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Large carbon dioxide emissions avoidance potential in improved commercial air transport efficiency

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Stefan Gössling[1], Milan Klöwer[2], Jorge Cardoso Leitão[3], Sebastian Hirsch[4], Dietrich Brockhagen[4] & Andreas Humpe[5]

Aviation's climate impact continues to grow, with little progress toward emission reductions aligned with global targets. While technological advances attract attention, operational efficiency across aircraft, airlines, airports, city pairs, and regions remains underexplored. Here we assess carbon dioxide efficiency for 27.5 million flights between 26,156 city pairs in 2023, using data from Airline Data, International Civil Aviation Organization, International Air Transport Association. Results show wide variation: 32–890 gram carbon dioxide per revenue passenger kilometres across routes and 60–360 gram carbon dioxide per revenue passenger kilometre across aircraft models. Efficiency differs by region and is lowest in Africa, Australia, and Norway, and highest in Brazil, India, and Southeast Asia. Operating all routes at their demonstrated optimum could cut emissions by 10.7%. A theoretical 50% reduction is possible with the most efficient aircraft, all-economy layouts, and 95% load factors. Efficiency-focused policy could swiftly reduce fuel use without limiting air transport capacity.

Global commercial aviation released between 892 and 936 Mt of carbon dioxide (CO_2) in 2019[1–3], contributing roughly 4% of the world's net human-driven effective radiative forcing[4,5]. Industry projections indicate that the sector is likely to see robust growth over the next twenty years[6,7]. As demand growth has outpaced efficiency gains in the past, emissions from the sector will continue to rise unless new technologies, including sustainable aviation fuels (SAF), become available at scale[8–10]. However, with recent Airbus' decision to delay work on hydrogen-electric aircraft; technical and economic barriers to e-fuel production[11,12]; and the cost and production limits to SAF[13,14], it is unlikely that the sector will decarbonize in line with global climate stabilization objectives[15,16].

Factors driving the growth of emissions in air transport include the expansion of airlines, airports, and the role of subsidies[17], as well as patterns of flight distribution and the influence of frequent fliers on demand generation[18]. Less attention has been given to the potential for reducing emissions, including through improved fuel efficiency in the air transport system. Fuel consumption can be optimized in four general ways: aircraft technology & design; alternative fuels & fuel properties; aviation operations & infrastructure; and socio-economic & policy measures[19]. *Aircraft technology & design* refers to airframe (weight, aerodynamics) and engine fuel efficiency. *New fuels* with properties similar to Jet A1 will reduce net CO_2 emissions. *Operations & infrastructure* refers to optimized flight routes, including altitude, air traffic control systems, dynamic scheduling, efficient ground handling, airport designs and airport congestion[20]. Higher passenger load factors reduce fuel consumption per passenger, as do economy-class only seating configurations[3,21,22]. Regarding *policies*, subsidies make air transport less efficient[23], while any form of charge directly or indirectly targeting emissions (SAF fuel quotas, landing fees, air passenger duties, emission trading) is an incentive for airlines to operate more efficiently. Efficiency gains will be an important pillar of any decarbonisation strategy for the sector[24], although growth rates have consistently outpaced efficiency gains in the past[25].

Historically, average passenger load factors have seen an upward trend, from 63.2% in 1980 to 82.4% in 2019, while emissions per RPK fell from 280 g CO_2 per RPK to 90 g CO_2 per RPK[25]. Yet, recent restrictions in airspace use due to military conflicts (specifically Russia-Ukraine) have increased flight distances and global fuel consumption[26]. Several large airlines have also started to introduce more premium travel options[27], decreasing fuel efficiency. In the future, avoidance of super-saturated flight zones to reduce contrail formation and subsequent non-CO_2 warming is projected to increase fuel use[28], while the introduction of supersonic aircraft will decrease fuel efficiency and accelerate radiative forcing[29].

While factors influencing fuel consumption have been discussed, differences in global operational efficiency appear to have never been

[1]School of Business and Economics, Linnaeus University, Kalmar, Sweden. [2]Atmospheric, Oceanic and Planetary Physics, University of Oxford, Clarendon Laboratory, Oxford, UK. [3]Jorge Leitão ApS, Copenhagen, Denmark. [4]atmosfair gGmbh, Berlin, Germany. [5]Munich University of Applied Sciences, München, Germany. e-mail: stefan.gossling@lnu.se

investigated. We analyze passenger air transport efficiency between aircraft, airlines, airports, city pairs, and geographical regions. The potential of three strategies—operating only the most efficient aircraft, adopting an all-economy class configuration, increasing load factors—is assessed to determine the hypothetical maximum efficiency for the current air transport system.

Results

Emissions and efficiency

Data is analysed for 27,451,887 flights (take-offs), operated between 26,156 bi-directional city pairs in 2023. Flights transported a total of 3,554,769,475 passengers over a total flown distance of 43,314,099,618 km (equivalent to 145 return journeys to the sun), or equalling 6,813,991,167,300 RPK (about 0.7 light years), causing emissions of 577,968,750 t CO_2.

Fig. 1 illustrates the relevance of the 20 highest emitting countries. The United States is responsible for 25% of global emissions (144.6 Mt), with an average weighted efficiency per RPK that is 14.3% higher than the weighted global average. The second largest emitting country, China, follows with 49.7 Mt CO_2, and an average weighted efficiency of 88.6 g CO_2 per RPK. Together, the 20 countries account for 74.9% (433 Mt CO_2) of global emissions from air passenger transport. Emissions on individual city pairs vary between a low of 31.6 g CO_2 per RPK (Milan, Italy to Incheon/Seoul, South Korea) and a high of 888.3 g CO_2 per RPK (Kavieng to Tokua Lakunai, within Papua New Guinea). The global average is 84.4 g CO_2 per RPK.

The global variation in efficiencies can also be illustrated by airports, and for the busiest routes (Fig. 2). Results show that inefficient flights dominate in Africa, Oceania, the Middle East, and Central Asia. They are also common in North America (particularly smaller airports, less busy flights), East Asia, and Western South America. In Europe, Norway is particularly inefficient. Efficient flights dominate in Brazil, India, and Southeast Asia, as well as on routes with high traveller volumes. Other regions, including Europe, have both more and less efficient routes.

Larger airports have a higher efficiency averaged across arriving and departing flights (Fig. 3a). The standard deviation of flight CO_2 intensities increases for larger airports too (Fig. 3b) as they serve more flights. This is statistically supported by rank correlations of (a) −0.57, (b) 0.54, and total CO_2 emissions are largely determined by RPK (Pearson: 0.98). Large variation in CO_2 intensity reflects on regional differences (Fig. 2).

Figure 4 further illustrates differences between the least and most efficient airports and airlines in the world. Average emissions between the least/most efficient airports and airlines (emissions of 0.1 Mt CO_2 or more in 2023) can be more than a factor two. For example, airline LATAM (Chile) caused average emissions of 69.1 g CO_2 per RPK, while Air Algerie (Algeria) emitted 115.0 g CO_2 per RPK; airport Abu Dhabi (United Arab Emirates) caused 67.5 g CO_2 per RPK and Atlanta 103.0 g CO_2 per RPK. There is also evidence that larger airlines are more efficient (Fig. 5a), and that passenger load factors influence efficiency (Fig. 5b).

Efficiency improvement potentials

These findings point to the importance of aircraft models, layouts, and load factors. These are analyzed to determine the theoretical maximum efficiency in the air transport system. Observed aircraft model efficiency varies considerably (Fig. 6). The most efficient models include Boeing 787–900 (55.4 g CO_2 per RPK), 787–800 (59.8 CO_2 per RPK), and Boeing 787–1000 (60.1 CO_2 per RPK), followed by Airbus A320 neo (61.4 g CO_2 per RPK), Airbus A321neo (64.1 CO_2 per RPK), and Airbus A350 (76.2 g CO_2 per RPK). If all aircraft were replaced with the Boeing 787-9 (long-haul) and the Airbus A321neo (short and medium-haul), this would result in fuel savings of −25% to −28% depending on respective market share (Fig. 7).

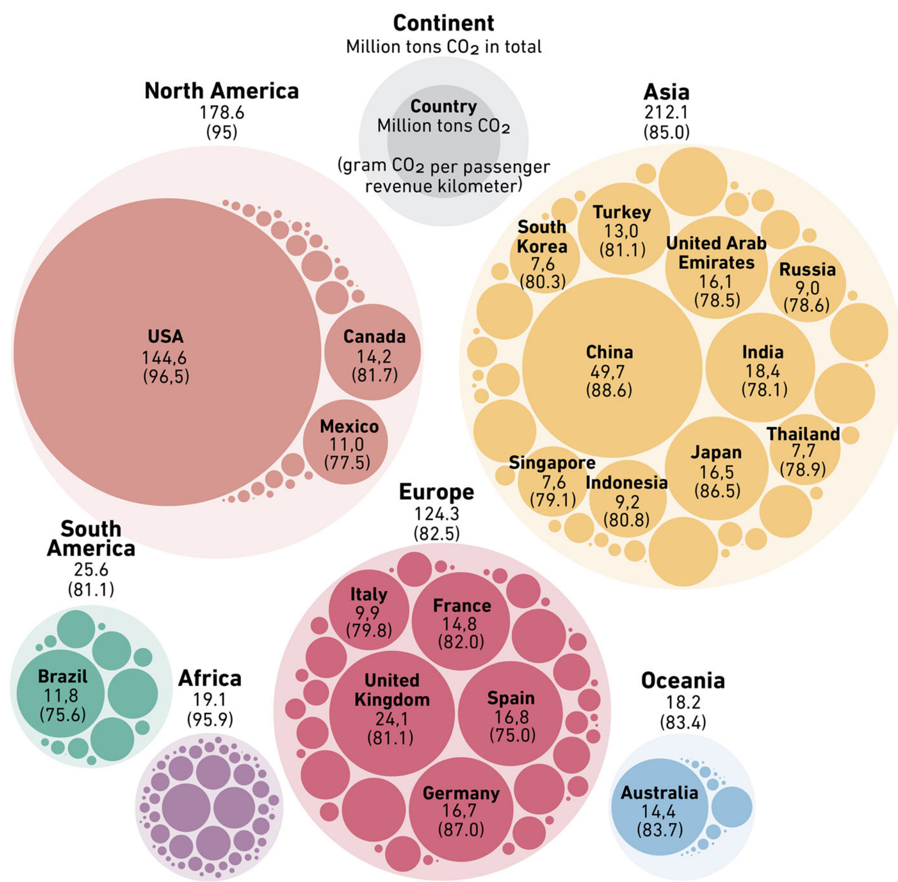


Fig. 1 | Aviation CO_2 emissions and averaged CO_2 intensity by country. CO_2 emissions from aviation across countries (aggregating airport emissions within national borders), showing both the total emissions and emissions per revenue passenger kilometre (RPK). The United States leads with the highest total emissions (144.6 Mt CO_2) and the highest per-passenger emissions (96.5 g CO_2 per RPK), followed by China and the United Kingdom. Countries are color-coded by continent, highlighting regional contributions to global aviation-related carbon emissions.

Fig. 2 | Flight CO_2 intensity by airport. Thin white lines denote the ideal flight path between two airports along the respective great circle, shown globally (**a**), and for North America (**b**), Europe (**c**), and East Asia (**d**). Airports are marked by location and colour-coded to show the CO_2 intensity (RPK-weighted average across arrivals and departures) and the marker size scales with the airport's CO_2 emissions (half of all arrivals and departures). Percentages in the legend correspond to emission percentiles, ranking airports from lowest to highest emissions.

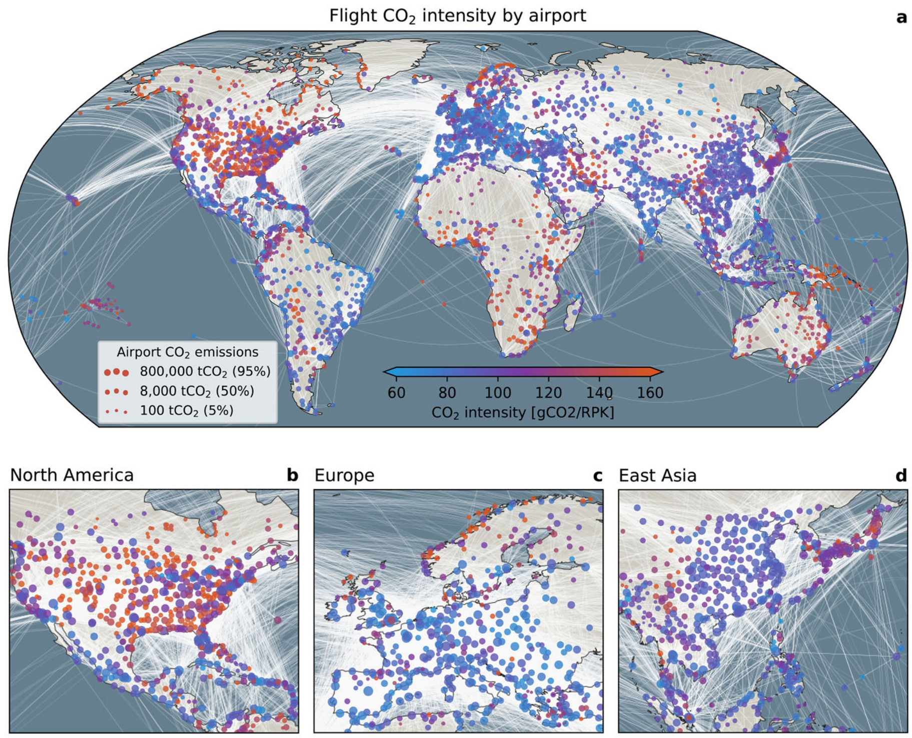
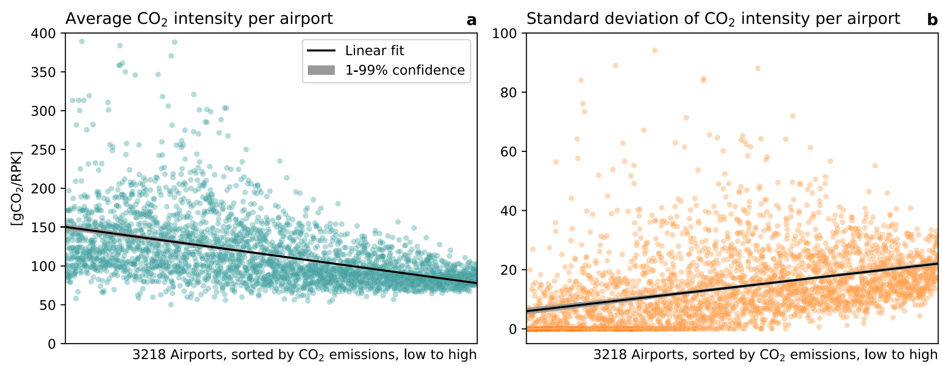


Fig. 3 | CO_2 intensity per airport. a Mean and (**b**) standard deviation of CO_2 intensities across all arriving and departing flights. Mean and standard deviations are RPK-weighted. Airports are sorted by their respective CO_2 emissions (half of all departures and arrivals), low to high. Linear least-square fits are applied with 1–99% confidence intervals obtained from bootstrapping 1000 random subsamples of 50% of the airports. Rank-correlation coefficients are (**a**) −0.57, (**b**) 0.54.



In regard to layouts, IATA[21] suggests that business and first class seats are up to 5 times more CO_2-intense than economy class seats. Premium class seating is more common in wide-bodied aircraft and on long-haul flights, as well as among specific airlines including American Airlines, United Airlines, Delta Air Lines, Emirates, Singapore Airlines, and Swiss International Air Lines[30]. An all-economy class configuration would consequently reduce emissions. Here, results suggest that increasing passenger numbers to the maximum seating configuration for the most efficient aircraft (Airbus 350 and Boeing 787) would further reduce emissions by 21.5% to 56.7%, assuming no changes in the load factor.

In 2023, average passenger load factors were 78.9% for flown kilometers, with a range from 20.1% to 100% between individual flights. Increasing this load factor to 95% would further reduce emissions by 16.1%. Overall, emissions in 2023 could have been 54.5% to 76.0% lower, though a modest fuel penalty would have to be considered (see Methods). This suggests that transporting the same number of passengers over the same distances would be possible with less than half the current fuel consumption, if airlines only operated the most efficient aircraft models, switched to an all-economy layout, and increased the load factor to 95% (Fig. 7).

While this is the hypothetical maximum, analysis for 13,666 city pairs (52.2% of all city pairs) that are served by more than one airline or aircraft configuration suggests that operating these city pairs by the most efficient configuration currently in use would reduce emissions by 10.7%. This represents the already demonstrated efficiency gain in the air transport system, with airlines operating under their economic constraints.

Further analysis confirms that CO_2 intensity strongly depends on passenger load factors and flight distance (Fig. 8). A least-squares linear regression with load factor and distance as predictors shows that a full flight (load factor 100%) covering 10,000 km emits, on average, 57 g CO_2 per RPK. This almost doubles to 109 g CO_2 per RPK for a half full flight (load factor 0.5) or increases to 83 g CO_2 per RPK for a reduced flight distance of 1000 km at full capacity. However, there is considerable variation around this average (Fig. 8) likely highlighting the importance of aircraft models. Neglecting possible changes in passenger load, if every flight's intensity was capped at this average (the *medium cap model*), increasing efficiency for approximately the lower half of flights would save 8.6% in emissions (or 50 Mt CO_2). A low cap model, allowing average intensities (from the medium cap model) and up to 33% higher, would only affect the most inefficient flights, consequently saving only 1.1% of emissions. A high cap model, however, which requires every flight to be at least 33% more efficient than the average (of the medium cap model), effectively requiring the highest industry standards, would save 34.6% of emissions or 200 Mt CO_2. These scenarios are more realistic compared to those discussed around Fig. 7 as they acknowledge constraints many airlines face when operating.

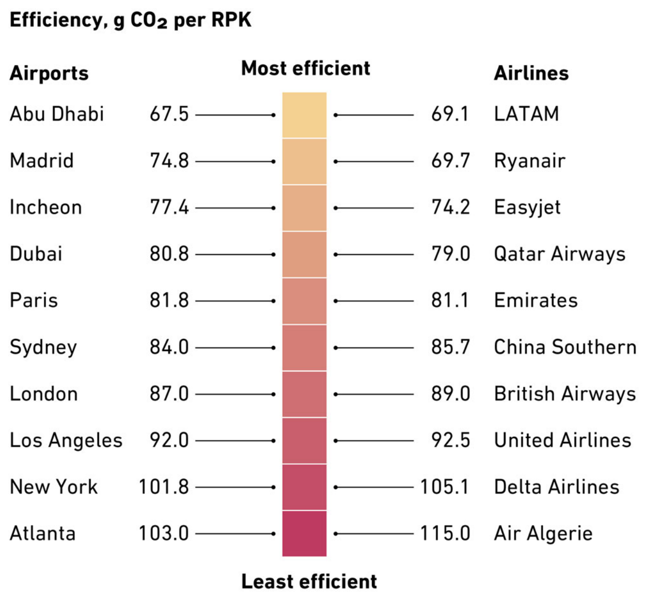


Fig. 4 | Variation in efficiency for airports and airlines. Ranking of airports (n = 575) and airlines (n = 266) with emissions exceeding 0.1 Mt CO_2 in 2023. Includes the largest airport/airline by total emissions within each decile. Calculation based on half of aggregated emissions from incoming/outgoing traffic (airports), and total emissions (airlines). Some cities have several airports, airport codes are AUH, MAD, ICN, DXB, CDG, SYD, LHR, LAX, JFK, ATL, more to less efficient.

Conclusions

Further growth in aviation will make the sector increasingly relevant for climate change mitigation. Efficiency gains have importance, because the replacement of Jet A1 with SAF does not eliminate non-CO_2 components, even though lower soot particle emissions can reduce effective radiative forcing[31]. Strategies minimizing fuel use are thus preferable, as they contribute to a reduction in CO_2 as well as non-CO_2 effects. This article highlights the considerable potential for efficiency gains in the sector: higher load-factors, the scaling back of premium-class seating, or the replacement of inefficient aircraft models with efficient ones provide opportunities for considerable fuel savings.

While airlines often claim that fuel savings are in their own economic interest, the reality is that many airlines continue to fly with old aircraft, low load factors, or growing shares of premium-class seating. For example, aircraft remain in service for 25 years[32]. Global passenger load factors have generally increased over time, but have yet to surpass the 85% threshold[25]. New policies and policy corrections are needed to accelerate efficiency gains in aviation. For example, low load factors may be a result of public service obligations and other subsidies provided by governments[23], encouraging - and even forcing - airlines to fly even though demand is marginal. Another example is the hub-and-spoke model, under which airlines fly passengers from smaller airports to central hubs where they can transfer to other flights. Spoke routes may be served with smaller, less efficient aircraft, have lower load factors, and not be profitable on their own[33].

Climate policies, where they exist, currently focus on decarbonizing air transport through the adoption of SAF. For example, the European Union's ReFuel programme forces airlines to adopt greater shares of SAF[34], defined

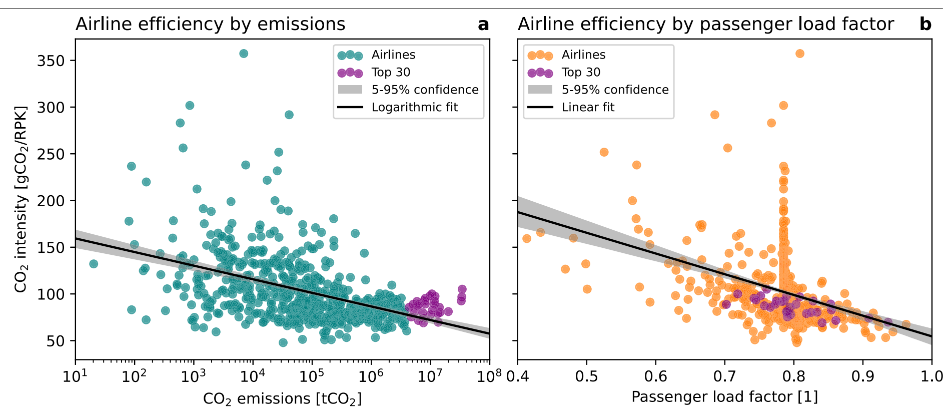


Fig. 5 | Airline efficiencies. The emission intensity (g CO_2 per RPK) of 590 airlines as a function of (**a**) total emissions (t CO_2) and (**b**) passenger load factor. The 30 largest airlines by total emissions (>4 Mt CO_2) are marked in purple and account for 60.7% of all emissions. **a** Logarithmic and (**b**) linear least-squares fits are applied with 5–95% confidence intervals via bootstrapping 1000 subsamples of a random 50% of the airlines. Frequent passenger load factors around 0.79 in (**b**) are due to data limitations (see Methods).

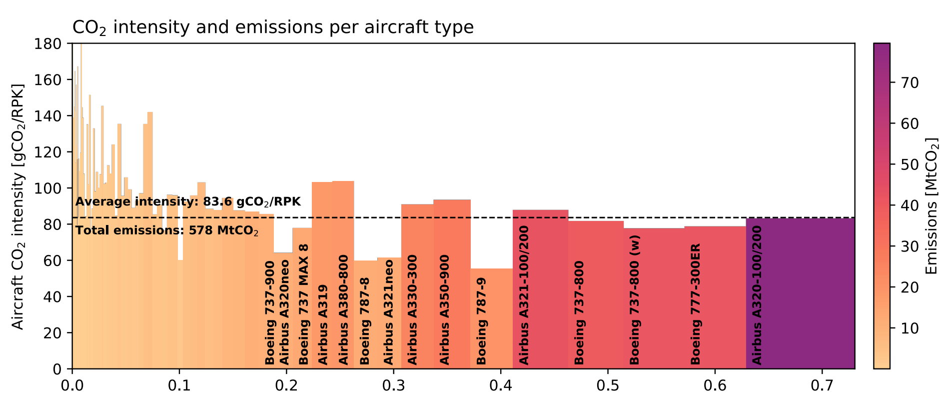


Fig. 6 | Efficiency by aircraft type. Aircraft are sorted by revenue RPK share (denoted in light-years, 1 light-year ≈9.5 · 10^{12} km) and horizontally stacked on the x-axis (accumulating RPK). The height of each bar denotes the aircraft's CO_2 intensity, the area is proportional to the CO_2 emissions from that aircraft type and colored accordingly. The 15 most prominent aircraft types (in RPK) are labelled, (w) stands for (winglets). Average intensity is given as a horizontal dashed line and the total emissions across all aircraft is proportional to the area below.

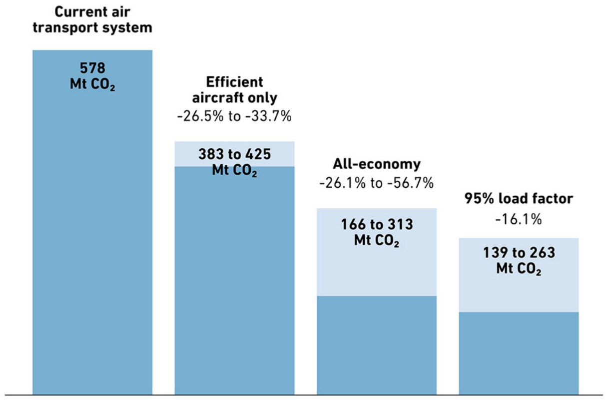


Fig. 7 | Overview of savings potential. The current air transport system in our study causes emissions of 578 Mt CO_2 (see Methods for system boundaries). Replacing less efficient aircraft with only the two most efficient models (Boeing 787-9 and Airbus A350) would reduce emissions by 26.5% to 33.7% to 383 to 425 Mt CO_2. Changing these aircraft from their current layout (premium and economy class seating) to an all-economy class layout would further reduce emissions in the range of 26.1 to 56.7%, or 166 to 313 Mt CO_2. Last, increasing the load factor to 95% would further reduce emissions to a range of 139 to 263 Mt CO_2. The fuel penalty incurred in additional weight is not considered, but small (see Methods, Fig. 9).

as a percentage share of total fuel use. Paradoxically, this legislation could lead to an increase in overall warming, even if quotas are successfully met, if total fuel use increases faster than the share replaced with SAF. Inefficiency considerations in air transport are an alternative climate governance inroad: as the CO_2 intensity cap model illustrates, efficiency-based policies have a great potential to curb emissions. These may include soft policies (a public airline efficiency rating), market-based measures (phasing out subsidies, higher landing fees for inefficient airlines or aircraft), or regulatory approaches (CO_2 intensity caps). Notably, there is precedent for such policies in other sectors: the EU energy label and minimum performance standards for white appliances[35], bonus-malus systems in vehicle insurance[36] or fuel economy standards[37], as recently approved by the Marine Environment Protection Committee for international shipping[38]. Resistance to any such policies must be expected, as airlines operate within economic constraints, a business environment shaped by subsidies, expectations of continued growth, and limited ambition for climate change mitigation.

Methods

Efficiency model

The comparison of commercial passenger air transport efficiencies requires a comparable indicator. CO_2 intensity, i.e. *Emissions per revenue passenger kilometer* (g CO_2 per RPK) can be calculated for aircraft, airports, and city pairs. This indicator is directly proportional to fuel use per revenue passenger kilometer (kg fuel per RPK). It is influenced by many factors, including the aircraft design (airframe, engine type, winglets), operational aspects (distance, speed, flight route, flight altitude, weather, detours, holding patterns, green flying techniques), as well as on-the-ground conditions (taxiing, ground power supply). Energy use per passenger also depends on aircraft layout (seat numbers), load factors, and co-loaded cargo. Data is limited to aircraft with 30 seats and more, i.e., private aircraft and business jets are not part of the analysis. Data allows us to calculate average load factors for each city pair, from which global load factors and fuel use can be derived.

To factor these aspects into the calculation of emissions per RPK, an efficiency model is used that considers distance, aircraft type, and payload (passenger and cargo weight). 2023 data for the efficiency model is derived from:

1) T100I (AirlineData): flight-specific load factors for flights to and from the USA and Canada, annual means.
2) ICAO TFS (Traffic by Flight Stage): similar to T100I with global coverage, though not for all airlines.
3) IATA WATS (World Air Transport Statistics): annually averaged, airline-specific load factors (i.e., not disaggregated by city pair or aircraft type), further split into international and domestic services, for about 219 airlines.
4) FlightGlobal: similar to IATA WATS, with airline-level data (annual mean load factors) for 178 airlines.

Data consequently has three levels of granularity for load factors:

- **Level 1**: Airline average over one year (52% of all flights).
- **Level 2**: Airline–city pair average over one year (12.4%).
- **Level 3**: Airline–aircraft–city pair average over one year (15.2%).

T100I and ICAO TFS provide level 3 data. From these, level 2 and level 1 averages can be derived by averaging revenue passenger kilometers (RPK) and available seat kilometers (ASK) across aircraft serving a given city pair (level 2) and additionally across all city pairs (level 1, ICAO TFS only). By contrast, IATA WATS and FlightGlobal only provide level 1 data.

For each individual flight, the highest level of load factor is sought, following a fallback cascade across the data sources. When IATA WATS is established as the best data source, the corresponding value for either domestic or international flights is used. As a last fallback, a global load factor over all airlines is calculated for three distance categories: short-haul (≤1500 km), medium-haul (1501−3500 km) and long haul (>3500 km). This load factor is used when no other load factor (level 1–3) can be found.

The induced error can be calculated for using global means instead of level 3 values. When bootstrapping 100,000 samples, the per-flight absolute error mean is 0.0406, and the median is 0.0145. The bootstrapped 95% CI for the absolute error mean is [0.0389, 0.0423]. This corresponds to a relative error of 5.38% with a 95% CI of [5.15%, 5.62%]. Notably, this error affects 20.4% of the load factor, as a higher-level granularity for load factors is available for 79.6% of flights.

Total fuel use is a function of total load and aircraft-specific performance data. Seat-classes are weighted by multiplying average per-passenger emissions with a seat-class factor based on IATA's cabin class method[21]. This method considers the number of seats per class in a given aircraft configuration. The formula for this calculation is provided in (Eq. (1)); the passenger share of fuel use in (Eq. (2)), also involving data from Flight Global, which provides passenger data. Fuel use is transformed into CO_2 in (Eq. (3)).

More specifically, fuel consumption is calculated for each individual flight, accounting for the specific aircraft model, cabin layout, and passenger/cargo load factors. Fuel consumption is derived from a physical aircraft performance model, which calculates fuel consumption for a given aircraft model, considering flight distance and takeoff weight. The total fuel consumption of the flight is then broken down into fuel use per passenger and converted to CO_2 emissions per passenger. All subsequent analyses are based on these individual-flight emission characteristics, allowing for more nuanced results than calculations based on airline-average or city pair-average load factors or performance data.

Allocation of total fuel burn of a given flight to individual passengers and subsequent conversion to CO_2 emissions follows these steps:

(a) Calculation of fuel use for payload in ton kilometres (tkm)

$$fuel\ per\ tkm = (total\ fuel)/(flight\ distance \times payload) \tag{1}$$

(b) Calculation of fuel per passenger (pax)

$$\text{fuel per pax} = \text{fuel per tkm} \times \text{distance} \times 100\ \text{kg} \times \text{freight correction freight correction} = \frac{m_{\text{pax}} + 0.5 \times m_{\text{cargo}}}{m_{\text{pax}} + m_{\text{cargo}}} \tag{2}$$

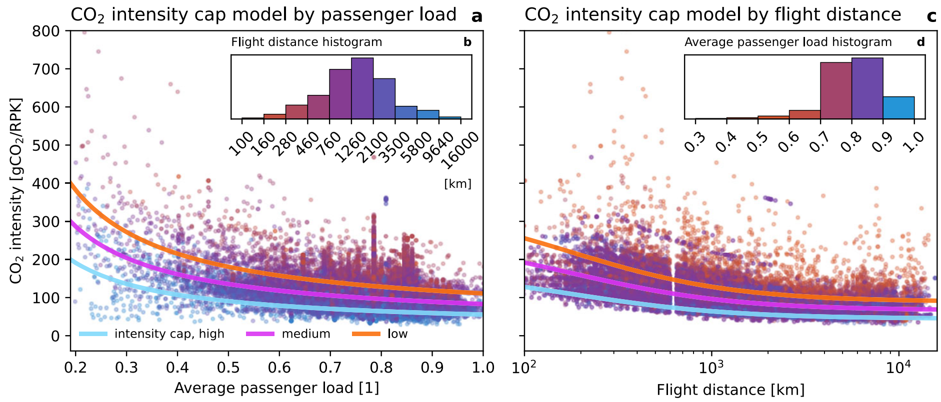


Fig. 8 | CO_2 intensities against passenger load and flight distance. CO_2 intensity of flight connections as a function of (**a**) average passenger load and (**c**) flight distance (including detours and holding). Each marker denotes one flight connection between two airports. Markers are color-coded with flight distance in (**a**) and passenger load in (**c**), with colors visualized as a histogram in (**b**, **d**) respectively for (**a**, **c**). Note that (**b**, **c**) show flight distance on a logarithmic axis. A CO_2 intensity cap model (blue, purple, orange lines) is added as a simple model to represent an approximate industry standard of operational low, medium and high CO_2 intensities for civil aviation. The medium cap model is fitted via least-squares, the low (high) cap model is 33% higher (lower) intensity. The data gap in (**c**) is an artefact resulting from the ICAO correction factor (see Methods).

Here, passenger emissions and 50% of the emissions from freight transport are allocated to passengers, assuming a passenger (including baggage) weighs 100 kg[39].

(c) Calculation of CO_2 per Passenger (pax)

$$CO_2 \text{ per pax} = \text{fuel per pax} \times 3.16 \tag{3}$$

The resulting per-passenger emission intensity enables comparisons of flight efficiency. Figure 8 illustrates the inherent dependence of emission intensity on flight distance, with longer flights generally exhibiting lower emission intensities. This is because takeoff and ascent to cruising altitude - the most fuel-intensive phase of a flight - account for a larger proportion of total fuel burn on short-haul routes.

These data are used to assess all flights; where no data for a specific flight is available, global mean values are used for three distance classes (short-/medium-/long-haul). Flight distances are based on great circle distances, which are converted to flown distances by using ICAO's correction factor: +50 km for flights up to 550 km, + 100 km for flights between 550 and 5500 km, and +125 km for flights >5500 km[40]. Data is available for 26,155 city pairs and 61,607 'flights', with one flight being defined as a unique combination of departure airport, arrival airport, airline, and aircraft type. Non-operational code-sharing flights have been removed from the dataset; only the airline carrying out the flight is considered. A weakness of the dataset is that it includes mostly scheduled flights.

Validation checks

The dataset comprises 27,451,887 flights in 2023, carrying a total of 3,554,769,475 passengers over a distance of 6,813,991,167,301 RPK, and causing emissions of 577,968,750 t CO_2. This is less than the 35.3 million flights, 4.319 billion passengers, 8232 billion RPK, and the 530 Mt CO_2 reported through the CORSIA Central Registry (said to cover 99% of total 2023 emissions on scheduled services reported for 2023 by ICAO[41])[42,43]. Our data consequently covers 83% of RPK and 82% of passengers in comparison to ICAO data. A potential explanation is that there are data gaps related to the reporting of charter operators.

Consistency analysis of our database shows that the number of seats in aircraft is always higher than the number of passengers. Airline load factor comparison with three airlines, Ryanair, Lufthansa, and American Airlines, for which data is publicly available, also suggests that variation is within 10%. For example, in 2023, Ryanair reported a 93% load factor, whilst the model suggests 93.6%; Lufthansa reported 82%, whilst the dataset is 78.9%; and American Airlines reported 83.5%, whilst the model suggests 81%. It is difficult to validate emission intensities for airlines due to variable operating conditions and inconsistent reporting standards. Annual reports may not include RPK numbers, refer to financial years rather than calendar years, combine data on operational fuel use for cargo and passengers, combine different accounting scopes, deduct sustainable aviation fuel emission "savings", or calculate CO_2e rather than CO_2. Airlines also have subsidiaries that may have been included/excluded in the accounting. However, the communication teams of all airlines mentioned in this article (LATAM, Ryanair, EasyJet, Qatar Airways, Emirates, China Southern, British Airways, United Airlines, Delta Air Lines, Air Algérie) were provided with the data sources used in our analysis, as well as the airline-specific emission efficiencies (g CO_2 per RPK) calculated, and were asked to comment. LATAM responded by saying that it does not wish to comment. EasyJet provided a link to their own calculations, suggesting slightly lower emission efficiencies (66.64 g CO_2 per RPK) than calculated using our model (74.2 CO_2 per RPK).

Emission attribution

Emissions are assessed at different scales of analysis, for airports, airlines, or countries. For airports, emissions are calculated by aggregating half the emissions from all incoming and outgoing flights. This ensures that half of the emissions for each city pair are attributed to the respective departure and arrival airports. The approach addresses that fuel use can vary between incoming and outgoing flights due to differences in flight paths or weather. Airline emissions consider all emissions from flights operated by an airline, with intensities calculated by dividing the total amount of CO_2 by the number of RPK. Country emissions are calculated by aggregating emissions from all airports within national borders.

Efficiency calculations

The efficiency of air transport is calculated for aircraft, airlines, airports, city pairs, and countries, using the same indicator (g CO_2 per RPK). Airport emissions are calculated for 3218 airports by summing up the CO_2 for all departures and arrivals from/at each airport, and dividing the value by two to assign half the emissions from every flight to this airport. In an identical approach, half of all RPKs for every departure and arrival are calculated. The mean CO_2 intensity (g CO_2 per RPK) is then derived by dividing an airport's CO_2 emissions by its RPK. Aircraft comparisons are based on city pairs, for which data is available for all aspects of the flight. For these, fuel consumption per RPK can be calculated for each aircraft based on fuel use, emissions, and RPK. On this basis, aircraft can be ranked by observed efficiency.

Optimum efficiencies on city pairs can be calculated for all routes served by more than one flight configuration (13,666 out of 26,156 city pairs, or 52.2%). Avoided CO_2 can be determined by dividing the most efficient average (g CO_2 per RPK) by the average efficiency on the city pair, multiplied with CO_2 emissions on this city pair. Values can then be aggregated for all city pairs, and total emission be compared to current emissions in the system. This can be expressed as (Eq. (4)):

E_{best} = Best (minimum) efficiency for a given route (e.g., fuel per tkm)
E_i = Efficiency of airline i on the same route

Table 1 | Actual max and theoretical maximum number of seats

IATA	Model	Observed max. seats OAG/FA	Average observed seats	Theoretical max seats (OAG/FA)	Certified maximum	Assumed maximum	% more seats*
351	A350-1000	429/480	349	501/500	440	440	26.1
359	A350-900	432/432	313	342/432	440	432	38.0
781	Boeing 787-1000	344/367	315	458/439	420	420	33.3
788	Boeing 787-800	335/335	254	398/398	420	398	56.7
789	Boeing 787-900	375/395	283	375/449	420	420	48.4

*increase in seat number as percentage of average observed to assumed maximum seat number.
OAG OAG data, *FA* FleetsAnalyzer data.

$CO2_i$ = Current CO_2 emissions of airline i
$CO2_{best,i}$ = CO_2 emissions at best efficiency for airline i
Then, the formula for CO_2 emissions at the best efficiency is:

$$CO_{2,\text{best,i}} = \left(\frac{E_{\text{best}}}{E_i}\right) \times CO_{2,\text{i}} \tag{4}$$

If there are multiple airlines on a city-pair, the total emissions improvement can be calculated as (Eq. (5)):

$$\text{Total } CO_2 \text{ reduction} = 1 - \frac{\sum \text{r}CO_{2,\text{best,i}}}{\sum \text{r}CO_{2,\text{i}}} \tag{5}$$

Assuming that only the most efficient aircraft were operated on all city pairs served by more than one carrier, emissions would be 10.66% lower than current emissions (517 Mt CO_2, rather than 578 Mt CO_2). This is the lower theoretical threshold for emission reductions based on observed operational efficiency.

Theoretical maximum efficiency. There are three ways to increase the efficiency of air transport: using only the most efficient aircraft, switching to one flight class (economy); and increasing load factors. The maximum efficiency for the year 2023 can be calculated in three steps.

Step 1: Global fleet of most efficient aircraft models. The effect of replacing the entire 2023 fleet with the two most efficient models - the Boeing 787-9 (55.4 g CO_2 per RPK) and the Airbus A321neo (61.4 g CO_2 per RPK) would lead to emission reductions in the range of 26.6% (all Airbus) to 33.7% (all Boeing), compared to the current fleet average of 83.6 g CO_2 per RPK, with (Eq. (6)):

I_{avg} = average CO_2 intensity (gCO_2 per RPK)
I_{opt} = CO_2 intensity of the Boeing 787-9 (gCO_2 per RPK)
S = relative savings

$$S = 1 - \frac{I_{\text{opt}}}{I_{\text{avg}}} \tag{6}$$

Step 2: Economy class only configuration. To determine the difference between an air transport system consisting only very efficient aircraft models, we calculate frequency weighted averages for average seat numbers in economy, business, and first class for the five configurations of the most efficient aircraft models (A350-1000; A350-900; Boeing 787-1000; Boeing 787-800; and Boeing 787-900). As Table 1 illustrates, first class seating is uncommon in these aircraft, partially explaining their efficiency.

The difference in space use between all-economy vs. business and first class aircraft layout can be calculated using current economy to business to first ratios, with each first class seat equalling 5 economy seats, and every business class seat 4 economy class seats[21]. The percentage increase in seat numbers can be calculated based on data from Official Airline Guide (OAG) and FleetsAnalyzer (FA) for models A350 and B787, which represent the range of most efficient aircraft. In contrast to FA, OAG does not distinguish economy and economy-premium class; this might explain some of the difference in observed maximum seat numbers. OAG data refers to the 2023 flight schedule that lists the actual cabin layout for every flight; FA data considers actual aircraft configurations in fleets of various airlines (2023 data).

Table 1 shows the observed *maximum* seat number for the different models for both databases, and the *average* seat numbers for each model. The theoretical maximum number of seats can be calculated based on the following formula (Eq. (7)):

$$S_{\max} = S_{\text{eco}} + 1.5 \cdot S_{\text{prem.eco}} + 4 \cdot S_{\text{bus}} + 5 \cdot S_{\text{first}} \tag{7}$$

where *S* is the number of seats per class, and the factors are the IATA seat class factors, and economy (eco), premium-economy (prem.eco), business (bus) and first (first).

The increase in seat numbers in an all-economy layout is then determined based on an "assumed maximum", representing either the calculated theoretical maximum seat number or the certified maximum seat number (whichever is lower). Certified maximums refer to type certification that are based on emergency evacuation demands[13]. This means that the number of seats in the Airbus A350-1000 is capped at 440, and at 420 seats for Boeing 787-1000 and 787-900.

Results suggest that an all-economy layout would allow airlines to carry 26% to 57% more passengers, which is equivalent to the theoretical reduction in fuel use of an all-economy layout.

Step 3: 95% load factor. Limiting capacity growth in global air transport will lead to higher load factors. In particular low-cost carriers have reported load factors of up to 94%[44]. Here we assume a hypothetical maximum load factor of 95% that would reflect on an air transport system with considerably reduced capacity[25]. Given the current load factor of 78.9%, aircraft could carry 16.1% more passengers if available capacity was utilized at 95%.

Fuel penalty. Calculations in Step 2 and 3 do not consider that optimization for efficiency will incur a fuel penalty due to the additional weight carried. Analysis for the two aircraft models characterizing the range of layout gains, i.e., A350-1000 and Boeing 787-800 (26.1–56.7% more seats), suggests that this fuel penalty is small. This is illustrated in Fig. 9 for the A350-1000: depending on distance, fuel consumption increases by 5.8% to 13.9%, implying a small fuel-penalty even in comparison of a near-empty (20% load factor) to a close to full (80% load factor) aircraft. We conclude that increasing seat numbers or load factor will marginally increase fuel use. The potential reduction in fuel consumption in an optimized air transport system is thus in the range of −55% to −75%, not considering the fuel penalty.

CO_2 intensity cap model

A CO_2 intensity cap model illustrates how much emissions from global aviation would fall if flights were required to operate at a mandated maximum CO_2 intensity. However, considering such a cap as constant is largely unrealistic as it is strongly dependent on flight distance and load factors. Ignoring changes to load factors or flight distance, we isolate the variation

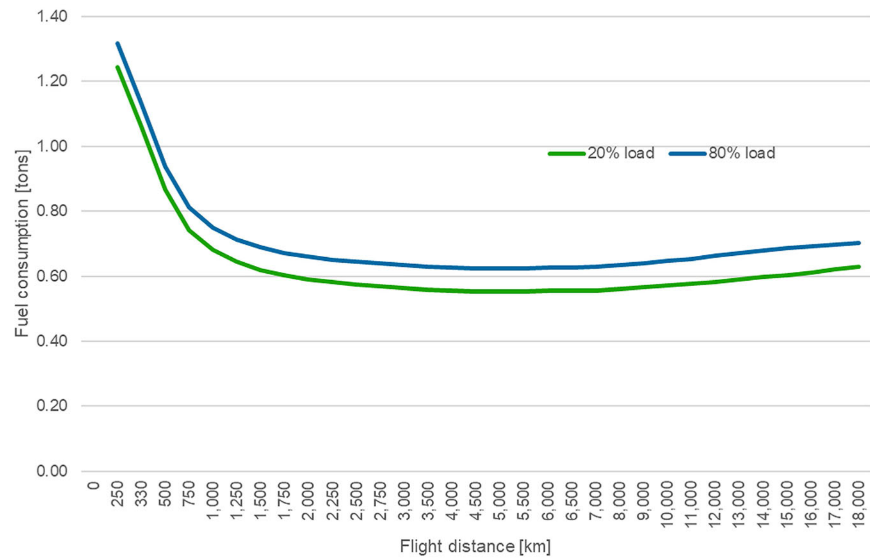


Fig. 9 | Fuel consumption increase as a function of load factor. Fuel use increases as a function of load, here illustrated for the A350-1000. The difference in fuel consumption between a near-empty (20% load factor, lower green curve) and near-full (80% load factor, upper blue curve) ranges between 5.8% and 13.9%, suggestion that the fuel penalty for additional weight carried is small.

independent of those. Other scenarios investigate increasing load factors (in exchange for fewer aircraft, see above).

The CO_2 intensity c is therefore modelled as a function of load factor l and flight distance d, linear in both predictors (Eq. (8)):

$$c = \frac{a}{l + l_0} + \frac{b}{d + d_0} \tag{8}$$

Inverse proportionality is assumed as increasing load decreases the intensity, so does a longer flight (larger aircraft, less resistance at higher altitude, smaller contribution of fuel-intensive takeoff). This model is fit via least-squares, estimating the constants to (rounded) a = 54 g CO_2 per RPK, b = 35,000 g CO_2 per pax, d_0 = 180 km. The offset in load factor l_0 is manually set to 0.01 to prevent intensities going to infinity for very low load factors which is not well constrained with the data given how few flights operate that empty. This model is considered to be the *medium cap model* representing an average intensity. The low c_{low} and high cap model c_{high} are defined as $c_{low} = 4c/3$, $c_{high} = 2c/3$, representing 33.3% lower/higher efficiency, respectively. Theoretically, for very long flight distances fuel consumption increases due to the additional weight of large amounts of fuel. This motivates to add a term proportional to distance d, which however, does not yield a positive proportionality constant, contradicting this theory with data. In that sense, higher intensities for very long flight distances are not supported with the data here.

Limitations

Findings are characterized by the following limitations: Our data comprises only a share of global commercial passenger air transport (83% of RPK and 82% of passengers in comparison to ICAO[42,43]). It is unclear how the difference affects the representativeness of our findings for commercial passenger air transport. We also acknowledge that ICAO's distance correction is crude, as the ratio of actual flight distance to great-circle distance depends on multiple factors such as weather, airspace restrictions, or airport congestion. Load factors are calculated based on three levels of granularity, and a fallback option that is the global average. Analysis suggests that the error affects in particular small, remote, or politically isolated territories (Nauru, St. Pierre and Miquelon, Wallis and Futuna, Bhutan, or Greenland), countries where reporting is more limited (China, Russian Federation, India), or specific airlines and airline subsidiaries (e.g., Sichuan Airlines, TUI Airways Ltd., Interglobe Aviation Ltd.). Last, our proposed strategies to increase efficiencies in global aviation will in practice be met with various economic and political challenges. Airlines operate within economic constraints and a business environment shaped by subsidies, limited ambition for climate change mitigation, and expectations of continued growth. Efforts to enhance air transport efficiency will have to be addressed within this multifaceted context.

Data availability

All data is available through the following link: https://github.com/jorgecardleitao/aviation There are no restrictions to data access.

Code availability

The code is available at Klöwer, M. and Leitão, J.C. 2025. jorgecardleitao/aviation: v1.0.0. Zenodo. https://doi.org/10.5281/zenodo.17525494.

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Author contributions
S.G., M.K., A.H., and J.C.L. conceived and designed the study. D.B. and S.H. provided the data and model. M.K., S.H., A.H., J.C.L., and S.G. performed the analysis. S.G. and M.K. wrote the paper.

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Additional information

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Correspondence and requests for materials should be addressed to Stefan Gössling.

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