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Optimizing Carbon Dioxide Removal Portfolios Considering the Cost of Permanent Removal

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Negative emission technologies (NETs) are now considered essential for achieving net-zero emissions by mid-century. These technologies work by removing carbon dioxide from the atmosphere and storing it in various mediums, such as biomass, soil, deep underground, or the ocean. Rather than relying on a single large-scale NET, portfolios offer a way to manage the risks and sustainability issues associated with these technologies. Optimizing the deployment of NET portfolios is an emerging area of research. One challenge in this optimization is considering the permanence of carbon dioxide removal (CDR) for different technologies, as some NETs are more susceptible to reversal (e.g., forests are at risk of fires) than others (e.g., geological storage has a lower risk of reversal). CDR permanence is crucial in NET portfolio optimization because it affects the actual CDR potential of the portfolio over time. Currently, there is a lack of studies considering the permanence of NETs in portfolios. One approach to address this is by using time-evaluated costs, where the various NETs have different costs of permanent removal (CPR) depending on the considered planning horizon or time of permanence. This work aims to bridge the research gap by applying the concept of CPR in optimizing NET portfolios. Two mixed-integer linear programming models are used to optimize a NET portfolio under CPR, resource, budget, and capacity constraints, subject to target CDR. Different times of permanence (from 25 to 1,000 y) are investigated. The results show varying NET portfolios depending on the time of permanence considered. This work contributes to the analysis of decarbonization portfolios for decision-making to mitigate climate change.

1. Introduction

Carbon dioxide removal (CDR) technologies, also known as negative emissions technologies (NETs), are now necessary to meet the Paris Agreement goals of limiting global warming to 1.5 or 2 °C (IPCC, 2022). Common land-based NETs include afforestation/reforestation (AR), biochar (BC) incorporation in the soil, direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS), and enhanced weathering (EW) (The Royal Society, 2018). Rather than implementing NETs individually over large areas, it is recommended to deploy a mix of different NETs in portfolios for sustainability and risk management (Minx et al., 2018). While integrated assessment models have included individual NETs, optimizing NET portfolios using other frameworks is an emerging research area (Migo-Sumagang et al., 2023a).

A major concern rarely addressed in NET portfolio optimization is the permanence and saturation of carbon sinks for these technologies. Some NETs are less permanent than others (Smith et al., 2016). For example, geological storage is generally considered more permanent than biomass storage due to the risk of reversal in the latter (Fuss et al., 2018). Reasons for CDR reversal include sink saturation for biogenic NETs (e.g., forests saturate within decades), changes in land use management, and disturbances like forest fires (Smith et al., 2019). Although geological storage is subject to leakage, substantial research exists on monitoring, detection, and remediation of such leaks (Bui et al., 2018). While studies have optimized multi-period NET portfolios until 2100 (Migo-Sumagang et al., 2023b), CDR permanence remains a challenge and knowledge gap in optimizing these portfolios, affecting long-term investment decisions.

One approach to evaluating the permanence of CDR is through time-evaluated costs. The time of permanence (TP) is defined as the required horizon for CDR, a concept first introduced by Prado and Mac Dowell (2023). The cost of permanent removal (CPR) can be calculated as a function of TP, the economic lifetime (NE), and

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the physical lifetime (NP) of the NET, using Eq(1) from Prado and Mac Dowell (2023) as will be further elaborated in the following sections. Different NETs exhibit varying cost behaviors depending on the TP considered. The CPR values for various NETs have been initially estimated for TP horizons up to 1,000 y (Prado and Mac Dowell, 2023).

While studies have investigated the carbon dioxide removal supply chains from industrial resources (Cristiu et al., 2022), the evaluation of NET portfolios while considering CDR permanence is currently lacking in the literature. One way to incorporate CDR permanence into NET portfolio modeling is by using CPR in the cost calculations. This work bridges the knowledge gap by developing models that utilize CPR in optimizing NET portfolios. Two linear programming models with different objectives are developed. The first minimizes the total portfolio cost while targeting a CDR capacity, and the second maximizes the portfolio's CDR capacity while limiting the total portfolio cost. The models also consider capacity limits, environmental footprints of NETs, and resource constraints. The models are demonstrated through case studies of land-based NETs, considering different times of permanence. This work is important because CPR affects the optimal technology mix of NET portfolios, and this information is useful for investment decisions. The rest of the paper is structured as follows. Section 2 describes the problem statement. Section 3 presents the optimization models. Section 4 illustrates the models in case studies by investigating the optimal technology mix with varying times of permanence. Section 5 presents the sensitivity analysis. And Section 6 provides the conclusions.

2. Problem statement

The formal problem is as follows.

- Given a set of NETs. Each NET i is characterized by its environmental footprints ($\mathrm{M_{ij}}$) and the cost of the permanent removal ($\mathrm{CPR_i}$) at a considered time of permanence (TP), evaluated using Eq(1).
- Given a set of resources. Each resource j is characterized by its resource constraint ($\mathrm{F_j}$).
- Given the upper ($\mathrm{x_i^U}$) and lower ($\mathrm{x_i^L}$) capacity limits of each NET i.
- Given a target carbon dioxide removal G and a budget limit B.

The objective is to determine the optimal CDR allocation ($\mathrm{x_i}$) of each NET to minimize the total cost of the NET portfolio while targeting a minimum CDR (Model 1) for a given TP. It is also desired to determine the optimal allocation to maximize the total CDR under a budget limit (Model 2) for a given TP.

3. Optimization models

The following section describes two single-objective optimization models employed in this study. Model 1 minimizes the total cost of the NET portfolio, subject to constraints on the CDR target, technology capacities, and resource availability. Model 2 maximizes the total CDR of the NET portfolio, subject to constraints on the available budget, technology capacities, and resource availability.

3.1 Model 1

To calculate the cost of permanent removal (CPR), Eq(1) from Prado and Mac Dowell (2023) is used.

$$\mathrm{CPR} = \frac{\mathrm{TC}}{\widehat{\mathrm{CB}}} = \frac{\mathrm{I}\left(\frac{(1+\mathrm{i})^{\mathrm{NE}}}{(1+\mathrm{i})^{\mathrm{NE}}-1}\right)+\sum_{\mathrm{t}=1}^{\mathrm{NP}}\frac{\mathrm{OM}-\mathrm{R}}{(1+\mathrm{r})^{\mathrm{t}}}+\sum_{\mathrm{t}=1}^{\mathrm{NP}}\frac{\mathrm{MRV}}{(1+\mathrm{r})^{\mathrm{t}}}}{\sum_{\mathrm{t}=1}^{\mathrm{NP}}\mathrm{CS}-\sum_{\mathrm{t}=1}^{\mathrm{TP}}\mathrm{CE}+\mathrm{CL}(1-\mathrm{CRV})}\ \mathrm{s} \qquad (1)$$

In Eq(1), TC represents the total cost and $\widehat{\mathrm{CB}}$ is the total carbon balance. The total cost comprises the investment cost (I), total operating and maintenance costs (OM), revenues like electricity from BECCS (R), and monitoring, reporting, and verification (MRV) costs. The investment cost is annualized using a weighted average cost of capital (i). The operating, maintenance costs, revenues, and MRV costs are subject to a discount rate (r), making TC a net present cost. The total carbon balance includes the total carbon stored (CS), total carbon emissions (CE) from the supply chain, and carbon leakage during TP (CL). The leaked carbon is multiplied by (1-CRV), where CRV is the climate repair value, factoring in the reduced damage from temporary removal (Prado and Mac Dowell, 2023). As shown in Eq(1), CPR is a specific cost.

Model 1 is represented by Eq(2) to Eq(6). The objective function in Eq(2) minimizes the total cost of the NET portfolio. Eq(3) ensures that the target CDR (G) is achieved. Eq(4) evaluates the environmental footprints of each NET, subject to a resource constraint ($\mathrm{F_j}$). Eq(5) and Eq(6) ensure that the CDR allocation to each NET does not exceed the NET's maximum capacity ($\mathrm{x_i^U}$), and does not go below the minimum capacity ($\mathrm{x_i^L}$).

$$\min \sum_{\mathrm{i}} \mathrm{CPR_i x_i} \qquad (2)$$

$$\sum_{\mathrm{i}} \mathrm{x_i} \geq \mathrm{G} \qquad (3)$$

$$\sum_i M_{ij} x_i \leq F_j \quad , \forall j \tag{4}$$

$$x_i \leq x_i^U \quad , \forall i \tag{5}$$

$$x_i \geq x_i^L \quad , \forall i \tag{6}$$

3.2 Model 2

Model 2 is depicted by Eq(7), Eq(8), and Eq(4) to Eq(6). Eq(7) replaces Eq(2) as the objective function to maximize the total CDR. It is subject to a budget constraint in Eq(8). It is also subject to resource and capacity constraints in Eq(4) to Eq(6).

$$\max \sum_i x_i \tag{7}$$

$$\sum_i CPR_i x_i \leq B \tag{8}$$

4. Case studies

The following section illustrates the two models in case studies with different objectives. The last subsection includes a discussion.

4.1 Case Study 1

The case study investigates the technology mix that would minimize the cost while achieving a target CDR, using Model 1. The case study considers five CDR technologies: afforestation/reforestation (AR), biochar (BC) incorporation into soil, direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS), and enhanced weathering (EW). The environmental footprints, capacities (Table 1), and resource constraints (Table 2) for these NETs are based on a previous study in the Association of Southeast Asian Nations (ASEAN) region (Migo-Sumagang et al., 2023b). The lower capacity limit is assumed to be zero, allowing the solution to exclude technologies from the portfolio if needed. It is assumed that energy from BC cannot be utilized within the system. The CPR estimates are taken from the study by Prado and Mac Dowell (2023), as shown in Table 3. The target annual CDR is set at 0.725 Gt CO_2, based on the Intended Nationally Determined Contributions (INDCs) of ASEAN countries compiled in the literature (Fulton et al., 2017).

Table 1: Environmental footprints and upper capacities of NETs

NET	Land (Mha/Gt CO_2)	Water (km^3/Gt CO_2)	Energy (EJ/Gt CO_2)	Nitrogen (Mt/Gt CO_2)	Phosphorus (Mt/Gt CO_2)	Capacity (Gt CO_2)
BECCS	113.85	574	0.605	9.57	6.65	0.682
AR	2.95	1575	0	0.1125	0.1325	0.205
BC	58	0	0	8.2	2.7	0.192
DAC	0.1365	4.415	14.65	0	0	0.409
EW	84.65	1.5	6.35	0	0	0.660

Table 2: Annual resource constraints

NET	Constraint
Land	20 Mha
Water	1135 km^3
Energy	19.5 EJ
Nitrogen	6.2 Mt
Phosphorous	6.2 Mt

Solving Eq(2) to Eq(6) (Model 1), the resulting optimal technology mix and total costs for varying times of permanence (TP) are shown in Figure 1. Note that as per Eq(1), the total cost represents a net present cost. If the TP considered is between 25 and 500 y, the optimal technology mix consists of AR (28 %), BC (26 %), DACCS (32 %), and EW (14 %). The total cost increases from USD $227x10^9$ to USD $285x10^9$ within this range. If the TP considered is between 500 and 1,000 y, the technology mix shifts to AR (28 %), DACCS (40 %), and EW (32 %), excluding BC and increasing the shares of DACCS and EW. The total cost reaches up to USD 333 $x10^9$. BECCS is completely excluded from the technology mix for all TPs considered.

Table 3: Cost of permanent removal (USD/t CO_2) at different TP horizons

NET/TP (y)	25	50	100	250	500	750	1000
BECCS	150	150	150	150	150	150	150
AR	45	45	50	90	200	300	400
BC	125	140	150	200	300	400	500
DACCS	745	745	745	745	745	745	745
EW	225	150	150	150	150	150	150

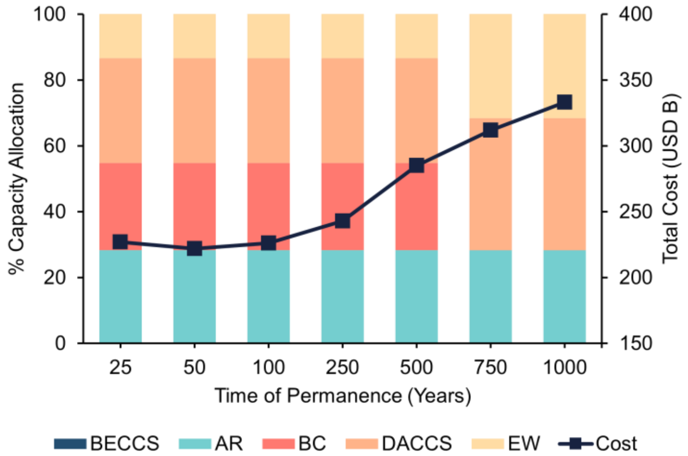

Figure 1: Results of case study 1

4.2 Case study 2

Case Study 2 investigates the technology mix that would maximize the CDR capacity under a budget limit. The same data as Tables 1 to 3 are used, except for the land use constraint, which was increased to 45.7 Mha. A budget limit of USD $75x10^9$ is imposed, based on 15 % of the global budget for climate change adaptation in 2050 (UNEP, 2016). Due to infeasibilities caused by the decreased budget, the land constraint was increased. Solving Eq(7), Eq(8), and Eq(4) to Eq(6) (Model 2), two alternative solutions are presented in Figure 2. Figure 2a is dominated mostly by EW, while Figure 2b is dominated by both BECCS and EW. DACCS is completely excluded due to the tight budget limit, in contrast with Case Study 1, where the budget exceeds USD $300x10^9$. The portfolio's CDR capacity decreases with increasing TP. At TP of 25 y, the CDR capacity is 0.68 Gt CO_2 decreasing to 0.5 Gt CO_2 at TP of 500 y and remaining constant. Although lower than the 0.725 Gt CO_2 target in Case Study 1, this CDR level still falls within the range of the ASEAN total INDCs of 0.375 to 0.725 Gt CO_2.

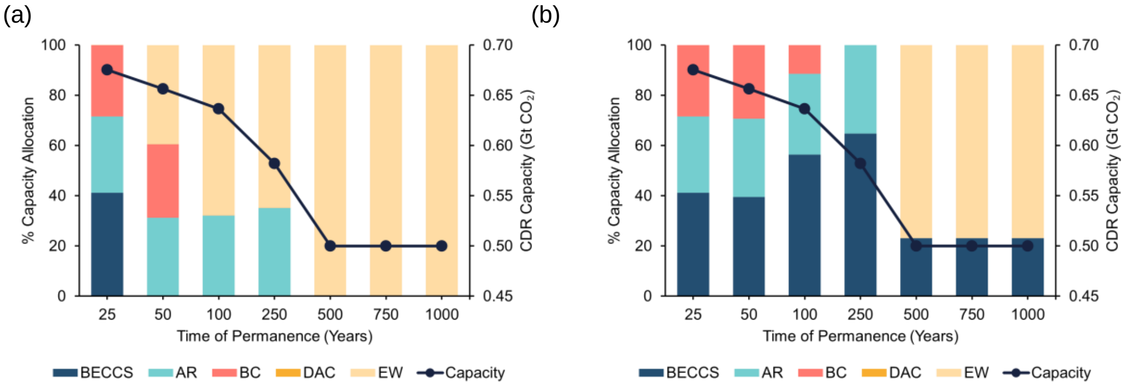

Figure 2: Results of case study 2 (a) and alternative solution (b)

4.3 Discussion

For both case studies, technology shifts occur when longer TP horizons of 500 y and above are considered. These shifts happen due to the cost behaviour considering the time of permanence (CPR). At shorter TP horizons, AR and BC have lower CPRs. However, when longer TP horizons are considered, AR and BC become more expensive, as shown in Table 3. On the other hand, DACCS and BECCS have constant CPRs, while EW has an initially high CPR that decreases and remains constant over time. This is because the current energy-intensiveness of the technology is high, but is projected to improve over time, along with the projected decrease in renewable energy cost (Creutzig, 2019). Therefore, the optimal technology mix choice depends on the TP horizon considered. For minimizing cost given a target CDR capacity, AR, DACCS, and EW are consistent choices at short or long TP horizons. BC is only a good choice if the TP is in the range of 500 y. For maximizing CDR capacity under a budget limit, AR and BC are only good choices at short TP horizons of 50 to 250 y. DACCS is not a good choice if the budget is tight. Overall, EW is the best choice for maximizing capacity in longer TP horizons due to its permanence and cost over time. Alternatively, BECCS is a good choice if the land resource is not binding, as discussed in the next section.

5. Sensitivity analysis

A sensitivity analysis is conducted using dual prices. The dual price refers to the change of the optimal objective value per unit change in each of the right-hand side parameters of the constraints. A zero value implies that the objective value is not bound by that constraint. Table 4 shows the dual prices in USD x10^9 for the total cost objective in Case Study 1. The objective value is only affected by the CDR target, upper capacity constraints for AR and BC, and land resource constraints. The rest of the constraints have zero dual prices and are excluded. Increasing the CDR target by 1 Gt CO_2 will increase the total portfolio cost by USD 745.84 x10^9. Increasing the AR and BC capacities and land limit will decrease the total cost, as indicated by their negative dual prices. A non-zero dual price also signifies that the allocations for AR, BC, and land use have reached their maximum limits in the portfolio.

Table 4: Dual prices (USD x10^9) for case study 1

Constraint/TP(y)	25	50	100	250	500	750	1,000
CDR target	745.84	745.96	745.96	745.96	745.96	745.96	745.96
Capacity							
AR	-682.69	-680.19	-675.19	-635.19	-525.19	-425.19	-325.19
BC	-263.97	-197.62	-187.62	-137.62	-37.62	0	0
Resource							
Land	-6.15	-7.04	-7.04	-7.04	-7.04	-7.04	-7.04

For a maximization problem like Case Study 2, improvement is reflected as an increase in the objective value (positive sign). Table 5 presents the dual prices in Gt CO_2 for Case Study 2. The objective value is only affected by the budget limit and AR and BC capacity constraints (for TP horizons up to 100-250 y). The zero dual prices for resource constraints indicate that those limits are not binding. BECCS, usually considered a resource-intensive NET, is included in alternative solution 2 (Figure 2b) due to the non-binding resource constraints.

Table 5: Dual prices (Gt CO_2) in case study 2

Constraint/TP(y)	25	50	100	250	500	750	1,000
Budget limit	0.0067	0.0067	0.0067	0.0067	0.0067	0.0067	0.0067
Capacity							
AR	0.7	0.7	0.67	0.4	0	0	0
BC	0.17	0.067	0	0	0	0	0

6. Conclusions

Two linear programming models for optimizing NET portfolios while considering the costs of permanent removal were developed and applied to case studies. Model 1 minimizes the total cost subject to a target CDR, while Model 2 maximizes the CDR capacity subject to a budget constraint. Both models also consider resource and capacity constraints. The optimal choice of CDR technology mix depends on the TP horizon considered. AR, DACCS, and EW are consistent choices for minimizing cost in short or long-TP horizons. BC is only a good choice if the TP is in the range of 500 y. AR and BC are good choices for maximizing CDR capacity under a budget limit if the TP is in the range of 50 to 250 y. BECCS is a good choice if the land resource limit is not binding. Overall, EW is the best choice for maximizing CDR capacity in longer TP horizons. This work demonstrates that the optimal NET technology mix is affected by the costs of permanent removal, which is an important consideration for making investments with long-lasting impact. Future work may include additional constraints such as storage limits and other performance aspects like social acceptance and governance feasibility.

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Nomenclature

AR - Afforestation/Reforestation
ASEAN - Association of Southeast Asian Nations
BC - Biochar incorporation in the soil
BECCS - Bioenergy with Carbon Capture and Storage
CDR - Carbon Dioxide Removal
CPR - Cost of Permanent Removal
DACCS - Direct Air Carbon Capture and Storage
EW - Enhanced Weathering
NET - Negative Emissions Technologies
TP - Time of Permanence

Parameters
C_i - Cost of CDR technology i
B - Budget limit
F_j - Limit of resource j
G - Negative emissions capacity target
M_{ij} - Footprint of CDR technology i on resource j
x_i^U - Upper capacity limit of CDR technology i
x_i^L - Lower capacity limit of CDR technology i
Variables
x_i - Capacity allocation of CDR technology i

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