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DOI

[10.1016/j.trd.2024.104215](https://doi.org/10.1016/j.trd.2024.104215)

Publication date

2024

Document Version

Final published version

Published in

Transportation Research Part D: Transport and Environment

Citation (APA)

Simorgh, A., Soler, M., Castino, F., Yin, F., & Cerezo-Magaña, M. (2024). Concept of robust climate-friendly flight planning under multiple climate impact estimates. *Transportation Research Part D: Transport and Environment*, 131, Article 104215. <https://doi.org/10.1016/j.trd.2024.104215>

Important note

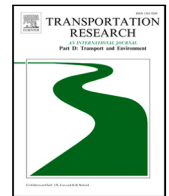
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Concept of robust climate-friendly flight planning under multiple climate impact estimates

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ARTICLE INFO

Keywords:

Climate change
Aircraft trajectory optimization
Aviation-induced non-CO₂ climate effects
Multiple climate impact estimates
Robust optimization

ABSTRACT

The spatiotemporal dependency of aviation-induced non-CO₂ climate effects can be incorporated into flight planning tools to generate climate-friendly flight plans. However, estimating climate impact is challenging and associated with high uncertainty. To ensure the effectiveness of such an operational measure, sources that induce uncertainty need to be identified and considered when planning climate-aware trajectories. The mismatch between different assessments of climate impact is an important indicator of uncertainty. This study introduces a concept aimed at planning robust climate-optimized aircraft trajectories under multiple climate impact estimates. The objective is to generate climate-optimal trajectories that achieve mitigation potential consistent with all available assessments. Case studies show that, even when there is a significant discrepancy between input models in specific regions, the proposed approach can effectively generate trajectories to mitigate the climate impact with a high level of confidence.

1. Introduction

In spite of being seriously affected by the COVID-19 pandemic, the aviation industry is estimated to fully recover by 2024 and grow by 1.2% annually (International Air Transport Association (IATA), 2022). Such a growth rate is creating severe environmental challenges, requiring short-term actions to mitigate their associated effects (Eurocontrol, 2022). The non-CO₂ climate effects caused by aviation include the emissions of nitrogen oxides (NO_x) (leading to changes in the concentrations of ozone (O₃) and methane (CH₄)) (Köhler et al., 2008), water vapor (H₂O), hydrocarbons (HC), carbon monoxide (CO), sulfur oxides (SO_x), and increased cloudiness due to contrail formation (Kärcher, 2018). The climate impact of non-CO₂ species strongly depends on the atmospheric conditions at the location and time of the emissions. Such spatiotemporal dependency enables planning aircraft trajectories with less impact on climate change compared to the current business-as-usual routing options (Teoh et al., 2020; Dietmüller et al., 2023). The feasibility of this measure has been explored in several studies (see Simorgh et al. (2022b) for a review). Despite the possibility of mitigating the climate effects caused by non-CO₂ species with flight planning, one needs to consider the challenges with modeling and predicting their impact (Lee et al., 2021; Dahlmann et al., 2016).

The assessment of climate effects caused by the aviation industry, from emissions to changes in a green gas component, changes in radiation and temperatures, and ultimately evaluating the efficiency of a mitigation strategy (e.g., flight planning), is a complex task due to significant uncertainties involved in calculating the atmospheric changes induced by emissions. This can be validated

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<https://doi.org/10.1016/j.trd.2024.104215>

Received 27 September 2023; Received in revised form 26 February 2024; Accepted 16 April 2024

Available online 4 May 2024

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Nomenclature

Abbreviations

aCCF	Algorithmic Climate Change Function
AIC	Aviation-Induced Cloudiness
ATM	Air Traffic Management
ATR	Average Temperature Response
BFFM2	Boeing Fuel Flow Method 2
CoCiP	Contrail Cirrus Prediction Model
EPS	Ensemble Prediction System
OLR	Outgoing Longwave Radiation
PCFA	Persistent Contrail Formation Areas
POTCOV	Potential Contrail Coverage
ROOST	Robust Optimization of Structured Trajectories
SOC	Simple Operating Cost
USD	US Dollar

Symbols

(w_x, w_y)	Components of wind
χ	Heading
γ	Flight path angle
λ	Longitude
\mathbf{f}	Vector of dynamical functions
\mathbf{f}_a	Augmented vector of dynamical functions
\mathbf{u}	Vector of controls
\mathbf{u}_a	Augmented vector of controls
\mathbf{x}	Vector of states
\mathbf{x}_a	Augmented vector of states
Ω_j	A set of models, estimating the climate impact of species j
ϕ	Latitude
ψ	Course
\mathbf{w}_{m_i}	Weather variables associated with the i th climate impact estimation model
$\mathbf{CM}_{m_i}^j$	i th inputted climate impact estimation model for species j .
\mathbf{L}	Atmospheric location of a flight
T	Thrust force
ζ	Vector of uncertain parameters
C_L	Coefficient of lift
C_T	Coefficient of thrust
D	Drag force
d_a	Derivative of altitude
d_v	Derivative of true airspeed
f_c	Fuel flow
h	Flight altitude
M	Mach number
m	Aircraft mass
n	Number of inputted climate impact estimation models
n_m^j	Number of models, estimating the climate impact of species j
R_M	Ellipsoid radius of curvature in the meridian
R_N	Ellipsoid radius of curvature in the prime vertical
S	A set of CO ₂ and non-CO ₂ species used within flight planning
s	Distance flown along the route

by referring to the uncertainty ranges on the latest available estimates of the climate effects induced by aircraft operations reported by Lee et al. (2021). For instance, in terms of the impact of NO_x emissions, the effective radiative forcing has been measured at 17.5 [mW/m²] as the best estimate and (0.6, 29) [mW/m²] confidence interval. Such low confidence is also observed in the impact

S_{c_i}	A set of CO ₂ and non-CO ₂ species estimated by the model i th
T	Temperature
t	Time
v_{cas}	Calibrated airspeed
v_{gs}	Ground speed
v_{tas}	True airspeed

of contrail cirrus. The best estimate of the corresponding radiative forcing is 57.4 [mW/m²] with (17, 98) [mW/m²] uncertainty ranges. Considering such low confidence in the estimated climate effects induced by some forcing agents, a question arises: To what extent can we mitigate aviation-induced climate effects by changing the traffic pattern? In case of employing inaccurate climate impact estimation models for flight planning, in addition to not mitigating climate effects, the Air Traffic Management (ATM) system performance will be degraded in some other aspects, e.g., an increase in operational cost (Niklaß et al., 2021, 2019) and instability of aerial traffic (Baneshi et al., 2023). In parallel with the necessity for further research to better understand and quantify aviation-induced climate effects (Lee et al., 2021), a direction of research to increase the reliability of climate impact estimation and, in turn, the reliability of the achieved mitigation potential with climate-friendly trajectories is to identify sources of uncertainty and try to reduce their effects on climate impact quantification through robust flight planning.

There are several approaches to considering climate impact in planning climate-aware trajectories. The early attempts were based on reducing emissions or avoiding ice-supersaturated areas (Sridhar et al., 2011; Celis et al., 2014). Such methods can lead to increased climate effects, as reducing emissions does not necessarily reduce the net climate impact due to the high spatiotemporal dependency of non-CO₂ climate effects (van Manen and Grewe, 2019; Niklaß et al., 2021). In addition, in the case of avoiding ice-supersaturated areas, not all contrails have a warming impact (or significant warming impact) that needs to be mitigated. The other methods were based on calculating climate metrics such as radiative forcing and global warming potential from emissions using constant factors multiplied by fuel consumption (Rosenow et al., 2017; Vitali et al., 2021). As for contrails, a positive constant is applied to ice-supersaturation areas (Soler et al., 2014; Rosenow et al., 2017). In such a modeling approach, if included in flight planning, the optimizer tries only to reduce fuel consumption by generally flying at higher altitudes within vertical constraints. However, due to high weather and spatial dependencies of non-CO₂ climate impacts, there is a risk of increasing their adverse climate effects and, therefore, overcompensation for emissions reduction. For flight planning, models detailing spatiotemporal dependency of non-CO₂ climate effects are required. In the literature, there exist only two modeling approaches that provide such information in real-time compatible with flight planning tools: Algorithmic Climate Change Functions (aCCFs) (van Manen and Grewe, 2019; Yin et al., 2023; Dietmüller et al., 2023; Matthes et al., 2023) and the Contrail Cirrus Prediction (CoCiP) Model (Schumann, 2012). CoCiP provides estimates only for contrails, while aCCFs, in addition to contrails, quantify the climate effects of the most relevant species, including ozone, methane, CO₂, and water vapor.

These state-of-the-art approaches to quantify non-CO₂ climate effects (i.e., aCCFs and gridded CoCiP) require specific meteorological variables as input for predicting the climate sensitivity of aircraft emissions. As these meteorological variables are retrieved from standard weather forecasts, they are inevitably uncertain. The ensemble prediction system (EPS), as the main state-of-the-art framework in the meteorological community, provides insight into probable deviations in the state of the atmosphere by generating N_{EPS} predictions (so-called ensemble members) through slightly perturbing the initial state of the atmosphere or/and parameters of a numerical weather integration model (WMO, 2012). The use of EPS enables capturing meteorological uncertainty effects on the quantified climate effects. In this direction, recently, a few studies have emerged to incorporate weather forecast uncertainty quantified using EPS to plan robust climate-optimal aircraft trajectories. In Simorgh et al. (2022a), we employed robust tracking optimal control theory for the first time to formulate a 2D flight planning problem by assuming constant altitude within the context of future fully free-routing airspace. The information on climate effects was provided using aCCFs. Later, within the framework of EU-Project FlyATM4E,¹ we developed a fast heuristic-based robust optimization algorithm called ROOST² (robust optimization of structured trajectories) capable of optimizing full 4D aircraft trajectory considering the current structured airspace, as well as meteorological uncertainty, quantified using EPS. Both studies highlighted that high deviations in the relative humidity field characterized using ensemble prediction weather forecasts are magnified when calculating persistent contrail formation areas and, in turn, climate effects of contrails. The aim of the flight planning problems in the mentioned studies was to determine climate-optimal trajectory with minimum sensitivity to meteorological uncertainty.

In addition to weather forecast uncertainty, representation of background conditions in numerical models (Hersbach et al., 2020), estimation of aircraft emissions (DuBois and Paynter, 2006; Jelinek, 2004) and uncertainties related to estimating the overall climate effect in Earth-System climate models, e.g., caused by radiative transfer calculation, by the representation of atmospheric processes, or by choice of the used physical climate metric, act as other important sources of uncertainty (Lee et al., 2021). By referring to the study conducted by Lee et al. (2021), it can be understood that the uncertainty ranges of the climate effects induced by individual species are quantified by performing statistical analysis on the available estimates of climate effects based on a wide range of global

¹ <https://flyatm4e.eu>

² An open-source python library has been developed, which can be accessed using DOI: <https://doi.org/10.5281/zenodo.7495472>.

atmospheric chemistry/climate models and a broad range of present-day aviation emission inventories (e.g., in the case of NO_x emissions, analysis was performed on an ensemble of 20 available measurements to determine the best estimate and confidence interval). In this respect, if different models provide similar estimates for a species, it is said that the impact can be quantified with high confidence. For example, this is the case for the climate impact of CO_2 emissions. Otherwise, high uncertainty exists in estimating the effect of particular species. This fact motivated us to generalize the concept of robustness of climate-optimized aircraft trajectories by directly accounting for the spread in the climate impact estimations measured with different approaches, which can simultaneously account for other sources, including meteorology (e.g., the data source and resolution that each model is compatible with (Dietmüller et al., 2023)), emission calculation model, and climate indicator. Our goal is to plan aircraft trajectories, which take into account different estimations of climate effects and focus on those climate-sensitive areas that are identified in good agreement with all considered approaches. With the proposed concept, we rely on the fact that aircraft trajectories optimized considering more possible climate impact estimates are expected to be more reliable than focusing on only one model.

In this respect, climate effects quantified with different approaches are accounted for in order to create a robust planning framework that can be used to generate climate-optimized aircraft trajectories with less sensitivity to discrepancies between climate impact estimation models. The models selected to estimate climate impact can be represented with different sets of meteorological data, resolutions, emission calculation models, and assumptions in order to consider different aspects that introduce uncertainty. We formulate ensemble aircraft dynamical model and path constraints to capture the effects of different weather datasets (corresponding to different models) on aircraft performance variables. A weighted sum of the expected values and variances of the climate impact and operating costs are defined as the objective function of the optimization problem. The flight planning problem is formulated based on the robust tracking optimal control framework (González-Arribas et al., 2018; Simorgh et al., 2022a). The variables included in the flight plan (i.e., lateral path, speed schedule, and altitude profile) are designated as “tracked variables” in order to be optimized uniquely despite uncertainty effects for the operational applicability of the approach. All in all, this study’s main contributions are two-fold: (1) Introducing the concept of robustness to multiple climate impact estimates. (2) Formulating the proposed concept within the context of robust tracking optimal control framework, aiming at optimizing operationally applicable and feasible 4D aircraft trajectories within the free-routing airspace, considering reduced climate effects with a high confidence level as the main flight planning objective.

To show the effectiveness of the introduced concept, we use the climate effects measured employing the prototype algorithmic climate change functions (aCCFs-V1.0a) (Matthes et al., 2023) with the meteorological information provided by the ECHAM/MESSy Atmospheric Chemistry (EMAC) model (Jöckel et al., 2010) and the ERA-Interim reanalysis data product (Simmons, 2006). The aCCFs with ERA-Interim data are calculated using the recently developed Python library called CLIMaCCF³ (Dietmüller et al., 2023), while submodels CONTRAIL and ACCF (see Yin et al. (2023), Yamashita et al. (2020)) are used for the EMAC model. A mismatch between the considered climate impact estimates is expected mainly due to differences in the meteorological data and resolution, and different approaches to identifying where persistent contrails are expected to form. In a previous study (Matthes et al., Unpublished results), such potential inconsistencies were quantified when optimizing the top 100 routes (ranked using the average seat kilometers in 2018) using these two approaches separately. Results showed that in some scenarios, discrepancies can be observed. In the current study, the aim is not only to quantify the difference between estimations but also to control them. In simulations, we first show that optimizing the aircraft trajectory based on only one of the models may not necessarily result in mitigation potential when the climate impact is assessed with the other model. Therefore, despite the probability of increasing the operating cost and challenging the ATM system due to deviation from business-as-usual trajectories, there is a risk of not mitigating climate effects. By employing the proposed robust flight planning method, we show that there is potential to plan trajectories that mitigate climate impact with reduced discrepancies between estimations.

The rest of the paper is organized as follows. Section 2 states the robust climate-optimal flight planning concept, considering different models for estimating climate impact. Section 3 deals with flight planning problem formulation by accounting for the objectives presented in Section 2. The case studies and simulation results are provided in Section 4.

2. Concept of robust aircraft trajectory optimization & multiple estimates of climate impact

According to the latest estimations, the aviation industry is responsible for about 3.5% of global warming (Lee et al., 2021). Mitigating the climate impact of CO_2 emissions requires moving towards developing more efficient aircraft, using alternative fuels or novel propulsion (Durdina et al., 2021; Schripp et al., 2018; Teoh et al., 2022). The aviation-induced non- CO_2 climate effects are highly dependent on atmospheric conditions at the time and location of emissions (van Manen and Grewe, 2019). Therefore, in addition to the mentioned mitigation measures for CO_2 emissions, there is a possibility to reduce their impact by planning aircraft trajectories to avoid areas of airspace with high sensitivity to aircraft emissions in terms of climate change (e.g., the formation of persistent contrails can be avoided by re-routing ice-supersaturated areas (Gierens et al., 2008; Yin et al., 2018)). Operational strategies such as flight planning to reduce non- CO_2 climate effects can be considered as a relatively shorter-term action compared to technical ones (due to the aircraft’s long life service and long phases in development, production, and certification) towards mitigating climate effects.

³ Available via <https://github.com/dlr-pa/climaccf>.

To enable climate-optimized flight planning, information on climate-sensitive areas is required in the first step. An appropriate model to estimate non-CO₂ climate effects should take the weather and spatiotemporal information as inputs and be able to estimate climate effects in almost real-time to be suitable for flight planning (i.e., having fast function evaluation in the optimization process). In the next sections, we first discuss the existence of uncertainty in estimating the climate impact of aviation with the available models (Section 2.1), and then propose a framework to increase the confidence level of mitigation potential achieved with flight planning (Section 2.2).

2.1. Uncertainty in estimating the climate impact of aviation

The assessment of climate effects is very challenging as it is a very complex multi-disciplinary topic, including estimation of aircraft emissions, weather forecast and representation of background conditions in numerical models, and climate science (e.g., chemical transformations, microphysics, radiation) (Matthes et al., 2023). Therefore, high uncertainty is expected in estimating the climate effects induced by aviation, as pointed out by Lee et al. (2021). Such potential uncertainty needs to be carefully considered when planning aircraft trajectories (Dahlmann et al., 2016). As a matter of fact, deviating from business-as-usual routes for the benefit of climate has some side effects on the ATM system in terms of operational cost (Niklaß et al., 2021) and stability (Baneshi et al., 2023). Therefore, we need to be more confident about the mitigation that can be achieved by re-routing aircraft trajectories. This calls for robust flight planning, considering different sources of uncertainty affecting the estimation of climate effects.

In order to address potential uncertainties when planning flights in a climate-friendly manner, we first need to identify and quantify them. Looking at the estimations reported by Lee et al. (2021), it can be understood that a large part of the uncertainties in estimating climate impact is due to variations in model results from different calculation methods, such as different chemistry or cloud schemes (Lee et al., 2009). This implies that the confidence level of climate impact estimations can be improved by having consistent assessments from different models. In the context of climate-optimal flight planning, we interpret such an existence of uncertainty as the mismatch between climate-sensitive areas identified with different approaches. One direction of study to increase the reliability of the climate impact assessment is, therefore, to perform further research to better understand and quantify aviation-induced climate effects in order to reduce discrepancies between available models, as climate impact estimates with different approaches should ideally provide consistent measurements. The other direction, which we aim to introduce and explore in this study, is to consider all possible estimations of climate effects in flight planning in order to reduce the mismatch between estimations by flying in areas with a good level of agreement with all considered models for estimating climate effects.

Several approaches exist to quantify the climate effects of non-CO₂ species (see Simorgh et al. (2022b), Section 3). The difference between these approaches can be attributed to the required inputs and/or models themselves. The inputs are generally meteorology (e.g., source of weather forecast and resolution) and emissions (e.g., DLR method (Deidewig et al., 1996) and Boeing Fuel Flow Method 2 (DuBois and Paynter, 2006)), and parameters representing the model (e.g., forcing efficacy (Lee et al., 2021)), modeling approach (e.g., contrails aCCF and CoCiP), assumptions (e.g., contrail properties and lifetime in terms of contrails impact), and the physical climate metric (e.g., ATR, energy forcing (Schumann, 2012), global warming potential (Vitali et al., 2021)) are some factors introducing uncertainty to the model. Such variations can lead to different estimates of climate effects.

So far, a spread in climate impact estimations due to meteorological uncertainty (as inputs to one model, i.e., aCCFs) has been addressed in the literature employing EPS weather forecast (see Simorgh et al. (2023, 2022a)). Here, we propose a novel flight trajectory calculation approach, considering all the probable factors as a form of uncertainty during the optimization process. Eventually, we aim to deliver climate-optimized trajectories with a robust performance to potential sources of uncertainty.

2.2. Robustness of aircraft trajectories to multiple climate impact estimates

In this section, we introduce a framework for planning climate-optimal trajectories, which perform robustly under different estimates of climate effects. With robustness, we refer to reduced discrepancies across various climate impact estimates, thereby achieving higher consensus among multiple models rather than relying on a single model's estimates. We start by defining a set of available climate impact estimation models considered for flight planning. Let us define $S = \{O_3, CH_4, H_2O, CO_2, AIC\}$ as a set, including relevant species to be mitigated by flight planning and consider n models as follows:

$$CM_{m_1}(L, t_{m_1}, w_{m_1}, EI_{m_1}), \quad \dots, \quad CM_{m_n}(L, t_{m_n}, w_{m_n}, EI_{m_n}) \quad (1)$$

where L includes the atmospheric location of a flight, i.e., λ, ϕ, h corresponding to latitude, longitude, and altitude. $CM_{m_i}(\cdot)$ is the i th available model and $CM_{m_i}(\cdot) := \{CM_{m_i}^j\}_{j \in s_{c_i}}$, where the set $s_{c_i} \subset S$ includes the species provided by the model i th, implying that each model does not necessarily estimate the climate effects of all species. Each model can use a specific source of weather data and emission calculation model, i.e., set of weather variables w_{m_i} and set of emission indices EI_{m_i} are associated with the i th model (i.e., $CM_{m_i}(\cdot)$). Finally, t_{m_i} is the flight time predicted using weather variables of the i th model: w_{m_i} . Notice that the models may produce climate impact estimates in terms of different units. For such cases, in addition to metric conversion, an alternative is to normalize models results with respect to their maximum values without loss of generality.

The objective is to determine a flight plan in 4D to reduce the associated climate effects with all n models considered to estimate non-CO₂ climate effects. This concept has been graphically presented in Fig. 1. It can be seen that the optimal trajectory planned with respect to Model 1 still crosses areas identified as hotspots with Model 2. Similarly, if we employ Model 2 to perform trajectory optimization, the aircraft will fly in the climate hotspots associated with Model 1. However, there is a possibility to avoid both hotspots by a slight deviation from the trajectory optimized w.r.t one of the models if the optimizer is aware of other estimates. It is worth mentioning that this problem cannot be addressed by solving n optimization problems, each considering one model. This

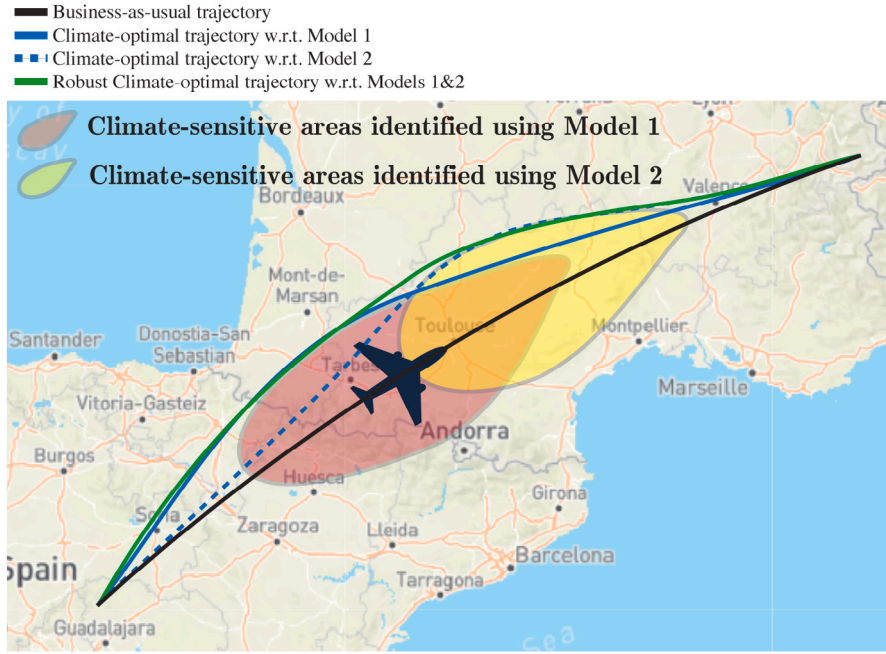


Fig. 1. Concept of robust climate-optimal flight planning with respect to multiple climate impact estimates.

is because, as shown in Fig. 1, $n = 2$ (in this case) flight plans are generated. Therefore, one optimization problem needs to be formulated to deliver a unique (or deterministic) flight plan while delivering optimal performance for all available estimates. The optimality in our context is interpreted as climate impact mitigation with a high level of confidence at a reasonable cost increase.

3. Robust climate-friendly aircraft trajectory optimization

In this section, the concept of robustness of aircraft trajectory presented in Section 2 is formulated based on the optimal control theory by assuming a future fully free-routing airspace. Here, we directly employ the approach we developed for modeling and solving robust aircraft trajectory optimization problems, taking into account meteorological uncertainty. Interested readers are referred to González-Arribas et al. (2018) and Simorgh et al. (2022a) for a detailed description of the methodology. With this approach, a robust aircraft trajectory optimization is formulated to generate a unique flight plan for all possible uncertainty realizations, called a robust tracking optimization problem. In the following, we briefly present the robust flight planning approach and how it can be adapted to the flight planning problem proposed in this study.

Let us consider a 4D point-mass aircraft dynamical model as (Simorgh et al., 2023):

$$\frac{d}{dt} \begin{bmatrix} \phi \\ \lambda \\ h \\ v_{ias} \\ m \end{bmatrix} = \begin{bmatrix} \frac{v_{ias} \cos(\gamma) \cos(\chi) + w_y(\phi, \lambda, h, t)}{R_M(\phi) + h} \\ \frac{v_{ias} \cos(\gamma) \sin(\chi) + w_x(\phi, \lambda, h, t)}{(R_N(\phi) + h) \cos(\phi)} \\ \frac{v_{ias} \sin(\gamma)}{T(C_T) - D(C_L) - g \sin(\gamma)} \\ \frac{m}{-f_c(T(\phi, \lambda, h, t), C_T)} \end{bmatrix} \quad (2)$$

where m , t , C_T , C_L , χ , γ , v_{ias} , and f_c are aircraft mass, flight time, thrust coefficient, lift coefficient, flight heading angle, flight path angle, true airspeed, and fuel flow, respectively. The Earth's ellipsoid radii of curvature in the meridian and the prime vertical are denoted with R_M and R_N , respectively. The BADA4.2 model is used to represent aerodynamic and propulsive performance (Gallo et al., 2006). With such a representation of aircraft dynamical model, the state (\mathbf{x}) and control (\mathbf{u}) vectors are selected as:

$$\text{State vector: } \mathbf{x} = [\phi \quad \lambda \quad v_{ias} \quad h \quad m]^T, \quad \text{Control vector: } \mathbf{u} = [\gamma \quad C_T \quad \chi]^T. \quad (3)$$

It can be seen in Eq. (2) that the dynamical model requires specific atmospheric variables, including components of wind (w_x , w_y), and temperature T . For representing multiple climate impact estimates in Section 2.2, we assume that each model can use a specific source of weather data, leading to m_n possible realizations of the required variables, i.e., $(w_{x,m_1}, w_{y,m_1}), \dots, (w_{x,m_n}, w_{y,m_n})$, and $(T_{m_1}, \dots, T_{m_n})$. Such potential realizations of atmospheric variables can be considered as uncertainty, affecting the aircraft's dynamical behavior (e.g., flight time and fuel consumption (Simorgh et al., 2023)). In a previous study, we proposed a general framework for integrating meteorological uncertainty in planning aircraft trajectories (González-Arribas et al., 2018; Simorgh et al., 2022a). In this approach, a general formulation of robust tracking optimal control problem with uncertain parameters given in a continuous distribution is formulated. Then, the uncertain parameters are approximated with a discrete probability distribution, enabling the conversion of the stochastic optimal control problem to a deterministic optimization problem with a larger dimension, which can be solved efficiently using well-known deterministic optimal control approaches, including direct optimal control (Betts, 2010).

To illustrate that, let us consider ζ as a vector including uncertain variables assumed to have known probability distribution functions. The uncertainty vector affects the system dynamics (e.g., aircraft dynamical model) through $\dot{\mathbf{x}}(t) = \mathbf{f}(t, \mathbf{x}(t), \mathbf{u}(t), \zeta)$, where \mathbf{x} and \mathbf{u} are the state and control vectors of a dynamical model, and \mathbf{f} is a vector of dynamical functions. By discretizing uncertain parameters (i.e., ζ_k for $k = 1, \dots, n$), which can be performed using different approaches (e.g., Monte-Carlo (Chai et al., 2019)), an augmented dynamical model can be built, including dynamics for each realization of discrete samples (ζ_k), i.e., $\dot{\mathbf{x}}_k(t) = \mathbf{f}(\mathbf{x}_k(t), \mathbf{u}_k(t), \zeta_k, t)$, leading to:

$$\mathbf{x}_a(t) = \mathbf{f}_a(\mathbf{x}_a(t), \mathbf{u}_a(t), t) := [\mathbf{f}(\mathbf{x}_i(t), \mathbf{u}_i(t), t)]_n \quad (4)$$

where $\mathbf{x}_a := [\mathbf{x}_i]_n$ and $\mathbf{u}_a := [\mathbf{u}_i]_n$ are augmented vectors of states and control inputs, respectively. Due to the discretization, the realizations of uncertainty are now limited, and the corresponding effects are reflected in additionally defined state, control, and algebraic variables. Now, all the elements of the robust optimal control problem with uncertainty can be represented in a deterministic manner. Under our problem setting, as the atmospheric variables constitute a discrete collection, this methodology is well-suited for the flight planning problem proposed in this study.

Generally, to formulate aircraft trajectory optimization within the context of optimal control theory, we require the aircraft dynamical model (or dynamical constraints), (equality and inequality) path constraints, boundary conditions, and performance index representing flight planning objectives. In the following, we present these elements by directly considering available models for estimating climate impact.

3.1. Dynamical constraints

Given the unpredictable nature of uncertainties prior to finalizing a flight plan (e.g., weather conditions), it is essential to optimize a deterministic flight plan that remains effective under potential uncertainty effects. However, with the ensemble formulation of the optimal control problem briefly presented in Section 3, determining a unique flight plan is not directly possible. For instance, by considering m_n realizations of meteorological variables associated with different climate impact estimation models, m_n optimized flight plans will be determined after solving the optimization problem (i.e., optimized augmented state vector (\mathbf{x}_a) includes m_n samples of trajectories (e.g., latitude and longitude)). In order to address the uniqueness of the flight plan when solving the proposed flight planning problem under different probable realizations of atmospheric variables, it is necessary to make adjustments to the aircraft's dynamical model. For this purpose, two types of variables are defined: tracked and untracked variables (González-Arribas et al., 2018). The tracked variables exclude the uncertainty effects and need to be considered once when building the augmented aircraft dynamical model. The remaining variables, on the other hand, can take different values depending on the realization of uncertainty, referred to as untracked variables. For the uniqueness of flight plan variables (i.e., lateral path, flight altitude profile, and speed schedule), they are defined as tracked variables. The aircraft dynamical model given in Eq. ((2)) is based on time as the independent variable. This can lead to infeasibility of the flight planning problem because considering the effects of different realizations of wind for the unique time and unique lateral path is only feasible if all realizations of wind are identical.

To feasibly exclude the uncertainty effects on the tracked variables, we define the ground speed v_{gs} as an algebraic variable and the course ψ as an additional control variable, with the standard composition of velocities relating the additional variables to the airspeed, heading, and wind: $v_{gs} \cos(\psi) - v_{tas} \cos(\chi) \cdot \cos(\gamma) - w_y = 0$ and $v_{gs} \sin(\psi) - v_{tas} \sin(\chi) \cdot \cos(\gamma) - w_x = 0$. Now, we can change the independent variable of the aircraft dynamical model from time to distance flown along the route (s), i.e., $(dt)(ds)^{-1} = v_{gs}^{-1}$, and considering time as a new untracked state variable. The derivatives of true airspeed and flight altitude with respect to distance as d_h and d_v (i.e., $(dv_{tas})(ds)^{-1} = d_v$ and $(dh)(ds)^{-1} = d_h$) are defined as additional control variables with a similar justification given in González-Arribas et al. (2018) (for the true airspeed), while moving the dynamic relationships to two new equality constraints (see Section 3.2).

Now, we can build an augmented state-space by considering m_n copies of the untracked state and control variables, with each corresponding to a possible realization of weather variables:

$$\frac{d}{ds} \begin{bmatrix} \phi \\ \lambda \\ h \\ v_{tas} \\ m_{m_1} \\ \vdots \\ m_{m_n} \\ t_{m_1} \\ \vdots \\ t_{m_n} \end{bmatrix} = \begin{bmatrix} \cos(\psi)(R_M(\phi) + h)^{-1} \\ \sin(\psi)\left((R_N(\phi) + h)\cos(\phi)\right)^{-1} \\ d_h \\ d_v \\ -f_c(T_{m_1}, C_{T,m_1})v_{gs,m_1}^{-1} \\ \vdots \\ -f_c(T_{m_n}, C_{T,m_n})v_{gs,m_n}^{-1} \\ v_{gs,m_1}^{-1} \\ \vdots \\ v_{gs,m_n}^{-1} \end{bmatrix} \quad (5)$$

with the following state (\mathbf{x}_a) and control (\mathbf{u}_a) vectors:

$$\begin{aligned} \text{State vector: } \mathbf{x}_a &= [\phi \quad \lambda \quad v \quad h \quad m_{m_1} \quad \cdots \quad m_{m_n} \quad t_{m_1} \quad \cdots \quad t_{m_n}]^T \\ \text{Control vector: } \mathbf{u}_a &= [d_v \quad d_h \quad \psi \quad \gamma_{m_1} \quad \cdots \quad \gamma_{m_n} \quad C_{T,m_1} \quad \cdots \quad C_{T,m_n} \quad \chi_{m_1} \quad \cdots \quad \chi_{m_n}]^T. \end{aligned} \quad (6)$$

The augmented dynamical model is formulated in this form (Eq. (5)) mainly to generate a unique flight plan while reflecting the effects of different realizations of temperature and wind on the flight performance variables such as flight time and fuel consumption. It should be noted that to exclude the effects of uncertainty on variables of flight plan within the proposed formulations, the uncertainties are transferred onto the remaining control and state variables (i.e., those repeated m_n times). Regarding the operational applicability of the approach when having uncertainty effects reflected in control variables (e.g., thrust and heading and path angles), in our practical context, the autopilot can compute the controls needed for the aircraft to track the optimized flight plan in real-time at a shorter timescale than that of the optimal control problem without causing a considerable error in performance. A detailed description of the practical concept and conversion of the point-mass dynamical model to Eq. (5) can be found in [González-Arribas et al. \(2018\)](#).

3.2. Path constraints

For the feasibility of the constructed ensemble dynamical model (Eq. (5)), some equality type path constraints need to be imposed. In addition, a valid trajectory must fulfill a set of constraints representing the flight envelope. In particular, the limitations should be imposed for calibrated airspeed (v_{cas}), thrust and lift coefficients (C_T , C_L), Mach (M), and altitude. In the following, constraints representing the feasibility of the augmented dynamical model and flight envelope are given:

$$\begin{bmatrix} v_{gs,m_1} \cos(\psi) \\ \vdots \\ v_{gs,m_n} \cos(\psi) \\ v_{gs,m_1} \sin(\psi) \\ \vdots \\ v_{gs,m_n} \sin(\psi) \\ d_v \cdot v_{gs,m_1} \\ \vdots \\ d_v \cdot v_{gs,m_n} \\ d_h \cdot v_{gs,m_1} \\ \vdots \\ d_h \cdot v_{gs,m_n} \end{bmatrix} - \begin{bmatrix} v_{tas} \cos(\chi_{m_1}) \cdot \cos(\gamma_{m_1}) + w_{y,m_1} \\ \vdots \\ v_{tas} \cos(\chi_{m_n}) \cdot \cos(\gamma_{m_n}) + w_{y,m_n} \\ v_{tas} \sin(\chi_{m_1}) \cdot \cos(\gamma_{m_1}) + w_{x,m_1} \\ \vdots \\ v_{tas} \sin(\chi_{m_n}) \cdot \cos(\gamma_{m_n}) + w_{x,m_n} \\ T(C_{T,m_1}) - D(C_{L,m_1})m_{m_1}^{-1} - g \sin(\gamma_{m_1}) \\ \vdots \\ T(C_{T,m_n}) - D(C_{L,m_n})m_{m_n}^{-1} - g \sin(\gamma_{m_n}) \\ v_{tas} \sin(\gamma_{m_1}) \\ \vdots \\ v_{tas} \sin(\gamma_{m_n}) \end{bmatrix} = \mathbf{0}, \quad \begin{bmatrix} v_{cas,stall} - v_{cas}(v_{tas}) \\ v_{cas}(v_{tas}) - v_{cas,max} \\ C_{T,min} - C_{T,m_1} \\ \vdots \\ C_{T,min} - C_{T,m_n} \\ C_{T,m_1} - C_{T,max} \\ \vdots \\ C_{T,m_n} - C_{T,max} \\ C_{L,m_1} - C_{L,max} \\ \vdots \\ C_{L,m_n} - C_{L,max} \\ M(v_{tas}) - M_{max} \\ -v_{gs,m_1} \\ \vdots \\ -v_{gs,m_n} \\ h - h_{max} \end{bmatrix} \leq \mathbf{0} \quad (7)$$

where w_x, w_y are components of wind.

3.3. Boundary conditions

The boundary constraints imposed on the tracked and untracked state variables for the proposed aircraft trajectory planning are given in the following:

• **Tracked states:**

$$\begin{aligned} [\phi(0) \quad \lambda(0) \quad v_{tas}(0) \quad h(0)] &= [\phi_0 \quad \lambda_0 \quad v_{tas,0} \quad h_0], \\ [\phi(s_f) \quad \lambda(s_f) \quad v_{tas}(s_f) \quad h(s_f)] &= [\phi_f \quad \lambda_f \quad v_{tas,f} \quad h_f] \end{aligned} \quad (8)$$

• **Untracked states:**

$$\begin{aligned} t_i(0) &= 0, \quad t_{f,\min} \leq t_i(s_f) \leq t_{f,\max} \\ m_i(0) &= m_0, \quad m_{f,\min} \leq m_i(s_f) \end{aligned} \quad (9)$$

for $i \in \{m_1, \dots, m_n\}$.

As can be seen, the flight's initial and final atmospheric locations are fixed (e.g., location of origin and destination airports). The initial flight mass and flight departure time are also predefined. However, their final conditions are selected free and determined based on the objective of the optimization problem.

3.4. Objective function

The dynamical and path constraints presented in Sections 3.1 and 3.2 were defined in a manner that allows for capturing the effects of uncertainty in meteorological conditions characterized by employing weather data from different sources. The other source of uncertainty considered in this work, related to the mismatch between models to quantify climate effects, is considered when defining the cost functional (or performance index) of the optimal control problem. In fact, in order to mitigate climate effects through aircraft trajectory optimization, models to estimate climate impact need to be included in the objective function of the optimization problem.

To define an objective function within the context of optimal control theory, we need to consider two terms: Mayer and Lagrange. The Mayer term is used to represent objectives that are evaluated only at boundaries. However, those objectives evaluated and accumulated over the trajectory are defined as a Lagrange term. Within our context, we use both terms for flight planning. In fact, the climate effects are evaluated over the trajectory and, thus, should be defined in the Lagrange form. In addition, we are interested in generating robust climate-optimal trajectories that are economically acceptable. Therefore, the operating cost is also selected as a flight planning objective. In this study, we use simple operating cost (SOC), representing the operational cost in USD (Yamashita et al., 2020). As for evaluating SOC, the duration of the flight and consumed fuel are required, which are evaluated at boundaries and thus defined in the Mayer form.

We start by defining the Lagrange term, including objectives related to climate effects. First of all, it should be noted that the climate effects of CO₂ emissions and non-CO₂ emissions, except for contrails, are evaluated based on fuel consumption rate since they are initiated by emissions. However, in the case of aviation-induced cloudiness (AIC), the impacts are not simply related to a single emissions quantity. Therefore, they are typically evaluated based on the distance flown within areas favorable for forming persistent contrails. For species $j \in S := \{O_3, CH_4, H_2O, CO_2, AIC\}$, we calculate the expected climate response (\overline{CR}) evaluated taking the average between all estimates as:

$$\overline{CR}^j = \frac{1}{n_m^j} \sum_{i \in \Omega_j} \int_0^{s_f} CM_i^j(\mathbf{L}, t_i, \mathbf{w}_i, El_i^j) \cdot f_{c,i} \cdot ds \quad (10)$$

where $\Omega_j \subset \mathbf{M} := \{m_1, \dots, m_n\}$ is a set of models including species j , in which the number of models is specified by n_m^j . Note that, in case of $j = AIC$, we divide CM_i^{AIC} by $f_{c,i} := f_c(T_{m_i}, C_{T,m_i})$. In order to control the level of discrepancy between different climate impact estimates when planning climate-optimized trajectories, we define the variance of climate effects and include it in the objective function as:

$$\sigma_{CR}^2 = \frac{1}{n_m^j} \sum_{i \in \Omega_j} \left(\int_0^{s_f} CM_i^j(\mathbf{L}, t_i, \mathbf{w}_i, El_i^j) \cdot f_{c,i} \cdot ds - \overline{CR}^j \right)^2 \quad (11)$$

which is the variance of climate response of species j with respect to the set of models Ω_j . Now, the net climate response can be calculated as follows, which we will consider as the term representing climate impact in the cost functional of the robust flight planning problem:

$$J_{\text{lagr}} = C_{\overline{CR}} \sum_{j \in S} \overline{CR}^j + C_{\sigma_{CR}} \sum_{j \in S} \sigma_{CR}^2 \quad (12)$$

where $C_{\overline{CR}}$ and $C_{\sigma_{CR}}$ are weighting parameters adjusting the relative importance of reducing average climate response and dispersions of climate impact estimated with different models, respectively. Notice that we assume similar units and equal weights for calculating the average and variance of climate effects. With current formulations, it is possible to use models with different units.

In such cases, normalized climate effects can be used. For models of different importance levels, weighted average and weighted variance can be simply calculated.

To represent the operating cost in a simplified manner, we rely on the metric simple operating cost (SOC),⁴ estimating operating cost with linear relation to fuel consumption and flight time as:

$$\text{Simple Operating Cost [USD]} = 0.75 [\text{USD/s}] \cdot \text{Flight time [s]} + 0.51 [\text{USD/kg}] \cdot \text{Fuel Consumption [kg]} \quad (13)$$

which quantifies cost in USD (Yamashita et al., 2020). Due to uncertainty in flight time and fuel burn, similar to climate effects, we consider two terms, i.e., the average and variance of SOC:

$$\begin{aligned} \overline{\text{SOC}} &:= \frac{1}{n} \sum_{i=1}^n 0.75(t_{m_i}(s_f) - t_0) + 0.51(m_0 - m_{m_i}(s_f)) \\ \sigma_{\text{SOC}}^2 &:= \frac{1}{n} \sum_{i=1}^n \left(0.75(t_{m_i}(s_f) - t_0) + 0.51(m_0 - m_{m_i}(s_f)) - \overline{\text{SOC}} \right)^2 \end{aligned} \quad (14)$$

allowing us to define the Mayer term of the cost functional as

$$J_{\text{may.}} = C_{\overline{\text{SOC}}} \cdot \overline{\text{SOC}} + C_{\sigma_{\text{SOC}}} \cdot \sigma_{\text{SOC}}^2 \quad (15)$$

where $C_{\overline{\text{SOC}}}$ and $C_{\sigma_{\text{SOC}}}$ are parameters weighting the average and variance of SOC in the objective function. These weighting parameters, together with those previously introduced for penalizing climate impact, are important for studying existing trade-offs between objectives.

Finally, the optimal control problem formulated to address the concept of robust flight planning problem under multiple models for estimating climate impact can be summarized as follows: The cost functional given in Eqs. (15) + (12) is to be minimized while respecting dynamical constraints (Eq. (5)), path constraints (Eq. (7)), and boundary constraints (Eqs. (8), (9)). This problem is in the form of deterministic dynamic optimization problems that can be solved with optimal control methods.

4. Case studies

In this section, we employ the proposed flight planning approach to optimize the trajectories of two flights as case studies. The experiment setups for simulations are given in Section 4.1, and Section 4.2 presents the simulation results.

4.1. Climate impact estimation models

To explore the potential of the presented concept, we require different climate impact estimates. In this study, we employ the climate effects measured using the prototype aCCFs V1.0a (Matthes et al., 2023) with the meteorological information provided by ECHAM/MESy Atmospheric Chemistry (EMAC) model (Jöckel et al., 2010) and ERA-Interim (Simmons, 2006) (see Table 1).

In the following, we describe the part of the objective function representing the climate effects (Eq. (12)). Notice that the aCCFs with the EMAC model are calculated from submodels CONTRAIL and ACCF (see Yin et al. (2023), Yamashita et al. (2020)), while the python library CLIMaCCF (Dietmüller et al., 2023) is used to calculate the aCCFs with ERA-Interim weather data. We use “CLIMaCCF-Interim” in the following to refer to the aCCFs calculated using the CLIMaCCF library with ERA-Interim weather data. Some user-defined options need to be defined for aCCFs based on the application. For studying the mitigation potential of constantly applying a routing option, the business-as-usual future emission scenario is suggested (Grewé and Dahmann, 2015). Therefore, in this study, we use the latest version of aCCFs (V1.0a) for the business-as-usual emission scenario over the time horizon of 20 years. The aCCFs are further scaled with the forcing efficacy factors reported by Lee et al. (2021). Interested readers are referred to the study conducted in Dietmüller et al. (2023) for a detailed explanation of the required parameters.

Let us define the subscript m_1 for the weather data obtained from EMAC model and subscript m_2 for ERA-Interim, i.e., $\mathbf{w}_{m_1} := \mathbf{w}_{\text{EMAC}}$ and $\mathbf{w}_{m_2} := \mathbf{w}_{\text{Int.}}$. Under similar definitions for aCCFs and NO_x emission index, for all species except for contrails, we have

$$\text{aCCF}_{m_i}^j(\mathbf{L}, t_{m_i}, \mathbf{w}_{m_i}) \cdot \text{EI}_{m_i}^j(\mathbf{L}, t_{m_i}, \mathbf{w}_{m_i}, f_{c,i}) := \text{CM}_{m_i}^j(\mathbf{L}, t_{m_i}, \mathbf{w}_{m_i}, \text{EI}_{m_i}^j) \quad (16)$$

for $i \in \{1, 2\}$. As the formulations of aCCFs for CO_2 and H_2O include the emission indices and thus, given in K/kg(fuel) , we assign $\text{EI}_{m_i}^j = 1$ for $j \in \{\text{H}_2\text{O}, \text{CO}_2\}$. However, due to high spatial and engine dependencies of NO_x emissions, it is generally not represented with a constant emission index. In this respect, we employ Boeing Fuel Flow Method 2 (BFFM2) (DuBois and Paynter, 2006) to consider such dependencies in calculating actual NO_x emissions. All in all, we can estimate the average temperature response over 20 years time horizon (ATR) for each model as:

$$\begin{aligned} \text{ATR}_{m_i}^{\text{NO}_x} &:= \text{CR}_{m_i}^{\text{NO}_x} = \int_0^{s_f} \text{aCCF}_{m_i}^{\text{NO}_x}(s, \mathbf{x}_{m_i}(s), \mathbf{w}_{m_i}(\mathbf{x}_{m_i}(s))) \cdot \text{EI}_{m_i}^{\text{NO}_x}(s, \mathbf{x}_{m_i}(s), \mathbf{w}_{m_i}(\mathbf{x}_{m_i}(s)), f_{c,i}(s)) \cdot f_{c,i}(s) \cdot ds \\ \text{ATR}_{m_i}^{\text{H}_2\text{O}} &:= \text{CR}_{m_i}^{\text{H}_2\text{O}} = \int_0^{s_f} \text{aCCF}_{m_i}^{\text{H}_2\text{O}}(s, \mathbf{x}_{m_i}(s), \mathbf{w}_{m_i}(\mathbf{x}_{m_i}(s))) \cdot f_{c,i}(s) \cdot ds \\ \text{ATR}_{m_i}^{\text{CO}_2} &:= \text{CR}_{m_i}^{\text{CO}_2} = \int_0^{s_f} \text{aCCF}_{m_i}^{\text{CO}_2} \cdot f_{c,i}(s) \cdot ds \end{aligned} \quad (17)$$

⁴ The term used in this study to represent the operational cost can be written in the form of conventional cost metric with cost index as: $\text{CI} \cdot \text{Flight Time} + \text{Fuel Consumption}$, where $\text{CI} \approx 1.5 [\text{USD/s}]$.

Table 1

Information on the approaches used in this study to estimate climate effects. A detailed explanation of the parameters used to represent aCCFs can be found in [Dietmüller et al. \(2023\)](#).

Models	Model 1 (EMAC)	Model 2 (CLIMaCCF-Interim)
MET Data		
Source of MET data	ECHAM5 (Jöckel et al., 2010 ; Roeckner et al., 2006)	ERA-Interim (Simmons, 2006)
Resolution of MET data	Horizontal: T42 ($2.8^\circ \times 2.8^\circ$) Vertical: 31 pressure levels up to 10 hPa	Horizontal: $0.75^\circ \times 0.75^\circ$ Vertical: 37 pressure levels up to 1 hPa
Climate Impact		
Prototype	aCCF V1.0a	aCCF V1.0a
Tool	ACCF, CONTRAIL (Yin et al., 2023)	CLIMaCCF (Dietmüller et al., 2023)
Climate indicator	ATR	ATR
Time-horizon	20 years	20 years
Forcing efficacy	Included	Included
Emission scenario	Future emission scenario	Future emission scenario
Contrail formation	Potcov (Burkhardt et al., 2008)	ISSRs + SAC (Appleman, 1953)
NO _x emission	BFFM2 (DuBois and Paynter, 2006)	BFFM2

Table 2

Routing options considered for optimizing the aircraft trajectory.

Routing tag	$C_{\text{SOC,EMAC}}$ [-]	$C_{\text{SOC,Int.}}$ [-]	C_{SOC} [USD]	$C_{\text{CR,EMAC}}$ [-]	$C_{\text{CR,Int.}}$ [-]	C_{CR} [USD/K]	$C_{\sigma_{\text{CR}}}$ [USD/K ²]
Cost opt. (EMAC)	1	0	1	0	0	0	0
Climate opt. (EMAC)	1	0	1	1	0	$1e^{13}$	0
Cost opt. (CLIMaCCF-Interim)	0	1	1	0	0	0	0
Climate opt. (CLIMaCCF-Interim)	0	1	1	0	1	$1e^{13}$	0
Cost opt. (AVG)	1	1	1	0	0	0	0
Climate opt. (AVG)	1	1	1	1	1	$1e^{13}$	0
Climate opt. (AVG + Var)	1	1	1	1	1	$1e^{13}$	$1e^{26}$
Climate opt. (AVG + higher Var)	1	1	1	1	1	$1e^{13}$	$1e^{27}$

where $\mathbf{x}_{m_i}(\cdot) := [\lambda(\cdot) \ \phi(\cdot) \ h(\cdot) \ t_{m_i}(\cdot)]$ is a vector including tracked variables (e.g., atmospheric location of flight) and flight time (as an untracked variable) associated with model m_i required to calculate aCCFs and emission indices. For the climate response of contrails, aCCF of contrails needs to be multiplied by areas favorable for the formation of persistent contrails (denoted by “Contrails”), i.e.,

$$\text{aCCF}_{m_i}^{\text{AIC}}(\mathbf{L}, t_{m_i}, \mathbf{w}_{m_i}) \cdot \text{Contrails}(\mathbf{L}, t_{m_i}, \mathbf{w}_{m_i}) \cdot f_{c,i}^{-1} := \text{CM}_{m_i}^{\text{AIC}}(\mathbf{L}, t_{m_i}, \mathbf{w}_{m_i}). \quad (18)$$

To identify areas where persistent contrails are formed, two different approaches are used with the data retrieved from EMAC and ERA-Interim. With ERA-Interim, ice-supersaturated conditions, jointly with the Schmidt-Appleman criterion (SAC), are used to determine persistent contrail formation areas ([Appleman, 1953](#)). Engine specifications and meteorological parameters such as temperature and relative humidity over ice are required. In contrast, due to the coarse resolution of the EMAC model ($\approx 2.8^\circ \times 2.8^\circ$), a fractional scheme is used to determine such areas, called potential contrail coverage (POTCOV) (see [Burkhardt et al. \(2008\)](#)). In other words, $\text{Contrails}_{\text{EMAC}}(\cdot) \in [0, 1]$ and $\text{Contrails}_{\text{Int.}}(\cdot) \in \{0, 1\}$. In this respect, we define the ATR of contrails as:

$$\text{ATR}_{m_i}^{\text{AIC}} := \text{CR}_{m_i}^{\text{AIC}} = \int_0^{s_f} \text{aCCF}_{m_i}^{\text{AIC}}(s, \mathbf{x}_{m_i}(s), \mathbf{w}_{m_i}(\mathbf{x}_{m_i}(s))) \cdot \text{Contrails}(s, \mathbf{x}_{m_i}(s), \mathbf{w}_{m_i}(\mathbf{x}_{m_i}(s))) \cdot ds \quad (19)$$

which is only evaluated in areas with the possibility of forming persistent contrails.

4.2. Simulation results

In order to showcase the proposed methodology, based on the geographical distribution of the estimates discrepancies, we selected two flights on January 4, 2018, departing at 1200UTC:

- **Case I:** Warsaw-Rennes Flight,
- **Case II:** Palermo-London Flight.

The selection of weighting parameters in the objective function plays an important role in achieving the desired performance in flight planning. Due to the varying magnitudes of objectives across different flights and scenarios, weights may need to be

selected scenario-specific to ensure meeting the flight planning criteria. This is particularly relevant when having climate impact as a flight planning objective; the climate impact of different non-CO₂ species can change significantly for different scenarios (due to dependency on meteorological conditions, aircraft type, etc.). A common approach for weight selection of terms behaving in a conflicting manner (e.g., operating cost and climate effects) involves adjusting one weighting parameter while keeping others constant. This method generates a Pareto frontier, a curve depicting the trade-offs between different objectives. By examining the Pareto frontier, one can identify the most suitable solution that meets flight planning criteria. Such a process can be performed iteratively to fine-tune the weights applied to different objectives. For an effective selection of weights in constructing the Pareto frontier, it is necessary to consider the relative magnitudes of terms in the objective function. For example, insights from the magnitudes of climate effects and operating cost when using ATR and SOC as metrics reveal that they are in the order of 10^{-9} and 10^4 , respectively. Thus, applying weight on the order of 10^{13} to the average climate impact scales its magnitude to be comparable to that of operating costs. In this study, after conducting experiments with the aforementioned approach, details of which are provided in [Appendix A](#), we select eight different sets of weights for both case studies, summarized in Table 2. These routing options are:

- **Deterministic optimization (EMAC):**

Considering the EMAC model to determine cost-optimal (tagged as “Cost opt. (EMAC)”) and climate-optimal trajectories (tagged as “Climate opt. (EMAC)”).

- **Deterministic optimization (CLIMaCCF-Interim):**

Considering the CLIMaCCF-Interim to determine cost-optimal (tagged as “Cost opt. (CLIMaCCF-Interim)”) and climate-optimal trajectories (tagged as “Climate opt. (CLIMaCCF-Interim)”).

- **Robust optimization (Average):**

Considering both models to determine cost-optimal (tagged as “Cost opt. (AVG)”) and climate-optimal trajectories based on the average of climate effects (tagged as “Climate opt. (AVG)”).

- **Robust optimization (Average and Variance):**

Considering both models to determine climate-optimal trajectories with two different weights for penalizing the variance of climate effects (tagged as “Climate opt. (AVG + Var)” and “Climate opt. (AVG + higher Var)”, respectively).

For presenting the results, as will be shown, if we use one of the estimations to optimize aircraft trajectory, we also provide the assessment of climate effects w.r.t. the other model to quantify the mismatch and explore the robustness of the determined trajectories.

4.2.1. Deterministic optimization (EMAC)

In the first scenario, we optimize aircraft trajectory considering cost-optimal and climate-optimal routing options for the EMAC model. The lateral paths and vertical profiles are given in [Figs. 2, 3](#), respectively, for both flights. It can be seen that when the optimization objective is the operating cost, aircraft select the shortest path and tend to fly at high altitudes (≈ 12 – 13 km). However, large deviations (from the cost-optimal routing option) in altitude and lateral path are seen when the climate impact is penalized in the objective function. Such behaviors can be justified by referring to the climate effects of individual species provided in [Fig. 4](#). Adopting the climate-optimal routing option reduces the net climate effects mainly by increasing the cooling impact of contrails; For Case I, the net cooling contrails increase, and warming contrails turn to cooling for Case II. Due to the role of contrails in the achieved mitigation potential, the lateral paths given in [Fig. 2](#) have been depicted with the aCCF of contrails. The right-hand side plots in [Fig. 2](#) show the aCCF of contrails at different flight altitudes for the EMAC model. By relating the selected flight altitude ([Fig. 3](#)) and flown lateral path ([Fig. 2](#)), we conclude that the optimizer tries to maximize generating cooling contrails by deviating from the shortest path.

The results presented so far were based on the climate effects optimized and assessed using the EMAC model. Now, let us assess the performance of the optimized trajectory in terms of the CLIMaCCF-Interim model. By looking at the assessment of climate effects using the ERA-Interim weather data (the columns with dashed boxes) in [Fig. 4](#), a discrepancy between estimations is observed. Such a mismatch is mainly related to the climate impact of contrails. As the flights are during daytime, the aCCF of daytime contrails is used, requiring the meteorological variable relative humidity over ice and temperature (which are used to determine where persistent contrails are formed), and outgoing longwave radiation (OLR) to quantify the climate impact of the formed contrails. In [Appendix B](#), [Fig. 10](#), it can be seen that a part of the difference in the climate impact of contrails is related to the relative humidity provided by EMAC and ERA-Interim and the resolution of data, leading to implementing different approaches to determine persistent contrail formation areas. In addition, one can see some areas with inconsistent climate effects ([Fig. 2](#)), i.e., one shows a cooling impact while the warming impact is estimated with the other. Such a mismatch is related to the parameter outgoing longwave radiation. Based on the aCCF of daytime contrails ([Yin et al., 2023](#)), for the outgoing longwave radiation with a magnitude larger than -193 [W/m^2], cooling contrails are generated. In [Fig. 10](#), the OLRs provided by ERA-Interim and the EMAC model are depicted, showing a significant difference in the spatial distribution of areas with $\text{OLR} < -193 \text{ W/m}^2$. Therefore, in addition to the mismatch in PCFA, the variability of the OLR field is significant.

For Case I, the mismatch between estimations for the climate-optimal routing option is critical, in which the trajectory that maximized generating cooling contrails for the EMAC model caused a warming impact of contrails for ERA-Interim weather data (see [Fig. 4](#)). This can be validated by referring to [Fig. 2](#); the aCCFs of contrails for the EMAC and CLIMaCCF-Interim models at altitudes 10 – 11 km show a mismatch in terms of sensitivity to generate cooling and warming contrails for almost two-thirds of distance flown. Such a difference between estimations can also be seen for the cost-optimal routing option and Case II. However,

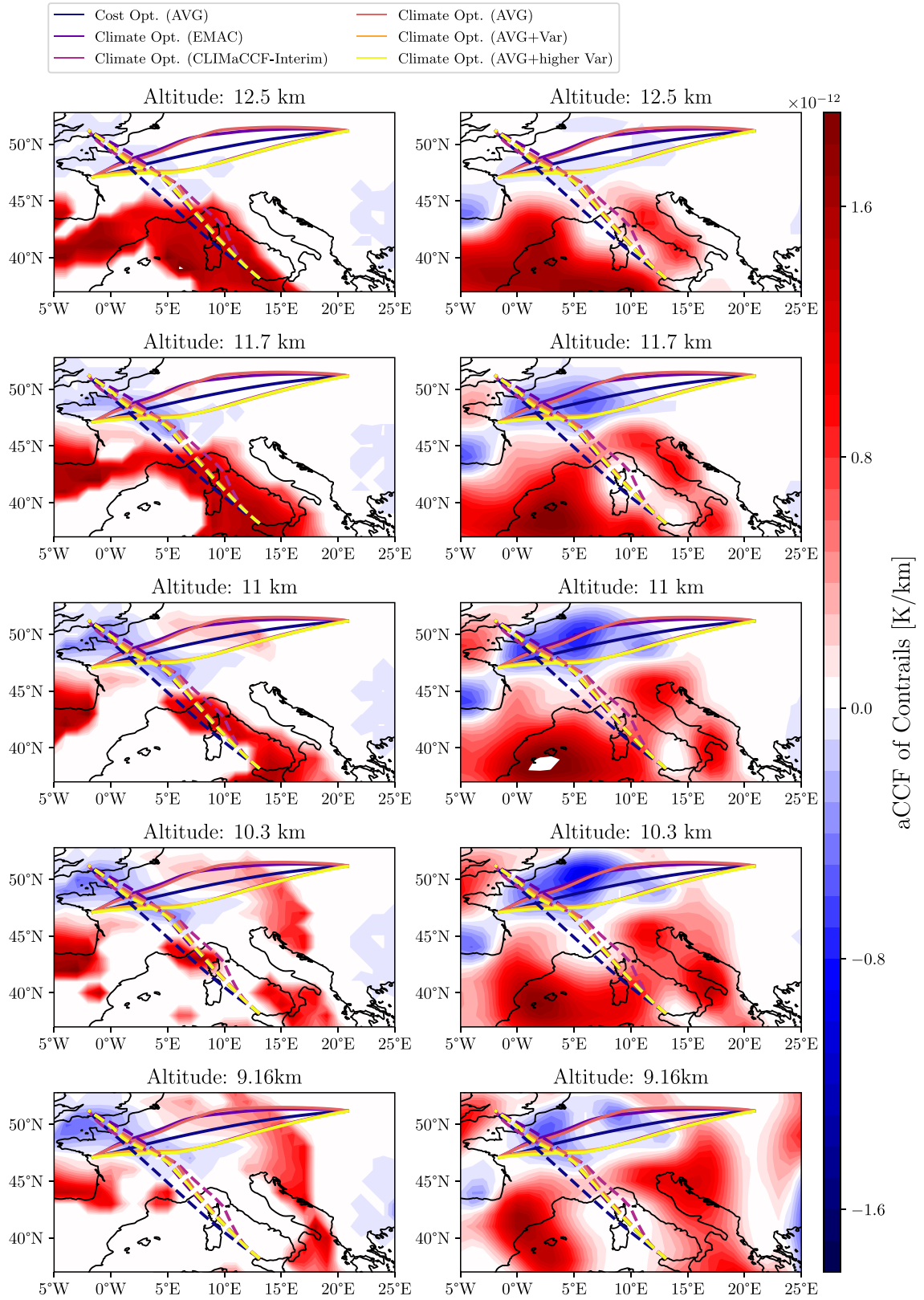
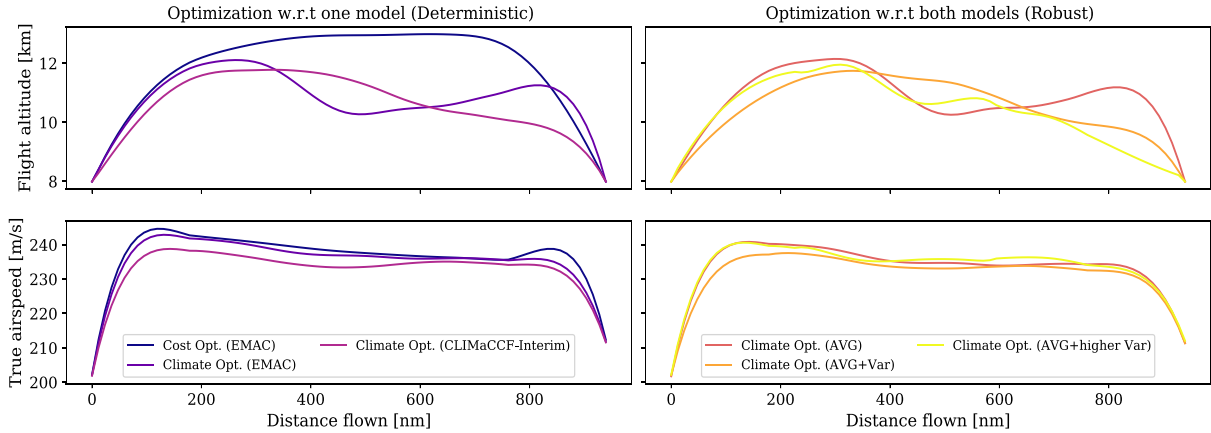


Fig. 2. Lateral paths for different routing options (LHS: CLIMaCCF-Interim, RHS: EMAC).

Case I



Case II

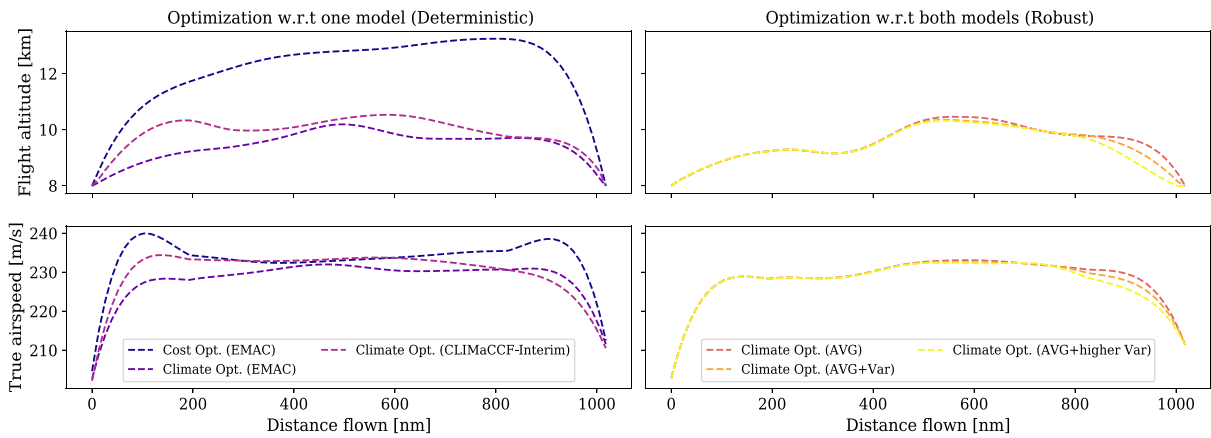


Fig. 3. Airspeed and flight altitude for different routing options.

the level of discrepancy changes. For instance, in Case II, the results show a better consistency for the climate-optimal routing option than for Case I.

Such a potential difference between different estimations needs to be taken into account because if the optimization is based on one model and the other models (which are not used for optimization) are more representative of aviation-induced climate effects for particular scenarios, besides increasing the operating cost (due to re-routing), the main objective is not achieved, i.e., we may not significantly reduce the climate impact (e.g., see the assessments of climate impact based on CLIMaCCF-Interim for Case 1 when the optimization is based on EMAC model). It should be noted that the estimations of other species, such as CO_2 , NO_x , and water vapor emissions, are very similar. This is due to the fact that the meteorological variables required for these aCCFs are in good consistency (e.g., temperature (see Fig. 10)).

4.2.2. Deterministic optimization (CLIMaCCF-Interim)

In this scenario, we perform trajectory optimization considering only the CLIMaCCF-Interim model. For the cost-optimal routing option, a similar trajectory to the previous scenario is determined. When the optimization objective is the operating cost, only meteorological variables used in the dynamical model of aircraft are required, i.e., temperature and wind. As shown in Appendix B, Fig. 10, temperature and wind are very similar for the areas covering the origins and destinations. Therefore, similar trajectories are expected. In contrast, penalizing climate effects leads to different trajectories compared to the scenario with the EMAC model. Here, the flight altitude and lateral path are obtained so that the climate impact measured using CLIMaCCF-Interim is minimized, which is achieved mainly by deviating from the shortest path to generate cooling contrails. For Case I, unlike the previous scenario with the EMAC model (i.e., warming contrails were generated for the assessment based on ERA-Interim weather), the regions where cooling contrails can form according to the ERA-Interim weather are also confirmed as such as by the EMAC model, leading to more consistent results for the climate-optimal routing option. However, such consistency cannot be seen in Case II. Climate-optimized trajectory leads to net cooling impact with the ERA-Interim weather data while warming contrails are estimated with the EMAC model. Such inconsistency can also be seen in Case II when the optimization objective is the operating cost.

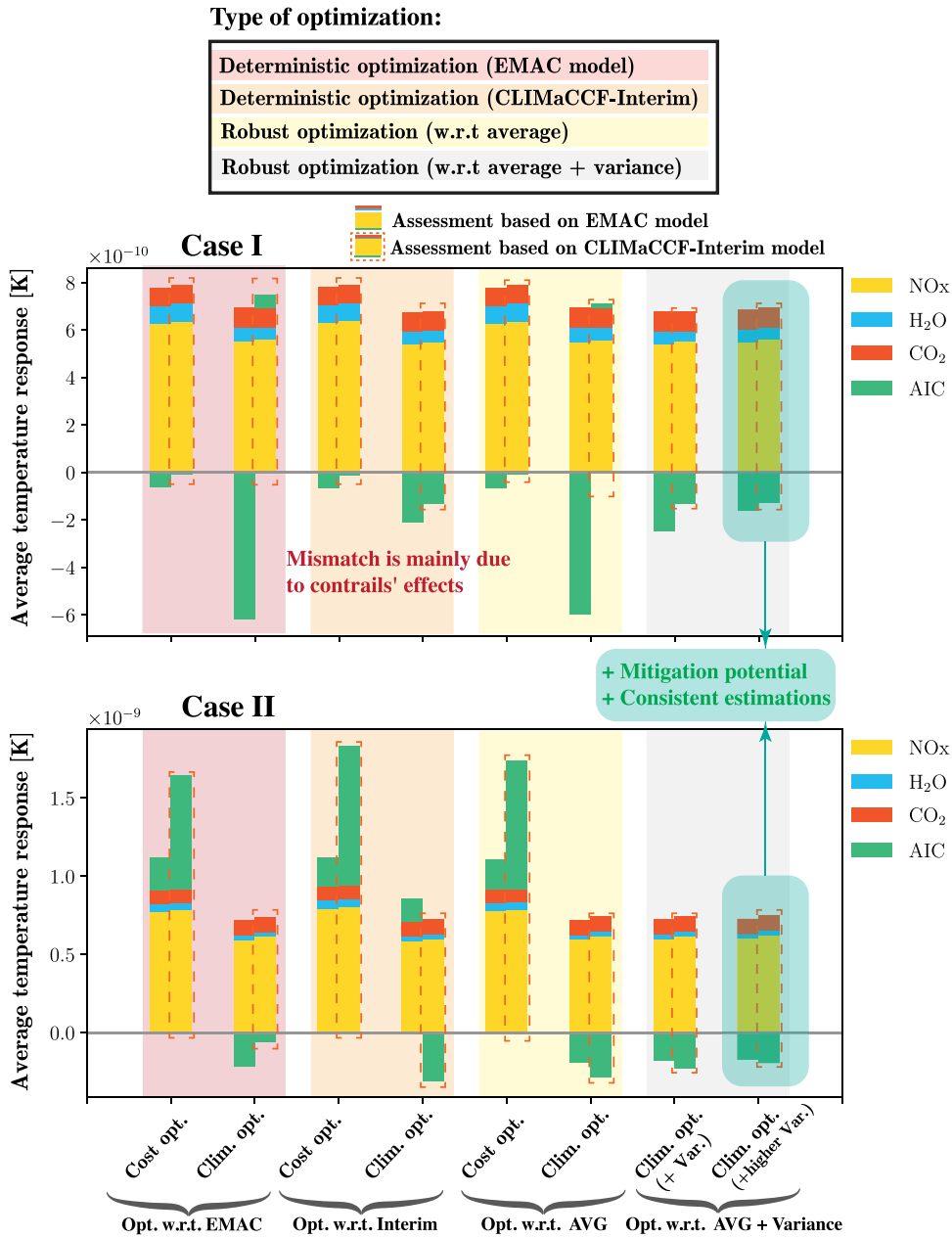


Fig. 4. Climate effects of individual species assessed with the EMAC model and CLIMaCCF-Interim (red dashed box) for different routing options. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2.3. Robust optimization (Average)

So far, we have explored that the optimization based on considering one of the models, despite providing mitigation potentials for the considered model, could lead to significant discrepancies when the assessment is performed using the other model.

We want to explore how the proposed methodology can deal with such significant differences between estimations and directly determine climate-optimal trajectories, resulting in more consistent estimations. We expect that the optimizer avoids warming contrails for both models and considers those cooling areas in good agreement for estimations. To this end, we perform trajectory optimization considering both models at the same time. We start by penalizing the average of both estimations.

As mentioned earlier, the only difference between these two models for the cost-optimal routing option is the meteorological variables temperature and wind. As these variables are in good agreement with the EMAC model and ERA-Interim weather data, the cost-optimal trajectory is achieved similarly to the previous cases. Regarding the climate-optimized routing option, different trajectories are determined. For Case I, it can be seen in Fig. 4 that as we penalize the average performance with a large weight

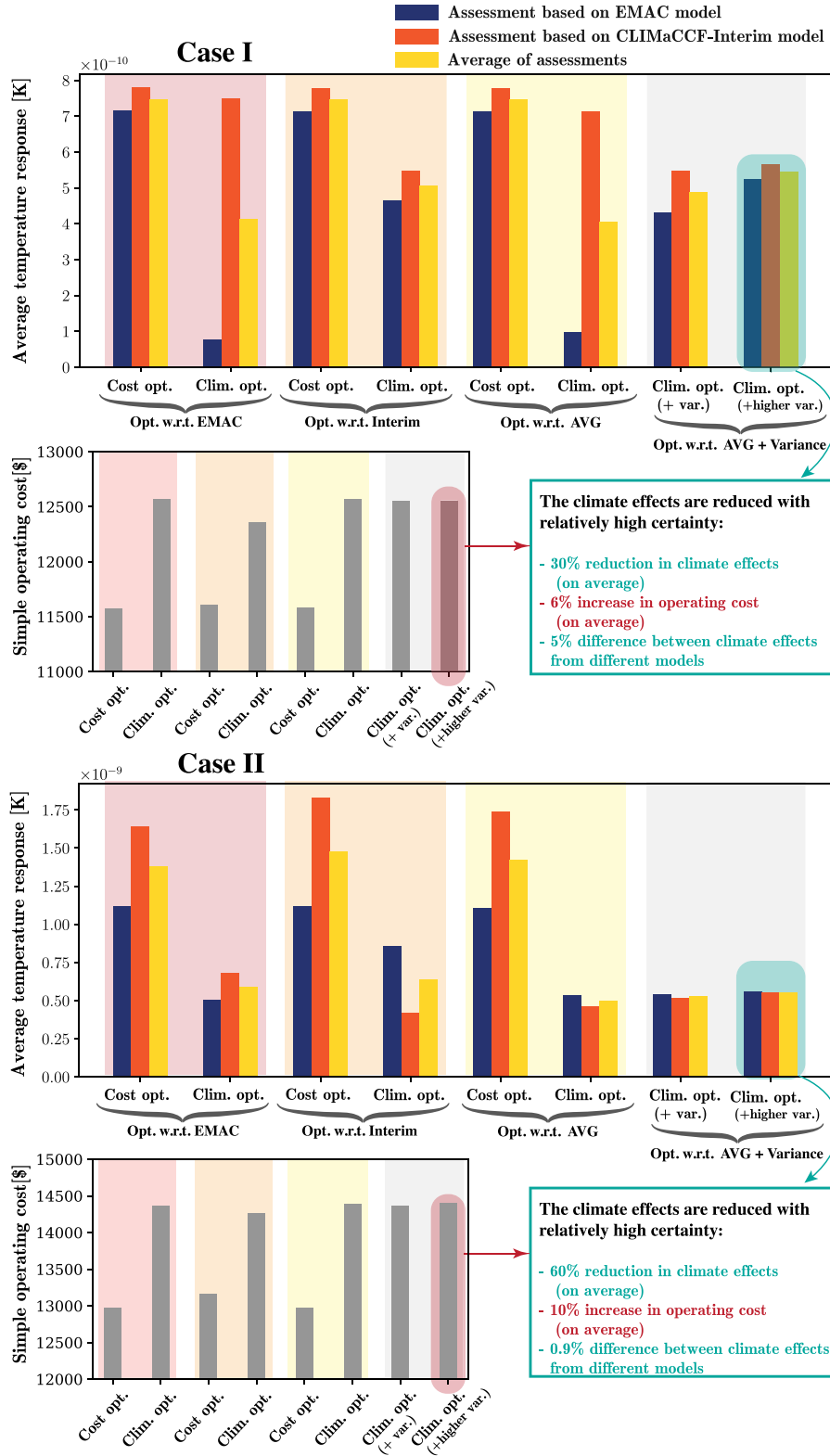


Fig. 5. Climate impact and operating cost for different routing options.

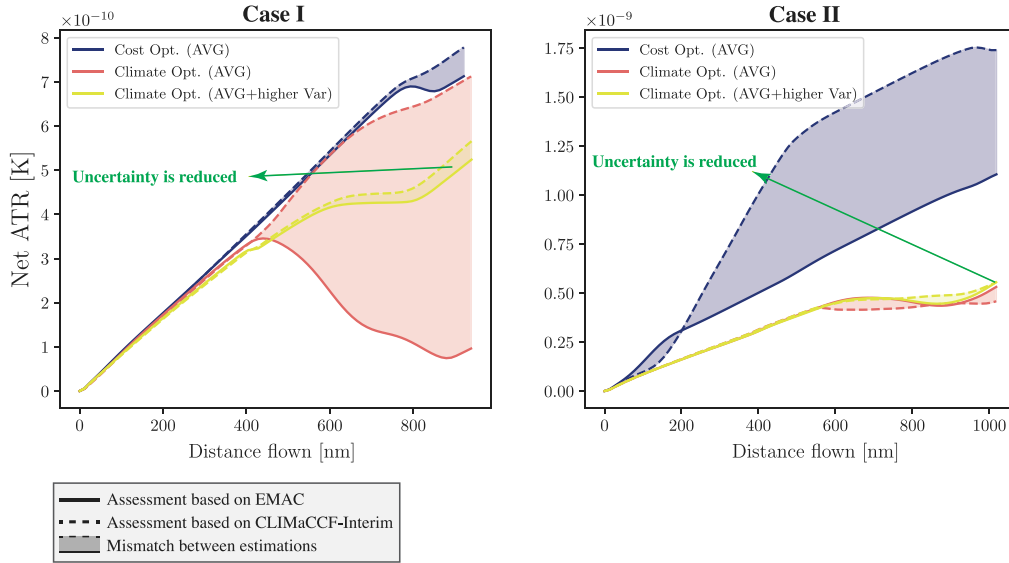


Fig. 6. Accumulated values of the net ATR along the route for three routing options. Shaded areas show mismatches between estimations.

(i.e., climate-optimal routing option), the climate effects associated with both models are mitigated. However, the optimizer relies on the climate impact estimate showing a higher possibility of forming cooling contrails (i.e., EMAC model, in this case (see the lateral path and flight altitude in Figs. 2, 3, respectively)). This, in turn, leads to an increased dispersion between the estimated climate effects. Therefore, despite the mitigation potential for the two considered models, the difference between the estimated impact is relatively high. For Case II, penalizing average climate effects provides mitigations for both models with good consistency. Such consistency can be seen in Fig. 2 at altitudes 9–11 km, where the aircraft flies in areas with similar climate effects.

4.2.4. Robust optimization (Average and Variance)

The penalization of the average performance, as depicted in the previous section, does not necessarily provide consistent estimations. This is reasonable as the optimizer focuses on finding a trajectory yielding the highest mitigation potential on average.

Here, we penalize the variance of climate effects with two different weights in addition to the average performance. Fig. 4 shows that there is a trade-off between average performance and consistency of climate effects. As we penalize the variance of the climate effects with larger weights, the dispersion between estimated climate impacts reduces at the cost of decreasing average mitigation potential. For Case I, as we expected, the aircraft trajectory for such routing options is in the vicinity of the trajectory optimized considering only the CLIMaCCF-Interim model since the formation of cooling contrails estimated with the CLIMaCCF-Interim model is also consistent with the EMAC model (see Fig. 2). For Case II, the optimization based on average climate effects already provided robust solutions. However, by penalizing the variance of climate effects, it is possible to maintain the average mitigation potential (achieved by penalizing only the average of climate impacts) with less discrepancy between estimations (less than 1% difference). Such consistency is achieved by avoiding warming contrails for both estimates (flying at ≈ 9 km) and flying through areas with a high degree of concurrence for cooling contrails.

The difference between estimations along the route for three different routing options is illustrated in Fig. 6. It can be seen that the proposed robust optimization with penalizing average and variance of climate effects leads to reducing climate effects and uncertainty from the beginning of both flights by seeking those climate-sensitive areas with acceptable agreements.

The simulation results for both cases underscore the importance of appropriate weight selection in the flight planning objective function. It can be seen in Figs. 2, 3 that similar weights do not necessarily provide similar results in terms of performance for the considered flights. For instance, for the climate-optimal routing option, when the objective is to minimize the average climate effects, trajectory optimization for Case 1 (i.e., Warsaw-Rennes flight) mitigated climate impact with reduced discrepancies between the two models. In contrast, with the same routing option (i.e., the same weighting parameters), a large discrepancy was observed when optimizing the flight trajectory from Palermo to London. This is mainly related to the high variability of non-CO₂ climate effects across different scenarios, highlighting the necessity for scenario-specific weight selection.

The mitigation potentials are obtained by accepting additional increases in the operating cost. This is because penalizing climate effects can significantly change flight plans compared to the cost-optimal routing option (see lateral paths and flight altitudes in Figs. 2, 3). In this respect, we assess the cost increase for all routing options in USD together with the net climate impacts, which is illustrated in Fig. 5. It can be concluded that when climate effects are penalized, the operating cost increases. The relative increases compared to cost-optimal scenarios are considerable (i.e., $\approx 6\%$ for Case I, and $\approx 10\%$ for Case II) as we penalized the climate effects with relatively large weights. In Appendix A, we perform optimizations for Case I using more weighting parameters in order to

build Pareto-frontiers, allowing for studying the existing trade-offs as a decision-making aid. The difference between the operating cost increase corresponding to optimizing one model in a deterministic manner and the proposed robust approach is insignificant. Therefore, with almost the same operating cost increase compared to focusing only on one model, the optimizer is able to find trajectories that mitigate the climate effects of the considered models with a slight difference between the estimated impacts.

4.3. Discussion

As highlighted in the introduction, only two approaches in the literature provide spatiotemporal dependency of non-CO₂ climate effects in real-time, i.e., aCCFs and gridded CoCiP. The aCCF of contrails and gridded CoCiP are different in several respects, which can lead to differences in their climate impact estimates. The modeling approach (i.e., aCCF of contrails was derived based on radiative forcing calculations on Lagrangian trajectories (Yin et al., 2023), while the gridded CoCiP (Shapiro et al., 2022) is a domain-filling version of the Lagrangian CoCiP (Schumann, 2012)), contrail properties assumptions (e.g., lifetime), inputs (e.g., meteorological variables and the required time steps, and specific emissions) are some factors that can introduce mismatch in the estimates. The other main difference is related to the physical climate metric. The aCCFs estimate climate effects using the state-of-the-art metric ATR. In contrast, CoCiP estimates the climate effect of contrails using the metric energy forcing (Schumann, 2012). In this study, we focused on the aCCFs calculated using two sources of atmospheric conditions: the ECHAM/MESSy Atmospheric Chemistry model and global atmospheric reanalysis data called ERA-Interim. Since we used the aCCFs in both approaches, two possible estimates in the same unit [K] were provided. The comparison of the aCCF of contrails and CoCiP and the representation in the same physical unit is ongoing research (e.g., within the CICONIA⁵ project).

With the growing concern over aviation's climate impact, the research and development community is actively working towards creating more sophisticated models to improve climate impact predictions. For instance, commercial models have recently been developed or are currently under development for the forecast of contrails forming areas, including SATAVIA's⁶ high-resolution contrail forecasting tool and Google's⁷ artificial intelligence-based contrail prediction model that can be used along with aCCF of contrails or CoCiP in order to enhance the prediction of contrails forming areas. Given the inherent complexities of climate impact modeling and the likely persistence of discrepancies, the proposed flight planning framework will be effective in mediating between differing estimates, offering a balanced and more reliable mitigation strategy. In case of the availability of these tools and/or other newly developed models, as a future direction of our research, we will assess the proposed methodology considering more climate impact estimates.

The weather data sources used in this study are suitable to assess the savings (in terms of climate impact), and the associated cost the flight could have achieved in reality (which is important for quantifying the cost of climate impact mitigation and establishing policy-based incentives) as they do not provide real-time information (e.g., ERA-Interim is a reanalysis data product). They were employed in this study to show the applicability of the proposed approach when having a mismatch in different climate-impact estimates. However, as can be seen in the formulations presented in Section 3, the method is generic in terms of weather data and climate impact estimation model, and one can use forecast data without loss of generality to illustrate the robust flight planning approach as potential flight dispatching applications.

The initial selection of case studies was based on the geographical distribution of model discrepancies (see Fig. 2), identifying two specific flights that could effectively demonstrate the concept of robustness. In the following, the proposed methodology is evaluated by considering more flights, and the performance of the optimized trajectories is assessed in an aggregated manner. We utilize a subset of a fictitious route network generated within the EU-project FlyATM4E, approximating aerial traffic flow with fewer routes (Mendiguchia Meuser et al., 2022). We have selected 95 flights within a geographical area bounded by latitudes 30° to 60° and longitudes -10° to 45°, on January 4, 2018 (i.e., the same day as individual cases explored in this study). The obtained lateral paths and distributions of flight altitude and true airspeed are depicted in Fig. 7. In addition, Fig. 8 shows the assessment of climate effects of individual non-CO₂ species and the net climate impact with both considered models. The aggregated results corroborate the conclusions previously drawn from the individual flights discussed in the paper, e.g., when focusing on one model for climate-optimal flight planning does not consistently mitigate climate with the other model (e.g., warming and cooling impact of contrails), while the proposed robust approach can result in mitigation potential with reduced discrepancies between both estimates.

The flight planning method proposed in this study is based on the concept of a fully free-routing airspace, allowing for unconstrained optimization of both altitude and lateral paths. Such a routing strategy enables greater flexibility to avoid areas with significant discrepancies in climate impact estimates. However, given the structured nature of today's airspace, the proposed robustness concept needs to be explored by accounting for real operational constraints.

The trajectory optimizations performed in this study were computationally acceptable. Full 4D flight planning problems for cases considering a single model and multiple models were generally solved in a minute. Nonetheless, the computational performance of the proposed methodology can be highly affected by the number of inputted weather data associated with each model. This is because, to account for the effects of using different weather sources, the dimensions of the optimization problem (e.g., aircraft dynamical model, path and boundary constraints, and decision variables) are expanded linearly with the number input weather data, degrading the computation performance mainly in terms of function evaluation and therefore convergence speed. Implementing

⁵ <https://sesarju.eu/projects/CICONIA>

⁶ <https://satavia.com/contrail-forecasting/>

⁷ <https://sites.research.google/contrails/>

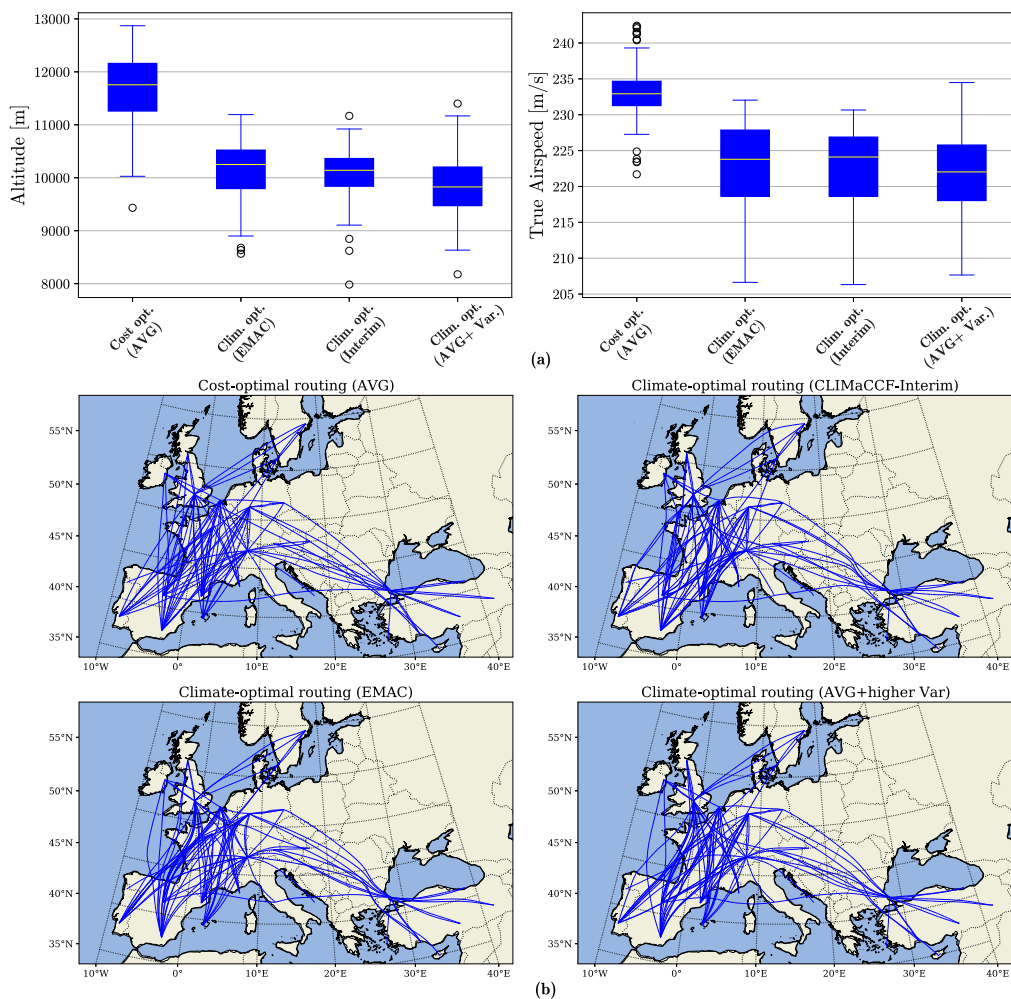


Fig. 7. (a) Distributions of flight altitude and true airspeed, (b) and the lateral paths for different routing options considering a fictitious route network, including 95 flights.

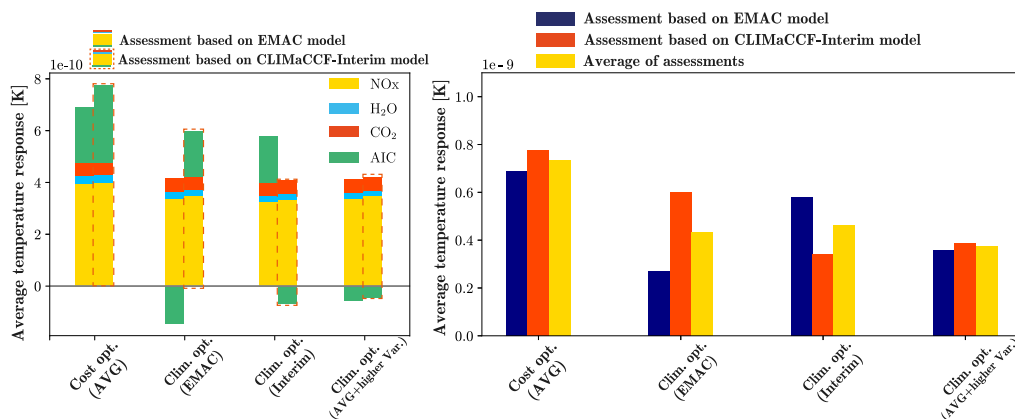


Fig. 8. The climate impact of individual species and the net climate impact for different routing options considering a fictitious route network, including 95 flights. The assessments are reported per flight.

a parallelization scheme could address this challenge by enabling parallel function evaluation. It is worth mentioning that if different climate impact estimation models considered for robust climate-optimal flight planning use the same weather data, the computational performance is expected not to be significantly affected by the number of models, as the problem's dimension remains unchanged.

5. Conclusions

This study presented a methodology for planning robust climate-optimal aircraft trajectories, taking into account multiple approaches to assess the climate impact of aviation. For the case studies, we employed algorithmic climate change functions (aCCFs) calculated using meteorological data from both the EMAC model and ERA-Interim reanalysis, providing two possible estimates for climate impacts. A significant mismatch was observed in the contrails climate impact for the considered models. This discrepancy was attributed to a mismatch in the required meteorological variables, such as relative humidity and outgoing longwave radiation. Furthermore, the coarse resolution of data from the EMAC model necessitated adopting a different approach to identify persistent contrail formation areas. The performance of the proposed approach to deal with climate-optimal flight planning under multiple estimates of climate effects was explored by optimizing two different flights. Case studies revealed that optimizing aircraft trajectory based on one of the estimates did not consistently reduce climate impacts when assessed using the other approach. For instance, in the case of the Palermo to London flight (Case II), optimizing solely based on the CLIMaCCF-Interim model resulted in forming persistent contrails exhibiting cooling effects in the assessment using the CLIMaCCF-Interim model, whereas they showed warming effects when assessed using the EMAC model (Fig. 4). By using the proposed robust approach, considering both estimates when planning aircraft trajectory, we were able to ensure the climate mitigation potential with a good level of confidence. It should be noted that, despite providing more confident solutions, the operating cost increase as the existing trade-off for reducing climate effects was almost similar to the deterministic optimizations considering only one of the models. All in all, the concept introduced in this study offers a promising remedy for flight dispatchers aiming to increase the reliability of climate-optimized flight plans in cases where there is a significant discrepancy between climate impact estimation models.

To illustrate the concept of robustness, we used data sources that do not provide real-time information, and the prototype aCCFs, with only differences in the approach to identify where persistent contrails are formed, were employed to estimate climate impact. As for a future line of research, we aim to include more climate impact estimation models, particularly the CoCiP model, due to the high uncertainty in quantifying the climate impact of contrails. In addition, the input weather data in the form of an ensemble weather forecast and different emission index calculation methods (e.g., DLR method) will be used in order to showcase the concept for real flight dispatching applications.

Funding

This research was supported by funding from the EU-Project RefMAP. RefMAP has received funding from the Horizon Europe program 2022 under grant agreement No 101096698. The opinions expressed herein reflect the author's views only. Under no circumstances shall the Horizon Europe program be responsible for any use that may be made of the information contained herein.

CRedit authorship contribution statement

Abolfazl Simorgh: Conceptualization, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Manuel Soler:** Conceptualization, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing. **Federica Castino:** Data curation, Visualization, Writing – original draft, Writing – review & editing. **Feijia Yin:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing. **María Cerezo-Magaña:** Methodology, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix A. Pareto-frontiers

We presented the results in Section 4.2 with two sets of weighting parameters for each considered optimization type. We observed that increases in the operating cost for climate-optimized routing options were relatively high. This was due to penalizing the climate impact with large weights. However, in order to make more efficient decisions, one needs to assess other alternative solutions by varying weighting parameters in the defined objective function. To this end, we solve the trajectory optimization problem for Case 1 using more sets of weighting parameters in order to study the existing trade-offs by generating Pareto-frontiers, depicted in Fig. 9.

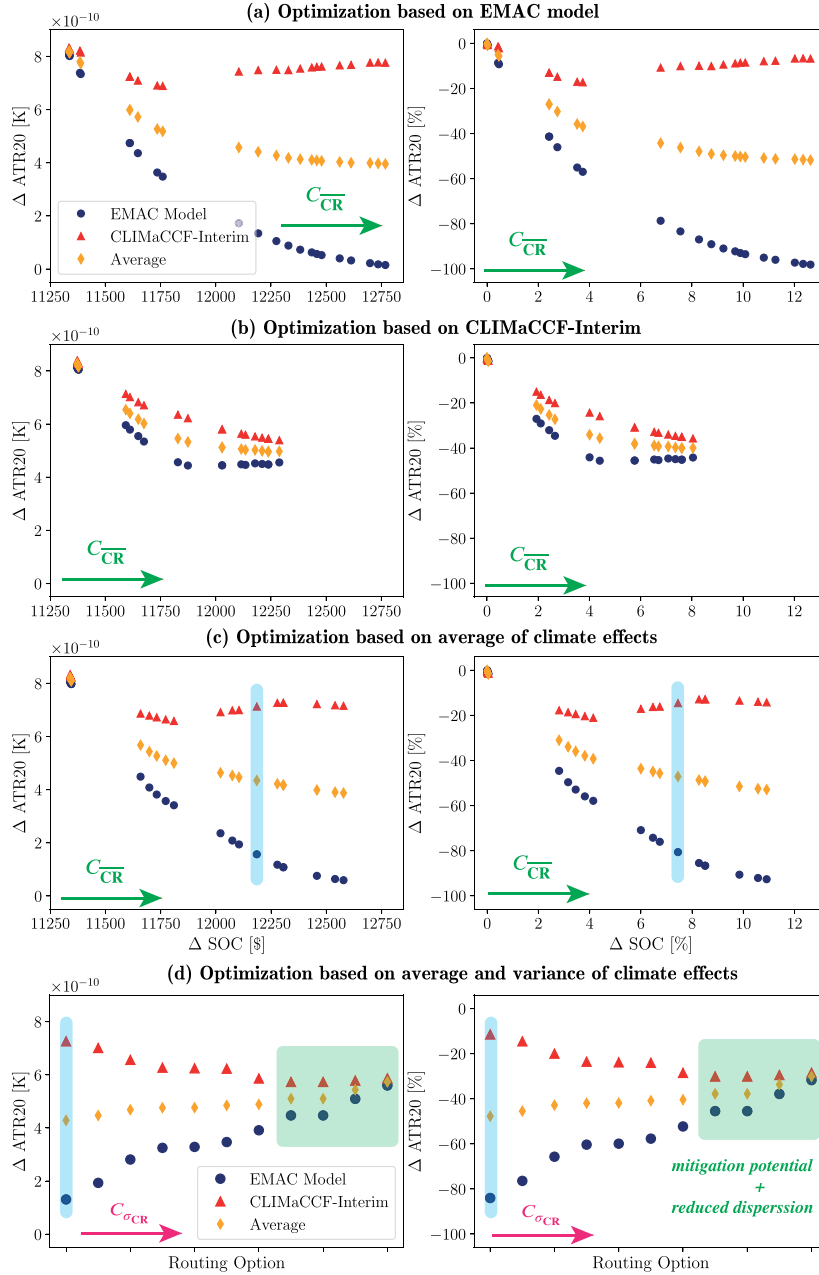


Fig. 9. Results of Case I: Pareto-optimal solutions generated by varying weighting parameters in the defined cost functional.

Appendix B. Meteorological variables provided by the EMAC model and ERA-interim reanalysis

The sources of meteorological data used in this study are different. In Fig. 10, differences between some of the required variables for calculating aCCFs and integrating the aircraft dynamical model can be observed. It can be seen that the discrepancy is mainly related to relative humidity and outgoing longwave radiation. Such a mismatch biases the estimation of contrails' climate effects, as was shown in Section 4.2 for both flights.

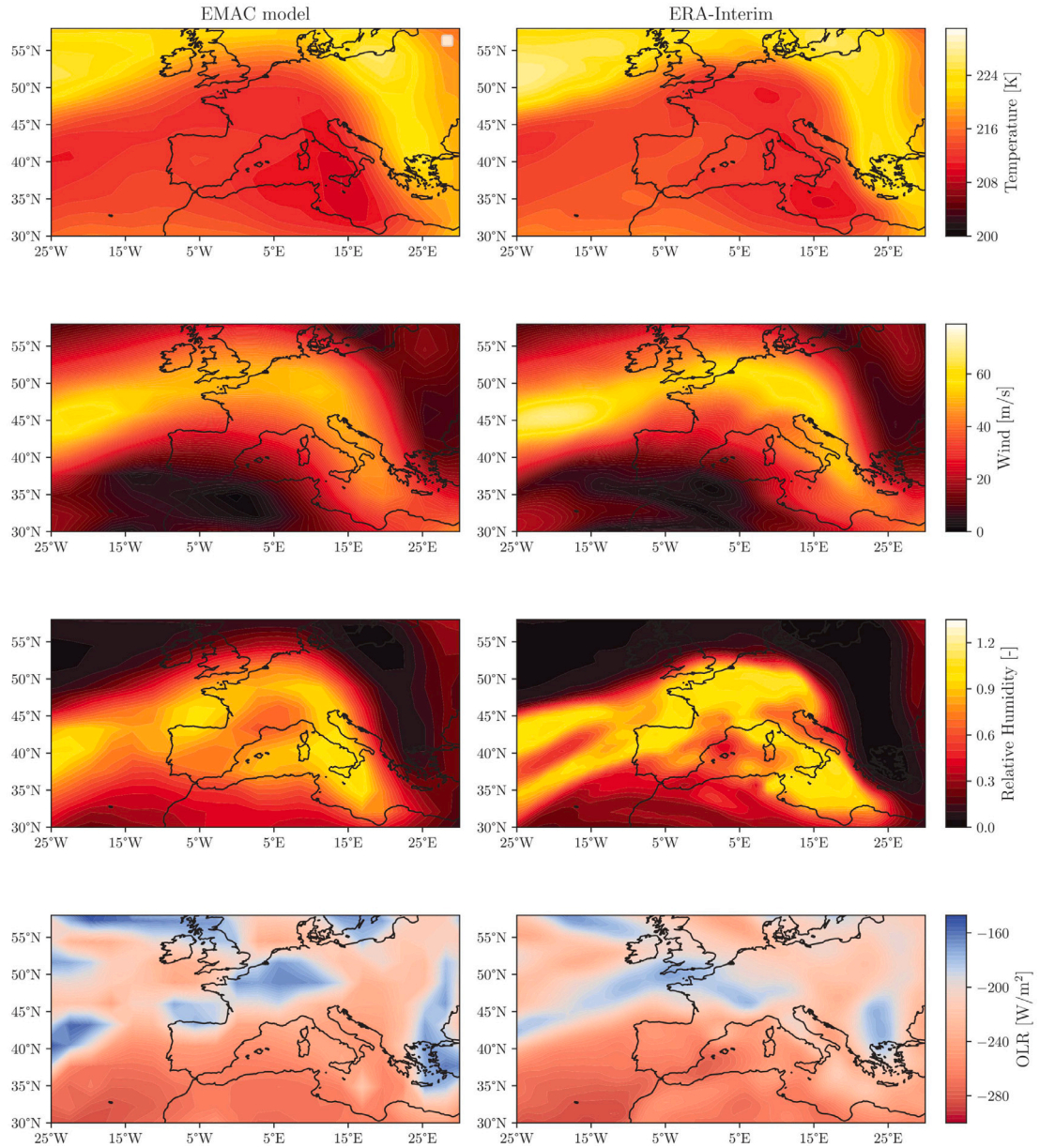


Fig. 10. Meteorological conditions on January 4, 2018, 1200UTC (LHS: EMAC, RHS: ERA-Interim). The pressure level variables are plotted at 250 hPa.

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