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Title Page

From Physics to AI: A Multidisciplinary Review of Contrail Prediction Models

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Declaration of competing interest

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

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During the peer review process, author Longfei Chen has officially taken up a full-time position at the National Natural Science Foundation of China (NSFC).

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In accordance with the official regulations and conflict-of-interest policies for NSFC staff, he is not permitted to be listed as an author on any academic papers during his term of service.

Therefore, we respectfully request to remove Longfei Chen from the author list in the revised version of this manuscript.

All other authors agree to this change, and the scientific content and conclusions of the paper remain unchanged.

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From Physics to AI: A Multidisciplinary Review of Contrail Prediction Models

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Abstract: Aviation-induced condensation trails (contrails) and contrail cirrus represent a dominant yet uncertain component of effective radiative forcing (ERF), potentially exceeding the warming impact of accumulated carbon dioxide. As the aviation sector targets climate-optimal operations by 2030, the demand for scalable, real-time contrail forecasting has driven a fundamental paradigm shift in modeling strategies. This review provides a comprehensive analysis of contrail prediction methodologies spanning eight decades, classifying the evolution into five distinct epochs: (1) Thermodynamic and Analytical Foundations (1940s–1990s), rooted in the Schmidt-Appleman Criterion (SAC) for binary formation thresholds; (2) Microphysical Simulation (1990s–2010s), exemplified by the Contrail Cirrus Prediction (CoCiP) and APCEMM models, which resolve complex particle dynamics and lifecycle evolution; (3) NWP-Integrated Frameworks (2000s–Present), such as ECMWF IFS and WRF-Chem, which embed contrail parameterizations into global weather systems; (4) Satellite-Empirical Models, leveraging AVHRR, MODIS, and CALIOP data to establish climatological baselines and validate physical assumptions; and (5) AI-Driven and Hybrid Frontiers (2020–2026), where deep learning architectures, including U-Net segmentation, Physics-Informed Neural Networks (PINNs), and the Google-DLR hybrid system, are revolutionizing real-time detection and flight attribution. By critically evaluating the trade-offs between physical interpretability and computational scalability, this paper identifies the emerging consensus that future operational systems must adopt hybrid architectures—merging the robust constraints of first-principles physics with the adaptive precision of artificial intelligence—to enable verifiable contrail avoidance and sustainable flight planning.

1 Introduction

Aviation has become an increasingly important focus in climate policy due to its growing share of global greenhouse gas emissions and high-altitude impacts. Organizations such as the International Civil Aviation Organization (ICAO), The Intergovernmental Panel on Climate Change (IPCC), the European Union Aviation Safety Agency (EASA) and national bodies like National Aeronautics and Space Administration (NASA) (Li et al., 2025) and the U.S. Federal Aviation Administration (FAA) (Brasseur et al., 2016) are actively engaged in monitoring, modeling, and mitigating aviation-induced climate effects.

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In 2025, these agencies have taken concrete steps to address contrail-related warming: ICAO introduced contrail avoidance guidelines into its global environmental strategy; NASA and the FAA expanded operational trials of real-time flight rerouting algorithms targeting ice-supersaturated layers; and the EU's Clean Aviation program launched funding initiatives for developing AI-based contrail forecasting tools aimed at integration by 2030**.** Aircraft emit a complex mixture of gases and particles—including Carbon Dioxide (CO_2), Water / Water Vapor (H_2O), Nitrogen Oxides (NO_x), Sulfur Oxides (SO_x), particulate matter (PM), and hydrocarbons (HC) (Lee et al., 2009).

Table 1 List of Aviation Emissions, their source and effects on climate

Emission	Source / Mechanism	Climate Effect	Residence Time	Altitude Sensitivity	Ref
CO_2	Complete combustion of jet fuel	Long-term warming (GHG)	~100 years	Global (not altitude-dependent)	(Aamaas et al., 2025)
H_2O	Combustion product	Contrail & cirrus formation	Days to weeks	Strong effect at high altitudes	(Gaillot et al., 2023)
NO_x	High-temp combustion	Forms ozone (warming) & reduces CH_4 (cooling) → net warming	Days to weeks	Amplified at high altitudes	(Lee et al., 2021)
SO_x	Sulfur in fuel	Sulfate aerosols (cooling)	Days	Moderate	(Lu et al., 2011)
PM	Incomplete combustion, soot	Ice nuclei for contrails, some warming	Days	High at cruise altitude	(Whitby, 1977)
HCs	Incomplete combustion	Minor ozone formation	Hours to days	Minor at high altitude	(Oh, 2020)
CO	Incomplete combustion	Minor indirect effect	Weeks	Mostly low-altitude	(Ning et al., 2024)
N_2O	Trace from combustion	Strong long-lived GHG	~120 years	Global	(Filonchyk et al., 2024)
Short Contrails	H_2O vapor condensing on soot	Short-lived warming	Minutes to <1 hour	Requires cold/moist conditions	(Kärcher et al., 2015)
Persistent Contrails	Sustained formation under specific conditions	Net warming (trap IR, reflect sun)	Hours to day(s)	Strong high-altitude dependency	(Schumann et al., 2017)
Contrail Cirrus Clouds	Spread & evolution of persistent contrails	Significant net warming	Hours to days	Only at cruise altitude	(Minnis et al., 2004)
Chemiions	Ion emission from hot exhaust	Enhance aerosol nucleation, may affect contrail microphysics	Seconds to minutes	High at cruise altitude	(Yu and Turco, 1997)
Volatile particles	Homogeneous nucleation of H_2SO_4-H_2O	Provide additional ice nuclei, influence contrail onset	Minutes to hours	Strong at high altitude	(Yu and Turco, 1998)
Organic compounds	Unburned hydrocarbons / lubricants	May coat soot, alter ice-nucleating efficiency	Hours to days	Cruise altitude	(Yu et al., 1999)

Each of these emissions influences the Earth's climate through distinct physical mechanisms and atmospheric interactions. Their impact varies significantly depending on altitude, chemical reactivity, and residence time in the atmosphere(Lee et al., 2009; Lee et al., 2021). Table 1 provides a list of aviation emissions and their effects on climate, including their sources, climate mechanisms, and altitude sensitivities as shown Figure 1 which highlight the roles of different compounds in warming or cooling, and their interactions with cloud processes.

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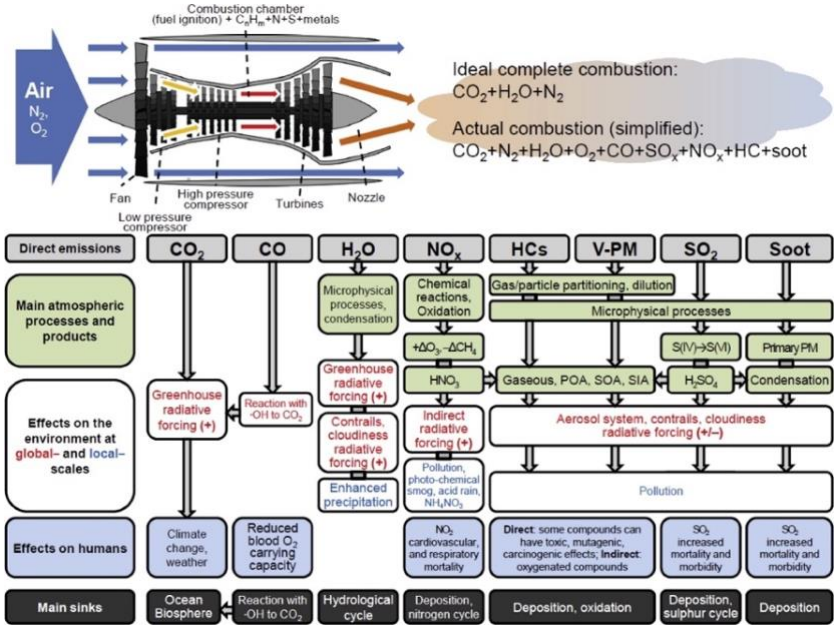

Figure 1 Complex mixture of gases and particles emits from aircraft turbofan engine (Lee et al., 2009)

A more quantitative picture of aviation's climate impact is illustrated in Figure 2, showing effective radiative forcing (ERF) components from 1940 to 2018. Contrail cirrus (CC) dominates the non-CO_2 contribution with an estimated Radiative Forcing (RF) of 111.4 mW/m², exceeding that of CO_2 itself (34.3 mW/m²) (Lee et al., 2021).

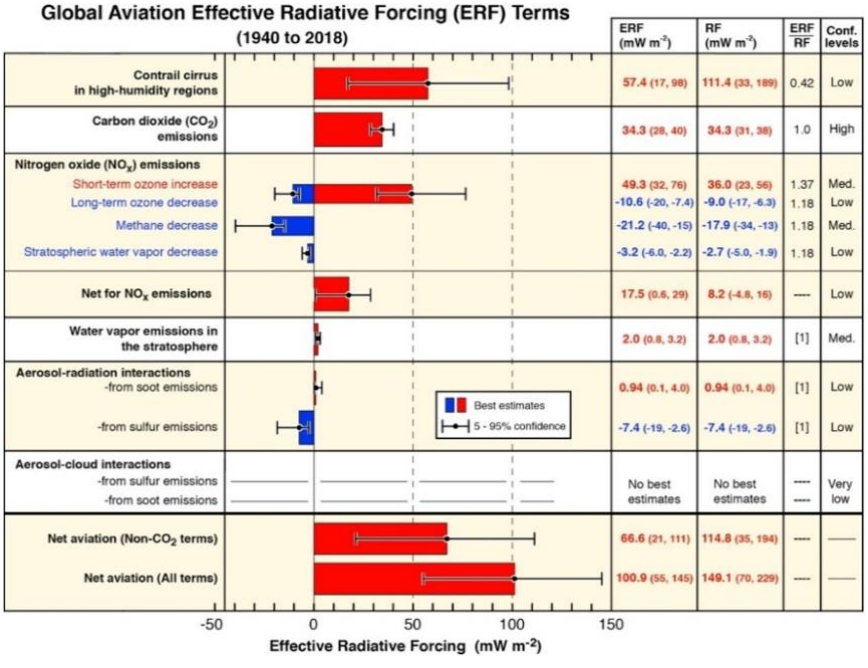

Figure 2 Global Aviation Effective Radiative Forcing (ERF) Terms (1940 to 2018) (Lee et al., 2021)

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To contextualize aviation within global emissions, Figure 3a show that it contributes ~90 mW/m² of the total ~2.29 W/m² anthropogenic RF. However, Figure 3b reveals that aircraft-induced cloudiness (AIC)—primarily persistent contrails and CC accounts for more than half of aviation's total RF (50–150 mW/m²). A breakdown in Figure 3c shows that CC contributes ~40 mW/m², while persistent contrails add ~10 mW/m², highlighting their disproportionate role in aviation-related climate effects (Karcher, 2018).

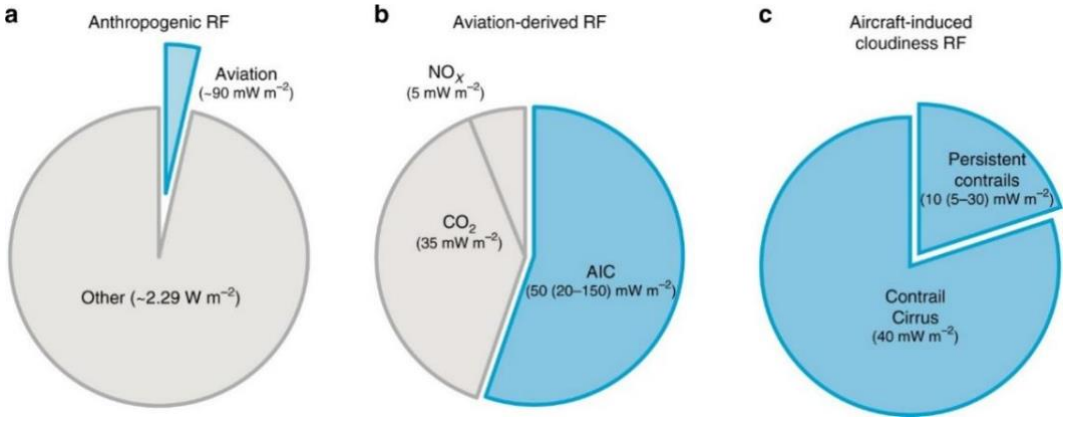

Figure 3 Aviation RF (a) Aviation's contribution to global RF in 2011 relative to pre-industrial times. (b) Forcing components within aviation, with AIC accounting for over half. (c) Breakdown of AIC RF into contrail cirrus and persistent contrails (Karcher, 2018).

The European airspace represents one of the most critical geographical focal points for contrail research due to its extreme traffic density. Data from EUROCONTROL indicates that the region sustained an average of approximately 28,000 flights per day throughout 2023, creating a near-constant saturation of aircraft within the upper troposphere. This high volume of traffic, as visualized in Figure 4, underscores the significant challenge of managing climate impacts. Europe serves as a primary "living laboratory" for validating advanced prediction models—ranging from thermodynamic criteria to AI-driven avoidance strategies as even minor tactical rerouting to avoid Ice supersaturated regions (ISSRs) (Raumfahrt, 2023a).

Figure 4 The airspace over Europe is one of the busiest. According to EUROCONTROL, there were an average of around 28,000 flights per day in 2023 (Raumfahrt, 2023b).

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Contrails form when aircraft engines emit hot, moist exhaust into cold, supersaturated air at cruise altitudes, creating linear ice clouds that may persist and spread, forming optically thin but radiatively significant (Petzold et al., 2025). These clouds trap outgoing longwave radiation more effectively than they reflect incoming solar radiation, leading to a net warming effect, particularly at night. Unlike CO_2, contrails exert a short-lived but intense radiative forcing, making their prediction and mitigation a high-priority research area (Singh et al., 2024).

Over the decades, contrail modeling has evolved through five distinct categories, as depicted in Figure 5. The earliest are thermodynamic or analytical models, based on the Schmidt–Appleman Criterion (SAC) developed in the 1940s–1950s (M.Bjormson, 1992; Ernst 1941), which assess whether atmospheric conditions favor contrail formation. These include plume mixing models, Eulerian models, and threshold-based maps, including variants for alternative fuels. While computationally efficient, these models offer only binary outputs and limited physical realism. Building on this, microphysical models emerged in the 1980s and 1990s, simulating the lifecycle of ice particles nucleation, growth, sublimation, and deposition through tools like Large Eddy Simulation (LES) models, the Unterstrasser-Gierens model, and Lagrangian cloud modules. The Contrail cirrus prediction (CoCiP) model, developed by (Schumann, 2012), became widely used for its integration of microphysics with global meteorological fields, offering more realistic simulations of contrail evolution and radiative effects. A more recent advancement in this category is the Aviation Particle and Chemical Emissions Model (APCEMM), developed at Massachusetts Institute of Technology (MIT), which provides plume-resolved simulations of gas-phase chemistry, aerosol dynamics, and contrail ice formation. APCEMM models the near-field evolution of aircraft exhaust, capturing sub-grid chemical and microphysical processes critical for accurate radiative forcing estimation (Fritz et al., 2020). As meteorological data and computing resources advanced, Numerical Weather Prediction (NWP) integrated models developed during the 1990s and 2000s began embedding contrail parameterizations into operational weather forecasting systems. These include European Centre Hamburg General Circulation Model (ECHAM) Series (Stevens et al., 2013), Global Forecast System (GFS) + SAC (M.Bjormson, 1992), Series of Community Earth System Model (CESM) (Hurrell et al., 2013), Weather Research and Forecast (WRF) and SAC (Mazon and Pino, 2016), and UK Met Office Unified Model (UKMO) contrail layers(Zhang, 2025), providing global or mesoscale forecasts that consider vertical motion, wind shear, and humidity fields, though often limited by the accuracy of upper-tropospheric humidity. Parallel to this, the rise of satellite-based models in the late 1990s and 2000s enabled large-scale detection of contrails using sensors such as Advanced Very High Resolution Radiometer (AVHRR) (Kalluri et al., 2021), Moderate Resolution Imaging Spectroradiometer (MODIS) (Patrick Minnis, 2013), Geostationary Operational Environmental Satellite (GOES) (Euchenhofer et al., 2025), and Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) (Winker et al., 2004), employing techniques like split-window algorithms and optical thickness thresholds. Although excellent for retrospective climatology and monitoring, these models are observational, not predictive and depend on overpass timing and clear sky conditions. The most recent generation includes hybrid AI models, which integrate physical knowledge with machine learning to deliver high-resolution, near-real-time predictions. Starting in the late 2010s, models such as Predictive Real-time Emissions Technologies Reducing Aircraft Induced Lines in the Sky (PRE-TRAILS) (Bock, 2024), Global Aviation

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emissions Inventory (GAIA) (Teoh et al., 2024a), and Convolutional Neural Network (CNN)-AVHRR have applied deep learning to satellite and meteorological data (Zhang et al., 2018). A major leap came in 2024, when Google AI, in collaboration with Breakthrough Energy and Deutsches Zentrum für Luft- und Raumfahrt (DLR) a German aerospace Center, released an enhanced hybrid contrail prediction system that combined CoCiP with satellite detection and aircraft routing algorithms, enabling real-time contrail avoidance strategy development (Zebediah Engberg, 2025). Additionally, Physics-Informed Neural Networks (PINNs), introduced in the early 2020s, such as those by (Raphael Alamu, 2025), embed thermodynamic constraints directly into neural architectures to ensure physically consistent predictions—offering a promising solution to the "black box" challenge in AI systems.

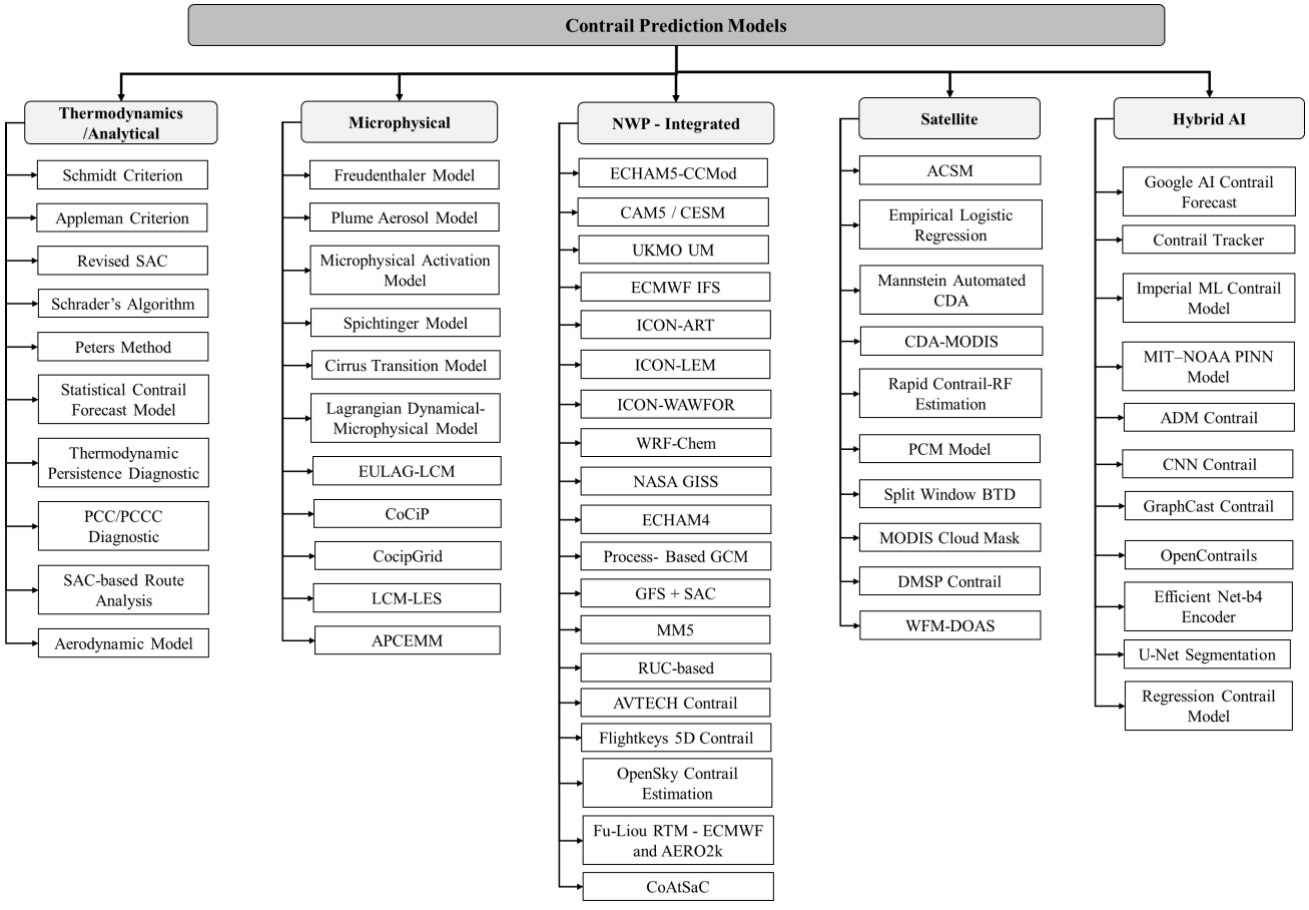

Figure 5 Tree diagram of contrail prediction models

In summary, the development of contrail prediction models spans five major categories, which are illustrated in Figure 5. Thermodynamic/analytical, microphysical, NWP-integrated, satellite-empirical, and AI-driven—each characterized by distinct methodologies and trade-offs. Thermodynamic models are computationally efficient but overly simplistic; microphysical models provide high accuracy and process-level detail but are computationally intensive; NWP-integrated models offer realistic meteorological integration but are limited by data resolution and forecast uncertainty; satellite-based

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models enable large-scale observational insight but lack forward-looking predictive capability; and AI-driven models deliver rapid, high-resolution forecasts but depend heavily on large training datasets and robust validation. Understanding the strengths and limitations of each model type is essential for their effective use in climate assessments, aviation regulation, and operational strategy. This review systematically evaluates these modeling approaches, comparing their architectures, predictive performance, and roles within the broader context of climate mitigation—especially as the aviation sector moves toward AI-integrated environmental forecasting systems and next-generation sustainable flight planning.

2 Fundamentals of Contrail

Contrails are the visible by-products of aircraft engine emissions interacting with the ambient conditions of the upper troposphere. Their formation, evolution, and eventual impact on climate are governed by a combination of atmospheric thermodynamics, microphysical processes, and operational parameters. This section reviews the fundamental mechanisms underlying contrail formation and sets the stage for subsequent discussions on predictive modeling.

2.1 Mechanism of contrail

Contrail formation is a thermodynamic and microphysical process initiated by the combustion of hydrocarbon jet fuels (typically Jet A-1), which react with atmospheric oxygen to produce CO_2, H_2O, NO_x, soot, and heat (Gierens and Schumann, 1996).

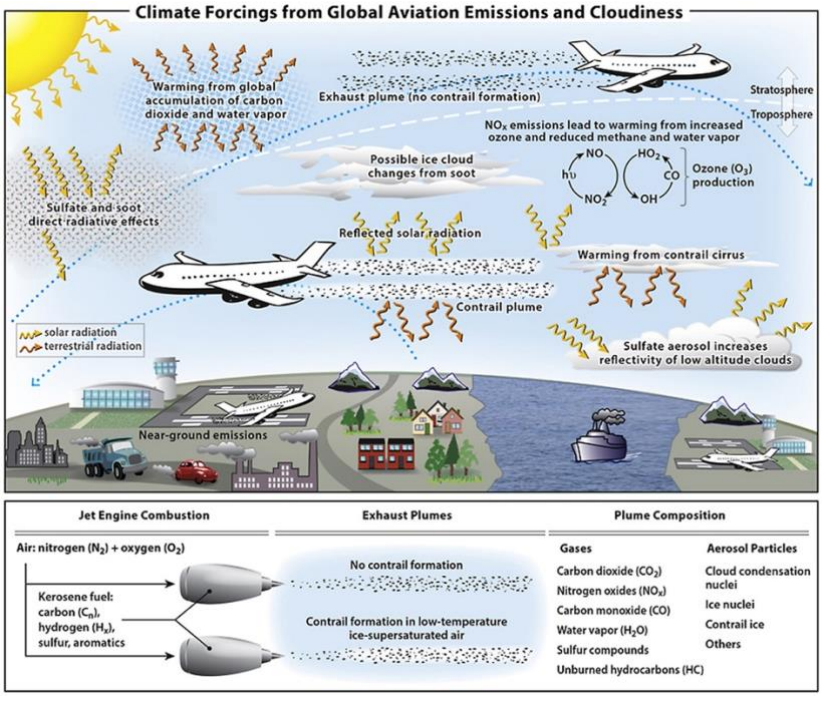

Figure 6 Schematic overview of the processes by which aviation emissions and increased cirrus cloudiness affect the climate system (Lee et al., 2021).

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$$C_xH_y + \left(x + \frac{y}{4}\right) O_2 \rightarrow xCO_2 + \frac{y}{2} H_2O + \text{Heat} \quad (1)$$

For every kilogram of fuel burned, approximately 1.2–1.3 kg of water vapor is emitted (Steven L. Baughcum, 1994). At cruise altitudes (~8–12 km), ambient temperatures are extremely low (often below −40 °C), and the air may be supersaturated with respect to ice (RHi > 100%). As the hot, moist exhaust mixes with this cold ambient air, conditions favorable for ice nucleation may be achieved, particularly if the SAC is satisfied, which defines the threshold temperature below which contrail formation is thermodynamically possible.

$$T < T_{crit} = T_{\infty} - \frac{(1-\eta)Q}{C_p} \quad (2)$$

The critical temperature for contrail formation (T_{crit}) is calculated by taking the ambient air temperature (T_{∞}) and subtracting a term that represents the warming effect of the engine's waste heat. That term is $(1-\eta)Q/Cp$), where η is the engine's propulsion efficiency (the fraction of fuel energy converted to thrust), Q is the specific combustion heat of the fuel (about 43 MJ/kg for kerosene), and Cp is the specific heat capacity of air at constant pressure (approximately 1005 $J \cdot kg^{-1} \cdot K^{-1}$). Thus, the waste heat fraction $(1-\eta)$ times the fuel energy Q gives the waste heat per unit mass, and dividing by Cp converts that energy into a temperature increase. The ambient air must be colder than T_{crit} for the mixed exhaust to reach ice supersaturation (U.Schumann, 1996).

Soot particles within the exhaust serve as effective ice nuclei, triggering heterogeneous nucleation, wherein water vapor deposits directly onto particulate surfaces and freezes into ice crystals (Testa et al., 2024).Volatile particles formed in the plume can also contribute to contrail ice particles, especially when fuel sulfur content is high (Yu and Turco, 1998) or soot concentrations are low (Kärcher and Yu, 2009). These initial ice particles grow via vapor deposition if ambient supersaturation is sustained, forming line-shaped contrails that may persist and spread under the influence of atmospheric shear and turbulence. In such conditions, contrails evolve into contrail cirrus extensive, optically thin ice clouds that can trap outgoing longwave radiation, contributing significantly to short-term positive radiative forcing. The net climatic impact of contrails depends on multiple factors, including ambient humidity, particle number concentration, and the vertical structure of the atmosphere, making accurate prediction a complex yet critical component of aviation climate impact assessments (Singh et al., 2024). Figure 5 illustrates the overall effect of climate forcing from global aviation emission and cloudiness, including the formation mechanism of contrails.

2.2 Atmospheric Conditions

The likelihood of contrail formation depends on several atmospheric parameters, with the most important being temperature and humidity. For a contrail to form, the atmosphere must be cold enough to allow the water vapor in the exhaust to condense and freeze. The ambient temperature typically needs to be below -40°C at the altitude of the aircraft for contrail formation to occur, as the water vapor needs to reach its frost point to transition into ice (Kameníková et al., 2024).

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Equally important is the RHice, which measures how much water vapor is present in the atmosphere compared to the maximum amount the air can hold at a given temperature. Contrails will only form if the surrounding air is sufficiently supersaturated with respect to ice (i.e., $RH_i > 100\%$), which allows the water vapor to condense onto ice nuclei. This is why contrails tend to form at altitudes where the air is both cold and saturated or supersaturated with respect to ice.

The Schmidt-Appleman Criterion illustrated in Figure 7, developed in 1953, provides an empirical model for predicting when contrails will form based on the temperature and relative humidity with respect to ice. According to this criterion, contrails are most likely to form when the ambient temperature is below −39°C and the relative humidity with respect to ice exceeds a certain threshold. This criterion is widely used in contrail prediction models to estimate when and where contrails are likely to form under various atmospheric conditions.

$$RH_i > RHt_{threshold}, T_{ambient} \leq -39°C \quad (3)$$

According to Appleman's criterion, contrails could form when the ambient temperature was below −39°C and the RH_i exceeded a certain threshold, typically around 100% supersaturation. This criterion was revolutionary, providing a fundamental understanding of the basic conditions necessary for contrail formation. Figure 7 shows the dependence of contrail formation on altitude, temperature, and RH_i. It divides the atmosphere into three zones: "Always Contrails," "Possible Contrails," and "Never Contrails." Contrails always form in cold, high-altitude conditions and never form in warmer, low-altitude areas. The contour lines represent different RH_i levels, indicating that higher humidity allows contrails to form at higher temperatures. The dashed gray line shows the standard atmospheric temperature profile, helping identify where contrails are likely to occur under typical conditions.

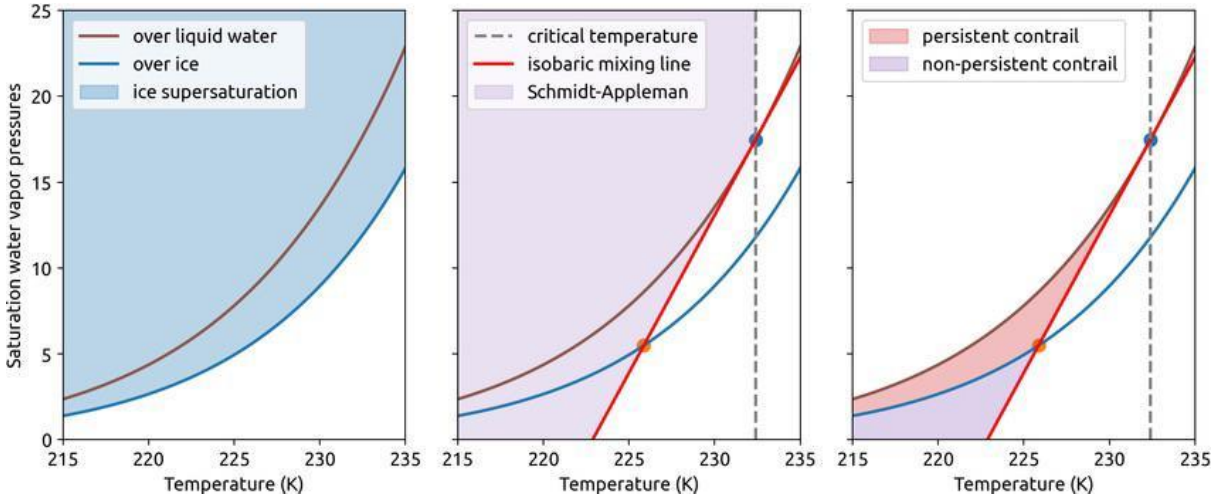

Figure 7 Schmidt-Appleman criterion (Sun and Roosenbrand, 2023)

2.3 Microphysical Processes

The microphysical processes that govern the evolution of contrails are crucial for understanding their formation, persistence, and eventual climatic effects (Singh et al., 2024). These processes are driven by the interaction between the aircraft exhaust,

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which contains water vapor, soot, and aerosols, and the surrounding atmosphere at high altitudes (Alsante and Cheng, 2024). Once the contrail forms, a series of nucleation, crystal growth, and sedimentation processes take place, shaping the characteristics of the contrail and determining its lifetime and radiative impact (Rubin-Zuzic et al., 2025). Below, we delve into the key microphysical processes that contribute to the formation and evolution of contrails. As shown in Table 2, the evolution of a contrail is categorized by distinct chronological stages, from initial engine emission to its final impact on the global climate.

Table 2 In depth Microphysical process

Stage	Process	Main Mechanism	Key Controls	Impact on Contrail
Emission & mixing	Exhaust dilution	Turbulent mixing and rapid cooling	Engine efficiency, ambient T, pressure	Determines supersaturation
Supersaturation	Water supersaturation	Schmidt–Appleman criterion	Ambient T, humidity	Enables contrail formation
Droplet Activation	Condensation	Heterogeneous condensation on soot/acid aerosols	Aerosol number, supersaturation	High droplet number density
Ice Nucleation	Freezing	Immersion freezing of soot-containing droplets	T < −38 °C, particle properties	Formation of ice crystals
Volatile Particle Formation	Homogeneous / ion-induced nucleation	Gas-to-particle conversion of H_2SO_4-H_2O or organics	Fuel sulfur content, soot concentration, ion emissions	Provides additional ice nuclei, especially when soot is low or sulfur high
Initial Growth	Deposition growth	Vapor diffusion onto ice	Ice supersaturation, T	Controls early crystal size
Persistence Check	Growth vs sublimation	Deposition (ISSR) or sublimation	RH with respect to ice	Short-lived or persistent
Crystal Evolution	Habit change & aggregation	Shape transitions, collisions	Supersaturation, turbulence	Alters optical properties
Sedimentation	Gravitational settling	Size- and shape-dependent fall speed	Crystal mass, air density	Vertical spreading, decay
Spreading & Aging	Contrail → cirrus	Wind shear and dilution	Wind gradients, stability	Long-lived contrail cirrus
Radiative Effect	Cloud–radiation interaction	SW scattering, LW trapping	Crystal size, optical depth	Net warming effect

2.3.1 Ice Nucleation

Governed by the Schmidt-Appleman criterion, contrail ice formation is a thermodynamic process that occurs when hot engine exhaust mixes with cold ambient air, leading to ice supersaturation. This supersaturation drives nucleation, which requires soot or metallic aerosols emitted by the engine to act as condensation nuclei. The process follows a condensation-freezing mechanism: water vapour first condenses onto the surfaces of these particles to form liquid droplets, which subsequently freeze as the plume rapidly cools.

The nucleation rate (J) can be described mathematically as:

$$J = AS_x^n N_s \tag{4}$$

where A is constant related to the nucleation efficiency, S_x is the supersaturation with respect to ice. while N_S is the number of soot particle or nuclei per unit volume, n is an exponent typically around 1 for ice nucleation (Spichtinger et al., 2023).

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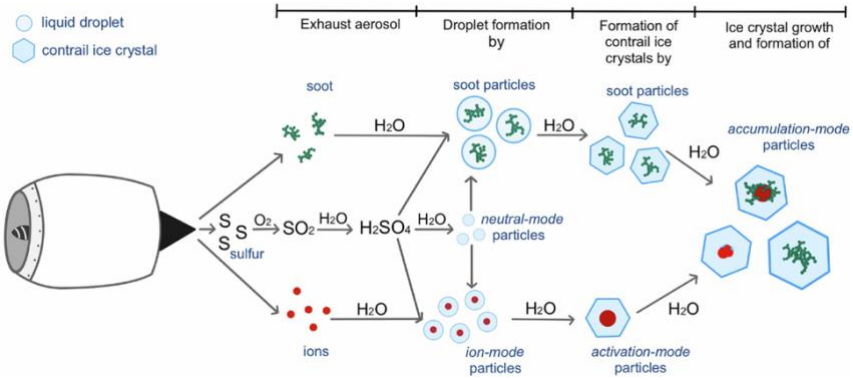

Figure 8 Formation of contrail ice particles for a fuel with medium to high sulfur content (Dischl et al., 2025)

Recent research has shown that this process is strongly modulated by fuel sulfur content, which influences nucleation in two distinct ways. Combustion converts fuel sulfur into SO_x and H_2SO_4, which condense onto soot particles. This liquid coating enhances the hygroscopicity and effective size of the soot, rendering it a more efficient nucleus (Comstock et al., 2008). Under high-sulfur conditions (e.g., >500 ppm), excess sulfuric acid and water vapour can generate new volatile aerosol particles via homogeneous nucleation or heterogeneous nucleation on chemiions (Yu and Turco, 1997, 1998). These volatile particles can grow sufficiently to act as additional cloud condensation nuclei, producing a bimodal distribution of ice crystals. The competition between soot and volatile liquid plume particles is a key dynamic; for current engine emission levels, soot typically controls ice formation (Kärcher and Yu, 2009).

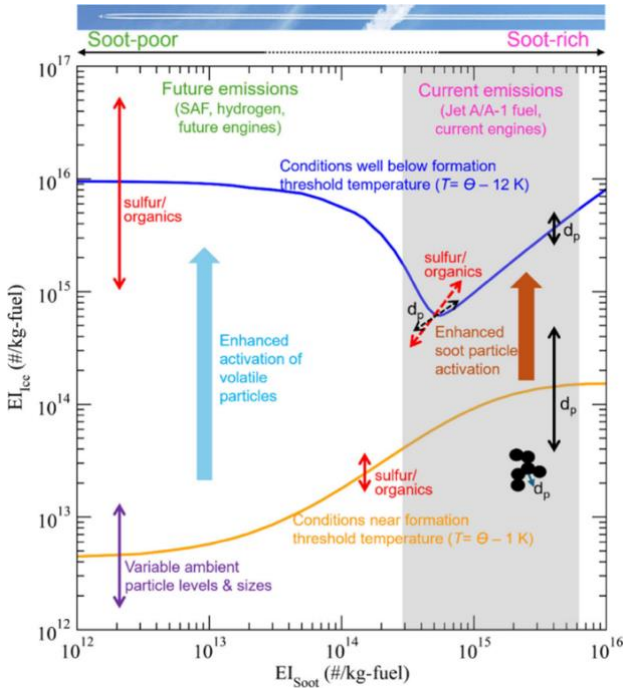

Figure 9 Nucleation of ice crystals in jet aircraft exhaust plumes (Yu et al., 2024a).

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However, a transition to sustainable aviation fuels, which often emit smaller primary soot particles, may increase supersaturation within the plume and render the contribution of volatile particles more significant (Yu et al., 2024a). As the exhaust plume mixes with ambient air (typically between 8–12 km), the density of soot determines the nucleation regime (Ponsonby et al., 2024). Abundant soot particles serve as effective nucleation sites, leading to efficient ice crystal formation where crystal counts can reach 10^{16} (Mahrt et al., 2018). In these conditions, ice crystal numbers correlate linearly with soot emissions. When soot is scarce, ice nucleation becomes less efficient and is driven partially by ultrafine aqueous particles, depending strongly on ambient temperature and aerosol levels, resulting in lower crystal concentrations of around 10^{12}. Nevertheless, high fuel sulfur content can offset the lack of soot: volatile particles may then cause ice crystal numbers to exceed the number of emitted soot particles(Yu et al., 2024a).

2.3.2 Crystal Growth

The growth of ice crystals in contrails begins after nucleation, when the ice crystals grow through the deposition of water vapor from the surrounding supersaturated air (Laaksonen and Malila, 2022). This growth is driven by the degree of supersaturation with respect to ice (S_x), where water vapor condenses onto the crystals, causing them to grow larger (Verma and Burkhardt, 2022). The rate of crystal growth depends on the supersaturation level and is typically expressed as:

$$G = K_1(S_X - 1) \tag{5}$$

where, G is the growth rate of ice crystals (m/s), K_1 is the deposition coefficient (ranging from 10−8 to 10−7 m/s depending on atmospheric conditions (Libbrecht and Rickerby, 2011).

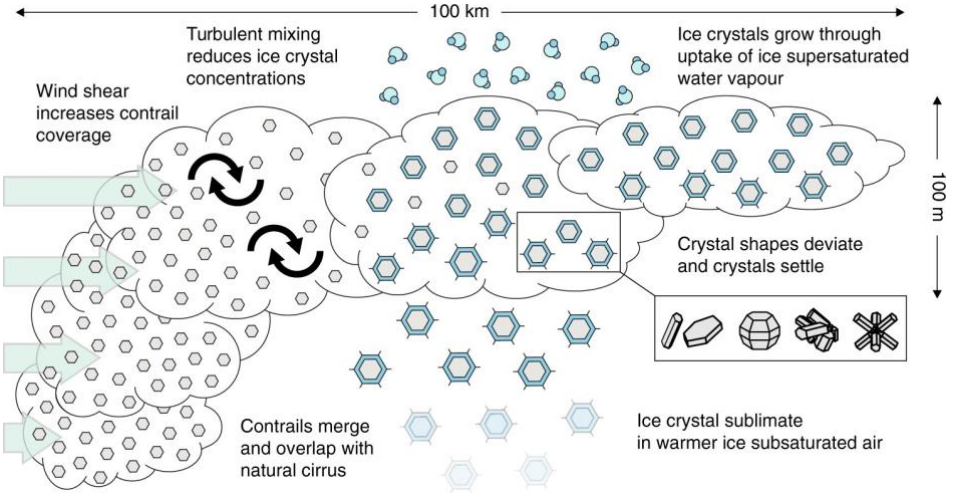

Figure 10 Factors affecting the development of aircraft-induced clouds (Karcher, 2018)

In conditions of high supersaturation, ice crystals grow rapidly, typically at a rate of 10–100 nm per second, and can reach sizes around 1000 nm (1 micron) in 1–10 seconds as shown in Figure 11 (Wex et al., 2015). As the crystals grow, they begin to deviate from simple hexagonal shapes, transitioning into more complex forms such as droxtals, columns, and bullet rosettes, depending on the level of supersaturation and the surrounding temperature (Wolf et al., 2023). The optical properties of the

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contrail are influenced by these growth processes, as larger ice crystals scatter more solar radiation and absorb more longwave radiation (Rubin-Zuzic et al., 2025). Wind shear plays a key role in increasing the lateral spread of the contrail, which enhances contrail coverage (Kärcher et al., 2009). This spread is due to horizontal movement, and as the contrail mixes with the ambient air, turbulent mixing occurs, which reduces the ice crystal concentrations (Lewellen, 2014). While mixing dilutes the contrail and reduces its density, it also causes it to spread, potentially merging with natural cirrus clouds, which increases the overall cloud coverage (Lewellen, 2014). Table 3 summarizes the four primary factors that dictate contrail crystal growth. It outlines how the soot emission index determines crystal size and density, how ambient temperature and humidity govern nucleation rates and long-term persistence, and how aircraft wake dynamics influence early crystal loss during the initial downwash.

Table 3 Factors effecting crystal growth

Factor	Influence on Growth
Soot Emission Index EI_{soot}	High soot = many nuclei = high competition = **smaller, more numerous crystals**. Low soot = fewer nuclei = **larger, fewer crystals**.
Ambient Temperature	Controls nucleation threshold and growth rate. Lower T = faster nucleation but slower diffusive growth dynamics.
Ambient Humidity RH_i	The fuel for growth. High RH_i leads to rapid growth and long persistence. RH_i < 100% causes immediate sublimation.
Aircraft Wake Dynamics	Determines the depth of the "downwash" and therefore how much adiabatic heating (and crystal loss) occurs in the first 2 minutes.

As the crystals grow larger, they experience sedimentation due to gravity. Larger crystals, typically those greater than 30 µm, fall at speeds greater than 100 m/h, which is described by the fall speed equation (Jensen et al., 2018).

$$v_f = \frac{2}{9}\frac{(\rho_c - \rho_f)gr^2}{\mu} \tag{6}$$

Where, v_f is all speed of a crystal , where ρ_c the density of the crystal while ρ_f is the density of the fluid surrounding.

2.3.3 Sedimentation

As the ice crystals in contrails grow, they eventually reach a size where they begin to fall out of the contrail, a process known as sedimentation (Singh et al., 2024). Sedimentation is driven by the gravitational pull acting on the ice crystals, causing them to fall toward the Earth's surface. The rate of sedimentation depends on the size of the ice crystals and the surrounding atmospheric conditions. Larger crystals, typically those greater than 30 µm, settle more quickly due to their increased mass. The fall speed of these crystals can be described using the following equation (Mahowald et al., 2014).

$$v_f = \frac{d^2}{\rho}\left(\frac{g}{\eta}\right) \tag{7}$$

where V_f is fall speed, d is the diameter of the ice crystal, p is the density of ice an η is dynamic viscosity of air. Smaller crystals, with diameters typically less than 30 µm, experience slower fall speeds due to their lower mass and larger surface area-to-volume ratio (Libbrecht, 2017). These smaller crystals may remain suspended in the atmosphere for a longer period

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unless the surrounding air is sufficiently supersaturated with water vapor to maintain their growth. The vertical wind shear in the atmosphere can influence the rate and direction of sedimentation (Podglajen et al., 2018). Wind shear, which refers to the variation in wind speed and direction at different altitudes, can alter the trajectory of the ice crystals (Corbosiero and Molinari, 2002). In turbulent conditions, vertical wind shear can cause the ice crystals to disperse more widely or remain aloft for a longer duration. If the wind shear is weak, the contrail ice crystals are more likely to remain concentrated, leading to a more persistent contrail. In areas with strong wind shear, the ice crystals may spread out or dissipate more quickly (Jensen et al., 2025). In some cases, the ice crystals in a contrail may grow large enough to fall out and contribute to precipitation at the Earth's surface (Singh et al., 2024). However, in most instances, especially in persistent contrails that evolve into contrail cirrus, the ice crystals remain suspended in the atmosphere for an extended period (Petzold et al., 2025). The sublimation of ice crystals in warmer, ice-sub-saturated air may also occur, further reducing their size. This process influences the persistence and spatial extent of contrail cirrus clouds, which can significantly affect their optical properties and radiative forcing (Bock and Burkhardt, 2016).

Sedimentation plays a key role in determining the lifetime, size distribution, and spatial spread of contrails and contrail cirrus, influencing their eventual dissipation or expansion and their impact on the climate. The larger crystals fall at higher speeds and can lead to the gradual dissipation of the contrail, while smaller crystals remain suspended, contributing to cloud persistence and long-term radiative effects (Kärcher and Corcos, 2025).

2.4 Evolution of Contrail Cirrus

The evolution of contrail cirrus begins with the formation of contrails when jet aircraft exhaust, consisting of water vapor and particulate matter, cools upon mixing with the ambient air at altitudes typically between 8–12 km (Schumann and Heymsfield, 2017).. This cooling leads to ice nucleation on exhaust particles, forming ice crystals of approximately 1000 nm in size as illustrated in Figure 11 (Kärcher et al., 2018). These crystals grow through sublimation and deposition, depending on the surrounding supersaturation levels of water vapor, with growth rates of about 10–100 nm per second under favorable conditions (Magee et al., 2014). Once the contrail forms, it may expand laterally due to wind shear, with horizontal spreading rates of 0.1–1 km per hour depending on atmospheric turbulence and vertical wind profiles (Unterstrasser, 2020).. However, the evolution does not stop with this initial spreading; the subsequent vortex phase, occurring during the first seconds to minutes after emission, plays a decisive role in dictating the contrail's vertical dispersion and ice crystal survival (Saulgeot et al., 2023). During this phase, a pair of counter-rotating wingtip vortices descends and wraps around the exhaust plume, carrying ice crystals several hundred meters below the flight altitude into warmer, drier air, which can cause substantial sublimation and reduce the ice crystal number by up to 75 % compared to the initial emission (Unterstrasser and Gierens, 2010b; Kleine et al., 2018). Large-eddy simulations show that when the ambient temperature exceeds 225 K or when the initial ice crystal concentration is very high, adiabatic heating within the vortex core can evaporate most of the ice before the vortices break up (Bier et al., 2024). After the vortex pair decays (≈30–60 s), the remaining ice crystals enter the diffusion phase, where turbulent mixing and wind shear broaden the contrail horizontally at rates that increase with vertical wind shear and decrease with

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atmospheric stability (Duda et al., 2004; Duda et al., 2001; Unterstrasser and Stephan, 2020). If the contrail encounters a persistent ice-supersaturated layer, it transitions into contrail cirrus—a diffuse, irregular cloud no longer recognisable as a linear trail—typically within 10–30 min (Heymsfield et al., 2010). During this transition, ice crystal effective diameters grow from 1–5 µm to 20–100 µm, while number concentrations drop from >100 cm^{-3} to <1 cm^{-3} (Magee et al., 2014).The transformation involves depositional growth, aggregation, and sometimes secondary ice nucleation, though the latter is rare at typical cruise altitudes (Unterstrasser and Gierens, 2010a). Under strong vertical wind shear, the contrail cirrus elongates into thin filaments; under weak shear, it forms a compact cloud patch (Singh et al., 2024). The cloud can persist for up to 12 hours if the ice-supersaturated layer remains continuous, but sedimentation of larger ice crystals (diameter >50 µm) falling at 0.1–0.5 m s^{-1} leads to sublimation in warmer, subsaturated layers below (Kärcher et al., 2009). In situ measurements reveal that ice water content in contrail cirrus can vary by two orders of magnitude over just a few kilometres, reflecting the patchy nature of supersaturated regions and turbulent mixing (Seelig et al., 2025). The complete evolution—from jet exit to eventual sublimation or sedimentation—is thus controlled by a cascade of factors: initial particle number and composition (engine type and fuel), vortex dynamics (aircraft weight, engine spacing, atmospheric stratification), ambient ice supersaturation (meteorology), and wind shear (governing spreading and dilution), each introducing uncertainties that make contrail evolution a central challenge in cloud microphysics(Kärcher et al., 2018).

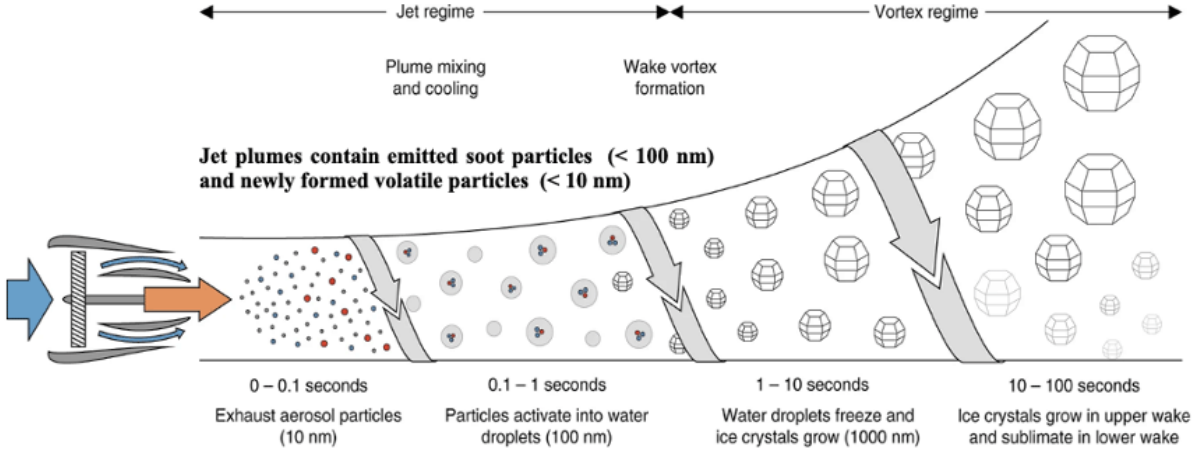

Figure 11 Processes influencing the contrail formation stage (Kärcher et al., 2018).

2.5 External Influences

Besides the inherent atmospheric conditions, various operational and external factors influence contrail formation which include aircraft and engine characteristic variations in engine design, emission profiles, and operational altitudes affect the temperature and composition of the exhaust plume (Epa, 2025). Modern engines with improved combustion efficiencies may alter the number and quality of ice nuclei produced (Korhonen et al., 2022). Environmental variability localized variations in atmospheric conditions such as temperature inversions and humidity fluctuations can lead to heterogeneous contrail behavior

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(Peter et al., 2025). This variability adds complexity to the prediction of contrail formation across different flight routes and conditions.

2.6 Implications for Predictive Modeling

Advancing contrail prediction requires modeling approaches that not only reproduce the initial formation conditions but also resolve the temporal and spatial evolution of contrail ice particles under realistic atmospheric variability (Kärcher and Corcos, 2025). Each class of model thermodynamic/analytical, microphysical, NWP-integrated, satellite-empirical, and AI-driven carries specific implications for predictive accuracy, interpretability, and operational utility.

Thermodynamic and analytical models, based on closed-form criteria like the Schmidt-Appleman formulation, remain valuable for rapid assessment of contrail formation thresholds. Their simplicity enables large-scale screening and climatological mapping, but their binary logic and lack of temporal dynamics restrict their use in forecasting persistence or radiative effects (Cannon et al., 2024).

Microphysical box models simulate particle-scale processes such as nucleation, coagulation, sublimation, and ice growth under controlled thermodynamic conditions (Pal et al., 2025). These models offer fine-scale insights into contrail microstructure, especially when parameterized with laboratory-derived aerosol properties. However, their reliance on high-resolution input data and limited scalability reduce their practical application in real-time systems (Bier et al., 2024).

NWP-integrated models bridge physical realism with spatial coverage, embedding contrail schemes into regional or global atmospheric simulations. Their ability to capture atmospheric heterogeneity including vertical motion, wind shear, and ambient humidity makes them well-suited for studying contrail coverage and radiative forcing. However, uncertainties in upper tropospheric humidity fields and the reliance on parameterizations for plume-scale processes introduce notable errors in persistence estimation (Randall et al., 2019).

Satellite-based empirical models contribute observational validation and climatological baselines, essential for calibrating physical and AI models. Their integration into machine learning workflows allows pattern recognition on a global scale. Still, their passive nature and limitations in cloud-type discrimination reduce their standalone forecasting potential.

AI-driven models particularly those incorporating ensemble reanalysis, satellite data, and flight trajectories enable spatial generalization and short-term forecasting (Riggi--Carrolo et al., 2023). PINNs and hybrid frameworks combine thermodynamic laws with learned patterns, improving robustness in data-sparse regions (Hashemi et al., 2025). These models are increasingly being explored for optimizing flight paths to reduce climate impact. Their main limitations include reduced interpretability, dependence on training data quality, and difficulties in propagating observational uncertainty through learned parameters.

Effective contrail prediction in future frameworks will likely rely on hybrid systems that leverage the physical grounding of first-principles models (Di Giusto et al., 2024), the scalability of NWP systems, the observational fidelity of satellites, and the adaptive intelligence of AI (U.Schumann, 1996). Model coupling strategies that support uncertainty quantification, high-

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resolution inputs, and multi-objective optimization (e.g., fuel burn vs. radiative forcing) are critical for deployment in operational decision-making environments.

3 Overview of Contrail Prediction Models

Contrail prediction models have evolved along five major methodological lines, reflecting increasing sophistication in both atmospheric science and computational modeling (Engberg et al., 2025). Thermodynamic and analytical models, grounded in the Schmidt–Appleman Criterion, are among the earliest approaches used for predicting contrail formation (U.Schumann, 1996). These models rely on threshold-based formulations involving ambient temperature, pressure, and aircraft exhaust characteristics to determine the likelihood of contrail initiation. While they are computationally efficient and valuable for rapid assessments, their simplified structure fails to account for spatial variability and offers limited insight into the dynamic evolution of contrails after formation.

Building on this foundation, microphysical box models provide a more detailed representation of contrail processes by simulating ice nucleation and growth within aircraft exhaust plumes (Ponsonby et al., 2025). These models incorporate aerosol microphysics and conservation equations as in Table 4. to capture particle behavior at high temporal and spatial resolution. Despite offering granular insights into the physical mechanisms of contrail development, they demand substantial computational power and high-resolution atmospheric data, which constrains their operational deployment.

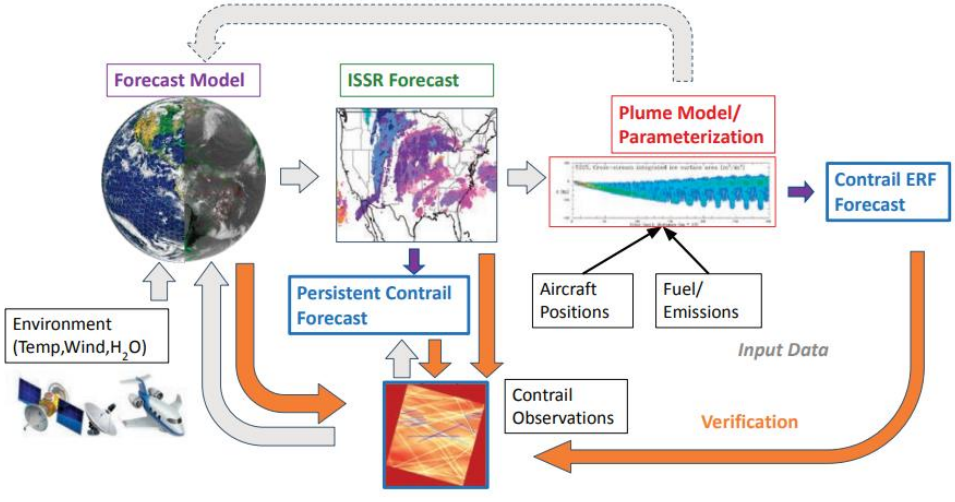

Figure 12 Schematic elements of a contrail forecasting and verification system (Timothy C. Lieuwen (Nae), 2025)

A further step in model complexity is represented by contrail schemes integrated into NWP systems. These models embed contrail-related processes within mesoscale or global circulation frameworks such as ECHAM4/5 or MM5 (P. Stier 2005). The advantage of this approach lies in its ability to provide spatially and temporally resolved forecasts under realistic meteorological conditions. However, model performance is sensitive to uncertainties in upper-tropospheric humidity fields and the simplifications inherent in parameterization schemes used to represent sub-grid scale processes (Peter et al., 2025).

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In parallel, satellite-empirical models have emerged as a valuable tool for identifying contrail occurrence and building climatological datasets (Jarry et al., 2026). These models utilize remote sensing data from instruments such as AVHRR (Yu et al., 2024b), MODIS (Duda et al., 2013), and CALIPSO (Singh et al., 2024), often applying pattern recognition algorithms and statistical inference methods to detect linear contrail features. Although these approaches are highly effective for retrospective analysis and model validation, they lack forward predictive capabilities and are prone to misclassification, particularly under conditions of complex cloud backgrounds or low sensor resolution (Yu et al., 2024b).

Table 4 Core Aerosol Microphysics and Conservation Equations in Contrail Modeling

S.No	Equation Type	Mathematical Expression	Eq.no	Ref
1	Mass Continuity (Air/Plume)	$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho u) = 0$	(8)	(Lewellen, 2014; R.Paoli, 2002)
2	Water Vapor Conservation	$\frac{Dq_v}{Dt} = S_{comb} - S_{cond} - S_{dep}$	(9)	(Schumann et al., 1996)
3	Energy (Thermodynamic) Conservation	$\rho c_p \frac{DT}{Dt} = -p(\nabla \cdot u) + L_{sub} \frac{Dq_i}{Dt} + Q_{rad}$	(10)	(Burkhardt and Kärcher, 2009; Chen and Gettelman, 2013)
4	Particle Number Conservation	$\frac{\partial n(r,t)}{\partial t} + \nabla \cdot (nu) = J_{nuc} + \frac{1}{r^2} \cdot \frac{\partial}{\partial r}(r^2 G(r) n) + S_{coag}$	(11)	(Jensen et al., 1998; Kärcher et al., 2018)
5	Condensational Growth of Ice Particles	$\frac{dr}{dt} = \frac{S_i - 1}{\frac{L_{sub}}{R_v T} \cdot \frac{L_{sub} D_v}{kT} + \frac{R_v T}{pD_v}}$	(12)	(Huebsch et al., 2014)
6	Ice Mass Mixing Ratio	$M_i = \int_0^\infty \frac{4}{3} \pi \rho_i r^3 n(r) dr$	(13)	(Chen and Gettelman, 2013; Burkhardt and Kärcher, 2009)
7	Optical Depth of Contrail	$\tau = \int \int_0^\infty Q_{ext}(r) \pi r^2 n(r) dr$	(14)	(Chen and Gettelman, 2013; Teoh et al., 2024a)

More recently, AI-based models have gained prominence in the field. Leveraging techniques such as random forests (Kameníková et al., 2024), deep learning (Lin et al., 2024), and PINNs (Raphael Alamu, 2025), these models utilize large, multi-source datasets to forecast contrail formation and evolution with high spatial and temporal fidelity. They frequently outperform traditional models in predictive accuracy and operational feasibility, yet they introduce challenges in model interpretability, robustness under unseen conditions, and dependence on the quality and representativeness of training data. In response to these limitations, hybrid approaches that integrate physical modeling with machine learning have been increasingly proposed. These methods aim to combine the generalizability and physical interpretability of mechanistic models with the data-driven precision of AI, marking a significant frontier in current contrail prediction research (Zebediah Engberg, 2025). Figure 12 illustrates the architecture of a modern contrail prediction system that incorporates environmental data (e.g., temperature, humidity, wind) sourced from satellite and reanalysis datasets. These inputs feed into weather forecast models, which in turn enable (ISSRs. The primary atmospheric condition supporting persistent contrail formation. This information,

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combined with aircraft position data and engine emissions profiles, is processed through plume evolution models or parameterizations to estimate contrail characteristics and their ERF. The final outputs are compared against satellite-based contrail observations for model verification and performance evaluation, forming a feedback loop for continuous improvement. Complementing this structure,

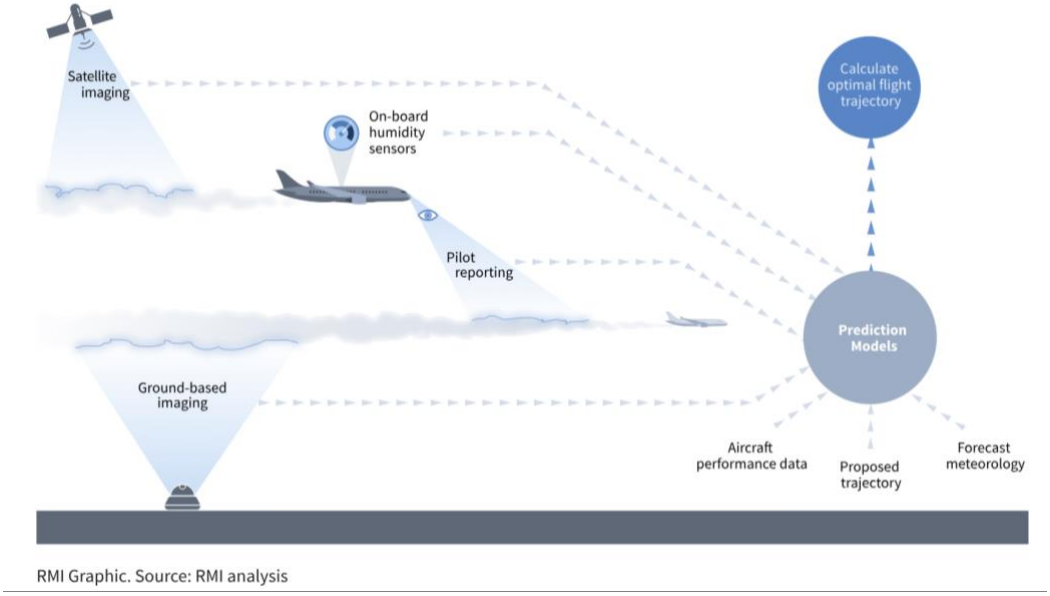

Figure 13 Different technique used for contrail prediction (Grewe et al., 2017)

Figure 13 highlights various observational techniques that support contrail detection and prediction model refinement. Satellite imaging, ground-based instruments, and on-board humidity sensors contribute to real-time or retrospective identification of contrail events. Additionally, pilot reports serve as qualitative sources of observational input. These heterogeneous data streams are fed into prediction models that also ingest aircraft performance data, forecast meteorology, and proposed flight trajectories. The integration of these elements allows for the calculation of optimized flight paths that minimize contrail formation potential. Such predictive and prescriptive capabilities are central to emerging climate mitigation strategies aimed at reducing aviation-induced radiative forcing by avoiding contrail-prone airspaces.

3.1 Thermodynamic and analytical models

Thermodynamic and analytical models form the conceptual foundation of contrail prediction science. These models provide a physically grounded and mathematically tractable framework for identifying the atmospheric conditions under which contrails are expected to form. At their core lies the Schmidt Criterion (U.Schumann, 1996), the first theoretical formulation to describe contrail formation based on plume mixing and the derivation of a critical temperature threshold (Ulrish Schuman, 1997). This foundational work did not consider atmospheric humidity, limiting its predictive capacity. Building on this, the SAC introduced fuel efficiency and ambient pressure dependencies, enabling graphical representations of contrail formation potential under simplified conditions. These models gained popularity for operational forecasting due to their simplicity. However, they

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retained core limitations such as assumption of a static atmosphere, homogeneous plume behavior, and a binary output (formation vs. no formation), without accounting for contrail persistence or radiative impacts. A concise summary of key models, their features, and limitations is provided in Table 5.

Table 5 List of Thermodynamic and Analytical Contrail Prediction Models

Model / Framework	Year / Developer	Key Features	Limitations	Ref
Schmidt Criterion	1941 / E. Schmidt	Established the mixing-line theory: exhaust and air mix isobarically to reach water saturation.	Lacked modern engine physics; did not account for pressure/altitude effects.	(Ernst 1941)
Appleman Criterion	1953 / H. Appleman	First graphical tool (Appleman Charts) used by pilots; introduced pressure/altitude as a variable.	Assumed fixed engine heat/water ratios; ignored modern propulsion efficiency η.	(N, 1953)
Revised SAC	1996 / U. Schumann	**The Current Standard.** Introduced η. Proved efficient engines (cooler exhaust) form contrails more easily.	Highly sensitive to humidity data errors in NWP models.	(U.Schumann, 1996)
Schrader's Algorithm	1997 / M. L. Schrader	The Gold Standard numerical solver used to find the tangent point (T_{crit}) on the vapor curve.	Iterative nature can be computationally slow for large-scale real-time simulations.	(Schrader, 1997)
Peters Method	1993 / Rich F. Coleman	A modified forecasting technique that used a different "Contrail Factor" for engine specific heat.	Criticized for errors in basic physics (requiring ice saturation instead of liquid for formation).	(Coleman, 1996)
Statistical Contrail Forecast Model	2001 / Jackson	Logistic regression relates contrail probability to radiosonde temperature/humidity	Small dataset (557 observations), limited geographically (New England) and seasonally	(Jackson, 2001)
Thermodynamic Persistence Diagnostic	2024 / Hofer - DLR	Validates thermodynamic contrail prediction using ERA5 vs. radiosondes	High false alarm rates due to unresolved humidity variability	(Hofer et al., 2024)
PCC/PCCC Diagnostic	2022 / Dischl - DLR	Diagnoses potential contrail/cirrus cover using ERA5 thermodynamic fields	Represents potential areas only , depends on reanalysis humidity accuracy	(Dischl et al., 2022)
SAC-based Route Analysis	2021 / Choi et al.	Applies SAC to sounding data for the Tokyo-Qingdao route to suggest altitude changes	Relies on sparse sounding data (low spatial resolution); limited to single route case study	(Choi et al., 2021)
Aerodynamic Model	2009 / K. Gierens et al.	Thermodynamic model for **Aerodynamic Contrails**; based on pressure drop over wings, not exhaust.	Only applies to specific high-humidity conditions; often invisible or very short-lived.	(Jansen and Heymsfield, 2015)

In the following decades, analytical plume mixing models extended SAC through adiabatic cooling and isobaric mixing formulations, offering improved thermodynamic realism (Khangaonkar et al., 2024). Despite these advancements, they remained limited by their exclusion of microphysical processes such as ice nucleation, growth, and sublimation necessary for studying contrail evolutions.

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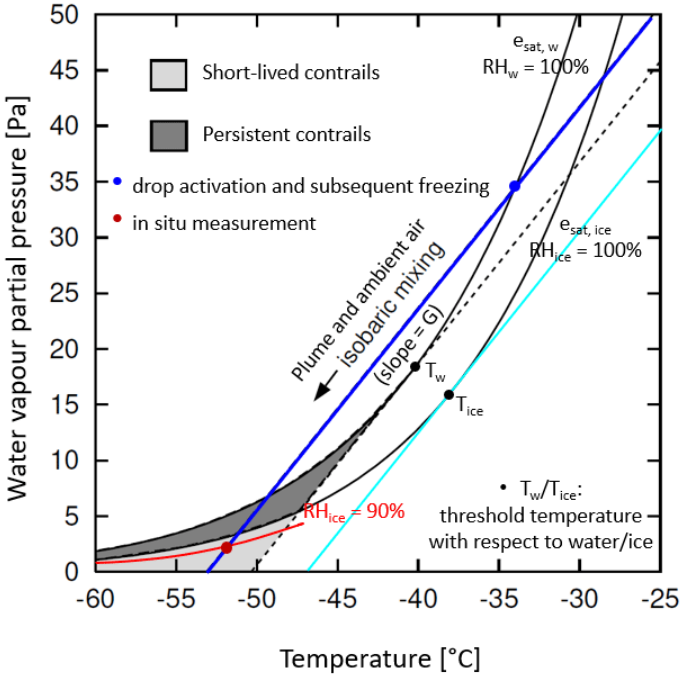

Figure 14 Schmidt-Appleman Criterion(Li et al., 2023b)

A significant step toward more dynamic modeling came with Lagrangian plume models (Anfossi et al., 2005) as shown in Figure 15. These models simulate the trajectory of aircraft exhaust as an evolving parcel, incorporating environmental factors such as wind shear, ambient humidity, and temperature gradients. By tracking plume dispersion over time, Lagrangian approaches capture spatial temporal variations and nucleation thresholds with greater fidelity. However, they are still constrained by computational complexity and a lack of full radiative feedback or comprehensive microphysics.

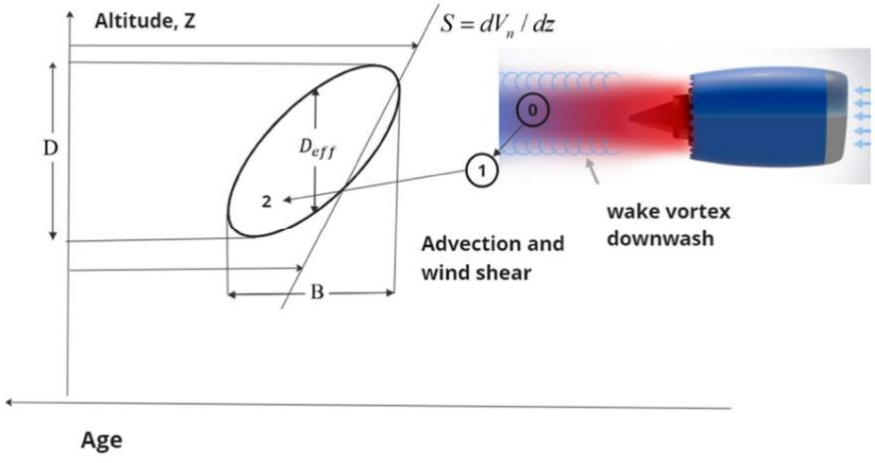

Figure 15 Lagrangian plume model

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Parallel to these advancements, operational agencies such as FAA (Brasseur et al., 2016), DLR (Raumfahrt, 2023a), and ICAO developed threshold-based formation maps (1990s–2020s), translating SAC outputs into global screening tools using standard atmospheric profiles. These maps continue to support large-scale climatological assessments but struggle with mesoscale resolution and real-time adaptability. With growing emphasis on sustainable aviation, modified SAC models emerged to incorporate the effects of SAFs. Schumann proposed adjustments based on altered soot and water vapor emission indices, reflecting new contrail behavior under SAF scenarios. These models, however, face uncertainties due to evolving fuel chemistry and combustion characteristics. Finally, SAC-based diagnostics have been embedded in NWP models by institutions like DLR, ECMWF, and NASA since the early 2000s. By integrating SAC into systems such as GFS, WRF, and CESM, these frameworks enable large-scale contrail prediction. However, they rely heavily on the accuracy of upper-tropospheric humidity data, and they function only as diagnostic modules not as standalone predictive models.

The statistical contrail forecast model was developed by Artie Jackson, Brian Newton, Doug Hahn, and Allan Bussey at the Air Force Research Laboratory (Hanscom AFB, Massachusetts) in 2001. Moving away from purely thermodynamic thresholds, the authors utilized logistic regression techniques to correlate specific atmospheric variables with the presence or absence of contrails. The model was trained on a dataset from the "Contrail Field Program," which consisted of 557 coincident aircraft observations and radiosonde measurements collected in eastern Massachusetts. By analyzing predictors such as temperature and relative humidity, the model achieved a correct diagnosis rate of 85%, significantly outperforming the standard Schrader (Appleman-based) algorithm, which had only 58% accuracy. The primary limitation of this model is that it was developed using a relatively small dataset collected only during September in New England, which may restrict its applicability to other geographic regions or seasons (Jackson et al., 2001).

A study was conducted by Sina Hofer,at the DLR and Forschungszentrum Jülich in 2024 about How well can persistent contrails be predicted? The authors assessed the accuracy of predicting persistent contrails by applying the standard SAC and Ice Supersaturation thresholds to ERA5 reanalysis data. The methodology involved comparing these diagnostic predictions against high-resolution radiosonde measurements (treated as ground truth) to quantify performance metrics like the Probability of Detection and False Alarm Rate. A primary limitation identified is that despite using state-of-the-art reanalysis ERA5, the prediction of persistent contrails remains challenging because current models cannot sufficiently resolve the small-scale spatial and temporal fluctuations of ice supersaturation, leading to significant uncertainties and high false alarm rates (Hofer et al., 2024).

ERA5-based PCC/PCCC thermodynamic Diagnostic study was conducted by Rebecca Dischl, Stefan Kaufmann at DLR and Johannes Gutenberg-Universität Mainz in 2022. The authors developed a methodology to quantify the Potential Contrail Cover (PCC) and Potential Contrail Cirrus Cover (PCCC) over Europe and the North Atlantic by analyzing 10 years of ERA5 reanalysis data. The methodology applies the thermodynamic SAC to determine regions of formation and uses varying thresholds of Relative Humidity over Ice to identify areas capable of supporting persistent contrail cirrus. By processing high-resolution meteorological fields, the study establishes a climatology of favorable contrail conditions. A primary limitation of

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this approach is that it calculates only the potential for coverage based on atmospheric state, ignoring actual air traffic density and the microphysical lifecycle (advection, spreading, aging) of the contrails, and is ultimately constrained by the accuracy of the moisture fields in the ERA5 reanalysis (Dischl et al., 2022).

The SAC Based route analysis study was conducted by Jun-Young Choi at the Korea National University of Transportation in 2021. The authors developed a basic contrail prediction model to support future aircraft certification for contrail reduction. The methodology involves applying the SAC to atmospheric sounding data (temperature, pressure, and humidity profiles) obtained from the University of Wyoming database. The study focused on the commercial flight route between Tokyo (Narita) and Qingdao, analyzing vertical profiles to identify contrail-forming layers. The results demonstrated that adjusting flight altitude—specifically descending or ascending by approximately 2,000 ft to 4,000 ft—could effectively move the aircraft out of ice-supersaturated regions, thereby preventing persistent contrail formation. A primary limitation is the reliance on radiosonde point data, which lacks the high spatial and temporal resolution of modern numerical weather prediction models necessary for global trajectory optimization (Choi et al., 2021).

Collectively, these thermodynamic and analytical models define the parameter space within which all subsequent modeling microphysical, satellite, and AI-based operates. While their simplifications limit predictive power, their physical interpretability and computational efficiency make them valuable for screening, sensitivity testing, and as benchmarks for advanced systems. As the field moves toward hybrid frameworks, there is growing interest in SAC-informed AI architectures, where machine learning systems are constrained by physical laws to improve generalizability and transparency. Thus, these models continue to serve as essential but increasingly complementary tools within the modern contrail modeling hierarchy.

3.2 Microphysical Box Models

Microphysical box models have evolved as a cornerstone of contrail modeling by providing detailed, process-level simulations of ice nucleation, growth, and optical development within the aircraft exhaust plume. These models go far beyond threshold-based frameworks like the SAC by resolving the fundamental microphysical processes that govern contrail life cycles. A representative list of these microphysical models, including their approaches and primary foci, is provided in **Error! Reference source not found.**. Their development reflects increasing sophistication in how we understand the formation, persistence, and climatic impacts of aircraft-induced clouds. Table 6 summarizes key microphysical contrail prediction models developed primarily at DLR, MIT, and other institutes. These models resolve ice nucleation, growth, optical properties, and lifecycle dynamics using Lagrangian, LES, or spectral bin approaches, enabling process-level simulations beyond simple threshold-based formation criteria.

The Freudenthaler Model (optical parameterization), established through the extensive lidar research of Volker Freudenthaler and colleagues serves as the definitive analytical framework for bridging the gap between microphysical simulation and remote sensing observations. Unlike dynamic growth models, this parameterization solves the inverse scattering problem by employing advanced geometric optics (ray-tracing) and T-matrix codes to correlate the physical morphology of ice crystals specifically their aspect ratios and surface roughness—with their optical signatures, most notably the linear depolarization

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ratio (δ). The model operates on the principle that non-spherical ice crystals scramble the polarization of incident laser light (unlike spherical liquid droplets which return linear depolarization ratio equal to zero, and it quantifies this effect by calculating the ratio of perpendicular to parallel backscatter intensity.

$$\delta = P_{\perp} / P_{\parallel} \quad (15)$$

A critical contribution of this work is the definition of the "Freudenthaler Limit" or characteristic curves, which demonstrate that fresh contrails, composed of small, highly irregular, and randomly oriented crystals (e.g., droxtals or complex aggregates), exhibit significantly higher depolarization values $\delta \sim 0.4$ - 0.5 compared to the lower values $\delta < 0.3$ typical of aged, oriented crystals in natural cirrus; this optical distinction provides the essential validation metric for checking if the size distributions and habit assumptions in microphysical box models are physically consistent with real-world lidar measurements from platforms like CALIPSO or EARLINET.

Table 6 List of Microphysical Contrail Prediction Models

Model	Developer Institute	Approach	Primary Focus	Ref
Freudenthaler Model	LMU Munich / DLR	Lidar/Optical Theory	Optical properties & Lidar validation	(Freudenthaler et al., 1996)
Plume Aerosol Model	DLR	Near-field chemistry	Particle activation & soot-ice link	(Kärcher et al., 1998)
Microphysical Activation Model	DLR / Imperial College of London	Lagrangian parcel	Quantifying the contribution of volatile particles to contrail ice crystal numbers	(Ponsonby et al., 2025)
Microphysical Pyrcel	DLR / NASA	0D/1D Lagrangian	Jet-phase ice nucleation (<1s)	(Kärcher et al., 2015; Ponsonby et al., 2025)
Spichtinger Model	JGU Mainz / DLR	Advanced Microphysics	Competition between soot & ambient ice	(Spichtinger and Gierens, 2009)
Cirrus Transition Model	DLR	Cloud Dynamics	Linear-to-circular shape transition	(S. Unterstrasser, 2009; Unterstrasser and Gierens, 2010b)
Lagrangian Dynamical-Microphysical Model	DLR / NWRA	Lagrangian	Investigating physical controls on contrail lifetime statistics	(Bier et al., 2022)
EULAG-LCM	DLR	LES / Lagrangian	Vortex-phase crystal loss & survival	(S. Unterstrasser, 2009)
CoCiP	DLR	Lagrangian / Bulk	Life-cycle prediction & flight routing	(Schumann, 2012)
CocipGrid	Breakthrough Energy	4D spatiotemporal grid	Generate pre-computed global maps of Contrail Energy Forcing	(Engberg et al., 2025)
LCM-LES	DLR	High-Res Particle Tracking	Turbulence-microphysics interaction	(Unterstrasser and Sölch, 2010)
APCEMM	MIT	2-D Spectral Bin	Detailed chemistry & vertical advection	(Fritz et al., 2020)
ACM	DLR	Lagrangian parcel	Contrail ice formation on volatile particles	(Voigt et al., 2026)

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Recent Advances have expanded these parameterizations to multi-wavelength applications (e.g., combining 355nm, 532nm, and 1064nm) to retrieve crystal size distributions from spaceborne platforms like CALIPSO or EarthCARE. Its primary Limitation is that it is non-predictive; it acts only as a translator between optical signals and physical shapes and cannot simulate the time-evolution, formation, or atmospheric life cycle of the contrail itself (Freudenthaler et al., 1996).

The Plume Aerosol Model (frequently associated with the foundational work of Kärcher, Fahey, and Yu) functions as the critical "initialization" module for contrail simulation, grounded in a Theoretical Foundation of Explicit Non-Equilibrium Microphysics that governs the chaotic interaction between exhaust particulates and condensing vapors in the first few seconds of plume evolution. This model captures the "Supersaturation Pulse," a violent transient event where the rapid mixing of hot exhaust with cold ambient air drives the saturation ratios of water and sulfuric acid to extreme levels, forcing them to condense onto hydrophobic soot particles. The model's Governing Equations couple the kinetic uptake rates of sulfuric acid (H_2SO_4) and water vapor with the thermodynamic Kelvin Effect, calculating the precise energy barrier r_{crit} that a wetted soot particle must overcome to "activate" into a freezing droplet; this determines the "Apparent Emission Index of Ice," or the fraction of soot that successfully becomes a contrail. Recent Advances (Yu et al., 2024a) have adapted these schemes to account for Sustainable Aviation Fuels (SAF) and hydrogen combustion, focusing on the formation of volatile particulate matter (vPM) droplets in the absence of soot. However, the model is strictly bound by its Limitations, specifically its validity only within the "jet regime" (0–100m behind the engine), as it neglects the macroscopic wake vortex dynamics and wind shear that dominate the subsequent lifecycle of the contrail (Kärcher et al., 1998).

The Microphysical Parcel model simulate two distinct models specifically for particle activation in contrails: the extended K15 model, designed for efficient integration into global simulations, and the modified pyrcel model, a high-fidelity benchmark adapted from cloud physics to simulate isobaric mixing. The extended K15 model builds upon the framework by (Kärcher et al., 2015) by introducing a third particle mode for vPM alongside soot and ambient particles and replacing analytical approximations with exact numerical solutions ; however, because it omits the Kelvin effect in droplet growth equations, it overestimates growth rates and systematically underpredicts peak plume supersaturations by 10%–70% compared to the benchmark. In contrast, the modified pyrcel model explicitly accounts for the Kelvin effect and homogeneous ice nucleation, as well as kinetic vapor feedbacks like the Wegener-Bergeron-Findeisen process where growing ice crystals deplete moisture from evaporating droplets which highlights the K15 model's inability to accurately simulate competition between particle types in soot-rich regimes. While both models utilize Köhler theory (Konopka and Vogelsberger, 1997) to describe water saturation , the authors caution that even the benchmark is limited by discretization errors of approximately ±10% and, more critically, by the highly uncertain nature of prescribed volatile particle properties, necessitating urgent in situ validation to improve accuracy (Ponsonby et al., 2025).

The Spichtinger Microphysics Scheme (developed by Peter Spichtinger and Klaus Gierens) is a specialized Double-Moment ice nucleation code, built on a Theoretical Foundation of Competitive Nucleation Physics that rigorously models the thermodynamic "tug-of-war" between Heterogeneous Nucleation (ice forming on soot) and Homogeneous Nucleation

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(spontaneous freezing of liquid droplets below -38 C). The model simulates the "Supersaturation Pulse" as a competitive event: as the air parcel cools, if soot-induced freezing occurs early and abundant crystals grow rapidly, they deplete the water vapor—this "depletion effect" suppresses the supersaturation peak below the critical threshold (S_{crit} ~1.5) required for homogeneous freezing. Its Governing Equations typically employ a two-moment approach, predicting both the Crystal Number Density (N_c) and Ice Mass Mixing Ratio (q_c), while utilizing the Koop parameterization to calculate the stochastic probability of liquid freezing based on water activity. Recent Advances have made this scheme central to Clean Aviation research (e.g., hydrogen combustion), as it allows researchers to predict whether removing soot will eliminate contrails or simply shift the formation mechanism to homogeneous freezing of background aerosols. However, its Limitations lie in its high computational cost and complexity; it is rarely used as a standalone predictor but rather as an embedded microphysics module within high-resolution LES codes like EULAG or COSMO (Spichtinger and Gierens, 2009).

The Cirrus Transition Model (often implemented via LES codes like *Méso-NH* or *EULAG*) addresses the critical Dispersion Phase of contrail evolution, grounded in a Theoretical Foundation of Shear-Driven Turbulence and Radiative Transfer that governs the transformation of a linear contrail into a diffuse cirrus cloud. Unlike early-stage models, it views the Supersaturation Pulse not as a formation event, but as a maintenance mechanism driven by localized updrafts; as the ice crystals absorb upwelling terrestrial infrared radiation, they heat the air inside the contrail, creating a "secondary circulation" or buoyant rise that generates fresh supersaturation and sustains crystal growth against sublimation. Its Governing Equations couple the Navier-Stokes equations for atmospheric turbulence with the Radiative Transfer Equation (RTE), explicitly solving for the Optical Depth (τ) evolution and the vertical spread caused by wind shear (dU/dz). Advances by (R.Paoli, 2002) and (Unterstrasser and Sölch, 2010) have incorporated synoptic-scale forcing"into these models, allowing researchers to simulate how contrails originating in the same corridor merge into contrail outbreaks or homogeneous cirrus decks over hours. However, the model faces significant Limitations due to its computational intensity; resolving the turbulent eddies across a domain large enough to capture dispersion (10–50 km) requires massive resources, restricting its use to fundamental process studies rather than operational global forecasting (S. Unterstrasser, 2009; Unterstrasser and Gierens, 2010b).

This Lagrangian Dynamical-Microphysical Model microphysical model was developed by Bernd Kärcher at DLR and Milena Corcos at NorthWest Research Associates (USA) in 2025. The authors devised a quasi-one-dimensional, Lagrangian dynamical-microphysical model to investigate the lifetime statistics of persistent contrails. The methodology involves initializing a contrail layer with a specific ice crystal size distribution and tracking the evolution of "Simulation Ice Particles" (SIPs) as they undergo entrainment, dilution, depositional growth, sublimation, and gravitational settling. A key innovation is the inclusion of stochastic vertical wind forcing to represent synoptic motions, mesoscale gravity waves, and microscale turbulence, which drives rapid fluctuations in supersaturation. A primary limitation of this model is the assumption of a vertically homogeneous layer, which neglects vertical variations in temperature and pressure, as well as the exclusion of wind shear effects and internal radiative heating, which could potentially prolong contrail lifetimes (Kärcher and Corcos, 2025).

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The Unterstrasser-Gierens Model (formally *EULAG-LCM*) represents the gold standard for the Vortex Phase of contrail evolution, distinguished by a Theoretical Foundation of LES coupled with Lagrangian Particle Tracking that resolves the complex 3D interaction between fluid dynamics and ice microphysics. Unlike simpler models that assume a static plume, this model simulates the Supersaturation Pulse as a spatially heterogeneous event that is often violently reversed; it captures the adiabatic compression caused by the aircraft's wake vortices dragging the exhaust plume downward (by 200–500m), which generates localized heating that crushes the relative humidity and sublimates a significant portion of the ice crystals. Its Governing Equations explicitly couple the anelastic or compressible Navier-Stokes equations (solved by the *EULAG* fluid driver) with the Lagrangian trajectory equations for millions of individual simulation particles (SIPs), calculating the mass evolution of each crystal based on its unique path through the turbulent, subsaturated vortex core. Recent Advances (e.g., Unterstrasser et al., 2020) have applied this framework to assess mitigation via formation flight (wake surfing) and the impact of reduced soot emissions on crystal survival rates, fundamentally quantifying the Survival Fraction, the finding that up to 50% of crystals are destroyed in the first 3 minutes. However, the model is bound by Limitations of scale such as the extreme computational cost of resolving fine-scale turbulence restricts its temporal scope to the first 5–10 minutes of flight, making it unsuitable for simulating the hours-long dispersion or global radiative forcing of contrails (S. Unterstrasser, 2009).

The CoCiP Model, developed by DLR (Schumann et al.), stands as the operational standard for global-scale assessment, built on a Theoretical Foundation of Lagrangian Particle Tracking coupled with a Gaussian Puff approximation that prioritizes computational efficiency over microphysical granularity. Unlike explicit parcel models that resolve the initial Supersaturation Pulse directly, CoCiP treats the formation event parametrically typically utilizing the SAC to trigger formation and relying on sub-grid parameterizations (e.g., Kärcher et al.) to determine the initial ice crystal number thereby bypassing the millisecond scale physics to focus on the macroscopic lifecycle. Its Governing Equations employ a bulk microphysics scheme that tracks only two prognostic variables per flight segment. Total Ice Water Content (IWC) and Crystal Number (N_{ice})—evolving them via simplified integral equations for depositional growth, sedimentation loss, and turbulent mixing, while the plume's spatial extent is defined by analytically updating the Gaussian width (σ_y) and depth (σ_z). Recent Advances (e.g., Teoh et al., 2024; Breakthrough Energy trials) have coupled CoCiP with real-time flight data and high-resolution reanalysis (ERA5) to validate contrail avoidance strategies and estimate ERF for entire aviation fleets. However, the model is fundamentally constrained by its Limitations, particularly the Gaussian assumption which enforces a simplified elliptical cross-section, rendering it incapable of simulating complex internal structures like fall streaks, bi-modal size distributions, or the asymmetric shearing effects critical for precise optical depth calculations (Schumann, 2012).

This CoCiP grid-based microphysical model was developed by Zebediah Engberg, and Roger Teoh, at Breakthrough Energy (USA) and Imperial College London (UK) in 2025. The authors extended the existing Lagrangian CoCiP framework into a grid-based forecasting tool (CocipGrid) to facilitate integration with air traffic management systems. The methodology involves initializing infinitesimal contrail segments at every point in a 4D spatiotemporal grid and simulating their full microphysical evolution including wake vortex dynamics, ice crystal survival, and radiative forcing using numerical weather

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prediction inputs (e.g., ECMWF/ERA5). To maintain computational efficiency for operational use, the model categorizes aircraft into simplified groups (e.g., N=3) based on mass and emissions. A primary limitation of this approach is that simplifying the diverse global fleet into fewer aircraft-engine groups introduces prediction errors (approximately 13% for N=3), and the model remains highly sensitive to biases in the forecast humidity fields (Engberg et al., 2025).

The Lagrangian Cloud Module (LCM-LES) (exemplified by codes like *EULAG-LCM* or the simpler LCM coupled to COSMO) represents the theoretical pinnacle of microphysical fidelity, established on a Theoretical Foundation of Hybrid Eulerian-Lagrangian Dynamics that discards the traditional grid-based approach for ice physics to instead track the individual histories of millions of SIPs. Unlike bulk models that average the Supersaturation Pulse across a grid cell, the LCM resolves the pulse as a unique, spatially heterogeneous experience for every crystal; it captures the stochastic nature of turbulent fluctuations where two nearby particles might experience completely different growth histories due to sub-grid eddies. Its Governing Equations are bifurcated: the 3D wind field is solved via the Eulerian Navier-Stokes equations, while the ice phase is governed by Lagrangian trajectory equations and explicit mass growth equations calculated along these trajectories, effectively eliminating the numerical diffusion errors that blur cloud edges in grid models.

$$\frac{d\vec{x}}{dt} = \vec{u} \tag{16}$$

Recent Advances (e.g., Sölch & Kärcher, Unterstrasser) have leveraged this method to resolve the entrainment interface, the exact boundary where dry air mixes into the plume providing the first detailed quantification of how turbulence spectrums influence crystal size distribution broadening and optical depth. However, this precision comes with severe Limitations in computational scalability; the memory and processing power required to track millions of SIPs restrict its application to fundamental process studies on supercomputers, rendering it infeasible for real-time forecasting or global climate simulations (Unterstrasser and Sölch, 2010).

The APCEMM (Aircraft Plume Chemistry, Emissions, and Microphysics Model), developed by MIT (Fritz et al., 2020), occupies a critical intermediate fidelity niche, distinguished by its Theoretical Foundation of 2-D Spectral Bin Microphysics that bridges the gap between simple box models and expensive LES. Unlike 0-D models that homogenize the plume, APCEMM simulates a cross-sectional slice perpendicular to the flight path, allowing it to resolve the "Supersaturation Pulse" spatially; it captures how the pulse decays faster at the plume edges due to entrainment while persisting in the core, a gradient essential for accurate crystal survival rates. Its Governing Equations explicitly solve the Smoluchowski Coagulation Equation for roughly 40 discrete size bins (spanning from nanometers to 50+ microns), coupling this microphysics with a detailed chemical solver that tracks the heterogeneous uptake of species like HNO_3 and SO_2 on ice surfaces. Recent Advances have leveraged this structure to simulate precipitation plumes (fall-streaks) where large crystals settle out of the contrail core providing the first computationally efficient method to quantify how these falling crystals dehydrate the upper troposphere and alter local cirrus properties. However, the model retains specific Limitations tied to its dimensionality; by assuming the

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atmosphere is uniform along the flight track (the infinite cylinder assumption), it cannot account for variations in weather conditions, wind shear changes, or vortex instabilities that occur along the length of a single flight segment (Fritz et al., 2020). Microphysical Activation Model study was published by Joel Ponsonby, Roger Teoh, Bernd Kärcher, and Marc E. J. Stettler at Imperial College London and DLR Oberpfaffenhofen in 2025. The authors updated a microphysical model to challenge the prevailing assumption in global simulations that only nvPM and ambient aerosols act as condensation nuclei for contrails. The methodology involved extending the governing equations of particle activation to explicitly include vPM—ultrafine particles formed from fuel sulfur and organic emissions—and benchmarking this updated framework against more complex detailed microphysical simulations. The study demonstrated that vPM can contribute significantly to ice crystal numbers, particularly in low-soot emission scenarios (e.g., using Sustainable Aviation Fuels), thereby altering the optical properties and radiative forcing of the resulting contrails. A primary limitation is the increased complexity required to model the formation and growth of these volatile modes, which depends heavily on accurate characterization of fuel sulfur content and organic emission indices (Ponsonby et al., 2025).

The ACM (Aerosol and Contrail Microphysics) model, originally developed by Fangqun Yu and Richard Turco in the late 1990s (Yu and Turco, 1997, 1998) and substantially extended for the (Voigt et al., 2026) study, occupies a critical niche as a Lagrangian parcel model that explicitly simulates the formation and activation of volatile particles in aircraft exhaust plumes, particularly in the low-soot regime characteristic of modern lean-burn engines. Unlike models that assume ice nucleation occurs solely on emitted soot particles, ACM's theoretical foundation includes ion-mediated nucleation, binary homogeneous nucleation of H_2SO_4-H_2O, condensation of low-volatility organic vapours from unburned fuel, and nucleation of lubrication oil vapours vented into the hot core flow. The governing equations track the evolution of particle number and size distributions across multiple modes (soot, volatile sulfate, organics, and oil droplets) coupled to plume dilution, adiabatic cooling, and ice nucleation via immersion freezing or homogeneous freezing of deliquesced volatile particles. A key recent advance, as reported in (Voigt et al., 2026), was the ability of ACM to reproduce measured contrail ice number emission indices ($\approx 10^{15}$ kg^{-1}) behind an A321 neo with LEAP-1A lean-burn engines, despite soot emissions being three orders of magnitude lower ($\approx 10^{12}$ kg^{-1}). The model demonstrated that volatile particles formed from fuel sulfur (192 ppm) dominate ice nucleation in the low-soot regime, and that for ultralow-sulfur fuels (2–3 ppm), lubrication oil and organic vapours become the primary ice-nucleating sources. However, the model retains limitations tied to its zero-dimensional nature: it assumes homogeneous dilution of the plume within a Lagrangian parcel, does not resolve spatial gradients such as vortex dynamics or entrainment at plume edges, and its predictions depend heavily on uncertain emission indices for organic compounds and lubrication oil vapours, which are not routinely measured in flight campaigns (Voigt et al., 2026).

3.3 NWP Integrated models

NWP integrated models form an essential category within the broader hierarchy of contrail prediction systems. These models embed thermodynamic criteria and simplified microphysical processes into global and regional weather forecasting

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frameworks. Unlike box or Lagrangian models which offer high-resolution but spatially limited simulations, NWP-based systems operate over continental to global domains and exploit real-time meteorological inputs, enabling spatially and temporally consistent evaluations of contrail formation across diverse atmospheric conditions. Table 7 provides a representative list of these NWP-integrated systems, ranging from global climate models (ECHAM5, CAM5, UKMO UM) to operational forecast models (ECMWF IFS, GFS, ICON) and commercial flight-planning tools (AVTECH, Flightkeys). Their strengths lie in scalability, data assimilation capabilities, and compatibility with long-term climate modeling and operational forecasting systems. Table 7 summarizes NWP-integrated contrail prediction models developed at DLR, ECMWF, NOAA, NCAR, and other institutions. These systems embed SAC diagnostics or simplified microphysics into global/regional weather models to enable large-scale contrail forecasting, climate impact assessment, and operational avoidance trials. The ECHAM5-CCMod (ECHAM5-Cirrus), developed at DLR in collaboration with the Max Planck Institute for Meteorology (MPI-M) (notably by (Burkhardt and Kärcher, 2011), represents a paradigm shift in aviation climate modeling as the first GCM to treat Contrail Cirrus not as a static parameter but as a fully prognostic cloud class distinct from natural cirrus. Methodologically, the model modifies the standard ECHAM5 two-moment microphysics scheme (originally from MPI-M) to introduce a new prognostic variable—the contrail cirrus fractional coverage (b_{cc}) which allows the model to simulate the complete lifecycle of aviation-induced cloudiness, from initial linear formation via the SAC to the shear-driven spreading into aged cirrus decks. Technically, it solves specific transport equations for contrail ice mass and crystal number density, enabling the simulated clouds to compete with natural cirrus for water vapor and evolve independently based on local thermodynamic conditions. This approach led to the critical scientific advancement of quantifying that the global net radiative forcing of aged contrail cirrus (approx. 50 mW/m²) is roughly nine times larger than that of line-shaped contrails alone, fundamentally redefining the scope of aviation's climate impact. However, the model is constrained by significant limitations, primarily its coarse global resolution (typically T42 or T63, which necessitates heavy reliance on sub-grid parameterizations to estimate the initial plume expansion and makes it incapable of resolving individual flight tracks or regional corridor dynamics with high precision (Burkhardt and Kärcher, 2011).

The CAM5 / CESM (+ Contrail Module), primarily developed by researchers at the National Center for Atmospheric Research (NCAR) (notably (Chen and Gettelman, 2013), with contributions from MIT), approaches contrail simulation through a distinct Methodology of Source Term Injection rather than creating a separate cloud class. Unlike the ECHAM approach which isolates contrail ice, this model directly modifies the standard Morrison-Gettelman two-moment microphysics scheme to inject specific bursts of ice crystals into the grid cells where aircraft fly, based on global emissions datasets and thermodynamic criteria. Technically, this allows the model to rigorously simulate the "Indirect Effect"—the complex aerosol-cloud interaction where the high number density of contrail ice crystals (N_{ice}) competes with natural cirrus clouds for the available supersaturated water vapor. A key scientific advancement from this framework was the revelation of a dehydration effect, where persistent contrails effectively starve nearby natural clouds of moisture, potentially reducing their optical thickness—a negative feedback loop that simpler models often miss. However, the model faces inherent limitations related to its grid scale; because it injects

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the ice into large grid boxes, it artificially smears narrow contrails instantly across a vast area, leading to potential inaccuracies in calculating the local optical depth and radiative forcing of young, line-shaped plumes (Chen and Gettelman, 2013).

Table 7 List of NWP-Integrated Contrail Prediction Models

Model System	Developer Institute	Methodology	Primary Role	Ref
ECHAM5-CCMod	DLR / MPI-M	Prognostic Cloud Class	Global Climate Impact	(Burkhardt and Kärcher, 2011)
CAM5 / CESM	NCAR / MIT	Source Term Injection	Aerosol-Cloud Interaction	(Chen and Gettelman, 2013)
UKMO UM	UK Met Office	Contrail Sheet Parameterization	Radiative Forcing Efficacy	(Rap et al., 2010)
ECMWF IFS	ECMWF	Operational SAC Diagnostic	Real-time Avoidance Trials	(Gruber et al., 2018; Forbes et al., 2011)
ICON-ART	DWD / KIT / MPI-M	Icosahedral-Nonhydrostatic	Global Chemistry & Soot Tracking	(Gruber et al., 2018; Rieger et al., 2015)
ICON-LEM	MPI-M / DWD	Large-Eddy Simulation	High-Res Process Physics	(Verma and Burkhardt, 2022)
ICON-WAWFOR	DLR	Statistical Diagnostic Modeling	Probabilistic Contrail Forecasting	(Von Bonhorst et al., 2025)
WRF-Chem	NCAR / NOAA	Regional High-Res Eulerian	Local Corridor Dynamics	(S. Gruber, 2015)
NASA GISS	NASA GISS	Empirical/GCM Parameterization	US Climate Policy	(Hansen et al., 2005)
ECHAM4	DLR / MPI-M	Diagnostic Parameterization	Historic Climate Baseline	(M. Ponater, 1996)
Process- Based GCM	DLR	Prognostic simulation of contrail life cycle, spreading, and microphysics	Sensitive to optical depth thresholds and air traffic inventory quality	(Burkhardt and Kärcher, 2009)
GFS + SAC	NCEP (NOAA)	Global Diagnostic Post-process	Global Flight Planning	(Yoo and Li, 2012)
MM5	PSU / NCAR	Mesoscale Diagnostic	Regional Outbreak Studies	(Martin Stuffer, 2004; Carleton et al., 2008)
RUC-based	NASA	Estimates coverage (2005) and predicts probabilistic occurrence (2009	diagnose and estimate regional persistent contrail coverage	(Duda et al., 2005; Duda and Minnis, 2009)
AVTECH Contrail Prediction	AVTECH/ KTH	Integrates SAC with real-time weather forecasts into a vertical trajectory optimize	operational tool for commercial airlines to minimize persistent contrails	(Kundgol et al., 2025)
Flightkeys 5D Contrail	Flightkeys / Breakthrough Energy	Integrates CoCiP and ECMWF into the Flightkeys 5D flight planning system	pre-tactical contrail avoidance	(Martin Frias et al., 2024)
OpenSky Contrail Estimation	TU Delft	SAC applied to interpolated ERA5 data	Rapid, scalable diagnostic tool for flight trajectory analysis	(Sun and Roosenbrand, 2023)
Fu-Liou RTM coupled with ECMWF and AERO2k data	University of Reading (UK)	Radiative transfer calculations applied to NWP-derived contrail maps	Assessing the climate impact of changing flight cruise altitude	(Rädel and Shine, 2008)
CoAtSaC	Google Research	Temporal clustering of advected tracks using RANSAC optimization	Automating the attribution of satellite-observed contrails to the specific flights that formed them	(Sarna et al., 2025)

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The UKMO UM (Unified Model) with its contrail parameterization, developed primarily by the UK Met Office in collaboration with the University of Leeds (notably (Rap et al., 2010), stands as a distinct Aerosol Climate approach to aviation simulation. Methodologically, rather than simply injecting ice water like CESM, the model integrates a specialized "contrail sheet" parameterization directly into its Edwards Slingo radiation scheme; it diagnoses the potential coverage of line-shaped contrails based on the Schmidt-Appleman Criterion and traffic density, but crucially treats this coverage as a separate cloud layer for radiative transfer calculations to avoid the overlap error common in other GCMs. Technically, the model is often coupled with the UKCA (UK Chemistry and Aerosols) module, enabling it to rigorously simulate the microphysical link between aviation soot emissions (number density) and the optical depth of the resulting ice crystals, using specific scaling factors to account for the smaller crystal size of contrails compared to natural cirrus. A key scientific advancement from this system was its robust quantification of the efficacy of contrail forcing demonstrating that a Watt of forcing from contrails produces a different surface temperature response than a Watt of forcing from CO_2, largely due to the specific vertical profile of heating. However, it is subject to limitations, particularly its reliance on diagnostic traffic inventories which are often static time-slices, and the computational expense of the full UKCA chemistry package, which restricts the model's ability to run high-resolution, multi-decadal simulations for rapid policy assessment (Rap et al., 2010).

The ECMWF IFS (Integrated Forecasting System), developed and operated by the ECMWF (Reading, UK / Bonn, Germany), stands as the undisputed global standard for Operational Contrail Forecasting, serving as the meteorological engine behind recent high-profile avoidance trials (e.g., with Breakthrough Energy and Google). Methodologically, the model distinguishes itself by its superior handling of ISSR within its prognostic cloud scheme (originally based on Tiedtke/Tompkins); unlike lower-fidelity models that immediately convert supersaturation into natural cirrus, the IFS is tuned to sustain high humidity levels in clear air, enabling it to accurately map the Potential Contrail Cirrus Coverage that aircraft will encounter. Technically, the operational implementation employs a diagnostic post-processing (or semi-prognostic) approach that applies the SAC to high-resolution thermodynamic fields (HRES, currently ~9 km resolution), calculating the specific critical temperature at every flight level to determine if exhaust plumes will persist. A major scientific advancement has been the recent integration of these persistent contrail maps into real-time flight planning software, demonstrating the first viable climatological to operational bridge for contrail mitigation. However, it faces limitations typical of operational constraints; the standard forecast output is often diagnostic (a snapshot of potential formation) rather than fully prognostic (tracking the drift and aging of the contrail over hours), and its bulk microphysics cannot resolve the specific optical depth variations caused by different engine soot profiles without external parameterizations (Forbes et al., 2011).

The ICON-ART (ICOsahedral Nonhydrostatic model with Aerosols and Reactive Trace gases), developed through a partnership between the German Weather Service (DWD), the MPI-M, and the Karlsruhe Institute of Technology (KIT), represents the next generation of unified atmospheric modeling for both weather and climate. Methodologically, the system replaces the traditional latitude-longitude grid with an icosahedral-triangular Arakawa-C grid, which provides exact local mass conservation and eliminates the "pole problem" inherent in older global models. Technically, ICON-ART integrates the ART

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module to resolve the lifecycle of aerosols (including aviation soot) and their chemical interactions online, utilizing a state of the art two moment cloud ice microphysics scheme that explicitly predicts both ice mass and crystal number density to skillfully resolve ISSRs. A significant scientific advancement of this model is its two-way coupling capability, where the model can exchange variables with the CoCiP to account for direct contrail-weather interactions, such as the local warming of ambient air and the butterfly effect where contrail-induced disturbances alter subsequent weather patterns. However, it faces limitations related to computational complexity; the high numerical cost of its non-hydrostatic core and detailed aerosol-chemistry modules often requires a trade-off between the length of the simulation and the horizontal resolution, and like other NWP systems, it still relies on subgrid scale parameterizations for processes like homogeneous ice nucleation which can be sensitive to unresolved vertical velocity fluctuations (Rap et al., 2010).

The ICON-LEM (ICOsahedral Non-hydrostatic Large-Eddy Model), developed by MPI-M and the DWD (with specialized contrail implementations by Verma and Burkhardt, 2022), serves as a high-fidelity cloud-resolving atmospheric model. Unlike coarse NWP models, it is built on a Theoretical Foundation of Resolved Large-Eddy Dynamics, where the most energy-containing turbulent motions are explicitly calculated rather than parameterized. Methodologically, the system solves the non-hydrostatic equations on a triangular icosahedral grid, typically at horizontal resolutions ranging from 156 m to 625 m. This allows for the Scientific Advancement of simulating contrails within complex, heterogeneous environments, such as pre-existing natural cirrus clouds. Technically, the model implements a specialized contrail parameterization that accounts for ice nucleation in the jet phase and ice crystal survival during the vortex phase, while uniquely considering how "contrail-on-cirrus" interactions (e.g., the sublimation of natural ice in the engine and competition for water vapor) alter the resulting cloud's optical depth. However, its Limitations are centered on its massive computational demand; while it can be run in "weather forecasting mode" for specific regional domains (e.g., over Germany), it is currently too resource-intensive to serve as a global operational forecast tool or for multi-year climate assessments (Verma and Burkhardt, 2022).

The ICON-WAWFOR forecast evaluation study was conducted by Georg von Bonhorst, at DLR in 2025. The authors investigated the reliability of contrail predictions under realistic operational conditions using the WAWFOR (World Aviation Weather Forecast) dataset produced by the global ICON numerical weather prediction model. The methodology compared two different cloud microphysics schemes—a standard one-moment scheme and a more complex two-moment scheme—to assess their ability to forecast ISSR. By validating against high-resolution radiosonde data, the study demonstrated that even advanced NWP models suffer from the Double Penalty problem, where predicted features are spatially or temporally shifted from reality. Consequently, the authors conclude that precise, trajectory-based contrail avoidance is currently unrealistic due to these non-linear forecast errors; instead, avoidance strategies should focus on broader zones of potential contrail formation (Von Bonhorst et al., 2025).

The WRF-Chem (Weather Research and Forecasting with Chemistry) model, developed by a broad consortium led by the National Center for Atmospheric Research (NCAR) and the National Oceanic and Atmospheric Administration (NOAA) (with specific contrail implementations by researchers such as Gruber et al. and Unterstrasser), serves as the premier tool for

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Regional Scale contrail assessment. Methodologically, unlike global models that must parameterize the entire world at coarse resolution, WRF-Chem employs a high-resolution Eulerian grid (typically 1–5 km) to simulate specific high-traffic flight corridors (e.g., Central Europe or the North Atlantic) with convection permitting fidelity. Technically, the model integrates contrail physics by modifying advanced microphysics schemes such as the Morrison 2 moment scheme to include a prognostic source term for aircraft ice; when a flight track intersects a grid cell satisfying the SAC, the model injects a precise mass and number of ice crystals directly into the cloud variables, allowing them to interact online with local mesoscale dynamics like gravity waves and frontal systems. A key scientific advancement of this framework is its ability to validate satellite observations directly because it resolves the exact weather patterns at the time of flight, it allows researchers to perform point to point comparisons with Lidar or camera data from campaigns like *ML-CIRRUS*, which is impossible with statistical global models. However, it is constrained by limitations of scope; as a limited-area model, it relies on external global models for its lateral boundary conditions and cannot capture the global climate feedback loops or the long-range inter-hemispheric transport of aviation pollutants (S. Gruber, 2015).

The NASA GISS ModelE, developed by the NASA Goddard Institute for Space Studies (GISS) in New York, represents a cornerstone of U.S. climate research, used extensively in IPCC assessments to quantify the global radiative forcing of aviation. Methodologically, the model utilizes an Empirical Statistical Parameterization that differs from European prognostic approaches; it defines the potential for contrail formation and persistence using the SAC but scales the resulting coverage and optical depth based on high-resolution satellite correlations (e.g., from MODIS and CALIPSO data). Technically, the model represents contrails as a diagnostic cloud fraction within its grid boxes , where the ice water content and effective radius are constrained by local temperature and humidity fields, allowing the contrails to participate in the model's full radiative transfer calculations. A major scientific advancement of ModelE has been its focus on Climate Sensitivity; by performing perturbed-parameter ensemble runs, NASA researchers (notably Rind, Minnis, and Diedenhoven) have been able to isolate the hemispheric asymmetry of contrail warming, showing that the concentrated flight corridors of the Northern Hemisphere drive a disproportionate surface temperature response compared to uniform greenhouse gas forcing. However, the model faces inherent limitations, primarily its reliance on prescribed traffic inventories and its diagnostic nature, which means it cannot fully simulate the dynamic "spreading" of a single contrail over multiple hours into a sprawling cirrus deck contrail cirrus without simplified statistical scaling factors (Hansen et al., 2005).

The ECHAM4(+Contrail Parameterization), developed at the DLR (notably by Ponater et al., 2002) in conjunction with the MPI-M, represents the foundational era of global contrail climate modeling. Methodologically, the model treats contrails through a diagnostic parameterization rather than a separate cloud class; it calculates potential contrail coverage based on the SAC and local humidity, then scales this by a time-dependent air traffic density inventory to estimate actual coverage. Technically, the model introduces a sub-grid scale modification to the cloudiness parameterization, allowing a grid box to contain both natural clouds and a linear contrail fraction, which influences the radiative transfer code. A major scientific advancement provided by this system was the first comprehensive global estimate of Radiative Forcing (RF) from line-shaped

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contrails, providing the baseline figure of approx. 3.5 to 10 mW/m^2 that served as the primary reference for the IPCC Special Report on Aviation. However, the model is subject to significant limitations, specifically its memoryless nature; because it lacks a prognostic variable for contrails, it cannot simulate the advection, spreading, or aging of contrails into cirrus clouds effectively ignoring the vast majority of aviation's warming impact that occurs after the initial linear phase (M. Ponater, 1996). The Process-based Contrail Cirrus Parameterization (ECHAM4 GCM) was developed by Ulrike Burkhardt and Bernd Kärcher at the DLR in 2009. The authors developed a novel parameterization scheme within the ECHAM4 general circulation model that introduces contrail cirrus as a separate, prognostic cloud class. The methodology simulates the entire life cycle of contrails, initializing them based on thermodynamic formation criteria and calculating their evolution as they spread due to wind shear and grow within fractional ice-supersaturated areas. This approach allows the model to capture the transition from young line-shaped contrails to aged contrail cirrus and their interaction with the global water budget. A key limitation of this model is that the global distribution of young contrail coverage tends to be smoothed out due to grid-scale transport, and the accuracy is fundamentally limited by the host model's ability to represent upper-tropospheric humidity and sub-grid scale supersaturation (Burkhardt and Kärcher, 2009).

The GFS+SAC (Global Forecast System+SAC) represents the primary operational diagnostic tool for the aviation industry, developed and maintained by the National Centers for Environmental Prediction (NCEP) under the NOAA. Methodologically, the system does not function as a standalone microphysical model but rather as a post processing algorithm that applies the classic thermodynamic mixing equations of the SAC to the 3D output fields (temperature, pressure, and relative humidity) of the GFS weather model. Technically, the model evaluates the mixing line between hot, moist engine exhaust and cold ambient air to determine if liquid saturation is reached (the formation condition) and subsequently checks if the environment is supersaturated with respect to ice to predict contrail persistence. A significant scientific advancement of this system has been its evolution from a course 1.0° grid to the current high-resolution 0.25° (approx. 28 km) spectral grid, coupled with ensemble forecasting techniques (GEFS) that allow airlines to calculate Contrail Frequency Indices (CFI) and assign a probability of persistence for specific flight routes. However, the system faces critical limitations, primarily the persistent humidity bias found in most global NWP models; the GFS often struggles to accurately resolve the vertical depth and horizontal extent of the thin, ISSRs layer where contrails live. Furthermore, because it is a diagnostic tool, it cannot simulate the prognostic lifecycle of the contrail—such as its drift, transition into a cirrus deck, or its complex radiative feedbacks making it useful for immediate flight planning but insufficient for long-term climate impact assessments (Yoo and Li, 2012).

The MM5+SAC (Fifth-Generation Penn State/NCAR Mesoscale Model + SAC) represents the foundational era of regional NWP for aviation. Developed primarily by Pennsylvania State NCAR, this system was among the first to move contrail prediction from simple global averages to high-resolution regional grids. Methodologically, the system functions as a diagnostic tool where the MM5 serves as the atmospheric engine, providing high resolution 3D fields of temperature and relative humidity. The SAC is then applied as a post-processing algorithm to these fields to calculate the thermodynamic mixing of aircraft exhaust with the environment. Technically, the model solves non-hydrostatic, terrain-following equations

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that allow it to resolve mesoscale features (like mountain waves or local fronts) which dictate the formation of ISSRs. A significant scientific advancement was the application of Arctic MM5 and other regional versions to study specific contrail outbreaks over areas like Alaska and the contiguous US, proving that regional NWP could achieve a high probability of detection (over 80% in some studies) by accurately capturing synoptic-scale humidity variations. However, the system faces notable limitations: as a precursor to the modern WRF model, its microphysics are less sophisticated, often leading to threshold errors where small inaccuracies in humidity lead to binary (yes/no) failures in predicting persistence. Furthermore, in its standard SAC diagnostic form, it does not track the life cycle of the contrail (drift, spreading, or sublimation) but rather provides a "snapshot" of potential formation at a single point in time (Martin Stuffer, 2004; Carleton et al., 2008).

The Rapid Update Cycle (RUC) NWP-integrated diagnostic model was developed by David P. Duda at the NASA Langley Research Center in 2005. The authors developed a method to estimate persistent contrail coverage over the United States by integrating commercial air traffic data with hourly meteorological analyses from the RUC numerical weather prediction model. The methodology calculates Potential Contrail Frequency based on modified Appleman thermodynamic criteria within the RUC model grid, and then converts this to contrail coverage using air traffic density data. The model was tuned empirically by comparing the results against satellite-derived contrail coverage from NOAA-16 AVHRR data, leading the authors to conclude that a fourth root relationship between flight path length and contrail coverage provided the most accurate results. A primary limitation of this model is its dependence on the accuracy of the underlying NWP humidity fields, which suffer from a known dry bias, as well as uncertainties inherent in the satellite observations used for tuning and the lack of military air traffic data (Duda et al., 2005).

The evolving body of diagnostic modeling was developed by David P. Duda at NASA Langley Research Center and the National Institute of Aerospace between 2005 and 2009. The initial 2005 methodology integrated commercial air traffic data with hourly Rapid Update Cycle (RUC) meteorological analyses to estimate persistent contrail coverage, utilizing a modified Appleman criterion. This model was empirically tuned against NOAA-16 AVHRR satellite data, establishing a fourth root relationship between flight path length and contrail coverage (Duda et al., 2005). In 2009, the authors refined this into a probabilistic forecasting methodology by applying logistic regression to high-resolution RUC and Advanced Regional Prediction System (ARPS) analyses. This study derived distinct "SURFACE" (ground-observation based) and "OUTBREAK" (satellite-observation based) models, identifying upper-tropospheric temperature, humidity, and wind direction as key predictors. A primary limitation of this collective framework is its purely diagnostic nature—predicting occurrence at fixed locations without explicitly modeling physical advection or spreading—and its sensitivity to known dry biases in the underlying NWP humidity fields (Duda and Minnis, 2009).

This AVTECH prediction and optimization Model was developed by Chirag Bipinchandra Kundgol, and David Rytter, at KTH Royal Institute of Technology and AVTECH Sweden AB in 2025. The authors presented a real-time contrail management tool designed for commercial airline fleets. The methodology calculates the critical temperature for contrail formation using the SAC Critera applied to high-resolution weather forecasts from the UK Met Office. These predictions are integrated into a

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Dynamic Programming (DP) algorithm that optimizes the aircraft's vertical flight profile to minimize a combined cost function of fuel, time, and contrail persistence. A primary limitation of this model is its direct dependence on the accuracy of the underlying weather forecast data (particularly relative humidity). additionally, the current iteration focuses only on avoiding persistent contrails without calculating their specific radiative forcing or climate impact (Kundgol et al., 2025).

The Flightkeys 5D Contrail operational analysis was conducted by Alejandra Martin Frias and Marc Shapiro, at Flightkeys (Austria) and Breakthrough Energy (USA) in 2024. The authors integrated the CoCiP model (via the Contrails API) into the Flightkeys 5D (FK5D) commercial flight planning system to evaluate the feasibility and cost of contrail avoidance. The methodology involved simulating 84,839 American Airlines flights from June 2023 and January 2024 using ECMWF HRES weather forecasts to identify regions of high contrail energy forcing. Flights predicted to form warming contrails were re-optimized using *Dijkstra's and A algorithms** to navigate around these regions (defined as hard constraints). The study found that navigational avoidance could reduce contrail energy forcing by approximately 73% with a minimal increase in fuel (0.11%) and total cost (0.08%). A primary limitation of this study was the use of simplified "hard" avoidance polygons, which may be less efficient than a continuous cost-based optimization approach (Martin Frias et al., 2024).

OpenSky Contrail Estimation is a data-driven diagnostic study which was conducted by Junzi Sun and Esther J. Roosenbrand at Delft University of Technology (TU Delft) in 2024. The authors presented a computationally efficient framework to estimate persistent contrail formation by integrating open-source flight trajectories from the OpenSky Network with meteorological reanalysis data from ERA5. The methodology applies the SAC implemented via the pycontrails Python library to high-resolution ADS-B data, enabling large-scale assessments of contrail coverage without relying on proprietary airline flight recorders. A primary limitation of this approach is its reliance on the spatiotemporal resolution and humidity accuracy of the ERA5 dataset, which limits the precision of individual flight-level predictions compared to models using higher-fidelity weather inputs (Sun and Roosenbrand, 2023).

The radiative forcing assessment was conducted by Gaby Rädel and Keith P. Shine at the Department of Meteorology, University of Reading (UK) in 2008. The authors developed a framework to quantify the global RF of persistent contrails and its sensitivity to cruise altitude changes. The methodology involved deriving global contrail coverage by combining the AERO2k aviation emissions inventory (2002) with meteorological data from ECMWF analyses, using thermodynamic criteria tuned to match independent satellite observations. These coverage maps were then processed through the Fu-Liou delta-4-stream radiative transfer model to calculate Shortwave and Longwave effects. The study performed perturbation experiments, increasing air traffic in 2,000 ft vertical layers and found that contrails formed at approximately 10 km (33,000 ft) altitude produce the largest net radiative forcing per kilometer flown. A primary limitation of this model is the high uncertainty (estimated at ~60%) resulting from the necessary assumptions regarding constant contrail optical depth and the scarcity of global observational data for validation (Rädel and Shine, 2008).

CoAtSaC (Contrail Attribution Sample Consensus) & SynthOpenContrails is a methodological study was conducted by Aaron Sarna and Vincent Meijer at Google Research, TU Delft, and ONERA in 2025. The authors addressed the lack of ground truth

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for contrail attribution by developing SynthOpenContrails, a large-scale synthetic dataset generated by filtering CoCiP microphysical simulations to match the statistical properties of satellite observations. Furthermore, they introduced CoAtSaC, a highly scalable attribution algorithm that employs RANSAC (Random Sample Consensus) to robustly identify physical contrails by analyzing the temporal evolution of the "W" parameter (cross-track advection error). By grouping single-frame matches that form coherent linear structures over time, the algorithm effectively distinguishes true flight sources from coincidental overlaps. A primary limitation of this approach is its inability to attribute contrails detected in only a single satellite frame (resulting in lower recall for short-lived contrails) and its inherent dependence on the accuracy of the ERA5 wind fields used for advection (Sarna et al., 2025).

3.4 Satellite-Based and Empirical Models

Satellite-based and empirical contrail prediction models have played a foundational role in mapping contrail occurrence, validating physical simulations, and generating training datasets for AI development. Early efforts used thermal infrared channels to detect linear contrails against natural cloud backgrounds, enabling the first contrail climatologies over North America and Europe. Subsequent models incorporated automated detection algorithms, statistical regression methods, and radiative transfer calculations to estimate contrail properties and their climate impacts. Despite their utility for large-scale and long-term studies, these models generally lack vertical resolution, struggle to distinguish contrails from thin cirrus, and depend heavily on manual validation or training data quality. Table 8 summarizes representative satellite-based and empirical contrail models, including automated detection systems (Mannstein CDA, MODIS), empirical logistic regression, radiative forcing estimators (Rapid Contrail-RF), multi-sensor cloud masks, and historical climatology products (DMSP, ACSM).

One of the earliest large-scale efforts was led by (Minnis et al., 1998), who used NOAA's AVHRR split-window infrared channels to detect contrails based on brightness temperature differences (BTD) between 10.8 μm and 12.0 μm bands. These models enabled the construction of contrail climatologies over North America and Europe but lacked vertical resolution and struggled to distinguish contrails from overlapping cirrus. A similar approach was extended through AVHRR split-window threshold algorithms, forming the basis for multiple empirical detection frameworks used during the 1980s and 1990s.

The MODIS-based contrail detection system developed by NASA Ames improved spatial and spectral resolution by incorporating aircraft trajectory overlays and cloud phase information, supporting event-based analysis and radiative forcing estimates. MODIS cirrus optical thickness algorithms, while not contrail-specific, have been adapted to estimate the microphysical properties of persistent contrail cirrus. In geostationary orbit, GOES-based systems like the NASA GOES split-window tracker and studies by (Li et al., 2023a).offered temporal continuity, enabling lifecycle monitoring of contrail persistence and spreading, though resolution constraints and variable background conditions limit their reliability in tropical and polar regions (Li et al., 2023a).

For vertical profiling, CALIOP lidar aboard CALIPSO introduced a major advancement by detecting contrails using backscatter and depolarization ratio signatures. These measurements enabled studies like (Burkhardt et al., 2010) to compare modeled contrail cirrus with observed vertical structures, thereby informing global climate models. However, CALIOP's low

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temporal coverage (1–2 overpasses/day) and narrow swath limit real-time applications. More recently, VIIRS-based experimental models and MISR angular radiance techniques have expanded detection capabilities through multi-angle and multispectral sensing, providing improved estimates of contrail shape, albedo, and radiative impact (Meyer et al., 2025). Similarly, SCIAMACHY contributed early spectral insights into cirrus-aerosol overlap, though not specifically optimized for contrail analysis.

Operationally, NOAA and DoD have employed empirical contrail forecast products based on vertical profiles of RH_i and temperature, derived from radiosonde and satellite data, to support aviation planning. These empirical forecasts remain in limited use for military and strategic purposes. Importantly, many of these satellite-based models are now integrated into AI workflows—MODIS and AVHRR data feed into neural networks developed by Teoh et al. and Zhang & Li, while CALIOP vertical profiles have been used to benchmark CoCiP and PINN-based models. Additionally, synthetic datasets derived from these satellite products are often used to validate hybrid AI-physics architectures such as GAIA and Google's recent transformer-based platforms.

The Ames Contrail Simulation Model (ACSM) was developed by (Li et al., 2023a) at NASA Ames and Langley Research Centers in 2023 . The authors designed the ACSM to support Strategic Traffic Flow Management (STFM) by providing a computationally efficient tool to estimate the global climate impact of aviation. The methodology integrates the Schmidt-Appleman Criterion for formation with Lagrangian particle advection equations to track contrail position and evolution driven by RUC, RAP, or MERRA meteorological data. The model adapts the physics from the DLR CoCiP model but introduces significant simplifications for speed: it models the contrail cross-section as a rectangle with uniform ice density (rather than a Gaussian ellipsoid) and assumes all ice particles are spherical throughout their lifecycle. A primary limitation of ACSM is the exclusion of explicit wake vortex downwash modeling; instead, it initializes contrails with fixed average dimensions and neglects the specific sinking dynamics that affect early-stage ice crystal survival, while also relying on the inherent accuracy of the input NWP humidity fields (Li et al., 2023a).

The empirical model to predict widespread occurrences of contrails was developed by lead author (Travis et al., 1997) from the Department of Geography at the University of Wisconsin-Whitewater. This logistic regression model is designed to forecast the probability of widespread contrail clusters outbreaks rather than individual plumes by analyzing specific atmospheric conditions. The model calculates persistence probability using three statistically significant variables: the column-integrated water vapor counts (WV) for the 700–100-mb layer derived from GOES 6.7μm satellite imagery, the interaction between this moisture count and the mean 300–100-mb temperature (WVT) from NWS rawinsondes, and WVT^2 to account for the non-linear middle range of conditions where contrails thrive. However, the model has several limitations. It becomes less reliable for predicting small outbreaks (under 100 km), struggles with accuracy when contrails are located near or within multilayered natural clouds, is highly sensitive to the low spatial density of rawinsonde temperature data, and cannot be easily applied to regions lacking consistent data, such as coastal waters or outside national borders (Travis et al., 1997).

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Mannstein Automated Contrail Detection Algorithm (CDA) is classical satellite detection algorithm was developed by (Mannstein et al., 2010) at DLR in 1999. The authors presented a fully automated scheme to detect linear contrails using infrared data from the Advanced Very High-Resolution Radiometer (AVHRR). The methodology utilizes the "split-window" technique, exploiting the brightness temperature difference between the 11µm and 12µm channels to identify thin ice clouds, followed by morphological filtering to isolate linear structures with specific width and length criteria. This algorithm was applied to derive the first diurnal and seasonal climatologies of contrail coverage over Central Europe. A primary limitation of this approach is its deliberate tuning for a low false-alarm rate, which significantly reduces detection efficiency (missing optically very thin or non-linear aged contrails) and makes the derived coverage values lower bound estimates (Mannstein et al., 2010).

CDA-MODIS is satellite-based observational study was conducted by (Minnis et al., 2013) at the NASA Langley Research Center in 2013. The authors sought to reduce the uncertainty in contrail climate forcing by quantifying the properties of contrail cirrus. the spreading, aged phase of contrails that is often missed by standard linear detection algorithms. The methodology involved analyzing 21 cases of spreading contrails using Terra and Aqua MODIS data; they applied a standard CDA to identify linear segments and manually tracked their evolution into irregular cirrus shapes. By retrieving microphysical properties from the satellite radiances, the study established that contrail cirrus has significantly higher optical depths (2–3 times) and larger effective particle sizes (20% larger) than the adjacent linear contrails, and that accounting for this spreading phase increases calculated contrail coverage by a factor of 2.4 to 7.6. A primary limitation of this method is the difficulty in automating the detection of these older, shapeless contrails, particularly in regions of dense air traffic where overlapping plumes reduce the sensitivity of current detection algorithms (Minnis et al., 2013).

Rapid Contrail - RF is satellite based observational study which was conducted by (Dimitropoulou et al., 2026) at the Royal Meteorological Institute of Belgium in 2025. The authors developed a Rapid Contrail-RF Estimation Approach to quantify the radiative forcing of contrail cirrus using geostationary Meteosat Second Generation (MSG/SEVIRI) data. The methodology involved visually identifying days with intense contrail activity and utilizing the Optimal Cloud Analysis (OCA) product provided by EUMETSAT to retrieve ice cloud properties (optical thickness, effective radius, pressure). These observed properties were processed through Look-Up Tables (LUTs)—constructed using the libRadtran radiative transfer model—to compute Shortwave and Longwave fluxes, while a separation scheme was applied to isolate the specific radiative contribution of the contrails from natural cirrus. A primary limitation of this approach is its reliance on visual identification to select analysis days, which limits automation and global scalability, as well as the dependency on the accuracy of the OCA retrieval product which can have uncertainties for multi-layer or optically thin clouds(Dimitropoulou et al., 2026) .

The probabilistic detection model was developed by (Musial et al., 2014) at the University of Bern in 2014. The authors designed the Probabilistic Cloud Mask (PCM) to resolve the ambiguity of binary cloud masks by employing a multidimensional information space. The methodology involves constructing extensive Look-Up Tables (LUTs) where spectral features enhanced by an Invariant Coordinate System (ICS) transformation to improve thin cirrus and snow separation

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are binned alongside ancillary data (solar angles, texture, and land cover). Probabilities are derived by analyzing the frequency of cloud/snow occurrences within these bins based on a training dataset composed of PPS and MODIS masks. A primary limitation of this approach is the subjectivity involved in selecting binning intervals and the computational constraint on LUT size, which limits the resolution of the probability estimates, as well as the fact that the model's maximum accuracy is inherently capped by the quality of the reference masks used for training (Musial et al., 2014).

Split Window Brightness Temperature Difference (BTD) is a satellite detection methodology developed by (Lee, 1988) at the Naval Environmental Prediction Research Facility (Monterey, California) in 1989. The author addressed the difficulty of detecting thin, narrow contrails in standard infrared imagery by utilizing the "Split Window" technique applied to AVHRR (Advanced Very High-Resolution Radiometer) data. The methodology involves co-registering digital data from Channel 4 (11μm) and Channel 5 (12μm), converting raw gray shades to calibrated brightness temperatures, and subtracting the Channel 5 value from the Channel 4 value to create a difference image. The study demonstrated that while the Earth's surface and thick clouds exhibit small temperature differences (+1 to +2 K), newly formed contrails and thin ice clouds show significantly larger positive differences (+2 to +6 K) due to the differential transmissivity of ice particles, making them appear bright against a dark background. A primary limitation of this technique is that natural thin cirrus clouds share similar spectral properties with contrails, making it difficult to distinguish anthropogenic plumes from natural high clouds solely based on brightness temperature differences without additional geometric analysis (Lee, 1988).

MODIS Cloud Mask All Tests Consolidation (ATC) satellite validation study was conducted by Żaneta Nguyen Huu, at the Institute of Geography and Spatial Management, Jagiellonian University (Poland) in 2025. The authors evaluated the utility of the MODIS operational Cloud Mask (MYD35 Collection 6.1) for creating a global cirrus mask by validating it against 136 million observations from the CALIOP lidar. To improve detection reliability, they introduced the ATC approach, which aggregates results from six standard spectral tests (including the 1.38 μm "cirrus band" and 11–12 μm split-window) into a unified boolean flag. The study established that while ATC achieves a Probability of Detection (POD) of roughly 81% during the daytime, it suffers from a high False Alarm Rate (FAR) of ~35% and performs significantly worse at night (POD ~25%) due to the unavailability of solar channels. A primary limitation of this framework is its inability to reliably detect optically thin cirrus (COT < 0.4), which active sensors like CALIOP easily identify, leading to a substantial underestimation of global nighttime cirrus coverage compared to lidar climatologies (Nguyen Huu et al., 2025).

Defense Meteorological Satellite Program (DMSP) Contrail is an extensive climatological analysis conducted by James Q. DeGrand et al. at The Ohio State University, Pennsylvania State University, University of Wisconsin-Whitewater, and the University of Oklahoma in 2000. The authors developed a satellite-based climatic description of jet contrails over the contiguous United States by manually analyzing very high resolution (0.6 km) thermal-infrared imagery from the DMSP polar orbiters. The methodology involved the visual identification of contrails on hard-copy film strips for the midseason months (January, April, July, October) of the period 1977–1979, validating these observations against ground-based records to establish spatial distribution patterns. A primary limitation of this study is the inherent subjectivity of the manual identification

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technique and the restricted temporal coverage (limited to specific months and satellite overpass times), which prevents a continuous assessment of diurnal or long-term trends (Degrand et al., 2000).

WFM-DOAS (Weighting Function Modified Differential Optical Absorption Spectroscopy) v2.1 is a satellite retrieval validation study conducted by J. Heymann et al. at the Institute of Environmental Physics (IUP), University of Bremen in 2012. The authors assessed the global quality of the WFM-DOAS retrieval algorithm (version 2.1), which determines atmospheric CO_2 columns from SCIAMACHY near-infrared spectra. The methodology involved minimizing the difference between the logarithm of the measured sun-normalized radiance and a linearized radiative transfer model to retrieve vertical column densities. These retrievals were then compared globally against the CarbonTracker model to quantify systematic biases. The study found that while the retrieval captures the seasonal cycle well, it suffers from significant systematic errors (typically underestimations) due to light path shortening by thin cirrus clouds and aerosols, necessitating rigorous filtering to achieve sufficient accuracy for surface flux inversion.

Table 8 List of Satellite-Based and Empirical Contrail Prediction Models

Model System	Developer Institute	Key Features	Limitations	Ref
ACSM	NASA	Full lifecycle simulation optimized for Strategic Traffic Flow Management	simplified rectangular cross-section; no wake vortex downwash modeling	(Li et al., 2023a)
Empirical Logistic Regression	1996/ David J. Travis	Predicts outbreak probability using GOES water vapor counts and rawinsonde temperatures via a non-linear equation.	Unreliable for small areas (<100 km), obscured by natural clouds, and sensitive to input data density	(Travis et al., 1997)
Mannstein Automated CDA	1999 / - DLR	Uses infrared brightness temperature difference (T_4 - T_5) and morphological line filters	Tuned for low false alarms resulting in low detection efficiency; misses wide/aged contrails	(Mannstein et al., 2010)
CDA-MODIS	2013 - NASA	Quantifies optical depth and particle size of spreading contrail cirrus	Reduced detection sensitivity in dense air traffic or overlapping cirrus	(Minnis et al., 2013)
Rapid Contrail-RF Estimation	2025 -RMI Belgium	Quantifies RF using geostationary OCA products and radiative transfer LUTs	Relies on manual visual identification; limited to specific case studies	(Dimitropoulou et al., 2026)
PCM Model	2014 / University of Bern	Provides continuous probability estimates for cloud, snow, and clear-sky	Accuracy limited by training data quality; LUT size constraints	(Musial et al., 2014)
Split Window BTD	1989 / Thomas F. Lee	Enhances contrail visibility by subtracting 12µm from 11µm radiances	Difficult to distinguish contrails from natural thin cirrus clouds	(Lee, 1988)
MODIS Cloud Mask	2025 / Nguyen Huu et al.	Validates passive cirrus detection using active lidar (CALIOP) ground truth	Low nighttime reliability; misses optically thin cirrus ($\tau < 0.4$)	(Nguyen Huu et al., 2025)
DMSP Contrail	2000 / DeGrand et al.	High-resolution (0.6 km) mid-season contrail climatology over the US	ubjective manual identification; limited to 1977-79 mid-season months	(Degrand et al., 2000)
WFM-DOAS	2012 / Heymann et al.	Retrieves XCO_2 from NIR spectra; assesses aerosol/cloud induced biase	Significant systematic errors (~1%) caused by thin cirrus and aerosols	(Heymann et al., 2012)

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3.5 AI-Driven Contrail Prediction Models

In recent years, AI has emerged as a transformative paradigm for contrail prediction, enabling scalable, high-resolution, and near real-time modeling capabilities that extend beyond the limitations of traditional physics-based approaches. AI-driven models are particularly well suited to handling large, heterogeneous datasets—combining meteorological fields, flight trajectories, and satellite observations—while offering new pathways for operational contrail mitigation. These models range from computer vision systems for contrail detection in satellite imagery to random forest classifiers for formation probability, physics-informed neural networks that embed thermodynamic constraints, and deep learning architectures for altitude estimation and flight attribution .Table 9 summarizes representative AI-driven contrail models, including Google's contrail forecast system, Eurocontrol's Contrail Tracker, Imperial College's random forest model, MIT–NOAA's PINN, and various deep learning segmentation approaches (U-Net, EfficientNet, OpenContrails).

One of the earliest operational AI-based contrail prediction systems was introduced by (Engberg et al., 2025) who developed a Random Forest classifier trained on ERA5 meteorological reanalysis, aircraft trajectory data, and satellite-derived contrail labels. The model demonstrated practical applicability in real-time contrail avoidance strategies by identifying contrail-favorable atmospheric regions. Similarly, (Heni et al., 2025) proposed a feedforward neural network using ERA5 data and satellite observations to predict global contrail-prone regions. While effective at large scales, this approach remains constrained by its reliance on historical datasets and limited physical interpretability. A significant advance toward improving physical consistency in AI models was achieved through the introduction PINNs by (Raphael Alamu, 2025). By embedding thermodynamic constraints most notably the SAC directly into the learning architecture, these models reduced prediction errors relative to unconstrained deep networks while maintaining adherence to established contrail formation physics. However, PINNs introduce increased training complexity and sensitivity to hyperparameter selection, which remain active challenges. It is notable that many AI-driven contrail prediction frameworks including those developed by (Engberg et al., 2025), and Google rely heavily on global reanalysis datasets such as ERA5 or MERRA-2 as their meteorological backbones. Furthermore, established physical models, particularly the CoCiP, continue to serve as critical benchmarks and are frequently used to generate synthetic training data. As hybrid AI–physics frameworks mature, they offer a promising route to combining the interpretability of physical models with the scalability and adaptability of machine learning, enabling real-time contrail mitigation in next-generation flight management systems.

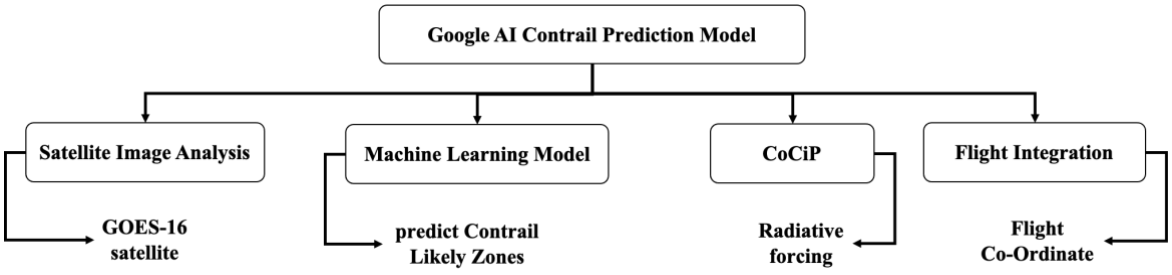

Figure 16 Google AI Contrail model framework

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The Google contrail framework emerged from a recent collaboration between Google Research, DLR, American Airlines, and Breakthrough Energy (2023–2024). To address the interpretability limitations of purely data-driven algorithms, the authors designed a hybrid, dual-component architecture that integrates a Machine Learning-based Contrail Likely Zone (CLZ) model with the physics-based CoCiP model. The CLZ model was trained on over 1.3 million flight tracks using high-resolution meteorological features from ECMWF HRES. Crucially, to mitigate observational blind spots and ensure rigorous validation, the system was calibrated against both passive geostationary data MODIS and independent active spaceborne lidar CALIPSO. The methodology calculates the final climate impact by multiplying the ML-derived formation probability by the CoCiP-simulated energy forcing, which is subsequently adjusted by a 0.42 conversion factor to estimate ERF. Furthermore, the framework introduced the Global AI Aviation model, a transformer-based architecture designed for multi-objective flight trajectory optimization. Despite its high predictive capability, critical limitations remain. The system is proprietary, limiting independent verification, and currently struggles to provide robust probabilistic uncertainty quantification. Consequently, managing the operational "regret factor"—ensuring that automated avoidance maneuvers do not incur a net climate penalty via excess CO_2 emissions due to deterministic false-positive forecasts—remains a primary challenge for real-world integration (Zebediah Engberg, 2025).

To bridge the gap between theoretical forecasting and empirical validation, an AI-driven ADM system was introduced by (Geraedts et al., 2024). Unlike prognostic microphysical models, this scalable framework operates retrospectively, employing a computer vision algorithm to process passive infrared imagery from the GOES-16 ABI. By advecting historical ADS-B flight trajectories using numerical weather data, the system physically aligns individual flights with observed persistent contrails. This generated a massive empirical dataset of over 1.6 million flight segments, providing a critical baseline to directly benchmark predictive frameworks like CoCiP. However, significant observational constraints remain. The computer vision architecture exhibits a 30% error rate (false positive and negative) relative to human labeling. Furthermore, the reliance on passive geostationary sensors restricts detection to optically thick, horizontally expansive contrails. The system cannot resolve sub-pixel formations, optically thin cirrus, or precise vertical profiles, highlighting the necessity of integrating active spaceborne lidar (e.g., CALIOP) to mitigate these fundamental observational blind spots (Geraedts et al., 2024).

Addressing the vertical placement errors frequently encountered in NWP-integrated models, an AI-driven Contrail Altitude Estimation framework was introduced by (Meijer et al., 2024) at MIT in 2024. Utilizing a CNN, this approach bypasses traditional thermodynamic parameterizations to estimate altitudes directly from passive thermal infrared imagery GOES-16 ABI. Crucially, to overcome the inherent vertical resolution limits of geostationary sensors, the model was rigorously trained and validated against coincident, active spaceborne lidar CALIPSO to establish high-precision ground-truth labels. While the CNN efficiently generates pixel-wise altitude maps from spatial patches of brightness temperatures, critical operational constraints persist. The model's accuracy degrades significantly in complex, multi-layer cloud scenes, particularly where contrails overlap with underlying meteorological layers. Furthermore, the architecture is fundamentally restricted to identifying the visible contrail top rather than resolving the full vertical depth. For tactical flight avoidance, this lack of

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volumetric boundary data presents a severe limitation; aircraft require precise bottom-edge altitudes to execute minimal-descent rerouting without incurring unnecessary aerodynamic and fuel penalties (Meijer et al., 2024).

GraphCast Contrail AI-integrated simulation framework was developed by Najrane Heni at the University of Stuttgart in 2025. The authors presented the first study integrating GraphCast, a deep learning-based weather forecasting model, with the CoCiP to estimate contrail formation and radiative forcing. The methodology involves a multi-source data pipeline that combines flight trajectories from OpenSky with meteorological data from both GraphCast and ERA5 reanalysis. By replacing traditional numerical weather prediction inputs with AI-generated forecasts, the study aims to enhance computational efficiency and prediction skill. A primary limitation of this approach is that GraphCast currently operates at a lower vertical resolution (13 pressure levels) compared to ERA5 (37 levels), which can reduce the accuracy of detecting thin ice-supersaturated regions critical for persistent contrail formation (Heni et al., 2025).

OpenContrails AI-based detection study was conducted by Joe Yue-Hei Ng, and Kevin McCloskey at Google Research and MIT in 2024. The authors introduced OpenContrails, a publicly available dataset of human-labeled contrails derived from GOES-16 ABI data. The methodology employs a deep learning model—specifically a U-Net architecture with a ResNet-18 backbone—that utilizes a sequence of satellite images (temporal context) to distinguish persistent linear contrails from natural cirrus clouds and surface features. By training on over 40,000 labeled scenes and using hard-example mining, the model achieves significantly higher accuracy than single-frame approaches. A primary limitation is the inherent subjectivity and potential inconsistency of human annotations used for ground truth, as well as the restriction of the dataset to the geographical coverage of the GOES-16 satellite (primarily the Americas) (Ng et al., 2024).

EfficientNet-b4 Encoder with Pseudo-Labeling study was conducted by Qunwei Lin from Trine University in 2024. The authors developed an optimized framework for contrail detection using the EfficientNet-b4 architecture as a feature extraction encoder, chosen for its balance of accuracy and efficiency using compound scaling. The methodology integrates three novel techniques to enhance performance: Misalignment Correction, which applies a 0.5-pixel shift to counteract errors introduced by polygon-to-mask conversions; Soft Labeling, which utilizes the average vote of multiple human annotators to provide confidence gradients rather than binary hard labels; and Pseudo-labeling, a two-phase training strategy that uses the model's own predictions on unlabeled data to enrich the training set. A primary limitation addressed by the authors is the model's high sensitivity to geometric inconsistencies (e.g., from flip/rotation augmentations), necessitating precise alignment corrections to maintain cross-validation performance (Lin et al., 2024).

U-Net Segmentation combining Hough Transform Matching is an observational study conducted by Emmanuel Riggi-Carrolo and Thomas Dubot at the French Civil Aviation Authority (DGAC) and ONERA (The French Aerospace Lab) in 2024. The authors developed a hybrid detection and identification pipeline designed to associate persistent contrails observed in GOES-16 satellite imagery with their specific source aircraft. The methodology first employs a U-Net deep neural network to segment contrail pixels from the satellite images, followed by a Hough Transform to extract linear features from these masks. To identify the source flight, the system utilizes ADS-B air traffic data and ERA5 meteorological reanalysis wind fields to advect

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potential candidate trajectories to the time of the satellite image, matching the geometric alignment of the flight path with the detected contrail line. A primary limitation of this approach is the challenge of accurately distinguishing contrails from natural cirrus clouds in the segmentation phase, as well as the dependence on precise wind data to correctly link the advected flight path to the observed contrail position over time (Riggi--Carrolo et al., 2023).

Table 9 List of AI-Driven Contrail Prediction Models

Model	Developer / Institution	Method	Input Data Sources	Key Feature	Ref
Google AI Contrail Forecast	DLR / Google Research / American Airlines	thermodynamic + microphysical simulation AI-assisted classification	Aircraft trajectory, temperature, relative humidity, soot emissions	Provides labeled contrail datasets and probabilistic forecasts; supports operational contrail avoidance	(Engberg et al., 2025; Geraedts et al., 2024)
Contrail Tracker	Eurocontrol	Computer Vision / AI (Multi-Modal)	Ground-based visible & IR cameras + MTG geostationary satellite data	Automates contrail-to-flight attribution for real-time validation of mitigation strategies	(Jarry et al., 2026)
Imperial ML Contrail Model	Imperial College London / DLR	Random Forest Classifier	ERA5 reanalysis + flight path data	Predicts contrail formation probability and persistence; used for eco-routing	(Teoh et al., 2024b)
MIT–NOAA PINN Model	MIT / NOAA	PINN	Atmospheric reanalysis + thermodynamic constraints	Embeds Schmidt–Appleman physics in neural nets; reduces forecast error by ~40%	(Di Giusto et al., 2024)
ADM Contrail	Google, MIT	Computer vision detects contrails in satellite images; physics-based algorithms match them to flights	GOES-16 infrared imagery, ADS-B flight paths, and ECMWF weather data	Created a massive 1.6-million-flight empirical dataset to benchmark contrail prediction models	(Geraedts et al., 2024)
CNN Contrail	MIT	CNN	GOES-16 ABI, CALIPSO/CALIOP, LIDAR)	Predict directly from geostationary satellite imagery	(Duda et al., 2005)
GraphCast Contrail	University of Stuttgart	Integrates AI weather forecasting (GraphCast) with CoCiP	OpenSky, GraphCast, ERA5	Integrates GraphCast with CoCiP	(Heni et al., 2025)
OpenContrails	Google Research & MIT	Spatio-Temporal Deep Learning	GOES-16 ABI, OpenContrails Dataset	Uses temporal context & OpenContrails	(Ng et al., 2024)
EfficientNet-b4 Encoder	Trine University	Deep learning segmentation with semi-supervised training	Satellite imagery with human-annotated polygon masks	EfficientNet-b4 backbone, misalignment correction, soft labeling	(Lin et al., 2024)
U-Net Segmentation	DGAC & ONERA	U-Net architecture for semantic segmentation	GOES-16 AB, ADS-B, ERA5	Automates the attribution of satellite-detected contrails to specific flights	(Riggi--Carrolo et al., 2023)
Regression Contrail Model	MIT	deep learning regression trained on geometric stereo-derived altitude labels	GOES-16 ABI	Estimates contrail altitude from single-view geostationary thermal imagery	(Meijer et al., 2024)

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Deep Learning Regression Model (GOES-16 ABI) is an AI-based retrieval study conducted by Vincent R. Meijer et al. at the MIT Laboratory for Aviation and the Environment in 2024. The authors developed a Deep Learning model designed to estimate the altitude of persistent contrails using only single-view multispectral data from the GOES-16 ABI. The methodology involved training a neural network to identify the spectral signatures associated with different cloud top heights, effectively overcoming the limitations of traditional thermal brightness temperature methods which struggle with optically thin contrails that transmit radiation from warmer lower layers. By learning from a dataset of accurate altitude labels (likely derived from geometric stereo methods or active lidar), the model can assign altitude values to contrail pixels in real-time. A primary limitation of this approach is its dependence on the quality and representativeness of the ground truth training data, as well as reduced performance in scenes with low thermal contrast between the contrail and the underlying surface or cloud layers (Meijer et al., 2024).

4 Key Findings

This multidisciplinary review of contrail prediction methodologies (1940–2026) synthesizes eight decades of research to highlight five critical insights that define the current state and future trajectory of aviation climate mitigation. First, microphysical box and plume models (e.g., APCEMM, LCM-LES) achieve high fidelity by resolving ice crystal growth, sedimentation, and spreading using either size-resolved sectional schemes APCEMM or particle-based stochastic nucleation LCM-LES, yet neither resolves nanometer-scale nucleation from first principles; APCEMM relies on a prescribed black-carbon activation parameterization, while LCM-LES uses empirical nucleation laws without explicit treatment of volatile species. By contrast, the ACM model explicitly simulates binary homogeneous and ion-mediated nucleation of H_2SO_4–H_2O, condensation of organic vapors, and nucleation of lubrication oil droplets, and was validated against in-flight data from a lean-burn A321neo, proving that contrail ice crystals in low-soot regimes form predominantly on newly nucleated volatile particles rather than on emitted soot. All such microphysical models remain computationally prohibitive for global fleet forecasting, underscoring the need for hybrid architectures. Second, regardless of model sophistication, prediction accuracy is fundamentally capped by the quality of upper-tropospheric humidity data; the systematic “dry bias” in reanalyses like ERA5 prevents reliable identification of ice-supersaturated regions, causing either underestimation of contrail persistence or high false-alarm rates. Even the ACM model’s success depended on accurate meteorological inputs, making improved humidity observations the primary bottleneck for real-time contrail avoidance. Third, the period 2020–2026 has seen a decisive shift toward hybrid AI systems that embed physical laws into neural networks (e.g., Google-DLR, PINNs, CoCiP Grid), overcoming the lack of thermodynamic consistency in purely data-driven models. ACM’s explicit nucleation schemes provide a physically grounded target for such hybrid AI, enabling machine learning to learn the mapping from fuel properties and meteorology to ice crystal numbers without sacrificing interpretability. Fourth, modern climate models (e.g., ECHAM5-CCMod) confirm that a strong Pareto distribution governs contrail forcing: approximately 2–10% of global flights cause 80% of the total energy forcing, because aged, spreading contrail cirrus dominate warming. Fleet-wide avoidance is therefore inefficient; operational systems must minimize the “regret factor” by targeting only high-impact flights. ACM’s finding that low-sulfur fuels greatly

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reduce ice crystal numbers adds a new lever to target those flights. Fifth, satellite validation has evolved from retrospective climatologies to active calibration for deep learning networks (e.g., OpenContrails), yet a "nighttime blind spot" persists. Transitioning from passive sensors to active spaceborne lidar (e.g., CALIOP, EarthCARE) is essential to benchmark vertical profiles and optical depths. ACM's predictions of bimodal ice crystal size distributions under low-soot, high-sulfur conditions provide specific, testable hypotheses for such active sensors. Together, these insights chart a course toward accurate, scalable, and operationally viable contrail mitigation.

5 Future Research Directions

As the aviation sector transitions from theoretical climate assessment to operational mitigation, the focus of contrail prediction research must pivot from simple detection to actionable, high-confidence forecasting. The current reliance on purely data-driven, "black box" deep learning models presents a severe safety certification challenge for aviation authorities. When current AI networks encounter noisy training data, they frequently predict contrail formation in physically impossible conditions, such as warm or dry air masses. To overcome this, future research must prioritize "glass box" hybrid architectures where the AI component handles non-linear pattern recognition—such as satellite texture analysis—while a differentiable physics layer mathematically constrains the output. Specifically, the development of PINNs that strictly enforce thermodynamic laws, including mass conservation and the Clausius-Clapeyron relation, directly within the loss function will ensure that predictions always adhere to the physical reality of the Schmidt-Appleman criterion. However, even a perfectly constrained AI is ultimately limited by its meteorological inputs. The systematic underestimation of upper-tropospheric humidity in NWP models, such as the ECMWF and GFS, remains the single largest source of forecast error. Merely correcting this bias post-hoc is proving insufficient for tactical flight routing because current operational models do not effectively assimilate high-resolution water vapor radiances at flight levels. Moving forward, researchers must investigate machine learning techniques designed to assimilate real-time satellite radiances (from instruments like GOES-16 and Meteosat) directly into the initial conditions of weather models. The ultimate goal is to create a dynamic "humidity nowcasting" system capable of identifying ISSR with kilometre-scale precision before an aircraft ever enters them. Furthermore, predicting initial formation is no longer sufficient; the modeling focus must shift to lifetime prediction. Given that approximately 10 % of flights cause roughly 80 % of contrail-induced warming, the current binary focus on simply avoiding all contrails is operationally inefficient and potentially counterproductive due to the inherent CO_2 penalty of diversions. We currently lack robust tools to predict which specific contrails will harmlessly dissipate and which will spread into warming cirrus outbreaks. Future algorithms must be tailored to specifically identify "big hitter" flights—those traversing regions of deep supersaturation and high wind shear where contrails are predicted to persist for more than four hours. By shifting the focus in this way, operational trials can finally test "severity-based" avoidance rather than "frequency-based" avoidance. Validating these severity-based predictions requires overcoming the severe limitations of passive thermal imagery. The current reliance on passive sensors creates a significant "nighttime blind spot" and fails to resolve the vertical depth of contrails, which is critical for accurate radiative forcing calculations. Because passive sensors cannot accurately measure the optical depth of thin contrails or distinguish vertically

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overlapping layers, it is essential to integrate data from next-generation active spaceborne lidar, such as EarthCARE, to validate the vertical profiles in AI and NWP models. Simultaneously, research should focus on developing multispectral algorithms for geostationary satellites that can detect optically thin contrails at night, potentially utilizing machine learning to artificially enhance thermal contrast. ACM specifically call for additional targeted experiments: exploring how reductions in volatile particles (apart from soot) affect contrail ice formation, testing sulfur-free fuels to further reduce ice crystal numbers in lean-burn engines, better quantifying the role of organic fuel constituents and lubrication oil vapours, updating global fleet models that currently underestimate the climate impact of lean-burn aircraft, and addressing the complete data gap for emerging technologies such as hydrogen-powered aircraft. Finally, if these predictive tools are to be adopted by pilots and airline dispatchers, the output format must evolve. Operators require probabilistic risk assessments, not deterministic "yes/no" forecasts that are highly prone to false alarms. The community must transition toward ensemble prediction systems that replace single deterministic outputs with a clear "Probability of Persistence" and defined confidence intervals. Only with these probabilistic metrics can the industry define precise "Regret Factor" thresholds: determining the exact probability of formation at which the climate benefit of avoidance mathematically outweighs the fuel cost of the maneuver. Achieving this will require coupling advanced contrail prediction models directly with aerodynamic fuel-burn performance models to ensure every diversion results in a verifiable, optimized net climate benefit per flight.

6 Conclusion

The evolution of contrail prediction modeling from 1940 to 2026 represents a fundamental transition from theoretical atmospheric science to operational climate engineering. This review has critically examined the five dominant modeling paradigms Thermodynamic, Microphysical, NWP-Integrated, Satellite-Empirical, and AI-Driven revealing that no single approach suffices on its own. Instead, the field is converging toward a hybrid methodology that leverages the strengths of each era to solve the aviation climate challenge. For over half a century, the SAC provided the necessary thermodynamic boundary conditions for understanding formation, but it could not address the critical issue of persistence. The subsequent rise of Microphysical Box Models (e.g., CoCiP, APCEMM) successfully resolved the complex lifecycle of ice crystals, establishing that aged Contrail Cirrus—not the initial linear plume—is the primary driver of radiative forcing. However, the computational cost of these physical simulations rendered them impractical for global, real-time fleet management. The integration of NWP and Satellite Observation bridged this gap by enabling global climatologies, yet these systems hit a glass ceiling imposed by the Upper-Tropospheric Humidity dry bias and the observational blind spot" of passive sensors. Operational validation remains hindered by the difficulty of detecting optically thin plumes at night, creating a significant verification gap. The profound disruption of the 2020s driven by Artificial Intelligence—has fundamentally altered this landscape. AI and Deep Learning have surpassed traditional physical schemes in detection speed and pattern recognition, yet they face the Black Box interpretability challenge that limits their certification for safety-critical operations. Consequently, the most viable path forward, as demonstrated by recent breakthroughs from Google Research and DLR, lies in Physics-Informed Hybrid Architectures. By using satellite data to correct NWP biases and physical laws to constrain AI predictions, these systems offer

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the first scalable solution for operational contrail avoidance. Ultimately, the science of contrail prediction has matured from a diagnostic discipline into a prescriptive one. The discovery that a mere 2–10% of Big Hitter flights drive 80% of the warming has redefined the operational goal: we do not need to avoid all contrails, only the most damaging ones. The future of sustainable aviation therefore depends on minimizing the Regret Factor deploying high-precision hybrid models that can surgically divert these high-impact flights without incurring unnecessary carbon penalties. As aviation targets net-zero emissions, integrating these intelligent forecasting tools into global Air Traffic Management will be as critical as the development of new fuels or airframes.

7 Appendices

7.1 Appendix A: Model Comparison Tables

TABLE A1. Comprehensive Comparison of Contrail Prediction Models

Model Name	Developer(s)	Model Type	Purpose/Contribution	Limitations
SAC	Schmidt & Appleman (1940s–50s)	Thermodynamic	Established threshold conditions for contrail formation	Binary output; ignores microphysics and plume evolution
Freudenthaler Model	Freudenthaler et al. (1995)	Microphysical Box	Simulated particle growth and lidar backscatter for early detection	Lacks full lifecycle modeling; optical only
Plume Aerosol Model	Kärcher et al. (1996, 1998)	Lagrangian Microphysical	Simulated soot–ice nucleation and aerosol microphysics	Assumes steady state; simple entrainment
Microphysical Parcel Model	Jensen et al. (1998)	Microphysical Box	Included supersaturation feedback; validated with SUCCESS campaign data	No turbulence modeling; simplified dispersion
Spichtinger Model	Spichtinger et al. (2005)	Microphysical Box	Simulated contrail–cirrus transition using relative humidity feedback	Less focused on young plume evolution
Cirrus Transition Model	Kärcher & Burkhardt (2008, 2010)	Time-Resolved Cirrus	Parameterized aged contrail cirrus in climate models (e.g., ECHAM)	Not plume-resolving; needs external initialization
Unterstrasser-Gierens	Unterstrasser & Gierens (2010)	Eulerian Microphysical	Captures coagulation, vertical structure, entrainment, and decay	Limited meteorological coupling
CoCiP	Schumann / DLR (2011–Present)	Global Lagrangian	Simulates contrail evolution with weather data; predicts radiative impact	Simplified particle physics; relies on global reanalysis
Lagrangian Cloud Module (LES)	Lewellen (2014)	LES-Coupled Microphysical	Resolves turbulence, shear, and anisotropic dispersion	High computational cost
APCEMM	MIT (Fritz et al., 2020)	Modular Plume-Scale	Simulates gas-phase chemistry, aerosol evolution, plume microphysics	Requires detailed input; high complexity
ECHAM4/5	MPI Hamburg	NWP-Integrated	Embeds contrail cirrus physics into global circulation model	Limited resolution; approximated humidity
MM5 + SAC	NCAR	NWP-Integrated	Mesoscale contrail forecasts under realistic conditions	Dependent on SAC thresholds
GFS + SAC	NOAA	NWP-Integrated	Operational-scale contrail prediction with global coverage	Simplistic contrail formation logic
CESM Contrail Layer	NCAR	Climate Model Integration	Enables contrail radiative forcing in Earth system model	Coarse resolution; assumes parameterized microphysics

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WRF-SAC	NOAA/Community	NWP-Integrated	High-resolution contrail formation within mesoscale weather forecasts	Lacks full lifecycle evolution
UKMO Contrail Layer	UK Met Office	NWP-Integrated	Introduced climatological contrail layers in unified model	Static layers; lacks dynamic prediction
CNN-AVHRR	Zhang & Li (2021)	AI-Driven	Uses CNN to detect contrails in AVHRR imagery	Dependent on clear-sky imagery
PRE-TRAILS	Teoh et al. (2020)	AI-Driven Hybrid	Uses deep learning for contrail detection from multi-sensor data	Needs curated training datasets
GAIA	GAIA Consortium (2021–)	AI Hybrid Forecasting	Learns contrail patterns across spatial–temporal scales	Black box nature; explainability issues
Google AI + CoCiP	Google, Breakthrough Energy, DLR (2024)	Hybrid (AI + Physics)	Real-time contrail prediction & aircraft rerouting tool	Requires massive compute and integration
PINNs for Contrails	Wang et al. (2023)	Physics-Informed AI	Embeds SAC thermodynamics in neural architecture	Still under research; not widely validated

TABLE A2. Critical Synthesis and Comparative Matrix of Contrail Prediction Paradigms

Modeling Paradigm	Spatial Scale	Computational Cost	Prediction Accuracy & Lifecycle Evolution	Suitability for Operational Forecasting	Key Operational Limitations
Thermodynamic / Analytical (e.g., SAC)	Local to Global	Very Low	**Low:** Binary formation thresholds only. Cannot simulate lifecycle aging or persistence.	**High** for rapid climatological screening; **Low** for active flight routing.	Incapable of simulating advection, spreading, or the resulting radiative forcing.
Microphysical Box & Plume Models (e.g., APCEMM, LES)	Plume-scale (0–100 km)	Very High	**Very High:** Rigorously resolves nucleation, wake vortex dynamics, and long-term crystal survival.	**Very Low:** Computationally prohibitive for global fleet integration.	Requires massive supercomputing resources; highly sensitive to local boundary conditions.
NWP-Integrated (e.g., ECMWF IFS, WRF-Chem)	Regional to Global	Moderate to High	**Moderate:** Captures advection, wind shear, and weather interactions, but relies on bulk parameterizations.	**Moderate:** Currently used in pre-tactical flight planning and research trials.	Heavily constrained by persistent "dry biases" and resolution limits of upper-tropospheric humidity.
Satellite-Empirical (e.g., MODIS, CALIOP)	Global (Swath-dependent)	Low	**None:** Strictly observational and retrospective. Cannot simulate future evolution.	**Low:** Cannot forecast future atmospheric states for avoidance.	Plagued by "nighttime blind spots"; struggles to distinguish aged contrails from natural cirrus.
Hybrid AI-Driven (e.g., PINNs, Google/DLR)	Global	Low (Inference) / High (Training)	**High:** Combines physical constraints (like SAC) with pattern recognition for accurate lifecycle tracking.	**Very High:** Rapid real-time inference enables active, tactical flight rerouting.	"Black-box" interpretability issues; predictions degrade sharply if flight enters unrepresented atmospheric conditions.

7.2 Appendix B: Dataset Catalog

TABLE B1. Dataset for contrail prediction models

Dataset Name	Source/Agency	Type	Purpose in Contrail Research	Temporal Coverage	Notes

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MODIS	NASA (Terra/Aqua Satellites)	Satellite Imagery (VIS/IR)	Contrail detection, optical depth, cirrus classification	2000–Present	Used in many ML and empirical models
CALIOP (CALIPSO)	NASA & CNES	Active Lidar	Vertical profiling of contrails and cirrus clouds	2006–Present	High vertical resolution
AVHRR	NOAA/NASA	Satellite Imagery	Retrospective contrail climatology, pattern recognition	1978–Present	Legacy dataset for detection
GOES-16/17	NOAA	Geostationary Satellite	Real-time contrail detection in Western Hemisphere	2016–Present	High temporal resolution
ERA5	ECMWF	Reanalysis (Atmospheric Fields)	Provides humidity, wind, and temperature inputs for contrail models	1979–Present	Used in CoCiP and APCEMM
MERRA-2	NASA GMAO	Reanalysis	Atmospheric initialization for global-scale models	1980–Present	High compatibility with ECHAM, CESM
AIRS	NASA (Aqua)	IR Sounding	Retrieves temperature and humidity profiles at flight altitudes	2002–Present	Complements MODIS and ERA5
SUCCESS Campaign Data	NASA (1996)	Field Campaign (In-situ)	Contrail microphysics and plume chemistry calibration	1996	Used in Jensen (1998), Kärcher models
FAAM Aircraft Data	UK Met Office	In-Situ Aircraft Measurements	Provides aerosol and humidity data for contrail modeling	2004–Present (Campaigns)	Irregular temporal coverage
NOAA GFS Forecasts	NOAA	Operational Weather Model	Inputs for SAC, MM5, WRF-based contrail predictions	Real-time	Available for AI hybrid models
ADS-B Flight Data	OpenSky Network, FlightRadar24	Aircraft Trajectories	Contrail path mapping, emissions modeling, routing optimization	Varies	May require commercial license
CIRA Contrail Climatology	Cooperative Institute for Research in the Atmosphere (CIRA)	Remote Sensing	Long-term climatological analysis of persistent contrails	1980s–Present	Derived from satellite synthesis

7.3 Appendix C: Abbreviations

TABLE C1. Comprehensive List of Abbreviations

Abbreviation	Full Name / Description
ABI	Advanced Baseline Imager
ACSM	Ames Contrail Simulation Model
ADM	Automated Detection and Matching
ADS-B	Automatic Dependent Surveillance–Broadcast
AHI	Advanced Himawari Imager (on Himawari satellite)
AI	Artificial Intelligence
AIC	Aircraft-Induced Cloudiness
AIRS	Atmospheric Infrared Sounder
APCEMM	Aviation Particle and Chemical Emissions Model
ARPS	Advanced Regional Prediction System
ART	Aerosols and Reactive Trace gases
ATC	All Tests Consolidation
AVHRR	Advanced Very High Resolution Radiometer
BADA	Base of Aircraft Data

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BTD	Brightness Temperature Difference
CALIOP	Cloud-Aerosol Lidar with Orthogonal Polarization
CALIPSO	Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation
CAMS	Copernicus Atmosphere Monitoring Service
CC	Contrail Cirrus
CDA	Contrail Detection Algorithm
CESM	Community Earth System Model
CFI	Contrail Frequency Indices
CI	Cirrus
CLZ	Contrail Likely Zone
CNN	Convolutional Neural Network
CoAtSaC	Contrail Attribution Sample Consensus
CoCiP	Contrail Cirrus Prediction Model
COT	Cloud Optical Thickness
DLR	Deutsches Zentrum für Luft- und Raumfahrt (German Aerospace Center)
DMSP	Defense Meteorological Satellite Program
DNB	Day/Night Band (part of VIIRS)
DP	Dynamic Programming
DWD	Deutscher Wetterdienst (German Weather Service)
EASA	European Union Aviation Safety Agency
ECHAM	European Centre Hamburg Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA5	ECMWF Reanalysis v5 (climate reanalysis dataset)
ERF	Effective Radiative Forcing
FAA	Federal Aviation Administration
FAR	False Alarm Rate
FK5D	Flightkeys 5D
GAIA	Global AI Aviation
GEFS	Global Ensemble Forecast System
GEOS-5	Goddard Earth Observing System Model, Version 5
GFS	Global Forecast System
GHG	Greenhouse Gas
GISS	Goddard Institute for Space Studies
GOES	Geostationary Operational Environmental Satellite
HC	Hydrocarbons
ICAO	International Civil Aviation Organization
ICS	Invariant Coordinate System
IFS	Integrated Forecasting System (ECMWF)
IPCC	Intergovernmental Panel on Climate Change
ISSR	Ice-Supersaturated Region
IUP	Institute of Environmental Physics
IWC	Ice Water Content
KIT	Karlsruhe Institute of Technology
LCM	Lagrangian Cloud Model
LES	Large Eddy Simulation
LUT	Look-Up Table
MERRA	Modern-Era Retrospective analysis for Research and Applications
MISR	Multi-angle Imaging SpectroRadiometer
MIT	Massachusetts Institute of Technology
ML	Machine Learning
MM5	Fifth-Generation Penn State/NCAR Mesoscale Model
MODIS	Moderate Resolution Imaging Spectroradiometer
MODTRAN	Moderate Resolution Atmospheric Transmission
MPI-M	Max Planck Institute for Meteorology
MSG	Meteosat Second Generation

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NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NOAA	National Oceanic and Atmospheric Administration
NWP	Numerical Weather Prediction
OCA	Optimal Cloud Analysis
PCC	Potential Contrail Cover
PCCC	Potential Contrail Cirrus Cover
PCM	Probabilistic Cloud Mask
PINNs	Physics-Informed Neural Networks
PM	Particulate Matter
POD	Probability of Detection
PPS	Polar Platform System
PRE-TRAILS	Pre-trained Radiative AI Layered System
RANSAC	Random Sample Consensus
RAP	Rapid Refresh
RF	Radiative Forcing
RHi	Relative Humidity with respect to Ice
RRTM	Rapid Radiative Transfer Model
RRTMG	Rapid Radiative Transfer Model for GCMs
RTE	Radiative Transfer Equation
RTMs	Radiative Transfer Models
RUC	Rapid Update Cycle
SAC	Schmidt-Appleman Criterion
SAF	Sustainable Aviation Fuel
SCIAMACHY	Scanning Imaging Absorption Spectrometer for Atmospheric Chartography
SEVIRI	Spinning Enhanced Visible and Infrared Imager
SIPs	Simulation Ice Particles
SST	Supersonic Transport
STFM	Strategic Traffic Flow Management
SUCCESS	Subsonic Aircraft: Contrail and Cloud Effects Special Study
TOMS	Total Ozone Mapping Spectrometer
TUV	Tropospheric Ultraviolet and Visible Radiation Model
UKCA	UK Chemistry and Aerosols
UKMO	UK Met Office Unified Model
VIIRS	Visible Infrared Imaging Radiometer Suite
vPM	Volatile Particulate Matter
WAWFOR	World Aviation Weather Forecast
WFM-DOAS	Weighting Function Modified Differential Optical Absorption Spectroscopy
WRF	Weather Research and Forecasting Model
WRF-Chem	Weather Research and Forecasting model coupled with Chemistry
WV	Water Vapor

Code availability

No original code was developed for this review article. Details, algorithms, and source code availability for the various contrail prediction models discussed in this manuscript can be found within their respective cited literature.

Data availability

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No new primary datasets were generated or analysed in this study. All data, literature metadata, and model information synthesized in this review are publicly available and properly cited in the reference list.

Author's contributions

Najeeb Ullah conducted the primary literature investigation, performed the core research synthesis, and wrote the original draft of the manuscript. Meiyin Zhu and Liuyong Chang provided overall supervision for the project. Meiyin Zhu acquired the research funding and contributed to the conceptualization and critical review. Hongwei Deng and Shengnan Yang contributed to the formal analysis and methodology of the reviewed models. Aman Ullah and Jiaqi Yin assisted with data curation (literature selection) and visualization. Muhammad Owais Ghani and Tianxu Huang contributed to the investigation. All authors participated in the critical review and editing of the final manuscript.

Declaration of competing interest

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

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