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Master of Science in Energy Engineering

Master Thesis

The role of carbon capture and storage for climate stabilization: a numerical assessment

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Abstract

The goal of limiting global temperature increase below 2°C above the pre-industrial level will require overcoming significant economic and technological challenges. According to the Intergovernmental Panel on Climate Change (IPCC), Carbon Capture and Storage (CCS) technologies will play a role of primary importance in this context. However, one of the major issues related to the adoption of CCS technologies is their cost and deployability. Using the World Induced Technical Change Hybrid (WITCH) energy climate model framework, we aim at deepening the understanding of the role of CCS technologies in the electric sector. Our contribution is the following: (1) improve the representation of CCS available technologies in the power sector, with the related performance parameters and costs, (2) model technological improvements (learning by doing) on CCS deployment over time, (3) better represent storage availability, costs of CO_2 storage chain and leakage of stored CO_2 and (4) evaluate CCS deployment in the overall energy mix and associated emissions reduction, in relation with different temperature targets and climate policies. We approach these research questions by providing an extensive literature review, developing analytic expressions, implementing the improvements in the WITCH Integrated Assessment Model (IAM) and by running a set of policy scenario to quantify robust findings. The main conclusions can be summarized as follow. Both investment cost and storage related cost heavily impact on future of CCS deployment: learning by doing, and the cost reduction associated, could therefore influence the role of CCS as a climate change mitigation option. Retrofitting existing coal power plant proves to be a valuable CCS solution to avoid carbon intensive power plants to be shut down, especially in countries like China. Reliability of storage sites appears to be an extremely important parameter in driving CCS deployment: even small yearly leakage rates of CO_2 from underground reservoirs significantly lowers the benefits of CCS. Finally, the importance of CCS as a mitigation option varies significantly with the temperature target. The validity of the results is checked through some sensitivity analyses and a Monte Carlo simulation, whose outcomes provide a robustness check of our research.

Keywords: Carbon Capture and Storage; Climate change mitigation; Integrated Assessment Models; Electricity sector.

Sommario

L'obbiettivo di limitare l'incremento di temperatura sotto la soglia dei 2°C rispetto ai livelli pre-industriali comporterà futuri considerevoli sforzi economici e tecnologici. Secondo l'Intergovernmental Panel on Climate Change (IPCC), le tecnologie con Carbon Capture and Storage (CCS) hanno, in questo contesto, un ruolo di primaria importanza. Tuttavia, una delle maggiori criticità relative all'adozione di queste tecnologie a basse emissioni di carbonio è legata al costo rilevante. Utilizzando il modello World Induced Technical Change Hybrid (WITCH), intendiamo comprendere meglio il ruolo delle tecnologie con CCS nel settore elettrico. Il nostro contributo è il seguente: (1) migliorare la rappresentazione delle tecnologie CCS disponibili nel settore elettrico, con i rispettivi parametri di performance e costi, (2) modellizzare l'influenza dei progressi tecnologici (learning by doing) sullo sviluppo della CCS nel tempo, (3) perfezionare la rappresentazione della disponibilità di siti di stoccaggio, i costi di trasporto e stoccaggio della CO_2 e la possibilità di fuoriuscite di carbonio e (4) valutare lo sviluppo della CCS nel mix energetico e la riduzione di emissioni associate, in relazione a diversi obbiettivi di temperatura e politiche climatiche. Affrontiamo queste domande di ricerca presentando un approfondito studio della letteratura, sviluppando espressioni analitiche poi implementate nell'Integrated Assessment Model (IAM) WITCH e infine, sperimentando diversi scenari di policy per quantificare la solidità dei risultati. Le più importanti conclusioni che otteniamo sono le seguenti. Sia i costi di investimento che i costi relativi allo stoccaggio hanno un forte impatto sul futuro sviluppo della CCS: il learning by doing, e la riduzione di costi associata, potrebbe di conseguenza influenzare l'importanza della CCS tra le opzioni di mitigazione dei cambiamenti climatici. Inoltre, i retrofitting sembra essere una valida strategia per evitare la dismissione degli impianti tradizionali, ad elevate emissioni di carbonio. L'affidabilità dei siti di stoccaggio sembra essere un parametro altrettanto importante: persino ridotti tassi di fuoriuscite di CO_2 dai siti di stoccaggio, riducono in modo significativo i benefici legati alla CCS. Infine, l'importanza della CCS come opzione di mitigazione varia notevolmente a seconda dell'obbiettivo di temperatura. La validità dei risultati è messa in discussione attraverso una analisi di sensitività e una simulazione Monte Carlo, i cui risultati forniscono un test di robustezza della nostra ricerca.

Parole chiave: Carbon Capture and Storage; Mitigazione dei cambiamenti climatici; Integrated Assessment Models; Settore elettrico.

Extended Summary

Scope of the work

The goal of limiting global temperature increase below 2°C above the pre-industrial level will require overcoming significant economic and technological challenges. According to the Intergovernmental Panel on Climate Change (IPCC), Carbon Capture and Storage (CCS) technologies will play a role of primary importance in this context.

However, one of the major issues related to the adoption of CCS technologies is their cost and deployability. Using the World Induced Technical Change Hybrid (WITCH) energy climate model framework, we aim at deepening the understanding of the role of CCS technologies in the electric sector. Our contribution is the following: (1) improve the representation of CCS available technologies in the power sector, with the related performance parameters and costs, (2) model technological improvements (learning by doing) on CCS deployment over time, (3) better represent storage availability, costs of CO_2 storage chain and leakage of stored CO_2 and (4) evaluate CCS deployment in the overall energy mix and associated emissions reduction, in relation with different temperature targets and climate policies.

CCS has already been the central topic of several studies and policy analysis, including a special report of the IPCC. However, the uncertainties surrounding CCS costs and implementability call for additional work. The originality of our work consists in considering several key aspects, such as retrofitting of coal plants, technical improvement, storage and leakage, in an Integrated Assessment Model (IAM) for inter-sectoral analysis. To the best of our knowledge, there are no studies that explicitly considered all these CCS realistic features interdependence in models for climate policy scenarios.

Structure

Considering the chapters division, the work is structured as follows. In Chapter 2, we introduce the tool of analysis we use and present the major features and working principles. Chapter 3 summarizes the technology analysis and presents the most important parameters that influence the future scenarios of CCS. Chapter 4 is related to the future cost trends of CCS, and its consequences on CCS penetration. Chapter 5 focuses on CO_2 storage and transport features. The results on policy implications are reported in Chapter 6, while conclusions are summarized in Chapter 7. Chapters 3, 4 and 5 are organized in this way. The initial part summarizes the related literature and its main conclusions. Follows the description of the associated implementation. The last section of each chapter reports some preliminary results and a robustness check.

Methodology

The main instrument we use to perform our analysis is the WITCH IAM, which is an optimization model addressing the complex and multi-layered issue of global warming.

IAMs schematize and simplify complex dynamics so to ease the interpretation of multiple dependent phenomena, such as the relationship among climate, energy and economy. WITCH is designed to analyze climate change mitigation and adaptation policies, and it is developed at Fondazione Eni Enrico Mattei (FEEM) and Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC). WITCH is a dynamic global model integrating in a single framework the most significant aspects of economy, energy and climate change.

The methodology we adopted for the research can be summarized as follows. We first performed a literature review, gathering and organizing information and data, that we subsequently analyzed and arranged as inputs for our model. We then designed model equations, translating into mathematical terms raw data from the literature. The designed analytical structure is then implemented in GAMS language. We finally tested the implementation through robustness checks (sensitivity analysis and Monte Carlo simulations) and analysed the results, drawing the conclusions.

One of the major challenges encountered during our work concerns the lack of data in literature on breakthrough technologies such as CCS. In particular, data concerning future cost trend and CO_2 storage are subjected to high uncertainty. Another difficult task, frequent in integrated assessment modelling, consists in finding an acceptable compromise between technical details and simplifications that fits to the aggregated model structure. During our research, we tried to focus on the most recent data analyzing the latest technical publications, with the objective to obtain suitable information for the global scale and the regional differentiation of our model.

In order to answer to the formerly introduced questions, we included the following new features into the WITCH model:

(1) Technology options that are likely to be part of the future energy mix (retrofitting existing coal plants, coal oxyfuel, coal and gas post-combustion and IGCC with CCS, biomass CCS), with a focus on the main related parameters (investment and *O&M* costs, capture ratio, plant efficiency, capacity factor).

(2) Technological improvement over time for CCS options (learning by doing), determining all the significant related parameters (learning rate, spillover rate, floor cost).

(3) Bottom-up designed CO_2 storage and transport system, with seven types of CO_2 storage options, each characterized by different costs and average distances from CCS plants, that allows to build regional cost curves and have regional specific results on storage use.

The validity of the results is assessed through some robustness checks, that aim to identify the key parameters affecting the results and to assess the uncertainties due to our assumptions.

As a matter of clarification, we mainly address fossil fuel CCS and marginally deal with biomass CCS. The reason behind this choice is the following: as biomass CCS future looks very uncertain, we believe that this topic should be addressed in a more extensive and independent work.

Main results and conclusions

The main conclusions we achieve are the following. CCS achieves an important role among the climate mitigation options. Emissions captured by CCS in the electricity sector range from 10% to 20% of the overall emissions reduction with respect to the Business As Usual (BAU) scenario, in the investigated cases. Among coal options, the model prizes mostly oxyfuel plants, whose capture rate is high. Gas CCS and biomass CCS have a leading role in the energy mix, as they have low (gas) or even negative (biomass) carbon emissions. CO_2 capture rate, investment costs and electric efficiency are the main drivers for the technology adoption. Also retrofitting existing coal power plants seems to be a convenient strategy for reducing CO_2 emissions, especially in more stringent scenarios. CCS deployment could have also an impact on renewable technologies: the model results show some substitutability between CCS technologies and renewable energy sources.

Technological improvement, and specifically learning by doing, could significantly impact on CCS future perspectives: the trend over time of costs could be crucial for CCS deployment and adoption. Development of a single CCS technology could favour the others to a limited extent (thanks to the spillover effect). However, learning rate has the greatest impact on plants cost reduction. We notice that the share of CCS technologies and the relative importance of a technology with respect to the others is heavily influenced by learning. If at a first approximation coal oxyfuel appeared to be the most convenient coal technology, learning rates could prize other options (i.e. coal IGCC with CCS and coal post-combustion).

Three aspects of the storage and transport chain could mainly impact on CCS deployment: storage costs, transport costs and storage capacity. Among these, high storage costs greatly hinder CCS deployment, as some other low carbon options (i.e. Nuclear, Renewable technologies) could become more competitive from the economic point of view.

Our results indicate that availability of capacity is not a binding constraint, even in the most strict policy scenario, as estimates of available capacity are far higher than the average capacity required by CCS. However, as each storage type is characterized by different storage costs, availability of cheap storage capacity is strongly influencing the results. Therefore, we can conclude that storage costs and available capacity are the features with greatest impact on CCS production.

On the other hand, reliability and safety of storage sites are essential for CCS importance in the energy mix. Including in the simulations leakage of CO_2 from storage sites, we obtain that CO_2 leakage greater than 1%/yr of the stored quantity would strongly hinder CCS deployment. This would lead to a shift towards other technologies, more or less carbon intensive, depending on the policy scenario.

We also report results concerning policy and energy costs. Considering the role of CCS in different policy scenarios, we achieve the following results. We find that the importance of CCS plants is maximum for medium-stringent scenarios, with temperature increase around 2.5°C. To maintain the temperature increase below 2°C, fossil-fuelled plants with CCS lose importance and biomass with CCS becomes the most suitable technology, due to its negative carbon emissions.

Thanks to the robustness analysis we performed, we can state that our conclusions are quite robust, especially concerning results on emissions and economic trends. Moreover, in our work we provide some uncertainty ranges for several parameters related to CCS.

In conclusion, we also report some specific data concerning China, which is likely to be a leading country in CCS development. Retrofitting seems to be a key technology for this country, due to the recent fleet of coal power plants.

In this way, we can value the regional differentiation we introduced in our modelling work, and we give an insight on some results that can lose of significance if aggregated at a global level. Regional results are also useful for assessing the role of CCS in international climate policies, such as those ratified under the Paris climate agreement.

Sommario esteso

L'obbiettivo di limitare l'incremento di temperatura sotto la soglia dei 2°C rispetto ai livelli pre-industriali comporterà considerevoli futuri sforzi economici e tecnologici. Secondo l'Intergovernmental Panel on Climate Change (IPCC), le tecnologie con Carbon Capture and Storage (CCS) hanno in questo contesto un ruolo di primaria importanza. Tuttavia, una delle maggiori criticità relative all'adozione di queste tecnologie a basse emissioni di carbonio è legata alla fattibilità e al costo rilevante di queste tecnologie.

Usando il modello World Induced Technical Change Hybrid (WITCH), intendiamo comprendere meglio il ruolo delle tecnologie con CCS nel settore elettrico. Il nostro contributo è il seguente: (1) migliorare la rappresentazione delle tecnologie CCS disponibili nel settore elettrico, con i rispettivi parametri di performance e costi, (2) modellizzare l'influenza dei progressi tecnologici (learning by doing) sullo sviluppo della CCS nel tempo, (3) perfezionare la rappresentazione della disponibilità di siti di stoccaggio, i costi di trasporto e stoccaggio della CO_2 e la possibilità di fuoriuscite di carbonio e (4) valutare lo sviluppo della CCS nel mix energetico e la riduzione di emissioni associate, in relazione a diversi obbiettivi di temperatura e politiche climatiche.

La CCS è stata già oggetto di molti studi e analisi di policy, incluso uno special report dell'IPCC. L'originalità del nostro lavoro consiste nel considerare vari aspetti chiave, tra cui retrofitting di impianti a carbone, i progressi tecnologici, lo stoccaggio e le fuoriuscite di CO_2, in un Integrated Assessment Model utilizzato per analisi intersettoriali. Infatti, in base alle nostre conoscenze, non ci risultano esservi studi che considerano esplicitamente l'interdipendenza di tutte queste caratteristiche in modelli che studiano politiche sui cambiamenti climatici.

Struttura

Considerando la suddivisione in capitoli, la tesi è strutturata come segue. Nel Capitolo 2 introduciamo il nostro strumento di analisi ed i suoi principi di funzionamento. Il Capitolo 3 presenta le più importanti tecnologie di CCS disponibili e i principali parametri operativi che influenzano gli scenari futuri. Il Capitolo 4 è relativo ai possibili andamenti di costi futuri della CCS e le conseguenze sulla penetrabilità nel mix energetico. Il Capitolo 5 si concentra sul trasporto e lo stoccaggio della CO_2. I risultati sulle implicazioni delle policy sono raccolti nel Capitolo 6, le conclusione sono riassunte nel Capitolo 7. I Capitoli 3, 4 e 5 sono organizzati nel seguente modo. La sezione iniziale riporta la nostra rassegna bibliografica e le principali conclusioni che ne traiamo. Segue la descrizione del lavoro di definizione delle equazioni e di implementazione nel modello. L'ultima sezione di ogni capitolo riporta i risultati preliminari e delle analisi sull'incertezza dei risultati.

Metodologia

Lo strumento principale che usiamo per le nostre analisi è l'Integrated Assessment Model WITCH, un modello di ottimizzazione che affronta il complesso e stratificato tema del riscaldamento globale. Gli IAM schematizzano e semplificano dinamiche complesse così da facilitare l'interpretazione di fenomeni dipendenti da multiple forze, come le relazioni tra clima, energia ed economia. WITCH è stato progettato per analizzare le politiche di mitigazione e di adattamento al riscaldamento globale, ed è stato sviluppato dalla Fondazione Eni Enrico Mattei (FEEM) e dal Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC). WITCH è un modello dinamico globale che integra in una unica struttura gli aspetti più significativi dell'economia, dell'energia e del cambiamento climatico.

La metodologia che adottiamo per la nostra ricerca può essere riassunta in questo modo. Per prima cosa, abbiamo effettuato uno studio della letteratura, raccogliendo e riorganizzando concetti e dati, che abbiamo in seguito analizzato e inserito come input nel nostro modello. Abbiamo successivamente ideato le equazioni del modello, traducendo in termini matematici i dati grezzi ottenuti dalla letteratura. La struttura analitica è stata poi implementata in GAMS. Abbiamo infine testato l'implementazione con dei test di robustezza (analisi di sensitività e simulazioni Monte Carlo) e analizzato i risultati, traendo le conclusioni.

Uno dei maggiori ostacoli incontrati durante il nostro lavoro riguarda la mancanza di dati in letteratura su una tecnologia all'avanguardia come la CCS. In particolare, i dati riguardanti i futuri andamenti di costi e lo stoccaggio della CO_2 sono soggetti a grande incertezza. Un altro difficile compito, frequente nell'ambito degli IAM, è stato trovare un compromesso accettabile tra dettagli tecnici e semplificazioni che si adatti alla struttura aggregata del modello.

Nel corso della nostra ricerca, abbiamo cercato di concentrarci sui dati più recenti analizzando report tecnici, con l'obbiettivo di ottenere informazioni adatte alla scala globale e alla differenziazione regionale del nostro modello.

Per rispondere alle domande precedentemente introdotte, abbiamo incluso i seguenti nuovi aspetti in WITCH:

(1) Opzioni tecnologiche che probabilmente faranno parte del futuro mix energetico (retrofitting degli impianti a carbone esistenti, impianti oxyfuel a carbone, post-combustione e IGCC con CCS di gas e carbone, CCS a biomassa), con particolare attenzione ai parametri relativi più importanti (costi di investimento e di $O\&M$, efficienza di cattura e di impianto, capacity factor).

(2) Progresso tecnologico nel tempo per le opzioni CCS (learning by doing), determinando tutti i significativi parametri relativi (learning rate, coefficienti di spillover, floor cost).

(3) Sistema di trasporto e stoccaggio della CO_2 implementato con logica bottom-up, con sette opzioni di stoccaggio della CO_2, ognuna caratterizzata da differenti costi e distanze medie dagli impianti CCS che consentono di costruire curve regionali di costo e di ottenere risultati regionalizzati sull'uso dei siti.

La validità dei risultati è messa in discussione attraverso alcuni test di robustezza, con lo scopo di identificare i parametri chiave che più influenzano i risultati e di stimare le incertezze dovute alle nostre assunzioni.

Chiariamo che ci occuperemo maggiormente di CCS con combustibili fossili e solo marginalmente di CCS con biomassa. La ragione di questa scelta è la seguente: dal momento che il futuro della CCS con biomassa appare molto incerto, siamo convinti che questo tema dovrebbe essere trattato in modo più esteso e in un lavoro indipendente.

Risultati principali e conclusioni

Le più importanti conclusioni che abbiamo tratto sono le seguenti. La CCS ha un importante ruolo tra le opzioni di mitigazione dei cambiamenti climatici. Le emissioni catturate dalla CCS nel settore elettrico vanno dal 10% al 20% della riduzione di emissioni complessiva rispetto al caso Business As Usual (BAU), nei casi da noi studiati.

Tra le tecnologie a carbone, il modello premia maggiormente gli impianti oxyfuel, che hanno alto coefficiente di cattura. CCS con gas e con biomassa hanno un ruolo centrale nel mix energetico, dal momento che hanno emissioni basse (gas) o addirittura negative (biomassa).

L'efficienza di cattura della CO_2, i costi di investimento e l'efficienza di impianto sono i fattori più importanti che influenzano l'adozione delle tecnologie.

Anche il retrofitting ti impianti a carbone esistenti sembra essere una strategia conveniente per ridurre le emissioni di CO_2, specialmente negli scenari stringenti.

Lo sviluppo della CCS potrebbe anche avere un impatto sulle tecnologie rinnovabili: i risultati del modello mostrano una certa sostituibilità tra tecnologie CCS e fonti di energia rinnovabile.

Il progresso tecnologico, e nello specifico il learning by doing, potrebbe avere un impatto significativo sulle prospettive future della CCS: il trend nel tempo dei costi potrebbe essere cruciale per lo sviluppo e l'adozione della CCS.

Lo sviluppo di una singola tecnologia CCS potrebbe favorire le altre in misura limitata (grazie agli spillover). Tuttavia, il learning rate ha una influenza maggiore sulla riduzione di costi di impianto. Notiamo che lo share di tecnologie CCS e la loro importanza relativa rispetto alle altre è fortemente influenzato dal learining. Se a una prima approssimazione gli impianti oxyfuel a carbone sembravano essere la tecnologia a carbone più conveniente, i rate di learning potrebbero favorire altre opzioni (IGCC e post-combustione con CCS a carbone).

Tre aspetti della catena di trasporto e stoccaggio potrebbero influenzare maggiormente lo sviluppo della CCS: costi di trasporto, costi di stoccaggio e capacità dei siti di stoccaggio. Tra questi elementi, alti costi di stoccaggio ostacolano maggiormente l'adozione di CCS, dal momento che altre opzioni a basse emissioni di carbonio (nucleare, rinnovabili) potrebbero risultare più competitive dal punto di vista economico.

Possiamo affermare che la disponibilità di capacità di stoccaggio non rappresenta un vincolo, anche negli scenari più stringenti, dal momento che le stime di capacità disponibile sono molto maggiore della capacità media richiesta dalla CCS. Tuttavia, dal momento che ogni tipologia di sito è caratterizzata da costi diversi, la disponibilità di siti economici influenza fortemente i risultati. Possiamo concludere di conseguenza che i costi di stoccaggio e la capacità disponibile sono le caratteristiche che influenzano di più la produzione degli impianti a CCS.

D'altro canto, l'affidabilità e la sicurezza dei siti di stoccaggio sono essenziali per l'importanza della CCS nel mix energetico. Se includiamo nelle simulazioni le fuoriuscite di CO_2 dai siti di stoccaggio, otteniamo che valori maggiori dell'1% annuo della quantità stoccata possono fortemente ostacolare lo sviluppo della CCS. Questo significherebbe uno spostamento su altri tipi di tecnologie, ad alta o bassa intensità di carbonio, a seconda dello scenario.

Considerando i costi legati alla policy, quelli dell'energia e il ruolo della CCS in diversi scenario climatici, otteniamo i seguenti risultati. L'importanza degli impianti CCS è massima per scenari mediamente stringenti, con incremento di temperatura attorno a 2.5°C. Invece, per mantenere l'incremento di temperatura al di sotto dei 2°C, gli impianti a combustibili fossili con CCS perdono importanza e la CCS con biomassa diventa la tecnologia più adatta, grazie alle sue emissioni negative.

Grazie ai test di robustezza che abbiamo effettuato, possiamo affermare che le nostre conclusioni sono piuttosto robuste, specialmente per quanto riguarda i risultati dei trend economici e di emissioni. In più, nel nostro lavoro includiamo alcuni range di incertezza per diversi parametri relativi alla CCS.

In conclusione, riportiamo anche dei dati specifici sulla Cina, che è un paese che verosimilmente avrà un ruolo centrale nello sviluppo della CCS. Il retrofitting sembra essere una tecnologia chiave per questo paese, grazie alla quantità di recenti impianti a carbone.

In questo modo, possiamo valorizzare la differenziazione regionale che abbiamo introdotto nel nostro lavoro di modellazione, e dare un'idea di quei risultati che perdono di significato se aggregati a valori globali. I risultati regionalizzati sono anche utili per valutare il ruolo della CCS nelle policy internazionali sul clima, come quelle ratificate con l'accordo di Parigi.

Contents

Chapter 1

Introduction and motivations

1.1 Climate change framework

Nowadays, the link between climate warming and anthropogenic Greenhouse Gases (GHG) is widely recognised [32, 46, 63]. There is little doubt that the increasing trend in average atmospheric temperature and anthropogenic GHG levels are correlated (see Figure 1.1). The increasing awareness of the possible irreversible damages of global warming pushed, especially in recent years, both public opinion and governments towards the adoption of temperature increase countermeasures. This path culminated in 2015 with the COP21, that lead to the formulation of the Paris agreement, setting ambitious targets of emissions reduction. The COP21 marked a very important change in the shared concern about climate change possible future damages and the design of possible mitigation and adaptation policies. A year later, the COP22 in Marrakesh consolidated the determination of countries in ratifying the Intended Nationally Determined Contributions (INDC) developed for the COP21. However, the path towards the control of temperature increase is anything but straightforward. First of all, the adoption of climate policies is correlated to both technological and economic challenges [50]: at the current state of the art, energy options do not allow a systematic shift towards low carbon alternatives without strong increase in expenses [65]. The future benefits linked to a limited temperature increase imply, therefore, higher present costs. Moreover, according to the scientific community, there is not a unique solution for contrasting global warming, rather a system of consistent energy measures, which combined effect would limit the temperature increase [32]. This many-sided portfolio should take into account the different technology dimensions (among the others, renewables, nuclear, Carbon Capture and Storage (CCS), efficiency increase and energy savings, switch towards less carbon intensive fuels). As a final remark, it is worth underlining that the different economic sectors (mainly heat and power, transportation, agriculture, industry, building) weigh differently on the global Carbon Dioxide (CO_2) emission level, and need therefore, focused and coherent policies aiming at meeting the temperature target.

1.1.1 Electric sector

The electric sector is responsible for a large share of the global CO_2 emissions. In particular, electricity, together with heat production, was in 2013 responsible for more than 49% of CO_2 emissions (source: World Bank [79]). The carbon intensity of power system is strictly related to the fuel mix and the penetrability of low carbon technologies (Renewable Energy Sources (RES), nuclear, CCS): despite the recent efforts in reducing carbon emissions, the current global energy mix is in fact heavily based on fossil fuels. Coal, the most carbon intensive fossil fuel (with more than 0.35 $kgCO_2$ per kWh) accounts today for about 40% of the global electric energy production, and together with oil and gas their

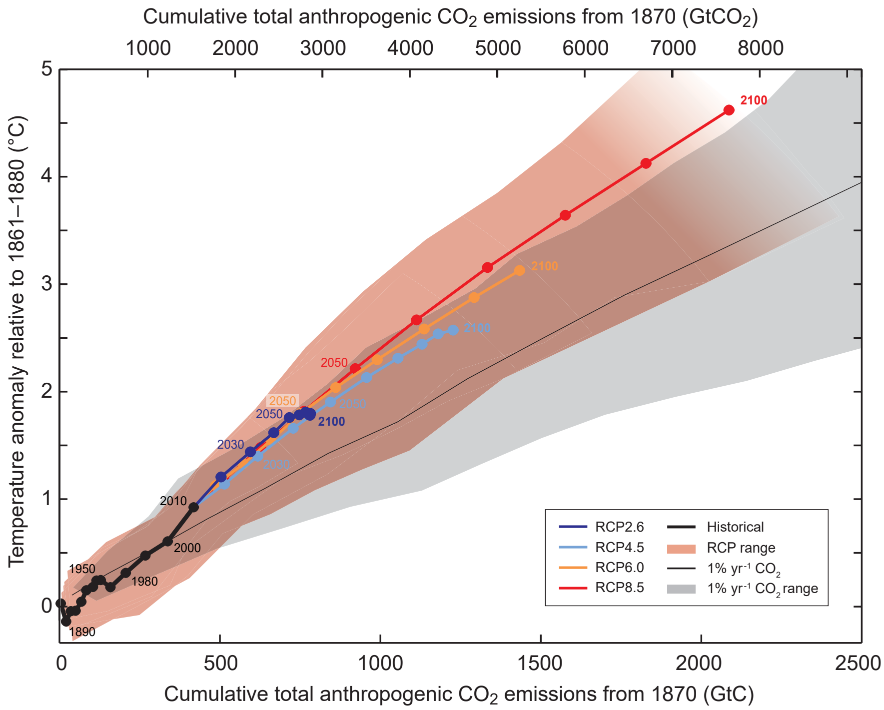

Figure 1.1. Global mean surface temperature increase as a function of cumulative total global CO_2 emissions. Besides the historical emissions, the Representative Concentration Pathways (RCPs) are reported: RCPs are GHG concentration possible future trajectories adopted by the Intergovernmental Panel on Climate Change (IPCC). The acronyms are related to the possible values of Radiative Forcing (RF) in 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2).
Source: IPCC 2013 [49]

share reaches more than 65%. Our society strongly depends on fossil fuels and it seems unlikely that this dependency, or the energy demand, will sharply decrease in the short term. The energy mix is likely going to be dominated by fossil fuels, at least in the next few decades: CCS could be therefore a useful option to facilitate the stabilization targets [63]. Many sources agree that fossil CCS could represent a valuable energy alternative, being low carbon intensive but fossil fuel based [32]. According to the International Energy Agengy (IEA) [33], CCS potential could have an important influence on the electricity carbon intensity. Especially in the short term, CCS might thus represent a considerable share of emission reduction in the energy field [13, 21]. The IPCC special report on CCS, 2005 [63] provides some illustrative examples of CCS possible role as a carbon mitigation option in the energy mix (see Figure 1.2). The importance of CCS is evident both from the energy mix (reaching almost 100 $EJyr^{-1}$ in both cases) and also from the avoided emission point of view (CCS seems to be responsible for almost one third of emissions reduction in each forecast).

However, the future of CCS is still highly uncertain, due to the early stage of technology development and the lack of studies aiming at assessing the potential health and environmental impact of CO_2 leakage [32].

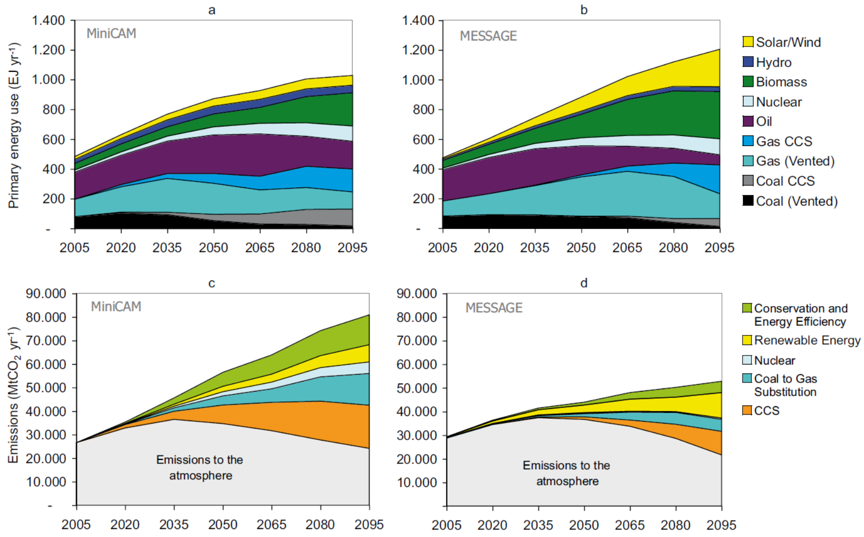

Figure 1.2.
Primary energy use according to two Integrated Assessment Models, MESSAGE and MiniCAM, adopting the same assumptions for the main emissions drivers, in a single scenario.
Source: IPPC special report on CCS [63]

1.1.2 Current CCS overview

CCS could be considered a relatively young technology. Even though CCS applications have been operating since many years, this technology has been mainly applied on a small scale. Today, only a few large-scale projects are in operation, under construction or planned: the Global CCS Institute accounts for 38 projects in 2016 [21]. As stated in the *Global Status of CCS: 2016* report, at the beginning of 2016 there were 15 large-scale CCS projects in operation around the world, with a CO_2 capture capacity close to 30 million tonnes per annum [$MtCO_2$/yr]. Considering the plants that became operational in 2016 and early 2017, plus those expected to become online during this year, the number of large-scale operational CCS projects is expected to increase to 21 by the end of 2017, with a CO_2 capture capacity of approximately 40 [$MtCO_2$/yr].

Figure 1.3 and 1.4 show what was the existing capacity of CCS plants in 2015 and information on the planned projects up to 2020. At a first sight, it clearly appears that most of the operating plants have been realized for the non-electric sector, mostly in applications related to the Oil&Gas industry. However, from 2015 onward, several projects are planned to become operative even in the power generation sector. In Figure 1.4 we can see which countries invested in CCS application in past and future projects. US and Canada are the countries where largest projects came in operation. China, Europe and few other countries are also planning to install considerable capacity.

This capacity appears to be still too low in order to consistently contribute to reducing global carbon emissions, especially compared to the traditional plants that CCS could potentially substitute.

1.2 Main questions and methodology

Given the complexity of assessing CCS role in the climate change scenario and the multiple possible research themes, in this thesis work we only address CCS applications in

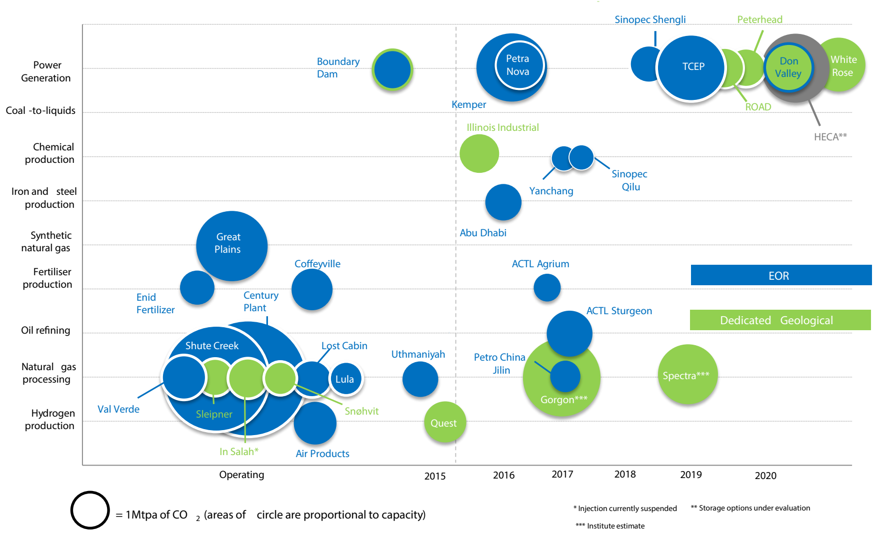

Figure 1.3. Actual and expected operation dates for large-scale CCS projects in the Operate, Execute and Define stages by industry and storage type.
Source: The Global Status of CCS 2015, Global CCS Institute [20]

the power sector. We bring particular attention to the possible future consequences of the adoption of this energy alternative, and we aim at assessing CCS future performances and importance within the climate change context. The main questions that lead our research are the following:

(1) Which are CCS available technologies in the power sector? What is the role of performance parameters and costs in assessing plants competitiveness in scenarios with carbon price?

(2) What is the influence of technological improvements (learning by doing) on CCS deployment over time?

(3) How do storage availability, costs of CO_2 storage chain and leakage occurrences impact the CCS potential?

(4) What is CCS deployment impact on the overall energy mix and the associated emissions reduction, in relation with different temperature targets and climate policies?

We are aware that CCS deployment is going to have an impact on the overall electric mix: therefore, as further developments, we test the links between CCS technologies and intermittent RES (solar and wind), and between CCS and traditional fossil fuel plants. We conclude with a case study focused on China, showing in detail the results we obtain for this region, which is likely to be a leading country for CCS deployment.

1.2.1 Research methodology

The main instrument we use for to perform our analysis is the World Induced Technical Change Hybrid (WITCH) model, which is an optimization Integrated Assessment Model (IAM) addressing the complex and multi-layered issue of global warming. IAMs schematize and simplify complex dynamics so to ease the interpretation of multiple dependent phenomena, such as the relationship among climate, energy and economy. WITCH is

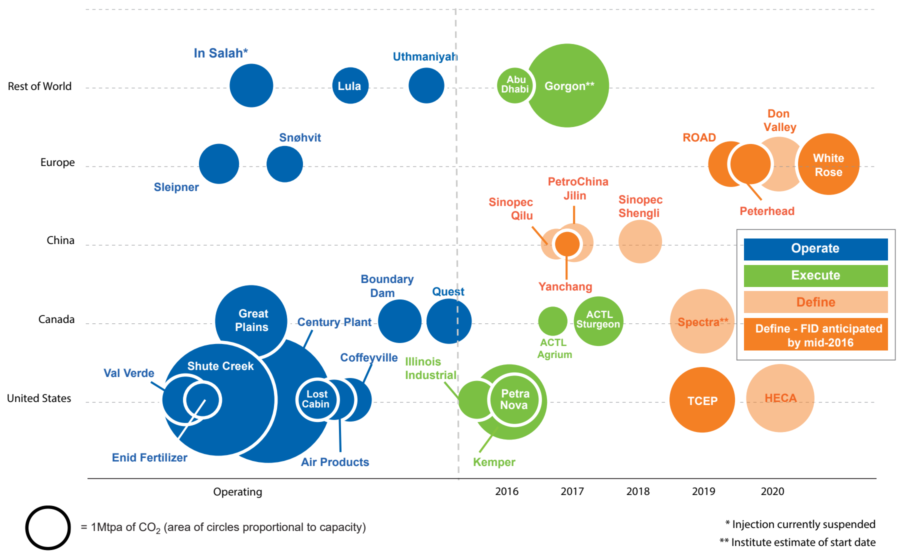

Figure 1.4. Actual and expected operation dates for large-scale CCS projects in the Operate, Execute and Define stages by region and project lifecycle stage.
Source: *The Global Status of CCS 2015*, Global CCS Institute [20]

designed to analyze climate change mitigation and adaptation policies, integrating in a single framework the most significant aspects of economy, energy and climate change. In the next chapter we will better describe the model and its main working principles.

One of the major challenges encountered during our work concerns the lack of data in literature about breakthrough technologies such as CCS. In particular, data concerning future cost trend and CO_2 storage are subjected to high uncertainty. Another difficult task, frequent in integrated assessment modelling, consists in finding an acceptable compromise between technical details and simplifications that fits to the aggregated model structure. During our research, we tried to focus on the most recent data analyzing the latest technical publications, with the objective to obtain suitable information for the global scale and the regional differentiation of our model.

The whole work we did can be structured as follows:

(1) Literature review: gathering and organization of information and data, analyzed and arranged to be used as input for the implementation.

(2) Design of model equations: raw data and concepts from literature are translated into mathematical terms and a mathematical structure is developed.

(3) Implementation in analytical form of the equations and translation in General Algebraic Modeling System (GAMS) language. This phase required particular attention as our final implementation of the CCS section, after the supervision of other researchers, is going to be used in the official version of the WITCH model.

(4) Robustness check of the results: sensitivity analysis in two stages, first with a detailed analysis on all possible *low*, *best*, *high* values for every parameter we introduce followed by a Monte Carlo analysis on the most important features, assuming probability distributions.

(5) Analysis and discussion of the results.

1.2.2 Thesis structure

Considering the chapters division, we followed this scheme. In Chapter 2, we introduce the tool of analysis we use and present the major features of its structure. The following three chapters are the core of the thesis. Chapter 3 summarizes the technology analysis and presents the most important parameters that influence the future scenarios of CCS. Chapter 4 is related to the future cost trends of CCS, and its consequences on CCS penetrability. Chapter 5 focuses on CO_2 storage and transport features. The results are reported in Chapter 6, while conclusions are summarized in Chapter 7. Each core chapter is organized in this way. The initial part summarizes the related literature and its main conclusions. Follows the description of the associated implementation. The last section of each chapter reports some preliminary results and a robustness check.

Chapter 2

Model description

In the previous chapter, we brought the attention on the potential of CCS technologies in limiting the global temperature increase. We also underlined the complexity of the climate related issues and the uncertainty behind the forecast of the future impact of energy choices. A major issue when considering this kind of long term forecasts is the uncertainty behind the governing dynamics of the climate, energy and economy interrelationships. Moreover, we underline also the possible critical arising of nonlinear dynamics in the ecosystem and positive or negative feedbacks [4]. A powerful tool to address this complex and multi-layered problem is represented by IAM. IAMs schematize and simplify the complex dynamics so to ease the interpretation of multiple dependent phenomena. In the following sections, we briefly describe the main features of IAM in general and we then introduce the WITCH IAM that we used for this thesis work.

2.1 IAM main features

Integrated assessment is, by definition, the process of combination and synthesis of information deriving from different research fields [45]. Focusing on climate change, the different disciplines that are involved in the process are mainly social sciences (such as economics and political science) and earth sciences (especially atmospheric chemistry and biochemistry): the aim of the study is the analysis of GHG emissions drivers and their consequences on human life and environment. IAM are mathematical computer models that try to portray the observed reality through assumptions and mathematical expressions, so to recreate the interaction among the different observed factors and obtain forecasts of the future system behavior. This characteristic makes IAMs very important tools for policy design because they provide a wide range of information in a synthetic way, avoiding the typical fragmentation of sectoral expert advices.

Generally speaking, IAM can be divided into top-down and bottom-up models [51], depending on the adopted strategy to analyze the linkages among the economic sector, the energy sector and emissions. Top-down approach starts from some aggregated variables (such as the discounted utility and the damage variable) which already synthesize various aspect of reality and optimize them. On the contrary, bottom-up approach requires a precise description of technology characteristics, and once the technological options are settled, it is possible to determine economical and environmental consequences.

We want to stress that IAM output results are not to be considered as exact prediction of the future or solution of complex problems. Intrinsic characteristic of predicting climate change is the presence of three important sources of uncertainty [26, 49]:

1. Internal climate system variability: the climate system is subjected to internally induced changes due to the interaction among the different climate components (i.e.

the El Niño-Southern Oscillation (ENSO), deriving from the interaction between atmosphere and ocean).

2. Model uncertainty: includes uncertainties introduced by errors in the model representation of the climate system and the response to external forcing.

3. Scenario uncertainty: the limited knowledge of future emissions pathways and forcing trajectories impacts on the reliability of models predictions.

2.2 The WITCH IAM

Among the existing IAMs, for the purposes of this thesis work we use the WITCH model. WITCH is an IAM developed to analyze climate change mitigation and adaptation policies, designed at Fondazione Eni Enrico Mattei (FEEM) and Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC). WITCH is a dynamic global model integrating in a single framework the most significant aspects of economy, energy and climate change. WITCH can be considered a top-down model, but the design of energy sector is bottom-up. Projections range from 2005 (the base year) up to 2150, with time steps of 5 years. The world is represented through a set of 13 (or 14) regions, which regroup countries according to the economic situation, the structure of energy sector and geographical similarities (see Figure 2.1). Regions can cooperate among each other creating coalitions or behave independently: the model maximises the welfare of each region or coalition simultaneously and strategically.

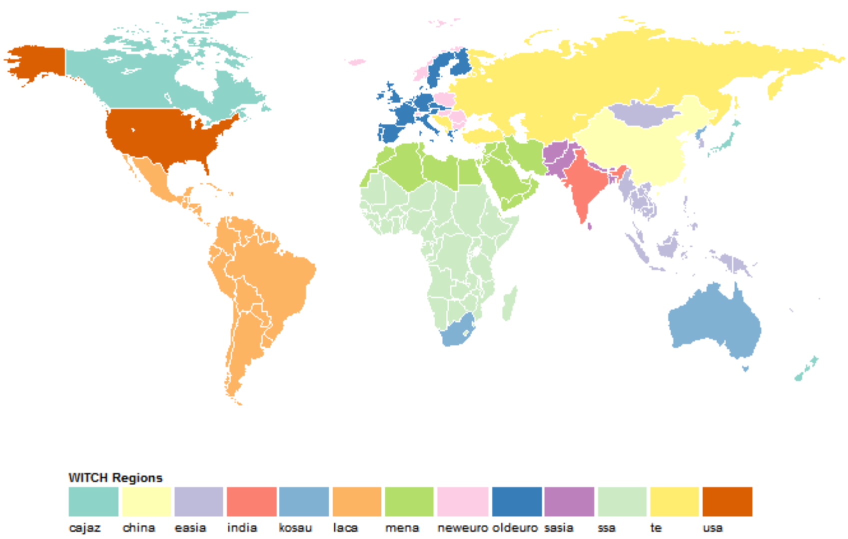

Figure 2.1. WITCH regions.

In this work, we refer to regions with the letter n and to time steps with the letter t. In the following paragraphs, we define the most important features of the model. The model structure is not the main subject of this work: for a comprehensive description of WITCH, please refer to the model documentation [78]. We provide a brief description of the model structure and main equations in Sections **??** and A.2 of Appendix A.

2.2.1 WITCH main sectors description

Economy

The objective function of the model is the maximization of the sum over time of regional discounted utility. The main component of the utility function is per-capita consumption of a representative agent per region. This term includes the net output and some relevant investment costs (for example, investments in energy technology, in the extraction sector, in infrastructures for the electric grid). The net output is a final good derived from capital and labour (linked with a Cobb-Douglas function) combined with energy services through a Constant Elasticity of Substitution (CES) function. As the base year of the model is 2005, in this thesis work we refer to 2005 USD when we represent economic values. In Appendix A we provide a more detailed description of these features.

Emissions and Climate Change

GHG emissions are responsible for climate change, and can be generated by energy sector, land use, transportation and industry. GHG emissions include CO_2, Nitrous Oxide (N_2O), Carbon Dioxide (CH_4) and F-gases (targets of Kyoto Protocol). The estimates of agriculture, forestry and bioenergy emissions are provided in input from Global Biosphere Management Model (GLOBIOM), a land-use model soft-linked with WITCH. Concerning the link between temperature and atmospheric concentrations, WITCH can internally convert regional emissions or can alternatively be soft-linked with a climate model, Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC).

Energy sector

WITCH includes a detailed system of energy technologies, describing both the energy resources availability and the electricity generation. The energy sector is modelled with a bottom-up approach and provides a detailed description of the different technology options. Each technology facility can participate to the energy mix production via a CES structure implementation. A CES structure is a production function that aggregates factors at different levels and represents the possibility to switch between alternatives with elasticities of substitution ρ.

Both the electric and the non-electric sector (comprising transportation, industry, residential and commercial energy use) are accounted into energy demand and supply. As the energy sector is hard-linked with the economic sector, the optimal solution pursued by the model involves management of energy investments and choices of technology adoptions. This sector has a bottom-up design, with a detailed description of the different technologies performances, primary fuel requirements and pollutant emissions.

As the modelled scenarios cover a wide time range (i.e. 50 or 100 years), energy technologies are supposed to improve over time. In Table 2.1, a representation of the possible technological and socio-economic improvements is provided.

2.2.2 WITCH initial setup

WITCH model has several set-up options, depending on the modelling purpose. The main options can be referred to the following topics:

1. Regional subdivision and cooperation in coalitions
2. Climate policies dimension

Table 2.1
Description of WITCH possible technical improvements

Description of the parameter	Quantities subjected to the technological change
LbD, Learning by doing: endogenous improvement, accumulation of experience leading to a cost reduction (investment costs decrease with the progressive technology deployment and the global cumulative capacity increase)	Advanced biofuels, solar, wind
LbR, Learning by researching: endogenous improvement, accumulation of knowledge, produced by investments in research and development	Advanced biofuels, general energy efficiency, batteries
Performances improvements, exogenously determined, related to a better employment of resources or a reduction in consumption due to more efficient production methods	Plant efficiency, productivity of energy services, capital and labour productivity

3. Socio-economic assumptions

Due to the large number of possible set-up options, in Table 2.2 we synthesize the selected options for each topic. Considering the socio-economic assumptions, an important setting concerns the selection of the Shared Socio-economic Pathways (SSPs). SSPs can be described as narratives or story-lines qualitatively representing the possible relationships among future socio-economic situation and policy options, leading to different climate change scenarios [57].

2.2.3 Low carbon target scenarios

We consider two possible policy instruments to enforce low carbon scenarios: the first process imposes an initial global carbon tax equal to 30 $/t$CO_{2,eq}$, that exponentially grows over time, and the model finds the optimal economic solution; the second imposes a temperature or carbon budget target that must be achieved following the most convenient solution and calculate what is the carbon price that allows reaching the target. In both cases, the default year of carbon tax introduction is 2020. If we change some important setting on energy technologies (i.e efficiency of power plants) keeping the same policy options, the first type of scenario will always have the same carbon price trend, but will reach different emission levels. On the contrary, the target scenarios will always achieve similar emission levels (or average temperature), with changes on the resulting carbon price.

The relationship between GHG concentration in the atmosphere and temperature increase has been an important topic of discussion concerning climate change. In fact, it strongly affects the results of energy-climate models as IAMs. It is not the purpose of our thesis to study this relationship, but it is important to define common references so to avoid any misunderstanding. In this framework, the IPCC, 2007 report shows the probability of limiting the temperature increase from pre-industrial levels in function of

Table 2.2
Description of WITCH initial settings

Parameter	Set-up	Description
Regions	WITCH13	`cajaz` (Canada, Japan, New Zeland), `china` (China and Taiwan), `easia` (South East Asia, including Indonesia), `india` (India), `kosau` (South Korea, South Africa, Australia), `laca` (Latin America, Mexico and Caribbean), `mena` (Middle East and North Africa), `neweuro` (EU new countries), `oldeuro` (EU 15 countries + EFTA), `sasia` (South Asia (excluding India)), `ssa` (Sub Saharan Africa), `te`(Non-EU Eastern European countries, including Russia), `usa` (United States of America)
SSPs	SSP2	Also called Middle of the Road, it is characterized by a continuity with the recent global trend, with some achievements in the Sustainable Development Goals (SDGs) but also some inequalities within contries and a fossil fuel share remaining relevant in the energy mix
Policy	`BAU`	There are no carbon related policies, energy needs increase in time due to an increase in population and the Gross Domestic Product (GDP) is not reduced by carbon taxes
	`ctax`	The carbon tax starts in 2020 from 30 \$ per tonCO_2 and increases afterwards, with a smooth growth rate
	`2DC`	The modeller defines the maximum average temperature increase in 2100 with respect to pre-industrial level (in this case 2°C), and the model finds the carbon tax that should be applied so to achieve this target

the $CO_{2,eq}$ concentration in the atmosphere of the RF stabilization levels [W/m^2] [47].

In the WITCH model, we calculate the $CO_{2,eq}$ budget and we use the MAGICC model (version 5.3) in order to perform the conversion to concentration, RF, or temperature. Using the MAGICC model, we can provide information in terms of global average temperature and RF that are comparable with results from other researchers and modellers.

Figure 2.2 shows the average temperature increase from pre-industrial level, with confidence intervals, for the baseline scenarios resulting from our modelling implementation. The `ctax` scenario reaches an average global temperature of 2.5°C while the `2DC` remains below 2°C for the median value. The MAGICC model also provides values of average global RF. While gross RF accounts for the contribution of CO_2, CH_4 and N_2O as GHG into the atmosphere, the net value takes into account the effect due to Areosol (subtracted to the gross RF). However, due to large uncertainties on estimation of the Areosol effect, we will only refer to the gross RF in this thesis. The resulting values of gross RF for our scenarios are 4.08 [W/m^2] in 2100 for `ctax` and 3.11 [W/m^2] for `2DC`. For more information regarding the assumptions used in MAGICC, please see the documentation web-page [61].

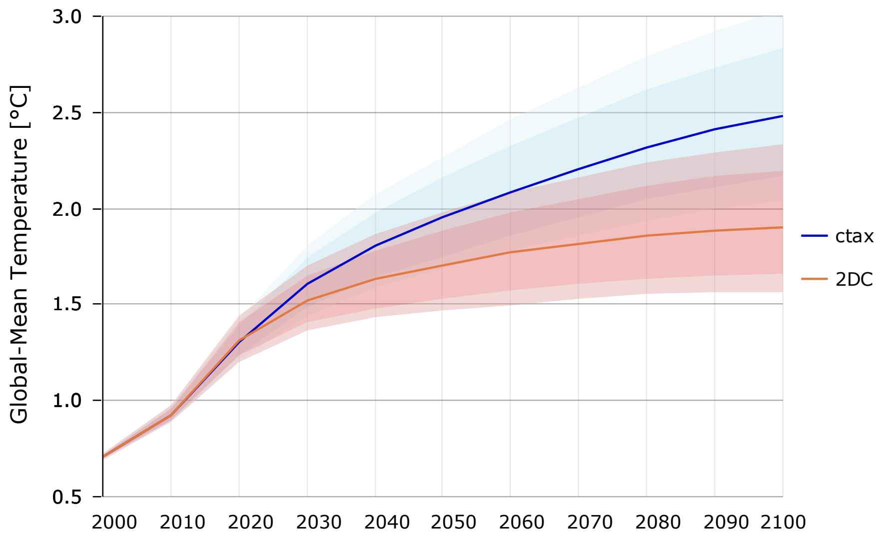

Figure 2.2. Average temperature increase for `ctax` and `2DC` scenarios with two confidence interval areas. The dark shading denotes the 25%/75% percentile region, and the light shading the 17%/83% percentile region. The lines in the middle represent the median.

2.3 WITCH structure

WITCH is mainly written in GAMS, a high-level modeling system particularly suitable for mathematical and economical optimization. The GAMS modelling language is based on the definition of some elements - namely *parameters*, *variables* and *equations*. GAMS solves the *equations* as a function of the *variables*. It converts the program in a form which is suitable to a solver (CONOPT in the case of WITCH), and the solver optimizes the objective function, under a set of constraints defined by the equations. The mentioned elements are usually defined with respect to *sets*: the same object (e.g. variable or parameter) has different values for different set elements (e.g. each region, technology, time step). Sets are useful to synthetically represent this dependency. Finally, constraints, or mathematical *equations*, establish relationships between parameters and variables that the model solves looking for the optimal solution. Even though most of the code is implemented in GAMS, it requires inputs from the softwares R and Python. The programming part of this thesis work has been carried out in both GAMS and R coding.

2.4 CCS overview in the model

As stated, the focus of this thesis work is CCS role assessment in the electric sector. The model presents some CCS technologies, both in the electric and in the non-electric sector (see Appendix A for the single CCS technologies representation). The technology portfolio in WITCH considers a single coal CCS option (coal Integrated Gasification combined cycle (IGCC) with CCS), a gas CCS option and a biomass one (biomass IGCC with CCS). We think this CCS technologies portfolio could be integrated with other CCS based plants, that are today drawing the attention for their future perspectives, such as post combustion and oxyfuel power plants. As it is possible to see in Figure 2.4 and Figure 2.3, the current model implementation already puts in evidence the importance of CCS technological options in low carbon scenarios. From the emission reduction point of view, CCS is responsible for 20% (`ctax`) or 14% (`2DC`) of the cumulated avoided emissions up to 2100. Considering the technology portfolio, we notice that both fossil CCS and biomass CCS shares gradually increase in time. On the other hand, traditional coal electricity production remains crucial in the energy mix up to many decades in `ctax` case, while the phase out in `2DC` case is fast and dramatic. This specular behaviour could be linked to the absence in the model of the retrofitting option (i.e. traditional power plants equipped with CO_2 abatement): without retrofitting, the model has to choose between heavily rely on traditional coal plants (strongly carbon intensive), or switching them off (with a critical loss in economic terms, because the phase out happens regardless the theoretical lifetime of plants). We are therefore convinced that retrofitting would be a valuable addition to the current implementation. Considering technology related costs, the current implementation considers constant costs in time, regardless the installed capacity. This aspect might affect the future perspectives of CCS options: as relative young technologies, their costs could be not competitive within the energy mix even in the future. We think that the introduction of a cost reduction linked to the increase in installed capacity (learning by doing) would better portray the future cost behaviour. Moreover, the storage implementation in WITCH is conceived with a top-down approach: as we are aware of the key importance of storage sites characteristics and CO_2 transportation issues, we aim at redesigning the storage and transport implementation in order to assess more in detail storage impact on CCS adoption.

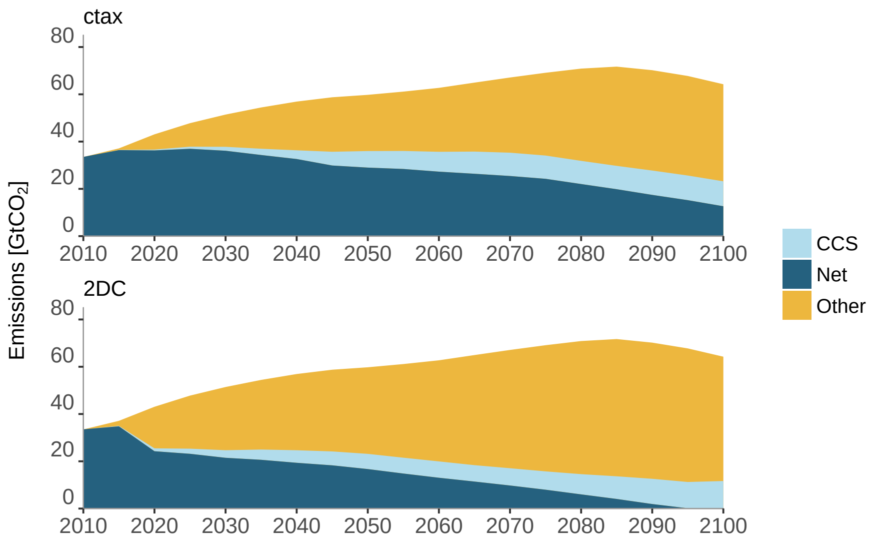

Figure 2.3. Emissions reduction with respect to `BAU` in `ctax` and `2DC` cases, as an output of the original implementation. The light blue area represents the amount of emissions captured by CCS.

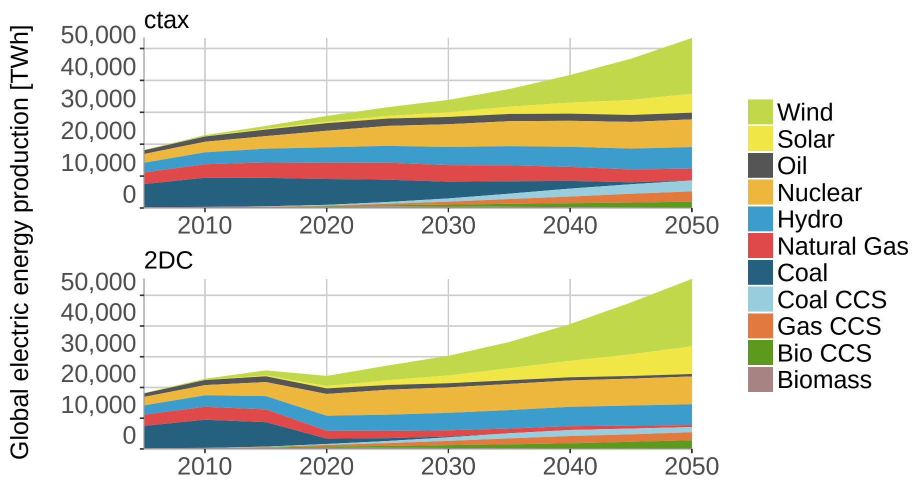

Figure 2.4. Electric energy production by technology according to the WITCH model (`ctax` and `2DC` scenarios).

Chapter 3

CCS Technologies

3.1 Technological assessment

In this chapter, we will provide an overview of the currently most promising carbon capture technologies, reviewing several reports and papers of experts in the sector. For the purposes of our modelling work, we are mostly interested in identifying a number of main features for each technology. In particular, we focus on investment costs, operating and maintenance costs, plant efficiency, CO_2 capture rate efficiency, average operating hours per year, current state and possible progress of the technology development. In the following sections, we describe the main types of power plants with carbon capture and their main performance parameters. The results are summarized in Table 3.2 and 3.1 Afterwards, we discuss the outcomes of our literature review concerning costs.

3.1.1 Technology description and performance parameters

Pre-combustion, Coal-fired Integrated Gasification Combined Cycle with CCS (C-IGCC)

Pre-combustion capture of CO_2 can be performed through gasification of coal 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 (i.e. Methyl diethanolamine (MDEA) or other amines) or physical (i.e. Selexol) solvent [18]. Existing C-IGCC power plants with carbon capture feed the gasification process with a mixture of air and pure oxygen produced in the Air Separation Unit (ASU), which is a very energy intensive element of the plant and accounts for a significant share of the total investment cost [10, 18, 43].

Plant efficiency penalty due to the CO_2 capture unit is around eight percentage points compared to a C-IGCC plant without CCS [43, 59]. Considering several sources quoted in Table C.1 in Appendix C, we evaluated an average net electric efficiency of C-IGCC plant of 33.88% on Lower heating value (LHV) basis. As an insight into future perspectives, Siemens has estimated that five net efficiency percentage points can be gained back with the use of advanced hydrogen fired gas turbine in the near future [18].

Pulverized coal plant with post combustion with CCS (C-post)

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. Monoethanolamine (MEA)) or membranes (not yet developed for large scale applications [7]). If required, this type of technology can

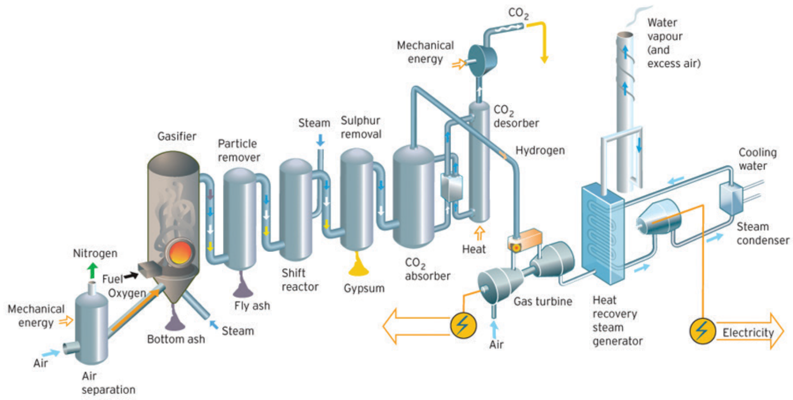

Figure 3.1. Illustration of a C-IGCC plant with CCS. Source: NACAA

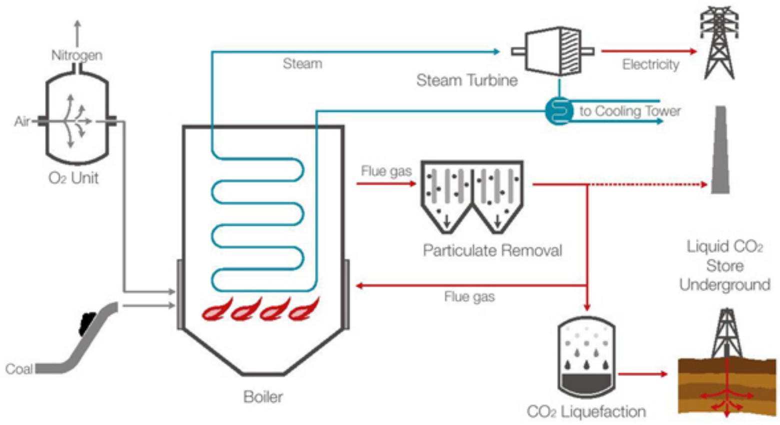

Figure 3.2. Scheme of an Oxyfuel power plant with CCS. Source: CS Energy

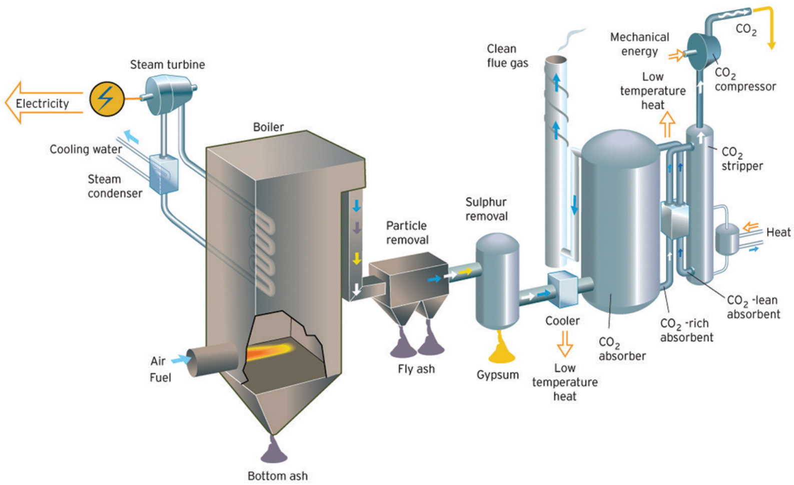

Figure 3.3. Simplified scheme of a Pulverized coal with post-combustion carbon capture. Source: NACAA

be implemented on existing power plants (retrofitting), offering the opportunity to reduce plant emissions.

Retrofitting an existing plant or installing a new plant with post-combustion technology imply additional costs with respect to a conventional coal power plant and a significant efficiency loss of about 9-10 percentage points, due to the large amount of energy used for solvent regeneration [13, 17, 41, 67, 70]. This leads to achieve an average plant efficiency of 33.7%. In this thesis we will also notice how the expected high costs and low efficiency of this technology negatively affect the possible development of new C-post plants in the future.

Different studies agree on the fact that C-post power units seem not to have great potential of technological improvement and cost reduction in the near future. On the other hand, major contribution in improvements might come from the use of new and less energy intensive solvents or membrane technologies (even 2% of net efficiency points) [17, 83].

Oxyfuel coal plant with CCS (C-OXY)

Oxyfuel power plants work with combustion of pulverized coal with pure oxygen in a special boiler or furnace, usually with recirculation of exhaust gases [38]. 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. The pure oxygen for the combustion is provided by the ASU which, compared to the previously seen technologies, is the greatest energy consuming and costly component of the plant, due to its large size. The ASU cost can account for 20% up to more than half of the total capital cost of the plant [43, 60].

An average efficiency penalty compared to a plant without CCS is around seven percentage points on LHV efficiency [16, 83]. Beside these negative aspects, burning coal with high purity oxygen allows a more performing capture rate ratio. Therefore, a great advantage of C-OXY is that CO_2 can be captured with a capture rate up to 99%, even if most studies are based on an average capture rate of 95%. For C-IGCC and C-post a commonly accepted value of Carbon Capture Rate Ratio CRR is 90% [16, 63, 67].

Oxyfuel capture option is the newest and the least developed among the three investigated above [16, 67]. From our perspective, this aspect has two main consequences: first of all, the uncertainty on information concerning C-OXY is wider than other technologies (Table 3.1); secondly, technological improvement is more uncertain but might have a greater potential. For instance, Hammond et al. assert that a possible development of high pressure oxyfuel cycle might lead to a 5% increase in net electric efficiency [25].

Retrofitting existing coal power plants

We implemented coal power plants with CCS above mentioned as newly built power technologies. This means that our tool of analysis is able to make distinction between these three coal technologies, but CCS share would be represented only by the installation of new power plants with high investment costs, while the large power capacity of existing coal power plants in 2015 remains incapable to adapt in case of strict climate policy scenario. For this reason, it is important to consider retrofitting of existing power plants as an alternative option to installing new plants and phasing out the old plants before the end their lifetime [30]. The WITCH model has an existing capacity of pulverized coal plants and we introduced in the model a post-combustion unit that can be applied to existing plant.

Actually, not all the power plants working in 2015 are compatible with retrofitting:

some plants are old and not very efficient, and problems of space around the industrial area or distance from the storage site might arise. The NETL, 2011 study suggests some criteria for screening suitable power plants in a fleet: nominal capacity greater than 100 MW, a thermal efficiency greater than 27.3% (Higher heating value (HHV) basis) and an average storage distance shorter than 40 km [8]. Applying these conditions, the potential for the US appears to be 85% of the total capacity. A publication from EPRI, 2009 and an IEA, 2012 study consider as suitable plants with power capacity greater than 300 MW [30, 69]. The first report also suggests to screen only plants less than 35 years old, while the latter chooses three case analyses screening all the plants with less than 30, 20 and 10 years old respectively. The data used in the IEA study come from a large database on global power plants, the UDI World Electric Power Plants Data Base (WEPP) Data Base 2011. We included similar information in the model, in order to realistically constrain the retrofitting potential.

As we have access to the same database updated to the 2015 version, we used these data to set and calibrate the installed power capacity in the model. Therefore, we have the possibility to screen the plants suitable for retrofitting according to the IEA approach. In Appendix B we explain the screening criteria we adopted. The final results are reported in Figure B.2 and show strong differences in regional retrofitting potential, mainly due to the age of power fleets. In the US and China 7.8% and 83.4% respectively of the national coal power plants is suitable for retrofitting in 2015, since it is greater than 300 MW and less than 25 years old.

Further details concerning the modelling of retrofitting are reported in Section 3.2.1.

Nevertheless, in the literature it is possible to find new C-post plants and the retrofitting case studies analyzed together, as the lack of practical experience is a limit for studies on new plants [17]. The IEAGHG, 2011 report on integration of CCS component highlights how a new plant can lead to an overall higher electric efficiency with respect to old plants with retrofitting, but also the investment costs and $LCOE$ are higher [30, 40].

For seek of consistency with the existing data in the model, we make some simplifications on the performance definition for the CCS integration, carefully checking to be coherent with the information gathered from our sources. In particular, we set an efficiency loss of 10 percentage points on power plants that integrate carbon capture, considering 90% of carbon capture ratio. The additional cost of retrofitting is assumed to be equal to the difference between a new Pulverized Coal (PC) with and without CCS. However, considering that in the model the existing power plants are the cheapest, we obtain that investment cost for a plant with retrofitting is lower than a new built C-post plant. We will refer to plants that integrate a capture unit as Coal-fired power plant retrofitted with a CCS unit (C-retro)

Natural Gas Combined Cycle with CCS (NG-CCS)

Natural Gas (NG) combined cycle is a mature technology that can currently achieve more that 50% net efficiency [7]. Analogously to coal, it is possible to perform carbon capture from natural gas combustion with different technologies. Pre-combustion with gasification, oxyfuel combustion and post-combustion capture are all feasible and studied options. However, most of studies focus on post-combustion capture technology, which is very similar to PC: this process utilizes a chemical solvent that separates the CO_2 during an absorption process and release it after regeneration [41, 59]. As a result of our literature review we consider 48% of LHV efficiency for a generic gas combined cycle with CCS, NG-CCS.

From Table 3.2 it is noticeable that NG-CCS investment cost is significantly lower than coal based power plants with carbon capture. This aspect reflects the actual difference in investment cost between conventional coal-fired and natural gas-fired power plants.

Bio-Energy with Carbon Capture and Storage (BECCS)

The idea of combining biomass fired power plants with carbon capture and sequestration became, in recent years, topic of engineering and integrated assessment studies. Indeed it shows a great potential for reducing carbon dioxide in the atmosphere [39, 71, 77]. Several papers and reports refer to BECCS as a Negative emission technology (NET) and as a mean of Carbon Dioxide Removal (CDR). In facts, burning biomass generally leads to almost neutral or slightly positive emissions in the atmosphere (considering the plant life-cycle and the harvesting and transportation chain). When this potential is coupled with carbon capture from exhaust gases and geological storage, it leads to overall negative emission [22, 42, 48, 53, 86]. Apart from demonstration projects, BECCS technology for electricity production has not found commercial realization yet. Some barriers to the deployment of the technology are the supply of sustainable biomass, public acceptance and, most importantly, the immaturity of both biomass power plants and CCS technologies [39]. A first use of bio-energy sources coupled with CCS are experimented in co-firing plants that work with coal and biomass [24].

However, when referring to biomass we include a large variety of fuels that have biological origin, such as liquid bio-fuels, methane produced by anaerobic digestion, municipal solid waste and other farmed solid biomass, such as sugar cane or wood [86]. Great part of these fuels demand belongs to the non-electric sector, such as transportation or local heat production. The IEA World Energy Outlook, 2010 accounts for 11.3 EJ/yr of modern biomass primary energy supply, 4 EJ/yr of which is from electricity and Combined Heat and Power (CHP) [29, 48].

As the scope of this thesis is addressing CCS in the electricity sector, we will focus specifically on power plants. Despite narrowing the gap of our research, uncertainty on the topic of BECCS for electricity remains vast. This uncertainty is due to the large variety of biomass used in the energy sector and prospected for the future: even excluding sources devoted to liquid bio-fuel production, it ranges from wood to charcoal, from agricultural wastes to livestock manure [24]. Moreover, different types of CCS processes can be applied to biomass plants, exactly as to coal power plants: post-combustion capture, pre-combustion or oxyfuel combustion are all attainable solutions [24, 39, 86].

However, due to the scarcity of deployment projects and the early stage of research, we believe that this topic should be addressed on its own in a more extensive work other than this thesis project.

The WITCH model has already implemented a BECCS technology with input data updated in recent years. Therefore, we decide to use BECCS as it is already implemented and to carry out some researches on parameters update, in order to be consistent with the other data and the rest of the model.

We used the parameters and costs already present in the model with the exception of the investment cost that we recalibrated according to information found in literature. Table 3.1 and 3.2 report the input data for BECCS used in the model. In particular, the WITCH model assumed 4000 $/KW as investment cost for BECCS power plants, though several case studies and expert elicitations suggest lower costs for such technologies, which remain however more expensive than coal plants with CCS. Therefore, we assumed a reasonable updated value to be around 3700 $/kW. Other parameters seem to be consistent with data found in literature [11, 14, 39, 53].

To sum up, biomass with CCS power plant will be touched only marginally within this work. On the other hand, we are aware of its significant role in combination with other

CCS technologies in the electricity sector (i.e. Research and Development in CCS involves also biomass plants). For this reason we make some uncertainty analysis on the parameters related to BECCS, assuming boundary ranges similar to those of other CCS technologies. In this work we will refer to biomass fired power plants with CCS as Biomass-fired plant with CCS (Bio CCS)

Table 3.1
Main performance parameters of power plants with CCS as results of the literature review (sources in Table C.1).

	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						0.45
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						0.5
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 actually 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 3.2
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]		
Technology	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
C-post	1400	4627	3063	3.8	22.8	13.4
C-OXY	1127	5034	3253	1.7	20.5	9.5
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
Bio CCS			3693			10.3

[a] Values actually used in the model, not output of literature review
[b] Summed costs of old power plants and retrofitting unit

3.1.2 Cost of carbon capture plants

As already mentioned, Table 3.2 shows investment and aggregated fixed and variable operating and maintenance costs ($O\&M$) (considering plants working for the maximum available hours per year) for the technologies described in Section 3.1.1, as outcome of our literature review. In addition, the costs for the respective technologies without CCS present in the WITCH model are also reported. Concerning the traditional plants, we do not apply any modification to the originally implemented values. It is important to specify that in the WITCH model investment costs are differentiated across regions, considering the differences in manufacturing costs across countries. In Table 3.2 we report the costs for Oldeuro expressed in 2005 USD. For converting costs from different sources, we referred to USforex [81] for Euro-Dollar conversion and to International Monetary Fund [80] for the dollar deflation in different years.

Looking at the table, it is possible to notice the difference between coal and gas power plant investment costs. Moreover, the additional cost due to a switch towards carbon capture is greater in case of coal plants, even though the effect on CO_2 capture are usually more significant in case of fuels with high carbon content, such as coal.

Oxyfuel power plants are slightly more expensive than the other alternatives, and the uncertainty gap for C-OXY is certainly the largest.
Finally, costs for C-Retro are reported as the sum of old plant costs plus the integration of the capture unit, even though the investment for building the power plant and the one related to retrofitting are usually done in distinct moments, meaning different overall costs according to depreciation of the initial investments.

In the next paragraph we introduce some additional indicators that give us further useful information for the comparison between technologies.

LCOE and other indicators

$LCOE$ is an important indicator for assessing the cost of electricity produced by a power plant, especially when we want to underline the differences between new plants with carbon removal and a reference traditional plant. Follows the definition of $LCOE$ related to CO_2 capture:

$$LCOE_{capt}\left[\frac{\$}{MWh_{el}}\right] = \frac{I_{cost} \cdot FCF}{CF \cdot 8760 \cdot Q_{EN}} + O\&M + FC \tag{3.1}$$

Where I_{cost} [\$] is the investments cost, FCF is the fixed charge factor (dependent on lifetime and interest rate), $O\&M$ [\$/MWh] considers both fixed and variable operating and maintenance cost, Q_{EN} [$\mathrm{MWh_{el}}$] is the electricity produced in a year, assuming the plant operating hour ($CF \cdot 8760$) given a capacity factor CF and FC [\$/MWh] is the fuel cost computed as the product of a specific fuel cost multiplied by the heat ratio required by the plant. $LCOE$ in Table 3.3 is evaluated with an average interest rate of 7% and a mean FCF around 15%, and it is expressed in 2005 USD with a conversion factor to 2015 USD equal to 1.193 [\$2015/\$2005] for each type of plant.

The average emission factor for each type of fuel is a parameter already present in the WITCH model and accounts for 0.343 [$\mathrm{tCO_2/MWh_{th}}$] for coal and 0.198 [$\mathrm{tCO_2/MWh_{th}}$] for natural gas. Dividing the emission factor by the electric efficiency and, in case of plant with CCS, multiplying it by $(1 - CRR)$, it is possible to account for the specific CO_2 emissions e_{CO_2} [$\mathrm{tCO_2/MWh_{el}}$].

Once we calculate an average $LCOE_{capt}$ and emission rate, it is beneficial to consider additional indicators that highlight the effects due to carbon capture in comparison with a reference plant without CCS. In our example the reference plants are pulverized coal plants with steam turbine for each coal technology and NGCC for gas.

The Cost of CO_2 Captured (CCC) is evaluated as the difference in $LCOE$ between the CCS case and the reference plant divided by the amount of CO_2 captured. It only considers the carbon dioxide removed by the plant with CCS.

$$CCC\left[\frac{\$}{tCO_2}\right] = \frac{LCOE_{capt} - LCOE_{ref}}{e_{CO_2}(capt)} \tag{3.2}$$

The Cost of CO_2 Avoided (CCA) gives a measure of the effective cost of reducing carbon emissions considering the reference as a base case. Compared to CCC, it takes into consideration the effect of the efficiency loss on emissions. In case of a Carbon Tax or Cap and Trade scenario, the CCA can be directly compared to the carbon price and gives an idea on whether CCS is an economically convenient solution:

$$CCA\left[\frac{\$}{tCO_2}\right] = \frac{LCOE_{capt}{}^{CC} - LCOE^{ref}}{e_{CO_2}{}^{ref} - e_{CO_2}{}^{CC}} \tag{3.3}$$

Finally, the Specific Primary Energy Consumption for CO_2 Avoided ($SPECCA$) is similar to the CCA, but it reports the additional energy expenditure per kg of CO_2 due to carbon capture. In the following expression, HR is the heat ratio and η_{el} is the net electric efficiency of the plant:

$$SPECCA\left[\frac{MJ_{th}}{kgCO_2}\right] = \frac{HR^{CC} - HR^{ref}}{e_{CO_2}{}^{ref} - e_{CO_2}{}^{CC}} \quad \text{where} \quad HR\left[\frac{MJ_{th}}{MWh_{el}}\right] = \frac{3600}{\eta_{el}} \tag{3.4}$$

Table 3.3 reports the above mentioned indicators for a representative case for each new CCS plant in our model. For $LCOE$ calculation, only capture cost are considered, while transport and storage costs for the CO_2 captured are excluded. These numbers are to be meant as average results of the nominal data obtained in the literature review.

The most remarkable aspect is that C-OXY has the lowest CCC and CCA despite the highest investment cost. However, values related to each coal technology remain within a similar range. Whereas NG-CCS shows lower $LCOE$ than coal plants, the amount of CO_2 captured is significantly lower, therefore CCA for NG-CCS stays in the range of 60 $/$tCO_2$ and CCC is the highest between CCS technologies.

Concerning energy consumptions, $SPECCA$ shows similar increases in energy penalty for all coal technologies, with post combustion being slightly more consuming. NG-CCS shows less energy consumption per ton of CO_2 avoided.

It would be interesting to investigate any change on these parameters in case of different carbon tax scenarios. Some influencing variables might be the energy production per year, the technological learning and different emission targets fixed for the future. In Chapter 5 we will introduce costs of CO_2 transport and storage. These components can be added to the $LCOE_{capt}$ providing a total $LCOE_{capt,st}$ where $c_{t\&s}$ [$/$tCO_2$] is the specific cost of transport and storage and the $E_{CO_2,capt}$ are the absolute emissions captured by the plants [tCO_2]:

$$LCOE_{capt,st} = LCOE_{capt} + \frac{c_{t\&s} \cdot E_{CO_2,capt}}{Q_{EN}} \tag{3.5}$$

Another possible way to calculate the differences in costs between plants with and without CCS in a scenario with carbon price in [$/$tCO_2$] (alternative to the CCA), is to integrate the emission costs in the $LCOE$ formulation. We will refer to this version of levelised cost as $LCOE_{CO_2}$, defined as:

$$LCOE_{CO_2} = LCOE_{capt,st} + \frac{ctax \cdot E_{CO_2}}{Q_{EN}} \tag{3.6}$$

3.2 Implementation and methodology

3.2.1 Implementation in the WITCH model

One of the main purposes of this thesis is to assess the role of CCS technologies for the next decades according to different climate polices for the reduction of anthropogenic

Table 3.3
Emissions, $LCOE_{capt}$ and other indicators related to CCS technologies (2005 USD).

Technology	LCOE[a] [$/MWh]	e_{CO_2} [$t\,CO_2$/MWh]	$e_{CO_2}(capt)$ [$t\,CO_2$/MWh]	CCC [$/t CO_2]	CCA [$/t CO_2]	SPECCA [MJ/kg CO_2]
C-IGCC	97.71	0.111	0.901	47.10	65.16	4.0
C-post	99.05	0.102	0.916	47.77	66.25	4.1
C-OXY	99.16	0.052	0.982	44.69	61.73	4.0
PC w/o CCS[b]	55.28	0.763				
NG-CCS	87.47	0.045	0.367	53.53	62.46	3.0
NG w/o CCS[b]	67.82	0.360				

[a] CO_2 transport and storage costs are not included
[b] Reference technologies without carbon capture

carbon dioxide. We use WITCH integrated assessment model as a tool for this analysis, therefore we need to interact with the model framework and modify it every time we need to introduce some new features, parameters or equations.

3.2.2 New CCS technologies implementation

Considering the power plant technologies with CCS described in the previous section, we introduce all the performance parameter, assumptions and necessary equations in the model structure. Following the model structure introduced in Section 2.3, we consider the performance characteristics as *parameters*, they can be fixed or variable with respect to different dimension (*sets*), namely time, regions or technologies.

Concerning C-OXY, C-IGCC, Bio CCS, C-post and NG-CCS, the implementation in the model is facilitated by the model structure and simply requires the definition of the performance parameters listed above. A particular remark can be done on electric efficiency: the WITCH model assumes an increase in efficiency of 10% by 2050 for coal technologies. However, in order to take into account the particular predictions mentioned in Section 3.1, we consider a slightly higher efficiency increase for CCS technologies as default condition.

3.2.3 Retrofitting implementation

We use a different approach for implementing the retrofit of an existing power plant with respect to new CCS plants. In fact, in this case, we relate the investment cost to the integrative unit that is installed a posteriori, while we link the effects of retrofitting to the operation of the existing power plants, according to the following equations:

$$Q_{IN}(old) = \frac{Q_{EN}(old)}{\eta_{el}} \quad \text{and} \quad Q_{IN}(retro) = \frac{Q_{EN}(retro)}{\eta_{el} - \Delta\eta_r} \tag{3.7}$$

Where Q_{IN} [$\mathrm{TWh_{th}}$/yr] is the primary energy provided to the plant in form of heat potential, Q_{EN} [$\mathrm{TWh_{el}}$/yr] is the electric energy produced, η_{el} is the net electric efficiency of the plant and $\Delta\eta_r$ is the efficiency loss due to retrofitting. With the term *old* we refer to the plant without CCS, with *retro* we refer to the plant that integrates carbon capture.

However, the model is structured in aggregated form, without considering the single power plant dimension, but solely the overall effects for each type of technology in terms of energy production, investments, emissions, etcetera. For this reason, we implement $Q_{EN}(retro)$ as an additional variable that accounts for the energy produced by the plants with CCS integration and, as a subset of the overall energy produced by the existing power plants. Hence, the final equation implemented in the model considers the differential effects due to retrofitting accounted within the category of old plants. When $Q_{EN}(retro) = Q_{EN}(old)$, it means that all the energy is produced by plants with retrofitting. Therefore:

$$\begin{cases} Q_{IN}(old) = \frac{Q_{EN}(old)}{\eta_{el}} - \frac{Q_{EN}(retro)}{\eta_{el}} + \frac{Q_{EN}(retro)}{\eta_{el}-\Delta\eta_r} = \frac{Q_{EN}(old)}{\eta_{el}} + \frac{Q_{EN}(retro)\Delta\eta_r}{\eta_{el}(\eta_{el}-\Delta\eta_r)} \\ Q_{EN}(retro) \leq Q_{EN}(old) \end{cases} \tag{3.8}$$

Another important variable in the model is the installed capacity K_{EN} [TW/yr], which is strictly related to the investment. In case of the retrofitting, $K_{EN}(retro)$ refers to the integration unit that is added to a plant. It has a relation with $K_{EN}(old)$ and it is also correlated to Q_{EN} according for the following equations:

$$\begin{cases} Q_{EN}(old) \leq CF \cdot 8760 \cdot K_{EN}(old) \\ Q_{EN}(retro) \leq CF \cdot 8760 \cdot K_{EN}(retro) \\ K_{EN}(retro) \leq lk_{retro} \cdot K_{EN}(old) \end{cases} \tag{3.9}$$

lk_{retro} is an important parameter that takes into account the share of power plants of the existing fleet in 2015 that is suitable for retrofitting (see Appendix B). As mentioned in the paragraph about retrofitting in Section 3.1.1, we calculated this limits from the WEPP database, screening data according to the specification suggested by IEA, 2012 and EPRI, 2009.

Carbon Dioxide emissions for a plant without CCS and with carbon capture are evaluated according to the following expression:

$$\begin{cases} E_{CO_2}(old) = Q_{IN}(old) \cdot e_{fuel}(coal) \\ E_{CO_2}(retro) = Q_{IN}(retro) \cdot e_{fuel}(coal)(1 - CRR) \end{cases} \tag{3.10}$$

Where the emissions are expressed in [$GtCO_2$], $e_{fuel}(coal)$ [$GtCO_2/TWh_{th}$] is the average stoichiometric emission coefficient for coal and CRR is the carbon capture rate ratio. Similarly to energy production, also the emission equation is formulated accounting for the differential effect or retrofitting.

3.3 Results and robustness analysis

Figure 3.4 shows the resulting output of the model in terms of electricity production from plants with CCS in the `ctax` and `2DC` scenarios. At a first sight, we notice that CCS plays a greater role in the `ctax` scenario, as there is not a constraining emission budget. On the other hand, CCS based production starts earlier in `2DC` case with a great demand for retrofitting: this is due to the higher carbon tax with respect to the previous scenario. This plot gives an insight of the order of magnitude that characterize CCS energy production. In Chapter 6 we will discuss in detail these results.

In the previous sections, we underlined the importance of uncertainty behind the gathered data. A valuable approach for assessing this uncertainty is to perform a sensitivity analysis on the ranges that characterize each parameter mentioned in this chapter. In particular, we want to assess what is mostly affecting the WITCH results in terms of output variables such as investments, energy cost, emissions and energy production from fossil fuel.

As an investigation, we run a sensitivity analysis using the *Low*, *High* and *Best* values reported in Tables 3.1 and 3.2 for each performance parameter and type of cost, with the

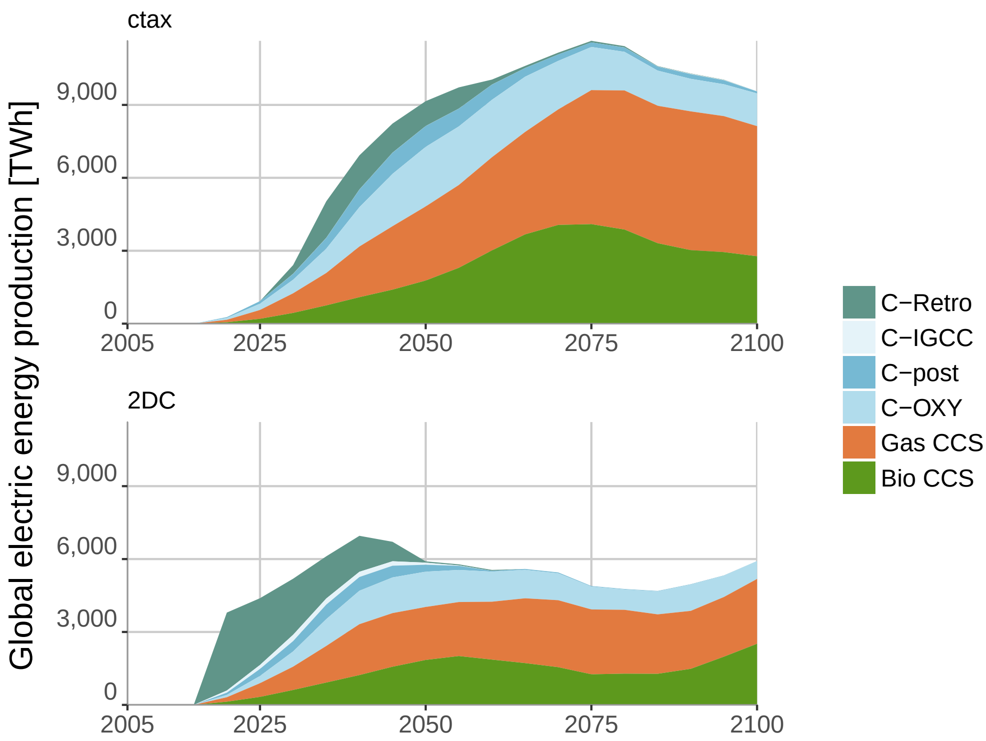

Figure 3.4. Electric energy production from CCS plants in two different climate policy scenarios.

exception of the low investment cost case. Indeed, we consider it an excessive assumption to have investment costs lower than the conventional power plants without CCS. Therefore, where the *low* case from our data crossed the respective cost of traditional plants, we used this last value during the sensitivity analysis.

We run the model several times, testing the effect on single technologies, groups of technologies with the same fuel (natural gas, coal or biomass) or the overall group of plants with carbon capture. In this way, we can assess whether the variations affect every technology identically or not.

Figure 3.5 shows the results of a sensitivity analysis focusing on: impact of the performance parameters and costs on the energy produced by CCS plants, emissions related to these plants and energy system expenditure resulting from the different climate scenarios. It is worth underlining that the results strongly depend on the selected representative scenario. In this specific case, we select the `ctax` scenario, with an initial carbon tax value of 30 $/t$CO_2$ and the retrofitting option set to OFF, as we will analyze retrofitting separately. In the graph, the horizontal black line tracks the results of the base case. The plot shows the variation of three model variables when we vary the parameters of interest for all the CCS technologies at the same time. Subsequently in this chapter we will study the different impact for categories of power plants. The average yearly electric energy is the total electricity Q_{EN} produced in a time period (shown in Figure 3.4) , divided by the numbers of years. The *ese* is the Total Energy System Expenditure [T$/yr], it is evaluated by the model including the investment cost in technology development and research, O&M, fuel and storage costs.

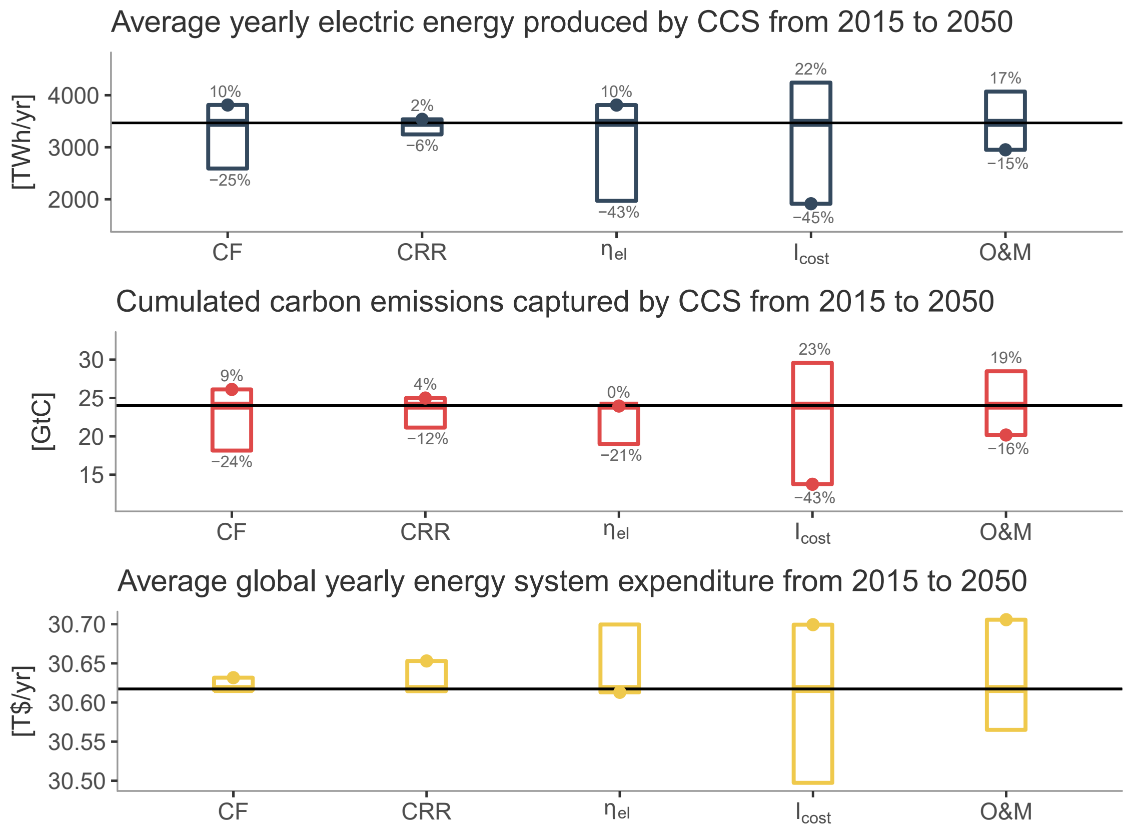

Figure 3.5. Impact of significant parameter on: Average yearly electricity produced by power plants with CCS; cumulative captured carbon emission; *ese*. Year 2050. The dots represent the maximum values in the uncertainty range (i.e. maximum cost of investment, maximum efficiency, etcetera). The middle black line indicates the representative value of a `ctax` scenario with the retrofitting option set OFF.

Capacity factor (CF)

The net capacity factor of a power plant is the ratio of its actual output, to its potential output as if it were possible to operate it at nominal capacity continuously over a period of time. If we multiply the capacity factor by the number of hours in a year, we obtain the equivalent hours of plant operation in nominal conditions. The values of capacity factor are similar for every type of plant analyzed, and most of our sources agree in assessing an average value around 80% for every CCS technology.

We notice an impact due to the variation of the capacity factor, especially considering the lower bound. The effect is however lower compared to other parameters, like investment costs.

Carbon dioxide capture rate ratio (CRR)

This parameter does not show any particular results and the influence on the three output variables is negligible. This is mainly due to the fact that the uncertainty range is extremely small. In fact larger variations of capture rate visibly affect CCS captured emissions, but there is a technical limit that contains CRR around 0.9. By looking at Equation 3.11, considering the same amount of energy produced, carbon emissions into the atmosphere strongly depend on the capture ratio. $e_{CO_2}(fuel)[GtCO_2/TWh_{th}]$ is the emission coefficient.

$$E_{CO_2,capt} = \frac{Q_{EN}}{\eta_{el}} \cdot e_{CO_2}(fuel) \cdot CRR \tag{3.11}$$

Net electric plant efficiency (η_{el})

The changes in efficiency seem to have significant impacts especially on the energy production. The scenario with low efficiency shows a drop in electricity production from CCS plants of 43.2%. Concerning ese, we must underline that every variation showed in the plot is lower than 0.001%. As ese depends on a large number of variables of the optimization process, it not easy to predict the reasons behind such a particular and small variation. The values are practically negligible for every performance parameter.

Investment costs (I_{cost})

Investment cost is the parameter that most resolutely affects the results of the model. At a first sight to the graph, it is noticeable how the ranges in the results vary significantly for all the three variables. As expected, high costs lead to a reduction of CCS deployment.

The electric energy produced adequately represents the importance of CCS in a specific scenario. This uncertainty analysis shows how the upper and lower bounds in investment costs make the energy vary from +22% to -45% of the representative value.

In this case we notice a similar trend for the captured emission, that proportionally follows the energy production (see Figure 3.5). Only in case of efficiency and capture rate variation, this linear correlation is not exhibited, as expected considering Equation 3.11.

Operating and maintenance costs ($O\&M$)

Concerning $O\&M$, what we just said for investment costs is still valid, but the impacts on the three variables is less appreciable.

3.3.1 Group of technologies by fuel

In this section we analyse biomass, coal and gas fired power plants with CCS separately and we perform some sensitivity analysis on the capture rate, plants efficiency and investment cost with two main objectives. First of all, we want to understand which parameters, technology, and combination of both mostly affect the model results. Secondly, we want to highlight whether there is substitutability among CCS technologies or between CCS and renewable energy sources with intermittency, such as solar and wind power plants.

Table 3.4 reports the results of different scenarios where efficiency changes for CCS technologies with different fuels. The results refer to the total energy produced by the whole electric sector from 2020, year in which CCS is set to be able to start, to 2050. The other columns show the percentage on the total of all plant with CCS, wind and solar plants, and subgroups of technologies by fuel.

It is noticeable how, in particular for low efficiency settings, the total amount of energy produced lowers and how there is not great substitutability among CCS technologies. By contrast, especially when the coal with CCS efficiency is very low, the share of intermittent renewables increases.

Table 3.4
Results on the global electric energy production [1000 TWh] and share for type of fuel [%] in response to net efficiency variation.

Scenario	**El [PWh]**	**CCS %**	**W&S %**	**Bio CCS %**	**Coal-CCS %**	**NG-CCS %**
Rep Case	1497.158	8.41	19.86	1.64	3.74	3.02
Bio High η_{el}	1497.64	8.52	19.81	1.77	3.72	3.03
Bio Low η_{el}	1495.70	8.05	19.97	1.29	3.75	3.01
Coal High η_{el}	1498.96	9.05	19.70	1.64	4.39	3.02
Coal Low η_{el}	1493.94	7.24	20.16	1.65	2.58	3.02
Gas High η_{el}	1498.16	8.64	19.81	1.64	3.73	3.26
Gas Low η_{el}	1495.11	7.67	19.94	1.64	3.64	2.40

El refers to the overall total global electric energy produced resulting up to 2050, CCS includes the sum of all CCS power plants, W&S stands for wind and solar power plants, follow biomass, coal and gas fired plants with CCS

We complete this analysis reporting the effects due to investment cost variation on the power plant installed capacity in 2050. From Table 3.5, trends similar to the previous cases are confirmed. Cost settings seem to affect particularly coal technologies. Substitution occurs more evidently between W&S and CCS rather than among CCS technologies. This might be also due to some spillovers between CCS plants, as will be explained in the next chapter.

In conclusion, this analysis highlights some relations between CCS and renewable energy plants in carbon constrained scenario, that we will deepen in more detail in the next chapters.

Table 3.5
Results on the global installed capacity K_{EN} [TW/yr] in the energy sector in response to investment costs variation.

Scenario	Total	CCS	W&S	Bio CCS	Coal-CCS	NG-CCS
Rep Case	16.45	1.26	9.25	0.26	0.57	0.42
Bio High cost	16.55	1.21	9.36	0.21	0.58	0.42
Bio Low cost	16.40	1.29	9.20	0.29	0.57	0.47
Coal High cost	16.88	1.01	9.70	0.26	0.34	0.41
Coal Low cost	16.17	1.42	8.95	0.26	0.75	0.42
Gas High cost	16.58	1.16	9.38	0.26	0.56	0.34
Gas Low cost	16.43	1.28	9.20	0.26	0.57	0.45

Total refers to the overall global power generation fleet resulting in 2050, CCS includes the sum of all CCS power plants, W&S stands for wind and solar power plants, follow biomass, coal and gas fired plants with CCS

3.3.2 Retrofitting

In order to complete the assessment of uncertainty due to our implementation, we analyze the effects of efficiency loss and additional investment cost for retrofitting existing power plants. We perform several runs of our model varying the efficiency loss from 7 to 12 percentage points: the first case leads to overall high efficiency, the second to low efficiency, the representative case having a penalty loss of 10 percentage points.

Figure 3.6 illustrates what is the optimal solution that the WITCH model finds concerning integrating existing power plants with post-combustion capture units. By looking and the installed capacity over time, it is noticeable that, in the representative case, retrofitting is smoothly introduced from 2025 to 2035, reaching a peak of 200 GW of retrofitted capacity. The curves in the plot decrease after reaching a peak, as a consequence of depreciation and lifetime expiration. In case of efficiency variation, we don't notice great differences in terms of the absolute capacity, but some delay in the case of high efficiency loss, meaning that the initial carbon tax is not sufficient to make retrofitting convenient before.

It's worth remarking that the `ctax` scenario introduces a carbon price that gradually increases over time, starting in 2020 with 30 $/t$CO_2$ and reaching around 90 $/t$CO_2$ in 2050.

By looking at specific regions, great part of retrofitting is concentrated in China (around 150 GW), while mainly US, India, and Russia share the remaining 50 GW. The resulting installed capacity is well below the maximum potential, which globally accounts for 600 GW in 2025. This is also due to the fact that in the WITCH model, power plants built before 2005 are assumed to have lower efficiency, and, with additional efficiency loss, become economically disadvantageous.

The second plot in Figure 3.6 shows the effects due to investment cost change, from a case where the cost of retrofitting is halved, to the case where it is doubled. However, we consider the most representative boundaries being `x 0.5` and `x 1.5`, as they are similar to the bounds evaluated for the new technologies in our literature review. We notice strong impacts due to investment costs. In fact, in case of doubled cost retrofitting becomes uncompetitive, while in the `x 0.5` scenario, we notice an anticipation and an increase in the global installed capacity. As in the representative scenario, the results show China leading with more than 200 GW installed in the most optimistic scenario.

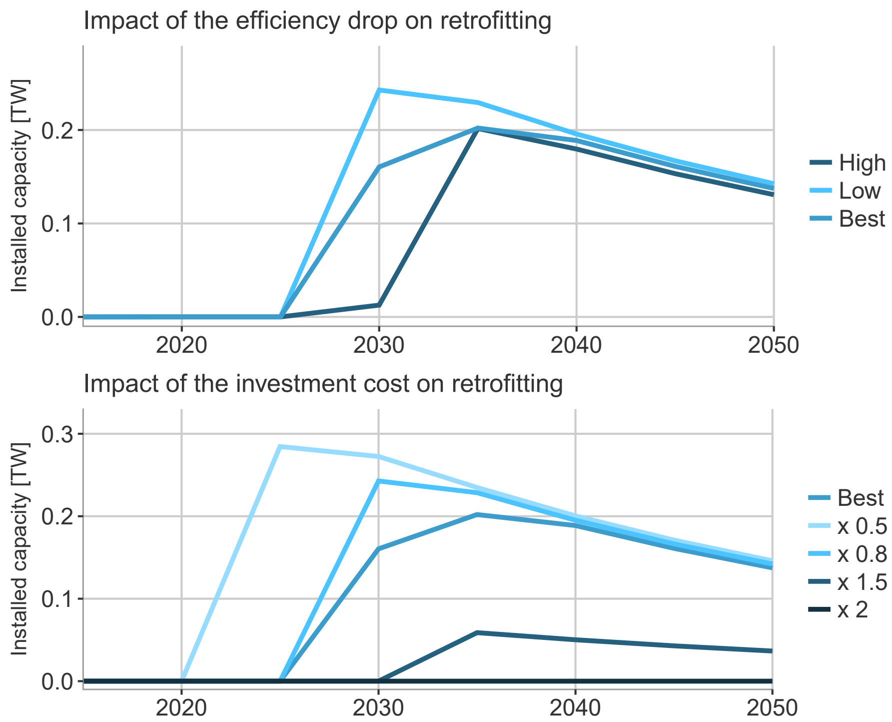

Figure 3.6. Variation of optimal retrofitting capacity due to efficiency and investment costs change. `ctax` scenario.

3.3.3 Results with the `2DC` scenario

The analyses performed until now referred to the `ctax` scenario. However, in this thesis we also want to investigate more stringent climate scenarios such as the `2DC` scenario. Therefore, it is important to assess whether the conclusions drawn in the previous sections holds.

In Figure 3.4 the main differences between `ctax` and the `2DC` scenarios arise. The former has a gradual increase of CCS that leads to a greater amount of energy produced in 2050. The latter shows a sudden increase in retrofitting adoption, due to a drastic emissions reduction requirement, but on the long term, fossil fuel CCS seems to decrease, with the exception of BECCS. This is probably because, in order to reach low target of emissions, every fossil fuel plant is penalized.

From the plot we can notice how coal, gas and biomass plants contribute almost equally until 2050 to electricity production. Breaking down the coal fired power plant category, it is striking how C-OXY seems to be the dominant technology. As we could have expected by looking at CCA in Table 3.3, oxyfuel plants become the most competitive in carbon tax scenarios, because of the high capture rate. In the `2DC` scenarios, post-combustion and C-IGCC plants enter more resolutely in the energy mix, probably thanks to the economic incentive and the spillovers across CCS technologies.

Comparing Figure 3.7, the `2DC` scenario, with Figure 3.5, we notice slightly different results. In the `2DC` scenario the carbon capture rate has a larger impact both on the energy production, which oscillates from -12.5% to +5.5%, and the captured emissions. The extent of variation on the output variables remains practically unchanged in case of efficiency and investment cost variation between the two scenarios.

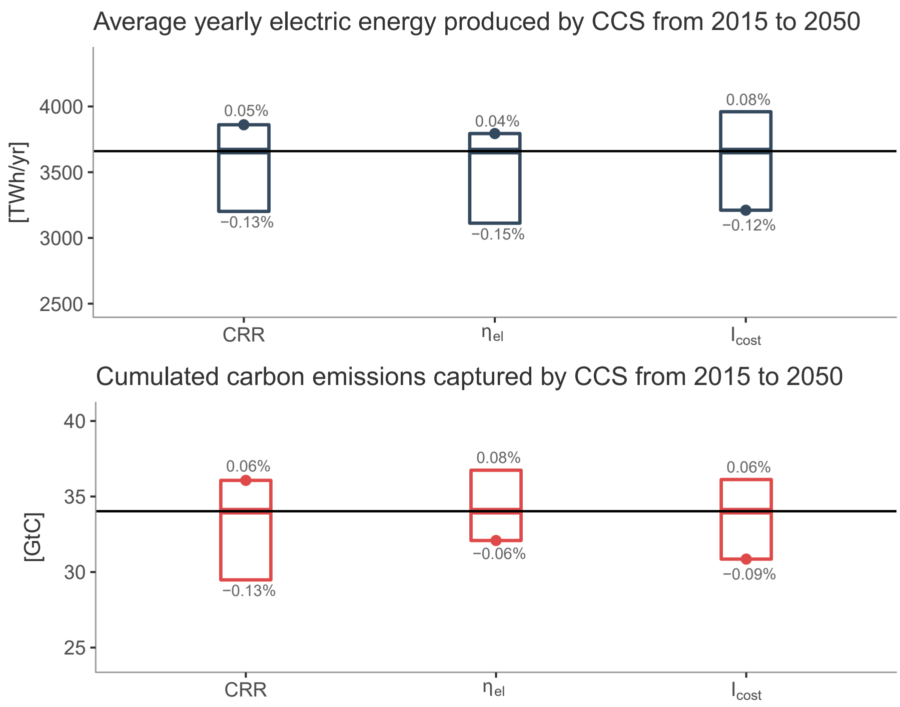

Figure 3.7. Impact of significant parameter on: Average yearly electricity produced by power plants with CCS; cumulative captured carbon emission. Year 2050. The dot represent the maximum bounds in the uncertainty range. The middle black line indicates the representative value of a `2DC` scenario with the retrofitting option set OFF.

Retrofitting

As we expected looking at the energy mix comparison between scenarios, upgrading power plants seems to gain importance in carbon constrained scenarios such as the `2DC`. As a matter of fact, the retrofitting capacity reaches its limit for what concerns plants built after 2005. Due to a differentiation in the WITCH model of older power plants, the model chooses to switch off most of this older capacity and only partially retrofit it.

Finally, looking at Figure 3.8, it is not distinguishable any strong impact of investment cost on retrofitting optimal capacity. The case with halved costs shows the same results as the representative case because, as already mentioned, great part of the potential capacity reaches its upper limit.

3.4 Main Chapter conclusions

- Among coal technologies, oxyfuel plants seem to be the favourable choice of our model in scenarios with carbon taxes.
- Retrofitting existing coal power plants seems to be a convenient strategy for reducing CO_2 emissions, especially in the `2DC` scenario.
- Investment cost is the parameter that mostly affect the results related to CCS technologies.
- Our model results shows some substitutability between CCS technologies and renewable energy sources.

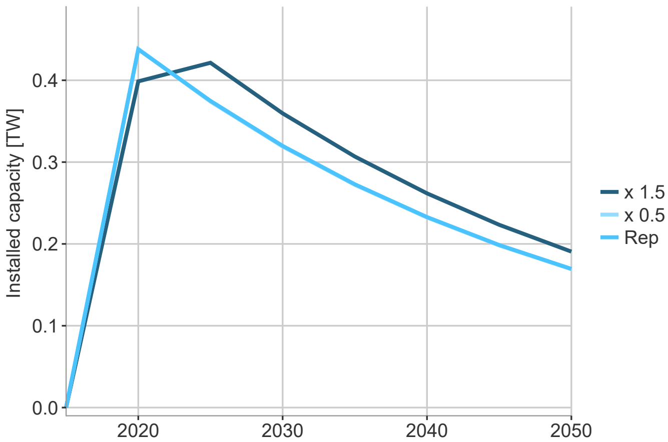

Figure 3.8. Variation of optimal retrofitting capacity due to efficiency and investment costs change for the 2DC.

Chapter 4

Technological Learning

In the following chapter, we aim at analysing possible paths of cost reduction for CCS options in the future. These reductions are likely to take place: it is often observed that costs decrease with an increase in installed capacity. The relationship between cumulative capacity and cost can be described as learning by doing. This phenomenon is particularly significant at an early stage of technology development, when the market offers more opportunities of learning by doing [64]. Considering CCS, this could be the case: therefore, it is worth focusing our attention on learning as it could positively affect CCS potential in the future. In this chapter, we will investigate the technological improvement and consequent cost reduction considering investment costs of the power plants. From the previous chapter, we know in fact that $O\&M$ costs play a niche role on the overall costs of CCS compared to the investment costs.

4.1 Learning curve definition and properties

4.1.1 Model context

As already described, the WITCH model provides different CCS technologies, synthesized in Table 4.1. We aim at introducing learning by doing for each technology (except for retrofitted power plants), in order to better understand the competitiveness among CCS solutions and to figure out the most promising technologies. As they show some similarities (e.g. CO_2 capture component), we assume that they are linked by some spillover effects. Therefore, in our implementation, advancement in one technology are going to positively influence other similar technologies. Another important aspect that should be underlined is that we assume a delay in the learning phenomenon occurrence, marked by a minimum installed capacity [68]. The reason behind this assumption is the following. For some newly implemented technologies, an initial cost increase could take place, instead of the above mentioned cost reduction. This increase could be related to the use of components that have never been implemented on a large-scale: for CCS technologies this could be the case. This issue is addressed assuming that the start of cost decrease is delayed until a large scale capacity is operating.

4.1.2 Methodology description

Currently, the prevailing method for representing the electricity costs dependence on technological change is through log-linear equations called learning curves [82]. We define learning rate the percentage reduction in cost corresponding to a doubling in capacity. It is worth underlining that at the moment only very few plants with CCS are operating [1]. The calculation of the learning rate for such young technologies poses strong challenges as

Table 4.1
CCS technologies options implemented in WITCH and corresponding fuel

Technology		Fuel
Natural Gas Combined Cycle with capture	NG-CCS	Natural gas
Integrated Gasification Combined Cycle with capture	C-IGCC	Coal
Pulverized Coal Oxyfuel	C-OXY	Coal
Pulverized coal Post Combustion[a]	C-post	Coal
Biomass fired Integrated Gasification Combined Cycle	Bio CCS	Biomass

[a] either with retrofitting or as a new technology

it is traditionally based on historical trends. In absence of historical values, this fitting process is infeasible. Therefore, we follow another approach derived from a report by IEAGHG, 2006, which takes into account similarities among different technologies, in order to determine possible learning rates for CCS options [36]: we base the implementation on this study. In this study, the authors develop learning curves for some technologies somehow related to CCS plants. Afterwards, they consider these components as subsystems of the overall plant, the total cost is represented by the sum of the single components. As the historical value of single components installed capacity can be calculated, the overall learning curve calculation is straightforward.

4.1.3 Description of components and relevant characteristics

In the following section, we describe each element, the analogy between components and the reason why they have been selected in order to represent CCS plants learning behaviour. In Table 4.2 CCS plants components and the analogous elements adopted in the approximation are synthesized.

Gas Turbine Combined Cycle (GTCC)

A combined cycle power plant main components are a gas turbine, a Heat Recovery Steam Generator (HRSG) and a steam turbine. Even though HRSG and steam turbine technologies could be considered mature, GTCC advancements are still possible due to gas turbine improvements. Learning rates related to GTCC could therefore influence some CCS technologies requiring a gas turbine.

Flue Gas Desulfurization (FGD)

This technology is used to control sulphur oxide emission level in thermal power plants. Concerns related to corrosion potential of Sulfur Dioxide (SO_2) pushed the research in this post-combustion technology, available in wet and dry applications. FGD is usually applied in coal based power plants, as an after treatment of flue gases. As CCS CO_2 post-combustion removal options, FGD has high costs and high efficiency of removal.

Selective Catalyst Reduction (SCR)

SCR is a technology used in coal power plants as an after treatment in order to control Nitrogen Oxides (NO_x) emissions. Similarly to post-combustion CO_2 capture and FGD technology, the pollutant abatement is performed treating flue gases with chemical agents.

Table 4.2
Definition of each plant component and analogous technology

NG-CCS Plant	GTCC (power block)	GTCC
	CO_2 capture (amine system)	FGD
	CO_2 compression	CO_2 compression
	Fuel cost	
C-post	PC Boiler/turbine-generator area	PC boiler
	AP controls (SCR, ESP, FGD)	FGD/SCR
	CO_2 capture (amine system)	FGD
	CO_2 compression	CO_2 compression
	Fuel cost	
C-IGCC Plant	Air separation unit	O_2 production
	Gasifier area	LNG production
	Sulphur removal/recovery	FGD
	CO_2 capture (WGS/Selexol)	FGD/SCR
	CO_2 compression	CO_2 compression
	GTCC (power block)	GTCC
	Fuel cost	
C-OXY	Air separation unit	O_2 production
	PC boiler/turbine generator area	PC boiler
	AP controls (ESP, FGD)	FGD
	CO_2 distillation	LNG production
	CO_2 compression	CO_2 compression
	Fuel cost	

The table is taken from [36]

This technology has high abatement rates and high costs, trends comparable with CCS options.

PC boiler

One of the major components of coal based plants is the PC boiler. The basic principle is the following: solid fuel (coal) needs to be pulverized and transferred with combustion air to the furnace, where the ignition starts. An increase in performance for this technology can be historically linked to some technical improvements (e.g. super alloys used in the surface of the furnace, ultra-super critical cycles, air pre-heating). As the cost of this component is significant with respect to the overall plant, the associated learning rate is relevant.

O_2 production

Oxygen production is performed through ASU units. The main goal is separating oxygen from other ambient gases (such as N_2), so to avoid the presence of inert gases in the burning phase and in the water gas shift reactions. The main steps that should be performed are the following: air requires an initial filtration, followed by a compression and a purification [72]. Heat is recovered and a distillation allows to separate the gases with different boiling points. This technology is costly and energy intensive: when required in a power plant, ASU costs and performances are highly relevant.

Liquified Natural Gas (LNG) production

LNG production is a process through which natural gas is firstly purified and than liquefied so to ease the storage and transportation processes. The technical requirements of this component shows evident similarities with CO_2 compression and liquefaction.

4.2 Implementation

4.2.1 Pre-existing modelling context

As already reported in Chapter 2, in the WITCH model framework learning by doing is taken into account for solar, wind and advanced biofuels. Through our implementation, we add CCS to the set of technologies subjected to Learning by doing (see Table 2.1).

4.2.2 Main equations

The mathematical model that we follow for the implementation is represented by the one factor learning curve:

$$\frac{I_{cost}(j,t,n)}{I_{cost}(j,0,n)} = \left(\frac{wcum(j,t)}{wcum(j,\bar{t})}\right)^{-b(j)} \tag{4.1}$$

Where $I_{cost}(j,t,n)$ [\$/W] represents the investment cost for the j-th CCS technology in country n at time t, $I_{cost}(j,0,n)$ refers to the same variable at the initial time step, $wcum(j,t)$ [TW] refers to the global cumulative capacity of j-th technology at time t, $wcum(j,\bar{t})$ is the global capacity at which learning starts, and $b(j)$ is a parameter which depends on the technology. It is worth underlining that we assume full spillover across regions: the capacity installed in a region allows to benefit to the same extent in each world region. In WITCH, the initial investment cost is exogenously determined and it is characterized by a regional differentiation. In our implementation, it is assumed to be constant and equal to $I_{cost}(j, 0, n)$ until the installed capacity reaches a minimum value (represented by $wcum_{min}(j) = wcum(j, \bar{t})$), at time step $\bar{t}$. The initial capacity of CCS technologies is null, but the model is allowed to invest in CCS options in order to meet climate scenario requirements making the capacity increase.

In order to calculate the factor $b(j)$, we need to determine the learning rate $LR(j)$ and the progress ratio $PR(j)$ for each technology. These parameters are linked as follows:

$$PR(j) = 1 - LR(j) \tag{4.2}$$

$$LR(j) = 1 - 2^{b(j)} \tag{4.3}$$

As already mentioned, there is a positive effect on similar technologies spreading from investments in one technology (spillover effect). In order to take into account this aspect, the cumulative installed capacity is determined as follows:

$$\forall j, \quad wcum(j, t) = \sum_i spill_{rate}(i, j) \cdot wcum_{single}(i, t) \tag{4.4}$$

where $wcum_{single}(i, t)$ refers to the single technology cumulative installed capacity and $spill_{rate}(i, j)$ represents the spillover effect between the j-th and the i-th technology. This parameter is comprised between 0 (absence of spillover) and 1 (total benefit transfer). Another constraint is assumed to be related to a minimum cost that CCS technologies could not reach, the so called floor cost $floor_{cost}(n, j)$, in [\$/W]. The floor cost imposition is necessary in order to avoid excessively decreasing costs with an increase in installed capacity. We assume that a meaningful floor cost is equal to the investment cost of a new plant without CCS built in the same region and fired with the same fuel, namely a new coal plant for C-IGCC, C-OXY, C-post, a new gas power plant for NG-CCS and a new biomass-fired plant for Bio CCS. If a learning curve crosses such cost, $I_{cost}(j, t, n)$ is calculated as:

$$I_{cost}(j, t, n) = floor_{cost}(n, j) \tag{4.5}$$

4.2.3 Data gathering and literature review

In order to determine the parameters in Equation 4.2 and Equation 4.3, we performed a literature review focused on CCS learning rates [36, 64, 66, 68]. The resulting values are reported in Table 4.3. It is worth underlining that data in literature are characterized by a strong variability [66], mainly due to the early stage of development of the technologies and the absence of historical data. We address this issue performing a sensitivity analysis on the most important values. For example, C-IGCC has the highest learning rate, but also the highest uncertainty range. On the other hand, C-OXY shows the lowest learning rate. Concerning the minimum installed capacity before learning, C-OXY and Bio CCS have the highest value, meaning that they require more deployment of new plants before cost start decreasing.

The initial representation of the implemented values is provided in Figure 4.1.

As already mentioned, we represent cross benefits among technologies through the parameter $spill_{rate}(i, j)$. In Table 4.4 we synthesize the first attempt values implemented.

We estimated and hypothesized the values, based on similarities among technologies. In particular, the higher the similarity, the higher is the spillover value: it means that an increase in $wcum_{single}(j, t)$ is basically as much effective on the i-th technology as an equivalent increase in $wcum_{single}(i, t)$. This is the case of C-IGCC and Bio CCS, which

Table 4.3
Learning related parameters for each technological option

	LR [%]			b			$wcum_{min}$
Technology	Low	High	Best	Low	High	Best	[TW]
C-IGCC	2.5	20.0	6.7	0.037	0.322	0.100	0.007
Bio CCS	0.0	10.0	5.0	0.000	0.152	0.074	0.010
NG CCS	1.2	12.0	4.2	0.017	0.184	0.062	0.003
C-post	1.1	9.9	3.8	0.016	0.150	0.056	0.005
C-OXY	1.4	7.0	2.8	0.020	0.105	0.041	0.010

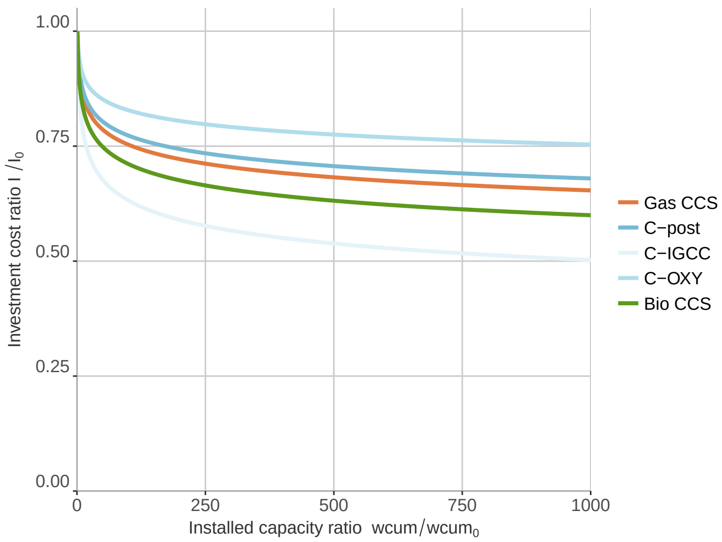

Figure 4.1. Learning curve representation for each CCS technology in the *best* case.

Table 4.4
Coefficients of spillover $spill_{\text{rate}}(i, j)$ matrix.

	C-IGCC	**Bio CCS**	**NG CCS**	**C-post**	**C-OXY**
C-IGCC	1	0.8	0.7	0.5	0.6
Bio CCS	0.8	1	0.7	0.5	0.2
NG CCS	0.7	0.7	1	0.7	0.2
C-post	0.5	0.5	0.7	1	0.2
C-OXY	0.6	0.2	0.2	0.2	1

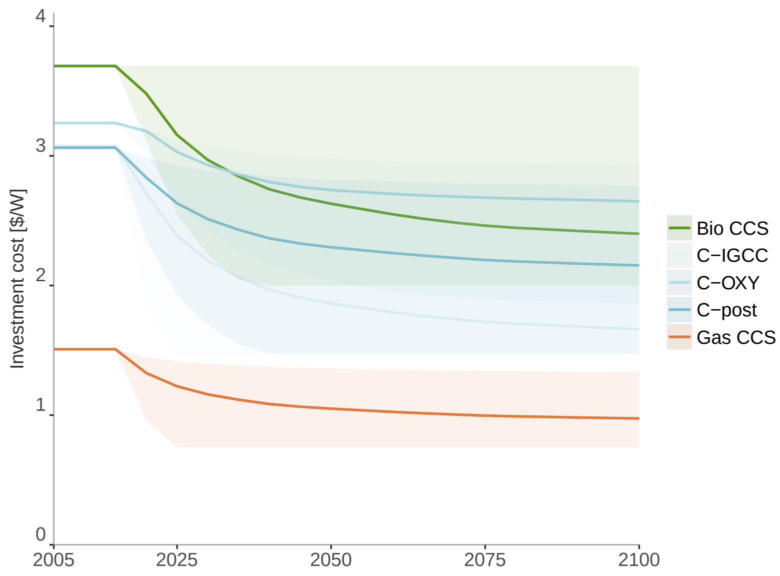

Figure 4.2. Learning curve with uncertainty area depending on $b(j)$ estimates for each CCS technology in time, region Oldeuro, `ctax` scenario.

essentially require the same carbon capture system. It is noticeable how, also in this case, C-OXY is unprivileged. We estimated the spillover coefficients with other technologies quite low, since C-OXY plants present some important structural differences.

4.3 Results and robustness analysis

As already mentioned, there is high uncertainty concerning the parameters included in the implementation. In order to address this issue, we perform a sensitivity analysis testing a range of maximum and minimum value of each key parameter. The firs results are shown performing a `ctax` scenario, subsequently we also show the differences with the `2DC` scenario. By looking at the bar *Best* in Figure 4.3 we can have an idea of what is the total electricity produced by CCS plants by 2050.

4.3.1 Spillover importance and effect

First of all, a strong assumption that we introduced is the spillover effect among the various technologies. In this regard, we would like to test the model response to a strong reduction and increase in spillover values and the importance of the spillover effect in the absolute decrease in investment cost for each technology. The representative values are reported in Table 4.4, while as a lower bound we consider the total absence of spillovers, while as upper bound we impose $spill_{rate}(i,j)$ equal to 1. This means that every investment in a specific CCS technology contributes in the same way to the cost decrease of every plant with CCS: this is not likely to occur, but can be a useful case study.

Testing the three sets of spillover factor value, we do not appreciate any significant variation in the results. We notice that, in case of absence of spillover, some technologies reach $wcum_{min}$ with some delay. Calculating the cumulated installed capacity $wcum(j,t)$ for all the technologies in 2050, the variation with respect to the representative case are +2% for $spill_{rate}(i,j)$ equal to 1, and -2% for $spill_{rate}(i,j)$ equal to 0. In conclusion, spillover does not allow strong variations in investment costs and, as a consequence, the difference in terms of installed capacity is minimal. Probably, the underlying reason is linked to the myopic behaviour of the model concerning this part of the implementation. Equation 4.1 is calculated at the end of each model iteration (time t), and the results updates the value of $I_{cost}(j, t+1, n)$. Therefore, at the beginning of each iteration, the model is not aware that an increase in capacity is potentially leading to a future cost reduction.

4.3.2 Floor cost and minimum capacity before learning

As already mentioned, the floor cost importance is related to the competition among CCS and traditional technologies. If it is not realistic to assume CCS technologies becoming more convenient than traditional options (base case), it could be interesting to test an higher floor costs case. An increase in the floor cost can also be considered a test from a modeling point of view, since crossing the floor cost introduces a discontinuity in the learning function. However, performing the `ctax` scenario setting floor costs 1.5 time higher than the reference case, does not show significant changes in the results. In particular, C-OXY and C-post do not reach the floor cost, so they behave identically as in the reference case.

The minimum capacity before learning starts also does not meaningfully affect the results, especially considering our time frame. Doubling the start capacity we delay of one period of time (5 years) the introduction of most CCS technologies, but results in 2050 remain almost unchanged.

4.3.3 Learning rate

A very important aspect of learning is the fastness of cost decrease. This is mainly linked to the assumptions on the parameter $b(j)$. Therefore, a variation in a maximum-minimum range of this values is important to assess how much this parameter influences the delay in the technology adoption. The selected ranges are derived from the data collected during the literature review. As an example, in Figure 4.2 a representation of the effect of $b(j)$ variation on the investment cost curves is reported. As already mentioned, investment cost values depend on the selected region, but also on the capacity installed (which depends on the carbon tax): for example, this is a `ctax` scenario for the region Oldeuro.

An increase in $b(j)$ values with respect to the base case determines a faster reduction in costs of the technologies. We expect this evident cost decrease to result in higher CCS penetration. The implemented values of $b(j)$ correspond to the maximum values found in literature. Symmetrically, a slower decrease in investment costs should lead to a reduction in CCS share in the energy mix, because of the cost optimization process pursued by the model. Similarly to the previous case, the values are based on the literature review.

From the data we use in this analysis, it is evident that C-IGCC and C-post are greatly advantaged compared to C-OXY in case of high cost reduction (therefore high $b(j)$). This trend affects the result leading to a reduction in oxyfuel power plant and an increase of C-IGCC and post-combustion technologies. Figure 4.3 shows the differences in energy production from CCS technologies for the `ctax` and `2DC` scenarios. As expected, with an increase of the learning factor $b(j)$ all CCS technologies become more convenient, and therefore contribute more to electricity production. Moreover, we can notice that the technologies that mostly benefit from learning variation are gas and coal fired technologies. This is a consequence of our strict assumptions on biomass with CCS and the absence of technical improvement for retrofitting. Finally, considering the reference cases, they only slightly deviate from the case with no learning, while the main changes arise only

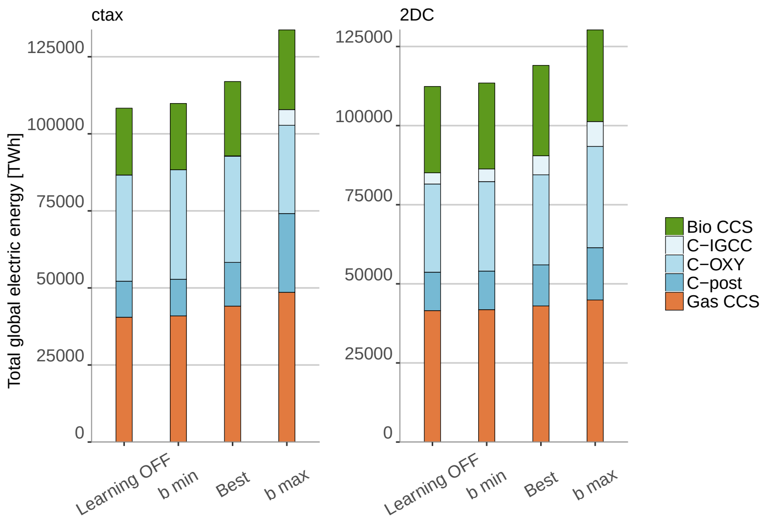

Figure 4.3. Cumulative energy produced up to 2050 by CCS technologies considering different values of $b(j)$. `ctax` and `2DC` scenario results are compared.

considering the maximum learning.

We are also interested in assessing whether learning rate variation also affects the results concerning other power technologies. Concerning Solar and Wind power plants, the same considerations made in the previous chapter are confirmed: whenever CCS plants become more or less competitive, there is direct substitution with intermittent renewables. Moreover, we notice also very small changes in traditional fossil fuel production. As shown in Figure 4.4, electricity produced by conventional coal and gas plants slightly lowers while CCS total production increases thanks to learning. Considering case *b max*, it is possible to see that while the total production of CCS technologies increases, total production by traditional coal and gas plants remains almost constant.

4.3.4 The `2DC` scenario

Following the same procedure used in Chapter 3, we perform the sensitivity analysis also considering the `2DC` scenario.

The main conclusions we drew in the previous sections remain valid. As previously stated, even in this case the most important parameter is the learning rate. However, considering that in this scenario retrofitting has an important role, but no learning, the overall effect of $b(j)$ on CCS technologies is restrained, as shown in Figure 4.3.

4.4 Main Chapter conclusions

- Technological improvements have a relevant impact on the overall usage of CCS technologies.
- According to our implementation and the data we found, some scenarios are less optimistic on the role of oxyfuel coal plants compared to our reference setting. On the other hand, IGCC and post-combustion technologies might gain more importance.

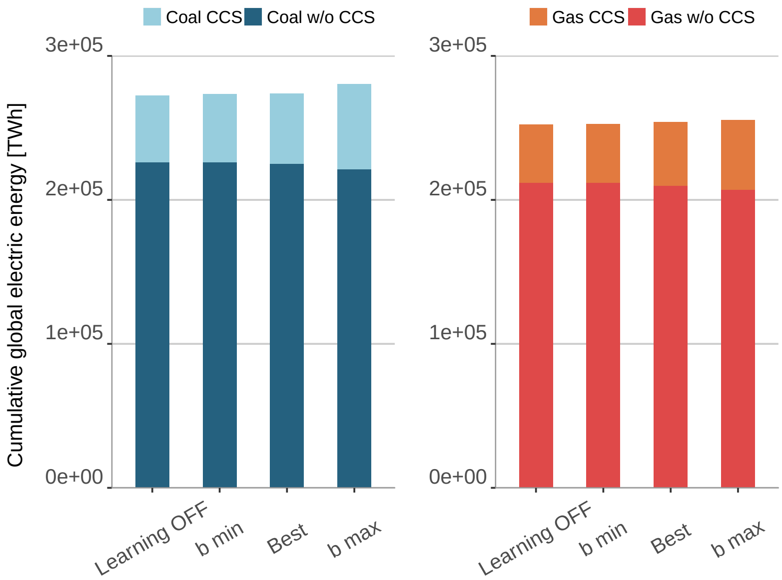

Figure 4.4. Total energy produced in 2050 by fossil fuel technologies considering different values of $b(j)$, `ctax` scenario.

Chapter 5

CO_2 Transport and Storage

In the previous chapters, we analysed in detail CO_2 capture phase, considering different capture technologies performances and costs (see Chapter 3), and the possible behaviour of investment costs in the future (see Chapter 4). However, another important aspect of CCS power chain is CO_2 storage. First of all, it is worth underling that anthropogenic carbon dioxide, once removed from the other exhaust gases of a power plant, can be stored or re-used for industry purposes. Besides plant related costs, these processes imply the deployment of additional infrastructures construction and maintenance, and, consequently, additional costs [3, 15, 63]. Even though CO_2 is required in many industrial sectors, such as oil and gas, chemical and pharmaceutical, food processing and many others [15], in this work we focus only on geological storage and do not consider reuse. In this chapter, we therefore consider CO_2 transport and storage features, including leakage. Follows a description of the implementation, a sensitivity analysis and some result. We then deepen the leakage theme, presenting at first the results related to constant yearly leakage rate, and secondly the results imposing different trends to the rate.

5.1 Overview of CO_2 transport and storage options

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 [23, 34].

The most diffused transportation technique of CO_2 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. high carbon price and remote offshore distance from the producer to the storage site) [85]. In this thesis work we deal with pipeline transportation only.

Another important aspect of CCS 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. However, we mainly focus our attention on leakage from storage sites.

Considering storage available options, we identify the main types of possible geological storage solution: aquifers, oil and gas fields and coal seams. Figure 5.1 schematizes these three possible storage solutions.

Aquifers

Aquifers could be defined as a geological formation of porous rocks, permeable and saturated with water, that allows the water withdrawal [2]. Aquifers are already exploited

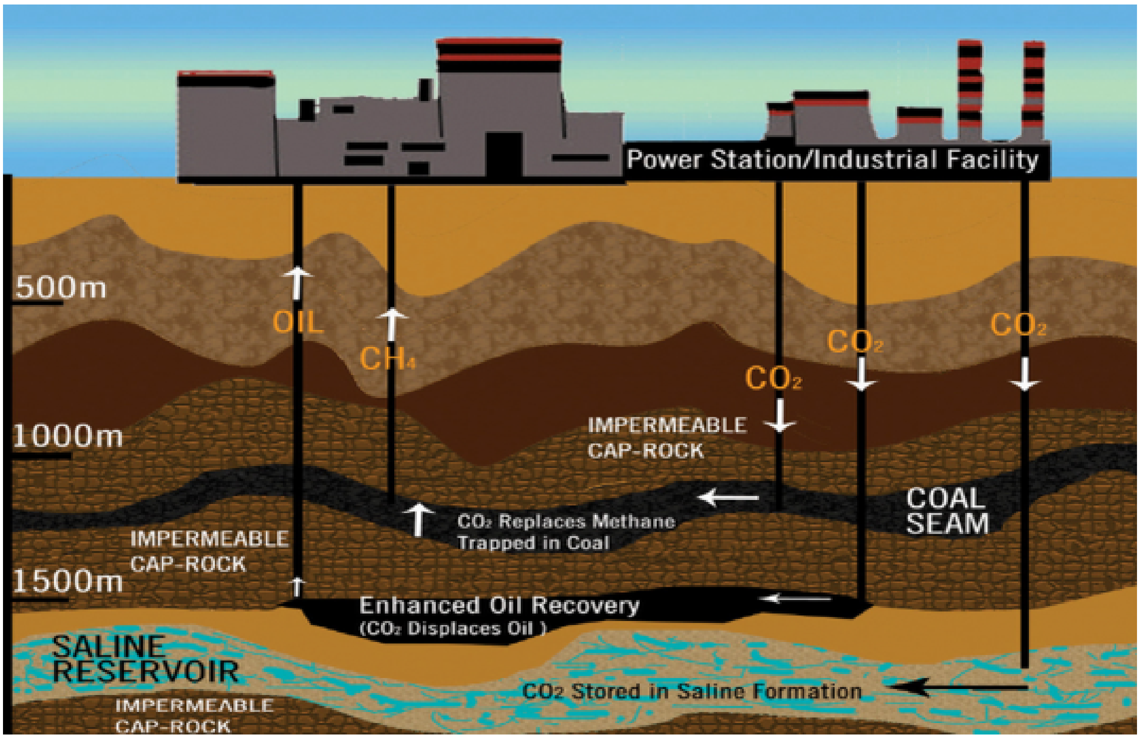

Figure 5.1. A simplified representation of the three types of storage that we consider. Source: Energy-Without-Carbon

for their storage potential (i.e. for waste water, seasonal CH_4 storage, CO_2) but a careful management of these resources is required due to the complex geological water system. Only deep saline aquifers are taken into account for the storage purpose. As most of deep saline aquifers have not been fully characterized yet, the assessment of suitable storage sites would require accurate studies.

Oil and gas fields

Oil and gas fields, where extraction is declining, are interesting options for CO_2 storage. First of all, it is economically convenient to apply EOR technique, which extra oil production revenues overcome costs. Carbon storage is today mainly applied to EOR in oil and gas fields. CO_2 injection helps the oil release due to fluids pressure. Great part of the injected CO_2 is still recoverable and can be reused by the operator for other re-injections, while a small part of CO_2 is trapped. The operator can, once the field is depleted, use it as a long term CO_2 storage [34]. Depleted fields can be a valuable storage site: they are reasonably reliable, as they naturally stored gas for thousands years, and they have been geologically fully characterized.

Coal seams

Coal seams are coal beds where mining is profitable. Coal seams that are not advantageously exploitable are in general considered as unmineable, even though some methane is trapped in coal pores. The technique of Enhanced Coal Bed Methane (ECBM), which consists of injecting CO_2 in the coal bed, contributes to CH_4 release. The ratio between stored moles of CO_2 and released CH_4 moles is about two [35].

Another storage option studied and experimented in the past is deep ocean storage. However, most of recent studies don't consider this option as a resource for the future, due to problems of public acceptance and uncertainty of impacts on ecosystems [28]. As a consequence, in our modelling work we don't consider deep ocean storage. In order to give a more detailed representation of storage sites, we further split aquifers and oil and gas fields categories into onshore and offshore options. Another distinction we apply is related to depleted oil and gas fields and active sites (suitable for EOR).

5.1.1 Storage and transport cost in integrated modelling

The WITCH model, as well as other integrated assessment models, has a specific section devoted to CCS. Storage and transport costs are implemented according to an approach by Hendriks et al, 2004 [27]. The study assesses the global storage capacity for different reservoirs and provides also storage and transport costs differentiated per region. Figure 5.2 shows a global total cost curve from Hendriks, where a base capture cost of 38.5 €/tCO_2 is summed up with the variable storage and transport cost.

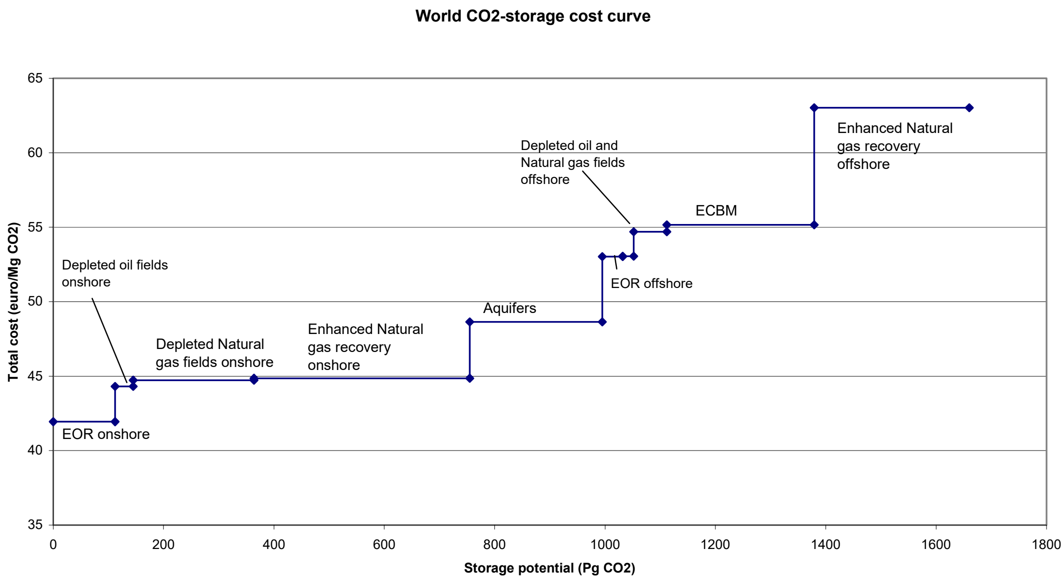

Figure 5.2. Global fixed capture cost plus variable transport and storage cost. Hendriks et al, 2004 [27]

The current implementation in the model gathers data of costs and capacities from this report. We think that the current implementation is worth updating due to some important reasons. First of all, we find in recent studies some discrepancies from the mentioned source, especially in terms of global and regional storage potential and storage costs. Moreover, other reports study in detail CO_2 transport in pipelines and precisely assess the related costs [5, 9, 58, 62]. Secondly, we think that an important information that the current implementation loses is the record of timing and location of the stored CO_2. As a consequence, as it will be extensively explained in Section 5.4, we decide to model the storage system in WITCH differently from the past. Our main purpose is to find a technique meant to keep track of what type of storage is used in the different regions for every period of time. Furthermore, in the current implementation leakage of CO_2 from CCS chain is not included. As we think leakage could have a crucial role in CCS future deployment, we include them in the model.

The first step of the process is a literature review focused on storage potential, typologies of storage site, storage cost and transportation cost, leakage phenomenon. The results of the literature review are summarized in the following sections.

5.2 Assessment of storage potential and costs

The first and probably most important issue regarding carbon capture and sequestration is the assessment of how much CO_2 can be stored worldwide and how this capacity is distributed across regions. Indeed, carbon capture would be worthless if there was not a secure place where to convey CO_2 that guarantees good seal and no leakage into the atmosphere. The International Energy Agency carried out in 2013 a very extensive study about this topic. Their report reviews a large number of storage capacity related studies, in order to derive the principles for a common method of storage capacity assessment. It puts in evidence the major constraints for evaluating the performances of a storage sites: geological characteristics and ground surface structure; engineering considerations (such as technology availability); economics and socio-political factors (i.e. public acceptance) [31].

5.2.1 Global storage potential

As already specified, most studies agree to consider a bunch of storage types that comply with the just mentioned criteria. These types of storage sites are: depleted or remaining oil and gas fields, coal beds and underground aquifers (saline aquifers, not used for drinkable water). Due to the uncertainty in the assessment in available capacity, some authors provide low, best and high estimation. Dooley, 2013 considers a theoretical capacity of 35300 $GtCO_2$ that is reduced to an effective and then a practical potential of 13500 and 3900 $GtCO_2$ respectively [12]. Manipulating data provided by the literature, we obtain an average global capacity of 11096 $GtCO_2$, even though a more pessimistic estimation is by Hendriks et at., 2004 (476 $GtCO_2$) and the very optimistic estimation is by Benson, 2012 (33153 $GtCO_2$) [3, 27, 44]. As a check, we find that Koelbl et al., 2014 and the Ecofys report for IEAGHG, 2011 suggest default values for global storage capacity very close to the average value that we obtain [39, 54].

5.2.2 Regional storage capacity divided by type

When dealing with regional capacity differentiation, we decide to mainly rely on the IEAGHG, 2011 report. In Table 5.1 we synthesize the values taken from this report and used as a base for the model input. Considering these data, we can notice that aquifers are the most widespread storage type worldwide, covering the 85.6% of global capacity, followed by Oil and Gas (O&G) fields with 10.8% and finally coal seams with 3.6%.

The IEAGHG 2011 report summarizes the low, best and high estimates of storage capacity for seven regions and three storage types (O&G fields, coal beds and aquifers). It is striking to notice that the assumed capacity for North America accounts for 8333 $GtCO_2$ in the *best* case, which represents 74% of the total global capacity. In Appendix D, we report in Table D.1 the *low*, *best*, *high* estimates they provide. This trend is confirmed by NETL, 2015 report that assesses in an extensive way the potential for North America, and by Benson 2012 that, although showing different absolute numbers, assign most of the global capacity to the US [3, 6].

However, as already explained, we would like to introduce some other categories among the storage options. In particular, O&G fields is quite a general category that could be analysed with further detail, distinguishing depleted fields from EOR. IEA, 2015 and

Table 5.1
IEA GHG capacity divided per region in *best* case in $GtCO_2$.

	O&G	Coal beds	Aquifers
Africa and ME	522	8	588
Asia	91	179	370
Oceania	20	11	2
Latin America	89	2	121
non OECD and Former Soviet Union	310	25	379
North america	156	176	8001
OECD Eu	19	1	82

Godec, 2011 both provide some estimation of the EOR potential capacity with regional differentiation [23, 34]. In our implementation, we account for this analysis and originate a new category from the branch of O&G fields.

Finally, IEAGHG, 2009 shows other data from Hendriks, 2004 and Dooley, 2005, reporting an estimation of the onshore and offshore storage reservoir for oil and gas fields and aquifers [37] (see Table D.2 in Appendix D).

Combining all these data, we are able to assess for each region what is the storage capacity of seven different type of reservoir: EOR onshore and offshore, O&G fields onshore and offshore, aquifers onshore and offshore and finally only onshore ECBM. Our resulting data are reported in Table D.5 in Appendix D. Some important conclusions can be drawn from the data. In Figure 5.3, global quantities are calculated from the regional capacities: it is clear that the highest uncertainty is related to aquifers, especially onshore. They represent however the highest available storage capacity in each case (low/best/high), while EOR represents a very small share of the overall available capacity.

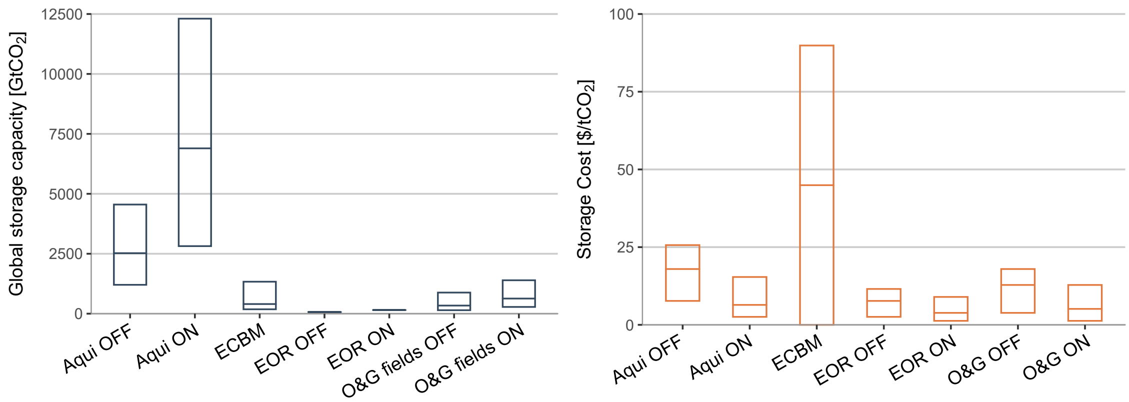

Figure 5.3. Global storage capacity and storage costs for each storage type according to a low/best/high estimation. ON and OFF refer to "Onshore" a "Offshore" storage sites.

5.2.3 Storage cost

The variability for geological storage costs in literature is very high, because many studies describe specific sites that might have different properties one from another, such as storage type, regional geology, pre-built infrastructure. For example, Rubin, 2015 shows costs range between 1 and 18 $/tCO_2$ [67]. Due to the variability in gathered data, we

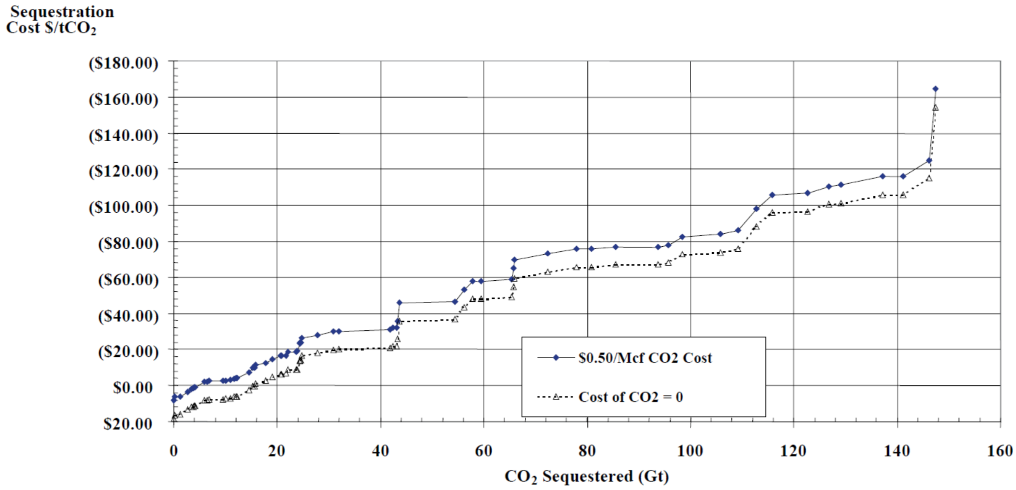

Figure 5.4. ECMB cost-capacity curve according to Gale, 2006

consider in our model only the values supplied by a study by ZEP and IEAGHG regarding storage costs for all the storage types we selected [39, 84] (see Table D.3), except for ECBM. For this last storage type, we rely on another report [52], according to which ECBM cost shows a peculiar behaviour as it ranges from slightly negative to highly positive values (see Figure 5.4). It is worth underlining that, in our model, costs of storage cannot be negative without consequences on the gas market (gas price would be influenced by a gain from ECBM-gas producers). However, as it is possible to see in Figure 5.4, only a low storage capacity is characterized by negative costs. Therefore, we believe a feasible approximation is having ECBM costs ranging from 0 to almost 90 $\$/tCO_2$ (see Figure 5.3). The same reasoning holds for EOR impact on oil market: according to some sources, EOR cost could range from highly negative to highly positive values [54, 55]. However, we consider an acceptable approximation the adoption of very low costs of EOR storage sites in the low cost estimation, as in the report by ZEP and IEAGHG. The obtained costs estimates are reported in Figure 5.3.

5.2.4 Transport costs

As already mentioned, another critical aspect in the current implementation is related to CO_2 transport towards storage sites. In particular, the current model takes into account an overall cost value representing both transport and storage. In our implementation, as we would like to trace CO_2 flows, we need to separately represent transportation costs.

Generally speaking, CO_2 transportation costs via pipeline can be related to the infrastructure costs: pipelines construction, pipe coating, protection system. On the other hand, costs of allowances, surveillance, expert supervision should also be taken into account [62]. In addition to the complex transport cost composition, the CO_2 network system is, at the moment, strongly undersized (with the only exception of the United States), if we take into consideration a future development of CCS technologies. As a consequence, we need to make some assumptions on the transport cost behaviour. According to several sources, two important variables mainly affect the transport cost: mean pipeline length and average CO_2 mass flow rate [5, 9, 58, 67]. The relationship between the variables is the following: the proportionality between mean pipeline length and transport cost is direct, while there is a decrease in costs with respect to an increase in mass flow rate. From Correia, 2011, we understand that from a certain pipeline length on, the specific cost per km is constant. Moreover, all sources agree that for mass flow rates high enough, costs can be considered constant with respect to mass flow rate. Combining these considerations, we represent specific transport costs as a coefficient depending only on the average pipeline length: we calculate it manipulating data provided by Rubin, 2015 (see Table D.4) and find a value equal to 0.006667 $/t$CO_2$km. In order to determine the total transport cost, we need therefore estimates of the mean pipeline length in each region. We obtain these data manipulating information provided by Hendriks, 2004. In Table 5.2 we report the mean distances covered by pipelines in each region.

Table 5.2
Mean source to storage distances in each country expressed in [km].

	Aquifers	O&G fields Onshore	O&G fields Offshore	ECBM
Canada	350	350	1250	350
U.S.A.	350	350	2000	350
Central Am.	125	25	350	1250
South Am.	125	125	125	25
Northern Afr.	125	125	125	2000
Western Afr.	125	350	350	2000
Eastern Afr.	350	350	2000	2000
Southern Afr.	125	350	125	125
Western Eur.	125	350	125	125
Eastern Eur.	1250	25	2000	125
Former S.U.	1250	1250	2000	2000
Middle East	125	25	125	2000
Southern Asia	350	1250	125	350
Eastern Asia	1250	350	1250	125
South East. Asia	350	125	125	1250
Oceania	125	2000	1250	350
Japan	350	2000	1250	125
Greenland	1250	2000	1250	2000

We use these values to derive the mean distances towards all the seven storage sites: the values for Aquifers is assigned to aquifers onshore and offshore, and the same for O&G and EOR, both onshore and offshore.

5.3 CO_2 leakage

As already mentioned, CCS safety and mitigation potential is strictly dependent on leakage risk. Leakage could be originated by CO_2 transportation, underground injection, or storage. Leakage from transportation is due to eventual pipeline losses, but can be considered unlikely to occur due to pipeline monitoring systems that measure pressure losses and potentially harmless, due to the pressure drops control systems [19]. Injection process can lead to unwanted CO_2 leaks: injection requires a wellbore, a conduit where eventual upward flows are possible. Finally, undesired loss of CO_2 from storage sites can occur due to the imperfect storage sealing. The main features of these different leakage occurrences are the following. Both pipeline and injection leakage take place in the same time period of the emission, before the CO_2 is stored. This means that, in principle, the amount and effect of leakage could be instantly assessed. The coincidence between t of emission and t of leakage is absent when dealing with CO_2 loss from storage sites, i.e. the leakage is related to the cumulative quantity of CO_2 that has been stored in the past. This aspect is critical as one of the main issues related to CCS deployment is the long term suitability of storage options [63, 75]. Moreover, according to the literature, there is still high uncertainty about the true reliability of storage sites [75]. As the long term response of storage sites could hinder CCS effectiveness as a mitigation option, we decided to focus our attention in assessing the impact of storage leakage.

5.3.1 Leakage estimate

According to our literature review, leakage rate could be related to CO_2 quantity present within the storage site [74, 75]. The behaviour of leakage rates could depend also on time: in particular, the percentage of CO_2 lost with respect to the total stored amount could exponentially decay or show an S-Shaped behaviour. These complex paths try to portray some important geological and fluid-dynamic aspects of CO_2 leakage. For example, the exponentially decaying curve stands for a storage site where CO_2 leaks at first easily, then increasingly more scarcely due to the fact that only the best trapped CO_2 remains in the storage site. An S-Shaped curve would represent the CO_2 leaking through multi-layers media. However, as in van der Zwaan, 2007, leakage rate could be also represented as a constant percentage of the cumulative stored quantity within the storage site. We base our analysis on this paper, assigning a constant annual value to leakage rate [76]. As a first approximation, due to this high variability and uncertainty in leakage rates, we consider a null default value. This hypothesis is plausible if we consider that, according to the IPCC, 2005 report, storage sites are highly probably reliable and safe [63]. We then test this major assumption testing the model with different yearly leakage rates. In particular, we assign it values ranging from 1% to 0% and test the robustness of the main thesis conclusions. The selected values range from the default leakage percentage (0%) to the maximum acceptable value of 1% year, according to van der Zwaan, 2007 [76]. We then test higher values, aiming at understanding the model behaviour in some extreme cases. Our implementation of leakage equations is explained in the next section. As a final test, we analyse the model response to non-constant leakage rates.

5.4 Implementation in the model

In the following section we provide a description of the implementation procedure we applied in order to include all the transport and storage related information in WITCH.

First of all, most of the gathered data are region specific, but world countries are grouped differently with respect to WITCH regions. Therefore, we need to convert all the data following the ISO-3 regional decomposition, and, as a second step, regroup the regions according to WITCH criteria. This process could lead to some misunderstanding of the original data, since in the reports there is no description of the region composition: therefore, we don't know how to split each region a priori. Moreover, besides selecting the subregions, we don't know how to disaggregate the given value and redistribute it. For example, if we consider Asian aquifers storage capacity (370 $GtCO_2$, see Table 5.1), we first have to determine which countries are included in the region Asia, and then we have to select a weighting criterion that defines how the single countries contributes to the overall Asia value. In order to do so, we use a script developed in R that interacts with the model and redistribute data according to a weighting factor and a mathematical calculation. The weighting factor is chosen from a set of available options: therefore, we have to select the most suitable factor case by case, trying to find a good proxy of the original value. In

Table 5.3 we report the parameters included in the model compared to the parameter used as a weight.

Table 5.3
Weights used to include data related to CO_2 transport and storage in the model.

Parameter	Weight
Storage capacity O&G fields	O&G extraction in 2000
Storage capacity of ECBM	Coal extraction in 2000
Storage capacity of Aquifers	Hydroelectric production in 2005
Storage capacity of EOR	Oil extraction in 2005
ON-OFF storage share	Oil and gas extration in 2000
Average distance	Land area

5.4.1 Main equations

The following section reports the main equations implemented in the model to include the previously described transport and storage features. We will refer to the different storage types with the expression k_{st}. First of all, the capacity constraint for each storage typology in each country can be expressed as:

$$CUM_{EMI,st}(k_{st},t,n) \leq cap_{max}(k_{st},n) \tag{5.1}$$

Where $CUM_{EMI,st}(k_{st},t,n)$ [$GtCO_2$] stands for the cumulative emission stored in country n and time t in the k_{st}-th storage type, with an initial value in the first time period equal to zero. The capacity constraint $cap_{max}(k_{storage},n)$ [$GtCO_2$] corresponds to the maximum regional storage capacity we derived from the literature. $CUM_{EMI,st}(k_{st},t,n)$ account for the already stored CO_2 quantity $CUM_{EMI,st}(k_{st},t-1,n)$, reduced by the leakage factor λ_{lk}, and the CO_2 amount that is stored at time t, $Q_{EMI,st}(k_{st},n,t)$ [$GtCO_2$/yr]:

$$\begin{aligned} CUM_{EMI,st}(k_{st},t,n) =& CUM_{EMI,st}(k_{st},t-1,n)\cdot(1-\lambda_{lk}) \\ &+ tstep \cdot Q_{EMI,st}(k_{st},n,t) \end{aligned} \tag{5.2}$$

$Q_{EMI,st}(k_{st},n,t)$ represents an annual quantity, and should be therefore multiplied by *tstep* so to evaluate the 5 years time step equivalent. λ_{lk} stands for the percentage of CO_2 stored in the previous time period that is lost due to leakage and emitted in the atmosphere.

The costs of captured CO_2 transport and storage $C_{t\&s}$ [\$/yr] is evaluated according to the following equation:

$$\begin{aligned} C_{t\&s}(t,n) =& \sum_{k_{st}} \Big(c'_{tr} \cdot Q_{EMI,st}(k_{st},n,t) \cdot l_{tr}(n,k_{st}) \\ &+ Q_{EMI,st}(k_{st},n,t) \cdot c_{st}(k_{st}) \Big) \end{aligned} \tag{5.3}$$

Where c'_{tr}=0.006667 [\$/tCO_2km] is the specific transport cost, $l_{tr}(n,k_{st})$ [km] represents the average distance derived from Table 5.2, and c_{st} [\$/tCO_2] is derived by our literature review (see Figure 5.3).

Another equation introduced in the implementation takes into account the flow of captured CO_2 at time t from the emitting plants $E_{CO_2,capt}(t,n)$ [$GtCO_2$/yr] and set it equal to the overall gas streams that are to be stored:

$$E_{CO_2,capt}(t,n) = \sum_{k_{st}} Q_{EMI,st}(k_{st},n,t) \quad (5.4)$$

The last equation takes into account the increase in GHG emissions due to leakage:

$$Q_{EMI,leak}(t,n) = \lambda_{lk}(k_{st},t,n) \cdot \sum_{k_{st}} CUM_{EMI,st}(k_{st},t,n); \quad (5.5)$$

where $Q_{EMI,leak}(t,n)$ is the amount of CO_2 leaked and adds up to the other emissions sources in the equation of the model accounting for emissions into atmosphere.

5.4.2 Storage cost-potential curves

In order to have a clearer representation of the storage and transport cost behaviour with respect to the capacity, we report some interesting cost curves. The global curve is represented in Figure 5.5. We can see that a very large portion of the overall global capacity is below 10 \$ /tCO_2. Some interesting regional curves are plotted in Figure 5.6. We can see that the transport costs varies with the average distance, even decreasing with an increase in capacity, but the sum of storage and transport cost is always increasing. The model optimises the overall cost.

From Figure 5.7 it is possible to notice how, using the low, best or high values of the data we gathered can differently impact the storage cost curves. In particular, changing the storage capacity the curves are compressed along the x axis, therefore in case of low capacity the cost increases rapidly. Varying the storage (or the transport) costs have a different impact on the curves, as the capacity remain the same, the values on the y axis are reduced or increased. As the costs vary across the ranges we obtained from literature, the order from most convenient, to more expensive storage might change according to the scenario.

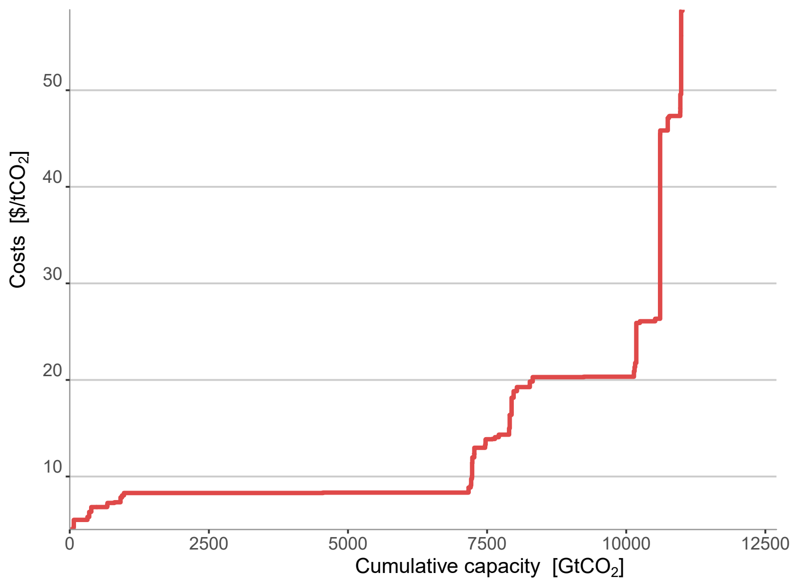

Figure 5.5. Global storage curve storage costs versus cumulative capacity $CUM_{EMI,st}$.

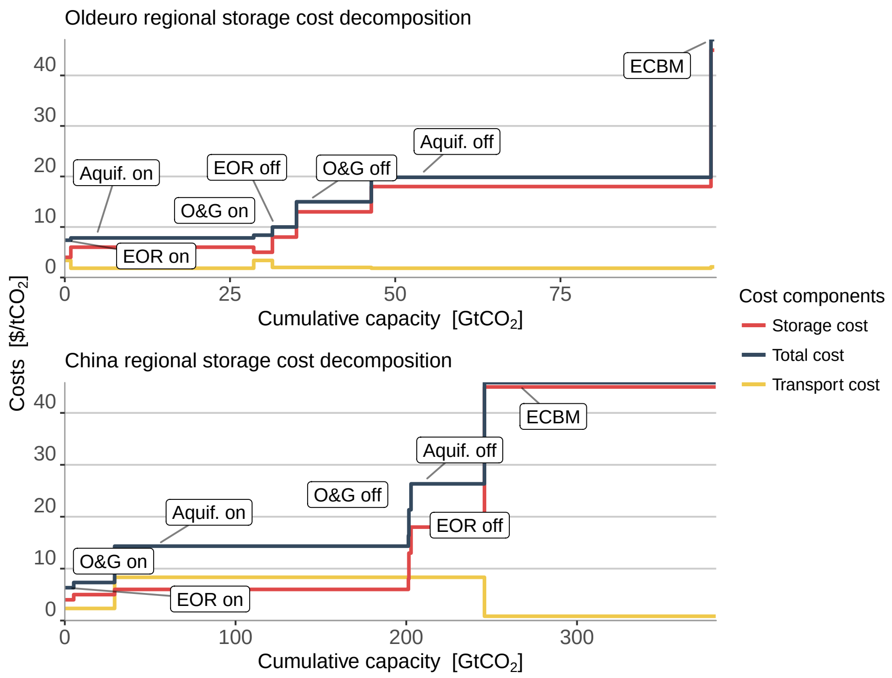

Figure 5.6. Regional cost curves for CO_2 transport and storage versus cumulative capacity $CUM_{EMI,st}$, region Oldeuro and China.

5.5 Results and robustness analysis

In this section, we provide some results following the storage and transport implementation and a robustness check. In Figure 5.8, we can see how the model allocates in time the stored CO_2. In both `ctax` and `2DC` scenarios, EOR ON results the most convenient storage site, with a used capacity in 2100 of more than 60% in both cases. The total amount of stored CO_2 is lower in the `2DC` case (in 2100, there is almost 100 $GtCO_2$ of difference from the `ctax` case), but the storage starts earlier and with more significant quantities. In both cases, barely 4% of Aquif. ON is used, but as the capacity is extremely high, the quantity of CO_2 there stored is by far the highest among the various options.

More results are reported and discussed in Chapter 6.

Following the same procedure we applied in the previous chapters, we now test the introduced parameters, in particular analysing the differences in output according to the low-best-high estimates concerning costs and storage capacities. We at first consider a `ctax` scenario and then a `2DC` scenario.

5.5.1 Storage costs and capacities importance

As already mentioned, storage costs have very important consequences on CCS adoption. Moreover, another interesting aspect of a variation in CCS share is represented by RES penetration, especially intermittent ones (solar and wind). The relative energy mix share is represented in Figure 5.9. In particular, comparing low storage costs with respect to high storage costs we get an increase in CCS share in 2050 of more than 5% (from 15% to 20.1%) and a corresponding decrease in penetration of RES of about 4% (from 43.5% to 39.6%). This result is coherent with the economic optimization shift in the energy mix: if CCS results more convenient (low storage costs), the model is pushed towards CCS to the detriment of RES. If on the contrary storage costs are higher, the model shifts

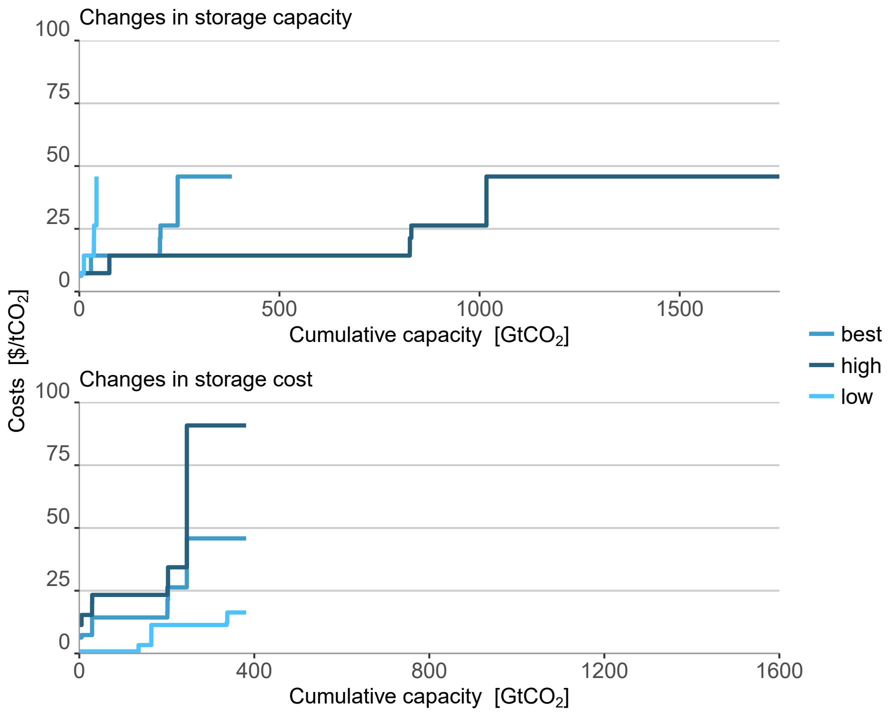

Figure 5.7. Storage and transport cost ($c_{t\&s}$) curves variation due to capacity or storage cost effect, region China

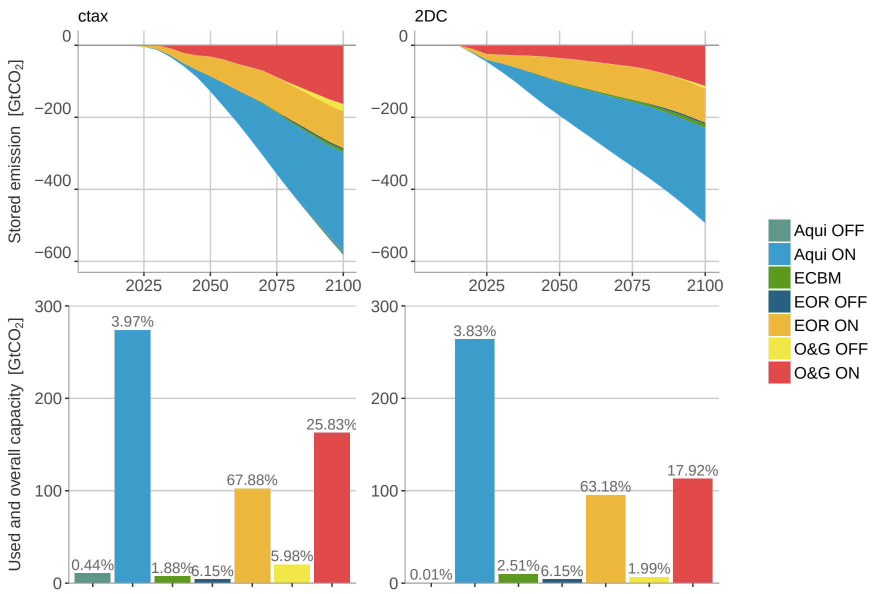

Figure 5.8. Quantity of global CO_2 stored: in function of time (top charts); and as the percentage in 2100 of the overall maximum capacity (bottom plots) for `ctax` and `2DC` scenarios.

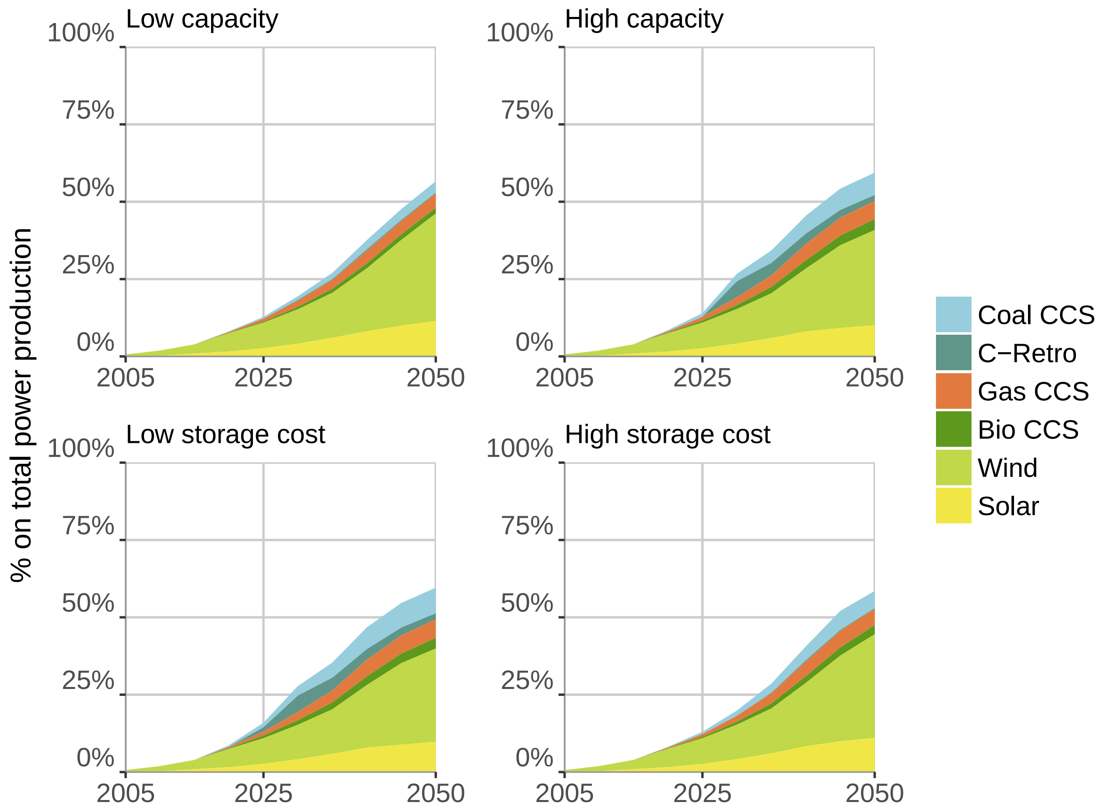

Figure 5.9. Comparison between high and low estimations of storage cost and capacity: consequences on CCS and RES share in a `ctax` scenario.

towards RES. The largest variation in penetration considering CCS options is related to retrofitting.

When dealing with storage available capacity, the main driving force of energy mix adoption is the high or low availability of cheap storage capacity (see Figure 5.9). Retrofitting is the most influenced technology, as it almost disappears from the energy mix when dealing with a low capacity case. Comparing the low-high capacity cases, we find out that CCS share varies in a range of 5.7 percentage points, increasing from 12.9% to 18.6%. RES penetration is even more influenced than in case of storage cost variation: it increases from 40.8% to 45.5% when storage capacity is low. Besides the electric energy mix, another interesting consequence of the profitability of CCS is related to primary energy consumption. We tested the impact of a variation in storage costs and in storage capacity on the coal and gas needs: with a decrease in CCS production, we have a decrease in primary fuel needs. Coal consumption for electricity production in case of low capacity of storage is 6% lower than the base case coal consumption, while gas decreases of 1% both in case of high costs of storage and low capacity availability.

5.5.2 Influence of transport and storage costs

We now aim to understand which one between storage and transport costs have a greater impact on CCS deployment. As already mentioned, considering storage costs we have some different estimates (the low-best-high cases). Concerning transport cost, however, we derived a single specific cost from Rubin, 2015. We assumed therefore a range for transport cost too. In order to be consistent with the storage cost estimates, we

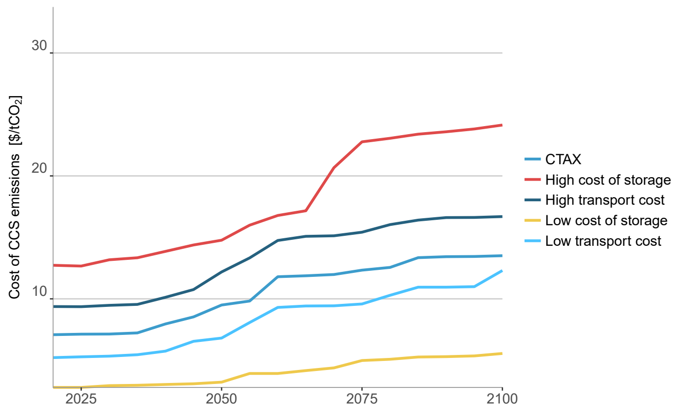

Figure 5.10. Cost of CO_2 transport and storage in different costs scenarios, global average.

multiply the specific cost, in the high case by the average ratio between the high and the best storage cost estimates, while for the low case by the average ratio between the low and best estimates. The variations are calculated as an average of values reported in Figure 5.3

As we can see from Figure 5.10, the impact on costs of CO_2 emissions related to CCS strongly varies according to the estimates of storage costs. In particular, in 2100, the difference between the high and low estimates of storage costs is around 20 $/t$CO_2$, while the same value for transport is less than 10 $/t$CO_2$. Moreover, from Figure 5.11, we can see that the use of storage capacity is more influenced by a storage costs variation than transport costs one: in high and low storage cost cases, the percentage of used capacity oscillates more (almost ± 1%). Another interesting result from the same plot is related to the capacity constraint importance. As we can see, storage capacity seems to be a not binding constraint in each tested case. In Figure 5.11 we can see that the overall available capacity is significantly higher than the utilized capacity. In the most pessimistic case, the percentage of used capacity barely overcomes 6%. However, it significantly affects CCS production and the related captured emission, since we see that, in case of low capacity, the total CO_2 stored is significantly lower compared to any other case. This is expected as, by looking at the curves in Figure 5.7, we have very squeezed cost curves with high prices in case of low capacity scenario. As a final remark, we can state that the overall increase in costs or a decrease in available capacity has a direct consequences on storage use: the model optimizes for each country a certain quantity of CO_2 to store in the base case, and oscillates around this value.

5.5.3 The `2DC` scenario

Considering the `2DC` scenario, the results on the electricity mix of 2050 are quite similar to the `ctax` option. In particular, the strongest impact on CCS and RES deployment is given by the low capacity case. Considering a comparison with the base case, the decrease in CCS share is equal to 4.3%, while the increase in RES is equal to 4.9% in 2050. However, the CCS share in high available capacity case reaches 12.7%, almost 6 percentage points lower than the same case with `ctax`. The total share of RES in this case reaches 61%, higher than the same value in the `ctax` case (46.2%). This is due to the already underlined preference for carbon neutral option in the budget scenario.

Considering the used capacity, the trends observed for the `ctax` are maintained. We have therefore an higher impact on capacity used in case of storage costs oscillations than

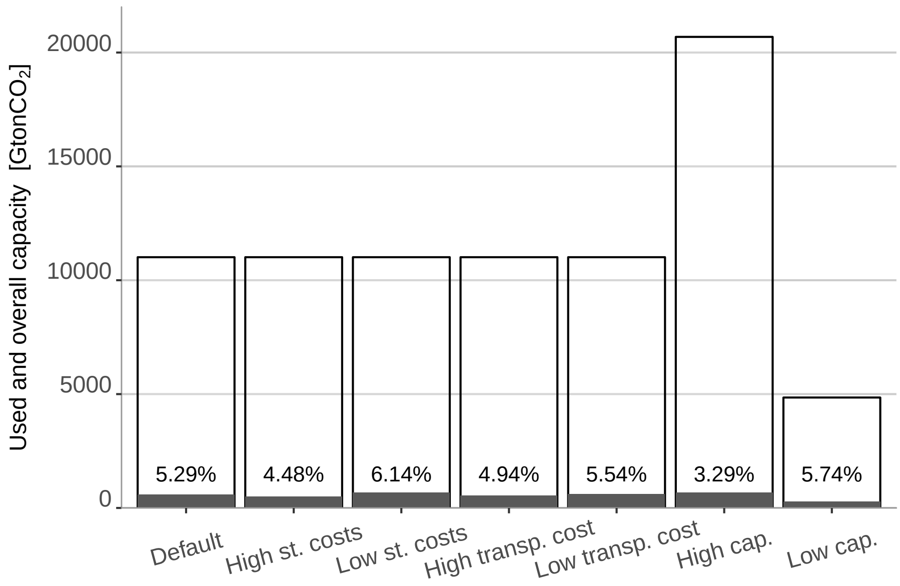

Figure 5.11. Storage capacity used up to 2100 in a `ctax` scenario for different storage cost and storage capacity assumptions.

in case of transport cost variations. As the cumulative CCS share is lower in the `2DC`, the percentage of CO_2 stored in 2100 is also lower. The emission costs follows the same trends of Figure 5.10. The relative importance of storage cost on transport cost holds.

5.6 Analysis on leakage

As previously specified, we want to study the impact of leakage from CO_2 storages in climate policies. Considering the high uncertainty in literature, we execute the model several times varying the leakage factor, which represents the leaked percentage of the stored quantity. In the following section, we present the model answers to variations in leakage.

5.6.1 Constant leakage rates

A first important issue when dealing with leakage phenomenon is the assessment of the impact on CCS energy production.

Let's at first consider a `ctax` scenario. Looking at Figure 5.12, it is evident that leakage factors greater then 0.01 (1%/yr) almost hinder CCS as a solution for reducing carbon emissions. Moreover, we notice that, when the leakage factor increases, retrofitting is the first technology that recedes, followed by the other coal options. On the contrary, biomass and gas fired plant are the last technologies phasing out. This is probably due to the fact that Bio CCS contributes to negative emissions, while NG-CCS is less carbon intensive than coal power plants.

Considering the `2DC` scenario, we notice a similar trend of the electricity production from plants with CCS. However, two main differences emerge. First of all, the role of retrofitting is more important even with leakage factors greater than 0.1%. Secondly, the leakage factor is impacting the CCS with lower extent compared to the `ctax`, and therefore with leakage factor equal to 2% we still have some CCS produced. The phase out occurs with values greater than 3%.

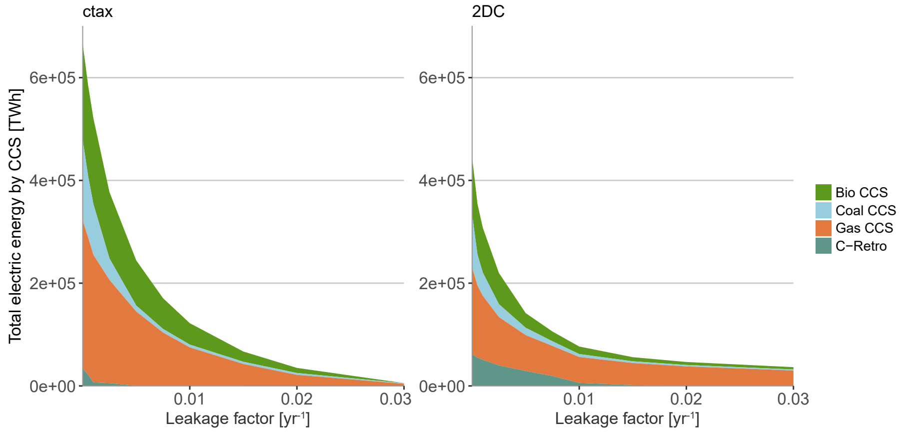

Figure 5.12. Total electricity produced by CCS plants up to 2100 as function of the leakage rate.

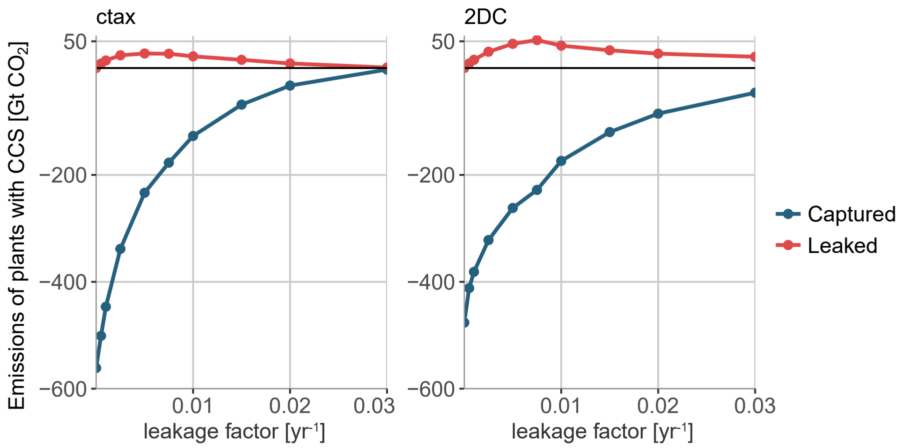

Figure 5.13. Cumulative leaked ($Q_{EMI,leak}$) and captured ($E_{CO_2,capt}$, negative axis) CO_2 emission in 2100 as function of the leakage rate.

Another major consequence of leakage is the variation in cumulated captured and leaked emissions. Figure 5.13 shows the quantity of CO_2 leaked into atmosphere $Q_{EMI,leak}$ and the amount of CO_2 captured and sent to the storage sites $E_{CO_2,capt}$, as functions of different values of leakage factor λ_{lk}. Considering the `ctax` scenario, with leakage from storage sites equal to 1% per year, we already know that the total electricity produced up to 2100 with CCS results low (see Figure 5.12). The cumulative carbon captured at the same year accounts for 127.10 $GtCO_2$. Of this CO_2, 17% is re-emitted into atmosphere because of leakage. On the other hand, in case of 0.1% of leakage, we obtain 446.62 $GtCO_2$ with only 0.5% of it that leaks from the reservoirs.

From Figure 5.13, we understand that captured CO_2 follows a trend similar to the energy production, while the shape of the curve of $Q_{EMI,leak}$ as a function of leakage is particular and deserves further attention. The curve shows a peak around 0.05%, and then decreases. We can explain this trend looking at Equation 5.5. $Q_{EMI,leak}$ should rise as the leakage rate increases, but in the same time the usage of CCS and $E_{CO_2,capt}$ lowers. The peculiar trend is therefore the result of the optimization process: the model accepts to have more absolute CO_2 leaking when the leakage factor is comprised between 0%/yr and 1%/yr, while the value lowers with higher leakage, because the difference between the advantages of capturing and the cost of leaking tends to zero. The same reasoning holds for the `2DC` scenario (right hand side of the Figure).

A first conclusion is therefore that leakage could have major consequences on the emissions pathways. This impact is clearly visible in Figure 5.14. The Figure shows the trends of CO_2 emissions when the leakage factor increases (`ctax` scenario, left hand side), and the carbon tax trends in time with different leakage rates (`2DC` scenario, right hand side). Considering the `ctax` case, It is evident that, when leakage increases and CCS share decreases, we have a substantial increase in CO_2 emissions mainly due to fossil fuel power plants increase.

The `2DC` scenario shows a different behaviour: CO_2 emissions follow a unique path also when the leakage factor increases and CCS disappears from the energy mix. The `2DC` scenario has a carbon budget constraint that do not allow evident variations on the emission path. On the other hand, the carbon tax is not fixed and changes with leakage rate in order to always satisfy the carbon budget. From Figure 5.14, we see that higher leakage leads to an increase in carbon prices to achieve the same temperature target. Comparing the absence of seepages with the case with λ_{lk}=3%/yr, we have a delta in carbon taxes of about 54.29 $/$tCO_2$ in 2020 that grows up to 763.41 $/$tCO_2$ in 2100.

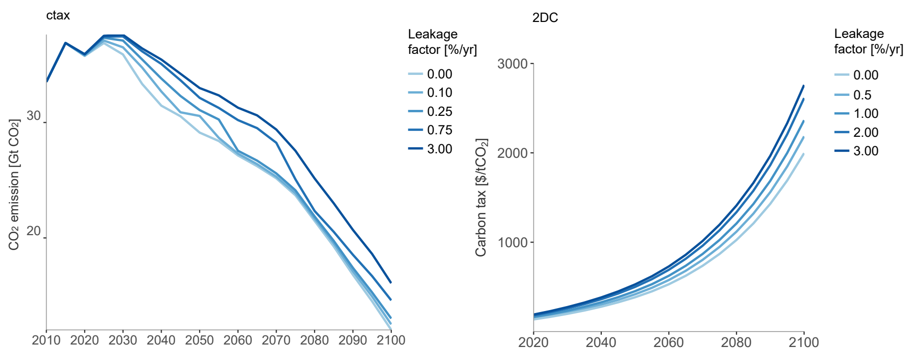

Figure 5.14. CO_2 emission (`ctax` scenario, left) and carbon tax trends (`2DC` scenario, right) for different leakage factors λ_{lk}.

The behaviour of the emissions can be explained looking at Figure 5.15, where we see what type of energy sources substitute CCS plants in case of high leakage. We notice

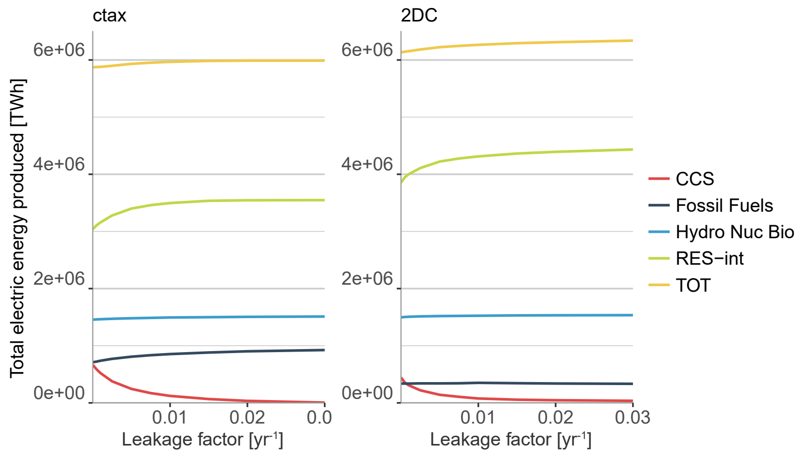

Figure 5.15. Cumulative electricity produced by groups of plants as function of the leakage rate.

that in case of `ctax` scenario fossil fuelled plants represent the most competitive solution and replace CCS, while the total energy production (equal to the consumption) remains unchanged. However, in the `2DC` scenario there is a carbon budget as a target for the optimization solution. Therefore, the alternatives to CCS are all low carbon technologies, such as Solar and Wind, Nuclear or Hydroelectric plants. When leakage is high, the two solutions adopted to fill the energy gap left by CCS are low carbon technologies and reduction of the total energy consumption.

In conclusion, we want to give an idea of the temporal dimension. Let's consider the `ctax` scenario. Figure 5.16 shows the trend of $E_{CO_2,capt}$ with different leakage rates. It is important to remember that as time goes by the carbon tax increases (see Figure 6.1). This is a driving factor for CCS increase: in fact, with an higher tax, it is more convenient to adopt low carbon technologies. A remarkable conclusion we can draw from the Figure is that, for every scenario, there is a carbon tax value that makes the CO_2 emission higher than 4 $GtCO_2$ around 2100. This holds for every case but the 3%/yr leakage factor scenario. Another important aspect revealed by this graph is that the differences between high and low seepage scenarios are much greater for low values of carbon prices (i.e. around 2050), rather than for high carbon prices (i.e. around 2100). Therefore, if we consider the plot up to 2050, we see almost no energy produced by CCS plants for λ_{lk} around 1 %/yr.

5.6.2 Non-constant leakage rates

As explained in Section 5.3, according to the literature, we should not take for granted the assumption of constant leakage factor. Testing the different assumptions, we found on leakage trends as a function of time or storage use, we implemented four different leakage trends. Two scenarios assume linearly decaying or increasing seepages, while in the other cases the trends show parabolic shapes. For each scenario, the leakage rate varies from 0.05 %/yr to 1 %/yr, depending on the amount of CO_2 stored in the k_{st}-th storage site in the n-th region at time-step t. We implemented the following quadratic equation that, according to the values of a_{lk}, b_{lk} and c_{lk}, can define each type of curve:

$$\lambda_{lk}(k_{st}, t, n) = a_{lk} \cdot \left(\frac{CUM_{EMI,st}(k_{st}, t, n)}{cap_{max}(k_{st}, n)} \right)^2 + b_{lk} \cdot \frac{CUM_{EMI,st}(k_{st}, t, n)}{cap_{max}(k_{st}, n)} + c_{lk} \quad (5.6)$$

The curves are represented in Figure 5.17.

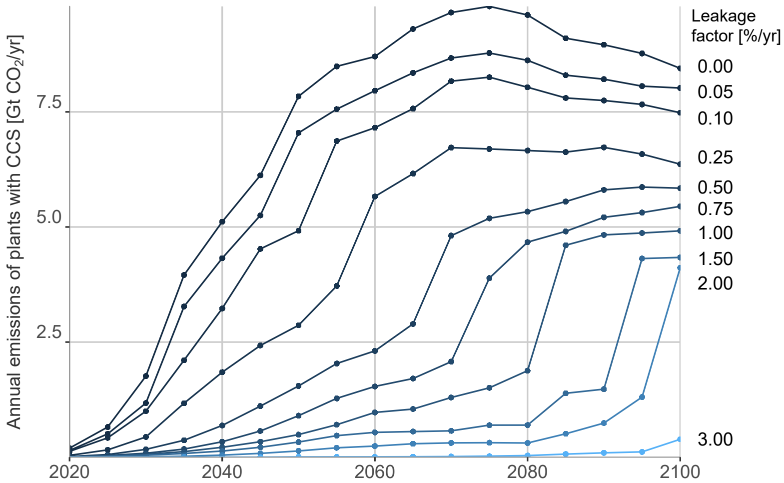

Figure 5.16. Annual CO_2 emission captured by CCS plants with different leakage rates λ_{lk}. `ctax` scenario.

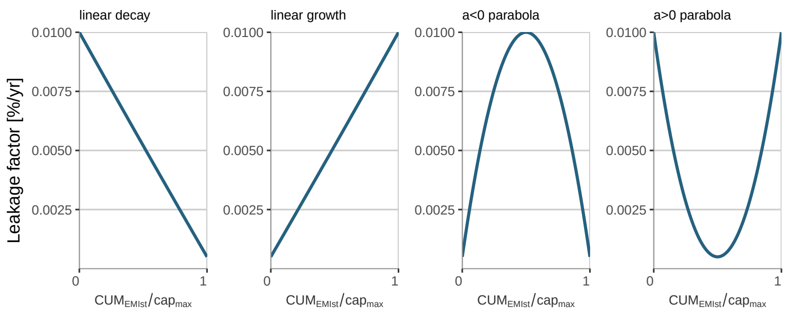

Figure 5.17. Four pattern of the leakage factor in non-constant scenarios.

The `linear decay` case represents a situation where, when we start filling the storage sites, the leakage factor is high, and it decreases as the reservoir fills with CO_2 (i.e. only the best trapped CO_2 remains within the storage site). The opposite trend (`linear growth` curve) stands for sites where seepages are more intense with an higher stored quantity (i.e. an excessive use of the storage site). Different combinations of the two effects are represented by the two parabolic curves.

We performed different runs with these curves both in `ctax` and `2DC` scenarios. As the analyses lead to similar conclusions, we only report the results for the `ctax` case. The main results are represented in Figure 5.18, where the global amount of CO_2 stored is represented as a function of time and as percentage of the maximum available storage capacity.

Moreover, we can underline that in `linear growth` and `a<0 parabola` scenarios, CCS has a significantly more marginal role with respect to the other cases. The `linear decay` scenario shows the maximum deployment of CCS technologies accounting for 400 $GtCO_2$ stored in 2100.

It is not straightforward to understand why the different trends lead to such peculiarities in the results, in particular for the parabolic trends. Comparing the two linear cases, we observe high variability of storage types for the `linear growth` case. This behaviour happens because once a storage site (or category) gets filled up, it also leaks more into the atmosphere, making it convenient to switch to different types of storage, even though they are more expensive. In this context, we notice an important use of ECBM, which is usually the most expensive storage option in the model, and hardly taken into consideration in the zero leakage case. By contrast, in the `linear decay` scenario, the initially high leakage rates do not have particular impacts on the choice of storage: the mostly adopted solutions are those with lower costs. In fact, Onshore EOR, which is on average the least expensive option, reaches 54.7 % of the global available capacity.

Similar conclusions can be drawn for the two parabolic trends. However, we notice that the behaviour of `a<0 parabola` is very similar to the `linear growth` case, as if just the first half of the parabola were considered during the optimization process (up to $CUM_{EMI,st}/cap_{max}$=0.5). This is due to the high leakage rate at the maximum value that hinders CCS deployment. The positive slope parabola shows results similar to the `linear decay`: the main difference is given by the growing leakage factor after the minimum point, that leads to higher storage diversification in `a>0 parabola` and less use of EOR ON.

5.7 Main Chapter conclusions

- Storage costs and storage available capacity are the features with greatest impact on CCS production.
- Storage capacity is particularly binding in terms of cost increase (Figure 5.7) and not for what concerns the filling capacity of storage sites (Figure 5.11).
- CO_2 leakage greater than 1%/yr of the stored capacity, could strongly hinder CCS deployment.

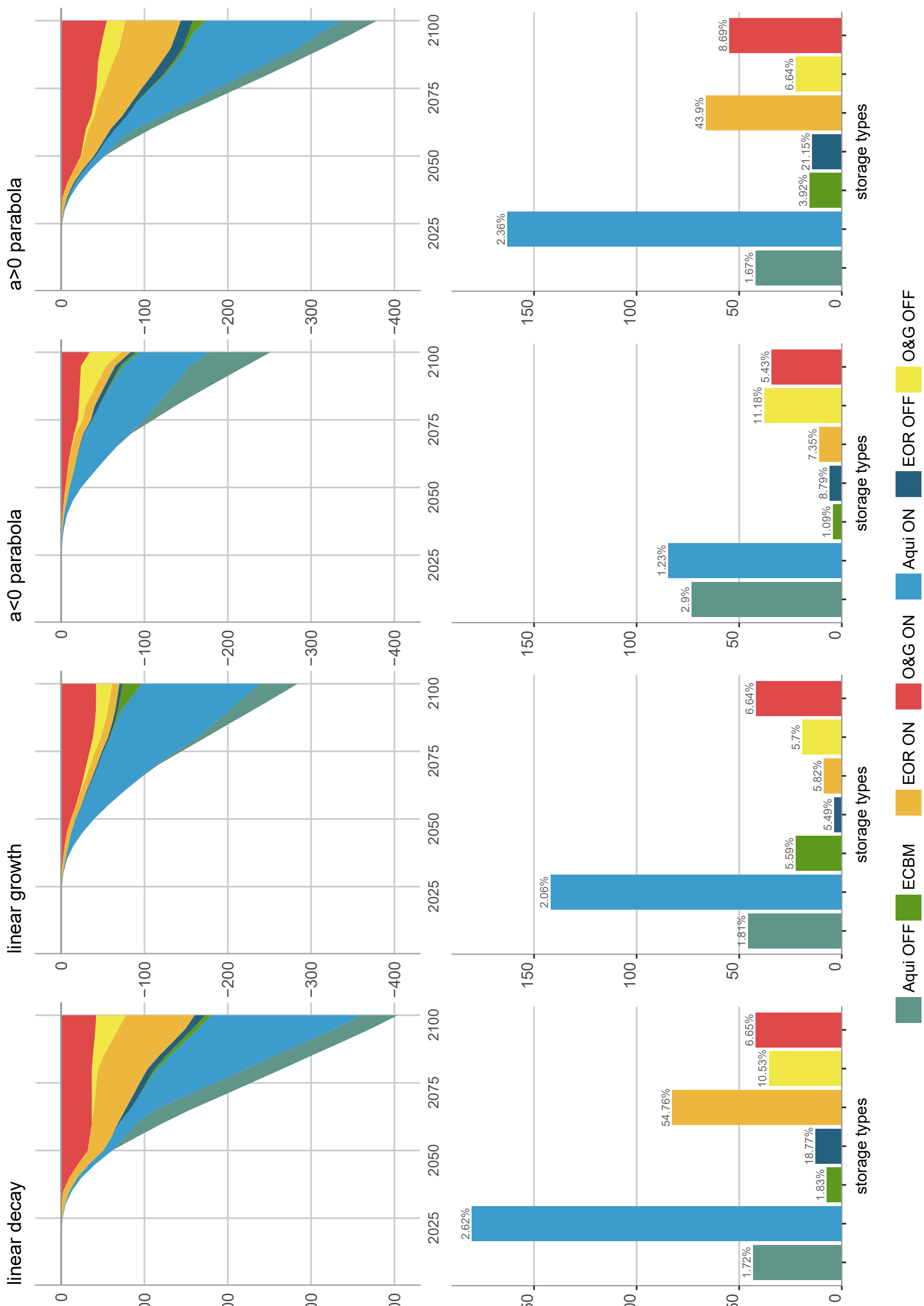

Figure 5.18. Quantity of global CO_2 stored: as a function of time (top charts) and as the percentage in 2100 of the overall maximum capacity (bottom plots) for the four non-constant leakage curves, in `ctax` scenario.

Chapter 6

Policy analysis

In this chapter, we will present the output results concerning policy adoption consequences. As already specified in the previous sections, these results are not to be considered as predictions of future behaviours or the reflection of reality. They only provide an idea of possible future paths. We at first provide the base case results, comparing the main scenarios that we selected (`BAU`, `ctax` and `2DC`). We then analyse the differences among them, with a specific attention about the assumptions and uncertainties behind the numbers that we report.

Our interest on uncertainty assessment comes straightforward: we focus on the uncertainty introduced with our implementation, performing two Monte Carlo simulations for the policy scenarios. We then analyze the importance of CCS in achieving different temperature increase targets. In conclusion, we will report a case study on China, showing more in details results concerning costs and storage for this country, which is likely to play a significant role in reducing emission from coal power plants by means of CCS technologies.

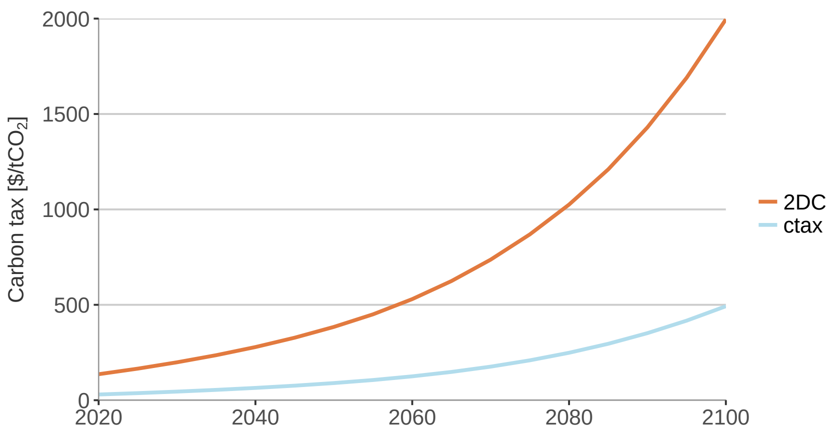

Figure 6.1. Trend of the carbon tax in the `ctax` and `2DC` scenarios.

6.1 Reference scenarios pathways

In this section, we show the reference results concerning energy and electricity consumptions, CO_2 emissions, and costs related to the three baseline scenarios, `BAU`, `ctax` and `2DC`. The main driver of diversification in the results is the different carbon tax, which is absent in the `BAU` scenario and for the other two cases follows the trend represented in Figure 6.1.

6.1.1 Energy consumption and production

In Figure 6.2, a representation of the electric energy mix in each scenario is provided. As we can see, in the `BAU` case the total energy production continuously grows in time. Fossil fuel based power plants represent the largest share of the total (63% in 2020 and 57% in 2050): their production gradually increases in time, with a negligible CCS share. The total energy supply is higher with respect to the low carbon scenarios, and W&S share represents a small but significant component of the energy mix, with a share increasing in time.

Considering the `ctax` scenario, the introduction of the carbon tax results in a lower total production, with a bend in the growth rate around 2020, with the tax introduction. Traditional Coal gradually decreases and phases out around 2040. Solar and Wind shares rapidly increase in time, and simultaneously CCS production becomes quite significant with respect to the overall share.

The same patterns appear in the `2DC` scenario, even more evidently. The initial decrease in energy production (starting in 2020) leads to a very fast phasing out of traditional coal, and retrofitting gains strong importance especially up to 2025. CCS technologies share gradually increases in time, but the growth of Wind and Solar share is faster and leads to a 56% share of W&S in the overall energy mix of 2050.

From the Figure, it is clear how CCS could be a really significant component of the energy mix, in case of low carbon scenarios. However, not all the regions are going to adopt CCS as a low carbon technology: as we can see from Figure 6.4, CCS power plants are mainly concentrated in two regions: China and USA. The other regions are optimizing their energy mix in case of carbon tax relying mainly on other technologies (i.e. RES, Nuclear). Even in regions where CCS production is important, we can underline some important differences. The regional composition of the CCS share is in fact strictly dependent on local economic features and resource availability. As an example, we notice that retrofitting is mainly applied in countries where the coal plant fleet is quite recent (China, India), as reported in the Appendix B. In Latin America, due to the large availability of biomass, a large percentage of the overall CCS share is represented by Bio CCS.

6.1.2 GHG emissions

We draw the attention on the variation of energy mix composition in the different policy scenarios (`BAU`, `ctax` and `2DC`). The CO_2 emissions associated to each scenario varies accordingly. In Figure 6.5 we report the CO_2 equivalent emissions: the `BAU` case is associated with strongly increasing emissions peaking around 2090, when RES share becomes more significant in the energy mix. Due to the increase in coal and gas consumption, in fact, their prices grow in time, and the economic optimal reduces the amount of fossil fuel in the energy mix. The introduction of a carbon tax results instead in a decrease in emissions, gradual in the `ctax` case (less stringent) and dramatic in the `2DC` case: in the period comprised between 2015 and 2020, emissions are strongly reduced, and the decrease continues less steeply afterwards. As we can see from Figure 6.6, CCS is responsible for a significant share of emission reduction by 2100: 20% in the `ctax` case, 12% in the `2DC` scenario.

6.1.3 Main policies costs

Assessing the cost of a climate policy is a complex issue, especially when we consider a global level. GDP is usually considered a valuable indicator for global economic expenditures due to the introduction of a policy. From Figure 6.7, we can notice that scenarios with

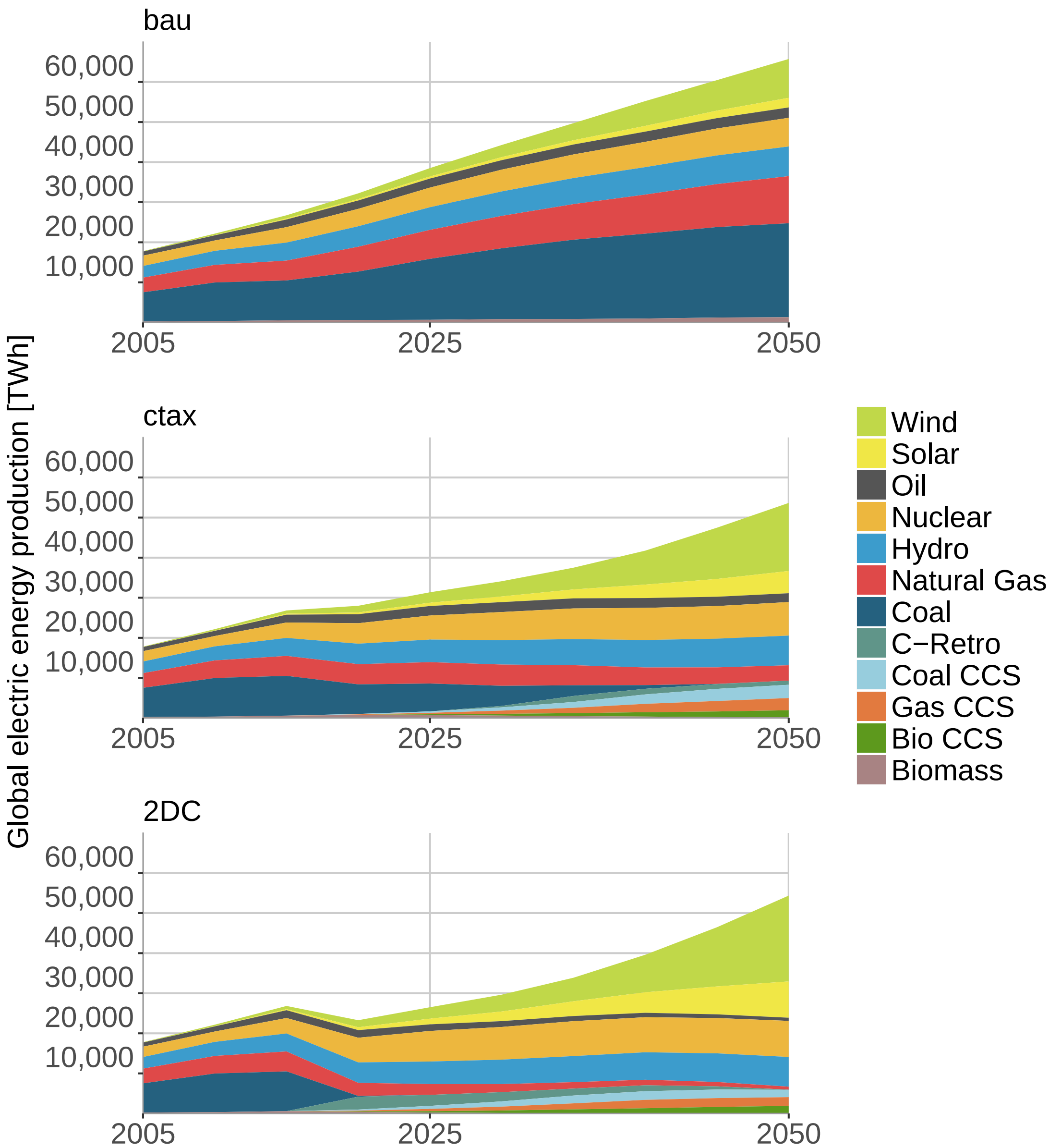

Figure 6.2. Electric energy production by technology in `BAU`, `ctax` and `2DC` scenarios.

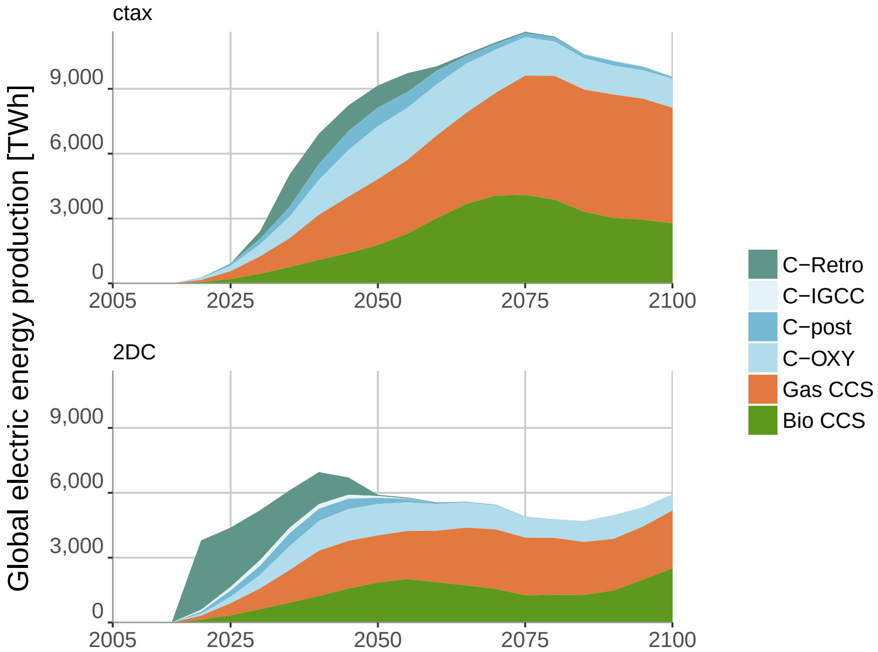

Figure 6.3. Electric energy production from CCS plants in `ctax` and `2DC` climate scenarios.

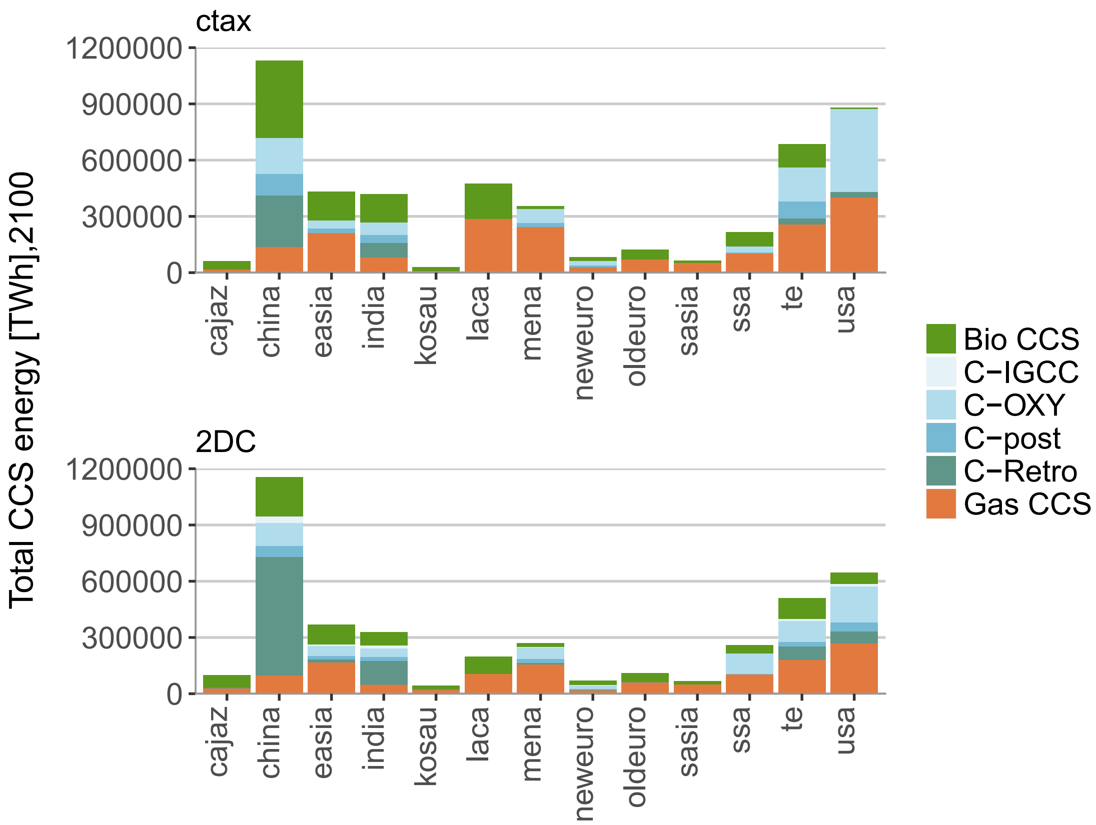

Figure 6.4. Total energy production from CCS sources by 2050, divided by region.

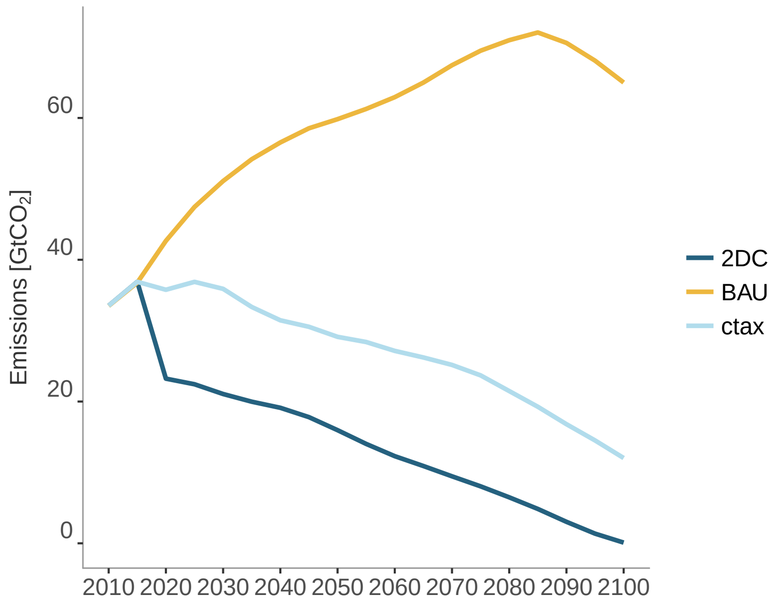

Figure 6.5. Global emissions on time in `BAU`, `ctax` and `2DC` case.

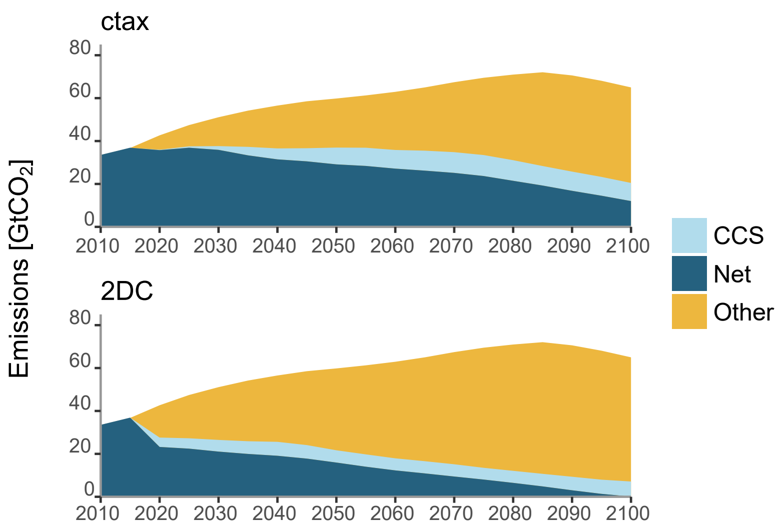

Figure 6.6. Emissions reduction with respect to `BAU` in `ctax` and `2DC` cases, as an output of the final implementation. The light blue area represents the amount of emissions captured by CCS.

carbon prices lead to higher costs, and a consequent reduction in global GDP with respect to the BAU scenario.

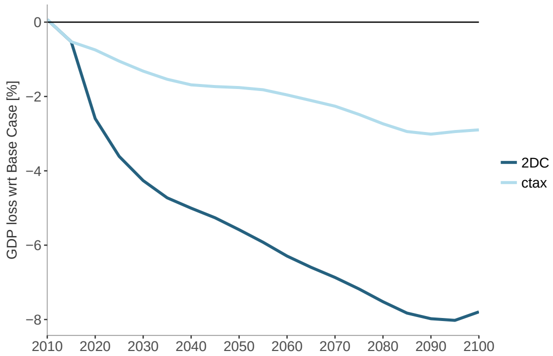

Figure 6.7. GDP loss with respect to the `BAU` case in percentage points, `ctax` and `2DC` cases.

In particular, we notice that the `2DC` scenario leads to more than twice the GDP losses of the `ctax` case, accounting for about 8 percentage points in 2100. Another useful cost indicator is the energy system expenditure (ese) which accounts for the overall expenditure in the energy system, without considering any cost related to the carbon price. This indicator puts in evidence whether the technology transition imply significant cost variations for the energy system.

Figure 6.8 represents the ese divided by the overall energy produced (including the non electric sector) per year, providing a global average cost of energy. The plot clearly shows that the introduction of carbon tax and the consequent switch to low carbon technologies lead to an increase of system cost. Moreover, the higher is the carbon tax (therefore, in the `2DC` case), the higher is ese/Q_{EN}, at the same year. From the Figure, we can see that costs for the `BAU` scenario increase starting from 2050: this is probably due to a late transition to renewable sources that partially substitute the fossil fuel based energy sources.

In the previous chapters, we investigated the importance of different cost component for CCS technologies, such as the investment cost and the infrastructural costs for transportation and storage of the CO_2. We also highlighted the importance of $LCOE$ as a cost indicator. Nevertheless, WITCH provides values of $LCOE$ at a regional level, and they are not suitable for a global overview. The levelized cost of electricity can in fact be calculated only in regions where the technology is adopted and is actually producing energy. For this reason, we are showing the main results concerning $LCOE$ in the case study relative to China, in Section 6.4.

6.2 Sensitivity analysis for uncertainty assessment

6.2.1 Description of Monte Carlo procedure

In addition to the sensitivity analysis performed for each parameter of interest (see Sections 3.3, 4.3, 5.5), we want to understand how the complementary variation of some key parameters affects the results. As previously mentioned, among the most important values we assumed in the implementation we find the initial investment costs of CCS plants $I_{cost}(j, 0, n)$, the learning exponent $b(j)$ and the storage costs $c_{st}(k_{st})$. Therefore, we perform a Monte Carlo analysis where the contemporary variation of such parameters is taken into account. The analysis consists of 2000 runs, 1000 for the `ctax` scenario and 1000 for the `2DC` scenario, using as starting values for the above mentioned parameters samplings

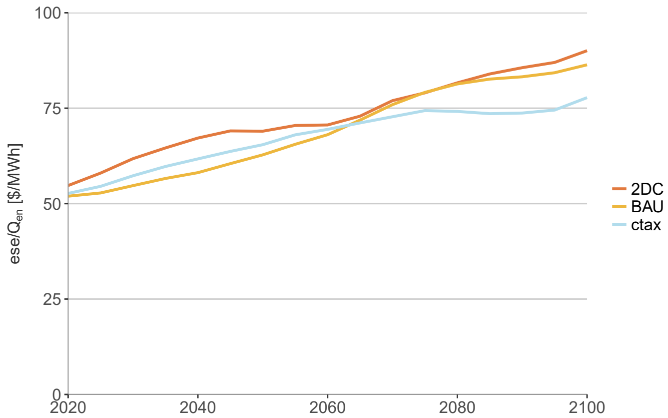

Figure 6.8. Energy System Expenditure trend on time for our three baseline scenarios.

from statistical distributions. A first issue is to reasonably select the starting distribution for each parameter: for all of them, we have confidence intervals derived by the literature, already reported as *low*, *best*, *high* values in the respective chapters. However, as we have not enough data to statistically determine the distributions, we assume these values as the 5% (*low* value) and 95% (*high* value) percentiles of normal distributions, centred on the *best* value. Since the confidence intervals determined from literature are not necessarily symmetric, we assume a symmetric confidence interval about the mean as follows:

$$\begin{aligned} I_{cost}(j,0,n) &= \mathcal{N}(\mu_I,\, \sigma_I^2) \\ b(j) &= \mathcal{N}(\mu_b,\, \sigma_b^2) \\ c_{st}(k_{st}) &= \mathcal{N}(\mu_s,\, \sigma_s^2) \end{aligned} \tag{6.1}$$

where:

$$\begin{aligned} \mu_I &= I_{cost}^{best}(j,0,n) \\ \mu_b &= b^{best}(j) \\ \mu_s &= c_{st}^{best}(k_{st}) \end{aligned} \tag{6.2}$$

and:

$$\begin{aligned} \sigma_I &= 0.5 \cdot min(I_{cost}^{best}(j,0,n) - I_{cost}^{low}(j,0,n), I_{cost}^{high}(j,0,n) - I_{cost}^{best}(j,0,n)) \\ \sigma_b &= 0.5 \cdot min(b^{best}(j) - b^{low}(j), b^{high}(j) - b^{best}(j)) \\ \sigma_s &= 0.5 \cdot min(c_{st}^{best}(k_{st}) - c_{st}^{low}(k_{st}), c_{st}^{high}(k_{st}) - c_{st}^{best}(k_{st})) \end{aligned} \tag{6.3}$$

Moreover, when dealing with $I_{cost}(j,0,n)$, the 5% percentiles is given by:

$$I_{cost}^{low}(j,0,n) = max(floor_{cost}(n,j), I_{cost}^{low}(j,0,n)) \tag{6.4}$$

because, since we defined the floor cost as the likely lowest possible value, we have to proceed as in Section 3.3. In Figure 6.9 we can see the representation of the normal distributions related to I_{cost}, $c_{st}(k_{st})$ and $b(j)$. The very few values below 0 are considered equal to 0, for sake of simplicity. Values below zero should be considered meaningless for the considered quantities.

A final remark is related to the mechanism of representation of the link between the different technologies. We already underlined in the previous chapters that the different CCS technologies future deployment is strictly related: therefore, in order not to lose this link, we extract the samplings for all the $I_{cost}(j, 0, n)$ distributions from a uniform distribution defined between 0 and 1. In the same run, the samplings from each normal distribution $I_{cost}(j, 0, n)$ is at the same percentile as the sampling from the starting uniform distribution. Therefore, in the same run all the plants samplings share the same selected percentile.

Considering the retrofitting cost, as already mentioned in Chapter 3, we calculate it as a difference between a traditional plant and a C-post plant in 2005. However, with the samples from the normal distribution of C-post investment cost (see Figure 6.9 (A)), the possibility of witnessing to unreliable values of $I_{cost}(Retro, t, n)$ is not so low. For example, the resulting value when the sampling is towards the lower tail, retrofitting could be unlikely cheap. On the other hand, when the sampling is towards the upper tail, the cost of retrofitting could be too high. In order to avoid this kind of situations, we put an upper and a lower bound on $I_{cost}(Retro, t, n)$, using the same values reported in the sensitivity analysis on retrofitting cost (see Section 3.3). Therefore, we assume that the cost of retrofitting is given by the following expression:

$$\begin{aligned} I_{cost}(Retro, t, n) =& min\Big(max(I_{cost}(C\text{-}post, 0, n) - I_{cost}(Coal, 0, n), \\ & 0.5 \cdot I^{base}_{cost}(Retro, t, n)), 1.5 \cdot I^{base}_{cost}(Retro, t, n)\Big) \end{aligned} \tag{6.5}$$

Considering the normal distributions for the $b(j)$ values, the only remark is given by the fact that for Bio CCS the probability of having lower that 0 values is high (about 5%), as the lower bound is equal to 0. Applying the simplification of putting equal to 0 the values lower than 0, we find an heavy tailed distribution (many samplings are likely to be equal to the lower bound, 0). In Figure 6.9 (B) and (C) we report the distributions for $b(j)$ and $c_{st}(k_{st})$.

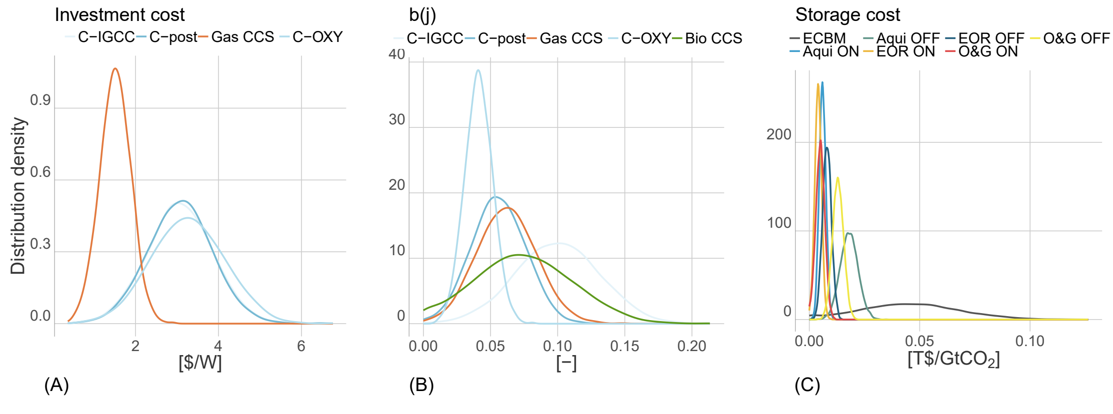

Figure 6.9. Normal distributions for the selected variables $I_{cost}(j, 0, n)$, $b(j)$, $c_{st}(k_{st})$.

6.2.2 Discussion of the results

Energy production from CCS sources

One of the most important results of this Monte Carlo analysis is the assessment of the variation in energy production by CCS technologies. In Figure 6.10 we can see that, especially in the `ctax` scenario, electricity production by CCS strongly deviates from the base case. In Table 6.1 some numerical results are summarized. In 2050, the percentage variation with respect to base case of the maximum value is about 28% in both `ctax` and `2DC` cases. In the same year, the minimum value variation from the base case is equal to -21% in the `2DC` case while it reaches -43% in the `ctax` case. In 2100, the variability with respect to `ref` case is again higher for the `ctax` scenario. The range of variations in `ctax` scenario is therefore clearly wider than in the `2DC` case.

It is also interesting to understand which values of investment cost, learning rate or storage cost characterize the extremes of the Energy production uncertainty boundaries. In particular, we find that the scenario leading to less deployment of CCS has very high investment cost, with values above the 95% percentile, while $b(j)$ and the storage costs are close to the median. This holds for both scenarios, in 2050 and 2100. Considering the maximum energy from CCS in 2050, in the `ctax` case we have values of $b(j)$ slightly higher than the median, while storage costs for ECBM is almost 0 T\$/GtCO_2 and investment costs are around two thirds of the reference values. Considering 2100 in the `2DC` scenario, we have different conditions of the three variables in the extreme bounds. This means that multiple combinations lead to high or low CCS deployment, and there is not one driver prevailing on the others.

Table 6.1
Electric energy by CCS and GDP loss variations with respect to the reference case, `ctax` and `2DC` scenarios.

		2050		2100	
		CCS energy	GDP	CCS energy	GDP
2DC	$\frac{\Delta(MAX-ref)}{ref}$	28.15%	0.11%	6.98%	0.09%
	$\frac{\Delta(min-ref)}{ref}$	-21.40%	-0.02%	-11.68%	-0.02%
ctax	$\frac{\Delta(MAX-ref)}{ref}$	27.61%	0.09%	22.38%	0.04%
	$\frac{\Delta(min-ref)}{ref}$	-43.90%	-0.06%	-22.33%	-0.05%

Impact on GHG emissions

In Figure 6.11 we can see a representation of emission trends in both `ctax` and `2DC` scenarios. Variability is more evident in the `ctax` case, especially in the period ranging from 2020 to 2060. Considering the `2DC` case, the variation with respect to the reference case is almost negligible, and all the simulations collapse on the reference line. We can therefore conclude that from the point of view of the emissions level, our conclusions are quite robust.

Policy cost variations

Figure 6.12 reports the range of variation in GDP loss expected in the `ctax` and `2DC` cases. In both scenarios the results presented in Section 6.1.3 are quite robust, as the variation is limited to a fraction of percentage point as maximum. Table 6.1 reports the values of absolute GDP in 2050 and 2100, we notice that the variations are quite low.

Considering the values of our three input variables $I_{cost}(j, 0, n)$, $b(j)$, $c_{st}(k_{st})$, we notice that most of the cases that turn to be the upper or lower bound in GDP, are also the

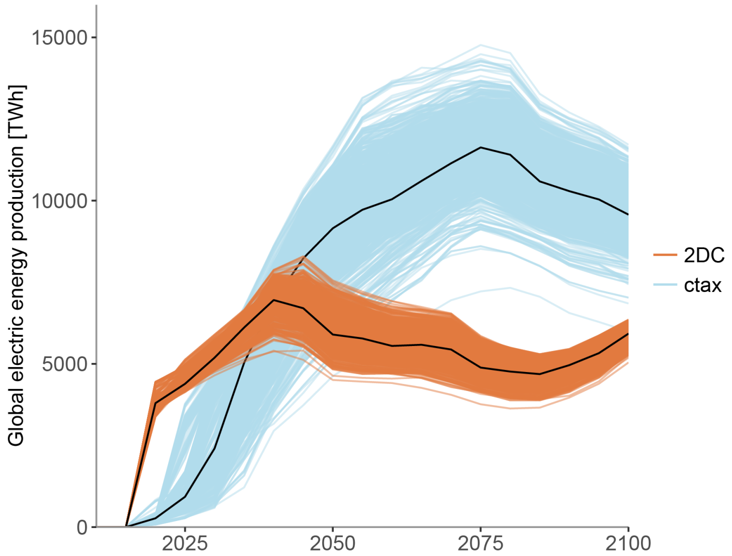

Figure 6.10. CCS total electric energy production for the Monte Carlo simulations in `ctax` and `2DC` scenarios. The respective base cases are the black lines while the coloured areas represent the output of the simulations.

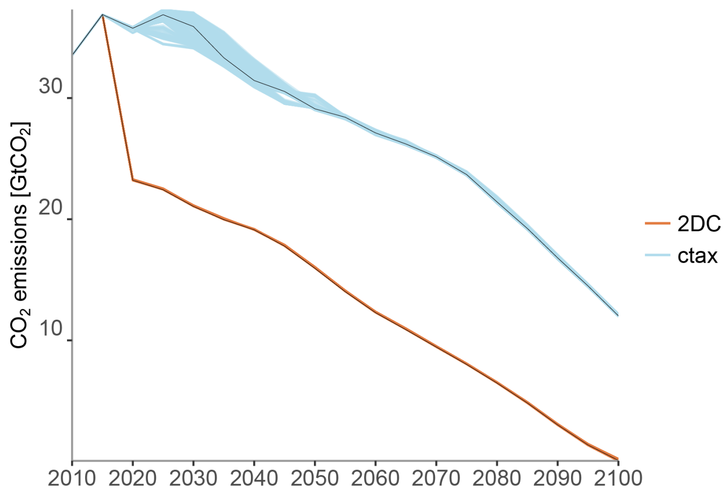

Figure 6.11. CO_2 emissions for the Monte Carlo simulations in `ctax` and `2DC` scenarios. The respective base cases are the black lines while the coloured areas represent the output of the simulations.

extreme conditions in terms of electricity production from CCS. To higher CCS energy productions correspond therefore higher values of GDP, and vice versa.

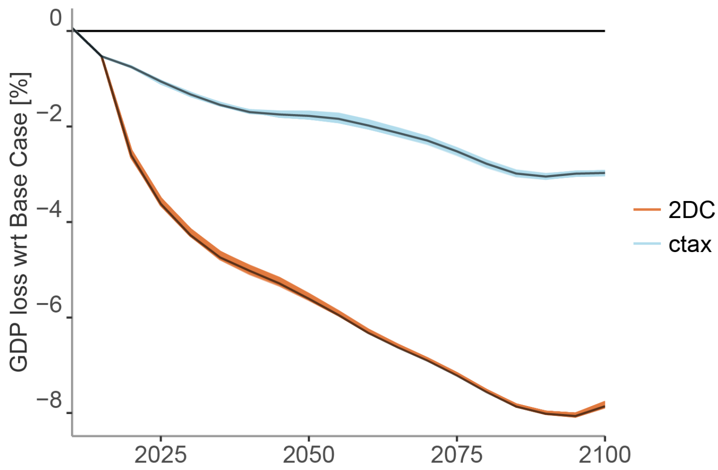

Figure 6.12. GDP loss with respect to the `BAU` case for the Monte Carlo simulations in `ctax` and `2DC` scenarios. The respective base cases are the black lines while the coloured areas represent the output of the simulations.

6.2.3 Influence on W&S deployment

We already underlined the possible substitutability between Wind&Solar and CCS: an interesting output of the Monte Carlo analysis could be the impact assessment on W&S with variations on CCS share. In particular, it could be important to understand whether a variation in TWh produced by CCS results in a similar alteration in terms of W&S TWh. In Figure 6.13, we see the behaviour of overall electric energy produced up to 2100 by W&S as a function of electric energy produced by CCS. The trend is linear in both `ctax` and `2DC` scenarios. The range of variations in the `ctax` scenario is wider than in the `2DC` scenario, as already underlined in Section 6.2.2. We notice that in the `ctax` case a relatively large delta on the x axis corresponds to a slightly lower delta on the y axis. In the `2DC` case instead, we see a steeper slope: a smaller delta on the x axis corresponds to a larger delta on the y axis, i.e. W&S production is more sensitive to variations in CCS production.

6.3 CCS behaviour on temperature reduction

Until now, we only discussed the two references scenarios that we chose (`ctax` and `2DC`) that have different characteristics in terms of optimal solution and temperature targets. We now aim at investigating which is the response in terms of CCS production with a variation of the temperature target (or radiative forcing) across a large range. From the charts previously plotted in this chapter, we in fact noticed different trends in the adoption of CCS for reducing GHG emission: `2DC` shows a sudden introduction of CCS when the carbon tax starts (2020), but `ctax` leads to an higher total use of CCS technologies in the long term.

Let's keep in mind that the `ctax` scenario leads in 2100 to an average global temperature increase around 2.5°C, with a gross radiative forcing of 4.08 W/m^2, while the `2DC` results

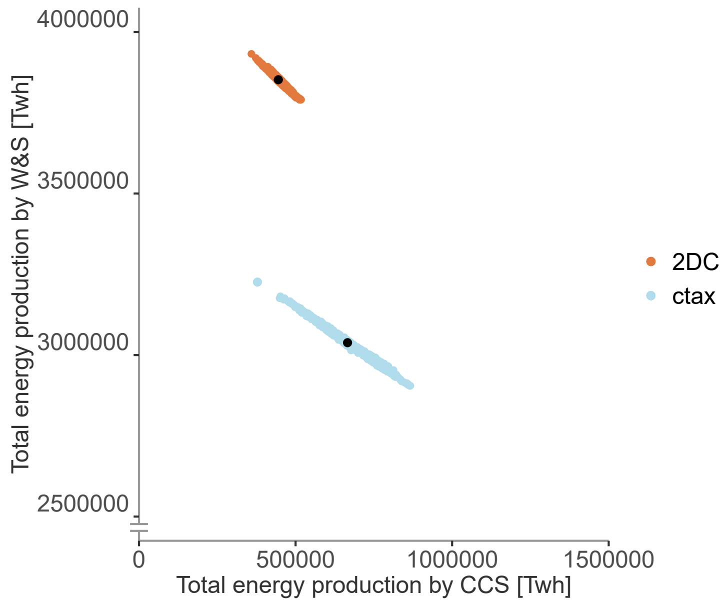

Figure 6.13. RES dependency on CCS in 2100. The respective base cases are the black points while the coloured points represent the output of the simulations.

in less than 2°C of temperature increase and RF equal to 3.11 W/m^2 (Figure 2.2 in Section 2.2.3). In order to understand the pattern of CCS deployment with respect to the RF, we range from a scenario with negligible difference from the `BAU` in terms of target, with 6.4 W/m^2, to the most strict scenario that our model can run, with RF equal to 2.47 W/m^2 and an equivalent average global temperature increase of 1.5°C.

Figure 6.14 shows the total electric energy produced by CCS up to 2100, for different climate targets, expressed with the radiative forcing. The CCS energy production starts with RF equal to 5.69 W/m^2, corresponding to the introduction of a carbon tax in 2020 of 3.19 $/t$CO_2$. We notice a monotonic increase in energy production, for each CCS plant, from values of radiative forcing ranging from the maximum to 4.07 W/m^2, which is almost equal to the `ctax`. For stricter scenarios (left in the chart), the total energy from CCS lowers but retrofitting gains importance. At the same time, Bio CCS is reducing until we get close to 3 W/m^2. In these scenarios, C-Retro is necessary to achieve a fast reduction in emission before 2050, while Bio CCS usually enters in the energy mix later in time (see Figure 6.3). This might explain the reduction in biomass with CCS.

Nevertheless, for achieving very low targets (RF lower than 3 W/m^2), we see a strong reduction in electricity production from fossil fuel plants, while Bio CCS increases significantly, as it is the only technology that guarantees negative emissions. Therefore, we can conclude that fossil fuel fired plants with CCS are optimal for achieving medium-strict targets. In order to limit the temperature increase below 1.5°C from pre-industrial level, biomass CCS is the only optimal alternative. As a consequence, the total amount of CCS electricity production in the most stringent scenario depends almost only on the biomass availability and cost.

Figure 6.15 shows the cumulative captured emissions by CCS plants up to 2100. We can draw the same conclusions of the electricity production, as the two variables are strictly correlated. However, in this Figure we can appreciate also the temporal dimension. For the scenarios with the highest CO_2 captured, we see that CCS in 2025 is almost null and

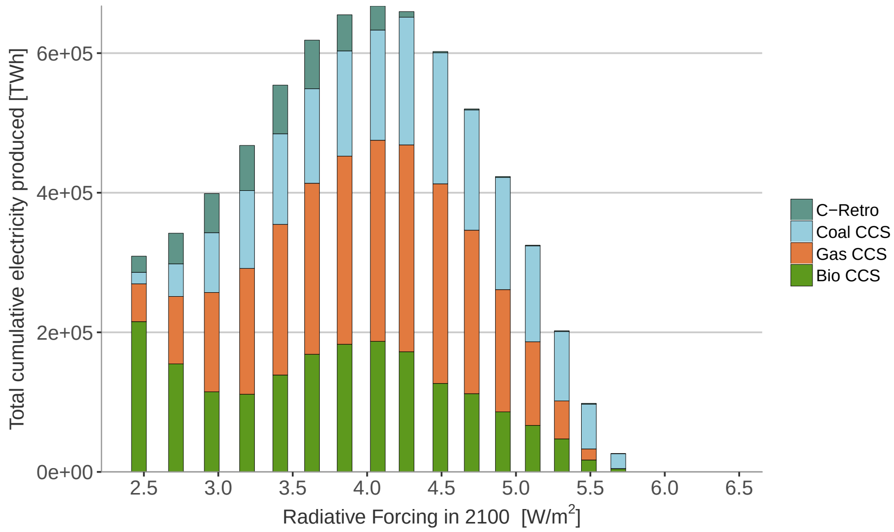

Figure 6.14. Total electric energy production by CCS plants in different climate scenarios in 2100. The lowest scenario (RF=2.47 W/m^2) corresponds to an average temperature increase around 1.5°C. The radiative forcing values for our references scenarios are: 6.92 W/m^2 for `BAU`, 4.08 W/m^2 for `ctax` and 3.11 W/m^2 for `2DC`. Note: to ease the comprehension of the graph, the first value on the x axis is not set to zero.

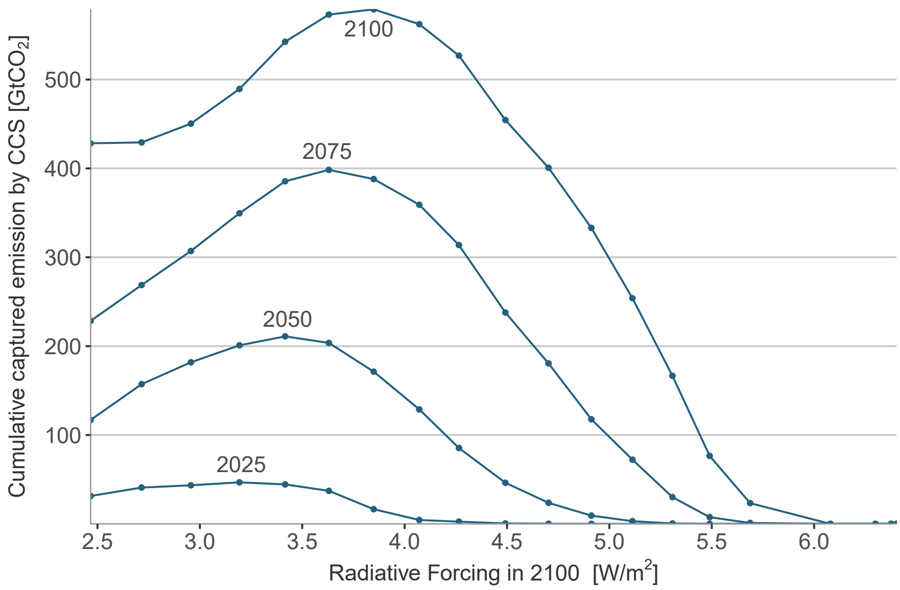

Figure 6.15. Cumulative CO_2 emission captured by CCS plants in different climate scenarios in 2025, 2050, 2075 and 2100. The lowest scenario (RF=2.47W/m^2) corresponds to an average temperature increase around 1.5°C. The radiative forcing valued for our references scenarios are: 6.92 W/m^2 for `BAU`, 4.08 W/m^2 for `ctax` and 3.11 W/m^2 for `2DC`. Note: to ease the comprehension of the graph, the first value on the x axis is not set to zero.

gains importance mostly after 2050. On the other hand, stricter scenarios capture around 50 $GtCO_2$ by 2025 thanks to retrofitting. Looking at the curves at different years, we also notice that the peaks with maximum deployment of CCS shift to the right: this confirms the fact that in the short terms CCS is important for low temperature targets, while the opposite is true for long terms results.

Figure 6.16 condenses the main results of the first three chapters, including the dimension of climate target. It shows the variation of the curve in Figure 6.15 at 2100, using the low and high values for I_{cost}, $b(j)$ and c_{st} seen in the previous chapters. We notice that the conclusions on the key importance of the three parameters are still valid: the learning factor affects less the results, while the investment cost introduces the greatest variation especially for high radiative forcing targets. For both I_{cost} and storage costs, we clearly see that high costs cases require more strict targets and therefore higher carbon tax, to obtain the same CCS energy production of the reference case.

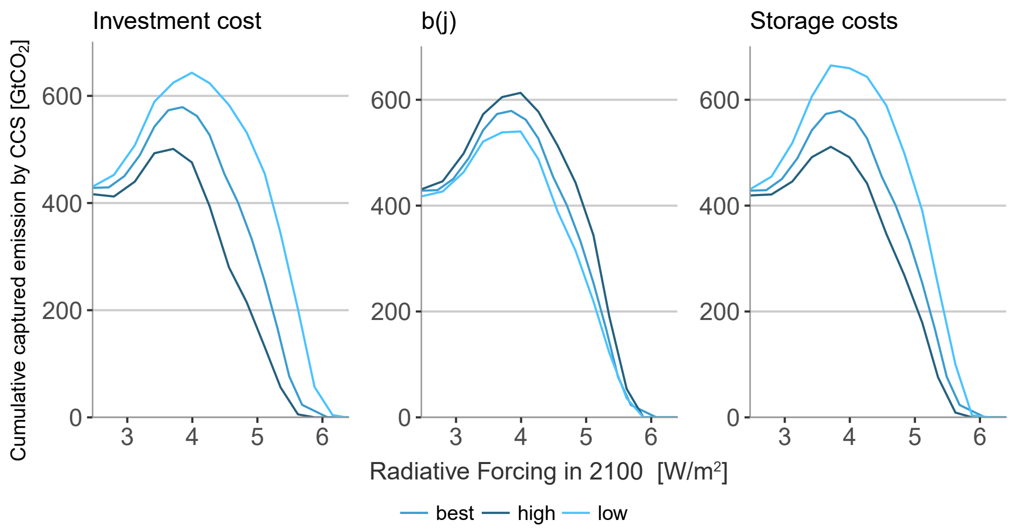

Figure 6.16. Cumulative CO_2 emission captured by CCS plants in different climate scenarios in 2100, considering low, best, high assumptions for the most significant parameters. The lowest scenario (RF=2.47W/m^2) corresponds to an average temperature increase around 1.5°C. The radiative forcing valued for our references scenarios are: 6.92 W/m^2 for `BAU`, 4.08 W/m^2 for `ctax` and 3.11 W/m^2 for `2DC`. Note: to ease the comprehension of the graph, the first value on the x axis is not set to zero.

6.4 Case Study: CCS in the Chinese electricity sector

As already mentioned, the WITCH model version that we used for this work has thirteen different regions. Up to now, we reported mainly global values and results. However, when disaggregating the global results into the world regions, we notice that strong differences exist in terms of output, input data and performances parameters. For instance, the representation of technology related costs (such as $LCOE$) loses its significance if we try to draw a global picture, as it heavily depends on the regional technology portfolio.

We therefore report some of the results for a single country, in order to give an overview of those parameters that are strongly regional specific. For this purpose, China represents an ideal case study, as we observed an high CCS potential in general, and coal retrofitting in particular. Moreover, we prefer to focus on the `ctax` scenario, as it shows a greater involvement of CCS and at the same time a more heterogeneous energy mix, compared to the 2DC.

6.4.1 Electric sector

Figure 6.17 gives a representation of the electricity supply by technology in China in a ctax scenario. On the left-hand side, the overall energy mix is provided, while on the right hand side we report a focus on CCS technologies. Electric sector appears to be strongly dominated by traditional coal power plants up to 2015. Low carbon technologies (Nuclear, Solar, Wind, Hydro, CCS) then gradually gain more significant shares of the energy mix. Wind alone is responsible for more than 40% of the overall electric production in 2050. CCS, and retrofitting in particular, seems to substitute the traditional coal power plants electricity production.

Considering the energy produced with retrofitting, we witness to an increase in the ratio between the energy produced by traditional plants and the energy produced by retrofitted plants. In 2035, more than 43% of the total traditional coal plants in operation is retrofitted; this percentage increases to 62% in 2040, and in 2045 the total electricity production from traditional coal plants is from retrofitted units. Retrofitting allows therefore a delay in the shut down of traditional plants. In the following decades, Bio CCS importance increases with respect to fossil CCS, peaking around 2070. In the longer term, renewables are the most important low carbon technologies, and the overall share of CCS gradually decreases.

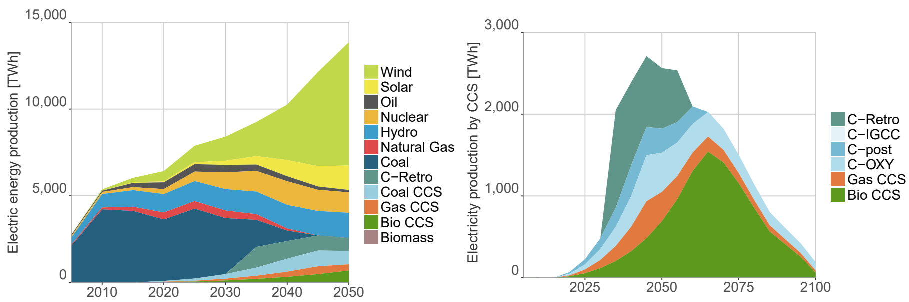

Figure 6.17. Chinese energy mix until 2050 (left) and breakdown for CCS technologies until 2100 (right), in a ctax scenario.

6.4.2 Storage capacity and use

In Chapter 5 we gave an overview of storage costs and capacities mainly at a global level. We now aim at understanding the regional dynamics of the CO_2 storage process. In Figure 6.19 we report the storage cost-capacity curve for China. This available capacity is gradually filled in time, with cost criteria: increasingly expensive storage sites are used. This mechanism is evident when analysing the storage capacity used: in Figure 6.18, we can see that the cheapest storages (O&G on, EOR on, Aquif. ON) are the first to be gradually filled.

6.4.3 LCOE

The levelized cost of electricity can be evaluated only for technologies that are actually in operation in a specific year. Therefore, *LCOE* value is not available for each technology in every year. In the case of China, C-IGCC technology is not used, and we cannot calculate

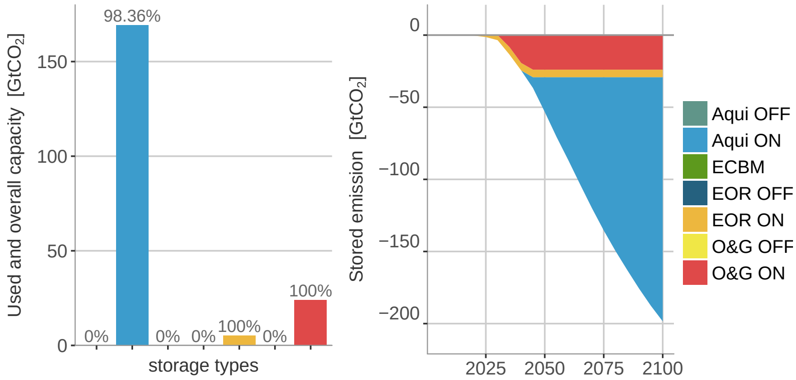

Figure 6.18. Quantity of CO_2 stored in China `ctax` scenario.

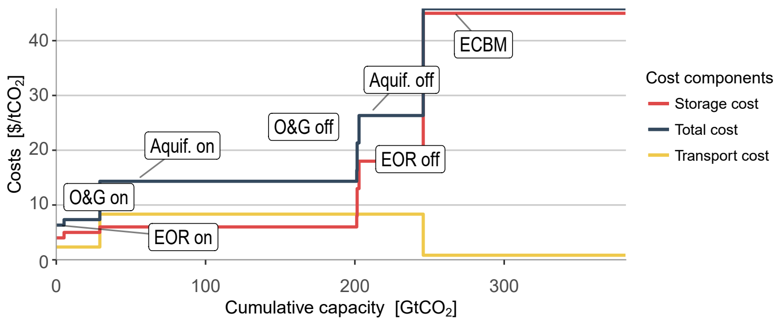

Figure 6.19. Regional cost curves for CO_2 transport and storage versus cumulative capacity in China.

the $LCOE$. The same holds also for conventional fossil fuel technologies, that get switched off quite soon because of the high carbon prices.

Figure 6.20 pictures twenty years during which traditional technologies coexist with plants with CCS. On the left hand plot, $LCOE_{CO_2}$ trends are represented. This variable stands for the sum of costs related to plants with capture technology, storage infrastructure and the cost of emitting CO_2 with the carbon tax. It is important to remind that if CCS plants appear in the energy mix, it means that they are more advantageous than plants without CCS. In fact, the $LCOE_{CO_2}$ starts from similar values for plants with the same fuel in 2020, but CCS plants become much cheaper than traditional plants in 2040 thanks to the carbon tax increase. On the right hand figure, the same information is given plotting the CCA (defined in Section 3.1.2) for plants with CCS in comparison with the carbon tax trend. The drop in CCA explains the phase out of gas and coal plants in China by 2040 shown in Figure 6.17.

Cost of retrofitting is not reported, as it is not possible to evaluate it precisely: the investment cost of the existing coal power fleet is not accountable in the model.

Figure 6.21 shows a breakdown of $LCOE_{CO_2}$ components of all CCS technologies that are present in the Chinese energy mix except for retrofitting. From this Figure, we can notice some important effects linked to our implementation. First of all, the investment cost reduction due to technological learning is strongly evident: for each type of plant, the investment component of $LCOE$ is almost halved by 2035 and in 2050 it becomes around 40% of the initial value (Gas CCS has the strongest reduction, reaching 38.6% of the initial value). The second dynamic cost component resulting from our implementation is the transport and storage cost. From Figure 6.21, we see that it increases over time for each technology. This is due to the switch to more expensive storage sites, once the cheapest options are totally filled: this result matches with the storage behaviour we see in Figures 6.19 and 6.18.

Finally, from the $LCOE$ bar chart we also see quantitatively why Bio CCS might be a very competitive technology in a carbon tax scenario: even if it has the highest $LCOE_{capt,st}$, the advantage due to negative emissions makes it the most competitive technology among the CCS options. However, we also recognize a steep raise in fuel cost related to biomass, that might be a consequence of the limited availability. There considerations lead to interesting discussions on biomass with CCS that we hope we will be able to address in further future work.

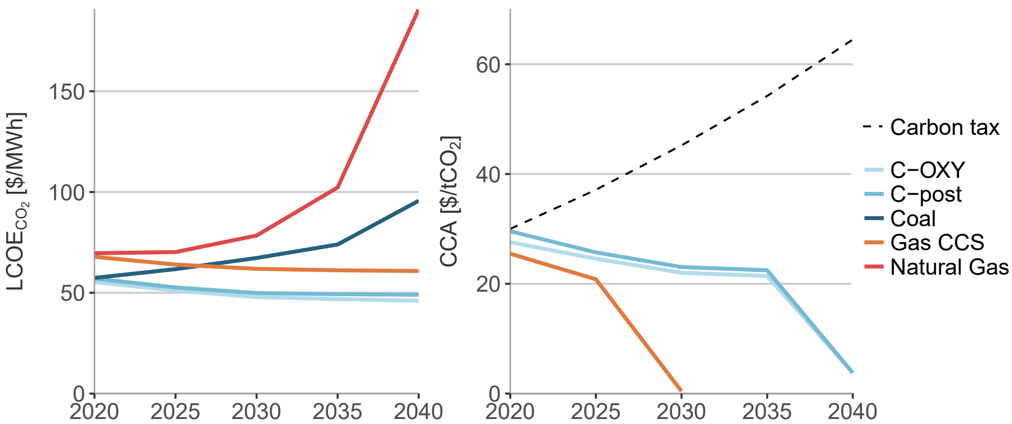

Figure 6.20. LCOE and CCA in China `ctax` scenario.

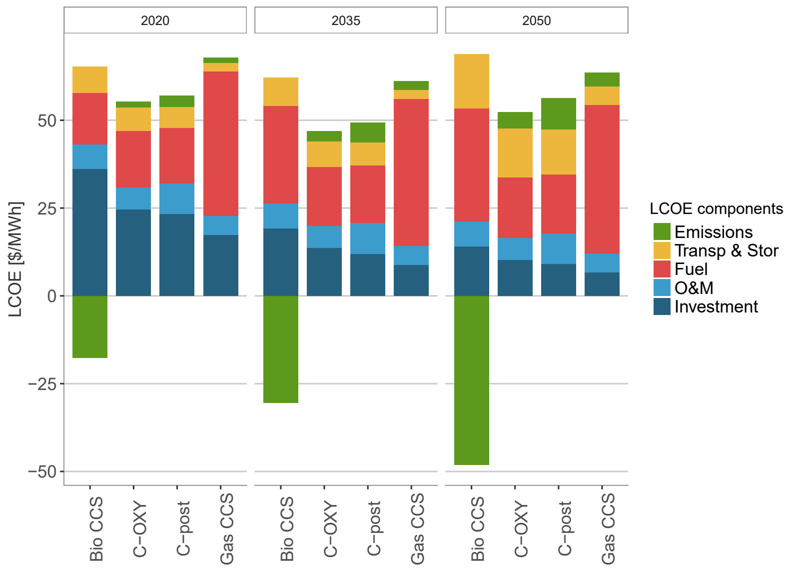

Figure 6.21. Breakdown in the LCOE for CCS tech `ctax` scenario.

Chapter 7

Conclusion

In this chapter, we sum up the most important results we achieved from our work and present in a synthetic form the main conclusions, providing the answers to the questions that motivated our research. We report the main questions for sake of simplicity:

(1) Which are CCS available technologies in the power sector? What is the role of performance parameters and costs in assessing plants competitiveness in scenarios with carbon price?

(2) What is the influence of technological improvements (learning by doing) on CCS deployment over time?

(3) How do storage availability, costs of CO_2 storage chain and leakage occurrences impact the CCS potential?

(4) What is CCS deployment impact on the overall energy mix and the associated emissions reduction, in relation with different temperature targets and climate policies?

Main questions discussion

Technological assessment

First of all, we determined the CCS technology options that are likely to be part of the future energy mix (coal oxyfuel, coal and gas post-combustion, coal and gas IGCC with CCS, biomass CCS) and focused on the main related parameters (investment and $O\&M$ costs, capture rate, plant efficiency, capacity factor). Among coal options, the model prizes mostly oxyfuel plants, which capture rate is high. Gas CCS and biomass CCS have an important role in the energy mix, as they have low (gas) or even negative (biomass) carbon emissions. CO_2 capture rate, investment costs and electric efficiency are the main drivers for the technology adoption. However, analyzing the uncertainty ranges, investment cost is the most influencing parameter on CCS deployment.

Considering the overall energy mix, we can draw some important conclusions. Traditional coal power plants could have an important role in future energy portfolio even in low carbon scenarios, thanks to retrofitting. Retrofitting existing coal power plants seems to be a convenient strategy for reducing CO_2 emissions, especially in more stringent scenarios: without retrofitting, traditional coal plants are rapidly shut down, regardless their potential lifetime. This would have consequences from the economic point of view (i.e. these plants are closed long before it would be convenient to stop the production). CCS deployment could have also an impact on renewable technologies: the model results show some substitutability between CCS technologies and renewable energy sources.

Learning by doing consequences

Technological improvement, and specifically learning by doing, could heavily impact on CCS future perspectives: the trend over time of costs could be crucial for CCS deployment and adoption. Even though spillovers among the different technologies seem not to be particularly relevant, the learning rate impact on single technologies could assume a key importance. Both the overall share of CCS technologies and the relative importance of a technology with respect to the others could be heavily influenced by learning. If at a first approximation coal oxyfuel appeared to be the most convenient coal technology, learning rates could prize other options (i.e. coal IGCC with CCS and coal post-combustion).

Storage costs and potential

Three aspects of the storage and transport chain could mainly impact on CCS deployment: storage costs, transport costs and storage capacity. High costs could hinder CCS deployment, as some other low carbon options (i.e. Nuclear, Renewable technologies) could become more competitive from the economic point of view. On the other hand, availability of reliable storage capacity is essential for CCS importance in the energy mix. Without a sufficient and secure storage capacity, CO_2 captured could not be safely stored: CCS utility as a low carbon technology would be neutralized.

We can conclude that costs of storage impact more than transport related costs: storage costs are the main cost driver. Concerning capacity, we can assess that capacity availability is not a binding constraint, even in the most strict climate scenario, as estimates of available capacity are far higher that the average capacity required by CCS. However, as each storage type is characterized by different storage costs, availability of cheap storage capacity is strongly influencing the results. Therefore, we can conclude that storage costs and available capacity are the features with greatest impact on CCS production.

This conclusions refer to zero-leakage scenarios. Including in the simulations leakage from storage sites, we achieve further results. In particular, depending on the stringency of the scenario, CO_2 leakage greater than 1%/yr of the stored capacity, could strongly hinder CCS deployment. Should not the storage sites be reliable, the energy mix would shift towards other technologies, more or less carbon intensive, depending on the climate scenario, and CCS importance would be strongly downscaled.

Role of CCS in the energy portfolio

We now discuss the importance of CCS technologies in the electricity sector and assess to what extent they can be considered a suitable option in the energy portfolio.

First of all, in climate constrained scenarios CCS plays an increasingly important role, since the introduction of the carbon tax until the period between 2050-2075. Afterwards, its energy production remains almost constant. The higher the temperature reduction we aim to achieve, the earlier the start of CCS introduction, with a stronger contribution of coal retrofitting. Considering the regional dimension, China and US are expected to be the two leading countries in CCS development.

The emissions captured by CCS in the electricity sector range from 10% to 20% of the overall emissions reduction with respect to the `BAU` scenario, in the investigated cases. The variation in the percentage depends on the difference in temperature targets.

Finally, we found a remarkable relation between climate target and the importance of CCS. The share of CCS plants is maximum for medium-stringent scenarios, with temperature increase around 2.5°C. When the climate policy aims at maintaining the temperature increase below 2°C, we notice a strong reduction in fossil-fueled plants with

CCS, while biomass with CCS gains significant importance, with an overall drop in CCS development.

Robustness analysis

During our work, we performed several sensitivity analysis in order to identify the key parameters affecting the results and to assess the uncertainties due to our assumptions.

We can state that our conclusions are quite robust, especially concerning results on CO_2 emissions and GDP trend. Furthermore, confidence interval narrows for more strict climate scenarios.

The most remarkable variations in the results concerns electricity production by CCS plants, followed by the Solar and Wind energy production in substitution to CCS. However most of the output variables of our model do not vary significantly.

Scientific contributions provided

To come to a conclusion, we believe this work makes a twofold contribution to the climate mitigation context. The first aspect is related to energy modelling framework. We improved the WITCH power sector and the CO_2 storage system, updating input data and implementing a more careful representation of CCS technologies. The model is expected, therefore, to more realistically outline CCS perspectives. The second contribution addresses questions posed by policy makers: we analyzed in detail many aspects of CCS technologies in the electric sector, examined the possible relationships among CCS features (i.e. technologies main parameters, future cost trend, storage and leakage) and provided an evaluation of the uncertainty underlying the estimates. We believe therefore that this work could provide some useful information and help in the design of climate policies.

Further developments

Besides the results we achieved so far, we think that other important research themes would complete this work and add an important contribution to better assess CCS perspectives in low carbon scenarios. We can group future possible developments in two main categories: the first includes some possible continuations of the current work, deepening other aspects of CCS, and requires further implementation in our model. The second group refers to research themes that might be addressed using the actual state of the WITCH model as analysis tool, but we did not investigate in this work as they deviate from our key research questions.

Concerning the first category we selected the following research themes:

(1) Biomass with CCS: we are aware that this work is mainly focused on fossil fuel CCS, while biomass CCS issue is only marginally addressed. However, our results show the key role of biomass CCS especially in very strict climate scenarios. Therefore, a detailed analysis on biomass with CCS perspectives would be an asset for further work.

(2) Industrial applications of Carbon Capture and Storage: since most of current CCS plant are not devoted to power production and CCS applications in the industrial sector could have a relevant role in the future, we think that studying and modelling industrial application would add strong relevance to our work. In the WITCH model there is already a general coal CCS technology not related to the electric sector, but the topic is certainly worth further development.

(3) Extension of the retrofitting implementation to gas plants and new plants: in our work, we only considered retrofitting of coal power plants that were already operating in 2015. This choice was due to technical modelling reasons. However, it would be interesting in the future to extend the retrofitting option to plants that will be installed later, as well as to gas and biomass plants.

(4) Study the case of negative CO_2 storage cost for EOR and ECBM types of storage: eventual benefits from enhanced oil and gas extraction impact on the market could provide incentives to CCS adoption.

Follow some interesting research topics that could be potentially investigated using our new version of the WITCH model, and could lead to meaningful results thanks to the work we did on CCS implementation:

(5) Relation between RES with intermittencies and CCS technologies: we addressed this theme only marginally, even though RES are implemented in detail in the WITCH model. We however underline that WITCH optimizes with time steps of five years, making critical the study of base and peak load variations in the electricity market with renewables. This could represent a limit for this kind of research.

(6) Relation of CCS technologies with traditional power plants: fossil fuel based options are certainly going to have a key role in future electric mix, due to their reliability. CCS plants, like traditional plants, can supply the necessary base load to the electric system. We only marginally investigated the partial substitutability between the two categories that could arise.

(7) CCS role in other policy frameworks: CCS importance could be also affected by specific policy requirements, such as the INDCs defined at the COP21 in 2015 or air quality related policies, which focus on pollutant emissions other than CO_2.

Appendix A

The WITCH model

A.1 Model structure

In the flowchart reported in Figure A.1 it possible to see WITCH model structure. WITCH has a modular organization where each module focuses on a key topic (i.e. solar

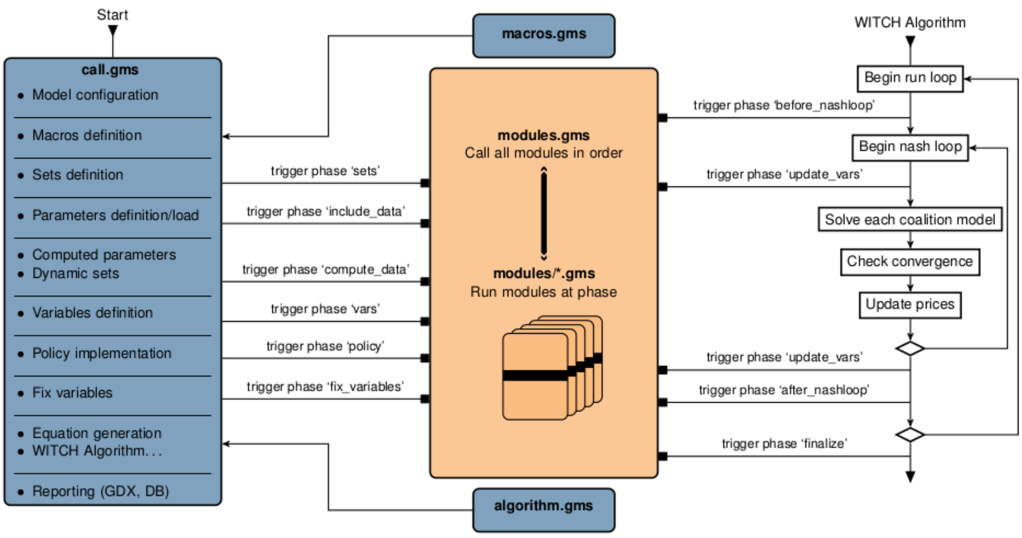

Figure A.1. WITCH flowchart.

energy, CCS). From the algorithmic point of view, each module is divided in phases: the model solves the optimization problem phase by phase, therefore it goes through phases in each module. The solving process is an iterative process that gradually converges. The model optimizes the discounted utility of each region independently (in the open loop Nash equilibrium), and at the end of each iteration it checks if there is an equilibrium between import and exports of oil, a the output oil market price. If the condition is not met, the model updates the oil price and the iteration restarts.

A.2 Main equations of the model

The objective function of the model is the maximization of the sum over time of regional discounted utility:

$$W(n) = \sum_t l(t,n) \frac{\left(\frac{C(t,n)}{l(t,n)}\right)^{1-\eta} - 1}{1-\eta} \beta^t \tag{A.1}$$

Where $W(n)$ is the discounted utility, $C(t,n)$ is the consumption of the final good, η represents the inverse of the intertemporal elasticity of substitution, $l(t,n)$ stands for the population β is the pure time preference discount factor. β be calculated as:

$$\beta = (1+\rho)^{\Delta t} \tag{A.2}$$

where ρ is the discount rate and Δt corresponds to a time range of 5 years. For each region, a representative consumer is taken into account. This agent is responsible for the consumption of $C(t,n)$ which is derived as the difference between net output $Y(t,n)$ and investments:

$$C(t,n) = Y(t,n) - \sum_t I \tag{A.3}$$

Net output is a function of capital (K) and labour (l) (linked with a Cobb-Douglas function) combined with energy services (ES) through a CES function. The upper node of the CES function represents how capital, labour and energy services influence the GDP:

$$Y(t,n) = f(K(t,n), l(t,n), ES(t,n), \rho) - \sum_{fuels,GHG} c(t,n) \tag{A.4}$$

$\sum_{fuels,GHG} c(t,n)$ is the sum of the expenditure devoted to fuel demand and GHG emissions. All the other nodes follow the same principle. As an example, let's consider the nodes linking $EL(t,n)$ (Electric energy) and $NEL(t,n)$ (Nonelectric energy) and the way they contribute to the composition of $EN(t,n)$ (Energy):

$$EN(t,n) = f(EL(t,n), NEL(t,n), \rho_{EN}) \tag{A.5}$$

This function aggregates different factors at various levels, associating them with particular elasticities of substitution (the number below each node). In the CES structure, both electric and non electric sectors are included. The CES structure is represented in Figure A.2. All the acronyms appearing in the figure and their meaning are reported in Table A.1.

Table A.1
Main WITCH variables relevant in this thesis

Abbreviation	Name	Abbreviation	Name
KL	Capital-labor aggregate	ELNUKE& BACK	Electricity generated with nuclear and backstop
K	Capital invested in the production of the final good	ELBACK	Electricity generated with backstop
L	Labor	ELNUKE	Electricity generated with nuclear
ES	Energy services	ELW& S	Wind turbines and photovoltaic panels
RDEN	Energy R&D capital	NEL	Nonelectric energy
EN	Energy	TradBiom	Traditional Biomass
EL	Electric energy	COALnel	Coal for nonelectric energy
ELYHYDRO	Electricity generated with hydroelectric	OGB	Oil, backstop, gas, and biofuel
EL2	Electricity generation	GASnel	Gas for nonelectric energy
ELFF	Fossil fuel electricity	OIL&BACK	Oil and backstop for nonelectric energy
ELCOALBIO	Electricity generated with Coal and Biomass	BACKnel	Backstop for nonelectric energy
EPC	Electricity generated with pulverized coal	OILnel	Oil for nonelectric energy
ELIGCC	Electricity generated with integrated gasification combined cycle coal plus carbon capture and storage	Biofuels	Traditional and advanced biofuels
ELOIL	Electricity generated with oil	Trad Bio	Traditional biofuels
ELGAS	Electricity generated with gas	ELWIND	Electricity generated with Wind Energy
ELGASTR	Electricity generated with Gas turbines	ELPV	Electricity generated with Photovoltaics
ELGASCCS	Electricity generated with Gas with CCS	ELCSP	Electricity generated with Concentrated Solar Power
WINDON	Electricity generated with Onshore Wind	WINDOFF	Electricity generated with Offshore Wind
ELPC	Electricity generated with Pulverised Coal	ELCIGCC	Electricity generated with Coal IGCC plus CCS
ELPB	Electricity generated with biomass	ELBIGCC	Electricity generated with Biomass with CCS

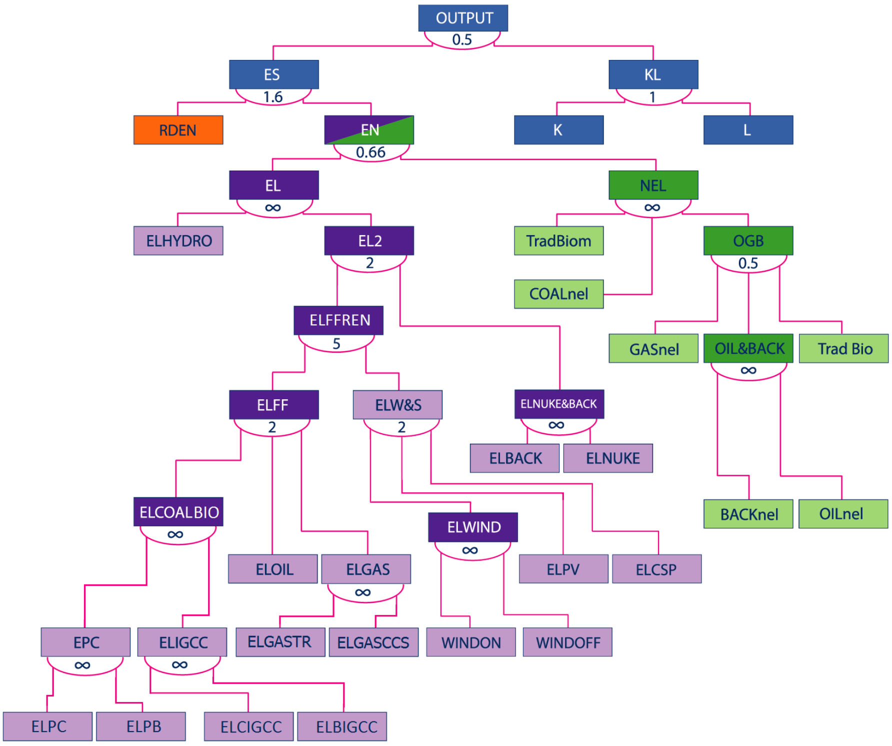

Figure A.2. WITCH CES

Appendix B

World Electric Power Plants Data Base

The UDI World Electric Power Plants Data Base (WEPP) is a global inventory of electric power generating units. It contains country specific data concerning ownership, location, engineering design data of power plants of all sizes and technologies managed by regulated utilities, private companies, and industrial autoproducers. The WEPP is edited and maintained by the UDI Products Group of Platts, the energy information division of McGraw Hill Financial.

The WEPP database covers in an exhaustive way all the power plants with a prime mover connected to a generator, such as steam, gas or hydraulic generators, as well as reciprocating engines. Coverage for wind turbine, diesel engines, photovoltaic systems and every generating unit less than 25 kW is representative, but not exhaustive.

For the purpose of our thesis we deal with the WEPP database in order to provide updated and reliable historical data as input to the WITCH model. In particular, we focus on the generating power capacity in 2005 and 2010 for some specific technologies reported in the database: coal-fired, gas-fired, oil-fired, nuclear and hydroelectric power plants.

B.1 Initial installed capacity

The WEPP database does not only include data for operating power plants, but also information on retired plants as well as planned and under construction infrastructures: we will refer to these different conditions as "status". When dealing with a large number of generating unit types, with different status, fuels and other conditions, we must carefully chose which data are we interested in and what processes of the data selection introduce errors.

As an example, we group by technology those data that have specific characteristics (i.e. plants with *uranium* as fuel are assigned to nuclear, those with fuel *coal* or *coke* and with steam turbines to coal power plants). However, some data entries cannot be classified because of lack of information: these are sources of uncertainty that we must consider.

We account for different type of uncertainty that are summarized in Table B.1. Those categories with "NO impact" are data from the database that we exclude with high certainty because not pertinent with our selection. Figure B.1 shows the results of our data analysis, it represents the installed power capacity in 2005 divided by the five categories of power plant across the thirteen WITCH region. It also provides informations on the total uncertainty for each region and breakdown on the error source.

Data concerning `oldeuro` and `cajaz` regions show the highest level of uncertainty, respectively 10.8% and 15.7% of the total capacity in each region. Thanks to the breakdown into different error types, we can assess which are the main sources of uncertainty. Concerning `oldeuro`, the error if given both by data with *Shutdown* status and with

Table B.1
Description uncertainty sources

Error type	Impact	Description
Autoproducers	NO	Industrial or commercial enterprise that generates its own electricity, usually without energy sales to the grid, though the plants might be grid-connected. We do not consider these data as uncertainty because we think that autoproducers should not be included in the country electricity generating fleet.
Unknown	YES	All the generating units whose status is unknown and we can not know if the units are in effect operating.
Shutdown	YES	All the generating units that in 2015 are considered as off, mothballed, deactivated or canceled. This category includes two types of uncertainty. The first is intrinsic in the database, especially nuclear and hydroelectric plants may be offline for few years for safety modification or retrofit. The latter error arises as we are defining an overview of the generating fleet in 2005, while the status specification are referred to 2015, therefore it is impossible to determine whether a plant that is off in 2015 for the mentioned reasons was actually operating in 2005 or not. Shutdown error is one of the major sources of uncertainty.
Other status	NO	Power plants with different status specification are not considered as source of uncertainty. This category includes planned, under construction or delayed units.
NOtech	YES	Every power units that can not be assigned to a technology.
NOyear	YES	Data entry where the year is missing and we can not define if the plant is operating.

unknown technology. Instead, concerning `cajaz` the major source of error are the data related to nuclear power plants in Japan that were switched off temporarily or permanently from 2005 to 2015.

B.2 Assessing retrofitting potential for coal power plants

As explained in Section 3.1.1, we use the WEPP data base also for assessing the share of the existing coal power plant fleet that is suitable for retrofitting, according to two criteria: power capacity greater than 300 MW and lifetime shorter that 25 year. These conditions are a simplification of a complex set of situations that vary for every power plant, from the public acceptance, to technical or space issues.

For this analysis we consider the latest data available in the database, which covers until the end of 2014. In this way we can reduce the *Shutdown* type uncertainty, as the status in the database is referring to the same year we are analyzing.

Figure B.2 shows the existing capacity for coal power plants in 2014 and the share that is potentially suitable for retrofitting according to our conditions. From these data, we calculate the percentage share and we use this value as boundary condition for the model.

Let's remind that we only implement retrofitting for existing power plant in 2015, therefore the share that we estimate is a reasonable representative value. Nevertheless, although we are using this ratio as a static parameter, it would be plausible that the number of existing suitable plants will lower in the future, as old plants get switched off. However, by looking at the model results running carbon tax scenarios, we notice that retrofitting is always a choice limited to the first years of policy introduction, usually 2020 or lately 2025. Therefore, we can consider our assumptions admissible in our model framework.

The most striking results are that, while in China 83.4% of more than 800 GW installed meets the retrofitting criteria, in the US and in `te` (Russia) the share accounts for only 7.8% of around 400 GW and 13.8% of 100 GW installed respectively. This is due do the large number of old power plants in these regions. By contrast, most of Chinese coal plant were built recently. In `oldeuro`, on 200 GW of installed capacity, 13% results suitable for retrofitting.

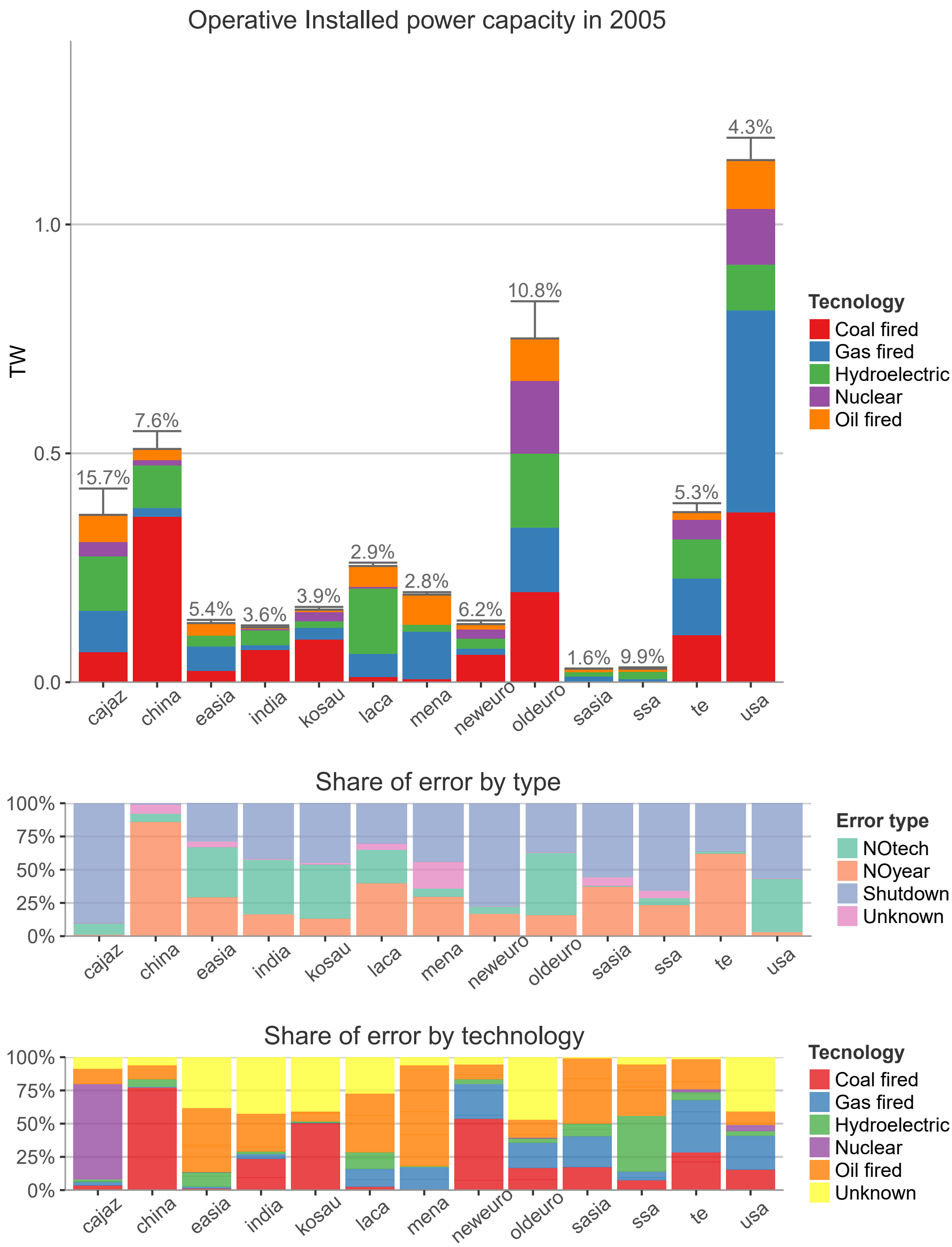

Figure B.1. Results of our analysis on the installed capacity for power generation.

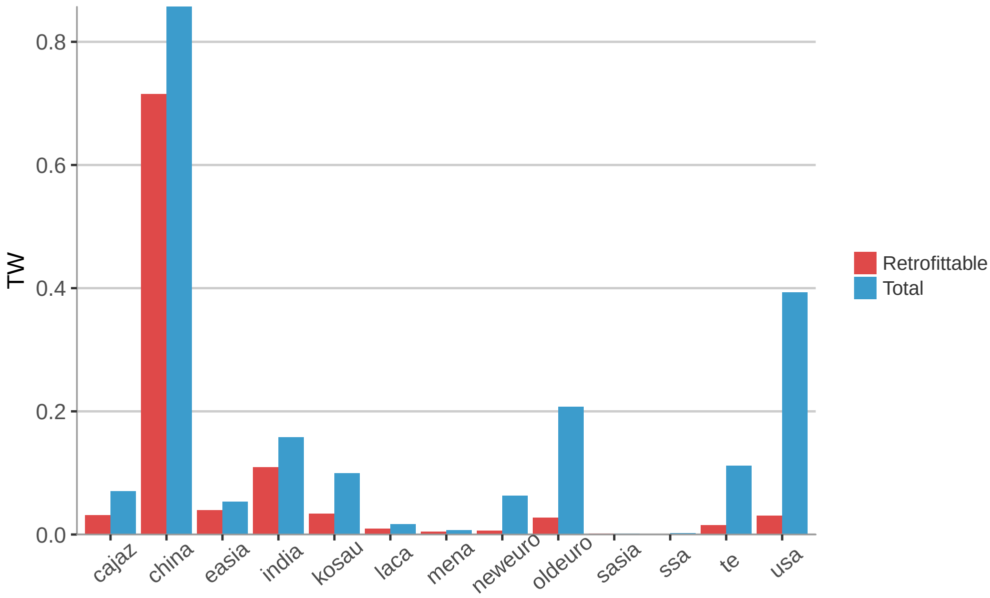

Figure B.2. Total and retrofittable installed coal capacity in 2014.

Appendix C

Data on carbon capture plants

Table C.1
Data gathered during our literature review.

	Rubin 2015 [67]		GCCSI 2012 [16]		Leung 2014 [59]	IEA 2013 [32]	IPCC 2005 [63]		Koelbl 2016 [56]		van den Broek 2011 [73]	IEAGHG 2012 [41]		Catalanotti 2012 [7]	NETL 2011 [10]
	best	[low-high]	best	[low-high]	best	best	best	[low-high]	best	[low-high]	best	best	[low-high]	best	best
η_{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] η_{el} is the net electric plant efficiency on LHV basis; CRR is the carbon capture rate ratio; CF is the capacity factor.

Appendix D

Data on CO_2 storage and transport

Table D.1
IEA GHG capacity divided per region in *low*, *best*, *high* cases in [$GtCO_2$] [39].

	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 D.2
Percentage of onshore and offshore capacity for storage potential of O&G and Aquifers [37].

	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 D.3
Cost of storage for O&G sources and Saline formations [$/t$CO_2$] [84].

			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 D.4
Transport costs on a common basis for onshore and offshore pipelines at three different capacities [$/t$CO_2$/250km] [67]. 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		
[MtCO_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			

Table D.5
Maximum regional storage capacity for each storage type in [$GtCO_2$]

		cajaz	china	easia	india	kosau	laca	mena	neweuro	oldeuro	sasia	ssa	te	usa
	low	1469.0	24.6	1.9	4.1	0.0	26.4	69.3	13.2	27.7	1.2	46.1	68.8	1065.2
Aquif. ON	best	3576.0	172.1	13.6	28.9	0.2	96.8	188.7	13.2	27.7	8.1	125.4	68.8	2577.2
	high	5800.0	750.6	59.2	126.2	0.5	383.2	557.1	13.2	27.7	35.2	370.1	68.8	4114.6
	low	377.4	6.2	2.9	4.1	0.1	6.6	12.5	24.6	51.4	1.7	85.5	275.3	355.1
Aquif. OFF	best	918.6	43.0	20.3	28.9	0.3	24.2	34.0	24.6	51.4	12.1	232.8	275.3	859.1
	high	1489.9	187.6	88.7	126.2	1.0	95.8	100.5	24.6	51.4	52.8	687.4	275.3	1371.5
	low	0.6	6.3	2.6	1.7	0.1	7.6	56.8	1.6	2.8	0.4	7.0	193.5	0.0
O&G fields ON	best	33.3	24.0	8.1	5.6	0.3	31.6	245.0	1.6	2.8	0.9	19.7	193.5	64.2
	high	39.0	69.8	22.3	15.8	0.7	128.4	790.9	1.6	2.8	2.3	56.7	193.5	70.2
	low	0.0	0.3	10.6	0.9	0.2	11.3	26.6	4.8	11.3	1.4	13.0	64.5	0.0
O&G fields OFF	best	2.1	1.3	32.4	3.0	0.6	47.3	114.5	4.8	11.3	3.6	36.6	64.5	16.1
	high	2.4	3.7	89.3	8.5	1.5	192.5	369.8	4.8	11.3	9.2	105.3	64.5	17.5
	low	5.4	5.2	0.9	0.8	0.0	4.0	68.9	0.0	0.9	0.0	1.5	34.4	28.9
EOR ON	best	5.4	5.2	0.9	0.8	0.0	4.0	68.9	0.0	0.9	0.0	1.5	34.4	28.9
	high	5.4	5.2	0.9	0.8	0.0	4.0	68.9	0.0	0.9	0.0	1.5	34.4	28.9
	low	0.3	0.3	3.8	0.4	0.0	6.1	32.2	0.1	3.6	0.0	2.8	11.5	7.2
EOR OFF	best	0.3	0.3	3.8	0.4	0.0	6.1	32.2	0.1	3.6	0.0	2.8	11.5	7.2
	high	0.3	0.3	3.8	0.4	0.0	6.1	32.2	0.1	3.6	0.0	2.8	11.5	7.2
	low	9.5	0.0	0.0	0.0	0.0	0.0	0.0	1.6	0.5	0.0	0.0	23.9	147.5
ECBM	best	11.0	135.4	14.6	27.7	19.3	2.0	0.0	1.6	0.5	0.2	0.2	23.9	165.4
	high	16.0	731.7	79.0	149.8	101.5	12.0	0.3	1.6	0.5	1.3	1.3	23.9	215.2

Appendix E

GAMS code

During this thesis work we have been programming in R for data analysis and manipulation, and in GAMS for what concerns the model implementation. The WITCH model is structured in several modules, so to ease the understanding and the editing. We have brought several important change in different modules, but in particular we have almost completely developed the CCS module, which code is following.

```
$ifthen %phase%=='conf'

$setglobal ccs_setup ccs_default
$setglobal learning_ccs  learning_ccs_default
$setglobal storage_capacity_ccs   best_storage_ccs
$setglobal storage_cost_ccs    best_storage_cost
$setglobal retro_ccs retro_def_limk

*---------------------
$elseif %phase%=='sets'

set j / elretro_old, elretro_vint /;              # provide a Q_EN
set jreal(j) / elretro_old, elretro_vint /;       # provide a K_EN, MCOST_
    INV, delta_en and oem
set jel(jreal) / elretro_old, elretro_vint /;     # provide a mu and flex_
    coeff
*set jfed(jreal) /elretro_old /;
set jinv(jreal) / elretro_old, elretro_vint /;    # provide a I_EN

set e /
ccs      # Sequestered CO2
co2leak     # CO2 leakages
/;

set map_e(e,ee) 'Relationships between Sectoral Emissions' /
co2.co2leak
/;
set sink /ccs/;

set jccs(jfed) 'Electrical Actual Energy Technology Sectors with CCS' /
elcigcc
elbigcc
elgasccs
elpc_ccs
elpc_oxy
/;

set cost(e) 'Emissions-related entities that cost' /
ccs
```

```
/;

*learning curves
set jlccs(jinv) 'Set of Electrical CCS technology with learning by doing' /
elcigcc
elbigcc
elgasccs
elpc_ccs
elpc_oxy
/;

alias(jlccs,jllccs);

set jretro_un(jel) 'unit of retrofitting that will have K_EN and I_EN but
    not Q_EN' /
elretro_old
elretro_vint/;

set map_retro(jretro_pl,jretro_un) /
elpc_old.elretro_old
elpc_vint.elretro_vint/;

set k_storage   'different storage technologies' /
aqui_on
aqui_off
oil_gas_no_EOR_on
oil_gas_no_EOR_off
EOR_on
EOR_off
ECBM
/;


set j_aqui_shore(k_storage) 'aquifer storage ON and OFF'/
aqui_on
aqui_off
/;

set j_OandG_EOR_shore 'oil and gas storage ON and OFF, including EOR'/
oil_gas_on
oil_gas_off
/;

set j_OandG_shore(k_storage) 'oil and gas storage ON and OFF, including EOR
    '/
oil_gas_no_EOR_on
oil_gas_no_EOR_off
/;

set j_EOR_shore(k_storage) 'oil and gas storage ON and OFF, including EOR'/
EOR_on
EOR_off
/;


set j_lbh 'low, best, high case of storage capacity'/
low
best
high
/;
```

```
set j_dist 'how distances are referred to in the make data file' /
aquif
oil_gas_onshore
oil_gas_offshore
coal_beds
/;

set map_storage_OandG(j_OandG_shore,j_OandG_EOR_shore,j_EOR_shore) /
oil_gas_no_EOR_on.oil_gas_on.EOR_on
oil_gas_no_EOR_off.oil_gas_off.EOR_off
/
;

set map_storage_eor(j_EOR_shore,j_OandG_EOR_shore) /
EOR_on.oil_gas_on
EOR_off.oil_gas_off
/
;

set map_storage_dist(j_dist,k_storage) /
aquif.(aqui_on,aqui_off)
oil_gas_onshore.(oil_gas_no_EOR_on,EOR_on)
oil_gas_offshore.(oil_gas_no_EOR_off,EOR_off)
coal_beds.ECBM
/;

set map_cca_lcost(j,jj)/
elpc.(elpc_ccs,elpc_oxy,elcigcc)
elgastr.elgasccs
elpb.elbigcc
/;
set map_fuel_j(f,j)/
coal.(elpc,elpc_ccs,elpc_oxy,elcigcc)
gas.(elgastr,elgasccs)
wbio.(elpb,elbigcc)
/;

*--------------------
$elseif %phase%=='include_data'
parameters co2_emissionj(j,t,n) 'emission from plant involved in CCA
    calculation [tCO2/MWh]'
co2_capturej(j,t,n) 'co2 captured by plant [tCO2/MWh]'
cca_ccs(j,t,n) 'cost of co2 avoided $/tCO2'
ccc_ccs(j,t,n)  'cost of co2 captured $/tCO2'
specca_ccs(j,t,n) 'specific energy consumption per co2 avoided [MJ/kgco2]';
parameter retro_limk0(*,n);
parameter retro_limk(*,t,n);

parameter eff_loss 'efficiency loss due to retrofitting' / 0.1/;

$gdxin '%datapath%data_mod_ccs'

parameter ccs_capture_eff(*) /
elcigcc    0.89
elbigcc    0.90
elgasccs   0.89
elpc_ccs   0.90
elpc_oxy   0.95
nelcoalccs 0.90/;

parameter ccs_quantity(*,n) 'CCS quantities for the CCS cost function';
```

```
$loaddc ccs_quantity

parameter emi_ct(f);
$loaddc emi_ct

parameter stor_cap_aqui(n,*) 'storage capacity for aquifers storage';
$loaddc stor_cap_aqui

parameter stor_cap_ecbm(n,*) 'storage capacity for coal bed storage';
$loaddc stor_cap_ecbm

parameter stor_cap_OandG(n,*) 'storage capacity for oil and gas fields
    storage';
$loaddc stor_cap_OandG

parameter stor_cap_eor(n) 'storage capacity for EOR storage';
$loaddc stor_cap_eor

parameter stor_share_ONOFF(n,*) 'share of storage capacity ONshore and
    OFFshore';
$loaddc stor_share_ONOFF

parameter stor_distance(n,*) 'average distance in the country for different
     storage types in [km]';
$loaddc stor_distance
$gdxin

******* LEARNING *********
*definition of spillovers for learning

table ccs_spill_factor(jlccs,jllccs) 'Matrix of share in learning
    contribution between ccs technologies'
elcigcc  elbigcc  elgasccs  elpc_ccs  elpc_oxy
elcigcc   1        0.8      0.7       0.5       0.6
elbigcc   0.8      1        0.7       0.5       0.2
elgasccs  0.7      0.7      1         0.7       0.2
elpc_ccs  0.5      0.5      0.7       1         0.2
elpc_oxy  0.6      0.2      0.2       0.2       1
;
*acronym low, high;

*definition of floor costs for each country and technology (as their costs
    are not decreasing in time, we consider mcost_inv0
*corresponing to each reference technology and for each country)

table floor_costs_ccs(*, n) 'Cost of investment [T$/TW]'
usa    oldeuro    neweuro      kosau      cajaz         te       mena
          ssa      sasia       china      easia        laca      india
elpc_ccs          1.4365     1.4721     1.3629     1.1599     2.0723
    1.4378     2.0723     2.0723     1.0013     0.9657     0.9835
    1.5076     1.0013
elbigcc           2.0000     2.0000     2.0000     2.0000     2.5000
    2.0000     2.5000     2.5000     1.6000     1.6000     1.6000
    2.0000     1.6000
elgasccs          0.6637     0.7500     0.7513     0.6294     1.0495
    0.7310     1.0495     1.0495     0.7398     0.7398     0.7398
    0.9835     0.7398
elpc_oxy          1.4365     1.4721     1.3629     1.1599     2.0723
    1.4378     2.0723     2.0723     1.0013     0.9657     0.9835
    1.5076     1.0013
elcigcc           1.4365     1.4721     1.3629     1.1599     2.0723
```

```
   1.4378     2.0723     2.0723     1.0013     0.9657     0.9835
   1.5076     1.0013
;

***********table of b values for each tech

parameter b_learn0(jlccs) /
elcigcc     0.0997
elbigcc     0.074
elgasccs    0.0615
elpc_ccs    0.0559
elpc_oxy    0.041
/;

parameter b_learn(jlccs,t);

parameter wcum_start(jlccs) 'minimum installed cumulated capacity after
   which learning starts [TW]'/
elcigcc     0.007
elbigcc     0.01
elgasccs    0.003
elpc_ccs    0.005
elpc_oxy    0.01
/;

parameter wcum_ccs_spillover(jlccs,t) 'installed capacity at each time step
    considering spillover effect among technologies [TW]'
;

************ STORAGE **********

parameter average_distance2(n,k_storage) 'Avg distance from CCS power
   plants to storage sites [km] from Hendriks 2004';


loop((j_dist,k_storage)$(map_storage_dist(j_dist,k_storage)),
average_distance2(n,k_storage)=stor_distance(n,j_dist)
);


parameter cost_storage (k_storage) 'storage cost, [T$/GtonCO2]' /
aqui_on              0.006
aqui_off             0.018
oil_gas_no_EOR_on    0.005
oil_gas_no_EOR_off   0.013
EOR_on               0.004
EOR_off              0.008
ECBM                 0.045
/;


parameter transp_coeff2 'coefficients of transport costs, considering that
   it is almost constant for large mass flow rates [$/(tonCO2*km)]'/
0.006667034
/;

parameter stor_cap_OandG_ONOFF(n,j_lbh,j_OandG_EOR_shore)'storage capacity
   of oil and gas fields divided into ONshore and OFFshore';
parameter stor_capacity_max_ONOFF(n,j_lbh,k_storage)'storage capacity of
   each storage type';
parameter capacity_maximum(k_storage,n)'capacity_maximum available for each
```

```
    tehcnology according to the selected option C';
parameter leakage_factor(t) '% of cumulated stored CO2 leakages';
*--------------------------
$elseif %phase%=='compute_data'
*Calculation of storage capacity total of aquifer dividing into ON and OFF
stor_capacity_max_ONOFF(n,j_lbh,j_aqui_shore)=stor_cap_aqui(n,j_lbh)*stor_
   share_ONOFF(n,j_aqui_shore);
*Calculation of storage capacity total of OandG, EOR included
stor_cap_OandG_ONOFF(n,j_lbh,j_OandG_EOR_shore)=stor_cap_OandG(n,j_lbh)*
   stor_share_ONOFF(n,j_OandG_EOR_shore);
*Calculation of storage capacity total of ECBM which is ON only
stor_capacity_max_ONOFF(n,j_lbh,'ECBM')=stor_cap_ecbm(n,j_lbh);

*Calculation of storage capacity total of EOR dividing into ON and OFF
loop((j_EOR_shore,j_OandG_EOR_shore)$(map_storage_eor(j_EOR_shore,j_OandG_
   EOR_shore)),
stor_capacity_max_ONOFF(n,j_lbh,j_EOR_shore)=stor_cap_eor(n)*stor_share_
   ONOFF(n,j_OandG_EOR_shore)
);
*Calculation of storage capacity total of OandG, EOR excluded
loop((j_OandG_shore,j_OandG_EOR_shore,j_EOR_shore)$(map_storage_OandG(j_
   OandG_shore,j_OandG_EOR_shore,j_EOR_shore)),
stor_capacity_max_ONOFF(n,j_lbh,j_OandG_shore)=max(stor_cap_OandG_ONOFF(n,j
   _lbh,j_OandG_EOR_shore)-stor_capacity_max_ONOFF(n,j_lbh,j_EOR_shore),1e
   -7)
);

capacity_maximum(k_storage,n)=max(stor_capacity_max_ONOFF(n,'best',k_
   storage)*12/44,1e-5);

retro_limk0('elpc_old',n)=k_elpc_retro_platts_old('elpc','3',n)/k_en_valid_
   platts_old('elpc','3',n);
retro_limk0('elpc_vint',n)=k_elpc_retro_platts_vint('elpc','3',n)/max(1e
   -8,(k_en_valid_platts_tot('elpc','3',n)-k_en_valid_platts_old('elpc
   ','3',n)));
retro_limk0(jretro_pl,n)$(retro_limk0(jretro_pl,n) eq 1 and (k_elpc_retro_
   platts_vint('elpc','3',n) eq 1e-8 or k_elpc_retro_platts_vint('elpc
   ','3',n) eq 1e-8))=1e-8;
retro_limk(jretro_pl,t,n)=retro_limk0(jretro_pl,n);

emi_ct('coal') = emi_st('coal');
emi_ct('gas') = emi_st('gas');

delta_en(jretro_un,t,n) = delta_en0(jretro_un,n);
delta_lcost(jretro_un,t,n) = delta_en0(jretro_un,n);
mcost_inv0(jretro_un,n)=mcost_inv0('elpc_ccs',n)-mcost_inv0('elpc_new',n);
oem(jretro_un,t,n)=oem('elpc_ccs',t,n)-oem('elpc_new',t,n);
mu('elretro_old',t,n)=mu('elpc_old',t,n);
mu('elretro_vint',t,n)=mu('elpc_vint',t,n);

*Leakage rate
leakage_factor(t)=1e-8;
*learing rate
b_learn(jlccs,t)=b_learn0(jlccs);
*-------------------------
$elseif %phase%=='vars'

positive variable Q_EN_RETRO(jretro_pl,t,n) 'part of Q_EN of exixting plant
    that is doing retrofitting';
loadvarbnd(Q_EN_RETRO, '(jretro_pl,t,n)',1e-5,1e-8,+inf);
```

```
positive variable MCOST_EMI(e,t,n) 'Average cost of emission-related
    entities [T$/GTonC]';
loadvarbnd(MCOST_EMI,'(e,t,n)',1e-5,1e-8,+inf);

positive variable Q_STORED(k_storage,n,t) 'quantity of co2 that is stored
    for each storage type [GtonC]';
loadvarbnd(Q_STORED, '(k_storage,n,t)',1e-5,1e-8,+inf);

positive variable CUM_Q_STORED(k_storage,t,n) 'cumulative quantity of co2
    that is stored for each storage type [GtonC]';
loadvarbnd(CUM_Q_STORED, '(k_storage,t,n)',1e-5,1e-8,+inf);

CUM_Q_STORED.up(k_storage,t,n)=capacity_maximum(k_storage,n);
CUM_Q_STORED.fx(k_storage,t,n)$(year(t) eq 2005)=CUM_Q_STORED.lo(k_storage,
    t,n);
MCOST_EMI.scale('ccs',t,n) = 1e-3;
CUM_EMI.lo('ccs',t,n) = 1e-8;
Q_EMI.lo('ccs',t,n) = 1e-8;

I_EN.up(jlccs,t,n)$(year(t) le 2010) = I_EN.lo(jlccs,t,n);
I_EN.up('elretro_old',t,n)$(year(t) le 2010) = I_EN.lo('elretro_old',t,n);
I_EN.up('elretro_vint',t,n)$(year(t) le 2010) = I_EN.lo('elretro_vint',t,n)
    ;

*---------------------
$elseif %phase%=='eql'

eqq_emi_ccs_%1
*eqcum_emi_ccs_%1
*eqmcost_emi_ccs_%1
eqcost_emi_sinks_%1
eqcapacity_retro_%1
eqenergy_retro_%1
eqkq_retro_%1
eqq_in_retro_%1
*eq_stor_ccs_cost_%1
eq_stor_ccs_cum_%1
eq_emi_stor_ccs_%1
eq_emi_leak_ccs_%1
*-----------------------
$elseif %phase%=='eqs'

eqq_emi_ccs_%1(t,n)$(mapn_tfix('%1'))..
Q_EMI('ccs',t,n) =e=
sum((f,jfed)$(jccs(jfed) and csi(f,jfed,t,n)),
Q_IN(f,jfed,t,n)* emi_sys(t,n) * emi_ct(f) * ccs_capture_eff(jfed))
+ sum(jretro_pl,
div0(Q_EN_RETRO(jretro_pl,t,n),csi('coal',jretro_pl,t,n)-eff_loss)*emi_sys(
    t,n) * emi_ct('coal') *ccs_capture_eff('elpc_ccs'));

eqcapacity_retro_%1(jretro_un,jretro_pl,t,n)$(mapn_tfix('%1') and map_retro
    (jretro_pl,jretro_un))..
K_EN(jretro_un,t,n) =l= retro_limk(jretro_pl,t,n)*K_EN(jretro_pl,t,n)
    +10**(-5);

eqkq_retro_%1(jretro_pl,jretro_un,jreal,t,n)$(mapn_tfix('%1') and sameas(
    jreal,jretro_un) and map_retro(jretro_pl,jretro_un))..
Q_EN_RETRO(jretro_pl,t,n) =l= mu(jretro_un,t,n) * K_EN(jreal,t,n);

eqenergy_retro_%1(jretro_pl,t,n)$(mapn_tfix('%1'))..
Q_EN_RETRO(jretro_pl,t,n) =l= Q_EN(jretro_pl,t,n);
```

```
eqq_in_retro_%1(jretro_pl,t,n)$(mapn_tfix('%1') and (sum(f$csi(f,jretro_pl,
    t,n),1)))..
Q_IN('coal',jretro_pl,t,n) =e= div0(Q_EN(jretro_pl,t,n),csi('coal',jretro_
    pl,t,n))+
div0(Q_EN_RETRO(jretro_pl,t,n)*eff_loss,csi('coal',jretro_pl,t,n)*(csi('
    coal',jretro_pl,t,n)-eff_loss));

*eqcum_emi_ccs_%1(t,n)$(mapn_tfix('%1'))..
*                CUM_EMI('ccs',t,n) =e= sum(tt$(tperiod(tt) le tperiod(t)),
     tstep * sum(sink,Q_EMI(sink,tt,n)));

* Keep the explicit whole equation in order to help the solver
eqcost_emi_sinks_%1(t,n)$(mapn_tfix('%1'))..
COST_EMI('ccs',t,n) =e=
sum(k_storage, (transp_coeff2*Q_STORED(k_storage,n,t)*(44/12)*1e-3*average_
    distance2(n,k_storage)+
Q_STORED(k_storage,n,t)*(cost_storage(k_storage)*44/12)))
;
eq_stor_ccs_cum_%1(k_storage,t,tm1,n)$(mapn_tfix('%1') and tnofirst(t) and
    pre(tm1,t) )..
CUM_Q_STORED(k_storage,t,n) =e= CUM_Q_STORED(k_storage,tm1,n)*(1-leakage_
    factor(tm1))+
tstep * Q_STORED(k_storage,n,t);

eq_emi_stor_ccs_%1(t,n)$(mapn_tfix('%1'))..
Q_EMI('ccs',t,n)=e=sum(k_storage, Q_STORED(k_storage,n,t));

eq_emi_leak_ccs_%1(t,n)$(mapn_tfix('%1'))..
Q_EMI('co2leak',t,n)=e=leakage_factor(t)*sum(k_storage,CUM_Q_STORED(k_
    storage,t,n));
*---------------------
$elseif %phase%=='fix_variables'

tfixvar(MCOST_EMI,'(e,t,n)')
tfixvar(Q_EN_RETRO,'(jretro_pl,t,n)')
tfixvar(Q_STORED,'(k_storage,n,t)')
tfixvar(CUM_Q_STORED,'(k_storage,t,n)')

*--------------------

$elseif %phase%=='before_nashloop'


wcum(jlccs,tfirst) = sum(n,K_EN.l(jlccs,tfirst,n));

*--------------------

$elseif %phase%=='before_solve'

*CUM_Q_STORED.fx(k_storage,t,n)=CUM_Q_STORED.l(k_storage,t,n)*(1-leakage_
    factor(t));
*CUM_EMI.fx('ccs',t,n)=CUM_EMI.l('ccs',t,n)*(1-leakage_factor(t));

MCOST_EMI.fx('ccs',t,n)=COST_EMI.l('ccs',t,n)/Q_EMI.l('ccs',t,n);

Q_EN.fx(jretro_un,t,n)$(not t_fix(t)) = 0;

loop((tnofirst(t),tm1)$pre(tm1,t),
wcum(jlccs,t) = wcum(jlccs,tm1) + tstep*sum(n, I_EN.l(jlccs,tm1,n)/MCOST_
    INV.l(jlccs,tm1,n));
```

```
);


wcum_ccs_spillover(jlccs,t)=sum(jllccs, ccs_spill_factor(jlccs,jllccs)*(
    wcum(jllccs,t)));


MCOST_INV.fx(jlccs,t,n)$(wcum_ccs_spillover(jlccs,t) gt wcum_start(jlccs))
    = max(floor_costs_ccs(jlccs,n), mcost_inv0(jlccs,n)*(wcum_ccs_spillover
    (jlccs,t)/wcum_start(jlccs))**(-b_learn(jlccs,t)));

*-------------------
$elseif %phase%=='summary_report'
loop((f,j)$map_fuel_j(f,j),
co2_emissionj(j,t,n)= emi_sys(t,n) * emi_ct(f) * (1-ccs_capture_eff(j))
    *1000*44/12
);

loop((f,j)$map_fuel_j(f,j),
co2_capturej(j,t,n)= emi_sys(t,n) * emi_ct(f) * ccs_capture_eff(j)
    *1000*44/12
);

ccc_ccs('elpc_ccs',t,n)$(lcost_jel('elpc_ccs','level_cost',t,n) lt 1)=div
    0((lcost_jel('elpc_ccs','level_cost',t,n)-lcost_jel('elpc_new','level_
    cost',t,n))*1e6,
co2_capturej('elpc_ccs',t,n));
ccc_ccs('elpc_oxy',t,n)$(lcost_jel('elpc_oxy','level_cost',t,n) lt 1)=div
    0((lcost_jel('elpc_oxy','level_cost',t,n)-lcost_jel('elpc_new','level_
    cost',t,n))*1e6,
co2_capturej('elpc_oxy',t,n));
ccc_ccs('elcigcc',t,n)$(lcost_jel('elcigcc','level_cost',t,n) lt 1)=div0((
    lcost_jel('elcigcc','level_cost',t,n)-lcost_jel('elpc_new','level_cost
    ',t,n))*1e6,
co2_capturej('elcigcc',t,n));
ccc_ccs('elgasccs',t,n)$(lcost_jel('elgasccs','level_cost',t,n) lt 1)=div
    0((lcost_jel('elgasccs','level_cost',t,n)-lcost_jel('elgastr_new','
    level_cost',t,n))*1e6,
co2_capturej('elgasccs',t,n));
ccc_ccs('elbigcc',t,n)$(lcost_jel('elbigcc','level_cost',t,n) lt 1)=div0((
    lcost_jel('elbigcc','level_cost',t,n)-lcost_jel('elpb_new','level_cost
    ',t,n))*1e6,
co2_capturej('elbigcc',t,n));

cca_ccs('elpc_ccs',t,n)$(lcost_jel('elpc_ccs','level_cost',t,n) lt 1) =div
    0((lcost_jel('elpc_ccs','level_cost',t,n)-lcost_jel('elpc_new','level_
    cost',t,n))*1e6,
co2_emissionj('elpc_new',t,n)-co2_emissionj('elpc_ccs',t,n));
cca_ccs('elpc_oxy',t,n)$(lcost_jel('elpc_oxy','level_cost',t,n) lt 1)=div
    0((lcost_jel('elpc_oxy','level_cost',t,n)-lcost_jel('elpc_new','level_
    cost',t,n))*1e6,
co2_emissionj('elpc_new',t,n)-co2_emissionj('elpc_oxy',t,n));
cca_ccs('elcigcc',t,n)$(lcost_jel('elcigcc','level_cost',t,n) lt 1)=div0((
    lcost_jel('elcigcc','level_cost',t,n)-lcost_jel('elpc_new','level_cost
    ',t,n))*1e6,
co2_emissionj('elpc_new',t,n)-co2_emissionj('elcigcc',t,n));
cca_ccs('elgasccs',t,n)$(lcost_jel('elgasccs','level_cost',t,n) lt 1)=div
    0((lcost_jel('elgasccs','level_cost',t,n)-lcost_jel('elgastr_new','
    level_cost',t,n))*1e6,
co2_emissionj('elgastr_new',t,n)-co2_emissionj('elgasccs',t,n));
cca_ccs('elbigcc',t,n)$(lcost_jel('elbigcc','level_cost',t,n) lt 1)=div0((
```

```
    lcost_jel('elbigcc','level_cost',t,n)-lcost_jel('elpb_new','level_cost
    ',t,n))*1e6,
co2_emissionj('elpb_new',t,n)-co2_emissionj('elbigcc',t,n));
*----------------
$elseif %phase%=='gdxitems'

* Sets
jccs

* Parameters
co2_emissionj
co2_capturej
ccc_ccs
cca_ccs
ccs_capture_eff
ccs_quantity
emi_ct
retro_limk
stor_capacity_max_ONOFF
stor_cap_OandG_ONOFF
capacity_maximum
average_distance2
cost_storage
leakage_factor

wcum_start
wcum_ccs_spillover
b_learn

* Variables
MCOST_EMI
Q_EN_RETRO
CUM_Q_STORED
Q_STORED
$endif
```

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CCA	Cost of CO_2 Avoided	[$/t$CO_2$]
CCC	Cost of CO_2 Captured	[$/t$CO_2$]
CF	Capacity Factor	
CRR	Carbon Capture Rate Ratio	
$\Delta\eta_r$	Efficiency penalty due to retrofitting	
$E_{CO_2,capt}$	Absolute CO_2 captured emissions	[tCO_2/yr]
FCF	Fixed Charge Factor	
FC	Fuel Cost	[$/MWh$_{\mathrm{th}}$]
HR	Heat Ratio	[MJ$_{\mathrm{th}}$/MWh$_{\mathrm{el}}$]
I_{cost}	Plant Investment Cost	[$/W]
K_{EN}	Installed power plant capacity	[TW/yr]
$LCOE_{capt}$	LCOE considering the power plant and the CO_2 capture costs	[$/MWh$_{\mathrm{el}}$]
$LCOE_{CO_2}$	LCOE that includes costs of emitting CO_2 with carbon tax	[$/MWh$_{\mathrm{el}}$]
$LCOE_{capt,st}$	LCOE that includes capture, transport and storage costs	[$/MWh$_{\mathrm{el}}$]
$LCOE$	Levelized Cost of Electricity	[$/MWh$_{\mathrm{el}}$]
Q_{EN}	Electric Energy Production	[TWh$_{\mathrm{el}}$/yr]
Q_{IN}	Thermal energy input to a power plant	[TWh$_{\mathrm{th}}$/yr]
$SPECCA$	Specific Primary Energy Consumption for CO_2 Avoided	[MJ$_{\mathrm{th}}$/kgCO_2]
$c_{t\&s}$	Specific cost of CO_2 transport and storage	[$/yr]
e_{CO_2}	Specific CO_2 emission per MW$_{el}$ produced	[tCO_2/MWh$_{\mathrm{el}}$]
ese	Energy system expenditure	[T$/yr]
η_{el}	Net electric efficiency of power plants	
lk_{retro}	Share of coal plants suitable for retrofitting	
$O\&M$	Operation and Maintenance Costs	[$/MWh]
$LR(j)$	Learning rate	
$PR(j)$	Progress ratio	
$b(j)$	Learning curve parameter	
$floor_{cost}$	Floor cost of CCS technologies in learning formulation	[$/W]
$spill_{rate}$	Learning spillover parameter between technologies	
$wcum$	Global cumulative installed power capacity	[TW]
$CUM_{EMI,st}$	Cumulative CO_2 stored	[GtCO_2]
$C_{t\&s}$	Absolute cost of CO_2 transport and storage	[$/yr]
$Q_{EMI,leak}$	Quantity of CO_2 leaked	[GtCO_2/yr]
$Q_{EMI,st}$	Quantity of CO_2 stored	[GtCO_2/yr]

c_{st}	Specific storage cost on stored quantity	[$/t$CO_2$]
cap_{max}	Maximum regional storage capacity	[GtCO_2]
c'_{tr}	Specific transport cost on distance and quantity	[$/t$CO_2$km]
l_{tr}	Average distance from plant to storage site	[km]
λ_{lk}	Leakage factor, % of emission leaked per year	[%/yr]
$tstep$	Time step interval adopted in our model, five years	[yr]
a_{lk}	First coefficient of the quadratic leakage function	
b_{lk}	Second coefficient of the quadratic leakage function	
c_{lk}	Third coefficient of the quadratic leakage function	

Acronyms

CO_2 Carbon Dioxide

N_2O Nitrous Oxide

CH_4 Carbon Dioxide

SO_2 Sulfur Dioxide

NO_x Nitrogen Oxides

IEA International Energy Agengy

RF Radiative Forcing

INDC Intended Nationally Determined Contributions

LHV Lower heating value

HHV Higher heating value

WITCH World Induced Technical Change Hybrid

CCS Carbon Capture and Storage

IGCC Integrated Gasification combined cycle

C-IGCC Coal-fired Integrated Gasification Combined Cycle with CCS

NG-CCS Natural Gas Combined Cycle with CCS

C-post Pulverized coal plant with post combustion with CCS

Bio CCS Biomass-fired plant with CCS

C-OXY Oxyfuel coal plant with CCS

C-retro Coal-fired power plant retrofitted with a CCS unit

CES Constant Elasticity of Substitution

MDEA Methyl diethanolamine

IAM Integrated Assessment Model

GLOBIOM Global Biosphere Management Model

MAGICC Model for the Assessment of Greenhouse-gas Induced Climate Change

GHG Greenhouse Gases

ASU Air Separation Unit

IPCC Intergovernmental Panel on Climate Change

NG Natural Gas

HRSG Heat Recovery Steam Generator

FEEM Fondazione Eni Enrico Mattei

CMCC Centro Euro-Mediterraneo sui Cambiamenti Climatici

LNG Liquified Natural Gas

GTCC Gas Turbine Combined Cycle

FGD Flue Gas Desulfurization

SCR Selective Catalyst Reduction

PC Pulverized Coal

MEA Monoethanolamine

BECCS Bio-Energy with Carbon Capture and Storage

CDR Carbon Dioxide Removal

NET Negative emission technology

CHP Combined Heat and Power

EOR Enhanced Oil Recovery

SSPs Shared Socio-economic Pathways

GAMS General Algebraic Modeling System

SDGs Sustainable Development Goals

ECBM Enhanced Coal Bed Methane

WEPP World Electric Power Plants Data Base

GDP Gross Domestic Product

RES Renewable Energy Sources

RCPs Representative Concentration Pathways

EOR Enhanced Oil Recovery

O&G Oil and Gas

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