Comparative net energy analysis of renewable electricity and carbon capture and storage

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Abstract

Carbon capture and storage (CCS) for fossil fuel power plants is perceived as a critical technology for climate mitigation. Nevertheless, limited installed capacity to date raises concerns about CCS ability to scale sufficiently. Conversely, scalable renewable electricity installations –solar and wind - are already deployed at scale and have demonstrated a rapid expansion potential. Here we show that power sector CO_2 emission reductions accomplished by investing in renewable technologies generally provide a better energetic return than CCS. We estimate the electrical Energy-Return-on-Energy-Invested ratio of CCS projects accounting for their operational and infrastructural energy penalties to range between 6.6:1 and 21.3:1 for 90% capture ratio and 85% capacity factor. These values compare unfavorably to dispatchable scalable renewable electricity with storage, which ranges from 9:1 to 30+:1 under realistic configurations. Therefore, renewables plus storage provide a more energetically effective approach to climate mitigation than constructing CCS fossil power stations.

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1 Introduction

Current consensus towards climate change mitigation significantly relies on carbon capture and storage (CCS) from existing and future fossil-fueled plants, recognizing it as a major component in future energy portfolios. In IEA's 2012 2DS scenario that lays out an energy system emissions trajectory consistent with 50% chance of staying below 2°C average global temperature rise, CCS contributes around 14% of needed emissions reductions by 2050[1]. Integrated Assessment Models (IAMs) estimate CCS contribution from 5% to 55% of the total primary energy with the regressed average exceeding 20% for cumulative emissions of 1000Gt CO_2 or less for 66% chances of staying below the 2°C target[2,3]. These results form the basis for claims that CCS is a fundamental option for climate mitigation[4]. Nevertheless, general equilibrium IAMs may have their own biases that prevent them from validly considering energy portfolio mixes that diverge radically from the current one, implicitly endorsing CCS simply as an extension of the current system with added costs[5].

Other indicators contradict the postulated ability of CCS to scale in the timeframes involved. Current deployment figures lag noticeably, with only 110MW_e of power CCS installed by 2016[6]. Notably, China, the world's single largest emitter is expected to develop 349GW_e of CCS power by 2050 in the IEA 2DS. Nevertheless, despite interest in CCS[7], currently China does not have any large-scale CCS in operation and has not included CCS in the nationally determined contributions (NDC) submission to the 22nd Conference of the Parties or in its (current) 13th five year plan.

Worldwide, a significant gap between modeled expectations for CCS and practice emerges when comparing the 110MW_e of CCS to the 227,000 MW_p of PV and 433,000 MW_p of wind cumulatively installed by 2016[8] (shown in Supplementary Table 1). Of course, in itself, the fact that CCS deployment is minuscule today doesn't mean that the technology is unviable, but it raises the issue of whether it can be timely scaled-up to the level of having a cumulative adoption comparable to scalable renewable electricity (sRE). When the discrepancy between actualized CCS projects and expectations is acknowledged, it is explained by a lack of coordinated policy support and very high initial large-scale demonstration project costs[9] while the issue of energy losses appears to be treated as trivial[10].

In contrast, we believe that properly accounting for these energy losses offers important insight in the relative performance of the two options to date and is a good predictor of their future deployment. Energy return on energy invested (EROEI)[11,12] is the ratio of the energy made available to society over the energy invested in the construction, operation and fuel procurement for the powerplants (see Eq. 1 in Methods). Since EROEI is a ratio, it would be formally reported as X:1. For simplicity and following common practice, we omit the unitary denominator and just report the numerator as EROEI. EROEI provides a measure of the relative utility of an energy technology[13]. *Ceteris paribus* and with limited resources, for a given energy investment, society should prioritize the option that offers a higher EROEI. As such, a worse net energy performance of CCS electricity compared to sRE may explain its lackluster deployment. For greenhouse gas emission mitigation technologies of equivalent impact, the technology with the better net energy performance, if chosen to *replace* existing conventional options, facilitates a transition trajectory with higher chances to stay within emissions limits. Quantitative modeling of net energy availability indicates that the EROEI of renewable energy is sufficiently large to make the transition possible within the current emission constraints[14].

There exist several life cycle assessments (LCA) for CCS at the regional level[15],[16],[17]. A net-energy study of coal liquefaction in China reported a considerable reduction of the EROEI of the process if CCS was added to the plant which could lead to “extremely low, even negative” net energy returns although this is a fundamentally different application to electricity generation[18]. A 2006 CCS and sRE life cycle comparison in the German context did not evaluate net-energy performance but found that, on a lifecycle basis, CCS emissions are considerably greater compared to off-shore wind farms in the North Sea and concentrated solar power (CSP) plants in North Africa per unit of energy delivered[19]. Nevertheless, there are limited studies discussing the EROEI of CCS[20] or comparing the net energy performance of CCS and sRE.

Here, we cover this gap by presenting a general framework for consistently calculating the EROEI of CCS energy systems and of dispatchable (i.e. coupled with storage) RE resources. We use as basis prior EROEI estimates for the fuel and sRE converters and adjust for the addition of CCS and storage options respectively. This approach allows us to consistently compare *CCS for electricity generation* with sRE from a net-energy perspective. We estimate the EROEI of electricity from fossil-based powerplants with CCS ranging between 6.6 and 21.3 assuming that 90% of CO_2 is captured ratio and the plants operate at 85% capacity factors. These values compare unfavorably to the current

EROEI of scalable renewable energy resources without storage. The EROEI of fully dispatchable RE with storage ranges from 9 to 30+ for average quality PV and wind and realistic efficiency and storage fraction levels. To facilitate reading of the following sections we summarize all acronyms and symbols with their units in Supplementary Table 2.

2 Estimating CCS energy penalties and EROEI

The thermal powerplant energy return ($EROEI_{el}$), based on its net electricity output, can be estimated using Eq. 3 in Methods. Adding CCS introduces operational and capital energy penalties, shown in Fig. 1 for an illustrative case of an amine-based CCS plant. These penalties are a result of the energy required to build and operate the four CCS process steps (separation, compression, transport, and storage). Operational energy penalties result from: *i*) the withdrawal of thermal energy from the steam-cycle, usually for amine regeneration, thus reducing *gross* electricity output *and ii*) from the use of electric power to operate ancillary equipment for capture and transport processes like pumps and compressors that also reduces *net* electricity output. Dedicated infrastructure investment for the capture system, the compressors, and the pipelines translate into additional embodied energy. While there are several alternative CCS options that differ by the type of fuel and capture process, they all introduce penalties that can be generalized into operational and capital ones. The operational energy penalty (f_{op}) is the reduction in *net* electricity output *with* CCS (E_{red} in Fig.1) over the *net* electricity output *without* CCS (E_{el} – E_{AUX}) for constant fuel input. Similarly, the capital energy penalty (f_{cap}) is the ratio of the additional energy embodied in the CCS system (E_{CCS} + $E_{O\&M,CCS}$) over the energy embodied in a conventional power plant (E_{CAP} + $E_{O\&M}$) at constant fuel input.

Accounting for these, Eq. 6 in Methods estimates the $EROEI_{el\_CCS}$ (referred to as $EROEI_{CCS}$ onwards) with reference to the $EROEI_{el}$ of the non-CCS system when the value of these penalties is known. The values of the penalties depend on the concentration of the CO_2 in the flue-gas stream that is process and fuel dependent, the capture ratio *(CR)*, i.e. the ratio of the CO_2 that is captured from the flue-gas stream, the fuel type, and the power generation and capture processes[21]. Once a plant is configured, the f_{cap} can be estimated using a detailed process-based LCA[22] or through proxy use of environmentally-extended input-output analysis[23].

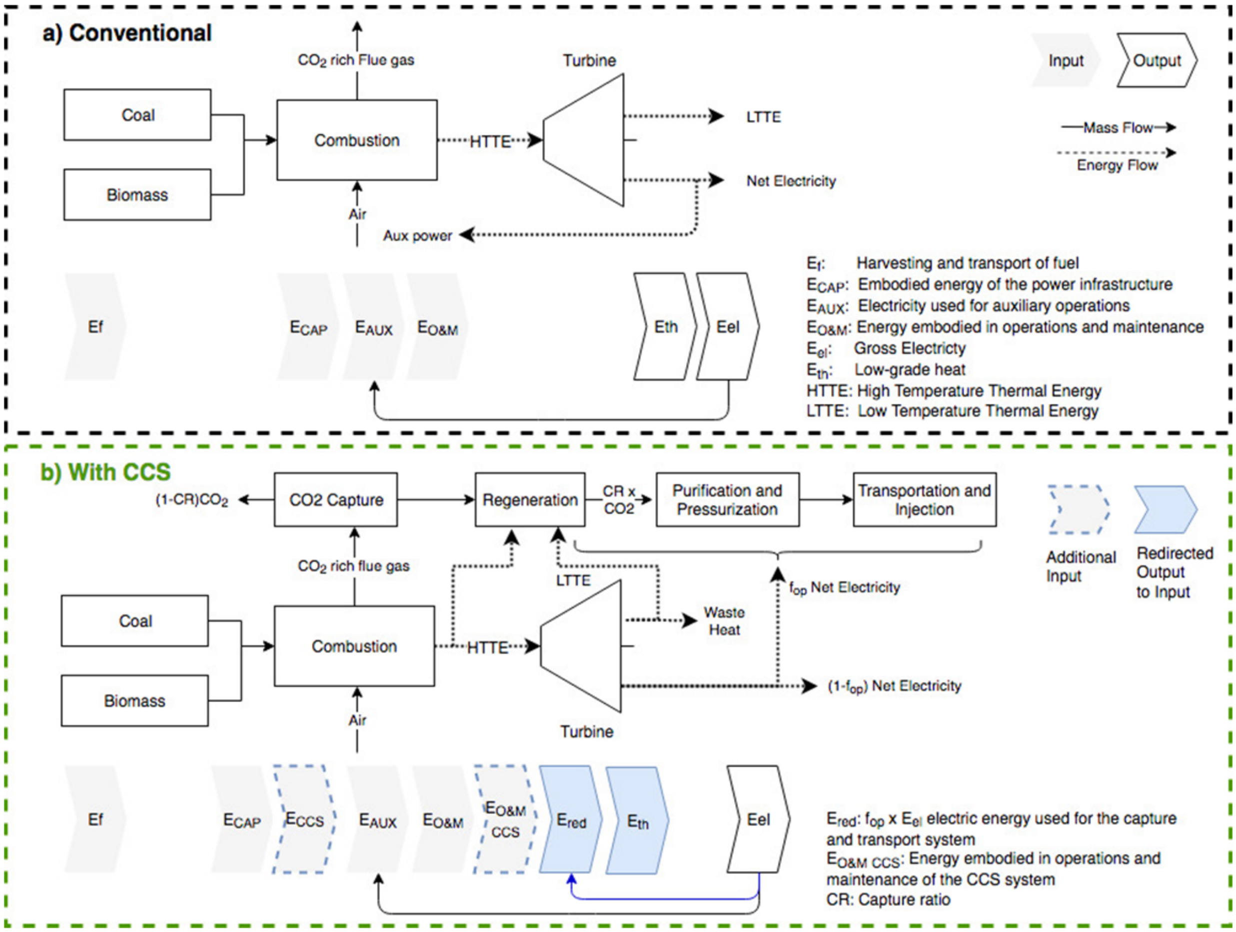

Figure 1 Difference in process mass and energy flow between conventional powerplant and one with carbon capture and sequestration. The diagrams show the mass flow for a conventional powerplant (a) and one with post-combustion CCS (b) of fuel, air and CO2 (solid lines) and the energy flows (dotted lines) in both configurations emphasizing the changes. CCS powerplants redirect energy flows utilizing high and low temperature steam and electricity from the turbine to operate the capture and transport of CO_2 from the fuel combustion flue gases. They also require additional embodied energy inputs for the construction and operation of the CCS-related equipment as additional energy investment streams.

Significant progress has been achieved in mitigating operational penalties; for example the energy needed for solvent regeneration has been halved from 450 kWh/tCO_2 in 2001 to 200 kWh/tCO_2 in 2012[24]. Nevertheless, the operational energy penalty for a complete CCS cycle remains significant. Applying first principles to a pulverized coal (PC) system, the absolute lower bound for f_{op} was estimated at 11% while 29% is considered a reasonable target for 90% *CR*[25]. For consistency and broad technology coverage we rely on detailed process simulations[26] which for 90% *CR* indicate an average f_{op} of 28.3% for pulverized coal (PC), 21.3% for coal gasification combined cycle (IGCC) and 14.7% for natural gas combined cycle (NGCC) (see Table 1 and Supplementary Table 3). The optimal energy penalty per kg of CO_2 for pulverized coal plants is achieved at *CR* between 65% and 80%[27] - though most designs aim for the higher practical *CR* of 90%. Although higher capture rates are technically possible[28] they have not yet been introduced in planned designs. We model the effect of different capture ratios (*CR*) on f_{op} using the relationship shown in Supplementary Figure 1[27]. Finally, once captured CO_2, must be purified to avoid two-phase flow problems and compressed as a supercritical fluid transported by pipeline to the storage site. Indicatively, a CO_2 flow of about 1.5Mt per year, produced from a baseload 530MW natural gas combined cycle (NGCC) plant, requires compression power of about 23MW or 4.3% of its output[29]. For distances greater than 100km, this becomes insufficient and repressurization stations would be needed along the way. In addition to these costs, monitoring of the injection site needs to be included as an operational investment.

Table 1 Normalized Detailed Performance Characteristics of Coal and Natural Gas Plants with and without CCS. The table shows the detailed simulated characteristics and lifetime energy flows of fossil powerplants for 90% Capture Rates, 85% and 55% Capacity Factor, and 80km pipeline to injection. These are used to calculate energy penalties and the corresponding EROEIs based on Eq. 1 and confirming Eq. 6 in Methods. (Based on NETL simulations[26] and author calculations)

		Coal Integrated Gasification Combined Cycle (Based on NETL Exhibit 3-101 *and normalized for coal flowrate =500000 lb/hr*)						**Pulverized Coal** (Based on NETL Exhibit 4-58 *and normalized for coal flowrate =500000 lb/hr*)				**Natural Gas Combined Cycle** (Exhibit 5-27)	
	Case number	**1**	**1a (CCS)**	**2**	**2a (CCS)**	**3**	**3a (CCS)**	**4**	**4a (CCS)**	**5**	**5a (CCS)**	**6**	**6a (CCS)**
	Gross Power Output (kW_e)	800,812	753,576	802,465	726,645	843,933	723,675	666,014	546,916	708,621	585,699	564,700	511,000
	Aux Power Requirement (kW_e)	134,665	195,837	122,989	196,288	123,693	189,720	37,245	99,790	37,128	99,705	9,620	37,430
	Net Power Output (kW_e)	666,148	557,739	679,475	530,357	720,240	533,955	628,770	447,126	671,493	485,994	555,080	473,570
	Net Plant HHV Efficiency (%)	39.0%	32.6%	39.7%	31.0%	42.1%	31.2%	36.8%	26.2%	39.3%	28.4%	50.2%	42.8%
	Plant Overnight Unit Cost (2007$/kW)	1,987	2,711	1,913	2,817	2,217	3,181	1,622	2,942	1,647	2,913	584	1,226
	Total Plant Costs (Millon$)	1,591	2,043	1,535	2,047	1,871	2,302	1,080	1,609	1,167	1,706	330	626
cf =85%	E_{out} (GWh)	178,885	168,334	179,255	162,318	188,518	161,655	148,774	122,170	158,292	130,833	126,143	114,147
	$E_{cap-ccs}$ (GWh)		688		780		657		806		821		452
	E_{cap} (GWh)	2,425	2,425	2,339	2,339	2,851	2,851	1,646	1,646	1,778	1,778	503	503
	$E_{O\&M}$	*2,910*	*3,736*	*2,807*	*3,743*	*3,421*	*4,209*	*1,975*	*2,942*	*2,134*	*3,120*	*603*	*1,146*
	E_f (GWh)	*7,908*	*7,908*	*7,785*	*7,785*	*7,720*	*7,720*	*6,970*	*6,970*	*6,944*	*6,944*	*2,888*	*2,888*
	Fuel $EROEI_{th}$	58		58		58		58		58		87	
	$EROEI_{el}$ (Eq. 1&6)	**11.2**	**8.4**	**11.7**	**8.1**	**11.5**	**7.7**	**13.3**	**8.1**	**13.8**	**8.6**	**31.0**	**21.2**
	R (from Eq. 6)		1.48		1.51		1.23		1.92		1.77		2.61
cf =55%	E_{out} (GWh)	115,749	108,922	115,988	105,029	121,982	104,600	96,266	79,051	102,424	84,657	81,622	73,860
	$E_{cap-ccs}$ (GWh)		688		780		657		806		821		452
	E_{cap} (GWh)	2,425	2,425	2,339	2,339	2,851	2,851	1,646	1,646	1,778	1,778	503	503
	$E_{O\&M}$	*2,910*	*3,736*	*2,807*	*3,743*	*3,421*	*4,209*	*1,975*	*2,942*	*2,134*	*3,120*	*603*	*1,146*
	E_f (GWh)	5,117	5,117	5,037	5,037	4,996	4,996	4,510	4,510	4,493	4,493	1,869	1,869
	Fuel $EROEI_{th}$	58		58		58		58		58		87	

$EROEI_{el}$ (Eq. 1&6)	**9.2**	**6.7**	**9.6**	**6.4**	**9.2**	**6.1**	**11.2**	**6.5**	**11.6**	**6.9**	**27.0**	**17.3**
R (from Eq. 6)		0.96		0.98		0.80		1.25		1.15		1.69
f_{op}		***16.3%***		***21.9%***		***25.9%***		***28.9%***		***27.6%***		***14.7%***
f_{cap}		***28.4%***		***33.3%***		***23.0%***		***48.9%***		***46.2%***		***90.0%***

The capacity factor (*cf*), another parameter that significantly influences $EROEI_{el}$ varies widely as shown in Supplementary Figure 2. Due to low gas prices, *cf* for US coal plants declined over the period 2005-2015 from a mean of 62% to below 50%, with an attendant rise for gas *cf*. While it could be assumed that CCS-enabled plants would tend to have higher capacity factors (to justify the investment cost), the increasingly lower cost of sRE[30] will constrain dispatchable fossil powerplants to peaker duty thus tending to lower their *cf*.

In order to assess the influence of these set of factors we conduct a parametric analysis using realistic ranges for their values constructed from the max and minimum reported estimates in the literature as summarized in Supplementary Table 3. Figure 2 shows the relationship of the $EROEI_{CCS}$ calculated using Eq. 6 in Methods under realistic ranges of operational energy penalty f_{op} and capital energy penalty f_{cap} for each thermal CCS technology. We show two representative values for capture ratios (CR) 60% and 90%, capacity factors (*cf*) 55% and 85%, and the correspondent variable (fuel) to capital and fixed operating costs ratio (R). These values are shown for a base $EROEI_{el}$ estimated from the upper range value of the $EROEI_{th}$ of the fuel (58 for coal and 87 for gas). In order to complete the analysis we also vary $EROEI_{th}$ within the reported estimates (see Methods) to create a comprehensive boundary of feasible $EROEI_{CCS}$ for each technology. This is used to generate the trapezoidal profiles in Figure 4.

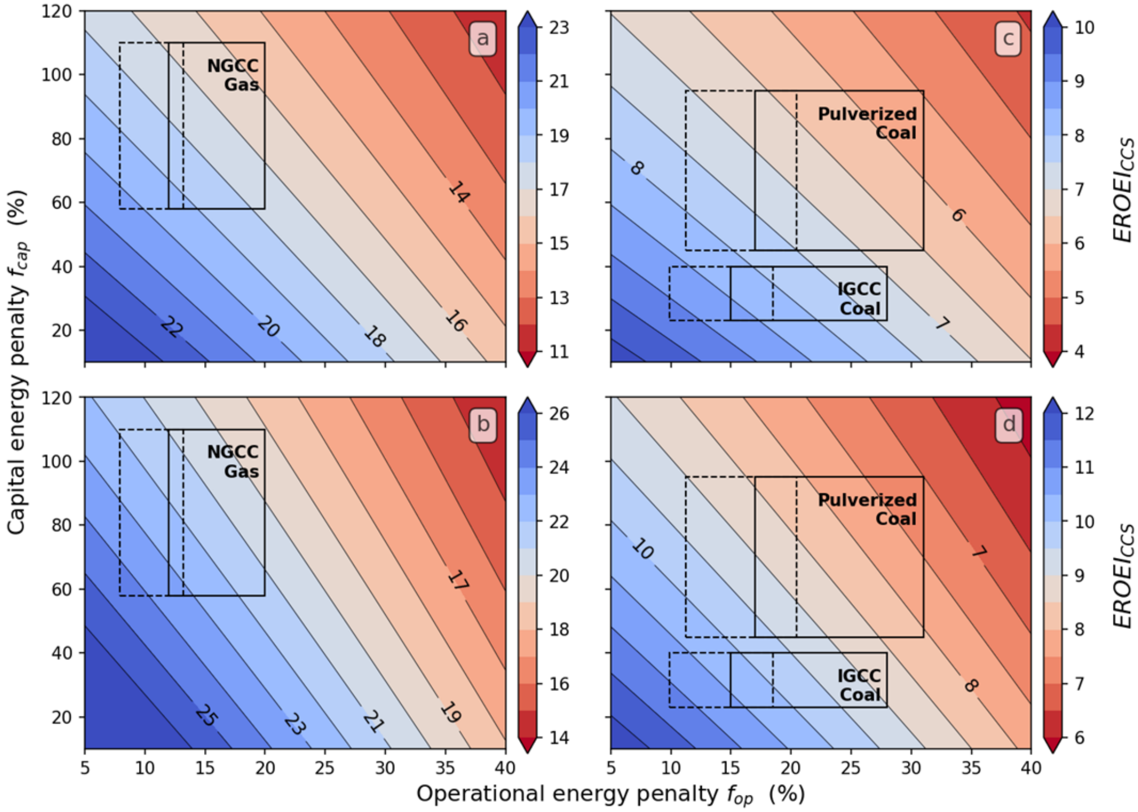

***Figure 2** Energy Return on Energy Invested for coal and gas powerplants under a range of CCS energy penalties. The rectangles in the contour plots represent the $EROEI_{el}$ for wide capital energy penalty (f_{cap}) and operational energy penalty (f_{op}) range for each technology for a capture ratio CR=90 (solid) and CR=60 (dashed). Natural Gas Combined Cycle (NGCC) assumes a fuel $EROEI_{th}$=87. Coal pathways assume a fuel $EROEI_{th}$=58 for both the pulverized coal and the integrated gasification combined cycle (IGCC). Capacity factors (CF) shown are for 55% (a,c) and 85% (b,d). We represent the minimum and maximum encountered $EROEI_{CCS}$ values in each of these rectangles as extent edges in Figure 4 replicating this analysis for a range of $EROEI_{th}$ forming the shaded trapezoids.*

3 EROEI Comparison of Dispatchable sRE and CCS

For the case of sRE, EROEI depends both on the energy costs to build the plant but also on the resource quality of the area the system is installed. A meta-analysis based on 2011 data harmonized the inputs of several assessments and found that the average EROEI of PV at the inverter output ranges from 8.7 for mono-Si to 34.2 for CdTe for average insolation (1700kWh/m^2)[31], while an analysis using more recent data of ground-mounted systems estimated a range of 25-48 for moderate and 34-65 for high insolation[32]. However, these values represent primary energy EROEI and should be adjusted into $EROEI_{el}$ for consistency with Section 2. Multiplying with 0.35, the same factor used in ref.[32] to adjust electricity to primary energy, we get current $EROEI_{el}$ ranges of 9-17 and 12-23 correspondingly. While there is some controversy on the PV EROEI with some studies finding lower values, a detailed response confirmed a value of 9.7 in 2016 for Switzerland's low to moderate insolation[33]. Given the steep learning and scale economies curves, a normalization study demonstrated the importance of using the latest information for accurately representing the state-of-the-art[34]. Using the historical learning curve, $EROEI_{el}$ for PV is expected to range between 20 to 40 in areas of moderately good insolation once cumulative PV capacity reaches 1.3TW[35] which should happen by 2022 at current growth rates. For wind energy, similar meta-analyses found normalized $EROEI_{el}$ in the 20-60 range for large turbines, with several studies reporting values over 100[36,37,38]. However, the maximum global capacity of wind farms with $EROEI_{el}$ higher than 10 may be limited to 31TW[39] constrained by the availability of high-quality locations. In summary, the two RE technologies that offer the highest scaling potential, solar PV and wind both exhibit $EROEI_{el}$ greater than 10 even when installed in moderate resource quality areas.

An argument often raised against sRE resources is their variability and inability to be dispatched on demand[40]. At current adoption levels (less than 20% contribution), variable renewable electricity is integrated directly into the electricity grid without the need for deploying significant additional storage simply by utilizing the extant abilities of the power system to modulate supply and demand. Such facilities include utilizing electricity trade and long-distance transmission lines[41], dispatchable and flexible powerplants (mostly hydro and gas), existing low-cost storage options like pumped-hydro, and demand response through wholesale electricity markets that may include curtailment[42]. At higher adoption rates, integration will become increasingly challenging[43] but manageable by using storage more extensively[44]. Therefore, in order to compare fossils and renewables on an equal basis, we account for the use of energy storage systems that can make them fully dispatchable[45].

To do this on a net-energy basis, we use the energy-stored-on-energy-invested (ESOI) (Eq. S8)[46], the storage fraction (φ), roundtrip efficiency (η), and any potential curtailment (k) to estimate the $EROEI_{disp}$ (for dispatchable RE electricity) of the combined generation plus storage system for a combination of sources and storage options as shown in Eq. S11. This approach is agnostic to the storage medium and since it assumes electricity to electricity conversions, it broadly satisfies ancillary and grid-balancing requirements[47]. Figure 3 visualizes the relationship of $EROEI_{el}$ to $EROEI_{disp}$ for different storage types and a range of base $EROEI_{el}$ that covers that reported for the sRE spectrum. The high-end of storage fraction of 35% means that more than a third of the produced energy is stored. A high ESOI and high roundtrip efficiency, typical of pumped hydro systems (d) has limited impact on $EROEI_{disp}$ even for high storage fractions. Low ESOIs with high efficiency, typical of batteries (a), would only be reasonable for limited ESOIs of 10% or less. Medium ESOIs with low efficiencies, typical of large-scale power to hydrogen (P2H) (c) exhibit more manageable impacts as a φ of 30% drops $EROEI_{disp}$ by less than 25%.

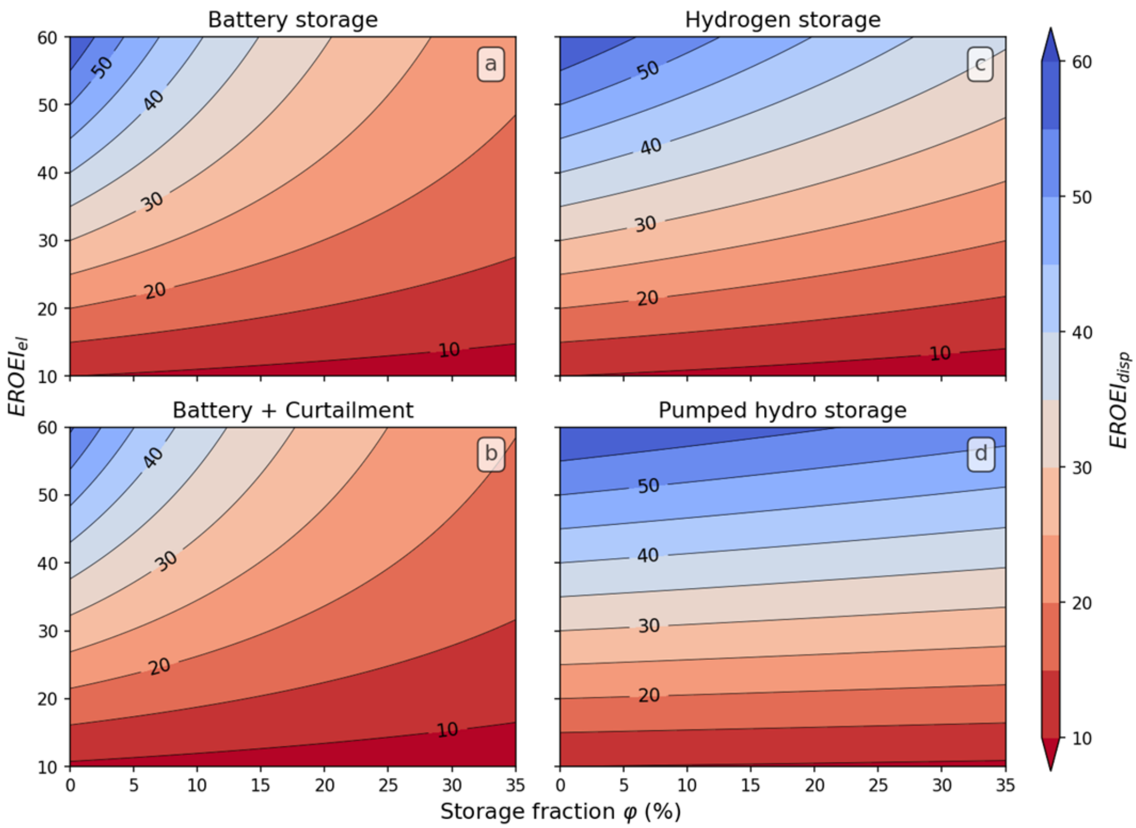

Figure 3 Energy Return on Energy Invested contours for scalable dispatchable renewables for a range of energy storage configurations. Each plot shows the EROEI of scalable renewables when dispatchable with storage ($EROEI_{disp}$) under technology representative configurations of energy stored on invested (ESOI) and roundtrip efficiencies η, across a range of $EROEI_{el}$ values: battery storage with (b) and without (a) curtailment, hydrogen (c) and pumped hydro (d) storage (both uncurtailed). Battery storage assumed ESOI=11 and η=83% for (a), and additional curtailment ratio of k=7% in (b). Hydorgen assumed an ESOI of 24 and η=30% (c), and pumped hydro ESOI of 249 and η=80% (d).We represent the minimum and maximum encountered $EROEI_{disp}$ values in each of these rectangles as extent edges in Figure 4 creating the shaded ranges for renewables.

In order to specifically assess the impact of the critical parameters and compare them to the performance of renewable systems, we also visually present them across the plausible ranges for the different technology options.

Figure 4 summarizes these results and compares the estimates for the $EROEI_{CCS}$ and $EROEI_{disp}$ under a range of reported values by extending and merging Figures 2 and 3.

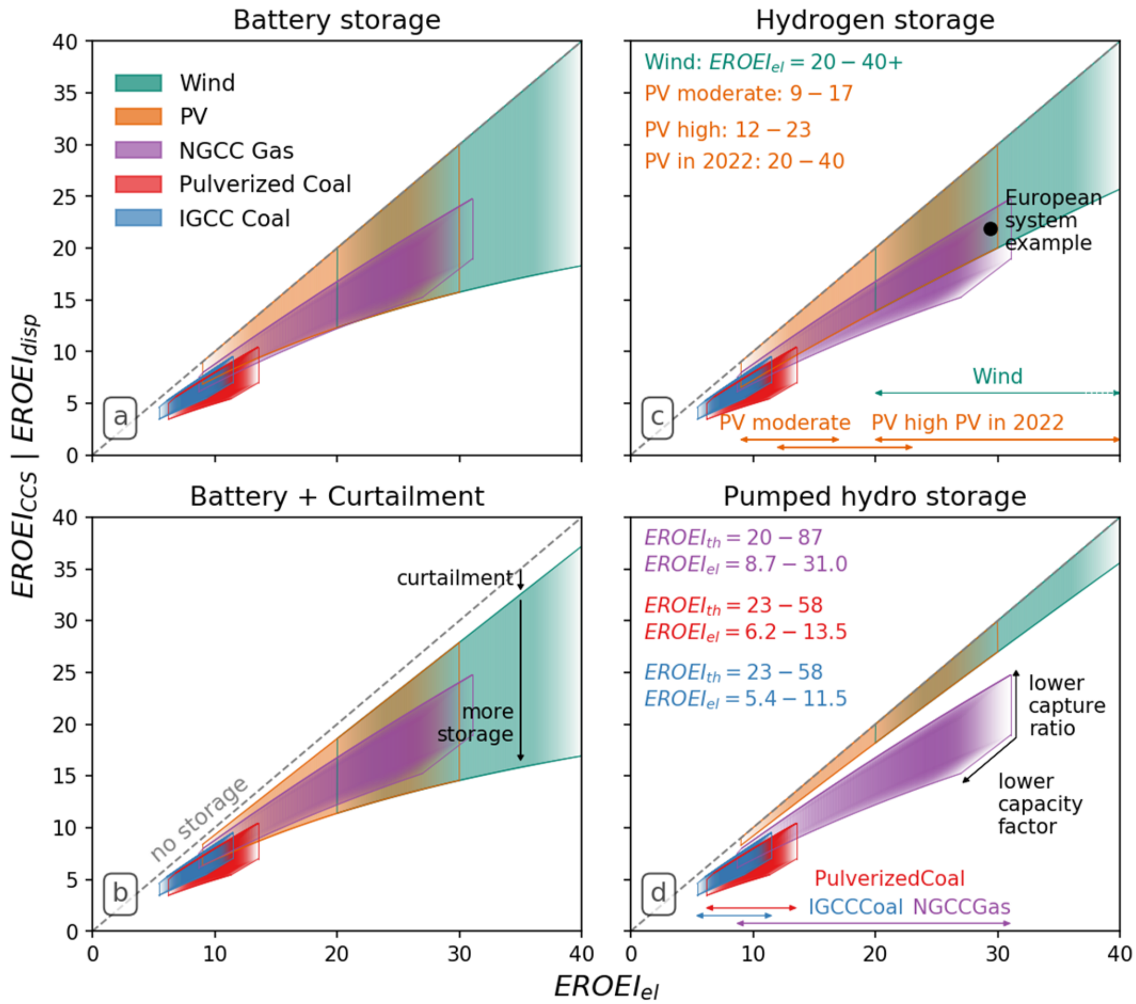

Figure 4 Comparison of adjusted Energy Return on Energy Invested for carbon capture and dispatchable renewables with energy storage. Shaded areas represent the extents of adjusted EROEIs by taking the minimum and maximum values of each individual contour plot in Figures 2 and 3 while covering the range of reported base $EROEI_{el}$ shown in plot (c) for sRE options and $EROE_{th}$ for CCS options shown in plot (d). The energy storage configurations maintain their parameters presented in Figure 3.The European system example refers to the composite $EROEI_{disp}$ of an 100% RE configuration for a future hypothetical configuration where PV and Wind contribute 33% and 67% of sRE supply, they are 2.1% curtailed, and stored in batteries, PHS and P2H at 5.5%, 2.6%, and 5.5% storage fractions respectively (see Supplementary Table 5).

We observe that for the same base EROEI, sRE when stored in high ESOI media Fig. 4d outperforms CCS in all cases. $EROEI_{CCS}$ of PC and IGCC is inferior to practically any moderate or higher quality sRE configuration, and only the best PC_{CCS} compares to the lower-end sRE resources with high storage fractions *and* low ESOI (Fig. 4b and 4c). Nevertheless, $NGCC_{CCS}$ becomes competitive especially for lower capture ratios and the higher range of $EROEI_{th}$. We examine indicative limit cases of these relationships in detail in Supplementary Table 4 for CCS plants with 85% cf and 90% CR. SRE with $EROEI_{el}$ of 21.3 or higher exceeds the best NGCC case without storage and with an $EROEI_{el}$ of 30 they can provide 16% storage fraction (φ) in batteries and 29.9% in P2H. If they are stored in PHS, then $EROEI_{el}$ of 23.5 suffices to reach φ of 35%. These $EROEI_{el}$ values are available to moderate wind and good solar resources. The medium case of NGCC will be matched by an $EROEI_{el}$ of 20 stored at φ of 16.5%.

Since, the better $NGCC_{CCS}$ becomes competitive with battery-stored, medium quality sRE for storage fractions higher than 20% and low ESOIs (Fig. 4a,b,c) it would be important to examine their likelihood under high sRE penetration. Storage factions are not explicitly reported in current studies. The ratio of energy storage capacity over total demanded is reported and a recent review indicates values ranging from 1% to 6% for 80% RE penetration and up to 14% for 100% penetration[48] consistent with a range between 10-20% by global region based on an hourly model of an 100% RE trade-connected energy system[49]. Such a system would utilize a portfolio of batteries, thermal, P2H and mechanical (pumped-hydro and compressed-air) storage systems with different sizes and utilization patterns – i.e. batteries for multiple hourly/daily cycles, P2H for seasonal storage with 3-5 cycles, and mechanical with daily/weekly cycles. The exact composition would be system specific but the $EROEI_{disp}$ of any combination can be estimated using Eq. 11 in Methods. Notably, we calculate a portfolio $EROEI_{disp}$ of 21.9 (Fig. 4c) for a European 100% RE scenario (described in detail in Methods and Supplementary Table 5) that is on par with the best $NGCC_{CCS}$ estimates but further examination exceeds our purview.

4 Conclusions

In summary, the net-energy losses in the fossil primary energy resources from implementing CCS in power generation systems for most current deployment of RE exceed the benefits of simply directing these resources towards building a self-sustaining renewable energy infrastructure, an approach previously termed "*the sower's strategy*"[14]. Even when RE penetrations may reach or exceed 80%, there are indications that the system EROEI may be equal with the better $EROEI_{CCS}$ without the reliance on depleting resources and the non-energetic biophysical complications discussed in the Supplementary Note 1.

The $EROEI_{CCS}$ of electricity from fossil-based powerplants (IGCC, PC, and NGCC) with CCS is between 6.6 and 21.3 at 90% capture ratio and 85% capacity factors. This is lower to the current $EROEI_{el}$ of scalable renewable energy resources without storage for a scale of deployment that is less than 30% of electricity dispatched. The $EROEI_{disp}$ of dispatchable RE with storage ranges from 9 to 30+ for average quality PV and wind and realistic efficiency and storage fraction levels (see Fig. 4). We estimated the $EROEI_{disp}$ of a portfolio of energy and storage options simulated to provide 100% RE electricity in Europe at 21.9 – a value that exceeds any $EROEI_{CCS}$. Given that the higher EROEI ranges for CCS are achieved only for natural gas systems under base-load assumptions for capacity factor (85%) and high $EROEI_{th}$, we conclude that it is more valuable, energetically, to invest the available energy resources directly into building new renewable electricity (and storage) capacity rather than building new fossil fuel power plants with CCS. The better net energy return of investing in RE, makes it more likely to meet emissions targets without risking a reduction in energy availability due to depletion. Of course, this does not mean that sRE allows perpetual growth for the energy system but it does allow it to reach a steady state that could be higher than current[14].

Given its net energy disadvantages, we consider CCS development for electricity as a niche and supplementary contributor to the energy system rather than as critical technology option. This does not preclude biomass-based, negative emission technologies from serving as an atmospheric carbon removal mechanism for a climate emergency. Nevertheless, we recognize such measures as an energetically intensive carbon management tool rather than an energy resource.

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Methods

Energy return on energy investment

The energy return on energy investment (EROEI/ERoEI or EROI) is a measure of the ratio of available energy that a process provides (E_{out}) over the energy that needs to be expended for that process (E_{in}). As a physical measure, EROEI presents an alternative to monetary-based comparisons with distinct advantages[13]. Nevertheless, determining the EROEI of a process requires attention because it depends on the boundary of the analysis and it is specified in five accounting levels: internal energy, external energy, material energy, labor, and ancillary services of energy use[12]. The common accounting boundary proposed as standard[12] includes the first three. The energy investment includes the capital energy investment embodied in the materials and used for the construction and eventual decommission (E_{cap}), the energy needed for operating the powerplant ($E_{O\&M}$), and for procuring and distributing the fuel (E_f) (Eq. 1).

$$EROEI = \frac{E_{out}}{E_{in}} = \frac{E_{out}}{E_{cap} + E_{O\&M} + E_f} \qquad \text{Eq. 1}$$

A subtle but important consideration in the calculation of the EROEI for chained, multi-step processes is how to handle internal energy use. Should the high-quality energy that becomes available from an upstream step but is then used in a transformation at a downstream step be considered as an input or not? In essence, choosing to ignore internal energy use omits the opportunity cost of directing that energy to other purposes[50]. This results in masking the overall process actual energy costs potentially overestimating its energetic performance[51]. While we recognize this potential weakness, we opt to assess fossil system EROEI using only the *net* energy outputs and without accounting for the internal energy streams. This option offers a simple energetic calculus clearly indicating how much energy needs to be invested to deliver a given amount of electricity. Moreover, for electricity generating systems, process efficiency can increase by adding internal energy exchange steps (e.g. using a combined Rankine and Brayton cycle system) as opposed to operating them individually. Considering such internal process energy flows outside the boundary, would lead to, counterintuitively, lower EROEI for the combined system. Finally, the choice of omitting internal energy streams is conservative as it provides the higher range of estimates of EROEI for CCS processes. We use this approach to develop a generalizable approach to estimate the EROEI of CO_2 harvesting processes with CCS.

Power CCS Processes and Steps

The first step of CCS, capture, is well understood and there exist a variety of technology options for carbon capture from fossil fuel combustion [52] [24]. In IGCC plants, pre-combustion of the carbon components through gasification of coal and a subsequent water-gas-shift reaction of the syngas leaves hydrogen for powering the gas turbine while the CO_2 can be separated and captured. Post-combustion, which is the foremost currently commercialized process, separates the CO_2 present in concentrations of 5-15% from the flue gases of conventional combustion systems. It is also possible to utilize oxy-fuel combustion, that is combustion with high oxygen concentration, to produce effluent gas with correspondingly high concentrations of CO_2. Post-combustion processes include physical methods, such as cryogenic separation, chemical capture in solvents such as amine solutions, ionic liquids, electrochemical or plasma activation of CO_2, and more. In practice, the commercially considered methods are either post-combustion separation via amine solutions or oxy-combustion although in practice the latter seems to face additional obstacles in utility-scale deployment.

The captured CO_2 needs to be transported, compressed for ease of handling, via pipeline or ship to the location where it will be processed and stored. The final step involves storing the CO_2 in forms expected to remain stable at least for a few centuries. Storage may be achieved by pumping the CO_2 gas into an appropriate geologic formation, usually saline aquifers, depleted oil and gas reservoirs, or active oil reservoirs for enhanced oil recovery (EOR). Other proposed methods involve storage in abandoned mines, the injection of liquefied CO_2 in deep ocean, and chemical sequestration, that is transforming CO2 into a solid product such as pure carbon or carbonates. This diversity in possible combinations of capture and storage makes a comprehensive and detailed net energy analysis of each combination impractical leading us to create a generalized CCS EROEI methodology.

Energy penalties

In the post- and pre-combustion cases, the fuel type plays a significant role on the energy requirements of the capture process. The theoretical estimates referenced in Section 2 are confirmed from the detailed simulations of several IGCC (integrated gasification combined cycle), PC, and NGCC (natural gas combined cycle) configurations with and without CCS, shown in Table 1. These values include the pressurization, transportation and injection components for a favorable saline aquifer injection site served by an 80km pipeline. While we cannot exclude that scaled deployment and technological progress could lead to more favorable parameters for fossil/CCS power plants, current project prices are much higher (see Supplementary Note 1).

While it may be possible to mitigate fossil fuel energy penalties by integrating lower-grade heat sources like solar thermal in the plant design[53] such strategies increase the capital costs and introduce an additional energy resource in the denomination indicating that the overall system $EROEI_{el}$ may not be improved significantly. Improvements by optimizing process integration[54] at minimal additional costs are possible but do not drastically change the process energy balances.

Capital Cost Penalties

Based on the plant costs presented in Table S1, we use the US2002 producer model to estimate the energy requirements of the plant investment. Assuming that 60% of the investment is in construction (Sector #230102: Nonresidential manufacturing structures) and 40% is in machinery (approximated by Sector #333611:Turbine and turbine generator set units manufacturing), the energy intensity is 6.042TJ per million 2002 US dollars (US2002 428-sector producer model[55]). Accounting for inflation to 2007 using the producer price index (PCU3336: PPI industry group data for Turbine and power transmission equipment manufacturing[56]) the intensity is 5.49TJ per million 2007 USD. Using this approximation, the average f_{cap} estimates for the systems in Table S1 are 28% for IGCC, 48% for PC, and 90% for NGCC.

These estimates account only for short transport pipelines and compression under favorable conditions, actual values in large-scale adoption would likely be higher as a longer transportation network would be needed. Widely-used approximation models to estimate pipeline capital and operation costs can be simplistic and lead to underestimating the costs unless based on pipeline weight[57]. The optimal design of a complete pipeline network relies on pooling together several sources and build trunk pipelines to utilize scale economies[58,59]. In practice though, project costs and risks favor an incremental project-based approach with point-to-point pipeline as developments depend on future carbon price expectations that can be subject to significant uncertainty at the time of investment decisions. In this case, the per stored tonne cost of a point-to-point system may be anywhere from 30% to 350% higher than would be the case for an optimal network[60]. Compounding the uncertainty is the level of renewable energy adoption and the concomitant reduction in the utilization of CCS fossil-fired power plants favoring a smaller size pipeline investment[61]. These factors suggest that initial deployment of CCS is highly unlikely to be part of a scale-optimized network and, in the absence of enforceable planning legislation, it will be difficult to reverse the trend in the future.

Given the differences in design and assumptions, we use a review study that normalized the data from several CCS studies, including the one reviewed in details in Table 1 to obtain ranges for f_{op} and f_{cap} shown in Table Supplementary Table 3. The ranges used in Figure 2 cover the min and max reported f_{op} and f_{cap}. The f_{cap} in Supplementary Table 3 is approximately estimated as $f_{cap} = \frac{(CCS_{cost} - Conventional_{cost})}{Conventional_{cost}}(1 - f_{op})$ in the absence of the detailed data used in Table 1 for all cases but the wide range coverage negates any potential shortcoming of this assumption since the range well encompasses the values of Table 1.

EROEI of fuels and thermal electricity generation systems

In order to evaluate their relative performance, this section reviews the EROEI of the fossil options (IGCC, PC, and NGCC) together with the EROEI of dispatchable scalable RE. The EROEI of the fuel is reported separately and we denote that with the suffix *th*. The $EROEI_{el}$, referring to the electricity output, additionally accounts for the conversion efficiency (η), the power-plant invested energy (E_{cap}) and the operations and maintenance expenses ($E_{O\&M}$). There is significant divergence in the literature reported $EROEI_{th}$ for fuels. Using a monetary basis for the calculation, Freise estimates the Canadian conventional natural gas $EROEI_{th}$ in 2009 as 20 from a peak of around 80 in 1970s[62]. A more detailed material analysis estimated the average $EROEI_{th}$ of tight gas wells drilled in Indiana in the period between 1985 and 2003 at 87[63]. On the other hand, a study of the combined oil and gas sector estimated a current EROEI of 11 for Canada[64] and around 10 for China[65]. Since both these studies report the combined sectors, we do not lower the EROEI range for gas below 20. The most recent estimates for coal $EROEI_{th}$ range from 23 to 58[66] while for China coal EROEI at 24 falls on the lower end of the range[65]. We use these values as $EROEI_{th}$ ranges for completing the comparative Figure 4. The general trend is that resource depletion increases the energy intensity of the extraction processes and the fuel's EROEI deteriorates.

Figure 1 shows a schematic fossil-fuel fired coal/biomass plant along with a CCS option. This arrangement shows the corresponding energy flows and the EROEI estimation after accounting for the process energy penalty flows. Eq. S1 shows the conventional EROEI estimate. The energetic cost of the power-plant infrastructure is a product of the installed capacity (*P*) and the unit energy intensity (*ε*) or embodied energy of capital per installed unit of power. Operation and maintenance ($E_{O\&M}$) is referenced as a share ($s_{O\&M}$) of the investment cost. Over its lifetime, the powerplant will generate electrical energy E_{el} and will consume fuel with a thermal energy content E_{th} as shown in Eq. 2. From the EROEI definition the fuel procurement energy (E_f) is calculated by dividing the thermal energy content (E_{th}) of the fuel used with its $EROEI_{th}$. Expanding Eq. 1 with Eq. 2 provides the relationship of $EROEI_{el}$ to cycle efficiency (*η*), plant-lifetime (*L*), and capacity factor (*cf*) that becomes independent of capacity (*P*) (see Eq. 3).

$$E_{out} = P\,cf\,L, and\ E_{th} = \frac{P\,cf\,L}{\eta} \qquad \text{Eq. 2}$$

$$EROEI_{el} = \frac{P\,cf\,L}{P\,\varepsilon\,(1+L\,s_{O\&M}) + P\,cf\frac{L}{\eta\,EROEI_{th}}} = \frac{cf\,L}{\varepsilon\,(1+L\,s_{O\&M}) + cf\frac{L}{\eta\,EROEI_{th}}} \qquad \text{Eq. 3}$$

Using Eq. S1 to include the CCS process leads to Eq. S4. The re-purposed energy flows that were previously available as an output are subtracted from the numerator (energy out) while the additional capital and operating investments for the CCS plants are added to the denominator. We can then divide Eq. 4 and Eq. 1, generalizing, for a given capture ratio (*CR*) and assuming the same fuel input we can derive Eq. 5. Defining the reference ratio of fuel to capital and non-fuel operating energetic costs of the conventional plant as R, we can simplify Eq. 5 to Eq. 6.

$$EROEI_{CCS} = \frac{E_{el}\,[1-f_{op}(CR)]}{E_{cap}(1+f_{CAP}) + E_{CCS\,O\&M} + E_f} = \frac{E_{el}\,[1-f_{op}(CR)]}{E_{cap}(1+f_{CAP})(1+Ls_{O\&M}) + E_f} \qquad \text{Eq. 4}$$

$$EROEI_{CCS} = [1-f_{op}(CR)]\frac{E_{cap}(1+Ls) + E_f}{E_{cap}(1+f_{cap})(1+Ls_{O\&M}) + E_f}EROEI_{el} \qquad \text{Eq. 5}$$

$$EROEI_{CCS} = [1-f_{op}(CR)]\frac{R+1}{R+1+f_{cap}}EROEI_{el},\ R = \frac{E_f}{E_{cap}(1+Ls_{O\&M})} \qquad \text{Eq. 6}$$

From Eq. S2 and Eq. S6 we can therefore determine the primary drivers for the $EROEI_{CCS}$ processes and their relationship to conventional. Expectedly, the $EROEI_{CCS}$ is higher when the conventional process has a high $EROEI_{el}$. High capacity factors, long asset life, low O&M costs and especially a high $EROEI_{th}$ are positively contributing factors. If the capital and operating energy expenses increase as a result of less favorable injection locations, then they would negatively impact the CCS EROEI. Finally, lower capture ratios, decrease both the operational and capital penalties at the expense of more atmospheric carbon release and higher unit carbon costs as shown in Supplementary Figure 1. Table 1 also provides the detailed estimation of the $EROEI_{el}$ of six simulated conventional and CCS cases demonstrating that Eq.1 and Eq. 6 are fully compatible. Since both $EROEI_{el}$ and R depend on the capacity factor (graphically shown in Supplementary Figure 2 for the USA), we use these relationships to estimate $EROEI_{CCS}$ for a continuous capacity factor range from 55% to 85% in line with Supplementary Figure 2 and populate the CCS shaded regions in Figure 4.

EROEI of Dispatchable RE

In order to compare fossils and renewables on an equal basis for high RE adoption rates, we should account for the use of energy storage systems that can make them fully dispatchable[45]. Prior work developed an equation that provided an upper limit on the EROEI of the combined RE and storage system[46]. It assumed that storage is fully utilized to its lifetime limit and that there is no curtailment. We extend it to relax these assumptions. We use the concept of energy-stored-on-energy-invested (ESOI), for a storage fraction (φ) and storage cycle efficiency (η), and curtailment ratio (k), to estimate the EROEI of the combined generation plus storage system using Eq. 7[46]. ESOI is defined as the ratio of energy stored under *full* utilization (i.e. exhaustion of designed cycles) of the storage system over the energy invested in its construction[67] which is shown in Eq. 7 where ε is the embodied energy as above.

$$ESOI = \frac{C\lambda_c\eta D}{C\varepsilon} = \frac{\lambda_c\eta D}{\varepsilon}\left[\frac{kWh_e\ stored}{kWh_e\ embodied}\right] \qquad \text{Eq. 7}$$

The ESOI for storage systems depends on the number of capacity cycles (λ_c), the storage efficiency (η) and the depth of discharge (D). Storage systems that are designed for medium or longer term (weeks to months) storage like

PHS, CAES and P2X demonstrate a large energy capacity to power ratio. Unlike short- and medium-term storage that could be utilized over several hundred cycles a year, reversible P2X system cycles may see fewer than 5 storage capacity cycles per year. This creates the impression of under-utilization, but these systems comprise of energetically expensive power converters, i.e. power-limited charge/discharge systems with a relatively shorter lifetime (e.g. electrolyzer and fuel-cell stacks) and a storage system (at this scales caverns and large tanks) exhibiting strong economies of scale and long lifetimes. As a result, the actual capacity/volume of energy storage is not the limiting parameter in estimating net energy performance but rather the charge/discharge power and power cycles (λ_p). To represent this, we separate the embodied energy of the power system (ε_p) from the storage system (ε_s), a distinction that is not relevant for solid batteries (in which case we consider that $\varepsilon_s = 0$) but can become significant for systems that utilize liquids, gases or chemicals for storage modifying ESOI as in Eq. 8.

$$ESOI = \frac{C\lambda_c\eta D}{P\varepsilon_p + C\varepsilon_s} = \frac{P\lambda_p\eta D}{P\varepsilon_p(1+\frac{C\varepsilon_s}{P\varepsilon_p})} = \frac{\lambda_p\eta D}{\varepsilon_p u}\left[\frac{kWh_e\ stored}{kWh_e\ embodied}\right],\quad u = \frac{C}{P}\frac{\varepsilon_s}{\varepsilon_p} + 1 \qquad \text{Eq. 8}$$

Eq. 9 represents the total EROEI of the dispatchable sRE system. We allow a portfolio of energy generation (i) and energy storage (j) types.

$$EROEI_{disp} = \frac{E_{out} - \sum_j (1-\eta_j)\varphi_j E_{out} - cE_{out}}{\sum_i E_{in\_i} + \sum_j E_{in\_j}}\ \forall\, i,j \qquad \text{Eq. 9}$$

Substituting from the definition of EROEI (Eq. 1) and ESOI (Eq. 8) weighted by their fractional contribution (α), we get Eq. 10 which simplifies to 11. For a single sRE system and storage system combination that is fully utilized without curtailment Eq. 11 becomes equivalent to the previously developed Eq. 12[67]. We note that ESOI is independent of the storage fraction and curtailment but is dependent on the roundtrip efficiency.

$$EROEI_{disp} = \frac{E_{out}[1 - \sum_j (1-\eta_j)\varphi_j - k]}{\sum_i \frac{E_{out}\alpha_i}{EROEI_i} + \sum_j \frac{E_{out}\eta_j\varphi_j}{ESOI_j}}\ \forall\, i,j \qquad \text{Eq. 10}$$

$$EROEI_{disp} = \frac{1 - \sum_j (1-\eta_j)\varphi_j - k}{\sum_i \frac{\alpha_i}{EROEI_i} + \sum_j \frac{\eta_j\varphi_j}{ESOI_j}}\ \forall\, i,j \qquad \text{Eq. 11}$$

$$EROEI_{disp} = \frac{1 - \varphi + \eta\varphi}{\frac{1}{EROEI_{el}} + \frac{\eta\varphi}{ESOI}} \qquad \text{Eq. 12}$$

This approach is agnostic to the storage medium and can work equally well for batteries, thermal storage, pumped-hydro, and their combinations. Since it assumes electricity to electricity conversions, it satisfies all other ancillary balancing requirements. In practice as sRE become adopted the systems will progressively evolve. At the current low sRE penetration (<30% of total supply), there is limited to no need for storage and the network can accept the sRE without additional configuration[48]. SRE in this case are simply handled as negative loads (they subtract from the load curve) and the system operates by using existing flexible load followers (hydro and gas turbines) essentially reducing the fuel use of these resources. Some limited curtailment during very high SRE events becomes acceptable (<2%). Utilization of conventional generation is reduced. As penetration increases to 30-80%, storage dedicated to equalizing the sRE supply intra-day and up to a week becomes necessary. This role would be filled by batteries along with PHS and thermal storage depending on which storage type is conducive for the system's location and morphology. The "long-gaps" and load peaks that do not coincide with VRE supply would be filled by conventional generation at low utilization factors (which also implies low $EROEI_{el}$ for them, cf. Eq. S3). Given the lower fuel demand, biofuels like bio-gas could also cover a sizable part of this demand. For systems where RE exceeds 80% and up to 100%, peak generation will need to be supplied from a combination of biofuels and P2H or P2X storage.

One such reversible P2X proposal envisions a two-tank, closed loop system that circulates carbon as the carrier molecule through a reversible solid oxide fuel cell. In charging mode, stored CO_2 and water are processed through fuel cell stacks with electricity input to generate a mix of methane, hydrogen and carbon monoxide that is stored under pressure. The reverse process takes place in discharging mode with electricity as output estimating a 70% round-trip efficiency at intermediate cell temperatures (680°C)[68]. A similar open cycle process using ammonia as the hydrogen carrier would also have low storage costs would require nitrogen air separation and a single reservoir.

A detailed analysis of different levels of RE penetration is system and context specific. The ESOEI of different options is practically bimodal with batteries exhibiting low values, while pumped-hydro and compressed-air high values[46]. We use the values reported by Pellow et al. (Table 2 in ref.[69]). Since these were estimated with the embodied energy transformed into electric – we revise them to be consistent with our use of primary energy in the EROEI/ESOI denominator by multiplying by 0.3 - the same factor used by Pellow et al.. For P2H we use their estimate for large-scale cavern storage at 78 (Section 4.3 in the citation). The resultant ESOI values we use are Batteries 11, P2H 24, PHS 249.

In order to investigate the effect of combinations of sRE supply and storage types at very high sRE penetrations, we would need the supply shares and storage fractions by storage technology to apply Eq. S11. We provide an example system-level $EROEI_{disp}$ scenario shown in Supplementary Table 5 based on the detailed values estimated from a global model of 100% sRE deployment that utilizes hourly resolution and includes storage and regional trade[49]. In this configuration the system EROEIdisp reaches a respectable 21.9 illustrated in Fig. 4 for comparison. A broader more detailed analysis of storage combinations in 100% sRE configurations is suggested as an avenue for future exploration.

Finally, in order to provide some detail on the overlap between the $EROEI_{sRE}$ and $EROEI_{CCS}$ in Figure 4, Supplementary Table 4 shows the min $EROEI_{el}$ for sRE and the storage fraction it can accommodate (if any). In addition, the table shows the $EROEI_{el}$ for sRE that can match the CCS powerplant performance while still achieving the max storage fraction (up to 35%) and at what $EROEI_{el}$ it can be achieved in order to match the max and mid $EROEI_{th}$ of the range of each CCS option.

Data Availability Statement

All data used in this analysis were based on published studies that are duly referenced in the text and the related tables. Any assumptions, adjustments and normalizations are described in the captions or the text. The annotated code used to run the analysis and develop the figures can be openly accessed on Github (http://nbviewer.jupyter.org/github/csaladenes/sustainable-energy-transitions/blob/master/ccs/eroei-ccs-workbook.ipynb). The corresponding author will make available any additional information upon reasonable request.

Competing interests

- The authors declare no financial and non-financial competing interests.

Author contributions

- SS conceived of the research idea, conducted the initial analysis, collected data and authored the majority of the text. MD authored parts of the text, reviewed the analysis, proposed changes, contributed to data collection. DC developed the sensitivity analysis models, the code for the figures, checked and contributed to the analysis. UB reviewed and edited the manuscript and contributed parts of the text. MC reviewed and edited the manuscripte and proposed changes for its organization and structure.
- The corresponding author for any questions, comments and request for materials is Sgouris Sgouridis (Sgouris.sgouridis@ku.ac.ae, sgouris@alum.mit.edu).

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