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Article

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Posted Date: November 27th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11786787/v1

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Additional Declarations: No competing interests reported.

Modelling intercity and long-distance passenger travel decarbonisation pathways

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Abstract

This study addresses the imperative to decarbonise intercity and long-distance travel in alignment with the Paris Agreement—a transport segment that is frequently overlooked. Focusing on global intercity transport, this paper assesses the impacts on travel demand and related CO_2 emissions of two future scenarios using a global multimodal model representing five transport modes (air, rail, car, bus, and motorcycle). Projections indicate that demand will grow through 2060 under both scenarios, with the Increased Ambition (IA) scenario reducing projected total travel volume by 18% by 2060 compared to the Business-as-Usual (BAU) scenario. Decoupling travel demand growth from emissions requires accelerating the adoption of clean fuels and vehicle fleets. The paper examines the scope and implementation challenges of decarbonisation policies aimed at promoting modal shift toward lower-emission modes and reducing each mode's carbon intensity. Finally, we show that intercity and long-distance travel accounts for 24% of global passenger transport CO_2 emissions, yet these emissions are driven by a small minority of the world's population—underscoring the pronounced socio-economic disparities inherent in long-distance travel behaviour, where individuals in affluent regions exhibit substantially higher travel propensity.

Keywords: long-distance travel · decarbonisation · scenario modelling · decarbonising aviation

Introduction

Meeting the 2015 Paris Agreement target to limit global warming within 1.5 to 2°C above pre-industrial levels[1] demands a significant and urgent change in the transport sector, steering it away from its current trajectory. Reducing emissions from intercity and long-distance travel will be a key and challenging part of passenger transport decarbonisation. This study focuses on global intercity domestic and international trips irrespective of distance. While these trips represent less than 1% of the global passenger trips, given that long distances and carbon-intense modes characterise them, they yield 21% of the global passenger-kilometres and 24% of total passenger transport CO_2 emissions[2]. Despite intercity and long-distance transport being a significant source of CO_2 emissions, policy discussions and research aimed at decarbonising transport have predominantly focused on urban transport systems[3].

Multiple factors contribute to the complexity of the low-carbon transition in long-distance passenger transport. In first place, long trips are highly reliant on aviation without any modal alternatives. Flying requires an enormous amount of energy, which positions aviation as the mode with the highest energy consumption and CO_2 emissions per passenger-kilometre[4–6]. Secondly, due to the inherent difficulty of allocating CO_2 emissions from international transport (and specifically from aviation) to countries, ICAO has been assigned the responsibility to ensure the reduction of emissions from international aviation. The organisation presented its Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA)7 in 2016, which is legally non-binding and has been heavily criticised for its low reliability and effectiveness in reducing emissions[7–9]. Finally, developing and constructing the required infrastructure to promote alternative, cleaner modes of aviation for medium-distance trips carries high levels of capital investment. High-speed rail is frequently seen as a promising alternative because of its environmental advantage and competitive service; however, the development of an extensive network with strong integration and rail interoperability entails high public investments[10,11]. Range anxiety has been identified as the main barrier to electric vehicles (EV) adoption for long-distance travel[12,13]. The rollout of fast charging facilities to guarantee coverage on main roads and highways is associated with high capital costs and important uncertainties given EVs' early market stage and the varying conditions of the local power grids in different countries of the world[14–16]. Strong policy regulations and incentives would generally be required to support a fair deployment of fast-charging infrastructure[17,18].

Under the current paradigm, demand for long-distance travel is set to keep growing in developed economies[19] and could potentially grow faster in developing economies as population and GDP per capita increase faster than travelling costs[20]. Aligning this expected growth with decarbonising ambitions is a challenge, if even possible. Technologies to deliver cleaner fuels and fleets need to be introduced and upscaled extremely fast, with significant associated costs and uncertainties of markets and resources availability[21–23]. According to the International Energy Agency (IEA)[24], a major shift towards electromobility and the use of biofuels can drive the reduction of fossil fuels use in road transport already by 2030, if

supported by electromobility incentives and internal combustion engine vehicles phase-out dates. Oppositely, the projected reduction of fossil fuels demand in non-road transport towards 2030 is negligible. Rail is the most electrified transport mode today, with fossil fuels representing approximately 50% of the demand, but with limited potential for further reduction until 2030. Fossil fuels will still account for most of the energy demand in aviation to 2030 and the sector will require a variety of parallel strategies to decarbonise[20]. These strategies will be highly reliant on cleaner fuels and technologies: the use of drop-in sustainable aviation fuels (SAF) on existing aircrafts such as biofuels and synthetic fuels (also known as electrofuels or e-fuels), the continued improvement in fuel efficiency of new aircrafts[25,26], and the development of new electric[27,28] and hydrogen [29] propelled aircrafts.

Undoubtedly, long-distance travel presents formidable challenges in terms of abatement. The difficulty in achieving decarbonisation targets by 2050 has been documented in the literature (specifically for aviation). It has highlighted the need for a combination of policies that incentivise technology development and adoption and regulatory measures that manage demand growth and mode choice[20,30]. Despite the essential role of travel demand models as tools to assess the global impact of such policies[31], long-distance travel demand models and the assessment of its derived externalities is relatively scarce[32]. The conventional approach has been the development of global (or regional) models for a single transport mode, or national (or corridor-based) models that develop a multimodal approach. The development of global (or regional) multimodal transport demand models is mostly inexistent. A major barrier is the lack of robust datasets used for calibration and validation of modal and routing choices, where intermediate nodal attributes (such as stations or airports) and network developments that affect pricing (such as hub and spoke)[33,34] are included. The modelling of long-distance multimodal trips, especially when air travel represents the main trip leg, has been identified as an essential area for research, with a call for more detailed representation and integration into large-scale transport models[35].

In what respects to unimodal demand models, specifically the aviation sector has recently observed a substantial increase of interest in assessing demand and the pathways to achieve the low-carbon targets set for this hard-to-abate sector[20,21,33,36,37]. Several technological development pathways have been tested to assess the compatibility of the set targets with the technological constraints and envisaged performance improvements of the sector[27,34,38,39]. While most of the scenario-based studies rely on forecasting methods[21], one recent study developed a backcasting approach to assess what would be required from the aviation sector to achieve full decarbonisation by 2060[20]. It tests different scenarios and identifies the main challenges each one would have in achieving the required changes to meet the decarbonisation objective. This body of the aviation literature agrees on the difficulty to achieve decarbonisation targets by solely relying on technological improvements and highlights the importance of demand management policies. The aviation literature has also investigated connectivity and market structure by analysing the derived implications for prices and market development of airline companies and alliances evolution and change of size[40].

Research has also explored the impact of airport development strategies on air travel demand, and showed the potential constraints it could impose to the sector growth and pattern of development[41]. Regarding the unimodal travel demand forecast models, they tend to rely on time series methods, estimating the future demand based on past data, being complex to forecast demand in an uncertain and different economic and policy context, where premises to the stability of the models are not met[42].

National (or corridor-based) multimodal models have higher resolution and are extensively used in developed countries (e.g. USA, UK, France, Denmark, China) to evaluate investments and anticipate the effects of public- and private-sector decisions on the transport system[43,44]. Some regions, such as Europe, with a substantial permeability of the borders, also developed dedicated models as Transtools[45]. Yet, these models can reproduce current demand and assess externalities but present limited capability of accounting for changes in the economic, social and technological context when forecasting travel demand. Most of the efforts to model multimodal activity in long-distance travel have focused on mode choice and trying to understand the competition and co-operation features of different transport modes such as high-speed rail and aviation[46]. These models typically rely on more or less sophisticated forms of discrete choice models that include mode choice decisions or combined mode and route choice decisions.

This paper contributes to covering the research gap on assessing future intercity and long-distance travel demand and emissions by relying on a global multimodal model. It estimates global intercity (domestic and international) travel by 5 different transport modes (air, rail, car, bus and motorcycle) under two different policy scenarios. These policy scenarios include demand-side solutions that target behaviour, end-user technology adoption and lifestyles, as well as infrastructure and technology development. The policy scenarios are defined by a bundle of policy measures that are implemented in different years and with a different intensity in the different world regions (see Table 2).

- The *BA* scenario is constructed based on existing national policies and recent historical trends. It intentionally excludes future commitments and aspirations that have not yet been codified into active legislation or definitive policy packages. Consequently, this scenario represents the most conservative approach to transport development, derived from extensive desk research analyzing current transport frameworks and technological advancements.
- The *IA* scenario assumes that policymakers implement accelerated actions to decarbonize the transport sector. This pathway is developed under the 'High-with-Low' narrative, which targets high levels of equitably distributed global well-being alongside a drastic reduction in contemporary energy consumption[47]. The practical implementation of these policies and aspirations is informed by an expert survey conducted across the network of the International Transport Forum (ITF).

The global intercity model of the ITF PASTA modelling framework[48] follows a four-step modelling approach and represents travel activity between 1,191 centroids distributed across the world. The paper further examines how travel activity and emissions vary from 2025 (baseline year) to 2060 under the two policy scenarios and explores the contribution of each world region to global totals. Further details of model components, data inputs and policy scenario definitions can be found in the Methods section.

The scenario results presented in this paper are derived from the global modelling exercise developed for the ITF Transport Outlook 2025 at the International Transport Forum (ITF-OECD). Although both works rely on the same simulation outputs, that report is not available to the general public. Beyond making these projections accessible, this article documents the full mathematical specification and calibration of the non-urban passenger model, breaks down demand and emission drivers across world regions and transport modes, and discusses the policy and equity implications of long-distance travel disparities in greater detail.

Results

Definition of policy scenarios

Designing scenarios for long-term outlook analysis is a complex exercise that translates abstract concepts or aspirations into concrete metrics capable of generating distinct quantitative outcomes. For the development of the ITF Transport Outlook 2025, the International Transport Forum (ITF) implemented a participatory process involving experts and policymakers from various global regions to construct two contrasting scenarios. Crucially, neither scenario utilised a "target-based" approach. Instead, the ITF defined regional pathways and timelines for policy implementation, incorporating technological advancements, demand management, and socio-behavioural adaptations across different levels of political and economic commitment to climate change mitigation. These two distinct policy pathways were designated as the Business-as-Usual (BA) scenario and the Increased Ambition (IA) scenario.

The BA scenario provides insights into how transport demand and emissions could evolve over the coming decades if transport policy continues along its current path and already agreed and active commitments. The measures in the BA scenario include the current policies inertia and technological penetration that is replacing internal combustion engine (ICE) vehicles, maintaining a similar pace; limited demand management and mode shift, where active examples were already taking place; and limited investment in attractive and sustainable alternatives to the private car; and improving efficiency and operations to reduce carbon intensity are very limited and restricted where regulation or legal commitments have been done (i.e. European Union).

The IA scenario, by contrast, looks at the impact of adopting more ambitious policies to decarbonise the transport sector. The IA scenario takes all the known or policies under research for implementation and imagines a policy pathway with accelerated implementation timelines,

geographical distribution and ambitious targets. It factors in the impacts of bolder policies aimed at encouraging more sustainable developments and travel behaviour. It also takes into account the scale of ambition set by the Breakthrough Goals for the global transport sector [49]. The Breakthrough Goals include ambitious targets for ending new sales of ICE vehicles for both passenger and freight road fleets, the rollout of sustainable aviation fuels and the uptake of zero-emission fuels for maritime shipping.

The scenarios are set differently for nine World regions: **Europe** (EUR): EU 27, Ukraine, UK, Switzerland and Turkey; **East and North East Asia** (ENEA): China, Japan and South Korea; **Latin America and the Caribbean** (LAC): Mexico, Central America, South America and the Caribbean; **Middle East and North Africa** (MENA): including Middle Eastern countries, Algeria, Djibouti, Egypt, Libya, Mauritania and Morocco; South East Asia (SEA); **Sub-Saharan Africa** (SSA**); South and South West Asia** (SSWA): Afghanistan, Bangladesh, Bhutan, India, Iran, the Maldives, Nepal, Pakistan and Sri Lanka; **Transition Economies and the Pacific** (TAP): including Russia, North Korea, Pacific island states and former Soviet Republics in Central Asia; and finally a group including the **USA, Canada, Australia and New Zealand** (UCAN). The different measures and their level of implementation are presented in Table 1. The details about the detailed implementation of scenarios are presented in Table 2.

Demand and CO_2 emissions projections

Global intercity travel demand is projected to increase under both policy scenarios. Under the BA scenario, passenger-kilometre projections for 2060 increase by a factor of **2.2** relative to 2025. In contrast, under the IA (IA) scenario, this growth factor is limited to **1.80** —representing an 18% reduction in projected total travel volume by 2060 (a 33% reduction in demand growth) (Figure 1). This deceleration of travel activity under the IA pathway is driven by the implementation of targeted demand-side measures. These include a reduced propensity to travel induced by "fly-shaming" behavioural shifts, the widespread adoption of teleconferencing for business travel, and escalating travel costs resulting from mandated clean fuels and the implementation of carbon taxes and distances charges for road vehicles.

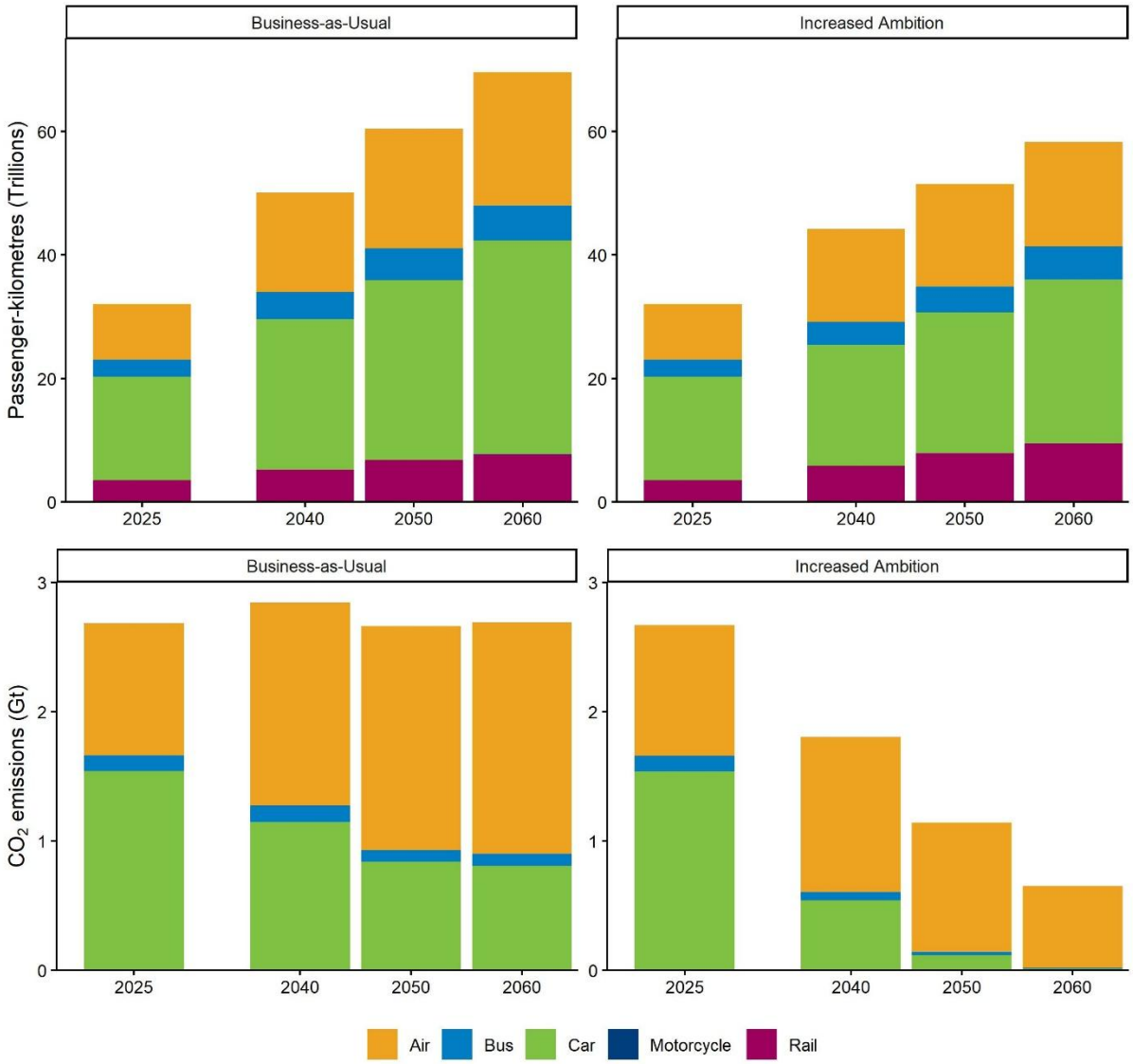


Figure 1: Projections of travel activity and CO_2 emissions under Business-as-Usual and Increased Ambition policy scenarios

However, the largest CO_2 emissions savings under the *IA* policy scenario for intercity travel does not come from suppressed demand growth but from the reduced carbon intensity of the transport modes. The *IA* scenario incorporates ambitious policy goals for technologies and fuels that decouple demand growth from emissions and determine a 76% reduction in total CO_2 emissions by 2060 with respect to 2025.

Figure 1 illustrates the relative modal split in terms of passenger-kilometres and emissions across the analysed years and scenarios. In 2025, air travel is not the predominant mode in intercity transport, representing only 28% of passenger-kilometres and 38% of CO_2 emissions. However, by 2060, the carbon landscape changes drastically under the BA scenario: aviation's share of CO_2 emissions surges to 67%, while its share of passenger-kilometres remains relatively stable at 31%. This stark divergence underscores the high carbon intensity inherent

to air travel. Conversely, rail accounts for 11% of passenger-kilometres in 2060 under the BAU scenario but contributes less than 1% of total CO_2 emissions.

Under the IA scenario, the 2060 projections reveal that aviation becomes virtually the sole hard-to-abate mode, concentrated at 97% of global intercity transport CO_2 emissions. Meanwhile, rail expands its role to encompass 16% of passenger-kilometres, while maintaining its minimal environmental impact at less than 1% of CO_2 emissions.

Decarbonisation policies vary by trip length

Shifting trips from carbon-intensive transport modes to less polluting ones is not always possible. The mode alternatives in intercity and long-distance travel are highly conditioned by the length of the trip. When discussing decarbonisation of long-distance travel and specifically when assessing the potential for mode shift, it becomes imperative to conduct the analysis by trip length.

Figure 2 represents on the top the total number of passenger-kilometres in 2025 by trip distance segment and the contribution of each mode to the total value, and on the bottom the projection of passenger-kilometres from 2025 to 2060 under the *BA* scenario for each trip distance segment. While road (car and bus) and rail are the prevalent modes for short (<500 km) and mid-short (500-1000 km) distance trips, air transport accounts for more than 66% of mid-long (1000-3000 km) and almost all the long (>3000 km) distance trips.

Given that aviation is the most carbon-intense transport mode and the recent momentum gained by policies aiming to restrict air transport when rail alternatives available[50], a measure that bans short-haul flights (<500 km) when good-quality rail connectivity exists is included in the *IA* policy scenario. Implementing such a ban globally could potentially shift 49% of the passenger-kilometres generated by short-haul flights to rail by 2060. However, reaching this figure relies on further expansion and improvements of the global rail network. Since passenger-kilometres from short-haul flights represent 2.6% of total air travel, such ban would only affect 1.2% of the total passenger-kilometres generated by air travel. Moreover, if this ban was only applied when a high-speed rail alternative was available, the affected air passenger-kilometres would be limited to 0.1%.

Accelerating the technological and fuel transition of aviation and road fleets toward low- and zero-emission options is imperative to decouple travel demand growth from emissions. Under the BA scenario, zero-emission passenger cars are projected to represent 72% of the total car fleet by 2060, a share that rises to 97% under the IA scenario. Consequently, the global average carbon intensity of passenger vehicles decreases by 75% between 2025 and 2060 under the BA scenario, whereas the IA scenario achieves a virtually carbon-neutral fleet by the same year, therefore reducing the car's contribution to intercity transport CO2 emissions from 57% in 2025 to less than 2% in 2060 in the IA scenario (Figure 3). Bus fleets are mostly powered by fossil fuels and commitments to transition to cleaner fleets are far

behind those of passenger cars. Therefore, under the BA scenario only 26% of the global bus fleet would be zero emission by 2060. The IA scenario assumes higher emission-reduction targets aligned with the 2030 Breakthrough [49] target for buses and, therefore, yields over 85% of zero-emission buses by 2060. Even if buses significantly reduce their carbon intensity under the IA policy scenario, their percentual contribution to intercity transport CO_2 emissions between 2025 and 2060 is equal given the increase of bus transport demand (Figure 3).

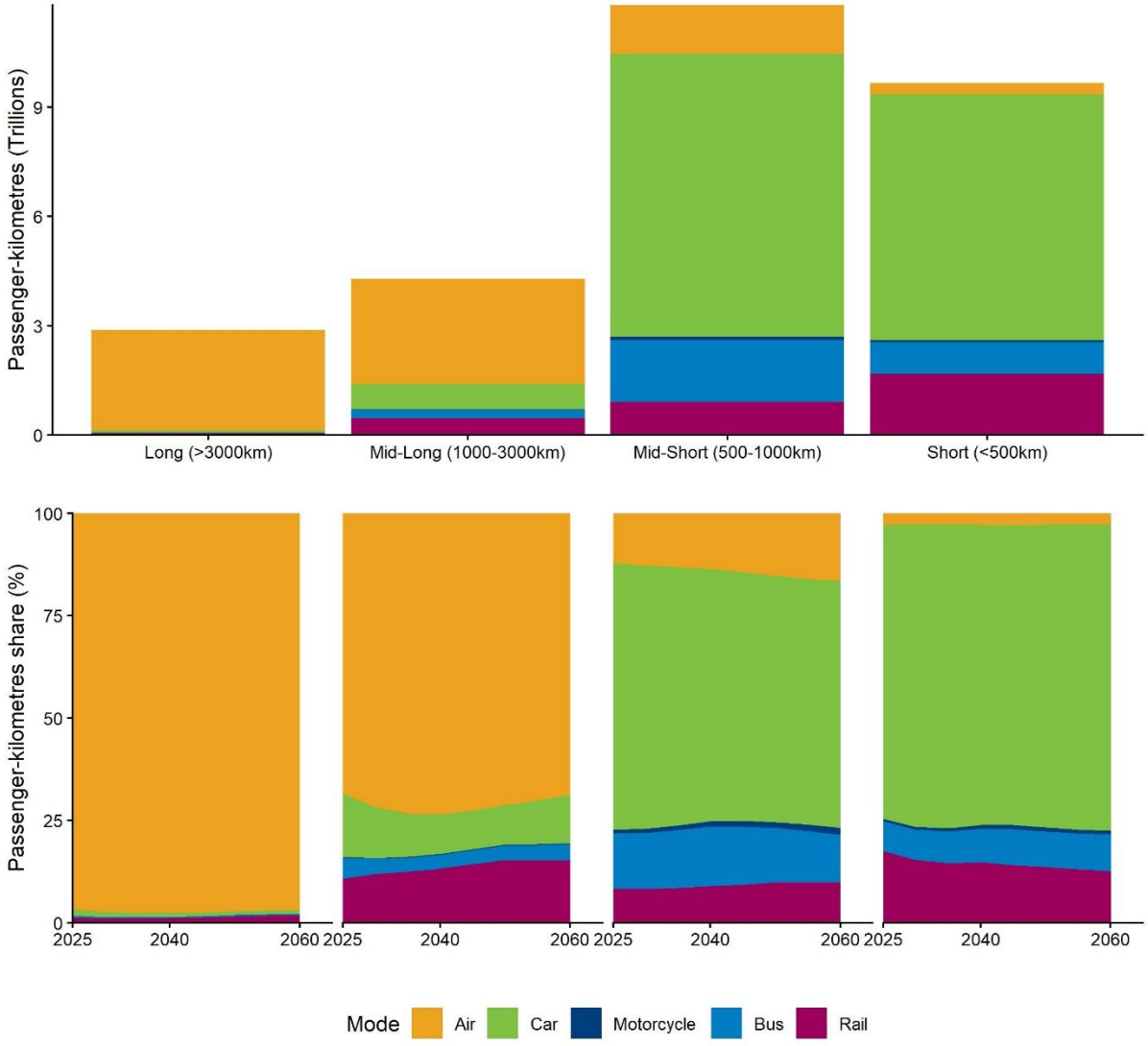
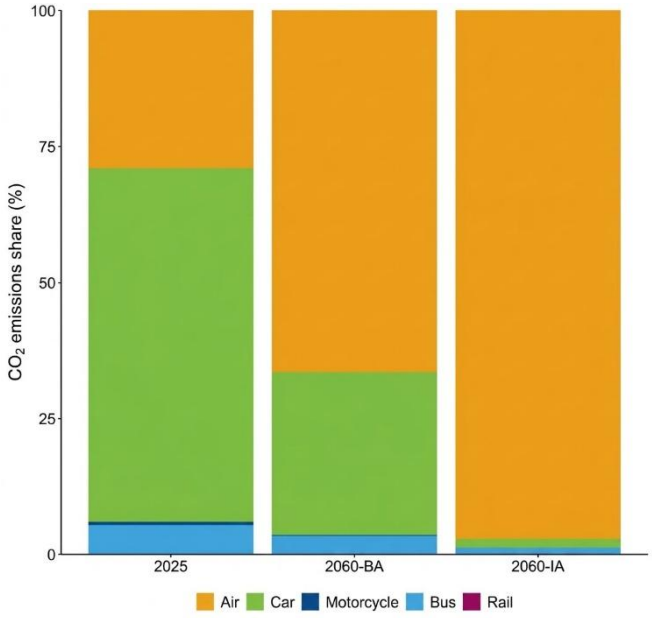


Figure 2: Travel activity by trip distance under the Business-as-Usual policy scenario

Air is the hardest to abate long-distance passenger mode due to its difficulty to electrify and its requirement for high-density fuels. The *BA* scenario already includes significant improvements in the carbon intensity of the fuel mix based on the EU's "Refuel EU" policy. This policy envisages a massive scale-up in the share of SAF (biofuels and electrofuels). The *IA* scenario applies similar levels of ambition in the use of SAF globally, rather than limited to the EUR region, and assumes an ambitious rate of technological development of battery-electric

and hydrogen propelled aircraft. Assuming hydrogen aircraft capable of transporting 165 passengers on a maximum range of 3,700 km[51] under the BA scenario and 4,260 km under the IA scenario, and battery-electric aircraft carrying 19 passengers on a maximum range of 350 km[51] would be commercially available by the 2040s, the *IA* scenario finds that by 2060, hydrogen and battery-electric aircraft could transport 6% and almost 1% of the global air passenger-kilometres, respectively. Most of the reduction in aviation emissions will come from the use of SAF as drop-in fuels in conventional aircraft to reduce air transport carbon intensity. The *IA* scenario includes stringent policy measures for aviation, as the introduction of global mandates for use of SAF (although it assumes different shares of SAF use in different world regions), which drives a 77% reduction in aviation carbon intensity between 2025 and 2060. Even under this exceedingly ambitious goal to decarbonise aviation, its contribution to intercity transport CO_2 emissions increases from 38% in 2025 to 67-97% in 2060 (BA and IA scenarios respectively) as road transport modes decarbonise faster (Figure 3).

Figure 3: Share of CO2 emissions by mode in 2025 and 2060 under both policy scenarios



Unequal distribution between world regions

Intercity and long-distance travel activity is mostly concentrated in three world regions (EUR, ENEA, UCAN). The policy measures included in the *IA* policy scenario are not enough to rebalance the global distribution of long-distance travel, showing that by 2060 still 54% of the total passenger-kilometres take place in EUR, ENEA and UCAN (travel activity is attributed to trips origin).

Figure 4 shows the global distribution of air trips in 2025 and 2060 by representing the total number of annual trips projected for each airport. As for long-distance travel distribution, air trips are mostly concentrated in North America, Europe, Asia and the Middle East to a lesser

extent. Europe presents the highest number of intermodal trips, while the Middle East is characterised by airports operating as hub-and-spoke.

Figure 5 shows the global distribution of rail trips in 2025 and 2060 by representing the total number of annual trips projected for each train station. Rail intercity trips are mainly limited to Europe and Asia (China, Japan and India). The projected growth of rail transport activity by 2060 in other regions remains limited, even under the *IA* policy scenario. The *IA* policy scenario includes further investments in network integration and the creation of multimodal hubs, which will yield an increase in rail travel demand by 2060 in places where intercity rail systems are already in place.

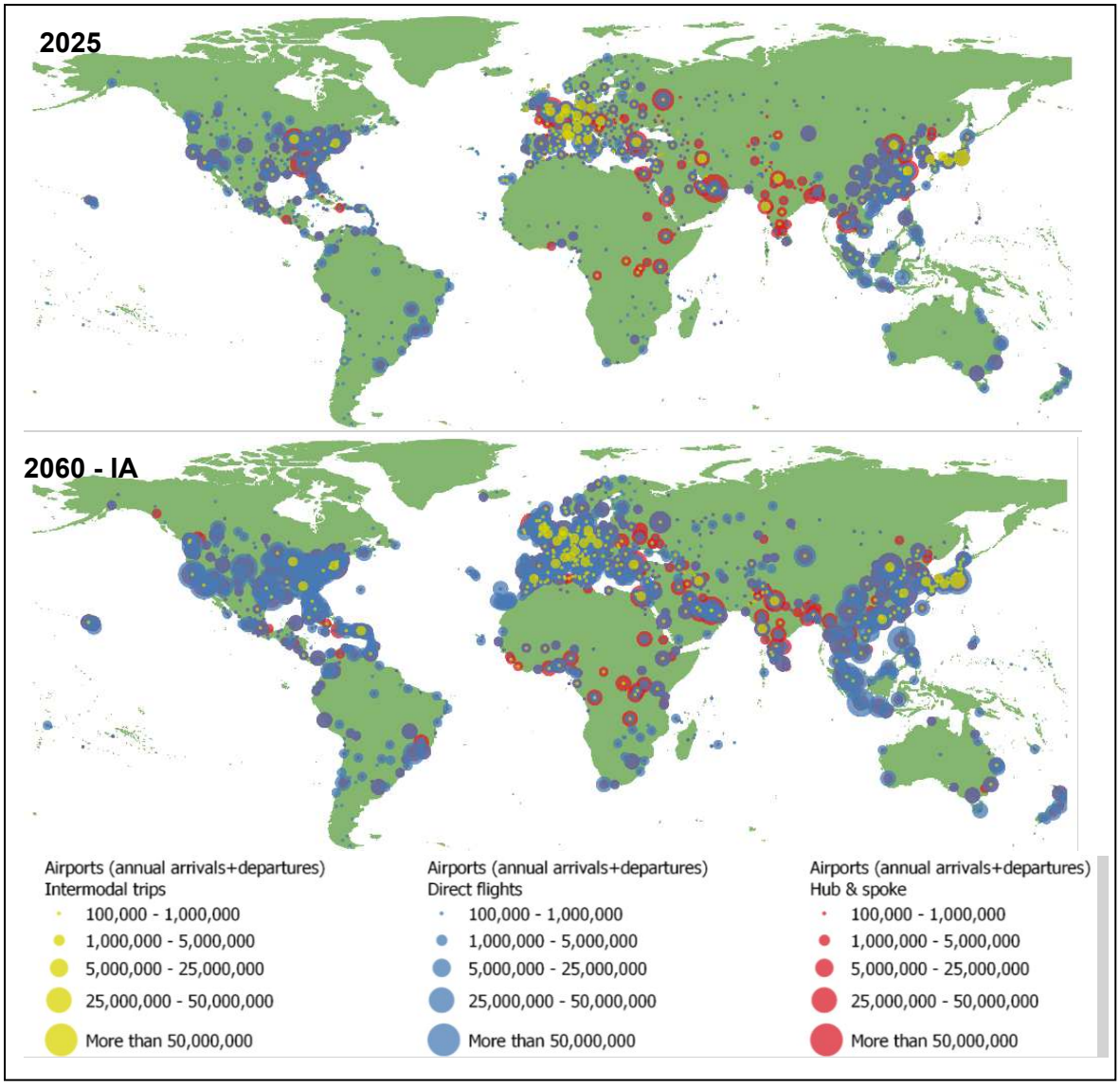


Figure 4: Global distribution of number of air trips in 2025 and 2060 under the IA policy scenario

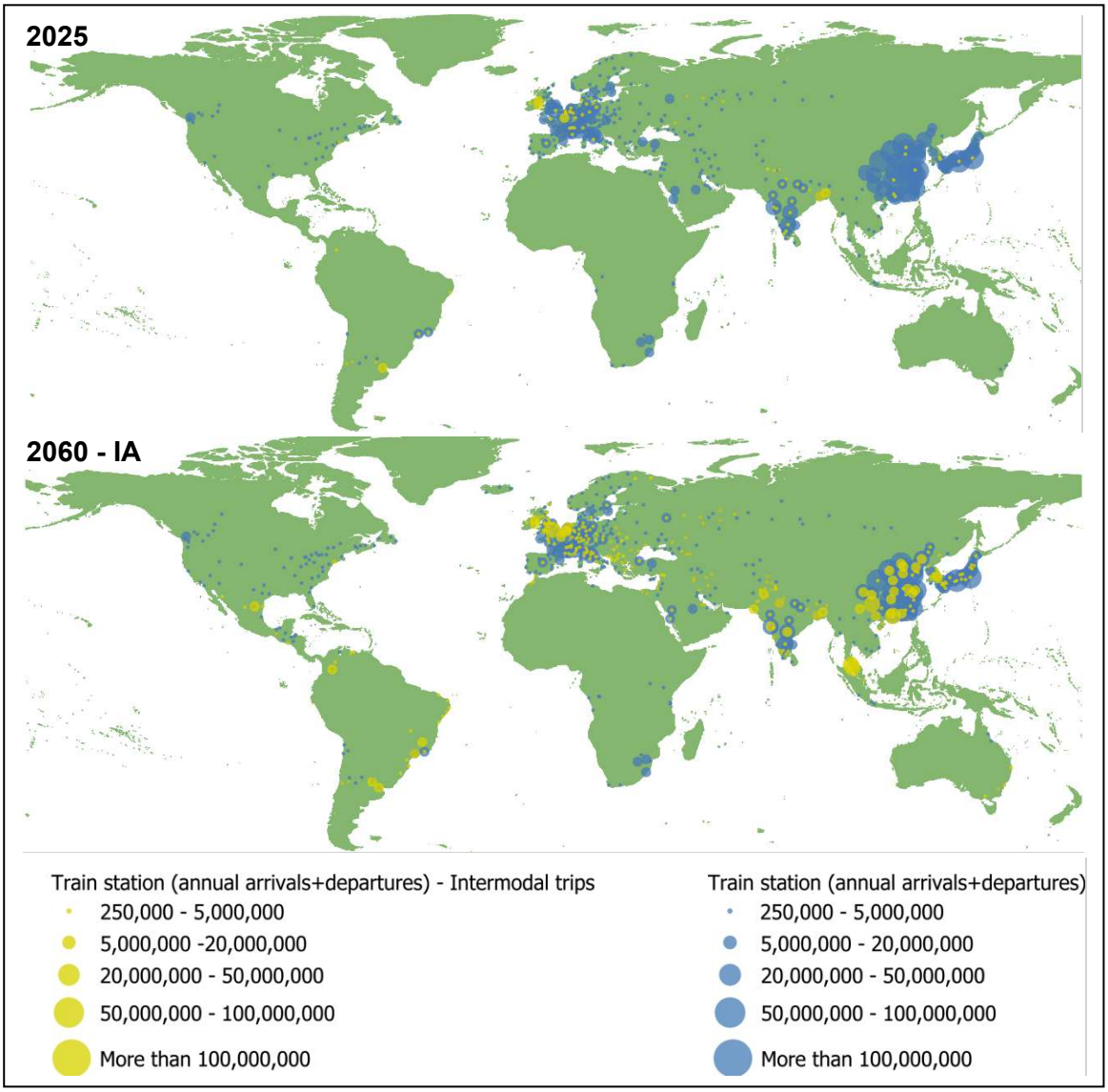


Figure 5: Global distribution of number of rail trips in 2025 and 2060 under the IA policy scenario

Travel activity and its corresponding emissions are typically analysed at the location where the activity takes place. Nonetheless, intercity and long-distance travel encompass both domestic and international travel, which implies that in numerous cases, travel activity takes place in one country but is performed by people from other countries. The unequal distribution of global intercity and long-distance travel is even reinforced when attributing travel activity to world regions according to people's place of residence rather than the trip origin.

Figure 6 represents the relative travel activity and CO_2 emissions per inhabitant for each world region. The average values for each world region are divided by the value for SSA in 2025 (the world region with the lowest value) to calculate the relative factors. As noted, differences in travel activity across the different world regions are enormous. Intercity travel of a person living in UCAN is on average 54 times more than that from someone living in SSA, while for a person living in Europe it is 24 times more (measured in passenger-kilometres; corresponding to 85

times and 58 times more in terms of annual trips). While regional differences in travel activity persist by 2060, regional differences regarding per inhabitant CO_2 emissions reduce substantially between 2025 and 2060 under the IA scenario. This change is triggered by stricter decarbonisation policies in leading markets such as UCAN, ENEA and EUR compared to the rest of the world.



Figure 6: Average trips, passenger-kilometres, and CO_2 emissions per inhabitant by world region in 2025 and 2060 under the BA and IA policy scenarios (ratio with values SSA 2025)

Disaggregating intercity and long-distance travel across global income percentiles reveals acute socio-economic disparities in non-urban mobility (Figure 7). In 2025, the top 5% of the global income distribution accounts for 62% of aviation passenger-kilometres (Gini = 0.80) and 53% of surface transport and ferry activity (Gini = 0.73), concentrated predominantly in UCAN, ENEA, and EUR, which together comprise 33.2% of the world's population. Conversely, the bottom 50% generates just 1.4% of air travel and 3.9% of surface and ferry travel, occurring largely in SSWA. Under the 2060 BA scenario, rising incomes in emerging economies, notably ENEA and SSWA, expand travel volumes within the middle and upper-middle income brackets and lower the Gini coefficient for surface and ferry travel to 0.70, whereas global aviation remains heavily skewed toward the top 5% (Gini = 0.80). In the 2060 IA scenario, carbon pricing, aviation ticket taxes, and modal shift measures curb aggregate demand growth while disproportionately moderating long-distance travel among the highest-income cohorts: aviation demand in the top 5% contracts by 36% relative to 2060 BA, reducing its share of global air travel from 63% to 52% and lowering the global aviation Gini coefficient to 0.75, while surface and ferry travel in the top bracket declines by 11% (Gini = 0.70) without curtailing mobility gains among lower-income groups.

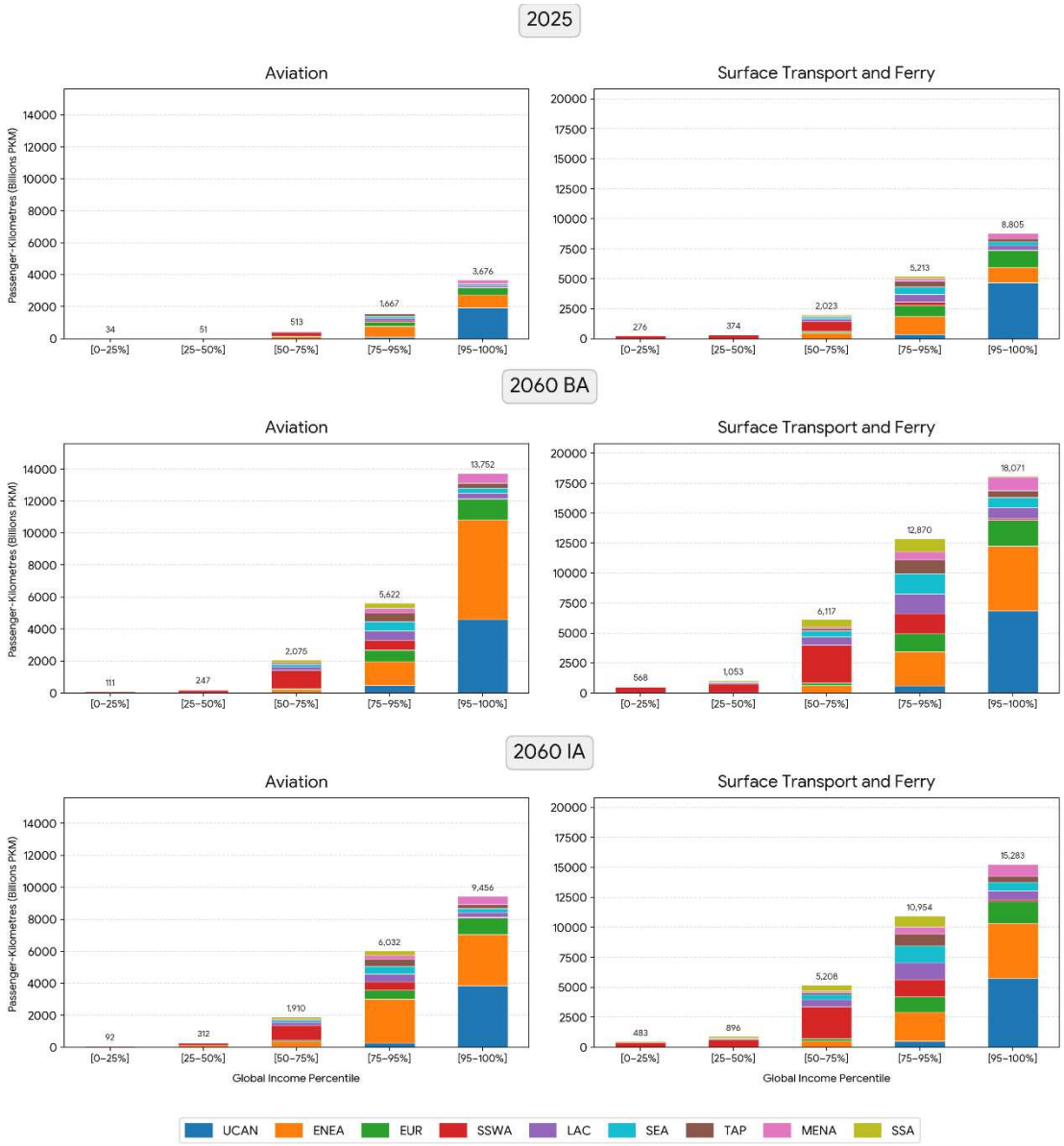


Figure 7: Passenger-kilometres by global income percentile, mode category, and world region in 2025 and the tested 2060 (BA and IA scenarios).

Discussion

Intercity and long-distance passenger transport poses a formidable challenge in the pursuit of decarbonisation. It is not only a cornerstone of economic development but also a facilitator of social opportunities, yet it is a substantial contributor to global CO_2 emissions. This study introduces a global multimodal approach for simulating intercity and long-distance travel and its related CO_2 emissions under two policy scenarios. It establishes a baseline for 2025 and assesses the impact of two scenarios of differing decarbonisation ambitions that integrate plausible technological advancements, innovations, and policy regulations: *BA* and *IA*. The *BA* scenario builds on countries existing policies, commitments and aspirations, while the *IA* scenario assumes policy makers take accelerated action to decarbonise transport. The purpose

is not to predict an uncertain future but rather to elucidate the potential impacts of two distinct policy scenarios.

The projected intercity and long-distance travel activity to 2060 reveals a persistent growth trend across all policy scenarios. Under the *BA* scenario, long-distance travel shows an average compound annual growth of 2.2%, while air transport grows at a rate of 2.5%. The *IA* scenario exhibits a reduction of 18% in projected total travel volume by 2060 compared to the *BA*. Notably, these figures diverge from projections posited by the aviation sector itself, which based on unimodal time series analysis, estimates annual growth at 3.4%-4.5%[51,52]. Growth projections that exceed the BA scenario, combined with the baseline's limited capacity for significant emissions abatement, signal a profound discrepancy. Specifically, a mismatch emerges between aspirational decarbonisation targets and the aviation industry's demand forecasts. These projections clash not only with the general willingness to travel but also with the capacity of frequent flyers to continuously expand their annual mileage as they approach a travel saturation point. Consequently, sustaining larger cohorts of hyper-frequent flyers—defined as individuals travelling more than 50 times a year—becomes highly challenging due to inherent time constraints that prevent further mileage expansion. Similarly, expanding the broader base of passengers flying more than 10 times annually becomes increasingly difficult in a market characterised by escalating aviation and fuel costs[55].

Decarbonisation efforts hinge significantly on the widespread adoption of clean fuels and the transition to zero and low-emission fleets. While rail emerges as the least carbon-intensive mode for long-distance travel at present, cars and buses see a significant reduction (97% and 85%) of their carbon intensity by 2060 under the *IA* scenario. CO_2 emissions savings from passenger cars are mostly achieved through direct electrification. The uptake of EVs is accelerating, especially in leading markets. However, meeting the *IA* scenario requires binding targets for the phase-out of ICEs, which need to be set and met worldwide. Moreover, many countries in the world heavily rely on the import of used vehicles, which constitutes a major barrier to achieve clean fleets. Clean bus fleets also rely on technology options such as direct electrification. While it is already underway for city buses, intercity buses are significantly harder to electrify due to range requirements. Therefore, achieving clean fleet rates as required in the *IA* scenario, may require anticipated fleet renewal measures through policy incentives, such as anticipated scrappage schemes combined with purchase incentives.

The need to decarbonise aviation becomes apparent when considering its dominance in facilitating long and mid-long-distance travel. Mode-shift policies to less polluting modes become less applicable as trip distances grow and fewer viable alternatives exist. Achieving this goal requires either a reduction of the carbon intensity or of the travel itself. Travel activity reductions can be promoted by substituting trips for shorter ones (e.g. via a paradigm shift toward localised or sustainable tourism frameworks, promoting a lower annual frequency of trips paired with prolonged durations of stay) or eliminating travel needs altogether (e.g. by replacing business trips with teleconferencing or reducing the propensity to travel because of

flight shaming behaviour). However, such measures have limited impact and could have potential consequences for people, countries (particularly those reliant on tourism), economic development, and connectivity. SAF emerge as a promising path for decarbonising aviation, yet their current use represents only 0.2% of total aviation fuels. The incipient stage of Sustainable Aviation Fuel (SAF) production requires substantial capital investment and infrastructure development, raising significant uncertainties regarding its scalability and timely availability to meet decarbonisation targets. Scaling up production faces severe resource constraints across both production pathways: bio-based SAF is limited by the finite global supply of sustainable waste lipids and non-food lignocellulosic feedstocks, while synthetic electrofuels (e-SAF) demand massive quantities of additional low-carbon electricity, green hydrogen, and captured carbon. Furthermore, stringent sustainability criteria must be enforced to ensure the genuine efficacy of SAF in reducing lifecycle emissions, including safeguards against indirect land-use change (ILUC), mandates for low-carbon electricity inputs, and strict additionality criteria to avoid diverting renewable energy from other decarbonising sectors.

While accounting for 24% of global passenger transport CO_2 emissions, intercity and long-distance travel is driven by a minority of the world's population. This underscores the socio-economic disparities inherent to long-distance travel behaviour, with individuals in affluent regions exhibiting higher travel propensity. Findings suggest that individuals living in UCAN, EUR or ENEA travel 85, 58, 11 times more than those in SSA (measured in trips and 54, 24, 6 in passenger-kilometres). Furthermore, under the *IA* decarbonisation scenario, where regulatory measures (such as carbon taxes, SAF mandates and air ticket taxes) affect transport pricing with differentiated levels between world regions. However, these regional inequalities persist if the implemented instruments rely mostly on economic deterrence, rather than on direct constraints to mitigate excessive travel. Addressing these disparities requires further exploration. A potential policy intervention that has been recently documented in the literature to address a just decarbonisation transition for long-distance travel is frequent flying levies[54,55] or even the establishment of flight quotas[56].

In conclusion, decarbonising intercity and long-distance travel represents a multifaceted challenge that requires concerted efforts across technological, policy and socio-economic domains. Our study highlights the need for global and holistic tools able to simultaneously assess the impact of changes in travel behaviour, vehicle fleets and regulations on the transition to decarbonise intercity and long-distance travel.

Methods

Modelling framework

The intercity passenger model of the ITF PASTA modelling framework is a strategic tool that tests the impacts of multiple policies and trends on the intercity passenger sector. The model provides scenario forecasts for intercity transport activity and its related CO_2 emissions by transport mode (air, rail, car, bus and moto) up to 2060. The model is computed sequentially in 5-year intervals as presented in Figure 8.

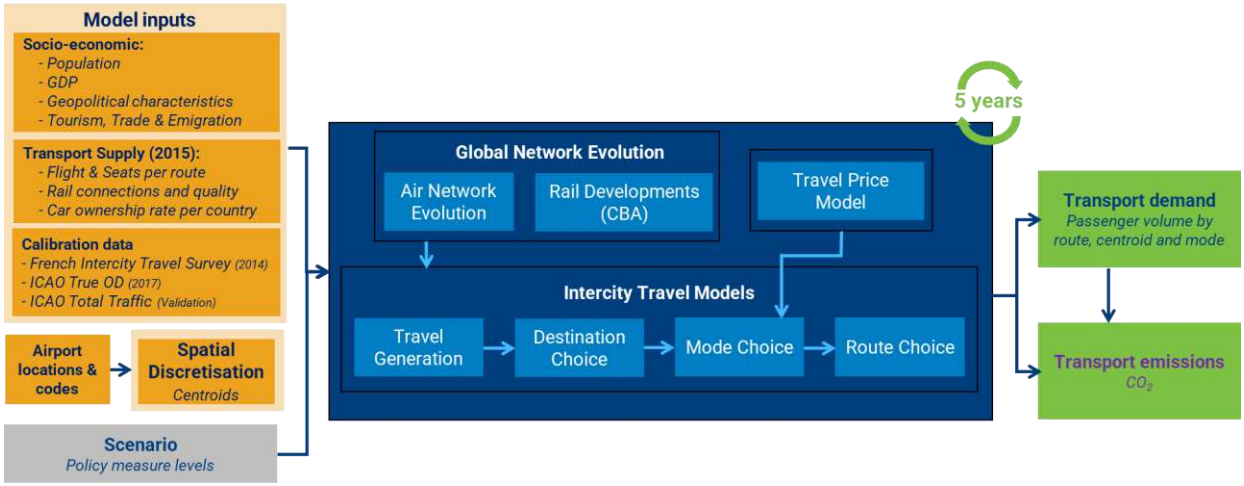


Figure 8: PASTA – Intercity passenger model framework

Spatial discretisation model

This model defines the centroids used to estimate transport flows between world regions. The centroids are defined by all large and medium-sized airports with international operating codes as classified by IATA[57]. They are clustered by city airport codes where several airports exist in the same city or where airports are within 100 km of the main airport and within the same country. This results in a total of 1,191 centroids with a significant world coverage. The influence areas around the centroid are defined using a raster-based world surface map. Each raster cell is assigned to a centroid based on its distance from the centroid and considering country borders. Each centroid is characterised by its raster-based population[58] and GDP estimates[59] for the baseline year and then updated based on population [60] and GDP [61] forecasts for regions.

Other attributes relevant to travel demand generation and attraction of each centroid are also included. Geopolitical characteristics of the city-centroid such as islands (which have higher reliance on air modes) and capitals (which have higher attraction than others with equal size). Tourism estimates that are complimentary to the population and increase intercity activity compared to others with equal population size. Trade and emigration estimates between

countries that influence the number of people travelling from one to another for business purposes.

Global network evolution model

This model component creates a transport network between the 1,191 centroids to accommodate intercity travel activity and determines the evolution of the global network over time. A connection between two centroids is assumed to be possible by road (for car, bus and motorcycle) if there is a continuous surface transport connection, and if the Euclidian distance is less than 2000 km (or 3000 km in case both centroids are in the same country). A rail connection exists when rail infrastructure connecting the respective two centroids exists in the baseline year. The quality of the rail connection corresponds to the frequency of service and the type of service in terms of speed, distinguishing slow (<100 km per hour), fast (<200 km per hour), and high speed (>200 km per hour). For connections by air, a different approach is taken. Information on all international and domestic flights and seats operated for 2015 (obtained from the Innovata Schedules Reference Service database) is aggregated at the OD pair level.

The global network evolves over time either by including additional direct links or by improving the existing connections. Surface road modes may benefit from increased infrastructure availability or frequency improvements. Changes for rail accounted for in the model are potential developments of the rail network over time. The development plans are estimated exogenously to the main model in a simple cost-benefit analysis (CBA) and inputted into the main model. The CBA explores whether the demand generated or shifted to high-speed rail (HSR) due to travel time savings would outweigh the high fixed costs and make the Net Present Value of the project greater than 0 or not.

The main evolution of the air network is assumed to be the addition of new direct links or removal of existing ones between OD pairs. The module creates new links based on a binomial regression analysis. This likelihood to create new links is defined as a function of economic mass (the product of the GDP at the origin and the GDP at the destination), cultural connection and distance. A link is removed in case the travel demand on the link in the previous iteration did not reach a minimum passenger threshold. The existence (and introduction) of low-cost carriers (LCC) links are also updated at each iteration. A higher economic mass is required for a LCC link to be created. LCC links are constrained to distances of up to 3500 km. A new LCC link starts with an initial share between 2.5% and 10%. This value may grow over time to represent 25% of the market, or more if the prospective demand of the OD pair grows. The frequency of air connections is updated at each iteration based on the new demand with the use of elasticity values. These elasticities are extracted by the Innovata Schedules Reference Service database and are differentiated by two parameters:

- High frequency (> 2,000 flights/year) and short/medium-haul (<= 3,500 km): 0.6;
- High frequency (> 2,000 flights/year) and long-haul (> 3,500 km): 0.5;

- Low frequency (<= 2,000 flights/year) and short/medium-haul (<= 3,500 km): 0.8;
- Low frequency (<= 2,000 flights/year) and long-haul (> 3,500 km): 0.7.

Travel price model.

The travel price model estimates travel prices across different modes. Car and bus travel prices depend on two components. The first component is the price of gasoline in a country (relevant time series data, including forecasts, stem from the IEA[62]). The second component is a fixed price component that depends on distance ranges and reflects toll costs. For both these modes, prices are affected by vehicle load factors, which may change over time. Rail travel costs are estimated on a per passenger kilometre basis. Data for rail fares in France are used to compute the cost structure. Prices are indexed for the type of service (slow, fast, and high-speed). The costs are also indexed to the GDP per capita of France, which allows the extrapolation of these costs to the rest of the world.

The estimation of air travel prices does not include price differentiation across different airlines; price variations between two centroids, however, do exist by itinerary. The estimation procedure presents a refinement of the model discussed in Benezech et al.[63]. The data used to calibrate the airline route price setting module was provided by the operators of the website Skyscanner (www.skyscanner.com). Competition and low-cost carriers have a very significant impact on prices. The price model does not attempt to explain prices between competitors realistically - this would require airline modelling and game theoretical approaches[64,65]. However, the model does attempt to reflect the main impacts of competition levels and low-cost carriers on the different routes. The base prices for the model are obtained from the average prices observed in the dataset. The prices are grouped by origin-destination pair differentiated by the number of transfers. Therefore, for a given origin-destination pair, all itineraries with the same number of stops are assumed to have the same price. Price plays a vital role in the propensity to travel (i.e. in generation models), mode choice and route choice components.

Travel activity generation model

The travel generation model estimates how many trips are generated by a given region for each of the four types of intercity travel: domestic trip, an international trip without border controls (e.g. Schengen zone, US-Canada), short and medium-haul international trips (less than 4 hours flight time), and long-haul international trips (more than 4 hours flight time).

It is handled via a generalised linear regression model where the link function follows a Poisson distribution. The propensity to travel of region i for intercity travel type j is given by:

$$\mathrm{GD}_{ij} = (1 - \mathrm{Rtel}_i \cdot \alpha_{0j}) \cdot \left(1 - FSh_i \cdot \alpha_{1j}\right) \cdot (POPreg_i \cdot \alpha_{2j} + Tour_i \cdot \alpha_{3j}) \cdot e^{ASC_i + LNGDPcap_i \cdot \alpha_{4j} + Island_i \cdot \alpha_{5j} + Cap_i \cdot \alpha_{6j} + HSR_i \cdot \alpha_{7j} + AS_i \cdot \alpha_{8j}} \quad (1)$$

The exposition factor of the Poisson model is defined by the population ($POPreg_i$), the number of tourist visitors ($Tour_i$), and the scenario variables related to teleconferencing ($Rtel_i$) and flight shaming (FSh_i) in region i. The exponential function is defined by the logarithmic transformation of GDP per capita in region i ($LNGDPcap_i$), dummy variables for islands ($Island_i$) and country capitals (Cap_i) and transport connectivity variables (HSR_i and AS_i). HSR_i is a dummy variable that takes value 1 when HSR is available in region i and AS_i represents the airport throughput of region i.

Income constraint analysis

The endogenous income distribution constraint analysis jointly shapes travel generation and trip distribution. The proposed tool allocates observed passenger activity and trips to income groups and infers the country of residence of travellers for each origin–destination (OD) pair. OD pairs are constructed to be symmetric with respect to underlying passenger activity, ensuring consistency between the two travel directions.

The share of total trips and passenger-kilometres assigned to each income group is assumed to be proportional to that group's effective capacity to travel, defined by its available income and available time budgets. This capacity is evaluated relative to the total observed country-level demand for each travel type, acknowledging that average generalised costs differ substantially across modes and by travel type and distance band. For each income quantile, travel mode, and travel type, the model computes the maximum number of equivalent trips that could be undertaken subject to: (i) the available income budget and (ii) the available time budget. The binding (i.e., more restrictive) of these two constraints determines the feasible number of trips for that group, mode, and travel type.

The income assessment proceeds in two stages. First, the annual travel budget is allocated across five travel categories: rural travel, domestic intercity travel, international short-distance travel, international medium-distance travel, and international long-distance travel. Second, annual income-expenditure thresholds—expressed as percentages of annual income and reported in Table 3—are applied to constrain feasible travel demand by income group, thereby embedding the endogenous income distribution constraint within the generation and distribution components of the model.

Time constraints are imposed in parallel with income constraints. The model assumes that, at most, 33% of total tourism-related time (for both work and leisure purposes) can be devoted to travelling. In addition, total time spent on tourism activities (including both travel time and time at the destination) is capped at 200 days per year. The binding constraint—either the 33% travel-time share or the 200-day annual tourism cap—limits the feasible number of trips for each income group, mode, and travel type.

Table 3. Income thresholds used in ITF modelling for non-urban passenger transport

Type of non-urban travel	Income groups [0,25%]	Income groups [25,50%]	Income groups [50,75%]	Income groups [75,95%]	Income groups [95,100%]
Rural travel	5.00%	5.00%	5.00%	5.00%	5.00%
Domestic travel	5.00%	5.00%	5.00%	5.00%	5.00%
International short-distance travel (<1 000 km)	3.75%	3.75%	3.75%	6.25%	6.25%
International medium-distance travel (1 000<x<3 000 km)	0.50%	1.00%	1.50%	3.00%	3.00%
International long-distance travel (>3 000 km)	0.50%	1.00%	1.50%	4.00%	5.00%

Destination choice model

The destination choice model relies on a multinomial logit model (MNL) that distributes the trips generated by a given region for a given types of intercity travel across the different destinations. The model uses a non-linear utility function with a scale parameter calibrated to match observed data in the aviation sector. The number of alternatives for each origin, can reach more than 300 compatible alternatives, which increases the model complexity. The utility function for this model is defined as:

$$\begin{aligned} \mathrm{V}_{od} = {} & (\mathrm{C}_d \cdot \alpha_0 + I_d \cdot \alpha_1) \cdot (FF_{od} \cdot \alpha_2 + HSR_{od} \cdot \alpha_3) \\ & \cdot (T_{od} \cdot \alpha_4 + pop_{od} \cdot \alpha_5 + E_{od} \cdot \alpha_6) \\ & \cdot (Rf_{od} \cdot \alpha_7 + Rh_{od} \cdot \alpha_8 + LCC_{od} \cdot \alpha_9 + L_{od} \cdot \alpha_{10}) \cdot e^{TTair_{od} \cdot \alpha_{11}} \end{aligned} \quad (2)$$

$$P_{od} = \frac{e^{Sc \cdot V_{od}}}{\sum_{j \in D} e^{Sc \cdot V_{oj}}} \quad (3)$$

where o is the origin and d the destination. The model variables are *socio-economic variables* (population – pop, trade – T, and emigration – E), geopolitical and *cultural variables* (use of same language – L, being a capitol – C, and being an island – I), and *transport services provision* for each OD pair (road highway connection – Rh, rail travel time – Rf, frequency of services of high speed rail services – HSR, direct daily flight frequency – FF, availability of low cost carriers – LCC, and air travel time – TTair).

Mode choice models

The mode choice model relies on a multinomial logit model with 5 mode alternatives (car, moto, bus, rail, and air). The utility functions for this model component are defined as:

$$\begin{aligned} \mathrm{V}_{ODi} = {} & ASC_i + \mathrm{Cost}_{ODi} \cdot \alpha_0 + T_{ODi} \cdot \alpha_1 + NTransf_{ODi} \cdot \alpha_2 + Freq_{ODi} \cdot \alpha_3 \\ & + Regional\ panel_i \end{aligned} \quad (4)$$

$$P_{ODi} = \frac{e^{Sc \cdot V_{ODi}}}{\sum_{j \in D} e^{Sc \cdot V_{ODj}}} \quad (5)$$

The utility function includes regional mode preferences (panel terms), specific attributes of the best route that represents the mode (price (Cost_{ODi}), travel time (T_{ODi}), minimum and number of transfers ($NTransf_{ODi}$)) and indicators of connectivity that highlight the role of frequent connections and reliability in intercity mode choice ($Freq_{ODi}$). The most interesting results from the intercity mode choice sub-model are the differences between the regions in the panel terms and the variables. North America has a highly positive panel term for car and air travel, which can be associated with the driving culture and the high distances involved, respectively. China, on the other hand, has a positive panel term for bus and a negative one for air, whereas India and Russia have a positive panel term for rail travel. Finally, in Europe, the highly developed rail network and the ease of travelling within the Schengen zone give favourable panel terms for rail and air travel and negative ones for buses and cars. The other variables, such as price, travel time, and the number of transfers, are all significant and negatively impact the choice of each mode, while flight frequency and high-speed rail frequency are positive for air and rail, respectively.

Route choice model for intercity travel

The route choice model, which is only implemented for air travel, allocates passengers on the different possible itineraries for each origin-destination pair. Rail, car, bus and motorcycle, on the other hand, are assigned to the shortest path between each OD pair.

The route choice model has a nested structure based on the number of minimum stops for the itinerary. The utility functions for this model component are defined as:

$$\mathrm{V}_{R0i} = \mathrm{BCcost}_{Ri} \cdot \alpha_0 + T_{Ri} \cdot \alpha_1 + Freq_{Ri} \cdot \alpha_2 + Transf_{R0i} \cdot \alpha_3 + Transf_{R0i} \cdot \alpha_4 \quad (6)$$

(

$$\mathrm{V}_{R1i} = \mathrm{BCcost}_{Ri} \cdot \alpha_0 + T_{Ri} \cdot \alpha_1 + Freq_{Ri} \cdot \alpha_2 + Transf_{RN1i} \cdot \alpha_5 + Transf_{RN1i} \cdot \alpha_6 \quad (7)$$

$$BCcost_{Ri} = \begin{cases} \dfrac{(BCcost_i{}^{\lambda} - 1)}{\lambda}; \lambda \neq 0 \\ logBCcost_i; \lambda = 0 \end{cases} \quad (8)$$

$$P_{Ri} = \frac{\sum_m (\alpha_{im}\, e^{V_{Ri}})^{\frac{1}{\mu_m}} \cdot \left(\sum_{n' \epsilon N_m} (\alpha_{n'm} \cdot \mathrm{e}^{V_{Rn'}})^{\frac{1}{\mu_m}} \right)^{\mu_m - 1}}{\sum_m \left(\sum_{n' \epsilon N_m} (\alpha_{n'm} \cdot \mathrm{e}^{V_{Rn'}})^{\frac{1}{\mu_m}} \right)^{\mu_m}} \quad (9)$$

The variables in the utility function for each route are travel time (including the estimated transfer time), price, frequency, and a transfer penalty. A Box-Cox transformation is applied to travel cost to account for the diminishing marginal sensitivity to cost changes as total trip expenditure increases. For example, a cost saving of €20 is perceived as substantially more relevant for a trip costing €50 than for one costing €500. The generated routes are limited to three legs, while a quality-of-service index characterises each of them. This index considers the various characteristics of each route: travel time, frequency, and transfer time. In an improvement from the pre-existing international aviation model, air travel can also use surface modes as feeders. For example, a traveller might travel by road or rail to a centroid nearby and then fly to their destination. This feeder mode is counted as one of the possible three legs that are allowed for in the route choice model for aviation.

Calibration process

The main source of calibration data is the on-flight origin-destination counts for all international air links and the proportion of direct, one-stop and two-stop flights between large markets (Europe-North America for instance). Additionally, information from UIC regarding rail intercity passenger activity and national statistics and travel surveys of United States and European Union regarding long distance travel, and with OD pairs detail for the case of France[66]. As a result, all models are calibrated simultaneously with a joint calibration. The problem is similar to the question of estimating an origin-destination matrix on the road network using traffic counts coming from cordon survey and the methodology adopted closely resembles that explained by Cascetta, Russo [67]. Schematically, the procedure finds the set of parameters which minimise the difference between the observed demand and the estimated demand on all arcs.

Given a set of values for the parameters, the estimated demand d_k for each link k, by summing up the demand for all paths that use link k is:

$$d_k = \sum_{i,j} \sum_{\substack{p \in P_{ij} \\ k \in p}} \pi_p d_{ij} \tag{10}$$

The objective function to minimise is then the sum of absolute errors for all links:

$$\Delta = \sum_{k} |d_k - {d^0}_k| \tag{11}$$

where ${d^0}_k$ is the observed demand for link k. This gives a set of parameters that are later slightly modified by rerunning the calibration but adding to the objective function a comparison between estimated and observed proportions of direct trips.

Following this calibration procedure multiple times with different set of parameters allows for variable selection. Two considerations are important in this process:

- The quality of the fit, as measured by the goodness-of-fit function as well as other measures of calibration quality.
- Avoiding over-fitting. The problem is especially acute for the selection of supply variables in the generalized cost. Including frequency, or the log-sum, yield extremely high level of fit but only reflect the adaptation of supply to demand rather than the impact of supply on demand.

Emissions model

The intercity passenger travel demand model provides passenger-kilometres (pkm) and vehicle-kilometres (vkm) for each OD pair and centroid, disaggregated by transport mode.

CO_2 emissions by mode are estimated via transport activity expressed in either pkm or vkm, depending on the mode. For road transport (car, moto and bus), CO_2 is estimated via vkm, assuming vehicle load factors (to get from pkm to vkm) defined by:

$$\begin{aligned} car\ load\ factor_{\ ij} \\ &= \min(4, 1.306 \cdot (1 - \%SM_{ij}) + 0.0006 \cdot distance_{ij} \\ &+ 2.800 \cdot \%SM_{ij} + 0.101 \cdot \%Saut_{ij} \end{aligned} \quad (12)$$

$$bus\ load\ factor_{ij} = \min(50, 22.544 + 0.006 \cdot distance_{ij}) \quad (13)$$

These load factors are estimated on data stemming from ITF member countries and depend on the average distance driven and the effect of potential organisational or technological disruptive elements. These are shared mobility (identified as SM in equation 12) and automation (identified as Saut in equation 12). For other modes, CO_2 estimates are estimated via transport activity in pkm.

CO_2 intensities per vkm (for bus, moto and car) and pkm (for rail and air) and the future development of these CO_2 intensities for the different modes are calculated within the framework of the ITF fleet model [48], applying a feedback loop between the demand evolution of different vehicles and fleet dynamics in terms of quantity, age, and technological composition.

Table 1: Implementation of policy measures within the model structure

Measures and Disruptions	Propensity to travel			Destination choice			Modal split				Routing choice		Vehicle activity	Energy/CO_2 performance
	Alternative specific constant	High-speed rail station	Air connectivity (H index)	Connectivity (by mode)	High-speed rail connection	LCC	Availability	Travel time	Cost	Frequency	Connectivity (# links, frequency, Cost, TT)	Cost	Load factor	Fleet composition
Enhancement of Infrastructure														
Development of high-speed rail (HSR)	-	Endogenous update of rail network development	-	Endogenous by rail network development		-	Endogenous by rail network development	Update to rail high-speed value	Change ticket price to high-speed	Set initial or development of high-speed rail frequencies	Update for unimodal and multimodal routes	Change ticket price to high-speed	-	Electric rail share
Rail frequency improvement and electrification	-	-	-	Endogenous by rail network development		-	-	Update to rail electrified (good rail)	-	Endogenous update	Update for unimodal and multimodal routes	-	-	Electric rail share
Multimodality improvement	-	-	-	-	-	-	-	Improve performance of routes	Adjust costs of multimodal routes	Adjust the frequency of routes	Adjust the performance of multimodal routes	Adjust costs of multimodal routes	-	-
Economic instruments														
Carbon pricing	-	-	-	-	-	-	-	-	Add computed tax	-	-	Add computed tax	-	-
Ticket taxes (air travel)	-	-	-	-	-	-	-	-		-	-		-	-
Regulatory instruments														
Sustainable Aviation Fuel (SAF) mandates	-	-	Endogenous by air network development		-	-	-	-	Add SAF surcharge	-	-	-	-	CO_2 intensity per km
Short-haul flight (<500 km) ban	-	-			-	-	Air alternative erased if targeted	-	-	-	-	-	-	-
Stimulation of innovation and development														
Shared mobility	-	-	-	-	-	-	-	-	Adapt to load factor	-	-	-	% change	-
Vehicle automation	-	-	-	-	-	-	-	-	Adjust costs	-	-	-	-	-
Electric vehicles	-	-	-	-	-	-	-	-	Adjust to electric vehicles' price and energy cost	-	-	-	-	Endogenous update to fuel blend and engine type (CO_2 intensity per km)
New propulsion aircrafts	-	-	Endogenous by air network development		-	Endogenous by air network update	-	-	Adjust ticket price to new aeroplane and fuel cost	-	-	-	-	
Trends														
Reduced propensity to fly	% variation	-	Endogenous by air network development		-	-	-	-	-	-	-		-	-
Reduction in business travel due to teleconferencing	% variation	-	Endogenous by air network development		-	-	-	-	-	-	-	-	-	-

Table 2: Levels and calendar of policy measures implementation by world region

Measures and Disruptions	Variable updated (Initial year)	Scenario	World Regions								
			EUR	ENEA	LAC	MENA	SEA	SSA	SSWA	TAP	UCAN
Enhancement of Infrastructure											
Development of high-speed rail (HSR)	Intensity of investment (cost-benefit ratio)	Business-as-Usual	No line beyond projects under constructions								
		Increased Ambition	Planned calendar of cost-benefit ratio <=1.25 or planned HSR announced or in construction								
Rail frequency improvement and electrification	First quality improvement (2025)	Business-as-Usual	2035	2030	2040	2035	2050	2050	2035	2035	2030
		Increased Ambition	2030	2025	2030	2030	2040	2040	2030	2030	2030
	Second quality improvement (2025)	Business-as-Usual	-	-	-	-	-	-	-	-	-
		Increased Ambition	2040	2030	2050	2040	-	-	2040	2045	2040
Multimodality improvement	Transfer time between modes (hours) (2025)	Business-as-Usual	-								
		Increased Ambition	2 hours								
Economic instruments											
Carbon pricing	Cost ($/tonne CO2) (2025)	Business-as-Usual	200	-	-	-	-	-	-	-	-
		Increased Ambition	500	500	300	300	300	300	300	300	500
Ticket taxes (air travel)	Cost (2025)	Business-as-Usual	+15%	+10%	+5%	+3%	+7%	+3%	+5%	+5%	+10%
		Increased Ambition	+45%	+37.5%	+25%	+8%	+15%	+8%	+15%	+15%	+45%
Regulatory instruments											
Sustainable Aviation Fuel (SAF) mandates	Mandate of blend share (2025)	Business-as-Usual	5% -> 63%	0%	0%	0%	0%	0%	0%	0%	0%
		Increased Ambition	11% -> 73%	15.7% - >86.5%	15.7% - >86.5%	15.7% - >86.5%	15.7% - >86.5%	15.7% - >86.5%	15.7% - >86.5%	15.7% - >86.5%	20.4%->100%
	Cost (2025)	Business-as-Usual	0.016	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.006
		Increased Ambition	0.016	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.006
Short-haul flight (<500 km) ban	Year of start of implementation	Business-as-Usual	2030	-	-	-	-	-	-	-	-
		Increased Ambition	2030	2035	2040	2040	2040	2040	2040	2040	2035
Stimulation of innovation and development											
Shared mobility	Car load factor (2025)	Business-as-Usual	-								
		Increased Ambition	+ 30%	+ 20%	+ 20%	+ 20%	+ 20%	+ 20%	+ 20%	+ 20%	+ 30%
Vehicle automation	Share of car PKM (2025)	Business-as-Usual	2.5%	1.3%	1.3%	0%	0%	0%	0%	0%	2.5%
		Increased Ambition	2.5%	1.3%	1.3%	0%	0%	0%	0%	0%	2.5%
Electric vehicles	Electric fleet (2025)	Business-as-Usual	13%	18%	2%	2%	3%	2%	10%	0%	2%
		Increased Ambition	51%	54%	34%	38%	39%	38%	45%	31%	36%
New propulsion aircraft (Hydrogen)	Cost (surcharge) (2035)	Business-as-Usual	3.5 -> 2.5	2.6 -> 1.5	5 -> 2.8	5 -> 2.8	5 -> 2.8	5 -> 2.8	2.6 -> 1.5	5 -> 2.8	2.6 -> 1.5
		Increased Ambition	3 -> 2.2	2.6 -> 1.3	5 -> 2.5	5 -> 2.5	5 -> 2.5	5 -> 2.5	2.6 -> 1.3	5 -> 2.5	2.6 -> 1.3
	Range (km) (2035)	Business-as-Usual	3700								
		Increased Ambition	4260								
New propulsion aircraft (Electric)	Cost (2035)	Business-as-Usual	A surcharge evolves from (2.03 -> 1.5) compared to the standard kerosene cost								
		Increased Ambition	A surcharge evolves from (1.8 -> 1.2) compared to the standard kerosene cost								
	Range (km) (2035)	Business-as-Usual	350								
		Increased Ambition	350								
Trends											
Reduced propensity to fly	Demand reduction (2025)	Business-as-Usual	0	0	0%	0%	0%	0%	0%	0%	0%
		Increased Ambition	-2.1%	-1.4%	0%	0%	0%	0%	0%	0%	-1.4%
Reduction in business travel due to teleconferencing	Demand reduction (2025)	Business-as-Usual	-5%	-5%	-2.5%	-2.5%	-2.5%	-2.5%	-2.5%	-2.5%	-5%
		Increased Ambition	-12.5%	-12.5%	-2.5%	-2.5%	-2.5%	-2.5%	-2.5%	-2.5%	-12.5%

Data and code availability

The baseline demographic, economic, and spatial inputs used in this study are publicly available from the United Nations World Population Prospects (UN DESA), OECD long-term economic projections, and the Gridded Population of the World (GPWv4). Specific input datasets and scenario parameter tables that are not subject to third-party or commercial restrictions are documented in the main text, Methods, and Tables 1 and 2, and are available from the corresponding author upon reasonable request. By contrast, base-year transport schedules, ticket fares, and origin–destination demand matrices rely on proprietary third-party datasets of commercial value (such as OAG/Innovata, Skyscanner, and ICAO True OD) used under institutional licence at the International Transport Forum (ITF-OECD); due to commercial licensing agreements, these raw inputs cannot be shared publicly and must be obtained directly from the respective data providers. The aggregated simulation results and source data underlying the figures and tables in this manuscript can be provided by the corresponding author upon reasonable request. The source code for the global non-urban passenger simulation model is proprietary to the International Transport Forum (ITF-OECD) and cannot be made publicly available due to institutional access restrictions; however, all mathematical formulations, utility functions, and calibration equations required to implement the modelling framework are detailed in the Methods section, and the calibrated model parameters can be provided by the corresponding author upon reasonable request.

Acknowledgements

This work was supported by funding from the Energy Demand changes Induced by Technological and Social innovations (EDITS) project, which is part of the initiative coordinated by the Research Institute of Innovative Technology for the Earth (RITE) and International Institute for Applied Systems Analysis (IIASA), and funded by the Ministry of Economy, Trade, and Industry (METI), Japan.

This work builds on a previous modelling work developed by ITF under its Decarbonising Transport initiative, in the "Decarbonising Transport in Europe" (DTEU) project, funded by the European Union Horizon 2020 Programme under grant agreement no. 831743.

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