Sustainable Aviation Fuel Use at a Washington State International Airport: Regional Air Quality Benefits

Submitted: December 1, 2024

Period covered: Year 2023

Prepared by the Department of Environmental & Occupational Health Sciences at the University of Washington

ENVIRONMENTAL & OCCUPATIONAL HEALTH SCIENCES
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Authors: Elena Austin, Yeon Cheong, Ningrui Liu, Timothy Larson, Timothy Gould, Edmund Seto

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Preamble

This is the first in a series of annual reports mandated by the Washington State Legislature under **SB 5447** to quantify the benefits of alternative jet fuels (AJFs) compared to fossil jet fuel. This initial report focuses on **sustainable aviation fuels (SAFs)**, a subset of AJFs, to assess their emissions benefits and potential to improve regional air quality. While the legislative directive under SB 5447 encompasses all alternative jet fuels, this report focuses on SAFs as the most immediately viable subset of AJFs, aligning with the Port of Seattle's reporting framework and regional sustainability goals.

The Port of Seattle has set ambitious targets for SAF adoption at Seattle-Tacoma International Airport (SEA), aiming for 10% SAF use by 2028 and 25% by 2035. SAFs, which include fuel types such as Hydroprocessed Esters and Fatty Acids (HEFA) and Alcohol-to-Jet (ATJ), are derived from renewable resources and offer significant environmental benefits. These fuels are compatible with existing aviation infrastructure and engines, making them a practical and impactful choice for immediate emissions reductions.

This work evaluates emissions of particulates and sulfur oxides from SAF blends compared to conventional Jet A fuel and explores their implications for regional air quality. It also identifies gaps in understanding, particularly around the specific blends and operational contexts that optimize emissions reductions, to guide future research and reporting.

The University of Washington's Department of Environmental & Occupational Health Sciences developed this foundational report based on a comprehensive review of existing published literature, while Washington State University contributed by reporting on the current usage of conventional jet fuel and SAFs at Sea-Tac International Airport.

This report serves as a groundwork for future evaluations, identifying current knowledge, methodologies, and data gaps. Through an extensive literature review and synthesis, the University of Washington team provides insights into the state of SAF research and outlines potential directions for future studies and reporting.

Sustainable Aviation Fuels Usage

For the calendar year 2023, the Port of Seattle reported to partners at the University of Washington, for the purpose of generating this report, that 664,998,063 gallons of conventional petroleum Jet A fuel were uplifted at Sea-Tac. **No sustainable aviation fuels were used in 2023.** These use figures were reported in accordance with the requirements of SB5447 in July 2024 by the Port of Seattle to the University of Washington team, through coordination with the WA State Alternative jet fuels work group.

Executive Summary

In response to the legislative directive, this report explores potential regional air quality benefits of adopting sustainable aviation fuels (SAF) at Sea-Tac International Airport, focusing on reductions in ultrafine particles and sulfur oxide emissions compared to emissions from Jet A fuel. *The Port of Seattle reported that no SAF were used in 2023.* The legislative directive provided guidance to consider the benefits of all alternative jet fuels (AJF). This report focuses on SAF use as this was the subset of AJF reported by the Port of Seattle. The SAF focus also aligns with the Alternative Jet Fuels Work Group 2022 report, *Sustainable Updates and Recommendations (Opportunities for Washington)* (WSU, 2022).

Although no SAF usage was reported in 2023, this report synthesizes literature on potential SAF emission reductions, health impacts of SAF adoption, and modeling and monitoring approaches that can be applied to better quantify future impacts and benefits. It also identifies knowledge gaps and recommends important next steps to better quantify SAFs' real-world benefits.

Key findings suggest that SAFs have the potential to reduce regional air pollution in airport-impacted communities, improve health outcomes, and assess environmental justice impacts. There are significant potential benefits but also uncertainties in quantifying these benefits. The magnitude of the benefits will depend on various factors, including SAF production methods, blend ratios, fuel additives, and sulfur content. Landing flights are a significant contributor to regional ultrafine particle concentrations, underscoring the need to consider fueling locations.

Recommended next steps to support future reports include enhancing SAF usage tracking, expanding emissions monitoring, and evaluating policies to support SAF adoption. Recommended next steps include enhancing SAF usage tracking, expanding emission monitoring, and encouraging policies to support SAF adoption.

Legislative Directive

A new section is added to chapter 28B.20.545 RCW to read as follows:

(1) To assess the potential co-benefits of alternative jet fuel for Washington's communities, by December 1, 2024, and December 1 of each year until such time as the joint legislative audit and review committee has completed its final report on the tax preferences contained in sections 9 through 12 of this act, the University of Washington's Department of Environmental and Occupational Health Sciences, in collaboration with Washington State University, ***shall calculate emissions of ultrafine and fine particulate matter and sulfur oxides from the use of alternative jet fuel as compared to conventional fossil jet fuel, including the potential regional air quality benefits of any reductions***. This emissions calculation shall be conducted for alternative jet fuel used from an international airport owned by a port district in a county with a population greater than 1,500,000. The University of Washington may access and use any data necessary to complete the reporting requirements of this section.

(2) To facilitate the calculation required in subsection (1) of this section, an international airport owned by a port district in a county with a population greater than 1,500,000 must report to the University of Washington the total annual volume of conventional and alternative jet fuel used for flights departing the airport by July 1, 2024, and July 1st of each year until such time as the joint legislative audit and review committee has completed its final report on the tax preferences contained in sections 9 through 12 of this act.

Abbreviation Key

AJF: Alternative Jet Fuels
ATJ: Alcohol-to-Jet
BC: Black Carbon
CO: Carbon Monoxide
CO_2: Carbon Dioxide
EIM: Emission Indices for Mass
EIN: Emission Indices for Number
EPA: Environmental Protection Agency
FAA: Federal Aviation Administration
FT: Fischer-Tropsch (fuel type)
GMD: Geometric Mean Diameter
HEFA: Hydroprocessed Esters and Fatty Acids
ICAO: International Civil Aviation Organization
Jet A: Conventional jet fuel
LDSA: Lung Deposited Surface Area
LTO: Landing and Takeoff
MOV-UP: Mobile Observations of Ultrafine Particles
nvPM: Non-Volatile Particulate Matter
NO: Nitrogen Oxide
NO_x: Nitrogen Oxides
PAH: Polycyclic Aromatic Hydrocarbons
PHSKC: Public Health Seattle & King County
PM: Particulate Matter
PM_{10}: Particulate Matter with diameters ≤10 micrometers
$PM_{2.5}$: Fine Particulate Matter (particles with diameters ≤2.5 micrometers)
PNC: Particle Number Count
SAF: Sustainable Aviation Fuels
SO_x: Sulfur Oxides
UFP: Ultrafine Particles
vPM: Volatile Particulate Matter
VOC: Volatile Organic Compounds

Introduction

The legislative directive under SB 5447 calls for an evaluation of **alternative jet fuels (AJFs)** to mitigate aviation emissions and improve regional air quality. AJFs encompass a broad category of non-conventional aviation fuels, including biofuels, synthetic fuels, and other innovative pathways. Among these, **sustainable aviation fuels (SAFs)** represent the most immediately viable option for real-world application, given their compatibility with existing aviation infrastructure and engines, and their established environmental benefits.

SAFs, produced using pathways such as HEFA and ATJ, are particularly promising for reducing emissions of ultrafine particles (UFPs), fine particulate matter (PM2.5), and nitrogen oxides (NOx) during critical phases of aircraft operation, such as taxiing, takeoff, and landing. For this reason, a growing number of recent policies support the adoption of sustainable aviation fuels and low-emission fuels, including biofuels and synthetic fuels, to reduce aviation's impact on the climate, improve overall air quality, and protect human health. The FAA has committed to transitioning to unleaded aviation gasoline by 2030 and initiated a grant program called Fueling Aviation's Sustainable Transition to support SAF production and deployment. The FAA also recently finalized a rule requiring reductions in emissions of ultrafine carbon particles and non-volatile particulate matter from U.S. civil aircraft engines.

At the State level, the Port of Seattle has demonstrated leadership by setting a goal of 10% SAF-blend fuel usage at Sea-Tac International Airport by 2028, making it the first U.S. airport to set a target and timeline for SAF adoption. In 2024, the Washington State Legislature introduced, but did not pass, a bill (SB6114) that would have mandated a 10% SAF blend for certain aircraft, depending on local production capacity. The 2022 report from the Alternative Jet Fuels Work Group underscores the importance of SAF adoption for reducing greenhouse gas emissions and aligning with Washington State's broader decarbonization and clean energy goals, emphasizing the need for continued investment in SAF production and infrastructure to achieve these targets (WSU 2022).

This report presents current evidence and approaches for calculating and reporting changes in emissions of ultrafine and fine particulate matter and sulfur oxides from the use of sustainable aviation fuels, as compared to conventional fossil jet fuel, as well as the potential regional air quality benefits of reductions in Jet A fuel usage. We also report on the current usage of SAFs at Sea-Tac International Airport, which is the only airport in Washington State owned by a port district in a county with a population greater than 1.5 million. The reporting from the Port of Seattle to the University of Washington was provided in the context of SAF use. This focus aligns with the Port's reporting and supports the broader goals of the Washington State Alternative Jet Fuels Work Group to promote the adoption of sustainable aviation fuels and reduce aviation-related emissions in the region.

Report goals

This initial report sets the stage for subsequent evaluations mandated under SB 5447 by the Washington State Legislature. Given the absence of Sustainable Aviation Fuel (SAF) usage at Sea-Tac Airport in 2023, this report focuses on foundational analysis and lays the groundwork for future reports by focusing on four key sections:

Section 1 Emissions: Reviews existing literature on estimated differences in pollution emissions for SAF blends compared to conventional Jet A fuel. Identifies blend ratios that have been reported to produce measurable emissions reductions.

Section 2 Human Health: Examines current evidence on the health impacts of conventional Jet A emissions and potential benefits of SAF adoption. Proposes some suggested scale of impacts from different blend ratios.

Section 3 Air Quality Modeling: Discusses approaches to modeling ground-level concentrations of aviation emissions near airports.

Section 4 Air Quality Monitoring near Airport Communities: Discusses current approaches to monitoring ground-level concentrations of aircraft emissions along the landing and takeoff paths.

Section 5 Implications and Next Steps: Outlines the University of Washington perspective on implications and next steps, offering a framework for future reports and ongoing discussions with state-level stakeholders.

This December 1, 2024, report will be shared with the State Legislature. The materials therein are suggested as technical guidance in developing and reporting benefits of different SAFs production and SAF use scenarios.

Report highlights

Reduction in Ultrafine Particle Emissions with SAF Adoption: Sustainable aviation fuels (SAFs) can have significantly lower sulfur and aromatic content compared to conventional jet fuels. Low SAF blends (e.g., 5–10%) significantly reduce ultrafine particle (UFP) emissions by up to 90% during low-thrust operations such as idling and taxiing. This has meaningful implications for improving air quality in communities near airports, which face heightened exposure to UFP pollution.

Health Benefits for Airport-Adjacent Communities: Communities near airports experience higher rates of respiratory and cardiovascular illnesses, adverse birth outcomes, and reduced life expectancy as compared to other communities in King County. These communities also face elevated exposures to UFP and other regional pollutants. SAF adoption has the potential to mitigate exposures by reducing emission of pollutants, particularly when high-blend SAF ratios are used in conjunction with low-emission additives. Aircraft emissions during landing are a concern, and without guidance on fuel use for incoming flights, the full benefits of SAF adoption may not be realized.

Importance of Comprehensive Monitoring and Data Sharing: Assessing SAF co-benefits requires enhanced air quality monitoring near airports to capture pollutant concentrations and composition. Data-sharing protocols, including SAF blend ratios, flight activity, and fuel sulfur content, are needed to validate predictions and quantify health benefits.

Refinement of Air Quality Modeling Approaches: Current models like AERMOD and CMAQ must be improved to assess SAF-specific emissions and their regional level impacts. Combining these models with monitoring data and hybrid modeling approaches could enhance accuracy, particularly for high-spatial resolution exposure assessments.

Research Gaps in SAF Emission Characterization: Real-world monitoring of SAFs' ground level impacts during operational cycles (e.g., landing and takeoff) is essential. This knowledge will help quantify the health and environmental benefits of SAF adoption and inform robust cost-benefit analyses for policy development.

Considerations for SAF Implementation: Collaboration among airport authorities, research institutions, and public health agencies is crucial to support SAF adoption. Policymakers could consider prioritizing initiatives like high-blend SAF usage, expanded monitoring networks, and structured reporting systems to maximize health and environmental co-benefits for airport-impacted communities.

This report underscores the potential of SAFs in reducing pollution, the importance of evaluating benefits to community health, and establishes some approaches that could allow for these findings to be considered when planning for SAF adoption and implementation. Real-world emission profiles and minimum effective SAF blend thresholds remain critical knowledge gaps for understanding regional air quality benefits.

Section 1. Emissions from Sustainable and Traditional Jet Fuels

Highlights

- The highest impacts on communities from aviation emissions occur during aircraft idle, landing, and takeoff.
- As compared to conventional fuels, SAFs typically have lower sulfur and aromatic content. Thus, SAFs have the potential to significantly reduce both volatile UFP and sulfur dioxide emissions.
- Aviation fuels with even relatively low proportions of SAF (e.g., 5%) offer significant emissions reductions.
- Different production methods and different additives blends significantly modify the emission profiles of SAFs. Thus, potential impacts are dependent on detailed SAF profiles.
- SAFs emissions and particle size distributions differ from those of conventional Jet A fuels. Thus, these must be explicitly reported to capture the correct impact on community health.
- A comprehensive evaluation—considering factors such as aircraft operating modes (taxi, landing, takeoff), airport traffic volume, flight paths, and the fuel types used for inbound and outbound flights—is essential to accurately assess exposure risks in nearby communities.

Background

Aviation emissions have an impact on climate change, local air quality, and human health (Bookstein et al., 2024; Carter et al., 2023; Hsu et al., 2012; D. S. Lee et al., 2021; Westerdahl et al., 2008). Aviation emissions accounted for 2% of the total greenhouse gas emitted globally in 2018 (Abrantes et al., 2021). Although the number of flights dramatically decreased during the coronavirus pandemic, the aviation industry has rapidly recovered, reaching 2019 levels by November 2023 (IATA, 2024).

In 2021, the International Air Traffic Association (IATA) committed to reducing aviation carbon dioxide (CO_2) emissions by 50% by 2050 relative to 2005 levels, thus capping emissions at 2020 levels. This would be achieved primarily through the widespread adoption of sustainable aviation fuels (IATA, 2021). From a lifecycle analysis perspective, SAFs have the potential to reduce aviation-related CO_2 emissions by about 80% (IATA, 2017). While reducing greenhouse gas emissions is the main goal of SAF adoption, it also offers significant benefits for community health by lowering sulfur dioxide and particulate emissions, thus improving air quality around airports and flight paths. In part to support the implementation of the IATA, the quantity of studies on SAFs feasibility, production and benefits has increased since 2020 (Yaşar Dinçer et al., 2024).

Aircraft emit various pollutants, including particulate matter, both volatile and non-volatile; carbon monoxide; carbon dioxide; nitrogen oxides; sulfur dioxide; water vapor; and unburned hydrocarbons. Aircraft engine lubrication oils have also been detected in exhaust plumes (Fushimi et al., 2019; Ungeheuer et al., 2022; Yu et al., 2019). These emissions affect both the upper troposphere and ground-level air quality. At higher altitudes, CO_2 and particulates contribute to climate change through radiative forcing—that is, by increasing the energy balance within the Earth's atmosphere by increasing energy capture from the CO_2 and through the atmospheric impact of aviation-related contrails. At ground level, elevated concentrations of ambient pollutants, including ultrafine particles, sulfur dioxide, and nitrogen dioxide, pose significant concerns for community health. SAF adoption is a pathway to remediating both climate and health impacts.

Below we review the types of SAFs and their impacts on ultrafine particle emissions, as well as relevant regulatory frameworks.

Fuel types

To ensure stable operation at high altitudes, all aviation fuels must satisfy certain parameters regarding composition, volatility, fluidity, combustion, corrosion, thermal stability, contaminants, and additives. The specific chemical content of fuels (i.e. fuel composition), particularly the sulfur and aromatic content, govern ambient emissions, including ultrafine particle (UFP) emissions.

Conventional (Jet A) fuels

Jet A fuels are kerosene-based and widely used in aviation. Because these fuels are fossil fuel based, there is increased interest in developing alternative and sustainable alternatives. Jet A-1 is the standard fuel for international flights in most regions. Jet A is commonly used for domestic flights within the U.S. In Canada, Jet B is preferred for cold-weather operations due to its lower freezing point (Raji et al., 2024). The sulfur content of these fuels is usually less than 0.3% by weight (3000 ppm), although the exact amount can vary depending on the fuel type and regional regulations. Jet A fuels contain approximately 17% aromatics by volume, crucial for promoting seal swell and preventing fuel leaks. A lack of aromatics can lead to seal failure and leakage. However, the incomplete combustion of these aromatics contributes to undesirable soot emissions (Hamilton et al., 2024).

Sustainable aviation fuels

Rising fuel costs, climate goals, stricter regulations, and energy security factors have led airlines to explore SAFs, also referred to as 'drop-in' fuel, because they can be used without any engine modifications. SAFs are derived from various feedstocks, including sugar, plant-based oils, animal fats, algae-derived oils, and waste oils (Raji et al., 2024; Watson et al., 2024).

The American Society for Testing and Materials (ASTM) evaluates and certifies SAF production technologies. Well-recognized ASTM-certified SAFs include hydroprocessed esters and fatty acids (HEFA), Fischer-Tropsch synthesis (FT), alcohol-to-jet (ATJ), and synthesized iso-paraffins (SIP) processes (Khujamberdiev & Cho, 2024; Raji et al., 2024).

When blended with Jet A fuel, SAFs typically comprise 10% to 50%, depending on the type of SAF and its aromatic content (ASTM D7566). For example, SIP fuels are allowed a maximum of 10% blend, while FT, HEFA, and ATJ fuels can be blended up to 50%. Among these, HEFA is considered the most commercially viable, though challenges such as high production costs, hydrogen requirement, and economic feasibility persist (M. J. Watson et al., 2024). It is worth mentioning that studies on SAF production, life cycle analysis, and economic analyses for feedstocks using lignin, forest residue, and municipal solid wastes exist (Ahire et al., 2024; Yang et al., 2022; L. Zhang et al., 2024). SAFs typically contain lower levels of sulfur and aromatics, depending on the feedstock used. However, given the specific requirements of jet fuels, achieving 100% SAF conversion is challenging.

SAFs hold significant potential to reduce CO_2 emissions by using renewable feedstocks like waste oils or biomass. However, their adoption is contingent upon sustainable feedstock availability, technological viability, economic feasibility, and supportive policies. While a growing body of literature explores the pollutant-reduction potential of SAFs compared to conventional jet fuels, there is a notable gap in research on the potential health benefits associated with SAF adoption—an area that warrants further investigation.

Emissions regulations

Before 2016, the only emission standard related to particulate matter (PM) emissions from aircraft was the Smoke Number Regulation, an international standard which ensured that engine emissions were invisible (ICAO). However, as concerns about the health impacts of ultrafine particles, particularly non-volatile particulate matter (nvPM), grew, more stringent measures were implemented. In response, the International Civil Aviation Organization's Committee on Aviation Environmental Protection (ICAO-CAEP) introduced the CAEP/10 certification standard in 2016 (ICAO, 2016). This new standard focused specifically on nvPM emissions and required not only measurement of nvPM mass concentration, but also the reporting of nvPM mass and number emission indices (total emissions per kg of fuel burned) during landing and takeoff. This marked a significant step forward in addressing the environmental and health risks associated with UFP emissions from aircraft. The ICAO nvPM standard applies to turbojet and turbofan engines with a rated thrust greater than 26.7 kN (typical of medium to large commercial jets) that were certified after January 1, 2020. While manufacturers were required to comply with the standard from 2020 onward, the regulation became fully effective and enforceable as of January 2023.

In the U.S., the Environmental Protection Agency has finalized PM and nitrogen oxide (NO_x) standards, aligning its PM standards and test procedures with those adopted by ICAO in 2017 and 2020 (US EPA, 2022). This alignment was part of the Final Rule for Control of Air Pollution from Aircraft Engines: Emission Standards and Test Procedures (2022/11). The final rule also applied Smoke Number standards, but not PM standards, to engines with a rated thrust less than or equal to 26.7 kN, such as those used on smaller private jets and on supersonic airplanes.

While these emission standards apply to most aviation fleets, they exclude aircraft with rated thrusts of less than 26.7 kN, including small business jets. Research indicates that small jets can emit as much nvPM as larger airliners (Durdina et al., 2019). This suggests that in addition to accounting for emissions from larger aircrafts, in the future it may also be important to consider not only rated thrust but also the frequency and purpose of aircraft operations in order to effectively manage nvPM emissions and community impacts.

Aircraft emissions measurement

This section provides a focused literature review of aircraft emissions research, specifically examining studies that involve direct measurements.

We identified a preliminary set of 58 journal articles using Web of Science and the following keywords: “sustainable aviation fuels”; “ultrafine particles”; and “emissions." To align with the primary objective of this report—understanding ultrafine particle reductions associated with SAF adoption—we excluded studies that focused on volatile emissions from aircraft, as well as those that relied on modeling or prediction. After applying these exclusions, a final set of 25 articles remained.

Experimental methods for measuring aircraft emissions can be categorized into three approaches: in-flight measurements, ground-based measurements, and test cell experiments. Due to logistical challenges and safety concerns related to in-flight measurements, researchers have concentrated primarily on ground-based measurements and test cell experiments. These studies typically examine emissions from turbofan jet engines, which are common in civilian aircraft (Durdina et al., 2014; Jasiński & Przysowa, 2024; Lobo et al., 2015; Wey et al., 2007).

Non-volatile particulate matter (nvPM) is a key focus of these studies. In test cell experiments, inline instrumentation (e.g. Scanning Mobility Particle Sizer, Engine Exhaust Particle Sizer, Differential Mobility Spectrometer, and Electrical Low Pressure Impactor, Real time gas analyzers) is used to measure gasses, particulate number and mass, and particle size distribution (C. Zhang et al., 2022). To minimize the formation of volatile particulate matter (vPM) by condensation, the exhaust gas is maintained at 160°C upstream of the diluter and subsequently diluted and kept above ambient temperature (e.g., 60°C) downstream of the diluter (Saffaripour et al., 2020; Smith et al., 2024). Heated sampling systems are also employed to keep volatile species in the gas phase during measurement (Stacey, 2019).

For ground-based measurements, the exhaust gas is sampled behind the aircraft, with the distance between the engine exhaust axis (also referred to as "exhaust plane") and the sampling probe varying from approximately 1–40 meters (Schripp et al., 2022; Turgut et al., 2015; Wey et al., 2007). The exhaust then undergoes a sampling process similar to that used in test cell experiments for nvPM analysis. The sampling distance is critical, as it is closely related to the age of the exhaust plume, which affects the behavior of vPM. vPM is highly sensitive to environmental conditions and can condense or agglomerate as the plume disperses, potentially altering the total PM measurement. Additionally, nvPM emitted from aircraft is often coated with sulfuric acid and water, making it essential to carefully consider the sampling distance to avoid interference from these coatings (Owen et al., 2022).

Engine emissions are analyzed at various thrust levels, with studies typically following the landing and takeoff (LTO) cycles used by the ICAO engine certification process. The ICAO LTO cycle includes taxi (7% thrust for 26 minutes), approach (30% for 4 minutes), climb (85% for 2.2 minutes), and takeoff (100% for 0.7 minute). Additionally, thrust levels of around 60% are sometimes tested to simulate emissions during cruise, although this is less common (Lobo et al., 2015; Z. Xu et al., 2024).

Jet A-1 is typically used as a reference fuel to evaluate the emission characteristics of SAFs, both pure and 50% blends. Emission indices (EI) are assessed across various thrust levels across the LTO cycle, as defined by ICAO (ICAO, 2016)

Particulate matter types

Current research finds that aircraft UFP emissions typically range in size from 10–20 nm (Austin et al., 2021; Shirmohammadi et al., 2017; Stacey, 2019). These UFPs are a significant health concern for communities near airports. While SAFs are effective in reducing CO_2, PM, and sulfur dioxide (SO_2) emissions, they do not appear to significantly impact carbon monoxide (CO) or nitrogen oxide (NO_X) emissions, as these are primarily influenced by engine operating conditions (Schripp et al., 2022; Song et al., 2024). Therefore, this report focuses on particulate matter; the terms "PM" and "UFP" are used interchangeably for the remainder of this section.

Aircraft PM is primarily composed of refractory carbon soot with organic and/or sulfate coatings (Onasch et al., 2009; Timko et al., 2010). At ground level, these emissions affect air quality and health (Austin et al., 2021; Hsu et al., 2012; Westerdahl et al., 2008). At high altitudes, they contribute to contrail formation and radiative forcing (Testa et al., 2024).

Aircraft total PM consists of both volatile and non-volatile components. nvPM refers to solid particles that exist at the plane of the engine exhaust at 350°C (ICAO, 2016). Typically, it is carbonaceous in nature and is commonly referred to as soot, black carbon, or elemental carbon (Durdina et al., 2014; Saffaripour et al., 2020; Stacey, 2019). Due to its relative sampling simplicity, nvPM is used as a basis for ICAO emissions standards.

vPM refers to particles that do not exist at the engine exit plane at 350°C. It forms through condensation and nucleation within the exhaust plume, resulting in smaller geometric mean diameters and geometric standard deviations (Lobo et al., 2015).
vPM is predominantly composed of sulfuric acid and organic materials. The sulfur content of fuels determines the amount of sulfuric acid droplets present to act as condensation nuclei. Thus, sustainable aviation fuels, which contain virtually no sulfur, can significantly reduce both vPM and SO_2 emissions. However, studies in the early 2000s found that, at very low sulfur levels (e.g.,100 ppm), non-sulfate fuel compounds such as non-methane hydrocarbons can also contribute to vPM (Brock et al., 2000; Schröder et al., 2000).

In summary, total aircraft particulate emissions are a complex mixture of both volatile and non-volatile particulate matter, making measurement challenging. While nvPM is well-defined and regulated, vPM also plays a crucial role and must be considered in emissions assessments. Additionally, the measurement of total PM is sensitive to factors such as distance from the exhaust plane and plume age. These complexities underscore the need for more comprehensive measurement approaches to fully understand aircraft emissions and their impacts on air quality and climate.

Emission indices—pollutant emissions per unit of fuel burned

An important benefit of SAF adoption is the reduction in ultrafine particles. Owing to their ultrafine size (less than 100 nm in diameter), particle number is regarded as a more relevant metric than mass-based measurements for climate and health assessments (Abdillah & Wang, 2023; Z. Xu et al., 2024). Emission indices (EI) are metrics used to quantify the amount of a specific pollutant emitted per unit of fuel burned. EI provide valuable insight into the effectiveness of SAFs in reducing UFP emissions compared to conventional

Jet A fuels. This section will discuss the emission indices (EI) of UFP for both particulate number and mass, emphasizing the complementary perspective provided by number-based measurements, which capture the high particle counts characteristic of ultrafine emissions.

Particulate number emission indices

Studies of nvPM emission indices for different fuel types and thrust settings consistently report U-shaped curves in relation to thrust (or fuel flow) for particulate number EI (EI_N). Emission metrics such as the EI_N are key indicators of an aircraft's emissions relative to fuel consumption. The EI_N quantifies the amount of particulate matter emitted per kilogram of fuel burned, which helps assess the impact of fuel types on pollution levels and are particularly important for understanding ultrafine particle (UFP) concentrations. These metrics are crucial for determining how SAFs, compared to conventional Jet A fuel, reduce harmful particulate emissions in the surrounding environment. For Jet A fuels, the EI_N typically ranges from 10^{15}–10^{17} particles/kg of fuel burned (Jasiński et al., 2021; Kinsey et al., 2010; Wey et al., 2007). Variations in EI_N values are influenced by fuel type, combustion conditions, and thrust settings, with fuel flow rate and engine operating conditions playing a significant role.

Conventional fuels such as Jet A-1 show EI_N values increase with thrust, peaking at higher thrust levels as high as 1.33×10^{17} particles/kg fuel burned (Jasiński et al., 2021)j and Przysowa, 2024). SAFs including hydroprocessed esters and fatty acids (HEFA) (both neat and blends) and alcohol-to-jet (ATJ) blends demonstrate significant reductions in EI_N compared to Jet A-1. For example, 30% HEFA blends with Jet A-1 showed up to 90% reduction in EI_N across all thrust levels, with values ranging from 2.83×10^{15} (10% thrust) to 1.04×10^{16} particles/kg fuel (70% thrust) (Jasiński & Przysowa, 2024). Similarly, 30% ATJ blends with Jet A-1 resulted in a 50% median reduction in EI_N (Jasiński et al., 2021).

For Fischer-Tropsch (FT) fuels, natural gas-derived and coal-derived FT exhibited median reductions in EI_N of 70% and 73%, respectively, across all thrust levels. In contrast, 50:50 blends of these FT fuels with JP-8, a kerosene fuel with additives intended to provide properties important for military uses, showed more modest EIN reductions of 15% for natural gas FT and 20% for coal-derived FT (Kinsey et al., 2010). Additionally, reductions in particle number emissions were greater at higher thrust levels, indicating improved emissions performance at higher power settings, particularly with FT blends. These reductions were consistent across thrust levels, reflecting the beneficial impact of SAFs on reducing particle emissions.

Particulate mass emission indices

Non-volatile particulate matter (nvPM) mass EI (EI_M) generally shows a monotonic increase. Reported EI_M values vary widely, ranging from as low as 6.88–600 mg/kg of fuel burned, suggesting that EI_M is influenced by multiple factors and may not serve as a reliable metric for direct comparison (Xu et al., 2024; Lobo et al., 2015). The sampling distance, fuel type, effective density, and varying particle size distribution with thrust all play a role in how EI_M is calculated. Despite these complexities, several general trends can be observed.

Compared to conventional aviation fuel, SAFs typically show lower EI_M values across all thrust levels, with more significant reductions at low thrusts (Jasiński & Przysowa, 2024; C. Zhang et al., 2022). For instance, Kinsey et al. (2019) reported a median reduction of 94% in nvPM EI_M for both natural gas-derived and coal-derived FT compared to JP-8 under similar operating conditions. They also observed a median reduction of at least 56% in EI_M for FT blends with JP-8 (50:50 blend ratio).

Similarly, ATJ blend fuels (5%, 20%, and 30%) showed notable reductions in EI_M, with a median reduction of 53% for the 30% blend; 47% for the 20% blend; and 22% for the 5% blend across all thrust levels (Jasiński et al., 2021). When considering specific thrust levels, the 5% ATJ blend fuel exhibited the highest reduction (61%) in EI_M. These findings suggest that SAFs, particularly at lower blend ratios, may offer significant benefits in reducing nvPM emissions in low-thrust conditions.

Therefore, even 5% SAF blends have the potential to significantly reduce emissions, particularly during idle phases such as taxiing. As such, the Port of Seattle's goal of 10% SAF-blend fuel use at Sea-Tac by 2028 provides a strong starting point for mitigating aircraft emissions in the vicinity of the airport.

Particle size and other characteristics of SAF

Compared to Jet A fuel, SAFs not only reduce PM emissions but also affect particle size distribution (PSD) and characteristics such as density and particle reactivity. The size and reactivity of particles from aircraft emissions have implications for community exposure. This section summarizes the general PSD and morphological characteristics of aircraft UFPs from Jet A fuel combustion and explores how SAFs influence these parameters.

The PSD shows both dominant particle size and magnitude of emissions. For Jet A fuels at idle thrust, the PSD follows a lognormal distribution, with most primary particles (75–85%) in the 5–10 nm range and mobility diameters of 30–75 nm (Abegglen et al., 2015; Durdina et al., 2019; Liati et al., 2019). Mobility diameter in this context refers to the diameter of a spherical particle with the same aerodynamic behavior as the measured soot particle. At higher thrust levels, the PSD becomes less lognormal, with 60% of particles in the 10–25 nm range, and mobility diameters extending to 20–150 nm at thrusts above 67% (Abegglen et al., 2015; Durdina et al., 2019). A significant soot mode appears at high thrusts (> 85%) with JP-8 fuel, and the soot mode intensifies with higher fuel flow, resulting in larger and more numerous particles (Jasiński et al., 2021; Kinsey et al., 2019; Z. Xu et al., 2024). Overall, the PSD is lognormal across all thrusts, but particle size and distribution vary with fuel type and thrust setting (Abegglen et al., 2015; Kinsey et al., 2019).

SAFs follow a similar trend, while PSD shifts to a finer range. At low thrust, HEFA (100%) shows a peak at 7.5 nm, shifting to 20.8 nm at high thrust, with a nucleation mode between 7.5–25 nm (Z. Xu et al., 2024). HEFA blends (5%, 20%, 30%) exhibit a lognormal distribution in the 5–30 nm range, with bimodal volume-based PSDs showing peaks at 10 nm and 200 nm, especially at 30% HEFA (Jasiński & Przysowa, 2024).

The ATJ blends (5%, 20%, 30%) also have a nucleation mode (5–30 nm), with a 50% reduction in magnitude at 5% ATJ and a distinct soot mode around 50–560 nm for volume-based PSD (Jasiński et al., 2021). HEFA blend (32%) has primary particles in the 5–10 nm range at low thrust, with a shift to 10–25 nm at high thrust, showing larger agglomerates than Jet A-1 (Liati et al., 2019). FT fuels produce smaller particles and lower particle numbers than JP-8, with natural gas-derived FT showing a larger proportion of soot particles but a smaller overall magnitude (Kinsey et al., 2019).

Blended fuels tend to alter particle size and distribution compared to neat HEFA and JP-8. The geometric mean diameter (GMD) is an important parameter that indicates the dominant particle size and represents the central tendency of a PSD, which is critical for assessing inhalation exposure. The GMD increases with higher thrust (Abegglen et al., 2015; Durdina et al., 2019; Liati et al., 2019; Lobo et al., 2015; Z. Xu et al., 2024).

For Jet A fuels, these studies reported GMD typically ranging from 15–45 nm, with values rising at higher thrusts. In contrast, SAFs, including both neat and blends, produce smaller GMD across all thrust levels. For neat HEFA, the GMD is 7.7 nm at low thrust (7%) and increases to 20.3 nm at high thrust (100%) (Z. Xu et al., 2024). HEFA blends (17%, 30%, 49%) show a decrease in GMD as the blend concentration increases (Schripp et al., 2022). For a 32% HEFA blend, the GMD is 14.7 nm at low thrust (7%) and increases to 44.6 nm at high thrust (85%), with corresponding geometric standard deviations of 1.71 and 1.83 (Liati et al., 2019). Overall, the GMD increased with thrust for all fuel types. However, SAFs produced smaller particles and resulted in lower GMDs compared to Jet A fuels. This trend is attributable to differences in fuel composition.

The effective density of particles is also important, as it influences the particle-to-gas conversion rate, which in turn affects nvPM emissions. Studies have shown that particle effective density generally decreases with increasing thrusts using conventional jet fuels. Durdina et al. reported a decrease in effective density from 1100 kg/m^3 at ground idle to ~900 kg/m^3 at takeoff using Jet A-1 fuel (Durdina et al., 2014). As thrust increases, the composition of ultrafine particles (UFPs) shifts from organic carbon (OC) to elemental carbon (EC), which is associated with larger primary particle sizes and, consequently, a lower effective density. The effective density of small particles (e.g., 30 nm) ranged from

1075–1490 kg/m^3 at all thrust levels, while particles larger than 100 nm showed as low as 800 kg/m^3 at thrust levels above 67% (Abegglen et al., 2015). While SAFs produce fewer and smaller particles, the increase in effective density may be linked to a less pronounced reduction in EI_M at higher thrust levels (C. Zhang et al., 2022).

Particle reactivity, or soot reactivity, refers to the oxidative capacity of soot particles, which is influenced by their size, structure, and surface composition. Soot reactivity decreases with increasing thrust. At idle conditions, particle reactivity is highest for Jet A-1 fuel, while HEFA blends slightly reduce reactivity (Liati et al., 2019). Although particle reactivity for HEFA blends was found to be higher than Jet A-1 during climb conditions, the reduced quantity of UFP emissions from the blended fuels suggests that SAFs could help mitigate particle toxicity at ground idle. This reduction in UFP emissions could potentially protect the health of airport workers and nearby communities (Delaval et al., 2022).

In summary, particle size increases with thrust for Jet A fuels, while SAFs tend to reduce particle size and increase effective density, with changes in soot reactivity also observed. These effects are more pronounced at low thrust levels, which could have beneficial implications for reducing exposure to UFPs for airport personnel and nearby communities. Therefore, UFP emission indices and particle characteristics should be considered together to fully assess the potential health benefits of SAF adoption. Integrating these factors provides a more comprehensive understanding of how SAFs can contribute to improved air quality and public health outcomes.

Summary of findings — Section 1

While extensive research has focused on nvPM, there is limited literature on the characterization of vPM. This is likely due to the complexities discussed above associated with measuring vPM, which is not currently included in ICAO emissions regulations.

Table 1 summarizes the primary findings related to particle emission, fuel type and engine thrust level that were identified through the literature review discussed above. While EI_N consistently shows a U-shaped curve with increasing thrust, the trends for EI_M are variable. This variability stems from the dynamic relationships between particle number emissions, GMD, and particle formation processes. Even a small shift in GMD can lead to significant changes in the volume and mass distribution of particles. As a result, EI_N is a more relevant metric for evaluating the co-benefits of SAF adoption.

This literature review of reported emissions benefits of SAFs highlights both the potential of SAFs to decrease ambient emissions as well as some gaps in understanding the full emissions benefits of specific blends under specific use cases. These gaps represent a key area for further investigation. To fully capture the potential of SAFs, particularly in reducing air pollution in local communities, it is essential to fully describe the emission characteristics of different SAF blends to assess their specific impacts on regional air quality and community exposures.

Aircraft engines are optimized for cruising at high altitudes, which leads to inefficiencies during low and high thrust conditions, particularly during takeoff. Even low blends of SAFs can significantly reduce emissions during these low-thrust phases, potentially offering health benefits due to lower air pollution. The exact threshold value for the lower bound of SAFs blend expected to provide significant benefit is not yet known, in part due to uncertainties presented in the upcoming sections.

Additionally, this section suggests that continued review and study of emission characteristics is important to capture emerging science. Such a review should consider aircraft operating modes (taxi, landing, takeoff), airport traffic volume, flight paths, and the fuel types. Accurately characterizing emissions profiles for inbound and outbound flights could provide additional information important for accurately assessing exposure profiles in communities. This will provide the information needed to assess the evidence for the health benefits of SAF and also inform strategies to protect community health and address climate change.

Table 1. Summary of SAF impact on nvPM characteristics by thrust compared to Jet A fuel.

Fuel type	Thrust level	Particle Size Dist. (PSD)	Geometric Mean Diameter (GMD)	Particulate Number Emission indices (EI_N)	Particulate Mass Emission indices (EI_M)	Morphology	References
Jet A fuel (or similar grade such as JP-8)	Low	Lognormal distribution with nucleation mode between 5 – 100 nm	10 – 30 nm at low thrusts (7%, 30%)	5.83×10^{14} – 2.20×10^{17} at low thrust (Xu et al., 2024; Jasiński et al., 2021)	6.88 – 180 mg/kg (Xu et al., 2024; Jasiński et al., 2021)	Effective density decreases with increasing thrust (Durdina et al., 2014)	Xu et al., 2024; Jasiński et al., 2021; Lobo et al. 2015
	Medium		42 nm (Durdina et al., 2019)	Lowest at 15 – 30% thrust (Lobo et al., 2015)	82 – 150 mg/kg (Jasiński and Przysowa, 2024; Durdina et al., 2019)		

Fuel type	Thrust level	Particle Size Dist. (PSD)	Geometric Mean Diameter (GMD)	Particulate Number Emission indices (EI_N)	Particulate Mass Emission indices (EI_M)	Morphology	References
Jet A Fuel (cont.)	High		30 – 60 nm (> 85% thrust)	10^{15} - 10^{17} (Lobo et al., 2015)	100 – 600 mg/kg (Lobo et al., 2015)		
HEFA (100%)	Low	Similar PSD of Jet A, but smaller particle size in nucleation mode (5 – 30 nm) and reduced magnitude of particle counts	7.7 nm (7% thrust)	1.91×10^{14} (7% thrust)	1.36 mg/kg (7% thrust)	Smaller size, primarily chain-like with some surface pores	Xu et al., 2024
	High		20.3 nm (100% thrust)				
HEFA blend	Low	Similar PSD of Jet A, but smaller particle size in nucleation mode (5 – 30 nm) and reduced magnitude of particle counts	14.7 nm (7% thrust) (32% HEFA) (Liati et al., 2019)	2.83×10^{15} (10% thrust) (30% HEFA) (Jasiński and Przysowa, 2024)	14.0 mg/kg (10% thrust) (30% HEFA) (Jasiński and Przysowa, 2024)	Smaller soot agglomerates (40 – 100 nm) and more reactive primary particles (32% HEFA)	Liati et al., 2019 Jasiński and Przysowa, 2024
	Medium			Reduced EI_N at medium thrust for HEFA blend with higher hydrogen content (Schripp et al., 2022).	Up to 70% reduction in EI_M at medium thrust (53% N1) (Schripp et al., 2022).		Schripp et al., 2022)

Fuel type	Thrust level	Particle Size Dist. (PSD)	Geometric Mean Diameter (GMD)	Particulate Number Emission indices (EI_N)	Particulate Mass Emission indices (EI_M)	Morphology	References
HEFA blend (cont.)	High		44.6 nm (85% thrust) (32% HEFA) (Liati et al., 2019)	Not Reported	Not Reported	30~40% of particles with amorphous outer shell (32% HEFA)	Liati et al., 2019
ATJ blend	Low	Similar PSD of Jet A, but smaller particle size in nucleation mode (5 – 30 nm) and reduced magnitude of particle counts		1.1×10^{17} (30% ATJ)			Jasiński et al., 2021
	Medium			4.7×10^{16} – 1.1×10^{17} (30% ATJ)	117 mg/kg (30% ATJ)		
FT (100%)	Low to mid	Similar PSD of Jet A, but smaller particle size in nucleation mode (5 – 30 nm) and reduced magnitude of particle counts		2.7×10^{16} (Coal-derived FT) at low thrust	Minimum EI_M at medium thrust		
	General			Median reduction of 70 – 73% at all thrusts for two neat FT fuels, 15 - 20% for 50% FT blends	Median reduction of 94% at all thrusts for two neat FT fuels, 56 – 61% for FT blends		Kinsey et al., 2019

Section 2. Human Health: Impacts of Conventional Jet Fuels and Benefits of Sustainable Aviation Fuels

Highlights

- Ground-level monitoring shows that communities near airports are exposed to elevated ultrafine particle (UFP) emissions.
- Landing aircraft contribute to UFP exposures within communities.
- Airport-adjacent communities experience health disparities that are compounded by air and noise pollution from airport activities.
- Exposure to UFP increases the risks of respiratory and cardiovascular illness, preterm birth and low birth weight, and all-cause mortality.
- An optimized SAF strategy—including high blend ratios, selection of low-emission SAF types, and careful additive choices—could yield significant health improvements for airport-adjacent communities.

Background

Communities living near airports face unique challenges due to their proximity to significant sources of air pollution, including ultrafine particles (UFPs) and noise from aircraft and airport-related sources. These pollutants have been linked to respiratory and cardiovascular illnesses, adverse birth outcomes, and reduced life expectancy. Socioeconomically vulnerable populations are disproportionately affected by the health impacts of airport operations.

Sustainable aviation fuels (SAFs) offer a promising avenue to mitigate these impacts, with potential to significantly reduce UFP emissions and improve air quality in airport-adjacent neighborhoods. This section examines the health disparities linked to conventional jet fuel emissions, highlights the role of UFPs in adverse health outcomes, and explores how SAF adoption could address these concerns to enhance public health outcomes.

Particle matter concentrations near airports

The Mobile Observations of Ultrafine Particles (MOV-UP) Study (Austin et al., 2019), funded by the Washington State Legislature and conducted by the University of Washington, monitored the distribution and characteristics of ultrafine particles (UFPs) generated by emissions from conventional Jet A-1 fuel in communities surrounding Seattle-Tacoma International Airport (Sea-Tac). The study collected UFP data in areas under Sea-Tac flight paths, many of which are densely populated and socioeconomically vulnerable.

Using both mobile and fixed-site monitoring, the MOV-UP Study (Austin et al., 2021) gathered time-resolved UFP measurements over a representative sampling period in 2018. Mobile monitoring along designated north and south transects provided a detailed spatial analysis of pollutant concentrations, identifying distinct UFP sources from both roadway traffic and aircraft emissions. In addition, this study demonstrated that the impacts of landing aircraft on ambient air quality is substantial, particularly with respect to ultrafine particle concentrations.

While the highest UFP concentrations were near major roadways such as Interstate 5, the data also showed that aircraft landing operations at Sea-Tac significantly elevated ground-level UFP concentrations, particularly in the 10–20 nm range, illustrating the environmental impact of regular flight activities on nearby communities.

Annual UFP concentrations reported in Blanco et al. (2022) further estimated high particle levels around Seattle, with annual exposures of more than 10,000 particles per cubic centimeter in areas near aviation sources (Blanco et al., 2022a). This supports the previous findings that airport-impacted communities are exposed to elevated UFP emissions compared to other Puget Sound locations. Similar studies around major airports such as Los Angeles, Atlanta, Boston, and New York also found elevated UFP concentrations in communities impacted by conventional jet fuel emissions (Gualtieri et al., 2022; Hudda et al., 2014, 2016, 2018; Hudda & Fruin, 2016; Kerckhoffs et al., 2022).

Health disparities in airport-adjacent communities

The 2020 Public Health Seattle & King County (PHSKC) report to the Washington Legislature (Johnson et al., 2020) highlights health disparities among communities within a ten-mile radius of Sea-Tac airport, attributing these disparities to exposure to pollutants such as UFPs and black carbon from airport activities. These neighborhoods are home to high proportions of Black, Hispanic/Latino, and Native Hawaiian/Pacific Islander residents, who face socioeconomic conditions such as higher poverty and uninsured rates that may increase their vulnerability to pollution-related health issues.

Similarly, research in Rochester, New York, found that airport emissions contribute significantly to pollutant loads, as measured by exposure biomarkers, in people residing in adjacent communities (Y. Lin et al., 2024)**.** They also reported that UFP and polycyclic aromatic hydrocarbons (PAHs) exposure from airport sources aligns closely with socioeconomic factors, indicating that communities near airports, especially those with limited healthcare access and resources, face heightened cumulative exposure. This distribution pattern highlights how socioeconomic conditions can amplify the adverse effects of airport pollutants, increasing health risks for vulnerable populations living close to Sea-Tac.

Respiratory health impacts of ultrafine particle exposure

Although the MOV-UP Study recorded elevated UFP levels under Sea-Tac flight paths, it did not directly assess health outcomes. Prior research shows that UFPs—particles between 10 and 100 nm—can penetrate deep into lung tissue and potentially enter the bloodstream. Toxicological studies suggest that UFPs can induce cellular inflammation and oxidative stress, contributing to cardiovascular and respiratory issues (Oberdörster et al., 2005; Ohlwein et al., 2019; Peters et al., 2011; Qin et al., 2024).

More recent studies provide further evidence of the inflammatory response associated with UFPs from conventional jet fuel (Habre et al., 2018; He et al., 2020). Even low UFP concentrations can stimulate pro-inflammatory responses in lung epithelial cells, aligning with the increased respiratory risks reported for populations near airports (He et al., 2020). Important differences in the short-term inflammatory response of healthy participants exposed to near-road UFP and near-aircraft UFP have also been observed (Habre et al., 2018). Similarly, UFP exposure triggers inflammatory responses in lung and bronchial cells, supporting the view that prolonged exposure to aviation-related UFPs may weaken lung function and increase susceptibility to respiratory illnesses over time (Delaval et al., 2022) (Delaval et al., 2022).

Reproductive and developmental effects of ultrafine particles

Research on reproductive and developmental health impacts from UFPs and related emissions, including those from aircraft, highlights significant risks for communities near airports.

According to the PHSKC report, mothers living within one mile of Sea-Tac have a 43% higher likelihood of preterm births compared to those in other parts of King County. Proximity to the airport and ongoing exposure to UFPs, black carbon, and noise pollution from aircraft may contribute to these risks based on epidemiological studies described below.

Other studies support this association, finding that chronic UFP exposure is linked to higher risks of preterm birth and low birth weight (Carter et al., 2023; Stettler et al., 2013; Wing et al., 2022). UFPs from aircraft emissions are known to increase oxidative stress and systemic inflammation in pregnant individuals, which are factors that complicate fetal growth and delivery. PAHs and other byproducts from jet fuel combustion can disrupt hormonal balance, contributing to adverse birth outcomes (Y. Lin et al., 2024). This issue is particularly pronounced in economically disadvantaged communities near airports, where mothers experience disproportionate exposure to these pollutants, potentially leading to more frequent cases of low birth weight and developmental delays. Delaval et al. (2022) also provide biological insights, showing that UFPs can disrupt placental function, impairing nutrient and oxygen exchange and possibly contributing to growth restrictions and preterm delivery.

Mortality and life expectancy impacts

The PHSKC report indicates that residents near Sea-Tac face a life expectancy of 2 to 5 years fewer than residents in areas of King County less impacted by airport operations. Studies increasingly link exposure to UFPs, black carbon, and pollutants from aircraft emissions to higher mortality risks, particularly from cardiovascular and respiratory diseases.

Long-term exposure to aviation-related UFPs is associated with increased cardiovascular and all-cause mortality rates (Klemick et al., 2022; Qi et al., 2024). UFP exposure intensifies inflammatory and oxidative stress responses, which can worsen cardiovascular conditions and lead to fatal outcomes (Qi et al., 2024). Similarly, prolonged UFP exposure is linked to higher rates of respiratory and cardiovascular mortality (Beelen et al., 2014). Extended UFP and PAH exposure is also associated with an elevated risk of developing lung and brain cancers (Beelen et al., 2014; Wu et al., 2021).

Expected health benefits from increased SAF use

To fully realize the health benefits of SAFs for communities surrounding airports, it is essential to consider the types of SAFs used, the blend ratios with conventional Jet A-1 fuel, and any additives incorporated into these fuels. These factors influence the magnitude of UFP and particulate matter (PM) reductions, which directly impact the health benefits achievable for airport-adjacent populations. Additionally, given the impact of landing flights on ambient air quality, quantifying the SAFs usage for incoming flights is important in order to fully understand health benefits.

Variability in sulfur content

As discussed in the previous section on emissions, fuel sulfur content plays a critical role in the volume and composition of UFP emissions from aircraft.

The low-sulfur content of SAFs compared to conventional jet fuel results in substantially lower particle emissions, which is beneficial for improving local air quality and reducing UFP-related health risks in nearby communities. For example, Schripp et al. (2022) showed that SAFs with low sulfur content can reduce UFP emissions by up to 90% in some cases, especially at low-thrust settings where exposure levels are highest near airports. Such reductions could significantly lower the incidence of respiratory and cardiovascular diseases for populations living close to airports, as fewer and less reactive particles enter the ambient air (Schripp et al., 2022).

The lower sulfur content of SAFs also contributes to a finer particle size distribution in exhaust emissions, which is associated with decreased oxidative stress upon inhalation, further mitigating potential inflammatory responses in the respiratory tract (Delaval et al., 2022; Durdina et al., 2014).

For communities exposed to chronic, high sulfur-related pollution, switching to low-sulfur SAFs may represent a critical step in reducing sulfur-related health risks and enhancing the quality of life for residents near major airports. As SAF production scales and higher blend ratios become feasible, the cumulative health benefits associated with these low-sulfur fuels are expected to grow, contributing to long-term respiratory and cardiovascular health improvements across regions impacted by airport operations.

Variability in health benefits based on SAF type

Different types of SAFs have distinct chemical compositions that affect emissions. Hydroprocessed Esters and Fatty Acids (HEFA), Fischer-Tropsch (FT) fuels, and Alcohol-to-Jet (ATJ) fuels vary in their aromatic and sulfur content, which are key drivers of UFP and PM emissions.

Studies show that HEFA fuels, which are the most commercially viable, consistently reduce UFP emissions by lowering sulfur and aromatic content. HEFA blends reduce the number of particles emitted and shift the size distribution toward smaller, less reactive particles, which may reduce oxidative stress upon inhalation (Schripp et al., 2022; Z. Xu et al., 2024). This shift could help reduce inflammation and cardiovascular risk for nearby residents.

FT fuels derived from natural gas or biomass also show promising reductions in particle emissions, but the extent of these benefits varies based on the feedstock and processing method. FT fuels can achieve up to 70% reductions in emission indices (EIs) for particle number and mass, particularly when derived from natural gas (Kinsey et al., 2019). However, FT fuels from coal, for example, may provide less substantial emission benefits due to differences in particle composition and reactivity.

Choosing SAF types with consistently lower sulfur and aromatic contents, such as HEFA, will maximize community health benefits by reducing exposure to pollutants that are highly associated with respiratory and cardiovascular conditions.

Influence of blend ratios on health benefits

The blend ratio of SAF with conventional jet fuel significantly impacts the volume of UFP reductions and the associated health benefits.

Studies indicate that higher SAF blend ratios lead to more substantial reductions in UFP emissions. For instance, a 30% HEFA blend has been shown to reduce particle number emissions by up to 90% during low-thrust operations, such as idling and taxiing, compared to conventional Jet A-1 fuel (Jasiński et al., 2021). In these operational stages, when emissions most directly affect ground-level air quality and nearby communities, high SAF blend ratios offer the greatest potential to decrease exposure to harmful pollutants.

However, the health benefits associated with higher SAF blends must be weighed against their economic feasibility, as the production costs of SAFs are currently higher than conventional fuels. Consequently, airports that implement lower SAF blend ratios may experience smaller, though still meaningful, reductions in UFP and PM emissions. A 10% SAF blend, for example, may reduce particle emissions by 30–40%, still offering respiratory and cardiovascular health benefits (Schripp et al., 2022). Increasing the blend ratio as SAF production becomes more economically viable will enhance health benefits for airport-adjacent populations by further reducing pollutant exposure.

Role of additives

The choice of additives in SAFs can also influence emissions and associated health impacts.

Additives may be included to improve fuel stability, enhance performance at high altitudes, or address specific requirements of aircraft engines. However, some additives can increase aromatic content or sulfur levels, potentially diminishing the UFP reduction benefits otherwise achievable with SAFs.

For instance, certain antioxidant additives, while necessary for maintaining fuel stability, can raise the overall UFP and PM emission indices, especially at low thrust levels (Durdina et al., 2019). To maximize health benefits, selecting low-emission additives compatible with SAFs and limiting their use at ground-level operations could help airports further reduce emissions and health risks.

Conversely, innovations in additive technologies are also underway to enhance emissions reductions. Some additive formulations aim to reduce particle reactivity and increase particle density, which could further lower health risks by decreasing particle deposition in the respiratory tract. Adoption of novel additives may provide incremental health benefits, though research is ongoing to validate their efficacy in reducing UFP-related health impacts in real-world airport settings (Liati et al., 2019).

Projected scale of health benefits with optimized SAF adoption

An optimized SAF strategy—including high blend ratios, selection of low-emission SAF types such as HEFA or FT from clean feedstocks, and careful additive choices—could yield significant health improvements for airport-adjacent communities.

Studies suggest that with high SAF blends, communities near high-traffic airports could see a significant reduction in respiratory and cardiovascular hospital admissions over time (Delaval et al., 2022; Qi et al., 2024). This scale of impact would translate to thousands of avoided cases annually across communities near major U.S. airports, potentially improving life expectancy and reducing healthcare costs.

The potential reduction in developmental and reproductive health risks also becomes more pronounced with optimized SAF use. Given that communities near Sea-Tac, for instance, show elevated preterm birth rates linked to UFP exposure, a significant shift to high-SAF blends could lower these rates by decreasing airborne particulate exposure during critical stages of fetal development (Carter et al., 2023; Wing et al., 2020). The combined effect of optimized SAF strategies could provide enduring health benefits for vulnerable populations, while also supporting climate goals and improving air quality.

In summary, the degree of health benefits for communities near airports depends on the specific choices made regarding SAF types, blend ratios, and additives. A carefully chosen, high-blend SAF strategy tailored to maximize emission reductions will most effectively lower health risks and support long-term improvements in air quality for residents near airports. The continued development of cost-effective, low-emission SAF options will be crucial in enabling broader adoption and extending these benefits across high-traffic airport regions.

Summary of findings — Section 2

Table 2 provides an overview of the expected scale and types of health benefits associated with various SAF scenarios. The adoption of different types of SAFs presents varied potential health benefits for communities near airports.

HEFA SAFs: Known for their very low sulfur and low aromatic content, can reduce UFPs by up to 90% at low-thrust operations, resulting in substantial respiratory and cardiovascular health benefits. This reduction could significantly improve air quality in high-traffic airport areas, especially those with vulnerable populations.

Fischer-Tropsch (FT) SAFs: Derived from natural gas or biomass, also demonstrate strong reductions in particle emissions, with up to a 70% decrease in particle number. These SAFs can reduce inflammatory and oxidative stress responses, which may lessen respiratory symptoms for airport-adjacent communities, particularly at higher blend levels.

Alcohol-to-Jet (ATJ) SAFs: With moderate aromatic content, provide 50–60% reductions in UFP emissions, especially effective at a 30% blend ratio, offering moderate respiratory and cardiovascular benefits for communities with intermittent high exposure.

Coal-derived FT fuels: With low-to-moderate sulfur and moderate aromatic content, yield a more modest 15–20% reduction in UFP emissions, which could provide limited health improvements, mainly in highly impacted areas.

HEFA blends: At lower ratios (10–30%) maintain a 30–90% reduction in UFP emissions, with higher blends delivering more substantial respiratory and cardiovascular health benefits in airport communities.

Low-sulfur Jet A blends: Also offer partial health benefits by reducing UFP emissions by 20–50%, providing moderate interim improvements for sensitive populations near airports until more effective SAF solutions are widely adopted.

Table 2: Expected co-benefits of SAF adoption

SAF Type	Sulfur Content	Aromatic Content	Emission Reductions	Potential Health-Related Benefits	Scale of Impact
HEFA (100%)	Very low	Low (varies by blend)	Up to 90% reduction in UFPs at low thrust (Schripp et al., 2022)	Substantial reduction in respiratory and cardiovascular risks due to lower particle numbers and smaller particle size distribution	High: Significant improvement in air quality for high-traffic airports with vulnerable communities. Current regulations do not allow for 100% HEFA blend.
FT (Fischer-Tropsch) (from natural gas or biomass)	Very low	Very low	Up to 70% reduction in particle number emissions (Kinsey et al., 2019)	Some decreases in inflammatory and oxidative stress responses, reduced respiratory symptoms	Moderate to High: Varies with blend ratio, significant impact at higher blends
ATJ (Alcohol-to-Jet)	Very low	Moderate	UFP emissions reduction increases with blend percentage (Jasiński et al., 2021)	Moderate improvement in respiratory health, reduced cardiovascular risk with regular exposure	Moderate: Best suited for areas with intermittent high exposure rather than constant
FT (Coal-derived)	Low to moderate	Moderate	Reductions of 15–20% reduction in UFP emissions; lower reduction relative to other SAFs (Kinsey et al., 2019)	Limited health benefits; potential to reduce exposure-related symptoms, less impactful for cardiovascular and respiratory outcomes	Low to Moderate: Minor improvements in heavily impacted areas
HEFA Blends (10–30%)	Very low	Low (varies by blend)	Reductions of 30–90% in UFP emissions, depending on blend ratio (Schripp et al., 2022)	Variable benefits in respiratory and cardiovascular health, with high-blend ratios offering the most impact	High with 30% blend: Effective in reducing both acute and chronic health effects near major airports
Low-Sulfur Jet A Blends	Low	Moderate	Reduction of 20–50% in UFP emissions; sulfur-related UFP decreases	Partial benefit to respiratory health, slight reduction in inflammatory responses in sensitive groups	Moderate: Suitable for interim improvements, not a long-term solution

Section 3. Aviation–Related Air Quality Modeling

Highlights

- Commonly used aviation-related air quality models include plume dispersion models, chemical transport models, receptor models, and other monitor-based models.
- Modeling results suggest that aviation emissions have a substantial impact on ambient community-level air pollution, such as NO_x, UFP counts, and CO, near airports.
- Many studies show good agreement between air quality modeling results and measurement data, but more comprehensive comparisons between different air quality models are required. Most air quality modeling approaches can be extended to sustainable aviation fuels in future studies.
- Air quality monitoring data are necessary for aviation–related air quality modeling from the perspective of model input or validation.

Background

Quantifying the impact of aviation emissions on community-level air pollution exposures is very important to assess the corresponding health risks. There are several widely used air quality modeling (AQM) approaches, and some of them have been applied to aviation-related air quality modeling. The most common approaches can be classified into dispersion models, chemical transport models, receptor models, and other monitor-based models.

Plume dispersion models

Plume dispersion models are one of the most commonly used approaches for air quality modeling. These models use mathematical equations to describe mainly the transport and fate of air pollutants emitted from various sources, including gaseous pollutants and particulate matter mass concentrations (US EPA, 2024a).

Compared to the chemical transport models, plume dispersion models focus more on the physical atmospheric processes, such as diffusion and advection, and less on the atmospheric chemistry. For particle number concentrations, additional aerosol dynamics modeling should be integrated into the dispersion modeling.

Since aviation-related studies are mostly centered on regional impact, this section will put more emphasis on regional models instead of small-scale models such as those used for street environments.

Gaussian plume models

Among all plume dispersion models, Gaussian models are the most widely used modeling approach for air quality prediction. Gaussian models assume a Gaussian distribution of aviation plumes in both horizontal and vertical directions. And the normal distribution can be modified at larger distances from the sources because of the turbulent reflection at the boundary layer and from the earth surfaces (Holmes & Morawska, 2006).

These models mainly rely on emission source information (e.g., emission rate, source height), meteorological parameters (e.g., wind speed, wind direction), and the receptor’s distance to the source. Gaussian models include many famous plume dispersion models, such as Industrial Source Complex Version 3 (ISC3), American Meteorological Society /U.S. Environmental Protection Agency Regulatory Model (AERMOD), Atmospheric Dispersion Modeling System (ADMS), California Line Source Dispersion Model (CALINE), etc.

ISC3 is a steady-state Gaussian plume model for simulating both short-term and long-term air pollutant concentrations from a wide variety of industrial sources. This model considers particle deposition, downwash, plume rise as a function of downwind distance, different geometric characteristics of sources, and limited terrain adjustment (US EPA, 2024b). The Emissions Modeling System for Hazardous Pollutants (EMS-HAP) is used to provide an emission inventory for ISC3 models. ISC3 was the U.S. Environmental Protection Agency's preferred model until 2006 which was then gradually replaced by AERMOD.

Compared to ISC3, AERMOD is a bi-gaussian model that has an advantage in its capability of addressing complex terrain, considering state-of-the-art turbulence algorithms for meteorological conditions, and various emission sources besides industrial sources (Kalhor & Bajoghli, 2017; Salva et al., 2023). It performs much better than ISC in predicting near-source, downwind concentrations and was therefore adopted as EPA’s official Gaussian dispersion model. The AERMOD model includes a meteorological data preprocessor, AERMET, for describing the air dispersion based on planetary boundary layer turbulence structure and scaling concepts, and a terrain data preprocessor, AERMAP, for addressing complex terrain (US EPA, 2024b). The AERMOD model is also used by Aviation Environmental Design Tool (AEDT) from U.S. Federal Aviation Administration to model the dispersion of aviation emissions.

Many studies have applied ISC3 and AERMOD models to quantify the impact of aviation emissions on ambient air quality. Some studies only reported the air quality simulation results attributable to aviation emissions.

Makridis et al. evaluated the hourly average ground-level concentrations of carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO2), carbon dioxide (CO_2), fine inhalable particulates ($PM_{2.5}$), and Particle Number Concentration (PNC) due to aircraft emissions from landing and takeoff (LTO) cycles at Chania Airport in Greece, which are then compared with relevant air quality standards (Makridis & Lazaridis, 2019). PNC are all particles below 1000 nm in diameter, and include a broader range of sizes than UFP.

Rather than modeling relatively local impacts near the airport, Moradi et al. used both AERMOD and ISC3 model to quantify the distribution of several air pollutants (i.e., NO_x, CO, SO_2) in a much wider radius (i.e., 50 km) of an international airport in Iran (Moradi et al., 2024).

However, the above two studies did not evaluate the model performance by using monitoring data, which has been covered by several other studies. For example, Wing et al. used the AERMOD model to predict the UFP exposures within a 15–km buffer of geocoded addresses around Los Angeles International Airport (Wing et al., 2020). They found that AERMOD predictions agreed well with the direct downwind measurements (R^2 = 0.71, RMSE = 2300 #/cc). They further revealed a significantly positive association between aircraft-origin UFP concentrations and preterm births (Odds ratio (OR) = 1.04, 95% CI = 1.02-1.06).

Popescu et al. applied the AERMOD model to assess the concentrations of aircraft-related CO, NO_x, and VOCs around Traian Vuia International Airport in Timisoara, Romania (Popescu et al., 2011). The comparison with direct measurements shows that the model works well with hourly average concentrations of CO (relative error for maximum: 7.1%) and NO_x (13.1%).

Some studies additionally observed inconsistent results between AERMOD predictions and monitoring data in some scenarios. Penn et al. found that AERMOD underestimated the black carbon (BC) and NO_x concentrations during the daytime, but overestimated them during late night hours at Los Angeles International Airport (Penn et al., 2015). They explained that this deviation probably results from the inappropriate treatment of plume buoyancy and related dynamics by AERMOD. Pandey et al. also found that AERMOD overestimated the hourly SO_2 concentrations near Los Angeles International Airport during early morning and late-night hours (Pandey et al., 2023). That could be due to AERMET in AERMOD failing to account for the unique meteorological features in Los Angeles, such as proximity to the ocean and the high density of buildings downtown.

ADMS is a UK regulatory air quality model widely used in Europe. It has broadly similar principles as AERMOD, such as the boundary layer structure characterization based on Monin-Obuhkov theories and Gaussian profiles for concentration distributions (skewed distribution for vertical profiles).

Nevertheless, the two models differ significantly in the meteorological preprocessing of surface heat flux, boundary layer height, and mixed layer velocity scale, as well as the dispersion algorithms, such as the plume rise algorithm (Carruthers et al., 2011). ADMS is also better at addressing more intricate terrains, such as the effect of buildings, by taking building downwash into account (Holmes & Morawska, 2006). When it comes to aviation emissions, an advanced model, ADMS-Airport model, has been established based on the ADMS-Urban model. The ADMS-Airport model considers aviation-related emission sources such as aircraft traffic, auxiliary power units, and ground support equipment.

A series of studies employed ADMS-Airport model to estimate the aviation-related air pollution near the airports. Based on actual flight data and emission inventory, Wang et al. used ADMS-Airport to evaluate the influence of airport emissions on ambient air quality (e.g., PM, NO_x, SO_2, HC) around Beijing Daxing International Airport (Wang et al., 2023). Their simulation results reveal that the aviation emissions mainly affect the air quality within 15 km of the airport.

Popoola et al. applied ADMS-Airport to London Heathrow Airport and found that airport emissions contributed about 36% of total NO_2 observed (Popoola et al., 2018). They also adopted a low-cost air quality sensor network to validate the model performance and found a very good agreement between model predictions and measurements. Mokalled et al. compared the ADMS-Airport model NO_2 concentration prediction for the Beirut International Airport with sensor measurements and also found a strong correlation ($r = 0.85$) between prediction and observation for NO_2 (Mokalled et al., 2022).

Besides ISC3, AERMOD, and ADMS, there are other Gaussian plume models which are less frequently used. Voogt et al. used the STACK+ dispersion model commonly used in the Netherlands to compare the modeled PNC with the measured PNC surrounding the Schiphol Airport (Voogt et al., 2023). They found that the Pearson and Spearman correlations between model prediction and measurements were 0.88 and 0.83, which were relatively high. However, this study pointed out that the STACK+ model does not consider more complex aircraft plume dynamics. Keuken applied an hourly version of a Gaussian plume model called SRM3 to calculate the particle dispersion (Keuken et al., 2015). Their results suggest that more than 200,000 addresses were exposed to increased PNC levels due to aviation emissions from Schiphol Airport.

There are some limitations for Gaussian plume models (Holmes & Morawska, 2006). First, most Gaussian plume models are steady-state models and are applicable for the time required for air pollutants to travel from sources to receptors. In the case of overhead jet emissions during landing and takeoff, the plume's vertical transport times to reach the ground are typically less than an hour for emissions within the boundary layer. Second, the models assume no interaction between multiple plumes. Third, they do not include the important chemical and physical aerosol processes for regional modeling, which will be addressed by the chemical transport model below. Fourth, Gaussian plume models will overestimate the air pollution exposures under very low wind speeds.

Lagrangian dispersion models

Lagrangian dispersion models follow the trajectory of a small region of air when it moves in space and time. These models perform well for both flat and complex terrain, and for both stable and unstable conditions (Holmes et al., 2006). They allow the source to move through space, unlike the steady-state models that assume a stationary source geometry. Several examples of Lagrangian dispersion models are Graz Lagrangian model (GRAL), California puff model (CALPUFF), and stochastic particle Lagrangian air dispersion model (SPRAY).

The GRAL model was used by Zhang et al. coupled with GRAMM, a Eulerian mesoscale weather prediction model, to estimate the PNC near Zurich International Airport (X. Zhang et al., 2020). It was found that the PNC exposures caused by aviation emissions are 2–10 times the background level (104 particles/cm^3) for nearby communities.

CALPUFF is another important Lagrangian dispersion model. Some limitations of Gaussian plume models can be overcome by considering the continuous plume as a series of puffs over time and allowing a variable wind speed (Holmes & Morawska, 2006). CALPUFF is a multi-layer non-steady-state puff dispersion model which takes the space- and time-varying meteorological conditions into account, according to emission strength, pollutant transport, transformation, and removal (US EPA, 2024b). Patino-Aroca et al. applied the CALPUFF model with WRF/CALMET meteorological model to estimate the contribution of various urban sources to particulate matter and gaseous pollutants in Guayaquil, Ecuador (Patiño-Aroca et al., 2024). They found that the airport contributed 1.3% to SO2; 3.8% to NO_2; 1.4% to CO; <0.1% to $PM_{2.5}$; and <0.1% to PM_{10} for 14 sites in the city, while road traffic dominated the air pollution. They did not evaluate ultrafine particle impacts.

In addition, Pecorari et al. adopted the SPRAY5 model, which is a Lagrangian stochastic model that characterizes turbulence by spatiotemporal random variation of fluid-dynamic variables based on Thomson's theories (Pecorari et al., 2016). This study evaluated the NO_x, CO, and HC dispersion from aircraft exhausts near Marco Polo Airport in Venice, Italy. They found that the model underestimated the pollutant concentrations compared to the measurements, and aircraft taxiing contributed the most to air pollution exposures in the immediate area.

The Lagrangian dispersion models also do not consider the effect of atmospheric chemistry. Compared to Gaussian plume models, Lagrangian dispersion models characterize the atmospheric physical process in more detail, but that also leads to higher computational costs and requires more professional knowledge.

Chemical transport models / photochemical models

In contrast to the above dispersion models, chemical transport models (CTMs) have a stronger capability to model the atmospheric chemical processes, such as photochemistry and chemical reactions between different air pollutants. Therefore, CTMs are often regarded as the gold standard of air quality modeling (Gardner-Frolick et al., 2022). Since Lagrangian CTM cannot describe these processes comprehensively, most of the latest CTMs employ the three-dimensional Eulerian grid modeling approach (US EPA, 2024e). Some commonly used CTMs include Community Multiscale Air Quality Model (CMAQ), Comprehensive Air Quality Model with extensions (CAMx), and Global Atmospheric Chemistry Model (GEOS-Chem) (Li et al., 2021).

As one of the most widely used CTMs, the CMAQ model is a three-dimensional Eulerian CTM which calculates the mass balance over each grid by taking transport across the grid boundaries and source/sink characteristics within each grid over time into consideration (US EPA, 2024d). CMAQ incorporates a series of atmospheric processes, including diffusion, advection, cloud dynamics and aqueous chemistry, gas-phase chemistry, and aerosol dynamics and thermodynamics (Zhao et al., 2020). There are two important inputs for the CMAQ model: meteorological information and emission rates from sources. Therefore, Weather Research and Forecasting Model (WRF) is often coupled with CMAQ to provide gridded meteorological information, and Sparse Matrix Operation Kernel for Emissions (SMOKE) model is integrated with CMAQ to provide the source emission information (US EPA, 2024d).

The CMAQ model with relevant extensions has been applied to aviation-related research. Lawal et al. applied WRF-SMOKE-CMAQ model to evaluate the aviation impacts around Atlanta Hartsfield-Jackson Airport (Lawal et al., 2022). This study developed a 3-D emission inventory instead of a surface source for aircraft LTO processes. They discovered that the aviation emissions elevated the UFPs count, $PM_{2.5}$ mass, and O_3 by 38%, 8%, and 4%, respectively.

Furthermore, Benosa et al. employed the CMAQ model to quantitatively assess the benefits of several aviation emission reduction strategies in the South Coast Air Basin of California (SoCAB), including aviation biofuel implementation (SAF use), ground support equipment electrification, and taxi-out times reduction (Benosa et al., 2018). Their findings suggest that the use of SAFs can reduce $PM_{2.5}$ emissions from aircraft by 55%, and reduce the aviation-attributable PM2.5 exposure by 28% in summer and 19% in winter. However, SAF use was found to increase the ozone exposure by 9% in winter. This study can provide valuable insights into the benefit analysis of SAF.

Some studies applied hybrid models, combining CMAQ and plume dispersion models, to increase the near-source spatial resolution of CMAQ alone for air quality modeling. For instance, Woody et al. used CMAQ to estimate the aviation-attributable $PM_{2.5}$ concentrations across the contiguous U.S. according to emissions from 99 major U.S. airports (Woody et al., 2016). In order to improve the spatial resolution of CMAQ grids, this study combined CMAQ with the plume-in-grid (PinG) treatment, allowing the chemical evolution of aircraft emissions in a plume before dilution into the grid. In addition, this study applied the Aerosol Dynamics Simulation Code (ADSC) model to account for the formation of secondary organic aerosols in PM2.5. They found that the average aviation-attributable $PM_{2.5}$ reached 2.7 and 2.6 ng/m^3 in January and July 2005, which corresponded to increases of 40% and 12%, respectively. The relatively small increase in the $PM_{2.5}$ mass concentrations was probably due to the very small ultrafine particles usually emitted by aviation, which do not contribute too much to the total $PM_{2.5}$ concentrations. However, this study did not report any aviation impacts on UFP counts.

The CAMx model is another Eulerian CTM, which assesses a wide variety of inert and chemically active pollutants, including ozone, PM, other toxics and their complex chemical interactions. CAMx can simulate the air quality across different geographical scales and be also coupled with the WRF and SMOKE models. Several previous studies have used the CAMx model to quantify the impact of aviation emission on ambient air quality (Bo et al., 2019; Bossioli et al., 2013; De Foy et al., 2015). A recent review paper pointed out that CAMx is used less frequently than that of CMAQ, which basically covers and extends the CAMx applications (Gao & Zhou, 2024).

The GEOS-Chem model can numerically simulate the atmospheric composition from regional to global scales. It can be used either off-line with meteorological data from NASA's Goddard Earth Observing System (GEOS), or on-line coupled with other climate and weather models, such as WRF-GEOS-Chem model (H. Lin et al., 2020). Compared with CMAQ at the regional level, GEOS-Chem usually focuses on global-scale air quality but with lower spatial resolution. Since CMAQ cannot reflect the time-varying boundary conditions of the focused region, GEOS-Chem model can also be linked to CMAQ to more accurately describe the pollutant transport through boundaries (D. Lee et al., 2012).

Eastham et al. used the GEOS-Chem High-Performance model to simulate the impact of aviation on global air quality ($PM_{2.5}$ and O_3) at three different resolutions (50 km, 100 km, and 400 km) (Eastham et al., 2024). This study ran simulations with all aviation emissions enabled and disabled and considered the aviation contributions to $PM_{2.5}$ and O_3 exposures. They found that the $PM_{2.5}$ and O_3 attributable to aviation caused 21,200 (95% confidence interval (CI): 19,400-22,900) and 53,100 (95% CI: 36,000-69,900) premature deaths in 2015 globally.

Purpose-specific CMTs have been developed by some research groups to answer specific air quality research questions. For example, the aircraft contribution to ambient UFP in the California South Coast Air Basin was estimated using a fit-for-purpose CTM that considered emissions, transport, dry/wet deposition, gas-phase chemistry, gas-to-particle conversion, coagulation, and some condensed-phase chemical reactions (Yu et al., 2019). The results agreed well with a source-apportionment model of measured PM data collected from four receptor sites, and showed that aircraft accounted for 2–6% of UFP mass concentration.

Another effort to develop custom CMT allowed for tracking of primary particles across California (Hu et al., 2014). This updated model neglects the formation of secondary PM to focus on estimating the spatial impact of primary PM trace chemicals. Unfortunately, this study did not discuss the aviation impacts in particular; however, this model could be used in the future to better understand this question.

Receptor models

Plume dispersion models and chemical transport models are deterministic models and rely on emission inventory, meteorological information, and atmospheric physical and chemical processes to predict the transport behaviors of air pollutants. In contrast, another type of aviation-related air quality model is based on measurement data from stationary and mobile monitoring. These models do not require emission source information. This section will focus on the most important monitor-based approach, i.e., the receptor models. Other common monitor-based approach will be covered in the next section.

Receptor models are mathematical or statistical approaches to identify and quantify the presence and contributions of multiple sources of air pollution based on measurements of various species at one or multiple receptor locations (US EPA, 2024a). The fundamental principle of receptor models is the mass balance, where the species concentrations are composed of source profiles and source contributions.

The mass balance principle can be shown as:

Equation 1

$$x_{ij} = \sum_{k=1}^{K} f_{kj} \times g_{ik}$$

where x_{ij} is the measured j_{th} species (e.g. pollutant) concentration in the i_{th} sample, f_{kj} is the j_{th} species concentration in the k_{th} source (source profile), and g_{ik} is the contribution of the kth source to the i_{th} sample (source contribution). The chemical mass balance model can be specified if the number and profile of sources are known. If they are unknown, multivariate models are preferred (Hopke, 2016).

Chemical mass balance (CMB) model

If the source information is available, the CMB model can be specified for source apportionment of air pollution. In other words, x_{ij}, f_{kj}, and K are known in equation (1), and g_{ik} must be derived. The effective variance least squares (EVLS) algorithm is used to account for measurement errors in both dependent and independent variables (Hopke, 2016; J. G. Watson et al., 1984). The U.S. Environmental Protection Agency has developed relevant software for the CMB model and provided various source profiles comprised of particulate matter and volatile organic compounds (VOCs) in the U.S. (US EPA, 2024a, 2024c).

CMB models have been applied to apportion air pollutants into various urban sources including traffic-related sources. For example, Xue et al. collected samples of UFP in multiple California cities over one year and found that meat cooking and gasoline combustion were the most significant sources of UFP organic carbon (Xue et al., 2019). However, few studies have used CMB for aviation-related sources. Shirmohammadi et al. used CMB to evaluate the impacts of aviation emission on ambient $PM_{0.25}$ OC around Los Angeles International Airport (Shirmohammadi et al., 2018). The profiles of mobile emissions (gasoline and diesel vehicles), wood smoke, vegetative detritus, road dust, and ship emissions were input into CMB. The contribution of aviation emissions was derived from the un-apportioned OC after adjustment of secondary OC. They concluded that aviation emissions contributed about 36% of $PM_{0.25}$ OC at Los Angeles International Airport.

The most challenging issue in using CMB approaches for aviation-related impacts is the scarcity of aviation-related source profiles, which is necessary for CMB analysis. In many developing countries, few or no profiles are available even for other common sources such as vehicle emission and wood combustion. Inappropriate source profiles that do not represent local source characteristics well can introduce large errors in source apportionment with CMB models.

Multivariate models

When the number and nature of emission sources are unknown, multivariate factor analysis approaches are an alternative way to apportion sources. These multivariate models rely on the covariance structure between different pollutants or species to derive the source profile as well as source contribution simultaneously. Then the researchers need to take full advantage of their prior knowledge to interpret these sources as realistic emission sources in the physical world (Hopke, 2016). Common multivariate models include principal component analysis (PCA) / absolute principal component score (APCS) and positive matrix factorization (PMF).

PCA transforms a large set of original pollutant/species concentrations into a small set of variables, which are linear combinations of the original variables, through the eigenvector decomposition of the correlation matrix. The first several components usually account for the majority of total variance in the observations. Nevertheless, the factor scores of PCA only provide the relative impact of different air pollution sources, and there may be large negative values in the PCA results. Therefore, the APCS approach can be further used to derive the source contribution and subsequent source-specific air pollution exposures (Thurston & Spengler, 1985).

Austin et al. conducted a mobile monitoring campaign of size-resolved UFPs, CO_2, and BC concentrations in the northern and southern area of Sea-Tac International Airport (Austin et al., 2021). Then they used PCA to derive two different components and their corresponding factor scores. Based on the above results, they recognized one component as aviation emissions and another as road traffic. Doubleday et al. also used mobile monitoring in Seattle and PCA to identify three important features, one of which was likely from aircraft emissions, and two others from gasoline and diesel vehicle emissions (Doubleday et al., 2023). However, their subsequent APCS analysis focused on road traffic instead of aircraft emissions.

Lai et al. applied the PCA/APCS model for source apportionment of VOCs near Taipei International Airport (Lai et al., 2013). They identified that aircraft and heavy-duty gasoline vehicle emissions contributed 47%, 42%, and 34% of total VOCs in summer, autumn, and early winter.

However, PCA/APCS models do not consider different weights for observations according to their measurement uncertainties. And the orthogonality of factors obtained by PCA does not necessarily reflect real world conditions where there may be overlap in pollutant profiles between sources. These limitations can be overcome by PMF.

PMF has become the most widely used receptor model for source apportionment of air pollution. Based on equation (1), PMF minimizes the residuals weighted by the uncertainties to simultaneously derive the source profile and contribution (Paatero & Tapper, 1994). Most aviation-related source apportionment studies applied PMF to stationary monitoring data near the airport to quantify the impact of airport emissions (Masiol et al., 2016, 2017; Pirhadi et al., 2020; Stacey et al., 2020; Yin et al., 2024).

For instance, Masiol et al. used PMF and two sampling sites near the Venice airport to obtain six different factors (Masiol et al., 2016). According to particle size distribution, diurnal variation, traffic volume, wind direction, and other information, these factors were identified as nucleation, traffic, airport, nighttime nitrate, regional pollution, and local resuspension. The airport-related source had a mode of around 80 nm, and another smaller than 14 nm, and contributed about 20% of total PNC. Similarly, through PMF analysis, Masiol et al. found that airport emissions accounted for 30–35% of total particles in both warm and cold seasons at the Heathrow Airport (Masiol et al., 2017).

Aviation emissions were also found to contribute 59% of $PM_{2.5}$ near Tianjin Binhai International Airport in China, outweighing other identified factors including fugitive dust, biomass combustion, vehicle emission, and secondary emission (Yin et al., 2024).

A few studies further classified airport emissions according to different courses during the LTO cycle. Pirhadi et al. identified five PMF factors at Schiphol Airport in the Netherlands, among which aircraft arrivals, aircraft departures, and ground service equipment are all related to aviation (Pirhadi et al., 2020). They found that the largest contributors of PNC are aircraft departures (46%) and arrivals (27%).

Recent studies have started to combine PMF with mobile monitoring campaigns, but few have covered aviation-related sources. Liu et al. applied PMF to a time-balanced mobile monitoring dataset from 2019 to 2020 across 309 sites in the greater Seattle area (Liu et al., 2024). Six sources were identified, including aviation, diesel trucks, gasoline vehicles, accumulated mode aerosols, oil combustion, and wood combustion. They found that aviation emissions contributed the most to UFPs within 10–13 nm (83%) and 13–18 nm (52%) in this area. The annual average contribution of aviation-related sources was higher around and to the north of Sea-Tac International Airport, which was quite different from the spatial patterns of other sources. Although the PMF model is widely employed, it should be noted that mis-specified uncertainties will cause large errors in the results.

Other monitor-based models

Besides the receptor models, there are other monitor-based models which do not rely on the measurements of different species. These approaches usually rely on some external information, such as land use variables and wind direction and speed to build statistical models. This section will introduce two common models related to aviation emissions: the land-use regression model and models leveraging local wind data.

Land-use regression (LUR) model

The LUR model usually associates the measured air pollutant concentrations with land use variables to obtain the concentration estimates with a higher spatial resolution. Both simple regression models and more complicated machine learning algorithms can be used (Gardner-Frolick et al., 2022). In the aviation-related studies, some specific covariates are included, such as the distance to the airports.

Saha et al. provided a large-scale, population-level UFP exposure map across the U.S. based on regulatory and mobile monitoring data with a LUR model (Saha et al., 2021). Some monitoring stations near the airport were included in this study. Various land-use covariates are included in the LUR model, including the distance to airports. Although this study focused on the UFP prediction instead of the impact of airports, the regression coefficient can be used to quantify the contribution of airports to UFP exposures.

Similarly, Weichenthal et al. developed a LUR model for ambient UFPs in Toronto, Canada, based on mobile monitoring across one year (Weichenthal et al., 2016). The distance to the airport was also included in this LUR model. Venuta et al. used machine learning algorithms, such as random forest models, with land-use covariates to provide daily spatiotemporal estimates of ambient UFPs in Toronto and Montreal (Venuta et al., 2024). The cross-validation shows good performance of this model (R^2 = 0.73 in Montreal and 0.72 in Toronto). Although no aviation-related variables were included, this study can provide some useful insights for future aviation studies.

The LUR model is simple to use and validate and can be adapted to various monitoring designs. However, it may be difficult to acquire the high-resolution geospatial covariates in some countries or regions. The LUR model also requires that the variation of the modeled air pollutants should be related to land use, otherwise the LUR model does not work, since it does not reflect the underlying atmospheric processes.

Models leveraging local wind data

Among all models using local wind data, conditional probability function (CPF) is the most widely used. CPF uses source contributions (obtained from other models) as well as wind direction to analyze the point-source impacts from different wind directions on the receptor site (Kim & Hopke, 2004). The CPF for wind sector $\Delta\theta$ is defined as the ratio between the number of occurrences exceeding the threshold (such as 90th percentile of the source contribution) and the total number of data from this wind section (Hopke, 2016; Kim & Hopke, 2004). The CPF can further incorporate the wind speed to obtain the conditional bivariate probability function (CBPF), which has been used in aviation studies (Masiol et al., 2017).

Nonparametric regression (NPR) is another model using local wind data. The NPR model uses a Gaussian kernel as a non-subjective alternative to the bar chart, which is highly dependent on the location and size of $\Delta\theta$. Compared to CPF, NPR can obtain confidence intervals and the exact location of peaks for source contributions (Kim & Hopke, 2004). NPR can be further improved to nonparametric wind regression (NWR) when wind direction and speed information are incorporated into the model (Henry et al., 2009).

Summary of findings — Section 3

Various air quality models have been used to quantify the impacts of aviation emissions on ambient air quality. Table 3 provides an overview of those models and how they are applied to aviation-related studies. For each class of model, we present overall approaches, major assumptions and specific use examples to provide context.

Different types of models apply different estimation strategies. Plume dispersion models usually track the pollutants in the plume from aircraft emissions to predict the aviation-attributable pollutant exposure levels. After considering complex chemical interactions, chemical transport models often evaluate the aviation impact using the difference of simulation results with and without aviation emission sources. Plume dispersion and chemical transport model predictions show good agreement with measurement data in most studies. In contrast, receptor models use multi-species monitoring data near the airport and their covariance structure to derive the profile and contributions of aviation.

Most available studies obtained the aviation contribution under baseline conditions in which conventional aviation fuels were used, but these approaches can be extended to the scenario of using SAF. The study from Benosa et al. (2018), which calculated air pollutant exposure predictions between baseline and SAF use scenarios, provides a good example of using air quality models to evaluate the SAF benefits on air quality (Benosa et al., 2018). Future research could combine this framework with various air quality models to assess the impact of SAF on communities.

Table 3. Summary of aviation-related air quality modeling.

Model	Approach	Assumptions	Use examples
Plume dispersion models (ISC3, AERMOD, AEDT, ADMS, GRAL, CALPUFF, etc.)	**Both:** **Rely** on emission inventory, meteorological information, and atmospheric physical process mechanism (e.g. diffusion and advection) **Gaussian plume models:** Calculate the pollutant concentrations based on statistical distribution **Lagrangian models:** Track the trajectory of air pollutants from emission sources	**Both:** Not consider the atmospheric chemistry Not consider the interaction between multiple plumes **Gaussian plume models:** Gaussian distribution of plumes in both horizontal and vertical directions Steady-state models not considering the transport time Not accurate for low wind speeds	Predict air pollution impacts, including ground level aviation related air pollutant concentrations, through modeling plume dispersion of aviation emissions (e.g. emission rate, source position, source height).

Model	Approach	Assumptions	Use examples
Chemical transport models (CMAQ, CAMx, GEOS-Chem, etc.)	Employ the 3-d Eulerian modeling approach to model both the atmospheric physical and chemical processes for air pollutants	Simplify the atmospheric chemical reactions, which differs according to different models Homogeneous physical and chemical properties within each grid Rely heavily on accurate meteorological data	Evaluate the aviation impact using the difference of simulation results with and without aviation emission sources.
Receptor models (CMB, PCA/APCS, PMF, etc.)	**Both:** Identify and quantify the contribution of various sources based on multi-pollutant or multi-species monitoring data and mass balance principle **Chemical mass balance model:** Derive the source contribution when source profile is provided. **Multivariate models:** Derive the source profile and contribution simultaneously based on the covariance structure of multiple pollutants or species	Emission source profiles are constant spatially and/or temporally. Measurements of air pollutants are linear combinations of different source contributions. Not consider the chemical reactions between pollutants	Distinguish aviation-specific contributions to total regional air pollution measured at specific sites by using particle size distribution, chemical composition, diurnal variation, flight data, and other external information. Identify aviation-specific factors and estimate both the multi-pollutant profile of aviation emissions and the percentage contribution to each individual regional pollutant.
Land use regression models	Associate the measured pollutant concentrations with land use variables, such as the distance to airport Both regression and machine learning algorithms can be applied.	The modeled air pollutants should be related to land use.	Incorporate aviation-related land use variables, such as proximity to the airport and landing/takeoff paths, to predict pollutant concentrations.
Other models leveraging local wind data (CPF, CBPF, NPR, NWR, etc.)	Plot and fit the probability of high concentrations (> threshold) at a location categorized by wind direction and speed	The pollutant concentration should be related to wind direction and speed.	Use aviation-related source contributions and wind data to plot the Conditional Probability Function (CPF) or fit a nonparametric regression model.

Section 4. Monitoring Approaches

Highlights

- Ambient air pollutant monitoring results from airports using SAF are unavailable due to lack of significant SAF adoption for fueling aircraft.
- Particulate matter monitoring results near airports show consistent trends, with higher concentrations observed downwind of the airport.
- Ultrafine particle (UFP) size distribution is a critical component of ambient monitoring near airports, as very small particles (10-20 nm) serve as a marker for jet engine emissions and present health concerns.

Monitoring importance and data transparency

Relevant and representative ambient monitoring results are required to validate modeling approaches. Transparent data reporting is key to integrating monitoring results with air quality models, enabling a clearer understanding of aviation emissions' impacts on ambient pollutant concentrations and the health of impacted populations.

However, as noted in this report, to date no SAF fuel conversions have occurred in Washington at major airports, so there is no ambient monitoring data available in-state that can represent pollutant concentrations due to SAF use by aircraft flying to and from regional airports.

Existing monitoring studies as a baseline

The contribution of aviation emissions to regional air quality and near Sea-Tac has been previously documented. Key studies include:

- The MOV-UP report (University of Washington), which details emissions and impacts in the vicinity of Sea-Tac (Austin et al., 2019, 2021).
- Additional monitoring studies in the Puget Sound region, conducted by UW investigators between 2018 and 2023, such as the ACT-TRAP study and the Healthy Schools Project (Blanco et al., 2022b; Carmona et al., 2022; Liu et al., 2024).

These studies occurred between 2018 and 2023, when the aircraft fuel used was all standard jet-A fuel. Future monitoring once SAFs are employed in Sea-Tac operations can be compared with this body of previous work, with relevant adjustments for aircraft volume, meteorological conditions, and other pertinent factors.

Approaches to monitoring and measurement considerations

Monitoring approaches include mobile, fixed site, dense network for areal coverage, and aerial surveys, all of which can be applied near airport settings to characterize ambient air pollution levels resulting from aviation operations. The types of equipment used for these different approaches will vary in sophistication, quality, and ease of deployment, depending on the number of different monitors used and the monitoring objectives.

Measurement averaging time is an important consideration to capture the effects of short-term events such as plumes generated from the emissions of individual aircraft. Often trade-offs exist among averaging time, concurrent detection of multiple pollutants, resolution and precision of the acquired measurements, duration of monitoring operation, and the cost of instrumentation.

Ambient concentrations of air pollutants can be quite different at ground-level sites under similar emission profiles on account of meteorological influences that impact pollutant dispersion. Therefore, monitoring data and study design need to account for possible significant effects from seasonal differences in temperature, relative humidity, and mixing height of the atmospheric boundary layer.

Ultrafine particles are important to understanding fine PM

Ambient monitoring conducted near airports demonstrates the impact from flight operations in the surrounding areas and has identified ultrafine particles (UFP) in a very small size range (<20 nm) as an important marker for the impact of particulate pollutants from airport operations. Monitoring locations that characterize the impacts on air quality of road traffic and of aircraft can differentiate the sources of elevated particulate matter, black carbon (BC), and UFPs based largely on dominant particle size, along with wind profiles relative to the position of data collection sites, airport runways, typical flight paths, and major highways.

Comprehensive atmospheric aerosol monitoring should include a diverse set of characteristics. Harm-Altstädter et al. (2024) recommends simultaneous measurements of aerosol particles in different size ranges (10–20 nm for aircraft emissions; 20–100 nm for roadway traffic emissions), along with black carbon, and the fraction of volatile constituents (Harm-Altstädter et al., 2024).

In the Helsinki metropolitan area, departing planes were a major contributor near the airport to particle number (PN), and most particles were smaller than 10 nm, similar to those measured in the city center. Departing aircraft caused significant peaks in PN concentration, and the World Health Organization (WHO) definition of high concentration (20,000 particles/cm^3) was clearly exceeded. However, BC or $PM_{2.5}$ were not detected at similarly elevated concentrations, which emphasizes the role of air traffic as a source of ultrafine particles, but not as a major source of particle mass (Lepistö et al., 2023).

Lung deposited surface area (LDSA), a measure of the surface area concentration of particles of a size that deposit in the alveolar region of the human respiratory tract, per unit $PM_{2.5}$ was 1.4 and 2.4 times higher near the airport than in the city center and in the residential area, respectively. This variation indicates that health effects of $PM_{2.5}$ depend on the location and dominant emission sources. The surface area of the smallest particles per unit of $PM_{2.5}$ is not constant. The urban environment and regional background aerosol also affect the LDSA per unit of $PM_{2.5}$. These findings emphasize the importance of PN monitoring to fully understand the impact of aviation on ambient pollutants (Lepistö et al., 2023).

Aircraft particle emissions are dominated by UFPs smaller than 50 nm, with most particles smaller than 10 nm. Monitoring using non-volatile particle metrics (nvPM) found that sub-10 nm particles were significantly higher at airport sites compared to traffic dominated street canyons, emphasizing air traffic as a source of the smallest UFPs (Lepistö et al., 2023). These results emphasize the need for long-term measurements of UFP, especially the sub-10 nm fraction and highlight the importance of considering regional differences in particle size. By focusing only on $PM_{2.5}$ in monitoring, the effects of UFP from different emission sources may be overlooked.

Samad et al. (2022) conducted a study near Stuttgart airport, the sixth largest airport in Germany, with over 12.7 million passengers in 2019 (Samad et al., 2022). UFP concentrations near the airport reached up to 800,000 particles/cm^3, with elevated levels (300,000 particles/cm^3 at 10 nm median diameter) detectable up to 2.7 km away (Samad et al. 2022). Distinct patterns allowed differentiation between emissions from aircraft and vehicles based on particle count and peak diameter (Dp), showing the need for detailed size-resolved monitoring.

A Berlin airport study by Stacey et al. (2023) showed the highest concentrations of UFP at a size of 10 nm (mobility diameter) occurred during departures and arrivals, consistent with other airport studies (Stacey et al., 2023). By contrast, emissions originating from roadway traffic were characterized by larger UFP sizes and higher concentrations of black carbon (BC) relative to aircraft emissions.

High UFP concentrations were observed by Lopes et al. (2019) in the Lisbon Airport vicinity. The UFP 10-minute average count increased 18–26-fold at locations immediately downwind of the airport, and four-fold at locations up to 1 km from the airport. This airport is located within the city center and surrounded by residences, businesses, schools, sport complexes and hospitals, so it significantly impacts surrounding populations. Monitoring results showed that particle count increased with the number of flights and decreased with distance from the runway and the altitude of aircraft (Lopes et al., 2019).

Westerdahl et al. (2008) measured average concentrations of UFP of 5×10^4 particles/cm^3 at 500 meters downwind of Los Angeles International Airport. They determined that very small particles with a size of 10–15 nm dominated the ambient PM number count (Westerdahl et al., 2008).

Air quality variation near airports dependent on flight volume variations

Several studies have compared the measured pollutant levels and associated flight volumes before, during, and after the COVID-19-related downturn in travel, highlighting the contribution of aircraft emissions to regional ambient air quality. Reduced emissions through use of SAF rather than less flight traffic has the potential for lessening the impact on regional ambient air quality.

The contribution of aircraft emissions to the concentrations of various pollutants is well demonstrated by the reductions observed near airports in China during the height of the COVID-19 pandemic. Table 4 shows the percentages by which several pollutants fell at monitoring sites near these airports.

Table 4: Reduction in average pollutant concentrations near Shanghai (SHA) and Wuhan (WUH) airports associated with major reductions in flight traffic due to Covid-19.

Pollutant	SHA Reduction vs. 2018*	SHA Reduction vs. 2019*	WUH Reduction vs. 2019*
NO	78.0%,	62.3%	
NO2	47.9%	34.8%,	79.3%,
NOx	57.4%	41.8%	
CO			21.5%
$PM_{2.5}$			28.4%,
PM_{10}			32.4%

*Reported by (H. Xu et al., 2023)

At Logan International Airport, located 1.6 km east of downtown Boston, Mueller et al. (2022) monitored ambient particle number count (PNC) from January 2017 to September 2018, and from March 2020 through June 2021. Under wind conditions that placed the monitor downwind from the airport, mean PNC more closely followed flight activity volume patterns. Proximate sources of highway traffic and aircraft operations in a near-airport setting exhibited different activity profiles and different associations with wind speed and direction, which enabled this study to better differentiate their relative impacts on ambient PNC. Mean PNC was 48% lower during the first three months of the COVID-19 state of emergency than pre-pandemic, consistent with 74% lower flight activity and traffic volume that was 39% (local) to 51% (highway) lower. Traffic volume and mean PNC for all wind directions returned to pre-pandemic levels by June 2021; however, when the monitoring site was downwind from Logan Airport, PNC remained 23% lower than pre-pandemic levels, consistent with lower-than-normal flight activity (44% below pre-pandemic levels) (Mueller et al., 2022).

The Samad et al. (2022) Stuttgart airport study found that during the airport's closure for construction, peak particle diameters ranged from 27–86 nm, falling to 27–35 nm during the COVID-19 lockdown, and further to 11 nm during peak holiday travel periods after the lockdown. These smaller particle sizes are indicative of aircraft contribution to UFP. Post-lockdown, UFP concentrations near the airport reached up to 800,000 particles/cm^3, with elevated levels (300,000 particles/cm^3 at 10 nm median diameter) detectable up to 2.7 km away (Samad et al., 2022).

Meteorology and site characteristics influence pollutant levels

Stability of the atmospheric boundary layer is a key factor in the vertical distribution of aerosols, with the highest concentrations close to the ground. Inversion layers enhance horizontal transport, so that airport pollutants can move farther away. Therefore, the relative size of the airport and its typical meteorology can influence the ambient levels of pollutants observed in the surrounding region.

At a mid-sized airport in Luxembourg, Trebs et al. (2023) observed that mixed layer development and near-surface turbulence promoted aircraft plume dispersion, thereby causing a dilution of gaseous and particulate pollutants. Pollutant concentrations (except ozone), including UFP, dropped substantially during the day, although flight frequency was highest during that time. This contrasts with results found at larger airports, where the temporal variation of pollutant concentrations generally correlates with flight activity (Trebs et al., 2023).

At Amsterdam's Schiphol Airport, Voogt et al. (2023) quantified the contribution of aviation, urban background and road traffic to PNC. Annual average exposure due to aircraft emissions rapidly decreased with the distance from Schiphol. For residential areas that are closest to the airport, the annual average contribution of approximately 10,000 particles per cm^3 (Voogt et al., 2023).

A study near Boston's Logan Airport with sites selected for aviation attribution, Chung et al. (2023) found that PNC was elevated during the hours with high aircraft activity (Chung et al., 2023). Sites closest to the airport showed stronger signals when downwind of operations, with intermittent contributions from arriving aircraft accounting for up to 50% of total ambient PNC at a monitor 3 km away. However, this study measured total PNC without differentiating particle size distributions. Future studies should include particle size data to differentiate between aircraft and traffic source contributions.

Summary of findings—Section 4

This section describes diverse monitoring approaches that could help enhance the understanding of SAF adoption on regional air quality near airports. Mobile, fixed-site, and dense network monitoring methods provide complementary insights into the spatial and temporal variability of pollutants like ultrafine particles (UFPs), fine particulate matter ($PM_{2.5}$), black carbon, and sulfur oxides (SO_x). Advanced monitoring tools that distinguish volatile and non-volatile components or characterize UFP size distributions may further contribute to identifying aviation-specific emission reductions.

Studies near airports consistently show that aircraft emissions significantly elevate ambient concentrations of UFPs, $PM_{2.5}$, BC, and NO_x, especially downwind of runways and beneath landing paths. Seasonal and meteorological factors, such as boundary layer mixing dynamics, temperature, chemical reactions of pollutants in the atmosphere, and wind direction, further influence pollutant dispersion and concentration, and can be incorporated into study designs for robust data collection.

Evidence from reduced flight activity during the COVID-19 pandemic demonstrates the effectiveness of monitoring in capturing declines in pollutant concentrations during periods of decreased flight activity, demonstrating the effectiveness of monitoring in capturing benefits of changing emissions. This highlights the potential for SAF adoption to improve ambient air quality and the value of monitoring to accurately quantify that improvement. Future monitoring should integrate temporal and spatial variability, including particle size distributions, to better differentiate emissions from aircraft, road traffic, and urban backgrounds.

Expanding monitoring efforts near airports, where feasible, could complement modeling tools and provide valuable information to guide decision making and priorities for SAFs adoption with the goal of cleaner, healthier airport communities.

Section 5: Implications and Next Steps

This report is not intended to provide recommendations to the State Legislature. Rather, in order to prepare for future reports under scenarios where SAF use has been reported in Washington, this report lays the groundwork necessary to contextualize potential emissions benefits of different SAF blends, and to identify pollutants with potential to be reduced or modified by SAF use. The report also describes possible modeling and monitoring approaches that could quantifiably generate results to describe "regional air quality benefits", as per the Legislative directive.

Overarching findings

SAF adoption appears to offer potential benefits for reducing UFP pollution in airport-impacted communities. The following points would facilitate the University of Washington team to provide more specificity regarding "regional air quality benefits" in future years:

- Continue supporting collaborative partnerships among airport authorities, research partners, and public health agencies to document exposures before and after SAF adoption.
- Implement SAF blend reporting protocols for modeling efforts.
- Quantify use of high-blend SAFs (e.g., 30% HEFA blends) that may maximize particulate emission reductions.
- Characterize any incentivizing of SAF use for incoming aircraft.
- Develop tools to identify threshold blend quantities producing regional air quality benefits.
- Explore the potential value of ambient air monitoring near airports to assess real-time SAF benefits, despite challenges associated with limited characterization methods.

Key areas for future discussion

Assessing the co-benefits of sustainable aviation fuels

Future reports could integrate air quality modeling with health impact assessments to evaluate SAF co-benefits. This combined approach could enable the direct assessment of SAF-related emission reductions on ground-level pollutants such as (UFPs), nitrogen oxides (NO_x), and sulfur dioxide (SO_2), enabling a more accurate quantification of health benefits. An analysis of the change in pollutant exposure distributions in communities near airports can help identify regional air quality benefits of SAFs. It may also help quantify benefits to communities, particularly in areas currently experiencing the highest pollutant concentrations, as suggested by Keuken et al. (2015) and Liu et al. (2024) (Keuken et al., 2015; Liu et al., 2024).

Enhancing monitoring and data collection

Continue to review the findings of SAF research that could include improved multipollutant monitoring near airports to refine model inputs and validate predictions. Mobile monitoring efforts, such as those by Austin et al. (2021) and Blanco et al. (2022), have isolated aviation-related air pollutants, but more comprehensive, long-term datasets could allow for generalization of findings (Austin et al., 2021; Blanco et al., 2022b). Time-resolved data on pollutant concentrations and chemical compositions near major airports, such as Sea-Tac, offers insights into exposure trends and air quality improvements from SAF adoption.

Addressing data gaps in emission characterization

Significant gaps remain in characterizing SAF emissions under real-world conditions. Current models often rely on conventional jet fuel emission profiles, though SAFs produce different pollutant compositions. Developing SAF-specific emission factors, particularly for landing and takeoff (LTO) cycles, is essential for accurately assessing their environmental and health benefits. Additionally, considering fuel blends used in takeoff and landing cycles is critical to fully understanding benefits.

Improving exposure assessment from air quality modeling

Plume dispersion models (e.g., AERMOD) and chemical transport models (CTMs) provide differing predictions of pollutant concentrations. Although prior studies have compared these models, results are inconsistent. More research is needed to validate models with monitoring data and improve exposure assessment accuracy. Enhanced spatial resolution, applicable at the address level, is critical for epidemiological analyses. Combining strengths of existing models could result in more robust hybrid approaches.

Assessing exposure and health outcomes

Continue to review population-level studies that integrate exposure estimates from air quality models with epidemiological data. Using exposure-response functions, researchers could quantify SAF-related health benefits, including reductions in mortality and improvements in respiratory and cardiovascular health outcomes. Relying on the future improved accuracy of these studies will support more robust estimations of SAF co-benefits.

Future efforts should focus on integrating published emissions data, refining SAF-specific model inputs for key operational cycles such as landing and takeoff, and bridging air quality models with health assessments. These steps will help quantify community-level co-benefits such as reduced mortality and improved health outcomes. Expanding community monitoring near Sea-Tac and addressing data gaps will enhance model accuracy and relevance for public health assessments.

Future opportunities for data sharing

Tracking SAF use
A comprehensive initiative to gather time-resolved data on SAF blend ratios (e.g., 10%, 30%, or 50%), SAF types (e.g., HEFA, FT, ATJ), and their compositional characteristics will support accurate emissions assessments and identification of SAF blends yielding the greatest health benefits.

Flight activity and fuel usage records
Recording incoming flights and their fueling port, along with data on flights using SAF versus conventional Jet A-1 fuel, will enable robust exposure assessments and modeling of SAF impacts on air quality.

Jet A-1 fuel sulfur composition
Detailed records of Jet A sulfur content will allow precise comparisons with SAFs, which are typically low in sulfur, enabling accurate quantification of health benefits.

Annual reporting and data sharing with DEOHS
Annual reporting protocols, established through the Washington Legislature, will include SAF usage and could be expanded to include projections, flight activity, and fuel characteristics.

Enhanced monitoring and data collection
Monitoring at sensitive locations, such as schools and healthcare facilities near airports, will help validate models and assess exposure levels with greater precision. As previously demonstrated in other localities, direct measurement approaches can be used to link emission rates to community level concentrations. These measurements could inform modeling approaches and provide clear information on blend thresholds and impacts.

Research needs and knowledge gaps

Initial studies suggest SAF adoption could reduce ultrafine particle and sulfur emissions. However, additional data is needed to quantify these benefits. Robust cost-benefit analyses and assessments of health improvements will provide essential data for decision-makers and policy development.

Ongoing efforts by the UW research team are focused on SAF-specific emission modeling, including real-world simulations of pollutant dispersion and community exposure assessments. These efforts aim to quantify the minimum SAF blend thresholds necessary for meaningful regional air quality improvements. Results from this work will be incorporated into future reports as they become available.

Future reports will focus on spatial distributions and health impacts of reduced exposures due to SAF adoption. These benefits will be driven by SAF composition, usage, and blend characteristics. Direct links between SAF-driven emission reductions and community and regional exposure levels are essential for understanding their benefits. The current literature does not provide clear guidance on the threshold of SAF use that will drive impacts and benefits. This question can be addressed through the proposed methods identified in this report including, careful comparison of expected emission inventory impacts, continued review of health impacts literature, refinement of modeling approaches to directly assess regional pollutant benefits, particularly with respect to ultrafine particle distribution as well as consider pairing regional monitoring to capture benefits of SAF adoption and identify critical threshold values.

Conclusion

In 2023, no SAF usage was reported at Sea-Tac airport. Structured data collection, transparent reporting, and public health-oriented decision-making are critical for realizing the full benefits of SAF adoption. Coordinated efforts involving DEOHS, the Port of Seattle, WSU, and other stakeholders will ensure reliable reporting of the impacts of SAF adoption on regional air quality near Sea-Tac and other airports.

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Contact Information

Elena Austin, ScD
Department of Environmental and Occupational Health Sciences
School of Public Health
University of Washington

elaustin@uw.edu