carbon Capture and Storage (BECCS), and Direct Air Carbon Capture and Storage (DACCS) (IPCC, 2022). Negative emission practices are essential for reaching net-zero targets by offsetting residual emissions from hard-to-abate sectors in the short term and for achieving net-negative emissions in the long term. Integrated Assessment Model scenarios estimate that 190 to 1,190 $GtCO_2$ of cumulative removal will be needed by 2100 (Huppmann et al., 2018,Rogelj et al., 2018). The magnitude of these deployment needs raises numerous economic and policy concerns pertaining to: the important cost of that deployment, the fierce competition for resources it may create, the societal demand for social justice, and possible threats on biodiversity (Fuss et al., 2018, Heck et al., 2018, P. Smith et al., 2016).

The purpose of this study is to broaden the understanding of the conditions for a massive deployment of these technologies. More specifically, it focuses on the optimal deployment of two key engineered and novel CDR technologies BECCS and DACCS with the aim of minimizing total economic costs. BECCS is needed for achieving negative emissions, particularly in the European Union (ERCST, 2025). The costs and scalability of both BECCS and DACCS are subject to significant uncertainties, with BECCS costs starting lower but decreasing more slowly compared to DACCS, which has higher initial costs but steeper cost reductions over time (Abegg et al., 2024a). Rather than assessing global or purely technological feasibility, the analysis concentrates on determining where, when and at what cost these technologies should be deployed in Europe to support climate targets aligned with the Paris Agreement. The geographical scope is limited to seven strategically selected regions and regions: France, the United Kingdom, Germany, the Benelux countries (considered as one region), Sweden, Norway, and Denmark. These countries were chosen based on their potential for CDR deployment with respect to storage sites (Terlouw et al., 2024).

In recent years, the European Union has increasingly acknowledged the importance of CDR in achieving net-zero emissions by 2050 and net-negative trajectories thereafter (Presty et al., 2024; Schenuit, 2021). The EU estimates that residual emissions will range between 390 and 1,165 million tonnes of $CO_2$ equivalents, requiring CDR solutions to offset these emissions (Cario, 2024).

Scenarios suggest that CDR will need to remove between 400 and 500 million tonnes annually by 2050 (Parmiter et al., 2021). Novel CDR, should account for one quarter of that amount (EU-Commission, 2018). Initiatives such as the European Climate Law, the Net Zero Industry Act, and the Innovation Fund explicitly recognize the need to scale up negative emissions technologies (European Commission, 2023, Delafalize, 2023). These instruments are accompanied by emerging proposals for a European Carbon Removal Certification Framework, designed to standardize monitoring, reporting, and verification of removals, and to lay the groundwork for future incentive structures, such as credit markets or procurement schemes (Global CCS Institute, 2024). However, CDR deployment remains at an early stage and faces a wide range of techno-economic, political, and institutional barriers (Quadrature Climate Foundation, 2024). In this context, integrated assessment models (IAMs) have played a central role in projecting the long-term role of CDR technologies within global mitigation portfolios. Several studies have shown that CDR can account for up to 20–30% of cumulative mitigation under 1.5°C pathways, with BECCS dominating early and DACCS emerging after (IPCC, 2018).

Our analysis concentrates on the economics of large-scale deployment of CDR technologies in the context of achieving European climate targets. We adopt a spatially explicit, dynamic cost-optimization framework. This model is designed to minimize the total economic cost per ton of $CO_2$ of deploying BECCS and DACCS across selected European countries between 2025 and 2050. It allows us to investigate the following core research questions: Which novel CDR technologies should be deployed? Where and when should this deployment take place? In what quantities? This research aims to answer those questions under our European objectives of net zero by 2050.

While the importance of CDR technologies is increasingly recognized in global climate mitigation scenarios, there remains a limited understanding of how, where, and when these technologies should be deployed in a cost-effective manner within specific regional contexts (Köberle, 2019). Most IAMs, such as those used by the IPCC, operate at a global or continental scale (IPCC, 2022, Butnar et al., 2020, Van Sluisveld et al., 2018, Fajardy et al., 2018, S. Smith et al., 2024). While these models are essential to map global CDR needs, they often lack the spatial granularity and sectoral resolution necessary to inform national investment strategies, infrastructure planning, or region-specific technology choices. By offering a geographically explicit, microeconomic optimization model, the model captures heterogeneity and techno-economic potential. In addition to complementing global IAMs, this study fills a gap left by previous national or regional assessments that typically focus on theoretical potential, costs and trajectories, but do not quantify least-cost deployment pathways (Ganti et al., 2024, Rosa et al., 2021, Abegg et al., 2024a). By producing detailed cost trajectories associated with BECCS and DACCS. This is particularly relevant in the context of the European Union and neighboring states, where climate neutrality targets require coordinated but cost-efficient planning, as evidenced by recent multinational agreements on $CO_2$ transport and storage infrastructure (CMCC, 2024). The model also contributes to the ongoing debate regarding the relative merits and limitations of BECCS and DACCS. While BECCS is often considered a lower-cost option, it faces structural constraints related to sustainable biomass supply and land-use competition (Schenuit, 2021, Lehtveer and Emanuelsson, 2021). Conversely for DACCS, though currently more costly, is geographically more flexible but heavily reliant on low-carbon electricity and still undergoing technological maturation (Abegg et al., 2024a). By simulating deployment under real-world constraints and cost dynamics, this study helps to identify at what point in time and space each technology becomes preferable.

Our results present a sequenced deployment meets the 2050 target of 100 $MtCO_2$/yr of engineered removals: BECCS scales earlier on biogenic point sources and accessible storage, while DACCS becomes the marginal option after 2040 as costs decline and grids decarbonize. BECCS supplies 78% of cumulative removals to 2050, whereas it reaches 60% of annual removals in 2050. Deployment is also spatially asymmetric: Sweden and the United Kingdom specialize in early BECCS, while Norway initiates DACCS first followed by France and Sweden post-2040. The average cost is ≈ €231 per net $tCO_2$, with cumulative removals of 0.998 $GtCO_2$ and electricity demand rising to ~76 TWh/yr by 2050 (~615 kWh per net $tCO_2$). These results raise two central questions: how to incentivize such investments, and how to equitably share the burden of large-scale deployment.

The paper is organized as follows. In the next section, we present description of the CDR options and our motivations for the one that are used in our model. The third section describes our model and its specificity. The fourth section presents the area of study and the data used in our model. Finally, we present a conclusion that discuss our method and results while commenting on future work and limitations.

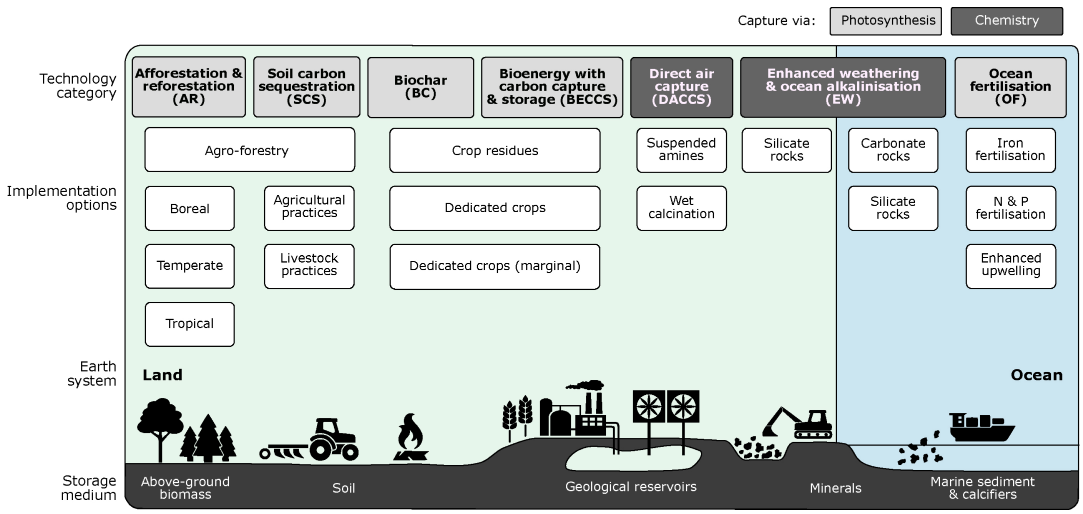


*Figure 1: A taxonomy of negative emissions technologies (NETs) IPCC, 2022*

## 2 Description of CDR options

CDR methods compared to Carbon Capture and Storage (CCS) do not only reduce emissions but enable negative emissions, a necessary step for true carbon neutrality (Masson-Delmotte et al., 2018). Those technologies capture $CO_2$ through photosynthesis or chemical processes on land or in the oceans to store the $CO_2$ in geological storage, biomass, soil, mineral, marine sediments and calcifiers J. C. Minx et al., 2018. There are eight main CDR technologies which includes natural methods: 1. Coastal blue carbon, 2. Soil carbon sequestration, 3. Afforestation/Reforestation, 4. Ocean fertilization, 5. Biochar, 6. BECCS, 7. DACCS, and 6. Mineralization, 8. Enhanced weathering and alkalinisation. Each one of these technologies has different risks, verification challenges, and costs but some portfolio of them, perhaps different for each region, could be a viable way to meet climate change/decarbonization goals (Mace et al., 2021).

Our study investigate BECCS and DACCS, they are novel CDR technologies that provide opportunities for the development of new markets, making them not only technologically feasible but also economically attractive. They can generate economic interactions and strategic behaviors among countries, regions, markets, and industries. As a consequence, they can be integrated in policy discussions and be incentivized/monitored by policy instruments (IPCC, 2022). CCS has the quality of inducing a carbon capture monitored and a carbon permanently stored (Giannaris et al., 2020) which makes it simpler for regulations.

We restrict the analysis to engineered carbon dioxide removals (BECCS and DACCS). These technologies deliver durable storage via geological sequestration and already align with EU-ETS expectations for permanence, liability, and robust MRV, which the EU Carbon Removal Certification Framework (CRCF) seeks to formalize (Rickels et al., 2021; Kalkuhl et al., 2022; Edenhofer et al., 2023; Normec Verifavia, 2025). Crucially for a cost-minimization model, BECCS and DACCS have well-characterized, decomposable cost components and transparent physical constraints that can be represented with convex cost curves and linear/convex constraints, enabling a clear, comparable euro-per-tonne least-cost allocation across countries and technologies (Donnison et al., 2020; Fajardy et al., 2018; Hale et al., 2022; Sacchi et al., 2023). By contrast, nature-based options (e.g., afforestation/soils) are essential for mitigation and co-benefits but pose higher risks of impermanence and reversal over policy-relevant horizons and exhibit heterogeneous MRV and additionality. A faithful treatment would require risk-adjusted permanence discounts, buffers/insurance, and intertemporal stochastic constraints, which are outside our scope (P. Smith et al., 2016; Theuer et al., 2021).

# 3 The model

This section first describes the real-world setting captured by our model, then formalizes it mathematically, and finally lists the notation used throughout.

## 3.1 Overview and Objective

The model represents a coordinated European effort to deploy engineered CDR at least cost. Economically, it can be read as a social planner (or an EU-level agency) that chooses when, where, and how much to invest in two novel CDR technologies (BECCS and DACCS) across a set of cooperating countries bordering the North Sea (France, United Kingdom, Germany, Benelux, Denmark, Sweden, Norway). Politically, this corresponds to a cooperative burden-sharing arrangement under which countries pool access to transport and storage infrastructure and commit to a common net-removal requirement by 2050, while allowing location-specific costs and constraints to determine who deploys what and when.

Time is discrete and annual from 2025 to 2050. In each year the planner decides the number of BECCS and DACCS plants to commission in each country. Investments face a two-year construction delay: capacity committed in year $t$ becomes operational in $t+2$. Once online, plants deliver gross $CO_2$ capture that is converted to certified net removals via technology, country, and time specific netting factors. These factors deduct lifecycle emissions, specifically electricity-related emissions that depend on each country's grid emission intensity and on the electricity intensity of the technology, and therefore improve over time with power-sector decarbonization.

We do not model the electricity-generation side of BECCS and therefore do not include any electricity-sales revenue in the optimisation: electricity prices $p^{\text{el}}_{k,t}$ and grid emission factors $e^{\text{grid}}_{k,t}$ are treated as exogenous inputs and only electricity $\gamma^{\text{el}}_{k,t}$ used by the capture process enter the cost terms. This choice rests on a perfect-competition assumption for the power market: firms are price-takers so $p = MC(q)$, and free entry implies zero long-run economic profit $\pi = p \cdot q - C(q) \approx 0$. Under these conditions any persistent rent from electricity generation is negligible for allocation decisions in our model, so we focus solely on the capture-related costs and on netting of lifecycle emissions.

The planner's objective is a levelized measure: minimize the present value of total system costs divided by total net removals over the horizon. This choice makes the objective comparable across scenarios and emphasizes the long-run budgetary burden of achieving net-negative goals. The result of the program is an internally consistent deployment pathway: technology and country-specific investment schedules over 2025–2050, implied net removals, and a decomposition of the levelized system cost into capital, operating, and TS components. This pathway can be interpreted as the cost-efficient division of labor among selected cooperating European countries under shared access to storage, given heterogeneous costs, energy systems, learning dynamics, and frictions.

## 3.2 Mathematical Formulation

The objective is to minimize the discounted cost per tonne of net $CO_2$ removed:

$$\min_{n} \quad z = \frac{\sum_{t \in \mathcal{T}} z_t}{R_{\text{total}}}, \tag{1}$$

where $z_t$ is the total discounted cost incurred in year $t$, and $R_{\text{total}}$ is the total net $CO_2$ removed across all countries and years. In this context, $\sum_{t \in \mathcal{T}} z_t$ is a present value (PV) of costs: each future cost is converted to its present value using the discount factor $(1+\rho)^{-(t-t_0)}$.

The discounted cost in each year $t$ is defined as:

$$z_t = \frac{1}{(1+\rho)^t} \sum_{k \in \mathcal{K}} \left( \frac{C_{k,t}^{\text{BECCS}}}{\nu_{k,\text{BECCS},t}} + \frac{C_{k,t}^{\text{DACCS}}}{\nu_{k,\text{DACCS},t}} \right), \tag{2}$$

where $C_{k,t}^{\text{BECCS}}$ and $C_{k,t}^{\text{DACCS}}$ are the total BECCS and DACCS costs in country $k$ and year $t$, and $\nu_{k,\text{BECCS},t}$, $\nu_{k,\text{DACCS},t}$ are the effective net capture efficiencies. These efficiencies translate gross captured $CO_2$ into certified net removals by deducting lifecycle emissions specific to each technology, country, and year. For BECCS, the deduction reflects emissions from the biomass supply chain (cultivation, harvesting, processing, and transport), residual process and capture bypass during combustion and separation, electricity and heat use for capture, compression, and auxiliaries, and $CO_2$ transport and storage operations. Taken together these components form a lifecycle emission factor $\theta_{k,\text{BECCS},t}$ so that $\nu_{k,\text{BECCS},t} = 1 - \theta_{k,\text{BECCS},t}$. For DACCS, the deduction is driven primarily by energy requirements to operate air-contacting fans, regenerate sorbents through heat and/or vacuum, compress $CO_2$, and run auxiliaries, with additional contributions from transport and storage; hence $\nu_{k,\text{DACCS},t} = 1 - \theta_{k,\text{DACCS},t}$ where $\theta_{k,\text{DACCS},t}$ depends strongly on electricity use. In both cases, the electricity-related term scales with the country- and time-specific grid emission intensity $e_{k,t}^{\text{grid}}$, so expected power-sector decarbonization reduces $\theta_{k,j,t}$ over time and increases $\nu_{k,j,t}$.

The cost components are modeled as follow:

$$\mathrm{C}_{k,t}^{\text{BECCS}} = \mathrm{K}_{k,t}^{\text{BECCS}} + O_{k,t}^{\text{BECCS}} + V_{k,t}^{\text{BECCS}} + T_{k,t}^{\text{BECCS}}, \tag{3}$$

$$\mathrm{C}_{k,t}^{\text{DACCS}} = \mathrm{K}_{k,t}^{\text{DACCS}} + O_{k,t}^{\text{DACCS}} + V_{k,t}^{\text{DACCS}} + T_{k,t}^{\text{DACCS}} \tag{4}$$

Here, $K_{k,t}^{j}$ is the capital expenditure (CAPEX), it covers the upfront investment to build capture and conditioning assets. $O_{k,t}^{j}$ is the fixed operating expenditure (Fixed OPEX), it comprises costs that do not scale with annual output: staffing, routine maintenance and inspections, insurance, environmental compliance and monitoring, etc... In our implementation this is represented as a proportion of the capital stock. The variable operating expenditure (OPEX) $V_{k,t}^{j}$ gathers costs that scale approximately linearly with captured tonnes such as solvent/sorbent, reagents, water use, and process electricity/heat. Transport and Storage $T_{k,t}^{j}$ accounts for moving $CO_2$ from the plant to the storage site and permanent sequestration.

We model the CAPEX as a declining cost through a combination of exogenous and endogenous learning-by-doing (LBD). LBD relates to learning that arises through production and investment:

costs fall as cumulative capacity production increases and technology becomes more mature. The most common specifications scale costs with a learning factor linked to capacity accumulation for endogenous LBD (Schopp et al., 2015). Formally, for each country $k$ and year $t$ we write:

$$K_{k,t}^{\mathrm{BECCS}} = \alpha\,\mathrm{CAPEX}_{k,t_0}^{\mathrm{BECCS}}\big(Q_{\mathrm{BECCS},t-3}^{\mathrm{cum}}/w_{\mathrm{BECCS}}\big)^{-\lambda_{\mathrm{BECCS}}} + (1-\alpha)\,\mathrm{CAPEX}_{k,t}^{\mathrm{BECCS}} \tag{5}$$

$$K_{k,t}^{\mathrm{DACCS}} = \beta\,\mathrm{CAPEX}_{k,t_0}^{\mathrm{DACCS}}\big(Q_{\mathrm{DACCS},t-3}^{\mathrm{cum}}/w_{\mathrm{DACCS}}\big)^{-\lambda_{\mathrm{DACCS}}} + (1-\beta)\,\mathrm{CAPEX}_{k,t}^{\mathrm{DACCS}} \tag{6}$$

The terms $w_{\mathrm{BECCS}}$ and $w_{\mathrm{DACCS}}$ are the capacities of a representative large-scale BECCS and DACCS plant ($tCO_2$/yr per plant) used for normalization. Thus $Q_{j,t}^{\mathrm{cum}}/w_j$ measures the cumulative number of equivalent large-scale plants deployed up to year $t-2$, and the factor $\big(Q_{j,t-3}^{\mathrm{cum}}/w_j\big)^{-\lambda_j}$ applies endogenous learning to the unit CAPEX as deployment scales. The exogenous component $\mathrm{CAPEX}_{k,t}^{j}$ captures time trends unrelated to cumulative deployment. The parameter $\lambda_j > 0$ is the learning exponent implied by an assumed learning rate $\mathrm{LR}_j$ via $\lambda_j = \ln(1-\mathrm{LR}_j)/\ln(2)$. The Two-year lag $t-2$ reflects a commissioning delay: investments undertaken at $t$ begin contributing to cumulative operating capacity and to learning only after they are built and enter service. $\alpha, \beta \in [0,1]$ are the shares of total cost decline allocated to endogenous learning-by-doing effects for BECCS and DACCS, respectively.

Cumulative global deployment of each technology is computed as the sum, across countries and commissioning years, of the number of plants invested ($n_{k,j,\tau}$) multiplied by the capacity per plant ($w_j$, $tCO_2$/yr); equivalently, $Q_{j,t}^{\mathrm{cum}}/w_j$ is the cumulative number of equivalent large-scale plants online after the two-year delay:

$$Q_{\mathrm{BECCS},t}^{\mathrm{cum}} = \sum_{k\in\mathcal{K}}\sum_{\tau\le t-2} n_{k,\mathrm{BECCS},\tau}\cdot w_{\mathrm{BECCS}}, \tag{7}$$

$$Q_{\mathrm{DACCS},t}^{\mathrm{cum}} = \sum_{k\in\mathcal{K}}\sum_{\tau\le t-2} n_{k,\mathrm{DACCS},\tau}\cdot w_{\mathrm{DACCS}}. \tag{8}$$

Fixed operational costs are modeled as a constant annual fraction of the capital stock. Specifically, $o^j$ is the fixed O&M factor for technology $j \in \{\mathrm{BECCS}, \mathrm{DACCS}\}$, so that

$$\mathrm{O}_{k,t}^{\mathrm{BECCS}} = \mathrm{K}_{k,t}^{\mathrm{BECCS}}\cdot o^{\mathrm{BECCS}}, \tag{9}$$

$$\mathrm{O}_{k,t}^{\mathrm{DACCS}} = \mathrm{K}_{k,t}^{\mathrm{DACCS}}\cdot o^{\mathrm{DACCS}}. \tag{10}$$

Because $\mathrm{K}^j_{k,t}$ denotes the CAPEX for installed capacity at $(k,t)$, these expressions capture that fixed O&M scales with the assets. Since $\mathrm{K}^j_{k,t}$ declines over time with learning-by-doing and exogenous time trends, fixed O&M inherits the same decline: lower CAPEX from cumulative deployment implies proportionally lower fixed O&M in subsequent years.

Variable operating costs scale directly with output. Let $q_{kjt}$ denote gross tonnes captured and sent to storage in $(k,j,t)$ ($tCO_2$/yr). The variable cost per tonne combines a non-energy marginal component and energy purchased at local prices multiplied by technology intensities:

$$\mathrm{V}^{\mathrm{BECCS}}_{k,t} = q_{k,\mathrm{BECCS},t}\left[v^{\mathrm{BECCS}}_{k,t} + p^{\mathrm{el}}_{k}\,\gamma^{\mathrm{el}}_{\mathrm{BECCS}}\right], \tag{11}$$

$$\mathrm{V}^{\mathrm{DACCS}}_{k,t} = q_{k,\mathrm{DACCS},t}\left[v^{\mathrm{DACCS}}_{k,t} + p^{\mathrm{el}}_{k}\,\gamma^{\mathrm{el}}_{\mathrm{DACCS}}\right]. \tag{12}$$

Here, $v^j_{k,t}$ (EUR/$tCO_2$) collects non-energy consumables. The term $p^{\mathrm{el}}_{k,t}$ (EUR/MWh) is the country specific electricity price, and $\gamma^{\mathrm{el}}_j$ (MWh/$tCO_2$) is the technology-specific electricity intensity per tonne captured. This formulation makes explicit that variable OPEX depends on local electricity prices and on the electricity intensity of each technology.

Transport and storage costs are modeled with increasing marginal unit costs that scale with the project's share of national transport–storage capacity utilized in year $t$. Early projects access shorter routes and proximate storage, while later projects face longer hauls or scarcer injection capacity (Abegg et al., 2024b; (IEA), 2022).

$$\mathrm{T}^{\mathrm{BECCS}}_{k,t} = n_{k,\mathrm{BECCS},t}\,w^{\mathrm{BECCS}}_{k,t}\left[T^{\mathrm{BECCS,min}}_{k} + \left(\frac{n_{k,\mathrm{BECCS},t}\,w^{\mathrm{BECCS}}_{k,t}}{Q^{\mathrm{BECCS,max}}_{k}}\right)\left(T^{\mathrm{BECCS,max}}_{k} - T^{\mathrm{BECCS,min}}_{k}\right)\right], \tag{13}$$

$$\mathrm{T}^{\mathrm{DACCS}}_{k,t} = n_{k,\mathrm{DACCS},t}\,w^{\mathrm{DACCS}}_{k,t}\left[T^{\mathrm{DACCS,min}}_{k} + \left(\frac{n_{k,\mathrm{DACCS},t}\,w^{\mathrm{DACCS}}_{k,t}}{Q^{\mathrm{DACCS,max}}_{k}}\right)\left(T^{\mathrm{DACCS,max}}_{k} - T^{\mathrm{DACCS,min}}_{k}\right)\right]. \tag{14}$$

where $T^{\min}_k$ and $T^{\max}_k$ are the minimum and maximum unit TS costs (EUR/$tCO_2$) for country $k$, $Q^{\max}_k$ is the national TS capacity limit ($tCO_2$/yr), and $n_{k,\mathrm{BECCS},t}\,w^{\mathrm{BECCS}}_{k,t}$ is the BECCS flow in year $t$ ($tCO_2$/yr). The same applies for DACCS.

Define the netting factors as:

$$\nu_{k,\mathrm{BECCS},t} = 1 - \left(\gamma^{\mathrm{proc}}_{\mathrm{BECCS}} + e^{\mathrm{grid}}_{k,t}\,\gamma^{\mathrm{el}}_{\mathrm{BECCS}}\right), \tag{15}$$

$$\nu_{k,\mathrm{DACCS},t} = 1 - \left(\gamma^{\mathrm{aux}}_{\mathrm{DACCS}} + e^{\mathrm{grid}}_{k,t}\,\gamma^{\mathrm{el}}_{\mathrm{DACCS}}\right), \tag{16}$$

where $e^{\text{grid}}_{k,t}$ is the electricity emission intensity in country $k$ and year $t$ ($tCO_2$/MWh). The term $e^{\text{grid}}_{k,t}$ is an exogenous input and declines over time according to the country-specific decarbonization path. $\gamma^{\text{el}}_j$ is the technology-specific electricity intensity (MWh/$tCO_2$ gross), and $\gamma^{\text{proc}}_{\text{BECCS}}$ and $\gamma^{\text{aux}}_{\text{DACCS}}$ collect non-electric lifecycle deductions per gross tonne. These factors satisfy $0 < \nu_{k,j,t} \leq 1$ and increase over time as $e^{\text{grid}}_{k,t}$ declines with power-sector decarbonization.

Given the netting factors $\nu_{k,j,t}$ defined above, net removals are obtained by applying these factors to gross output after the commissioning delay: for BECCS,

$$r_{k,\text{BECCS},t} = \sum_{\tau \leq t-2} n_{k,\text{BECCS},\tau}\, w_{\text{BECCS}}\, \nu_{k,\text{BECCS},t}, \tag{17}$$

$$r_{k,\text{DACCS},t} = \sum_{\tau \leq t-2} n_{k,\text{DACCS},\tau}\, w_{\text{DACCS}}\, \nu_{k,\text{DACCS},t}. \tag{18}$$

The model imposes four constraint families. (i) A terminal requirement ensures adequacy by mandating that aggregate net removals in year $T$ meet or exceed the policy target $\bar{R}_T$. (ii) Country-level capacity bounds limit cumulative operational BECCS and DACCS to technical potentials $Q^{\max}_{\text{BECCS},k}$ and $Q^{\max}_{\text{DACCS},k}$. (iii) Deployment ramping constraints restrict year-over-year expansions via technology-specific growth rates $g_{\text{BECCS}}$ and $g_{\text{DACCS}}$, capturing delivery and supply-chain limits. (iv) Non-negativity of investment decisions rules out disinvestment within the horizon.

$$\sum_{k \in \mathcal{K}} \left( r_{k,\text{BECCS},t} + r_{k,\text{DACCS},t} \right) \geq \bar{R}_T, \tag{(i)}$$

$$\sum_{\tau \leq t} n_{k,\text{BECCS},\tau} \cdot w_{\text{BECCS}} \leq Q^{\max}_{\text{BECCS},k}, \tag{(ii)}$$

$$\sum_{\tau \leq t} n_{k,\text{DACCS},\tau} \cdot w_{\text{DACCS}} \leq Q^{\max}_{\text{DACCS},k}, \tag{19}$$

$$\sum_{\tau \leq t} n_{k,\text{BECCS},\tau} \cdot w_{\text{BECCS}} \leq (1 + g_{\text{BECCS}}) \left( \sum_{\tau \leq t-1} n_{k,\text{BECCS},\tau} \cdot w_{\text{BECCS}} \right), \tag{(iii)}$$

$$\sum_{\tau \leq t} n_{k,\text{DACCS},\tau} \cdot w_{\text{DACCS}} \leq (1 + g_{\text{DACCS}}) \left( \sum_{\tau \leq t-1} n_{k,\text{DACCS},\tau} \cdot w_{\text{DACCS}} \right), \tag{20}$$

$$n_{k,\text{BECCS},t} \geq 0, \qquad n_{k,\text{DACCS},t} \geq 0. \tag{(iv)}$$

## 3.3 Notations

**Objective function:**

$$\min_{\{n_{kjt}, q_{kjt}, r_{kjt}\}} \quad J = \frac{1}{R_{\text{total}}} \sum_{t\in\mathcal{T}} \sum_{k\in\mathcal{K}} \sum_{j\in\mathcal{J}} \delta_t \, C^{\text{rem}}_{kjt}(r_{kjt}) \tag{21}$$

$$\text{where} \quad R_{\text{total}} = \sum_{t\in\mathcal{T}} \sum_{k\in\mathcal{K}} \sum_{j\in\mathcal{J}} r_{kjt}, \qquad \delta_t = (1+\rho)^{-(t-t_0)}. \tag{22}$$

**subject to:**

(Terminal requirement) $$\sum_{k\in\mathcal{K}} \sum_{j\in\mathcal{J}} r_{kjT} \geq \bar{R}_T \tag{23}$$

(Commissioning delay) $$q_{kjt} = \sum_{\tau\le t-2} n_{kj\tau}, \qquad \forall\, k, j, t \tag{24}$$

(Netting / lifecycle emissions) $$r_{kjt} = \nu_{kj,t}\, q_{kjt}, \qquad 0 < \nu_{kj,t} \le 1, \qquad \forall\, k, j, t \tag{25}$$

$$\nu_{k,\text{BECCS},t} = 1 - \left(\gamma^{\text{proc}}_{\text{BECCS}} + e^{\text{grid}}_{k,t}\, \gamma^{\text{el}}_{\text{BECCS}}\right), \tag{26}$$

$$\nu_{k,\text{DACCS},t} = 1 - \left(\gamma^{\text{aux}}_{\text{DACCS}} + e^{\text{grid}}_{k,t}\, \gamma^{\text{el}}_{\text{DACCS}}\right), \tag{27}$$

(BECCS potential) $$0 \le r_{k,\text{BECCS},t} \le \bar{R}^{\text{BECCS}}_{kt}, \qquad \forall\, k, t \tag{28}$$

(Electricity availability) $$\sum_{j\in\mathcal{J}} \gamma^{\text{el}}_j\, q_{kjt} \le \bar{E}^{\text{el}}_{kt}, \qquad \forall\, k, t \tag{29}$$

(Growth / monotonicity) $$q_{kjt} \ge q_{kj,t-1}, \qquad \forall\, k, j,\ t > \min(\mathcal{T}) \tag{30}$$

$$q_{kjt} - q_{kj,t-1} \le g_j\, q_{kj,t-1} + \delta_j, \qquad \forall\, k, j,\ t > \min(\mathcal{T}) \tag{31}$$

(Non-negativity) $$n_{kjt} \ge 0, \quad q_{kjt} \ge 0, \quad r_{kjt} \ge 0, \qquad \forall\, k, j, t \tag{32}$$

*Table 1: Notation: indices, variables, costs, parameters, and constraints.*

| Symbol | Description | Units / Notes |
|---|---|---|
| **Indices and Sets** | | |
| $k$ | Country (capture region) index; elements of $\mathcal{K}$. | — |
| $j$ | Technology index; $j \in \{\text{BECCS}, \text{DACCS}\} = \mathcal{J}$. | — |
| $t$ | Year index; horizon $t \in \mathcal{T}$ (2025–2050), terminal year $T$. | — |
| $\tau$ | Lagged year index used for a two-year commissioning delay. | — |
| **Decision Variables** | | |

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| Symbol | Description | Units / Notes |
|---|---|---|
| $n_{kjt}$ | Plants invested in year $t$. Becomes operational at $t+2$. | Count |
| $q_{kjt}$ | Gross $CO_2$ captured and sent to storage in $(k,j,t)$. | $tCO_2/yr$ |
| $r_{kjt}$ | Net removals certified in $(k,j,t)$ after lifecycle netting. | $tCO_2/yr$ |
| **Objective and Intermediate Quantities** | | |
| $z$ | Average discounted cost per net tonne over the horizon. | EUR per $tCO_2$ (net) |
| $z_t$ | Discounted system cost incurred in year $t$. | EUR (present value) |
| $R_{\text{total}}$ | Total net $CO_2$ removed across all $k,j,t$. | $tCO_2$ |
| $\delta_t$ | Discount factor for year $t$ (base year $t_0$). | $(1+\rho)^{-(t-t_0)}$ |
| **Cost Terms (per $(k,j,t)$)** | | |
| $C_{kjt}$ | Total cost for $(k,j,t)$: capital, fixed OPEX, variable OPEX, TS. | EUR |
| $K^j_{k,t}$ | Capital cost term used in $C_{kjt}$ (computed from unit CAPEX and capacity). | EUR |
| $\text{CAPEX}^j_{k,t}$ | Unit overnight CAPEX entering learning equations. | EUR per $(tCO_2/yr)$ |
| $O^j_{k,t}$ | Fixed operating expenditure. | EUR |
| $V^j_{k,t}$ | Variable operating expenditure. | EUR |
| $T^j_{k,t}$ | Transport and storage (TS) expenditure. | EUR |
| **Learning, Capacity, and Flows** | | |
| $Q^{\text{cum}}_{j,t}$ | Cumulative global deployment for technology $j$ up to $t$ (after delay). | $tCO_2/yr$ |
| $w_j$ | Nameplate capacity per plant/module of technology $j$. | $tCO_2/yr$ per plant |
| $\lambda_j$ | Learning exponent implied by learning rate $\text{LR}_j$. | $\lambda_j = \ln(1-\text{LR}_j)/\ln(2)$ |

Continued on next page

| Symbol | Description | Units / Notes |
|---|---|---|
| $\alpha, \beta$ | Shares of endogenous LBD in CAPEX decline for BECCS and DACCS. | In $[0, 1]$ |
| **Energy Prices and Intensities** | | |
| $p^{\mathrm{el}}_{k,t}$ | Electricity price in country $k$, year $t$. | EUR/MWh |
| $\gamma^{\mathrm{el}}_{j}$ | Electricity intensity per gross tonne for technology $j$. | MWh per $tCO_2$ |
| $v^{j}_{k,t}$ | Non-energy variable cost per gross tonne. | EUR per $tCO_2$ |
| **Netting and Emissions** | | |
| $e^{\mathrm{grid}}_{k,t}$ | Grid emission factor for country $k$, year $t$. | $tCO_2$/MWh |
| $\gamma^{\mathrm{proc}}_{\mathrm{BECCS}}$ | Non-electric lifecycle deduction per gross tonne (BECCS). | $tCO_2$ per $tCO_2$ (gross) |
| $\gamma^{\mathrm{aux}}_{\mathrm{DACCS}}$ | Non-electric lifecycle deduction per gross tonne (DACCS). | $tCO_2$ per $tCO_2$ (gross) |
| $\nu_{kjt}$ | Netting factor linking gross to net removals. | In $[0, 1]$ |
| **Transport and Storage Parameters** | | |
| $T^{\min}_{k,j}, T^{\max}_{k,j}$ | Lower/upper bounds of unit TS cost in country $k$ for technolgy $j$. | EUR per $tCO_2$ |
| **System Constraints and Limits** | | |
| $\bar{R}_T$ | Net-removal requirement in terminal year $T$. | $tCO_2$/yr |
| $Q^{\max}_{\mathrm{BECCS},k}$ | BECCS technical potential (capacity bound) in country $k$. | $tCO_2$/yr |
| $Q^{\max}_{\mathrm{DACCS},k}$ | DACCS technical potential (capacity bound) in country $k$. | $tCO_2$/yr |
| $\bar{E}^{\mathrm{el}}_{k,t}$ | Electricity available for removals in country $k$, year $t$ (if used). | MWh/yr |
| $g_j$ | Maximum year-over-year proportional growth for technology $j$. | — |
| **Miscellaneous** | | |
| $\rho$ | Real discount rate; discount base year $t_0$. | — |
| $t_0$ | Base year for discounting. | Year |

# 4 Area and Data

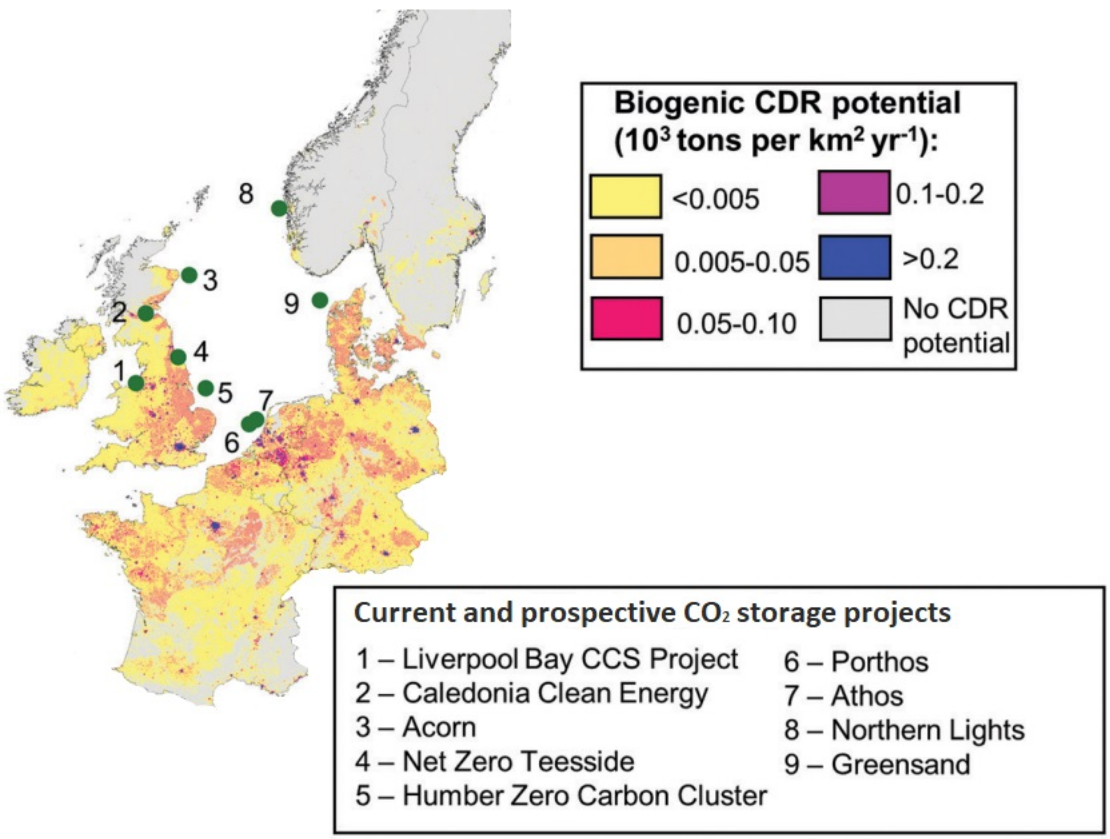
This section documents the datasets, construction steps, and harmonization choices used to parameterize the model. The geographical scope includes seven North Sea–adjacent regions: France, the United Kingdom, Germany, the Benelux (Belgium, the Netherlands, Luxembourg), Denmark, Sweden, and Norway. These countries are selected for their direct access to North Sea $CO_2$ storage and for the plausibility of coordinated planning under a shared terminal net-removal requirement. In the model they are treated as cooperating under pooled planning with country-specific costs and constraints. All data with their sources are presented in the appendix.

The model is based on a network of $CO_2$ storage in the North Sea. The transport and storage infrastructure represented in our model present actual projects currently under development or already contracted. In our main scenario, we do not assume any potential additional storage projects nor new pipeline routes. The main European project in terms of $CO_2$ storage is the Northern lights. Aiming to store over 5 million tons of $CO_2$ per year during the initial phase, the projects aims to deliver reliable and safe $CO_2$ transport and storage to various countries across Europe. Our transport and storage data corresponds to the transportation and storage of $CO_2$ to the projects described in Figure 2.

BECCS opportunities are constructed from biogenic point sources reported in the literature in Europe, including pulp and paper, municipal solid-waste incineration, bio-power, wastewater treatment, and selected agricultural residues (Rosa et al., 2021). Facilities with annual biogenic emissions at least 0.1 $MtCO_2/yr$ are retained, they are presented in Figure 2. The resulting spatial distribution defines country-level BECCS potential and capture siting. This opportunity set is held constant over 2025–2050, acknowledging uncertainty about future competition for biomass, we do not assume more biogenic CDR potential to be available.

DACCS has no intrinsic siting potential. However, we limit its deployment by electricity availability up to a maximum of 10% of national electricity production to protect electric systems. Studies show that while DACCS lacks intrinsic siting limitations, large-scale deployment is fundamentally constrained by the availability of low-carbon electricity, and excessive demand by DACCS threatens to compromise grid reliability and displace renewable resources required for other decarbonization

*Figure 2: Geospatial distribution of biogenic carbon dioxide removal potential from existing point sources in Europe in 2018. The figure shows incinerators, pulp and paper, and bio-power facilities emitting more than 0.1 Mtons $CO_2$ per year, and wastewater treatment plants processing more than 100 000 population equivalent of wastewater per day. Biogenic CDR potential data from (Rosa et al., 2021). The figure also present current $CO_2$ storage project in the North Sea that are included in our data. A higher resolution figure is available in the appendix* **??**.



priorities (Bisotti et al., 2023; Terlouw et al., 2024). For instance, this study (Bisotti et al., 2023) demonstrates that scenarios permitting DACCS to consume 14–25% of national electricity, as in Norway, risk undermining the operational resilience of energy systems. Scientific assessments recommend robust upper bounds as prudent measures (McQuillen et al., 2025).

Electricity price $p^{\mathrm{el}}_{k,t}$ and grid emission factor $e^{\mathrm{grid}}_{k,t}$ are exogenous, country-specific inputs. For prices, we take the 2025 country values from the IEA Energy Prices database and hold them constant over the horizon (EUR/MWh) (International Energy Agency, 2025b). For grid emission factors, we take 2025 country values ($tCO_2$/MWh) and impose an exogenous linear decline of 90% by 2050. This assumption is consistent with power-sector decarbonization pathways underlying EU long-term strategy and infrastructure scenarios, which converge to a near-zero-carbon electricity system by mid-century (EUCommission, 2018; International Energy Agency, 2021).

Cost data on BECCS and DACCS up to 2050 primarily come from a comprehensive dataset by the Danish Energy Agency (Danish Energy Agency, 2024) and various studies (Krey et al., 2019, Chris, 2018, Viebahn et al., 2019, Fasihi et al., 2019, Keith et al., 2018, McQueen et al., 2021, Evans, 2017, L. Jiang et al., 2023, Sciences et al., 2019, Ozkan et al., 2022, Madhu et al., 2021, Shayegh et al., 2021) [1]. We also use a learning by doing ratio given by different studies that suggest a 5% for BECCS and 15% for DACCS (Danish Energy Agency, 2022, (IEA), 2022, Rubin et al., 2015, G. F. Nemet et al., 2018). We make the assumptions that chemicals have no limit and are at a fixed cost. Also, while water and land use might be an issue, we do not integrate them in our model. The discount rate is set to 3.4%, in line with EU member states social perspective (Hermelink and Jager, 2015) and the WITCH model's average discount rate on CDR (Emmerling et al., 2019).

The European Commission indicates that achieving climate neutrality will require 400–500 $MtCO_2$/yr of CDR by 2050, with roughly three quarters delivered by nature-based options and the remaining 100–125 $MtCO_2$/yr by engineered approaches (BECCS and DACCS) (Parmiter et al., 2021; EUCommission, 2018). Accordingly, we set a baseline terminal requirement of 100 $MtCO_2$/yr of engineered removals in 2050.

[1] All monetary inputs are converted to euros 2020. When studies report ranges or multiple technology variants, central values are selected for the baseline. Only the transport and storage costs are taken as highest due to being low or high.

# 5 Results

The following section presents the results of the model. We aim to answer the question: When, where and at what cost can we achieve our 2050 $CO_2$ removal target in Europe ?

## 5.1 When?

The model's results are presented as a deployment trajectory from 2025 to 2050. We first examine aggregate investments in Figure 3, which shows annual net $CO_2$ removals from BECCS and DACCS. Because the model is calibrated to achieve 100 $MtCO_2/yr$ by 2050, investments reach this target mechanically by construction. However, the path towards this objective is the interesting part. The curves show a clear sequencing in the deployment: BECCS is deployed and scaled earlier, with removals gradually increasing from the early 2030s, while DACCS accelerates significantly after 2040. The model identifies BECCS as a more mature candidate for early-stage negative emissions due to its integration with existing biomass energy infrastructure and near-term cost advantage. In the literature, Almena-Ruiz et al., 2021 and Mander et al., 2017 explain the advantages of BECCS to capitalize on existing infrastructure to have lower costs. However, the deployment of BECCS is ultimately constrained by sustainable biomass availability and potential competition with other biomass intensive technologies (Jones and Albanito, 2020). Looking at our results, BECCS follows a saturating (approximately logarithmic) trajectory, while DACCS exhibits an exponential take-off. DACCS would likely overtake BECCS shortly after 2050. DACCS deployment proceeds in three phases: first, a negligible "exploration phase" begins alongside first BECCS investments. Those essential investments comes from a willingness to reduce future cost through learning-by-doing. In the second phase, around 2040, DACCS becomes cost-competitive as capital costs fall and electricity grids are sufficiently decarbonized to make the technology viable from a net removal standpoint. Deployment begins to scale in high-efficiency countries with favorable cost profiles. After 2045, the large-scale deployment of DACCS begins, becoming the dominant novel CDR technology in terms of annual investments. This acceleration is essential given BECCS's constraints that cannot keep up with the removal objective and its associated increasing marginal cost.

Those results imply important observations: early investments are efficient in order to progress through learning by doing. BECCS is cheaper than DACCS in early period. BECCS is largely constrained by biogenic CDR availability which creates a large increase in cost, making DACCS potentially more cost-efficient at some point (2045 in our model). DACCS can scale exponentially but is largely limited through assumptions of high decreasing costs.

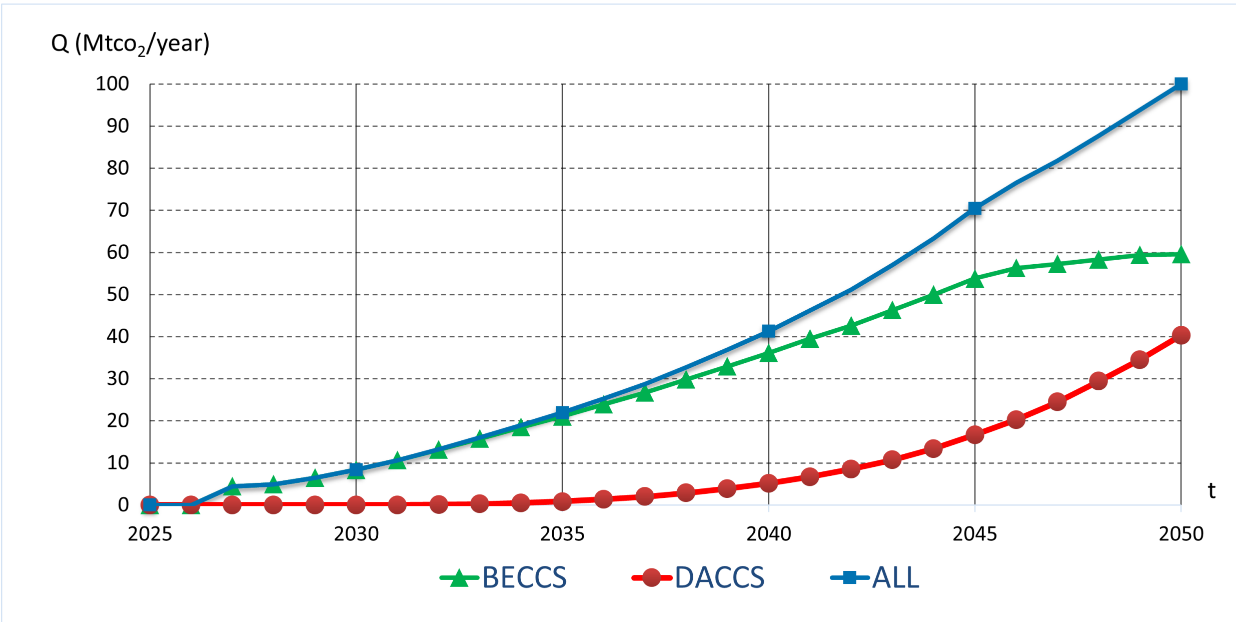



*Figure 3: Annual net $CO_2$ removals from BECCS and DACCS over the 2025–2050 period.*

### 5.2 Where?

This deployment of engineered CDR also raises the question on where are the removals done. Spatial heterogeneity in resource availability, transport and storage access and cost and electricity mix play an important role in shaping this optimal distribution of CDR. In addition to present where the investments would be on average the most profitable, the geographic distribution allows to better understand, design and address an equitable, efficient and feasible strategy. The total net negative emissions from each country are represented on Figure 4, at first sight, asymmetries in deployment patterns are clearly observable. Trends that are driven by their respective local conditions. Sweden clearly is set as the principal land for CDR investments in those regions, while Denmark struggles to be competitive in this regard. UK follows a similar pattern as Sweden but in lower volumes, while France has a low investments start with the highest increase in the later period.

BECCS deployments on Figure 5 present a dominant portion of initial investments done in Sweden and the UK. They both benefit from a robust and sustainable biomass supply with a relatively easy access to transport and storage infrastructure. This access to the North Sea infrastructures enhance BECCS feasibility by reducing transport costs. The Benelux, Norway, and Denmark share the same advantage as the UK in terms of proximity to transport and storage infrastructure. However, Norway and Denmark have limited biomass availability (see appendix), which directly constrains their BECCS deployment. In other countries, BECCS investments struggle to take-off, especially in Germany where it becomes relevant after 2035. France and the Benelux still have some impact in this deployment in early period. But while the Benelux is constrained by its biogenic CDR potential capacity, France's investments are targeted towards DACCS rather than BECCS, as shown in Figure 6.

During the initial period, DACCS investments remain extremely limited, consistent with a testing and pilot phase. Norway is the first country to initiate a DACCS hub around 2035, leveraging its nearly carbon-neutral electricity mix combined with an advantageous access to storage sites. Strategically, those investments serves as cost reductions through learning-by-doing. Once DACCS costs decline sufficiently, France, followed by Sweden and then the UK begin their large-scale investments. The timing and scale of DACCS adoption are strongly conditioned by electricity-related constraints: the emission intensity of electricity is critical for ensuring net-negative outcomes, and DACCS's high energy demand requires a sufficiently large and decarbonized power grid. It shows the importance of considering the net negative emission compared to the negative emission that might lead to totally different results.

Overall, we observe that Sweden and the UK have the highest potential for BECCS, in terms of cost-efficiency, due to their biogenic CDR potential. BECCS investments only take-off after 2035 in other countries. DACCS are largely cost-efficient in Norway at first but rapidly becomes competitive in France and Sweden. However, DACCS depends largely on the cost reductions and the grid decarbonization, thus it only becomes relevant after the 2040s.

### 5.3 At what cost ?

This massive deployment of engineered CDR has low probability to be deployed totally liberally, without subsidies or any kind of help from governments. And even in the case of direct cost of zero for the governments, indirect costs are still going to be a fair part of the burden. In this regard, it seems important to assess the burden implications of such deployment.

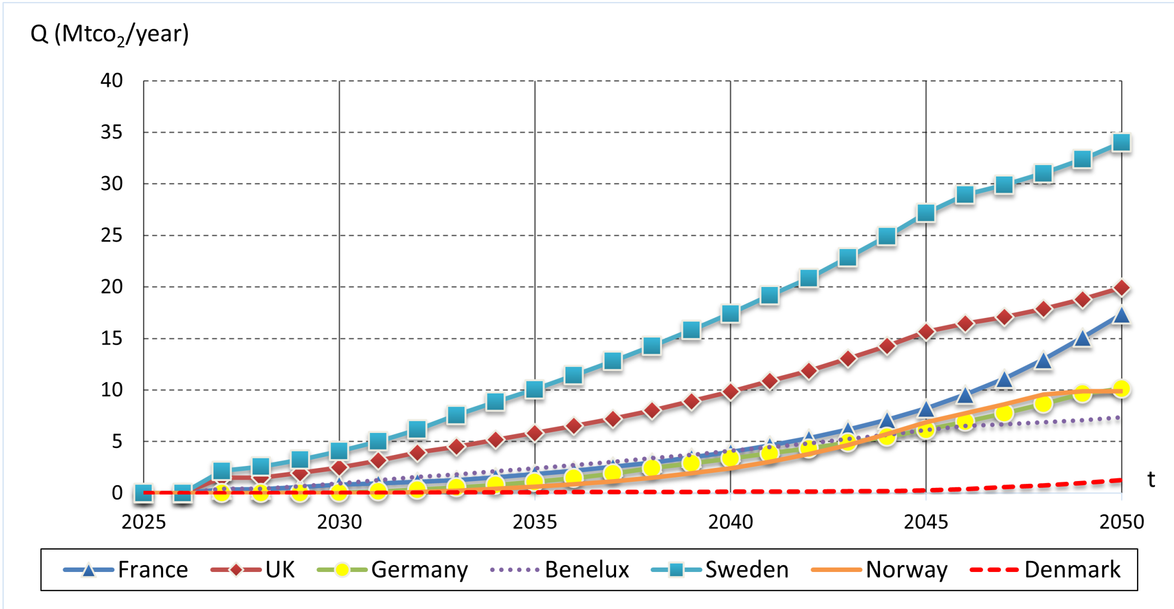



*Figure 4: Annual net $CO_2$ removals by country between 2025 and 2050.*

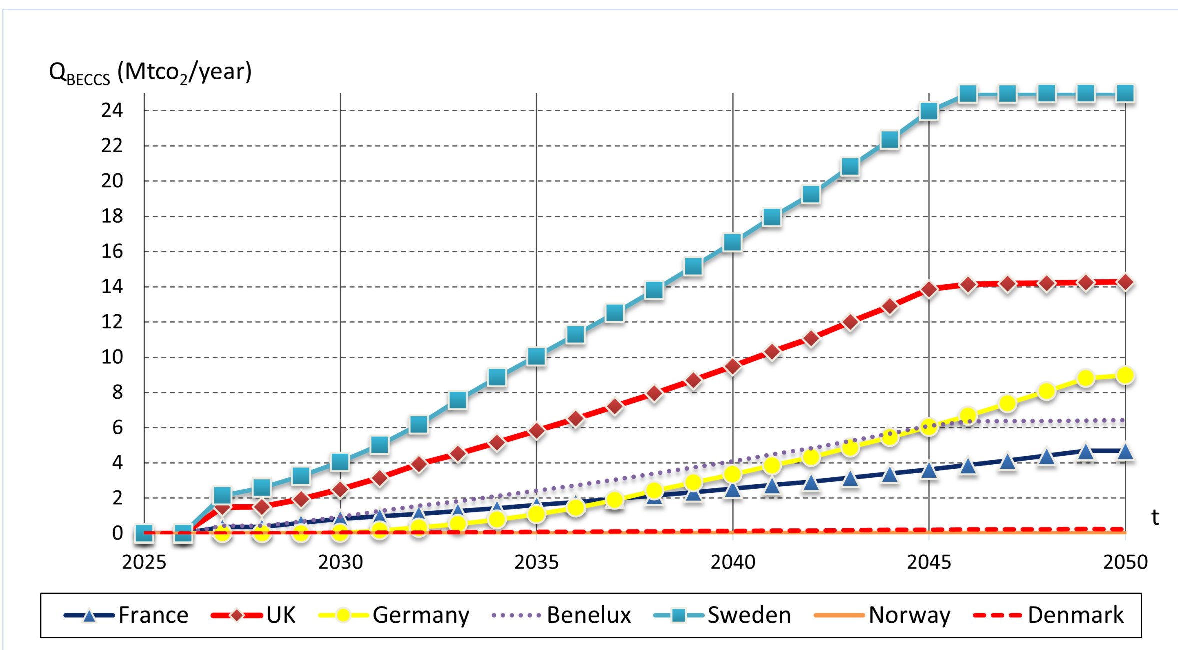



*Figure 5: Annual net $CO_2$ removals from BECCS by country between 2025 and 2050.*

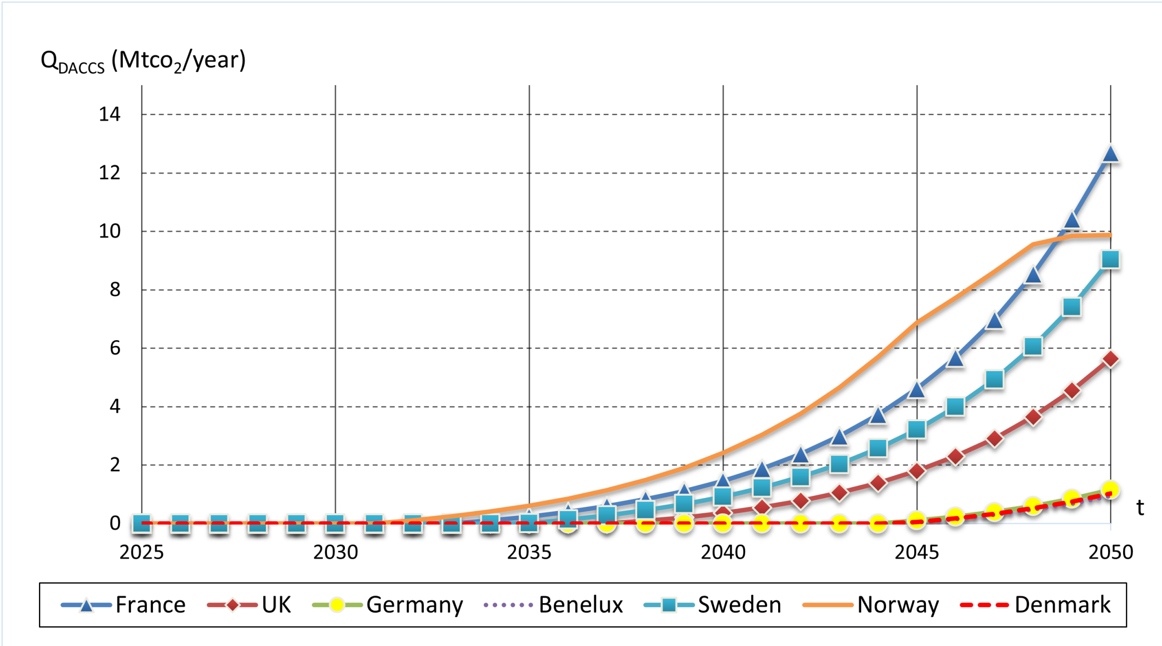



*Figure 6: Annual net $CO_2$ removals from DACCS by country between 2025 and 2050.*

At the system level, annual spending shown in Figure 7 rises from negligible levels to a peak in the second half of the 2040s on the order of a couple tens of billions of euros per year, before stabilizing by 2050 as BECCS saturates and DACCS growth partially offsets declining unit costs. Those curves represent the sum of heterogenous profiles.

In the early years, BECCS dominates expenditures because it is the least-cost source of net removals where biogenic point sources are available and $CO_2$ transport and storage can be accessed at moderate cost. This is visible in Figure 8: Sweden and the United Kingdom bear the largest BECCS spending, with Sweden's annual costs rising toward the mid-2040s and then plateauing, the United Kingdom following a similar but lower trajectory, and Germany and the Benelux cluster increasing along smoother, mid-range paths. France's BECCS costs remain comparatively modest, and Norway and Denmark contribute little by construction because of scarce or absent biogenic potential.

The DACCS cost trajectories in Figure 9 show the delayed but rapid rise of expenditures after 2040 in countries with favorable combinations of electricity price and access to storage. At first, Norway incur the earliest costs for DACCS deployment, however, France and Sweden display the sharpest late-period DACCS spending. This creates a sequential strategy in which Norway undertakes early, high-value investments to generate learning effects, allowing other countries to scale up deployment later as costs decline.

Technology–location interactions matter for system cost. Countries specializing in BECCS (Sweden, UK) bear large early and cumulative expenditures in the BECCS cost panel, while DACCS-heavy countries (France, Norway) see expenditures surge later as DACCS scales. The total-cost figure thus reflects a dynamic burden-sharing pattern: early-mover BECCS hosts finance the initial net-removal ramp; later, as DACCS becomes net-efficient and cheaper per net tonne, financial responsibility shifts toward countries with low-carbon grids.

However, Figure 10 better represent the share of the burden for each country. The cumulative perspective reveals an uneven distribution of lifetime financial burdens. By 2050, Sweden accumulates the highest total cost, followed by the United Kingdom and France, while other countries remain materially lower. This concentration is an endogenous outcome of the least-cost allocation: countries with relatively abundant, low-cost options in one technology become workhorses for the cooperative system and thus shoulder more investment. The policy implication is that a strictly national perspective on expenditures will diverge from the cooperative optimum. In addition, while costs and investments curve follow similar patterns, the order of magnitudes are different. For example, the relative difference between France and UK negative emissions are lower than their relative difference in costs, such that, on average, a net negative emission in France was more expansive than in the UK. The same applies for Sweden, the relative costs of Sweden is way higher than the relative net negative emissions they are producing compared to other countries. For France, the difference is created through large DACCS investments that represent the most costly ones, while Sweden for later DACCS investments but mostly BECCS early investments. Those remarks are important in a cooperation setup.

For engineered CDR, direct costs are not the only factor that is relevant to address for analyzing the financial burden. Electricity consumption of those technologies are extremely high and correspond to one of their main limits, especially for DACCS. Additional electricity demand can creates additional cost for increasing grid capacities, especially for low carbon grids. Our model cannot endogenize those extra costs but we can still quantify them through energy demand. The corresponding electricity demand in Figure 11. That total electricity use for BECCS and DACCS together reaches several tens of TWh/year by 2050 across the seven countries, with DACCS accounting for a growing share after 2045 (Figure 13). In some countries this load corresponds to a non-trivial fraction of current national generation, implying the need to integrate CDR deployment with power-sector expansion plans. While BECCS is aimed at creating additional electricity through burning biomass, its impact on electricity demand is lower than DACCS, even with higher deployment (Figure 12). Therefore, DACCS adds non negligible demand that must be served without delaying decarbonization in other sectors.

Two further observations follow those analysis. First, the apparent late-period decline in DACCS cost lines in some countries despite rising electricity use indicates effective learning-by-doing dominating the impact of growing volumes on variable costs. Second, the timing of the crossover in spending varies by country in line with local constraints: where BECCS potential is scarce or quickly exhausted, the switch arrives earlier and more abruptly; where BECCS resources are ample, the portfolio remains more balanced through 2050. Both features suggest that early investment in BECCS is valuable to meet near-term targets at moderate cost, but parallel, earlier-than-market DACCS deployment is also warranted to unlock learning benefits and prepare for the post-2040 scale-up. Second, the model yields a geographically differentiated but complementary division of labor. BECCS concentrates where biogenic $CO_2$ is abundant and storage access is favorable, delivering early, scalable removals that anchor the trajectory to mid-century. DACCS concentrates where electricity is both clean and affordable, taking over the marginal tonne as learning and decarbonization reduce its net cost. Under cooperative planning with shared access to transport and storage, this spatial specialization minimizes system cost but creates asymmetric national expenditure profiles, arguing for coordinated financing and accounting rules that separate the location of removal from the beneficiary of the credit.

# 6 Sensitivity analysis

This section presents a set of sensitivity analysis that are designed to test the robustness of the baseline results but also to interrogate the results on different assumptions. Each sensitivity scenario perturbs a single modeling assumption or input and the outcomes are summarized in Table 2. We compare scenario outcomes across multiple metrics in order to identify how those assumptions

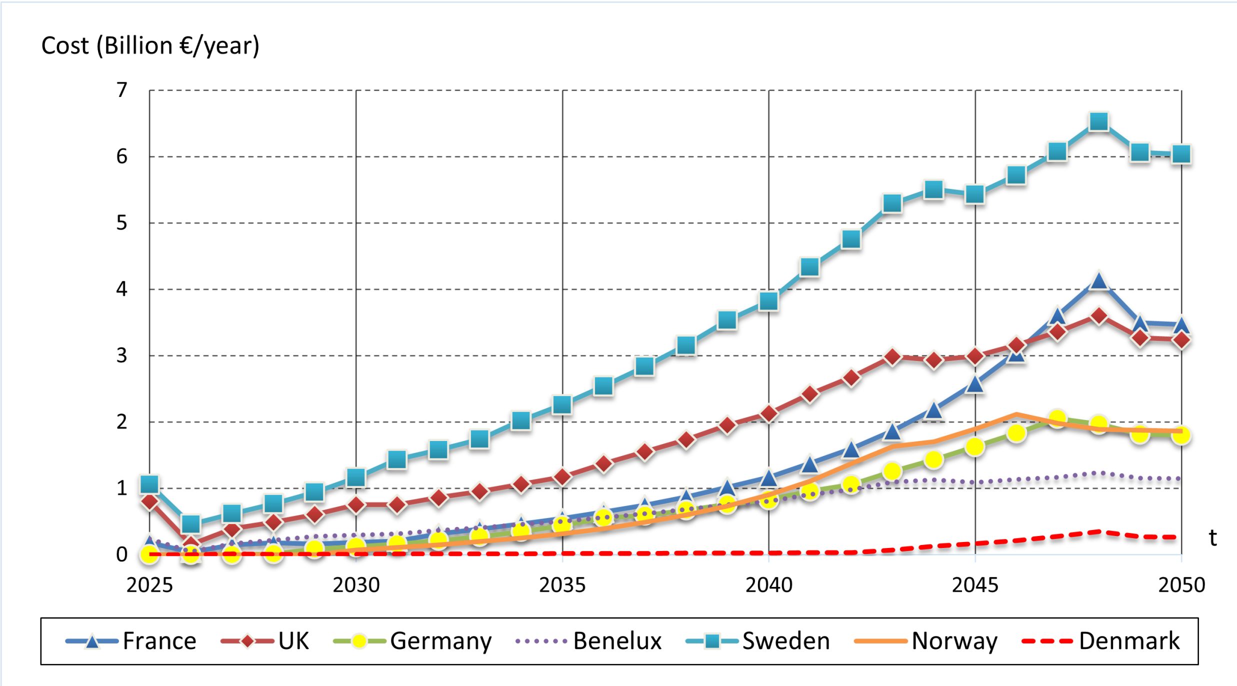



*Figure 7: Total annual cost by country (billion euro per year).*

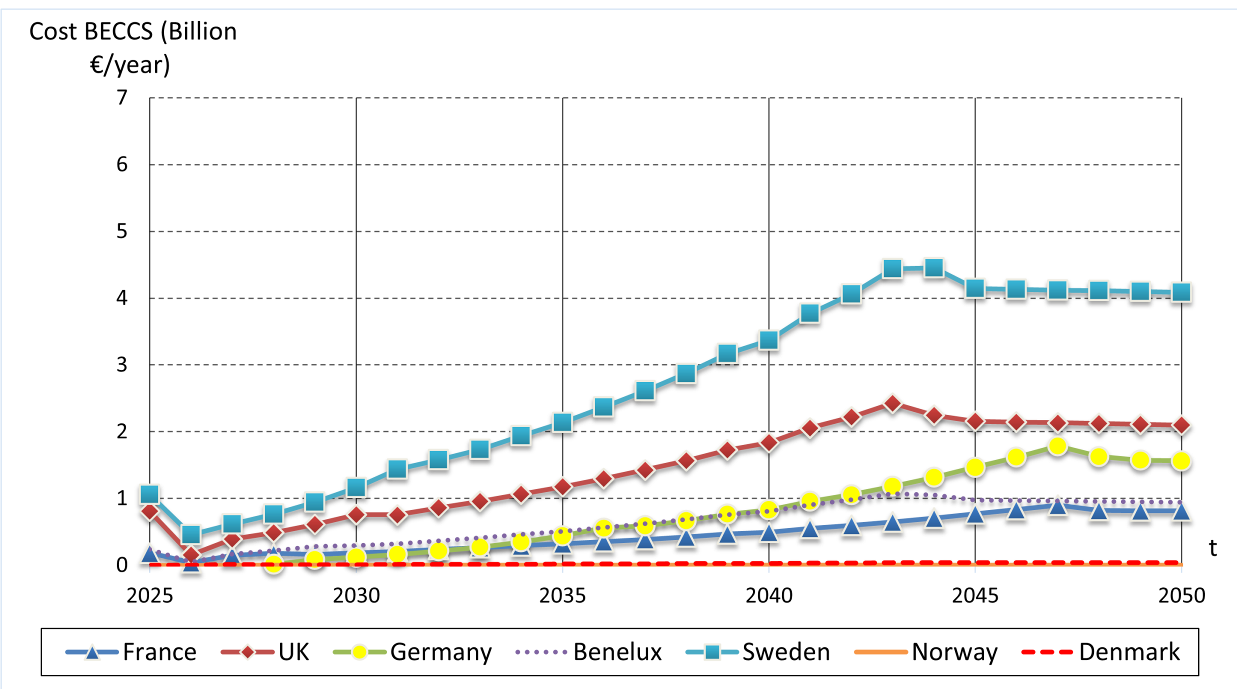



*Figure 8: Annual BECCS cost by country (billion euro per year).*

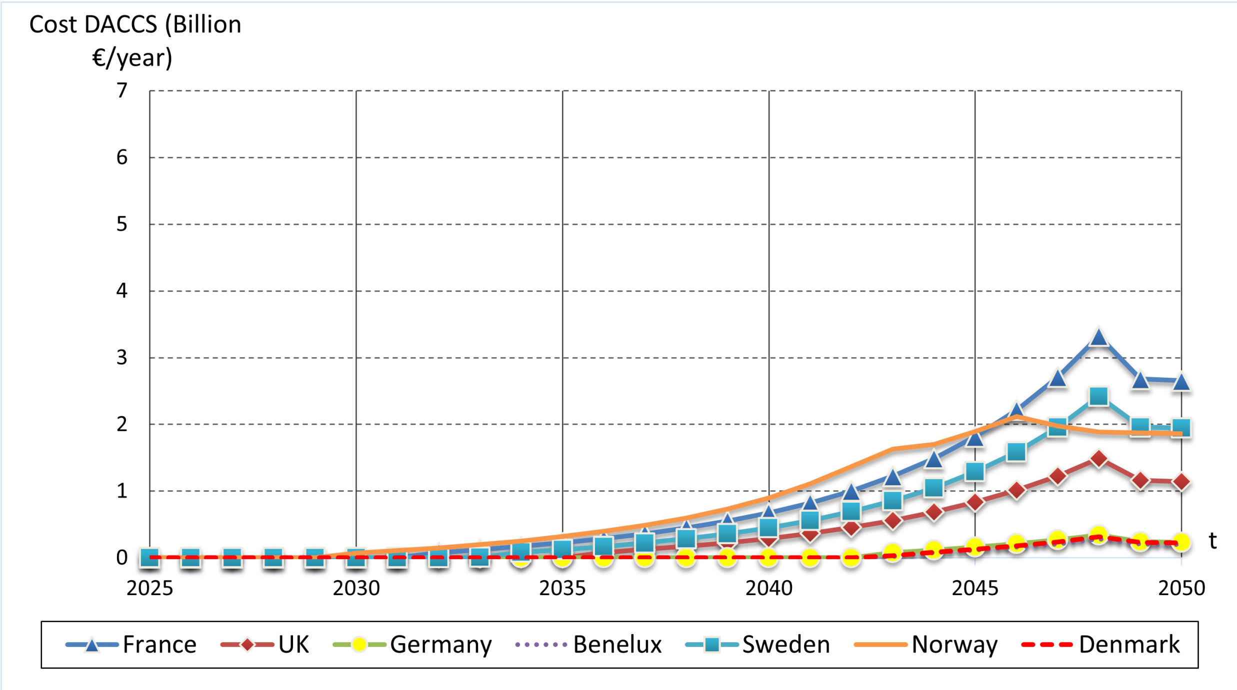



*Figure 9: Annual DACCS cost by country (billion euro per year).*

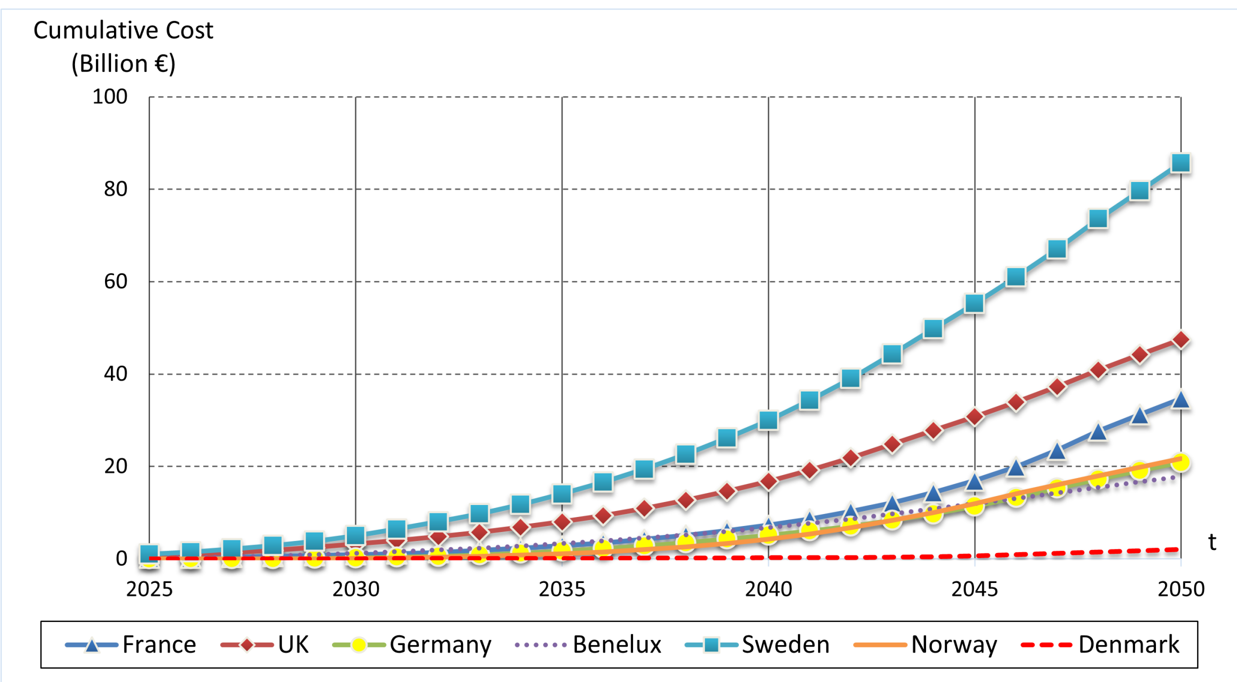



*Figure 10: Cumulative cost to 2050 by country (billion euro).*

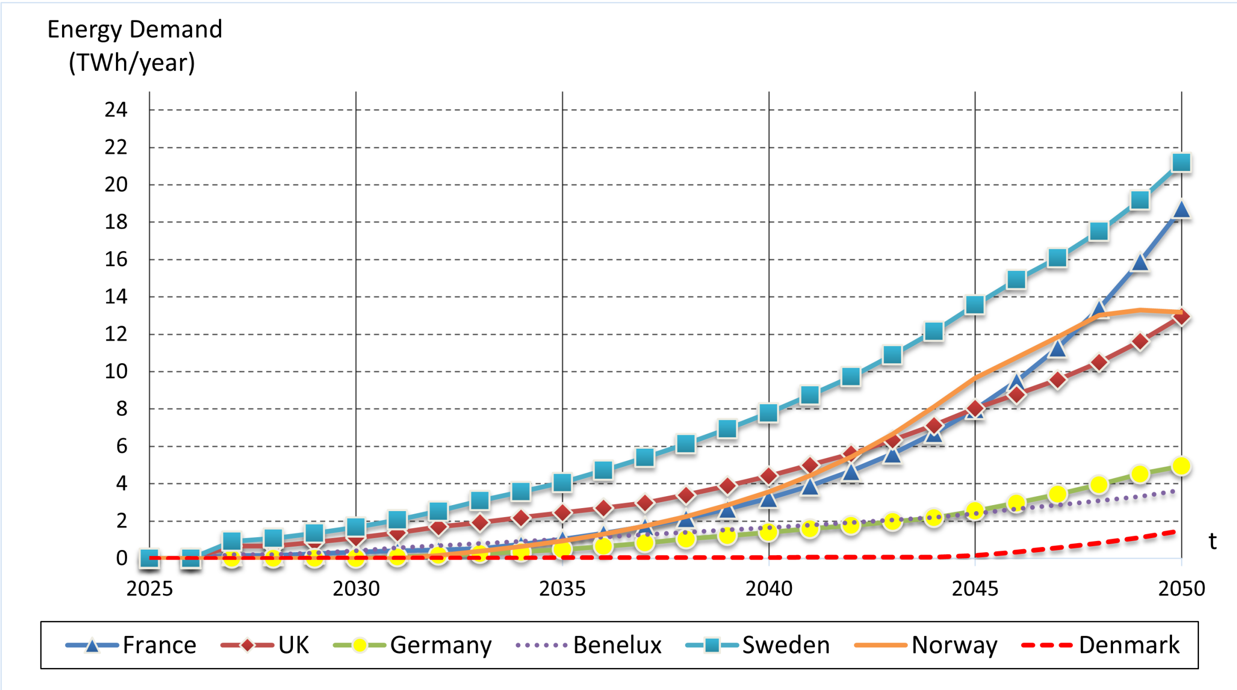



*Figure 11: Electricity demand by country (TWh per year).*

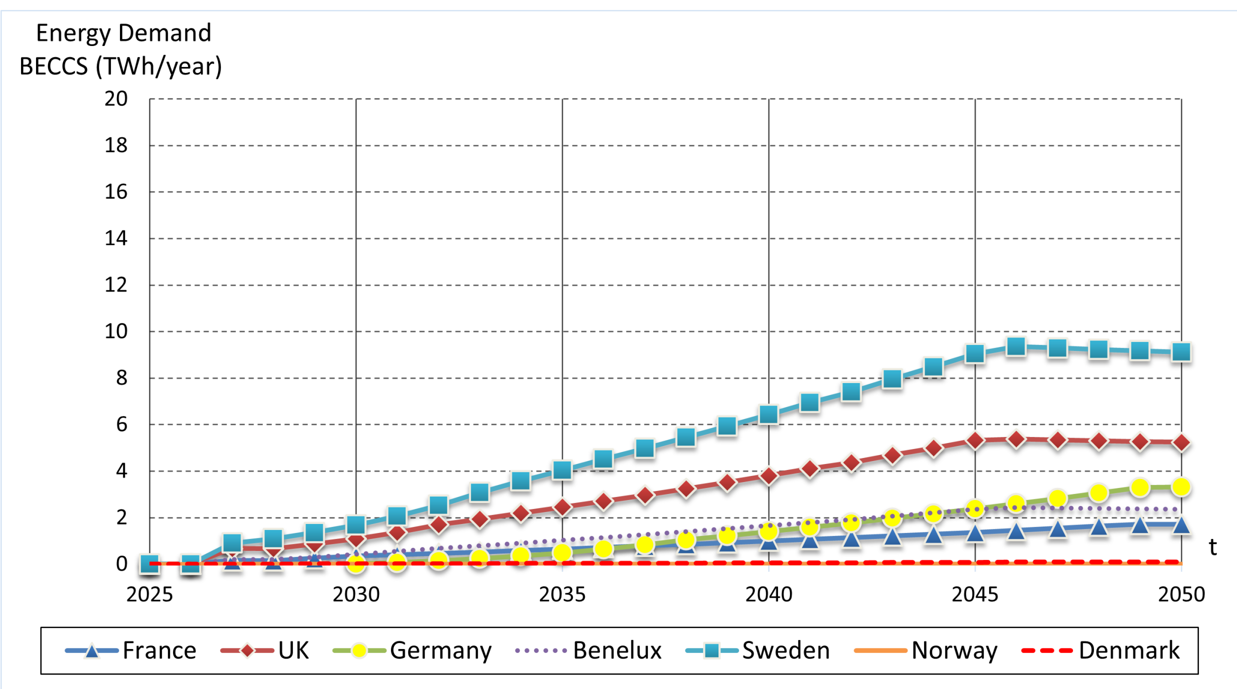



*Figure 12: Electricity demand from BECCS by country (TWh per year).*

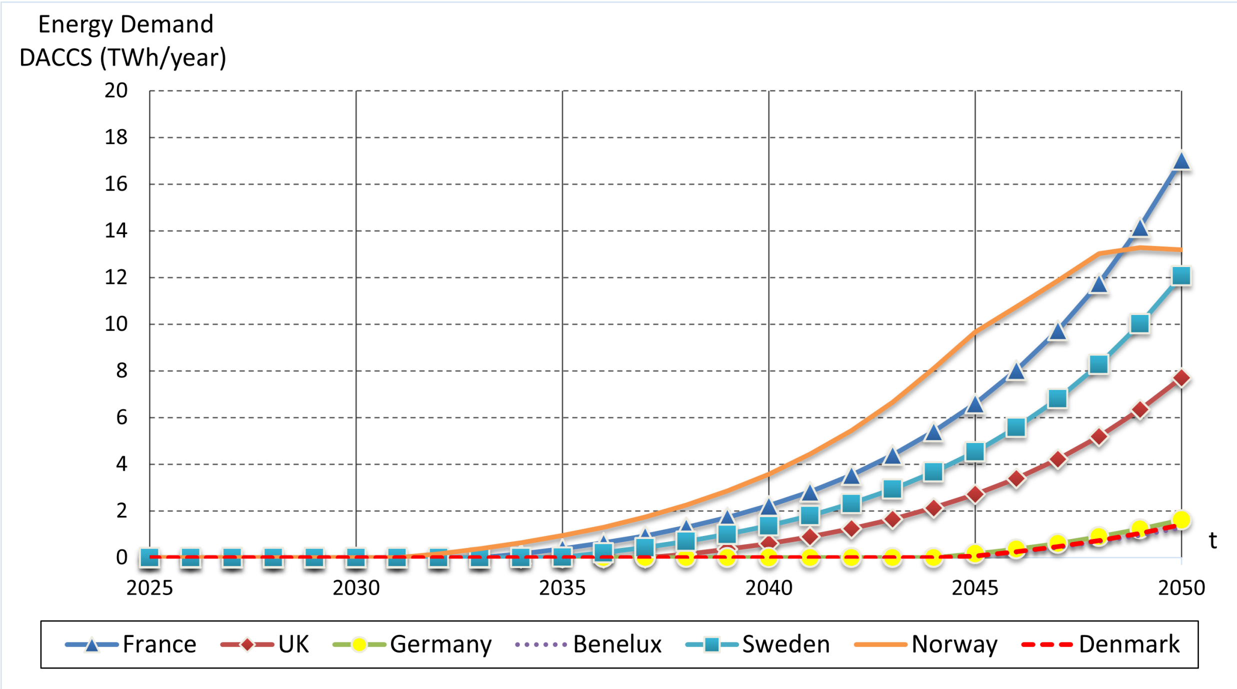



*Figure 13: Electricity demand from DACCS by country (TWh per year).*

drives changes in deployment timing, spatial allocation and system costs. The section has three aims: first, to establish which uncertainties most affect the feasibility and cost of reaching the 2050 removal objective; second, to evaluate how technological learning and grid decarbonization interact to shift the burden between BECCS and DACCS. And third, to draw implications for policy design, in particular for the timing of supply-side support, investments in transport and storage infrastructure, and the need for cooperative financing arrangements under spatially asymmetric cost burdens.

We measure spatial concentration with the Herfindahl–Hirschman Index (HHI), computed on country shares of cumulative net removals as

$$\mathrm{HHI}_{\mathrm{raw}} = \sum_{k=1}^{N} s_k^2, \qquad s_k = \frac{Q_k}{\sum_k Q_k},$$

where $Q_k$ is the quantity attributed to country $k$ and $N$ is the number of countries. Because $\mathrm{HHI}_{\mathrm{raw}}$ depends on $N$ (it ranges from $1/N$ for perfectly even distribution to 1 for a single-country monopoly), we report a normalized index on the unit interval,

$$\mathrm{HHI}_{\mathrm{norm}} = \frac{\mathrm{HHI}_{\mathrm{raw}} - 1/N}{1 - 1/N},$$

so that $\mathrm{HHI}_{\mathrm{norm}} = 0$ indicates perfectly even distribution and $\mathrm{HHI}_{\mathrm{norm}} = 1$ indicates complete concentration in a single country. In interpreting the index, focus less on absolute cut-offs and more on relative differences across scenarios and technologies: increases in $HHI_{norm}$ signal greater geographic concentration (higher resilience and equity risks, and larger asymmetric fiscal burdens), while declines indicate a more sparsed allocation of deployment.

Table 2 reports six counterfactual analyses relative to the baseline pathway. In the first case (1), we integrate a cost-minimization objective, removing the per-ton $CO_2$ efficiency objective. This creates incentives to invest in the later period to reduce cumulative variable costs. In the second case (2), we reduce the objective in net-removal obligation by setting $\bar{R}_T = 50$ Mt, keeping all other model settings equal. It evaluates the sensitivity to the ambition of the policy target. In the third case (3), we impose a slower power-sector decarbonization path by attenuating the baseline grid-emission factor trajectory (a 60% reduction compared to 2025 levels), thus testing the dependence of DACCS viability on the pace of grid decarbonization. In the fourth case (4), we lower the transport–and–storage cost schedules used in the model; this situation would occur in the case of a high deployment of CCS in Europe in terms of both infrastructure and legal framework (Clean Air Task Force, 2023). In the fifth case (5), we switch off cost declines for the technologies by holding CAPEX and OPEX parameters constant through time, setting learning rates (both exogenous and endogenous) to zero, which isolates the role of technological-progress assumptions in driving timing and technology choice. Finally, in the sixth case (6), we replace the baseline combining exogenous and endogenous learning specification with a fully endogenous learning-by-doing formulation. This scenario tests sensitivity to a fully endogenous learning specification in a non-cooperative European setting.

The cost-minimization case (1) yields much smaller removals over 2025–2050, with cumulative net removals falling to 0.488 $GtCO_2$ but total spending to 147.5 billion euros. Compared to other scenarios, the amount of removals is even lower than with a reduced 2050 objective by half. However, costs decline by around 80 billion euros and the average cost per net tonne rises to 302 €/t. Investments are delayed as much as possible to minimize total variable costs, using the exogenous decrease in costs and grid decarbonization to make investments when they are most efficient. This creates fewer cost reductions through learning-by-doing, which makes BECCS relatively more efficient compared to DACCS with respect to the baseline scenario, since BECCS has lower cost-reduction potential than DACCS. Interestingly, this scenario has the best HHI index, probably due to later investments being less impacted by differences in grid emissions. However, because the total DACCS share in terms of total removals is the highest, the energy intensity of those removals is the largest (714.4 kWh/t$CO_2$).

Scenario (2) halves the objective in 2050. With linear costs, one would expect results to be halved similarly. However, we observe convex outcomes: total net removals are about 10% higher than half of previous levels (0.554 Gt$CO_2$) and similarly for total spending (107.9 billion euros). These are the result of a relatively higher amount of BECCS investments (92% of cumulative removals and 87% in 2050), which mechanically lowers the energy intensity to 465 kWh/t$CO_2$. However, concentration increases markedly: when the program is small, the planner selects a narrow set of very favorable BECCS sites.

The two previous sensitivity scenarios are based on different modeling assumptions, which respond to different questions. The following scenarios are based on different datasets; here the objective is to observe the robustness of our results. Scenario (3) creates a higher emission intensity for electricity in our data. However, the energy-intensity values do not change substantially. The results show investments are partially shifted toward highly decarbonized-grid countries. Differences in decarbonization data create similar results overall (except for higher costs), but Germany's DACCS investments are eliminated and Denmark's are reduced. Assuming lower transport-and-storage costs (4) has a high impact on both costs and timing of deployment. As it becomes cheaper to produce negative emissions, investments begin earlier toward additional BECCS. This situation creates a double advantage for the cost per t$CO_2$: costs are directly lower, and increasing early investments yields higher total net removals. It amplifies the early-mover role of Sweden and the United Kingdom. Mechanically, having a higher share of BECCS produces a lower energy intensity for the grid. In a similar way, non-declining costs (5) incentivize early investments for per-t$CO_2$ efficiency, since fewer gains come from waiting. Total cost increases substantially, as does the BECCS deployment share. Finally, endogenizing learning-by-doing completely (6) produces outcomes very close to the baseline. Our results corroborate the findings of studies that estimate global learning-by-doing.

Some implications follow from these sensitivities. First, our objective on engineered CDR is not entirely dependent on the successful decarbonization of the grids, provided our objectives do not increase. Each marginal addition of removals has an increasing impact on the grid and on costs. Second, additional reliance on BECCS, due to lower costs or higher DACCS constraints, creates higher early investments, a positive feedback for cumulative removals. Therefore, penalties on DACCS can create a positive situation in terms of grid reliance and limiting temperature levels. Third, deployment cost is strongly convex: a lower objective reduces costs by more than one-to-one.

## 7 Discussion

At the system level, annual deployment rises to the high tens of billions of euros per year in the late 2040s. The average cost per net tonne remains in the €230s, with DACCS systematically costlier than BECCS, consistent with cost estimates from systematic analyses (Fuss et al., 2018). While non-negligible, these magnitudes are commensurate with other strategic decarbonization investments and well within the scale of EU-level innovation and infrastructure programs if spread over decades (EUCommission, 2018; Parmiter et al., 2021). However, our results present considerable disparities in cost and deployment responsibilities across countries. They imply a need for coordinated EU-level policies that ensure equitable burden sharing while maximizing efficiency. Financial designs matters for both efficiency and fairness. Without mechanisms for redistribution, early investors or countries with specific techno-economic advantages may be overburdened in the case of a subsidy-based deployment. Conversely, if a market for CDR emerge to be profitable, lock-in effects could concentrate technological and financial advantages in a few regions, potentially reinforcing regional inequities in cost and capacity distribution. The concentrated burden and collective benefit of such investments argue in favor of cooperation to align national contributions with broader European climate goals. In a cooperative setting, these asymmetries present the need for EU-level instruments that decouple the location of physical removal from the distribution of fiscal and physical responsibility (Schenuit, 2021; Global CCS Institute, 2024). Market commitments or EU-level contracts-for-difference can reduce financing costs and align private incentives with social value (Schenuit, 2021). EU-wide auctions or contracts-for-difference could procure removal services from the least-cost sites while allocating costs (and benefits) across member states according to equity or efficiency rules. A robust registry under the emerging CRCF would be needed to avoid double counting and to ensure durable MRV. Complementary public investment in transport and storage networks can lower early BECCS costs and lower the risk of private capital (Terlouw et al., 2024; CMCC, 2024).

Electricity consumption is a first-order driver of feasibility, particularly for DACCS. Decarboniza-

*Table 2: Comparison of the different scenarios.*

| | Baseline | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| **A. Net Removals** | | | | | | | |
| Total net removals ($GtCO_2$) | 0.998 | 0.488 | 0.554 | 1.022 | 1.207 | 1.090 | 1.017 |
| Total DACCS share (%) | 22.2 | 35.4 | 7.9 | 22.2 | 13.6 | 19.7 | 22.0 |
| Total BECCS share (%) | 77.8 | 64.6 | 92.1 | 77.8 | 86.4 | 80.3 | 78.0 |
| DACCS share in 2050 (%) | 40.4 | 37.4 | 12.9 | 38.8 | 33.9 | 34.4 | 39.8 |
| BECCS share in 2050 (%) | 59.6 | 62.6 | 87.1 | 61.2 | 66.1 | 65.6 | 60.2 |
| **B. Cost composition** | | | | | | | |
| Total cost (B€) | 230.3 | 147.5 | 107.9 | 244.1 | 177.0 | 263.3 | 234.3 |
| DACCS share (%) | 32.5 | 42.3 | 10.9 | 32.2 | 27.1 | 30.4 | 32.5 |
| BECCS share (%) | 67.5 | 57.7 | 89.1 | 67.8 | 72.9 | 69.6 | 67.5 |
| Avg cost per $tCO_2$ (€/t) | 230.8 | 302.0 | 194.6 | 238.8 | 146.6 | 241.6 | 230.4 |
| Avg cost per $tCO_2$, DACCS (€/t) | 336.8 | 360.8 | 269.2 | 346.0 | 291.9 | 372.8 | 341.4 |
| Avg cost per $tCO_2$, BECCS (€/t) | 200.4 | 269.7 | 188.3 | 208.2 | 123.7 | 209.3 | 199.1 |
| **C. Concentration** | | | | | | | |
| Normalized HHI (0–1) | 0.098 | 0.066 | 0.129 | 0.104 | 0.104 | 0.092 | 0.096 |
| **D. Energy** | | | | | | | |
| Peak energy demand (TWh/yr) | 76.2 | 73.4 | 24.6 | 76.4 | 69.7 | 70.3 | 75.7 |
| Energy intensity ($kWh/tCO_2$) | 615.2 | 741.4 | 465.1 | 625.1 | 527.2 | 590.7 | 612.6 |

(1) Cost-minimisation.

(2) $\bar{R}_T = 50Mt$ target.

(3) Lower-decarbonization, 60% decreased compared to 2025 levels .

(4) Low Transport and Storage costs.

(5) Technologies costs are non declining.

(6) Fully endogenous learning-by-doing cost.

Note: A similar table normalized at the baseline level is available in the appendix for easier comparison.

tion plays a dual role: it reduces direct national emissions and enhances the viability of DACCS by lowering its operational carbon intensity and cost. Where DACCS scales rapidly, late-period electricity demand implies a non-trivial share of national generation and grid capacity. These loads must be integrated with concurrent electrification of transport, buildings, and industry if CDR is not to displace decarbonization elsewhere (International Energy Agency, 2021). Our stylized cap on DACCS electricity use prevents extreme concentration but also reveals the shadow value of flexible siting and cross-border power trade. The decarbonization sensitivity show the dependence of DACCS on clean grids: slower declines in grid-emission factors shift deployment toward the cleanest systems, increase average costs, and delay the hand-off from BECCS. Planning implications include early reinforcement of grid infrastructure in prospective DACCS hubs, streamlined permitting for co-located renewables and storage, and compatibility between CDR procurement and national resource-adequacy targets. As such, legal frameworks aiming to support DACCS deployment should be aligned with renewable energy policies and grid decarbonization targets. Regulatory and financial support for low-carbon electricity can serve as an indirect but powerful lever to unlock DACCS investments. For BECCS, ensuring sustainable biomass availability require dedicated European coordination mechanisms, such as the Renewable Energy Directive that forbid biomass electricity generation without carbon capture (IEA Bioenergy, 2024) or Voluntary Certification Schemes that ensure sustainability criteria for biomass (ISCC System GmbH, 2024).

The sequencing observed here aligns with comparative advantages identified in prior work (Almena-Ruiz et al., 2021; Mander et al., 2017; (IEA), 2022). BECCS leverages concentrated $CO_2$ streams and existing bioenergy assets; its netting penalty is dominated by non-electric lifecycle components and rises with TS distance and congestion. DACCS is geographically flexible and avoids biomass constraints, but its netting factor is tightly coupled to electricity carbon intensity and price. These trade-offs suggest that policy should avoid technology monocultures. A mixed portfolio hedges against uncertainty in biomass availability, technology learning, and power-sector trajectories, and reduces exposure to any single supply-chain risk (IPCC, 2022; Abegg et al., 2024a). Taken together, the results argue for a staged policy: immediate BECCS deployment where durable feedstock and storage access are verified, plus steady DACCS procurement to unlock learning and prepare for a post-2040 expansion consistent with clean-grid availability.

Several modeling choices bound external validity. Electricity prices and decarbonization paths are exogenous and stylized; joint planning with the power sector could alter relative economics and siting. Biomass availability is treated as exogenous and constant, whereas future land-use competition or climate effects may reduce supply or the opposite increase availability. Some models integrates biomass competition through a market with cross-sector demand, prices, and sustainability criteria. Transport–storage costs follow national schedules without endogenizing network expansion options or cross-border pipeline optimization. The model also abstracts from non-$CO_2$ co-impacts (air quality, water, land) and from siting frictions, public acceptance, and permitting delays, all of which may affect feasible ramps (Quadrature Climate Foundation, 2024). The CDR target of 100 $MtCO_2$/year is conservative and reflects the minimum required to stay on a net-zero trajectory. However, delays in other sectors or greater ambition may require significantly higher removal volumes. In addition, the model assumes full international cooperation and perfect knowledge spillovers across countries and technologies. This includes post-Brexit collaboration between the UK and EU a potentially fragile assumption given geopolitical uncertainties. Finally, permanence and liability are incorporated implicitly via technology choice rather than explicit risk premium.

A natural extension would co-optimize CDR deployment with power-sector capacity expansion under decarbonization and resource constraints. Such an integrated model would capture the two-way feedback between DACCS siting, power-sector build-out and wholesale price formation, and would allow explicit quantification of the system cost of supplying large, new electrified loads. Similarly, replacing fixed BECCS potentials with dynamic, regionally disaggregated biomass supply curves—subject to sustainability criteria and inter-sectoral competition—would let prices, trade and policy endogenously determine feasible BECCS volumes (Schenuit, 2021; Lehtveer and Emanuelsson, 2021; IEA Bioenergy, 2024). Likewise, endogenizing $CO_2$ transport and storage infrastructure (cross-border pipeline routing, terminal sizing, shipping versus pipeline trade-offs, and storage-site learning), together with investment timing and permitting lags, would change marginal transport and storage costs and therefore the spatial division of labor among countries (Terlouw et al., 2024; CMCC, 2024). To address deep uncertainty, multi-stage stochastic or robust optimization could be used to represent uncertain technology learning, transport and storage deliverability, grid decarbonization and biomass supply, thereby quantifying the option value of diversified early pilots. Future work could also explicitly price permanence risk (for example via discounting or insurance buffers), align modeled outcomes with the evolving EU CRCF, and test how alternative liability regimes influence optimal technology mixes and siting. Finally, embedding explicit policy instruments such as reverse auctions and integration with the EU ETS would permit non-cooperative distributional analyses. Each model, coupled with a formal evaluation of burden-sharing rules (ability-to-pay, polluter-pays, per-capita or Shapley-value allocations), could use dual variables as shadow prices to design compensation mechanisms that decouple the physical location of removals from their fiscal incidence.

## 8 Conclusion

This paper develops a geographically explicit, dynamic cost-optimization model to assess how, where, and when engineered carbon removals could be deployed efficiently to support European climate neutrality. Three system-level results emerge. First, achieving 100 $MtCO_2$/yr of engineered removals by 2050 calls for a sequenced portfolio: BECCS scales earlier by leveraging concentrated biogenic point sources and existing infrastructures, while DACCS scales later as grids decarbonize and capital costs fall through learning. This sequencing is robust across sensitivities and aligns with the qualitative literature (Almena-Ruiz et al., 2021; Mander et al., 2017; (IEA), 2022). Second, spatial heterogeneity is material. Sweden and the United Kingdom specialize in early BECCS, while Norway initiates DACCS earliest due to very low grid-carbon intensity and storage access. France and Sweden undertake larger DACCS investments post-2040 as electricity decarbonizes further. Denmark's participation remains limited by land and biomass constraints, and Germany's contributions rise later as BECCS becomes competitive at the margin. Third, system costs are important but tractable: average costs stay in the mid-€200s per net tonne, with total annual spending peaking in the late 2040s at the level of several tens of billions of euros before stabilizing as BECCS saturates and DACCS learning deepens. Electricity demand for removals reaches the high tens of TWh/yr by 2050 across the case countries, increasingly dominated by DACCS, creating a need for coordinated power-sector planning (International Energy Agency, 2021).

Sensitivity analyses indicate that (i) Slower grid decarbonization delays DACCS and shifts activity toward the cleanest systems. (ii) Cheaper transport and storage accelerates BECCS and lowers average costs. (iii) Suppressing technological progress raises total costs by only 10% but increase biomass dependency and limits future potential scaling. (iv) A pure cost-minimization objective lowers backloads investment, creating lower cumulative CDR at a lower total cost but increasing average costs. These patterns support a two-track policy: accelerate near-term BECCS where sustainable feedstock and storage are verified, while procuring steady DACCS volumes to unlock learning and prepare for a post-2040 scale-up.

The paper contributes a transparent, microeconomic lens to complement global IAM insights (IPCC, 2022; Butnar et al., 2020; Van Sluisveld et al., 2018; Fajardy et al., 2018; S. Smith et al., 2024). By integrating spatial heterogeneity and temporal decisions, it clarifies when, where and how BECCS and DACCS are most valuable and the consequences of such deployment in the North-Sea area.

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*Figure 14: Geospatial distribution of biogenic carbon dioxide removal potential from existing point sources in Europe in 2018. The figure shows incinerators, pulp and paper, and bio-power facilities emitting more than 0.1 Mtons $CO_2$ per year, and wastewater treatment plants processing more than 100 000 population equivalent of wastewater per day. Biogenic CDR potential data from (Rosa et al., 2021).*

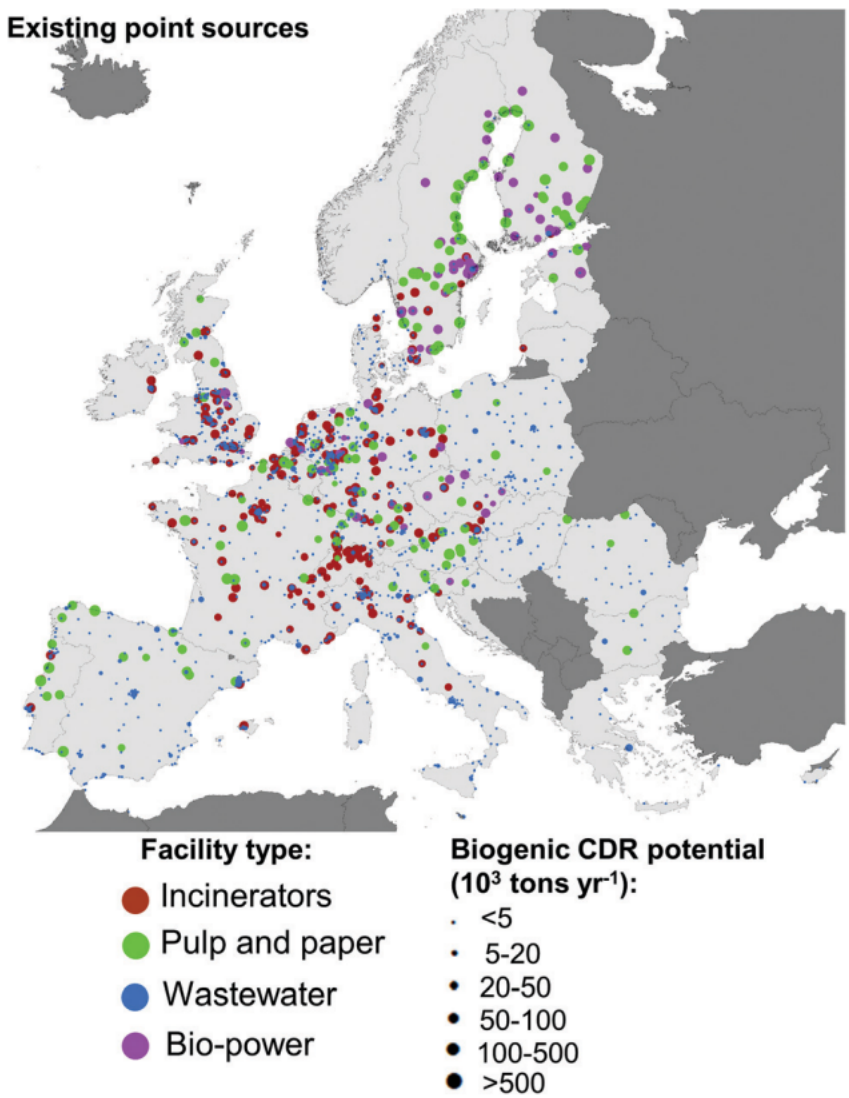

*Table 3: Model parameters. Parameters that are non-country/time-specific.*

| Parameter | Value (units) | Source |
|---|---|---|
| $r$ | 0.034 | Hermelink and Jager, 2015; Emmerling et al., 2019 |
| $w_{\text{BECCS}}$ | 1.505 $\text{MtCO}_2$/yr per plant | Danish Energy Agency, 2024 |
| $w_{\text{DACCS}}$ | 1.075 $\text{MtCO}_2$/yr per plant | Danish Energy Agency, 2024 |
| $\lambda_{\text{BECCS}}$ | 0.074 (implied by LR = 5%) | Danish Energy Agency, 2022; (IEA), 2022 |
| | | Rubin et al., 2015; G. F. Nemet et al., 2018 |
| $\lambda_{\text{DACCS}}$ | 0.234 (implied by LR = 15%) | Danish Energy Agency, 2022; (IEA), 2022 |
| | | Rubin et al., 2015; G. F. Nemet et al., 2018 |
| $g_{\text{j}}$ | 0.20 $\text{yr}^{-1}$ | Projekt, 2023 |
| $z_{B,2025}$ | 0.0421 $\text{yr}^{-1}$ | Danish Energy Agency, 2024 |
| $z_{D,2025}$ | 0.2000 $\text{yr}^{-1}$ | Danish Energy Agency, 2024 |
| $\epsilon_{B,2025}$ | 2 $\text{EUR/tCO}_2$ | Danish Energy Agency, 2024 |
| $\epsilon_{D,2025}$ | 5 $\text{EUR/tCO}_2$ | Danish Energy Agency, 2024; Keith et al., 2018 |
| $\nu_{\text{BECCS,proc}}$ | 0.85 | Literature synthesis |
| $\text{CAPEX}_{k,t_0}^{\text{BECCS}}$ | 414,473,684 Euros | Danish Energy Agency, 2024 |
| $\text{CAPEX}_{k,t_0}^{\text{DACCS}}$ | 631,578,947 Euros | Danish Energy Agency, 2024 |
| $R_T$ | 100 Mt | Parmiter et al., 2021; EUCommission, 2018 |
| $\alpha$ | 0.5 | — |
| $\beta$ | 0.5 | — |

### Electricity Price Assumptions for the Benelux Region

To represent the electricity cost in the Benelux region (Belgium, the Netherlands, and Luxembourg), we construct a weighted average of wholesale electricity prices for the year 2025. The International Energy Agency reports indicate the following estimated wholesale electricity prices for 2025 International Energy Agency, 2025b:

- Belgium: €80/MWh,
- Netherlands: €85/MWh,
- Luxembourg: €90/MWh.

To ensure that differences in national electricity demand are accounted for, we apply a weighted average using 2022 national electricity consumption data: 85 TWh for Belgium, 110 TWh for the Netherlands, and 7 TWh for Luxembourg (International Energy Agency, 2025a). The weighted average electricity price is thus calculated as follows:

$$\text{Price}_{\text{Benelux}} = \frac{(85 \times 80) + (110 \times 85) + (7 \times 90)}{85 + 110 + 7} = \frac{16780}{202} \approx 83\,€/\text{MWh}$$

This value is used as the electricity cost input for CDR operations in the Benelux region.

*Table 4: Country-specific data. Electricity prices are 2025 values. Sources - $p^{\text{el}}_{k,2025}$: International Energy Agency, 2025b / $T_k^{\text{BECCS,min}}$, $T_k^{\text{BECCS,max}}$: Clean Air Task Force, 2023 / $Q^{\max}_{\text{BECCS},k}$: Derived from Rosa et al., 2021 / $Q^{\max}_{\text{DACCS},k}$: Using International Energy Agency, 2025a.*

| | France | UK | Germany | Benelux | Sweden | Norway | Denmark |
|---|---|---|---|---|---|---|---|
| $p^{\text{el}}_{k,2025}$ (EUR/MWh) | 78.8 | 97.2 | 91.8 | 83.1 | 75.6 | 64.8 | 102.6 |
| $T_k^{\text{BECCS,min}}$ (EUR/tCO$_2$) | 34 | 19 | 32 | 21 | 43 | 21 | 21 |
| $T_k^{\text{BECCS,max}}$ (EUR/tCO$_2$) | 129 | 69 | 112 | 71 | 89 | 74 | 74 |
| $Q^{\max}_{\text{BECCS},k}$ (MtCO$_2$/yr) | 8.61 | 16.91 | 15.32 | 7.63 | 29.41 | 0.01 | 0.29 |
| $Q^{\max}_{\text{DACCS},k}$ (MtCO$_2$/yr) | 33.10 | 16.62 | 30.76 | 1.52 | 10.69 | 10.41 | 2.27 |

*Table 5: Time series data from Danish Energy Agency, 2024. CAPEX in EUR; $\gamma^{el}$ in MWh/t$CO_2$*

| Year | CAPEX BECCS | CAPEX DACCS | $\gamma^{el}_{BECCS}$ | $\gamma^{el}_{DACCS}$ | $\nu_{DACCS}$ |
|---|---|---|---|---|---|
| 2025 | 414,473,684 | 631,578,947 | 0.3600 | 1.5900 | 0.9000 |
| 2026 | 410,789,473 | 584,210,526 | 0.3580 | 1.5666 | 0.9020 |
| 2027 | 407,105,263 | 536,842,105 | 0.3560 | 1.5432 | 0.9040 |
| 2028 | 403,421,052 | 489,473,684 | 0.3540 | 1.5198 | 0.9060 |
| 2029 | 399,736,842 | 442,105,263 | 0.3520 | 1.4964 | 0.9080 |
| 2030 | 396,052,631 | 394,736,842 | 0.3500 | 1.4730 | 0.9100 |
| 2031 | 393,289,473 | 382,894,737 | 0.3480 | 1.4622 | 0.9120 |
| 2032 | 390,526,315 | 371,052,632 | 0.3460 | 1.4514 | 0.9140 |
| 2033 | 387,763,157 | 359,210,526 | 0.3440 | 1.4406 | 0.9160 |
| 2034 | 384,999,999 | 347,368,421 | 0.3420 | 1.4298 | 0.9180 |
| 2035 | 382,236,841 | 335,526,316 | 0.3400 | 1.4190 | 0.9200 |
| 2036 | 379,473,683 | 323,684,211 | 0.3380 | 1.4082 | 0.9220 |
| 2037 | 376,710,525 | 311,842,105 | 0.3360 | 1.3974 | 0.9240 |
| 2038 | 373,947,367 | 300,000,000 | 0.3340 | 1.3866 | 0.9260 |
| 2039 | 371,184,209 | 288,157,895 | 0.3320 | 1.3758 | 0.9280 |
| 2040 | 368,421,052 | 276,315,789 | 0.3300 | 1.3650 | 0.9300 |
| 2041 | 363,815,789 | 272,368,421 | 0.3280 | 1.3551 | 0.9320 |
| 2042 | 359,210,526 | 268,421,053 | 0.3260 | 1.3452 | 0.9340 |
| 2043 | 354,605,263 | 264,473,684 | 0.3240 | 1.3353 | 0.9360 |
| 2044 | 350,000,000 | 260,526,316 | 0.3220 | 1.3254 | 0.9380 |
| 2045 | 345,394,736 | 256,578,947 | 0.3200 | 1.3155 | 0.9400 |
| 2046 | 340,789,473 | 252,631,579 | 0.3180 | 1.3056 | 0.9420 |
| 2047 | 336,184,210 | 248,684,211 | 0.3160 | 1.2957 | 0.9440 |
| 2048 | 331,578,947 | 244,736,842 | 0.3140 | 1.2858 | 0.9460 |
| 2049 | 326,973,684 | 240,789,474 | 0.3120 | 1.2759 | 0.9480 |
| 2050 | 322,368,421 | 236,842,105 | 0.3100 | 1.2660 | 0.9500 |

*Table 6: Electricity emission factors (kg $CO_2$/kWh) by year and country International Energy Agency, 2025a.*

| Year | France | UK | Germany | Benelux | Denmark | Sweden | Norway |
|---|---|---|---|---|---|---|---|
| 2025 | 0.0570 | 0.1810 | 0.4000 | 0.2317 | 0.1820 | 0.0200 | 0.0100 |
| 2026 | 0.0549 | 0.1745 | 0.3856 | 0.2234 | 0.1754 | 0.0193 | 0.0096 |
| 2027 | 0.0529 | 0.1680 | 0.3712 | 0.2150 | 0.1689 | 0.0186 | 0.0093 |
| 2028 | 0.0508 | 0.1615 | 0.3568 | 0.2067 | 0.1623 | 0.0178 | 0.0089 |
| 2029 | 0.0488 | 0.1549 | 0.3424 | 0.1983 | 0.1558 | 0.0171 | 0.0086 |
| 2030 | 0.0467 | 0.1484 | 0.3280 | 0.1900 | 0.1492 | 0.0164 | 0.0082 |
| 2031 | 0.0447 | 0.1419 | 0.3136 | 0.1817 | 0.1427 | 0.0157 | 0.0078 |
| 2032 | 0.0426 | 0.1354 | 0.2992 | 0.1733 | 0.1361 | 0.0150 | 0.0075 |
| 2033 | 0.0406 | 0.1289 | 0.2848 | 0.1650 | 0.1296 | 0.0142 | 0.0071 |
| 2034 | 0.0385 | 0.1224 | 0.2704 | 0.1566 | 0.1230 | 0.0135 | 0.0068 |
| 2035 | 0.0365 | 0.1158 | 0.2560 | 0.1483 | 0.1165 | 0.0128 | 0.0064 |
| 2036 | 0.0344 | 0.1093 | 0.2416 | 0.1399 | 0.1099 | 0.0121 | 0.0060 |
| 2037 | 0.0324 | 0.1028 | 0.2272 | 0.1316 | 0.1034 | 0.0114 | 0.0057 |
| 2038 | 0.0303 | 0.0963 | 0.2128 | 0.1233 | 0.0968 | 0.0106 | 0.0053 |
| 2039 | 0.0283 | 0.0898 | 0.1984 | 0.1149 | 0.0903 | 0.0099 | 0.0050 |
| 2040 | 0.0262 | 0.0833 | 0.1840 | 0.1066 | 0.0837 | 0.0092 | 0.0046 |
| 2041 | 0.0242 | 0.0767 | 0.1696 | 0.0982 | 0.0772 | 0.0085 | 0.0042 |
| 2042 | 0.0221 | 0.0702 | 0.1552 | 0.0899 | 0.0706 | 0.0078 | 0.0039 |
| 2043 | 0.0201 | 0.0637 | 0.1408 | 0.0816 | 0.0641 | 0.0070 | 0.0035 |
| 2044 | 0.0180 | 0.0572 | 0.1264 | 0.0732 | 0.0575 | 0.0063 | 0.0032 |
| 2045 | 0.0160 | 0.0507 | 0.1120 | 0.0649 | 0.0510 | 0.0056 | 0.0028 |
| 2046 | 0.0139 | 0.0442 | 0.0976 | 0.0565 | 0.0444 | 0.0049 | 0.0024 |
| 2047 | 0.0119 | 0.0376 | 0.0832 | 0.0482 | 0.0379 | 0.0042 | 0.0021 |
| 2048 | 0.0098 | 0.0311 | 0.0688 | 0.0399 | 0.0313 | 0.0034 | 0.0017 |
| 2049 | 0.0078 | 0.0246 | 0.0544 | 0.0315 | 0.0248 | 0.0027 | 0.0014 |
| 2050 | 0.0057 | 0.0181 | 0.0400 | 0.0232 | 0.0182 | 0.0020 | 0.0010 |

*Table 7: Comparison of scenarios (Baseline = 1.00). Values are indices relative to the Baseline.*

| | Baseline | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| **A. Net removals (index)** | | | | | | | |
| Total net removals ($GtCO_2$) | 1.00 | 0.49 | 0.56 | 1.02 | 1.21 | 1.09 | 1.02 |
| Total DACCS share (%) | 1.00 | 1.59 | 0.36 | 1.00 | 0.61 | 0.90 | 0.99 |
| Total BECCS share (%) | 1.00 | 0.83 | 1.18 | 1.00 | 1.11 | 1.03 | 1.00 |
| DACCS share in 2050 (%) | 1.00 | 0.93 | 0.32 | 0.96 | 0.84 | 0.85 | 0.99 |
| BECCS share in 2050 (%) | 1.00 | 1.05 | 1.46 | 1.03 | 1.11 | 1.10 | 1.01 |
| **B. Cost composition (index)** | | | | | | | |
| Total cost (B€) | 1.00 | 0.64 | 0.47 | 1.06 | 0.77 | 1.14 | 1.02 |
| DACCS share of cost (%) | 1.00 | 1.30 | 0.34 | 0.99 | 0.83 | 0.94 | 1.00 |
| BECCS share of cost (%) | 1.00 | 0.86 | 1.32 | 1.00 | 1.08 | 1.03 | 1.00 |
| Avg cost per $tCO_2$ (€/t) | 1.00 | 1.31 | 0.84 | 1.04 | 0.64 | 1.05 | 1.00 |
| Avg cost per $tCO_2$, DACCS (€/t) | 1.00 | 1.07 | 0.80 | 1.03 | 0.87 | 1.11 | 1.01 |
| Avg cost per $tCO_2$, BECCS (€/t) | 1.00 | 1.35 | 0.94 | 1.04 | 0.62 | 1.04 | 0.99 |
| **C. Concentration** | | | | | | | |
| Normalized HHI (0–1) | 1.00 | 0.67 | 1.32 | 1.06 | 1.06 | 0.94 | 0.98 |
| **D. Energy** | | | | | | | |
| Peak energy demand (TWh/yr) | 1.00 | 0.96 | 0.32 | 1.00 | 0.91 | 0.92 | 0.99 |
| Energy intensity (kWh/$tCO_2$) | 1.00 | 1.21 | 0.76 | 1.02 | 0.86 | 0.96 | 1.00 |

Note: Each entry is the scenario value divided by the Baseline value (Baseline = 1.00). Values rounded to two decimals.

(1) Cost-minimisation.

(2) $\bar{R}_T$ = 50 Mt target.

(3) Lower-decarbonization.

(4) Low Transport and Storage costs.

(5) Technology costs are non-declining.

(6) Fully endogenous learning-by-doing cost scenario.

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