ENVIRONMENTAL RESEARCH
LETTERS

LETTER • **OPEN ACCESS**

Beyond the single-basket mindset: a multi-gas approach to better constrain overshoot in near term warming

To cite this article: Julie S Miller *et al* 2024 *Environ. Res. Lett.* **19** 094011

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
24 January 2024

REVISED
7 June 2024

ACCEPTED FOR PUBLICATION
17 July 2024

PUBLISHED
8 August 2024

LETTER

Beyond the single-basket mindset: a multi-gas approach to better constrain overshoot in near term warming

Julie S Miller[1,*], Gabrielle B Dreyfus[1], John S Daniel[2], Stephen Willis[3] and Yangyang Xu[3]

[1] Institute for Governance & Sustainable Development, Washington, DC, United States of America
[2] National Oceanic and Atmospheric Administration, Chemical Sciences Laboratory, Boulder, CO, United States of America
[3] Department of Atmospheric Sciences, Texas A & M University, College Station, TX, United States of America
[*] Author to whom any correspondence should be addressed.

E-mail: jmiller@igsd.org

Keywords: carbon dioxide, methane, overshoot, near-term warming, climate mitigation

Supplementary material for this article is available online

Abstract

The remaining carbon budget framework tracks progress towards the Paris Agreement's goal to limit longer-term warming to well below 2 °C, but no analogous framework exists for constraining mid-century warming. Established single-basket methods of combining gases into CO_2-equivalents using Global Warming Potentials (GWPs) lead to ambiguity over what combination of short- and long-lived emissions reductions are needed because they obscure the distinct warming impacts of each. We investigate to what extent a multi-basket approach that separates short-lived and long-lived pollutants can better estimate the likelihood for emission pathways to meet a near-term warming goal. We develop logistic regression models to categorize IPCC emission pathways (AR6) based on whether they exceed a mid-century temperature threshold. We focus on two baskets, using CO_2 for long-lived and methane (CH_4) for short-lived gases. For comparison, we consider several single-basket approaches (e.g. GWP100, GWP20, GWP*). We further apply our framework to a synthetic dataset covering a broader emissions space. Across both datasets, the two-basket outperforms all single-baskets. Using an illustrative near-term goal (1.7 °C), the two-basket approach reduces the magnitude of overshoot by a factor of 7 compared with the traditional single-basket. The two-basket's advantage is smaller with the AR6 pathways, which we attribute to the high correlation between CO_2 and CH_4 emissions and confounding effects from other pollutants. Our results indicate that the two-basket approach better constrains overshoot magnitude, particularly if future emissions deviate from the AR6 assumption of correlated CO_2 and CH_4 reductions. Our approach allows the determination of a metric value and reduction target in the context of a chosen set of scenarios and temperature threshold; the outcome is a near-term methane-specific emissions budget that can be adopted by decisionmakers in a way that is analogous and complementary to the carbon budget. Future work could consider a third basket for very short-lived pollutants.

1. Introduction

The remaining carbon budget for staying below 1.5 °C could be exhausted within five years or less (Lamboll *et al* 2023). There is growing consensus that minimizing overshoot by slowing the warming rate in the coming decades is critical to reducing losses and damages to human and natural systems and the risk of irreversible changes (Future Earth *et al* 2023, Lee *et al* 2023), including the risk of triggering irreversible tipping points (Armstrong Mckay *et al* 2022, Wunderling *et al* 2023, Lenton *et al* 2023). As such, limiting overshoot could be considered an implicit near-term temperature goal. Approaches that favor longer-term impacts, i.e. 100 year global warming potential (GWP100), obscure policy-relevant information on the role of non-CO_2 climate pollutants on the timing, duration, and magnitude of the anticipated overshoot of 1.5 °C.

Identifying emissions pathways that have high likelihood of staying within the near- and longer-term temperature limits requires the development of a more inclusive framework that considers the distinct warming impacts of short-lived and long-lived climate pollutants (Shindell *et al* 2017, Fesenfeld *et al* 2018). The conventional framework for assessing emissions pathways adopts a single-basket (1B) approach, in which all greenhouse gas (GHG) emissions are converted into CO_2 equivalents (CO_2-eq), predominantly using GWP100, and very short-lived pollutants such as sulfate aerosols and volatile organic compounds are largely ignored. While 1B approaches offer efficiency for least-cost optimization by providing a simple exchange value between pollutants, they create ambiguity in warming outcome because scenarios having the same CO_2-eq emissions pathways, but with different mixes of short- vs. long-lived pollutants, can lead to very different warming trajectories (Fuglestvedt *et al* 2000, Daniel *et al* 2012). This ambiguity, especially when using GWP100, prevents an accurate evaluation of which mitigation strategies would be most effective at limiting warming over the next several decades to stay within a near-term temperature limit.

Furthermore, a limitation of the 1B approach is that it trades off nearer-term and longer-term impacts. For example, scenarios focused on meeting the longer-term Paris temperature goal (i.e. limiting the temperature increase this century to a maximum of 1.5 °C, or allowing for a temporary overshoot of 1.5 °C while always holding temperature this century to 'well below' 2 °C, Schleussner *et al* 2022) using 1B approaches often 'overshoot' these temperature targets in the mid-century by up to 0.3 °C (Lee *et al* 2023). Such levels of sustained overshoot increase the risk climate change impacts could be much larger than anticipated based on using the 1B cumulative emissions consistent with meeting the long-term climate target. Greater climate impacts fall disproportionately on the poorest and most vulnerable people (IPCC 2022). A key feature of climate metrics is their implications for climate justice and equity principles, specifically the mandate to protect the vulnerable (Dooley *et al* 2021).

Climate pledges and stocktaking almost exclusively use the 1B approach based on CO_2-eq, despite increasing calls for separate reporting of short- and long-lived pollutants due to their differential impacts (Jackson 2009, Balcombe *et al* 2018, Allen *et al* 2022), in particular the potential for short-lived pollutant mitigation to slow global warming in the near term (Xu and Ramanathan 2017, Dreyfus *et al* 2022, Cohen-Shields *et al* 2023). Wood *et al* (2023) call for separate targets and accounting for short-lived pollutants using GWP20 or GWP* (an alternative 1B metric that favors rate of change in short-lived pollutants, e.g. Cain *et al* 2019) as part of a framework to measure near-term impacts. Further, net-zero GHG target setting using CO_2-eq lack clarity and imply trade-offs of individual GHGs, especially when trading residual non-CO_2 emissions against negative CO_2 emissions (Rogelj *et al* 2021, Buck *et al* 2023) and are unable to incorporate the fact that mitigation strategies targeting long- versus short-lived gases are not interchangeable (Shoemaker *et al* 2013, Dreyfus *et al* 2022).

1B approaches allow for trading between mitigation measures to optimize mitigation costs. However, their shortcomings have been recognized since GWP was first proposed (Intergovernmental Panel on Climate Change 1990, Balcombe *et al* 2018). Notably, the Montreal Protocol did not adopt an approach that allowed for trading between ozone-depleting substance groups, which are characterized by substantially different lifetimes in many cases. Daniel *et al* (2012) detailed how this multi-basket approach reduced ambiguity and avoided the potential for greater ozone depletion.

Given the well-recognized ambiguities and limitations in assessing warming outcomes using a 1B approach, we investigate to what extent a multi-basket approach would provide more robust estimates of the chances for certain emission pathways to meet climate targets. As a proof of concept, here we focus on two baskets (2B), using CO_2 as a proxy for long-lived gases and methane (CH_4) for short-lived gases. This work aims to refine CO_2 and CH_4 emissions metrics to *probabilistically* distinguish emission pathways with a higher chance of meeting a given near-term warming threshold and limiting the magnitude of overshoot in the interim of reaching long-term climate stabilization. This is in line with Allen *et al* (2022) in recognizing the need to track long- and short-lived pollutants separately, but we do not aim to *deterministically* quantify the warming trajectories based on emission pathways. To establish this probabilistic approach, we built a suite of logistic regression models containing one or more predictors (emission based) to distinguish between emission pathways that go above or stay below a set warming threshold.

Our refined implementation of the 2B approach identifies different time periods for different baskets that can collectively best predict warming outcomes. While 1B approaches generally require choosing a single time horizon for all emissions because they are represented in an aggregated equivalent quantity by design, our 2B approach allows for a CH_4-specific emissions metric and time horizon optimized for a given climate goal. By identifying metrics and emissions levels for each basket that are specific to meeting a particular climate goal, this framework is conceptually analogous to how the remaining carbon budget is formulated, where the chosen long-term warming threshold determines the allowable remaining cumulative CO_2 emissions.

2. Methods

2.1. Data

Two sets of future climate scenarios are used in the analysis. One set is from the SSP scenarios used in the Sixth Assessment Report (AR6) of the International Panel on Climate Change (IPCC) (SM 1.1). Global averaged surface air temperatures (GSAT), and corresponding CO_2 and CH_4 emissions data, are taken from the AR6 Scenario Explorer and Database hosted by IIASA, release version 1.1 (Byers *et al* 2022). The second set, the 'synthetic' scenarios, were generated for this work using absolute global temperature change potentials (AGTPs; SM 1.2; Miller *et al* 2024).

2.2. Setting mid-century warming goals to construct emission pathway categories

We bin all AR6 and synthetic pathways into two categories based on whether they stay below or exceed a mid-century (MC) temperature threshold. Additionally, we consider the MC threshold both with and without an end-of-century (EoC) constraint (figures 1(B) and (D)) to account for the Paris Agreement long-term temperature goal.

These categories are used in logistic regression-based classification models (section 2.4) to predict pathway category based on each pathway's emissions. The construction of contrasting categories aims to test which accounting approach, i.e. 1B or 2B, better predicts whether an emission pathway would stay below the set warming threshold.

We divide AR6 pathways into two categories that stay below or exceed 1.8 °C in 2050 (MC threshold in figure 1(C)). We also select pathways that are below 1.8 °C in 2095 and categorize them based on staying below or exceeding 1.7 °C in 2050 (MC + EoC threshold in figure 1(D)). These illustrative warming thresholds are chosen to allow for a statistically meaningful total number of scenarios and relatively even numbers between the two categories. The general results, however, do not depend on the choice of warming thresholds. Our criteria create contrasting categories that are similar to the category designations of the AR6 pathways (Riahi *et al* 2022), such as C1-'below 1.5 °C (>50%) with no/limited overshoot' and C2-'below 1.5 °C (>50%) after a high overshoot', but capture a greater diversity of pathways, including those from C3-'Likely below 2 °C (>67%)' and C4-'Below 2 °C (>50%)' (SM 2 and figure S1).

Similarly, we divide synthetic pathways into roughly equal-sized categories that stay below or exceed a 2.0 °C threshold in 2050 (figure 1(A)). We repeat the analysis with a subset of pathways limited to those below 1.9 °C in 2095, and categorized with a 1.8 °C threshold in 2050 (figure 1(B)).

2.3. Emissions metrics for 1B and 2B models

We first adopt the traditional 1B metric, in which we aggregate the cumulative CO_2 and CH_4 emissions into CO_2-equivalents using GWP100 = 27.9 (Smith *et al* 2021a). We also consider alternative 1B renderings that were designed to better account for near-term warming impacts using GWP20 and GWP* (table 1).

For both 1B and 2B approaches, we use the cumulative sum of annual CO_2 emissions starting in 2000 as a metric to describe CO_2's contribution to future warming. The cumulative sum CO_2 emissions has a well-established relationship with warming (Collins *et al* 2013). Using a starting year prior to 2000 does not change our results since all pathways are identical before 2000 and our model is constructed to be linear.

For the 2B model, we test two CH_4 metrics separately from CO_2's metric. First, we use the cumulative sum of annual CH_4 emissions over the prior 44 years (lag44). We choose 44 years as the aggregation period of CH_4 emissions because it best predicted CH_4's contribution to future warming in our linear regression models ($R^2 = 0.93$; SM 3). As an additional CH_4 metric, we consider the 20 year change in annual emissions (delta20), following the convention used for GWP* (Allen *et al* 2018, Cain *et al* 2019). While we find that emission changes over 31 years best predicted warming rates for the scenarios considered here, we opted for the shorter 20 year window based on our recognition that pathways with abrupt cuts to methane by 2030 were a key feature of AR6 pathways identified as limiting overshoot by 2050 (SM 4).

2.4. Evaluation of 1B and 2B models

We build 1B and 2B logistic regression models to distinguish pathways that stay below or exceed a temperature threshold using the 'glm' function in *R*. The 1B logistic models contain one aggregated predictor: cumulative summed CO_2 annual emissions plus cumulative CH_4 in CO_2-eq as described in section 2.3 and table 1. The 2B logistic models contain two predictors: (1) cumulative summed CO_2, and (2) one CH_4 emissions metric—either lag44 or delta20. We did not include both lag44 and delta20 in the same model due to their high covariance in the AR6 pathways. We thus examined two potential 2B models. We also consider a model containing only cumulative CO_2 emissions to determine the extent to which a separate CH_4 predictor improves its predictive power.

Because CO_2 and CH_4 metrics (and their combinations) are constructed to identify pathways meeting a climate threshold rather than predicting warming in all years, there is flexibility in assigning *specific* time periods for *individual* metrics. For each of the above metrics and targets, we identify the year when the ratio of a metric's between-category variance to within-category variance was maximized (i.e. a higher ratio indicates a cleaner separation between

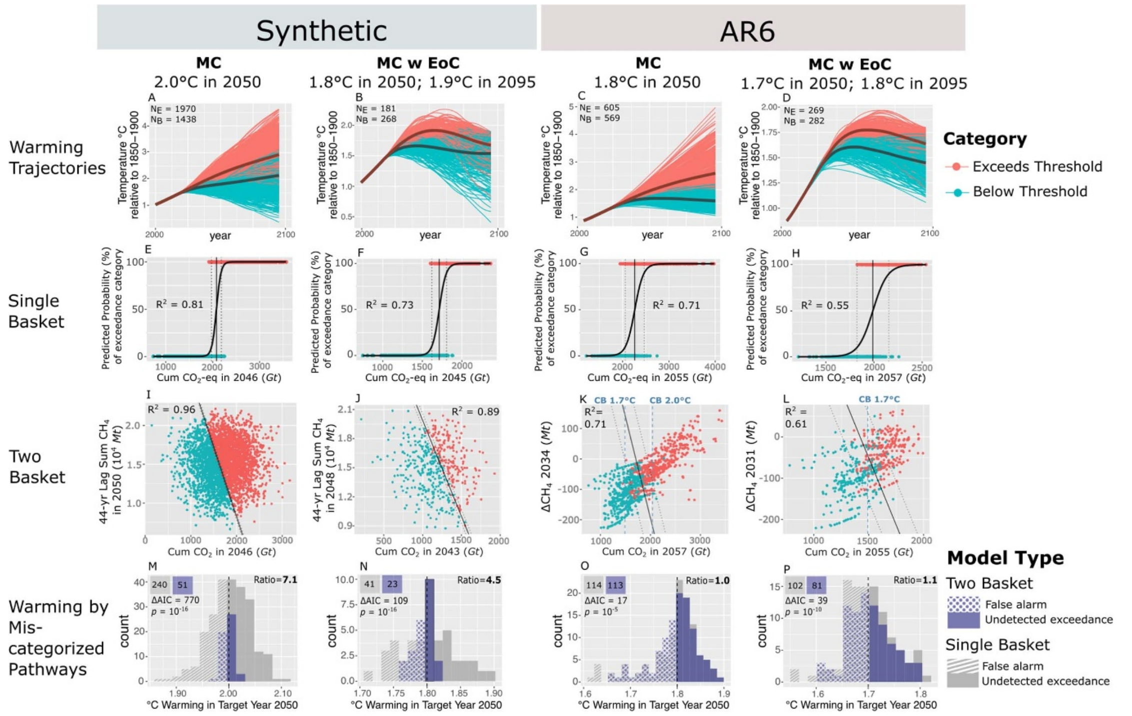

Figure 1. Warming trajectories for synthetic and AR6 pathways, and results from the GWP100 single-basket (1B) model and the best-performing two-basket (2B) model. (A)–(D) Warming trajectories colored according to category. Heavy lines are category means. N_E and N_B are the number of pathways in the exceeds-threshold and below-threshold categories, respectively. (A), (E), (I), (M) All synthetic pathways separated by a mid-century (MC) threshold only. (B), (F), (J), (N) A subset of synthetic pathways constrained by an end-of-century (EoC) threshold and separated by a mid-century threshold. (C), (G), (K), (O) All AR6 pathways separated by a mid-century threshold only. (D), (H), (L), (P) The subset of AR6 pathways constrained by an end-of-century threshold and separated by a mid-century threshold. (E)–(H) Logistic curves for the 1B models with data points from each pathway. (I)–(L) Logistic results of the 2B model plotted in 2D, with cumulative CO_2 (starting from 2000 and ending in various years) on the *x*-axis and the best-performing CH_4 metric on the *y*-axis. In (E)–(L), the solid line indicates the 50% chance of belonging to the exceeds-threshold category, and dotted-lines are the 10% and 90% predicted probabilities. R^2 of the corresponding model is reported. (K), (L) Blue vertical dashed lines indicate carbon budget (CB, cumulated starting from 2000) for a 50% likelihood of staying below the indicated temperature (Forster *et al* 2023). CB amounts are the sum of 2000–2019 CO_2 emissions from LULUCF (Land Use, Land-Use Change and Forestry) and FFI (Fossil Fuel and Industry) sources (742 GtCO2; Smith *et al* 2023) and the remaining carbon budget in 2020 given in the post AR6 scenario (table 7 in Forster *et al* 2023). (M)–(P) Histograms showing the range of warming levels in the pathways miscategorized by the 1B and 2B models (grey and purple, respectively). Vertical dashed line indicates the warming goal in 2050; pathways to the right of this line are missed detections of overshoot (solid bars) and pathways to the left are overshoot false alarms (textured bars). The number of miscategorized pathways for each model is shown in the squares in the upper-left. Two metrics comparing 1B and 2B models are reported: ΔAIC is AIC_{1B}—AIC_{2B}, a measure of model performance, with larger values depicting the advantage of the 2B model; and a *p*-value resulting from an analysis of model deviance testing significant difference between models. The exceedance ratio reported in the upper right in bold is the ratio of the maximum degrees of undetected exceedance of the 1B vs. 2B models (solid bars to the right of the temperature threshold), with the larger values indicating an advantage of the 2B model relative to the 1B.

categories). We conduct this selection procedure for each metric separately, such that the time period for summing cumulative CO_2 is allowed to differ from the time period during which the CH_4 emissions are derived (lag44 or delta20). In the 1B cases, we use the same procedure to identify the optimal time period for the summed CO_2-eq.

We assess model performance using Akaike Information Criterion (AIC), a goodness-of-fit metric that estimates how much variation is explained by the model, and R^2 (SM 5). We also discuss model results in terms of their errors, or mis-categorizations. There are two types of mis-categorizations: (1) false negatives, in which the model mis-categorizes a pathway as below-threshold when it is an exceedance (missed exceedance); and (2) false positives, in which the model mis-categorizes a pathway as above-threshold when it is below (false alarm). False negative pathways raise the magnitude of maximum overshoot, and these errors are therefore most relevant to the model's utility in constraining overshoot.

3. Results

3.1. Comparison of 2B vs. 1B models

For both datasets and all categorizations, including for IPCC's C1 and C2 categories (figure S1; SM 2), the best-performing 2B model predicts a reduced or equal warming magnitude above the mid-century threshold relative to the 1B scaled by GWP100 (figure 2; figures 1(M)–(P)). The best 2B model better distinguishes categories than any of the

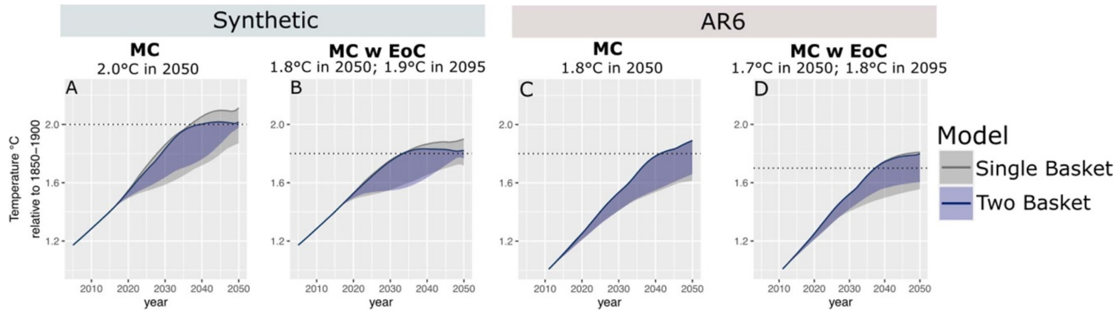

Figure 2. Warming trajectories up to 2050 from pathways miscategorized by the GWP100 single-basket (1B, grey) and two-basket (2B, purple) models. Models applied to (A), (B) synthetic and (C), (D) AR6 datasets, with corresponding temperature thresholds indicated above each plot, as in figure 1, and by the horizontal dotted lines. Shaded area contains the upper and lower bounds of temperatures in the miscategorized pathways from each model (individual pathways not shown). Area above the dotted line indicates when and to what extent miscategorized pathways exceed the 2050 warming threshold, which are presented in the histograms in figure 1. Synthetic data temperatures are about 0.2 °C warmer than AR6 temperatures likely due to only including CO_2 and CH_4 and excluding other positive and negative climate pollutants.

Table 1. Summary of all 2B and 1B models and their predictors. Predictors are listed in bold; the specific year for each predictor is chosen because it best distinguished between categories. Under the predictor(s) is each model's AIC score and R^2; AIC scores are only comparable for a given dataset and temperature target combination, i.e. within a column. The best performing model per dataset and temperature target combination is highlighted in green, which has the lowest AIC score.

	Models	Synthetic 2.0 °C in 2050	Synthetic 1.8 °C in 2050; 1.9 °C in 2095	AR6 1.8 °C in 2050	AR6 1.7 °C in 2050; 1.8 °C in 2095
2B	**44 yr lag sum CH_4+ cum CO_2**	**44 yr-CH_4(2050) + CO_2(2046)** 221; 0.96	**44 yr-CH_4 (2048) + CO_2(2043)** 81; 0.89	**44 yr-CH_4 (2059)+ CO_2 (2057)** 566; 0.71	**44 yr-CH_4 (2043)+ CO_2 (2055)** 386; 0.56
	20 yr ΔCH_4+ cum CO_2	**ΔCH_4 (2035) + CO_2 (2046)** 714; 0.87	**ΔCH_4 (2034) + CO_2(2043)** 151; 0.79	**ΔCH_4 (2034)+ CO_2 (2057)** 552; 0.71	**ΔCH_4 (2031)+ CO_2 (2055)** 351; 0.61
1B	**GWP100** $cumCO_2 + cumCH_4{}^* GWP_{100}$	**CO_2-eq (2046)** 991; 0.81	**CO_2-eq (2045)** 191; 0.73	**CO_2-eq (2055)** 569; 0.71	**CO_2-eq (2057)** 390; 0.55
	GWP20 $cumCO_2 + cumCH_4{}^* GWP_{20}$	**CO_2-eq (2047)** 541; 0.90	**CO2-eq (2045)** 133; 0.82	**CO_2-eq (2054)** 594; 0.69	**CO_2-eq (2056)** 422; 0.51
	44 yr lag GWP100 $cumCO_2$ + (44 yr lag sum $CH_4{}^* GWP_{100}$)	**CO_2-eq (2046)** 991; 0.81	**CO_2-eq (2045)** 191; 0.73	**CO_2-eq (2056)** 565; 0.71	**CO_2-eq (2058)** 390; 0.55
	44 yr lag GWP20 $cumCO_2$ + (44 yr lag sum $CH_4{}^* GWP_{20}$)	**CO_2-eq (2047)** 541; 0.90	**CO_2-eq (2045)** 133; 0.82	**CO_2-eq (2056)** 586; 0.70	**CO_2-eq (2060)** 422; 0.51
	GWP* $cumCO_2 + cum(CH_{4(t)}{}^* GWP_{100}{}^* 0.25^* 1.13 + 20yr\Delta CH_4{}^* GWP_{100}{}^* 0.75{}^* 1.13^* 100/20)$	**CO_2-eq (2047)** 819; 0.85	**CO_2-eq (2045)** 167; 0.77	**CO_2-eq (2050)** 630; 0.67	**CO_2-eq (2047)** 445; 0.49
	CO_2 only $cumCO_2$	**CO_2 (2046)** 1744; 0.67	**CO_2 (2043)** 330; 0.51	**CO_2 (2057)** 573; 0.70	**CO_2 (2055)** 388; 0.55

Calculation for GWP* from (Smith *et al* 2021b).

1B models, including those using GWP100, GWP20, or GWP* (table 1; figure 1), according to model metrics AIC and R^2. The number of miscategorized scenarios is always smaller when using the best 2B model, regardless of dataset (figures 1(M)–(P)).

The 2B model's advantage over the 1B approach is particularly substantial when using the synthetic scenarios (figure 1, left two columns). The 2B model had up to 5 times fewer mis-categorizations than the 1B model (figure 1(M)). The histograms in the bottom row of figure 1 show both types of mis-categorizations: pathways to the right of the threshold are missed detections of threshold exceedance (i.e. false negatives) and pathways to the left are false alarms (i.e. false positives). Relative to the 1B model, the 2B models reduced the magnitude of mid-century overshoot (°C in 2050) in the miscategorized pathways by a factor of 4.5 and 7.1 with and without an EoC constraint, respectively (cf 'Ratio' in figures 1(M) and (N)). This 'exceedance ratio' is the ratio of the maximum warming level above threshold for the 1B vs 2B models, with larger values indicating the advantage of the 2B model relative to the 1B in limiting mid-century warming above a temperature goal.

There is a smaller advantage for the 2B model when using the AR6 data than the synthetic data (figure 1, right columns). The 2B models reduce overshoot magnitude of the miscategorized pathways only by a factor of 1.1 with an EoC constraint (Exceedance Ratio; figure 1(P)). However, the miscategorized pathways from the 1B and 2B models predict nearly the same overshoot magnitude without an EoC constraint (Exceedance Ratio; figure 1(O)). The weaker superiority of the 2B approach when using the AR6 data is explored in section 3.2.

Performance of the 1B models also depend on the dataset. Using the synthetic dataset, the GWP20 model outperforms all other 1B models, including GWP*; the GWP100 is the worst performing 1B model, but it still outperforms the CO_2-only model (table 1). When applied to the AR6 dataset, the GWP100 model is the best performing 1B model, and GWP* is the worst performing, below even the CO_2-only model. We note that the AR6 dataset, unlike the synthetic dataset, includes other gases and pollutants, which may influence the year with greatest separation between categories identified for the 1B models.

The best-performing 2B model using AR6 pathways incorporates the delta20 metric (table 1; Y-axis label in figures 1(K) and (L)), whereas the model containing the lag44 metric performs best when using the synthetic data (table 1; figures 1(I) and (J) note the Y-axis label). In each of the 2B models, the target year for CH_4 is different from that for cumulative CO_2, and varies according to the specific scenarios and category definition (table 1).

While it may be tempting to use the slope of the solid black line in figures 1(I)–(L) to combine CH_4 and CO_2 into a 1B model, we note that the slope is dependent on the magnitude and timing of warming thresholds and metrics chosen (e.g. lag44, delta20). Furthermore, when seeking to simultaneously meet near-term and longer-term temperature goals, adding the remaining carbon budget constraint (figures 1(K) and (L)) imposes an additional restriction on potential trading between baskets that would be obscured if collapsed into a single basket.

3.2. Causes of differences between synthetic and AR6 results

3.2.1. Confounding by species other than CO_2 and CH_4

To investigate whether the weaker advantage of the 2B models when using the AR6 dataset could be due to the confounding influence of all other species, we repeated our analysis in their absence (SM 6). Following the same procedure outlined above (sections 2.3 and 2.4), we run both forms of the 2B models and the GWP100 1B model.

Models fit to the warming driven only by AR6's CO_2 and CH_4 emissions trajectories as calculated with the AGTP approach (hereafter AR6 CO_2/CH_4 only) perform better than the models fit to the full AR6 warming outputs (contrasting R^2 in figures 3(C)–(F) with figures 1(G), (H), (K) and (L). Consistent with a better overall fit for all models, miscategorized pathways from both 1B and 2B models had a smaller overshoot size when applied over AR6 CO_2/CH_4 only data (contrasting figures 3(G), (H) with figures 1(O), (P)).

The relative advantage of the 2B model also increases for the AR6 CO_2/CH_4 only dataset. The 2B model predicts lower overshoot by a factor of 1.7 (2.2) relative to the 1B model with (and without) an EoC constraint (figures 3(G) and (H)), which is substantially larger than for the original AR6 data at 1.1 and 1.0, respectively (figures 1(O) and (P)). These results confirm that accounting for CO_2 and CH_4 in separate baskets reduces the chances of mis-categorizing pathways that exceed the near-term warming threshold and indicate that the focus on these two gases is justified. It further shows that efforts to incorporate other gases into the multi-basket approach offer the potential for identifying pathways that avoid overshoot with even more precision. It is also notable that the advantage of the 2B approach remains substantially weaker, even in the simplified case of considering only CO_2 and CH_4 emissions, than was found when using the synthetic data; this is further explored in section 3.2.2.

The delta20 metric performs best among the 2B models when using the full AR6 or the AR6 CO_2/CH_4 only datasets with an EoC constraint (table 1; figure 3(F); $\Delta AIC_{lag44\text{-}delta20} = 35$). When lacking an EoC constraint, the delta20 metric still performed best using the full AR6 dataset (figure 1(I); table 1), while the delta20 and the lag44 metrics performed equally well with the AR6 CO_2/CH_4-only dataset ($AIC_{lag44} = 73$, $AIC_{delta20} = 68$; $\Delta AIC_{lag44\text{-}delta20} = 5$; figure 3(E)). In section 3.2.3 we explore why the delta20 2B model is generally favored when using the AR6 emissions data, while lag44 performs best when using the synthetic data (table 1).

3.2.2. Covariance between CO_2 and CH_4 emissions

CO_2 and CH_4 emissions trajectories are reduced over a similar timeframe across most of the AR6 dataset (2020–2050), leading to a strong positive emissions correlation (mean correlation = 0.83, figure 4(C)). This is not a characteristic of the synthetic data by design (mean correlation = 0.06, figure 4(C)). While the simultaneous steep reductions in CO_2 and CH_4 are perhaps desired to meet climate goals, such correlated reductions are not guaranteed in the coming

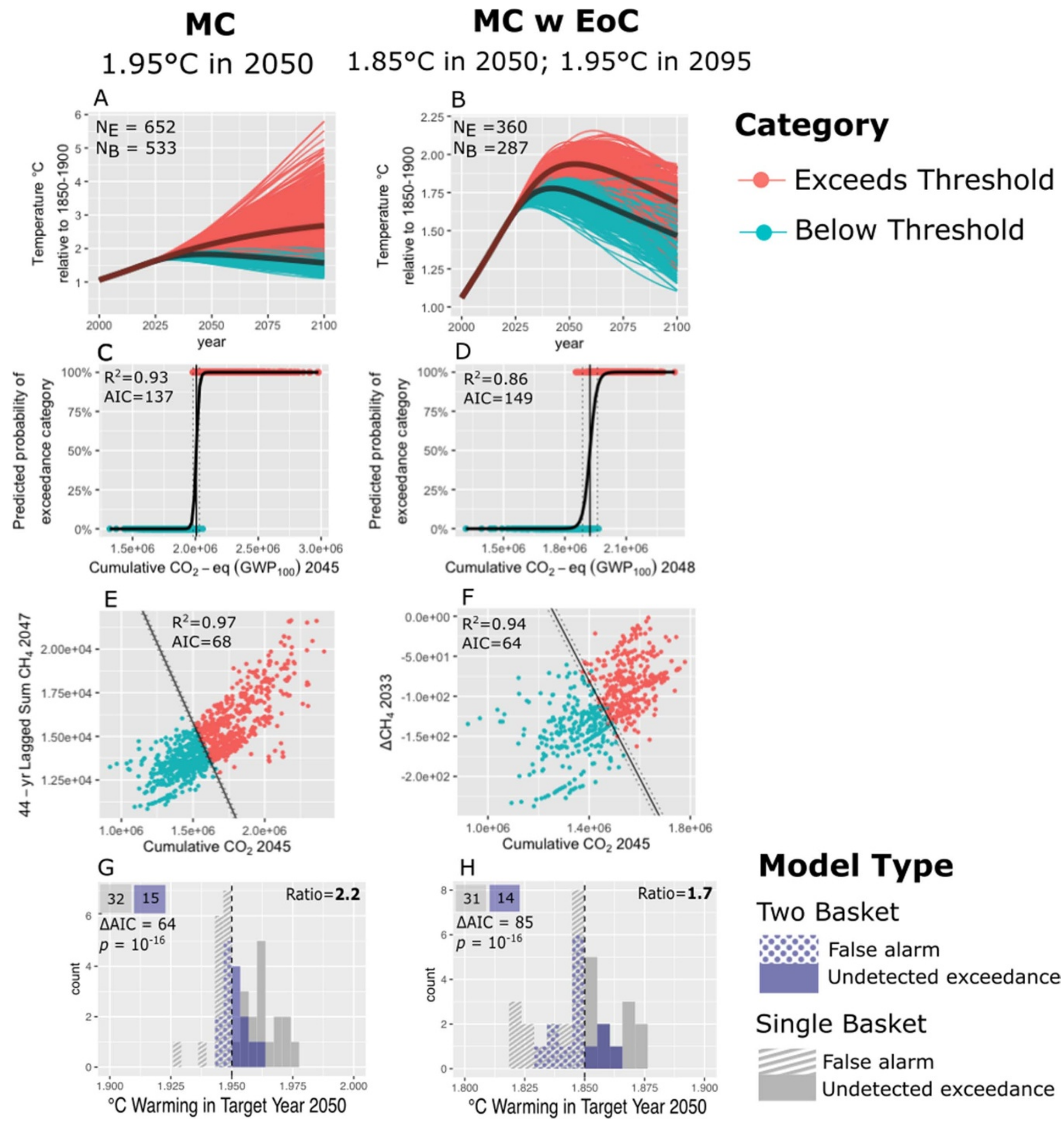

Figure 3. Warming trajectories driven by CO_2 and CH_4 only in AR6 pathways, and results from 1B and 2B models. (A)–(B) Warming trajectories colored according to category. Heavy lines are means for each category. (A) All pathways separated by a mid-century threshold, (B) a subset of pathways constrained by an end-of-century threshold and separated by a mid-century threshold. (C)–(D) Logistic curves for the 1B models with data points from each pathway. (E)–(F) Results of the 2B model plotted in 2D, with the CO_2 metric on the *x*-axis and the CH_4 metric on the *y*-axis. In (C)–(F), the solid line indicates the 50% predicted probability of belonging to the exceeds-target category, and each dotted-line is the 10% and 90% predicted probability; R^2 of each model is in the upper-left of each plot. (G)–(H) Histograms showing the range of warming levels in the pathways miscategorized by the 1B and 2B models (grey and purple, respectively), as in figure 1.

decades (Nisbet *et al* 2020, Olczak *et al* 2023). To test whether the high correlation in the AR6 dataset could explain why the 2B's advantage over the 1B is diminished, we compare model performance using two subsets of the full synthetic dataset: a subset with large positive CO_2/CH_4 correlation and a low correlation subset (SM 7).

Our analysis shows that the high correlation between CO_2 and CH_4 emissions diminishes the relative advantage of 2B. The 2B loses its advantage when using the high-correlation dataset (exceedance ratio = 0.8), but increases when using the low-correlation pathways (exceedance ratio = 12.6); the 2B advantage falls in-between when using the full synthetic dataset (exceedance ratio = 7.1; figure 1(M)).

The negative impact of the CO_2/CH_4 correlation on the 2B model's performance reveals that a 1B approach may be sufficient if it is known that CO_2 and CH_4 emissions will be highly correlated in the coming decades. But current commitments, including the relative paucity of binding commitments on CH_4 emissions, suggest that concomitant reductions in CO_2 and CH_4 cannot be assumed.

3.2.3. Abrupt CH_4 emission cuts

To investigate why the 2B models favor different CH_4 metrics when applied to the AR6 and synthetic data

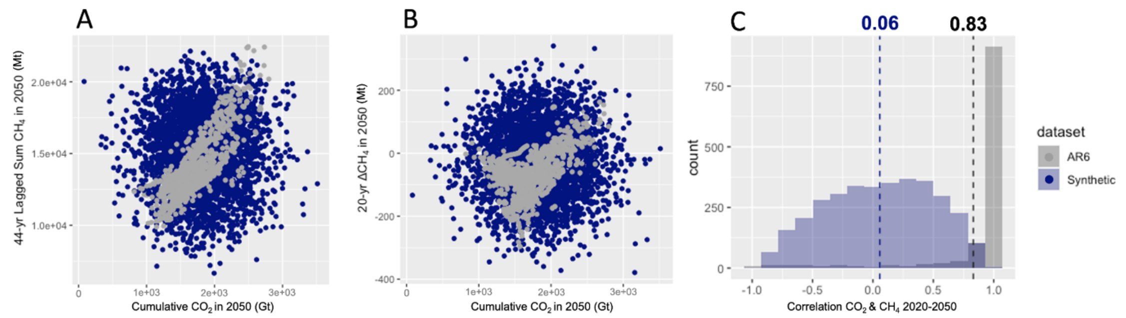

Figure 4. (A) Scatterplot of cumulative emissions of CO_2 and 44 year lagged sum of CH_4, both in 2050 for the scenarios considered here. (B) Scatterplot of cumulative CO_2 and 20 year ΔCH_4, both in 2050. Blue points are synthetic and grey points are AR6 pathways. The synthetic scenarios of CO_2 and CH_4 emissions were developed to encompass the range of the AR6 scenarios over the time period up to 2050, while covering a fuller range of CO_2 and CH_4 emissions combinations. (C) Histogram of the correlation coefficients between CO_2 and CH_4 emission pathways between 2020 and 2050. Dotted vertical lines indicate the mean correlation coefficient of each dataset. Note the much higher correlation between CH_4 and CO_2 emissions in the AR6 data compared with the synthetic data.

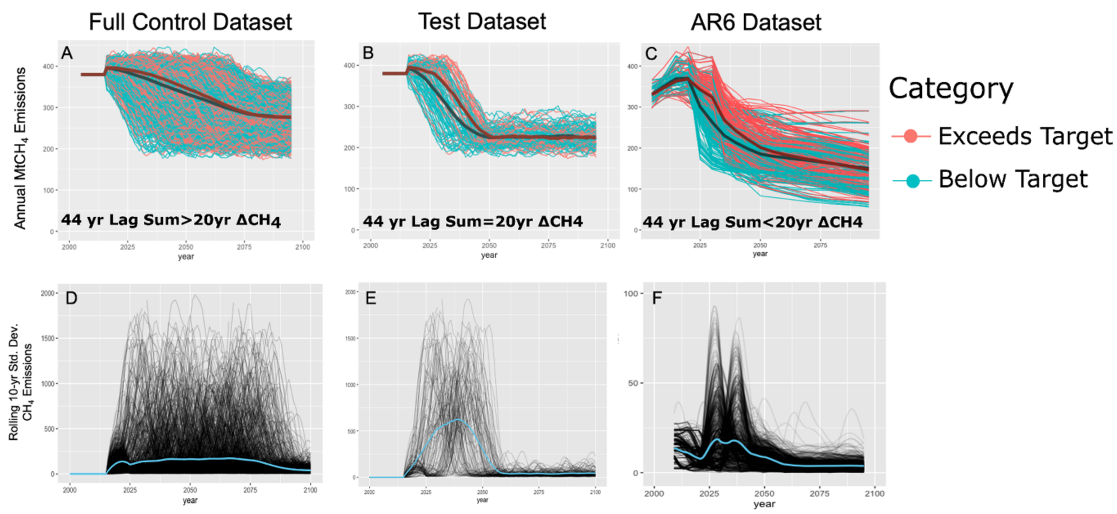

Figure 5. (A-C) CH4 emissions trajectories for each data subset: (A) control dataset of synthetic pathways, (B) synthetic subset with abrupt reductions in CH_4 emissions similar to those in AR6 (categories defined based on the 2.0 °C threshold in 2050), and (C) AR6 dataset (categories defined based on the 1.7 °C threshold in 2050 and 1.8 °C in 2095). Each pathway is colored according to its exceedance category, and heavy lines are annual means for each category. Relative performance of the 2B models containing the indicated methane metrics are summarized by the inequality: (A) 2B model using the lag44 out-performs the delta20 2B model; (B) the delta20 2B model performance improves relative to the control dataset, but the lag44 2B model performs equally well; and (C) the delta20 model out-performs the lag44 model. (D)–(E) Rolling 10 year standard deviation of annual CH_4 emissions. Each black line represents a pathway, and the light blue line is the mean of all pathways.

(green cells in table 1), we compare CH_4 emissions trajectories between datasets (SM 8). CH_4 emissions in AR6 pathways are generally reduced earlier and more abruptly than in the synthetic data, implying that the delta20 metric would more accurately capture the full magnitude of emission reduction than in scenarios with more gradual reductions, and thus that these more abrupt CH_4 cuts amplify the between-category variance of delta20 (figure 5(C)). Meanwhile, the lag44 metric may result in smaller differences between categories as variation in emissions are aggregated equally across a longer time span, diminishing the small differences in the timing and magnitude of abrupt cuts between categories.

We find that the 2B models applied to a dataset containing only abrupt CH_4 cuts leads to improved performance of the delta20 metric (figure 5(B); SM 8) relative to the control dataset across all mid-century targets (table S4). Using the control dataset, the lag44 is the favored metric (i.e. lag44 has a lower AIC score than delta20, table S4). When the analysis is run using the abrupt cuts subset, the models adopting the detla20 tend to perform as well as the lag44 (difference in AIC scores <10; table S4). In this case, they have an $R^2 = 1$, indicating that both models perfectly categorize all pathways and one model could not outperform the other. These results are unaffected by imposing an EoC constraint (table S5).

These results show that the delta20 metric performs better when applied to scenarios with abrupt reductions in CH_4 emissions and help explain why the delta20 metric is the better-performing 2B metric the AR6 scenarios. While these results show that metric performance is sensitive to the assumptions of the considered pathways, they do not unequivocally establish the superiority of one CH_4 metric over another for the purposes of setting a near-term CH_4 emissions target.

4. Discussion

The climate policy discourse has focused almost exclusively on longer-term climate goals with concerns over limiting overshoot mostly emerging since the Paris Agreement (Riahi *et al* 2021); however, there have been many calls for setting specific targets for short-lived climate pollutants aimed at reducing the rate of warming in addition to a target for long-lived pollutants (Fuglestvedt *et al* 2000, Jackson 2009, Shindell *et al* 2017). Our premise is that if limiting the magnitude of overshoot is desired, a near-term goal is needed even when there is an established EoC goal. Our approach is consistent with calls to separate long-lived and short-lived climate forcers to reduce ambiguity in assessing global temperature impact (Allen *et al* 2022, Wood *et al* 2023). Where our approach differs is the use of a 2B probabilistic framework in which we seek to identify a simple set of emission-related metrics that better differentiates between emissions pathways that lead to overshoot (e.g. exceed 1.7 °C mid-century) and those that do not. Our metrics are designed to categorize pathways with respect to fulfilling near- and/or long-term temperature goals. This differs from previous attempts to derive metrics that act as 'mini-models' (Smith *et al* 2012, Allen *et al* 2022, Meinshausen and Nicholls 2022) that quantify the aggregated impacts of emissions on future global temperature.

We show that a 2B approach can reduce the magnitude of overshoot above an illustrative near-term temperature threshold (1.7 °C) by up to a factor of 7 compared with the 1B approach using GWP100. The improvement in classification of the 2B approach relative to the 1B approach is greatest when CO_2 and CH_4 emissions are not assumed to be highly correlated.

A key finding of this framework is that it makes explicit the magnitude and timing of methane emissions reductions needed to meet a specific policy goal. Taking staying below 1.7 °C in 2050 as an illustrative near-term goal, the implied reduction target can be inferred for the AR6 pathways as follows. Assuming that cumulative CO_2 emissions are capped at the carbon budget for 1.7 °C, scenarios that avoid overshoot reduce methane by the amounts summarized in table 2 (Two-Basket AR6; SM 9). When applied to the AR6 data, the early 2030s are identified as the decisive emissions reduction target years that distinguish between overshoot outcomes in 2050. We emphasize that the methane metric and reduction target should apply to *net additional* methane emissions; this is, if natural emissions increase due to anticipated climate feedbacks (Kleinen *et al* 2021), anthropogenic emissions would have to be further decreased by an equivalent amount. These results are consistent with the findings by Rogelj and Lamboll (2024) for non-CO_2 emissions reductions implied by the 1.7 °C remaining carbon budget, and with AR6 Working Group III on pathways that limit EoC warming to 2 °C or below with limited mid-century overshoot (table 2). This is also consistent with implementation of the Global Methane Pledge, which calls for at least a 30% reduction in CH_4 emissions below 2020 levels by 2030 (GMP 2022). Although the values from Rogelj and Lamboll (2024) are similar to ours, they may be lower because their results include compensatory reductions in other non-CO_2, non-methane emissions, whereas our probabilistic approach considers only the contribution of CH_4 and CO_2 to the likelihood of overshoot.

The 2B framework we present here allows for developing a set of emission metrics for tracking national and sectoral progress towards meeting a specified near-term climate goal simultaneously with a longer-term goal. Like the carbon budget framework, by starting with a chosen goal, our multi-basket classification framework yields emissions metrics and targets that essentially shift the use of metrics to the design level in climate policy (Tanaka *et al* 2010). Many studies and the IPCC conclude that the 'choice of metric, including time horizon, should reflect the policy objectives for which the metric is applied' (Dhakal *et al* 2022). However, if there are two policy objectives, in this case constraining near-term and longer-term temperature, a 1B framework will result in ambiguity regardless of metric by imposing a single choice of time horizon or temporal weighting (e.g. Collins *et al* 2020).

While our probabilistic approach can identify metrics that effectively distinguish between categories, such metrics are not necessarily practical for policy or good temperature proxies. Our delta20 metric is a powerful predictor for the AR6 dataset but makes a poor metric when considering the desirable features for GHG emission metrics (Tanaka *et al* 2010, Meinshausen and Nicholls 2022). The lag44 metric, on the other hand, possesses many desirable features, including that it accurately represents differences in physical climate impacts (i.e. global temperature) between a scenario with and without the emissions, applies equally at regional and sectoral levels, is simple and transparent, has the potential to act like a currency converter (while not explored here, the 2B classification approach can yield a conversion factor to CO_2-eqs that is associated with a specific climate target), is compatible with existing

Table 2. Results of the magnitude of methane reductions from this study compared with those implied by the remaining carbon budget (Rogelj and Lamboll 2024) and IPCC WGIII Report (Riahi *et al* 2022). Reductions listed across three periods of different length between 2020 and 2050. For Two-Basket AR6 results, median annual methane emissions values from the 184 pathways correctly classified as below-threshold are used to calculate reductions, with median 2020 emissions levels equal to 363 $MtCH_4$, which is comparable with GMP and WGIII. Note that the reduction magnitudes are substantially driven by the specific pathways assumed in AR6.

	% Emissions Change		
Years	Two-Basket AR6 <1.7 °C by 2050	Non-CO_2 Reductions for 1.7 °C RCB (Rogelj and Lamboll 2024)	IPCC WGIII limited overshoot (Riahi *et al* 2022)
2020–2030	−32%	−18%	−35%
2020–2040	−43%	−35%	−46%
2020–2050	−50%	−44%	−53%

climate policy environment, has year-to-year stability for target-setting and tracking purposes, and by analogy with conventional GWP, is compatible with least-cost economic analysis. Below we compare lag44 with existing methane metrics as they pertain to some of these features.

From a physical perspective, lag44 is similar to GWP* in that it is a better temperature indicator than cumulative GWP100 or GWP20 because it can decrease in value when emissions decrease. Whether lag44 or GWP* is a superior temperature indicator will be addressed in a companion study (Miller *et al* in prep). In practice, lag44 has greater year-to-year stability than GWP* (Meinshausen and Nicholls 2022), an advantage it shares with conventional GWPs. To provide a more stable conversion factor between long-lived and short-lived GHGs, Collins *et al* (2020) proposed a 'combined global temperature change potential' (CGTP). While stable and designed for consistency with the Paris Agreement, we suggest that the CGTP is less simple and transparent than the set of metrics for the 2B approach proposed here.

Metrics used for climate policy should also enable the core principles of equitable climate action, specifically protection of the poor and differentiation based on need, responsibility, capacity, and equity (Dooley *et al* 2021). Like conventional GWPs, lag44 applies equally at global, sectoral and enterprise scales. We assess that the effect of 'forgetting' emissions older than 44 years has limited impact (SM 10; figure S6). In contrast the choice of baseline year for GWP* can change the resulting GWP* value, and when applied at a sub-global level, newer emitters are penalized compared with 'grandparenting' of historical emitters (Rogelj and Schleussner 2019, 2021). Our alternative metric, delta20 presents a similar equity problem as GWP* because it ignores historical emissions beyond 20 years and those between the first and twentieth year, thus delta20's contribution could be zero if the emissions remain constant, even if they are large; therefore, delta20 lacks transparency about an emitter's actual contribution to warming (Meinshausen and Nicholls 2022). Lag44 contains no ambiguity about what historical data gets included and attributed to warming (Donnison and Murphy-Bokern 2023), and its relative year-to-year stability enables progress tracking (Meinshausen and Nicholls 2022). These features of stability and more equal treatment of historical and more recent emitters also make lag44 more appropriate to use in 'fair share' allocation discussions (e.g. Rajamani *et al* 2021).

The lag44 metric for CH_4 is particularly practical for policy adoption because it can be expressed as a percentage reduction in emissions relative to a base period and as a methane budget, both of which can be applied at global, regional, or individual entity levels. For example, a lag44 methane budget for a temperature target in 2050 could be derived from our results by summing methane emissions in the 44 years between 2007 and 2050. Using the same illustrative example as above for 1.7 °C in 2050, the remaining methane budget would be 6022 Mt (after subtracting emissions from 2007–2023). This is analogous to the net-zero CO_2 metric in the carbon budget framework that offers the practical ability to scale across potential implementers, meaning the lag44 metric allows for target setting across enterprise, sub-national, national and global levels in a comparable and additive way.

The results here should be considered with respect to assumptions of the pathways used. One limitation of the synthetic pathways is that they lack the practical constraints and underlying storylines that have been built into AR6 scenarios. Nevertheless, we maintain they have the advantage of allowing CO_2 and CH_4 reductions to be uncorrelated, and thus they allow a broader sampling of the CO_2/CH_4 emissions phase space. The magnitude of the reductions inferred from the AR6-based analysis also depends on the GSAT percentile level. Repeating the analysis with a higher GSAT estimate (e.g. 67th percentile instead of 50th percentile) requires CH_4 and CO_2 reductions be more ambitious (SM 11.1, figure S7); however, the advantage of the 2B is robust to GSAT percentile levels.

Future work could build on the framework presented here to explore the value of a three-basket approach that separately accounts for long-lived greenhouse gases (i.e. CO_2, N_2O, CFCs, PFCs, etc), shorter-lived gases (CH_4, HFCs, etc), and a third basket for very short-lived pollutants (ozone precursors and tropospheric aerosols) that affect regional air quality and temperature (e.g. Stohl *et al* 2015, Nair *et al* 2023, Persad *et al* 2023). The choice of weighting within each basket and lifetime thresholds separating each basket would be part of further study and should consider response timescales of the climate system (e.g. Smith *et al* 2012). While multi-basket approaches may not be as cost-efficient as 1B approaches, they offer greater precision in assessing multiple policy goals, and linkages between global and regional policy regimes could improve cost effectiveness (Rypdal *et al* 2005).

5. Conclusion

We show here the value in adopting a 2B approach with separate CO_2 and CH_4 metrics to identify emissions pathways that are consistent with staying below a near-term warming threshold. Compared to the commonly adopted 1B approach, this 2B approach reduces the magnitude of overshoot above a near-term warming threshold by up to a factor of 7, depending on the extent to which future CO_2 and CH_4 emissions are correlated, with higher performance in the case of lower correlation. While the 1B approach still performs well under the assumptions of highly correlated CO_2 and CH_4 emissions trends in the AR6 pathways, it leads to substantial ambiguity in assessing future climate goals compared with a 2B approach under a broader range of emissions scenarios. Rapid, deep, and sustained reductions at the pace needed for both long-lived and short-lived climate pollutants are far from assured, and the 2B approach offers a more precise and robust approach to address the full range of future possible scenarios.

Our analysis introduces two potentially useful methane metrics for near-term target-setting: the lag44 and the delta20 (consistent with Allen *et al* 2018, Cain *et al* 2019). Our analysis shows that the abrupt cuts to CH_4 in the AR6 pathways favor the use of the delta20 metric, but this metric has disadvantages in policy applications. The lag44 is more precise in more general cases that do not predominately include abrupt CH_4 cuts. Similar to the well-adopted concept of the remaining carbon budget of CO_2, the lag44 metric can be tabulated and tracked by policymakers against a pre-determined threshold. Its simple and intuitive nature provides ample flexibility for reinforcement. at the regional and sectoral levels. Future work could consider a third basket for very short-lived pollutants.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: 10.5281/zenodo.10558229.

The code used in the analyses of this study is openly available at the following URL/DOI: https://zenodo.org/records/13001713.

Acknowledgments

We thank three anonymous reviewers for their valuable comments.

Funding

We acknowledge Spark Climate Solutions for funding this work.

ORCID iDs

Julie S Miller https://orcid.org/0000-0002-2301-1955
Gabrielle B Dreyfus https://orcid.org/0000-0002-5863-0924
Yangyang Xu https://orcid.org/0000-0001-7173-7761

References

Allen M R *et al* 2022 Indicate separate contributions of long-lived and short-lived greenhouse gases in emission targets *npj Clim. Atmos. Sci.* **5** 1–4

Allen M R, Shine K P, Fuglestvedt J S, Millar R J, Cain M, Frame D J and Macey A H 2018 A solution to the misrepresentations of CO_2 -equivalent emissions of short-lived climate pollutants under ambitious mitigation *npj Clim. Atmos. Sci.* **1** 16

Armstrong Mckay D I, Staal A, Abrams J F, Winkelmann R, Sakschewski B, Loriani S, Fetzer I, Cornell S E, Rockström J and Lenton T M 2022 Exceeding 1.5 °C global warming could trigger multiple climate tipping points *Science* **377** eabn7950

Balcombe P, Speirs J F, Brandon N P and Hawkes A D 2018 Methane emissions: choosing the right climate metric and time horizon *Environ. Sci. Process. Impacts* **20** 1323–39

Buck H J, Carton W, Lund J F and Markusson N 2023 Why residual emissions matter right now *Nat. Clim. Change* **13** 351–8

Byers E *et al* 2022 AR6 scenarios database (available at: https://zenodo.org/record/5886911)

Cain M, Lynch J, Allen M R, Fuglestvedt J S, Frame D J and Macey A H 2019 Improved calculation of warming-equivalent emissions for short-lived climate pollutants *npj Clim. Atmos. Sci.* **2** 29

Cohen-Shields N, Sun T, Hamburg S P and Ocko I B 2023 Distortion of sectoral roles in climate change threatens climate goals *Front. Clim.* **5** 1163557

Collins W J, Frame D J, Fuglestvedt J S and Shine K P 2020 Stable climate metrics for emissions of short and long-lived species—combining steps and pulses *Environ. Res. Lett.* **15** 024018

Collins W J, Fry M M, Yu H, Fuglestvedt J S, Shindell D T and West J J 2013 Global and regional temperature-change

potentials for near-term climate forcers *Atmos. Chem. Phys.* **13** 2471–85
Daniel J S, Solomon S, Sanford T J, McFarland M, Fuglestvedt J S and Friedlingstein P 2012 Limitations of single-basket trading: lessons from the Montreal Protocol for climate policy *Clim. Change* **111** 241–8
Dhakal S *et al* 2022 Emissions trends and drivers *IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press) (available at: www.ipcc.ch/report/ar6/wg3/)
Donnison C L and Murphy-Bokern D 2023 Are climate neutrality claims in the livestock sector too good to be true? *Environ. Res. Lett.* **19** 011001
Dooley K *et al* 2021 Ethical choices behind quantifications of fair contributions under the Paris Agreement *Nat. Clim. Change* **11** 300–5
Dreyfus G B, Xu Y, Shindell D T, Zaelke D and Ramanathan V 2022 Mitigating climate disruption in time: a self-consistent approach for avoiding both near-term and long-term global warming *Proc. Natl Acad. Sci.* **119** e2123536119
Fesenfeld L P, Schmidt T S and Schrode A 2018 Climate policy for short- and long-lived pollutants *Nat. Clim. Change* **8** 933–6
Forster P M *et al* 2023 Indicators of global climate change 2022: annual update of large-scale indicators of the state of the climate system and human influence *Earth Syst. Sci. Data* **15** 2295–327
Fuglestvedt J S, Berntsen T K, Godal O and Skodvin T 2000 Climate implications of GWP-based reductions in greenhouse gas emissions *Geophys. Res. Lett.* **27** 409–12
Future Earth, The earth league and WCRP 2023 *10 New Insights in Climate Science 2023/2024* (Future Earth, The Earth League, World Climate Research Programme) (https://doi.org/10.5281/zenodo.10034364)
GMP 2022 Global methane pledge (available at: www.globalmethanepledge.org/)
Intergovernmental Panel on Climate Change 1990 *Climate Change: the IPCC Scientific Assessment* ed J T Houghton, G J Jenkins and J J Ephraums (Cambridge University Press) (available at: www.ipcc.ch/site/assets/uploads/2018/03/ipcc_far_wg_I_full_report.pdf)
IPCC 2022 *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* ed H-O Pörtner *et al* (Cambridge University Press) p 3056
Jackson S C 2009 Parallel pursuit of near-term and long-term climate mitigation *Science* **326** 526–7
Kleinen T, Gromov S, Steil B and Brovkin V 2021 Atmospheric methane underestimated in future climate projections *Environ. Res. Lett.* **16** 094006
Lamboll R D, Nicholls Z R J, Smith C J, Kikstra J S, Byers E and Rogelj J 2023 Assessing the size and uncertainty of remaining carbon budgets *Nat. Clim. Change* **13** 1360–7
Lee H *et al* 2023 AR6 synthesis report: climate change 2023 pp 1–85 (available at: https://report.ipcc.ch/ar6syr/pdf/IPCC_AR6_SYR_LongerReport.pdf)
Lenton T M *et al* 2023 Global tipping points report 2023 (available at: https://global-tipping-points.org/)
Meinshausen M and Nicholls Z 2022 GWP*is a model, not a metric *Environ. Res. Lett.* **17** 041002
Miller J S, Dreyfus G B, Daniel J S and Xu Y 2024 Synthetic datasets for multi-basket approach (available at: https://zenodo.org/records/10558229)
Miller J S, Dreyfus G B, Daniel J S and Xu Y in prep An alternative methane metric conducive to setting near-term climate goals: the 44-year sum
Nair H R C R, Budhavant K, Manoj M R, Andersson A, Satheesh S K, Ramanathan V and Gustafsson Ö 2023 Aerosol demasking enhances climate warming over South Asia *npj Clim. Atmos. Sci.* **6** 39
Nisbet E G *et al* 2020 Methane mitigation: methods to reduce emissions, on the path to the Paris Agreement *Rev. Geophys.* **58** e2019RG000675
Olczak M, Piebalgs A and Balcombe P 2023 A global review of methane policies reveals that only 13% of emissions are covered with unclear effectiveness *One Earth* **6** 519–35
Persad G *et al* 2023 Rapidly evolving aerosol emissions are a dangerous omission from near-term climate risk assessments *Environ. Res. Clim.* **2** 032001
Rajamani L, Jeffery L, Höhne N, Hans F, Glass A, Ganti G and Geiges A 2021 National 'fair shares' in reducing greenhouse gas emissions within the principled framework of international environmental law *Clim. Policy* **21** 983–1004
Riahi K *et al* 2021 Cost and attainability of meeting stringent climate targets without overshoot *Nat. Clim. Change* **11** 1063–9
Riahi K *et al* 2022 Mitigation pathways compatible with long-term goals *Climate Change 2022—Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* ed P R Shukla *et al* (Cambridge University Press) pp 295–408 (available at: www.cambridge.org/core/product/identifier/9781009157926%23c3/type/book_part)
Rogelj J, Geden O, Cowie A and Reisinger A 2021 Net-zero emissions targets are vague: three ways to fix *Nature* **591** 365–8
Rogelj J and Lamboll R D 2024 Substantial reductions in non-CO_2 greenhouse gas emissions reductions implied by IPCC estimates of the remaining carbon budget *Commun. Earth Environ.* **5** 35
Rogelj J and Schleussner C-F 2019 Unintentional unfairness when applying new greenhouse gas emissions metrics at country level *Environ. Res. Lett.* **14** 114039
Rogelj J and Schleussner C-F 2021 Reply to Comment on `Unintentional unfairness when applying new greenhouse gas emissions metrics at country level' *Environ. Res. Lett.* **16** 068002
Rypdal K, Berntsen T, Fuglestvedt J S, Aunan K, Torvanger A, Stordal F, Pacyna J M and Nygaard L P 2005 Tropospheric ozone and aerosols in climate agreements: scientific and political challenges *Environ. Sci. Policy* **8** 29–43
Schleussner C-F, Ganti G, Rogelj J and Gidden M J 2022 An emission pathway classification reflecting the Paris Agreement climate objectives *Commun. Earth Environ.* **3** 1–11
Shindell D, Borgford-Parnell N, Brauer M, Haines A, Kuylenstierna J C I, Leonard S A, Ramanathan V, Ravishankara A, Amann M and Srivastava L 2017 A climate policy pathway for near- and long-term benefits *Science* **356** 493–4
Shoemaker J K, Schrag D P, Molina M J and Ramanathan V 2013 What role for short-lived climate pollutants in mitigation policy? *Science* **342** 1323–4
Smith C *et al* 2023 Github Climate Indicator Repository (available at: https://github.com/ClimateIndicator/GHG-Emissions-Assessment)
Smith C, Nicholls Z R J, Armour K, Collins W, Forster P, Meinshausen M, Palmer M D and Watanabe M 2021a The Earth's energy budget, climate feedbacks and climate sensitivity *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press) ch 7 supplementary material (available at: www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_Chapter07_SM.pdf)
Smith M A, Cain M and Allen M R 2021b Further improvement of warming-equivalent emissions calculation *npj Clim. Atmos. Sci.* **4** 19
Smith S M, Lowe J A, Bowerman N H A, Gohar L K, Huntingford C and Allen M R 2012 Equivalence of greenhouse-gas emissions for peak temperature limits *Nat. Clim. Change* **2** 535–8

Stohl A *et al* 2015 Evaluating the climate and air quality impacts of short-lived pollutants *Atmos. Chem. Phys.* **15** 10529–66

Tanaka K, Peters G P and Fuglestvedt J S 2010 Policy Update: multicomponent climate policy: why do emission metrics matter? *Carbon Manage.* **1** 191–7

Wood S A, Hayhoe K, Bradford M A, Kuebbing S E, Ellis P W, Fuller E and Bossio D 2023 Mitigating near-term climate change *Environ. Res. Lett.* **18** 101002

Wunderling N, Winkelmann R, Rockström J, Loriani S, Armstrong Mckay D I, Ritchie P D L, Sakschewski B and Donges J F 2023 Global warming overshoots increase risks of climate tipping cascades in a network model *Nat. Clim. Change* **13** 75–82

Xu Y and Ramanathan V 2017 Well below 2 °C: mitigation strategies for avoiding dangerous to catastrophic climate changes *Proc. Natl Acad. Sci.* **114** 10315–23