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Deploying direct air capture at scale: How close to reality?

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ABSTRACT

The role of negative emissions in achieving deep decarbonization targets has been demonstrated through Integrated Assessment Models (IAMs). While many studies have focused on bioenergy with carbon capture and storage (BECCS), relatively little attention has been given to direct air capture (DAC) in IAMs beyond assessing the role of low-cost DAC with carbon storage (DACCS). In this study, we employ an economy-wide model to more fully explore the potential role of DAC, considering the full range of cost estimates (\$180–\$1000/tCO_2), DAC units supplied by either dedicated renewables or grid electricity, and both the storage of captured CO_2 (DACCS) or its utilization (DACCU) to produce fuels. Our results show that the deployment of DAC is driven by its cost and is dominated by DACCS, with little deployment of DACCU. We analyze the technical and policy conditions making DACCS compete with BECCS, investigating scenarios in which BECCS is limited and there is no emissions trading across countries. With an international emissions trading system (ETS), we find that Africa takes advantage of its large and cheap renewable potential to export emissions permits and contributes more than half of total global negative emissions through DAC. However, DAC also proves essential when no ETS is available, particularly in Asian countries due to scarce and expensive access to land and bioenergy. Our analysis provides a comprehensive evaluation of the impact of DAC on the power system, economy, and land use.

1. Introduction

Since the 1970s and the first oil crisis, energy models have been employed for energy planning (Herbst et al., 2012; Pohekar and Ramachandran, 2004; Rath-Nagel and Voss, 1981), and more recently to develop strategies to combat climate change (Kang et al., 2020; Subramanian et al., 2018). Integrated assessment models (IAMs) connect the energy system to the broader economy and the Earth system. By projecting the future of the global economy and energy system, these models can evaluate what policies and technologies should be developed throughout the 21st century to meet specific climate commitments such as net-zero emission (NZE) targets or limiting global temperature increase to 1.5 °C. IAMs are as numerous as they are diverse (IAMC-Documentation Contributors, 2021), some focusing more on energy economics than the technologies of the energy system, with different modeling paradigms and assumptions. With the wide variety of IAMs, differences in the treatment and consideration of systems arise, but the modeling community recognizes the critical role played by negative emissions in climate mitigation strategies (Fuhrman et al., 2019; Fuss et al., 2018; IPCC, 2022; IPCC, 2018; Iyer et al., 2021; Rickels et al., 2018; Schweizer et al., 2020).

Negative emissions represent greenhouse gas (GHG) fluxes directed from the atmosphere to the biosphere or the geosphere, or from the biosphere to the geosphere. In other words, negative emissions account for GHG removed from the atmosphere, enabling a net reduction of the concentration of those GHGs in the air. Several pathways exist to remove CO_2 from the atmosphere with different implications in terms of economics, land use, water use, removal efficiency, and energy consumption (Chiquier et al., 2022; Gabrielli et al., 2020; IEA, 2022). These carbon dioxide removal (CDR) techniques can be divided into two categories: natural climate solutions (NCS) or engineered negative emission technologies (NETs). The first category employs and enhances natural phenomena to remove carbon dioxide. The most known are afforestation and reforestation which consist of increasing the photosynthesis of the biosphere. Emerging NCS are ocean-based approaches and soil carbon sequestration (SCS), respectively stimulating the fertilization of oceans,

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and increasing plant yields and carbon storage of soil by amending pyrolyzed biomass – or biochar – (Hepburn et al., 2019; NASEM, 2019).

The second category relies on industrial processes involving mechanical and chemical engineering techniques. The most known of engineered NETs is bioenergy with carbon capture and storage (BECCS). It consists of burning, gasifying, or fermenting biomass, which results both in energy generation and the production of CO_2 that is subsequently captured and stored underground. As the captured CO_2 originated from the atmosphere, the CO_2 removed is considered a negative emission. However, concerns have been raised regarding land use, water use, biodiversity, and the economic implications of this technique. On the other hand, direct air capture (DAC) is, as its name suggests, filtering the ambient air to recover pure CO_2 at the end of the process. There are two types of DAC technology: the low-temperature (LT) process with solid sorbents or the high-temperature (HT) process with liquid solvents that feature different properties in terms of kinetics and heat transfers (McQueen et al., 2021b). The principle is to make the CO_2 react with solid or liquid sorbent, and regenerate these sorbents in an endothermic reaction. Then, the CO_2 is compressed to be stored or used. As the CO_2 in the air is more diluted than in the biomass flue gas, much higher amounts of energy are required to capture the CO_2 – in the range of 4–6 GJ/tCO_2 and 8–12 GJ/tCO_2 respectively for LT and HT compared to 1.0–2.6 GJ/tCO_2 for BECCS (NASEM, 2019). In contrast, much less land and water are required for DAC compared to BECCS which needs substantial amounts of both to grow dedicated biomass. Regarding the costs, there are large uncertainties, with estimates ranging from \$20 to \$1000/tCO_2 captured for DAC (Fasihi et al., 2019; IEAGHG, 2021a; IPCC, 2018; Keith et al., 2018; McQueen et al., 2021b), and about \$30 to \$400/tCO_2 for BECCS (Fuss et al., 2018; Hepburn et al., 2019; IEAGHG, 2021b), mainly depending on how biomass is transformed (e.g., electricity, ethanol, hydrogen). Thus, there are large uncertainties and trade-offs regarding the performance, economics, and implications of NETs, especially for DAC.

BECCS has been widely studied in IAMs (Minx et al., 2017), which have demonstrated its large potential contribution to mitigating CO_2 emissions while delivering energy services (Bauer et al., 2020; Rogelj et al., 2018), even when biomass availability and CO_2 storage are limited (Selosse, 2019), with moderate impacts on food prices (Fajardy et al., 2021; Muratori et al., 2016). Recent efforts have been made to consider other CDR solutions beyond BECCS and afforestation in IAMs (Köberle, 2019), including DAC.

In the following sections, we review the literature that has modeled and studied DAC in IAMs, focusing on the assumptions and the results. This leads us to the identification of research gaps and the motivation of our study. In the third section, we describe the IAM employed in this study, the MIT Economic Projection and Policy Analysis (EPPA) model, how we modeled DAC, and what scenarios we considered. We then present our results, exploring the policy and technical conditions for the emergence of DAC in the future, as well as the implications on the rest of the energy system, the economy and land use. In the final section, we offer our conclusions.

2. How DAC is considered in global energy models

This section provides an overview of 1) how DAC is modeled in the existing literature, 2) the main findings regarding DAC, and 3) the research gaps. Of the 34 models in the IAMC database, we found that 13 include DAC as a CDR technology in their framework (IAMC-Documentation Contributors, 2021), of which 6 were employed in a peer-reviewed study exploring DAC deployment in the future. We review these 6 studies, as well as two additional studies – one by the International Energy Agency (IEA, 2021a) and one by Galimova et al. (2022).

2.1. How DAC is modeled

Capital costs and energy consumption are the main contributors that determine the overall cost of DAC. As shown in Table 1, the range of the assumed cost of DAC in 2050 is wide, reflecting the uncertainty behind these costs. The range is displayed for 2050 because it is information that is available in each referenced study, which allows us to compare the assumptions on the same basis. These costs only include capital and labor, not the cost of fuel as it is an endogenous output of the models. Even when fuel costs are accounted for, the costs assumed are rather on the low end, given the full range of uncertainty for DAC costs found in the literature – from \$20 to \$1000/tCO_2 captured. While the vast majority of DAC cost assumptions in these IAM studies are below \$500/tCO_2, some have expressed skepticism that DAC can be cheaper than \$600/tCO_2 (Herzog, 2022).

The cost of fuel strongly depends on the nature of the energy purchased, namely electricity, heat, or natural gas - depending on the region they are produced, as well as the type of process design (LT or HT). Overall, the assumptions in the energy models in terms of DAC energy needs are no higher than 10 GJ/tCO_2 captured, but the lower end may vary substantially among studies depending on the process design, from 2.5 to 6.8 GJ/tCO_2. It is not often explicit whether a model took into account the operational cost and energy needed to compress the CO_2 once it is captured, which is estimated to increase energy needs by 0.42 GJ/tCO_2 (APS, 2011). It is also generally unclear how the models consider energy consumption and intermittency, i.e., whether dedicated renewable assets – with or without batteries – are installed, or DAC units are connected to the grid. Chen and Tavoni (2013) explicitly use only zero-to low-carbon electricity to run DAC plants, including nuclear, intermittent renewables or fossil fuels combined with CCS, which raises questions about how the distribution and allocation are managed.

An option often cited in the literature to further reduce the cost of DAC is to use excess heat (Beuttler et al., 2019; Fasihi et al., 2019; Wevers et al., 2020), which consists of taking advantage of free waste heat generated by some industrial processes locally, thus benefiting from low-cost energy. For LT processes, Realmonte et al. (2019) consider waste heat recovery from industrial processes using natural gas by defining an industry-dependent recovery factor between 20 and 40% of the energy input. Waste heat recovery is also considered for nuclear and concentrated solar plants, such that for each PJ of electricity generated from them, respectively 1.3 and 4.5 PJ of waste heat can be recovered. There is no record of the capital and operational costs of the recovery process. Another option often considered to generate heat is natural gas, which increases the cost of net CO_2 removed, as additional fossil CO_2 is generated from the combustion (NASEM, 2019).

In some cases, models consider a full electric supply involving heat generated from heat pumps. However, there is little information on how electricity is provided. It seems the models do not consider dedicated renewable assets to feed DAC plants, but rather assume grid electricity distribution. This assumption is reasonable as long as the electricity used is carbon-free – which is not made explicit in all publications. If it is envisioned to supply DAC with grid electricity, then it may be credible from a certain time frame when the grid is expected to be decarbonized (2050 for instance). Otherwise, dedicated intermittent and low-carbon renewable assets are needed, which would require the installation of batteries and/or the construction of excess capacity to ensure the energy needs of the DAC units can be met, thereby increasing the cost of capital. Marcucci et al. (2017) acknowledge a limitation of their modeling as the simplistic representation of intermittency of solar and wind.

Each model considers regional costs for energy generation, as it is determined endogenously through the cost of fuels. Three studies of the panel also include regional costs for the transport and storage of CO_2. However, none of the studies consider regional variation for capital expenditures of the DAC process itself. The last column of Table 1 specifies the assumption about GHG trade. In general, this information is not easy to recover, however the assumption is important as it influences demand for DAC. For studies that assume a carbon market, it is not mentioned whether trade is allowed between CO_2 and other GHGs.

In terms of the purpose of the CO_2 captured, seven studies consider

Table 1
Techno-economic assumptions of existing studies modeling DAC. Economic values are in USD 2018.

Study	DAC technology modeled	Range of DAC cost in 2050 [$/t$CO_2$]	Range of energy needs in 2050 [/tCO_2]	Energy consumption	Includes CO_2 compression?	Regional variation of capital costs	GHG Trade
(Chen and Tavoni, 2013)	HT	379–509	8.1 GJ	High-temperature heat	Yes	Included for transport and storage	Carbon market among regions
			490 kWh	Zero to low-carbon electricity			
(Marcucci et al., 2017)	HT	350–470	5.0–8.1 GJ	Natural gas	Yes	Not included	Carbon market among regions
			500 kWh	Grid electricity			
(Realmonte et al., 2019)	HT	106–318	5.3–8.1 GJ	Natural gas	Lack of evidence / Not explicit	Not mentioned	Not mentioned
			361–500 kWh	Electricity			
	LT	53–371	4.4–7.2 GJ	Natural gas and waste heat			
			167–306 kWh	Electricity			
(Fuhrman et al., 2021)	HT	78–296	5.3–8.1 GJ	Natural gas	Lack of evidence / Not explicit	Not mentioned	Carbon market among regions starting from 2025
			361–500 kWh	Electricity			
	HT	101–384	1389–1667 kWh	Electricity			
	LT	137–402	694–1528 kWh	Electricity			
(Akimoto et al., 2021)	HT	226–831	1535 kWh	Grid electricity	Lack of evidence / Not explicit	Not mentioned	Not mentioned
	LT	203–744	6.3 GJ	Natural gas and heat			
			250 kWh	Electricity			
(Strefler et al., 2021)	HT	103	10 GJ	Natural gas or hydrogen	Lack of evidence / Not explicit	Not mentioned	Global uniform carbon prices
			556 kWh	Electricity			
(Galimova et al., 2022)	Not mentioned	38–84*	4.6–4.7 GJ**	Not mentioned	Lack of evidence / Not explicit	Not included	Not mentioned
(IEA, 2021a)	Not mentioned	123–335 (DAC report)	6.6–10.0 GJ (DAC webpage)	Not mentioned	Yes	Not mentioned	Not modeled

* Values including the cost of fuel.
** Values mentioned in the reference associated (Fasihi et al., 2019) but not specified in the article.

DAC as a means to get negative emissions and three of them consider the utilization of CO_2 (Table 2). Although DACCU has been less of a focus in models, it is important to include as it is a potentially important pathway to producing valuable low-carbon fuels, chemicals, or building materials that could be helpful in decarbonizing other sectors. The models considering DACCU also consider other options for capturing CO_2, such as CCS applied to power plants or industrial assets. All studies also consider opportunities other than DAC for generating negative emissions. Specifically, BECCS is always considered and found to compete with DACCS. Afforestation techniques are also considered and found as potent as BECCS in generating negative emissions (Fuhrman et al., 2021; Realmonte et al., 2019).

2.2. Main findings from the existing studies

In Table 2, we report the results obtained by the studies reviewed in the preceding section, along with information regarding the modeling paradigm employed. The latter refers to whether the models consider energy systems with high levels of engineering details but in isolation from other economic sectors (bottom-up) or in a more aggregated fashion but with interactions and feedbacks with the rest of the economic sectors (top-down), inter alia. Being aware of the modeling paradigm is of importance as it influences the results (Böhringer and Rutherford, 2008; Hourcade et al., 2006). For instance, bottom-up models are known to underestimate the abatement costs (Assoumou et al., 2018; van Vuuren et al., 2009), and the modeling assumptions of DAC tend to be in its favor, both on the technical-economic assumptions and on how energy is delivered to the facilities, making the resulting outcomes rather optimistic. In all studies, the role of DAC was studied in the context of deep decarbonization targets consistent with 1.5 °C or 2 °C temperature elevation, but with different assumptions related to the shared socioeconomic pathways (SSPs) considered (Fuhrman et al., 2021), the cost of renewables (Akimoto et al., 2021), or the growth rate of DAC (Realmonte et al., 2019).

For models projecting the energy system to 2100, the quantity of negative emissions generated from DAC is very high, exceeding the current levels of CO_2 emissions globally. As a result, DACCS delays the phase-out of fossil fuels since DACCS acts as backstop technology to

Table 2
Deployment rate of DAC in existing studies.

	Features			Peak deployment [Gt/y]		Reduction of CO_2 abatement cost
Study	Model	Modeling paradigm	Fate of CO_2	2050	2100	
(Chen and Tavoni, 2013)	WITCH	Hybrid	Storage	1	16–37	N/A
(Marcucci et al., 2017)	MERGE-ETL	Hybrid	Storage	*	14–38	19 to 35%
(Realmonte et al., 2019)	WITCH & TIAM-Grantham	Hybrid & Bottom-up	Storage	0	20–30	60 to 90%
(Fuhrman et al., 2021)	GCAM	Bottom-up	Storage	0.24–12	4.6–32	N/A
(Akimoto et al., 2021)	DNE21+	Bottom-up	Storage	5–21	10–44	50 to 90%
			Utilization	<0.07	0.05–1	
(Strefler et al., 2021)	REMIND-MAgPIE	Hybrid	Storage	1–5	1.5–3.5	25%
(Galimova et al., 2022)	LUT Energy Transition Model	Bottom-up	Utilization	3.6	N/A	N/A
(IEA, 2021a, 2021b)	WEM/ETP	Hybrid	Storage	0.63	N/A	N/A
			Utilization	0.37		

* The deployment of DAC is allowed by the modelers after 2065.

fulfill climate ambitions. The range displayed for peak DAC deployment refers to climate scenarios that are more or less stringent, or to various assumptions about DAC performance and deployment rates, but the orders of magnitude across studies are similar in 2100. Overall, these studies are unanimous: DAC is needed to achieve deep decarbonization targets. Without DAC, the targets become either infeasible (Akimoto et al., 2021; Realmonte et al., 2019), or costlier (Marcucci et al., 2017). The results of the studies show that the more stringent the climate policy, the greater the need for DAC. In other words, the zero-carbon transition is more difficult to achieve without DACCS. The studies that assess the impact of DAC deployment on the rest of the energy system observe that BECCS power generation decreases substantially compared to a scenario when DAC is not available (Akimoto et al., 2021; Fuhrman et al., 2021). Moreover, DAC was proved to be a mitigating factor in land-use change and water withdrawals compared to scenarios in which DAC is not available (Fuhrman et al., 2021; Fuhrman et al., 2020; Realmonte et al., 2019). As the models all optimize the cost of the energy transition, if DAC appears as a major backstop solution, it is due to its economic benefits: the models estimate reductions in CO_2 abatement costs between 19% and 90% (Table 2). Similar findings were also made in a model focusing on the UK (Daggash et al., 2019).

Nevertheless, there are some divergences in the results. The temporality and rate of DAC deployment vary substantially. While long-term projections deploy DACCS after 2050 and even 2065, mid-term projections reveal an earlier penetration starting from 2030. If studies claim that the role of BECCS is reduced with DACCS, then the profile of power generation should be altered as BECCS is a net supplier while DACCS is a net consumer of electricity. However, some studies report that global electricity increases (Fuhrman et al., 2021; Realmonte et al., 2019), and others report a decrease in power supply (Akimoto et al., 2021; Marcucci et al., 2017). Regarding the utilization of CO_2 captured from DAC, both the short-term and long-term of the deployment rate are uncertain, but DACCU still remains less important than DACCS. Thus, there is no clear future for DACCU, especially in the mid-term. Several sensitivities were carried out to identify key drivers of DAC deployment with different lessons. On the one hand, Akimoto et al. (2021) and Fuhrman et al. (2021) show that low costs for DAC may triple its contribution in generating negative emissions. On the other hand, Marcucci et al. (2017) and Realmonte et al. (2019) argue that costs have barely any impact on DAC deployment. However, they demonstrate that controlling the deployment rate of DACCS, e.g. through capacity limits or growth rates, and the availability of CO_2 storage greatly impact the investments in DACCS. Finally, as global energy models disaggregate the world energy system in different regions, they are able to explore the contribution of DAC in each one. However, there are no clear leading regions for DAC that emerge across these studies. Chen and Tavoni (2013) emphasize that energy exporting regions such as the Middle East play a key role related to DAC and the achievement of climate targets, because they possess the highest storage capacities for moderate DAC costs. Similar results are observed in Marcucci et al. (2017) with the exception that China also becomes a leader in DAC deployment. Conversely, in Akimoto et al. (2021) and Galimova et al. (2022), the American continent and the former Soviet Union are the main leaders. These results diverge firstly due to the difficulty of representing DAC regionally, and secondly because DAC investments are decoupled from the specific emissions sources (Chen and Tavoni, 2013), so DAC can be invested where it is more convenient to do so when GHG trade is available. Therefore, the assumptions related to the international emission trading system (ETS) and the regionalization of costs appear critical.

2.3. Research gaps and motivation of the study

The previous sections allow us to identify divergences between studies, but also convergences that can be questioned. The motivation for our study is twofold: we want to address the gaps regarding the modeling of DAC, and to explore new scenarios to better understand the future of DAC under different assumptions.

From the literature review, we identify several research gaps regarding the techno-economic modeling of DAC. Firstly, the techno-economic literature acknowledges that the cost range for capturing CO_2 from the air is wide and uncertain, and yet studies tend to focus primarily on the lower end of this range ($50–500/t$CO_2$ captured), leaving the implications of higher DAC costs largely unexplored. Secondly, the energy consumption of DAC is also subject to considerable uncertainty and there is a need to further investigate how energy would be supplied to DAC units, whether with dedicated intermittent electricity or grid electricity. In general, the cost of DAC is only regionalized in studies through the cost of electricity, heat, and natural gas. Besides, the impact of regional capital costs on DAC deployment has not been studied. Thirdly, studies generally use an exogenous cost decrease that depends only on time, or a cap on the deployment of DAC. Studies have not investigated a more realistic setting in which the cost and rate of deployment endogenously depend on demand for the technology and past investments in DAC. Finally, DACCU is understudied, particularly in top-down models. In terms of policy considerations, we note that the role of international emissions trading in driving deployment of DAC has not been explored.

In Section 3, we explore these gaps employing an economy-wide model. We investigate the potential role of DAC considering the full range of cost estimates ($180–$1000/tCO_2), DAC units supplied by either dedicated renewables or grid electricity, both the storage of captured CO_2 (DACCS) or its utilization (DACCU) to produce fuels, regionalized capital costs, and the implications of assumptions about international emissions trading. The literature does not seem to be in agreement regarding the early deployment of DAC while international companies currently show their interest in investing in DAC now. Our study aims at delivering new insights about the policy and technical conditions necessary to have DAC deployed at scale, i.e., with capacities approaching 1 Gtpa globally by mid-century. Our comprehensive analysis evaluates the implications of DAC in terms of the energy system requirements, economics, and land use. For the energy system, we explore interlinkages of DAC deployment with other electricity uses and BECCS: given the high energy requirements of DAC, it can be expected that the deployment of DAC would stress the power sector, whereas electricity could potentially be used to decarbonize other sectors more effectively.

3. Methods

We use and enhance the MIT Economic Projection and Policy Analysis (EPPA) model by implementing different DAC technologies that either generate negative emissions or provide pure CO_2 as a raw material for Fischer-Tropsch processes to produce synthetic fuels.

3.1. EPPA model

EPPA is a top-down multi-region multi-sector computable general equilibrium (CGE) model of the world economy (Chen et al., 2022). The model provides projections of world economic development at a regional and sectoral level, including the economic implications of GHG emissions, conventional air pollution, land-use change, food demand, and natural resource use. It simulates the evolution of economic, demographic, trade and technological processes involved in activities that affect the environment. The EPPA model chooses the least-cost production opportunities based on zero profit conditions (the cost of inputs should not exceed the price of the output), market clearance conditions (supply must equal demand), and income balance conditions (expenditures must equal income, accounting for savings, subsidies, and taxes). Therefore, production technologies are chosen based on their relative competitiveness. The 18 regions represented in the model are given in Appendix A. For the base year, 2014, the model uses the GTAP dataset (Chepeliev, 2020), for 2015 and 2020 it is calibrated for economic and energy data from (IMF, 2019) and (IEA, 2021b), and then it solves recursively in 5-year time steps up to 2100. Additional information about the EPPA model can be found in (Chen et al., 2022). Coupled with the MIT Earth System Model (MESM, Sokolov et al., 2018), it captures the level of GHG emissions due to human activity and assesses the impact on the global temperature rise. In previous work, BECCS, afforestation and reforestation were incorporated into the EPPA model as negative emission technologies (Fajardy et al., 2021; Morris et al., 2019a). In the following sections we describe how we introduced DAC into the EPPA model.

3.2. DAC modeling in EPPA

Top-down models represent technologies in an aggregate way. Currently, the only operational technology for DAC is the solid sorbent technology, which is a low-temperature (LT) process. Potentially, it would operate at lower costs than high-temperature processes. Hence, in our study we choose to focus on the LT technology. Therefore, we consider the DAC facility that includes heat pumps that provide low-temperature heat to regenerate the sorbent. Although this is a less mature technology, it is also the most promising because it avoids the need for high temperature heat generally provided by natural gas, thereby increasing net CO_2 removal compared to HT processes.

While we limit ourselves to one DAC technology, we model two types of facilities: one powered by grid electricity, and the other one powered by dedicated variable renewable assets (VRA), namely solar photovoltaics and wind. This distinction is made since delivering CO_2-rich electricity to DAC plants can have the opposite effect of CO_2 removal as certain grids in the world are still carbon intensive, such that the CO_2 emissions associated with electricity generation would exceed the CO_2 removed from the air. Thus, modeling DAC plants with dedicated assets would increase the chances of DAC being deployed before the grid is decarbonized, at the expense of much higher capital costs.

The capital and operational costs in this study are extracted from the National Academies of Sciences, Engineering, and Medicine study (NASEM, 2019) using their low, high, and worst cases. The energy requirements are taken from (Herzog, 2022), calculating that 1071 kWh/tCO_2 are required using a heat pump with a coefficient of performance (COP) of 3.5. For the "High" scenario, the COP of the heat pump is assumed to be 3, increasing the energy consumption to 1167 kWh/tCO_2. If the CO_2 is to be stored, we add to these consumptions 120 kWh/tCO_2 representing the electricity necessary for the compression of CO_2 (APS, 2011), and we include the cost of CO_2 transport and storage based on (Smith et al., 2021). All DAC plants have a 1 Mtpa capacity and are designed for 20 years of operation with a capacity factor of 90% and a discount rate of 8.5% (NASEM, 2019). In the cases where power is supplied to DAC plants by VRA, we include additional capital costs to reflect the need for batteries and the construction of excess VRA capacity to ensure the energy needs of the DAC units can be met given the intermittency of the VRA. As we want the plants to run 90% of the time, the renewable capacities need to be oversized according to their capacity factor.

$$C_{VRA} = \frac{Tec \times C_{DAC}}{8760 \times CF_{VRA}} \# \tag{1}$$

Where Tec is the total energy consumption in MWh/tCO_2, C_{DAC} is the capacity of the DAC plant in Mtpa, and CF_{VRA} equals to 35% and 20% capacity factors respectively for wind and solar (Morris et al., 2019a). The required battery capacity $C_{battery}$ is then calculated estimated as follows:

$$C_{battery} = C_{VRA} \times 24 \times (1 - CF_{VRA}) \# \tag{2}$$

The costs for batteries are assumed to be equal to \$300/kWh (McQueen et al., 2021a). The main techno-economic parameters of DACCS are shown in Tables 3 and Table 4 with grid electricity supply and with VRE supply, respectively. The techno-economic parameters of DACCU exclude costs and energy consumption related to storage. The tables include the estimated total CO_2 capture cost in the four scenarios, and Table 3 displays the total cost of net CO_2 removed calculated using a cost factor that transforms cost of capture into the cost of removal based on the carbon footprint of the electricity running DAC units (NASEM, 2019). Note that, in the model, we assume no indirect emissions due to solar and wind power generation.

We distinguish three DAC processes, depending on how they are powered. First, SDACCS and SDACCU are DAC units with dedicated solar assets generating respectively CO_2 permits and CO_2 as a raw

Table 3
Techno-economic parameters of DACCS (NASEM, 2019) fed with grid electricity in \$2018 in the US.

	Units	VeryLow	Low	Medium	High
Power		Grid	Grid	Grid	Grid
"Overnight" Capital Cost	\$/tpa	132	720	1944	5186
Total Capital Requirement	\$/tpa	142	777	2099	5601
Fixed O&M* (FIXOM)	\$/tpa	11	11	22	48
Scaled Capital Recovery Requirement	\$/tCO_2	17	91	246	658
FIXOM Recovery Required	\$/tCO_2	19	19	31	60
Variable O&M* (VAROM)	\$/tCO_2	8	8	8	8
Electricity input	MWh/tCO_2	1,2	1,2	1,2	1,2
Fuel cost	\$/tCO_2	122	122	122	122
Total capture cost	\$/tCO_2	177	252	419	859
Indirect CO_2 emissions**	tCO_2/tCO_2	0,58	0,58	0,58	0,58
Cost factor***		2,38	2,38	2,38	2,38
Total cost of net CO_2 removed	\$/tCO_2	439	616	1014	2058

* O&M denotes Operational and Maintenance.
** The average carbon intensity of global electricity is 475 $kgCO_2$/MWh (IEAGHG, 2021b) O&M denotes Operational and Maintenance.
*** The cost factor denotes the factor to which multiply the cost of capture to retrieve the cost of removal considering the carbon footprint of the electricity running DAC units. The cost factor equals 1/(1-Indirect CO_2 emissions from electricity generation). This cost factor is indicative and is not an input of EPPA as the model endogenously considers indirect emissions.

Table 4
Techno-economic parameters for DACCS (NASEM, 2019) fed with solar photovoltaics VS wind in \$2018 in the US.

	Units	VeryLow	Low	Medium	High
Power		Solar/Wind*	Solar/Wind*	Solar/Wind*	Solar/Wind*
"Overnight" Capital Cost	\$/tpa	915/830	1382/1284	2482/2384	5456
Total Capital Requirement	\$/tpa	988	1492/1386	2680/2575	5892
Fixed O&M	\$/tpa	11	11	22	48
Scaled Capital Recovery Requirement	\$/tCO_2	127	195/181	350/336	770
FIXOM Recovery Required	\$/tCO_2	19	20	32	61
Variable O&M	\$/tCO_2	8	8	39	41
Electricity input	MWh/tCO_2	1.2	1.2	1.2	1.3
Fuel cost	\$/tCO_2	172/127	172/127	172/127	186/137
Required installed VRE capacity	MW/Mtpa	544/386	544/386	544/389	588/420
Battery capacity	MWh/Mtpa	2448/2122	2448/2122	2448/2122	2644/2291
Total capture cost	\$/tCO_2	327/263	407/348	605/574	1069/1036

* All techno-economic properties regarding solar and wind are taken from (Morris et al., 2019a).

material. Second, WDACCS and WDACCU are DAC units with dedicated wind assets generating respectively CO_2 permits and CO_2 as a raw material. Finally, EDACCS and EDACCU are DAC units powered with grid electricity respectively delivering negative emissions in the form of CO_2 permits, and CO_2 as a raw material. The techno-economic properties of DAC units supplying CO_2 as an input for generating low-carbon fuels (DACCU) are given in Appendix B.

The nesting structures of DAC processes implemented in EPPA are shown in Fig. 1. As a CGE model, EPPA uses nested constant elasticities of substitution (CES) functions to specify production technologies and substitution possibilities between inputs. The monetary inputs used by a DAC plant are capital, labor (including fixed and variable operating costs), and grid electricity, or solar or wind. At the top-level nest of the production function enters the Technology-Specific Factor (TSF), representing the adjustment cost for technology diffusion. The TSF limits the penetration of new technologies such as DAC, based on empirical evidence on the penetration of past technologies (Morris et al., 2019b).

We assume that capital and labor nests are Cobb-Douglas functions (Balistreri et al., 2003) and the elasticity of substitution for TSF is based on Morris et al. (2019b). The function between the energy input (either solar, wind or grid electricity) and the Capital-Labor nest is assumed to be a Leontief function, meaning that they are needed in fixed proportions and cannot be substituted. As such, technology energy efficiency improvements are not considered. We do not account for the land use of the DAC unit itself or the land used by dedicated solar and wind, as we assume that the land used by solar or wind farms do not compete with crop land.

There are two options for the CO_2 that is captured from DAC: either it is compressed by the DAC plant and sent to storage to generate CO_2 permits, or it is used onsite by a Fischer-Tropsch process comprised of an electrolyzer and a compressor train, generating a slate of fuels made up of 47% sustainable aviation fuels (SAF) for the aviation sector, and 53% refined oil for other sectors, following the techno-economic properties found in (Zang et al., 2021) and detailed in Appendix C.

3.3. Scenarios

With an assumption that DAC is commercially available from 2030, we use an illustrative scenario targeting net-zero anthropogenic GHG emissions by 2070 in all regions of the world (see regional emission permits allowances in Appendix D). According to the MIT Earth System Model (MESM, Sokolov et al., 2018), this emissions scenario results in an end-of-century global average temperature increase of below 1.5 °C. Global emissions and the resulting temperature trajectory for this scenario are discussed in MIT Global Change Outlook (MIT Joint Program, 2021). All GHGs are included in this target except land-use CO_2 emissions, which fall to near-zero by 2070. We compare two climate policy settings related to the trading of GHGs: either GHGs can be traded across regions of the model (*GT*) or they cannot (*NoGT*). In both cases, GHGs are tradeable among each other, i.e. the emission of 1 tCO_{2eq} of methane can be exchanged with the removal of $1tCO_{2eq}$ of carbon dioxide.

To these climate policy scenarios, we apply cost cases related to the cost of DAC (see Table 3 and Table 4) and the impact of limited BECCS capacities (*BECPen*). The former refers to the cost cases of Tables 3 and 4, and the latter assumes that BECCS costs increase linearly with the share of cropland used for BECCS if BECCS exceeds >5% of the regional cropland area. This case provides a proxy for factors that could limit the deployment of BECCS, including the effect of climate change on land productivity (Günther and Ekardt, 2022) and potential environmental and societal concerns about biomass competing with food production and the provision of ecosystem services. The reference scenario (*NoDAC*) is consistent with achieving the net-zero target by 2070 with international emissions trading and without DAC available.

The costs displayed in Table 3 and Table 4 above are consistent with the US case albeit we apply a regional variation to the cost of CO_2 transport and storage based on Smith et al. (2021), the levelized cost of wind and solar based on (Morris et al., 2019a), and the price of electricity for the base year of the model (2014) from (Chepeliev, 2020). In additional scenarios, we briefly explore the impact of regional variation in the cost of capital for DAC assets (Table 5) based on (Ferrari et al., 2019) in scenarios with "_R" as suffix (see Appendix E).

4. Results and discussion

First, we analyze how the deployment of DAC is affected by assumptions about the cost of DAC, the availability of BECCS and the presence of international emissions trading. We then discuss the induced requirements on the energy system and impacts on the economy, land use, and food prices. The scenarios can be compared with the reference scenario which does not allow for DAC investments (*NoDAC*). Consequently, only BECCS and afforestation/reforestation can be deployed in order to generate negative emissions, as Fig. 2 shows. The modeling of BECCS in EPPA and its contribution to reach the 1.5 °C target were discussed in Fajardy et al. (2021).

4.1. DAC deployment

4.1.1. Cost of DAC and BECCS availability

Introducing a high-cost DAC as a new technology in EPPA for a *NZ70* scenario does not impact the resulting solution, i.e. DAC is not found competitive for a cost close to $860–1000/$tCO_2$, either to generate negative emissions or produce synthetic fuels. For a medium cost ($420–570/$tCO_2$), DACCS is slightly penetrating the generation mix of negative emissions, proving competitive only in Africa and Indonesia and providing 1.3% of total global negative emissions (Fig. 3). At this level, DAC is not deployed at scale: at best, DACCU provides 90 $MtCO_2$ in

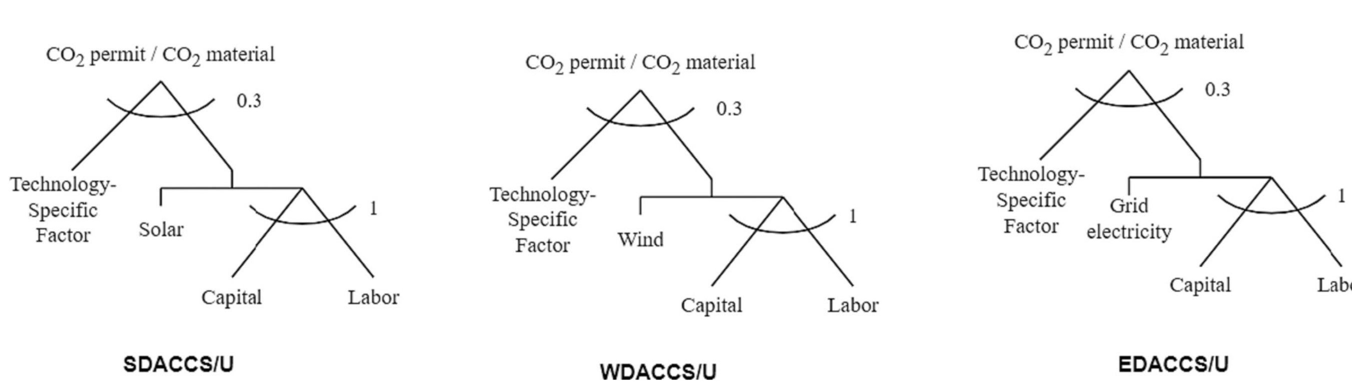

Fig. 1. Nested CES fuction of DAC processes implemented in EPPA DAC units can either use solar or wind dedicated assets (left and middle) or grid electricity (right) For SDACCS, WDACCS and EDACCS, the output is a CO_2 permit, but for SDACCU, WDACCU, and EDACCU, the output is pure CO_2 ready to be converted into synthetic fuels.

Table 5
Regional variation of DAC according to the cost of capital.

Region	USA	CAN	MEX	JPN	ANZ	EUR	ROE	RUS	ASI
Capital scalar relative to USA	1,00	1,14	1,03	0,97	1,06	1,06	0,98	0,98	0,98
Region	CHN	IND	BRA	AFR	MES	LAM	REA	KOR	IDZ
Capital scalar relative to USA	0,82	0,99	1,03	1,10	0,97	1,03	0,98	0,97	0,98

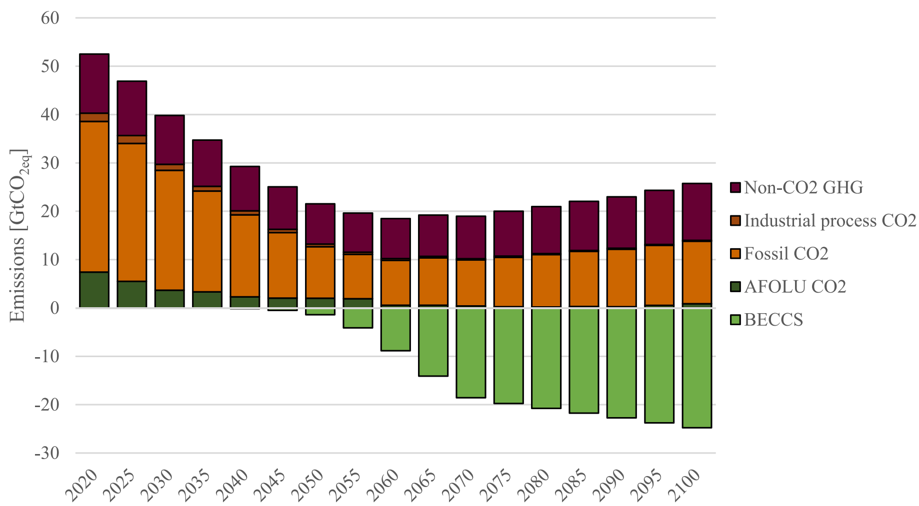

Fig. 2. Emissions profile of the reference scenario with no DAC (NoDAC).

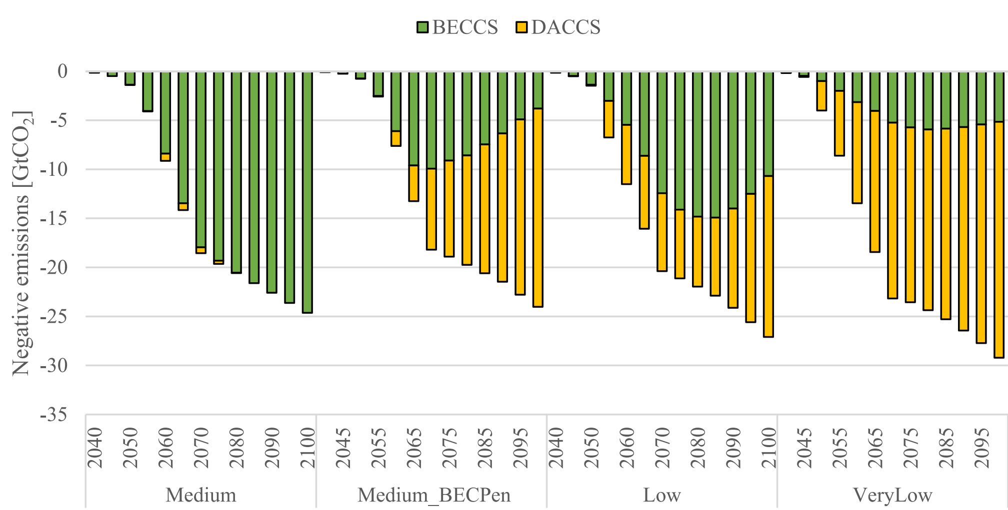

Fig. 3. Temporal generation of negative emissions of for a medium, low, and very low cost of DAC.

2075 and DACCS provides 730 $MtCO_2$ in 2060. The total amount of negative emissions is unchanged compared to the *NoDAC* scenario, suggesting that DACCS substitutes BECCS in these regions.

Assuming a low cost (~\$250–400/tCO_2), DACCS contributes by generating 44% of the cumulative amount of negative emissions, or 435 $GtCO_2$ over the century, especially deploying in Africa and other regions having affordable access to large renewable potentials. In this configuration, the cost of DACCS is comparable to the cost of BECCS, although BECCS is still dominating the generation of negative emissions in regions with large biomass potentials such as Africa, Latin America, Indonesia and Brazil. For a very low cost of DACCS (~\$180–330/tCO_2), it finally overcomes BECCS: 875 $GtCO_2$ of negative emissions are produced through 2100, and Africa clearly dominates the market (Fig. 4). We find that DAC is deployed at scale at a cost of less than \$380/tCO_2 for EDACCS, (resp. \$450/tCO_2 and \$520/tCO_2 for wind and solar). However, the 1 Gtpa rate is reached only in 2065 and 2070 (Appendix F).

The major regions involved in the generation of negative emissions through DACCS are Africa, Indonesia, Canada, and Brazil. Canada is generating all its negative emissions from DAC with grid electricity which is fully decarbonized by 2035 and sold at prices that are 10–26% lower than the US thanks to cheap wind and large hydroelectricity capacities. Africa initially relies on grid electricity to run DACCS units through mid-century, benefiting from a fully decarbonized power system, but as the price of renewables continues to decline (reaching around \$30/MWh by the end of the century), it becomes more competitive to run stand-alone DACCS units powered with dedicated wind or solar. We observe the same in Indonesia and Brazil. Thus, employing dedicated renewables for DACCS presents an opportunity to generate massive amounts of negative emissions late in the century.

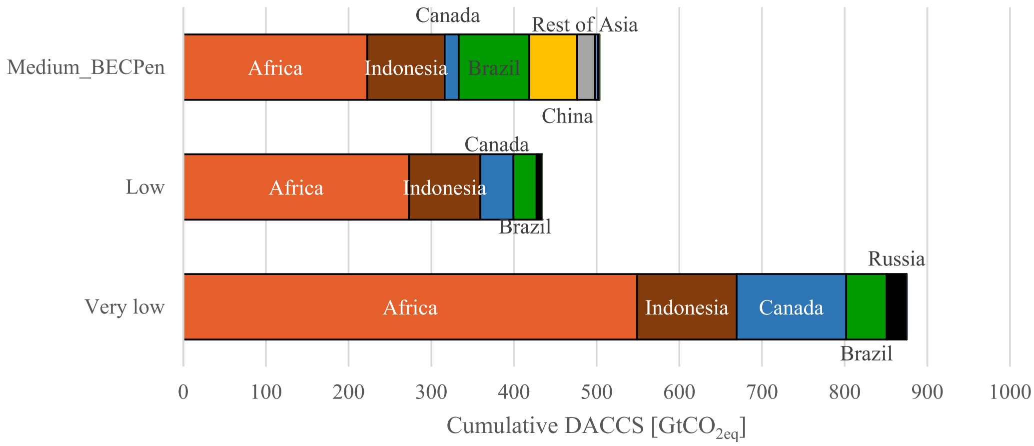

Fig. 4. Cumulative regional negative emissions through DACCS for different cases with GHG trade across regions and between GHGs.

Synthetic fuels generation with DAC remains small, even in the *VeryLow* cost case, utilizing <0.7% of the total amount of carbon captured from the air over the century. This represents 6.1 $GtCO_2$ turned into 1 EJ of synthetic fuels, of which 93% is generated between 2095 and 2100. These results contrast with the ones of Akimoto et al. (2021).

The above results assume globally uniform capital costs for DAC units themselves, but do factor in regional variation for the cost of the electricity needed to run the units and for the cost of CO_2 transport and storage (see Section 3.3). However, it is questionable that DAC costs are uniform globally, and so we also consider regionalized capital costs for DAC based on the capital scalars presented in Table 5. In Appendix E, we present the difference in regional deployment of DACCS when the capital cost is regionalized compared to uniform capital costs. For the *Low* scenario, the regions deploying DAC are the same, but the levels differ, especially in China and Africa. For a low cost, the overall global deployment slightly decreases (from 435 $GtCO_2$ to 384$GtCO_2$) with the regionalized capital costs. There is less of a difference for the *VeryLow* cost scenario. Thus, considering regionalized capital costs for DAC impacts the regional deployment but does not change the global quantity significantly.

In order to enlarge the window of uncertainty related to the potential of DAC, we consider another scenario with a medium cost and a limited expansion of BECCS (*Medium_BECPen)*. It reveals that DACCS deployment is very sensitive to the availability of BECCS, as 59% of the cumulated negative emissions is generated from DACCS compared to 1.3% in the original case (Fig. 3), which represents 504 and 12 $GtCO_2$ of cumulative negative emissions, respectively. Even for a high-cost DAC, the technology competes with BECCS when the latter is constrained, i.e., DACCS contributes 24% of total negative emissions, but deploys after 2080 with 173 $GtCO_2$ cumulated.

4.1.2. *What if no international ETS emerges?*

The results in the previous section all assume GHG trading across regions. In that setting, several regions produce negative emissions for sale abroad, especially Africa, Latin America, Brazil and Indonesia. Under the *Medium* cost case, nearly all of the negative emissions are from BECCS, so the countries benefiting most from the sale of offsets abroad are those rich in land and biomass resources. When BECCS is limited, many of the regions that would have produced more BECCS if possible switch to DACCS to continue to sell permits abroad. Indonesia and Brazil are examples (Fig. 5). Whether produced by BECCS or DACCS, the trade of negative emissions depends on a high level of international

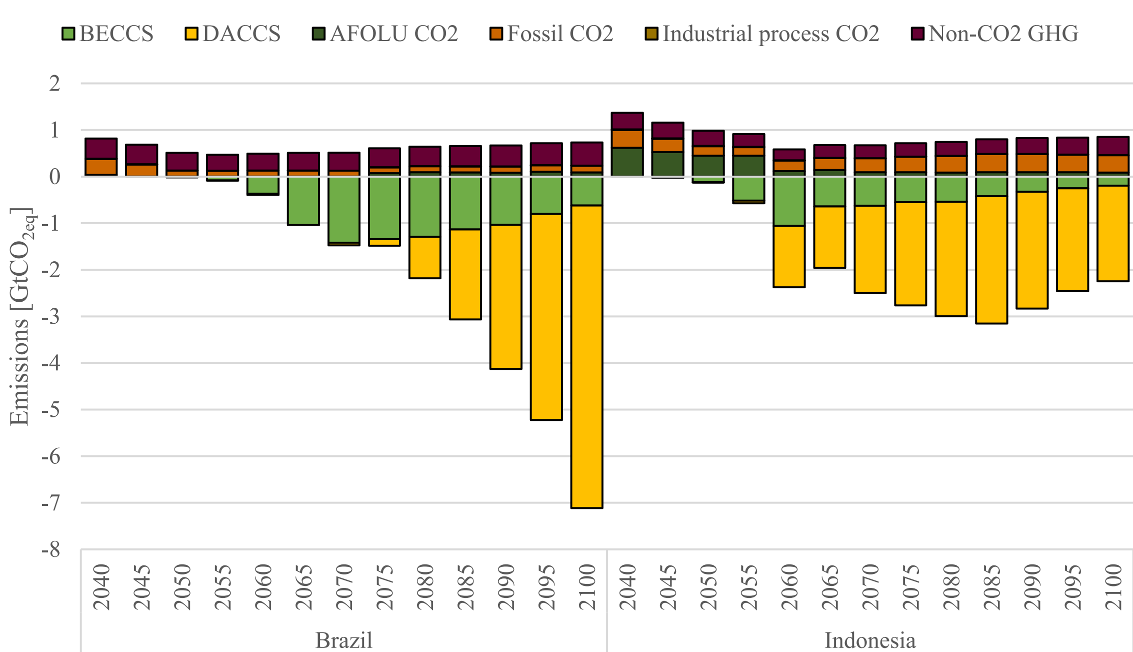

Fig. 5. Temporal GHG emissions in Brazil and Indonesia with Medium cost of DAC and penalty on BECCS.

cooperation and the establishment of an emissions trading system (ETS) that is maintained over the century. This leads to the question of how realistic the assumption of a global emissions trading system is.

One can imagine a future in which no international emissions trading scheme ever emerges, considering the slow pace of discussions currently and the wide range of political relations between countries. Therefore, we explore the deployment of DAC in scenarios where GHG trading is only allowed between GHGs within a region, but not between different regions, focusing on the *Medium* cost case. Under these assumptions, DACCS appears essential in achieving the climate target, (Fig. 6), especially for countries having low access to BECCS and afforestation solutions, such as South Korea and Japan, and those for which land-based NET options are expensive or cannot compete with other demands for land (e.g. for food), such as China and India. Thus, DACCS availability is beneficial to some regions more than others when international GHG trading is not allowed. Without GHG trading, regions or countries such as the US, Rest of Europe (ROE), Rest of Asia (REA), Mexico (MEX), Brazil (BRA) or Latin America (LAM) can no longer export permits generated from BECCS, and many other regions will not deploy their own BECCS due to scarce and/or expensive access to land and bioenergy, and so the global amount of BECCS over the course of the century is reduced significantly (from 891 $GtCO_2$ with international emissions trading to 347 $GtCO_2$ without trading). In Indonesia (IDZ) and Africa (AFR), the permits generated from DACCS were being produced for export, so are no longer generated without global emissions trading. Conversely, in the absence of global emissions trading, China (CHN), India (IND), Korea (SKO), Japan (JPN), and the Middle East (MES) deploy DACCS either because BECCS cannot fulfill their own demand for offsets, or because DACCS is more competitive than BECCS. China and India alone generate 73% of global negative emissions from DACCS in that case, and globally the cumulative amount of negative emissions from DACCS increases significantly (from 12 $GtCO_2$ with international emissions trading to 300 $GtCO_2$ without trading). Nevertheless, BECCS still dominates the market globally. Note that, even for a high-cost DAC, the technology is deployed at scale in the aforementioned countries and regions with 135 $GtCO_2$ cumulatively over the century, of which 49% are in India (resp. 30% in China).

The magnitude of these results raises questions about the feasibility of storing such amounts of CO_2. Based on the regional CO_2 storage assessment of (Kearns et al., 2017), the limited availability of CO_2 storage capacities of India, South Korea and Japan might compromise the deployment of DACCS in these regions. Indeed, the storage capacities of these countries were assessed at 99, 8, and 6 $GtCO_2$ respectively in the lower estimate (Kearns et al., 2017), while our results show 130, 10, and 12 $GtCO_2$ of negative emissions, thus ignoring additional CCS requirements in other sectors to capture fossil carbon.

4.2. Implications of DAC deployment

To discuss the implications of DAC deployment, we focus on the *Medium* cost case, as it appears to us as a reasonable assumption for the future techno-economic performances of this technology.

4.2.1. Energy system

Although important in some scenarios to achieve the climate target, DACCS also stresses the power sector, as illustrated in Fig. 7. In the *Medium* cost case with a penalty on BECCS, the electricity dedicated to DACCS uses up to 13% of total electricity generation. As the deployment of BECCS is limited, less power is generated from this process, and additional power is needed to run DAC units, which explains why the total power is higher than in the baseline *Medium* cost case (+10%), but the total electricity supplied to other sectors is reduced (−4%). However, this profile can be very different at the country level. For instance, Indonesia and Brazil generate more electricity for the DAC units than for their own consumption (Fig. 8). The electricity used to run the DAC units comes from dedicated wind and solar, which suggests that these countries take advantage of their huge and cheap renewable potential to generate profits from selling permits to other countries. Nevertheless,

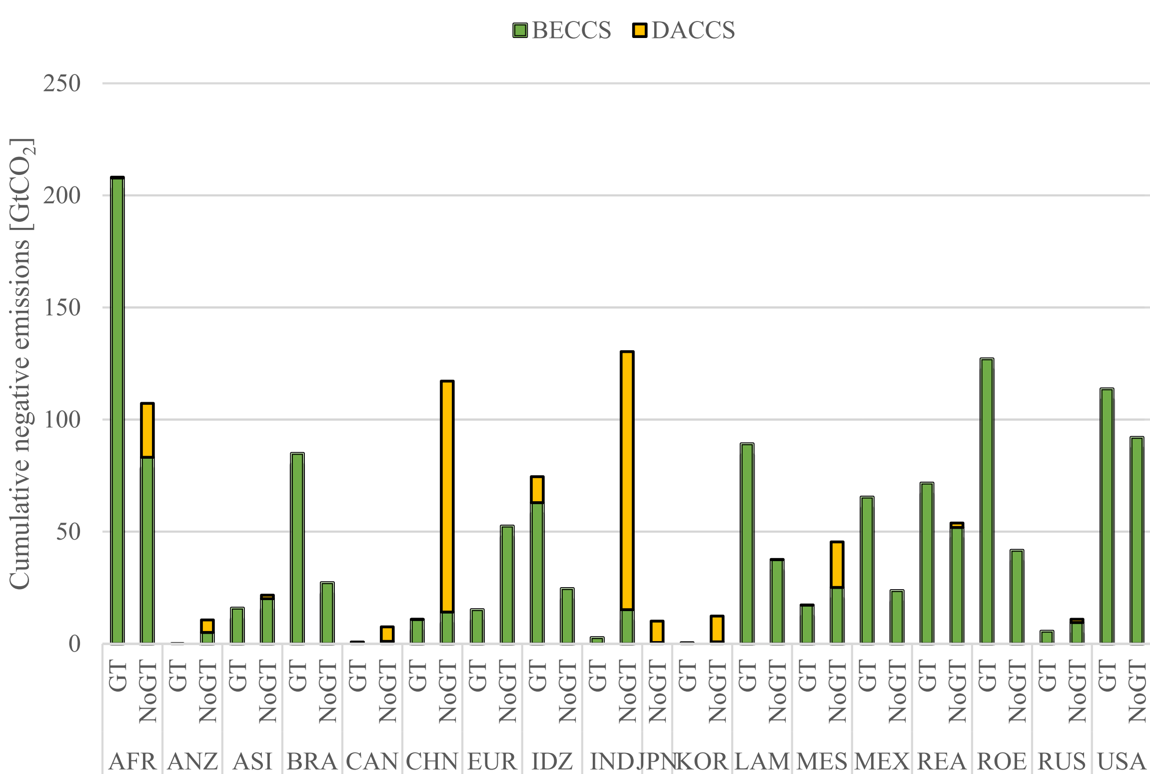

Fig. 6. Cumulative regional generation of negative emissions in scenarios with GHG trading across regions (*GT*) and without GHG trading across regions (*NoGT*) in a *Medium* cost DAC case.

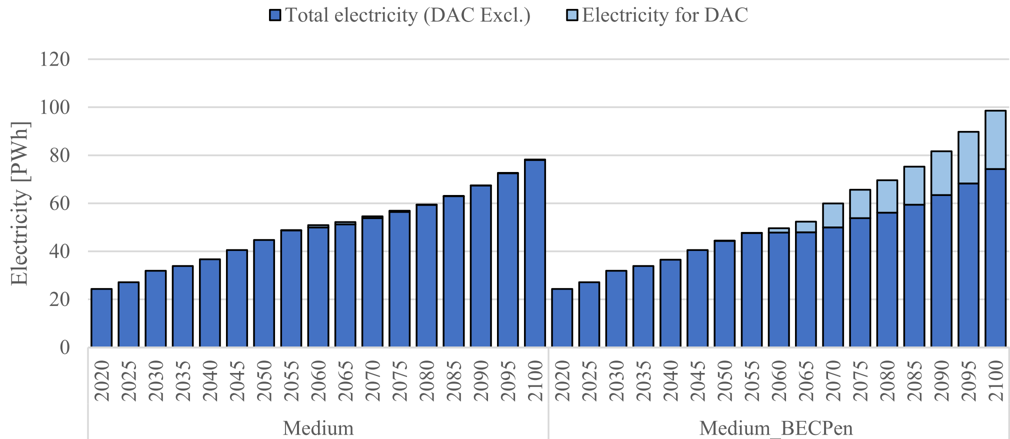

Fig. 7. Global electricity generation in a *Medium* cost with BECCS penalty (right) or not (left).

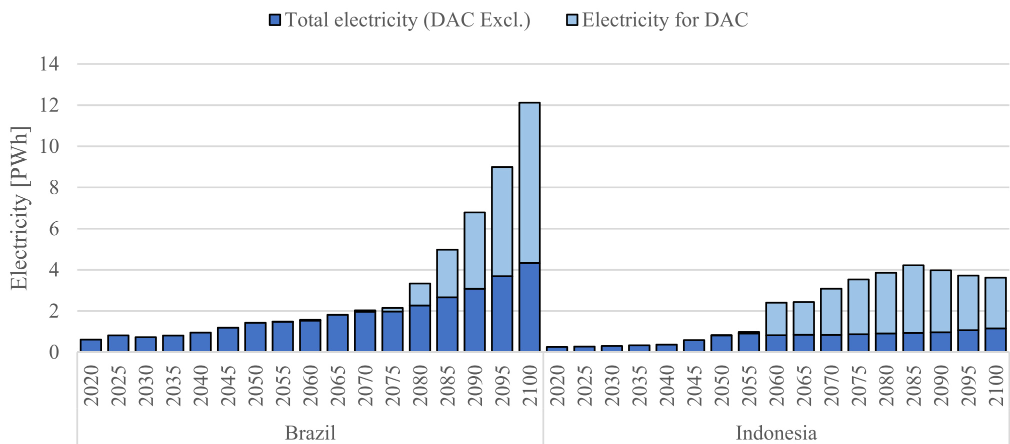

Fig. 8. Electricity generation in Brazil and Indonesia in the *Medium_BECPen* scenario.

the profile of the Brazilian and Indonesian power systems raises questions about the consistency of such a strategy with other development goals and social/political acceptance of such a huge roll-out of wind turbines and solar farms just to generate emissions permits.

4.2.2. Economics

In terms of economic implications, the stakes are high if DACCS is to be deployed at scale. When comparing the price of CO_2 in cases where DAC is available or not, we observe a clear decoupling of the values at the moment DACCS is deployed (Fig. 9), with DAC reducing the long-run carbon price from \$250/tCO_2 in the *NoDAC* case to about \$150–200/

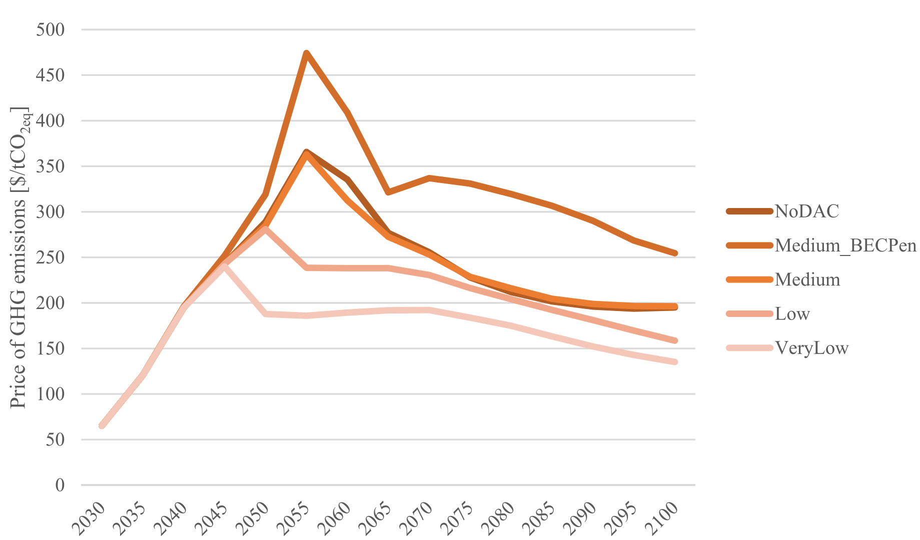

Fig. 9. Effect of DACCS deployment to the global price of GHG emissions.

tCO_2, depending on the cost assumption for DAC, which is consistent with other findings (e.g. Akimoto et al., 2021; Marcucci et al., 2017; Realmonte et al., 2019). The question arises as to why the prices shown in Fig. 9 are lower than the techno-economic assumptions on DAC displayed in Tables 3 and 4. In these tables, the cost of DAC is given for the US and the base year (2014) of the model. However, in the model we consider regionalized costs for DAC (meaning that costs shown in Tables 3 and 4 are not globally applicable), and the costs of the DAC processes change endogenously over time as the prices of inputs (e.g. capital, labor, energy, etc.) change and efficiency improvements occur. In particular, in achieving the net-zero target by 2070, the model decarbonizes the global power sector and electricity prices decrease, especially for solar (−64%) and wind (−53%), thereby the electricity expenditures of DAC processes decrease too and so does the GHG price.

The lowest GHG prices only occur when the cost of DAC is considered low to very low. Focusing on the *Medium* case with BECCS restricted, it is clearly favorable to consider implementing DACCS as BECCS cannot provide enough emissions permits to cap the price of CO_2. Consequently, gains in GDP can be as high as 11% at the global level when comparing the *Medium_BECPen* scenario with a scenario when there is no DAC and a BECCS penalty. Regarding the *Medium* case, we note that the price of GHG emissions largely follows the one of the *NoDAC* case, with both converging towards $\$200/tCO_{2eq}$. This corresponds to the CO_2 removal price through BECCS since in this case DACCS cannot compete with BECCS.

The benefits of DACCS are even more substantial at the national level for regions relying substantially on NETs to achieve their decarbonation when international GHG trading is not allowed, namely South Korea, Japan, China and India. In Fig. 10, we observe a clear decoupling between the solid lines, representing the price of CO_2 without ETS and DAC, and the dashed lines when there is no ETS but DACCS is deployed. In turn, over the century, China, and India could save between 4% and 8% of their GDP if DAC is available in a world without global emissions trading compared to if DAC is not available. Therefore, for some regions, the issues behind DAC availability may be of great importance if no international ETS emerges. In Appendix G, we show for the setting with no international ETS how the development trajectories of selected regions and countries vary based on whether or not DAC is available.

4.2.3. *Land use*

As some scenarios deploy large amounts of DACCS, we evaluate the land use requirements ad hoc. Based on NREL data, we assume that the total land use of wind (resp. solar PV) power requires 16 ± 10 ha/GWh.y^{-1} (resp. 1.8 ha/GWh.y^{-1}) and installing a 1Mtpa low-temperature DAC unit requires 81–506 ha (NASEM, 2019). With these values, we evaluate the land footprint of all DAC units – no matter how they are supplied – plus the dedicated renewables required to supply them (but we do not consider the incremental land increases embedded in grid electricity that is distributed to DAC units as we do not know the origin of electrons in this case). Depending on the assumptions (low end or high end of the range), we estimate that land requirements can vary by up to three times (Fig. 11). These values should be compared with the land use of BECCS in the scenario where there is no DAC, which is 8.4 Mkm^2. In the *VeryLow* case with no global emissions trading (*VeryLow_NoGT*), the land use required reaches up to 1.14 Mkm^2, of which 37% is allocated to India, which suggests that 13% of the country would be used to generate emissions permits through DAC. Our results appear more realistic in the *Medium_NoGT* scenario, where the maximum land use for DACCS and its power supply is 0.48 Mkm^2 dispatched over regions (Fig. 12). Nonetheless, 0.2% of China's territory would be covered by large machines scrubbing CO_2 from the air (dark blue bar), excluding the land footprint of grid electrons. Japan would need to develop wind energy massively to supply its DAC units, representing 13% of its territory (marine areas excluded) but the land use of DACCS would be less threatening if the wind turbines were installed offshore, or if solar panels substituted wind turbines.

Overall, our assessment is very sensitive to the type of energy consumed by DAC units, reflecting the assumptions on wind and solar above, but, contrary to the land required by BECCS, the land required by DAC does not compete with crop areas, as wind turbines can be installed in agricultural fields. If one needs to limit the impact of DAC on total land use, alternative energies to wind power (e.g., nuclear) should be considered, or wind turbines should be set up offshore, when possible, although it would increase the cost of electricity supply.

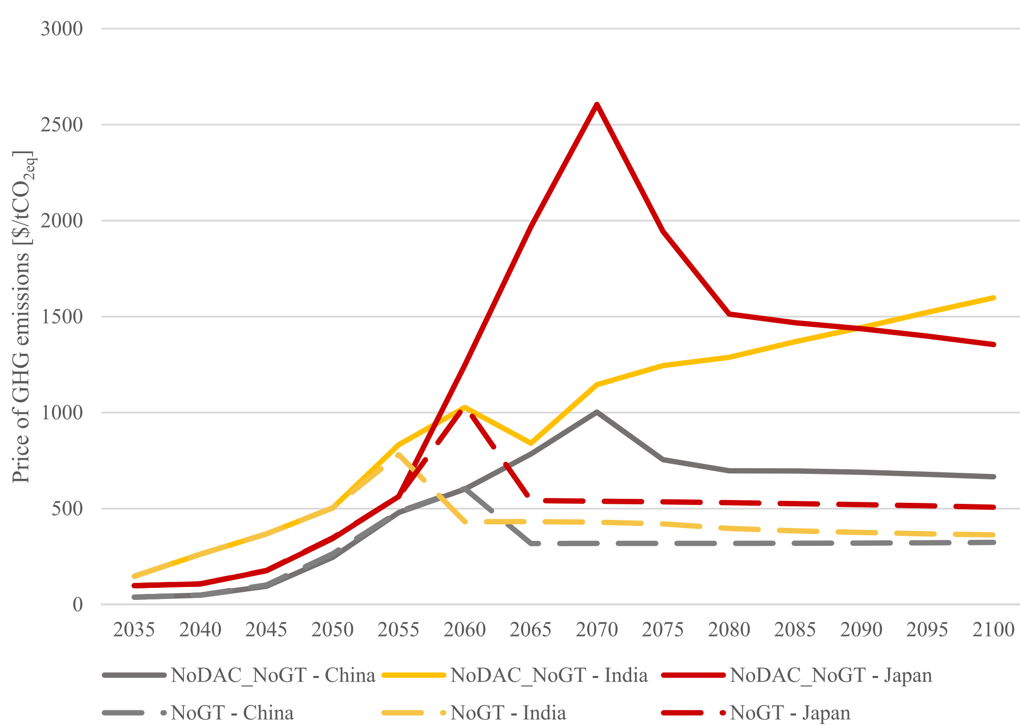

Fig. 10. Effect on DACCS deployment to the price of GHG emissions when emissions trading across regions is disabled.

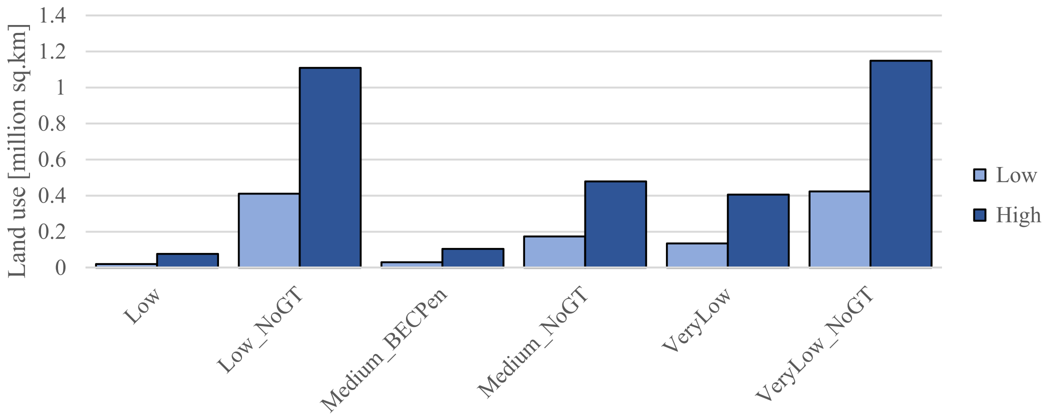

Fig. 11. Range of land use requirements for DACCS units and their power supply (wind or solar) in 2070.

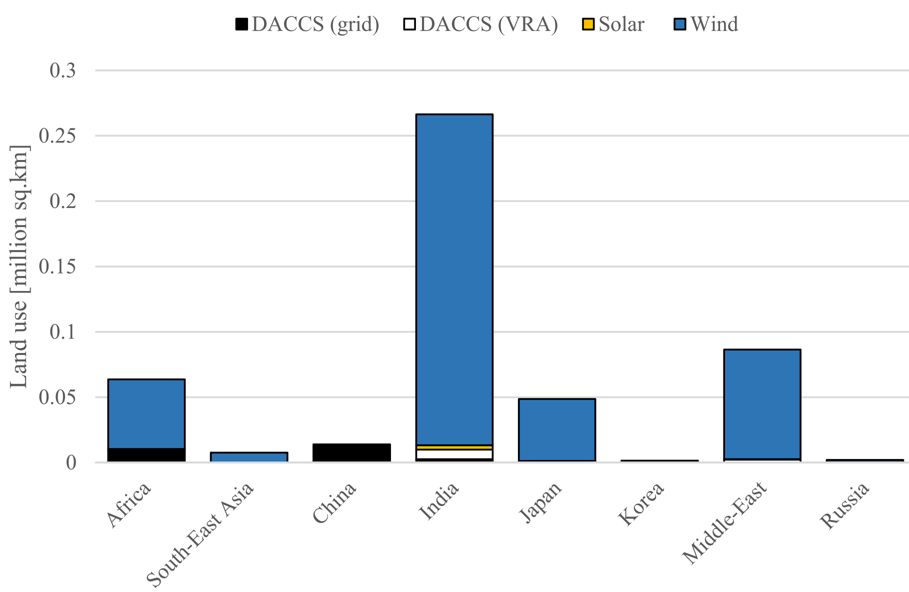

Fig. 12. Regional land use requirements for DACCS in the *Medium_NoGT* scenario in 2070 (high estimate).

4.3. DAC in advanced countries

One can see that the US and Europe are not deploying DAC in the results displayed above, while these two regions are currently developing projects and funding research programs related to DAC (Clean Air Task Force, 2022; DOE, 2022). Besides, the US is currently subsidizing DAC through tax credits contained in the Inflation Reduction Act (Global CCS Institute, 2022). In this section, we explore the policy and technical conditions to have DAC deployed in these two regions.

The results of Section 4.1 do not reveal any deployment of DAC in the US or Europe, even for the *VeryLow* cost case (in which the US and Europe still entirely rely on BECCS to provide both power and CO_2 removal at a price that cannot compete with DACCS), and even in the case where BECCS is penalized. When we assume that no international GHG trading would occur, these regions require a very cheap DAC technology to be competitive with BECCS, and even then, DAC only represents 5% (resp. 2%) of the total negative emissions of Europe (resp. USA). If we assume both a BECCS penalty and no international GHG trading, then DACCS at low or very low cost (see Table 3 and Table 4) becomes competitive with BECCS in the US and Europe, i.e. low cost DACCS contributes to >95% of European and American negative emissions. Thus, if BECCS capacities would be limited in the US and Europe, and there was no global emissions trading, then DACCS would replace BECCS for costs approaching \$250/tCO_2. The maximum DACCS deployment observed in these regions, is when BECCS is not available at all, in a world where international GHG trading is not allowed: the US and Europe deploy respectively 89 and 59 Gt of negative emissions cumulated from DACCS, but 99% of that is generated after 2050. Thus, our results suggest that DACCS would only compete with BECCS in Europe and the US if there is no international trading, BECCS is either limited or unavailable, and DAC technology costs fall below \$400/tCO_2.

For Europe, our results contrast with the estimates of Lux et al. (2023), who claim that up to 288 Mtpa DAC capacities would be required by 2050, with a cost between 66 and 104 €/tCO_2. Although the emissions reduction target in that study is carbon neutrality by 2050, we argue that their results would be worth discussing with a higher cost of DAC. For the US, Williams et al. (2021) also found that DAC would be necessary if land use was limited.

5. Conclusion

To reach climate neutrality, negative emissions undoubtedly will contribute significantly as they are indispensable in offsetting hard-to-abate emissions. Our study discusses the technical feasibility and economic viability of negative emissions technologies, focusing on DAC. Past studies have emphasized the importance of BECCS, and more recent studies have argued that DACCS would rival BECCS as it required less land, less water, with more flexibility in exchange for a much higher energy-intensity. However, such findings were often made under favorable economic assumptions about DAC that have not been demonstrated yet and may never be reached. Our research provides further insights about the potential future of DAC by considering a wide cost range from \$180–1000/tCO_2. In addition, we consider dedicated renewable assets equipped with batteries to supply the DAC units. In this techno-economic context, we explored the contribution of DAC to reach carbon neutrality, either as a negative emission technology or a supplier of CO_2 for the production of climate-neutral fuels, under different scenarios varying assumptions about the availability of BECCS and the presence of a global emissions trading system.

In view of our results, we argue that the potential of DAC should be discussed relative to the assumed cost, as its deployment is very sensitive to this assumption. For instance, under the considered scenarios, we have observed that DAC contributes to 78% of global negative emissions when its cost is \$180/tCO_2, but the share drops to 1% when the cost is \$420/tCO_2. We need to assume that DACCS is cheaper than \$380/tCO_2 to have units generating >1 Gtpa of negative emissions. However, DAC employed as a supplier of CO_2 to produce Fischer-Tropsch fuels is not found cost-effective in any case. Results also demonstrate that DAC units supplied with dedicated renewable assets are worth modeling as they impact the deployment of DAC. In the midterm (2050), DAC powered by dedicated wind or solar can drive the deployment of DACCS in regions where the grid is not sufficiently decarbonized, and in the long run it could bring additional negative emissions because the cost of renewables becomes extremely cheap. Thus, the regions and countries that are projected to invest the most in DACCS are either the ones that have a cheap decarbonized grid, like Canada, or those that have large and cheap potentials for wind and solar, such as Africa, Brazil and Indonesia.

As we realized that these regions and countries were big exporters of emissions permits, we explored a scenario in which no international ETS is set up. Because DACCS can theoretically be installed anywhere as long as sufficiently CO_2 storage capacities exist, our results show that in the absence of global emissions trading DACCS is an essential technology in regions and countries that have low and/or expensive access to bioenergy or land, such as Australia, Japan, China, and India, even for a high-cost DAC. We observe the same results in a scenario with trading but BECCS being limited; even for a medium cost DACCS could provide 1 Gtpa of negative emissions as of 2050. It could arguably be even more important if all bioenergy processes were limited (e.g. liquid biofuels), and not only BECCS. Thus, the availability of biomass and international emissions trading are two big drivers of DACCS deployment. It took assuming a low cost of DACCS, BECCS penalty, and scenarios with no international GHG trading all together to have DAC invested in the US and Europe, otherwise it could not compete with BECCS. Incidentally, the regionalization of DAC capital costs can slightly impact the regional deployment of DAC, but the global quantity is not significantly affected.

Since DAC proves competitive in some techno-economic contexts and policy scenarios, it means that it can be economically viable under certain conditions. If inexpensive DAC machines can be built, it would halve the global price of GHGs, and in scenarios without international emission trading, it could avoid the very expensive price of GHGs in Asian countries, with substantial GDP savings. However, the technical feasibility is not guaranteed when looking at the implications on land use and the power system. Although the land use requirements of DACCS are lower than BECCS even with conservative assumptions, it could be problematic in some countries, especially if wind turbines supply energy for DAC units. In fact, the land footprint of DAC units is not the main concern, but the land used by electricity generators matters, due to the high energy intensiveness of DAC. Consequently, the impact on the power system is huge, with roughly a third of total electricity supply dedicated to DAC in a scenario with BECCS limited. The more DACCS is deployed, the more it increases power consumption, and the more it reduces power generation as DACCS replaces BECCS.

Given the few operational DAC units in the world, we believe it is essential to reduce DAC cost at least below \$500/tCO_2. In making this assumption, it is also important to ensure that DAC is sufficiently competitive with other CDR options for it to be deployed at scale. Our study considers only BECCS and afforestation/reforestation, but other options (e.g. blue carbon, enhanced weathering, biochar) may change the game.

In future works, other CDR options should be considered to better assess each CDR's potential, role, and implications. Regarding DAC, it would be valuable to update the results with more granular regional availability factors for wind and solar as those play a role in the capital cost of the batteries and the cost of electricity to run DAC units. Indeed, we considered a uniform availability factor of solar and wind (resp. 20% and 35%), but some studies suggest different regional values across regions of the world (IRENA, 2019), which would also have a large impact on land use. Furthermore, our study does not include meteorological performances of DAC that were found to be more effective in dry and cold climate conditions (Sendi et al., 2022). Finally, the aggregation of countries into big regions like Africa or Latin America suggests implicitly that there is emission trading internally for these. While our results show an important role for DACCS in Africa, information about the location of DAC investments is missing and it may hide the fact that some African countries could actually sell permits to others. Thereby, the potential of DACCS in scenarios with no trading may be even more important.

The answer to the question of how close we are to deploying DAC at scale depends on three items. The first two, which we examined in detail in this paper, are the cost of DAC and how that cost compares to other negative emissions technologies. However, even if DAC costs decrease so they are competitive, there still is an outstanding question on whether people will be willing to pay the price for DAC. Our modeling imposed a stabilization criterion to reach net-zero emissions by 2070, but in the real world, policies must be put in place to achieve global decarbonization and these policies will have a price. If there is not the will to pay that price among the populace, then politicians will not enact the policies required to reach net-zero emissions. The bottom line is that the more the costs of DAC can be driven down, the closer we will be to deploying it at scale. While we can model scenarios that give us insight to the question of how close we are to deployment at scale, no one has a crystal ball that can predict the future cost trajectory of DAC. Therefore, we cannot state when, or even if, DAC will be deployed at scale.

CRediT authorship contribution statement

Lucas Desport: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Angelo Gurgel:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Jennifer Morris:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Howard Herzog:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Yen-Heng Henry Chen:** Methodology, Writing – review & editing. **Sandrine Selosse:** Supervision, Writing – review & editing. **Sergey Paltsev:** Conceptualization, Methodology, Supervision, Writing – review & editing.

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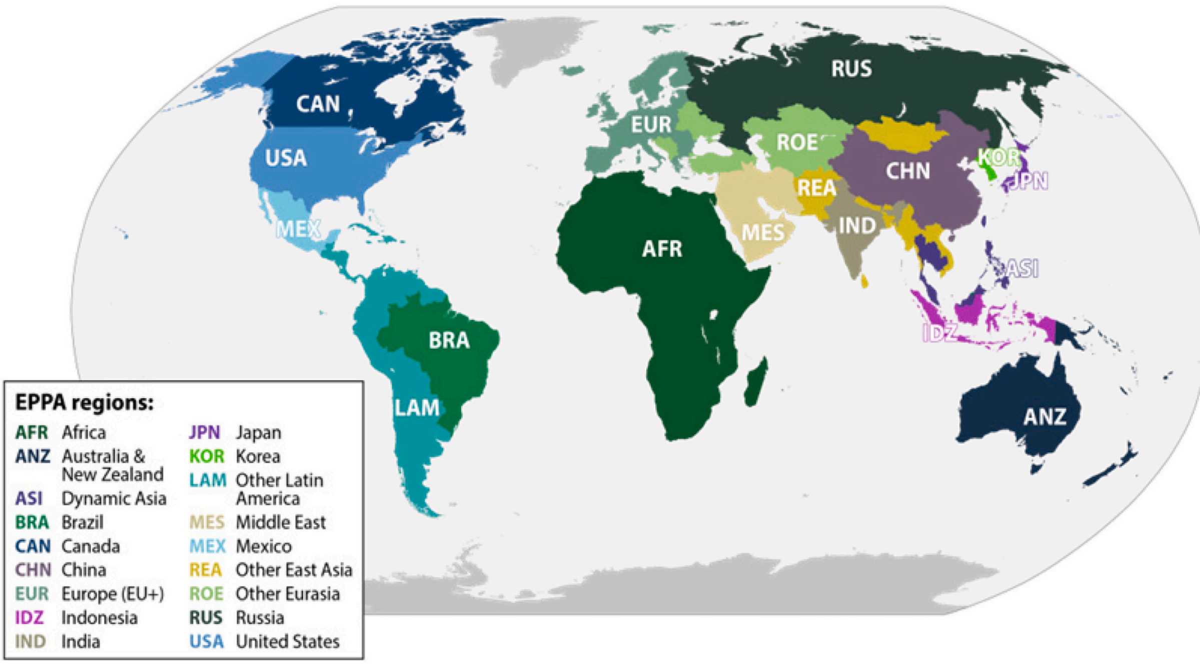
the funder.

Appendix A. Regions of EPPA



Appendix B. Techno-economic parameters of DAC with CO_2 utilization (DACCU)

Cost scenario	Units	Very low	Low	Medium	High
Power		Grid	Grid	Grid	Grid
"Overnight" Capital Cost	\$/tpa	132	720	1944	5186
Total Capital Requirement	\$/tpa	142	777	2099	5601
Fixed O&M (FIXOM)	\$/tpa	11	11	22	48
Scaled CRR	\$/tCO_2	17	91	246	658
FIXOM Recovery Required	\$/tCO_2	13	13	25	53
Variable O&M (VAROM)	\$/tCO_2	8	8	8	8
Electricity input	MWh/tCO_2	1,1	1,1	1,1	1,1
Fuel cost	\$/tCO_2	110	110	110	110
Total capture cost	**\$/tCO_2**	**147**	**222**	**389**	**828**

Power		Solar/Wind	Solar/Wind	Solar/Wind	Solar/Wind
"Overnight" Capital Cost	\$/tpa	836/704	1424/1292	2648/2516	5891/5759
Total Capital Requirement	\$/tpa	903/761	1538/1396	2860/2717	6362/6220
Fixed O&M (FIXOM)	\$/tpa	11	11	22	48
Scaled CRR	\$/tCO_2	106/89	181/164	336/319	747/730
FIXOM Recovery Required	\$/tCO_2	13	13	25	53
Variable O&M (VAROM)	\$/tCO_2	8	8	8	8
Electricity input	MWh/tCO_2	1,1	1,1	1,1	1,1
Fuel cost	\$/tCO_2	155/114	155/114	155/114	155/114
Required installed VRE capacity	MW/Mtpa	612/349	612/349	612/349	612/349
Battery capacity	MWh/Mtpa	2348/1908	2348/1908	2348/1908	2348/1908
Total capture cost	**\$/tCO_2**	**282/228**	**356/304**	**524/474**	**963/920**

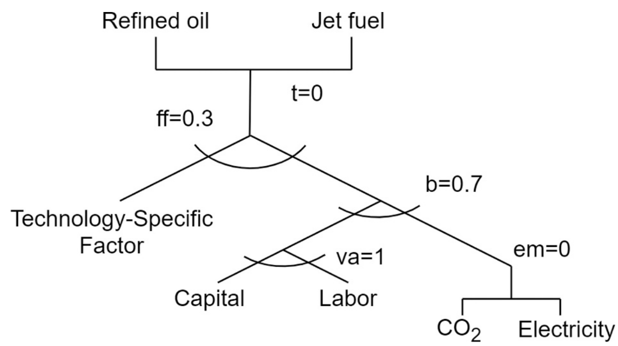
Appendix C. Techno-economic properties of the Fischer-Tropsch process using CO_2 from DACCU

As modeled in EPPA, the Fischer-Tropsch (FT) process that uses CO_2 from DACCU generates a slate of liquid fuels, including diesel, gasoline, and jet fuels made out of hydrogen and CO_2. The CO_2 is first converted into CO through a RWGS reactor and then mixed with hydrogen to form a syngas that will react in the presence of a catalyst at temperatures between 150 and 200 °C, following an endothermic reaction:

$nCO + (2n)H_2 \leftrightarrow C_nH_{2n+1}OH + (n+1)H_2O$

The products of the FT process are carbon chains whose output share depends on the catalyst and the temperature employed. Following the findings of (Zang et al., 2021) jet fuel, diesel, and gasoline are all generated from this process, respectively comprising 47%, 27%, and 26% of the energy output. As EPPA does not differentiate diesel and gasoline but denote them as refined oil, the two outputs of the process modeled are jet fuel by 47% and refined oil by 53% (as the sum of diesel and gasoline). We assume that there is no trade-off for the product slate, meaning that the chemical behavior of the FT plant is constant and always delivers the same share of fuels. All techno-economic properties were taken from Zang et al. (2021) and they are displayed in Table 5.

The version of EPPA employed here does not model hydrogen so we considered that the FT process is run along with and electrolyzer whose techno-economic properties were taken from (Schweizer et al., 2020). The capital cost of the PEM process (1463 \$2016/kW$_{el}$) corresponds to the average value of the "2020 capital cost range" (first column, 50th percentile of Table D.1) and the efficiency was assumed equal to 70%. The electricity used to run the FT process and the electrolyzer was assumed to be grid electricity or solar or wind. Thus, the production of jet fuels and refined oil through the FT process in EPPA combines CO_2, electricity, capital and labor, and the so-called Technology-Specific Factor (TSF) using a series of nested CES functions, as illustrated in Fig. 1.



Nested CES structure of the Fischer-Tropsch process

C.1. Nesting structure of the Fischer-Tropsch process modeled in EPPA

We represent trade-off possibilities among products using a sequence of nested constant elasticity of transformation (CET) functions. We also assume that there is no trade-off between CO_2 and electricity, i.e. the process cannot perform energy or material efficiency to optimize the use of CO_2 or electricity. However, we consider a value-added elasticity equal to 1 (Balistreri et al., 2003; Hertel, 2019). The TSF was introduced by (Morris et al., 2019b) to represent the penetration of a backstop technology. This factor is required to operate the FT process, but its supply is limited, especially at the early stage. As is standard in EPPA, we apply the markup shown into the output of our FT process, which determines the cost of e-fuels compared to a conventional process. In addition, the cost shares were used to represent the weight of each input in the total cost. The techno-economic assumptions were used to calculate the cost of economic inputs as implemented in the model to characterize the techno-economic behavior of FT processes.

C.2. Techno-economic properties of the Fischer -Tropsch process (electrolyzer excluded)

	Parameter	Units	Zang et al. (2021)
[01]	"Overnight" Capital Cost	\$/GJ_a	107.7
[02]	Total Capital Requirement	\$/GJ_a	116.3
[03]	Capital Recovery Charge Rate	%	10.6%
[04]	Fixed O&M (FIXOM)	\$/GJ_a	5.5
[05]	Variable O&M (VAROM)	\$/GJ	1.7
[06]	Project Life	years	20
[7]	Capacity Factor	%	90%
[8]	Annual Capacity	PJ/y	5.15
[9]	Capital Recovery Required	\$/GJ	12.3
[10]	FIXOM Recovery Required	\$/GJ	6.1
[11]	CO_2 input	t/GJ	0.152
[12]	CO_2 cost	\$/t	100
[13]	Total CO_2 cost	\$/GJ	15.2
[14]	H_2 input	kg/GJ	14.3
[15]	H_2 cost	\$/kg	3
[16]	Estimated hydrogen cost	\$/GJ	43
[17]	Estimated fuel cost	\$/GJ	58.2
[18]	Estimated production cost	\$/GJ	78.3

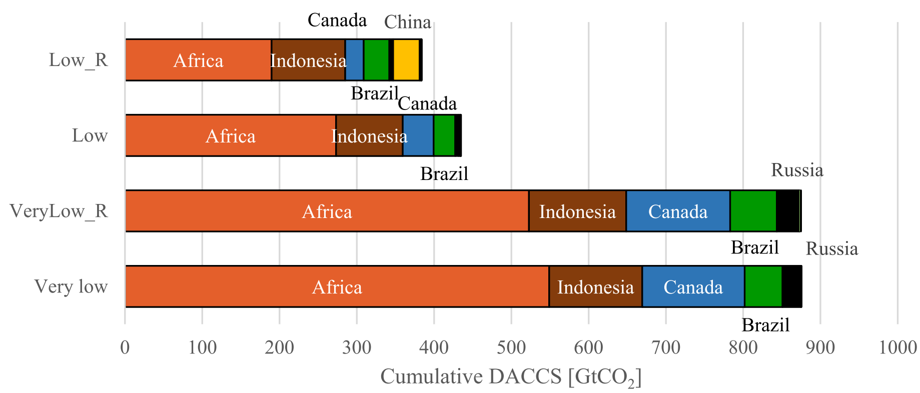
Appendix D. Regional emissions permits allowances

This table shows the level of permits attributed to each country or region to achieve the net-zero target by 2070, in $MtCO_2$.

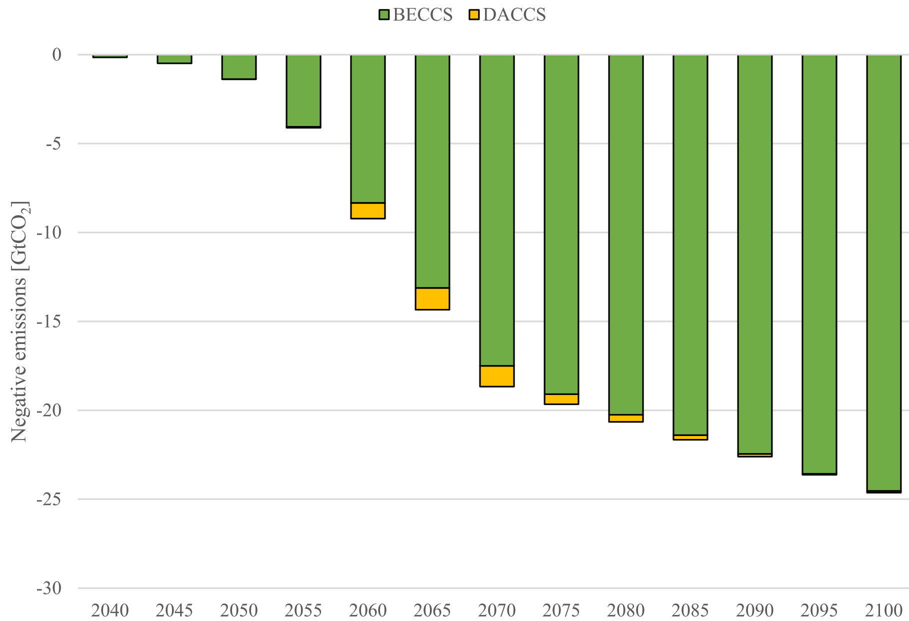
	2020	2030	2040	2050	2060	2070	2080	2090	2100
USA	1625	943	660	377	189	0	0	0	0
CAN	569	422	269	115	57	0	0	0	0
MEX	508	406	298	189	95	0	0	0	0
JPN	1071	677	523	326	163	0	0	0	0
ANZ	518	387	241	96	48	0	0	0	0
EUR	3324	1915	1530	797	399	0	0	0	0
ROE	1166	916	705	493	247	0	0	0	0
RUS	1372	1223	1063	902	452	0	0	0	0
ASI	1365	1092	826	561	281	0	0	0	0
CHN	9914	7849	5466	3072	1531	0	0	0	0
IND	2469	2349	1619	1071	535	0	0	0	0
BRA	2442	3242	2705	1685	840	0	0	0	0
AFR	5075	6423	6041	5660	2833	0	0	0	0
MES	1346	1388	1175	962	480	0	0	0	0
LAM	2682	2886	2289	1384	694	0	0	0	0
REA	1544	1901	1584	1428	713	0	0	0	0
KOR	759	605	539	478	239	0	0	0	0
IDZ	2988	2976	2272	1565	783	0	0	0	0

Appendix E. Regionalization of the cost of DAC

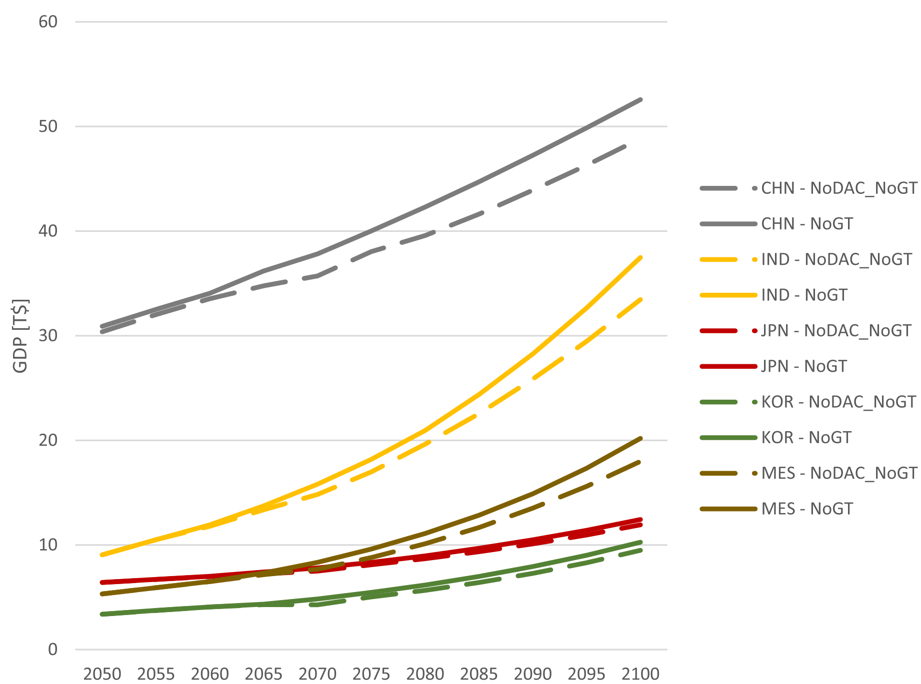
The suffix "_R" refers to scenarios in which costs are regionalized. The graph illustrates that we do not note significant difference when the cost of DAC is regionalized by its capital cost or not.



Appendix F. Deployment of DAC at $380/t$CO_2$



Appendix G. Development trajectories of selected countries in a scenario without GHG trading. The solid line denotes GDP projections for a *Medium* cost of DAC assumed while DAC is not available in the scenario denoted by dashed lines



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