

Supplementary Information

for

Climate-optimized flight planning can effectively reduce the
environmental footprint of aviation in Europe at low operational
costs

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Table S1: **Classification of recent studies (from 2020 to March 2024) on optimizing aircraft trajectories for climate impact mitigation.** Notably, many of these studies overlook airspace structure and uncertainty and limit their scope to a few weather scenarios. Therefore, they may lack the comprehensive indicators needed to evaluate the mitigation potential achievable through the climate-optimized flight planning measure, which is essential for guiding more informed policy decisions. A review of initial efforts up to 2022 is detailed in Simorgh et al. (2022)¹.

Work	Forcing agents	Climate impact est. modeling	Uncertainty	Degrees of freedom	Routing	Case study
Luhrs et al. (2021) ²	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	No	Lateral path, speed, and altitude	Unconstrained	1 day
Matthess et al. (2020) ³	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	No	Lateral path, speed, and altitude	Unconstrained	1 day
Yamashita et al. (2020) ⁴	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	No	Lateral path, and altitude	Unconstrained	1 day
Yamashita et al. (2021) ⁵	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	No	Lateral path, and altitude	Unconstrained	8 days
Vitali et al. (2021) ⁶	CO ₂ , NO _x , H ₂ O, AIC, Soot, and SO2	Emission/ISSR-based (GWP)	No	Lateral path, speed, and altitude	Unconstrained	1 day
Baneshi et al. (2023) ⁷	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	No	Lateral path, and speed	Unconstrained	1 day
Yin et al (2023) ⁸	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	No	Lateral path, and altitude	Unconstrained	1 day
Castino et al. (2023) ⁹	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	No	Lateral path, and altitude	Unconstrained	31 days
Simorgh et al. (2023) ¹⁰	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	Meteorological uncertainty Initial flight conditions	Lateral path, speed, and altitude	Structured airspace	2 days
Simorgh et al. (2024) ¹¹	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	Meteorological uncertainty	Lateral path, speed, and altitude	Unconstrained	3 days
Martin Frias et al. (2024) ¹²	CO ₂ and AIC	CoCiP (AGWP)	No	Lateral path, speed, and altitude	Structured airspace	30 days
This study	CO ₂ , NO _x , H ₂ O, and AIC	aCCF (ATR)	Meteorological uncertainty	Lateral path, speed, and altitude	Structured airspace	1 year
			Initial flight conditions			
Climate imp. estimation assum. (assessment)						
AIC: Aviation-induced cloudiness; ISSR: ice-supersaturated areas; GWP: Global warming potential; AGWP: Absolute global warming potential; The emission/ISSR-based approach for climate impact estimates ignore the spatiotemporal dependency of non-CO ₂ climate effects and their climate impacts are calculated by multiplying constant factors by fuel consumption; Unconstrained routing: lateral path and altitude are optimized freely.						

Table S2: Fleet-aggregated results for cost-optimal and climate-optimal (w.r.t. an additional 2.0% cost and up to 30% rerouting) routing options: operational-related performance variables and aircraft emissions. The values shown in the table represent the average per flight. The reported values support the conclusion drawn in this study. For instance, in months exhibiting high mitigation potentials (such as May and October), aircraft typically fly at lower altitudes and slower speeds, resulting in higher portions of extra cost (mainly due to increased flight time), compared to months with generally lower mitigation potential (like July and August).

Operational-related performance variables & Aircraft emissions												
Distance Flown [NM]	835.77	836.52	835.41	835.8	835.77	835.51	834.83	835.03	835.48	835.95	835.93	835.83
	838.28	840.09	839.6	840.38	839.64	837.31	835.32	836.31	838.16	840.9	841.0	841.87
	+0.3%	+0.43%	+0.5%	+0.55%	+0.46%	+0.21%	+0.06%	+0.15%	+0.32%	+0.59%	+0.61%	+0.72%
Fuel Cons. [kg]	4388.35	4406.25	4363.47	4380.27	4408.09	4409.68	4391.47	4397.34	4406.1	4453.67	4423.77	4429.92
	4426.31	4450.65	4408.63	4444.22	4482.12	4442.51	4398.43	4413.95	4442.04	4526.46	4494.17	4493.97
	+0.86%	+1.01%	+1.04%	+1.46%	+1.68%	+0.74%	+0.16%	+0.38%	+0.82%	+1.63%	+1.59%	+1.45%
Flight Time [Min.]	115.15	115.27	114.58	114.44	114.46	113.8	112.97	112.87	113.54	114.63	114.88	115.65
	117.25	117.66	117.21	117.47	117.99	116.2	114.33	115.0	116.25	118.54	118.3	119.06
	+1.83%	+2.07%	+2.3%	+2.65%	+3.09%	+2.11%	+1.21%	+1.89%	+2.38%	+3.41%	+2.97%	+2.94%
Flight level [hft]	348.83	348.65	352.77	351.14	346.85	346.68	346.05	345.06	346.1	343.08	347.5	348.04
	339.24	337.57	341.08	335.21	327.9	334.81	340.03	335.72	333.26	324.05	331.47	334.35
	-2.75%	-3.18%	-3.31%	-4.54%	-5.46%	-3.42%	-1.74%	-2.71%	-3.71%	-5.55%	-4.61%	-3.93%
Mach Num. [hft]	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77
	0.76	0.76	0.76	0.76	0.75	0.76	0.76	0.76	0.75	0.75	0.75	0.76
	-1.32%	-1.44%	-1.49%	-1.97%	-2.8%	-1.9%	-1.07%	-1.67%	-2.05%	-2.99%	-2.29%	-2.0%
Oper. Cost (SOC) [tUSD]	7.42	7.43	7.38	7.38	7.4	7.37	7.32	7.32	7.36	7.43	7.43	7.46
	7.53	7.56	7.52	7.55	7.6	7.49	7.39	7.43	7.5	7.64	7.62	7.65
	+1.54%	+1.75%	+1.92%	+2.29%	+2.66%	+1.69%	+0.89%	+1.42%	+1.9%	+2.87%	+2.55%	+2.49%
CO ₂ Emiss. [kg(CO ₂)]	13845.26	13901.73	13766.74	13819.74	13907.53	13912.53	13855.08	13873.6	13901.25	14051.34	13956.99	13976.39
	13965.01	14041.79	13909.24	14021.51	14141.1	14016.12	13877.04	13926.02	14014.62	14280.99	14179.12	14178.49
	+0.86%	+1.01%	+1.04%	+1.46%	+1.68%	+0.74%	+0.16%	+0.38%	+0.82%	+1.63%	+1.59%	+1.45%
H ₂ O Emiss. [kg(H ₂ O)]	5428.39	5450.53	5397.61	5418.39	5452.81	5454.77	5432.25	5439.51	5450.35	5509.19	5472.2	5479.81
	5475.35	5505.45	5453.48	5497.5	5544.39	5495.39	5440.85	5460.06	5494.8	5599.24	5559.29	5559.05
	+0.86%	+1.01%	+1.04%	+1.46%	+1.68%	+0.74%	+0.16%	+0.38%	+0.82%	+1.63%	+1.59%	+1.45%
	January	February	March	April	May	June	July	August	September	October	November	December

Table S3: Fleet-aggregated results for cost-optimal and climate-optimal (w.r.t. an additional 2.0% cost and up to 30% rerouting) routing options: the distances forming persistent contrails and their associated climate impact for departures at midnight and noon. The values shown in the table represent the average per flight. The table demonstrates the effectiveness of climate-optimized trajectory planning in reducing the climate impact of contrails by avoiding the formation of warming contrails at both night and day and, where feasible, promoting the formation of cooling contrails during the day. Detailed daily results are presented in Figure S5.

Cost-optimal (business-as-usual)				Climate-optimal (2.0% SOC & Max. 30% rerouting)									Contrail properties		Difference (related to routing options) [%]
Formed Cont. (Day) [%]	4.88	5.19	6.07	7.19	7.4	2.78	1.15	2.71	4.72	10.1	8.25	9.67			
	6.08	6.37	8.53	7.79	3.69	2.0	0.63	2.14	3.38	7.12	8.56	11.16			
	-16.08%	+22.8%	+40.7%	+8.31%	-50.1%	-28.31%	-45.61%	-21.08%	-28.55%	-29.46%	+3.76%	+15.45%			
Formed Cont. (Night) [%]	3.95	4.1	4.65	5.63	6.94	2.77	0.95	2.12	3.8	8.28	5.95	6.68			
	0.92	1.02	1.5	1.35	0.56	0.17	0.1	0.13	0.26	0.44	0.77	1.44			
	-76.73%	-75.24%	-67.65%	-76.02%	-91.98%	-93.85%	-89.77%	-94.07%	-93.12%	-94.63%	-87.06%	-78.44%			
F-ATR20 of Cont. (Day) [1e-10K]	0.38	0.19	0.01	0.53	1.27	0.48	0.26	0.36	0.6	1.0	0.57	0.16			
	-0.21	-0.43	-0.65	-0.49	-0.15	-0.12	-0.02	-0.15	-0.28	-0.57	-0.76	-1.04			
	-154.83%	-323.48%	-5726.98%	-192.01%	-112.01%	-125.02%	-107.52%	-141.06%	-146.77%	-156.92%	-233.73%	-735.01%			
F-ATR20 of Cont. (Night) [1e-10K]	0.81	0.89	0.94	1.24	1.67	0.81	0.3	0.66	1.08	2.09	1.44	1.37			
	0.21	0.25	0.35	0.36	0.17	0.06	0.03	0.04	0.09	0.14	0.23	0.34			
	-73.51%	-71.36%	-62.61%	-70.91%	-89.97%	-93.1%	-89.33%	-93.78%	-91.59%	-93.28%	-84.4%	-75.37%			
	January	February	March	April	May	June	July	August	September	October	November	December			

Table S4: Fleet-aggregated results for cost-optimal and climate-optimal (w.r.t. an additional 2.0% cost and up to 30% rerouting) routing options: climate effects of different species in terms of average temperature response over 20 years and 100 years with the future emission scenario. The values shown in the table represent the average per flight. The table indicates that the mitigation potential is mainly achieved by reducing the climate impact of contrails. Due to the long atmospheric lifetime of CO₂ compared to non-CO₂ effects, extending the analysis to a 100-year time horizon shows a decrease in mitigation potential. It is also noted that the mitigation potential is slightly higher over 100 years for the climate impact of NO_x emissions due to the longer atmospheric lifetime of methane (which has a cooling effect) compared to ozone (which contributes to warming).



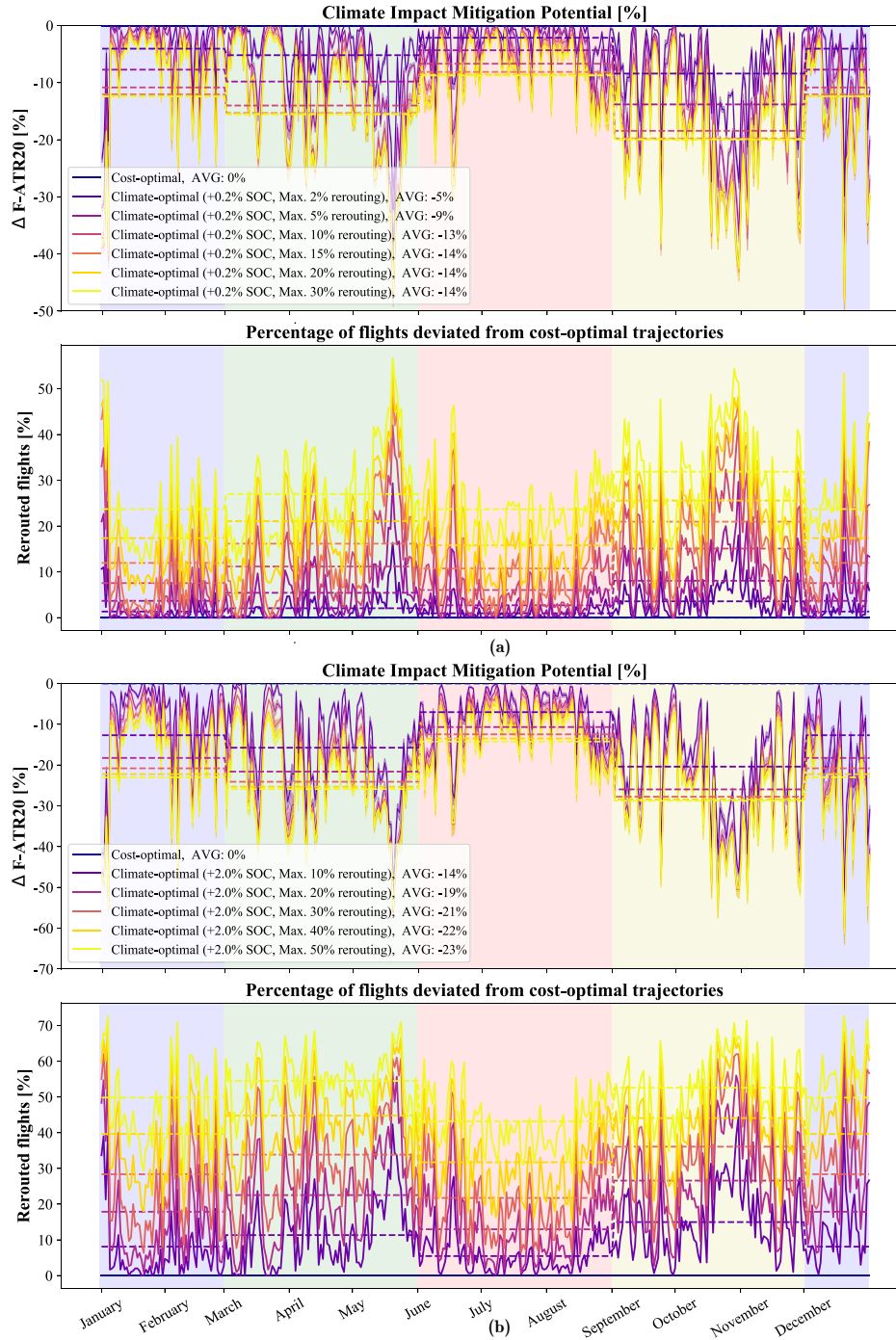


Figure S1: Climate impact mitigation potential and the proportion of flights requiring rerouting for climate-optimized routing options w.r.t. (a) 0.2% and (b) 2.0% extra operating costs, under different rerouting constraints. Solid lines represent daily results, while dashed lines indicate seasonally averaged results. The values shown in the table represent the average per flight. The yearly averaged mitigation potential for each assumption is reported in the legend of the subfigures. The figure demonstrates that the allowance for more flights to be rerouted correlates with an increase in mitigation potential. However, it is important to note that the rate of climate impact reduction begins to decrease beyond certain rerouting thresholds, a factor that should be considered for more effective decision-making.

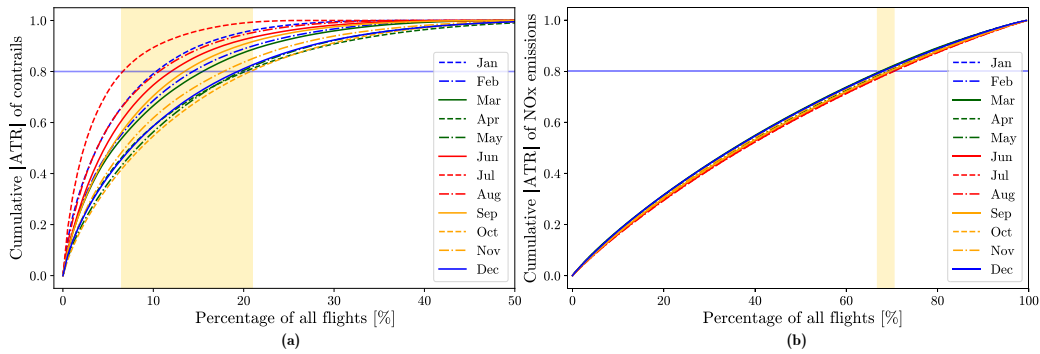


Figure S2: The proportion of flights accounting for 80% of the climate impact associated with (a) contrails and (b) NO_x emissions. Different months are represented with different colors and different line styles shown in the legend of the figure: blue lines show winter months, light green lines show spring months, red lines show summer months, and light orange lines show autumn months. Analyzing the fraction of flights that drive large climate effects from specific species provides important insight into mitigation opportunities. Since a relatively small subset of flights disproportionately contributes to a large climate impact of contrails, targeting these flights for rerouting can substantially reduce the associated climate effects with minimal additional costs. As depicted in this study's figures, mitigating the climate effects of contrails is more cost-effective than addressing NO_x emissions and is the main priority of the optimizer for large penalties on additional cost or the number of flights being rerouted.

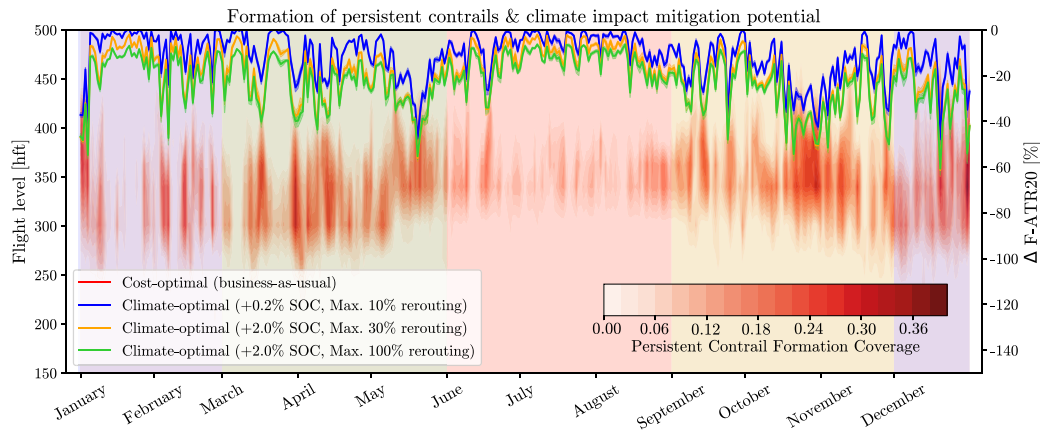


Figure S3: Correlation between the possibility of forming contrails and the achieved mitigation potential. The color coding for routing options and the shaded areas are consistent with those in Figure 3 of the main manuscript. The coverage of persistent contrails at each flight level is determined by calculating the ratio of grid cells that satisfy both the Schmidt-Appleman criterion and ice-supersaturation condition to the total number of grid cells across areas encompassing all flights. The figure demonstrates that days with a higher likelihood of contrail formation present an increased potential for climate impact mitigation. This potential is linked to strategies of either avoiding contrail formation or intentionally generating contrails. If cost-optimal flight paths lead to the formation of warming contrails (which is related to the vertical extent of contrail coverage and cruising altitude), rerouting flights to avoid contrail formation can substantially reduce their climate impact. Furthermore, the possibility of generating cooling contrails introduces additional mitigation opportunities. Summer generally exhibits a smaller horizontal extent of contrail coverage, leading to a decreased formation of contrails in this season¹³ (Figure S5). It is important to highlight that the large spatial gradient in the climate impact of contrails, driven by the Schmidt-Appleman criterion and conditions of ice supersaturation, is favorable for climate-optimized flight planning, as slight route adjustments can lead to high climate impact reduction.

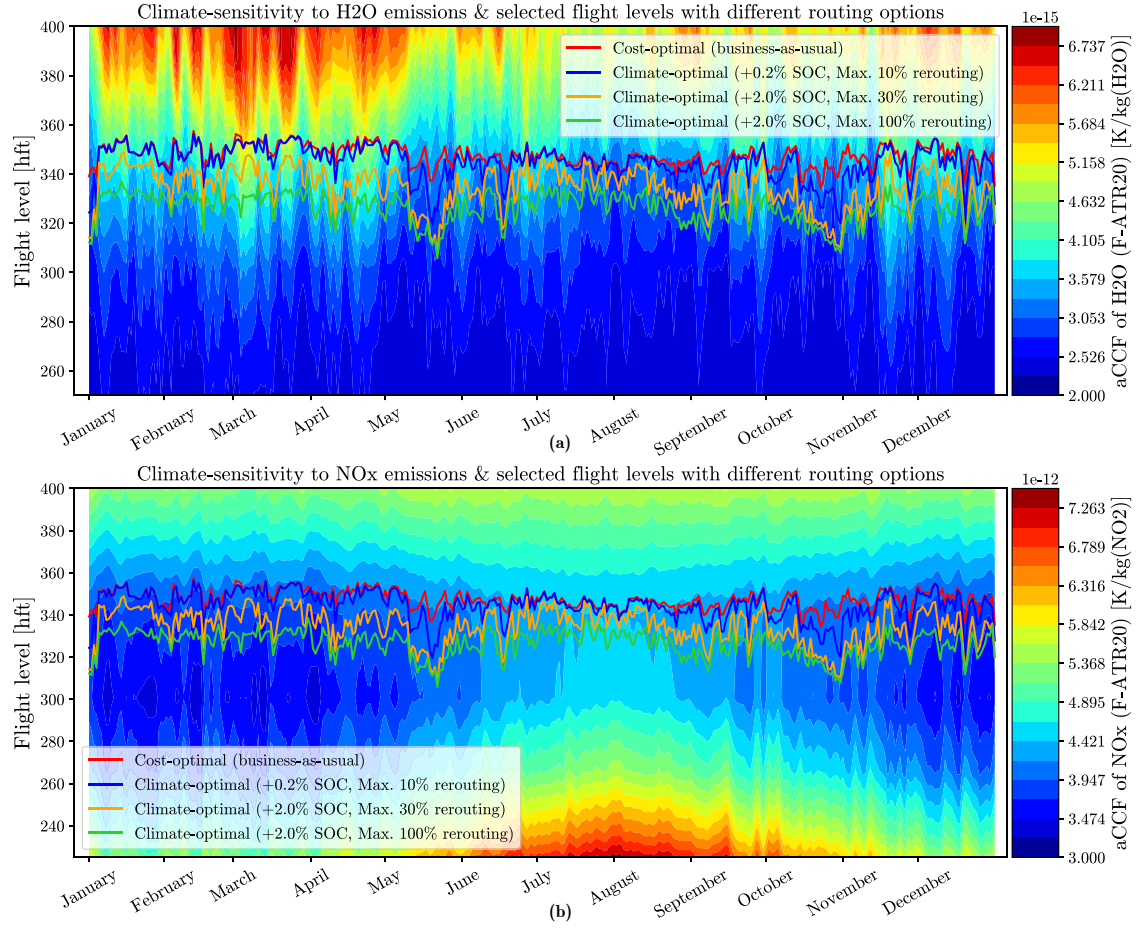


Figure S4: Climate sensitivity to H₂O and NO_x emissions. The figure illustrates the climate sensitivity to (a) H₂O emissions and (b) NO_x emissions, as well as the selected flight levels for different routing options. The color coding for routing options is consistent with those in Figure 3 of the main manuscript. These sensitivity maps are generated using the algorithmic climate change functions^{8,14}. Consistent with the literature, reducing flight altitudes within the typical cruising range can reduce the climate impact of both H₂O and NO_x emissions^{8,15–17}. These altitudes are selected with the climate-optimal routing options, particularly when a cost increase limit of 2.0% is applied, prompting the optimizer to consider these emissions' climate effects. However, it is observed that the rate of change in climate impact for H₂O and NO_x emissions with altitude is relatively low, making them less efficient targets for climate impact mitigation.

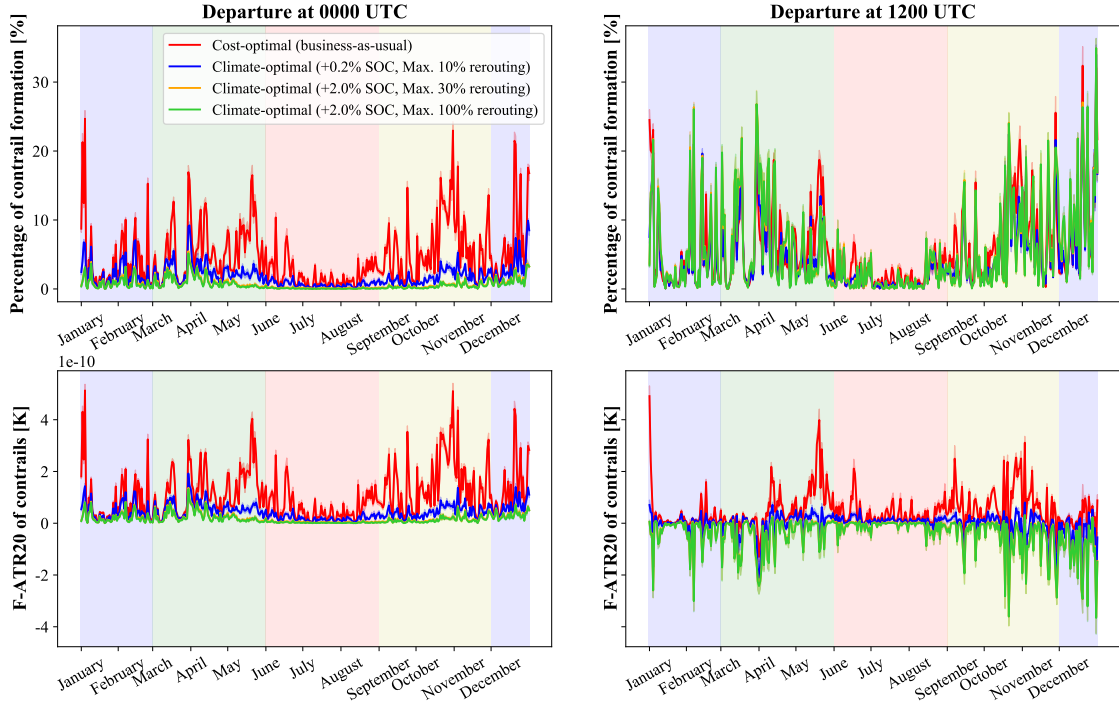


Figure S5: Distances forming persistent contrails and contrails climate impact for midnight and mid-day flights (daily basis). The color coding for routing options and the shaded areas are consistent with those in Figure 3 of the main manuscript. The figure illustrates that for nighttime flights, the adoption of climate-optimal trajectories reduces the percentage of contrail formation due to their warming impact. Conversely, climate-friendly routing options for flights departing at noon do not necessarily seek to avoid contrail formation, given the potential for generating cooling contrails during daylight hours.

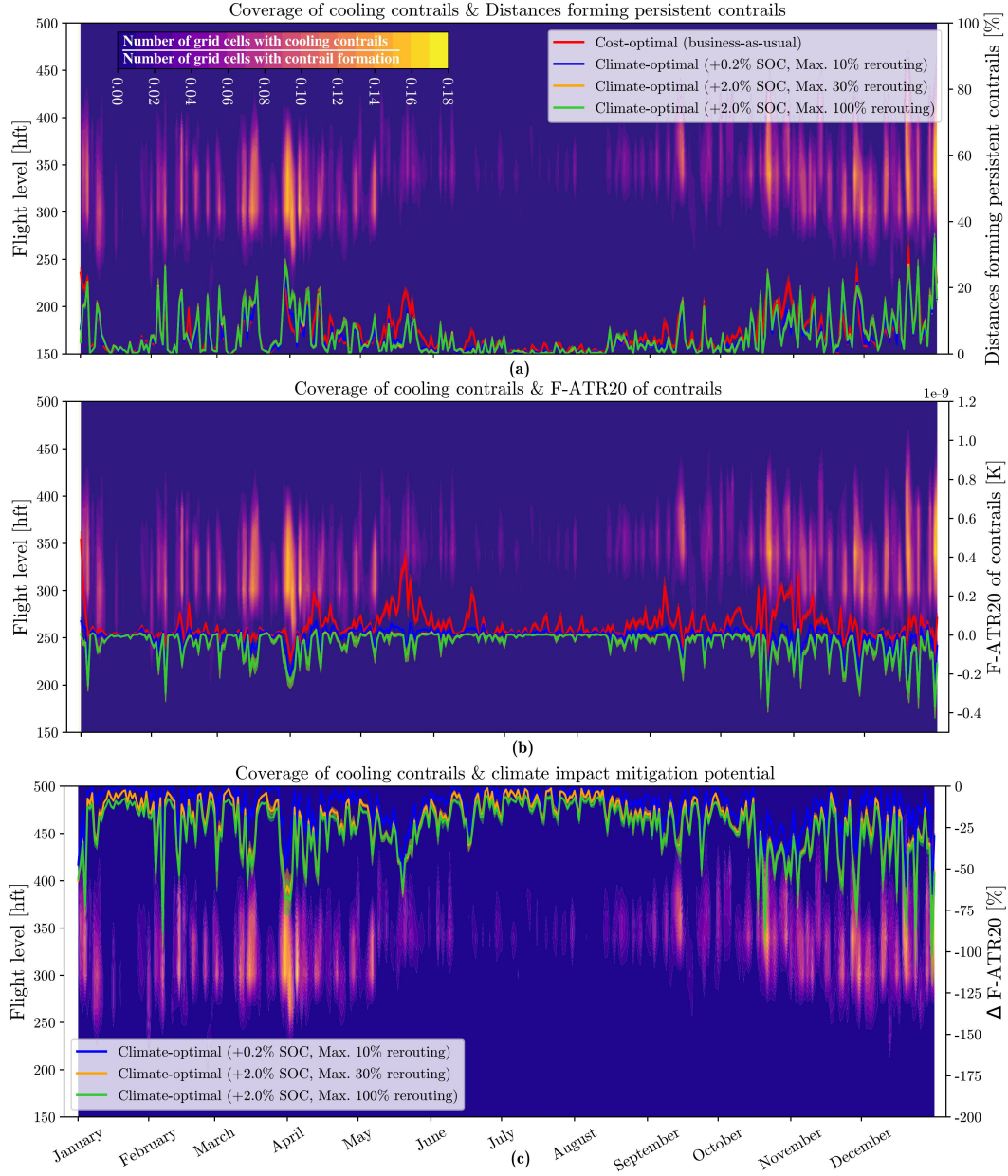


Figure S6: Correlation between the possibility of cooling contrails formation and climate impact mitigation potential. The color coding for routing options and the shaded areas are consistent with those in Figure 3 of the main manuscript. This figure analyses the likelihood of cooling contrails formation and its correlation with the optimizer's behavior, particularly in terms of the distances forming persistent contrails (subfigure (a)), the climate impact of contrails (subfigure (b)), and the potential for climate impact mitigation (subfigure (c)). The results are based on flights departing at midday (1200 UTC). Subfigure (a) reveals that on days with a higher probability of generating cooling contrails, the trajectory optimization tends to favor flight paths generating contrails. This, in turn, contributes to the cooling effect of contrails, as illustrated in subfigure (b), and mitigation potential (see subfigure (c)).

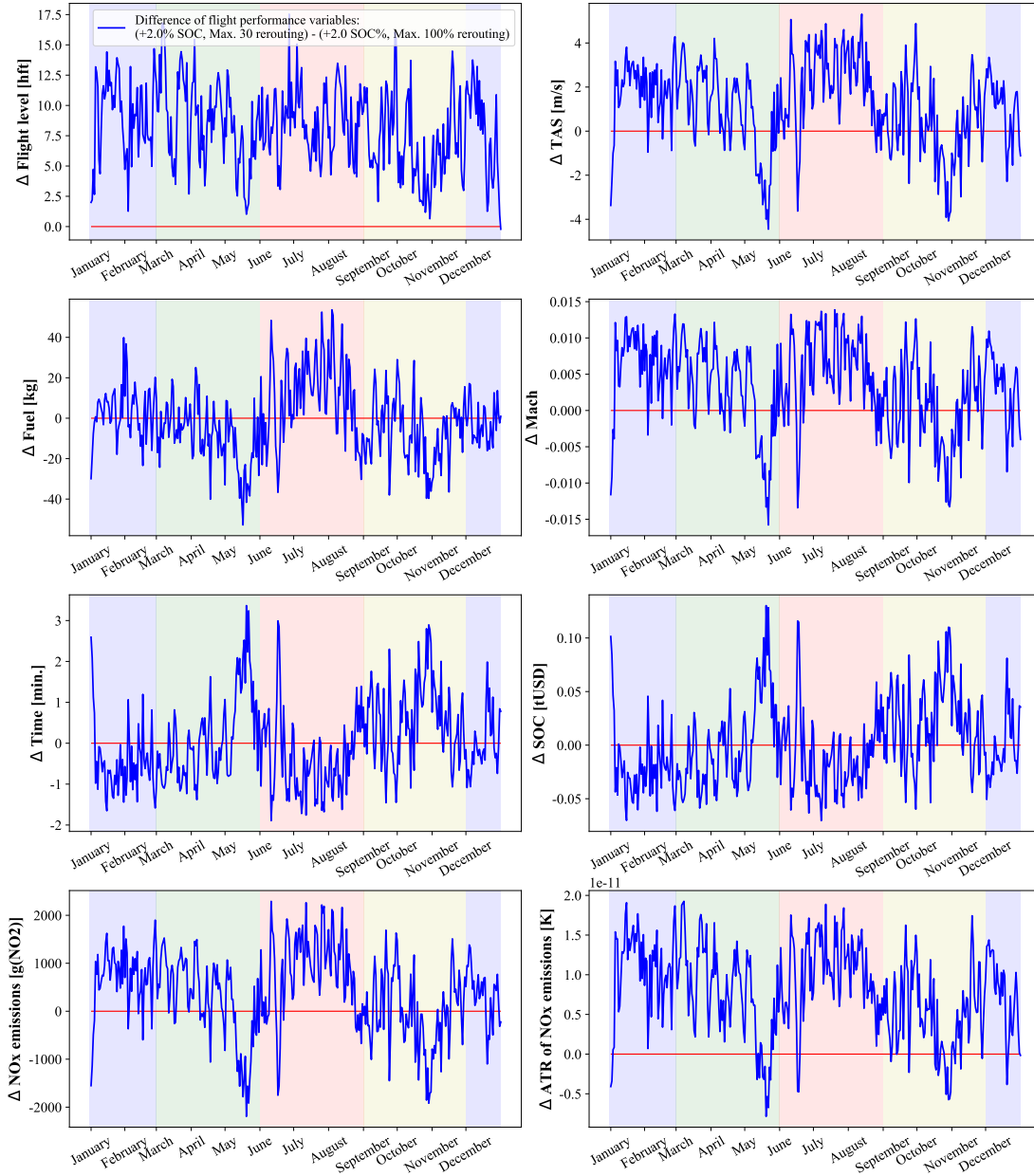


Figure S7: Comparison of climate-optimized trajectories considering an additional 2.0% operating cost under two rerouting limits: 30% and 100% (i.e., no penalization). The figure highlights the difference in flight performance variables between the option permitting up to 30% rerouting and the unrestricted rerouting scenario. The findings support the conclusion drawn in this study that the restricted rerouting approach prioritizes days with the highest mitigation potential, consequently allocating extra costs predominantly to these days. When the number of flights is restricted, the optimizer selects routing options that maximize climate impact mitigation among the set of optimized alternatives. The selected trajectories aim to minimize NO_x emissions' climate impact (in addition to contrails), typically through speed reductions, reducing NO_x emissions. Therefore, on days with substantial mitigation potentials, this routing option leads to flying at lower speeds relative to the scenarios with unrestricted rerouting, resulting in increased operating costs.

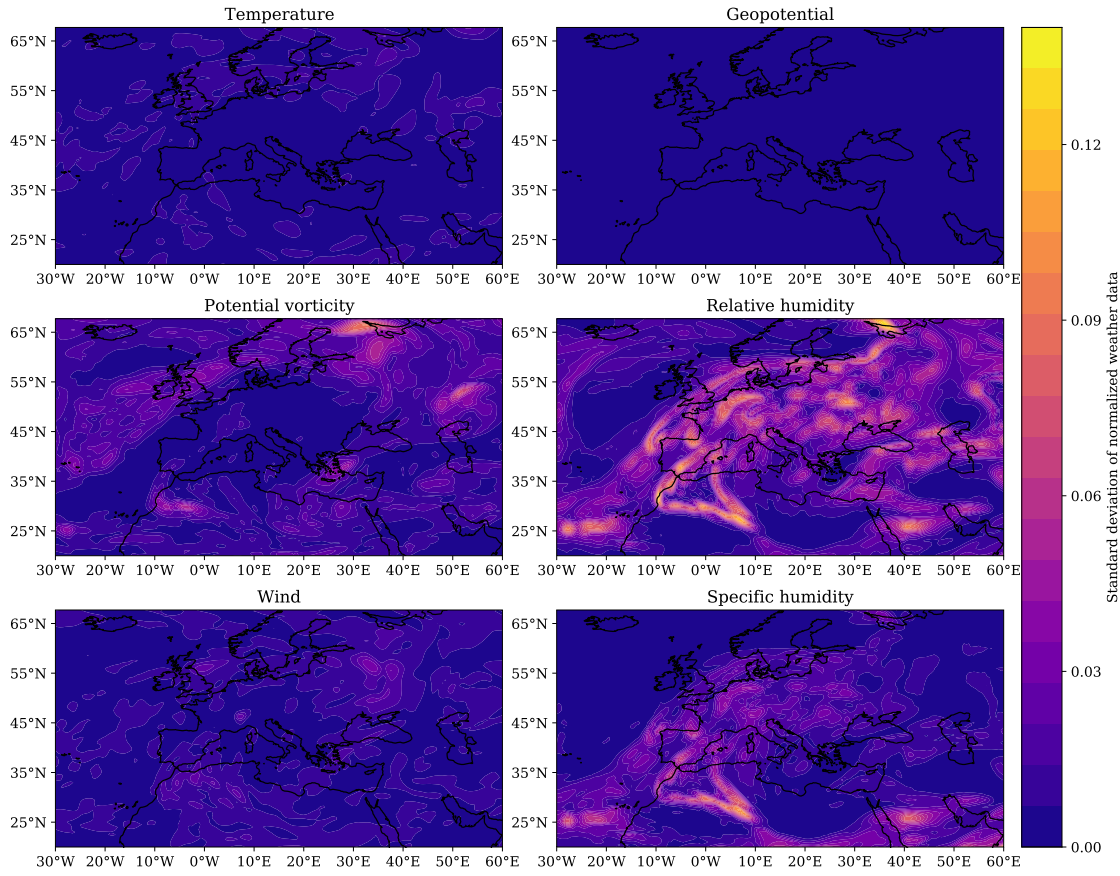


Figure S8: Sensitivity analysis of the required meteorological variables for a specific scenario. The figure shows the variability (quantified using standard deviation) of the meteorological variables on January 1, 2023, over European airspace at 250 hPa, calculated using the ERA5 reanalysis data product, containing 10 ensemble members. The standard deviation is taken from normalized variables for comparison purposes. The figure shows that the variability in meteorological variables is low, except for the humidity fields.

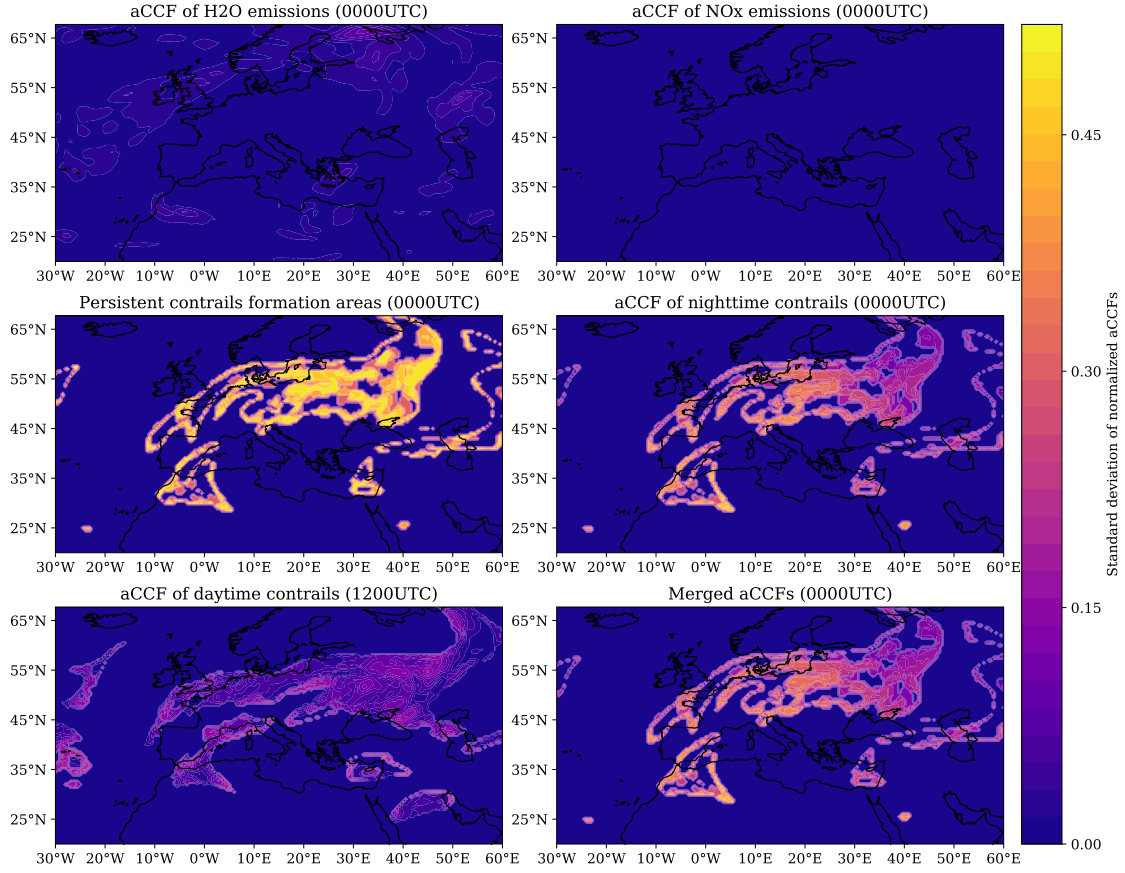


Figure S9: **Sensitivity analysis of the aCCFs for a specific scenario.** The figure shows the variability (quantified using standard deviation) of aCCFs on January 1, 2023, over European airspace at 250 hPa, calculated using the ERA5 reanalysis data product, containing 10 ensemble members. The figure shows that persistent contrail-forming areas and the aCCFs of daytime and nighttime contrails are highly uncertain. This is due to the high variability in the relative humidity, as shown in Figure S8. Due to the large contribution of contrails to net climate effects, the merged aCCFs, combining the effects of all individual non-CO₂ emissions, has a high degree of uncertainty.

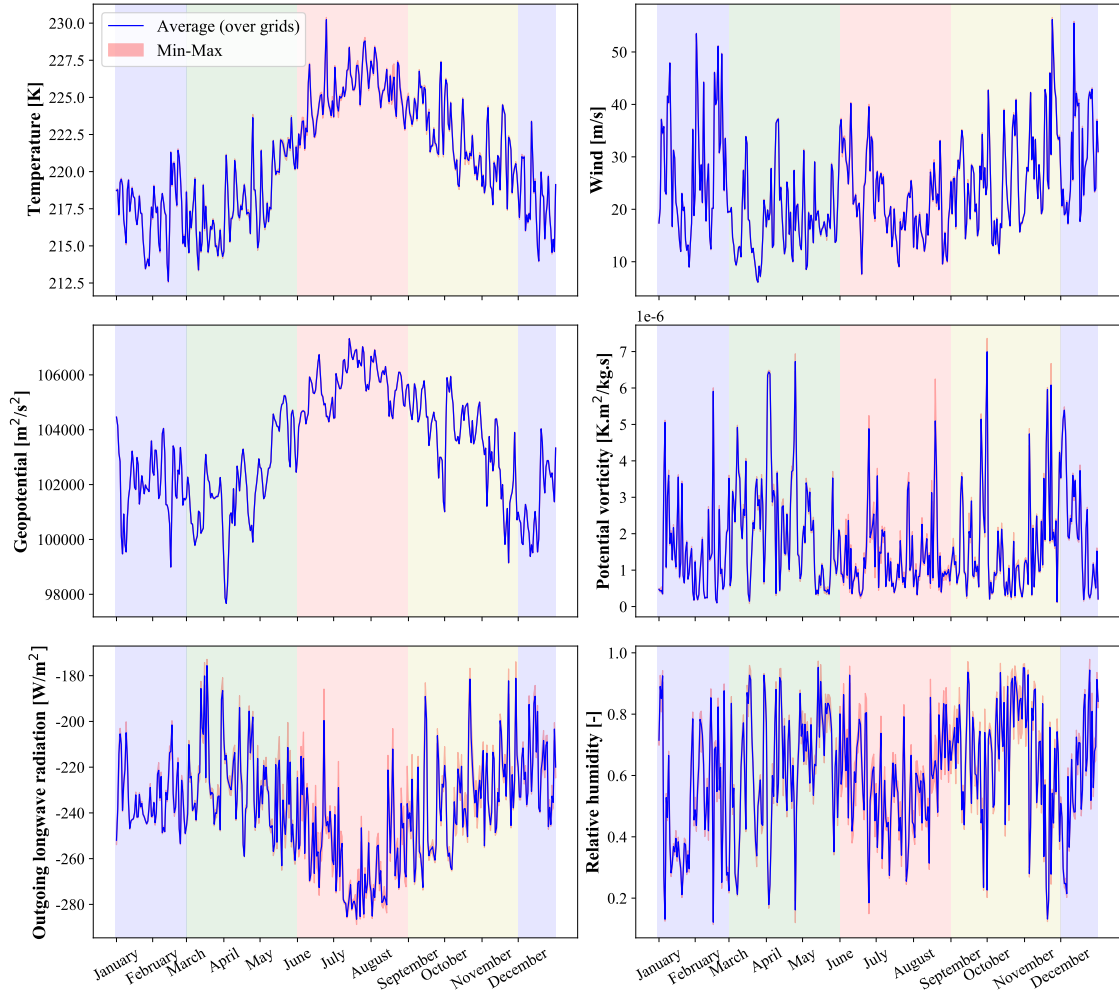


Figure S10: Sensitivity analysis of the required meteorological variables over the year 2022. The figure shows average and min-max ranges of meteorological variables at 250 hPa over 2022 (0000 UTC), calculated using the ERA5 reanalysis product with 10 ensemble members. The results illustrate low variability among ensemble members for temperature, wind, geopotential, and potential vorticity, while relative humidity and outgoing longwave radiation exhibit higher variability, consistent with the analysis in Figure S8 for a particular day.

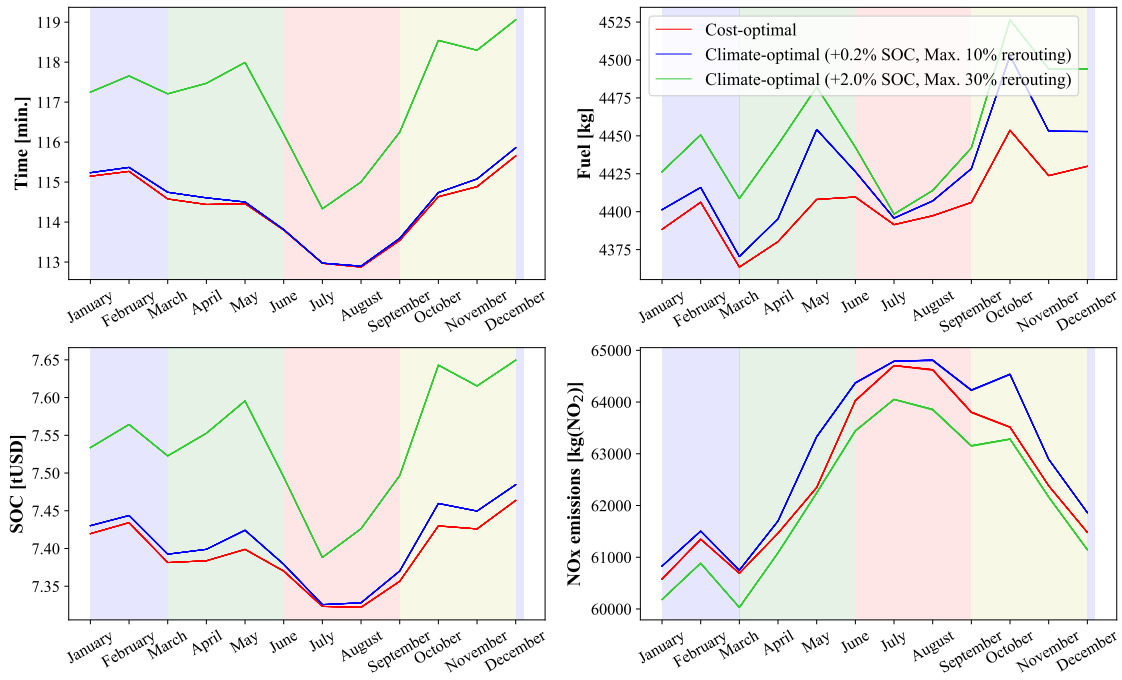


Figure S11: The sensitivity of flight performance variables, NO_x emissions, and operating costs to meteorological uncertainty. The figure shows variability of flight performance variables and NO_x emissions due to meteorological uncertainty characterized by using the ERA5 reanalysis data product, containing 10 ensemble members. No variability in response to meteorological uncertainty is seen, which is attributed to the high agreement among the ensemble realizations of the required weather variables (e.g., wind and temperature), as shown in Figures S8 and S10.

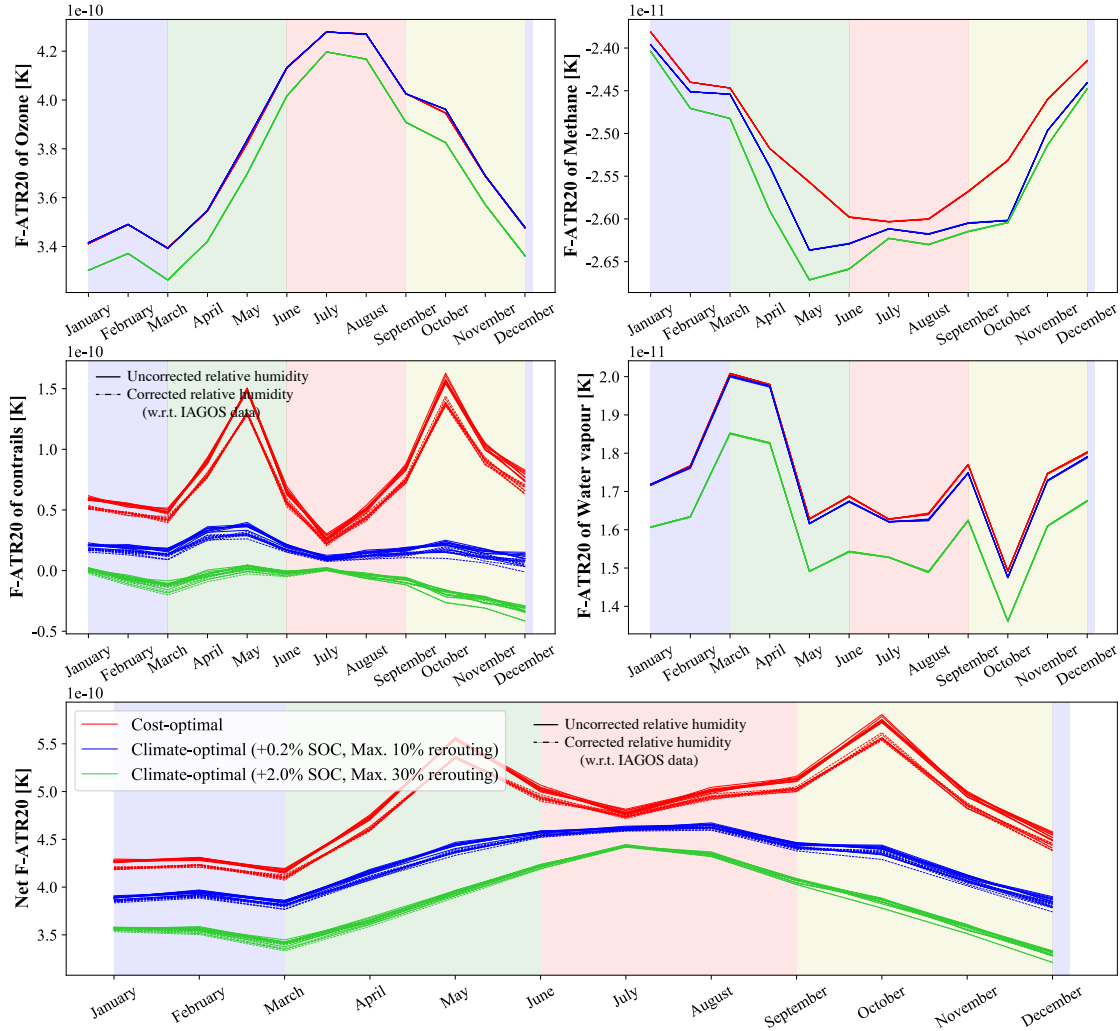


Figure S12: The sensitivity of the climate effects of different species to meteorological uncertainty. The figure shows the variability of the climate impact of different non-CO₂ species due to meteorological uncertainty, characterized by using the ERA5 reanalysis data product for calculating aCCFs, containing 10 ensemble members. No (or very small) variability is seen in response to meteorological uncertainty for ozone, methane, and water vapor, which is attributed to the high agreement among the ensemble realizations of required weather variables (e.g., geopotential, temperature, and potential vorticity). However, for contrails, a relatively larger variability is observed, which is due to higher deviations between ensemble members in the relative humidity field, required for identifying where persistent contrails are expected to form, and in outgoing longwave radiation, needed for estimating the climate effects of contrails during daytime. It is also important to note that, for contrails, solid lines represent climate effects calculated using uncorrected relative humidity, while results using corrected relative humidity are shown with dashed lines. The net climate effects also exhibit sensitivity to meteorological uncertainty, mainly due to the large contribution from contrails.

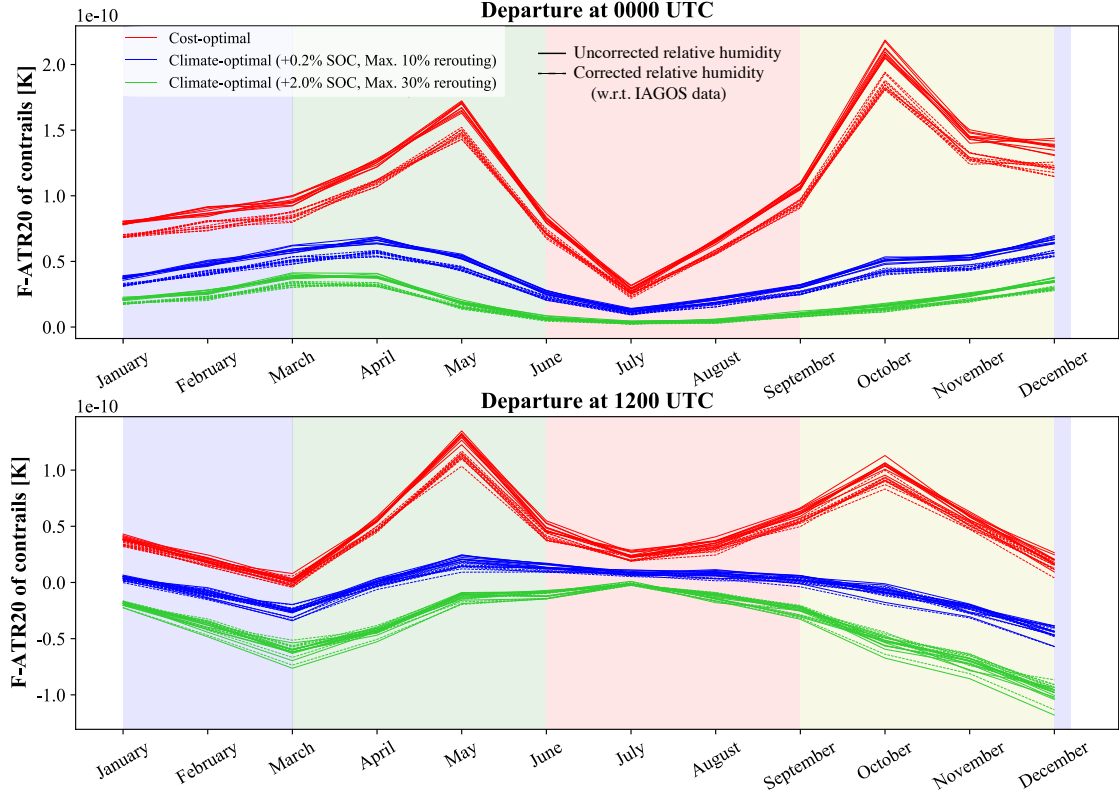


Figure S13: **Sensitivity of contrails climate impact to daytime and nighttime flights.** The figure illustrates the variability of the climate impact of nighttime and daytime contrails due to meteorological uncertainty, characterized by using the ERA5 reanalysis data product to calculate persistent contrails-forming areas and the corresponding aCCFs. The figure shows relatively large variability in the climate effects of contrails, as analyzed in Figure S12. We observe differing sensitivities for daytime and nighttime flights for the climate-optimized routing option (i.e., green lines, whether based on corrected or uncorrected relative humidity). During nighttime, as contrails have warming effects, the optimizer tends to avoid forming contrails for all ensemble weather scenarios, thereby avoiding uncertain contrail-forming areas, leading to reduced variability in the results. However, for daytime flights, in scenarios where cooling contrails can form (e.g., March and December), the uncertainty level increases as the aircraft tends to fly through contrail-forming areas to generate cooling contrails.

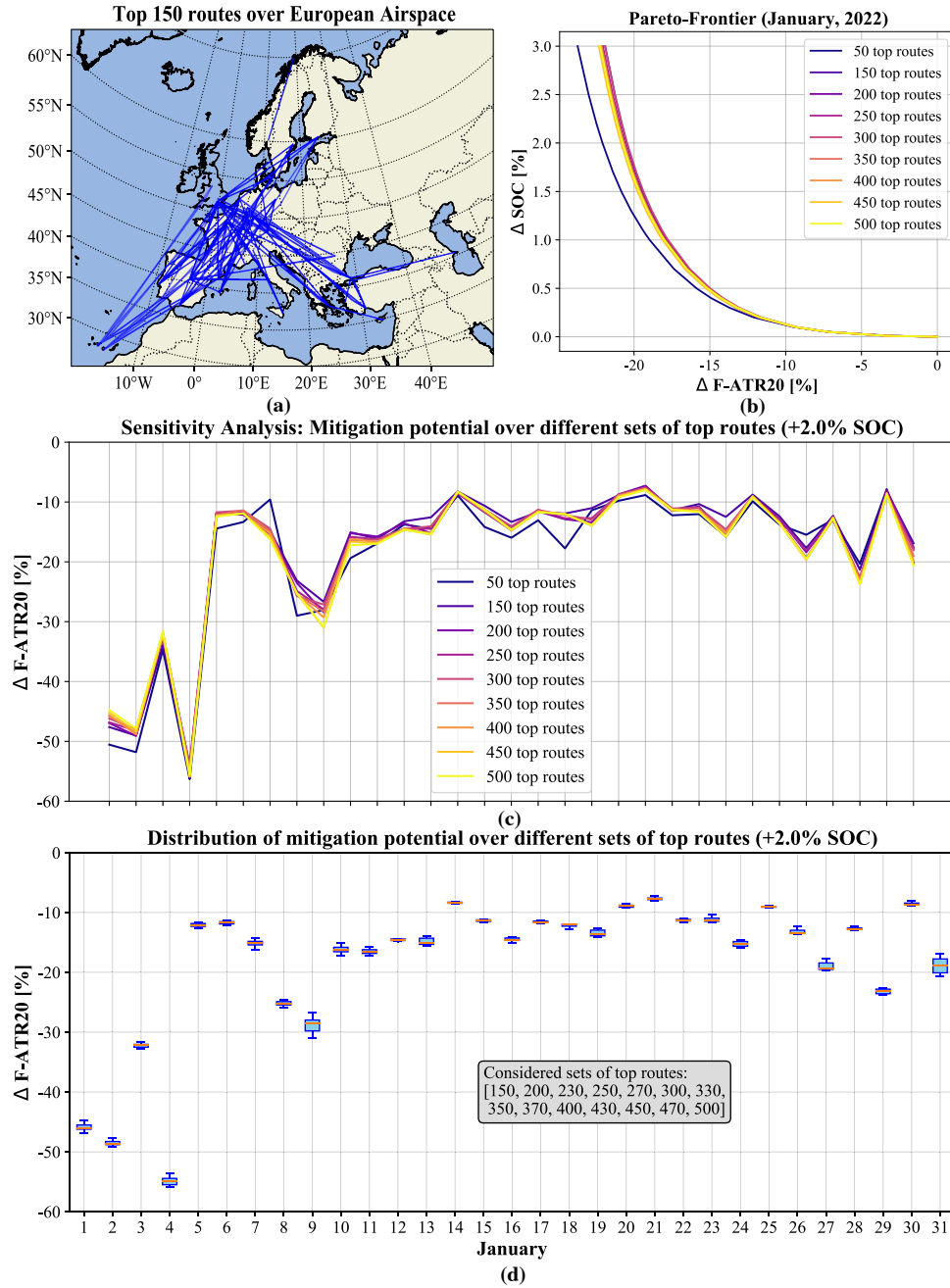


Figure S14: **Sensitivity analysis for the traffic scenario.** Subfigure (a) depicts the traffic scenario used for trajectory optimization in this study, including the top 150 routes of 2018 within European airspace, ranked by Available Seat Kilometers (ASK). Subfigure (b) displays the Pareto frontier calculated for all days in January 2022 for the chosen 150 routes, along with a sensitivity analysis for various sets of top routes extending to the top 500. The daily sensitivity analysis for the climate-optimal routing option w.r.t. a 2.0% extra operating cost is depicted in subfigure (c). Subfigure (d) illustrates the distribution of mitigation potential obtained from sets of top routes ranging from 150 to 500, presented through box plots. Each box represents the interquartile range of daily mitigation potential, with whiskers indicating data within 1.5 times this range. The horizontal line within each box marks the median. Analysis from subfigures (b) to (d) reveals that the top 150 selected routes reflect the mitigation potential across broader flight sets.

Contribution of each forcing agent to the net achieved mitigation potential

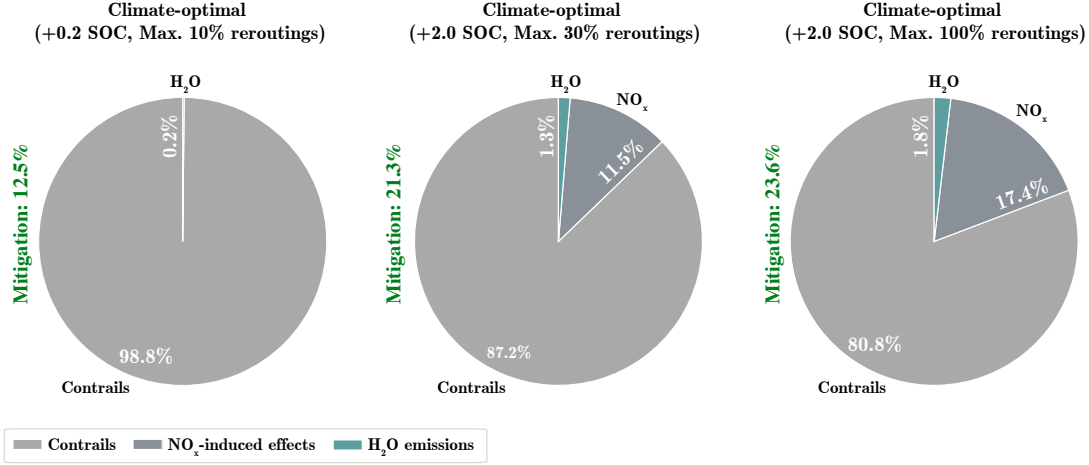


Figure S15: **Contribution of each forcing agent to the net achieved mitigation potential.** The figure shows that the majority of the mitigation is achieved through contrails. In more constrained scenarios (e.g., a 0.2% limit on extra cost), the optimizer focuses only on mitigating the climate effects of contrails. However, as we allow for higher extra costs and additional rerouting, the optimizer begins to consider other species. Despite this, the mitigation potential remains dominated by contrails. These results suggest that flight planning is most effective at mitigating the climate impact of contrails.

1 Supplementary Methods: Flight planning approach

Modeling flight planning problem primarily involves the aircraft’s dynamical model, flight planning objectives, and the relevant physical and operational constraints, briefly discussed in the following.

1.1 Airspace Structure and Flight Plan Definition

The optimization performed in this study focuses on structured airspace, requiring consideration of specific constraints within this operational context (e.g., the air traffic service (ATS) route network). In the following, we briefly present our proposed airspace structure and flight plan modeling.

We model the airspace as a directed acyclic graph $G = (V, E)$, where V represents the navigation waypoints, and E consists of the airway edges connecting these waypoints. The flight trajectory is assumed to begin at the end of the Standard Instrument Departure (SID) procedure (climb phase) and end at the beginning of the Standard Instrument Arrival (STAR) procedure at the destination airport (descent phase). For the route graph, we extract a subgraph from the complete airspace structure of June 2018. This subgraph consists of paths, each no longer than 105% of the length of the shortest ground distance path.

We define the flight plan, as a tuple $F := (R, \overline{FL}, \overline{M}, C, D, d_D)$, where the lateral path, R , is a sequence of waypoints $R := (r_0, r_1, \dots, r_{n_r})$, the vertical cruise profile, $\overline{FL}$, is defined as an ordered sequence of tuples (r_k, FL_k) , and the Mach schedule, $\overline{M} := (M_0, M_1, \dots, M_{n_r})$, specifies the target Mach number. Additionally, the climb and descent profiles, C and $D : \mathbb{R} \rightarrow \mathbb{R}$, are represented by continuous, piecewise-differentiable functions that map altitude to the target airspeed for the climb and descent phases, respectively. During the cruise phase, flight level changes are made in increments or decrements of 2,000 feet, while Mach profile adjustments are performed in steps of 0.01. Furthermore, for the practicality of the optimized trajectory (e.g., maintaining passenger

comfort), rapid changes are restricted.

The objective is to determine an optimal flight plan, i.e., F^o , such that a given objective function, including flight planning objectives (e.g., operational cost and climate effects), gets minimized while respecting a set of constraints (e.g., aircraft dynamics and flight envelope) to ensure feasibility from physical and operational perspectives.

1.2 Aircraft Dynamical Model and Flight Envelope

For a given flight plan, to obtain the required flight performance variables needed to evaluate the defined objective function (e.g., fuel consumption, flight time, and climate effects in Eq. (1) of the main manuscript), trajectory integration needs to be performed based on the aircraft dynamics. For this study, the aircraft dynamical model is represented using the three-degrees-of-freedom (3DoF) point-mass model, which is commonly employed in ATM studies:

$$\frac{d}{dt} \begin{bmatrix} \phi \\ \lambda \\ h \\ v_{tas} \\ m \end{bmatrix} = \begin{bmatrix} (v_{tas} \cos(\gamma) \cos(\chi) + w_y) (R_M(\phi) + h)^{-1} \\ (v_{tas} \cos(\gamma) \sin(\chi) + w_x) \left((R_N(\phi) + h) \cos(\phi) \right)^{-1} \\ v_{tas} \sin(\gamma) \\ (T(C_T) - D(C_L)) m^{-1} - g \sin(\gamma) \\ -f_c(C_T) \end{bmatrix} \quad \begin{array}{l} \text{Latitude, Longitude : } \phi, \lambda \\ \text{Altitude, True airspeed : } h, v_{tas} \\ \text{Mass, Fuel flow : } m, f_c \\ \text{Thrust \& Drag forces : } T, D \\ \text{Thrust \& Lift coefficients : } C_T, C_L \\ \text{Components of wind : } w_x, w_y \\ \text{Heading \& Path angles : } \chi, \gamma \end{array} \quad (1)$$

where $C_L(\gamma) = (2mg \cos(\gamma)) / (\rho v_{tas}^2 S)$, g is the gravitational acceleration, S is the wetted wing surface, ρ is the air density, R_M and R_N are the radii of curvature of the meridian's ellipse and the radius of curvature in the prime vertical, respectively. The aerodynamic and propulsive performance are modeled utilizing BADA4.2. The following set of constraints are considered for the flight envelope:

$$\begin{aligned} v_{CAS, stall} &\leq v_{CAS}(v) \leq v_{CAS, max} \\ C_{T, min} &\leq C_T \leq C_{T, max} \\ M(v_{tas}) &\leq M_{max} \\ C_L &\leq C_{L, max} \\ h &\leq h_{max} \end{aligned} \quad (2)$$

where M is the Mach number and v_{CAS} is the calibrated airspeed. For more details on the optimization approach, interested readers are referred to Simorgh et al. (2022)¹⁰.

1.3 Augmented Random Search

The proposed flight planning problem within the structured airspace involves a combination of both discrete and continuous decision variables, resulting in a mixed-integer nonlinear programming problem, which is mathematically complex and computationally intensive¹⁸. To efficiently address the proposed flight planning problem, the optimization is represented in an equivalent form, which enables searching in the space of probability distributions defined over flight plans (i.e., $\min_{p(F)} \mathbb{E}_{p(F)} \{J(F)\}$) rather than directly searching for the optimal flight plan (i.e., $\min_F J(F)$), thus yielding a continuous search space. To facilitate this search, the probability distribution is parameterized by a vector of parameters, θ . From θ , flight plans can be sampled randomly¹⁰, leading to the following stochastic optimization problem:

$$\min_{\theta} \mathbb{E}[J(\theta)] \quad (3)$$

To solve the resulting stochastic optimization problem, we utilize the Augmented Random Search (ARS) algorithm for its sample efficiency and, most notably for the purpose of this study, its scalability properties. In ARS, the algorithm generates multiple perturbations δ_i ($i = 1, \dots, N$) around the current policy parameters θ (or decision variables). For each perturbation, two policy evaluations $\theta + \nu\delta_i$ and $\theta - \nu\delta_i$ are performed independently to obtain the corresponding rewards r_i^+ and r_i^- . Since these evaluations are independent of each other, they can be distributed across multiple GPU cores to evaluate several perturbed policies in a parallel fashion (i.e., $2N$ parallel evaluations). After obtaining the rewards for all perturbations, the algorithm aggregates the results to determine the update direction for the decision variables. The update rule is:

$$\theta_{k+1} = \theta_k + \frac{\alpha}{N\sigma_r} \sum_{i=1}^N (r_i^+ - r_i^-) \delta_i$$

where:

- θ_k is the current policy parameter vector.
- θ_{k+1} is the updated policy parameter vector after iteration k .
- α is the step size (learning rate).
- N is the number of perturbations.
- σ_r is the standard deviation of the rewards r_i^+ and r_i^- .
- r_i^+ and r_i^- are the rewards obtained from the positive and negative perturbations, respectively.
- δ_i is the perturbation vector sampled from a standard normal distribution.

By implementing the flight planning method on GPUs, multiple flight plans across various scenarios are run in parallel, enabling the robust climate-optimized flight plan to be delivered within seconds. It is important to note that, for each search direction, evaluating the performance associated with each flight plan requires performing N_{EPS} trajectory integrations, one for each ensemble member. Consequently, a total of $2N \times N_{EPS}$ parallel simulations are executed. The computational efficiency of the robust flight planning method enabled the large-scale analysis conducted in this study.

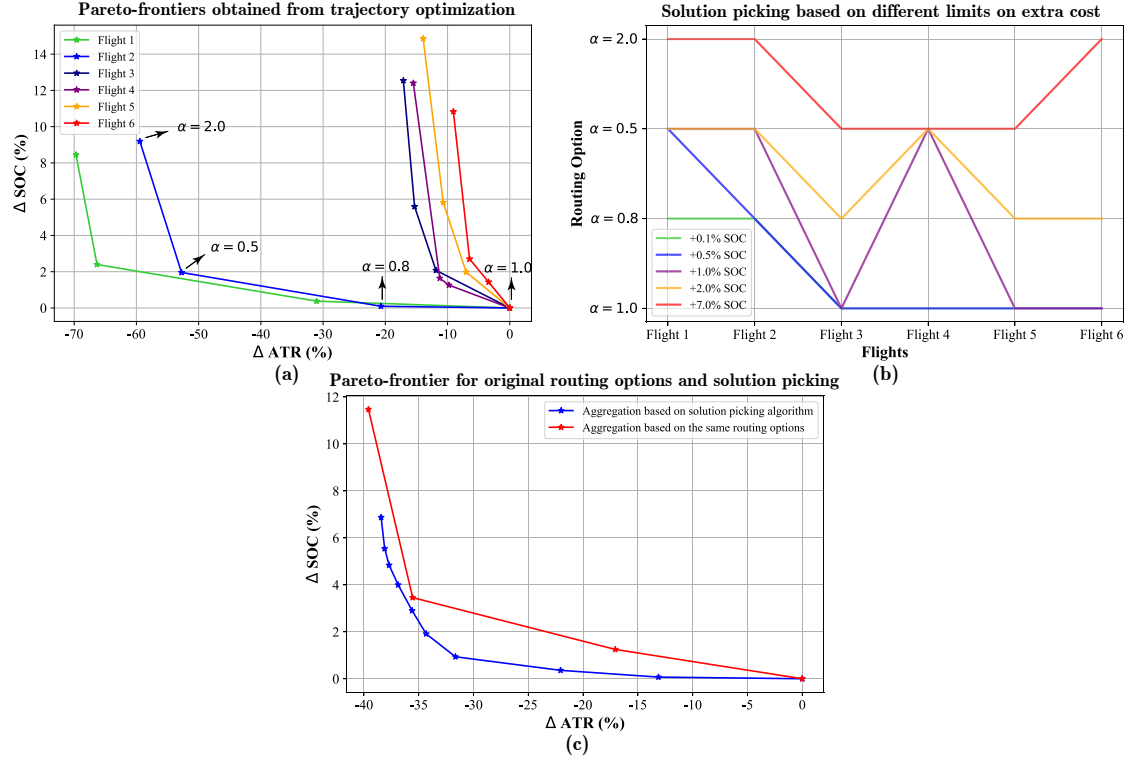


Figure S16: **Illustration of the solution-picking algorithm.** (a) Pareto frontiers generated for six flight samples considering four values of α (i.e., $\alpha \in \{1.0, 0.8, 0.5, 0.2\}$). (b) Selected routing options for each flight under different extra cost limits, determined by the solution-picking algorithm. (c) Comparison of the aggregated Pareto frontier, obtained by summing the performance of trajectories with the same α values versus using the solution-picking algorithm with varying extra cost limits. Subfigure (b) shows that the solution-picking approach prioritizes selecting flights with a large mitigation potential to allocate additional costs. For instance, with cost increases of 0.1% and 0.5%, only flights 1 and 2 are selected, while the others maintain their cost-optimal routing options. Subfigure (c), which shows the aggregated Pareto frontiers, clearly illustrates that the solution-picking approach is more effective at identifying big-hit flights for rerouting and allocating additional costs than aggregating based on the same weights.

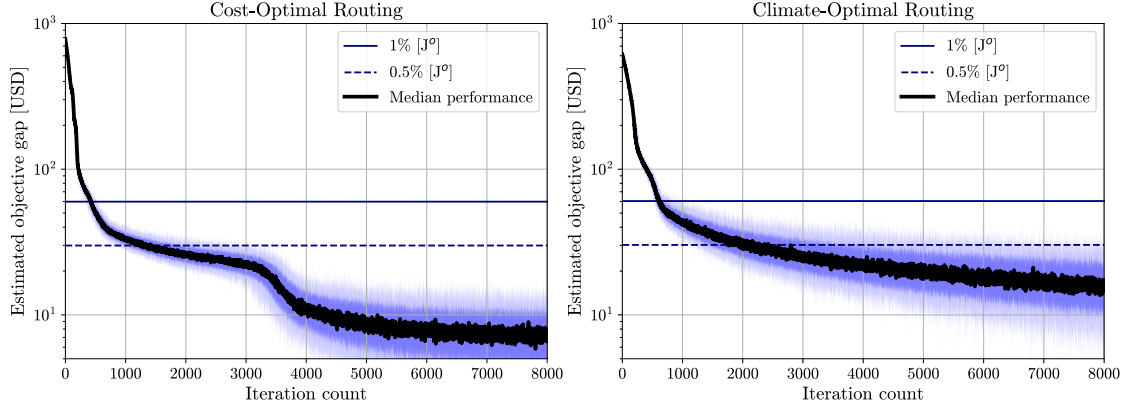


Figure S17: Convergence Performance. The sensitivity of the optimization algorithm’s convergence performance was evaluated over 50 executions for both the cost-optimal and climate-optimal routing options. The objective gap is calculated by measuring deviations from the best performance achieved across the 50 runs (i.e., the minimum value of J), which served as the baseline. At each iteration, the value of the objective function is compared with the minimum value of other executions. The mean performance is represented by a solid black line, while the 0th, 10th, 90th, and 100th percentiles are shown using different colored bands. It can be observed that after approximately 4,000 iterations, near-optimal performance is achieved, with a maximum deviation of +0.5% from the best-obtained value (i.e., the most optimal case). Since the climate-optimal routing option accounts for climate effects, the optimization becomes more complex, requiring a higher number of iterations to converge to an optimal solution.

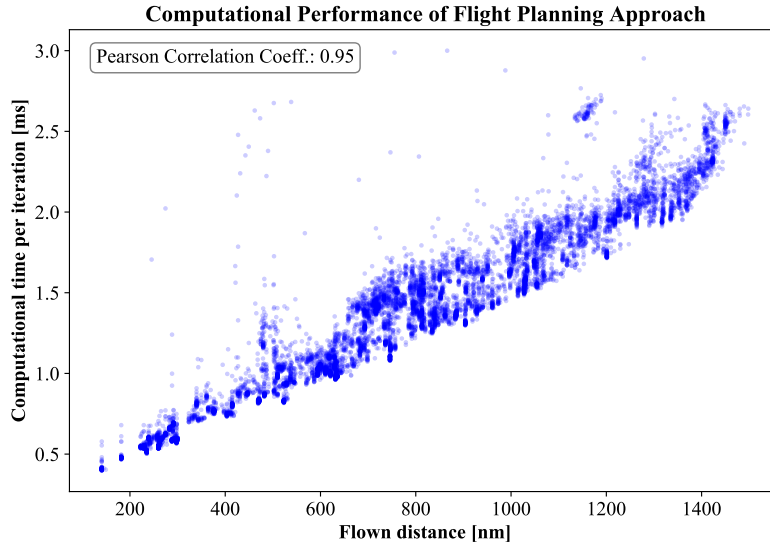


Figure S18: Computational Performance. The algorithm’s iteration speed was recorded over ten days of trajectory optimization in January 2022. A clear linear relationship is observed between iteration speed and trajectory length. This is reasonable, as at a fixed grid resolution, the number of integration steps required for the simulation is approximately proportional to the length of the flight path. The optimizations are launched on a NVIDIA GeForce RTX 3090 graphics card, featuring 10496 CUDA cores at a clock speed of 1.4 to 1.7 GHz. For the optimizations performed in this study, we selected 4,000 iterations.

Supplementary References

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