# Degrees of Uncertainty

Quantifying Uncertainties of
Temperature Alignment Metrics
for Climate Risk Management

right.
based on science

# Knowledge is an unending adventure at the edge of uncertainty.

**Dr. Jacob Bronowski**
"The Ascent of Man", 11th Essay, BBC, 1973

right. based on science GmbH (2022) Degrees of Uncertainty. Quantifying Uncertainties of Temperature Alignment Metrics for Climate Risk Management. Frankfurt am Main.

Contributors:
Tobias Baumann (right. based on science GmbH); Prof. Heikki Haario, Ph.D. (Lappeenranta-Lahti University of Technology LUT); Dr. Hans-Peter Hafner (right. based on science GmbH); Dr. Jacopo Pellegrino (right. based on science GmbH); Prof. Dr. Martin Simon (Frankfurt University of Applied Sciences); Hannah Stringham (right. based on science GmbH); Aleksandr Zinovev.

Based on research conducted in a Master thesis by **Aleksandr Zinovev** and supervised by Prof. Heikki Haario, Ph.D. at Lappeenranta-Lahti University of Technology within the right. open initiative.

# Content

4 Executive Summary

6 Introduction

8 Method

11 Results

16 Discussion

17 Outlook

18 References

20 Appendix

# Executive Summary



Climate risk is increasingly understood as a major threat to the stability of the financial system. It is unique in both its potential scale (recent estimates say the impacts of climate change could shrink the global economy by one fifth - Swiss Re Institute, 2021) and its inherent uncertainties and non-linearities. As public awareness and regulatory scrutiny rise, financial institutions face multifaceted pressure to progress on the task of managing climate risks. Integrating climate risks into existing risk management systems and organisations has evolved from a fringe issue addressed by a small number of front-running institutions to a sector-wide task (e.g., European Central Bank, 2022). One of the biggest challenges in determining the best methodologies and models to measure climate risk is the quantification of uncertainties. This is a crucial step toward one day reliably assessing the scope and impact of these risks – and pricing them accordingly.

While physical risks (caused by, e.g., acute extreme weather events or permanent shifts in weather patterns and sea levels) are already beginning to materialise today, it is transition risks that are expected to dominate in their financial impact in the short and medium term. These include policy and legal actions, technology changes, market responses, and reputational considerations as part of societal efforts to mitigate and adapt to global warming (TCFD, 2017; TCFD, 2021b). With this in mind, a company's or portfolio's own contribution to climate change, i.e., its climate impact, is a significant and material factor in climate risk assessment.

Among the available methodologies to measure climate impact, so-called 'temperature alignment' (TA) or 'implied temperature rise' (ITR) approaches (TCFD, 2021a) are moving to the forefront. TA tools allow investors to benchmark the greenhouse gas (GHG) emission trajectory of an entity or a portfolio against normative decarbonisation pathways with the result expressed in expected global temperature rise (Helmke et al., 2020; TCFD, 2021a). One such methodology is the X-Degree Compatibility (XDC) Model, developed by right. based on science GmbH. The model calculates the temperature alignment of portfolios as well as single securities from various asset classes (listed equity, private equity, corporate debt, sovereign bonds, and real estate), centring on the question: "How much global warming could be expected, if the world exhibited the same climate performance as the entity in question?"

Making the XDC metric useful to and applicable in risk management processes will require reliable quantification of the inherent uncertainties. One source of these uncertainties lies in the conversion of emissions to temperature. For this, the XDC Model draws on the Finite Amplitude Impulse Response (FaIR) climate model (Leach et al., 2021; Smith et al. 2018; Millar et al., 2017). As a first step to investigating the various sources of uncertainty in XDC Model results, this paper first explores parametric uncertainty quantification for the FaIR Model.

We apply the Markov Chain Monte Carlo (MCMC) method, which is also commonly adopted for uncertainty quantification of financial risk measures (Chib, Nardari, and Shephard, 2002; Raggi and Bordignon, 2006), in combination with the Delayed Rejection Adaptive Metropolis (DRAM) algorithm (Haario et al. 2001, 2006).

We select two scenarios to evaluate the validity of the results:

- Emissions from Representative Concentration Pathway (RCP) 8.5, a global emissions scenario according to which the radiative forcing will reach 8.5W/m² by the end of the century. This can be considered a business-as-usual scenario with high baseline emissions.
- Emissions of a sample company from the chemicals sector. Starting from 2017 as the base year, the emissions are assumed to grow according to a business-as-usual scenario until the target year.

These two scenarios were chosen because the XDC Model aims to provide an entity-specific perspective which enables both comparability among assets as well as steering. This is achieved by mapping emissions from one single entity, such as a company, to the world. However, the resulting upscaled global emissions may be exceptionally high (imagine the entire world emitting greenhouse gases at the rate of a chemical plant). Therefore, the validity of the XDC Model calculations through FaIR must be tested both for a 'moderate' scenario and for extreme emissions and temperatures.

Emission data from both scenarios are provided as input to 5,000 MCMC simulations, in which the FaIR model is used to visualize the temperature evolution according to various parameter samples. The calculations provide a minimum and maximum temperature value for each point in time, yielding a temperature bandwidth. For the timeframe from 1850-2005, the results of these model simulations show a good fit to observed temperatures, serving as a calibration (see Fig. 1). The further the projections move into the future, the wider the span between minimum and maximum becomes (see Fig. 2 and Fig. 4). This increased range in possible temperatures shows that the MCMC simulation results can capture the uncertainties of a forward-looking methodology.

For the RCP 8.5 scenario, the interval of possible temperatures in the target year 2050 is [2.3° C, 2.6° C] with a mean of 2.4° C. Viewed as a histogram (see Fig. 3), it is evident that the distribution is markedly skewed towards higher temperatures, showing that more parameter combinations result in an estimate above the mean than below it.

The same is true for the second scenario for a chemicals company: Since there is a much larger quantity of emissions in this scenario, the estimated temperature increase is about twice as high. The temperature interval in the target year 2050 is [3.8° C; 4.9° C] with a mean of 4.3° C. Here, too, the distribution of values is skewed towards the higher end of the range (see Fig. 5).

The implication here for risk managers would be to apply more conservative assessments, as companies may need to reduce emissions further than their decarbonisation target pathway might indicate. More importantly, this investigation shows that the uncertainties arising from the conversion of emissions to degrees Celsius through the FaIR Model can be reliably quantified to enhance the transparency of the metric. Further investigations into other sources of uncertainty within the model, such as the definition of sectors, input data, further model parameters (outside the climate-related elements), and scenario uncertainty will be needed. Finally, model uncertainty with regard to the underlying climate model will also need to be quantified.

Addressing these points will contribute to providing richer and more robust information to practitioners, which is vital to allowing business leaders to identify and implement effective decarbonisation measures, while also enabling financial actors to make sound choices on where to direct capital and how to both manage and price their climate risk. Underlying methodologies must be sufficiently reliable, broadly applicable across asset classes, and scalable, while eschewing oversimplification. Positioned at the intersection of financial decision making and climate science, TA approaches like the XDC Model can promote better understanding of the effects of business activities and assets on climate change and global temperature rise.

Evaluating TA approaches with concepts and frameworks already familiar to financial institutions, such as MCMC (Chib, Nardari, and Shephard, 2002; Asai, McAleer, and Yu, 2006), facilitates the integration of climate risks into organisations struggling with limited resources and capabilities for addressing the daunting task of managing climate risks.

The unprecedented uncertainties that climate change brings with it will not be resolved by any model or metric. However, providing clarity and transparency on their extent, their sources, and their impact on results is crucial to creating a metric that is suitable for practical use and integration into risk management processes. The work presented here, as well as further collaborative investigations between business, finance, and academia, will bring us closer to this aim – degree by degree.

# Introduction

During the 2008 Global Financial Crisis, financial institutions were pushed to the brink of collapse and temporarily unable to adequately assess and manage their risk exposure, owing to their use of oversimplified measures and models about the behaviour of housing and mortgage markets (Nickerson and Griffin, 2017). In the space of two years, that crisis sent global GDP plummeting from +4.4 % in 2007 to -1.3 % in 2009 (World Bank, 2022). What followed was a global recession, the Euro crisis, and food shortages in several developing nations, to name just a few consequences. However, as disastrous as this was, it is dwarfed by the potential economic effects from increasing atmospheric greenhouse gas (GHG) concentration and rising global temperatures, which could cause the global economy to shrink by almost one fifth (Swiss Re Institute, 2021). Within financial risk management, one of the key lessons drawn from the 2008 crisis is the need for uncertainty quantification (UQ) for risk measures and models (Moshirian, 2011; Chen, Flood, and Sowers, 2017). Given the potentially crippling effects of climate change on the global financial – as well as planetary – system, the urgent need to reliably assess the associated financial risks, and therefore to also quantify inherent uncertainties could not be clearer.

## Putting a Price on Climate Risk

The Task-Force on Climate-Related Financial Disclosures (TCFD) divides climate risk into two categories: Physical risks, resulting from 'chronic' changes in weather, precipitation patterns, or rising sea levels, as well as 'acute' events such as floods, wildfires, droughts, or heatwaves. In contrast, transition risk refers to asset revaluation occurrences due to societal and regulatory efforts to limit global warming, including policy and legal actions, technology changes, market responses, and reputational considerations (TCFD, 2017; TCFD, 2021b). The contribution of a company or portfolio to climate change is a significant and material factor in climate risk assessment. While both risk types are interdependent, transition risks are expected to dominate in the short and medium term, coming with deep uncertainties about their exact timing and magnitude (Gambhir et al., 2022). Regulators and banking institutions recognise the immense challenges in managing transition risks and are striving for methodological guidance and best practices for risk management (TCFD, 2021a).

The German banking regulator BaFin guides banking institutions to integrate sustainability risks, including climate and related reputational risks, into existing risk management frameworks and risk categories (BaFin, 2019). In addition, recently published reports and guidelines from the Basel Committee on Banking Supervision and the European Banking Authority (EBA) highlight the necessity of science-based quantitative risk measures for effectively measuring, managing, and communicating transition risks (Basel Committee on Banking Supervision, 2021; EBA, 2021). Useful climate risk metrics must be both quantitative and seamlessly integrated into existing risk management practices and frameworks of the financial sector. A metric that satisfies both aspects would allow bank risk managers to work toward putting a price tag on climate risks and integrating this risk type into existing asset pricing and risk models.

## Temperature Alignment for Risk Management

Among the available methodologies to measure climate impact, so-called 'temperature alignment' (TA) or 'implied temperature rise' (ITR) approaches (TCFD, 2021a) are moving to the forefront. TA tools allow investors to benchmark the GHG emission trajectory of an entity or a portfolio against normative decarbonisation pathways with the result expressed in expected global temperature rise (Helmke et al., 2020; TCFD, 2021a). Regulatory bodies and standard-setting institutions recognise temperature alignment metrics as a methodological approach for financial institutions to evaluate and manage climate risks (EBA, 2021). On a global level, the TCFD's Portfolio Alignment Team, in a recently published report, suggests to financial institutions the deliberate use of TA methodologies, particularly in cases where the necessity for insights about the degree of alignment or misalignment of a portfolio to the goals of the Paris Climate Agreement is required or where there is a need for an effective climate performance comparison of different investing strategies (TCFD, 2021a). These recommendations were also welcomed by the United Nations Environment Programme - Finance Initiative (UNEP FI), a strategic public-private partnership that comprises 400 global financial institutions (UNEP FI, 2021).

One such methodology is the X-Degree Compatibility (XDC) Model developed by right. based on science GmbH. The XDC Model calculates the temperature alignment of portfolios as well as single securities from various asset classes (listed equity, private equity, corporate debt, sovereign bonds, and real estate), centring on the question: "How much global warming could be expected, if the world exhibited the same climate performance as the entity in question?" By scaling from a company or asset to the world, the XDC Model is geared towards understanding that single entity's climate impact, its alignment to the Paris Agreement goal, as well as assessing its exposure to inside-out climate risks at a preliminary stage. It is not designed to predict realistic planetary warming scenarios, but rather extrapolated results, to enable risk management and steering at a company- or portfolio-level. To calculate this 'extrapolated warming effect', the XDC Model draws on a climate model, the Finite Amplitude Impulse Response (FaIR) Model (Leach et al., 2021; Smith et al. 2018; Millar et al., 2017). As a first step to investigating the various sources of uncertainty in XDC Model results, this paper explores parametric uncertainty quantification for the FaIR Model. Other analyses on these uncertainties have been conducted (Leach et al., 2021; Smith et al., 2018), which form the foundation of the work presented here. The work discussed in this paper intends to extend those previous analyses by using a different statistical framework, different data, and a different cost function with the aim of significantly reducing the uncertainty intervals.

This investigation is thus a first step towards fully quantifying uncertainties within XDC results and thereby lays the foundation for the integration of climate risks into risk management frameworks through TA tools like the XDC Model.

The research described here was conducted in a Master thesis by Aleksandr Zinovev, supervised by Prof. Heikki Haario, Ph.D. at Lappeenranta-Lahti University of Technology as well as Dr. Jacopo Pellegrino and Dr. Hans-Peter Hafner of right. based on science GmbH within the right. open initiative (Zinovev, 2021).

## The X-Degree Compatibility (XDC) Model

The X-Degree Compatibility (XDC) Model calculates the temperature alignment of an economic entity, such as a company (public or private), a building, a sovereign / state, or a portfolio covering one or several of these asset classes. The calculation steps are as follows:

1. Determine the emission intensity in a given base year of the asset / portfolio in question. This is defined as the ratio of GHG emissions (the 'carbon footprint') to either gross value added (GVA), square metres (for buildings), or population (for sovereign bonds).

2. Project the future development of this emission intensity over time based on scenario assumptions and compare this trajectory to benchmarks drawn from recognised climate change mitigation scenarios (e.g., those provided by the International Energy Agency (IEA), the Network for Greening the Financial System (NGFS), or the Carbon Risk Real Estate Monitor (CRREM)) to establish the climate performance.

3. Assume the world would perform equally over the same timeframe and derive a time series of global emissions.

4. Input this data into the FaIR Model to obtain the resulting global mean temperature time series.

There are several sources of uncertainty in the XDC Model, as in all TA methodologies and climate metrics: The first is the measurement or estimation of the GHG emissions (or 'carbon footprint') attributed to a particular entity. This is especially challenging for Scope 3 emissions (GHG Protocol, 2015), which are not directly caused by the entity of interest but come from many different sources along its upstream and downstream value chain. Further uncertainties relate to the projection of future growth and emissions at the entity level as well as on a broader sectoral and global scale (scenario assumptions). Finally, there are model uncertainties associated with converting emissions to temperature, including the uptake of $CO_2$ emissions by the ocean and land, as well as the magnitude and timescale of warming, associated with the emissions that remain in the atmosphere. Most TA methodologies draw on target emission pathways derived from emission budgets in different mitigation scenarios. However, as these budgets are themselves uncertain, the uncertainties are 'hidden' in these TA approaches, making them difficult to quantify. To the best of our knowledge, the XDC Model is the only TA / ITR methodology to use an iterative climate model (FaIR), i.e., one that updates the state of the climate system for each year of input emissions and considers multiple different gases explicitly. There are many advantages to this approach, one of which is the ability to quantify the different impacts of early mitigation of emissions versus later use of negative emission technologies as well as the effect of uncertainties on the TA calculation. This study provides a first step towards quantifying these uncertainties. In order to provide a proof of concept in a generalisable computational framework, we focus here on parametric uncertainty, i.e., uncertainty with regard to the physical input parameters of the FaIR model which needs to be propagated to its output. In future research, we hope to use this framework to account for data, scenario, and model uncertainty.

XDC

## The Finite Amplitude Impulse Response (FaIR) Climate Model

FaIR is a simplified climate model. This means, it is less computationally intensive than complex climate models while still being able to emulate the global mean temperature response of such models. Thus, FaIR is perfectly suited for use by decision makers to test and validate potential climate strategies or possible investment decisions. Likewise, FaIR is ideal for integrating large probabilistic ensembles and quantifying uncertainties. FaIR has been used by the UN Intergovernmental Panel on Climate Change (IPCC) and features in its recent report on the Mitigation of Climate Change (IPCC, 2022).

The process of the FaIR model can be summarized in the following three steps:

1. A simplified representation of the carbon cycle determines how many $CO_2$ emissions per year remain in the atmosphere and how many are taken up by the land and ocean.

2. Calculation of radiative forcing, or in other words, how much the energy balance of the planet is affected by the change in atmospheric GHG concentration. Several sources such as methane and nitrous oxide are considered in addition to $CO_2$.

3. Computation of the global mean temperature anomaly compared to the pre-industrial as a function of time resulting from total radiative forcing. In FaIR, the temperature anomaly in any particular year depends on the temperature anomaly in the previous year, the current emissions, and the radiative forcing in the current year.

Every stage of the process from emissions to temperature change bears uncertainties. For example, there are uncertainties associated to the share of emissions taken up by the ocean and land, which is expected to decrease in the future, as increasing temperatures reduce the efficiency of uptake. Another example is the radiative forcing caused by a doubling of atmospheric $CO_2$ concentration. This can be affected by other factors like clouds, which can act to mask the forcing. Finally, arguably the largest and most important uncertainties of FaIR come from the Equilibrium Climate Sensitivity (ECS) and the Transient Climate Response (TCR): two parameters that determine how quickly and how much the global mean temperature responds to the radiative forcing.

FaIR

## Markov Chain Monte Carlo (MCMC) Method

In order to determine how large these uncertainties are and how much they affect the XDC Model results, this research applies the so-called Markov Chain Monte Carlo (MCMC) method, which is also commonly adopted for uncertainty quantification of financial risk measures (Chib, Nardari, and Shephard, 2002; Raggi and Bordignon, 2006). The idea behind this approach is the following: FaIR has approximately 20 main physical parameters which are used for the calculation of atmospheric concentration, radiative forcing, and temperature increase. For these parameters, the exact values are not known, but, from experiments and theoretical considerations, ranges for the parameters can be estimated, and thus a theoretical distribution can be defined for each. These theoretical distributions are called prior distributions or priors. The goal is, given the priors, to find a feasible posterior distribution of model parameters such that the temperature values which FaIR estimates for historical periods are in line with observed temperature measurements.

The non-linearity of the FaIR model together with noise in the data raise severe identifiability issues, which are amplified as the number of parameters grows, thus rendering the problem of designing an efficient MCMC sampling algorithm a challenging task. By combining state of the art Delayed Rejection Adaptive Metropolis (DRAM) MCMC sampling (Haario et al. 2001, 2006) with novel ideas to pre-process the available temperature data and modelling of the cost function, we found a framework to produce superior estimates of the parameter posterior distribution in the sense that it provides tighter uncertainty bounds. An introduction to the MCMC methodology as well as a workflow summarizing the posterior estimation can be found in the Appendix.

By employing this estimation framework, a distribution of possible values for each parameter is obtained. Starting from these distributions, point and spread estimates at any wanted accuracy, such as 90% confidence intervals (5% - 95% quantile), can be used to define the accepted parameter combinations to propagate parametric uncertainty to the outputs of the FaIR Model.

MCMC

To investigate the parametric uncertainty in the FaIR Model, the MCMC methodology described in the previous section was applied using two different scenarios and prior distributions according to the findings of Smith et al. 2018. (Other assumptions for the priors were tested and then discarded, as they lead to either physically impossible results or calculation overflow.) While some interesting observations on the accuracy of the MCMC simulation results can be made across the full timeframe from 1850 to 2050, the crucial year to better understand the uncertainties that affect XDC Model results and climate risk management is the target year (in this case, 2050 was chosen). The histograms Fig. 3 and Fig. 5 show the distribution of results for the target year.

## Scenarios

In selecting scenarios for this analysis, it is important to bear in mind that the XDC Model maps emissions from one single entity, such as a company, to the world to provide an extrapolated metric that can be used not only by the finance and investment side, but also by companies themselves, to steer their climate strategies. By moving a step beyond the carbon footprint (i.e., absolute emissions in a particular year) to a forward-looking climate impact measurement which is upscaled to a global level, the XDC metric provides comparability among various companies and assets.

This metric is intended as an assessment and comparison tool, not as a realistic projection of the future that awaits us. In fact, for emission-intensive entities and sectors, the calculation may produce extremely high upscaled emissions and temperature values. Therefore, the scenarios chosen for this analysis must ensure validity of the results not only in a 'moderate' emissions scenario, but also for extreme emissions and temperatures. These scenarios are:

- Emissions from Representative Concentration Pathway (RCP) 8.5, a global emissions scenario according to which the radiative forcing will reach 8.5W/m$^2$ by the end of the century. This can be considered a business-as-usual scenario with high baseline emissions.
- Emissions of a sample company from the chemicals sector. Starting from 2017 as the base year, the emissions are assumed to grow according to a business-as-usual scenario until the target year.

## Temperature dataset

In this study, a temperature dataset consisting of the temperature output of 11 different climate models during the period 1850-2005 was used (see Fig. 1). The model parameters were calibrated to a composite temperature time series obtained by averaging over the different climate model outputs. The mean annual variance divided by the number of measurements was used as measurement error variance. We found that using this pre-processed composite dataset has a significant stabilizing effect on the parameter calibration.

## Results of MCMC calibration

Using the framework described above (see Method), emission data from both scenarios were provided as input to 5,000 MCMC simulations each, in which the FaIR model was used to determine the temperature evolution according to the various parameter samples. The calculations provide a minimum and maximum temperature value for each point in time, which serve as a bandwidth (shaded green area in Fig. 1, Fig. 2, and Fig. 4). A well-calibrated approach would be indicated by the actual (observed) temperature values of past years falling within this bandwidth. As shown in Fig. 1, the results of the model simulations with parameters drawn from the posterior (shaded green area) show a good fit to the observed composite data (black dots). This is especially true for more recent years, in which observations are assumed to be more accurate than in the past.

**Calibration data: minimum to maximum temperatures range of simulations and observed data**

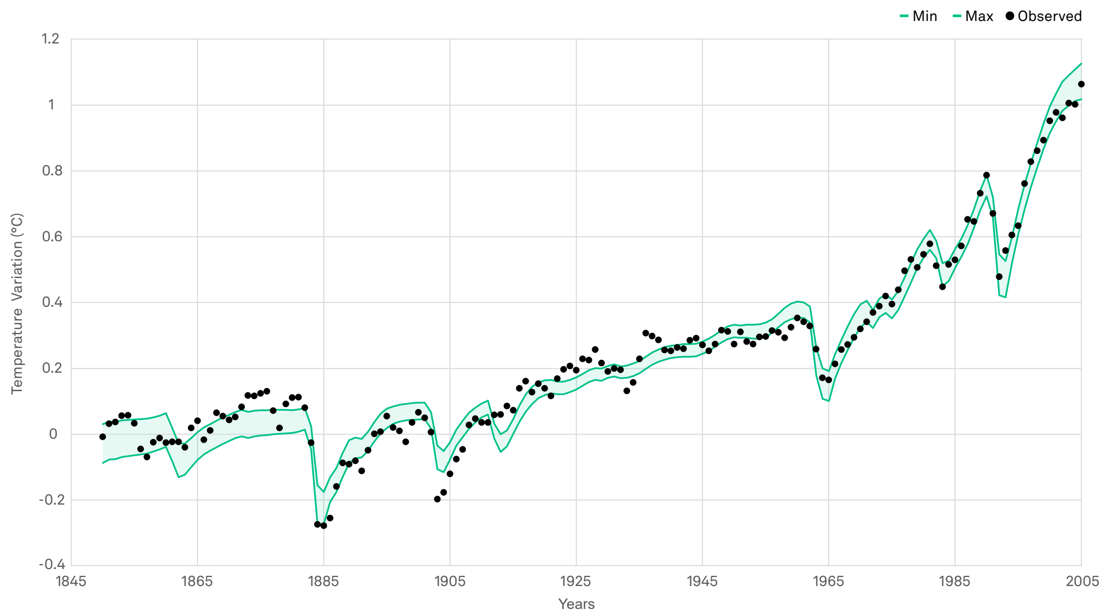



**FIGURE 1:** **Evolution of simulated and observed temperatures starting from 1850 (beginning of observations) until 2005. Data are compared to the minimum and maximum values obtained via the MCMC experiments.**

## Forward-looking FaIR results with uncertainty quantification

Shifting focus towards the time ahead, the results show that the more projections move into the future, the wider the span between minimum and maximum becomes. This demonstrates that the MCMC simulation results can capture the uncertainties of a forward-looking methodology (see Fig. 2 and Fig. 4).

## RCP 8.5 scenario

Based on the parameter combinations obtained as previously described, the interval of possible temperatures in the target year 2050 is [2.3° C, 2.6° C] with a mean of 2.4° C. This is also depicted by the histogram of temperature values in 2050 in Fig. 5. It is noteworthy that the histogram is markedly skewed to the right, showing that more parameter combinations result in an estimate above the mean than below it. The implication for risk managers is to apply more conservative assessments, as companies may need to reduce emissions further than their decarbonisation target pathway might indicate. Considering two different target pathways for a company, one for the lower and one for the upper boundary of the interval, there is a higher probability of reaching a temperature close to the upper bound than one closer to the lower bound.

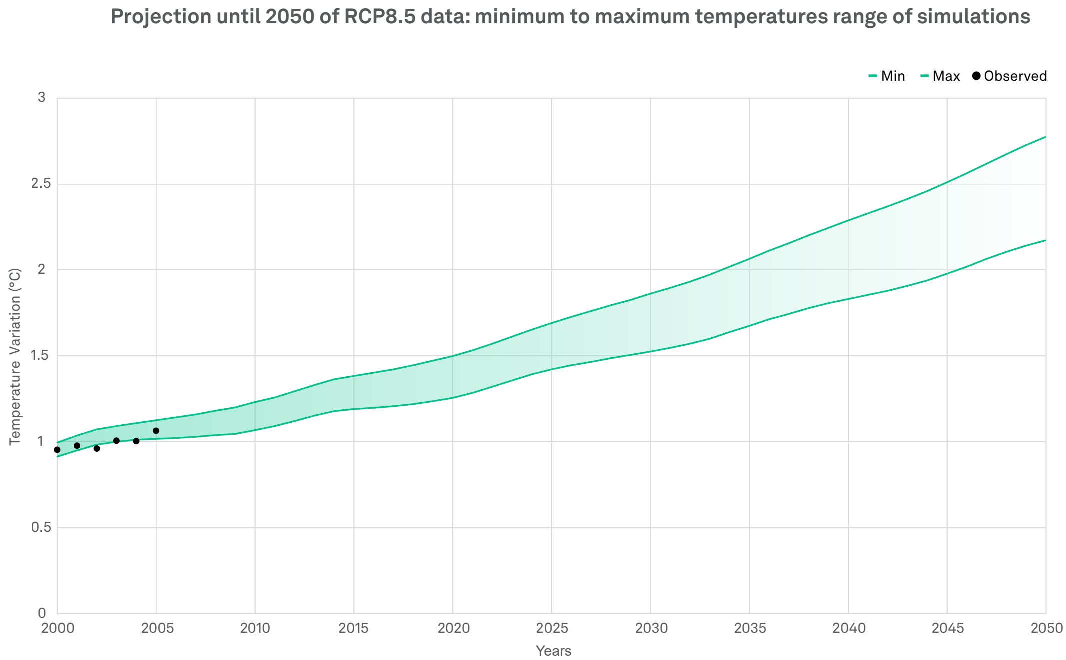



FIGURE 2: Temperature projection according to RCP8.5 data. The bandwidth between minimum and maximum grows when moving forward into the future.

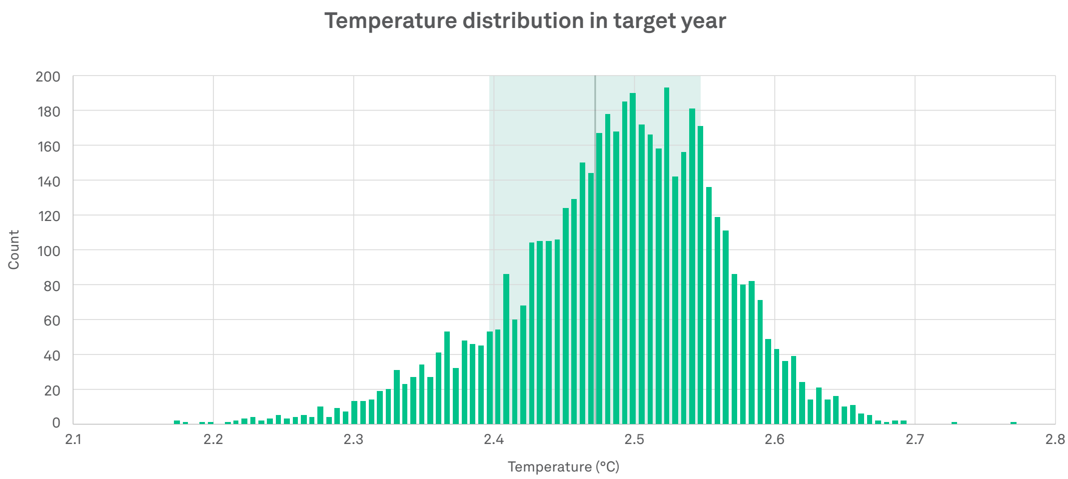



FIGURE 3: Temperature distribution in target year based on RCP8.5 data. Shaded green area indicates the centre of distribution (dark grey line) and a ±1 standard deviation interval.

## Chemicals company scenario

For the second scenario (upscaled emissions of a company from the chemicals sector) the results look similar. Since there is a much larger amount of $CO_2$ emissions in this scenario, the estimated temperature increase is about twice as high. With the same constraints on the model parameters, providing this sample company dataset as input to the FaIR model leads to a temperature interval in the target year of [3.8° C; 4.9° C] with a mean of 4.3° C. As the histogram shows (Fig. 5), the distribution of the values is again skewed to the right. At first glance, this effect is less pronounced than in Fig. 4. However, as the temperature values overall are higher here, this still points to a greater likelihood of actual temperatures landing on the higher end of the scale and hence would imply a more conservative assessment for risk management purposes.

**Projection until 2050 of sample chemicals company data: minimum to maximum temperatures range of simulations**

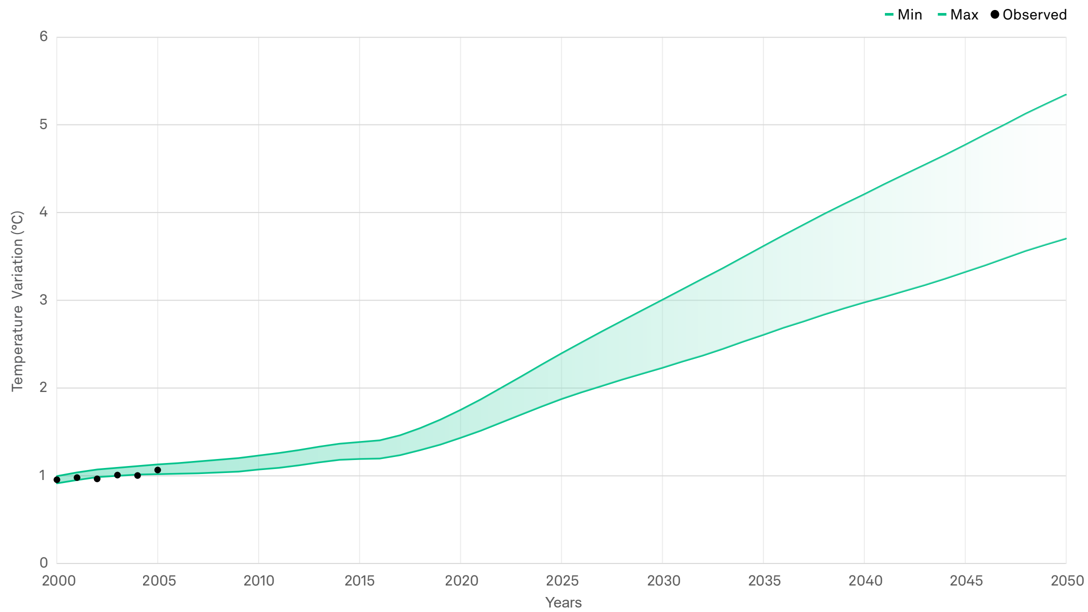



FIGURE 4: **Temperature projection according to sample chemicals company data. The bandwidth between minimum and maximum grows when moving forward into the future. Compared to the RCP8.5 case, temperatures are also higher overall due to greater emissions in this scenario.**

**Temperature distribution in target year**

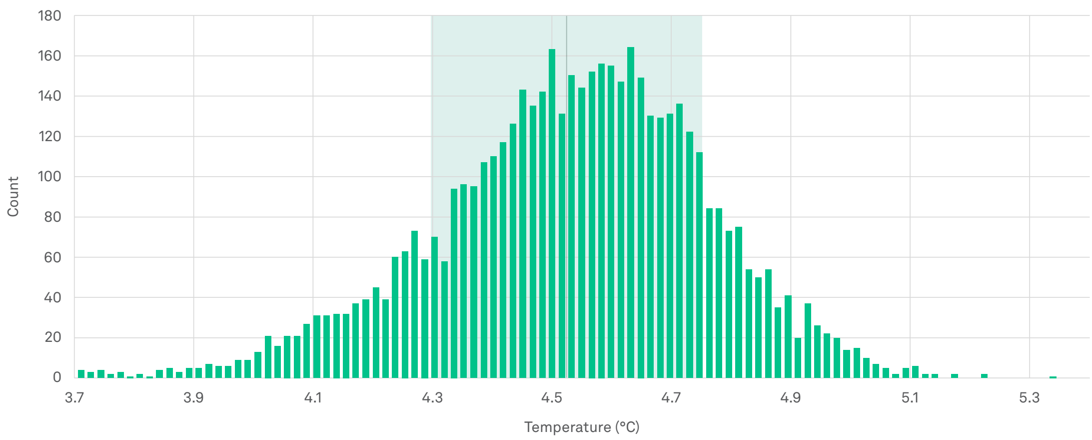



FIGURE 5: **Temperature distribution in target year based on the $CO_2$ concentration increase following the sample chemicals company. Shaded green area indicates the centre of distribution (dark grey line) and a ±1 standard deviation interval.**

The results discussed above show a rather narrow range for the temperature estimates compared to some other climate change studies. This is likely due to the following:

- The only uncertainties considered here are the parametric ones originated by the FaIR climate model. Due to the limited current knowledge about several physical processes of the climate system (such as the behaviour of clouds), different representations in other climate models are possible.

- FaIR works with the assumption that most processes within the climate system will remain stable in the future. In reality, there are likely to be many different feedback loops due to global heating, which may accelerate some developments of the system, leading to a steeper rise in temperatures.

Therefore, a model uncertainty analysis based on an ensemble of climate models would almost certainly lead to wider confidence intervals. Nevertheless, this initial investigation shows that even for a high-emission scenario, the parametric uncertainty margins arising from the conversion of global emissions to temperature rise through the FaIR Model are not overly large and can therefore be used to provide valuable information within risk assessment processes.

# Discussion



Financial institutions face multifaceted pressure to progress on the task of managing climate risks. With global warming reaching the top of the regulatory agenda, integrating climate risks into existing risk management systems and organisations has evolved from a fringe issue addressed by a small number of front-running institutions to a sector-wide task (e.g., European Central Bank, 2022). The effects of *physical* climate risks are already beginning to materialise today, with assets lost, supply chains impacted, and businesses hurt by floods, fires, storms, and drought. However, already in the short and medium term, seismic shifts in public opinion and scrutiny as well as rising regulatory pressure will bring *transitional* climate risks to the fore. In face of this new reality, risk management functions will urgently need to identify and implement forward-looking methodologies that will allow them to reliably assess the scope and impact of these risks – and price them accordingly. These methodologies must be sufficiently reliable, broadly applicable across asset classes, and scalable. That being said, the temptation to oversimplify should be resisted if robust risk assessments are to be achieved. Positioned at the intersection of financial decision making and climate science, TA approaches like the XDC Model can serve to promote better understanding of the effects of business activities and assets on climate change and global temperature rise.

Though sometimes decried as too complex for practical use at scale, scientifically sound TA metrics may prove to be well suited to fulfil the requirements expressed by the TCFD's Portfolio Alignment Team, which advises financial institutions to 'include a statement in their portfolio alignment disclosures regarding uncertainties arising from the methodology' (TCFD, 2021a).

With regards to the XDC Model in particular, this analysis has shown that the uncertainties arising from the conversion of emissions to degrees Celsius through the FaIR Model can be reliably quantified to enhance the transparency of the metric. Further investigations into other sources of uncertainty within the XDC Model calculations will serve to further support its use in risk management (see Outlook).

The research conducted here also contributes to transparency on the uncertainties of climate risk metrics in general. The MCMC approach is a methodology that has become familiar to risk management academics and practitioners when it comes to volatility modelling (Chib, Nardari, and Shephard, 2002; Asai, McAleer, and Yu, 2006). Evaluating TA approaches with concepts and frameworks already familiar to financial institutions, such as MCMC (Chib, Nardari, and Shephard, 2002; Asai, McAleer, and Yu, 2006), facilitates the integration of climate risks into organisations struggling with limited resources and capabilities for addressing the daunting task of managing climate risks (European Commission, 2021).

# Outlook



The investigation described in this paper can be considered a first and important step towards a wider coverage of uncertainties in the XDC Model. However, as described above, further sources of uncertainty will need to be considered and investigated before XDC results can be further qualified with, e.g., a margin of error and before this additional information can then be integrated into the software and products that draw on the XDC Model. Uncertainties may originate from the definition of sectors (with implications for classification and data availability), the input data, further model parameters (outside the climate-related elements), and scenarios. Finally, model uncertainty with regard to the underlying climate model will also need to be quantified.

Arguably the greatest challenge here will be to cope with uncertainties in input data, especially for emissions. Work to model and estimate emission data from company financial information and reporting has already begun. Advances here will improve the control and standardisation of input data and allow for uncertainty quantification in this crucial first calculation step.

Addressing all of these points will contribute to providing richer and more robust information to practitioners from across finance, investment, and business through the XDC Model. Such information is vital to allowing business leaders to identify and implement effective decarbonisation measures, while also enabling financial actors to make sound choices on where to direct capital and how to both manage and price their climate risk.

The unprecedented uncertainties that climate change brings with it will not be solved by any model or metric. However, providing clarity and transparency on their extent, their sources, and their impact on results is crucial to creating a metric that is suitable for practical use and integration into risk management processes. The work presented here, as well as further collaborative investigations between business, finance, and academia, will bring us closer to this aim – degree by degree.

# References




Asai, M., McAleer, M., and Yu, J. (2006) ‘Multivariate Stochastic Volatility: A Review’, Econometric Reviews, 25(2–3), pp. 145–175.

BaFin (2019) 'Merkblatt zum Umgang mit Nachhaltigkeitsrisiken'. Available at: https://www.bafin.de/SharedDocs/Downloads/DE/Merkblatt/dl_mb_Nachhaltigkeitsrisiken.html?nn=9021442 (Accessed: 26 March 2022).

Bank of England (2019) ‘The 2021 Biennial Exploratory Scenario on the Financial Risks From Climate Change’, Discussion Paper, pp. 1–30. Available at: https://www.bankofengland.co.uk/-/media/boe/files/paper/2019/the-2021-biennial-exploratory-scenario-on-the-financial-risks-from-climate-change.pdf?la=en&hash=73D06B913C73472D0DF21F18DB71C2F454148C80. (Accessed: 21 October 2021)

Basel Committee on Banking Supervision (2009) 'Revisions to the Basel II Market Risk Framework – Final Version'. Available at: http://www.bis.org/publ/bcbs158.htm. (Accessed: 7 October 2021)

Basel Committee on Banking Supervision (2021) 'Climate-related Financial Risks – Measurement Methodologies'. Available at: https://www.bis.org/bcbs/publ/d518.pdf. (Accessed: 26 March 2022)

BlackRock (2021) 'Larry Fink’s 2021 Letter to CEOs'. Available at: https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter (Accessed: 7 October 2021).

Board of Governors of the Federal Reserve and Office of the Comptroller of the Currency (2011) 'Supervisory Guidance on Model Risk Management'. Available at: https://www.occ.treas.gov/news-issuances/bulletins/2011/bulletin-2011-12a.pdf. (Accessed: 9 November 2021)

Carbon Disclosure Project (2019) 'Climate Change Report 2018: Major Risk or Rosy Opportunity: Are Companies Ready for Climate Change?'. Available at: https://cdn.cdp.net/cdp-production/cms/reports/documents/000/004/588/original/CDP_Climate_Change_report_2019.pdf?1562321876 (Accessed: 4 October 2021).

Chen, J., Flood, M. D., and Sowers, R. B. (2017) ‘Measuring the Unmeasurable: An Application of Uncertainty Quantification to Treasury Bond Portfolios’, Quantitative Finance, 17(10), pp. 1491–1507. doi: 10.1080/14697688.2017.1296176.

Climate Action Tracker (2021) 'Global Update: Climate Summit Momentum'. Available at: https://climateactiontracker.org/publications/global-update-climate-summit-momentum/ (Accessed: 5 October 2021).

Diebold, F. X., Doherty, N. A., and Herring, R. J. (2010) 'The Known, the Unknown, and the Unknowable in Financial Risk Management: Measurement and Theory Advancing Practice'. Princeton, N.J.: Princeton University Press.

European Banking Authority (2021) 'EBA Report: On Management and Supervision of ESG Risks for Credit Institutions and Investment Firms'. Available at: https://www.eba.europa.eu/sites/default/documents/files/document_library/Publications/Reports/2021/1015656/EBA Report on ESG risks management and supervision.pdf. (Accessed: 19 April 2022)

European Central Bank (2022) 'Supervisory assessment of institutions’ climate-related and environmental risks disclosures. ECB report on banks’ progress towards transparent disclosure of their climate-related and environmental risk profiles'. Available at: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.ECB_Report_on_climate_and_environmental_disclosures_202203~4ae33f2a70.en.pdf?2e88c1605db8adf0b748ad4aeb8721d7 (Accessed: 24 March 2022)

European Commission (2021) ‘Final Study on the Development of Tools and Mechanisms for the Integration of ESG Factors into the EU Banking Prudential Framework and into Banks’ Business Strategies and Investment Policies’. Available at: https://ec.europa.eu/info/publications/210827-final-study-esg-factors-banking_en. (Accessed: 15 March 2022)

European Parliament (2014) 'Directive 2014/95/EU of the European Parliament and of the Council of 22 October 2014 amending Directive 2013/34/EU as regards disclosure of non-financial and diversity information by certain large undertakings and groups'. Available at: https://eur-lex.europa.eu/eli/dir/2014/95/oj. (Accessed: 29 March 2022)

Chen, J., Flood, M. D., and Sowers, R. B. (2017) ‘Measuring the Unmeasurable: An Application of Uncertainty Quantification to Treasury Bond Portfolios’, Quantitative Finance, 17(10), pp. 1491–1507. doi: 10.1080/14697688.2017.1296176.

Chib, S., Nardari, F., and Shephard, N. (2002) ‘Markov Chain Monte Carlo Methods for Stochastic Volatility Models’, Journal of Econometrics, 108(2), pp. 281–316.

Forster, P. M., Maycock, A. C., McKenna, C. M., and Smith, C. J. (2020) 'Latest climate models confirm need for urgent mitigation', Nature Climate Change 10(1), pp. 7–10, Available at: https://doi.org/10.1038/s41558-019-0660-0.

Gambhir, A., George, M., McJeon, H., Arnell, N. W., Bernie, D., Mittal, S., Köberle, A. C., Rogelj, J., and Monteith, S. (2022) ‘Near-term Transition and Longer-term Physical Climate Risks of Greenhouse Gas Emissions Pathways’, Nature Climate Change, 12(1), pp. 88–96. doi: 10.1038/s41558-021-01236-x.

Greenhouse Gas Protocol (2015) 'A Corporate Accounting and Reporting Standard'. Revised Edition. Available at: https://ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf (Accessed: 9 November 2021)

Haario, H., Saaksman, E., and Tamminen, J. (2001) 'An adaptive Metropolis algorithm', Bernoulli, 7(2), pp. 223–242.

Haario, H., Laine, M., Mira, A., and Saaksman, E. (2006) 'DRAM: Efficient adaptive MCMC'. Statistics and Computing, 16, pp. 339–354. doi: 10.1007/s11222-006-9438-0.

Helmke, H., Hafner, H. P., Gebert, F., and Pankiewicz, A. (2020) ‘Provision of Climate Services - The XDC Model’, in Leal Filho, W. and Jacob, D. (eds) Handbook of Climate Services. Cham: Springer, pp. 223–249.

Intergovernmental Panel on Climate Change (2022) 'Climate Change 2022: Mitigation of Climate Change. Working Group III contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change'. Available at: https://www.ipcc.ch/report/ar6/wg3 (Accessed: 3 May 2022)

Leach, N. J., Jenkins, S., Nicholls, Z., Smith, C. J., Lynch, J., Cain, M., Walsh, T., Wu, B., Tsutsui, J., and Allen, M. R. (2021) 'FaIRv2.0.0: a generalized impulse response model for climate uncertainty and future scenario exploration', Geoscientific Model Development, 14, 3007–3036, Available at: https://doi.org/10.5194/gmd-14-3007-2021

Metropolis, N., Rosenbluth, A., Rosenbluth, M., Teller, A., and Teller, E. (1953) 'Equation of State Calculations by Fast Computing Machines'. The Journal of Chemical Physics 21(6), pp. 1087–1092.

# References



Millar, R. J., Nicholls, Z. R., Friedlingstein, P., and Allen, M. R. (2017) 'A modified impulse-response representation of the global near-surface air temperature and atmospheric concentration response to carbon dioxide emissions', Atmospheric Chemistry and Physics, 17, pp. 7213–7228, Available at: https://doi.org/10.5194/acp-17-7213-2017

Moshirian, F. (2011) 'The Global Financial Crisis and the Evolution of Markets, Institutions and Regulation', Journal of Banking & Finance, 35(3), pp. 502–511. doi: 10.1016/j.jbankfin.2010.08.010.

Nickerson, J. and Griffin, J. M. (2017) 'Debt correlations in the wake of the financial crisis: What are appropriate default correlations for structured products?', Journal of Financial Economics, 125(3), pp. 454–474, Available at: https://doi.org/10.1016/j.jfineco.2017.06.011.

Raggi, D. and Bordignon, S. (2006) 'Comparing stochastic volatility models through Monte Carlo simulations', Computational Statistics & Data Analysis, 50(7), pp. 1678–1699, Available at: https://doi.org/10.1016/j.csda.2005.02.004.

Smith, C. J., Forster, P. M., Allen, M., Leach, N., Millar, R. J., Passerello, G. A., and Regayre, L. A. (2018) 'FAIR v1.3: A simple emissions-based impulse response and carbon cycle model', Geoscientific Model Development, Available at: https://doi.org/10.5194/gmd-11-2273-2018

Swiss Re Institute (2021) 'The economics of climate change: no action not an option'. Available at: https://www.swissre.com/dam/jcr:e73ee7c3-7f83-4c17-a2b8-8ef23a8d3312/swiss-re-institute-expertise-publication-economics-of-climate-change.pdf. (Accessed: 19 March 2022)

TCFD (2017) 'Final Report: Recommendations of the Task Force on Climate-related Financial Disclosures'. Available at: https://assets.bbhub.io/company/sites/60/2020/10/FINAL-2017-TCFD-Report-11052018.pdf (Accessed: 28 May 2021).

TCFD (2021a) 'Measuring Portfolio Alignment: Technical Considerations'. Available at: https://www.tcfdhub.org/wp-content/uploads/2021/10/PAT_Measuring_Portfolio_Alignment_Technical_Considerations.pdf (Accessed: 19 March 2022)

TCFD (2021b) 'Implementing the Recommendations of the Task Force on Climate-related Financial Disclosures. Appendix 3: Glossary and Abbreviations'. Available at: https://www.tcfdhub.org/wp-content/uploads/2022/04/Glossary-and-Abbreviations.pdf (Accessed: 21 April 2022)

United Nations Environment Programme - Finance Initiative (2021) 'UNEP FI Responds to the TCFD's Consultation on its Proposed Guidance on Climate-related Metrics, Targets, and Transition Plans and Measuring Portfolio Alignment: Technical Supplement'. Available at: https://www.unepfi.org/news/unep-fi-responds-to-tcfd-consultation-on-proposed-guidance/ (Accessed: 8 October 2021).

World Bank (2022) 'GDP Growth (annual %)' Available at: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG (Accessed: 13 April 13, 2022).

World Economic Forum (2021) 'The Global Risk Report 2021'. Available at: https://www.weforum.org/reports/the-global-risks-report-2021 (Accessed: 6 October 2021).

Zinovev, A. (2021) 'Uncertainty quantification of FaIR climate model'. Master's Thesis. Lappeenranta-Lahti University of Technology LUT. Available at: https://urn.fi/URN:NBN:fi-fe2021062139081

Consider a non-linear model

$$\mathbf{y} = f(\mathbf{x} \mid \theta) + \epsilon$$

where y are the measurements, f is a non-linear function with parameters $\theta$ and design variables x, and ☒ is the error term. Due to the error, it is impossible to estimate $\theta$ with total precision, but it is possible to calculate the probability distribution of $\theta$.

For this non-linear model, Bayes' theorem can be written as

$$p(\theta \mid \mathbf{y}) = \frac{p(\mathbf{y} \mid \theta)p(\theta)}{\int p(\mathbf{y} \mid \theta)p(\theta)d\theta}$$

where p($\theta$ | y) is the posterior distribution of the parameter $\theta$ given the observation y, p(y | $\theta$) is the likelihood of y occurring given that the parameter values are $\theta$, p($\theta$) is a prior distribution of $\theta$, the integral is a normalization constant and equal to the prior distribution p(y).

*Markov Chain Monte Carlo (MCMC)* is a method that allows one to sample a posterior distribution by generating a sequence (chain) $(\theta_i)_{i=1}^{N}$ which asymptotically approaches the posterior distribution. The chain is generated randomly (hence the term Monte Carlo) and every member except the first depends only on the previous member (hence the term Markov Chain). The main advantage of MCMC is the ability to sample the posterior distribution (in this case p($\theta$ | y)) without computing a multidimensional integral.

Several algorithms exist to generate a MCMC chain. One of the most frequently used is the Metropolis Hastings (MH) algorithm (Metropolis et al. 1953). It starts with the initial point $\theta_1$ and it repeats the following steps until a chain of the required length is generated (the distribution of the sequence is close to the posterior distribution):

- Choose a candidate $\hat{\theta}$ with respect to the proposal distribution $q(\hat{\theta}, \theta_n)$
- Accept the candidate with probability

$$\alpha(\theta_n, \hat{\theta}) = \min\left(1, \frac{p(\hat{\theta})q(\theta_n, \hat{\theta}))}{p(\theta_n)q(\hat{\theta}, \theta_n)}\right)$$

The choice of the proposal distribution affects the speed of convergence and varies from case to case. Often a multivariate normal distribution is used as the first proposal and then the choice of the covariance matrix can heavily influence the optimal length of the chain and therefore the calculation time. To deal with that problem, the Adaptive Metropolis (AM) algorithm can be used (Haario, H., Saaksman, E., and Tamminen, J., 2001).

The main idea of the AM is to update the covariance matrix during the chain generation. After the initial covariance matrix $C_0$ is proposed, the chain is generated until the $n_0$-th member (so-called 'burn-in' period), and then every few steps the covariance is updated.

Another advanced method is the Delayed Rejection (DR) algorithm. It is the same as MH except in the case of rejection of a candidate $\widehat{\theta_{(1)}}$ where the second candidate $\widehat{\theta_{(2)}}$) is generated from the proposal distribution $q_2(\hat{\theta}^{(2)}, \hat{\theta}^{(1)}, \theta_n)$ with respect to the rejected candidate. The probability of acceptance is

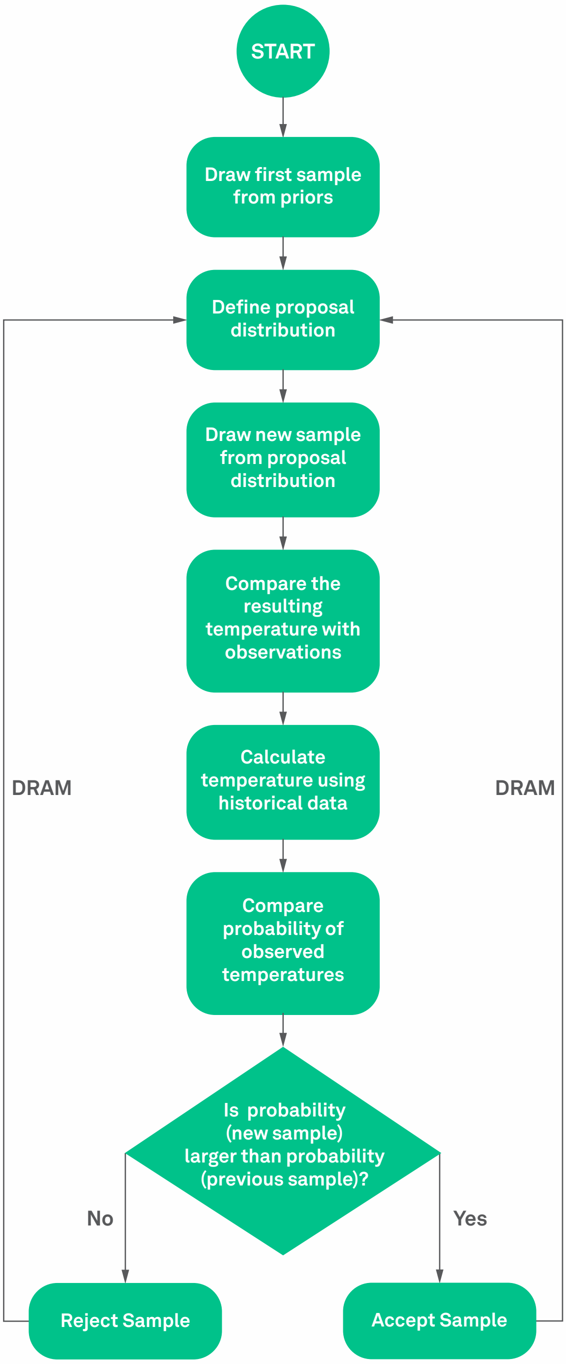
$$\alpha_2(x, y_1, y_2) = \min\left(1, \frac{p(y_2)q_1(y_2,y_1)q_2(y_2,y_1,x)[1-\alpha_1(y_2,y_1)]}{p(x)q_1(x,y_1)q_2(x,y_1,y_2)[1-\alpha_1(x,y_1)]}\right)$$

where $\alpha_1$ is calculated like the acceptance probability of the MH algorithm.

The combination of the above-mentioned methods is the *Delayed Rejection Adaptive Metropolis (DRAM)* algorithm (Haario et al. 2006). The algorithm is the same as the AM algorithm except when a candidate is rejected (first step of DR), then the further candidates are generated with respect to the scaled covariance matrix. In other words, in the first step of DR the candidate $\widehat{\theta_{(1)}}$ is generated from the proposal distribution $q_1(\cdot, \theta_n \mid \mathbf{C}_n^1)$, and in the further steps the candidates ^{θ}_{(i)} are generated from $q_i(\cdot, \hat{\theta}^{(i-1)}, \dots, \hat{\theta}^{(1)}, \theta_n \mid \mathbf{C}_n^i)$, where $\mathrm{C}_n^i = \gamma_i \mathbf{C}_n^1$ is a scaling parameter that can be chosen freely.

For the calculations, the MCMC Toolbox for MATLAB written by Marko Laine was used. For the code and examples, see https://mjlaine.github.io/mcmcstat/. This package allows one to use MH and AM algorithms as well.

1. A first sample (i.e., a set of parameters) is drawn from the prior distribution.
2. For the first iteration, a proposal distribution is defined which will be updated after the sample is accepted or rejected.
3. A new sample is drawn from the proposal distribution.
4. The set of parameters is applied to the FaIR model and the temperature on historical data is calculated.
5. The new sample is accepted when the probability of the observed data (temperatures and concentrations) given the new parameter sample is larger than for the previous parameter set (i.e., when the deviation between the observed temperature values and the ones estimated with FaIR gets smaller). In case the probability isn't larger, a probability for the acceptance of the new sample is computed.
6. The proposal distribution is updated according to the Delayed Rejection Adaptive Metropolis (DRAM) algorithm to improve the efficiency of the sampling process (see above for more details).



# Disclaimer

right. based on science GmbH is not an investment advisor and makes no representation regarding the advisability of investing in any particular company, investment fund, or other vehicle. A decision to invest in any such investment fund or other entity should not be made based on any of the statements set forth in this publication. While right. based on science GmbH has obtained information believed to be reliable, right. based on science GmbH shall not be liable for any claims or losses of any nature in connection with information contained in this publication, including but not limited to, lost profits or punitive or consequential damages. Some of the content of this paper may be proprietary and belong to right. based on science GmbH.
The information contained in this whitepaper does not constitute an offer to sell securities or the solicitation of an offer to buy, or recommendation for investment in any securities within any jurisdiction. The information is not intended as financial advice. This whitepaper provides general information only. The information and opinions constitute a judgment at the date indicated and are subject to change without notice. The information may therefore not be accurate or current. The information and opinions contained in this whitepaper have been compiled or derived from sources believed to be reliable and in good faith, but no representation or warranty, express or implied, is made by right. based on science GmbH as to their accuracy, completeness, or correctness. Finally right. based on science GmbH does not warrant that the information is up to date.


Layout & Design: Orange Hive

right. based on science GmbH
Intzestraße 1 | 60314 Frankfurt am Main
CEO: Hannah Helmke
Registry Office: Amtsgericht Frankfurt am Main HRB 106032
www.right-basedonscience.de