



Predicting Contrails and Their Potential Climate Impact With Uncertainty In Mind

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Abstract. Pre-tactical contrail avoidance is a promising near-term strategy for reducing aviation's non-CO₂ climate impacts, but its effectiveness depends strongly on the accuracy of upper-tropospheric humidity forecasts. Because persistent contrails only occur in ice-supersaturated air, even small humidity errors can shift regions between contrail-forming and contrail-free states. To quantify how this uncertainty affects predicted contrail formation and potential climate impact, we apply a Monte Carlo framework in which spatially correlated, time-varying humidity perturbations are calibrated to published cruise-altitude forecast-error statistics and propagated through the Contrail Cirrus Prediction model (CoCiP) using ERA-5 meteorology and observed flight trajectories. The resulting ensemble simulations show that CoCiP's deterministic estimates can misrepresent both the magnitude and robustness of contrail climate impact, particularly near the relative-humidity threshold for persistent contrail formation. For high-impact warming flights, ensemble impacts are often lower than the deterministic estimate even when all ensemble members remain warming, reflecting the asymmetric response introduced by the saturation threshold. For cooling flights, deterministic estimates can likewise overstate the magnitude of expected cooling. At the fleet level, humidity uncertainty changes the ranking of flights by predicted climate impact and alters which flights remain strong candidates for mitigation under risk-based decision criteria. A simple altitude-modification example further shows how uncertainty-aware evaluation can identify trajectory changes that remain beneficial across plausible humidity realizations while preserving favorable cooling effects elsewhere. Overall, these results demonstrate that probabilistic impact estimates provide a more useful basis for contrail mitigation planning than deterministic predictions alone.

1 Introduction

Pre-tactical contrail avoidance has emerged as a promising near-term option to reduce aviation's non-CO₂ climate impacts, but its effectiveness depends critically on the ability to anticipate contrail formation and persistence from upper-tropospheric humidity forecasts (Teoh et al. 2022). Ice supersaturation as defined by relative humidity with respect to ice (RH_{ice}) greater than one hundred percent is a threshold condition for persistent contrails wherein small humidity errors can shift regions



between contrail-promoting and contrail-prohibiting states (e.g., Schumann 1996, 2012; Kärcher 2018). This sensitivity is compounded by the fact that ice-supersaturated regions (ISSRs) are often sub-grid, intermittent, and spatially patchy, which remains challenging for numerical weather prediction (NWP) systems to represent accurately (Tompkins et al. 2007; Lamquin et al. 2009). Consistent with these difficulties, verification studies have reported low skill in pointwise ISSR prediction and have consequently questioned whether current forecast quality is sufficient to deliver meaningful climate benefits from contrail avoidance (Gierens et al. 2020).

However, conclusions drawn solely from point-wise verification metrics may be overly pessimistic for operational contrail mitigation. Recent studies indicate that forecast errors in ISSR position are often dominated by spatial displacement, with characteristic offsets that can be small relative to feasible rerouting distances. This suggests that contrail avoidance may remain effective if optimization strategies explicitly exploit the spatial proximity between forecast and actual contrail-forming regions (Thompson et al. 2024). Dean et al. (2025), for example, proposed a robust trajectory optimizer, but noted that their approach relies on hand-tuned choices and that operational deployment would benefit from a more formal representation of forecast uncertainty. Other recent demonstrations have similarly highlighted the practical feasibility of contrail avoidance in the presence of meteorological uncertainty (Martin Frias et al. 2024; Sonabend-W et al. 2024), while leaving the uncertainty in the resulting climate benefit largely unquantified.

A growing body of work has therefore begun to formalize uncertainty-propagation within contrail modeling frameworks. Platt et al. (2024) evaluated the ability of the Contrail Cirrus Prediction Model (CoCiP) to identify flight segments with large contrail energy forcing under uncertainty in both meteorological inputs and internal model parameters. They represented humidity-driven uncertainty using the ECMWF ERA-5 ensemble reanalysis as Monte Carlo inputs and calibrated ensemble humidity by correcting bias and under-dispersion to match cruise-altitude in situ humidity distributions, thereby emphasizing that humidity uncertainty used for contrail prediction must be statistically representative. Simorgh and Soler (2025) similarly incorporated meteorological uncertainty using the 10 member ERA-5 ensemble to derive distributions of persistent contrail-forming regions and overall mitigation potential.

In this study, we addressed the need for uncertainty-aware contrail mitigation by introducing a probabilistic representation of upper-tropospheric humidity uncertainty targeted to conditions relevant for contrail formation and persistence. We created spatially-correlated and time-varying RH_{ice} perturbations, calibrated to observed NWP humidity error statistics, and propagated this uncertainty through CoCiP simulations. Using this Monte Carlo ensemble of humidity-perturbed simulations, we quantified uncertainty in each contrail's radiative forcing and resulting climate impact through a measure of carbon dioxide equivalent (CO_{2e}) greenhouse gas forcing (Teoh et al. 2024). This framework enables risk-based interpretation of contrail impact estimates and provided a basis for designing avoidance strategies that are more robust to forecast uncertainty. The data and methodology used in this study are described in the next section. The uncertainty quantification analysis is presented in Section 3 including illustrative examples of specific flights, followed by a discussion and conclusions in Section 4.



2 Data and Methodology

65 Because persistent contrails occur only where $RH_{ice} > 100\%$ and humidity errors are far larger than temperature errors (Thompson et al. 2024), we focused on propagating humidity uncertainty through CoCiP to determine contrails' radiative forcing in a Monte Carlo framework. The CoCiP model requires meteorological data of pressure, temperature, humidity, winds, cloud content, and pre-existing radiative fluxes together with an aircraft trajectory and various aircraft-specific data such as fuel flow, take-off weight, etc. The subsections below provide more detail of the input datasets and the framework
70 of an ensemble of perturbations.

2.1 Meteorological data

Meteorological fields were obtained from the ECMWF ERA-5 reanalysis through the Copernicus Climate Data Store. The data were retrieved in GRIB format with hourly temporal resolution and horizontal resolution of $0.25 \times 0.25^\circ$. Vertical native model-level data were retained so that atmospheric fields preserve all available vertical structure in the upper
75 troposphere. This was important because coarser pressure-level interpolated data can reduce the maximum humidity peaks present in the actual data.

ERA-5 serves as the baseline atmospheric state from which the humidity ensemble is constructed. Across ensemble members, only the humidity field was modified. Temperature, pressure, winds, radiation, and the remaining meteorological fields required by CoCiP were held fixed at their original values. This construction allows the effect of humidity uncertainty
80 to be examined separately from uncertainties in the other meteorological variables and from uncertainty in the CoCiP model internal parameters. The resulting impact distributions are thus conditional on the prescribed RH_{ice} perturbation model. They do not constitute estimates of total meteorological or contrail model uncertainty. The same perturbation framework could be applied independently to, or jointly with, other meteorological fields or CoCiP internal parameters.

2.2 Flight trajectory data

85 Aircraft trajectories were obtained from globally distributed Automatic Dependent Surveillance – Broadcast (ADS-B) dataset from 2019. The simulations reported in this study were restricted to two mid-month days from February and two mid-month days from June. These days provide contrasting seasonal meteorological conditions for evaluating the uncertainty-propagation framework. The final dataset contains approximately 300,000 flight trajectories, half from each month.

90 2.3 Deterministic CoCiP simulation

Contrail formation, evolution, and radiative impact are simulated using the trajectory-based implementation of CoCiP available in the open-source `pycontrails` library (Schumann 2012; Shapiro et al. 2026). The ADS-B observations



provide the aircraft position, altitude, and time information required to define each trajectory, while ERA-5 supplies the corresponding meteorological and radiation fields.

95 For each flight, CoCiP simulates the formation and subsequent evolution of individual contrail segments and calculates their associated radiative forcing and energy forcing. The signed energy forcing contributions from all simulated contrail segments are aggregated to obtain a cumulative value. Positive values indicate a net warming effect, whereas negative values indicate a net cooling effect. The cumulative energy forcing is subsequently converted to metric tons of carbon dioxide equivalent, CO_2e , using the 100-year CO_2 *absolute* global warming potential $AGWP_{CO_2,100} = 92.5 \times$
 100 $10^{-15} \text{ yr } W \text{ m}^{-2} \text{ kg}_{CO_2}^{-1}$ (Joos et al. 2013).

2.4 Ensemble of CoCiP simulations

We propagate uncertainty in upper-tropospheric RH_{ice} using a Monte Carlo framework that applies spatially correlated, time-varying perturbations to the ERA-5 humidity field while holding all other meteorological inputs fixed. The perturbation method and humidity-adjustment procedure are described below. For each flight, CoCiP is run for $N = 50$ humidity
 105 realizations, yielding an ensemble of radiative-forcing and CO_2e outcomes in addition to the deterministic baseline estimate.

2.4.1 Perlin noise perturbations of humidity

Humidity uncertainty is introduced by applying additive stochastic perturbations to the baseline ERA-5 RH_{ice} field. The perturbations are generated using the Perlin gradient noise algorithm (Perlin 1985). Perlin noise produces smooth pseudo-random fields with spatially coherent structures, rather than the discontinuous grid-scale variations generated by
 110 independently sampled, or “gray noise” perturbations. Such structured fields can be used to represent cloud-like or otherwise coherent geophysical variability and have previously been applied to perturb atmospheric initial conditions in ensemble forecasting contexts (Bi et al. 2023; Chen et al. 2023). Perlin noise was therefore selected to introduce spatially organized humidity variability, while retaining control over the magnitude and characteristic scale of the imposed perturbations.

115 For each ensemble member $m = 1, \dots, N$, a single-octave, three-dimensional Perlin noise field is generated using the `perlin-numpy` implementation (Vigier 2026). The three dimensions correspond to the two horizontal coordinates and time. The full field has dimensions $(2048, 2048, t)$, where t is the number of hourly time indices in the meteorological dataset. The Perlin resolution parameter is specified as $(64, 64, t)$, corresponding to 64 noise cells along each horizontal dimension. Each horizontal noise cell therefore spans 32 grid points, which at the ERA-5 horizontal resolution corresponds
 120 to approximately $8 \times 8^\circ$.

Along the temporal dimension, the number of noise periods is set equal to the number of hourly time indices, which was 48 in this study. The perturbation therefore varies at the finest available Perlin lattice scale in time, producing distinct spatial



patterns between consecutive hourly fields rather than imposing a smooth multi-hour correlation structure. The generated perturbations are thus spatially correlated within each time slice and time-varying across the simulation period.

125 Let $P^{(m)}(i, j, n)$ denote the cropped Perlin field for ensemble member m , where i and j are horizontal grid indices and n is the time index. The scaled perturbation is defined as

$$\Delta RH_{ice}^{(m)}(i, j, n) = s \times P^{(m)}(i, j, n) \quad (1)$$

where s is the perturbation scale factor. The three-dimensional (x, y, time) perturbation is then repeated across all vertical model levels. The perturbation is therefore not independent between model levels; the same scaling field is applied at every
 130 level, giving perfectly correlated noise in the vertical. Throughout the numerical implementation, RH_{ice} is represented as a dimensionless ratio, such that a value of 1 or 100% corresponds to ice saturation and values greater than 1 or 100% correspond to ice supersaturation. The perturbed humidity field is computed as

$$RH_{ice}^{(m)}(i, j, k, n) = \text{clip}[RH_{ice}^0(i, j, k, n) + \Delta RH_{ice}^{(m)}(i, j, n), 0.01, 1.60] \quad (2)$$

where RH_{ice}^0 is the baseline ERA-5 field. The lower and upper bounds correspond to 1% and 160%, respectively, and
 135 prevent the additive perturbations from producing values outside a prescribed physical range.

The perturbation amplitude is calibrated using the RH_{ice} forecast-error statistics described by Thompson et al. (2024), who compared spatially and temporally interpolated S-WRF forecasts with approximately 1.5 million radiosonde measurements collected over Europe and the Middle East during a ten-month period in 2022. The analysis was restricted to the cruise-altitude range from FL250 to FL450 and produced a pointwise S-WRF minus radiosonde RH_{ice} error distribution with mean
 140 bias of 2.3%, standard deviation of 23.2%, and mean absolute error of 16.7%.

A perturbation scale factor of $s = 1.5$ is applied to the raw Perlin field so that the variance of the resulting pre-clipping perturbations matches the variance of the reference RH_{ice} forecast-error distribution. The reported mean forecast bias is not imposed; the synthetic perturbations remain approximately zero-centered. Thus, the Thompson et al. (2024) error variance determines the magnitude of the imposed uncertainty, whereas the selected Perlin configuration determines its horizontal
 145 structure and time variation.

Repeating this procedure using independent Perlin-noise realizations produces the Monte Carlo humidity ensemble. The analyses presented in this study used $N = 50$ ensemble members. Sensitivity tests with $N = 200$ showed little change in the reported statistics, suggesting that 50 was sufficient for the present analysis. Fig. 1 illustrates the resulting spatial variability in ISSR occurrence over a representative portion of the trans-Atlantic corridor. The baseline ERA-5 ISSR is shown together
 150 with the fraction of ensemble members satisfying $RH_{ice} > 100\%$ at each grid location.

2.4.2 Ensuring thermodynamic consistency

Instead of the RH_{ice} variable, CoCiP internally requires specific humidity, q , as a meteorological input. To maintain consistency between the perturbed RH_{ice} field and the humidity supplied to CoCiP, each ensemble realization is converted to



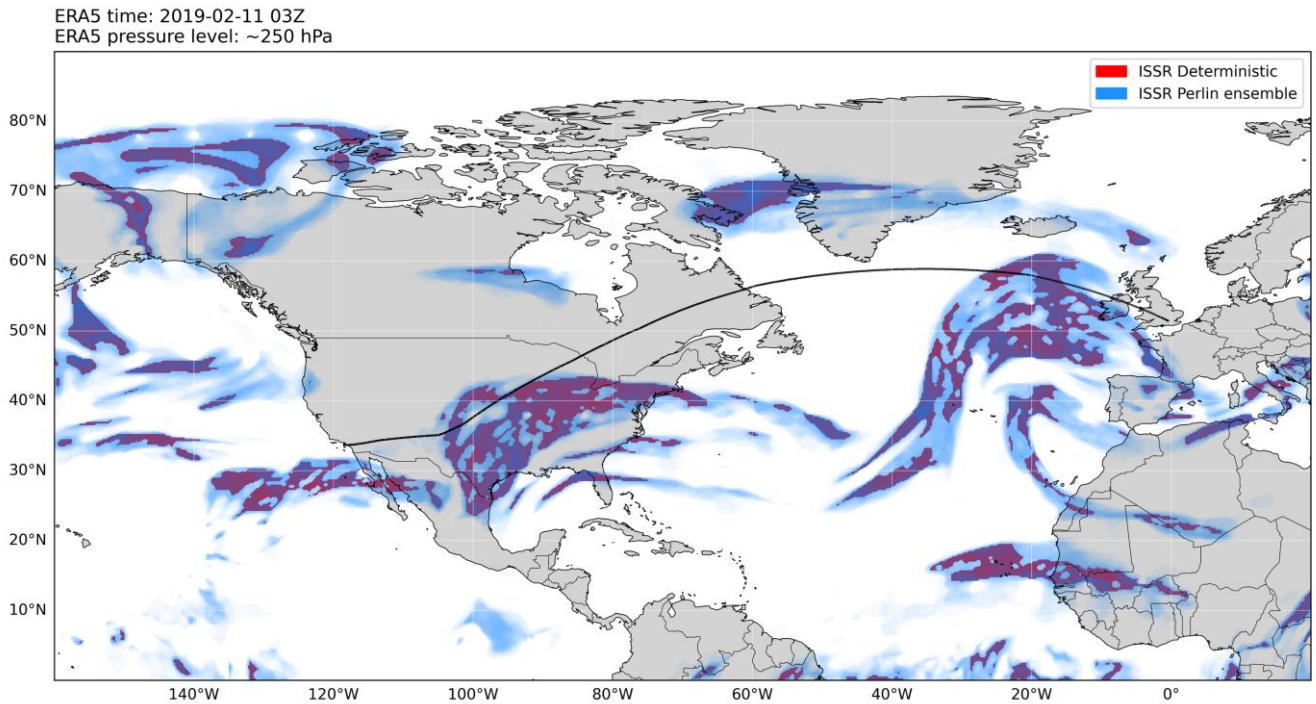
a corresponding specific humidity while retaining the ERA-5 temperature and pressure fields. The conversion follows the
 155 thermodynamic relationships implemented in `pycontrails` (Shapiro et al. 2026) as repeated here:

$$RH_{ice} = \frac{P_{vap}}{e_{sat,i}(T)} \quad (3)$$

where P_{vap} is the water vapor partial pressure and $e_{sat,i}(T)$ is the saturation vapor pressure over ice at temperature T using the formula of Murphy and Koop (2005). Using P_{vap} and total atmospheric pressure, p , the specific humidity is calculated from:

$$q = \frac{0.622 P_{vap}}{p - 0.378 P_{vap}} \quad (4)$$

160 where the constants 0.622 and 0.378 arise from the molecular weight ratio of water vapor to dry air and its complement respectively.



165 **Figure 1: Visualization of deterministic ISSR (red) at the 250 hPa level at 0300 UTC 11 February 2019 and ISSR occurrence from the 50-member ensemble (blue) shaded as a fraction of members exceeding $RH_{ice} = 100\%$.**

3 Analysis

The analysis follows the propagation of humidity uncertainty from local conditions encountered along a flight trajectory to the cumulative climate impact assigned to the complete flight. At trajectory level, waypoint-sampled RH_{ice} and the



corresponding contrail segment-level energy forcing identify where humidity perturbations alter contrail persistence and radiative impact. At flight level, the segment contributions are aggregated to obtain a distribution of cumulative climate impact. Since the same distinction is used throughout the following case studies, we introduce a consistent notation for the two levels of analysis.

For flight f , let r index the waypoints along the aircraft trajectory and let $m = 1, \dots, N$ index the humidity ensemble members as before. For each waypoint, CoCiP calculates the lifetime-integrated energy forcing associated with the contrail segment initialized at that location. This waypoint-indexed segment energy forcing is denoted by $EF_{f,r}^{(m)}$ with $EF_{f,r}^0$ denoting the corresponding deterministic value. Segment-level energy-forcing contributions are subsequently aggregated along the trajectory and converted to CO_2e units to obtain the cumulative flight-level climate impact. The CO_2e cumulative flight-level impact associated with each ensemble member is denoted by $I_f^{(m)}$, whereas I_f^0 denotes the corresponding deterministic ERA-5-based estimate. Positive values of I_f indicate net warming, whereas negative values indicate net cooling.

For each flight, the ensemble distribution is summarized using its mean and the 10th–90th percentile interval, $[Q_{0.10,f}, Q_{0.90,f}]$, where $Q_{\alpha,f}$ denotes the empirical α quantile of $\{I_f^{(1)}, \dots, I_f^{(N)}\}$. To characterize the likelihood that cumulative flight-level impact exceeds a specified threshold x , the empirical exceedance probability is defined as

$$\text{PR}(I_f \geq x) = \frac{1}{N} \sum_{m=1}^N \mathbb{I}[I_f^{(m)} \geq x] \quad (5)$$

where $\mathbb{I}[\cdot]$ is the indicator function. Evaluating $\text{Pr}(I_f \geq x)$ over a range of thresholds defines the flight-level exceedance-probability curve. A threshold exceeded by 90% of the ensemble members is referred to as a 90% exceedance threshold and corresponds approximately to the lower 10th percentile of the cumulative flight-level impact distribution.

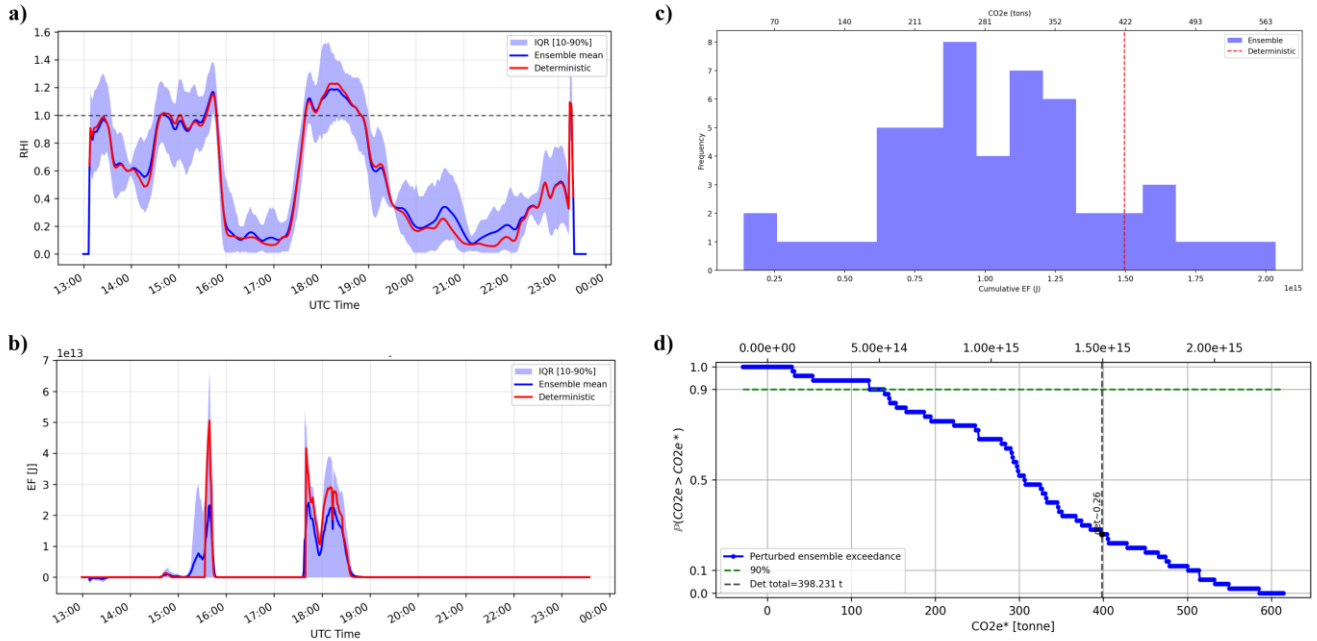
3.1 High contrail warming impact

We began with a flight that the deterministic ERA-5 simulation identified as high-impact warming. Fig. 2 shows the RH_{ice} and segment energy forcing along the trajectory. The aircraft crosses an extended ISSR during mid-cruise, and the spread in segment energy forcing (EF) is largest there, where the 10th–90th percentile band of the perturbed RH_{ice} straddles the saturation threshold. This behavior arises from the threshold itself: a realization that falls below saturation shortens the contrail's lifetime and its energy forcing drops to zero, while a higher moisture realization does not produce a proportional increase, since the lifetime-integrated forcing also depends on the conditions the segment encounters after formation. Humidity perturbations that are approximately zero-centered therefore produce an EF distribution that is shifted downward relative to the deterministic value, not just widened.

These segment-level shifts accumulate at the flight level. All 50 ensemble members remain warming (Fig. 2c), but only about a quarter of them (26%) match or exceed the deterministic estimate of $I_f^0 \approx 398$ tons CO_2e while most of the ensemble lies below it. The exceedance curve in Fig. 2d gives the complementary reading: 90% of the members reach at least 120 tons



200 CO_2e . The ensemble is therefore confident that the flight warms, but much less confident that it warms by the full deterministic amount.



205 **Figure 2: Example of a warming, high-impact flight. (a) Waypoint-sampled RH_{ice} along the aircraft trajectory; (b) Waypoint-indexed lifetime-integrated energy forcing (EF) associated with the simulated contrail segments; (c) Histogram of cumulative flight-level energy forcing across the $N = 50$ humidity ensemble members, with the corresponding CO_2e values shown on the secondary axis; and (d) Empirical exceedance-probability curve of cumulative flight-level climate impact. In panels (a) and (b), the red line denotes the deterministic outcome, the blue line denotes the ensemble mean, and the shaded region denotes the pointwise 10th–90th percentile interval. In panel (c), the blue bars show the ensemble distribution, and the red dashed line marks the deterministic result. In panel (d), the vertical dashed line marks the deterministic cumulative impact, while the horizontal dashed line indicates a 90% exceedance probability.**

This is the information an operator needs when screening flights for pre-tactical avoidance. A risk tolerance can be set directly on the exceedance curve — for example, intervening only when 90% of the members exceed a chosen impact threshold, which is equivalent to requiring $Q_{0.10,f}$ to exceed that threshold. Under such a rule, this flight would be assessed at roughly 120 tons of avoidable warming rather than the 398 tons indicated by the deterministic simulation.

215 3.2 High contrail cooling impact

Cooling flights require one additional step of care in interpretation. Because the cumulative impact is signed, a high exceedance probability at a negative threshold x means that most outcomes are no more cooling than x ; it does not mean that a cooling benefit of magnitude $|x|$ is likely. We illustrate this with a flight identified as strongly cooling under the deterministic simulation.



Fig. 3 shows the same along-track behavior as the warming case, with the sign reversed. The humidity band crosses the saturation threshold over parts of the trajectory, and the EF spread concentrates there: members that fall below saturation lose their negative forcing to zero, while members that remain supersaturated retain strong cooling contributions, so the EF response is again asymmetric despite the approximately zero-centered perturbations. The deterministic run gives $I_f^0 \approx -14.5$ tons CO_2e , close to the ensemble median, so about half the members cool more than this and half cool less.

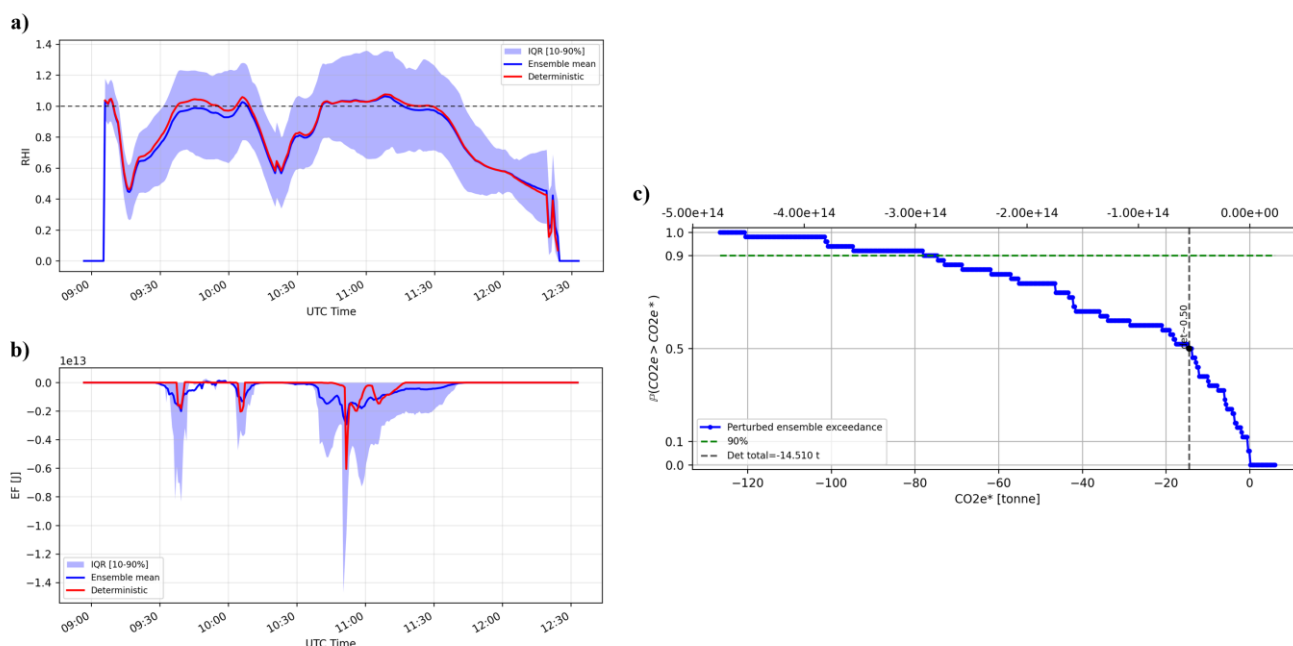


Figure 3: As in Fig. 2a, b, and d except for an example of high impact cooling flight.

The more useful quantity for a decision-maker is how much cooling the ensemble supports with high confidence. This is set by the upper quantile: a cooling benefit supported by 90% of the members corresponds to $Q_{0.90,f}$, provided $Q_{0.90,f} < 0$, and here $Q_{0.90,f} \approx -1$ ton CO_2e . The ensemble agrees on the sign, but only about one ton of cooling is supported at that confidence level — far less than the deterministic value. At the other tail, 90% of the members are no more cooling than $Q_{0.10,f} \approx -78$ tons CO_2e .

3.3 Synthetic altitude modification experiment

The framework to evaluate a candidate intervention for contrail warming mitigation is easily demonstrated. The experiment is deliberately simple — a manually specified altitude change rather than a complete trajectory optimization. Starting from the original ADS-B trajectory of a high-impact warming flight, the cruise altitude was raised by roughly 2,000 ft (610 m)



over the portion of the flight responsible for the dominant warming contribution, with the horizontal route and departure time left untouched.

Fig. 4 shows why this particular flight trajectory and altitude change were chosen. The flight intersects two distinct ISSRs: one during mid-cruise and another shortly before descent. The altitude change lifts the aircraft above the first ISSR, into subsaturated air that does not support persistent contrails; the second region, which produces mostly cooling contrails, is left alone. Both trajectories are then evaluated against the same $N = 50$ humidity realizations, with $I_{f,original}^{(m)}$ and $I_{f,modified}^{(m)}$ denoting the cumulative impacts of the original and modified route for member m , and $I_{f,original}^0$, $I_{f,modified}^0$ their deterministic counterparts.

For the original routing, the central ISSR dominates the positive EF (Fig. 5a,b) while the later region contributes mostly negative forcing. The deterministic impact is $I_f^0 \approx 780$ tons CO_2e (Fig. 5c), exceeded by about a third (34%) of the ensemble members — the now-familiar pattern of a deterministic estimate lying in the upper reaches of its own ensemble.

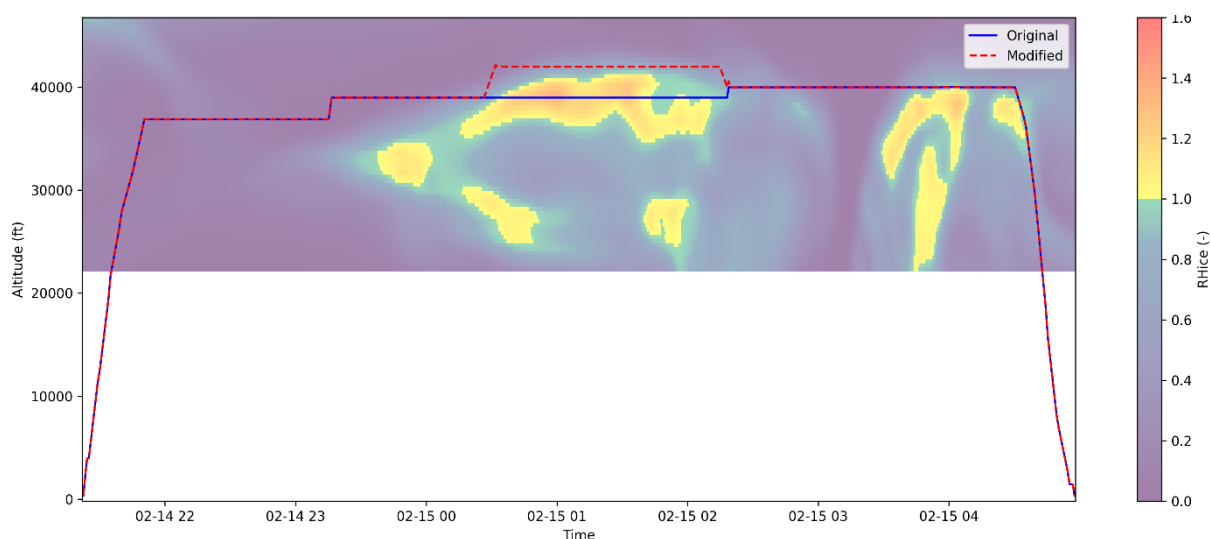


Figure 4: Time-height view of RH_{ice} along an actual flight trajectory (black) and hypothetical modified (red) trajectory going above an ISSR.

The altitude modification substantially reduces the positive EF contribution associated with the central portion of the flight, while the negative contribution near the end of cruise is retained (Fig. 5, right column). Under the deterministic ERA-5 simulation, the resulting cumulative impact is $I_f^0 \approx -28$ tons CO_2e (Fig. 5f). The deterministic comparison therefore indicates a reduction of approximately 808 tons CO_2e relative to the original trajectory. The humidity-ensemble results support an equally significant, although smaller, overall reduction in impact of approximately 400 tons CO_2e . Relative to the original trajectory, the modified trajectory distribution is shifted markedly toward lower cumulative impacts.



From an operational perspective, this experiment demonstrates the value of combining segment-level *EF* information with uncertainty-aware evaluation. The deterministic simulation identifies the portion of the trajectory responsible for the dominant warming contribution, while the ensemble quantifies the range of impacts that remains after the modification. A relatively small and localized altitude change can therefore avoid the principal warming region while retaining a cooling contrail contribution elsewhere along the flight. The framework provides a means of evaluating whether such a candidate modification remains beneficial across plausible humidity realizations, rather than judging its effectiveness from the deterministic simulation alone.

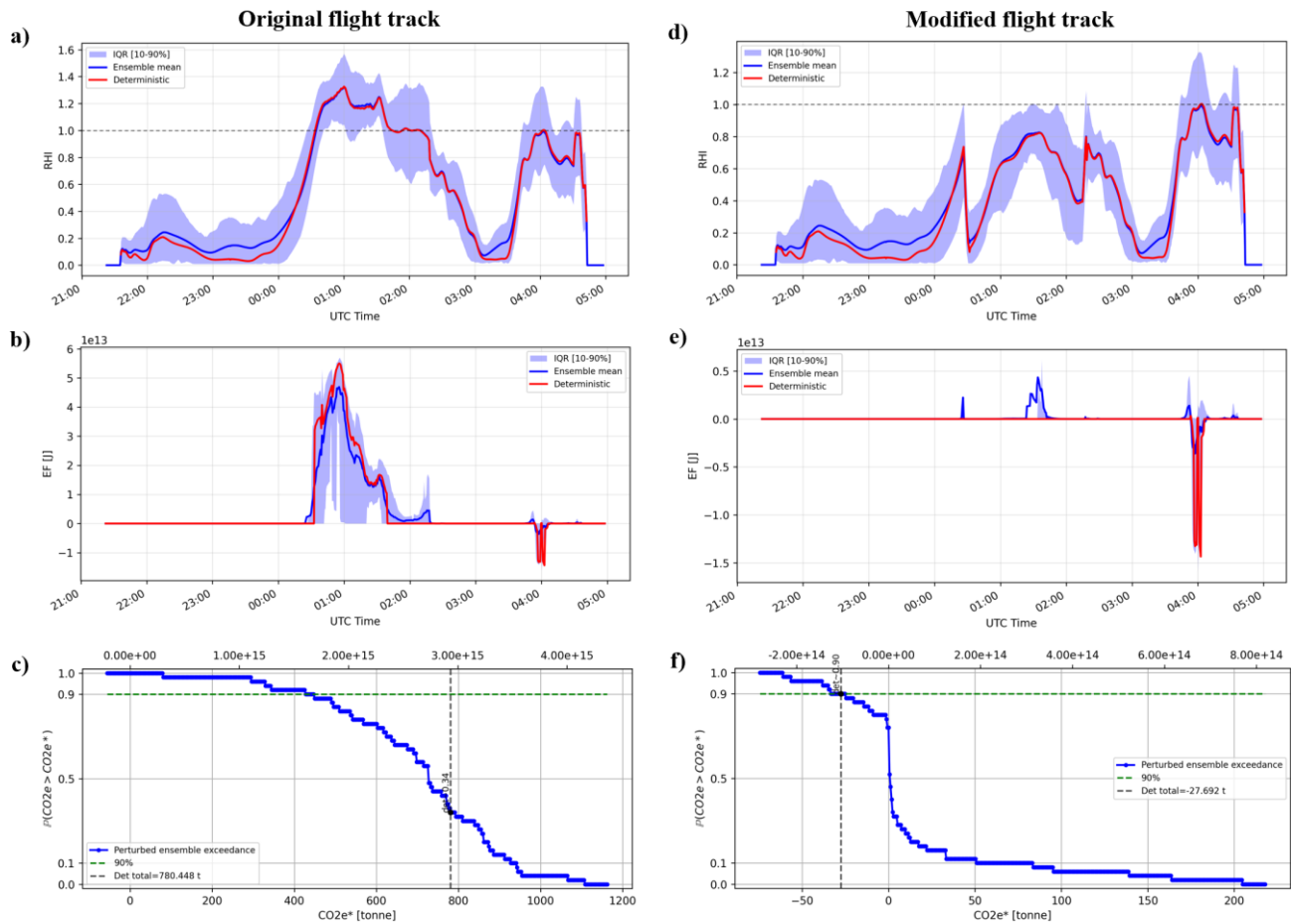


Figure 5: As in Fig. 3, except for a different flight trajectory (left column) and a hypothetical altitude-modified flight (right column).



3.4 Aggregate flight analysis

- 270 This analysis aims to answer the following question: do the patterns seen in the individual cases persist across many flights? To check, we ranked the flights in each sampled period by deterministic cumulative warming impact I_f^0 , retained the top 500 of each month and compared each deterministic value against the flight's ensemble median $Q_{0.50,f}$ and 10th–90th percentile interval $[Q_{0.10,f}, Q_{0.90,f}]$ (Fig. 6). By construction the deterministic curves decrease monotonically with rank, whereas the ensemble medians are not expected to preserve the same ordering.
- 275 Three patterns emerge from Fig. 6. First, the February flights show larger deterministic impacts than the June flights across most of the ranked set. This is consistent with physical expectations, as wintertime contrails are expected to cause larger warming impact than summertime contrails — since high sun angles can produce more solar reflection contributing to potential cooling. The ensemble medians show the same seasonal contrast, and the February uncertainty intervals are wider in absolute terms. Second, the deterministic estimate lies above the ensemble median for most flights in both periods. The
- 280 downward shift seen in the individual warming cases therefore holds at the aggregate level: even though the humidity perturbations are approximately zero-centered, the threshold behavior at ice saturation lowers the central impact estimates relative to the deterministic run. Third, the ensemble medians do not follow the deterministic ranking. Flights with similar deterministic impacts can have very different medians and intervals, and for some warming flights $Q_{0.10,f}$ approaches or crosses zero, indicating limited assurance that these flights are robustly warming under humidity uncertainty.
- 285 Fig. 7 further summarizes deterministic-ensemble agreement across the full sample of flights. Each point corresponds to a single flight, positioned by its deterministic impact on the x-axis (tons CO_2e) and by the ensemble-derived probability of a warming contrail on the y-axis, defined here as the fraction of ensemble members (out of 50) with $I > 5$ tons CO_2e . Points are colored according to agreement between deterministic classification and ensemble support. Flights classified as warming deterministically ($I_f^0 > 5$ tons CO_2e) are labeled as robust warming (green) when more than 80% of ensemble members also
- 290 exceed 5 tons CO_2e , and as non-robust warming (red) when more than 80% of ensemble members instead fall below this threshold (i.e., near-zero or cooling). Conversely, flights classified as near-zero/cooling deterministically ($I_f^0 < 5$ tons CO_2e) but supported as warming by more than 80% of the ensemble are labeled non-robust cooling (blue). These blue cases are rare and are less operationally relevant for pre-tactical avoidance because ensemble exceedance beyond $I_f^0 > 5$ tons CO_2e may be marginal, making prioritization ambiguous. Remaining flights that do not meet these confidence criteria are shown in gray.
- 295 Two qualitative features are apparent. First, the distribution is asymmetric in that high-probability warming outcomes tend to occur at larger absolute impacts than high-probability cooling outcomes, consistent with warming contrails having larger magnitude tail behavior than cooling contrails in this sample. Second, agreement between deterministic and ensemble classifications is generally strong for deterministically cooling flights and especially for deterministically high-impact warming flights. Together with Fig. 6, this indicates that the principal operational value of the ensemble is not to
- 300 fundamentally overturn the deterministic assessment, but to identify where deterministic rankings are insufficiently robust and where uncertainty-aware screening can improve prioritization.



For mitigation planning, the robustness question is the operative one. A deterministic ranking will promote some flights whose warming is not robust under humidity uncertainty and demote others whose warming is; screening instead by a 90% exceedance threshold — requiring $Q_{0.10,f}$ to clear a prescribed intervention level – retains the robust candidates and filters out the fragile ones, at the cost of a more conservative estimate of total avoidable impact. The contrast between the sampled February and June periods suggests that the size of that conservatism will itself vary with meteorological regime, which argues for flight-specific impact distributions, rather than deterministic rank alone, as the basis for prioritization.

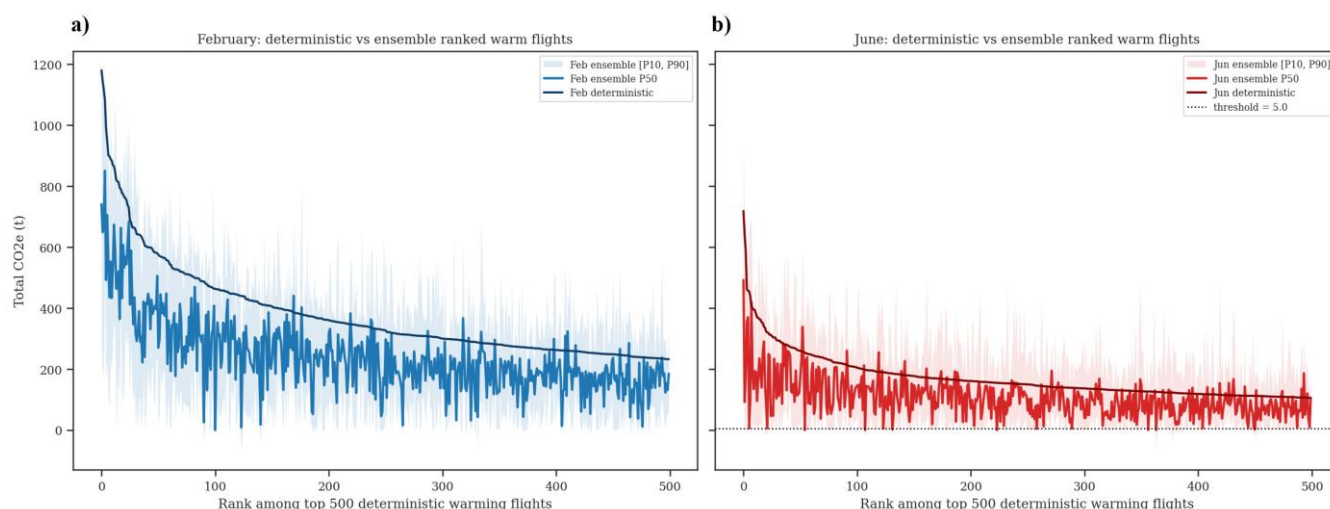


Figure 6: Cumulative flight-level climate impact for the 500 highest-impact warming flights in the sampled February and June periods, ranked in descending order according to the deterministic ERA-5-based estimate. (a) February flights; (b) June flights. In each panel, the dark line denotes the deterministic impact, the colored line denotes the ensemble median $Q_{0.50,f}$, and the shaded region denotes the flight-specific 10th–90th percentile interval, $[Q_{0.10,f}, Q_{0.90,f}]$, across the $N = 50$ humidity ensemble members.

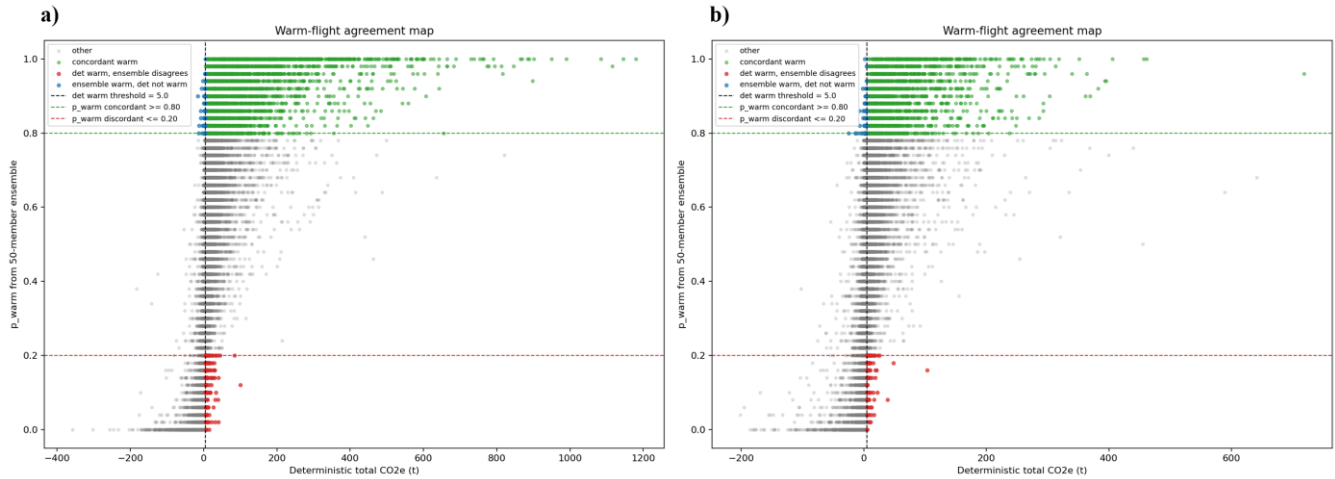


Figure 7: Deterministic-ensemble consistency for cumulative flight-level climate impact across ~150,000 flights sampled in (a) February and (b) June 2019. Each point represents a single flight. Points are colored by agreement between deterministic and ensemble classification: green indicates robust warming cases ($I_f^0 > 5$ tons CO_{2e} and $\Pr(I_f > 5 \text{ tons } CO_{2e}) > 0.8$), red indicates non-robust warming cases ($I_f^0 > 5$ tons CO_{2e} and $\Pr(I_f > 5 \text{ tons } CO_{2e}) < 0.2$), blue indicates non-robust cooling cases ($I_f^0 < 5$ tons CO_{2e} and $\Pr(I_f > 5 \text{ tons } CO_{2e}) > 0.8$), and gray indicates intermediate cases not meeting these confidence thresholds.

4 Discussion and Conclusions

Most prior analyses treated flight optimization deterministically and ignored uncertainty effects. The Monte Carlo humidity perturbation approach presented in this work directly responds to explicit call for ensemble representation of humidity uncertainty.

4.1 Strengths of the methodology

Perturbing deterministic meteorology with a Perlin noise model to represent meteorological uncertainty offers several advantages over relying directly on available NWP ensembles. First, the approach is portable and efficient: Perlin-based perturbations can be generated from any deterministic meteorological product (e.g., a single forecast run or a reanalysis) without requiring access to, storage of, or processing for multi-member NWP ensembles, making it a more computationally and data efficient alternative for large simulation campaigns. It also provides flexible sampling, since the ensemble size N can be selected to match the needs of the uncertainty analysis, whereas operational ensembles are often constrained to relatively small member counts (e.g., 10-50). This flexibility is particularly valuable when estimating tail behavior, such as P_{90} thresholds or exceedance curves, which benefits from larger N .

Second, a Perlin-based uncertainty model makes it possible to enforce statistically representative humidity uncertainty when operational ensembles can still contain systematic biases. As an example, Thompson et al. (2024; Fig. 3) clearly showed an unrealistically high peak frequency of occurrence of RH_{ice} near 104% in the ECMWF's Integrated Forecast System (IFS) model which lowers to almost exactly 100% in the ERA-5 data. Neither of these two datasets match the observations in their



distribution of RH_{ice} compared with the observations. Since ERA-5 ensembles are predicated on the IFS underlying first-guess forecast, this incorrect distribution remains in all ensemble members. NWP humidity ensembles may also exhibit under-dispersion, which can yield overconfident predictions of ISSRs and, by extension, contrail occurrence. By contrast, Perlin noise parameters can be calibrated to match an observation-based humidity error distribution and prescribed spatiotemporal correlation scales, providing targeted control over the coherence of RH_{ice} uncertainty that strongly influences contrail formation and persistence near the $RH_{ice} = 100\%$ threshold.

4.2 Operational applications

The results of this study demonstrate that incorporating humidity-driven uncertainty into contrail impact estimates provides an actionable basis for safe and risk-aware operational decision-making. By replacing single deterministic outputs with likelihood distributions and exceedance probabilities, the framework enables operators to identify flights (or trajectory segments) for which contrail impacts are consistently high across plausible meteorological simulations. This supports “safe rerouting” in the decision-analytic sense: interventions can be prioritized when the likelihood of achieving a climate benefit exceeds a chosen confidence level, reducing the risk of unnecessary or counterproductive route changes.

A key strength of the approach is that it is applicable in both forecast and hindcast settings. In forecast mode, ensemble-derived impact distributions can inform pre-tactical navigational contrail avoidance by quantifying the probability that candidate route modifications reduce contrail climate impact relative to the baseline plan. In hindcast mode, the same methodology can be applied to reanalysis-driven ensembles to support monitoring, reporting, and verification (MRV) by providing uncertainty-bounded estimates of contrail impacts and mitigation benefits in a retrospective evaluation.

Operationally, the framework also provides operators with a flexible lever for optimization. Rather than prescribing a single rerouting rule, it offers a quantified trade space in which airlines can select a risk tolerance (e.g., using percentile thresholds or exceedance criteria) consistent with their operational constraints, cost priorities, and environmental objectives. This allows decision-makers to tailor interventions to different contexts, such as fuel price regimes, airspace constraints, or sustainability targets, while maintaining transparent confidence bounds on expected climate outcomes.

Finally, the methodology can be extended to leverage cooling contrail opportunities. By identifying situations in which cooling impacts are not only predicted but predicted with high confidence, operators could avoid inadvertently eliminating beneficial cooling while still mitigating robust warming cases. This enables a more nuanced strategy that prioritizes net climate benefit under uncertainty, rather than uniformly minimizing contrail occurrence.

4.3 Limitations and future work

Humidity uncertainty was the focus of this uncertainty-quantification framework because humidity is the key driver of contrail formation and persistence. However, contrails depend on more than humidity; the Perlin-based NWP ensembles could naturally be extended to additional atmospheric variables (e.g. temperature, winds, radiation) to preserve multivariate relationships. A similar methodology could also be applied to other parametric uncertainties.



The present approach differs from that of Platt et al. (Platt et al. 2024), who used ERA-5 ensemble members to represent meteorological uncertainty while also propagating parametric uncertainty within the contrail model. Here, humidity and model uncertainty were deliberately decoupled by prescribing a synthetic, correlated RH_{ice} perturbation model while holding the CoCiP configuration fixed. A natural extension would combine the two approaches by incorporating model-parameter uncertainty together with the humidity uncertainty developed in this study.

Code and data availability

The custom code and some of the data underlying this study are subject to propriety and commercial confidentiality restrictions and therefore cannot be released publicly. However, samples of the data can be made available to the journal editors and reviewers upon request for evaluation purposes during the peer-review process.

Author contributions

CS and MKRP both led the simulations, data curation, formal analysis, investigation, software, visualization and writing – original draft. GT funding acquisition, supervision, conceptualization, methodology and writing – review and editing. GK and JC funding acquisition, supervision, conceptualization and methodology.

Competing interests

The authors declare that they have no conflict of interest.

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References

- Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., and Tian, Q.: Accurate medium-range global weather forecasting with 3D neural networks, *Nature*, 619, 533–538, <https://doi.org/10.1038/s41586-023-06185-3>, 2023.
- Chen, L., Zhong, X., Zhang, F., Cheng, Y., Xu, Y., Qi, Y., and Li, H.: FuXi: a cascade machine learning forecasting system for 15-day global weather forecast, *npj Clim. Atmos. Sci.*, 6, 190, <https://doi.org/10.1038/s41612-023-00512-1>, 2023.



- 395 Dean, T. R., Abbott, T. H., Engberg, Z., Masson, N., Teoh, R., Itcovitz, J. P., Stettler, M. E. J., and Shapiro, M. L.: Impact of
 forecast stability on navigational contrail avoidance, *Environ. Res.: Infrastruct. Sustain.*, 5, 045008,
<https://doi.org/10.1088/2634-4505/aelda5>, 2025.
- Gierens, K., Matthes, S., and Rohs, S.: How Well Can Persistent Contrails Be Predicted?, *Aerospace*, 7, 169,
<https://doi.org/10.3390/AEROSPACE7120169>, 2020.
- 400 Joos, F., Roth, R., Fuglestad, J. S., Peters, G. P., Enting, I. G., von Bloh, W., Brovkin, V., Burke, E. J., Eby, M., Edwards,
 N. R., and Friedrich, T.: Carbon dioxide and climate impulse response functions for the computation of greenhouse gas
 metrics: a multi-model analysis, *Atmos. Chem. Phys.*, 13, 2793-2825, <https://doi.org/10.5194/acp-13-2793-2013>, 2013.
- Kärcher, B.: Formation and radiative forcing of contrail cirrus, *Nat. Commun.*, 9, 1824, <https://doi.org/10.1038/s41467-018-04068-0>, 2018.
- 405 Lamquin, N., Gierens, K., Stubenrauch, C. J., and Chatterjee, R.: Evaluation of upper tropospheric humidity forecasts from
 ECMWF using AIRS and CALIPSO data, *Atmos. Chem. Phys.*, 9, 1779-1793, <https://doi.org/10.5194/acp-9-1779-2009>,
 2009.
- Martin Frias, A., Shapiro, M., Engberg, Z., Zopp, R., Soler, M., and Stettler, M. E. J.: Feasibility of contrail avoidance in a
 commercial flight planning system: an operational analysis, *Environ. Res.-Infrastructure and Sustainability*, 4, 015013,
 410 <https://doi.org/10.1088/2634-4505/ad310c>, 2024.
- Murphy, D. M. and Koop, T.: Review of the vapour pressures of ice and supercooled water for atmospheric applications, *Q.
 J. Roy. Meteor. Soc.*, 131, 1539-1565, <https://doi.org/10.1256/qj.04.94>, 2005.
- Perlin, K.: An image synthesizer, *ACM SIGGRAPH Comput. Graph.*, 19, 287-296, <https://doi.org/10.1145/325165.325247>,
 1985.
- 415 Platt, J., Shapiro, M., Engberg, Z., McCloskey, K., Geraedts, S., Sankar, T., Stettler, M. E. J., Teoh, R., Schumann, U., Rohs,
 S., Brand, E., and Van Arsdales, C.: The effect of uncertainty in humidity and model parameters on the prediction of
 contrail energy forcing, *Environ. Res. Commun.*, 6, 095015, <https://doi.org/10.1088/2515-7620/ad6ee5>, 2024.
- Schumann, U.: A contrail cirrus prediction model, *Geosci. Model Dev.*, 5, 543-580, <https://doi.org/10.5194/gmd-5-543-2012>, 2012.
- 420 Schumann, U.: On conditions for contrail formation from aircraft exhausts, *Meteorol. Z.*, 5, 4-23,
<https://doi.org/10.1127/metz/5/1996/4>, 1996.
- Shapiro, M. L., Engberg, Z., Teoh, R., Stettler, M., Dean, T., and Abbott, T.: Pycontrails: Python library for modeling
 aviation climate impacts, *Zenodo*, <https://doi.org/10.5281/ZENODO.20836452>, 2026.
- Simorgh, A. and Soler, M.: Climate-optimized flight planning can effectively reduce the environmental footprint of aviation
 425 in Europe at low operational costs, *Commun. Earth Environ.*, 6, 66, <https://doi.org/10.1038/s43247-025-02031-8>, 2025.
- Sonabend-W, A., Elkin, C., Dean, T., Dudley, J., Ali, N., Blickstein, J., Brand, E., Broshears, B., Chen, S., Engberg, Z.,
 Galyen, M., Geraedts, S., Goyal, N., Grenham, R., Hager, U., Hecker, D., Jany, M., McCloskey, K., Ng, J., Norris, B.,
 Opel, F., Rothenberg, J., Sankar, T., Sanekommu, D., Sarna, A., Schütt, O., Shapiro, M., Soh, R., Van Arsdales, C., and



- 430 Platt, J. C.: Feasibility test of per-flight contrail avoidance in commercial aviation, *Commun. Eng.*, 3, 1–7,
<https://doi.org/10.1038/s44172-024-00329-7>, 2024.
- Teoh, R., Engberg, Z., Schumann, U., Voigt, C., Shapiro, M., Rohs, S., and Stettler, M. E. J.: Global aviation contrail climate
effects from 2019 to 2021, *Atmos. Chem. Phys.*, 24, 6071–6093, <https://doi.org/10.5194/acp-24-6071-2024>, 2024.
- Teoh, R., Schumann, U., Gryspeerdt, E., Shapiro, M., Molloy, J., Koudis, G., Voigt, C., and Stettler, M. E. J.: Aviation
contrail climate effects in the North Atlantic from 2016 to 2021, *Atmos. Chem. Phys.*, 22, 10919–10935,
435 <https://doi.org/10.5194/acp-22-10919-2022>, 2022.
- Thompson, G., Scholzen, C., O'Donoghue, S., Haughton, M., Jones, R. L., Durant, A., and Farrington, C.: On the fidelity of
high-resolution numerical weather forecasts of contrail-favorable conditions, *Atmos. Res.*, 311, 107663,
<https://doi.org/10.1016/j.atmosres.2024.107663>, 2024.
- Tompkins, A. M., Gierens, K., and Rädcl, G.: Ice supersaturation in the ECMWF integrated forecast system, *Q. J. Roy.*
440 *Meteor. Soc.*, 133, 53–63, <https://doi.org/10.1002/qj.14>, 2007.
- Vigier, P.: Perlin-Numpy; a fast and simple Perlin noise generator using NumPy, GitHub, <https://github.com/pvigier/perlin-numpy>, 2026.