# Global Solutions for Carbon Removal

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## Executive Summary

Carbon dioxide removal (CDR) will be an important tool in climate change mitigation. It is possible, if not likely, that active removal of carbon from the atmosphere will eventually be a necessary step in limiting global heating to acceptable levels. Nevertheless, the technological immaturity and uneven distribution of CDR resources serve as barriers to the deployment of large-scale CDR. The global nature of climate impacts will further disincentivize countries from pursuing CDR independently.

In this report, we outline measures designed to facilitate international cooperation on CDR activities and present cost-optimal CDR technology portfolios based on expected emissions trajectories and end-of-century target temperatures. Our novel approach to CDR quota allocation considers countries' responsibility for emissions and total economic ability, with relative weights determined by per-capita GDP. A global CDR trading system ensures efficient use of limited CDR resources, and optimization modeling provides cost-optimal technology portfolios for 176 countries. We find that ensuring universal access to the CDR resource base leads to optimal outcomes and that the global cost of CDR necessary to limit warming to $2^oC$ with 50% certainty is roughly \$3.9 trillion per year.


# 1 Introduction

Greenhouse gas (GHG) emission reductions alone may be insufficient in mitigating the worst impacts of climate change. Furthermore, implementation of clean technologies, while cost-effective, does nothing to reverse historical emissions. It will likely be necessary to *remove* carbon dioxide ($CO_2$) from the atmosphere in order to hit global climate targets. According to some emissions trajectories, we may need to remove hundreds or thousands of gigatons of $CO_2$ from the atmosphere before 2100 [15, 16].

How this massive undertaking should be accomplished, and by whom, is the subject of ongoing debate [8, 9, 24]. CDR incurs costs locally and distributes benefits globally, disincentivizing individual action [9]. International accord and cooperation will thus be essential if the world is to meet its climate change mitigation goals. Beyond the problem of allocating responsibility for CDR, the act of removing carbon itself will present challenges. There are a range of CDR technologies available, each with costs and biophysical limitations on total capture potential [23, 16]. Particular CDR resources are also highly location-dependent, with some countries having significantly lower or higher local potential for a given CDR technology [24]. Developing a framework for sharing available technologies to meet global CDR goals optimally will be critical to the success of this project.

In this report, we propose and justify national CDR quotas and analyze five major CDR technologies: Afforestation and Reforestation (AR), Soil Carbon Sequestration (SCS), Enhanced Weathering (EW), Bioenergy with Carbon Capture and Storage (BECCS), and Direct Air Capture (DAC). We develop global supply curves for each with country-level resolution. We then use a proprietary optimization framework to model the global CDR trading system, meeting CDR goals while minimizing cost. We present least-cost global CDR portfolios and demonstrate how these change based on technology performance assumptions and quota designs. Finally, we show that offshoring at least some CDR will likely be key to successfully meeting global climate goals.

## A Global CDR Framework

In this report, we consider carbon mitigation and removal to be an inherently global problem with a necessarily collaborative solution. Our analysis does not place special weight on the interests of any individual country. As a guiding principle, we assume that social welfare is maximized when the global costs of CDR are minimized. We therefore propose a global CDR "trading" framework resembling modern carbon markets. Countries may fill their CDR quota either by performing CDR locally or by purchasing credits from abroad. This second option is equivalent to direct investment in foreign CDR. This system ensures that global CDR resources do not go to waste, and that countries have an option to finance cost-effective CDR abroad rather than investing in less-efficient technologies locally.

We describe a model wherein quotas - based on established fairness metrics - are updated annually. Quotas will rise and fall as industrialization intensifies globally. International financing prevents over- or undershooting (nations over-filling their falling quotas, or being prevented from filling a rising quota due to geographic limitations). Note that such a system will also encourage investment (prompting economic stimulus) in countries with geographic room for CDR which their economies cannot sustain.

# 2 International Emissions Quotas

Allocating the onus of CDR internationally is easier said than done. At its core, any CDR allocation schema must promote fairness. Yet it is difficult to define a "fair" solution, let alone implement it optimally. There are three main fairness metrics that are commonly considered [24]:

- *The Responsibility Principle:* The parties culpable for climate change should be the ones responsible for its resolution. Within this metric, we must also resolve whether onus lies with those who produce or those who consume.
- *The Capability Principle:* Countries more able to contribute to climate solutions, (i.e. countries able to shoulder a greater fiscal burden) should be responsible for contributions to CDR and emissions mitigation.
- *The Equality Principle:* Every person should have equal stake in the costs and benefits of CDR. Countries with a higher population should pay more without consideration for these first metrics of fairness.

We heavily investigated, analyzed, and debated scenarios that emphasized stronger weights on responsibility or capability in delineating countries' CDR quotas. An industrialized country of modest means will bear responsibility for its emissions and will also have a deontoligical obligation to contribute to this global crisis according to its ability. Neither of these duties clearly outweighs the other; putting an exact number on these relative weights is a job for a moral philosopher and would provide fodder for an entire PhD thesis.

We do, however, push back on the notion that per-capita CDR is an appropriate means of fairly distributing carbon capture quotas. While there are benefits to CDR that may prove boons for local communities (employment opportunities are one such example) there are risks involving any large scale national financial investment; overburdening impoverished communities would cause undue and unfair strain.

This is not to say that population should not be a consideration in assigning quotas. On the contrary, in order to ensure fairness, we consider population as it relates to per-capita GDP. This is how we ensure that countries are not overburdened with CDR as they begin industrialization.

The metrics we use as proxies for fairness, capability, and equality are historical emissions, national GDP, and population size (here incorporated specifically as per-capita GDP) respectively. Because we allow foreign investments, GDP is a proper stand-in for capability: inability to fulfill CDR quotas due to geographic limitations can be overcome through investment. Historical emissions represent culpability, as it is precisely these same $CO_2$ emissions which we are forced to counteract. We selected per-capita GDP to stand in for populations' poverty rates as it

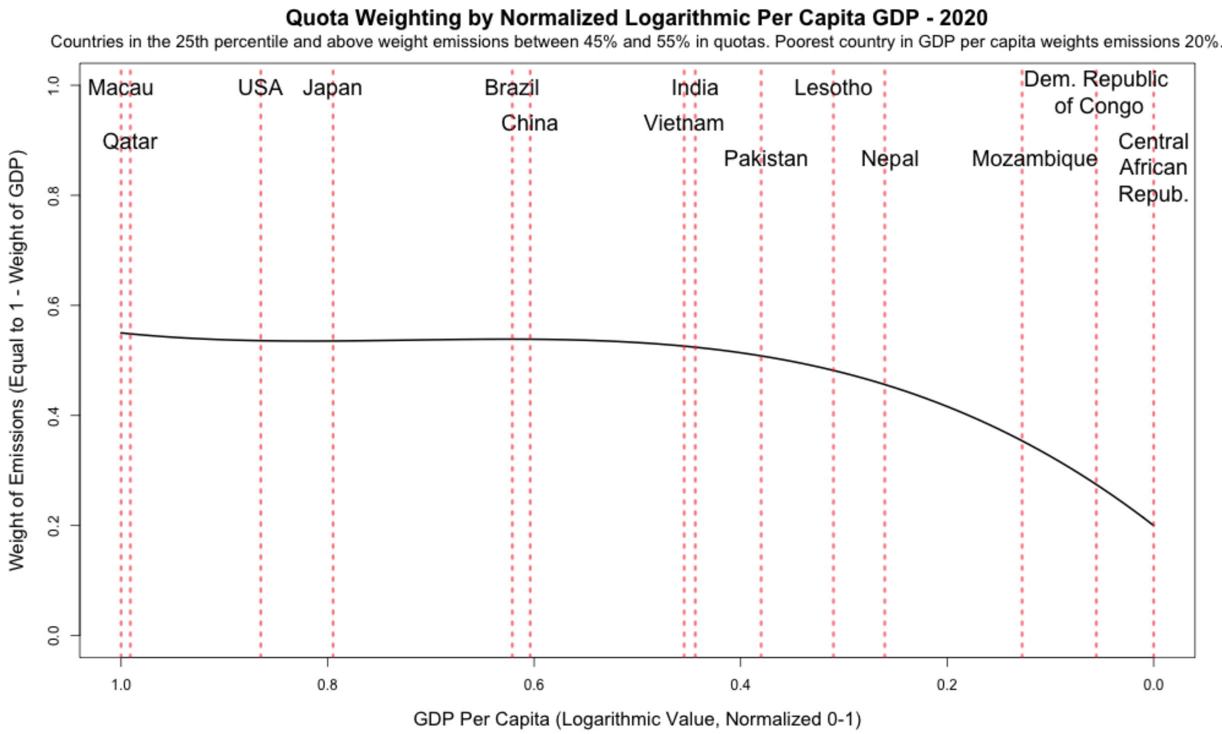


Figure 1: Relative weighting of historical emissions and GDP for CDR quota allocation as a function of GDP-per-capita.

represents the average financial standing of a nation's citizens; much other international poverty data we found (e.g. percentage of a population living under the poverty line) was too sparse to be usable.

Let $e$ represent the historical emissions of a given country $c$, normalized such that the heaviest-emitter has $e(c) = 1$ and the lightest emitter has $e(c) = 0$. Let $g$ and $p$ represent national GDP and GDP per capita, similarly normalized. We will create a fair CDR quota by weighting a vector $\alpha$ of weighting variables as follows:

$$quota(c) = \alpha_1 \cdot e(c) + \alpha_2 \cdot g(c)$$

$$\alpha_1 + \alpha_2 = 1$$

We decided that a fair solution to CDR quota allocations has the following qualities:

1. For countries in the top 75% of the range of per-capita GDP seen globally, the weight of emissions ($\alpha_1$) should be between 0.45 and 0.55. Barring extreme poverty, capability and responsibility should have similar weight.
2. For poorer per-capita countries ($p(c) < 0.25$), GDP is weighted at 0.8, emissions are weighted as 0.2.

A heavier weight is assigned to $g$ in poorer countries to ensure that impoverished and industrializing nations are not financially overburdened as they develop; their quotas will more strongly consider their GDPs regardless of their historical emissions. As GDP grows, countries' emissions will become a larger and larger portion of their CDR quota, enabling countries' development while still encouraging investment in low-carbon technologies.

We found the following formulae (see Figure 1) which met the requirements enumerated above:

$$\alpha_1(c, y) = 0.948p(c, y)^3 - 2.052p(c, y)^2 + 1.454p(c, y) + 0.2$$

$$\alpha_2(c, y) = 1 - \alpha_1(c, y)$$

$$quota(c, y) = \alpha_1 e(c, y) + \alpha_2 g(c, y)$$

Where $(c, y)$ represents a pair of a country and a year, $p$ represents a nation's per-capita GDP in a given year, $g$ represents a nation's overall GDP in a given year, and $e$ represents a nation's historical emissions up to the given year. Additionally, note that:

- Assigned quotas were normalized to form a percentage before being multiplied by our total quota.
- GDP per-capita measurements were included as their logarithmic values before being normalized when calculating $\alpha_1$ in order to compensate for the heavy skew induced by small and rich countries - predominantly oil producing and exporting (OPEC) nations. See the dotted red lines in Figure 1.

## 2.1 Quotas Over Time

These quotas will be updated every 1-5 years. If a quota decreases such that a given country has already surpassed its new quota, it can "sell" its CDR surplus so that a nation with biophysical CDR limitations can purchase credit for it. Figure 2 shows mappings of per-capita CDR responsibilities developed using this methodology for both 2020 and 2100, demonstrating how quotas can shift dynamically over time. Country-level quota values for baseline CDR goals are given in Appendix 1.

## 2.2 Net Quotas

We selected a net sequestration goal of 1400 gigatons of $CO_2$. This number considers the amount of CDR needed to be 50% confident that temperature increases are kept to within 2°C by 2100 under the global emissions pathways delineated in [15]. To allocate emissions to each country, we used baseline future emission projections from Shared Socioeconomic Pathway (SSP) 1, a set of future emissions scenarios prepared by climate scientists that anticipates some degree of climate action by countries. Each SSP contains multiple potential trajectories based on the level of warming desired; this level of warming is described by the Representative Concentration Pathway (RCP), a set amount of GHG emissions established by the IPCC [30]. We selected SSP1 under the assumption that if countries are engaging in CDR, they will also be engaging in some level of GHG mitigation measures. Depending on the RCP chosen, SSP1 future emissions levels may already have some CDR built in. To avoid "double counting" of this CDR, we selected a high warming scenario of SSP1, RCP6.0, that includes no CDR [18]. Without any additional CDR, RCP6.0 will result in about 2.8°C of warming [18]. We then took emissions trajectories of SSP1 under RCP6.0 that were downscaled to the country level [17] and adjusted these totals downward on a country-weighted basis to be in line with the 2°C compliant scenario developed by Friedlingstein *et al.* [15]. GDP and population data for future country-level projections were also obtained from [17].
As emissions trajectories and global climate trends become more clear over time, it is likely that total CDR targets will shift. The global total will be updated alongside national quota allocations every 1-5 years, and will reflect humanity's best understanding of the total CDR needed to meet climate targets.

## 2.3 Emissions Accounting: Production vs. Consumption

In a production-based model, the nation producing a good is held accountable for the emissions involved in its manufacturing. In a consumption-based model, the nation consuming the good is ultimately responsible for these emissions.

According to the *Impact = Population* · *Affluence* · *Technology* (IPAT) equation [5], affluence (amount consumed) and technology (emissions per unit consumption) are key in determining responsibility due to environmental impact. In a production-based model, we cannot account for culpability via affluence: it is the affluence of another country determining quantities of production. According to a consumption-based model, affluence is easy to ascertain (how much of the good does the country demand?). Technology is also a culpability in a consumption-based model, as consumers have the ability to vote with their wallets by purchasing from a cleaner supply chain in order to subsidize clean production mechanisms. Consumption-based accounting is thus a more just means of emissions-tracking, as its actors have more agency over their environmental impact.

# 3 Modeling CDR Deployment

Once quotas were derived, we used the Julia language [2] to create a least-cost optimization model determining how nations should meet their respective quotas. This model, dubbed "*decarb.jl*," optimizes national CDR investments to mimic an efficient global CDR trading system. We model CDR implementation from 2050 to 2100, with each country responsible for meeting its total quota by 2100. We assign costs and limitations for each form of CDR based on techno-economic analysis in all countries. Countries may meet their quotas by funding CDR locally or by making foreign direct investments to fund CDR internationally. Recognizing that self-interest will make a perfectly efficient global CDR market improbable,

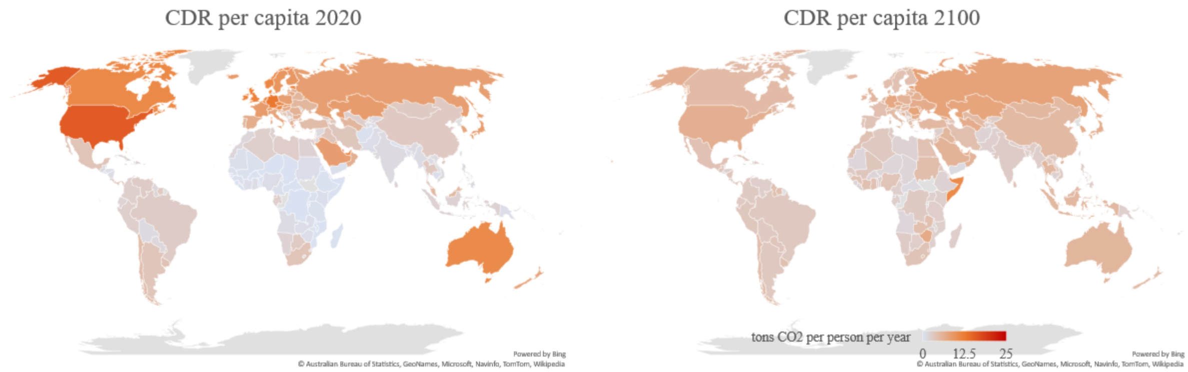


Figure 2: Maps of CDR responsibilities per capita for our reference case in the year 2020 (left), and the year 2100 (right). Both maps use the same scale, in units of tons $CO_2$ sequestered per person per year.

we include a "hurdle rate" of \$10/t$CO_2$ which biases countries toward performing CDR locally before investing abroad. This hurdle rate only serves to influence the model objective function, and is not included in any of our final reported CDR costs. Adjusting the hurdle rate allows us to assess the impact of foreign investments on global CDR costs. All CDR is modeled as an average rate over the 50 year model period. Final results are based on projected quota allocations for the year 2100. The following subsections describe the model formulation and assumptions for relevant CDR technologies.

## 3.1 Model Framework

The least-cost optimization model *decarb.jl* uses the Julia for Mathematical Programming (JuMP) [11] mathematical optimization suite. The following paragraphs provide a brief overview of the model's indices, decision variables, expressions, constraints, and objective function. The listed expressions and constraints are not exhaustive, and are meant to provide insight into the model's framework. The full model code can be found in Appendix 2.

**Indices:** A single index is used within the model, namely that of the 176 countries modeled. This index is denoted $N$.

**Decision Variables:** All primary decision variables in the model are of the form $X[i \in N, j \in N]$, and use the standard acronyms for each technology. For biofuels, $i$ represents the country where the fuel is produced and $j$ represents the country where the fuel is used for BECCS. For all other technologies, $i$ represents a country where the respective technology's CDR occurs, and $j$ represents the country funding that CDR.

**Expressions:** The following expressions are common to all technologies, except biofuels.

$eX_{in}[i] = \sum_{j \in N} X[i,j]$ – the total CDR from technology $X$ occuring in country $i$.

$eX_{by}[j] = \sum_{i \in N} X[i,j]$ – the total CDR from technology $X$ funded by country $j$.

$eX^{cost}_{outside}[j] = \sum_{i \in N, i \neq j} X[i,j] \times (pX_{Price}[i] + pHurdle)$ – the total cost of foreign CDR from technology $X$ funded by country $j$, including hurdle costs.

$eX^{cost}_{country}[j] = X[j,j] \times pX_{Price}[j] + eX^{cost}_{outside}$ – the total cost of all CDR from technology $X$ funded by country $j$.

$eX^{cost}_{total} = \sum_{j \in N} eX^{cost}_{country}[j]$ – the total global cost of CDR from technology $X$.

For biofuels, we include similar expressions for the total biofuel production of a given country ($eBF_{from}[i]$) and the total biofuel use for BECCS within a given country ($eBF_{for}[i]$). Biofuels are not subject to hurdle rates, but are subject to a 15% additional fee if imported to a country. The cost of biofuel production is assigned to the country responsible for the corresponding BECCS investment.

For geologic storage of captured $CO_2$, costs are assigned to the country responsible for the corresponding BECCS or DAC.

**Constraints:** *decarb.jl* constrains CDR in each country based on local biophysical limits of each technology. The following constraints apply to AR, EW, SCS, biofuel production, and geologic sequestration:

$eX_{in}[i] \leq pX_{Limit}[i]$ – the amount of sequestration by technology $X$ occuring in country $i$ is less than the total biophysical limit on sequestration by technology $X$ in country $i$.

The following constraint applies only to BECCS:

$eBECCS_{in}[i] \leq eBF_{for}[i]$ – total BECCS in country $i$ is no greater than the amount of biofuels produced in or imported to country $i$.

Finally, biofuel production and AR compete for land in countries where both are available. For countries where more land is available for AR than for biofuels:

$eAF_{in}[i] + \alpha/\beta \times eBF_{from}[i] \leq pAF_{Limit}[i]$ – land use from both AR and biofuels production must not exceed total land available in country $i$. $\alpha$ and $\beta$ are the land use intensities of biofuels and AR, respectively.

For countries where more land is available for biofuels than AR, a similar constraint is used:

$\beta/\alpha \times eAF_{in}[i] + eBF_{from}[i] \leq pBF_Limit[i]$.

**Objective Function:** The objective seeks to minimize total global cost for all CDR, including technology, fuel, and sequestration costs:

$$\min \left( eAF_{total}^{cost} + eSCS_{total}^{cost} + eEW_{total}^{cost} + eBECCS_{total}^{cost} + eBF_{total}^{cost} + eDAC_{total}^{cost} + eGS_{total}^{cost} \right)$$

## 3.2 CDR Technologies

We considered the following CDR technologies in this analysis: AR, EW, SCS, DAC, and BECCS. For each technology, we give an overview of the baseline assumptions made regarding costs and biophysical limits. See Table 1 for global costs and limits, and Appendix 1 for country-level CDR limits. Because CDR technologies are generally immature, there are frequently significant disagreements in the literature as to the costs and sequestration potentials of these technologies. In our model, we assume costs for the years 2050-2100. We assume more optimistic costs and limitations for technologies that are better characterized in the literature. For technologies that have not been studied at scale or with high granularity we ascribed mid-range values based on the literature. For the three "high-tech" technologies, namely EW, BECCS, and DAC, we ensured a fair comparison by isolating costs (or revenues in the case of BECCS) from electricity and fuel use and assuming consistent values for these across all technologies. We adopt a universal cost for electricity of 9.8¢/kWh From Fajardy *et al.* [12], and a cost for natural gas of \$7.54/MMBTU from the EIA's Long-Term Natural Gas Price Projections for Henry Hub [29].

There are some technologies we omit in this study. Ocean fertilization is a process wherein iron and other nutrients added to ocean waters induce carbon-removing biological activity. This technology was not considered as a resource for the model due to the significant uncertainties surrounding the impacts of ocean fertilization on ecosystems [16]. Biochar, used to increase soil sequestration capacities, was also omitted: biochar competes with BECCS for resources and is generally regarded to be more costly. While there may be cases where biochar is preferred (including situations without long-term crop availability), these differences and opportunities require more granular data and higher modeling resolution for future work [16].

### 3.2.1 Afforestation & Reforestation

Afforestation & Reforestation is among the simplest, cheapest, and most generally beneficial CDR technologies. AR either by natural forest regrowth or by active tree planting has the potential to cost-effectively sequester a significant amount of carbon over periods of 50 to 100 years, while improving local biodiversity [23].

**Sequestration Potential:** We adopt country-level annual sequestration limits from AR from a highly granular study conducted by Cook-Patton *et al.* [10]. This study assessed rates of carbon accumulation over a thirty-year period from natural forest regrowth, and concluded that most forest types see consistent accumulation for up to one hundred years. Based on this observation, and the fact that natural forest regrowth is easy to accomplish and may well start before our official start year of 2050, we adopt carbon sequestration rates by country directly from Cook-Patton *et al.*, leading to an annual sequestration potential of 8.85 Gt/yr $CO_2$. This rate assumes a total land availability of 678 Mha, an assumption which requires much of the world's marginal or unproductive farmland and grazing land be returned to

Table 1: Baseline cost and sequestration potential assumptions used in the *decarb.jl* model. For relevant technologies, costs are divided between fuel, plant, and sequestration. All costs are given in 2021 USD. *AR and biofuels compete for land in countries where both are available.

| Technology | Baseline Cost ($/t$CO_2$) | Annual Sequestration Potential (Gt/yr $CO_2$) |
|---|---|---|
| Afforestation & Reforestation | 15.13 | 8.85* |
| Soil Carbon Sequestration | 57.42 | 1.40 |
| Enhanced Weathering | 208.48 | 2.99 |
| BECCS (Plant) | 15.29 | Unlimited |
| BECCS (Biofuels) | 152.88 | 18.51* |
| DAC (Plant) | 267.73 | Unlimited |
| Geologic Sequestration (Low) | 10 | 157.39 |
| Geologic Sequestration (High) | 40 | 1106.06 |

forest. While such an assumption is ambitious, this same land may also potentially be used for biofuels. Depending on the relative economics of each, the use of one may limit the total sequestration potential of the other.

**Cost:** Our assumptions of global CDR potential from AR relies on natural forest regrowth. The only cost of this approach is the opportunity cost of land used. This land may otherwise have been used for agriculture, industry, etc. Based on a review of literature values, we assume an opportunity cost for land of $209/ha/yr [27], leading to an average cost for sequestration of $15.13/t$CO_2$.

#### 3.2.2 Soil Carbon Sequestration

Intensive use of land for agricultural purposes has the potential to dramatically reduce carbon levels in the soil, and serves as a significant source of emissions in today's world [23]. Soil Carbon Sequestration (SCS) describes the use of regenerative farming practices such as planting cover crops, using low- or no-till techniques, and leaving crop residues in the field to replenish carbon levels in depleted soils. SCS represents a low-tech option for large-scale CDR with benefits for soil chemistry and agricultural yields.

**Sequestration Potential:** Ideal practices for SCS are well understood, but there has been little large-scale testing of combinations of practices. It is unclear how efficiently carbon can be sequestered under optimal conditions. Based on a review of global sequestration potentials in Fuss *et al.* [16], we adopt a mid-range global annual sequestration potential of 3.5 Gt/yr $CO_2$. Because soil carbon becomes saturated after a period of 20 years, we adjust this rate to 1.4 Gt/yr for our 50 year model. This global potential is divided between countries in proportion to total cropland as given by the Food and Agriculture Organization of the United Nations [14].

**Cost:** The cost of SCS is uncertain due to the large number of potential practices that can be used. Given this uncertainty, we adopt a mid-range estimate from Fuss *et al.* of $57.42/t$CO_2$ [16].

#### 3.2.3 Enhanced Weathering

Enhanced Weathering (EW) describes artificial acceleration of natural weathering processes by which exposed rock reacts with air to remove carbon from the atmosphere. Minerals with appropriate chemical properties are mined and crushed down to a fine grain which is dispersed to weather over time. In this report, we focus on farmland dispersal, as it has potential benefits for soil chemistry and does not have an impact on ocean ecosystems.

**Sequestration Potential:** There is significant disagreement regarding the total sequestration potential from EW and its primary limiting factors. Potential may be limited by land or rock availability, energy requirements for grinding and transportation, or overall sequestration effectiveness per unit area seeded with crushed rock. There is uncertainty regarding rates of capture in particular. Given this uncertainty, we assume a mid-range global annual sequestration potential given by Fuss *et al.* of 3 Gt/yr $CO_2$ [16]. This global potential is divided between the modeled countries in proportion to total cropland, as is done for SCS.

**Cost:** The costs for EW were estimated in this model using the results of Strefler *et al.* [28]. Costs for EW come from mining, grinding the rocks, and transport to the field for distribution. This amounted to a low-cost estimate of $63/t$CO_2$ and a mid-cost estimate of $208/t$CO_2$, accounting for differences in weathering method, materials, and grain sizes. The highest-cost

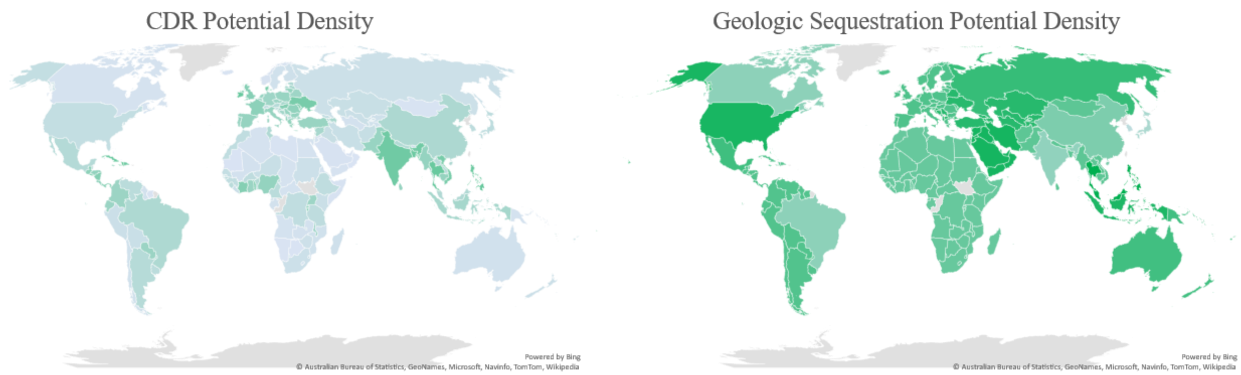


Figure 3: Potential densities (total potential divided by land area) for a combination of AR, SCS, EW, and biofuels (left), and for worst-case geologic sequestration (right). Darker colors indicated greater potential, and both maps use the same scale.

estimate of EW was pulled from Kirchofer *et al.* 's life cycle assessment on various mineral carbonation technologies [21]. While Strefler's paper assumed the EW would be decentralized such that transport distances were not significantly long distances, Kirchofer's life cycle assessment included the use of more remote fields that would be brought into use if EW were to be deployed at large scales.

#### 3.2.4 Direct Air Capture

Direct air capture has been explored significantly in CDR literature to facilitate better understanding of its potential and likely costs [3, 4, 25]. In different studies, either high-temperature (HT) processes or low-temperature processes are utilized for direct air capture. HT processes rely on increased water inputs and higher temperatures, while LT technologies are less mature and require less heat to run [4]. After conducting a literature review and cost analysis of possible electricity and fuel costs to run a DAC plant, our calculations for HT and LT costs were similar for the projected time period, assuming that LT technologies mature quickly. In this report, we define one decision variable to describe DAC costs, which could fit either HT or LT technologies. Our sensitivity analysis ensures that we are accounting for a range of DAC costs with consideration of the ceiling and floor for both HT and LT DAC.

**Potential:** Carbon sequestration from DAC is limited only by regional geologic sequestration potential. See Section 3.2.6.

**Cost:** To calculate the \$/t$CO_2$ for DAC, we adopt an estimate from Realmonte *et al.*'s recent analysis for DAC costs and assumptions. To ensure the final costs accounted for electricity and fuel costs, we used Realmonte *et al.*'s projected electricity and fuel consumption alongside projected electricity and fuel prices [25]. From our bottom-up analysis of considering the overnight capital costs, electricity consumption and cost per t$CO_2$, and fuel consumption and cost per t$CO_2$, we calculated the overall DAC \$/t$CO_2$. Various scenarios assumed different overnight capital costs, electricity consumption, and fuel consumption. From our calculations for the reference case, we assumed the capital costs translated to roughly \$194.4/t$CO_2$, electricity consumption was 1.3 GJ/t$CO_2$, and fuel consumption was 5.3 GJ/t$CO_2$. These costs and consumption led to a reference cost of DAC of \$267.73/t$CO_2$. Since DAC is a relatively immature technology in terms of scale and deployment when compared to other CDR technologies, the cost estimates fluctuate significantly in the literature from \$25/t$CO_2$ to \$1000/t$CO_2$ [16]. Thus, a sensitivity analysis of reference, high, and low DAC costs was conducted. Reference costs were \$267.73/t$CO_2$, high costs were \$644.70/t$CO_2$, and low costs were \$54/t$CO_2$.

#### 3.2.5 BECCS and Biofuels

Bioenergy with carbon capture and storage is among the most oft-cited and most thoroughly studied CDR technologies. By using biofuels to generate electricity and then capturing the resulting point source carbon stream, the $CO_2$ absorbed by the biofuel crops during growth is effectively removed from the atmosphere. BECCS can potentially provide a significant amount of CDR, though at higher cost than some low-tech options and subject to land use constraints.

**Potential:** CDR from BECCS is technically limited by total geologic storage available in the given region, but the primary limitation is land availability for biofuel production. Based on analysis in Smith *et al.*, we assume a land use efficiency from biofuel production for BECCS of 18.33 $tCO_2$/ha/yr [26]. We adopt land availability values from Cai *et al.*, who provide these values for multiple land categories. We assume that only marginally productive cropland and land with mixed crops and vegetation are available for biofuel production, so as to avoid competition with productive food resources and natural ecosystems. For countries which were excluded from the analysis in Cai *et al.*, we extrapolate biofuel land availability based on the relative proportion of total cropland (as given by the FAO [14]) to those countries that were included, generally the country's closest geographic neighbor. The total land available for biofuel production is therefore 1010 Mha worldwide. Using the sequestration efficiency given above, the global annual sequestration potential from BECCS is 18.51 Gt/yr $CO_2$. Because some land available for biofuels may alternatively be used for AR, there will be competition for land between the two technologies.

**Cost:** BECCS is a well-studied yet immature technology. Here, we use detailed cost breakdowns provided by Fajardy *et al.* to isolate the capital costs from the BECCS power plant, ongoing fuel costs, and revenues from electricity sales. The cost of the plant is \$84.04/$tCO_2$, which falls to \$15.29/$tCO_2$ after electricity revenues are considered. The cost of fuel is \$3.43/GJ, or \$152.88/$tCO_2$ when plant heat rate and capture efficiency are taken into account. We assume that this rate is paid for all biofuels produced within the country where the BECCS is occurring. Performing BECCS with imported biofuels adds a 15% surcharge to the fuel costs.

#### 3.2.6 Geologic Sequestration

When carbon is captured directly, as in BECCS and DAC, it must then be utilized or sequestered. Because industrial uses for carbon are currently limited, we focus here entirely on geologic sequestration of captured carbon.

**Potential:** The coverage of global potential by existing studies of geologic sequestration potential is sparse and the methodological differences make results difficult to compare [7]. For this report, we use a single source analyzing global storage potential with a consistent methodology. We adopt the results of Kearns *et al.*, who estimated carbon sequestration potential in deep saline aquifers globally [20]. These results include both low and high estimates for total sequestration potential, reflecting differing assumptions with respect to storage efficiency and energy requirements. The results of Kearns *et al.* are designed as inputs to MIT's EPPA model and assigned to EPPA regions. For this report, we divide the potentials given in Kearns *et al.* among the countries in each EPPA region in proportion to total landmass.

**Cost:** Though the costs of geologic sequestration are uncertain and location-dependent, several sources cite \$10/$tCO_2$ as a good estimate [12, 16]. We adopt this value for all geologic sequestration of carbon from both BECCS and DAC up until the "low" local storage potential is reached. We take into account the need to increase pumping power or drill new injection wells to make up for reduced storage efficiency at this stage by adding an additional \$10/$tCO_2$ for all sequestration between the low potential and the midpoint between the low and high potentials. Finally, we account for rapidly increasing storage costs by adding an additional \$20/$tCO_2$ for all sequestration between the midpoint potential and the high potential. The high potential serves as a hard cap on geologic sequestration in a given country.

Overall, we find that geologic sequestration potential is hardly a limiting factor. Figure 3 shows the minimum local potential for geologic sequestration in every country alongside the combined potential of AR, SCS, EW, and BECCS. Given the stark difference, DAC effectively has unlimited potential relative to the other technologies.

# 4 Projections for Optimal Global CDR Deployment

## 4.1 Costs and Distribution of CDR

Overall, we find that global carbon dioxide removal activities in the latter half of the $21^{st}$ century will likely come at a substantial but not insurmountable cost. In our reference case, which targets a 50% chance of limiting warming to $2^oC$ by the end of the century, an average of 28 Gt of $CO_2$ must be removed from the atmosphere annually between 2050 and 2100. Doing so requires a global investment of \$3.9 trillion annually over this period. This annual cost is equivalent to roughly 5% of global GDP today, or 1% of projected GDP in 2100.

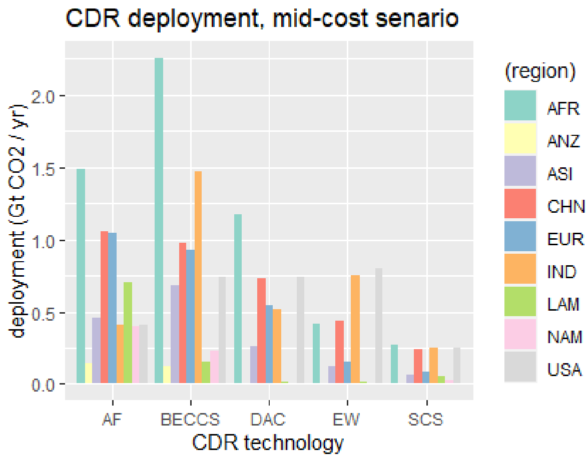


Figure 4: Total CDR deployment by technology and region in the reference case.

Looking at distribution trends, we find that CDR technologies are deployed one after the other in order of cost. AR and SCS are the most cost-effective technologies and are always deployed. These are followed by BECCS, EW, and finally DAC. As CDR quotas increase, we find that all technologies except DAC are pushed to their maximum biophysical limits everywhere in the world. Though hurdle rates incentivize countries to invest locally where possible, the high cost of DAC means that all countries will choose to make foreign investments in other technologies before investing in DAC locally. Therefore, CDR activities for non-DAC technologies are distributed around the world according to the local availability of these technologies. AR and biofuels compete for land in our model where both are available, and we find that AR wins this competition in almost all cases. While biofuels make more efficient use of the available land, potentially reducing the amount of CDR that must be contributed by more expensive technologies like DAC, the large cost gap between AR and BECCS outweighs this advantage.

Figure 4 gives the total CDR located in each EPPA region [20] for all technologies. The physical distribution is uneven, with Latin America for example being host to a disproportionate amount of AR. Nevertheless, the ability of countries to make foreign investments to secure CDR credits for themselves ensures that limited global CDR resources are used efficiently.

This efficiency can also be seen in the total cost that each country incurs in filling its CDR quota. As illustrated in Figure 5, the cost per ton of $CO_2$ sequestered is fairly consistent worldwide. Some countries with ample cheap CDR resources (e.g. Brazil) do end up paying less than the global average, but few end up paying more. Going forward, it may be prudent to include countries' cost-effective CDR potential as a factor in quota allocation.

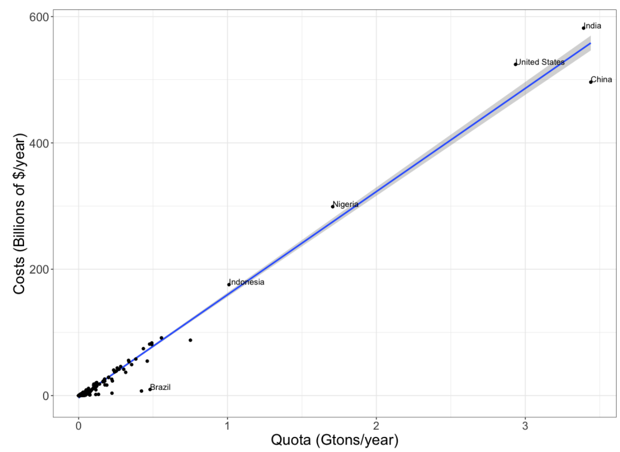


Figure 5: Scatter plot of national CDR quotas and costs for the reference case. A trend line indicates the average cost of $CO_2$ sequestration, equal to roughly $140 per ton.

## 4.2 The Impact of Quotas

Changes in the total CDR goal for the global community have a large effect on CDR cost. For an ambitious CDR goal targeting 2$^o$C of warming with a 66% chance, global removal is 34 Gt/yr $CO_2$ and costs rise to $5.6 trillion per year. Thus a ∼20% increase in annual removal leads to a ∼40% increase in cost compared to the base case. For a less ambitious scenario targeting between 2$^o$C and 3$^o$C of warming, global annual removal is 14 Gt/yr $CO_2$ at an annual cost of $0.9 trillion. Halving the CDR goal here reduces costs by more than 75%. These results, shown in Figure 6, illustrate the nonlinearly increasing costs of meeting greater global CDR quotas. This phenomenon can be ascribed to the limited availability of "cost-effective" CDR options such as AR and SCS. These technologies allow the first chunk of CDR quotas to be filled at relatively low cost. However, once the biophysical limits of these methods are reached, the marginal cost of additional CDR rises rapidly. This becomes most extreme once all non-DAC resources are exhausted, which occurs at 24-30 Gt of annual removal. After this point, any additional CDR must be accomplished by DAC at a high cost. It will be important for decision makers to consider this decreasing return on investment when setting global CDR targets.

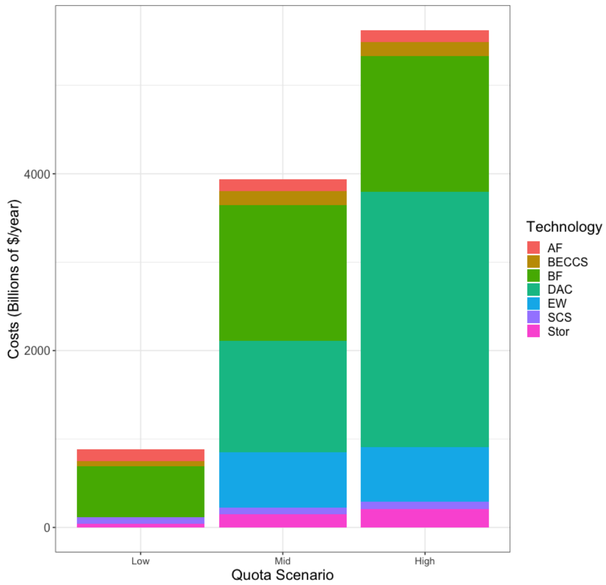


Figure 6: Global cost of CDR, broken down by category, for three quota scenarios. The columns correspond to total sequestration over 50 years of 700 Gt, 1400 Gt, and 1704 Gt of $CO_2$, respectively.

## 4.3 Sensitivity Analysis

We analyzed several alternative cases with differing technology costs and availabilities to better understand the impact of these parameters on model outcomes. The first major sensitivity we investigated was land availability, which affects all four non-DAC CDR resources. Our base-case biophysical limits assume that all marginally productive cropland, mixed crop and vegitation land, grazing land, and other nonessential deforested land is available for CDR activities. This baseline assumes a major reduction in global meat production, and may be overly ambitious. When the amount of available land for non-DAC resources is reduced by half, we find that annual CDR costs increase substantially to \$5.9 trillion. This is entirely due to an increased reliance on DAC, which is significantly more expensive than the land-constrained technologies.

With DAC cost projections subject to high variability, we also investigated how substantially higher and lower DAC costs would affect the composition of technologies built globally. For a very low DAC cost of \$54/t$CO_2$, total costs are dramatically lower. The effectively limitless capacity of DAC means that EW and BECCS are both entirely displaced, and total annual costs decrease to \$1.4 trillion. If DAC costs increase substantially to \$645/t$CO_2$, total costs in turn rise to \$5.5 trillion. One interesting phenomenon of note in this case is a switch in land-use priority between AF and BECCS. Whereas previously the cost advantage of AF made it the preferred choice, here the higher land use efficiency of BECCS reduces system cost by a greater amount by minimizing the remaining CDR that needs to be accomplished by expensive DAC.

## 4.4 Foreign Investment Rates

As noted in Section 4.1, foreign investments allow for the efficient use of unevenly distributed CDR resources. Countries with high quotas but low local CDR potential are able to meet these quotas by investing in unused CDR elsewhere. Countries with high local potential are able to use as much of this potential as they require and open up the rest to foreign investment. Figure 7 illustrates the distribution of foreign direct investments globally in the reference case. Some countries are net sources of foreign investments, while others are net sinks. In total, foreign investments in the reference case amount to \$0.6 trillion/yr, or roughly 16% of global CDR investments.

Though foreign investments make up a relatively small portion of total global investments, they are incredibly important for ensuring efficient use of CDR resources and minimizing global costs. To illustrate this, we model a scenario in which hurdle rates are extremely high, incentivizing countries to onshore as much CDR as possible. This scenario effectively eliminates foreign investments, but also forces countries to make use of expensive local resources like DAC instead of cheaper foreign CDR. The total global cost of CDR in this scenario is roughly 17% higher than in the reference case. Thus, while foreign investments make up a small portion of total investment, they have an outsized impact when it comes to reducing global CDR costs.

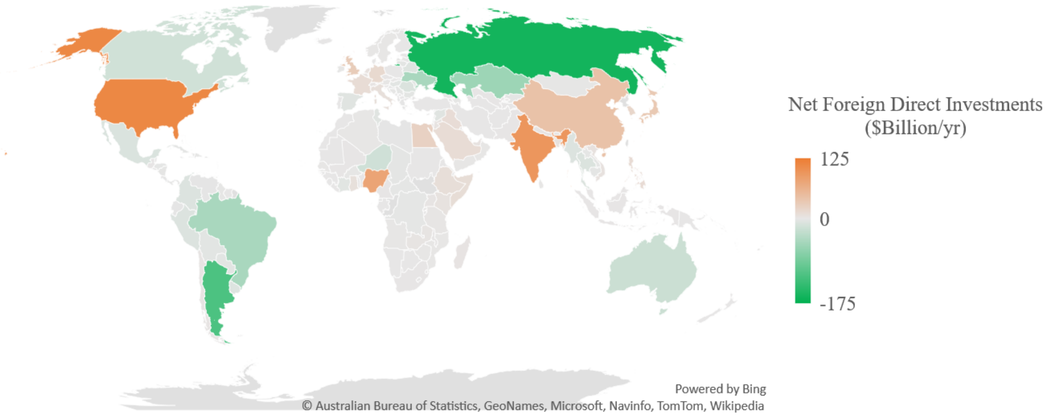


Figure 7: Sources and sinks of foreign direct investments. Countries in orange have greater total investment than local investment, while those in green have greater local investment than total investment.

# 5 Conclusion

We aimed to create a quota metric that allocated CDR responsibility fairly. When quotas are assessed in the year 2020, 42% of the onus of CDR rests on the shoulders of the United States, China, and India (19%, 17%, and 6% respectively.) Industrialized nations like Japan, Australia, Mexico, and most of the European Union are each responsible for somewhere in the ballpark of 2% of CDR: a quantity in line with their smaller size.

Our formula was built to encourage clean industrialization. Were we to overweight GDP, we would likely encourage expansion that relied on high-emitting technologies. Were we to overweigh emissions, we would encourage expansion but would likely over-penalize historic polluters, perhaps even causing CDR to outpace the economies of industrializing nations without the financial wiggle-room to bear the extra cost.

We analyzed all-GDP and all-emissions formulas to qualitatively see where major differences lay. Focusing purely on GDP, for example, takes India from paying for 6.2% of global CDR in 2020 under our formula to paying for 7.6% of global CDR, even though India is only responsible for 3.3% of emissions to date. Under our formula, Aruba pays for 0.0002% of global CDR in 2020. Under an all-emissions schema, Aruba would be responsible for 0.02%: a 100-fold increase in responsibility for a nation with a 2020 GDP only 1/5000 that of the United States. This extra cost would be an enormous burden for such a small nation.

While it is impossible to provably justify the fairness of any given metric, we are confident that our formula is more fair than either of the two strategies posited above. Furthermore, we posit that our cubic weighting system which more heavily considers GDP for countries with low GDP per capita will relieve nations with large impoverished populations from undue burden.

Our proposed global CDR trading framework is based on the principles of maximizing resource utilization efficiency and global social welfare. We constructed an optimization model mimicking this system to derive optimal CDR technology mixes under various scenarios. We found that the cost of global CDR increases nonlinearly with respect to the total CDR target, and that low-tech technologies like AR and SCS provide much more cost-effective CDR than high-tech solutions like EW, BECCS and DAC. The interface between DAC and non-DAC technologies is important when determining total system cost: DAC is likely to be the most expensive technology but the least limited. Outcomes therefore have strong sensitivity to both the cost of DAC and the availability of non-DAC resources.

Finally, we find that a system which allows CDR resources to be efficiently exploited by means of foreign direct investments delivers optimal results. Sharing CDR resources through a global marketplace reduces total costs significantly compared to scenarios where each country meets its goal independently. These results demonstrate the necessity of international cooperation in the face of the global climate crisis.

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# 6 Appendix

## 6.1 Country Quotas and Biophysical Limits

Table 2: Country quotas (based on GDP and emissions projections for 2100) and biophysical limits for various CDR methods, in units of Gt/yr $CO_2$.

| Country | Quota | AF | SCS | EW | BF | GS_min | GS_max |
|---|---|---|---|---|---|---|---|
| Afghanistan | 0.121614 | 0.00011 | 0.007246 | 0.015528 | 0.095404 | 0.750555 | 5.273203 |
| Albania | 0.004529 | 0.009809 | 0.00063 | 0.001349 | 0.007713 | 0.044891 | 0.315622 |
| Algeria | 0.123094 | 0.007759 | 0.007705 | 0.01651 | 0.074769 | 2.51244 | 17.65941 |
| Angola | 0.090106 | 0.004904 | 0.004718 | 0.010109 | 0.045781 | 1.315113 | 9.243655 |
| Argentina | 0.115924 | 0.079495 | 0.030487 | 0.06533 | 0.728307 | 3.410443 | 23.95752 |
| Armenia | 0.005473 | 0.00161 | 0.000457 | 0.000979 | 0.005597 | 0.046644 | 0.327947 |
| Aruba | 0.003561 | 0 | 1.81e-6 | 3.88e-6 | 0 | 0 | 0 |
| Australia | 0.226771 | 0.149548 | 0.027972 | 0.059939 | 0.368276 | 10.78461 | 75.83666 |
| Austria | 0.047209 | 0.007576 | 0.00126 | 0.002699 | 0.015431 | 0.105262 | 0.738923 |
| Azerbaijan | 0.027072 | 0.004429 | 0.002132 | 0.004568 | 0.026115 | 0.135415 | 0.952095 |
| Bahamas | 0.001193 | 0 | 1.09e-5 | 2.33e-5 | 8.78e-5 | 0.012474 | 0.08763 |
| Bahrain | 0.01471 | 0 | 4.16e-6 | 8.92e-6 | 5.48e-5 | 0.001412 | 0.009915 |
| Bangladesh | 0.303227 | 0.00011 | 0.007958 | 0.017053 | 0.104778 | 0.149793 | 1.052409 |
| Barbados | 0.00029 | 0 | 7.24e-6 | 1.55e-5 | 5.85e-5 | 0.000536 | 0.003764 |
| Belarus | 0.031113 | 0.030305 | 0.005265 | 0.011282 | 0.0645 | 0.332526 | 2.337964 |
| Belgium | 0.081077 | 0.003477 | 0.000797 | 0.001708 | 0.009763 | 0.038625 | 0.271141 |
| Belize | 0.000653 | 0.005636 | 0.00011 | 0.000236 | 0.000892 | 0.028426 | 0.199683 |
| Benin | 0.047664 | 0.000659 | 0.003076 | 0.006591 | 0.029848 | 0.118948 | 0.836059 |
| Bhutan | 0.002642 | 0.002306 | 9.05e-5 | 0.000194 | 0.001191 | 0.04389 | 0.308357 |
| Bolivia | 0.031288 | 0.061342 | 0 | 0 | 0.103452 | 1.350001 | 9.48342 |
| Bosnia and Herzegovina | 0.008688 | 0.011492 | 0.001014 | 0.002173 | 0.012423 | 0.083883 | 0.589775 |
| Botswana | 0.005899 | 0 | 0.000237 | 0.000508 | 0.0023 | 0.597829 | 4.202018 |
| Brazil | 0.479952 | 1.827182 | 0.057461 | 0.123131 | 1.372687 | 5.94 | 41.74 |
| Brunei Darussalam | 0.00278 | 0 | 0 | 0 | 0.000119 | 0.010638 | 0.074557 |
| Bulgaria | 0.02555 | 0.017971 | 0.003283 | 0.007035 | 0.040218 | 0.138478 | 0.972098 |
| Burkina Faso | 0.066477 | 0 | 0.005518 | 0.011825 | 0.05355 | 0.288614 | 2.028607 |
| Burundi | 0.030735 | 0.000622 | 0.001402 | 0.003005 | 0.013607 | 0.027089 | 0.190404 |
| Cambodia | 0.026287 | 0.051862 | 0.003678 | 0.007882 | 0.048428 | 0.203131 | 1.427143 |
| Cameroon | 0.076136 | 0.047031 | 0.007011 | 0.015024 | 0.068035 | 0.49865 | 3.504907 |
| Canada | 0.271112 | 0.038723 | 0.035114 | 0.075244 | 0.283868 | 6.36 | 44.72 |
| Cape Verde | 0.000873 | 0.001574 | 4.89e-5 | 0.000105 | 0.000474 | 0.004251 | 0.02988 |
| Central African Republic | 0.006871 | 0.010358 | 0.001701 | 0.003644 | 0.016504 | 0.657166 | 4.619084 |
| Chad | 0.04982 | 0.000329 | 0.004739 | 0.010154 | 0.045983 | 1.328299 | 9.336336 |
| Chile | 0.058402 | 0.02584 | 0.001498 | 0.00321 | 0.035788 | 0.926584 | 6.509025 |
| China | 3.440044 | 1.060229 | 0.122738 | 0.26301 | 2.456667 | 8.06 | 56.6 |
| Colombia | 0.133664 | 0.39367 | 0.008931 | 0.019137 | 0.213344 | 1.382651 | 9.71278 |
| Comoros | 0.003449 | 0 | 0.000105 | 0.000225 | 0.001018 | 0.001963 | 0.013798 |
| Congo | 0.014983 | 0.073859 | 0.000568 | 0.001217 | 0.005513 | 0.36024 | 2.532051 |
| Democratic Republic of the Congo | 0.461006 | 0.220588 | 0.012032 | 0.025782 | 0.116757 | 2.391455 | 16.80904 |
| Costa Rica | 0.012057 | 0.028768 | 0.000521 | 0.001116 | 0.004209 | 0.063631 | 0.446989 |
| Côte d'Ivoire | 0.11543 | 0.154928 | 0.007237 | 0.015508 | 0.07023 | 0.33545 | 2.35781 |
| Croatia | 0.009598 | 0.011639 | 0.000811 | 0.001739 | 0.009941 | 0.091688 | 0.644652 |
| Cuba | 0.014774 | 0.072834 | 0.003313 | 0.0071 | 0.026786 | 0.129355 | 0.908686 |
| Cyprus | 0.003684 | 0 | 0.000112 | 0.00024 | 0.00137 | 0.011786 | 0.082739 |
| Czech Republic | 0.076684 | 0.007064 | 0.00229 | 0.004908 | 0.028059 | 0.098483 | 0.691335 |

Table 3: Continued: country quotas (based on GDP and emissions projections for 2100) and biophysical limits for various CDR methods, in units of Gt/yr $CO_2$.

| Country | Quota | AF | SCS | EW | BF | GS_min | GS_max |
|---|---|---|---|---|---|---|---|
| Denmark | 0.038055 | 0.002379 | 0.002189 | 0.00469 | 0.026812 | 0.051024 | 0.358179 |
| Djibouti | 0.002129 | 0 | 1.81e-6 | 3.88e-6 | 1.76e-5 | 0.024452 | 0.171868 |
| Dominican Republic | 0.02312 | 0.036014 | 0.001115 | 0.002388 | 0.00901 | 0.060204 | 0.422915 |
| Ecuador | 0.046639 | 0.084912 | 0.002197 | 0.004709 | 0.052493 | 0.309504 | 2.174192 |
| Egypt | 0.435041 | 0 | 0.00347 | 0.007436 | 0.033675 | 1.050076 | 7.380762 |
| El Salvador | 0.007496 | 0.010504 | 0.000797 | 0.001708 | 0.006443 | 0.025821 | 0.181387 |
| Equatorial Guinea | 0.004812 | 0.00022 | 0.000163 | 0.000349 | 0.00158 | 0.029589 | 0.207977 |
| Eritrea | 0.018782 | 0 | 0.000626 | 0.001341 | 0.006075 | 0.127828 | 0.898479 |
| Estonia | 0.00941 | 0.007137 | 0.00063 | 0.001351 | 0.007722 | 0.05545 | 0.389251 |
| Eswatini | 0.004691 | 0 | 0.000172 | 0.000368 | 0.001668 | 0.018144 | 0.127529 |
| Ethiopia | 0.338471 | 0.073273 | 0.016196 | 0.034705 | 0.157166 | 1.190492 | 8.367716 |
| Fiji | 0.001906 | 0 | 0.000226 | 0.000485 | 0.002978 | 0.025615 | 0.180126 |
| Finland | 0.031143 | 0.000805 | 0.002035 | 0.004362 | 0.024936 | 0.38769 | 2.721533 |
| France | 0.38427 | 0.120487 | 0.017256 | 0.036978 | 0.211404 | 0.698458 | 4.903084 |
| Gabon | 0.00567 | 0.01259 | 0.000448 | 0.00096 | 0.004345 | 0.27181 | 1.910494 |
| Gambia | 0.005301 | 0 | 0.000403 | 0.000863 | 0.003907 | 0.010675 | 0.075035 |
| Georgia | 0.009725 | 0.008235 | 0.000387 | 0.000829 | 0.004741 | 0.113848 | 0.800459 |
| Germany | 0.491546 | 0.02767 | 0.010777 | 0.023094 | 0.132026 | 0.445678 | 3.128603 |
| Ghana | 0.170524 | 0.072614 | 0.004723 | 0.010121 | 0.045834 | 0.240026 | 1.687095 |
| Greece | 0.039235 | 0.041797 | 0.002914 | 0.006245 | 0.035703 | 0.164424 | 1.154231 |
| Grenada | 0 | 0 | 6.33e-6 | 1.36e-5 | 5.12e-5 | 0.000424 | 0.002976 |
| Guatemala | 0.065274 | 0.055266 | 0.00185 | 0.003964 | 0.014956 | 0.133542 | 0.9381 |
| Guinea | 0.052723 | 0.012773 | 0.003438 | 0.007366 | 0.033359 | 0.259204 | 1.82189 |
| Guinea-Bissau | 0.006174 | 0.001098 | 0.000498 | 0.001066 | 0.004828 | 0.029663 | 0.208496 |
| Guyana | 0.001613 | 0.003989 | 0.000416 | 0.000892 | 0.009941 | 0.245313 | 1.723263 |
| Haiti | 0.01982 | 0.021448 | 0.001221 | 0.002617 | 0.009873 | 0.034345 | 0.241266 |
| Honduras | 0.02219 | 0.057316 | 0.001444 | 0.003094 | 0.011672 | 0.139437 | 0.979507 |
| China, Hong Kong Special Administrative Region | 0.024297 | 0 | 0 | 0 | 0 | 0 | 0 |
| Hungary | 0.038211 | 0.007503 | 0.00406 | 0.0087 | 0.049738 | 0.11641 | 0.817185 |
| Iceland | 0.002807 | 0 | 0.000109 | 0.000235 | 0.001341 | 0.128618 | 0.902879 |
| India | 3.391639 | 0.391474 | 0.153172 | 0.328225 | 2.016667 | 1.98 | 13.94 |
| Indonesia | 1.009904 | 0.130735 | 0.046408 | 0.099446 | 0.611014 | 3.26 | 22.88 |
| Iran | 0.259224 | 0.006771 | 0.015864 | 0.033994 | 0.208864 | 2.937793 | 20.62426 |
| Iraq | 0.335529 | 0 | 0.004749 | 0.010177 | 0.062531 | 0.783036 | 5.49717 |
| Ireland | 0.038718 | 0.06599 | 0.000402 | 0.000861 | 0.004921 | 0.087875 | 0.616874 |
| Israel | 0.093946 | 0.000146 | 0.000433 | 0.000927 | 0.005698 | 0.039032 | 0.274018 |
| Italy | 0.243691 | 0.053143 | 0.008439 | 0.018085 | 0.103389 | 0.377214 | 2.64799 |
| Jamaica | 0.004069 | 0.00527 | 0.000194 | 0.000417 | 0.001572 | 0.013496 | 0.094808 |
| Japan | 0.491421 | 0.030817 | 0.003978 | 0.008524 | 0.052371 | 0.16 | 1.18 |
| Jordan | 0.058784 | 0 | 0.000261 | 0.000559 | 0.003434 | 0.160158 | 1.124359 |
| Kazakhstan | 0.117051 | 0.005051 | 0.02713 | 0.058135 | 0.357189 | 4.423026 | 31.09797 |
| Kenya | 0.201178 | 0.010358 | 0.005726 | 0.012271 | 0.055569 | 0.600372 | 4.219887 |
| Kuwait | 0.03899 | 0 | 1.27e-5 | 2.71e-5 | 0.000167 | 0.032142 | 0.225647 |
| Kyrgyzstan | 0.01297 | 0.000329 | 0.001234 | 0.002644 | 0.016246 | 0.314234 | 2.209353 |
| Lao People‘s Democratic Republic | 0.01795 | 0.045274 | 0.001555 | 0.003332 | 0.020474 | 0.265594 | 1.865991 |
| Latvia | 0.005616 | 0.009187 | 0.001201 | 0.002574 | 0.014718 | 0.079376 | 0.55721 |
| Lebanon | 0.014397 | 0.000805 | 0.000233 | 0.0005 | 0.003073 | 0.018452 | 0.129538 |
| Lesotho | 0.007771 | 0 | 0.000128 | 0.000275 | 0.001247 | 0.032026 | 0.225104 |
| Liberia | 0.022083 | 0.005344 | 0.000633 | 0.001357 | 0.006145 | 0.101606 | 0.714164 |
| Libyan Arab Jamahiriya | 0.014651 | 0.000146 | 0.001855 | 0.003974 | 0.017996 | 1.856095 | 13.04611 |
| Lithuania | 0.008083 | 0.008418 | 0.002033 | 0.004356 | 0.024902 | 0.079877 | 0.560729 |
| Luxembourg | 0.007248 | 0 | 5.75e-5 | 0.000123 | 0.000704 | 0.003284 | 0.023053 |
| China, Macao Special Administrative Region | 0.002179 | 0 | 0 | 0 | 0 | 0 | 0 |
| Madagascar | 0.102163 | 0.017422 | 0.003257 | 0.006979 | 0.031603 | 0.613726 | 4.313755 |
| Malawi | 0.081266 | 0.000586 | 0.003438 | 0.007366 | 0.033359 | 0.099454 | 0.699039 |
| Malaysia | 0.165495 | 0.001867 | 0.007496 | 0.016063 | 0.098691 | 0.663227 | 4.648165 |
| Maldives | 0.001301 | 0 | 4.89e-6 | 1.05e-5 | 6.43e-5 | 0.000421 | 0.002958 |
| Mali | 0.117897 | 0 | 0.005935 | 0.012719 | 0.057597 | 1.287148 | 9.047096 |
| Malta | 0.001346 | 0 | 9.39e-6 | 2.01e-5 | 0.000115 | 0.000408 | 0.002865 |
| Mauritania | 0.009067 | 0 | 0.000372 | 0.000797 | 0.003608 | 1.08726 | 7.642123 |
| Mauritius | 0.004424 | 0 | 7.15e-5 | 0.000153 | 0.000694 | 0.002141 | 0.015051 |
| Mexico | 0.422238 | 0.449997 | 0.020019 | 0.042898 | 0.161838 | 2.76 | 19.34 |
| Moldova | 0.007459 | 0.002306 | 0.001738 | 0.003725 | 0.021297 | 0.041949 | 0.294476 |
| Mongolia | 0.014331 | 0.006661 | 0.001207 | 0.002586 | 0.015886 | 1.792019 | 12.59025 |
| Montenegro | 0.001394 | 0.004612 | 1.36e-5 | 2.91e-5 | 0.000166 | 0.017157 | 0.120438 |
| Morocco | 0.100884 | 0.004685 | 0.007791 | 0.016694 | 0.075602 | 0.470791 | 3.30909 |
| Mozambique | 0.099442 | 0.000439 | 0.005383 | 0.011534 | 0.052233 | 0.829533 | 5.830613 |
| Myanmar | 0.076043 | 0.225602 | 0.011308 | 0.024232 | 0.148887 | 0.751096 | 5.277003 |
| Namibia | 0.007626 | 0 | 0.000733 | 0.00157 | 0.007111 | 0.868468 | 6.104282 |
| Nepal | 0.077651 | 0.018154 | 0.002104 | 0.004508 | 0.0277 | 0.16496 | 1.158968 |
| Netherlands | 0.102114 | 0.006625 | 0.000949 | 0.002033 | 0.011623 | 0.042949 | 0.301497 |
| New Zealand | 0.031122 | 0.026535 | 0.000561 | 0.001202 | 0.007385 | 0.369174 | 2.596009 |
| Nicaragua | 0.016066 | 0.07686 | 0.001619 | 0.00347 | 0.013091 | 0.149967 | 1.05348 |
| Niger | 0.101972 | 0 | 0.016119 | 0.034541 | 0.15642 | 1.336211 | 9.391945 |
| Nigeria | 1.706727 | 0.112435 | 0.036638 | 0.07851 | 0.355539 | 0.960749 | 6.752902 |
| North Macedonia | 0.005857 | 0 | 0.000416 | 0.000892 | 0.005098 | 0.041319 | 0.29051 |
| Norway | 0.039382 | 3.66e-5 | 0.000726 | 0.001557 | 0.008899 | 0.46571 | 3.26922 |

Table 4: Continued: country quotas (based on GDP and emissions projections for 2100) and biophysical limits for various CDR methods, in units of Gt/yr $CO_2$.

| Country | Quota | AF | SCS | EW | BF | GS_min | GS_max |
|---|---|---|---|---|---|---|---|
| Oman | 0.030483 | 0 | 9.99e-5 | 0.000214 | 0.001315 | 0.558245 | 3.919061 |
| Pakistan | 0.556369 | 0.002379 | 0.028315 | 0.060676 | 0.372802 | 0.887092 | 6.232474 |
| Panama | 0.014417 | 0.048458 | 0.000678 | 0.001454 | 0.005485 | 0.092443 | 0.649386 |
| Papua New Guinea | 0.022537 | 0.008528 | 0.000905 | 0.001939 | 0.011911 | 0.634933 | 4.464808 |
| Paraguay | 0.0249 | 0.110898 | 0.004364 | 0.009351 | 0.104251 | 0.495112 | 3.478042 |
| Peru | 0.075031 | 0.037808 | 0.005137 | 0.011008 | 0.122714 | 1.595127 | 11.20537 |
| Philippines | 0.316135 | 0.153171 | 0.009897 | 0.021207 | 0.130302 | 0.601901 | 4.218363 |
| Poland | 0.163502 | 0.026059 | 0.010308 | 0.022089 | 0.126285 | 0.390471 | 2.741054 |
| Portugal | 0.036083 | 0.031 | 0.001536 | 0.003292 | 0.01882 | 0.116851 | 0.82028 |
| Qatar | 0.029549 | 0 | 1.54e-5 | 3.30e-5 | 0.000202 | 0.020725 | 0.145493 |
| Romania | 0.065392 | 0.024961 | 0.008484 | 0.018179 | 0.103932 | 0.293488 | 2.060245 |
| Russia | 0.75092 | 0.2984 | 0.111671 | 0.239295 | 1.470268 | 24.68 | 173.46 |
| Rwanda | 0.040375 | 0 | 0.001268 | 0.002717 | 0.012305 | 0.026024 | 0.182916 |
| Samoa | 7.87e-5 | 0 | 5.75e-5 | 0.000123 | 0.000758 | 0.003968 | 0.027901 |
| Saudi Arabia | 0.282494 | 0 | 0.003255 | 0.006975 | 0.042854 | 3.877394 | 27.22057 |
| Senegal | 0.061134 | 0 | 0.002965 | 0.006354 | 0.028777 | 0.203095 | 1.427513 |
| Serbia | 0.021028 | 0.015152 | 0.002519 | 0.005399 | 0.030865 | 0.143289 | 1.007456 |
| Sierra Leone | 0.020429 | 0.00172 | 0.001582 | 0.00339 | 0.015354 | 0.076141 | 0.535178 |
| Singapore | 0.023999 | 0 | 5.97e-7 | 1.28e-6 | 7.86e-6 | 0.001445 | 0.01013 |
| Slovakia | 0.025168 | 0.003989 | 0.001237 | 0.00265 | 0.01515 | 0.06133 | 0.430531 |
| Slovenia | 0.00863 | 0.002891 | 0.000212 | 0.000455 | 0.002598 | 0.025686 | 0.180311 |
| Solomon Islands | 0.000793 | 3.66e-5 | 9.86e-5 | 0.000211 | 0.001298 | 0.039243 | 0.275957 |
| Somalia | 0.174713 | 0.004502 | 0.001018 | 0.002181 | 0.009876 | 0.661765 | 4.651411 |
| South Africa | 0.201416 | 0.006954 | 0.011229 | 0.024063 | 0.10897 | 1.279659 | 8.994453 |
| Republic of Korea | 0.222675 | 0.002782 | 0.00143 | 0.003065 | 0.018831 | 0.0268 | 0.215 |
| Spain | 0.176737 | 0.079019 | 0.015162 | 0.032489 | 0.185741 | 0.637247 | 4.473386 |
| Sri Lanka | 0.055767 | 0.003148 | 0.002145 | 0.004597 | 0.028247 | 0.071191 | 0.500167 |
| Sudan | 0.235387 | 0 | 0.018085 | 0.038753 | 0.175497 | 1.950711 | 13.71114 |
| Suriname | 0.002002 | 0.001281 | 6.15e-5 | 0.000132 | 0.00147 | 0.194406 | 1.365655 |
| Sweden | 0.063484 | 0.000366 | 0.002301 | 0.004931 | 0.028188 | 0.519527 | 3.64701 |
| Switzerland | 0.055565 | 0.003184 | 0.000383 | 0.000822 | 0.004697 | 0.050406 | 0.353845 |
| Syria | 0.051507 | 0.000878 | 0.005186 | 0.011114 | 0.068283 | 0.331213 | 2.325225 |
| Tajikistan | 0.015157 | 0.00011 | 0.000771 | 0.001653 | 0.010156 | 0.227385 | 1.598729 |
| Tanzania | 0.252309 | 0.048641 | 0.014158 | 0.030338 | 0.137387 | 0.934409 | 6.567762 |
| Thailand | 0.224165 | 0.213451 | 0.019278 | 0.04131 | 0.253815 | 1.031308 | 7.227822 |
| Timor-Leste | 0.013947 | 0.006515 | 0.000208 | 0.000446 | 0.002739 | 0.020849 | 0.146605 |
| Togo | 0.027977 | 0.010541 | 0.002551 | 0.005467 | 0.024756 | 0.057375 | 0.403275 |
| Trinidad and Tobago | 0.011018 | 0 | 0 | 0 | 0 | 0 | 0 |
| Tunisia | 0.02631 | 0.001061 | 0.004517 | 0.009679 | 0.043832 | 0.163885 | 1.151916 |
| Turkey | 0.356037 | 0.11917 | 0.020896 | 0.044778 | 0.275123 | 1.260915 | 8.865405 |
| Turkmenistan | 0.029328 | 0 | 0.001809 | 0.003877 | 0.023821 | 0.769905 | 5.413146 |
| Uganda | 0.241626 | 0.004319 | 0.008232 | 0.017641 | 0.079887 | 0.211524 | 1.486755 |
| Ukraine | 0.17561 | 0.051057 | 0.030556 | 0.065478 | 0.374334 | 0.949254 | 6.674137 |
| United Arab Emirates | 0.083237 | 0 | 8.18e-5 | 0.000175 | 0.001077 | 0.128099 | 0.899295 |
| United Kingdom | 0.476851 | 0.099881 | 0.005547 | 0.011886 | 0.067953 | 0.308603 | 2.166355 |
| United States | 2.934825 | 0.320579 | 0.145138 | 0.311011 | 1.173333 | 16.24 | 114.16 |
| Uruguay | 0.008099 | 0 | 0.001852 | 0.003968 | 0.044238 | 0.218109 | 1.532159 |
| Uzbekistan | 0.119371 | 0 | 0.004014 | 0.008602 | 0.052851 | 0.721779 | 5.074774 |
| Vanuatu | 0.000462 | 0.002086 | 0.000131 | 0.000281 | 0.001727 | 0.017091 | 0.120183 |
| Venezuela | 0.074097 | 0.186111 | 0 | 0 | 0.071316 | 1.099204 | 7.721638 |
| Vietnam | 0.189383 | 0.110532 | 0.010626 | 0.02277 | 0.139902 | 0.360679 | 2.534037 |
| Yemen | 0.054874 | 0 | 0.001314 | 0.002815 | 0.017294 | 0.952299 | 6.685449 |
| Zambia | 0.140532 | 0.002599 | 0.00347 | 0.007436 | 0.033675 | 0.784184 | 5.511864 |
| Zimbabwe | 0.070489 | 7.32e-5 | 0.003709 | 0.007948 | 0.035993 | 0.408079 | 2.868299 |

## 6.2 Least-Cost Model Source Code

```julia
using JuMP
using LinearAlgebra
using DataFrames
using CPLEX
using CSV

decarb = Model(CPLEX.Optimizer)

#read in list of countries, quotas, costs, potentials
countries = CSV.read("CDRdata/country.csv", DataFrame; header=true)

#a set of all countries in the model
N = countries.id

#a dummy set to help distribute CDR between countries
S = range(0,1,length=100)

#a flat hurdle rate imposed on foreign investments
pHurdle = 10
#an additional cost multiplier for imported biofuels
pImport = 0.15

#Penalties for using more than a certain amount of available storage capacity
pStor_Penalty_0 = 10
pStor_Penalty_1 = 10
pStor_Penalty_2 = 20

#a parameter limiting potential from AF, SCS and Biofuels
pLand_Efficiency = 1

countries.quota = 1*countries.quota/1e6
countries.AF = countries.AF*pLand_Efficiency/1e6
countries.EW = countries.EW*pLand_Efficiency/1e6
countries.SCS = countries.SCS*pLand_Efficiency/1e6
countries.BF = countries.BF*pLand_Efficiency/1e6


@variables(decarb, begin
    #CO2 removal from afforestation indexed by (country_in, country_by)
    vAF[N,N] >= 0

    #CO2 removal from enhanced weathering indexed by (country_in, country_by)
    vEW[N,N] >= 0

    #CO2 removal from soil carbon sequestration indexed by (country_in, country_by)
    vSCS[N,N] >= 0

    #CO2 removal from DAC indexed by (country_in, country_by)
    vDAC[N,N] >= 0

    #CO2 removal from BECCS indexed by (country_in, country_by)
    vBECCS[N,N] >= 0

    #total biofuel production indexed by (country_from, country_for)
    vBF[N,N] >= 0
end)

### AFFORESTATION ###
#Afforestation occurring in each country
@expression(decarb, eAF_in[i in N], sum(vAF[i,j] for j in N))

#Afforestation funded by each country
@expression(decarb, eAF_by[j in N], sum(vAF[i,j] for i in N))

#Afforestation in each country is limited by natural constraints
@constraint(decarb, cAF_max[i in N], eAF_in[i] <= countries.AF[i])

#small escalating penalty for using the same CDR in a single country.
#this encourages distributing CDR over all available countries if costs are equal
@variable(decarb, vAF_esc[j in N, s in S] >= 0)
@constraint(decarb, cAF_esc[j in N, s in S], vAF_esc[j,s] >= 0.001*(eAF_by[j]-s))
@expression(decarb, eAF_esc_cost[j in N], sum(vAF_esc[j,s] for s in S))

#Total cost of FDI in Afforestation by each country
@expression(decarb, eAF_outside_cost[j in N], sum(vAF[i,j]*(countries.AF_price[i]+pHurdle+0.004) for i in N if i != j))

#Total cost of afforestation funded by each country (including internal)
@expression(decarb, eAF_country_cost[j in N], vAF[j,j]*countries.AF_price[j] + eAF_outside_cost[j] + eAF_esc_cost[j])

#Total global cost from afforestation
@expression(decarb, eAF_total_cost, sum(eAF_country_cost[i] for i in N))
```

Figure 8: Source code for the *decarb.jl* model, part 1.

```julia

### ENHANCED WEATHERING ###

@expression(decarb, eEW_in[i in N], sum(vEW[i,j] for j in N))
@expression(decarb, eEW_by[j in N], sum(vEW[i,j] for i in N))
@constraint(decarb, cEW_max[i in N], eEW_in[i] <= countries.EW[i])
@variable(decarb, vEW_esc[j in N, s in S] >= 0)
@constraint(decarb, cEW_esc[j in N, s in S], vEW_esc[j,s] >= 0.001*(eEW_by[j]-s))
@expression(decarb, eEW_esc_cost[j in N], sum(vEW_esc[j,s] for s in S))
@expression(decarb, eEW_outside_cost[j in N], sum(vEW[i,j]*(countries.EW_price[i]+pHurdle+0.001) for i in N if i != j))
@expression(decarb, eEW_country_cost[j in N], vEW[j,j]*countries.EW_price[j] + eEW_outside_cost[j] + eAF_esc_cost[j])
@expression(decarb, eEW_total_cost, sum(eEW_country_cost[i] for i in N))

### SOIL CARBON SEQUESTRATION ###

@expression(decarb, eSCS_in[i in N], sum(vSCS[i,j] for j in N))
@expression(decarb, eSCS_by[j in N], sum(vSCS[i,j] for i in N))
@constraint(decarb, cSCS_max[i in N], eSCS_in[i] <= countries.SCS[i])
@variable(decarb, vSCS_esc[j in N, s in S] >= 0)
@constraint(decarb, cSCS_esc[j in N, s in S], vSCS_esc[j,s] >= 0.001*(eSCS_by[j]-s))
@expression(decarb, eSCS_esc_cost[j in N], sum(vSCS_esc[j,s] for s in S))
@expression(decarb, eSCS_outside_cost[j in N], sum(vSCS[i,j]*(countries.SCS_price[i]+pHurdle+0.003) for i in N if i != j))
@expression(decarb, eSCS_country_cost[j in N], vSCS[j,j]*countries.SCS_price[j] + eSCS_outside_cost[j] + eSCS_esc_cost[j])
@expression(decarb, eSCS_total_cost, sum(eSCS_country_cost[i] for i in N))

### DIRECT AIR CAPTURE ###

@expression(decarb, eDAC_in[i in N], sum(vDAC[i,j] for j in N))
@expression(decarb, eDAC_by[j in N], sum(vDAC[i,j] for i in N))
@variable(decarb, vDAC_esc[j in N, s in S] >= 0)
@constraint(decarb, cDAC_esc[j in N, s in S], vDAC_esc[j,s] >= 0.001*(eDAC_by[j]-s))
@expression(decarb, eDAC_esc_cost[j in N], sum(vDAC_esc[j,s] for s in S))
@expression(decarb, eDAC_outside_cost[j in N], sum(vDAC[i,j]*(countries.DAC_price[i]+pHurdle) for i in N if i != j))
@expression(decarb, eDAC_country_cost[j in N], vDAC[j,j]*countries.DAC_price[j] + eDAC_outside_cost[j] + eDAC_esc_cost[j])
@expression(decarb, eDAC_total_cost, sum(eDAC_country_cost[i] for i in N))


### BIOFUELS (FOR BECCS) ###

@expression(decarb, eBF_from[i in N], sum(vBF[i,j] for j in N))
@expression(decarb, eBF_for[j in N], sum(vBF[i,j] for i in N))
@constraint(decarb, cBF_max[i in N], eBF_from[i] <= countries.BF[i])
@expression(decarb, eBF_outside_cost[j in N], sum(vBF[i,j]*countries.BF_price[i] for i in N if i != j)*(1+pImport))
@expression(decarb, eBF_country_cost[j in N], vBF[j,j]*countries.BF_price[j] + eBF_outside_cost[j])
@expression(decarb, eBF_total_cost, sum(eBF_country_cost[i] for i in N))

#biofuels and afforestation compete for limited land in each country
for i in N
    if countries.BF[i]/18.33 > countries.AF[i]/13.11
        @constraint(decarb, eBF_from[i]/18.33 + eAF_in[i]/13.11 <= countries.BF[i]/18.33)
    else
        @constraint(decarb, eBF_from[i]/18.33 + eAF_in[i]/13.11 <= countries.AF[i]/13.11)
    end
end


### BECCS ###+ eAF_in[i]*18.33/13.11

@expression(decarb, eBECCS_in[i in N], sum(vBECCS[i,j] for j in N))
@expression(decarb, eBECCS_by[j in N], sum(vBECCS[i,j] for i in N))
@constraint(decarb, cBECCS_max[i in N], eBECCS_in[i] <= eBF_for[i])
@variable(decarb, vBECCS_esc[j in N, s in S] >= 0)
@constraint(decarb, cBECCS_esc[j in N, s in S], vBECCS_esc[j,s] >= 0.001*(eBECCS_by[j]-s))
@expression(decarb, eBECCS_esc_cost[j in N], sum(vBECCS_esc[j,s] for s in S))
@expression(decarb, eBECCS_outside_cost[j in N], sum(vBECCS[i,j]*(countries.BECCS_price[i]+pHurdle+0.002) for i in N if i != j))
@expression(decarb, eBECCS_country_cost[j in N], vBECCS[j,j]*countries.BECCS_price[j] + eBECCS_outside_cost[j] + eBECCS_esc_cost[j])
@expression(decarb, eBECCS_total_cost, sum(eBECCS_country_cost[i] for i in N))


### SEQUESTRATION ###

#Hard sequestration limit per country
@constraint(decarb, cStorMax[i in N], eDAC_in[i] + eBECCS_in[i] <= countries.stor_max[i])

#Increasing penalties applied as max. storage is approached
@variable(decarb, vSTORCOST1[i in N] >= 0)
@variable(decarb, vSTORCOST2[i in N] >= 0)
@constraint(decarb, cStorCost1[i in N], vSTORCOST1[i] >= pStor_Penalty_1*(eDAC_in[i] + eBECCS_in[i] - countries.stor_min[i]))
@constraint(decarb, cStorCost2[i in N], vSTORCOST2[i] >= pStor_Penalty_2*(eDAC_in[i] + eBECCS_in[i] - (countries.stor_min[i] + countries.stor_max[i])/2))

#total storage cost by country
@expression(decarb, eStor_local_cost[i in N], pStor_Penalty_0*(eDAC_in[i]+eBECCS_in[i]) + vSTORCOST1[i] + vSTORCOST2[i])
@expression(decarb, eStor_total_cost, sum(eStor_local_cost[i] for i in N))

### QUOTA CONSTRAINT ###

#Each country must fulfill its removal quota
@constraint(decarb, cQuotas[j in N], eAF_by[j] + eEW_by[j] + eSCS_by[j] + eDAC_by[j] + eBECCS_by[j] == countries.quota[j])



### OBJECTIVE FUNCTION ###

#Objective is to minimize total costs
@objective(decarb, Min, eAF_total_cost + eEW_total_cost + eSCS_total_cost + eDAC_total_cost + eBECCS_total_cost + eBF_total_cost + eStor_total_cost)

optimize!(decarb)
```

Figure 9: Source code for the *decarb.jl* model, part 2.