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Greta Savitsky

gsavitsk@uvm.edu

University of Vermont

Brian Beckage

University of Vermont <https://orcid.org/0000-0002-5908-6924>

Dale Rothman

George Mason University <https://orcid.org/0000-0003-1479-2849>

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Mechanistic Ecological Feedbacks in DICE 2023: Physical Divergence and Welfare Sensitivity

Greta Savitsky^{a,b,*}, Dale S. Rothman^c, Brian Beckage^{a,b,d,e}

^a Department of Plant Biology, University of Vermont, Burlington, Vermont, USA

^b Gund Institute for Environment, University of Vermont, Burlington, Vermont, USA

^c Computational and Data Sciences Department, George Mason University, Fairfax, Virginia, USA

^d Department of Computer Science, University of Vermont, Burlington, Vermont, USA

^e Vermont Complex Systems Institute, University of Vermont, Burlington, Vermont, USA

* Corresponding author: greta.l.savitsky@uvm.edu

Abstract

The interconnected relationships among climate change, global economies, and mitigation policies will shape the future of anthropogenic greenhouse gas emissions. Understanding these dynamics is critical for designing optimal policy, but structural limitations in the benefit–cost integrated assessment models used to measure them could lead to underestimates of future temperature increases and their economic impacts. Often these models, including DICE 2023, represent ecological feedbacks through aggregated emulators that preclude mechanistic attribution to individual ecological pathways. We replaced DICE 2023’s native DFAIR carbon module with a simple carbon cycle model (SCM), yielding extended configuration DICE-C. DICE-C results in a similar temperature trajectory to DICE 2023, suggesting that the SCM functions similarly to DFAIR. We then augmented this configuration with gradual and abrupt permafrost thaw dynamics, yielding another extended configuration: DICE-CP. DICE-CP results in higher temperatures than DICE 2023 or DICE-C due to permafrost carbon release, a lagged but persistent reinforcing feedback, with DICE-CP maintaining a mean global atmospheric temperature of 1.8°C above pre-industrial by 2300 compared to 0.57°C under DICE 2023. Permafrost carbon release depends on a temperature threshold and a 200-year lagged response to warming, so near-term emissions decisions determine whether this feedback engages decades before its economic consequences. Despite this physically meaningful divergence, cumulative discounted welfare changes under the standard DICE damage function remain small: +0.02% for DICE-C and −0.21% for DICE-CP relative to the DICE 2023 baseline. Replacing the standard quadratic damage coefficient with an updated empirical estimate raises welfare losses by 1.56% for DICE 2023 alone and 1.96% for DICE-CP, exceeding any ecological feedback-driven welfare loss under standard damage assumptions. These results demonstrate that the apparent insensitivity of DICE welfare projections to ecological feedback-driven temperature increases reflects structural choices in the damage function and discount convention.

1 Introduction and Overview of Results

1.1 Climate impacts on the global economy

Global economies are projected to be negatively impacted by a rapidly changing climate over the next four hundred years [9, 11]. Quantifying this impact is difficult due to significant uncertainty in carbon-climate dynamics, human behavior and policy, and economic resilience. Carbon-climate

feedbacks such as permafrost thaw introduce nonlinear and threshold-dependent behavior that standard integrated assessment models often do not explicitly represent [25, 1, 12]. Additionally, models generally treat policy response as exogenous or driven by simplified behavioral rules rather than by the feedback between climate outcomes and the processes of policy creation, implementation, and adherence [5]. The sociopolitical processes that determine the effectiveness of a policy are treated as exogenous in almost all climate change modeling, despite documented socioecological and socioeconomic feedbacks across individual, community, national, and global scales [29]. Adherence to adopted policies depends on social and institutional dynamics, such as norm change and collective action, that are absent from standard IAM formulations [32]. The relationship itself between temperature and economic output loss is also not well constrained empirically and varies substantially across model specifications [18]. These complex and interconnected facets compound in their uncertainty, yet must be explicitly represented in predictive models to accurately quantify uncertainty and plausible trajectories [36, 30].

1.2 Ecological feedbacks and nonlinear earth system dynamics

Increasing temperatures due to anthropogenic greenhouse gas (GHG) emissions can trigger ecological feedbacks that alter the capacity of ecosystems to sequester carbon. These feedbacks can amplify warming by reducing the ability of several earth system components to retain and absorb carbon [10, 14], with sequestration losses propagating through vegetation, soil, and ocean systems via phenological mismatches, range shifts, biodiversity loss, extinctions, and loss of photosynthetic capacity [1, 13, 33, 38, 41]. Reinforcing feedbacks can cause climate tipping points, i.e. the exponential, compounding increase of emitted carbon and consequential warming, if they pass a threshold temperature [25, 24, 1]. Examples of climate tipping points include ocean buffer saturation, terrestrial sequestration loss, and permafrost thaw. Simultaneously, reinforcing feedbacks, like carbon fertilization [16, 21], can counteract this warming. The magnitude of these carbon cycle feedbacks is large enough to shift atmospheric carbon trajectories [25] and, consequently, the projected economic damages from climate change.

1.3 Integrated Assessment Models and ecological carbon feedbacks

Integrated Assessment Models (IAMs) are the primary tool linking physical climate projections to economic policy [40]. Benefit–cost IAMs weigh benefits and drawbacks of climate change mitigation spending, calculating an optimal spending plan to maximize global or regional welfare. Higher projected temperatures increase climate damages to the economy, raising optimal spending toward combating climate change and informing optimal climate policy. Standard IAMs, including the Dynamic Integrated Climate-Economy (DICE) model, often simplify ecological feedbacks and tipping points into statistical emulators [8], though some scientists argue that the nuances and nonlinearities of these dynamics are essential to accurate climate projections [7, 27, 42]. Several studies have examined the consequences of incorporating ecological feedbacks into coupled socioecological models and IAMs, consistently finding that their omission leads to underestimated warming. CMIP5 and CMIP6 Earth system models consistently predict future net reinforcing ecological feedbacks that amplify warming [2] and more recent work demonstrates that ecosystem carbon fluxes exhibit uncertain thermal response thresholds [44], indicating that simple, opaque parameterizations used in IAMs may fail to capture changes in the sign and strength of ecological feedbacks at high temperatures.

1.4 Feedback-Driven Tipping Points and the DICE Damage Function

DICE 2023 partially addressed this gap with the introduction of ecological feedbacks in the DFAIR carbon module [3], but its aggregated structure precludes mechanistic attribution of individual ecological feedbacks. A previous study indicated that including permafrost carbon release in DICE 2013 raises optimal mitigation rates up to 2.7% [42], and a structural meta-analysis incorporating eight additional feedback-driven climate tipping points across a range of IAMs resulted in up to 25% higher social costs of carbon [12]. These two results indicate that the omission of physically-grounded feedbacks from standard IAM accounting could cause underestimates of the social cost of carbon and the optimal mitigation rate. In addition, DICE’s damage function is calibrated to project roughly 3.1% of GDP loss at 3°C of warming, which sits at the lower end of the plausible spectrum of damage intensities [3, 18]. Whether this calibration understates true climate damages remains an active debate. Several empirical studies argue for substantially higher damage estimates [6, 17, 18, 34], while others, including DICE 2023, arrive at comparably low figures [3, 30]. The omission of realistic carbon cycle feedbacks and uncertain assumptions in damage estimates from IAMs like DICE 2023 are limitations with direct consequences for climate policy, particularly given that cascading effects can begin without warning [15].

1.5 Approach

In this paper, we address DICE 2023’s carbon feedback limitations by replacing its carbon model with a more physically based, mechanistic representation (Figure 1). We integrate a simple carbon cycle model [23], which represents nonlinear changes in soil respiration, plant respiration, photosynthesis, and ocean carbon cycling with changing climate and ambient CO₂ concentration; the Woodard et al. (2021) mechanistic representation of gradual permafrost thaw, which captures the short-term dynamics; and abrupt permafrost thaw quantified by Armstrong McKay et al. (2022), which accounts for episodic, high-magnitude carbon releases that gradual thaw models cannot represent alone. This yields two extended configurations: DICE-C (DICE 2023 with the SCM) and DICE-CP (DICE-C with additional permafrost dynamics) (Table 1). Both configurations were forced with DICE 2023’s optimal emissions control and savings trajectories [3], analogous to a policy-making scenario without full information about the underlying ecological feedbacks. We conduct a full factorial sensitivity analysis across the six individual feedback mechanisms in the SCM to attribute the divergence between DICE-C and DICE 2023 to specific carbon cycle pathways. We additionally examine how DICE’s damage function specification and discount convention mediate welfare sensitivity to the resulting physical changes.

Table 1: Components of each model configuration used in this study.

Configuration	Carbon cycle model	Climate model	Economic model
DICE 2023	DFAIR [3]	DFAIR [3]	DICE 2023 [3]
DICE-C	Lenton simple carbon model [23]	DFAIR [3]	DICE 2023 [3]
DICE-CP	Lenton simple carbon model [23] + gradual permafrost [43] + abrupt permafrost [1]	DFAIR [3]	DICE 2023 [3]

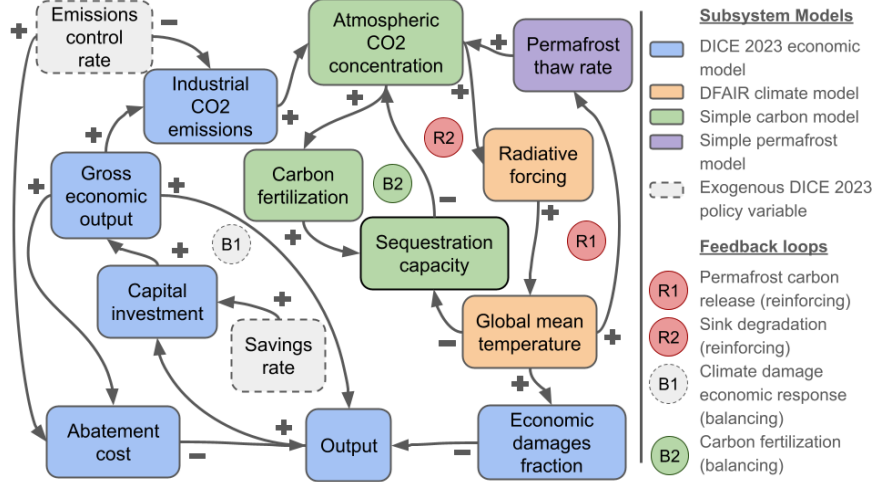


Figure 1: **Causal loop diagram of the simple carbon model (SCM) coupled to DICE 2023.** Signs and arrows denote the sign and direction of the relationship between two variables. Important feedbacks are labeled reinforcing (R) and balancing (B). Feedback loops: (B1) represents the balancing effect on warming of decreased economic output resulting from damages from climate change, (B2) represents the balancing effect on atmospheric carbon of carbon fertilization, (R1) represents the reinforcing effect on atmospheric carbon of permafrost melt, and (R2) represents the reinforcing effect on atmospheric carbon of decreased carbon sequestration.

While the DICE-C model yields a similar temperature trajectory to DICE 2023, the DICE-CP model produces higher atmospheric carbon concentrations, radiative forcing, and temperatures than the DICE 2023 trajectory. DICE 2023 cools to 0.57°C above pre-industrial by 2300 after peaking at 2.60°C in year 2111, while DICE-CP sustains 1.8°C above pre-industrial by 2300 after peaking at 3.39°C in year 2125, demonstrating that physical feedbacks can fundamentally undermine the effectiveness of mitigation on century timescales. The factorial sensitivity analysis presented later reveals that this divergence is driven predominantly by permafrost carbon release, and that terrestrial CO₂ fertilization acts as the dominant balancing feedback, cooling the system relative to DICE 2023 in early decades and substantially offsetting the warming signal from reinforcing loops.

Under the standard DICE damage function, these physical changes translate into small cumulative, discounted welfare effects: +0.02% for DICE-C and -0.21% for DICE-CP relative to the DICE 2023 optimal control trajectory. This implies minimal changes in the optimal trajectory. Replacing the DICE 2023 quadratic coefficient with a DICE-equivalent quadratic coefficient derived from the preferred damage estimate of Howard and Sterner at 3°C (2025) [18] raises welfare losses by 1.56% under DICE 2023 alone and 1.96% under the DICE-CP configuration.

2 Model overview and methods

2.1 DICE 2023

2.1.1 Time step conversion

All DICE 2023 equations were converted to single year time steps from the original five year time step to make DICE 2023 compatible with the SCM. We then implemented this version of DICE 2023 in STELLA [19] and checked the results against those from the original implementation in GAMS

when we exogenously imposed the emissions control and savings choices from the Cost-Benefit Optimal scenario [3].

2.1.2 DICE 2023 Economic framework

The DICE model is an integrated assessment model used to simulate an efficient climate control strategy. It assumes the global population has well-defined preferences represented by a dynamically optimized welfare function. The model uses the basic Ramsey model of optimal economic growth with adjustments to calculate the optimal path for savings (s), investment (I), and GHG-emission abatement (μ), optimizing cumulative discounted utility (U_{acc}).

In DICE 2023, optimization occurs over climate change abatement control rate (μ) and savings rate (s), adjusting the yearly investment in mitigating climate change and the amount withheld from consumption and invested in physical capital like machinery or infrastructure. Industrial CO₂ emissions in DICE 2023 are determined by the product of gross economic output (Y_{gross}), the emission control rate (μ), and the carbon intensity of production (σ). The latter parameter is exogenous and represents the carbon emissions per unit of GDP produced. Carbon intensity of production declines over time, reflecting the decarbonization of the economy through technological innovation independent of explicit abatement policy. Gross economic output (Y_{gross}), or economic output before accounting for climate damages, is calculated as

$$Y_{gross} = TFP \cdot (L/1000)^{1-\gamma} \cdot K^\gamma \quad (1)$$

where γ is capital elasticity. Total factor productivity (TFP) growth, population (L), Capital stock (K) and emissions intensity (σ) trajectories are exogenous.

Climate affects the economy in two ways: investment in climate change abatement (C_{abate}) and physical damages to the economy (D_{frac}). Investment in climate change abatement reduces climate damage to the economy, but at the cost of climate change mitigation (C_{abate}). C_{abate} is represented by an abatement cost function that relates the fraction of emissions abated (μ) to a corresponding reduction in economic output dependent on the cost of the backstop, or non-fossil fuel, technology (p_{back}), which is also exogenously provided and decreases over time.

$$C_{abate} = \frac{\sigma \cdot p_{back} \cdot Y_{gross} \cdot \mu^{\theta_2}}{\theta_2 \cdot 1000} \quad (2)$$

Damages from climate change affect economic output through a damage function that relates increases in global mean temperature (T) to a fractional reduction in economic output (D_{frac}):

$$D_{frac} = a_1 \cdot T + a_2 \cdot T^{a_3} \quad (3)$$

where a_1 , a_2 , and a_3 control the slope and degree of nonlinearity in the relationship between damages and warming. This damage function is calibrated for approximately 3.1% of GDP loss at 3°C. Climate damages are reflected directly in economic output (Y):

$$Y = Y_{gross} \cdot (1 - D_{frac}) - C_{abate} \quad (4)$$

which in turn affects cumulative discounted utility (U_{acc}), the primary outcome variable for all welfare comparisons in this study. Per period per capita utility is calculated as a function of per capita consumption and the elasticity of marginal utility of consumption (η):

$$U = \frac{\left(\frac{C \cdot 1000}{L}\right)^{1-\eta} - 1}{1 - \eta} \quad (5)$$

where L is population and η is the elasticity of marginal utility. Accumulated utility integrates period utility weighted by population and the social time preference factor with precautionary adjustment (STP) over the simulation horizon:

$$U_{\text{acc}} = \int_{t_0}^T U \cdot L \cdot \text{STP} \, dt \quad (6)$$

All welfare changes reported in this study are expressed as percentage changes in U_{acc} for the period 2020-2420 relative to the DICE 2023 baseline.

2.1.3 DFAIR

The central structural difference motivating this analysis is the way that feedbacks are represented in each model. DFAIR is the simple climate emulator adapted from the Finite Amplitude Impulse-Response (FAIR) model [28] for DICE 2023. Ecological feedbacks modify the effective atmospheric retention of CO_2 , which DFAIR represents through an impulse response function (IRF_{100}) parameterized by accumulated atmospheric carbon C_{acc} and temperature (T):

$$\text{IRF}_{100}(t) = \text{irf}_0 + \text{ir}_C \cdot C_{\text{acc}}(t) + \text{ir}_T \cdot T \quad (7)$$

where irf_0 is pre-industrial IRF_{100} , ir_C is the increase in IRF_{100} with cumulative carbon uptake (years to sequester 1 GtC), ir_T is the increase in IRF_{100} with warming (years per degree K rise in mean global atmospheric temperature) [3]. IRF_{100} is itself measured in years, representing the effective 100-year atmospheric retention time of a CO_2 pulse. DFAIR represents the global carbon cycle as four reservoirs (R_0 through R_3), each corresponding to a physically motivated component of the Earth system's carbon sinks: a quasi-permanent atmospheric fraction (R_0 , decay timescale = 1,000,000 years), the deep ocean (R_1 , = 394.4 years), the terrestrial biosphere (R_2 , = 36.53 years), and the ocean mixed layer (R_3 , = 4.304 years) [28]. Each year's emissions are partitioned across these four reservoirs according to fixed shares (emshare_i), and each reservoir decays exponentially according to its own characteristic timescale (τ_i):

$$R_i(t+1) = \left(\text{emshare}_i \cdot \tau_i \cdot \alpha(t+1) \cdot \frac{E_{\text{CO}_2}(t+1)}{3.667} \right) \left(1 - e^{-\Delta t / (\tau_i \alpha(t+1))} \right) + R_i(t) e^{-\Delta t / (\tau_i \alpha(t+1))} \quad (8)$$

for $i \in \{0, 1, 2, 3\}$, where $E_{\text{CO}_2}(t)$ is total CO_2 emissions and Δt is the model timestep. Atmospheric carbon concentration is the sum of all four reservoirs plus the pre-industrial equilibrium concentration. Ecological feedback enters through $\alpha(t)$, the carbon decay time scaling factor, which multiplies every reservoir's decay timescale identically and is solved each period by equating the 100-year integrated impulse response (IRF_{100}) implied by the four-reservoir structure to a target value that increases with accumulated sink carbon (C_{acc}) and temperature (Equation 7). Because $\alpha(t)$ is a single scalar applied uniformly across all four reservoirs at every timestep, DFAIR has no mechanism by which the atmosphere, deep ocean, terrestrial biosphere, and ocean mixed layer reservoirs can respond independently to a changing climate; any divergence in how these sinks behave under warming is invisible to the model.

2.2 Simple Carbon Model

The simple carbon model (SCM) [23] used in this study represents an analogous set of physical compartments (atmosphere, vegetation, soil, and multiple ocean layers) but assigns each its own mechanistic flux equation rather than a shared exponential decay scaled by a single feedback

parameter. Fluxes between these SCM pools are proportional to empirical ecological and biochemical relationships, including changes in soil and vegetation respiration, ocean-atmosphere gas exchange, and photosynthesis as explicit functions of temperature and atmospheric CO₂ concentration (Equations 9–14). Because each pool’s flux is governed by its own equation, these pathways can strengthen, weaken, or move in opposing directions independently of or in tandem with one another as the climate changes, and each pathway can be isolated and tested individually. DFAIR’s single shared scaling factor cannot represent this kind of structural divergence between sinks; it can only make all reservoirs collectively more or less efficient at absorbing carbon in lockstep. This is the central structural distinction motivating the substitution of the mechanistic carbon cycle for DFAIR in this study.

2.2.1 Terrestrial CO₂ Fertilization and Photosynthesis

Gross photosynthetic uptake (J_{photo}) follows a Michaelis-Menten function of atmospheric CO₂ concentration and a temperature-dependent scaling term:

$$J_{\text{photo}} = k_p C_{v(s)} k_{MM} \cdot \frac{p\text{CO}_2 - k_c}{K_M + (p\text{CO}_2 - k_c)} \cdot \frac{(15 + \Delta T)^2 (25 - \Delta T)}{5625} \quad (9)$$

where k_p is the photosynthesis rate, $C_{v(s)}$ is the vegetation carbon stock, k_{MM} is the normalizing constant, k_c is the CO₂ compensation point, K_M is the half-saturation concentration, and ΔT is the atmospheric temperature anomaly. The terrestrial CO₂ fertilization feedback operates through atmospheric partial pressure ($p\text{CO}_2$).

2.2.2 Vegetation Respiration

Vegetation respiration ($J_{\text{veg resp}}$) follows an Arrhenius temperature-dependent rate:

$$J_{\text{veg resp}} = k_r C_v k_A \cdot \exp\left(\frac{-E_a}{R T_s}\right) \quad (10)$$

where k_r is the plant respiration rate, C_v is vegetation carbon, k_A is the normalizing constant, E_a is the plant respiration activation energy, R is the universal gas constant, and T_s is surface temperature in Kelvin.

2.2.3 Soil Respiration

Soil respiration ($J_{\text{soil resp}}$) follows a Lloyd-Taylor temperature-dependent rate:

$$J_{\text{soil resp}} = k_{sr} C_s k_B \cdot 2.7^{-\frac{308.56}{T_s - 227.13}} \quad (11)$$

where k_{sr} is the soil respiration rate, C_s is soil carbon, and k_B is the normalizing constant.

2.2.4 Ocean CO₂ Solubility

Ocean-atmosphere carbon flux (J_{ocean}) is driven by the air-sea partial pressure gradient in two ocean carbon compartments (warm ocean and cold ocean):

$$J_{\text{ocean}} = k_s a_O A_h b_c (p\text{CO}_2 - p\text{CO}_2(c)) \cdot 12 \times 10^{-15} \cdot \rho + k_s a_O A_l b_w (p\text{CO}_2 - p\text{CO}_2(w)) \cdot 12 \times 10^{-15} \cdot \rho \quad (12)$$

where k_s is the piston velocity, a_O is the ocean fraction, A_h and A_l are high and low surface area, respectively, b_c and b_w are solubility coefficients, ρ is seawater density, and $p\text{CO}_2(c)$ and $p\text{CO}_2(w)$ are the cold ocean surface partial pressure and ocean surface partial pressure, respectively. The ocean surface partial pressure evolves nonlinearly with ocean carbon concentration via the Revelle factor:

$$p\text{CO}_2(c) = p\text{CO}_2(c)_0 \cdot \left(\frac{C_{\text{cold ocean}}}{C_{\text{cold ocean},0}} \right)^\beta \quad (13)$$

$$p\text{CO}_2(w) = p\text{CO}_2(w)_0 \cdot \left(\frac{C_{\text{warm ocean}}}{C_{\text{warm ocean},0}} \right)^\beta \quad (14)$$

where β is the Revelle factor exponent. This power-law relationship produces a reinforcing feedback loop: as the ocean absorbs carbon, outgassing pressure rises nonlinearly, progressively narrowing the air-sea gradient and weakening the ocean sink.

2.3 Representation of Permafrost Dynamics

The SCM does not originally include explicit permafrost dynamics. Therefore, we use Woodard et al.'s representation of gradual permafrost thaw, originally implemented as an extension of the object-oriented simple carbon-climate emulator HECTOR [43]. This permafrost submodel adds two extra carbon pools: frozen permafrost (C_{perm}) and thawed soil (C_{thawed}), and can be engaged or disengaged independently of the SCM carbon cycle feedbacks.

Carbon moves from frozen permafrost to thawed soil as a function of the fraction of permafrost remaining frozen (f_{frozen}), which follows a log-normal cumulative distribution function of high-latitude temperature anomaly ($T_{HL} = 2 \cdot T_{\text{atm}}$):

$$f_{\text{frozen}} = \Phi \left(\frac{\ln(1 + T_{HL}) - 1.67}{0.99} \right) \quad (15)$$

The gradual thaw flux from frozen to thawed permafrost (ΔC_{perm}) is then:

$$\Delta C_{\text{perm}} = - (f_{\text{frozen}}(t) - f_{\text{frozen}}(t - \Delta t)) \cdot C_{\text{perm}}(t - \Delta t) \quad (16)$$

In addition, we include the abrupt permafrost thaw tipping point (J_{abrupt}) as quantified by Armstrong McKay et al.: after crossing a temperature anomaly threshold of 2°C , the rate of frozen permafrost thawing increases by 40% [1]:

$$J_{\text{abrupt}} = \begin{cases} 0.4 \cdot \Delta C_{\text{perm}} & \text{if } T_{\text{atm}} > 2^\circ\text{C} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

Carbon flux from thawed soil to the atmosphere is driven by a Q_{10} temperature sensitivity applied to the labile fraction of thawed carbon ($C_{\text{labile}} = (1 - f_{\text{static}}) \cdot C_{\text{thawed}}$, where $f_{\text{static}} = 0.74$):

$$J_{\text{thawed} \rightarrow \text{atm}} = C_{\text{labile}} \cdot Q_{10}^{T_{200}/10} \quad (18)$$

where $Q_{10} = 2$ is the temperature sensitivity coefficient and T_{200} is a 200-year delayed temperature anomaly capturing the slow thermal response of deep permafrost to surface warming. A fixed fraction ($F_{CH_4} = 0.023$) of this flux is released as methane; the remainder is released as CO_2 . Both contribute to the atmospheric carbon pool. This entire module can be engaged or disengaged independently of the SCM feedbacks.

2.4 Model Coupling Strategy

This coupling runs on a one year time step, with all model components solved jointly at each timestep, instead of DICE 2023’s native 5-year discrete timestep formulation. The SCM is coupled with the DICE 2023 economic model, replacing the DFAIR carbon cycle (Figure 1). In place of the DFAIR atmospheric CO₂ concentration parameter (MAT_D), the SCM atmospheric CO₂ concentration parameter (MAT_S) is substituted into the DFAIR radiative forcing (F) equation:

$$F = f_{\text{co22x}} \cdot \frac{\ln(\text{MAT}_S / M_{\text{eq}})}{\ln(2)} + F_{\text{misc}} + F_{\text{GHG}} \quad (19)$$

where f_{co22x} is the forcing from equilibrium CO₂ doubling, M_{eq} is the pre-industrial equilibrium atmospheric carbon concentration, F_{misc} is miscellaneous forcings, and F_{GHG} is forcing from non-CO₂ greenhouse gas emissions. Both F_{misc} and F_{GHG} are exogenous variables retained from DICE 2023.

Anthropogenic CO_{2E} emissions (E_{CO2E}), comprising both industrial emissions and land-use change emissions from DICE 2023, flow into the SCM atmospheric carbon pool. The resulting atmospheric CO₂ concentration propagates through the SCM carbon cycle, modifying internal carbon fluxes, and through the radiative forcing equation above, which drives the DFAIR temperature module. Temperature changes subsequently enter the DICE 2023 damage function, affecting economic output. This coupling is fully simultaneous, with all model components solved jointly at each timestep.

2.5 Model Parameterization and Sensitivity

The emissions abatement rate and savings rate were held fixed at values pre-optimized under the standard DICE 2023 framework using General Algebraic Modeling System (GAMS), such that observed differences in model output reflect the influence of ecological feedbacks rather than re-optimization of economic controls. Under this forcing, atmospheric CO₂ concentration, global mean temperature, and economic damages were recorded as time series, enabling direct parameter sweep comparisons across the three model configurations: DICE 2023, DICE-C, and DICE-CP.

2.5.1 Individual Feedback Sensitivity Analysis

To attribute the divergence between DICE-C, DICE-CP, and DICE 2023 to individual carbon cycle feedback pathways, we conducted a full factorial sensitivity analysis across the six feedback mechanisms in the SCM: ocean CO₂ solubility, photosynthesis temperature response, soil respiration temperature response, vegetation respiration temperature response, terrestrial CO₂ fertilization, and permafrost carbon release (Table 2). Each feedback was independently engaged or disengaged across all combinations, yielding 64 unique SCM configurations paired against the DFAIR baseline. The economic system, emissions trajectory, and damage function were held constant across all runs (Figure 4).

Table 2: Individual feedback mechanisms in the Lenton carbon module included in the full factorial sensitivity analysis.

Feedback	Description	Reference	Disengagement Mechanism
Terrestrial CO ₂ fertilization	Photosynthetic uptake increases with rising atmospheric CO ₂	Eq. 9	$p\text{CO}_2$ fixed at 4.165×10^{-4} atm
Photosynthesis temperature response	Temperature-dependent scaling of gross photosynthetic uptake	Eq. 9	ΔT fixed at zero
Vegetation respiration	Arrhenius temperature-dependent plant respiration flux	Eq. 10	T_s fixed at 288 K
Soil respiration	Lloyd-Taylor temperature-dependent soil carbon decomposition	Eq. 11	T_s fixed at 288 K
Ocean CO ₂ solubility	Nonlinear ocean buffer saturation via Revelle factor	Eq. 12 – 14	Atmospheric $p\text{CO}_2$ fixed at 4.165×10^{-4} atm
Permafrost carbon release	Gradual and abrupt thaw-driven carbon flux from frozen permafrost to atmosphere	Eq. 15 – 18	$F_{\text{thawed} \rightarrow \text{atm}} = 0$

2.5.2 Welfare and Discounting sensitivity analysis

These three model configurations were tested for their sensitivity to DICE damage and discounting conventions. For an alternative damage function, we used a damage coefficient derived from Howard & Sterner (2025) ($a_2 = 0.01$) (Eq. S1), which projects economic losses approximately three times greater than the DICE-2023 default ($a_2 = 0.0035$) at 3°C of warming. For the discounting sensitivity, we set the pure rate of time preference (ρ) and climate beta coefficient (β_{clim}) to zero, retaining consumption-growth discounting through the elasticity of marginal utility ($\eta = 0.95$). These two alternatives were applied across all three physical model configurations, yielding twelve runs in total. The emissions control trajectory and savings rate were held at their GAMS-optimized values in all cases; welfare is not re-optimized under the alternative damage or discounting specifications.

Table 3: Sensitivity analysis parameter specifications.

Specification	a_2	Rationale	
DICE default	0.0035	Baseline DICE-2023 calibration	
Howard-Stern	0.01	Three times larger than the DICE default; calibrated to macroeconomic evidence considered more consistent with observed impacts at 3–4°C	

Specification	ρ	β_{clim}	Rationale
Ramsey	0.001	0.5	Baseline DICE-2023 discounting
Zero time preference	0	0	Removes pure time preference and climate risk premium; retains consumption-growth discounting

The Howard-Stern damage coefficient is derived from the growth-inclusive estimate in Howard and Stern’s (2025) preferred damage specification. We use the upper end of the non-catastrophic damage range they report at 3°C [18]. See Eq. S1 for the derivation.

3 Results

Including ecological feedbacks in DICE 2023 produces up to 0.79°C of additional peak warming. This physical divergence translates into welfare losses of at most 0.21% under the standard damage function.

3.1 Temperature and Atmospheric Carbon

Ecological feedbacks lead to increased radiative forcing due to increased atmospheric carbon (Figure 2), with peak temperature increasing from DICE 2023 by 0.24 °C for DICE-C and 0.79 °C for DICE-CP (Table 4). These feedbacks also lead to later peak temperatures, with DICE-C temperature peaking in 2121 and DICE-CP peaking in 2125, while DICE 2023 temperature peaks in 2111 (Table 4, Figure 2). DICE 2023 atmospheric carbon peaks at approximately 1,200 GtC before declining as aggressive mitigation removes carbon from the atmosphere, while DICE-C reaches approximately 1,300 GtC at peak and DICE-CP reaches approximately 1,600 GtC (Figure 2). The latter increase in atmospheric carbon compared to DICE 2023 is largely driven by permafrost carbon release, which introduces a sustained carbon flux. Under Nordhaus’s optimized solution, DICE 2023 cools to 0.57 °C above pre-industrial by 2300. DICE-C follows a similar trajectory, cooling to approximately 0.82 °C by 2300 and 0.62 °C by 2420, but DICE-CP sustains 1.8 °C (Figure 2). In DICE-CP, thawed permafrost continues releasing carbon into the atmosphere well after industrial emissions have declined, maintaining radiative forcing at levels that mitigation cannot counteract on century timescales.

Table 4: Summary of peak temperature (T_{peak}), year of T_{peak} , temperature change relative to DICE 2023, damage fraction of gross output (D_{frac}) at peak, change in damage fraction, and social time preference at peak across the three model configurations.

Configuration	T_{peak} (°C)	Peak Year	ΔT_{peak} from DICE (°C)	D_{frac} at Peak (% Y_{gross})	ΔD_{frac} from DICE (pp)	STP at Peak
1 – DICE 2023	2.60	2111	—	2.35%	—	0.0645
2 – DICE-C	2.84	2121	+0.24	2.79%	+0.44%	0.0456
3 – DICE-CP	3.39	2125	+0.79	3.99%	+1.64%	0.0396

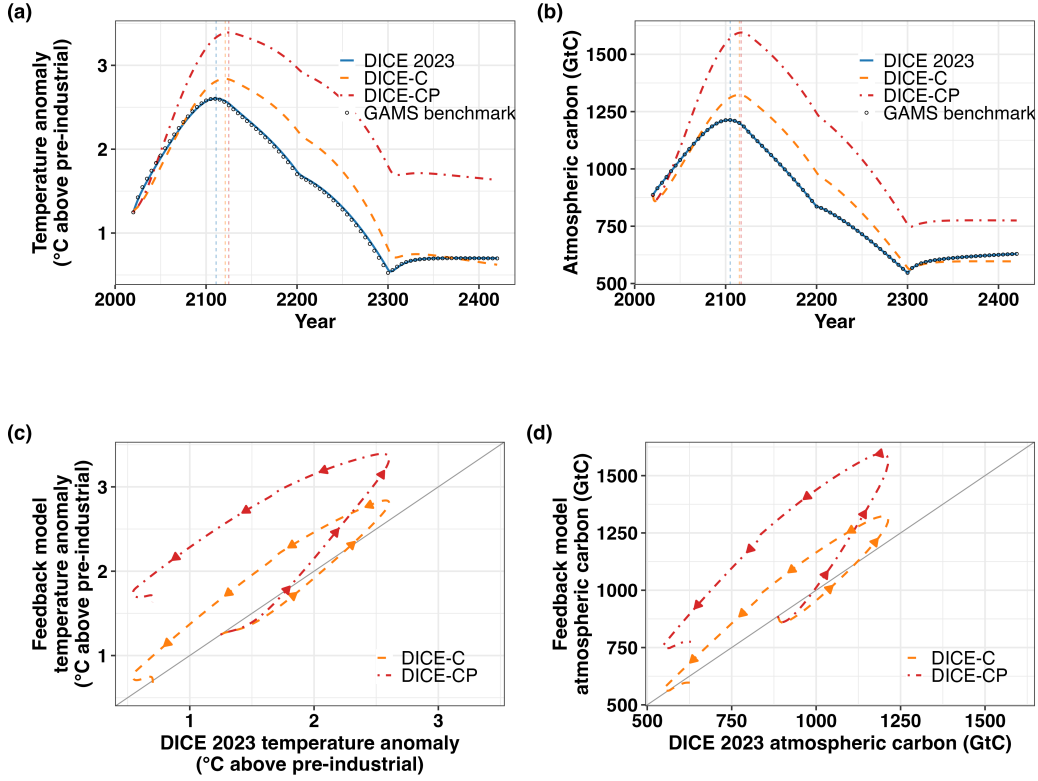


Figure 2: **Projected atmospheric temperature anomaly and atmospheric carbon concentration under three model configurations, 2020–2420.** Upper panels show time series of (a) temperature anomaly (°C above pre-industrial levels) and (b) atmospheric carbon concentration (gigatons of carbon). Lower panels show 1:1 comparisons of feedback model output against the DICE 2023 baseline for (c) temperature anomaly and (d) atmospheric carbon. Open circles indicate GAMS (General Algebraic Modeling System) benchmark values from the discrete-time DICE 2023 optimization, provided for model validation. Vertical dashed lines mark the year of peak temperature or carbon concentration for each configuration. In lower panels, the solid line is the 1:1 reference; points above this line indicate higher values in the feedback model relative to DICE 2023. Arrows indicate the direction of time along each parametric trajectory.

3.1.1 Comparison to CMIP6 Earth System Models

To assess whether the physical trajectories produced by these three configurations fall within a plausible range of climate outcomes, we compare projected temperature anomalies against ensemble mean trajectories from four Coupled Model Intercomparison Project Phase 6 (CMIP6) Shared Socioeconomic Pathways: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 [26] (Figure 3). DICE 2023 and DICE-C remain close to one another and to the lower bound of the CMIP6 envelope through 2100, consistent with their representation of an optimized mitigation pathway rather than a no-policy baseline. DICE-CP, by contrast, tracks between the SSP2-4.5 and SSP3-7.0 ensemble means by the end of the century, indicating that the addition of permafrost dynamics shifts the model’s physical trajectory into closer alignment with a moderate-emissions Earth system model scenario. This comparison places all three configurations within the plausible range spanned by contemporary climate model ensembles, and indicates that the warming amplification introduced by permafrost dynamics does not push the model into a physically implausible regime relative to CMIP6.

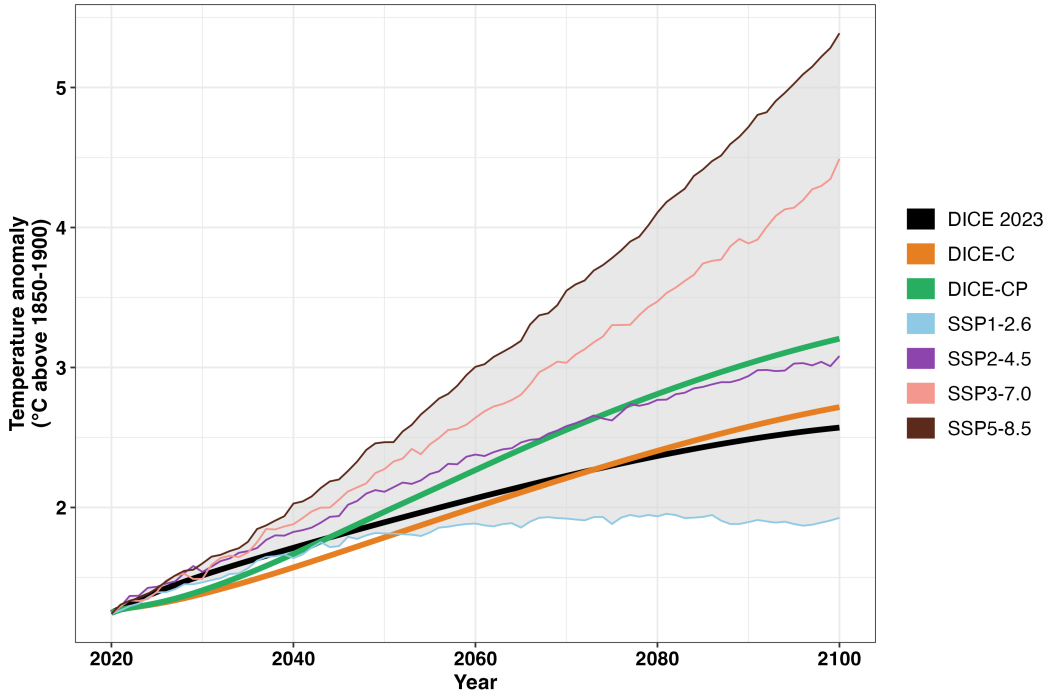


Figure 3: **DICE configurations compared against CMIP6 SSP ensemble means, 2020–2100.** Colored shading indicates the full range spanned by the four illustrated CMIP6 Shared Socioeconomic Pathway (SSP) ensemble means [26], from SSP1-2.6 (lowest) to SSP5-8.5 (highest). Temperature anomalies are expressed relative to a 1850–1900 baseline, calculated from the CMIP6 historical ensemble mean over that period.

3.1.2 Feedback Analysis Findings

The factorial feedback sensitivity analysis reveals the relative contributions of individual carbon cycle feedbacks within the DICE-C and DICE-CP configurations (Figure 4). Terrestrial CO₂ fertilization dominates all other feedbacks as a balancing mechanism: removing it raises peak temperature by 3.52°C and peak atmospheric carbon by approximately 2,395 GtC (Figure S1). The temperature dependence of photosynthesis functions as the second-largest balancing feedback, raising peak tem-

perature by 0.54°C when removed. Permafrost carbon release is the largest reinforcing feedback, lowering peak temperature by 0.71°C when removed, and reducing peak atmospheric carbon by approximately 471 GtC. Soil respiration and vegetation respiration contribute smaller reinforcing effects of 0.37 and 0.29°C respectively. Ocean CO_2 solubility shows the smallest contribution among all feedbacks, adding a balancing increment of 0.14°C .

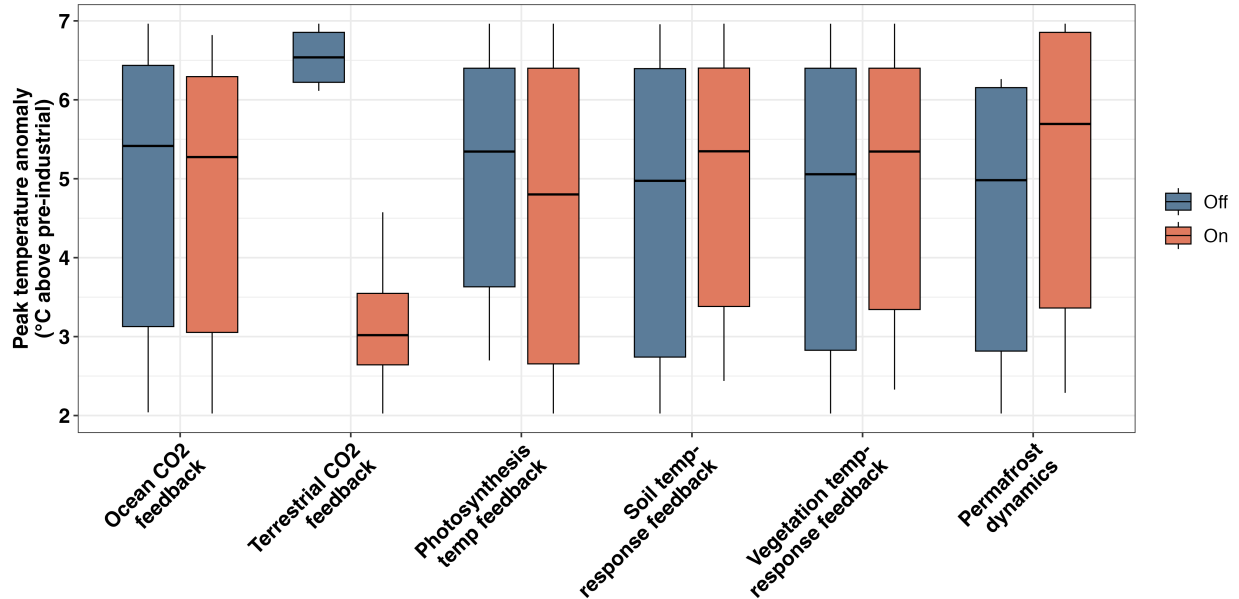


Figure 4: **Contributions of individual Lenton carbon cycle feedbacks to peak temperature anomaly.** A full factorial sensitivity analysis highlights the contributions of each feedback on peak temperature over the 400 year simulation period. Each bar is colored by the inclusion or disengagement of individual feedbacks and represents the average peak temperature for that configuration.

3.2 Climate Damages

The inclusion of climate-carbon feedbacks also led to increased damage costs. DICE-C showed a 0.44% increase in damages as compared to DICE 2023 at peak temperature, and DICE-CP showed an increase of 1.64% (Table 4, Figure 5).

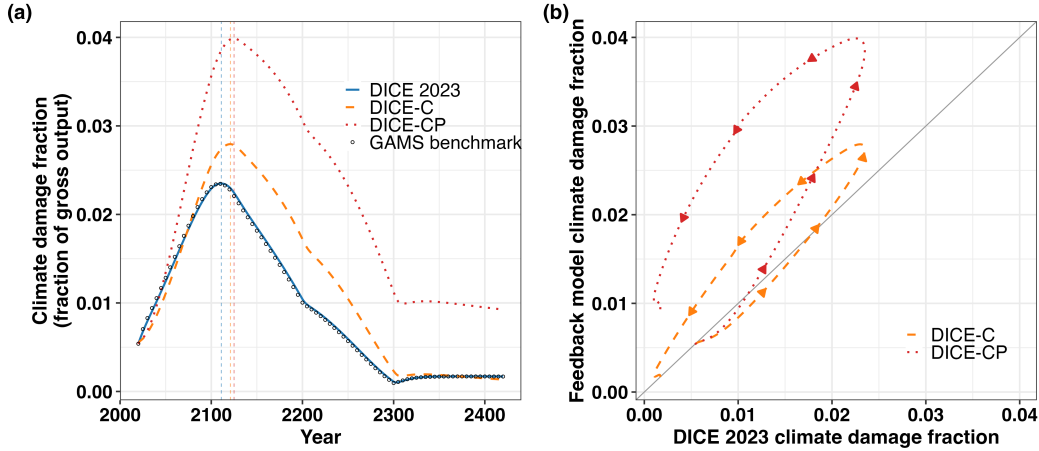


Figure 5: **Climate damage fraction under three model configurations, 2020–2420.** Panel (a) shows time series of the damage fraction (percentage of gross economic output) under each model configuration. Panel (b) shows a 1:1 comparison of feedback model damage fraction against the DICE 2023 baseline; points above the solid 1:1 reference line indicate greater climate damages in the feedback model relative to DICE 2023. Open circles in panel (a) indicate GAMS benchmark values from the discrete-time DICE 2023 optimization. The damage fraction D_{frac} is defined as $D_{\text{frac}} = a_1 T_{\text{ATM}} + a_2 T_{\text{ATM}}^{a_3}$, where T_{ATM} is the global mean surface temperature anomaly and a_1 , a_2 , a_3 are calibrated damage coefficients [3]. Arrows in panel (b) indicate the direction of time along each parametric trajectory.

3.3 Economic Output and Social Welfare

Climate damages affect economic output and social welfare through two channels operating on different timescales. In the short term, higher damages reduce net output, and since population, total factor productivity, and carbon intensity are held fixed across configurations, lower net output reduces consumption and welfare. In the longer term, higher damages in a given year reduce savings, which reduces capital available in future years, reducing future gross output. Reduced capital availability also reduces future abatement spending, since abatement cost scales with gross output. The net effect on future net output, consumption, and welfare therefore depends on which of these offsetting forces is larger.

With a fixed emissions reduction rate, the extended model responds to higher temperature scenarios through a decrease in abatement spending. Overall economic output was essentially unchanged for DICE-C and approximately \$800 trillion lower for DICE-CP by 2420. Cost of abatement follows the same trajectory, as DICE-C feedbacks decrease spending, especially at peak temperature, but ultimately regress back to just above DICE 2023 values by 2420. DICE-CP results in approximately \$0.9 trillion less abatement spending (Figure 6). Because this study uses precomputed emissions control and savings rates, it represents DICE 2023 optimum with no policy response to additional warming.

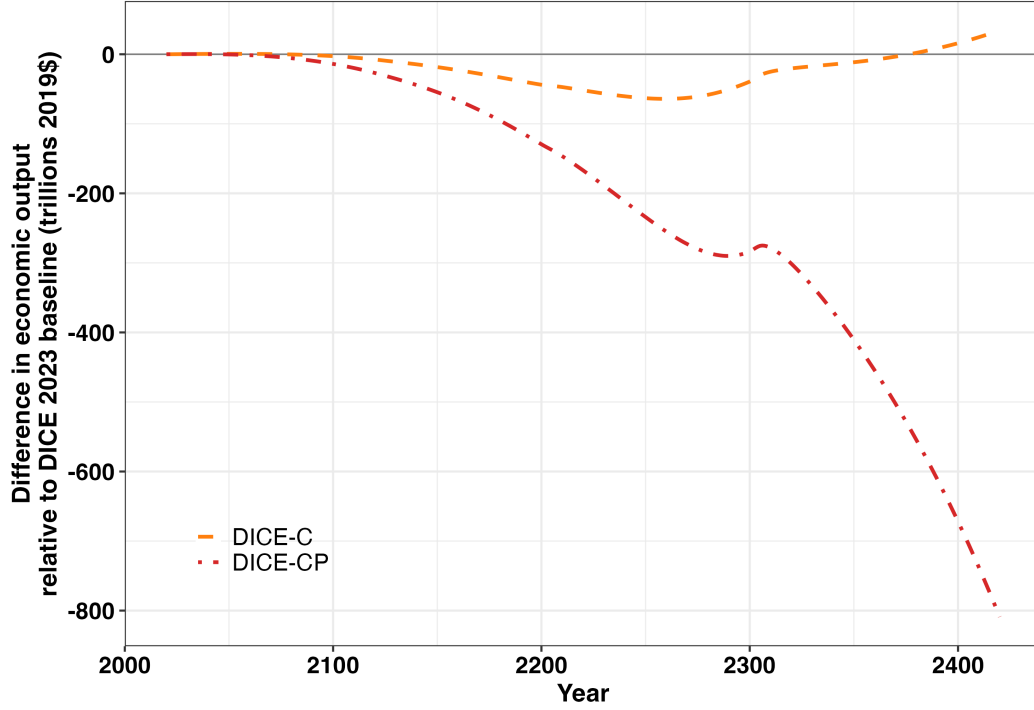


Figure 6: **Difference in economic output relative to the DICE 2023 baseline, 2020–2420.** Computed as the feedback model value minus the DICE 2023 value; negative values indicate losses relative to the baseline. The solid horizontal line at zero indicates the DICE 2023 baseline.

Gross economic output, abatement cost, and discounted social welfare per year follow nearly identical trajectories across all three configurations (Figure 7), reflecting that the differences documented above are small relative to the growth in output projected over the 400 year simulation horizon.

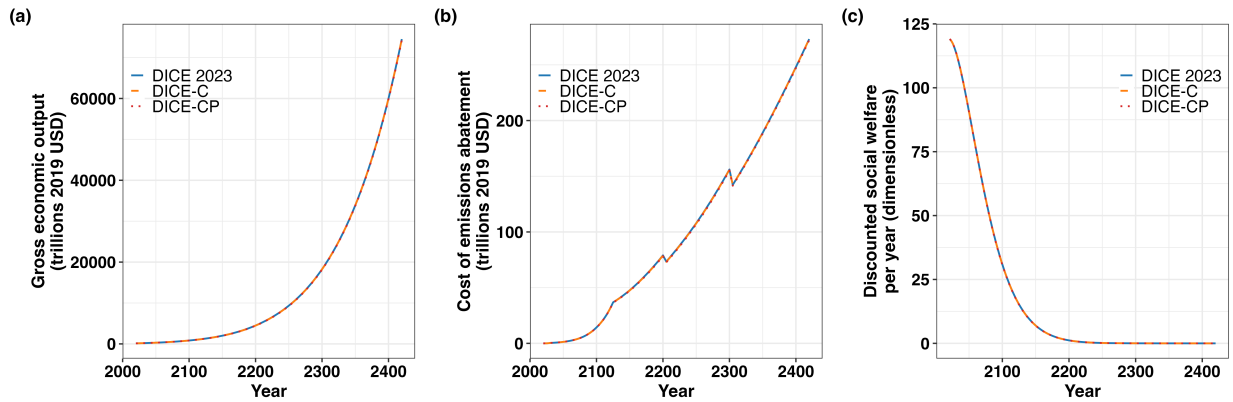


Figure 7: **Gross economic output, abatement cost, and discounted social welfare per year under three model configurations, 2020–2420.** Panel (a) shows gross economic output; panel (b) shows the cost of emissions abatement; panel (c) shows discounted social welfare per year, computed as the year-to-year change in accumulated utility U_{acc} .

DICE-C shows a negligible welfare difference of +0.02% relative to DICE 2023, and DICE-CP decreases 2420 welfare by 0.21% (Figure 8). Because early-period welfare carries substantially greater discount weight than late-period welfare, the early cooling advantage of DICE-C offsets the later warming penalty, producing a near-zero net welfare effect.

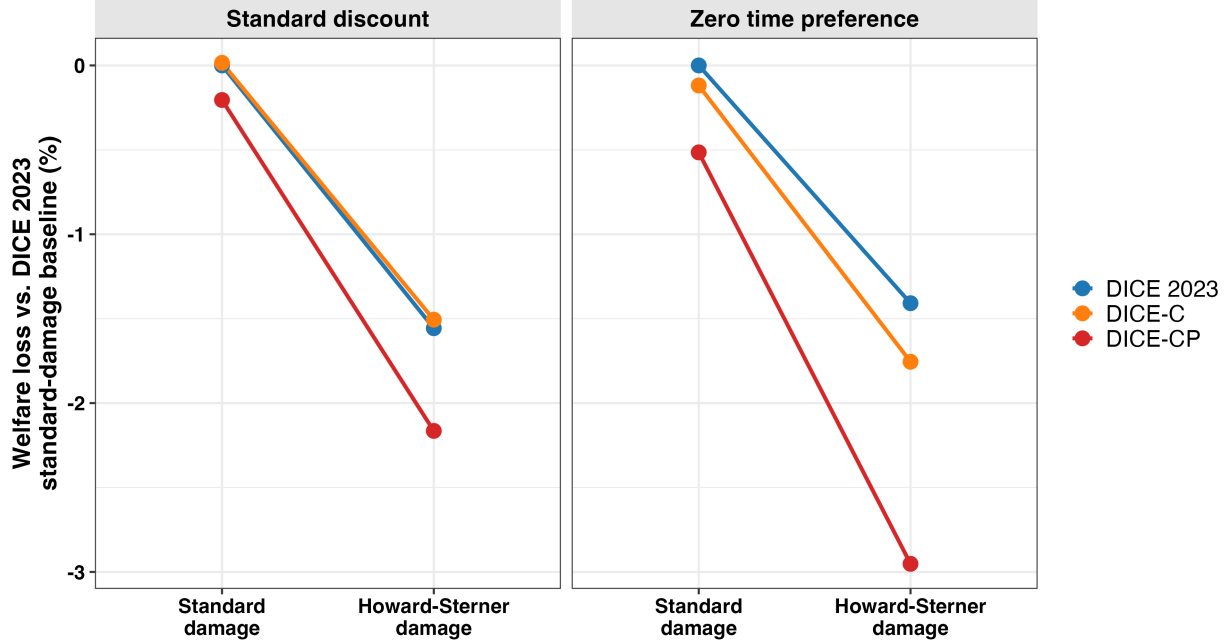


Figure 8: **Welfare loss relative to the DICE 2023 standard-damage baseline by physical model configuration, damage function, and discount convention.** Points show the percentage reduction in accumulated utility U_{acc} at year 2420 relative to the DICE 2023 standard-damage baseline within each discount convention. Negative values indicate welfare losses. Panel (a) uses standard DICE 2023 discounting. Panel (b) removes explicit time preference ($\rho = 0$, $\beta_{clim} = 0$).

Replacing the DICE 2023 damage function with the Howard-Stern (2025) specification [18] (Table 3, Eq. 3) reduces welfare across all three physical model configurations (Figure 8). Within each configuration, switching from standard to Howard-Stern damage and holding the physical model fixed produces a welfare decrease of 1.56% under DICE 2023 alone, 1.51% under DICE-C, and 1.96% under DICE-CP, under standard discounting. In each case this damage-function effect exceeds the physical feedback effect reported above. Discounting convention changes which configuration retains the most welfare. Under standard discounting, DICE 2023 and DICE-C remain nearly identical across both damage functions (-1.56% vs. -1.51% under Howard-Stern damage), while DICE-CP consistently loses the most welfare. Under zero time preference, DICE 2023 retains the most welfare under both damage functions, with the gap widening most under Howard-Stern damage (1.41% for DICE 2023 vs. -1.76% and -2.95% for DICE-C and DICE-CP) (Figure 8). Physical feedbacks contribute at most 0.52% of welfare loss relative to DICE 2023 under any tested combination, while the additional welfare loss from switching to the Howard-Stern damage coefficient ranges from 1.41% to 2.44% depending on configuration and discount convention. The decrease in welfare under the Howard-Stern damage function is largest when physical feedbacks are strongest.

3.4 Continuous-Time Implementation and GAMS Benchmark Comparison

The continuous-time version of DICE 2023 coupled with the DFAIR climate-carbon model produced almost identical temperature, atmospheric carbon, and economic trajectories to the discrete time version (temperature maximum absolute deviation: 0.043°C , occurring around year 2300 during the cooling phase). Welfare estimates from the continuous-time STELLA implementation exceed the GAMS benchmark by approximately 6.6%, reflecting the difference between continuous integration and Nordhaus’s 5-year discrete timestep formulation. Because this discrepancy applies to the underlying DICE 2023 welfare calculation itself, it is not specific to the ecological feedbacks introduced in this study; however, it is present in the DICE-C and DICE-CP welfare comparisons as well, since all three configurations are implemented in the same continuous-time framework. Therefore, we report comparisons between the three configurations, since the same continuous-time integration error applies uniformly across all of them, but these estimates should not be compared against GAMS-based DICE 2023 results.

4 Discussion

Ecological feedbacks introduced in DICE-C and DICE-CP produce nonlinear trends in global warming, including early-period cooling and late-period heating, that DICE 2023’s DFAIR does not capture. However, these climate differences translate to small changes in global welfare. We identify how the damage function, the discounting convention, and the fixed policy trajectory contribute to this insensitivity.

4.1 Physical feedbacks produce meaningful but structurally invisible divergence

Including ecological feedbacks in DICE increases peak global temperature by up to 0.79°C , yet climate damages remain modest (by at most 1.64% of gross economic output) in all three configurations. Replacing the DFAIR carbon cycle with the SCM raises peak atmospheric temperature by $+0.24^{\circ}\text{C}$, and the addition of permafrost dynamics raises it by an additional $+0.55^{\circ}\text{C}$ relative to DICE 2023 alone (Table 4).

The divergence persists and grows when viewed on centennial timescales. DICE 2023 cools to 0.57°C above pre-industrial by 2300. DICE-C follows this trajectory while DICE-CP maintains 1.80°C . This gap widens after 2200 as permafrost emissions continue even as anthropogenic emissions decrease and society becomes carbon negative, demonstrating that physical feedbacks can erode the effectiveness of mitigation over centuries.

Welfare differences across configurations nonetheless remain modest under standard economic conventions despite these temperature differences. We identify three non-exclusive structural reasons why welfare accounting fails to register physical changes of this magnitude.

4.2 The damage function is the binding structural constraint

Warming of the magnitude resulting from DICE-C and DICE-CP does not produce correspondingly large welfare consequences. The majority of this is attributable to the calibration and functional form of the DICE damage function. Under the standard quadratic specification, physical feedbacks produce welfare changes of approximately $+0.02\%$ (DICE-C) and -0.21% (DICE-CP) relative to DICE 2023 under standard discounting. We tested the sensitivity of these relationships to the damage function by substituting the Howard-Stern (2025) damage coefficient [18] (Eq. 3, Table 3). Holding each physical configuration fixed and comparing its own standard damage function

and alternative damage function runs, this substitution raises welfare losses by 1.56% for DICE 2023, 1.51% for DICE-C, and 1.96% for DICE-CP. In every configuration the damage function effect exceeds the ecological feedback effect, consistent with Kessler (2017) [20], who finds that the welfare impact of permafrost carbon feedbacks is highly sensitive to damage function convexity.

This insensitivity of standard DICE welfare projections is therefore due to the convexity of the quadratic specification: marginal damages increase with temperature, so the welfare cost of feedback-driven warming depends critically on where in the trajectory the additional increment falls. Under a sufficiently steep damage function, ecologically-driven temperature increments that appear physically modest become economically significant. The choice of damage coefficient therefore determines the magnitude of projected welfare losses and whether ecological feedbacks register as consequential at all. The welfare signal from physically realistic feedbacks is suppressed by the damage function.

4.3 Discounting interacts with feedback timing in configuration-specific ways

Feedback-driven warming accumulates and peaks late in the simulation, precisely when Ramsey discounting suppresses the cost of damages. Under zero time preference, welfare losses from physical feedbacks expand relative to the Ramsey baseline across all model configurations, with DICE-CP showing the largest expansion. This pattern reflects the timing of climate divergence: removing explicit time preference transfers welfare weight to these later periods, amplifying the economic effects from late-term feedbacks that standard discounting obscures. The qualitative finding of ecological feedback insensitivity under standard damage specifications is robust to the discounting assumption tested here.

4.4 The fixed policy trajectory represents a structurally realistic but physically miscalibrated scenario

The emissions control and savings rates used throughout this study are pre-optimized under standard DICE physics. When these trajectories are imposed on DICE-C and DICE-CP, abatement remains lower than the feedback-driven warming would warrant: under optimal DICE policy, DICE-CP reaches temperatures 0.79°C higher at peak, with no corresponding increase in mitigation effort. This scenario is still policy-relevant. The flat optimization landscape documented in Barrage and Nordhaus (2024) [3] means that DICE-projected welfare is relatively insensitive to moderate deviations from the DICE optimum across a wide range of policy scenarios. This structural insensitivity is therefore compounded by the insensitivity of the damage function. We hypothesize that the policy differences from re-optimizing under feedback-corrected physics would be unlikely to produce substantially different welfare outcomes.

4.5 Abatement costs and the limits of fixed-trajectory analysis

Even though including permafrost feedbacks led to higher temperatures (Figure 6), abatement spending decreased by approximately \$900 billion (2019\$) by 2420 as compared to DICE 2023, a direct consequence of lower economic output under elevated damages. Climate-related damages can decrease the capacity of a society to manage the impacts of climate change, increasing the intensity of the damages. It can also limit the resources allocated to transitioning to more sustainable, less carbon-intense infrastructure, making it difficult to reduce emissions [22].

This could partially be a structural artifact of holding policy fixed, representing a scenario in which information about ecological feedbacks is either unknown or does not affect policy. The additional warming introduced by feedbacks could plausibly raise optimal abatement rates instead

if the new configuration were optimized similarly to DICE 2023, although this assumes decision-makers respond with the same perfect-information, optimizing behavior that DICE’s social planner does, rather than the bounded rational behavior that actually characterizes policy response to new climate information [5, 4].

4.6 Near-Term Emissions Control and the Timing of Threshold-Crossing Risk

The abrupt permafrost threshold (Eq. 17) and the 200-year delayed temperature term governing labile carbon release (Eq. 18) mean that whether and when this feedback engages is determined by cumulative emissions decades before its economic or ecological consequences are realized. Because welfare under Ramsey discounting compresses the visibility of damages arriving late in the simulation, avoiding threshold crossing in the near term carries physical significance that a discounted cost-benefit framework will tend to undervalue. A model can be welfare-optimal by construction and still cross a physical threshold that its objective function ignores. This dynamic suggests that near-term abatement may be more consequential for avoiding physically irreversible outcomes than standard IAMs project.

4.7 Limitations and future directions

DICE relies on a globally aggregated welfare optimizing function rather than any representation of socio-political processes that yield and enforce climate policy, including public opinion formation, technology adoption, and institutional responsiveness. Integrated assessment models offer prescriptive suggestions based on perfect information availability instead of forecasting actual human behavioral responses. Moore et al. [29] model these processes directly and find a structurally similar dependence on near-term conditions: century-end warming in their coupled climate-social model ranges from 1.8°C to 3.6°C depending on whether early action triggers self-reinforcing opinion dynamics, or political status quo stagnates opinions. Coupling mechanistic ecological feedbacks of the kind developed here with an endogenous socio-political representation of policy formation of the kind Moore et al. develop would address two distinct sources of structural simplification in standard IAM practice jointly: the physical carbon cycle and the policy-generating process.

Additionally, both the DICE model and the SCM [23, 3] are global mean-field formulations and do not capture regional heterogeneity in carbon flux or economic infrastructure, which vary considerably across space [35]. Regional carbon cycle models suggest that high-latitude feedbacks, including permafrost melt, may be substantially stronger than global mean estimates imply [37, 39], so present results may understate feedback-driven welfare losses even under the Howard-Stern specification. Nordhaus & Yang (1996) developed a regional dynamic integrated climate-economic model [31] to address this uncertainty, and we suggest that future work should leverage this to investigate the implications of regional feedbacks on climate-economy dynamics.

5 Conclusions

The results of this study demonstrate that including ecological feedbacks in IAMs produces meaningful divergence, including (1) about 0.79°C of additional peak warming, (2) 1.64% more economic damage, and (3) sustained temperatures of above 1.5 °C under DICE 2023 optimal abatement. These consequences translate to small welfare losses under standard economic conventions. This reflects the damage function’s calibration to the low end of empirical estimates, rather than any lack of physical significance in the feedbacks themselves. Substituting the Howard-Stern damage

coefficient raises each configuration’s welfare loss by between 1.51 and 1.96%, exceeding the physical feedback effect in every tested configuration, regardless of discount convention. Improvements in ecological realism may not produce appropriate welfare signals under this structural constraint, including under alternative policy trajectories. Because DICE-projected welfare is relatively insensitive to moderate deviations from the optimum, we expect that re-optimizing under feedback-corrected physics would not substantially alter these conclusions, though this hypothesis warrants testing in future work.

These findings have direct implications for climate policy modeling. Standard IAMs are routinely used to derive the social cost of carbon, evaluate emissions targets, and assess the costs and benefits of mitigation pathways. If the welfare signals those models produce are systematically suppressed by structural choices in the damage function then the policy prescriptions derived from them will systematically undervalue both the physical risks from ecological feedbacks and the mitigation investments required to address them. Closing this gap requires not only the physical model improvements demonstrated here, but renewed attention to the economic architecture through which physical forcing is translated into welfare consequences.

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7 Data availability

Models, data, results, and code can be found at github.com/gsavitsky/DICE-eco-feedbacks.

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S1 Initial conditions

Table S1: Initial conditions (year 2020) for all model stocks.

Symbol	Description	Initial value	Units
Simple carbon model (Lenton) pools			
$C_{a,0}$	Atmospheric carbon (SCM)	887	PgC
$C_{v,0}$	Vegetation carbon	550	PgC
$C_{s,0}$	Soil carbon	1,500	PgC
$C_{ol,0}$	Low-latitude (warm) surface ocean carbon	730	PgC
$C_{oh,0}$	High-latitude (cold) surface ocean carbon	140	PgC
$C_{oi,0}$	Intermediate ocean carbon	10,040	PgC
$C_{od,0}$	Deep ocean carbon	23,860	PgC
Deforestation ₀	Cumulative deforestation	0	PgC
Permafrost pools			
$C_{perm,0}$	Frozen permafrost carbon	1,035	PgC
$C_{thawed,0}$	Thawed soil carbon	0	PgC
DFAIR carbon reservoirs			
$R_{0,0}$	Reservoir 0	150.093	GtC
$R_{1,0}$	Reservoir 1	102.698	GtC
$R_{2,0}$	Reservoir 2	39.534	GtC
$R_{3,0}$	Reservoir 3	6.1865	GtC
$C_{tot,0}$	Cumulative carbon emissions	633.5	GtC
Climate module			
$T_{1,0}$	Deep ocean temperature anomaly	0.1477	°C from 1765
$T_{2,0}$	Upper ocean temperature anomaly	1.099454	°C from 1765
$FGHG_0$	Non-CO ₂ GHG forcing	0.518	W/m ²
Economy			
K_0	Capital stock	295	trillion 2019 USD
$U_{acc,0}$	Accumulated utility	0	unitless

S2 Howard-Sternier damage estimate

We approximate the Howard and Sterner (2025) growth-inclusive damage estimate as a DICE-equivalent quadratic coefficient by evaluating their preferred specification [18] at $T = 3^\circ\text{C}$ and solving for a_2 such that $a_2 \cdot 3^2$ reproduces their implied damage fraction:

$$a_2 = \frac{(0.622 \cdot 3^{1.5} + 1.997 \cdot 3)/100}{3^2} \approx 0.0102 \quad (\text{S1})$$

S3 Damage function–discounting sensitivity results

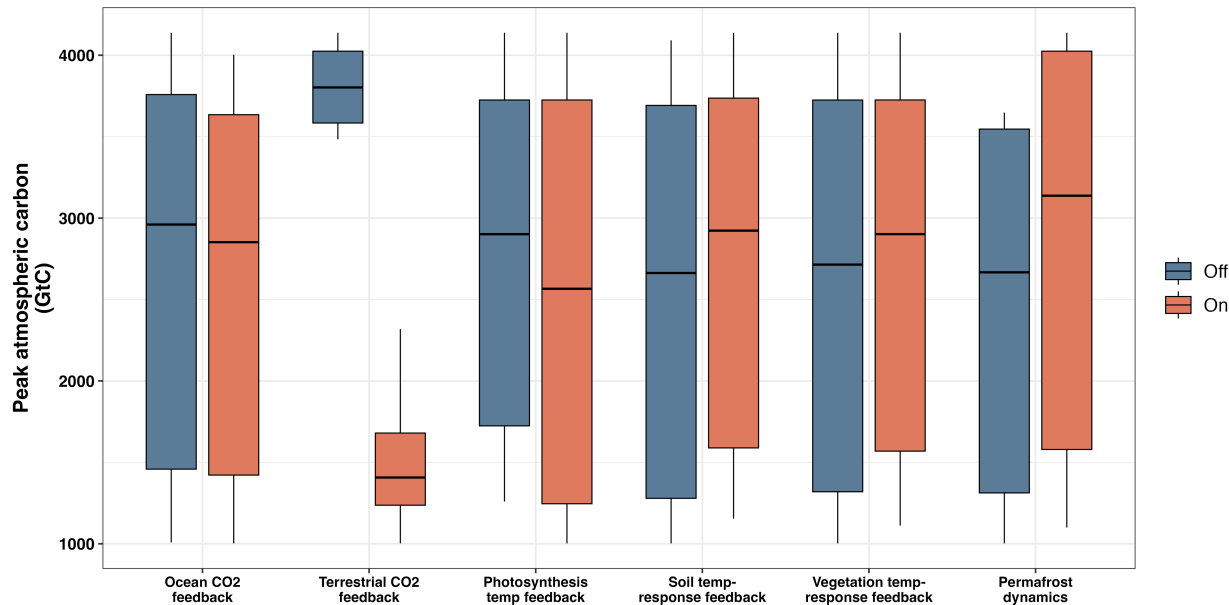


Figure S1: **Isolated and conditional contributions of individual Lenton carbon cycle feedbacks to peak atmospheric carbon.** A full factorial sensitivity analysis highlights the contributions of each feedback on peak atmospheric carbon over the 400 year simulation period. Each bar is colored by the inclusion or disengagement of individual feedbacks and represents the average peak atmospheric carbon for that configuration.

Table S2: Accumulated welfare (U_{acc} , dimensionless) at year 2420 by physical model configuration, damage function, and discount convention. Loss values are percentage reductions relative to the DICE 2023 standard-damage run, computed consistently within each discount convention for both the Standard-damage and Howard-Stern rows.

Configuration	Damage	Standard discount		Zero time preference	
		U_{acc}	Loss	U_{acc}	Loss
DICE 2023	Standard	7,102	—	45,257	—
	Howard-Stern	6,991	−1.56%	44,619	−1.41%
DICE-C	Standard	7,103	+0.02%	45,203	−0.12%
	Howard-Stern	6,995	−1.51%	44,462	−1.76%
DICE-CP	Standard	7,087	−0.21%	45,024	−0.52%
	Howard-Stern	6,948	−2.17%	43,921	−2.95%