Environment International 158 (2022) 106958

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

# Air quality and health-related impacts of traditional and alternate jet fuels from airport aircraft operations in the U.S.

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ARTICLE INFO

Handling Editor: Xavier Querol

*Keywords:*
Aircraft emissions
$PM_{2.5}$
$NO_2$
$O_3$
Air quality
CMAQ
Alternative jet fuel
Health impacts

ABSTRACT

Aviation emissions from landing and takeoff operations (LTO) can degrade local and regional air quality leading to adverse health outcomes in populations near airports and downwind. In this study we aim to quantify the air quality and health-related impacts from commercial LTO emissions in the continental U.S. for two recent years' inventories, 2011 and 2016. We quantify the LTO-attributable $PM_{2.5}$, $O_3$, and $NO_2$ concentrations and health outcomes for mortality and multiple morbidity health endpoints. We also quantify the impacts from two scenarios representing a nation-wide implementation of 5% or 50% blends of sustainable alternative jet fuels. We estimate 80 (68–93) and 88 (75–100) $PM_{2.5}$-attributable and 610 (310–920) and 1,100 (570–1,700) $NO_2$-attributable premature mortalities in 2011 and 2016, respectively. We estimate a net decrease of 28 (14–56) and 54 (27–110) in $O_3$-attributable premature mortalities across the U.S. in 2011 and 2016, respectively due to the large $O_3$ titration effects near the airports. We also find that the asthma exacerbations due to $NO_2$ exposures from LTO emissions increase from 100,000 (2,500–200,000) in 2011 to 170,000 (4,400–340,000) in 2016. Implementing a 5% or 50% blend of sustainable alternative jet fuel in 2016 results in a 1% or 18% reduction, respectively in $PM_{2.5}$-attributable premature mortalities. Monetizing the value of avoided total premature mortalities, we find that a 50%-blended sustainable alternative jet fuel results in a 19% decrease in $PM_{2.5}$ damages per ton of fuel burned and a 2% decrease in total damages per ton of fuel burned as compared to damages from traditional jet fuel. We also quantify health impacts by state and find California to be the most impacted by LTO emissions. We find that LTO-attributable $PM_{2.5}$ and $NO_2$ premature mortalities increase by 10% and 80%, respectively from 2011 to 2016 and that $NO_2$-attributable premature mortalities are responsible for 91% of total LTO-attributable premature mortalities in both 2011 and 2016. And since we find LTO-attributable $NO_2$ to be unaffected by the implementation of sustainable alternative jet fuels, additional approaches focused on $NO_X$ reductions in the combustor are needed to mitigate the air quality-related health impacts from LTO emissions.

## 1. Introduction

Commercial aviation emissions' impact on air quality has been estimated to be responsible for approximately 16,000 premature mortalities each year globally (Yim et al., 2015; Grobler et al., 2019). Both international and domestic forecasts for aviation traffic call for continued growth, 2.1% and 3.5% growth in revenue passenger miles over the next 20 years, respectively (FAA, 2014), with total fuel burn from commercial aircraft globally increasing by 71% between 1992 and 2006 (Olsen et al., 2013) and increasing by 28% between 2006 and 2015 (Grobler et al., 2019). Modeling studies have aimed to quantify air quality impacts and climate effects from all stages of an aircraft's flight trajectory, often looking at impacts at the landing and takeoff (LTO) stages (Arunachalam et al., 2011; Unal et al., 2005; Woody et al., 2011; Levy et al., 2012b; Lee et al., 2013; Woody and Arunachalam, 2013; Wolfe et al., 2014; Vennam et al., 2015; Woody et al., 2015; Woody et al., 2016; Penn et al., 2017) (below 3,000 ft) and full-flight (cruise) stages (Barrett et al., 2010; Barrett et al., 2012; Koo et al., 2013; Caiazzo et al., 2017; Cameron et al., 2017; Vennam et al., 2017; Grobler et al., 2019; Quadros et al., 2020; Lee et al., 2021).

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https://doi.org/10.1016/j.envint.2021.106958
Received 13 July 2021; Received in revised form 21 October 2021; Accepted 22 October 2021
Available online 26 October 2021

A recent paper by Dedoussi et al. 2021 (Dedoussi, 2021) has highlighted the important research questions surrounding aviation-attributable air pollution such as global impacts versus local impacts, aviation's impact in a changing atmosphere, and emission reduction strategies focused on technological changes such as alternative jet fuels. Recent modeling studies have aimed to quantify global impacts from full-flight cruise emissions; with over 75% of health impacts due to aviation-attributable air pollution estimated to be from full-flight emissions (Barrett et al., 2010; Yim et al., 2015; Dedoussi, 2021). However, global studies may not be capturing the local impacts due to limited chemistry and coarser model grid cell resolutions (Barrett et al., 2010; Levy et al., 2012b; Dedoussi et al., 2020). Local to regional scale modeling efforts to quantify health impacts from aviation-attributable pollution in the U.S. have utilized emission inventories from the early 2000s (Ratliff et al., 2009; Levy et al., 2012b; Lee et al., 2013; Koo et al., 2013; Ashok et al., 2013; Wolfe et al., 2014; Yim et al., 2015; Penn et al., 2017) which do not represent the impacts of the economic recession in 2007–2009 and the impacts of a changing U.S. atmosphere (Pye et al., 2020; Dedoussi, 2021). In fact, the recession in 2007–2009 had slowed aviation growth such that U.S. commercial air carriers' total number of domestic departures had not increased above 2007 levels until 2016 (FAA, 2014). And as far as the authors are aware, no study that has looked at health impacts from aviation-attributable air pollution have quantified the impacts from aviation-attributable $NO_2$, a potentially dangerous local-scale pollutant from mobile sources (Khreis et al., 2017; Atkinson and Butland, 2018; Achakulwisut et al., 2019; Mohegh et al., 2020). And while one study has looked at the air-quality-related health benefits from desulfurizing jet fuel (Barrett et al., 2012), and two others have looked at the non-volatile particulate matter (nvPM) emissions reductions from alternative jet fuels (Speth et al., 2015; Lobo et al., 2011), no study has looked to quantify the air-quality-related health benefits from fleet-wide implementation of sustainable alternative jet fuel.

This study aims to address some of the gaps of the prior studies by quantifying LTO aviation-attributable fine particulate matter ($PM_{2.5}$), ozone ($O_3$), and nitrogen dioxide ($NO_2$) concentrations and health impacts in the continental U.S. (CONUS) for the two most recent U.S. Environmental Protection Agencies' (EPA) National Emissions Inventories' (NEI) years of 2011 and 2016. Two additional 2016 LTO emission inventories have been generated and modeled to quantify the air quality impacts of a 5% and 50% blend of sustainable alternative jet fuel implemented across the U.S. This will be the first study to quantify the impacts from aviation-attributable $NO_2$ in the U.S. and the implementation of sustainable alternative jet fuel blends nationwide. We hope these results can add to the growing list of literature surrounding aviation-attributable air pollution and associated health impacts.

## 2. Methods

We utilize a modeling platform consisting of the Weather Research and Forecasting (WRF) model (Skamarock et al., 2008) to process meteorology inputs, the Sparse Matrix Operator Kernel Emissions (Baek and Seppanen, 2018) (SMOKE) model to process background emissions, and the Community Multi-Scale Air Quality Model (CMAQ) to estimate LTO aviation-attributable $PM_{2.5}$, $O_3$, and $NO_2$ across the continental U.S. (CONUS) for the years 2011 and 2016. CMAQv5.2 (US EPA Office of Research and Development, 2017) with the Carbon Bond 6 revision 3 mechanism (CB6r3) (Luecken et al., 2019) is used to quantify pollutant concentrations across our modeling domain. Our modeling domain covers the continental U.S. with 12 km × 12 km horizontal grid cell resolution. Background emissions (all sectors excluding commercial aviation) are from the U.S. EPA's 2011 (2011 NEI v2) (US Environmental Protection Agency, 2011) and 2016 (2016 NEI v1) (US Environmental Protection Agency, 2016) National Emissions Inventories. Aircraft emissions in this study were constructed from the FAA's Aviation Emission Design Tool (AEDT) (FAA-AEDT, 2016) for National Air Space (NAS)-wide LTO aircraft activity for the years 2011 and 2015. LTO segments from AEDT datasets (Wilkerson et al., 2010) were processed into gridded emission rate files using AEDTProc (Baek et al., 2012) such that LTO emissions of nitrogen oxides ($NO_X$) (speciated to nitrogen oxide (NO), $NO_2$, and nitrous acid (HONO)), carbon monoxide (CO), sulfur dioxide ($SO_2$), total organic gases (TOG) (speciated to CB6r3 model species according to EPA's speciation profile (US Environmental Protection Agency and Federal Aviation Administration, 2009)), and primary PM (sulfate, organic aerosols, and elemental carbon (Wayson et al., 2009; Wilkerson et al., 2010)) are allocated to CMAQ-ready emission input files. Two additional LTO emissions inventories were generated to represent the expected emissions if sustainable alternative jet fuels (AJFs) were implemented across the U.S. as a 5% blend of existing jet fuel and a 50% blend of existing jet fuel. These inventories were generated by scaling hourly emission rates of the 2015 LTO inventory by fractional impact factors (values in S8) derived from field studies as defined in a recent synthesis study from the Airports Cooperative Research Program (ACRP) that quantified emissions reductions due to use of sustainable alternate jet fuels (Hamilton, 2019). AJFs are produced from non-petroleum sources which reduces the life-cycle greenhouse gases (Pavlenko and Searle, 2021; Martinez-Valencia et al., 2021) and when burned in aircraft engines, AJFs emit less air pollutants. In this study we are concerned with the latter as it pertains to air quality impacts from airport aircraft operations. AJF use has been shown to reduce emissions of sulfur oxides ($SO_X$) and nvPM significantly (~90% and ~50% $SO_X$ reductions for 100% and 50% blends of AJFs, respectively (Beyersdorf et al., 2014; Corporan et al., 2010) and ~65% nvPM reductions for 50% blends (Beyersdorf et al., 2014; Chan et al., 2015; Lobo et al., 2011)) and to a lesser extent, CO (~10% CO reductions for 50% blends of AJF (Shouse et al., 2012)). There are currently three potential routes for AJFs: synthetic liquid fuels manufactured from current fossil fuels or biomass, bio-jet fuels made from agricultural oil crops, and hydrogen. Current use of AJFs requires a certain percentage to be blended with conventional petroleum-based jet fuel. Hence, the 5% and 50% impact factors derived in the ACRP report are from field campaigns that quantify the emissions and effects of different AJFs at specified blends up to 50%. In addition to the two NEI background emission inventories and LTO emission inventories, we made use of two meteorology datasets for 2011 and 2016. Details regarding model settings and datasets used can be found in tables S1–S2 and details regarding model evaluation against observations can be found in figures S1-S7 and table S5.

The health impact assessment tool BenMAPR is used to quantify the expected mortalities and morbidities due to LTO-attributable pollutants. Similar to the U.S. EPA's Benefits Mapping and Analysis Program (BenMAP) (Sacks et al., 2018), BenMAPR is a geospatial air pollution health impact assessment modeling platform written in the statistical computing language R (R Core Team, 2017) that links air pollution exposures to data on exposed populations and their background health. It then calculates the health impacts of these exposures using concentration response functions (CRFs) from the epidemiological literature. BenMAPR has been used in other health impact analyses (Arter et al., 2021) and relies on the same calculations and datasets used in BenMAP. For quantifying $PM_{2.5}$-attributable premature mortalities, we make use of a CRF from a recently published meta-analysis (Vodonos et al., 2018) that found a 1.29% (95% CI 1.09–1.5) increase in all-cause mortality per 10 $\mu g/m^3$ increase in $PM_{2.5}$. For $O_3$-attributable premature mortalities, we use a CRF associating all-cause mortality to long-term $O_3$ exposure with a hazards ratio of 1.02 (95% CI 1.01–1.04) per 10 ppb increase in $O_3$ (Turner et al., 2016). For $NO_2$-attributable premature mortalities, we use a CRF from a meta-analysis that found a pooled effect on mortality to be 1.04 (95% CI 1.02–1.06) with an increase in 10 $\mu g/m^3$ in $NO_2$ (Faustini et al., 2014). In addition to mortality estimates, we expand the analysis to incorporate multiple morbidity estimates such as: respiratory and cardiovascular hospitalizations (Levy et al., 2012a; Zanobetti et al., 2009), non-fatal heart attacks (Mustafić et al., 2012), and asthma

hospitalizations, emergency department visits, and exacerbations in those ages 5 to 17 (Orellano et al., 2017). Information regarding the morbidity CRFs and the underlying datasets used can be found in table S4. We chose CRFs in studies that best represent present day health outcomes and North American populations. If no suitable CRF could be found, we then relied on the CRFs that are currently used in BenMAP.

## 3. Results

### 3.1. Emissions

Table 1 shows the number of arrivals and departures at CONUS airports and annual emissions of CONUS LTO CO, $NO_X$, primary elemental carbon (PEC), and $SO_2$ for each simulation year. While the total number of arrivals and departures slightly decrease from 2011 to 2016, total fuel burned increases by ~10% (from ~4.66 Tg in 2011 to ~5.13 Tg in 2016) resulting in emissions increasing from 2011 to 2016. Emissions of CO, PEC, and $SO_2$ decrease under the 5% and 50% 2016 AJF scenarios with the amount decreased given by the impact factors in the ACRP report (table S8). It is important to note that other emission species, such as $NO_X$, HAPs, and volatile organic compounds (VOC) were estimated to be negligibly impacted by currently approved blend percentages (up to 50%) of sustainable alternative jet fuels. The ACRP report found no statistically significant impact for $NO_X$ and HAPs and no statistically meaningful results for VOCs from their fitting of the experimental data. Hence, the authors cautioned applying impact factors for those species and we left those emission species unchanged from 2016 in the 5% and 50% blend scenarios.

We are able to quantify airport level emissions by looking at the emissions in the airport-containing grid cell. Fig. 1 shows the CO, $NO_X$, primary elemental carbon (PEC), and $SO_2$ emissions at the airport-containing grid cells for the top 28 airports in terms of passenger boardings (Air Carrier Activity Information System (ACAIS), 2015). The ORD (Chicago O'Hare International)-containing grid cell has the most $NO_X$ emissions at 2,184 tons in 2011 and the JFK (John F. Kennedy International)-containing grid cell has the most $NO_X$ emissions at 2,880 tons in 2016. The ATL (Hartsfield-Jackson Atlanta International)-containing grid cell has the most CO emissions at 1,421 tons in 2011 and the LAX (Los Angeles International)-containing grid cell has the most CO emissions at 1,519 tons in 2016. The ATL-containing grid cell has the most PEC emissions at 3.7 tons in 2011 and at 3.7 tons in 2016. The ORD-containing grid cell has the most $SO_2$ emissions at 172 tons in 2011 and at 192 tons in 2016. Emissions at the grid cell level are largely linear with respect to the number of flights at these airports. Figures S8-S11 show the number of arrivals and departures at 66 airports across the U.S. versus emissions of $NO_X$, CO, $SO_2$, and PEC in the airport-containing grid cell.

### 3.2. Air quality

Table 2 shows the CONUS-averaged population-weighted concentrations for LTO-attributable $PM_{2.5}$, $O_3$, and $NO_2$. $PM_{2.5}$ and $NO_2$ concentrations represent the annual average while $O_3$ concentrations represent the annual average of the daily 8 h maximum. $PM_{2.5}$ population-weighted concentrations increase by 7.7% from 2011 to 2016. $PM_{2.5}$ population-weighted concentrations are expected to decrease in 2016 by 2.4% if a 5% blend of sustainable alternative jet fuel is implemented and by 18.4% if a 50% blend is implemented. $O_3$ population-weighted concentrations are negative in both 2011 and 2016, meaning that LTO emissions near the airport are removing $O_3$. This is due to localized $NO_X$/VOC ratios impacting whether $O_3$ formation is limited by $NO_X$ or VOC concentrations and as it is often the case for densely populated urban areas; $NO_X$ emissions can lead to a reduction in $O_3$ in VOC-limited areas. From Table 1 we can see that $NO_X$ emissions from LTO across the U.S. are larger in 2016 than 2011 which corresponds to an 82% decrease in $O_3$. As both $NO_X$ and VOC emissions are unaffected by the implementation of sustainable alternative jet fuels, $O_3$ concentrations are not impacted. $NO_2$ population-weighted concentrations increase by 77% from 2011 to 2016 and are also unaffected by the implementation of sustainable alternative jet fuels.

Figs. 2–4 show the LTO-attributable $PM_{2.5}$, $O_3$, and $NO_2$ concentrations, respectively across the continental U.S. aggregated to the county scale for both 2011 and 2016. Impacts are mostly seen in counties either containing an airport or surrounding an airport. Large negative $O_3$ concentrations (in blue in Fig. 3) outweigh positive $O_3$ concentrations that are occurring downwind of the airports in $NO_X$-limited areas. In 2016, two counties in Northwest Washington, Pierce and Island Counties, have negative LTO-attributable $PM_{2.5}$ due to the negative LTO-attributable nitrate ($NO_3^-$), ammonium ($NH_4^+$), and organic matter (OM) components of $PM_{2.5}$. These components are reduced with LTO emissions due to LTO emissions of $NO_X$ reacting with available $O_3$ and gas phase $NO_3^-$ near the airport to form nitrogen pentoxide ($N_2O_5$); resulting in a reduction of both gas phase $NO_3^-$ and oxidants available to form SOA (Woody and Arunachalam, 2013). In the summer, warmer temperatures can limit the particle-phase partitioning of ammonium nitrate ($NH_4NO_3$) resulting in negative LTO-attributable $NH_4^+$. The higher temperatures limiting the partitioning of $NH_4NO_3$ into particle phase can also make the impacts on aerosol sulfate ($SO_4^{2-}$) formation more pronounced. Aerosol $SO_4^{2-}$ formation can be reduced by the additional LTO $NO_X$ increasing aqueous-phase acidity and subsequently reducing the dissolution of $SO_2$ in the aqueous-phase; as well as LTO $NO_X$ limiting the oxidants available to oxidize $SO_2$ to sulfuric acid ($H_2SO_4$). And while these impacts are seen across the U.S. for other grid cells, these two Washington counties that are north and south of the Seattle-Tacoma airport are impacted enough by these effects to cause each county to have on average negative LTO-attributable $PM_{2.5}$.

Figs. 5–7 show the monthly LTO-attributable $PM_{2.5}$, $O_3$, and $NO_2$ concentrations, respectively across the continental U.S. for 2011 and 2016 as boxplots for all grid cells within the continental U.S. (top of each figure) and the monthly mean LTO-attributable concentrations (bottom of each figure). Figures S17 and S18 show the monthly mean LTO-attributable $PM_{2.5}$ component concentrations for 2011 and 2016, respectively. In 2011, LTO-attributable $NO_3^-$ and $NH_4^+$ are largest in the month of March due to the most LTO $NO_X$ being emitted in March. The LTO $NO_X$ can positively impact $NO_3^-$ and $NH_4^+$ formation far enough downwind of airports in the month of March where the competition for available oxidants between LTO $NO_X$ and $SO_2$ to form $NO_3^-$ and $SO_4^{2-}$, respectively, and the competition of the subsequent nitric acid ($HNO_3$) and $H_2SO_4$ for available $NH_3$ to determine the phase state of $HNO_3$ and subsequent aerosol phase $NH_4NO_3$ near the airport is no longer occurring. In cooler months, limited $NH_3$ near the airports will keep $HNO_3$ in the gas phase and $H_2SO_4$ neutralized. But downwind of the airports, LTO $NO_X$ can positively impact $NH_4NO_3$ concentrations where this competition is no longer occurring. And while $NO_X$ emissions are also large in the summer months, we see $NO_3^-$ being a much smaller portion of the LTO-attributable $PM_{2.5}$ due to effects that occur near the airport and the

**Table 1**
LTO emissions in the U.S. for each scenario, [a] percent change from 2011, [b] percent change from 2016.

| | 2011 | 2016 | 2016AJF5 | 2016AJF50 |
|---|---|---|---|---|
| Arrivals and Departures | 24,151,176 | 24,141,257 (−0.04%)[a] | 24,141,257 | 24,141,257 |
| CO (Tons/year) | 44,637 | 49,382 (11%)[a] | 48,888 (−1%)[b] | 44,049 (−11%)[b] |
| $NO_X$ (Tons/year) | 64,056 | 73,926 (15%)[a] | 73,926 (0%)[b] | 73,926 (0%)[b] |
| PEC (Tons/year) | 161 | 164 (2%)[a] | 149 (−9%)[b] | 58 (−65%)[b] |
| $SO_2$ (Tons/year) | 5,481 | 6,038 (10%)[a] | 5,814 (−4%)[b] | 3,773 (−38%)[b] |

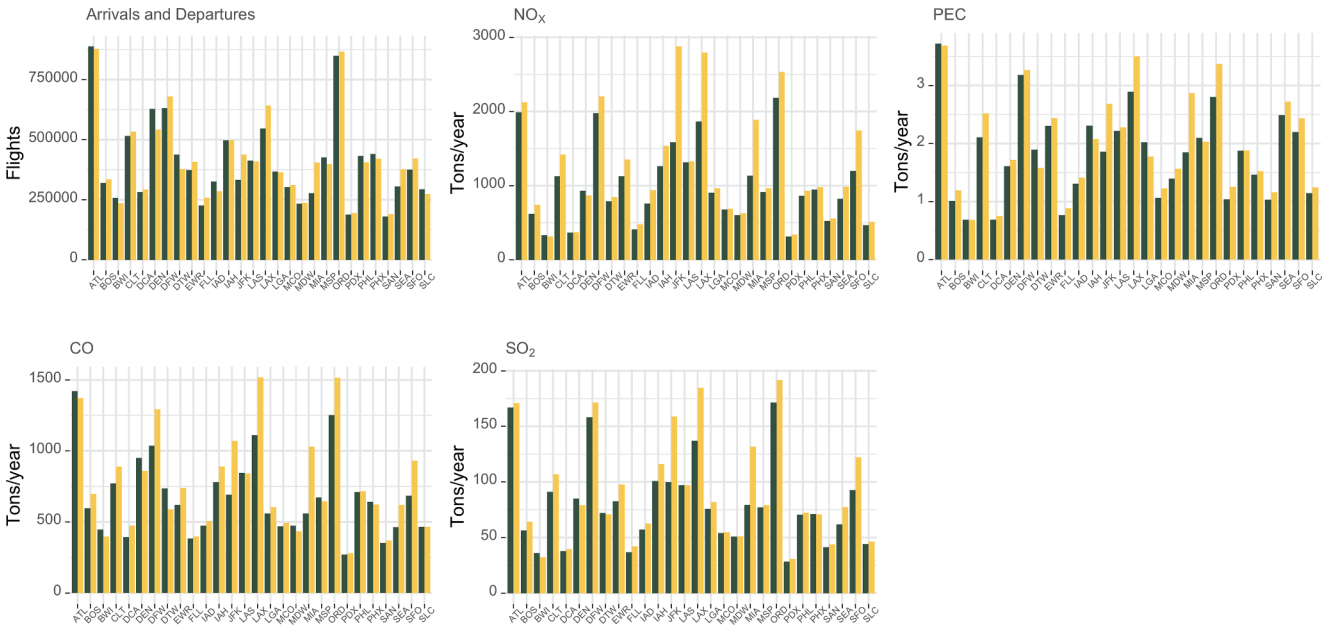


**Fig. 1.** Number of arrivals and departures and the LTO emissions in the airport-containing grid cells, table S6 describes the full names associated with each of the airport ID codes.

**Table 2**
Annual average population weighted concentrations due to LTO emissions in the U.S.

| | 2011 | 2016 | 2016AJF5 | 2016AJF50 |
|---|---|---|---|---|
| $PM_{2.5}$ (μg/m$^3$) | 2.72E−03 | 2.93E−03 | 2.86E−03 | 2.39E−03 |
| $O_3$ (ppb) | −8.24E−03 | −1.50E−02 | −1.50E−02 | −1.50E−02 |
| $NO_2$ (ppb) | 3.92E−02 | 6.93E−02 | 6.94E−02 | 6.94E−02 |

warmer temperatures impacting the particle-phase partitioning of $NH_4NO_3$ and reduced formation of $SO_4^{2-}$ as described in the previous paragraph. The distribution of grid cell concentrations shows the localized impacts of LTO emissions with outlier points' absolute values being order of magnitudes larger than the mean values and indicative of airport-containing grid cells (Figures S13-S15 show the monthly LTO-attributable $PM_{2.5}$, $O_3$, and $NO_2$ concentrations for airport-containing grid cells). These outliers drive the population-weighted exposures and as we will see, the health outcomes. Mean values of $O_3$ and $NO_2$ show opposite monthly trends with mean LTO-attributable $O_3$ concentrations peaking in the summer and diminishing in the winter and LTO-attributable $NO_2$ exhibiting the opposite. Both LTO-attributable $O_3$ and $NO_2$ impacts are driven by LTO $NO_X$ emissions.

Similar to individual airport's emissions, we can look at the concentrations of $PM_{2.5}$, $O_3$, and $NO_2$ at the airport-containing grid cell level. It is important to note that the airport-grid cell concentrations are not indicative of the total impacts felt by LTO emissions near an airport, and this analysis is simply a comparison of concentrations in the grid cells containing the top 28 airports in terms of passenger boardings. Fig. 8 shows the pollutant concentrations at the airport-containing grid cell level for the same group of airports in Fig. 1. The SFO (San Francisco International)-containing grid cell has the largest increase in $PM_{2.5}$ concentration of 5.4E-02 $\mu g/m^3$ in 2011 and the LAX-containing grid cell has the largest increase in $PM_{2.5}$ concentration of 4.9E-02 $\mu g/m^3$ in 2016. $O_3$ titration impacts are seen at the airport-containing grid cell level where $O_3$ concentrations are decreased by the addition of LTO emissions. The SFO-containing grid cell has the largest decrease in $O_3$ concentration at −1.13 ppb in 2011 and −1.86 ppb in 2016. The LAX-

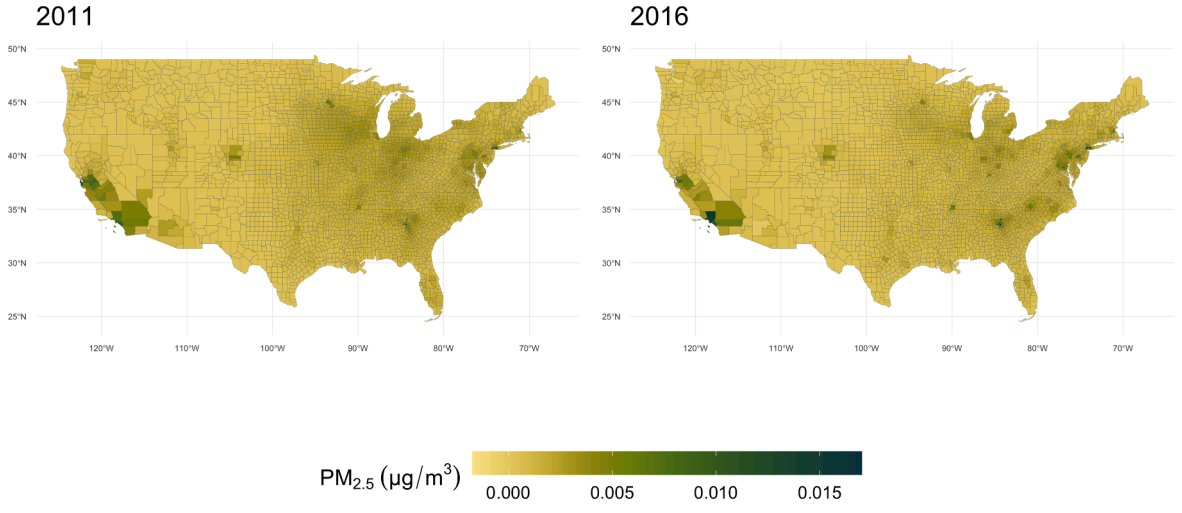


**Fig. 2.** LTO-attributable $PM_{2.5}$ concentrations in 2011 (left) and 2016 (right).

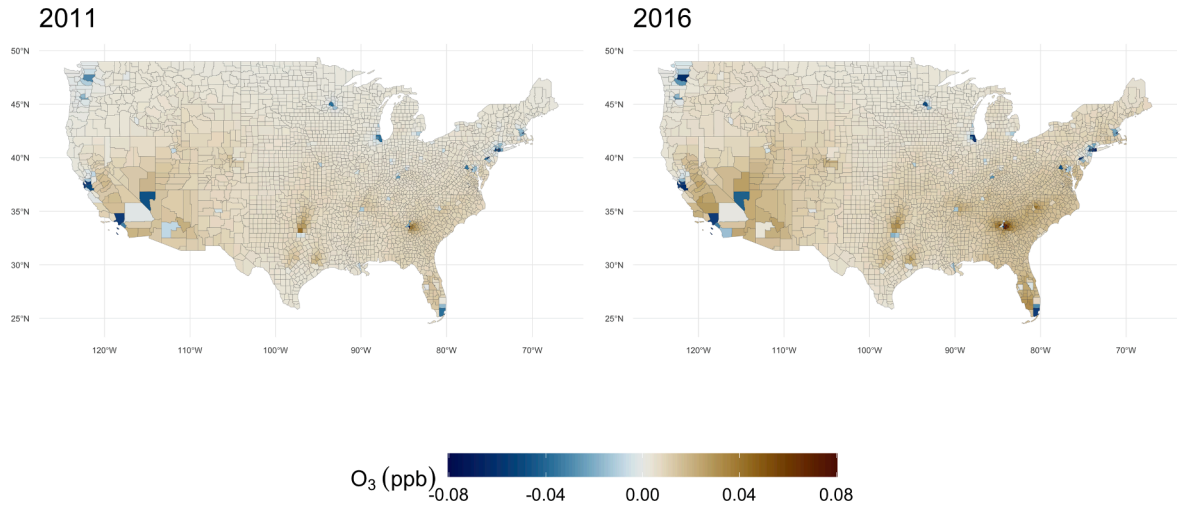


**Fig. 3.** LTO-attributable $O_3$ concentrations in 2011 (left) and 2016 (right).

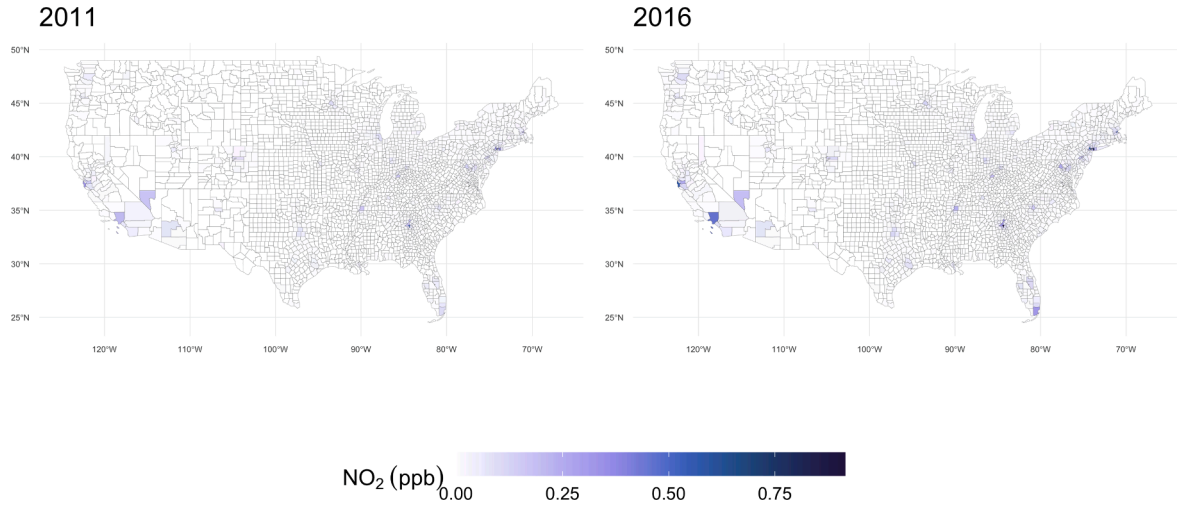


**Fig. 4.** LTO-attributable $NO_2$ concentrations in 2011 (left) and 2016 (right).

containing grid cell has the largest increase in $NO_2$ concentration at 1.76 ppb in 2011 and 4.44 ppb in 2016. Impacts in the SFO-containing grid cell may not be entirely due to LTO activity from SFO due to the close proximity to OAK (Oakland International) (see figure S12). Figure S16 breaks down the $PM_{2.5}$ at the airport-containing grid cell level into concentrations of $NH_4^+$, $NO_3^-$, $SO_4^{2-}$, elemental carbon (EC), and OM chemical constituents. LTO emissions are positively contributing to concentrations of $NH_4^+$, $SO_4^{2-}$, EC, and OM while concentrations of $NO_3^-$ are negatively impacted. Decreases in $NO_3^-$ and $O_3$ concentrations at the grid cell level can be explained by LTO emissions of NO being converted to $NO_2$. This process is possible due to the reaction of NO with $O_3$, which results in $O_3$ concentrations being reduced and $NO_2$ concentrations increasing. $NO_2$ is able to react with $NO_3^-$ to form $N_2O_5$. Hence, the reduction of both $NO_3^-$ and $O_3$ can also impact secondary organic aerosol (SOA) formation as both $NO_3^-$ and $O_3$ are precursors needed for SOA formation (Woody and Arunachalam, 2013); which we are able to see by looking at the few cases in which OM is negatively impacted in 2016 in the ATL, IAH (George Bush Intercontinental/Houston), MCO (Orlando International), and SFO-containing grid cells. LTO emissions of $NO_X$ at the airport-containing grid cell level are fairly linear with $NO_2$ concentrations (Figure S19) and $O_3$ concentrations (Figure S20) with opposite correlations.

### 3.3. Health impacts

Table 3 shows the total adverse health outcomes due to air quality degradation from LTO emissions in the U.S. in 2011 and 2016 and under two sustainable alternative jet fuel implementation scenarios in 2016. $PM_{2.5}$-attributable premature mortalities increase by 10% from 2011 to 2016. We estimate a net decrease in $O_3$-attributable premature mortalities across the U.S. in both 2011 and 2016 due to the large $O_3$ titration effects near the airports. Hence, the titration of $O_3$ in heavily populated regions around airports outweigh the formation of $O_3$ downwind. That is not to say that there are no adverse $O_3$ health outcomes in communities downwind of airports as we will see for health outcomes broken down by state in the next section. $NO_2$-attributable premature mortalities increase by 80% from 2011 to 2016 and are responsible for 91% of total premature mortalities in both 2011 and 2016. Implementing a 5% or 50% blend of sustainable alternative jet fuel in 2016 results in a 1% or 18% reduction, respectively in $PM_{2.5}$-attributable premature mortalities in 2016.

Figs. 9–11 show the number of $PM_{2.5}$, $O_3$, and $NO_2$-attributable mortalities, respectively in each state. California saw the most $PM_{2.5}$-attributable mortalities in 2011 and 2016 with 17.7 (14.9–20.6, 95% CI) and 23.7 (20.0–27.5) mortalities, respectively. Texas saw the most $O_3$-attributable mortalities in 2011 with 2.0 (1.0–4.1) mortalities while Georgia saw the most $O_3$-attributable mortalities in 2016 with 3.3

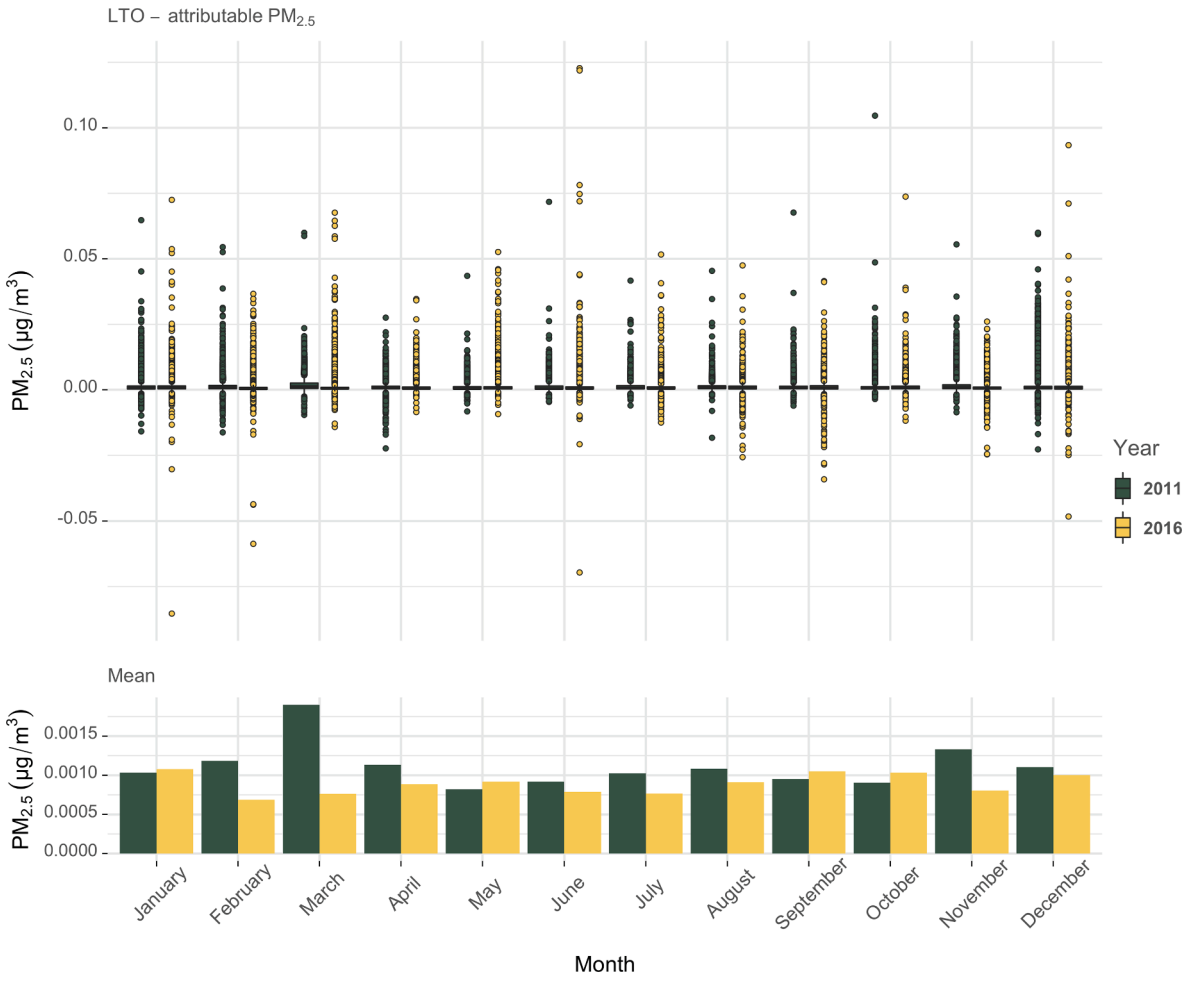


**Fig. 5.** Monthly LTO-attributable $PM_{2.5}$ concentrations for the grid cells that comprise the continental U.S.

(1.6–6.6) mortalities. California saw the most $NO_2$-attributable mortalities in 2011 and 2016 with 155 (78–233) and 323 (161–484) mortalities, respectively.

We can monetize the value of avoided mortalities by applying a value of statistical life (VSL) approach as recommended by the EPA (US Environmental Protection Agency, 2010) and divide by the estimated fuel burned to approximate the economic damages per ton of fuel burned. We multiply the number of $PM_{2.5}$ and total (the sum of $PM_{2.5}$, $O_3$, and $NO_2$) attributable premature mortalities in 2016 by a 2016 USD income-adjusted value of $10.3 million and divide by the total fuel burn estimated through the total $SO_2$ emitted. We do this for our three scenarios in 2016 representing the economic damages per ton of traditional jet fuel burned, 5%-blended sustainable alternative jet fuel, and 50%-blended sustainable alternative jet fuel. We find LTO activity in 2016 to be responsible for 177 (90–292) USD $PM_{2.5}$ damages per ton of fuel burned. Implementing a 5% or 50% blend of sustainable alternative jet fuels results in 175 (88–292) and 144 (74–234) USD $PM_{2.5}$ damages per ton of fuel burned, respectively. Total damages per ton of fuel burned in 2016 are 2,211 (738–4,850) USD and drop to 2,209 (736–4,850) and 2,178 (723–4,791) USD for a 5% and 50% blend, respectively. The values in parentheses indicate an uncertainty in the willingness to pay for a reduction in mortality risk as given in table S3. Hence, a 50%-blended sustainable alternative jet fuel results in a 19% decrease in $PM_{2.5}$ damages per ton fuel burned from traditional jet fuel and a 2% decrease in total damages.

## 4. Discussion

We can compare health outcome estimates from prior studies that aimed to quantify the impacts from LTO-attributable $PM_{2.5}$ and $O_3$. Levy et al. 2012 (Levy et al., 2012b) utilized a 36 km × 36 km CMAQ platform for 99 airports in the U.S. that account for 94% of passenger enplanements in 2005 and quantified the LTO-attributable $PM_{2.5}$ premature mortalities to be 75. Ashok et al. 2013 (Ashok et al., 2013) and Ratliff et al. 2009 (Ratliff et al., 2009) also utilized a 36 km × 36 km CMAQ platform for a 2005 LTO inventory and quantified 195 and 160 $PM_{2.5}$ premature mortalities, respectively. Each of these studies utilized different CMAQ versions and emissions inventories which owe to the variation in results. Barrett et al. 2010 (Barrett et al., 2010) utilized GEOS-Chem at a 1° × 1° resolution for a 2006 LTO inventory and quantified the LTO-attributable $PM_{2.5}$ premature mortalities to be ~ 92 (20% of 458 premature mortalities due to full flight emissions). Koo et al. 2013 (Koo et al., 2013) utilized an adjoint of GEOS-Chem to quantify 20 $PM_{2.5}$ premature mortalities from LTO $SO_2$ emissions and 150 from LTO $NO_X$ emissions in 2006. These studies both relied on global simulations in GEOS-Chem with limited chemistry and coarser model resolution. We estimate 80 and 88 LTO-attributable $PM_{2.5}$ premature mortalities in 2011 and 2016, respectively which are in line with the findings of these prior studies.

Fewer studies have aimed to quantify LTO-attributable $O_3$ mortalities. Yim et al. 2015 (Yim et al., 2015) utilized a 36 km × 36 km CMAQ platform for a LTO inventory in 2006 and quantified LTO-attributable premature mortalities from both $PM_{2.5}$ and $O_3$ to be 650 in North America. Dedoussi et al. 2020 (Dedoussi et al., 2020) utilized GEOS-

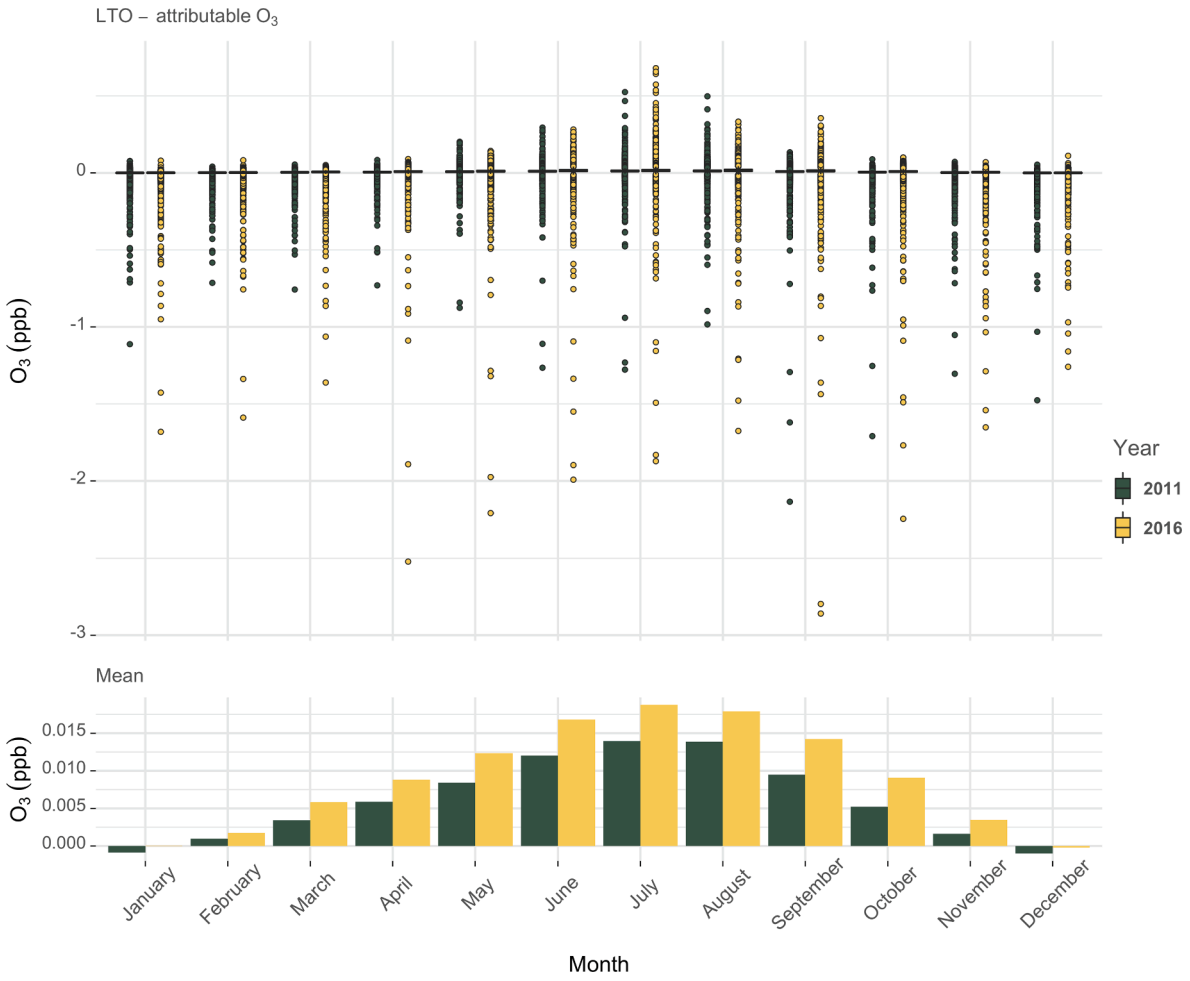


**Fig. 6.** Monthly LTO-attributable $O_3$ concentrations for the grid cells that comprise the continental U.S.

Chem at 0.5° × 0.67° resolution for a LTO inventory in 2011 and quantified LTO-attributable premature mortalities from both $PM_{2.5}$ and $O_3$ to be 209 in the U.S. Both of these studies have quantified total $O_3$ mortalities from LTO to be positive. However, these studies also highlight the impact of coarser model resolutions not being able to capture LTO $NO_X$ emissions decreasing $O_3$ formation in VOC-limited areas. A recent global aviation sensitivity study by Qaudros et al. 2020 (Quadros et al., 2020) stated that LTO emissions cause close to zero net increase in surface level ozone over the year due to airports often being located in areas with high $NO_X$ surface level concentrations and the additional $NO_X$ from aircraft is able to decrease $O_3$, especially in the winter. Two CMAQ-DDM studies aimed at quantifying sensitivities to individual airports (Penn et al., 2017; Arter and Arunachalam, 2021) also found $O_3$ depletion at airports from LTO $NO_X$ emissions, with Penn et al. 2017 claiming that the 36 km × 36 km model resolution used may still be reducing the likelihood of $NO_X$-saturated/VOC-limited conditions (Penn et al., 2017). Missing from all of these studies is the quantification of LTO-attributable $NO_2$ adverse health outcomes which is closely tied to the localized $O_3$ impacts. In VOC-limited areas, $NO_2$ and $O_3$ will often be inversely correlated as a reduction in $NO_X$ emissions can lead to an increase in $O_3$. Hence, additional $NO_X$ from LTO activity in VOC-limited areas will impact both $NO_2$ and $O_3$ concentrations. A recent study in Hong Kong (Hossain et al., 2021) has aimed to quantify the added health risk (AR) associated with $NO_2$ and $O_3$ in a VOC-limited, heavily populated city and found the decrease of AR from ambient $NO_2$ from decreased $NO_X$ emissions measured at roadside stations was considerably higher than the increase in AR associated with increased ambient $O_3$ in those urban areas. Another recent study (Mohegh et al., 2020) aimed to quantify the sensitivity of estimated $NO_2$-attributable health outcomes to grid resolution and found performing their analyses across U.S. cities at 10 km and 100 km resulted in 6% and 32% fewer adverse health outcomes, respectively than the analysis being performed at 100 m up to 1 km. Hence, by not taking into account LTO-attributable $NO_2$, especially at the resolutions needed to capture $NO_X$-saturated/VOC-limited conditions, we may be underestimating the air-quality related health impacts from LTO emissions.

Yim et al. 2015 (Yim et al., 2015) and Grobler et al. 2019 (Grobler et al., 2019) monetized the damages from LTO-attributable $PM_{2.5}$ and $O_3$ premature mortalities. Yim et al. 2015 estimated 439 USD per ton of fuel burned in North America and Grobler et al. 2019 estimated 320 USD per ton of fuel burned in the U.S. for damages from $PM_{2.5}$ and $O_3$. We estimate 177 USD per ton of fuel burned for damages from $PM_{2.5}$ and 2,211 USD for damages from $PM_{2.5}$, $O_3$, and $NO_2$. We did not apply a cessation lag as was done in Yim et al. 2015 (Yim et al., 2015) and Grobler et al. 2019 (Grobler et al., 2019) when monetizing the damages. As we are comparing LTO-attributable $PM_{2.5}$, $O_3$, and $NO_2$ premature mortalities across LTO inventories, a PM cessation lag used in the results would not vary between the comparisons, and not match the CRF used here. In addition, the authors are unaware of research pertaining to cessation lags for use in $NO_2$-attributable premature mortalities. Future work can make use of proposed cessation lags for $PM_{2.5}$-attributable premature mortalities (Walton, 2010). While no other studies have quantified the impacts due to implementation of sustainable alternative jet fuel blends, Barrett et al. 2012 quantified the air quality related health impacts from implementation of ultra low sulfur fuel by reducing aircraft $SO_2$ emissions by 97.5% and found ~120–230 avoided $PM_{2.5}$ mortalities in the U.

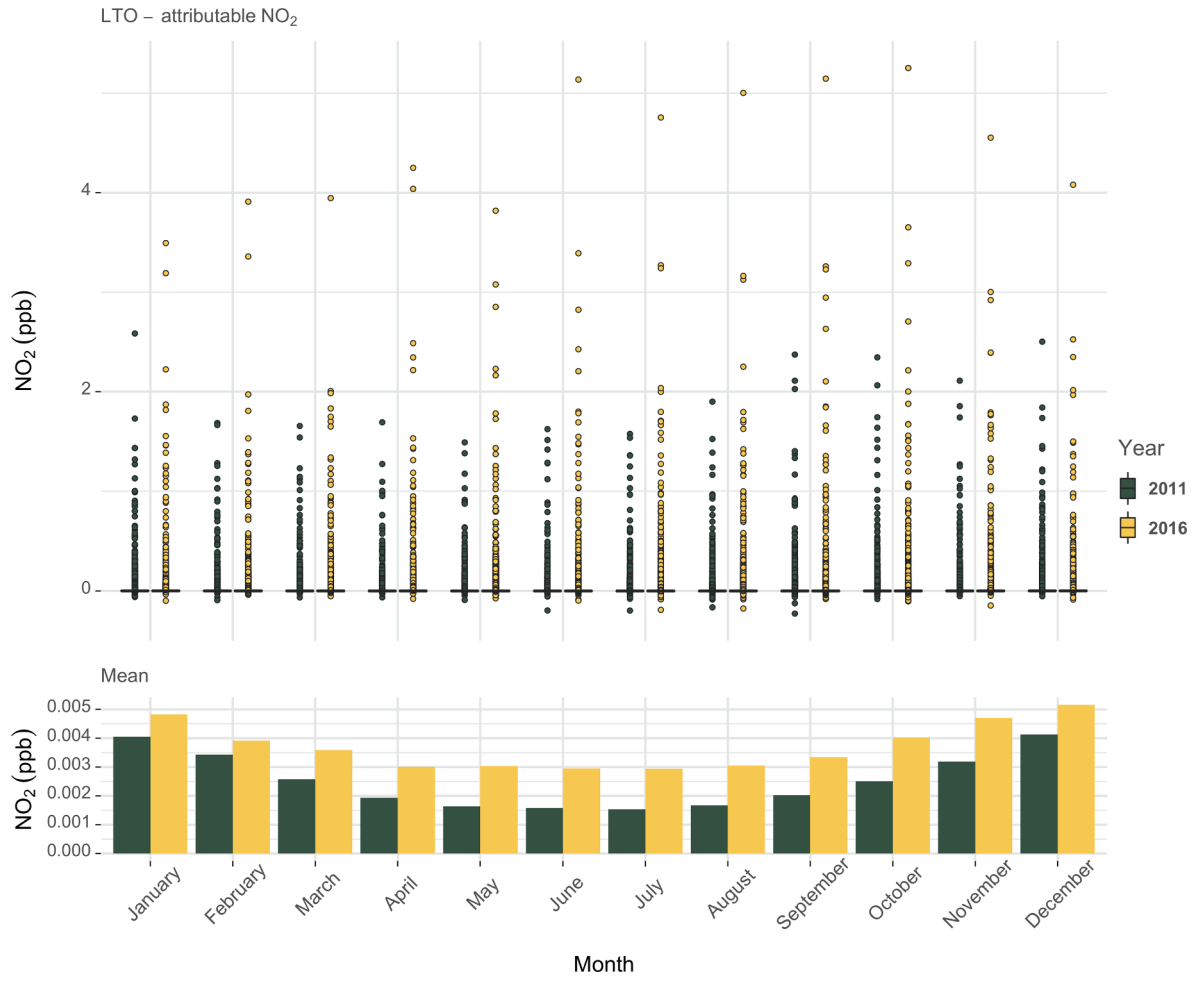


**Fig. 7.** Monthly LTO-attributable $NO_2$ concentrations for the grid cells that comprise the continental U.S.

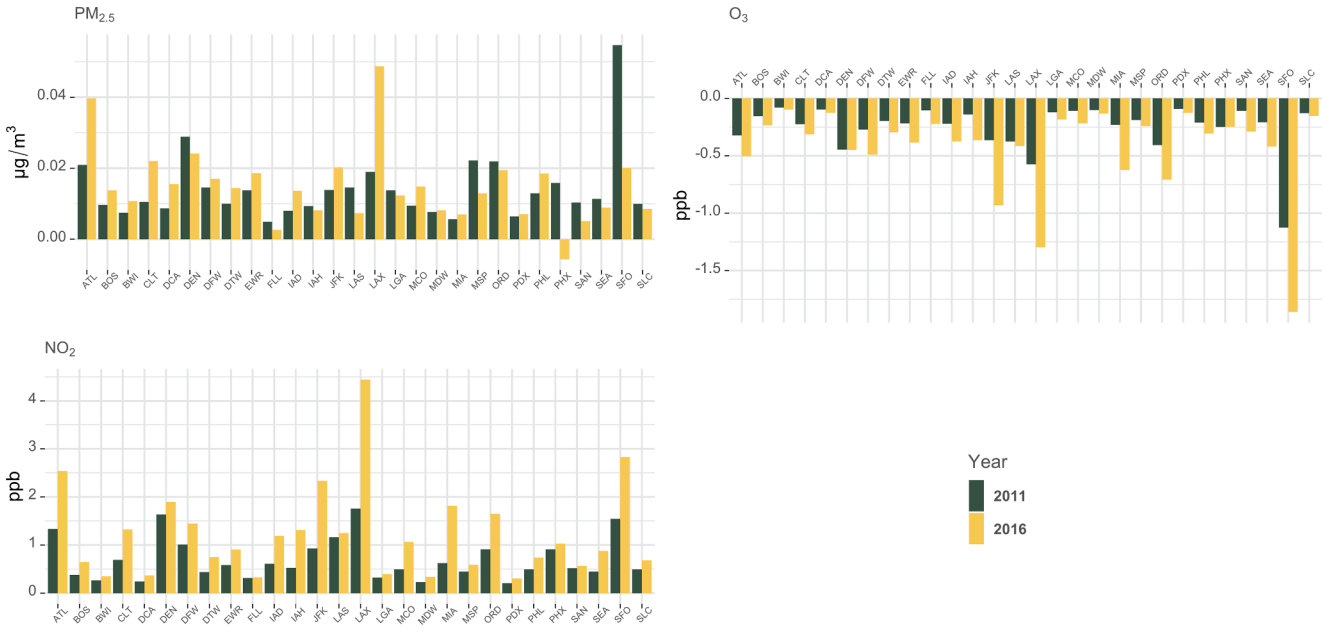


**Fig. 8.** LTO-attributable $PM_{2.5}$, $O_3$, and $NO_2$ concentrations in the airport-containing grid cells.

**Table 3**
Total U.S. LTO-attributable air quality-related mortality and morbidity outcomes for each scenario (Values in parentheses reflect the 95% confidence intervals from the uncertainties in the CRFs, and estimates are rounded to two significant figures).

| | | 2011 | 2016 | 2016AJF5 | 2016AJF50 |
|---|---|---|---|---|---|
| Premature Mortalities | $PM_{2.5}$ | 80 (68–93 ) | 88 (75–100) | 87 (73–100) | 72 (61–84 ) |
| | $O_3$ | −28 (−14 to −56) | −54 (−27 to −110 ) | −54 (−27 to −110 ) | −54 (−27 to −110 ) |
| | $NO_2$ | 610 (310–920) | 1,100 (570–1,700 ) | 1,100 (570–1,700 ) | 1,100 (570–1,700 ) |
| | Total | 670 (360–960) | 1,200 (610–1,700 ) | 1,200 (610–1,700 ) | 1,100 (600–1,700 ) |
| Cardiovascular Hospitalizations | $PM_{2.5}$ | 3.7 (2.6–4.9) | 4.6 (3.1–6 ) | 4.5 (3.1–5.9) | 3.7 (2.6–4.9) |
| Respiratory Hospitalizations | $PM_{2.5}$ | 3.7 (1.9–5.4) | 4.5 (2.3–6.6) | 4.4 (2.3–6.5) | 3.7 (1.9–5.4) |
| | $O_3$ | −12 (−4.5 to −20) | −25 (−8.9 to −40) | −25 (−8.9 to −40) | −25 (−8.9 to −41) |
| | Total | −8.7 (−2.6 to −15) | −20 (−6.6 to −34) | −20 (−6.6 to −34) | −21 (−7 to −35) |
| Non-fatal Heart Attacks | $PM_{2.5}$ | 3.7 (2.2–5.3) | 4.1 (2.5–6 ) | 4.1 (2.4–5.8) | 3.4 (2–4.9) |
| | $NO_2$ | 41 (22–59 ) | 75 (41–110) | 75 (41–110) | 75 (41–110) |
| | Total | 44 (24–65 ) | 79 (43–110) | 79 (43–110) | 78 (43–110) |
| Asthma Hospitalizations Ages 5 to 17 | $PM_{2.5}$ | 0.27 (0–0.54 ) | 0.28 (0–0.57 ) | 0.28 (0–0.56 ) | 0.23 (0–0.46 ) |
| | $NO_2$ | 14 (0.35–27 ) | 23 (0.6–47 ) | 23 (0.6–47 ) | 23 (0.6–47 ) |
| | Total | 14 (0.35–28 ) | 24 (0.6–47 ) | 24 (0.6–47 ) | 24 (0.6–47 ) |
| Asthma Emergency Department Visits Ages 5 to 17 | $PM_{2.5}$ | 2.6 (0–5.3) | 2.7 (0–5.5) | 2.7 (0–5.4) | 2.2 (0–4.5) |
| | $NO_2$ | 130 (3.2–250) | 220 (5.6–430) | 220 (5.6–430) | 220 (5.6–430) |
| | Total | 130 (3.2–260) | 220 (5.6–440) | 220 (5.6–440) | 220 (5.6–440) |
| Asthma Exacerbations Ages 5 to 17 | $PM_{2.5}$ | 2,100 (0–4,300 ) | 2,300 (0–4,600 ) | 2,200 (0–4,500 ) | 1,900 (0–3,800 ) |
| | $NO_2$ | 100,000 (2,500–200,000) | 170,000 (4,400–340,000) | 170,000 (4,400–340,000) | 170,000 (4,400–340,000) |
| | Total | 100,000 (2,500–200,000) | 170,000 (4,400–340,000) | 170,000 (4,400–340,000) | 170,000 (4,400–340,000) |

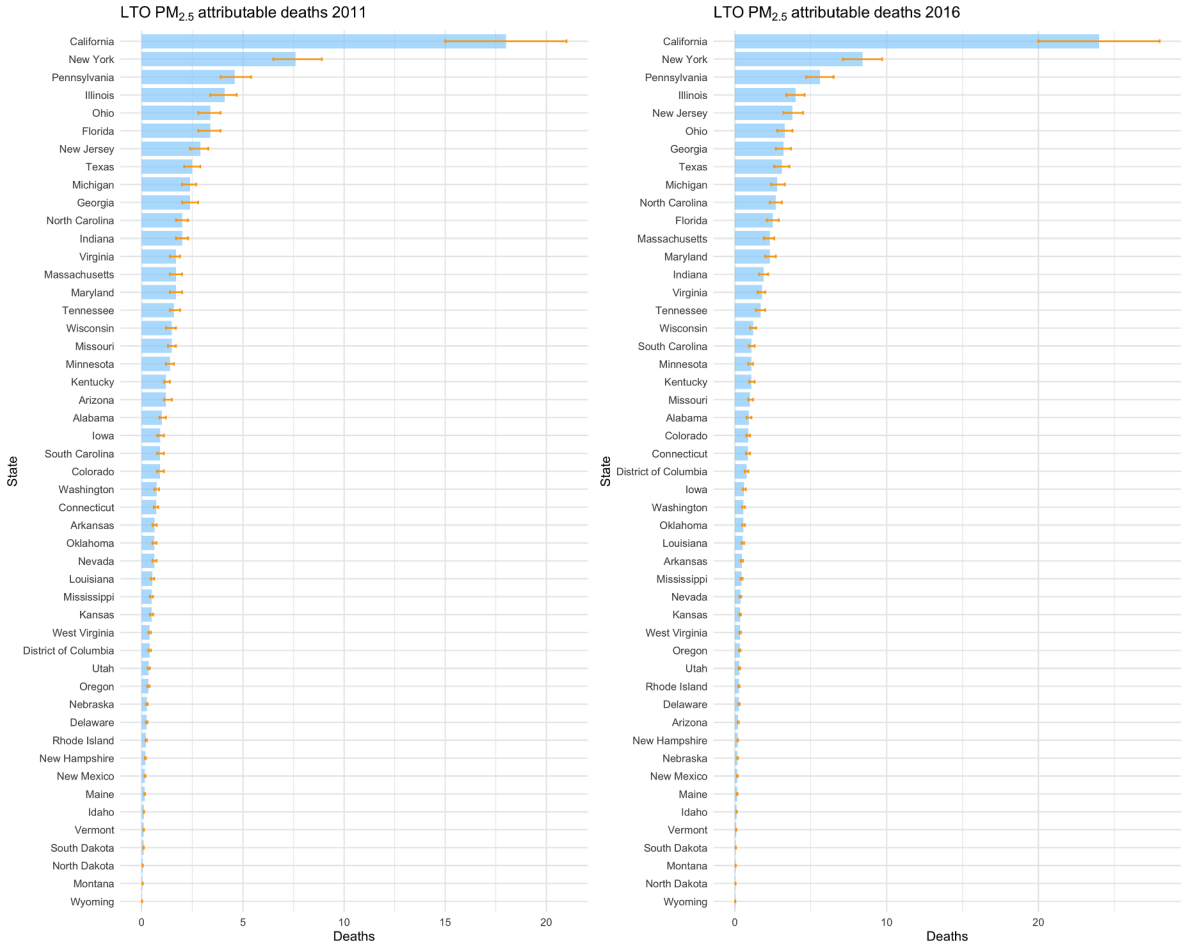


**Fig. 9.** $PM_{2.5}$-attributable mortalities in each state in 2011 (left) and 2016 (right), the orange bars reflect the 95% confidence intervals from the uncertainties in the CRFs.

S. depending on model choice and CRF. Barrett et al. 2012 (Barrett et al., 2012) estimated $PM_{2.5}$ exposure to be reduced by 6% globally by using ultra low sulfur fuel. We estimate a reduction in $PM_{2.5}$ population-weighted concentrations of 2.4% and 1 fewer $PM_{2.5}$ mortalities in the U.S. if a 5% blend of sustainable alternative jet fuel is implemented and an 18.4% reduction in $PM_{2.5}$ population-weighted concentrations and 16 fewer $PM_{2.5}$ mortalities if a 50% blend is implemented.

To account for uncertainty in the health outcome estimates, we have included results from the 95% confidence intervals in the CRFs. The confidence intervals for each mortality and morbidity outcome reflect

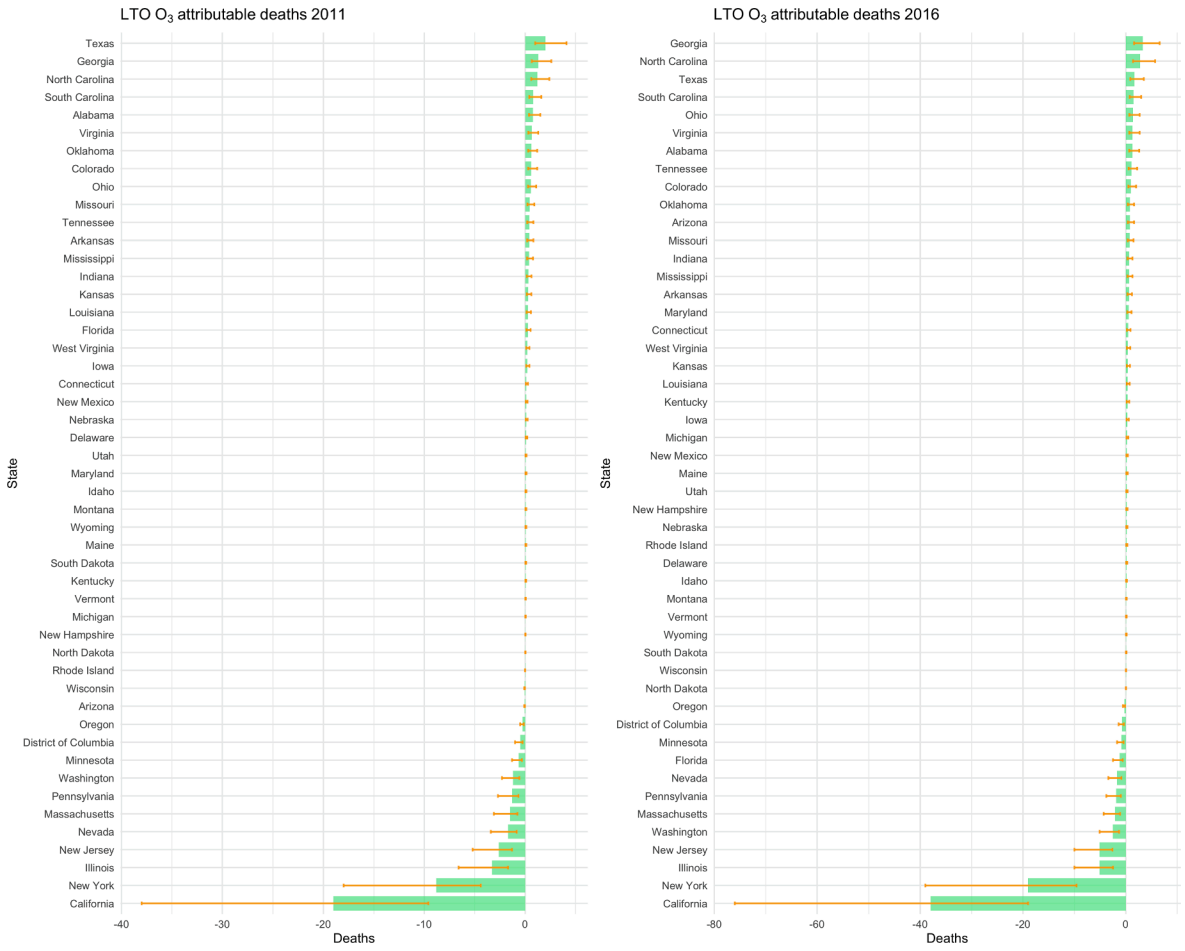


**Fig. 10.** $O_3$-attributable mortalities in each state in 2011 (left) and 2016 (right), the orange bars reflect the 95% confidence intervals from the uncertainties in the CRFs.

the variability in the results from the epidemiological studies used to construct the CRFs. We accounted for uncertainty in the damages per ton of fuel burn by including lower and upper bounds for the 2016 USD ($) income-adjusted value of $10.3 million as given in table S3. Additional uncertainties exist in each stage of the emission-to-health outcome modeling chain. Uncertainties in the emission inventories and the air quality model outputs are not accounted for in this study as the focus is a comparison of emission inventories. Additional work is needed to asses the uncertainty surrounding the emission inventories and air quality model outputs. Follow up studies should also look to distinguish the impacts from various types of sustainable alternative jet fuels. The impact factors used in this work are derived from multiple types and blends of sustainable alternative jet fuels. Next steps in this work should aim to quantify the impacts by fuel, engine, and aircraft type to get a better estimate of local air quality impacts from an airport's fleet makeup and choice of sustainable alternative jet fuel.

In this study we compare impacts of the LTO emission sector between two years, 2011 and 2016, that have varying background and LTO emission inventories, meteorological datasets, and population estimates. We did not perform sensitivity analyses that determine the impacts due to each of those varying datasets. Hence, when we make comparisons between the two years we are assuming that we are capturing the most accurate representations of each modeling year. Additional work can quantify the impacts due to each variable similar to the work done in Levy et al. 2012 (Levy et al., 2012b) which quantified LTO impacts by varying background emissions, LTO emissions, and populations in 2005 and projected 2025 values. However, that study also did not quantify impacts due to changing meteorology which can be significant especially for timeframes indicative of changing climates (Fann et al., 2021).

While we are the first to report large adverse health outcomes from LTO-attributable $NO_2$, other studies have started to include $NO_2$ in traffic-related pollution health burden studies (Atkinson and Butland, 2018; Mohegh et al., 2020; Hossain et al., 2021; Southerland et al., 2021). As $NO_2$ is a localized to the emission source, coarsely resolved modeling efforts may not capture the spatial variability of $NO_2$ (Anenberg et al., 2017) and its health impacts (Mohegh et al., 2020). While 12 km × 12 km resolution is not as fine as 4 km× 4 km or 1 km × 1 km, the results from this study are more finely resolved than results from prior aviation-related health impact modeling studies. That being said, 12 km × 12 km resolution may still be missing the fine resolution needed to capture $NO_2$ variability leading to an underestimation of impacts. And while other studies have quantified the impact of LTO emissions on $PM_{2.5}$ concentrations at varying grid cell resolutions (Arunachalam et al., 2011; Woody et al., 2016; Rissman et al., 2013) and found $PM_{2.5}$ population exposure to be mostly unaffected by grid cell resolution, $NO_2$ exposure is dependent on grid cell resolution. In addition, 12 km × 12 km resolution may still be too coarse to accurately describe the $NO_X$-saturated/VOC-limited conditions that govern $O_3$ response near airports. Future modeling studies should continue to move to finer spatial resolutions when estimating $NO_2$ and $O_3$ concentrations. In addition to finer spatial resolutions, incorporating plume level processes may improve LTO-attributable $NO_2$ and $O_3$ estimates. Two studies (Cameron et al., 2013; Fritz et al., 2020) have looked at the impacts of including plume level treatment for aircraft sources as compared to instant mixing within a photochemical model's grid cell. Both of these studies found an

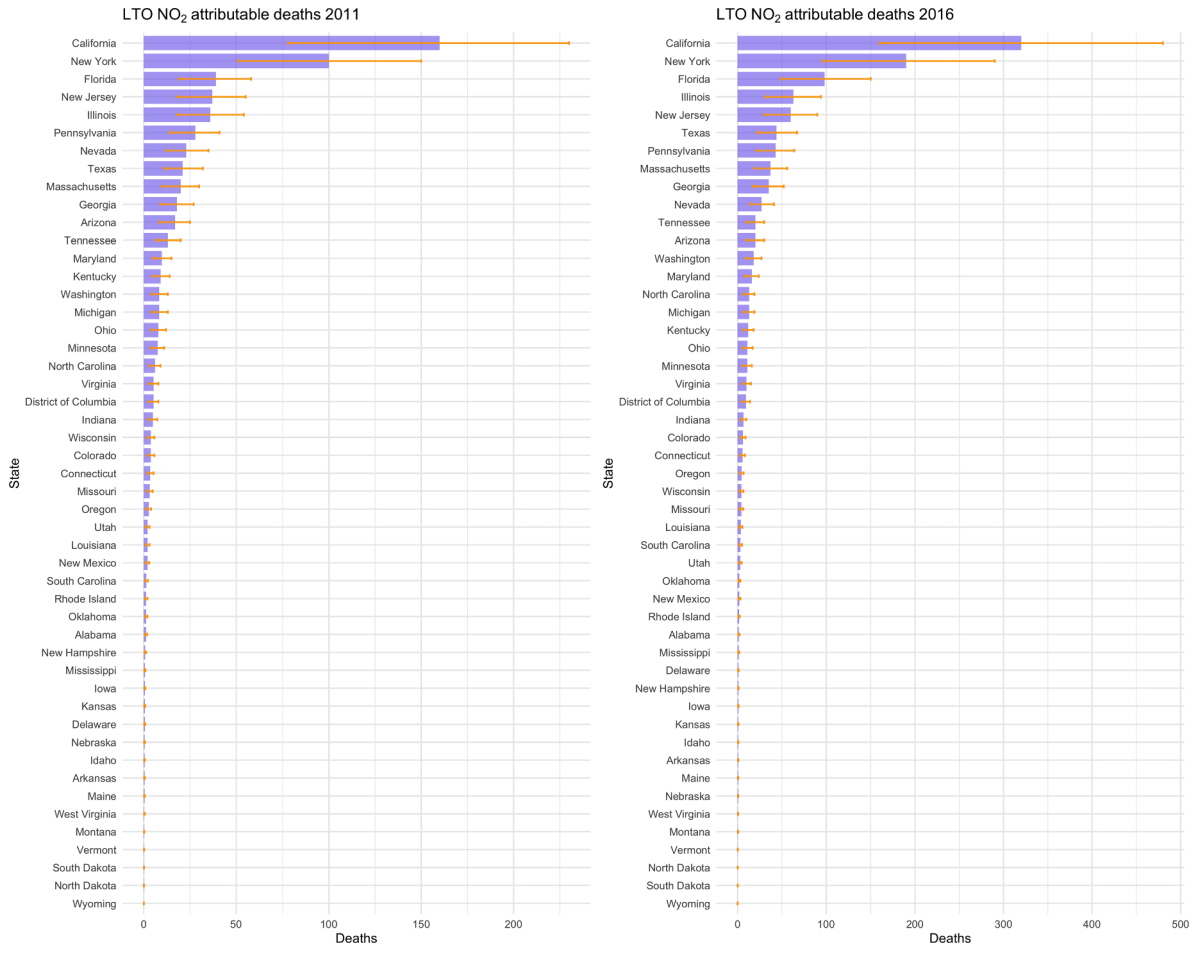


**Fig. 11.** $NO_2$-attributable mortalities in each state in 2011 (left) and 2016 (right), the orange bars reflect the 95% confidence intervals from the uncertainties in the CRFs.

overestimation of $O_3$ production without plume level treatment and an underestimation of the remaining $NO_X$. In addition these studies also quantified the conversion of $NO_X$ into reservoir species with and without plume treatment, with one study (Cameron et al., 2013) finding the plume treatment results in more $NO_X$ remaining in the plume than compared to the grid treatment, and the other study (Fritz et al., 2020) finding that plume treatment results in $NO_X$ to $HNO_3$ conversion being reduced by 16% and $NO_X$ to $N_2O_5$ by 37%. Hence, we can surmise that by not including plume level treatment, we are underestimating $NO_2$ impacts.

From this study we have two rather impactful findings: 1. LTO-attributable $NO_2$ is responsible for 91% of total LTO-attributable premature mortalities in the U.S. and 2. Implementing a 5% or 50% blend of sustainable alternative jet fuels leaves LTO-attributable $NO_2$ concentrations untouched as sustainable alternative jet fuels do not reduce $NO_X$ emissions. Table 10 in the ACRP report (Hamilton, 2019) shows the impact factors for $NO_X$ for each experimental study considered. Of the 34 distinct measurements made with varying engine type, conventional jet fuel, sustainable alternative jet fuel, and blend percentage cited in Table 10 of the ACRP report; only 5 measurements showed non-zero impact factors, and after the ACRP authors attempted to construct a fit of the data, the uncertainty was greater than the absolute value of the impact factor. Hence, the authors of the ACRP report concluded that there is no statistically significant impact associated with sustainable alternative jet fuels for $NO_X$. As LTO $NO_X$ emissions are almost entirely responsible for LTO-attributable $NO_2$, we find that sustainable alternative jet fuel implementation will do little to mitigate the $NO_2$ air quality-related health impacts from LTO emissions in the U.S. $NO_X$ emissions are primarily due to combustion in the air flow, and compared to nitrogen content in the fuel; atmospheric nitrogen is the dominant source of $NO_X$ (National Academies of Sciences, Engineering, and Medicine, 2018). Hence, to reduce LTO $NO_X$ emissions and the associated adverse air quality-related health outcomes, technologies aimed at combustion modifications such as Lean Premixed Prevaporized (LPP) combustion (Sattelmayer et al., 1998; Anacleto et al., 2003), Lean Direct Injection (LDI) combustion (Liu et al., 2017), and water/steam injection (Block Novelo et al., 2019; Golzari et al., 2021) need to be explored.

As recent studies surrounding aviation-related environmental impacts have shifted toward the impacts from full flight emissions at global scales, the results from this study hope to highlight the importance of a continued effort in reducing the air quality-related impacts from LTO emissions on vulnerable populations near airports. By including LTO-attributable $NO_2$ health burden estimates, we introduce an additional factor to consider when assessing the public health impact of the aviation sector. This study also shows the benefits of implementing sustainable alternative jet fuel blends at a national scale which can help to inform aviation sustainability efforts while also protecting public health.

## CRediT authorship contribution statement

**Calvin A. Arter:** Methodology, Investigation, Data curation, Software, Formal analysis, Writing – original draft. **Jonathan J. Buonocore:** Software, Data curation, Writing – review & editing. **Chowdhury Moniruzzaman:** Software, Investigation, Data curation. **Dongmei Yang:** Software, Investigation, Data curation. **Jiaoyan Huang:** Conceptualization, Methodology. **Saravanan Arunachalam:**

Conceptualization, Methodology, Validation, Supervision, Project administration, Resources, Funding acquisition, Writing – review & editing.

## Declaration of Competing Interest

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

## Acknowledgments

This research was funded by the U.S. Federal Aviation Administration Office of Environment and Energy through ASCENT, the FAA Center of Excellence for Alternative Jet Fuels and the Environment, project 19 through FAA Award Number 13-C-AJFE-UNC under the supervision of Jeetendra Upadhyay. The aircraft emissions inventories used for this work were provided by the U.S. Department of Transportation's Volpe Center. We also thank the U.S. EPA for providing access to the 2016 modeling platform with various inputs including the meteorology, background emissions and boundary conditions from the Hemispheric scale simulations. Any opinions, findings, conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the FAA or Volpe.

## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.envint.2021.106958.

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# Technical Report Documentation Page

| 1. Report No. | 2. Government Accession No. | 3. Recipient's Catalog No. |
|---|---|---|
| j.envint.2021.106958 | | |

| 4. Title and Subtitle | 5. Report Date |
|---|---|
| Air quality and health-related impacts of traditional and alternate jet fuels from airport aircraft operations in the U.S. | October 2021 |
| | 6. Performing Organization Code |

| 7. Author(s) | 8. Performing Organization Report No. |
|---|---|
| Calvin A. Arter, Jonathan J. Buonocore, Chowdhury Moniruzzaman, Dongmei Yang, Jiaoyan Huang, Saravanan Arunachalam | |

| 9. Performing Organization Name and Address | 10. Work Unit No. (TRAIS) |
|---|---|
| Center of Excellence for: Alternative Jet Fuels and Environment<br><br>The University of North Carolina at Chapel Hill, Chapel Hill, NC 27599, USA | 11. Contract or Grant No.<br><br>13-C-AJFF-UNC-010, 012 |

| 12. Sponsoring Agency Name and Address | 13. Type of Report and Period Covered |
|---|---|
| Federal Aviation Administration<br>Office of Environment and Energy | Journal Article |
| | 14. Sponsoring Agency Code |

15. Supplementary Notes

16. Abstract

Aviation emissions from landing and takeoff operations (LTO) can degrade local and regional air quality leading to adverse health outcomes in populations near airports and downwind. In this study we aim to quantify the air quality and health-related impacts from commercial LTO emissions in the continental U.S. for two recent years' inventories, 2011 and 2016. We quantify the LTO-attributable PM2.5, O3, and NO2 concentrations and health outcomes for mortality and multiple morbidity health endpoints. We also quantify the impacts from two scenarios representing a nation-wide implementation of 5% or 50% blends of sustainable alternative jet fuels. We estimate 80 (68–93) and 88 (75–100) PM2.5-attributable and 610 (310–920) and 1,100 (570–1,700) NO2-attributable premature mortalities in 2011 and 2016, respectively. We estimate a net decrease of 28 (14–56) and 54 (27–110) in O3-attributable premature mortalities across the U.S. in 2011 and 2016, respectively due to the large O3 titration effects near the airports. We also find that the asthma exacerbations due to NO2 exposures from LTO emissions increase from 100,000 (2,500–200,000) in 2011 to 170,000 (4,400–340,000) in 2016. Implementing a 5% or 50% blend of sustainable alternative jet fuel in 2016 results in a 1% or 18% reduction, respectively in PM2.5-attributable premature mortalities. Monetizing the value of avoided total premature mortalities, we find that a 50%-blended sustainable alternative jet fuel results in a 19% decrease in PM2.5 damages per ton of fuel burned and a 2% decrease in total damages per ton of fuel burned as compared to damages from traditional jet fuel. We also quantify health impacts by state and find California to be the most impacted by LTO emissions. We find that LTO-attributable PM2.5 and NO2 premature mortalities increase by 10% and 80%, respectively from 2011 to 2016 and that NO2-attributable premature mortalities are responsible for 91% of total LTO-attributable premature mortalities in both 2011 and 2016. And since we find LTO-attributable NO2 to be unaffected by the implementation of sustainable alternative jet fuels, additional approaches focused on NOX reductions in the combustor are needed to mitigate the air quality-related health impacts from LTO emissions

| 17. Key Words | 18. Distribution Statement |
|---|---|
| Aircraft emissions, PM2.5, NO2, O3, Air quality, CMAQ, Alternative jet fuel, Health impacts, ASCENT |  |

| 19. Security Classif. (of this report) | 20. Security Classif. (of this page) | 21. No. of Pages | 22. Price |
|---|---|---|---|
| Unclassified | Unclassified | | |