Methodology:

Oxari Temperature Score

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Introduction

This document lays out the methodological framework for the development of the new *Oxari Temperature Score*[1] (OTS). It partially builds on Carbon Disclosure Project (CDP) and World Wide Fund for Nature's (WWF) open-source Temperature Rating Methodology[2] (TRM), in which the underlying idea is to deduct a unique temperature score from the varying company greenhouse gas (GHG) emission targets to have one single indicator that is easily comparable and entails the aggregated information of climate scenario research.

The OTS builds on this framework adjusting it in two ways:

1. Temperature Score based on Technology & Policy scenarios

In the TRM, the temperature score is assigned through a linear regression which is based on a set of climate scenario pathways[3]. It essentially applies different filters to the entire scenario database, builds subsets and then takes the subset that produces the best-fitting linear regression. While this yields one single score per company, it is rather rigid. The OTS allows for some degree of flexibility. It introduces two variables that allow the user to distinguish different climate scenarios. One is policy risk, based on the scenario's assumed carbon price, and the other one is technology dependency, focusing on the mitigation scenario set's reliance on carbon dioxide removal (CDR).

2. Increase Coverage

The TRM is only suited to assign temperature scores to companies which actually publish carbon emission targets. Companies that fail to do so get a default score. AI predictions from the *Oxari Corporate Carbon Estimator* fill gaps in historic and current company CO_2 emissions data. These reported or predicted historic emission values in turn are used to generate a company's temperature score. While the SBTi database has 4,237 companies with reported targets in the data, 2,081 of them approved, the OTS provides temperature scores on over 30,000 companies worldwide[4].

The final outcome is a tool, in which users can browse through a database of companies and obtain estimates on their temperature score depending on different assumptions concerning policy pathways and technology dependency. Both variables have three levels resulting in nine possible policy-technology scenario combinations. In the following, we provide a detailed description of the underlying methodology.

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[1] Corporate Environmental and Finance Dashboard. 2022. Oxari B.V. https://www.oxari.io/dashboard

[2] Science based targets. 2021. Temperature Rating Methodology. https://sciencebasedtargets.org/resources/legacy/2020/09/Temperature-Rating-Methodology-V1.pdf

[3] *Integrated Assessment Modeling Consortium*. 2019. IAMC 1.5°C Scenario Explorer https://data.ene.iiasa.ac.at/iamc-1.5c-explorer/#/login?redirect=%2Fworkspaces

[4] Science based targets, Companies taking action. https://sciencebasedtargets.org/companies-taking-action#table, Accessed on 27/12/2022

Temperature Score Estimation

The estimation of the Oxari temperature scores consists of two main parts. Firstly, the prediction & extrapolation of CO2 emissions and secondly, the choice of scenarios. The former concerns individual companies, while the latter is about building a meaningful average pathway from the large number of climate scenarios that the IAMC 1.5°C Scenario Explorer[5] provides, given the aforementioned policy and technology-dependency assumptions. The corporate emissions and climate scenarios are matched through a common variable, the linear annual reduction (LAR, in %) in CO2 emissions.

Prediction & Extrapolation

Many companies do not report their CO2 emissions and only a few set reduction targets. This makes it intrinsically difficult to get an understanding of their performance in terms of climate change and future environmental developments. To overcome the lack of data, the OTS uses Oxari's Corporate Carbon Estimator, which predicts Scope 1-3 emissions of non-reporting companies by using public company-, industry-, and country-level data and machine learning models trained on large corporate emission datasets. In this methodology, 2016 serves as the starting point for the time series, as the Paris Agreement[6] shifted the focus to carbon reduction drastically and globally. As a result, there has been an increasing number of companies reporting on carbon emissions[7]. Based on the historical and current reported and predicted values, the LAR is calculated and matched with the average annual reduction derived from the scenarios as described in the next section.

Scenario Choice

Research on future pathways of the world's climate is manifold. Release 2.0 from the Integrated Assessment Modeling Consortium (IAMC) contains 417 different scenarios, with each scenario containing a different set of underlying assumptions concerning climate-related and socio-economic factors[8].

[5] IXMP Scenario Explorer developed by IIASA. (n.d.). IAMC https://data.ene.iiasa.ac.at/iamc-1.5c-explorer/#/login?redirect=%2Fworkspaces

[6] United Nations / Framework Convention on Climate Change. 2015. Paris Agreement https://unfccc.int/sites/default/files/english_paris_agreement.pdf

[7] KPMG, Key Global Trends in Sustainability Reporting. https://home.kpmg/xx/en/home/insights/2022/09/survey-of-sustainability-reporting-2022/global-trends.html

[8] Rogelj, J., D. Shindell, K. Jiang, S. Fifita, P. Forster, V. Ginzburg, C. Handa, H. Kheshgi, S. Kobayashi, E. Kriegler, L. Mundaca, R. Séférian, and M.V. Vilariño, 2018: Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development. In: *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 93-174, doi:10.1017/9781009157940.004.

Based on these underlying assumptions, conclusions concerning global warming can differ substantially. While this myriad of information is certainly valuable for climate researchers, it is essential for our task to find a meaningful average scenario, given the policy and technology filters, that incorporate as much information as possible while removing outliers. The TRM finds a meaningful and realistic average scenario by applying various filters and picking the set that has the largest R2 when regressing LAR on the global temperature in 2100 (see Table 1). One of these variables is the type of emissions. While this can make sense when finding a scenario set on purely statistical grounds, we follow a different approach. In our opinion, it makes sense for this application to choose the variable beforehand based on qualitative arguments.

Because we want a temperature score representative of a wide variety of companies in various industries, we opt to work with *Kyoto Gases*[9] as the emissions variable. The goal is to find a scenario set that realistically forecasts the relationship between LAR and the global temperature by 2100. Because there is a high degree of variability among the different climate scenarios, depending largely on the underlying assumptions, we would like to refrain from estimating only one number. Instead, we follow an approach, where the users can choose a path that suits their expectations.

Table 1. TSM scenario filters

Variable/ Filter	Peak_yrv	Peak_varv	Applied	Cdr_lim	Cdr_var
1	2020	Emissions | Kyoto Gases	1.5C	cdr|max	-10
2	2025	Emissions | CO2 | Energy and Industrial Processes	1.5C and 2C	minimum.net.CO2.e missions. (Gt.CO2/yr)	-1000
3	2030		1.5C and lower 2C		-15
4	2100				-20

Step 1: Building the scenario sets

To do so, we split the scenarios into three policy categories, represented by the upper, middle and lower tercile of carbon prices. These groups are considered strong, average and weak political action, respectively. We then follow a similar approach for the technology-dependency categories, using a cumulative CDR variable, which allows us to measure the degree of technological development and timing. This leads to more variability in the forecasted temperature score. Each company receives nine theoretical scores based on the chosen policy and technology dependency category. This procedure, in combination with how we choose the emissions variable, highlights our approach of combining thorough statistical analysis while also making decisions based on qualitative arguments where it makes sense.

[9] *Total Kyoto GHG emissions, including CO2, CH4, N2O and F-gases (based on 100-year GWPs from AR5 for aggregation of different gases) (Mt CO2-equiv/yr)*

Step 2: Estimating regressions

We start by calculating the LAR for each scenario. Subsequently, we use bounded linear regressions (see below) to correlate the resulting LAR with the global temperature in 2100 (66% probability) within each scenario set. Based on the adjusted-R2 as a goodness-of-fit measure we choose nine scenario sets, one for each combination of our two socio-economic variables: (i) policy and (ii) technology. The reason for choosing the scenario sets as such is to have a selection of model-scenario combinations that represents the respective level of policy stringency and technological development. This should also be reflected in the set of possible temperature scores within a scenario set. For example, the range of temperature scores in a low policy intervention and low technological development scenario set, should be systematically lower than for the opposite case of high policy intervention and high technological development.

We introduce minimum and maximum temperature score boundaries that a company can reach within any given scenario set. The reason for this is that simple unbounded linear regressions, in some cases, result in unrealistically large and scientifically ungrounded temperatures for some companies. Figures 1 and 2 show that this is ensured by setting minimum and maximum boundaries.

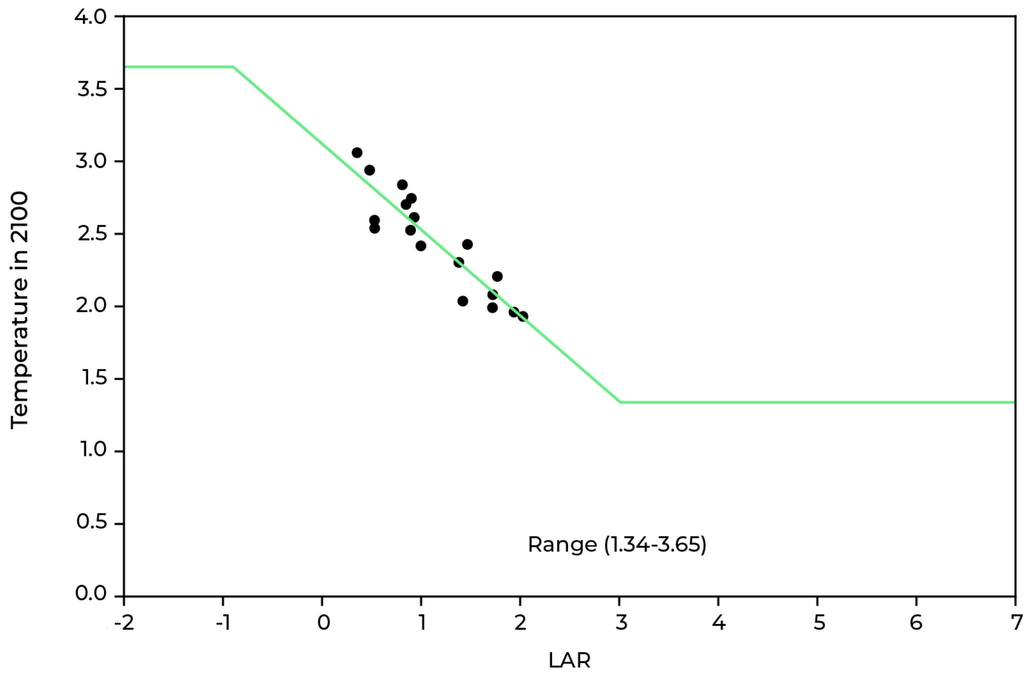

Figure 1. Bounded function for low policy stringency and low technological advancement scenarios

These minimum and maximum boundaries should incorporate two main sources of information/uncertainty: (i) the minimum and maximum temperature among all scenarios in a given set, and (ii) the marginal effect of an increase in LAR on the temperature in 2100. We ensure both by making the boundaries for each scenario set as a function of the regression slope. This implies that the minimum/maximum boundaries of scenario sets with a relatively steeper slope are further from the minimum/maximum observations than those with a flatter slope (see Figures 1 and 2).

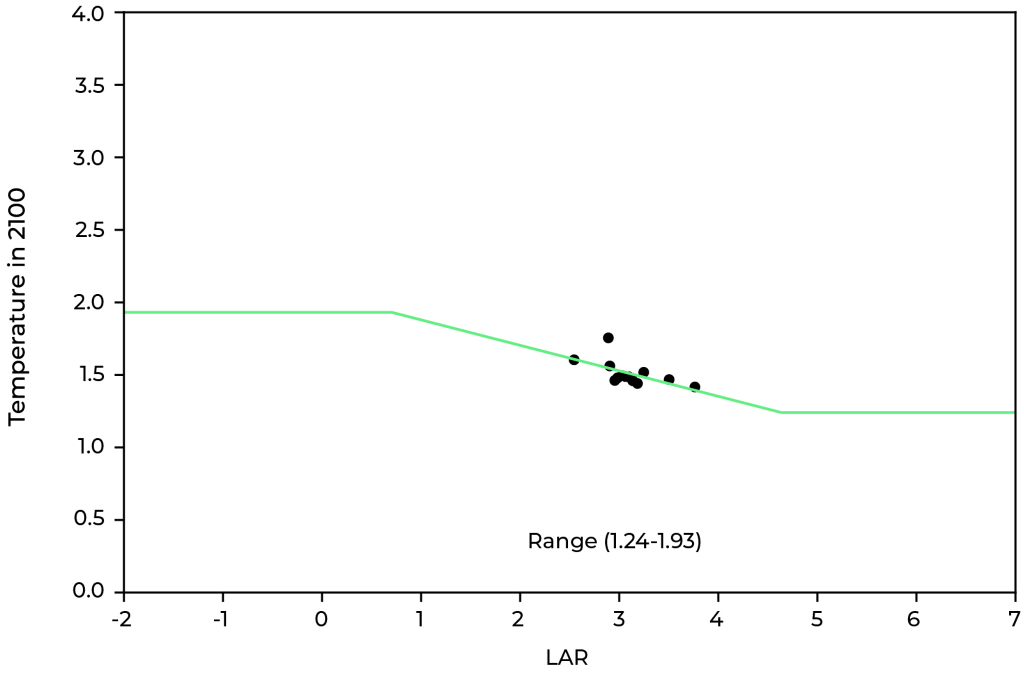

Figure 2. Bounded function for high policy stringency and high technological advancement scenarios

Company temperature scores

The final step matches the company-level LAR, with the predictions obtained for the global warming scenarios to determine the corresponding temperature score. As there are 9 different technology/policy scenario sets to choose from, the users can see their idea of the future political and technological development reflected in the displayed temperature score.

Final Comments

The OTS enables the classification of over 30,000 companies in the macro-political climate framework and therefore covers large parts of listed companies. This number is set by the capacity of Oxari's Corporate Carbon Estimator to predict emissions from reporting and non-reporting companies. The method of the OTS is based on historic and current performance, instead of only company targets. This makes data more trustworthy, through context-relating and eliminates possible self-reporting bias as far as possible. However, to provide multi-perspective insights, OTS future versions will also provide the temperature scores from company targets. By providing unique data, the OTS helps evaluate single stocks and investment portfolios, exposing laggards and leaders. The data can be viewed based on examples on Oxari Dashboard and accessed & purchased via the Oxari API. The OTS is targeted at investment & sustainability professionals as well as policymakers to enable a quick and comprehensive analysis of corporate carbon emissions and their impacts on the global environment.