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# The Role of Carbon Capture and Storage Electricity in Attaining 1.5 and 2°C

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**Summary**

The climate targets defined under the Paris agreement of limiting global temperature increase below 1.5 or 2°C require massive deployment of low-carbon options in the energy mix, which is currently dominated by fossil fuels. Scenarios suggest that Carbon Capture and Storage (CCS) might play a central role in this transformation, but CCS deployment is stagnating and doubts remain about its techno-economic feasibility. In this article, we carry out a throughout assessment of the role of CCS electricity for a variety of temperature targets, from 1.5 to above 4°C, with particular attention to the lower end of this range. We collect the latest data on CCS economic and technological future prospects to accurately represent several types of CCS plants in the WITCH energy-economy model, We capture uncertainties by means of extensive sensitivity analysis in parameters regarding plants technical aspects, as well as costs and technological progress. Our research suggests that stringent temperature scenarios constrain fossil fuel CCS based deployment, which is maximum for medium policy targets. On the other hand, Biomass CCS, along with renewables, increases with the temperature stringency. Moreover, the relative importance of cost and performance parameters change with the climate target. Cost uncertainty matters in less stringent policy cases, whereas performance matters for lower temperature targets.

**Keywords**: Carbon Capture and Storage, Integrated Assessment Model, Climate Mitigation Policies, Electricity Sector, Low-carbon Technology

**JEL Classification**: O33, Q42, Q43, Q54

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# The role of Carbon Capture and Storage electricity in attaining 1.5 and 2°C

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**Abstract**

The climate targets defined under the Paris agreement of limiting global temperature increase below 1.5 or 2°C require massive deployment of low-carbon options in the energy mix, which is currently dominated by fossil fuels. Scenarios suggest that Carbon Capture and Storage (CCS) might play a central role in this transformation, but CCS deployment is stagnating and doubts remain about its techno-economic feasibility. In this article, we carry out a throughout assessment of the role of CCS electricity for a variety of temperature targets, from 1.5 to above 4°C, with particular attention to the lower end of this range. We collect the latest data on CCS economic and technological future prospects to accurately represent several types of CCS plants in the WITCH energy-economy model, We capture uncertainties by means of extensive sensitivity analysis in parameters regarding plants technical aspects, as well as costs and technological progress. Our research suggests that stringent temperature scenarios constrain fossil fuel CCS based deployment, which is maximum for medium policy targets. On the other hand, Biomass CCS, along with renewables, increases with the temperature stringency. Moreover, the relative importance of cost and performance parameters change with the climate target. Cost uncertainty matters in less stringent policy cases, whereas performance matters for lower temperature targets.

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## 1 Introduction

Following a continuous increase in scientific awareness of anthropogenic climate change, in 2015 the Paris agreement opened a call for policies more ambitious than ever before, aimed at limiting global temperature increase well below 2°C, and in the direction of 1.5°C (IPCC, 2014a). Such stringent targets usually involve scenarios of limited reliance on fossil fuels. This implies a non-trivial transformation of the status quo, where these fuels account for more than 80% of the global primary energy supply (IEA, 2016) due to their dispatchability, economic convenience and technological maturity.

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Given that the dependence on fossil fuels is not likely to decline in the short term (IEA, 2013a), many sources agree that CCS, among the possible low-carbon options available for energy production, might provide an important contribution to the sector decarbonization (IPCC, 2014b; IEA, 2013a, 2010). Some multi model comparisons show that CCS might represent from 30% to 40% of the primary energy use (Koelbl et al., 2014), and biomass is likely to be the most used fuel combined with CCS, especially at the end of the century (Van Der Zwaan et al., 2013). Krey et al. (2014), showed that CCS and biomass constrains are those mostly influencing the results of the 2°C climate mitigation scenario. Little is however known about CCS potential in below 2 degrees scenarios, and different outcomes in models results seems to be dependent on CCS-related assumptions. The authors themselves suggest that further research would be advisable in order to provide a more detailed intra-model sensitivity analysis. Within this work we aim at contributing in addressing these literature gaps, providing a single model CCS centered analysis.

CCS consists of separating and capturing fuel $CO_2$ content at energy production and industrial facilities. CCS can be coupled with both fossil fuels and biomass (Bio CCS): if coupled with biomass, a negative emission level can be achieved (Kemper, 2015; IEAGHG, 2014a; Chum et al., 2011). Zero or negative emissions technologies are supposed to be crucial in limiting the temperature increase to 1.5°C in the next decades (Rogelj et al., 2015). Captured $CO_2$ is later transported towards storage sites for long term confinement. CCS technologies offer some major advantages. First of all, they can significantly decrease emission levels without the need of shifting away from the currently used carbon-rich fuels. Secondly, power production is provided on-demand, being CCS a dispatchable technology. Furthermore, part of the literature suggests that, considering technology related LCOE, CCS would be potentially competitive with other low-carbon technologies in case of carbon pricing policy (IEA, 2013a). Despite these advantages, safety concerns about storage sites, public acceptance and high technology costs (see for example Karayannis et al. (2014)) are often mentioned as major drawbacks. Indeed, so far, CCS adoption is still limited to small scale plants, especially in the industrial sector, and its potential is subjected to large uncertainties (GCCSI, 2016).

It is therefore not yet clear to what extent CCS can effectively contribute to climate change mitigation effort (Koelbl et al., 2013, 2014; Metz et al., 2005b), and in particular if large scale applications will make inroads in the electric sector (Whittaker and Kneppers, 2013). Moreover, particularly stringent climate targets, such as the 1.5°C, could hinder fossil fuel based CCS deployment, encouraging a shift towards carbon neutral or carbon negative options (van der Zwaan and Tavoni, 2011; De Cian and Tavoni, 2012). This paper aims at contributing to the debate on the potential impact of CCS adoption on both the energy and the economic sector, offering a quantitative assessment of optimal CCS mitigation strategies in different future scenarios, with an emphasis on the role of $CO_2$ capture rather than underground storage.

In particular, we tackle the following questions:

1. what is the state of the art of CCS technological options in the power sector and what are the most promising CCS alternatives according to the literature?

2. to what extent could uncertainty of future cost and performances estimates impact CCS adoption?

3. how sensitive is CCS deployment to the climate policy target?

The first question is more qualitative and is best answered by reviewing the relevant literature. The data collected in the process was then implemented in the WITCH energy climate model to answer the remaining questions. Previous analyses have compared CCS potential in the 2°C scenario resulting from different Integrated Assessment Models, including WITCH (Luderer et al., 2012). This latter model resulted to have quite simplified and conservative assumptions concerning CCS, which have been expanded and updated for the purpose of this study. Moreover, the analysis presents extensive sensitivity analysis over input techno-economic parameters, as well as climate policy objectives, providing an exhaustive evaluation of CCS uncertainties for low end climate targets,

The paper is structured as follows. In Section 2, we present an overview of the CCS state of the art in the power sector. We also describe the WITCH model and the main changes included for this study. In Section 3 we present the results we obtained both from the literature review and the model output, providing answers to the research questions. In Section 4 we draw the conclusions.

# 2 Materials and Methods

## 2.1 WITCH model

WITCH is a dynamic global model, developed at Fondazione Eni Enrico Mattei (FEEM) and Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) and extensively used for cost-effective analyses of mitigation portfolios (Emmerling and Drouet, 2016). The model fully integrates a top-down description of the economy sector with a bottom-up representation of the energy sector. Projections range from 2005 (the base year) up to 2150, with time steps of 5 years. The world economy is divided into 13 regions, where countries are clustered according to economic, energy and geographical similarities. Each region acts as a forward-looking planner, who optimizes the allocation of investments in final goods, innovation (R&D) and energy technologies, with the objective to maximize social welfare. The overall solution is obtained via an open loop non-cooperative game among the regions. The game is solved through iterations as some decisions spill over on the decisions of other players. For example, investments in R&D of one party not only improves the technologies in its energy system, but also those in other regions according to a given knowledge diffusion dynamics. The resulting investment paths define energy portfolios and associated costs, as well as the consequent greenhouse gas emission profiles into the climate system. GHG emissions affect global temperature, and in case of climate policies, are considered as environmental externalities.

The energy sector is designed through a nested CES production function, whose elasticities of substitution represent the observed heterogeneity in the energy system. Economic growth is driven by a mix of electric and non-electric energy services, which are supplied by a variety of options. Among the options to produce power with carbon capture, WITCH includes different coal based CCS alternatives, a generic natural gas technology and a generic biomass fueled plant. Each option group together power plants of similar type, which are then defined by a common set of key features, namely investment and operation and maintenance costs, plant net electricity efficiency (on LHV basis), carbon capture rate ratio (or capture efficiency), lifetime and capacity factor (annual operative hours). CCS technologies compete with all the other power technologies, spanning from fossil fuel oil, coal and gas plants, to nuclear and renewable technologies, such as hydropower, solar and wind. Technologies are subjected also to future progress, either via learning by doing or learning by researching. The former results in a cost reduction of CCS and solar plants as function of the installed capacity. The latter involves specific investments to reduce the cost of breakthrough advanced biofuels, or increase the efficiency of the energy system as a whole.

## 2.2 CCS assumption

Most of the assumptions on CCS (such as costs, technical parameters and technological learning), have been updated or introduced in the model for the purposes of this study, after an extensive literature review. Follows an extract of this research, that highlights the main sources we referred to.

### 2.2.1 CCS technologies overview

According to (Metz et al., 2005b), a $CO_2$ capture system can follow three possible layouts: post-combustion, pre-combustion and oxyfuel combustion. Each configuration can be applied to both fossil fuel and biomass combustion plants (Metz et al., 2005b; IEAGHG, 2011a; ZEP/EBTP, 2012). CCS plants can moreover be built ex-novo or by means of retrofitting existing plants. Also in terms of fuel use, different possible configurations are available. In this research, only coal, gas and biomass are considered as possible fuels, excluding for example waste or combinations of coal with biomass.

Pre-combustion capture of $CO_2$ consists of separating $CO_2$ before the fuel is burnt. Capture can be performed through gasification of fuel by means of steam reforming and water-gas-shift reactions, which produce syngas rich of hydrogen and $CO_2$. Carbon capture is then accomplished by an acid gas removal process of absorption and stripping with a chemical or physical solvent (GCCSI, 2012).

The post-combustion carbon capture technology aims to remove $CO_2$ content from the stream of exhaust gases at the end of flue gases cleaning process. The separation of $CO_2$ is usually performed using chemical solvents (i.e. MEA) or membranes. If required, this type of technology can be implemented on existing power plants (retrofitting), offering the opportunity to reduce plant emissions.

Oxyfuel power plants work with combustion of fuel with pure oxygen in a special boiler or furnace, usually with recirculation of exhaust gases (IEAGHG, 2010). The product of combustion after the exhaust treatment is mainly water and $CO_2$. Water is easily condensed and separated, while $CO_2$ is compressed and stored. Oxyfuel capture option is newer and less developed than pre- and post-combustion technologies (GCCSI/EPRI, 2012; Rubin et al., 2015). As a consequence, uncertainty on available data concerning oxyfuel is wider than other technologies.

The introduction of climate policies is likely to result in the premature shutdown of existing fossil fuel plants (IEAGHG, 2011b). Retrofitting them to operate with CCS could therefore represent in some cases a cost effective alternative to a full replacement with lower carbon options (Gibbins et al., 2011; Johnson et al., 2015), despite the additional cost and the efficiency loss drawbacks.

In this study, we consider a generic gas combined cycle with CCS, NG-CCS, which parameters are obtained averaging values related to different plant designs. We similarly include a generic biomass-fueled power plant, Bio CCS. Thanks to a larger data availability, we are able to disaggregate coal based power plants according to the categories previously mentioned. Finally, only one retrofitting technique is considered, applicable only for coal CCS plants.

### 2.2.2 Technical progress

As CCS technologies are at an early stage of development, it is legitimate to hypothesize that technological improvements over time could impact their cost and performance. In particular, a large body of literature advocates that an increase in installed capacity restrain the technology associated costs, and one of the most diffused mathematical method for endogenously representing this phenomenon is through learning curves (Rubin et al., 2015). The correlation between cumulative installed capacity and cost decrease is in this case represented by an exponentially decreasing curve. Even though the correlation is generally based on historical observations, literature suggests a possible method for extending the concept of learning curves based on the learning of single technology subcomponents (Rubin et al., 2015). This method has been applied to young technologies such as CCS power plants due to the lack of empirical data. Often, literature reports the technology associated *learning rate*, representing the reduction in cost corresponding to a doubling in installed capacity. In this study, we gathered estimates and projections of learning rates and determined uncertainty ranges for each power plant category included in the model.

#### 2.2.3 Parameters of interest

Tables 1 and 2 report the final results of our technological assessment in terms of nominal values and uncertainty ranges for each CCS technology considered in this study. Ranges are based on quantities reported from different sources. Regarding Bio CCS, literature provide scarce and less reliable estimates concerning plants costs, efficiencies and learning rates. In this case we derived lower and upper bounds for each parameter, consistently with the ranges obtained for the other CCS technologies.

Base on these data we can draw some preliminary insight on the current state of the art of CCS options in the power sector. First of all, the values of capacity factor and electric efficiency seem comparable among coal fired plant technologies. Oxyfuel deviates from the others with a higher capture rate and investment cost, and a slightly lower O&M cost.

Secondly, the type of fuel has apparently important consequences both in terms of efficiency and costs. Natural gas combined cycle plants usually have higher efficiency and lower investment cost compared to coal plants (Beér, 2007). This holds true also for plants with carbon capture. Capture efficiency is instead comparable to coal options, with the exception of Oxyfuel.

Finally, Bio CCS shows in absolute terms the highest costs and lowest efficiency.

Looking at future perspectives, Oxyfuel is characterized by both the lowest learning rate and the narrowest range of uncertainty. This might appear to constrast with Oxyfuel being the currently least developed technology among the reported selection. However, the number of studies providing uncertainty assumptions for Oxyfuel learning rates is limited compared to other technologies, and the cost trend is mainly influenced by two expensive components, the Air Separation Unit (ASU) and the boiler, while other technologies have more heterogeneous cost drivers (IEAGHG, 2014b; MacDonald, 2012). This second aspect might influence the learning rate component based calculation.

Focusing on uncertainty ranges, Tables 1 and 2 show considerable variation in O&M costs, investment costs and learning rates, while capture rates exhibit narrower ranges. Again, Oxyfuel departs from the others with more uncertain capital costs and more conservative electrical efficiency values.

#### 2.2.4 Storage, transport and leakage

Part of our modelling work aimed at including in WITCH costs, availability and reliability of carbon dioxide storage in geological reservoirs and transport through pipelines. Although our research focuses on the capture side of CCS, we recognize that storage is a potential driver of uncertainty in long-term projections and consider it an important avenue for future research.

Nowadays, $CO_2$ transport and storage technologies are mature and mainly applied to Enhanced Oil Recovery (EOR) $CO_2$ supply. Particularly in the United States, $CO_2$ from natural sources has been injected for decades into expiring oil fields for enhancing the extraction (IEA, 2015; Godec et al., 2011).

Table 1: Main performance parameters of power plants with CCS as results of the literature review.

| | Capacity Factor [%] | | | $CO_2$ CRR [%] | | | Net efficiency [%][a] | | |
|---|---|---|---|---|---|---|---|---|---|
| Technology | Low | High | Best | Low | High | Best | Low | High | Best |
| PC w/o CC[b,c] | | | 85 | | | | | | 45.0 |
| C-IGCC | 65 | 85 | 81 | 85 | 91 | 89 | 31.0 | 40.0 | 33.9 |
| C-post | 65 | 90 | 83 | 80 | 90 | 90 | 28.5 | 38.5 | 33.7 |
| C-OXY | 67 | 91 | 83 | 90 | 98 | 95 | 23.4 | 35.5 | 33.2 |
| NGCC w/o CC[b,d] | | | 70 | | | | | | 50.0 |
| NG-CCS | 65 | 95 | 84 | 85 | 90 | 89 | 43.7 | 52.1 | 48.0 |
| Bio CCS | | | 80 | | | 90 | | | 28.0 |

[a] on LHV basis; [b] Values currently used in the model, not output of literature review
[c] same values for C-retro, with CCR=90% and 10 pp efficiency loss
[d] includes single gas turbines still widely used globally, with low capacity factor

Table 2: Investments and O&M cost of Power plants with and w/o CCS as results of the literature review (2005 USD).

| | $I_{cost}$ [$/kW] | | | O&M costs [$/MWh] | | | LR [%] | | |
|---|---|---|---|---|---|---|---|---|---|
| Technology | Low | High | Best | Low | High | Best | Low | High | Best |
| PC new w/o CC[a] | | | 1472 | | | 8.9 | | | |
| C-IGCC | 1310 | 4648 | 3078 | 2.0 | 19.1 | 10.1 | 2.5 | 20.0 | 6.7 |
| C-post | 1400 | 4627 | 3063 | 3.8 | 22.8 | 13.4 | 1.1 | 9.9 | 3.8 |
| C-OXY | 1127 | 5034 | 3253 | 1.7 | 20.5 | 9.5 | 1.4 | 7.0 | 2.8 |
| C-retro[b] | | | 2302 | | | 13.4 | | | |
| NGCC w/o CC[a] | | | 750 | | | 5.6 | | | |
| NG-CCS | 774 | 2268 | 1508 | 4.6 | 8.3 | 6.4 | 1.2 | 12.0 | 4.2 |
| Bio CCS[c] | | | 3693 | | | 10.3 | 0.0 | 10.0 | 5.0 |

[a] Values currently used in the model, not output of literature review
[b] Summed costs of old power plants and retrofitting unit
[c] We assumed uncertainty ranges consistent with other CCS technologies

Most studies agree to consider a set of storage option: depleted or remaining oil and gas fields, coal beds and underground saline aquifers, not used for drinkable water.

For this work we derived an average storage capacity for each region in the model and for seven different types of storage reservoir, including onshore and offshore options. Any detail concerning the assumption we adopted for the $CO_2$ storage side are reported in the Appendix.

Regarding the transportation of $CO_2$, the most diffuse technique is liquefaction and conveyance through pipelines. Although some other options are available, mainly ships transport, they prove not to be economically convenient apart from particular cases (i.e. remote offshore distances) (ZEP, 2011b).

$CO_2$ transportation costs via pipeline are mainly related to the infrastructure costs, followed by costs of allowances, surveillance and expert supervision (McCoy and Rubin, 2008). Our implementation introduced an average distance between storage site and power plant with CCS per each type of storage and region, that, combined with an average transportation cost per km, provides the cost of $CO_2$ transport.

A final aspect of $CO_2$ storage and transportation is the leakage risk. The term leakage refers to undesired $CO_2$ losses due to imperfect sealing or infrastructures damages. Leakage could be originated by $CO_2$ transportation, underground injection, or storage.

According to the IPCC, 2005 report, storage sites are highly probably reliable and safe, meaning to release practically zero leakages (Metz et al., 2005a). Therefore for this study we considered the leakage rate equal to zero.

## 2.3 Scenarios description

In this study, climate policy scenarios are identified by temperature targets, i.e. a limit on temperature increase with respect to the preindustrial level over the century. This constraint can be conveniently added to the WITCH model in the form of a cap on cumulative GHG emissions (carbon budget). The higher the carbon budget, the higher the temperature increase, and the lower the associated policy stringency. The model iteratively searches for an global price on anthropogenic GHG emissions that eventually achieves the desired carbon budget. This price is implemented as a carbon tax that comes into force in 2020 and rises over time at the interest rate of the global economy.

In order to have a more reliable estimate of the resulting temperature pathways, we take advantage of the soft link between WITCH and the MAGICC climate model (Meinshausen et al., 2011). MAGICC receives as input the GHG emission levels obtained by WITCH and provides values of average global temperature increase, radiative forcing and average concentration of $CO_2$ in the atmosphere. MAGICC produces a reference temperature pathway leading to a certain temperature increase in 2100: this baseline corresponds to the median of temperature increase distribution, and represents therefore a scenario with 50% of probability of meeting a certain temperature target. In this study, we adopt a conservative approach: instead of considering the median of the distribution as a baseline, we use as reference pathways where the probability of meeting a certain temperature target exceeds 60%. We name each scenario after the temperature increase resulting from this procedure, i.e. if WITCH emissions pathway output determines a MAGICC 1.5 °C temperature increase with a probability exceeding 60%, the scenario is called 1.5DC.

We consider several scenarios imposing different carbon budgets on overall GHG emissions, reporting commonly used metrics such as the $CO_2$ emissions from 2010 to 2100 from anthropogenic sources, or the mean global temperature increase. As already underlined, we are particularly interested in analyzing scenarios in line with the Paris agreement. We therefore investigate in greater detail two representative scenarios, called 1.5DC and 2DC according to our notation. 1.5DC scenario imposes a $CO_2$ budget from 2010 to 2100 of around 500 $GtCO_2$, with a 60% chance of containing warming below 1.5 °C. In the 2DC scenario, the budget by the end of the century is less than 1200 $GtCO_2$, with a temperature increase in 2100 lower than 2°C with a 60% chance. We also explore larger budgets. More details are shown in Figure 6 in the Appendix.

### 2.4 Robustness checks

Due to the scarce penetration of CCS in the current power fleet and the uncertainty of its future development, we perform a robustness check on cost and performance assumptions. In particular, we focus on six parameters: plant capacity factor, net efficiency, capture rate ratio, investment and operation and maintenance costs and learning rate (for a description of the learning rate, see Section 2.2.2). For the selected scenarios (1.5DC and 2DC), we perform a sensitivity analysis on each of these parameters in turn (ceteris paribus) to test how the model output changes in case of nominal, low and high estimates. This kind of analysis puts in evidence which parameters are most notably affecting outcomes in terms of installed CCS power capacity. A further robustness check addresses the third research question. In particular, once the most significant parameters are identified by the procedure above, we extend the sensitivity analysis to additional scenarios with different carbon budgets. We consider temperature increase targets between 1.5 to 4°C, the latter being consistent to our BAU case. This will reveal whether the response to the parameters variation have different impacts on the outcomes according to the target.

## 3 Results

In the following Section, we introduce the reference results, i.e. those obtained with central values for the parameters of interest, under the 1.5DC and 2DC scenarios. For those same scenarios, we further perform a parametric uncertainty analysis. We conclude extending the study of CCS deployment under a wider range of policies.

### 3.1 CCS in 1.5DC 2DC scenarios

#### 3.1.1 Reference results

Figure 1 shows the amount of electricity generated by CCS plants over time in the 2DC (upper panel) and 1.5DC (lower panel) scenarios. Considering the 2DC case, retrofitting existing coal power plants seems a cost effective choice just after the carbon tax introduction, for a few decades until 2050. A first peak in CCS deployment occurs before 2050, followed by decrease driven by retirement of retrofitted capital and shifting towards renewable energy technologies. Considering the whole available power technologies, CCS plants contribute to 8% of the yearly electricity generation in 2050, compared to around 16% of nuclear and 73% of wind solar and hydroelectric technologies. In the long run, CCS production increases again as investments are focused on Bio CCS, the only technology in the model capable of achieving negative emissions. Concerning non-retrofitted coal fueled options, Oxyfuel seems the most promising technology, despite its high costs and limited learning improvement. Yet its high capture rate compensates for such drawbacks, especially in the context of a rather stringent scenario like the 2DC one.

Looking at the 1.5DC target, we notice an almost total absence of fossil fueled CCS plants, while negative emission technologies gain significant importance growing steadily until 2100. We point out that due to the capture rates lower 100%, both fossil and biomass fueled plants with CCS emit a small amount of carbon into the atmosphere. Considering Bio CCS however, net $CO_2$ emissions are negative. Differently from the

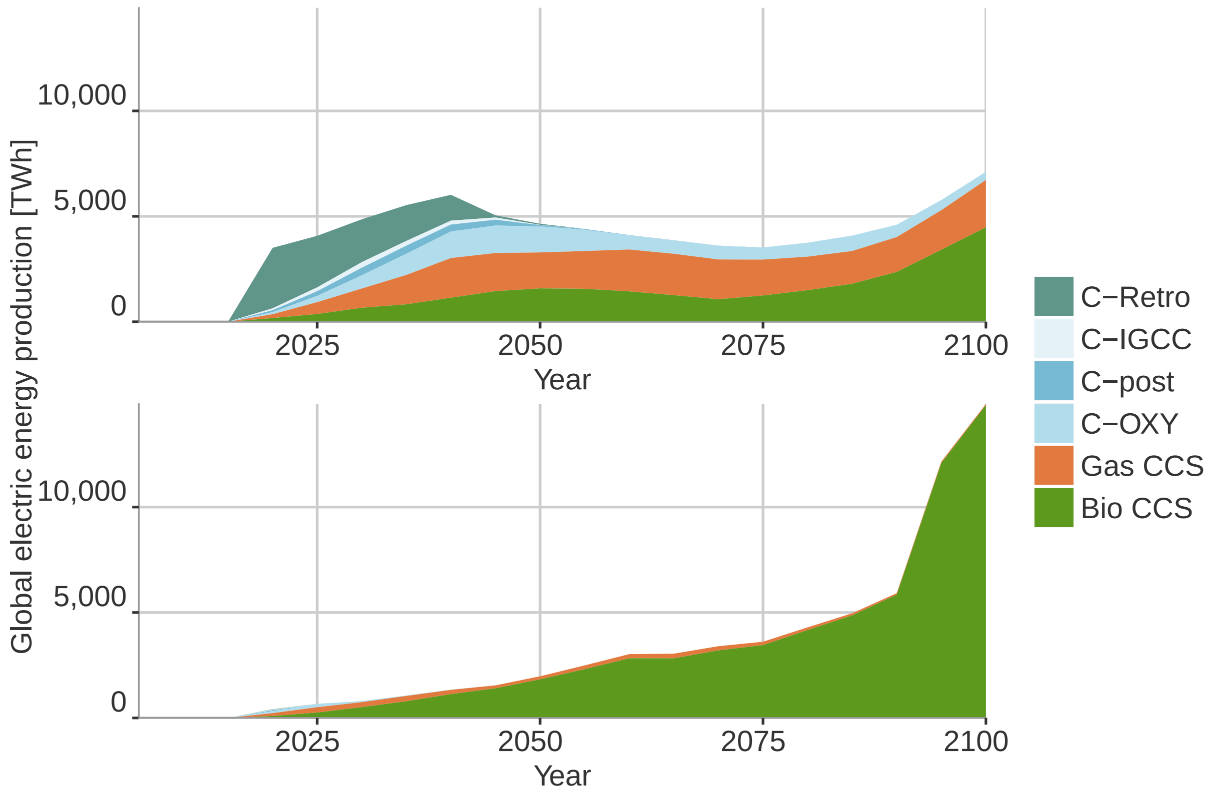


Figure 1: Electricity generation mix by CCS plants over time, for the 2DC(A) and the 1.5DC (B) scenarios

2DC, 1.5DC does not leave room for net emitting technologies, so that Bio CCS, renewables and nuclear are the preferred low carbon alternatives (respectively 4%, 80% and 16% of the electricity generation in 2050). As already specified, the contribution of Bio CCS becomes increasingly relevant approaching 2100, when it accounts alone for 11% of the electricity generation.

#### 3.1.2 Parametric uncertainty

In order to test the model response to different input estimates, we analyzed how the installed capacity of CCS power plants changes in both 2DC and 1.5DC scenarios using minimum and maximum values for the parameters of interest as reported in Tables 2 and 1. Results are shown in Figure 2, where bars represent the percentage variation in cumulative installed capacity of all CCS plant categories with respect to the nominal case, which corresponds to the central a black line. Measures span periods ranging from 2015 to 2050 and from 2015 to 2100. For each parameter, the results corresponding to the maximum value (referred to as "High" in the tables) is marked with a dot.

In general, efficiency, capture rate and investment cost lead to broader deviation in the output, whereas learning rate, capacity factor and O&M cost almost always cause variation lower than 10%.

Among others, the impact of Capture Rate Ratio (CRR) is particularly remarkable considering that this parameter has the narrowest uncertainty gap. Its effect grows over time for the 2DC scenario, producing variation from -15% to +12% in the installed CCS capacity. An opposite trend holds for the 1.5DC scenario, where Bio CCS is extensively used early in the century to achieve global negative emissions, and an extreme realization of CRR levels can either significantly interfere or align with this goal.

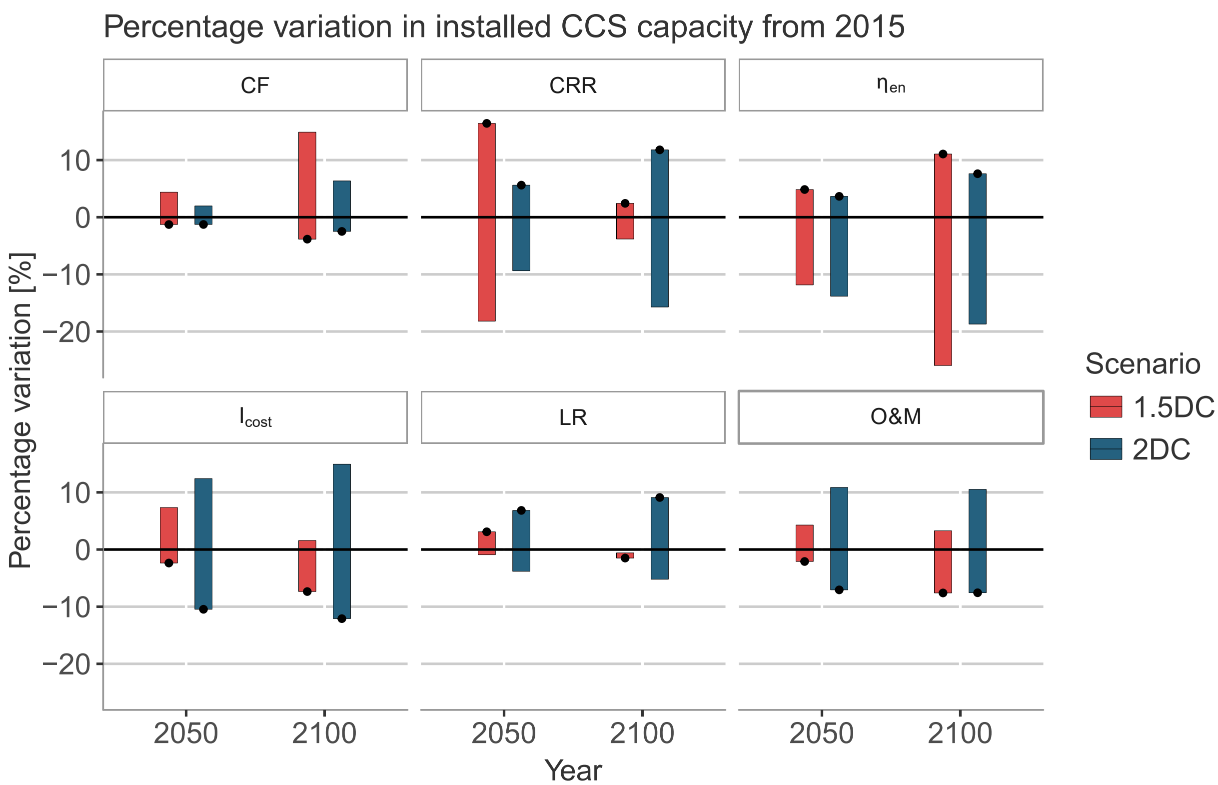


Figure 2: Percentage variation in cumulative installed CCS capacity in response to changes in six performance parameters

The second most influential parameter, at least for the 2DC case, is the investment cost. Higher CCS capital costs make the construction and use of this type of plants less preferable, as other available low-carbon options keep their nominal costs. The response is weaker in the more stringent case. The latter involves higher policy costs, against which capital cost variations impact relatively less. Similar results hold for the other monetary parameter of the group, namely O&M costs, but with a minor response, as installation costs dominate operation costs for these types of plant.

Considering electric efficiency, we notice how a low value is particularly detrimental for CCS development in both climate scenarios, showing a tumble of -26% for 1.5DC in 2100. Efficiency links energy production with plant emissions, so that a lower value implies higher $CO_2$ emissions per unit of energy produced, reducing the mitigation benefits of CCS. On the other hand, higher efficiencies can translate into either keeping the same amount of energy with less associated emission, or producing more energy (and installing more plants) while keeping the same absolute level of emissions. Our model suggests the latter to be the most convenient strategy.

Although the capacity factor establishes the relation between installed capacity and electricity generation (hence the amount of captured emissions), the variation in this parameter does not affect particularly the stock of CCS installed. Either its uncertainty range or its unitary impact is smaller with respect to the others, with the exception of 1.5DC by 2100. In this case, higher stress is put on the yearly generation of large capacities of biomass plants to keep global cumulative emissions below the budget, and the sensitivity is higher.

Effects of alternative assumptions in technological improvement seem also small with respect to the others. Learning rate shares similar trends across time and policy stringency with the other two monetary metrics, as it is intimately related to costs in our implementation. The impact is negligible in the 1.5DC case, where the range of variability does not seem to justify a change in a strategy already with little room for deviations over time.

To sum up, uncertainty in capture rate ratio investment costs drives changes in CCS development the most under a 2°C temperature increase target, while costs becomes less relevant for 1.5 degrees, and the uncertainty on technological parameters affecting emissions are more critical. In this latter case, cost assumptions do matter for the overall policy costs, but not as much in determining the optimal CCS strategy. Comparing 2050 to 2100 metrics, the impact of parameter variability tends to grow over time, with the most notable exception of CRR under 1.5DC.

## 3.2 CCS across different temperature targets

In this section we consider how CCS utilization changes across a continuum of temperature targets, where the most stringent one is the 1.5DC used before, and the most lenient one corresponds to an average temperature increase of around 4°C in 2100, which is the climate outcome of a BAU.

Figure 3 shows the cumulative electric energy produced by CCS plants up to 2100 in our range of scenarios. At the extreme right we have a BAU world, where no CCS generation is needed. Going towards the left, climate stringency increases, and CCS energy production starts to be positive for targets below 3.4°C, corresponding to the introduction of a carbon tax in 2020 of at least 2.7 \$/tCO2. As temperature falls, we notice a monotonic increase in energy production, for each type of CCS plant, down to around 2.5°C. As we go further to the left of the chart, the total energy from CCS lowers, while retrofitting gains importance to the detriment of Bio CCS. In these scenarios, the level of carbon price at the introduction of the tax is high enough to make C-Retro highly competitive, triggering a fast reduction in emission before 2050, with

Bio CCS entering the energy mix later in time (see Figure 1). The abatement provided by retrofitting is enough to reduce the need for Bio CCS negative emissions. For achieving very low targets (T less than 2°C), we see a strong reduction in electricity production from fossil fuel plants, which follows a general reduction in total energy supply. Nonetheless, Bio CCS increases significantly, as it is the only technology that provides negative emissions.

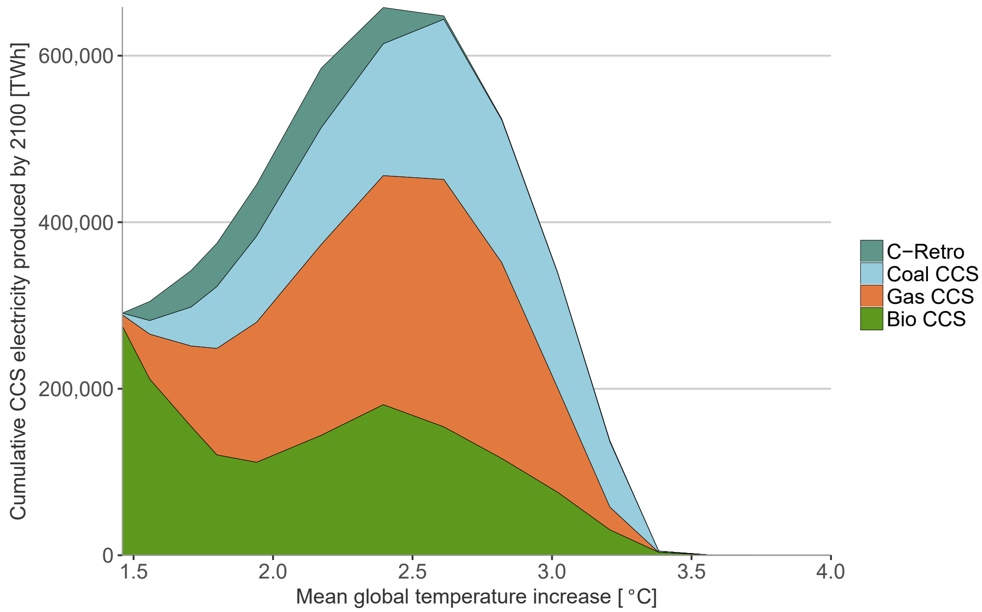


Figure 3: Cumulative electricity generation from CCS plants by 2100 for different temperature increase targets

Thus, fossil fuel fired plants with CCS are optimal for achieving targets of medium to medium-high stringency, around 2.5°C. In order to limit the temperature increase below 1.5°C from pre-industrial level with mitigation measures alone, biomass with CCS is the most economically efficient alternative. In this case, the total amount of CCS electricity production depends mostly on biomass availability and cost.

Figure 4 shows the total CCS installed capacity up to 2100 for different climate scenarios, and how this deviates from the nominal case (black dotted line) when considering either high or low efficiencies and capital costs. First of all, the effect of varying climate policy dominates the effect of alternative parameterizations, which share similar concave curves with a peak around 2.5°C. As confirmed by our previous analysis, the variation in investment costs determines the greatest change in output for medium-stringent scenarios. Moving below 2°C, the outcomes of alternative costs converge, while the impact of efficiency becomes more pronounced.

The right panel of Figure 4 helps to understand how the model optimizes under stringent scenarios. On one hand, cumulative $CO_2$ emissions captured by CCS plants by 2100 across investment assumptions exhibits the same trend of installed capacity (left panel): higher costs means higher capacity installed and higher CO2 captured. The two output variables are proportionally correlated. On the other hand, the stock of captured emissions does not react to variation in efficiency as shown for capacity: the model adjusts the amount of capacity installed so that the same net of ghg emission captured (and emitted) by CCS plants is ensured.

Finally Figure 5 compares the share yearly global electricity generation for CCS and renewable technologies with intermittences (solar and wind). This analysis considers al the different temperature targets examined

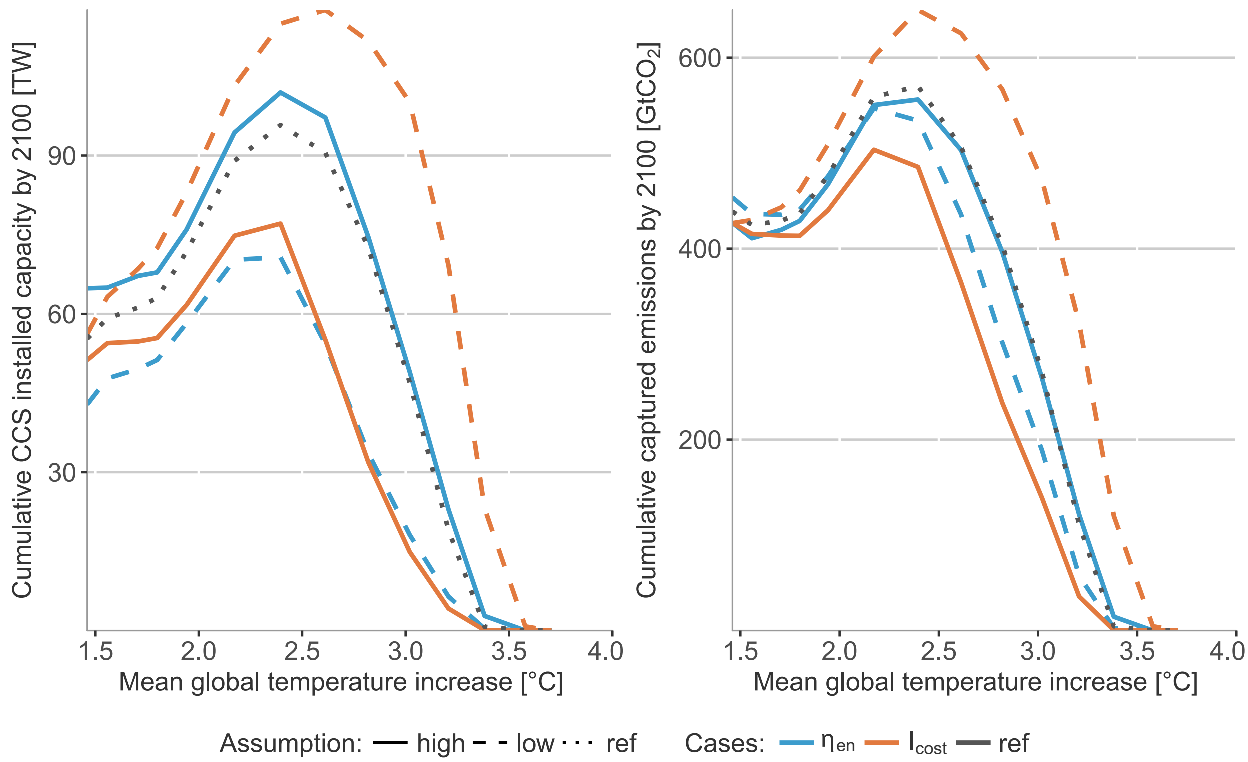


Figure 4: Variation in installed CCS capacity and $CO_2$ captured emissions over temperature increase, in response to changes in efficiencies and investment cost

in Figure 3 and three periods, 2030, 2050 and 2100. First of all, the bell shape behaviour of CCS share across climate policies is verifiable in this chart. By contrary, renewables follow a continuous increase as the temperature target enhances, exhibiting complementarity with CCS options. This trend stand true over time, with renewables becoming predominant in the energy mix as moving to the end of the century. The 2100 curve presents some differences compared to the other two, first of all the maximum share of CCS considering all the scenarios is around 10%, while in 2030 and 2050 it esceeds 15%. Moreover in 2100, in case of very stringent scenarios, Bio-CCS grows significantly, while the share of RES remains around 80%.

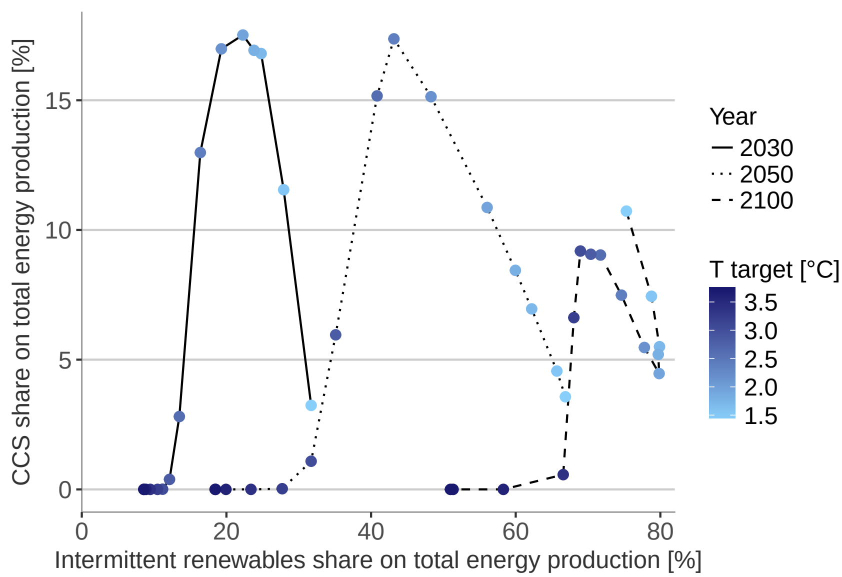


Figure 5: Comparison of CCS and intermittent RES share of yearly total electricity generation, across different climate targets.

# 4 Conclusions

With this study, we aim at contributing to the debate about fossil CCS potential as a low carbon technology in medium- to long-term scenarios, when considering techno-economic and policy uncertainties. The analysis is carried out with the WITCH model and spans a range of temperature targets, with a focus on scenarios consistent with the Paris agreement. Results indicate that the policy stringency could significantly affect the future deployment of fossil CCS, in terms of i) amount installed capacity, ii) technology mix and iii) sensitivity to input data variations. Concerning the impact on installed capacity value, our analysis suggests a concave relation between CCS deployment and policy stringency, with a maximum deployment of CCS for intermediate climate targets such as 2.5°C, rapidly falling for lower as well as higher temperatures. The technological mix is affected both in terms of fuel use and adopted technology options: among fossil-based plants, Oxyfuel appears to be the most promising alternative, and retrofitting an interesting medium-stringency option that might offset Bio CCS deployment, mitigating the existing capacity. Bio CCS remains however the uncontested best option in most stringent scenarios. Finally, sensitivity to plant characteristic parameters is mainly influenced by costs in medium-stringent scenarios while efficiencies prevail at lower carbon budgets. Time seems to be a determinant factor when analyzing the sensitivity, as sensitivity appears to be more significant in the long run. In the medium-stringent scenarios however, as an early strong mitigation is introduced by retrofitting, this dependency appears to be less evident.

# 5 Limitations and further developments

Even though in our understanding this research provides some valuable insights on CCS perspectives, we acknowledge some major limitations.

First of all, even if the modeling phase has implied a careful representation of both capture and storage processes of CCS technologies, in the results we exclusively focus on the capture side, neglecting the significant sensitivity of the output with respect to storage and leakage related parameters. We plan to address this issue in a future research, providing an analysis on storage costs and capacity and leakage values and trends. Other applications of CCS technologies are also overlooked in the current model version, namely carbon capture in industrial applications and CCS in the production chain of secondary energy carries other than electricity (hydrogen and synfuels). These aspects, together with carbon utilization, might be included in the model to improve the current carbon capture and storage representation.

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## Appendix

Resulting temperature increase for the adopted scenario, output of the MAGICC climate model having in input the WITCH GHG emission levels .

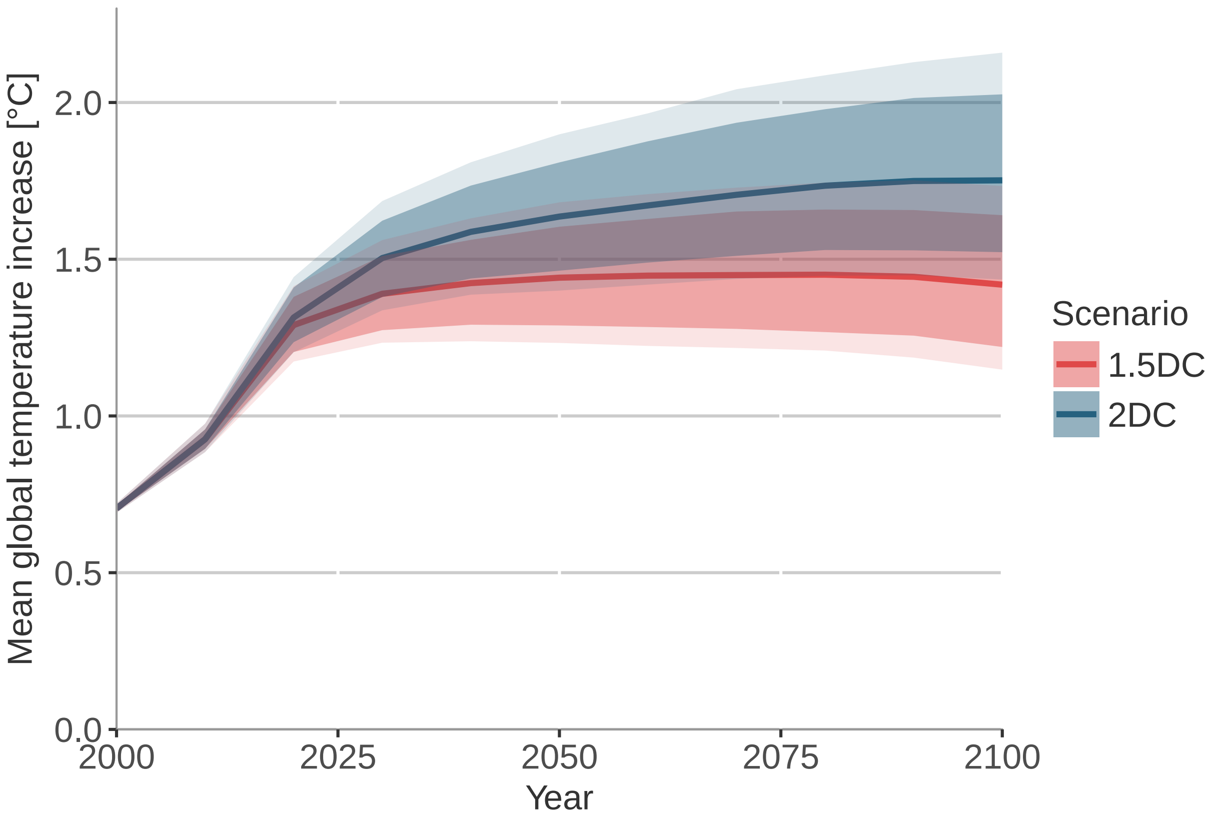


Figure 6: Average temperature increase for 2DC and 1.5DC scenarios with two confidence interval areas. The dark shading denotes the 25%/75% percentile region, and the light shading the 17%/83% percentile region. The lines in the middle represent the median.

### Data from literature review

Table 3: Data gathered during our literature review.

| | Rubin 2015 [43] | | GCCSI 2012 [9] | | Leung 2014 [34] | IEA 2013 [14] | IPCC 2005 [39] | | Koelbl 2016 [32] | | van den Broek 2011 [44] | IEAGHG 2012 [21] | | Catalanotti 2012 [2] | NETL 2011 [5] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | best | [low-high] | best | [low-high] | best | best | best | [low-high] | best | [low-high] | best | best | [low-high] | best | best |
| **$\eta_{el}$[a][%]** | | | | | | | | | | | | | | | |
| C-IGCC | 32.7 | 31.5-34.4 | 31.8 | | 31.5 | 33.1 | 35.5 | 31-40 | 33.7 | 32-35.7 | 38 | 35.1 | | | |
| C-post | 33.7 | 28.7-38.5 | 32.2 | 28.5-35.8 | 34.8 | 30.9 | 33.1 | 30-35 | | | 36 | 35.2 | | | |
| C-OXY | 33.4 | 31.3-35.5 | 32.9 | | 35.4 | 31.9 | 29.6 | 23.4-35.4 | | | | 35.7 | | | |
| NG-CCS | 48.7 | 47-52.1 | | | 44.45 | 48.4 | 48.2 | 47-50 | 46.2 | 43.7-48 | 49 | 51.4 | 51-52 | | |
| **CRR[a][%]** | | | | | | | | | | | | | | | |
| C-IGCC | 89.0 | 86-90 | 90 | | | | 88.2 | 85-91 | | | | | | | |
| C-post | 90.0 | | 90 | 80-90 | | | 88.8 | 85-90 | | | | | | | |
| C-OXY | 92 | 90-98 | 98 | | | | | | | | | | | | |
| NG-CCS | 90 | | | | | | 87.7 | 85-90 | | | | | | | |
| **CF[a][%]** | | | | | | | | | | | | | | | |
| C-IGCC | 80 | | | | | | 77.7 | 65-85 | | | | | | 85 | 80 |
| C-post | 86 | 80-90 | | | | | 75.8 | 65-85 | | | | | | 85 | 85 |
| C-OXY | 86 | 85-90 | | | | | 80.5 | 67-91 | | | | | | | |
| NG-CCS | 84 | 75-90 | | | | | 81.7 | 65-95 | | | | | | 85 | 85 |

[a] $\eta_{el}$ is the net electric plant efficiency on LHV basis; CRR is the carbon capture rate ratio; CF is the capacity factor.

Table 4: IEA GHG capacity divided per region in *low*, *best*, *high* cases in [Gt$CO_2$] (IEAGHG, 2011a).

| | O&G | | | Coal beds | | | Aquifers | | |
|---|---|---|---|---|---|---|---|---|---|
| | low | best | high | low | best | high | low | best | high |
| Africa and ME | 209 | 522 | 1430 | 0 | 8 | 46 | 216 | 588 | 1736 |
| Asia | 36 | 91 | 234 | 0 | 179 | 967 | 53 | 370 | 1614 |
| Oceania | 8 | 20 | 49 | 0 | 11 | 54 | 0 | 2 | 9 |
| Latin America | 29 | 89 | 331 | 0 | 2 | 12 | 33 | 121 | 479 |
| non OECD & ex USSR | 310 | 310 | 310 | 25 | 25 | 25 | 379 | 379 | 379 |
| North america | 22 | 156 | 166 | 157 | 176 | 229 | 3307 | 8001 | 12774 |
| OECD Eu | 19 | 19 | 19 | 1 | 1 | 1 | 82 | 82 | 82 |

Table 5: Percentage of onshore and offshore capacity for storage potential of O&G and Aquifers (IEAGHG, 2009).

| | O&G | | Aquifers | |
|---|---|---|---|---|
| | onshore | offshore | onshore | offshore |
| Canada | 95% | 5% | 80% | 20% |
| USA | 80% | 20% | 75% | 25% |
| Latin America | 40% | 60% | 80% | 20% |
| Eastern Europe | 25% | 75% | 35% | 65% |
| Former SU | 75% | 25% | 20% | 80% |
| Middle East | 75% | 25% | 95% | 5% |
| India | 65% | 35% | 50% | 50% |
| China | 95% | 5% | 80% | 20% |
| Australia and New Zealand | 0% | 100% | 30% | 70% |
| South East Asia | 20% | 80% | 40% | 60% |
| Western Europe | 20% | 80% | 35% | 65% |
| Africa | 35% | 65% | 35% | 65% |

Table 6: Cost of storage for O&G sources and Saline formations [\$/t$CO_2$] (ZEP, 2011a).

| | | | low | high | best |
|---|---|---|---|---|---|
| Onshore | Depleted O&G | reuse | 1.28 | 8.98 | 3.85 |
| | Depleted O&G | no reuse | 1.28 | 12.83 | 5.13 |
| | Saline formations | | 2.57 | 15.39 | 6.41 |
| Offshore | Depleted O&G | reuse | 2.57 | 11.54 | 7.70 |
| | Depleted O&G | no reuse | 3.85 | 17.96 | 12.83 |
| | Saline formations | | 7.70 | 25.65 | 17.96 |

Table 7: Transport costs on a common basis for onshore and offshore pipelines at three different capacities [\$/t$CO_2$/250km] (Rubin et al., 2015). Original sources are reported in the first column: the values have been converted in the same unit of measure by the author to ease the comparison.

| | ONSHORE | | | OFFSHORE | | |
|---|---|---|---|---|---|---|
| [Mt$CO_2$/yr] | 3 | 10 | 30 | 3 | 10 | 30 |
| IPCC | 5.75 | 2.95 | 1.75 | 8.05 | 3.85 | 2.15 |
| ZEP | 10.9 | 3.3 | 0 | 14.8 | 4.8 | |
| USDOE | 4.9 | | 1.7 | | | |

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