The influence of speed and scale of carbon dioxide removal on overshoot peak temperature and duration.

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Abstract

CO_2 emissions are pushing global temperatures higher, with the Paris Agreement temperature target of limiting warming to no more than 1.5°C above the preindustrial average likely to be exceeded within the next two decades. Overshooting this target before reducing global temperature by the end of the century is increasingly viewed as a potential pathway to still meet the Paris Agreement target, however this approach would require significant carbon dioxide removal. Yet, how the speed and scale of carbon dioxide removal deployment affects overshoot peak temperature and duration is not well understood. Here we use a climate-economic model to investigate peak temperature and overshoot duration across a range of deployment rates for the five baseline Shared Socioeconomic Pathways. We find that the speed of deployment, is the primary determinant of overshoot magnitude, with peak temperatures reaching 2.46°C under slow deployment and overshoot duration varying from 19 to 59 years. Fast deployment speeds limit peak temperature to 1.58°C, while high maximum capacity leads to temperature peaking at 1.88°C. Together, these results provide a clear direction for carbon dioxide removal efforts.

1. Introduction

Given continually rising anthropogenic CO_2 emissions, current governmental Nationally Determined Contributions (NDCs) are no longer sufficient to keep global mean surface temperatures below 1.5°C [1], with exceedance now expected within the next two decades [1], [2]. As a result, overshoot - the temporary exceedance of a warming target prior to reducing temperature to that target - is now being explored as a solution to meeting the 1.5°C Paris Agreement target [3], [4]. Given that exceeding 1.5°C now appears inevitable, questions remain about whether temperature can return to target by the end of the century, and what the likely duration and peak temperature of the overshoot will be [3], [4].

Carbon dioxide removal (CDR) is considered fundamental to lowering global temperature [5], but this success will depend on how quickly CDR can be scaled up and deployed. CDR deployment affects peak temperature timing by controlling when maximum cumulative emissions occur. It also influences overshoot duration by determining how quickly excess emissions are removed from the atmosphere. Crucially, delaying emissions reduction in the short term affects the CDR needed to meet the Paris Agreement by increasing the cumulative CO_2 emissions that CDR must ultimately offset [6], [7], [8]. Therefore, a critical question is how the speed of implementing CDR and the scale, or maximum capacity, of CDR deployment affect overshoot magnitude and duration [4].

Previous research has shown that overshoot peak temperature is more sensitive to emissions reduction than to CDR removal of emissions already in the atmosphere, while overshoot duration is primarily controlled by total CDR capacity [9], [10]. Likewise, lower peak temperature has also been linked to the early deployment of CDR [3], [10]. Limited research has comprehensively explored the speed and scale of CDR deployment to understand how these factors control the peak temperature and duration of an overshoot, or whether a selected temperature target can be reached by the end of the century.

The speed and scale of CDR deployment affect the environmental impacts of overshoot through their influence on peak temperature and duration. Although temperature is expected to fall rapidly in response to reductions in cumulative CO_2 emissions [11], [12], climate-sensitive systems, as well as large-scale climate tipping elements may not recover as quickly, and even risk irreversible impacts once critical temperature thresholds are crossed [13]. Fast-responding ecosystems and species are more sensitive to peak temperature, while slow-responding ecosystems, such as the Antarctic ice sheet, are more sensitive to the duration of overshoot above 1.5°C [7], [12]. The speed and scale of CDR deployment is therefore an important factor in what environment impacts may occur.

Our aim is to understand how the speed and scale of CDR deployment affect overshoot duration and peak temperature under a specific end-of-century temperature target. To address this, we apply a climate-economic model [14] to explore the duration and peak temperature of overshoot across a wide range of CDR deployment speeds and scales, taking a technology-agnostic approach following Ricke et al. (2017), and using the Paris Agreement target of 1.5°C by 2100 as a case study. We find that different combinations of speed and scale can produce the same final temperature, but with markedly different overshoot trajectories. Furthermore, we find that faster deployment speed is more effective than higher scale in minimising the duration and magnitude of overshoot.

2. Methods

2.1 MACROM model

MACROM (Mitigation and Carbon Removal Optimisation Model) [14] uses optimal control to identify least-cost trajectories of emissions mitigation and CDR deployment to achieve a specific temperature target. MACROM captures the trade-offs between the costs of emissions mitigation and CDR deployment, and the economic damages of climate inaction, determining the optimal timing and scale of climate abatement. MACROM assumes an increasing marginal unit cost for emissions mitigation and CDR deployment, using a quadratic to describe the relationship. This parameterisation of marginal cost makes CDR more costly per tonne of CO_2 removed when deployed at large scales, favouring balanced usage over time. The economic damage of climate change is calculated as a percentage reduction in gross world product per degree Celsius of warming formulated as a quadratic, favouring early action to keep temperature low. However, these drivers are counteracted by discounting in the model, which favours delayed expenditure [14].

MACROM uses forecasts of CO_2 emission and Gross World Product (GWP) forecasts from the IPCC Shared Socioeconomic Pathways (SSPs) as exogenous model inputs. For this study, we use the five baseline SSPs, which represent different projections of population growth, economic development, fossil fuel usage and land-use change [15]. SSP1 and SSP4 assume an energy-mix with a decreasing reliance on fossil fuels, SSP3 and SSP5 assume increasing fossil fuel use, while SSP2 assumes an energy-mix similar to the present. These differing energy-mix assumptions produce divergent CO_2 emission trajectories across the 21st century. For example, SSP1 projects annual emissions 24 $GtCO_2$ in 2100, compared to 126 $GtCO_2$ under SSP5. MACROM uses both emissions mitigation and CDR as control variables; however, since our purpose here is to explore the effect of changes in CDR deployment speed and scale on overshoot duration and magnitude, we assume no additional emissions mitigation beyond what is already given in the changing energy-mix assumptions in each SSP projection.

2.2 CDR capacity function

To explore the impact of changing CDR deployment speed and scale, we extended MACROM with a CDR capacity function imposing an exogenous upper bound on maximum annual deployment of CDR. This extension is conceptually distinct from, and operates alongside, MACROM's endogenous cost-benefit constraints on deployment. It is therefore useful to be explicit about what each element of the model represents and which sources motivate it.

Endogenous determination of CDR deployment: Within MACROM, CDR deployment at each time step is the outcome of an optimal control problem that balances the marginal cost of CDR (rising quadratically with deployment) against the marginal economic damage of warming, subject to discounting [14]. Once marginal costs of an additional tonne of removal exceeds marginal climate benefit, the optimiser chooses not to deploy further, even if more capacity is physically available. MACROM therefore contains an internal, demand-side ceiling on CDR deployment, arising endogenously from the cost/benefit structure of the economic problem. This is analogous to the role consumer demand plays as a saturation level in the technology-diffusion literature [16].

Exogenous capacity constraint: Separately, CDR deployment is bounded above by physical and biological constraints outside of the cost/benefit calculation. For example, land availability, geological storage limits or nutrient limitations in marine geoengineering. While the precise values of these limits are poorly understood [17], [18],

[19], their existence is clear: regardless of how economically valuable an additional tonne of removal might be, deployment cannot exceed what the physical world permits.

Functional form: To represent CDR's approach to this exogenous ceiling, we assume CDR deployment will follow a logistic (S-shaped) trajectory, consistent with historical energy technology transitions [20], [21]. The curve captures an initial low deployment, a phase of rapid growth, and decreasing growth as the trajectory approaches the asymptote, reflecting the period of experimentation and development, alongside the build-up of industrial and workforce capacity, before successful large-scale deployment is achieved [9], [22], [23].

Interaction of the two mechanisms: In MACROM, the logistic capacity function defines the physical maximum CDR achievable in any given year; the optimal control routine determines the economically optimal level; and the realised deployment in each year is the minimum of the two. When the model selects deployment at the logistic ceiling, CDR is being exogenously constrained by the assumed biophysical and industrial limits; when it selects a level below the ceiling, deployment reflects the endogenous economic optimum derived from balancing marginal abatement costs against avoided climate damages.

The logistic curve at each time step *t* is given as,

$$g(t) = \frac{K}{1 + \left(\frac{K}{g_{initial}} - 1\right) e^{-r(t-t_0)}},$$

where K is the scale (maximum capacity) of CDR ($GtCO_2$ $year^{-1}$), $g_{initial}$ is the CDR capacity already deployed at the start of the time horizon ($GtCO_2$ $year^{-1}$), r is the speed (intrinsic growth rate) of CDR deployment ($year^{-1}$), t is the year, and t_0 is the starting year of the simulation [24].

2.3 Representative CDR deployment scenarios

We parameterised three representative growth rates, informed by research technology transitions and CDR deployment [16], [18], [25], [26]. We selected representative slow ($r = 0.05$), moderate ($r = 0.07$) and fast ($r = 0.11$) speeds, combined with a maximum scale (K) of 100 $GtCO_2$ $year^{-1}$ applied uniformly across all speeds. The moderate speed approximates the historical growth rate of steam engines or hydropower; the fast growth rate is close to that of coal power plants [27]. These values were chosen to ensure a 2050 CDR capacity of 6.6 $GtCO_2$ for slow growth, 10.5 $GtCO_2$ for moderate growth and 24.2 $GtCO_2$ for fast growth, covering the estimated 2050 plausible range of 6-24 $GtCO_2$ from Fuss et al., (2018). Further, Nemet et al, (2023) studied historical technology transitions, finding a median logistic coefficient of 0.13 $year^{-1}$, and a range of 0-0.69 $year^{-1}$. This logistic coefficient corresponds with the speed (r) in our logistic function and places our intrinsic growth rates within the range of historical transitions. Higher intrinsic growth rates have been observed for recent technologies, including 0.29 $year^{-1}$ for offshore wind power and 0.31 $year^{-1}$ for solar photovoltaics [27], indicating that our values are conservative relative to the upper bounds of historically observed transitions. Projecting the logistic growth function to 2100 yields maximum scales of 46.5, 79.6 and 98.7 $GtCO_2$ respectively for the slow, moderate and fast growth rates (Fig 1).

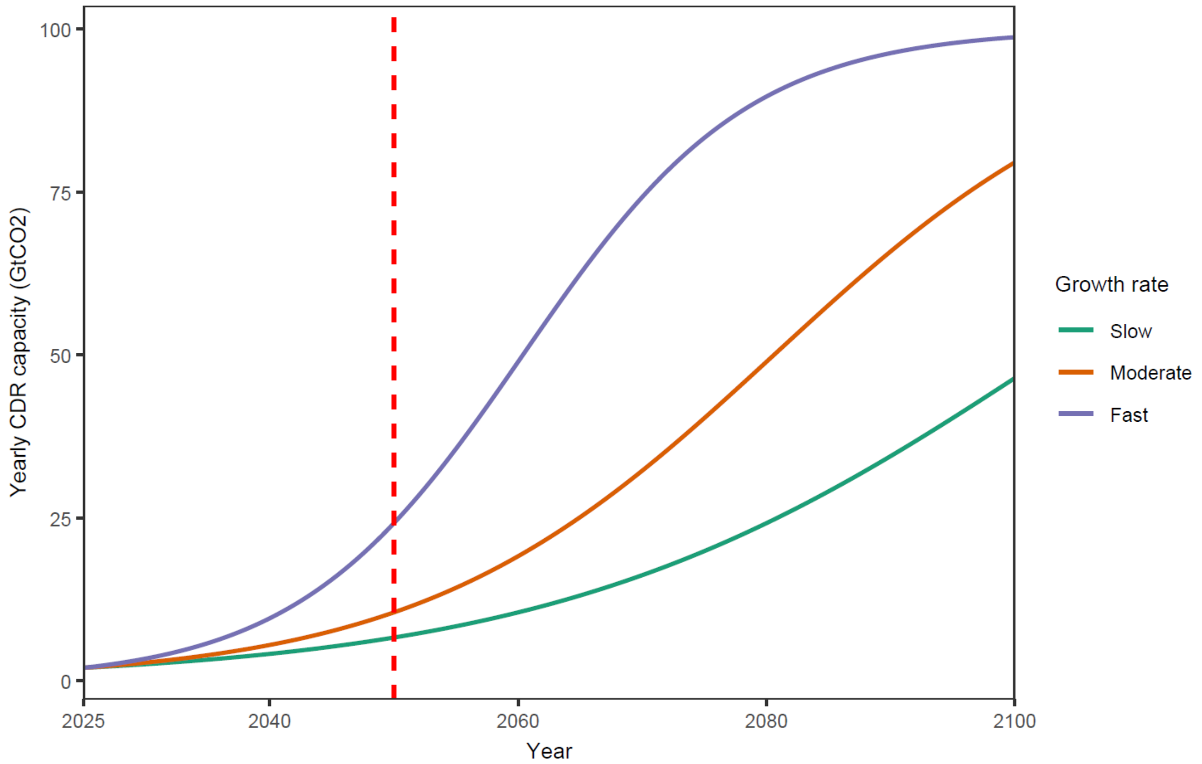


Fig 1. **Yearly maximum capacity**. Modelled yearly carbon dioxide removal (CDR) capacity over time for three growth rate scenarios — slow ($r = 0.05\, year^{-1}$), moderate ($r = 0.07\, year^{-1}$) and fast ($r = 0.11\, year^{-1}$) — with an initial CDR deployment of 2 $GtCO_2\ year^{-1}$, and a maximum yearly capacity (K) of 100 $GtCO_2\ year^{-1}$. Vertical dashed line marks 2050, which corresponds to Fuss et al.'s (2018) plausible range.

From MACROM we derived the cost-optimal deployment of CDR from 2025-2100 to limit warming to 1.5C by 2100, without exceeding the yearly maximum capacity, for each of the five baseline SSPs. MACROM attempts to find solutions that meet the temperature target, and when it fails to do so, the cost-optimal solution yielding the lowest final temperature is returned.

2.4 Sensitivity of overshoot outcomes to CDR speed and scale

We also explored a wider range of deployment rates to investigate how variation in CDR deployment speed and scale affects peak temperature, overshoot duration, and the likelihood of recovery within this century. Fuss et al. (2018) reported a range of CDR capacity values of 4-287 GtCO2 in 2050, based on a comprehensive literature review of the potential and costs of seven different CDR methods (bioenergy with carbon capture and storage, afforestation and reforestation, direct air carbon capture and storage, enhanced weathering, ocean fertilisation, biochar, and soil carbon sequestration).

The parameter ranges for r and K were determined using the range reported by Fuss et al. (2018). Given the CDR deployment initial conditions ($g_{initial} = 2 \text{ GtCO}_2$), achieving 287 GtCO_2 in 2050 requires speed $r > 0.23$ and scale $K > 500 \text{ GtC0}_2$. Therefore, we used this to set an upper limit on r and K. Preliminary results showed that near identical outcomes occurred where $r > 0.2$ and $K > 200 \text{ GtC0}_2$. On this basis, we set the speed (r) in the range 0.02-0.2 $year^{-1}$ and scale (K) in the range 25-200 GtCO_2 $year^{-1}$. We selected 51 independent, uniformly distributed samples for r and K, creating 2601 unique capacity constraint curves, and solved the optimal control problem using each constraint, for the five baseline SSPs.

Peak and final temperatures for each optimal solution were recorded, and peak temperature was classified into one of three categories: 1) no overshoot, where peak temperature remained below 1.5°C for the full period from 2025-2100; 2) recoverable overshoot, where peak temperature exceeded 1.5°C for at least one year before returning to 1.5°C in 2100; and 3) unrecoverable overshoot, where peak temperature exceeded 1.5°C and could not return back to target before 2100.

3. Results

3.1 Representative CDR deployment scenarios

A consistent pattern was observed across all SSPs in the representative CDR deployment scenarios – CDR deployment rates with slower speed but higher scale resulted in longer, hotter overshoots than deployment rates with faster speed but lower scale (Fig 2, Fig 3, Table 1, Table 2). For example, moderate and fast growth rates for SSP1 to SSP4 reached the same final temperature via different trajectories, with peak temperatures varying by up to 0.19°C, despite nearly identical total CDR deployment (Fig 2, Table 2). Across all SSPs and representative CDR deployment scenarios, temperatures continued to rise until CDR capacity exceeded emissions and excess CO_2 could be removed from the atmosphere (Figure 2).

For the representative slow ($r = 0.05$), moderate ($r = 0.07$) and fast ($r = 0.11$) growth rates, only SSP1 returned to a final temperature of 1.5°C by 2100 across all 3 growth rates (Fig 2, Table 2). SSP2 to SSP4 achieved the 1.5°C target under fast and moderate growth rates, while SSP5 returned to target only under the fast growth rate (Fig 3). Under the slow growth rate peak temperature ranged from 1.6°C under SSP1 to 2.46°C under SSP5, with overshoot durations between 49 and 61 years (Table 2). For SSP5, overshoot duration varied little across growth rates (between 58 and 61 years), while peak temperature varied substantially differing by 0.83°C, from 1.63°C under the fast growth rate, to 2.46°C under the slow growth rate.

Figure 2 shows the CDR deployed (coloured lines) as well as the yearly maximum capacity for each growth rate (grey lines). For the slow growth rate, SSP2 to SSP5 used maximum CDR capacity, but still fail to meet the 1.5°C temperature target. Conversely, for all growth rates where the full CDR capacity is not required, the solutions prioritise using CDR earlier rather than later in the century (Fig 2).

3.2 Sensitivity of overshoot outcomes to CDR speed and scale

We identified separately the lowest speed and lowest scale CDR trajectories for each SSP where temperature was 1.5°C in 2100. These results also showed the same pattern of slower speed but higher scale deployment resulting in longer, hotter overshoots, consistent with the representative growth rates findings (Fig 3, Table 1). When comparing the overshoot peak temperature and duration, we found that the lowest scale trajectories reached peak temperatures between 1.51°C and 1.58°C, compared with peak temperatures between 1.63°C and 1.88°C for lowest speed trajectories (Table 1, Fig 3). Overshoot duration was also shorter for lowest scale solutions (19-51 years) compared to lowest speed solutions (52-59 years) (Table 1, Fig 3).

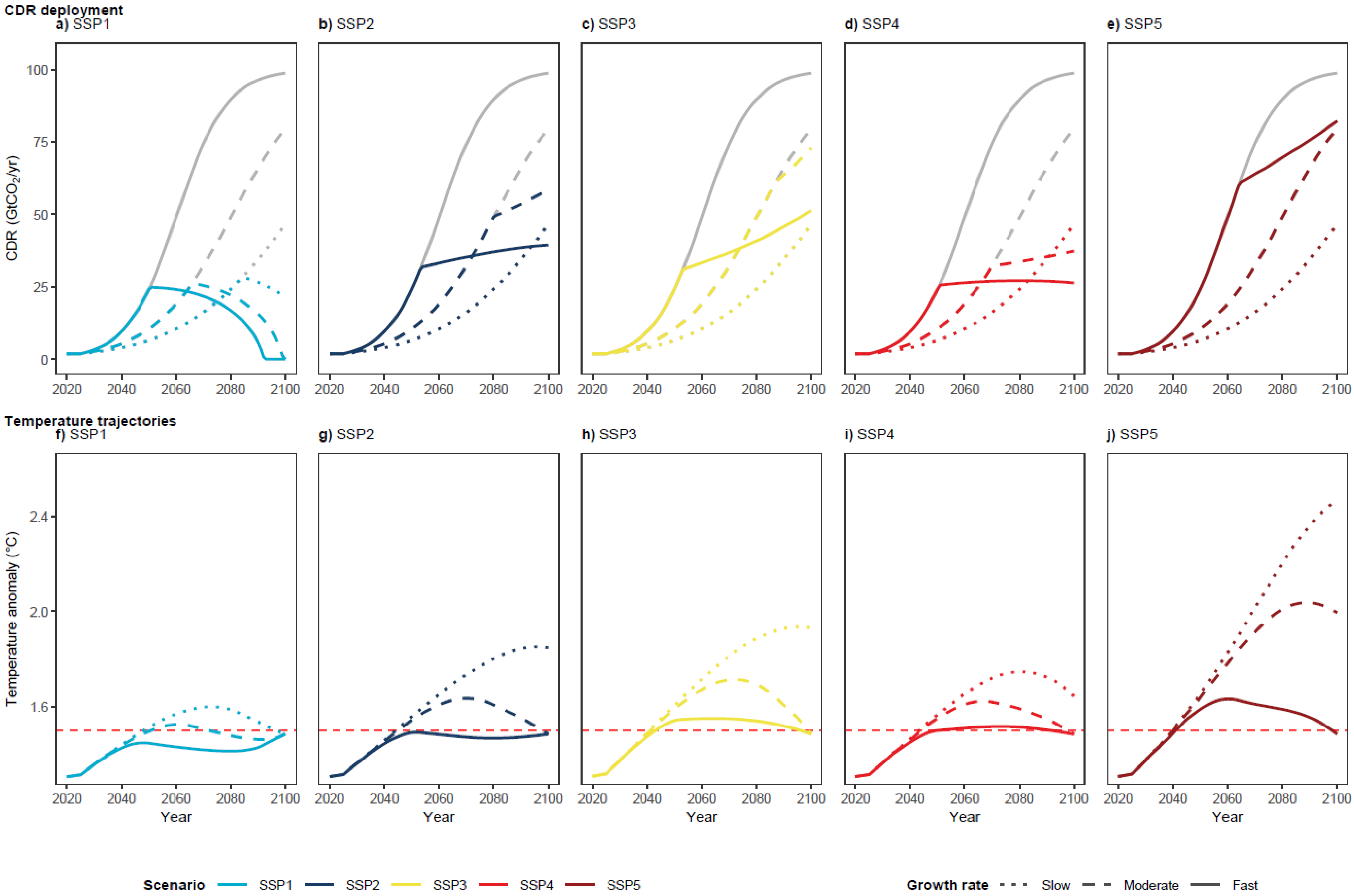
Under SSP1, achieving a recoverable overshoot required either a speed of at least $r = 0.045$ paired with a scale of at least $K = 95\ \mathrm{GtCO_2}$, or a scale as low as $K = 25\ \mathrm{GtCO_2}$ provided the speed was at least $r = 0.07$, illustrating that a higher scale can compensate for a slower speed, and vice versa (Table 1). For SSP2 to SSP5, recoverable overshoot required speeds between $r = 0.052$ and $r = 0.074$, paired with scales between $K = 144\ \mathrm{GtCO_2}$ and $K = 186\ \mathrm{GtCO_2}$ (Table 2). Alternatively, where scale was $25 < K < 63.5\ \mathrm{GtCO_2}$ the speeds needed were between $0.11 < r < 0.189$ (Table 1). Figure 4 shows that for $K \leq 40\ \mathrm{GtCO_2}$ there was no recoverable overshoot possible for SSP2, SSP3 and SSP5.

Table 1. Parameter combinations yielding the lowest speed (r) and lowest scale (K) solutions for each SSP baseline scenario, where temperature exceeded, then returned to 1.5°C by 2100.

Scenario	Maximum Growth Rate (%)	Maximum Capacity ($GtCO_2$/year)	Peak Temp. (°C)	Years above 1.5°C	CO_2 Removed (Gt)
Lowest recoverable growth rate solution					
SSP1	4.5	95.0	1.63	52	1,014
SSP2	6.0	161.5	1.70	55	2,016
SSP3	6.3	144.0	1.75	58	2,203
SSP4	5.2	182.5	1.72	57	1,555
SSP5	7.4	186.0	1.88	59	3,397
Lowest recoverable maximum capacity solution					
SSP1	7.0	25.0	1.58	50	1,013
SSP2	11.0	42.5	1.53	32	2,032
SSP3	12.8	42.5	1.55	51	2,197
SSP4	18.9	25.0	1.51	33	1,557
SSP5	15.7	63.5	1.52	19	3,397

Table 2. Peak temperature and overshoot duration across SSP baseline scenarios and CDR growth rates. Peak temperature (°C) represents the maximum annual temperature anomaly relative to pre-industrial levels achieved under the optimal control solution. Overshoot duration (years) is the number of years the temperature anomaly exceeds 1.5°C. Results are shown for three CDR logistic growth rates slow ($r = 0.05$), moderate ($r = 0.07$) and fast ($r = 0.11$), applied across five Shared Socioeconomic Pathway (SSP) baseline emission scenarios.

Baseline SSP	Growth	Peak Temperature (°C)	Years above 1.5°C	CO_2 Removed (Gt)
SSP1	Slow	1.60	49	1,040
	Moderate	1.52	22	1,039
	Fast	1.49	0	1,039
SSP2	Slow	1.85	56	1,235
	Moderate	1.64	54	2,039
	Fast	1.49	0	2,038
SSP3	Slow	1.94	60	1,235
	Moderate	1.71	58	2,224
	Fast	1.52	54	2,224
SSP4	Slow	1.75	57	1,235
	Moderate	1.62	54	1,587
	Fast	1.52	43	1,587
SSP5	Slow	2.46	61	1,235
	Moderate	2.04	61	2,281
	Fast	1.63	58	3,408



CDR deployment
a) SSP1
b) SSP2
c) SSP3
d) SSP4
e) SSP5
CDR ($GtCO_2$/yr)
100
75
50
25
0
2020
2040
2060
2080
2100
Temperature trajectories
f) SSP1
g) SSP2
h) SSP3
i) SSP4
j) SSP5
Temperature anomaly (°C)
2.4
2.0
1.6
Year
Scenario
SSP1
SSP2
SSP3
SSP4
SSP5
Growth rate
Slow
Moderate
Fast

Fig 2. Trajectories for 3 representative growth rates. Comparison of optimal control results across SSP emissions scenarios (SSP1–SSP5), under different CDR capacity and growth rate parameterisations. Upper panels (a–e) show annual CDR deployment ($GtCO_2$ $year^{-1}$) and lower panels (f–j) show temperature anomaly trajectories (°C) over time, with each column corresponding to one SSP scenario. Within each panel, dotted, dashed, and solid lines represent rates slow ($r = 0.05$), moderate ($r = 0.07$) and fast ($r = 0.11$) CDR speed respectively. Scale was set to $K = 100\ \mathrm{GtCO_2}\ year^{-1}$ across all scenarios. The horizontal dashed red line in temperature panels indicates the 1.5°C Paris Agreement target. The grey lines indicate the maximum CDR deployment possible each year.

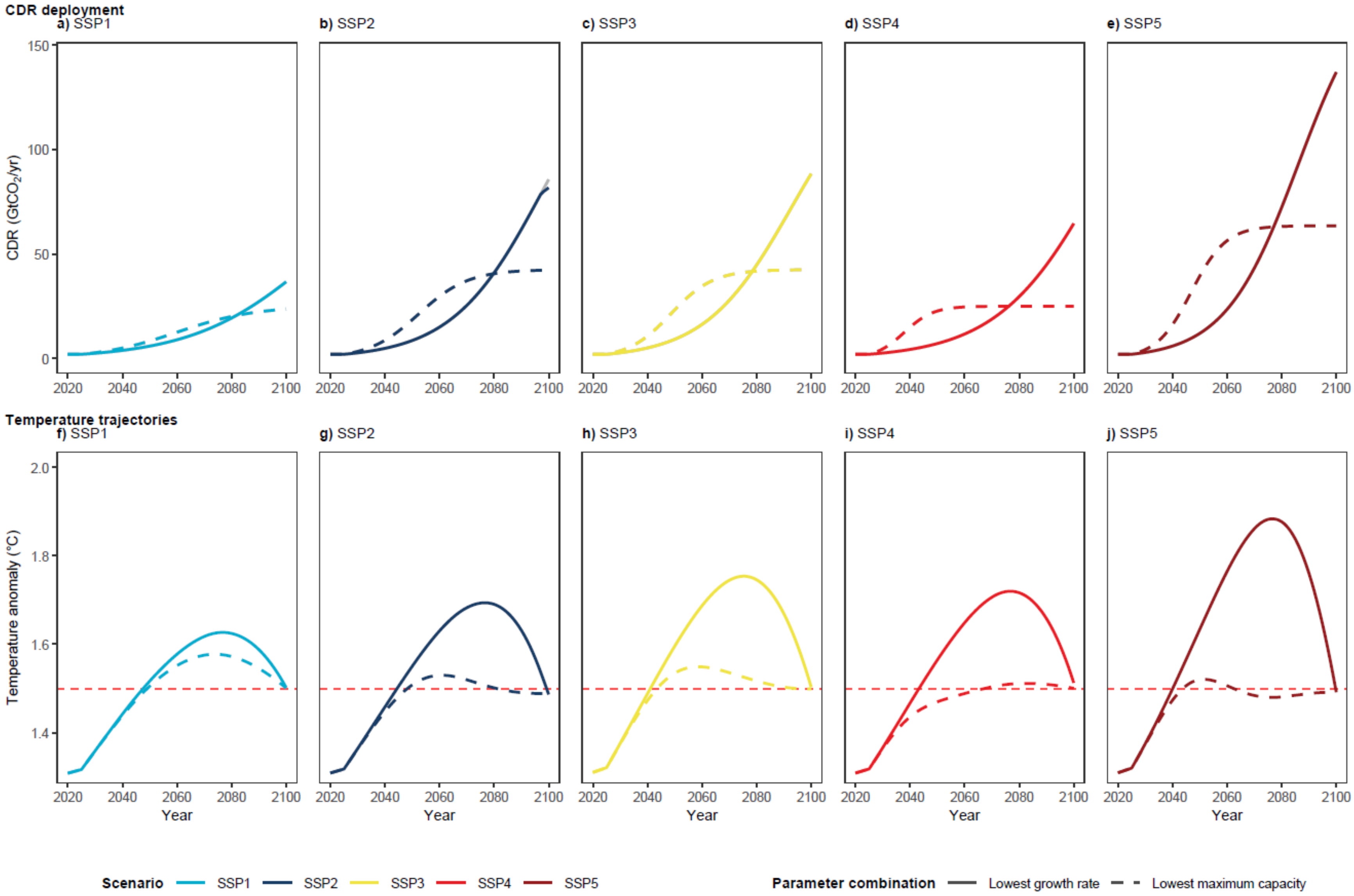


Fig 3. Trajectories for lowest recoverable growth rate and lowest recoverable maximum capacity. Comparison of optimal control results across SSP emissions scenarios (SSP1–SSP5). Within each panel, solid and dashed lines represent the trajectories for the lowest recoverable speed and lowest recoverable scale, respectively. Upper panels (a–e) show annual CDR deployment ($GtCO_2$ $year^{-1}$) and lower panels (f–j) show temperature anomaly trajectories (°C) over time, with each column corresponding to one SSP scenario. The horizontal dashed red line in panels (f-j) indicates the 1.5°C Paris Agreement target.

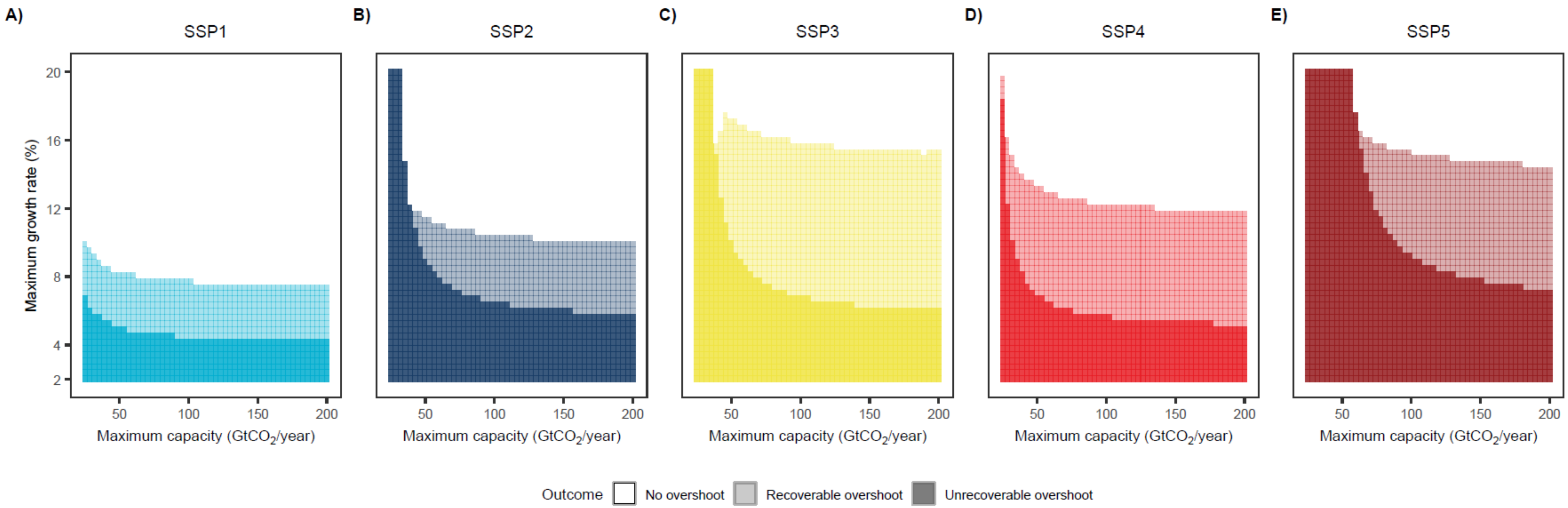


Fig 4. Overshoot outcome across CDR scale sensitivity parameters for five SSP scenarios. Each panel shows the combinations of scale ($GtCO_2$ $year^{-1}$) and speed that produce each of three overshoot outcomes by 2100, under a given emissions scenario. White regions indicate parameter combinations where peak temperature remains below 1.5°C (no overshoot). Light shading indicates recoverable overshoot, where peak temperature exceeds 1.5°C but returns below 1.5°C by 2100. Dark shading indicates unrecoverable overshoot, where temperature remains above 1.5°C at 2100.

4. Discussion

This study set out to determine how the speed and scale of CDR deployment influence peak temperature and overshoot duration. Our results demonstrate that the speed of CDR deployment is more important for minimising peak temperature and overshoot duration than the scale. While the interplay between speed and scale determines the specific optimal trajectory, for the likely feasible parameter ranges explored, faster speed with lower scale typically resulted in more favourable outcomes (lower peak temperature and shorter overshoots) than higher scale but slower speed of deployment.

Faster CDR deployment speed minimises peak temperature by allowing cumulative emissions to be reduced sooner, thereby limiting how high cumulative emissions climb. Additionally, by reaching net-negative emissions sooner, earlier CDR deployment allows more time to reduce temperature to target if necessary. Slow CDR speeds, even when combined with large scale in the long-term, result in hotter and longer overshoots. When speed is less than $r = 0.04$ (i.e., when CDR doubles approximately every 17 years in the early growth phase), our results indicate it is not possible to recover from a temperature overshoot this century irrespective of scale. We note that this speed of deployment is already high compared to current growth rates. Existing CDR (for example afforestation and land-use changes) growth has been steady for several years, and new CDR technology, although growing more rapidly, is increasing from a very low base of 0.0013 $GtCO_2$ $year^{-1}$ [26]. Under these conditions, achieving even the lowest identified recoverable speed would require substantial increases in deployment.

Under longer, hotter overshoots brought about by low CDR deployment speed there are more likely to be long-lasting environmental and societal impacts during and beyond the overshoot period [4], [12]. Sea level rise, polar ice loss and ecosystem degradation can persist well beyond the overshoot period [12], [28], [29], [30], [31]. Even when different speed and scale combinations remove the same volume of CO_2, the different temperature trajectories produced can result in changing risk of crossing tipping point thresholds [13], [30].

Faster deployment speed also results in more achievable scale requirements, reducing potential reliance on novel CDR technology and land-use conflicts with agriculture [17], [18], [32]. Therefore, our results have important implications for climate policy, suggesting that the rapid rollout of CDR deployment, even when paired with lower total capacity, is a priority to limit the impacts of overshoot on the environment and climate, and to maximise the usefulness of CDR for achieving the Paris Agreement target.

Here, we used a logistic function to set an upper bound on CDR capacity. Although the logistic function is a well-established model of technology transition [16], real-world adoption is rarely smooth and can be influenced by policy-driven decisions and investments, a factor particularly relevant given the urgency of meeting the Paris Agreement targets [33]. Additionally, the transition away from fossil fuels may not reflect historical transitions, given that it is being uniquely hastened by scientific urgency and increasing climate change impacts, rather than purely economic forces. Similar analogues include off-shore wind power and solar photovoltaics, where initial deployment was driven by policy incentives to increase early deployment, and which have subsequently achieved significantly higher growth rates than considered in our model [27]. Our results show that only a small change in speed or scale can make the difference between a recoverable and unrecoverable overshoot this century. Therefore, if real-world deployment speed or scale is faster than expected, overshoot peak temperature and duration will be minimised. Despite these factors, our key finding – that earlier and faster speed of CDR deployment reduces overshoot duration and peak temperature – should be robust to variations in real-world deployment trajectories.

While this update of MACROM is designed to isolate the effects of the speed and scale of CDR deployment, several simplifying assumptions made by our model and parameterisation may influence results. The first set of limitations concerns the physical representation of the climate system within MACROM. The model assumes instantaneous and symmetric equilibration between atmospheric CO_2 and temperature, meaning temperature responds immediately and equally to changes in cumulative CO_2 emissions, whether rising or falling. This overlooks the inertia, lagged ocean heat uptake, and hysteresis inherent in the climate system [29]. Consequently, the model likely underestimates peak temperature and duration, as real-world temperatures would decline more slowly following reductions in atmospheric CO_2 concentrations than MACROM assumes.

The second set of limitations concerns the socioeconomic representation of emissions mitigation and CDR deployment. Emissions mitigation is assumed to be limited to the reductions embedded within each SSP, primarily driven by changes to the energy-mix and land-use [15]. In MACROM, CDR deployment is more expensive per tonne CO_2 removed than emissions mitigation, implying that lower-cost pathways may exist that rely more heavily on mitigation than the SSPs and our modelling assume, rather than relying solely on CDR to meet the temperature target [14]. Furthermore, the model includes two distinct mechanisms constraining CDR expansion: an explicit cap on maximum deployment rates, and a quadratic increase in marginal deployment costs with scale. Both mechanisms act to suppress large-scale CDR deployment, and may therefore bias the model towards longer and higher overshoots.

A third set of limitation concerns the structural assumptions of the model. MACROM works at a global scale and does not capture regional heterogeneity in either climate impacts or economic damages. Optimal global solutions may have negative consequences at a regional scale, especially in developing nations [28], [30], [34]. Additionally, the model does not account for biophysical feedbacks resulting from large scale CDR rollout, including changes in surface albedo and hydrological cycles [31], [35]. Lastly, our model does not represent political factors, including questions of generational equity, feasibility or political instability, despite being likely to influence real-world CDR deployment [36], [37]. Due to these limitations, our results should be considered indicative of general trends, rather than precise estimates suitable for policy decisions.

We used the Paris Agreement as a case study, but MACROM allows for customisation in setting initial conditions and targets. In future investigations, we can set different temperature targets to assess speed and scale limits that lead to a successful overshoot recoverability when targeting a different final temperature. Similarly, extending simulations beyond 2100 would allow us to assess the impact of less ambitious CDR deployment scenarios on overshoot duration and magnitude. This future research could also help assess the risks to ecosystems and climate for longer overshoots. Given current emissions trajectories make the Paris Agreement target increasingly unlikely, exploring overshoot scenarios beyond 2100 would provide a better understanding of alternative future outcomes.

5. Conclusion

This study set out to assess how different combinations of CDR deployment speed and scale affect overshoot duration and peak temperature. This study has shown that faster speed, over greater scale minimises the duration and magnitude of an overshoot. Additionally, removing the same volume of CO_2 emissions can result in different overshoot trajectories, despite reaching the same final temperature, with earlier CDR deployment most advantageous. Our results suggest that the speed of CDR rollout is more important than scale to avoid the worst effects of an overshoot. Ramping up CDR deployment as early as possible should therefore be a policy priority to achieve lower peak temperature, shorter overshoot duration and lower required CDR capacity.

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Bibliography

[1] UNEP, “Emissions Gap Report 2025: Off Target - Continued Collective inaction puts Global Temperature Goal at Risk,” Nov. 2025, [Online]. Available: https://wedocs.unep.org/20.500.11822/48854

[2] E. Bevacqua, C.-F. Schleussner, and J. Zscheischler, “A year above 1.5 °C signals that Earth is most probably within the 20-year period that will reach the Paris Agreement limit,” *Nat. Clim. Change*, vol. 15, no. 3, pp. 262–265, Mar. 2025, doi: 10.1038/s41558-025-02246-9.

[3] C.-F. Schleussner *et al.*, “Overconfidence in climate overshoot,” *Nature*, vol. 634, no. 8033, pp. 366–373, Oct. 2024, doi: 10.1038/s41586-024-08020-9.

[4] A. Reisinger *et al.*, “Overshoot: A Conceptual Review of Exceeding and Returning to Global Warming of 1.5°C,” *Annu. Rev. Environ. Resour.*, vol. 50, no. Volume 50, 2025, pp. 185–217, Oct. 2025, doi: 10.1146/annurev-environ-111523-102029.

[5] W. F. Lamb *et al.*, “The carbon dioxide removal gap,” *Nat. Clim. Change*, vol. 14, no. 6, pp. 644–651, Jun. 2024, doi: 10.1038/s41558-024-01984-6.

[6] J. Rogelj *et al.*, “Scenarios towards limiting global mean temperature increase below 1.5 °C,” *Nat. Clim. Change*, vol. 8, no. 4, Art. no. 4, Apr. 2018, doi: 10.1038/s41558-018-0091-3.

[7] A. Reisinger and O. Geden, “Temporary overshoot: Origins, prospects, and a long path ahead,” *One Earth*, vol. 6, no. 12, pp. 1631–1637, Dec. 2023, doi: 10.1016/j.oneear.2023.11.008.

[8] G. Ganti *et al.*, “Evaluating the near- and long-term role of carbon dioxide removal in meeting global climate objectives,” *Commun. Earth Environ.*, vol. 5, no. 1, pp. 1–7, Jul. 2024, doi: 10.1038/s43247-024-01527-z.

[9] K. L. Ricke, R. J. Millar, and D. G. MacMartin, “Constraints on global temperature target overshoot,” *Sci. Rep.*, vol. 7, no. 1, Art. no. 1, Nov. 2017, doi: 10.1038/s41598-017-14503-9.

[10] R. Prütz, J. Strefler, J. Rogelj, and S. Fuss, “Understanding the carbon dioxide removal range in 1.5 °C compatible and high overshoot pathways,” *Environ. Res. Commun.*, vol. 5, no. 4, p. 041005, Apr. 2023, doi: 10.1088/2515-7620/accdba.

[11] M. R. Allen *et al.*, “Net Zero: Science, Origins, and Implications,” *Annu. Rev. Environ. Resour.*, vol. 47, no. 1, pp. 849–887, Oct. 2022, doi: 10.1146/annurev-environ-112320-105050.

[12] A. L. S. Meyer and C. H. Trisos, “Ecological impacts of temperature overshoot: The journey and the destination,” *One Earth*, vol. 6, no. 12, pp. 1614–1617, Dec. 2023, doi: 10.1016/j.oneear.2023.11.014.

[13] N. Wunderling *et al.*, “Global warming overshoots increase risks of climate tipping cascades in a network model,” *Nat. Clim. Change*, vol. 13, no. 1, Art. no. 1, Jan. 2023, doi: 10.1038/s41558-022-01545-9.

[14] N. Rynne, M. Bode, M. E. Roberts, and R. F. Heneghan, “MACROM: An Optimal Control Model for Balancing Climate Change Abatement and Damage Trade-offs,” Feb. 12, 2026, *EarthArXiv*. doi: https://doi.org/10.31223/X5SB5W.

[15] K. Riahi *et al.*, “The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview,” *Glob. Environ. Change*, vol. 42, pp. 153–168, Jan. 2017, doi: 10.1016/j.gloenvcha.2016.05.009.

[16] N. Meade and T. Islam, “Modelling and forecasting the diffusion of innovation – A 25-year review,” *Int. J. Forecast.*, vol. 22, no. 3, pp. 519–545, Jan. 2006, doi: 10.1016/j.ijforecast.2006.01.005.

[17] L. R. Boysen, W. Lucht, D. Gerten, V. Heck, T. M. Lenton, and H. J. Schellnhuber, “The limits to global-warming mitigation by terrestrial carbon removal,” *Earths Future*, vol. 5, no. 5, pp. 463–474, 2017, doi: 10.1002/2016EF000469.

[18] S. Fuss *et al.*, “Negative emissions—Part 2: Costs, potentials and side effects,” *Environ. Res. Lett.*, vol. 13, no. 6, p. 063002, May 2018, doi: 10.1088/1748-9326/aabf9f.

[19] M. J. Gidden *et al.*, “A prudent planetary limit for geologic carbon storage,” *Nature*, vol. 645, no. 8079, pp. 124–132, Sep. 2025, doi: 10.1038/s41586-025-09423-y.

[20] P. A. Geroski, “Models of technology diffusion,” *Res. Policy*, vol. 29, no. 4, pp. 603–625, Apr. 2000, doi: 10.1016/S0048-7333(99)00092-X.

[21] A. Grubler, “Energy transitions research: Insights and cautionary tales,” *Energy Policy*, vol. 50, pp. 8–16, Nov. 2012, doi: 10.1016/j.enpol.2012.02.070.

[22] A. Grubler, N. Nakicenovic, and D. G. Victor, “Dynamics of energy technologies and global change,” *Energy Policy*, vol. 27, no. 5, pp. 247–280, May 1999, doi: 10.1016/S0301-4215(98)00067-6.

[23] G. J. Kramer and M. Haigh, “No quick switch to low-carbon energy,” *Nature*, vol. 462, no. 7273, pp. 568–569, Dec. 2009, doi: 10.1038/462568a.

[24] J. D. Murray, Ed., *Mathematical Biology: I. An Introduction*, vol. 17. in Interdisciplinary Applied Mathematics, vol. 17. New York, NY: Springer, 2002. doi: 10.1007/b98868.

[25] G. Nemet, J. Greene, F. Müller-Hansen, and J. C. Minx, “Dataset on the adoption of historical technologies informs the scale-up of emerging carbon dioxide removal measures,” *Commun. Earth Environ.*, vol. 4, no. 1, p. 397, Oct. 2023, doi: 10.1038/s43247-023-01056-1.

[26] S. Smith *et al.*, Eds., “The State of Carbon Dioxide Removal 2024 - 2nd Edition,” 2024, doi: 10.17605/OSF.IO/F85QJ.

[27] M. R. Edwards *et al.*, “Modeling direct air carbon capture and storage in a 1.5 °C climate future using historical analogs,” *Proc. Natl. Acad. Sci.*, vol. 121, no. 20, p. e2215679121, May 2024, doi: 10.1073/pnas.2215679121.

[28] S.-K. Kim *et al.*, “Widespread irreversible changes in surface temperature and precipitation in response to CO2 forcing,” *Nat. Clim. Change*, vol. 12, no. 9, Art. no. 9, Sep. 2022, doi: 10.1038/s41558-022-01452-z.

[29] J. Schwinger, A. Asaadi, N. J. Steinert, and H. Lee, “Emit now, mitigate later? Earth system reversibility under overshoots of different magnitudes and durations,” *Earth Syst. Dyn.*, vol. 13, no. 4, pp. 1641–1665, Nov. 2022, doi: 10.5194/esd-13-1641-2022.

[30] N. Bauer *et al.*, “Exploring risks and benefits of overshooting a 1.5 °C carbon budget over space and time,” *Environ. Res. Lett.*, vol. 18, no. 5, p. 054015, May 2023, doi: 10.1088/1748-9326/accd83.

[31] A. Marshall, E. Grubert, and S. Warix, “Temperature Overshoot Would Have Lasting Impacts on Hydrology and Water Resources,” *Water Resour. Res.*, vol. 61, no. 1, p. e2024WR037950, 2025, doi: 10.1029/2024WR037950.

[32] S. Smith *et al.*, “State of Carbon Dioxide Removal - 1st Edition,” Jan. 2023, doi: 10.17605/OSF.IO/W3B4Z.

[33] B. K. Sovacool, “How long will it take? Conceptualizing the temporal dynamics of energy transitions,” *Energy Res. Soc. Sci.*, vol. 13, pp. 202–215, Mar. 2016, doi: 10.1016/j.erss.2015.12.020.

[34] L. Drouet *et al.*, “Net zero-emission pathways reduce the physical and economic risks of climate change,” *Nat. Clim. Change*, vol. 11, no. 12, Art. no. 12, Dec. 2021, doi: 10.1038/s41558-021-01218-z.

[35] J. Hilaire *et al.*, “Negative emissions and international climate goals—learning from and about mitigation scenarios,” *Clim. Change*, vol. 157, no. 2, pp. 189–219, Nov. 2019, doi: 10.1007/s10584-019-02516-4.

[36] S. Asayama and M. Hulme, “Engineering climate debt: temperature overshoot and peak-shaving as risky subprime mortgage lending,” *Clim. Policy*, vol. 19, no. 8, pp. 937–946, Sep. 2019, doi: 10.1080/14693062.2019.1623165.

[37] J. Fuhrman, H. McJeon, P. Patel, S. C. Doney, W. M. Shobe, and A. F. Clarens, “Food–energy–water implications of negative emissions technologies in a +1.5 °C future,” *Nat. Clim. Change*, vol. 10, no. 10, Art. no. 10, Oct. 2020, doi: 10.1038/s41558-020-0876-z.