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Climate uncertainty impacts on optimal mitigation pathways and social cost of carbon

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Abstract

Emissions pathways used in climate policy analysis are often derived from integrated assessment models. However, such emissions pathways do not typically include climate feedbacks on socioeconomic systems and by extension do not consider climate uncertainty in their construction. We use a well-known cost-benefit integrated assessment model, the Dynamic Integrated Climate-Economy (DICE) model, with its climate component replaced by the Finite-amplitude Impulse Response (FaIR) model (v2.1). The climate uncertainty in FaIR is sampled with an ensemble that is consistent with historically observed climate and Intergovernmental Panel on Climate Change (IPCC) assessed ranges of key climate variables such as equilibrium climate sensitivity (ECS). By varying discounting assumptions, three scenarios are produced: a pathway similar to the 'optimal welfare' scenario of DICE that has similar warming outcomes to current policies, and pathways that limit warming to 'well-below' 2 °C and 1.5 °C with a short-term overshoot, aiming to meet Paris Agreement long-term temperature goals. Climate uncertainty alone is responsible for a factor of five variation (5%–95% range) in the social cost of carbon (SCC) in the 1.5 °C overshoot scenario, with the spread in SCC increasing in relative terms with increasing stringency of climate target. CO_2 emissions trajectories resulting from the optimal level of emissions abatement in all pathways are also sensitive to climate uncertainty, with 2050 emissions ranging from -12 to $+14$ $GtCO_2$ yr^{-1} in the 1.5 °C scenario. ECS and the strength of present-day aerosol effective radiative forcing are strong determinants of SCC and mid-century CO_2 emissions. This shows that narrowing climate uncertainty leads to more refined estimates for the social cost of carbon and provides more certainty about the optimal rate of emissions abatement. Including climate and climate uncertainty in integrated assessment model derived emissions scenarios would address a key missing feedback in scenario construction.

1. Introduction

Integrated Assessment Models (IAMs) can be categorized into two broad types: process-based (PB-IAMs) and cost-benefit (CB-IAMs) [1]. PB-IAMs model the energy system, technology, economy, agricultural productivity and land use across a number of world regions, are used to construct possible future emissions scenarios, and have extensive policy reach [2], partly as a consequence of their ubiquity across IPCC reports [3]. PB-IAMs produced the Shared Socioeconomic Pathways (SSPs) used to drive Earth System model projections of future climate [4], providing a large base of model evidence to the

Intergovernmental Panel on Climate Change (IPCC) Working Group 1 (WG1) report. Analysis of future potential technological and social developments in a large number of PB-IAMs are assessed in IPCC Working Group 3 (WG3) [3].

CB-IAMs are simpler and often used to model climate change effects on the global economy at a macro level. One area in which CB-IAMs have had extensive policy reach is in determining the social cost of carbon (SCC), describing the marginal time-discounted climate damages suffered by society for each additional ton of CO_2 emitted [1]. CB-IAMs perform a cost-benefit analysis that balances the foregone present-day economic consumption (which under the current global energy mix, is CO_2-intensive) that is instead invested in emissions abatement technologies, with benefits future avoided climate damages from warming. The SCC forms a central component of climate policy in several countries, most notably the United States [5]. In a hypothetical efficient market, the SCC could be used to set the optimal global carbon price or carbon taxation level.

A CB-IAM requires a simple climate module as an integral part of the model in order to calculate global warming and hence climate damages. While their model dynamics are highly aggregated and parameterised, CB-IAMs tend to include a two-way coupling between emissions and climate. PB-IAMs may also include climate modules and may calculate climate damages [6] allowing determination of SCC, and may also be run in an optimization framework in order to produce cost-optimal energy transition pathways [7], but at present typically do not consider climate change effects on technology availability, energy demand, agriculture, or the factors of productivity when used to construct community emissions scenarios [8–10]. This potentially excludes important feedbacks between climate and human decision-making in scenario design.

Additionally, the relative simplicity of CB-IAMs means that an optimal solution (e.g. from an iterative optimization process) can be found relatively quickly. Therefore, uncertainty analysis can be undertaken by varying model parameters and re-running many times using variance-based sensitivity analyses or Monte Carlo sampling [11, 12]. The properties of economic-climate coupling and efficiency make CB-IAMs useful tools for exploring the impact of climate uncertainty on emissions scenarios and SCC.

It has recently been observed that climate module components of CB-IAMs are performing poorly with respect to full-complexity Earth System models and observations [13]. CB-IAM climate modules can be improved if model parameters are better calibrated [14], though key Earth System processes such as the carbon cycle feedback are often missing [15]. As climate damages (and therefore SCC) in CB-IAMs depend on global mean surface temperature, it is important to use an appropriate and well-calibrated simple climate model within a CB-IAM to prevent biased estimates of SCC [13].

An additional consideration for SCC is that of uncertainty in climate. Several climate variables including ECS and the magnitude of present day aerosol forcing have large uncertainty bounds [16] and varying the climate response in CB-IAMs can lead to differing estimates of the SCC [5, 17, 18]. We extend this previous work by producing a systematic assessment of climate uncertainty using a calibrated probabilistic ensemble of the FaIR v2.1.0 simple climate model [19] coupled to the DICE-2016R CB-IAM [20], focusing on allowable CO_2 emissions under Paris Agreement consistent mitigation scenarios in addition to the effect of climate uncertainty on the present-day SCC.

2. Methods

2.1. DICE integrated assessment model

The starting point for this work is the DICE-2016R model of William Nordhaus [20, 21] with some additional updates and modifications (supplementary material section 1). We reduce the model timestep in DICE from 5 years to 3 years, and use 2023 as the first period (updated from 2015 in DICE-2016R). We run DICE to 2500 for a total of 160 periods (DICE-2016R runs to 2510 for a total of 100 periods). A 3-year time step allows for more responsive emissions reductions in the near term, without significantly adding to the computational burden.

Gross world economic output Y is determined with a Cobb-Douglas production function

$$Y(t) = A(t)K(t)^{\gamma}L(t)^{1-\gamma} \tag{1}$$

where K is global capital stock, L is global labour stock, $\gamma = 0.3$ is the output elasticity to capital and A is total factor productivity. $t = 1\ldots160$ is the period. $L(t)$ is assumed to scale proportionally with global population.

The projections of world population from DICE-2016R are updated with the median projection of 10 000 scenarios from the Resources For the Future Socioeconomic Pathways (RFF-SPs) [5, 22]. Global capital stock $K(t)$ and total global product $Y(t)$ are updated to use 2019 figures from the International Monetary Fund (IMF) reported in 2017\$ and re-indexed to give $K = \$341$tn and $Y = \$133$tn for 2023 in 2020\$. Total factor productivity $A(t)$ in 2023 is calculated by rearrangement of equation (1) using the re-indexed 2019 estimates of $K(t)$ and $Y(t)$ from the IMF data and $L(t)$ from the RFF-SP timeseries.

CO_2 emissions from fossil fuel and industrial processes (E_{FFI}) are given by

$$E_{\mathrm{FFI}}(t) = \sigma(t)Y(t)(1-\mu(t)) \tag{2}$$

where $\sigma(t)$ is the emissions intensity of GDP [kg CO_2 \$$^{-1}$]. $\sigma(t)$ includes a baseline improvement

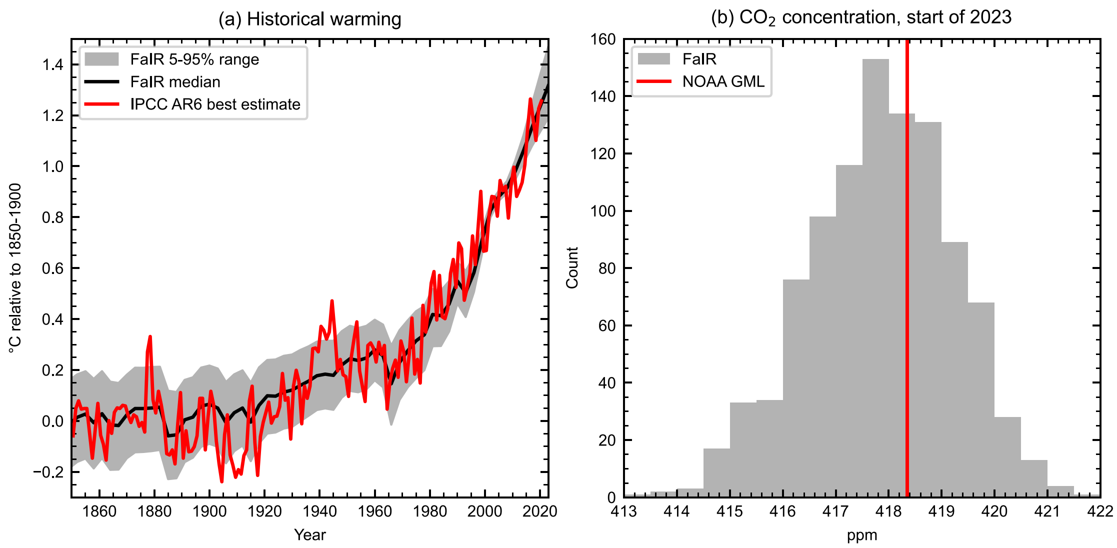

Figure 1. (a) Historical global mean surface temperature in FaIR (5%–95% range in grey shading, median in black) compared to the IPCC's best estimate time series (red) from Gulev *et al* [31]. Temperatures use a baseline of 0.85 °C above pre-industrial for 1995–2014, following IPCC. Widening spread near the beginning of the time series relates to observational uncertainty in present-day warming included in the ensemble. (b) Distribution of atmospheric CO_2 concentration at the start of 2023 from FaIR initialised in 1750 (grey histogram) compared to NOAA's global mean surface dataset (red line). Start of year 2023 CO_2 concentrations were estimated from extrapolating the 12-month trend value from December 2022 forward for half a month. Data was obtained from https://gml.noaa.gov/webdata/ccgg/trends/co2/co2_mm_gl.txt (accessed 3 April 2023).

in energy efficiency over time in the absence of any climate policy. We update E_{FFI} to be 36.6 Gt CO_2 yr^{-1} in 2023, which is the estimate of 2022 fossil fuel emissions from the Global Carbon Project (GCP) [23].

$\mu(t)$ is the emissions abatement fraction. In DICE-2016R, net negative emissions ($\mu > 1$) are not allowed until 2160. We relax this assumption, allowing net zero CO_2 emissions ($\mu = 1$) in 2040 and net negative emissions thereafter. While the feasibility of achieving net zero CO_2 emissions in 2040 is debatable [24–26], many PB-IAM scenarios in the IPCC WG3 database have already reached net negative emissions by 2040 [3, 27]. In order to construct sensible transition pathways, we impose an upper limit of $\mu(t) = 0.15t$ for $1 \leqslant t \leqslant 7$ and retain DICE-2016R's maximum allowable abatement of $\mu(t) = 1.2$ for $t \geqslant 8$. We use $\mu = 0.15$ in 2023 rather than DICE-2016R's $\mu = 0.03$ in 2015. A present-day emissions abatement level of 15% can be justified on the basis that some limited emissions mitigation has occurred. Around 10% of global primary energy supply is renewable [28], and a significant coal-to-gas shift has occurred over the last 30 years in the energy sector.

Total CO_2 emissions are given by $E = E_{FFI} + E_{AFOLU}$. E_{AFOLU} is the CO_2 emissions from agriculture, forestry and other land use (AFOLU). DICE-2016R uses an exogenous pathway of AFOLU CO_2 emissions. We replace this with a regression-based relationship of E_{AFOLU} with E_{FFI} and t that is derived from 1202 PB-IAM scenarios from the IPCC WG3 database (supplementary material section 1.3).

2.2. The calibrated FaIR v2.1 climate model

FaIR is described in [19, 29, 30]. Unlike the DICE-2016R climate module, FaIR includes carbon cycle feedbacks simulating the declining efficiency of land and ocean carbon sinks (increasing airborne fraction) with increasing emissions of CO_2. A recent update, DICE-2023R, incorporates FaIR inside its climate module and therefore does include carbon cycle feedbacks. Comparisons with DICE-2016R and DICE-2023R are shown in supplementary figure 6. The version of FaIR v2.1.0 used inside DICE is a reduced version that includes just the carbon cycle and temperature response to forcing (supplementary material section 2).

We produce a 1001 member posterior sample of FaIR parameters from a 1.5 million member prior ensemble. The 1001 ensemble members simultaneously span IPCC assessed ranges of ECS (e.g. 90% of the distribution lying within 2 °C–5 °C), transient climate response (TCR), ocean heat content change from 1971–2018, global mean surface temperature from 1995–2014 relative to 1850–1900, aerosol effective radiative forcing (ERF; 2005–2014 relative to 1750), CO_2 concentrations in 2014 and future warming projected under SSP2-4.5 in 2081–2100 (supplementary material section 3). We verify that FaIR reproduces historical observed warming including its uncertainty (figure 1(a)) and present-day CO_2 atmospheric concentrations (figure 1(b)) when run with historical emissions from 1750 at a 3-year timestep.

As DICE only models CO_2 emissions, non-CO_2 emissions are treated as an external forcing so that the total forcing $F = F_{CO_2} + F_{ext}$. To generate F_{ext} for our scenarios we run FaIR offline using the 1001-member posterior ensemble under SSP2-4.5, SSP1-2.6 and SSP1-1.9 emissions. These three SSP scenarios are used in our study to model Nordhaus' 'welfare optimal', 2 °C and 1.5 °C overshoot scenarios respectively for 1750–2500 [32] (section 2.3) which have similar warming levels to each SSPs. For 2023 onwards we export F_{ext} from each ensemble member and each scenario and use this as an exogenous input to the DICE runs. This captures uncertainty in the strength of non-CO_2 forcing, including aerosols, but not uncertainties in future emissions. We use GCP CO_2 emissions from 1750–2022 and non-CO_2 emissions from the RCMIP dataset [33–35]. For CO_2, we harmonize [36] the CO_2 emissions to ensure a smooth transition between the GCP historical and the SSP future for CO_2.

FaIR v2.1.0 uses the Meinshausen *et al* [37] relationship of ERF from concentrations of CO_2, CH_4 and N_2O which includes radiative band overlaps between gases. As DICE only models CO_2 concentrations explicitly we revert to the logarithmic formula for CO_2 forcing [38]

$$F_{CO_2} = F_{2\times CO_2} \frac{\log(C_{CO_2}/C_{CO_2,\mathrm{ref}})}{\log 2} \quad (3)$$

where C_{CO_2} is the CO_2 concentration in parts per million volume (ppm) and $C_{CO_2,\mathrm{ref}}$ is the pre-industrial concentration. $F_{2\times CO_2}$ is the ERF from a doubling of CO_2 above pre-industrial concentrations. To transition from the Meinshausen formula to the logarithmic formula we calculate an effective $F_{2\times CO_2}$ from each historical ensemble member to use in the corresponding DICE simulation by rearranging (3) and using 2023 values of F_{CO_2} and C_{CO_2}.

For computing the temperature response to ERF, FaIR uses an impulse-response formulation of the well-known n-layer energy balance model [39]. We use $n = 3$, expected to be sufficient to capture short- and long-term climate responses to forcing [19, 40]. Results from the offline historical FaIR runs are saved out for 2023 and used as initial conditions for DICE. The temperatures of the three ocean layers in 2023 are re-baselined such that the uppermost layer (a proxy for global mean near-surface air temperature) is defined to be 0.85 °C above pre-industrial over the 1995–2014 mean, this being the best estimate assessed warming in the IPCC AR6 WG1 [31] and following the treatment of scenario assessment in IPCC AR6 WG3 [3, 27, 41]. The other two ocean layers are adjusted by the same amount that was required to fix the uppermost layer at 0.85 °C, maintaining relative differences.

FaIR uses four atmospheric boxes to model CO_2 concentrations (supplementary material section 2.1). The carbon mass in each box is also saved out of the historical run and used for initialising DICE in 2023. The sum of the atmospheric boxes (a mass anomaly above pre-industrial) and the pre-industrial mass (a probabilistic parameter sampled in [32]) gives the initial atmospheric CO_2 concentration at the start of 2023 (figure 1(b)).

2.3. Scenario construction

The three scenarios (Nordhaus' 'optimal', well-below 2 °C and 1.5 °C overshoot) are differentiated solely by their discount parameters and the SSP scenario chosen to represent their non-CO_2 forcing.

DICE uses Ramsey-style discounting [42] to express future values in today's equivalents. The social discount rate r is

$$r = \rho + \eta g \quad (4)$$

where ρ is the pure rate of time preference, η is the elasticity of marginal utility of consumption and g is per-capita growth in consumption in percent. In Nordhaus' 'optimal' scenario we use the default DICE-2016R parameters of $\rho = 1.5\%$ and $\eta = 1.45$ resulting in social discount rates around 3.1%. The 2 °C scenario uses $\rho = 0.35\%, \eta = 0.35$ and the 1.5 °C scenario uses $\rho = 0.12\%, \eta = 0.12$, resulting in very low social discount rates centred around 1.4% and 0.6% respectively. These parameters have been selected solely to achieve the goals of constructing scenarios that meet the Paris Agreement targets and are not necessarily constructed to be economically meaningful.

3. Results

3.1. CO_2 emissions pathways

Figure 2 shows the headline projections for the three scenarios, which are summarized in table 1. In each scenario, a wide range of allowable CO_2 emissions consistent with the ensemble warming classification are shown. The Nordhaus 'optimal' pathway produces a level of total CO_2 emissions ranging from 5–41 Gt CO_2 yr^{-1} in 2100 (5%–95% range), with a relatively smaller spread in 2050. In contrast, the 2 °C and 1.5 °C scenarios show larger spreads in their 2050 CO_2 emissions (2–24 and −14 to +12 Gt CO_2 yr^{-1} respectively). This suggests that climate uncertainty alone can either demand high levels of net negative emissions or permit substantial residual positive emissions in mid-century. By the end of the century, a majority of 1.5 °C scenarios approach the maximum abatement level allowed in DICE (120% of gross emissions), evidenced by the 5th and 50th percentile being at the same −23 CO_2 yr^{-1} level.

Table 1. Key results from the three scenarios. All correlations are significant at the 1% level.

Variable	Nordhaus 'optimal'	Well below 2 °C	1.5 °C overshoot
CO_2 emissions 2050 (Gt CO_2 yr^{-1})	45 (39–49)	15 (2–24)	2 (−14 to +12)
CO_2 emissions 2100 (Gt CO_2 yr^{-1})	25 (5–41)	−19 (−23 to −5)	−23 (−23 to −13)
Net zero CO_2 year	2129 (2105–2152)	2077 (2053–2094)	2054 (2040–2079)
Social cost of carbon 2023 (2020$ (t CO_2)$^{-1}$)	26 (15–44)	439 (237–934)	1759 (821–4434)
Peak warming (°C relative to 1850–1900)	3.1 (2.7–3.7)	1.8 (1.5–2.2)	1.6 (1.3–2.1)
Warming 2100 (°C relative to 1850–1900)	2.9 (2.4–3.6)	1.7 (1.5–2.0)	1.4 (1.2–1.7)
Effective radiative forcing 2100 (W m^{-2})	5.2 (4.4–5.9)	2.7 (1.9–3.3)	1.9 (1.4–2.6)
ECS/SCC correlation coefficient	.51	.74	.74
ECS/2050 CO_2 emissions correlation coefficient	−.48	−.72	−.76
2014 aerosol forcing/SCC correlation coefficient	−.64	−.60	−.59
2014 aerosol forcing/2050 CO_2 emissions correlation coefficient	.61	.59	.56
Near-term discount rate (%)	3.1 (3.1–3.2)	1.4 (1.2–1.6)	0.6 (0.2–0.8)

The observation that all 1.5 °C and 2 °C pathways follow the emissions abatement upper bound of $\mu(t) = 0.15t$ (emissions lower bound) for the first few periods (figure 2(a)) demonstrates that decarbonizing as rapidly as possible in the near term is welfare-optimal under Paris Agreement long-term temperature constraints.

3.2. Timing of net zero CO_2

The 1.5 °C scenario reaches net zero CO_2 emissions with an ensemble median year of 2054, which is consistent with the C1 scenario category of IPCC AR6 WG3. The well-below 2 °C ensemble has a median net zero CO_2 emissions year of 2077, which is a little later than the IPCC's C3 scenario category. The 'optimal' ensemble does not reach net zero CO_2 emissions this century, but does reach net zero with a median year of 2129. This demonstrates the utility of extending scenarios beyond 2100 to consider longer-term impacts.

3.3. Global mean surface temperature

Global mean surface temperature reaches 2.9 °C above pre-industrial in the 'optimal' pathway, peaking at 3.1 °C in the 22nd century (figure 2(b)). The 2 °C and 1.5 °C scenarios exhibit peak warming this century, consistent with net-zero CO_2 dates well before 2100. The 1.5 °C overshoot ensemble has a peak warming of 1.6 °C. As more than 33% of the ensemble members have a peak warming above 1.5 °C, this ensemble does not meet the IPCC definition of 'low overshoot' (category C1 in [3]) and would fall into the C2 (1.5 °C high overshoot) category. Indeed, it is difficult to avoid overshooting 1.5 °C at all from today's starting level of warming, even under very rapid emissions phase-out scenarios [43]. The 2 °C scenario is within in the definition of C3 from the IPCC (67% of the ensemble remaining below 2 °C).

3.4. Effective radiative forcing

The total median ERF (figure 2(c)) in 2100 is 5.2 W m^{-2} in the 'optimal' scenario, 2.7 W m^{-2} in the 2 °C scenario and 1.9 W m^{-2} in the 1.5 °C scenario. Non-CO_2 forcing pathways were provided from SSP2-4.5, SSP1-2.6 and SSP1-1.9 respectively, though the total ERF is dominated by the CO_2 component. In the 2 °C and 1.5 °C scenarios, the median ERF in 2100 is very similar to the non-CO_2 scenario nameplate forcing in 2100. SSP1-2.6 and SSP1-1.9 were designed to be 'well-below 2 °C' and 1.5 °C-consistent scenarios respectively and our ERF results are therefore consistent with the SSP scenario framework [4].

3.5. Social cost of carbon

The SCC shows a wide uncertainty range for each scenario, with the spread increasing for stronger mitigation (lower discount rates) (figure 2(d)). The 5%–95% uncertainty range is approximately a factor of three (15–44$ (t CO_2)$^{-1}$), four (237–934$ (t CO_2)$^{-1}$) and five (821–4434$ (t CO_2)$^{-1}$) for the 'optimal', 2 °C and 1.5 °C cases respectively (values are reported in 2020 US dollars). Our findings that lower discount rates show more spread in the relative range of SCC when climate uncertainty is taken into account is consistent with [5, 14]. Our hypothesis for this is that for higher discount rates, some of the long-term costs of climate damages are discounted away leading to a greater spread in long-term warming (figure 2(b)), a lesser spread in near-term mitigation effort (figure 2(a)), and hence a smaller spread in SCC.

3.6. Relationships between climate sensitivity, aerosol radiative forcing and social cost of carbon

There is a strong positive correlation between SCC and ECS [11], particularly in 1.5 °C and 2 °C mitigation scenarios (figure 3(a)). This follows from the fact that if climate sensitivity is high, emissions need to be abated more aggressively to maintain a similar

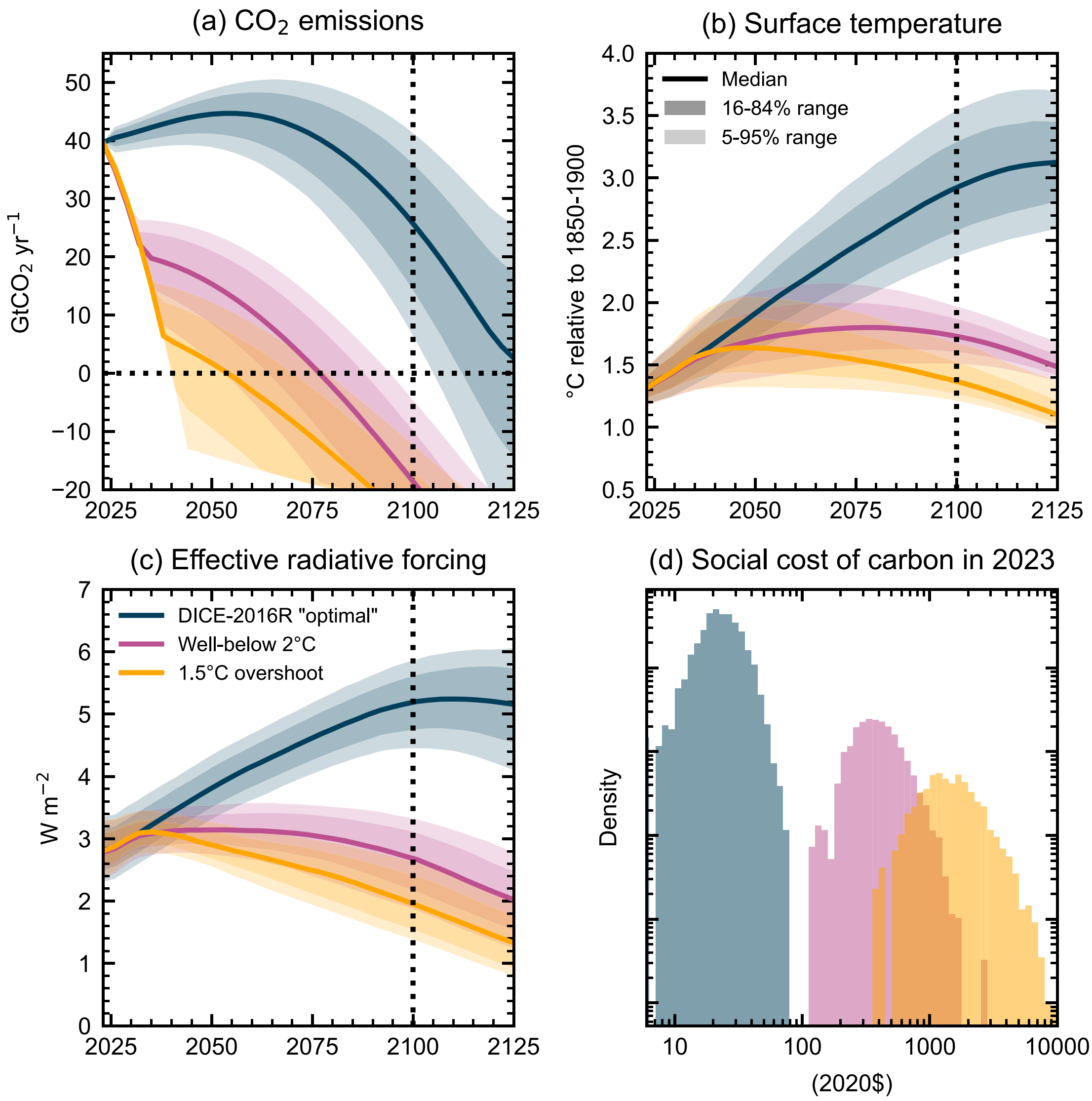

Figure 2. Emissions, climate and economic projections for three scenarios using FaIR-DICE. (a) CO_2 emissions from energy and industrial processes for the 'optimal' (blue), 2 °C (pink) and 1.5 °C (yellow) scenarios. (b) Temperature projections. (c) Total effective radiative forcing projections. (d) Histogram of year-2023 SCC (in 2020$) on a log-log scale. In (a)–(c), light shading shows 5%–95% range, darker shading shows 16%–84% range and solid lines show ensemble medians.

warming level (and similar level of associated climate damages) compared to a case where climate sensitivity is low. Stronger abatement necessitates a higher social cost of carbon. This also confirms that reducing climate sensitivity uncertainty can lead to better informed estimates of the social cost of carbon and net present benefits [44].

The negative correlation between ECS and net CO_2 emissions in 2050 is shown in figure 3(b), showing that stronger emissions abatement is required if climate sensitivity is high as a corollary of the discussion above. In 2050, the maximal level of mitigation (net emissions of -14 $GtCO_2$ yr^{-1}) is reached in several of the 1.5 °C ensemble members. These tend to be clustered towards higher values of ECS, though moderate ECS between 3 and 4 °C could still require very high levels of abatement.

Alongside climate sensitivity, present-day aerosol ERF is a strong predictor of 21st century warming [45, 46]. In figure 3(c) there is a negative correlation between aerosol ERF in 2014 and social cost of carbon, and in figure 3(d) a positive correlation between aerosol ERF and 2050 CO_2 emissions. These are the opposite signs to the correlations related to ECS in figures 3(a), (b), and is due to ECS and aerosol ERF being negatively correlated in observationally consistent climate simulations [30]. A strong negative aerosol forcing is associated with a sensitive climate, as historical greenhouse gas warming has been offset by cooling aerosols. Aerosol forcing may be easier to constrain than ECS, and this indicates there are also net present economic benefits to reducing uncertainty in aerosol forcing [46].

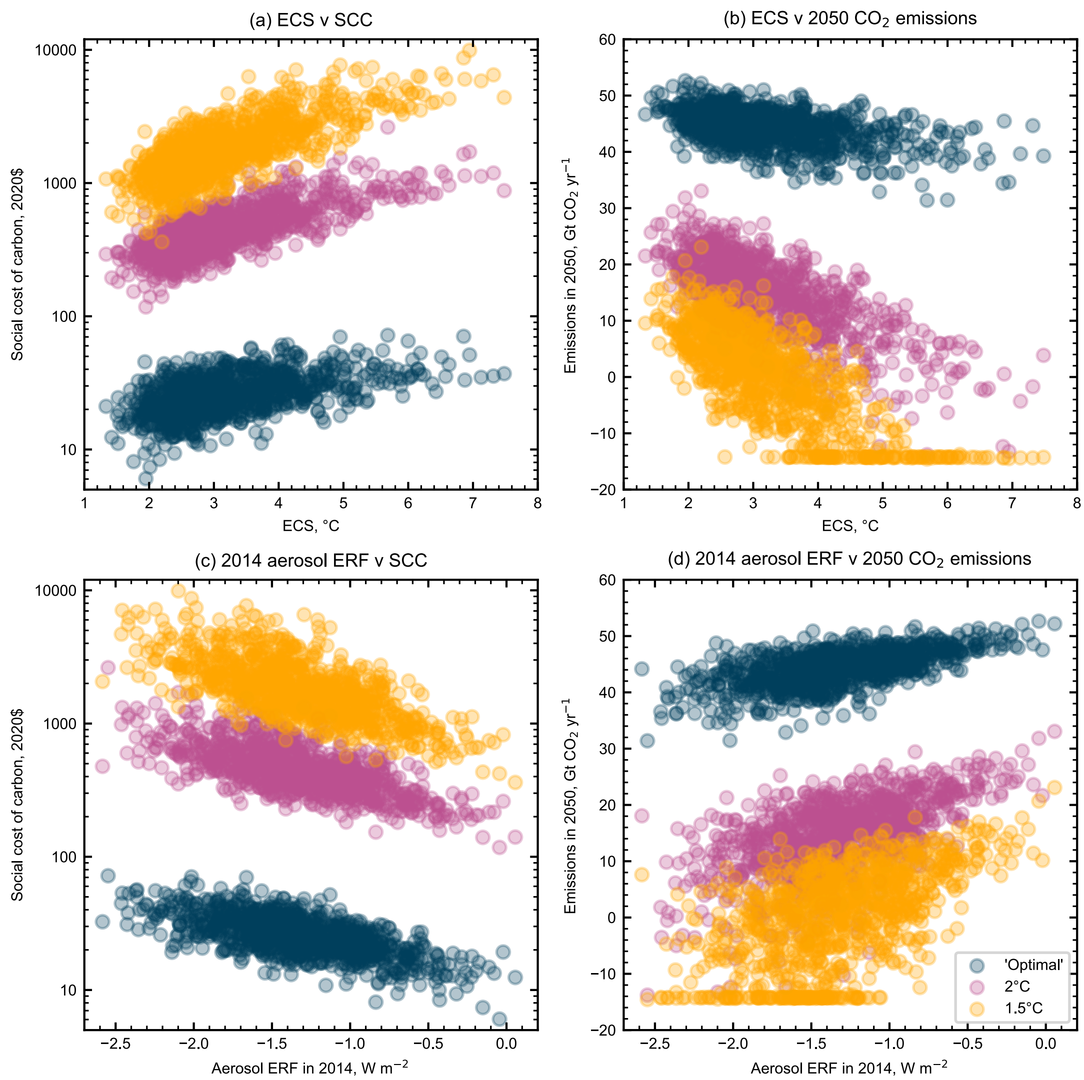

Figure 3. Relationship between parameters. (a) ECS versus social cost of carbon; (b) ECS versus CO_2 emissions in 2050; (c) 2014 aerosol ERF versus social cost of carbon; (d) 2014 aerosol ERF versus CO_2 emissions in 2050.

4. Discussion and conclusions

We show that the optimal CO_2 emissions pathways and social cost of carbon are sensitive to physical climate uncertainty, including ECS and present-day aerosol forcing. Due to climate uncertainty alone, a range of CO_2 emissions pathways could be consistent with a 1.5 °C future, ranging from requisition of a high level of net negative emissions to allowance of a substantial level of residual positive emissions. However, there are few plausible climate states forgiving enough to allow achieving Paris-compliant climate goals (well-below 2 °C or 1.5 °C) without net negative emissions in the second half of the century, evidenced by the emissions in the 95th percentile of the 2 °C scenario being below zero in 2100 (figure 2(a)). Net negative emissions in 2100 are at −23 Gt CO_2 yr^{-1} in more than half of the 1.5 °C ensemble, this being the maximum abatement of 120% of gross emissions assumed in DICE. We note that this level of net negative emissions may not be achievable in reality due to feasibility constraints [25, 47].

There is a strong positive correlation between SCC and ECS, and negative correlation between aerosol forcing and ECS, where high climate sensitivity or strong aerosol forcing leads to aggressive abatement being socially optimal, and hence leads to a higher SCC. Owing to this, there is a relationship between climate sensitivity (or aerosol forcing) and emissions which can be contextualised as a climate-abatement feedback. This feedback is straightforward to demonstrate in DICE but is missing from PB-IAMs, at least when being used to construct emissions scenarios for IPCC [3] and policymaking.

In PB-IAMs, there exists the opportunity to consider the processes under which climate change causes economic losses (or benefits). Climate change may lead to impacts on energy generation [48], heating and cooling demand [10], labour productivity, agriculture, bioenergy, and sea-level rise [5], in addition to remedial costs resulting from climate catastrophes that will likely increase in severity and frequency [49]. While in some cases difficult, incorporation of these effects into PB-IAMs will lead to more realistic emissions scenarios, particularly in high emissions pathways where high levels of warming increases climate damages, reduces GDP and consumption, and hence is a negative feedback onto emissions [15].

Our 'optimal' scenario has a lower median SCC at \$26 than DICE-2016R which is \$31 in 2015\$ (\$34 in 2020\$). This is despite the lower effective discount rate in our study (3.1% versus DICE-2016R's 4.25%), driven by lower near-term per-capita consumption growth rates. An updating and recalibration of the economic assumptions used in DICE partly accounts for the differences, particularly our lower future population projections compared to DICE-2016R (section 2.1). The social discount rates required to construct our scenarios are significantly lower than those used in the literature for mitigation scenarios. Our 2 °C scenario uses the same discount rate, by coincidence, as Stern's assessment of the costs of climate change [50]. As the social discount rate relies on the growth in consumption, and consumption is affected by both by investment diverted towards emissions abatement and climate damages, the near-term discount rate is affected by climate uncertainty in our scenarios and is not a single value across all ensemble members (table 1). Our analysis shows that meeting 1.5 °C with limited overshoot would require a very high carbon price, with a median estimate of \$1759 $(\mathrm{t\ CO_2})^{-1}$ and 95th percentile of \$4434 $(\mathrm{t\ CO_2})^{-1}$.

The social discount rate is one of the most contested and controversial parameters in climate economics [51]. Nordhaus [20] suggests the discount rate should be a continuation of the real risk-free interest rate in the recent past, and opts for a discount rate in DICE-2016R of 4.25%. Stern [50] argues that the discount rate is a subjective valuation of the welfare of future generations compared to the present, and is a normative choice, putting forward an ethical basis for lower discount rates [52]. A recent evaluation of the SCC for recommendation to US policymakers uses a preferred discount rate of 2% [5]. Our use of the discount rate as a control dial on the acceptable level of future warming puts us more in the 'normative choice' camp of Stern. Regardless of viewpoint, the fact that three very different scenarios are achievable by modifying the discount rate confirms that discounting is one of the most influential parameters controlling emissions pathways and social cost of carbon [11, 12, 53].

In every ensemble member, a cost-benefit optimal emissions pathway is constructed, with the assumption that in each of these 1001 different 'worlds' the social planner knows the state of the climate system in advance. It is likely that as climate change unfolds over the coming decades, uncertainty in emergent parameters in the climate system such as the ECS will reduce; we will simply have more observational evidence to draw upon [44]. This reduction in uncertainty or updating of knowledge over time would be a useful future analysis. Another additional avenue of future study is the relative contributions of socioeconomic (e.g. growth in population, carbon intensity, total factor productivity, discount rate) and climate uncertainties on total variation in social cost of carbon and emissions pathways, including their time dependence. Although we include their forcing contributions and uncertainties and report on the dependency of SCC on aerosol ERF, non-CO_2 emissions are not calculated endogenously. Doing so from a process perspective would require modelling of cost-abatement curves in several sectors and substantially increase the complexity of the analysis, but relationships between key important non-CO_2 forcers and fossil CO_2 could be sought from a large database of PB-IAM scenarios [54, 55] at a relatively low computational cost, as we do for land-use CO_2. Notwithstanding its simplicity, this study highlights the importance of incorporating climate uncertainty into IAM-derived emissions scenarios.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.8155285 [56].

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