Updated Version

Robust 4D Climate Optimal Flight Planning in Structured Airspace using Parallelized Simulation on GPUs: ROOST V1.0

We greatly appreciate both the editor and the reviewers for the complimentary and constructive suggestions on our paper entitled "Robust 4D Climate Optimal Flight Planning in Structured Airspace using Parallelized Simulation on GPUs: ROOST V1.0". The manuscript has been modified following the reviewers' comments and resubmitted for consideration for publication. Please find attached a point-by-point response to the reviewer's concerns. We hope that you find the responses satisfactory and that the manuscript is now acceptable for publication.

For the sake of clarity the following criteria has been adopted throughout this document:

- Reviewer's comments
- Authors' responses
- Words changed or added to the paper after revision

Reviewer 1

Simorgh et al. present ROOST v1.0, an open-source Python library for 4D climate optical flight planning in structured airspace with the capability for using GPUs for efficient augmented random search. The authors introduce robust planning through the consideration of uncertainties in standard weather forecasts using an ensemble prediction system. The manuscript presents evaluation of the new model software through the planning of a flight from Frankfurt to Kyiv using a Airbus A320-214 on two different departure times representing scenarios with and without formation of persistent contrails, and demonstrates a climate impact reduction of 15-55% corresponding to 0.8-4% increase in operating cost. The work is novel and represents a significant new model software development, especially its consideration of sources of uncertainty, and is thus well fit for the scope of Geoscientific Model Development. I have minor comments regarding the manuscript before recommending it for publication.

- **One of the main contributions in the study (L89-L92) is the determination of optimized trajectory with fast computational efficiency. Could the authors elaborate on this fast computational efficiency, e.g., (1) how fast does the model run for a given scenario for prediction:**
  Response: Thanks for this comment. Each iteration within optimization takes $\approx$ 4ms. Thus, the computational time is almost proportional to the number of iterations specified by the user. In Fig. (8) of the paper, it is shown that an acceptable optimality is achieved with a maximum of 4000 iterations (i.e., $\approx$ 16s).

- **(2) considering the use of GPUs, the GPU (particularly memory) requirements for the model**
  Response: The GPU memory requirements for the cases we run are essentially determined by the size of the meteorological data in single-precision format (4 bytes per entry), which comprises more than 90% of the total memory usage of the algorithm. Thus, for our case, with a resolution of 12 variables per location, 8 time steps, 30 pressure levels, a latitude-longitude grid with 106×176 points, and 10 ensemble members, we require:

  $$12 \times 8 \times 30 \times 106 \times 176 \times 10 \times 4 \approx 2149 \text{ million bytes} = 2 \text{ GB}$$

  plus around 300 MB to store the trajectories. Thus, a dataset of this size allows the algorithm to run on any modern graphics card in the market, while an input dataset with denser resolution could require a higher-end card. As long as the memory requirements are met, the algorithm will run, with the main potential difference between models being faster or slower execution (as well as allowing a more powerful card to increase the number of search directions at a small penalty in iteration time).

- **and (3) the data requirements (e.g., EPS forecast data) for running the model?**
  Response: For running ROOST, we need an ensemble weather forecast in order to feed the performance model with the meteorological variables (temperature, wind, geopotential) and calculate aCCFs; a standard GRIB file in ECMWF format can be used and the preprocessing routines within ROOST will generate the required arrays in the internal layout. In addition, as ROOST considers the structured airspace, the route network needs to be inputted by the user.

- **If the computational efficiency is notable compared to other studies, it will be useful to include comparisons to prior work as well, as flight planning is a time sensitive operational task and would greatly benefit from improved computational efficiency if the improvements are significant compared to prior work or those currently used in the aviation industry.**
  Response: Regarding a potential comparison with previous studies, we cannot easily offer such a comparison; for, as we note in the introduction, we could not find any method in the literature that addresses the full formulation of the problem that we tackle (as opposed to partial formulations where, for example, the problem is solved only in the 2D case or in the fixed-airspeed context). Outside the scientific literature, flight service providers do have systems capable of computing realistic flight plans, but their exact capabilities, features, performance, and algorithmic basis are not public. Therefore, we cannot make such a comparison either.

- **In this case, a brief description of how GPUs are used in the work and specific optimizations for future readers' reference will be very useful as well.**
  Response: Regarding how the code is implemented on GPUs and why it is beneficial, we added the following text on Page 22:

  As can be concluded, at each iteration, we generate $2n$ different vectors of decision variables (i.e., n search directions with $\theta + \mathbf{S}\omega$ and $\theta - \mathbf{S}\omega$), and for each decision variable, we sample N_{EPS} flight plans. Therefore, we need to perform trajectory evaluation (i.e., TI) $2n \times N_{\text{EPS}}$ times for each iteration. As these calculations are similar (or very similar) and independent from each other, the parallelization on GPUs is beneficial, enabling very fast function evaluation.

  We also included the information on the GPU model used for optimizing the case studies in the paper:
  Simulations are launched on the NVIDIA GeForce RTX 3090 graphics card, providing 10496 CUDA cores at a clock speed of 1.4 to 1.7 GHz.

- **A specific note on the code reproducibility. Because ROOST requires the BADA license for representation of aircraft aerodynamics, the code provided cannot be evaluated as it is incomplete. I understand the authors are not totally in control of this but it would be reassuring for the open-source nature of the software to include a paragraph on potential future implementations of other open-source aircraft performance models within ROOST, and if ROOST has the capability/interfaces for it.**

  Response: This is unfortunately the case, we can not share BADA. We have taken the suggestion into consideration and added the following paragraph in the code availability section.

  It should be noticed that the optimizer ROOST uses BADA4.2 (license granted for the activities developed within FlyATM4E project) to represent the aerodynamic and propulsive performance of the aircraft. Due to restrictions imposed by the BADA license, the current version (in the GitHub repository) is incomplete, as three python scripts related to the used aircraft performance model have been excluded (i.e., bada4.py, apm.py, and badalib.cu). We are currently assessing the existing open-source aircraft performance models in order to make the complete library available to the public. In principle, it is possible to use other performance models as long as the functional specification (not necessarily the internal implementation) is the same as the BADA point-mass model, i.e., the drag polar is a function of the same variables, and so on. Otherwise, probably small modifications to the code would have to be applied. Potential alternatives include the OpenAP model [1] and the model in [2].

- **L79: "These studies suffer mainly from computational perspectives and some restrictive assumptions (see Simorgh et al...)" could you briefly include some examples of these restrictive assumptions? Also, it is unclear what is being referred to as "computational perspectives".**

  Response: We apologize for not being clear on this. The following examples have been added to the revised version of the manuscript.
  However, these studies suffer mainly from computational perspectives (i.e., the computational time of the optimizer when considering weather uncertainty) and some restrictive assumptions (e.g., inaccurate modeling of the aircraft dynamical model or ignoring important decision variables such as the flight altitude) (see [3], Subsection 5.3). For instance, in [4], a robust aircraft trajectory optimization problem is solved using the direct optimal control approach within fully free-routing airspace. In this study, the effects of uncertainty are included in the optimization problem by expanding the dynamical model of the aircraft (almost) linearly to the number of ensemble members, resulting in a larger dimensional deterministic optimization problem. Thus, it requires a higher computational time compared to the deterministic flight planning problem. Besides, the flight planning problem is limited to optimizing only the lateral path. As for the structured airspace, Franco et al. ([5]) proposed uncertain flight plan optimization using mixed-integer linear programming (MILP). Similarly, the optimization in this study is performed in 2D airspace. In addition, the fuel burn and its associated nonlinearities are ignored, and it has a sizeable computational cost of several minutes.

- **Page 4, Table 1 - I suggest including "This work" for easy comparison.**

  Response: Thanks for your suggestion. A row has been added to the table in the revised version of the manuscript.

- **L98: "optimized trajectory is tracked as determined" is unclear. Do you mean the optimized trajectory is deterministic but in fact takes into account the un-**

certainty of the weather forecasts? Please clarify.

Response: Yes, exactly. In fact, with the proposed trajectory optimization, the aim is to determine a unique (or deterministic) flight plan optimized with respect to the performance variables (e.g., operating cost and climate effects) obtained from all ensemble members. We emphasized this part because one can solve n deterministic trajectory optimizations, each considering one ensemble member, but in the end, n different flight plans will be generated. This does not address the robust trajectory optimization problem, as the realization of uncertainty is not known before committing to a specific plan. Therefore, a robust optimization problem needs to be formulated aiming at delivering a unique flight plan (including lateral route, altitude profile, and speed schedule). In our practical context, the track of the determined flight plan is enforced by an online controller (such as the autopilot and Flight Management System).

- **L190: How are Ψ_{CST} and Ψ_{CLM} selected?**

  Response: In the original version of this manuscript, we presented the approach we used for selecting Ψ_{CST} and Ψ_{CLM}. Generally, there is a trade-off between the operating cost and climate effects, and they are also of different orders. The approach we used is to have only one controlling parameter, called α, enabling the generation of alternative trajectories. Just to state it more clearly, a detailed description of the approach has been included in the revised version of the paper as follows:

  The weighting parameters of the objective function are selected as: $\psi_{\mathrm{CST}} = \alpha$ [-] and $\psi_{\mathrm{CLM}} = (1-\alpha)\mathrm{K}$ [USD/K], where K is a scaling (or conversion) factor determined as

  $$\mathrm{K} = \frac{\mathrm{SOC}_{\mathrm{climate}} - \mathrm{SOC}_{\mathrm{cost}}}{\mathrm{ATR}_{\mathrm{cost}} - \mathrm{ATR}_{\mathrm{climate}}} \tag{1}$$

  where for instance, $\mathrm{SOC}_{\mathrm{climate}}$ is the SOC calculated when the optimization objective is only the climate impact or $\mathrm{ATR}_{\mathrm{cost}}$ is the ATR when the objective is only SOC. $\alpha \in [0, 1]$ is a weighting parameter that penalizes cost versus climate impact in which $\alpha = 0$ is the pure cost optimal and $\alpha = 1$ is the pure climate optimal routing strategies. In the simulations, we consider five different values for α in order to explore the trade-off between operating cost and climate impact represented by SOC and ATR, respectively.

- **The use of altitude and pressure in figures could be more consistent. e.g., Figure 2 uses 250 hPa which is standard for science but later results e.g., Figure 10 use FL360, FL340, etc. which is standard for the aviation industry. To help readers, it may be useful to add estimate of altitude in the Figure 2 legend (250 hPa is approx. FL340), and vice-versa in other figures to help context.**

  Response: The authors agree with the reviewer. In the revised version of the paper, we have presented them in flight levels.

- **L227: "nigh-time" → "night-time".**

  Response: Thanks for your precise look. The typo has been corrected.

- **Figure 7: "expected perfromace" → "expected *performance*"**

  Response: Thanks. The typo has been corrected.

Reviewer 2

The paper by Simorgh and colleagues describes a python library for the climate-optimal planning of flight trajectories within the structured airspace taking uncertainties in weather forecasts into account. The library is designed for parallel simulation on GPUs. The cost function of the optimization problem considers operational costs and climate impacts of aircraft emissions, whereas both factors can be weighted individually. From what is written in the introduction, the presented work seems to represent an important and novel contribution in the field of optimal flight planning. Overall the paper is relatively clearly written and the performance of the tool is nicely demonstrated by two examples, a night-time flight from Frankfurt to Kyiv during summer and a day-time flight on the same route during winter. My major point of criticism is related to the length of the paper, which hinders readability. Section 2 starts with a formulation of the deterministic climate-optimal flight planning problem, followed by the description of the aircraft dynamical model and the cost function, which is to be minimized in the optimization problem. This subsection (2.1.2) includes a rather detailed description on how the climate impact of aircraft emission is determined. If I understand this correctly, this part has already been published elsewhere. The paper continues with a section on uncertainties in weather forecasts and how optimal flight planning problem has to be reformulated taking these uncertainties into account. This means that several equations occur twice in the paper, once with and once without uncertainty parameters. In my view this is a bit confusing and the reader might easily lose the thread. Maybe the authors find a more concise way to present their method, e.g. by moving some of the equations into the appendix. Also, a short overview/schematic of the approach at the beginning of Section 2 might help the reader to better understand the individual parts and how they are connected. After some minor modifications (for details see attached pdf) I recommend the manuscript for publication in GMD.

Response: Thanks a lot for your valuable suggestions. Thanks a lot for your valuable suggestions. We have enhanced the readability of the paper. For instance, we divided Section 2 into two sections. We now start with the problem statement to provide a clear paper overview. Then, we directly formulate the robust climate optimal trajectory planning problem instead of presenting the deterministic version. Thus, we avoid repeating formulations.

- **Which version of the aCCFs are used in ROOST? According to the statement in L94 it is aCCFV1.1, but as far as I know CLIMaCCFv1.0 still uses the previous version of the aCCFs? Please clarify.**

  Response: The CLIMaCCF V1.0 is the first release of the python library, which includes both versions of aCCFs, i.e., V1.0 and V1.1. The selection of the version is a user-defined option. The aCCFs V1.1 was published in Yin et al. 2022 and aCCF V1.1 is in preparation to be submitted to GMDD within the next weeks [6]. We clarified it in the revised manuscript.
  It should be noticed that CLIMaCCF V1.0 is the first release of the python library, which includes both versions of aCCFs, i.e., V1.0 and V1.1. For performing aircraft trajectory optimization in this study, we use aCCFs V1.1.

- **I think it would be nice to present a very short discussion (i.e., trajectory optimization methods used for climate optimal flight planning) of the different strategies, how they differ and their pros and cons.**

  Response: Thanks for your suggestion. In the revised version of the manuscript, the following paragraph has been added to the introduction.
  The mathematical programming methods only apply to the simplified aircraft trajectory optimization problems (e.g., in [7], the aircraft dynamics is represented with a linearised

model). The meta-heuristic methods (e.g., Genetic algorithm) require very fast aircraft trajectory prediction in order to find an optimal solution with a large number of iterations; thus, the flight planning problem is usually approximated with a simplified but representative enough problem (e.g., in [8], the optimization is defined with 11 decision variables to characterize lateral path and flight altitude, and the speed profile is considered constant). Finally, with the optimal control methods, the capability to model more accurate aircraft trajectory optimization problems is provided since the problem is represented as a dynamical optimization problem. However, there are some drawbacks to solving the formulated problem. The dynamic programming method (as an optimal control approach) results in the "curse of dimensionality" for complex problems (e.g., a full 4D aircraft trajectory optimization problem). Regarding the indirect optimal control approach, deriving analytical solutions using Pontryagin's maximum principle is daunting, especially for problems with singularities (e.g., only a 2D trajectory optimization problem has been addressed in the literature [9]). The direct optimal control approach, despite being very flexible in modeling aircraft trajectory optimization problems (e.g., considering a full 4D dynamical model with nonlinear path and boundary constraints [10]), has a high sensitivity to initial conditions and, thus, local optimality is its main drawback. Besides, considering the airspace structure with indirect and direct optimal control methods is not straightforward. Readers are referred to [3] for a more detailed description of these methodologies and a review of studies employing them.

- **Does this mean that crew salaries are also related to flight time and burned fuel?**

  Response: Crew salaries are calculated based on flight time (generally by a constant index [x EUR/hour] * flight time [hour]). In the original version of the paper, it was written:

  "In spite of considering only flight time and fuel burn to represent the operating cost, it was reported in Table 4 of Yamashita et al. (2021) [8] that employing simple operating cost (SOC) and a more comprehensive metric such as cash operating cost (COC) within trajectory optimization delivered almost similar results. This is mainly related to the consideration of time and fuel burn to calculate costs of other aspects such as crew's salaries."

  In fact, if we look into all the terms of both functions, we find that SOC and COC are functions of "flight time" and "burned fuel". Therefore, the crew salaries are considered in SOC and also COC; the salaries are calculated using flight time. In the revised version of the manuscript, we clarified this.
  This is because these two metrics, in the end, consider flight time and fuel consumption as inputs to estimate the operating cost.

- **The aCCFs by default use a pulse emission scenario, which is not suited for assessing climate impacts of aviation? Why is P-ATR20 then used? And what is the advantage of F-ATR20? And how is the conversion done? Please provide more information here, this section is very confusing.**

  Response: Thanks for this comment. We have modified the section related to aviation-induced climate effects according to your suggestion. For instance, regarding this comment, we added the following paragraph in the revised manuscript:
  The selection of a suitable metric depends on the question to be answered (see Grewe & Dahlmann 2015 [11] for more details); therefore, different questions require the use of different metrics. The P-ATR20 metric was selected as a metric for the aCCFs, to assess the impact of a simple pulse emission. However, factors are available (see [12]) to convert P-ATR20 to other available metrics, for example, assuming the future emission scenario or longer time horizons. This way, one can select the emission scenario and time horizon that are best suited for their question. In this study, the F-ATR20 metric is used to assess the climate effect reduction obtained by steadily applying a specific routing strategy under the assumption of a future business-as-usual emission scenario. The climate metric conversion

factors were derived by simulations with the climate response model AirClim ([13]): one simulation with pulse emission and one with the future emission scenario. By comparing the two simulations, the factors can be derived.

- **I checked the paper by Dietmuller et al., but could not find a detailed description. Again, please provide some more information here. It is a bit tedious for the reader to check several other studies just to get an idea of how certain things are done.**

  Response: We added the following paragraph in the revised manuscript.
  Efficacies were introduced to take into account that the radiative forcing of some non-CO2 forcing agents (e.g., ozone, methane, contrails) is less or more effective in changing the global mean near-surface temperature per unit forcing compared to the response of CO2 forcing (see [14], [15]). In Dietmuller et al. ([12]), the efficacy parameters reported by Lee et al. 2021 [16] are summarized. For a detailed explanation of efficacy, the reader is referred to the state-of-the-art literature (e.g., Ponater et al. 2006 [15]; Rap et al. 2020 [17]; Bickel et al. 2020 [18]).

- **educated guess factors, What is meant here?**

  Response: The educated guess factors describe the calibration factors that were used to develop aCCF-V1.1. The aCCF-V1.1 has been calibrated to the state-of-the-art climate response model AirClim (Dahlmann et al., 2016 [13]). A detailed description of this calibration process will be given in the publication of Matthes et al. 2023 (in preparation for GMDD [6]). We changed "educated guess factors" to "AirClim calibration factors." In the case of aCCF-V1.1, we also use the term "aCCFs calibrated to AirCLim" or simply aCCF-V1.1.

- **Methane is not induced by NOx.**

  Response: Here with "NOx-induced methane" we referred to the NOx-induced effect on methane, i.e., the decrease in atmospheric concentration of methane due to NOx emissions from aircraft [19]. In the revised manuscript, we reformulate to "NOx-induced ozone (production), NOx-induced methane (destruction)".

- **typical transatlantic fleet mean values, Typical values of what?**

  Response: As aCCFs are given in different units (see Yin et al. 2022), we need to convert them to the same unit in order to combine them into a merged aCCF (See Dietmueller et al. 2022 [12]). This conversion is done by multiplying the individual aCCFs by using typical transatlantic fleet mean values from the literature. Here we use 13 g(NO2)/Kg(fuel) (Graver and Ruherford, 2018 [20]) for NOx emission indices (in case of the aCCF of ozone and methane) and 0.16 km/kg(fuel) (Penner et al., 1999 [21]) for flown distance per kg burnt fuel (in case of contrail aCCF).

  It should be noted that such a conversion is done only to show the pattern of the merged aCCFs. In the optimization, we use Boeing Fuel Flow Method 2 to calculate the NOx emission index, distance flown in persistent contrail formation areas, and fuel consumption to represent climate effects associated with all species in Kelvin.

- **(ICAO) data bank, Is there a citation for this?**

  Response: We have cited the ICAO data bank in the revised manuscript.

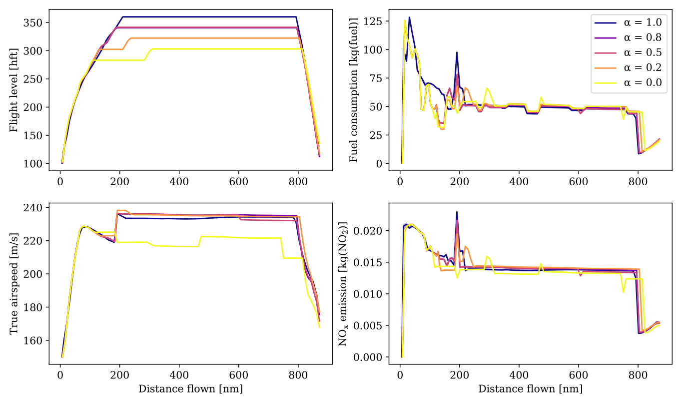
- **I do not understand why you do not simply use a current weather forecast ensemble. If you want to provide an example, I think it should be as close as possible to a real application case.**

- **Again, I would prefer an example with real weather forecast data and not ERA5 reanalysis data. I would assume that the spread in forecasts is larger, although I have to admit that this depends probably strongly on the weather situation. Please comment on this.**

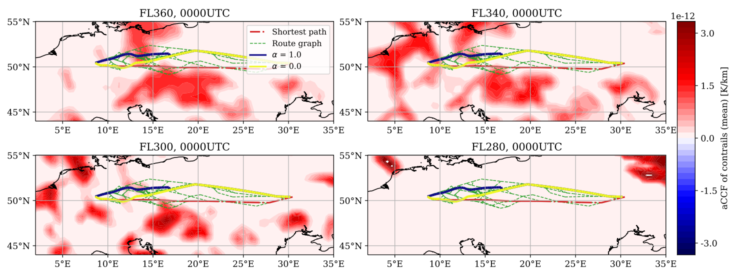
  Response: We provide our answer to the two comments since they are related. First, it should be mentioned that we are aiming at quantifying the mitigation potential. Thus, we want to assess the savings (in terms of climate impact) and the associated cost the flight could have achieved in reality. To that end, using the weather (the reanalysis, with assimilated values) that provides the best approximation to reality seems plausible. This is important for quantifying the cost of mitigation climate and establishing policy-based incentives. Otherwise, we would be incorporating the uncertainties associated with the errors in the weather prediction systems, resulting in biased results. The decision to use ERA5 reanalysis data products was taken in the framework of the FlyATM4E project. In addition to this, there is a practical reason: ERA5 is publicly available (which is not the case of high resolution EPS), allowing the inclusion of the data in the repository of the library for reproducing the results.

  From the computational perspective, using forecast data with more ensemble members does not introduce challenges. Within ROOST, one needs only to specify the number of ensemble members. In the following, we present an example of ROOST with the ECMWF forecast data containing 50 ensemble members.

  It can be seen that results (given in Figs. (1,2)) are similar to those presented in the paper using reanalysis data. For instance, the aircraft reduces its altitude mainly to avoid forming warming contrails. Looking at the Pareto frontier, it can be seen that the uncertainty in the operating cost is relatively higher than the results in the paper with reanalysis data. This mainly related to the higher variability in the components of wind compared to the scenarios considered in the original manuscript (see Fig. (3)).

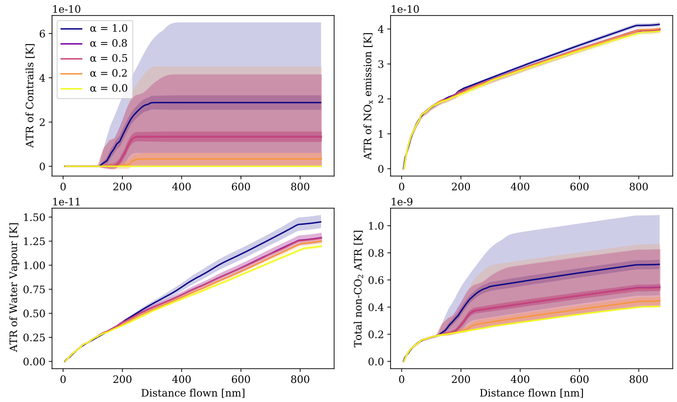


(a) Flight level, fuel consumption, true airspeed, and NO_x emissions.

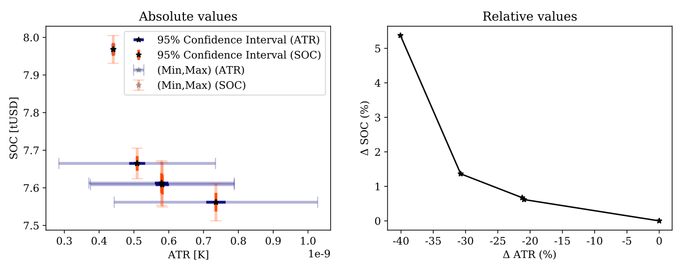


(b) Lateral paths depicted with aCCF of contrails as colormaps.

Figure 1: Results of ROOST using ECMWF forecast data containing 50 ensemble members (9th of June 2018, 0000UTC) for different routing options (i.e., α's).



(a) ATR of persistent contrails, ATR of NO_x emissions, ATR of water vapor emissions, and net ATR of non-CO_2 emissions (accumulated values along the route). The shaded regions show the ranges of uncertainty associated with uncertain meteorological conditions (outer lighter areas show the minimum and maximum values while the inner darker ones represent 95% confidence interval).



(b) Pareto-frontiers considering absolute and relative values.

Figure 2: Results of ROOST using ECMWF forecast data containing 50 ensemble members (9$^{\text{th}}$ of June 2018, 0000UTC) for different routing options (i.e., α's).

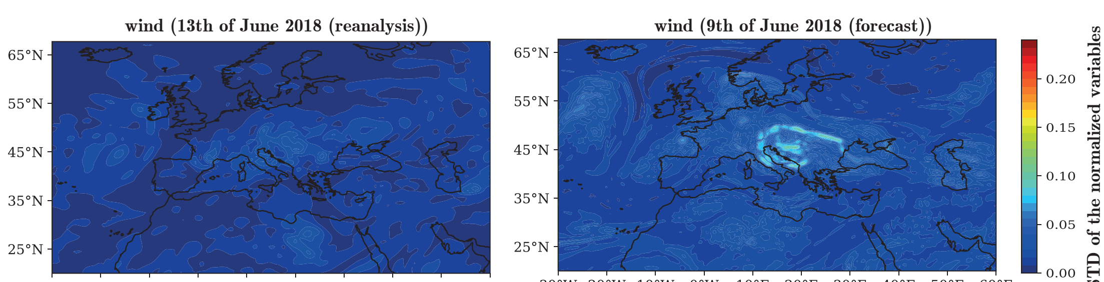


Figure 3: Comparison of the variability of wind components characterized using reanalysis and forecast data.

- **What does TI stand for? Time integration?**

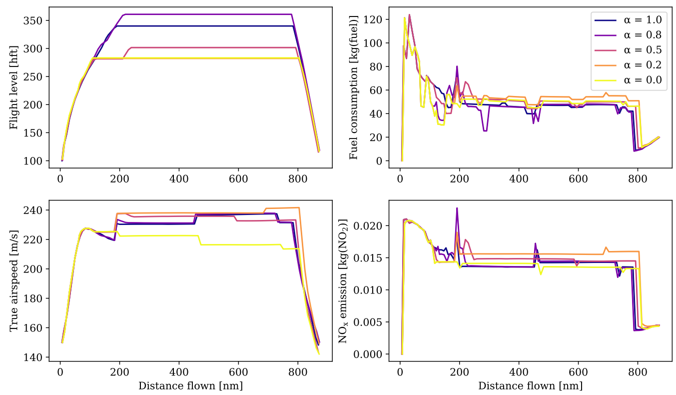
  Response: TI stands for trajectory integration of the aircraft dynamical model with respect to a given flight plan, a realization of weather data, and initial flight conditions. We change the independent variable from flight time to distance flown mainly to consider the effects of wind uncertainty on flight time. Thus, the integration is performed with respect to the distance flown along the route. In the revised version of the paper, we have introduced TI.

- **How is a NOx-sensitive region defined? Is not any region more or less NOx-sensitive?**

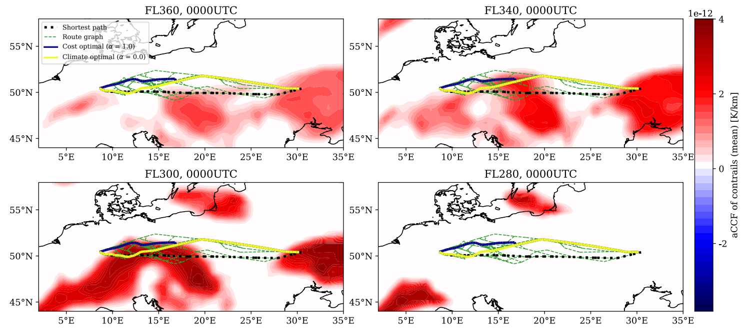
  Response: The aCCF of NOx emissions provides spatiotemporally resolved information on the sensitivity to aircraft NOx emissions in terms of climate change. Thus, with NOx-sensitive regions, we are referring to the climate impact evaluation using the aCCF of NOx emissions.

- **I have no experience/feeling for the variability in the initial mass of an aircraft at departure, but a standard deviation of 10 kg, given a mean of 61600 kg seems to be very small.**

  Response: Thanks for mentioning this. The selected standard deviation of initial aircraft mass does not have a practical justification and was chosen only to consider uncertainty in initial flight conditions. In the revised version of the paper, we rerun the simulations considering the standard deviation of 11 min for initial flight time in order to make the associated mean absolute error (MAE) match the corresponding MAE in take-off time prediction closest to the estimated off-block time in [22]. Regarding the initial mass, we use the standard deviation of 162 Kg, a number that has been derived for a passenger count of 140 by assuming that their weights are independent samples from the anthropometric tables of the adult Spanish population [23], plus baggage with a standard deviation of 5 Kg. Here we present the results of scenario 13$^{\text{th}}$ of June 2018, 0000UTC. In the revised version of the manuscript, we have updated the results with the new simulations.
  It can be seen in Figs. (4, 5) that the results are similar to the previous case (i.e., with a standard deviation of 10kg). This is because the defined objective function for the trajectory optimization considers the average fuel consumption and the average flight time to quantify the operating cost, and since, in this scenario, the impact of wind uncertainty is not considerable, almost similar results were obtained. It is also worth mentioning that by comparing the Pareto-frontiers, we can conclude that the simulations with the standard deviations of 10kg and 10s for initial aircraft mass and initial flight time provide slightly better solutions (in terms of climate impact mitigation potential and relative increase in cost) for both considered scenarios.

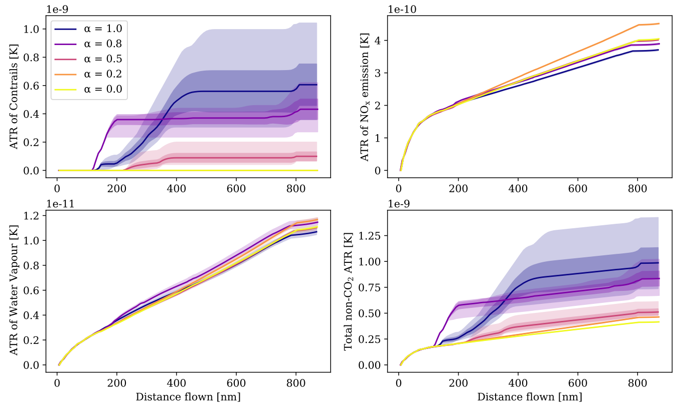


(a) Flight level, fuel consumption, true airspeed, and NO_x emissions.

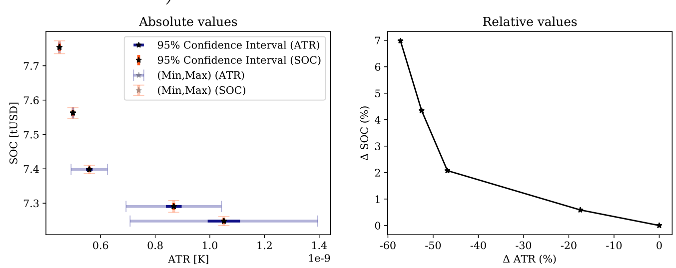


(b) Lateral paths depicted with aCCF of contrails as colormaps.

Figure 4: Results of ROOST: (13$^{\text{th}}$ of June 2018, 0000UTC) for different routing options (i.e., α's).



(a) ATR of persistent contrails, ATR of NO_x emissions, ATR of water vapor emissions, and net ATR of non-CO_2 emissions (accumulated values along the route). The shaded regions show the ranges of uncertainty associated with uncertain meteorological conditions (outer lighter areas show the minimum and maximum values while the inner darker ones represent 95% confidence interval).



(b) Pareto-frontiers considering absolute and relative values.

Figure 5: Results of ROOST: (13^{th} of June 2018, 0000UTC) for different routing options (i.e., α's).

- **What are acceptable increases in operating costs, and who defines what is acceptable? Airlines might have a different definition than climate scientist.**

  Response: The authors agree with the reviewer. In fact, the main reason that we generate alternative solutions (i.e., Pareto-optimal solutions) is to study the existing trade-off between the operating cost and climate effects for each scenario, enabling more efficient decision-making. In the text, by the acceptable increase in operating cost, we refer to those points in Pareto-frontiers with relatively large climate effects mitigation potential at a limited cost increase (typically less than 3%).

- **I am wondering how applicable this optimization procedure is in real life? In the shown examples, only one flight track has been optimized, but in reality there are hundreds of flights at the same time and aircrafts have to stick to a certain schedule. So how much flexibility is there in reality for such an optimization approach?**

  Response: Thanks for raising this point. In the paper, with operational applicability, we are referring to the consideration of the full 4D aircraft dynamical model, the current structure of airspace, and the generation of unique (or deterministic) flight plans despite considering all potential weather scenarios characterized using ensemble weather forecasts and being computationally very fast.

However, we need to mention that in this study, we dealt with climate-optimal trajectory planning from the micro-scale (i.e., trajectory level) perspective. The following paragraph has been added to the revised paper (Discussion section) about the operational feasibility of climate optimal routing strategy at the network scale.

One of the next steps should be analyzing the feasibility of such a routing strategy for real traffic scenarios. In fact, the air traffic managment (ATM) is a complex multi-agent system that cannot be represented by individual elements but by their collective behavior at the network scale. It was shown in the paper that for the climate-optimal routing options, the aircraft tends to fly at relatively lower altitudes compared to the cost-optimal one. Such behavior to avoid climate-sensitive areas may result in more congested areas, raising some challenges, particularly the increased workload, complexity, and conflicts. Thus, the mitigation potentials reported at the micro-level may not be achievable considering real traffic scenarios. Therefore, after generating climatically optimal flight plans, one needs to assess the fostered effects at the network scale and perform a resolution (typically modeled as an optimization problem) to re-stabilize ATM system by compensating for the negative impacts while keeping the modified trajectories as close as possible to inputted climate-optimized ones. The assessment of manageability of climate-optimal trajectory planning at the ATM system is called macro-scale analysis and lies outside the scope of this paper (see [24]) for a study in this area.

- **Are all daytime contrails cooling contrails, or only when they exceed a certain optical thickness? Could you add a reference?**

  Response: No, not all daytime contrails are cooling. The net radiative forcing from contrail results from the combined effects of interacting with the incoming short-wave (SW) solar radiation and with the outgoing long-wave (LW) radiation. Therefore, a contrail during daytime can have a cooling effect, but only if the negative (cooling) SW radiative forcing exceeds the positive (warming) LW radiative forcing. The values of the SW and LW radiative forcings depend, for example, on the contrail optical thickness and the solar zenith angle (see [25], [26] (BOX 2), and [27] (diurnal cycle of contrails RF))

- **Would you expect different aCCFs for other regions? If so, why? And would it be necessary to have different aCCFs for different regions or would it be possible to come up with a globally valid aCCF?**
  Response: aCCFs have been developed for the North Atlantic Flight Corridor during typical synoptical summer and winter situations. Thus aCCFs at other locations or seasons should be carefully evaluated. For the geographical region of Europe, we are quite confident that the aCCFs are valid, as the summer and winter days were characterized by weather patterns that also highly influence the weather of Europe. However, e.g., in the tropics region, we expect significant differences in the aCCFs, as here, the synoptical situation is different. Further research is needed to expand the geographical location and time coverage of the aCCFs.

- **This sentence is almost identical to the first sentence of the discussion section. In general, there is a lot of redundant information, which makes the paper rather lengthy. In my opinion, the paper would benefit from some shortening and a more concise language. For example, Section 4 and 5 could be merged.**

  Response: We considered the reviewer's suggestion to increase the readability of the paper. In addition, we have merged Sections 4 and 5.

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Once again, we express our sincere gratitude to the reviewers and the editor-in-chief for the time they spent to review this paper and for their useful and constructive comments. We hope that the revised version of the paper addresses the concerns of the reviewers.

The authors

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