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Aviation fuel and emissions in air markets with interregional passenger leakage

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Abstract

Attractive air services at large airports in the U.S., over the last two decades, have encouraged interregional air passenger leakage, a phenomenon in which air travelers abandon their nearby small airports in favor of starting their air journeys from large hub airports farther away. The disparities between small and large airports, in terms of air services, are expected to widen because of COVID-19 and further exacerbate passenger leakage. This study estimates the differences in mean aviation fuel consumed and pollutants emitted between air routes from small and large airports in the U.S. Midwest region – routes that are known to be contested according to results from an air ticket dataset. Findings indicate that air journeys originating from large airports result in 24% less aviation fuel consumption and considerably lower emissions at the passenger-kilometer level, offering additional insight toward better understanding the environmental impact of a geographically shifting air travel demand.

Keywords: Interregional passenger leakage, small airports, large (hub) airports, aviation fuel, emissions.

1. Introduction

This study estimates the differences in the quantity of aviation fuel consumed and pollutants emitted per passenger-kilometer (pkm), between air routes originating from small and large airports in the U.S. Midwest region to a number of domestic destination airports. Based on an analysis of a large air ticket dataset, air travelers fly to these destinations by foregoing use of their nearby small (local) airports and driving to distant large hub airports in neighboring regions, sometimes hundreds of miles away. We aim to quantify the aviation fuel and emissions differences of these trips from small versus large airports – specifically, how significant they might be by also recognizing the fuel consumption and emissions associated with the longer ground trips made to access distant large hub airports.

Consolidated air services allow large hub airports to reap the benefits of economies of density, in which the cost of operating more traffic on the same network decreases, both at the airline (Gillen, Oum, & Tretheway, 1990) and route (Brueckner & Spiller, 1994) levels. As such, higher density leads to more enplanement, which in turn results in better air services (more frequency, lower fares, more direct routes, larger aircraft), in a positive demand-and-supply feedback pattern (Zou & Hansen, 2012; Hansen, 1995). Higher load factors (LFs) on larger aircraft are expected to result in consumption of less aviation fuel and emission of lower amounts of pollutants on a pkm basis, compared to regional (or other smaller) aircraft.

Higher enplanements at large airports offering consolidated air services are achieved by attracting air travelers from farther away through cheaper fares, and more frequent as well as direct flights (Gao, 2020; Lieshout, Malighetti, Redondi, & Burghouwt, 2016; Fu & Kim, 2016; Phillips, Weatherford, Mason, & Kunce, 2005; Suzuki, Crum, & Audino, 2003). The resulting passenger leakage has detrimental effects on the economy of regions served by small airports (Naczek, 2019) as it takes away employment and tourism opportunities. It may also contribute significant vehicle volumes and emissions to already busy interstate highways, given that these leaking passengers often drive considerable distances to access out-of-region large airports (Ryerson & Kim, 2018). The environmental implications of interregional passenger leakage (both the ground access and air travel portions) have not been explicitly examined so far. Thus, this study takes a first step by estimating the differences in aviation fuel consumed and pollutants emitted between domestic routes at small airports experiencing leakage and large airports in the U.S. Midwest, and by recognizing the carbon emissions resulting from the excess ground access trips. The estimated emissions will also help airlines establish appropriate customer emissions charges as they commit to support the development of carbon capture technology and sustainable aviation fuel (SAF) (ICAO, 2021) in support of the 2050 net zero carbon goal (United Nations Framework Convention on Climate Change, 2016).

Given the limited resilience of small airports to external shocks (Atallah & Hotle, 2019), the current COVID-19 global pandemic is expected to result in partial loss of services at some small U.S. airports in the near future (Hotle & Mumbower, 2021), leading to more air passengers making longer drives to reach large airports. The emergence of plug-in hybrid and battery electric (R.Gopal, Park, Witt, & Phadke, 2018) as well as connected-and-autonomous vehicles (CAVs) (Perrine, Kockelman, & Huang, 2020) that lower the environmental and operational cost of driving may also play a role in promoting long distance travel including interregional passenger leakage. Thus, this study provides timely environmental insight into the issue of passenger leakage, interregionally and within megaregions, and the evolution of the aviation hub system.

2. Literature Review

Greenhouse gases (GHGs) such as carbon dioxide (CO_2) and water vapor (H_2O), and other pollutants like nitrogen oxides (NO_X), sulphur oxides (SO_X), carbon monoxide (CO), hydrocarbons (HC), and particulate matters including PM_{25} which are emitted by aircraft operation are recognized and have been studied both at the airport and flight route levels. What remain unknown are the potential shifts in aviation fuel consumption and emission of the aforementioned pollutants (both in terms of volume and geography) caused by interregional passenger leakage whereby air travelers choose distant large hub airports over their nearby small airports for reasons of accessing better air services.

2.1 Aviation Fuel and Emissions

The potential effects of airline hub concentration (due to the limitedness of services at surrounding smaller airports) are observed in megaregions and across national borders. One of the main outcomes that researchers have studied for decades in North America is the behavior of air travelers driving long distances to reach these hub airports. This shifting demand in turn causes further network reorganization and other service changes (i.e. upgauging/downgauging of aircraft and flight frequency adjustments), which then result in shifting aviation fuel consumption and emissions. Several studies have estimated the mass of aviation fuel burned and carbon (as well as other pollutants) emitted for different routes (Jemiolo, 2015; Howe, Kolios, & Brennan, 2013; Spielmann, Bauer, Dones, & Tuchschmid, 2007; Peeters, Szimba, & Duijnisveld, 2007; Delft, C.E., 2005; Gössling, et al., 2005). Nonetheless, there are no comparisons that actually estimate the differences in aviation fuel consumption and emissions among neighboring airports (particularly those that compete) in serving the same destinations. The potential savings in aviation fuel that could be achieved by hub reorganization, however, have been estimated at the airline level (Ryerson & Kim, 2014) only.

Airlines are aware of their carbon footprints and are increasingly involved in upgrading their fleet, engaging passengers (customers) in carbon offset charges and supporting research into: carbon capture; SAF; and efficient aircraft technology. Although SAF accounts for just under 1% of jet fuel globally (Dichter et al. 2020), it has recently received promising boosts - for instance, Delta committed over 1B USD to be invested over 10 years toward supporting SAF and carbon removal research while FedEx pledged 2B USD to be disbursed over 20 years toward the same. JetBlue (in collaboration with Boeing) partnered with SkyNRG, America's SAF production project with the goal of converting 10% of total jet fuel to SAF by 2030. United placed 100 orders for the hydrogen powered Heart Aerospace ES-19 while also placing a total of 270 orders for the new-generation fuel efficient Airbus Neo A321 and Boeing 737 Max variants in June 2020 (ICAO 2021). Air Canada also committed to net zero in March 2021 by announcing a 50M USD initial investment in SAF and carbon capture technology, and plans to deploy more new-generation aircraft on its network (MacGregor 2021). Singapore airlines has launched a voluntary customer emissions charge where passengers can offset their carbon footprints by supporting various accredited carbon removal projects and SAF research (ICAO 2021). Overall, SAF implementation depends on how quickly and successfully it becomes available to the wider aviation industry.

Aviation emissions have been measured through remote sensing and Fourier transform infrared spectroscopy (Schäfer, Jahn, Sturm, Lechner, & Bacher, 2003; Schäfer, 2001), chromatography analysis of carbon species emissions (Anderson, Chen, & Blake, 2006), open path devices for real time emission indices (Schürmann, et al., 2007) and sample collection from engines through a probe fixed on exhaust nozzles (Agrawal, Sawant, Jansen, Miller, & Cocker III, 2008). Other analytical methods of estimating aviation fuel and emissions have been documented by the European Monitoring and Evaluation Programme (EMEP) / European Environment Agency (EEA) Air Pollutant Emission Inventory Guidebook (European Environment Agency, 2013) and International Civil Aviation Organization (ICAO) Engine Exhaust Emission Databank (ICAO, 2009). These documents provide procedures to estimate fuel and emissions from the landing-takeoff (LTO) and climb-cruise-descent (CCD) phases of flying, with estimates from these phases aggregated to determine total quantities (Kurniawan & Khardi, 2011). LTO includes aircraft operations (taxi out, take off, climb to 914 m above runway, final approach, land and taxi in) that take place below 914 m altitude, while all activities above this altitude are classified under CCD (ICAO, 1993). In our study, we apply an existing generalized fuel/emissions model that was developed by Cox et al. (2018) based on EMEP/EEA's database, and implemented in the life cycle assessment of the Swiss commercial aircraft fleet.

2.2 Interregional Passenger Leakage

Interregional passenger leakage is defined as the phenomenon in which an air traveler from one airport's (often a small airport) catchment chooses an airport farther away (often a large airport) in a different region (Suzuki, Crum, & Audino, 2003). Based on various airport catchment definitions, the underlying drivers of passenger leakage have been investigated over decades of research (Gao, 2020; Ryerson & Kim, 2018; Fu & Kim, 2016; de Luca, 2012; Phillips, Weatherford, Mason, & Kunce, 2005; Suzuki, Crum, & Audino, 2003; Innes & Doucet, 1990). Research results show, time and again, that air service characteristics such as airfare, flight frequency, availability of direct services, and frequent flyer programs influence travelers to leak, in addition to airport access and parking costs. The disparities in such service variables between large and small airports have significantly increased in the U.S. following airline mergers in the

2000s (Brueckner, Lee, & Singer, 2013), with the 2015 merger between U.S. Airways and American Airlines being the most significant one.

Small airports – already prone to experiencing loss of air passengers to larger airports – are also less resilient to shocks (Atallah & Hotle, 2019). In response to the COVID-19 global pandemic (which has caused unprecedented depression in the air travel industry (ICAO, 2020)), the U.S. government provided small airports some protection through the Coronavirus Aid, Relief, and Economic Security (CARES) Act, requiring certain airlines to maintain service to small cities served pre-pandemic (U.S. Congress, 2020). However, some of these small airports are expected to lose partial services once the CARES Act regulations end (Hotle & Mumbower, 2021). Under those circumstances, air travelers will look for alternate departure airports, which are likely to be the larger hub airports. Airlines' network models are fundamental to the air services offered, which in turn impact passenger leakage. Wong et al. (2019) documented weakening of major hubs at the global level, due to low cost carriers (LCCs) using point-to-point services to bypass these major hubs and thus further penetrate the existing passenger markets of legacy carriers (Vowles and Lück 2013). However, concentration of passenger traffic continues to be the case in the U.S. (Wong et al. 2019). Emissions charges, which have an impact on the network model of airlines, also affect passenger leakage. Higher emissions charges sometimes result in preference for the hub-and-spoke model (Brueckner & Zhang 2010), which could mean further strengthening of hubbing. Further hub strengthening (and thus, improved services at hubs) will attract more passengers from afar (Yirgu, Kim, & Ryerson 2021). Additionally, the hub-and-spoke model has been re-emerging as a result of some measures taken by airlines during COVID-19 (Curran, 2020). These developments, in turn, may encourage further passenger leakage in markets throughout the US. This study contributes to the literature on passenger leakage by focusing on the air side fuel use and emissions.

3. Study Design

3.1 Study Airports

Our study focuses on domestic routes between 2013 and 2018 originating from small and neighboring large airports in parts of Minnesota, Wisconsin, Illinois, Iowa, Indiana and Michigan centered around Chicago, as shown in Fig. 1. Airport categorization in the figure follows the Federal Aviation Administration's (FAA's) classification system[1]. However, for the purpose of this study, we refer to all airports that are not large or medium hubs as small airports.

This region is chosen for different reasons. First, it centers around the two large hub airports of Chicago – O'Hare International (ORD) and Chicago Midway International (MDW) - that attract air travelers throughout the region because of superior air services including direct and frequent flights as well as attractive airfares (Yirgu, Kim, & Ryerson, 2021; Gao, 2020). Second, there are a considerable number of small airports in the study region that offer few daily flights, connecting mainly to the large hub airports of ORD, MDW, Detroit Metropolitan Wayne County (DTW), Minneapolis–St Paul International (MSP) and Atlanta (ATL). This limited service is expected to drive air travelers toward the region's large hubs due to previously documented evidence of leakage; for example, residents of Madison served by the small airport of Dane County Regional Airport (MSN) drive over 200 km to ORD, while passengers originating from Milwaukee similarly abandon Milwaukee Mitchell International Airport (MKE) in favor of ORD over 120 km away (Naczek, 2019).

Although MSP appears to be quite distant from the smaller airports in Fig. 1 (320 km or greater), Suzuki, Crum, & Audino (2003) discovered that travelers in the expected service area of

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[1] https://www.faa.gov/airports/planning_capacity/categories/

DSM in Iowa leaked to MSP by driving in excess of 3.5 hour. In our analysis of the Market Locator data, we observe leakage from the expected service areas of CWA and DBQ toward MSP as well.

3.2 Study Approach

The approach is based on an individual passenger level analysis. We consider a passenger (whose true point of origin is home) who has the option of choosing either a small/medium local airport or a distant large hub in order to fly to some final destination as shown in Fig. 2. We aim to compare the difference in emissions from these two options. By choosing the local airport, the passenger will contribute to some emissions based on the details (connections, aircraft size, LF, and flight distance) of Flight 1. On the other hand, by choosing a distant large hub, the passenger will travel (y-x) km excess distance from home, and thus will contribute to emissions both from excess driving as well as flying, with the flying portion based on the details of Flight 2. In Fig. 3, we provide a methodological process diagram.

For the air travel portion, we adopt a model structure from a previous study (Cox, Jemiolo, & Mutel, 2018) whose parameters we estimate based on: the aviation fuel/emissions reported in the EMEP/EEA database for representative aircraft; and details such as operating empty weight (OEW) and seating capacity of these representative aircraft. Routes for which interregional leakage is taking place from small to large airports are then identified from the Market Locator data which is the primary ticket purchases data used in this study. Inputs such as aircraft operating weight (AOW) and flight distance which are required in order to apply the model on the study routes (per route segment) are directly taken or computed from publicly available aviation datasets such as the DB1B and T-100. Aviation fuel and emissions are then estimated for these routes, beginning at both nearby small/medium airports and their surrounding large airports. The resulting differences, in combination with estimates for the excess ground travel portion, are finally presented and discussed.

4. Data Description and Processing

4.1 Data Sources

Passenger ticket data is acquired from the Airlines Reporting Corporation (ARC), a consortium of major North American air carriers that report ticket transactions processed through travel agencies (online and otherwise). Called Market Locator data, it contains the following information on millions of sampled air travel ticket purchases: origin airport; destination airport; route flown; number of travelers; month and year of flight; and billing ZIP code of credit card used for ticket purchase. Given that travel agencies are preferred by leisure travelers much more than business travelers, we assume the ZIP codes of the credit cards used to purchase tickets represent the residential/home addresses of travelers rather than companies.

To establish proximity based service areas (discussed in Section 4.2), we also extract coordinates of ZIP codes' centroids and airports, and road shapefiles from various sources. Table 1 provides a summary of all data sources and information extracted.

The chosen fuel/emissions model (Cox, Jemiolo, & Mutel, 2018), further discussed in Section 5.1 is based on 78 representative aircraft reported in the EMEP/EEA Emission Inventory database[2]. Because the chosen model's parameters are functions of AOW and flight distance, the

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[2] The database reports the weights of aviation fuel consumed and pollutants emitted by 78 representative aircraft in flying various distances ranging from 125 nautical miles (nm) (231.5 km) up to 8,180 nm (15,149.36 km). Information reported includes aircraft model, flight distance, and weights of the following for both the LTO and CCD phases: aviation fuel, CO_2, CO, H_2O, NO_X, SO_X, HC, and PM_{25}, among others. The database assumes a LF of 0.6, combined with an average passenger weight of 95 kg. Additionally, aircraft engine performance is based on 2004 technology, and engine thrust settings as well as duration of all LTO activities follow ICAO standard taxi time. Reported values for CCD phases are based on 4D flight trajectories (the three spatial dimensions defining trajectories integrated with time) extracted from the Central Flow Management Unit (CFMU). Furthermore, the database's CCD phase fuel burn values use the altitude and attitude dependent parameters from Eurocontrol's Base of Aircraft Data (BADA).

former of which is not available in the Inventory database, we first extract OEW and seating capacity of all 78 aircraft from various sources (Appendix A. Supplementary Data Sources) and compute useful payload (based on the specified LF and weight per passenger). This payload is then added with OEW to determine AOW. Lastly, we estimate fuel consumption and CO_2 emissions from the ground travel portion of leakage based on values reported by the 2019 Fuel Consumption Guide (Natural Resources Canada, 2019) for over one thousand vehicle models. These estimates are normalized by the average vehicle occupancy taken from the 2017 National Household Travel Survey (NHTS) Weighted Vehicle Occupancy Factors (Federal Highway Administration, 2017) to determine results on a per pkm basis.

4.2 Travel Itineraries

The Market Locator dataset was downloaded in May 2019 using “origin airport” as a key filtering criteria for the years 2013–2018. We first remove itineraries with zero passenger and/or itineraries where the departure airport did not match with the first airport in the ‘route’ field in which case the airport chosen for departure could not be conclusively identified. We then exclude travelers residing in states other than Minnesota, Wisconsin, Iowa, Illinois, Indiana and Michigan, and determine that a total of 4.6 million records comprising over 6 million passengers with 4,600 different ZIP codes remain. It is noted that the dataset does not contain LCCs such as Southwest (which has a dominant presence at MDW), Allegiant, Spirit and Sun Country Airlines (although JetBlue is included), and thus is not an unbiased representation of air ticket purchases. However, the aim of using the itinerary data is to identify routes on which leakage is observed so that the model inputs required to estimate aviation fuel and emissions can be extracted from other aviation data sources which include all carriers that operate domestically.

We establish a proximity based service area for each study airport as follows. First, for all ZIP codes which had passengers reported in the Market Locator data, we compute access distance from the centroid of each ZIP code to each study airport using a road network built in ArcMap, ArcGIS. Second, we cluster ZIP codes closest (based on the access distance computed) to a given airport into a single service area belonging to that particular airport as shown in Fig. 4. Previous studies defined service areas (more commonly known as "airport catchment") using: a multi-airport systems approach based on temporal distance (Sun et al. 2017); various airport access times such as 1 hour (Suzuki, Crum, & Audino 2003), 2 hour (Marcucci & Gatta 2011) and 2.5 hour (Zhou et al. 2018); and circles of various radii such as 25/50/100 km (Suau-Sanchez, Burghouwt, & Pallares-Barbera 2014) and 120 km (Fuellhart 2007). We choose to use airport access distance over travel time to define services areas, because the latter can vary quite significantly depending on the time of travel, and geographic location. With the service areas defined based on proximity, we analyze the airport choice distribution of all sampled travelers in each service area during the six-year study period, and determine that the 14 small airports and one medium airport (MKE) shown in Table 2 lost at least 25% of the air travelers in their respective service areas due to leakage, mainly to large hub airports. The remaining small airport of DSM lost only 10% of its local market, while medium airports Indianapolis International (IND) and St Louis Lambert International (STL) lost less than 5% travelers in their respective service areas. Note that service areas shown in Fig. 4 are only for those airports that experienced passenger losses of at least 25%.

Table 2 shows basic descriptive statistics of travelers from the service areas of the 15 airports that exhibited leakage (14 small and one medium, i.e. MKE).

As Table 2 indicates, hundreds of final domestic destination airports are recorded for a total of 2.32 million travelers originating from over 1,800 ZIP codes for the 15 airports (out of the total

6 million sampled travelers throughout the study region). For each destination airport, there are records showing that both nearby small/medium and neighboring large airports were used by travelers. Thus, all routes are contested and considered in our study. In Fig. 5, we present the airport choices of all travelers from Table 2 over the six-year study period.

From Fig. 5, it is observed that ORD drew air travelers from 14 of the 15 small/medium airport service areas. It attracted as much as: 42% of travelers from SBN's service area; over 20% of travelers from service areas CMI, MSN, BMI, MLI and DBQ; and 7-19% at the remaining eight service areas. On the other hand, MSP and DTW were generally less attractive to travelers in our region, likely due to location. MSP attracted 43% and 26% of travelers from the service areas of CWA and DBQ, respectively, which are the closest, while drawing only 2% from the more distant MKE. DTW drew a substantial number of air travelers from AZO's and GRR's service areas (at just over 30% for both), but only 6% from the more distant FWA. Due to the absence of itineraries on Southwest Airlines (which has a dominating presence at MDW), passenger leakage toward MDW is not captured in our dataset. The medium airport of IND attracted a significant proportion of travelers from FWA and CMI at 38% and 26% respectively, while MKE drew 32% and 19% of travelers from service areas GRB and MSN. STL attracted 43% from SPI's service area. The passenger leakage to medium airports could support the observations made by Wong et al. (2019) in which secondary airports' (corresponding to medium airports) air traffic growth is outpacing that of major hubs'. Secondary airports, which attract passengers through point-to-point services operated by LCCs (Vowles and Lück 2013), are also known for drawing passengers from the service areas of major hubs in some cases (Kimley-Horn & Associates 2015). Asides from an overall growth in air travel demand, the growth at medium hubs could be attributed to them attracting more passengers from further afield. However, further investigations are required to verify this. Overall, the data confirms that air passenger leakage mainly took place from small and medium airports toward the large hubs of ORD, MSP and DTW, although there is ample evidence of leakage from small to medium airports as well.

4.3 Aviation Fuel/Emissions Model Inputs

In this section, we provide a short description of input data required to apply the chosen aviation fuel/emissions model to the routes recorded in the Market Locator dataset – flight distance and AOW of all flight operations involved in all segments of a route (whether direct or connecting). We focus on domestic routes for two reasons. First such trips (including inter-city air trips) are believed to be the leading causes of emissions regionally (Wang, O'Sullivan, & Schäfer, 2019; Aamaas, Borken-Kleefeld, & Peters, 2013), offsetting reduced emissions from shorter (but far more prevalent) daily trips (Ottelin, Heinonen, & Junnila, 2014). Second, supplementing these domestic itineraries with publicly available aviation data can be done in a more complete manner compared with international itineraries. Flight distance for all routes (which is listed as "Market Miles Flown" and "Non Stop Miles" in the DB1B dataset) is taken from the DB1B dataset. However, AOW is not directly available and in order to calculate it, we first filter the T-100 dataset based on route segments, and compute mean LF as well as mean weight per passenger on a quarterly basis. Mean LF is computed as the ratio of mean number of seats occupied to mean number of seats available, while mean weight per passenger is determined by dividing mean available payload (directly taken from T-100) by mean number of seats occupied. The average mean weight per passenger at the four large airports of ORD, MDW, MSP and DTW over the entire six-year study period (24 quarters) was 116 kg/passenger, which is six kg more than 110 kg/passenger that was suggested for the Swiss commercial air market (Cox, Jemiolo, & Mutel, 2018). Mean LFs remained around 0.8 and 0.77 for large and small airports, respectively, while mean non-stop distances were 1,533 km and 1,438 km. And itineraries originating from small airports had a mean number of leg of two compared with 1.4 for those originating from large ones. Furthermore, large airports offered services on larger aircraft compared with small ones in terms of mean number of available seats (110 vs 102).

We then estimate OEW from number of seats available (Cox, Jemiolo, & Mutel, 2018) since such an approach allows a continuous computation of mean OEW even when a route is served by more than one kind of aircraft (which is common as different airlines use different aircraft models). Based on the 78 representative aircraft in the EMEP/EEA database, we formulate **Eq. (1)**.

$$OEW_y = 222.28 * (s_y)^{1.035} \tag{1}$$

Where

$OEW_y =$ operating empty weight (kg) of aircraft y, and

$s_y =$ seat available (based on single class configuration) on aircraft y.

The multiplicative and power parameters in Eq. (1) have standard errors of 3.89 and 0.0044 respectively, and are significant at the 99% confidence level. The equation has a goodness of fit (R^2) of 0.97. Mean AOW for any segment in any of our study routes for a known quarter is finally determined as the sum of mean OEW and mean useful payload on that route according to Eq. (2).

$$\overline{AOW}^{qi}_{o-d} = (\overline{OEW}^{qi}_{o-d} + (\overline{LF}^{qi}_{o-d} * \bar{s}^{qi}_{o-d} * \overline{w}^{qi}_{o-d}))/1000 \tag{2}$$

Where

$\overline{AOW}^{qi}_{o-d} =$ mean aircraft operating weight (ton) on flight segment i (between o and d) during quarter q,

$\overline{OEW}_{o-d}^{qi}$ = mean operating empty weight (kg) of aircraft on flight segment i (between o and d) during quarter q,

$\overline{LF}_{o-d}^{qi}$ = mean load factor on flight segment i (between o and d) during quarter q,

$\bar{s}_{o-d}^{qi}$ = mean number of available seats on flight segment i (between o and d) during quarter q, and

$\overline{w}_{o-d}^{qi}$ = mean weight per passenger (kg) on flight segment i (between o and d) during quarter q.

5. Fuel and Emissions Modeling

5.1 Aviation Fuel and Emissions Model

5.1.1 Model Setup

We apply a generalized aviation fuel/emissions model from a previous study (Cox, Jemiolo, & Mutel, 2018). The model is based on 78 representative aircraft whose fuel consumption and pollutant emissions are reported for flight distances ranging from 125-8,180 nm in the EMEP/EEA database (European Environment Agency, 2013). As described in Footnote 2, the values reported assume the following: 0.6 LF at 95 kg/passenger; standard ICAO taxi time and engine thrust settings during LTO; CCD emissions based on BADA's altitude and attitude dependent parameters; cruise altitudes that follow CFMU's typical 4D trajectories; and aircraft engine performance based on 2004 technology. We adopted this generalized fuel model because it allows a macroscopic level analysis in cases such as our study where aircraft taxi duration, engine thrust settings, altitude/attitude dependent parameters and other operational details are not available. In assessing the lifecycle of the Swiss commercial aircraft fleet, Cox, Jemiolo, & Mutel (2018) first used the values reported by the EMEP/EEA database to estimate a set of modified Breguet range equations (basic aerodynamic equations that predict how far an aircraft can fly given a set of constraining parameters) that model aviation fuel consumed and pollutants emitted as functions of AOW and flight distance. The models can be used to estimate fuel/emissions of an aircraft with any specified payload operating a known flight distance. Cox, Jemiolo, & Mutel (2018) then applied their model to the Swiss commercial aircraft fleet, and estimated national aviation fuel consumption to within 7% accuracy for a 25-year period. In this paper, we re-estimate the model parameters in order to retain certain aircraft models that are still used in the U.S. which Cox, Jemiolo, & Mutel (2018) removed in their study.

Eqs. (3) – (6), taken from Cox, Jemiolo, & Mutel (2018), show that aviation fuel consumption and emissions during the LTO phase depend only on AOW, while they depend on both flight distance and AOW in the CCD phase. Indeed, flight distance is irrelevant during LTO as aircraft will always have to taxi out, take off, climb up to 914 m above runway, approach, land and taxi in irrespective of destination's distance. The energy required to climb to cruise altitude also heavily depends on the AOW, while the cruise stage depends mainly on flight distance.

$$LTO_x = \alpha_x * AOW^{\beta_x} \tag{3}$$

$$CCD_x = \gamma_x * d + \delta_x \tag{4}$$

$$\gamma_x = \varepsilon_x * AOW^{\zeta_x} + \eta_x \tag{5}$$

$$\delta_x = \theta_x * AOW^{\iota_x} \tag{6}$$

Where

$x \in$ {aviation fuel, CO_2, H_2O, NO_X, SO_X, HC, CO, PM_{25}},

$LTO_x =$ aviation fuel burned/pollutant emitted per LTO cycle (kg),

$CCD_x =$ aviation fuel burned/pollutant emitted during CCD (kg),

$d =$ flight distance (km),

$\alpha_x, \beta_x, \gamma_x, \delta_x, \varepsilon_x, \zeta_x, \eta_x, \theta_x, \iota_x =$ estimated parameters, and

$AOW =$ aircraft operating weight (ton).

For the LTO phase of Eq. (3), we directly estimate model parameters by using values of fuel and emissions reported as well as AOW computed for all 78 representative aircraft. However, for the CCD phase (Eqs. (4) – (6)), we first plot fuel consumption and emission of each pollutant to determine slope (γ_x) and intercept (δ_x). This is because CCD values, unlike LTO, depend not only on AOW but also on flight distance, and there are multiple observations for the same aircraft model with various flight distances. γ_x represents fuel and emissions per km of flight while δ_x represents the energy required to accelerate the aircraft to speed and climb up to cruise altitude (Cox, Jemiolo, & Mutel, 2018). Parameters in Eqs. (5) – (6) are then estimated based on AOW, γ_x and δ_x. All model parameters are estimated using the “mosaic” library in R Studio and verified with “curve_fit” from scipy.optimize in Python. Table 3 presents parameters estimated for the LTO phase. All parameters are significant at the 99% confidence level unless otherwise indicated. Model parameter estimates for the CCD phase are presented in Table 4.

Insignificant parameter estimates may be due to the fact that estimating CO, HC and other atmospherically processed emissions not included in this study such as CH_4 and cirrus clouds have always presented challenges, mainly because these emissions depend on operational and ambient conditions more than on volume of aviation fuel burned (Scheelhaase, et al., 2016; Fuglestvedt, et al., 2010; Lee, et al., 2009). Nonetheless, such insignificant model parameters have been used to estimate average aviation fuel consumption/pollutant emissions in the past (Cox, Jemiolo, & Mutel, 2018) and we also use them in this study. The θ estimate for CO is significant at the 90%

confidence level, while the ζ and ι estimates for PM25 and HC respectively are significant at the 95% confidence level. All other estimates are significant at the 99% confidence level.

5.1.2 Model Application

We use the model estimated in Section 5.1.1 to estimate the mean weight of aviation fuel burned and pollutants emitted per pkm for all routes exhibiting leakage (whether direct or connecting) as observed from the Market Locator dataset according to Eq. (7).

$$\bar{x}_q^r = \sum_{i=1}^{I} \frac{LTO_x(\overline{AOW}_{o-d}^{qi})}{d_{o-d}^{i} * \bar{s}_{o-d}^{qi} * \overline{LF}_{o-d}^{qi}} + \sum_{i=1}^{I} \frac{CCD_x(\overline{AOW}_{o-d}^{qi}, d_{o-d}^{i})}{d_{o-d}^{i} * \bar{s}_{o-d}^{qi} * \overline{LF}_{o-d}^{qi}} \tag{7}$$

Where

$\bar{x}_q^r$ = mean aviation fuel/emission in kg/pkm associated with route r during quarter q,

I = all flight segments involved in flying route r,

$i \in \{ I$, with origin o and destination $d\}$,

d_{o-d}^{i} = flight distance (km) on flight segment i (between o and d),

$\overline{AOW}_{o-d}^{qi}$, $\bar{s}_{o-d}^{qi}$, $\overline{LF}_{o-d}^{qi}$ as defined in Eq. (2), and

LTO_x, CCD_x = model functions from Eqs. (3) – (4).

If route flown is direct, aviation fuel and emissions from both LTO and CCD phases will be computed based on a single mean operating weight of the aircraft used from the origin to destination, and flight distance. If the route is indirect (i.e., requiring a connection at an intermediate airport), both LTO and CCD fuel/emissions will be generated for each flight leg of the itinerary.

While we focus on the difference in aviation fuel/emissions per pkm between routes originating from small and large airports, we also compute values for routes starting at medium airports as some leakage took place from small airports toward these medium airports. Nonetheless, the data analysis in Section 4.2 showed that most leakage was from small and medium airports toward large ones.

5.2 Vehicular Fuel and Emissions

To estimate the passenger level impact associated with the ground travel portion of interregional passenger leakage, we rely on vehicular fuel consumption and CO_2 emissions reported in the 2019 Fuel Consumption Guide published by Natural Resources Canada (Natural Resources Canada, 2019). We choose this source because it is extensive, containing over a thousand vehicle models. The Guide reports volume of diesel/gasoline burned per 100 km and CO_2 weight emitted per km. We use the volume and weight reported for combined city and highway trip which is representative of leakage trips in which travelers drive through both cities and on inter-state highways to access distant large hubs. Because existing vehicle fleet composition requires extensive research, we only provide a very basic approximation by simply computing average values that incorporate cars (617 models), pickup trucks (91 models), sport utility vehicles (SUVs) (287 models), plug-in hybrid electric vehicles (26 models) and battery electric vehicles (35 models) included in the guide. However, we removed exotic models (Alfa Romeo, Aston Martin, Bentley, etc.) which are unlikely to constitute more than a tiny proportion of vehicles. Volume of diesel/gasoline reported by the dataset is converted into weight using density at 15 degree Celsius. We make a further assumption of 1.54 passenger per vehicle as per the Federal Highway Administration’s 2017 National Household Travel Survey (NHTS) Weighted Vehicle Occupancy Factors (Federal Highway Administration, 2017) to determine fuel consumption and CO_2 emission per pkm.

6. Results and Discussion

For the ground travel portion, we estimate fuel consumption of 0.048 kg/pkm and CO_2 emission of 0.15 kg/pkm. This value of CO_2 emission is comparable with 0.13 kg/km which is proposed by the 2019 EEA Greenhouse Gas – Data Viewer (EEA, 2019). With regard to the air travel portion, we present the mean value of aviation fuel/emissions per pkm for routes originating at small airports (Case 1), medium airports (Case 2) and large airports (Case 3) in Fig. 6.

We observe that the mean weight of aviation fuel burned and pollutants emitted per pkm decrease as airport size increases. This finding is intuitive insofar as large airports operate more air services at a reduced unit cost (Zou & Hansen, 2012; Brueckner & Spiller, 1994; Gillen, Oum, & Tretheway, 1990; Caves, Christensen, & Tretheway, 1984). Small airports offer very limited direct flights, mainly to neighboring large airports; as such, most passengers that are destined to airports other than these large airports connect through these airports. In doing so, these passengers often travel on multiple flight legs that generate more than one LTO cycle, which would be more emissions intensive. Recall from Section 4.3 that the mean number of flight legs for routes originating from small airports was two (compared to 1.4 for routes originating from large hubs). Previous research has shown that a 25% increase in LTO cycle leads to an increase of 11% in common pollutants (Yilmaz, 2017). Additionally, flights originating from these small airports, because of more connections, involve a mean non-stop flight distance which is lower than those from large airports by 95 km. We also showed in Section 4.3 that LFs and aircraft size at small airports were lower, contributing to the increased per pkm fuel consumption in trips started at these airports. Medium airports offer more direct services in comparison with small airports, and thus passengers have fewer connecting itineraries from medium airports compared with small (and thus, less LTO cycles from which significant emissions are generated). For instance, MKE and STL, on average, offer direct services to over 25 and 35 domestic destinations, respectively, compared to the neighboring small airports that offer direct services only to ORD, MDW, DTW, MSP, ATL and a few other large airports. On the other hand, large airports offer far more direct routes with higher mean non-stop flight distances compared to both medium and small airports, and thus on a route-pkm basis, expend less aviation fuel and emit lower pollutants.

Our fuel estimate of 0.106 kg/pkm for trips beginning at medium airports is comparable with 0.109 kg/pkm which was suggested for intra-European flights (Spielmann, Bauer, Dones, & Tuchschmid, 2007). For trips starting at large airports, our estimate of 0.088 kg/pkm is halfway between 0.109 kg/pkm (suggested for intra-European flights) and 0.070 kg/pkm that was reported for short intercontinental flights (Spielmann, Bauer, Dones, & Tuchschmid, 2007). With regard to CO_2, our estimate for large airports is close to the upper value of 0.24 kg/pkm suggested for short haul European flights (Gössling & Upham, 2009), but those for medium and small airports are significantly higher compared to other studies that estimated under 0.2 kg/pkm (Miyoshi & Mason, 2009; Peeters, Szimba, & Duijnisveld, 2007). Nonetheless, values as high as 0.35 kg/pkm have been reported for regional aircraft with LFs between 0.5 and 0.6 (Miyoshi & Mason, 2009). The relatively higher CO_2 emissions, particularly for routes originating from small and medium airports (where more connections are required) in this study are justified because our analysis is itinerary-based (while previous works are single flight leg-based) which is critical for comparing the impacts of trips from small versus large airports (the former tends to require connections, while the latter do not – by not accounting for full itineraries, these trips cannot be compared). For instance, these existing studies investigate emissions per pkm on a single flight leg with different distances such as 500 km, 500 – 1000 km, etc., while our study accounts for a complete itinerary in which a single passenger may connect and fly on multiple legs to arrive at the final destination. For similar reasons, our NO_X estimates are also higher than the $1.03x10^{-3}$ kg/pkm suggested for short haul European flights (Peeters, Szimba, & Duijnisveld, 2007). Other sources of differences include assumptions of LF, aircraft engine performance and altitude/attitude dependent paramters. Comparisons of CO, SO_X, HC and PM_{25} with other studies are not possible because these pollutants are rarely directly reported throughout the literature, at least in part due to the uncertainties involved in their estimation (Scheelhaase, et al., 2016; Fuglestvedt, et al., 2010).

In Fig. 7, we show the percentage differences in mean aviation fuel and emissions per pkm for routes originating from small and medium airports, comparing against those of large airports. Trips originating at small airports, on average, consumed 31.8% more aviation fuel per pkm at the route level and emitted between 27.3-49.4% additional pollutants compared to those originating at large airports. This means that air trips originating from large airports expend 24.1% less aviation fuel on a pkm basis at the route level compared with those from small airports, indicating that hubbing at large airports results in considerable operational cost savings. This is also supported by Ryerson & Kim (2014). Trips originating at medium airports resulted in 20.5% more aviation fuel and between 19.1-39% additional pollutants per pkm compared with large airports.

The savings in aviation fuel and emissions per route-pkm at large airports cannot be discussed without considering the other negative externalities of large airports and air passenger leakage to them, including: high noise pollution as well as local concentration of harmful pollutants due to airport scale; the economic weakening of regions served by small airports; fuel and emissions of the ground portion of leakage trips (often up to several hundreds of kilometers in private vehicles); and the fate of these smaller airports post COVID-19. Noise pollution is a serious concern among communities living proximate to airports with higher air traffic movement (Lawton & Fujiwara, 2016; Bartels, Márki, & Müller, 2015). Airside concentration of harmful pollutants that directly affect human health is also another concern in the vicinity of airports (Schlenker & Walker, 2016; Westerdahl, Fruin, Fine, & Sioutas, 2008).

Unlike Europe which has a fairly well connected airport-city transit link, long distance transit service in the U.S. remains the exception rather than the norm (Augustin, Gerike, Sanchez, & Ayala, 2014; Sperry, Larson, Leucinger, Janowiak, & Morgan, 2012), meaning that interregional passenger leakage is overwhelmingly facilitated via private vehicles. Accordingly, leaking passengers that drive long distances to large airports may constitute up to 2.75% of the average annual daily traffic on interstate highways (Ryerson & Kim, 2018), which we estimate is accompanied by a fuel consumption of 0.048 kg and CO_2 emission of 0.15 kg per passenger for every extra km driven. Emissions from driving are expected to decrease into the future due to the adoption of rapidly developing plug-in hybrid electric, battery electric (R.Gopal, Park, Witt, & Phadke, 2018) and CAV technologies (Perrine, Kockelman, & Huang, 2020) (although also expected to increase total long-distance driving), potentially making passenger leakage beneficial to the environment in terms of total emissions.

The passenger level outputs from this study can be readily adopted by researchers and environmental agencies toward estimating the total environmental impact associated with interregional passenger leakage on a megaregional or even national level with the appropriate scaling up mechanism that includes: total air travel demand estimation for the megaregion; airport market share modeling for this total demand so that the leaking demand can be determined; and supply-demand feedback analysis which captures changes in aircraft size and LF (in response to changing demand) which in turn affect aviation emissions.

As recognized by the place based approach to net zero emissions (Krabbe 2021; Wildfire et al. 2019), passenger leakage from small to large airports leads to carbon leakage at the city/state level. Passenger leakage, in turn, is driven by the services offered by airlines (which are in part determined by the airlines' network model – i.e., hub-and-spoke or point-to-point) in response to potential emission charges among other things, although these charges do not lead to a clear-cut shift toward one network model over another when emission charges are varied (Brueckner & Zhang 2010). In general, stronger hubbing at major cities leads to more aviation related carbon leakage toward these cities from surrounding regions due to increased volume of leaking as well as connecting travelers. As supported by our results and a previous study (Ryerson and Kim 2014), consolidated hubbing allows airlines to reduce their fuel consumption. Thus, from a profit perspective, legacy carriers might prefer concentrating their services at hub cities unlike LCCs that rely on point-to-point services to stay competitive. Besides considering fuel efficiency in planning their networks, airlines are engaging their customers in carbon offsetting through voluntary emissions charges (ICAO 2021). Thus, this study's passenger-level analysis and resulting estimates may be used to inform customer emissions charges.

7. Conclusions

This paper estimates mean aviation fuel consumption and emissions of GHGs such as CO_2 and H_2O, and other pollutants (CO, NO_X, SO_X, HC and PM_{25}) for hundreds of air routes originating from small airports and neighboring large airports, specifically comparing the fuel/emissions impact of air passengers that leak to these large airports from the service areas of smaller airports. Our analysis is based on a large sample of air ticket purchases over a six-year period, in a study region centered around Chicago O'Hare International Airport in the U.S. Midwest. Our results show that air trips originating from large airports, in comparison with those from small airports, consume 24.1% less aviation fuel on average and emit considerably lower pollutants on a pkm basis at the route level.

The results from this study demonstrate that there may be some environmental advantages, from an overall regional and megaregional perspective, afforded by large airports and interregional passenger leakage. However, these results must also be qualified by the other impacts, which include increased local concentration of aviation-based emissions and noise pollution around large airports, to more fully understand the impacts of airport service consolidation, passenger leakage and the associated environmental impacts in a holistic manner.

The estimated emissions on itineraries departing from airports of different sizes can also be helpful inputs to airlines that have been more widely supporting the development of SAF and carbon capture technology in order to gradually reduce aviation emissions they produce.

We recognize several ways by which to improve on this work. First, the proximity-based service area approach (which assumes each region is served by a single airport) can be overcome by defining areas served by a system of multiple airports as multi-airport regions. For such regions, leakage occurs only when passengers abandon all airports in the system to depart from a hub airport elsewhere. This will overcome the limitation in the current “leakage” definition which, for instance, assumes passengers leak if they choose an airport that is 60 km away while their closest airport is 50 km away. Second, there are additional ways to build on this study that include: presenting temporal analysis of market shares at airports in the study region to better understand the evolution of leakage; and investigating how the emissions from excess ground trips (made to large hubs while “leaking”) compare against the lower (per passenger-km) pollutants from the air travel portion, particularly by considering vehicle fleet composition, emerging plug-in hybrid electric and battery electric vehicles. Furthermore, it is possible to investigate airlines’ preferences for network models by accounting for both fuel savings and the effect of potential emissions charges. This will allow air passenger leakage trends to be more conclusively predicted into the future.

Overall, we recognize there are major changes in the air travel industry both now and in the near future, between the impacts of the COVID-19 pandemic and rapid technological development and adoption of plug-in hybrid electric and battery electric vehicles as well as hydrogen-fueled and electric commercial aircraft. Consequently, we are likely to see airlines reorganize their networks and aircraft fleet composition, and such analyses as the one presented in this paper will need to be revisited.

CrediT authorship contribution statement

Kaleab Woldeyohannes Yirgu: Conceptualization, Methodology, Formal analysis, Writing – original draft. Amy M. Kim: Conceptualization, 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.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2021.103092.

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Table 1 Data Sources

Data/document	**Source**	**Information/data extracted**
Market Locator	Airlines Reporting Corporation (ARC)	Origin, final destination, route flown, residential ZIP code of traveler
DB1B	https://www.transtats.bts.gov/DatabaseInfo.asp?DB_ID=125	Market mile and non-stop market per route – referred to as "flight distance" throughout our study
T-100	https://www.transtats.bts.gov/Fields.asp	Available seat, occupied seat, available payload (all per segment of route)
Airports' locations	https://openflights.org/data.html	Geographic coordinates of airports
ZIP codes' locations	https://public.opendatasoft.com/explore/dataset/us-zip-code-latitude-and-longitude/table/	Geographic coordinates of ZIP codes' centroids
Road shapefiles	https://catalog.data.gov/dataset/tiger-line-shapefile-2016-nation-u-s-primary-roads-national-shapefile	Primary and secondary road shapefiles of the six study states
EMEP/EEA Emission Inventory Guidebook and Database	European Environment Agency, 2013.	Aviation fuel consumed and pollutants emitted by 78 representative aircraft at specified payloads (for different flight distances)
Aircraft characteristics	Appendix A. Supplementary Data	Operating empty weight (OEW) and seating capacity of the 78 representative aircraft in the EMEP/EEA Emission Inventory Guidebook
2017 National Household Travel Survey (NHTS) Weighted Vehicle Occupancy Factors	Federal Highway Administration	Average number of passenger per vehicle
2019 Fuel Consumption Guide	Natural Resources Canada	Vehicular fuel consumption and CO_2 emissions

Table 2 Descriptive Statistics of Small/Medium Airport Markets based on the Market Locator Data, 2013-2018

ZIP codes closest to:	Number of ZIP codes	Total travelers on sampled tickets	Number of final destinations (domestic itineraries)	Other departure airports chosen
ATW	75	131,864	188	MKE, ORD, GRB
AZO	75	100,041	212	DTW, GRR, ORD
BMI	62	52,455	176	ORD, PIA, STL
CMI	174	98,613	134	IND, ORD, BMI, STL
CWA	94	110,873	194	MSP, MKE, MSN
DBQ	231	109,810	130	ORD, MSP, MLI, DSM, MSN
FWA	134	136,702	228	IND, ORD, DTW
GRB	56	101,545	189	MKE, ORD, ATW
GRR	161	221,349	267	DTW, ORD
MKE*	132	480,894	278	ORD, MSP
MLI	175	147,105	195	ORD, DSM, PIA
MSN	133	351,665	255	ORD, MKE
PIA	111	85,971	184	ORD, BMI, STL
SBN	107	126,510	164	ORD, IND, MDW
SPI	112	62,622	127	STL, BMI, ORD, PIA

* Medium airport; all others are small.

Table 3 LTO Model Parameter Estimates

x	α		β	
	estimate	**t value**	**Estimate**	**t value**
Fuel	48.79	15.08	0.77	59.53
NO_X	0.29	8.09	0.97	41.04
CO_2	153.68	15.08	0.77	59.53
SO_X	0.04	15.08	0.77	59.53
H_2O	60.00	15.08	0.77	59.53
CO	2.95	5.82	0.41	11.60
HC	2.22	4.57	$0.03^{n/s}$	0.58
PM_{25}	0.01	7.70	0.50	19.02

$^{n/s}$ not significant at 90% confidence level; all other parameters are significant at the 99% confidence level

Table 4 CCD Model Parameter Estimates

x	ε		ζ		η		θ		ι	
	estimate	**t value**	**estimate**	**t value**	**estimate**	**t value**	**estimate**	**t value**	**estimate**	**t value**
Fuel	0.12	2.67	0.83	12.45	0.23$^{n/s}$	0.79	45.80	3.01	0.56	8.02
NO_X	0.00*	2.09	1.21	13.93	0.00$^{n/s}$	0.82	0.09	2.78	1.24	18.07
CO_2	0.38	2.67	0.83	12.45	0.73$^{n/s}$	0.79	144.26	3.01	0.56	8.02
SO_X	0.00	2.67	0.83	12.46	0.00$^{n/s}$	0.79	0.04	3.01	0.56	8.02
H_2O	0.15	2.67	0.83	12.46	0.28$^{n/s}$	0.79	56.33	3.01	0.56	8.02
CO	-3.83$^{n/s}$	-0.83	0.00$^{n/s}$	1.20	3.85$^{n/s}$	0.71	0.20**	1.72	0.78	6.65
HC	-2.97$^{n/s}$	-0.76	0.00$^{n/s}$	-1.11	2.98$^{n/s}$	0.71	0.13$^{n/s}$	1.14	0.43*	2.25
PM_{25}	0.00$^{n/s}$	0.80	0.40*	2.07	0.00$^{n/s}$	-0.76	0.00$^{n/s}$	0.50	0.66$^{n/s}$	1.61

* significant at the 95% confidence level

** significant at the 90% confidence level

$^{n/s}$ not significant at 90% confidence level

All other parameters are significant at 99% confidence level

Fig. 1. Study airports.

Fig. 2. Illustration of passenger “leakage”

Fig. 3. Methodological process diagram.

Fig. 4. Proximity based service areas.

Fig. 5. Airport choice distribution at study airport service areas.

Fig. 6. Aviation fuel/pollutants results.

Fig. 7. Aviation fuel/pollutants increase (large vs small and medium airports).

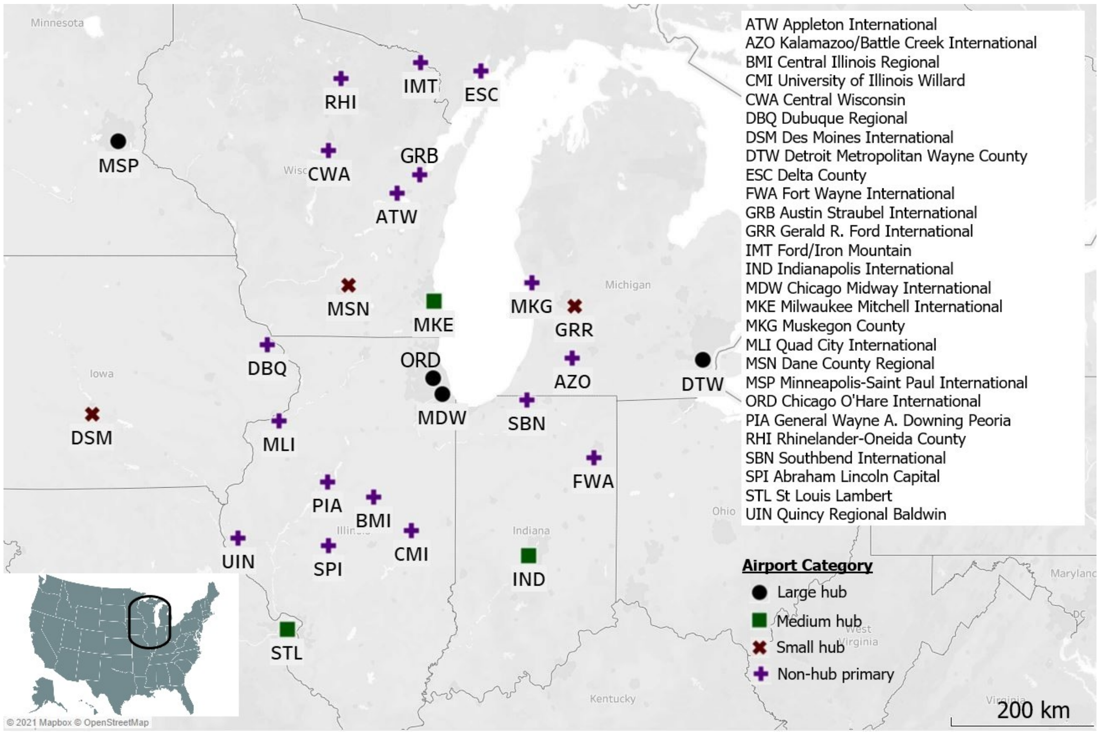

MSP
RHI
IMT
ESC
CWA
GRB
ATW
MSN
MKE
MKG
GRR
DBQ
ORD
MDW
AZO
DTW
DSM
MLI
SBN
FWA
PIA
BMI
CMI
SPI
UIN
IND
STL
Minnesota
Iowa
Illinois
Indiana
Michigan
Ohio
Kentucky
West Virginia
Maryland
DC
ATW Appleton International
AZO Kalamazoo/Battle Creek International
BMI Central Illinois Regional
CMI University of Illinois Willard
CWA Central Wisconsin
DBQ Dubuque Regional
DSM Des Moines International
DTW Detroit Metropolitan Wayne County
ESC Delta County
FWA Fort Wayne International
GRB Austin Straubel International
GRR Gerald R. Ford International
IMT Ford/Iron Mountain
IND Indianapolis International
MDW Chicago Midway International
MKE Milwaukee Mitchell International
MKG Muskegon County
MLI Quad City International
MSN Dane County Regional
MSP Minneapolis-Saint Paul International
ORD Chicago O'Hare International
PIA General Wayne A. Downing Peoria
RHI Rhinelander-Oneida County
SBN Southbend International
SPI Abraham Lincoln Capital
STL St Louis Lambert
UIN Quincy Regional Baldwin
Airport Category
● Large hub
🟩 Medium hub
✖ Small hub
✚ Non-hub primary
200 km
© 2021 Mapbox © OpenStreetMap

Fig. 1.

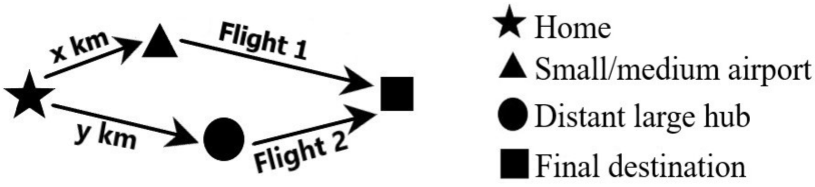

x km
Flight 1
y km
Flight 2
★ Home
▲ Small/medium airport
● Distant large hub
■ Final destination

Fig. 2.

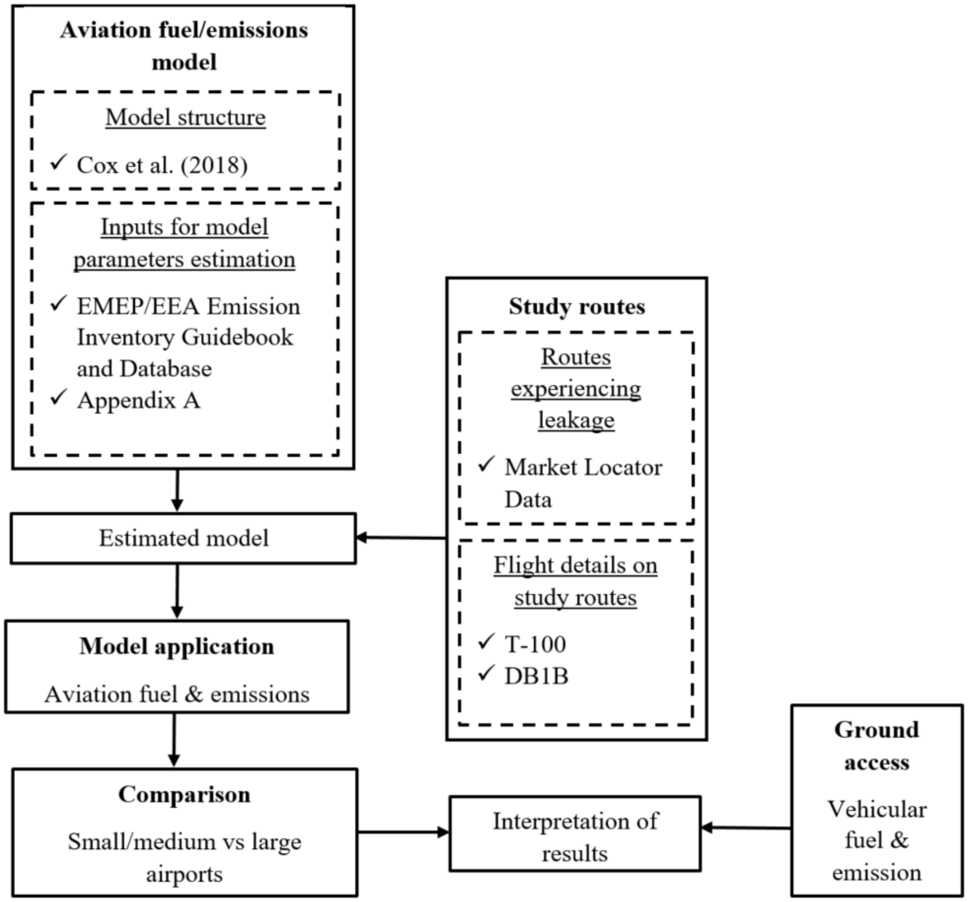

Aviation fuel/emissions model
Model structure
✓ Cox et al. (2018)
Inputs for model parameters estimation
✓ EMEP/EEA Emission Inventory Guidebook and Database
✓ Appendix A
Estimated model
Model application
Aviation fuel & emissions
Comparison
Small/medium vs large airports
Study routes
Routes experiencing leakage
✓ Market Locator Data
Flight details on study routes
✓ T-100
✓ DB1B
Interpretation of results
Ground access
Vehicular fuel & emission

Fig. 3.

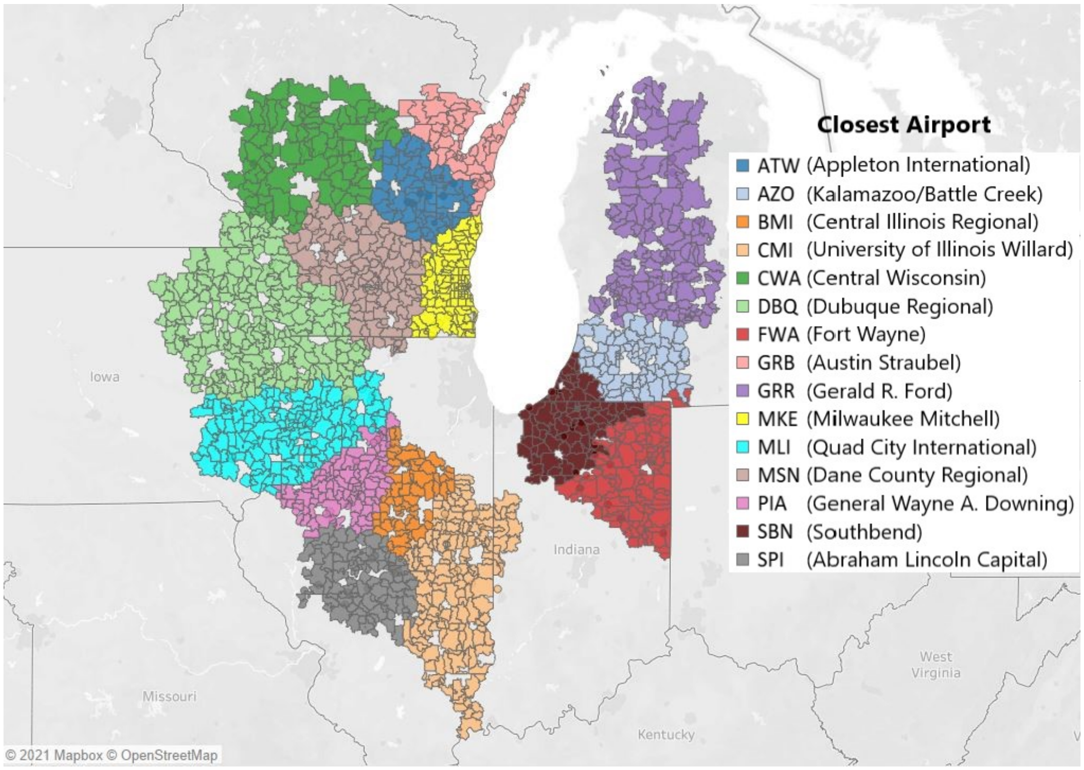
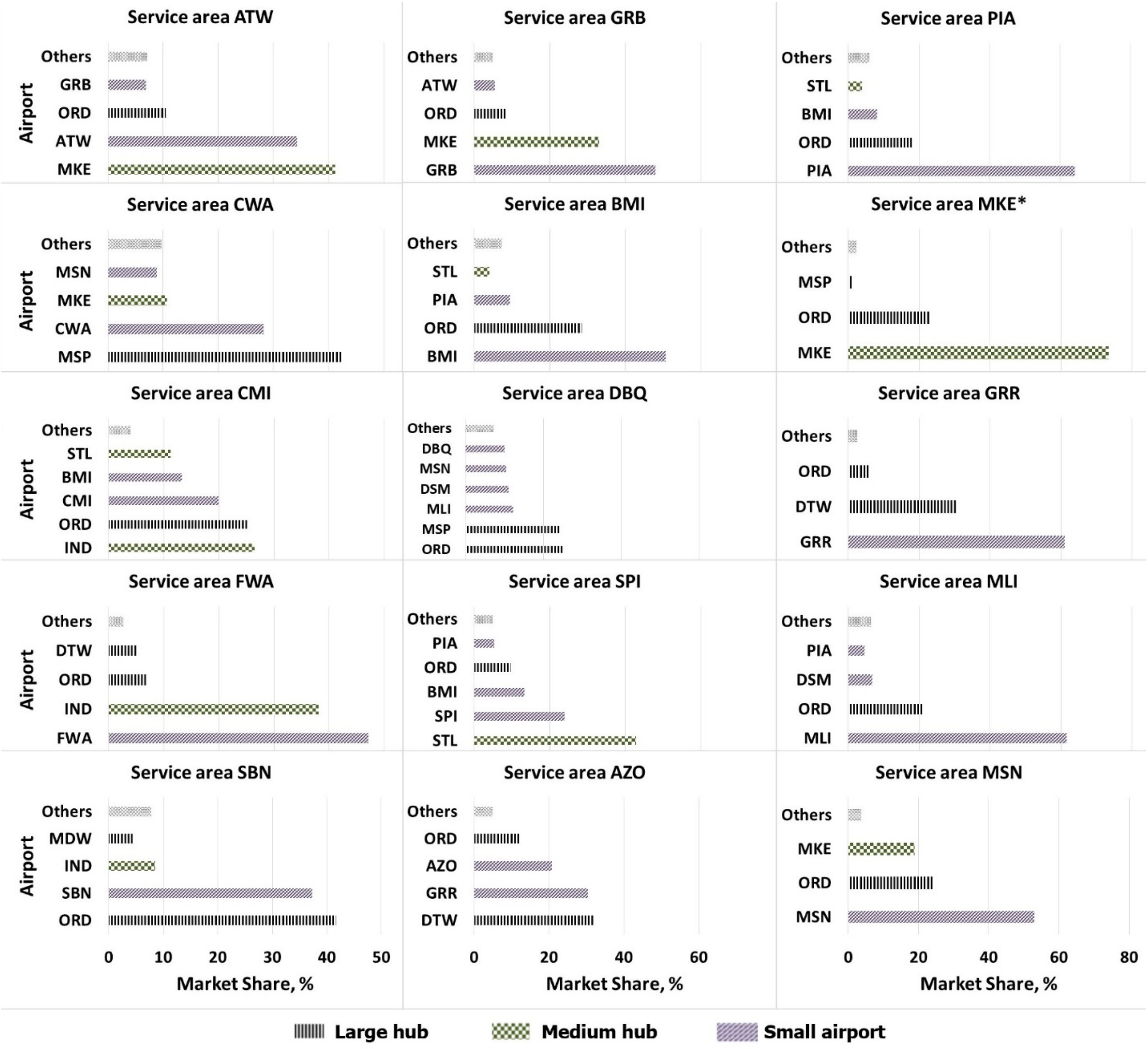

Closest Airport
ATW (Appleton International)
AZO (Kalamazoo/Battle Creek)
BMI (Central Illinois Regional)
CMI (University of Illinois Willard)
CWA (Central Wisconsin)
DBQ (Dubuque Regional)
FWA (Fort Wayne)
GRB (Austin Straubel)
GRR (Gerald R. Ford)
MKE (Milwaukee Mitchell)
MLI (Quad City International)
MSN (Dane County Regional)
PIA (General Wayne A. Downing)
SBN (Southbend)
SPI (Abraham Lincoln Capital)
Iowa
Indiana
Missouri
Kentucky
West Virginia
© 2021 Mapbox © OpenStreetMap

Fig. 4.



* MKE is the only medium airport in the study whose service area exhibited passenger leakage; all other service areas in the figure correspond to small airports

Fig. 5.

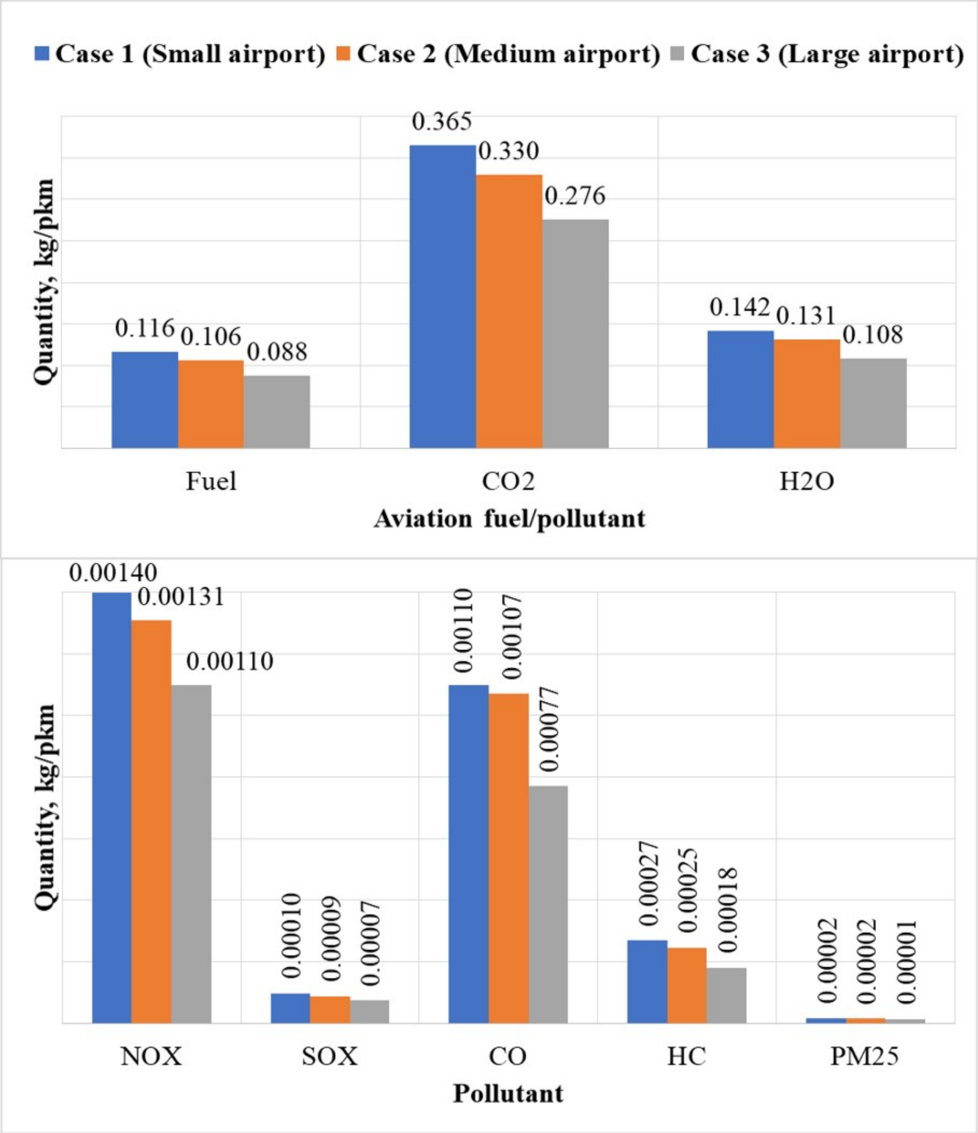
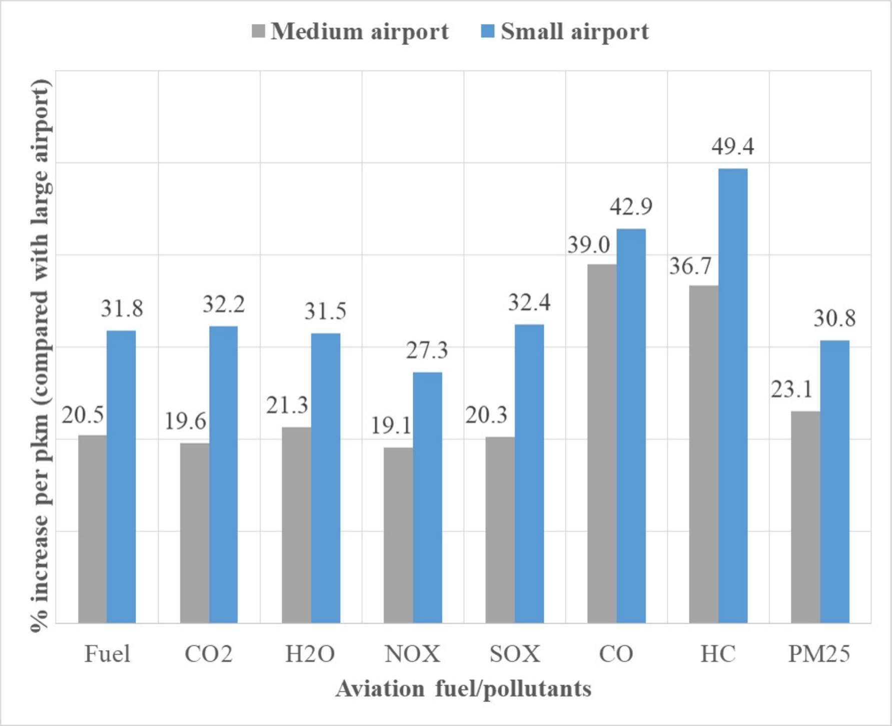

■ Case 1 (Small airport) ■ Case 2 (Medium airport) ■ Case 3 (Large airport)
Quantity, kg/pkm
0.116
0.106
0.088
0.365
0.330
0.276
0.142
0.131
0.108
Fuel
CO2
H2O
Aviation fuel/pollutant
Quantity, kg/pkm
0.00140
0.00131
0.00110
0.00010
0.00009
0.00007
0.00110
0.00107
0.00077
0.00027
0.00025
0.00018
0.00002
0.00002
0.00001
NOX
SOX
CO
HC
PM25
Pollutant

Fig. 6.



Medium airport
Small airport
% increase per pkm (compared with large airport)
20.5
31.8
19.6
32.2
21.3
31.5
19.1
27.3
20.3
32.4
39.0
42.9
36.7
49.4
23.1
30.8
Fuel
CO2
H2O
NOX
SOX
CO
HC
PM25
Aviation fuel/pollutants

Fig. 7.