

**Informing climate policy through advancements in our understanding of the Earth system
response to emissions, temperature overshoot, and temporary carbon storage**

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Abstract

Informing climate policy through advancements in our understanding of the Earth system response to emissions, temperature overshoot, and temporary carbon storage

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Limiting global warming to the temperature thresholds outlined in the Paris Agreement requires a clear understanding of the relationship between cumulative CO₂ emissions and temperature, the consequences of temporarily exceeding these thresholds, and the role of carbon dioxide removal in achieving temperature stabilization. This thesis advances understanding of the Earth system response to CO₂ emissions and removals through three complementary manuscripts. First, I provide a review of the Remaining Carbon Budget (RCB) framework where I examine how methodological choices and uncertainty affect its use as a decision-making tool, highlighting the importance of transparent communication of likelihoods and assumptions in setting net-zero targets. Second, I use an Earth system climate model to quantify the reversibility of climate responses following temperature overshoot, showing that slow-responding variables exhibit irreversible changes that scale linearly with the time-integrated magnitude of overshoot. Third, I investigate the climate value of temporary carbon storage, demonstrating that storage-years of carbon yield proportional short-term benefits across the same slow-responding variables, but that some of these benefits decline over multi-century timescales. Collectively, these studies reveal that the magnitude of positive emissions and the magnitude, timing, and durability of removals play an important role in determining climate outcomes. This research underscores the urgency of rapid and durable emissions reductions.

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Dedication

I dedicate this thesis to my late uncle, Neil Barker. Near the end of my undergraduate degree, I told Uncle Neil that I regretted not having focused more and not having studied science. He shared how he himself had only become serious about his studies late in his degree, which led him to write and publish an honours thesis on pinecones. That paper helped him land his first job in forestry and launched a career that spanned three decades. Uncle Neil encouraged me to follow a similar path, which inspired me to seek out a someone to supervise an honours thesis. My eventual thesis on the effect of climate change on outdoor skating in Montréal was later published and propelled me into grad school. Without his encouragement and support, I doubt I would have pursued an honours thesis or found my way to this PhD.

Contribution of Authors

Manuscript 1 (Chapter 2):

The conceptualization of this manuscript was jointly developed by myself and Dr. H. Damon Matthews. I was responsible for the analysis and writing, under Dr. Matthews' supervision. Prior to submission and publication in *Current Climate Change Reports* in August of 2022, Dr. Kasia Tokarska and Dr. Matthews contributed substantially to the editing of the manuscript. The published article can be found at: <https://doi.org/10.1007/s40641-022-00184-8>.

Manuscript 2 (Chapter 3):

Under the supervision of Dr. H. Damon Matthews, I was responsible for the conceptualization, experimental design, analysis, and writing of this manuscript. In preparation for submission, Dr. Kirsten Zickfeld and Dr. Matthews provided high-level feedback and editorial input. As of August 2025, the manuscript is under peer review for consideration in *Nature Climate Change*.

Manuscript 3 (Chapter 4):

This manuscript was co-authored by myself and Dr. H. Damon Matthews. We jointly developed the study concept. I conducted the experiments and analysis and wrote the manuscript, while Dr. Matthews contributed to editing.

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List of Abbreviations

AMOC	Atlantic meridional overturning circulation
AR6	The United Nations Sixth Assessment Report
BECCS	Bioenergy with carbon capture and storage
CDR	Carbon dioxide removal
CMIP5	Couple Model Intercomparison Project Phase 5
CMIP6	Couple Model Intercomparison Project Phase 6
CO₂	Carbon dioxide
DACCS	Direct air carbon capture and storage
DIC	Dissolved inorganic carbon
ECS	Equilibrium climate sensitivity
ENSO	El Nino Southern Oscillation
ESM	Earth system model
GHG	Greenhouse gas
GSAT	Global surface air temperature
GWP	Global warming potential
IAM	Integrated assessment model
ML	Machine learning
Non-OS	Non-overshoot
OCO-2	NASA's Orbiting Carbon Observatory -2
OS	Overshoot
PFT	Plant functional type
RCB	Remaining carbon budget
RCP	Representative concentration pathway
SAT	Surface air temperature
SLR	Sea level rise
SR1.5	United Nations Special Report on Global Warming of 1.5°C
SSP	Shared socioeconomic pathway
TCR	Transient climate response
TCRE	Transient climate response to cumulative CO ₂ emissions
UNFCCC	United Nations Framework Convention on Climate Change
UVic-ESCM	University of Victoria Earth system climate model

1 Introduction

1.1 Earth's natural climate variability and its effect on ancient humans

Palaeoclimatological research reveals that Earth's climate has undergone profound changes since the evolution of modern humans approximately 300,000 years ago¹⁻⁴. These changes have been driven by processes that occur across a broad range of timescales. On the longest timescales, variations in Earth's orbit change the distribution and intensity of insolation at the surface, driving glacial-interglacial cycles that occur roughly every 23,000 to 100,000 years⁵. Similarly, natural fluctuations in atmospheric greenhouse gas (GHG) concentrations, such as carbon dioxide (CO₂), have contributed to gradual natural climatic transitions over thousands of years⁵. On shorter timescales, internal modes of climate variability – like the El Niño Southern Oscillation (ENSO) – have caused pronounced variations in global and regional temperature and precipitation patterns on interannual to decadal timescales⁵. Episodic volcanic eruptions have also caused powerful short-term cooling by injecting aerosols into the stratosphere that reflect solar radiation, however, their influence typically diminishes within a few years⁵. Together, these processes demonstrate that Earth's climate system over the course of human history has been dynamic, shaped by the interplay of slow, long-term forcings and transient perturbations.

These climatic fluctuations have had major implications for life on Earth. Over geological time, before the evolution of modern humans, large and abrupt shifts in global temperature and atmospheric composition have triggered mass extinction events, reshaping the trajectory of evolution⁶⁻⁸. In the more recent past – since the Last Glacial Maximum approximately 21,000 years before present, and even within the very stable last 7000 years of the Holocene – archaeological, historical, and genetic evidence suggests that humans have been strongly influenced by climate variability⁹. Climatic changes such as cooling or warming phases and shifts in precipitation patterns have been linked to mass migrations, the collapse of settlements and civilizations, transitions in dominant modes of subsistence from mobile hunter gatherer societies to sedentary agrarian societies, and even genetic mutations in humans⁹. These examples highlight that human societies, even before industrialization, were intimately coupled with their climatic conditions.

1.2 Anthropogenic climate change

The Industrial Revolution marked the beginning of large-scale anthropogenic CO₂ emissions and coincided with the scientific discovery that greenhouse gases warm the planet. The first recorded suggestion that Earth's atmosphere could substantially increase surface temperatures was made by Joseph Fourier in 1827¹⁰. Roughly three decades later, Eunice Foote demonstrated that carbon dioxide absorbs thermal radiation, an observation that provided experimental evidence of the greenhouse effect¹¹. Soon afterward, John Tyndall became the first to quantify infrared absorption by various atmospheric gasses¹². By the end of the nineteenth century, Svante Arrhenius produced the first quantitative estimates of the climate response to increased atmospheric CO₂, laying the foundation for modern climate science¹³.

Since the onset of large-scale industrialization around 1850, human activities have also caused approximately 2.5 trillion tonnes of CO₂ emissions¹⁴. The combustion of fossil fuels has been the principal driver of these emissions, accounting for roughly 1.8 trillion tonnes of CO₂¹⁴. By burning fossil fuels, humans have transferred carbon that was stored for millions of years within Earth's crust into the fast-responding reservoirs of the carbon cycle – the atmosphere, the surface ocean, and the terrestrial biosphere. As a consequence, atmospheric CO₂ concentrations have risen by more than 140 parts per million, from approximately 280 ppm in 1750 to over 420 ppm today¹⁵. This unprecedented increase has produced about 1.36°C of human-caused global mean temperature increase relative to pre-industrial levels and has already caused some individual years to temporarily exceed 1.5°C of warming¹⁶. When placed in the context of Earth's climatic history, the speed of anthropogenic warming is extraordinary: whereas the transition from the Last Glacial Maximum to the pre-industrial Holocene produced roughly 5°C to 7°C of warming over 14,000 years³, nearly 3°C of warming is projected to occur from 1850 until 2100 within a span of just 250 years¹⁷.

1.3 Impacts of anthropogenic climate change

Despite our remarkable technological abilities as a species, anthropogenic climate change is producing challenges to human societies that echo the disruptions experienced by past civilizations. Increasing temperature and its associated climate changes are already forcing populations to migrate and exacerbating conflicts over resources¹⁸. Critical infrastructure is being damaged or rendered obsolete by rising sea levels and extreme weather, while crop failures, water scarcity, and the degradation of ecosystems essential to human well-being threaten food

security¹⁸. These impacts are distributed unevenly: some regions, particularly low-lying coastal zones, and small island states, face disproportionately severe risks¹⁸. Moreover, adaptive capacity is strongly correlated with wealth, governance, and institutional strength, meaning that the poorest and most vulnerable populations – both between and within nations – bear the greatest burden of climate change impacts¹⁸. Consequently, anthropogenic climate change has become, alongside the threat of nuclear conflict, one of the foremost existential risks to human civilization.

1.4 Tracking progress towards international climate targets

The unprecedented scale, pace, and impacts of anthropogenic climate change underscore the urgent need for coordinated global mitigation efforts. In recognition of this, the international community has established several frameworks and agreements designed to limit greenhouse gas emissions. Milestones in pursuit of this effort include the ratification of United Nations Framework Convention on Climate Change (UNFCCC) in Rio de Janeiro in 1992, Kyoto Protocol (1997), and most notably the Paris Agreement (2015), which commits nations to limiting global warming “to well below 2°C above pre-industrial levels” and pursue efforts “to limit the temperature increase to 1.5°C above pre-industrial levels”¹⁹.

Tracking progress toward these targets requires a quantitative understanding of how CO₂ emissions and other anthropogenic forcings translate into temperature change. This task would seem to be difficult given that the climate system contains many non-linearities that respond to anthropogenic emissions dynamically. However, despite the complexity of the climate system, two remarkable features of the Earth system response to anthropogenic CO₂ emissions help simplify the relationship between CO₂ emissions and warming. First, that each tonne of CO₂ emitted causes approximately the same amount of warming regardless of the background atmospheric CO₂ concentration²⁰. Second, that warming caused by CO₂ persists over millennial timescales^{21,22}. These characteristics mean that, remarkably, CO₂ induced warming scales with cumulative CO₂ emissions^{23–26}, and that stabilizing global temperature will therefore require CO₂ emissions to reach net-zero²⁷. Because CO₂ is the dominant driver of anthropogenic climate change, these properties enable the quantification of a finite budget of allowable CO₂ emissions compatible with limiting warming to a given temperature, referred to as the remaining carbon budget (RCB). While the RCB focuses on the transient climate response to CO₂ emissions,

methods for quantifying the RCB also account for other important anthropogenic forcers, such as non-CO₂ greenhouse gasses like methane and nitrous oxide, and any inertial warming or cooling post net-zero CO₂^{i 28–30}. Although there is uncertainty in RCB estimates due to methodological choices, future emissions, and uncertainty in the physical response to emissions, the RCB is still an invaluable tool. The RCB translates complex Earth system dynamics into a probabilistic framework that links cumulative emissions to temperature outcomes and thus highlights the emissions reductions required – within a known range of uncertainty – to meet a given temperature limit.

1.5 How much warming should we expect?

Our understanding of the climate response to CO₂ emissions provides a clear framework for what must be done to achieve international climate goals: CO₂ emissions must reach net-zero and cumulative CO₂ emissions between the present and when we reach net-zero CO₂ must remain within the limits defined by the RCB for “well-below 2.0°C”. Despite this conceptual clarity, the world remains off track to meet these targets. Annual CO₂ emissions continue to rise¹⁴, global temperature continues to increase¹⁶, and investment in fossil fuels exceeds one trillion U.S. dollars per year³¹.

This reality prompts a pressing question: how much additional warming should we expect? One way to answer this question is to examine RCB estimates and their associated uncertainty for different temperature targets to assess what is physically possible based on those estimates. Even if global CO₂ emissions were to cease tomorrow, RCB estimates demonstrate that committed warming from past emissions and Earth system inertia may have already pushed the 1.5°C target out of reach¹⁶. However, limiting warming to below 2.0°C remains physically achievable, though the window of opportunity is rapidly narrowing given that the RCB for a two-thirds chance of limiting warming to 2.0°C is equal to about twenty-two years of emissions at the 2024 rate from the end of 2025 onwards¹⁶.

ⁱ Our best estimate of temperature change following net-zero CO₂ is zero, although the multi-model range is approximately $\pm 0.3^\circ\text{C}$, and some models show substantial continued climate changes over a millennium following net-zero CO₂¹³⁹

A second way to evaluate expected warming is to consider what is socio-economically likely. This approach is inherently uncertain because future CO₂ emissions depend on complex, interlinked human systems – population growth, technological innovation, cultural norms, and policy decisions³² – all of which are shaped by unpredictable human behavior and lack fixed cause-and-effect relationships. With this caveat in mind, the best available projections of future emissions indicate that current national pledges and observed socioeconomic trends place the world on a trajectory toward roughly 3°C of warming by 2100¹⁷. Analyses from both physical and socioeconomic perspectives therefore converge on a sobering conclusion: the temperature targets of the Paris Agreement are becoming increasingly difficult to achieve unless there is drastic action taken to rapidly reduce emissions.

1.6 Increasing likelihood of temperature overshoot

Despite decades of international pledges, our continued rise in annual emissions and subsequent dwindling RCBs suggest that the probability of exceeding 1.5°C and “well below 2.0°C” temperature targets is increasing. This trajectory has prompted the critical question: can we return to these temperature targets if they are temporarily breached? From a physical standpoint, the answer is yesⁱⁱ. Earth system model experiments demonstrate that negative CO₂ emissions have a cooling effect on global temperature that is nearly symmetrical to the warming effect of positive emissions^{33,34}. These model simulations suggest that, if CO₂ emissions could be reduced to net-negative through large-scale carbon dioxide removal, global temperatures would be expected to decrease correspondingly. The notion that humankind could subsequently reduce global mean temperature after surpassing a target level using net-negative CO₂ emissions has popularized the concept of temperature overshoot, in which global warming first temporarily exceeds a threshold and later declines to meet the same threshold.

The temperature overshoot scenarios have become increasingly prominent in scenario development. In the Intergovernmental Panel on Climate Change Special Report on Global Warming of 1.5°C (SR1.5), nearly all the scenarios consistent with limiting warming to 1.5°C by

ⁱⁱ It should be noted that while reducing temperature is physically possible, many arguments have been made challenging the feasibility of achieving large scale net-negative emissions from socioeconomic, technological, and ecological perspectives^{140,141}.

2100 included some degree of temperature overshoot³⁵. Similarly, in the IPCC Sixth Assessment Report (AR6), a substantial proportion of scenarios compatible with the Paris Agreement targets also involved overshoot trajectories³⁶. These scenarios typically assume large-scale deployment of carbon dioxide removal (CDR) technologies – such as bioenergy with carbon capture and storage (BECCS), reforestation and afforestation, or direct air carbon capture and storage (DACCS) – to reverse the temperature rise later in the century³⁶. The growing prevalence of overshoot scenarios in the literature reflects the reality that the RCBs consistent with the Paris Agreement temperature thresholds are small, making it increasingly difficult to limit warming to stringent targets without first exceeding them.

1.7 Understanding the consequences of temperature overshoot

The growing likelihood that global temperature will temporarily exceed the Paris Agreement thresholds makes it increasingly important that we understand the impacts of first overshooting a temperature. Until the past decade, most research in Earth system science and climate impacts has concentrated on scenarios in which global temperature rises and then stabilizes, rather than those involving temperature overshoot. For instance, the Representative Concentration Pathways (RCPs) developed for the fifth phase of the Coupled Model Intercomparison Project (CMIP5) all depicted temperature trajectories in which temperature levels off after reaching a given value, leading to stable temperatures³⁷. These scenarios informed much of the literature on long-term climate responses, ecosystem change, and socio-economic impacts in the IPCC's Fifth Assessment Report (AR5). However, the sixth phase of CMIP (CMIP6) introduced the Shared Socioeconomic Pathways (SSPs), which included two scenarios that explicitly feature temperature overshoot followed by subsequent cooling – SSP1-1.9 and SSP5-3.4-OS³². The inclusion of these scenarios has enabled researchers, for the first time within a coordinated multi-model comparison project, to systematically examine how Earth system components respond to a period of temperature decline after overshoot.

Research based on these overshoot scenarios has substantially expanded our understanding of the climate system and its long-term inertia. Studies have explored how overshoot affects components of the Earth system including ocean heat uptake and thermal expansion, the reversibility of permafrost carbon release, regional temperature and precipitation, sea ice, thermohaline circulation, and biogeochemical cycling^{33,38–50}. This emerging body of

work has clarified that some components of the Earth system respond quasi-symmetrically to warming and cooling, while others – such as sea level or ice sheet extent – exhibit hysteresis or irreversible change following overshoot. While these efforts have yielded valuable insights, they have been conducted within a relatively narrow experimental and scenario framework: many studies rely on the two SSP overshoot scenarios, employ highly idealized experiments, or utilize reduced-complexity climate emulators rather than fully coupled Earth system models. A clear gap remains in the literature regarding the overshoot responses across Paris compatible mitigation pathways. Addressing this gap is essential for accurately evaluating the physical and societal consequences of meeting the Paris Agreement targets only after first exceeding them.

1.8 Net-Zero, Net-Negative, and Carbon Storage Durability

Our understanding of the Earth system response to CO₂ emissions indicates that achieving a stable global temperature requires CO₂ emissions to eventually reach net-zeroⁱⁱⁱ. Net-zero CO₂ emissions imply that positive anthropogenic emissions are balanced by equivalent anthropogenic removals. The most robust means of achieving this – bringing CO₂ emissions to zero and thus negating the need for anthropogenic removals – remains extraordinarily difficult given the persistence of hard-to-decarbonize sectors such as heavy industry, and agriculture⁵¹. Consequently, even under ambitious mitigation efforts, some portion of residual CO₂ emissions will likely need to be offset through carbon dioxide removal. In a world where global temperature stabilization follows a period of temperature overshoot, CO₂ removals will need to go beyond net-zero and reach net-negative – at least temporarily – to compensate for exceedance of the RCB and to draw temperatures back down.

Any large-scale carbon dioxide removal will introduce substantial new uncertainties into our understanding of both present and future climate change and into tracking progress towards

ⁱⁱⁱ Given that there is uncertainty in the Earth system response following net-zero CO₂ emissions (i.e., the ZEC previously discussed), it is possible that either: 1) a small amount of positive emissions could be sustained without causing further warming, or 2) a small amount of net-negative CO₂ emissions would be required to keep global temperature from continuing to rise. It is also possible that non-CO₂ emissions reductions could offset warming from continued CO₂ emissions. However, even if this occurs, eventually CO₂ emissions would have to be brought to net-zero given that non-CO₂ emissions would eventually reach zero and therefore could not offset continued CO₂ emissions forever.

limiting emissions to a given RCB. One of these key uncertainties is the durability of carbon storage. Given that the warming effect of CO₂ persists for millennia, accurately quantifying both the magnitude of removal and the longevity of storage is of great importance if carbon removal is meant to provide a robust offset to emissions or act to decrease temperature by reaching net-negative emissions. Without accurate quantification and verification, we risk perceiving that net-zero has been achieved when net CO₂ emissions are still positive, which would result in continued warming. This uncertainty could undermine the reliability of the RCB as a policy and mitigation tool: if the true balance between emissions and removals is unknown, the correspondence between emissions pathways and temperature outcomes becomes ambiguous.

1.9 Implications of temporarily stored carbon

This potential ambiguity in the durability of carbon storage is relevant to all CDR methods. Commonly proposed methods involve sequestering carbon in geologic reservoirs, the terrestrial biosphere, or the ocean. If CDR fails to ensure storage over millennial timescales, it will not truly offset the enduring warming impact of fossil fuel emissions unless any re-release of carbon is measured and fully re-compensated by additional removal. Uncertainty in the durability of carbon storage is particularly important for nature-based approaches because terrestrial ecosystems respond dynamically to ongoing climate change in ways that can decrease carbon storage⁵², and because future anthropogenic land-use changes may reverse previously achieved removals. Furthermore, of all CDR methods, nature-based carbon removal is featured the most heavily in national climate pledges⁵³. Consequently, developing a robust understanding of how the durability of carbon storage influences the climatic outcomes of CDR is essential for assessing mitigation pathways.

2 Research objectives

The overarching motivation of my research is to advance our understanding of future climate change from an Earth system perspective, with a specific focus on questions central to climate mitigation. These include: How much carbon can humankind emit while remaining within the temperature limits of the Paris Agreement? How does the pathway we take to reach a given RCB influence climate outcomes if that budget is first exceeded? And if net-zero CO₂ emissions are achieved while relying on nature-based carbon storage and removal that may only provide temporary storage, will this storage provide any lasting climatic benefit? By addressing these questions, this thesis aims to contribute to the understanding of how the physical climate system responds to emissions, overshoot trajectories, and temporary carbon storage, thereby improving the scientific basis for setting and evaluating mitigation strategies.

Manuscript 1 (Chapter 2) is a comprehensive review paper on the concept of the RCB. In this chapter, I examine the theoretical foundations of the RCB and synthesize how it arises from the near-linear relationship between cumulative CO₂ emissions and global mean temperature change. I discuss how different methodologies for quantifying the RCB produce distinct estimates and uncertainty ranges. I also analyze how these methodological choices influence policy-relevant outcomes. This study was published in *Current Climate Change Reports* in August, 2022.

In manuscript 2 (Chapter 3), I investigate the reversibility of climate change following temperature overshoot, addressing a set of interrelated questions: Which aspects of the climate system are reversible or irreversible after overshoot? What drives irreversible or reversible behavior? And can the impacts of overshoot on irreversible variables be predicted based on the characteristics of the overshoot pathway? Using an intermediate-complexity Earth system climate model, I simulate a suite of overshoot and non-overshoot scenarios to quantify the degree of reversibility across a range of key climate variables. I identify the physical processes that drive reversibility or irreversibility in these variables and demonstrate that many irreversible outcomes scale with the time-integrated magnitude of temperature overshoot. This relationship provides a novel framework for predicting certain irreversible effects based on the temporal and temperature characteristics of overshoot trajectories. The overarching aim of this study is to

improve understanding of the Earth system consequences of temperature overshoot in scenarios compatible with the Paris Agreement and to highlight the factors that govern the persistence of overshoot impacts. This study was submitted to Nature Climate Change in July of 2025 and is currently in review.

In manuscript 3 (Chapter 4), I investigate the climate response to temporary carbon storage. The central questions guiding this analysis are: Are there measurable climate benefits to storing carbon temporarily? How do these benefits depend on the magnitude and duration of storage? And how do they evolve over multi-century timescales? Building upon the findings in Chapter 3 showing that irreversible climate outcomes scale with time-integrated magnitude of temperature overshoot, I demonstrate that irreversible climate variables also scale with time-integrated carbon storage in the Earth system model used here. This relationship establishes a quantitative link between temporary carbon storage resulting from either carbon removal or avoided land emissions, and long-term climate outcomes. The goal of this manuscript is to determine whether temporary carbon storage can provide lasting mitigation benefits despite eventual re-emission and to develop a framework for comparing the climate effectiveness of different CDR methods that operate on varying timescales. In doing so, this study contributes to ongoing debates about the value and limitations of temporary carbon storage within global mitigation strategies.

3 Chapter 2: The Role of Remaining Carbon Budgets and Net-Zero CO₂ Targets in Climate Mitigation Policy

3.1 Abstract

Purpose of Review:

Here, we review recent estimates of the remaining carbon budget, with a focus on characterizing key uncertainties and assessing the implications for net-zero CO₂ targets and climate policy.

Recent Findings:

Recent analyses offer a range estimates of remaining allowable CO₂ emissions for the 1.5°C and well-below 2°C climate targets, though the treatment and coverage of key sources of uncertainty vary considerably among studies. We recommend that net-zero CO₂ targets be set with explicit recognition of the uncertainty associated with carbon budget estimates and be updated regularly as this uncertainty is better constrained. Allocating the remaining carbon budget among countries or other entities, as well as monitoring progress at the subnational level, represents additional key challenges in applying a carbon budget framework to climate policy.

Summary:

Despite these challenges, recent advances in quantifying carbon budget uncertainty demonstrate that the concept is well-suited to inform climate policy and to evaluate whether net-zero CO₂ targets are consistent with the goals of the Paris Agreement.

3.2 Introduction

A remaining carbon budget (RCB) defines the amount of remaining allowable CO₂ emissions that is consistent with limiting global warming to a specified temperature target (such as 1.5°C warming above the pre-industrial) with a given probability. The RCB could be an effective tool for policymaking and science communication, and its conceptual similarity to a financial budget makes it intuitive and easy to understand (e.g. ^{29,54}). Since the concept of a budget implies a finite quantity that is available to be “spent” in the future, the RCB also clearly underscores that stabilizing global temperatures will require either eliminating global CO₂ emissions, or balancing CO₂ emissions with CO₂ removal, to stop warming. The RCB is therefore a key rationale for countries, corporations and other jurisdictions to set net-zero CO₂ emission targets in order to meet the temperature goals of the Paris Agreement.

Matthews et al.²⁹ clarify the definition of RCB that would limit global warming to a given temperature limit as “*the amount of CO₂ that can still be emitted from the present day onwards ... up to the point in time that CO₂ emissions reach net-zero.*” While this definition of the RCB is specific to CO₂ emissions, the climate response (i.e. potential additional warming) to other non-CO₂ greenhouse gas or aerosol emissions is accounted for when the RCB is estimated. In other words, these future non-CO₂ emissions themselves are not included as part of the RCB estimate, but the net warming effect from them is accounted for. Therefore, the RCB is relevant for mitigation of both CO₂ and non-CO₂ emissions, even though it is expressed only in remaining amount of CO₂. The RCB definition also does not include any information about the trajectory of emission after the point of net-zero CO₂ emissions. Given that peak temperature change in future scenarios occurs close to the time of net-zero CO₂ emissions⁵⁵, this definition of the RCB is consistent with limiting peak warming to the desired temperature limit, with a given level of probability. The trajectory of global CO₂ emissions after the point of net-zero CO₂ (i.e. whether they remain at net-zero or become net-negative) would determine whether CO₂-induced temperature change remains approximately stable at the peak temperature level, or decrease from this peak in response to net-negative global CO₂ emissions (e.g.^{29,30,56–58}).

In this review, we focus on three broad topics. First, we provide an overview of methods that can be used to estimate the RCB, how these methods differ across studies, and what conclusions we can draw from the RCB in light of the range of different methods that have been used in recent literature. Second, we discuss how net-zero CO₂ targets should be informed by the RCB, recognizing the important implications of uncertainty in RCB estimates. Finally, we consider the challenges and opportunities for implementing the RCB and net-zero CO₂ targets in climate mitigation policy.

3.3 The Remaining Carbon Budget: Estimates, Methods, and Uncertainties

3.3.1 The Climate Response to Cumulative CO₂ Emissions

The climate system includes many non-linear processes that respond to different forcings (such as anthropogenic emissions) in a dynamic way. However, despite the complexity of the climate system and the non-linearity of individual processes, the relationship between total (or cumulative) CO₂ emissions and CO₂-induced global temperature change has been shown to be approximately linear (e.g.^{23–25,59}). This approximately linear relationship is known as the

transient climate response to cumulative CO₂ emissions (TCRE), and is evident across climate models of different complexities and in the observational record (e.g. ^{60–62}).

The near-linear climate response to CO₂ emissions emerges from the finding that an emission of CO₂ produces the same amount of warming regardless of the background atmospheric concentration of CO₂ at the time of emission, combined with the fact that CO₂ induced warming persists in the climate system for millennia ^{20,27}. The resulting linear TCRE relationship demonstrates that: (1) CO₂-induced warming is independent of the CO₂-emissions pathway, and (2) the warming impact from CO₂ emissions can be estimated based on cumulative CO₂ emissions (e.g. ^{24–27,63}). As a result, the TCRE forms the scientific basis for the RCB. By using the TCRE, a finite amount of cumulative CO₂ emissions can be directly related to CO₂-induced warming regardless of the timing and rate of CO₂ emissions (e.g. ^{23,25,64}).

3.3.2 Carbon Budget Uncertainty in a Real-World Setting

In a real-world setting, a carbon budget estimate for a particular temperature target cannot be calculated using the TCRE alone as there are other factors that contribute both to uncertainty in the estimated temperature change and uncertainty related to emission estimates. Overall carbon budget uncertainty can be understood to span two distinct categories: geophysical uncertainty and socioeconomic uncertainty²⁹. Geophysical uncertainty relates to climate system processes that are not fully understood and that affect the climate response to both CO₂ and non-CO₂ emissions. Socioeconomic uncertainty relates to human systems and decision-making processes that will determine future emissions pathways of non-CO₂ emissions; these non-CO₂ emissions pathways are an important determinant of the warming that will be caused by emissions other than CO₂, and hence affect the allowable CO₂ emissions that can be emitted to limit total warming to a particular target level. The primary factors contributing to RCB uncertainty are listed in Table 3–1, all of which could either decrease or extend the remaining carbon budget by a substantial amount.

<i>Sources of uncertainty</i>		<i>Description</i>
<i>Geophysical uncertainty</i>	<i>TCRE</i>	Uncertainty in the value of the TCRE includes: (1) <i>physical climate uncertainty</i> that reflects the climate response to atmospheric CO ₂ changes, including CO ₂ forcing uncertainty and all physical climate feedbacks that affect the climate response, and (2) <i>carbon cycle uncertainty</i> that reflects how atmospheric CO ₂ changes in response to CO ₂ emissions and carbon cycle feedbacks.
	<i>Non-CO₂ forcing and response</i>	This includes uncertainty in the radiative forcing associated with non-CO ₂ emissions (greenhouse gases and aerosols) as well as the climate response to this forcing. This uncertainty affects the estimated future warming caused by emissions other than CO ₂ and hence the amount of available future CO ₂ -induced warming that is used to estimate the RCB.
	<i>Unrepresented Earth system feedbacks</i>	This source of uncertainty relates to feedbacks that are not fully represented in the climate models that are used to estimate the value of the TCRE or the non-CO ₂ contribution to warming. The most important of these feedbacks is the permafrost carbon feedback. This source of uncertainty only applies when a model-based TCRE estimate is used to estimate the RCB; when using observational data to estimate the TCRE, all feedbacks are in principle included in the observed climate response.
	<i>Zero emissions commitment (ZEC)</i>	The ZEC represents the amount of committed temperature change from past emissions after net-zero CO ₂ emissions has been reached. The ZEC is distinct from the TCRE uncertainty because the TCRE measures only the transient (i.e. instantaneous) climate response to cumulative CO ₂ emissions, and not the longer-term temperature changes that may arise from inertia associated with the climate response to emissions.
<i>Socioeconomic uncertainty</i>	<i>Non-CO₂ emissions pathway</i>	The future contribution to temperature change from non-CO ₂ emissions depends on the species emitted and the timing and rate of emissions leading up until net-zero CO ₂ is reached, both of which will depend on socioeconomic rather than geophysical processes. This source of uncertainty applies primarily to emissions of short-lived non-CO ₂ species (e.g. aerosols and methane) whose climate effect is sensitive to near-term changes in emission rates, rather than to longer-lived species (e.g. nitrous oxide) whose climate effect is more strongly determined by cumulative emissions as is the case of CO ₂ .

Table 3-1 – The major sources of geophysical and socioeconomic RCB uncertainty.

3.3.3 Methods of Estimating the Remaining Carbon Budget

In Table 3–2, we show the range of RCB estimates that is available in recent literature for temperature targets of 1.5°C and 2.0°C. The spread of individual RCB estimates is affected by the uncertainty sources listed in Table 3–1. However, the spread of estimates among studies is caused by methodological differences, including the adoption of different definitions of the RCB, as well as the exclusion (or only partial representation) of particular sources of uncertainty. Here,

we have adopted the formal definition of the RCB following Matthews et al.²⁹ and Rogelj et al.³⁰, the latter of which defines the RCB as “*the finite total amount of CO₂ that can be emitted into the atmosphere by human activities while still holding global warming to a desired temperature limit.*” This RCB definition implies that the temperature target in question is avoided, meaning that warming from slow responding processes in the climate system are considered, and is therefore consistent with the definition of the “avoidance budget” that was defined in Rogelj et al.⁶⁵. Alternatively, some studies have estimated the amount of CO₂ emissions up until the point when a particular temperature target is reached (and subsequently exceeded), which Rogelj et al.⁶⁵ termed an “exceedance budget” (e.g.^{66,67}). Peak warming expected from an exceedance budget would likely exceed the associated temperature target due to inertia in the climate system, and as such, exceedance budgets are generally larger than avoidance budgets. The definition of the RCB therefore influences the size of the RCB estimate.

Some sources of uncertainty (e.g. ZEC-related uncertainty) are explicitly included or omitted depending on the definition of the RCB that is applied in a particular study^{29,30}. Other methodological choices are also important, such as the choice of whether RCB estimates reflect warming from a particular choice of pre-industrial reference period or from a particular definition of observed warming (e.g.^{30,66,68}), or whether sources of uncertainty are represented as a single estimate (e.g. a ZEC of zero) or by a range of values (e.g. a ZEC ranging from ± 0.3 as in ZECMIP⁶⁹). Building on previous analyses (e.g.³⁰), we show in Figure 3–1 which sources of uncertainty from Table 3–1 are included in RCB estimates in the literature published between 2014 and 2021. The inconsistent coverage of uncertainty sources across studies demonstrates that many RCB estimates are not easily compared largely because of methodological differences rather than because of scientific uncertainty. The inclusion or exclusion of individual sources of uncertainty in a RCB estimate can alter the size of the budget substantially, especially for inconsistent treatment of permafrost (e.g.^{48,70}) and non-CO₂ emissions pathway uncertainty (e.g.^{28,55,62,71}). Estimates that account for the range of possible values for each source of uncertainty are more robust but will have a larger range of uncertainty as a result. Similarly, using probabilistic approaches to assess the RCB distribution (e.g. MCMC sampling or Bayesian methods) provides a more holistic view of the RCB than approaches that use a limited set of models or single set of parameters.

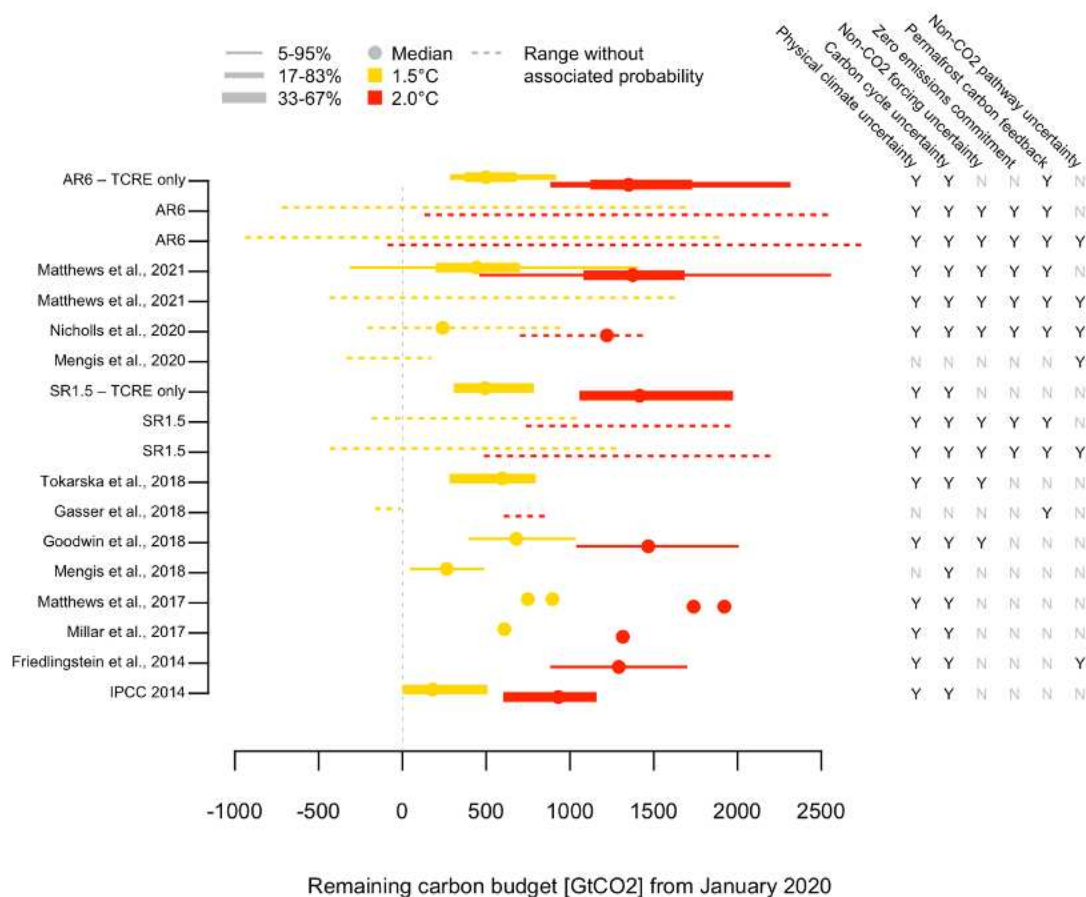


Figure 3-1 – Estimates of the remaining carbon budget for 1.5°C and 2.0°C targets across various studies.

Estimates of RCB from different studies were adjusted using the observed global emissions up to the year 2020 (from the Global Carbon Project⁸⁹ to reflect the RCB from January 2020 onwards). Columns on the right indicate whether primary sources of RCB uncertainty are included in a particular study's RCB estimate with "Y" indicating that a particular source of uncertainty is included and "N" indicating that a particular source of uncertainty is excluded. Here, physical climate uncertainty is listed as included for a particular study if the ranges of possible values for equilibrium climate sensitivity (ECS) and the transient climate response (TCR) are considered. Similarly, carbon cycle uncertainty is considered included in a particular estimate if the range of possible changes to land and ocean carbon uptake is considered. Non-CO₂ forcing uncertainty reflects the uncertainty in the climate response a particular non-CO₂ scenario, but not differences in non-CO₂ forcing across scenarios. Non-CO₂ pathway uncertainty is marked as included if a range of plausible future non-CO₂ pathways that reflect varying decarbonization pathways are considered in a RCB estimate.

*Given that the IPCC SR1.5 and AR6 reports did not provide a way to assess the full uncertainty as a single distribution, the range presented here represents the sum of all individual uncertainty ranges. However, this likely exaggerates the uncertainty in the RCB because it assumes that the uncertainties are independent, which may not be the case in reality.

Estimates that include all major sources of uncertainty as well as the ranges of uncertainty of each source can be considered “best estimates” – for instance the estimates by Canadell et al.⁶² in the IPCC Sixth Assessment Report (AR6), the estimates by Nicholls et al.⁷², and the estimates by Matthews et al.²⁸. However, even amongst these “best estimates” we identify three important differences. The first is whether sources of uncertainty are considered to be independent. In some studies the effect of different sources of geophysical uncertainty on the RCB is quantified using an integrated framework that accounts for possible interdependence between sources (e.g.²⁸), while in other studies the effects of sources of geophysical uncertainty on the RCB are quantified using a segmented framework where sources of uncertainty are assumed to be independent and are assessed individually (e.g.^{55,62,72}). Sources of uncertainty are most likely to be interdependent (e.g. if non-CO₂ forcing is more positive, the TCRE would be smaller) and thus an integrated framework may be better suited to capture this interdependence. Another advantage of the integrated framework is that the RCB and the associated geophysical uncertainty can be represented as a single distribution.

The second important difference between “best estimates” is how the relationship between CO₂-induced warming and cumulative CO₂ emissions is represented. Canadell et al.⁶² use a strictly linear TCRE. In Nicholls et al.⁷², a weakly non-linear TCRE is derived from the relationship between CO₂-induced warming and cumulative emissions of CO₂ when net-zero CO₂ is reached in mitigation scenarios as simulated by a simple climate model (that is calibrated to ESMs). Finally, in Matthews et al.²⁸, the TCRE is derived using observations of warming since a pre-industrial period, estimates of cumulative emissions of CO₂ since a pre-industrial period, and estimates of the forcing fraction of CO₂ to non-CO₂ emissions. As Nicholls et al.⁷² point out, these varying representations of the relationship between CO₂-induced warming and cumulative CO₂ emissions are often referred to simply as the TCRE in the literature despite being somewhat distinct.

A third important difference between “best estimates” is how the warming contribution from the future non-CO₂ emissions pathway is included. In some studies, the warming contribution of non-CO₂ emissions at net-zero (as simulated in a simple climate model) is converted to an equivalent amount of cumulative CO₂ emissions using the TCRE (e.g. ^{62,72}). In the integrated framework by Matthews et al. ²⁸, the non-CO₂ contribution to warming is represented by the non-CO₂ fraction of total anthropogenic forcing, averaged over the 30 years before net-zero is reached.

The differences between frameworks for estimating the RCB cause non-negligible differences in RCB estimates (e.g. ^{28,72}), especially in mitigation scenarios where the RCB is already small (i.e. only several hundred Gt CO₂). Some of these differences have been investigated (e.g. Nicholls et al. ⁷² demonstrate how using a non-linear TCRE produces RCB estimates more closely aligned with the RCB in simple climate model simulations). However, further analysis of all various frameworks for estimating the RCB would be valuable as it could clearly define the advantages or disadvantages of each framework and identify whether there is one particular framework that produces more accurate RCB estimates.

3.3.4 Important Takeaways from RCB Estimates

It is important to emphasize that despite these methodological inconsistencies across studies that complicate direct comparisons of RCB estimates, the following general conclusions are consistent across the studies represented in Figure 3–1: (1) the RCB for 1.5°C is small, and on the order of several hundreds of Gt CO₂, (2) the RCB for 2°C is expected to be in between 1000 and 1500 Gt CO₂, (3) the RCB for 2°C has a wider range of uncertainty than 1.5°C RCB, and (4) there is a low (but non-zero) probability that the RCB for 1.5°C has already been exceeded (e.g. ^{28,55,62,72}).

Figure 3–2 demonstrates another important point: the RCB is not a single number (of how much CO₂ still could be emitted before a given level of warming is reached) but rather, needs to be interpreted in probabilistic terms (i.e. what is the probability of meeting or exceeding a given target if a certain amount of Gt CO₂ is emitted). There are several ways to understand RCB estimates that account for all sources of uncertainty together and have enough samples to assign a reliable probability range. First, the RCB estimate can be understood as a probability distribution, which illustrates the likelihood that the RCB for a particular temperature target is

equal to a particular quantity of cumulative CO₂ emissions (see Figure 3–2 A). Alternately, the RCB estimate can be shown as a cumulative probability distribution which shows the likelihood that a given amount of cumulative CO₂ emissions will succeed in limiting warming to below the desired temperature target (see Figure 3–2 B). Finally, the RCB estimates for a range of temperature targets can also be plotted to show the likely range of temperature outcomes that would result from a given amount of cumulative CO₂ emissions (see Figure 3–2 C).

Because of the range of uncertainty of RCB estimates, RCB estimates for one temperature target overlap the range of RCB estimates of other nearby temperature targets. Consequently, a given quantity of emissions can represent the RCB estimate for a range of temperature targets, but with different associated likelihoods of not exceeding the target (see Table 3–2). For example, the RCB estimates that gives a 50% chance of limiting warming to 1.5°C (GtCO₂ from 2020 onwards; Table 3–2) would correspond to an 81% chance of limiting warming to 1.75°C, and a 96% chance of limiting warming to 2.0°C.

<i>Amount of total emissions</i> [Gt CO ₂]	<i>Chance of limiting warming to:</i>		
	1.5 °C	1.75 °C	2.0 °C
230	67%	91%	98%
440	50%	81%	96%
670	33%	67%	89%
910	20%	50%	79%
1110	12%	36%	67%
1370	5%	22%	50%

Table 3-2 – Estimates of the RCB starting from January 2020, with corresponding likelihood of not exceeding 1.5°C, 1.75° and 2°C above the 1850-1900 temperatures

Red (blue) cells highlight RCBs with a 67% (50%) probability of limiting warming to each temperature threshold (values from Matthews et al. ²⁸).

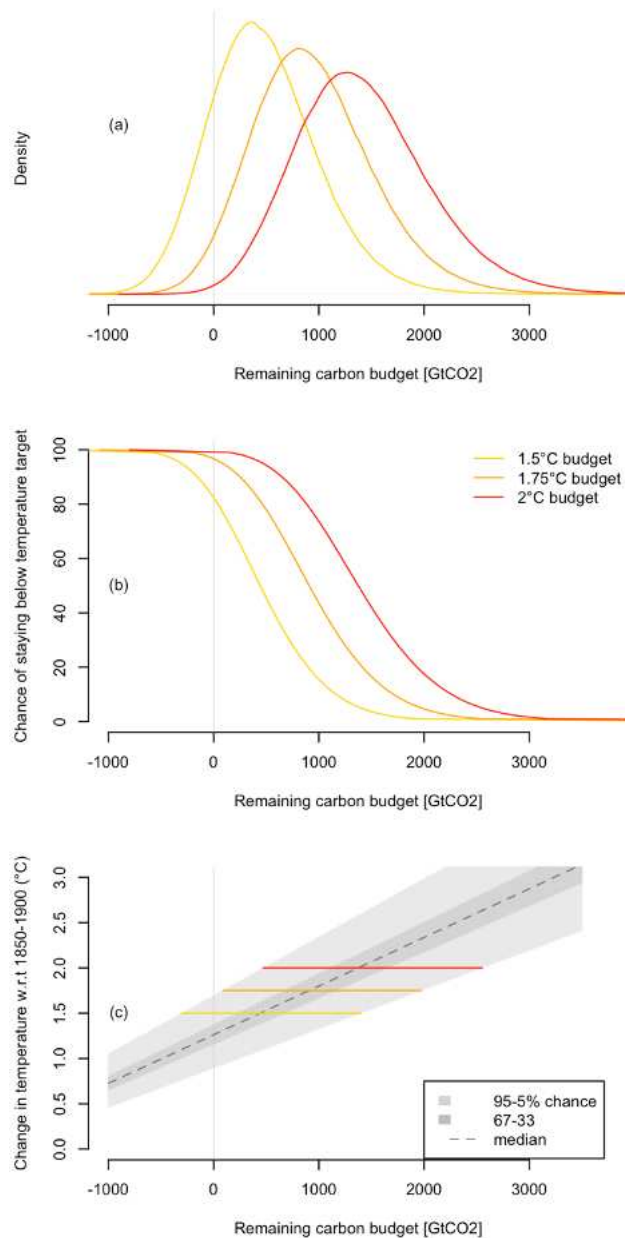


Figure 3-2 – Visualizing the probabilistic understanding of the remaining carbon budget estimates for 1.5°C, 1.75°C and 2 °C warming targets

The three panels demonstrate three ways to visualize the RCB for 1.5°C, 1.75°C and 2 °C warming targets (indicated by yellow, orange and red lines, respectively): (a) probability distribution of RCB for a given target, (b) likelihood of not exceeding a particular temperature target (cumulative probability distribution of RCB estimates), and (c) likely range of temperature outcomes as a function of total future CO₂ emissions. The grey areas in panel (c) represent the 33-67% (dark grey) and 5-95% (light grey) uncertainty range associated with the RCB

distributions shown in panels (a) and (b). RCB distributions shown here are taken from Matthews et al.²⁸, representing total CO₂ emissions from 2020 onwards.

3.4 Implications of RCB Uncertainty for Net-Zero CO₂ Targets

The RCB and net-zero CO₂ targets share the same scientific foundation. Both concepts arise from the fact that the minimum requirement to stabilize global temperature is for CO₂ emissions to reach zero or be balanced by equal amounts of CO₂ removals (assuming CO₂ removals are permanent). Since the RCB defines the remaining allowable CO₂ emissions for a given temperature target, once the RCB is “spent” emissions must reach net-zero CO₂ for the temperature target not to be exceeded. The timing of global net-zero CO₂ targets can therefore be informed by the RCB.

Rogelj et al.⁵⁷ propose a best practice for setting net-zero targets that calls for the scope, fairness, and plan for reaching and/or maintaining net-zero to be explicit. The scope of net-zero targets refers to what emissions are included or excluded. For example, a net-zero target for CO₂ would imply stabilized global temperature, whereas a net-zero greenhouse gas (GHG) could imply declining global temperature driven by net-negative CO₂ emissions. The fairness of a net-zero target refers to the logic used in determining the target. For example, does a net-zero target reflect an entity’s (e.g. a nations or corporations) historical responsibility for climate change based on their past emissions or their financial or physical capacity to mitigate or offset their emissions? Finally, the authors recommend that targets should include a plan for reaching net-zero so that the cumulative emissions (i.e. proportion of the RCB “spent”) up to net-zero are defined, and a plan post net-zero CO₂ that demonstrates whether an entity’s warming contribution is intended to be stable (e.g. by maintaining net-zero CO₂) or to decline post net-zero (e.g. through net-negative CO₂ emissions or declining rates of short-lived non-CO₂ emissions).

We propose two additional recommendations for setting net-zero CO₂ targets to account for the wide range of RCB uncertainty and variety of methods of estimating the RCB that we have discussed here. Our first recommendation is that the likelihood of the RCB limiting temperature to a chosen threshold be considered when setting net-zero CO₂ targets and be made explicit. For instance, it should be made clear if a net-zero CO₂ target is consistent with a 50% likelihood of limiting warming to 1.5°C or, if a more precautionary approach is taken, with a

66% or higher likelihood of limiting warming to 1.5°C. As discussed above, not all frameworks allow for geophysical uncertainty to be presented as a single distribution and uncertainty associated with future non-CO₂ emissions pathways is difficult to quantify owing to its dependence on socioeconomic processes. However, if a net-zero CO₂ target is informed by an RCB estimate from a segmented framework that does not allow for geophysical uncertainty to be presented in a single distribution, the likelihood of the TCRE value used to set the net-zero CO₂ target should be made explicit.

Our second recommendation is that net-zero CO₂ targets be informed by what we have categorized here as “best estimates” – RCB estimates that include all major sources of uncertainty as well as the ranges of uncertainty of each source – and be adjusted to reflect changes in our understanding of RCB uncertainty and reduced RCB uncertainty as we approach a target. Figure 3–2 A demonstrates that there is less geophysical uncertainty in RCB estimates for temperature targets that are closer to observed temperature (e.g. the distribution of the 1.5°C RCB is narrower than the distribution for the 2.0°C RCB), given that climate feedbacks generally become more uncertain at higher levels of warming. Socioeconomic uncertainty affecting the RCB should also decrease as we approach a given temperature threshold because the non-CO₂ pathway and non-CO₂ contribution to warming will have less time to evolve before net-zero CO₂ is reached. Therefore, net-zero CO₂ targets should be set with the intention that they are periodically adjusted to reflect how geophysical and socioeconomic uncertainty related to the RCB become more constrained as we approach a given temperature threshold.

3.5 Challenges and Opportunities in Using the RCB to Inform Net-Zero CO₂ Targets in Climate Mitigation Policy

3.5.1 *Accounting for the Large Spread of RCB Uncertainty*

Even if there were a cooperative global climate mitigation effort, the difficulty in implementing a precise plan consistent with the RCB for the temperature target in question is complicated by the large uncertainty associated with RCB estimates. Wherever possible, climate policy should favour an RCB value that carries a higher likelihood of not exceeding the temperature target in question, hence requiring an earlier net-zero CO₂ target. As mentioned above, entities (e.g. nations, corporations) should explicitly state the likelihood associated with the RCB that is being used to inform net-zero CO₂ targets and emission reduction pathways (i.e.

cumulative CO₂ emissions). To reflect different contributions to climate change and different capacities for mitigating emissions, we recommend that entities with high responsibility for climate change and high capacity to mitigate emissions could reach net-zero CO₂ before it is met globally, remove CO₂ from the atmosphere, or use smaller RCB values to inform their climate mitigation policy.

3.5.2 *Accounting for Non-CO₂ Emissions*

Non-CO₂ emissions have contributed significantly to anthropogenic temperature change⁷³ and thus their temperature impacts must be considered in estimating the RCB, especially for ambitious climate mitigation targets such as 1.5°C in which they have greater influence (e.g.⁷¹). However, in contrast to the impact of CO₂ emissions on temperature which can be estimated based on cumulative emissions using the TCRE, the impacts of many non-CO₂ emissions on peak temperature and on the RCB relate to the timing and rate of emissions^{74,75}. Previous approaches (e.g.^{45,48,66,71,76}) used only one or a few scenarios, which are subject to a specific choice of non-CO₂ pathway, and calculated RCB directly from the resulting scenario(s). The approach used in recent IPCC assessments is to use a simple climate model to estimate the temperature impact of non-CO₂ on the RCB from a larger range of plausible future non-CO₂ emissions pathways (e.g.^{30,55,62}). However, this approach results in the uncertainty associated with both non-CO₂ forcing and scenario uncertainty being quantified separately, rather than being included in the RCB uncertainty distribution itself. Matthews et al.²⁸ proposed a new framework that integrates non-CO₂ forcing uncertainty into the estimate of RCB uncertainty distribution, but still calculated the scenario-related (socioeconomic) uncertainty separately using a range of available future non-CO₂ scenarios.

The above approaches to accounting for the non-CO₂ emissions contribution to temperature change using simple climate models (e.g.^{28,62,72}) use scenarios developed with energy-economy-land models known as integrated assessment models (IAM) that require socioeconomic (e.g. whether new technologies are adopted) and technological (e.g. on the future capacity of carbon dioxide removal (CDR)) assumptions. As a result of the uncertainty of socioeconomic and technological input parameters in IAMs, IAM scenarios are not representative of what future non-CO₂ emissions are plausible or likely, but rather demonstrate a possible pathway that reflects the assumptions used in the IAM setup. Huppmann et al.³⁵

provided a set guidelines that outline how scenarios are and are not meant to be interpreted. They caution against interpreting an ensemble of scenarios in probabilistic terms and drawing conclusions about the plausibility of scenarios based on the frequency in which they appear in the literature (e.g. the absence of a scenario in the literature does not signify that it is impossible). Furthermore, they recommend that scenario ensembles should be considered as a whole, arguing that drawing conclusions from any particular scenario could be considered “cherry-picking”. While these recommendations by Huppmann et al.³⁵ were in reference to the scenarios included in the IPCC Special Report on 1.5°C of Global Warming (SR1.5), they apply to the use of scenarios in the literature more generally.

An alternative approach to using a simple climate model and IAMs scenarios to account for the temperature impacts of non-CO₂ emissions is to use emissions metrics, such as global warming potential (GWP), GWP*, or combined step-pulse metrics, which are used to compare the impacts of non-CO₂ emissions on radiative forcing to those of CO₂^{73,77,78}. GWP represents the time-integrated radiative forcing of a given mass of a species of non-CO₂ emission normalized to the radiative forcing of a pulse of CO₂ of equal mass⁷⁹. A limitation of GWP is that the chosen time horizon, which has a significant impact of GWP values, is an arbitrary decision with no scientific basis⁸⁰. The most common time horizon of 100 years dilutes the effects of short-lived emissions in the short-term and overestimates their effects in the long-term⁷⁷. To account for this limitation of GWP, Allen et al.⁷⁷ developed GWP* in which changes to sustained rates of short-lived non-CO₂ emissions are normalized to pulses of CO₂ emissions of equal mass. Using GWP* forcing from short-lived non-CO₂ emissions can be assumed to be permanent and is therefore comparable to forcing from CO₂ on a multi-century timescale. Alternatively, “combined step-pulse metrics” make use of combined global warming potential and combined global temperature change potential, which account both for rate and pulses in emissions as a way of aggregating long-lived and short-lived contributions to warming into one metric⁷⁸.

Emissions metrics such as GWP, GWP*, and combined step-pulse metrics have limitations due to their simplicity. For instance, GWP is incompatible with the RCB framework because non-CO₂ emissions cannot be accounted for cumulatively using GWP and estimating the temperature impact of emissions using GWP can result in temperature changes of the wrong sign when rates of non-CO₂ emissions are decreasing⁷⁷. Alternatively, while CO₂ equivalent

emissions calculated using GWP* or combined step-pulse metrics can be accounted for cumulatively and are compatible with a RCB framework, comparing the temperature impacts of non-CO₂ and CO₂ emissions using these metrics could, depending on how they are interpreted, reward countries that have historically emitted a high proportion of short-lived non-CO₂ emissions if applied on a country level ⁸¹. Furthermore, net-zero CO₂ equivalent emissions calculated using GWP* or combined step-pulse metrics are inconsistent with the goal of balancing anthropogenic sources and sinks of greenhouse gasses outlined in Article 4 of the Paris Agreement since, by using GWP* or combined step-pulse metrics, there would be a sustained rate of short-lived non-CO₂ at net-zero causing an imbalance in anthropogenic sources and sinks of some gasses ⁸². As a result, GWP* and the combined step-pulse metrics are less useful to track progress towards meeting international agreements ⁸².

Another method to account for the contribution of non-CO₂ emissions is to use a climate model to diagnose CO₂ forcing equivalent emissions of non-CO₂ emissions ⁸³. CO₂ forcing equivalent emissions represent the amount of cumulative CO₂ emissions required in a particular climate model to cause the same amount of warming that is caused by non-CO₂ emissions in a given scenario. Cumulative CO₂ forcing equivalent emissions scale linearly with temperature change and therefore are compatible with the RCB framework. However, as with other methods of accounting for the temperature impact of non-CO₂ emissions, there are important limitations to using CO₂ forcing equivalent emissions. First, it is relatively inaccessible to policymakers as it requires a climate model that can diagnose emissions. Second, using CO₂ forcing equivalent emissions would not allow for the temperature impacts of non-CO₂ emissions to be estimated at a country level as the global emissions pathway is needed to have an accurate estimate. A third limitation of CO₂ forcing equivalent emissions is that forcing from non-CO₂ emissions is treated the same as CO₂ even though there are differences between the climate feedbacks that result from different types of emissions.

Finally, another relevant method of accounting for the temperature impact on non-CO₂ emissions in a RCB estimate is to adjust the quasi-linear relationship of the TCRE to represent how cumulative emissions of CO₂ scale to global warming from all anthropogenic sources – this variation is known as the “effective TCRE” and can be used to estimate cumulative emissions of CO₂ consistent with global warming from CO₂ and non-CO₂ emissions (e.g. ⁶⁴). Since the temperature impact of non-CO₂ emissions is dependent on the time and rate of emissions (e.g.

⁷⁷), the effective TCRE is subject to change as the proportion of temperature change from CO₂ and non-CO₂ emissions changes ⁶⁴. However, despite the variability of the effective TCRE, RCB estimates can be made using the effective TCRE if the changing proportions of temperature change between the present and when net-zero CO₂ is reached are considered (e.g. ²⁸).

These methods of accounting for the warming contribution of non-CO₂ emissions all have limitations in the scientific sphere and/or the climate mitigation policy sphere. Using simple climate model simulations of IAM generated scenarios is a scientifically robust way of estimating the contribution of non-CO₂ emissions to the RCB. However, this method may obscure the full range of climate mitigation policy options due to the limitations of IAMs as discussed above, and is not applicable to emissions accounting at sub-global scales. Emissions metrics have either scientific (e.g. whether metrics track temperature change) or policy (e.g. inconsistent with the Paris Agreement) limitations depending on the choice of metric. Furthermore, CO₂ forcing equivalent emissions or the effective TCRE are limited in their use for policy and emissions accounting since they require global emission pathways to account for warming from non-CO₂ emissions. Overall, the question of how to treat non-CO₂ emission remains a barrier to easily applying RCB estimates to climate policy, and there remains a need to develop a method to account for non-CO₂ emissions within RCB estimates that is consistent with international agreements and can be used for emissions accounting on global and local scales.

3.5.3 Allocating a Remaining Global Carbon Budget to Countries or Other Entities

The RCB represents the amount of allowable global cumulative CO₂ emissions that is consistent with limiting warming to a given temperature target. Distributing a global RCB to individual countries (with a sum that adds up to the RCB) presents challenges related to equity and cooperation among different countries. Different methods of quantifying fair-share allocations of the RCB for 1.5°C and 2.0°C targets to form national carbon budgets have been explored (e.g. ⁸⁴⁻⁸⁷), which can produce substantially different national budget allocations depending on the allocation method that is used ²⁹. Subnational government and corporate carbon emissions reduction pledges are also becoming increasingly common, and such entities have potential to contribute to national emission reduction efforts (e.g. ⁸⁸). As such, there is a need to further explore the equity issues that arise when allocating a portion of the global budget to non-governmental entities such as corporations and industries, or when distributing national carbon

budgets among subnational jurisdictions or economic sectors. For example, what are potential methods of quantifying fair-share allocations of a national carbon budget among economic sectors and what are the equity implications of allocating national carbon budgets using particular methods? Should historical responsibility for past emissions be taken into consideration when making allocations, either within countries, or to multinational corporations? And once decided, how should corporate or sub-national allocations be enforced?

3.5.4 Monitoring How Much of a Remaining Carbon Budget Is “Spent”

Aside from the challenges associated with accounting for non-CO₂ emissions in RCB estimates and the allocation of the RCB, another obstacle to applying the RCB will be tracking how much of a RCB has already been “spent” as we approach a given temperature target. In general, our knowledge of how much RCB has been spent can be tracked via existing annual inventories of national emissions estimated using monthly energy data such as that organized via the Global Carbon Project ⁸⁹. However, as we approach temperature targets, uncertainties associated with national emissions inventories will become increasingly important, especially the large uncertainties associated with land-use and land cover change emissions. For the RCB to be an effective tool for climate mitigation, reducing uncertainty with emissions estimates will be crucial.

One area of opportunity and for further research is in improving tracking of the RCB through the monitoring emissions from space. New approaches using remote sensing, such as NASA’s Orbiting Carbon Observatory-2 (OCO-2), or remote sensing and machine learning (ML) techniques, such as those used by ClimateTRACE (climatetrace.org), have the potential to allow for detailed global maps of sources and sinks of carbon. Tools that enable observations of emissions will help reduce uncertainty associated with annual emissions, and thus will also help accurately track progress towards net-zero CO₂ emissions and the RCB for a particular warming target. Such tools could be also used for monitoring (and potentially reinforcing) the remaining carbon budget parts attributed to different nations or sub-national entities (e.g. corporations and industries).

Another important consideration in tracking emissions is CDR (i.e. the removal of CO₂ from the atmosphere aimed at decreasing temperature or offsetting emissions), which is prominent in the literature for mitigation pathways in line with the goals of the Paris Agreement

(e.g. ⁵⁵). If CDR is meant to offset emissions of CO₂ from fossil fuels, the permanence of carbon storage should last for a similar period as the temperature impact of CO₂ emissions, i.e. on the order of centuries or longer ^{21,22}. However, if CDR is implemented using natural climate solutions such as reforestation or agricultural soil carbon sequestration (e.g. ⁹⁰), guaranteeing this sort of permanent storage is difficult since natural carbon reservoirs are vulnerable to disturbances arising from both climate and human-driven threats (e.g. ^{52,91}) such as wildfires. In scenarios that are in line with the temperature targets of the Paris Agreement, temporary CO₂ removal may still reduce peak temperature, but temporary CO₂ removal in scenarios with higher peak temperatures that occur later in the twenty-first century will likely only delay peak temperature rather than lower it ⁹². We recommend that natural solutions (such as afforestation), while beneficial for restoring ecosystems, should therefore not be used to “offset” fossil fuel emissions or “extend” the RCB due to the uncertain permanence of CO₂ storage offered by these natural methods.

For other potentially permanent methods of CDR, such as bioenergy with carbon capture and storage (BECCS) or direct air carbon capture and storage (DACCS), guaranteeing permanent storage hinges on whether geological reservoirs (used to store the extracted CO₂) are immune to leaks and effectively trap CO₂ on long timescales. One method to reduce CO₂ leakages in geologic storage reservoirs and to maximize the positive impacts of CDR is to ensure that geologic reservoirs used for carbon storage are well-suited for long-term use and are the least likely to experience leakages. For example, ML models trained with geologic data from naturally occurring deposits of CO₂ could help identify which geologic reservoirs most effectively store CO₂ ⁹³. Once geologic storage sites are in use, it is important to monitor for leaks to ensure that the net quantity of CO₂ captured and stored can be quantified and considered in the tracking of the RCB. Examples of monitoring techniques include using instruments to measure the concentration of gases ⁹⁴, using ML models trained with data from pressure sensor within geologic reservoirs ⁹⁵, and using computer vision ML models ⁹⁶. Applying these techniques to CDR represents an opportunity to reduce uncertainty in tracking progress towards the RCB as we approach net-zero as well as increase the potential efficacy of CDR efforts.

Finally, CDR using BECCS may also complicate monitoring of emissions. Specifically, accurately tracking the net contribution to the RCB is complicated by the difficulty of estimating and tracking the emissions that would likely result from BECCS-related land use change. One

study suggests that BECCS would initially be a source of emissions in many regions as a result of a loss of land carbon storage from the initial land use change ⁹⁷. If BECCS is utilized at scale as suggested in much of the mitigation pathway literature (e.g. ⁵⁵), then considering and tracking the emissions from its implementation will be important for quantifying the net effect of BECCS and for tracking progress toward the depletion of the RCB.

3.5.5 Missing the Target – Overshoot of a Given Temperature Level

Another obstacle to tracking the RCB is the possibility of temperature overshoot. The RCB for a particular temperature target is equal to the total amount of cumulative CO₂ emissions up to the point at which net-zero CO₂ emissions is reached. Tracking emissions to measure progress towards meeting the RCB is increasingly complicated in overshoot scenarios which temporarily exceed the RCB and reach higher peak temperatures before returning to the intended RCB via net-negative emissions using CDR. The inclusion of net-negative emissions in scenarios introduces a new source of uncertainty to the RCB because it is unclear whether the reversibility of CO₂-induced warming via net-negative emissions is proportional to the warming effect of positive emissions (i.e. whether one unit of negative CO₂ emissions counteracts the temperature response to one previous unit of positive CO₂ emissions) ⁹⁸. Some climate models exhibit a delayed response to net-negative CO₂ emissions owing to inertial processes in the climate system (e.g. ^{34,58}) while others exhibit a response that is proportional to or larger than the effect of positive CO₂ emissions (e.g. ⁹⁸). However, it is important to emphasize that models that include representation of the permafrost carbon feedback demonstrate that the permafrost carbon feedback is sensitive to the magnitude of peak temperature in an overshoot scenario: with a higher peak temperature, the warming contribution from permafrost thaw is larger, meaning that a greater quantity of CO₂ would have to be sequestered via CDR than the amount by which anthropogenic CO₂ emissions exceed the RCB ^{48,70}. These uncertainties related to temperature overshoot emphasize the need to reach net-zero CO₂ emissions as soon as possible to stabilize CO₂-induced warming and minimize the added uncertainty associated with the climate response to net-negative CO₂ emissions from CDR.

3.6 Conclusion

The RCB is a valuable tool for climate mitigation policy and setting net-zero CO₂ targets: it is easily conceptualized, has a strong scientific foundation, and clearly demonstrates the need to reduce CO₂ emissions to net-zero. Since there have been a range of methods used to estimate the RCB in the literature, it is important to consider methodological choices researchers have made when comparing RCB estimates, particularly regarding which sources of uncertainty are included or excluded. We caution that only RCB estimates from studies using similar frameworks should be compared directly, as otherwise it is not a like-to-like comparison. Furthermore, RCB estimates must also be understood as associated with a likelihood of limiting warming to a particular temperature threshold rather than as a single value of cumulative CO₂ emissions. As we demonstrated in Section 2.3 (Figure 3–2 and Table 3–2), estimates can also be contextualized by highlighting the likelihoods of an amount of cumulative CO₂ emissions being consistent with a range of nearby temperature targets. The variety of methods and wide range of uncertainty in the RCB must be considered when using RCB estimates to inform net-zero CO₂ targets and net-zero CO₂ targets should be set with the intention that they are adjusted to accommodate expected changes to methods of estimating the RCB and changes to RCB uncertainty.

Future research priorities include a need to address the question of how national (or other sub-global scale) emissions of non-CO₂ gases can be integrated with CO₂ targets that are informed by RCB estimates. Another opportunity to improve the RCB framework, especially when CDR is used to achieve given RCB, is to quantify the magnitude and effectiveness of CDR as a means of returning from an RCB overshoot. For BECCS and DACCS, this means prioritizing monitoring and in-depth suitability analyses for geologic storage and bioenergy crop sites. We also argue that natural climate solutions, while having potential for both climate and non-climate benefits, should not be considered as a CDR method or offset to ongoing fossil fuel emissions owing to the difficulty in quantifying the carbon stored by natural climate solutions, as well as its likely ephemeral nature. Furthermore, temperature overshoot scenarios generally exacerbate some of the difficulties in applying the RCB to climate policy and introduce new sources of uncertainty to RCB estimates. As a result, we caution against planning for overshoot scenarios in climate mitigation discussions, and rather suggest that reaching net-zero global CO₂ emissions on a timescale that does not result in emissions that exceed the RCB should be the primary goal of national and international climate mitigation efforts.

4 Chapter 3: Irreversible climate changes driven by degree-years of temperature overshoot

4.1 Abstract

It is becoming increasingly likely that meeting the long-term temperature goal of the Paris Agreement will involve a period of temperature overshoot. Understanding the differences in climate outcomes between overshoot and non-overshoot scenarios requires an assessment of the reversibility of climate changes along an overshoot pathway. Using an intermediate-complexity Earth system model, we quantify the reversibility of a suite of climate variables and investigate the factors driving differences in reversibility across an ensemble of 42 pairs of overshoot and non-overshoot scenarios. For highly irreversible climate variables like permafrost and ocean changes, we show that the long-term outcome is linearly related to the time-integrated overshoot magnitude, which we define here as the degree-years of temperature overshoot. Our results show that degree-years of overshoot can be used to predict the changes of a range of irreversible ocean and permafrost variables in overshoot scenarios, therefore offering important insights into the difference in climate outcomes of overshoot compared to non-overshoot scenarios.

4.2 Introduction

Current climate policies have global emissions on track to push global warming well beyond 2.0°C⁹⁹. As a result, it is becoming increasingly likely that if we are to meet the 1.5°C to well-below 2.0°C temperature goal of the Paris agreement, there will first be a period of prolonged temperature overshoot (OS). The increasing likelihood of OS highlights the importance of understanding the climate outcomes of OS compared to non-OS scenarios that achieve the same temperature target by the end of the century. A key question is how the severity of climate changes will differ as a function of the duration and magnitude of OS across a range of policy-relevant 1.5°C to 2.0°C scenarios.

Previous work has shown that OS leads to additional climate changes and associated impacts due to hysteresis (or irreversibility) in the climate system^{39,43}. These changes can be broadly categorized into two groups: those affecting slow-responding variables, which exhibit significant hysteresis or are sensitive to tipping points, and those affecting fast-responding variables, which tend to exhibit less or no hysteresis. Slow-responding climate variables that

show pronounced hysteresis following OS include permafrost carbon loss, ocean temperature, ocean oxygen content, ocean pH, thermosteric sea level rise (SLR), and ice sheet loss along with the associated SLR^{39,44,47–50,58,70,100–102}. These variables exhibit hysteresis because they involve large thermal or physical inertia. For instance, once permafrost thaws during OS, the carbon loss is irreversible from a policy perspective since carbon buildup in soils and vegetation and subsequent refreezing would take millennia⁴⁷. Ocean temperature and thermosteric SLR are governed by the slow penetration of heat into the deep ocean, which takes centuries to equilibrate even if surface temperatures are reduced¹⁰². Similarly, changes in ocean oxygen content and pH that occur during the period of OS can become effectively locked in when surface waters are downwelled, transporting these altered conditions into the deep ocean^{49,50}. Once subducted, this water is isolated from the atmosphere for centuries, preventing rapid re-equilibration and delaying recovery of the deep ocean for centuries after surface temperatures have stabilized. Ice sheet loss is marked by threshold behavior and self-reinforcing feedbacks, such as the ice-albedo effect, which make ice sheet recovery impossible on timescales of centuries after substantial loss has occurred⁴⁷.

Fast-responding climate variables that exhibit little to no hysteresis following OS include surface air temperature, precipitation, Arctic sea ice, and sea surface pH^{34,39,44,58}. Surface air temperature is closely tied to radiative forcing – as CO₂ concentrations decline, temperatures begin to decrease rapidly due to the relatively low thermal inertia of the atmosphere and upper ocean^{43,45}. Precipitation also adjusts relatively quickly as surface temperatures change, with reversal occurring slightly after changes in temperature⁴⁴. However, for both temperature and precipitation, even though global mean values show high reversibility, there is evidence that the regional response following OS can exhibit more path dependence^{42,103}. Arctic sea ice, while sensitive to warming, can regrow rapidly during cooler periods because it is driven by short-term surface energy fluxes⁴⁴. Sea surface pH, which reflects the balance of CO₂ between the surface ocean and atmosphere, also responds relatively quickly as well – when atmospheric CO₂ levels decline, the surface ocean can begin to outgas CO₂ and partially recover its pH due to rapid gas exchange and mixing in the upper ocean layers^{39,44}. These variables tend to lack the deep memory, physical inertia, or strong reinforcing feedbacks that characterize slower components of the climate system, allowing them to more closely track changes in forcing and exhibit minimal hysteresis.

Finally, some climate variables do not fit neatly into the categories of fast- or slow-responding. One such example is the Atlantic Meridional Overturning Circulation (AMOC), which is sensitive to rate of temperature change during OS, and can substantially influence both global and regional climate patterns, particularly in the North Atlantic and surrounding areas³⁸. In some models, the AMOC recovers within two to three centuries after the peak of OS, suggesting it exhibits less hysteresis than slower-responding variables like permafrost carbon release or deep ocean heat content³⁹. At the same time, this recovery time is slower and more path-dependent than that of fast-responding variables such as surface temperature or precipitation. As such, the AMOC occupies an intermediate position – demonstrating a moderate level of hysteresis that depends on both the magnitude and duration of OS, as well as the rate of temperature change^{38,104}.

Existing modelling studies on the climate impacts of OS have used: 1) idealized CO₂ only scenarios that are concentration driven or driven by emission pulses^{34,39,44,45,58,103,105–107}, 2) a limited number of scenarios (e.g., SSP5-3.4OS and/or SSP1-1.9^{33,40,42,49,108}), or 3) an ensemble of realistic scenarios that are simulated in a climate emulator rather than a more complex and spatially explicit Earth system model (ESM)¹⁰⁹. There has yet to be a study that investigates climate outcomes of OS in relation to the magnitude and duration of OS across an ensemble of policy-relevant (i.e., 1.5° to 2.0°C) multi-gas scenarios in a spatially explicit Earth system model.

In this study, we investigate the climate outcomes of OS occurring this century in the University of Victoria intermediate complexity Earth System Climate Model (UVic-ESCM). We simulate 42 pairs of scenarios – one non-OS reference scenario and one OS scenario – with peak temperatures ranging from ~1.5 to ~2.0°C (Fig. 4–1). To explore how the duration and magnitude of OS affects the climate outcomes, we calculate the degree-years of OS, which we define here as the time integrated difference in global surface air temperature (GSAT) between an OS scenario and its non-OS pair. We then quantify the reversibility of a suite of different climate variables and show that the degree-years of OS are a robust predictor of the changes that occur across a range of highly irreversible climate variables.

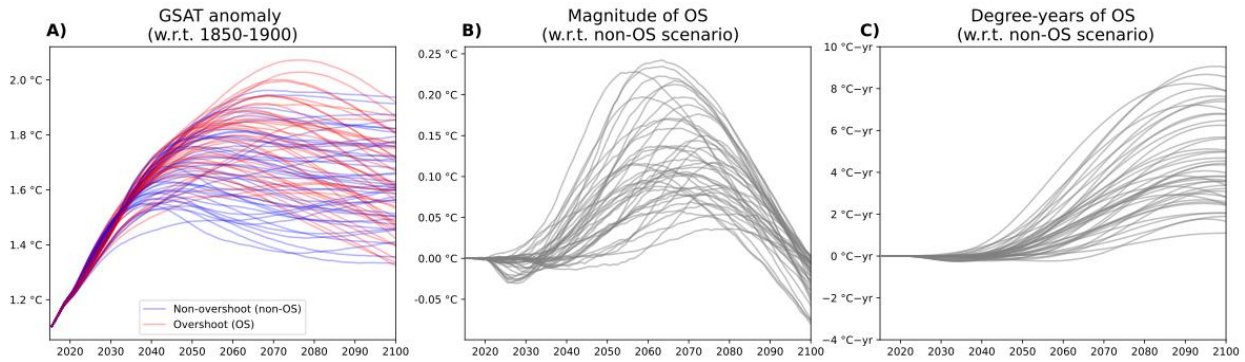


Figure 4-1 – Paired OS and non-OS scenarios used in this study which achieve a long-term temperature target of less than 2°C with peak temperatures in the OS scenarios ranging from 1.5 to 2.0°C.

Panel (A) shows the average global surface air temperature (GSAT) anomalies in OS (red lines) and their paired non-OS (blue lines) scenarios with respect to a 1850-1900 baseline. Panel (B) shows the magnitude of OS relative to the paired non-OS reference scenarios. Panel (C) shows the degree-years of OS (i.e., the time integrated difference in temperature change between an OS and non-OS scenario pair).

4.3 Results

The climate outcomes of OS are often defined in terms of reversibility/irreversibility^{39,42,44,50}. For a given climate variable, if there is a difference between the OS and non-OS reference scenario values during the period of OS, and if there is no difference between the scenarios after the period of OS, then this climate variable would be considered fully reversible and OS would be considered to have no impact on long-term change. Conversely, if there is still a difference in a given variable following OS, then the variable would be considered to have some degree of irreversibility.

Here, we define the reversibility of a suite of climate variables relative to that of global mean temperature in a series of OS scenarios that return to a target global temperature of between ~1.4 and ~1.9°C before the end of the century. We quantify reversibility for each climate variable at the return year, which is defined as the year that global mean temperature in the OS scenario returns to the same temperature as in the paired non-OS scenario. In the scenarios used here, the return years fall between 2086 and 2100. Despite pairs of scenarios having equal cumulative CO₂ emissions by the end of the century, return years do not necessarily align with the year when cumulative CO₂ emissions become equal because non-CO₂ forcing in all OS scenarios falls below levels found in the non-OS scenarios after 2090 (SM Fig. 8-1).

To calculate reversibility, we first calculate the maximum difference ($diff^{max}$) for each variable between the OS and non-OS value during the period of OS. Second, we calculate the difference between the OS and non-OS values of a variable at the return year ($diff^{return\ year}$). Using the $diff^{max}$ and $diff^{return\ year}$ we define the reversibility of a given climate variable at the return year as:

$$reversibility = \frac{diff^{max} - diff^{return\ year}}{diff^{max}} \quad \text{Equation 4-1}$$

We calculated the reversibility of 30 globally-averaged climate variables simulated by the UVic-ESCM, in addition to the spatial pattern of surface air temperature. Given our representation of reversibility (illustrated in Fig. 4–2 A), global mean temperature itself is by definition 100% reversible. In addition to the magnitude of temperature OS, we further calculated the time-integral of the global mean temperature OS, which we define here as the degree-years of OS (Fig. 4–2 B).

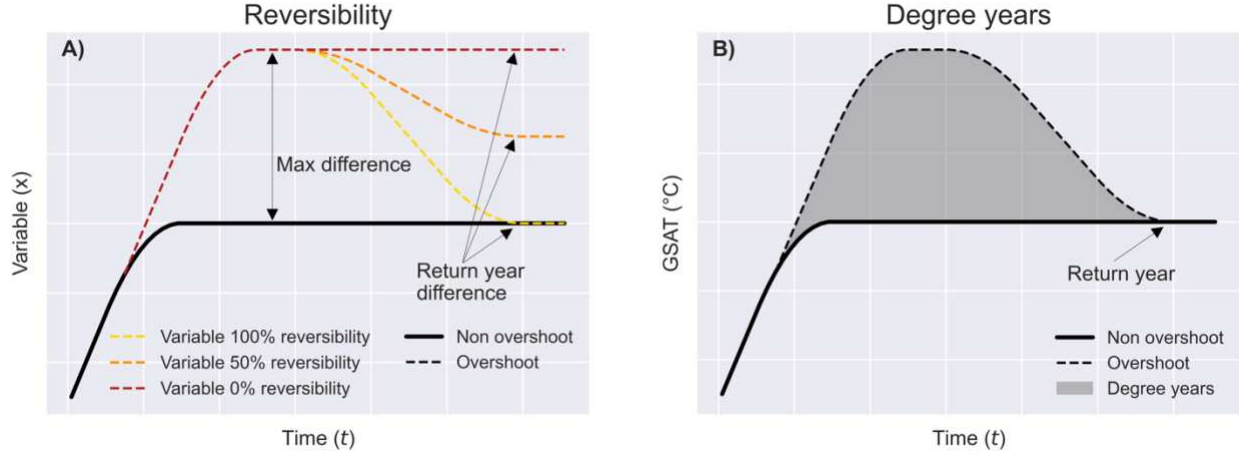


Figure 4-2 – Illustrative examples of reversibility and degree-years

Figure A) illustrates how reversibility is defined for climate variables. Figure B) illustrates degree-years of OS, which is the time-integrated difference in global surface air temperature (GSAT) between an OS and non-OS pair of scenarios.

4.3.1 *Reversibility of Climate Outcomes*

Across the 30 globally-averaged climate variables simulated by the UVic ESCM, the median reversibility across scenarios ranged from 0% (fully irreversible) to 120% (more reversible than global average temperature) (Fig. 4–3). Slow responding climate variables are the least reversible, particularly those associated with the ocean and with permafrost (boxplots 1–6 Fig. 4–3). Climate variables with median reversibility above 100% include the atmospheric concentration of CO₂, surface ocean carbon cycle variables that follow atmospheric CO₂ levels closely, and global average ocean alkalinity (boxplots 27–30 Fig. 4–3). For atmospheric CO₂, sea surface pH and sea surface dissolved inorganic carbon (DIC), greater than 100% median reversibility reflects the understanding that, due to carbon cycle inertia, the ocean continues to take up CO₂ following peak OS as temperatures decline, resulting in lower atmospheric CO₂ at the return year relative to non-OS scenarios⁴⁵. As a result, temperature reversal lags changes to atmospheric CO₂ concentration in OS scenarios, so achieving 100% reversible temperature requires more than a 100% reversal of atmospheric CO₂ concentration.

Many of the climate variables presented here exhibit high uncertainty in reversibility across scenarios (Fig. 4–3). To investigate the drivers of uncertainty in reversibility for variables with high uncertainty – defined as those with an interquartile range in reversibility exceeding 10% (SM Table 8–1) – we calculated the linear correlation between the absolute values of each variable at the return year in individual OS and non-OS scenarios (i.e., without taking the difference between OS and non-OS) and several potential explanatory variables: peak and return-year for temperature and atmospheric CO₂ concentration, the rates of change in temperature and atmospheric CO₂ concentration during the OS period, and the average temperature and atmospheric CO₂ concentration over the OS period (SM Table 8–2 and SM Fig. 8–2).

Variables with high uncertainty in reversibility fall into two general groups. The first group includes atmospheric CO₂ as well as most carbon cycle variables: global average ocean DIC, total ocean carbon, total land carbon, total soil carbon, total vegetation carbon, and global average sea surface DIC and pH (boxplots 11, 12, 15–17, 27, 28, 30 Fig. 4–3). Sea surface DIC and pH are almost perfectly correlated with atmospheric CO₂ at the return year ($R^2 = 0.99$) because the rapid exchange of CO₂ between the sea surface and the atmosphere allows for these variables to respond to changes in atmospheric CO₂ with almost no delay. Uncertainty in the

reversibility of the other carbon cycle variables mentioned here – global average ocean DIC, total ocean carbon, total land carbon, total soil carbon, and total vegetation carbon – are most highly correlated with average CO₂ concentrations during the OS period, indicating that they are more sensitive to the pathway of atmospheric CO₂ than to its present value alone (Table 8–2).

The range in atmospheric CO₂ reversibility is driven by varying contributions to temperature change from non-CO₂ forcing between OS and non-OS pairs, and this uncertainty is propagated to carbon cycle variables that respond directly to atmospheric CO₂ changes. We would expect greater reversibility of atmospheric CO₂ in scenarios where non-CO₂ forcing in the OS and non-OS pair are equal and where the reduction in temperature following OS is caused by net-negative CO₂ emissions because, if the reduction in temperature is caused by net negative CO₂ emissions rather than a reduction in non-CO₂ forcing, more carbon would be removed from the atmosphere¹⁵. Alternatively, if temperature reduction following OS is caused by a reduction in non-CO₂ forcing in the OS scenario relative to the non-OS scenario, temperature can be reversed before cumulative CO₂ emissions in the OS scenario are equal to those of the non-OS scenario. This results in higher atmospheric CO₂ concentrations in the OS scenario at the point of temperature return, and thus reduced CO₂ concentration reversibility.

This relationship between the CO₂ and non-CO₂ forcing fraction and the reversibility of atmospheric CO₂ and related carbon cycle variables becomes clear when comparing two key milestones: the *return year* – when temperature in the OS scenario matches that of the non-OS scenario – and the year when cumulative CO₂ emissions in the OS scenario equal those in the non-OS scenario. When these two milestones occur at the same time, or when cumulative CO₂ emissions in the OS scenario are equal to the non-OS scenario *before* the return year, reversibility of atmospheric CO₂ and related carbon cycle variables is highest (SM Fig. 8-3). Conversely, as the cumulative emissions year occurs increasingly *after* the return year due to lower non-CO₂ forcing in OS scenarios relative to their non-OS pairs, reversibility declines (SM Fig. 8-3).

Reversibility in atmospheric CO₂, sea surface DIC, and sea surface pH show the strongest correlations with the difference between the return year and the cumulative emissions year. Global average ocean DIC and ocean total carbon also correlate strongly with this difference, though their reversibility is notably lower, reflecting the greater reversibility of surface ocean changes compared to those in the deep ocean. Finally, carbon cycle variables associated with the

land reservoir also show a clear relationship, but with lower correlations, reflecting the understanding that these variables are also strongly influenced by temperature, and that less of their reversibility can be explained by a metric tied to differences in CO₂ and non-CO₂ forcing fractions between scenario pairs.

The second group of variables with high uncertainty in reversibility across scenarios includes those strongly influenced by temperature: permafrost global area, global total sequestered frozen carbon, and global snow volume (boxplots 9, 10, 14 in Fig. 4–3). In individual OS and non-OS scenarios, these variables show strong linear correlations between their values at the return year and the average temperature over the OS period ($R^2 = 0.95\text{--}0.97$; Table 8–2). Return year values in these temperature-sensitive variables also correlate strongly with peak and return year temperatures, which is expected given the high inter-correlation among the temperature metrics themselves. However, peak and return year temperatures exhibit lower correlations than average OS-period temperature (SM Table 8–2), suggesting that reversibility in these variables has a significant inertial component. Since average temperatures across individual scenarios vary widely – from 1.4°C to 2.0°C – we can conclude that the high uncertainty in the reversibility of permafrost area, frozen carbon, and snow volume is driven by differences in average temperatures between OS and non-OS scenario pairs.

Two other variables with high uncertainty in reversibility – global average ocean alkalinity and salinity – do not fit neatly into one of the above two groups of variables. For global ocean alkalinity, the absolute changes following OS are small – the median impact of OS on ocean alkalinity at the return year is only an increase of 2.4×10^{-7} mol m⁻³ (range: -4.8×10^{-7} to 1.6×10^{-6} mol m⁻³). Similarly, the absolute changes in global average ocean salinity following OS are also all – the median impact of OS on salinity at the return year is an increase of 7.0×10^{-6} grams of salt per 1000 grams of water (psu), with range of 7.2×10^{-8} to 1.2×10^{-5} psu. For ocean alkalinity, there is no strong correlation with any of the independent variables considered here (SM Table 8–2). In contrast, average ocean salinity shows a strong linear correlation ($R^2 = 0.90$) with average temperature (SM Table 8–2). Since OS and non-OS scenarios differ in their average temperatures during this period, it is unsurprising that variables like average ocean salinity, which are strongly correlated with average temperature, exhibit a wide range of reversibility outcomes. However, because changes in average ocean alkalinity and salinity are small in absolute terms, the associated uncertainty in reversibility – when expressed as a

percentage – is amplified, making it difficult to interpret. As a result, findings related to these variables should be interpreted with caution.

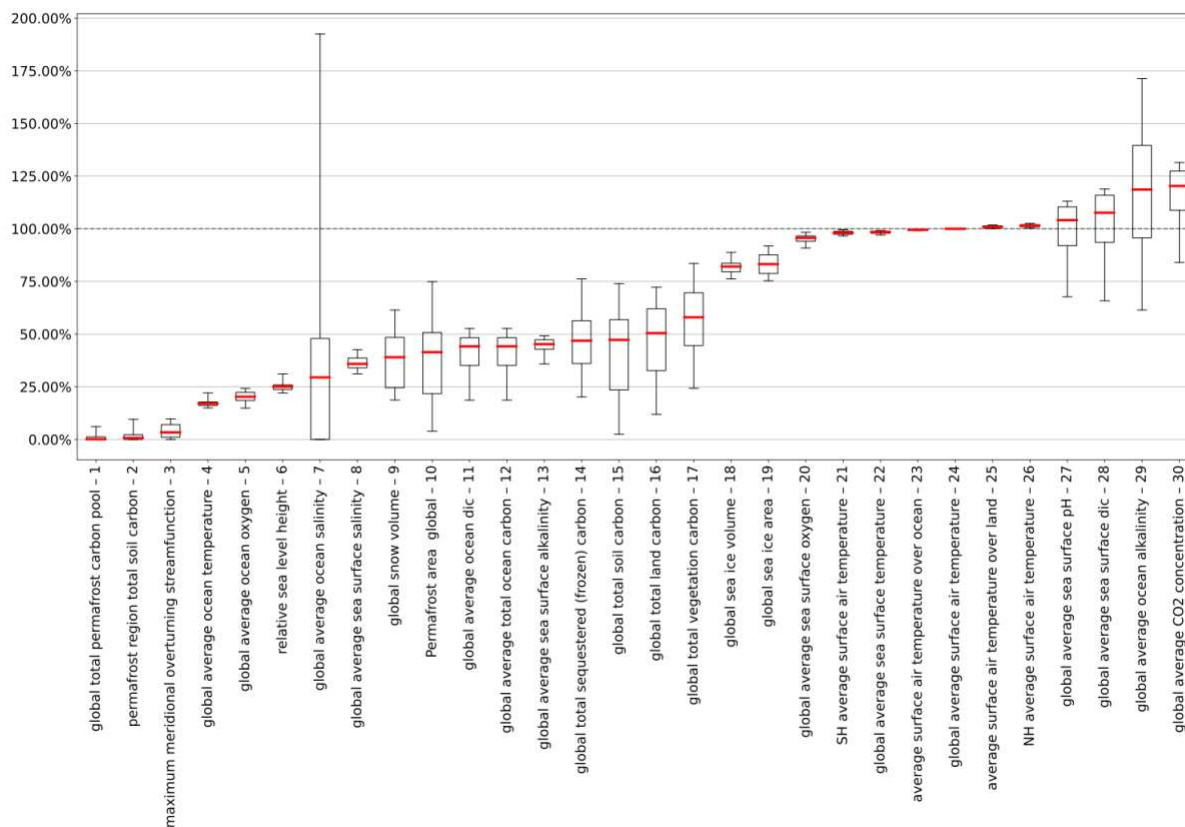


Figure 4-3 – Reversibility of variables in the UVic-ESCM.

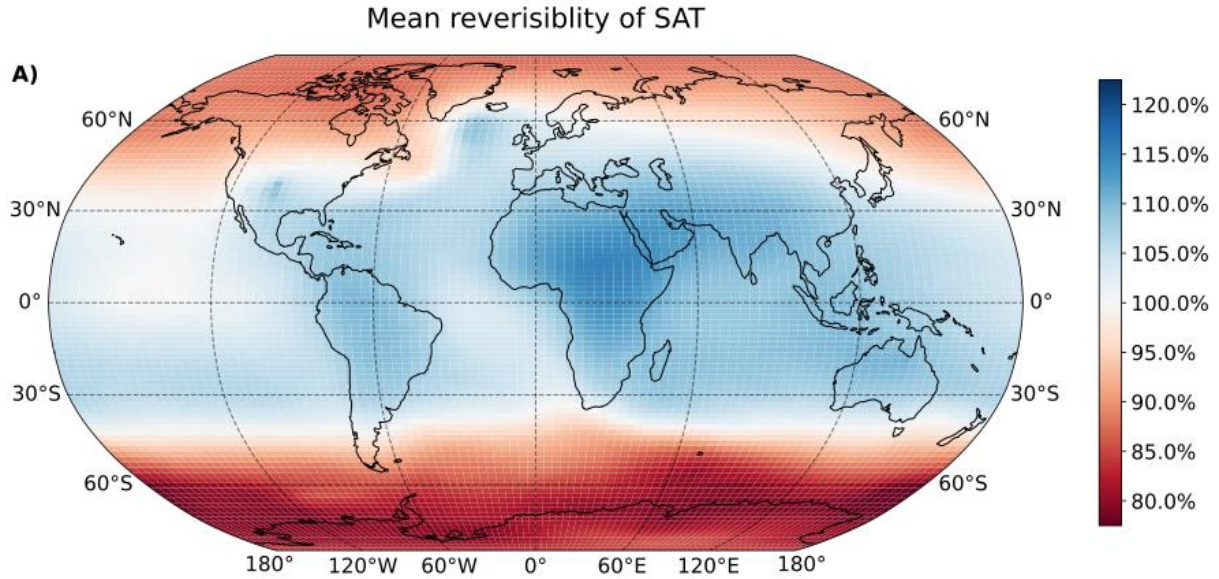
Median reversibility across all pairs of scenarios for each variable is represented by red lines. Each box represents the 1st and 3rd quartiles of reversibility for a given variable. The whiskers represent the 5th and 95th percentiles of reversibility.

4.3.2 Reversibility in the Spatial Warming Pattern

A grid-cell by grid-cell analysis surface air temperature reversibility shows that regional temperatures vary in their level of reversibility relative to the reversibility of global mean temperature change (which is 100% reversible based on the definition of reversibility used here) (Fig. 4–4 A). Reversibility values range from about 80% at high latitudes to about 110% across tropical continental regions. In other words, OS scenarios lead to warmer high latitudes and cooler equatorial and middle latitudes compared to non-OS scenarios at the same global warming

level. Increased warming in high latitudes is consistent with spatial changes in SAT following OS in idealized simulations¹⁰⁵, as well as with long-term averages in some CMIP6 models simulating SSP5-3.4OS and SSP1-1.9 scenarios⁴². In agreement with previous work^{42,103}, our results show that the lower reversibility at high latitudes is slightly more pronounced in the Southern Hemisphere, where hemispheric average temperature is slightly less than 100% reversible, compared to the Northern Hemisphere, where temperature reversibility is slightly above 100% on average (boxplots 21 & 26 Fig. 4–3). Irreversible warming at high latitudes is related to polar feedbacks such as the ice albedo feedback. Based on our definition of reversibility, irreversible warming at the poles necessitates greater than 100% reversible changes to temperature in the middle and lower latitudes.

The ranges in reversibility values across scenarios are generally low ($\leq 10\%$ range between 5th and 95th percentiles over 82% of grid cells; Fig. 4–4 B), which demonstrates that the spatial distribution of SAT reversibility is relatively independent of the peak temperature or the magnitude of OS for most regions in the scenarios used here. Ranges of reversibility tend to be lower over the oceans than over land which reflects how land surfaces experience higher rates of warming from transient climate change due to the continental and maritime effects. Ranges in reversibility are high (i.e., $>15\%$) in the North Atlantic, high elevation regions of the central United States, and in the Southern Ocean, particularly near the West Antarctic (Figure 4–4 B). We would expect these areas to experience regional changes that act as feedbacks on temperature change – the slowdown of AMOC reducing the rate of heat transport to the North Atlantic, the disappearance of ice and snow in the central United States, and the melting of sea ice as in the western Southern Ocean – which explains higher ranges in reversibility in these regions.



Difference in range of reversibility of SAT (i.e, 95th subtracted by 5th percentile)

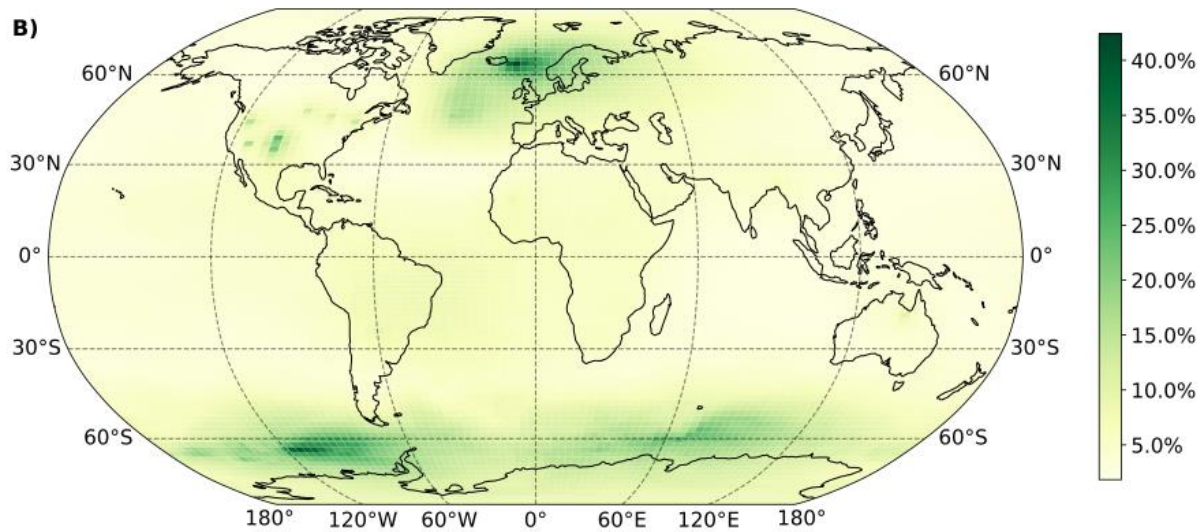


Figure 4-4 – Mean reversibility of surface air temperature (SAT) and difference in the range of reversibility of SAT

Figure A) shows the mean reversibility of surface air temperature (SAT) across all pairs of scenarios at each grid cell. The equatorial latitudes and the middle latitudes show greater than 100% reversibility which demonstrates that, following OS, temperature is lower in those regions relative to non-OS scenarios. At the poles, temperature is less than 100% reversible which demonstrates that, following OS, temperatures remain higher in these regions relative to non-OS reference scenarios. Figure B) shows the range of the 5th and 95th percentiles of SAT reversibility across all pairs of scenarios at each grid cell. Most regions show low ranges in reversibility (<10%). Regions where this range is higher (i.e., > 15%) include the North Atlantic, Northern

Europe, the central United States, and the Southern Ocean, particularly in the Western Hemisphere.

4.3.3 Predicting the Outcome of Irreversible Variables Using Degree-Years of OS

Simulated changes in many of the most irreversible variables in our study can be well characterized by the time-integrated temperature difference – the degree-years of overshoot – associated with each OS/non-OS scenario pair. In the pairs of scenarios used in this study, degree-years of OS range from approximately 1°C-yr to 9°C-yr (Fig. 4–1C). We investigated the relationship between the magnitude of irreversibility in climate variables and the degree-years of OS by performing a linear regression between degree-years of OS and the difference between OS and non-OS for each variable at the return year.

We found robust relationships ($R^2 > 0.9$) between degree-years of OS and the magnitude of irreversibility for several permafrost and ocean variables (Fig. 4–5). Interestingly, for variables in which there is a strong relationship between degree-years of OS and the magnitude of irreversibility, the relationship appears to be fairly independent of the peak temperature achieved in the OS scenario, which demonstrates that degree-years of OS is a good predictor of the effect of OS on highly irreversible climate variables across a range of OS scenarios compatible with the Paris Agreement (Fig. 4–5).

For globally averaged ocean variables – ocean oxygen, ocean temperature, and relative sea level height – the difference in absolute values between OS and non-OS scenarios grows before partially reversing as the return year is approached (Fig. 4–5 B, E, G). As previously discussed, the ocean interior and surface exhibit different responses to net-negative emissions and cooling^{39,49,50}. For instance, with thermosteric sea level rise, sea surface water warms, undergoes thermal expansion, and downwells, causing irreversible change in the short-term because the downwelled water can no longer exchange heat with the atmosphere. However, thermosteric sea level rise caused by sea surface warming before downwelling has occurred is easily reversible in the short-term because heat can still be exchanged between the sea surface and the atmosphere.

The difference in sea surface salinity between OS and non-OS pairs also increases before beginning to decrease as the return year is approached which suggests that there are both more easily and less easily reversible factors influencing change. Some of the decreased salinity in the OS scenario is easily reversed as sea ice refreezes – the loss of sea ice is mostly reversible on

short timescales since it responds quickly to changes in temperature (boxplots 18 & 19 Fig. 4–3). However, decreased salinity caused by an influx of fresh water from melting sea ice during OS is not fully reversed because polar regions experience less regional temperature reversibility (Fig. 4–4 A). Given that changes in sea surface alkalinity covary with salinity^{110,111}, sea surface alkalinity exhibits similar patterns of change as sea surface salinity.

Unlike the other variables which exhibit robust relationships between degree-years of OS and the magnitude of irreversibility, maximum meridional overturning, permafrost carbon pool, and total permafrost region carbon all exhibit more linear patterns of irreversibility as it relates to degree-years of OS (Fig. 4–5 C, D, H). We argue that degree-years of OS can be thought as a proxy for accumulated energy in the Earth system and that these forementioned variables are likely correlated with Earth energy imbalance during OS relative to the non-OS reference scenario.

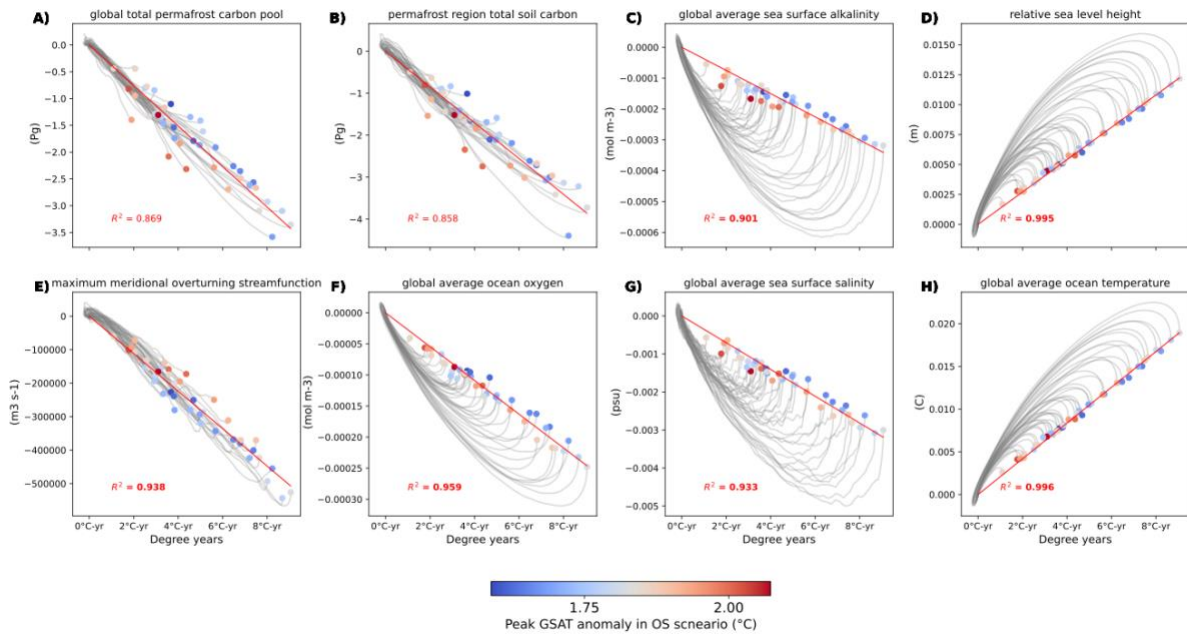


Figure 4-5 – The difference between ocean and permafrost variables in the OS and non-OS pairs of scenarios plotted against degree-years of OS.

The difference between OS and non-OS of a given variable at the return year is represented by the coloured points in which the colours indicate the peak temperature anomaly reached in the OS scenario. Grey lines represent the relationship between the difference between OS and non-OS of a given variable and degree-years of OS from 2015 until the return year.

4.4 Discussion

Due to the lack of progress on reducing emissions, it is increasingly important that we understand the climate effects of OS scenarios across a range of climate variables. An important question in furthering our understanding of the climate outcomes of OS is the question of how the severity of changes relates to the magnitude and duration of OS. Here, we confirm that there are nonnegligible climate effects of OS, especially for slow-responding variables, leading to path dependent climate outcomes. We show that high uncertainty in reversibility is primarily caused by differences in the forcing fractions of CO₂ and non-CO₂ forcings across scenarios (i.e., whether CO₂ or non-CO₂ forcing is what is responsible for OS and its reversal) or by average temperature differences across the pairs of scenarios.

We also find that degree-years of OS is linearly related to the outcome of many slow responding irreversible permafrost and ocean variables. Surprisingly, the relationship between degree-years of OS and the outcome of irreversible variable appears to be relatively independent of the peak temperature reached in the 42 pairs of below 2.0°C scenarios simulated here. This finding demonstrates that degree-years of OS could potentially be used to capture the impact of OS for slow responding variables in a range of scenarios compatible with the Paris Agreement.

We acknowledge that our definition of reversibility is based on decadal OS timescales that are shorter than the equilibration time for many climate variables. However, defining reversibility at a point in time this century immediately following a period of OS is relevant from climate impact and adaptation planning perspectives. This is particularly important for the practice of communicating climate impacts in terms of global warming levels¹¹², which is problematic in OS scenarios given that the path to a given level of warming is an important determinant of climate outcomes. Our finding that degree-years of OS is a strong predictor of the effect of OS for several irreversible climate variables suggests that degree-years of OS could be used to predict the difference in climate outcomes between a stabilization scenario and an OS scenario for the most irreversible set of climate variables.

4.5 Methods

4.5.1 Scenarios

We use 42 pairs of scenarios from the ENGAGE project. In the ENGAGE project, Riahi et al.¹¹³ developed pairs of scenarios using several IAMs where one scenario was constrained by a remaining carbon budget (RCB) that cannot be exceeded at any point before 2100 (i.e., the non-OS scenario) and one scenario where the same RCB could be temporarily exceeded but must be returned to by 2100 (i.e., the OS scenario). The RCB constraints in the 42 scenarios used range from 450 Gt CO₂ to 1600 Gt CO₂. Forcing from non-CO₂ emissions was determined by assumptions embedded in individual IAMs, therefore IAMs simulated different temperature outcomes for the same RCBs. Pairs of scenarios in the ENGAGE ensemble were excluded from our analysis if: 1) annually averaged GSAT in the OS scenario failed to return to GSAT in the non-OS scenario before 2100, or 2) the OS scenario had less than one degree-year of OS. We did not need to control for internal climate variability using multi-year averages, since our results are averaged across an ensemble of scenarios and the intermediate complexity model we use does not exhibit much internal variability^{114,115}.

4.5.2 Model

The University of Victoria Earth System Climate Model (UVic-ESCM) is an intermediate complexity climate model with a spatial resolution of 3.8° of longitude and 1.8° of latitude¹¹⁴. The model couples atmospheric, oceanic, land surface, and sea ice components while maintaining relatively low computational demands compared to more complex Earth System Models¹¹⁴. The atmospheric component uses a two-dimensional single-layer energy-moisture balance model, effectively simulating large-scale heat and moisture transport without detailed atmospheric circulation¹¹⁴. Thus, surface wind and cloud albedo are both held static at prescribed values based off observations. In contrast to the atmosphere, the ocean representation is more comprehensive, featuring a three-dimensional general circulation model that resolves major ocean currents and includes dynamic sea ice and marine biogeochemistry modules¹¹⁴. The land component incorporates vegetation dynamics by simulating competition between five plant functional types (PFTs) – shrubs, C3 and C4 grasses, and needleleaf and broadleaf trees – and their response to environmental changes¹¹⁴. The land model is coupled to carbon cycle models

representing the marine terrestrial carbon cycles ^{114,115}. The interactive carbon cycle includes physical and biological ocean carbon cycling, sedimentary carbon cycling, and a representation of land carbon via the forementioned PFTs, permafrost carbon storage, and soil carbon storage ^{46,115–117}.

The UVic-ESCM's coarse resolution and simplified atmosphere enable computationally efficient century-long simulations of ensembles of scenarios, making it well-suited for this study. However, two key limitations should be noted: 1) the non-dynamic atmosphere means changes in precipitation are not well captured, and 2) only thermosteric sea-level rise is represented. Therefore, changes in precipitation are ignored in this study and all sea-level rise results in this study refer exclusively to thermosteric changes.

4.5.3 *Simulations*

Future simulations in the UVic-ESCM were driven by fossil and land use change CO₂ emissions as well as aggregated non-CO₂ forcing from the ENGAGE project, the latter being estimated using MAGICC¹¹³. Given that the scenarios from the ENGAGE project do not include spatially explicit land cover change ¹¹³, land cover in our simulations was held static at preindustrial values. Similarly, the scenarios used here do not include spatially explicit changes to aerosol emissions, so only the aggregate globally averaged forcing of aerosols is included. For consistency, the historical simulation used to calculate temperature anomalies in Fig. 4–1 A was emissions driven with static land cover and prescribed globally-averaged aerosol forcing. The combined non-CO₂ greenhouse gas and aerosol forcing for the historical simulation was harmonized with the future scenarios non-CO₂ GHG and aerosol aggregated forcing in the year 2015. Solar forcing was held constant in both the historical and future simulations. Volcanic forcing was included in the historical simulations, but was held constant at the average historical value after the year 2015.

5 Chapter 4: Temporary land carbon storage can avoid slow-responding climate changes

5.1 Abstract

Nature-based carbon removal and storage is central to many net-zero commitments, yet its durability is uncertain due to risks such as wildfires and deforestation. Even if carbon is stored only temporarily however, this storage can still produce climate benefits, such as by lowering peak warming in net zero scenarios. Previous work shows that carbon storage-years (the time-integrated quantity of land carbon storage) are proportional to time-integrated avoided warming, which in turn is closely related to avoided changes in slow-responding climate variables. Here we show that this proportionality between carbon storage-years and avoided changes in inertial climate variables holds across a wide range of removal amounts and emissions scenarios. Across scenarios, carbon storage-years scale quasi-linearly with avoided changes in permafrost carbon, ocean carbon, AMOC, ocean temperature, and thermosteric sea-level rise. These relationships remain strong until 2100. On multi-century timescales, some of these relationships weaken and the impact of temporary storage decreases.

5.2 Introduction

Nature-based carbon removal and storage has emerged as a prominent element in climate mitigation portfolios for both nations¹¹⁸ and corporations¹¹⁹. However, carbon removed from the atmosphere and stored in the terrestrial reservoir is vulnerable to disturbances such as fire, disease, or land-use change^{52,120}. Because the durability of nature-based carbon storage is uncertain due to these threats, and because the durability of carbon storage dictates the persistence of the temperature effects of nature-based carbon removal and storage^{92,121}, the extent to which nature-based storage can reduce climate risk is difficult to quantify. In contrast, the climate impacts of fossil CO₂ emissions remain for thousands of years^{21,22}. This asymmetry creates a fundamental challenge: carbon removal achieved through nature-based means is unlikely to provide a lasting offset to the warming and subsequent climate changes driven by fossil CO₂ emissions.

Nevertheless, even temporary carbon storage, either from avoided emissions or from carbon removal, yields measurable and meaningful climate benefits by reducing peak global temperature in ambitious climate mitigation scenarios and by delaying global temperature

changes in less ambitious scenarios⁹². These outcomes can be significant, as the magnitude and timing of peak warming influence both the severity of climate impacts and the time available for adaptation and mitigation responses. The potential that nature-based carbon storage may only be temporary should therefore not lead to the conclusion that nature-based solutions are ineffectual. Rather, nature-based storage should be recognized an important contribution to climate risk reduction, while acknowledging the fundamental asymmetry between temporary carbon storage and the long-lived effects of fossil CO₂ emissions^{121–123}.

Efforts to formalize this contribution have demonstrated a consistent relationship between the magnitude and duration of temporary carbon storage and the effect of this storage on temperature, and that time-integrated measures of storage capture this relationship more effectively than simple stock measures^{124–129}. Matthews et al.¹²⁸ showed that temporary storage-years (a.k.a. tonne-years) of carbon, which represent the time integrated amount of annual additional carbon storage, are approximately proportional to degree-years of avoided warming, which represent the time-integrated amount of avoided warming. This proportionality provides a framework for quantifying the climate value of non-permanent sequestration. Extending this work, Dickau et al.¹³⁰ establish that degree-years or avoided warming are proportional to avoided changes in a suite of inertial climate system variables in scenarios with temperature overshoot. Together, these findings imply that carbon storage-years provide a metric for linking temporary sequestration to a broad set of climate outcomes. This framework offers a rigorous basis for evaluating the role of nature-based carbon storage in climate mitigation and for comparing the climate benefits of temporary and permanent forms of carbon storage.

Here, we use an intermediate-complexity global climate model – the University of Victoria Earth System Climate Model (UVic-ESCM)^{114,115} – to investigate the proportionality between temporary land carbon storage, expressed in storage-years, and changes in highly inertial components of the climate system. We simulated a suite of idealized temporary storage pathways (with decreased emissions followed by re-emission of stored carbon) applied to eight baseline Shared Socioeconomic Pathway (SSP) scenarios. Maximum rates of carbon removal and re-emission ranged from $\pm 3.64 \text{ Gt CO}_2 \text{ yr}^{-1}$, which is consistent with a conservative estimate of afforestation and reforestation potential¹³¹, to $\pm 10.4 \text{ Gt CO}_2 \text{ yr}^{-1}$, which is consistent with an optimistic estimate of nature-based avoided emissions and removal from all sources (hereinafter referred to as temporary carbon storage)⁹⁰. These perturbations were used to approximate the

effect of time-limited carbon storage interventions. Given that cumulative CO₂ emissions reductions occurring in the first half of the 21st century are balanced by additions of CO₂ emissions in the second half of the century, each of the storage pathways applied to the SSPs have identical cumulative CO₂ emissions relative to their SSP baseline from 2100 onwards. Our simulations include six temporary storage pathways and one baseline simulation for each of the SSPs – SSP1-1.9, SSP1-2.6, SSP4-3.4, SSP5-3.4OS, SSP2-4.5, SSP4-6.0, SSP 3-7.0, and SSP5-8.5 – to generate an ensemble of 48 temporary storage simulations (hereinafter storage SSPs) and eight baseline simulations (hereinafter baseline SSPs). See Methods for more detail.

We then quantify the effect of this temporary carbon storage on changes in key slow-responding climate system variables. We focus here on changes in permafrost carbon, ocean temperature, total ocean carbon, thermosteric sea level rise, and maximum meridional overturning (hereinafter referred to as AMOC), which represent the available climate variables in the UVic-ESCM that include a high inertial component in their response to changing climate forcing. Our results show a clear proportionality between storage-years of temporary carbon storage and degree-years of avoided warming, with measurable benefits for both global temperature and avoided changes in slow-responding climate variables. For temperature, the effect is most apparent in ambitious mitigation scenarios, where temporary removal reduces peak warming. For slow-responding variables, avoided changes scale proportionally with storage-years. Consequently, the relative benefits of temporary storage by 2100 are greatest under stringent mitigation pathways. On multi-century timescales, benefits largely disappear in stabilization scenarios, while peak-and-decline scenarios retain some persistent small legacy effects particularly for avoided permafrost carbon loss.

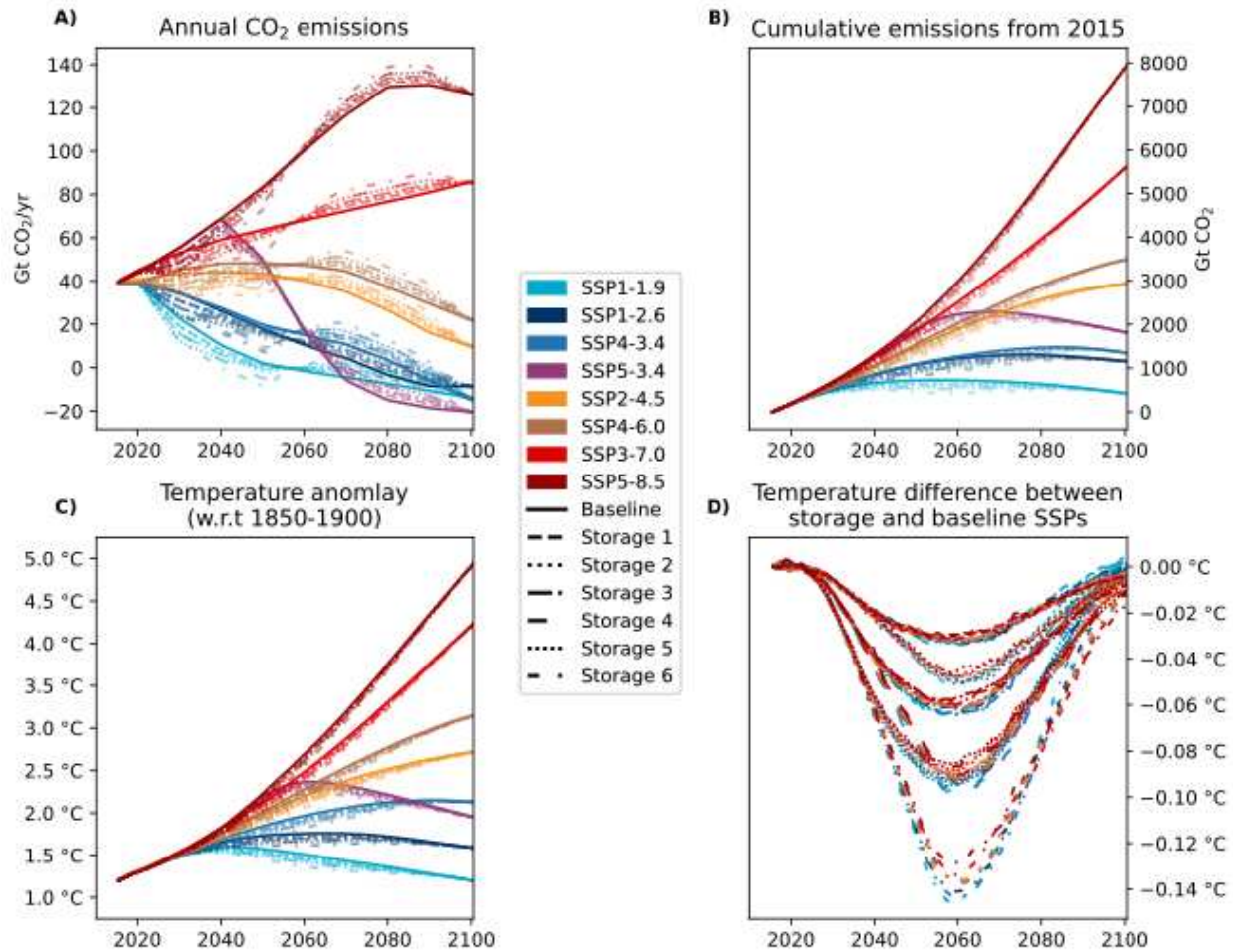


Figure 5-1 – 21st-century CO₂ emissions and temperature responses in baseline and storage SSPs.

(A) Annual anthropogenic CO₂ emissions from fossil fuels and land-use change. (B) Cumulative CO₂ emissions from 2015 to 2100. (C) Global mean surface air temperature anomaly relative to a 1850-1900 preindustrial baseline. (D) Temperature difference between storage SSPs and their corresponding baseline SSPs. Colours indicate SSP ensembles, with solid lines showing baseline simulations and dashed/dotted lines showing the six storage pathways applied to each SSP.

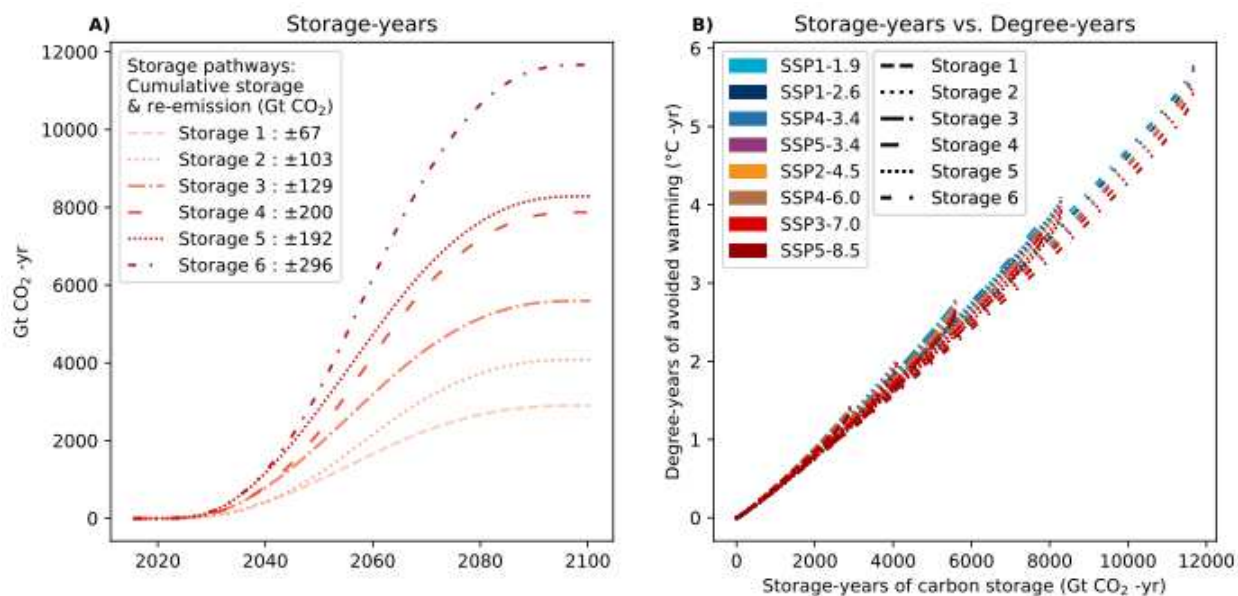


Figure 5-2 – Storage-years in storage pathways and their relationship to degree-years of avoided warming in storage SSPs up until 2100.

(A) Storage-years of the six storage pathways applied to each SSP baseline, with cumulative removals/re-emissions listed in the figure legend. (B) The quasi-linear relationship between degree-years of avoided warming and storage-years of temporary carbon storage across all 48 storage SSPs.

5.3 Results

5.3.1 Temperature effect of temporary carbon storage

Our simulations confirm that temporary carbon storage occurring in the first half of the 21st century decreases peak temperature in scenarios with a peak-and-decline temperature trajectory (i.e., SSP1-1.9, SSP1-2.6, SSP4-3.4, SSP5-3.4; all are scenarios that reach net zero followed by net negative CO₂ emissions this century), but only delays warming in scenarios with continued temperature increase throughout the century (i.e., SSP2-4.5, SSP4-6.0, SSP3-7.0, SSP5-8.5). By 2100, nearly all the temperature difference between storage and baseline SSPs is reversed, leaving only a small residual cooling effect in some storage SSPs (<0.02 °C) (Fig. 5–1 D). This residual temperature difference between storage SSPs and baseline SSPs is larger in scenarios with higher end-of-century warming and scales with the magnitude of temporary storage (e.g., Fig. 5–1 D; SSP5-8.5 Storage 6 has the largest residual temperature difference).

Regional temperature difference following 2100 between storage and baseline SSPs is most pronounced at the poles, where slight cooling is evident, while the lower and middle latitudes experience little change or very slight warming (SM Fig. 8-4). This regional pattern of temperature difference is consistent with several studies which show that the poles are generally warmer following temperature overshoot^{42,103,130}. Here, however, baseline SSPs act as overshoot scenarios relative to the storage SSPs, which is why the poles in storage SSPs are cooling following temporary carbon storage. As with global mean temperature, these regional patterns become more pronounced with larger magnitudes of temporary carbon removal (SM Fig. 8-4).

We calculate the storage-years of temporary carbon storage and the degree-years of avoided warming of the storage SSPs relative to their baseline SSPs. Consistent with previous work¹²⁸, we find a quasi-linear relationship between storage-years of temporary carbon removal and degree-years of avoided warming in our simulations (Fig. 5–2 B), across a wider range of SSPs and temporary storage pathways as compared to previous work. This proportionality indicates that the duration and magnitude of carbon storage directly determine the duration and magnitude of avoided warming. This proportionality is grounded in the linear relationship between global mean temperature increase and cumulative CO₂ emissions, as described by the transient climate response to cumulative carbon emissions (TCRE)^{23–26,62}. The linearity in the TCRE arises because each tonne of CO₂ produces a similar amount of warming regardless of when it is emitted or the background climate state²⁰, and because warming from CO₂ persists for thousands of years^{21,22,27}. Consequently, a CO₂ removal (or additional avoided emission) and an additional emission exert nearly equal but opposite effects on global temperature regardless of the timing of emissions or the background concentration of CO₂^{33,34}. When time-integrated, this TCRE relationship extends to a proportionality between carbon storage-years and degree-years of avoided warming (Fig. 5–2 B).

5.3.2 *Effect of temporary carbon removal on slow-responding variables*

Unlike the effects of temporary carbon storage on temperature, slow-responding climate variables exhibit persistent changes that are not reversed once temporary carbon storage is re-emitted by 2100 (Fig. 5–3). Figure 3 shows the difference between slow-responding variables in the storage SSPs relative to their baseline SSPs over the 21st century. Across all variables, the

magnitude of avoided change relative to baseline SSPs increases with the magnitude of temporary carbon storage (Fig. 5–3). All variables also see some reversal of avoided change in the second half of the century when storage SSPs have higher emissions relative to baseline SSPs (Fig. 5–3). For thermosteric sea level rise, total ocean carbon, and global ocean temperature, the end-of-century impacts are determined primarily by the magnitude of storage and show little dependence on the baseline SSP (Fig. 5–3). In contrast, the responses of the AMOC and permafrost carbon depend on both the magnitude of storage as well as the baseline SSP. In these cases, particularly for the AMOC response and less so for the permafrost carbon response, the general effect of temporary storage is negatively correlated with end-of-century warming, such that larger climate changes diminish the relative influence of temporary carbon storage (Fig. 5–3), which demonstrates that the permafrost carbon and AMOC responses to temporary carbon storage are scenario dependent.

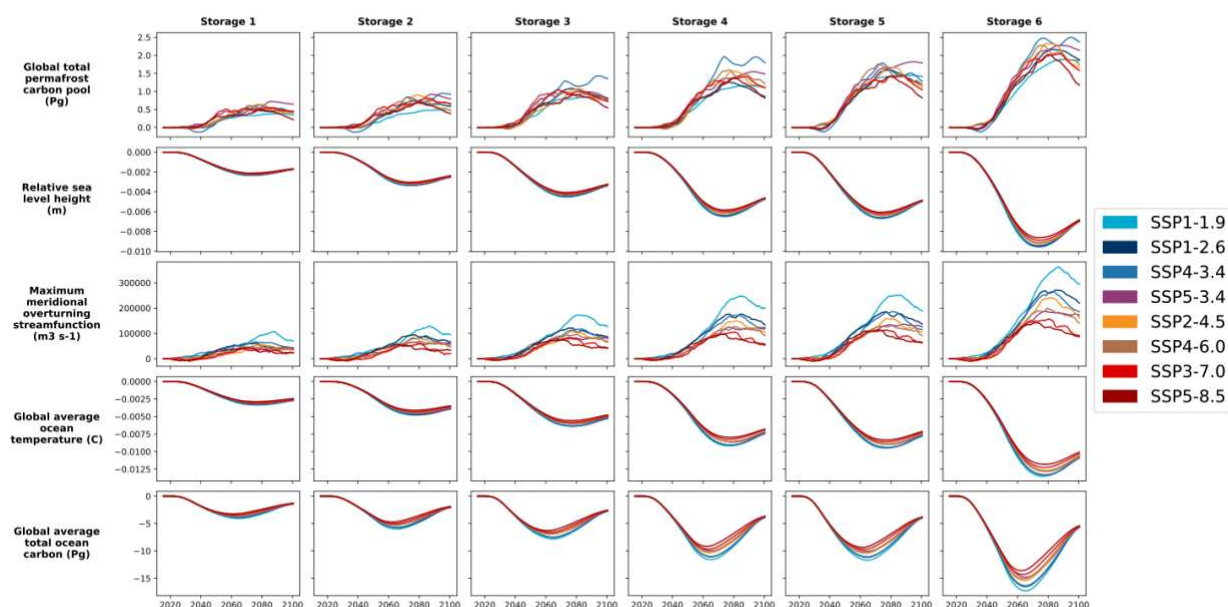


Figure 5-3 – Differences in slow-responding climate variables between storage and baseline SSPs for each of the six storage pathways to 2100.

Each subplot shows the difference between storage SSPs and baseline SSPs for a single slow-responding variable under one storage pathway. Rows correspond to climate variables (listed on the left), and columns correspond to storage pathways (listed above). All variables show avoided change from temporary carbon storage up to 2100, with the magnitude of avoided change increasing under storage pathways with greater storage. Coloured lines in each subplot indicate the underlying SSP for each of the storage simulations.

5.3.3 Proportionality between storage-years and climate effects of temporary storage

Across scenarios, avoided changes in slow-responding variables at the end of the century are proportional to the quantity of temporary carbon storage-years (Fig. 5–4). For total ocean carbon, thermosteric sea-level rise, and average ocean temperature, responses are proportional to storage-years and are also independent of the baseline SSP (Fig. 5–4 B, D, & E). This suggests that avoided end-of-century changes in these variables can be inferred directly from the magnitude and duration of carbon storage measured using storage years, regardless of the background emissions scenario.

Permafrost carbon and the AMOC also scale proportionally with storage-years, but only within each SSP ensemble, with a different proportionality relationship for different baseline SSP scenarios (Fig. 5–4 A & C). This indicates that the relationship between storage-years and variable response is scenario dependent. For the AMOC, this dependence is closely linked to end-of-century warming: while the AMOC remains stronger relative to SSP baselines in all storage scenarios, the strength of the storage-year response declines in SSP ensembles with higher end-of-century warming (Fig. 5–4 C). For permafrost carbon, SSPs with greater warming generally show less benefit per storage-year of temporary storage, although this dependence is not explained by end-of-century warming alone. For example, SSP2-4.5 storage scenarios yield less permafrost carbon savings per storage-year than SSP4-6.0, while SSP4-3.4 and SSP5-3.4 yield more benefit per storage-year than SSP1-1.9 (Fig. 5–4 A). Instead, the scenario dependence of the permafrost carbon response is likely also influenced by the shape of the temperature pathway, such as differences in peak warming or the rate of warming leading up to 2100.

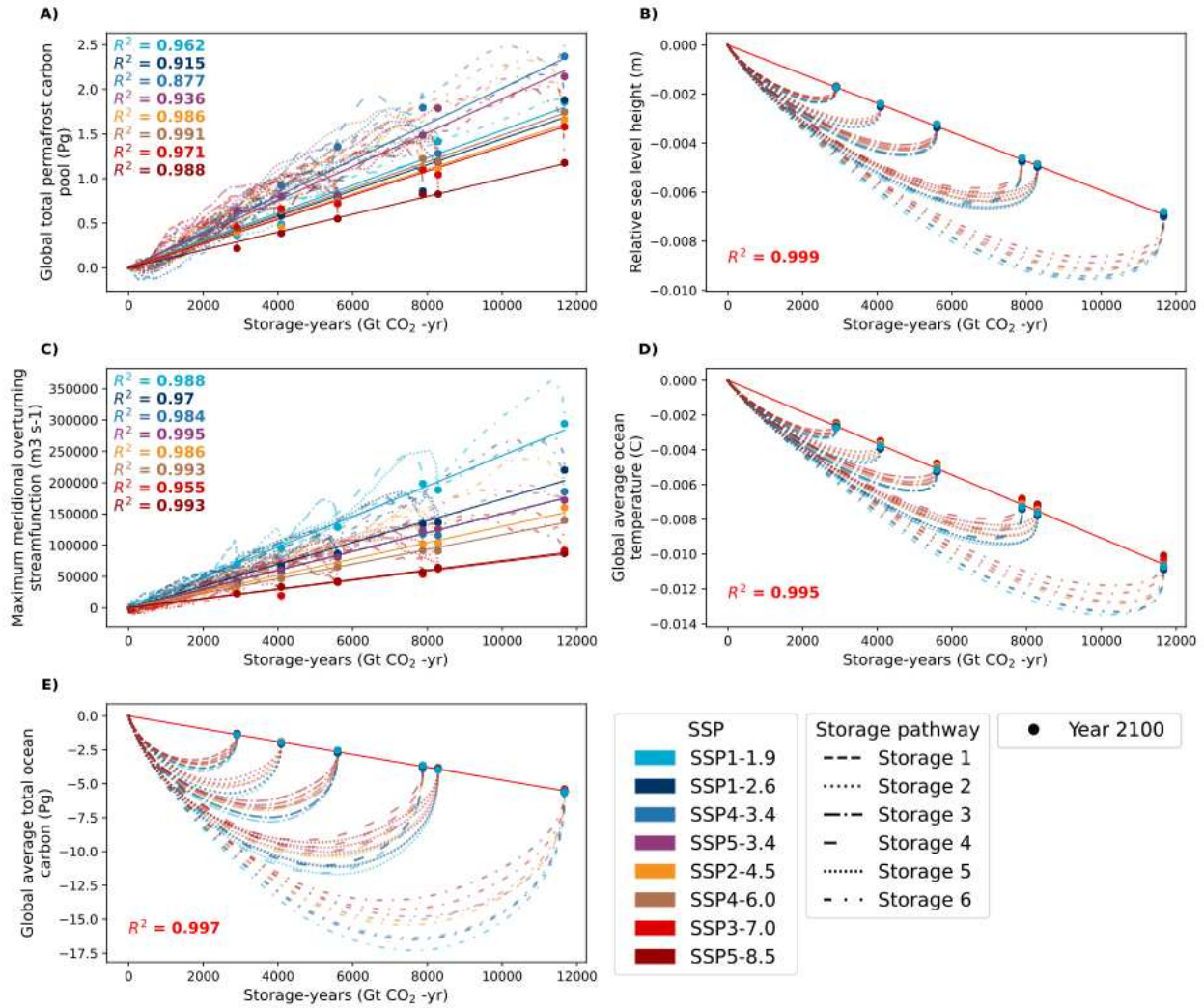


Figure 5-4 – Relationship between storage-years and avoided change of slow-responding variables in storage SSPs relative to their baseline SSPs to 2100.

Figure 5–4 shows the relationship between storage-years of temporary carbon storage and avoided change in: (A) permafrost carbon, (B) thermosteric sea level rise, (C) AMOC, (D) average ocean temperature, and (E) total ocean carbon. Non-linear dashed/dotted lines represent SSP ensembles (colours) and storage pathways (line types), with coloured dots marking 2100 values for each storage SSP. Solid lines indicate linear relationships between storage-years and avoided change. In panels (B), (D), and (E), these linear fits are shown in red, with R^2 values displayed on the left. Linear correlations in panels (B), (D), and (E) are calculated across all storage SSPs, whereas correlations in panels (A) and (C) are calculated within each SSP ensemble, with solid lines and R^2 colours corresponding to each SSP ensemble.

5.3.4 *Contextualizing the climate benefits of temporary carbon storage*

To contextualize the impact of temporary carbon storage on slow-responding variables, we compare avoided changes in storage SSPs in 2100 to the total changes in the baseline SSPs between 2015, the year when baselines diverge from the historical simulation, and 2100. Since the impact of temporary carbon storage on slow-responding variables scales with storage-years, and since the same six storage pathways are applied to each baseline SSP, the relative avoided change from temporary carbon storage in storage SSPs declines as end-of-century temperature increases. As a result, the relative mitigating effect of temporary carbon storage is strongest in ambitious mitigation scenarios (e.g., SSP1-1.9) and weakest in high-emissions scenarios (e.g., SSP5-8.5) (Fig. 5–5). Permafrost carbon and the AMOC see the most benefit from temporary carbon storage, particularly in more ambitious mitigation SSPs where temperatures peak-and-decline. In SSP ensembles with the highest end-of-century warming, there is less variability in the relative avoided change across variables – e.g., SSP5-8.5 storage pathways avoided 0% to 2.5% across all variables. It is notable that the least ambitious storage pathways (e.g., Storage 1) provide almost no benefit when paired with the least ambitious SSPs (e.g., SSP5-8.5)(Fig. 5–5).

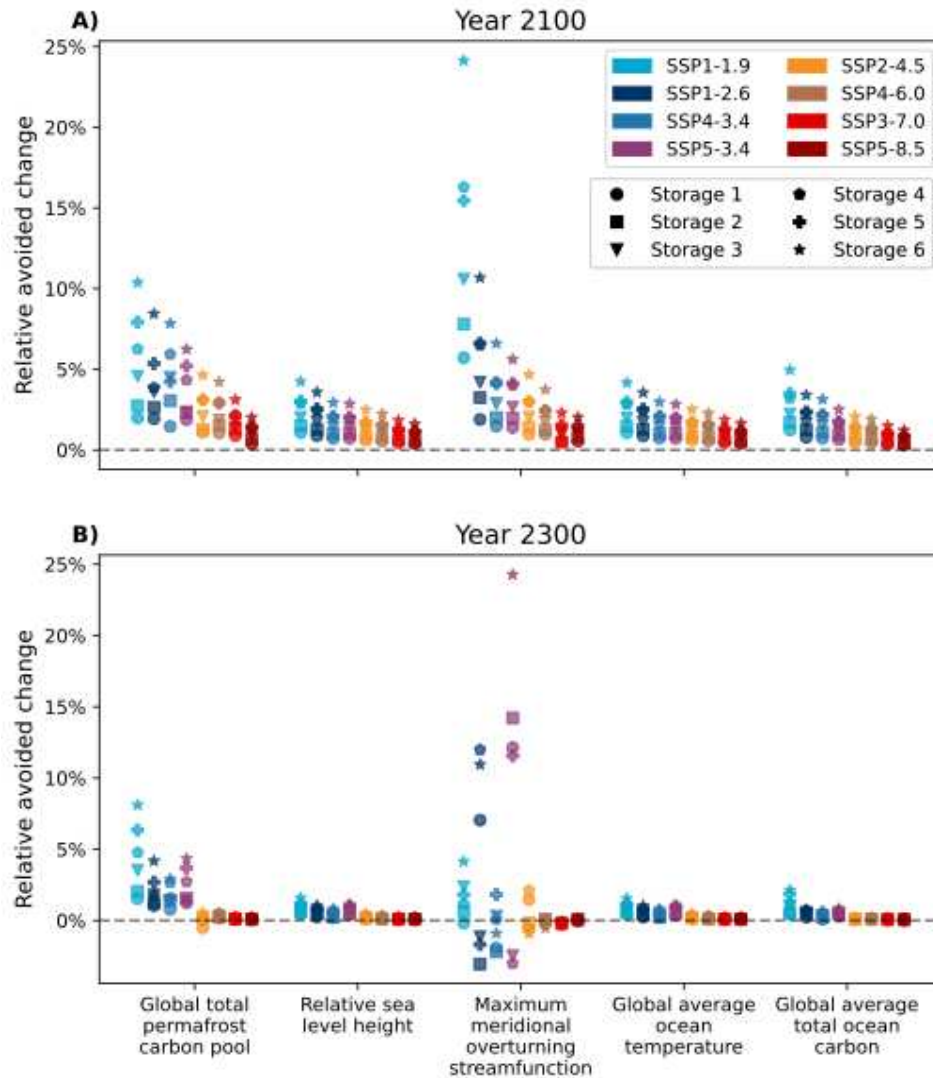


Figure 5-5 – Relative avoided change from temporary carbon storage in A) 2100 and B) 2300.

Figure 5–5 shows how avoided changes in storage SSPs compare to total changes in baseline SSPs from 2015 to 2100 (A) and from 2015 to 2300 (B) for slow-responding variables. Colours denote SSP ensembles, and marker styles denote storage pathways. By 2100, relative avoided change increases with the magnitude of temporary carbon storage and decreases under baseline SSPs with higher end-of-century forcing. Accordingly, the largest relative avoided changes occur in high-storage pathways paired with ambitious mitigation SSPs. This pattern largely persists to 2300 for SSPs that reach net-negative emissions (SSP1-1.9, SSP1-2.6, SSP4-3.4, SSP5-3.4). In contrast, for SSPs that do not reach net-negative CO₂ emissions before 2300 (SSP2-4.5, SSP4-6.0, SSP3-7.0, SSP5-8.5), relative avoided change is close to zero. AMOC and permafrost carbon exhibit the highest relative avoided changes in both 2100 and 2300. However, some baseline SSP and storage pathway combinations show negative avoided change for the AMOC by 2300, underscoring that the AMOC response to temporary carbon storage is highly variable as a flux variable and can rebound over time to produce more change than in the corresponding baselines.

5.3.5 *Multi-century response to temporary carbon storage*

We extend our simulations to 2300 to assess which of our findings hold on multi-century timescales (SM Fig. 8-5). Because storage SSPs remain slightly cooler than their corresponding baselines after 2100 ($\sim \leq 0.015$ °C) (SM Fig. 8-5D), degree-years of avoided warming continue to accumulate between 2100 and 2300 (SM Fig. 8-6 B). As a result, each unit of storage-years yields progressively more degree-years of avoided warming as 2300 is approached even though storage-years remain constant after 2100 (SM Fig. 8-6 A & B). This effect is slightly more pronounced in peak-and-decline SSPs likely due to more long-term avoided permafrost carbon loss (discussed below).

The effect of temporary carbon storage on slow-responding variables also evolves in the extended simulations. By 2300, variables exhibit greater variability in their responses across storage SSPs than in 2100, indicating that their sensitivity to temporary storage becomes increasingly scenario dependent (SM Fig. 8-7). This scenario dependence is most pronounced in peak-and-decline scenarios (SM Fig. 8-7). In contrast, a given amount of temporary carbon storage produces similar changes across stabilization SSPs, which are defined here as SSPs where CO₂ emissions never reach net-negative and where temperatures rise and then stabilize before 2300 (i.e., SSP2-4.5, SSP4-6.0, SSP3-7.0, and SSP5-8.5; SSPs) (SM Fig. 8-7). Among the peak-and-decline SSPs, the largest effects occur in the SSP5-3.4 ensemble, whose baseline features a pronounced temperature overshoot, characterized by the most rapid increase, steepest subsequent decline, and highest rate of net-negative CO₂ emissions (SM Fig. 8-5 A).

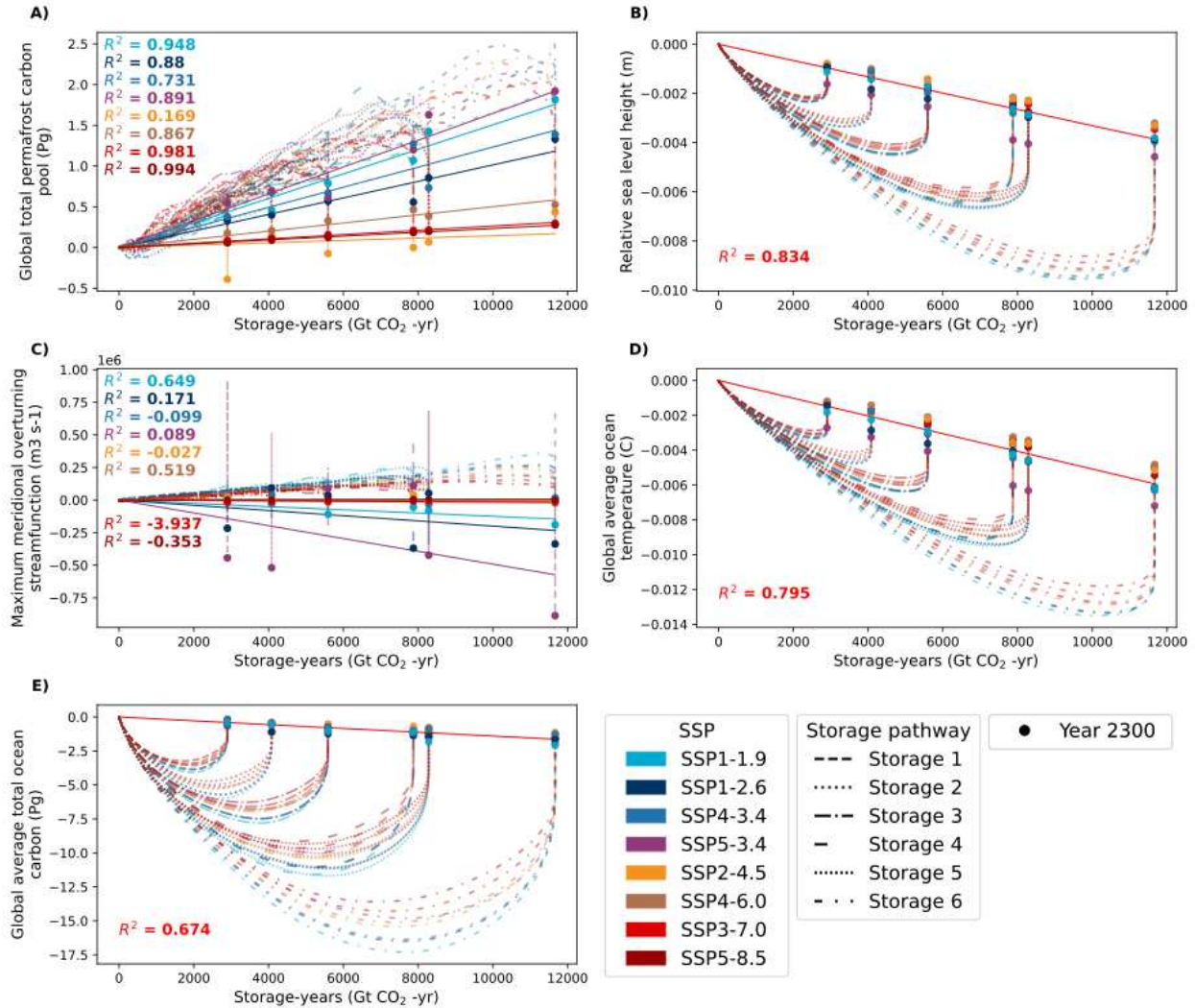


Figure 5-6 – Relationship between storage-years and avoided change of slow-responding variables in storage SSPs relative to their baseline SSPs to 2300.

Figure 5–6 shows the relationship between storage-years of temporary carbon storage and avoided change in: (A) permafrost carbon, (B) thermosteric sea level rise, (C) AMOC, (D) average ocean temperature, and (E) total ocean carbon. Non-linear dashed/dotted lines represent SSP ensembles (colours) and storage pathways (line types), with coloured dots marking 2300 values for each storage SSP. Solid lines indicate linear relationships between storage-years and avoided change. In panels (B), (D), and (E), these linear fits are shown in red, with R^2 values displayed on the left. Linear correlations in panels (B), (D), and (E) are calculated across all storage SSPs, whereas correlations in panels (A) and (C) are calculated within each SSP ensemble, with solid lines and R^2 colours corresponding to each SSP ensemble.

Despite this increasing scenario dependence by 2300, some proportionality between storage-years and avoided changes remains for thermosteric sea-level rise, ocean temperature,

total ocean carbon, and permafrost carbon, the latter of which retains ensemble-level proportionality rather than proportionality across all SSPs (Fig. 5–6). Across these variables, the magnitude of avoided change per storage-year is reduced as storage SSPs equilibrate with baseline SSPs over time, effectively erasing some of the avoided change achieved in 2100. The strength of these linear relationships between storage-years and avoided change tend to be weaker in 2300 than in 2100, largely because of differences in the responses of peak-and-decline SSPs relative to stabilization SSPs (Fig. 5–6; Fig. 5–4). For example, in stabilization SSPs, most of the avoided permafrost carbon loss accumulated during the 21st century is erased, leaving only a small residual effect (Fig. 5–6 A). Conversely, in peak-and-decline SSPs, much of the avoided permafrost carbon loss achieved by 2100 persists to 2300 (Fig. 5–6 A). For ocean temperature and thermosteric sea-level rise, peak-and-decline SSPs – particularly the SSP5-3.4 variants – show greater avoided change in 2300 compared to stabilization SSPs (Fig. 5–6 B, E).

In contrast, there is no proportionality between avoided change in the AMOC and storage years by 2300 (Fig. 5–6 C). However, there is still a notable difference between the responses to temporary carbon storage in peak-and-decline SSPs relative to stabilization SSPs. In stabilization SSPs, there is practically no legacy effect of temporary carbon storage, whereas in peak-and-decline SSPs the AMOC response is highly variable, exhibiting both positive and negative responses across peak-and-decline SSPs and storage pathways (Fig. 5–6 C). As the only flux variable considered here, the difference in the multi-century responses of the AMOC between storage and baseline SSPs should be interpreted with caution.

Comparing avoided changes in slow-responding variables to total baseline changes from 2015 to 2300 shows that relative avoided change declines by 2300 as storage SSPs gradually equilibrate with their baselines (Fig. 5–5). In stabilization SSPs, relative avoided change for all variables in 2300 is close to zero (Fig. 5–5 B). In peak-and-decline SSPs, the relative avoided change in thermosteric sea-level rise, ocean temperature, and total ocean carbon, decreases from a maximum of 5.0% in 2100 to a maximum of 2.5% in 2300 (SSP1-1.9 Storage pathway 6 in Fig. 5–5). For permafrost carbon, relative avoided change sees only a slight decrease between 2100 and 2300 in peak-and-decline storage SSPs (e.g., SSP1-1.9 Storage 6 sees a decline from $\approx 11\%$ to $\approx 8\%$ avoided change), indicating that the effect of temporary carbon storage on permafrost carbon persists on multi-century timescales (Fig. 5–5). For the AMOC, the relative

avoided change in peak-and-decline SSPs by 2300 is highly variable, exhibiting both positive and negative responses change across scenarios, making it difficult to interpret (Fig. 5–5).

5.4 Discussion

The potential for nature-based carbon storage to only be temporary in nature makes it increasingly important to understand the climate impacts of temporary carbon storage so that nature-based approaches and their associated risks can be fairly weighed against other mitigation options. Our results show that temporary carbon storage delivers measurable climate benefits this century. For temperature, temporary storage can lower peak warming when combined with ambitious mitigation, which previous work shows would reduce the risk for triggering climate tipping points¹³². For the slow-responding variables examined here, temporary carbon storage reduces impacts by the end-of-century, with avoided changes by 2100 scaling proportionally with the magnitude and duration of storage, expressed in storage-years. For thermosteric sea level rise, ocean temperature, and total ocean carbon, this proportionality is independent of the SSP baseline. In contrast, the proportionality between storage-years and avoided change in the AMOC and permafrost carbon depends strongly on the baseline scenario, with more ambitious SSPs generally showing the largest avoided changes per storage-year. Our results also demonstrate that by 2300, however, the benefits of temporary carbon storage on slow-responding variables diminish, particularly in stabilization SSPs, where temperature continues to increase following 2100.

Conservative estimates of countries' Nationally Determined Contributions under the Paris Agreement indicate that approximately one billion hectares of land have been pledged to be used for carbon dioxide removal or storage projects by 2060⁵³. Our results indicate that if these pledges are fulfilled, but some of the carbon is only temporarily stored, there are still measurable twenty-first century climate benefits. By providing a measure of avoided change for climate outcomes in slow-responding variables, the metric of storage-years offers a framework to weigh these benefits of nature-based storage against the benefits of more permanent mitigation options, such as sustained reductions of fossil CO₂ emissions or durable geologic storage.

Our results also demonstrate that the climate benefits of temporary carbon storage increase when paired with ambitious emissions reductions but diminish substantially in scenarios where emissions continue to rise. For example, they show that the avoided change caused by

temporary carbon storage depends strongly on the magnitude and duration of storage – in SSP1-1.9, the relative avoided change of permafrost carbon in Storage pathway 1 is less than 2.5%, while it is approximately 11% in Storage pathway 6 (Fig. 5–5). This implies that in a world where global CO₂ emissions do not decline or decline slowly and where the highest estimated rates of nature-based carbon storage are not achieved, the climate benefits of temporary storage will be limited. Given these findings, we echo the conclusions of other studies^{121–123} and argue that nature-based carbon storage should be regarded as a complement to, rather than a substitute for, sustained fossil CO₂ emissions reductions and the deployment of more durable carbon removal approaches.

5.5 Methods

We developed six temporary carbon storage pathways to apply to each SSP baseline. These are based on three hypothetical maximum CO₂ storage rates – 3.64 Gt CO₂ yr⁻¹, 7.02 Gt CO₂ yr⁻¹, and 10.4 Gt CO₂ yr⁻¹ – and by two distinct pathways of storage and re-emission. In both pathways, CO₂ is removed, or emissions are avoided, and stored until 2056 and then re-emitted in equal cumulative amounts between 2057 and 2100, so that the total negative emissions are balanced by positive emissions. The first pathway consists of five phases: (1) a linear decrease in emissions from zero in 2020 to the maximum removal rate in 2030; (2) a linear increase back to zero by 2056; (3) a 12-year linear increase to the maximum rate of positive emissions; (4) 20 years of constant positive emissions at that maximum rate; and (5) a 12-year linear decline back to zero. The second pathway is identical except that, instead of emissions linearly increasing to zero from 2030 to 2056 (step 2), the maximum storage rate is sustained until 2050 before increasing rapidly to zero between 2050 and 2056. The two distinct storage and re-emission pathways represent varying temporal patterns of storage which result in different cumulative removals and re-emissions. Each of the three storage rates is paired with both pathways, yielding six storage pathways in total. When applied to the eight SSP baselines, these scenarios generate 48 temporary carbon storage pathways.

For our simulations, we used the UVic-ESCM version 2.10. The UVic-ESCM is an intermediate-complexity coupled climate-carbon cycle model designed to simulate interactions between the atmosphere, ocean, terrestrial, and sea ice systems at a resolution of 3.8° of longitude and 1.8° of latitude^{114,115}. The atmospheric component is a simplified two-dimensional,

single-layer energy–moisture balance model that captures large-scale heat and moisture fluxes without simulating detailed atmospheric circulation, thereby improving computational efficiency. The ocean is represented by three-dimensional ocean general circulation model with 19 vertical layers, a marine sediment model, as well as a marine biogeochemical model which represents the cycling of inorganic and organic carbon, nitrogen, phosphorus, and oxygen. The terrestrial system includes a land surface model simulating the physical exchanges of energy, heat, and moisture with the atmosphere, a dynamic vegetation model representing five plant functional types, a multi-layer soil model that captures freeze–thaw processes and carbon cycling, and a permafrost module. The relatively low computational cost of the UVic-ESCM enables the simulation of large ensembles and of multi-century experiments while including key processes governing global temperature, ocean circulation, and carbon fluxes, which makes it well-suited for our study. The model has been widely applied to investigate scenarios of anthropogenic emissions, carbon removal, and long-term climate response^{34,47,70,92,133,134}.

The eight baseline SSP simulations were emissions driven. Forcings included fossil and land-use change CO₂ emissions, aggregated non-CO₂ greenhouse gas radiative forcing, and aerosol emissions from Mathesius et al.¹³⁵. The 48 storage SSP simulations are identical to their baseline counterparts, except that temporary storage (and subsequent re-emissions) were subtracted from (and added to) prescribed land-use CO₂ emissions. By modulating prescribed land-use CO₂ emissions rather than explicitly including the land-use and land-cover changes that would accompany many forms of nature-based carbon removal, our results reflect the biogeochemical effect of temporary carbon storage but not biogeophysical effects such as altered surface albedo or cloud cover^{136–138}. Solar and volcanic forcing varied transiently in the historical simulations but were held constant in both baseline and storage SSP experiments. Land cover was prescribed and held fixed throughout all historical and future simulations.

6 Conclusion

Throughout human history, slow natural changes in Earth's climate have been a fundamental force shaping the trajectory of our species, at times creating existential challenges for individual societies. Today, we face a profoundly different challenge: climate change is unfolding at an unprecedented pace, and for the first time, humanity itself has become the primary driver of global climate changes¹⁶. To address this reality, effective policymaking demands a rigorous scientific understanding of the climate response to emissions. Important questions include how the Earth system responds to our emissions, how different pathways toward climate stabilization influence long-term outcomes, and how might tools to mitigate emissions differ in their long-term effect. In this thesis, I have examined three interconnected dimensions of this challenge.

In Manuscript 1 (Chapter 2), I reviewed the scientific foundation, methods, and policy relevance of the RCB) framework. By synthesizing recent literature, I demonstrated that while the near-linear relationship between cumulative CO₂ emissions and global temperature forms a robust physical basis for the RCB, substantial uncertainty remains in its estimation due to both geophysical factors – climate sensitivity, carbon cycle feedbacks, non-CO₂ forcing, and zero-emission commitment – and socioeconomic factors – future non-CO₂ emissions pathways. My meta-analysis showed that methodological differences across studies – particularly in the inclusion or exclusion of specific uncertainties and in the treatment of interdependencies – lead to variation in RCB estimates, emphasizing that only comparable frameworks should be directly contrasted. Despite these challenges, I argued that the RCB remains a powerful tool for informing net-zero CO₂ targets, linking temperature goals to allowable cumulative emissions in an accessible way. In the review, I recommended that net-zero CO₂ targets explicitly state their associated likelihood of meeting temperature thresholds, be informed by “best-estimate” RCBs that incorporate all major uncertainty sources and be periodically updated as these uncertainties narrow as we approach relevant temperature thresholds. Finally, I identified key challenges for future research and for the use of the RCB, including integrating non-CO₂ emissions into RCB-based frameworks, improving our confidence in the quantification and durability of CDR, and the possibility of temperature overshoot scenarios that would exceed the RCB before stabilization.

In Manuscript 2 (Chapter 3), I explored the reversibility of climate responses in temperature overshoot scenarios compatible with the goals outline in the Paris Agreement using an ensemble of 42 paired overshoot and non-overshoot simulations in the UVic-ESCM. In my analysis I quantified how a wide range of climate variables respond to and recover from transient exceedances of temperature thresholds from approximately 1.5°C to 2.0°C. The results showed that while fast-responding variables such as surface temperature and sea ice are largely reversible on decadal timescales, slow-responding components of the Earth system – particularly permafrost and ocean variables – exhibit strong hysteresis and limited reversibility. Importantly, I identified that the degree-years of overshoot serves as a robust predictor of the magnitude of irreversible change across these slow-responding variables, largely independent of the peak temperature reached. This finding implies that the long-term consequences of overshoot in some slow-responding variables could be estimated based off the magnitude and duration the overshoot period relative to a baseline scenario. In this study I also demonstrated that uncertainty in reversibility for many variables arises primarily from variations in the relative contributions of CO₂ and non-CO₂ forcing across scenarios, emphasizing the need to better constrain future non-CO₂ emissions trajectories to understand the climate outcomes of overshoot. Collectively, these results advance understanding of path dependence in Earth system responses, demonstrate a quantitative framework for predicting irreversible climate impacts of overshoot scenarios, and highlight the importance of minimizing both the magnitude and duration of future temperature overshoot to reduce long-term climate risks.

In Manuscript 3 (Chapter 4), I assessed the climate benefits and limitations of temporary carbon storage, focusing on how carbon storage affects slow-responding components of the Earth system. Using the UVic-ESCM, I simulated an ensemble of idealized temporary storage pathways across eight SSP scenarios to quantify how the magnitude and duration of nature-based carbon storage influence temperature and key inertial climate variables. The results showed that temporary storage – expressed as carbon storage-years, a time-integrated measure of stored carbon – produces measurable short-term climate benefits by reducing peak global warming and delaying some long-term impacts. Across scenarios, I found that storage-years scale quasi-linearly with degree-years of avoided warming, as well as with avoided changes in slow-responding variables such as permafrost carbon loss, ocean temperature, thermosteric sea-level rise, total ocean carbon, and the strength of the AMOC. These relationships were strongest under

ambitious mitigation scenarios that limit peak warming in the twenty-first century and weakest in high-emission pathways with continued warming, demonstrating that the climate value of temporary storage is conditional on broader mitigation efforts. On multi-century timescales, the benefits of temporary storage diminish as the climate system equilibrates, though modest residual effects persist for some variables, particularly permafrost carbon. Overall, this study establishes that even temporary carbon storage yields quantifiable near-term climate benefits, provides a framework for comparing nature-based and durable carbon removal approaches, and reinforces that nature-based storage should complement rather than replace deep, sustained reductions in fossil CO₂ emissions.

Taken together, the work I presented in this thesis highlights the complex interplay between scientific understanding and policy relevance in efforts to limit global warming. The RCB provides an elegant and intuitive link between cumulative emissions and temperature outcomes, yet uncertainties arising from both physical and socio-economic processes are still an important consideration. By examining how different pathways toward net-zero influence long-term climate outcomes, I demonstrated that mitigation decisions – whether characterized by temperature overshoot or a reliance on CDR that may only provide temporary carbon storage – will shape future climate outcomes. These findings reveal that while the physics of cumulative carbon emissions define the boundaries of what is possible, the path we take within those boundaries determines the legacy of human influence on the Earth system. Ultimately, this thesis underscores that the challenge of climate change is not simply one of reaching a destination – whether net-zero CO₂ emissions, a temperature target, or a particular atmospheric CO₂ concentration. Instead, I showed here how the way we arrive at that destination will shape the world we will inhabit. The decisions we make in the coming years – how quickly we reduce emissions, how much we allow temperature to overshoot, and how we deploy carbon removal – will leave a lasting imprint on the Earth system.

7 References/Bibliography

1. Judd, E. J. *et al.* A 485-million-year history of Earth's surface temperature. *Science* (1979) **385**, (2024).
2. Snyder, C. W. Evolution of global temperature over the past two million years. *Nature* **538**, 226–228 (2016).
3. Osman, M. B. *et al.* Globally resolved surface temperatures since the Last Glacial Maximum. *Nature* **599**, 239–244 (2021).
4. Schlebusch, C. M. *et al.* Southern African ancient genomes estimate modern human divergence to 350,000 to 260,000 years ago. *Science* (1979) **358**, 652–655 (2017).
5. Masson-Delmotte, V. *et al.* Information from Paleoclimate Archives. in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Stocker, T. F. *et al.*) 383–464 (Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2013). doi:10.1017/CBO9781107415324.013.
6. Bond, D. P. G. & Grasby, S. E. On the causes of mass extinctions. *Palaeogeogr Palaeoclimatol Palaeoecol* **478**, 3–29 (2017).
7. Penn, J. L., Deutsch, C., Payne, J. L. & Sperling, E. A. Temperature-dependent hypoxia explains biogeography and severity of end-Permian marine mass extinction. *Science* (1979) **362**, (2018).
8. Davies, J. H. F. L. *et al.* End-Triassic mass extinction started by intrusive CAMP activity. *Nat Commun* **8**, 15596 (2017).
9. Degroot, D. *et al.* The history of climate and society: a review of the influence of climate change on the human past. *Environmental Research Letters* **17**, 103001 (2022).
10. Fleming, J. R. Joseph Fourier, the 'greenhouse effect', and the quest for a universal theory of terrestrial temperatures. *Endeavour* **23**, 72–75 (1999).
11. Foote, E. Circumstances affecting the heat of the sun's rays. *American Journal of Science and Arts* **22**, (1856).
12. Tyndall, J. The Bakerian Lecture.—On the absorption and radiation of heat by gases and vapours, and on the physical connexion of radiation, absorption, and conduction. *Philos Trans R Soc Lond* **151**, 1–36 (1861).
13. Arrhenius, S. XXXI. On the influence of carbonic acid in the air upon the temperature of the ground. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science* **41**, 237–276 (1896).
14. Friedlingstein, P. *et al.* Global Carbon Budget 2024. *Earth Syst Sci Data* **17**, 965–1039 (2025).

15. Lan, X., Tans, P. & Thoning, K. W. Trends in globally-averaged CO₂ determined from NOAA Global Monitoring Laboratory measurements. *NOAA* (2025) doi:<https://doi.org/10.15138/9N0H-ZH07>.
16. Forster, P. M. *et al.* Indicators of Global Climate Change 2024: annual update of key indicators of the state of the climate system and human influence. *Earth Syst Sci Data* **17**, 2641–2680 (2025).
17. Olhoff, A. *et al.* *Emissions Gap Report 2024: No More Hot Air ... Please! With a Massive Gap between Rhetoric and Reality, Countries Draft New Climate Commitments*. (United Nations Environment Programme, 2024). doi:10.59117/20.500.11822/46404.
18. IPCC. Summary for Policymakers. in *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Pörtner, H. O. *et al.*) In Press (Cambridge University Press, Cambridge, UK, 2022).
19. UNFCCC. *Adoption of the Paris Agreement*. (2015).
20. Caldeira, K. & Kasting, J. F. Insensitivity of global warming potentials to carbon dioxide emission scenarios. *Nature* **366**, 251–253 (1993).
21. Eby, M. *et al.* Lifetime of anthropogenic climate change: Millennial time scales of potential CO₂ and surface temperature perturbations. *J Clim* **22**, 2501–2511 (2009).
22. Solomon, S., Plattner, G.-K., Knutti, R. & Friedlingstein, P. Irreversible climate change due to carbon dioxide emissions. *Proceedings of the National Academy of Sciences* **106**, 1704–1709 (2009).
23. Meinshausen, M. *et al.* Greenhouse-gas emission targets for limiting global warming to 2 °C. *Nature* **458**, 1158–1162 (2009).
24. Matthews, H. D., Gillett, N. P., Stott, P. A. & Zickfeld, K. The proportionality of global warming to cumulative carbon emissions. *Nature* **459**, 829–832 (2009).
25. Zickfeld, K., Eby, M., Damon Matthews, H. & Weaver, A. J. Setting cumulative emissions targets to reduce the risk of dangerous climate change. *Proc Natl Acad Sci U S A* **106**, 16129–16134 (2009).
26. Allen, M. R. *et al.* Warming caused by cumulative carbon emissions towards the trillionth tonne. *Nature* **458**, 1163–1166 (2009).
27. Matthews, H. D. & Caldeira, K. Stabilizing climate requires near-zero emissions. *Geophys Res Lett* **35**, L04705 (2008).
28. Matthews, H. D. *et al.* An integrated approach to quantifying uncertainties in the remaining carbon budget. *Commun Earth Environ* **2**, 7 (2021).
29. Matthews, H. D. *et al.* Opportunities and challenges in using remaining carbon budgets to guide climate policy. *Nat Geosci* **13**, 769–779 (2020).
30. Rogelj, J., Forster, P. M., Kriegler, E., Smith, C. J. & Séférian, R. Estimating and tracking the remaining carbon budget for stringent climate targets. *Nature* **571**, 335–342 (2019).
31. IEA. *World Energy Investment 2025*. <https://www.iea.org/reports/world-energy-investment-2025> (2025).

32. Riahi, K. *et al.* The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change* **42**, 153–168 (2017).
33. Koven, C. D. *et al.* Multi-century dynamics of the climate and carbon cycle under both high and net negative emissions scenarios. *Earth System Dynamics* **13**, 885–909 (2022).
34. Zickfeld, K., MacDougall, A. H. & Damon Matthews, H. On the proportionality between global temperature change and cumulative CO₂ emissions during periods of net negative CO₂ emissions. *Environmental Research Letters* **11**, 055006 (2016).
35. Huppmann, D., Rogelj, J., Kriegler, E., Krey, V. & Riahi, K. A new scenario resource for integrated 1.5 °C research. *Nat Clim Chang* **8**, 1027–1030 (2018).
36. Byers, E. *et al.* AR6 Scenarios Database. Preprint at <https://doi.org/10.5281/zenodo.5886912> (2022).
37. van Vuuren, D. P., Edmonds, J. A., Kainuma, M., Riahi, K. & Weyant, J. A special issue on the RCPs. *Clim Change* **109**, 1 (2011).
38. Schwinger, J., Asaadi, A., Goris, N. & Lee, H. Possibility for strong northern hemisphere high-latitude cooling under negative emissions. *Nat Commun* **13**, 1095 (2022).
39. Schwinger, J., Asaadi, A., Steinert, N. J. & Lee, H. Emit now, mitigate later? Earth system reversibility under overshoots of different magnitudes and durations. *Earth System Dynamics* **13**, 1641–1665 (2022).
40. Asaadi, A. *et al.* Carbon cycle feedbacks in an idealized simulation and a scenario simulation of negative emissions in CMIP6 Earth system models. *Biogeosciences* **21**, 411–435 (2024).
41. Santana-Falcón, Y. *et al.* Irreversible loss in marine ecosystem habitability after a temperature overshoot. *Commun Earth Environ* **4**, 343 (2023).
42. Pflöiderer, P., Schleussner, C.-F. & Sillmann, J. Limited reversal of regional climate signals in overshoot scenarios. *Environmental Research: Climate* **3**, 015005 (2024).
43. Schleussner, C.-F. *et al.* Overconfidence in climate overshoot. *Nature* **634**, 366–373 (2024).
44. Boucher, O. *et al.* Reversibility in an Earth System model in response to CO₂ concentration changes. *Environmental Research Letters* **7**, 024013 (2012).
45. Tokarska, K. B., Zickfeld, K. & Rogelj, J. Path Independence of Carbon Budgets When Meeting a Stringent Global Mean Temperature Target After an Overshoot. *Earths Future* **7**, 1283–1295 (2019).
46. MacDougall, A. H. & Knutti, R. Projecting the release of carbon from permafrost soils using a perturbed parameter ensemble modelling approach. *Biogeosciences* **13**, 2123–2136 (2016).
47. MacDougall, A. H. Reversing climate warming by artificial atmospheric carbon-dioxide removal: Can a Holocene-like climate be restored? *Geophys Res Lett* **40**, 5480–5485 (2013).

48. Gasser, T. *et al.* Path-dependent reductions in CO₂ emission budgets caused by permafrost carbon release. *Nat Geosci* **11**, 830–835 (2018).
49. Mathesius, S., Hofmann, M., Caldeira, K. & Schellnhuber, H. J. Long-term response of oceans to CO₂ removal from the atmosphere. *Nat Clim Chang* **5**, 1107–1113 (2015).
50. Li, X., Zickfeld, K., Mathesius, S., Kohfeld, K. & Matthews, J. B. R. Irreversibility of Marine Climate Change Impacts Under Carbon Dioxide Removal. *Geophys Res Lett* **47**, (2020).
51. IPCC. Summary for Policymakers. in *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Shukla, P. R. *et al.*) (Cambridge University Press, Cambridge, UK and New York, NY, USA, 2022). doi:10.1017/9781009157926.001.
52. Anderegg, W. R. L. *et al.* Climate-driven risks to the climate mitigation potential of forests. *Science (1979)* **368**, (2020).
53. Dooley, K., Christiansen, K. L., Lund, J. F., Carton, W. & Self, A. Over-reliance on land for carbon dioxide removal in net-zero climate pledges. *Nat Commun* **15**, 9118 (2024).
54. Asayama, S., Hulme, M. & Markusson, N. Balancing a budget or running a deficit? The offset regime of carbon removal and solar geoengineering under a carbon budget. *Clim Change* **167**, (2021).
55. Rogelj *et al.* Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development. *Special Report, Intergovernmental Panel on Climate Change* (2018).
56. Jones, C. D. *et al.* Simulating the Earth system response to negative emissions. *Environmental Research Letters* **11**, (2016).
57. Rogelj, J., Geden, O., Cowie, A. & Reisinger, A. Net-zero emissions targets are vague: three ways to fix. *Nature* **591**, (2021).
58. Tokarska, K. B. & Zickfeld, K. The effectiveness of net negative carbon dioxide emissions in reversing anthropogenic climate change. *Environmental Research Letters* **10**, 094013 (2015).
59. Tokarska, K. B., Gillett, N. P., Weaver, A. J., Arora, V. K. & Eby, M. The climate response to five trillion tonnes of carbon. *Nat Clim Chang* **6**, 851–855 (2016).
60. Gillett, N. P., Arora, V. K., Matthews, H. D. & Allen, M. R. Constraining the ratio of global warming to cumulative CO₂ emissions using CMIP5 simulations. *J Clim* **26**, 6844–6858 (2013).
61. Collins, M. *et al.* Long-term Climate Change: Projections, Commitments and Irreversibility. in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Stocker, T. F. *et al.*) 1029–1136 (Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2013). doi:10.1017/CBO9781107415324.024.

62. Canadell, J. G. *et al.* Global Carbon and other Biogeochemical Cycles and Feedbacks. in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Masson-Delmotte, V. *et al.*) (Cambridge University Press, 2021).
63. Zickfeld, K., Arora, V. K. & Gillett, N. P. Is the climate response to CO₂ emissions path dependent? *Geophys Res Lett* **39**, (2012).
64. Matthews, H. D. *et al.* Estimating Carbon Budgets for Ambitious Climate Targets. *Curr Clim Change Rep* **3**, 69–77 (2017).
65. Rogelj, J. *et al.* Differences between carbon budget estimates unravelled. *Nat Clim Chang* **6**, (2016).
66. Millar, R. J. *et al.* Emission budgets and pathways consistent with limiting warming to 1.5 °C. *Nat Geosci* **10**, 741–747 (2017).
67. Tokarska, K. B., Gillett, N. P., Arora, V. K., Lee, W. G. & Zickfeld, K. The influence of non-CO₂ forcings on cumulative carbon emissions budgets. *Environmental Research Letters* **13**, 034039 (2018).
68. Tokarska, K. B. *et al.* Recommended temperature metrics for carbon budget estimates, model evaluation and climate policy. *Nat Geosci* **12**, 964–971 (2019).
69. MacDougall, A. H. *et al.* Is there warming in the pipeline? A multi-model analysis of the Zero Emissions Commitment from CO₂. *Biogeosciences* **17**, 2987–3016 (2020).
70. MacDougall, A. H., Zickfeld, K., Knutti, R. & Matthews, H. D. Sensitivity of carbon budgets to permafrost carbon feedbacks and non-CO₂ forcings. *Environmental Research Letters* **10**, 125003 (2015).
71. Mengis, N., Partanen, A. I., Jalbert, J. & Matthews, H. D. 1.5 °C carbon budget dependent on carbon cycle uncertainty and future non-CO₂ forcing. *Sci Rep* **8**, 5831 (2018).
72. Nicholls, Z. R. J., Gieseke, R., Lewis, J., Nauels, A. & Meinshausen, M. Implications of non-linearities between cumulative CO₂ emissions and CO₂-induced warming for assessing the remaining carbon budget. *Environmental Research Letters* **15**, (2020).
73. Forster, P. M. *et al.* The Earth's Energy Budget, Climate Feedbacks, and Climate Sensitivity. in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Masson-Delmotte, V. *et al.*) (Cambridge University Press., 2021).
74. Bowerman, N. H. A. *et al.* The role of short-lived climate pollutants in meeting temperature goals. *Nat Clim Chang* **3**, 1021–1024 (2013).
75. Rogelj, J., Meinshausen, M., Schaeffer, M., Knutti, R. & Riahi, K. Impact of short-lived non-CO₂ mitigation on carbon budgets for stabilizing global warming. *Environmental Research Letters* **10**, (2015).
76. Goodwin, P. *et al.* Pathways to 1.5 °C and 2 °C warming based on observational and geological constraints. *Nat Geosci* **11**, (2018).

77. Allen, M. R. *et al.* A solution to the misrepresentations of CO₂-equivalent emissions of short-lived climate pollutants under ambitious mitigation. *NPJ Clim Atmos Sci* **1**, 16 (2018).
78. Collins, W. J., Frame, D. J., Fuglestedt, J. S. & Shine, K. P. Stable climate metrics for emissions of short and long-lived species—combining steps and pulses. *Environmental Research Letters* **15**, 024018 (2020).
79. Shine, K. P., Fuglestedt, J. S., Hailemariam, K. & Stuber, N. Alternatives to the Global Warming Potential for Comparing Climate Impacts of Emissions of Greenhouse Gases. *Clim Change* **68**, 281–302 (2005).
80. Shine, K. P. The global warming potential—the need for an interdisciplinary retrieval. *Clim Change* **96**, 467–472 (2009).
81. Rogelj, J. & Schleussner, C.-F. Unintentional unfairness when applying new greenhouse gas emissions metrics at country level. *Environmental Research Letters* **14**, 114039 (2019).
82. Schleussner, C.-F., Nauels, A., Schaeffer, M., Hare, W. & Rogelj, J. Inconsistencies when applying novel metrics for emissions accounting to the Paris agreement. *Environmental Research Letters* **14**, 124055 (2019).
83. Jenkins, S., Millar, R. J., Leach, N. & Allen, M. R. Framing Climate Goals in Terms of Cumulative CO₂-Forcing-Equivalent Emissions. *Geophys Res Lett* **45**, 2795–2804 (2018).
84. Alcaraz, O. *et al.* Distributing the Global Carbon Budget with climate justice criteria. *Clim Change* **149**, (2018).
85. Gignac, R. & Matthews, H. D. Allocating a 2°C cumulative carbon budget to countries. *Environmental Research Letters* **10**, (2015).
86. Holz, C., Kartha, S. & Athanasiou, T. Fairly sharing 1.5: national fair shares of a 1.5 °C-compliant global mitigation effort. *Int Environ Agreem* **18**, (2018).
87. van den Berg, N. J. *et al.* Implications of various effort-sharing approaches for national carbon budgets and emission pathways. *Clim Change* **162**, (2020).
88. Hultman, N. E. *et al.* Fusing subnational with national climate action is central to decarbonization: the case of the United States. *Nat Commun* **11**, (2020).
89. Friedlingstein, P. *et al.* Global Carbon Budget 2020. *Earth Syst Sci Data* **12**, (2020).
90. Griscom, B. W. *et al.* Natural climate solutions. *Proceedings of the National Academy of Sciences* **114**, 11645–11650 (2017).
91. Erb, K.-H. *et al.* Unexpectedly large impact of forest management and grazing on global vegetation biomass. *Nature* **553**, (2018).
92. Matthews, H. D. *et al.* Temporary nature-based carbon removal can lower peak warming in a well-below 2 °C scenario. *Commun Earth Environ* **3**, 65 (2022).
93. Aviso, K. B., Janairo, J. I. B., Promentilla, M. A. B. & Tan, R. R. Prediction of CO₂ storage site integrity with rough set-based machine learning. *Clean Technol Environ Policy* **21**, (2019).

94. Moriarty, D., Dobeck, L. & Benson, S. Rapid surface detection of CO₂ leaks from geologic sequestration sites. *Energy Procedia* **63**, (2014).
95. Zhong, Z., Sun, A. Y., Yang, Q. & Ouyang, Q. A deep learning approach to anomaly detection in geological carbon sequestration sites using pressure measurements. *J Hydrol (Amst)* **573**, (2019).
96. Wang, J. *et al.* Machine vision for natural gas methane emissions detection using an infrared camera. *Appl Energy* **257**, (2020).
97. Harper, A. B. *et al.* Land-use emissions play a critical role in land-based mitigation for Paris climate targets. *Nat Commun* **9**, (2018).
98. Koven, C. *et al.* 23rd Century surprises: Long-term dynamics of the climate and carbon cycle under both high and net negative emissions scenarios. *Earth Syst. Dynam. Discuss.* **2021**, 1–32 (2021).
99. UNEP. *Emissions Gap Report 2023: Broken Record – Temperatures Hit New Highs, yet World Fails to Cut Emissions (Again)*. (United Nations Environment Programme, Nairobi, 2023). doi:10.59117/20.500.11822/43922.
100. de Vrese, P. & Brovkin, V. Timescales of the permafrost carbon cycle and legacy effects of temperature overshoot scenarios. *Nat Commun* **12**, 2688 (2021).
101. Comyn-Platt, E. *et al.* Carbon budgets for 1.5 and 2 °C targets lowered by natural wetland and permafrost feedbacks. *Nat Geosci* **11**, 568–573 (2018).
102. Ehlert, D. & Zickfeld, K. Irreversible ocean thermal expansion under carbon dioxide removal. *Earth System Dynamics* **9**, 197–210 (2018).
103. Kim, S.-K. *et al.* Widespread irreversible changes in surface temperature and precipitation in response to CO₂ forcing. *Nat Clim Chang* **12**, 834–840 (2022).
104. Herrington, T. & Zickfeld, K. Path independence of climate and carbon cycle response over a broad range of cumulative carbon emissions. *Earth System Dynamics* **5**, 409–422 (2014).
105. Jeltsch-Thömmes, A., Stocker, T. F. & Joos, F. Hysteresis of the Earth system under positive and negative CO₂ emissions. *Environmental Research Letters* **15**, 124026 (2020).
106. Wei, T., Chen, Y. & Wang, H. Hysteresis of Northern Hemisphere permafrost to carbon dioxide emissions. *Environmental Research Letters* **19**, 094032 (2024).
107. Keller, D. P. *et al.* The Carbon Dioxide Removal Model Intercomparison Project (CDRMIP): rationale and experimental protocol for CMIP6. *Geosci Model Dev* **11**, 1133–1160 (2018).
108. Melnikova, I. *et al.* Carbon Cycle Response to Temperature Overshoot Beyond 2°C: An Analysis of CMIP6 Models. *Earths Future* **9**, (2021).
109. Drouet, L. *et al.* Net zero-emission pathways reduce the physical and economic risks of climate change. *Nat Clim Chang* **11**, 1070–1076 (2021).
110. Millero, F. J., Lee, K. & Roche, M. Distribution of alkalinity in the surface waters of the major oceans. *Mar Chem* **60**, 111–130 (1998).

111. Lee, K. *et al.* Global relationships of total alkalinity with salinity and temperature in surface waters of the world's oceans. *Geophys Res Lett* **33**, (2006).
112. IPCC, 2022: Summary for Policymakers. in *Climate Change 2022 – Impacts, Adaptation and Vulnerability* (eds. H.-O. Pörtner *et al.*) 3–34 (Cambridge University Press, Cambridge, UK and New York, NY, USA, 2022). doi:10.1017/9781009325844.001.
113. Riahi, K. *et al.* Cost and attainability of meeting stringent climate targets without overshoot. *Nat Clim Chang* **11**, 1063–1069 (2021).
114. Weaver, A. J. *et al.* The UVic earth system climate model: Model description, climatology, and applications to past, present and future climates. *Atmosphere-Ocean* **39**, 361–428 (2001).
115. Mengis, N. *et al.* Evaluation of the University of Victoria Earth System Climate Model version 2.10 (UVic ESCM 2.10). *Geosci Model Dev* **13**, 4183–4204 (2020).
116. Schmittner, A., Oeschies, A., Matthews, H. D. & Galbraith, E. D. Future changes in climate, ocean circulation, ecosystems, and biogeochemical cycling simulated for a business-as-usual CO₂ emission scenario until year 4000 AD. *Global Biogeochem Cycles* **22**, (2008).
117. Matthews, H. D., Weaver, A. J. & Meissner, K. J. Terrestrial Carbon Cycle Dynamics under Recent and Future Climate Change. *J Clim* **18**, 1609–1628 (2005).
118. Government of Canada. 2 Billion Trees Commitment. (2025).
119. Smith, B. Microsoft will be carbon negative by 2030. *Official Microsoft Blog* (2020).
120. McDowell, N. G. *et al.* Pervasive shifts in forest dynamics in a changing world. *Science (1979)* **368**, (2020).
121. Brunner, C., Hausfather, Z. & Knutti, R. Durability of carbon dioxide removal is critical for Paris climate goals. *Commun Earth Environ* **5**, 645 (2024).
122. Allen, M. R. *et al.* Geological Net Zero and the need for disaggregated accounting for carbon sinks. *Nature* **638**, 343–350 (2025).
123. Seddon, N. Harnessing the potential of nature-based solutions for mitigating and adapting to climate change. *Science (1979)* **376**, 1410–1416 (2022).
124. Sierra, C. A., Crow, S. E., Heimann, M., Metzler, H. & Schulze, E.-D. The climate benefit of carbon sequestration. *Biogeosciences* **18**, 1029–1048 (2021).
125. Metzler, H., Launiainen, S. & Vico, G. Amount of carbon fixed, transit time and fate of harvested wood products define the climate change mitigation potential of boreal forest management—A model analysis. *Ecol Modell* **491**, 110694 (2024).
126. Minasny, B. & McBratney, Alex. B. Soil carbon tonne-year accounting: Crediting the additional time-integrated amount of carbon captured in soil. *Soil Security* **15**, 100153 (2024).
127. Alexander, J. R., Gamble, J. D. & Venterea, R. T. Stock change accounting overestimates the potential climate benefit of soil carbon storage. *Soil Science Society of America Journal* **88**, 745–752 (2024).

128. Matthews, H. D., Zickfeld, K., Koch, A. & Luers, A. Accounting for the climate benefit of temporary carbon storage in nature. *Nat Commun* **14**, 5485 (2023).
129. Sierra, C. Integrating time in definitions of carbon sequestration and greenhouse gas removals and reversals. *R Soc Open Sci* **12**, (2025).
130. Dickau, M., Zickfeld, K. & Matthews, H. D. *Irreversible Climate Changes Driven by Degree-Years of Temperature Overshoot*. Preprint at doi:10.21203/rs.3.rs-7603499/v1.
131. Roe, S. *et al.* Contribution of the land sector to a 1.5 °C world. *Nat Clim Chang* **9**, (2019).
132. Ritchie, P. D. L., Huntingford, C. & Cox, P. M. ESD Ideas: Climate tipping is not instantaneous – the duration of an overshoot matters. *Earth System Dynamics* **16**, 1523–1526 (2025).
133. Matthews, H. D. & Zickfeld, K. Climate response to zeroed emissions of greenhouse gases and aerosols. *Nat Clim Chang* **2**, 338–341 (2012).
134. Zickfeld, K., Azevedo, D., Mathesius, S. & Matthews, H. D. Asymmetry in the climate–carbon cycle response to positive and negative CO₂ emissions. *Nat Clim Chang* **11**, 613–617 (2021).
135. Mathesius, S. *et al.* CMIP6 scenarios’ radiative forcing of non-CO₂ greenhouse gases and aerosols for UVic ESCM simulations (1850-2500). *Zenodo* (2024).
136. Betts, R. A. Offset of the potential carbon sink from boreal forestation by decreases in surface albedo. *Nature* **408**, 187–190 (2000).
137. Jayakrishnan, K. U. & Bala, G. A comparison of the climate and carbon cycle effects of carbon removal by afforestation and an equivalent reduction in fossil fuel emissions. *Biogeosciences* **20**, 1863–1877 (2023).
138. Bala, G. *et al.* Combined climate and carbon-cycle effects of large-scale deforestation. *Proceedings of the National Academy of Sciences* **104**, 6550–6555 (2007).
139. Borowiak, A., King, A. D., Brown, J. R. & Ziehn, T. Revised estimates of temperature changes under net zero CO₂ emissions. *NPJ Clim Atmos Sci* **8**, 275 (2025).
140. Fuss, S. *et al.* Betting on negative emissions. *Nat Clim Chang* **4**, 850–853 (2014).
141. Fuss, S. *et al.* Negative emissions—Part 2: Costs, potentials and side effects. *Environmental Research Letters* **13**, 063002 (2018).

8 Supplementary Material

8.1 Supplementary Material for Chapter 3: Irreversible climate changes driven by degree-years of temperature overshoot

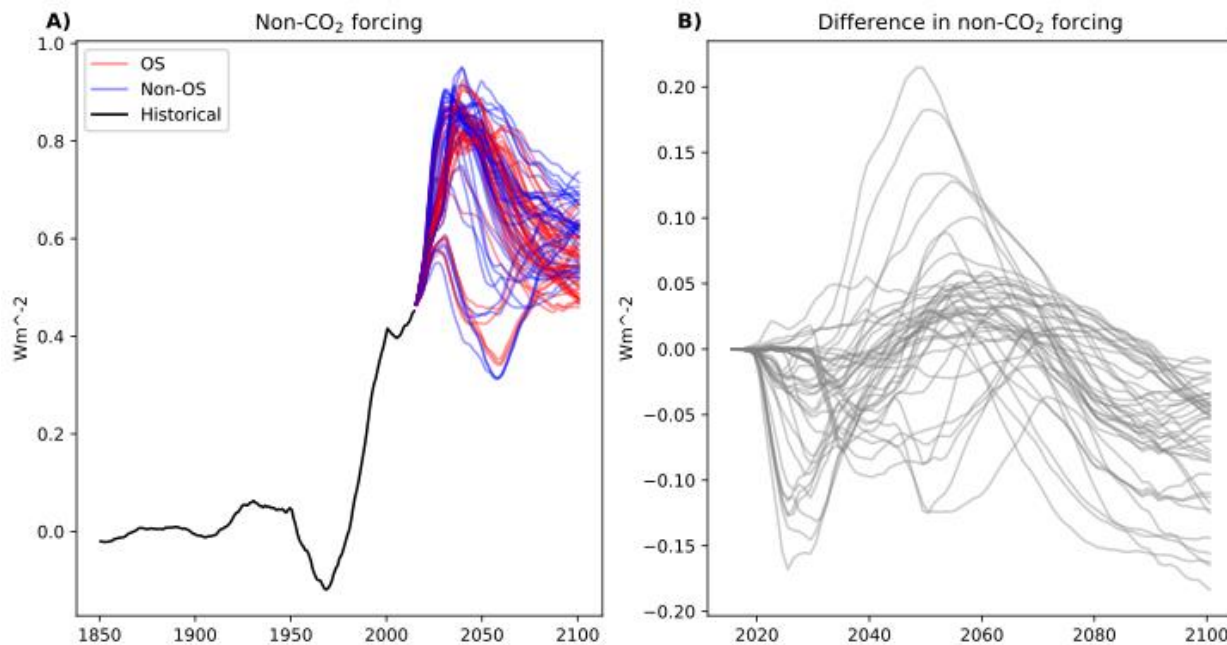


Figure 8-1 – Non-CO₂ forcing in OS and non-OS simulations from 1850 to 2100 and the difference in non-CO₂ forcing between OS and non-OS simulations

Figure A) shows the evolution of non-CO₂ forcing (i.e., non-CO₂ GHGs and aerosols) for the historical, OS, and non-OS simulations. Figure B) shows the difference between the non-CO₂ forcing in OS and non-OS scenarios (i.e., OS non-CO₂ forcing subtracted by non-OS non-CO₂ forcing). Figure B) demonstrates that non-CO₂ forcing in the OS scenarios is equal to or lower than non-CO₂ forcing in non-OS scenarios by 2090.

	Variable	5th_p	95th_p	IQR	median
A_co2	global average CO ₂ concentration	84.02	131.43	18.60	120.33
A_sat	global average surface air temperature	100.00	100.00	0.00	100.00
A_satL	average surface air temperature over land	100.09	101.78	0.90	100.89
A_satN	NH average surface air temperature	100.36	102.59	1.07	101.49
A_satO	average surface air temperature over ocean	99.05	99.95	0.47	99.52
A_satS	SH average surface air temperature	96.62	99.54	1.42	98.05
L_permacarb	global total permafrost carbon pool	0.00	6.10	1.22	0.10
L_PFGLOBAL	Permafrost area global	3.93	74.89	29.05	41.42
L_PFregcarb	permafrost region total soil carbon	0.00	9.58	2.25	0.73
L_soilcarb	global total soil carbon	2.44	74.00	33.30	47.27
L_squedcarb	global total sequestered (frozen) carbon	20.17	76.23	20.38	46.88
L_totcarb	global total land carbon	11.90	72.26	29.37	50.47
L_vegcarb	global total vegetation carbon	24.25	83.58	25.08	58.00
O_alk	global average ocean alkalinity	61.44	171.35	43.95	118.62
O_alksur	global average sea surface alkalinity	35.82	49.18	4.50	45.24
O_dic	global average ocean dic	18.64	52.69	13.18	44.19
O_dicsur	global average sea surface dic	65.85	118.88	22.36	107.64
O_dsealev	relative sea level height	22.01	31.15	2.20	25.05
O_icearea	global sea ice area	75.32	91.84	8.87	83.24
O_icevol	global sea ice volume	76.23	88.80	4.05	82.08
O_motmax	maximum meridional overturning streamfunction	0.00	9.77	5.96	3.35
O_o2	global average ocean oxygen	14.86	24.22	3.85	20.26
O_o2sur	global average sea surface oxygen	90.88	98.32	2.59	95.66
O_phsur	global average sea surface pH	67.74	113.10	18.43	104.12
O_sal	global average ocean salinity	0.00	192.50	47.93	29.45
O_salsur	global average sea surface salinity	31.13	42.64	4.71	35.87
O_snovol	global snow volume	18.70	61.44	23.93	39.02
O_temp	global average ocean temperature	14.98	22.06	1.64	17.10
O_tempsur	global average sea surface temperature	97.09	99.21	0.93	98.48
O_totcarb	global average total ocean carbon	18.65	52.69	13.21	44.20

Table 8-1 – The 5th and 95th percentiles, interquartile range , and median values of reversibility of climate variables in the UVic-ESCM.

Interquartile range above 10% of reversibility are highlighted in red.

Variable	Peak temp.	Peak CO ₂	Return temp.	Return CO ₂	Rate temp.	Rate CO ₂	Avg. temp.	Avg. CO ₂
A_co2	0.49	0.55	0.96	1.00	0.42	0.18	0.65	0.73
L_PFGLOB AL	0.91	0.79	0.73	0.60	~~0.09~~	~~0.00~~	0.95	0.83
L_soilcarb	0.40	0.70	0.66	0.72	0.42	0.03	0.47	0.78
L_squedcarb	0.88	0.80	0.85	0.73	0.17	~~0.01~~	0.97	0.88
L_totcarb	0.49	0.75	0.77	0.80	0.43	~~0.04~~	0.58	0.85
L_vegcarb	0.61	0.78	0.90	0.89	0.39	0.06	0.73	0.91
O_alk	0.13	0.06	0.32	0.29	0.20	0.12	0.20	0.15
O_dic	0.73	0.87	0.86	0.82	0.29	~~0.02~~	0.81	0.94
O_dicsur	0.53	0.62	0.96	0.99	0.42	0.14	0.68	0.79
O_phsur	0.57	0.65	0.97	0.99	0.41	0.13	0.72	0.82
O_sal	0.89	0.88	0.65	0.54	0.08	~~0.01~~	0.90	0.87
O_snovol	0.89	0.81	0.87	0.75	0.19	~~0.01~~	0.95	0.89
O_totcarb	0.73	0.87	0.86	0.82	0.29	~~0.02~~	0.81	0.94

Table 8-2 –Correlation of highly uncertain variables with various metrics.

This table shows UVic-ESCM variables with high uncertainty in reversibility and the R² values of the linear correlation between the absolute values of these variables at the return year in individual OS and non-OS scenarios (i.e., not taking the difference between OS and non-OS) against peak and return year temperatures and atmospheric CO₂ concentrations, the rate of temperature and atmospheric CO₂ concentration change during the OS period, and the average temperature and atmospheric CO₂ concentration during the OS period. Values with a strikethrough indicate that these R² were not statistically significant (i.e., p value > 0.05). Values in red indicate the highest R² value that is statistically significant for each UVic-ESCM variable

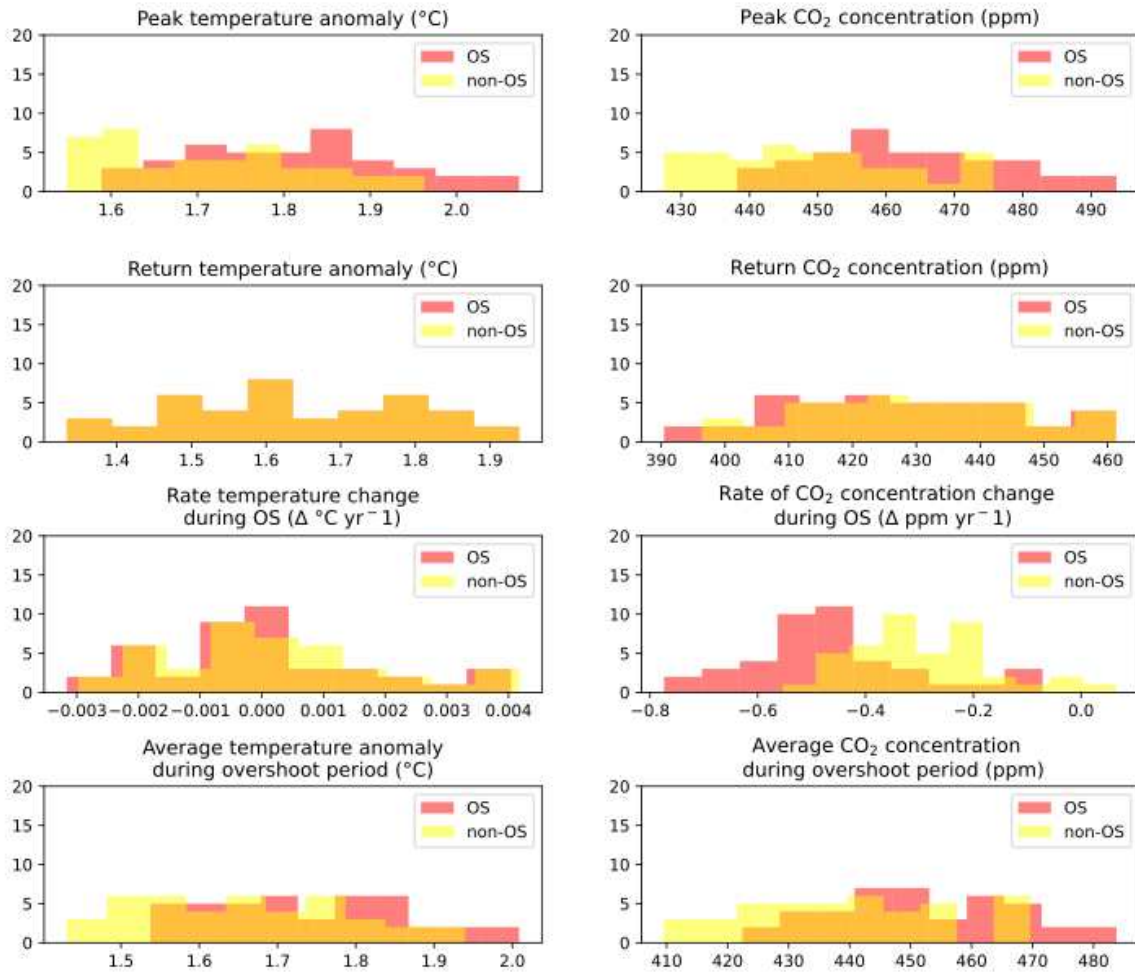


Figure 8-2 – The distributions of independent variables from SM Table 8.2 across 84 individual OS and non-OS scenarios

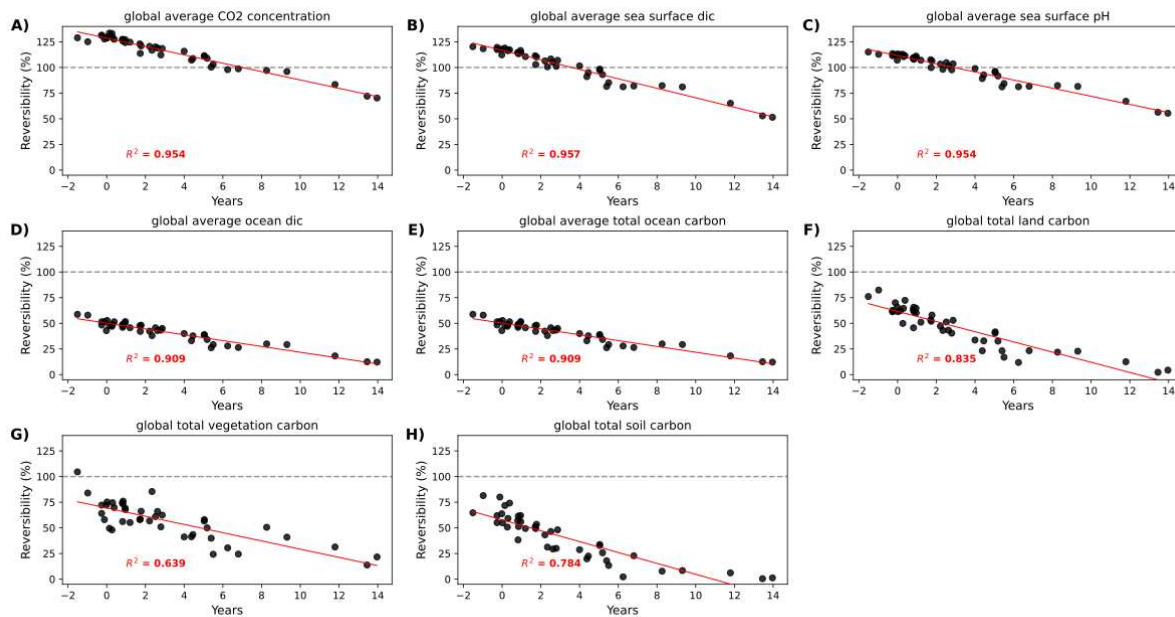


Figure 8-3 – Reversibility of carbon cycle variables plotted against the time difference between the return year and the year when cumulative emissions are equal.

Reversibility of atmospheric CO₂ concentration and other carbon cycle variables relative to the difference between the return year – when temperature in the OS scenario reaches that of the non-OS scenario – and the year that cumulative CO₂ emissions in the OS scenario become equal to cumulative emissions in the non-OS scenario. When the return year and the cumulative emissions year are nearly equal (i.e., values of near zero on the x-axis), there is high reversibility. However, reversibility declines when cumulative CO₂ emissions in the OS scenario reach cumulative CO₂ emissions of the non-overshoot scenario after

8.2 Supplementary Material for Chapter 4: Temporary land carbon storage can avoid slow-responding climate changes

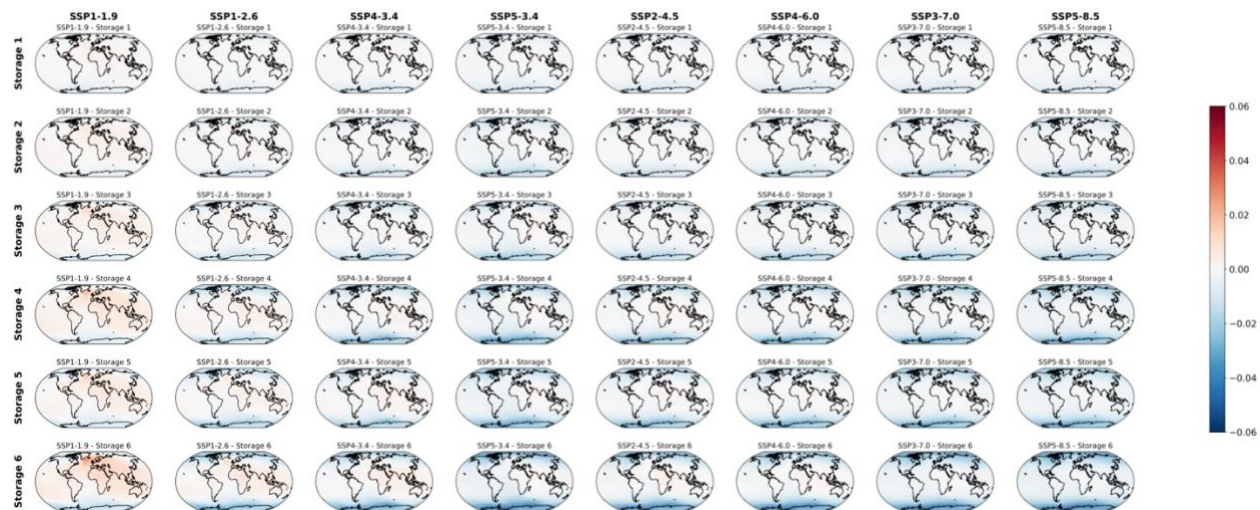


Figure 8-4 – Average difference in surface air temperature between storage SSPs and baseline SSPs between 2100 to 2120.

Shown is the 20-year mean difference in surface air temperature (SAT) between storage and baseline SSPs (i.e., storage SAT subtracted by baseline SAT) for the period 2100–2120, corresponding to the two decades following the re-emission of all temporarily stored carbon. Columns indicate baseline SSPs (listed above), and rows indicate storage pathways (listed to the left). In general, storage SSPs remain cooler at high latitudes and exhibit equal or slightly warmer temperature in equatorial and mid-latitude regions relative to their baselines. This regional warming pattern strengthens with increasing magnitude of temporary carbon storage.

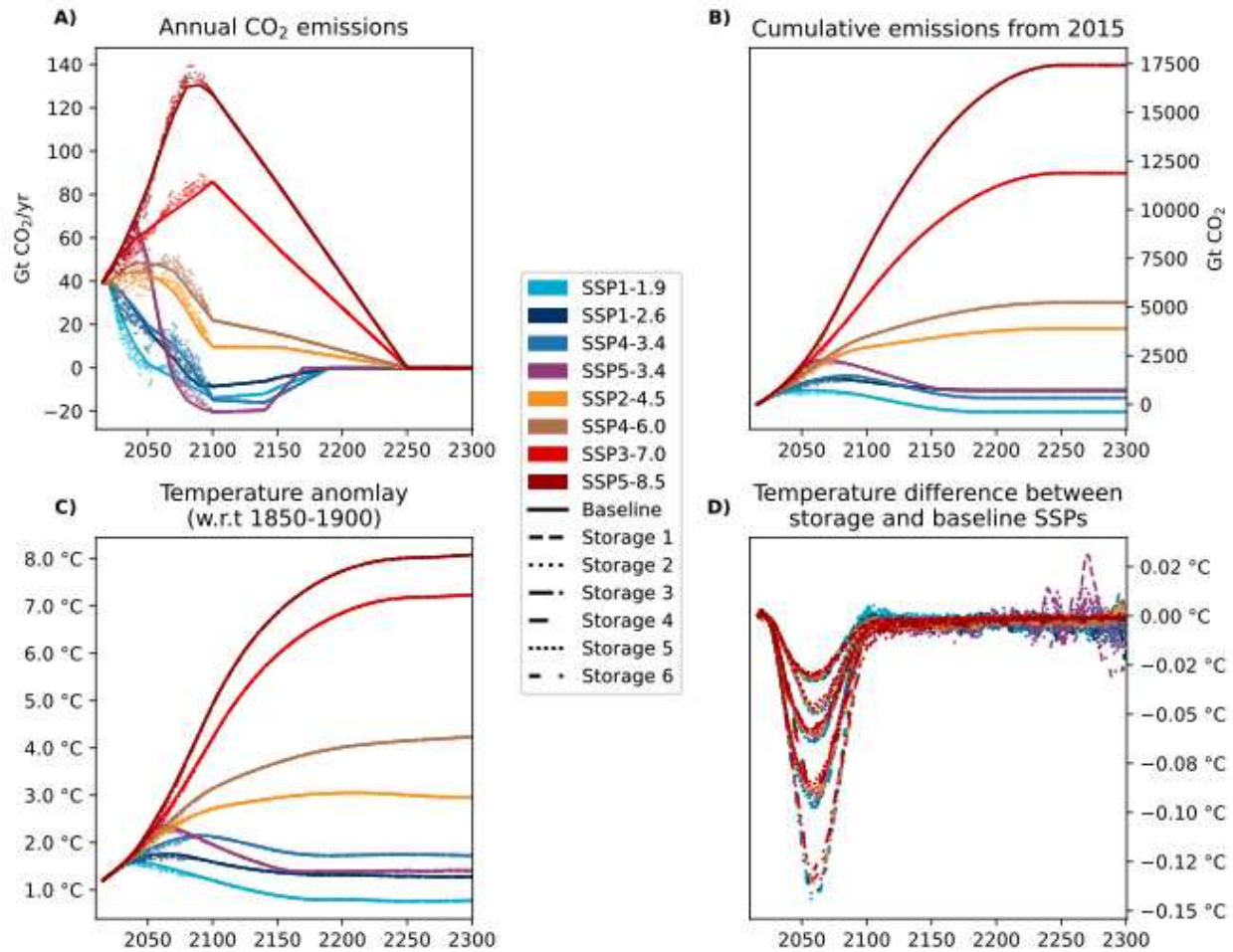


Figure 8-5 – CO₂ emissions and temperature responses in baseline and storage SSPs up until 2300.

(A) Annual anthropogenic CO₂ emissions from fossil fuels and land-use change. (B) Cumulative CO₂ emissions from 2015 to 2300. (C) Global mean surface air temperature anomaly relative to a 1850-1900 preindustrial baseline. (D) Temperature difference between storage SSPs and their corresponding baseline SSPs. Colours indicate SSP ensembles, with solid lines showing baseline simulations and dashed/dotted lines showing the six storage pathways applied to each SSP.

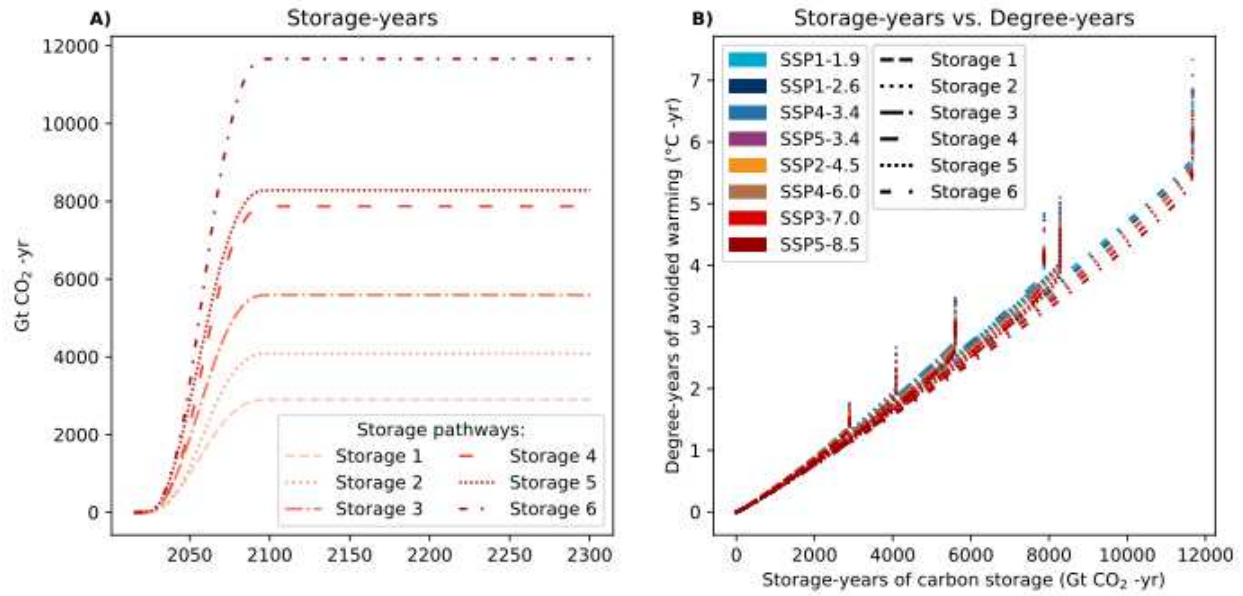


Figure 8-6 – Storage-years in storage pathways and their relationship to degree-years of avoided warming in storage SSPs up until 2300.

(A) Storage-years of the six storage pathways applied to each SSP baseline. (B) The quasi-linear relationship between degree-years of avoided warming and storage-years of temporary carbon storage across all 48 storage SSPs.

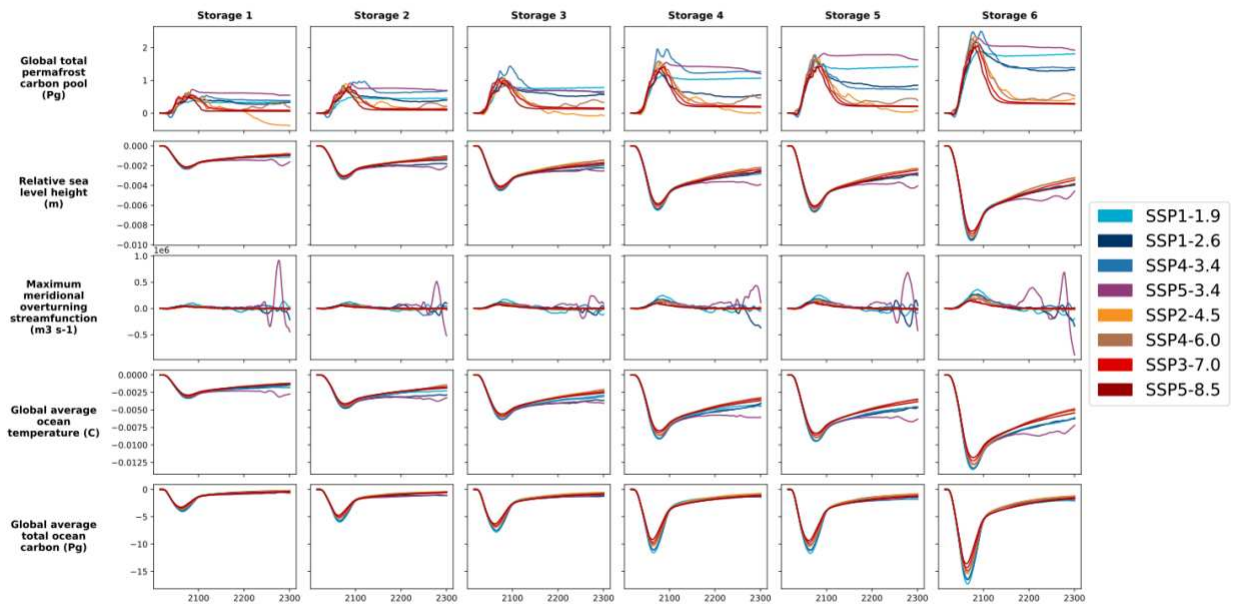


Figure 8-7 – Differences in slow-responding climate variables between storage and baseline SSPs for each of the six storage pathways to 2300.

Each subplot shows the difference between storage SSPs and baseline SSPs for a single slow-responding variable under one storage pathway. Rows correspond to climate variables (listed on the left), and columns correspond to storage pathways (listed above). Aside from meridional overturning (a.k.a. AMOC), all variables show avoided change from temporary carbon storage up to 2300, with the magnitude of avoided change increasing under storage pathways with greater storage. The AMOC response to temporary carbon storage by 2300 is more variable. There is almost no effect in stabilization SSPs – i.e. SSP2-4.5, SSP4-6.0, SSP3-7.0, SSP5-8.5 – and both positive and negative responses in peak-and-decline SSPs – i.e. SSP1-1.9, SSP1-2.6, SSP4-3.4, SSP5-3.4. Coloured lines in each subplot indicate the storage SSPs.