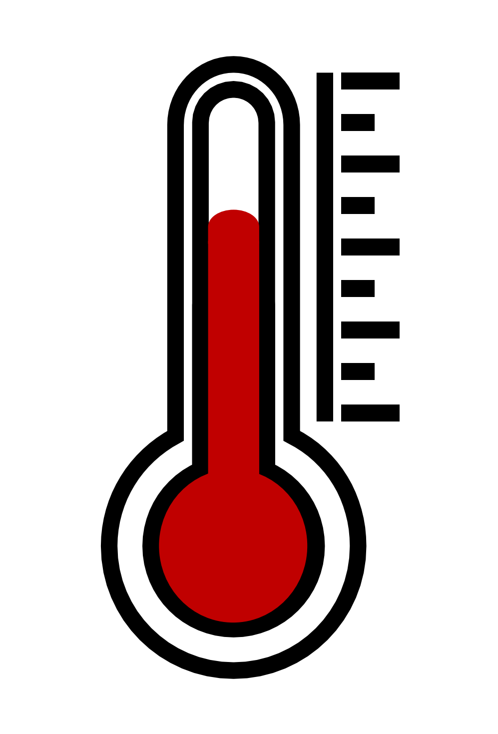

Temperature Rating Methodology

A temperature rating method for targets, corporates, and portfolios

Open source methodology to translate the ambition of corporate GHG emission reductions into temperature ratings for corporates and investment portfolios

CDP Worldwide and WWF International

Version 1.0.

TEMPERATURE RATING METHODOLOGY

A TEMPERATURE RATING METHOD FOR TARGETS, CORPORATES, AND PORTFOLIOS

BETA VERSION

October 01, 2020

CDP Worldwide and WWF International

This method is an open source framework to enable the translation of corporate GHG emission reduction targets into temperature scores at a target, company, and a portfolio level. The method can be used to generate temperature scores for individual targets to translate target ambition to a common intuitive metric.

The method provides a protocol to enable the aggregation of target level scores to generate a temperature rating for a company based on the ambition of its targets. Finally, the method defines a series of weighting options that can enable financial institutions and others to

Built on the work of the Science based targets initiative, the methodology provides a public, transparent, and science-based protocol to assess the ambition of corporates and portfolios based on the ambition of targets. It enables users to assess the ambition of any public GHG emission reduction target and can help users compare the relative ambition of one company versus another. The method may also be used to temperature score investment portfolios and allow Financial Institutions to calculate the current temperature score of portfolio, which is a key starting point for aligning the portfolio with long term temperature goals such as 1.5C

About CDP

CDP is an international non-profit that drives companies and governments to reduce their greenhouse gas emissions, safeguard water resources and protect forests. Voted number one climate research provider by investors and working with institutional investors with assets of US$106 trillion, we leverage investor and buyer power to motivate companies to disclose and manage their environmental impacts. Over 8,400 companies with over 50% of global market capitalization disclosed environmental data through CDP in 2019. This is in addition to the over 920 cities, states and regions who disclosed, making CDP's platform one of the richest sources of information globally on how companies and governments are driving environmental change. CDP is a founding member of the We Mean Business Coalition. Visit https://cdp.net/en or follow us @CDP to find out more.

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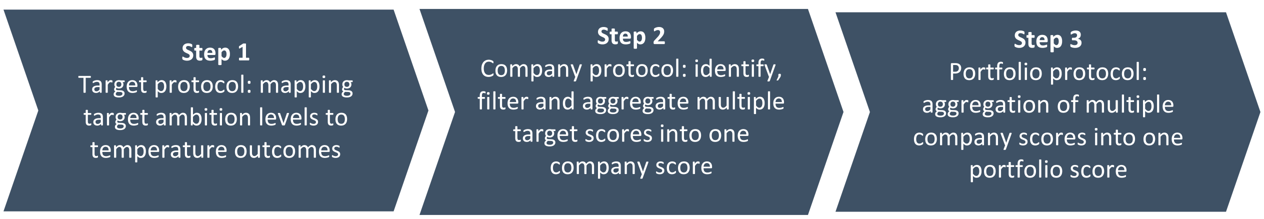
Contents

Methodological Overview

Through the Science Based Targets initiative (SBTi), a large number of companies have been able to set approved science-based targets since 2015. Building on the work of the SBTi, the temperature rating methodology presented in this document expands the temperature assessment of short- and medium-term corporate ambition against a wide range of end of century (2100) temperature outcomes, between 1.5 – 5°C. It therefore aims to translate reported corporate targets into long-term temperature trajectories. Assessing the ambition of corporate targets has traditionally been very complex, as targets can be expressed with different units, over multiple timeframes covering various types of scopes. The goal of a temperature rating is to translate targets into a single common and intuitive metric that is linked to the long-term temperature outcomes associated with the ambition of the target.

The methodology is composed of three distinct steps:



The target protocol represents the first step of the process, which is to convert individual targets of various formats into temperature scores. This is achieved by generating simple regression models for estimated warming in 2100 from climate scenarios with short, medium, and long-term trends in metrics like absolute emissions or emissions intensities. Regression models are generated based on scenarios in the IPCC Special Report on 1.5°C scenario database. In addition to defining methods for disclosed targets, this step outlines the methodology used to define a default score to be applied to all non-disclosing companies.

Since companies have multiple climate targets, covering different scopes and timeframes, a protocol is then used to aggregate all target data into scores at a company level (step 2). This protocol defines the minimum quality criteria for determining the acceptability of a target to be scored and the steps required to identify and aggregate multiple targets to produce an overall company score.

The final step is used to weight company scores when assessing an index or portfolio of companies, such as in the context of financial portfolios. Figure 1 presents an overview of how the three protocols fit together to form the temperature rating methodology.

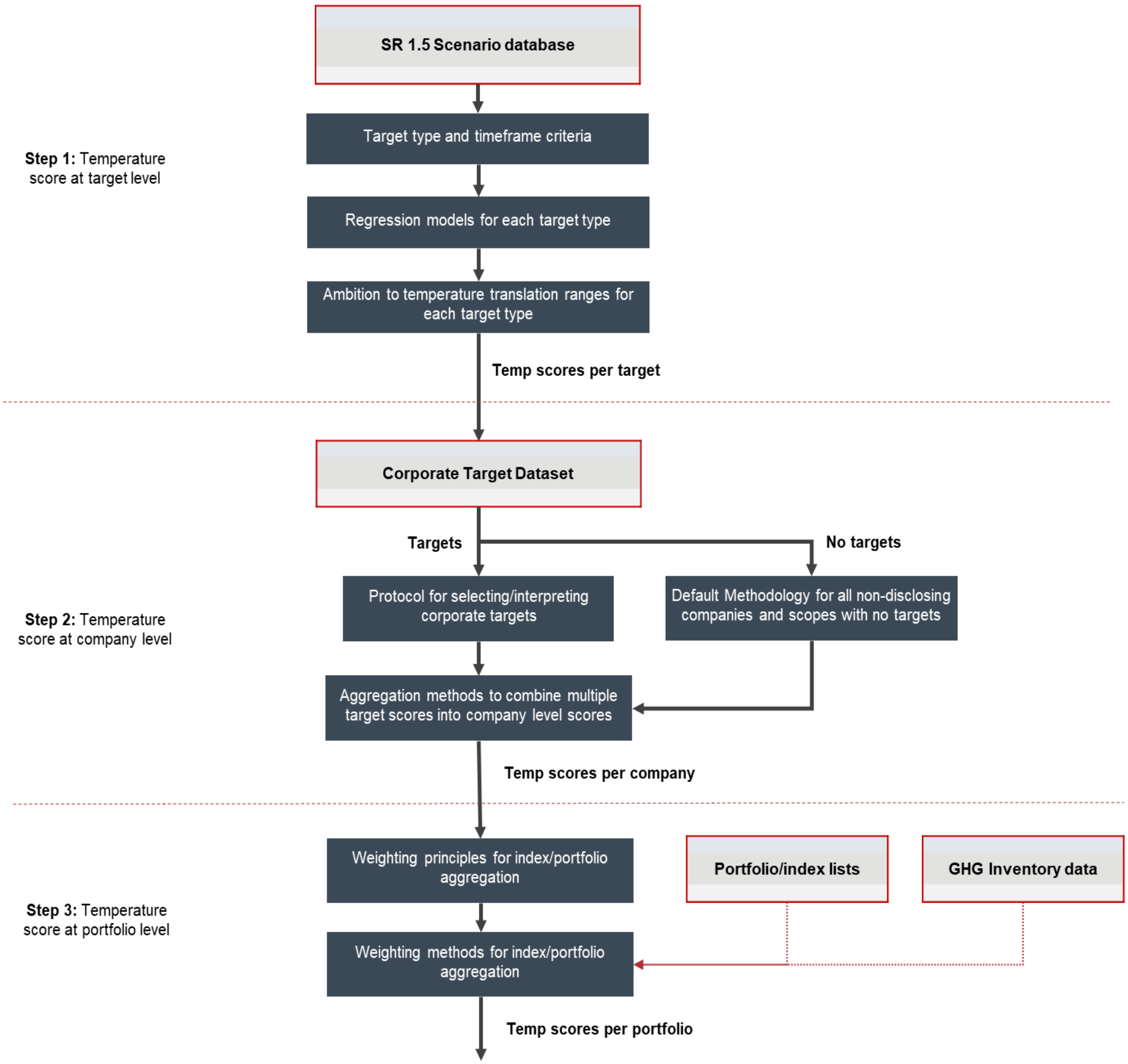


Figure 1. Temperature rating methodology overview

1. Target protocol

1.1. Introduction

Companies are directly responsible for a significant portion of global GHG emissions and bear substantial influence over energy and land-use systems that will need to transform to meet the goals of the Paris Agreement. In 2019, more than four thousand companies covering seven GT CO2e emissions, publicly reported emissions targets through CDP. Emissions targets are a partial, but relatively crucial and forward-looking marker of a company’s ambition to mitigate its climate impact. In this document, a protocol for expressing (‘rating’) individual climate targets as temperature outcomes (warming in 2100) is presented.

1.2. Overview of methodology

In support of the IPCC’s Special Report on Global Warming of 1.5°C, the Integrated Assessment Modelling Consortium (IAMC) compiled a database of over 400 scenarios produced by models across different experimental frameworks (Huppman et al., 2018). The scenarios cover a wide range of temperature outcomes, which may be classified based on global warming in 2100 compared to pre-industrial temperatures. Our method assumes that there is a linear relationship between the change (slope) in common target metrics (e.g., absolute emissions; emissions intensity of revenue or sold product) over specific timeframes relevant to corporate target setting horizons (e.g., 2020-2035) and the resulting global warming in 2100. The concept builds on descriptive statistical summaries of the IAMC SR1.5 database (Huppman et al., 2018; Rogelj et al., 2018) and the simple analysis presented in Weber et al. (2018) relevant to corporate targets and scenario variables. See for instance Figure 2 (b), which shows the 20 year slope in relevant scenario variables for different end of century temperature outcomes (<1.5°C to 4°C) from the Shared Socioeconomic Pathways (SSP) database.

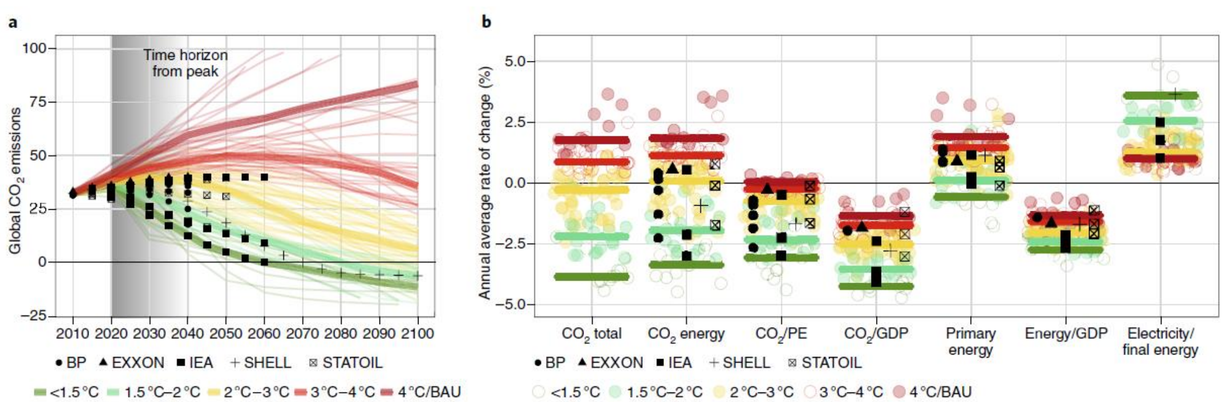


Figure 2. Illustration of underlying scientific scenarios and corporate and industry scenarios (black markers) for one global control variable (CO2 emissions; panel a) and summaries of the 20 year slope of such variables vs. end of century temperature outcomes (b)

Traditionally, scenario databases are analysed using a variety of descriptive statistical approaches. In the SR1.5 for instance, scenarios were binned according to their end of century temperature outcome and level of overshoot (Below 1.5C, 1.5C low overshoot, etc.; see Figure 3 below). While valuable to describe the range of uncertainty and variability between scenarios, such an approach has several main drawbacks for the intended use here:

1) In order to apply a 'score' to targets, a method must return a single unambiguous score, which is not possible using descriptive binning approaches
2) the IPCC tends to be very inclusive of any scenario meeting certain minimum quality criteria, but there are normative reasons to prefer certain scenarios given both the potential climate impacts of overshoot (e.g. Anderson et al., 2019) and concerns over the feasibility of large scale CO2 removal (Fuss et al., 2018; Andersen et al., 2019) especially in the context of "delay" scenarios that do not begin aggressive mitigation until later years, e.g. 2030. (Strefler et al., 2018).
3) Results can be difficult to understand for non-experts, since bins tend to have overlapping ranges (see Fig 3)

For these reasons we instead apply a simple two step approach to temperature rating: first, the creation of a scenario set that matches a normative precautionary preference in regard to overshoot and CDR; and second, develop best-fitting linear regression models to describe the relationship between scenario variables (matching the general structure of corporate GHG targets) and end of century temperature outcomes. As described below, the two steps were further applied iteratively to test different normative choices surrounding CDR and overshoot and the resulting regression fits for select scenario metrics.

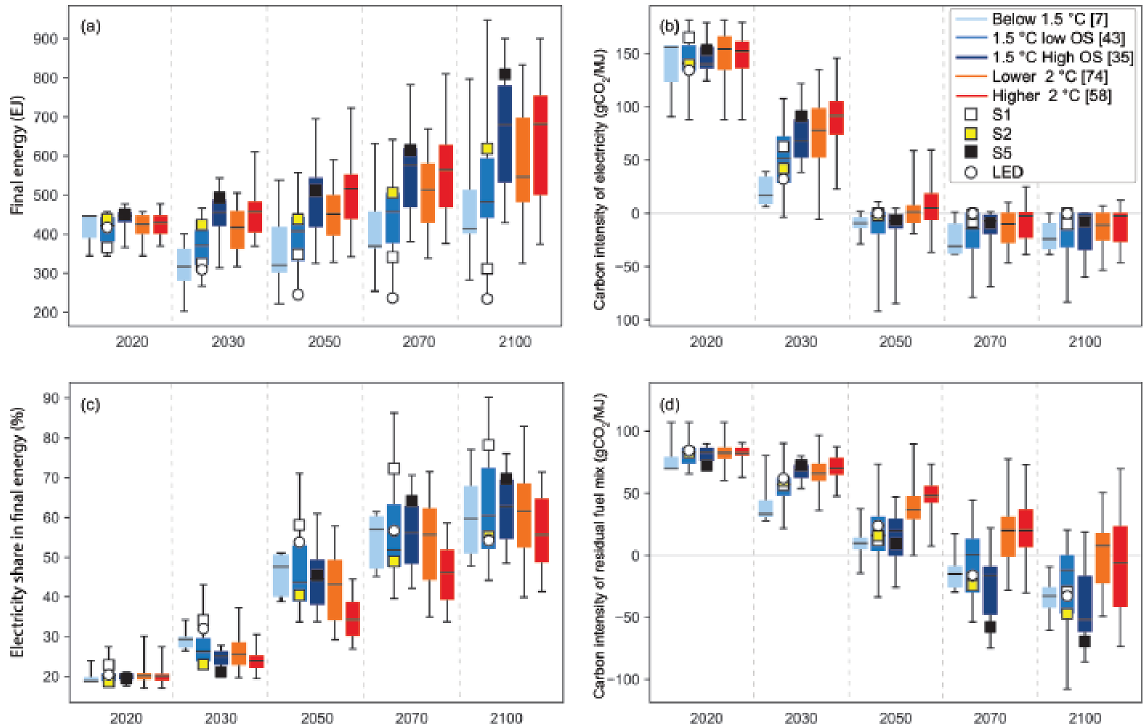


Figure 2.14 | Decomposition of transformation pathways into (a) energy demand, (b) carbon intensity of electricity, (c) the electricity share in final energy, and (d) the carbon intensity of the residual (non-electricity) fuel mix. Box plots show median, interquartile range and full range of pathways. Pathway temperature classes (Table 2.1) and illustrative pathway archetypes are indicated in the legend. Values following the class labels give the number of available pathways in each class.

Figure 3: SR1.5 analysis of scenarios using descriptive binning, here analyzing decomposition of energy system CO2 emissions

The methodology is subject to notable limitations that reflect trade-offs between specificity and applicability. First, any generalized metric is inherently a summary of sub-metrics that are potentially diverse (e.g., global GHG emissions pathways are the sum of all regional or country-level pathways, which can also be subdivided into emissions associated with different physical processes). Many companies operate across a diverse range of geographies and/or activities, but in some cases, using a generalized metric that is not consistent with the company's geographies or activities might lead to biased results. Sensitivity analyses have been included, where possible, to assess the significance of such potential biases. Second, in cases where the metric is appropriate, the assessment of one target is still an incomplete picture of the company's alignment with long-term or structural changes needed to meet the goals of the Paris Agreement. For example, two approaches to reducing power-related emissions by 30% in ten years (e.g., 2018-2028) may correspond to very different outlooks for the subsequent ten years (e.g., 2028-2038) based on the lifespan of assets, etc., which are not captured by emissions targets. This uncertainty can be reduced by assessing the temperature alignment of both short/mid-term targets and long-term targets for a single company, in cases where both have been reported.

Third, there are inherent issues with the use of linear regression of a scenario set, since scenarios are by their nature not a random statistical sample—one of the inherent assumptions of a regression. We contend this general limitation would be true of nearly any reasonable approach that 'scores' GHG targets, since benchmarks for rating short-term targets must either be based on a single scenario or some statistical averaging of scenario results.

Fourth, rating companies based on stated targets assumes inherently that the targets will be met—if targets are missed, companies may be given unfairly low temperature scores. Of course, the converse is also true—if companies exceed GHG reduction targets, their scores are biased high.

Finally, and perhaps most importantly, the approach only scores companies based on their forward-looking ambition (as indicated by GHG targets) rather than based on prior actions the company has taken to reduce emissions. This naturally penalizes those companies that have already reduced emissions considerably, since generally the cost of emissions reductions for most companies will increase as low-cost/high-return options are exhausted.

There are approaches that could be used to ameliorate the fourth (assumption of target compliance) and final (disregard for past action) weaknesses—for instance, rating approaches can use a combination of forward-looking and backward-looking indicators, including cross-sectional comparisons to competitors. Further iterations of this method will test such approaches, but this initial version should be understood in the context of these limitations.

In the next section of this methodology, regression models for absolute emissions reduction targets and intensity targets are introduced.

1.3. Assigning a temperature score to disclosed targets

The first step in assigning temperature scores to disclosed targets was to assess which types of corporate GHG targets (absolute GHG reductions and GHG intensity reductions, following CDP 2018 Climate Change questionnaire) can be adequately matched to scenario variables (e.g. global GHG emissions) or benchmarks constructed using scenario variables (e.g. global GHG intensity, GHG/GDP). Using GHG targets disclosed to CDP in 2018, common target types were identified and mapped to scenario variables or derived benchmarks. Annex 1 shows the results of this mapping, but some of the most common scenario benchmarks are shown in Table 1.

Table 1: Target typology and matched scenario benchmark

Target Class	Example Target wording	SR1.5 Scenario variable/ benchmark
Absolute GHG reduction	Company X commits to reduce absolute scope 1 and 2 emissions 30% by 2030 from a 2018 base year	Emissions|Kyoto Gases (AR5-GWP100)
GHG Economic Intensity	Company X commits to reduce scope 1 and 2 emissions 30% per unit of added value by 2030 from a 2018 base year	Emissions|Kyoto Gases (AR5-GWP100)/ GDP|PPP
GHG Physical Intensity, cement	Company X commits to reduce scope 1 emissions 30% per tonne of cement by 2030 from a 2018 base year	Emissions|CO2|Energy|Demand|Industry *Materials production*|*Cement*
GHG Physical Intensity, steel	Company X commits to reduce scope 1 emissions 30% per tonne of steel by 2030 from a 2018 base year	Emissions|CO2|Energy|Demand|Industry *Materials production*|*Crude steel*
GHG Physical Intensity, power generation	Company X commits to reduce scope 1 emissions 30% per MWh by 2030 from a 2018 base year	Emissions|CO2|Energy|Supply|Electricity

In order to assess the temperature alignment of targets, each class of target needs to be mapped to an SR15 variable (or quotient of two SR15 variables, in the case of intensity targets). Each target "class" is a combination of a CDP- Industry classification, target type (including denominator for intensity targets), and scope(s) covered. In Annex1, relevant target classes are mapped to SR15 variables.

The second step was identifying potential scenario subsets from the entire SR1.5 database to be included in subsequent regressions. This step was treated iteratively, through code that subsetted the entire database using different combinations of three key variables that collectively describe the normative scenario types SBTi aligns itself with (those most likely to result in long term temperature target given potential limits to late century CDR, see The SBTi Foundations of target setting paper, SBTi, 2019). Specifically, scenarios were filtered using combinations of the following variables:

- Peak emissions year (using values of 2020, 2025, 2030, and 2100), applied to both CO2 from energy/industry and Kyoto GHGs from mitigation scenarios
- Maximum annual CDR (10, 15, or 20 Gt CO2/year, as well as no constraint (1000 Gt CO2/yr)

The combinations of these variables resulted in 192 different scenario sets, though with many duplicates (for instance, because peak year 2020 and peak year 2025 filters removed the same scenarios). In total 56 unique scenario sets resulted after deduplication, summarized in Annex 2. The scenario sets ranged from a minimum of 213 to a maximum of 416 scenarios after filters were applied. These numbers were further reduced by removing baseline scenarios from each set (as defined by SR1.5 metadata field "baseline scenario", i.e. scenarios where no deliberate mitigation action is taken), as baseline scenarios are not appropriate benchmarks for corporate mitigation actions (though these were utilized in the development of the default score, as described below in Section 1.4).

Regression models were then developed for each unique combination of key scenario variables or benchmarks, each unique scenario set (56 unique sets, Annex 2) and developed for six key time horizons relevant to corporate targets, ranging from 5 years to 30 years, starting from base year 2020 (the most common mitigation start year for mitigation scenarios in the SR1.5 database). Thus a total of 2016 regression models were constructed. Here we focus especially on results for "medium term" targets (15 years, 2020-2035 slopes) and "long term" targets (30 years, 2020-2050., though results for each time horizon will also be made available upon publication.

Code written in R to process the SR1.5 scenario data into the distinct scenario subsets and run and visualize the regressions will also be freely available online upon publication.

Sample results are shown for the most common scenario benchmark (global GHGs) over the six time horizons and one scenario set (4) in Figure 4. Results for each scenario set and variable followed a similar logical pattern, with fits increasing and slopes of the regression lines increasing over longer time horizons (slope –0.23, R2 0.64 for 5 year; slope –0.52, R2 0.93 for 30 year). This is logical, since the required ambition over a longer time horizon will be smaller, since it averages over more years, and the degree of variability between scenarios decreases over longer horizons as more of the scenario is 'baked in' by 2050 than by 2030.

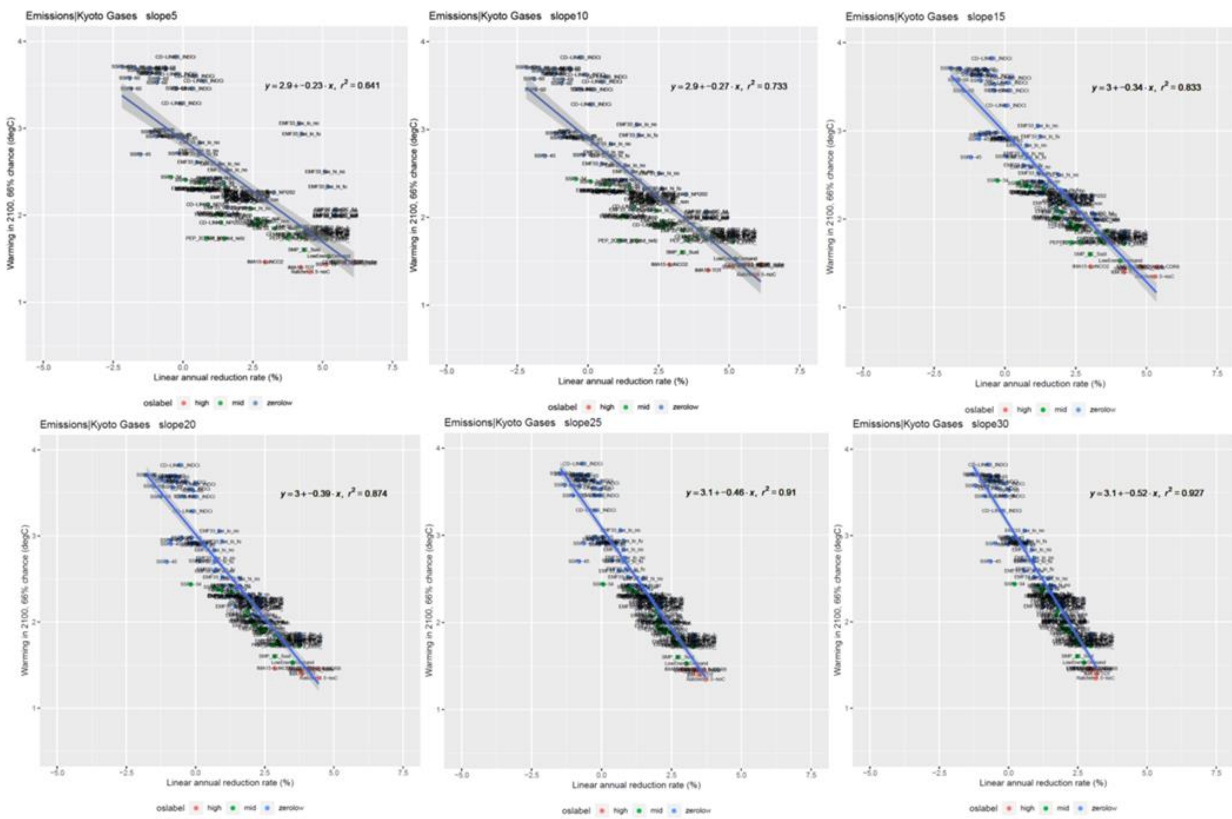


Figure 4: Scatter plots with linear fit for global GHG variable ('Emissions|Kyoto Gases') over six time horizons for Scenario set 4

Following the development of regression models, the final input scenario set (and thus regression results) was chosen based on a combination of two factors: first, best fit over medium and long term horizons (15 and 30 year); and second, consistency with SBTi's scenario preferences for lower-risk (low overshoot/low CDR) scenarios (see SBTi, 2019). Common regression diagnostics (leverage, Cook's D) were also consulted.

Fortunately these factors pointed in similar directions, as generally the scenarios sets that were more constrained for peak year and particularly for CDR tended to find better regression fits—this is shown in Annex 2, which sorts the scenario sets by average R^2 values for the three most common target variables (GHGs, GHG/GDP, and CO2/MWh from power) over 15 and 30 year horizons. Comparing the number of scenarios in each set with average fits shows a high degree of correlation, as shown in Figure 5. This is logical, as most scenarios that represent outliers between near term scenario variables and end of century warming are those that delay ambition and make up for it through later CDR (Rogelj et al., 2018). This trend is further shown in Figure 5, which shows the relationship between the sample size and resulting fit for the 56 scenarios sets, coloured by each scenario variable. (NB: sample sizes in this graphic are different from those shown in Annex 2 because not all scenarios contain every variable).

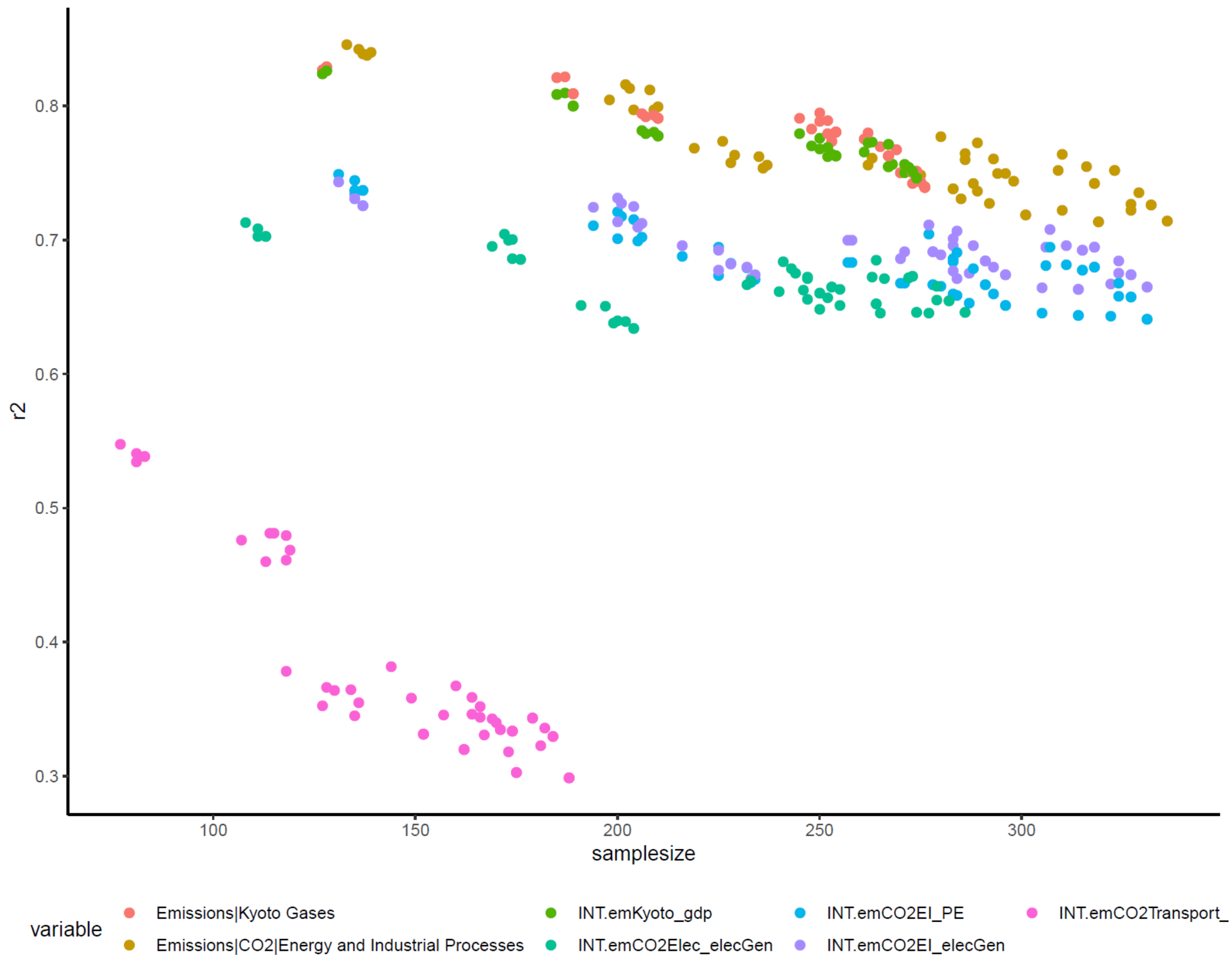


Figure 5: Regression fit (R2) as a function of sample size of regression, by scenario variable/benchmark.

The chosen scenario set (104) is constrained to a peak year of 2020 for maximum CO2 emissions from energy and industry, and a maximum CDR of 10 Gt/yr. Regression results for the chosen scenario subset are shown in Table 2.

Table 2: Regression results for Scenario set 4

	15-year horizon (targets < 15 year)			**30-year horizon (targets < 30 year)**		
Regression Model	Intercept	Slope	R^2	Intercept	Slope	R^2
GHG (Kyoto Gases)	2.7	-0.31	0.83	2.84	-0.48	0.93
CO2 (Energy and Industrial Processes)	2.62	-0.31	0.85	2.72	0.44	0.9
GHG/GDP	4.11	-0.53	0.83	4.93	-1.1	0.9
CO2/MWH (Electricity generation)	3.33	-0.33	0.71	3.9	0.78	0.89
CO2/PE (primary energy)	3.00	-0.51	0.75	3.21	0.66	0.84

Annex 1 provides a complete overview of how these five regression models can be used to map target ambition to a temperature outcome, depending on the time horizon, sector, and scope coverage of the target.

The target ambition is first converted into linear annual reductions, defined below:

$$Linear\ annual\ reductions = \frac{\%\ emission\ reduction\ from\ base\ year\ to\ target\ year}{target\ year - base\ year}$$

The linear annual reductions of the target are then used to in the regression equations to convert target ambition to temperature ratings. For example, an absolute target of 30% reduction between 2015 and 2030 mapped to the Kyoto gases regression model would result in a linear annual reduction of 2%. Using the Kyoto gases regression equation, this ambition would translate to a 2.08°C temperature rating.

1.4. Default temperature score for companies without disclosed targets

1.4.1. Default score approaches

Companies without any relevant, publicly disclosed targets, or without targets covering an important GHG emissions scope, are still assigned a temperature score ("default temperature score") to enable the useful comparison of portfolios that may differ in terms of target coverage, in addition to company-by-company comparisons.

In the absence of targets, companies are assumed to follow a business as usual pathway, as they have not stated publicly (through a GHG emission reduction target) how they intend to reduce their emissions over time. Default scores therefore represent an expected business as usual trajectory for the company.

Business as usual trajectories can be defined at a company, sector, and economy wide level. This methodology first focuses on uniform default scores at an economy wide level. While, economy wide default scores assume the company's temperature score is aligned with that of the global economy, sector specific approaches define business as usual pathways at a sector level and assume the company's trajectory is consistent with that of the sector.

1.4.1.1. Economy wide default scores

An economy wide default score applies the score uniformly to all companies, regardless of sector or current performance. The scores are based on 2100 warming projections. Using the climate action trackers 2100 warming projections (Figure 6), based on current pledges, a range of warming between 2.8°C and 3.2°C is expected by the end of the century (66% probability) [1].

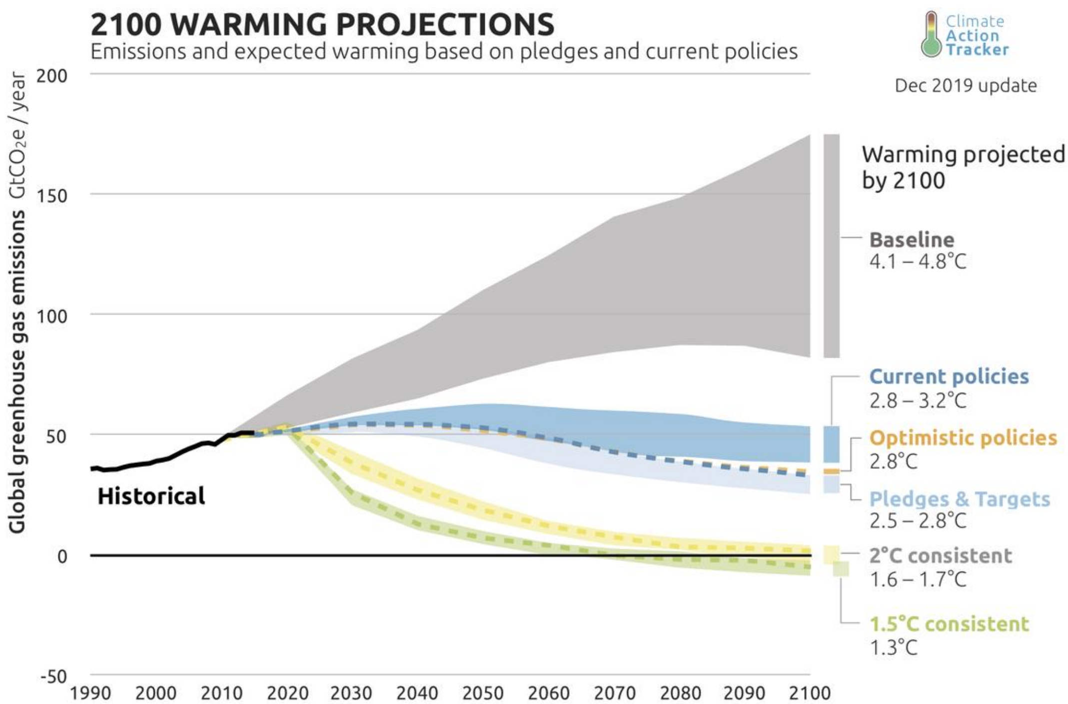


Figure 6: 2100 warming projections based on a range of future scenarios (Climate Action Tracker)

This aligns with the UNEP Emissions Gap Report 2019 finds that even if all unconditional Nationally Determined Contributions (NDCs) under the Paris Agreement are implemented, the world is on course for a 3.2°C temperature rise by 2100 (UNEP, 2019). The most recent review of business as usual pathways from the UNEP Emissions Gap Report and IEA World Energy Outlook puts the temperature value at around 3°C when projected out to end of century using different approaches, or when comparing emissions levels in 2040, with no further policy and only reflecting market changes.

Other estimates for business as usual pathways also exist. The 2019 UN Emissions Gap Report highlighted that a continuation of current policies would lead to a global mean temperature rise of 3.5°C by 2100 (range of 3.4–3.9°C, 66 per cent probability). The IPCC's RCP 8.5 pathway delivers a temperature increase of about 4.3˚C by 2100, relative to pre-industrial temperatures.

[1] Based on a likely (≥66%) probability that if the projected emissions are accurate, warming would not exceed 3.2°C, which is consistent with the scenario temperature classifications used throughout.

The temperature rating methodology will use a 3.2°C value as an interim solution to derive temperature scores for companies with no forward-looking targets. This implies that these companies are expected to decarbonise along a 3.2°C pathway, consistent with global policies implemented to ensure reduction of emissions at this rate. Section 4 outlines the plan for future methodological development, which will include generating more detailed uniform and sector specific default scores for companies with no valid GHG emission reduction targets.

2. Company protocol

The company protocol enables the generation of a company level temperature score based on the temperature scores of the company's targets. Targets are usually expressed using different units, can cover various types of GHG emission scope, and can be set over multiple timeframes. Hence, this protocol is used to select and aggregate different target scores in order to produce consistent and comparable score at a company level.

A set of quality criteria is first established to identify the target types and target formulations that can be scored. This is followed by a series of classification and aggregation steps based to produce the finals scores per company.

2.1. Target quality criteria

Targets can be classified in terms of five key attributes, presented in Table 3.

Table 3. Target criteria

Criteria	Description
Target Type	Defines whether the target ambition is based on an absolute, intensity, or other format e.g. % procurement.
Target scope coverage	Targets can be set across individual or combined GHG emission scopes (as defined in the GHG protocol) e.g. scope 1, scope 2, scope 3, scope 1+2, scope 1+2+3 etc.
Boundary coverage	Within a given emissions scope, companies define how much of that scope will be included in the boundary of the target e.g. 50% of scope 1 is covered by the target, or 95% of combined scope 1+2 is covered by the target.
Target timeframe	Targets can be reported across timeframes ranging from the reporting year up to 2100.
Target progress	Describes the rate of achievement of the target e.g. 30% of the target has been achieved by the current reporting year

2.1.1. Target types

Only GHG emission reduction targets are currently acceptable for rating. All procurement, engagement, or renewable electricity targets are currently not accepted. Long-term ambitious or aspirational targets that are not quantitative (e.g. climate neutral/net-zero in 2050) are not scored at this time due to the lack of definition of these terms.

Of the valid GHG emission reduction target types, these can be broadly divided into absolute and intensity GHG targets.

All types of absolute targets based on GHG emissions and intensity targets based on GHG reductions per unit of X are valid, such as

- Physical intensity pathways of SDA sectors: Cement, Power Generation, Iron and Steel, Aluminium, Fossil Fuels, Transport Services
- Economic intensity targets: based on GEVA or Revenue.
- Any intensity targets where the conversion to absolute emissions is disclosed

2.1.2. Scope coverage

Targets covering scope 1 and 2, and scope 3 emissions will be assessed and scored separately. Temperature scores will be produced for each company by either rating the targets or using a default rating in the absence of a valid target.

Scope 3 targets will be scored using the same approach as scope 1 and 2 targets. The SBTi target classification approaches currently apply only to scope 1 and 2 targets, meaning that only scope 1 and 2 targets can be classified against temperature goals. Future target classifications approaches developed by the SBTi can be incorporated into this methodology to ensure alignment.

If a company's relevant and mandatory scope 3 emissions are 40% or more of total scope 1, 2, and 3 emissions, a scope 3 target is also required. For companies whose scope 3 emissions represent less than 40% of total emissions, scores at both the scope 1+2 and scope 1+2+3 levels will be based on the scores of the scope 1+2 ambition. If no scope 3 target is disclosed, or the target is deemed insufficient from a coverage or timeframe perspective, a default score is provided.

The individual scores for scope 1+2 and scope 3 can be aggregated to produce an overall scope 1+2+3 score. This is completed with GHG inventory data. The following equation highlights the weighting approach to produce scope 1+2+3 scores, where TS is temperature score:

$$Scope\ 1+2+3\ TS = \frac{(Scope\ 1+2\ \ TS)\times(Scope\ 1+2\ GHG\ emissions)+(Scope\ 3\ TS)\times(Scope\ 3\ GHG\ emissions)}{Scope\ 1+2+3\ GHG\ emissions}$$

2.1.3. Boundary coverage

The boundary coverage criterion defines the minimum acceptable coverage of emissions in scopes covered by targets. The SBTi uses a minimum coverage approach where at least 95% of scope 1 and 2 emissions must be covered by targets. For scope 3 emissions, this minimum coverage threshold is 67% of emissions.

As the goal of the temperature rating approach is to score any public GHG targets, no minimum scope coverage thresholds will be applied for targets. The ambition of the target is however, normalised to the relative boundary coverage of the target. For all scope 1+2 targets under 95% coverage, and scope 3 targets under 67% coverage, the ambition of the target is therefore linked to the coverage. This means an ambitious target covering only a small portion of the scope emissions would be weighted lower as a result of the reduced coverage.
For example, consider an absolute target of 30% reduction of scope 1+2 emissions over 12 years, with 20% coverage. The target LAR would be 2.5% (30%/12 years). This LAR is then normalised to the emissions coverage, 2.5% * 20% giving a coverage normalised LAR of 0.5%.

The temperature score for the scope is computed using the following equation, where LAR is the linear annual reduction of the target:

$$Normalised\ LAR = (\%\ emissions\ in\ scope\ covered\ by\ target) \times (target\ LAR)$$

Targets can only be assessed if the boundary coverage can be quantified. In the case of single scope 1 or scope 2 target, the GHG emissions coverage of the target, compared to the overall scope 1+2 emissions of the company must be known to determine its scope coverage. If this GHG emissions data is not available, the target cannot be rated.

For combined scope 1+2+3 targets, the coverage of the target is defined by GHG emissions coverage of the stated target divided by the total reported or estimated scope 1+2+3 GHG emissions of the company.

2.1.4. Target timeframe

The timeframe criterion defines the range of acceptable target timeframes. Targets up to and including the current reporting year are not forward-looking and hence are not considered valid. The regression models outlined in Section 1 highlight that a 15-year regression time horizon is used for all targets with target years less than 15 years in the future. A 30-year time horizon is used for all targets with target years more than 15 years in the future. The 15-year time horizon can be further split into short term and mid-term timeframes.

Target timeframes are divided into the following three categories:

- Short-term: target years up to 4 years from the reporting year e.g. 2021-2024
- Mid-term: target years between 5-15 years from the reporting year e.g. 2025-2035
- Long-term: target years greater than 15 years from the reporting year e.g. 2036-2050

Targets can be scored across these 3 different timeframes providing insights on the short, mid, and long-term ambition of companies.

2.1.5. Target progress

Scores will be based on the ambition over the timeframe of the target (base year to target year), and not just on the forward-looking portion (current year to target year). Therefore, companies reporting some progress towards achieving their targets (as long as it is not 100% achieved) will not be penalised for early action. Target must not already have already been completed i.e. a target that has already been achieved would not be acceptable for rating.

2.2. Target aggregation

The target aggregation process describes the steps taken to classify and score targets to generate one company score per scope and timeframe. The following steps are conducted to arrive at the final scores:

1) Classify companies in terms of scope 1+2 and scope 3. For targets combining aspects of scope 1+2 with scope 3 combined targets, the coverage must be split between scopes 1+2 and scope 3. Where the underlying composition is not clear e.g. the amount of scope 3 emissions covered by the target is not disclosed, then the ambition is applied only to the scope 1+2 portion, and the if no details on scope 3 coverage are provided, the scope 3 portion would receive the default score.

2) Group the targets into timeframes: short-term (2021-2024), mid-term (2025-2035), and long-term (2036-2050).

3) Determine the boundary coverage of the targets and apply the normalisation step as outlined in Section 2.1.3.

4) Filtering multiple targets. Many companies report multiple targets within the same scope and timeframe. e.g. two midterm targets covering scope 1+2. In these cases, multiple scores per category would be produced. To generate just one representative score per category, a series of filtering steps is performed to arrive at a single score for each timeframe/scope category:

    4.1. Boundary coverage – select the target with the highest boundary coverage.
    4.2. Timeframes – If the boundary coverage is the same, later target years within the timeframes are given precedence. Longer-term perspectives are preferred as it means that targets are more forward-looking e.g. in a case where a company has a valid 2030 and 2035 targets covering scope 1+2, the 2035 temperature score would be used to represent the company's midterm score. In cases where target years are the same, but the additional target uses a different base year, the target with the later base year is given precedence.

4.3. Target type – in cases where both timeframe and boundary coverage are the same, absolute targets are given precedence over intensity targets

Figure 7 displays a summary of the protocol steps:

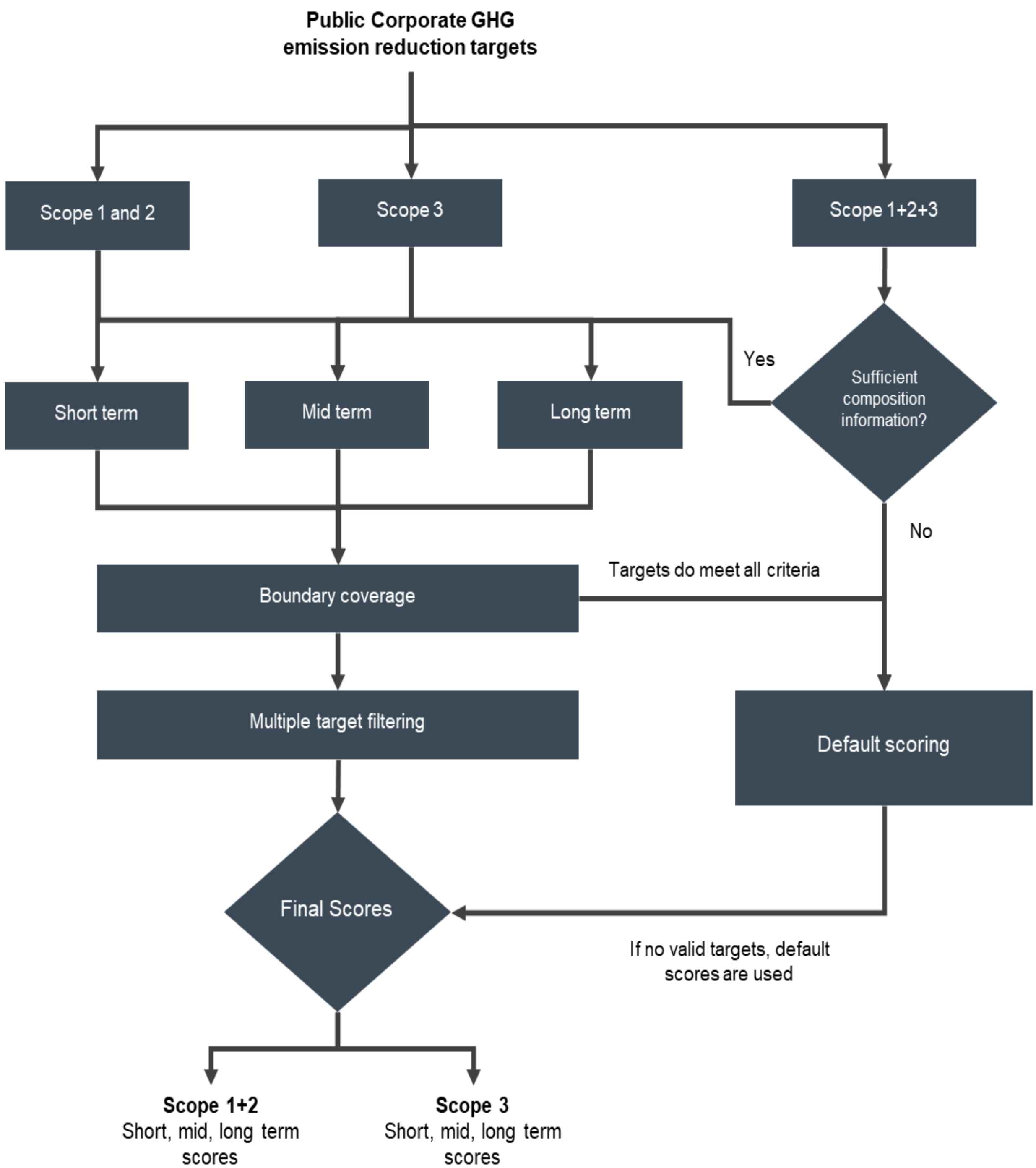


Figure 7. protocol steps to generate temperature scores at a company level, based on either valid, publicly disclosed targets or a default approach for n companies with no valid targets.

2.3. Using temperature scores

Depending on the option chosen for timeframe coverage, up to six temperature scores can be produced per company based on target timeframe and GHG emission scope coverage. Table 4 presents the six categories that can be scored at the company level.

Table 4. Six categories for each company based on GHG emission scope coverage and target

	Short-term 2021-2024	Mid-term 2025-2035	Long-term 2035-2050
Scope 1+2	Temp score	Temp score	Temp score
Scope 3	Temp score	Temp score	Temp score

timeframe.

The scope 1+2 temperature scores can then be combined with the scope 3 temperature scores to generate a scope 1+2+3 score. Table 5 illustrates how these scores would be presented for one example company. In this case, the company has only publicly disclosed valid targets covering scope 1+2 for the mid-term and long-term timeframes. The company has not disclosed any short-term targets or any scope 3 targets.

The mid-term timeframe is considered the key timeframe as it currently represents the main time period for corporate ambition and aligns with the SBTi's target setting criteria of between 5-15 years from the reporting year. The short and long-term scores can be used to better understand if companies have more immediate and longer-term goals in place.

	Short-term 2021-2024	Mid-term 2025-2035	Long-term 2035-2050
Scope 1+2 GHG: 450,000t	No target/default score: 3.2°C	1.8°C	1.9°C
Scope 3 GHG: 2,100,000t	No target/default score: 3.2°C	No target/default score: 3.2°C	No target/default score: 3.2°C
Scope 1+2+3 GHG: 2,550,000t	No target/default score: 3.2°C	GHG weighting applied to produce a composite score: $\frac{(450{,}000 * 1.8°C) + (2{,}100{,}000 * 3.2°C)}{450{,}000 + 2{,}100{,}000} = 2.95°C$	GHG weighting applied to produce a composite score: $\frac{(450{,}000 * 1.9°C) + (2{,}100{,}000 * 3.2°C)}{450{,}000 + 2{,}100{,}000} = 2.97°C$

Table 5. Example output of temperature scores at the company level

3. Portfolio protocol

The final step of the temperature rating method describes the different options for aggregating temperature scores of companies at an index or portfolio level. Several weighting options have been proposed that may be used in different applications.

3.1. Weighting objectives and principles

Before developing weighting approaches, a set of objectives were first developed that to help evaluate proposed weighting options (Table 6).

Table 6. Default weighting method objectives

Objective	Description
Enable Net-zero / Paris alignment	The method should emphasize climate impact and support investors in accurately assessing the °C warming potential of an index or a portfolio and to align their investments with a 1.5° pathway.
Support better disclosure of GHG emissions by corporations	The method should foster more and higher quality disclosure of GHG emissions along the entire value chain (Scope 1+2+3) by global corporations.
Support standardisation of methods	The method should be aligned with existing portfolio GHG accounting methods.

In addition to meeting these objectives, the default weighting method should best adhere to a set of weighting principles, presented in Table 7.

Table 7. Default weighting principles

Principle	Description
Comparability	Results should be comparable across different asset classes and investment products.
Applicability	Investors should be able to perform the aggregation at a reasonable cost with public/accessible data.
Reliability	The method should produce results which are reliable and verifiable.
Clarity	The method should be understandable and practical to implement.
Timeliness	The method should produce results that are timely and current.
Completeness	The method should allow for complete portfolio assessments.

3.2. Weighting Options

Seven potential options for aggregating individual company temperature scores at the index/portfolio are presented for consultation. These include:

- Option 1: Weighted average temperature score (WATS)
- Option 2: Total emissions[1] weighted temperature score (TETS)
- Option 3: Market Owned[2] emissions weighted temperature score (MOTS)
- Option 4: Enterprise Owned[3] emissions weighted temperature score (EOTS).
- Option 5: EV + Cash emissions weighted temperature score (ECOTS)
- Option 6: Total Assets emissions weighted temperature score (AOTS)
- Option 7: Revenue owned emissions weighted temperature score (ROTS)

Table 8 provides a description and formula for calculating the portfolio temperature scores using each of these options.

[1] Reported and modelled GHG emissions of the latest reporting period.
[2] Based on a company's market capitalisation, i.e. the total euro market value of a company's outstanding shares of stock. Commonly referred to as "market cap," it is calculated by multiplying the total number of a company's outstanding shares by the current market price of one share.
[3] Based on Enterprise value (EV). EV is a measure of a company's total value and includes in its calculation the market capitalisation of a company but also short-term and long-term debt.

Table 8: Details of portfolio aggregation methods

Option	Method	Temperature score formula (where TS = Company temperature score)
Weighted average temperature score (WATS)	Temperature scores are allocated based on portfolio weights.	$\sum_{n}^{i}(Portfolio\ weight_i \times TS_i)$
Total emissions weighted temperature score (TETS)	Temperature scores are allocated based on historical emission weights using total company emissions.	$\sum_{n}^{i}\left(\frac{Company\ emissions_i}{Portfolio\ emissions} \times TS_i\right)$
Market Owned emissions weighted temperature score (MOTS)	Temperature scores are allocated based on an equity ownership approach.	$\sum_{n}^{i}\left(\left(\frac{\frac{Investment\ value_i}{Company\ market\ cap} \times Company\ emissions_i}{Portfolio\ market\ value\ owned\ emissions}\right) \times TS_i\right)$
Enterprise Owned emissions weighted temperature score (EOTS)	Temperature scores are allocated based on an enterprise ownership approach	$\sum_{n}^{i}\left(\left(\frac{\frac{Investment\ value_i}{Company\ enterprise\ value} \times Company\ emissions_i}{Total\ enterprise\ owned\ emissions}\right) \times TS_i\right)$
Enterprise Value + Cash emissions weighted temperature score (ECOTS)	Temperature scores are allocated based on an enterprise value (EV) plus cash & equivalents ownership approach	$\sum_{n}^{i}\left(\left(\frac{\frac{Investment\ value_i}{Company\ EV + Cash} \times Company\ emissions_i}{Total\ EV + Cash\ owned\ emissions}\right) \times TS_i\right)$
Total Assets emissions weighted temperature score (AOTS)	Temperature scores are allocated based on a total assets ownership approach	$\sum_{n}^{i}\left(\left(\frac{\frac{Investment\ value_i}{Company\ Total\ Assets} \times Company\ emissions_i}{Total\ Assets\ owned\ emissions}\right) \times TS_i\right)$

Revenue owned emissions weighted temperature score (ROTS)	Temperature scores are allocated based on the share of revenue	$\sum_{n}^{i}\left(\left(\frac{\frac{Investment\ value_i}{Company\ Revenue}\times Company\ emissions_i}{Total\ Revenue\ owned\ emissions}\right)\times TS_i\right)$

The denominators in the formulas presented in Table 8 are defined as follows:

TETS: portfolio emissions are the sum of the portfolio company emissions

MOTS: Portfolio market value owned emissions is the sum of portfolio company owned emissions weighted on the market cap of investee companies.

EOTS: Total enterprise owned emissions is the sum of portfolio company owned emissions weighted on the enterprise value of investee companies.

ECOTS: Total EV + Cash owned emissions is the sum of portfolio company owned emissions weighted on the enterprise value + cash of investee companies.

AOTS: Total Assets owned emissions is the sum of portfolio company owned emissions weighted on the total assets of investee companies.

ROTS: Revenue owned emissions is the sum of portfolio company owned emissions weighted on the share of revenue of investee companies.

3.3. Method Assessment

Each proposed weighting method is compared against the objectives outlined in Section 3.1 (Table 10). WATS, TETS, and MOTS all have some downsides when it comes to certain objectives. The ownership methods (EOTS, ECOTS, AOTS, ROTS) all perform well against the stated objectives.

Table 10: Assessment of options against weighting objectives

Objective	WATS	TETS	MOTS	EOTS	ECOTS	AOTS	ROTS	Comment
Enable Net-zero / Paris alignment	✓	✓✓✓	✓✓	✓✓✓	✓✓✓	✓✓✓	✓✓✓	Exposure to high impact companies is best reflected under TETS; exposure under the ownership methods could be masked by high market cap/EV/revenue etc. of these companies.
Support better disclosure of GHG emissions by corporations	✓	✓✓✓	✓✓✓	✓✓✓	✓✓✓	✓✓✓	✓✓✓	WATS does not take current GHG emissions into account, therefore the incentive for companies to report is lower.
Support standardisation of methods	✓✓✓	✓	✓✓✓	✓✓	✓✓✓	✓✓	✓✓	WATS aligned to TCFD's[4] main recommended WACI method for measuring the carbon intensity of a portfolio. MOTS aligned to TCFD's approach for carbon footprinting. ECOTS aligned to PCAF[5] method for carbon footprinting of listed equities and corporate debt.

[4] TCFD (Task Force on Climate-related Financial Disclosures, 2017): Implementing the Recommendations of the Task Force on Climate-related Financial Disclosures

[5] PCAF (Partnership for Carbon Accounting Financials, 2019): Accounting GHG emissions and taking action: harmonised approach for the financial sector in the Netherlands

Table 11 provides an assessment of each option against the principles outlined above.

Table 11: Assessment of options against weighting principles

Objective	WATS	TETS	MOTS	EOTS	ECOTS	AOTS	ROTS	Comment
Comparability	✓✓✓	✓✓✓	✓	✓✓✓	✓✓✓	✓✓✓	✓✓✓	MOTS cannot be applied to corporate bonds
Applicability	✓✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	TETS requires GHG data, the ownership methods require GHG and additional corporate financial data. Specific corporate financial data may be difficult to obtain for non-listed companies
Reliability	✓✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	All options besides WATs are based on self-reported and modelled GHG data.
Clarity	✓✓✓	✓✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	Ownership based methods reduces transparency / results are somewhat less intuitive.
Timeliness	✓✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	All options besides WATs are dependent on timely GHG data
Completeness	✓✓✓	✓✓	✓	✓	✓	✓	✓	TETS dependent on GHG data for all portfolio companies; The ondership approaches require additional corporate financial data.

The EOTS/ECOTS/AOTS/ROTS methods best support the stated objectives whereas WATS is the least supportive method. In contrast, WATS is significantly better aligned to the principles compared to the ownership approaches. Yet, some of the principles related disadvantages of EOTS/ECOTS/AOTS/ROTS would be less significant if corporate reporting of GHG emission inventories were better. As better disclosure is generally supported through these approaches, an ownership approach is recommended to be applied in the temperature rating of portfolios.

3.4. Additional notes on the portfolio protocol

Double counting: In the absence of an appropriate accounting standard, double counting of GHG emissions and their respective targets shall not be considered at this stage.

Avoided emissions: as with the temperature scores at the company level, avoided emissions from low-carbon products or services shall not be considered.

4. Method Evolution

This version represents a first version of the methodology. This method will evolve over time to include updates from the latest climate science in addition to further methodological improvement.

Two key aspects of the method that are still under development are the default scoring and portfolio aggregation steps.

4.1. Default scoring

A uniform default score is first selected as an interim solution to enable the generation of portfolio level temperature scores by also weighting companies that do not have valid, forward looking targets. A 3.2°C score is first applied as a default score, based on current pledges at a 66% probability.

Various other “business as usual” scenarios exist that could also serve as a credible default score for non-reporting companies. For example, a continuation of current policies would lead to a global mean temperature rise of 3.5°C by 2100 (range of 3.4–3.9°C, 66% probability). Future work on rating non-reporting companies, will focus on a twostep approach

1. Determining the most representative economy wide average temperature, expected by the end of the century, based on the latest climate science.
2. Determining a series of default scores for non-target disclosing companies based on a distribution around the economy wide average. A sector specific approach will be explored to enable the generation of a default temperature score for each sector. Companies operating in these sectors that have no valid targets would then be assumed to decarbonise along the sector averages.

Future versions of the temperature rating approach will seek to incorporate these sector specific default scores in order to provide more granularity that better reflect actual sector emission pathways.

4.2. Portfolio weighting

Section 3 of this methodology outlines several approaches to weighting company level scores to produce portfolio level temperature scores. The beta version of this method can be used to test these weighting methods to better understand their relevance for specific applications e.g. rating an equity portfolio vs. an index.

Future versions of the method will recommend specific weighting options for specific applications e.g. target setting via the SBTi

4.3. Version Control

Version Name	Description	Date published
Consultation method	Draft method published to coincide with the method consultation period which ran from April 30 – May 22, 2020.	April 30, 2020
Beta method	Beta version to be used for testing	June 30, 2020
Version 1.0	Updated methodology incorporating feedback from beta testing process	October 01, 2020

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Annex 1: Target class to SR15 variable mapping

Target class			
CDP-ACS Industry	**Target type**	Scope 1+2 Regression Model **SR15 variable match**	Scope 3 Regression Model **SR15 variable match**
All industries except Fossil Fuels, Cement & Concrete, Steel & Iron, Aluminum, Power, and Transportation Services (below)	Absolute	Emissions|Kyoto Gases (AR5-GWP100)	Emissions|Kyoto Gases (AR5-GWP100)
	Intensity	INT.emKyoto_gdp	INT.emKyoto_gdp
Power Generation	Absolute	Emissions|CO2|Energy and Industrial Processes	Emissions|Kyoto Gases
	Intensity	INT.emCO2Elec_elecGen	INT.emCO2Elec_elecGen
Cement/Steel/Aluminium	Absolute	Emissions|CO2|Energy and Industrial Processes	Emissions|Kyoto Gases
	Intensity	INT.emKyoto_gdp	INT.emKyoto_gdp
Primary Energy	Absolute	Emissions|Kyoto Gases	Emissions|Kyoto Gases
	Intensity	Emissions|Kyoto Gases (AR5-GWP100)/Primary Energy	Emissions|Kyoto Gases (AR5-GWP100)/Primary Energy
Transportation	Absolute	Emissions|Kyoto Gases	Emissions|Kyoto Gases
	Intensity	INT.emKyoto_gdp	INT.emKyoto_gdp

Annex 2: Scenario sets used for regression models

Scenario Set	Average R2, 15 year	Rank R2, 15 year	Average R2, 30 year	Rank R2, 30 year	Peak Emissions year	Peak Emissions variable	Peak filter applied to	CDR filter variable	CDR Limit (Gt CO2/yr)	Number scenarios in set
4	0.799879	1	0.903919	1	2100	Year of max Kyoto emissions	1.5C and 2C	cdr|max	-10	213
104	0.795081	3	0.903357	2	2020	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-10	216
20	0.795777	2	0.902727	4	2100	Year of max Kyoto emissions	1.5C and lower 2C	cdr|max	-10	217
136	0.792082	5	0.902217	5	2020	Year of max EI CO2 emissions	1.5C	cdr|max	-10	218
36	0.793902	4	0.903104	3	2100	Year of max Kyoto emissions	1.5C	cdr|max	-10	219
3	0.777904	9	0.880951	11	2100	Year of max Kyoto emissions	1.5C and 2C	cdr|max	-15	278
103	0.787263	6	0.887937	6	2020	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-15	282
119	0.786006	7	0.88724	8	2020	Year of max EI CO2 emissions	1.5C and lower 2C	cdr|max	-15	283
19	0.77443	10	0.879555	19	2100	Year of max Kyoto emissions	1.5C and lower 2C	cdr|max	-15	284
107	0.785552	8	0.887556	7	2025	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-15	288
35	0.77296	12	0.879204	20	2100	Year of max Kyoto emissions	1.5C	cdr|max	-15	289
99	0.773886	11	0.879661	18	2100	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-15	290
52	0.754887	16	0.872668	39	2100	Year of max Kyoto emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-10	297
152	0.756133	15	0.871872	45	2020	Year of max EI CO2 emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-10	304
68	0.748917	24	0.870096	53	2100	Year of max Kyoto emissions	1.5C and lower 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-10	306

168	0.751037	20	0.869931	54	2020	Year of max EI CO2 emissions	1.5C and lower 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-10	307
156	0.751247	19	0.87071	50	2025	Year of max EI CO2 emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-10	313
84	0.746734	27	0.869693	56	2100	Year of max Kyoto emissions	1.5C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-10	314
148	0.747671	26	0.870142	52	2100	Year of max EI CO2 emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-10	315
51	0.745919	28	0.873163	38	2100	Year of max Kyoto emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-15	340
2	0.747949	25	0.876861	25	2100	Year of max Kyoto emissions	1.5C and 2C	cdr|max	-20	343
50	0.73639	38	0.875866	27	2100	Year of max Kyoto emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-20	354
18	0.743356	32	0.875174	30	2100	Year of max Kyoto emissions	1.5C and lower 2C	cdr|max	-20	355
151	0.760699	13	0.879948	15	2020	Year of max EI CO2 emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-15	358
53	0.732392	41	0.875519	28	2020	Year of max Kyoto emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-1000	361
5	0.732392	42	0.875519	29	2020	Year of max Kyoto emissions	1.5C and 2C	cdr|max	-1000	363
167	0.749913	22	0.876825	26	2020	Year of max EI CO2 emissions	1.5C and lower 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-15	364
1	0.725108	47	0.87488	32	2100	Year of max Kyoto emissions	1.5C and 2C	cdr|max	-1000	365
118	0.752599	17	0.880982	10	2020	Year of max EI CO2 emissions	1.5C and lower 2C	cdr|max	-20	366
83	0.736425	37	0.869926	55	2100	Year of max Kyoto emissions	1.5C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-15	367
34	0.740188	36	0.874516	34	2100	Year of max Kyoto emissions	1.5C	cdr|max	-20	368

106	0.75928	14	0.882794	9	2025	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-20	369
66	0.731086	43	0.873351	37	2100	Year of max Kyoto emissions	1.5C and lower 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-20	370
122	0.751381	18	0.880862	13	2025	Year of max EI CO2 emissions	1.5C and lower 2C	cdr|max	-20	373
134	0.742193	34	0.874171	35	2020	Year of max EI CO2 emissions	1.5C	cdr|max	-20	374
138	0.74275	33	0.874797	33	2025	Year of max EI CO2 emissions	1.5C	cdr|max	-20	376
98	0.741272	35	0.874971	31	2100	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-20	378
65	0.720008	51	0.872412	40	2100	Year of max Kyoto emissions	1.5C and lower 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-1000	379
17	0.720008	52	0.872412	41	2100	Year of max Kyoto emissions	1.5C and lower 2C	cdr|max	-1000	381
166	0.745421	29	0.878488	21	2020	Year of max EI CO2 emissions	1.5C and lower 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-20	387
82	0.727532	46	0.872221	44	2100	Year of max Kyoto emissions	1.5C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-20	388
101	0.75022	21	0.880894	12	2020	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-1000	390
154	0.749474	23	0.880441	14	2025	Year of max EI CO2 emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-20	394
165	0.73327	39	0.877332	23	2020	Year of max EI CO2 emissions	1.5C and lower 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-1000	396
81	0.716454	55	0.87124	48	2100	Year of max Kyoto emissions	1.5C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-1000	397
117	0.73327	40	0.877332	24	2020	Year of max EI CO2 emissions	1.5C and lower 2C	cdr|max	-1000	398
33	0.716454	56	0.87124	49	2100	Year of max Kyoto emissions	1.5C	cdr|max	-1000	399
153	0.744722	30	0.879869	16	2025	Year of max EI CO2 emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-1000	401
105	0.744722	31	0.879869	17	2025	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-1000	403

146	0.728335	45	0.873519	36	2100	Year of max EI CO2 emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-20	405
133	0.722674	50	0.870676	51	2020	Year of max EI CO2 emissions	1.5C	cdr|max	-1000	407
121	0.730413	44	0.877402	22	2025	Year of max EI CO2 emissions	1.5C and lower 2C	cdr|max	-1000	409
185	0.722961	48	0.871709	46	2025	Year of max EI CO2 emissions	1.5C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-1000	410
137	0.722961	49	0.871709	47	2025	Year of max EI CO2 emissions	1.5C	cdr|max	-1000	412
145	0.717115	53	0.872394	42	2100	Year of max EI CO2 emissions	1.5C and 2C	minimum.net. CO2.emissions .(Gt.CO2/yr)	-1000	414
97	0.717115	54	0.872394	43	2100	Year of max EI CO2 emissions	1.5C and 2C	cdr|max	-1000	416