Carbon Footprints and Financial Performance of Transport Infrastructures: the Case of Airports

Transition risk assessment using traffic and geospatial data

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Executive Summary

Carbon emissions and the so-called "transition risks" they create is a concern from an investment standpoint. Investors in infrastructure and their regulators require better data to understand the implications of climate risks for assets that are highly connected to climate change.

In this paper, we develop a methodology to estimate the carbon footprint of thousands of airport infrastructures around the world and test for the existence of a relationship between carbon emissions and realised or expected returns in the private airport investment sector.

Not all airports emissions are equal

Company emissions can be broken down into several types defined by the GHG Protocol: Scope 1 emissions are direct emissions from combustion of fossil fuels; Scope 2 emissions, the indirect emissions from purchase of electricity, heat and cooling; and Scope 3 the indirect emissions from upstream and downstream activities.

In the case of infrastructure companies, while some investors have started reporting their scope 1 and 2 emission, data remains scarce and difficult to use for benchmarking or analytical purposes. Meanwhile, almost no one reports scope 3 emissions and methods vary when they do.

We propose a consistent methodology to assess the scopes 1, 2 and 3 of infrastructure companies (in this case Airports) and implement it for several thousands entities around the world. We use detailed geospatial and traffic data to predict scope 1 and 2 emissions for several thousands airports across the globe. We also derive scope 3 emissions from highly granular cruise, landing and take-off (LTO) data for more than 8,000 airports globally. We find that cruise emissions dominate LTO emission by almost an order of magnitude for the largest airports, showing the relevance of reporting this source of emissions to provide a better estimate of transition risks exposure to investors.

We show that the results are robust and allow computing a carbon-intensity metric: grams of CO2 per passenger/kilometre (gCO2/pkm) that provides a powerful benchmark to compare individual airports.

Is there a carbon factor in infrastructure equity returns?

We then analyse the link between carbon emissions and financial performance: we build a so-called factor replicating portfolio of high minus low carbon intensity using monthly price return data for private airports provided by infraMetrics® and attempt to determine whether this potential 'factor' has predictive power in terms of airports equity returns.

We show that whether we take Scopes 1&2 or Scope 3 into account, the carbon intensity of airports is not a significant determinant of their realised financial performance once traditional pricing factors such as size or profit have been taken into account. We also find that expected returns are not driven by the different degrees of carbon intensity whether they are measured in terms of Scopes 1 and 2 or Scope 3.

We conclude that transition risk, as proxied by the carbon intensity of airports, is not integrated in asset prices today.

1. Introduction

In this paper, we develop a methodology to estimate the carbon footprint of airport infrastructure around the world (scopes 1, 2 and 3) and test for the existence of a relationship between carbon emissions and realised or expected returns in the private airport investment sector.

In what follows, we consider why the issue of carbon emissions and the so-called "transition risks" they create is a concern from an investment standpoint and the relevance of this issue in the case of airport infrastructure.

Transition risks are defined by the G20's Task Force on Climate-related Financial Disclosure (TCFD) as the combination of policy and legal, technology, market, and reputation risks to which companies are exposed due to climate change. These risks relate either directly or indirectly to carbon and other greenhouse gases (GHG) emissions, and stand at the center of new regulations developed by major institutions such as the Securities and Exchange Commission (SEC), the European Sustainability Reporting Standards (ESRS), or the International Sustainability Standards Board (ISSB).

Company emissions, namely their carbon footprint, can be broken down into several types defined by the GHG Protocol. These are called Scope 1: the direct emissions from combustion of fossil fuels; Scope 2: the indirect emissions from purchase of electricity, heat and cooling; and Scope 3: the indirect emissions from upstream and downstream activities. These different sources of emissions are reported by companies in sustainability reports and their estimate allows the assessment of the short-term exposure to transition risks.

Airports, the infrastructures supporting air transports and classified as IC601010 under EDHECinfra's Taxonomy (TICCS®), have seen a fast increase in activities over the last few decades. Overall, the aviation sector is responsible for around 2.5% of global CO_2 emissions. Airports' activities, highly regulated and homogeneous across countries thanks to their international nature, are now seriously exposed to transition risks. The Airports Council International (ACI) and International Civil Aviation Organization (ICAO) have already expressed their intentions to transform airport activities and reach a net-zero model by 2050. However, most of the forty thousand and more airports in activity in the world remain far from the objective.

In this context of opportunities and risks, infrastructure investors are increasingly aware and concerned with the necessity of assessing the carbon footprint of their owned assets, including airports, and to take into consideration carbon emissions in their decisions. Nevertheless, the current ESG data available to investors is insufficient to satisfy this demand. For this reason, a global estimate of airports emissions, with a uniform treatment of data and highest possible accuracy, is of real interest in order to compare the value of these assets, understand their risk exposure, and decarbonize portfolios. The goal of this publication is to present a methodology that responds to this demand and estimates emission metrics for airports with a global coverage, showing accurate and robust predictions, and easily applicable to other infrastructure sectors. The year of focus is 2019, as it represents a normal ("pre-covid") year of activity, but can be translated to any recent years where data is available.

We first present models for scope 1 and 2 emissions of airports based on a variety of factors suggested by the literature. These include airport characteristics, operations and climate data, and they serve as independent variables for a linear regression of reported emissions. Several steps are carried out to select the best combination of explanatory variables. Once models are trained, they are used to establish predictions on non-reporting airports with the same set of independent variables, thus filling the void of currently unavailable data.

The model for scope 1 emissions shows promising results, explaining about half the variability observed in reported data. We find that the most relevant factors are temperature variations and airport geolocated characteristics such as the size of the aerodrome and terminals. The predictions also appear consistent with what we would expect for smaller airports. A similar model is employed for scope 2 emissions, but shows less predictability. Despite this fact, the explanatory variables appear to make sense, showing in particular the importance of airport terminal characteristics as well as number of passengers. Finally, a model of scope 1+2 is derived as well and shows results complementary to the two others.

Based on these models, we are able to predict scope 1 emissions for more than 3,000 airports, scope 2 emissions and scope 1+2 emissions for more than 1,700 airports across the globe. These predictions are discussed in details and prove their relevance from the insight that they already provide on airport activities and emissions. They also allow the derivation of intensity metrics of potential interest regarding future regulatory frameworks and investment decisions.

In a second part of the publication, we present models developed for scope 3 emissions. We consider two dominant sources of emissions coming from aircraft cruises (distance-based model), plus the landing and take-off (LTO) cycle (time-based model) which is the mainly reported source of scope 3. The models differ from scope 1 and 2 models in many ways. Indeed, contrary to the statistical approach of regression against reported data, the method employed here is predictive in its design. Several reasons justify this difference. First, less airports report scope 3 emissions than scope 1 and 2, second, precise data on air traffic can easily be found.

We obtain scope 3 emissions from cruise and LTO for more than 8,000 airports globally. We find that cruise emissions dominate LTO emission by almost an order of magnitude for the largest airports, showing the relevance of reporting this source of emissions to provide a better estimate of transition risks exposure to investors. Several metrics are derived and it is easy to see that these models can be employed for a large variety of applications towards sustainable investments. Despite the lack of data to assess the quality of the predictions accurately, the results of the models appear to show very promising levels of reliability.

With carbon disclosures and alternative data taking a growing role in investors' decisions, these types of models are of increasing relevance for assessing the sustainability of assets and their exposure to different types of risks, including transition risks. Due to the current lack of regulations, though numerous indications show that they will soon be enforced, it is still a challenge to know which metric would turn out to be the most relevant for investors. In addition, data is still lacking, and this explains the current limitations in modelling, as illustrated by our scope 2 emissions model.

Nevertheless, the growth in data access and increase in data accuracy gives high confidence in the establishment of even more precise models and accurate predictions. Our generated predictions for scope 1, 2 and 3 emissions far exceed the current available data on airport emissions, and this study constitute a proof of the numerous benefits that large datasets can bring for the evaluation of companies and assets, their use in sustainability assessment, and the ability to better inform investors in their decisions.

Finally, we analyse the link between carbon emissions and financial performance: we build a so-called factor replicating portfolio of high minus low carbon intensity using monthly price return data and attempt to determine whether this 'factor' has predictive power in terms of airports equity returns.

We show that whether we take Scopes 1&2 or Scope 3 into account, the carbon intensity of airports is not a significant determinant of their realised financial performance once traditional pricing factors such as size or profit have been taken into account.

We also find that expected returns are not driven by the different degrees of carbon intensity whether they are measured in terms of Scopes 1&2 or Scope 3. We conclude that transition risk, as proxied by the carbon intensity of airports, is not integrated in asset prices today.

The rest of this publication will address the topic of airports emissions as follows. In Chap. 3 the data processing and regression models for scope 1 and 2 emissions are described in details. Chap. 4 describes the models for scope 3 emissions, following a similar structure in the description but with a fundamentally different type of modelling involved. In Chap. 5, results of analysis are presented and discussed in great details, presenting results for scope 1, 2 and 3 models, interpreting and confronting their predictions. Chap. 6 then analyses the relationship between realised and expected returns in private airports and their level of emissions. Chap. 7 concludes.

2. Transition Risks and Transport Infrastructures

2.1 Transition risks evaluation for infrastructure investors

The most recent report from the Intergovernmental Panel on Climate Change (IPCC) addressed the current and future impacts of climate change and considered possible adaptation measures to avoid losses on natural and human systems. The current level of global warming is around 1°C above pre-industrial period (1880-1900), and projections suggest that a 1.5°C warming could be reached before 2040. The IPCC warns that a warming higher than this level would *"cause unavoidable increases in multiple climate hazards and present multiple risks to ecosystems and humans"*, and limiting these emissions to that level would *"substantially reduce projected losses and damages related to climate change"* (Cf. Pörtner et al. (2022); Reisinger et al. (2020)). The IPCC's last report mentions concerns regarding infrastructures multiple times. For this reason, and others developed in this section, reduction of emissions is very likely to take a growing importance in infrastructure investors' decisions.

2.1.1 Defining transition risks, carbon footprint and scope emissions

Transition risks, or more precisely climate-related transition risks, are given a precise definition from the G20's Task Force on Climate-related Financial Disclosures (TCFD). According to TCFD (2021, 2017), transition risks are made up of 4 components:

- **Policy and Legal risk:** relates to litigation risk and the emergence of new regulations put in place to tackle climate change.
- **Technology risk:** relates to new technologies and innovations necessary for reducing carbon emissions.
- **Market risk:** relates to shifts in supply and demand curves due to changes in activities in relation with climate change.
- **Reputation risk:** relates to the public sentiment towards a brand value from climate change considerations.

The 2° Investing Initiative (Cf. Thomä et al. (2020)) defines a simpler and unique transition risk as the *"financial risk associated with the transition to a lower economy"*, but accounts for similar components in its description of relevant modelling parameters. Consequently, one can see transition risks as a set of risks emerging from exposure to climate change, as seen through the prism of several socio-economic and financial actors.

How can we measure such risks? The assumption employed in this work is that transition risks are directly represented by GHG emission metrics such as levels of emissions in tons of CO_2 equivalent (tCO_2e), namely the carbon footprint of assets owned by companies. This carbon footprint can be assessed through direct and indirect emissions measured at a certain frequency (e.g. yearly); intensity metrics representing emissions relative to certain amounts of goods, services, or operational characteristics; and their evolution or projections over time. This assumption makes intuitive sense given the components of transition risks presented above, and is supported by literature. Indeed, this approach is taken by Bolton and Kacperczyk (2021b,a) where it is shown that the carbon risk premium of listed companies relate primarily to levels of emissions as a reflection of long-term exposure to transition risks. Monasterolo and de Angelis (2020) shows that investors have started to integrate carbon emissions in their considerations after the Paris Agreement at COP21 in 2015, but Reboredo and Ugolini (2022) states that transition risks have only been partially integrated in market prices. These studies, among numerous others, confirm that carbon footprints and their time evolution play a significant role in the assessment of transition risks. However, and as described in Thomä et al. (2020), transition risk scenarios and their associated models must rely on a much larger set of metrics reflecting the complexity and uncertainties related to future policies, markets, new technologies and macro-economic trends. In this sense, the use of carbon footprints is a highly reliable but narrow assessment of short-term transition risk, as opposed to lower-accuracy but broad long-term projection models.

Following this definition, we understand that measuring GHG emissions is of primary importance in order to evaluate the associated carbon footprints. Following the GHG Protocol Corporate Standard (Cf. WBCSD (2004)), it is common to categorise emissions in 3 different scopes:

- **Scope 1**: direct emissions, including emissions from facilities and vehicles (usually from the combustion of fossil energies);
- **Scope 2**: indirect emissions from purchased electricity, steam, heating or cooling, ventilation and lighting;
- **Scope 3**: indirect emissions from other sources, including upstream and downstream activities (e.g. purchased goods and services, transportation and distribution, employees commute, generated waste, etc.).

The GHG Protocol focuses on 7 types of GHGs, and these GHGs are usually emitted in smaller quantities than CO_2. However, their global warming potential (GWP) [1] is much higher. These gases are the following:

- **CO_2:** carbon dioxide (GWP = 1 by definition),
- **CH_4:** methane (GWP $\simeq$ 28),
- **N_2O:** nitrous oxide (GWP $\simeq$ 265),
- **HFCs:** hydro-fluorocarbons (GWP $\simeq$ 4-12,400),
- **PCFs:** per-fluorocarbons (GWP $\simeq$ 6,630-11,100),
- **NF_3:** nitrogen trifluoride (GWP $\simeq$ 16,100),
- **SF_6:** hexa-fluoride (GWP $\simeq$ 23,500).

(Source of GWP values: IPCC, AR5). Water vapour is also emitted in addition to these gases, e.g. when an aircraft generates contrails and clouds, but the GWP of water vapour is low considering its short lifetime into the atmosphere. In general, all the different impacts of GHGs are gathered together by the use of GWP in order to report their impact under the same unit, so-called CO_2-equivalent (CO_2e) emissions.

As illustrated in Fig. 1, the general functioning of infrastructures can be described through a physical approach. Indeed, an infrastructure can in general be seen as a set of geo-located physical assets which operate individually or in association, transforming primary resources through specific operations in order to provide goods or services to human users and which, by this process, generate certain amounts of wastes. It is precisely this generation of wastes that exposes infrastructures to sustainability-related risks, and since no system is perfect all infrastructures possess some level of exposure. Nevertheless, different natures of wastes often leads to difficult comparisons. As an example, nuclear energy production emits very low amounts of carbon during operations, but the generation of nuclear

1 - The GWP corresponds to the amount of energy absorbed by 1 ton of a gas over a period of time, usually taken as 100 years, relative to the same evaluation for CO_2. GWP is a function of radiative efficiency and lifetime in the atmosphere. See e.g. IPPC for more details.

wastes is often a major source of safety concerns.

2.1.2 Current and future regulations

In order to limit future emissions and mitigate climate related risks on societies and economies, institutions around the world are putting in place new regulations and setting new reporting standards. These standards belong to the general concept of Environmental, Social and corporate Governance (ESG) which is increasingly more relevant to businesses and investors. Consequently, the regulations are evolving in parallel to numerous ESG schemes intended to provide ratings of companies, including the coverage of infrastructure assets as described in Blanc-Brude and Manocha (2021). The regulations and ESG schemes are still actively developed and are expected to converge with time as knowledge in the field increases. Despite the need for more consistency, it is the amount of research and data being produced which testifies about the current rapid developments in the ESG landscape.

The TCFD standards, already mentioned above and established in 2017, have for example been used as a reference for disclosure regulation in the UK[2]. As another example, the Securities and Exchange Commission (SEC) recently proposed a set of rules for climate-related risks disclosure in the reports of registered companies, including estimates of GHG emissions and climate-related financial metrics (Cf. Securities and Commission (2022)). Similarly, the European Financial Reporting Advisory Group (EFRAG) has developed the European Sustainability Reporting Standards (ESRS) (Cf. PTF-ESRS (2022)). At roughly the same time, the International Sustainability Standards Board (ISSB) published the IFRS's Sustainability Disclosure Standard (Cf. (ISSB) (2022a)). Though still in construction, these standards are undoubtedly going to advance the amount of disclosure in place, improve the reliability of reported data, and improve the convergence towards more consistency in reporting (Cf. also Persefoni (2022)).

In parallel with better reporting standards, governments are implementing actions to decarbonize their economies. One method that appears to be efficient for this goal is carbon pricing, either through emission trading systems (ETS), or through carbon taxes[3]. With ETSs, the total amount of emissions is fixed and businesses emitting more than their allowed permits have to buy extra permits from low emitters, creating a market of emissions and effectively making a fluctuating carbon price. With carbon taxes, governments fix the price of carbon emissions and give an incentive for companies to reduce their emissions in order to pay less taxes. These two approaches in carbon reduction are under consideration in multiple countries4 and their impact on the long run will directly depend on the price of carbon they create. However, these implementations and the associated risks for large emitters are likely to grow.

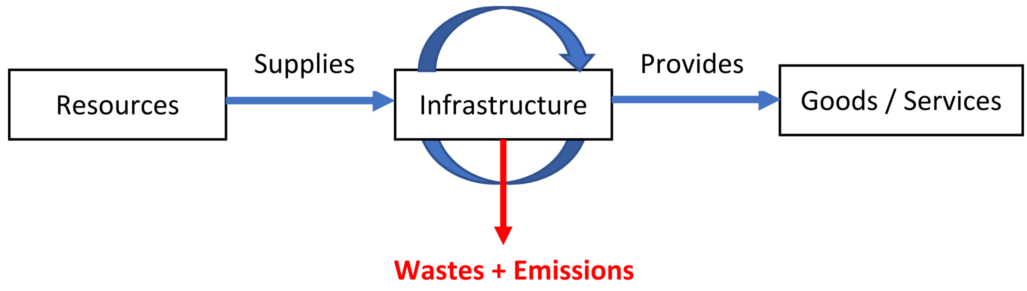
As described by TCFD (Cf. TCFD Board et al. (2017)), climate change is not only a source of risk, but also of opportunities for companies. These opportunities include a better management of resources across production and distribution of goods and services, reducing costs and increasing production. It also includes the development and usage of superior technologies, as well as cleaner sources of energy, reducing exposure to fossil fuel prices and improving their reputation. Opportunities aiming at attracting new customers and new markets will develop as consumers and infrastructure users shift their preferences due to climate change considerations, increasing their revenues. These adaptation measures can be a motivation for businesses to improve

2 - FT.com

3 - c2es

4 - World Bank

Figure 1: Physical description of an infrastructure



resilience and evolve towards new future demands.

2.1.3 ESG and investors preferences

Since ESG regulations are still in development, the main driver of interest from investors towards ESG data relates to risk management. Numerous investors have growing concerns towards the impact of companies and assets on climate change, and the "double-materiality" aspect of their activities implies that non-material factors today (such as carbon emissions), could become material in the future (either through regulations or environmental factors impacting activities and revenues). In this context, carbon footprints are primordial to consider due to their direct link with global warming. This necessity of risk management is also becoming material at the portfolio level through frameworks like the Paris Aligned Investment Initiative (PAII) and the Net-Zero Asset Owner Alliance (NZAOA), as described in Ducoulombier (2022).

In addition, other types of risks related to ESG issues matter to investors (Cf. Blanc-Brude et al. (2022)). This is the case of physical risks which cover different types of hazards such as storms, floods, droughts, wild fires, extreme temperatures, earthquakes, etc. Some of these hazards, seen either as chronic or acute risks, have a strong dependence on global warming and could significantly impact business activities as well as cause physical damage to assets, with potential losses involving repair, adaptation, lifespan, or insurance premium.

Furthermore, businesses undeniably value their reputation. As certain as it is that climate change will have an impact on businesses, it will also have an impact on societies. Hence, it is fair to say that social acceptability risks will also play a role in investors' future considerations of transition risks, with a growing number of citizen asking for companies and infrastructures to improve on their emissions. These potential social concerns will, in return, be accompanied by new regulations as well as potential litigations, increasing the pressure not only to do well, but also to do good for the planet.

2.2 Transports infrastructures, the case of airports

We will briefly present airports in this section, providing a short description of their structure. One should keep in mind that airports come in multiple sizes and shapes, with the largest airports employing several tenth of thousands people and serving tenth of millions passengers per year, while the smallest ones can employ as little as few dozens of people and serve only a few thousands of passengers a year.

2.2.1 TICCS taxonomy and transports

As any other infrastructure, airports are classified under the TICCS taxonomy (Cf. Documentation (2022)). They fall under the Industrial Asset Subclass code IC601010, and they belong to airport companies (Industrial Class code IC6010), itself belonging to the Industrial Superclass of Transport (code IC60). Other classes in this superclass include Car Park Companies (IC6020), Port Companies (IC6030), Road Companies (IC6040) and Urban Commuter Companies (IC6060). Airport companies are often the owners of a single airport which they operate. However, there exists also a significant number of airport companies owning, in part or fully, a larger number of airports.

In 2020, although significantly impacted by the Covid-19 pandemic, aviation still represented about 8% of global emissions from transports5. Hence, the aviation sector amounts for about one tenth of transport emissions, while the transport sector represented about 7.2 Gt CO2 in 2020 (falling by 10% from the previous year, due to Covid)6. When taking the main GHGs into account, the transport sector represents more than 15% of global emissions, making the contribution of aviation around 2.5% of the total globally, closely followed by shipping, but smaller than road transport of passengers and freight (about 6 times larger than the airport contribution).

2.2.2 Airports structure and operations

As airports constitute the infrastructure connecting aircraft vehicles with their passengers (or cargo) to provide air transport services, their structure is mainly determined by this mandate. Airports are thus made of an aerodrome on which is built one or several runways for aircraft fleets to land and take-off. Aircraft are parked at aprons and connect to the runways through taxiways. Aprons are usually situated close to airport terminals to easily board or disembark passengers. Airport terminal buildings welcome passengers and offer a space to operate the necessary security checks, baggage handling and waiting. Airports operate on tight schedules, so airport terminals need to be of an important size to provide services to a large number of users. Since airports are usually located at a distance far enough from cities to afford their large land usage while close enough to remain attractive to passengers, they also have infrastructures for users to reach them, including often bus stations, train stations as well as road accesses and parking lots.

The airport operations are thus shaped by their two main actors: airline companies and passengers. The first actor requires airports to handle aircraft schedules properly, guiding aircraft during their approach until they reach the arrival gate, and equivalent procedures for take-off. They also provide all the necessary support such as fire fighters, accompanying passengers, loading and unloading freight, deicing, or dealing with rough climate conditions. On the passenger side, airports operate the terminal building and numerous other buildings related to passengers access as well as necessary activities such as waste management, heat production and in some cases on-site energy production. Let us add that passenger activities represented about 80% of airport activities in 2018, hence cargo operations only remained close to 20%.

2.2.3 Regulations, initiatives and reported metrics

The IFRS's Sustainability Disclosure Standard (Cf. (ISSB) (2022a)) contains a selection of industry-based disclosure requirements in its Volume B, which include Infrastructure as well as Transportation categories. In the transportation category are present both *"Air Freight & Logistics"* (Cf. (ISSB) (2022b)) and *"Airlines"* (Cf. (ISSB) (2022c)) which are closely associated to airport activities. This first document requires air freight companies to report scope 1 emissions, fuel consumption as well as the intensity metric of revenue ton kilometers (RTK). The second document for airlines requires the reporting of identical metrics, as well as additional metrics: available seat kilometers (ASK), passenger load factor, and revenue

5 - Statista
6 - IEA

passenger kilometers (RPK), average age of fleet and number of departures. Hence, noticing the closeness with airport activities, one can argue that these standards may also define precise metrics for airports in a near future.

Despite the lack of regulatory framework on sustainability disclosure of airports, numerous actors among them have already taken the lead towards carbon transition. Indeed, on June 2021 the Airports Council International (ACI), which defines standards and policies for airports as well as represents nearly 2,000 of them around the globe, has pledged that its member airports commit to reach net zero carbon emissions by 2050[7], and published a plan to show the feasibility of this goal (Cf. ACI (2021)). Furthermore, the Airport Carbon Accreditation (ACA), created by ACI EUROPE in 2009, accompanies more than 400 airports in this transition through 6 level of certification, with probably more soon to join the program. Similar pathways have been acknowledged by the International Air Transport Association[8], and the International Civil Aviation Organization (ICAO) has defined the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) [9].

In addition to the initiatives of airport groups, individual airports have also taken preventive measures to protect themselves from transition risks. As an example, Sydney Airport (SYD) has published regular responses to TCFD (Cf. e.g. Sydney Airport Limited (2021)), defining its carbon reduction and physical risk mitigation strategies, and committed to net zero emissions (scope 1 and 2) by 2030. The Groupe ADP, owner of Charles De Gaulle (CDG) airport and others, has committed to carbon neutrality by 2030[10]. In addition to official commitments, airports also show growing efforts in reporting their emissions with great details. As an example, one can cite Heathrow Airport (LHR) which, to the authors' knowledge, is the first one to report departing cruise emissions in its scope 3 inventory of carbon emissions. These examples, among numerous others, show the intention of the airport sector to tackle emissions and build more efficient and resilient infrastructures.

7 - ACI
8 - IATA
9 - ICAO
10 - Paris Airport

2.3 Size of emissions, metrics and limitations of data

Despite the ambitions of numerous airports to assess their emissions and reach a lower level of pollution, the large number of airports in activity around the globe (estimated at more than 41,000) unavoidably makes their total contribution to global warming non negligible and likely to grow even further.

2.3.1 Airport emissions

In 2019, the global emissions of the aviation sector reached an estimated 920 million tons of CO2 (Mt CO_2)[11], with a global passenger count of 4.56 billion. In 2018, the aviation contribution was about 2.5% of the total 36.7 billion tons of emitted CO_2 that year[12], and estimates including the effect of contrails and other GHGs indicate a contribution of about 3.5% to global warming (Cf. Lee et al. (2021)). It is estimated that there is around 1,500 airlines operating a fleet of more than 33,000 commercial aircraft to service the most important airports. As a consequence, the aviation sector represents nearly 10% of transport emissions globally.

Among the different countries where passenger employ air transports the most are the United States (179 Mt CO_2, 23% of airports emissions), the European Union (152 Mt CO_2, 19%) and China (103 Mt CO_2, 13%)[13]. The use of air transport correlates

11 - EESI
12 - Statista
13 - ICCT

with consumer habits, with large countries more likely to develop domestic air traffic. Their level of economic development is also an important component. For example, China currently has about 250 civil airports while the U.S. has close to 20,000, with around 5,000 public airports, but China's passenger market is rapidly growing and predicted to outperform the U.S. around 2030[14]. As for the breakdown of commercial operations, the bulk of it comes from passenger travels (80-85% depending on estimates) and the rest (15-20%) being represented by freight.

The aviation sector has invested a lot of efforts to reduce the amount of emissions per passenger over the last decades. On average, it is estimated that in 2019 aviation emitted about 90 grams of CO_2 per passenger-kilometer (pkm). Obviously, this number significantly increases for premium class passengers, where it can exceed 350 grams CO_2 pkm. It also varies depending on types of aircraft, engine, employed fuel, seat configurations and occupancy of aircraft (for which the global average is around 83%). The steady increase of commercial aviation emissions over the last decades[15], only recently put on hold because of the Covid-19 pandemic, thus appears to be driven by a high user demand that reduction of emissions per passenger have not been able to compensate.

Despite the low number of airports publicly reporting their emissions, an analysis of their sustainability reports and Corporate Social Responsibility (CSR) reports allows a certain level of understanding of airports' main sources of emissions. Scope 1 and 2 emissions are reported in a more consistent manner than scope 3, and this relates to their better coverage in terms of guidance and regulatory frameworks. As these emissions directly depend on airport activities, they are also easier for airport owners to access, process and report. As for scope 3 emissions, the airport sector still lacks a consensus on which sources to report. Most airports publishing reports take into consideration the emissions from the LTO cycle as well as some emissions related to ground vehicles. Cruise emissions, which are believed to dominate scope 3 emissions, are on the other hand almost never reported.

14 - ACI
15 - Statista

2.3.2 Reported metrics

As mentioned earlier, no regulatory framework at the moment imposes specific metrics to airports in their disclosures. However, one can define metrics that represent accurately the important sources of emissions of airports based on the metrics which are already reported, and metrics which are likely to be imposed by regulators. The most obvious metrics are scope 1 and 2 emissions, as they relate directly to airport emissions and consumption. Scope 3 emissions are also of great significance considering that they are much larger than scope 1 and 2. However, few airports still report these sources of emissions, in part due to their diversity of sources. We should add here that airports generate and monitor numerous kind of pollutants in their vicinity, such as nitrogen dioxide (NO_2), carbon monoxide (CO), nitric oxide (NO), particular matter such as $PM_{2.5}$ and black carbon, or ultra fine particles. One can thus think of having metrics for each type of GHG.

As for intensity metrics, one can think of different quantities based on airport operations. An example is to assess airports from their emissions relative to their revenues to account for their profits, or with respect to their number of passengers (pax) or passenger-kilometer (pkm) to evaluate their efficiency in terms of services. Another similar quantity can be the estimate of emissions per number of flights in order to test the capacity of airports. Finally, some metrics specific to the source of emissions can be derived, in scope 1 and scope 2, with scope

2 distinguishing already from location-based and market-based estimates, as well as scope 3 for which even more sources can be tested.

2.3.3 ESG data providers and limitations

Due to their private ownership nature, infrastructure assets and their operating companies often lack a good coverage on data. This fact applies to airports as well. As a consequence, only few data vendors provide ESG data on airports, and the number of assets under consideration is in the order of tenth. The current availability of data is thus unsatisfactory when it comes to building systematic studies. As an example, leaders in ESG data such as the Carbon Disclosure Project (CDG)[16], Sustainalytics[17] or Arabesque[18] put together seem to provide data on less than 30 individual airports and contain about 13 airport groups representing around 240 airports. However, most of these airports within groups do not disclose their individual emissions, which makes them unexploitable. In fact, the limitation of ESG data is not only affecting infrastructure companies, but numerous activity sectors (Cf. e.g. Ducoulombier (2021)).

We will show in this publication that models of emissions can be established based on substantial efforts to retrieve more data from reporting airports, and providing enough confidence to use these models on a larger set of assets. This approach not only improves the understanding of factors influencing airport emissions, but also opens the door to the prediction of emissions on a large amount of non-reporting assets. Hence, this approach shifts the perspective from small-data to big-data analysis, and it is likely to have an impact on how investors will make their investment decisions in a context where comparison of assets with respect to each other becomes available.

16 - CDP
17 - Sustainalytics
18 - Arabesque

As always the case when designing models, the right level of precision needs to be assessed based on the availability of data, its granularity, limiting assumptions and the desired level of description. For example, it is inefficient and time-consuming to develop a detailed description of some features in a model when limiting factors impose an over-simplification in another component of that model. Similarly, and because airports possess numerous intrinsic differences (such as those emerging from their design, their countries, the decisions of their operators, etc.), there exists a trade-off between the global reach of a model and its precision. As will later be shown, this trade-off exists in the academic literature as well, with authors e.g. studying a small number of airport terminals or cruise flights in great details, or a larger number of them with possibly larger deviations on individual cases.

Having mentioned these trade-offs, it is important to mention that our approach intends to be global in order to tackle the problem of low statistics. Hence, this design choice enforces a lower level of accuracy unless more data becomes available, implying also potential deviations between predictions and reality for some individual cases. This will be true for scope 1 and 2 modes, where for example the inaccuracy of terminals data may lead to large variations for certain airports, and for scope 3 emissions where a given flight may have characteristics deviating significantly from our estimate. However, if the models are not biased one should expect the errors to cancel out when aggregating predictions (e.g. by adding emission of a large number of flights).

In addition, let us also mention that several GHGs can be modelled to describe the total emissions of airports. However, this complexity also has a cost to consider. Since the effects of GHGs other than CO_2 mostly come from cruise emissions and are difficult to predict (Cf. Penner et al. (1999)), we have neglected the presence of other GHGs than CO_2 in our scope 3 models. As for scope 1 and 2, multiple GHGs are indirectly included from the fact that reported emissions of airports used in our model dataset are consistently expressed in CO_2-equivalent units. Hence, when mentioning CO_2 in our scope 1 and 2 models, one should in fact understand that it is CO_2-equivalent emissions which are being considered.

3. Modelling scope 1 and 2 emissions

This section is devoted to the modelling of scope 1 and scope 2 emissions of airport infrastructures. Scope 1 emissions are composed of direct emissions from mobile combustion, fugitive and process emissions. As for scope 2, they are made of indirect emissions from purchased electricity, steam, heat and cooling. Due to the commonality of sources composing scope 1 and scope 2 emissions, it is expected that the method described here will translate to other types of infrastructures as well, with possible variations in the quality of predictions depending on the predictability of the regressors at play.

3.1 Literature review and approach

The airport sector is not exempt of research studies addressing its emissions, and these studies bring an important support when it comes to evaluate scope 1 and 2 emissions.

3.1.1 Airport operations

Airports are infrastructures providing air transport services around the globe. From their nature, most operations at airports directly or indirectly relate to the provision of this service to users. Hence runways, taxiways, aprons and control towers make the landing and take-off of aircraft possible. On the other hand, access services, parking lots, water/waste management systems and terminal buildings provide services to users before and after their flights. Since an aircraft require strict safety measures and numerous support operations (refueling, deicing, loading passengers and cargo, etc.), and because of the international nature of this transportation mean, airports of similar capacity share common features both in size, physical characteristics as well as operations.

As the rest of the transport sector, the operations at airports rely heavily on fossil fuels combustion. We can distinguish 4 types of combustion:

- stationary combustion which uses natural gas, liquefied petroleum gas (LPG), oil or coal, to serve in boilers and furnaces providing heat for buildings;
- mobile combustion where petrol and diesel is used to operate cars and trucks;
- fugitive emissions which come from leaks in GHGs such as refrigerant gases;
- process emissions related to the production of cement and construction in general.

The different sources of direct emissions mentioned above compose scope 1 emissions and take place at airports through the use of heavy heating, ventilation and air conditioning (HVAC) systems, operated vehicles such as ground support equipment[1] (when owned by the airport), and the use of refrigerants. As some of these operations are gradually transitioned from fuel-based to electricity-based systems and vehicles, these direct emissions are likely to decrease (depending on airport policies) and be partially transferred into scope 2 emissions.

3.1.2 Airport terminals

Airport terminals are known to be some of the most energy-intensive buildings in the world (Cf. e.g. Ahn and Cho (2015)), especially due to the enormous volumes of air for which temperature needs to be accurately controlled. They also represent a significant part of the electric consumption of airports, sometimes reaching up to 80% of the airport consumption (Cf. e.g. Ortega Alba and Manana (2016)). But airport terminals have benefited from a good attention in

1 - The Points Guy

academic literature, with several in-depth studies analysing their consumption, and hence giving useful guidelines to estimate their consumption.

Some studies on airport terminal buildings (ATBs) focus on single terminals with high-frequency and detailed monitoring of consumption. For example, Kang et al. (2017) shows the importance of time of the day or week and outside temperature to predict terminal consumption, but it does not see a strong correlation with the number of flights. Xianliang et al. (2021), on the other hand, finds that the energy consumption of Nanning Airport Terminal 2 mainly depends on passenger flow, meteorological parameters and supply fan frequency.

Other authors take a statistical approach to the problem by studying several terminals and regressing their consumption against numerous parameters. This is the case of Ahn and Cho (2015); Kim et al. (2020) where 20 ATBs in the United States are considered, with a breakdown of terminals areas, enplanement, days of cooling and heating, etc. Li et al. (2017) studies the energy consumption of ATBs in China, considering the influence of local climates and revealing the importance of heating days against cooling days as the temperature variation to produce during winters is higher than the one to produce in summers.

These studies, among many others (cf. e.g the general guide of World Resources Institute and Team (2013)), all suggest natural variables to understand the electric consumption of terminals, and thus sources of scope 2 emissions. It also explains part of scope 1 emissions when fossil fuels are used at terminals. Hence the literature allows us to think that potentially relevant parameters include the dimensions of terminal buildings, the age of facilities, climate conditions and well as significant operational parameters.

3.1.3 Proposed methodology

Based on the literature described above, the method proposed is to estimate scope 1 and 2 emissions as a regression of several factors relating to airport characteristics, operations, consumption and local climates. Hence, the collected data falls into similar categories and is combined with scope 1 and 2 emissions of airports to train a model. The reported values for these scopes, i.e. the dependent variables, are found in sustainability reports of numerous airports, many of which are taking part in the Airport Carbon Accreditation (ACA) program (Cf. ACA (2021)). Once the best model is found from this training (and the best regressors are identified), it is then used to predict emissions on a much larger dataset on which the same explanatory variables have been collected. Again, these variables are composed of:

- airport physical characteristics (e.g. terminals area),
- airport operations (e.g. passenger data),
- data on closely located power plants,
- local climate data (e.g. temperature).

Other geolocation data such as latitude and longitude or categorical variables such as the countries where airports are located can be added to the above. Nevertheless, we assume that airports scope 1 and 2 emissions do not primarily depend on the country where they are located as we are interested in their intrinsic characteristics. Official types of airports is another categorical variable that could be considered as well, but we will use it instead as a validation parameter when displaying our results.

The data employed is the present work is based on year 2019, but other years can be covered in a similar way. However, due to the Covid 19 pandemic, airport activities have been significantly reduced in years 2020 and 2021, and for that reason these 2 years are not appropriately adapted for such an estimate. Indeed, not only airports were impacted differently by the pandemic based on local sanitary measures as well as political choices, they were also affected by other airports they had operations with (cascading impact) as well as individual choices of maintaining or interrupting their activities. This complexity of individual choices and the abnormality of the situation can have a significant biasing effect in the predictions, and for that reason is best to avoid to establish the models.

3.2 Data collection

Since the modelling involves a combination of numerous factors, it is important to make a careful analysis of each data sources, proceeding to a careful cleaning on each of them in order to reach a merged dataset with maximum coverage. Indeed, each feature of the dataset that translates into a regressor in the model becomes a limiting feature if improperly cleaned (high percentage of error) or if it has a low coverage (high percentage of missing values). Such a scenario significantly impacts the model training, which relies on a limited number of data points, but also reduces the number of airports for which scope emissions can be estimated.

3.2.1 Data sources

The most important source of data here is the dependent variable, namely scope 1 and 2 emissions collected from sustainability reports. The targeted airports were mainly composed of airports taking part in the Airport Carbon Accreditation (ACA) program (Cf. ACA (2021)). This program includes 395 airports and 6 levels of accreditation[2], for which combined operations amount to about 48% of global air passenger traffic. Unfortunately, most of these reported emissions remain undisclosed. This list was then extended to any other airport for which sustainability reports could be found online.

As it is important to notice, scope 2 emissions are generally reported as location-based or as market-based. Location-based estimates rely on grid-averaged emission factors while market-based estimates reflect the emissions from electricity that emitters have chosen from their contractual purchases[3]. Scope 2 emissions collected from there reports were location-based estimates, as the model intends to understand the real electricity consumption of airport facilities and put aside their compensations through commercial agreements. Other potentially interesting features were extracted, such as scope 3 emissions, numbers of passengers and aircraft movements. The year of focus was 2019 as it can be considered to be a "normal" year (before the Covid pandemic), but other years were also collected. Finally, this data was checked and completed when other sources were found.

Airport characteristics were obtained from OpenStreetMap4 and WikiData5, and required numerous cleaning as well as consistency checks based on geospatial analysis. Most of these characteristics carry a quasi-permanent aspect, i.e. they do not change over time other than a timescale of a decade, hence time considerations are not needed here. Another characteristic of airports is the shape of their terminal buildings. To assess this quantity, we define the shape parameter of a geo-referenced polygon as follows:

$$\text{shape} = 4\pi\frac{A}{p^2},$$

where A stands for the area of a polygon and p for its perimeter. From this definition, a circular building has a shape parameter of 1, and since a circle maximizes the area at constant perimeter this is a maximum value. A square building has a shape of $\pi/4 \simeq 0.78$ while an excessively extended building sees its shape tend to zero. Fig. 2, produced from

2 - Ariport Carbon Accreditation

3 - GHG Protocol

4 - OSM

5 - Wikidata

about 14,000 aerodrome and 7,000 terminals, shows that most aerodromes are rectangular with a median value corresponding to a ratio of 8.8 between the length and width. As for terminals, they can take more diverse shapes, but are almost never too close to a circle. The reason behind this reality can be related to the need to maximize perimeter of buildings since aircraft have a large span that imposes a certain extension, as well as constraints such as simplicity of design with rectangular buildings.

Airport operations were evaluated from a mix of WikiData, such as patronage, and other data sources. A strongly correlated feature that can be considered is aircraft movements, available from traffic data such as OAG data. Some features, like the number of passengers, required more processing than others and were then aggregated into yearly estimates, again focusing on year 2019.

Though most airports buy electricity from their local power grid, a few are producing their own electricity (Cf. e.g. ICAO (2017a)). Assuming a close distance of these power plants to the airport facilities, we can sporadically add the generation capacity of these plants (in 2019) to the regression model and improve scope 2 estimates. The Global Power Plant Database of the World Resources Institute (WRI) was used to accomplish this task.

Indicators of local climates are also believed to be important for scope 1 and 2 estimates. Consequently, a dataset from the European Union's Climate Change Service was extracted, the global dataset being based on the Copernicus Programme6.

3.2.2 Data processing

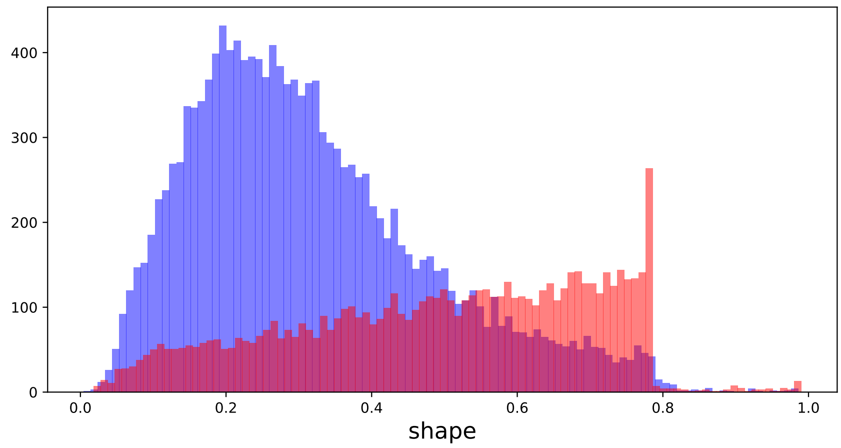
Since the modelling involves multiple data sources, the accurate combination of datasets is of primary importance in order to avoid data losses. When it comes to WikiData, the data is structured and identification features can be used. For airports, the natural identification is the International Air Transport Association (IATA) location identifier, in short "IATA code". Nevertheless, when it comes to geolocated data, label features can be missing and relying on incomplete features can lead to inconvenient losses. Hence, a very useful approach is to use geolocations to combine datasets (such as points closely located to a polygon's boundary or centroid).

Obviously, as accurate and careful the data processing can be done, the final dataset can still contain input errors or intrinsic biases from the lack of better data. For example, traffic data can give an accurate estimate of numbers of flights. However, such a number can be biased when traffic data focusses only on commercial flights, while some airports may have their activities specialised on cargo instead. In such a case, the concerned airport would be an outlier of the model as predictions may not reflect its true emissions. Such biases can be treated and corrected, at least partially and statistically, by using other highly correlated features (e.g. the number of passengers) in order to improve the quality of that data.

At the end of the process, our training dataset based on sustainability reports of year 2019 has 72 observations for which scope 1, 2 or 3 reported values were collected, and for which airports were not part of an airport group on which emissions are collectively reported. On a marginal number of values, some imputation is done to have the highest possible statistics. If questionable regarding a potential bias that it could bring into the modelling, the airport is discarded. This dataset serves as the training set (or rather called here "model dataset") in order to evaluate the best explanatory variables. Once the best fit model is identified, the larger

6 - https://www.copernicus.eu/en

Figure 2: Comparison of aerodrome (blue) and terminal buildings (red) shapes.



dataset holding the identically generated regressors is used for predictions.

Before describing the modelling, we can already notice some important facts from the reported data. Indeed, we can see that scope 2 emissions are in general larger than scope 1, with a ratio scope 2 / scope 1 $= 12.8 \pm 24.7$ (and a median value at 2.7). Furthermore, the two dependent variables have a good correlation, as visible already from the log-plot in Fig. 3. In fact, the Pearson correlation between the two is 0.87, but only 0.25 for their log. This suggests the idea that both scope 1 and scope 2 can be summed up and used in regression as a single dependent variable as well.

The reported data also contains a number of scope 3 emissions, 32 in total. From this data, we see that the correlation between scope 1+2 and scope 3 is only 0.15 (and 0.32 on the logs). This low correlation is a good support for our two different approaches in modelling scope 1 and 2 on the one hand, and scope 3 emissions on the other hand. One should keep in mind though that scope 3 emissions in sustainability reports mainly address the LTO cycle, surface access and other non-collected sources. The correlations between total scope 3 emissions and LTO cycle emissions is around 0.97, and this is justified from the fact that the main part of reported scope 3 emissions comes from the LTO cycle. Between total scope 3 and surface access emissions, the correlation is about 0.57, but this contribution is smaller than the LTO contribution (with a ratio of 0.65 ± 0.89 and a median value of 0.30).

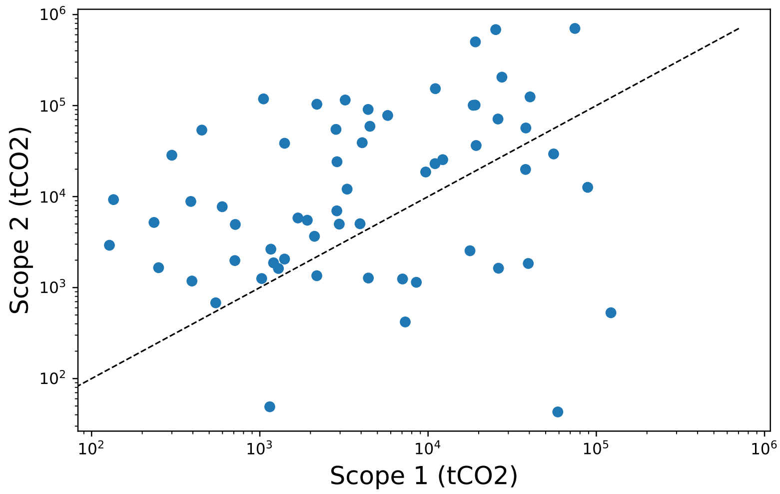
3.3 Regression model

We will now present the regression model and fitting method resulting in the most successful regression of the data. Since airports cover several orders of magnitude in size and as such have characteristics which often take a heavily skewed distribution, we find appropriate to take the log of the dependent variables as well as regressors. This transformation not only reshapes distributions of values closer to normal, they also significantly improve the regressions and facilitate the reading of results in terms of elasticities.

3.3.1 Main model

A regression with all parameters (14 in total) was first carried out for both scope 1, scope 2, and both combined (scope 1+2). As stated above, both regressors and the dependent variables where taken in log values. The obtained results and associated scores are presented in Table 1-I). As expected, the adjusted R^2 value is smaller than R^2, and considering all the available parameters

Figure 3: Scatter plot of scope 1 and scope 2 emissions in the model dataset (log scale). The dotted line represents the Scope 2 = Scope 1 axis.



maximizes the R^2 value without guaranteeing the best available adjusted R^2.

Considering the limited number of observations used in the regression, it is important to use data points of high quality. For that reason, some outliers were discarded, as already mentioned. In addition, it is important to verify that the remaining points have a distribution close to the large dataset values if we want the model to give robust predictions. This check was done and it reveals some differences between the two datasets. In fact, most of the airport characteristics and operations in the training dataset are larger than the bulk of global airports, and this simply relates to the fact that large airports have the capacity and incentive to report and publish their emissions, as opposed to smaller ones. This difference between the datasets is not detrimental to the robustness of predictions if the explanatory variables influence both populations in the same manner.

Finding the best adjusted R^2 is important as it allows to reach the best regression while minimizing the number of explanatory variables. This simplifies the model and reduces the risk of over-fitting, hence guaranteeing better predictions on the large dataset. But reducing the number of regressors carry another advantage. Since the large dataset has missing values that imputation would risk to bias, these values can't be completed. Consequently, the smaller the number of explanatory variables, the larger the number of airports on which a prediction can be made.

We consider all possible combinations of regressors (around 16 thousands), and for each combination we compute the score associated to the fit of data that it allows. Then, out of these generated combinations, the set of regressors corresponding to the top decile of the best adjusted R^2 is evaluated through the average of p-values for each explanatory variable, keeping only the variables of lowest p-values. The model made of these selected variables is then considered our best fit model, and later applied for predictions. The obtained scores can be seen in Table 1-II), and we should remark that here as well as the previous case, the scores are computed "in-sample", i.e. using the same data as employed during training. This choice is justified from the small size of the dataset and will be discussed soon after.

The threshold on p-values to select the best model is decided from the average p-values over the best decile described above. For the scope 1 model, the retained threshold is around 0.22, with some variables having much lower averages. In scope 2 it is reduced to 0.14 as the number of variables turns out to be larger, and for scope 1+2 it is taken as 0.16 as it offers a good separation of explanatory variables. Let us add to the discussion that our focus here is to maintain a good level of explanatory power in the models, while lowering the number of explanatory variables to increase the number of predictions. One could also think of optimizing the prediction dataset by considering only variables with the largest coverage. This choice, however, would result in less explanatory power from the models. Finally, let us recall here that since the models are trained on reported data estimating the CO_2-equivalent emissions of airports, these models are actually predicting the CO_2-equivalent emissions as well, hence partially including the effect of other GHGs as considered by airports in their inventories.

As explained, once these operations are done on the training dataset the model is employed on the large dataset for predictions. The best fit model for scope 1 has 3 explanatory variables and the large dataset covered by these features has 3069 instances for which we are able to obtain predictions. The best fit model for scope 2, on the other hand, has 4 regressors and 1749 airport predictions, the larger number of regressors having reduced the number of airports on which prediction could be made. Scopes 1+2 emissions were predicted with only 2 explanatory variables and reached 4908 airports. Let us note that since the log of a quantity Q has been taken as $\log(1 + Q)$, some predicted values under the regression can fall in the interval $[-1, 0]$. These values, corresponding to very small predictions of emissions, are discarded from the results. In the scope 1 model no such case is found, for the scope 2 model 107 of such cases appear, and only 10 for scope 1+2.

Finally, a K-fold cross validation was done on the model dataset, employing the best fit models of each case ("fixed-formula") as well as varying the set of regressors ("recomputing-best-fit"), this time selecting the best-only regressor based on the adjusted R^2. This validation is necessary in order to test the "in-sample" estimates earlier described. As for the meta-parameters employed here, the number of folds was set to $K = 20$ and for each fold the best fit model was estimated based on 5,000 random combinations of regressors. The estimates of adjusted R^2 scores for the fixed-formula and recomputed-best-fit are reported in Table 1-III). Looking at the values and their standard deviations, we can see that the in-sample estimates of scores were accurate enough, and the reasonably low standard deviation indicates robustness in the models.

3.3.2 Alternative models

Other regressors were added in order to build alternative models. In particular, the countries where airports are located were added in the regression in order to capture possible socio-economic variations. Models were trained after converting the country names through one-hot encoding, improving the fitting scores. Nevertheless, the large number of involved countries already present in the training dataset leads to over-fitting, and hence was not retained.

Another tested approach consisted in applying K-Means clustering on the large dataset in order to assess possible changes in regressors informing on the size of airports, or any other specific nature. Nevertheless, and as some scatter plots will reveal in Chap. 5, the differences between airports appear to be continuous and consequently make the clustering not so successful in splitting the total population in different groups.

Table 1: Summary of scope 1, scope 2 and scope 1+2 regressions

	Scope 1	Scope 2	Scopes 1 + 2
Number of data points	67	64	66
I) All 14 regressors			
R^2 score	0.507	0.319	0.388
Adjusted R^2	0.375	0.125	0.219
II) 16k regressions (combinations of regressors) + top decile regressors			
Number of regressors	3	4	2
R^2 score	0.471	0.261	0.328
Adjusted R^2	0.446	0.211	0.307
III) KFold Cross Validation			
Adjusted R^2 ("fixed-formula")	0.443 ± 0.026	0.214 ± 0.040	0.306 ± 0.021
Adjusted R^2 ("recomputed-best-fit")	0.446 ± 0.021	0.214 ± 0.030	0.306 ± 0.020

4. Modelling scope 3 emissions

After modelling scope 1 and 2 emissions of airports, we are now going to describe the modelling of scope 3 emissions. As these emissions concern indirect emissions not owned by airports, from upstream as well as downstream activities, it is fair to believe that the number of different sources of scope 3 is larger than sources of scope 1 and 2 emissions. A consequence of this multiplicity of sources is the larger variability in the reporting of these sources, going from absence of reporting for some airports, to detailed inventories for others. General information, with partial relevance for airport activities, can be found in Sotos (2015).

4.1 Literature review and approach

It is a priori difficult to know if one or several sources of emissions are dominating scope 3. However, simple reasoning and order of magnitude estimates are enough to get convinced that cruise emissions largely dominate passenger commutes to the airport. Also, emissions during the Landing and Take-Off (LTO) cycle of aircraft, even though performed at higher thrust than during the cruising phase, are not long enough to reach cruise emissions most of the time.

Consequently, and as supported by sustainability reports where the LTO cycle explains $67\% \pm 21\%$ of the total of non-cruise scope 3 emissions (relying on 15 observations), we will neglect any source of scope 3 emissions other than cruise and the LTO cycle. As a next order correction, passengers commute and other surface access emissions should probably be considered (but difficult in practice). Furthermore, since both cruise and LTO emissions directly relate to the performance of aircraft engines, and most of their combustion products being composed of CO_2 ($> 70\%$, with most of the rest in water vapour), we will consider only CO_2 emissions and neglect other possible sources of GHGs coming as products of non-ideal combustion, such as nitrous oxide (NO_2), methane (CH_4), etc.

4.1.1 Cruise emissions

Cruise is usually defined as the period of flight where an aircraft is above 3,000 feet (around 914 meters) of altitude. Obviously, an aircraft can adjust its trajectory and phases of flight are simplifications meant to capture the main picture. Following this description, cruise is made of 3 phases where an aircraft first goes through climbing from 3,000 feet to cruise altitude, cruises on a relatively horizontal trajectory with respect to the ground, and descends from cruise altitude back to 3,000 feet.

In addition, busy airports have put in place zones of aircraft rotations, called stacks, to regulate air traffic and optimize landing frequency. These stacks are separated by 1,000 feet between 8,000 feet and 16,000 feet of altitude and can be located at different localizations (e.g. Heathrow airport has 4 of them). Hence, stack emissions, though strongly related to airport activities, do not take part in the reported scope 3 emissions of airports.

Since cruise emissions are not yet reported by airports, one can argue that the incentive to research on them is less than for LTO emissions. However, and as we will show, cruise emissions are in general dominating aircraft emissions and as such are of primary importance for airline companies. Indeed, airlines are under increasing pressure to reduce their emissions, and a better understanding of these emissions is necessary to improve aircraft efficiency.

Estimates of aircraft emissions can span a vast scope of models, from the most granular description of fuel consumption from aircraft engines in Velásquez-SanMartín et al. (2021), to the most coarse-grained description from national fuel inventories in Rypdal (2000). Other publications on the topic relate to the development of software to compute emissions, such as Wasiuk et al. (2015) (based on aircraft schedules), or the use of altitude trajectories distinguishing between different types of aircraft as in Filippone et al. (2021). Finally, some research like Wells et al. (2021) focuses on aircraft efficiency through the use of alternative routes benefiting from wind currents.

4.1.2 LTO emissions

The Landing and Take-Off (LTO) cycle can be described as the sequence of aircraft operations taking place under 3,000 feet of altitude. These different phases include more precisely the following phases:

- taxi-out (departure),
- take-off (departure),
- climb-out (departure) to 3,000 feet,
- approach (arrival) from 3,000 feet,
- landing (arrival),
- taxi-in (arrival).

As we will see later, some of these phases are pretty homogeneous in terms of duration and thrust of engines. This regularity can be traced back to pilot instructions and training as well as similarity of aircraft, as well as the uniformization of airports operations (Cf. e.g. Yunos et al. (2017)). Such homogeneity is beneficial to the modelling process.

A vast literature of research has been written on LTO emissions, with numerous articles trying to refine the estimates of emissions for multiple aircraft types or even engines. For example, Chati and Balakrishnan (2014) estimates emissions from LTO cycle in operations from actual flight data as compared with engine emissions data. Winther et al. (2019a) offers detailed assessment of relevant factors as well as methodologies to estimate LTO emissions. Koudis et al. (2017) studies the correlation between emissions and thrust. Simaiakis and Balakrishnan (2010) studies the impact of airport congestion on taxi times as well as emissions of 4 U.S. airports. Khadilkar and Balakrishnan (2012) defines a model of fuel burn during taxi-out phase and Chati and Balakrishnan (2013) assess the real thrust and durations of LTO phases for an Airbus A330-223. Finally, one should mention Masiol and Harrison (2014) which provides an in-depth review on research regarding engine exhaust emissions and airport emissions.

4.1.3 Proposed methodology

The modelling of cruise emissions is based on distances between airports, assuming that aircraft follow the great circles (geodesic distances) between departure and arrival destinations. In practice, aircraft can deviate from these paths for numerous reasons such as safety, political events, weather conditions, air traffic control charges, or the attempt to reach higher fuel efficiency by exploiting wind currents. Simple corrections are used to account for these sources of extra travelled distance. Then based on distance, it is possible to compute the emissions of flights taking into account the type of aircraft carrying passengers and attribute yearly aggregated emissions to airports, in this case chosen to be the departing airports. One could choose the arrival airports as well, the difference in aggregation being very small over a year since airports have a limited parking capacity and high turnover of aircraft, which tend to make both estimates converging over long periods of time.

As for LTO emissions, the modelling that we propose is based on tables of LTO emissions for different aircraft, extrapolated to a larger population of aircraft and corrected from specific times of traffic data. These timestamps allow a partial account of the different phases of the LTO cycle, correcting the first estimate of LTO emissions, and separated into departure LTO and arrival LTO emissions. It is then possible to aggregate these emissions for each airport, here attributing to each of them both their departure and arrival contributions, and compute yearly estimates that represent the efficiency of airports to operate aircraft on their ground and vicinity.

For reasons already mentioned in the case of scopes 1 and 2, the year of focus is 2019 as it corresponds to a quasi-normal year in terms of traffics, as opposed to 2020 and 2021 strongly impacted by the Covid pandemic. Nevertheless, the method proposed here is perfectly applicable to any year of airport activities.

4.2 Data collection and processing

This section describes the data employed in the modelling of scope 3 emissions, for cruise as well as LTO cycle emissions. Other sources of emissions such as surface access are neglected.

4.2.1 Data sources

The modelling of cruise emissions is based on a distance estimate of fuel burnt by different types of aircraft. The source of flight schedule data employed by the model is the Official Airline Guide (OAG) data[1], starting from year 2019. This data contains, among numerous features, a detailed description of flights with timestamps associated to certain phases of landing and take-off operations. The coverage of flights appears to be very good, with OAG's number of flights reaching on average of 98% reported flights (with dispersion of 17%, based on 28 data points). The tail number of aircraft, though potentially interesting, was not retained due to inconsistencies with the aircraft type. The aircraft identification is done based on the aircraft type, other sources of data gathered online, and Ch-Aviation data[2]. Finally, but not the least, a table of distance to fuel consumption from the International Civil Aviation Organization (ICAO) was used in order to convert distances into emissions (Cf. ICAO (2017b)). The number of airports involved reaches around 8,800 and the number of flights processed is around 44 million.

The source of data for the LTO cycle estimates first relies on a table from the European Monitoring and Evaluation Programme (EMEP) and the European Environment Agency (EEA), providing the LTO emissions of several aircraft (Cf. Winther et al. (2019b)). This table is leveraged and completed in order to predict the typical LTO cycle for more aircraft. This first estimate of LTO emissions is thus independent from the airport where the aircraft is operating. The emissions are then refined through the integration of time-schedule data from OAG, specializing the estimate to the airport itself through this integration of operational efficiency measure.

4.2.2 Data processing and modelling

Several operations are required to clean air traffic data and the distance between airports. When missing, distances are imputed based on geolocations of airports and the great circle (GC) distance separating them. In-house methods have been developed to identify aircraft types, and a description of an average aircraft has been designed to evaluate emissions of unidentified aircraft. Less than 10% of scheduled aircraft fall into that category, and the identification will improve over time. As mentioned before, distances are corrected by simple factors depending on

1 - OAG

2 - CH Aviation

their values, and an interpolation is done from the distance-to-fuel table provided by ICAO. Finally, a simple emission factor is applied to estimate the amount of CO_2 emitted from flights. Estimates of errors are also implemented in the process. Following this prediction, emissions are aggregated for each departure airports and saved for a given year of traffic data (here representing 2019). Statistical errors due to approximations, unless affected by bias, are expected to average out and to be further reduced with the improvement of different steps in the process.

The processing and modelling for the LTO cycle has been partially described in the previous section. As it is the case for cruise emissions, the LTO estimates rely on an accurate identification of aircraft operating at airports. One accurate estimate of emissions during the LTO cycle, as well as for any operation, is through the integration of the fuel flow rate. Since the fuel flow rate $W_{ff}^{(P)}(t) \equiv dm_f/dt$ describes the amount of fuel burnt per unit of time, the LTO emissions can be written as a sum of integrals over the different phases of the LTO cycle:

$$\text{LTO emissions} = e_{\text{CO}_2} \sum_{P \in \mathcal{P}} \int_{T^{(P)}} W_{ff}^{(P)}(t)dt,$$

where $\mathcal{P} \equiv \{D_1, D_2, D_3, A_1, A_2\}$ is the set of departure phases (D_1: taxi-out; D_2: take-off; D_3: climb-out) and arrival phases (A_1: approach and landing; A_2: taxi-in) composing the LTO cycle of that aircraft. Furthermore, $T^{(P)}$ is the duration of phase P and e_{CO_2} = 3.16 kg CO_2 / kg fuel burnt is the emission factor converting mass of fuel burnt into mass of CO_2 emitted. It is assumed here that all fuel is burnt by combustion in the aircraft engines.

In the absence of engine consumption data of aircraft, this equation can be simplified under the assumption of constant thrust of engines. Indeed, the fuel flow rate relates directly to thrust through the thrust specific fuel consumption (TSFC) as $W_{ff}^{(P)}(t) = c_{\text{TSFC}}F(t)$ (with c_{TSFC} in $kg/N = s/m$ and $F(t)$ in newtons $N = kgm/s^2$), and assuming a constant thrust simplifies the above relation as:

$$\text{LTO}^{(A)} = e_{\text{CO}_2} c_{\text{TSFC}}^{(A)} \sum_{P \in \mathcal{P}} F^{(A,P)} T^{(P)}.$$

Since the TSFC depends on engines, and so on aircraft types, the LTO emission also depends on the aircraft itself, as stated through the exponent (A). Obviously, this approximation corresponds to perfect conditions and can only be valid on average, assuming that proper estimates of thrust $F^{(A,P)}$ is used for each phase. We further express the thrust relatively to its maximum value, $F^{(A,P)} = f^{(A,P)} F_{max}^{(A)}$ (with $f^{(A,P)}$ in percent). One other assumption that can be employed here is that the thrust is the same for each aircraft during the same phase of the LTO cycle, hence $f^{(A,P)} \equiv f^{(P)}$. This is supported from the fact that pilots of different aircraft still follow similar procedures and the fact that known values of LTO emissions assume common values of relative thrust. Consequently, the LTO emissions are given by:

$$\text{LTO}^{(A)} = e_{\text{CO}_2} c_{\text{TSFC}}^{(A)} F_{max}^{(A)} \sum_{P \in \mathcal{P}} f^{(P)} T_{ICAO}^{(P)},$$

with $f^{(P)}$ coefficients known from ICAO and reported in Table2.

Based on the equation above, the LTO emissions from actual schedule data can be related to the standard ICAO estimate by equating the aircraft-only part of the equation (which is actually unknown), finding that:

$$\text{LTO}^{(A)} = \text{LTO}_{ICAO}^{(A)} \frac{\sum_{P \in \mathcal{P}} f^{(P)} T^{(P)}}{\sum_{P \in \mathcal{P}} f^{(P)} T_{ICAO}^{(P)}}.$$

where $T_{ICAO}^{(P)}$ are the standard durations of the LTO phases as defined by ICAO and reported in Table2, and $T^{(P)}$ are the actually measured durations of these phases when available (cf. Table2 as well).

Finally, and thanks to the linearity of the equation that we have derived, we can split

Table 2: Thrusts and durations of LTO cycle phases from ICAO and in our model.

LTO Phase P	Relative Thrust $f^{(P)}$ (%)	Duration $T^{(P)}_{ICAO}$ (s)	Duration $T^{(P)}$ (s) in model
Taxi-Out (D_1)	7	780	Measure + estimate
Take-Off (D_2)	100	42	42
Climb-Out (D_3)	85	132	132
Approach + Landing (A_1)	30	240	240
Taxi-In (A_2)	7	780	Measure

the emissions for both departing and arrival phases of the LTO cycle, as follows:

$$\mathrm{LTO}^{(A)}_{\mathrm{dep}} = \mathrm{LTO}^{(A)} \frac{\sum_{P \in [D_1, D_2, D_3]} f^{(P)}\, T^{(P)}}{\sum_{P \in \mathcal{P}} f^{(P)}\, T^{(P)}},$$

$$\mathrm{LTO}^{(A)}_{\mathrm{arr}} = \mathrm{LTO}^{(A)} \frac{\sum_{P \in [A_1, A_2]} f^{(P)}\, T^{(P)}}{\sum_{P \in \mathcal{P}} F^{(P)}\, T^{(P)}},$$

guaranteeing that:

$$\mathrm{LTO}^{(A)} = \mathrm{LTO}^{(A)}_{\mathrm{dep}} + \mathrm{LTO}^{(A)}_{\mathrm{arr}}.$$

This method allows in particular the estimate from airport congestion, where aircraft can spend a long time taxiing-in or taxiing-out, representing sometimes an important part of emissions despite the low thrust used during these phases. Finally, and in the same manner as cruise emissions, these estimates are aggregated for each airport, for both departure, arrival and total contributions, hence establishing yearly frequency metrics that allow direct comparison of airports as well as validation from the use of reported data.

5. Results

This section is devoted to the discussion of results from the scope 1, 2 and 3 emissions models described in chapters 3 and 4. We will first discuss results from the models separately, followed by a comparisons of the different types of emissions against each other.

5.1 Scopes 1 and 2 emissions

This section reports the results from the method described in Chap. 3 to estimate scope 1 and scope 2 emissions from regressions of a set of characteristic explanatory variables.

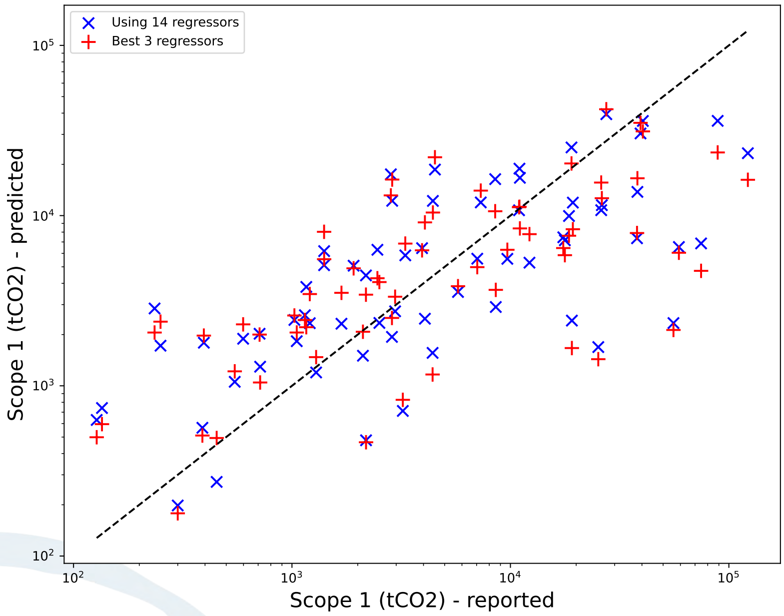
5.1.1 Global predictions for scope 1 emissions

As stated in Table 1, the use of all 14 regressors returns a prediction with an in-sample $R^2 = 0.507$, and an adjusted $R^2 = 0.375$. Following the method described in Chap. 3, the regression applied to 10,000 random combination of regressors and the selection of the best explanatory variables from their p-value averaged among to top decile scores (with a threshold around 0.2), leads to a model with only 3 variables (and the intercept). The score of this model is $R^2 = 0.471$, and an adjusted $R^2 = 0.446$, which shows the benefits of this approach in increasing the adjusted R^2 value. One should keep in mind that the motivation here is not only to increase this quantity, but to capture the best model for a reduced set of parameters, as the less parameters the larger the amount of airports on which we will be able to establish a prediction (airports for which missingness affects some variables).

As it can be seen in Fig. 4, the two regressions appear to be qualitatively similar, despite their different scores. One should note however that the largest scope 1 emitters are not so well captured by the models, and will require more attention in the future. Nevertheless, the model captures part of the complexity of airports emissions. Indeed, we find that the best parameters are consistent with previous literature. For example, we find that the size of the aerodrome and temperature variations are the most important factors, with characteristics of the terminals as well. Hence, the model assesses correctly that scope 1 emissions relate to activities on the airport ground as well as heating of terminal buildings.

The model is then used to predict emissions for the large set of airports with no reported scopes. Due to the reduction in number of explanatory variables, the model can be applied on as much as 3,069 airports. Using all 14 regressors would lead to a prediction on only about 1,600 airports. Scope 1 emissions are plotted against the most important regressors in Fig. 5 and Fig. 6. Information regarding the type of airport (large, medium, small, etc.) has been obtained from ICAO and employed as color-coding in order to check the consistency of results. As it can be seen, the model data and predictions appear to be consistent, except potentially for large variations in temperatures for which the model may not be representative of the large dataset. The biggest emitters in the predictions do not exceed the biggest emitters in the model dataset, which appear consistent with the fact that the largest airports report their emissions. As for the color coding, it tells us that few small airports have large scope 1 predictions and few large airports have small predictions. Globally, the different types of airports are well separated by the predictions, which is a proof of model accuracy and consistency (since the color coding is

Figure 4: Prediction of scope 1 emissions against reported values, for two sets of regressors.



independent from the model). Furthermore, many airports receive smaller emissions than the model dataset values, as it is expected from the large population of small and medium operating airports and confirmed through the color coding. The distribution of predictions is presented in the histogram of Fig. 7. Predicted airports are displayed on a map in Fig. 8, and it reveals the global coverage of the predictions.

5.1.2 Global predictions for scope 2 emissions

As in the case of scope 1 emissions, scope 2 emissions are first estimated from the 14 regressors at our disposal. The quality of the fit is less than for scope 1, showing $R^2 = 0.319$ and adjusted $R^2 = 0.125$, as reported in Table 1. The 10,000 regressions based on random combinations of regressors lead us to select 4 best explanatory variables (with p-value averages less than 0.15), in addition to the intercept. The selected model now has $R^2 = 0.261$ and adjusted $R^2 = 0.211$, which reveals the less accurate nature of our model when it comes to scope 2 emissions. This difference with the scope 1 modelling could be related to several explanations, one of which being the different energy mixes in the countries where airports are located, as this mix plays an important role in the calculation of reported emissions and can impact the predictability of the model.

The in-sample predictions for the two regressions (with respectively 14 and 4 regressors) are presented against their reported values in Fig. 9. As we can see from this plot, the regression is less accurate than scope 1 and sometimes problematic for larger emitters, with some airports appearing as outliers. The most relevant parameters involve the characteristics of airport terminals as well as operational quantities like the number of passengers, which appears to have a positive influence on scope 2 emissions.

As before, the model is used to predict emissions for the large set of airports. Due to more missing values on these regressions, the number of airports receiving a prediction is only 1,749. Scope 2 emissions are plotted against estimates of the number of passengers in Fig. 10 and we can see that airports reporting emissions have a bias towards large number of passengers. As before, the airport type from ICAO is imported for color-coding, and it confirms a lesser quality of the estimates here. Despite the presence of outliers at large scope 2

Figure 5: Scope 1 emissions against aerodrome surface for both model (crosses) and prediction on large dataset (colored circles).

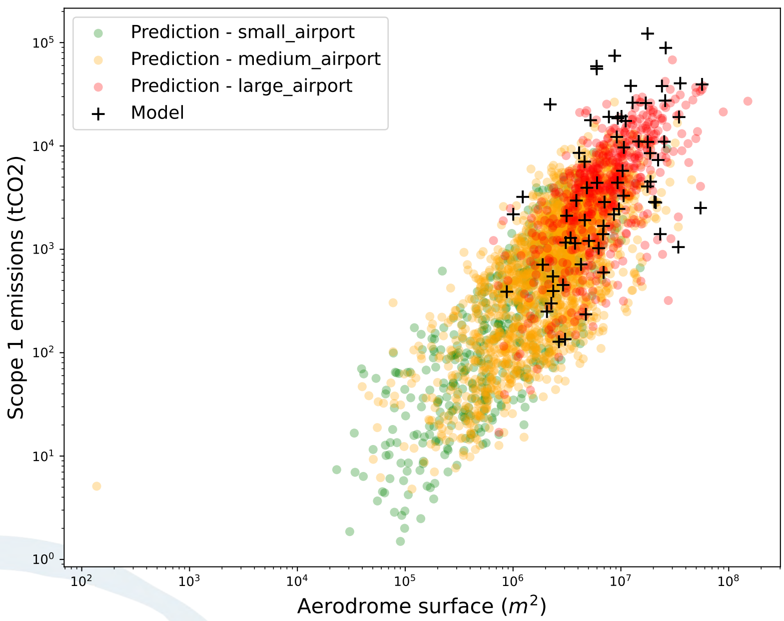


Figure 6: Scope 1 emissions against monthly temperature variation for both model (crosses) and prediction on large dataset (colored circles).

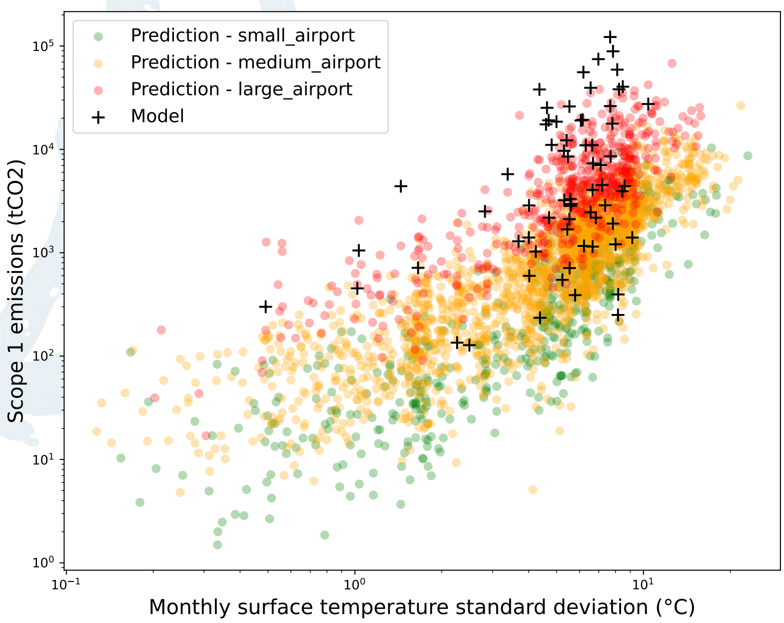


Figure 7: Scope 1 emissions distributions for both model (red) and prediction on large dataset (blue).

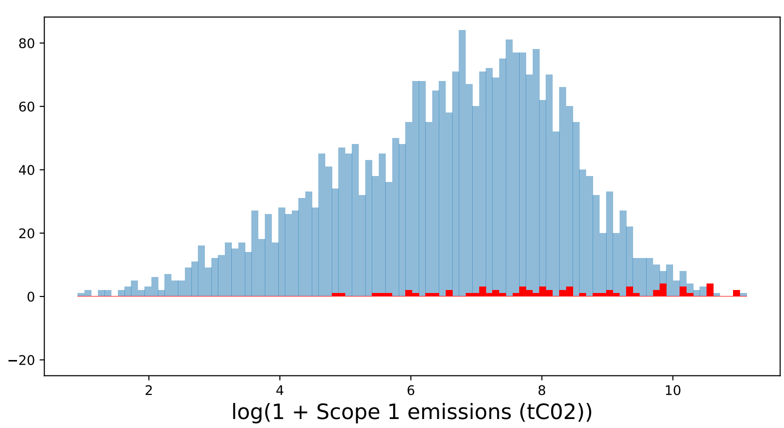


Figure 8: Map of airports from the large dataset receiving a scope 1 prediction.

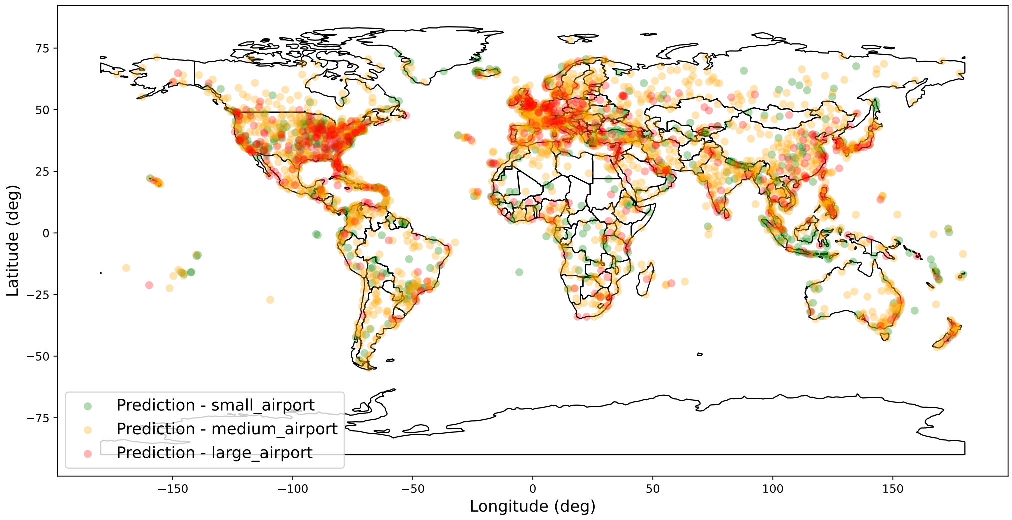
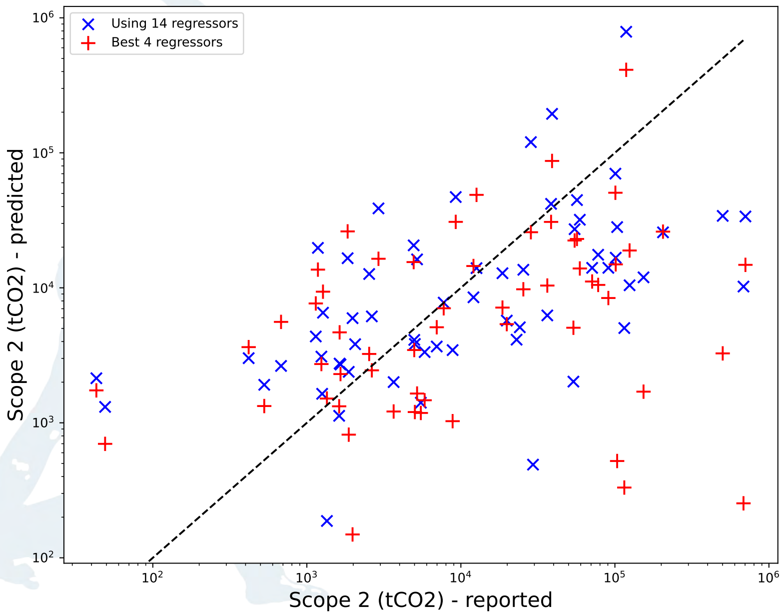


Figure 9: Prediction of scope 2 emissions against reported values, for two sets of regressors.



estimates, due to the lack of precision of the model, one can still be satisfied with the trend extracted by the model for a smaller amount of passengers. This model is expected to improve with a better coverage of airports in the model dataset. The distribution of predictions is shown as above in the histogram of Fig. 11, and predicted airports are displayed on a map in Fig. 12.

5.1.3 Global predictions for scope 1+2 emissions

Since regressions were done on scope 1 and scope 2 emissions individually, and because some airports may sometimes report their emissions as the sum of scope 1 and 2, it is interesting to build a model for scope 1 + 2 as well. Based on the totality of regressors, i.e. 14 of them, we find a model with $R^2 = 0.388$ and adjusted $R^2 = 0.219$. When running 10,000 regressions and selecting the best explanatory variables from the top decile, we find that 2 variables (plus the intercept) with average p-value less than 0.15 are enough to capture most of the explanatory power. Based on this set of regressors, the scores remain high with $R^2 = 0.328$ and adjusted $R^2 = 0.307$, as summarized in Table 1. Interestingly, the 2 explanatory variables involved are not common to the two other models, but now involve the temperature average and another characteristic of aerodromes.

Figure 10: Scope 2 emissions against number of passengers for both model (crosses) and prediction on large dataset (colored circles).

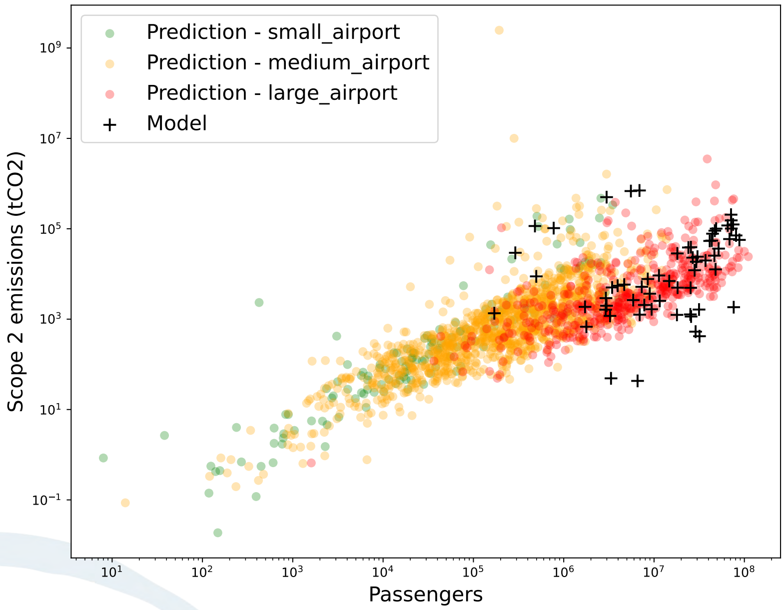


Figure 11: Scope 2 emissions distributions for both model (red) and prediction on large dataset (blue).

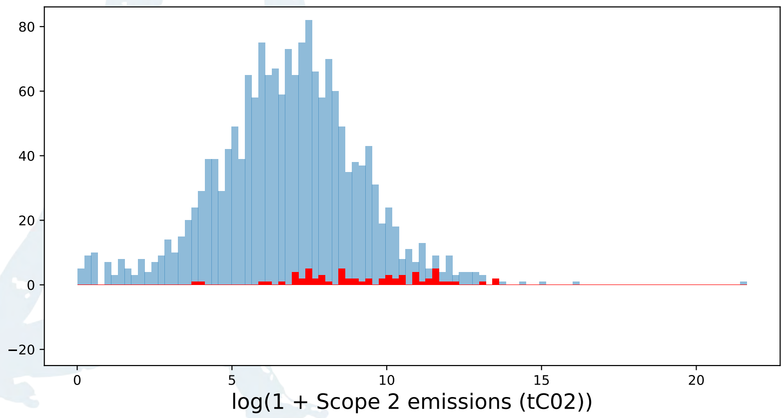
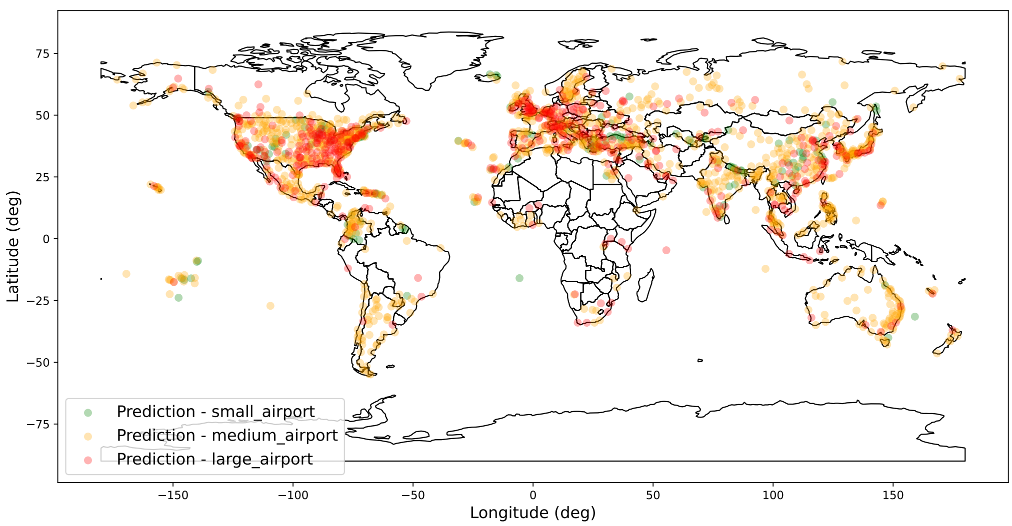


Figure 12: Map of airports from the large dataset receiving a scope 2 prediction.



Despite scope 2 emissions being on average 12 times larger than scope 1 in the model dataset, it appears that the regressors capturing less of scope 2 variability make the model of scope 1+2 "in between" the two other models. Following the same method as before, we predict the values of scope 1+2 emissions on 4,908 airports around the globe. The distribution of predicted values appears more reasonable than for scope 2, as expected from the better scores of the fits, and the number of outliers is likely to be less. The histogram of values is shown in Fig. 13.

As we can conclude from these 3 analyses, this method allows global predictions of emissions on airports based on a small amount of reported data. The distributions of values of the model dataset display positive skewness and kurtosis further emphasized in the prediction datasets. This presence of fat-tail distributions reveals the fact that airport emissions are made from very different types of actors, going from very large emitting hubs to only satellite contributors in the global network of airports. The acquisition of more observations with the inclusion of new explanatory variables, as currently carried on in parallel to this publication, will further improve the modelling of emissions and reach even higher precision.

5.1.4 Relevance in the ESG market

As we already mentioned in Chap. 2, the main ESG data providers do not offer much data on airport emissions despite their large coverage across companies. As a consequence, it can be interesting to compare our method with the best data available on the market. To do this, we have considered the list of airport companies covered by these providers, and retained the emission values present in our model dataset. For CDP, that represents 3 airports, for Sustainalytics and Arabesque we have respectively 9 and 8 in common. These last two vendors also cover respectively 9 and 8 airport groups, and as such are not present in our dataset that focuses on individual airport emissions, except for two airport groups in which individual airport emissions were retrieved. This explains the lower representation of these datasets in our comparison. If these data vendors would have access to all emissions in the airport groups that they cover, their total number of airports would be respectively about a hundred and two hundreds airports. In practice though, the breakdown of emissions for individual assets is rarely available. We display our comparison of datasets in Fig. 14 based on our Scope 1+2 modelling of the last section. We can see that our approach relies on more disclosed data to build the model, and a much larger population when it comes to predictions.

5.2 Scope 3 emissions

As explained in Chap. 4, our modelling of scope 3 emissions relies on a predictive estimate of CO_2 emissions at the flight and aircraft levels, using a distance-based approach for cruise emissions and a time-based approach for LTO cycle emissions. Hence, the discussion of this section will focus on the extraction of knowledge from the estimates, and not on the interpretation of potential regressors like it was the case in the previous section. The number of airports on which emissions are computed is more than 8,000 airports globally.

5.2.1 Global predictions for scope 3 emissions from cruise

As intuitively known, the total distance of departure and arrival flights at airports is strongly correlated with their number of departure and arrival flights. This is illustrated in Fig. 15 where the correlation between the two variables is obvious. We have used like before a color coding from the type of airports defined by ICAO, and the colors logically display that larger airports have larger values of total distances flown by aircraft as well as larger number of flights. On

Figure 13: Scope 1+2 emissions distributions for both model (red) and prediction on large dataset (blue).

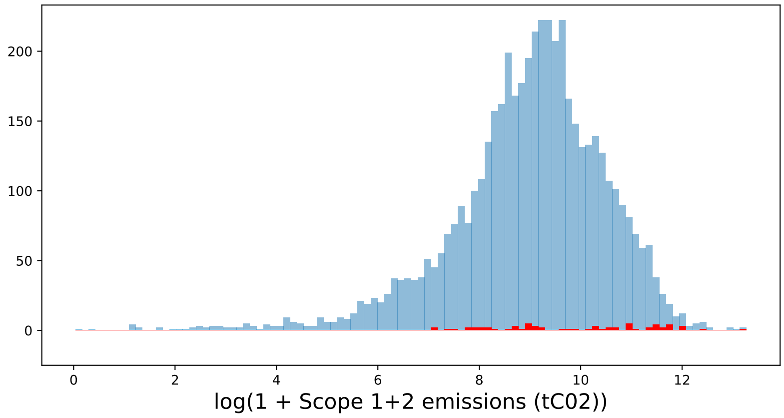
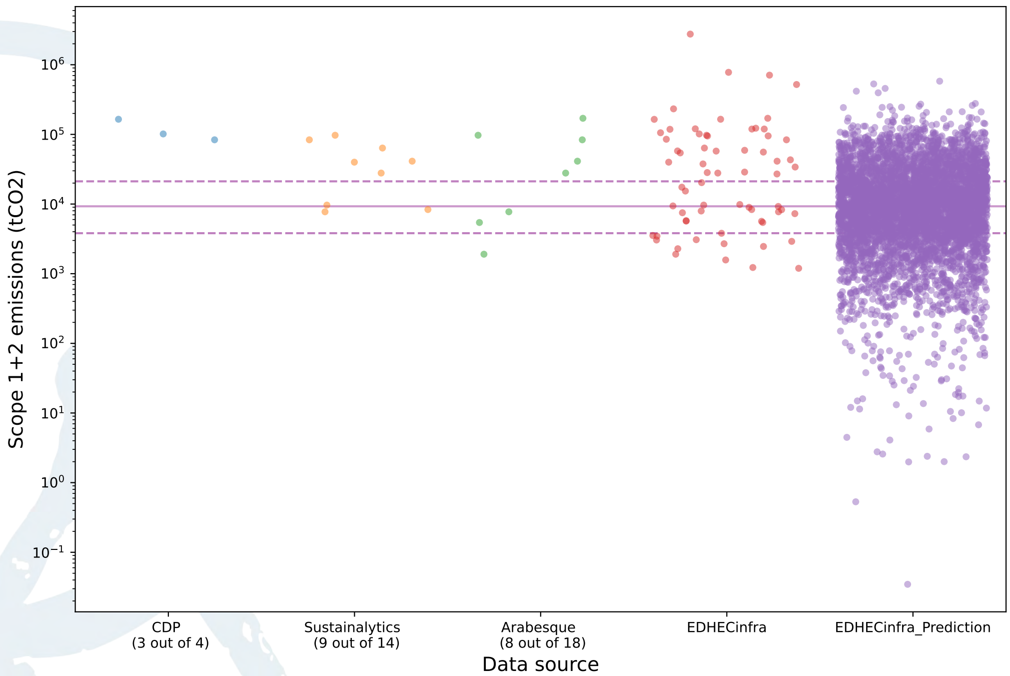


Figure 14: Scope 1+2 emissions for model (red), prediction on large dataset (purple), and other data vendors (blue, orange, green).



the other hand, we can see that the dispersion is larger for small airports, revealing the fact that some small airports concentrate their activities around short distance flights, while others, potentially located in isolated places, rather have a smaller number of flights of long distance trips.

We have chosen in this study to attribute all emissions to the airport of departure. Other choices could have been made, e.g. splitting cruise emissions of each flight in two equal contributions, with each airport involved getting one of them. Our choice was mainly motivated by simplicity and the fact that Heathrow's airport chooses to report emissions of its departing flights. However, since airports aprons and hangars have a limited storing capacity of aircraft and that airlines have an incentive to fly their fleet as much as possible, we can expect that any difference relating to cruise between departing and arrival flights would disappear. This is confirmed in Fig. 16, where we can see that the total departure and arrival distances are quasi-equal for large airports, i.e. the airports with high turnover of aircraft.

Since our model estimates the emissions from departure flights, it is worth asking the question of the relationship between the total departure distance of flights and the cruise emissions themselves. As we can see from Fig. 17, there is a strong linear depen-

Figure 15: Total number of flights against total distance (arrival and departure).

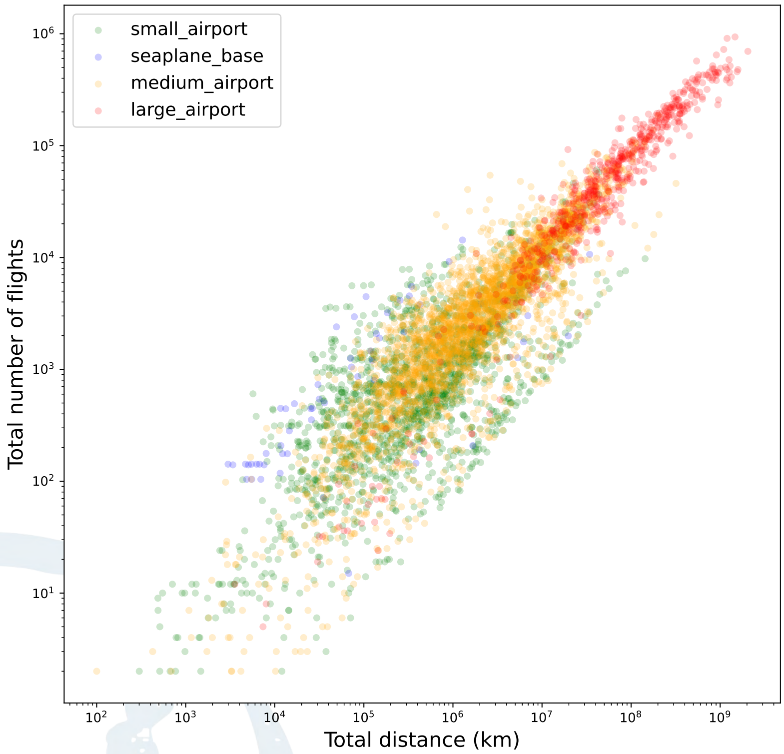
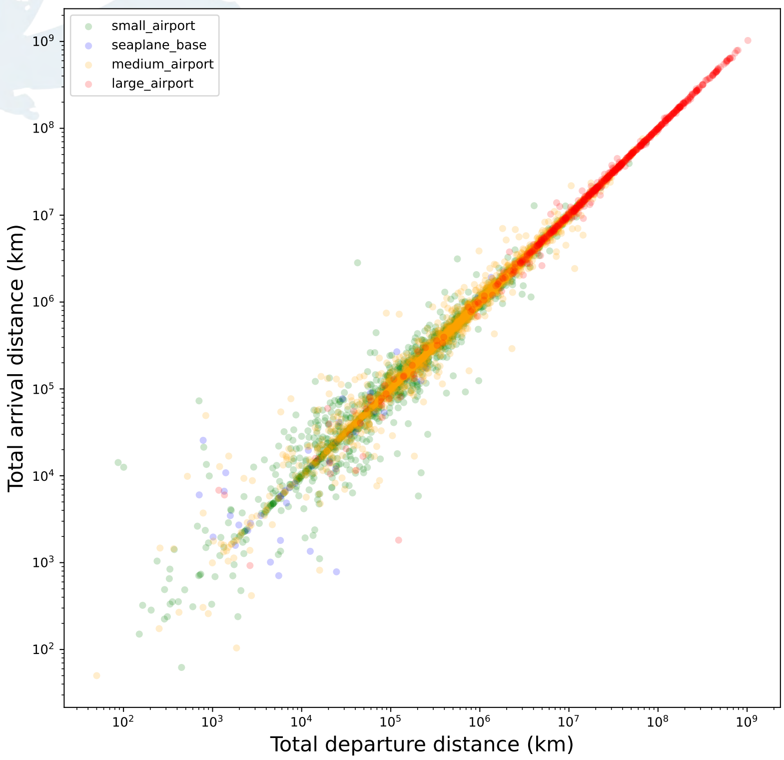


Figure 16: Total departure distance against total arrival distance.



dence between the two. This is obviously explained from the fact that our model of cruise emissions is based on distance, justifying the small dispersion on the plot. As for the nature of this dispersion, it relates to the different populations of aircraft visiting large and small airports. As we can notice also, medium size airports appear closer to large airports than small airports when it comes to this dispersion, probably traced back to the similarity of aircraft using them.

In a similar manner, and with some overlap with the previous figures, we can look at the relationship between departure cruise emissions of airports and their total number of flights (departure + arrival). What we find in such a case is displayed in Fig. 18, and it reveals that large international airports are more uniform than small airports. Indeed, the low dispersion in this relationship can be related to the presence of a more uniform population of aircraft and more regulated activities. On the other hand, smaller airports vary in size, shapes and levels of activities.

Another relationship of interest is the influence from the number of passengers on cruise emissions. Obviously, we also expect a strong correlation from the fact that an aircraft can carry roughly the same amount of passengers. However, as we can see in Fig. 19 there exists a sub-category of medium and small sizes airports for which the number of passengers is significantly lower than the generated emissions. Again, this has to relate to the fact that some small airports support small aircraft on small distance flights (possibly involving private jets also), while some others focus on long distance flights, probably in direct link with the major airports and thus much more in line with their emission pattern.

A similar relationship can be observed from the average distance of flights of airports (i.e. their total distance divided by their number of flights), as shown in Fig. 20. We see from this plot that medium and large airports can play a similar role in terms of distances, and rather differ from the number of operations they carry. However, the two populations of small airports are visible here as well. These two groups of small airports seem to confirm two different natures of activities, short-distance-small-emissions activities and long-distance-large-emissions activities.

5.2.2 Global predictions for scope 3 emissions from LTO cycle

A similar analysis can be drawn for LTO emissions, and this is the goal of this section. However, and as described in Chap. 4, the LTO cycle possesses intrinsic differences between arrival and departure due to the difference of operations involved at the aircraft level (thrust) and the airport level (efficiency in dealing with traffic, delays). We present in Fig. 21 the comparison of departure and arrival LTO emissions, where we directly see that departure emissions are larger than arrival emissions for the vast majority of airports. Two factors can explain this reality, the first one is that aircraft in general emit more during the LTO's departure phase than during the arrival phase, the second one is that airports are less efficient at dealing with departure traffic than arrival traffic, this due to the higher level of operations during departure.

In order to prove this argument, we have adjusted the departure and arrival LTO with factors directly extracted from Table 2. Assuming standard thrusts and durations for the LTO phases, it is expected that departure emissions should amount to 62.3% and arrival emissions to 37.7% of the LTO cycle. Hence, using these factors to re-balance their values and taking the difference of departure minus arrival, it is possible to separate (at least in theory) the influence from aircraft and the influence from airport (based on real time values of taxiing). When plotted against the number of flights, we obtain Fig. 22

Figure 17: Scope 3 cruise emissions against total departure distance.

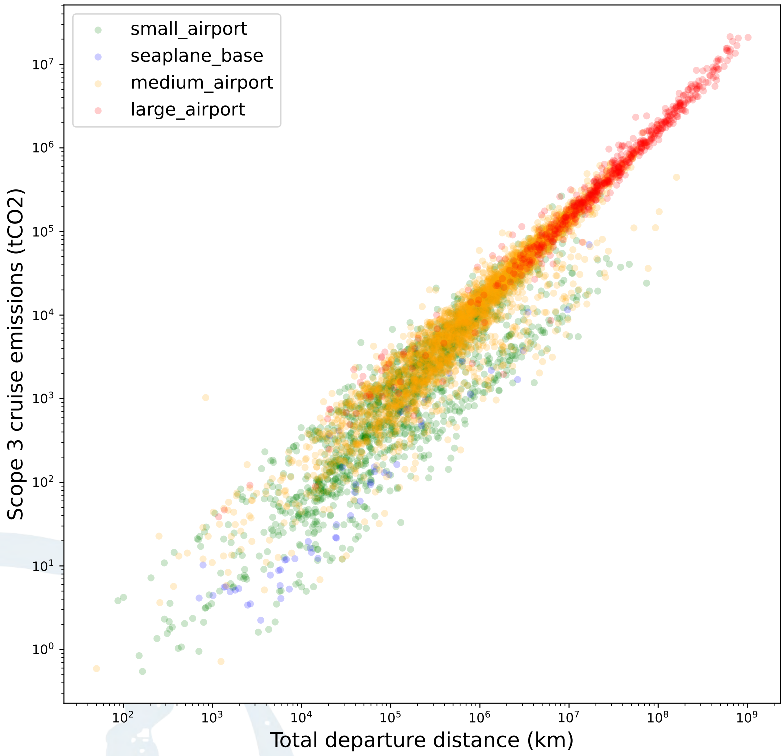


Figure 18: Scope 3 cruise emissions against total number of flights (departure + arrival).

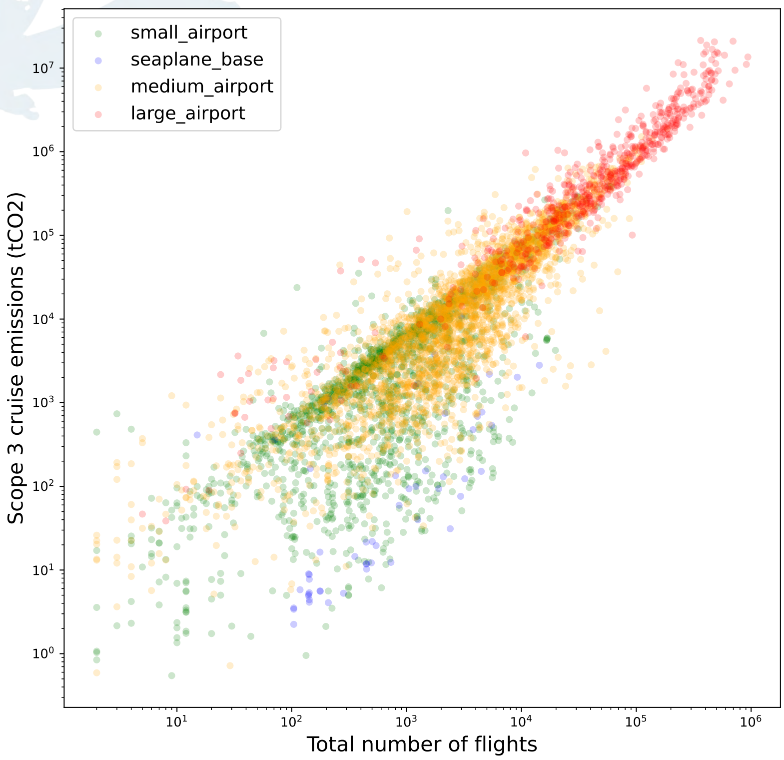


Figure 19: Scope 3 cruise emissions against total number of passengers.

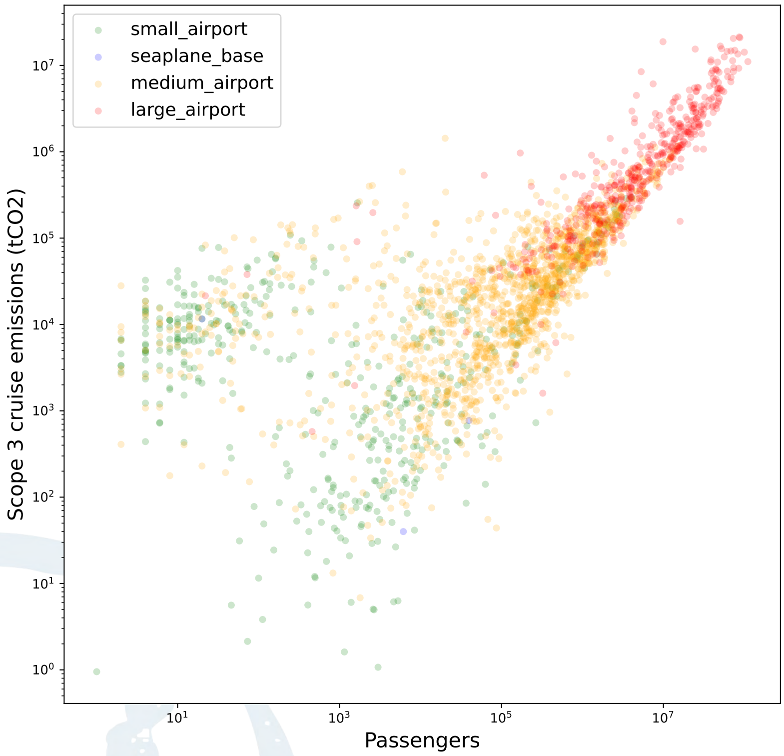


Figure 20: Scope 3 cruise emissions against average distance of flights.

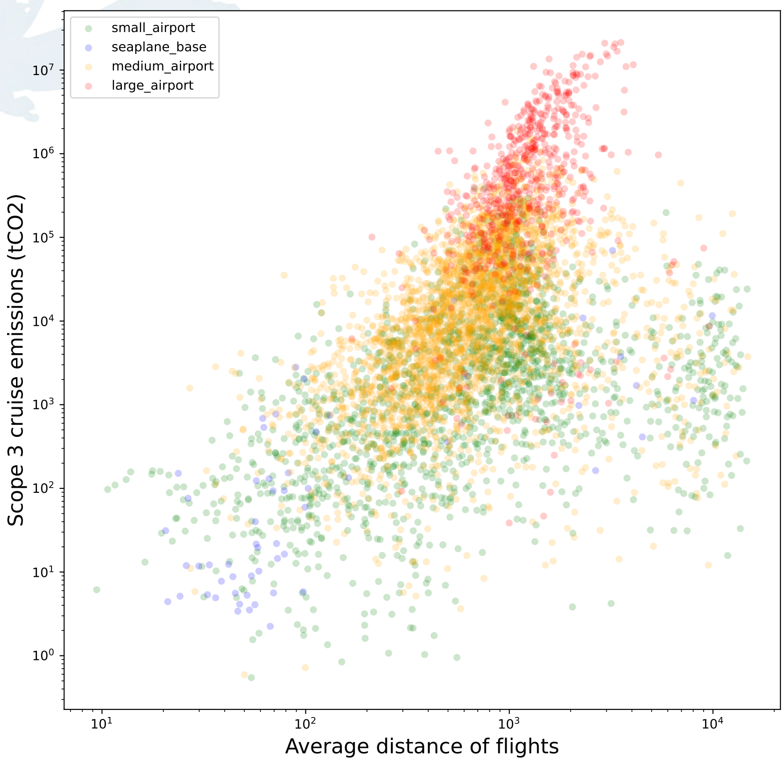
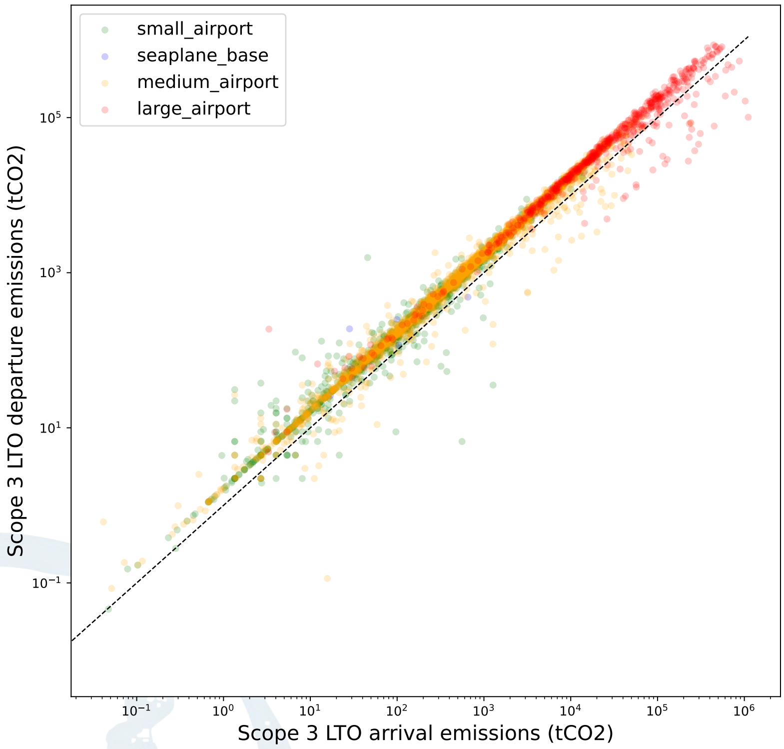


Figure 21: Scope 3 departure LTO emissions against arrival LTO emissions.



which clearly shows that the biggest airports generate larger departing LTO emissions than arrival LTO emissions. This excess of emissions is much less present for small airports, and this directly points to the fact that large airports are more likely to reach saturation of runways, giving the priority to arrival flights and thus creating an imbalance in the duration of taxi-out compared to taxi-in phases. In other words, emissions from LTO are amplified by long departing taxi times, and larger airports face difficult constraints to reduce them. One should add that these results are the outcome of both modelling and time schedule measurements.

When plotted against the total distance of departure flights, the total LTO emissions (departure + arrival) show a linear dependence in the same way as cruise emissions. This relationship can be seen in Fig. 23 and relates to the fact that airports with high number of flights mechanically generate more emissions. In addition to this fact, different populations of aircraft between airports have an influence on the amount of LTO emissions.

In a similar way, the LTO cycle emissions directly scale with the number of flights operated by airports. This can be seen in Fig. 24 where this relationship shows more uniformity for large airports again, and where small airports display lower LTO emissions. Once again, the nature of aircraft visiting small airports plays an important role as small airports carry less passengers at a slower rate, hence employing smaller aircraft fleets which use less fuel than larger aircraft.

Dividing now the emissions per the total number of flights and showing the result against the total distance of flights, we can see in Fig. 25 that large airports have larger LTO emissions than small airports due to the aircraft models operating on their aerodromes, which are on average bigger and heavier, hence consuming more fuel. Using the type of airport to divide the populations, we find 1.57 ± 0.95 tCO_2 emitted per LTO cycle for large airports. On the other hand, small airports show LTO cycle emissions of 1.00 ± 0.74 tCO_2 per flight and medium airports show 0.98 ± 1.17 tCO_2. Interestingly, and maybe due to the large variability

Figure 22: Scope 3 difference between adjusted departure LTO and adjusted arrival LTO emissions against total number of flights.

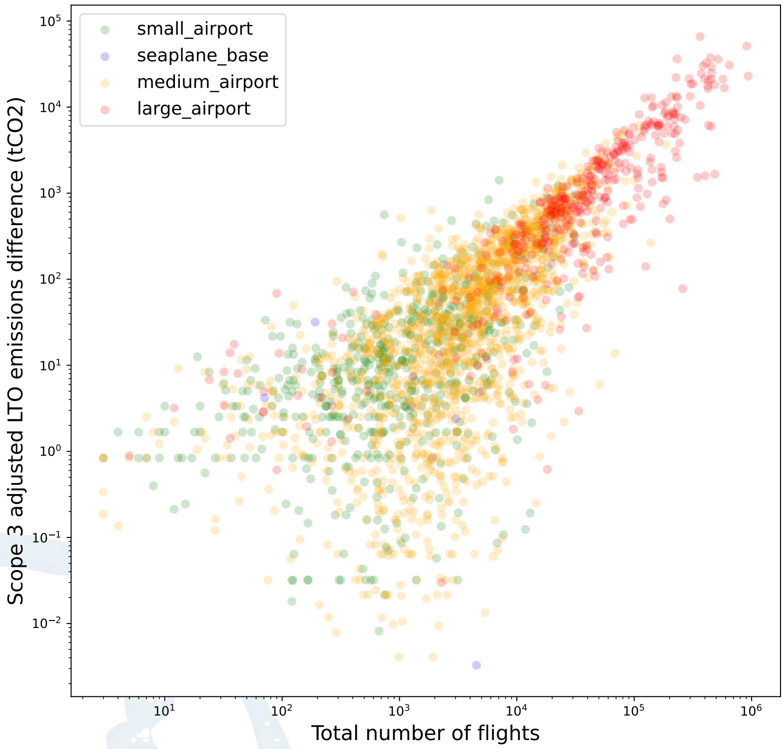


Figure 23: Scope 3 LTO total emissions (departure + arrival) against the total distance of departure flights.

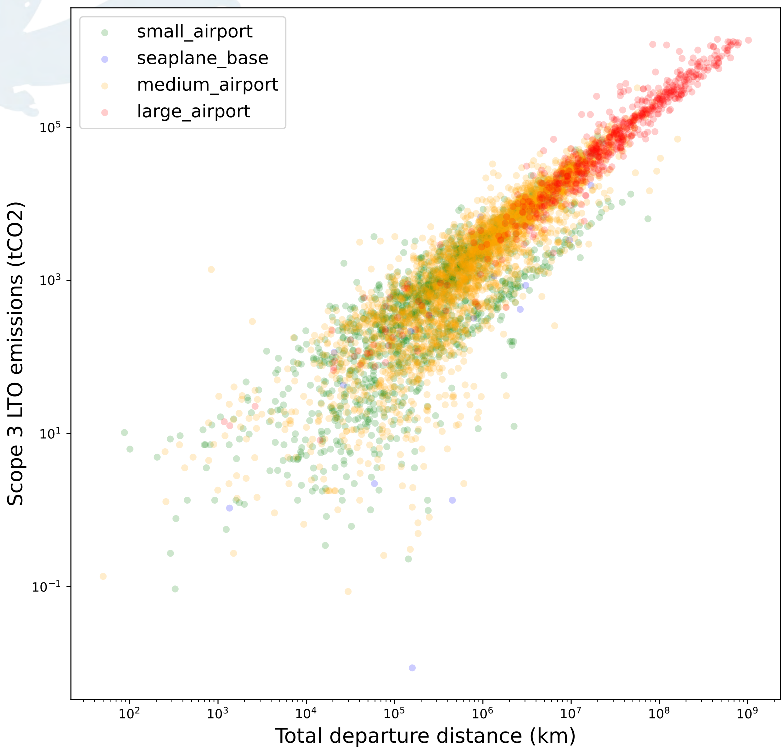
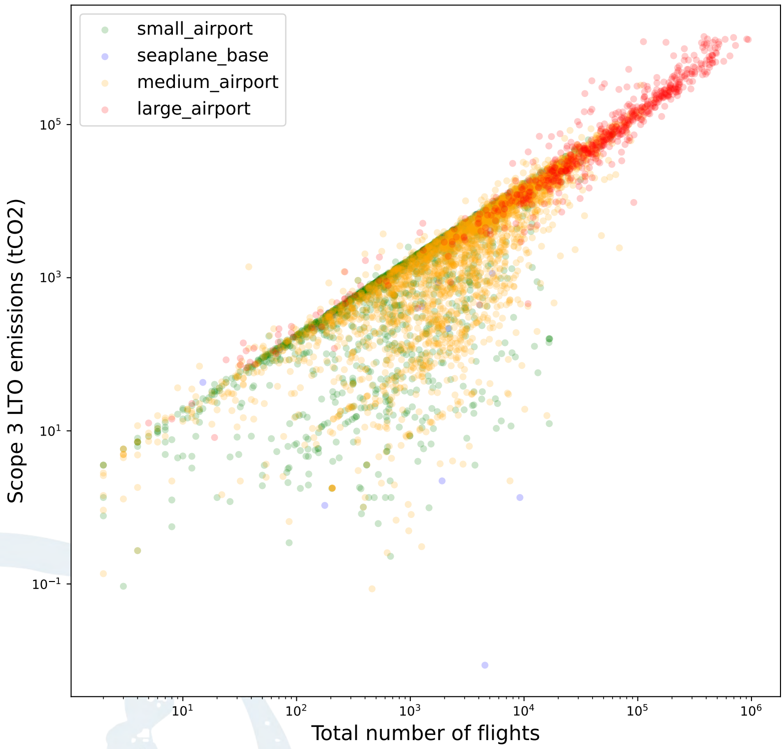


Figure 24: Scope 3 LTO total emissions (departure + arrival) against the total number of flights (departure + arrival).



of aircraft nature on medium airports, the standard deviation of the prediction for medium airports is larger than the rest.

As we have shown above, large airports have higher emissions per number of flights. However, one should not conclude that large airports are for that reason inefficient. Indeed, and as we know, large airports serve a much larger population than small airports. In Fig. 26 is displayed the total LTO emissions against the number of passengers. As we see, both are directly correlated since each LTO cycle brings its own contribution to the emissions.

As suggested above, large airports actually appear more efficient in their emissions than smaller ones. This is illustrated in Fig. 27, where large airports display a much higher efficiency from their LTO emissions, with on average 227 grams of CO_2 per passenger for an LTO cycle, and a median of 0.26 grams (due to the heavily skewed distribution of values). The values obtained from medium and small airports are much larger, with a median value of 4.01 grams of CO_2 per passenger for medium airports and 57.7 grams of CO_2 per passenger for small airports. Some of these values for small airports may be impacted by the aircraft identification process if their aircraft population is made of non-standard aircraft with respect to the LTO cycle's emission table used in our study. In addition, one should keep in mind that large values appearing for some medium and small airports could be due to uncertainty in passenger data, as data on small and medium airports is less likely to be accurate. Some partial accounting for error from LTO emissions is also assessed and reveals that small and medium airports are significantly more affected than large airports. Nevertheless, if such a trend is confirmed it would indicate that small airports are significantly more exposed to transition risk than larger airports based on their scope 3 LTO emissions.

5.2.3 Predictions for scope 3 cruise + LTO, intensity metrics

The comparison of cruise and LTO emissions is of major importance since almost no airport reports cruise emissions, but almost all airports reporting scope 3 emissions do

Figure 25: Scope 3 LTO total emissions (departure + arrival) per flight against the total distance of flights.

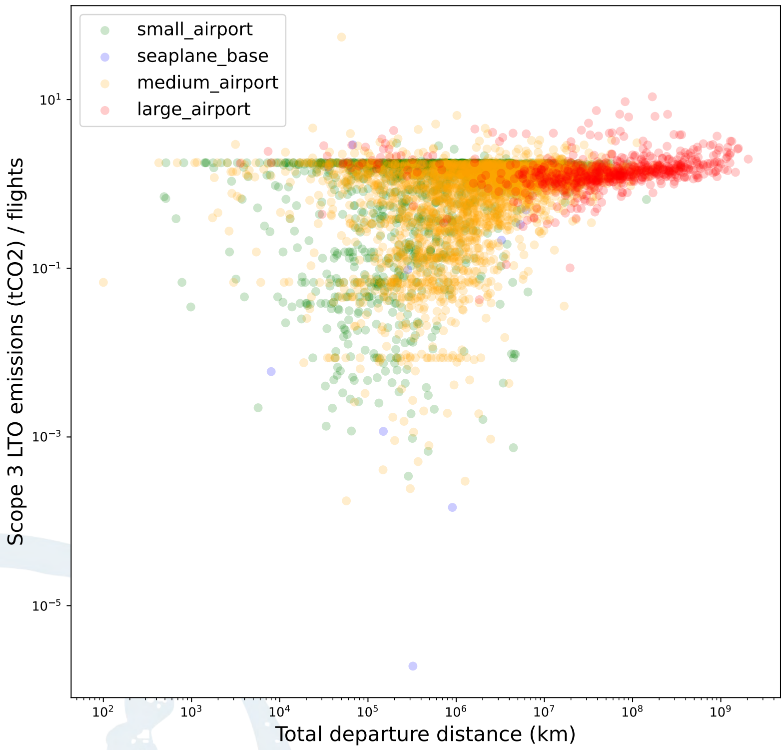


Figure 26: Scope 3 LTO total emissions (departure + arrival) against the total number of passengers.

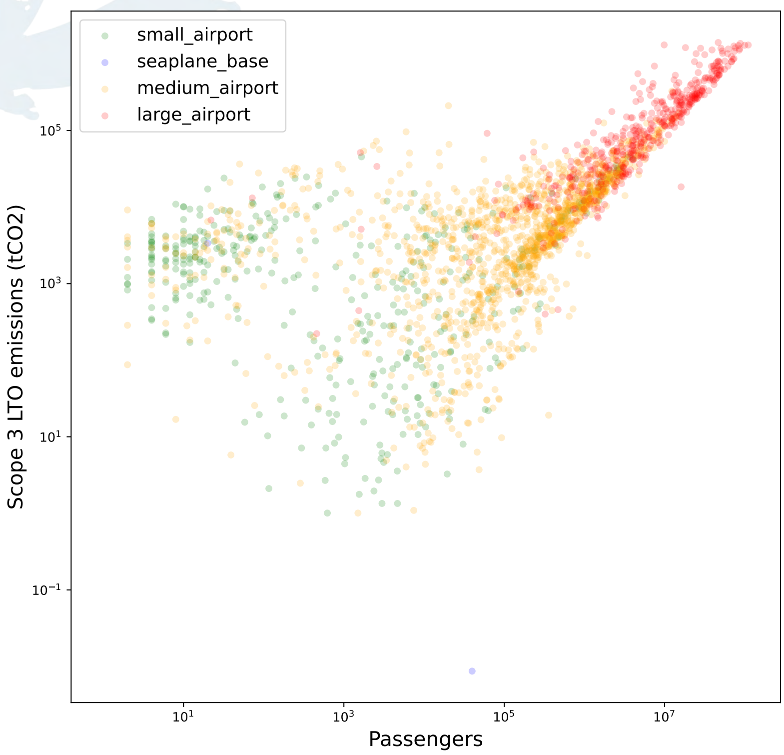
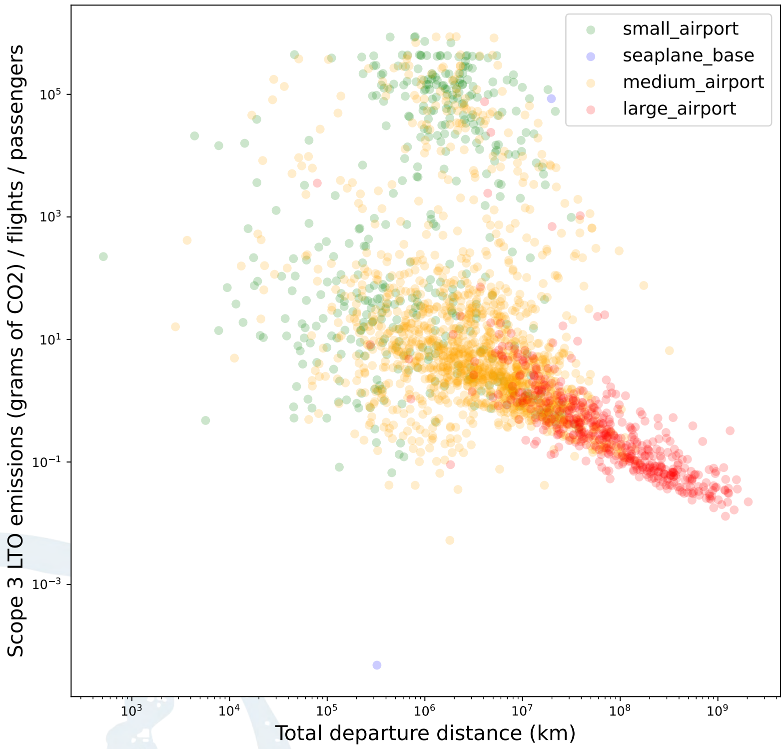


Figure 27: Scope 3 LTO total emissions (departure + arrival) per flight per passengers against total distance (departure + arrival).



provide an estimate of LTO emissions. Hence, we can say that airports recognize the LTO cycle as a major source of scope 3 emissions, but consider that cruise emissions should not be part of their scope 3 estimates. Heathrow airport has not taken this position though, and reports both cruise and LTO emissions as part of its scope 3 inventory. Fig. 28 shows the two main sources of scope 3 against each other, and we clearly see that cruise emissions almost always dominate the LTO cycle on average over airport activities. We also see that this is even more true for large airports as they focus on long distance flights. Taking ratios, we find that the LTO cycle represents $15.7\% \pm 9.4\%$ of the cruise emissions for large airports, $19.2\% \pm 13.0\%$ for medium airports, and $23.6\% \pm 33.8\%$ for small airports. In addition, we can compute the sum of airport emissions for both sources, as reported in Table 3 and find that large airports, despite their higher efficiency, are responsible for 86% for global cruise emissions (1,075 million tCO_2) and 80% of global LTO emissions (135 million tCO_2).

Let us now combine cruise and LTO in order to extract metrics which are more representative of the total scope 3 emissions. Obviously, and as already stated in Chap. 4, we are assuming that all scope 3 emissions from these two sources alone make other sources negligible. Though not true in theory, the cruise emissions, and to some extent the LTO emissions, are so important that such an approximation is good approximation in practice. This is especially true for airports focusing on long-distance for which the commute of passengers and employees cannot reach the same level as cruise emissions.

Despite the importance of evaluating airports on their absolute emissions as we have done until now, it is also important to evaluate them from intensity metrics. A natural metric to consider is the amount of emissions from cruise + LTO per flight against the average distance of flights for each airport. This metric is displayed in Fig. 29 and shows again that large airports specialize in long distances and thus large emissions per flight. As for small airports, it is interesting to see

Figure 28: Cruise emissions (departure) against Scope 3 LTO emissions (departure + arrival).

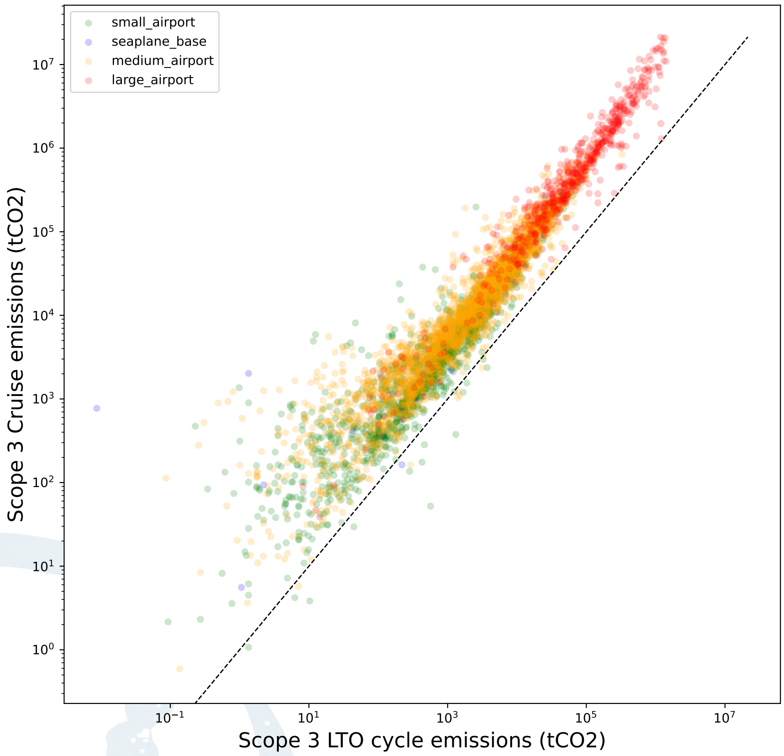


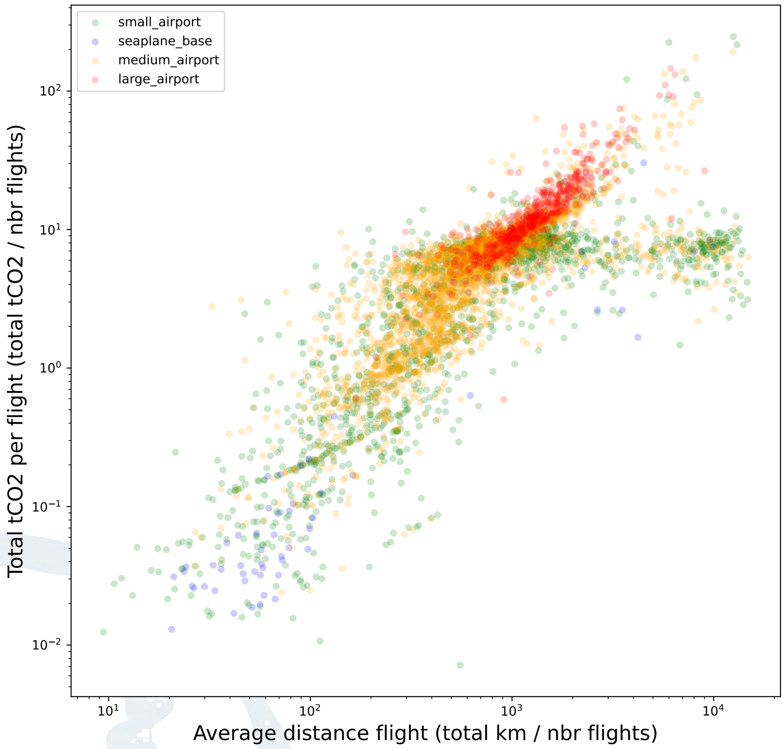
Table 3: Summary of global scope 3 emissions (cruise and LTO)

Type of airport	Global Scope 3 from Cruise ($mtCO_2$)	Global Scope 3 from LTO ($mtCO_2$)	Total Scope 3 from Cruise + LTO ($mtCO_2$)
Large airports	967	108	1075
Medium airports	140	24	164
Small airports	17	4	21
Total	1124	136	1260

again two different "branches", with some small airports having long flights and quite large emissions, possibly relating to private jet travel or connecting islands to larger airports, and smaller airports with small amount of emissions, possibly consisting of short flights of smaller aircraft. Seaplane bases, marginal in number and not discussed before, still compose an interesting isolated group of very low emissions and very short distances flights, as we would expect from the types of aircraft operating through them.

We consider also the total emissions (cruise + LTO) per passenger-kilometer (pkm) against the average distance of flights, as presented in Fig. 30. What we can see from this plot is the efficiency of large airports and their proximity with medium size airports, probably due to their common population of aircraft. Small airports show some differences, with some of them being much less efficient than others. When averaging over values by type of airport, we find the median value of emissions to be 104 grams of CO_2 per pkm for large airports, 164 grams of CO_2 per pkm for medium size airports, and a probably unrealistic value of $2,800$ grams of CO_2 per pkm for small airports. As we will show later, small airports estimates are likely to be more affected by aircraft misidentification, and hence have larger errors in their estimates. We are also dealing with skewed distributions that can easily shift averages and medians. Interestingly, the values for large and medium airports are in good agreement with reported values. Indeed, some authors talk about 90 grams of CO_2 per pkm for

Figure 29: Scope 3 total emissions (cruise + LTO) per flight against average distance of flights.



passenger aviation[1], others report higher values like 285 grams of CO_2 per pkm[2], with even around 420 grams for some private jets[3]. One should finally mention that mean values are much higher than the medians, this due to the heavily skewed distributions representing these quantities.

The numbers mentioned above can be verified and analysed through another calculation, based on averages over airports. Indeed, denoting by $\langle \ldots \rangle$ an average over airports of a certain type (large, medium or small), we can average the number of flights n, the emissions e (grams of CO_2), the distance d (km) or the number of passengers p, which can be seen as random variables over the population of airports within a given type. Based on this concept, we can define two types of average scope 3 emissions per passenger-kilometers $\mathcal{S}$:

- $\mathcal{S}_1 = \frac{\langle (e/n) \rangle}{\langle (d/n) \rangle \langle (p/n) \rangle}$,
- $\mathcal{S}_2 = \frac{\langle (\langle e \rangle / \langle n \rangle) \rangle}{\langle (\langle d \rangle / \langle n \rangle) \rangle \langle (\langle p \rangle / \langle n \rangle) \rangle} = \langle n \rangle \frac{\langle e \rangle}{\langle d \rangle \langle p \rangle}$.

1 - ICCT
2 - EEA
3 - Compare Private Planes

For a uniform population of airports, these two definitions would lead to the same result, but as populations vary they lead to different predictions, as summarized in Table 4. Interestingly, these definitions bring much more consistent results between the different types of airports, indicating less emissions for large airports than for small ones, but with a much more reasonable gap between the two.

The emissions per passenger-kilometer (pkm) can also be compared against the total number of passengers. Plotting this quantity gives the results shown in Fig. 31, where it appears again that large airports are more efficient than small airports. What may be interesting to point at is the fact that when plotted against passengers, the two populations of airports appear to form only one continuous distribution. In addition to this metric of emissions per pkm, other definitions of averages as illustrated above can be derived. What remains important here is that the predictions are consistent with reality and that they give an insight into airport operations.

Figure 30: Scope 3 total emissions (cruise + LTO) per passenger-kilometer against average distance of flights.

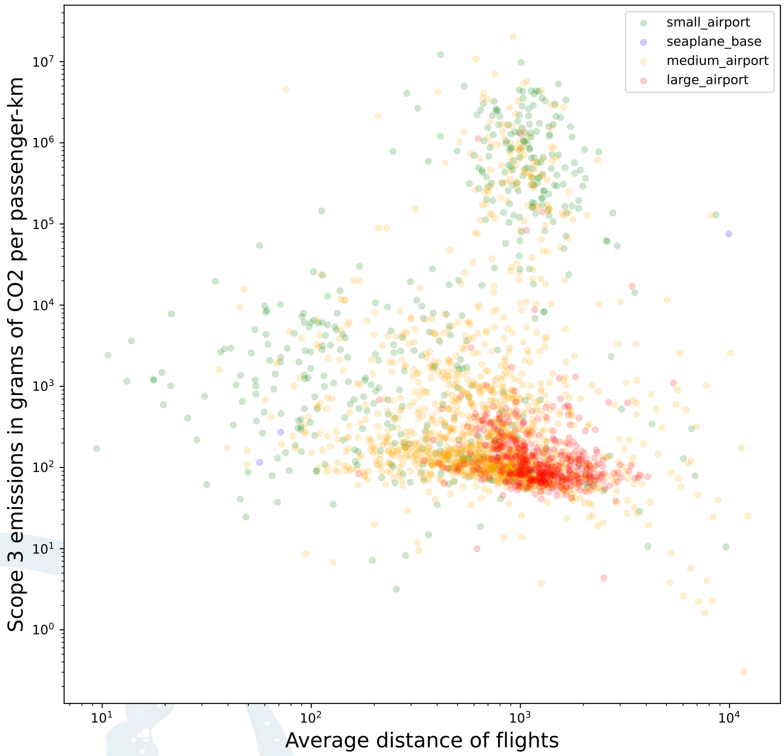
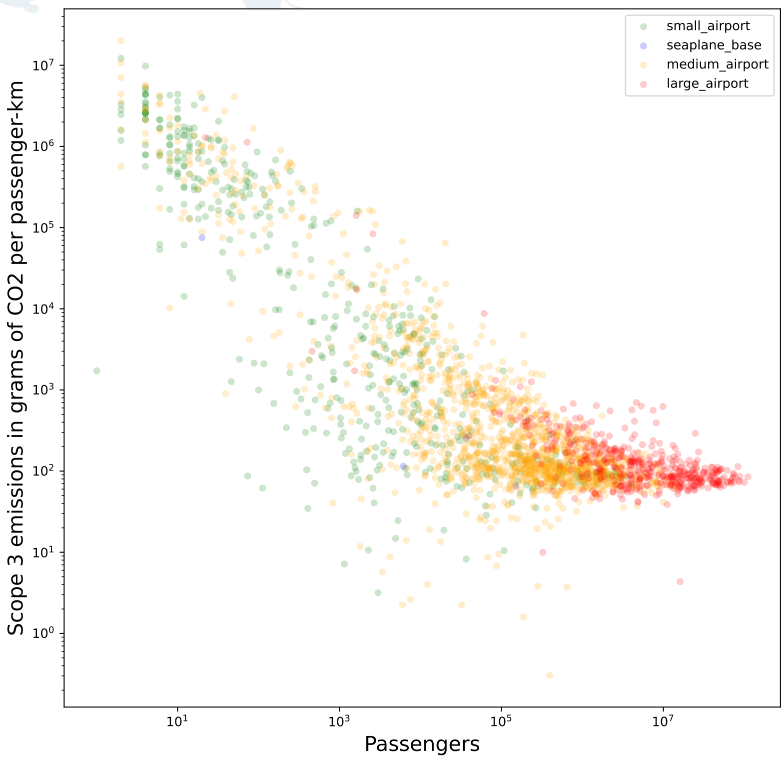


Table 4: Average Scope 3 emissions following two different definitions of averages.

Type of airport	$\mathcal{S}_1$ (grams CO_2 per pkm)	$\mathcal{S}_2$ (grams CO_2 per pkm)
Large airports	106	82
Medium airports	102	86
Small airports	124	86

Figure 31: Scope 3 total emissions (cruise + LTO) per passenger-kilometer against number of passengers.



Let us finish this section by displaying a map of some of the airports covered by the scope 3 emissions calculations. Out of the 8,000 airports for which we establish a prediction, about 5,300 of them have known geolocations that we can use to establish a map representing part of their population. This map is shown in Fig. 32. As we can see, our predictions are global and representative of the world population of airports.

5.3 Comparative analysis of scopes

Now that we have presented the results of our model for the computation of scope 1 and 2 emissions as well as scope 3 emissions from cruise and LTO cycle, we will gather these predictions together and compare their magnitudes in order to bring a better understanding of the most important sources of emissions.

5.3.1 Hierarchy of scope emissions

Having now predictions on scope 1, 2 and 3 emissions, it is interesting to represent their values on a common ground allowing for comparison. This is what Fig. 33 provides, showing the emissions as predicted by our different models. As we can see, scope 1 predictions are more concentrated than scope 2, as probably related to the lack of precision of the scope 2 model (and revealed by its large predicted values). Scope 3 emissions are larger than scope 1 and 2, as expected, but display a large dispersion due to the large number of airports it encompasses, including numerous small airports. The total number of airports, separated by their type, is summarized in Table 5.

Since these distributions represent different populations of airports, it is also interesting to plot the distribution of emissions for the subset of airports that has a full set of predictions. Doing this reduces the population of airports to 1515 mostly limited here by the scope 2 model, with 443 large airports, 967 medium airports, and 103 small airports. The corresponding distributions can be found in Fig. 34, and show much clearer separation of values. Indeed, scope 1 and 2 appear to have median values of similar magnitude, with scope 2 having a larger dispersion and skew towards large values due to a lesser precision in the model. On the other hand, the prediction of scope 3 emissions appears to have a median value an order of magnitude larger, with a ratio of about 40 times larger than the median of scope 1 and 70 times larger than the median of scope 2. These predictions and comparisons that they allow offer a very valuable insight into airport emissions for investors who want to limit their exposure to transition risks.

5.3.2 Interdependence between the different scopes

Now that we have seen the difference in magnitude of the different scopes of emissions, it is interesting to explore the relationship between them. As we can see from Fig. 35, scope 1 and scope 2 emissions are not strongly correlated. For large airports, we find a Pearson correlation of 0.10, possibly impacted by the quality of scope 2 predictions.

When comparing scope 1 predictions with scope 3 predictions from LTO, we find that the two are strongly correlated, as illustrated in Fig. 36. The correlation coefficient is 0.58 for large airports and 0.63 when gathering all predictions. When considering only airports having all predicted scopes, this coefficient is also 0.63. This interesting correlation appears to make sense since part of scope 1 emissions relate to the size of airports as well as ground vehicle activities, which are expected to scale with LTO emissions.

The correlation between scope 2 and scope 3 emissions from LTO is much less pronounced. For large airports, it is around 0.16, but this correlation disappears when considering all types of airports. This relationship is shown

Figure 32: Map of 5,300 airports covered by our scope 3 emissions estimates (out of 8,000).

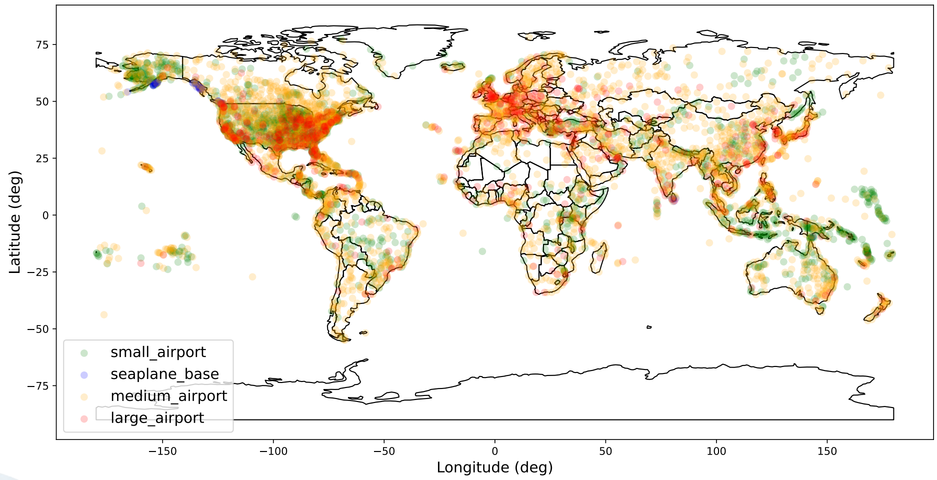


Figure 33: Histogram of Scope 1, 2 and 3 predictions for all predicted airports. Vertical lines represent the first and third quartiles of the distributions.

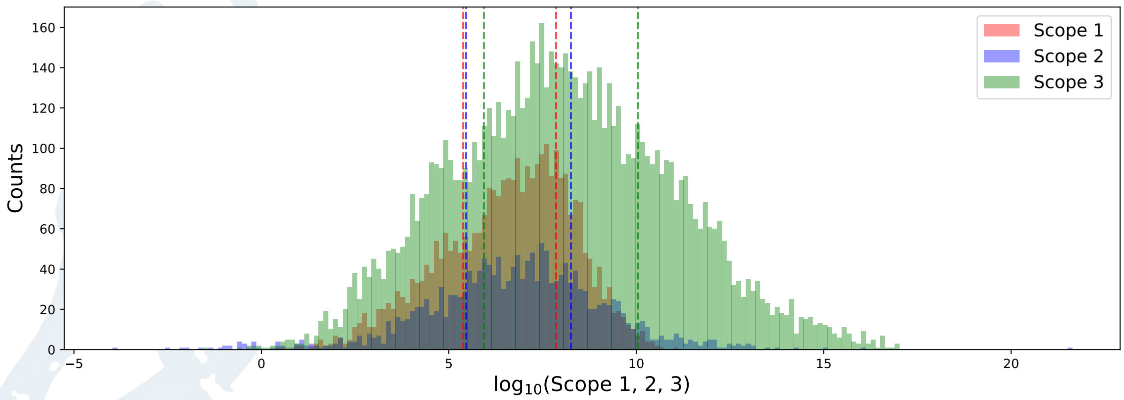


Table 5: Number of airports in each type for the different developed models of emissions.

Type of airport	Scope 1	Scope 2	Scope 3
Large airports	554	467	629
Medium airports	1954	1139	3024
Small airports	521	139	1666
Unknown / other type	40	4	2783
Total	3069	1749	8102

Figure 34: Histogram of Scope 1, 2 and 3 predictions for predicted airports that have all scopes predicted. Vertical lines represent the first and third quartiles of the distributions.

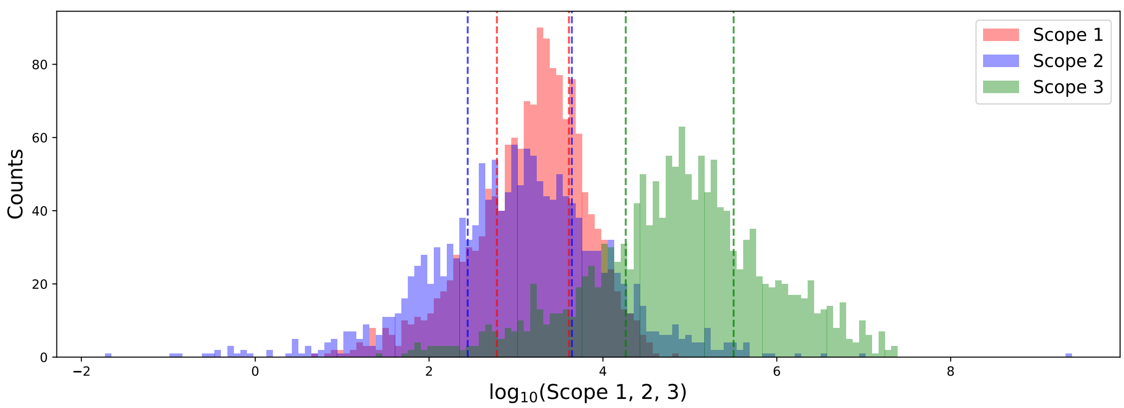


Figure 35: Scope 2 predictions against scope 1 predictions.

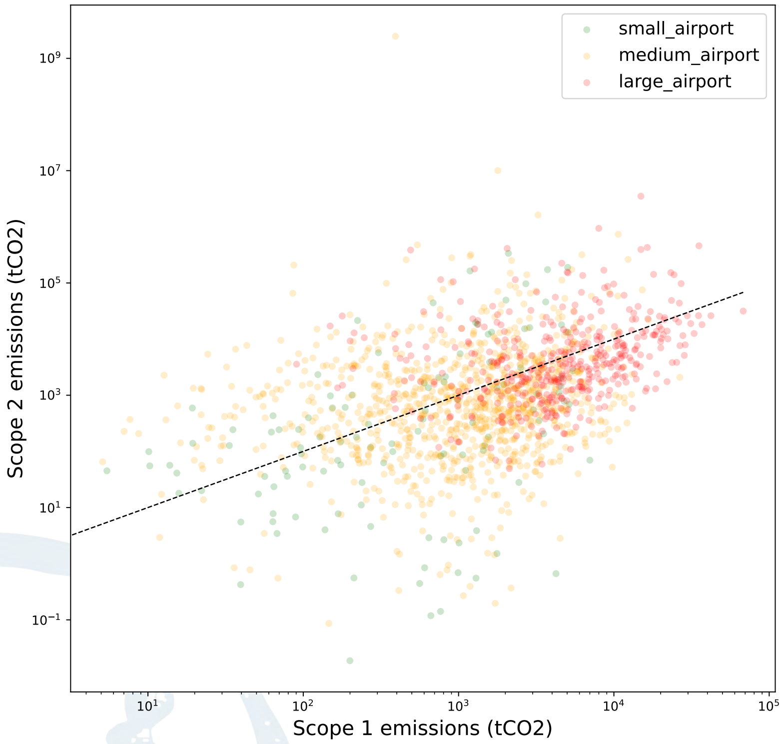
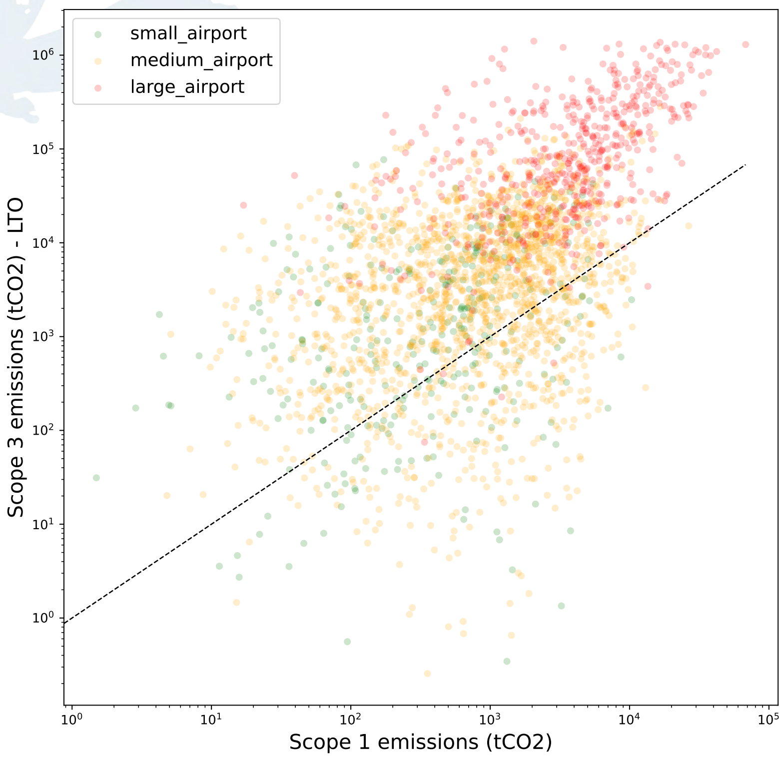


Figure 36: Scope 3 predictions from LTO against scope 1 predictions.



in Fig. 37, and the lack of correlation, aside from the low scope of the model, can be traced back to the fact that airport terminal buildings which compose most of scope 2 emissions would not have an electricity consumption primarily related to the number of aircraft on the airport ground.

Now that we have considered LTO emissions that are often reported in sustainability reports, but not cruise emissions, it is interesting to consider the correlation of scope 1 against LTO and cruise emissions together (total scope 3). The corresponding result for scope 1 is given in Fig. 38 and shows a correlation only slightly less than correlations reported between scope 1 and scope 3 from LTO (less than a 0.03 difference). This is not a surprise considering the correlation between scope 3 from LTO and scope 3 from cruise, which is around 0.9. The interpretation thus remains the same as above. It may be interesting to add that the median value for the ratio Scope 3 / Scope 1 is about 170 when it comes to large airports, 35 for medium airports, and 12 for small airports (values based on airports having all predictions).

We can draw very similar conclusion for the correlation of scope 2 emissions and total scope 3 emissions as the case of scope 2 against scope 3 from LTO. A correlation of 0.20 appears for large airports and around 0.58 for small airports, but almost disappears totally when combined together (as is also the case for medium airports alone). Results can be visualized in Fig. 39. The median value for the ratio of Scope 3 / Scope 2 turns out to be 263 for large airports, 43 for medium airports, and 14 for small airports. These values are quite sensitive to the modelling and may change with the improvement of the model.

Finally, and maybe most interestingly, we can explore the correlation between scope 1 + 2 emissions and total scope 3 emissions. This relationship is shown in Fig. 40 and resembles the relationship of scope 3 against scope 2, with correlations of 0.22 for large airports, 0.57 for small airports, and almost zero when it comes to medium airports or all airports combined. As for the ratio Scope 3 / Scope 1+2, we find a value of 80 for large airports, 13 for medium airports, and 4 for small airports.

5.4 Limitations and improvements

As any other study, this work has limitations which call for further improvements. We will review here some of the most appealing aspects of amelioration that could be implemented in order to reach higher accuracy and coverage from predictions.

5.4.1 Evaluation of errors

Evaluating the uncertainty of predictions is of primary importance in order to assess the quality of the models. When it comes to our statistical models of scope 1 and 2 emissions, the calculation of errors has partially been accounted for through the description of R^2 scores and the qualitative description of the models. As we have already described, the scope 1 model in its current stage provides better predictions than the scope 2 model.

When it comes to the estimate of errors for scope 3 models, we can first rely on approximations made by the models themselves. We thus considered the error in emissions when an average aircraft model was used (which as stated before appears in less than 10% of cases). This estimate has been made for both cruise and LTO emissions and appears to be reasonable in practice. Other sources of error were not considered as they were not measurable or estimated to be negligible. Based on what has been explained, Fig. 41 and Fig. 42 show the errors on scope 3 emissions respectively from cruise and the LTO cycle at airports. As we can see on both plots, the errors on the estimates are smaller than the estimates themselves. For cruise emissions on large airports, the error is on average of 14%,

Figure 37: Scope 3 predictions from LTO against scope 2 predictions.

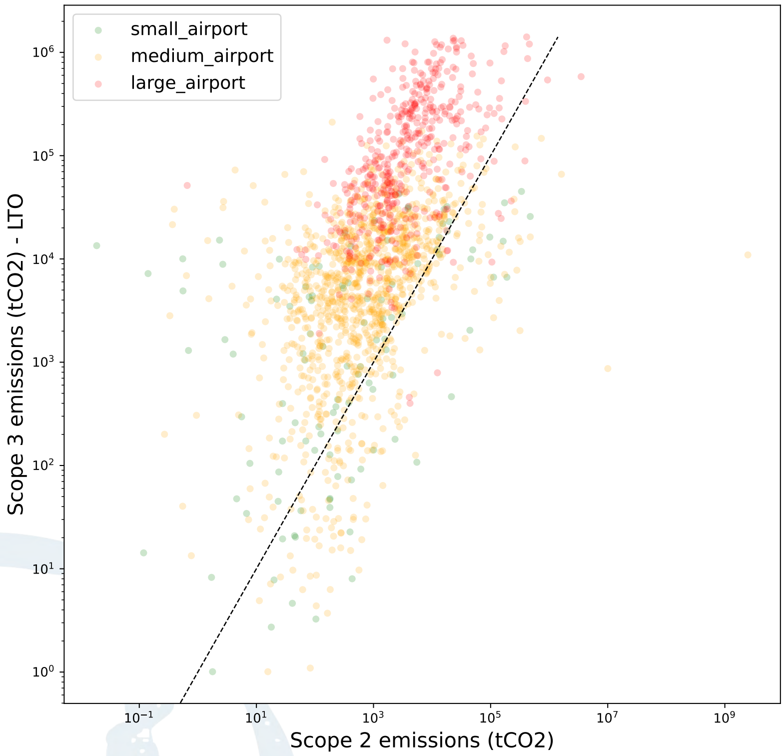


Figure 38: Scope 3 predictions against scope 1 predictions.

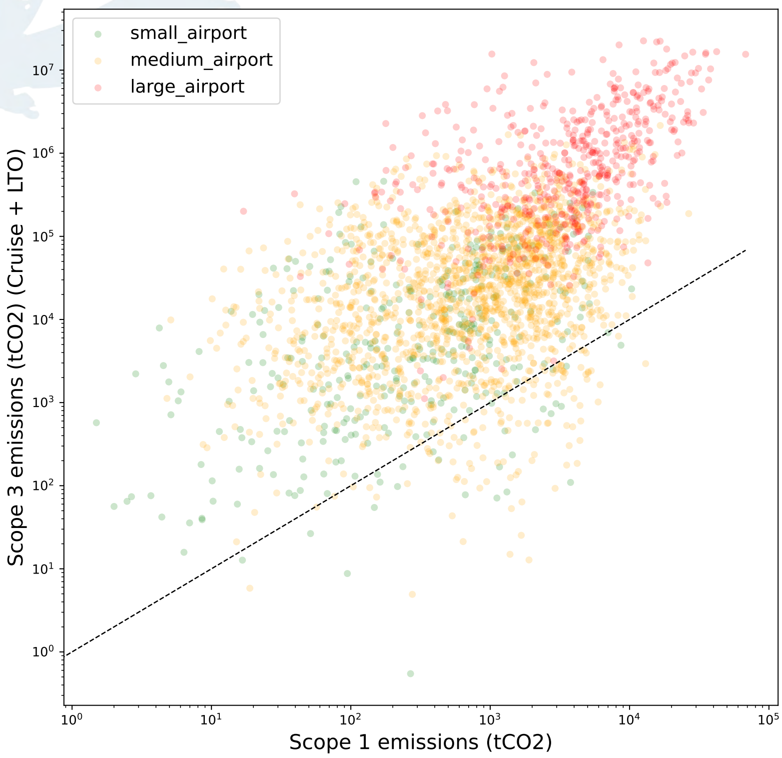


Figure 39: Scope 3 predictions against scope 2 predictions.

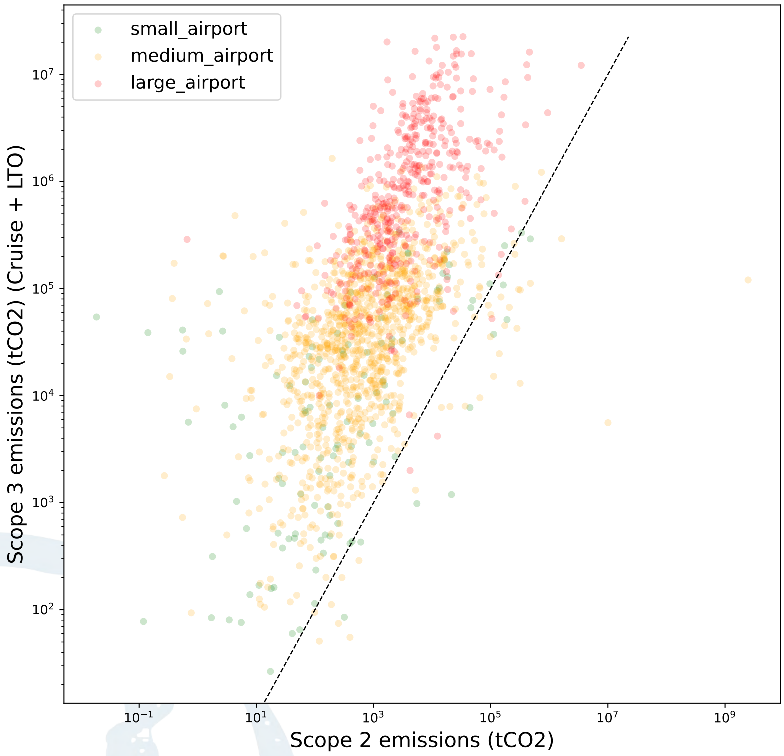
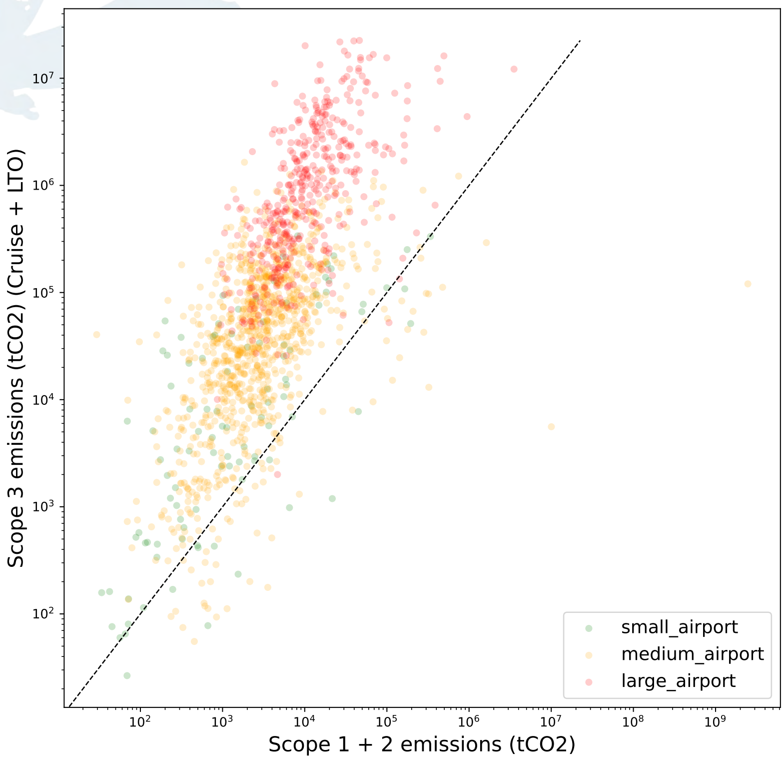


Figure 40: Scope 3 predictions against scope 1 + 2 predictions.



with median at 4%, while for LTO the values of mean and median are slightly above 10%. Errors are significantly larger when it comes to medium and small airports. Finally, let us add that the employed emission factor of 3.16 kg CO_2 / kg of fuel burnt is likely to have a relative 5% error on its value affecting all predictions.

As a final check of accuracy, one can use the small amount of reported scope 3 data in order to test our predictions. 15 airports where found reporting scope 3 LTO emissions and being present in our dataset. The ratio of predicted LTO emissions over the reported ones was found to be 1.7 ± 2.1, but after the removal of one outlier fell much closer to real values with a ratio of 1.2 ± 0.7. This result is satisfying considering the small number of data points as well as the sources of error discussed earlier. As for scope 3 emissions from cruise, the only airport known to the authors is Heathrow airport. According to Heathrow's sustainability report for year 2019, its estimated departure cruise emissions are 18,742 tCO_2e while our model gives a prediction of $20,561 \pm 900$ tCO_2 (recall that we assumed $CO_2e \equiv CO_2$), hence within 10% of the real value. As for the LTO emissions of Heathrow airport, our model predicts $1,268 \pm 82$ tCO_2 while the reported value is $1,250$ tCO_2e, hence falling at 1.5% close to the reported value.

5.4.2 Current limitations and improvements

As already mentioned, the statistical models for scope 1 and 2 can be improved with the inclusion of more data points to train the model efficiently. In particular, a potential source of concern is the absence of small airports in publicly reported data which can bias the predictions of the model as we have seen especially in the case of scope 2 predictions. Including more points in the modelling dataset should improve the quality of predictions further and this task is already under development. In addition to this increase in instances, the collection of additional features and in particular geospatial features will likely improve the estimates for both scope 1 and 2 models. This process of larger collection is already under way. As scope 2 emissions are related to electricity consumption, and thus are more likely to depend on socio-economic factors, new explanatory variables could be added in order to establish a better prediction. Finally, we have seen that the number of airports in the prediction dataset could be limited by some particular features. A better treatment of these variables could improve the situation and is under study as well. The application of several models on different instances of the prediction dataset, though diminishing the overall quality of predictions, is also a simple solution that would allow a full coverage of airports globally.

Since scope 3 modelling is significantly different from scope 1 and 2, the challenges to improve the predictions of scope 3 models are of different nature. One source of improvement is to perfect some of the steps in the calculation. Indeed, we already mentioned that the aircraft identification was not perfect and can be improved for a higher accuracy at the airport level (though potential miss-identifications statistically cancel-out over a large number of aggregated flights). This is true for both cruise and LTO models. As mentioned already as well, the use of great circles for the distance travelled by aircraft may slightly underestimate the real distance flown by aircraft, but some of this underestimate has already been factored out in our modelling through empirical corrections of distances. Finally, a mixed approach between distance and travel time could be integrated for a better modelling of particular routes and aircraft.

When it comes to the estimate of LTO emissions, similar comments can be made due to their reliance on a common subset

Figure 41: Errors of scope 3 predictions from cruise emissions against their estimates.

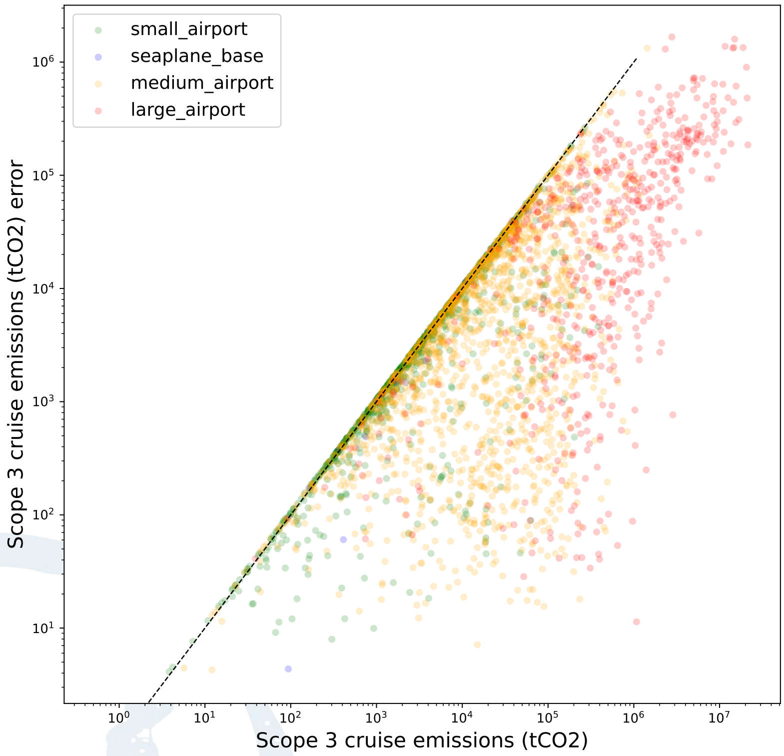
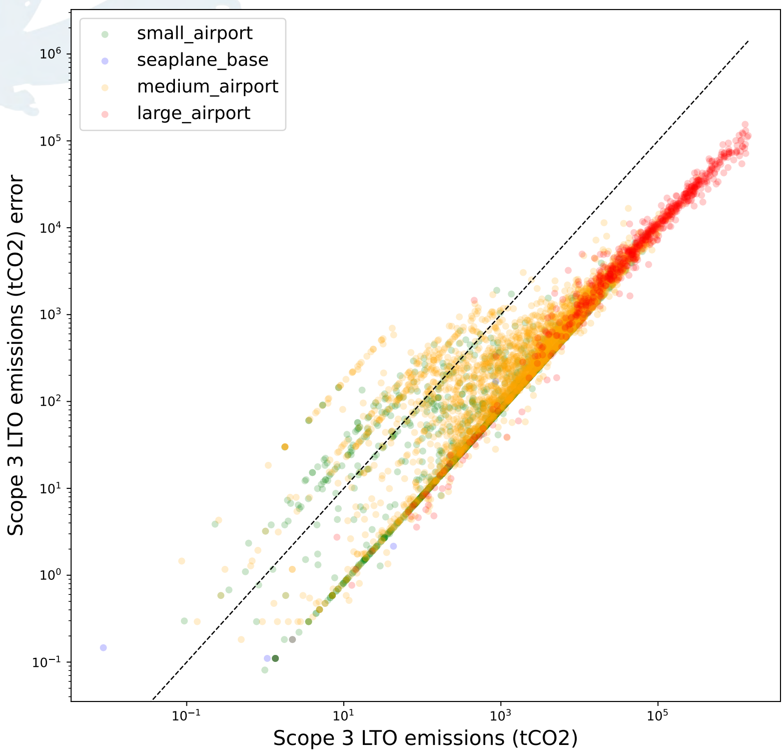


Figure 42: Errors of scope 3 predictions from LTO emissions against their estimates.



of data. The LTO estimate depending on schedule time data, the integration of complementary time features and data relating to the specific aspects of LTO emissions by multiple aircraft types could also bring more precision in the estimates. Finally, and as explained in the modelling part, the thrust of aircraft during the different LTO phases has been assumed constant and independent from aircraft types. More specific modelling of thrust at the aircraft level could be implemented in order to push further the precision of the model.

Final considerations regarding developments can be made based on the frequency of the extracted metrics. Since our estimates focus on airports and because reported data is available on an annual basis, the natural frequency of our estimates is yearly. We have focused on year 2019 since it was not significantly impacted by Covid 19 as compared to years 2020 and 2021, but our models are directly applicable to these years as well. However, thanks to the availability of most processed data at a higher frequency level (with high confidence for scope 1 and 2 models and great certainty for scope 3 models), it is also possible to predict scope 1, 2 and 3 emissions on a quarterly or monthly basis. This availability of predictions at higher frequency is potentially interesting for investors, especially in fast moving market conditions such as what we have seen during the Covid-19 crisis. It is also relevant for pre-quarter predictions. In general, these predictions of carbon footprints bring a new type of information to investors and could quickly become a requirement for the evaluation of assets before an eventual acquisition.

6. Carbon Emissions and Financial Returns

In this chapter, we take our findings one step further and investigate the relationship between the carbon emissions of airports and their financial performance.

If emissions represent a known factor of transition risk today, then financial markets should be pricing such transition risks consistently and require higher returns for investments that are more exposed to these risks, *ceteris paribus*. Conversely, if the financial returns of airports do not relate in any way with their level of emissions once other control variables have been taken into account, it suggests that transition risks are not priced.

We use data from infraMetrics® to match the financial performance of 25 large private airports with their scopes 1&2 and scope 3 emissions, as well as their carbon intensity for scopes 1&2 and scope 3.

We first examine the relationship between emissions and the capital returns of these airports, controlling for the presence of other factors that typically drive returns in infrastructure investments (6.1).

We then look at expected returns: a forward-looking view of the market the riskiness of an investment, and whether the level of emissions is related to the level of expected returns.

6.1 Realised (price) returns and emissions

6.1.1 Data

CO2 intensity is expressed in gCO2/pkm i.e. it is a reflection of the emissions of the airport by unit of output (or service) produced.

When expressed in terms of Scopes 1&2, it reflects the operational efficiency of the airport: higher Scopes 1&2 intensity indicates that the airport requires consuming more energy to deliver one unit of service.

When expressed in terms of Scope 3, it is a measure of the economies of scale achieved by the size of the airport: higher Scope 3 intensity indicates that fewer, smaller and/or shorter flights were using the airport, leading to a higher consumption of CO2 per unit of passenger/kilometre.

Since we have estimated carbon emissions for the year 2019, we use data going back 6 years until 2019 i.e., we assume that the relative level of emissions between airports in 2019 can be held constant going back several years. Going forward, because of the Covid-19 lockdowns and their differing impacts on airports, this assumptions cannot be held. Hence, our dataset spans 2013-2019 for realised returns.

The 25 airports for which infraMetrics reports monthly financial return represent a combined market capitalisation of USD50bn in 2019.

We examine price (or capital) returns to focus on the potential impact of emissions on the equity discount rate and avoid any noise from the large dividends paid by infrastructure investments in the relationship between returns and carbon emissions.

6.1.2 Sorted portfolios

We first sort assets into 'high' and 'low' portfolios by ranking each airport above the median metric as 'high' and below the median as 'low' of CO2 scopes 1&2.

Table 6: Mean and median monthly returns of scopes 1&2 sorted portfolios

Portfolio	Mean Return	Median Return
H/H	-0.0009	0.0043
H/L	0.0065	0.0080
L/H	0.0092	0.0124
L/L	0.0014	0.0068

Table 7: Mean and median monthly returns of scopes 3 sorted portfolios

Portfolio	Mean Return	Median Return
H/H	0.0075	0.0063
H/L	0.0064	0.0074
L/H	0.0055	0.0090
L/L	0.0005	0.0054

Next, we build four portfolios combining the carbon intensity (gCO2/pkm) and level of emissions (tCO2) thus:

- H/H : high carbon intensity & high emissions
- H/L : high carbon intensity & low emissions
- L/H : low carbon intensity & high emissions
- L/L : low carbon intensity & low emissions

The weighted geometric returns of portfolio H/H are then computed as:

$$Portfolio^{H/H} = exp\Big(\frac{1}{\sum_{i=1}^{N} \omega_i} \sum_{i=1}^{N} \omega_i . ln(r_{i,t}^{h/h})\Big)$$

where ω_i are the asset weights, and $r_{h/h}$ are the returns of the assets in the H/H portfolio with both high carbon intensity and high carbon emissions.

The price returns of the other three portfolios are computed in the same manner. Table 6 shows the mean and median monthly return of each sorted portfolio. When it comes to Scopes 1 and 2, we observe that low carbon intensity airports (i.e., more efficient airports) that, at the same time, are high emitters, have seen higher realised returns than high-intensity (i.e., less efficient) airports.

We repeat this exercise for scope 3 emissions. Table 7 shows the monthly returns for the same four portfolios sorted on the basis of scope 3 emissions. Here, low-intensity (i.e., large scale) airports that, at the same time, are high emitters, have performed the best in terms of price returns

6.1.3 Carbon factor portfolios

Following the literature on asset pricing, we create so-called factor mimicking portfolios, by subtracting the average of high intensity portfolios from that of low intensity ones, so that

$$CarbonFactor = \frac{1}{2}(H/H + H/L) - \frac{1}{2}(L/H + L/L)$$

Table 8 shows the descriptive statistics for each HML portfolio using scopes 1&2 or scope 3 respectively, as well as an index of all airports in the sample. Figure 43 shows the cumulative performance of all three portfolios.

We note that a high-minus-low Scopes 1&2 intensity portfolio of airports has negative average returns i.e., low CO2-intensity airports have higher price returns than higher CO2-intensity airports on a scope 1&2 basis. Conversely, the HML portfolio using scope 3 emissions exhibits positive returns and tends to track the all airport index over time on a cumulative basis. In other words, airports with high scope-3 emission intensity have tended to have higher price returns between 2013 and 2019.

Figure 43: High-minus-Low Carbon Airport Portfolios (Scopes 1&2, 3) and All Airports

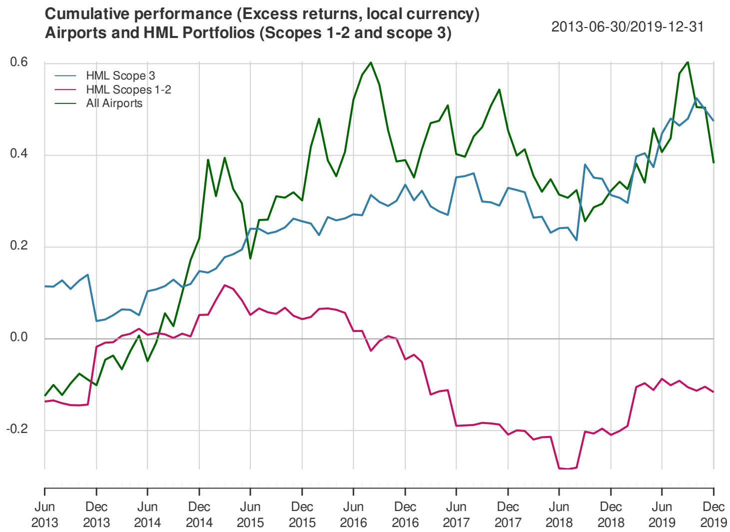


Table 8: Monthly returns of the HML and All Airports Portfolios

	HML Scope 3	HML Scopes 1-2	All Airports
Mean	0.004	-0.003	0.005
Median	0.002	0.000	0.010
StdDev	0.028	0.033	0.050
Semi-Variance	0.025	0.036	0.052
Sharpe ratio	0.112	-0.101	0.078
Kurtosis	4.846	7.586	-0.074
Skewness	0.821	0.086	-0.050

Since we are considering price or capital returns only, these results give a sense of the difference in capital gains over the period between high emissions and low emissions airports: the discount rate of low Scope 1&2 intensity and high scope 3 intensity airports decreased more (capital gains have been positive) over the period.

Hence, those airports that investors have found the most attractive have seen the highest capital gains i.e. yield compression, are the ones that exhibit higher operational efficiency (low scope 1&2 intensity) but also lower scale economies (higher scope 3 intensity).

This could suggest that investors value lower scopes 1&2 carbon intensity, which could be a signal of lower exposure to transition risks, but not scope 3 intensity, which is positively related with a reduction of the cost of capital.

6.1.4 Carbon factor regression

Other factors could explain this difference in the performance of airports that exhibit higher or lower carbon intensity. Next, we run the following regressions:

- A base regression of all airport price returns against the standard factors that explain the realised returns of infrastructure assets: Size, Leverage, Profit, Investment and Country risk.
- A similar regression using the HML Carbon factor portfolio as an additional explanatory variable, to determine whether this effect is also present in realised returns;
- A regression of the HML Carbon factor portfolio itself against the same factors to determine is it is driven by 'something else' than standard pricing factors: i.e. if there may be a 'carbon factor' in the price returns of unlisted airports.

Table 9: Regression of Airport Returns 2013-2019

	Beta	SE	p.value
(Intercept)	-0.0011	(0.0021)	0.61273
Market	1.25	(0.0563)	0
Size	-0.8322	(0.2395)	0.00087
Leverage	0.8972	(0.215)	0.00008
Investment	0.3568	(0.2636)	0.18018
Profit	0.7591	(0.1681)	0.00002
Ctry.Risk	-0.4185	(0.0857)	0.00001
Deg. freedom	72		
Adj-R2	94.04%		

Airport returns

Table 9 shows the results of the basic monthly return regression of all airport returns based on the standard infraMetrics factor returns, in local currency for the period 2013-2019. The construction of factors used in the regression loosely follows the Fama-French five-factor model. Factor computation details are described in the appendix.

Table 9 confirms that the monthly price returns of the infraMetrics airports index can be explained with a high degree of fit (Adjusted-R^2 of 94%) by an unlisted infrastructure market factor and 5 factors capturing the returns of key risk factors found in unlisted infrastructure investments.

All factors are highly significant except the investment factor. Indeed, the airports present in the index are all existing brownfield assets and, relative to the infrastructure market as a whole, they are all 'low investment' assets. As a result the returns of airports do not load on the investment factor.

The intercept of the regression is not statistically different from zero, meaning that the factors used in the model explain all the variance of the realised returns and there is no residual 'alpha' in the model.

Next, we examine the impact of the HML Carbon Factor we built above in this setting.

Airport returns with the HML Carbon factor

Tables 10 and 11 show the regression results for the same model with the addition of a High-minus-Low Carbon intensity factor for Scope 1&2 and scope 3 respectively.

Table 10: Regression of Airport Returns with HML Scopes 1&2 Factor

	Beta	SE	p.value
(Intercept)	-0.0017	(0.0021)	0.4235
HML Scopes 1&2	-0.0818	(0.0629)	0.19767
Market	1.2588	(0.0585)	0
Size	-0.7852	(0.2402)	0.00166
Leverage	1.0457	(0.2283)	0.00002
Investment	0.3331	(0.268)	0.21796
Profit	0.7775	(0.1699)	0.00002
Ctry.Risk	-0.3711	(0.089)	0.00009
Deg. freedom	71		
Adj-R2	93.03%		

Table 11: Regression of Airport Returns with HML Scope 3 Factor

	Beta	SE	p.value
(Intercept)	-0.0003	(0.002)	0.88187
HML Scope 3	-0.167	(0.0809)	0.04269
Market	1.2442	(0.0597)	0
Size	-0.7141	(0.2356)	0.0034
Leverage	0.8497	(0.2332)	0.00051
Investment	0.2662	(0.2747)	0.33577
Profit	0.606	(0.189)	0.00201
Ctry.Risk	-0.3348	(0.0875)	0.00028
Deg. freedom	71		
Adj-R2	91.51%		

Adding the HML Scopes 1&2 to the regression does not yield any additional significance to the model. The variable itself is not significant and the model adjusted-R^2 is slightly lower.

However, adding the HML Scope 3 to the regression does yield some extra statistical significance albeit limited and with a lower goodness-of-fit. The result suggests that airports returns may load negatively on a HML Scope 3 factor i.e. controlling for everything else, higher Scope 3 intensity airports would have slightly lower realised price returns i.e. a higher risk premia.

HML Carbon Factor Regressions

Finally, we regress the HML Carbon Factor returns against the same set of factors that explains airport returns. Results are shown in tables 12 and 13 for HML Scopes 1&2 and Scope 3, respectively.

The HML Scope 1&2 factor regression exhibits a low degree of fit and has a slightly significant intercept (at the 5% confidence level). HML Scope 1&2 returns load on leverage and

Table 12: Regression of HML Scope 1&2 Returns

	Beta	SE	p.value
(Intercept)	-0.0086	(0.0041)	0.0406
Market	0.1891	(0.1207)	0.12173
Size	-0.0555	(0.4025)	0.89074
Leverage	1.2377	(0.3813)	0.00178
Investment	-0.2419	(0.5285)	0.6486
Profit	0.2006	(0.2966)	0.50109
Ctry.Risk	0.3658	(0.1602)	0.02538
Deg. freedom	72		
Adj-R2	15.93%		

Table 13: Regression of HML Scope 3 Returns

	Beta	SE	p.value
(Intercept)	0.0042	(0.0029)	0.1468
Market	-0.0604	(0.0854)	0.48181
Size	-0.0237	(0.2845)	0.93374
Leverage	-0.9179	(0.2191)	0.00008
Investment	-0.367	(0.4037)	0.36634
Profit	-0.8805	(0.1635)	0
Ctry.Risk	0.1766	(0.1259)	0.16492
Deg. freedom	72		
Adj-R2	67.68%		

country risk with a positive sign, indicating that some of the difference in price returns between high and low carbon intensity airports is driven by higher exposures to these risk factors amongst the airports considered.

In the case of HML Scope 3, the expected value of the factor is not different from zero (the intercept is not significant) and 67% of its variance can be explained by differences in leverage and profit in the HML constituent airports. The coefficients for these two only significant factors are negative meaning that the difference in returns between high and low Scope 3 intensity airports hinges around these airports being more profitable (the profit factor has a negative sign) and less leveraged i.e. lower returns than the market, which is consistent with the evidence reported in table 8.

In conclusion, the combination of the results presented above suggests that there is not persistent, systematic difference in returns between high and low carbon intensity airports, whether one considers Scopes 1&2 or Scope 3.

Standard, well-documented pricing factors suffice to explain all the observed variance of realised price returns, suggesting that there is no 'carbon factor' or effect when investors set the price of such investments.

Finally, we look at expected returns and emissions.

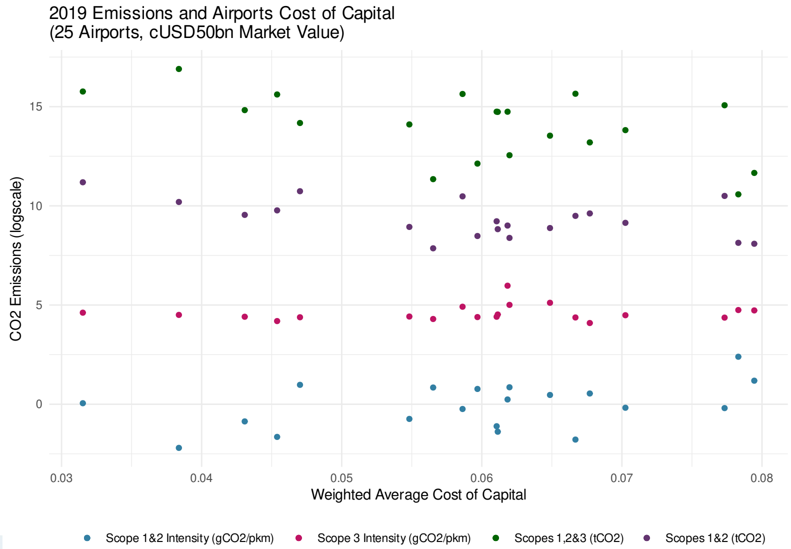
6.2 Expected returns and emissions

Figure 44 shows the relationship between the weighted-average cost of capital or WACC in 2019 for the airports in the sample on the horizontal axis, and their emissions both in absolute terms (Scopes 1&2 and Scope 3) and relative terms (Carbon intensity) on the vertical axis presented in logs.

Unlisted the realised returns considered above, the WACC is a combination of the cost of debt and cost of equity of the firm and a reflection of its forward looking or expected returns. It is therefore a candidate to try and detect the presence of a carbon-related risk premia.

However, it is quite clear from this chart that there is no relationship between the WACC of airports their emissions, which is also consistent with the evidence presented above.

Figure 44: Emissions and weighted average cost of capital



Source: infraMetrics®

7. Conclusions

We will now summarize the findings of this paper and recall its main implications regarding the use of such models and predictions for investor decisions. We will also discuss possible future improvements of our approach.

7.1 Why this study

This work addressed the estimate of carbon footprints in the airport sector. Transition risks have received growing consideration, especially since COP21 and the Paris Agreement in 2015, as investors have expressed increasing concerns and now demand more data to manage the associated risks in their investments. Carbon emissions have thus become central as they are believed to be a good proxy of transition risks. Sustainable investing has been growing in popularity as well in the recent years and there is a strong demand for estimates of climate-related risks.

Some of the motivations to study airports can be found in the fast growth of their sector of activity over the last few decades. Due to the relative importance of air transport emissions per passenger and the partial existence of alternatives to flights, airport activities may be more at risk than some other types of infrastructures regarding transition risks. Global warming is not only an economic threat to airports, it is also a magnifying factor of diverse hazards impacting their activities. Hence multiple airports have shown the will to transition to net zero by 2050, and will need important efforts to reach this target. This may explain the presence of a certain amount of sustainability reports in the sector, which are fundamental in order to establish or validate models of emissions.

Nevertheless, the number of publicly reported emissions is still limited and an increase in reporting is necessary for a better understanding of airports, especially when it comes to the smallest airports on which data is hard to obtain. However, since the main motivation is to understand the principal sources of emissions in the airport sector, large airports are by far the most important airports to capture. This lack of significant coverage of airport emission metrics is thus a problem which current ESG data vendors on the market do not satisfactorily handle. Solving this issue through the provision of transition risks estimates was the main motivation of the present work.

As these estimates are of relevance for a multiplicity of applications, they are of major importance for infrastructure investors who look for better data to evaluate the exposure of their assets to transition risks as well as acquiring new assets or reducing the carbon footprint of their portfolios. As a recent survey from EDHECinfra to infrastructure investors has revealed, the main ESG data needed by investors concerns climate impact, and in particular the impact of assets on climate change (before the impacts on natural resources, human well-being or economic development). The models presented here thus respond to the investors' main concern by providing climate-change impact-related predictions covering the majority of assets world-wide, and developing metrics of relevance for their decisions.

7.2 Main findings

We have shown here that it was possible to leverage geospatial data and traffic data to establish statistical and predictive models.

Our approach on scope 1 and scope 2 emissions have shown that a few data points of quality used to establish a statistical model was enough to reveal the importance of some explanatory variables, in agreement with the current literature and bringing its own contribution to the field. We have found that our model of scope 2 emissions was slightly weaker than scope 1, but we believe that the inclusion of more training data points will increase this precision in a very near future. As for scope 3 emissions, the models developed for cruise and LTO have shown equally, if not actually more promising results than scope 1 and 2 models. Hence, they offer an insight in sources of emissions which are still not consistently reported and bring new possibilities of insight regarding sustainability issues.

Using these models, we have found that scope 1 and 2 emissions were relatively similar in size, when considered on average. On the other hand, we have found that scope 3 emissions where much larger than the sum of scope 1 and 2 emissions. Having considered only two sources of emissions within scope 3, i.e. cruise and LTO cycle emissions, we have found that cruise emissions were significantly larger than LTO emissions. The two types of emissions have been logically found to have a very strong correlation. As for other correlations, we have found that scope 1 and 2 or scope 2 and 3 were not significantly correlated, but that scope 1 and 3 were interestingly correlated. Finally, by using a classification of airports in different types, we have shown that hierarchies could depend on the type of airport, and it was often found that the quality of modelling increased when considering large airports.

Furthermore, our analysis of carbon emissions estimations and financial performance generated several interesting results. First, low-carbon-intensity airports that are high emitters perform the best. In other words, airports that are high CO2 emitters but, nevertheless, are either energy-efficient or large-scale performed the best in terms of price returns.

Second, when looking only at carbon intensity and its link to performance, we found that low CO2-intensity airports, which are operationally more efficient, had higher price returns than high CO2-intensity airports on a scope 1&2 basis. This result may suggest that investors value lower scopes 1&2 carbon intensity, signaling a lower exposure to transition risk. However, once controlling for the standard factors explaining realized returns of infrastructure, this effect was found not to be statistically significant.

Likewise, higher CO2-intensity airports characterized by lower economies of scale achieved higher price returns on a scope 3 basis. However, once controlling for standard factors, higher scope 3 intensity airports are found to have a slightly lower realized returns, close to the non-significance threshold.

Overall, the combined results of the carbon-to-performance analysis suggests that there is not persistent, systematic difference in price returns between high and low carbon intensity airports, whether one considers Scopes 1&2 or Scope 3. In other words, carbon intensity as a proxy of transition risk is not priced in airport returns.

7.3 Implications for risk management and reporting

As already stated, the current ESG data market is insufficient to satisfy infrastructure investors in their risk management decisions. We have presented through this publication a methodology that is general and lead to robust predictions that can be extended to other types of assets. Thanks to their generality and simplicity, the models derived from this method are able to generate a large amount of data, reaching global coverage, and respond to the current need of infrastructure investors. Consequently, our predictions represent an important progress for investors in their risk management and provide a significant support for the reporting of emissions from assets which either do not estimate their emissions, or do not disclose them.

These developed models are very relevant for the assessment of carbon footprints and transition risks which directly relate to them. Hence they bring important information regarding assets, and due to the lack of reported data especially come in handy in a context where only a few assets publicly report their emissions. In addition to the raw estimates which are scope 1, 2 and 3, we have shown that intensity metrics could also be derived based on emissions combined with operational or physical variables. As models grow in coverage, complexity and accuracy, more metrics can be developed in order to refine the toolkit for investors willing to integrate sustainability considerations into their investment strategies.

As we described in the introduction, numerous regulatory frameworks are being put in place to uniformize the reporting of sustainability factors. These new regulations will not only set a path towards good-practice reporting for businesses, but also likely support the implementation of new laws regulating their activities, supporting carbon taxes or emission trading systems, and other very relevant aspects of business. At the moment, infrastructure assets are not all exposed in the same way to those frameworks, and a lot of progress remains to be made in order to establish the new standards. This work does not only provide a solution for airport investors and other stakeholders, but also shows that if estimates of emissions can be made, regulations based on them can also be implemented. In an epoch where big data has become the norm for business, this type of approach developed here is unavoidably going to become usual practice as well.

7.4 Future improvements

As any other type of modelling, our models rely on simplifying assumptions to establish their predictions. The current models already show important results and their weaknesses reveal potential opportunities of improvements. Some of these improvements are already under consideration by EDHECinfra and they intend to bring better coverage of assets globally as well as increase precision of the estimates. These models have strong potential for further improvements and several new features will be integrated into their design. A perfect example of new features is the integration of infrastructures' financial data in which EDHECinfra plays a significant role. As these models progress and get more complex, their performances will also improve, as we intend to show in the near future.

Our study has focused on the airport sector and its goal has been to show that an in-depth description of their carbon footprints to assess transition risks could be performed. As already explained, the airport sector is a good case study for other transport infrastructures which represent more than 10% of global emissions. As our approach combines statistical models, geospatial analysis and physics-based models, it is equally promising for numerous types of infrastructures, if not all. Hence, these models also compose a basis of understanding and set standards for the development of more models covering all types of infrastructure assets and companies at the global level.

A. Appendix: Factor Returns

In this section, we describe the computation of the factor returns used to decompose the performance of an infrastructure portoflio. The construction of the factor returns loosely follows the Fama & French approach to design factor replicating portfolios using sorted portfolios of asset returns.

The market factor is simply defined as the weighted geometric returns of all *N* assets in the universe. That is,

$$Market = exp\Big(\frac{1}{\sum_{i=1}^{N}\omega_i}\sum_{i=1}^{N}\omega_i.ln(r_{i,t})\Big)$$

Where r_i is the (excess or price) return of asset i and ω_i is the weight of asset i.

The Size factor or 'small minus big' (SMB) factor is the average return on nine small asset portfolios minus the average return on nine large asset portfolios.

Assets are sorted into small and large portfolios according to the median value of their total assets on the 30th of June of each year. This sort is then maintained until June of the following year, at which point the mediam breakpoint is estimated again and assets sorted again into small and large asset portfolios.

To build the nine portfolios, assets are also sorted into low, medium and high portfolios in terms of leverage, profitability and investment (capex), using the 33rd and 66th centile breakpoints on the 30 June of each year year. The returns of each of these High/Medium/Low portfolios are then combined thus:

$$\begin{aligned}SMB_{leverage} = &\frac{1}{3}(Small/HighLeverage+\\ &Small/MediumLeverage+\\ &Small/HighLeverage)-\\ &\frac{1}{3}(Big/HighLeverage+\\ &Big/MediumLeverage+\\ &Big/HighLeverage)\end{aligned}$$

$$\begin{aligned}SMB_{profit} = &\frac{1}{3}(Small/HighProfit+\\ &Small/MediumProfit+\\ &Small/HighProfit)-\\ &\frac{1}{3}(Big/HighProfit+\\ &Big/MediumProfit+\\ &Big/HighProfit)\end{aligned}$$

$$\begin{aligned}SMB_{investment} = &\frac{1}{3}(Small/HighInvestment+\\ &Small/MediumInvestment+\\ &Small/HighInvestment)-\\ &\frac{1}{3}(Big/HighInvestment+\\ &Big/MediumInvestment+\\ &Big/HighInvestment)\end{aligned}$$

Finally, the size fatcor is computed as:

$$SMB = \frac{1}{3}(SMB_{leverage} + SMB_{profit} + SMB_{investment})$$

The Profit factor is the average return on the two high profit portfolios minus the average return on the two low profit portfolios, using median breakpoints on the 30th of June.

$$Profit = \frac{1}{2}(Small/HighProfit + Big/HighProfit) - \frac{1}{2}(Small/LowProfit + Big/LowProfit)$$

Likewise, the returns of the investment (respectively, leverage or Term) factors are computed using the average return of two high investment (leverage or Term) portfolios minus the average return on the two low investment (leverage or Term) portfolios, using median breakpoints on the 30th of June.

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- ACA (2021). Airport carbon accreditation, annual report 2019-2021.
- ACI (2021). Long-term carbon goal study for airports - report 2021.
- Ahn, J. and S. Cho (2015, 12). Energy performance benchmark model for airport terminal buildings.
- Blanc-Brude, F. and N. Manocha (2021, March). Towards a scientific approach to esg for infrastructure investors. *EDHECinfra Research Publication*.
- Blanc-Brude, F., N. Manocha, and D. Marcelo (2022, June). Do financial investors need non-financial data? *EDHECinfra Research Publication*.
- Bolton, P. and M. Kacperczyk (2021a). Do investors care about carbon risk? *Journal of Financial Economics 142*(2), 517–549.
- Bolton, P. and M. Kacperczyk (2021b). Global pricing of carbon-transition risk. Technical report, National Bureau of Economic Research.
- Chati, Y. S. and H. Balakrishnan (2013). Aircraft engine performance study using flight data recorder archives. In *2013 aviation technology, integration, and operations conference*, pp. 4414.
- Chati, Y. S. and H. Balakrishnan (2014). Analysis of aircraft fuel burn and emissions in the landing and take off cycle using operational data.
- Documentation, E. (2022). The infrastructure company classification standard (ticcs®).
- Ducoulombier, F. (2021). Understanding the importance of scope 3 emissions and the implications of data limitations. *The Journal of Impact and ESG Investing*.
- Ducoulombier, F. (2022, February). Understanding net-zero investment frameworks and their implications for investment management. *Scientific Beta*.
- Filippone, A., N. Bojdo, S. Mehta, and B. Parkes (2021). Using the opensky ads-b data to estimate aircraft emissions. *Engineering Proceedings 13*(1).
- ICAO (2017a). A focus on the production of renewable energy at the airport site. *Québec, Canada: International Civil Aviation Organization*.
- ICAO (2017b, June). Icao carbon emissions calculator methodology. *Québec, Canada: International Civil Aviation Organization*.
- (ISSB), I. S. S. B. (2022a). [draft] ifrs s2 climate-related disclosures.
- (ISSB), I. S. S. B. (2022b). [draft] ifrs s2 climate-related disclosures - appendix b industry-based disclosure requirements - volume b60—air freight & logistics.

- (ISSB), I. S. S. B. (2022c). [draft] ifrs s2 climate-related disclosures - appendix b industry-based disclosure requirements - volume b61—airlines.
- Kang, M., M. Berges, and B. Akinci (2017). Forecasting airport building electricity demand on the basis of flight schedule information for demand response applications. *Transportation Research Record 2603*(1), 29–38.
- Khadilkar, H. and H. Balakrishnan (2012). Estimation of aircraft taxi fuel burn using flight data recorder archives. *Transportation Research Part D: Transport and Environment 17*(7), 532–537.
- Kim, S.-C., H.-I. Shin, and J. Ahn (2020). Energy performance analysis of airport terminal buildings by use of architectural, operational information and benchmark metrics. *Journal of Air Transport Management 83*, 101762.
- Koudis, G. S., S. J. Hu, A. Majumdar, R. Jones, and M. E. Stettler (2017). Airport emissions reductions from reduced thrust takeoff operations. *Transportation Research Part D: Transport and Environment 52*, 15–28.
- Lee, D., D. Fahey, A. Skowron, M. Allen, U. Burkhardt, Q. Chen, S. Doherty, S. Freeman, P. Forster, J. Fuglestvedt, A. Gettelman, R. De León, L. Lim, M. Lund, R. Millar, B. Owen, J. Penner, G. Pitari, M. Prather, R. Sausen, and L. Wilcox (2021). The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018. *Atmospheric Environment 244*, 117834.
- Li, B., W. Zhang, J. Wang, J. Xu, and J. Su (2017, nov). Research and analysis on energy consumption features of civil airports. *IOP Conference Series: Earth and Environmental Science 94*, 012134.
- Masiol, M. and R. M. Harrison (2014). Aircraft engine exhaust emissions and other airport-related contributions to ambient air pollution: A review. *Atmospheric Environment 95*, 409–455.
- Monasterolo, I. and L. de Angelis (2020). Blind to carbon risk? an analysis of stock market reaction to the paris agreement. *Ecological Economics 170*, 106571.
- Ortega Alba, S. and M. Manana (2016). Energy research in airports: A review. *Energies 9*(5).
- Penner, J., D. Lister, D. Griggs, D. Dokken, and M. McFarland (1999). Ipcc special report, aviation and the global atmosphere.
- Persefoni, T. S. I. b. E. (2022). The evolution of sustainability disclosure.
- PTF-ESRS, P. T.-F. o. E. s. r. s. (2022). Esrs e1, climate change.
- Pörtner, H. O., D. C. Roberts, H. Adams, C. Adler, P. Aldunce, E. Ali, R. A. Begum, R. Betts, R. B. Kerr, R. Biesbroek, et al. (2022). Climate change 2022: impacts, adaptation and vulnerability.
- Reboredo, J. C. and A. Ugolini (2022). Climate transition risk, profitability and stock prices. *International Review of Financial Analysis*, 102271.

- Reisinger, A., M. Howden, C. Vera, M. Garschagen, M. Hurlbert, S. Kreibiehl, K. J. Mach, K. Mintenbeck, B. O'Neill, M. Pathak, et al. (2020). The concept of risk in the ipcc sixth assessment report: A summary of cross-working group discussions. *Intergovernmental Panel on Climate Change*, 15.

- Rypdal, K. (2000). Aircraft emissions. *Good practice guidance and uncertainty management in national greenhouse gas inventories*, 93–102.

- Securities and E. Commission (2022). The enhancement and standardization of climate-related disclosures for investors.

- Simaiakis, I. and H. Balakrishnan (2010). Impact of congestion on taxi times, fuel burn, and emissions at major airports. *Transportation research record 2184*(1), 22–30.

- Sotos, M. E. (2015). Technical guidance for calculating scope 3 emissions.

- Sydney Airport Limited, S. (2021). 2021 response to the task force on climate-related financial disclosures.

- TCFD (2017). Tcfd final report, a summary for business leaders.

- TCFD (2021, oct). Task force on climate-related financial disclosures, guidance on risk management integration and disclosure.

- TCFD Board, F. S. et al. (2017). Recommendations of the task force on climate-related financial disclosures.

- Thomä, J., C. Weber, M. Fulton, S. Dupré, M. Allison, and H. Chenet (2020). Transition risk toolbox. *2° Investing Initiative*.

- Velásquez-SanMartín, F., X. Insausti, M. Zárraga-Rodríguez, and J. Gutiérrez-Gutiérrez (2021). A mathematical model for the analysis of jet engine fuel consumption during aircraft cruise. *Energies 14*(12).

- Wasiuk, D., M. Lowenberg, and D. Shallcross (2015). An aircraft performance model implementation for the estimation of global and regional commercial aviation fuel burn and emissions. *Transportation Research Part D: Transport and Environment 35*, 142–159.

- WBCSD, W. (2004). The greenhouse gas protocol. *A corporate accounting and reporting standard, Rev. ed. Washington, DC, Conches-Geneva.*

- Wells, C. A., P. D. Williams, N. K. Nichols, D. Kalise, and I. Poll (2021, jan). Reducing transatlantic flight emissions by fuel-optimised routing. *Environmental Research Letters 16*(2), 025002.

- Winther, M., K. Rypdal, L. Sørensen, M. Kalivoda, M. Bukovnik, N. Kilde, R. De Lauretis, R. Falk, D. Romano, R. Deransy, et al. (2019a). 1. a. 3. a aviation 2019—european environment agency [file].

- Winther, M., K. Rypdal, L. Sørensen, M. Kalivoda, M. Bukovnik, N. Kilde, R. De Lauretis, R. Falk, D. Romano, R. Deransy, et al. (2019b). Nfr: 1. a. 3. a, 1. a. 5. b* aviation, guidebook 2019.

- World Resources Institute, G. P. and C. T. Team (2013). Ghg protocol scope 2 guidance.

References

- Xianliang, G., X. Jingchao, L. Zhiwen, and L. Jiaping (2021). Analysis to energy consumption characteristics and influencing factors of terminal building based on airport operating data. *Sustainable Energy Technologies and Assessments 44*, 101034.
- Yunos, M., M. F. Abdul Ghafir, and A. ab wahab (2017, 04). Aircraft lto emissions regulations and implementations at european airports. Volume 1831, pp. 020006.

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