International Journal of Greenhouse Gas Control 27 (2014) 81–102

Contents lists available at ScienceDirect

International Journal of Greenhouse Gas Control

journal homepage: www.elsevier.com/locate/ijggc

Uncertainty in the deployment of Carbon Capture and Storage (CCS): A sensitivity analysis to techno-economic parameter uncertainty

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ARTICLE INFO

Article history:
Received 8 August 2013
Received in revised form 16 March 2014
Accepted 16 April 2014
Available online 24 June 2014

Keywords:
CCS deployment uncertainty
Sensitivity analysis
CO_2 storage and transport cost
CO_2 capture cost
CO_2 storage capacity
Power plant performance

ABSTRACT

Projections of the deployment of Carbon Capture and Storage (CCS) technologies vary considerably. Cumulative emission reductions by CCS until 2100 vary in the majority of projections of the IPCC-TAR scenarios from 220 to 2200 $GtCO_2$. This variation is a result of uncertainty in key determinants of the baselines of different models, such as, technological development (IPCC Special Report on Carbon Dioxide Capture and Storage. Prepared by Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York). Technological key parameters of CCS deployment are power plant efficiency and investment cost, capture cost, transport cost and storage capacity. This study provides insights in how uncertain the key parameters are and how this influences CCS deployment projections. For each parameter, ranges are determined on the basis of the existing literature. CCS deployment is systematically assessed for all of these parameter ranges in a global energy system model (TIMER). The results show that investment cost uncertainty causes the largest range in cumulative CO_2 captured from global electricity production (13–176 $GtCO_2$ in 2050) in a scenario with a medium fossil fuel price level. The smallest, but still significant range of 65–91 $GtCO_2$ cumulatively captured until 2050, is caused by the uncertainty in the efficiency of the power plant and capture unit.

1. Introduction

Carbon Capture and Storage (CCS) plays an important role in model-based climate policy scenarios targeting low greenhouse gas concentrations (Koelbl et al., 2014; Kriegler et al., 2014; van Vuuren et al., 2007). Interestingly, however the projected contribution of (CCS) varies widely. The Special Report of the IPCC (2005) states, for instance, that the cumulative CO_2 storage until 2100 for most[1] of the TAR-scenarios[2] ranged from 220 to 2200 $GtCO_2$ (for different mitigation targets and baselines). Recently, Koelbl et al. (2014) found a comparable range for a set of mitigation scenarios aiming at 450 and 550 ppmv CO_2-eq developed by 12 different models participating in the Energy Modeling Forum 27 (EMF27) study. Considerable differences in storage projections can also be found on the regional level. Odenberger et al. (2008), for instance, project that up to 39 Gt of CO_2 can possibly be stored in the EU under ambitious policy scenarios. The IEA (2012) projects under a similar target (2-degree) for the same period only about 10 Gt. Tzimas and Georgakaki (2010) find a similar range (7–12 Gt) as the IEA (2012) using a CO_2 price increase from 50 €/t in 2020 to 80 €/t in 2050 under different fossil fuel price and policy scenarios.

Technological development of CCS and other options is emphasized as an important determinant of CCS deployment projections (IPCC, 2005). The technological development is uncertain as reflected by the wide ranges of parameter values found in the literature for future power plant performance, investment, storage and transport costs, and storage capacity (Bradshaw et al., 2007; IEA, 2010a; IPCC, 2005). Costs and capacity estimates are according to Herzog (2011) "[t]he two areas of biggest concern" (Herzog, 2011:p. 603) for large-scale CCS development. The impacts of these techno-economic parameters, therefore, are expected to be important for the modeling results with respect to CCS deployment.

Few studies have looked systematically at the influence of such techno-economic parameters on the role of CCS. A number of studies looked at the influence of different policies and carbon prices on the role of CCS (e.g. Bennaceur and Gielen, 2010; van den Broek et al., 2011; Vrijmoed et al., 2009) and a wider set of technological parameters such as Bistline and Rai (2010), BMU (2008), Bauer

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[1] The total range varies from no storage to over 5500 $GtCO_2$ (IPCC, 2005).
[2] An overview can be found in Morita et al. (2000) as cited in (IPCC, 2005).

http://dx.doi.org/10.1016/j.ijggc.2014.04.024
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(2006), Akimoto et al. (2004) and Kurosawa (2004). However, these studies have some limitations. Some focus on sensitivity rather than uncertainty as reflected in the literature (Akimoto et al., 2004; Kurosawa, 2004). Bauer (2006) and BMU (2008), mostly look at different parameters than the cost and power plant performance or storage capacity. The only partial overlap is the analysis of the impact of the energy penalty (BMU, 2008) and the available storage capacity (Bauer, 2006). The latter study, however, only differentiates between two reservoirs and concentrates on the impact on the distribution of CO_2 between the two options. Finally, Bistline and Rai (2010) also find a large range of CCS-mitigation potential projections in the literature and consequently investigate the impact of uncertainty in parameters like the heat rate of CCS plants on the potential of CCS to contribute to CO_2-emission reduction in the United States. However, they make exogenous assumptions about the level of CCS deployment.

Insights into the impacts of techno-economic parameters on the CCS deployment would support policy makers when deciding on the focus of R&D investments along the CCS chain to reduce uncertainty and costs where impacts are most severe. This is important as adding CCS to the technology portfolio is associated with economic benefits of lower mitigation (e.g. IPCC, 2005) or electricity generation cost[3] (e.g. IEA, 2010b), which consequentially are also uncertain as long as the deployment of CCS is uncertain. It is especially interesting to investigate uncertainty in CCS technologies as CCS, unlike other mitigation options, is hardly deployed on a large scale (GCCSI, 2013; IEA, 2012).[4] Therefore, in this study, we aim to investigate effects of the uncertainty in the above-mentioned techno-economic parameters on CCS deployment at a global level. We further shed light into the effect on the technology choice in these scenarios, the direct and indirect effects on the CO_2 captured from industry, and the impact on the emission level. At the same time, we also aim to look into the regional differences in the response to parameter uncertainty. To assess the impacts in a consistent way, we use the TIMER global energy system model (de Vries et al., 2001; van Vuuren et al., 2006) that constitutes a part of the IMAGE model (Bouwman et al., 2006). This is a bottom-up model with a detailed representation of the global energy system for 26 regions. Using this model we evaluate the influence of uncertainty in techno-economic parameters on the cumulative CO_2 captured and the share of CCS in the electricity production capacity of 2050.

The paper is structured as follows: In Section 2 we will describe the methodology, the TIMER model, the data and assumptions used, the baseline scenario, and the parameter analysis. Results are presented in Section 3 and discussed in Section 4, while conclusions are drawn in Section 5.

2. Methodology

The analysis consists of the following steps:

- First, we assess the uncertainty for selected techno-economic parameters on the basis of a literature review.
- Second, we evaluate the impact of the uncertainties for different parameters using the TIMER model.
- Finally, we draw conclusions on the basis of the results of these experiments.

2.1. CCS in the TIMER model

A brief overview of relevant parts of the TIMER model is presented in Appendix and a full description can be found in de Vries et al. (2001), van Vuuren et al. (2006) and van Vuuren (2007). The standard/original parameterization and many equations for modeling the CCS chain are based on Hendriks et al. (2002) and Hendriks et al. (2004a,b). For this study, we change the value of the investigated CCS parameters and adjust the equations for the cost and efficiency calculations of CCS power plants.

As shown in Fig. 1 in TIMER CO_2 capture can be applied in the electricity and hydrogen production as well as to steel and cement production in the industry (see also van Vuuren, 2007). The electric power module of TIMER includes 24 technologies: in addition to PV, wind, hydro and nuclear power, 20 thermal electricity plant types are modeled for electricity production. The latter consists of combinations of fuels, with conventional or combined-cycle technology, combined-heat and power technology (CHP) and CCS. In total, eight plant types are equipped with CCS (coal, oil, natural gas and bio-energy fueled plants with and without CHP).[5] Investment costs and efficiency of the thermal power plants and CCS are exogenous inputs in contrast to renewable energy technologies for which endogenous learning is applied (van Vuuren et al., 2006). In the model, competition between the different technologies takes place, both, in the investment stage, and in the operation stage. In principle, these decisions are based on the relative generation costs using multi-nomial logit equations. While full generation costs are used in the investment stage, capital costs are not accounted for in the operation stage. In each decision, factors such as fuel preferences (as a result of environmental policies), indirect costs due to limited capacity credit and base load versus peak load suitability are also weighted (see de Vries et al. (2001), van Vuuren et al., 2006 and Appendix for a more description).

CO_2 storage can take place in eleven different storage reservoir types: on- and offshore natural gas and oil reservoirs, which can all be empty or full,[6] on- and offshore aquifers, and onshore Enhanced Coal Bed Methane (ECBM). The storage capacity of these reservoir types differs per region. In the TIMER model, in each region the reservoir type with the least overall cost is deployed first (van Vuuren, 2007). These are composed of storage as well as transport cost. Storage costs depend on the reservoir type, while transport takes place via pipelines and the costs depend on the average distance to each reservoir type in each region. For this purpose five distance categories are used (i.e. <50 km, 50–200 km, 200–500 km, 500–2000 km and >2000 km). Each reservoir type in each region has been assigned to one of these categories based on Hendriks et al. (2004a) who estimate the average proximity of each reservoir type in each region to large CO_2 sources. The overall costs for storing CO_2 is thus different per region and reservoir type.

2.2. Data and assumptions

For all these key input parameters that determine the use of CCS in the model we have performed a literature survey. For each variable, we identified low, medium[7] and high estimates. Also, all data needed to be projected into the future. The parameters we look at are: power plant cost and capture unit costs, power plant and

[3] Under the same carbon price, the average global electricity generation cost in 2050 increase by 19% compared to the baseline, if CCS is part of the portfolio and by 38%, if CCS is excluded (IEA, 2010b).

[4] GCCSI (2013) identified eight large-scale CCS plants (including transport and storage) globally in operation by January 2013.

[5] *Note*: TIMER does not include pulverized coal with CCS (see discussion on the implications for the results in Section 4.1).

[6] In case of oil, full reservoirs are used only for Enhanced Oil Recovery (EOR). However, only the fraction of the reservoir filled with CO_2 for recovering additional oil is assumed to become available as storage capacity.

[7] This refers to the arithmetic mean value of the variable.

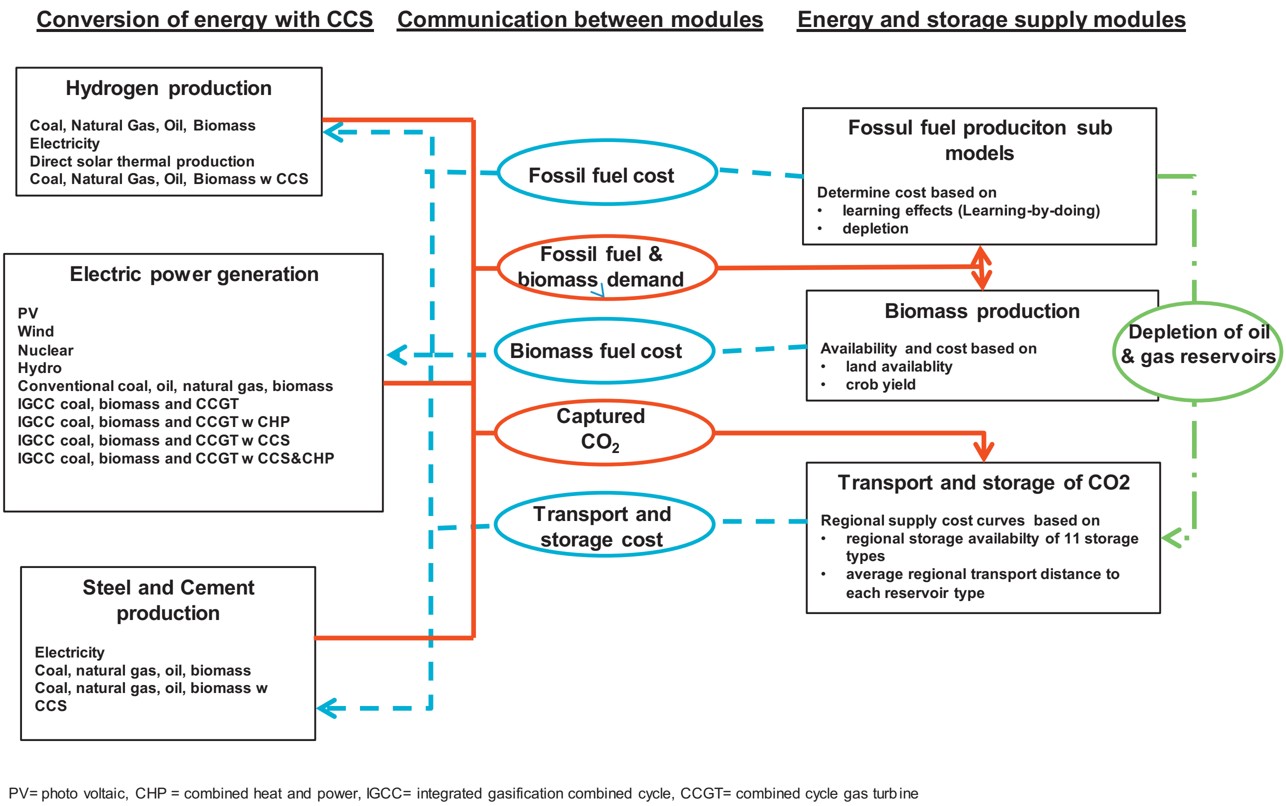

Fig. 1. Scheme of model parts of TIMER relevant to CCS applications and their interdependency.

capture unit efficiency, transport cost,[8] storage cost, and storage capacity (see Section 2.2). All costs from the literature were converted to USD_{2005} (fxtop.com, 2011) and the IHS CERA Power Plant Capital Costs Index (PCCI) of North America and the IHS CERA European Power Capital Costs Index (EPCCI) for power plant cost[9] and the IHS CERA Upstream Capital Costs Index (UCCI) for transport and storage cost (IHS, 2011).

2.2.1. Power plant investment cost and efficiency

The sources we used for power plant investment costs and efficiency, along with the original values and explanations of assumptions and adjustments can be found in the supplementary material. Some sources only provide cost and efficiency data for a certain year. To project a cost range over time, we calculate the annually compounded rate of change (CAGR) of the power plant investment cost and efficiency and capture unit investment costs and efficiency loss from sources that make explicit projections into the future for the period from 2000 to 2020 and 2020 to 2050 (sources in Tables 1a and 1b). For each of these two periods, the most pessimistic and optimistic CAGRs were selected, respectively, as shown for investment cost in Table 1a and for efficiency (loss) in Table 1b. The optimistic and pessimistic change rates where then used to calculate cost and efficiency (loss) values for 2020 and 2050 based on each value found in the literature for a given year. Out of the resulting range, we select the lowest and highest value of power plant and capture unit investment costs for the two points in time, which then respectively constitute the upper and lower cost development between 2020 and 2050. Similarly, the highest power plant efficiency and lowest capture efficiency loss give the upper range and the lowest power plant efficiency and highest capture efficiency loss make the lower range of efficiency values for

Table 1a
Pessimistic and optimistic CAGR for IGCC, CCGT and respective investment costs of capture unit.

Optimistic	IGCC (%)	Capture unit (%)	CCGT (%)	Capture unit (%)
2000–2020	−2.2	−1.5	−1.5	−2.2
2020–2050	−1.2	−2.3	−0.7	−2.4
Pessimistic				
2000–2020	−1.6	−0.8	−0.9	−0.4
2020–2050	−0.2	−0.3	−0.3	−0.5

Calculated from data found in van den Broek et al. (2009)[1], Riahi et al. (2012)[2] and Hendriks et al. (2004b).
Note: for BIGCC, the CAGR calculated for the coal IGCC are used.
[1]van den Broek et al. (2009) give estimates for 2001, which are assumed to be the same as in 2000.
[2]Only in case of investment cost for the year 2020–2050.

Table 1b
Pessimistic and optimistic CAGR for IGCC, CCGT pant efficiency and respective efficiency loss of capture unit.

Optimistic	IGCC efficiency (%)	Capture unit efficiency loss (%)	CCGT efficiency (%)	Capture unit efficiency loss (%)
2000–2020	0.99	−1.08	0.62	−0.76
2020–2050	0.29	−1.57	0.22	−0.94
Pessimistic				
2000–2020	0.59	−0.96	0.35	−0.70
2020–2050	0.21	0.00	0.10	−0.51

Calculated from data found in van den Broek et al. (2009), and Hendriks et al. (2004b).
Note: for BIGCC, the CAGR calculated for the coal IGCC are used.

[8] The range of transport cost has been generated using different models and has been compared to a range in the literature (see Section 2.2.2, and supplementary material).
[9] For both PCCI and EPCCI we used the indices excluding nuclear power. Because the indices were given in quarterly periods, and some periods were missing, we use the averages of the given periods.

Table 2
Ranges of investment costs for power plants and capture unit.

	USD_{2005} (kWe)	2020		2030		2040		2050	
		w/o CCS	Capture	w/o CCS	Capture	w/o CCS	Capture	w/o CCS	Capture
IGCC Coal	Min	749	219	666	140	593	111	527	88
	Max	2839	1212	2794	1177	2749	1142	2705	1109
IGCC Biomass	Min	1161	548	1032	435	918	345	817	273
	Max	3251	902	3199	875	3148	850	3098	825
CCGT	Min	436	266	404	208	378	163	354	128
	Max	949	1013	920	961	892	913	865	867

Values are rounded. The ranges are derived from the following sources: Damen et al. (2006), GCCSI (2011), Hendriks et al. (2004b), IEA (2010a), Klein et al. (2011), Larson et al. (2005), Mondol et al. (2009), Rhodes and Keith (2005), Riahi et al. (2012), van den Broek et al. (2009), van den Broek et al. (2011) and ZEP (2011a). The TIMER model adds to the capital costs the so-called interest-during-construction (IDC) assuming three years construction period (for thermal plants) and 5% interest rate, while the whole investment is undertaken in the first year. Therefore, the IDC costs had to be excluded from literature estimates on capital costs that implicitly or explicitly included IDC estimates (based on the description in the assumptions of these estimates). For those studies that suggested that IDC was included, we assumed that 4% (NGCC) and 9% (IGCC) of the total costs are IDC. This was based on the same assumptions as in van den Broek et al. (2008) using a discount rate of 10% (as generally used in TIMER (de Vries et al., 2001)). The input data was then converted accordingly to power plant costs excluding IDC, as this factor is added within the TIMER model. For further assumptions, original data, and specific values and corresponding sources see supplementary material.

Table 3
Ranges of power plant efficiency and capture unit efficiency loss (LHV).

		2020		2030		2040		2050	
		w/o CCS (%)	Capture (p.p.)	w/o CCS (%)	Capture (p.p.)	w/o CCS (%)	Capture (p.p.)	w/o CCS (%)	Capture (p.p.)
IGCC Coal	Min	38	4	39	4	40	3	40	3
	Max	52	11	53	11	56	10	58	9
IGCC Biomass	Min	32	5	33	4	34	3	35	3
	Max	50	11	51	9	53	8	54	7
CCGT	Min	48	6	49	5	49	5	50	5
	Max	64	11	65	10	66	10	67	9

p.p., percentage points of capture efficiency loss.
The ranges are derived from the following sources: Damen et al. (2006), GCCSI (2011), Hendriks et al. (2004b), IEA (2010a), Klein et al. (2011), Larson et al. (2005), Mondol et al. (2009), Rhodes and Keith (2005), van den Broek et al. (2009), van den Broek et al. (2011) and ZEP (2011a). For assumptions, original data, and specific sources, see supplementary material.
The range of efficiency and capture unit efficiency loss of coal and natural gas combined cycle plants have been verified by comparing the range to estimates of more recent publications by Knoope et al. (2013a), Meerman et al. (2013) and Rubin et al. (2012). This range covers all values.

Table 4
Ranges of CO_2 transport costs per distance category.

Distance in km	<50	50–200	200–500	500–2000	2000–∞
Min USD_{2005}/t CO_2	0.05	0.11	0.68	1.6	6
Max USD_{2005}/t CO_2	3.2	18	49	200	216
Min USD_{2005}/t CO_2/km	0.002	0.001	0.002	0.001	0.002
Max USD_{2005}/t CO_2/km	0.130	0.144	0.139	0.160	0.072

Costs per km are calculated based on the average distance of each distance category. Source: model runs by Knoope et al. (2013b). Models used: Chandel et al. (2010), Dahowski et al. (2004), Dahowski et al. (2009), ElementEnergy (2010), Gao et al. (2011), IEAGHG (2002), McCollum and Ogden (2006), McCoy and Rubin (2008), Ogden et al. (2005), Parker (2004), Piessens et al. (2008), Serpa et al. (2011) and van den Broek (2010). For comparison data from the literature and assumptions to generate this range, see supplementary material.

the experiment. The resulting ranges of cost and efficiency data are shown in Tables 2 and 3.

2.2.2. Transport cost

The data ranges of the transport cost per distance category (Table 4) were generated by running ten different diameter models and fourteen different cost models that are summarized in Knoope et al. (2013b). (See supplementary material for the input assumptions to generate these ranges).[10] The distance category of each reservoir type in each region was based on Hendriks et al. (2004a). An exception had to be made for aquifers, as information was only available for onshore aquifers. Therefore, we assumed that the offshore transport costs are three times as high as the transportation to the respective onshore option. This is in line with the data provided by Hendriks et al. (2004a). Finally, the data generated with this method, was compared to the data collected from the literature (see supplementary material for data and sources)[11] showing that they are larger than the ranges normally found in the literature.[12]

2.2.3. Storage cost

Table 5 and Fig. 3 show the data ranges for storage costs derived from the literature (for original data by source and assumptions see

[10] Data to make assumptions about some input parameter to these models was taken from Chandel et al. (2010), ElementEnergy (2010), IEAGHG (2002), McCollum and Ogden (2006), Wildenborg et al. (2004), Morbee et al. (2012), McCoy and Rubin (2008).

[11] Sources that used to compile a range for comparison to literature: ZEP (2011c), McCoy and Rubin (2008), GCCSI (2011), Koukouzas et al. (2011), GESTCO (2004), Chandel et al. (2010), McCollum and Ogden (2006), Hendriks et al. (2004a).

[12] No data could be found for the distance category of 2000 km and above. Therefore, we assume that the costs in this category are about three times as high as the cost in the previous category.

Table 5
CO_2 storage cost ranges per storage type.

USD_{2005}/tCO_2 stored	EOR, onshore	EOR, offshore	Rem. gas, onshore	Rem. gas, offshore	Depl. oil, onshore	Depl. oil, offshore	Depl. gas, onshore	Depl. gas, offshore	ECBM	Aquifer, onshore	Aquifer, offshore
Min	−106	−106	0.8	1.6	0.8	1.6	0.8	1.6	−30.3	0.4	0.8
Max	53	104	14	29	14	29	14	29	174	10	35

The ranges are derived from the sources GCCSI (2011), IPCC (2005), Koukouzas et al. (2011), McCoy and Rubin (2009) and ZEP (2011b).
EOR, Enhanced Oil Recovery; Rem., remaining; Depl., depleted; ECBM, Enhanced Coal Bed Methane. For assumptions, original data, and specific sources, see supplementary material.

Table 6
Global storage capacity ranges per storage type.

$GtCO_2$	EOR, onshore	EOR, offshore	Rem. gas, onshore	Rem. gas, offshore	Depl. oil, onshore	Depl. oil, offshore	Depl. gas, onshore	Depl. gas, offshore	ECBM	Aquifer, onshore	Aquifer, offshore
Low	110	30	168	126	33	60	95	11	171	2786	1054
Default	147	45	284	254	44	107	121	13	260	6912	2630

The ranges are derived from the sources Dahowski et al. (2009), Hendriks et al. (2004a), IEAGHG (2009a,b), IEAGHG (2011). Regional distribution based on Hendriks et al. (2004a); distribution between on- and offshore aquifers is based on Dooley et al. (2003).
EOR, Enhanced Oil Recovery; Rem., remaining; Depl., depleted; ECBM, Enhanced Coal Bed Methane. For assumptions, original data, and specific sources, see supplementary material.

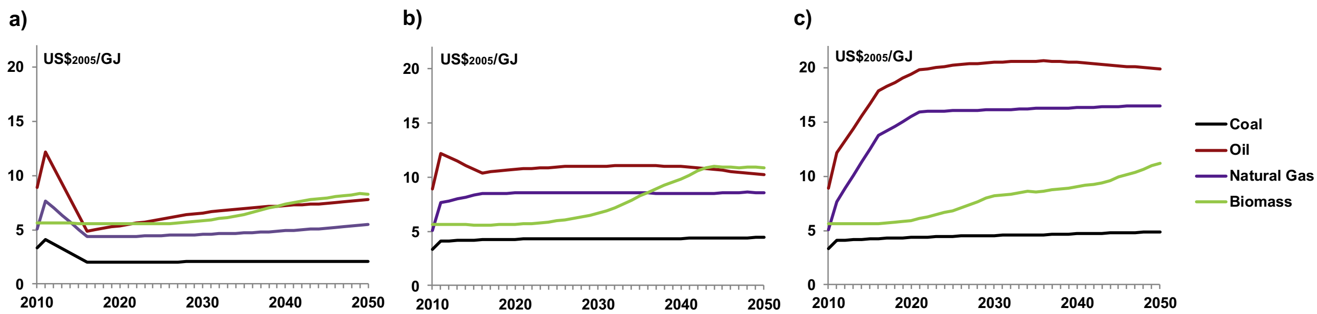

Fig. 2. Fossil and biomass fuel prices for electricity production for low, medium and high fossil fuel price development (Note: biomass prices are determined endogenously and are not amended exogenously to follow a high, medium or low price path) sources: see description.

supplementary material). Cost for EOR and ECBM reservoirs can be negative as there is a potential benefit from oil and gas extraction. These cost show large ranges as they strongly dependent on the natural gas and oil price as well as on the amount of CO_2 needed for the recovery of the fuel (Bock et al., 2003). The impact of oil and gas prices on these storage costs is treated exogenously in the sensitivity analysis as their impact is contained in the range of storage costs, which we use to determine the sensitivity of CCS deployment. Therefore, storage costs are not linked to the endogenously determined oil and gas prices.

2.2.4. Storage capacity

Table 6 presents the ranges of the storage capacity per reservoir type which were found in the literature (see supplementary material for original data by source and assumptions). The ranges roughly coincide with, and are partly based on, ranges in IEAGHG (2011).

Note that the source underlying the TIMER model for storage of CO_2 (Hendriks et al., 2004a) assumes that *all* oil fields that have not been exploited, yet, can be exploited by injecting CO_2 using Enhanced Oil Recovery. Besides the CO_2 that is injected for this purpose, it is assumed that no further storage space is used. The CO_2 storage space from EOR operations is estimated by (IEAGHG, 2009b) based on technical criterions likely to make EOR feasible and the amount of oil that can be recovered with EOR from reservoirs that fulfill these criterions. The capacity for CO_2 storage applies to the amount of CO_2 needed to recover additional oil and is eventually retained in the reservoir. The estimates for depleted oil fields stem from Hendriks et al. (2004a,b), which only apply to oil fields that were depleted at the time of the study. Hence, this limits the amount of future storage potential in oil reservoirs to the space that is used for EOR activity.

The availability of oil and gas fields for CO_2 storage depends on the use of these fuels in the model runs, which again depends on the cost of production[13] (de Vries et al., 2001) (see also Section 2.2.5).

2.2.5. Oil, gas and coal prices

The price scenarios for fossil fuels (coal, oil and gas) are determined in the liquid, gaseous and solid fuel sub-models in TIMER (see de Vries et al., 2001). In the low scenario, prices are based solely on the production cost, which decrease due to learning by doing, but increase with the level of depletion of the resource, as with higher cumulative production less economic reservoirs are exploited (e.g. deeper reservoirs) (de Vries et al., 2001).

For medium and high fossil fuel prices, the prices calculated by this method are amended with a markup-factor, such that the natural gas and oil prices are in line with the prices of van Ruijven and van Vuuren (2009), which cover the range of literature and are updated by resource estimates from the World Energy Outlook (WEO) (2008).[14] Coal price projections until 2035 provided by the 2011 WEO (2011)[15] were extrapolated to 2050 using the average growth rate of the given time series between 2010 and 2035. Again, these prices are used to supplement the endogenously determined coal prices for the low fossil fuel price scenario such that they approximate the price scenarios from the WEO (2011).[16]

The global average price development of fossil fuels and biomass for electricity production in the three price scenarios is presented in Fig. 2. In the low fossil fuel scenario, coal is the cheapest fuel (when taxes are not accounted for). Coal also remains comparatively cheap in the medium and high fossil fuel price scenario. Biomass is closely competing with oil, when fossils are cheap, and it is more competitive than natural gas and oil in the medium price scenario until mid-2030. When fossil fuel prices are on their high level, solid biomass feedstock are more competitive than oil and natural gas until the end of the modeling period, but it remains more expensive than coal if taxes are excluded.

If a carbon tax is included, bio-energy is the cheapest feedstock for electricity generation in the future in all price scenarios, although, biomass prices compete with coal prices in the beginning of the time horizon. When all fossil fuel prices follow a low price development, biomass prices are closest to natural gas prices when taxes are accounted for.

The global average[17] fuel costs (inclusive tax) for electricity generation in the *Base*(M) case rise from 8 (biomass), 10 (coal), 12 (natural gas) and 15 (oil) $\$_{2005}$/GJ in 2020 to 16 (biomass)[18], 21 (coal) 18 (natural gas) and 23 $\$_{2005}$/GJ (oil) in 2050. Biomass is most competitive after accounting for the carbon tax. Without the tax the feedstock price for solid fuel biomass in 2050 is about 11 $\$_{2005}$/GJ (global average).

Fuel prices vary regionally due to differences in production costs. The latter are determined largely by differences in learning rates and the depletion of resources. The model distinguishes multiple resources categories (based on fossil fuel resource estimates) and depletes cheaper resources first. The regional cost-supply

[13] In the TIMER model the EOR storage potential becomes available, according to the fraction of resource depletion. For instance, if 30% of the currently unexploited oil fields are exploited in 2030, 30% of the storage potential becomes available. Similarly, the potential for CO_2 storage in remaining gas reservoirs will become available according to the same principle.

[14] The values for 2010 for the present study were used from the 2011 version of the WEO (2011).

[15] The OECD steam coal import prices in WEO (2011) are deflated to USD_{2005} using the OECD CPI for energy goods from (OECD.stat). The conversion to USD/GJ was done by using a conversion factor of 23.9 GJ/t as given in IEA (2011).

[16] The exact price can deviate from the projections due to model dynamics. In the Base case the prices deviates by about 0.04 \$/GJ from the projection until 2030.

[17] Costs vary between regions.

[18] Net carbon emissions of biomass are slightly positive because emissions from land use change and the production of the biomass is accounted for.

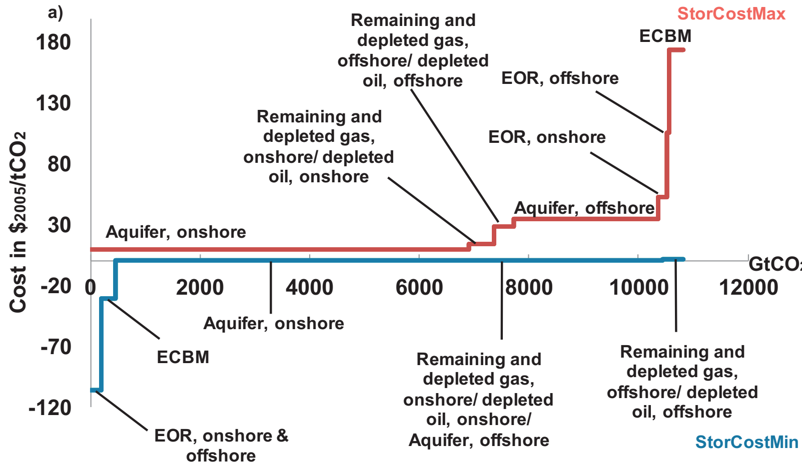

Fig. 3. Global storage cost-supply curves for high and low storage cost per reservoir type.

curves have been mostly derived from the USGS data (as collected in 2005 (in TNO, 2006)) following the same method as Rogner (1997). Fuel trade between regions depends on production and transport costs, while trade barriers are accounted for (see detailed descriptions in van Vuuren et al., 2006; de Vries et al., 2001). Fig. 15 (in Appendix) shows the regional price development for selected regions of the fossil fuel prices in the three price scenarios. The variation between the selected regions is largest in the low fossil fuel price scenario, since the medium and high price scenarios assumed comparably high prices for all regions. Also visible from the figures is the convergence of the prices in the selected region in the future, in many scenarios. The direction of price development can also differ per region. For instance, oil prices in the low fossil fuel price case (panel d) increase from 2020 onwards in the Middle east and Russia, but decrease in China from around 2030 onwards.

2.2.6. *Industry CCS assumptions*

The focus in this research is on the CCS deployment in the power sector. However, we indirectly analyze the effects on CCS in the industry production and show the respective cumulative CO_2 capture results. Tables 7 and 8 show the techno-economic data for CCS in the steel and cement industries with CCS, respectively. For hydrogen CCS assumptions see van Ruijven et al. (2007).

2.3. *Model analysis*

As indicated before, we use the TIMER model to explore the impact of the uncertainty ranges indicated above. Each parameter analysis is carried out for three different fossil fuel price levels. For each of these fuel price levels, each parameter is set to its minimum and maximum value, while keeping the values for all other parameters at their mean value. Table 9 gives an overview of the scenarios and their names as used in the remainder of this study.

The *Base*(M) case is a scenario with average parameter values and a carbon tax that is designed to approximately follow an emission pathway reaching a 450 ppmv target on the medium fossil fuel price level (in 2100).

Besides the *Base*(M) case, two further base cases (*Base*(H) and *Base*(L)) are created, where we keep all five parameter at their arithmetic mean value and vary only fossil fuel prices. The cost and performance variations will be done simultaneously for each power plant component and reservoir type. (e.g. all reservoir types are set to their minimum or maximum cost simultaneously; or power plant performance is decreased for all combined cycle plant types (coal, natural gas, biomass) simultaneously). Further note that power plant investment cost (e.g. *InvestMax*, etc.), or efficiency (e.g. *EffMax*, etc.) of combined cycle power plants are also changed at the same time as the cost, (or efficiency) of the capture unit. Therefore, in these experiments also the costs of the fossil and biomass fueled combined cycle plants without CCS are varied.

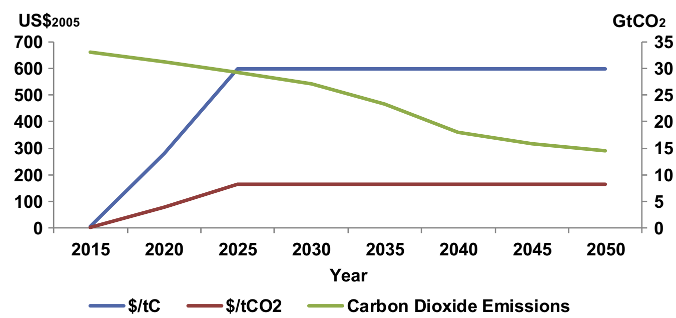

Fig. 4. Carbon tax and CO_2 emissions of the 450 ppmv scenario (*Base*(M) case).

The baseline assumptions are based on the baseline of the OECD Environmental Outlook to 2050 (OECD, 2012). The population size is assumed to grow to 9.2 billion until 2050, while the global economic yearly average growth rate is assumed to be 3.5% between 2010 and 2050 based on OECD (2012).[19] Running the baseline scenario with mean values for all parameters, results in global emissions and primary energy use as illustrated in Fig. 4. For the 2010–2050 period the cumulative emissions add up to almost 1780 $GtCO_2$ and fossil fuels make the largest share in primary energy use since without climate policy, fossil fuels are assumed to remain the cheapest source of energy (see Fig. 5).

We run all cases under a single global carbon tax, which produces the emission pathway to approximate a 450 ppmv concentration target in the *Base*(M) case. This carbon tax increases from zero 2015 to about 165 USD_{2005} in 2025 and stays on the same level until the end of the study horizon (Fig. 4). (The scenario was derived by imposing a carbon tax so that emissions approximately followed those of the 450 ppmv scenario of the OECD Environmental Outlook as calculated by FAIR[20] (Den Elzen and Lucas, 2006) (see Appendix), while taking into account the modification of the transport sector (Girod et al., 2012) and the change of the investigated parameters of this study to the

[19] Population growth projections in the OECD (2012) are based on UN (2009).

[20] Note: the cumulative emissions between 2010 and 2050 of the pathway in the *Base*(M) case are by about 1% (12 $GtCO_2$) lower than the cumulative emissions of this period when following the exact pathway calculated by FAIR.

Table 7
Techno-economic assumptions of steel production with CCS as in Boskaljon (2010).

	Investment costs ($/tonne production capacity/yr)	Annual O&M costs ($/tonne production capacity)	Minimum energy use (GJ/tonne)	Other energy use (GJ/tonne)[a]	Energy efficiency improvement (%/yr)	CO_2 captured	Effective operation time
Coal blast furnace + basic oxygen furnace + CCS	$623	$89	10.2	8.4	0.9%	80%	95%
Direct reduced iron + electric arc furnace + CCS	$422	$58	9.9	9.9	0.9%	80%	95%
COREX + CCS	$491	$88	9.2	11.2	1.1%	80%	95%

[a] Note that the total SEC for the year 2005 equals the sum of minimum energy use and other energy use.

Table 8
Techno-economic assumptions of cement production with CCS as in Boskaljon (2010).

	Investment costs ($/tonne production capacity/yr)	Annual O&M costs ($/tonne production capacity)	Minimum energy use (GJ/tonne)	Other energy use (GJ/tonne)[a]	Energy efficiency improvement (%/yr)	CO_2 captured	Effective operation time
On-site post-combustion CCS	$326	$10	2.0	1.3	0.6%	55%	95%
Oxy-combustion CCS	$558	$10	5.0	3.2	0.6%	86%	95%

[a] Note that the total SEC for the year 2005 equals the sum of minimum energy use and other energy use.

Table 9
Overview of scenarios.

Case	Value of varied variable	High fossil fuel prices	Medium fossil fuel prices	Low fossil fuel prices
Base cases	All variables at their mean values[a]	*Base*(H)	*Base*(M)	*Base*(L)
Investment cost of power plants and capture unit	High cost for all parts	*InvestMax*(H)	*InvestMax*(M)	*InvestMax*(L)
	Low cost for all parts	*InvestMin*(H)	*InvestMin*(M)	*InvestMin*(L)
Efficiency of power plants and capture unit	High efficiency for all parts	*EffMax*(H)	*EffMax*(M)	*EffMax*(L)
	Low efficiency for all parts	*EffMin*(H)	*EffMin*(M)	*EffMin*(L)
Storage cost	Low cost for all reservoirs	*StorCostMax*(H)	*StorCostMax*(M)	*StorCostMax*(L)
	High cost for all reservoirs	*StorCostMin*(H)	*StorCostMin*(M)	*StorCostMin*(L)
Transport cost	Low cost for all transport distances	*TranspCostMax*(H)	*TranspCostMax*(M)	*TranspCostMax*(L)
	High cost for all transport distances	*TranspCostMin*(H)	*TranspCostMin*(M)	*TranspCostMin*(L)
Storage capacity	Low storage capacity for all reservoirs	*StorCapacityMin*(H)	*StorCapacityMin*(M)	*StorCapacityMin*(L)
All parameter	High transport, storage, and power pant investment cost combined with low power plant efficiency; High storage capacity		*HighAll*(M)	
	Low transport, storage, and power pant investment cost combined with high power plant efficiency; High storage capacity		*LowAll*(M)	

[a] Refers to the arithmetic mean of the values found in the literature.

arithmetic mean of values found in the literature). Since the focus here is to evaluate the effect of the uncertainty in the parameters on the CCS deployment, and not on the cost of mitigating emissions, we conduct our research in a single policy environment. Hence, we use the same carbon tax for all scenarios. Consequently, emissions of the alternative scenarios deviate from the 450 ppmv scenario.

Finally note that CCS can become available as soon as it becomes competitive. Oil fired combined cycle plants (OGCC) with CCS are excluded in this analysis. Note also, that the emission pathway is calculated such that it becomes negative shortly after 2050 in order to achieve sufficiently low cumulative CO_2 emissions in 2100 to meet the target.

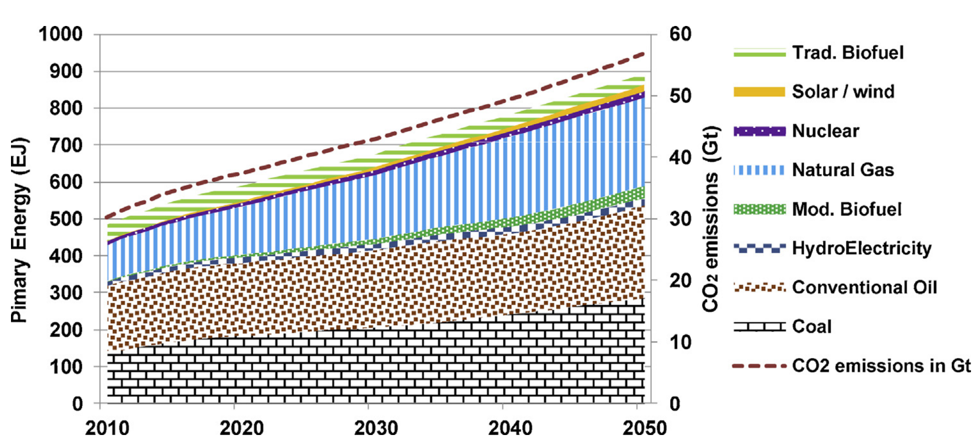

Fig. 5. CO_2 emissions and primary energy use in the Baseline scenario between 2010 and 2050.

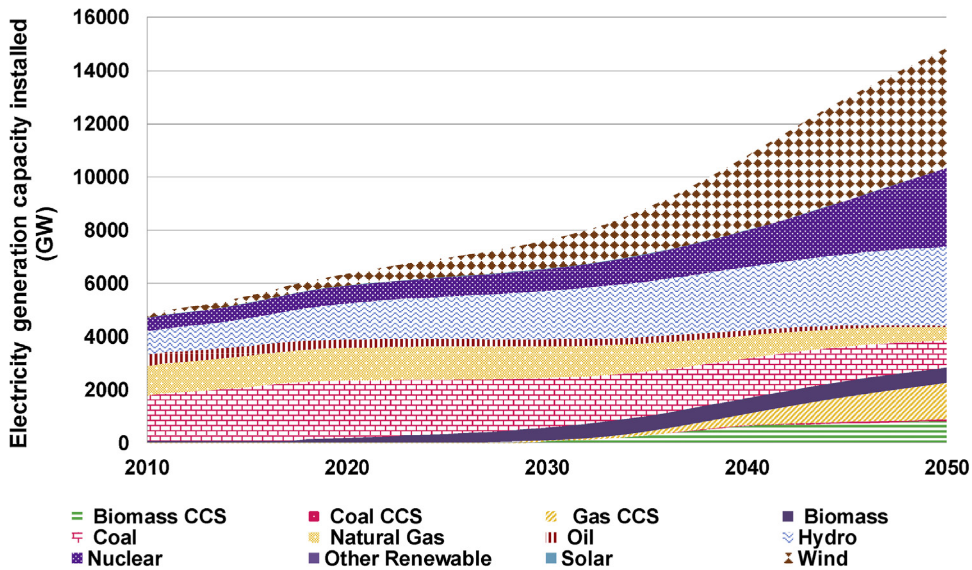

Fig. 6. Global installed capacity for electricity generation in the *Base*(M) case.

3. Results

3.1. Fossil fuel price variation – base cases

In the *Base*(M) case, the portfolio of total global installed capacity for electricity generation increases from about 5000 GW in 2010 to roughly 15,000 GW generation capacity installed in 2050 (see Fig. 6). The total CCS electricity generation capacity in this case is just above 2250 GW. This figure is about 2950 GW when fossil fuel prices are low and 600 GW in the *Base*(H) (Table 10).

The results clearly show that fossil fuel prices have a considerable effect on CCS deployment as well as on the emission level. The cumulative amount of CO_2 captured from electricity production until 2050 is lowest (25 $GtCO_2$) under high fossil fuel prices (Table 10). The reason is that high fossil fuel prices make fossil-fuel based technologies including those with CCS relatively unattractive compared to other options (renewables). Cumulative CO_2 captured from power production is almost the same (around 80 $GtCO_2$) between the *Base*(M) and the *Base*(L) case, because there is a shift from biomass CCS capacity in the *Base*(M) to more natural gas CCS generation capacity in the *Base*(L). The latter fuel has a lower carbon content and therefore producing more electricity with this CCS technology, instead of biomass CCS, decreases the total amount of CO_2 captured.

The share of CCS in the electricity production capacity of 2050 is highest in the *Base*(L) case (22%). Here, natural gas with CCS dominates over biomass CCS while the share of coal with CCS is low (less than 1%). Total electricity generation capacity from biomass in the three base cases requires global modern biomass consumption between 26 and 60 EJ/yr in that year (for a comparison of

Table 10
Results of Base cases under different fossil fuel price levels.

	2010	*Base*(H) 2050	*Base*(M) 2050	*Base*(L) 2050
Total global installed capacity (GW)	4850	16148	14848	13606
Total CCS capacity installed in (GW)	–	600	2263	2939
% Total share of thermal power plants w CCS	–	4	15	22
% Biomass CCS	–	1.4	6	5
% Coal CCS	–	1.3	0.5	0.7
% Natural gas CCS	–	1	9	15
% Total share of thermal power plants w/o CCS	69	11	14	19
% Biomass	1	3	4	5
% Coal	36	7	7	8
% Natural gas	23	2	3	6
% Oil	9	0	0	1
% Total share of renewables	21	52	50	46
% Hydro	18	20	20	19
% Other renewables	0.3	0.1	0.1	0.1
% Solar	0.2	0	0	0
% Wind	3	32	30	27
% Nuclear	10	33	20	13
Cumulative CO_2 emissions 2010–2050 (Gt)	–	919	1023	1195
Total cumulative CO_2 captured from all CCS applications until 2050 (Gt)	–	99	142	136
Cumulative CO_2 captured from power production until 2050 (Gt)	–	25	79	77
Biomass	–	14	63	38
Coal	–	8	2	3
Natural gas	–	3	14	36
Cumulative CO_2 captured from industry applications until 2050 (Gt)	–	73	62	59

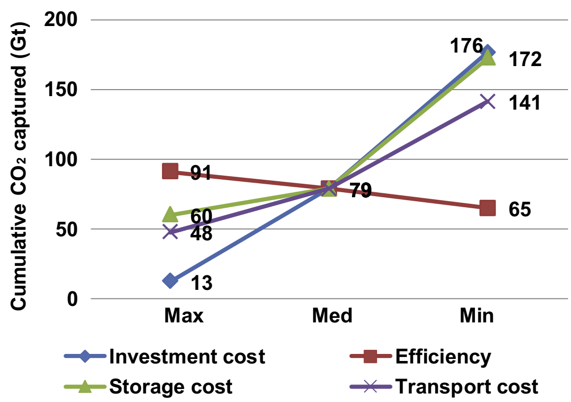

Fig. 7. Uncertainty in CCS deployment in the power sector due to parameter uncertainty; measured in global cumulative CO_2 captured from power production until 2050.

total global biomass use with estimates of biomass potentials see Section 4).

Interestingly, in the industrial sector the cumulative amount of CO_2 captured increases from the *Base*(M) to the *Base*(H) case. Here, the increase in fossil fuel prices leads to a shift from natural gas to coal. Since coal has a higher carbon content, the increase in CO_2 captured between the *Base*(H) and the *Base*(M) results from the fuel switch.

Fossil fuel prices clearly also influence the emissions. Besides higher shares of CCS in the electricity production capacity of 2050 with lower fossil fuel prices, there are also higher shares of thermal power plants without CO_2 capture (11% (H), 14% (M) and 19% (L)) when fossil fuel prices are lower. At the same time, the shares of renewable plants and nuclear obviously decrease with lower fossil fuel prices. Therefore, cumulative global CO_2 emissions from 2010 to 2050 are about 170 Gt higher in the *Base*(L) and roughly 100 Gt lower under high fossil fuel prices (*Base*(H)) compared to the *Base*(M) case (see Table 10).

3.2. Effects of techno-economic parameter uncertainty

The sensitivity of the CCS deployment in the electricity sector to the uncertainty in the techno-economic parameters is investigated by looking at the difference in the shares of the electricity production capacity and the difference in cumulative CO_2 captured until 2050 from electricity generation. Generally, the deployment of CCS decreases with higher investment cost, storage cost, transport cost, lower efficiency, or storage capacity.

The total range of global cumulative CO_2 captured from all CCS application of varying all parameter simultaneously (using the high storage capacity estimates) reaches from 50 to 296 $GtCO_2$ while the range for electricity production capture reaches from 8 to 244 $GtCO_2$. Varying the parameters individually shows (Fig. 7) that the effect is strongest for investment cost uncertainty, where the difference between the *InvestMin*(M) and the *InvestMax*(M) in cumulative CO_2 captured between 2010 and 2050 amounts to 164 $GtCO_2$ (see Table 11). The impact of investment cost uncertainty is about 46% larger than the spread caused by storage cost variations and roughly 75% higher than the difference in CCS deployment caused by transport cost ranges. The effect of the efficiency is smaller and shows a difference of 26 $GtCO_2$ between the maximum and minimum efficiency case. This is still a variation of +15% to −17% from the *Base*(M). The smallest effect is observed from decreasing the storage capacity to the lowest estimates found in the literature. Here, only a difference of 6 $GtCO_2$ in the electricity production CO_2 captured is observed. Similar as for the CO_2 capture, investment cost uncertainty also has the largest impact on the CCS shares of 2050 electricity generation capacity. The range due to the uncertainty in the other parameters is roughly similar in size (12%, 7% and 11% points, see Table 11), while again storage capacity has little influence (−2% compared to *Base*(M)).

In the *Base*(M) case, none of the regions run out of storage capacity until 2050. Neither does this happen under the same storage potential settings and low storage cost in the *StorCostMin*(M). When we assume low storage capacity in the *StorCapacityMin*(M), two regions, Korea and Japan, run out of storage capacity before 2050. Furthermore, the region of China only has 31% of its capacity left. This implies that effects of using the low storage capacity assumptions are quite likely to become stronger when running the experiment beyond 2050.

The most important explanation for the high sensitivity to uncertainty in the investment cost (Table 2) is the large uncertainty range, as cost variations are between ±42% (BIGCC-CCS in 2020) and ±72% (IGCC-CCS in 2050)[21] from the average value. Additionally, in the *Base*(M) case, the share of investment cost in the LCOE of CCS power plants is usually higher than the share of transport and storage cost.

The cost-supply-curves in Fig. 8, seem to suggest that the uncertainty in transport cost (Fig. 8(a)) is higher than for storage cost (Fig. 8(b)). However, this is not reflected in the results. The explanation is that the uncertainty for storage cost (Fig. 8(b)) is higher than for transport cost (Fig. 8(a)) for the first 300 Gt of storage capacity. The maximum amount of CO_2 captured in our experiments is only about 300 Gt until 2050. Therefore, the effect is strong for storage cost and mild for transport cost. Interestingly, this could change if the same investigation was executed for the time period until 2100, because with higher cumulative storage the uncertainty range is larger for transport cost than for storage cost. After 2050, therefore, transport cost uncertainty could become increasingly important.

Two factors are likely to be the reason why the uncertainty in the efficiency of the power plant has the least influence on total CO_2 captured from power generation on the global level. One factor is the comparatively low uncertainty, which is ±21% (CCGT-CCS 2050) and ±32% (BGCC-CCS 2020).[22] Secondly, biomass CCS has the largest share in cumulative electricity produced by CCS power plants (65–69%). At the same time, the fuel cost share in the production cost is comparatively low for biomass CCS plants.[23] Therefore, the decrease in the cumulative electricity production as a result of the efficiency decrease is lower for biomass CCS (−45% of biomass CCS compared to −56% of natural gas CCS and −60% of coal CCS).

3.2.1. Effects on technology choice

Natural gas is always the dominating technology in the installed electricity generation capacity that is equipped with CCS in 2050 in our calculations. Biomass CCS has the second largest share in 2050 electricity production capacity (sometimes close to the share of natural gas), while the share of coal is rather low in most cases (between <1% to 2%), except for the *InvestMin*(M) case where it reaches almost 5%. The low deployment of coal CCS is a result of the comparatively high investment cost share in the levelized cost of electricity (LCOE) of this technology in the average value case (Base case). Also, there is a preference for gas, as it can be used to satisfy peak load, as TIMER assumes a relative preference of natural gas over coal for peak load demand due to higher flexibility and a lower fixed-to-variable-cost-ratio. In the calculations, most of the cumulative CO_2 captured until 2050 comes from biomass with CCS (up to 142 Gt) except for the *InvestMax*(M) case (5 out of 13 Gt).

[21] This means, for example, that the uncertainty in the investment cost for an IGCC with coal in 2050 is a range of +75% to −75% of the average value.
[22] This is the lowest and highest uncertainty in the efficiency of a power plant with CCS. I.e. the lowest uncertainty is ±21% from the average value for IGCC-CCS plants in 2050, while the highest uncertainty is in the 2020 efficiency of a BIGCC plant.
[23] This is a result of the carbon tax credit, accounted for in fuel costs of biomass.

Table 11
Results of parameter variation on the medium fossil fuel price level–global results.

	2010	*Base*(M) 2050	*InvestMax*(M) 2050	*InvestMin*(M) 2050	*EffMax*(M) 2050	*EffMin*(M) 2050	*StorCostMax*(M) 2050	*StorCostMin*(M) 2050	*TranspCostMax* (M) 2050	*TranspCostMin*(M) 2050	*StorCapacityMin*(M) 2050
Total global installed capacity (GW)	4850	14848	15447	13364	14397	15165	15085	14179	15245	13959	14969
Total CCS capacity installed (GW)	–	2263	838	3515	3277	1633	1999	2911	1686	3050	1956
% Total share of thermal power plants w CCS	–	15	5	26	23	11	13	21	11	22	13
% Biomass CCS	–	6	1	11	9	4	4	9	3	10	5
% Coal CCS	–	0.5	0.1	5	0.7	0.3	0.4	2	0.3	1	0.4
% Natural gas CCS	–	9	5	11	13	6	9	10	8	11	8
Δ CCS (p.p.)	–	–	21		−12		7		11		
Deviation of CCS share from *Base*(M) (p.p.)	–	–	−10	11	8	−4	−2	5	−4	7	−2
% Total share of thermal power plants w/o CCS	69	14	19	13	13	15	15	11	17	13	16
% Biomass	1	4	10	2	2	5	5	1	7	2	4
% Coal	35	7	7	8	7	7	7	6	7	7	7
% Natural gas	23	3	3	4	4	3	3	3	3	3	4
% Oil	9	0	0	0	0	0	0	0	0	0	0
% Total share of renewables	21	50	53	43	48	52	51	48	51	46	51
% Hydro	18	20	20	19	19	20	20	20	20	19	20
% Other renewables	0.3	0	0	0	0	0	0	0	0	0	0
% Solar	0.2	0	0	0	0	0	0	0	0	0	0
% Wind	3	30	33	24	29	31	31	28	31	27	30
% Nuclear	10	20	22	18	16	22	20	21	21	19	20
Cumulative CO_2 Emissions 2010-2050 (Gt)		1023	1075	968	1011	1033	1041	951	1055	975	1029
Total cumulative CO_2 captured from all CCS applications until 2050 (Gt)		142	76	232	151	128	117	253	92	213	131
Cumulative CO_2 captured from power production until 2050 (Gt)		79	13	176	91	65	60	172	48	141	73
Biomass		63	5	142	71	53	45	136	34	122	59
Coal		2	0	19	3	1	2	23	1	5	2
Natural gas		14	7	15	18	11	14	14	12	14	13
ΔCO_2 cumulatively captured from power production until 2050 (Gt)			164		26		112		93		
Cumulative CO_2 captured from industry applications until 2050 (Gt)		62	63	55	60	62	56	79	44	70	57

p.p., percentage points.

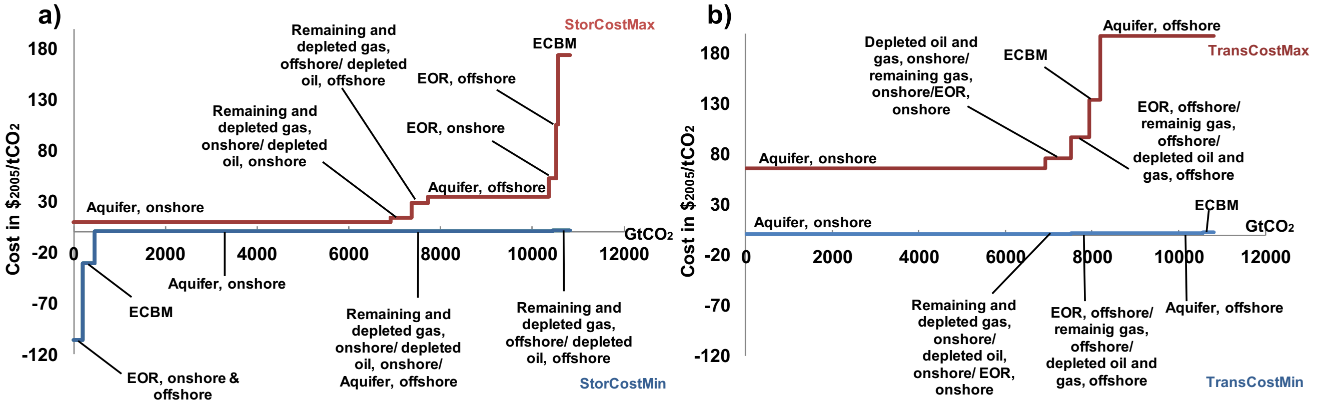

Fig. 8. Global storage (panel a) and transport cost (panel b) supply curves of storage capacity.

Obviously, the high carbon content of biomass plays a role in this result. TIMER here assumes 15.3 kgC/GJ for natural gas (de Vries et al., 2001), and 26 kgC/GJ for biomass. Still, this result indicates that biomass CCS plays an important role in almost all cases.

3.2.2. *Direct and indirect effects on the use of CCS in the industry*

Varying all cost and efficiency parameter at the same time has relatively mild effects on the cumulative CO_2 captured from industrial applications (note: investment cost and efficiency are only varied in the power sector). The values range only from 41 $GtCO_2$ to 51 $GtCO_2$ for pessimistic and optimistic values, while the amount found under mean values for all parameters (62 Gt), is even higher than under optimistic settings of all parameter. The detailed results show that the direct effects of storage and transport cost are somewhat less intense in the industry (−29% and −37% decrease of CO_2 captured from low to high cost case, respectively) than in the electricity sector (−65% and −66% decrease of CO_2 captured from low to high cost case, respectively). Indirectly, a slight increase in the cumulative capture activity in the industry of about 8 $GtCO_2$ (2 $GtCO_2$) is observed when investment cost in the power sector increase (efficiency decreases). Thus, there is a small compensation for the reduction of CCS in the power production sector by the industry.

3.2.3. *Emission levels and substitution effects*

The carbon tax was held at the level of the *Base*(M) case in all experiments. Emissions therefore also vary from the level in the *Base*(M) case (1020 $GtCO_2$). They are up to ∼50 $GtCO_2$ higher and by about −70 $GtCO_2$ lower due to individual parameter variations on the medium fossil fuel price level (c.a. +5% and −7%) (Table 11). The substitution effects between the shares of different technologies in electricity production capacity installed[24] in 2050 gives an idea how this comes about: CCS is not only replaced by renewables and nuclear when it becomes less competitive, but also by conventional fossil fuel based plants.

3.3. *Regional differences in the uncertainty of CCS deployment*

In order to look into the regional dimension, the standard deviations of the (relative) spreads[25] of cumulative CO_2 captured from the electricity sector are compared for each parameter. This measurement does not indicate the direct influence of each parameter, but whether their influence strongly varies across the regions.

The uncertainty in efficiency has by far the most regionally dependent impacts (for selected regions see Fig. 9). The standard deviation is 79% and the impact of efficiency, in fact, has different signs in different regions. In most regions, the efficiency decrease leads to lower CO_2 capture as a result of the reduced competitiveness of CCS. However, there are exceptions. In Western Europe more CO_2 is captured from electricity production when efficiency decreases (from about 15 to 19 $GtCO_2$). This is likely a product of several effects. First, the relative competitiveness of biomass fueled CCS plants (BECCS) does not decrease a lot as a result of the efficiency change, most likely because biomass CCS plants have relatively low fuel cost shares[26] and are thus less sensitive to changes in efficiency. In fact, after the efficiency change only one additional option (hydro power) is more competitive than BECCS (Fig. 10(a) and (b)), which constitutes no additional competition since deployment of hydro power is exogenously determined. Hence, the substitution effect is low, compared to, for instance, Russia. Here, the change in efficiency leads to a stronger decrease of relative competitiveness of the cheapest CCS option. Most likely because this option is natural gas fueled CCS which has high fuel cost shares in the cost of electricity per kWh (see Fig. 10(c) and (d)). Second, there is a small fuel switching effect between CCS technologies in Western Europe from natural gas with CCS to more carbon intensive biomass CCS. This contributes to higher capture per kWh of electricity produced. Finally, the efficiency decrease effect also makes the production of energy with fossil, or bio-energy fuels more carbon intensive and hence higher CO_2 amounts are captured per kWh. In total, the low substitution effect is probably canceled out by the small fuel switching effect and the direct efficiency effect.

For investment cost uncertainty the standard deviation of the regional impacts is comparatively low (13%) which implies that the impact is similar across the regions. An important reason is that in the model, investment costs for CCS power plants generally do not differ a lot per region. Therefore, changes in investment costs also change the competitiveness of CCS plants in each region in a similar way. Remaining differences mostly result from regional differences in fuel costs and the costs of competing plants.

The standard deviation of the uncertainty impact of transport costs (25%) is roughly twice as large as for investment cost uncertainty. Transport cost uncertainty has only a small impact in the Middle East (−15%), while a very large change (almost −91%) appears in the USA.[27] Both regions contribute considerably to global CO_2 captured, which declines from 141 to 48 $GtCO_2$ when

[24] This assumes that the electricity generation portfolios in 2050 are representative for the mix of installed capacity over the whole period.
[25] This is calculated as the difference between the maximum and minimum cost (efficiency) case, relative to the minimum cost (maximum efficiency) case.

[26] This is a result of the carbon tax credit, accounted for in fuel costs of biomass.
[27] The decrease in the USA is not the largest percentage decrease of all countries. Nevertheless, we pick this regions since it has a very high level of CCS activity in the *TranspCostMin*(M) scenario, which decrease substantially in the *TranspCostMax*(M).

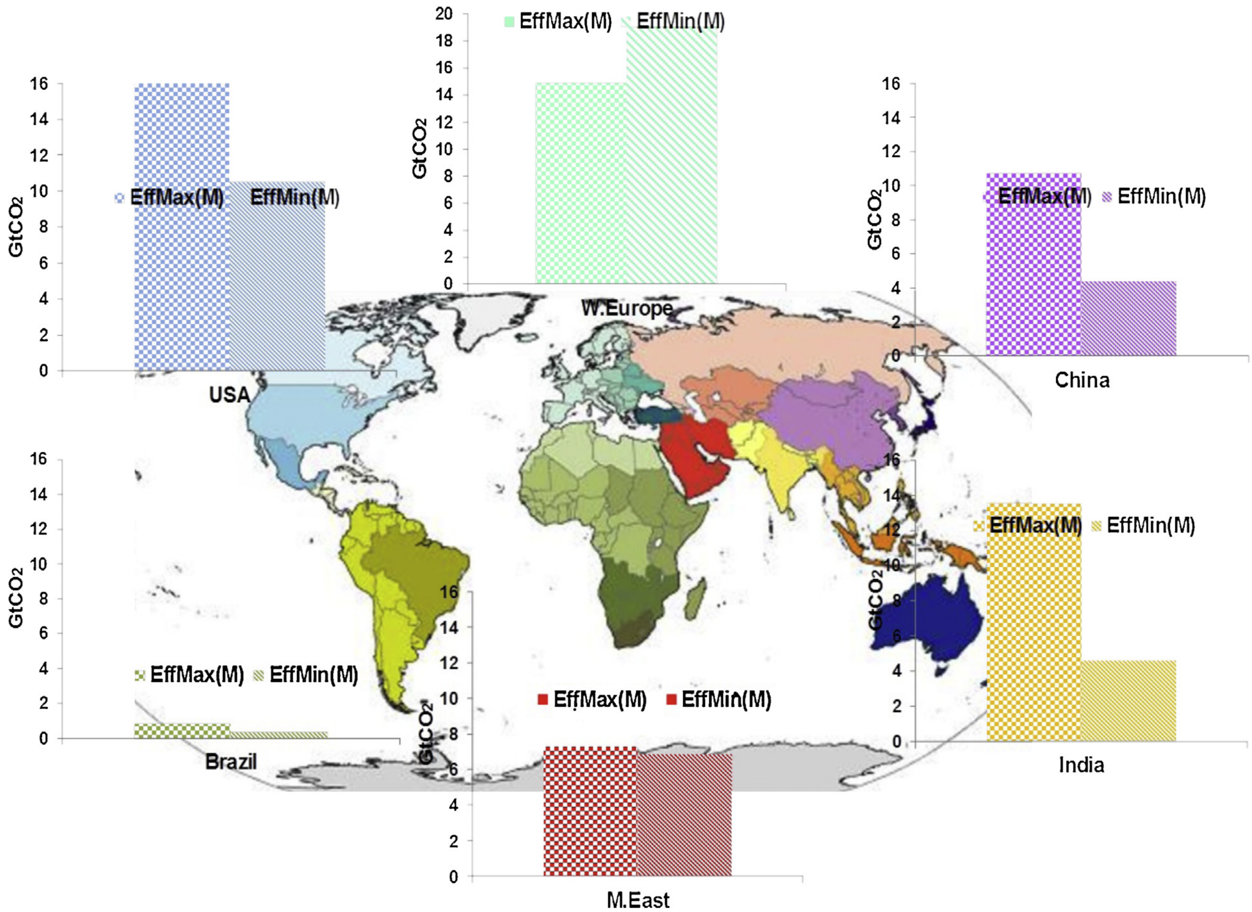

Fig. 9. Effect of CCS power plant performance uncertainty on cumulative CO_2 captured from power production in selected TIMER regions. Source of map with TIMER regions: http://themasites.pbl.nl/tridion/en/themasites/fair/definitions/datasets/index-2.html.

transport cost increase. In the USA it decreases from 26 to 2 $GtCO_2$, while in the Middle East only reduces CO_2 captured from electricity production from 8 to 7 Gt. This region is comparatively insensitive to transport cost and the large change on the global level is not mirrored in this region. Two reasons for this become apparent when looking at the regional cost-supply-curves for the high and low cost cases (Fig. 11(a)). First, the uncertainty in transport cost for most of the supply cost curve is much larger in the USA. Second, the overall and the upper price level are higher in the USA. This implies that CCS likely becomes a lot more unattractive compared to other options (e.g. renewables) than in the Middle East.

Storage cost variations also show considerable differences in regional impacts with a standard deviation of 28%. Two regions of interest (Fig. 12) are China, which experiences a very strong change (−85%), and the Middle East, with a comparatively mild change (−4%). Again, the differences in the storage cost and supply can explain the disparity of the impacts in the different regions (Fig. 11(b)). First, the cost-supply-curve for China is much steeper, because cheap storage potential is a lot more limited. Second, the cumulative baseline scenario emissions are around 470 and 90 $GtCO_2$ between 2010 and 2050 in China and the Middle East, respectively. Hence, the relative scarcity of storage capacity is much higher in China. Therefore, higher cost levels are reached at which China reacts very sensitive to a cost change.

Fig. 13 (a) and (b) shows the used reservoirs and the amount stored for the regions China and the Middle East in *StorCostMax*(M) and *StorCostMin*(M). When the storage costs are low in China (Fig. 13(b)), a great variety of storage options are used. Onshore aquifers are the mostly used reservoirs in this case (22 $GtCO_2$ stored). Because the cheapest option in the *StorCostMin*(M) case, namely ECBM, and on- and offshore EOR, are limited, they get used up completely in China. Then, storage potential that is located at a higher point in the cost-supply-curve is used. If storage costs are high (Fig. 13(a)) in China, the storage types used are onshore remaining gas, depleted oil and gas reservoirs, onshore remaining oil (EOR) (100% used up), and onshore aquifers (1% used up). In contrast, the Middle East switches from onshore EOR (16% used up) (Fig. 13(b)) to onshore depleted oil reservoir storage (63% used up) (Fig. 13(a)) when storage cost change. In both cost cases the respective cheapest option is large enough to store all the CO_2 captured of this region. This explains why the effect of the cost change is relatively moderate.

3.4. Robustness analysis – the results in light of different fossil fuel price levels

The tables presenting all results of the parameter variations on the low and high fossil fuel price level are presented in Appendix (Tables 12–14). Generally, the uncertainty in CCS deployment in electricity production caused by the uncertainty in the cost parameters is larger for lower fossil fuel prices.

Independent of the fuel price level, investment cost uncertainty remains to have the largest impact on total CCS deployment in the electricity sector measured in cumulative CO_2 captures, or in the 2050 shares of installed capacity. Also, the order of impacts of the four parameters on the cumulative CO_2 captured from electricity production is robust against different fossil fuel price levels. This is, however, not the case for the uncertainty range of CCS shares in total 2050 electricity production capacity. Out of the other four parameters, for example, the change in CCS shares in installed

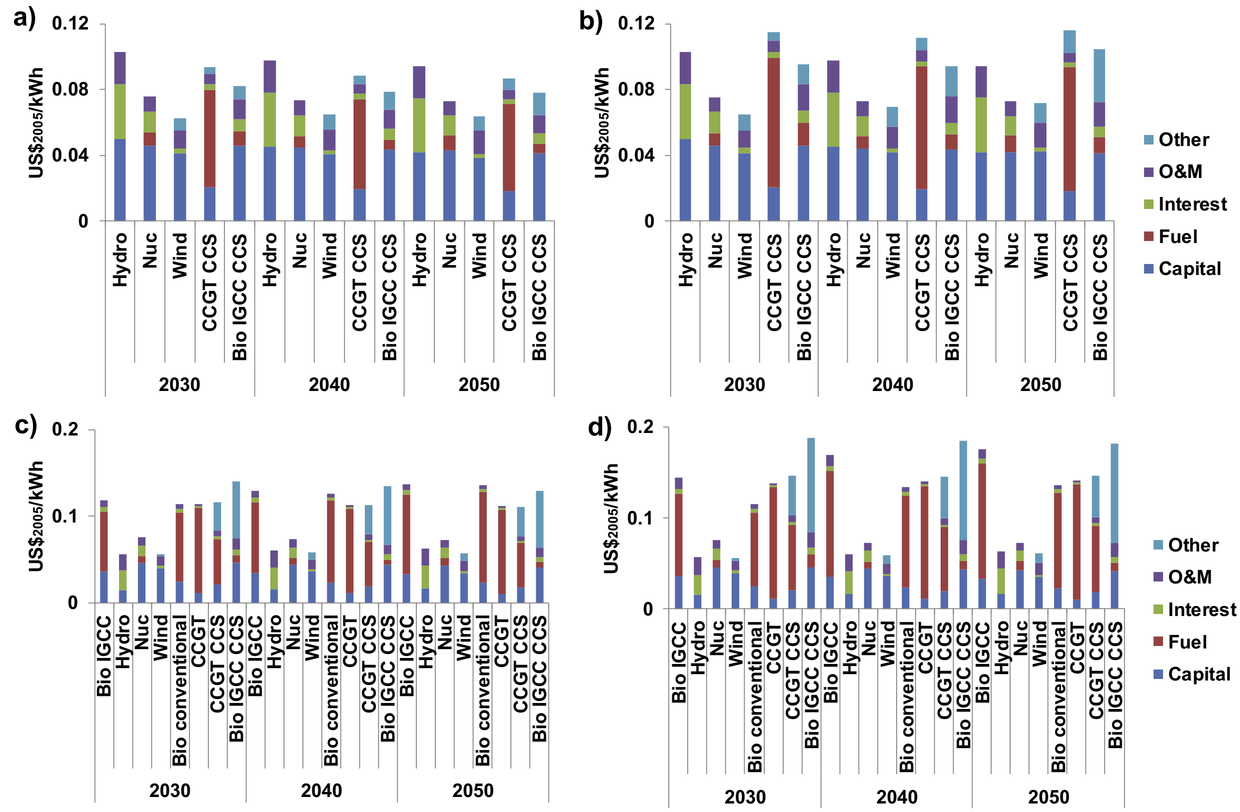

Fig. 10. Break down of cost per kWh of selected power production technologies in Western Europe (panel a and b) and Russia (panel c and d) under high and low power plant and capture unit efficiency assumptions.

capacity is second highest due to transport cost uncertainty under low fossil fuel prices. Under high fossil fuel prices, the strongest impact measured in the spread of CCS shares (after investment cost uncertainty) comes from power plant performance uncertainty.

Looking at the combined effect of fossil fuel price uncertainty and parameter uncertainty on cumulative CO_2 emissions (2010–2050) shows that: (1) cumulative emission levels decline with higher fossil fuel prices, and (2) emissions also decrease with more optimistic assumptions for CCS. Hence, the combination of high fossil fuel prices and optimistic CCS parameter leads to the lowest emission levels.

It also is a robust finding that less favorable conditions for CCS lead to less CCS shares and a more carbon intensive electricity portfolio (i.e. higher shares of CO_2 emitting plants in the electricity production capacity of 2050). However, the question whether the highest amounts of the CCS shares are replaced by CO_2 emitting, renewable or nuclear power plants, varies between cases and fossil fuel price levels. Only on the low fossil fuel price level the highest share of the CCS capacity goes to CO_2 emitting plants under all cost parameter variations but not under lower efficiency. However, the shares, which nuclear and renewables gain, are also often comparatively large.

The shares of fuel types with CCS in the electricity production capacity installed in 2050, also depends on the fossil fuel price level. Natural gas CCS is the preferred option in the medium fossil fuel price cases, and remains the dominant fuel in most of the low fossil fuel price cases with the exception of the *InvestMin*(L) *case*, where biomass is more dominant. On the high fossil fuel price level, the

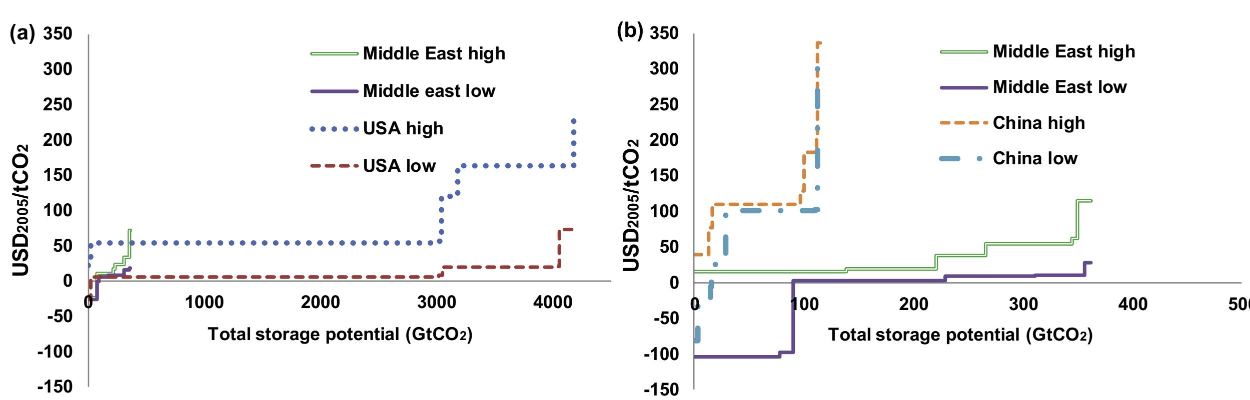

Fig. 11. Panel (a): Transport cost-supply-curves for the *TranspCostMin*(M) and *TranspCostMax*(M) in the USA and the Middle East. The transport cost-supply-curves were constructed using medium storage cost for each reservoir type. Panel (b): Storage cost-supply-curves for the *StorCostMin*(M) and *StorCostMax*(M) in the Middle East and China. The storage cost-supply-curves were constructed using medium transport cost for each region and reservoir type.

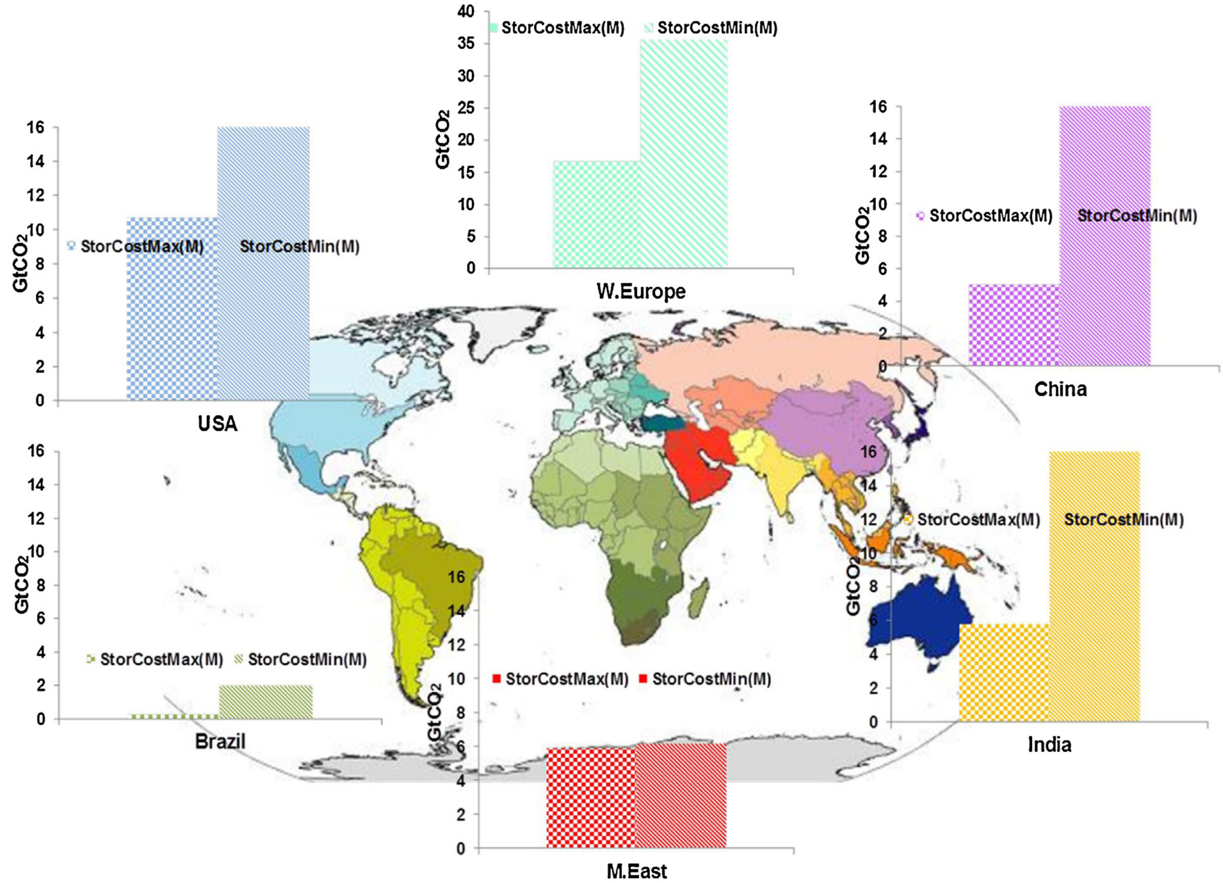

Fig. 12. Effect of CCS storage cost uncertainty on cumulative CO_2 captured from power production in selected TIMER regions. Source of map with TIMER regions: http://themasites.pbl.nl/tridion/en/themasites/fair/definitions/datasets/index-2.html.

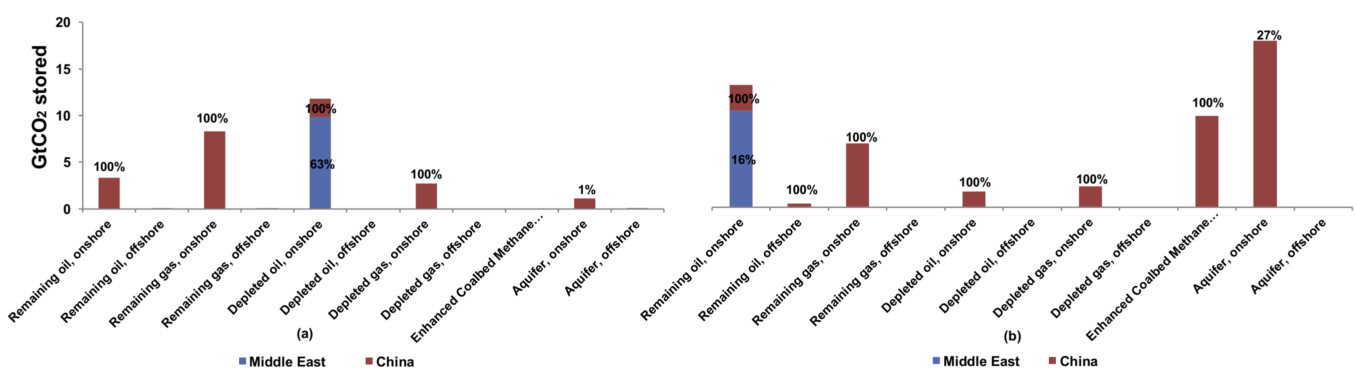

Fig. 13. Storage cost effects on reservoir use in China and the Middle East in the high (a) and low (b) storage cost case. Numbers in % indicate to what extend the reservoir options have been filled up with CO_2.

shares of the three technologies are similarly low (≤4%) except for the *InvestMin*(H), where coal with CCS is the preferred option (see Tables 12 and 13 in Appendix). Hence, under low investment cost and high fossil fuel prices, coal may have a dominant position in 2050.

Finally, the strength of the regional differences caused by the four variables is always highest for efficiency changes and lowest for investment cost uncertainty, while storage and transport cost uncertainty are in the middle. Therefore, on all fossil fuel price levels (see Table 14 in Appendix), the regionality of the impacts of the variables is the same relative to each other.

4. Discussion

4.1. Methodology

In this study we have looked at a single policy context (on a high carbon tax level). There are two key consequences of this approach. First, the cumulative emissions between 2010 and 2050 deviate from the *Base*(M) scenario by up to +52 and −72 $GtCO_2$ for individual parameter variations on the medium fossil fuel level and a much larger range when the fossil fuel price levels are varied in addition to the parameters. As we are interested in the influence of the CCS parameter uncertainty, the use of a single carbon tax scenario was preferred. This means, however, that we have not looked into the additional costs of mitigating CO_2 emissions at a similar target when CCS is expensive or cheap. Neither have we looked into the effects on the role of CCS of varying the parameters while keeping the target constant.

It should also be noted that the investigated parameters of this study are not independent of each other in their effect. For instance, the effect of limiting the storage potential to the minimum amount also depends on how much carbon is captured in each region. The latter is shown to be strongly dependent on, for example, the storage costs, which could then reinforce the effect of lower availability of storage capacity. Also, Bauer (2006) for instance, finds non-linearities of CO_2 captured for model parameters in the MIND model. Further, we have looked in the robustness analysis also to the cross effects of the parameters and fossil fuels, which has shown that the effect of optimistic CCS parameter assumptions in combination with low fossil fuel prices leads to the highest deployment results. It would thus be useful to study such combined effects further by varying different parameters simultaneously. Moreover, parameters of alternative power plants are not varied in this study. Since the electricity generation technologies compete with each other for market shares, the cost level of renewable energies also matters for the deployment of CCS. Abundance of cheap renewable electricity can make CCS an unimportant option even under low cost and vice versa. The effect of varying techno-economic parameters of renewable technologies on CO_2 captured by CCS has been investigated by BMU (2008). To investigate the combined effects of parameter uncertainty in renewable (or other) technologies and CCS would also be interesting for further studies.

We also did not include cases in which only the cost and efficiency of the capture unit where increased while keeping these constant for the other power plant parts. These experiments would provide further information about the uncertainty related only to the CCS technology, but not to the technological change in the rest of the power plants.

The absence of endogenous learning for performance and costs of thermal power plants in the model is a further caveat. Arguably, if learning is endogenous, the impact of an optimistic value for other variables (e.g. storage costs) can be stronger due to acceleration effects and vice versa less intense for pessimistic values due to deceleration effects. However, aside from the possible impact of endogenous learning on the uncertainty range due to interaction between the variables, the learning of the power plant investment costs, power plant efficiency and economies of scale in transport costs are explored exogenously in our analysis. Therefore, the direct impact of different cost developments is included in the analysis, which covers the range found in the literature. We would thus not expect that alternative formulations would lead to very different results. TIMER does not offer pulverized coal with CCS as an electricity production option. This might be unrealistic. Whether PC or IGCC shall be used for coal with CCS in the future cannot be determined, yet. Parallel deployment of both technologies in the future is possible. Currently, either technology has specific advantages. IGCC with CCS is less costly, but PC is currently more flexible, can burn lower quality coal and is more reliable as it is more mature (MIT, 2007). Nevertheless, we argue that adding capture from PC plants – in view of the purpose to explore overall long-term trends in the energy system – will not alter the results of our research.

The uncertainty range in learning potentials for complete IGCC CCS plants is likely to be larger (Rubin et al., 2007).[28] Similarly, IGCC plants might show higher learning rates in the future (Rubin et al., 2007). A comparison of LCOE from different sources as summarized in IEA (2010a) shows that differences in LCOE of IGCC and PC with capture are small on average and the range of LCOE they find for IGCC CCS is larger than for the PC. This implies that including PC CCS as an alternative option to supply power from coal would not change the results significantly (it would still lead to similarly competitive plants against other options, and a similar uncertainty range for coal CCS deployment). Only if the expectation is that the LCOE for PC with capture could be significantly lower, than for IGCC plants for the upper bound of the cost range, this would alter the range of outcomes of the uncertainty analysis. In that case, it would reduce the costs range (and thus the uncertainty range) for coal-based plants (as, PC capture would be preferred) in the high cost case. However, we compared the electricity cost for the plants from four different sources (GCCSI, 2011; IEA, 2010a; MIT, 2007; van den Broek et al., 2009; see supplementary material). In two of them, IGCC CCS is cheaper than PC CCS, whereof van den Broek et al. (2009) project cost of electricity for IGCC to be consistently lower than PC with capture during the time period used in this research. Only the oxy-combustion ultra supercritical pulverized coal technology could be considerably cheaper than IGCC plants with capture as expected by GCCSI (2011).

Furthermore, there are no feedback mechanisms between the cost of EOR storage and the oil price. EOR storage cost is oil price sensitive (Bock et al., 2003; Hendriks et al., 2004a) and therefore, the variation of oil prices in the model could change the cost and thus use of EOR storage in the scenarios. However, given the comparatively small portion of EOR storage capacity, this assumption is not expected to have significant impact on the outcome of the analysis. Furthermore, by varying the EOR storage costs we include this variation in oil prices exogenously.

It should further be noted here, that the carbon tax is designed such that the emissions have to become negative shortly after 2050 in order to meet the mitigation target until 2100. This implies that this carbon tax relies on the fact that biomass CCS has to be implemented on a large scale after 2050. A higher carbon tax would be necessary, if that option would not be available earlier in the century. This would likely increase the CCS deployment before 2050 and the significance of the effects of varying the techno-economic inputs will probably be influenced as well. It is, therefore, useful in subsequent work to look more into the influence of carbon tax levels. Furthermore, it has to be kept in mind that biomass CCS is even more uncertain than other CCS options as little large scale experience has been gained so far (IPCC, 2005). Also, on top of the technical and political uncertainties associated with CCS in general, biomass CCS is afflicted with concerns related to sustainable biomass availability (Dornburg et al., 2010; IPCC, 2011; van Vuuren et al., 2013).

The same considerations hold with respect to the fact that the biomass technology is assigned an important role in electricity generation capacity in most of the cases of this study. The bioenergy potential report of Dornburg et al. (2008) summarizes that the majority of bioenergy potential estimates in the current literature show a range between 300 and 800 EJ in 2050, while they find that under pessimistic assumptions about land availability, potentials sum up to about 220–260 EJ. Dornburg et al. (2010) indicates that more than 200 EJ/yr of biomass could be available in 2050, when excluding land with insufficient water supply, land for preservation of biodiversity, and unfruitful land, while satisfying demand for food. van Vuuren et al. (2009) give estimates of sustainable bioenergy potentials (from woody biomass) between 65 and 115 EJ for 2050, taking into account constraints with respect to water supply,

[28] By applying a ±50% sensitivity range to the "best estimate" of learning in different plant components for different CCS plants (IGCC, CCGT, PC and oxy-fuel plants), Rubin et al. (2007) find the widest range of learning rates for IGCC plants with capture.

biodiversity and low-quality land. The projection of primary energy use of modern biomass[29] of all sectors in the *Base* cases, here, is between 100 (*Base*(L)) and 144 EJ/yr (*Base*(M)) in 2050. While the first two estimates would cover this range, the latter range could be exceeded.

This leads to another important point not considered in this study. The sensitivity analysis does not include the biomass prices although, there is considerable uncertainty in this parameter. For instance, Hoogwijk et al. (2009) find a large range of production cost estimates of woody biomass in the project-based literature, while their generic global cost-supply-curve estimate strongly changes with different parameter assumptions. The global average price for solid bio-energy in 2050 is about 11$_{2005}$ in the *Base*(M) case. Conducting the experiments with higher biomass prices, would result in a lower amount of Biomass CCS deployment and when displaced by fossil fuels instead, stronger emission level overshooting is likely. Also, the outcome of the sensitivity analysis of efficiency could result in a larger range of deployment uncertainty as the cost share in LCOE would be higher. Obviously, we can expect the opposite when conducting the experiments with lower biomass prices.

Since the bioenergy use in the base case is already within the ranges of technical potential that can, according to the expert literature review of the IPCC-SRREN (2011), likely (under various conditions) be supplied sustainably by 2050 (100–300 EJ) (see IPCC, 2011), higher bioenergy prices in the model would logically keep the biomass use within this range. Lower biomass prices are still likely to produce global bioenergy use scenarios within this range. However, the IPCC-SRREN (2011) review about bioenergy potential also strongly emphasizes that manifold important advances in agricultural production in general (which are uncertain) and the administration of bioenergy production in particular are necessary in order to reach this potential in a socially and environmentally sustainable and beneficial manner (IPCC, 2011). For the uncertainty results of this study, this implies with respect to the BECCS deployment, that (some part) of the uncertainty range, might not be possible. However, taking such uncertainty into account, is beyond the scope of this research and should be investigated in future work.

Finally, projections of the IMAGE/TIMER model are in the medium to high range concerning the projections of CO_2 captured in comparison to other IAMS (Koelbl et al., 2014). Therefore, the absolute numbers could be lower in other models. However, the relative results are likely to still be indicative.

4.2. Data

Concerning the data for the experiments two aspects should be considered. First, our approach to estimate future cost and performance data for power plants may overestimate the uncertainty range. As described in Section 2.2.1, we calculate a pessimistic and optimistic growth rate for two periods (2000–2020 and 2020–2050). It is possible that some studies have assumed a fast growth rate in the first period and the opposite value in the second, while others assumed the contrary. Then, by taking the growth rates independently for both, the period before and after 2020, we chose the lowest and highest for each period. These constitute the low and high growth in both periods for the optimistic and pessimistic case. However, the true growth rates are still unknown and the development over the whole period could be both fast, or both slow.

Second, the availability of the data especially for the investment cost of biomass CCS is very limited. Therefore, the full uncertainty range is possibly not covered for this technology. This could also change the results to some extent. However, the aim of this paper was to assess the current uncertainty in the cost data and since not more estimates are available at this point in time, the available data does reflect the prevailing uncertainty.

4.3. Comparison of results

The global cumulative amount of $GtCO_2$ stored until 2050 from the production of electricity in the *Base*(M) case (79 $GtCO_2$) of this study is the same as the estimate reported in the IEA (2010b) (79 $GtCO_2$). Therefore, assuming the average values for the parameter range found in the literature for our study is yields comparable results to earlier projections assuming that the emission reduction targets are comparable.[30]

The range of CO_2 deployment projected by different models[31] that run the same scenario calculated from the EMF22[32] database is about 0–713 $GtCO_2$ (in a scenario with a comparable target[33]). In the EMF27 (Krey et al., 2013; Kriegler et al., 2014) the range projected by 10 models running a 450 ppmv scenario is about 75–340 $GtCO_2$ cumulative capture until 2050 (see also Koelbl et al., 2014). The range caused by varying the cost and efficiency parameter simultaneously in this study is 50–296 $GtCO_2$ (from all applications). This is about 35% of the EMF22 range and very similar to the EMF27 range. This shows that a considerable part of the variation may be caused by the uncertainty in techno-economic parameter assumptions.

5. Conclusion

In this study we analyzed the impacts of uncertainty in techno-economic input parameter of CCS on the worldwide role of CCS in climate mitigation until 2050. First, based on a literature review, we assessed the uncertainty ranges of the relevant parameters, i.e. the investment cost and efficiency of power plants, the CO_2 storage and transport cost, and the CO_2 storage capacity. Next, we evaluated the impacts on global CCS deployment in the electricity sector and the industry, the choice of CCS technology, the substitution of electricity generation technologies in 2050, the CO_2 emission level and also the regional differences of the impacts. The robustness of the results was then tested by investigating the impact also on a low and high fossil fuel price level. The results were obtained by varying the techno-economic parameter in the global, regionally explicit energy system model TIMER, which includes the whole CCS chain.

CCS parameter uncertainty and fossil fuel prices have a very large impact on its application rate. Consequently, emission levels are impacted considerably as well. The starting point of the analysis was a *Base* case. This is a scenario with average values for the CCS parameters and a carbon tax (165 $\$_{2005}/tCO_2$ in 2050) designed to achieve the 450 ppmv target under a medium fossil fuel price development. In this Base case, 142 $GtCO_2$ where stored cumulatively over the period 2010–2050. This amount varied from 50 to

[29] This excludes traditional biomass use. Modern biomass applications can be used for electricity and hydrogen production, in the industry, the service sector, and also by households.

[30] The target in the ETP BLUE Map is to reduce CO_2 emissions from energy by 50% in 2050 compared to 2005 levels (IEA, 2010b). The CO_2 emission reduction in 2050 compared to 2005 levels of the *Base*(M) case in this study is comparable about 47%.

[31] Results are provided for six different model runs stemming from four different models whereof two run twice with different technology assumptions.

[32] EMF22 refers to the 22 round of the Energy Modeling Forum (see Stanford University, accessed 12/2011; Clarke et al., 2009). Data is available at: http://emf.stanford.edu/files/evnts/5613/EMF_22_International_Data_Update_2009-10-22.xls.

[33] In a scenario, where they allow for overshoot of the target which is 450 ppm (for scenario descriptions see Clarke et al., 2009).

296 $GtCO_2$ when the combined uncertainty range of the cost and efficiency parameters was taken into account and high CO_2 storage capacity was assumed. In the electricity sector alone, this range was 8–244 $GtCO_2$. The uncertainty range in investment cost causes the widest spread (164 $GtCO_2$) in cumulative CO_2 stored from electricity production. This is followed by storage cost (112 $GtCO_2$), transport cost (93 $GtCO_2$), and efficiency (26 $GtCO_2$). The latter is still roughly one third of what the IEA (2010b) projects as the total amount of CO_2 captured from power production in the same period. In contrast, the uncertainty range of storage capacity results is only a variation of 6 $GtCO_2$ (11 Gt including all CCS applications) and thus seems not to be a significantly limiting factor until 2050. The order of the impact on cumulative capture until 2050 of these five variables is robust on all fossil fuel price levels.

Similar sensitivity is observed for the CCS share in capacity installed for power production. In the *Base* case the share of CCS capacity installed in 2050 in the power sector is 15%. Also here, uncertainty in investment cost has the strongest impact (a spread of 21% points). The spreads of the other three variables are between 9% and 14% points lower than the investment cost spread.

Less favorable conditions of CCS i.e. high cost or low efficiency also come with higher CO_2 emissions. This result is found on all fossil fuel price levels. Furthermore, the latter alone have a strong impact as well. This shows that the CO_2 price may have to be higher (or lower) than assumed here (165 $\$_{2005}/tCO_2$), in order to follow the emission pathway that is projected to reach the 450 target in 2100.

In our results, natural gas with CCS is the dominating CCS technology in the *Base*(M) case. However, this is sensitive to high fossil fuel prices. Natural gas with CCS is projected to present 9% of total installed capacity in the *Base* case in 2050, followed by BECCS (6%) and a small amount of coal CCS (0.5%). Natural gas has the largest shares in nearly all scenarios on the low and medium fossil fuel price level. On the high fossil fuel price level of this study all CCS shares are generally small ($\leq$4% per fuel), except for coal in the low investment cost case (*InvestMin*(H)). Here, coal CCS has 12% of the electricity production capacity in 2050 out of a total CCS share of 16%.

Strong regional differences in the impact of CCS uncertainty can be noted. The uncertainty impact of nearly all parameter varies per region. Most severely the power plant and capture unit efficiency uncertainty (on all fossil fuel price levels), while investment cost uncertainty had similarly strong impacts in different regions, because no large regional differences were assumed in these costs. As a consequence, the conclusions that are drawn here on the global level may not be applicable to certain regions. For instance, in the USA uncertainty in CO_2 captured cumulatively induced by storage cost uncertainty (64%) is lower than the uncertainty introduced by transport cost uncertainty (91%).

5.1. Future research and recommendations

We have shown here how uncertainty in CCS parameter assumptions and fossil fuel price assumptions can lead to widely varying application rates of this technology. There is quite some scope for future research. For instance, subsequent research should look into (1) the interdependency of the parameters analyzed in this study, to each other, (2) the parameters of competing technologies, (3) the influence on the carbon tax, and the influence on the parameters under the same target, (4) the influence of biomass prices and further investigate the impact of investment cost and performance data for biomass technologies on the CCS deployment. Finally, (5) it is highly recommended to investigate the sensitivity of results to storage capacity running scenarios also until 2100 since stronger impacts could be expected over this period, as China, for instance, only has 31% of its total capacity left after 2050.

The sensitivity to CCS parameter assumption might explain the wide ranges in CCS use in the literature. This research has shown that the uncertainty in the techno-economic parameter prevailing in the literature has severe impacts on the model projections. This implies that policies should be set up to reduce the uncertainties in the cost, and performance estimates, as well as to improve the techno-economic performance itself. For modeling studies, the results imply that the underlying data about the cost and performance parameters should always be published along with the main results.

Acknowledgements

This research has been carried out in the context of the CATO-2-program. CATO-2 is the Dutch national research program on CO_2 Capture and Storage. The program is financially supported by the Dutch Government (Ministry of Economic Affairs) and the CATO-2 consortium parties (http://www.co2-cato.nl/). Furthermore, this research was conducted with the support of The Netherlands Environmental Assessment Agency (http://www.pbl.nl/en/). We thank Sebastiaan Deetman and Jasper van Vliet, and the rest of the IMAGE team at PBL Netherlands Environmental Assessment Agency for technical and scientific support. Furthermore, we would like to thank Hans Meerman from Utrecht University for valuable advice.

Appendix.

A.1. Results robustness analysis

Tables 12–14 present the detailed outputs of the robustness analysis conducted using different fossil fuel price levels as discussed in Section 3.4.

A.2. The TIMER model

The schematic sketch of TIMER in Fig. 14 shows the different sub-modules which are described in detail in de Vries et al. (2001) and van Vuuren et al. (2006). The exogenous key inputs are the population size and the economic performance. Main output variables among many others are the primary and secondary energy use, greenhouse gas (GHG) emissions (de Vries et al., 2001) and specifically relevant for this study, the portfolio of energy conversion technologies, the amount of CO_2 captured and stored, as well as the reservoir use for CO_2 storage.

IMAGE and its sub-model TIMER have been used in numerous studies that are concerned with various issues connected to climate change mitigation and was, for instance, part of the 22nd Energy Modelling Forum[34] (EMF22).

A.3. Market shares for electricity production

Hydropower capacity shares are determined exogenously. The market shares of the electricity production technologies as well as the fuels used are determined by using a multinomial logit model. Thereby, the market share depends on the production cost of all competing technologies and the sensitivity to differences in the latter (van Vuuren et al., 2006). In addition to costs, premium factors can be added in these equations to reflect preferences for a certain technology (de Vries et al., 2001). In case of fuel choice premium factors can, for example, reflect insufficient infrastructure for some fuels (de Vries et al., 2001).

[34] EMF is an initiative where different integrated assessment models are deployed in order to run the same scenarios to yield coinciding results concerning climate change issues (see e.g. Stanford University, accessed 12/2011).

Table 12
Results of parameter variation on the low fossil fuel price level.

Year	2010	*Base*(L) 2050	*Invest Max*(L) 2050	*InvestMin*(L) 2050	*EffMax*(L) 2050	*EffMin*(L) 2050	*StorCostMax*(L) 2050	*StorCostMin*(L) 2050	*TranspCostMax*(L) 2050	*TranspCostMin*(L) 2050	*StorCapacityMin*(L) 2050
Total global installed capacity (GW)	4850	13606	14019	12187	13170	13883	13788	13088	13946	12619	13713
Total CCS capacity installed (GW)		2939	1076	4364	3866	2168	2541	3581	2042	4199	2544
% Total CCS share		22	8	36	29	16	18	27	15	33	19
% Biomass CCS		5	0	17	9	4	4	12	2	16	4
% Coal CCS		1	0	4	1	0	1	2	0	1	1
% Natural gas CCS		15	7	14	20	11	14	13	12	16	14
Delta CCS (p.p.)			28		−14		9		19		
Deviation of CCS share from *Base*(L)			−14	14	8	−6	−3	6	−7	12	−3
% Total share of thermal power plants w/o CCS	69	19	28	17	17	21	21	14	24	16	20
% Biomass	1	5	14	1	1	8	7	2	10	1	5
% Coal	35	8	8	9	8	8	8	7	8	9	8
% Natural gas	23	6	5	6	7	5	6	4	6	6	7
% Oil	9	1	1	1	1	1	1	1	1	1	1
% Total share of renewables	21	46	49	38	44	48	47	44	47	41	47
% Hydro	18	19	20	18	19	20	19	20	19	18	19
% Other renewables	0.3	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
% Solar	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
% Wind	3	27	29	20	25	28	28	25	28	23	27
% Nuclear	10	13	16	9	10	15	14	14	14	9	14

p.p., percentage points.

Table 13
Results of parameter variation on the high fossil fuel price level.

Year	2010	*Base*(H) 2050	*InvestMax*(H) 2050	*InvestMin*(H) 2050	*EffMax*(H) 2050	*EffMin*(H) 2050	*StorCostMax*(H) 2050	*StorCostMin*(H) 2050	*TranspCostMax*(H) 2050	*TranspCostMin*(H) 2050	*StorCapacityMin*(H) 2050
Total global installed capacity (GW)	4850	16148	16622	14276	15795	16377	16383	15601	16428	15281	16244
Total CCS capacity installed (GW)	–	600	151	2255	1367	348	523	1313	421	1041	561
% Total CCS share	–	3.7	1	16	9	2	3	8	3	7	3
% Biomass CCS	–	1.4	0.3	3.2	2.8	0.9	1.2	3.5	0.9	3.0	1.2
% Coal CCS	–	1.3	0.2	11.5	2.5	0.8	1.1	3.8	0.9	2.6	1.3
% Natural gas CCS	–	1.0	0.4	1.0	3.3	0.4	1.0	1.2	0.8	1.1	1.0
Delta CCS (p.p.)			15		−7		5		4		
Deviation of CCS share from *Base*(H)	–		−3	12	5	−2	−1	5	−1	3	−0.3
% Total share of thermal power plants w/o CCS	69	11	12	12	11	11	11	9	12	11	12
% Biomass	1	3	4	2	2	3	3	1	3	2	3
% Coal	35	7	6	7	7	6	6	6	6	7	7
% Natural gas	23	2	2	2	2	2	2	2	2	2	2
% Oil	9	0	0.3	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3
% Total share of renewables	21	52	54	44	51	53	53	50	53	48	52
% Hydro	18	20	21	18	20	20	20	19	20	19	20
% Other renewables	0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
% Solar	0	0	0	0	0	0	0	0	0	0	0
% Wind	3	32	33	25	31	32	32	31	33	29	32
% Nuclear	10	33	33	29	30	34	32	33	33	34	33

p.p., percentage points.

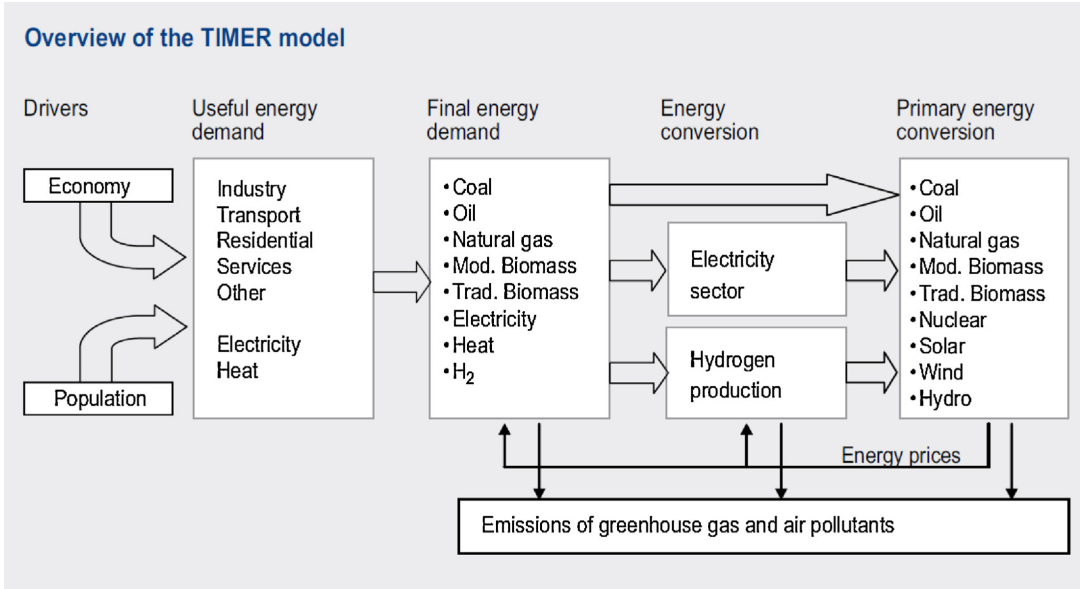

Fig. 14. Schematic representation of the TIMER model.
Source: van Vuuren et al. (2006).

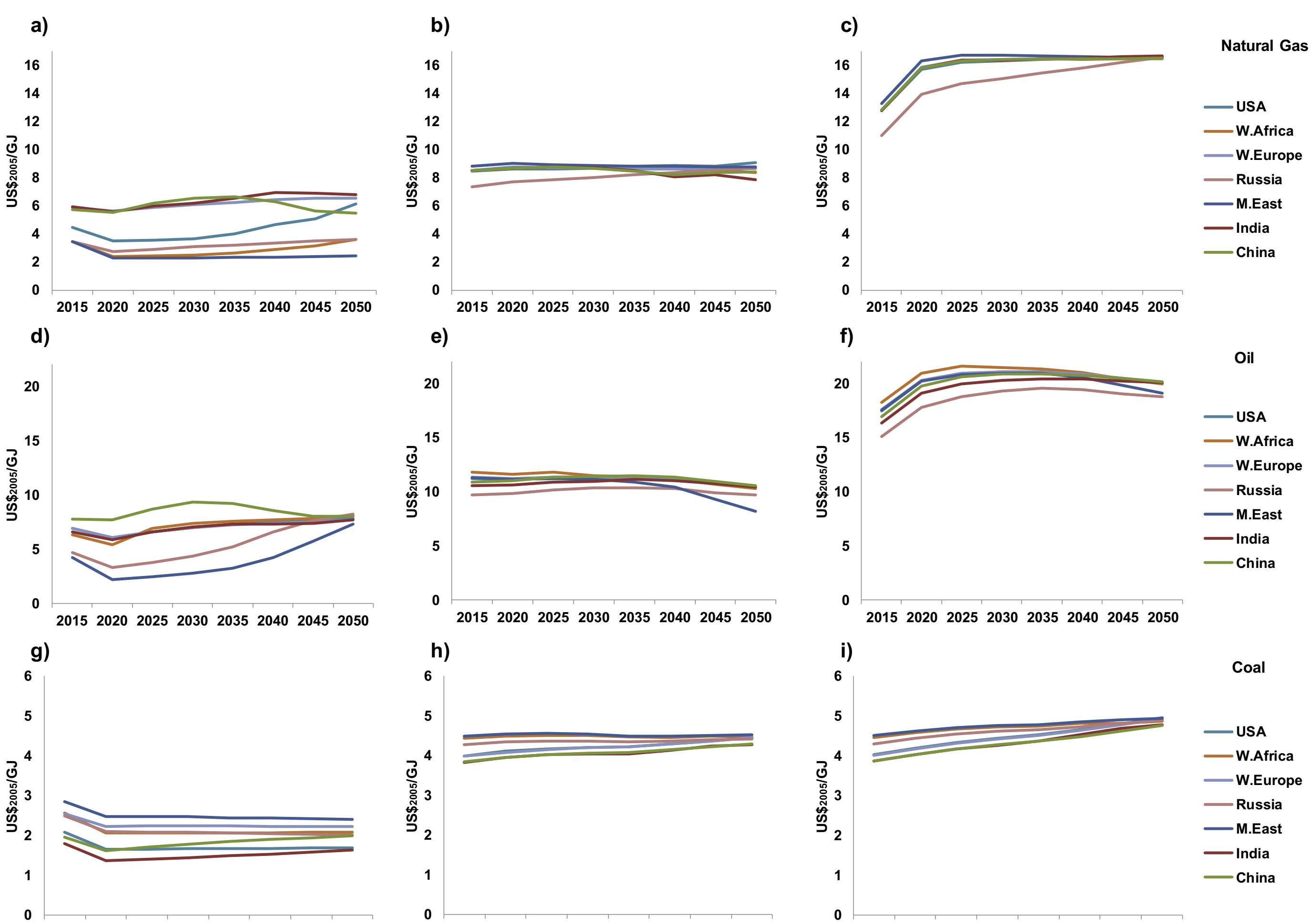

Fig. 15. Fossil fuel prices for selected regions: the panels show low (a), medium (b) and high (c) natural gas prices; low (d), medium (e) and high (f) oil prices and low (g), medium (h) and high (i) coal prices USA, W. Africa, W. Europe, Russia, M. East, India, and China.
For data sources and assumptions of regionalized prices, see de Vries et al. (2001) and van Vuuren et al. (2006).

Table 14
Standard deviation of regional impacts of parameter uncertainty.

		Standard deviation of varying			
		Efficiency	Investment cost	Storage cost	Transport cost
Fossil fuel price level	Low	38%	11%	28%	23%
	Medium	79%	13%	28%	25%
	High	90%	16%	24%	23%

A.4. Solar, wind and nuclear power costs

The costs for solar and wind depend on learning rates and resource assumptions based on Hoogwijk (2004) (see van Vuuren et al., 2006). Nuclear power costs are based on investment costs form literature sources (see van Vuuren et al., 2006: p. 42) and include endogenous learning as well, while the fuel costs change with the degree of resource depletion (van Vuuren et al., 2006).

A.5. The FAIR model

FAIR uses marginal abatement cost curves, based on the TIMER default settings and creates a cost optimal emission pathway over time with distinguished emission reduction distribution over CO_2 and other greenhouse gases. The emission pathway we follow in this paper is based on the Baseline of the OECD Environmental Outlook (OECD, 2012) modified by the transport sector as described in Girod et al. (2012) and calculated under TIMER default conditions. This pathway meets the 2.6 W/m^2 radiative forcing target, although this can be overshoot before 2100 (van Vliet et al., 2012; van Vuuren, 2007). The model also assumes considerable emission reduction outside the energy system. It should furthermore be noted that under the standard settings the emissions become negative shortly after 2050, as a result of the use of bio-energy with CCS. As the pathway we follow in the *Base*(M) case of this study is originally calculated under TIMER default conditions, this is not the cost optimal pathway for our parameter values, but is consistent with a 450 ppmv target.

A.6. Regional development of natural gas, oil and coal prices

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.ijggc.2014.04.024.

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