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Supplement of

GCAM-CDR v1.0: enhancing the representation of carbon dioxide removal technologies and policies in an integrated assessment model

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Supplemental Information

This Supplemental Information for "GCAM-CDR 1.0: Enhancing the Representation of Carbon Dioxide Removal in an Integrated Assessment Model" covers technical details of the new CDR technologies included in GCAM-CDR 1.0. Variants on these technologies, using different parameters and/or different inputs, can be added to the model fairly easily.

A Note on Implementation of Negative Emissions in GCAM-CDR

Like GCAM 5.4, GCAM-CDR calculates positive and negative emissions by tracking the carbon content of each technology's inputs and outputs. If the outputs of a technology (e.g., electricity) contain less carbon than its inputs (e.g., coal), then the difference is reported as emitted carbon, unless that carbon is captured and sequestered. If the outputs of a technology contain more carbon than its inputs, however, the difference is reported as negative emissions. In GCAM-CDR, all of the newly introduced CDR technologies consume an abstract input called "atmospheric CO_2" in the regional CDR sector, downstream from the technologies described below. The "atmospheric CO_2" input has a carbon coefficient of –1, and the output ("CDR_regional") has a carbon coefficient of 0, so that the model perceives the technology as creating negative emissions. This approach differs slightly from the one used in GCAM 5.4 to model negative emissions in its DAC technologies.

Technology Descriptions

This section describes the various CDR technologies introduced as part of GCAM-CDR, including the parameterization for each technology. Parameters are typically given in gigajoules (GJ) or metric tons (t) per gross metric ton of carbon dioxide (tCO_2) sequestered. Costs are adjusted to 2020 US dollars, although costs in the XML inputs to the model are given in 1975 dollars, as is customary in GCAM. See the "Note about Costs" at the end of this description for an important discussion of the technology costs implied by these parameterizations.

Table S1. Energy input-output coefficients for various CDR technologies. Bold-faced values are the default values in GCAM-CDR 1.0. Bracketed ranges indicate the range given in the reference(s) on which the input-output coefficients are based, as shown in Figures S1–S4.

Technology	Electricity (GJ/tCO_2)	Heat (GJ/tCO_2)
High-heat DAC (solvent)	**1.32** [1.32–1.8]	**5.2** [5.2–8.1]
Low-heat DAC (sorbent)	**0.7** [0.7–1.1]	**4.3** [4.3–7.2]
Terrestrial enhanced weathering	**1.5** [0.23–10]	N/A
Ocean liming	**0.97** [0.1–1.25]	**2.87** [0.62–5.61]

Direct Air Capture

GCAM-CDR includes two kinds of DAC, as described in Sect. 2.3.1 and 2.3.2 of the main text. Both are parameterized based on work by Realmonte et al. (2019), which is consistent with other published literature on these technologies. Note that we have chosen to use the lower estimates from Realmonte et al. (2019), reflecting an assumption that technological improvements between the time of their analysis of the time of deployment in the model will make the lower estimates a more reasonable prediction. Users can easily adjust those parameters to reflect lesser (or greater) levels of optimism.

Note that because the negative emissions for all new CDR technologies in GCAM-CDR are modeled downstream, in the regional CDR sector, both DAC technologies consume a dummy good (labeled "solvent" or "sorbent" but not reflecting any meaningful properties of those inputs in the real world) with a carbon coefficient of 1. Because that carbon is immediately sequestered, the model does not count it as emitted carbon or a negative emission. It is included to force the DAC technologies to internalize the endogenously calculated cost of carbon sequestration and to accurately track the amount of carbon that DAC technologies inject into geological reservoirs.

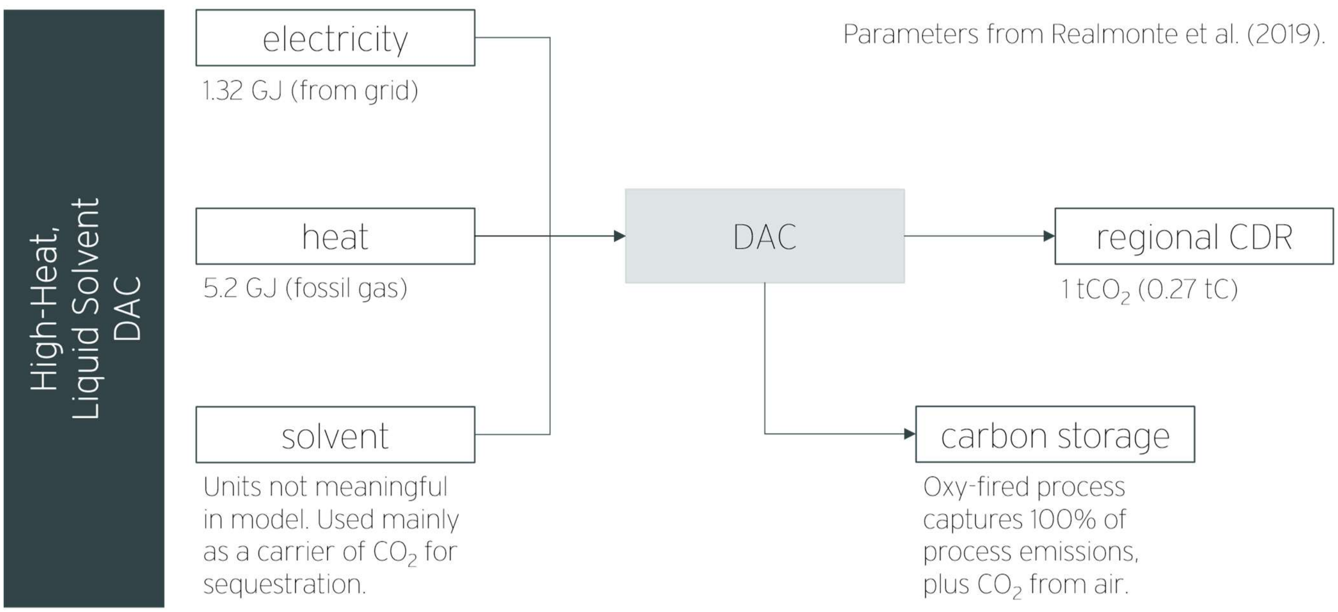

Figure S1. A diagram of the high-heat, liquid solvent-based DAC technology included in GCAM-CDR 1.0.

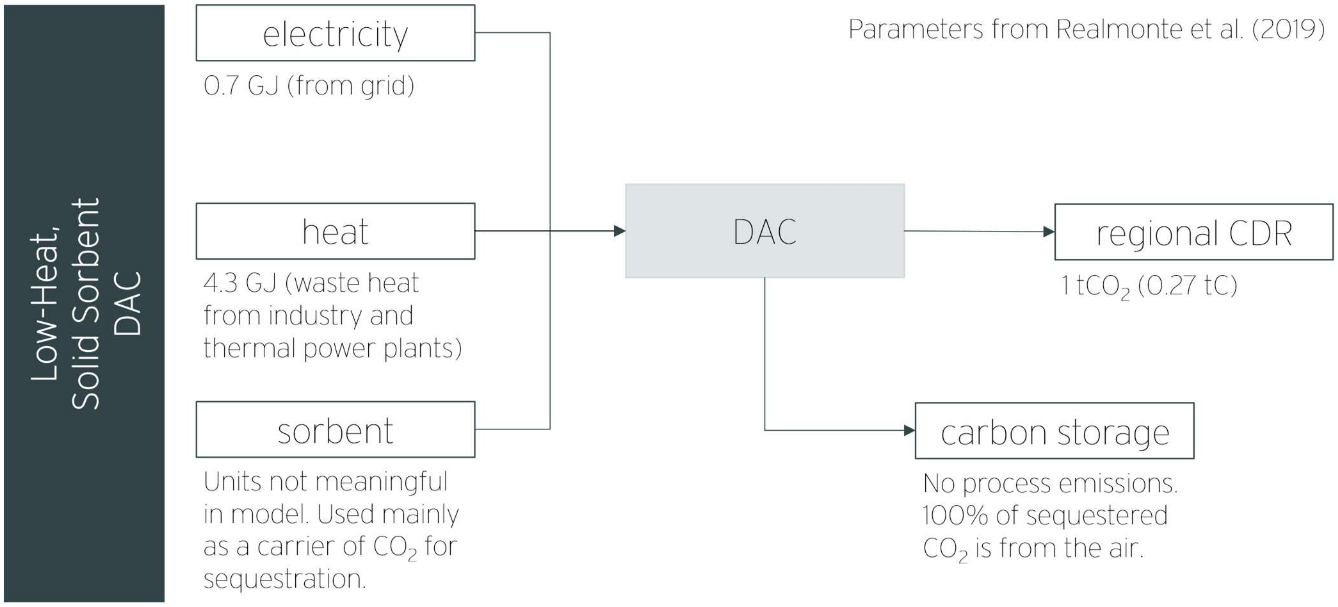

Figure S2. A diagram of the low-heat, solid sorbent-based DAC technology included in GCAM-CDR 1.0.

The quantity and cost of waste heat for solid sorbent DAC is modeled endogenously as a fractional secondary output of other processes in GCAM, such as electricity production. The waste heat output coefficients for each technology were estimated by calculating the difference in energy content between the inputs and outputs, and assuming that no more than 50% of that energy loss was recoverable as waste heat. The price of waste heat was calibrated to ensure that the cost of solid sorbent DAC would fall within the same ballpark as liquid solvent DAC, in keeping with independent cost estimates of the two technologies. Refining both the coefficients and costs may be a fruitful avenue for future research.

Terrestrial Enhanced Weathering

GCAM-CDR 1.0 includes one approach to terrestrial enhanced weathering (basalt application to cropland), as described in Sect. 2.3.3 of the main text. Parameters are based on work by Strefler et al. (2018).

Note that the "cropland" input (called "cropland_TEW" in model input files) is an abstract, finite, renewable resource that represents cropland available for basalt application. The maximum quantity available in a region is exogenously specified based on GCAM's reported cropland in each region in 2020. An upward-sloping supply curve for the resource represents the assumption that basalt will be applied to the most easily accessible croplands first, with additional application becoming increasingly more expensive because of the need to transport basalt to more distant or inaccessible areas.

The parameterization here assumes a grain size of 10 μm, which falls within the ranges examined by Strefler et al. (2018), and Beerling et al. (2020). Exploration of variations with different grain sizes may prove a fruitful avenue for future research, but experiments with smaller grain sizes during model development found them to be uncompetitive with other forms of CDR because of the higher energy requirements. Furthermore, smaller grain sizes increase the health risks associated with producing and spreading the silicate, providing additional reasons to explore larger grain sizes rather than smaller ones.

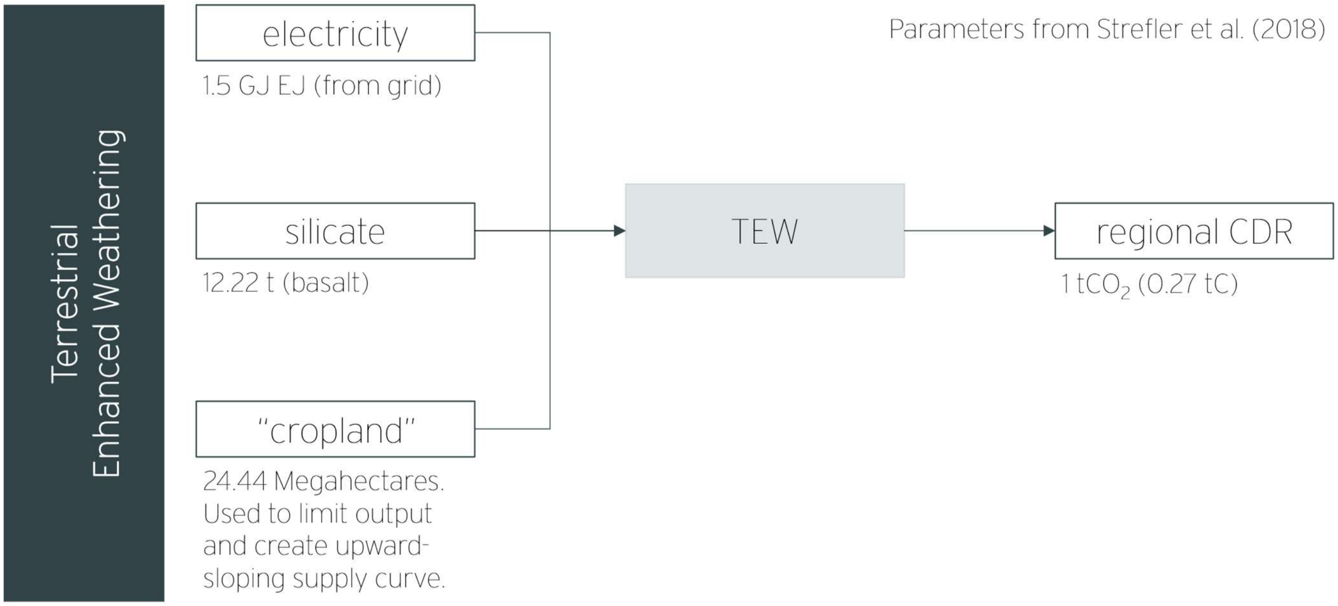

Figure S3. A diagram of the terrestrial enhanced weathering (TEW) technology included in GCAM-CDR 1.0.

Ocean Enhanced Weathering

GCAM-CDR includes one technology for ocean-based enhanced weathering (ocean liming), as described in Sect. 2.3.4 of the main text. Parameters for this technology are based mainly on the oxy-flash calcination process described by Renforth et al. (2013). This approach to lime production captures the process emissions from both combustion of natural gas and calcination of limestone simultaneously. Because we include shipping as a separate input from lime production, the input-output coefficients for electricity and natural gas shown in Figure S4 are slightly lower than the final electricity and thermal energy coefficients indicated in the Supplemental Information for Renforth et al. (2013), which include energy requirements for port operations and shipping.

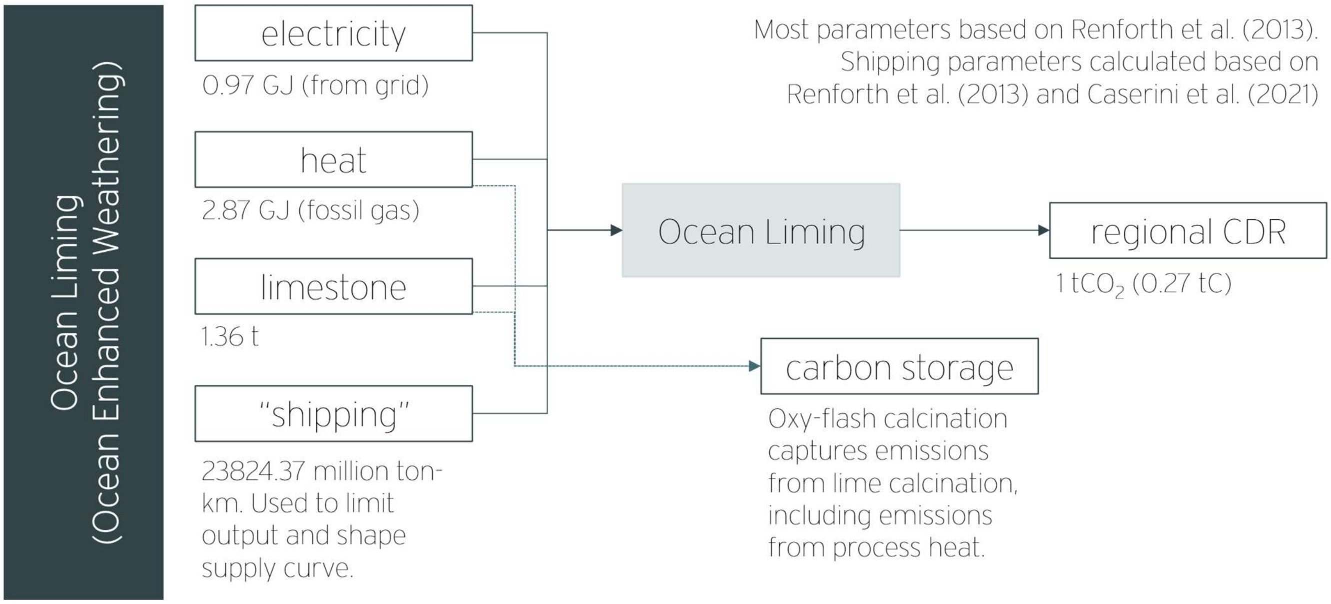

Figure S4. A diagram of the ocean liming technology included in GCAM-CDR 1.0.

GCAM-CDR 1.0 assumes that ocean liming is conducted using cargo ships, rather than a dedicated fleet of ocean liming vessels, and that this creates a potentially binding constraint on global capacity for ocean liming. To capture this constraint, we model ocean liming as requiring an abstract good, "OEW-shipping," that is produced as a byproduct of international maritime freight. GCAM measures maritime freight in million ton-kilometers and calculates the price per ton-km. The key exogenous parameters, for our purposes, are the number of ton-kms per ton of CDR and the maximum percentage of maritime freight that could be devoted to OEW.

We calculate the first parameter in two independent ways: bottom-up, using estimates from Renforth et al. (2013), and top-down, using estimates from Caserini et al. (2021). Caserini et al. estimate that bulk and container cargo ships could devote 13% of their tonnage to OEW, and that if all bulk and container cargo ships did so, they could deliver 1,700–4,000 Mt of lime into the ocean each year, depending on whether they stop to load more lime mid-route. Bulk and container cargo ships provide approximately 72% of maritime freight by ton-km (UN Conference on Trade and Development, 2020), implying that it would take approximately 9.36% of total global maritime freight capacity to release 1,700 Mt of lime into the ocean each year. GCAM estimates global shipping volume at 119,203,204 million ton-km annually in 2020, implying a rate of 6,563 million ton-km per Mt of lime released. At a rate of 3.63 Mt of slaked lime per MtC removed—as calculated by Renforth et al. (2013)—this implies a coefficient of 23,824.37 million ton-km per MtC removed. This is within 2% of our bottom-up estimate calculated based on parameters from Renforth et al. (2013). Strictly speaking, this is an overestimate of the number of ton-kms that would be needed, as the tonnage of slaked lime that needs to be moved would decline linearly during transit as it is dumped into the sea. As the purpose of this model input is to capture the way in which shipping *capacity* acts as a constraint on ocean liming, rather than just an additional cost to be born, we ignore this complication.

The second key parameter is the total fraction of maritime shipping that could be devoted to OEW. Here we follow Caserini et al. (2021) and impose an upper limit of 13%, but in interpreting this number, it is important to note two things. First, Caserini et al. (2021) assume that ships carry both lime and other cargo. Second, many cargo ships, especially bulk cargo ships, frequently sail empty because the countries that export bulk cargo, such as iron ore or wheat, tend not to import bulk cargo (Brancaccio et al., 2017). Thus, this number does not imply that 13% of other maritime freight would have been displaced. The estimates from Caserini et al. (2021) align reasonably well with earlier estimates from Köhler et al. (2013) that global shipping capacity in 2007 was sufficient to deliver approximately 10 Gt of material into the ocean.

Another important implication of the frequent mismatch because cargo ships and available cargo is carriers often ship goods at steep discounts on routes where they would otherwise sail empty (Brancaccio et al. 2017). To capture this, we assume that the costs of shipping for ocean liming begin well below the endogenously calculated cost of maritime freight, but rise to parity with shipping of other freight as ocean liming approaches the limit of 13% of global capacity. Technically, we accomplish this by modelling the OEW-shipping good as a fractional secondary output of international shipping, with a price starting at close to zero for very low quantities and rising as it approaches the capacity limit. This is the primary motivation for modeling this input as a byproduct of international shipping, rather than using shipping as a direct input.

Finally, note that because we model the OEW-shipping placeholder good as a by-product of maritime freight, the value of that good lowers the net cost of maritime freight. In GCAM, this induces a slight increase in maritime freight, so that the growth of ocean liming causes some growth in total maritime shipping.

Users wishing to remove this constraint can do so either by excluding the relevant XML file from their scenario and/or by introducing an additional ocean liming technology that takes international shipping as a direct input, which would endogenize the cost of shipping but impose no limit on the quantity that can be used.

A Note about Costs

GCAM-CDR's projected cost per ton of CO_2 removed for each of these technologies is higher than the costs estimated in the CDR literature, which we believe is an artifact of other parts of the model. A cost decomposition analysis reveals that the higher costs are caused by the fact that GCAM assumes higher energy prices than is typical in the CDR literature, and so fidelity to energy requirements exaggerates costs. Therefore, *we recommend against relying on GCAM-CDR's estimates of the costs of any CDR technology* because the high costs result from a forced choice between underestimating energy requirements and overestimating costs (relative to the CDR literature). Costs vary by region and by year and differ across scenarios, but as an example, for the USA in 2050 in our "Accumulated" CDR scenario, GCAM-CDR gives costs of approximately \$390/tCO_2 (liquid solvent DAC), \$290/tCO_2 (solid sorbent DAC using waste heat), \$370/tCO_2 (TEW), and \$245/tCO_2 (ocean liming).

Fortunately, the fact that absolute costs for CDR are higher than in the literature turns out to have relatively little impact on model results. This is partly because those costs reflect higher energy costs elsewhere in the system and partly because the drivers of CDR demand in GCAM-CDR 1.0 are largely insensitive to price. During model development, we explored some price-sensitive limits on and drivers of demand. We experimented with a cap on total spending on CDR as a percentage of regional income, which would be sensitive to absolute costs, but it was virtually never binding because constraining the growth of CDR to reasonable rates means that by the time the CDR sector has grown enough to absorb a non-negligible fraction of regional income, regional income has grown enough that the budget constraint is no longer binding for reasonable amounts of CDR. We also experimented with allowing emitters to choose to pay for CDR rather than paying a carbon price, but for technical reasons, this proved impractical to model. (Implementing this remains an important avenue of future research, though. See the model documentation for details.)

The relative costs of CDR technologies, compared to one another with the same scenario, do affect the model results. Since CDR costs are heavily influenced by energy costs, one implication of GCAM's high energy prices is that GCAM-CDR may exaggerate the economic advantage of less energy-intensive technologies over more energy-intensive competitors.

With respect to non-energy costs, we assume that such costs fall at different rates for different CDR technologies. The rationale for this is that the component technologies are at different levels of maturity. In particular, DAC technologies are less mature than the technologies for producing and spreading lime or crushing and distributing basalt. We use the rate of decline in non-energy costs for the DAC technologies from GCAM 5.4. The other new technologies' non-energy costs decline more slowly, akin to other technologies in GCAM, such as bioenergy with CCS. Figure S5 illustrates these declines.

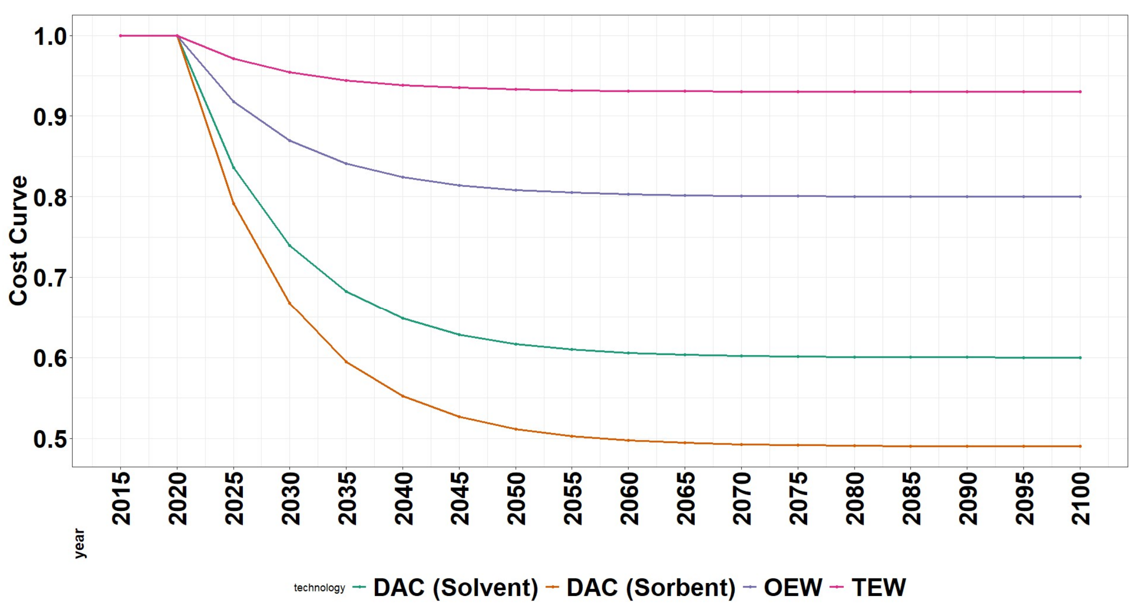

Figure S5. Assumed decline in non-energy costs of various CDR technologies in each future period as a fraction of their non-energy cost in 2020.

Constraining the Growth of CDR

In the real world, new technologies take time to grow. GCAM 5.4 includes various mechanisms that allow it to model such growth in a reasonable way for most technologies. These include having the costs of new technologies start high and gradually decline, which models the decline in costs that come from experience with a technology and general improvements in relevant technologies and processes; assigning new technologies less weight in the formula that apportions market share across technologies within a sector, which models gradual social uptake of novel technologies; and in some cases, the explicit representation of long-lived technologies, which models the gradual turnover of physical infrastructure needed to displace one technology with another. Users can also set quantity caps on technologies or sets of technologies, which GCAM implements by adjusting the price of those (sets of) technologies until that the algorithm for apportioning demand across competing technologies assigns them no more than the permitted quantity. (This follows a general principle that GCAM typically sets quantities by adjusting prices.)

The first three approaches are not suitable to constrain the growth of the CDR sector as a whole in GCAM-CDR because the CDR sector is a new, standalone sector. (Note, however, that in both GCAM 5.4 and GCAM-CDR, the growth of BECCS technologies is constrained by all of the first three approaches.) The first approach would not generally result in limits to the quantity produced because of the mechanisms by which GCAM-CDR sets demand for CDR, and at any rate, it assumes that funding is the binding constraint on the growth of CDR, which is not necessarily true. For technical reasons inside the model, the second and third approach work only in sectors in which the new technologies are competing with older technologies, enabling more established technologies to satisfy most of the demand in the sector.

In GCAM-CDR 1.0, we combine the fourth approach with the one developed by Fuhrman et al. (2019) to constrain the growth of DAC in GCAM 5.3.

Fuhrman et al. (2019) introduce an almost costless dummy technology that consumes no energy and removes no CO_2. Given GCAM's algorithm for apportioning demand between technologies in the same sector, this low-cost dummy technology initially dominates the DAC sector, so that the "real" DAC technologies supply little or no CDR. In the implementation by Fuhrman et al. (2019), which is now included as a standard option in GCAM 5.4, DAC becomes competitive with the dummy technology only when there is a sufficiently high carbon price. As the carbon price rises, the "real" DAC technologies receive increasingly large subsidies for sequestering carbon, such that they have a nominally negative cost in the model, causing GCAM to allocate more of the demand for DAC to the "real" DAC technologies.

In GCAM-CDR, we introduce an optional, expensive dummy technology that consumes no energy and removes no CO_2. We then use GCAM's quantity-capping mechanism to enable users to specify the maximum quantity of CDR achievable in each period. (Users could further refine this to set maximum quantities per technology and/or per region, but this incurs a performance penalty.) GCAM-CDR adjusts the prices of the various technologies in the CDR sector—DAC, OEW, and TEW—until they are expensive enough that the dummy technology can capture as much of the market as necessary to keep the "real" technologies from exceeding the user-specified quantity limit. This approach has the downside of causing the costs of those technologies to be unrealistically high during the period of initial growth, but internal limitations of GCAM make this the most efficient approach. Users can still extract the real costs by looking at the costs of the underlying sectors that supply those technologies.

GCAM-CDR 1.0 includes three off-the-shelf files for the constraining the growth of CDR. The central case somewhat arbitrarily assumes a growth rate of 15% per year, while the other files assume faster and slower growth, respectively. (For comparison, the 15% rate matches the average annual growth rate of installed wind capacity, globally, from 2011–2020, based on data from the International Renewable Energy Agency.) The actual growth rate remains highly uncertain, and users may wish to experiment with other growth and/or changing growth rates. For long-term scenarios, however, the growth rate usually matters less than the absolute level of demand for CDR over the long run.

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