



Uncertainty quantification in aviation climate impact: A stochastic approach to mission-specific CO₂ and non-CO₂ Effects

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ABSTRACT

The aviation industry significantly contributes to global climate change through both CO₂ and non-CO₂ effects. This study introduces a probabilistic framework that integrates flight mission, engine performance, emission, and simplified climate response models to quantify aviation's climate impact while accounting for uncertainties in emission and climate model parameters. In particular, uncertainties in emission indices and the contrail forcing factor are updated. Using Monte Carlo simulations, the framework provides probabilistic predictions of key climate metrics, offering insights into the sensitivity of predicted climate impacts to modeling uncertainties. A case study of a representative flight mission illustrates the framework's application and highlights the contributions of CO₂, NO_x, and contrails to mission-level climate forcing, revealing that uncertainties in non-CO₂ effects, particularly NO_x emissions and contrails, dominate the total uncertainty. The findings emphasize the need for improved modeling of non-CO₂ effects and demonstrate the framework's utility in evaluating current and future propulsion systems. By advancing uncertainty quantification in aviation climate impact assessments, this study provides a robust tool to inform sustainable aviation technologies, flight optimization strategies, and evidence-based policymaking.

1. Introduction

The aviation industry plays an increasing role in global anthropogenic climate change. It contributes to net surface warming through both CO₂ and non-CO₂ emissions (Lee et al., 2021). Emissions from conventional kerosene-burning jet engines include carbon dioxide (CO₂), nitrogen oxides (NO_x) leading to short-lived ozone (O_{3S}) production and affecting long-lived ozone (O_{3L}) and methane (CH₄) destruction, as well as water vapor (H₂O), soot, sulfate aerosols and oxides (SO_x), carbon monoxide (CO), and unburned hydrocarbons (UHC). These emissions interact with complex atmospheric processes, such as plume dynamics, chemical transformations, microphysics, radiation, and transport, leading to both immediate and long-term climate forcing and impacts (Lee et al., 2021). In addition, the formation of contrails and contrail-induced cirrus clouds (AIC - Aviation-Induced Cloudiness) significantly contribute to non-CO₂ climate forcing. Due to aviation's current reliance on fossil fuels, the projected fleet growth (Grewe et al., 2021), and the sector's substantial CO₂ and non-CO₂ effects, it is crucial to quantify both the magnitude and the drivers of climate forcing. This enables prioritization of mitigation pathways and identification of the technology and operational measures with the highest leverage for

reducing overall climate impact, as required to achieve the goals set for climate-neutral aviation (Advisory Council for Aviation Research and Innovation in Europe (ACARE), 2022).

Previous studies, such as the comprehensive meta-analyses by Lee et al. (2021) as well as others (Grewe et al., 2021; Lee et al., 2009; Dallara, 2011; Dahlmann et al., 2016; IPCC, 1999; Brasseur et al., 2016; Wuebbles et al., 2007; Sausen et al., 2005), have provided valuable assessments of aviation's global climate impact. However, these studies often focus on global averages and do not take into account the influence of local atmospheric conditions and operational variables. Despite their potential to significantly affect emissions and climate forcing, factors such as flight altitude, mission profiles, and engine characteristics are frequently underexplored. Moreover, these studies often neglect the variability and uncertainties associated with emission indices and climate model parameters. Addressing these uncertainties is essential for providing more reliable climate impact assessments and enabling accurate scenario analyses for aviation's future contributions to climate change. Furthermore, incorporating engine- and mission-specific effects into climate impact assessments is crucial for guiding

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the design of next-generation engines and aircraft with reduced climate impacts.

Existing tools for flight mission and engine performance modeling (GasTurb, 2020; Jones, 2007; Sun, 2019; Hendricks and Gray, 2019; Kyprianidis et al., 2009), as well as climate modeling frameworks (Lee et al., 2021; Dallara, 2011; Kyprianidis et al., 2009; Marais et al., 2008; Grewe and Stenke, 2008; Dietmüller et al., 2023), are highly efficient and accurate within their respective domains. Besides the tool EVA (Kyprianidis et al., 2009), which is not publicly available, none of these tools currently integrate flight mission, engine performance, and climate impact modeling into a unified framework. Such integration is necessary for making accurate climate impact predictions, and conducting comprehensive uncertainty assessments.

To address this gap, this study introduces a novel process chain that integrates flight mission, engine performance, emission, and climate impact modeling to then establish a probabilistic framework that incorporates uncertainty quantification for both emission and climate model parameters. By using Monte Carlo simulations (MCS), these uncertainties are propagated through emission and climate response models, enabling robust probabilistic predictions of aviation's climate impact and enhancing the reliability of these predictions. The results can be used to inform decisions on technologies, operational strategies, and evidence-based policymaking by quantifying trade-offs under uncertainty. Furthermore, this approach provides deeper insights into how sensitive aviation's climate impact is to various emission and climate parameters. Based on these sensitivities, guidelines for targeted measurements and model improvements can be derived to reduce critical uncertainties.

For this work, flight mission and engine performance analyses are conducted using MAPLE, a modular aircraft engine performance tool designed for sustainable aviation (Wiegand et al., 2024). MAPLE has been validated for both conventional gas turbines and novel propulsion concepts, demonstrating its efficiency and accuracy in modeling diverse configurations (Wiegand et al., 2024, 2025). This study couples MAPLE with statistical emission and climate models, enabling probabilistic assessment of representative flight missions and providing a comprehensive framework for evaluating aviation's climate impact at the mission scale.

The structure of this paper is as follows: after this introduction, Section 2 describes the uncertainty analysis methods employed in this study. Sections 3 and 4 provide overviews of the emission and climate models, respectively, along with their associated uncertainties. Section 5 presents the results of a case study of an exemplary flight mission and discusses the implications of the findings. Section 6 addresses limitations. Finally, Section 7 concludes with a summary of the key insights and potential directions for future research.

2. Uncertainty analysis methods

Reliable assessment of aviation's climate impact requires addressing the uncertainties inherent in performance, emission, and climate models. These uncertainties stem from variability in input parameters, such as emission indices and atmospheric conditions, as well as model assumptions, and can be classified as irreducible (aleatoric), reflecting inherent variability, or reducible (epistemic), arising from gaps in knowledge that can, in principle, be decreased through additional data or improved models. To ensure robust and reliable predictions, this study uses uncertainty quantification (UQ) techniques to propagate these uncertainties through the models and evaluate their influence on the results. The probabilistic outputs provide insights into the range and likelihood of potential outcomes, offering a more comprehensive understanding of aviation's climate impact.

2.1. Relative uncertainty

Uncertainties in the input parameters are expressed as relative uncertainties and are used to derive absolute distributions for specific values. The absolute distribution $\Psi(\bar{x})$ for a given parameter is calculated as

$$\Psi(\bar{x}) = M(\bar{x}) \cdot \Gamma(\mu_{\text{rel}}, \sigma_{\text{rel}}), \quad (1)$$

where $M(\bar{x})$ is the nominal value of the parameter and Γ represents the relative distribution function with mean μ_{rel} and standard deviation σ_{rel} . In this formulation, aleatoric (irreducible) uncertainty is encoded in relative distribution Γ , reflecting inherent variability, while epistemic (potentially reducible) uncertainty is associated with imperfect knowledge of the nominal value $M(\bar{x})$ and the dispersion parameters μ_{rel} and σ_{rel} , which can be updated as new data become available. This approach allows uncertainties to be propagated consistently across models and enables the deduction of output ranges rather than single point values.

2.2. Monte Carlo simulation

Monte Carlo simulation is a versatile UQ method that propagates uncertainties by generating a large sample of input parameters based on their probability distributions (e.g., normal, log-normal, uniform) and evaluating the model for each realization (Rubinstein and Kroese, 2008). This approach yields probabilistic outputs, enabling the estimation of key statistics, such as the mean, standard deviation, and confidence intervals (CI), which are then used to quantify the uncertainty in the results.

2.3. Sensitivity analysis

Sensitivity analysis complements Monte Carlo uncertainty analysis by identifying the input parameters that have the greatest influence on model outputs. This study uses global sensitivity indices, such as the coefficients of importance (CoI) (Bucher, 2009). CoI are applicable to cases with uncorrelated parameters and simple polynomial uncertainty spaces (Prots, 2023) and are calculated using ProSi (M. Voigt et al., 2021). By quantifying the relative importance of input parameters, sensitivity analysis highlights the key drivers of uncertainty, and guides efforts to refine models and reduce prediction errors.

3. Emission modeling

In order to evaluate the climate impact and its uncertainty along flight missions, the emissions from aircraft engines that cause the climate impact must be quantified, together with their associated uncertainty. For this purpose, emission models are developed and implemented in MAPLE.

Emissions are typically quantified based on the emission index EI

$$EI = \frac{m_{\text{emission}}}{m_{\text{fuel}}}, \quad (2)$$

which represents the mass of emissions m_{emission} over the mass of fuel burned m_{fuel} . The following section describes the methods used to quantify the emission indices for all relevant species.

3.1. Water vapor (H_2O)

Water vapor emissions result directly from the combustion process since nearly all of the fuel's hydrogen content w_{H_2} is oxidized to water vapor. Therefore, the H_2O emission index only depends on the fuel's hydrogen content and is constant for a given fuel, independent of the engine's operating conditions. However, there is uncertainty in the emission index due to variability in the hydrogen content of kerosene between fuel batches, caused by the crude oil sources and

Table 1
Examples of reported kerosene sulfur content in the literature.

Reference	w_S in %
Sutkus et al. (2001)	0.042
Wolters (2020)	0.094
Rachner (1998)	0.05
ICAO (International Civil Aviation Organization, 2016)	0.05
PQIS (Defense Logistics Agency Energy, 2011)	0.093, 0.1081 (Jet-A1, Jet-A)
EASA (2010)	0.04, 0.05, 0.08
CRC/EI (Coordinating Research Council and Energy Institute, 2022)	0.05, 0.044 (2016, 2017)
Lee et al. (2021)	0.06
C. Voigt et al. (2021)	0.135

refining processes. Rachner (1998) reported hydrogen content values ranging from 0.1310 to 0.1470 based on various studies in different regions. Rickard and Fulker (1997) analysis of 485 probes indicated a normal distribution with a mean value of $\mu(w_{H_2}) = 0.1384$ and a standard deviation of $\sigma(w_{H_2}) = 0.00204$, which is used as a basis for this work. The emission index is derived from the molar masses of hydrogen (M_{H_2}) and water vapor (M_{H_2O}) to

$$EI_{H_2O} = w_{H_2} \frac{M_{H_2O}}{M_{H_2}} \quad (3)$$

and leads to a nominal value of $EI_{H_2O} = 1.237 \frac{\text{kg}_{H_2O}}{\text{kg}_{\text{fuel}}}$ and a relative distribution with a mean value of $\mu_{\text{rel}} = 1.0$ and a standard deviation of $\sigma_{\text{rel}} = 0.0147$, Fig. A.1(a). This represents a relatively small uncertainty in the emission prediction of water vapor and is in good agreement with the emission indices provided in other studies (Rachner, 1998; Gordon and McBride, 1994; C. Voigt et al., 2021; Silberhorn et al., 2022), see Fig. A.1(a).

3.2. Sulfur compounds (SO_x)

Sulfur naturally exists in crude oil, which is used to produce kerosene. During refining, the sulfur content is reduced but usually not completely removed. It is regulated to a maximum mass fraction of $w_S < 0.003$, though actual levels are often lower. Values reported in the literature, Table 1, range from 0.00040 to 0.00135. In 2022, CRC and EI (Coordinating Research Council and Energy Institute, 2022) reported sulfur content values for more than 1200 fuel batches from 2016–2017. The distribution approximately follows a log-normal distribution with a mean value of $\mu(\ln(w_S)) = -7.7593$ and a standard deviation of $\sigma(\ln(w_S)) = 0.5304$, which is used in this work.

The sulfur content of kerosene is primarily oxidated to SO_2 and H_2SO_4 resulting in a mixture of sulfur oxides SO_x . The mole fractions of SO_2 and H_2SO_4 are expected to depend slightly on the specific engine and operating conditions but are in the range of 2%–5%. Lee et al. (2021) assumed 3% based on the results of Petzold et al. (2005) and this value is also used in this work. SO_x emissions also directly result from the combustion process and the emission index is approximately constant for a given fuel. It is given by

$$EI_{SO_x} = w_S \left(0.97 \frac{M_{SO_2}}{M_S} + 0.03 \frac{M_{H_2SO_4}}{M_S} \right). \quad (4)$$

Hence, the emission index has a nominal value of $EI_{SO_x} = 1.015 \frac{\text{g}_{SO_x}}{\text{kg}_{\text{fuel}}}$ and its relative distribution follows a log-normal distribution with $\mu_{\text{rel}} = -0.1439$ and $\sigma_{\text{rel}} = 0.5272$, Fig. A.1(b). The resulting distribution of the emission index is in good agreement with emission indices provided in the literature and with calculations of the emission index based on sulfur contents provided in the literature, Fig. A.1(b).

Although SO_x emissions are generally associated with a climate cooling effect, it is important to consider SO_2 and H_2SO_4 , as they are harmful to the environment and the human health (EASA, 2010).

3.3. Carbon dioxide (CO_2)

Similarly to H_2O and SO_x emissions, carbon dioxide emissions directly result from the combustion process and depend on the fuel's carbon content w_C . The carbon content of kerosene is not typically reported directly in literature. Some references report the hydrogen-to-carbon content ratio alongside the hydrogen content (Rachner, 1998; C. Voigt et al., 2021). Hence, the carbon content and its distribution can be determined from the hydrogen and sulfur content, as kerosene primarily consists of carbon, hydrogen, and sulfur, and contributions from other trace elements can be disregarded.

$$w_C = 1 - w_{H_2} - w_S. \quad (5)$$

The hydrogen content follows a normal distribution and the sulfur content a log-normal distribution. Since the mass fraction of hydrogen is significantly higher than that of sulfur, the carbon content also follows an approximately normal distribution with a mean value of $\mu(w_C) = 0.86111$ and a standard deviation of $\sigma(w_C) = 0.00206$. The emission index follows to

$$EI_{CO_2} = w_C \frac{M_{CO_2}}{M_C} \quad (6)$$

with a mean value of $EI_{CO_2} = 3.155 \frac{\text{kg}_{CO_2}}{\text{kg}_{\text{fuel}}}$ and a relative distribution with $\mu_{\text{rel}} = 1.0$ and $\sigma_{\text{rel}} = 0.0024$, Fig. A.1(c). As for H_2O , this represents a relatively small uncertainty in the emission prediction and is in good agreement with emission indices provided in other studies (Lee et al., 2021; Rachner, 1998; Gordon and McBride, 1994; C. Voigt et al., 2021; Silberhorn et al., 2022), Fig. A.1(c).

3.4. Nitrogen oxides (NO_x)

The combustion of kerosene can lead to nitrogen oxide and subsequent nitrogen dioxide, which are expressed as NO_x emissions. However, NO_x emissions cannot be estimated directly from the fuel chemistry as they do not depend on the nitrogen content of kerosene, but rather on the way the combustion is controlled (Chandrasekaran and Guha, 2012) and adequate models are required.

Some climate impact assessment studies assume a constant, globally averaged emission index EI_{NO_x} , e.g., Lee et al. (2021). Furthermore, constant fleet-average values have been proposed for each aircraft class, such as for single-aisle aircraft (F.D. Quadros et al., 2022). However, such approaches do not capture the altitude-dependent and engine operating condition-specific effects of NO_x emissions. Therefore, a variety of models exist in the open literature to calculate NO_x emissions of conventional engines in an engine operating condition-dependent manner, such as correlation-based models, p3-T3 methods, fuel flow/BFFM2-based methods, simplified physics-based models and high-fidelity simulations (Chandrasekaran and Guha, 2012). In addition, recent studies have explored data-driven approaches, such as convolutional neural networks, to estimate NO_x emissions across flight phases using high-resolution flight data (Chen et al., 2024). Many models are based on engine test data for a predefined landing and takeoff cycle from the ICAO databank (International Civil Aviation Organization, 2024).

While the BFFM2 method has previously been applied in emission inventories (F.D. Quadros et al., 2022; F.D.A. Quadros et al., 2022; Teoh et al., 2024b), the p3-T3 method and correlation-based models relying on the combustion chamber inlet conditions are the most promising of the presented methods, as they combine the advantages of low computational cost, relatively high accuracy, and the capability to be transferred for new engine designs without requiring engine-specific NO_x measurements from the ICAO databank. Three of the methods presented in Chandrasekaran and Guha (2012) are considered in this work. First, the method by Lipfert (Eq. (A.I.2) in Chandrasekaran and Guha (2012)), where NO_x emissions only depend on the combustion chamber inlet temperature T_{13} . Second, the method by AECMA (Eq. (A.I.3) in

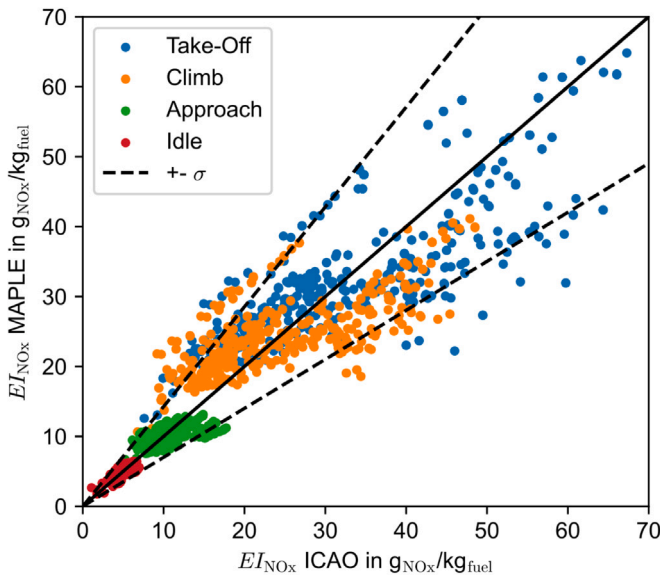


Fig. 1. Cross-correlation of MAPLE NO_x model compared to ICAO data (International Civil Aviation Organization, 2024).

Chandrasekaran and Guha (2012)) which additionally incorporates the impact of the combustion chamber pressure p_{t3} . Third, the method by (GasTurb, 2020)

$$EI_{NOx} = f_{NOx} \cdot S_{NOx} \quad (7)$$

with the severity parameter S_{NOx}

$$S_{NOx} = \left(\frac{p_{t3}}{2965 \text{ kPa}} \right)^{a_5} \cdot \exp \left(\frac{T_{t3} - 826 \text{ K}}{a_6} + \frac{6.29 - 100 \cdot WAR}{53.2} \right), \quad (8)$$

where WAR is the water-to-air mass ratio and $a_5 = 0.4$ and $a_6 = 194 \text{ K}$ are constants. GasTurb assumes the NO_x factor $f_{NOx} = 32$ for conventional and $f_{NOx} = 23$ for dual annular combustors.

The p3–T3 approach implemented in GasTurb and its severity parameter calculation is also applied in MAPLE. However, in early design stages the combustor design is usually unknown, making the assumption of a constant factor f_{NOx} too inaccurate. In this work, f_{NOx} is represented by a surrogate of existing engine and emission data from the ICAO databank (International Civil Aviation Organization, 2024). A sensitivity analysis of the available engine data and emission data showed that the bypass ratio λ and the overall pressure ratio Π_o have the highest impact for turbofan engines. These parameters were also selected because they are the only consistently available engine design parameters in the ICAO databank, which is used here as a reference dataset for validation. Therefore, the NO_x factor is calculated by

$$f_{NOx} = 10^{-3} \cdot \left[a_0 + a_1 \frac{\lambda}{\lambda_{ref}} + a_2 \frac{\Pi_o}{\Pi_{o, ref}} + a_3 \left(\frac{\lambda}{\lambda_{ref}} \right)^2 + a_4 \left(\frac{\Pi_o}{\Pi_{o, ref}} \right)^2 \right] \quad (9)$$

with $\lambda_{ref} = 6$ and $\Pi_{o, ref} = 30$. The coefficients a_0 – a_6 are fitted to minimize the summed squared error between the ICAO EI_{NOx} data and the modeled EI_{NOx} data according to Eq. (7) for turbofan engines available in the ICAO databank (International Civil Aviation Organization, 2024), across all available operating points. The required inputs for modeling the engines are either taken directly from the ICAO databank (λ and Π_o), or are calculated from the overall pressure ratio, atmospheric conditions, and an assumed compressor efficiency typical for turbofan engines to obtain p_{t3} and T_{t3} . The resulting coefficients are shown in Table 2. The model is valid for $1.26 < \Pi_o < 41.7$ and $2.1 < \lambda < 19.9$.

This model is applicable for all operating conditions for various combustor designs and only requires the combustor inlet temperature and pressure, water-to-air, bypass, and overall pressure ratio as inputs.

Table 2

Coefficients for factor for EI_{NOx} modeling.

a_0	a_1	a_2	a_3	a_4	a_5	a_6
55.66	−36.24	−19.18	19.71	4.46	0.90	1227.63

Table 3

Comparison of EI_{NOx} model accuracy for various models.

Model	Lipfert in Chandrasekaran and Guha (2012)	AECMA in Chandrasekaran and Guha (2012)	GasTurb (GasTurb, 2020)	MAPLE
R^2	0.40	0.68	0.65	0.80

All this information is available from the performance calculations in MAPLE.

The accuracy of the developed model is evaluated by linear correlation between the ICAO (International Civil Aviation Organization, 2024) reference values and the modeled results, as shown in Fig. 1. The improvements of the MAPLE model are evident from the higher cross-validated coefficient of determination R^2 in reproducing ICAO engine EI_{NOx} data, compared to other open-literature models, as shown in Table 3.

Most methods in the literature do not explicitly quantify the model prediction uncertainty when estimating the NO_x emission index (GasTurb, 2020; Chandrasekaran and Guha, 2012; Teoh et al., 2024b; F.D. Quadros et al., 2022; Chen et al., 2024; Simone et al., 2013). In this work, the deviations between the modeled and ICAO EI_{NOx} data are used as a practical input for uncertainty quantification, reflecting the surrogate model's ability to capture engine-level variations in the ICAO databank. Dividing the real over the modeled data, a relative metric is generated and it approximately follows a log-normal distribution with a mean value of $\mu(\ln(EI_{NOx, real}/EI_{NOx, model})) = -0.0330$ and standard deviation of $\sigma(\ln(EI_{NOx, real}/EI_{NOx, model})) = 0.2135$.

For predictions of new engines, the absolute distribution is derived with Eq. (1). First, the nominal emission index is determined with the new calculation method after Eqs. (7)–(9) and for the uncertainty quantification, the result is then multiplied with the sample of the relative distribution with a log-normal distribution and $\mu_{rel} = -0.0330$ and $\sigma_{rel} = 0.2135$. An example is shown in Fig. 2 for a CFM56 engine during climb. The nominal value from MAPLE is $EI_{NOx} = 0.0212 \frac{\text{kg}_{NOx}}{\text{kg}_{fuel}}$ and the result and its distribution, visualized by the orange bars representing a histogram from Monte Carlo sampling of the underlying log-normal relative distribution, are in good agreement with the actual value provided by the ICAO databank and from other methods (Lee et al., 2021; GasTurb, 2020; Chandrasekaran and Guha, 2012; International Civil Aviation Organization, 2024).

Overall, NO_x emissions are modeled as engine- and operating condition-dependent, using inlet temperature and pressure, bypass ratio, and overall pressure ratio, fitted to ICAO engine databank data. The model allows both deterministic and probabilistic predictions along the flight trajectory and is broadly applicable across different engine types. Nevertheless, it still has a higher uncertainty compared to CO₂ and H₂O emissions. Therefore, the predictions should be regarded as first-order estimates.

3.5. Soot

Soot emissions mainly consist of carbon (96%, Lefebvre and Ballal (2010)) and are not an equilibrium product of the combustion and thus cannot be predicted from kinetic or thermodynamic data. In practice it can be influenced by physical processes of atomization and fuel-air mixing (Lefebvre and Ballal, 2010). Many studies assume a constant emission index of $EI_{soot} = 0.03 \cdot 10^{-3} \frac{\text{kg}_{soot}}{\text{kg}_{fuel}}$ (Lee et al., 2021; Barrett et al., 2010). The German aerospace center (Wolters, 2020; Döpelheuer,

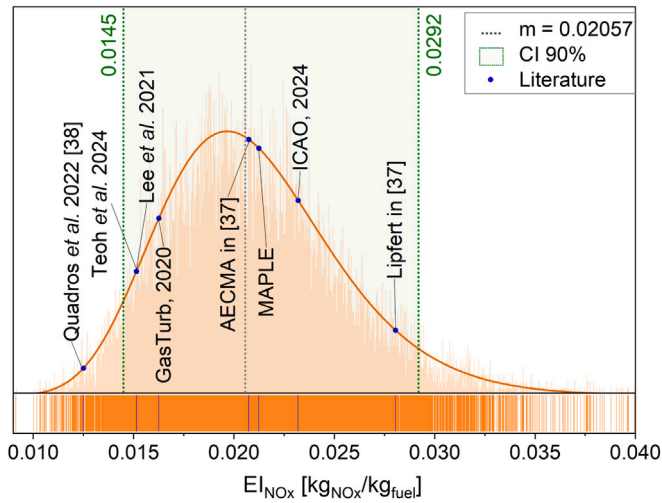


Fig. 2. Distribution of emission index of NO_x for CFM56 during climb.

Table 4

Overview emission models and relative uncertainties.

Emission	Method	$EI \left[\frac{\text{kg}}{\text{kg}_{\text{fuel}}} \right]$	Distribution	μ_{rel}	σ_{rel}
CO_2	constant	3.155	Normal	1.0	0.0024
H_2O	constant	1.237	Normal	1.0	0.0147
SO_x	constant	$1.015 \cdot 10^{-3}$	Log-normal	-0.1439	0.5272
NO_x	p3T3	Eq. (7)	Log-normal	-0.0330	0.2135
Soot	T3	Eq. (10)	Log-normal	0.0	0.9575

2002; Plohr, 2016) developed a p3-T3 method for soot estimation. However, proprietary engine data is required and not available in this work. In addition, recent studies have explored convolutional neural networks for soot estimation (Ge et al., 2022). In this work, reported soot emission data from ICAO (International Civil Aviation Organization, 2024) is analyzed and a correlation to the combustion chamber inlet temperature is found and defined by

$$EI_{\text{soot}} = 10^{-6} \cdot (a_0 + a_1 \cdot T_{t3} + a_2 \cdot T_{t3}^2 + a_3 \cdot T_{t3}^3) \quad (10)$$

with $a_0 = 323.44$, $a_1 = -1.5518$, $a_2 = 2.4450 \cdot 10^{-3}$, and $a_3 = -1.2054 \cdot 10^{-6}$. It is valid for $400 \text{ K} < T_{t3} < 1000 \text{ K}$.

Similar to the uncertainty quantification of NO_x emissions, the cross-correlation and resulting deviations between modeled and real data is also used to quantify the uncertainty of soot predictions. A log-normal distribution with a mean value of $\mu_{\text{rel}} = 0.0$ and standard deviation of $\sigma_{\text{rel}} = 0.9575$ results. An example is shown in Fig. A.1(d). This method has a large uncertainty and only provides a rough first estimate, but is more accurate than assuming a constant soot emission index.

The direct climate impact of carbon monoxide and unburned hydrocarbons resulting from the kerosene combustion process is expected to be negligible. Therefore, their developed emission models are explained in the supporting information in Appendix A.1. Table 4 shows an overview of all relevant emissions and their uncertainties.

4. Climate impact modeling

Aircraft engine emissions induce a radiative forcing (RF) in the atmosphere, resulting in climate responses such as changes in Earth's surface temperature (Dallara, 2011).

Due to the complex interaction between emissions and the atmosphere, simulating the Earth's total response requires comprehensive global climate models. Simplified linear climate models use direct relations and annually averaged parameters to directly evaluate the

climate response. Although these models are less accurate than three-dimensional global models, they adequately capture the first-order effects of emissions (Dallara, 2011). The main advantage is the reduced computational time, which allows for their application in uncertainty quantification and optimization. Therefore, this approach is employed in this work. Note that the climate response functions are applied using globally averaged parameters and thus do not resolve spatial or temporal meteorological variability.

Several alternative reduced-complexity frameworks exist for aviation climate-impact assessment and trade-off decisions. Grobler et al. (2019) compute marginal climate and air-quality costs of global aviation emissions using a reduced-order climate model, emphasizing flight-phase dependence and cost trade-offs. However, this approach does not allow for the evaluation of single missions or localized emission changes, e.g. those resulting from in-flight altitude changes. Prather et al. (2025) introduce the metric global warming per activity (GWA), defined as an integrated effective radiative forcing resulting from one year of flights, and derive climate trade-off risk curves to compare CO_2 and non- CO_2 mitigation efforts. The framework uses fleet-averaged values and does not incorporate engine- or mission-specific impacts, which the trajectory-resolved model described in this work can capture. Furthermore, Rao et al. (2024) propose an alternative surrogate model to increase the accuracy of evaluating the ozone radiative forcing of NO_x emissions. While this approach is promising for future analyses, it is currently only available for NO_x impacts and does not yet cover other emissions. Therefore, this work focuses on the linear approach of Dallara (2011) to ensure methodological consistency across the emissions evaluated.

4.1. Linear climate model

This work applies a linear response model to represent small perturbations of the climate system around an equilibrium state. The system response of a climate variable $\Phi(t)$ over time t in response to an external forcing $F(t)$, imposed at t_0 (with $F(t) = 0$ for $t < t_0$), is given by the convolution integral,

$$\Phi(t) = \int_{t_0}^t G_{\Phi}(t-t')F(t')dt', \quad (11)$$

where $G_{\Phi}(t)$ is the impulse response function (Green function), which describes the system's reaction to a δ -forcing. Both $F(t)$ and $\Phi(t)$ are defined as perturbations relative to the reference state.

The system response function characterizes both the radiative forcing caused by a climate forcer following from an emission impulse, as well as the global mean surface temperature change caused by a radiative forcing. It can be derived from carbon cycle models or comprehensive climate model simulations. For any non-degenerate linear system, the response is represented as a linear superposition of the responses of individual modes, which are typically exponential decays.

4.1.1. Radiative forcing

In order to calculate the radiative forcing of each forcer i , their corresponding impulse response and forcing functions are provided in Table 5. The forcing is represented by an emission impulse E , which is scaled by an altitude factor $s(h)$, if required. For emissions with long lifetimes, the impulse response function decays exponentially. For short life times (< 1 year), as observed in AIC, the model assumes a one-year step function, the indicator function $\chi_1(t)$, see Table 5. This is used because the instantaneous radiative forcing factors A_i are reported as annual averages in the literature. The instantaneous radiative forcing factors are summarized in Table A.1.

Most of the described emissions and climate impacts are assumed altitude-independent. However, the effects of certain emissions, such as NO_x or AIC, depend strongly on the flight altitude. Hence, their altitude dependence correction factors $s(h)$ are derived using Eq. (18) from Dallara et al. (2011) and are incorporated in the forcing functions,

Table 5
Lifetimes of aviation emissions/effects.

Emission	Mean lifetime (years)	Response function G_ϕ	Forcing function F	Reference
CO ₂	>100	$A_{\text{CO}_2} \cdot \left(\alpha_0 + \sum_{i=1}^3 \exp\left(-\frac{t}{\tau_i}\right) \right)$	E_{CO_2}	IPCC (2007)
CH ₄	12	$A_{\text{CH}_4} \cdot \exp\left(-\frac{t}{12}\right)$	$E_{\text{NOx}} \cdot s_{\text{CH}_4}(h)$	Dallara et al. (2011)
O _{3,short-life}	<1	$A_{\text{O}_3} \text{ (short-life)} \cdot \chi_1(t)$	$E_{\text{NOx}} \cdot s_{\text{O}_3\text{S}}(h)$	Dallara et al. (2011)
O _{3,long-life}	12	$A_{\text{O}_3} \text{ (long-life)} \cdot \exp\left(-\frac{t}{12}\right)$	$E_{\text{NOx}} \cdot s_{\text{O}_3\text{L}}(h)$	Dallara et al. (2011)
H ₂ O	<1	$A_{\text{H}_2\text{O}} \cdot \chi_1(t)$	$E_{\text{H}_2\text{O}}$	Dallara et al. (2011)
Soot	<1	$A_{\text{Soot}} \cdot \chi_1(t)$	E_{soot}	Dallara et al. (2011)
SO _x	<1	$A_{\text{SO}_x} \cdot \chi_1(t)$	E_{SOx}	Dallara et al. (2011)
AIC	<1	$A_{\text{AIC}} \cdot \chi_1(t)$	$L_{\text{AIC}} \cdot s_{\text{AIC}}(h)$	Dallara et al. (2011)

$\alpha_i = [0.217, 0.259, 0.338, 0.186]$.

$\tau_i = [172.9, 18.51, 1.186]$ years.

χ_i is the indicator function.

Table 5. The mission-averaged forcing factors are calculated using the altitude sensitivity dependence provided by Köhler et al. (2008) for NO_x and Rädcl and Shine (2008) for AIC. Similar to Dallara et al. (2011), for each mission, the averaged altitude forcing factor is determined from the proportion of the mission distance flown at cruise altitude relative to the total flight distance.

4.1.2. Global mean temperature change

Similarly to RF , the global mean surface temperature change ΔT_i is computed using the normalized effective radiative forcing ERF_i^* as the forcing function, and an impulse response function G_T

$$\Delta T_i(t) = \int_0^t G_T(t-t') ERF_i^*(t') dt'. \quad (12)$$

The normalized effective radiative forcing ERF_i^* follows from dividing the effective radiative forcing ERF of each species by the RF that would result from a doubling of CO₂ in the atmosphere, $RF_{2\times\text{CO}_2}$, whereas the ERF is obtained by multiplying the efficacy f_i of each forcer by its radiative forcing

$$ERF_i^* = \frac{ERF_i}{RF_{2\times\text{CO}_2}} = \frac{f_i \cdot RF_i}{RF_{2\times\text{CO}_2}}. \quad (13)$$

The efficacy $f_i = \lambda_i/\lambda_{\text{CO}_2}$ measures the atmosphere's sensitivity to a given forcer i , relative to the forcing of CO₂. It represents the atmosphere's actual response to a composition perturbation (Ponater et al., 2007; Frömming et al., 2012). Table A.2 shows the efficacies for all emissions and effects obtained from the literature.

The impulse response function G_T is given by two exponentially decaying modes

$$G_T(t) = S \cdot \left[\frac{\alpha_1}{\tau_{r1}} \exp\left(-\frac{t}{\tau_{r1}}\right) + \frac{1-\alpha_1}{\tau_{r2}} \exp\left(-\frac{t}{\tau_{r2}}\right) \right]. \quad (14)$$

These modes were derived from over 1000 simulated years using the HadCM3 climate model (Boucher and Reddy, 2008) and were later refined by Dallara (2011). The parameters are provided in Table A.3.

4.1.3. Validation

The developed methodology was validated using a simplified fuel-based model for historical aviation fuel consumption, similar to the approach of Lee et al. (2021). The resulting climate impacts, expressed in terms of RF and ERF , are generally consistent with those reported by Lee et al. (2021) for most climate forcers (e.g., <1% deviation in RF for CO₂), which reinforces the consistency and reliability of the proposed framework. However, notable differences are observed in the AIC results, with deviations of up to 14%, primarily due to the improved uncertainty characterization for AIC achieved in this study through the extended literature analysis, Section 4.2. Additionally, this analysis indicates a higher contribution from NO_x, which can be attributed to the adoption of higher instantaneous radiative forcing constants in this work (Table A.1) compared to Lee et al. (2021).

Summarized, the climate response is modeled linearly, with each forcer adjusted for altitude, lifetime, and CO₂-relative efficacy. Deterministic and probabilistic impacts are computed along the flight trajectory, showing good agreement with historical data and improved uncertainty treatment for AIC and NO_x.

4.2. Climate model uncertainty parameters and distributions

The RF and ΔT climate functions mainly depend on the fuel consumption m_{fuel} , flight distance L , emission indices EI_i , instant radiative forcing constants A_i , and efficacies f_i . The distributions of fuel consumption and emission indices are calculated using MAPLE and are shown in Figs. A.1, A.2. The instant radiative forcing constants and associated uncertainties are primarily based on values from the literature used by Dallara (2011) and Lee et al. (2021) and are presented in Table A.1 and Fig. A.3.

The radiative forcing contribution of contrails (AIC) is one of the most relevant parameters due to its large contribution to the overall climate impact. Fig. 3 presents a meta-analysis of the literature values (Teoh et al., 2024a; Quaas et al., 2021; Bier and Burkhardt, 2022; Stordal et al., 2005; Märkl et al., 2023; Bock and Burkhardt, 2019; Zhang et al., 2025; Schumann et al., 2015; Burkhardt and Kärcher, 2011; Chen and Gettelman, 2013; Gettelman et al., 2021) used to construct the distribution function of A_{AIC} , the yearly average radiative forcing per unit distance for the entire aviation sector. The resulting distribution has a nominal value of $A_{\text{AIC}} = 1.71 \cdot 10^{-15} \frac{\text{W}}{\text{m}^2}$ with a relative log-normal distribution with $\mu_{\text{rel}} = 0.0$ and $\sigma_{\text{rel}} = 0.515$, estimated using the method of moments.

The distributions of the efficacies are derived from the literature, Table A.2. All remaining climate model parameters are treated deterministically.

4.3. Integrated climate metrics

Integrated climate metrics provide a simplified way to relate emissions to their consequences on the climate, which stem from the complex interplay between gas and aerosol emissions and the atmosphere. These metrics allow the effect of various forcings to be compared on a common scale by integrating their effects over a defined time horizon (see Appendix A.2). Therefore, they are advantageous compared to climate metrics such as RF or ΔT .

One widely used metric is the Global Warming Potential (GWP). The GWP of a species is calculated by relating its absolute GWP (AGWP) to the AGWP of CO₂ (IPCC, 2007). The Average Temperature Response (ATR) directly quantifies the time-averaged change in the global mean surface temperature resulting from a pulse emission. The advantages and limitations of both metrics have been extensively discussed and quantitatively analyzed (Megill et al., 2024; Megill, 2022; Grewe and Dahmann, 2015). As a compromise, the efficacy-weighted GWP (f -GWP) has also been proposed. Similar to the ATR, it incorporates the

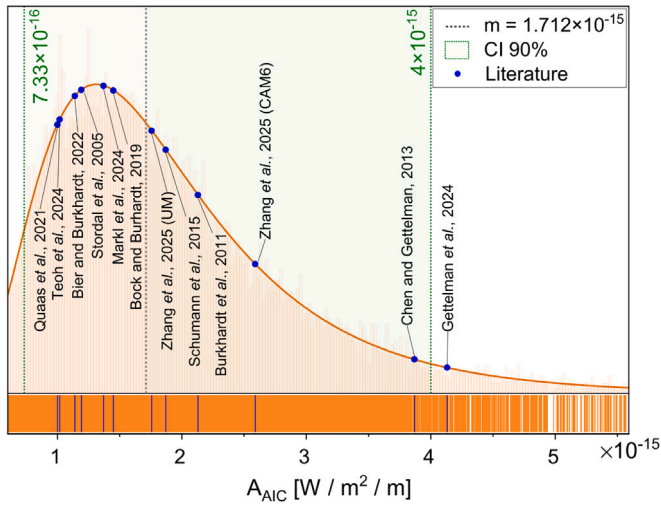


Fig. 3. Distribution of instantaneous radiative forcing constant per distance flown associated to AIC.

Table 6

Unitary integrated climate metrics per kg of CO₂.

Metric	Time Horizon	Median m	Units	Reference
$uAGWP_{100}$	100	$8.70 \cdot 10^{-14}$	$\frac{W \cdot yr}{m^2 \cdot kg_{CO_2}}$	IPCC (2007), This work
$f-uAGWP_{100}$	100	$8.70 \cdot 10^{-14}$	$\frac{W \cdot yr}{m^2 \cdot kg_{CO_2}}$	This work
$uATR_{100}$	100	$4.24 \cdot 10^{-16}$	$\frac{K}{kg_{CO_2}}$	This work

efficacy parameter as a scaling factor. Aviation-focused analyses suggest that horizons of at least 70 years improve neutrality and stability for ATR and f -GWP, while 100-year values remain the conventional anchor for GWP in policy and inventories (Megill et al., 2024). Hence, when coupled with a long time frame, such as $H = 100$ years, f -GWP provides additional insight into the climate impact of aviation emissions. This facilitates comparisons with other sectors and supports informed decision-making in policy and technology development.

In addition, the unitary u integrated metrics for CO₂ are derived in this work. They correspond to a pulsed emission of 1 kg of CO₂ and are required to calculate the respective kg CO₂-equivalent (eq) emissions, Table 6.

5. Application to exemplary flight mission

5.1. Setup

The developed emission and climate models are applied to an exemplary flight mission to demonstrate the methodology and evaluate its deterministic and probabilistic results. However, the framework is generally applicable to arbitrary aircraft types and flight missions.

An exemplary mission is generated with OpenAP (Sun, 2019) for a flight distance of 1400 km, a distance typical for a flight from Germany to Spain. A cruise altitude of 11,300 m and a maximum flight Mach number of 0.78 are assumed and the flight profile is discretized in time steps of 10 s. An Airbus A320-200 with a maximum takeoff weight of 78,000 kg is used, powered by two CFM56 engines. The engine is modeled as a two-spool turbofan in MAPLE and known engine characteristics are matched, such as a bypass ratio of $\lambda = 5.9$, total pressure ratio of $\Pi_t = 27.7$, and take-off thrust of $F = 120.10$ kN.

The performance models in MAPLE have been extensively validated in previous work against well-established tools, such as GasTurb (2020), showing deviations below 0.1% for design point and below 0.7% for off-design calculations (Wiegand et al., 2024). Calculations

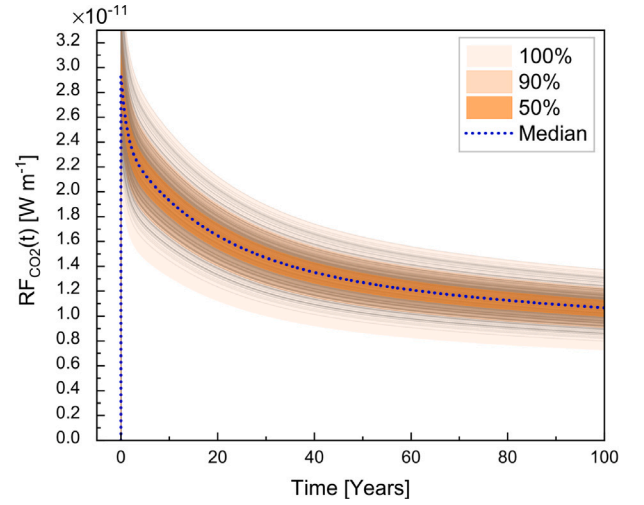


Fig. 4. Radiative forcing function of CO₂ for exemplary flight mission from Germany to Spain with A320-200.

of the fuel consumption for the CFM56 engine show small deviations compared to GasTurb (2020) and data provided in the ICAO databank (International Civil Aviation Organization, 2024), see Fig. A.2. In addition, previous comparisons of performance model data with measured engine data suggest that the modeling error is up to 2% (Göing, 2023). This study assumes a normal distribution for the error in modeled fuel consumption with a conservative 90% CI of $\pm 5\%$, represented by a relative distribution with $\mu_{rel} = 1.0$ and $\sigma_{rel} = 0.0304$, Fig. A.2.

In total, 21 uncertainty parameters are identified: the fuel consumption ($\dot{m}_{fuel}$), five emission indices (EI_{CO_2} , EI_{H_2O} , EI_{SO_x} , EI_{soot} , EI_{NO_x}), eight climate forcing factors (A_{CO_2} , A_{AIC} , A_{H_2O} , A_{SO_x} , A_{soot} , A_{CH_4} , A_{O_3L} , A_{O_3S}), and seven efficacies (f_{AIC} , f_{H_2O} , f_{SO_x} , f_{soot} , f_{CH_4} , f_{O_3L} , f_{O_3S}). They are sampled based on their derived distributions under the assumption of no correlation between them. This assumption is adopted because robust quantitative estimates of correlations are not available in the literature. A sample size of $n = 2500$ is used for the Monte Carlo analysis, and each realization is evaluated using the process chain developed for performance, emission, and climate modeling.

5.2. Results

The radiative forcing over time $RF(t)$ is obtained from the corresponding response function. Each forcer follows the characteristic shape defined in Table 5. Fig. 4 shows the probabilistic results of the RF of CO₂. Fig. 5 displays the results of ΔT_{CO_2} and ΔT_{AIC} as representative examples of forcers with different lifetimes. Each figure includes the realizations of the MCS (gray lines), the 90% confidence interval (orange area), and the median value (dotted blue line).

The RF slope of a single-mission (pulse) CO₂ emission at $t = 0$, shown for an exemplary A320-200 flight in Fig. 4, highlights both the immediate impact of the pulse emission and the persistent, long-term influence of CO₂, as well as the variability of the prediction. The RF peaks immediately and then declines rapidly over time at first, followed by a slow long-term decay. This behavior reflects the multi-timescale decay of CO₂, Table 5.

The atmosphere's temperature response ΔT to AIC is larger than the response to CO₂, Fig. 5. However, the impact of AIC decays quickly, while the temperature response of CO₂ stays high for many years. In addition, the confidence interval of the AIC temperature response prediction is larger than that of CO₂ due to the greater uncertainty in the AIC-related climate model parameters.

Table 7
Integrated climate impact metrics for exemplary flight mission from Germany to Spain with A320-200.

	AGWP ₁₀₀ ($\cdot 10^{-10}$ W m ⁻² years)		<i>f</i> -AGWP ₁₀₀ ($\cdot 10^{-10}$ W m ⁻² years)		ATR ₁₀₀ ($\cdot 10^{-12}$ K)	
	Median <i>m</i>	CI 90%	Median <i>m</i>	CI 90%	Median <i>m</i>	CI 90%
CO ₂	14.0	11.9, 16.1	14.0	11.9, 16.1	6.82	5.80, 7.84
AIC	22.4	9.73, 51.5	8.49	3.63, 19.9	4.65	1.99, 10.9
H ₂ O	0.486	0.067, 3.51	0.523	0.067, 4.10	0.287	0.037, 2.25
SO _x	-4.51	-32.6, -0.625	-3.81	-29.8, -0.486	-2.09	-16.3, -0.267
Soot	0.557	0.051, 6.05	0.397	0.029, 5.49	0.218	0.016, 3.01
CH ₄	-3.64	-22.7, -0.582	-4.28	-26.8, -0.681	-2.31	-14.5, -0.368
O _{3, long-life}	-0.869	-2.89, -0.261	-1.02	-3.45, -0.301	-0.552	-1.87, -0.163
O _{3, short-life}	6.28	1.85, 21.3	8.23	2.08, 32.5	4.51	1.14, 17.8
NO _x Net	1.08	-17.3, 15.5	2.07	-20.2, 23.1	1.17	-10.8, 12.7
Total	33.9	-2.76, 67.9	22.2	-15.3, 48.9	11.4	-8.96, 26.1

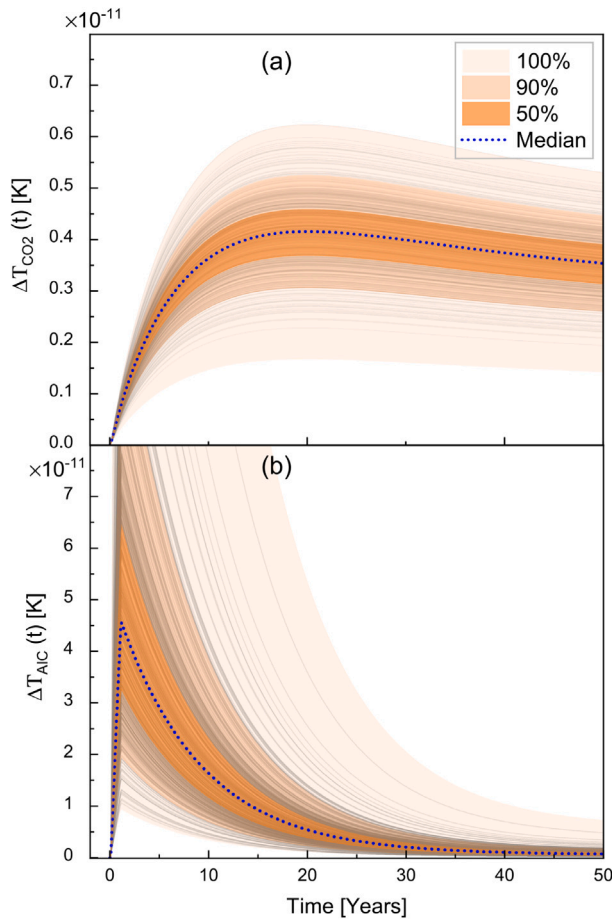


Fig. 5. Temperature change function of AIC and CO₂ for exemplary flight mission from Germany to Spain with A320-200.

Table 7 shows the calculated values of the integrated metrics AGWP, *f*-AGWP, and ATR for $H = 100$ years, as well as the 90% CI. Fig. 6 shows the *f*-AGWP₁₀₀ and the associated error for each forcer, as well as for the total impact. The distributions of ATR₁₀₀ for all forcings are shown in Fig. A.4.

The total climate impact of the exemplary mission, expressed through the three metrics, amounts to $3.39 \cdot 10^{-9} \frac{\text{W yr}}{\text{m}^2}$ for AGWP₁₀₀, $2.22 \cdot 10^{-9} \frac{\text{W yr}}{\text{m}^2}$ for *f*-AGWP₁₀₀, and $1.14 \cdot 10^{-11}$ K for ATR₁₀₀.

These contributions correspond to 38,966, 25,485, and 26,887 kg CO₂-eq for GWP₁₀₀, *f*-GWP₁₀₀, ATR₁₀₀, respectively, based on the unitary metrics listed in Table 6. The differences between these values

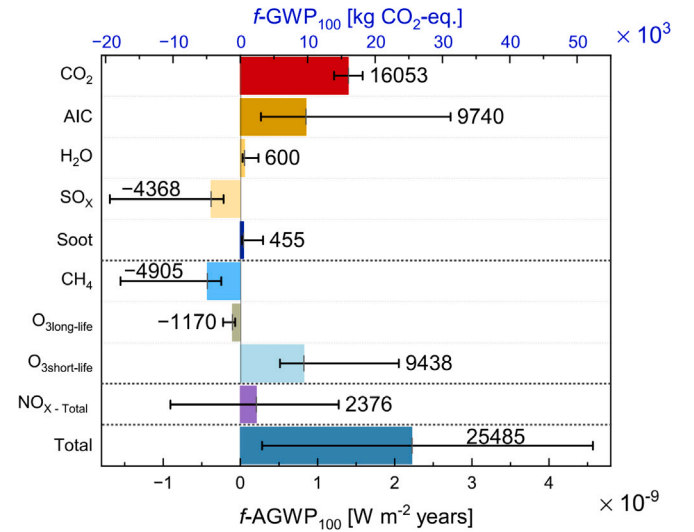


Fig. 6. Efficacy-weighted Global Warming Potential for all forcings and total impact for exemplary flight mission from Germany to Spain with A320-200 (*f*-AGWP₁₀₀ (bottom axis) and *f*-GWP₁₀₀ based kg CO₂-eq (upper axis)).

reflect the specific sensitivities of each metric. GWP emphasizes integrated radiative forcing, *f*-GWP incorporates the efficacy of non-CO₂ forcings, and ATR directly represents the associated temperature response. While the absolute magnitudes vary, the results, Table 7, consistently demonstrate the substantial contribution of non-CO₂ effects to aviation's overall climate impact.

The three main contributors to climate warming – CO₂, NO_x, and AIC – measured by *f*-GWP₁₀₀ correspond to 16,053 kg CO₂-eq, 2376 kg CO₂-eq, and 9740 kg CO₂-eq with proportions of 1 : 0.15 : 0.61. The impacts of soot and H₂O are negligible, whereas SO_x have a moderate cooling effect, Fig. 6.

5.3. Discussion

While Lee et al. (2021) focused on global aviation ERF for historical flights from 1940 to 2018, they also reported *f*-GWP₁₀₀ results (Table 5 in Lee et al. (2021)). This analysis aligns with theirs: for *f*-GWP₁₀₀, the relative contributions of CO₂, NO_x, and AIC are 1:0.16:0.63. For both ERF and *f*-GWP₁₀₀, CO₂ and contrails dominate warming, followed by NO_x. The relative contributions differ for ERF (1:0.51:1.67), as the radiative forcing of contrails and NO_x has a shorter lifetime than CO₂, Table 5. Lee et al.'s ERF analysis does not capture future effects of previously emitted CO₂, while past contrails and NO_x impacts have largely decayed, explaining the higher relative ERF contributions of contrails and NO_x. In contrast, this study evaluates the future climate

impact of a flight today, resulting in a relatively larger CO₂ contribution in integrated metrics.

Furthermore, the results of this work are more sensitive to operational effects, such as flight altitude and distance, because NO_x emissions are calculated locally along the trajectory. At cruise altitudes, the climate impact of NO_x is high, but the emission index is low ($EI_{NO_x} = 9 \frac{g_{NO_x}}{kg_{fuel}}$, consistent with PLOHR's results (Plohr, 2016)) due to reduced thrust settings and lower ambient temperature and pressure. Combined with lower fuel consumption, absolute NO_x emissions are limited, reducing their climate impact during cruise. In contrast, Lee et al. (2021) applied a constant global NO_x emission index of $EI_{NO_x} = 15 \frac{g_{NO_x}}{kg_{fuel}}$, which does not capture altitude-dependent emissions or climate effects.

In addition, this analysis investigated an exemplary A320 flight mission, and the relative contributions would vary with flight distance, aircraft type, and engine configuration. For instance, because the relative contribution of NO_x is highest at high altitudes, longer flights tend to have a greater relative NO_x impact.

Proper probabilistic frameworks are essential, as the median of a sum of distributions differs from the sum of individual medians. For NO_x, the sum of medians of individual contributors is 3363 kg CO₂-eq, whereas the median of the combined distribution is 2376 kg CO₂-eq, see Fig. 6, a deviation of over 40%. The total NO_x contribution is obtained by summing the distributions of CH₄, O₃long-life, and O₃short-life and then taking the median of the result. This reduces the median due to skewness, large uncertainties associated with the NO_x forcers, and non-linear effects in the summed distributions. Hence, using simple sums of medians can bias estimates, underscoring the need for rigorous probabilistic aggregation.

Taken together, this analysis demonstrates the sensitivity of the results to the selected climate metric and highlights the importance of using time- and altitude-resolved flight mission modeling, where emissions are calculated along the trajectory with a fine temporal resolution (10 s in this study), together with a rigorous probabilistic analysis.

Moreover, the aviation climate impact assessment by Lee et al. (2021) assumes constant emission indices for global air traffic and performs statistical analysis of *RF* contributions using results from various global climate models. However, some analyses rely on limited data points (e.g., only three for CO₂ and AIC), which constrains the robustness of their uncertainty quantification. This work improves upon the statistical assessment of aviation's climate impact by incorporating uncertainty propagation through MCS, and explicitly accounting for uncertainties in emission models and forcing factors, especially for AIC. By integrating high-fidelity flight mission and performance models directly into a linear climate model, this approach captures altitude-dependent effects and provides a more comprehensive and probabilistic evaluation of aviation's climate impact. In the future, this approach can be extended to the system level by aggregating scenario-based mission sets (e.g., stage-length distributions, routes, latitudes, and seasons), fleet mixes, technology variants, air traffic growth, and operations scenarios. This allows for more precise, probabilistic system-level estimates and sensitivity analyses, providing a more comprehensive evaluation than the frameworks employed in previous studies.

5.4. Sensitivity analysis

The error associated with each forcer contributes directly to the error propagation of the selected metric (*f*-GWP₁₀₀). Fig. 7 shows the sensitivity analysis using the coefficients of importance, see Section 2.3.

The dominant contributors to the total uncertainty of the climate impact assessment are the instantaneous forcing factors of SO_x (A_{SO_x}), the effects of NO_x (A_{CH_4} , A_{O_3S}), and contrails (A_{AIC}). Other parameters, such as the fuel flow rate ($\dot{m}_{fuel}$), emission indices for CO₂, H₂O, and soot, and most efficacies, have negligible impacts. This indicates that, of the three main climate warming forcers CO₂, NO_x, and AIC – the

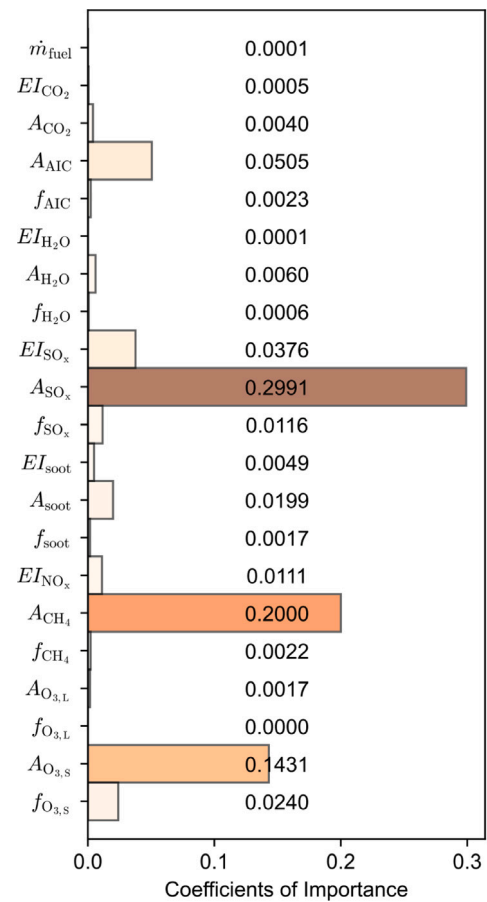


Fig. 7. Sensitivity analysis of the Monte-Carlo model.

impacts of NO_x and AIC are primarily responsible for the uncertainty in climate impact predictions.

Overall, the main factors contributing to the total uncertainty in the climate impact of the example mission are the instantaneous forcing factors A_i . The distributions of these factors were constructed based on literature values and require further refinement through improved data and modeling. Although A_{SO_x} may be of lower importance since SO_x emissions have a cooling effect on the climate, SO_x emissions should not be neglected since their uncertainty is large and they pose climate and health hazards beyond climate warming (EASA, 2010).

The results underscore the importance of reducing epistemic uncertainties in critical parameters, e.g., through targeted observations and model improvements, to enhance the reliability of climate impact assessments. Parameters with negligible contributions in the present mission and modeling approach may be deprioritized in subsequent studies, enabling resources to be allocated to the most impactful factors. However, it should be noted that contributions can shift based on assumptions, such as operational ones, so prioritization should be reassessed for other scenarios.

6. Limitations

Although this analysis extends previous climate impact analyses and their uncertainty analysis, several limitations are identified that should be addressed in the future.

The fuel consumption and thermodynamic data required for emission models are derived from MAPLE. Even though MAPLE is well-validated against established commercial tools (Wiegand et al., 2024), it is a simplified performance model that cannot represent the engine's

real, dynamic behavior. This error is accounted for by the conservative uncertainty estimation of the assumed fuel consumption but may still differ from experimental testing results. Similarly, the emission models and their uncertainties were validated based on existing engines. However, for evaluating the climate impact of future engines and technologies, their validity should be reassessed.

The linear climate model and altitude factors used in this analysis are simplified compared to those used in comprehensive, three-dimensional global climate models, as well as compared to actual climate behavior. These simplifications could lead to additional uncertainties in the results, as well as trends that do not accurately reflect reality. The models used are also unable to consider secondary climate effects, such as aerosol-cloud interactions originating from soot and SO_x . Similarly, this study does not consider climate impacts besides global warming, such as air pollution caused by SO_x and NO_x emissions. Nevertheless, linear climate models are capable of capturing first-order effects and are essential for probabilistic assessments due to their computational efficiency.

The distribution of A_{AIC} is derived from literature values. These values often represent the global average of contrail radiative forcing but do not consider the specific impact of engines or aircraft, such as fuel consumption, non-volatile particulate matter emissions, or aircraft size. Therefore, the contrail estimation should be improved in the future, e.g., through detailed analyses employing cloud-physics-based contrail models (e.g., pycontrails (Shapiro et al., 2025)).

Climate model parameters that were treated deterministically in this study, such as altitude dependence factors, also entail uncertainties. These uncertainties were not considered because there is insufficient data in the literature to perform appropriate uncertainty propagation. However, these uncertainties are expected to substantially affect the uncertainty of $f\text{-GWP}$ and ATR , particularly for NO_x and AIC . Therefore, incorporating the propagation of these uncertainties is an important priority for future research. Similarly, all uncertainty parameters were assumed to be uncorrelated due to the lack of reliable quantitative data describing potential correlations. In reality, correlations may exist, particularly among some climate response parameters (e.g., between CH_4 and O_3 responses to NO_x emissions or soot emissions and AIC). Incorporating such dependencies could influence the overall uncertainty and sensitivities and should therefore be investigated in future work once more robust data become available.

In addition, the probabilistic assessment of the climate impact is presented for an exemplary flight mission, and the contributions of each forcer, such as CO_2 , NO_x , and AIC , will differ for flight missions of various lengths and for different engines and aircraft. Similar results are expected, but have to be evaluated in the future to draw conclusions about the global climate impact of aviation. A global analysis would require detailed flight route data, engine parameters and emissions, as well as high-resolution fuel burn information.

7. Conclusions and outlook

Key Conclusions

- This paper introduces a probabilistic framework that integrates flight mission, engine performance, emission, and climate impact modeling to assess mission-level aviation climate impacts.
- Within this framework, uncertainties in model parameters, particularly in emission indices and the contrail forcing factor, are quantified based on literature findings as well as cross-correlations and resulting deviations between modeled and measured engine data.
- Monte Carlo simulations are employed to propagate uncertainties in emission and climate parameters across models, yielding probabilistic predictions of radiative forcing and temperature response metrics.

- The study highlights the significant contributions of both CO_2 and non- CO_2 emissions (e.g., contrails and NO_x) to aviation's climate forcing.
- Sensitivity analysis reveals that uncertainties in the climate forcing factors of NO_x emissions, contrails (AIC), and SO_x are the dominant contributors to the overall uncertainty.
- The results suggest that climate metric selection, altitude-dependent effects, and flight mission length significantly influence the relative climate impact of non- CO_2 emissions, which are found lower when using integrated climate metrics.
- The framework provides a robust tool for evaluating the climate impact of existing and future propulsion systems, enabling informed decision-making for sustainable aviation technologies and policies.

Future Recommendations

- Future studies should refine climate model parameters, particularly for non- CO_2 effects like contrail-induced cirrus clouds and NO_x emissions.
- Updating uncertainties and correlations of climate model parameters, as well as exploring more accurate altitude-dependence models, should be prioritized.
- Extending the framework to model global aviation scenarios with diverse aircraft and engine types will provide more comprehensive insights. However, detailed flight route data and engine parameters would be required.

CRedit authorship contribution statement

Marcus Wiegand: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lily Koops:** Writing – review & editing, Validation, Project administration, Funding acquisition, Conceptualization. **Ronald Mailach:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Rafael Balderas-Xicohtencatl:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

A.1. Carbon Monoxide (CO) and Unburned Hydrocarbons (UHC)

Carbon monoxide is formed due to the oxygen deficiency in fuel-rich combustion zones, where the complete reaction to CO_2 is not possible. In addition, CO is formed because of the dissociation of CO_2 at high temperatures (Lefebvre and Ballal, 2010). Similar to the NO_x emissions, an empirical model is created in MAPLE to fit the ICAO (International Civil Aviation Organization, 2024) data and the CO emissions are calculated by

$$\log(EI_{\text{CO}}) = a_0 + a_1 \cdot \log(EI_{\text{NO}_x}) . \quad (\text{A.1.1})$$

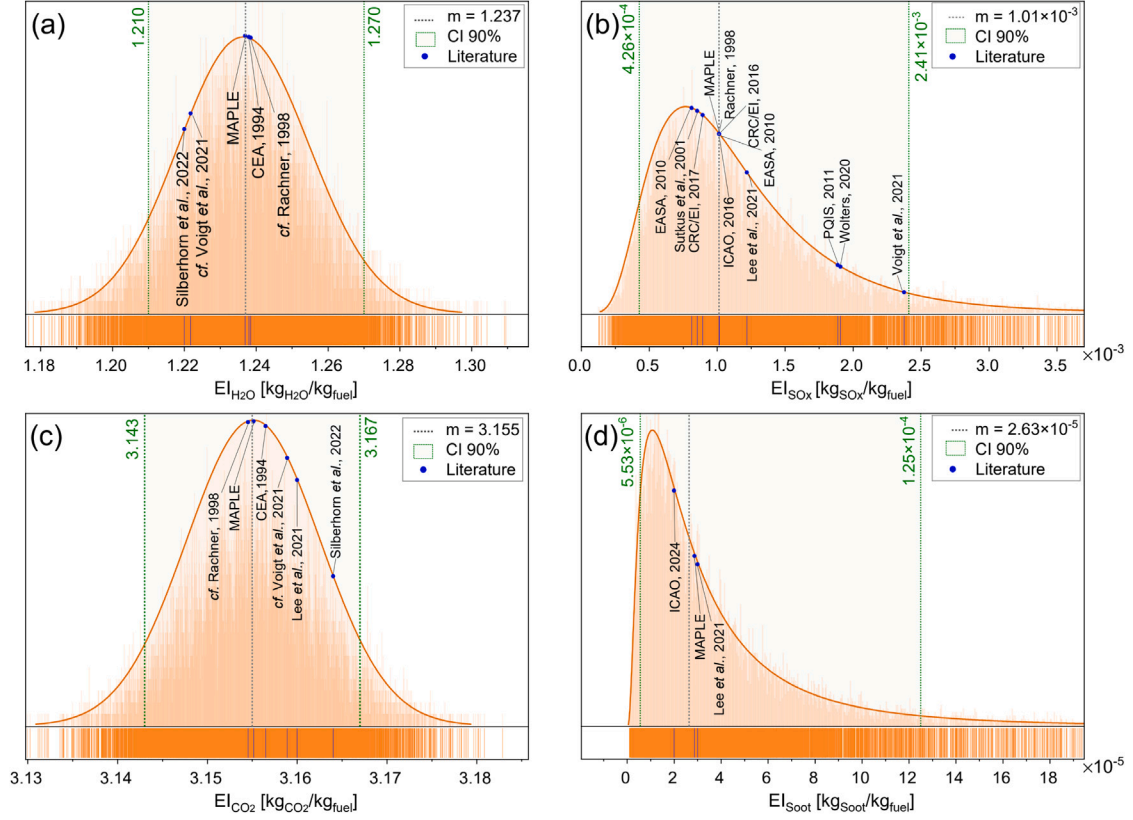


Fig. A.1. Distributions of emission index for H_2O , SO_x , CO_2 , and soot.

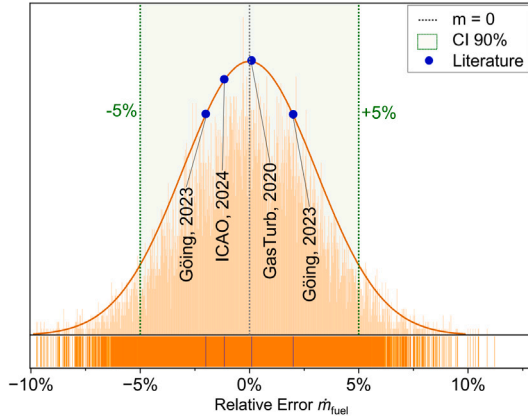


Fig. A.2. Distributions of the relative error of the fuel consumption.

with $a_0 = 2.5415$ and $a_1 = -2.1212$.

Several factors, such as poor fuel atomization, inadequate burning rates, or the chilling effects of film-cooling air, can cause unburned hydrocarbon (UHC) emissions. An exponential dependence is seen between the logarithmic emission indices of UHC and CO and is described by

$$\log(EI_{\text{UHC}}) = a_0 \cdot \exp(a_1 \cdot \log(EI_{\text{CO}}) + a_2) + a_3 \quad (\text{A.1.2})$$

with $a_0 = 0.3935$, $a_1 = 0.7985$, $a_2 = 0.5867$, and $a_3 = -1.8003$.

A.2. Climate impact metrics

Different metrics have been considered to quantitatively assess aviation's contribution to climate impact using one single numeric value. Systematic comparison can be found in the literature, e.g., Megill et al. (2024). This work used and compared three main metrics, Global Warming Potential (GWP), efficacy-weighted Global Warming Potential (f -GWP), and Average Temperature Response (ATR). For each forcer, they are calculated using the following three Eqs. (A.2.1)–(A.2.3), respectively.

$$\text{GWP}_i^{(H)} = \frac{\int_0^H RF_i(t) dt}{\int_0^H RF_{\text{CO}_2}(t) dt} \quad (\text{A.2.1})$$

$$f\text{-GWP}_i^{(H)} = \frac{\int_0^H f_i \cdot RF_i(t) dt}{\int_0^H RF_{\text{CO}_2}(t) dt} \quad (\text{A.2.2})$$

$$\text{ATR}_i^{(H)} = \frac{1}{H} \int_0^H \Delta T_i(t) dt \quad (\text{A.2.3})$$

where RF is the radiative forcing given by Eq. (11), $\Delta T(t)$ is the instantaneous temperature response at time t due to a pulse emission of species i , H is the time horizon (e.g., 20, 50, 100 years), and f is the efficacy.

A.3. Tables and figures

See Figs. A.1–A.4 and Tables A.1–A.3.

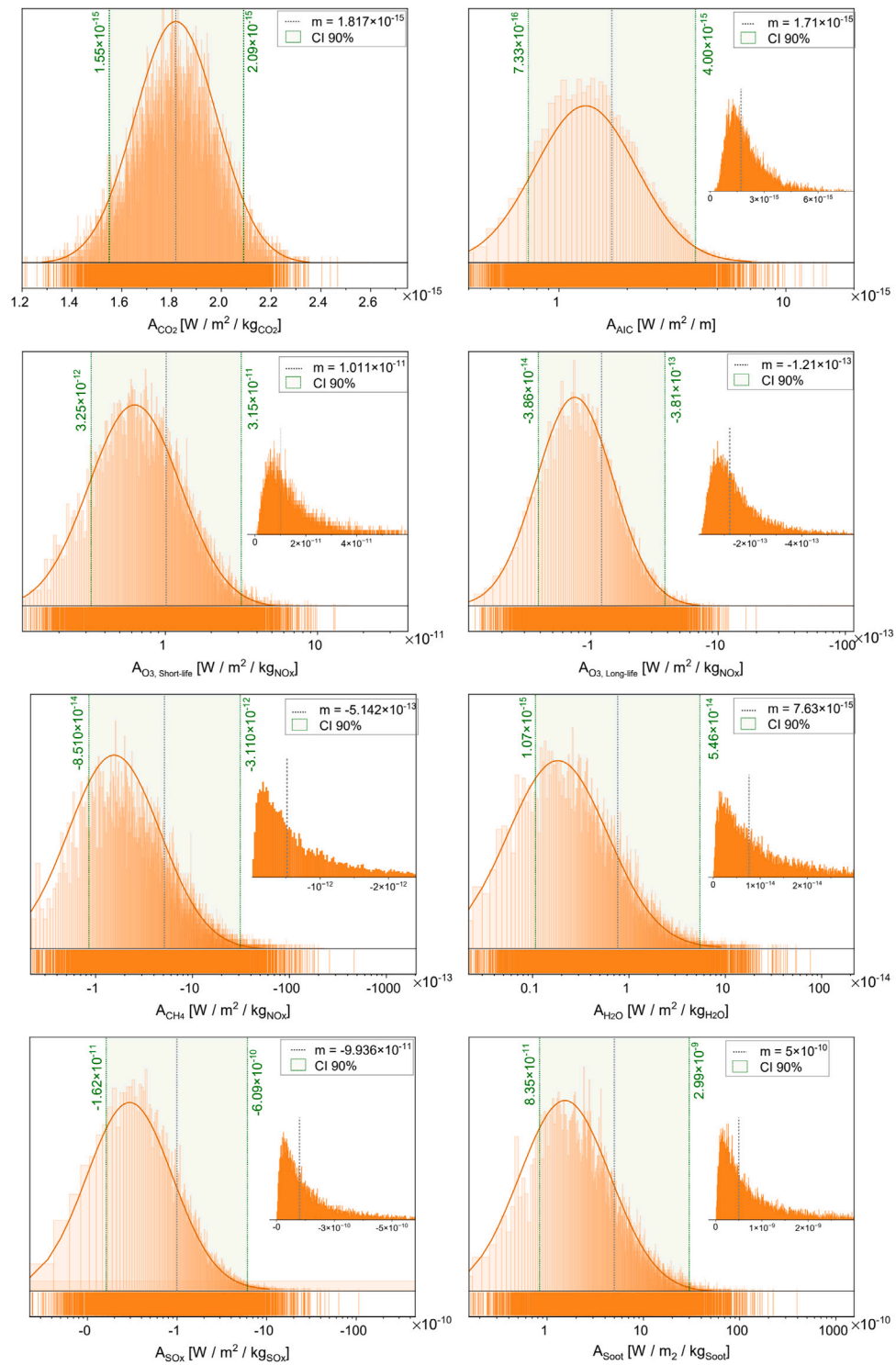


Fig. A.3. Distributions of instant radiative constant A for CO₂, AIC, O_{3,Short-life}, O_{3,Long-life}, CH₄, H₂O, SO_x, and Soot.

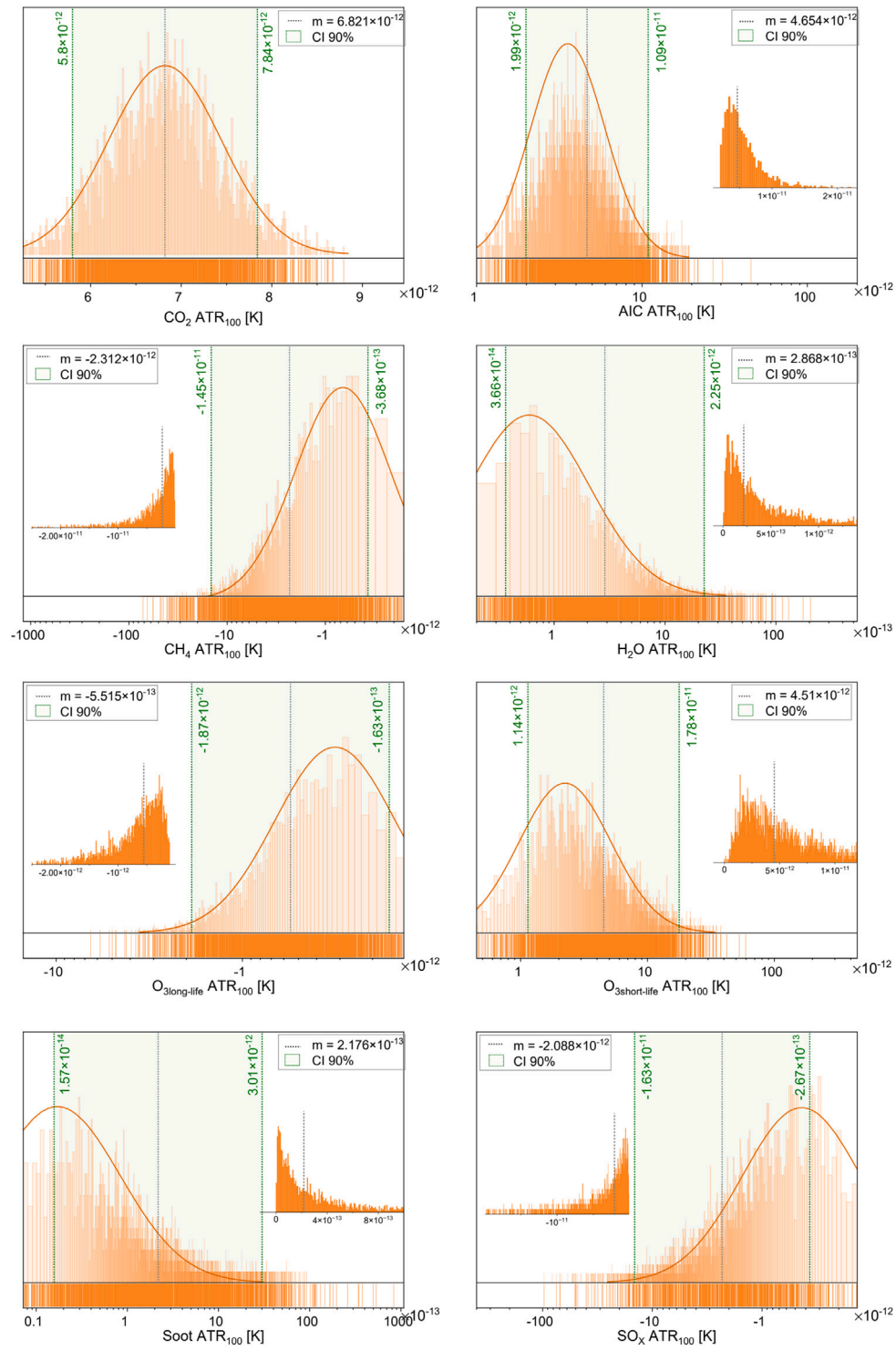


Fig. A.4. ATR₁₀₀ distributions for CO₂, AIC, CH₄, H₂O, O₃ (long-life), O₃ (short-life), soot, and SO_x.

Table A.1
Instantaneous radiative forcing constants.

Emission	A_i (median)	Dist.	μ_{rel}	σ_{rel}	90% Confidence Interval	References
CO ₂	$1.82 \cdot 10^{-15} \frac{\text{W}}{\text{m}^2 \text{ kg}}$	Normal	1.0	0.091	$1.5 \cdot 10^{-15}, 2.2 \cdot 10^{-15}$	Dallara et al. (2011)
CH ₄	$-5.16 \cdot 10^{-13} \frac{\text{W}}{\text{m}^2 \text{ kg}}$	Log-normal	0.0	1.09	$-3.1 \cdot 10^{-12}, -8.6 \cdot 10^{-14}$	Dallara et al. (2011), Lee et al. (2009) and Marais et al. (2008)
O _{3,short-life}	$1.01 \cdot 10^{-11} \frac{\text{W}}{\text{m}^2 \text{ kg}}$	Log-normal	0.0	0.693	$3.2 \cdot 10^{-12}, 3.2 \cdot 10^{-11}$	Grewe and Stenke (2008), Ponater et al. (2007) and Dallara et al. (2011)
O _{3,long-life}	$-1.21 \cdot 10^{-13} \frac{\text{W}}{\text{m}^2 \text{ kg}}$	log-normal	0.0	0.693	$-3.7 \cdot 10^{-13}, -3.8 \cdot 10^{-14}$	Dallara et al. (2011), Lee et al. (2009) and Marais et al. (2008)
H ₂ O	$7.43 \cdot 10^{-15} \frac{\text{W}}{\text{m}^2 \text{ kg}}$	log-normal	0.0	1.203	$1.1 \cdot 10^{-15}, 5.4 \cdot 10^{-14}$	Dallara et al. (2011), Lee et al. (2009) and IPCC (1999)
Soot	$5.0 \cdot 10^{-10} \frac{\text{W}}{\text{m}^2 \text{ kg}}$	log-normal	0.0	1.097	$8.3 \cdot 10^{-11}, 3.0 \cdot 10^{-9}$	Dallara et al. (2011), Lee et al. (2009) and IPCC (1999)
SO _x	$-1.0 \cdot 10^{-10} \frac{\text{W}}{\text{m}^2 \text{ kg}}$	log-normal	0.0	1.097	$-6.1 \cdot 10^{-10}, -1.6 \cdot 10^{-11}$	Dallara et al. (2011), Lee et al. (2009) and IPCC (1999)
AIC	$1.71 \cdot 10^{-15} \frac{\text{W}}{\text{m}^2 \text{ m}}$	log-normal	0.0	0.513	$7.3 \cdot 10^{-16}, 4.0 \cdot 10^{-15}$	This work

Table A.2
Efficacy parameter for each forcer.

Emission	Efficacy (median)	Dist.	μ_{rel}	σ_{rel}	90% confidence interval	References
CO ₂	1.0	–	–	–	–	–
CH ₄	1.18	Normal	1.0	0.1	0.977, 1.38	Ponater et al. (2007), Grewe and Stenke (2008) and Dallara (2011)
O _{3,short-life}	1.37	Normal	1.0	0.3	0.662, 2.08	Ponater et al. (2007), Grewe and Stenke (2008) and Dallara (2011)
O _{3,long-life}	1.18	Normal	1.0	0.1	0.977, 1.38	Lee et al. (2021), Grewe and Stenke (2008) and Dallara (2011)
H ₂ O	1.14	Normal	1.0	0.3	0.550, 1.73	Ponater et al. (2007), Grewe and Stenke (2008) and Dallara (2011)
Soot	0.7	Log-normal	0.0	0.7	0.212, 2.31	IPCC (2007) and Dallara (2011)
SO _x	0.9	Normal	1.0	0.3	0.412, 1.39	IPCC (2007) and Dallara (2011)
AIC	0.38	Normal	1.0	0.1	0.317, 0.443	Grewe and Stenke (2008), Dallara (2011) and Bickel et al. (2025)

Table A.3
Temperature change model parameters from Dallara et al. (2011).

Temperature model parameter	Best estimate
$RF_2 \times \text{CO}_2$	3.70 W m ⁻²
S	3.0 K
α_i	0.595
τ_1	8.4 yrs
τ_2	409.5 yrs

Data availability

Data will be made available on request.

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