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A million scenarios to identify conditions for robust bioenergy carbon capture in Sweden

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ABSTRACT

Large-scale bioenergy carbon capture and storage (BECCS) could be realized without escalating biomass use - under the right conditions. We apply robust decision-making theory to frame carbon capture as a decision problem. We then search for conditions of low costs and energy penalties by modelling the capture decision across a million scenarios of already-existing plants in Sweden. Mining the scenario data reveals that annual plant utilization, heat recovery via heat pumps and electricity prices constitute key conditions for combined heat and power plants. For pulp mills, key conditions are site-specific, but the availability of low-pressure steam and electricity prices are generally important. A sensitivity analysis supports these findings, but also identifies capture rates as key. About 19 $MtCO_2$ could be captured annually from the 113 plants studied while combusting zero additional biomass. Under the identified conditions, this would entail reduced power and district heating generation of 5.1-7.9 TWh per year – a modest penalty relative to the 220 TWh generated annually in Sweden.

1. Introduction

In 1959, Herbert A. Simon coined the term *satisficing* to describe how real decision-makers prefer to satisfy a range of objectives, rather than to maximize utility (Simon, 1959). This concept is worth reviving within contemporary research on bioenergy carbon capture and storage (BECCS) – a prominent method for delivering potentially gigatons of carbon dioxide removal (IPCC, 2023). Research involving BECCS has often relied on top-down, cost optimizing or integrated assessment modelling (cf. Azar et al., 2010; Klein et al., 2014; Muratori et al., 2020; Fajardy et al., 2021).

These research practices have been critically discussed for being overly speculative, sensitive to assumptions, normative, or deflective of fundamental critiques (Fuss et al., 2014, Creutzig, 2016; Haikola et al., 2019; Daioglou et al., 2020; Hansson et al., 2021). We see a risk of such models being detached from the realities of prospective BECCS operators (Haikola, 2019), who need to balance multiple contextual objectives (Rodriguez et al., 2021) rather than participating in a global optimization exercise. Despite this critique, we recognize the value in top-down studies but suggest that there is potential in methodological advancements.

That said, top-down approaches have contributed to the scientific consensus on the sustainability risks of BECCS (IPCC, 2023), notably the land-use impacts of potentially vast areas of energy crops (Anderson and Peters, 2016). When sustainability constraints are respected the potential of plantation-based BECCS could be close to zero (Koponen et al., 2024). However, given the substantial difference between global gross and net bioenergy use, there is likely scope for utilizing biomass residues for BECCS rather than dedicated crops (Slade et al. 2014; Calvin et al., 2021; Koponen et al., 2024).

Clearly, more research could demonstrate how risks of BECCS can be mitigated and benefits reaped (Smith et al., 2024). For this purpose, we see potential in framing bioenergy carbon capture as a site-specific decision problem and exploring this decision across many scenarios and sites. Our scope considers Sweden, and within this context, we argue that the risks of escalating land and biomass use can be avoided by efficiently integrating carbon capture into existing plants (cf. Gustafsson et al., 2021; Eliasson et al., 2022; Skoglund et al., 2023). This could require zero *additional* biomass feedstock as the plants already process substantial volumes of biomass.

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We rely on Robust Decision Making (RDM) theory. This and similar methodologies have been advocated by e.g. Creutzig (2016), Rodriguez Mendez et al. (2024) and Workman et al. (2021; 2024). RDM primarily uses models to explore and stress-test uncertain decisions against performance thresholds, and explicitly not to recommend or predict futures (Lempert, 2019). In this study, the decision to deploy carbon capture is considered robust if it achieves low costs and low energy penalty across many scenarios. These are common priorities of prospective BECCS operators (Rodriguez et al., 2021) so they constitute our satisficing criteria. While we apply RDM, our large scope (113 plants across Sweden) prevents full stakeholder engagement in the deliberation-with-analysis phase – an otherwise important aspect of the methodology (Workman et al., 2024). Instead, we illustrate how BECCS deployment scenarios can inform such deliberation.

As the outcomes of BECCS simulations are heavily dependent on underlying assumptions (Daioglou et al., 2020; Hansson et al., 2021), we focus on identifying key conditions for low costs and energy use. This shift from focusing on specific model outcomes to their underlying assumptions has been suggested by Creutzig (2016), exemplified for climate policies by Dekker et al. (2023), and is core to RDM (Lempert, 2019).

In summary, our research aims to apply an innovative methodology, RDM, to identify key conditions for robust bioenergy carbon capture. This lets us demonstrate how efficient integration of these technologies could result in insignificant increases of Swedish biomass demand. The following research questions support our aim:

1. Across many scenarios, what are key conditions for low capture costs and low energy penalties in Sweden, if diverse actors decide to deploy and operate bioenergy carbon capture?
2. How do these conditions change if the actors rely on zero additional biomass feedstock?
3. If many actors operate carbon capture under these conditions, using no additional biomass, how would Swedish electricity and district heating generation be affected?

Compared to other countries, Sweden has a very large forestry and biomass-based industry (Fuss and Johnsson, 2021; Petersson et al., 2022), where e.g. pulp and paper accounts for about 51 % of industrial energy use (Cruz, 2021). We study 7 kraft pulp mills and 106 combined heat and power (CHP) plants of various sizes and locations. Typically, CHP plants are woodchip- or waste-fired and provide district heating for cities. In Sweden, these co-generate approximately 15 TWh of power and 55 TWh of heat per year (Energimyndigheten, 2023a), and thus enable centralized low-fossil heating and waste treatment.

The considered plants are highly heterogenous, but all combust substantial amounts of biomass in boilers to power their processes. Therefore, we model how their boiler capacities can be retrofitted to power a basic monoethanolamine post-combustion capture process. Although the capture decision is our focus, other uses of the CO_2 than storage would be possible. However, we refer to the processes as carbon capture and storage (CCS) or BECCS for convenience.

The plant operators have various tools at their disposal to convert or transfer energy. These include e.g. heat exchange with district heating networks or process streams, operational strategies, additional boiler capacity or heat pumps (cf. Eliasson et al., 2022; Biermann et al., 2022, Kumar et al., 2023). Their utilization differs by scenario.

Notably, our research framing demands little consideration of temporality. The scenarios in this study should be thought of as snapshots, i.e. of a few years' time of operation. Furthermore, we do not consider transportation and storage of CO_2 (Karlsson et al., 2024), or interaction effects between sites, e.g. through cost learning rates (Reiner, 2016) or energy market dynamics (Levihn, 2017). We make no analysis of revenues, or reduced costs, from avoiding CO_2 emissions - while recognizing such incentives to be essential for developing CCS and BECCS at scale (cf. Lyngfelt et al., 2024; Bui et al., 2018; Zetterberg et al, 2021).

Finally, while RDM addresses many of the modelling critiques previously outlined, some still apply to our work. For example, similar to integrated assessment (Haikola et al., 2019), our work may support an imaginary of large-scale bioenergy carbon capture. This could be seen as narrow or technology optimistic, and other climate mitigation pathways may be preferred (Lefstad et al., 2024). Furthermore, in this context it seems warranted to consider the epistemology of simulations more generally. Not only does the quality of our results depend on underlying physical theories (e.g. the thermodynamics of steam cycles, generation of work or heat engines) but also on our calculation structure, choice of parameters and system boundaries, interpretations, and other critical aspects as outlined by Winsberg (1999).

To summarize, our main contribution is the application of RDM to study large-scale BECCS. This represents both a methodological advancement, and an opportunity to evaluate robust BECCS deployment in Sweden.

2. Methods and data

Our application of RDM is simplified, e.g. since no stakeholders of BECCS decisions are directly involved. But we are guided by the overall *framing, exploration* and *choosing* steps common to similar frameworks (Marchau et al., 2019). Respectively, these steps involve constructing models of CCS retrofits, sampling and running many scenarios, and then mining the resulting data set for insights. The steps are illustrated in Fig. 1.

For each plant studied, we assume the role of the plant owner. The decision to deploy CCS is framed using four components: exogenous uncertainties (X), which are factors more or less beyond our control; levers (L), representing actions or choices that should be explored; and model relationships (R), which defines how these factors interact (Lempert, 2019; Lempert et al., 2003). The decision is evaluated using measures of performance (M), which we refer to as Key Performance Indicators (KPIs). In each of many scenarios of this decision, a sample of uncertainties and levers is given as arguments to the model, which evaluates the KPIs. After evaluating all 113 plants, we identify what uncertainties and levers matter most by applying algorithms with roots in machine learning: Patient Rule Induction Method (PRIM) and random forest sensitivity analysis, as described in Sections 2.4 and 2.5.

2.1. Framing key performance indicators

The chosen KPIs are the cost of CO_2 capture, biomass penalties and energy services penalties, illustrated in Table 1. This choice represents a limitation of our methodology as it would ideally be customized to individual plant owners, which was not feasible when studying 113 plants. Costs and energy efficiency are, however, general priorities (Rodriguez et al., 2021) and align with our research interests.

Importantly, we are interested in a non-conventional view on energy efficiency in the context of a CCS retrofit: retrofitting with post-combustion capture incurs a considerable energy penalty, and this could either be managed by burning more fuel (upstream) or by reducing generation of electricity and/or district heating (downstream). The former is our biomass penalty, and the latter is our energy services penalty. We are interested in this latter aggregate of electricity and district heating penalties as it represents a summary of the lost useful energy incurred from a post-combustion retrofit. Dividing this KPI into separate heat and power KPIs would have been possible but would present significant challenges in determining appropriate satisficing thresholds and applying our scenario discovery algorithm, as described later.

Notably, the energy services penalty represents reduced heat and power generation, which could be undesirable or infeasible for many plant operators, implying foregone revenues or not meeting energy demands. This KPI can therefore be considered a demand that should be met by other means, e.g. by grid electricity and heat pumps, outside the

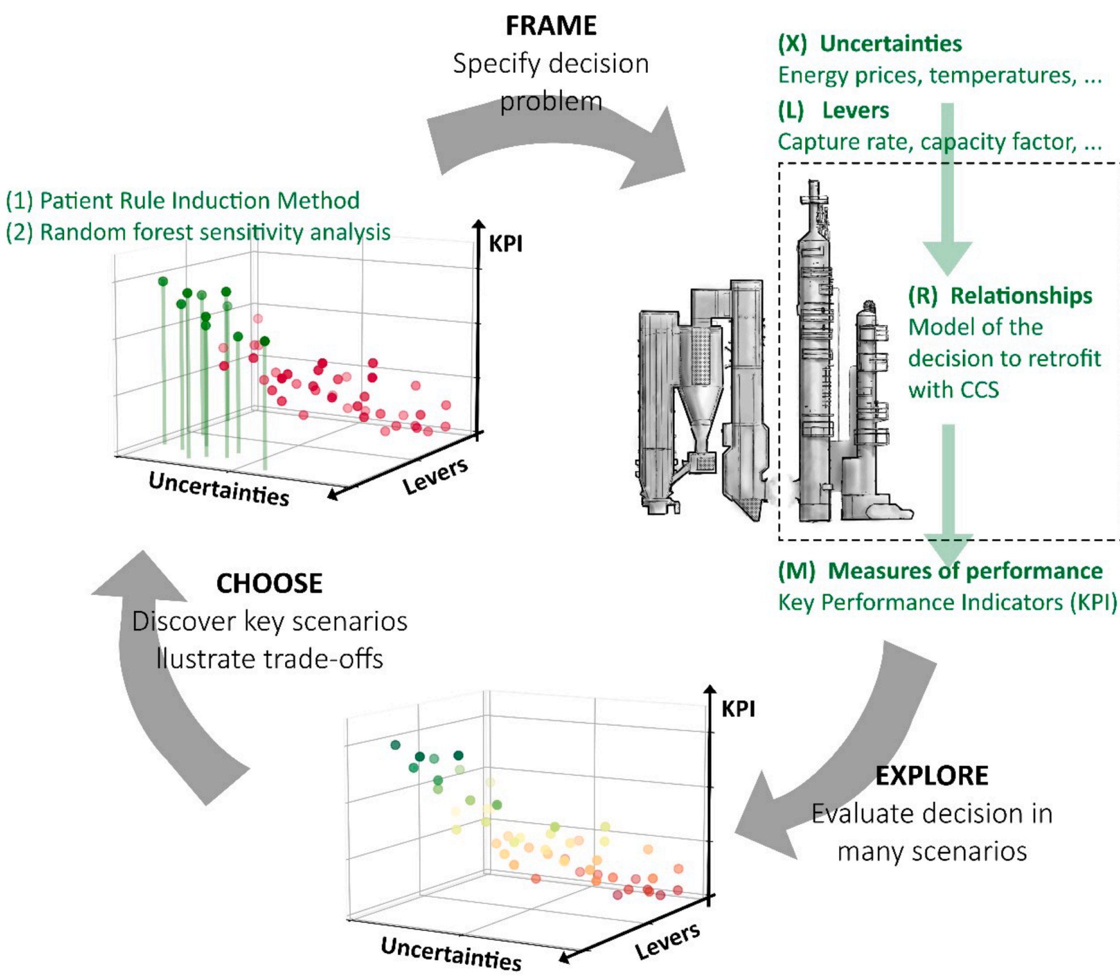

Fig. 1. The CCS deployment decision is iteratively framed within a model, explored across many scenarios and analyzed for key conditions and trade-offs.

Table 1
Key performance indicators and their thresholds for satisficing performance, by sector.

KPI	Equation [1]	Threshold Woodchip CHP	Threshold Waste CHP	Threshold Pulp Mills
Cost of CO_2 captured $\left[\frac{€}{t}\right]$	$capture\ cost = \frac{CAPEX_{annualized} + OPEX}{captured\ CO2}$ [2]	<120	<120	<80
Biomass penalty $\left[\frac{kWh}{t}\right]$	$biomass\ penalty = \frac{\Delta biomass\ combusted}{captured\ CO2}$	<500	≤0	<200
Energy services penalty $\left[\frac{kWh}{t}\right]$	$services\ penalty = \frac{\Delta power\ and\ district\ heating}{captured\ CO2}$	<350	<450	<450

[1] These equations are mainly illustrative. See Section 2.2 and Appendix B for detailed calculations.
[2] Capital expenditures (CAPEX) is annualized. Operational expenditures (OPEX) represent costs of additional energy or foregone revenues from selling energy. It also covers solvent makeup, fixed costs etc.

decision situation of the CCS retrofit. It therefore lies in the interest of the plant owner to reduce this penalty as much as possible - while not relying on combusting excessive amounts of biomass.

As mentioned, we seek robust rather than optimal decisions within RDM. If a decision is satisficing in most scenarios, it is robust. To be clear, the CCS retrofit decision is satisficing in a scenario if it meets the minimum acceptable threshold across all KPIs. These are calculated on an annual basis.

Choosing thresholds for satisficing performance is not trivial and would also ideally be set by the plant owners. We set these thresholds after iterative model runs and framings, as is common within RDM. For example, running thousands of scenarios and discovering that almost no scenarios achieve costs lower than 60 € per tCO_2 captured could lead to relaxing the cost threshold to 70 €. It could also lead to a review of the model input ranges – these are specified later in Tables 2 and 3 and were thus also iteratively adjusted to the best of our understanding.

The implications of the chosen thresholds are elaborated upon in the results and discussion. But e.g. the cost thresholds depend on possibilities for high plant utilization, and biomass thresholds on opportunities for increasing biomass feedstock. The thresholds can be compared to an upper cost estimate of ~100 € per tCO_2 captured (European Commission, 2024a) and a baseline energy demand, i.e. reboiler duty, of ~1000 kWh (3.6 GJ) per tCO_2 (cf. Biermann et al., 2022).

2.2. *Framing retrofit models of CHP plants and kraft pulp mills*

Our models rely on the data in Appendix A of CHPs and pulp mills. We refer to both types as “plants”. Two similar models of retrofitting a CHP with amine CO_2 capture were developed: one for woodchip-fired CHPs and one for waste-fired CHPs. Details of such a retrofit have

Table 2
The uncertainties and levers that constitute the parameters of the CCS retrofit models for woodchip- and waste-fired CHP plants.

Parameters Uncertainties	Low	High	Unit	Reference	Usage *
dT reboiler	7	14	°C	*Assumed*	*Dictates required reboiler steam temperature and the amount of waste heat that is recoverable for district heating*
T district heating (supply)	78	100	°C	Gustafsson et al. (2021)	
T district heating (return)	43	55	°C	Gustafsson et al. (2021)	
dT min for heat exchange	5	12	°C	*Assumed*	
U heat transfer coefficient	1300	1700	W/m2K	Biermann et al. (2022)	*Determines heat exchanger sizes*
Coefficient of Performance (COP)	2.3	3.8	-	Bergander and Hellander (2024)	*Ratio between useful output heat and input work for a heat pump*
CAPEX alpha constant	6	7	-	Eliasson et al. (2022), Fig. 6	*Estimates a baseline CAPEX for amine capture depending on flue gas volume*
CAPEX beta constant	0.6	0.7	-	Eliasson et al. (2022), Fig. 6	
CEPCI	780	830	-	University of Manchester (2024)	*Adjusts CAPEX to an assumed cost year of 2026*
Total overnight cost factor	10	30	%	Theis (2021)	*These factors escalate the CAPEX in-line with the NETL cost estimation methodology outlined by Ali et al. (2019) and Theis (2021).*
Weighted Average Cost of Capital	3	9	%	Mac Dowell and Fajardy (2017)	
Years of capital expenditure	3	6	years	Theis (2021)	
Cost escalation rate	0	6	%	Theis (2021)	
Discount rate	5	12	%	Ali et al. (2019)	*Annualizes the CAPEX*
Economic lifetime	20	30	years	Ali et al. (2019)	
Fixed cost (% of CAPEX)	4	8	%	Beiron et al. (2022)	*Estimates non-energy OPEX*
Price electricity	20	160	EUR/MWh	Gustafsson et al. (2021)	*Determines the price and cost of energy and solvents, and thus also energy- and solvent-related OPEX*
Price district heating (% of electricity price) **	25	100	EUR/MWh	*Assumed*	
Cost biomass	15	60	EUR/MWh	Bergander and Hellander (2024)	
Cost of solvent makeup	1.5	2.5	EUR/l	Ali et al. (2019)	
CAPEX constant heat pump	0.76	0.96	MEUR/MW	Bergander and Hellander (2024)	*Estimates heat pump and heat exchanger CAPEX*
CAPEX constant heat exchanger	470	670	EUR/m2	Eliasson et al. (2022)	
Plant utilization (woodchip)	4000	6000	hours/year	Beiron et al. (2022)	*Baseline operational hours per year before a CCS retrofit*
Plant utilization (waste)	7800	8200	hours/year	Beiron et al. (2022)	
Levers					
Plant utilization increase (woodchip)	0/1000/2000		hours/year	*Assumed*	*Increased operational hours per year following a CCS retrofit*
CO2 capture rate	78	94	%	*Assumed*	*Sets the fraction of CO_2 captured*
Heat pump utilization	True/False		-	*Assumed*	*Dictates if heat pumps are used to recover waste heat*

* For model details of how parameters are used, see Appendix B.

** The price of district heating is directly related to the electricity price, as local CHP operators adjust it based on regional electricity prices. Other dependencies between inputs are assumed to be less strong, and are thus not modelled.

been given elsewhere (Kumar et al., 2023; Biermann et al., 2019; Onarheim et al., 2017), but the models are described in Appendix B and the overall steps are illustrated in Fig. 2.

The steps involve: (1) estimating the nominal energy balance from the database parameters, (2) calculating flue gases, (3) sizing an Aspen Plus model of amine capture, compression and liquefaction, (4) determining the new energy balance after integrating the capture process and (5) estimating capital and operational expenditures. Aspen models were based on Kumar et al. (2023) and Deng et al. (2019).

Importantly, in the Swedish energy system, CHP plants fired by woodchips or by waste serve different purposes. The former typically operates flexibly on costlier fuels during colder months to balance heat demands in district-heating networks. The latter generates power and heat year-round, often as baseload in a district-heating network while earning revenue from waste incineration. If retrofitted with a capture unit, both can recover process heat of high temperatures via direct heat exchange, and of low temperatures via heat pumps (Kumar et al., 2023; Beiron et al., 2023; Gustafsson et al., 2021). Additionally, woodchip-fired plants could be operated for additional hours per year following a CCS retrofit, e.g. to reduce levelized costs.

These choices and the capture rate are considered levers. Along with the other uncertainties of Table 2, they form the parameters of the CHP models. One such parameter is the coefficient of performance (COP), which represents an (assumed constant) ratio between useful heat and input electricity for heat pumps. The COP and other parameters are either categorical or range between a low and a high value. We have iteratively adapted the ranges based on referenced sources and on our best judgment. The idea is to construct many scenarios by sampling from these ranges, as described in the following section, and to then identify which parameters matter most for satisficing performance.

A kraft pulp mill is a whole other story. These are heterogenous chemical plants which process biomass in stages, notably digestion, washing, bleaching and drying, while cooking chemicals are recovered from a black liquor treatment cycle (Svensson et al., 2021). The most substantial energy conversion step is the combustion of black liquor in recovery boilers. This generates steam that is primarily used to cover internal process demands. Any remaining steam is used to co-generate heat and power, as the mills are often equipped with auxiliary bark boilers, turbines and sometimes district heating connections. In the future, excess steam could be used for carbon capture.

Similar to CHP, a model of retrofitting kraft pulp mills with amine CO_2 capture was developed. For each mill, we first estimate the available steam that could be used to power the pulping and capture processes or for grid power generation, see Equation (1). Respectively, the recovery boiler generates 18 and the pulping process demands 11 GJ steam per t air dried pulp (EU Joint Research Centre, 2015). Bark boiler generation is then estimated as a plant-specific percentage of annual recovery boiler generation. The estimates are based on a set of case studies (Danielsson, 2018; Nihlmark and Mahmoud, 2017; Svensson, 2018; Ahlström and Benzon, 2015; Klugman et al., 2007; Lacaze-Masmonteil, 2024; Pedersén and Larsson, 2017). We regard the estimates as indicative but uncertain, so scenarios of bark boiler use could be interpreted as either utilizing existing boiler capacity or relying on expanded capacity.

$$Q_{available\ steam}[MWh\ p.a.] = Q_{recovery\ boiler} + Q_{bark\ boiler} - Q_{process\ demands} \tag{1}$$

The model treats most of the mills as a recovery and bark boiler of certain capacities and steam qualities, see Appendix A for this data. Based on the available steam from Equation (1) and the pressure levels of each mill we estimate their nominal energy balances. This is the first step in Fig. 3. The following steps are equivalent to the CHP models.

Table 3
The uncertainties and levers that constitute the parameters of the CCS retrofit models for pulp mills.

Parameters Uncertainties	Low	High	Unit	Reference	Usage *
Emission factor recovery boiler	0.38	0.43	tCO2/MWh	Onarheim et al. (2017)	*Estimated from Onarheim's et al. (2017) model and used to calculate CO_2 and flue gas volumes*
Emission factor bark boiler	0.29	0.34	tCO2/MWh	Onarheim et al. (2017)	
Flue gas volumes recovery boiler	10000	11000	kg(wet)/tpulp	Onarheim et al. (2017)	
Coefficient of Performance (COP)	2.3	3.8	-	Bergander and Hellander (2024)	*Ratio between useful output heat and input work for a heat pump*
k constant of excess heat	-217	157	GWh/year	Cruz et al. (2021)	*Estimates available excess heat above 60°C, using Equation (2).*
m constant of excess heat	0.918	1.578	GWh/tpulp	Cruz et al. (2021)	
CAPEX alpha constant	6	7	-	Eliasson et al. (2022), Fig. 6	*Estimates a baseline CCS CAPEX depending on flue gas volume ***
CAPEX beta constant	0.6	0.7	-	Eliasson et al. (2022), Fig. 6	
CEPCI	780	830	-	University of Manchester (2024)	*Adjusts CAPEX to cost year 2026*
Total overnight cost factor	10	30	%	Theis (2021)	*These factors escalate the CAPEX in-line with the cost estimation methodology outlined by Ali et al. (2019) and Theis (2021).*
Weighted Average Cost of Capital	3	9	%	Mac Dowell and Fajardy (2017)	
Years of capital expenditure	3	6	years	Theis (2021)	
Cost escalation rate	0	6	%	Theis (2021)	
Discount rate	5	12	%	Ali et al. (2019)	*Annualizes the CAPEX*
Economic lifetime	20	30	years	Ali et al. (2019)	
Fixed cost (% of CAPEX)	4	8	%	Beiron et al. (2022)	*Estimates non-energy OPEX*
Price electricity	20	160	EUR/MWh	Gustafsson et al. (2021)	*Determines the price and cost of energy and solvents, and thus also energy-related OPEX*
Cost biomass	15	60	EUR/MWh	Bergander and Hellander (2024)	
Cost of solvent makeup	1.5	2.5	EUR/l	Ali et al. (2019)	
CAPEX constant heat pump	0.76	0.96	MEUR/MW	Bergander and Hellander (2024)	*Estimates heat pump CAPEX*
Levers					
Energy supply strategy	SteamHP/ SteamLP/ HeatPumps		-	*Assumed*	*Dictates the supply strategy used for powering the reboiler*
CO2 capture rate	78	94	%	*Assumed*	*Sets the fraction of CO_2 captured*
Bark boiler utilization increase	0/30/60/90		%	*Assumed*	*Assumes any additional utilization of bark boiler capacity*

* For model details of how parameters are used, see Appendix B.
** Costs are estimated using the same methods as for CHP.

Notably, only CO_2 from the recovery boiler is considered for capture.

A differentiating aspect of the pulp model is that the mill owner could pick various energy supply strategies, and that these may or may not be sufficient for the capture process (Skoglund et al., 2023; Biermann et al., 2022). We limit the options to either using high pressure steam, low pressure steam or recovering low-grade process heat via heat pumps. This latter option has not been demonstrated but merits theoretical consideration, as it represents an electrified capture process utilizing excess heat (Jensen et al., 2024). Available excess heat above 60°C for the considered mills have been estimated by Cruz et al. (2021), see Equation (2). This heat estimate should be fairly accurate as the kraft process is similar across mills. And, in theory, the heat could be lifted to an appropriate reboiler temperature.

$$Q_{excess \geq 60^{\circ}C}[\boldsymbol{GWh\ p.a.}] = \boldsymbol{k} + \boldsymbol{m} * \boldsymbol{market\ pulp}[\boldsymbol{air\ dried\ tons\ p.a.}] \quad (2)$$

The energy supply strategy, extra boiler utilization and the capture rate constitute levers of the pulp model. These, the *k* and *m* constants of Equation (2) and other parameters are listed in Table 3. Again, scenarios will be generated by sampling from these ranges, as described in the following section.

2.3. Exploring the models' performance

The CHP and pulp models are written in Python and are available on GitHub (Stenström, 2024). They are wrapped inside helper functions of the EMA Workbench, an open-source toolkit for exploratory modelling and analysis (Kwakkel, 2017). For each of the 113 CHP and pulp plants, a new model is instantiated and run between 10 000 to 25 000 scenarios. Each scenario is constructed by Latin hypercube sampling (McKay et al., 1979) from the uncertainties and levers of the plant.

The sampling technique is common within RDM and does not rely on assumed probability distributions of inputs (cf. Roussanaly et al., 2020). Simply put, it instead divides all input ranges into bins and samples from all combinations of bins. This avoids bias around any specific scenario(s) and ensures that the full ranges of each input are evenly explored. This is an important feature of RDM, where modelling serves decision support rather than prediction (Lempert, 2019).

2.4. Identifying conditions for robust performance using scenario discovery

The resulting data set of over a million scenarios could now be analyzed to identify what conditions matter most for certain scenario outcomes, see Fig. 1. This operation is referred to as scenario discovery, and data mining algorithms are typically utilized. We use a Patient Rule Induction Method (PRIM) (Kwakkel, 2019; Friedman and Fisher, 1999).

To provide a crude description, PRIM recursively removes points from the data set by restricting the allowed input ranges. This increases *density*, the share of satisficing scenarios, but might reduce the number of satisficing scenarios. In each iteration the algorithm selects the restrictions that maximize density. Thus, inputs that are restricted are (generally) the most important for the models' performance. However, the algorithm could prioritize restrictions that do not result in the densest remaining data set after all iterations are completed. To circumvent this issue the algorithm can be run many times while alternating the input dimensions available to be restricted. Constraining

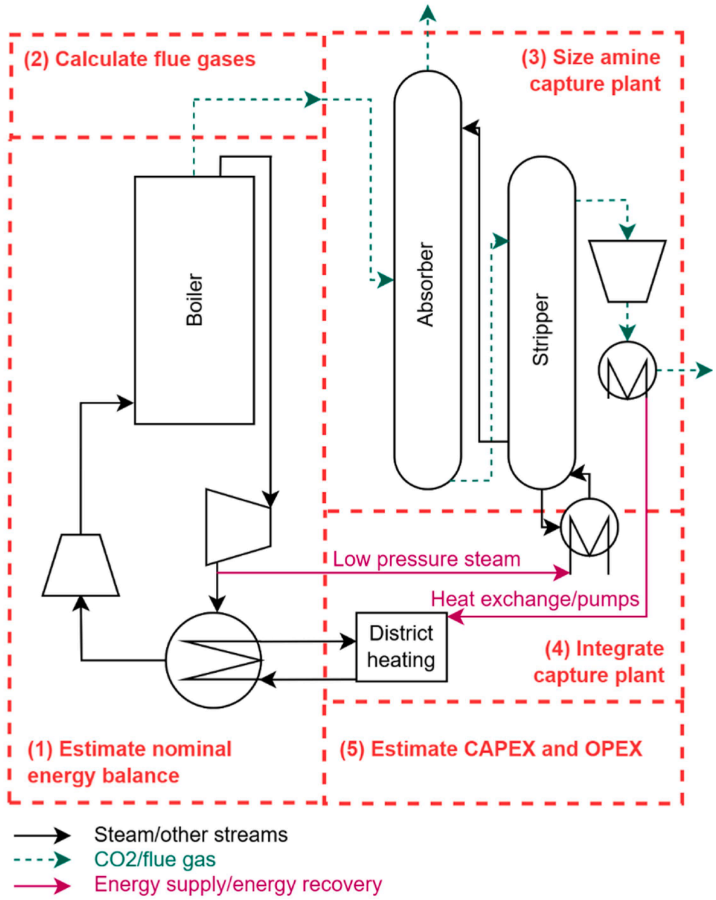

Fig. 2. Model outline for retrofitting a CHP plant with CCS.

the dimensions also makes the scenarios more interpretable. See Kwakkel (2019) for more details on PRIM.

Given this, we repeatedly ran PRIM on the CHP and pulp scenarios, alternating constraints on up to three dimensions at a time. To be clear, the algorithm thus identified input ranges, i.e. ranges of uncertainties and levers, that are good predictors for satisficing performance. The resulting input ranges represent key conditions for robust performance of bioenergy carbon capture and are presented as results.

2.5. Sensitivity analysis using a random forest algorithm

Conventional sensitivity analysis methods, e.g. One-at-a-Time or Sobol, are not well-suited for this study. Some reasons include: we evaluate 113 models (plants) rather than one; an ensemble of non-linear scenarios is explored rather than a point estimate; and the outcome of interest, i.e. satisficing performance, is binary but encompasses three performance indicators. While PRIM already identifies key conditions, offering a sensitivity-like analysis, it provides limited insight into the relative importance of parameters. However, our use of a million scenarios creates an opportunity to analyze this relative importance across the population of plants.

For the above reasons, our sensitivity analysis is based on random forest classification (Breiman, 2001; Antoniadis et al., 2021). The algorithm uses our modelled data to generate a set of decision trees which, given model inputs, aim to predict the output class. For example: "if capture rate > 0.90 and if electricity price < 40 and if… then the predicted outcome is (not) satisficing". To improve robustness, the decision trees are trained on different bootstrapped subsets and randomly selected parameters of the original data. They constitute a random forest, and their average prediction is the random forest prediction.

Importantly, instead of using the random forest to make predictions, its rules inform us of what parameters matter most for satisficing performance. For example, the rule "capture rate > 0.90" splits the data into two subsets, where one has higher and one has lower density of satisficing scenarios. This contribution to a purer data set is quantified within the random forest classifier of the Scikit-learn Python library (Pedregosa et al., 2011) – and we rely on this quantification. If a parameter contributes with substantial purity improvements across many decision trees, its importance is higher. The importances of all parameters were normalized, for comparability, and we analyzed whether they aligned with the key conditions found by PRIM. For more details on random forest sensitivity analysis, see Antoniadis et al. (2021).

3. Results

This section illustrates both our results and the strengths of applying RDM to a population of plants. In the following subsections, we first present BECCS decision tradeoffs for two illustrative cases: the biomass-fired CHP plant of Stockholm Exergi and the pulp mill of Östrand. We then visualize results for all 113 plants studied and the sensitivity analysis. Finally, we illustrate the total energy penalty if all plants would capture their CO_2.

3.1. Two illustrative cases of BECCS decision tradeoffs

To reiterate, the decision to deploy carbon capture was evaluated in terms of capture costs, biomass and energy services penalties – across many scenarios – for all studied plants. In Fig. 4 we illustrate these KPIs for the biomass-fired CHP of Stockholm Exergi (cf. Kumar et al., 2023)

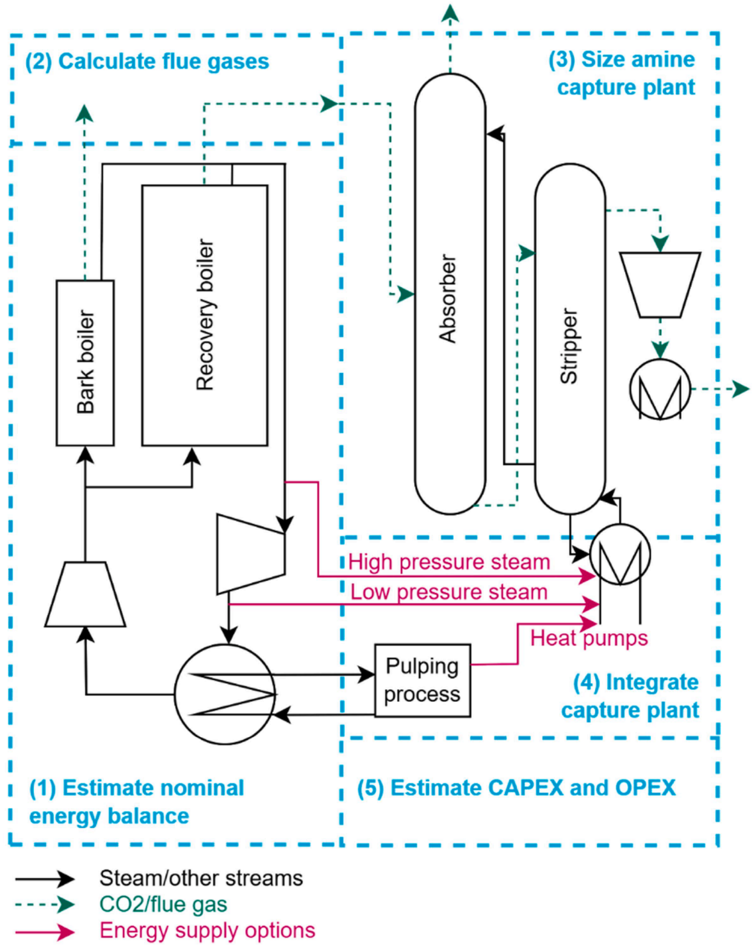

Fig. 3. Model outline for retrofitting a pulp plant with CCS.

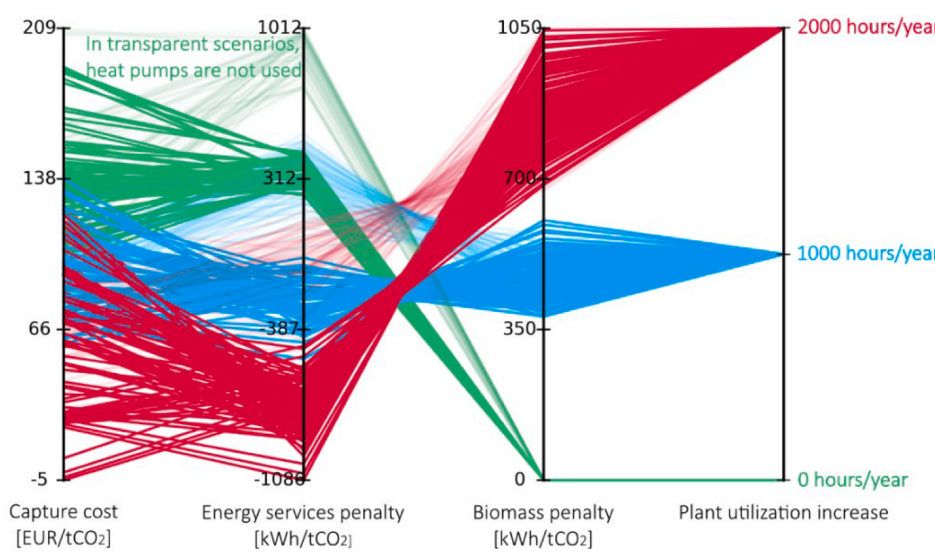

Fig. 4. KPI tradeoffs if Stockholm Exergi deploys amine BECCS. Each line represents a scenario, colored by the increase in plant utilization after the BECCS retrofit.

using a parallel coordinates plot. Each colored line connecting the four axes represents one scenario. For example, in transparent green scenarios, the decision-maker does not increase plant utilization after the BECCS retrofit and does not use heat pumps to recover low-temperature heat. These strategies result in no additional biomass penalty, but high energy services penalties around 700-1000 kWh/tCO_2 and high capture costs of maximum 209 EUR/tCO_2.

Contrastingly, an increase in utilization of 2000 hours per year (red scenarios) results in biomass penalties between 700-1000 kWh/tCO_2, low or negative energy services penalties, and capture costs below 120 EUR/tCO_2. Negative scenarios occur because – in our analysis – any additional heat and power generated over a year are subtracted from the capture cost and energy services penalty, and capture costs are annualized based on plant utilization.

This analysis exemplifies how RDM explicates decision-making tradeoffs under uncertainty. If Stockholm Exergi participated in deliberation-with-analysis, as is common in RDM (Lempert, 2019), they would identify the need to increase plant utilization to reduce costs – but that this strategy increases biomass penalties. To balance these priorities, a moderate increase of 1000 hours per year, combined with heat pumps for waste heat recovery, could be a robust strategy (blue scenarios).

Similarly, in Fig. 5, we illustrate tradeoffs when deploying BECCS at the Östrand pulp mill. Colors indicate what energy supply strategy is utilized for the capture process – low- or high-pressure steam or heat pumps – while transparent scenarios indicate that bark boilers utilization is increased by either 60 or 90 %. Clearly, in the upper panel, the biomass penalty is divided into distinct ranges (around 0, 200, 360 and 600 kWh/tCO_2) because the bark boiler increase is defined in steps (either 0, 30, 60 or 90 %). Lower boiler utilization implies lower biomass penalty. Contrastingly, it is difficult to distinguish what conditions lead to low capture cost and energy services penalties. This is where the data mining results are useful, as exemplified by the blue scenarios in the lower panel. If Östrand uses low-pressure steam for the capture process, avoids increasing bark utilization, and anticipates electricity prices below 74 EUR/MWh, they may achieve both lower costs and reduced energy penalties.

Again, RDM allows for deliberation-with-analysis. A strategy involving no increases in bark boiler utilization would ensure low biomass penalties but may result in high energy services penalties if high-pressure steam is used (red scenarios). Conversely, as mentioned, Östrand may balance all three KPIs if relying on low-pressure steam and not increasing bark boiler utilization – if anticipating electricity prices below 74 EUR/MWh. Notably, electricity prices are uncertain, impactful, and beyond the decision-maker's control, so RDM helps clarify how their expectations about such factors influence decisions.

3.2. Key conditions for robust BECCS across Sweden

Expanding on the two illustrative cases, this subsection presents conditions that balance KPI tradeoffs across all 113 plants studied. The aim was to identify conditions for robust performance. To reiterate, the conditions were identified by applying PRIM to the set of scenarios. While all identified conditions are reported as ranges in Appendix C for different plant types and sizes, we illustrate key results per sector below

For woodchip-fired CHP, the satisficing KPI thresholds were: capture costs below 120 EUR/tCO_2, biomass penalties below 500 kWh/tCO_2, and energy services penalties below 350 kWh/tCO_2. Meeting these criteria is mainly possible if operating many hours per year and using heat pumps to recover low-temperature heat (below ~47°C) from the capture process. This is illustrated in Fig. 6.

In panel (a) no conditions are applied, and most scenarios fail to meet the thresholds. In panel (b) we apply the following key conditions: all plants are operated around 6300-7000 hours; larger plants (with emissions above 200 ktCO_2 p.a.) use heat pumps, and smaller plants rely on lower discount rates between 5 and 7.7 %. This results in satisficing

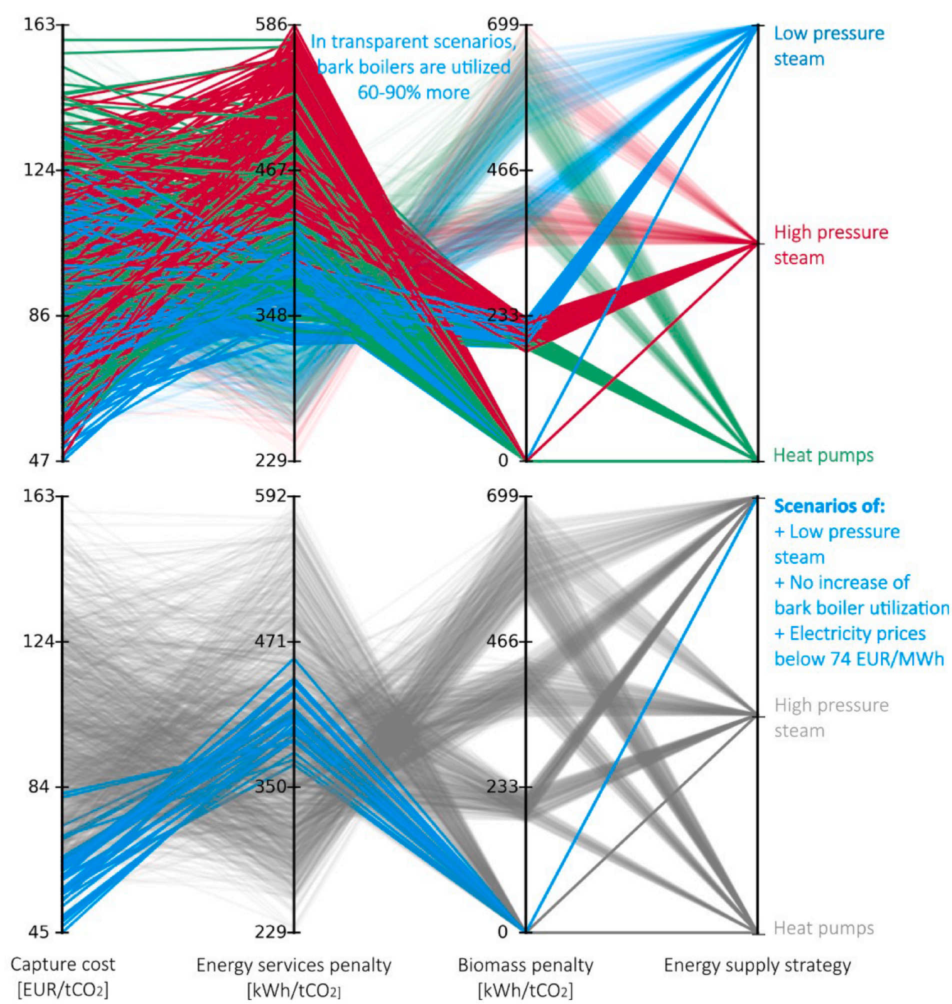

Fig. 5. KPI tradeoffs if Östrand deploys amine BECCS. The lower panel highlights a subset of scenarios identified through PRIM data mining.

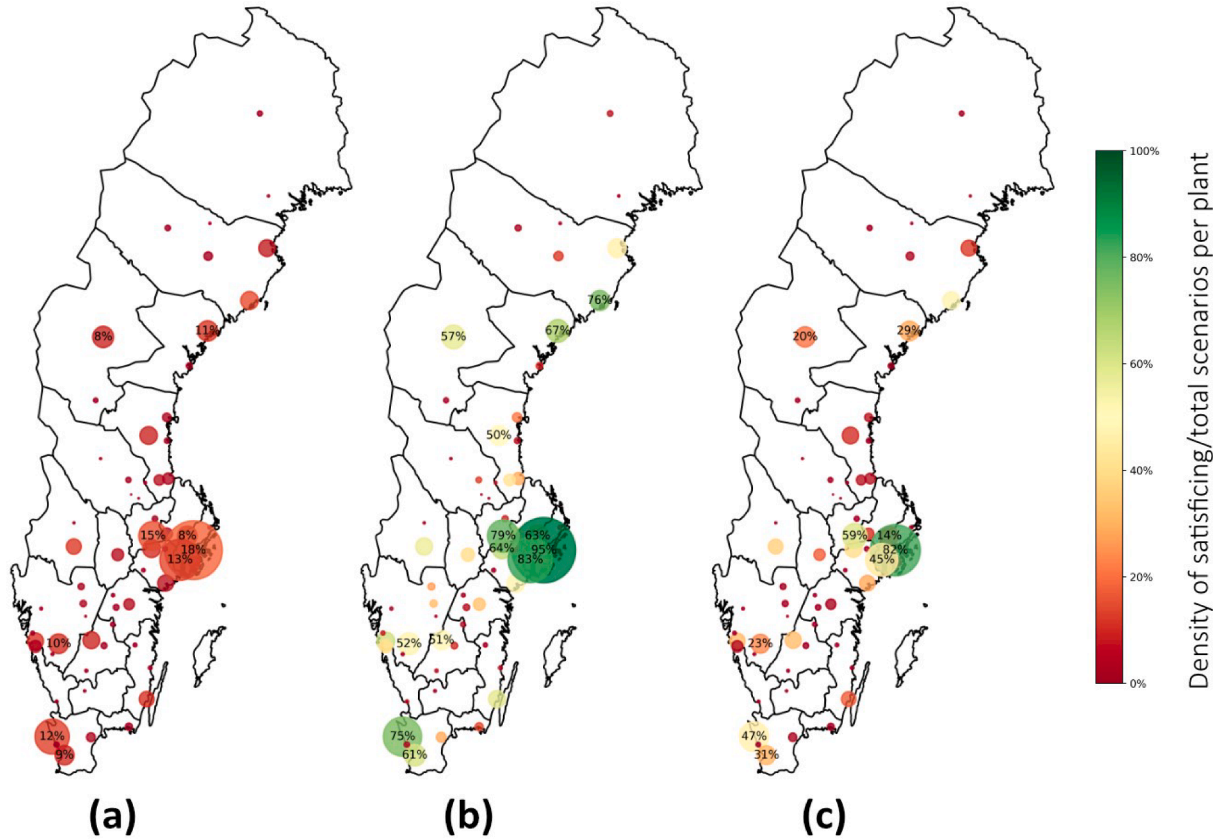

Fig. 6. Scenarios of woodchip-fired CHP plants. Radius represents gross CO_2 emissions. Color represents the share of scenarios which meet the performance criteria of low costs, biomass use and penalties on energy services. In panel (a), no conditions are applied to the scenarios. In panel (b), key conditions for robust performance are applied. In panel (c), similar conditions are applied but including a constraint of zero additional biomass use.

performance across most scenarios – around 75-90 % for larger plants. Thus, robust performance. However, while all medium and small plants perform more robustly after applying the abovementioned conditions, many still perform satisficing in fewer than 60 % of scenarios.

In panel (c) our 2nd research question is explored, as it illustrates conditions when no increase in biomass combustion is allowed. In such scenarios, plants with emissions lower than 300 ktCO_2 p.a. are not utilized for more than a baseline of 5400-6000 hours per year. Notably, this could be an overestimate for many plants. Furthermore, all plants rely on heat pumps to meet the performance criteria, and plants above 300 ktCO_2 p.a. achieve heat pump COPs between 3.14 and 3.8. These plants also assume constrained electricity prices, below 67 and 48 EUR/MWh, depending on the plant. Applying these conditions results in increased densities of satisficing scenarios compared to panel (a) where no conditions are applied. However, few plants achieve densities above 40 %.

For waste-fired CHP, the satisficing thresholds were: capture costs below 120 EUR/tCO_2, biomass penalties below or equal to 0 kWh/tCO_2, and energy services penalties below 450 kWh/tCO_2. The stricter biomass criterion is simply because the modelled plants already operate most of the year, so they never combust more biomass.

Similar to woodchip-fired CHP, a key condition for meeting these criteria is the utilization of heat pumps to recover waste heat. But electricity prices and discount rates are also important. Notably, these three are key conditions independently of plant size. The conditions are illustrated in Fig. 7. In panel (a) no conditions are applied. In panel (b) the following conditions apply: all plants use heat pumps; electricity prices are constrained to maximum 65 EUR/MWh; and discount rates are kept around 5 to 8 %. As mentioned, all waste-fired scenarios rely on zero additional biomass, so when illustrating these conditions in panel (c) all densities remain the same as in panel (b).

For pulp mills, the satisficing thresholds were: capture costs below 80 EUR/tCO_2, biomass penalties below 200 kWh/tCO_2, and energy services penalties below 450 kWh/tCO_2. Individual conditions for meeting these criteria were found for each of the seven mills illustrated in Fig. 8. Again, in panel (a), no conditions are applied, and the density of satisficing scenarios is low.

In panel (b), key conditions for robust performance are applied. All mills are favored by lower electricity prices. For example, prices below 74 EUR/MWh are key for the largest emitter Östrand, as shown in the previous subsection. To achieve satisficing performance, most mills with sufficient bark boiler capacity rely on a 0 or 30 % increase of this capacity, and of low-pressure steam to power the capture process. Mills with smaller bark capacities, such as Aspa and Värö, instead rely on excess heat and heat pumps to power the capture process, especially when biomass is constrained. Notably, this was a theoretically modelled option. Alternatively, these mills could also utilize low-pressure steam at the expense of greater losses of power output.

In panel (c) all scenarios of increased bark boiler capacity are removed, implying no additional biomass use. Under these conditions, the mills still perform satisficing across many scenarios when relying on either low-pressure steam or heat pumps; when electricity prices are limited to maximum 74 EUR/MWh; and when the CAPEX exponent beta is constrained to around 0.60-0.65 (refer to Table 3 of the present study, or Fig. 6 in Eliasson et al. (2022), for an interpretation of this exponent).

When searching for additional conditions, these vary substantially between sites. For example, capture rates between 80-90% is a key condition for Östrand, discount rates between 5-9% is important for Aspa and heat pump COP above 3.2 is important for Värö. Notably, applying these conditions in panel (c) results in the overall highest densities, which represents a reversed situation compared to woodchip-fired CHP in Fig. 6. This is because the biomass constraint enables more mills to meet the satisficing thresholds, mainly the biomass threshold, in

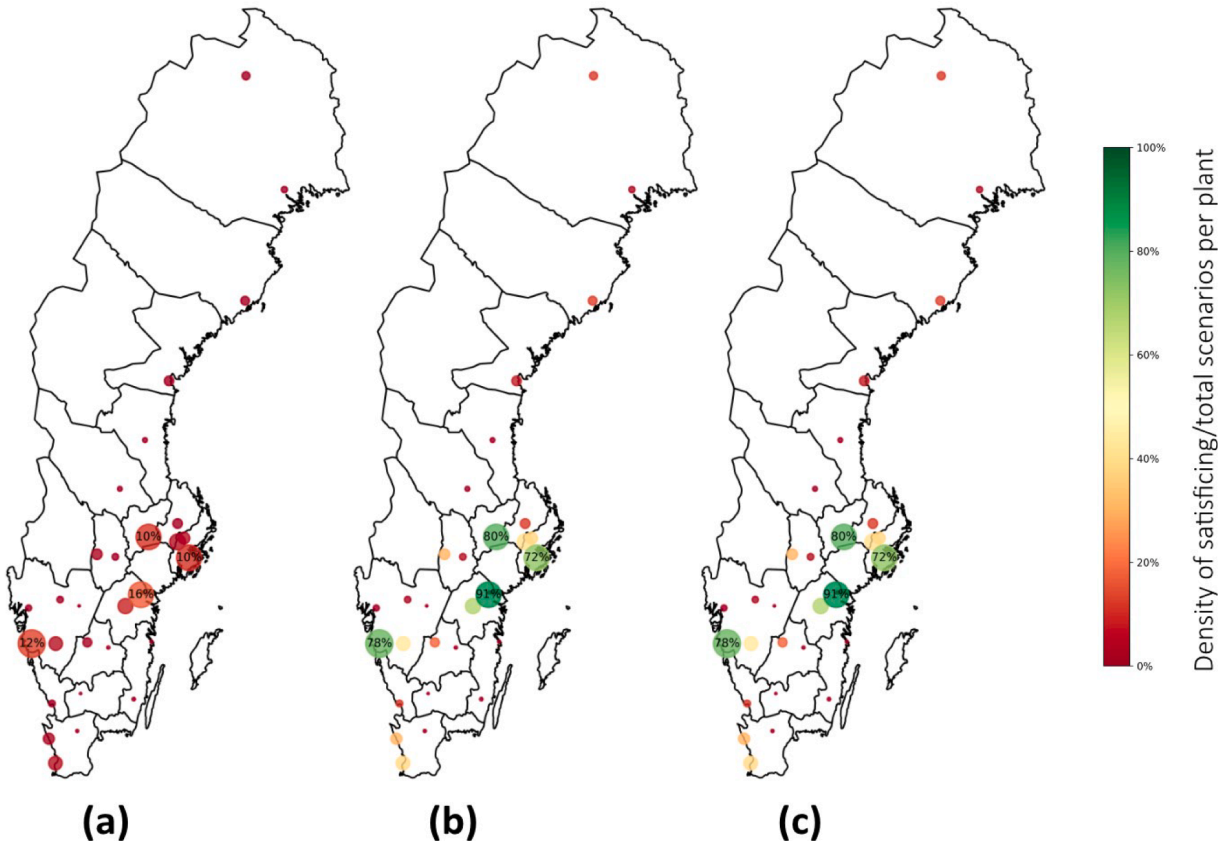

Fig. 7. Scenarios of waste-fired CHPs. Radius represents gross CO_2 emissions. Color represents the share of scenarios which meet the performance criteria. In panel (a), no conditions are applied to the scenarios. In panel (b), key conditions for robust performance are applied. In panel (c), a constraint of zero additional biomass use results in no change in density, as waste-fired plants anyway do not burn more biomass after a carbon capture retrofit.

more scenarios.

While these results indicate model sensitivity, they do not illustrate the relative importance between all model parameters. We estimated this relative importance using the random forest classifier of the Scikit-learn library, as outlined in Section 2.5. The results are illustrated in Fig. 9 and largely align with the key conditions found by PRIM: operating hours (plant utilization), discount rates, heat pump and bark boiler utilization and electricity prices. The main exception is the capture rate, which was given less importance by PRIM but more importance in this sensitivity analysis. Possible explanations are discussed in Section 4.

3.3. Illustrating total lost generation of electricity and district heating

To answer our 3rd research question, we compiled the total lost electricity generation and district heating if all plants would capture their CO_2 without combusting more biomass. This is illustrated in Fig. 10, which shows the energy services penalties against CO_2 capture capacity for each plant. This resembles a marginal abatement cost curve, where the plants are ordered from low to high penalties (cf. Beiron et al., 2022; Johnsson et al., 2020). The plants' mean penalties are illustrated by black horizontal lines, and their ranges are illustrated in grey. The red line represents the cumulative mean energy penalty if summarizing plants from left to right. Furthermore, the blue dashed lines illustrate two indicative Swedish BECCS targets of 1.8 and 10 Mt p.a. (Fuss and Johnsson, 2021; SOU, 2020).

To capture 1.8 $MtCO_2$ p.a. the cumulative penalty ranges between 270-540 (mean 400) GWh p.a. To capture 10 $MtCO_2$ p.a. the penalty ranges between 2050-3620 (mean 2770) GWh p.a. However, these summaries assume an "optimal" deployment order - a framing which we have criticized. The estimates should be referred to with caution. To answer our 3rd research question, we prefer discussing the cumulative penalty for capturing all 19 $MtCO_2$ p.a. This penalty ranges between 5110 and 7870 (mean 6350) GWh p.a., independently of deployment order.

Interestingly, Fig. 10 illustrates that carbon capture at pulp mills (large boxes to the top right) is costly in terms of lost energy services. Conversely, smaller CHPs retain more power and district heating production across our scenarios.

4. Discussion

The risks of large-scale BECCS are a prominent concern (IPCC, 2023). Our main research contribution is twofold. Firstly, we demonstrated that the risks of escalating land and energy use of BECCS in Sweden can be circumvented by efficiently integrating these technologies into existing bioenergy-intensive plants. If accepting this premise, BECCS can cause virtually zero *relative* increase in biomass demand. Secondly, we demonstrated a novel application of RDM theory. We framed BECCS as a decision problem for prospective operators and applied satisficing criteria and scenario discovery to balance multiple objectives across over a million scenarios.

Our application of RDM to BECCS serves several important purposes. Notably, it explicates assumptions often hidden in large-scale system models featuring BECCS, as problematized by e.g. Haikola et al. (2019) and Hansson et al. (2021). Relatedly, conventional modelling of large-scale carbon removal has been criticized for its predictive nature (Workman et al., 2024; Rodriguez Mendez et al., 2024), which could be risky if the promised outcomes fail to materialize, potentially leading to adverse consequences (Fuss et al., 2014). Our BECCS modeling therefore highlights assumptions and embraces uncertainties, focusing on the contingency of outcomes rather than making predictions.

Furthermore, our application of RDM illustrates its potential in

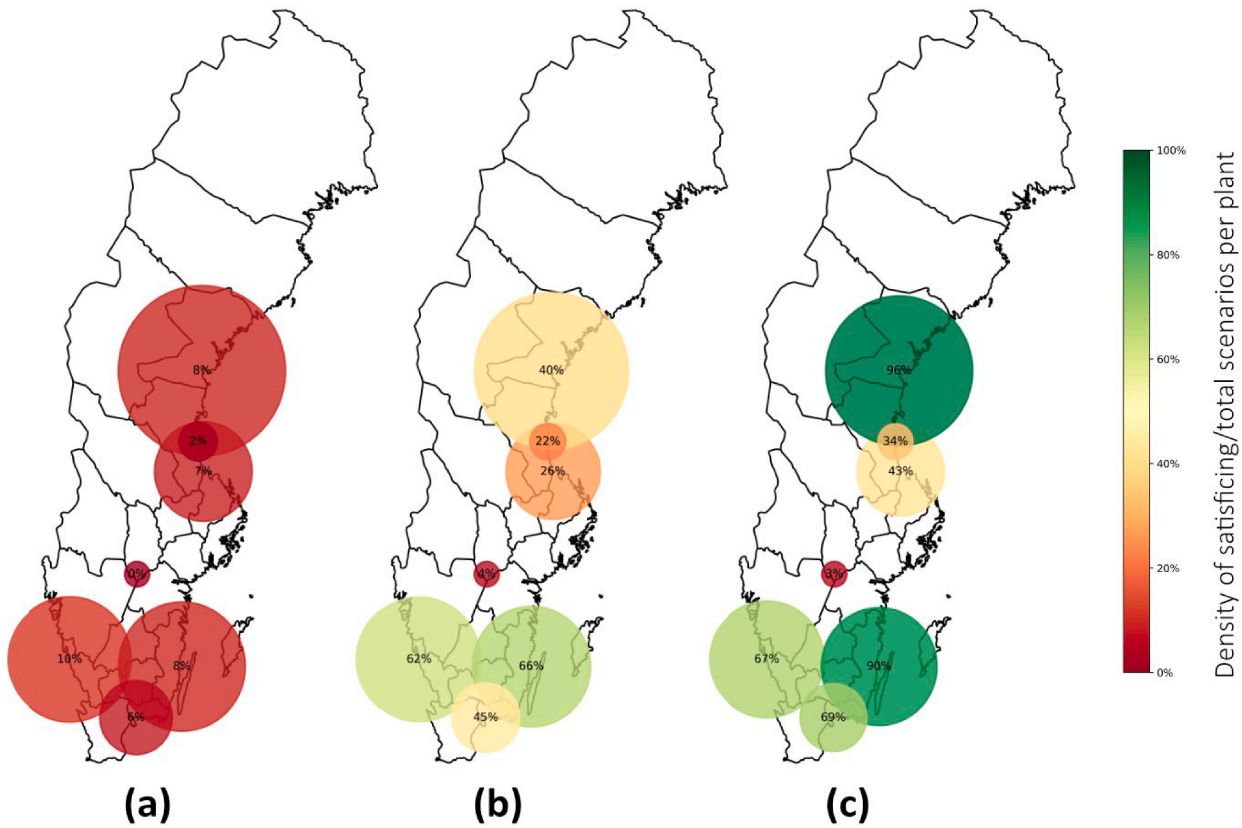

Fig. 8. Scenarios of pulp mills. Radius represents gross CO_2 emissions. Color represents the share of scenarios which meet the performance criteria. In panel (a), no conditions are applied to the scenarios. In panel (b), individual key conditions for robust performance are applied. In panel (c), similar conditions are applied but adapted to the zero additional biomass constraint.

engaging decision-makers in deliberation-with-analysis. For instance, Figs. 4 and 5 reveal KPI tradeoffs in utilizing additional biomass or recovering waste heat if Stockholm Exergi or Östrand would deploy amine-based BECCS. This analysis could be further improved if tailored to and directly engaging decision-makers – for example by defining plant-specific KPIs, scenarios and decision levers. Although initial steps toward such a deliberative analysis were taken in Stenström et al. (2024) for a BECCS investment decision and by Workman et al. (2024) for carbon removal policy, more research is needed to fully realize these participatory elements of RDM (Stanton and Roelich, 2021).

Considering our findings, these highlight key conditions for robust carbon capture, and the aggregate power and district heating losses from deploying these technologies at scale while combusting no additional biomass. These losses were estimated to 5110 and 7870 GWh p.a. (5th to 95th percentile range) when capturing 19 $MtCO_2$ p.a. from the 113 plants studied across Sweden. Naturally, large plants could be prioritized. For example, if only the 10 largest plants deploy BECCS the total energy penalty could be reduced to approximately 3350 GWh p.a. while still capturing 9 $MtCO_2$ p.a.

Obviously, an energy supply loss between 5.1 and 7.9 TWh could need compensation. For instance, district heating operators often need to supply a specified heat demand. In our analysis, we do not specify how this lost generation is replaced or any entailed system costs. Conceivably, wind, solar or nuclear could cover lost electricity generation, while heat pumps could cover lost district heating generation. Alternatively, energy demand could be reduced. While these alternatives are beyond the scope of our models, they suggest that scenarios without additional biomass use are possible.

Before discussing our results further, we will elaborate on key epistemological considerations as framed by Winsberg (1999).

Firstly, the degrees of freedom of the studied systems are both reduced and tailored towards energy conversion and engineering costs. Robust performance of bioenergy carbon capture may very well depend on other factors not studied, e.g. taxation, permitting, incentives, social acceptance etc. (Möllersten et al., 2021; Stenström et al., 2024). Another crucial factor is the availability of CO_2 transport and storage infrastructure (cf. Karlsson et al., 2024), which was outside our scope. Indeed, a comprehensive understanding of the feasibility of large-scale BECCS would require explicit analysis of transport and storage uncertainties (Hansson et al., 2022). Our choice of parameters – both uncertainties and levers – as well as their ranges are constrained, and consequently, so are our findings.

Secondly, the overall calculation structure and equations embedded in the models simplify each plant and their immediate surroundings with few site-specific considerations. This enables computationally efficient evaluations of many scenarios, but may misleadingly favor certain options (Kumar et al., 2024).

Thirdly, our capacity to validate the models is limited, and is arguably supposed to be (Winsberg, 1999), as detailed energy system data is not available for most of the plants studied. That said, the calculations primarily rely on fundamental thermodynamic relationships of steam cycles, in which we have high confidence.

Considering our results, low capture costs and energy penalties as defined in Table 1, and illustrated in Figs. 6-8, can be achieved across many scenarios under sector-specific conditions in Sweden. The definitions of satisficing thresholds shape the whole analysis, which is why they were iteratively adapted in-line with the RDM methodology. That said, more relaxed or stricter thresholds could be set – and their exact level could be endlessly debated. For instance, if prioritizing even lower costs, PRIM identifies CAPEX and discount rates as more important for many of the plants. If prioritizing lower energy penalties, COPs and district heating return temperatures emerge as more important. As

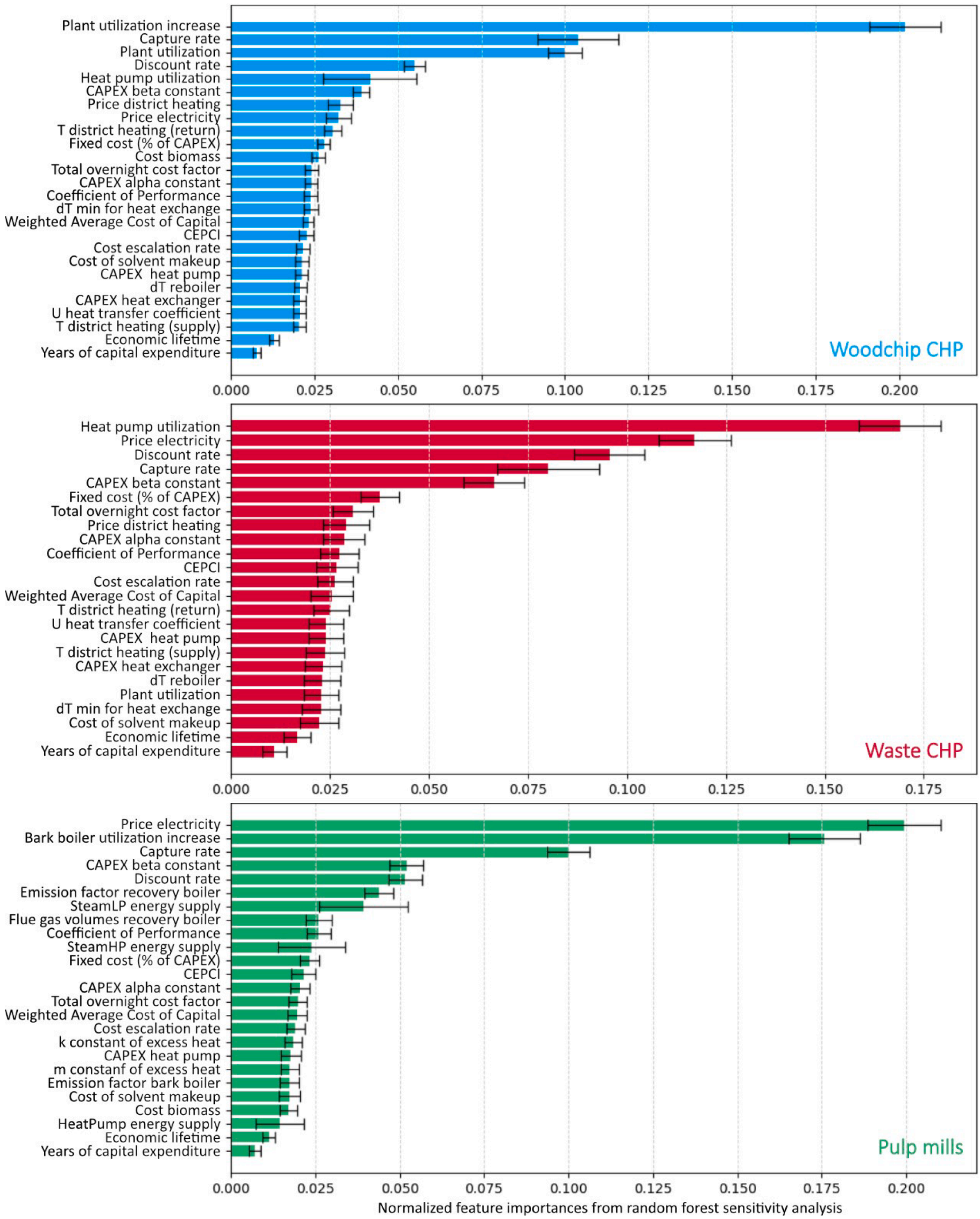

Fig. 9. Normalized, relative importance between parameters as estimated through random forest sensitivity analysis. The importance scores summarize to 1. Standard deviations are illustrated by black intervals. In addition to the parameters identified by PRIM, the capture rate is found to have great importance.

mentioned, this balance of objectives should ideally be framed by the actual plant owners. But the chosen thresholds adequately serve the purposes of this study.

For woodchip-fired CHPs, moderate increases in annual hours of operation (1000 additional hours), recovery of low-temperature heat and constraining electricity prices below 48 EUR/MWh constitute key conditions for robust carbon capture. The operational hours merit a critical discussion. We found operations of around 6300 and 7000 hours in total to be good predictors of robust performance. However, it is not certain that there will be sufficient demand to justify this increase in annual generation. That said, similar operational hours were explored by Beiron et al. (2022). Notably, they find that less integrated plants

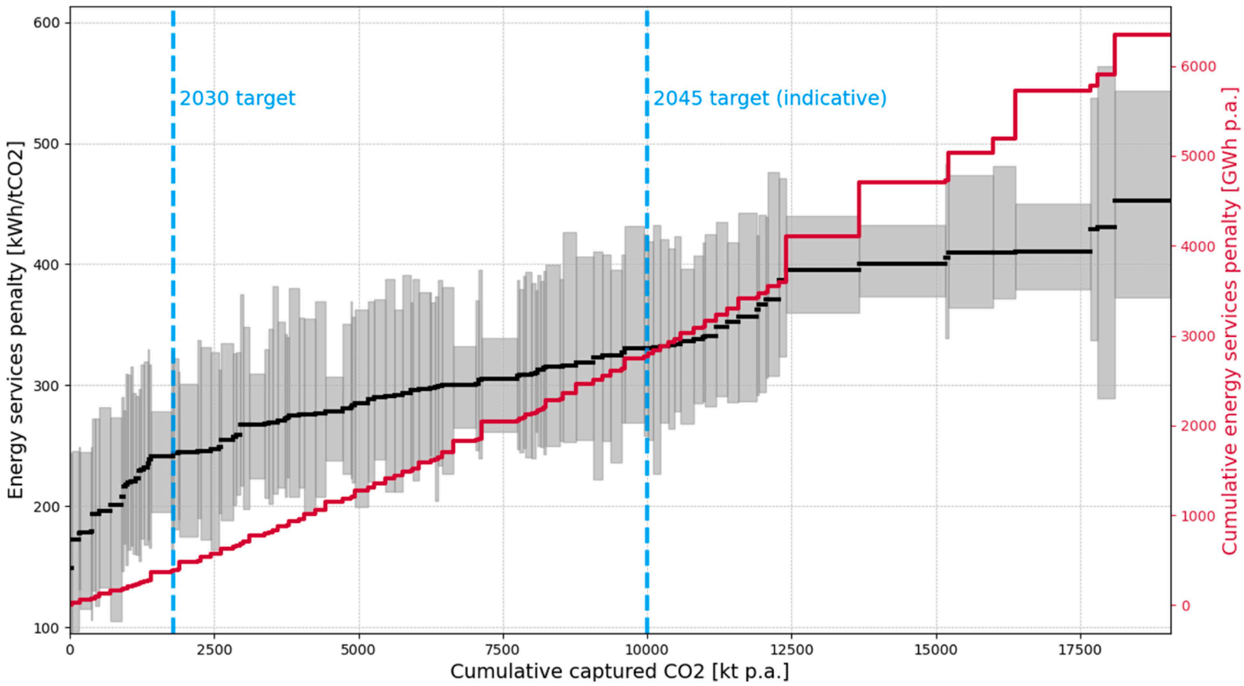

Fig. 10. When combusting no additional biomass, the total lost generation of electricity and district heating in Sweden mainly depends on the CO_2 capture volumes. Each grey box represents a plant. Respectively, box width and height represent mean CO_2 capture capacity, and the 5th to 95th percentile range of energy penalties. The red horizontal lines represent cumulative mean energy penalty, if summarizing plants from left to right. Blue dashed lines represent indicative Swedish BECCS targets (SOU, 2020).

tend to operate more hours to meet a given demand in a district heating system – a dynamic which we did not evaluate. Mac Dowell and Fajardy (2017) even suggest that *inefficient* plants, operated as baseload to capture CO_2 most of the year, would be "optimal". We question this logic, as energy efficiency is a priority among prospective BECCS operators, partly to maintain acceptance for bioenergy (Rodriguez et al., 2021).

Overall, a moderate increase in plant utilization would improve robustness by reducing costs of individual plants, see Fig. 6b. However, the option to *not* increase utilization could be cheaper from a systems perspective, as other production units are then used more. These could also have deployed carbon capture (Beiron et al., 2022). Although not increasing utilization resulted in less robust performance, as in Fig. 6c, it naturally conserves more biomass. All in all, the extent to which plant utilization can be increased depends on the dynamics between all production units in a given district heating system and the desired fuel use. As previously indicated, decision-maker deliberation could strengthen such an analysis and help identify infeasible scenarios for increasing plant utilization.

For carbon capture at waste-fired CHP plants to be robust, the utilization of heat pumps, electricity prices below 65 EUR/MWh and discount rates around 5-8 % constitute key conditions. This is a consequence of assuming that amine retrofitted waste-fired plants would be operated almost all year, meaning that profitability is mainly determined by such constant factors rather than operational decisions. This argument reveals a limitation of our models, i.e. that many parameters are treated as constant while in reality these would be subject to variation. A more developed model of greater time resolution could e.g. explore time-dependent electricity price or district heating scenarios, which could alter the results.

Given these conditions, most larger waste-fired plants (emissions above 250 $ktCO_2$ p.a.) could meet our satisficing conditions, see Fig. 7b. However, other conditions could be critical. Roughly half of the waste-fired plants' CO_2 emissions are biogenic, the other half are fossil. This has profound implications for how these emissions are governed within European and Swedish climate policy. For example, a planned incentive system for BECCS (Energimyndigheten, 2024a; European Commission, 2024b) would only apply to the biogenic share, whereas the European Emission Trading System incentive to reduce the fossil share (European Commission, 2024c) can arguably be considered inadequate. These shares may also change over time as society's waste fractions develop. Clearly, other factors than those we have evaluated may be key for robust carbon capture from waste CHP.

For pulp mills, we stress that the conditions for robust carbon capture are heterogeneous – more heterogeneous than could be demonstrated in this study. Skoglund et al. (2023) discussed many additional considerations: resource efficiency options, integration of lignin extraction or refinery concepts, lime kiln and bark boiler emissions, electrification, energy supply and heat integration options, increasing cross-sector demand for renewable carbon, and so on. Kumar et al. (2024) also discussed the importance of site-specific investment options, land utilization, costs of production stops or contingencies etc. for process industries.

Our study does not represent this plethora of scenarios for pulp mills. It mainly reveals trade-offs between utilizing available steam for CO_2 capture or for power generation. Most mills performed satisficing when supplying the capture process with low pressure steam, as this allows for co-generation of power. This concerned all mills with average bark boiler generation between 13-23 %, expressed as a percentage of annual recovery boiler generation. Mills with lower bark boiler generation, Värö and Aspa, have less steam available, and favoured the recovery of low-temperature heat (Cruz et al. 2021). This theoretical option of powering the capture process with heat pumps was introduced by Jensen et al. (2024) and illustrated for biogas upgrading. We make no claim of its actual applicability to pulp mills. But we conclude that mills with less available bark boiler capacity may require additional energy supply, e.g. from waste heat or increasing boiler capacity, to achieve low costs and energy penalties.

That said, the population of pulp mills performed more robustly in scenarios when bark boiler capacities were not increased, see Fig. 8c. This implies that the threshold on energy services penalties is relatively easy to meet – and combusting more biomass is not needed to keep electricity generation losses below 450 kWh/tCO_2. Given that mean penalties of pulp mills revolve around 400 kWh/tCO_2 in Fig. 10, we conclude that there could be scope for reducing the threshold of 450 kWh/tCO_2 in a future model iteration. The need for increased bark boiler generation could then be greater than what is shown in our analysis.

Across the sectors, a common condition for robust performance was the electricity price, especially for waste CHP and pulp mills. It is undisputably an important factor. Electricity generation represents the main energy tradeoff for amine carbon capture, and a major source of revenue and cost of capture. Electricity prices also determine district heating prices, as local CHP operators must adapt to regional electricity prices. Furthermore, a large range of 20-160 EUR/MWh was explored in the study. We see this as a major benefit of relying on RDM theory. As electricity prices are important yet subject to substantial uncertainty, it makes sense to explore a wide range of price scenarios. Naturally, the choice of the range to explore is a critical one, but we settled for a similar range as explored by Gustafsson et al. (2021).

Generally, the sensitivity analysis of Fig. 9 supports these findings. Operating hours, discount rates, utilization of heat pumps and bark boiler capacity, and electricity prices are key factors. We note that the electricity price is given less importance for woodchip CHP in this analysis, compared to the PRIM results for constrained biomass scenarios. This is mainly because the sensitivity analysis encompasses all scenarios, and not just those of constrained biomass. More importantly, we note that the capture rate is among the most sensitive parameters across all sectors - but the parameter was not identified by PRIM.

The random forest and PRIM algorithms quantify importance differently, which could explain why the capture rate was not identified by both as important. In the random forest analysis, parameter importance is represented by how well parameter splits (e.g., splitting scenarios based on whether capture rate > 0.90) separate satisficing from non-satisficing scenarios. In PRIM, parameter importance is represented by how well parameter restrictions (e.g., reducing the capture rate maximum by 5%) increase the density of satisficing scenarios. The random forest approach might more easily detect the impact of large changes in capture rate while PRIM, with its more lenient restrictions, might not. Other explanations could exist, but we suggest this is why PRIM fails to identify capture rate as important.

That said, identifying parameters that are *not* important for satisficing performance is also interesting. Notably, the economic lifetime used to annualize capture costs varies between 20-30 years, yet its precise value has little impact. Similarly, the cost of biomass contributes little to satisficing performance. This is likely because the biomass costs after a CCS retrofit are calculated as an increase relative to the biomass costs before the retrofit, meaning that when biomass feedstock increases are minimal or moderate, this cost parameter's influence is marginal. However, we do consider biomass costs important for the studied industries – they are just not fully allocated to the CCS decision.

Moreover, we evaluated the total energy penalty (electricity and district heating) to 5110-7870GWh, or about 6.3 TWh, when capturing and compressing 19 $MtCO_2$ p.a. from Swedish plants while relying on no additional biomass feedstock. For context, Sweden emits around 44 $MtCO_2$ p.a. of fossil origin. 6.3 TWh should also be compared with the total electricity production in 2022 and 2023, which respectively amounted to 170 and 163 TWh, and an annual district heating generation of around 55 TWh (Energimyndigheten, 2023a, 2024b). We conclude that, while 6.3 TWh is significant, it is small compared to the total electricity and district heating production of almost 220 TWh, and is comparable to historic annual fluctuations in electricity generation. This suggests that, in the Swedish context, the total energy penalty of capturing 19 $MtCO_2$ p.a. could be compensated by existing production units, if these are not reserved for redundancy and/or peak generation. As highlighted, the energy penalty of 6.3 TWh is contingent on plant operators prioritizing energy efficiency when integrating their processes.

6.3 TWh is also substantially lower than the increased electricity demand predicted for other energy intensive investments in Sweden – an increase of around 100-200 TWh by 2050 (Energimyndigheten, 2023b). Given that electricity supply could likely be constrained, expanded and highly demanded in the coming decades the capacity available to compensate for carbon capture should, however, be seen as uncertain. The same can be said for other nations. To resolve this tension, research has proposed more efficient capture technologies and applications compared to the studied amine technology. But major challenges remain in building investor confidence in such novel techniques (Bui et al., 2018).

On an endnote, research on novel capture technologies should, in our view, be more grounded in the decision situation of prospective operators and their contextual objectives. And research that portrays large-scale carbon capture should be reflexive about what views these portrayals enhance and marginalize (Lefstad et al., 2024), and what epistemological certainty they can claim (Haikola et al., 2019; Winsberg, 1999). Our study does illustrate that large-scale BECCS in Sweden could be realized while combusting no additional biomass and while entailing limited penalties on energy services. But this illustration is conditional.

5. Conclusions

Carbon capture was framed as a robust decision-making problem, and this decision was explored in over a million scenarios of 113 bioenergy-intensive plants in Sweden. This represents a methodological advancement, as the modeling focus was not on predicting large-scale BECCS deployment, but on highlighting the contingency of outcomes and the conditions underpinning robust performance. The scenarios mainly explore conditions for low energy penalties and capture costs, as these were the chosen indicators for robust performance. Unexplored conditions, e.g. incentives, CO_2 transport and storage, alternative investments or production units, biomass legislation, taxation, contingencies or social acceptance, could also be critical for prospective BECCS operators. Indeed, directly engaging BECCS operators in deliberation-with-analysis would strengthen the RDM process and the decision support it provides. This potential was suggested in our study but needs to be realized through research with a narrower scope.

For woodchip-fired CHP plants, increases in annual hours of operation, electricity prices and the recovery of low-temperature heat using heat pumps constitute key conditions for robust carbon capture. Increasing operations to between 6300 and 7000 hours per year reduces capture costs but entails combusting more biomass.

Like woodchip-fired CHP, waste-fired CHP plants perform robustly when recovering heat using heat pumps. Both types benefit from constrained electricity prices, e.g. 48 EUR/MWh for woodchip-fired and 65 EUR/MWh for waste-fired plants. These levels are relative to the wide range of 20-160 EUR/MWh explored. Another key condition for waste-fired CHP is a discount rate between 5-8 %.

For pulp mills, the key conditions for robust carbon capture are generally site-specific. But electricity prices are important for all mills. Furthermore, the amount of steam available from mill recovery and bark boilers determines whether it is robust to supply the capture process with low-pressure steam, thus enabling continued co-generation of electricity. If low-pressure steam is insufficient, utilization of excess heat or new capacity could be feasible but demands detailed studies.

Finally, it is possible to capture around 19 $MtCO_2$ annually from the 113 plants without increasing biomass feedstock. This would result in a reduction of electricity and district heating generation of 5.1-7.9 TWh p. a. – a modest penalty compared to the total generation of 220 TWh p.a. in Sweden. As this is an aggregate result of many scenarios of BECCS retrofit decisions, it is conditional on efficiency prioritization and biomass conservation.

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Data availability statement

The data and exploratory models are publicly available in the v1.0 release of the BECCS-Sweden GitHub repository (Stenström, 2024): https://doi.org/10.5281/zenodo.14236300.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used the generative artificial intelligence chatbot ChatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Oscar Stenström: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Tharun Roshan Kumar:** Writing – review & editing, Software, Methodology. **Magnus Rydén:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ijggc.2025.104411.

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