A Simulation of the Impacts of Climate Change on Civil Aircraft Takeoff Performance

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A Simulation of the Impacts of Climate Change on Civil Aircraft Takeoff Performance

Thomas D. Pellegrin

Dissertation Submitted to the College of Aviation in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Aviation

Embry-Riddle Aeronautical University

Daytona Beach, Florida

March 2023
A Simulation of the Impacts of Climate Change on Civil Aircraft Takeoff Performance

By

Thomas D. Pellegrin

This dissertation was prepared under the direction of the candidate’s Dissertation Committee Chair, Dr. Steven Hampton, and has been approved by the members of the dissertation committee. It was submitted to the College of Aviation and was accepted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Aviation.

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Climate change affects the near-surface environmental conditions that prevail at airports worldwide. Among these, air density and headwind speed are major determinants of takeoff performance, and their sensitivity to global warming carries potential operational and economic implications for the commercial air transport industry. Previous archival and prospective research observed a weakening in headwind strength and predicted an increase in near-surface temperatures, respectively, resulting in an increase in takeoff distances and weight restrictions. The main purpose of the present study was to update and generalize the extant prospective research using a more representative sample of worldwide airports, a wider range of climate scenarios, and next-generation climate models. The research questions included how much additional thrust and payload removal will be required to offset the centurial changes in takeoff conditions. This study relied on a quantitative method using the simulation instrument. Forecast climate data corresponding to four shared socioeconomic pathways (SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5) over the available 2015–2100 period were sourced from a high-resolution CMIP6 global circulation model. These data were used to characterize the six-hourly near-surface environmental conditions prevailing at all 881 airports worldwide having at least one million passengers in pre-COVID–19 traffic. The missing air density was
numerically derived from the air temperature, pressure, and humidity variables, while the headwind speed for each airport’s active runway configuration was triangulated from the wind vector components. Separately, a direct takeoff-dynamics simulation model was developed from first principles and calibrated against published performance data under international standard atmospheric conditions for two narrowbody and two widebody aircraft. The model was used to simulate 1.8 billion unique takeoffs, each initiated at 75% of maximum takeoff thrust and 100% of maximum takeoff mass. When the resulting takeoff distance required exceeded that available, the takeoff thrust was gradually increased to 100%, after which the takeoff mass was gradually decreased to an estimated breakeven load factor. In total, 65 billion takeoff iterations were simulated. Longitudinal changes to takeoff thrust, distance, and payload were recorded and examined by aircraft type, climate scenario, and climate zone. The results show that despite a marked centurial increase in the global mean air temperature of 9.4%–18.0% relative to the year 2015 under SSP2–4.5 and SSP3–7.0, air density will only decrease by 0.6%–1.1% due to its weak sensitivity to temperature. Likewise, mean headwinds were observed to remain almost unchanged relative to the 2015 baseline. As a result, the global mean takeoff thrust was found to increase by no more than 0.3 percentage point while payload removals did not exceed 1.1 passenger. Significant deviations from the mean were observed at climatic outlier airports, including those located around the Siberian plateau, where takeoff operations may become more difficult. This study contributes to the air transport climate adaption body of knowledge by providing contrasting results relative to earlier research that reported strong impacts of global warming on takeoff performance.

**Keywords:** adaptation, aviation, climate change, simulation, takeoff performance.
Dedication

To my parents for their gift and curse of intellectual curiosity. To Alex and Yulia for their unconditional support throughout this arduous journey. They collectively provided the ink to my words.
Acknowledgments

I am deeply grateful to all those whose contributions, direct and otherwise, enabled this academic endeavor. Dr. Steven Hampton provided unwavering mentoring and support throughout my Ph.D. candidacy. Other dissertation committee members, Drs. David A. Esser, Guy Gratton, and Marwa El-Sayed generously invested their time, consideration, and expertise in raising this work to scholarly standards. Prior researchers in climate change and takeoff performance provided the shoulders that this study stands on. Among them, Drs. Ethan D. Coffel and Radley M. Horton pioneered the line of inquiry, and Drs. Anil Padhra, Guy Gratton, and Paul D. Williams graced me with their advice. Fellow Ph.D. classmate Agatha Kessler was a steadfast source of camaraderie and encouragement. Joseph (Pat) Dunagan and Mark McCullins supported me with knowledge and constructive critiques. The World Climate Research Programme (WCRP)’s Working Group on Coupled Modeling (WGCM) made the sixth phase of the Coupled Model Intercomparison Project (CMIP6) possible, and the Max Planck Institute Earth System Model team produced the scenario runs on which this study relies. Drs. Junzi Sun, Jacco M. Hoekstra, and Joost Ellerbroek built the OpenAP aircraft model performance model from which this takeoff simulation model borrows. Lastly, Lufthansa Systems kindly contributed some of the runway data needed to accomplish this research. May they all receive my boundless gratitude.
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Climate change is likely to threaten transportation systems, both acutely through extreme weather events and chronically through gradual changes. Hazards are numerous: coastal and urban flooding, heat, cold, drought, and wind, to name a few. We are in the nascent stages of understanding how climate change might affect transportation systems. Although there is a growing body of knowledge related to how climate change might affect the transportation system . . . there still appears to be an opportunity to expand our understanding of vulnerabilities and adaptation strategies related to disruptions from behavioral, information, resource, and interconnected physical systems. (Markolf et al., 2019)
Chapter I: Introduction

The net increase in the global mean surface air temperature (GMST) of the Earth relative to a pre-industrial baseline, commonly known as global warming, is a widely-acknowledged manifestation and subset of climate change (Gettelman & Rood, 2016). The accumulation of greenhouse gases (GHG), such as carbon dioxide, in the troposphere traps some of the Sun’s reflected longwave radiation (Byrne & Goldblatt, 2014; Ramaswamy et al., 2019) and leads to positive radiative forcing, which is “an externally imposed perturbation in the radiative energy budget of the Earth’s climate system” (Intergovernmental Panel on Climate Change, IPCC, 2001, p. 353). Positive radiative forcing increases the mean tropospheric air temperature (Forster et al., 1997; Hansen et al., 1997), although unevenly across latitudes (Arnell et al., 2016; Suarez-Gutierrez et al., 2020).

Among the anthropogenic GHG emissions causal to positive radiative forcing, research has extensively quantified the historical contribution of the commercial air transport industry (Graver et al., 2019), although uncertainty remains over future levels (Terrenoire et al., 2019). Conversely, the effects and impacts of climate change on commercial air transport are an emerging research topic (Gratton et al., 2021; Ryley et al., 2020; P. D. Williams, 2016). Among them, the present study investigated the operational impacts of changes in air density and winds on takeoff performance at major commercial airports worldwide in the 21st century, extending prior research on the topic (Coffel et al., 2017; Coffel & Horton, 2015; Gratton et al., 2020; Ren et al., 2019; Y. Zhao & Sushama, 2020; T. Zhou et al., 2018; Y. Zhou et al., 2018). Figure 1 illustrates the context and scope of the present research.
Figure 1

*Context and Scope of the Present Research*

```
Climate change

Global warming

Effects on air transport

First-order effects

Impacts on takeoff performance

Operational impacts (takeoff distance increase, payload removal)

Economic impacts (revenue attrition and maintenance cost increase)

Other manifestations of climate change

Effects on other sectors

Second-order effects

Other first-order effects
```

*Note.* The boxes and arrows represent the order of precedence between climate change at the top and the scope of the present research in gray at the bottom.
Climatic Effects on Air Transport

The present study fits within the broader and emerging research context of how the effects of climate change impact air transport. Although the literature appears to be inconsistent in its use of both terms, the present study refers to climatic effects as changes in operating conditions due to climate change and impacts as the operational consequences to the air transport industry of those changes. The present study further categorizes climatic effects on the air transport industry into first- and second-order effects, borrowing from Birkmann’s (2011) adaptation taxonomy.

First-order effects in the present study refer to environmental changes proximate to the various physical manifestations of climate change, such as the increase in the GMST. They appear to be the most represented in the literature (Burbidge, 2018; Thompson, 2016). Among first-order effects, the present study explicitly focused on the atmospheric changes in takeoff conditions from global warming, including the near-surface air temperature $tas$, pressure $ps$, density $\rho$, relative humidity $hurs$, and eastward ($uas$) and westward ($vas$) wind components.

Second-order effects in the present study refer to institutional and behavioral changes toward air travel derived from the broader societal response to climate change, such as carbon taxation and flight shaming. Evidence shows that personal experience with climate change drives public concern and willingness to adapt (Weber, 2011; Whitmarsh, 2008); therefore, second-order effects tend to lag first-order effects. Chapter II briefly reviews the extant literature on both first- and second-order effects to anchor the present study in its context and suggest avenues for further research.
Climatic Effects on Takeoff Performance

The present study examined the degree to which net changes to the environmental conditions at airports influence the takeoff performance of representative fixed-wing civil transport aircraft with turbofan engines. This section introduces the relevant concepts of the takeoff sequence, distance, and performance, the environmental envelope, and the climatic effects on the forces of motion involved at takeoff.

The Takeoff Sequence

The Ground Run and Rotation. The present research refers to takeoff as a sequence comprised of two stages. The first is the ground run, which starts with the application of takeoff thrust while the aircraft is aligned and at rest or aligning with the runway’s centerline in a rolling takeoff. For simplicity, the present study combines the ground run with the rotation, which is the point at which the nose of the aircraft gradually rotates up to increase the angle of attack. This first takeoff stage ends when the aircraft becomes fully airborne at liftoff and the frictional forces at the tire-runway tribosystem disappear.

The First-Segment Climb. The second stage is the first-segment climb, which extends from liftoff to when the lowest point of the aircraft (typically, the main gear) clears a screen height of 35 ft (10.7 m) (Airbus, 2002).

The Takeoff Distance Required

The resulting takeoff distance required (TODR), assuming all engines are operating, is the greatest of the balanced field length or 115% of the horizontal distance covered by the aircraft during the ground run and first-segment climb, following E.U. and U.S. regulations (Certification Specifications and Acceptable Means of Compliance for
Large Aeroplanes, 2021; Takeoff Distance and Takeoff Run, 1998). Figure 2 illustrates the two stages and the regulatory factor applied to the takeoff distance. No consideration was made in this study of takeoffs with one engine inoperative (OEI), and thus of the Accelerate Stop Distance Required (ASDR) and of the balanced field length at which TODR equals the ASDR. Therefore, the TODR was assumed to always be 115% of the horizontal distance covered by the aircraft during the ground run and first-segment climb.

**The Takeoff Performance**

Lastly, *takeoff performance* in the present study refers to the *takeoff distance required* (TODR) to lift a given payload or, conversely, to the payload liftable within a *takeoff distance available* (TODA).

**The Environmental Envelope**

An aircraft’s *environmental envelope* defines “the extremes of the ambient air temperature and operating altitude for which operation is allowed” (Ambient Air Temperature and Operating Altitude, 2001, § 25.1527). The environmental envelope’s boundaries result from an aircraft design and certification process encompassing the range of operating conditions that operators are most likely to encounter. Figure 3 provides one such illustrative envelope and indicates a sea-level temperature limit of 55 °C (Lanson & von Wrede, 2017). Global warming may increase the frequency of envelope excursions at airports with extreme summer temperature maxima. In turn, envelope excursions prohibit takeoff operations, as happened in the U.S. Southwest in 2017 (Carpenter, 2019).
Figure 2

Takeoff Distance Used in the Present Study

Note. \( D_{GND} \) is the horizontal distance covered by the aircraft during the ground run, including the rotation up to liftoff. \( D_{AIR} \) is the horizontal distance covered by the airborne aircraft during the first-segment climb, from liftoff up to when the aircraft’s lowest point clears a screen height \( h \) of 35 ft (10.7 m). \( D_{REG} \) is the regulated horizontal distance equal to 15% of \( D_{GND} \) and \( D_{AIR} \) combined. \( \phi \) is the climb angle during the first-segment climb, which the present study assumes to be constant and invariant across takeoffs.
Figure 3

*Illustrative Environmental Envelope*

*Note.* Adapted from *Getting to Grips with Aircraft Performance*, by Airbus, 2002.
The Takeoff Forces

Takeoff performance is a function of gravitational, aerodynamic, frictional, and propulsive forces acting upon the aircraft (Sadraey, 2017). The gravitational or weight force $W$ is a function of the aircraft’s mass $m$ and the gravitational acceleration constant $g$, and has an opposite normal or reaction force $R$ from the runway surface (Eshelby, 2000). Except for the gravitational forces, all other forces involved in the takeoff sequence are sensitive to environmental conditions. It follows that global warming affects takeoff operations even within the boundaries of the environmental envelope.

Climatic Effects on Lift

The first component of the aerodynamic force involved in the takeoff sequence is the lift $L$, which is the typically-upward aerodynamic force resulting from the downwash generated by the airfoil as it travels through the air. The lift formula in Equation 1 evidences its relevance to the present study (Torenbeek & Wittenberg, 2009):

$$L = \frac{1}{2} \cdot \rho \cdot V^2 \cdot S \cdot C_L$$

where:

$L =$ The lift force in N.

$\rho =$ The air density in kg/m$^3$.

$V =$ The true airspeed of the aircraft in m/s.

$S =$ The wing surface area in takeoff configuration in m$^2$.

$C_L =$ The dimensionless lift coefficient derived from the static surface pressure distribution for a given angle of attack (Torenbeek & Wittenberg, 2009).
Equation 1 shows that $L$ is directly proportional to $\rho$, which is a function of $tas$, $ps$, and $hurs$. Therefore, it is possible to reformulate Equation 1 using the ideal gas law for moist air (Ambaum, 2010; Federal Aviation Administration [FAA], 2016):

$$L = \frac{1}{2} \left( \frac{ps_D}{hurs_D \cdot tas} + \frac{ps_V}{hurs_V \cdot tas} \right) \cdot V^2 \cdot S \cdot C_L$$

(2)

where:

$ps_D$, $ps_V$ = The partial pressures of dry air and water vapor in N/m$^2$.

$hurs_D$, $hurs_V$ = The specific gas constants for dry air and water vapor with respective values of 287.058 J/(kg·K) and 461.495 J/(kg·K).

$tas$ = The near-surface air temperature in K, not to be confused with the true airspeed of the aircraft $V_{TAS}$.

Equation 2 shows that an increase in $tas$ from global warming leads to a decrease in $\rho$, ceteris paribus. Likewise, at high latitudes, the expected decrease in $ps$ (IPCC, 2007) leads to a proportional reduction in $\rho$, while the expected increase in $ps$ at low-to-mid latitudes may be insufficient to offset the reduction in $\rho$ from warmer air (Y. Zhou et al., 2018). Lastly, global warming is likely to increase $hurs$ (Rastogi et al., 2020), although unevenly between inland and coastal areas (Byrne & O’Gorman, 2016; O’Gorman & Muller, 2010), further decreasing $\rho$ because the molar mass of water vapor (18.02 g/mol) is ~38% less than that of dry air (28.96 g/mol).

In combination, the net reduction in $\rho$ that might be expected from global warming eventually increases the takeoff speed at which the lift $L$ overcomes the weight $W$, extends the runway length required to achieve that speed, and decreases the permissible payload when the TODR exceeds the TODA.
Climatic Effects on Drag

The second force involved at takeoff is the drag $D$, which consists of (Eshelby, 2000): (i) the *lift-induced drag*, itself a function of $C_L$ which in turn is impacted by the angle of attack $\alpha$, the wing’s aspect ratio $AR$, and the Oswald efficiency factor $e$; and secondary lift from the tailplane; (ii) the lift-independent drag (surface friction and profile drag) that is quasi-constant at takeoff; and, (iii) the *compressibility-induced wave drag*, which is negligible at takeoff and thus ignored here. $D$ plays a far smaller role than $L$ in takeoff dynamics (Obert, 2009) due to the high lift-to-drag ratio $C_L/C_D$ of modern airliners where $C_D$ is the drag coefficient (Torenbeek & Wittenberg, 2009).

The sensitivity of $D$ to changing environmental conditions is identical to that of $L$, as evidenced by the drag formula shown in Equation 3:

$$D = \frac{1}{2} \cdot \rho \cdot V_{TAS}^2 \cdot S \cdot C_D$$

where:

$D =$ The drag force in N.

$\rho =$ The air density in kg/m$^3$.

$V_{TAS} =$ The true airspeed of the aircraft in m/s.

$S =$ The wing surface area in takeoff configuration in m$^2$.

$C_D =$ The dimensionless drag coefficient.

Equation 2 is identical to Equation 1 after substituting $D$ for $L$ and $C_D$ for $C_L$. It shows that $D$ is directly proportional to $\rho$ and its constituents *tas, ps*, and *hurs*. In practice, however, the effects on $D$ at takeoff of a net decrease in $\rho$ are inconsequential because of the high lift-to-drag ratio of modern commercial air transport aircraft and the negligible lift-induced drag due to the near-zero $\alpha$ prior to rotation.
Climatic Effects on Thrust

The third component of takeoff aerodynamics is the net propulsive force \( F \) generated by the engine thrust. It can be considered an aerodynamic force because of its interactions with \( L \) and \( D \) (Torenbeek & Wittenberg, 2009). Of relevance to the present study, the takeoff sequence requires the most thrust of all the flight stages, and thrust generation is sensitive to warmer environmental conditions in at least two ways described hereafter.

Air Density Effects. The turbofan engine is a volumetric device whose generated thrust is the difference between the stream forces entering and exiting the engine (Eshelby, 2000). Thrust production depends on the air mass going through the engine per unit of time and how fast the turbofan can accelerate it (Sadraey, 2017). The resulting \( F \) is the difference between the force of the streams entering and exiting the engine, as evidenced by Equation 4:

\[
F = \dot{m} \cdot V_j - \dot{m} \cdot V = \dot{m} (V_j - V)
\]

where:

- \( F \) = The net propulsive force in N.
- \( \dot{m} \) = The air mass flow passing by the engine, which is dependent on \( \rho \).
- \( V, V_j \) = The velocity in m/s of the intake and exhaust gas flow, respectively.

Equation 4 illustrates that a net reduction in \( \rho \) necessarily decreases \( \dot{m} \) and \( F \) (Koh et al., 2017; Takahashi, 2018; Torenbeek & Wittenberg, 2009). Indicatively, for a reference turbofan engine delivering 100 kN of thrust, such as mid-range variants of the CFM56 model commonly found on Airbus 320 and Boeing 737 aircraft, a \( tas \) of 35 °C above the International Standard Atmosphere (ISA) causes a 22% reduction in thrust.
from \( \rho \) effects alone relative to ISA conditions (Balicki et al., 2014). While ISA+35 \( ^\circ \text{C} \) represents a temperature maximum only found at a few tropical airports in the summer months today, the net increase in mean \( \text{tas} \) from global warming will make those occurrences more frequent and generally decrease the amount of engine thrust available at takeoff elsewhere. The decrease in thrust carries at least two operational implications, which are to increase the engine thrust where available and thus the wear and tear on the powerplant, and to decrease payload where necessary.

**Temperature Effects.** Independently of air density, warmer environmental conditions also increase the likelihood of engine throttling due to a design temperature excursion. The combustion chamber is the hottest section of a turbofan engine and, therefore, the most exposed to thermal stress. Its *exhaust gas temperature* (EGT) is measured using thermocouples at the engine’s low-pressure turbine inlet or outlet. To maintain a safe internal pressure and reduce thermal stress on the combustor, powerplant Original Equipment Manufacturers (OEMs) set a design limit for the EGT (Airbus, 2002), called the *exhaust gas temperature limit* (EGTL). Among all phases of flight, takeoffs are the most conducive to EGTL exceedance due to peak thrust, weak bypass air cooling, and surface-level air being typically warmer than at altitude.

To avoid EGTL exceedance and engine damage, OEMs certify engines to provide a flat-rated thrust independent of pressure and temperature conditions, but only up to a reference called the *corner point* or *thrust break* temperature or \( T_{\text{REF}} \). For example, the CFM LEAP–1A engine’s \( T_{\text{REF}} \) is 30 \( ^\circ \text{C} \) at takeoff (FAA, 2019). Above \( T_{\text{REF}} \), the Full Authority Digital Engine Control (FADEC) will throttle the fuel flow linearly to avoid an
EGTL excursion (Airbus, 2002; Takahashi, 2018). Therefore, a net increase in \( tas \) above \( T_{REF} \) decreases the available thrust and extends the TODR.

Furthermore, high temperatures correlate with the pilots’ use of pressurization air conditioning kits (packs) to cool the cabin and the cockpit in hot conditions. Packs rely on \textit{bleed air} drawn from the engines’ compressor section, diverting a non-trivial portion of the engine’s primary airflow, estimated at 15\% on a CFM LEAP–1B model (FAA, 2019). Therefore, the use of packs on warm days further reduces the thrust available for takeoff.

\textit{Climatic Effects on Runway Friction}

The final force involved in the takeoff sequence is the free-rolling friction at the tire-runway interface, which is a function of \( W \) and a dimensionless friction coefficient \( \mu \) for a given surface texture. \( \mu \) is subject to environmental conditions in two ways.

First, warmer air reduces the \textit{hysteretic friction} as the tire’s rubber softens and expends less energy deforming against the runway surface and bouncing back into shape during the wheel’s rotation (Kennedy et al., 1990; Young, 2017). While this effect is slightly favorable to takeoff performance, it is also deemed negligible as a 5 \( ^\circ \)C increase in \( tas \) reduces the friction force by an estimated 3\% only (E. Durand, Michelin, personal communication, November 5, 2020).

Second, other manifestations of climate change, such as a net increase in relative atmospheric humidity over land masses and its attendant precipitation, may lead to more frequent and more severe runway contamination. In turn, the resulting loss in braking efficiency in the event of a rejected takeoff extends the TODR.
Resulting Impacts

Operational Impacts on Takeoff Performance

The decrease in takeoff performance from global warming introduced earlier has several operational implications for operators, even within the environmental envelope.

**Geometric Limitations.** At certain runways, the TODR for a given mass \( m \) may exceed the TODA, in which case the takeoff becomes *runway-limited*. The aircraft may also fail to reach a screen height of 35 ft (10.7 m) above the end of the takeoff surface, in which case the takeoff is *climb-limited*. Lastly, the aircraft may fail to clear the vertical separation minimum above aerodrome-specific obstacles, in which case the takeoff becomes *obstacle-limited*.

**Tribological Limitations.** The higher groundspeed at liftoff increases the tires’ rotational speed, frictional heat, and centrifugal forces, which leads to more frequent tire servicing and raises the likelihood of catastrophic tread separation. To prevent the latter, OEMs set a maximum rotational speed above which the takeoff is *tire-limited* (Wakefield & Dubuque, 2009). Furthermore, braking heat accumulates in the carbon discs during consecutive short-haul sectors (Ahlers, 2011), which may lead to cool-down penalties, as the kinetic energy that brakes can absorb in a rejected takeoff is finite (Daidzic, 2017).

**Thermal Limitations.** Lastly, warmer air may lead to automatic engine throttling to prevent an EGTL excursion and prohibit the use of a reduced takeoff thrust setting above \( T_{REF} \). Such instances increase the thrust-specific fuel consumption (TSFC) and accelerate the engine fatigue by raising the combustor’s internal temperature (Balicki et al., 2014). The result is more frequent maintenance and a shortening of the engine’s service life.
Economic Impacts on the Air Transport Industry

These operational impacts may have economic consequences for airlines.

Revenue Attrition. Whenever takeoff limitations apply within the environmental envelope, an aircraft operator will likely favor increasing the takeoff thrust over removing revenue payload or rescheduling flights. However, even maximum takeoff thrust may be insufficient to overcome certain limitations, such as runway length or climb performance, and may exacerbate others, such as tire speed, brake disc heat, or EGTL exceedance. The operator must then remove any combination of fuel, passengers, or cargo to meet the takeoff performance requirements, each with economic implications.

First, corporate policy and regulatory requirements set a mandatory minimum for the required fuel, which takes priority over the commercial payload. Pilots can only elect to remove excess fuel above the reserve typically used for tankering, although this creates an opportunity cost to the operator (Eurocontrol, 2019). However, Tabernier et al. (2021) found that within the European Civil Aviation Conference (ECAC) countries, only 30% of short- and medium-haul flights in 2018 used partial or complete tankering, which suggests a low potential for discretionary fuel removal.

Second, passenger and cargo removals lead to an irreversible revenue loss, given the perishability of aircraft seats and belly space. The relative unpredictability of near-surface temperature conditions also suggests that such removals must happen close to departure time, maximizing opportunity costs both direct (e.g., refunds, monetary compensation) and indirect (e.g., customer inconvenience and increased churn rate). Lastly, canceling or rescheduling flights carries additional opportunity costs from downstream schedule disruptions and missed connections.
**Higher Fuel Costs.** Modern engines characteristically display a high *bypass ratio* (BPR), which is the proportion of air mass flow routed around the engine’s core rather than into it. A high BPR is a primary factor in improving turbofan efficiency by lowering the TSFC in turbofan engines (Dankanich & Peters, 2017). For example, the CFM–LEAP–1A engine has a BPR of 10.5–11.3, diverting proportionately twice as much air around the engine core as the older CFM56–5B with a BPR of 5.4–6.0. As a result, the CFM–LEAP’s takeoff TSFC is approximately 20% lower than the CFM56–5B’s (International Civil Aviation Organization [ICAO], 2021).

However, over time, a net increase in near-surface air temperature offsets some of these technological improvements by increasing the takeoff thrust required, ceteris paribus. For example, with two LEAP–1A29 engines, each delivering 75% of their maximum rated takeoff thrust of 130.3 kN at a mean takeoff TSFC of 14 g/kN (ICAO, 2021), and a Jet A fuel density of 820 g/L, the estimated fuel consumption over a three-minute takeoff sequence is given by Equation 5:

\[ 2 \times .75 \times 130.3 \times 14/820 \times 180 = .493 \text{ metric ton} \]  

(5)

Should the throttle be increased to 85% of its maximum setting, the fuel consumption is:

\[ 2 \times .85 \times 130.3 \times 14/820 \times 180 = .558 \text{ metric ton} \]  

(6)

At an indicative May 2022 jet fuel price of U.S. $1,314.05 per metric ton (International Air Transport Association [IATA], 2022), this 13.2% increase in fuel consumption converts to an opportunity cost of U.S. $85.4. While modest on a unit basis, this cost scales to nearly U.S. $3.42B industry-wide, considering that nearly 40 million commercial flights took off in 2019, prior to the coronavirus disease (COVID–19) pandemic.
**Higher Engine Life Cycle Costs.** Global warming also impacts the economics of engine operations in two significant ways described hereafter.

**Higher EGT From Warmer Air.** A net rise in near-surface air temperatures inexorably leads to an equivalent increase in the engine combustor’s internal temperature, as measured by the EGT (Balicki et al., 2014). The EGT correlates positively with engine severity, a Weibull-distributed measure of relative engine damage (Hanumanthan, 2009; Hanumanthan et al., 2011), and shop visit frequency (Seeman et al., 2011; Ting, 2009). The severity creep comes from compressor fouling, seal leakage, and fan blade airfoil erosion (Glowacki, 2016) and results in a net increase in the mean EGT for a given thrust (Yildirim & Kurt, 2018). Higher EGT correlates negatively with fuel burn (Stopkotte, 2003), economic life, and reliability (Ting, 2002; N. Zhao et al., 2014). Over time, these effects cumulatively narrow the *exhaust gas temperature margin* (EGTM), a common predictor of remaining engine life (Glowacki, 2016; Mungin & Maumy, 1988) that measures the difference between the EGT and the EGTL and indicates the need for an engine’s overhaul or retirement. Figure 4 compares an illustrative takeoff EGTM for new and deteriorated engines.

As a result from the marginal climate-induced severity, aircraft operators may experience decreased on-wing availability and economic returns from their assets. Likewise, the party responsible for keeping the engine in a serviceable state (which may be its manufacturer, lessor, or operator, depending on the contractual arrangement) will incur additional maintenance, repair, and overhaul (MRO) costs. Lastly, the engine owner (who may be a different party) will incur an impairment cost if the shortening of the engine’s economic life is not adequately predicted (IATA, 2016).
Higher EGT From Increased Thrust. A second economic impact of global warming on engine life cycle costs relates to the concept of reduced-thrust takeoff operations. In most takeoff situations, conditions allow pilots to decrease the thrust setting and save on engine life, maintenance, and fuel (Ting, 2002). Pilots can use the derated takeoff method, which reduces the full rated thrust by a fixed percentage. It is advantageous on short and contaminated runways where aerodynamic controllability is a concern because it lowers the aircraft’s minimum control speed. Alternatively, pilots can use the flexible (FLEX) or assumed temperature (ATM) takeoff described within the Airbus and Boeing operations manuals. Instead of lowering the rated thrust, this second method assumes the highest $tas$, above the corner point temperature, at which the aircraft can still produce the needed thrust. In this case, the crew first calculates the lowest thrust setting that enables a balanced-field takeoff using the full TODA. Regulations require
that the reduced thrust setting be at least 75\% of the maximum rated takeoff thrust (FAA, 1988). The crew then uses Regulatory Takeoff Weight (RTOW) lookup tables or takeoff planning software to identify the maximum temperature $T_{\text{FLEX}}$ at which the engine can still generate this thrust. $T_{\text{FLEX}}$ appears at the intersection of the actual thrust needed (horizontal line $A'$) and the $tas$-dependent, EGT-limited thrust (slope $C$) in Figure 5. Lastly, the crew enters $T_{\text{FLEX}}$ in the Flight Management Computer (FMC), which sets the thrust generation to the desired value below the maximum available thrust.

Both methods provide direct economic benefits to the operator. They reduce thermal and mechanical stress on the turbine, delaying the EGTM deterioration and decreasing fuel consumption and tire wear. The first 5\% thrust reduction yields most of the benefits (Airbus, 2011). A maximum 25\% reduction extends the engine’s mean time between failure fivefold, making takeoff thrust reduction the leading factor in turbine blade deterioration and failure mitigation (Stopkotte, 2003).

However, the net increase in near-surface temperatures has at least three detrimental effects on the pilots’ ability to reduce takeoff thrust. First, the effect of a decrease in $\rho$ can be expressed as a takeoff weight penalty, which raises the horizontal line $A'$ in Figure 5 and lowers the achievable $T_{\text{FLEX}}$. Second, if the $tas$ physically exceeds $T_{\text{FLEX}}$, the FADEC reduces the available thrust below the rated thrust as per slope $C$ in Figure 5. If the new permissible takeoff weight is below the aircraft’s actual takeoff weight, payload removal is necessary. Lastly, if $T_{\text{FLEX}}$ falls below either $T_{\text{REF}}$ or the prevailing $tas$ due to warm conditions, then a reduced-thrust takeoff is no longer permissible by regulations, thus negating all associated economic benefits to the operator.
Figure 5

Relationship Between Thrust, Engine Temperature, and Air Temperature

Note. Adapted from *Getting to Grips with Aircraft Performance*, by Airbus, 2002.
**Combined Economic Impacts.** The combined economic impacts of a net increase in mean engine combustor temperature and fewer reduced-thrust operations are challenging to quantify. Public data that relate EGTM deterioration with maintenance expenditures are scarce due to the proprietary nature of cost models for an engine’s life cycle. Hanumanthan (2009) found that an increase in $tas$ of 18–20 °C shortened the shop visit intervals by approximately 16% for a two-shaft turbofan engine similar to the CFM56–5B. Ting (2009) suggests that a 7–18% reduction in thrust yields a 25–40% decrease in maintenance material costs. Ackert (2015) quantified the maintenance cost per flight hour of a CFM56–5B engine in the U.S. $95–105 range for a new engine and U.S. $135–155 for a mature engine with deteriorated EGTM. This indicative increase of 42–48% in the engine maintenance cost may be considered an absolute upper bound for the economic consequences of premature EGTM deterioration and engine aging from climate change.

A more precise instrument to quantify the relationship between an EGT increase and maintenance cost is the severity curve, developed heuristically by powerplant OEMs to link thrust reduction levels with direct maintenance costs for each engine type (Seeman et al., 2011). The lower the EGT, the lower the severity factor (i.e., the penalty to engine life) applied to each flight hour or flight cycle. However, OEMs generally do not publicly disclose severity curves for commercial engines.
Statement of the Problem

Climate change is expected to impact the commercial air transport industry in the 21st century through several first- and second-order effects. Among those, a decrease in the near-surface air density from global warming could, in principle, adversely affect takeoff performance by raising the groundspeed at which liftoff happens, which extends the TODR, and by increasing the mean combustor temperature of the engines, ceteris paribus. In turn, geometrical, tribological, and propulsive limitations may increasingly constrain the achievable thrust reduction and liftable payload.

These limitations may force aircraft operators to increase the mean thrust setting at takeoff, which correlates with accelerated engine fatigue, shorter maintenance shop visit intervals, greater fuel consumption, added noise and greenhouse gas emissions, and faster tire wear. In some cases, operators may further need to remove revenue payload from the aircraft, which is disruptive to operations, inconvenient to passengers, and a source of opportunity costs.

Starting with Coffel and Horton (2015), recent research has evidenced the effects of global warming on takeoff performance and quantified their operational impacts, both retrospectively and prospectively, but mostly on a limited geographical scale and under extreme centurial climate scenarios. There remains a dual opportunity to generalize these findings to the broader set of airports worldwide throughout the 21st century. Doing so would enhance the aviation industry’s ability to anticipate and adapt, given that climatic adaptation requires understanding the opportunity cost of inaction (Leary, 1999; Moser & Ekstrom, 2010).
Purpose Statement

This study’s primary purpose is to quantify the impacts of global warming on commercial aircraft takeoff performance in the 21st century in the form of additional engine thrust and revenue payload removals. In pursuit of this purpose, the research has two practical goals. The first is to quantify the relationship between global warming scenarios and takeoff performance in operational terms of takeoff thrust setting and payload removal. The second is to generalize the findings and draw industry-level conclusions to inform relevant stakeholders about the materiality of the issue to their operations.

The present research will also serve three additional and indirect purposes. The first is to advance the climatic adaptation body of knowledge and governance agenda by quantifying the impacts of inaction in a specific context relevant to airlines, lessors, and engine manufacturers. The second indirect purpose is to extend the published literature with an exploration of global warming’s implications for air transport at a global and industry-wide scale. Lastly, the third indirect purpose is to make available to researchers a first-principles takeoff performance simulation model suitable for future climatic adaptation studies, extending the work of Sun et al. (2020b) in open-source aeronautical research.
Significance of the Study

The present study’s significance stems from its practical and theoretical implications explored in this section.

Practical Implications

The present research intends to quantify a specific aspect of global warming’s increasing burden on the air transport sector. In doing so, the study has several practical implications for decision-makers across the industry’s value chain.

Implications for Aircraft Engine Lessors and Operators. The net increase in the operating temperature of engines correlates positively with wear and tear and associated maintenance actions. The practical implication to engine owners, who may be lessors or airlines, is significant because powerplants incur 47% of all commercial aircraft MRO costs and are a significant determinant of an aircraft’s market value (Ackert, 2011). The spend on engine MRO amounted to U.S. $32B globally in 2018, projected to grow at 4.5% per annum to reach U.S. $50B in 2028 (IATA, 2021a), not accounting for COVID–19 effects. This U.S. $1.8B annual increase from fleet size growth alone does not account for incremental climate-related wear on the engines.

However, engine lessors typically charge maintenance reserves to the airlines to ensure that the asset, once returned, is in a physical condition consistent with the leasing contract’s depreciation assumptions. The maintenance reserves cover performance restoration shop visits and life-limited parts replacement (Ackert, 2011). In quantifying the marginal thrust required at takeoff, the present study may help lessors refine their maintenance reserve assumptions accordingly.
Implications for Engine Manufacturers. The significance of the present study also extends to powerplant OEMs. Outcome-based contracts (OBCs), which include power-by-the-hour and flight-hour-available, now govern most engine care arrangements. In an OBC, the OEMs’ value proposition shifts from delivering a product (i.e., an aircraft engine and its spare parts) to delivering an outcome (i.e., an engine’s availability for flight missions) (Grubic & Jennions, 2018). OEMs then bear the total life cycle costs (TLCC) of the engines on behalf of the airlines, who instead pay a flat rate per time unit of flight or availability. Such arrangements enhance the airlines’ MRO cost predictability and free up organizational resources while incentivizing the OEMs to create additional life cycle value in at least three ways. The first is to embed better reliability and maintainability engineering principles in the early design phase of an engine program, which determines 70% of the TLCC (Wong et al., 2008). The second is to accurately predict and iteratively optimize the TLCC to maximize contract value. The third is implementing effective engine remote monitoring technology and data analytics to mitigate delivery risks (Grubic & Jennions, 2018). Therefore, the study’s practical implication for powerplant OEMs is to better account for climate-related fatigue in the design-for-availability concept and OBT-type economic models.

Implications for Aircraft Manufacturers. Commercial aircraft design aims to accommodate the range of environmental conditions that operators are most likely to encounter. The design also aims to remain relevant for the aircraft platform’s entire life, which often spans decades. An analysis of the active Airbus A320 and Boeing 737 world fleet as of January 1, 2020 (pre-COVID–19) shows a 75th-percentile age of 14.0 and 17.4 years, respectively, and maximum values of 31.4 and 50.7 years (CAPA Center for
Aviation, 2020). Such timescales are long enough to witness the global mean surface temperature shifts expected from climate change, regardless of temporal uncertainty (Huber & Knutti, 2014). *Hot and high* conditions, characterized by an elevated temperature and density altitude, will become more frequent. Airports that operate at the edge of the environmental envelope of typical aircraft, such as Kuwait International Airport (OKKK), with a July mean temperature of 46.7 °C, will encounter more frequent envelope excursions that prohibit flight operations (Ryley & Chapman, 2012). Therefore, one practical implication of the present study is to raise awareness about climate considerations in future aircraft design.

**Implications for Aircraft and Airport Operators.** A net decrease in takeoff performance leads to revenue attrition for airlines, especially those based at airports where flight cancelations and aircraft payload removal are most likely. For example, in June 2017, an environmental envelope exceedance caused multiple flight cancelations and weight restrictions at Phoenix Sky Harbor International Airport (KPHX) (Carpenter, 2019; Hope, 2017; A. B. Wang, 2017). These restrictions are most likely to happen at airports characterized by a hot climate (e.g., Delhi, Dubai), a high elevation (e.g., La Paz, Lhasa), or both (Lanson & von Wrede, 2017). However, even a modest payload removal threatens the profitability of a flight, considering a 2019 mean breakeven load factor of 67.0% (IATA, 2021b). Restrictions also impact airport operators whose aeronautical revenue depends on passenger charges and the ability to attract airlines. Therefore, another practical implication of the present study is to enhance the airline and airport stakeholders’ awareness and understanding of climatic influences on profitability when forming their future network, fleet, and investment decisions.
There also exists an adjacent sustainability implication of a decrease in takeoff performance. An increase in the mean takeoff thrust correlates with higher fuel consumption, additional GHG emissions, and greater offset obligations for the airlines.

**Theoretical Implications**

The present study also carries theoretical implications for climatic adaptation and its applicability to commercial air transport, which have been insufficiently researched or considered (Ryley et al., 2020).

Among the multifaceted manifestations of climate change, the net increase in the GMST “could have severe consequences for aircraft takeoff performance” (ICAO, 2016, p. 205). The KPHX flight cancelations discussed earlier illustrate that the problem has already materialized, making the need for adaptation research even more pressing. The literature review in Chapter II shows that the extant research focused chiefly on demonstrating the existence of an adverse effect of global warming on takeoff performance and estimating the effect size on a limited sample. Among the studies reviewed, the most exhaustive ones simulated the takeoff performance of one or more aircraft types at several global airports against future emissions pathways (Coffel et al., 2017; Y. Zhou et al., 2018). Others were retrospective or limited to small airport samples (Gratton et al., 2020; Y. Zhao & Sushama, 2020).

In contrast, the present study extends the body of knowledge by quantifying the impacts of global warming on takeoff performance at an industry-wide level for a globally representative set of commercially relevant airports. Ultimately, the theoretical significance of the present study is to inform an approach to the adaptation conversation for air transport stakeholders.
Research Questions

The aero- and thermodynamic effects of temperature and air density variations on takeoff forces are generally well understood and do not need confirmatory analysis. However, the extent to which global warming will impact takeoff performance and the economics of commercial air transport in the 21st century is a research topic that lends itself to exploratory research, toward which the present study addressed three questions:

1. How much thrust increase will be required to lift an equivalent payload?
2. How much payload removal will be required when thrust is insufficient?
3. How much additional cost will the air transport industry incur as a result?

**How much thrust increase will be needed to lift an equivalent payload?**

The first research question considered how much marginal thrust increase will be required to compensate for the deterioration in takeoff conditions in the 21st century. Considering that takeoff performance is highly dependent on aircraft characteristics, the present study focused on four common narrowbody and widebody models as a representative sample of the world’s commercial fleet. Furthermore, the present research answered the research question under a gamut of four plausible future GHG concentration levels and associated warming scenarios adopted by the IPCC and commonly reported in the climatic adaptation literature. The takeoff simulation used in this study assumed a starting thrust of 75% TOGA for all takeoffs, which is the lowest permissible setting under reduced-thrust takeoff operations, and increased the thrust incrementally as needed until the TODR was less or equal to the TODA. By comparing the resulting mean thrust per takeoff longitudinally, it was possible to measure the difference attributable to changes in the near-surface air temperature, density, and winds.
**How much payload removal will be needed when thrust is insufficient?**

The second research question examined those cases in which a takeoff at MTOM is impossible even when using TOGA thrust (i.e., the TODR still exceeds the TODA despite the thrust having been incrementally increased from its 75% baseline to its maximum setting). In such cases, the takeoff simulation used in this study decremented the takeoff mass by one passenger equivalent at a time until the TODR was less or equal to the TODA. By comparing the resulting takeoff mass across the 21st century, it was possible to measure the revenue payload attrition caused by unfavorable climatic conditions.

**How much additional cost will the air transport industry incur?**

The third research question depended on converting the operational impacts on takeoff performance, expressed as marginal thrust increase and payload removal, into economic terms. The answer to this question enables an industry-level cost-benefit evaluation of the adaptation efforts required to mitigate the takeoff impacts of global warming. The study attempted to procure industry archival data to correlate thrust settings, engine severity, and maintenance spending to estimate the opportunity cost of increasing the mean takeoff thrust. Separately, the study leveraged published industry-standard passenger weight assumptions to convert the observed revenue payload removal into an opportunity cost. Other possible marginal costs, such as excess fuel consumption, tire wear, and flight schedule disruptions, were not considered in this research question and could benefit from further examination.
Delimitations

This section describes the inclusions and exclusions to the study’s scope.

Climatic Effects

The present study used a computer-assisted simulation as a suitable method to address the prospective nature of the research, which constrains the ability to collect data, and the intrinsic complexity in the relationship between atmospheric causal factors and takeoff performance. The simulation method requires selecting input variables. This research retained four such variables: the near-surface air temperature \( tas \), pressure \( ps \), relative humidity \( hurs \), and circulation (expressed as wind vector’s direction and speed) at each sampled airport throughout the 21st century. Conversely, the present research did not consider other expected effects of climate change, such as variations in the precipitation level and their attendant impact on runway contamination or the intensity of extreme weather events and how they disrupt airport operations.

Climate Scenarios

Climate scientists evaluate potential future GHG concentrations and attendant warming levels through shared socioeconomic pathways (SSPs), which are plausible demographic, societal, economic, and policymaking scenarios of anthropogenic emissions in the 21st century (Meinshausen et al., 2020). The present research simulated aircraft takeoff performance against four tier-one SSPs most common in the climatic adaptation literature: SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5. Table 1 shows that these SSPs cover a range of approximately 1.3 °C–5.7 °C of GMST increase by the year 2100 relative to the mean value for the years 1850–1900. Other common SSPs, such as SSP1–1.9, were not considered.
Table 1

*Shared Socioeconomic Pathways Considered in the Present Study*

<table>
<thead>
<tr>
<th>Name</th>
<th>Very likely range of GMST increase in °C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2021–2040</td>
</tr>
<tr>
<td>SSP1–2.6</td>
<td>1.2–1.5–1.8</td>
</tr>
<tr>
<td>SSP2–4.5</td>
<td>1.2–1.5–1.8</td>
</tr>
<tr>
<td>SSP3–7.0</td>
<td>1.2–1.5–1.8</td>
</tr>
<tr>
<td>SSP5–8.5</td>
<td>1.3–1.6–1.9</td>
</tr>
</tbody>
</table>

*Note.* Each range contains the minimum, best estimate (bold), and maximum likely values. The last two digits of each SSP refer to the forcing levels in W/m² by the year 2100. Adapted from *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, by IPCC, 2021, Cambridge University Press.

*a* “Very likely” is congruent with IPCC’s terminology.

*Takeoff Limitations*

Table 2 summarizes the geometric, tribological, and propulsive takeoff limitations introduced earlier. For simplicity and practicality, the present study only considered the *runway length*, expressed as the declared TODA for a given runway, as a limiting factor in the takeoff simulation. The angle of the first-segment climb, although not independent of air density conditions, was assumed to be constant, in line with Gratton et al. (2020). The simulation did not account for aerodrome-specific obstacles nor the aircraft’s ability to clear them. The research also excluded from the simulation model tribological and thermal limitations, which could be an area for future research.
Table 2

*Takeoff Limitations*

<table>
<thead>
<tr>
<th>Geometric</th>
<th>Tribological</th>
<th>Propulsive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climb limitation</td>
<td>Brake heat limitation</td>
<td>EGT limitation</td>
</tr>
<tr>
<td>Obstacle limitation</td>
<td>Tire speed limitation</td>
<td>Environmental envelope limitation</td>
</tr>
<tr>
<td>Runway limitation</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Only the runway length limitation (bottom row) is in scope of the present research.

**Operational Impacts**

The present study considered two operational impacts of global warming on takeoff performance from runway length limitations. The first is a decrease in the mean takeoff thrust reduction, expressed in percentage points (p. p.) of full takeoff/go-around (TOGA) thrust. The second is an increase in the mean revenue payload removal, expressed in kg. Other operational impacts were not considered, including but not limited to a fuel consumption increase at takeoff, additional GHG emissions and attendant carbon offset obligations, flight schedule disruptions and passenger compensation, and a tankering volume decrease. Similarly, economic impacts were not quantified, including those on other value chain participants, such as aeronautical revenue attrition at airports, were not included but could be examined as an extension to the present study.

**Aircraft**

As of January 1, 2020, there were 33,531 aircraft in commercial service worldwide, comprised of 101 models (e.g., Boeing 737), 551 variants (e.g., Boeing 737–800), and 435 engine models and variants (e.g., Boeing 737–800 with CFM–567B)
(CAPA Center for Aviation, 2020). Four aircraft shown in Table 3 were chosen as a representative sample of the broader worldwide fleet to keep the simulation practical. The distinct performance characteristics of narrowbody and widebody airframes motivated the decision to select two of each.

### Table 3

<table>
<thead>
<tr>
<th>Type</th>
<th>Manufacturer</th>
<th>Model</th>
<th>Variant</th>
<th>Code</th>
<th>Engine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Narrowbody</td>
<td>Airbus</td>
<td>A320</td>
<td>neo</td>
<td>A20n</td>
<td>LEAP–1A29</td>
</tr>
<tr>
<td></td>
<td>Boeing</td>
<td>B737</td>
<td>MAX 9</td>
<td>B39m</td>
<td>LEAP–1B28</td>
</tr>
<tr>
<td>Widebody</td>
<td>Airbus</td>
<td>A350</td>
<td>350–900</td>
<td>A359</td>
<td>Trent XWB–84</td>
</tr>
<tr>
<td></td>
<td>Boeing</td>
<td>B787</td>
<td>787–9</td>
<td>B789</td>
<td>Trent 1000–K2</td>
</tr>
</tbody>
</table>

The four selected models represented 50.2% of the global fleet as of January 1, 2020. Among those models, the newest variants and engine options were selected to extend the future relevance of the study’s findings, considering the multi-decadal lifespan of a typical commercial aircraft program. All other aircraft in service, including similar models using alternate powerplants, unrelated turbofan models, and all turboprop aircraft, were not included. However, they could later be examined independently by repurposing the simulation code developed for the present research.

**Airports**

The year 2019 served as a datum for the present study because it was the last one in which commercial air traffic remained unaffected by the COVID–19 pandemic. In that year, 4,436 airports worldwide reported scheduled commercial passenger traffic (IATA,
Of those, the study considered a representative sample of only 881 airports to keep the computational requirements of the simulation reasonable. Future researchers could adapt the code from this research to simulate the takeoff performance at any other airport.

**Study Period**

The present study considered the climatic conditions at the sampled airports for eighty-six consecutive years (2015–2100 included). The year 2100 is a horizon commonly found in the literature and coincides with the last year for which climate data was available. It is also far enough in time to capture long-term climatic effects. The research did not include a reanalysis of the climate data using archival records for the historical period from 2015 to the year of the study’s conclusion (2022).

**Limitations and Assumptions**

The present section describes the methodological limitations related to the study’s internal and external validity and the implicit and explicit assumptions formed.

**Limitations**

**Political, Economic, and Social Influences.** Commercial air transport has experienced tremendous historical growth, with pre-COVID–19 forecasts pointing to a doubling of traffic every 20 years (IATA, 2019a). However, several market forces threaten its future, including aeropolitical restrictions on freedoms of the air and movement; public defiance towards carbon-intensive flying (e.g., flygskam and slow travel); the generalization of modal alternatives such as high-speed rail; onerous regulations and environmental policies, such as carbon taxation; and stochastic events such as global pandemics, acts of terror, and sustained financial crises. The present study
did not attempt to reduce this uncertainty and forecast air travel demand until the year 2100. Instead, the research quantified the operational consequences of atmospheric warming on takeoff performance in relative terms from the baseline year 2015.

**Technological Evolution.** While the physical laws involved in takeoff are immutable, the propulsive technology, material science, and aeronautical design involved in commercial air transport are likely to undergo a substantial evolution through the study period. For example, electric engines may render obsolete the EGTL and runway length restrictions. Predicting such innovations and their adoption is a speculative exercise beyond the intended scope of the present study. Instead, this research assumed a ceteris paribus approach to simulating takeoff performance over time based on contemporary technology. This approach possibly limits the generalizability over time and thus the external validity of the findings.

**Environmental Uncertainties.** Thirdly, 21st-century climate change is subject to uncertainty and variability. The present study leveraged published prospective climate data through the year 2100, which implies that it inherits the same limitations to internal validity as the climate data itself. The research modeled the takeoff performance against a range of four SSPs to mitigate that threat to internal validity. As time passes, the study’s findings related to the unrealized pathways will lose validity, while those related to the nearest surviving SSP will gain validity. Furthermore, the modular and flexible nature of the code developed for the present research allows the findings to be updated with new climate data as they become available in the future.
Assumptions

Flight Rescheduling and Cancelation vs. Payload Removal. In takeoff situations where warm weather imposes runway limitations, aircraft operators may elect to reschedule the flight to a more favorable time, such as evening or night. The present study assumed that this option is impractical for at least three reasons. First, nocturnal departures may conflict with slot congestion and airport curfews. Second, departure punctuality may be crucial to onward connections, especially in the case of banked flights, and delays may lead to costly missed transfers. Third, a nocturnal decrease in air temperature may not be sufficient to alleviate the restrictions. Instead, the present study assumed that runway length limitations systematically translate into increased takeoff thrust and payload removal.

Conversely, the study assumed that the breakeven load factor (BELF) constitutes a lower floor to payload removal, below which the aircraft might elect to cancel the flight. Beyond the economic argument, the motivation for this assumption is to substantially reduce the simulation’s execution time by limiting the number of iterative payload removals for a given takeoff. However, this assumption may not always be valid in practice, as airlines may be reluctant to cancel unprofitable flights for at least four reasons. First, the total economic value of downstream connections may incentivize the airline to operate a feeder or hub-bound flight even at a slight loss. Second, cancelations cause second-order customer churn and retention costs. Third, interline arrangements typically come with contractual service obligations and associated penalties that may exceed the marginal cost of operating the flight at an unprofitable load factor. Fourth, unused slots risk being canceled by airports and governments.
**Types of Payload Removal.** Payload removal involves offloading any combination of passengers, cargo, and non-essential fuel. The latter is a non-revenue payload, although removing fuel may incur a tankering opportunity cost. For simplicity, the present study assumed that all payload removal required by takeoff limitations came from offloading revenue payload. Furthermore, the use of belly space for cargo is opportunistic, and its commercial rates are highly dependent on undisclosed agreements between carriers and freight forwarders. For simplicity, this research assumed that all revenue payload removal came exclusively from offloading passengers. Both the fuel and cargo assumptions may not always be valid in practice. Coffel et al. (2017), for example, use a different assumption of 83% passenger and 17% fuel payload removal. In assuming the unit mass of passengers for payload removal, the present research used an adult inter-seasonal mean from an industry-standardized set published by Filippone (2012), shown in Table 4. Alternative values include up to 100 kg per passenger (Coffel et al., 2017).

### Table 4

*Standard Passenger Mass Assumed in the Present Study*

<table>
<thead>
<tr>
<th>Passenger</th>
<th>Mass in kg</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Summer</td>
<td>Winter</td>
</tr>
<tr>
<td>Average adult</td>
<td>86</td>
<td>88</td>
<td></td>
</tr>
<tr>
<td>Average adult male</td>
<td>91</td>
<td>93</td>
<td></td>
</tr>
<tr>
<td>Average adult female</td>
<td>81</td>
<td>83</td>
<td></td>
</tr>
<tr>
<td>Child (2–13 years)</td>
<td>37</td>
<td>39</td>
<td></td>
</tr>
<tr>
<td>Single value assumed in the present study</td>
<td>87</td>
<td>87</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Values are from Filippone (2012) and consistent with Coffel et al. (2015).
**Takeoff Performance Calculation Assumptions.** The present study relied on several assumptions in simulating the takeoff performance of the sampled aircraft.

**Takeoff Distance.** EASA CS–25.113 and U.S. 14 CFR § 25.113 define several takeoff distances depending on the presence of runway contamination and a clearway. This research assumed the absence of both and adopted the definition provided in (a)(2) of both regulations, which codifies the takeoff distance as “115 percent of the horizontal distance along the takeoff path, with all engines operating, from the start of the takeoff to the point at which the airplane is 35 feet above the takeoff surface” (Takeoff Distance and Takeoff Run, 2021; Takeoff Distance and Takeoff Run, 1998).

The runway dryness assumption is a notable methodological simplification, considering that a substantial share of takeoffs occurs with some degree of runway contamination. In the event of a rejected takeoff, runway contamination leads to a decrease in braking efficiency and an increase in the accelerate-stop distance (ASD) required. However, the present study did not consider rejected takeoffs and their attendant calculation of the balanced field takeoff distance at the intersection of the ASD and the one-engine-inoperative (OEI) distance. Instead, the study assumed only normal and successful all-engines-operating (AEO) takeoffs up to the screen height.

As for the clearway, its presence changes the takeoff distance definition by applying the 115% factor only up to a point equidistant between liftoff and the screen height. This slight difference in definitions was deemed immaterial to the present study, which considered the TODA (inclusive of any clearway) to quantify runway length limitations.
**Takeoff Path.** The present study relied on further assumptions about the takeoff path considerations in EASA CS–25.111 and U.S. 14 CFR § 25.111. In line with section (a), the research assumed all takeoffs to extend from a standing start at zero speed and idle thrust, deliberately ignoring the practice of rolling takeoffs. The simulation also did not use the various regulatory indicated airs speeds, such as $V_{MCG}$, $V_{EF}$, $V_1$, $V_R$, and $V_2$. In particular, the simulation did not consider whether the takeoff performance was sufficient that the aircraft could climb post-rotation to the screen height with OEI at the safety speed $V_2$.

**Other Considerations.** The study relied on several other methodological assumptions: a constant friction coefficient $\mu$ for dry concrete and asphalt of .02, in line with the value commonly found in the literature (Engineering Sciences Data Unit [ESDU], 1985; Gratton et al., 2020; Koudis et al., 2017; Mair & Birdsall, 1992); a flat runway slope; no aircraft mass decrease during the takeoff sequence from fuel burn; and no installation losses to engine thrust.

**Summary**

Among the multi-faceted climate change implications for the commercial air transport industry, the present research quantified the operational impacts on takeoff performance of a net increase in air temperature and decrease in air density. The extant literature previously evidenced the impact of warmer air on takeoff distance and weight restrictions. The present study extended the body of knowledge by generalizing the marginal takeoff thrust and payload removal findings to a worldwide sample of airports representative of the entire commercial air transport industry for the remainder of the 21st century.
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASD</td>
<td>Accelerate-stop distance on the runway</td>
</tr>
<tr>
<td>ATM</td>
<td>Assumed temperature method at takeoff (see FLEX)</td>
</tr>
<tr>
<td>BELF</td>
<td>Breakeven load factor of the aircraft</td>
</tr>
<tr>
<td>BPR</td>
<td>Bypass ratio of the engine</td>
</tr>
<tr>
<td>CG</td>
<td>Climb gradient of the aircraft after rotation</td>
</tr>
<tr>
<td>CIPM</td>
<td>Comité International des Poids et Mesures</td>
</tr>
<tr>
<td>CO</td>
<td>Atmospheric carbon monoxide</td>
</tr>
<tr>
<td>CO₂</td>
<td>Atmospheric carbon dioxide</td>
</tr>
<tr>
<td>Cₙₒₒₜ</td>
<td>Atmospheric soot carbon</td>
</tr>
<tr>
<td>CMIP</td>
<td>Coupled Model Intercomparison Projects of the WCRP</td>
</tr>
<tr>
<td>CORSIA</td>
<td>Carbon Offsetting &amp; Reduction Scheme for International Aviation</td>
</tr>
<tr>
<td>EASA</td>
<td>European Union Aviation Safety Agency</td>
</tr>
<tr>
<td>EGT</td>
<td>Exhaust gas temperature of the engine</td>
</tr>
<tr>
<td>EPR</td>
<td>Engine pressure ratio</td>
</tr>
<tr>
<td>ESGF</td>
<td>Earth System Grid Federation</td>
</tr>
<tr>
<td>FAA</td>
<td>U.S. Federal Aviation Administration</td>
</tr>
<tr>
<td>FADEC</td>
<td>Full authority digital engine control</td>
</tr>
<tr>
<td>FLEX</td>
<td>Flexible takeoff method at takeoff (see ATM)</td>
</tr>
<tr>
<td>FMC</td>
<td>Flight management computer</td>
</tr>
<tr>
<td>FOSS</td>
<td>Free and open-source software</td>
</tr>
<tr>
<td>GHG</td>
<td>Atmospheric greenhouse gases</td>
</tr>
<tr>
<td>GCM</td>
<td>General circulation climate model</td>
</tr>
<tr>
<td>GMST</td>
<td>Global mean surface temperature of the Earth</td>
</tr>
<tr>
<td>H₂O(g)</td>
<td>Atmospheric water vapor</td>
</tr>
</tbody>
</table>
HAPPI  Half a Degree Additional warming, Prognosis, & Projected Impacts climate model
HC       Atmospheric hydrocarbons
hdw      Headwind speed at takeoff
HLD      High-lift devices (flaps and slats)
hurs     Near-surface relative air humidity (CMIP 6 variable)
IATA     International Air Transport Association
IASB     International Accounting Standards Board
ICAO     International Civil Aviation Organization
INDC     Intended Nationally Determined Contribution
IPCC     Intergovernmental Panel on Climate Change
ISA       ICAO Standard Atmosphere of 15 °C and 1,013.25 mb at sea level
LEAP     CFM International Leading Edge Aviation Propulsion engine
LOESS    Locally estimated scatterplot smoothing
MCT      Maximum continuous thrust
MPI-ESM1-2-HR  Max Planck Institute Earth System Model version 1.2 High Resolution climate model
MRO      Engine maintenance, repair, and overhaul
MTOM     Maximum takeoff mass
MTOW     Maximum takeoff weight
NOx      Atmospheric nitrogen oxide
O3       Atmospheric ozone
OAT      Outside air temperature
OATL     OAT limit for a full-thrust takeoff
OBC      Outcome-based contract
OCTOPUS  Airbus’ Operational and Certified Takeoff and landing Performance Universal Software
OEI  One engine inoperative at takeoff
OEM  Original equipment manufacturer of aircraft or engine
OpenAP  Open-Source Aircraft Performance Model
OPT  Boeing’s Onboard Performance Tool (for takeoff calculations)
p. p.  Percentage points
Packs  Pressurization air conditioning kits
PPA  Passengers per annum (departing and arriving at an airport)
ps  Near-surface air pressure (CMIP6 variable)
RCM  Regional circulation climate model
RDBMS  Relational database management system (e.g., MySQL)
RPC  Representative concentration pathway of GHG (see SSP, SWL)
RTOW  Regulatory takeoff weight
SFC  Specific fuel consumption
sfcWind  Near-surface wind speed (CMIP6 variable)
SO\textsubscript{x}  Atmospheric sulfur oxides
SSP  Shared socioeconomic pathways (see RCP)
SWL  Specific warming level (see RCP)
tas  Near-surface air temperature (CMIP6 variable)
TLCC  Engine total life cycle costs
TODA  Takeoff distance available
TODR  Takeoff distance required
TOGA  Takeoff / go-around thrust (maximum thrust)
TSFC  Thrust-specific fuel consumption (fuel per unit of thrust-time)
\textit{uas}  Eastward component of the wind (CMIP6 variable)
UNFCCC  United Nations Framework Convention on Climate Change
\textit{vas}  Northward component of the wind (CMIP6 variable)
WCRP  World’s Climate Research Program
Chapter II: Review of the Relevant Literature

This chapter provides a review of the relevant extant literature to anchor the present study in peer-reviewed research, confirm its originality and significance, and validate its boundaries. The literature review integrates research conducted centrally and adjacently on the present study’s topic and identifies the main issues from the most generic to the most specific, following Creswell (2014).

First, a review of domain-specific literature identified drivers for variability in climate modeling and how they lead to uncertainty in the geographical and temporal distribution of atmospheric change. This uncertainty justifies the present research in coupling a scenario-based approach with the simulation method, which can test the sensitivity of takeoff performance to multiple future warming levels at once. Second, the literature review evidenced the recent emergence of a small but growing body of knowledge on climate change’s effects on aviation. The review’s original segmentation into first- and second-order effects revealed the topic’s breadth and gaps for future research and framed the present study within a broader conceptual context.

Next, a review of the technical literature on takeoff performance motivated using a first-principles approach to solving the direct takeoff-dynamics problem of calculating the distance required for a given aircraft mass. Lastly, a review of published studies on global warming’s consequences on takeoff performance confirmed the existence and direction of a measurable effect relevant to the aviation industry. The review also provided a theoretical framework for using existing climate models of projected environmental conditions at airports in the present research.
Uncertainty in Climate Modeling

Climatic science is concerned with minimizing uncertainty, which is “a fundamental characteristic of weather, seasonal climate, and hydrological prediction” (National Research Council, 2006, p. 98). The present research intends to be a consumer rather than a provider of climate projections. Therefore, it preoccupies itself less with why uncertainty exists than how it affects confidence in warming scenarios. This section reviews the extant literature for causal factors and implications to the present research of predictive uncertainty in the GMST increase, as illustrated in Figure 6.

Figure 6

Causal Factors and Implications of Predictive Uncertainty in a GMST Increase

Note. From top to bottom, the illustration to the right illustrates the macro-scale uncertainty (i.e., the range of GMST increase predictions), the micro-scale uncertainty (i.e., the range of near-surface temperature increase predictions at each airport individually), and the temporal uncertainty (i.e., the range of time-wise distributions of the GMST increase).
**Causal Factors**

GMST projections differ across climate models. At least three reasons account for this *inter-model spread* (Hawkins & Sutton, 2009). *Internal variability* refers to the long-scale stochastic nature of non-linear atmospheric processes (Deser et al., 2012; Hawkins & Sutton, 2012). *Model uncertainty* accounts for the discrepancies in numerical models’ parameterization of small-scale effects and response to external forcing inputs (Jakob, 2010). Continuous refinements to the scientific understanding of climate systems reduce the influence of both factors over time. Thirdly, *forcing uncertainty* refers to the range of plausible atmospheric GHG concentration scenarios in the 21st century (Meinshausen et al., 2020), underpinned by unknowns in the drivers of anthropogenic emissions, such as carbon policies. In response, contemporary climate models consider multiple pathways under the IPCC collaborative framework. Those SSPs assume varying rates of decline, stabilization, or growth in GHG outputs and resulting GMST increases by the year 2100 (Hausfather & Peters, 2020), as summarized in Table 1.

**Implications**

The predictive uncertainty in the distribution of the GMST increase throughout the 21st century carries at least three theoretical implications for the present research.

**Global Uncertainty.** The first implication stems from the range of plausible GMST increases by the year 2100 due to socioeconomic unknowns. The IPCC’s sixth assessment defined several SSPs starting in the year 2015, shown in Table 1, whose best estimates for warming relative to the mean 1850–1900 baseline range from 1.4 °C to 4.4 °C by the year 2100 (IPCC, 2021). Adjacent research suggested that the 2015 Paris Agreement signatories are likely to fall short of fulfilling their Intended Nationally
Determined Contributions (INDC) CO₂ reduction pledges (Hulme, 2016) to keep warming at no more than 1.5 °C above the baseline. Research further predicted an increase of 2.0 °C to 4.9 °C by the year 2100, with a median of 3.2 °C (Raftery et al., 2017). The implication for the present research is that it must account for this broad range of warming futures by simulating takeoff performance under several of the IPCC’s SSPs.

**Local Uncertainty.** The second implication stems from location-dependent deviations from the mean. There is evidence that the GMST, being a mean, obfuscates an uneven regional distribution in the increase of surface temperatures (IPCC, 2019; Seneviratne et al., 2016). Landmasses and higher latitudes will experience significantly more warming (Kettleborough et al., 2007; X. Wang et al., 2018). Furthermore, warming impacts will also be uneven due to non-uniform vulnerabilities and adaptability across countries (Harrington et al., 2018; Tol et al., 2003). For example, two airports may experience the same warming level differently depending on their respective elevation and runway length. A practical implication for the present research is that it must account for local climate projections and individual airport characteristics in its sampling strategy.

**Temporal Uncertainty.** The third implication is temporal uncertainty, which refers to the timewise distribution of warming in the 21st century. It involves subdecadal variability or year-over-year temperature fluctuations (Brown & Caldeira, 2020) and nonlinear step-changes in the multidecadal onset of global warming (Jones, 2012). There is evidence of a gradual oceanic heat buildup with sudden periodic releases (Jones & Ricketts, 2017), leading to abrupt climatic events that models typically underestimate (Jansen et al., 2020). The present study acknowledged this temporal uncertainty and used the latest CMIP6 framework to alleviate this uncertainty.
Effects of Air Transport on Climate Change

This section examines the reciprocal relationships between climate change and aviation. The current and projected contribution of commercial aviation to global warming is the subject of ample, established research (Grewe et al., 2019; Niklaß et al., 2019; Terrenoire et al., 2019). Among other GHGs, emissions of CO₂ from passenger and cargo aircraft operations grew by 32% over the 2014–2018 period and now account for 2.4% of all CO₂ emissions from fossil fuel use (Graver et al., 2019). The ICAO (2019) expects aviation’s CO₂ emissions to triple by 2050, relative to the 2015 baseline, and to account for 27% of the 2050 global carbon budget laid out by the 2015 Paris Agreement on climate change between the parties to the United Nations Framework Convention on Climate Change (UNFCCC) (ICAO, 2016).

Furthermore, aircraft engines emit other GHG species, including water vapor (H₂O), nitrogen oxides (NOₓ) and their byproduct ozone (O₃), sulfur oxides (SOₓ), soot or black carbon (Cₗₒₒₗ), hydrocarbons (HC), and carbon monoxide (CO) (Wuebbles et al., 2007). The IPCC (1999) has quantified these chemical species’ positive and negative contributions to radiative forcing. The resulting combined effect accounts for 3.5% of total anthropogenic forcing (D. S. Lee et al., 2009). Lastly, H₂O and NOₓ promote the formation of cirrus clouds and tropospheric ozone (O₃) (Brasseur & Gupta, 2010), respectively, which bring the indirect contribution of commercial aviation to as much as 4.9% of all anthropogenic forcing (D. S. Lee et al., 2009). These figures confirm that commercial aviation’s total contribution to positive radiative forcing is two to three times greater than that of its CO₂ emissions alone (J. Lee et al., 2004).
Effects of Climate Change on Air Transport

Conversely, the extant research on the reciprocal effects of climate change on aviation is scarcer and still emerging (Ren et al., 2019; Ryley et al., 2020; P. D. Williams, 2016). Topics such as the incidence of clear-air turbulence from climate change have seen pioneering research in the last decade (P. D. Williams & Joshi, 2013). The reviewed literature appears to have focused on the most direct and immediate hazards of climate change on aviation, usually grouped by industry sub-sector (Burbidge, 2018; Thompson, 2016). Instead, the present study offers an original framework that categorizes those climatic effects on aviation into first- and second-order effects, borrowing from Birkmann’s (2011) taxonomy of adaptation to climatic hazards.

First-order effects are operational hazards and associated risks to industry constituents, such as airports and airlines, immediately caused by varying physical manifestations of climate change. Those first-order effects appear to be the most widely reported in the extant literature. Among them are the adverse effects of warmer air on takeoff performance on which the present study focused.

Second-order effects include institutional and behavioral impediments to air travel, such as carbon taxation or demand attrition. Both indirectly derive from the broader societal response to the manifestations of climate change. There is evidence that personal experience with climatic hazards drives public concern and willingness to adapt (Weber, 2011; Whitmarsh, 2008) so that second-order effects tend to emerge after first-order effects have materialized. Figure 7 and the following two sections introduce both concepts to situate the present study in its broader context and suggest future research avenues.
**Figure 7**

*First- and Second-Order Effects of Climate Change on Air Transport*

<table>
<thead>
<tr>
<th>Effects of climate change on air transport</th>
<th>First-order effects</th>
<th>Second-order effects</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Radiative effects</strong></td>
<td></td>
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<td>Warmer surface temperatures</td>
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<td>Physical damage to infrastructure</td>
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<td>Shifts in climate zones</td>
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<td>Occupational health and safety hazards</td>
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<td>Increased airport noise pollution</td>
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<td>Decreased takeoff performance</td>
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<td><strong>Hydrologic effects</strong></td>
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<td>Rise in sea level</td>
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<td>Coastal airports flooding</td>
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<td>Extreme precipitations</td>
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<td>Fluvial airports flooding</td>
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<td>Post-glacial tectonic rebound</td>
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<td>Volcanic eruptions</td>
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<td><strong>Atmospheric effects</strong></td>
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<td>Upper atmospheric circulation and humidity changes</td>
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<td>Airway obsolescence</td>
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<td>Clear-air turbulence</td>
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<td>Lower atmospheric circulation and humidity changes</td>
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<td>Crosswind, gusts, microbursts, extreme weather events</td>
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<td>Tourism demand attrition</td>
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<td><strong>Societal effects</strong></td>
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<td>Policy shifts</td>
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<td>Industry restrictions and taxation, airfare inflation</td>
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<td>Behavioral shifts toward aviation</td>
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<td>Lower propensity to fly</td>
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<td>In hospitable climate conditions</td>
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*Note.* The present study focused on decreased takeoff performance in the lower-left corner of the figure.
First-Order Effects

This section introduces first-order climatic effects on aviation, which are the most researched, as evidenced in Burbidge (2018), Ryley et al. (2020), and Thompson (2016).

**Warmer Air and Physical Damage to Infrastructure.** Temperature extremes are projected to increase faster than the mean (Horton et al., 2015, 2016). The likelier exceedance of the air transport infrastructure’s design temperature will create hazards for airside personnel and increase cooling and maintenance costs (Hayhoe et al., 2010). For example, heat as low as 32 °C may cause airside pavements to degrade (Ryley & Chapman, 2012), melt (Burbidge, 2016), settle unevenly (Li et al., 2011), fatigue quicker (Xu et al., 2019), crack (Abreu, 2019; Instanes & Mjureke, 2005), and decrease aircraft braking effectiveness from friction loss (Konarski, 2014).

**Warmer Air and Shifts in Climate Zones.** Global warming will shift current climate zones toward dryer climates in the subtropics and warmer climates at high latitudes (Hanf et al., 2012), essentially changing the distribution of Köppen-Geiger zones by the end of the 21st century (Mahlstein et al., 2013). Snowfall will decrease on average, increase in the extremes, and extend to new areas (Burbidge, 2016). Airports that previously would rarely or never encounter snowfall may need to make capital investments, such as snowplows, and prepare for changing environmental conditions, including climate-induced changes in wildlife hazards (Burbidge, 2018; Moore, 2011).

**Warmer Air and Occupational Safety and Health.** Airside operations include manual activities such as aircraft marshaling and towing, jet bridge or stairs positioning, catering, fueling, baggage and cargo handling, water and lavatory servicing, and aircraft maintenance. These occupations typically expose ground personnel to the prevailing
environmental conditions for prolonged periods, including inside covered facilities that are not air-conditioned, such as MRO hangars and baggage screening areas (National Institute for Occupational Safety and Health, 2006). Global warming increases the frequency, intensity, and duration of heatwaves (Rastogi et al., 2020) and, therefore, the risk of heat-related illnesses such as cramps, exhaustion, rashes, and heat strokes.

**Warmer Air and Airport Noise Pollution.** Noise emissions from aircraft engine operations are measurably detrimental to near-airport residents’ subjective well-being (Lawton & Fujiwara, 2016), real estate prices (Zheng et al., 2020), and wildlife conservation (Alquezar & Macedo, 2019). Warmer air accentuates noise emissions in at least three ways. First, acoustic propagation increases with temperature (Wiseman, 2014). Second, warmer air requires additional engine thrust to offset the decreased takeoff performance introduced earlier, increasing noise emissions. Third, warmer air decreases aircraft climb performance, delaying engine noise dissipation (Wiseman, 2014).

**Warmer Air and Takeoff Performance.** Atmospheric temperature, pressure, density, and circulation are changing due to global warming. Archival temperature records indicate a historical GMST increase of 0.99 °C by 2019 relative to the 1951–1980 mean (NASA, 2019), and 1.2 °C compared to the 1880–1920 mean (Hansen et al., 2020). Future GMST increases are subject to uncertainty and variability introduced earlier. However, on average, aircraft will continue to take off in increasingly warmer atmospheric conditions, resulting in worse takeoff performance, ceteris paribus.

**Rise in Sea Level and Coastal Airports Flooding.** The melting of ice sheets and the seawater’s thermal expansion will cause the mean sea level to rise by 0.3 to 2.5 meters by the year 2100 (Center for Operational Oceanographic Products and Services,
This phenomenon threatens coastal and low-lying areas (Hinkel et al., 2014), from which airports will need to relocate or build expensive infrastructure to prevent and mitigate flooding from storm surges (Hu et al., 2016). Major international airports have already experienced flooding (Dolman & Vorage, 2020), which will likely become more frequent, intense, and widespread. Monioudi et al. (2018) found that Caribbean airports will witness severe disruptions with just a 1.5 °C increase. 

**Extreme Precipitations and Fluvial Airports Flooding.** Global warming disproportionately increases the water holding capacity of air by 7% for every extra 1.0 °C (Trenberth, 2011). Separately, oceans will experience more evaporation as their temperature rises. Both effects will significantly add water vapor to the atmosphere. Furthermore, the intensity of precipitation extremes is known to follow the proportion of atmospheric water vapor content (O’Gorman & Schneider, 2009), though unevenly (Dore, 2005). The more frequent and intense precipitation extremes (Sillmann et al., 2013) can cause fluvial flooding at airports near rivers (Dolman & Vorage, 2020).

**Post-Glacial Tectonic Rebound and Volcanic Eruptions.** As heavy glaciers melt from global warming, underlying landmasses rise in a process known as isostatic rebound. In turn, decompression melting of the mantle rock leads to excess magma formation and, eventually, volcanic eruptions (Schmidt et al., 2013). The air transport industry is highly susceptible to navigational disruptions caused by volcanic ash clouds resulting from volcanism, as evidenced by the 2010 eruption of Eyjafjallajökull in Iceland (Bolić & Sivčev, 2011; Budd et al., 2011), which cost the industry U.S. $1.7 billion in lost revenue (Ryley & Chapman, 2012). Volcanic activity and attendant airspace disruptions may occur more often due to climate change (Cooper et al., 2018).
**Upper Atmospheric Changes and Airway Obsolescence.** Understanding how the position and intensity of jet streams at high latitudes respond to climate change is one of the grand challenges of climate science (Tan et al., 2019). Williams (2016) calculated that a doubling in the atmospheric CO₂ concentration increased winds at cruise altitudes by 14.8% and will asymmetrically lengthen westbound trips and shorten eastbound trips, resulting in a net increase in travel time, fuel cost, and GHG emissions, and forcing adaptation of flight routes to new optima (World Meteorological Organization Secretariat, 2016).

**Upper Atmospheric Changes and Clear-Air Turbulence.** Anthropogenic climate change widens the atmospheric temperature gradient by warming the upper troposphere at low latitudes and cooling the stratosphere at high latitudes (G. Chen et al., 2020). This thermal imbalance increases the vertical shear intensity and causes more clear-air turbulence (S. H. Lee et al., 2019), especially at mid-latitudes (Kim et al., 2016; Storer et al., 2017; P. D. Williams & Joshi, 2013). Increased turbulence causes two-thirds of all weather-related commercial aircraft incidents (Sharman et al., 2006), lengthens journey times, and increases fuel consumption and emissions as flight paths become more convoluted to avoid patches of rough air (P. D. Williams & Joshi, 2013).

**Upper Atmospheric Changes and Engine Icing.** The increased atmospheric moisture and the tropopause rise due to warmer air lead to more intense convective activity at higher altitudes (World Meteorological Organization Secretariat, 2016). In turn, these conditions favor the formation of ice crystals. Ice shedding into the engine core can cause a loss of thrust by extinguishing the combustion (i.e., a flameout or thrust rollback) or causing a surge-stall (Mason, 2007), to which modern lean-burn powerplant
models are especially susceptible (World Meteorological Organization Secretariat, 2016). High-velocity ice impacts can also damage the engine blades, and water usually present in small quantities within jet fuel can freeze and cause a hazardous flow restriction in the fuel/oil heat exchanger (Air Accidents Investigation Branch, 2014).

**Lower Atmospheric Changes to Crosswind Operations.** Surface wind vectors will likely be affected by climate change. Gratton et al. (2020) found that the modest weakening of near-surface winds, known as global stilling (Ma et al., 2016; McVicar et al., 2012), is consistent with historical observations at Greek airports. Headwinds decrease the TODR by reducing the aircraft's required groundspeed at liftoff. If headwinds weaken, the TODR increases. Directional changes in prevailing surface winds may also create or increase a crosswind component (Burbidge, 2018; Y. Zhao & Sushama, 2020). Most airports were designed with the longest runways oriented to the prevailing winds. A change in wind direction can force those airports to use shorter, auxiliary runways that are unsuitable for larger aircraft types and heavy payloads.

**Lower Atmospheric Changes and Extreme Weather.** There is growing evidence that climate change triggers extreme meteorological events (Mann et al., 2017) that exceed transportation systems’ historical design parameters (Markolf et al., 2019). Some of them, such as heatwaves, thunderstorms, lightning (Yair, 2018), cold fronts, heavy rain, sand and dust storms, and intense winds, disrupt aircraft operations by reducing visibility and creating unsafe wind conditions (Gultepe et al., 2019) to which modal alternatives, such as high-speed rail, are less vulnerable (Z. Chen & Wang, 2019). Furthermore, there is evidence that the share of aircraft accidents and fatalities caused by weather has grown from 40% in 1967 to almost 50% in 2010 (Mazon et al., 2018).
Second-Order Effects

Second-order effects are those derived from a societal reaction to climate change. They are beyond the present study’s scope but could benefit from future research.

Policy Shifts, Industry Restrictions and Taxation, and Airfare Inflation.

Policy restrictions meant to curb GHG emissions may take the form of a blanket carbon fee (Kaufman et al., 2019), flight rerouting (Frömming et al., in press; V. Williams et al., 2002), progressive airfare taxation on frequent travel (Devlin & Bernick, 2015), and bans on domestic short-haul routes that offer greener modal alternatives (Baumeister & Leung, 2021; Prussi & Lonza, 2018). Further regulatory impositions on the industry may also originate from safety concerns caused by extreme weather intensification (Pümpel, 2016).

Behavioral Shits Toward Aviation and Lower Propensity to Fly.

Public sentiment, fueled by flygskam, or flight shaming (Mkono et al., 2020), may shift in favor of less carbon-intensive modal alternatives to flying, such as rail (Robertson, 2016), and away from loyalty schemes that focus on rewarding frequent flyers (Jochimsen, 2020). Touristic habits may also evolve organically or under external forces (Becken, 2013; Buckley, 2011), leading to markedly different patterns by 2050, depending on the decarbonization pathways (Vorster et al., 2012).

Inhospitable Climate Conditions and Tourism Demand Attrition.

Higher temperature and humidity maxima may alter air travel demand’s geographical and temporal distribution (Burbidge, 2018). For example, ski destinations may suffer from milder winters and lack of snow, and summer destinations may lose their touristic appeal or become entirely inhospitable due to unsafe wet-bulb temperature exceedance (Coffel et al., 2018; Ebi et al., 2018), reducing demand for air travel in both cases.
Effects of Climate Change on Takeoff Performance

The discipline of takeoff performance aims to assess “that the aircraft can be controlled safely and the distances required for the maneuvers do not exceed those available” (Eshelby, 2000, p. 110). Measuring takeoff performance requires solving one of two takeoff-dynamics problems, following Daidzic (2016). This section reviews both problems and how the extant literature on climatic effects on takeoff has addressed them.

The Takeoff-Dynamics Problems

The Direct Takeoff-Dynamics Problem. The direct takeoff-dynamics problem, sometimes called the critical field length problem, relates to calculating the TODR for a given aircraft weight, which is relevant to the present study for determining whether weight restrictions apply for a given TODA. Such a calculation is achievable through the stepwise integration of differential equations of motion (Daidzic, 2016). It applies acceleration (i.e., thrust minus drag over mass) to each discrete state’s speed to determine the next state’s speed. It can also account for subtle effects, such as the slight mass decrement from fuel consumption at every step of the takeoff sequence or the minor change in rolling friction during the ground run. Alternatively, closed-form solutions that approximate the integration method’s precision exist that “are useful for a first-order investigation of the field performance” (Filippone, 2012, p. 254). These simplified algebraic representations of direct takeoff dynamics rely on one or more assumptions, such as treating the thrust and headwind as constants over the takeoff sequence. For example, the thrust decreases quadratically with airspeed (Powers, 1981), but a simplified solution may instead use the mean thrust value over the takeoff sequence.
The Inverse Takeoff-Dynamics Problem. The reciprocal inverse takeoff-dynamics problem addresses the maximum permissible mass for an available takeoff distance. It helps determine the payload removal required in runway-limited takeoffs but is a nonlinear programming problem with no general analytical solution (Daidzic, 2016). The extant research seems to avoid the problem entirely by iteratively decrementing the takeoff mass in discrete steps and solving the direct takeoff-dynamics equations until the TODR fits the TODA. Computer-assisted models lend themselves well to this type of goal-solving iteration. Alternatively, lookup tables such as Regulatory Takeoff Weight (RTOW) charts issued for a specific aircraft, runway, and takeoff configuration, provide the maximum permissible mass for a given runway length. However, they depend on OEM-proprietary software generally unavailable to researchers, such as Airbus’s Operational and Certified Takeoff and landing Performance Universal Software (OCTOPUS) and Boeing’s Onboard Performance Tool (OPT). As a result, charts do not lend themselves well to research that entails large sample sizes or sensitivity modeling at scale, such as the one performed in the present study. However, they can help calibrate takeoff models.

Literature Overview

Seven studies on the effects of warmer air on takeoff performance were identified, as shown in Table 5. All were published in the six years preceding this research, confirming the relative newness of the topic. All studies, but one, borrow from each other. The following section examines their choices of population and sampling frame, timeframe, modeling, and variables to anchor the present study into its methodological context.
### Table 5

**Population and Sampling Frames Used in the Literature**

<table>
<thead>
<tr>
<th>Study</th>
<th>Aircraft</th>
<th>Airports</th>
<th>Time period</th>
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<tbody>
<tr>
<td>Present study (for comparison)</td>
<td>A320neo, A350–900, B737 MAX 9, B787–9</td>
<td>Top 881 airports worldwide by passenger traffic</td>
<td>2015–2100</td>
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</table>

**Note.** Sorting is chronological as the studies borrow successively from each other, except Y. Zhou et al. (2018), which is methodologically closer to Gratton et al. (2020) in examining takeoff distance rather than weight. Except for Gratton et al. (2020), all studies were prospective, and historical years correspond to reanalysis years only.
**Population and Sampling Frame**

The population in all seven studies consisted of hypothetical takeoffs conducted with turbofan and turboprop transport aircraft from various civilian airports. Six studies were prospective up to the year 2115, and one was retrospective, as shown in Table 5.

**Aircraft Types.** Six of the seven studies examined the takeoff performance of specific aircraft types, and one remained aircraft-agnostic. Four studies used the Boeing B737–800 narrowbody aircraft (Coffel et al., 2017; Coffel & Horton, 2015; T. Zhou et al., 2018; Y. Zhou et al., 2018), and two used its closest competitor, the Airbus A320 (Coffel et al., 2017; Gratton et al., 2020). Both aircraft types were chosen due to being typical of their segment and for having takeoff performance data publicly available (Coffel & Horton, 2015; Gratton et al., 2020). The underlying assumption is that the trends observed in the results hold with some variation for other aircraft types (Coffel & Horton, 2015), although narrowbody aircraft present substantially different characteristics than widebody aircraft. One study (Gratton et al., 2020) stood out for also modeling the performance of one turboprop aircraft. Coffel et al. (2017) expanded their sampling frame to include the Boeing B777–300, B787–8, and Airbus A380 widebody aircraft to extend their previous results (Coffel & Horton, 2015). The sixth study in this group (Y. Zhao & Sushama, 2020) used performance data taken from the Boeing B737–800 and B787–8 published performance charts to derive operational limits, which is implicitly equivalent to modeling these two aircraft types. In contrast, the remaining study (Ren et al., 2019) followed a unique approach of tabulating for 100 commercial transport aircraft types the payload equivalent of a reduction in near-surface air density, using the direct proportionality between the latter and the maximum permissible takeoff mass.
In selecting commercial aircraft currently in operations, all studies implicitly assumed that future aircraft would perform similarly at takeoff, and the findings would remain valid. Coffel & Horton (2015) acknowledged that “changes in technology will no doubt revolutionize the aviation industry in the next 50 years” (p. 99) and cited carbon fibers and new engines as examples of such future innovation. However, the authors also noted that fundamental tradeoffs in wing design between high-speed efficiency in cruise and low-speed lift generation at takeoff would limit the future ability to optimize takeoff performance. In response, Hane (2016) argued that retrofit options already available to the Boeing 737–800’s fuel control unit, leading-edge slats, and electronic engine control computer alleviate the effects of warmer air on takeoff performance, which he concludes to be “considerably less than the authors predict” (p. 206). Coffel and Horton (2016) subsequently addressed, but not substantially remedied, Hane’s (2016) commentary by acknowledging that their research was “an initial contribution, based on a few simplifying assumptions” to an insufficiently considered topic worthy of early investigation (p. 208).

In consideration of Hane’s (2016) comment, the present research used some of the latest available commercial aircraft models and turbofan engines in production at the time of writing: the A320neo with LEAP–1A29, the A350–900 with Trent XWB–84, the B737 MAX 9 with LEAP–1B27, and the B787–9 with Trent 1000–K2, in an attempt to strengthen the external validity of the findings for the next few decades during which these aircraft will continue to operate.
**Airport Locations.** Another crucial characteristic of the sampling frame is the choice of takeoff airports. Four studies considered airports within one country, including four airports in the United States (Coffel & Horton, 2015), seven in China (T. Zhou et al., 2018), 13 in Canada (Y. Zhao & Sushama, 2020), and 10 in Greece (Gratton et al., 2020). The three remaining studies (Coffel et al., 2017; Ren et al., 2019; Y. Zhou et al., 2018) used small samples of six to 30 airports worldwide. There are at least two methodological benefits to selecting a small airport sample. The first is to enable the use of RCMs, which model the atmospheric conditions at each airport more granularly than GCMs. The second is to permit the use of archival records from weather stations to reanalyze historical atmospheric conditions at each airport and decrease the climate models’ bias.

Motivations for including airports in the sample ranged from having extreme summer temperatures, high elevation, short runways, significant traffic, regional hub status, limited expansion space, and a particular susceptibility to temperature increases. None of the studies, except perhaps Y. Zhou et al. (2018), stated a compelling rationale for their sample selection. However, the deliberate choice of sampling *hot and high* airports introduces a methodological bias toward magnifying the effect on takeoff performance of increasing temperatures and limits the generalizability of the findings to the broader set of worldwide airports. Furthermore, such small samples lack representativity. For example, Coffel & Horton’s (2015) sample of four airports covers only 1.8% of the world’s 2019 passenger traffic. The present research followed a different strategy of selecting a much larger sample of airports (*n* = 881), but also one that is highly representative of the traffic and latitude characteristics of the broader population of 4,436 airports with passenger traffic in the reference year.
**Observations.** Coffel & Horton (2015) only examined daily temperature maxima between May and September because these months “capture the vast majority of weight-restriction events” (p. 95) in the 21st century. While this assumption is plausible for the few North American airports in scope (KPHX, KDEN, KLGA, and KDCA), it may not hold for airports in the tropical zone with elevated temperatures throughout the year. The methodological choice of observing only temperature maxima results in a binary indication of whether the airport will encounter at least one takeoff limitation that day. The authors note that it is impossible to determine the duration of the weight restrictions based on CMIP5 data. In contrast, the present study sampled four-daily observations of climatic conditions at each airport to increase the temporal resolution of the research.

**Research Variables**

**Independent Variables.** All seven studies explicitly acknowledged air density as a leading factor impacting aircraft performance at takeoff. However, only one (Ren et al., 2019) modeled air density directly, building it from its air temperature, pressure, and humidity constituents available from CMIP data, which is the approach followed by the present research. The other studies used air temperature (Coffel et al., 2017; Coffel & Horton, 2015; Gratton et al., 2020; Y. Zhao & Sushama, 2020; T. Zhou et al., 2018) or pressure altitude (Y. Zhou et al., 2018) as proxies for air density. In doing so, these remaining studies ignored the individual effects of air pressure on engine efficiency and air density, and humidity on air density. In contrast, the present research modeled both. Lastly, two studies modeled the effect of temporal changes to atmospheric circulation on takeoff performance. Gratton et al. (2020) did so retrospectively, using wind records at ten Greek airports, whereas Zhao and Sushama (2020) used prospective climate models.
**Dependent Variables.** Four of the seven studies (Coffel et al., 2017; Coffel & Horton, 2015; Y. Zhao & Sushama, 2020; T. Zhou et al., 2018) further considered weight-restriction days as their dependent variable, defined as “any day when the daily maximum temperature matches or exceeds the weight-restriction temperature threshold” (T. Zhou et al., 2018, p. 704). Two more (Gratton et al., 2020; Ren et al., 2019) calculated passenger payload removals, in line with the inverse takeoff-dynamics problem and the present research, while the remaining study (Y. Zhou et al., 2018) used takeoff distance as its dependent variable. Table 6 summarizes these choices of variables.

**Table 6**

*Independent and Dependent Variables Used in the Literature*

<table>
<thead>
<tr>
<th>Study</th>
<th>Independent Variables</th>
<th>Dependent Variables</th>
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</thead>
<tbody>
<tr>
<td>2. Coffel et al. (2017)</td>
<td>Air temperature</td>
<td>Takeoff weight restriction days</td>
</tr>
<tr>
<td>4. Ren et al. (2019)</td>
<td>Air temperature, surface winds</td>
<td>Takeoff weight restriction days</td>
</tr>
<tr>
<td>5. Y. Zhao &amp; Sushama (2020)</td>
<td>Air temperature, surface winds</td>
<td>Takeoff distance in m, climb rate in °</td>
</tr>
<tr>
<td>6. Y. Zhou et al. (2018)</td>
<td>Pressure altitude</td>
<td>Takeoff distance in m, takeoff weight removal in kg</td>
</tr>
<tr>
<td>7. Gratton et al. (2020)</td>
<td>Air temperature, surface winds</td>
<td>Takeoff distance in m, takeoff weight removal in kg</td>
</tr>
<tr>
<td>Present study (for comparison)</td>
<td>Air temperature, air pressure, air humidity, air density, surface winds</td>
<td>Takeoff distance in m, takeoff thrust in percentage, takeoff weight removal in kg</td>
</tr>
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</table>

*Note.* All other possible influences on the dependent variables, such as runway condition and slope, were considered invariant in the reviewed studies.
Climate Models

Frameworks. Six of the seven reviewed studies used prospective climate data from published model runs with a time horizon of 2100. Only one retrospective study (Gratton et al., 2020) used archival climate data from 1955 to 2017. Four of the prospective studies (Coffel et al., 2017; Coffel & Horton, 2015; Ren et al., 2019; Y. Zhou et al., 2018) used multi-model means from the CMIP5 framework, which CMIP6 (used in the present research) superseded. One other study (T. Zhou et al., 2018) used the Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI) framework, which includes a series of focused experiments that specifically examine warming levels of 1.5 °C to 2.0 °C by the year 2100. The predominance of CMIP among the reviewed literature justifies using this framework as a source of climate data in the present study.

Spatial Resolution. Those five CMIP and HAPPI studies also employed general circulation models (GCMs), which use a global grid and physics equations to estimate atmospheric states from initial conditions (Gettelman & Rood, 2016). A downside of GCMs is that their relatively large grid cell size can result in temperature biases wherever mesoscopic features locally affect the climate (Coffel et al., 2017). Among the models used by those studies, the horizontal resolution ranged from 1° to 1.875°, or approximately 111–208 km at the equator. Only one study (Y. Zhao & Sushama, 2020) used a regional circulation model (RCM) to simulate the future atmospheric conditions more finely. That model belongs to the Global Environmental Multiscale Model (GEM) framework and has a horizontal resolution of .5° or approximately 55 km at the equator. Such a granular resolution is beneficial “for representing the effects of surface features like mountains” (Gettelman & Rood, 2016, p. 68). RCMs also typically produce bias-
corrected outputs, which makes them desirable for improving the fidelity of simulations at airports that are subject to the climatic influence of a distinctive local topography (T. Zhou et al., 2018), such as a coast (van Schalkwyk & Dyson, 2013) or a mountain range (Díaz-Fernández et al., 2020). Beyond RCMs, airport research could benefit from ultra-high-resolution climate models that account for highly-local influences such as the runway’s albedo and surrounding buildings (Y. Zhao & Sushama, 2020). None of the reviewed studies employed such models, however. The large sample count and worldwide geographical distribution of the airports used in the present research did not lend themselves well to RCMs or ultra-high-resolution models, whose availability is generally limited to one region.

Model Members. Four studies (Coffel et al., 2017; Coffel & Horton, 2015; Ren et al., 2019; Y. Zhou et al., 2018) used multi-model means for their independent variables, with a mean of 24 models. A chief motivation for using a multi-model ensemble over a single model resides in the error compensation, bias correction, lower uncertainty, and greater consistency and reliability of combining different results (Hagedorn et al., 2005; Tebaldi & Knutti, 2007). It is perhaps no coincidence that all four studies used the CMIP framework, whose titular intercomparison feature comes from having common standards that facilitate systematic inter-model analysis (Eyring et al., 2016). However, the downside of multi-model work is the large size of the climate datasets and the computing requirements of averaging them. The present research used only one model due to the large airport sample size, in congruence with two studies that used only one to two models (Y. Zhao & Sushama, 2020; T. Zhou et al., 2018).
Scenarios. Three studies (Coffel & Horton, 2015; Ren et al., 2019; Y. Zhou et al., 2018) presented a bias in simulating only the Representative Concentration Pathway 8.5 (RCP 8.5) from CMIP5, which projects 8.5 W/m² of positive radiative forcing and 2.6–4.8 °C of atmospheric warming with a mean of 3.7 °C (IPCC, 2014) by the year 2100. The RCP 8.5 assumes significant growth in population and energy consumption, modest rates of energy intensity improvements, and a lack of climate policies (Riahi et al., 2011). It constitutes a worst-case scenario (Hausfather & Peters, 2020) whose plausibility is increasingly challenged (Ho et al., 2019). A more pronounced warming level leads to a more pronounced decrease in takeoff performance and thus more significant results but limits the external validity of the research.

In addition to modeling the RCP 8.5, two more studies (Coffel et al., 2017; Y. Zhao & Sushama, 2020) also modeled the RCP 4.5, which projects 4.5 W/m² of positive radiative forcing and 1.1–2.6 °C of atmospheric warming with a median of 1.8 °C (IPCC, 2014) by the year 2100, thereby reflecting a more plausible range of climatic outcomes.

The remaining prospective study (T. Zhou et al., 2018) presents the apparent reverse bias of modeling only a range of modest warming levels, from 1.5 °C to 2.0 °C relative to the pre-industrial baseline, which will be relevant for several decades but may be exceeded by the year 2100. The study used a Generalized Extreme Value (GEV) continuous probability distribution to simulate temperature extremes around the 1.5 °C and 2.0 °C means. This approach is consistent with the theoretical understanding that climate change will increase temperature extremes more than the mean (Coffel & Horton, 2015; Horton et al., 2016). However, there is increasing evidence that the implementation of pledged GHG reductions from the Paris Agreement, called Nationally Determined
Contributions (NDCs), is falling short of the goals (Jackson et al., 2019; Roelfsema et al., 2020) and that the choice of 1.5 °C and 2.0 °C warming scenarios may lead to underestimating the effect size in the second half of the 21st century.

In contrast, the present research simulated future takeoff temperatures across the four CMIP6 SSPs from Table 1, representing a very likely (in CMIP terminology) range of warming levels from 1.8 °C to 4.4 °C. Table 7 summarizes the climate models used in the reviewed studies.

**Table 7**

*Climate Models and Scenario Runs Used in the Literature*

<table>
<thead>
<tr>
<th>Study</th>
<th>Framework</th>
<th>Spatial resolution</th>
<th>Members</th>
<th>Scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>2. Coffel et al. (2017)</td>
<td>CMIP5</td>
<td>GCM</td>
<td>27</td>
<td>RCP 4.5, RCP 8.5</td>
</tr>
<tr>
<td>3. T. Zhou et al. (2018)</td>
<td>HAPPI</td>
<td>GCM</td>
<td>1</td>
<td>1.5 °C, 2.0 °C</td>
</tr>
<tr>
<td>4. Ren et al. (2019)</td>
<td>CMIP5</td>
<td>GCM</td>
<td>27</td>
<td>RCP 8.5</td>
</tr>
<tr>
<td>5. Y. Zhao &amp; Sushama (2020)</td>
<td>GEM</td>
<td>RCM</td>
<td>2</td>
<td>RCP 4.5, RCP 8.5</td>
</tr>
<tr>
<td>7. Gratton et al. (2020)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Present study (for comparison)</td>
<td>CMIP6</td>
<td>GCM</td>
<td>1</td>
<td>SSP1–2.6, SSP2–4.5, SSP3–7.0, SSP5–8.5</td>
</tr>
</tbody>
</table>

*Note.* Gratton et al. (2020) was a retrospective study using archival records of the climate instead of prospective simulation data.
Takeoff Performance Models

Takeoff Modeling. Next, a review was conducted on how the literature has modeled the sensitivity of takeoff performance to climatic variables. The review identified four distinct approaches that use air temperature, density, pressure, and wind speed as independent variables. This section contrasts those methodological choices.

Temperature Thresholds. Four studies (Coffel et al., 2017; Coffel & Horton, 2015; Y. Zhao & Sushama, 2020; T. Zhou et al., 2018) defined coarse weight restriction levels, ranging from 454 kg to 6,804 kg, to estimate how much payload must be removed from the aircraft in case of weight restrictions. Those studies employed OEM-published takeoff performance charts to identify the tas thresholds at which the takeoffs would be weight-limited at each airport. They then used the daily maximum temperature returned by the bias-corrected CMIP5 models (or GEM, in the case of Y. Zhao & Sushama, 2020) to test whether the airport would encounter at least one weight limitation each day. This methodology was first developed by Coffel and Horton (2015), extended to additional aircraft by Coffel et al. (2017), applied to Chinese airports by T. Zhou et al. (2018), and finally expanded to include the wind component by Y. Zhao and Sushama’s examination of Canadian airports (2020). This approach simplifies the modeling but informs of weight restrictions only at the time of the daily temperature maximum, which is likely to be near mid-day. In practice, the heaviest intercontinental flights are likely to depart in the morning or evening to accommodate operating hours and curfews at the destination. This approach also returns coarse results whereby weight restrictions fall into a few intervals, in contrast with other studies (such as Gratton et al., 2020), which modeled payload removals to a unit kg of precision.
**Air Density.** In contrast, Ren et al. (2019) used the *direct proportionality* between $\rho$ and the maximum permissible takeoff mass to estimate future payload removals. Chapter I already introduced the proportionality of $\rho$ to lift generation in Equation 1. Although the authors do not mention it explicitly, an environmental decrease in lift can be equivalently expressed as a *weight penalty* because $L$ and $W$ act in opposite directions during the ground run. Therefore, there is a proportional relationship between $\rho$ and $W$, *ceteris paribus*, which the authors assumed to be such that a 1% decrease in $\rho$ results in a 1% decrease in MTOW. The authors then examined the mean temporal variations in $\rho$ from 27 CMIP5 model runs under RCP 8.5 and found more pronounced changes at higher latitudes, with polar regions experiencing a decrease in $\rho$ (and thus MTOW) of more than 5% by the year 2100, leading to a reduction in the effective payload of 8.5–19% depending on the aircraft model.

**Air Pressure.** The takeoff performance modeling approach followed by Y. Zhou et al. (2018) stands out for using air pressure as its independent variable. Using prospective climate data up to the year 2100 returned by 25 CMIP5 model runs under the RCP 8.5 scenario, the authors converted the bias-corrected air temperature and barometric pressure at 30 airport locations worldwide into *pressure altitude*. A key benefit of this approach is that the relationship between pressure altitude and takeoff performance is well understood. The researchers then used a *Koch chart*, which is an empirical instrument that uses temperature and pressure altitude as inputs, to determine a coefficient applicable to the takeoff distance and climb rate relative to the same takeoff performed under ISA conditions. As acknowledged by the authors, a notable limitation of the Koch chart is that it only provides approximative results.
**Wind Speed.** Y. Zhao and Sushama (2020) and Gratton et al. (2020) considered the effects of both air temperature and wind speed on takeoff performance. Focusing on Canadian airports up to the year 2100, Y. Zhao and Sushama (2020) observed that the probability of crosswind and tailwind operations remained constant or decreased slightly at southern airports and increased at central and northern airports. However, the researchers only used temperature to quantify the occurrences of takeoff weight and left their observations of wind vector changes as a topic for future examination. Gratton et al. (2020) examined archival records between the years 2050 and 2020 at lower-latitude Greek airports and observed a modest decrease in the mean headwind component. However, unlike Y. Zhao and Sushama (2020), Gratton et al. (2020) used the wind speed alongside the air temperature as inputs in their takeoff performance model.

**Takeoff Mass.** As shown in Table 8, all but two studies (Coffel et al., 2017; Y. Zhou et al., 2018) assumed a takeoff mass equal to the OEM-published Maximum Takeoff Mass (MTOM). In a published commentary responding to Coffel and Horton (2015), Hane (2016) argued that this methodological choice leads to overstating the results because most flights do not involve a maximal payload of passengers, cargo, and fuel. Coffel et al. (2017) addressed this critique by modeling weight restrictions at several equally-spaced takeoff mass intervals below MTOM and measuring the weight restrictions for each before converting them into passenger and fuel equivalents. Y. Zhou et al. (2018) instead assumed a single takeoff mass of 70,000 kg or 88.6% of the MTOM of the B737–800 aircraft used in their research, presumably to address Hane’s (2016) commentary, which they reference elsewhere in the study. The researchers did not provide a rationale for choosing this rounded takeoff mass value.
Table 8

*Takeoff Modeling Assumptions Used in the Literature*

<table>
<thead>
<tr>
<th>Study</th>
<th>Starting mass</th>
<th>Starting thrust</th>
</tr>
</thead>
<tbody>
<tr>
<td>2. Coffel et al. (2017)</td>
<td>Intervals</td>
<td>TOGA</td>
</tr>
<tr>
<td>3. T. Zhou et al. (2018)</td>
<td>MTOM</td>
<td>TOGA</td>
</tr>
<tr>
<td>4. Ren et al. (2019)</td>
<td>MTOM</td>
<td>TOGA</td>
</tr>
<tr>
<td>5. Y. Zhao &amp; Sushama (2020)</td>
<td>MTOM</td>
<td>TOGA</td>
</tr>
<tr>
<td>6. Y. Zhou et al. (2018)</td>
<td>89% of MTOM</td>
<td>TOGA</td>
</tr>
<tr>
<td>7. Gratton et al. (2020)</td>
<td>MTOM</td>
<td>TOGA</td>
</tr>
<tr>
<td>Present study (for comparison)</td>
<td>MTOM</td>
<td>75% TOGA</td>
</tr>
</tbody>
</table>

**Takeoff Thrust.** Table 8 also shows that all studies have assumed the takeoffs to be performed at their maximum rated thrust, although only two studies made that assumption explicit (Coffel & Horton, 2015; Gratton et al., 2020). Coffel and Horton (2015) are the only ones to note that a derated thrust is often used to reduce fuel burn and engine wear. This absence of either derated or FLEX/ATM thrust modeling among the reviewed literature is notable because an increase in combustor severity caused by global warming carries significant cost implications to the engine owner. Ren et al. (2019) acknowledged this “hidden cost” (p. 1718) of extra maintenance but did not attempt to quantify it. The present study indirectly estimated this increase in severity by assuming a below-maximum starting takeoff thrust and gradually increasing it as required.
Payload Removal. The studies varied in how they handled payload removal from weight-limited takeoffs. All studies but one converted mass restrictions into payload in a top-down fashion; Gratton et al. (2020) is the only study that iteratively decreased the takeoff mass until the takeoff limitations no longer applied. Coffel and Horton (2015) noted that belly space cargo is likely to be displaced first, but converted the mass restrictions into passengers only at an industry-standard mean mass of 190 lb (87 kg) per person. That mass assumption was reused by T. Zhou et al. (2018), while Ren et al. (2019) appear to have used a much higher assumption of 159 kg per passenger. Coffel et al. (2017) took a more nuanced approach and partitioned the payload restrictions into 83% passengers and 17% fuel, using means calculated from Eurocontrol’s Base of Aircraft Data (BADA). Y. Zhao and Sushama (2020) acknowledged that takeoff limitations are usually solved by removing fuel or passenger and cargo, but did not convert their findings into any quantifiable payload unit. The present study followed a hybrid approach of decreasing the takeoff mass iteratively, congruent with Gratton et al. (2020), although by the mass equivalent of one passenger at a time to reduce the number of takeoff iterations.

Findings

All seven studies concurred that atmospheric warming has a measurable and nontrivial detrimental effect on takeoff performance, although with significant disparities across latitudes and elevations. Coffel and Horton (2015) concluded that the number of weight-restricted summer days would increase by 50–200% by the year 2070 at the four U.S. airports in scope. Furthermore, the authors acknowledged “a negative economic effect on the airline industry” (Coffel & Horton, 2015, p. 94) without quantifying it. In
their follow-up study, Coffel et al. (2017) noted that the effects of warmer air are more pronounced for near-MTOM widebody flights, which will eventually experience restrictions 30–40% of the time, with a resulting payload reduction of 3–5%. In contrast, restrictions will only impact 5–10% of near-MTOM narrowbody flights and result in a 0.5% payload removal. The authors also found a significant variance across airports, whereby narrowbody weight restrictions are more frequent and pronounced at hot airports, such as New York’s LaGuardia (KLGA) and Dubai International (OMDB).

T. Zhou et al. (2018) also concluded that the seven Chinese airports in their sample would experience different warming levels depending on their latitude and elevation, with three of them experiencing the most increase at 257% and 557%, respectively, in the number of weight-restricted days under 1.5 °C and 2.0 °C warming scenarios. In this context, weight-restricted days are those with at least 1,000 lbs (454 kg) in payload removal required. The researchers also noted a significant disparity across airports, with Lhasa Gonggar (ZULS, with an elevation of 3,570 m) seeing the most substantial decrease in takeoff performance.

Among the six worldwide airports in their sample, Ren et al. (2019) observed a more pronounced decrease in takeoff performance at high latitudes, where the payload reduction will reach 8.5–19% by the year 2100. The global mean payload reduction by the year 2100 is 5–8.3% across the 100 aircraft types examined in the study.

Zhao and Sushama (2020) found that weight-restricted summertime days would increase alongside temperature maxima, with significant variance across the Canadian airports in their sample, and much sooner under RCP 8.5 than under RCP 4.5. They further found that even takeoffs at the coolest time of the day would become subject to
weight restrictions. This finding materially extends the earlier research, which focused on summertime temperature maxima at *hot and high* airports for the most part. Airports such as Toronto Pearson International (CYYZ), Vancouver International (CYVR), and Montréal-Pierre Elliott Trudeau International (CYUL) are expected to experience weight-restriction days for the first time from the year 2040 onward under the RCP 8.5 scenario. High-elevation airports such as Calgary International (CYYC) and Saskatoon John G. Diefenbaker International (CYXE) will experience the largest increase in weight-restriction days, in line with T. Zhou et al. (2018)’s findings.

A key finding from the Y. Zhou et al. (2018) study is the asymmetrical projected evolution of air temperature and pressure throughout the 21st century and across the 30 worldwide airports in the sample. While the former increases everywhere, the latter decreases for almost half of the airports by mid-century and proportionately more so at high-altitude airports. The net effect is a lengthening of takeoff distances and a reduction in climb rates at all airports. The study also found that the decrease in takeoff performance would be more pronounced in the second half of the 21st century. The summertime TODR will increase by 0.9–6.5% from 2005 to 2050, and another 1.6–11.0% from 2050 to 2100. Similarly, the summertime climb rate will decrease by 0.7–3.4% in the first period and another 1.3–5.2% in the second. The maximum increase in TODR observed across the sample airports is 168.7 m for a B737–800 aircraft. The results from Gratton et al. (2020) are not directly comparable because they apply to a retrospective period from 1950 to 2020. The study observed a modest annual TODR increase of 0.1–0.2% over the archival period and a takeoff weight restriction, where the TODR exceeds the TODA, of 0.0–0.1% per year.
Gaps in the Literature

This section summarizes the under-explored areas in the reviewed literature.

**Aircraft Sample.** Five of the reviewed studies examined the effects of global warming on one or two types of aircraft, mostly narrowbodies. However, narrowbody and widebody aircraft may be affected differently by global warming. Narrowbodies tend to operate at smaller airports equipped with shorter runways, while widebodies operate on longer runways but take off with a significantly higher mass, so it is not obvious which ones will be the most affected. The present study modeled two narrowbody and two widebody aircraft to control for these factors.

**Airport Sample.** All seven reviewed studies used small airport samples with no obvious justification regarding their representativity of the overall population. However, the uneven distribution of global warming across latitudes and elevations implies that even airports with comparable runway characteristics will experience significantly different impacts on takeoff performance. The present study chose a significantly larger airport sample \( n = 881 \) to enhance the external validity of its findings.

**Independent Variables Disagreement.** Five of the seven reviewed studies chose air temperature as their independent variable. Of the two remaining studies, one chose air density, and the other air pressure, expressed as pressure altitude. No study modeled humidity as an influencer of takeoff performance.

However, Equations 1, 3, and 4 have shown that \( \rho \) is the main climatic variable affecting \( L, D, \) and \( T \), respectively. Equation 2 further showed that \( \rho \) is mediated by the air temperature, barometric pressure, and humidity. While global warming will increase the mean surface temperatures worldwide (albeit with regional variance around the
mean), barometric pressure will likely increase over low-to-mid latitudes and decrease over high latitudes (IPCC, 2007). Therefore, the net effect on $\rho$ over the 21st century is latitude-dependent and not straightforward. In line with Ren et al. (2019), the present research modeled $\rho$ from its constituents and used it to model the effects on lift, drag, and thrust. The study also considered the headwind component, in line with Y. Zhao and Sushama (2020) and Gratton et al. (2020). Lastly, the study accounted for temperature effects on the Mach number via the speed of sound, and pressure effects on engine thrust coefficients via the pressure ratio.

Furthermore, only two studies among those reviewed modeled the projected changes to the global near-surface atmospheric circulation patterns. In both studies, the airport sample size was small (13 Canadian and 10 Greek airports) and not necessarily representative of global trends in wind strength. However, headwind speed is a significant determinant of takeoff performance (FAA, 2016). The present study addressed this gap by considering headwind speeds at all airports in the worldwide sample, using direction and magnitude data returned by the CMIP6 model run.

**Dependent Variables Disagreement.** Four of the seven reviewed studies chose takeoff weight restriction days as the dependent variable, two chose takeoff weight removals in kg, and only one focused on takeoff distance and climb rate. As introduced in Chapter I, takeoff weight and distance are co-dependent variables because a runway length limitation requires a payload removal from the aircraft. None of the studies considered the amount of takeoff thrust reduction as a dependent variable. The present study focused on payload removal and takeoff thrust increase from the regulatory minimum to provide an indication about the materiality of both issues.
**Climate Model Frameworks.** Five of the reviewed studies used CMIP5 models initiated in 2008 and developed well ahead of the IPCC’s Fifth Assessment Report in 2014. Since then, climate simulations have improved, especially in modeling the upper atmosphere, atmospheric chemistry, ice sheets, and marine ecosystems (Gettelman & Rood, 2016), which led to the development of Phase 6 (CMIP6) models, whose ensemble is more skillful at simulating temperature extremes (Fan et al., 2020). The present study used a recent CMIP6 model to benefit from the latest climate science and enhance the internal validity of the research.

**Climate Assumptions.** Six of the seven reviewed studies are prospective and used published climate model runs to project atmospheric conditions over the 21st century. This approach required selecting one or more GHG emission and concentration pathways as model assumptions. Three studies used a worst-case scenario, RCP 8.5, whose plausibility is questionable (Hausfather & Peters, 2020; Ho et al., 2019). One study used a 1.5–2 °C assumption, in line with the Paris Agreement goals but likely to be outdated in the second half of the century. Only two studies assumed an intermediate scenario (RCP 4.5). In contrast, the present study chose four of the five tier-1 SSPs provided under the CMIP6 framework to estimate the effect size under multiple plausible climate scenarios.

**Instrumental Validity.** Six of the seven reviewed studies used empirical methods to measure climatic effects on takeoff performance. These methods included *lookup tables* that relate air temperature with weight restrictions for airport planning purposes (Boeing, 2020) and *Koch charts* that provide a correction coefficient for the takeoff distance and climb rate. Neither instrument is suitable for a large sample. Only Gratton et
al. (2020) used published performance data for the Dash 8 aircraft, and a validated bespoke model for the Airbus A320. The present study aimed to improve the internal validity of the findings by using a first-principles model applicable to two narrowbody and two widebody aircraft that are representative of the global fleet.

**Theoretical Framework**

The topic of takeoff performance presents the challenge of spanning two largely unrelated disciplines: aeronautical and climatic science. The former focuses on maximizing aircraft performance, which is the aircraft’s ability to carry out a specific task (Eshelby, 2000). Aeronautical science requires a high degree of certainty and exactitude to satisfy the safety imperative of aircraft operations. The underlying physics of flight are well understood and documented. In contrast, climate science deals with the uncertainty inherent to weather, seasonal climate, and hydrological predictions (National Research Council, 2006). It is also evolving rapidly as domain knowledge expands and computing power increases (Gettelman & Rood, 2016). The literature review covered both disciplines and identified significant contributions to the theoretical framework related to sampling strategy and modeling, as presented hereafter.

**Airport Population Sampling.** Several theoretical considerations related to airport sampling emerged from the literature review. First, the studies appeared to lack a robust airport sampling strategy. Four studies selected airports within a single country, with a sample size of four to 13, and three studies selected six to 30 global airports. Few studies articulated their criteria for selection. Most deliberately chose hot and high airports to demonstrate climate change’s effect on takeoff performance in locations where it is most prominent, at the expense of generalizability, which appeared to be a secondary
consideration. Therefore, the literature’s theoretical contribution has been to demonstrate, confirm, and size the deleterious effect of global warming on takeoff performance. What remains is an opportunity to define a robust airport sampling strategy that favors the generalizability of the findings and their quantification at the air transport industry level.

The review also evidenced significant inter-study and inter-airport variability in the effect size, which is expected considering the diverse local conditions, including the aerodrome’s latitude, climate, elevation, and runway length. This finding provides a theoretical justification for sampling a set of airports that adequately represent the geographical distribution of the population of commercial airports worldwide.

Third, the two studies that modeled the wind component as an independent variable identified nontrivial changes to historical and future circulation patterns. The studies also noted the importance of headwind speed to takeoff performance. Therefore, the present study is justified in considering a sampling frame unit consisting of takeoffs at individual runways with unique wind components and TODA lengths.

Lastly, the literature ignored the possibility of obstacle-limited takeoffs at airports where the climb rate becomes insufficient to clear natural or artificial obstacles along the departure path. Only one study considered the climb rate as a dependent variable. Modeling obstacles for every airport in the sample, and the ability of a departing aircraft to clear them, would require an extraordinary effort for a modest validity gain.

**Aircraft Population Sampling.** Most of the reviewed studies sampled takeoffs from one or two aircraft types. Four studies considered the B737–800 narrowbody aircraft for its ubiquity. Only one study modeled a mix of contemporary narrow- and widebodies (Coffel et al., 2017). The significant difference in takeoff mass and distance
between narrowbodies and widebodies justifies the present research modeling both aircraft types and measuring their sensitivity to global warming separately.

**Climate Modeling.** The present research leveraged prospective climate data from model runs for its independent variables of near-surface air temperature, density, humidity, pressure, and wind vectors throughout the 21st century. A crucial theoretical framework contribution from the reviewed forward-looking studies is that most relied on climate models from the CMIP framework for their independent variables. The present study is thus justified in using the latest iteration of the CMIP models, now in their sixth phase, and benefit from the models’ enhanced sensitivity (Zelinka et al., 2020).

**Aeronautical Modeling.** Most of the reviewed studies used algebraic simplifications, such as the direct proportionality of $\rho$ with MTOM, or empirical instruments, such as Koch charts, to estimate the decrease in takeoff performance from global warming. One study (Gratton et al., 2020) provided a theoretical justification for the present research to use a first-principles approach to takeoff performance calculations, which is more scalable than empirical techniques for large sample sizes.

**Research Model**

The present study combined a climate model of independent variables and an aeronautical model of dependent variables. The former is an existing high-resolution model developed by the Max Planck Institute under the CMIP6 framework. The climate data from this model’s runs under four SSPs were downloaded to provide the independent variables for this research. The aeronautical model, on the other hand, is a bespoke computer program developed for the present study, which borrows theoretical contributions from Blake (2009), Sun et al. (2020b), and Gratton et al. (2020). Using a
The bespoke model is likely less accurate than using the OEMs’ takeoff performance software, such as Airbus’ OCTOPUS or Boeing’s OPT. However, those are proprietary software generally unavailable to researchers, limiting the reproducibility of studies.

Congruent with SSP1–2.6 to SSP5–8.5, the present study posited a GMST increase of 1.3 °C to 5.7 °C and very likely values of 1.8 °C to 4.4 °C by the year 2100 and evaluated the impacts to takeoff operations across all four SSPs. However, the analysis of the results in Chapter IV focused on two middle SSPs (SSP2–45 and SSP3–70). The study further assumed that airports worldwide would experience this warming unevenly in space and time (Huber & Knutti, 2014; Kettleborough et al., 2007).

Depending on the aircraft and airport configuration, takeoffs may become increasingly runway-limited (Coffel & Horton, 2015, and subsequent studies), and air operators may need to remove payload and increase engine thrust to meet takeoff requirements. The resulting opportunity costs may constitute an increasing economic burden for industry participants in the 21st century.

**Summary**

All seven studies of central relevance to the present research confirmed a decrease in takeoff performance from global warming, both retrospectively from archival records and prospectively from predictive climate simulations. They all used some combination of air temperature, density (or density altitude), pressure (or pressure altitude), and wind strength to measure global warming's historical and projected intensity. All but two of the prospective studies used GCMs from the CMIP5 collaborative framework to capture future climate change at the sampled airports up to the year 2100. The studies then used the past and future atmospheric conditions as independent variables against which to
calculate the impact on takeoff performance. The dependent variables expressing the latter included takeoff restriction days, takeoff distance required (TODR), climb rate, and payload removal. All but one study used empirical methods, including lookup tables and Koch charts, to calculate the climatic influences on the dependent variables. Only one study used first-principles aerodynamic models. The review identified an inter-study consensus about the climatic effect’s directionality (i.e., a decrease in takeoff performance) but not about effect size, which depends on the airport's latitude and elevation, climate scenario assumptions, and models used. The present study’s theoretical framework is grounded in the scientific literature’s use of published climate model runs to predict values for atmospheric conditions that are relevant to takeoff performance. Using a first-principles aeronautical model to calculate takeoff performance also has a precedent in the literature.
Chapter III: Methodology

This chapter describes the research method and variables, the climate data preparation, the takeoff performance modeling, and the airport population assembly and sampling used in the present study.

Research Method

The present research is *quantitative* in that it aimed to quantify the opportunity cost of global warming on takeoffs using numerical data about the atmosphere and aircraft performance. It is also *predictive* in that it aimed to forecast the effect size of future global warming on takeoff performance across the remainder of the 21st century. The research used the *simulation method* because it is suitable for quantitative and predictive research. Simulations are “mathematical models whose equations depend on time and on variables that correspond to some actual properties of the system under examination, and are solved numerically by means of a computer” (Pasini, 2006, p. 109). The present study used two such simulations in separate ways.

The first was a *climate simulation* of 21st-century atmospheric conditions conducted in 2019 by participants in the World Climate Research Programme’s (WCRP) Working Group on Coupled Modeling’s (WGCM) CMIP6 collaborative framework. The present study leveraged a subset of that simulation’s outputs in the form of a multi-decadal time series of atmospheric variables relevant to takeoff performance. The second simulation was *aerodynamic* and based upon a first-principles model of takeoff performance adapted from extant research. The next two sections discuss both simulations and their models in further detail.
Climatic Simulation

Model Selection Criteria. It is beyond the present study’s intent to conduct primary research into global warming. Instead, the study leveraged existing simulations of the Earth’s climate for the 21st century, whose results are published and available to researchers. Those models were screened and selected based on six requirements for this research. First, they needed to demonstrate scholarly acceptance in the literature as a proxy for reliability and validity. Second, the models needed to be openly accessible and free of restrictive licensing for research reproducibility. Third, their outputs had to comprise the atmospheric variables relevant to takeoff performance, which are the near-surface air temperature \( \text{tas} \), pressure \( \text{ps} \), relative humidity \( \text{hurs} \), density \( \rho \) (optionally, since it can be derived from \( \text{tas} \), \( \text{ps} \), and \( \text{hurs} \)), and wind vectors \( \text{uas} \) and \( \text{vas} \). Fourth, the models needed to output data up to the year 2100 and across a range of SSPs.

Next, the spatial resolution of the candidate models, which is the horizontal granularity of the Earth’s grid system, had to be on a scale small enough for airport-level analysis. The study considered both Global Climate Models (GCMs) and downscaled Regional Climate Models (RCMs), which typically provide horizontal grid spacings of 100–300 km and 10–50 km, respectively (Sørland et al., 2018), making RCMs superior candidates in principle. However, the regional coverage of RCMs renders them unsuitable for global studies, which could explain why only one of the six prospective studies reviewed in Chapter II (Y. Zhao & Sushama, 2020) used them. Likewise, the temporal resolution of the candidate models had to be granular enough to reveal diurnal variations in takeoff conditions and not only seasonal and decadal variations. The most granular models provide hourly observations but at the expense of increased data size.
The Rationale for Selecting CMIP. The present study identified CMIP as a suitable framework within which to evaluate model candidates. CMIP was initiated in 1995 by the WCRP’s WGCM as a standardized protocol to compare coupled (i.e., atmospheric-oceanic) models (Eyring et al., 2016). The theoretical justification for leveraging the CMIP framework in the present research is threefold.

First, CMIP constitutes state of the art in climatic science (Meehl et al., 2014). Governing it is a joint scientific committee comprising climate scientists from the WMO, the International Science Council (ISC), and the Intergovernmental Oceanographic Commission (IOC). It forms the scientific basis for numerous climate studies, including five out of the six prospective takeoff performance studies reviewed in Chapter II. The IPCC uses CMIP for its Assessment Reports, which are “the best and most comprehensive entry point for looking at model predictions” (Gettelman & Rood, 2016, p. 200) and are foundational to climate policymaking. Such widespread acceptance of CMIP models satisfies the reliability and validity requirement stated earlier. Second, CMIP provides “common standards, coordination, infrastructure, and documentation” (Eyring et al., 2016, p. 1937), and its outputs are available through the Earth System Grid Federation’s (ESGF) file format standards, distributed data nodes, and application programming interfaces (APIs) (Cinquini et al., 2014). This combination of standardized formatting and unrestricted access satisfies the reproducibility criteria for this research.

Lastly, CMIP offers over 100 distinct simulation models from more than 50 climate institutes, each providing its own combination of output climate variables, spatial and temporal resolutions, forecast horizons, and SSPs, including those relevant to the present study.
The Rationale for Selecting CMIP6. The CMIP framework has gone through several iterations since its inception. Work on the latest phase (CMIP6) began after the IPCC’s Fifth Assessment Report’s publication in 2013 to pave the way for the IPCC’s Sixth Assessment Report’s publication released in 2022. The six prospective takeoff performance studies reviewed in Chapter II used CMIP5 simulation models, which assumed four RCPs to account for a range of climate forcings. The newer CMIP6 framework, on the other hand, combines those RCPs and five SSPs (shown in Table 1) into a more comprehensive scenario matrix comprised of forcing assumptions on one axis and socioeconomic pathways on the other (Riahi et al., 2011). CMIP6 further includes three times as many participants as CMIP5, a more comprehensive geophysical process modeling (Simpkins, 2017), a greater model variety, an enhanced grid resolution, and an increased sensitivity (Zelinka et al., 2020). Lastly, numerous studies have already examined the robustness of CMIP6 models relative to both earlier CMIP phases and historical records (for examples, see Papalexiou et al., 2020; Smith et al., 2020; Zelinka et al., 2020).

The Rationale for Selecting ScenarioMIP. CMIP6 endorses 23 specialized activities named Model Intercomparison Projects (MIPs). Among them, the Scenario Model Intercomparison Project (ScenarioMIP) is the primary activity within CMIP6 that provides “multi-model climate projections based on alternative scenarios of future emissions” (O’Neill et al., 2016, p. 3461). Other CMIP6 activities specialize in ways that are not directly relevant to the present research, including oceanic, polar, and volcanic studies. Therefore, the present study only considered candidate climate simulation models from the ScenarioMIP activity. Figure 8 shows ScenarioMIP’s relation to climate models.
**Figure 8**

*ScenarioMIP in the Context of Climatic Simulation Models*

Note. Climatic forecasts, such as those published in the IPCC’s Assessment Reports, inform the policymaking that, in a feedback loop, influences SSPs through energy mix choices, infrastructure investments, environmental subsidies, carbon taxation, and related policy instruments. Recent GCMs such as those present in the CMIP6 collaborative framework combine those SSPs with RCPs into multi-decadal scenarios used in the ScenarioMIP activity. Adapted from *From Observations to Simulations: A Conceptual Introduction to Weather and Climate Modelling*, (p. 169) by A. Pasini, 2006, World Scientific (https://doi.org/gdkp).
**ScenarioMIP Model Selection.** An iterative search for suitable ScenarioMIP candidate models was performed through the ESGF interface at [https://esgf-node.llnl.gov/search/cmip6/](https://esgf-node.llnl.gov/search/cmip6/) using the taxonomy described in Appendix Table A1. Parameters included four tier-1 pathways that are common in the literature: SSP1–26, which is an update of CMIP5’s RCP2.6; SSP2–45, which is an update of RCP4.5; SSP3–70, which is a gap-filling scenario reaching 7.0 W/m² of forcing in the year 2100; and SSP5–85, which is an update of RCP8.5. The finest spatial grid resolution at which the required atmospheric variables (\( \text{tas, ps, hurs, uas, vas} \)) are available was found to be 100 km. The model may not accurately account for each airport’s microclimatic and topological characteristics at such a resolution. As discussed earlier, this tradeoff results from using GCMs instead of RCMs. Likewise, the finest temporal resolution at which the required atmospheric variables are available was six-hourly, which only allows four takeoff simulations per airport per day, at 00:00, 06:00, 12:00, and 18:00 Coordinated Universal Time (UTC). Lastly, of all the available ensemble members, only the first (\( r1i1p1f1 \)) was retained to reduce download and processing requirements, as is common practice (Tebaldi et al., 2021).

The search returned one ScenarioMIP model containing the climatic variables required for the present study. \( \rho \) was missing but could be calculated from \( \text{tas, ps, and hurs} \). This model is the Max Planck Institute Earth System Model version 1.2 High Resolution (MPI-ESM1-2-HR), forming the baseline for the CMIP6 seasonal and decadal climate predictions (Müller et al., 2018). The R script shown in Appendix Code C3 was developed to perform the final ESGF query programmatically and parse its results.
**Climatic Data Preparation.** The ESGF query shown in Appendix Code C3 returned 20 datasets from the MPI-ESM1-2-HR model, each corresponding to temporal observations of one of five climatic variables \((tas, ps, hurs, uas, vas)\) for one of four tier-1 SSPs \((ssp126, ssp245, ssp370, \text{and } ssp585)\) described earlier in Table 1. In turn, each of the 20 datasets comprised 18 files in NetCDF binary format corresponding to 17 five-year periods between the years 2015 and 2099 inclusive, plus one one-year period for the year 2100. The query returned 360 NetCDF files in a binary format that weighed 355 GB. The files were downloaded to a computer using a script generated from the ESGF website.

**Data Extraction.** Next, the R script shown in Appendix Code C4 was developed to sequentially extract each climate variable’s time series from their respective NetCDF files for every airport in the sample and discard the rest of the data. The script locates in each NetCDF file the nearest set of the Earth’s grid spatial coordinates matching those of each airport in the sample, as shown in Figure 9. It then saves the six-hourly, timestamped observations of the climatic variables of interest and the airport code to a local instance of a MySQL 8.0 database. Five of the climatic variables \((tas, ps, uas, vas)\) were found to be measured as six-hourly means \((6hr\) in CMIP6’s controlled vocabulary) centered on 00:00, 06:00, 12:00, and 18:00 UTC. The remaining variable \((hurs)\), however, was found to be measured six-hourly at specific points in time \((6hrPt\) in CMIP6’s controlled vocabulary) at 03:00, 09:00, 15:00, and 21:00 UTC. A decision was made to average every two consecutive values of \(hurs\) to match the sampling timeframes of the other variables and ensure consistency across measurements (e.g., the 03:00 and 09:00 values were averaged and set to 06:00 UTC).
Figure 9

*Sample Airports Mapped Onto the MPI-ESM1-2-HR Spatial Grid*

*Note.* Each grid cell is 0.938 ° wide and 0.935 ° tall (approximately 100 km by 100 km). There are 72,728 cells in total. The 881 sample airports in this study occupy 823 unique grid cells (i.e., 58 neighboring airports are within the same grid cells).
**Data Importation and Transformation.** Upon execution, the R script shown in Appendix Code C4 wrote 2.2 billion climatic observations to the research database, corresponding to the product of 881 airports, 86 years (2015–2100 inclusive), 365.24 days per year, four measurements per day, five variables \( (tas, ps, hurs, uas, vas) \), and four climate scenarios \( (ssp126, ssp245, ssp370, \text{ and } ssp585) \). The resulting data occupy 212 GB of disk space, which is 40% less than the raw set of binary NetCDF data. Next, the R script shown in Appendix Code C5 was developed to pivot these data from long to wide format for efficient plotting and use in the takeoff simulation. The pivoted data contain 442.8 million entries, in which each row corresponds to a unique timestamped observation of takeoff conditions at an airport, and each column is a climatic variable \( (tas, ps, hurs, \rho, \text{ and } hdw) \). The resulting data occupies 65.4 GB of disk space, which is 82% less than the NetCDF data. The methods to calculate \( \rho \) and \( hdw \) are described next.

**Air Density Calculation.** The near-surface air density \( \rho \), which is required by the takeoff simulation but missing from the CMIP6 model’s output variables, was derived from its constituents using Equation 7 (Ambaum, 2010) converted to R code.

\[
\rho = \frac{P_D}{R_D \cdot tas} + \frac{P_V}{R_V \cdot tas}
\]

where:

\( \rho \) = The air density in kg/m\(^3\).
\( P_D \) = The partial pressure of dry air in N/m\(^2\).
\( P_V \) = The partial pressure of water vapor in N/m\(^2\).
\( R_D \) = The specific gas constant for dry air with a value of 287.058 J/(kg·K).
\( R_V \) = The specific gas constant for vapor with a value of 461.495 J/(kg·K).
\( tas_K \) = The prevailing air temperature in K as returned by the CMIP6 model.
Values for $P_D$ and $P_V$ come from a polynomial approximation for the saturation vapor pressure at 0 °C (List, 1951; Schlatter & Baker, 1981) shown in Equations 8–11.

\[ P_D = P_S - P_V \]

where:

$P_S$ = The total air pressure in N/m\(^2\) as output by the CMIP6 model.

and:

\[ P_V = e_s \times hurs \]

where:

$e_s$ = The saturation vapor pressure at the current temperature in mbar.

$hurs$ = The prevailing relative humidity in % as output by the CMIP6 model.

and:

\[ e_s = \frac{e_{s0}}{pol^8} \]

where:

$e_{s0}$ = The reference saturation vapor pressure at 0 °C with a value of 6.1078 mbar.

$pol$ = A polynomial applied to the prevailing air temperature $tas_K$ in K.

and:

\[
\text{pol} = 0.99999683 + tas_c \times (-0.90826951E - 02 + tas_c \times (0.78736169E - 04 + tas_c \times (-0.61117958E - 06 + tas_c \times (0.43884187E - 08 + }
\]

\[tas_c \times (-0.29883885E - 10 + tas_c \times (0.21874425E - 12 + tas_c \times \]

\[(-0.17892321E - 14 + tas_c \times (0.11112018E - 16 + tas_c \times \]

\[(-0.30994571E - 19))))))))) \]

where:

$tas_c$ = The prevailing air temperature in °C as converted from $tas_K$. 
Upon examining the observed values for *hurs* returned by the model, 2.2% (9.8 million cases out of 442.8 million) were found to exceed 100%, with a maximum of value of 151.8%, which is indicative of a phenomenon of supersaturation. The presence of non-trivial supersaturation in model outputs is a documented characteristic of CMIP, but its plausibility is unclear (Ruosteenoja et al., 2017). Supersaturation is known to occasionally occur in an atmosphere cold and clean enough that nucleation does not happen (Genthon et al., 2018). While 96.2% of the observed supersaturation cases returned by the MPI-ESM1-2-HR model occurred outside the tropical zone, where temperature conditions conducive to supersaturation are plausible, the near-surface atmosphere at airports is unlikely to be clean of foreign nuclei due to the proximity of combustion engine operations. Furthermore, standard computing packages for the calculation of $\rho$ typically require *hurs* values to be within the 0–100% range. For these reasons, a decision was made to recode all *hurs* observations where supersaturation occurred to a capped value of 100%, which is consistent with prior practice (Ruosteenoja & Jylhä, 2021).

$\rho$ was calculated twice, first by applying Equation 7 to recoded values of *hurs*, and then using a published R library as a control to enhance the instrumental validity of the research. The *masscor* package, which relies on the 2007 formulation by the Comité International des Poids et Mesures (CIPM) of the equation for the density of moist air (Picard et al., 2008), was selected for this purpose. High congruence was found between the method adapted from Ambaum (2010) in Equation 7 and that of Picard et al. (2008), with a mean difference of only .04% and a standard deviation of .01% between the two calculated sets of $\rho$, each containing 442.8 million entries.
Wind Calculation. Trigonometric functions were then used to calculate the headwind speed, which is also required by the takeoff simulation, using the prevailing wind speed and direction, themselves derived from the eastward \( uas \) and westward \( vas \) wind components returned by the CMIP6 model, as shown in Equations 12–14.

\[
wnd_{spd} = \sqrt{uas^2 + vas^2}
\]

(12)

where:

\( wnd_{spd} \) = The prevailing wind speed in m/s.

\( uas \) = The eastward component of the wind in m/s.

\( vas \) = The northward component of the wind in m/s.

and:

\[
wnd_{dir} = \mod\left(180 + \frac{180}{\pi} \times \tan^{-1}\left(\frac{vas}{uas}\right), 360\right)
\]

(13)

where:

\( wnd_{dir} \) = The prevailing wind direction in °.

\( uas \) = The eastward component of the wind in m/s.

\( vas \) = The northward component of the wind in m/s.

and:

\[
hdw = wnd_{spd} \times \cos\left(|hdg - wnd_{dir}| \times \frac{\pi}{180}\right)
\]

(14)

where:

\( hdw \) = The headwind speed in m/s.

\( wnd_{spd} \) = The prevailing wind speed in m/s.

\( hdg \) = The magnetic heading of the runway in °.

\( wnd_{dir} \) = The prevailing wind direction in °.
Takeoff Simulation

Model Selection Criteria. As discussed in Chapter II, the present study defines a takeoff simulation model as one that outputs the takeoff distance required (TODR) for a given aircraft mass from first-principle calculations of the forces exerted on the aircraft under a given set of environmental conditions. By contrast, empirical methods work by analogy and rely on available performance data. Such methods include regulatory takeoff weight (RTOW) lookup tables, Koch charts, and OEM-published performance plots. Lookup tables are the most precise, but they are specific to an aircraft type, engine model, takeoff configuration, runway, and atmospheric conditions. As a result, they lack instrumental generalizability and are suitable only for small-scale studies. Lookup tables also require access to proprietary OEM software, limiting their instrumental reproducibility. Similarly, Koch charts were deemed unsuitable for the present study because they only provide a temperature- and pressure-dependent coefficient applicable to the takeoff distance but not the baseline values themselves. Takeoff performance plots, such as those found in the OEMs’ airport planning guides for a given aircraft, provide takeoff distance and mass value pairs for only a limited set of pre-defined environmental scenarios, such as ISA and ISA+15 °C.

Consequently, the present study used a bespoke, first-principle, numerical takeoff performance model, inspired and adapted chiefly from Blake (2009), Filippone (2012), Gratton et al. (2020), and Sun et al. (2018, 2020a). The model was developed in R and consisted of three parts: a functional module (Appendix Code C6), a calibration module (Appendix Code C7), and a simulation module (Appendix Code C8). Each one is described in further detail in the next three sections.
**Functional Module Preparation.** The R script shown in Appendix Code C6 was developed to provide three functions for the takeoff simulation to call as needed.

**The Liftoff Speed Function.** The function `fn_vlof` returns the liftoff speed $V_{LOF}$, which marks the end of the ground run (inclusive of the rotation) and the start of the first-segment climb. This function is shown in Equation 15 and was adapted from Filippone (2012) and Sadraey (2017):

$$V_{LOF}^2 = \frac{2}{\rho} \times \frac{W}{S} \times \frac{1}{C_{L,LOF}} \Rightarrow V_{LOF} = \sqrt{\frac{2 \times g \times \text{tom}}{\rho \times S \times C_{L,LOF}}} \quad (15)$$

where:

$V_{LOF} = $ The liftoff airspeed in m/s at which the aircraft first becomes airborne. In principle, the aircraft can lift off earlier, as soon as $L = W$, which happens from the moment of reaching the stall speed $V_{STALL}$ onward. In practice, however, $V_{LOF}$ must be proportionally greater than $V_{STALL}$ (or $V_{MU}$, in the regulations) by a positive safety factor $k$, so that $V_{LOF} = k \, V_{STALL}$, to mitigate the safety risk of reasonably-expected variations from the established takeoff procedures, such as over-rotation and out-of-trim conditions (Takeoff Speeds, 2021; Takeoff Speeds, 2011). Values for $k$ found in the literature range from 1.1 (Filippone, 2012) to 1.2 (Eshelby, 2000). Sadraey (2017) recommends the latter for transport aircraft, which is the value used in the present study.

$C_{L,LOF} = $ The dimensionless lift coefficient at liftoff.

$g = $ The gravitational acceleration constant with a value of 9.806665 m/s².

$\text{tom} = $ The aircraft takeoff mass in kg.

$W = $ The aircraft's weight in N, which is the product of $g$ and $m$.

$\rho = $ The prevailing air density in kg/m³ from Equation 7.

$S = $ The surface area of the wings in m².
The Airborne Distance Function. The function \( fn\_dis\_air \) was developed as part of the R script shown in Appendix Code C6 to return the horizontal distance covered by the aircraft during the first-segment climb, as illustrated in Figure 2. The formula used is shown in Equation 32:

\[
D_{AIR} = \frac{h}{\tan(\phi \frac{\pi}{180})}
\]

(32)

where:

- \( h \) = The regulatory screen height of 35 ft (10.7 m) which the aircraft’s lowest point must clear at the end of the first-segment climb.
- \( \phi \) = The aircraft’s climb angle during the first-segment climb, with a value of 7.7° as taken by Gratton et al. (2020) from actual flight data, converted into radians using the \( \pi/180 \) term. This value is consistent with the technical literature, according to which the nose angle increases at a typical value of 2–3° per second from 0° at the start of the rotation and reaches a typical value of 7–9° at liftoff for narrowbody and widebody aircraft similar to those used in the present study (Wakefield & Dubuque, 2009).

The assumption of a constant first-segment climb angle is consistent with Filippone (2012), Ren et al. (2019), and Gratton et al. (2020). However, those sources differ slightly in their trigonometric calculation of the horizontal distance \( D_{AIR} \). Gratton et al. (2020) divide the screen height \( h \) by the cosine of the climb angle \( \phi \), whereas Filippone (2012) uses the tangent function in the denominator. Equation 32 is consistent with the latter method, considering that only the climb angle \( \phi \) and the length \( h \) of the side opposite to it are known in the right triangle shown in Figure 2, and \( D_{AIR} \) is the length of the adjacent side. Due to the small value of \( \phi \), however, this methodological
difference is not material, as the cosine and tangent functions return results for $D_{AIR}$ of 69.6 m and 78.9 m, respectively (i.e., a difference of 9.3 m only).

The assumption of a fixed horizontal distance covered during the first-segment climb carries several significant implications for the present study when considered in combination with the method for calculating the regulatory takeoff distance on a dry runway with all engines operating, which is shown in Equation 33:

$$D_{REG} = (D_{GND} + D_{AIR}) \times 115\%$$

where:

- $D_{REG}$ = The regulatory component of the TODR in m.
- $D_{GND}$ = The ground run component of the TODR in m.
- $D_{AIR}$ = The first-segment climb component of the TODR in m from Equation 32.

A direct implication of this methodological approach is that the environmental variability in the takeoff distances at the center of the present research comes exclusively from the ground run, measured as $D_{GND}$, because $D_{AIR}$ is constant and $D_{REG}$ is a fixed percentage applied to the sum of $D_{GND}$ and $D_{AIR}$. A second-order implication is that the calibration of the simulation model discussed in the next subsections only needs to be conducted on the ground portion of the takeoff sequence. Lastly, future studies using the same research method but not intending to compare the regulatory TODR to the TODA could ignore the first-segment climb and regulatory distances and report variations in $D_{GND}$ only under a range of environmental conditions.

**The Ground Run Distance Function.** Lastly, the function $fn\_dis\_gnd$ in Appendix Code C6 was developed to return the horizontal distance $D_{GND}$ in m covered by the aircraft between the start of the ground run and the liftoff, as shown in Figure 2. The
step integration method was used in line with Blake’s (2009, pp. 18–14) and Boeing’s own takeoff performance software algorithm. This method treats the ground run as a cumulative sequence of discrete speed intervals, each with a constant mean acceleration and velocity. This approach provides a simplified and closed algebraic solution to the direct takeoff-dynamics problem that would otherwise require integrating differential equations of motion (Daidzic, 2016).

Blake (2009) further showed that there are diminishing returns to increasing the resolution of the step integration method, whereby reducing the speed intervals from 20 to one kt improves the accuracy of \( D_{GND} \) by only five feet (1.52 m) (pp. 18–14). On the other hand, increasing the resolution adds disproportionately to the computational cost. As a baseline, the present study modeled 1,771,077,824 unique takeoffs, which are the product of six-hourly observations at 881 airports between the years 2015 and 2100, under four climate scenarios (SSPs) and across four aircraft types. Assuming a \( V_{LOF} \) of 160 kts (82.31 m/s), Blake’s (2009) 20-knot (10.29 m/s) resolution results in \( 14.2 \times 10^9 \) discrete intervals to process. Increasing the resolution to just one kt (1.94 m/s) yields \( 283.4 \times 10^9 \) intervals, a 20-fold increase in computational cost for only a marginal improvement in the ground distance accuracy. Considering that the present research is not intended for flight dispatch purposes and that relative increases in the mean TODR over time matter more than the accuracy of each TODR, a decision was made to set the resolution of the step-integrated model to 10, resulting in \( 17.8 \times 10^9 \) intervals.

The first step in programatically determining \( D_{GND} \) was, therefore, to decompose the takeoff speeds \( V_{TAS} \) and \( V_{GND} \) into 10 equally-spaced intervals, as shown in Equations 16–17.
\[ V_{TAS} = [hdw, V_{LOF}] \]  \hspace{1cm} (16)

where:

- \( V_{TAS} \) = The true airspeed of the aircraft in m/s.
- \( hdw \) = The starting airspeed in m/s (i.e., the headwind speed from Equation 14).
- \( V_{LOF} \) = The final airspeed in m/s, which is equal to the liftoff speed (Equation 15).

and:

\[ V_{GND} = [0, V_{LOF} - hdw] \]  \hspace{1cm} (17)

where:

- \( V_{GND} \) = The groundspeed of the aircraft in m/s.
- 0 = The starting groundspeed in m/s, which is zero in the case of a standing start.
- \( V_{LOF} - hdw \) = The final groundspeed in m/s (i.e., liftoff speed minus headwind).

The second step in building \( D_{GND} \) function was to determine the propulsive force \( F \) at each step of the ground run. The present study adapted in R the method presented by Sun et al. (2020b) and used in the Python Open-Source Aircraft Performance Model (OpenAP). First, the local speed of sound \( V_{SND} \) at the airport was calculated using Equation 18 from Eshelby (2000). \( V_{SND} \) is needed for the subsequent determination of the Mach number \( M \).

\[ V_{SND} = \sqrt{\gamma \, R_D \, tas} \]  \hspace{1cm} (18)

where:

- \( V_{SND} \) = The speed of sound in m/s.
- \( \gamma \) = The adiabatic index for dry air with a mean value for dry air of 1.40 at 15 °C.
- \( R_D \) = The specific gas constant for dry air with a value of 287.058 in J/(kg·K).
- \( tas \) = The prevailing air temperature in K from the CMIP6 model.
Next, the Mach number $M$, which is the ratio of the airspeed to the local speed of sound and is required for the subsequent determination of the engines’ thrust ratio, was coded using Equation 19 from Eshelby (2000).

$$M = \frac{V_{TAS}}{V_{SN}}$$  \hspace{1cm} (19)

where:

- $M$ = The dimensionless Mach number.
- $V_{TAS}$ = The true airspeed of the aircraft in m/s from Equation 16.
- $V_{SN}$ = The local speed of sound in m/s from Equation 18.

Then, the relative atmospheric pressure, which is the ratio of the prevailing air pressure to its sea-level ISA datum and is another determinant of engine thrust, was added to the ground distance function using Equation 20 from Eshelby (2000).

$$\delta = \frac{p}{p_0}$$  \hspace{1cm} (20)

where:

- $\delta$ = The dimensionless relative pressure.
- $p$ = The prevailing air pressure from the CMIP6 model.
- $p_0$ = The air pressure at ISA conditions with a value of 101,325 Pa.

The next step was to determine the thrust ratio of the engines, which is the amount of thrust delivered at each ground run interval relative to the maximum static thrust at sea level. The net thrust of a turbofan engine is proportional to the difference between the exhaust flow velocity and the true airspeed of the aircraft (Eshelby, 2000). As a result, the thrust ratio decreases considerably as the airspeed increases (Sadraey, 2017) or the relative pressure decreases. This relationship is evidenced by the presence of
the terms \( M \) and \( \delta \) in Equations 21–25, which provide an empirical polynomial approximation of the thrust ratio (Sun et al., 2020b).

\[
\frac{T}{T_0} = A - \frac{377(1+\lambda)}{\sqrt{(1+82\lambda)}G_0} Z \cdot V_{MACH} + (0.23 + 0.19\sqrt{\lambda})X \cdot V_{MACH}^2
\]  \hspace{1cm} (21)

where:

\[
\frac{T}{T_0} = \text{The dimensionless thrust ratio.}
\]

\( \lambda = \text{The engine bypass ratio from Appendix Table A2.} \)

\( M = \text{The dimensionless Mach number from Equation 19.} \)

and:

\[
A = -0.4327 \delta^2 + 1.3855 \delta + 0.0472
\]  \hspace{1cm} (22)

\[
Z = 0.9106 \delta^3 - 1.7736 \delta^2 + 1.8697 \delta
\]  \hspace{1cm} (23)

\[
X = 0.1377 \delta^3 - 0.4374 \delta^2 + 1.3003 \delta
\]  \hspace{1cm} (24)

where:

\( \delta = \text{The dimensionless relative pressure from Equation 20.} \)

and:

\[
G_0 = 0.0606 \lambda + 0.6337
\]  \hspace{1cm} (25)

where:

\( \lambda = \text{The engine bypass ratio from Appendix Table A2.} \)

The coding of Equations 21–25 into the script shown in Appendix Code C6 allowed for testing of the sensitivity of the thrust ratio to the airflow velocity. \( T/T_0 \) values were calculated at each airspeed interval for the Airbus A320neo’s CFM International LEAP–1A29 engine, which has a bypass ratio of \( \lambda = 10.7 \). Indicatively, the results show that the engine thrust decreases by 24.6\% from airspeed effects alone between the start and the end of the ground run under ISA conditions. A simulated
reduction by 10% of the atmospheric pressure was found to decrease the thrust ratio by another 6.8 p. p.

The penultimate step in the propulsive force determination was to code for the maximum takeoff thrust available at each ground run interval, which was included in the R script shown in Appendix Code C6 using Equation 26:

\[ F_{MAX} = slst \times n \times \frac{T}{T_0} \]  

(26)

where:

\[ F_{MAX} = \text{The maximum takeoff thrust available in N at each ground run interval.} \]

\[ slst = \text{The sea-level static thrust in N for which the engine is rated, as shown in Appendix Table A2. The present study assumed no installation loss, no electrical generator loss, and no bleed air loss to packs.} \]

\[ n = \text{The engine count, as shown in Appendix Table A2. The present study only considered twin-engine aircraft, so that } n = 2. \]

\[ \frac{T}{T_0} = \text{The dimensionless thrust ratio from Equation 21.} \]

Lastly, the reduced takeoff thrust in N was determined according to Equation 27.

As introduced in Chapter I, reduced takeoff thrust operations using either the FLEX/ATM or the derate method are common when the TODA exceeds the TODR for a given aircraft mass. The present study assumed that each takeoff would start with a takeoff reduced by the permissible limit of 25% from the maximum rated takeoff thrust (FAA, 1988). The simulation script, described later, decreases that takeoff reduction incrementally until the takeoff distance required fits into that available.

\[ F_{RTO} = F_{MAX} \times \frac{rto}{100} \]  

(27)

where:
$F_{RTO}$ = The reduced takeoff thrust in N at each ground run interval.

$F_{MAX}$ = The maximum takeoff thrust available in N from Equation 26.

$rto$ = The amount of thrust reduction with a value in the range [0, 25], starting at 25 and decreasing by one percentage point at each takeoff iteration until TODR ≤ TODA.

The third step in building the ground run distance function was to calculate the aircraft's acceleration in m/s² up to the liftoff, which involved two calculations. The first was to determine the dynamic pressure of the airflow $q$, which is proportional to the air density $\rho$ and the airspeed $V_{TAS}$ squared, as per Equation 28. Appendix Table A3 illustrates the calculation of $q$ assuming an ISA sea-level $\rho$ of 1.225 kg/m³.

$$q = \frac{1}{2} \rho V_{TAS}^2$$  \hspace{1cm} (28)

where:

$q$ = The dynamic pressure of the airflow in Pa.

$\rho$ = The air density of moist air in kg/m³ from Equation 7.

$V_{TAS}$ = The true airspeed of the aircraft in m/s from Equation 16.

Next, the acceleration $a$ itself was determined using Equation 29 as proposed by Blake (2009, pp. 18–11). Appendix Table A3 provides a worked example for $a$.

$$a = \frac{g}{W} (F_{RTO} - \mu W - (C_D - \mu C_L)qS - W \sin \theta)$$  \hspace{1cm} (29)

where:

$a$ = The horizontal acceleration of the aircraft along the runway in m/s².

$g$ = The gravitational acceleration constant with a value of 9.806665 m/s².

$W$ = The weight of the aircraft in N.

$F_{RTO}$ = The reduced takeoff thrust in N at each ground run interval.

$\mu$ = The runway friction coefficient set to a value of .02 in the present study.
\(C_D\) = The drag coefficient, as output by the calibration module (cf. next section).

\(C_L\) = The lift coefficient, as output by the calibration module (cf. next section).

\(q\) = The dynamic pressure of the airflow in Pa from Equation 28.

\(S\) = The surface area of the wings in takeoff configuration in m\(^2\).

Finally, the fourth and ultimate step in building the ground run distance function was to convert the acceleration results from Equation 29 into a horizontal distance \(D_{GND}\). Within each ground run interval, the distance \(\Delta D_{GND}\) is a function of time and the mean groundspeed \(\bar{V}_{GND}\) between each pair of interval boundaries. Time in each interval is indirectly available by dividing the groundspeed increment \(\Delta V_{GND}\), which is the length of each interval in Equation 16, by the mean acceleration \(\bar{a}\), which is the rate of change of the groundspeed in each interval. The mean groundspeed \(\bar{V}_{GND}\) and the mean acceleration \(\bar{a}\) in each interval were calculated using a rolling mean function with an adaptive window. The marginal distance in m covered during each ground run interval was then calculated using Equation 30 from Blake (2009, pp. 18–13).

\[
\Delta D_{GND} = \bar{V}_{GND} \times \frac{\Delta V_{GND}}{\bar{a}} \tag{30}
\]

where:

\(\Delta D_{GND}\) = The marginal distance in m covered during each ground run interval.

\(\bar{V}_{GND}\) = The mean groundspeed in m/s during each ground run interval.

\(\Delta V_{GND}\) = The groundspeed increment in m/s in each ground run interval.

\(\bar{a}\) = The mean horizontal acceleration in m/s\(^2\) for each ground run interval.

Finally, the distance covered during the ground run, \(D_{GND}\), was calculated by performing the cumulative sum of the incremental distances \(\Delta D_{GND}\), as shown in Equation 31. Values are provided in Appendix Table A3 for illustration.
\[ D_{GND} = \sum_i \Delta D_{GND} \] 

(31)

where:

\( D_{REG} \) = The regulatory component of the TODR in m.

\( i \) = The number of intervals used in the step integration method discussed earlier.

\( \Delta D_{GND} \) = The marginal distance in m covered during each ground run interval.

**Calibration Module Preparation.** The takeoff performance simulation model developed for the present study used the liftoff speed \( fn_vlof \) and ground distance \( fn_dis_gnd \) functions described earlier to return its results. As shown in Equations 15 and 29, both functions require the lift coefficient \( C_L \) as input. Its maximum value \( C_{L_{MAX}} \), which is achieved at \( V_{STALL} \), is a major factor in takeoff performance because it determines the minimum speed required to achieve flight (Houghton & Carpenter, 2003).

Empirical \( C_L \) values for common commercial air transport aircraft are available in proprietary databases, such as Eurocontrol’s BADA, which was used in Coffel et al. (2017) and Gratton et al. (2020). A request to Eurocontrol was submitted and subsequently denied to use the BADA data under license for the present research. As a result, plausible values for \( C_L \) had to be heuristically estimated and tested instead. To that end, a review of the determinants of \( C_L \) was conducted for the purpose of tuning the calibration model, and the corresponding R script shown in Appendix Code C7.

\( C_L \) at takeoff is a function of the prevailing air density \( \rho \), the design parameters related to the shape and configuration of the airfoil, and the angle of attack \( \alpha \), which depends on the point in the takeoff sequence and individual piloting technique. The present section briefly describes those determinants to contextualize the calibration methodology adopted in the present research.
**Air Density.** For a given airfoil, \( C_L \) depends on “the distribution of static pressures on the upper and lower surfaces of the wing” (Torenbeek & Wittenberg, 2009, p. 148). That distribution itself depends on \( \rho \), as shown in Equation 34 that reformulates Equations 1 and 28:

\[
C_L = \frac{L}{\frac{1}{2} \rho V_{TAS}^2 S} \Rightarrow \frac{L}{q S}
\]  

(34)

where:

- \( C_L \) = The dimensionless lift coefficient, which is unknown a priori.
- \( L \) = The lift force in N, which is equal to the weight of the aircraft \( W \) at \( V_{STALL} \).
- \( \rho \) = The air density in kg/m\(^3\), which is a known output of the CMIP6 model.
- \( V_{TAS} \) = The airflow velocity, which is the true airspeed of the aircraft in m/s. Of relevance to the model calibration, the numerator \( L \) and the denominator \( q \) both vary as a function of the square of \( V_{TAS} \), so that \( C_L \) itself remains invariant to \( V_{TAS} \) for a given angle of attack \( \alpha \).
- \( q \) = The dynamic pressure of the airflow in Pa, as shown earlier in Equation 28.
- \( S \) = The known wing surface area in m\(^2\).

**Design Parameters.** \( C_L \) values are unique to the shape and configuration of an airfoil. The four aircraft considered in the present study all share similar low, monoplane, cantilevered, sweepback, dihedral, and positive-camber wing designs, with comparable aspect ratios (\( \bar{x} = 9.89, \sigma = .36 \)) although the wing surface areas \( S \) shown in Appendix Table A2 vary by a factor of 3.26 between the narrowbody and widebody models. Those aircraft also possess high-lift devices (HLDs) that, upon extension, change the aerodynamic characteristics of the wings (Klug, 1991), as discussed in the next subsection.
\textit{Angle of Attack.} Lastly, $C_L$ varies with the angle of attack $\alpha$ along a lift curve whose slope is typically determined by OEMs using wind tunnel experiments or computational fluid dynamics simulations for a given configuration of HLDs. On that lift curve, the minimum value $C_{L,MIN}$ is reached at the zero-lift angle of attack $\alpha_0$, which is a \textit{negative} angle in the case of positively-cambered airfoils (Eshelby, 2000). Prior to rotation, $C_L$ is therefore positive at any nonzero airspeed, even though $\alpha$ remains near zero due to the relative airflow being practically parallel to the wing chord. That design lift characteristic of the wing is augmented by the deployment of \textit{trailing-edge flaps} at takeoff that \textit{shift} the lift curve up and to the left by increasing the wing’s area and camber, respectively (Eshelby, 2000; Houghton & Carpenter, 2003). While not all flap types increase $S$, all four aircraft considered in the present study use single- or double-slotted Fowler flaps, which do increase $S$ by first moving rearwards before moving downwards (Gunston, 2004). The resulting gain in $C_L$, and therefore $L$, is crucial to takeoff performance because it allows for a lower $V_{STALL}$ during the ground run, and therefore a shorter distance to $V_{LOF}$ in turn. Of relevance to the model calibration, however, Filippone (2012) notes that $C_L$ must be “referred to the original wing area” (p. 83), so that $S$ in Equation 34 is exclusive of the increase in wing area from the deployment of trailing-edge flaps.

Figure 10 encapsulates these concepts by illustrating how the deployment of HLDs raises the critical angle of attack at which stall occurs from $\alpha_S$ to $\alpha_{S'}$, allowing for lower takeoff speeds, and increasing the lift coefficient $C_L$ accordingly.
Figure 10

*Lift Curve in Clean and Takeoff Configurations*

Note. The two lift curves correspond to a clean configuration with HLDs retracted ($\delta = 0^\circ$) and a typical takeoff configuration with HLDs deployed ($\delta = 10^\circ$). Arrow A shows the upward and leftward shift in the lift curve consecutive to the deployment of trailing-edge flaps. Arrow B shows the extension of the lift curve to a higher stalling point following the deployment of leading-edge slats. The two black points show plausible $C_{L_{LOF}}$ values based on typical values of $k$. Slopes for $\delta$ and values for $\alpha$, and $C_L$, and $k$ are illustrative only and not plotted accurately to scale. Adapted from *Aircraft Performance: Theory and Practice* (p. 44), by M. E. Eshelby, 2000, Elsevier.
Upon rotation, the right side of the ordinate in Figure 10 becomes material for takeoff performance, as $C_L$ increases sharply in proportion to the nose-up attitude of the aircraft. In principle, the maximum lift coefficient value $C_{L_{MAX}}$ is attained at the critical angle of attack $\alpha_S$ beyond which airflow separation and aerodynamic stall occur (Eshelby, 2000). As the aircraft rotates to its final pitch-up attitude, assumed to be 7.7° in the present study, the resulting angle of attack yields a greater $C_L$, relative to a clean configuration, thanks to the deployment of the trailing-edge flaps discussed earlier. Additionally, the deployment of leading-edge slats at takeoff extends the lift curve by moving $\alpha_S$ further right (Eshelby, 2000). Finally, from liftoff and throughout the first-segment climb, $\alpha$ is assumed constant, which implies that $C_L$ also remains constant.

In summary, $C_L$ at takeoff can be conceptually simplified as being the weighted mean of three constant values, corresponding to the y-intercepts on the lift curve of $\alpha \approx 0^\circ$ throughout the ground run, $\alpha \approx 7.7^\circ$ throughout the first-segment climb, and $\alpha \approx 7.7^\circ / 2 = 3.85^\circ$ during the rotation, as shown in Figure 11. In calibrating this study’s model, a mean $C_L$ value was calculated at $V_{LOF}$ using a reformulation of $V_{LOF} = k V_{STALL}$, as per Equation 35.

$$C_{L_{LOF}} = C_{L_{MAX}} / k \quad (35)$$

where:

- $C_{L_{LOF}}$ = The dimensionless lift coefficient at liftoff obtained at $V_{LOF}$.
- $C_{L_{MAX}}$ = The maximum dimensionless lift coefficient obtained at $V_{STALL}$.
- $k$ = The $V_{LOF}$ safety factor applied over $V_{STALL}$ with a value of 1.2.

Equation 35 is consistent with Eshelby (2000), Filippone (2012), Roskam (2018), and Sadraey (2017), and results in $C_{L_{LOF}} \approx .83 \cdot C_{L_{MAX}}$ for $k = 1.2$. 
Figure 11

*Lift Coefficient Throughout the Takeoff Sequence*

*Note.* Values for $C_L$ during the ground run, rotation, and first-segment climb are illustrative and not plotted accurately to scale.
**Calibration Data Preparation.** OEM software that generates representative takeoff performance charts was unavailable for the present research. Instead, takeoff performance data were obtained for the four aircraft under study from the airport planning documentation published by Airbus (2020, pp. 3–3–1, 2021, pp. 3–3–0) and Boeing (2018, pp. 3–5, 2021, pp. 3–44). The data consist of value pairs of *takeoff mass* in kg and *regulatory takeoff distance required* in m for a given engine model and several *tas* conditions, including multiples of ISA. The value pairs are not available in tabulated format but are presented as line plots instead in the documents, which introduces some imprecision in the data transcription. For the uniformity of the calibration, only the lines related to ISA conditions were extracted from the documents. The images were then uploaded to an online plot digitizer tool (Rohatgi, 2021). Mass intervals of 250 kg were manually overlaid onto the sea-level performance plot, and their takeoff distance intercepts were calculated by the tool. The resulting 975 value pairs (before interpolation) were downloaded to four CSV format files (one per aircraft). The full data are tabulated in Appendix Table A4 and summarized in Appendix Table A5, where the upper and lower bounds show the maximum and minimum mass values, respectively, for which a corresponding TODR is available. The value pairs were further plotted in Figure 12.

As Appendix Table A5 and Figure 12 illustrate, the mass-TODR value pairs culminate at the aircraft’s declared maximum takeoff weight (MTOM) indicated in Appendix Table A2, but their ranges below MTOM are inconsistent. The calibrated value pairs for the Airbus A320neo exist for only 15.3% of the aircraft’s maximum takeoff mass, from 77,000 kg to 65,250 kg, compared to 48.3% for the Boeing 737 MAX 9, for example.
Figure 12

*Calibrated Takeoff Performance (Pre-Interpolation)*

Note. The solid vertical line indicates the takeoff mass at zero load factor (i.e., all passengers removed). The dashed vertical line indicates the takeoff mass at the BELF taken as the global industry mean for the year 2019, as shown in Appendix Table A11.
**Calibration Data Reduction.** Not all mass-TODR value pairs within these ranges are relevant to this research. There is a *physical limit* to how much payload can be removed from the aircraft, which is the totality of passengers on board (belly cargo notwithstanding). This lower bound, shown as the 0% load factor row in Appendix Table A5 and as solid vertical lines in Figure 12, was calculated using a mean inter-seasonal mass and a total seat count per aircraft from Appendix Table A2. The Airbus A320neo is the only aircraft whose calibrated takeoff mass does not extend to that lower bound.

There is also an *economic floor* to passenger removals, which is the BELF. Regional BELF data for the year 2019 was sourced from IATA (2021b). To calculate a global weighted mean for the BELF, the regional share of Revenue Passenger-Kilometers (RPKs) was taken from IATA (2019b). The result, shown in Appendix Table A11, is an industry-average BELF for the year 2019 of 67.0%. From there, the economic limit to passenger removals was calculated per aircraft, and the takeoff mass at BELF was reported into the last row of Appendix Table A5 and as dashed vertical lines in Figure 12.

There are several methodological benefits to demarcating this lower bound of payload removals. The first is to constrain the search space of the takeoff simulation. Whenever the ground run distance is calculated and the returned TODR exceeds the TODA, the simulation removes one passenger’s worth of takeoff mass (from Table 4) and calls the function again. In extreme environmental conditions of high *tas*, low *ρ*, low *ps*, and no or negative *hdw*, no amount of mass removal within the calibrated range may satisfy the TODR ≤ TODA condition. In such cases, the simulation for that particular takeoff will stop after 700 iterations, on average, across all four aircraft.
Capping the payload removal to only the mass of all passengers on board (i.e., a zero-load factor) reduces the mean number of iterations to 251 before failure. Finally, further limiting the payload removal to the breakeven load factor reduces the number of iterations to no more than 83 on average. Using this approach, the computing time required by the simulation is decreased by up to 88.3% in worst-case-scenario takeoffs where neither condition of distance (i.e., TODR \( \leq \) TODA) and profitability (i.e., the residual load factor is at least equal to breakeven) can be satisfied. Such a decrease is significant considering that 418 million takeoffs out of 1.77 billion (23.6%) were found to have no solution that satisfied those constraints.

Another methodological benefit was to reduce the processing time of the calibration script itself. Ahead of the \( C_L \) calibration, 861 out of the 975 mass-TODR value pairs below breakeven mass (i.e., left of the dashed vertical line in Figure 11) were discarded, allowing the calibration script to estimate \( C_L \) only for the remaining 114 value pairs. Lastly, this eight-fold reduction in the number of calibrated value pairs resulted in slightly faster lookups of \( C_L \) values for a given mass in the subsequent simulation. Those savings scaled up considering that the simulation processed almost 1.8 billion takeoffs.

**Interpolation of Missing Values.** Next, the missing mass-TODR value pairs within each of the remaining 114 250-kg intervals between BELF mass and MTOM were linearly interpolated, resulting in 28,627 continuous value pairs of one-kg increment for each aircraft. Those values were written to the research database for subsequent lookups by the simulation. The results of the interpolation are shown in Figure 13, which is to be compared with Figure 12 which had missing values.
Figure 13

**Calibrated Takeoff Performance (Post-Interpolation)**

Note. The solid vertical line indicates the takeoff mass at zero load factor (i.e., all passengers removed). The dashed vertical line indicates the takeoff mass at the breakeven load factor taken as the global industry mean for the year 2019.
Calibrated Distance Decomposition. As discussed earlier, the horizontal distance of the first-segment climb $D_{\text{AIR}}$, returned by Equation 32 and coded in the $\text{fn\_dis\_air}$ function, was set across all simulated takeoffs to a constant value of 78.9 m, itself a consequence of assuming a fixed climb angle of 7.7°. Furthermore, the regulatory safety factor applied to the horizontal distances in the ground run $D_{\text{GND}}$ and first-segment climb $D_{\text{AIR}}$ in an AEO takeoff also takes a constant value, regulatorily set at 1.15. These simulation model parameters have two implications. First, the calibration of $C_L$ for the present model is only dependent on the aircraft’s takeoff performance in the ground run, expressed as $D_{\text{GND}}$ for a given mass. Second, $C_L$ can be seen as a weighted mean of the near-constant lift coefficient prior to rotation and the rapidly increasing lift coefficient during rotation, which further narrows its definition from Equation 35.

Accordingly, the regulatory component of each of the 28,627 calibrated TODR from the OEM data was deducted in such a way that a factor of 1.15 applied to the remainder would yield the original TODR, and the ground run and airborne components were extracted from the remaining distance. Equations 35–36 illustrate those calculations.

\begin{equation}
D_{\text{REG}} = D_{\text{TODR}} - \frac{D_{\text{TODR}}}{115}\%
\end{equation}

\begin{equation}
D_{\text{GND}} = D_{\text{TODR}} - D_{\text{REG}} - D_{\text{AIR}}
\end{equation}

where:

$D_{\text{TODR}}$ = The calibrated TODR in m, interpolated from OEM plots.

$D_{\text{REG}}$ = The regulatory component of the TODR in m, so that the TODR is equal to 115% of the ground run and airborne distances.

$D_{\text{GND}}$ = The ground run component of the TODR in m.

$D_{\text{AIR}}$ = The first-segment climb component of the TODR in m from Equation 31.
**Drag Coefficient Calibration.** The next step in the calibration consisted in setting up the calculation of the drag coefficient $C_D$ for a given lift coefficient $C_L$. As introduced in Chapter I and shown in Equation 37, $C_D$ is the sum of the *lift-independent* and *lift-induced* drag coefficients.

\[ C_D = C_{D_0}^* + C_{D_i} \quad (37) \]

where:

- $C_D$ = The dimensionless total drag coefficient.
- $C_{D_0}^*$ = The dimensionless lift-independent drag coefficient at takeoff. Values for $C_{D_0}^*$ were calculated from first principles using the zero-lift drag in a clean configuration $C_{D_0}$, the additional drag $\Delta C_{D_F}$ attributable to HLD deflection, and the additional drag $\Delta C_{D_G}$ attributable to the undercarriage. However, the results were found to be 41.3–48.1% lower than those given by Sun et al. (2018). Eventually, the latter were used as inputs into the model.
- $C_{D_i}$ = The dimensionless lift-induced drag coefficient. Values for $C_{D_i}$ were calculated using Equation 38.

\[ C_{D_i} = k \frac{C_L^2}{\pi AR e C_L^2} \quad (38) \]

where:

- $C_L^2$ = The square of the lift coefficient returned by the calibration model.
- $k$ = The lift-induced drag coefficient factor in a given configuration.
- $AR$ = The aspect ratio, which is wingspan squared over wing area.
- $e$ = The Oswald efficiency factor in a given configuration, which indicates the deviation in drag relative to a wing having the same $AR$ but an ideal elliptical lift distribution.
Values for both \( k_0 \) and \( e_0 \) in a clean configuration were taken from Open AP (Sun et al., 2020b) and are shown in Appendix Table A2. However, the value for \( e \), and therefore for \( k \) as well, increases with flap deflection. Its marginal value was calculated using Equation 39 from Sun et al. (2020b).

\[
\Delta e_F = .0026 \sin \left( \delta_F \frac{\pi}{180} \right)
\]  

(39)

where:

\( \Delta e_F \) = The component of the Oswald efficiency factor attributable to flaps, so that the total value at takeoff is \( e = e_0 + \Delta e_F \).

.0026 = A standardized coefficient of increase in \( e \) for a given increase in \( \delta_f \), as determined empirically by Obert (2009) for wing-mounted engines.

\( \delta_f \) = The flap deflection angle in ° at takeoff, set to a single constant value of 10° in the present study and converted to radians in Equation 38.

With the updated value of \( e \) in a takeoff configuration, it was then possible to calculate the updated value for \( k \) as per Equation 40.

\[
k = k_0 + \frac{1}{\pi AR \Delta e_F}
\]  

(40)

where:

\( k_0 \) = The lift-induced drag coefficient factor in a clean configuration.

\( AR \) = The aspect ratio, which is wingspan squared over wing area.

\( \Delta e_F \) = The component of the Oswald efficiency factor attributable to flaps.

Lastly, \( C_{D_l} \) and \( C_D \) were calculated using Equations 38 and 37, respectively, using the updated \( k \) coefficient factor. Their values were found to be in the range .088–.095 and .156–.174, respectively, for optimized \( C_L \) values discussed in the next subsection.
**Maximum Lift Coefficient Calibration.** The penultimate step in the calibration consisted in using a one-dimensional optimizer in R to search for $C_{L_{MAX}}$ values which, when used to calculate a simulated TODR using the `fn_dis_gnd` function introduced earlier, returns the least absolute residual error relative to the calibrated TODR. The lower and upper bounds of the optimizer’s search interval were set to 1.6 and 2.2, respectively, in line with typical $C_{L_{MAX}}$ values for transport jets in takeoff configuration (Roskam, 2018). The optimizer’s tolerance was set to $10^{-3}$. The 28,627 calibrated mass-TODR value pairs extracted and interpolated from the OEM plots were each passed to the optimizer sequentially, and a local optimum for $C_{L_{MAX}}$ was found within the search interval in all cases. Figure 14 shows the range of $C_{L_{MAX}}$ solutions returned by the optimizer across the range of calibrated takeoff mass. Values for the mean lift coefficient during the ground run and up to liftoff were then determined using Equation 35 so that $C_{L_{LOF}} \approx .83 C_{L_{MAX}}$. Finally, the $C_L$ optima for all the takeoff mass values above BELF were recorded to the research database for subsequent lookups.

The use of linear optimization in the present research is a notable methodological departure from past studies, such as Gratton et al. (2020), which used a single mean $C_L$ for a given aircraft type at takeoff, resulting in strong model accordance with OEM TODRs (as low as .07%) for mean values of mass, but also non-trivial deviations (up to 4.49%) at MTOM. Decision was made to optimize $C_{L_{MAX}}$ for every calibrated mass-TODR pair because the simulation model assumes that all takeoffs start at the aircraft’s MTOM, and only decrement one passenger’s worth of mass when TODR exceeds the TODA. Therefore, accurate calibration of the simulation model to the OEM data at the high end of the mass range was especially crucial to the model’s validity.
Figure 14

Maximum Lift Coefficient Values Across the Calibrated Mass-TODR Range

Note. Mean $C_{l\text{MAX}}$ values for each aircraft are shown as dots inside each box plot. The wide range of $C_{l\text{MAX}}$ values for the Boeing 737 MAX 9 can be explained by the non-linear behavior of the mass-TODR relationship above BELF mass seen in Figures 12–13.
Figure 15 shows the excellent fitness of the simulated TODR (in gray) relative to the calibrated TODR taken from OEM data (in black) for each takeoff mass above BELF.

**Figure 15**

*Fitness of the Simulated TODR Over the Calibrated TODR*

*Note.* Only the mass-TODR value pairs above the BELF mass are shown here.
Figure 16 further shows that the accuracy of the simulated TODR using the $C_{L_{MAX}}$ optimum is within one meter of the calibrated TODR distance across all takeoff mass values above BELF, with a mean of .14 m and a maximum deviation of .65 m.

**Figure 16**

*Difference Between Calibrated and Simulated TODRs*
**Simulation Module Preparation.** The R script shown in Appendix Code C8 was developed to perform the takeoff simulations. The script imports from a local database the observations of the five climatic \((tas, ps, hrs, \rho, \text{ and } hdw)\) and two operational variables (the active runway, as defined by that with the strongest headwind, and its TODA) at each of the 881 airports in the sample. There are 502,576 such observations at each airport, corresponding to four six-hourly measurements per day under four SSPs, 365.24 days per year, for 86 years (2015–2100 inclusive). The observations are then combined with the four aircraft considered in the present research to form sets of 2,010,304 unique takeoffs per airport. Each of these sets is then assigned to a central processing unit (CPU) core for faster parallel processing.

Next, the starting mass is set to MTOM, and the takeoff thrust reduction is set to its maximum permissible value of 25\%, except in cases where the calibrated TODR exceeds the TODA, in which case it is set to 0\%. This exception is predicated on the assumption that the calibrated takeoff performance was recorded at full takeoff thrust, which was validated in private conversations with one OEM (Airbus, personal communication, April 4, 2022). The simulated TODR using a reduced takeoff thrust setting is unlikely to be less than the calibrated TODR, except in cases where exceptionally favorable climatic conditions (low temperature, high air density, and high air pressure) could more than offset the thrust reduction. This exception reduced the number of takeoff iterations by up to 25 times, corresponding to one-percentage-point increments from 75\% to 100\% of full thrust.

The script then looks up in a local MySQL database the optimized \(C_L\) and \(C_D\) values for the current takeoff mass found and recorded during the model calibration. The
TODR is then assembled from the $D_{GND}$ and $D_{AIR}$ distances, calculated respectively by the $fn\_dis\_gnd$ and $fn\_dis\_air$ functions described earlier, and $D_{REG}$ as the regulatory safety distance proportional to both by a factor of 1.15. The resulting TODR is then compared to the TODA for the active runway. If the TODR exceeds the TODA, the takeoff thrust is increased by one percentage point, and the TODR is calculated again. If TODR still exceeds the TODA while the takeoff thrust is at its maximum, the simulation starts removing one passenger’s worth of mass at each iteration. If the TODR exceeds the TODA after the BELF mass is reached, the iterations stop, and the takeoff is considered unsuccessful. If the TODR is less than or equal to the TODA at any point, the takeoff is considered successful, and the last TODR value is recorded. Figure 17 summarizes the conditional logic of the simulation script in flow chart format.

The script was executed and successfully simulated 1,771,063,728 unique takeoffs in approximately 48 hours of runtime across 23 CPU cores on the research computer. Each takeoff was iterated an average of 32.5 times, corresponding to 25 p. p. of thrust increase up to TOGA and another 6–7 passenger removals. The most iterations any takeoff required was 129. In total, 65,138,833,995 iterations were performed.

Appendix Table A6 summarizes the takeoff and iteration count by aircraft type, SSP, and climate zone. The data output by the simulation, including the takeoff’s date and time, airport code, climatic variables and SSP, active runway, TODA, TODR, liftoff speed, ultimate values for mass and thrust reduction, and iteration count, were recorded to a local MySQL database table amounting to 256 GB of disk space.
Conditional Logic of the Simulation Script

Start / For each unique takeoff

Calibrated TODR > TODA

Yes

Set thrust reduction to 0%

No

Set thrust reduction to 25%

Calculate the TODR

TODR > TODA

Yes

No

End / Record the TODR

No

Yes

Thrust < TOGA

Increase thrust by one p. p.

Set mass to MTOM

Lookup $C_D$ and $C_L$ values

Mass > BELF

Decrease mass by one passenger
Population/Sample

This section presents the method followed by the present study to assemble the population and subset the sample of airports and runways used in the takeoff simulation.

Population and Sampling Frame

The population comprises non-rejected AEO takeoffs of scheduled passenger flights operated with turbofan passenger aircraft between the years 2015 and 2100 inclusive. Because most of these takeoffs happen in the future, simulated takeoffs from a model were used rather than actual takeoffs from archival records. The sampling frame was taken from a list of all civilian and dual-use commercial airports worldwide that reported scheduled passenger traffic in the year 2019 (IATA, 2020a). Each sampling frame unit is characterized by its independent variables: the climatic conditions at each airport, the geometric and propulsive characteristics of each aircraft, and operational takeoff parameters such as mass and thrust, as shown in Table 10.
Table 10

*Characteristic Independent Variables of the Sampling Frame Units*

<table>
<thead>
<tr>
<th>Climatic conditions</th>
<th>Aircraft characteristics</th>
<th>Takeoff parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air density</td>
<td>Engine bypass ratio</td>
<td>Climb angle (^a)</td>
</tr>
<tr>
<td>Air pressure</td>
<td>Engine count</td>
<td>Flap deflection angle (^a)</td>
</tr>
<tr>
<td>Air temperature</td>
<td>Engine thrust (static)</td>
<td>Runway friction (^a)</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>Lift-induced drag coefficient factor</td>
<td>Runway slope (^a)</td>
</tr>
<tr>
<td>Headwind speed</td>
<td>Number of seats</td>
<td>Takeoff mass</td>
</tr>
<tr>
<td></td>
<td>Oswald efficiency factor</td>
<td>Takeoff thrust</td>
</tr>
<tr>
<td></td>
<td>Wingspan</td>
<td>TODA</td>
</tr>
<tr>
<td></td>
<td>Wing surface area</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Zero-lift drag coefficient</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* \(^a\) Assumed invariant across all sampling frame units.

*Population Assembly*

**Airport Runway Dataset.** Lufthansa Systems kindly provided its Lido database of worldwide runways as of December 2020 in comma-separated values (CSV) format. In the context of this study, each runway designator (e.g., RW17) and its opposite heading (e.g., RW35) are referred to as *distinct runways* despite sharing the same physical surface because their respective TODAs may differ due to the presence of asymmetrical clearways. The CSV file was loaded into R Studio for description and treatment. The file contains 29,904 observations, each representing a runway, and three variables, which are the aerodrome’s four-letter ICAO location designator (e.g., KATL); the runway designator (e.g., RW08L); and the runway TODA in feet. Next, 13,332 (44.6%) observations with a zero or null TODA value were removed. The remaining
16,572 runways belong to 6,542 unique aerodromes. The mean count of runways per aerodrome is 2.5, and the mean TODA length is 1,965 m, as shown in Table 11.

Table 11

Descriptive Statistics of the Population Runways’ TODA

<table>
<thead>
<tr>
<th>Statistic</th>
<th>TODA in m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>30</td>
</tr>
<tr>
<td>First quartile</td>
<td>1,199</td>
</tr>
<tr>
<td>Median</td>
<td>1,819</td>
</tr>
<tr>
<td>Mean</td>
<td>1,965</td>
</tr>
<tr>
<td>Third quartile</td>
<td>2,639</td>
</tr>
<tr>
<td>Maximum</td>
<td>5,700</td>
</tr>
</tbody>
</table>

Note. N = 16,572 runways at 6,542 aerodromes.

Airport Traffic Dataset. Next, the annual passenger traffic data for all airports worldwide in the reference year 2019 were exported from IATA’s AirportIS database to a UTF-8 CSV file and imported into R Studio for description and treatment. The year 2019 was chosen as the reference because it is the last year for which air travel remained unaffected by the confounding effects of COVID–19. The file contains 4,436 observations, each representing a commercial airport with scheduled air traffic, and two variables, which are the airport’s three-letter IATA code and the passenger headcount in units for the reference year. The total traffic was found to amount to 9.096 billion passenger movements (airports count the same round-trip passenger twice, once upon departure for the outbound leg and once upon arrival from the inbound leg at the origin airport, and similarly in reverse at the destination airport, for a total of four movements).
The statistics of the traffic variable were described and tabulated in Table 12. The data display substantial positive skewness with a value of 6.7, indicating an asymmetry of the traffic distribution in favor of a few large airports, as discussed in a later subsection.

**Table 12**

*Descriptive Statistics of the Population Airports’ Passenger Movements*

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Passenger movements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>1</td>
</tr>
<tr>
<td>First quartile</td>
<td>11,219</td>
</tr>
<tr>
<td>Median</td>
<td>86,446</td>
</tr>
<tr>
<td>Third quartile</td>
<td>645,403</td>
</tr>
<tr>
<td>Mean</td>
<td>2,050,418</td>
</tr>
<tr>
<td>Maximum</td>
<td>106,893,692</td>
</tr>
</tbody>
</table>

*Note.* $N = 9,095,655,262$ passenger movements (arrivals and departures) at 4,436 airports.

**Geolocation Dataset.** The runway and traffic datasets described earlier use incompatible ICAO and IATA location designators. A third dataset was needed to reconcile them. A list of geolocated worldwide aerodromes as of June 2021 was downloaded from the open data repository OurAirports.com to a UTF-8 CSV file and imported into R Studio for description and treatment. The file contains 65,642 observations, each representing an aerodrome, and 18 variables, five of which are of interest to the present research. They are the aerodrome’s name, latitude and longitude, and ICAO and IATA location designators. The remaining 13 variables were discarded to improve performance. Lastly, balloon ports, heliports, seaplane bases, closed aerodromes, and cases without a three-letter IATA code were removed, leaving 8,223 observations.
**Data Consolidation.** The last step in assembling the population was to combine the three datasets. First, the traffic dataset of 4,436 airports with scheduled traffic in the year 2019 was merged with the geolocation dataset of 6,542 aerodromes using a left join and the IATA code as the common key. The operation returned 4,441 airports, of which 416 were found to have a missing ICAO location designator (i.e., they had no matching entry in the geolocation dataset). Those cases required manual imputation or removal because the ICAO code is needed for later reconciliation with the runway population. Manual imputation was performed on three airports with traffic greater than one million passengers that were recently transferred to a new facility or were rebranded under a different name. The remaining 413 incomplete cases only accounted for 5.9 million passengers (0.1% of the population’s total traffic) and were subsequently removed, leaving 4,026 airports.

Five duplicates were identified. Two were decommissioned airports replaced by newer projects with the same ICAO code. Two more were duplicate entries for the same physical airport. The fifth was a case of two unrelated airports sharing the same IATA code, one of which being a minor domestic airport that was removed. After treatment, 4,021 airports remained. This population of geolocated airports was then combined with the Lido dataset of 16,572 runways. The operation returned 9,603 airport-runway combinations, of which 621 were found to have missing runway data, indicating the absence of a match. Those incomplete cases were removed. The final population contains 8,982 runways at 3,400 airports for reported traffic of 8,950 billion passengers. Runways with reciprocal headings (e.g., RW08 and RW26) and identical TODAs at each airport were identified. The analysis showed that 3,426 (38.1%) runways meet that definition,
and 5,556 unique runways (61.9%) have different TODAs despite sharing the same physical surface, which suggests the presence of asymmetrical clearways. The statistics of the final treated population were described and tabulated in Table 13.

Table 13

Descriptive Statistics of the Treated Population

<table>
<thead>
<tr>
<th>Statistic</th>
<th>TODA in m</th>
<th>Passenger movements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>199</td>
<td>1</td>
</tr>
<tr>
<td>First quartile</td>
<td>1,699</td>
<td>31,590</td>
</tr>
<tr>
<td>Median</td>
<td>2,368</td>
<td>176,092</td>
</tr>
<tr>
<td>Mean</td>
<td>2,377</td>
<td>2,632,286</td>
</tr>
<tr>
<td>Third quartile</td>
<td>3,016</td>
<td>1,084,615</td>
</tr>
<tr>
<td>Maximum</td>
<td>5,700</td>
<td>106,893,692</td>
</tr>
</tbody>
</table>

Note. N = 8,982 runways at 3,400 aerodromes.

Distribution Analysis. The population airports were then grouped by traffic size into nine logarithmic bins from $10^0$ to $10^9$ passenger movements for the year 2019 to explore further the distributional asymmetry detected earlier in the traffic dataset. The cumulative passenger traffic was tabulated by descending bin size in Table 14. The table shows that the passenger movement distribution across airports for the year 2019 follows a quasi-Pareto distribution, whereby the top airports by size account for a disproportionately large share of the overall traffic. A density plot was generated in Figure 18 and confirms a positively skewed and platykurtic distribution, revealing a long left tail of small airports with fewer than 1,000 passengers per annum. Finally, a
histogram of the airport count by bin was rendered in Figure 19 to confirm the distribution's characterization.

**Table 14**

*Cumulative Distribution of Passenger Movements at Population Airports*

<table>
<thead>
<tr>
<th>Bin size in passengers</th>
<th>Airport count</th>
<th>Passenger movements</th>
</tr>
</thead>
<tbody>
<tr>
<td>[100M–1B)</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>[10M–100M)</td>
<td>215</td>
<td>217</td>
</tr>
<tr>
<td>[1M–10M)</td>
<td>664</td>
<td>881</td>
</tr>
<tr>
<td>[100K–1M)</td>
<td>1,089</td>
<td>1,970</td>
</tr>
<tr>
<td>[10K–100K)</td>
<td>1,023</td>
<td>2,993</td>
</tr>
<tr>
<td>[1K–10K)</td>
<td>282</td>
<td>3,275</td>
</tr>
<tr>
<td>[100–1K)</td>
<td>66</td>
<td>3,341</td>
</tr>
<tr>
<td>[10–100)</td>
<td>28</td>
<td>3,369</td>
</tr>
<tr>
<td>[1–10)</td>
<td>31</td>
<td>3,400</td>
</tr>
</tbody>
</table>
Figure 18

*Density Distribution of 2019 Passenger Traffic at Population Airports*

*Note.* The dashed and solid vertical lines indicate the median of 176,092 and mean of 2,632,286 movements, respectively.
Figure 19

Quasi-Pareto Distribution of Passenger Traffic at Population Airports
Representative Sampling

Sampling Strategy. With the population finally assembled and its distribution explored, the next step consisted of subsetting a research sample from it. The sampling strategy used in the present research followed two imperatives. The first was for the sample to capture a representative share of the passenger traffic while maintaining the set of airports as small as possible for the simulation. The second imperative was for the sample to account for the uneven latitudinal distribution of climate change over the 21st century (Arnell et al., 2016; Suarez-Gutierrez et al., 2020). Unlike prior takeoff performance research that displayed a geographical bias, the present study intended to control for macroscopic variations in climate change by sampling from a representative set of the Earth’s climate zones.

Sampling by Passenger Traffic. The Pareto analysis in Table 14 and Figure 19 shows that the first three bins, which include all airports serving at least one million passengers per annum, accounted for 25.9% of population airports and 94.9% of all passenger movements in the reference year. Comparatively, the first two bins account for only 71.7% of the traffic, while the first four bins account for 99.5% of the traffic, but at the expense of more than doubling the sample size. Therefore, the first three bins were found to form an adequate sample for the research, small enough to be practical for simulation purposes and yet suitably representative of the passenger traffic. Subsetting the population of 3,400 airports assembled earlier according to this minimum traffic threshold of one million passengers returned a sample of 881 airports described in Table 15. The comparative statistics for the TODA and passenger traffic variables in the treated population and the sample are described in Appendix Table A7.
## Table 15

**Sample Size Relative to the Population**

<table>
<thead>
<tr>
<th>Sampling unit</th>
<th>$n$</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airports</td>
<td>881</td>
<td>25.9</td>
</tr>
<tr>
<td>Runways</td>
<td>2,787</td>
<td>31.0</td>
</tr>
<tr>
<td>Passenger traffic</td>
<td>8,497,031,226</td>
<td>94.9</td>
</tr>
</tbody>
</table>

## Sampling by Climate Zone

Next, a check was performed to verify that the sample is representative of the airport population’s climate zones and thus controls for latitudinal variations in the magnitude of global warming. Population and sample airports were grouped by climate zone in Table 16. The check reveals that the sample is within 2.05–4.47 p. p. of the population’s zonal distribution, except for the frigid zone where the sample under-represents the population by an order of magnitude (.2% vs. 2.6%). This discrepancy is explained by the relative scarcity of airports above one million passengers in the frigid zone (i.e., located within the Arctic and Antarctic circles). For simplicity in the subsequent analysis, a decision was made to recode the two frigid airports as temperate, considering that they are located near the Arctic circle.

## Table 16

**Zonal Distribution of Population and Sample Airports**

<table>
<thead>
<tr>
<th>Climate zones</th>
<th>Population airports</th>
<th>Sample airports</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$n$</td>
<td>%</td>
</tr>
<tr>
<td>Tropical</td>
<td>1,490</td>
<td>43.8</td>
</tr>
<tr>
<td>Temperate</td>
<td>1,820</td>
<td>53.5</td>
</tr>
<tr>
<td>Frigid</td>
<td>90</td>
<td>2.6</td>
</tr>
<tr>
<td>Total</td>
<td>3,400</td>
<td>100.0</td>
</tr>
</tbody>
</table>
Next, the zonal classification was disaggregated in Appendix Table A8 to reveal any hemispheric bias. The distribution of both population and sample airports was plotted onto world maps in Figures 20 and 21 using an equirectangular projection. The latitudinal distribution of airports was found to be negatively skewed with a northerly bias. The median latitude is approximately 781 and 713 km north of the mean latitude, which is approximately 2,774 and 2,927 km north of the equator, respectively, in the population and the sample. Therefore, half of the airports in the population and the sample are located to the north of two parallels situated 3,555 and 3,640 km north of the equator, respectively. Indicatively, the sample’s median parallel nearly intersects San Diego International Airport (KSAN) in California, Madeira Airport (LPMA) in Portugal, and Kumamoto Airport (RJFT) in Japan. The population’s northernmost airport, Svalbard Airport (ENSB) in Norway, is situated further north of the equator (78.25°N) than the southernmost airport, Guardiamarina Zañartu Airport (SCGZ) in Chile, which is south of the equator (53.93°S). This finding also applies to the sample, although the latitudinal amplitude is slightly narrower.

The binning analysis was then performed more granularly across 36 10°–latitude bins from 90°S to 90°N, and the results were plotted as histograms of airport count in Figure 22 and passenger traffic in Figure 23. The histograms confirm the negative skewness of the airport latitudinal distribution, by which more and larger airports are located in the Northern Hemisphere. They also confirm that the sample is acceptably representative of the population’s latitudinal distribution by airport count, and highly representative by passenger traffic.
Figure 20

Map of the Population Airports

Note. $N = 3,400$. The color and size aesthetics are both mapped to the traffic statistic in passengers per annum (PPA).
Figure 21

Map of the Sample Airports

*Note.* $n = 881$. The color and size aesthetics are both mapped to the traffic statistic in passengers per annum (PPA).
Figure 22

Latitudinal Distribution of Airports

Figure 23

Latitudinal Distribution of Passenger Traffic

Note. The population’s latitudinal distribution by airport count (left) and passenger traffic (right) is displayed in light gray bars. The sample’s latitudinal distribution by airport count (left) and passenger traffic (right) is displayed in overlapping dark gray bars.
**Sampling by Köppen-Geiger Zone Coverage.** The Earth’s climate is not uniform within the latitudinal bounds of a climate zone due to atmospheric circulation. Unlike the latitudinal zoning examined earlier, which correlates with solar intensity, the Köppen-Geiger system classifies the world’s climate based on air temperature and precipitation. It remains widely used today, including in climate change impact assessment studies (Beck et al., 2018).

To account for these longitudinal variations (in the geographical sense, not chronological), the Köppen-Geiger zones of the population and sample airports were computed. The climate zone information could not be identified for 128 and five airports of the population and sample, respectively. Among the remaining airports, the continental climate (C) is predominant and applies to 36.4% of the population and 51.5% of the sample airports. In traffic terms, airports under a continental climate handle 59.4% of the population traffic and 60.6% of the sample traffic. The difference between the population and sample traffic across the four other climate groups is also within one percentage point, which indicates that the sample is highly representative of the traffic by climate zone. The distribution of airports and traffic by Köppen-Geiger zone was tabulated in Appendix Table A9, and plotted in Figures 24 and 25, respectively.

**Research Variables**

Appendix Table A10 summarizes the main variables identified from the literature review and used in the present research. The climatic variables are those sourced from the CMIP6 climate simulation models to serve as inputs into the aeronautical model of takeoff performance.
*Note.* The population’s Köppen-Geiger distribution by airport count (left) and passenger traffic (right) is displayed in light gray bars.

The sample’s Köppen-Geiger distribution by airport count (left) and passenger traffic (right) is displayed in dark gray bars.
Data Collection Process

Design and Procedures

The present study collected existing data to serve as inputs into the calibration and simulation models. The climatic variables shown in Appendix Table A10 were sourced from a high-resolution CMIP6 model of Earth’s climate for the 21st century, except air density, which was derived from those same variables. The aircraft variables shown in Appendix Table A10 were sourced from the scholarly and grey literature. The data were then imported into a statistical software package for wrangling, processing, and analysis.

Apparatus and Materials

The present research used version 4.2.2 of the R language and environment for statistical computing (R Core Team, 2022) to import and treat the airport and climate data, execute the takeoff performance calibration and simulation, and generate plots. R packages used in the research are listed in Appendix Table A12. Lastly, Microsoft’s GitHub version control software was used to publish the R code.

Sources of the Data

The list of all airports worldwide with their corresponding scheduled commercial passenger traffic reported in the year 2019 came from IATA’s AirportIS database, and their geographic coordinates were sourced from OurAirports.com. Lufthansa Systems provided the list of runways and their respective TODAs. The time series of climatic variables for each airport’s coordinate came from the MPI-ESM1-2-HR model outputs hosted at the Lawrence Livermore National Laboratory’s CMIP6 node. Lastly, the geometric and propulsive characteristics of the four aircraft under consideration of the present study were taken from Sun et al. (2018, 2020b) and the technical literature.
Ethical Considerations

The present research did not use human participants nor any safety-related data attributable to any individual or company. Therefore, Institutional Review Board (IRB) approval was unnecessary. Furthermore, the only proprietary data used in the present research were the TODAs supplied by Lufthansa Systems. They were excluded from the present document and the GitHub repository to comply with non-disclosure.

Data Analysis Approach

The present research was characterized by its reliance on large datasets and onerous computational requirements. The climate data alone comprised 2.2 billion observations weighting 355 GB upon download and 236 GB after parsing. The number of unique takeoffs to be simulated amounted to 1.8 billion. Each one was iterated an average of 32.55 times for a total of nearly 58 billion distinct simulated takeoffs.

Several data analysis approach decisions were made to accommodate the large data size. The first was to use a local database engine, rather than flat CSV files, to store the airport population, the imported climate data in long format, the treated climate data in wide format, the takeoff mass and TODR calibration data, and the results of the takeoff simulation. Second, the resulting tables, which occupy 509 GB in total, were indexed on several key columns to vastly reduce subsequent query times. Third, in cases where the data size exceeded the amount of random-access memory available, data analysis was performed in the database engine itself using Structure Query Language (SQL), and the results were passed to R, instead of loading the data into R for downstream processing. Fourth, the functional and procedural programming paradigms used in building the R scripts followed a data-oriented approach by taking advantage of R’s efficient vectorized
operations and splitting the data in memory-optimal ways. The *data.table* package (Dowle & Srinivasan, 2022) was favored over R’s native data frames for its superior performance and ability to assign data by reference. Lastly, the *parallel* package (R Core Team, 2022) was used to distribute the intensive workload across multiple logical cores, which is not the default behavior in R.

**Summary**

The present research sourced and processed climate data from a high-resolution CMIP6 model to characterize the centurial near-surface environmental conditions prevailing at a commercially and geographically representative sample of 881 worldwide airports above one million passengers. Separately, a calibration model was designed and supplied with published OEM takeoff performance data to find optimal values for the lift coefficient of four common turbofan passenger aircraft in a takeoff configuration under ISA conditions. The calibrated results were then passed to a direct takeoff-dynamics simulation model designed from first principles and using the step integration method.

The model iteratively simulated nearly 1.8 billion unique takeoffs at the minimum permissible thrust setting and MTOM. When the resulting TODR exceeded the TODA, the takeoff thrust was increased gradually up to TOGA, and the takeoff iterated each time. At TOGA, the takeoff mass was then decreased gradually to its BELF value by the equivalent of one passenger at a time, and the takeoff was again simulated iteratively. If the TODR fit within the TODA, its value was recorded to the database and no further iteration was performed. If not, the final TODR value was recorded when the takeoff mass reached its BELF floor. In total, 58 billion takeoff iterations were performed.
Chapter IV: Results

The present chapter reports the findings from the research that was conducted in accordance with the methodology described in Chapter III. The chapter is divided into three parts. The first describes the longitudinal changes between the years 2015 and 2100 in the input (climatic) variables returned by the MPI-ESM1-2-HR model at the sample airports, globally and by climate zone. The second presents attendant changes in output (takeoff performance) variables returned by the takeoff simulation model. The third and final part answers the three research questions formulated in Chapter I.

Climate Change at the Sample Airports

Prior to answering the research questions, it is useful to contextualize the 21st-century changes in takeoff conditions at the sample airports. As a reminder, the present research did not produce any original climate data but instead leveraged extant data from a published model. Therefore, the present study’s ability to describe climate change at the sample airports is merely a methodological byproduct of the research rather than the answer to a research question. Nevertheless, those changes are worthy of examination because they influence the output variables returned by the takeoff simulation model. The maximum, mean, and minimum statistics of five climate variables were examined at all sample airports globally and for the temperate and tropical zones individually. These variables are the near-surface air temperature \((\text{tas})\), pressure \((\text{ps})\), relative humidity \((\text{hurs})\), air density \((\rho)\), and headwind speed \((\text{hdw})\). As explained in Chapter III, \(\rho\) was numerically derived from \(\text{tas}, \text{ps}\), and de-supersaturated \(\text{hurs}\); and \(\text{hdw}\) was triangulated from the eastward \((\text{uas})\) and northward \((\text{vas})\) wind components relative to the active runway at the time of each observation (i.e., the one with the strongest headwind).
Figure 26 provides a global overview of the annual changes in the mean statistic of those five climatic variables across the four tier-1 SSPs for the 2015–2100 study period at all sample airports. The thin black lines represent the annual mean of all six-hourly observations at the sample airports. The thick, blue-colored lines are a locally estimated scatterplot smoothing (LOESS) with a default span value of $\alpha = .75$ meant to dampen the sub-decadal volatility and enhance the readability of trends from the otherwise noisy signal. The grey area around the LOESS is the confidence interval at 95%.

All climatic observations discussed in this chapter and the next are based on those LOESS values. Likewise, both chapters only report results for the middle SSP2–45 and SSP3–70 pathways for conciseness and plausibility. However, Appendices A and B provide climatic variable values for all SSPs for complete reference. Appendix Table A13 tabulates the net difference observed in the LOESS values between the years 2015 and 2100 for each SSP and climate zone. Appendix Figures B1 through B15 show the annual average values for the maximum, mean, and minimum statistics of the five climate variables’ LOESS estimates, also faceted by SSP and climate zone. Appendix Figures B16 through B30 plot the net difference between the years 2015 and 2100 in each climate variable by SSP onto choropleth maps of the sample airports worldwide. The remainder of this section reports the observations about changes in the climatic conditions at sample airports through the 21st century.
Figure 26

Changes in the Mean Climatic Variables at the Sample Airports (2015–2100)
Changes in the Near-Surface Air Temperature

Mean. Figure 26 illustrates that the mean $tas$ was found to increase by the year 2100 across all SSPs and climate zones, which is consistent with expectations of global warming. The mean $tas$ was found to correlate perfectly with the SSPs in that it increases alongside positive radiative forcing in every climate zone. Worldwide, the mean $tas$ was found to rise by an average of 1.6 °C–3.1 °C over the 2015 baseline under the SSP2–45 and SSP3–70 middle pathways, respectively. Temperate airports were found to experience greater absolute warming with an average increase in mean $tas$ of 1.7–3.2 °C compared to 1.4–2.8 °C for tropical airports under both SSPs.

The top ten airports with the highest combined increase in mean $tas$ across the two middle SSPs were also examined and found to be latitudinally concentrated in the same temperate region of southern Siberia. Six are in central and eastern Russia (UNOO, UEER, UNNT, USTR, USCC, USSS), one in Kazakhstan (UACC), one in Mongolia (ZMUB), and two in northeastern China (ZBLA, ZYCC). They are shown as darker points in the respective SSP facets of Appendix Figure B17. These airports were found to experience a significant centurial increase in mean $tas$ of 2.5–5.4 °C, on average, under the two middle SSPs, and as much as 6.2 °C for UNOO (Omsk Tsentralny Airport) under SSP3–70.
**Maxima and Minima.** Several takeoff performance studies reviewed in Chapter II observed only summer days, in which temperature maxima typically occur, because they “capture the vast majority of weight-restriction events” (Coffel & Horton, 2015, p. 95). Congruent with these studies, mean changes to the maximum annual $tas$ were examined and plotted to Appendix Figures B1 and B16. The maximum $tas$ was found to increase by a greater absolute amount than the mean $tas$, with a range of 2.0–4.7 °C at temperate and 3.1–3.2 °C at tropical airports, on average, under the two middle SSPs. UNOO airport in Omsk, Russia, remains the leading airport in terms of magnitude of the change, with an increase in maximum $tas$ of 5.9 °C under SSP2–45 and as much as 11.3 °C under SSP3–70. Other top ten airports include CYEG in Canada, KBDL and KGEG in the United States, and LFBO in France, all in the temperate zone. These airports were observed to be exposed to summer $tas$ peaks potentially 4.2–7.9 °C above their 2015 baseline by the year 2100, on average, under the two middle SSPs.

Likewise, the minimum annual $tas$ recorded an even greater amount of warming of 0.5–9.2 °C at temperate and 1.8–5.2 °C at tropical airports. As a result, 27 airports under SSP2–45 and 61 airports under SSP3–70 will no longer experience subzero minimum $tas$ in winter, and attendant icing conditions, by the end of the century. A geographically diverse set of temperate airports was found to comprise the top ten for the largest increase in minimum $tas$. This set includes four airports in Scandinavia (ENBO, ENVA, EFOU, and ESPA), three in Northeastern America (CYUL, KBTV, and CYOW), and three in Central Asia (USTR, UACC, and UEEE). Those airports will experience an average increase in mean $tas$ of 2.5–10.8 °C by the year 2100. Appendix Figures B3 and B18 plot the changes in minimum $tas$ for all sample airports worldwide.
Changes in the Near-Surface Air Pressure

**Mean.** Changes to the near-surface air pressure $ps$ are relevant to this study because of their influence on the air density $\rho$ evidenced in Equation 2. The changes in mean $ps$ by the year 2100 are tabulated in Appendix Table A13 and plotted in Appendix Figure B5 by SSP and climate zone. The mean $ps$ was found to increase almost imperceptibly, by half an hPa, under the two middle SSPs. The increase, however modest, is slightly greater at temperate airports compared to tropical ones. Some airports will experience a rise in $ps$ well above average, as evidenced by the darker points in the choropleth map in Appendix Figure B20. Among them, Lhasa Gonggar Airport (ZULS), an elevated airport (3,570 m) in the Tibet Autonomous Region with the lowest baseline air pressure of the entire sample, will experience the strongest increase in mean $ps$ by the year 2100, of 2.3 and 3.9 hPa, respectively, under SSP2–45 and SSP3–70. Conversely, 178 airports under SSP2–45 and 149 under SSP3–70 will witness a decrease in mean $ps$, most pronounced at Siberian airports USRR and UEEE with a centurial reduction of no more than 1.3 hPa.

**Maxima and Minima.** As was the case for $tas$, the maximum and minimum $ps$ values were observed to fluctuate more than the mean. Under SSP2–45, the maximum $ps$ will increase by as much as 4.1 hPa at both Beijing airports (ZBAA and ZBAD). All top ten airports by maximum $ps$ amplitude are in China. Under SSP3–70, one Canadian airport (CYQR) will see its maximum $ps$ rise by as much as 5.6 hPa, followed by Siberian airports. Lastly, the minimum annual $ps$ at airports is marked by the greatest amplitude. Japanese and Korean airports will see the highest increase under SSP2–45 (up to 7.7 hPa), and Scandinavian and Baltic airports under SSP3–70 (up to 11.3 hPa).
Changes in the Near-Surface Relative Humidity

**Mean.** The relative humidity $\textit{hurs}$ is the third determinant of $\rho$ alongside $\textit{tas}$ and $\textit{ps}$. Annual changes to the mean $\textit{hurs}$ across all SSPs and climate zones are displayed in Appendix Table A13 and plotted in Appendix Figure B8 by SSP and climate zone. The mean $\textit{hurs}$ was found to decrease by the end of the century in every combination of climate scenario and zone. Globally, $\textit{hurs}$ will decrease by 1.5–2.1 p. p. under the middle scenarios. The change will be two to four times more pronounced at temperate airports than at tropical ones. Under SSP2–45, Central European and Chinese airports will experience the strongest reduction, led by Zagreb Franjo Tuđman Airport (LDZA) at -9.3 p. p. Under SSP3–70, the mean $\textit{hurs}$ will decrease the most at South American airports, by as much as 11.7 p. p. at Manaus International Airport (SBEG). Conversely, a minority of airports will see their mean $\textit{hurs}$ rise by as much as 5.3–5.9 p. p. under the two middle SSPs, primarily in Northern India and Eastern Africa. The choropleth map in Appendix Figure B23 illustrates those changes visually.

**Maxima and Minima.** Unlike $\textit{tas}$ and $\textit{ps}$, $\textit{hurs}$ maxima were found to decrease less than the mean and by no more than half a percentage point on average under any scenario, but with significant variance. Airports located around the Persian Gulf and the Red Sea, in particular, will see the greatest decreases in annual $\textit{hurs}$ maxima of up to 8.1–8.9 p. p. under the two middle SSPs. $\textit{hurs}$ minima, on the other hand, will decrease more sharply than the mean under every scenario. Airports in continental Europe, and Germany in particular, will see the greatest change under SSP2–45, while South American and Siberian airports will see the most drastic reduction under SSP3–70 of up to 31.6 p. p. Appendix Figures B22–B24 plot those changes by airport onto a world map.
Changes in the Near-Surface Air Density

Mean. The near-surface air density $\rho$ derived from its three constituents $tas$, $ps$, and $hurs$ returned by the MPI-ESM1-2-HR model was examined next. Mean changes in annual airport-level observations of $\rho$ in kg/m³ aggregated by SSP and zone are shown in Appendix Table A13 and Appendix Figure B11. The mean $\rho$ was found to decrease slightly by $6.5–12.6 \times 10^{-3} \text{kg/m}^3$ globally under the two middle SSPs. The reduction is more pronounced at temperate airports than it is at tropical ones, but the mean difference is marginal. Across all zones, the mean change is less than one percent from the sea-level ISA $\rho$ of 1.225 kg/m³. Siberian airports will experience the greatest reduction in mean $\rho$ under the two middle SSPs. Only one airport in the sample, Carrasco Airport in Uruguay (SUMU), was observed to experience a slight increase in mean $\rho$ under SSP2–45. Appendix Figure B26 shows a choropleth map of the changes in mean $\rho$ at the individual airport level, faceted by SSP.

Maxima and Minima. Changes in annual $\rho$ maxima are shown in Appendix Figures B10 and B25. The maximum $\rho$ was found to decrease by a greater amount than the mean $\rho$ by the end of the century with a range of $7.5–17.1 \times 10^{-3} \text{kg/m}^3$ under the middle scenarios, which is still less than 1.4% of the sea-level ISA datum. High-latitude airports such as Reykjavík–Keflavík Airport in Iceland (BIKF) and Québec City Jean Lesage Airport in Canada (CYQB) will see the most pronounced reduction in maximum $\rho$. Finally, the minimum $\rho$ was found to also decrease slightly overall, approximately on par with the mean in absolute terms. Siberian airports will be disproportionately affected, however, with as much as $45.4 \times 10^{-3} \text{kg/m}^3$ of decrease at Tsentralny Airport in Omsk, Russia, by the year 2100 under SSP3–70.
Changes in the Near-Surface Headwind

**Mean.** Lastly, the present study examined centurial changes to the prevailing headwinds $hdw$ trigonometrically derived from the active runway’s heading at the time of each observation and the $uas$ and $vas$ wind components returned by the MPI-ESM1-2-HR model. Appendix Table A13 and Appendix Figure B14 show those changes in m/s averaged annually across all sample airports by SSP and climate zone. The mean $hdw$ was observed to remain virtually invariant throughout the century, with a negligible increase of no more than .1 m/s at tropical airports under the two middle SSPs and no measurable change globally. Increases in mean $hdw$ in excess of .1 m/s, but not exceeding 1.6 m/s, were observed at 153 airports, and most strongly at Indonesian airports (WARR, WARA) and U.S. airports (KBDL, KBUF) under the two middle SSPs. Conversely, some airports will experience a modest decrease in mean $hdw$ of no more than .8 m/s under SSP2–45 and SSP3–70, including airports in Ireland and the UK (EICK, EGGD, EGNX), China (ZHHH), and Western Europe (LEXJ, LFQQ). The geographical patterns of change in mean $hdw$, however weak, are evidenced in Appendix Figure B29.

**Maxima and Minima.** The maximum annual $hdw$ was found to oscillate slightly and inconclusively, decreasing by as much as .4 m/s at temperate airports under SSP3–70 and increasing by no more than .2 m/s at tropical airports under SSP2–45. Appendix Figures B13 and B15 illustrate those changes by zone throughout the observation period, and B28 and B30 show a map of the net changes by sample airport in the year 2100 relative to the 2015 baseline.
Takeoff Performance at the Sample Airports

The present section examines the temporal changes in simulated takeoff performance at the sample airports to pave the way for answering the research questions. Takeoff outcomes (i.e., whether a takeoff could be successfully performed for the given runway length and environmental conditions) were reviewed first. Among the subset of successful takeoffs, temporal changes in the rate of minimum-thrust takeoffs and in the TODR were also described to contextualize the answer to the research questions.

As a methodological reminder, every one of the 1.77 billion simulated takeoffs was initiated at a thrust setting of 75% TOGA. As shown in Figure 27, only 15.1% of all takeoffs completed successfully (i.e., the TODR fit within the TODA) using this baseline thrust. For the remaining 84.9%, the thrust setting was iteratively increased in one-percentage-point increments as required. Eventually, another 4.0% of all takeoffs were completed successfully at TOGA (i.e., maximum thrust), and 40.0% completed using some intermediate thrust setting between those two extremes. Among the remaining 40.9% of all takeoffs that were yet to complete, the payload was iteratively decreased in one-passenger decrements until the BELF was reached. Some amount of payload removal above BELF was enough to complete another 17.3% of all takeoffs. In all those successful cases, amounting to a cumulative 76.4% of all takeoffs, the final thrust setting (expressed as a percentage of TOGA) and the final payload removal (expressed in passenger headcount) were recorded to the research database, and their changes relative to the 2015 baseline values were plotted in Figures 34–39 and tabulated in Appendix Table A14. What remained were 23.6% of all takeoffs that could not be completed under any mix of thrust increase and economically sensible payload removal.
Figure 27

Summary of the Takeoff Simulation Outcomes

<table>
<thead>
<tr>
<th>Category</th>
<th>Successful takeoffs:</th>
<th>Successful takeoffs at 75% TOGA:</th>
<th>Successful takeoffs at 75–100% TOGA:</th>
<th>Successful takeoffs at 100% TOGA w/o payload removal:</th>
<th>Successful takeoffs at 100% TOGA w/ payload removal:</th>
</tr>
</thead>
<tbody>
<tr>
<td>All simulated takeoffs:</td>
<td>1,352,594,361 (76.4%)</td>
<td>267,506,321 (15.1%)</td>
<td>708,905,011 (40.0%)</td>
<td>71,469,172 (4.0%)</td>
<td>304,713,857 (17.3%)</td>
</tr>
<tr>
<td>Successful takeoffs at 100% TOGA:</td>
<td>376,183,029 (21.3%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Successful takeoffs at 100% TOGA w/o payload removal:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unsuccessful takeoffs:</td>
<td>418,469,367 (23.6%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Values shown combine narrowbody and widebody aircraft, all SSPs, and all climate zones for the entire simulation period 2015–2100. Details for each of these dimensions are tabulated in Appendix Table A14.
Changes in the Takeoff Outcomes

As shown in Figure 27, approximately 418 million (23.6%) of all simulated takeoffs across the 2015–2100 period were unsuccessful (i.e., the resulting TODR still exceeded the TODA despite the thrust being iteratively increased up to TOGA and then payload being removed down to the BELF). Overall, narrowbody aircraft (Airbus A320neo and Boeing 737 MAX 9 averaged together) were observed to experience fewer unsuccessful takeoffs than widebody aircraft (Airbus A350–900 and Boeing 787–9) by a factor of approximately three due to their lower takeoff mass. Of major relevance to this study, Appendix Table A14 and Appendix Figures B31–B32 show that the share of unsuccessful takeoffs for both aircraft types and climate zone rises in the 21st century, albeit modestly, as a result of changes in the atmospheric conditions described earlier.

The proportion of failed takeoffs was found to correlate positively with the positive radiative forcing and warming intensity of the SSPs. The centurial increase in unsuccessful takeoffs was found to be in the range of 0.2–0.6 p. p. for narrowbody and 0.5–1.5 for widebody aircraft under SSP2–45 and SSP3–70, respectively. Zonal results show that temperate airports experience a greater rise in unsuccessful takeoffs than tropical ones by an average factor of 1.5. Only two South American airports (SPQT, SBCG) and two Indonesian airports (WILL, WAWW) will experience a double-digit increase (in p. p.) in unsuccessful narrowbody and widebody takeoffs, respectively, under the two middle SSPs. Conversely, several airports will see a decrease in unsuccessful takeoffs, albeit at an even smaller, single-digit amount of change (in p. p.) by the end of the 21st century. Figures 28–29 illustrate those changes visually; however, no obvious geographical distribution pattern emerges.
Figure 28

Figure 29

Changes in the Thrust Outcomes

The simulation returned 1.35 billion successful takeoffs (76.4% of all simulated takeoffs) for which the TODA equals or exceeds the simulated TODR. Successful takeoffs can complete at any thrust ranging from 75% to 100% of TOGA. Among them, 268 million (15.1% of all and 19.8% of successful takeoffs) completed at the minimum thrust setting of 75% TOGA, 376 million (21.3% of all and 27.8% of successful takeoffs) completed at the maximum thrust setting of 100% TOGA, and 709 million (40.0% of all and 52.4% of successful takeoffs) completed at some intermediate thrust. Minimum-thrust takeoffs are worth examining because they are the most economical for airlines.

The simulation outputs shown in Appendix Table A14 and Appendix Figures B35–B36 exhibit a slight decrease in the percentage of minimum-thrust takeoffs across all SSPs in the 21st century for both narrow- and widebody aircraft. The mean decrease is modest overall and does not exceed 0.8 percentage point for narrowbodies and 0.2 for widebodies under the two middle SSPs. The reduction is more pronounced at temperate airports than at tropical ones by a factor of two. None of the airports in the sample were observed to experience more than a single-digit decrease in minimum-thrust takeoffs, which highlights the weakness of the effect. Southeast Asian airports (WIEE, VLVT, WILL, WALL) will see the most change for narrowbody operations, while no pattern emerges among widebody takeoffs under the two middle SSPs. Conversely, some airports will see an increase in minimum-thrust takeoffs, but by a modest amount not exceeding 4.7 p. p. in the most pronounced case (MHLM airport in Honduras).

Figures 30–31 plot the airport-level changes in minimum-thrust takeoffs by the year 2100 relative to the 2015 baseline.
Figure 30

Figure 31

Changes in the Mean Takeoff Distance

As introduced in Chapter I, the net decrease in the near-surface air density $\rho$ that is expected from global warming is, in principle, equivalent to a takeoff weight penalty being imposed onto the aircraft, which increases the TODR in turn. Congruent with the observations made earlier of a modest reduction in $\rho$, the mean TODR of successful takeoffs was found to lengthen by a small amount in almost every combination of SSP, climate zone, and aircraft type, as shown in Appendix Table A14 and Appendix Figures B41–B42. Two exceptions involve widebody aircraft at tropical airports, for which the mean TODR was found to decrease slightly, by no more than 1.7 m.

For narrowbody aircraft, the mean TODR was otherwise found to increase by 5.7–11.4 m globally under SSP2–45 and SSP3–70, respectively, which is only 0.19–0.38% of the mean TODA of 2,973 m across all sample airports. Zonally, the added TODR is greater at temperate airports (7.4–13.2 m) than at tropical ones (1.8–7.0 m). For widebody aircraft, the global increase is less pronounced, ranging from 3.0 to 5.8 m globally (0.1–0.2% of the mean TODA across all sample airports). The zonal contrast is greater, however, considering that the mean TODR was observed to increase by 8.5–11.2 m at temperate airports and decrease by 1.6–1.7 m at tropical ones. Under the two middle SSPs, the greatest increases in TODR were observed at Birmingham–Shuttlesworth Airport in the US (KBHM) with 102.1 m and Vancouver Airport in Canada (CYVR) with 145.1 m, respectively, for narrowbody and widebody takeoffs. Some airports will experience shorter TODR, though not by as much; the most decrease was observed at Lisbon Airport (LPPT) with 99.1 m and 175.8 m reductions in TODR for narrowbody and widebody takeoffs, respectively. Changes are shown in Figures 32–33.
Figure 32

*Map of Changes in the Mean Narrowbody TODR in m*
Figure 33

Map of Changes in the Mean Widebody TODR in m
Answers to Research Questions

Answer to Research Question 1

The first research question examined in this study relates to the amount of additional takeoff thrust required to compensate for changes in environmental conditions throughout the remainder of the 21st century. As shown in Figure 27, 15.1% of all takeoffs successfully completed at the minimum thrust of 75% TOGA, 40.0% at some intermediate thrust setting, 4.0% at maximum thrust exactly, and 17.3% at maximum thrust plus some amount of payload removal. In total, 76.4% of all 1.8 billion simulated takeoffs had a successful outcome. The final thrust setting of each one, expressed as a percentage of TOGA, was recorded to the research database for further examination.

The mean thrust of successful takeoffs was found to increase under all SSPs, climate zones, and aircraft types, but only marginally so. Figure 34 shows that the mean takeoff thrust of narrowbody aircraft will increase in both climate zones and globally, by 0.1–0.2 p. p. under the two middle SSPs by the year 2100. The changes are slightly more pronounced in widebody aircraft with an increase of 0.1–0.3 p. p, as apparent in Figure 35. At the airport level, however, there is significant variance around that mean. The boxplot in Figure 36 summarizes the distribution of the net difference in takeoff thrust by airport between the years 2100 and 2015, grouped by climate zone and aircraft type. Some outliers were removed from the plot to accommodate a narrower vertical scale and enhance readability. The corresponding values for the global zone, including those of minimum and maximum outliers, are tabulated in Table 17. The distribution shows a small positive bias correlated with the positive radiative forcing of the SSPs, by which 75% or more of the centurial changes in thrust are between zero and one p. p.
Figure 34

Figure 35

Changes in the Mean Widebody Takeoff Thrust in p. p.
Figure 36

Distribution of Mean Takeoff Thrust Changes in p. p.
Table 17

*Descriptive Statistics of the Changes in Mean Takeoff Thrust*

<table>
<thead>
<tr>
<th>Statistic</th>
<th>SSP1‒26</th>
<th>SSP2‒45</th>
<th>SSP3‒70</th>
<th>SSP5‒85</th>
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<tbody>
<tr>
<td></td>
<td>NB</td>
<td>WB</td>
<td>NB</td>
<td>WB</td>
</tr>
<tr>
<td>Minimum</td>
<td>-5.2</td>
<td>-1.7</td>
<td>-5.9</td>
<td>-1.2</td>
</tr>
<tr>
<td>25&lt;sup&gt;th&lt;/sup&gt; quantile</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Median</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>75&lt;sup&gt;th&lt;/sup&gt; quantile</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>Maximum</td>
<td>4.4</td>
<td>2.0</td>
<td>5.7</td>
<td>1.3</td>
</tr>
</tbody>
</table>

*Note.* Values are for all sample airports globally (both climate zones combined). The mean is plotted in Figures 34 and 35. The other statistics are plotted in the Figure 36 boxplot. NB = narrowbody, WB = widebody.

The distribution also reveals notable outliers beyond the standard 1.5 times interquartile range (IQR) delimited by the whiskers in Figure 36. Under the two middle SSPs, the mean increase in takeoff thrust falls outside the IQR at 13.5–16.6% of sample airports for narrowbody takeoffs and 16.6–20.0% for widebody takeoffs. Maximum outliers include a 5.7 p. p. mean thrust increase for narrowbody takeoffs at Adisutjipto Airport in Indonesia (WAHH) and a 3.1 p. p. increase for widebody takeoffs at Lisbon Humberto Delgado Airport in Portugal (LPPT) under SSP2‒45 and SSP3‒70, respectively. Conversely, some airports will experience a *decrease* in mean thrust. Minimal outliers include a 6.4 p. p. thrust reduction for narrowbody takeoffs at José Joaquín de Olmedo Airport in Ecuador (SEGU) and a 1.2 p. p. reduction for widebody takeoffs at Vancouver Airport in Canada (CYVR).
**Answer to Research Question 2**

The second research question examined in this study pertains to the amount of revenue payload that must be removed from the aircraft when even the maximum thrust setting proves insufficient to perform the takeoff. As shown in Figure 27, 21.3% of all takeoffs or 27.8% of successful takeoffs were performed at TOGA thrust. Among those, 81.0% further required some amount of payload removal to satisfy the condition that the TODR does not exceed the TODA. In those cases, the excess takeoff mass to be removed was recorded to the research database in passenger headcount terms using an industry-standard mass-to-passenger conversion factor discussed in Chapter I and shown in Table 4. Net changes to the annual mean passenger removals were plotted by SSP, climate zone, and aircraft type in Figures 37–38, and the net differences between the years 2100 and 2015 were tabulated in Appendix Table A14.

It results from the analysis that the global mean payload removal by the end of the century exceeds that of the 2015 baseline year by no more than 0.4 passenger for narrowbody and 1.1 passengers for widebody takeoffs under the two middle SSPs. Narrowbody takeoffs will experience a slightly greater increase in passenger removals at temperate airports, whereas widebody takeoffs will see more payload restrictions at tropical airports. Changes to the global mean passenger removals by the year 2100 relative to the year 2015 are summarized in the boxplot in Figure 39, with some outliers removed for readability, and tabulated in Table 18. The distribution shows positive skewness with at least 75% of observations resulting in an increase in passenger removals by as many as 2.9 for widebody takeoffs under SSP3–70 at the 75th quantile.
Figure 37

Changes in the Mean Narrowbody Passenger Removals
Figure 38

Changes in the Mean Widebody Passenger Removals
Figure 39

Distribution of Mean Passenger Removals
Table 18

*Descriptive Statistics of the Changes in Mean Passenger Removals*

<table>
<thead>
<tr>
<th>Statistic</th>
<th>SSP1–26</th>
<th>SSP2–45</th>
<th>SSP3–70</th>
<th>SSP5–85</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
<td>WB</td>
<td>NB</td>
<td>WB</td>
</tr>
<tr>
<td>Minimum</td>
<td>-34.8</td>
<td>-38.2</td>
<td>-35.5</td>
<td>-32.5</td>
</tr>
<tr>
<td>25&lt;sup&gt;th&lt;/sup&gt; quantile</td>
<td>0.0</td>
<td>-0.1</td>
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<td>0.0</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>Median</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.0</td>
</tr>
<tr>
<td>75&lt;sup&gt;th&lt;/sup&gt; quantile</td>
<td>0.4</td>
<td>1.1</td>
<td>0.6</td>
<td>1.5</td>
</tr>
<tr>
<td>Maximum</td>
<td>33.6</td>
<td>42.8</td>
<td>34</td>
<td>36.1</td>
</tr>
</tbody>
</table>

*Note.* Values are for all sample airports globally (both climate zones combined). The mean is plotted in Figures 37 and 38. The other statistics are plotted in the Figure 39 boxplot. NB = narrowbody, WB = widebody. Negative passenger removals (minimum row) are equivalent to *additional* payload that the aircraft can lift at takeoff, relative to the year 2015.

Once again, multiple outliers were observed beyond the 1.5 × IQR whiskers. The percentage of sample airports with passenger removals in excess of this boundary is 12.4–17.9% for narrowbody and as many as 18.7–42.6% for widebody takeoffs under the two middle SSPs. St. Pete–Clearwater Airport in Florida (KPIE) and Sultan Thaha Syaifuddin Airport in Indonesia (WIJJ) will experience as many as 4.1 and 36.1 narrowbody passenger removals, respectively, under the two middle SSPs. Likewise, Jay Prakash Narayan Airport in India (VEPT) and Sibu Airport in Malaysia (WBGS) will see a *decrease* in passenger removals by as many as 35.5 and 32.5, respectively, compared to payload restrictions observed in the year 2015.
Answer to Research Question 3

The third and last research question that the present study ambitioned to address pertained to expressing the operational impacts of climate change on takeoff performance in economic terms. As observed earlier, the takeoff thrust and payload removal variables were found to increase negligibly by the end of the century because their underlying determinants $\rho$ and $h_{ddw}$ will themselves remain nearly stable on average. A centurial increase in the mean takeoff thrust of 0.1–0.3 percentage point under the two middle SSPs, as shown in Appendix Table A14, is not a matter of economic concern for air operators. Likewise, the average removal of one to two passengers from narrowbody and widebody aircraft respectively, after rounding up, is not material to the operators over the long run and falls within the error margin of the climatic and takeoff simulation models.

Separately, the net increase in the mean $tas$ by 1.6–3.1 °C under the two middle SSPs will raise the engine combustor’s temperature, as measured by the EGT, by an equivalent amount at takeoff. It is unlikely that such a slight increase will cause significant marginal severity to the powerplants. Attempts to verify that assumption by quantifying the associated maintenance costs were unsuccessful as engine OEMs refused to disclose severity curves out of intellectual property concerns.

Lastly, the issue of rising $tas$ may be of greater relevance to individual airports where the annual maxima may exceed the environmental envelope’s boundary. As shown in Appendix Table A13, the average peak annual $tas$ was observed to rise by as much as 2.9–3.7 °C at tropical and temperate airports, respectively, under the middle SSPs. For example, 19 airports (all but four in the Middle East) will experience peak $tas$ in excess of 50 °C in the year 2100 under SSP3–70, compared to only seven airports in 2015.
Reliability and Validity

Reliability

Reliability “refers to the consistency of coding and measurement” and is a necessary condition for validity, although not sufficient (Vogt et al., 2012, p. 320). In the context of the present research, reliability refers to the consistency over multiple runs of outputs returned by the main research instrument, which is the takeoff simulation model.

To facilitate the convenient reproducibility of the present study and the consistency of results over repeat experiments, an early design decision was made to build the entire research workflow using a programming language with wide academic adoption, R, and additional packages that extend its capabilities, as listed in Appendix Table A12. Similarly, a popular relational database management system (RDBMS), MySQL, was chosen for recordkeeping. The computational workflow consists of a sequence of R scripts that serve to initialize the necessary constants, build, and describe the sample taken from the population of worldwide airports, download and parse the climate data from the ESGF repository, derive second-order input variables such as \( \rho \) and \( h_{dv} \), design and calibrate the takeoff simulation model against OEM data, iteratively perform the takeoff simulations, and analyze and plot the output variables. Each script is amply commented to advise future researchers on its features. What motivated this research design decision is that capturing and sharing information about the computational environment and steps required to collect, process, and analyze data is known to improve reproducibility (National Academies of Sciences, Engineering, and Medicine, 2019) by enabling other researchers to replicate and verify all the steps on their own hardware using only free and open-source software (FOSS).
Furthermore, the R code was published under a permissive license at Microsoft Corporation’s GitHub (https://github.com/TheAviationDoctor/PhD/), itself based on the Git version control FOSS. Git is increasingly adopted by scientists as part of their reproducibility toolbox (National Academies of Sciences, Engineering, and Medicine, 2019) and its use is considered best-practice for scientific computing (Wilson et al., 2014). Lastly, the open-sourcing of the R code developed for this research is consistent with the approach followed by the Open Aircraft Performance Model (OpenAP) and Toolkit (Sun et al., 2020b) from which this research borrows some components for its first-principles takeoff simulation model. Publishing the code not only enhances reproducibility, but also offers the opportunity for other researchers to scrutinize, fix, improve, or expand its capabilities to the benefit of future research on takeoff performance. Independently from its outputs, the open-sourced code itself constitutes one of the theoretical contributions of this study to the takeoff performance body of knowledge.

The climatic data was sourced from a public CMIP6 model, MPI-ESM1-2-HR, whose code (https://code.mpimet.mpg.de/projects/mpi-esm-users/files) and data (https://esgf-node.llnl.gov/search/cmip6/) are publicly available for download at no cost. The exact search parameters needed to retrieve the data sets in question are provided in Chapter III for reproducibility purposes. The research database itself, comprised of eight MySQL tables totaling 322 GB of data including the 1.77 billion simulated takeoff outcomes, was too large to be made available online, but can be requested electronically from the principal author of the present study, or replicated by executing the R code.
Internal Validity

Internal validity refers to “the extent to which a study’s result can be correctly attributed to the treatment or independent variable” (Vogt et al., 2012, p. 53). In the context of the present study, this means whether conclusions drawn in this chapter about the effects of climate change on takeoff performance are accurate and justified. To motivate such a claim in the positive, the instrumental validity of the takeoff simulation model was examined in the following section.

Takeoff Model Validity. A first-principle takeoff simulation model was developed for four common air transport aircraft to return the output variables needed to answer the research question, such as the TODR, the final thrust setting, and, where applicable, the payload removal necessary to complete the takeoff. Three steps were taken to enhance the validity of this model’s outputs. The first was to borrow model elements from the extant peer-reviewed literature, including Sun et al. (2020b) and Gratton et al. (2020). These elements include, inter alia, thrust coefficients for the calculation of the propulsive force and simplifying trigonometric assumptions related to the initial climb. The second step was to calibrate the model against archival takeoff data published by the aircraft OEMs, using $C_L$ as the adjustment variable to achieve an optimum stepwise fit between the observed and simulated TODRs for each aircraft type and takeoff mass. The third step was to develop a second takeoff performance model in Microsoft Excel, distinct from the R code but following the same logic, to compare their respective output values for a sample of input conditions and thus rule out possible errors in the coding itself. The results were found to be consistent between the R and Excel models, and the latter was also published to GitHub for the benefit of other researchers.
External Validity

External validity refers to the “generalizability of the findings to cases other than those you have studied, from samples to generalizations about populations” (Vogt et al., 2012, p. 323). In the present context, this means the generalizability of the results to other airports, aircraft, and future climate scenarios. This section examines each one in turn.

Population Generalizability. The present research examined a sample of 881 airports taken from a larger population of 3,400 airports worldwide that reported commercial traffic in the year 2019. The sampling methodology described in Chapter III was meant to ensure, inter alia, that the sample is representative of the climatic distribution of the population airports. The sample’s distribution by latitudinal climate zone (frigid, temperate, and tropical) was found to be within 4.47 p. p. (except for the frigid zone, which was later recoded as temperate) of the population’s distribution. Similarly, the sample’s distribution by Köppen-Geiger zone was found to be within one p. p. of the population’s distribution. The present study’s findings are, therefore, likely generalizable to the larger set of worldwide commercial airports to a high degree of confidence on account of the climatic similarity between sample and population.

One limitation to consider, however, is that the 2,519 population airports that were excluded from the sample (i.e., those with fewer than one million passengers in the reference year 2019) are, on average, smaller aerodromes with less-developed infrastructure. Those airports have a mean TODA of 2,109 m and 1.23 physical runway on average, compared to 2,973 m and 1.58 physical runway for the sample airports. The shorter runways do not affect the generalizability of the findings, but the fewer runway options reduce the likelihood of a successful takeoff under adverse wind conditions.
**Aircraft Generalizability.** One aspect of the ecological validity of the present research is whether the findings are applicable to the real-world setting in which airlines operate, including the type of aircraft that they use. A research design decision was made to model the performance of only two narrowbody (Airbus A320neo and Boeing 737 MAX 9) and two widebody aircraft (Airbus A350–900 and Boeing 787–9) whose respective powerplant options are shown in Table 3. This decision stemmed from the necessity to find a reasonable research tradeoff between fidelity to the world’s fleet mix and practicality of collecting calibration data and performing the simulation within time and computational constraints. These four aircraft accounted for 50.2% of the global fleet as of January 1, 2020. They are also the newest representatives of their class at the time of the research, which means they will remain relevant for several decades. Furthermore, reasoning from first principles, the takeoff performance of other air transport aircraft should remain equally constant if changes to \( \rho \) and \( h_dw \) throughout the 21st century are as negligible as the climatic data from MPI-ESM1-2-HR indicates. In aggregate, the findings applicable to the four simulated aircraft are likely generalizable to all others.

**Temporal Generalizability.** A third and final external validity aspect of the present study is whether its findings are generalizable to climate outcomes other than those it assumed as inputs. A notable limitation of the present research is that it used only one ensemble member \((r1i1p1f1)\) of one model (MPI-ESM1-2-HR), and no bias correction, for practicality. Future research should consider bias-correcting the averaged outputs of a multi-model ensemble to increase the validity of the climatic assumptions. Likewise, future research would benefit from refining the climate input variables by using later-generation models and reanalyzing those using recent climate observations.
Summary

The key climatic determinants of takeoff performance considered in this study are the air density $\rho$ and the headwind component $hdw$. Both were numerically derived from their primary components ($tas, ps$, and $hurs$; and $uas$ and $vas$, respectively) returned by the MPI-ESM1-2-HR model at the 881 sample airports worldwide. The mean $\rho$ was found to decrease by a negligible amount of only 0.5–1.0% of the sea-level ISA datum under SSP2–45 and SSP3–70 respectively. The mean $hdw$ was found to remain virtually unchanged. Non-trivial inter-airport variance around the mean of both variables was observed, however, with as much as a 2.5% decrease below sea-level ISA $\rho$ and -0.8–+1.6 m/s change from the 2015 $hdw$ baseline at the most impacted airports. Siberian airports display the greatest centurial variance in $\rho$, while no clear geographical pattern emerges in $hdw$ changes.

It follows from this temporal stability in $\rho$ and $hdw$ that the takeoff simulation under the two middle SSPs yields only a negligible increase in the mean takeoff thrust of no more than 0.2–0.3 p. p. for narrowbody and widebody aircraft, respectively. In the 17.3% of all simulated takeoffs that completed successfully after a payload decrease, no more than 0.4–1.1 passenger needed removing, on average.

It also follows that the marginal cost to the industry, in terms of both additional thrust-related engine wear and passenger revenue attrition, is unlikely to become a meaningful consideration for air operators. On the other hand, location-dependent outliers in the mean and maximum $tas$ increase are likely to affect some aircraft operators more than the industry average, especially at airports where annual peaks may reach or exceed the thermal boundary of an aircraft’s environmental envelope.
Chapter V: Discussion, Conclusions, and Recommendations

The present chapter begins with a discussion of the findings reported in Chapter IV and attempts to explain how the observations from the MPI-ESM1-2-HR climatic model and bespoke takeoff simulation led to the answers to the three research questions formulated earlier. Congruent and contrasting findings from the extant literature reviewed in Chapter II are also examined. The remainder of the chapter then forms concluding remarks from the results, summarizes the main theoretical and practical contributions and limitations from the study, and issues recommendations for both industry stakeholders to take action and other researchers to extend this research into future avenues of scholarly investigation.

Discussion

This section reviews the key observations from the climate model and the main findings from the takeoff simulation model presented in Chapter IV, discusses their importance and relevance to the research questions, and contextualizes them in relation to the studies reviewed in Chapter II.

Climatic Considerations

Methodological Considerations. A first motivation for this study was to contribute to the body of knowledge by generalizing prior research into some of the impacts of climate change on takeoff performance at a worldwide population of airports. A second motivation was to address several methodological biases observed in the extant research. First, all seven previous studies expounded in Chapter II were found to have examined limited and latitudinally non-representative samples of four to 30 airports, many of which exhibited the climatic bias of being hot (VTBS, VABB, OMDB, KPHX).
and high (KDEN, ZBHH, ZPPP, ZULS, CYYC, CYXY). Second, five out of six of the forward-looking studies drew conclusions from the extreme, and arguably less plausible, SSP5–85 forcing scenario. Third, four of them observed only changes to temperature maxima instead of the mean. Therefore, these studies were arguably methodologically designed to demonstrate the existence of an effect of global warming on takeoff performance under maximal conditions, rather than to quantify the likely effect size on the real-world population of commercial airports worldwide under more plausible middle-of-the-road climate scenarios. Lastly, five of the six prospective studies also focused on the near-surface air temperature \( tas \) instead of the air density \( \rho \) and the headwind component \( hdw \), which are the key determinants of takeoff performance, ceteris paribus.

**Temperature Considerations.** A first observation from the examination of the MPI-ESM1-2-HR model outputs is the unmistakable positive signal in both mean and maximum \( tas \) changes that correlates directly with the amount of positive radiative forcing of the SSPs. The temporal rise in \( tas \) is highly consistent with all seven studies reviewed in Chapter II. Coffel and Horton’s (2016) reported increase of 3 °C–4 °C in the maximum \( tas \) at four U.S. airports (KDCA, KDEN, KLGA, and KPHX) by the year 2069 under SSP5–85 using a CMIP5 multi-model ensemble overlaps this study’s finding of a 2.8 °C–5.6 °C increase by the year 2100 at those airports under the same radiative scenario. Likewise, their follow-up study (Coffel et al., 2017) with a larger sample of 19 airports worldwide observed a mean rise in peak \( tas \) of 0.3 °C and 0.7 °C per decade by the year 2080 under SSP2–45 and SSP5–85, respectively, which is consistent with this study’s observation of 0.3 °C and 0.6 °C by the year 2100 at those same airports. An adjacent finding is the existence of climatic outliers in the intensity of the maximum \( tas \).
increase, particularly at high-latitude airports located in Canada, northeastern China, Siberia, and the Tibet Autonomous Region, as evidenced in Appendix Figure B17. Maximal warming levels congruent with those observed in this research were reported by Zhao and Sushama (2020) and by Y. Zhou et al. (2018) in their examination of summertime weight restriction at 13 Canadian and seven Chinese airports, respectively.

**Air Density Considerations.** The present study observed a modest centurial reduction in the global mean $\rho$. Under the two middle SSPs, the mean $\rho$ was seen to decrease by only 0.6–1.1%, respectively, by the year 2100 relative to the 2016 baseline, which is disproportionately less than the relative increase of 9.4–18.0% in the mean $tas$. Ren et al. (2019), whose focus on $\rho$ as the main predictor of takeoff performance is methodologically similar to that of the present study, found that the mean $\rho$ decreased moderately over lower latitudes and more strongly in polar regions. This observation is consistent with the findings presented in Chapter IV and exhibited in Appendix Figures B25–B27. Ren et al. (2019) observed a decrease in $\rho$ at six airports worldwide that is remarkably congruent with this study; both sets of results are within $0.07 \times 10^{-3} \text{ kg/m}^3$ of each other per year on average ($\sigma = 0.04$) under the worst-case scenario of SSP5–85. Such agreement in the results strengthens the validity of this study’s independent derivation of $\rho$ from its $tas$, $ps$, and $hurs$ constituents returned by the MPI-ESM1-2-HR model.

This modest reduction in $\rho$, however, may seem counter-intuitive considering the clear atmospheric warming signal discussed earlier. It is explained primarily by the limited sensitivity of $\rho$ to $tas$, and to a far lesser degree by the fact that changes in $tas$, $ps$, $hurs$. 
and \( hurs \) partially offset each other. Both effects are significant theoretical considerations for future research on takeoff performance and are discussed next.

**Air Density Sensitivity Analysis.** As shown in Appendix Figure B2, the mean \( tas \) was observed to increase from its 2015 baseline under all climate scenarios and zones, in line with expectations from global warming, and by as much as 9.4%–18.0% across all sample airports globally under the two middle SSPs, respectively. Yet, the mean global \( \rho \) was observed to decrease by only 0.6%–1.1%, as illustrated in Appendix Figure B11. The reason for this apparent disproportion is that \( \rho \) is only weakly sensitive to \( tas \). To illustrate this point, a 10% change to sea-level ISA values for the predictor variables \( ps \), \( tas \), and \( hurs \) was plotted in Figure 40. The \texttt{masscor} package of R introduced in Chapter III was then used to calculate the resulting dependent variable \( \rho \). The results show that a 10% change in \( ps \), \( tas \), and \( hurs \) yields a 10%, 0.5% and 0.1% change in \( \rho \), respectively, confirming the uneven sensitivity of air density to its constituents.

**Figure 40**

*Sensitivity Analysis of Air Density to its Constituents*
**Offsetting Effects of ps and hurs.** Separately, the global mean $ps$ at sample airports in Appendix Figure B5 was found to rise by 0.05% over the century under the middle SSPs. The modest increase in $ps$ counteracts that in $tas$ because both terms are a numerator and a denominator, respectively, in the air density formula contained in Equation 2. The slight change in $ps$ was found to offset by about one-tenth to one-twentieth the observed decrease in $\rho$ from warming alone. This observation of quasi-stability in $ps$ is generally consistent with Y. Zhou et al. (2018) who found from a multi-model ensemble mean of 25 CMIP5 GCMs that the temporal trend in sea-level air pressure at 30 airports worldwide was neither negative nor positive in aggregate. Likewise, the observed 2–3 p. p. decrease in the mean $hurs$ shown in Appendix Figure B8 would have canceled out some of the reduction in $\rho$, but the effect size is immaterial here due to the weak sensitivity of $\rho$ to $hurs$ evidenced in Figure 40. Ren et al. (2019) raised a similar observation about the offsetting role of $hurs$ in multi-decadal changes to $\rho$.

**Implications for Airports.** This examination of the uneven sensitivity of $\rho$ to its constituents $tas$, $ps$, and $hurs$ is of relevance to the present study because it explains the changes in climatic conditions observed at individual airports whose $tas$ deviates significantly from the global mean. For example, Lhasa Gonggar Airport in the Tibet Autonomous Region (ZULS) should have experienced a 1.4% decrease in $\rho$ under SSP3–70 by the year 2100 on account of atmospheric warming alone, but only saw a 0.8% reduction due to the offsetting effect of the strongest increase in $ps$ in the entire airport sample. Research that expects the future takeoff performance to vary based on $tas$ alone would fail to account for the compensating effects of changes in $ps$ and $hurs$. It follows that future takeoff performance studies aimed at extending the present research with
additional model runs, climate reanalysis, and updated archival data from weather
stations at airports for the year 2015 and beyond, should also consider factoring in \textit{ps} and
\textit{hurs} as additional model output variables instead of accounting only for changes in \textit{tas}. A
related consideration is that, while latitude is a strong predictor of the magnitude of
climate change, there is no obvious pattern in its distribution by longitude, and per-airport
analysis remains essential to adequately account for local effects, such as the influence of
a continental vs. oceanic climate and the orographic influence on atmospheric circulation.
Ren et al. (2019) came to a similar conclusion about local and regional analytical fidelity.

\textbf{Wind Considerations.} A final climatic consideration from the present research is
that the mean headwind strength will remain quasi-stable globally over the 21st century,
with some local variation around the mean. Two of the seven studies reviewed in
Chapter II considered changes to circulation patterns, but only on small and
geographically limited airport samples. The first, by Zhao and Sushama (2020), observed
at 13 Canadian airports an absolute centurial change of less than 0.5 m/s under SSP5–85.
This is consistent with the present study’s observation of $0.0 \pm 0.2$ m/s in \textit{hdw} change at
all 15 Canadian airports with more than one million passengers. The second is Gratton et
al. (2020), which retrospectively examined wind records at ten Greek airports since 1955
and found a measurable decrease at four of them, in the order of 0.25 m/s on average per
decade. This is more pronounced than the present study’s observations of a mean
reduction of 0.1 m/s over the entire 2015–2100 period at ten Greek airports (only five of
which overlap those in the Gratton et al. study). This discrepancy highlights the need for
localized airport-level research that bias-corrects RCM data with historical wind records.
Takeoff Considerations

This section discusses considerations related to the outcomes of the takeoff simulation described in Chapter IV, including the answers to the three research questions about thrust increase, payload removal, and the potential economic cost to the industry.

Takeoff Distance Considerations. This study found that the mean TODR would increase by 5.7–11.4 m under SSP2–45 and SSP3–70 for narrowbody aircraft and by 3.0–5.8 m globally for widebody aircraft. Y. Zhou et al. (2018) also reported a lengthening of the mean TODR, but only for summer days, making the mean results difficult to compare. However, their observation of a maximum global increase of 168.7 m for narrowbody takeoffs is comparable with the value of 118 m found in the present research.

Thrust Considerations. This study’s takeoff simulation was designed so that all non-climatic determinants of takeoff performance, such as aircraft characteristics, remain invariant. The modest increase of 0.1–0.3 p. p. in takeoff thrust shown in Figures 34–35 is, therefore, exclusively attributable to environmental changes in takeoff conditions. Those changes include the effect of \( tas \) on the Mach number \( M \) via the speed of sound; of \( ps \) on the engine thrust ratio for a given \( M \); of \( \rho \) on the dynamic pressure and groundspeed at which liftoff is achieved; and of \( hdw \) on the takeoff groundspeed and the TODR. The observed quasi-stability of simulated thrust outcomes is entirely consistent with that of \( \rho \) and \( hdw \). This finding is not directly comparable with the prior studies reviewed in Chapter II because they assumed the thrust setting to be invariant at TOGA.

Two engine-related implications for engine owners and operators can be derived from these simulation results. Both are related to powerplant severity. The first is that the marginal increase in the mean takeoff thrust alone is unlikely to add meaningful wear and
tear to the engines, except perhaps at specific airports where thrust will rise well above the global mean. Two such examples include Maharana Pratap Airport in India (VAUD) with a 4.4% thrust increase in narrowbody takeoffs and Lisbon Airport in Portugal (LPPT) with a 3.1% thrust increase in widebody takeoffs under SSP3–70. Further ad hoc investigation would be needed to assess the impact on domestic carriers with hub operations and multiple daily services at those airports.

The second implication is additional thermal stress to the engine’s combustor from a \( \text{tas} \) increase, regardless of changes in thrust settings. Siberian airports, in particular, will experience the greatest increase in mean \( \text{tas} \), by 5.2 °C–6.2 °C under SSP3–70. Furthermore, tropical airports that will experience a marked increase in their annual maximum (not mean) \( \text{tas} \) are more likely to encounter EGT exceedance conditions. One example is Manaus Airport in Brazil (SBEG), whose maximum \( \text{tas} \) will rise by as much as 11.3 °C under SSP3–70 by the year 2100 from a baseline value of 34.8 °C in 2015.

**Payload Removal Considerations.** The takeoff simulation pointed to a required payload reduction of 0.4–1.1 passengers for narrowbody and widebody takeoffs, respectively, by the year 2100. Such a modest decrease should not become a concern for the commercial air transport industry overall. However, disparities emerge at the individual airport level. The previously-mentioned VAUD airport, for example, will experience as many as 33.4 narrowbody passenger removals by the year 2100 under SSP3–70. Similarly, while the proportion of unsuccessful takeoffs will grow by only 0.3–1.4 p. p. overall, notable outliers include several South American airports that will
experience double-digit growth in unsuccessful takeoffs. Once again, a case-by-case examination of each airport is warranted, as the global mean obfuscates local variance.

This finding about payload removal is only indirectly comparable with the extant literature reviewed in Chapter II due to methodological differences. Coffel and Horton (2015) estimated the number of summer mass-restriction days, rather than the annual mean payload removal, and reported an increase of 50%–200% in the number of such days at four U.S. airports (KDCA, KDEN, KLG, KPHX) by the year 2070 under SSP5–85. A bespoke examination of the MPI-ESM1-2-HR model outputs at those airports showed that the temperature thresholds for a 10,000 lb (4,536 kg) and 15,000 lb (6,804 kg) mass restriction, respectively, are reached 100% to 200% more often by the year 2070 relative to the year 2015, which is consistent with the report by Coffel and Horton (2015). Separately, Ren et al. (2019) observed a global mean decrease in $\rho$ of 1% and translated that in a 8.5%–19% reduction in payload under SSP5–85. The present study measured a similar change in $\rho$ but used takeoff thrust as an additional adjustment variable, leading to a much smaller net reduction in payload.

**Economic Cost Considerations.** The observed increase in the global mean takeoff thrust and payload removal is modest enough that it is unlikely to be of economic concern to the air transport industry. At the local level, however, some airports and air operators will likely incur significant disruptions to their business model as weight restrictions and potential environmental envelope exceedance will become more prevalent. Between the years 2015 and 2100, the number of sample airports whose annual maximum $tas$ exceeds 50 °C will grow from six to nine under SSP2–45 and from seven to 19 under SSP3–70.
Conclusions

The present study set out to quantify the impacts of an increase in the global mean surface temperature of the Earth on takeoff performance in the 21st century using extant climatic data and a bespoke takeoff simulation model applied to a sample of 881 airports with at least one million passengers. Its main conclusions are as follows.

Climate Change

Significant Rise in Air Temperature. The mean near-surface air temperature at sample airports was observed to rise by a significant global mean of 1.6–3.1 °C by the year 2100 under the middle shared socioeconomic pathways (SSP2–45 and SSP3–70). Airports located in southern Siberia will be the most affected with an increase as high as 3.1–6.2 °C. Furthermore, the annual peak air temperature at airports was observed to rise even more, by 1.9–3.4 °C globally and as much as 5.9–11.3 °C at one airport, with possible implications to aircraft environmental envelope exceedance not considered in this study. Temperate airports were more affected than tropical airports.

Disproportional Quasi-Stability in Air Density and Headwinds. The mean near-surface air density was observed to vary far less than the air temperature, and to decrease by a non-significant global mean of 6.5–12.6 × 10^{-3} kg/m^3, which is only 0.5–1.0% of the sea-level ISA datum. This disproportion is explained by the greater sensitivity of air density to air pressure, which was observed to remain quasi-stable over the century, than to air temperature. Likewise, runway headwinds were observed to remain mostly unaffected by other environmental changes over the 21st century.
Takeoff Performance

Noticeable Reduction in Successful Takeoffs. Unsuccessful takeoffs, for which the simulated takeoff distance required exceeded that available despite increasing the takeoff thrust to TOGA and removing passengers down to the BELF, were found to increase by 0.2–1.5 percentage points under SSP2–45 and SSP3–70 on average globally. Temperate airports were found to be slightly more susceptible than tropical ones.

Non-Significant Increase in Mean Takeoff Thrust. Changes to takeoff thrust returned by the simulation are twofold. First, the share of takeoffs performed at the minimum thrust setting of 75% TOGA will decrease by 0.2–0.8 percentage points worldwide. Second, the global mean takeoff thrust across all successful takeoffs will increase by 0.1 to 0.3 percentage points under SSP2–45 and SSP3–70. Both findings are considered non-significant globally, but local variance around the mean indicates that some airports will be disproportionately affected.

Non-Significant Increase in Mean Payload Removal. The simulation resulted in 17.3% of all takeoffs requiring the removal of payload to complete successfully. On average, a non-significant 0.4–1.1 passenger had to be removed from narrowbody and widebody aircraft, respectively, under the two middle SSPs by the end of the century.

Economic Impact

Non-Significant Cost to the Industry. The economic cost to engine owners and operators of aircraft engines is difficult to quantify precisely due to lack of access to severity curves. The simulation results suggest that this cost may remain immaterial to the industry under the two middle SSPs due to the small effect size on both engine thrust and payload removal.
Theoretical Contributions

The present research contributed to the body of knowledge related to climatic impacts on takeoff performance in at least two meaningful ways described hereafter.

First, this research generalized the prior studies reviewed in Chapter II by extending their coverage to additional airports and climate scenarios. A representative sample of 881 airports worldwide accounting for 94.9% of all passenger movements for the year 2019 was used. This is meaningful because, as observed from the climatic model outputs described in Chapter IV, the centurial changes in the near-surface air temperature, pressure, humidity, density, and circulation are unevenly geographically distributed, and the extant studies could not reliably extrapolate their findings to the entire air transport industry level. By using a representative sample, the present research was able to evidence that the variables most causal to takeoff performance (i.e., air density and headwinds) will not change significantly in aggregate but will exhibit enough variance around the mean to warrant further research into specific airports that are climatic outliers, such as South Siberian airports.

Furthermore, the present research considered four shared socioeconomic pathways, instead of only the worst-case scenario of SSP5–85 examined in most of the other prospective studies. This is meaningful because both the takeoff simulation model’s climatic input variables and performance output variables exhibit strong sensitivity to positive radiative forcing. Here, the key theoretical contribution from the present research is that the effect size was found to be globally non-significant under the middle-of-the-road forcing scenarios (SSP2–45 and SSP3–70) which are arguably the most plausible, and potentially significant only under SSP5–85.
Second, the present research contributed an open-source programmatic framework in the R language to extract climatic predictions from CMIP6 models, derive from them second-order variables causal to takeoff performance (air density, headwind), simulate takeoffs using a bespoke first-principle model calibrated against manufacturer data, and visualize the results by SSP, airport, climate zone, and aircraft type. The R code is available online for other researchers to adapt and extend for their own purposes. This is meaningful because the only takeoff performance tools that appear to be available at the time of writing are proprietary software generally unavailable for academic research.

**Practical Contributions**

The responsibility borne by commercial air transport in greenhouse gas emissions causal to anthropogenic climate change presents a major challenge for airline, airport, and adjacent stakeholders who face the imperative of decarbonizing the industry. Conversely, the impacts of climate change on commercial air transport, and on takeoff performance, in particular, are still a nascent field of research, and not as pressing a concern for the industry’s constituents. The present study offers two practical contributions to this topic.

The first is to answer, in general terms, the emerging question of whether climate change will impact takeoff performance in a meaningful way. This study’s results will serve to reassure engine owners and operators that the net increase in takeoff thrust is unlikely to materially reduce the economic life of engines nor increase their maintenance cost. Likewise, this study will reassure airlines that payload removals from environmental takeoff limitations will remain economically unimportant in the 21st century. Both assertions assume a forcing pathway of either SSP2–45 or SSP3–70 and would be invalidated by the realization of SSP5–85.
The second practical contribution of this study is that it demonstrates the heterogeneity in the airport-level distribution of climate change. It is apparent from the observed variance in the minimum, mean, and maximum statistics of the climate variables examined in Chapter IV that some airports are outliers in how much change they will experience. This study used a high-resolution model of approximately 100 km by 100 km gridded cells, which is the finest granularity that general circulation models have to offer. The results should encourage an even more granular analysis, using regional circulation models that account for an airport’s topographical characteristics, to quantify the extent of climate change more precisely at those outliers.

**Limitations of the Findings**

The present research was quantitative and used simulation models to return both climate input and takeoff output variables. The simulation method is, by definition, a way to approximate real world phenomena, and thus inherently suffers from fidelity loss when mimicking behaviors such as those of the Earth’s atmosphere and an aircraft taking off. Both limitations are briefly discussed hereafter.

The present study’s takeoff simulation sourced its climate input variables from only one CMIP6 model, MPI-ESM1-2-HR, with no bias correction. It follows that the conclusions about takeoff performance drawn in this chapter depend on the presumed reliability and validity of that single model. However, single models are demonstrably less reliable than multi-model ensembles averaged together (Hagedorn et al., 2005; Tebaldi & Knutti, 2007). Future research would benefit from combining multi-model inputs when seeking to confirm the magnitude of climate change at fewer airports.
A second methodological limitation resides in the use of a bespoke takeoff simulation model developed from first principles for the purpose of this research. While the model borrows components from others published in the scholarly literature, including Sun et al. (2020b) and Gratton et al. (2020), and was carefully calibrated against takeoff performance data published by OEMs under ISA conditions, its accuracy is likely inferior to that of sophisticated aircraft manufacturer software used for field length calculations, such as Airbus’ OCTOPUS or Boeing’s OPT. Future research would benefit from working with OEMs to at least verify the validity its takeoff performance calculations for each set of environmental conditions and aircraft characteristics.

**Recommendations**

This section forms recommendations to three groups of stakeholders within the air transport industry and to future researchers based on the results from the present study.

**Recommendations for the Air Transport Industry**

A first recommendation is aimed at engine owners and operators, such as lessors and airlines, who are advised to work with powerplant manufacturers to confirm that no meaningful impact is expected to the engines’ economic life and maintenance costs over the lifetime of their assets. This recommendation is motivated by the lack of public disclosure of severity curves, which prevented the present study from quantifying the marginal engine wear and tear from an environmental increase in the EGT. This recommendation is especially important at those hub airports where the maximum temperature is expected to increase faster than the mean. Adjacently, a second recommendation is for engine manufacturers to account for increasingly hot takeoff conditions and attendant reliability issues in the design of their future engines. For
turbofans, the risk of EGT exceedance will be more than ever a constraining factor of takeoff performance. For hydrogen-powered short-to-medium-haul aircraft, storing H₂ under cryogenic conditions (-253 °C) will be challenged by the larger thermal difference with the \( \text{tas} \). For electric engines powering smaller aircraft, the increased \( \text{tas} \) may decrease battery performance and reduce the flight range.

A third recommendation is aimed at airports most affected by climate change and their based carriers. While the implications to TODR, thrust, and payload removal were found to be limited under the two middle SSPs, the increase in \( \text{tas} \) will affect operations in other ways introduced in Chapter II, including hazards to the occupational safety and health of ground staff. Airports, airlines, and regulators should commission research into the dynamics of climate change relevant to their locations. Such analysis should include changes to annual temperature maxima because the outputs of the climate model presented in Chapter IV indicate not only a marked increase in the mean \( \text{tas} \), but also a sharper rise in annual peaks. At some airports, \( \text{tas} \) maxima may exceed the boundaries of an aircraft’s environmental envelope and prevent takeoffs entirely. The associated recommendations are threefold. First, airports and airlines most likely to be affected should conduct granular analysis of their local climate using RCMs. Second, aircraft manufacturers should extend the environmental envelope of their aircraft to accommodate higher \( \text{tas} \) maxima, and work with regulators to re-certify their aircraft under those extreme conditions where required. Third, all stakeholders should monitor the greenhouse gas emission and forcing trends that underpin the climate pathways to refine over time the plausibility of each SSP and attendant climatic impacts.
Recommendations for Future Research

Several avenues for further research emerge from the present study. The first is to enhance the validity of the present findings at a global level by sourcing climate input variables from a multi-GCM ensemble and apply bias correction, as described in the Limitations section. Depending on the geographical spread of the airport sample, and whether it is at a regional or local level, the use of RCMs is recommended due to their finer granularity and ability to account. Regardless of model selection, a key recommendation is to consider air density and headwinds among the climate input variables, the importance of which to takeoff performance was demonstrated by Ren et al. (2019) and Gratton et al. (Gratton et al., 2020), respectively, as well as the present study. The modeling of near-surface winds, in particular, would benefit from a more bespoke and higher-resolution model that accounts for each airport’s specific topography.

A second avenue for research consists of working with aircraft manufacturers to test the likelihood that the centurial increase in temperature maxima will lead to environmental envelope excursions. This phenomenon was previously observed to cause multiple flight cancelations and weight restrictions at Phoenix Sky Harbor Airport (KPHX) in the US in 2019 (Carpenter, 2019; Hope, 2017; A. B. Wang, 2017) for regional jet aircraft not in scope of the present study. Future research could, therefore, separately explore the impacts of climate change on short-haul operations using smaller passenger aircraft such as the Airbus A220 and Embraer E-Jet family. A key methodological recommendation for such a study would be to use manufacturer-certified software to enhance the accuracy of the field length calculations.
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Wilson, G., Aruliah, D. A., Brown, C. T., Chue Hong, N. P., Davis, M., Guy, R. T.,
Haddock, S. H. D., Huff, K. D., Mitchell, I. M., Plumbey, M. D., Waugh, B.,


https://doi.org/gbqr
# Appendix A

## Tables

<table>
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<th>Requirements and Search Parameters for the Climate Model Candidates</th>
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</thead>
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</tr>
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<td>A10</td>
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<td>A12</td>
<td>R Packages Used in the Research</td>
</tr>
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<td>A13</td>
<td>Changes in the Input (Climatic) Variables (2015–2100) at the Sample Airports</td>
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<td>A14</td>
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</tr>
<tr>
<td>A15</td>
<td>List of Airports and ICAO Codes Referred to in this Study</td>
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Table A1

Requirements and Search Parameters for the Climate Model Candidates

<table>
<thead>
<tr>
<th>Model characteristic</th>
<th>Research requirement</th>
<th>ESGF search parameter</th>
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<tr>
<td>Era</td>
<td>Latest available</td>
<td>CMIP6</td>
</tr>
<tr>
<td>Activity</td>
<td>Plausible emissions futures between the years 2015 and 2100</td>
<td>ScenarioMIP</td>
</tr>
<tr>
<td>Horizontal spatial resolution</td>
<td>Highest available</td>
<td>100 km</td>
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<td>Experiment</td>
<td>Tier-1 SSPs</td>
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<tr>
<td>Ensemble member</td>
<td>First</td>
<td>r1i1p1f1</td>
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<tr>
<td>Frequency</td>
<td>Highest available</td>
<td>6hr</td>
</tr>
<tr>
<td></td>
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<td>6hrPt</td>
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<tr>
<td>Variables</td>
<td>Near-surface air temperature</td>
<td>tas</td>
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<tr>
<td></td>
<td>Near-surface air pressure</td>
<td>ps</td>
</tr>
<tr>
<td></td>
<td>Near-surface relative air humidity</td>
<td>hurs</td>
</tr>
<tr>
<td></td>
<td>Near-surface wind speed</td>
<td>sfcWind</td>
</tr>
<tr>
<td></td>
<td>Eastward component of the wind</td>
<td>uas</td>
</tr>
<tr>
<td></td>
<td>Northward component of the wind</td>
<td>vas</td>
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</table>

Note. The model characteristics in the first column are congruent with the CMIP6’s controlled vocabulary.
### Table A2

**Aircraft and Engine Characteristics Assumed in the Simulation**

<table>
<thead>
<tr>
<th>Type</th>
<th>Name</th>
<th>Model</th>
<th>Count</th>
<th>Static sea-level thrust (N)</th>
<th>Bypass ratio</th>
<th>Seats</th>
<th>Max. takeoff mass (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A20n</td>
<td>Airbus A320neo</td>
<td>LEAP–1A29</td>
<td>2</td>
<td>130,300</td>
<td>10.7</td>
<td>180†</td>
<td>77,000†</td>
</tr>
<tr>
<td>A359</td>
<td>Airbus A350–900</td>
<td>Trent XWB–84</td>
<td>2</td>
<td>379,000</td>
<td>9.01</td>
<td>315†</td>
<td>275,000†</td>
</tr>
<tr>
<td>B39m</td>
<td>Boeing 737 MAX 9</td>
<td>LEAP–1B27</td>
<td>2</td>
<td>124710</td>
<td>8.3</td>
<td>220†</td>
<td>88,000†</td>
</tr>
<tr>
<td>B789</td>
<td>Boeing 787–9</td>
<td>Trent 1000–K2</td>
<td>2</td>
<td>350,900</td>
<td>9.04</td>
<td>290†</td>
<td>254,000</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Type</th>
<th>Wingspan in m</th>
<th>Wing surface area in m²</th>
<th>$C_{D_0}^*$</th>
<th>$k_0$</th>
<th>$e_0$</th>
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<tr>
<td>A20n</td>
<td>35.8</td>
<td>124</td>
<td>.078</td>
<td>.038</td>
<td>.807</td>
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<tr>
<td>A359</td>
<td>64.75</td>
<td>442</td>
<td>.075</td>
<td>.043</td>
<td>.783</td>
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<tr>
<td>B39m</td>
<td>34.32</td>
<td>127†</td>
<td>.08</td>
<td>.042</td>
<td>.797</td>
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<tr>
<td>B789</td>
<td>60.12</td>
<td>377</td>
<td>.074</td>
<td>.042</td>
<td>.783</td>
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</tbody>
</table>

*Note.* Values are taken from Sun et al. (2020a) except † from the technical literature. $C_{D_0}^*$ is the lift-independent drag coefficient in a takeoff configuration. $k_0$ is the lift-induced drag coefficient factor in a clean configuration. $e_0$ is the Oswald efficiency factor in a clean configuration.
### Table A3

**Worked Example of the Ground Distance Calculation**

<table>
<thead>
<tr>
<th>Steps</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
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</thead>
<tbody>
<tr>
<td>$V_{TAS}$</td>
<td>0.0</td>
<td>8.8</td>
<td>17.6</td>
<td>26.4</td>
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<td>44.0</td>
<td>52.8</td>
<td>61.6</td>
<td>70.4</td>
<td>79.2</td>
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<td>$V_{GND}$</td>
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<td>17.6</td>
<td>26.4</td>
<td>35.2</td>
<td>44.0</td>
<td>52.8</td>
<td>61.6</td>
<td>70.4</td>
<td>79.2</td>
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<tr>
<td>$\bar{V}_{GND}$</td>
<td>0.0</td>
<td>4.4</td>
<td>13.2</td>
<td>22.0</td>
<td>30.8</td>
<td>39.6</td>
<td>48.4</td>
<td>57.2</td>
<td>66.0</td>
<td>74.8</td>
</tr>
<tr>
<td>$\Delta V_{GND}$</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
</tr>
<tr>
<td>$V_{SND}$</td>
<td>340.4</td>
<td>340.4</td>
<td>340.4</td>
<td>340.4</td>
<td>340.4</td>
<td>340.4</td>
<td>340.4</td>
<td>340.4</td>
<td>340.4</td>
<td>340.4</td>
</tr>
<tr>
<td>$M$</td>
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<td>0.03</td>
<td>0.05</td>
<td>0.08</td>
<td>0.10</td>
<td>0.13</td>
<td>0.16</td>
<td>0.18</td>
<td>0.21</td>
<td>0.23</td>
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<tr>
<td>$\delta$</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>$T/T_0$</td>
<td>1.00</td>
<td>0.97</td>
<td>0.94</td>
<td>0.91</td>
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<td>0.85</td>
<td>0.83</td>
<td>0.80</td>
<td>0.78</td>
<td>0.75</td>
</tr>
<tr>
<td>$F_{MAX}$</td>
<td>260.6</td>
<td>252.3</td>
<td>244.3</td>
<td>236.6</td>
<td>229.2</td>
<td>222.0</td>
<td>215.2</td>
<td>208.7</td>
<td>202.5</td>
<td>196.5</td>
</tr>
<tr>
<td>$F_{RTO}$</td>
<td>260.6</td>
<td>252.3</td>
<td>244.3</td>
<td>236.6</td>
<td>229.2</td>
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<td>215.2</td>
<td>208.7</td>
<td>202.5</td>
<td>196.5</td>
</tr>
<tr>
<td>$q$</td>
<td>0.0</td>
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<td>190</td>
<td>427</td>
<td>760</td>
<td>1,187</td>
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<tr>
<td>$L$</td>
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<td>233.1</td>
<td>335.6</td>
<td>456.8</td>
<td>596.6</td>
<td>755.1</td>
</tr>
<tr>
<td>$D$</td>
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<td>4.1</td>
<td>9.2</td>
<td>16.3</td>
<td>25.5</td>
<td>36.7</td>
<td>50.0</td>
<td>65.3</td>
<td>82.6</td>
</tr>
<tr>
<td>$a$</td>
<td>3.19</td>
<td>3.07</td>
<td>2.93</td>
<td>2.78</td>
<td>2.61</td>
<td>2.42</td>
<td>2.21</td>
<td>1.98</td>
<td>1.74</td>
<td>1.48</td>
</tr>
<tr>
<td>$\bar{a}$</td>
<td>3.19</td>
<td>3.13</td>
<td>3.00</td>
<td>2.86</td>
<td>2.69</td>
<td>2.51</td>
<td>2.31</td>
<td>2.10</td>
<td>1.86</td>
<td>1.61</td>
</tr>
<tr>
<td>$\Delta\text{DIS}_{GND}$</td>
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<td>12.0</td>
<td>39.0</td>
<td>68.0</td>
<td>101</td>
<td>139</td>
<td>184</td>
<td>240</td>
<td>312</td>
<td>409</td>
</tr>
<tr>
<td>$\Sigma\text{DIS}_{GND}$</td>
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<td>12.0</td>
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<td>220</td>
<td>359</td>
<td>543</td>
<td>783</td>
<td>1,096</td>
<td>1,505</td>
</tr>
</tbody>
</table>

**Note.** This worked example of the functional module’s ground distance function shown in Appendix Code C6 assumes an Airbus A320neo aircraft with a takeoff mass of 77,000 kg, no thrust reduction, sea-level ISA conditions, no headwind, a lift coefficient $C_{L_{MAX}} = 1.9$, a runway friction coefficient $\mu = .02$, a runway slope $\theta = 0^\circ$, and flaps at $10^\circ$ deflection.
### Table A4

Calibrated Takeoff Performance Data (Details)

<table>
<thead>
<tr>
<th>Mass (kg)</th>
<th>TODR (m)</th>
<th>Mass (kg)</th>
<th>TODR (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>45,500</td>
<td>A20n: 952.0</td>
<td>164,500</td>
<td>A359: 1,581.1</td>
</tr>
<tr>
<td>45,750</td>
<td>B39m: 953.7</td>
<td>164,750</td>
<td>1,581.1</td>
</tr>
<tr>
<td>46,000</td>
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<td>165,000</td>
<td>1,582.4</td>
</tr>
<tr>
<td>46,250</td>
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<td>165,250</td>
<td>1,582.4</td>
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<tr>
<td>46,500</td>
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<td>166,750</td>
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</tr>
<tr>
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Table A5

*Calibrated Takeoff Performance Data (Summary)*

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### Table A6

**Count of Simulated Takeoffs and Iterations**

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Table A7

*Comparative Statistics of the Population and Sample Airports*

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Table A9

*Köppen-Geiger Distribution of Population and Sample Airports*

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Table A10

*Calibration and Simulation Model Input Variables*

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</thead>
<tbody>
<tr>
<td>Climates variables&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Near-surface&lt;sup&gt;b&lt;/sup&gt; air temperature&lt;sup&gt;c&lt;/sup&gt;</td>
<td>$tas$</td>
<td>K</td>
<td>Mach number $M$, air density $\rho$.</td>
</tr>
<tr>
<td>Near-surface air pressure&lt;sup&gt;d&lt;/sup&gt;</td>
<td>$ps$</td>
<td>Pa</td>
<td>Thrust coefficients, air density $\rho$.</td>
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<tr>
<td>Near-surface relative humidity</td>
<td>$hurs$</td>
<td>%</td>
<td>Air density $\rho$.</td>
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<td>m/s</td>
<td>The headwind and crosswind components for a given runway heading.</td>
</tr>
<tr>
<td>Eastward wind component</td>
<td>$uas$</td>
<td>m/s</td>
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<tr>
<td>Northward wind component</td>
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<td>m/s</td>
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</tr>
<tr>
<td>Near-surface air density</td>
<td>$\rho$</td>
<td>kg/m³</td>
<td>The liftoff speed $V_{LOF}$ and dynamic pressure $q$.</td>
</tr>
<tr>
<td>Aircraft variables</td>
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</tr>
<tr>
<td>Engine bypass ratio</td>
<td>$bpr$</td>
<td>–</td>
<td>The thrust ratio for a given Mach number $M$.</td>
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<td>Engine count</td>
<td>$n$</td>
<td>Units</td>
<td>The maximum takeoff thrust $F_{MAX}$.</td>
</tr>
<tr>
<td>Engine thrust (static)</td>
<td>$slst$</td>
<td>N</td>
<td>The lift-induced drag coefficient $C_{Di}$.</td>
</tr>
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<td>Lift-induced drag coefficient factor</td>
<td>$k_0$</td>
<td>–</td>
<td>The BELF takeoff mass.</td>
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<tr>
<td>Number of seats</td>
<td>–</td>
<td>Units</td>
<td>The aspect ratio $AR$.</td>
</tr>
<tr>
<td>Oswald efficiency factor</td>
<td>$e_0$</td>
<td>–</td>
<td>The lift-induced drag coefficient $C_{Di}$.</td>
</tr>
<tr>
<td>Wingspan</td>
<td>–</td>
<td>m</td>
<td>The aspect ratio $AR$, acceleration $a$, lift $L$, and drag $D$.</td>
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<td>Wing surface area</td>
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<td>m²</td>
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<tr>
<td>Zero-lift drag coefficient</td>
<td>$C_{D_0}$</td>
<td>–</td>
<td>The total drag coefficient $C_D$.</td>
</tr>
<tr>
<td>Input variables</td>
<td>Symbols</td>
<td>Units</td>
<td>Required for</td>
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<td>---------</td>
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</tr>
<tr>
<td>Climb angle</td>
<td>$\theta$</td>
<td>°</td>
<td>The horizontal distance $D_{AIR}$ of the first-segment climb.</td>
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<td>Flap deflection angle</td>
<td>$\delta_f$</td>
<td>°</td>
<td>The Oswald efficiency factor component $\Delta e_F$ attributable to flaps.</td>
</tr>
<tr>
<td>Runway friction</td>
<td>$\mu$</td>
<td>–</td>
<td>The acceleration $a$.</td>
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<tr>
<td>Runway slope</td>
<td>$\gamma$</td>
<td>°</td>
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<tr>
<td>Takeoff mass</td>
<td>$m$</td>
<td>kg</td>
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</tr>
<tr>
<td>Takeoff thrust</td>
<td>$F$</td>
<td>N</td>
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<tr>
<td>TODA</td>
<td>$TODA$</td>
<td>m</td>
<td>Determining whether the takeoff is runway length-limited.</td>
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<th>Symbols</th>
<th>Units</th>
<th>Required for</th>
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<tr>
<td>Payload removal</td>
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<td>kg</td>
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Note. Except for the air density $\rho$, the intermediary variables calculated by the calibration and simulation models, their constant input coefficients, and any natural and calibration constants (such as the gravitational acceleration) are not shown here for conciseness.

a Symbols for the climatic variables are congruent with the CMIP6 taxonomy.

b Near-surface typically means measured at a height of two meters from the ground, except for wind speed which is measured at a height of ten meters.

c In the present research, the air temperature only affects the Mach number determination via the speed of sound calculation.

d In the present research, air pressure only affects the engine thrust coefficients via the pressure ratio calculation.
Table A11

*Breakeven Load Factor Assumptions*

<table>
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<tr>
<th>Region</th>
<th>Breakeven load factors in %&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Shares of RPKs in %&lt;sup&gt;b&lt;/sup&gt;</th>
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<td>Middle East</td>
<td>67.7</td>
<td>9.0</td>
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<td>5.1</td>
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<td>22.3</td>
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<tr>
<td>Europe</td>
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<td>26.8</td>
</tr>
<tr>
<td>World</td>
<td>67.0&lt;sup&gt;c&lt;/sup&gt;</td>
<td>100</td>
</tr>
</tbody>
</table>

*Note.* All data are for the reference year 2019.

<sup>a</sup> Sourced from IATA (2021b).

<sup>b</sup> Sourced from IATA (2019b).

<sup>c</sup> Calculated weighted mean.
### Table A12

**R Packages Used in this Research**

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<td>data.table</td>
<td>Dowle &amp; Srinivasan (2022)</td>
</tr>
<tr>
<td>DBI</td>
<td>R Special Interest Group on Databases (R-SIG-DB) et al. (2022)</td>
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<td>Wickham et al. (2022)</td>
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<td>e1071</td>
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<td>epwshifr</td>
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<td>kc</td>
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<td>magrittr</td>
<td>Milton Bache &amp; Wickham (2022)</td>
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<td>rnaturalearth</td>
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<tr>
<td>scales</td>
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</tr>
<tr>
<td>tidyverse</td>
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<td>viridis</td>
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<td>zoo</td>
<td>Zeileis &amp; Grothendieck (2005)</td>
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Table A13

Changes in the Input (Climatic) Variables (2015–2100) at the Sample Airports

<table>
<thead>
<tr>
<th>Climate variables</th>
<th>SSP1–26</th>
<th>SSP2–245</th>
<th>SSP3–70</th>
<th>SSP5–85</th>
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</thead>
<tbody>
<tr>
<td>Changes in $tas$ (in °C)</td>
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<tr>
<td>Global</td>
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<td>1.6 / 1.6 / 1.9</td>
<td>3.7 / 3.1 / 3.4</td>
<td>5.2 / 4.1 / 4.6</td>
</tr>
<tr>
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<td>0.6 / 0.3 / 0.4</td>
<td>1.5 / 1.7 / 2.1</td>
<td>4.0 / 3.2 / 3.7</td>
<td>5.8 / 4.4 / 5.0</td>
</tr>
<tr>
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<td>1.7 / 1.4 / 1.4</td>
<td>3.1 / 2.8 / 2.9</td>
<td>3.7 / 3.4 / 3.6</td>
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<tr>
<td>Changes in $ps$ (in hPa)</td>
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<td></td>
<td></td>
<td></td>
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<tr>
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<td>-0.2 / 0.4 / -0.6</td>
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<td>0.5 / 0.6 / 1.3</td>
</tr>
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<td>0.4 / 0.6 / 1.5</td>
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<td>0.6 / 0.6 / 0.8</td>
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<tr>
<td>Changes in $hurs$ (in p. p.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>-3.0 / -3.2 / -0.2</td>
</tr>
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<td>-2.4 / -2.5 / -0.2</td>
<td>-4.1 / -4.0 / -0.2</td>
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<td>-0.1 / -0.5 / -0.6</td>
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<tr>
<td>Changes in $\rho$ (in $10^{-3}$ kg/m$^3$)</td>
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</tr>
<tr>
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<td>-5.1 / -5.9 / -7.5</td>
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<td>Changes in $hdw$ (in m/s)</td>
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</table>

Note. Values shown are the net difference in the LOESS of the annual minimum / mean / maximum statistics of each climate variable between the years 2100 and 2015 for all sample airports grouped by SSP and climate zone, rounded to the nearest first decimal.
Table A14

*Changes in the Output (Takeoff) Variables (2015–2100) at the Sample Airports*

<table>
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<tr>
<th>Takeoff variables</th>
<th>Narrowbody aircraft</th>
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<tr>
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<tr>
<td>Changes in all successful takeoffs (in p. p.)</td>
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<tr>
<td>Changes in successful takeoffs at minimum thrust (i.e., 75% TOGA) (in p. p.)</td>
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<td>Changes in successful takeoffs at intermediate thrust (i.e., 75%–100% TOGA) (in p. p.)</td>
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<td>SSP3–70</td>
<td>SSP5–85</td>
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<td>-0.1</td>
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<td>0.0</td>
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Note. Values shown are the net difference in the LOESS of the annual minimum / mean / maximum statistics of each climate variable between the years 2100 and 2015 for all sample airports grouped by SSP and climate zone, rounded to the nearest first decimal.
**Table A15**

*List of Airports and ICAO Codes Referred to in this Study*

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Appendix B

Figures

B1 Changes in the Maximum Near-Surface Air Temperature ($tas$) in °C
B2 Changes in the Mean Air Near-Surface Temperature ($tas$) in °C
B3 Changes in the Minimum Air Near-Surface Temperature ($tas$) in °C
B4 Changes in the Maximum Near-Surface Air Pressure ($ps$) in hPa
B5 Changes in the Mean Near-Surface Air Pressure ($ps$) in hPa
B6 Changes in the Minimum Near-Surface Air Pressure ($ps$) in hPa
B7 Changes in the Maximum Near-Surface Relative Humidity ($hurs$) in %
B8 Changes in the Mean Near-Surface Relative Humidity ($hurs$) in %
B9 Changes in the Minimum Near-Surface Relative Humidity ($hurs$) in %
B10 Changes in the Maximum Near-Surface Air Density ($\rho$) in g/m3
B11 Changes in the Mean Near-Surface Air Density ($\rho$) in g/m3
B12 Changes in the Minimum Near-Surface Air Density ($\rho$) in g/m3
B13 Changes in the Maximum Near-Surface Headwind ($hdw$) in m/s
B14 Changes in the Mean Near-Surface Headwind ($hdw$) in m/s
B15 Changes in the Minimum Near-Surface Headwind ($hdw$) in m/s
B16 Map of Changes in the Maximum Near-Surface Air Temperature ($tas$) in °C
B17 Map of Changes in the Mean Near-Surface Air Temperature ($tas$) in °C
B18 Map of Changes in the Minimum Near-Surface Air Temperature ($tas$) in °C
B19 Map of Changes in the Maximum Near-Surface Air Pressure ($ps$) in hPa
B20 Map of Changes in the Mean Near-Surface Air Pressure ($ps$) in hPa
B21 Map of Changes in the Minimum Near-Surface Air Pressure ($ps$) in hPa
B25  Map of Changes in the Maximum Near-Surface Air Density ($\rho$) in g/m$^3$
B26  Map of Changes in the Mean Near-Surface Air Density ($\rho$) in g/m$^3$
B27  Map of Changes in the Minimum Near-Surface Air Density ($\rho$) in g/m$^3$
B28  Map of Changes in the Maximum Near-Surface Headwind ($hdw$) in m/s
B29  Map of Changes in the Mean Near-Surface Headwind ($hdw$) in m/s
B30  Map of Changes in the Minimum Near-Surface Headwind ($hdw$) in m/s
B31  Changes in the Unsuccessful Takeoffs of Narrowbody Aircraft
B32  Changes in the Unsuccessful Takeoffs of Widebody Aircraft
B33  Changes in the Successful Takeoffs of Narrowbody Aircraft
B34  Changes in the Successful Takeoffs of Widebody Aircraft
B35  Changes in the Minimum-Thrust Takeoffs of Narrowbody Aircraft
B36  Changes in the Minimum-Thrust Takeoffs of Widebody Aircraft
B37  Changes in the Intermediate-Thrust Takeoffs of Narrowbody Aircraft
B38  Changes in the Intermediate-Thrust Takeoffs of Widebody Aircraft
B39  Changes in the Maximum-Thrust Takeoffs of Narrowbody Aircraft
B40  Changes in the Maximum-Thrust Takeoffs of Widebody Aircraft
B41  Changes in the Mean Takeoff Distances Required by Narrowbody Aircraft
B42  Changes in the Mean Takeoff Distances Required by Widebody Aircraft
Figure B1

*Changes in the Maximum Near-Surface Air Temperature (tas) in °C*
Figure B2

Changes in the Mean Air Near-Surface Temperature (tas) in °C
Figure B3

Changes in the Minimum Air Near-Surface Temperature (tas) in °C
Figure B4

Changes in the Maximum Near-Surface Air Pressure (ps) in hPa
Figure B5

Changes in the Mean Near-Surface Air Pressure (ps) in hPa
Figure B6

Changes in the Minimum Near-Surface Air Pressure (ps) in hPa
**Figure B7**

*Changes in the Maximum Near-Surface Relative Humidity (hurs) in %*

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The graphs show the changes in maximum near-surface relative humidity (%) for different scenarios (SSP126, SSP245, SSP370, SSP585) across various years (2020, 2060, 2100).
Figure B8

*Changes in the Mean Near-Surface Relative Humidity (hurs) in %*
Figure B9

*Changes in the Minimum Near-Surface Relative Humidity (hurs) in %*
Figure B10

Changes in the Maximum Near-Surface Air Density ($\rho$) in g/m$^3$
Figure B11

Changes in the Mean Near-Surface Air Density ($\rho$) in g/m$^3$
Figure B12

Changes in the Minimum Near-Surface Air Density ($\rho$) in g/m$^3$
Figure B13

*Changes in the Maximum Near-Surface Headwind (hdw) in m/s*
Figure B14

Changes in the Mean Near-Surface Headwind (hdw) in m/s
Figure B15

Changes in the Minimum Near-Surface Headwind (hdw) in m/s
Figure B16

Map of Changes in the Maximum Near-Surface Air Temperature (tas) in °C
Figure B17

Map of Changes in the Mean Near-Surface Air Temperature (tas) in °C
Figure B18

Map of Changes in the Minimum Near-Surface Air Temperature (tas) in °C
Figure B19

Map of Changes in the Maximum Near-Surface Air Pressure (ps) in hPa
Figure B20

Map of Changes in the Mean Near-Surface Air Pressure (ps) in hPa
Figure B21

Map of Changes in the Minimum Near-Surface Air Pressure (ps) in hPa
Figure B22

Figure B23

*Map of Changes in the Mean Near-Surface Relative Humidity (hurs) in p. p.*
Figure B24

Figure B25

*Map of Changes in the Maximum Near-Surface Air Density ($\rho$) in g/m$^3$*
Figure B26

*Map of Changes in the Mean Near-Surface Air Density ($\rho$) in g/m³*
Figure B27

Map of Changes in the Minimum Near-Surface Air Density ($\rho$) in g/m$^3$
Figure B28

*Map of Changes in the Maximum Near-Surface Headwind (h_{dw}) in m/s*
Figure B29

Map of Changes in the Mean Near-Surface Headwind ($hdw$) in m/s
Figure B30

Map of Changes in the Minimum Near-Surface Headwind (hdw) in m/s
Figure B31

Changes in the Unsuccessful Takeoffs of Narrowbody Aircraft
Figure B32

Changes in the Unsuccessful Takeoffs of Widebody Aircraft
Figure B33

Changes in the Successful Takeoffs of Narrowbody Aircraft
Figure B34

*Changes in the Successful Takeoffs of Widebody Aircraft*
Figure B35

Changes in the Minimum-Thrust Takeoffs of Narrowbody Aircraft
**Figure B36**

*Changes in the Minimum-Thrust Takeoffs of Widebody Aircraft*

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<th>SSP585</th>
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*Temperature, Tropical, Global*
Figure B37

Changes in the Intermediate-Thrust Takeoffs of Narrowbody Aircraft
Figure B38

Changes in the Intermediate-Thrust Takeoffs of Widebody Aircraft
Figure B39

Changes in the Maximum-Thrust Takeoffs of Narrowbody Aircraft

![Graph showing changes in maximum-thrust takeoffs for different scenarios over time.](image)
Figure B40

Changes in the Maximum-Thrust Takeoffs of Widebody Aircraft
Figure B41

Changes in the Mean Takeoff Distance Required of Narrowbody Aircraft
Figure B42

Changes in the Mean Takeoff Distance Required of Narrowbody Aircraft
### Appendix C

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<tr>
<td>C8</td>
<td>8_simulate.R</td>
</tr>
<tr>
<td>C9</td>
<td>9_analyze.R</td>
</tr>
</tbody>
</table>

All this codebase is also available at [https://github.com/TheAviationDoctor/PhD](https://github.com/TheAviationDoctor/PhD).
# NAME: scripts/0_common.R
# INPUT: None
# ACTIONS: Set common settings used across the scripts
# OUTPUT: Set of global variables loaded into R's environment
# RUNTIME: N/A
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023

# 0 Directory locations

dir <- list(
  "cal" = "data/cal", # Calibrated takeoff performance data
  "cli" = "data/cli", # Climate data in NetCDF format
  "log" = "logs", # Log files
  "plt" = "plots", # Plots generated by R
  "res" = "data/res" # Results
)

# 1 File locations

fls <- list(
  "act" = "data/act/aircraft.csv", # Aircraft data from Sun et al. (2020)
  "net" = "data/cli/netcdf.csv", # List of NetCDF files from the ESGF
  "geo" = "data/pop/geolocation.csv", # Airport coordinates from OurAirports.com
  "rwy" = "data/pop/runways.csv", # Runways and TODA from Lufthansa Systems
  "tra" = "data/pop/traffic.csv" # 2019 traffic by airport from IATA
)

# 2 Database parameters

dat <- list(
  "cnf" = ".my.cnf", # File that contains the database connection parameters
  "grp" = "phd", # Group name within the cnf file
  "act" = "act", # Aircraft characteristics for the takeoff simulation
  "cal" = "cal", # Calibration data
  "cli" = "cli", # Climate data post-transformation
  "imp" = "imp", # Climate data imported from the NetCDF files
  "pop" = "pop", # Population and sample airports
  "tko" = "tko", # Takeoff performance calculation outputs
  "an_cli" = "an_cli", # Climate change summary
  "an_tko" = "an_tko", # Takeoff outcomes summary
  "an_res" = "an_res", # Research questions summary
  "idx" = "idx" # Index name
)

# 3 Aircraft types


act <- list(
  "Airbus A320neo" = "A20n", # With LEAP-1A29 engines
  "Airbus A350-900" = "A359", # With Trent XWB-84 engines
  "Boeing 737 MAX 9" = "B39m", # With CFM LEAP-1B27 engines
  "Boeing 787-9" = "B789" # With Trent 1000-K2 engines
)

bod <- list(
  "Narrowbody" = c("A20n", "B39m"),
  "Widebody" = c("A359", "B789")
)

# 4 Climate simulation parameters
# ==============================================================================

cli <- list(
  "tas" = "in °C", # Near-surface air temperature
  "ps" = "in hPa", # Near-surface air pressure
  "hurs" = "in p.p.", # Near-surface relative humidity
  "rho" = "in g/m³", # Near-surface air density
  "hdw" = "in m/s" # Near-surface headwind
)

go <- list(
  "Frigid" = c(-90L, -66.5635), # Antarctic zone
  "Temperate" = c(-66.5635, -23.4365), # South temperate zone
  "Tropical" = c(-23.4365, 23.4365), # Tropical zone
  "Temperate" = c(23.4365, 66.5635), # North temperate zone
  "Frigid" = c(66.5635, 90L) # Arctic zone
)

# 5 Takeoff simulation parameters
# ==================================================

sim <- list(
  # Calibration settings
  "clb_ang" = 7.7, # Average climb angle to screen height
  "flp_ang" = 10L, # Takeoff flap deflection angle in degrees
  "max_lof" = 1.2, # Ratio from Clmax to Cllof (Roskam, 2018, p 95)
  "opt_cls" = c(1.6, 2.2), # Range of cl inputs passed to the optimizer
  "opt_tol" = 10^-3, # Optimizer tolerance
  "rwy_frc" = .02, # Friction coefficient for dry concrete/asphalt
  "rwy_slp" = 0L, # Runway slope in °
  "scr_hgt" = 35L, # Minimum screen height above terrain
  "thr_rto" = 0L, # Thrust reduction used for calibration
  "tod_mul" = 1.15, # Regulatory takeoff distance multiplier

  # Model settings
  "int_stp" = 10L, # Integration steps (model resolution)
  "lf_belf" = .67, # Break-even load factor
  "pax_avg" = 87L, # Mean adult pax weight (Filippone, 2012, p. 52)
  "pop_thr" = 10^6, # Minimum passenger traffic for airport sample
  "thr_inc" = 1L, # Thrust increase at each iteration in % point
  "thr_ini" = 25L, # Thrust reduction for simulation in %

  # Natural constants
  "adb_idx" = 1.4, # Adiabatic index for dry air at ISA temperature
  "co2_ppm" = 441.10e-06, # Molar fraction of carbon dioxide in the air
"ft_to_m" = .3048,  # Number of m in one ft
"g" = 9.806665,  # Gravitational acceleration constant in m/s²
"isa_hdw" = 0L,  # ISA near-surface headwind in m/s
"isa_hur" = 0L,  # ISA sea-level relative humidity in %
"isa_ps" = 101325L,  # ISA sea-level air pressure in Pa
"isa_rho" = 1.225,  # ISA sea-level air density in kg/m³
"isa_tas" = 288.15,  # ISA sea-level air temperature in K
"k_to_c" = 273.15,  # Number of K in 0 °C
"ps_isa" = 101325L,  # Air pressure in Pa at sea level under ISA
"sat_ref" = 6.1078,  # Ref. saturation vapor pressure at 0°C in mbar
"rsp_air" = 287.058,  # Specific gas constant for dry air in J/(kg·K)
"rsp_h2o" = 461.495,  # Spec. gas constant for water vapor in J/(kg·K)
# Analysis settings
"quantiles" = seq(from = 0L, to = 1L, by = .25)  # For boxplot analysis

# 6 Plotting parameters
# =============================================
plt <- list(
  # Font size
  "axis.text" = 5L,
  "axis.title" = 6L,
  "label.text" = 2L,
  "legend.title" = 5L,
  "legend.text" = 5L,
  "strip.text" = 5L,
  "text" = 9L,
  # File
  "device" = "png",
  "path" = dir$plt,
  # Canvas
  "dpi" = "retina",
  "scale" = 1L,
  "height" = 5.2,
  "width" = 9L,
  "units" = "in"
)

# 7 Common functions
# =============================================
# 7.1 Function to distribute a computational task across cores. Parameters:
# crs = number of cores to use in the cluster
# lib = libraries required by each core
# lst = list to be distributed across cores
# fun = function to be applied to each list item
# =============================================
fn_par_lapply <- function(crs, pkg, lst, fun) {
  # Set the log file to the name of the function being passed
  log <- paste(dir$log, "/", substitute(fun), ".log", sep = ")
  # Clear the log file in case it is not empty
  close(file(description = log, open = "w"))
  # Build the cluster of workers
cl <- parallel::makeCluster(spec = crs, outfile = log)

# Have each worker load the required packages
parallel::clusterCall(
  cl = cl,
  fun = function() {
    suppressMessages(lapply(X = pkg, FUN = require, character.only = TRUE))
  }
)

# Pass all global variables to each worker
parallel::clusterExport(cl = cl, varlist = ls(.GlobalEnv))

# Distribute the task across the workers
parallel::parLapply(cl = cl, X = lst, fun = fun)

# Shut down the workers
parallel::stopCluster(cl = cl)

# 7.2 Function to execute a SQL query and retrieve the results. Parameters:
# statement = the SQL statement to pass to the database
# ------------------------------------------
fn_sql_qry <- function(statement) {
  # Connect to the database
  conn <- DBI::dbConnect(
    RMySQL::MySQL(),
    default.file = dat$cnf,
    group = dat$grp
  )

  # Send the query to the database
  res <- DBI::dbSendQuery(conn = conn, statement = statement)

  # Return the results to a data table
  dt_out <- suppressWarnings(
    data.table::setDT(
      DBI::dbFetch(res = res, n = Inf)
    )
  )

  # Release the database resource
  DBI::dbClearResult(res)

  # Disconnect from the database
  DBI::dbDisconnect(conn)

  # Return the data table
  return(dt_out)
}

# EOF
Code C1

scripts/1_population.R

# NAME: scripts/1_population.R
# INPUT: CSV files of passenger traffic, runways, and airport coordinates
# ACTIONS: Assemble the airport population and plot its characteristics
# OUTPUT: Two plots saved to disk and 8,982 rows written to the dat$pop table
# RUNTIME: ~3 seconds (3.8 GHz CPU / 128 GB DDR4 RAM / SSD)
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023

# Clear the environment
rm(list = ls())

# Load the required libraries
library(e1071)
library(DBI)
library(scales)
library(tidyverse)

# Import the common settings
source("scripts/0_common.R")

# Start a script timer
start_time <- Sys.time()

# Clear the console
cat("\014")

# Load the runway data
df_rwy <- read.csv(
  file = fls$rwy,
  header = TRUE,
  na.strings = c(0L, "NULL"),
  colClasses = c(rep("character", 2L), "integer")
)

# Describe the data
str(df_rwy)

# Count missing TODAs
sum(is.na(df_rwy$toda))

# Remove the missing TODAs
df_rwy <- na.omit(df_rwy)

# Convert the TODAs from feet to meters
df_rwy$toda <- floor(df_rwy$toda * sim$ft_to_m)
# Count remaining aerodromes
length(unique(df_rwy$icao))

# Count unique runways
nrow(df_rwy)

# Calculate mean count of runway headings per airport
nrow(df_rwy) / length(unique(df_rwy$icao))

# 2 Examine the traffic dataset
# -----------------------------------------------------------------------------------------------------------------

# Load the traffic data
df_tra <- read.csv(
  file = fls$tra,
  header = TRUE,
  colClasses = c("character", "integer")
)

# Describe the data
str(df_tra)

# Sum up the total traffic
sum(df_tra$traffic)

# Describe the traffic variable
summary(df_tra$traffic)

# Describe the skewness of the traffic variable
e1071::skewness(x = df_tra$traffic, type = 1L)

# Describe the kurtosis of the traffic variable
e1071::kurtosis(x = df_tra$traffic, type = 1L)

# 3 Examine the geolocation dataset
# -----------------------------------------------------------------------------------------------------------------

# Load the geolocation data
df_geo <- read.csv(file = fls$geo, header = TRUE)

# Describe the data
str(df_geo)

# Keep only non-closed airports with an IATA code
df_geo <- subset(
  x = df_geo,
  type %in% c("small_airport", "medium_airport", "large_airport") &
  icao != "" & nchar(iata) == 3L,
  select = c("name", "lat", "lon", "icao", "iata")
)

# Count the remaining observations
nrow(df_geo)

# Assign each airport to a climate zone based on its latitude
df_geo$zone <- names(  
  x = df_geo,  
  type %in% c("small_airport", "medium_airport", "large_airport") &
  icao != "" & nchar(iata) == 3L,
  select = c("name", "lat", "lon", "icao", "iata")
)

# Count the remaining aerodromes
length(unique(df_rwy$icao))

# Count unique runways
nrow(df_rwy)

# Calculate mean count of runway headings per airport
nrow(df_rwy) / length(unique(df_rwy$icao))
x = df_geo$lat,
vec = unique(unlist(x = geo, use.names = FALSE))
)
)
# 4 Combine the traffic and geolocation datasets into an airport dataset
# ==============================================================================

# Left join the traffic and geolocation datasets
df_apt <- merge(
  x = df_tra,
y = df_geo,
by.x = "iata",
by.y = "iata",
all.x = TRUE
)

# Count the resulting observations
nrow(df_apt)

# Check for missing ICAO codes
count(df_apt[!complete.cases(df_apt$icao), ])

# Describe the larger airports (>= sim$pop_thr passengers) missing an ICAO code
str(df_apt$iata[!complete.cases(df_apt$icao) & df_apt$traffic >= sim$pop_thr])

# Select the smaller airports (< sim$pop_thr passengers) missing an ICAO code
df_sma <- df_apt[!complete.cases(df_apt$icao) & df_apt$traffic < sim$popThr, ]

# Describe the smaller airports
str(df_sma$iata)

# Calculate the traffic at the smaller airports
sum(df_sma$traffic)

# Calculate the traffic share at the smaller airports
sum(df_sma$traffic) / sum(df_tra$traffic) * 100L

# Transfer traffic from two large airports to another that absorbed them
df_tra$traffic[df_tra$iata == "BER"] <- df_tra$traffic[df_tra$iata == "SXF"] +
df_tra$traffic[df_tra$iata == "TXL"]

# Remove those two larger airports
df_tra <- subset(x = df_tra, !(iata %in% c("SXF", "TXL")))

# Manually rename one larger airport whose IATA code changed
df_tra$iata[df_tra$iata == "TSE"] <- "NQZ"

# Remove the smaller airports
df_tra <- subset(x = df_tra, !(iata %in% df_sma$iata))

# Merge again now that the traffic dataset has been adjusted
df_apt <- merge(
  x = df_tra,
y = df_geo,
by.x = "iata",
by.y = "iata",
all.x = TRUE
)
# Count the resulting observations
nrow(df_apt)

# Check for duplicated IATA codes
df_apt[duplicated(df_apt$iata) | duplicated(df_apt$iata, fromLast = TRUE), ]

# Remove three false duplicates (i.e. different airports, same IATA code)
df_apt <- subset(
  x = df_apt,
  name != "Liuting Airport" &
  name != "Dewadaru - Kemujan Island" &
  name != "Yibin Caiba Airport"
)

# Remove first occurrence only of strict duplicates (i.e. keep one of each)
df_apt <- df_apt[!rev(duplicated(rev(df_apt$iata))), ]

# Count the resulting observations
nrow(df_apt)

# Order the population by decreasing traffic size
df_apt <- df_apt[order(df_apt$traffic, decreasing = TRUE), ]

# Reset the row index
row.names(df_apt) <- NULL

# Examine the resulting population
str(df_apt)

# 5 Combine the airport and runway datasets into the population dataset

# Left join the resulting airport dataset and runway dataset
df_pop <- merge(
  x = df_apt,
  y = df_rwy,
  by.x = "icao",
  by.y = "icao",
  all.x = TRUE
)

# Describe the data
str(df_pop)

# Count missing runways
count(df_pop[!complete.cases(df_pop$rwy), ])

# Remove missing runways
df_pop <- subset(x = df_pop, complete.cases(df_pop$rwy))

# Count the resulting runways
nrow(df_pop)

# Count the resulting airports
length(unique(df_pop$icao))

# Count the resulting traffic
sum(df_pop$traffic[!rev(duplicated(rev(df_pop$icao)))]))
# Create column to identify unique runways (i.e. reciprocal headings sharing the same physical surface and same TODA at a given airport).

df_pop_unique <- df_pop |
  mutate(rwy.recip = if_else(
    parse_number(rwy) <= 18L,
    paste("RW",
      formatC(parse_number(rwy) + 18L, width = 2L, format = "d", flag = "0"),
      case_when(
        str_sub(rwy, -1L, -1L) == "L" ~ "R",
        str_sub(rwy, -1L, -1L) == "R" ~ "L",
        str_sub(rwy, -1L, -1L) == "C" ~ "C", TRUE ~ ""
      ),
      sep = "" ),
    paste("RW",
      formatC(parse_number(rwy) - 18L, width = 2L, format = "d", flag = "0"),
      case_when(
        str_sub(rwy, -1L, -1L) == "L" ~ "R",
        str_sub(rwy, -1L, -1L) == "R" ~ "L",
        str_sub(rwy, -1L, -1L) == "C" ~ "C", TRUE ~ ""
      ),
      sep = "" )
  ),
  paste("RW",
    formatC(parse_number(rwy) - 18L, width = 2L, format = "d", flag = "0"),
    case_when(
      str_sub(rwy, -1L, -1L) == "L" ~ "R",
      str_sub(rwy, -1L, -1L) == "R" ~ "L",
      str_sub(rwy, -1L, -1L) == "C" ~ "C", TRUE ~ ""
    ),
    sep = "" )) |
mutate(rwy.concat = pmap_chr(list(rwy, rwy.recip), ~ paste(
  sort(c(...)),
  collapse = "," ) ) |
  unite("rwy.unique", c("icao", "rwy.concat", "toda"),
    sep = ",",
    remove = FALSE |
  ) |
  arrange(desc(traffic), rwy.unique) |
select(rwy.unique)

# Count unique runways
length(unique(df_pop_unique$rwy.unique))

# Count unique percentage
length(unique(df_pop_unique$rwy.unique)) / nrow(df_pop)

# Count non-unique runways
nrow(df_pop) - length(unique(df_pop_unique$rwy.unique))

# Non-unique percentage
(nrow(df_pop) - length(unique(df_pop_unique$rwy.unique))) / nrow(df_pop)

# Describe the TODA variable
summary(df_pop$toda)

# Order the merged dataset by decreasing traffic size and ICAO code
df_pop <- df_pop[order(df_pop$traffic, df_pop$icao, decreasing = TRUE), ]

# Reset the row index
row.names(df_pop) <- NULL

# 6 Plot the traffic distribution

# Reduce final population to unique airports again
df_plt <- df_pop[!duplicated(df_pop$icao),]

# Describe the traffic variable
summary(df_plt$traffic)

# Describe the skewness of the traffic variable
e1071::skewness(x = df_plt$traffic, type = 1L)

# Describe the kurtosis of the traffic variable
e1071::kurtosis(x = df_plt$traffic, type = 1L)

# Define the traffic bins (logarithmic sequence)
b breaks <-
c(1L %o% 10^(0:9))

# Define the bin labels
labels<-
c("[1-10]",
"[10-100]",
"[100-1K]",
"[1K-10K]",
"[10K-100K]",
"[100K-1M]",
"[1M-10M]",
"[10M-100M])

# Bin the airports by passenger traffic
df_bin <- df_plt |> mutate(
  bin = cut(x = df_plt$traffic, breaks = breaks, labels = labels, include.lowest = TRUE, right = FALSE ) |
) |> group_by(bin) |> dplyr::summarize(airports = n(), traffic = sum(traffic) ) |
arrange(-row_number()) |
mutate(airports_cum = cumsum(airports), airports_per = cumsum(airports) / sum(airports), traffic_cum = cumsum(traffic), traffic_per = cumsum(traffic) / sum(traffic) ) |
relocate(bin, airports, airports_cum, airports_per, traffic, traffic_cum, traffic_per )

# Display the traffic distribution table
df_bin

# Define a coefficient to scale the secondary y axis proportionally to the first
coeff <- max(df_bin$traffic_per) / max(df_bin$airports)
# Plot the Pareto chart of passenger traffic by airport bin

```r
ggplot(data = df_bin) +
  geom_col(mapping = aes(x = bin, y = airports)) +
  geom_text(
    mapping = aes(
      x = bin,
      y = airports,
      label = scales::comma(airports, accuracy = 1L)
    ),
    hjust = ifelse(df_bin$airports < 10L, -.5, .5),
    vjust = ifelse(df_bin$airports < 50L, -.5, 1.5),
    color = ifelse(df_bin$airports < 50L, "black", "white"),
    size = 3.5
  ) +
  geom_point(
    mapping = aes(x = bin, y = traffic_per / coeff),
    size = 1L
  ) +
  geom_text(
    mapping = aes(x = bin, y = traffic_per / coeff,
      label = scales::percent(traffic_per, accuracy = 0.1)
    ),
    nudge_x = -.275,
    nudge_y = 50L,
    color = "black",
    size = 3.5
  ) +
  geom_path(
    mapping = aes(x = bin, y = traffic_per / coeff, group = 1L),
    lty = 1L,
    linewidth = 0.5
  ) +
  scale_x_discrete(
    name = "Traffic bins (2019)",
    limits = rev,
    guide = guide_axis(n.dodge = 2L)
  ) +
  scale_y_continuous(
    name = "Count of airports (bars)",
    labels = scales::comma,
    breaks = seq(from = 0L, to = 1200L, by = 300L),
    sec.axis = sec_axis(~ . * coeff,
      name = "Cumulative percentage of passenger traffic (line)",
      labels = percent
    )
  ) +
  theme_light() +
  theme(
    panel.grid.minor.x = element_blank(),
    panel.grid.minor.y = element_blank()
  )

# Save the plot

ggsave(
  filename = "1_traffic_bins.png",
  plot = last_plot(),
  device = "png",
  path = dir$plt,
  scale = 1L,
)
```

# Save the plot

ggsave(
  filename = "1_traffic_bins.png",
  plot = last_plot(),
  device = "png",
  path = dir$plt,
  scale = 1L,
)
width = 6L,
height = 7L,
units = "in",
dpi = "print"
)

# Plot the density of traffic by airport size

ggplot(data = df_plt, mapping = aes(x = traffic)) +
geom_density(alpha = .75, fill = "lightgray") +
geom_vline(xintercept = mean(df_plt$traffic), color = "black") +
geom_vline(
    xintercept = median(df_plt$traffic),
    color = "black",
    linetype = "dashed"
) +
scale_x_continuous(
    name = "Passenger traffic (2019)",
    breaks = breaks,
    trans = "log10"
) +
scale_y_continuous(name = "Density") +
theme_light() +
theme(
    panel.grid.minor.x = element_blank(),
    panel.grid.minor.y = element_blank()
)

# Save the plot

ggsave(
    filename = "1_traffic_density.png",
    plot = last_plot(),
    device = "png",
    path = dir$plt,
    scale = 1L,
    width = 6L,
    height = NA,
    units = "in",
    dpi = "print"
)

# 7 Save the population to a database

# Drop the table if it exists

fn_sql_qry(
    statement = paste("DROP TABLE IF EXISTS ", tolower(dat$pop), ";", sep = "")
)

# Create the population table

fn_sql_qry(
    statement = paste("
CREATE TABLE ",
    tolower(dat$pop),
    "("
    id SMALLINT NOT NULL AUTO_INCREMENT,
    icao CHAR(4) NOT NULL,
    iata CHAR(3) NOT NULL,
    traffic INT NOT NULL,
    name CHAR("", max(nchar(df_pop$name)), ") NOT NULL,
    lat FLOAT NOT NULL,
")"
$\text{lon}$ FLOAT NOT NULL,
$\text{zone}$ CHAR(11) NOT NULL,
$\text{rwy}$ CHAR(5) NOT NULL,
$\text{toda}$ SMALLINT NOT NULL,
PRIMARY KEY (id)
);
}

# Connect the worker to the database
conn <- dbConnect(RMySQL::MySQL(), default.file = dat$cnf, group = dat$grp)

# Write the population data to the database
dbWriteTable(
  conn = conn,
  name = tolower(dat$pop),
  value = df_pop,
  append = TRUE,
  row.names = FALSE
)

# Disconnect the worker from the database
dbDisconnect(conn)

# 8 Index the database table
# ==============================================================================
# Create a composite index
fn_sql_qry(
  statement = paste(
    "CREATE INDEX idx ON", tolower(dat$pop), "(icao, zone, traffic, lat, lon);",
    sep = " "
  )
)

# 9 Housekeeping
# ==============================================================================
# Stop the script timer
Sys.time() - start_time

# EOF
scripts/2_sample.R

# NAME: scripts/2_sample.R
# INPUT: 8,982 rows read from the dat$pop table
# ACTIONS: Subset the airport sample and plot its characteristics
# OUTPUT: Five plots saved to disk
# RUNTIME: ~18 seconds (3.8 GHz CPU / 128 GB DDR4 RAM / SSD)
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023
# ==============================================================================

# 0 Housekeeping
# ==============================================================================

# Clear the environment
rm(list = ls())

# Load the required libraries
library(data.table)
library(DBI)
library(geosphere)
library(kgc)
library(maps)
library(rgeos)
library(rnaturalearth)
library(scales)
library(tidyverse)
library(tmaptools)
library(viridis)

# Import the common settings
source("scripts/0_common.R")

# Start a script timer
start_time <- Sys.time()

# Clear the console
cat("\014")

# 1 Load and describe the population
# ==============================================================================

dt_pop <- fn_sql_qry(
  statement = paste("SELECT  
    icao,  
    iata,  
    traffic,  
    name,  
    lat,  
    lon,  
    zone,  
    rwy,  
    toda")
FROM 
dat$pop, 
";", 
sep = " "
)
)

# Recast column types
set(x = dt_pop, j = "zone", value = as.factor(dt_pop[, zone]))

# Describe the population airports
summary(dt_pop)

# 2 Subset the sample from the population based on a minimum traffic threshold
# Select only airports above the minimum traffic threshold in passengers
dt_smp <- subset(dt_pop, traffic >= sim$pop_thr)

# Describe the sample airports
summary(dt_smp)

# 3 Test that the sample is representative of the population's traffic
# Describe the population vs. sample traffic
list(
  "Airport count (population, sample, percentage)" = 
  c(
    length(unique(dt_pop$icao)),
    length(unique(dt_smp$icao)),
    length(unique(dt_smp$icao)) / length(unique(dt_pop$icao))
  ),
  "Runway count (population, sample, percentage)" = 
  c(
    nrow(dt_pop),
    nrow(dt_smp),
    nrow(dt_smp) / nrow(dt_pop)
  ),
  "Passengers count (population, sample, percentage)" = 
  c(
    sum(dt_pop$traffic[!rev(duplicated(rev(dt_pop$icao)))]),
    sum(dt_smp$traffic[!rev(duplicated(rev(dt_smp$icao)))]),
    sum(dt_smp$traffic[!rev(duplicated(rev(dt_smp$icao)))]) / 
    sum(dt_pop$traffic[!rev(duplicated(rev(dt_pop$icao)))])
  )
)

# 4 Test that the sample is representative of the population's latitudes
# Define the traffic bins (logarithmic sequence)
b breaks <- c(1L %o% 10^(0:9))
# Define the bin labels
labels <- c(
    "[1-10]",
    "[10-100]",
    "[100-1K]",
    "[1K-10K]",
    "[10K-100K]",
    "[100K-1M]",
    "[1M-10M]",
    "[10M-100M]",
    "[100M-1B]"
)

# Describe the population's latitude variable (in °)
summary(dt_pop$lat[!rev(duplicated(rev(dt_pop$icao)))]))

# Describe the sample's latitude variable (in °)
summary(dt_smp$lat[!rev(duplicated(rev(dt_smp$icao)))]))

# Describe the population vs. sample latitudes (in km)
list(
    "Distance from the median latitude to the equator (population, sample)" =
    c(
        distm(
            c(0L, median(dt_pop$lat[!rev(duplicated(rev(dt_pop$icao)))])),
            c(0L, 0L),
            fun = distHaversine
        ) / 1000L,
        distm(
            c(0L, median(dt_smp$lat[!rev(duplicated(rev(dt_smp$icao)))])),
            c(0L, 0L),
            fun = distHaversine
        ) / 1000L
    ),
    "Distance from the mean latitude to the equator (population, sample)" =
    c(
        distm(
            c(0L, mean(dt_pop$lat[!rev(duplicated(rev(dt_pop$icao)))])),
            c(0L, 0L),
            fun = distHaversine
        ) / 1000L,
        distm(
            c(0L, mean(dt_smp$lat[!rev(duplicated(rev(dt_smp$icao)))])),
            c(0L, 0L),
            fun = distHaversine
        ) / 1000L
    ),
    "Distance from the median latitude to the mean (population, sample)" =
    c(
        distm(
            c(0L, median(dt_pop$lat[!rev(duplicated(rev(dt_pop$icao)))])),
            c(0L, mean(dt_pop$lat[!rev(duplicated(rev(dt_pop$icao)))])),
            fun = distHaversine
        ) / 1000L,
        distm(
            c(0L, median(dt_smp$lat[!rev(duplicated(rev(dt_smp$icao)))])),
            c(0L, mean(dt_smp$lat[!rev(duplicated(rev(dt_smp$icao)))])),
            fun = distHaversine
        ) / 1000L
    )
)
# Find the population's northernmost airport
dt_pop[which.max(dt_pop$lat), c(1L, 4L, 5L)]

# Find the sample's northernmost airport
dt_smp[which.max(dt_smp$lat), c(1L, 4L, 5L)]

# Find the population's southernmost airport
dt_pop[which.min(dt_pop$lat), c(1L, 4L, 5L)]

# Find the sample's southernmost airport
dt_smp[which.min(dt_smp$lat), c(1L, 4L, 5L)]

# Bin the population airports (not runways) by passenger traffic and geo. zones
dt_pop_binned <- dt_pop[!duplicated(dt_pop$icao),]

  mutate(
    bin = cut(
      x = traffic,
      breaks = breaks,
      labels = labels,
      include.lowest = TRUE,
      right = FALSE
    )
  )

  mutate(
    geo = cut(
      x = lat,
      breaks = unique(unlist(x = geo, use.names = FALSE)),
      labels = names(geo),
      include.lowest = TRUE,
      right = FALSE
    )
  )

# Bin the sample airports (not runways) by passenger traffic and geo. zones
dt_smp_binned <- dt_smp[!duplicated(dt_smp$icao),]

  mutate(
    bin = cut(
      x = traffic,
      breaks = breaks,
      labels = labels,
      include.lowest = TRUE,
      right = FALSE
    )
  )

  mutate(
    geo = cut(
      x = lat,
      breaks = unique(unlist(x = geo, use.names = FALSE)),
      labels = names(geo),
      include.lowest = TRUE,
      right = FALSE
    )
  )

# Count the population airports by geographical zone
dt_pop_binned %>%
  group_by(geo) %>%
  dplyr::summarize(n = n()) %>%
  mutate(per = n / nrow(dt_pop_binned) * 100L) %>%
  bind_rows(summarize_all(., ~ifelse(is.numeric(.), sum(.), "Total")))
# Count the sample airports by geographical zone
dt_smp_binned %>%
group_by(geo) %>%
dplyr::summarize(n = n() * 100L) %>%
mutate(per = n / nrow(dt_smp_binned) * 100L) %>%
bind_rows(summarize_all(., ~ifelse(is.numeric(.), sum(.), "Total")))

# Sum the population traffic by geographical zone
dt_pop_binned %>%
group_by(geo) %>%
dplyr::summarize(n = sum(traffic) / 10^6) %>%
mutate(per = n / sum(dt_pop$traffic) * 10^8) %>%
bind_rows(summarize_all(., ~ifelse(is.numeric(.), sum(.), "Total")))

# Sum the sample traffic by geographical zone
dt_smp_binned %>%
group_by(geo) %>%
dplyr::summarize(n = sum(traffic) / 10^6) %>%
mutate(per = n / sum(dt_smp$traffic) * 10^8) %>%
bind_rows(summarize_all(., ~ifelse(is.numeric(.), sum(.), "Total")))

# Define the world object from the Natural Earth package
world <- rnaturalearth::ne_countries(scale = "small", returnclass = "sf")

# Plot the population airports onto a world map
ggplot() +
  geom_sf(data = world, fill = "gray") +
  coord_sf(expand = FALSE) +
  # Define the scales
  scale_x_continuous(breaks = c(-180L, 180L)) +
  scale_y_continuous(
    breaks = unique(unlist(x = geo, use.names = FALSE)),
    limits = c(-90L, 90L)
  ) +
  scale_color_viridis(
    breaks = breaks,
    direction = -1L,
    labels = trans_format(trans = "log10", format = math_format(10^.x)),
    limits = c(dt_pop$traffic[which.min(dt_pop$traffic)],
               dt_pop$traffic[which.max(dt_pop$traffic)]),
    name = "PPA",
    trans = "log"
  ) +
  scale_size_continuous(name = "traffic", guide = "none") +
  # Add the airports
  geom_point(
    data = dt_pop[!duplicated(dt_pop$icao), ],
    mapping = aes(x = lon, y = lat, color = traffic, size = traffic),
    shape = 20L,
  ) +
  # Add parallels
  geom_hline(
    color = "black",
    linewidth = .25,
yintercept = c(
  dt_pop$lat[which.max(dt_pop$lat)],                 # Max latitude
  dt_pop$lat[which.min(dt_pop$lat)],                 # Min latitude
  mean(dt_pop[!duplicated(dt_pop$icao), ]$lat),      # Mean latitude
  as.numeric(
    crossprod(
      dt_pop[!duplicated(dt_pop$icao), ]$traffic,
      dt_pop[!duplicated(dt_pop$icao), ]$lat
    ) /
    sum(dt_pop[!duplicated(dt_pop$icao), ]$traffic)
  ),                                                 # PPA-weighted latitude
  median(dt_pop[!duplicated(dt_pop$icao), ]$lat)     # Median latitude
)

# Add parallel labels
geom_text(
  data = world,
  color = "black",
  hjust = 1L,
  label = paste(  
    "Max. latitude ",
    sprintf(    
      fmt = "%.2f",
      round(x = dt_pop$lat[which.max(dt_pop$lat)], digits = 2L)
    ),        
    "°",
    sep = ""
  ),  
  size = 1.5,
  x = 179L,
  y = dt_pop$lat[which.max(dt_pop$lat)] + 2L
) +
geom_text(
  data = world,
  color = "black",
  hjust = 1L,
  label = paste(  
    "Min. latitude ",
    sprintf(    
      fmt = "%.2f",
      round(x = dt_pop$lat[which.min(dt_pop$lat)], digits = 2L)
    ),        
    "°",
    sep = ""
  ),  
  size = 1.5,
  x = 179L,
  y = dt_pop$lat[which.min(dt_pop$lat)] + 2L
) +
geom_text(
  data = world,
  color = "black",
  hjust = 1L,
  label = paste(  
    "Mean latitude ",
    sprintf(    
      fmt = "%.2f",
      round(x = mean(dt_pop[!duplicated(dt_pop$icao), ]$lat), digits = 2L)
    ),        
    "°",
    sep = ""
  ),  
  size = 1.5,
  x = 179L,
  y = mean(dt_pop[!duplicated(dt_pop$icao), ]$lat) + 2L
) +
size = 1.5,
x = 179L,
y = mean(dt_pop[!duplicated(dt_pop$icao),]$lat) - 1.5
) +
geom_text(      data = world,      color = "black",      hjust = 1L,      label = paste(        "PPA-weighted mean latitude ",        sprintf(          fmt = "%.2f",          round(            x = as.numeric(crossprod(              dt_pop[!duplicated(dt_pop$icao),]$traffic,              dt_pop[!duplicated(dt_pop$icao),]$lat            ) / sum(dt_pop[!duplicated(dt_pop$icao),]$traffic)            ),            digits = 2L)          ),        "°",        sep = "")      ),      size = 1.5,
x = 179L,
y = as.numeric(      crossprod(          dt_pop[!duplicated(dt_pop$icao),]$traffic,          dt_pop[!duplicated(dt_pop$icao),]$lat          ) / sum(dt_pop[!duplicated(dt_pop$icao),]$traffic)      ) - 1.5
) +
geom_text(      data = world,      color = "black",      hjust = 1L,      label = paste(        "Median latitude ",        sprintf(          fmt = "%.2f",          round(x = median(dt_pop[!duplicated(dt_pop$icao),]$lat), digits = 2L)          ),        "°",        sep = "")      ),      size = 1.5,
x = 179L,
y = median(dt_pop[!duplicated(dt_pop$icao),]$lat) + 2L
) +
geom_text(      data = world,      color = "gray",      hjust = 0L,      label = "Arctic circle",      size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[5] - 2L
) +
color = "gray",
hjust = .5,
label = unique(names(geo))[3],
size  = 2.5,
x     = -175L,
y     = mean(
    c( 
      unique(unlist(x = geo, use.names = FALSE))[3],
      unique(unlist(x = geo, use.names = FALSE))[4] 
    )
  )
)+
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[2],
size  = 2.5,
x     = -175L,
y     = mean(
    c( 
      unique(unlist(x = geo, use.names = FALSE))[4],
      unique(unlist(x = geo, use.names = FALSE))[5] 
    )
  )
)+
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[1],
size  = 2.5,
x     = -175L,
y     = mean(
    c( 
      unique(unlist(x = geo, use.names = FALSE))[5],
      unique(unlist(x = geo, use.names = FALSE))[6] 
    )
  )
)+
theme_light() +
theme(
  axis.title     = element_blank(),
  axis.text      = element_blank(),
  axis.ticks     = element_blank(),
  legend.key.size= unit(.2, "in"),
  legend.title   = element_text(size = 5L),
  legend.text    = element_text(size = 5L),
  plot.margin    = margin(-.8, 0L, -.8, 0L, "in")
)

# Find the aspect ratio of the map
ar <- tmaptools::get_asp_ratio(world)

# Save the plot
ggsave(
  filename = "2_map_of_population_airports.png",
  plot     = last_plot(),
  device   = "png",
  width    = 10
)
path     = "plots",
scale    = 1L,
height   = 9L / ar,
width    = 9L,
units    = "in",
dpi      = "retina"
)

# Plot the sample airports onto a world map
ggplot() +
  geom_sf(data = world, fill = "gray") +
  coord_sf(expand = FALSE) +
  # Define the scales
  scale_x_continuous(breaks = c(-180L, 180L)) +
  scale_y_continuous(
    breaks = unique(unlist(x = geo, use.names = FALSE)),
    limits = c(-90L, 90L)
  ) +
  scale_color_viridis(
    breaks = breaks,
    direction = -1L,
    labels = trans_format(trans = "log10", format = math_format(10^.x)),
    limits = c(
      dt_pop$traffic[which.min(dt_pop$traffic)],
      dt_pop$traffic[which.max(dt_pop$traffic)]
    ),
    name = "PPA",
    trans = "log"
  ) +
  scale_size_continuous(name = "traffic", guide = "none") +
  # Add the airports
  geom_point(
    data = dt_smp[!duplicated(dt_smp$icao), ],
    mapping = aes(x = lon, y = lat, color = traffic, size = traffic),
    shape = 20L,
  ) +
  # Add parallels
  geom_hline(
    color = "black",
    linewidth = .25,
    yintercept = c(
      dt_smp$lat[which.max(dt_smp$lat)],  # Max latitude
      dt_smp$lat[which.min(dt_smp$lat)],  # Min latitude
      mean(dt_smp[!duplicated(dt_smp$icao), ]$lat),  # Mean latitude
      as.numeric(
        crossprod(
          dt_smp[!duplicated(dt_smp$icao), ]$traffic,
          dt_smp[!duplicated(dt_smp$icao), ]$lat
        ) /
        sum(dt_smp[!duplicated(dt_smp$icao), ]$traffic)
      ),  # PPA-weighted latitude
      median(dt_smp[!duplicated(dt_smp$icao), ]$lat)  # Median latitude
    )
  ) +
  # Add parallel labels
  geom_text(
    data = world,
    color = "black",
    hjust = 1L,
    label = paste(
      "Max. latitude ",
    )
  )
```r
sprintf(
    fmt = "%.2f",
    round(x = dt_smp$lat[which.max(dt_smp$lat)], digits = 2L)
),
  "\degree",
  sep = "",
),
size = 1.5,
x = 179L,
y = dt_smp$lat[which.max(dt_smp$lat)] + 2L
) +
geom_text(
  data = world,
  color = "black",
  hjust = 1L,
  label = paste(
    "Min. latitude ",
    sprintf(
      fmt = "%.2f",
      round(x = dt_smp$lat[which.min(dt_smp$lat)], digits = 2L)
    ),
    "\degree",
    sep = "",
    ),
  size = 1.5,
  x = 179L,
  y = dt_smp$lat[which.min(dt_smp$lat)] + 2L
) +
geom_text(
  data = world,
  color = "black",
  hjust = 1L,
  label = paste(
    "Mean latitude ",
    sprintf(
      fmt = "%.2f",
      round(x = mean(dt_smp[!duplicated(dt_smp$icao), ]$lat), digits = 2L)
    ),
    "\degree",
    sep = "",
    ),
  size = 1.5,
  x = 179L,
  y = mean(dt_smp[!duplicated(dt_smp$icao), ]$lat) - 1.5
) +
geom_text(
  data = world,
  color = "black",
  hjust = 1L,
  label = paste(
    "PPA-weighted mean latitude ",
    sprintf(
      fmt = "%.2f",
      round(as.numeric(crossprod(
        dt_smp[!duplicated(dt_smp$icao), ]$traffic,
        dt_smp[!duplicated(dt_smp$icao), ]$lat
      ) / sum(dt_smp[!duplicated(dt_smp$icao), ]$traffic)
    ),
    digits = 2L)
```
```r
size = 1.5,
x = 179L,
y = as.numeric(crossprod(
    dt_smp[!duplicated(dt_smp$icao),]$traffic,
    dt_smp[!duplicated(dt_smp$icao),]$lat
) / 
    sum(dt_smp[!duplicated(dt_smp$icao),]$traffic)
) - 1.35
+
geom_text(
data = world,
color = "black",
hjust = 1L,
label = paste(
    "Median latitude ",
    sprintf(fmt = "%,.2f",
        round(x = median(dt_smp[!duplicated(dt_smp$icao),]$lat), digits = 2L)
    ),"\n",
    sep = ""
),
size = 1.5,
x = 179L,
y = median(dt_smp[!duplicated(dt_smp$icao),]$lat) + 2L
) + 
geom_text(
data = world,
color = "gray",
hjust = 0L,
label = "Arctic circle",
size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[5] - 2L
) + 
geom_text(
data = world,
color = "gray",
hjust = 0L,
label = "Tropic of Cancer",
size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[4] - 2L
) + 
geom_text(
data = world,
color = "gray",
hjust = 0L,
label = "Tropic of Capricorn",
size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[3] - 2L
) + 
geom_text(
data = world,
color = "gray",
size = 1.5,
x = 179L,
y = median(dt_smp[!duplicated(dt_smp$icao),]$lat) + 2L
) + 
geom_text(
data = world,
color = "gray",
hjust = 1L,
label = paste(
    "Median latitude ",
    sprintf(fmt = "%,.2f",
        round(x = median(dt_smp[!duplicated(dt_smp$icao),]$lat), digits = 2L)
    ),"\n",
    sep = ""
),
size = 1.5,
x = 179L,
y = median(dt_smp[!duplicated(dt_smp$icao),]$lat) + 2L
)
```
hjust = 0L,
label = "Antarctic circle",
size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[2] - 2L
) +
# Add zonal labels
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[1],
size = 2.5,
x = -175L,
y = mean(c(
    unique(unlist(x = geo, use.names = FALSE))[1],
    unique(unlist(x = geo, use.names = FALSE))[2]
  )
)
) +
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[2],
size = 2.5,
x = -175L,
y = mean(c(
    unique(unlist(x = geo, use.names = FALSE))[2],
    unique(unlist(x = geo, use.names = FALSE))[3]
  )
)
) +
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[3],
size = 2.5,
x = -175L,
y = mean(c(
    unique(unlist(x = geo, use.names = FALSE))[3],
    unique(unlist(x = geo, use.names = FALSE))[4]
  )
)
) +
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[2],
size = 2.5,
x = -175L,
y = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[4],
    unique(unlist(x = geo, use.names = FALSE))[5]
  )
)
) +
geom_text(
  angle = 90L,
  data = world,
  color = "gray",
  hjust = .5,
  label = unique(names(geo))[1],
  size = 2.5,
  x = -175L,
  y = mean(
    c(
      unique(unlist(x = geo, use.names = FALSE))[5],
      unique(unlist(x = geo, use.names = FALSE))[6]
    )
  )
)
) +
theme_light() +
theme(
  axis.title = element_blank(),
  axis.text = element_blank(),
  axis.ticks = element_blank(),
  legend.key.size = unit(.2, "in"),
  legend.title = element_text(size = 5L),
  legend.text = element_text(size = 5L),
  plot.margin = margin(-.8, 0L, -.8, 0L, "in")
)

# Save the plot
ggsave(
  filename = "2_map_of_sample_airports.png",
  plot = last_plot(),
  device = "png",
  path = "plots",
  scale = 1L,
  height = 9L / ar,
  width = 9L,
  units = "in",
  dpi = "retina"
)

# Build a histogram of airports by latitude
ggplot() +
  geom_histogram(
    mapping = aes(x = dt_pop[!duplicated(dt_pop$icao),]$lat),
    fill = "black",
    alpha = .5,
    binwidth = 10L,
    na.rm = TRUE
  ) +
  geom_histogram(
    mapping = aes(x = dt_smp[!duplicated(dt_smp$icao),]$lat),
    fill = "black",
    alpha = .5,
library(tidyverse)

# Build a histogram of traffic by latitude

ggplot() +
  geom_histogram(
    mapping = aes(
      x = dt_pop[!duplicated(dt_pop$icao),]$lat,
      weight = dt_pop[!duplicated(dt_pop$icao),]$traffic
    ),
    fill = "black",
    alpha = 0.5,
    binwidth = 10L,
    na.rm = TRUE
  ) +
  geom_histogram(
    mapping = aes(
      x = dt_smp[!duplicated(dt_smp$icao),]$lat,
      weight = dt_smp[!duplicated(dt_smp$icao),]$traffic
    ),
    fill = "black",
    alpha = 0.5,
    binwidth = 10L,
    na.rm = TRUE
  ) +
  scale_x_continuous(
    name = "Latitude",
    breaks = seq(-90L, 90L, 10L),
    limits = c(-90L, 90L)
  ) +
  scale_y_continuous(
    name = "Sum of traffic",
    breaks = seq(0L, 10^10, 5L * 10^8),
    labels = label_number(scale_cut = cut_short_scale())
  ) +
  theme_light() +
  theme(panel.grid.minor = element_blank())

# Save the plot

ggsave(
  filename = "2_histogram_of_airports_by_latitude.png",
  plot = last_plot(),
  device = "png",
  path = "plots",
  scale = 1L,
  width = 4L,
  height = 4L,
  units = "in",
  dpi = "retina"
)

# Build a histogram of traffic by latitude

ggplot() +
  geom_histogram(
    mapping = aes(
      x = dt_pop[!duplicated(dt_pop$icao),]$lat,
      weight = dt_pop[!duplicated(dt_pop$icao),]$traffic
    ),
    fill = "black",
    alpha = 0.5,
    binwidth = 10L,
    na.rm = TRUE
  ) +
  geom_histogram(
    mapping = aes(
      x = dt_smp[!duplicated(dt_smp$icao),]$lat,
      weight = dt_smp[!duplicated(dt_smp$icao),]$traffic
    ),
    fill = "black",
    alpha = 0.5,
    binwidth = 10L,
    na.rm = TRUE
  ) +
  scale_x_continuous(
    name = "Latitude",
    breaks = seq(-90L, 90L, 10L),
    limits = c(-90L, 90L)
  ) +
  scale_y_continuous(
    name = "Count of airports",
    breaks = seq(-90L, 90L, 10L),
    limits = c(-90L, 90L)
  ) +
  theme_light() +
  theme(panel.grid.minor = element_blank())

# Save the plot

ggsave(
  filename = "2_histogram_of_airports_by_latitude.png",
  plot = last_plot(),
  device = "png",
  path = "plots",
  scale = 1L,
  width = 4L,
  height = 4L,
  units = "in",
  dpi = "retina"
)
theme(panel.grid.minor = element_blank())

# Save the plot

ggsave(
  filename = "2_histogram_of_traffic_by_latitude.png",
  plot     = last_plot(),
  device   = "png",
  path     = "plots",
  scale    = 1L,
  width    = 4L,
  height   = 4L,
  units    = "in",
  dpi      = "retina"
)

# 5 Calculate the Köppen-Geiger climate zones for population & sample airports
# ==============================================================================

# Pick a resolution for the KGC package processing, either "fine" or "course"
# (yes, "coarse" is misspelled in the package's source code).
res <- "course"

# Prepare the population data
df_kgc_pop <- dt_pop[
  !duplicated(dt_pop$icao),
  c("icao", "lon", "lat", "traffic")
] %>%
  mutate(rndCoord.lon = RoundCoordinates(lon, res = res, latlong = "lon")) %>%
  mutate(rndCoord.lat = RoundCoordinates(lat, res = res, latlong = "lat"))

# Compute the Köppen-Geiger climate zone for the population data
df_kgc_pop <- data.frame(
  df_kgc_pop,
  kgc = LookupCZ(df_kgc_pop, res = res, rc = FALSE)
)

# Summarize the Köppen-Geiger climate zonal distribution for the population data
df_kgc_pop <- df_kgc_pop %>%
  group_by(kgc) %>%
  dplyr::summarize(pop.airports = n(), pop.traffic = sum(traffic))

# Prepare the sample data
df_kgc_smp <- dt_smp[
  !duplicated(dt_smp$icao),
  c("icao", "lon", "lat", "traffic")
] %>%
  mutate(rndCoord.lon = RoundCoordinates(lon, res = res, latlong = "lon")) %>%
  mutate(rndCoord.lat = RoundCoordinates(lat, res = res, latlong = "lat"))

# Compute the Köppen-Geiger climate zone for the sample data
df_kgc_smp <- data.frame(df_kgc_smp,
  kgc = LookupCZ(df_kgc_smp, res = res, rc = FALSE)
)

# Summarize the Köppen-Geiger climate zonal distribution for the sample data
df_kgc_smp <- df_kgc_smp %>%
  group_by(kgc) %>%
  dplyr::summarize(smp.airports = n(), smp.traffic = sum(traffic))

# Merge the population and sample counts for row-wise comparison
df_kgc <- merge(df_kgc_pop, df_kgc_smp, by = "kgc", all = TRUE)

# Recode NAs with 0
df_kgc[is.na(df_kgc)] <- 0L

# De-factorize
df_kgc$kgc <- as.character(df_kgc$kgc)

# Recode missing Köppen-Geiger climate zones with Z
df_kgc$kgc[df_kgc$kgc == "Climate Zone info missing"] <- "Z"

# Re-factorize
df_kgc$kgc <- as.factor(df_kgc$kgc)

# Summarize the airport and traffic distribution by Köppen-Geiger climate zone
df_kgc %>%
group_by(group = substr(kgc, 1L, 1L)) %>%
dplyr::summarize(
  pop.airports = sum(pop.airports),
  pop.airports.per = sum(pop.airports) / sum(df_kgc$pop.airports),
  pop.traffic = sum(pop.traffic),
  pop.traffic.per = sum(pop.traffic) / sum(df_kgc$pop.traffic),
  smp.airports = sum(smp.airports),
  smp.airports.per = sum(smp.airports) / sum(df_kgc$smp.airports),
  smp.traffic = sum(smp.traffic),
  smp.traffic.per = sum(smp.traffic) / sum(df_kgc$smp.traffic)
)

# Plot the airport distribution by Köppen-Geiger climate zone
ggplot(data = df_kgc) +
geom_bar(
  mapping = aes(x = kgc, weight = pop.airports),
  fill = "black",
  alpha = .5,
  width = 1L
) +
geom_bar(
  mapping = aes(x = kgc, weight = smp.airports),
  fill = "black",
  alpha = .5,
  width = 1L
) +
  scale_x_discrete(guide = guide_axis(n.dodge = 2L)) +
  scale_y_continuous(trans = "log1p", breaks = c(2^(0:8))) +
  labs(x = "Köppen-Geiger climate zones", y = "Airport count") +
  theme_light() +
  theme(panel.grid.minor = element_blank())

# Save the plot
  ggsave(
    filename = "2_histogram_of_airports_by_koppen_geiger_zone.png",
    plot = last_plot(),
    device = "png",
    path = "plots",
    scale = 1L,
    width = 4.4,
    height = 4.4,
    units = "in",
    dpi = "retina"
  )
# Plot the traffic distribution by Köppen-Geiger climate zone

```r
ggplot(data = df_kgc) +
  geom_bar(
    mapping = aes(x = kgc, weight = pop.traffic),
    fill   = "black",
    alpha  = .5,
    width  = 1L
  ) +
  geom_bar(
    mapping = aes(x = kgc, weight = smp.traffic),
    fill   = "black",
    alpha  = .5,
    width  = 1L
  ) +
  scale_x_discrete(guide = guide_axis(n.dodge = 2L)) +
  scale_y_continuous(
    breaks = seq(from = 0L, to = 10^10, by = 5L * 10^8),
    labels = label_number(scale_cut = cut_short_scale())
  ) +
  labs(x = "Köppen-Geiger climate zones", y = "Sum of traffic") +
  theme_light() +
  theme(panel.grid.minor = element_blank())
```

# Save the plot

```r
ggsave(
  filename = "2_histogram_of_traffic_by_koppen_geiger_zone.png",
  plot     = last_plot(),
  device   = "png",
  path     = "plots",
  scale    = 1L,
  width    = 4.4,
  height   = 4.4,
  units    = "in",
  dpi      = "retina"
)
```

# 6 Housekeeping

```
# Stop the script timer
Sys.time() - start_time
```

# EOF
# NAME: scripts/3_download.R
# INPUT: Search criteria for the climate models, defined in section 1 below
# ACTIONS: Query the Earth System Grid Federation (ESGF) for fitting NetCDF data
# OUTPUT: CSV file listing the matching NetCDF results
# RUNTIME: ~4 seconds (3.8 GHz CPU / 128 GB DDR4 RAM / SSD)
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023

# Clear the environment
rm(list = ls())

# Load the required libraries
library(dplyr)
library(epwshiftr)

# Import the common settings
source("scripts/0_common.R")

# Start a script timer
start_time <- Sys.time()

# Clear the console
cat("\014")

# Query the ESGF server
nc_files <- rbind(
  # First query for the main climate variables of interest
  esgf_query(
    activity = "ScenarioMIP",
    variable = c("ps", "tas", "uas", "vas"),
    frequency = c("6hrPt"),
    experiment = c("ssp126", "ssp245", "ssp370", "ssp585"),
    source = "MPI-ESM1-2-HR",
    variant = "r1i1p1f1",
    replica = FALSE,
    latest = TRUE,
    resolution = "100 km",
    type = "File",
    limit = 10000L,
    data_node = NULL
  ),
  # Separate query for 'hurs', which is only available at the 6hr frequency
  esgf_query(
    activity = "ScenarioMIP",
    variable = c("hurs"),
    frequency = c("6hr"),
  )
)
```r
experiment = c("ssp126", "ssp245", "ssp370", "ssp585"),
source = "MPI-ESM1-2-HR",
variant = "r1i1p1f1",
replica = FALSE,
latest = TRUE,
resolution = "100 km",
type = "File",
limit = 10000L,
data_node = NULL
)

# Parse the results

# Remove duplicate tracking ids (there is a weird ESGF server-side issue with a few identical hrs files appearing twice with the same tracking_id).
nc_files <- nc_files[!rev(duplicated(rev(nc_files$tracking_id))),]

# Count number of unique datasets
length(unique(nc_files$dataset_id))

# Sum size of combined dataset in GB
sum(nc_files$file_size) / 10^9

# Average size per file
mean(nc_files$file_size)

# Count number of files
nrow(nc_files)

# Display the number of files by experiment (SSP) and variable
nc_files %%
  group_by(experiment_id) %>%
  summarize(
    hrs = sum(variable_id == "hrs"),
    ps = sum(variable_id == "ps"),
    tas = sum(variable_id == "tas"),
    uas = sum(variable_id == "uas"),
    vas = sum(variable_id == "vas"),
  )

# Save the query results to a file for later reference
write.csv(x = nc_files, file = fls$net)

# Housekeeping

# Stop the script timer
Sys.time() - start_time
```

Code C4

scripts/4_import.R

# NAME: scripts/4_import.R
# INPUT: NetCDF files downloaded from the Earth System Grid Federation (ESGF)
# ACTIONS: Extract time series of climate variables for each airport coordinates
# OUTPUT: 2,213,829,660 rows of climate data written to the database
# RUNTIME: ~7.2 hours (3.8 GHz CPU / 128 GB DDR4 RAM / SSD)
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023

# Clear the environment
rm(list = ls())

# Load the required libraries
library(data.table)
library(DBI)
library(parallel)
library(tidyverse)
library(tmaptools)

# Import the common settings
source("scripts/0_common.R")

# Start a script timer
start_time <- Sys.time()

cat("\n014")

crs <- 10L

# Set a time horizon for the climatic data
horizon <- as.POSIXct(
  x = "2101-01-01 00:00:00",
  tz = "GMT",
  format = "%Y-%m-%d %H:%M:%S"
)

# Set up the database table

# Drop the table if it exists
fn_sql_qry(
  statement = paste("DROP TABLE IF EXISTS ", tolower(dat$imp), ",",";", sep = "")
)

# Create the table
fn_sql_qry(
  statement = paste("CREATE TABLE", tolower(dat$imp),",")
)
"( 
  id   INT UNSIGNED NOT NULL AUTO_INCREMENT,
  obs  DATETIME NOT NULL,
  icao CHAR(4) NOT NULL,
  lat  FLOAT NOT NULL,
  lon  FLOAT NOT NULL,
  zone CHAR(11) NOT NULL,
  ssp  CHAR(6) NOT NULL,
  var  CHAR(4) NOT NULL,
  val  FLOAT NOT NULL,
  PRIMARY KEY (id)
 );",

# 2 Fetch the data that we need
# ===========================================================================
# Fetch the list of unique airports in the sample
dt_smp <- fn_sql_qry(
  statement = paste(
    "SELECT icao, lat, lon, zone",
    "FROM", dat$pop,
    "WHERE traffic >", sim$pop_thr,
    "GROUP BY icao;",
    sep = " ",
  )
)
# Recast column types
set(x = dt_smp, j = "zone", value = as.factor(dt_smp[, zone]))
# Index the data table to speed up subsequent lookups
setkey(x = dt_smp, cols = icao, verbose = TRUE)
# List the NetCDF files from which to extract the airports' climatic conditions
nc_files <- list.files(path = dir$cli, pattern = "\.nc\$, full.names = TRUE)
# 3 Parse the NetCDF files
# ===========================================================================
fn_import <- function(nc_file) {
  # 3.1 Parse the current NetCDF file
  # ===========================================================================
  # Offset the start of each worker by a random duration to spread disk I/O load
  Sys.sleep(time = sample(1:(crs * 10L), 1L))
  # Inform the log file
  print(
    paste(
      Sys.time(),
      " pid ",
      stringr::str_pad(
        Sys.getpid(),
        width = 5L,
        " ")
    )
  )

side = "left",
 pad = " ",
" is processing ", basename(nc_file),
"...", sep = ""
}

# Open the NetCDF file
nc <- ncd4::nc_open(
    filename = nc_file,
    write = FALSE,
    readunlim = FALSE
)

# Read the NetCDF file's attributes
nc_att <- ncd4::ncatt_get(nc = nc, varid = 0L)

# Read the name of the file's climatic variable
nc_var <- nc_att$variable_id

# Read the file's experiment variable (SSP)
nc_ssp <- nc_att$experiment_id

# Read the latitude vector
nc_lat <- ncd4::ncvar_get(nc = nc, varid = "lat")

# Read the longitude vector
nc_lon <- ncd4::ncvar_get(nc = nc, varid = "lon")

# Recode the longitude vector from 0°-360° to -180°-180°
nc_lon <- ((nc_lon + 180L) %% 360L) - 180L

# Read the time vector in PCICT (POSIXct-like) format
nc_obs <- ncd4.helpers::nc.get.time.series(
    f = nc,
    v = nc_var,
    time.dim.name = "time"
)

# Read the 3D climate array
nc_arr <- ncd4::ncvar_get(nc = nc, varid = nc_var)

# Release the NetCDF file from memory
ncdf4::nc_close(nc = nc)

# Check if the plot already exists
if (file.exists(
    paste(dir$plt, "4_map_of_climate_model_spatial_grid.png", sep = "/")
) == FALSE)
{
    # Find the grid cells occupied by sample airports
    grid <- expand.grid(lat = nc_lat, lon = nc_lon)
    match <- lapply(}
\[ X = \text{as.vector}(\text{dt_smp}\$\text{icao}), \]
\[ \text{FUN} = \text{function}(x) \{ \]
\[ \quad \text{which.min(} \]
\[ \quad \quad \text{abs(grid}\$\text{lat} - \text{dt_smp}[\text{icao} == x, \text{lat}]) + \]
\[ \quad \quad \text{abs(grid}\$\text{lon} - \text{dt_smp}[\text{icao} == x, \text{lon}]) \]
\[ \quad \} \]
\[ \} \]
\[ \text{match} <- \text{unique(\text{unlist(match)})} \]

# Find the mean distance between two grid cell latitudes
\[ \text{off_lat} <- \text{mean(} \text{abs(diff(\text{as.vector(nc_lat))}))} \]

# Find the mean distance between two grid cell latitudes
\[ \text{off_lon} <- \text{mean(} \text{abs(diff(\text{abs(as.vector(nc_lon))}))} \]

# Define the world object from the Natural Earth package
\[ \text{world} <- \text{rnaturalearth::ne_countries(scale = "small", returnclass = "sf"}) \]

# Plot the grid cells of the NetCDF file onto a world map
\[ \text{ggplot()} + \]
\[ \quad \text{geom_sf(data = world, fill = "white") +} \]
\[ \quad \text{coord_sf(datum = NA, expand = FALSE) +} \]
\[ \quad \text{# Add the airports} \]
\[ \quad \text{geom_rect(} \]
\[ \quad \quad \text{color} = \text{NA}, \]
\[ \quad \quad \text{fill} = "blue", \]
\[ \quad \quad \text{linewidth} = 0L, \]
\[ \quad \quad \text{data} = \text{data.frame(} \]
\[ \quad \quad \quad \text{xmin} = \text{grid}[\text{match, "lon"] - \text{off_lon / 2L}, \]
\[ \quad \quad \quad \text{xmax} = \text{grid}[\text{match, "lon"] + \text{off_lon / 2L}, \]
\[ \quad \quad \quad \text{ymin} = \text{grid}[\text{match, "lat"] - \text{off_lat / 2L}, \]
\[ \quad \quad \quad \text{ymax} = \text{grid}[\text{match, "lat"] + \text{off_lat / 2L} \]
\[ \quad \quad }, \]
\[ \quad \quad \text{mapping} = \text{aes(} \]
\[ \quad \quad \quad \text{xmin} = \text{xmin}, \]
\[ \quad \quad \quad \text{xmax} = \text{xmax}, \]
\[ \quad \quad \quad \text{ymin} = \text{ymin}, \]
\[ \quad \quad \quad \text{ymax} = \text{ymax} \]
\[ \quad \} + \]
\[ \quad \text{# Add the parallels} \]
\[ \quad \text{geom_hline(} \]
\[ \quad \quad \text{color} = "blue", \]
\[ \quad \quad \text{linewidth} = .05, \]
\[ \quad \quad \text{yintercept} = \text{nc_lat} - \text{off_lat / 2L} \]
\[ \quad \) + \]
\[ \quad \text{# Add the meridians} \]
\[ \quad \text{geom_vline(} \]
\[ \quad \quad \text{color} = "blue", \]
\[ \quad \quad \text{linewidth} = .05, \]
\[ \quad \quad \text{xintercept} = \text{nc_lon} - \text{off_lon / 2L} \]
\[ \quad \) + \]
\[ \quad \text{theme_light()} + \]
\[ \quad \text{theme(} \]
\[ \quad \quad \text{axis.title = element_blank()}, \]
\[ \quad \quad \text{axis.text.x = element_blank()}, \]
\[ \quad \quad \text{axis.text.y = element_blank()}, \]
\[ \quad \quad \text{plot.margin = margin(-.8, 0L, -.8, 0L, "in"}) \]
\]
# Find the aspect ratio of the map
ar <- tmaptools::get_asp_ratio(world)

# Save the plot
ggsave(
  filename = "4_map_of_climate_model Spatial_grid.png",
  plot = last_plot(),
  device = "png",
  path = "plots",
  scale = 1L,
  height = 9L / ar,
  units = "in",
  dpi = "retina"
)

# 3.2 Extract the climatic variables for each sample airport (inner loop)

dt_nc <- lapply(X = as.vector(dt_smp$icao),

  FUN = function(x) {
    # Find the row index of the latitude nearest to the airport's
    lat_idx <- which.min(abs(nc_lat - dt_smp[icao == x, lat]))

    # Find the row index of the longitude nearest to the airport's
    lon_idx <- which.min(abs(nc_lon - dt_smp[icao == x, lon]))

    # Extract the climate variable's time series at those spatial indices
    nc_val <- nc_arr[lon_idx, lat_idx, ]

    # Assemble the results into a data table
    dt_apt <- data.table(
      obs = PCICt::as.POSIXct.PCICt(
        x = nc_obs,
        tz = "GMT",
        format = "%Y-%m-%d %H:%M:%S"
      ),
      icao = as.factor(dt_smp[icao == x, icao]), # Airport's ICAO code
      lat = dt_smp[icao == x, lat],             # Airport's latitude
      lon = dt_smp[icao == x, lon],             # Airport's longitude
      zone = as.factor(nc_zone),                # Airport's climate zone
      ssp = as.factor(nc_ssp),                  # Experiment (SSP)
      var = as.factor(nc_var),                  # Climatic variable name
      val = as.vector(nc_val)                   # Climatic variable value
    )

    # All climate variables except 'hurs' are 6-hourly mean samples at 06:00
    # (i.e. a mean of 03:00-09:00), 12:00 (i.e. a mean of 09:00-15:00), 18:00
    # (i.e. a mean of 15:00-21:00), and 00:00 (i.e. a mean of 21:00-03:00).
    # 'hurs' is instead sampled 6-hourly at a specified time point within the
    # time period (03:00, 09:00, 15:00, 21:00). For the observation times to
    # line up with those of other variables, hurs must be normalized. To do so
# the rolling mean of time & value is computed for every row pair of hours
if (nc_var == "hurs") {
  # Advance the observation time by 3 hours (which is the same as
  # averaging the times of the current and next six-hourly observations)
  set(x = dt_apt, j = "obs", value = dt_apt[, obs] + 3600L * 3L)
  # Average the current and next observation values
  set(
    x = dt_apt,
    j = "val",
    value = frollmean(x = dt_apt[, val], n = 2L, align = "left")
  )
  # The last value of 'hurs' for every NetCDF file and airport (365.25
  # days x 5 years x 4 daily observations = every 7,305th observation)
  # would be empty as a result of the left-centered rolling mean, so we
  # impute it by carrying the last observation forward ("locf")
  setnafill(x = dt_apt, type = "locf", cols = "val")
} # End lapply function

# Remove cases beyond the time horizon
return(subset(x = dt_apt, subset = obs < horizon))

} # End lapply

# 3.3 Consolidate the outputs and write them to the database
# └─────────────────────────────
# Consolidate the data tables
dt_nc <- rbindlist(l = dt_nc, use.names = FALSE)

# Connect the worker to the database
conn <- dbConnect(RMySQL::MySQL(), default.file = dat$cnf, group = dat$grp)

# Write to the database
dbWriteTable(
  conn = conn,
  name = tolower(dat$imp),
  value = dt_nc,
  append = TRUE,
  row.names = FALSE
)

# Disconnect the worker from the database
dbDisconnect(conn)

} # End of the fn_import function

# 4 Handle the parallel computation
# └─────────────────────────────
# Distribute the NetCDF files across the CPU cores
fn_par_lapply(
  crs = crs,
  pkg = c(
    "data.table",
    "DBI",
    "ggplot2",
    "ncdf4",
    "parallel",
    "foreach"
  ),
  # Additional parameters for the parallel function
  # ...
"ncdf4.helpers",
"PCICt",
"rnaturalearth",
"stringr",
"tmaptools"
),
lst = nc_files,
fun = fn_import
)

# 5 Index the database table

fn_sql_qry(
    statement = paste(
        "CREATE INDEX idx ON",
        tolower(dat$imp),
        "(icao);",
        sep = " ",
    )
)

# 6 Housekeeping

# Stop the script timer
Sys.time() - start_time

# EOF
Code C5

scripts/5_transform.R

```r
# ============================================================================== # NAME: scripts/5_transform.R # INPUT: 2,213,829,660 long climate observations read from the dat$imp table # ACTIONS: Pivot the data # Calculate the air density, wind vector, and active runway # OUTPUT: 442,765,932 wide climate observations written to the dat$cli table # RUNTIME: ~4.25 hours (3.8 GHz CPU / 128 GB DDR4 RAM / SSD) # AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in> # YEAR: 2023 # ============================================================================== # Housekeeping # # Clear the environment rm(list = ls()) # Load the required libraries library(data.table) library(DBI) library(masscor) library(parallel) library(stringr) # Import the common settings source("scripts/0_common.R") # Start a script timer start_time <- Sys.time() # Clear the console cat("\014") # Set the number of CPU cores for parallel processing crs <- 16L
```

```r
# Fetch the list of airports and runways in the sample
dt_smp <- fn_sql_qry(
  statement = paste("SELECT
  icao,
  lat,
  lon,
  zone,
  rwy,
  toda
FROM ",
tolower(dat$pop),
"WHERE traffic >",
sim$pop_thr,
";",
```

sep = " "

# Recast column types
set(x = dt_smp, j = "icao", value = as.factor(dt_smp[, icao]))
set(x = dt_smp, j = "zone", value = as.factor(dt_smp[, zone]))

# Convert the runway's name (e.g., RW26R) to its magnetic heading in degrees
# (e.g., 260) for later headwind calculation
dt_smp[, hdg := as.numeric(substr(rwy, 3L, 4L)) * 10L]

# For two runways with the same magnetic heading at a given airport (e.g. RWY26R
# and RWY26L), keep the one with the longest TODA (i.e. the most favorable case)
dt_smp <- dt_smp[, .SD[which.max(toda)], by = .(icao, hdg)]

# Return the resulting count of runways to the console
nrow(dt_smp)

# ==============================================================================
# 2 Set up the database table to store the results in wide format
# ==============================================================================

drop the table if it exists
fn_sql_qry(
  statement = paste("DROP TABLE IF EXISTS ", tolower(dat$cli), ";", sep = "")
)

# Create the table
fn_sql_qry(
  statement = paste("CREATE TABLE",
    tolower(dat$cli),
    
    "(   
      id      INT UNSIGNED NOT NULL AUTO_INCREMENT,
      year    YEAR NOT NULL,
      obs     DATETIME NOT NULL,
      icao    CHAR(4) NOT NULL,
      lat     FLOAT NOT NULL,
      lon     FLOAT NOT NULL,
      zone    CHAR(11) NOT NULL,
      ssp     CHAR(6) NOT NULL,
      hrs     FLOAT NOT NULL,
      hrs_cap FLOAT NOT NULL,
      ps      FLOAT NOT NULL,
      tas     FLOAT NOT NULL,
      rho1    FLOAT NOT NULL,
      rho2    FLOAT NOT NULL,
      rho3    FLOAT NOT NULL,
      hdw     FLOAT NOT NULL,
      rwy     CHAR(5) NOT NULL,
      toda    SMALLINT NOT NULL,
      PRIMARY KEY (id)
    );", sep = " "
  )
)
fn_transform <- function(apt) {
  # Offset the start of each worker by a random duration to spread disk I/O load
  Sys.sleep(time = sample(x = 1L:(crs * 10L), size = 1L))

  # Inform the log file
  print(
    paste(
      Sys.time(),
      "pid",
      stringr::str_pad(
        Sys.getpid(),
        width = 5L,
        side = "left",
        pad = " ",
      ),
      apt,
      "(1/6) Fetching climate observations...",
      sep = " ",
    )
  )
}

# 3.1 Fetch and prepare the climate data for the current airport
# ==================================================================================================

# Fetch the climate data for the current airport
dt_nc <- fn_sql_qry(
  statement = paste(
    "SELECT
      obs,
      icao,
      ssp,
      var,
      val
    FROM ",
    tolower(dat$imp),
    " WHERE
      icao = '",
    apt,
    "',
    sep = " ",
  )
)

# Recast column types
set(x = dt_nc, j = "icao", value = as.factor(dt_nc[, icao]))
set(x = dt_nc, j = "ssp",  value = as.factor(dt_nc[, ssp]))
set(x = dt_nc, j = "var",  value = as.factor(dt_nc[, var]))

# Inform the log file
print(
  paste(
    Sys.time(),
    "pid",
    stringr::str_pad(
      Sys.getpid(),
      width = 5L,
      side = "left",
      pad = " ",
    )
  )
)
# Pivot the dataset from long to wide format
# Pivot the dataset from long to wide format
dt_nc <- dcast.data.table(
data = dt_nc,
formula = obs + icao + ssp ~ var,
value.var = "val"
)

# 3.2 Calculate the air density of moist air at the current airport
# ============================================================================
# Inform the log file
print(
paste(  
Sys.time(),
"pid",
stringr::str_pad(  
Sys.getpid(),
width = 5L,
side = "left",
pad = " ",
),
"apt",
"(3/6) Calculating air density for",
format(x = nrow(dt_nc), big.mark = ","),
"observations...",
sep = " ",
)
)

# Polynomial approximation for the saturation vapor pressure at 0°C in mbar
# Based on the ESW(T) function at https://icoads.noaa.gov/software/other/profs
pol <- -0.99999683 +
  (dt_nc[, tas] - sim$k_to_c) * (-0.00026951E-02 +
    (dt_nc[, tas] - sim$k_to_c) * (0.78736169E-04 +
      (dt_nc[, tas] - sim$k_to_c) * (-0.61117958E-06 +
        (dt_nc[, tas] - sim$k_to_c) * (0.43884187E-08 +
          (dt_nc[, tas] - sim$k_to_c) * (-0.29883885E-10 +
            (dt_nc[, tas] - sim$k_to_c) * (0.21874425E-12 +
              (dt_nc[, tas] - sim$k_to_c) * (-0.17892321E-14 +
                (dt_nc[, tas] - sim$k_to_c) * (0.11112018E-16 +
                  (dt_nc[, tas] - sim$k_to_c) * (-0.30994571E-19)))))))

# 3.2.1 Method 1: ideal gas law allowing for supersaturation (hurs > 100%)
# =========================================================================
# Calculate the partial pressure of water vapor in mbar
pv <- (sim$sat_ref / pol^8L) * (dt_nc[, hurs] / 100L)
# Calculate the partial pressure of dry air in mbar
pd <- dt_nc[, ps] / 100L - pv
356

# Calculate the air density in kg/m3
set(
x
= dt_nc,
j
= "rho1",
value = (
(pd / (sim$rsp_air * dt_nc[, tas])) + (pv / (sim$rsp_h2o * dt_nc[, tas]))
) * 100L
)
#
#
#
#
#
#

============================================================================
3.2.2 Method 2: ideal gas law, no supersaturation (hurs capped at 100%)
These additional methods are provided because occurrences of supersaturation
(hurs > 100%) were observed in MPI-ESM1-2-HR model outputs.
See https://doi.org/jmgx and https://doi.org/jmgw for further details.
============================================================================

# Cap hurs at 100% where supersaturation is observed
set(
x
= dt_nc,
j
= "hurs_cap",
value = fifelse(dt_nc[, hurs] > 100L, 100L, dt_nc[, hurs])
)
# Re-calculate the partial pressure of water vapor in mbar
pv <- (sim$sat_ref / pol^8L) * (dt_nc[, hurs_cap] / 100L)
# Re-calculate the partial pressure of dry air in mbar
pd <- dt_nc[, ps] / 100L - pv
# Calculate the air density in kg/m3
set(
x
= dt_nc,
j
= "rho2",
value = (
(pd / (sim$rsp_air * dt_nc[, tas])) + (pv / (sim$rsp_h2o * dt_nc[, tas]))
) * 100L
)
# ============================================================================
# 3.2.3 Method 2: CIPM-2007 method, no supersaturation (hurs capped at 100%)
# ============================================================================
# Alternate air density calculation based on https://doi.org/dqnsdj
set(
x
= dt_nc,
j
= "rho3",
value = masscor::airDensity(
Temp
= dt_nc[, tas],
p
= dt_nc[, ps],
h
= dt_nc[, hurs_cap],
unitsENV = c("K", "Pa", "%"),
x_CO2
= sim$co2_ppm,
model
= "CIMP2007" # Typo in the package (should be "CIPM2007")
) * 10^3
)
# ============================================================================
# 3.3 Merge with the list of runways
# ============================================================================


# Extract the list of runways for the current airport
dt_rwys <- dt_smp[icao == apt, ]

# Return the Cartesian product of observations times runway headings
dt_nc <- merge(x = dt_nc, y = dt_rwys, by = "icao", allow.cartesian = TRUE)

# Inform the log file
print(paste(Sys.time(), "pid", stringr::str_pad(Sys.getpid(), width = 5L, side = "left", pad = " "), apt, "(4/6) Calculating headwinds for", format(x = nrow(dt_nc), big.mark = ","), "observations...", sep = " ")

# 3.4 Calculate the wind vector for each runway
# 3.4.1 Calculate the airport's wind speed in m/s
set(x = dt_nc, j = "wnd_spd", value = sqrt(dt_nc[, uas]^2L + dt_nc[, vas]^2L))

# Calculate the airport's wind direction in °
set(x = dt_nc, j = "wnd_dir", value = (180L + (180L / pi) * atan2(dt_nc[, uas], dt_nc[, vas])) %% 360L)

# Calculate each runway's headwind speed in m/s
set(x = dt_nc, j = "hdw", value = dt_nc[, wnd_spd] * cos(abs(dt_nc[, hdg] - dt_nc[, wnd_dir]) * pi / 180L)

# Keep only the runway with the maximum headwind speed (presumed to be the active runway) for each observation and experiment (SSP)
dt_nc <- dt_nc[, .SD[which.max(hdw)], by = .(obs, ssp)]

# 3.4 Write the data in wide format to the database
# Inform the log file
print(paste(Sys.time(), "pid", stringr::str_pad(Sys.getpid(), width = 5L, side = "left", pad = " "), apt, "(4/6) Calculating headwinds for", format(x = nrow(dt_nc), big.mark = ","), "observations...", sep = " ")
Sys.getpid(),
width = 5L,
side = "left",
pad = " "
),
apt,
"(5/6) Writing",
format(x = nrow(dt_nc), big.mark = ","),
"observations to the database...",
sep = " "
)
)

# Create the year column
set(
  x = dt_nc,
  j = "year",
  value = format.Date(x = dt_nc[, obs], format = "%Y")
)

# Select which columns to write to the database and in which order
cols <- c(
  "year",
  "obs",
  "icao",
  "lat",
  "lon",
  "zone",
  "ssp",
  "hurs",
  "hurs_cap",
  "ps",
  "tas",
  "rho1",
  "rho2",
  "rho3",
  "hdw",
  "rwy",
  "toda"
)

# Connect the worker to the database
conn <- dbConnect(RMySQL::MySQL(), default.file = dat$cnf, group = dat$grp)

# Write the data
dbWriteTable(
  conn = conn,
  name = tolower(dat$cli),
  value = dt_nc[, ..cols],
  append = TRUE,
  row.names = FALSE
)

# Disconnect the worker from the database
dbDisconnect(conn)

# Inform the log file
print(
  paste(
    Sys.time(),
    "pid",
    ....
  )
)
stringr::str_pad(
    Sys.getpid(),
    width = 5L,
    side = "left",
    pad = " "
),
apt,
"(6/6) Written",
format(x = nrow(dt_nc), big.mark = ","),
"observations to the database.",
sep = " "
)

} # End of the fn_transform function

# 4 Handle the parallel computation
# #=============================================================================

# Distribute the sample airports across the CPU cores
fn_par_lapply(
    crs = crs,
    pkg = c("data.table", "DBI", "masscor", "stringr"),
    lst = unique(dt_smp[, icao], by = "icao"),
    fun = fn_transform
)

# 5 Index the database table
# #=============================================================================

# Create the index
fn_sql_qry(
    statement = paste(
        "CREATE INDEX idx ON",
        tolower(dat$cli),
        "(year, icao, zone, ssp);", sep = " "
    )
)

# 6 Housekeeping
# #=============================================================================

# Stop the script timer
Sys.time() - start_time

# EOF
# NAME: scripts/6_model.R
# INPUT: Aircraft characteristics & takeoff conditions from the calling script
# ACTIONS: Simulate takeoffs and return the ground distance required in m
# OUTPUT: A vector of ground distances for each takeoff
# RUNTIME: Variable based on input data table size
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023

# Define a function to calculate the liftoff speed based on:
# cllof = dimensionless lift coefficient at liftoff
# g     = gravitational acceleration constant in m/s²
# tom   = takeoff mass in kg
# rho   = air density in kg/m³
# s     = wing surface area in m²
# Adapted from Blake (2009).

def fn_vlof(DT)
    vlof <- sqrt((2L * DT[, tom] * sim$g) / (DT[, rho] * DT[, s] * DT[, cllof]))

# Define a function to calculate the horizontal dist. covered by the aircraft
during the first-segment climb, in m. Adapted from Filippone (2012, p. 258).

def fn_dis_air()
    dis_air <- sim$scr_hgt / tan(sim$clb_ang * pi / 180L) * sim$ft_to_m

# Define a function to calculate the ground distance required based on:
# bpr  = engine bypass ratio
# cd   = dimensionless drag coefficient
# cllof = dimensionless lift coefficient at liftoff
# g0   = thrust coefficient
# hdw  = headwind in m/s
# n    = engine count in units
# rho  = air density in kg/m³
# s    = wing surface area in m²
# slst = engine sea-level static maximum thrust in N (per engine)
# vlof = speed in m/s at which lift L equals weight W, plus a safety margin
# vsnd = speed of sound in m/s for the given temperature in dry air
# w    = aircraft weight in N
# x    = thrust coefficient
# y    = thrust coefficient
fn_dis_gnd <- function(DT) {
  # 3.1 Calculate the airspeed and groundspeed intervals in m/s
  # Groundspeed is airspeed plus headwind.
  
  # Calculate the airspeed in m/s for each simulation interval up to liftoff
  vtas <- as.vector(mapply(
    FUN = seq,
    from = DT[, hdw],
    to = DT[, vlof],
    length.out = sim$int_stp
  ))
  
  # Calculate the groundspeed in m/s for each simulation interval up to liftoff
  vgnd <- as.vector(mapply(
    FUN = seq,
    from = 0L,
    to = DT[, vlof] - DT[, hdw],
    length.out = sim$int_stp
  ))
  
  # 3.2 Calculate the propulsive force in N
  # Adapted from Sun et al. (2020).
  
  # Vectorize the speed of sound
  vsnd <- rep(sqrt(sim$adb_idx * sim$rsp_air * DT[, tas]), each = sim$int_stp)
  
  # Calculate the dimensionless Mach number for each airspeed interval
  vmach <- vtas / vsnd
  
  # Calculate the air pressure ratio
  dp <- rep(DT[, ps] / sim$ps_isa, each = sim$int_stp)
  
  # Vectorize the engine bypass ratio
  bpr <- rep(DT[, bpr], each = sim$int_stp)
  
  # Calculate the thrust coefficients
  g0 <- .0606 * bpr + .6337
  y <- -.4327 * dp^2L + 1.3855 * dp + .0472
  x <- .1377 * dp^3L - .4374 * dp^2L + 1.3003 * dp
  z <- .9106 * dp^3L - 1.7736 * dp^2L + 1.8697 * dp
  
  # Calculate the thrust ratio for each Mach number interval
  tr <- y - .377 * (1L + bpr) / sqrt((1L + .82 * bpr) * g0) * z * vmach + (.23 + .19 * sqrt(bpr)) * x * vmach^2L
  
  # Vectorize the sea-level static thrust in N
  slst <- rep(DT[, slst], each = sim$int_stp)
  
  # Vectorize the engine count
n <- rep(DT[, n], each = sim$int_stp)

# Calculate the maximum takeoff thrust in N for each airspeed interval
fmax <- tr * slst * n

# Vectorize the thrust reduction percentage
thr_red <- rep(DT[, thr_red], each = sim$int_stp)

# Apply the maximum takeoff thrust reduction permissible
frto <- fmax * (100L - thr_red) / 100L

# 3.3 Calculate the acceleration in m/s² up to liftoff
# Adapted from Blake (2009).
#========================================================================================================
# Vectorize the takeoff mass in kg
tom <- rep(DT[, tom], each = sim$int_stp)

# Calculate the aircraft weight in N
w <- tom * sim$g

# Vectorize the wing surface area in m²
s <- rep(DT[, s], each = sim$int_stp)

# Vectorize the lift coefficient
cllof <- rep(DT[, cllof], each = sim$int_stp)

# Vectorize the drag coefficient
cd <- rep(DT[, cd], each = sim$int_stp)

# Vectorize the air density in kg/m³
rho <- rep(DT[, rho], each = sim$int_stp)

# Calculate the dynamic pressure in N/m²
q <- .5 * rho * vtas^2L

# Calculate the acceleration in m/s²
acc <- (sim$g / w) * (frto - (sim$rwy_frc * w) - (cd - sim$rwy_frc * cllof) * q * s - (w * sin(sim$rwy_slp)))

# Check for negative accelerations (extreme cases of elevated temperature, low air density, low air pressure, max takeoff mass, and min thrust).
acc_neg <- sum(acc < 0L)

# Zero out negative accelerations in extreme cases environmental cases
if(acc_neg > 0L) {
  print(paste(acc_neg, "negative accelerations were zeroed out."), sep = " ")
  acc[acc < 0L] <- .10^-3
}

# 3.4 Increment the horizontal takeoff distances in m
# Adapted from Blake (2009).
#========================================================================================================
# Set the rolling window width
bar_width <- rep(
  x = c(seq.int(2L), rep(x = 2L, each = sim$int_stp - 2L)),
  times = nrow(DT)
)
# Calculate mean acceleration between two groundspeed increments
acc_bar <- frollmean(x = acc, n = bar_width, adaptive = TRUE)

# Calculate mean groundspeed between two groundspeed increments
vgnd_bar <- frollmean(x = vgnd, n = bar_width, adaptive = TRUE)

# Vectorize the liftoff speed
vlof <- rep(DT[, vlof], each = sim$int_stp)

# Vectorize the headwind speed
hdw <- rep(DT[, hdw], each = sim$int_stp)

# Calculate the size of each groundspeed interval
vgnd_int <- (vlof - hdw) / (sim$int_stp - 1L)

# Calculate the incremental distance in m covered in each groundspeed interval
inc <- vgnd_bar * vgnd_int / acc_bar

# Calculate the cumulative distance in m up to liftoff
cum <- frollsum(
  x = inc,
  n = rep(x = seq(1L:sim$int_stp), times = nrow(DT)),
  adaptive = TRUE
)

# 3.5 Assemble the takeoff distance required in m
# Adapted from Blake (2009) and Gratton et al (2020)

# Set the horizontal ground distance up to liftoff
dis_gnd <- cum[seq(sim$int_stp, length(cum), sim$int_stp)]

} # End of fn_dis_gnd function

# EOF
Code C7

scripts/7_calibrate.R

```
# NAME: scripts/7_calibrate.R
# INPUT: OEM takeoff performance data under ISA conditions in dir$cal
# ACTIONS: Optimize lift and drag coefficients in 6_model.R to fit the OEM data
# OUTPUT: 28,627 rows of takeoff calibration data written to the dat$cal table
# RUNTIME: ~50 minutes (3.8 GHz CPU / 128 GB DDR4 RAM / SSD)
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023

# Housekeeping

# Clear the environment
rm(list = ls())

# Load the required libraries
library(data.table)
library(DBI)
library(ggplot2)
library(magrittr)
library(parallel)
library(stringr)
library(zoo)

# Import the common settings
source("scripts/0_common.R")

# Import the takeoff performance model
source("scripts/6_model.R")

# Start a script timer
start_time <- Sys.time()

# Clear the console
cat("\014")

# Import the aircraft characteristics (from Sun et al., 2020)

# Load the file to a data table
dt_act <- fread(
  file = fls$act,
  header = TRUE,
  colClasses = c(rep("factor", 2L), rep("integer", 5L), rep("numeric", 5L)),
  key = "type"
)

dt_act <- dt_act[type %in% act]

# Set the mass corresponding to a break-even load factor
set(x = dt_act,
```
j     = "tom_belf",
value = dt_act[, tom_max - floor(seats * (1L - sim$lf_belf)) * sim$pax_avg]

# Set the mass corresponding to a zero load factor
set(
  x     = dt_act,
  j     = "tom_zero",
  value = dt_act[, tom_max - (seats * sim$pax_avg)]
)

# 2 Import the takeoff performance calibration data
# List the takeoff performance calibration data files
l0 <- paste(dir$cal, "/", act, ".csv", sep = "")
# Combine all the files into one list
l1 <- Map(
  cbind,
  type = sub(".csv", "", basename(l0)),
  lapply(,
    X = l0,
    FUN = fread,
    sep = ",",
    header = TRUE,
    col.names = c("tom", "todr_cal"),
    colClasses = c("integer", "numeric")
  )
)
# Convert the list to a data table for plotting
dt_cal <- rbindlist(l1)
# Plot the calibrated mass over TODR for each aircraft type (pre-interpolation)
ggplot(data = dt_cal) +
  geom_point(mapping = aes(x = tom, y = todr_cal), color = "black", size = .1) +
  geom_vline(
    data = dt_act,
    mapping = aes(xintercept = tom_belf),
    linetype = "longdash"
  ) +
  geom_vline(data = dt_act, mapping = aes(xintercept = tom_zero)) +
  scale_x_continuous("Takeoff mass in kg", labels = scales::comma) +
  scale_y_continuous("Regulatory TODR in m", labels = scales::comma) +
  facet_wrap(~type, ncol = 2L, scales = "free") +
  theme_light() )
ggsave(
  filename = "7_pre_interpol.png",
  device = "png",
  path = "plots",
  scale = 1L,
  width = 6L,
  height = NA,
  units = "in",
  dpi = "print"
)

# 3 Interpolate the takeoff performance calibration data
# List every integer between the minimum and maximum mass values by aircraft

```
l2 <- lapply(X = l1, FUN = function(x) {
    data.table(
        type   = first(x["type"])[1],
        tom    = seq(
            from = floor(min(x["tom"])),
            to   = ceiling(max(x["tom"])),
            by   = 1L
        ),
        todr_cal = NA
    )
})
```

# Combine both lists into a single data table

```
dt_cal <- rbindlist(c(l1, l2))
```

# Remove duplicates values of type and mass created in l2

```
dt_cal <- unique(dt_cal, by = c("type", "tom"))
```

# Reorder the resulting data frame

```
dt_cal <- dt_cal[order(type, tom)]
```

# Interpolate missing TODR values by aircraft type

```
dt_cal <- dt_cal[, lapply(.SD, zoo::na.approx), by = type]
```

# Plot the calibrated mass over TODR for each aircraft type (post-interpolation)

```
(ggplot(data = dt_cal) +
 geom_point(mapping = aes(x = tom, y = todr_cal), color = "black", size = .1) +
 geom_vline(
    data = dt_act,
    mapping = aes(xintercept = tom_belf),
    linetype = "longdash"
  ) +
 geom_vline(data = dt_act, mapping = aes(xintercept = tom_zero)) +
 scale_x_continuous("Takeoff mass in kg", labels = scales::comma) +
 scale_y_continuous("Regulatory TODR in m", labels = scales::comma) +
 facet_wrap(~type, ncol = 2L, scales = "free") +
 theme_light()) %>%
 ggsave(
    filename = "7_post_interpol.png",
    device = "png",
    path = "plots",
    scale = 1L,
    width = 6L,
    height = NA,
    units = "in",
    dpi = "print"
  )
```

# Decompose the calibrated TODR values into their components

```
# Calculate the regulatory component of the calibrated TODR

set(
  x     = dt_cal,
  j     = "dis_reg_cal",
  value = dt_cal[, todr_cal] - dt_cal[, todr_cal] / sim$tod_mul
)
```
# Calculate the airborne component of the calibrated TODR
set(
  x = dt_cal,
  j = "dis_air_cal",
  value = fn_dis_air()
)

# Calculate the ground component of the calibrated TODR
set(
  x = dt_cal,
  j = "dis_gnd_cal",
)

# 5 Set the takeoff conditions used for calibration
#---------------------------------------------------------------------------------#
set(x = dt_cal, j = "hurs", value = sim$isa_hur) # Relative humidity in %
set(x = dt_cal, j = "ps", value = sim$isa_ps)  # Air pressure in Pa
set(x = dt_cal, j = "tas", value = sim$isa_tas) # Air temperature in K
set(x = dt_cal, j = "rho", value = sim$isa_rho) # Air density in kg/m³
set(x = dt_cal, j = "hdw", value = sim$isa_hdw) # Headwind in m/s
set(x = dt_cal, j = "thr_red", value = sim$thr_rto) # Thrust reduction in %
#---------------------------------------------------------------------------------#
# 6 Assemble the calibration inputs
#---------------------------------------------------------------------------------#

dt_tko <- merge(x = dt_act, y = dt_cal, by = "type")

# Remove masses below the break-even load factor
dt_tko <- dt_tko[tom > tom_belf]

# 7 Calculate the lift-induced drag coefficient k in takeoff configuration
# Adapted from from Sun et al. (2020).
#---------------------------------------------------------------------------------#
set(x = dt_tko, j = "ar", value = dt_tko[, span]^2L / dt_tko[, s])

# Calculate the Oswald factor component attributable to flaps
set(x = dt_tko, j = "e_flaps", value = .0026 * sin(sim$flp_ang * pi / 180L))

# Calculate the total Oswald factor in takeoff configuration
set(x = dt_tko, j = "e_total", value = dt_tko[, e_clean] + dt_tko[, e_flaps])

# Calculate the total lift-induced coefficient k in takeoff configuration
set(
  x = dt_tko,
  j = "k_total",
  value = 1L / (1L / dt_tko[, k_clean] + pi * dt_tko[, ar] * dt_tko[, e_flaps])
)

# 8 Define a function to calibrate CL and CD for every TOM and TODR value pair
# Adapted from from Sun et al. (2020) and Blake (2009).
fn_calibrate <- function(clmax, i) {

  # Set the lift coefficient at maximum angle of attack
  set(x = dt_tko, i = i, j = "clmax", value = clmax)

  # Set the lift coefficient at liftoff
  set(x = dt_tko, i = i, j = "cllof", value = clmax / sim$max_lof)

  # Calculate the lift-induced drag coefficient
  set(
    x = dt_tko,
    i = i,
    j = "cdi",
    value = dt_tko[i, k_total] * dt_tko[i, ccllof]^2L
  )

  # Calculate the total drag coefficient
  set(
    x = dt_tko,
    i = i,
    j = "cd",
    value = dt_tko[i, cd0] + dt_tko[i, cdi]
  )

  # Calculate the liftoff speed in m/s
  set(x = dt_tko, i = i, j = "vlof", value = fn_vlof(DT = dt_tko[i, ]))

  # Calculate the ground component of the simulated TODR in m
  set(
    x = dt_tko,
    i = i,
    j = "dis_gnd_sim",
    value = fn_dis_gnd(DT = dt_tko[i, ])
  )

  # Set the airborne component of the simulated TODR in m
  set(
    x = dt_tko,
    i = i,
    j = "dis_air_sim",
    value = fn_dis_air()
  )

  # Calculate the regulatory component of the simulated TODR in m
  set(
    x = dt_tko,
    i = i,
    j = "dis_reg_sim",
    value = (dt_tko[i, dis_gnd_sim] + dt_tko[i, dis_air_sim]) * (sim$tod_mul - 1L)
  )

  # Calculate the simulated TODR in m
  set(
    x = dt_tko,
    i = i,
    j = "todr_sim",
    value = dt_tko[i, dis_gnd_sim] + dt_tko[i, dis_air_sim] +
      dt_tko[i, dis_reg_sim]
  )
}
# Calculate the absolute difference in m between calibrated and simulated TODR
set(
    x = dt_tko,
    i = i,
    j = "diff",
    value = abs(dt_tko[i, todr_sim] - dt_tko[i, todr_cal])
)

# Return the absolute residual error in m
return(dt_tko[i, diff])

# End of the fn_calibrate function

# 9 Run an optimizer to find the CL that minimizes the TODR residual error
# For each calibrated takeoff mass/distance pair
for (i in seq_len(nrow(dt_tko))) {
    # Run the optimizer to minimize the residual error
    optimize(
        f = function(clmax) fn_calibrate(clmax, i),
        interval = sim$opt_cls,
        tol = sim$opt_tol
    )

    # Output results
    print(
        paste(
            "i =",
            str_pad(i, width = 5L, side = "left", pad = " "),
            "/",
            str_pad(nrow(dt_tko), width = 5L, side = "left", pad = " "),
            "| type = ",
            str_pad(dt_tko[i, type],
            "| m =",
            str_pad(dt_tko[i, tom], width = 6L, side = "left", pad = " "),
            "| CLmax =",
            format(x = dt_tko[i, clmax], digits = 3L, nsmall = 3L),
            "| CD =",
            str_pad(
                format(x = dt_tko[i, cd], digits = 3L, nsmall = 3L),
                width = 6L, side = "right", pad = " "),
                "| Vlof =",
                format(x = dt_tko[i, vlof], digits = 1L, nsmall = 1L),
                "| diff =",
                format(x = dt_tko[i, diff], digits = NULL, nsmall = 0L),
                sep = " ",
            )
        )
    )
}

# End of the for loop

# 10 Save the results to the database
# 10.1 Set up the database table to store the calibration data
fn_sql_qry(
    statement = paste("DROP TABLE IF EXISTS ", tolower(dat$cal), ";", sep = "")
)

fn_sql_qry(
    statement = paste("CREATE TABLE",
                      tolower(dat$cal),
                      "(
                      "id INT UNSIGNED NOT NULL AUTO_INCREMENT,
                      type CHAR(4) NOT NULL,
                      tom MEDIUMINT NOT NULL,
                      todr_cal SMALLINT NOT NULL,
                      todr_sim SMALLINT NOT NULL,
                      vlof FLOAT NOT NULL,
                      clmax FLOAT NOT NULL,
                      cllof FLOAT NOT NULL,
                      cd FLOAT NOT NULL,
                      PRIMARY KEY (id));", sep = "")
)

10.2 Write the calibration results to the database

# Select which columns to write to the database and in which order
cols <- c("type", "tom", "todr_cal", "todr_sim", "vlof", "clmax", "cllof", "cd"

# Connect to the database
cnn <- dbConnect(RMySQL::MySQL(), default.file = dat$cnf, group = dat$grp)

# Write the data
dbWriteTable(
    conn = conn,
    name = tolower(dat$cal),
    value = dt_tko[, ..cols],
    append = TRUE,
    row.names = FALSE
)

# Disconnect from the database
dbDisconnect(conn)

10.3 Index the database table

# Create the index
fn_sql_qry(
    statement = paste("CREATE INDEX", tolower(dat$idx),
                      "ON", tolower(dat$cal), "(type, tom);", sep = "")
)
# 11 Output summary statistics to the console
# Summarize the takeoff speeds by aircraft type
dt_tko[, as.list(summary(vlof)), by = type]
# Summarize the lift coefficients by aircraft type
dt_tko[, as.list(summary(clmax)), by = type]
# Summarize the drag coefficients by aircraft type
dt_tko[, as.list(summary(cd)), by = type]
# Summarize the differences between calibrated & simulated TODR by aircraft type
dt_tko[, as.list(summary(diff)), by = type]

# 12 Generate and save plots
# Box-plot the lift coefficient by aircraft type
(ggplot(data = dt_tko[, .(type, clmax)], aes(x = type, y = clmax)) +
  geom_boxplot() +
  stat_summary(fun = mean) +
  labs(x = "Aircraft type", y = "Lift coefficient (CLmax)") +
  theme_light()) %>%
ggsave(
  filename = "7_clmax.png",
  device = "png",
  path = "plots",
  scale = 1L,
  width = 6L,
  height = NA,
  units = "in",
  dpi = "retina"
)

# Box-plot the drag coefficient by aircraft type
(ggplot(data = dt_tko[, .(type, cd)], aes(x = type, y = cd)) +
  geom_boxplot() +
  stat_summary(fun = mean) +
  labs(x = "Aircraft type", y = "Drag coefficient (CD)") +
  theme_light()) %>%
ggsave(
  filename = "7_cd.png",
  device = "png",
  path = "plots",
  scale = 1L,
  width = 6L,
  height = NA,
  units = "in",
  dpi = "retina"
)

# Box-plot the calibration accuracy in m by aircraft type
(ggplot(data = dt_tko[, .(type, diff)], aes(x = type, y = diff)) +
  geom_boxplot() +
  stat_summary(fun = mean) +
  labs( x = "Aircraft type"),
y = "Difference (in m) between calibrated and simulated TODR"
)

```
y = "Difference (in m) between calibrated and simulated TODR"

# Plot the takeoff speed for each aircraft type
(ggplot(data = dt_tko[, .(type, vlof)], aes(x = type, y = vlof)) +
  geom_boxplot() +
  stat_summary(fun = mean) +
  labs(
    x = "Aircraft type",
    y = "Liftoff speed in m/s"
  ) +
  theme_light()) %%%

ggsave(  
  filename = "7_vlof.png",
  device = "png",
  path = "plots",
  scale = 1L,
  width = 6L,
  height = NA,
  units = "in",
  dpi = "retina"
)

# Plot the calibrated vs. simulated mass over TODR for each aircraft type
(ggplot(data = dt_tko) +
  geom_point(mapping = aes(x = tom, y = todr_cal), color = "black", size = 2L) +
  geom_line(mapping = aes(x = tom, y = todr_sim), color = "gray", size = 1L) +
  scale_x_continuous("Takeoff mass in kg", labels = scales::comma) +
  scale_y_continuous("Regulatory TODR in m", labels = scales::comma) +
  facet_wrap(~type, ncol = 2L, scales = "free") +
  theme_light()) %%%

ggsave(  
  filename = "7_todr_mass.png",
  device = "png",
  path = "plots",
  scale = 1L,
  width = 6L,
  height = NA,
  units = "in",
  dpi = "retina"
)
```

```
# Stop the script timer
Sys.time()
```

```
# EOF
```
scripts/8_simulate.R

# NAME: scripts/8_simulate.R
# INPUT: 442,765,932 climatic observations read from the dat$cli table
# ACTIONS: Assemble the aircraft, calibration, and climate data
#          Perform simulated takeoffs for each aircraft type and climate obs.
#          Write the resulting takeoff distance required to the database
#          Index the database table
# OUTPUT: 1,771,063,728 takeoff observations written to the dat$tko table
# RUNTIME: ~66 hours (3.8 GHz CPU / 128 GB DDR4 RAM / SSD)
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023
#==============================================================================
# 0 Housekeeping
#================================================================================
# Clear the environment
rm(list = ls())
# Load the required libraries
library(data.table)
library(DBI)
library(parallel)
library(stringr)
# Import the common settings
source("scripts/0_common.R")
# Import the takeoff performance model
source("scripts/6_model.R")
# Start a script timer
start_time <- Sys.time()
# Clear the console
cat("\014")
# Set the number of CPU cores for parallel processing
crs <- 20L
#================================================================================
# 1 Import the simulation data
#==============================================================================
# 1.1 Import the aircraft characteristics
#================================================================================
# Fetch the aircraft data
dt_act <- fread(
  file    = fls$act,
  header  = TRUE,
  colclasses = c(rep("factor", 2L), rep("integer", 5L), rep("numeric", 5L)),
  key      = "type"
)
# Set the maximum mass to be the starting takeoff mass
setnames(x = dt_act, "tom_max", "tom")

# Keep only needed columns
dt_act <- dt_act[, .(type, n, slst, bpr, s, tom)]

# 1.2 Import the takeoff performance calibration data
# ==============================================================
# Fetch the calibration data
dt_cal <- fn_sql_qry(
  statement = paste(
    "SELECT type, tom, todr_cal, cllof, cd FROM ",
    tolower(dat$cal),
    " WHERE type IN (",
    paste("", act, ",", collapse = ",", sep = ""),
    ")"," sep = ""
  )
)

# Create keys on the data table
setkey(x = dt_cal, "type", "tom")

# Convert the type column to factor
set(x = dt_cal, j = "type", value = as.factor(dt_cal[, type]))

# Order by type and descending mass
dt_cal <- dt_cal[order(type, -rank(tom))]

# Set the minimum mass for which there is a calibrated TODR
dt_cal[, tom_belf := min(tom), by = type]

# 1.3 Import the list of sample airports
# ==============================================================
# Fetch the airport and runway data
dt_apt <- fn_sql_qry(
  statement = paste(
    "SELECT DISTINCT icao FROM ",
    tolower(dat$pop),
    " WHERE traffic >", sim$pop_thr, ","," sep = ""
  )
)

# Create a key on the data table
setkey(x = dt_apt, "icao")

# 1.4 Exclude airports already processed
# ==============================================================
# Create the takeoff outputs table unless it exists (for incremental runs)
fn_sql_qry(
  statement = paste(
    "CREATE TABLE IF NOT EXISTS ",
    tolower(dat$tko),
    " ("
id      INT UNSIGNED NOT NULL AUTO_INCREMENT,
year    YEAR NOT NULL,
obs     DATETIME NOT NULL,
icao    CHAR(4) NOT NULL,
lat     FLOAT NOT NULL,
lon     FLOAT NOT NULL,
zone    CHAR(11) NOT NULL,
ssp     CHAR(6) NOT NULL,
type    CHAR(4) NOT NULL,
hurs    FLOAT NOT NULL,
ps      FLOAT NOT NULL,
tas     FLOAT NOT NULL,
rho     FLOAT NOT NULL,
hdw     FLOAT NOT NULL,
rwy     CHAR(5) NOT NULL,
toda    SMALLINT NOT NULL,
todr    SMALLINT NOT NULL,
vlof    SMALLINT NOT NULL,
thr_red SMALLINT NOT NULL,
tom_rem SMALLINT NOT NULL,
itr     SMALLINT UNSIGNED NOT NULL,
PRIMARY KEY (id)
);

# Fetch the airports already processed, if any
dt_exc <- fn_sql_qry(
    statement = paste(
        "SELECT DISTINCT icao FROM", tolower(dat$tko), ";", sep = " 
    ")
)

# FOR TESTING ONLY
cat("\014")
print(dt_exc)

# Create a key on the data table
setkey(x = dt_exc, "icao")

# Remove the airports already processed
dt_apt <- dt_apt[!dt_exc]

# Define a function to simulate takeoffs at each airport
fn_simulate <- function(icao) {

    # Offset the start of each worker by a random duration to spread disk I/O load
    Sys.sleep(time = sample(x = 1L:(crs * 10L), size = 1L))

    # Inform the log file
    print(
        paste(
            Sys.time(),
            "pid", str_pad(Sys.getpid(), width = 5L, side = "left", pad = " 
            "),
            "icao", icao,
            "Loading simulation data",
            sep = " 
        ))

    # Inform the log file
    print(
        paste(
            Sys.time(),
            "pid", str_pad(Sys.getpid(), width = 5L, side = "left", pad = " 
            "),
            "icao", icao,
            "Loading simulation data",
            sep = " 
        ))

    # Inform the log file
    print(
        paste(
            Sys.time(),
            "pid", str_pad(Sys.getpid(), width = 5L, side = "left", pad = " 
            "),
            "icao", icao,
            "Loading simulation data",
            sep = " 
        ))

    # Inform the log file
    print(
        paste(
            Sys.time(),
            "pid", str_pad(Sys.getpid(), width = 5L, side = "left", pad = " 
            "),
            "icao", icao,
            "Loading simulation data",
            sep = " 
        ))
# 2.1 Import the climatic observations for the current airport

# Fetch the takeoff conditions at the airport
# Here we use air density estimates from method #2 in S_transform.R
dt_cli <- fn_sql_qry(
  statement = paste(
    "SELECT
    year,
    obs,
    icao,
    lat,
    lon,
    zone,
    ssp,
    hrs_cap AS hrs,
    ps,
    tas,
    rho2 AS rho,
    hdw,
    rwy,
    toda",
    " FROM ", tolower(dat$cli),
    " WHERE icao = ", icao, ";",
    sep = ""
  )
)

# Create a key on the data table
setkey(x = dt_cli, "toda")

# Recast column types
set(x = dt_cli, j = "obs", value = as.POSIXct(dt_cli[, obs]))
set(x = dt_cli, j = "icao", value = as.factor(dt_cli[, icao]))
set(x = dt_cli, j = "year", value = as.factor(dt_cli[, year]))
set(x = dt_cli, j = "zone", value = as.factor(dt_cli[, zone]))
set(x = dt_cli, j = "ssp", value = as.factor(dt_cli[, ssp]))
set(x = dt_cli, j = "rwy", value = as.factor(dt_cli[, rwy]))

# 2.2 Combine the airport, aircraft, calibration, and climate data

dt_tko <- dt_cli[, as.list(dt_act), by = dt_cli]

# Unload the climatic observations from memory
rm(dt_cli)

# Convert the airport code to a factor
set(x = dt_tko, j = "icao", value = as.factor(dt_tko[, icao]))

# Combine climatic observations with calibration data using the starting mass
dt_tko <- dt_cal[dt_tko, on = c("type", "tom")]

# 2.3 Initialize takeoff parameters for the first simulation iteration
# Initialize the thrust reduction. If the TODA is shorter than the calibrated TODR at MTOM (which was calibrated using TOGA thrust), then it is unlikely that a thrust-reduced takeoff could lead to TODR < TODA (short of a few cases of better-than-ISA takeoff conditions). In this case, set the thrust to TOGA, to save on takeoff iterations. Otherwise, set it to the lowest takeoff thrust permissible by regulations.

```r
set(
  x = dt_tko,
  j = "thr_red",
  value = fifelse(
    dt_tko[, toda] <= dt_tko[, todr_cal],
    0L + sim$thr_inc,
    sim$thr_ini + sim$thr_inc
  )
)
```

# Initialize a column to track how much takeoff mass was removed
```
set(x = dt_tko, j = "tom_rem", value = 0L)
```

# Initialize the starting TODR to a value greater than the max TODA
```
set(x = dt_tko, j = "todr", value = dt_tko[, toda] + 1L)
```

# Initialize a counter to track the number of iterations of each takeoff
```
set(x = dt_tko, j = "itr", value = 0L)
```

# Set the horizontal airborne component of the TODR in m
# Adapted from Gratton et al, 2020
```
set(x = dt_tko, j = "dis_air_sim", value = fn_dis_air())
```

# 2.4 Perform vectorized takeoff simulations iteratively until TODR < TODA

```
repeat {

  # 2.4.1 Prepare the data

  # Retrieve indices of observations where TODR > TODA and the current mass is not less than the minimum mass for which there is calibrated data
  i <- dt_tko[, .I[todr > toda & tom >= (tom_belf + sim$pax_avg)]]

  # As long as there are takeoffs that meet these conditions
  if (length(i) > 0L) {

    # Save the iteration
    set(x = dt_tko, i = i, j = "itr", value = dt_tko[i, itr] + 1L)

    # If thrust is already at TOGA, then decrease the mass by one passenger
    set(
      x = dt_tko,
      i = i,
      j = "tom",
      value = fifelse(
        dt_tko[i, thr_red] == 0L,
        dt_tko[i, tom] - sim$pax_avg,
        dt_tko[i, tom]
      )
    )
  }
}
```
# And also keep track of how much mass was removed
set(
  x = dt_tko,
  i = i,
  j = "tom_rem",
  value = fifelse(
    dt_tko[i, thr_red] == 0L,
    dt_tko[i, tom_rem] + sim$pax_avg,
    dt_tko[i, tom_rem]
  )
)

# Otherwise decrease the thrust reduction incrementally up to TOGA
set(
  x = dt_tko,
  i = i,
  j = "thr_red",
  value = fifelse(
    dt_tko[i, thr_red] > 0L,
    dt_tko[i, thr_red] - sim$thr_inc,
    dt_tko[i, thr_red]
  )
)

# Inform the log file
print(
  paste(
    Sys.time(),
    "pid", str_pad(Sys.getpid(), width = 5L, side = "left", pad = " "),
    "icao", icao,
    "itr", str_pad(
      dt_tko[i, mean(itr)], width = 3L, side = "left", pad = " 
    ),
    "t/o =", str_pad(
      format(length(i), big.mark = ","),
      width = 9L, side = "left", pad = " 
    ),
    sep = " 
  )
)

# Remove the existing cL and cD values
set(x = dt_tko, i = i, j = "cd", value = NA)
set(x = dt_tko, i = i, j = "cllof", value = NA)

# Add the calibration data (cD and cL) again for the new mass
set(x = dt_tko, i = i, j = "cd", value = fifelse(is.na(cd), i.cd, cd),
     on = c("type", "tom"))
set(x = dt_tko, i = i, j = "cllof", value = fifelse(is.na(cllof),
                                                  i.cllof, cllof),
     on = c("type", "tom"))

# Calculate the liftoff speed in m/s
set(x = dt_tko, i = i, j = "vlof", value = fn_vlof(DT = dt_tko[i, ]))
# 2.4.2 Calculate the takeoff distance required TODR in m
# ========================================================================

# Calculate the ground component of the TODR in m
set(
  x = dt_tko,
  i = i,
  j = "dis_gnd_sim",
  value = fn_dis_gnd(DT = dt_tko[i, ])
)

# Calculate the regulatory component of the TODR in m
set(
  x = dt_tko,
  i = i,
  j = "dis_reg_sim",
  value =
    (dt_tko[i, dis_gnd_sim] +
     dt_tko[i, dis_air_sim]) *
     (sim$tod_mul - 1L)
)

# Calculate the total TODR in m, rounded to the nearest higher integer
set(
  x = dt_tko,
  i = i,
  j = "todr",
  value = ceiling(
    dt_tko[i, dis_gnd_sim] +
    dt_tko[i, dis_air_sim] +
    dt_tko[i, dis_reg_sim]
  )
)

} else { # Once there are no more observations that meet the conditions
  break # End the repeat loop
} # End if-else

} # End repeat

# 2.5 Write the simulation results to the database
# ========================================================================

# Inform the log file
print(
  paste(
    Sys.time(),
    "pid", str_pad(Sys.getpid(), width = 5, side = "left", pad = " "),
    "icao", icao,
    "Writing",
    str_pad(  
      format(nrow(dt_tko), big.mark = ","),
      width = 9L, side = "left", pad = " ",
    ),
    "rows to the database",
    sep = " ",
  )
)
# Select which columns to write to the database and in which order
cols <- c(
  "year",
  "obs",
  "icao",
  "lat",
  "lon",
  "zone",
  "ssp",
  "type",
  "hurs",
  "ps",
  "tas",
  "rho",
  "ndw",
  "rwy",
  "tdoa",
  "todn",
  "vlof",
  "thr_red",
  "tom_rem",
  "itr"
)

# Connect the worker to the database
conn <- dbConnect(RMySQL::MySQL(), default.file = dat$cnf, group = dat$grp)

# Write the data to the database
dbWriteTable(
  conn      = conn,
  name      = tolower(dat$tko), value = dt_tko[, ..cols],
  append    = TRUE,
  row.names = FALSE
)

# Disconnect the worker from the database
dbDisconnect(conn)

# Inform the log file
print(
  paste(
    Sys.time(),
    "pid", str_pad(Sys.getpid(), width = 5L, side = "left", pad = " "),
    "icao", icao,
    "Wrote ",
    str_pad(
      format(nrow(dt_tko), big.mark = ","),
      width = 9L, side = "left", pad = " ",
    ),
    "rows to the database",
    sep = " "
  )
)

} # End of the fn_simulate function

# ==============================================================================
# 3 Run the simulation across multiple cores
# ==============================================================================

# 3 Run the simulation across multiple cores
# Distribute the work across the cluster
fn_par_lapply(
  crs = crs,
  pkg = c("data.table", "DBI", "stringr"),
  lst = dt_apt[, icao],
  fun = fn_simulate
)

# 4 Index the database table
# ==============================================================================
# Create the index
fn_sql_qry(
  statement = paste(
    "CREATE INDEX idx ON",
    tolower(dat$tko),
    "(ssp, zone, year, icao);",
    sep = " "
  )
)

# 5 Housekeeping
# ==============================================================================
# Stop the script timer
Sys.time() - start_time

# EOF
Code C9

scripts/9_analyze.R

```r
# NAME: scripts/9_analyze.R
# INPUT: Climate and takeoff data output by earlier scripts
# ACTIONS: Create summary tables in MySQL and associated plots
# OUTPUT: Plot and summary data files saved to disk
# RUNTIME: ~160 minutes if the summary tables do not yet exist in the database.
#          ~3.5 minutes otherwise. (3.8 GHz CPU / 128 GB DDR4 RAM / SSD)
# AUTHOR: Thomas D. Pellegrin <thomas@pellegr.in>
# YEAR: 2023
# ==============================================================================

# NOTE: Some of the SQL queries below are memory-intensive. If you encounter
# the MySQL error "The total number of locks exceeds the lock table size",
# log as admin into MySQL Workbench and increase the InnoDB buffer size to
# a value of X where X is how much RAM in GB you can allocate to the process:
# 'SET GLOBAL innodb_buffer_pool_size = X * 1024 * 1024 * 1024;'
# ==============================================================================

# 0 Housekeeping
# ==============================================================================

# Clear the environment
rm(list = ls())

# Load the required libraries
library(data.table)
library(DBI)
library(ggplot2)
library(masscor)
library(rnaturalearth)
library(scales)
library(viridis)

# Import the common settings
source("scripts/0_common.R")

# Start a script timer
start_time <- Sys.time()

# Clear the console
cat("\014")

# 1. Climate change summary
# ==============================================================================

# 1.1 Fetch and cleanse the climate model data. Variables:
# tas  = Near-surface air temperature in °C
# hurs = Near-surface relative humidity in % (de-saturated)
# ps   = Near-surface air pressure in Pa
# rho  = Near-surface air density in kg/m³
# hdw  = Near-surface headwind in m/s
```

```
# Create the summary table (runtime: ~15 minutes)
fn_sql_qry(
    statement = paste(
        "CREATE TABLE IF NOT EXISTS",
        tolower(dat$an_cli),
        "("
        year      YEAR,
        ssp       CHAR(6),
        zone      CHAR(11),
        icao      CHAR(4),
        lat       FLOAT,
        lon       FLOAT,
        max_tas   FLOAT,
        max_hurs  FLOAT,
        max_ps    FLOAT,
        max_rho   FLOAT,
        max_hdw   FLOAT,
        avg_tas   FLOAT,
        avg_hurs  FLOAT,
        avg_ps    FLOAT,
        avg_rho   FLOAT,
        avg_hdw   FLOAT,
        min_tas   FLOAT,
        min_hurs  FLOAT,
        min_ps    FLOAT,
        min_rho   FLOAT,
        min_hdw   FLOAT
    )
    AS SELECT
    year,
    ssp,
    zone,
    icao,
    lat,
    lon,
    MAX(tas)  AS max_tas,
    MAX(hurs_cap) AS max_hurs,
    MAX(ps)   AS max_ps,
    MAX(rho2) AS max_rho,
    MAX(hdw)  AS max_hdw,
    AVG(tas)  AS avg_tas,
    AVG(hurs_cap) AS avg_hurs,
    AVG(ps)   AS avg_ps,
    AVG(rho2) AS avg_rho,
    AVG(hdw)  AS avg_hdw,
    MIN(tas)  AS min_tas,
    MIN(hurs_cap) AS min_hurs,
    MIN(ps)   AS min_ps,
    MIN(rho2) AS min_rho,
    MIN(hdw)  AS min_hdw
    FROM",
    tolower(dat$cli),
    "GROUP BY
    year,
    ssp,
    icao
    "
    sep = " "
)
)
# Fetch the data
dt_cli <- fn_sql_qry(
    statement = paste(
        "SELECT *
        FROM",
        tolower(dat$an_cli),
        "", sep = " "
    )
)

# Recast column types
set(x = dt_cli, j = "year", value = as.integer(dt_cli[, year]))
set(x = dt_cli, j = "zone", value = as.factor(dt_cli[, zone]))
set(x = dt_cli, j = "ssp", value = as.factor(dt_cli[, ssp]))
set(x = dt_cli, j = "icao", value = as.factor(dt_cli[, icao]))

# Convert temperatures from K to °C
cols <- c("max_tas", "avg_tas", "min_tas")
dt_cli[, (cols) := lapply(X = .SD, FUN = "-", sim$k_to_c), .SDcols = cols]

# Convert near-surface air pressure from Pa to hPa
cols <- c("max_ps", "avg_ps", "min_ps")
dt_cli[, (cols) := lapply(X = .SD, FUN = "/", 10^2), .SDcols = cols]

# Convert near-surface air density from kg/m³ to g/m³
cols <- c("max_rho", "avg_rho", "min_rho")
dt_cli[, (cols) := lapply(X = .SD, FUN = "*", 10^3), .SDcols = cols]

# Recode frigid airports to temperate
dt_cli[zone == "Frigid", zone := "Temperate"]

# Save the base values to disk
fwrite(
    x = dt_cli,
    file = paste(dir$res, "dt_cli_base_values_by_airport.csv", sep = "/")
)

# Declare climatic variables and their statistics
cols <- list()
# Base values
cols$max <- paste("max", names(cli), sep = "_")
cols$avg <- paste("avg", names(cli), sep = "_")
cols$min <- paste("min", names(cli), sep = "_")
cols$all <- c(cols$max, cols$avg, cols$min)
# Locally-estimated scatterplot smoothing (LOESS) of base values
cols$max_loe <- paste(cols$max, "loe", sep = "_")
cols$avg_loe <- paste(cols$avg, "loe", sep = "_")
cols$min_loe <- paste(cols$min, "loe", sep = "_")
cols$all_loe <- paste(cols$all, "loe", sep = "_")
# Absolute changes to base values
cols$max_abs <- paste(cols$max, "abs", sep = "_")
cols$avg_abs <- paste(cols$avg, "abs", sep = "_")
cols$min_abs <- paste(cols$min, "abs", sep = "_")
cols$all_abs <- paste(cols$all, "abs", sep = "_")
# Relative changes to base values
cols$max_rel <- paste(cols$max, "rel", sep = "_")
cols$avg_rel <- paste(cols$avg, "rel", sep = "_")
cols$min_rel <- paste(cols$min, "rel", sep = "_")
cols$all_rel <- paste(cols$all, "rel", sep = "_")
# Absolute changes to LOESS values
cols$max_loe_abs <- paste(cols$max_loe, "abs", sep = "_")
cols$avg_loe_abs <- paste(cols$avg_loe, "abs", sep = "_")
cols$min_loe_abs <- paste(cols$min_loe, "abs", sep = "_")
cols$all_loe_abs <- paste(cols$all_loe, "abs", sep = "_")
# Relative changes to LOESS values
cols$max_loe_rel <- paste(cols$max_loe, "rel", sep = "_")
cols$avg_loe_rel <- paste(cols$avg_loe, "rel", sep = "_")
cols$min_loe_rel <- paste(cols$min_loe, "rel", sep = "_")
cols$all_loe_rel <- paste(cols$all_loe, "rel", sep = "_")

# 1.2 Summarize climate change by airport

# Create a new data table for summarizing by airport
dt_cli_apt <- copy(dt_cli)

# Add locally-estimated scatterplot smoothing (LOESS) to base values
dt_cli_apt[, (cols$all_loe) := lapply(
    X = .SD,
    FUN = function(x) {
        predict(loess(formula = x ~ year, span = .75, model = TRUE))
    },
    by = c("ssp", "icao"),
    .SDcols = cols$all
)]

# Save the LOESS values to disk
fwrite(
    x = dt CLI_apt[, !cols$all, with = FALSE],
    file = paste(dir$res, "dt CLI_loess_values_by_airport.csv", sep = "/")
)

# 1.2.2 Summarize the changes in LOESS values by airport

# Calculate the absolute difference between each year and the first, by airport
dt_cli_apt[, (cols$all_loe_abs) := lapply(
    X = .SD,
    FUN = function(x) {
        (x - x[1:1])
    },
    by = c("ssp", "zone", "icao"),
    .SDcols = cols$all_loe
)]

# Save the final-year changes in LOESS values by airport to disk
fwrite(
    x = dt_cli_apt[year == dt CLI_apt[which.max(year), year]
     ][, !(cols$all, cols$all_loe), with = FALSE
[, (cols$all_loe_abs) := round(.SD, 1L), .SDcols = cols$all_loe_abs
[, melt(.SD, id.vars = c("year", "zone", "ssp", "icao", "lat", "lon"))
[, dcast(.SD, formula = year + icao + zone + lat + lon + variable ~ ssp)
[, variable := gsub("_abs", ",", variable)
],
file = paste(dir$res, "dt_cli_loess_changes_by_airport.csv", sep = "/")
)

# 1.2.3 Plot the changes in LOESS values by airport onto a choropleth map
# ==============================================================

# Transform the data
dt_plt <- dt_cli_apt[year == dt_cli_apt[which.max(year), year]
][, !c(cols$all, cols$all_loe), with = FALSE]

# Define the world object from the Natural Earth package
world <- rnaturalearth::ne_countries(scale = "small", returnclass = "sf")

# Create a function to plot results
fn_plot <- function(col) {
  ggplot() +
  geom_sf(data = world, fill = "gray") +
  coord_sf(expand = FALSE) +
  # Define the scales
  scale_x_continuous(breaks = c(-180L, 180L)) +
  scale_y_continuous(breaks = unique(unlist(x = geo, use.names = FALSE)),
                      limits = c(-90L, 90L)) +
  scale_color_viridis(
    direction = -1L,
    name = cli[[gsub("max|avg|min|_|loe|abs", ",", col)]]
    option = "magma"
  ) +
  facet_wrap(facets = vars(toupper(ssp))) +
  geom_point(
    data = dt_plt,
    mapping = aes(x = lon, y = lat, color = get(col)),
    shape = 20L,
    size = 1L
  ) +
  # Add parallel labels
  geom_text(
    data = world,
    color = "gray",
    hjust = 0L,
    label = "Arctic circle",
    size = 1.5,
    x = -179L,
    y = unique(unlist(x = geo, use.names = FALSE))[5] - 2L
  ) +
  geom_text(
    data = world,
    color = "gray",
    hjust = 0L,
    label = "Tropic of Cancer",
    size = 1.5,
    x = -179L,
    y = unique(unlist(x = geo, use.names = FALSE))[4] - 2L
  )
}

geom_text(
    data = world,
    color = "gray",
    hjust = 0L,
    label = "Tropic of Capricorn",
    size = 1.5,
    x = -179L,
    y = unique(unlist(x = geo, use.names = FALSE))[3] - 2L
  ) +

geom_text(
    data = world,
    color = "gray",
    hjust = 0L,
    label = "Antarctic circle",
    size = 1.5,
    x = -179L,
    y = unique(unlist(x = geo, use.names = FALSE))[2] - 2L
  ) +

  # Add zonal labels
  geom_text(
    angle = 90L,
    data = world,
    color = "gray",
    hjust = .5,
    label = unique(names(geo))[1],
    size = 2L,
    x = -175L,
    y = mean(
      c(
        unique(unlist(x = geo, use.names = FALSE))[1],
        unique(unlist(x = geo, use.names = FALSE))[2]
      )
    )
  ) +

  geom_text(
    angle = 90L,
    data = world,
    color = "gray",
    hjust = .5,
    label = unique(names(geo))[2],
    size = 2L,
    x = -175L,
    y = mean(
      c(
        unique(unlist(x = geo, use.names = FALSE))[2],
        unique(unlist(x = geo, use.names = FALSE))[3]
      )
    )
  ) +

  geom_text(
    angle = 90L,
    data = world,
    color = "gray",
    hjust = .5,
    label = unique(names(geo))[3],
    size = 2L,
    x = -175L,
    y = mean(
      c(
        unique(unlist(x = geo, use.names = FALSE))[3],
        unique(unlist(x = geo, use.names = FALSE))[3]
      )
    )
  )
unique(unlist(x = geo, use.names = FALSE))[4]
)
)
)
geom_text(
  angle = 90L,
  data = world,
  color = "gray",
  hjust = .5,
  label = unique(names(geo))[2],
  size = 2L,
  x = -175L,
  y = mean(
    c(
      unique(unlist(x = geo, use.names = FALSE))[4],
      unique(unlist(x = geo, use.names = FALSE))[5]
    )
  )
)+
geom_text(
  angle = 90L,
  data = world,
  color = "gray",
  hjust = .5,
  label = unique(names(geo))[1],
  size = 2L,
  x = -175L,
  y = mean(
    c(
      unique(unlist(x = geo, use.names = FALSE))[5],
      unique(unlist(x = geo, use.names = FALSE))[6]
    )
  )
)+
theme_light() +
theme(
  axis.title = element_blank(),
  axis.text = element_blank(),
  axis.ticks = element_blank(),
  legend.key.size = unit(.2, plt$units),
  text = element_text(size = plt$text)
)

# Save the plot
ggsave(
  filename = paste(
    "9_cli_map_of_",
    gsub("_abs", "", col),
    ".png",
    sep = ""
  ),
  plot = last_plot(),
  device = plt$device,
  path = plt$path,
  scale = plt$scale,
  height = plt$height,
  width = plt$width,
  units = plt$units,
  dpi = plt$dpi
)
# End of the fn_plot function

# Generate the plots
mapply(
    FUN = fn_plot,
    col = cols$all_loe_abs
)

# 1.2.4 Plot the correlation between absolute latitude & changes in LOESS values

# Create a function to plot results
fn_plot <- function(col) {
  ggplot(
    data   = dt_plt,
    mapping = aes(x = abs(lat), y = get(col))
  ) +
  # Define the scales
  scale_x_continuous(
    breaks = seq(from = 0L, to = 70L, length.out = 8L),
    limits = c(0L, 70L),
    name   = "Latitude (absolute)"
  ) +
  scale_y_continuous(
    name = paste(
      "Changes in",
      gsub("_", " ", gsub("_loe_abs", ", ", col)),
      cli[[gsub("max|avg|min|_|loe|abs", ", ", col)]],
      sep = " ",
    )
  ) +
  facet_wrap(facets = vars(toupper(ssp))) +
  geom_point(
    shape    = 20L,
    size     = 1L
  ) +
  geom_smooth(formula = y ~ x, method = "loess", linewidth = 1) +
  theme_light() +
  theme(
    axis.text = element_text(size = plt$axis.text),
    axis.title = element_text(size = plt$axis.title),
    strip.text = element_text(size = plt$strip.text),
    panel.grid.minor = element_blank()
  )

  # Save the plot
  ggsave(
    filename = paste(
      "9_cli_correlation_plot_of ",
      gsub("_abs", " ", col),
      ", with_latitude.png",
      sep = " ",
    ),
    plot   = last_plot(),
    device = plt$device,
    path   = plt$path,
    scale  = plt$scale,
    height = plt$height,
    width  = plt$width,
  )
units = plt$units,
    dpi = plt$dpi
)  # End of the fn_plot function

# Generate the plots
mapply(
    FUN = fn_plot,
    col = cols$all_loe_abs
)

# 1.3 Summarize climate change by zone
# Create a new data table for summarizing by zone
dt_cli_zon <- copy(dt_cli)

# 1.3.1 Summarize base and LOESS values by zone
# Declare independent variables for grouping
grp <- c("year", "ssp", "zone")

# Average the max, mean, and min annual airport values by zone and globally
dt_cli_zon <- rbind(
    dt_cli_zon[, lapply(X = .SD, FUN = mean), by = grp, .SDcols = cols$all],
    dt_cli_zon[, zone := "Global"], lapply(X = .SD, FUN = mean),
    by = grp,
    .SDcols = cols$all
)

# Calculate LOESS values from the base values summarized by zone
dt_cli_zon[, (cols$all_loe) := lapply(
    X = .SD,
    FUN = function(x) {
        predict(loess(formula = x ~ year, span = .75, model = TRUE))
    },
    by = c("ssp", "zone"),
    .SDcols = cols$all
)

# 1.3.2 Plot a global overview of the mean of each climate variable by SSP
# Select base values for the global zone
dt_plt <- dt_cli_zon[zone == "Global" ][, c("year", "ssp", cols$avg), with = FALSE ][, melt(.SD, id.vars = c("year", "ssp")) ][, variable := gsub("avg_", ",", variable) ][, variable := factor(variable, gsub("avg_", ",", cols$avg)) ]

# Select the starting label data (LOESS instead of base values)
labs_start <- dt_cli_zon
zone == "Global", .SD[which.min(year)],
by = "ssp", .SDcols = c("year", cols$avg_loe)
][, melt(.SD, id-vars = c("year", "ssp"))
][, variable := gsub("avg", "", variable)
][, variable := gsub("_loe", "", variable)
][, variable := factor(
  variable,
  gsub("avg", "", gsub("_loe", "", cols$avg_loe))
)
]}

# Select the ending label data (LOESS instead of base values)
labs_end <- dt_cli_zon[  
  zone == "Global", .SD[which.max(year)],
  by = "ssp", .SDcols = c("year", cols$avg_loe)
][, melt(.SD, id-vars = c("year", "ssp"))
][, variable := gsub("avg", "", variable)
][, variable := gsub("_loe", "", variable)
][, variable := factor(
  variable,
  gsub("avg", "", gsub("_loe", "", cols$avg_loe))
)
]}

# Rename facet labels to include units
labs <- paste(names(cli), unlist(unname(cli)), sep = " ")
names(labs) <- levels(dt_plt$variable)

# Build the plot
ggplot(data = dt_plt) +
  geom_line(
    linewidth = .2,
    mapping = aes(
      x = year,
      y = value
    )
  ) +
  geom_smooth(
    formula = y ~ x,
    method = "loess",
    linewidth = .5,
    mapping = aes(
      x = year,
      y = value
    )
  ) +
  geom_label(
    data = labs_start,
    aes(
      x = year,
      y = value,
      label = sprintf(fmt = "%.1f", value)
    ),
    alpha = .5,
    fill = "white",
    label.r = unit(0L, "lines"),
    label.size = 0L,
    nudge_x = 1.5,
    size = plt$label.text
  ) +
# Ending value labels
geom_label(
  data = labs_end,
  aes(
    x = year,
    y = value,
    label = sprintf(fmt = "%.1f", value)
  ),
  alpha = .5,
  fill = "white",
  label.r = unit(0L, "lines"),
  label.size = 0L,
  nudge_x = -1.5,
  size = plt$label.text
) +
scale_x_continuous(name = "Year", n.breaks = 5L) +
scale_y_continuous(name = "Value") +
facet_grid(
  rows = vars(variable),
  cols = vars(toupper(ssp)),
  scales = "free_y",
  labeller = labeller(variable = labs)
) +
theme_light() +
theme(
  axis.title.y = element_blank(),
  text = element_text(size = plt$text)
)

# Save the plot
ggsave(
  filename = "9.cli_global_overview.png",
  plot = last_plot(),
  device = plt$device,
  path = plt$path,
  scale = plt$scale,
  width = plt$width,
  height = plt$height,
  units = plt$units,
  dpi = plt$dpi
)

# 1.3.3 Plot the annual base and LOESS values as line plots for all zones
# ==============================================================
# Order the zones so the facets display in alphabetical order
dt_cli_zon[, zone := factor(
  zone,
  levels = sort(unique(levels(dt_cli_zon[, zone])))
)]

# Define independent variables for grouping
grp <- c("ssp", "zone")

# Create a function to plot results
fn_plot <- function(col) {
  # Build the plot
  ggpplot("
data = dt_cli_zon,
mapping = aes(
    x = year,
    y = dt_cli_zon[[as.character(col)]]
)
+
# Plot the base values
geom_line(linewidth = .2) +
# Plot the LOESS values
geom_smooth(formula = y ~ x, method = "loess", linewidth = .5) +
# Starting value labels
geom_label(  
data = dt_cli_zon[, .SD[which.min(year)], by = grp],
    aes(  
        x = year,
        y = dt_cli_zon[, .SD[which.min(year)], by = grp][[paste(as.character(col), "loe", sep = "]")]],
        label = sprintf(fmt = "%.1f",
            x = dt_cli_zon[, .SD[which.min(year)], by = grp][[paste(as.character(col), "loe", sep = "")]])  
    ),
    alpha = .5,
    fill = "white",
    label.r = unit(0L, "lines"),
    label.size = 0L,
    nudge_x = 5L,
    size = plt$label.text  
) +
# Ending value labels
geom_label(  
data = dt_cli_zon[, .SD[which.max(year)], by = grp],
    aes(  
        x = year,
        y = dt_cli_zon[, .SD[which.max(year)], by = grp][[paste(as.character(col), "loe", sep = "]")]],
        label = sprintf(fmt = "%.1f",
            x = dt_cli_zon[, .SD[which.max(year)], by = grp][[paste(as.character(col), "loe", sep = "")]])  
    ),
    alpha = .5,
    fill = "white",
    label.r = unit(0L, "lines"),
    label.size = 0L,
    nudge_x = -5L,
    size = plt$label.text  
) +
# Define the scales
scale_x_continuous(name = "Year", n.breaks = 5L) +
scale_y_continuous(name = "Value", labels = label_comma(accuracy = .1)) +
facet_grid(
    rows = vars(zone),
    cols = vars(toupper(ssp)),
    scales = "free_y"
) +
theme_light() +
theme(  
    axis.title.y = element_blank(),
    text = element_text(size = plt$text)
)
# Save the plot

ggsave(
    filename = tolower(paste("9_cli_lineplot_of_", col, ".png", sep = "")),
    plot     = last_plot(),
    device   = plt$device,
    path     = plt$path,
    scale    = plt$scale,
    width    = plt$width,
    height   = plt$height,
    units    = plt$units,
    dpi      = plt$dpi
)

} # End of the fn_plot function

# Generate the plots
mapply(
    FUN = fn_plot,
    col = cols$all
)

# 1.3.4 Summarize the changes in LOESS values by zone

# Calculate the absolute difference between each year and the first, by zone
dt_cli_zon[,]
(col$all_loe_abs) := lapply(
    X   = .SD,
    FUN = function(x) {
        (x - x[1:1])
    },
    by   = c("ssp", "zone"),
    .SDcols = col$all_loe
)

# Save the final-year changes in LOESS values by zone to disk
fwrite(
    x = dt_cli_zon[,year == dt_cli_zon[which.max(year), year]]
    , !col$all, col$all_loe, with = FALSE
    , (col$all_loe_abs) := round(.SD, 1L)
    , melt(.SD, id.vars = c("year", "zone", "ssp"))
    , dcast(.SD, formula = year + zone + variable ~ ssp)
    , zone := factor(zone, levels = sort(unique(levels(dt_cli_zon[, zone]))))
    , variable := gsub("_abs", ",", variable)
    , variable := factor(
        variable,
        c(rbind(col$max_loe, col$avg_loe, col$min_loe))
    )
    , order(variable, zone)
    , file = paste(dir$res, "dt_cli_loess_changes_by_zone.csv", sep = "/")
)

# 1.4 Sensitivity analysis of rho to tas, ps, and hurs

# Set the number of data points to plot
res <- 1L

# Build a data table for the sensitivity analysis
dt_cli_sa <- data.table(
    # Set sea-level ISA values for air temperature, pressure, and rel. humidity
    isa_tas  = rep(x = sim$isa_tas, times = res) - sim$k_to_c,
    isa_ps   = rep(x = sim$isa_ps,  times = res) / 100L,
    isa_hurs = rep(x = sim$isa_hur, times = res),
    # Set the percentage of change in the independent variables
    scale    = seq(from = 0L, to = .1, length.out = res)
)

# Flex the independent variables
dt_cli_sa[, 
    var_tas  := isa_tas  * (1L + scale)   # Increase tas by 10%
][, 
    var_ps   := isa_ps   * (1L - scale)   # Decrease ps by 10%
][, 
    var_hurs := isa_hurs + (100L * scale) # Increase hurs by 10 p. p.
]

dt_cli_sa

# Calculate sensitivity of air density to air temperature
dt_cli_sa[, 
    rho_tas := masscor::airDensity(
        Temp     = var_tas,  # We increase tas
        p        = isa_ps,   # We keep ps constant
        h        = isa_hurs, # We keep hurs constant
        x_CO2    = sim$co2_ppm,
        model    = "CIMP2007"
    ) * 10^6
]

# Calculate sensitivity of air density to air pressure
dt_cli_sa[, 
    rho_ps := masscor::airDensity(
        Temp     = isa_tas,  # We keep tas constant
        p        = var_ps,   # We decrease ps
        h        = isa_hurs, # We keep hurs constant
        x_CO2    = sim$co2_ppm,
        model    = "CIMP2007"
    ) * 10^6
]

# Calculate sensitivity of air density to relative humidity
dt_cli_sa[, 
    rho_hurs := masscor::airDensity(
        Temp     = isa_tas,  # We keep tas constant
        p        = isa_ps,   # We keep ps constant
        h        = var_hurs, # We increase hurs
        x_CO2    = sim$co2_ppm,
        model    = "CIMP2007"
    ) * 10^6
]

# Calculate relative changes in the air density
dt_cli_sa[, 
    rho_tas_rel  := abs(rho_tas  / rho_tas[1:1] - 1L)
][, 
    rho_ps_rel   := abs(rho_ps   / rho_ps[1:1] - 1L)
rho_hurs_rel := abs(rho_hurs / rho_hurs[1:1] - 1L)

# Save the data to disk
fwrite(
  x    = dt_cli_sa,
  file = paste(dir$res, "dt_cli_rho_sensitivity_analysis.csv", sep = "/")
)

# Plot the relative changes in air density (DV) based on changes to the IVs
ggplot(
  data = dt_cli_sa,
  mapping = aes(x = scale)
) +
  # Add lines
  geom_line(mapping = aes(y = rho_tas_rel), linewidth = 1L) +
  geom_line(mapping = aes(y = rho_ps_rel), linewidth = 1L) +
  geom_line(mapping = aes(y = rho_hurs_rel), linewidth = 1L) +
  # Add labels
  geom_label(mapping = aes(x = .1, y = max(rho_tas_rel), label = "tas")) +
  geom_label(mapping = aes(x = .1, y = max(rho_ps_rel), label = "ps")) +
  geom_label(mapping = aes(x = .1, y = max(rho_hurs_rel), label = "hurs")) +
  # Define scales
  scale_x_continuous(
    name = "Absolute percentage of change in tas, ps, or hurs",
    labels = scales::label_percent()
  ) +
  scale_y_continuous(
    name = "Absolute percentage of change in rho",
    labels = scales::label_percent()
  ) +
  theme_light() +
  theme(
    text = element_text(size = plt(text))
)

# Save the plot
ggsave(
  filename = paste("9_cli_rho_sensitivity_analysis.png", sep = ""),
  plot    = last_plot(),
  device  = plt$device,
  path    = plt$path,
  scale   = plt$scale,
  height  = plt$height,
  width   = plt$width,
  units   = plt$units,
  dpi     = plt$dpi
)

# 2. Takeoff outcomes summary
# ---------------------------------------------------------------
# 2.1 Fetch and cleanse the takeoff simulation data. Variables:
# itr_avg              = Average count of iterations per takeoff
# itr_sum              = Count of all iterations performed
# tko_ok_thr_min       = Count of takeoffs performed using 75% TOGA
# tko_ok_thr_mid       = Count of takeoffs performed using 75%-100% TOGA
# tko_ok_thr_max_no_rm = Count of takeoffs performed using 100% TOGA and no
# payload removal
# tko_ok_thr_max_rm  = Count of takeoffs performed using 100% TOGA and
#                      payload removal not exceeding the BELF
# tko_ok_thr_max     = Count of all takeoffs performed using 100% TOGA
#                      (with or without payload removal)
# tko_ok             = Count of all successful takeoffs
#                      (regardless of thrust and payload removal)
# tko_unsuccessful   = Count of all unsuccessful takeoffs
#                      (despite 100% TOGA and payload removal down to BELF)
# tko                = Count of all takeoffs (whether successful or not)
# ==============================================================================#### Create the summary table (runtime: ~90 minutes)

fn_sql_qry(
    statement = paste(
        "CREATE TABLE IF NOT EXISTS",
        tolower(dat$an_tko),
        "(
            year                YEAR,
            ssp                 CHAR(6),
            zone                CHAR(11),
            icao                CHAR(4),
            lat                 FLOAT,
            lon                 FLOAT,
            type                CHAR(4),
            itr                 INT,
            tko_ok_thr_min      MEDIUMINT,
            tko_ok_thr_mid      MEDIUMINT,
            tko_ok_thr_max_no_rm MEDIUMINT,
            tko_ok_thr_max_rm   MEDIUMINT,
            tko_ok_thr_max      MEDIUMINT,
            tko                  MEDIUMINT,
        )
    )
    AS SELECT
        year,
        ssp,
        zone,
        icao,
        lat,
        lon,
        type,
        SUM(itr) AS itr,
        SUM(thr_red =", sim$thr_ini, ") AS tko_ok_thr_min,
        SUM(thr_red BETWEEN 1 AND", sim$thr_ini - 1L, ") AS tko_ok_thr_mid,
        SUM(thr_red = 0 AND todr <= toda AND tom_rem = 0) AS tko_ok_thr_max_no_rm,
        SUM(thr_red = 0 AND todr <= toda AND tom_rem > 0) AS tko_ok_thr_max_rm,
        SUM(todr <= toda) AS tko_ok,
        SUM(todr > toda) AS tko_ko,
        COUNT(*) AS tko
    FROM",
    tolower(dat$tko),
    "GROUP BY
        year,
        ssp,
        icao,
        type
    ;",
    sep = " "
)
# Fetch the data
dt_tko <- fn_sql_qry(
  statement = paste(
    "SELECT *
    FROM",
    tolower(dat$an_tko),
    ",",
    sep = " ",
  )
)

# Recast column types
set(x = dt_tko, j = "year", value = as.integer(dt_tko[, year]))
set(x = dt_tko, j = "zone", value = as.factor(dt_tko[, zone]))
set(x = dt_tko, j = "ssp", value = as.factor(dt_tko[, ssp]))
set(x = dt_tko, j = "icao", value = as.factor(dt_tko[, icao]))
set(x = dt_tko, j = "type", value = as.factor(dt_tko[, type]))

# Recode frigid airports to temperate
dt_tko[zone == "Frigid", zone := "Temperate"]

# Replace the aircraft types by their body types
levels(dt_tko$type) <- bod

# Summarize the data by body type
dt_tko <- dt_tko[, 
  lapply(X = .SD, FUN = sum),
  by = c("year", "ssp", "zone", "icao", "lat", "lon", "type")
]

# Save the base values to disk
fwrite(
  x = dt_tko,
  file = paste(dir$res, "dt_tko_base_values_by_airport.csv", sep = "/")
)

# Declare output variables
cols <- list()
cols$bas <- grep("tko", names(dt_tko), value = TRUE) # Absolute base values
cols$rel <- paste(cols$bas, "rel", sep = ") # Relative base values
cols$loe <- paste(cols$rel, "loe", sep = ") # LOESS values
cols$dif <- paste(cols$loe, "dif", sep = ") # Changes in LOESS values

# 2.2 Summarize takeoff outcomes by airport

# 2.2.1 Calculate LOESS values by airport

# Create a new data table for summarizing by airport
dt_tko_apt <- copy(dt_tko)

# Add locally-estimated scatterplot smoothing (LOESS) to base values
dt_tko_apt[, 
  # Convert absolute values to relative (percentage)
(cols$rel) := lapply(
  X = .SD,
  FUN = function(x) {
    x / tko * 100L
  }
),
.SDcols = cols$bas
# Add LOESS values
][, (cols$loe) := lapply(
  X = .SD,
  FUN = function(x) {
    predict(loess(formula = x ~ year, span = .75, model = TRUE))
  }
),
by = c("ssp", "zone", "icao", "type"),
.SDcols = cols$rel
][,
# Remove unneeded columns
c("itr", cols$bas, cols$rel) := NULL
]

# Save the base values to disk
fwrite(
  x = dt_tko_apt,
  file = paste(dir$res, "dt_tko_loess_values_by_airport.csv", sep = "/")
)

# 2.2.2 Summarize the changes in LOESS values by airport
# 2.2.2.1 Calculate the absolute difference between each year and the first, by airport
dt_tko_apt[, (cols$dif) := lapply(
  X = .SD,
  FUN = function(x) {
    (x - x[1:1])
  }
),
by = c("ssp", "zone", "icao", "type"),
.SDcols = cols$loe
][, (cols$loe) := NULL]

# Save the final-year changes in LOESS values by airport to disk
fwrite(
  x = dt_tko_apt[year == dt_tko_apt[which.max(year), year]
  ][, (cols$dif) := round(.SD, 1L), .SDcols = cols$dif
  ][,
  melt(
    data   = .SD,
    id.vars = c("year", "ssp", "zone", "icao", "lat", "lon", "type")
  )
  ][,
  dcast(
    data   = .SD,
    formula = year + zone + icao + lat + lon + variable ~ type + ssp
  ),
  file = paste(dir$res, "dt_tko_loess_changes_by_airport.csv", sep = "/")
)

# 2.2.3 Plot the changes in LOESS values by airport onto a choropleth map
# Define the world object from the Natural Earth package
world <- rnaturalearth::ne_countries(scale = "small", returnclass = "sf")

# Create a function to plot results
fn_plot <- function(body, cols) {
  ggplot() +
  geom_sf(data = world, fill = "gray") +
  coord_sf(expand = FALSE) +
  # Define the scales
  scale_x_continuous(breaks = c(-180L, 180L)) +
  scale_y_continuous(breaks = unique(unlist(x = geo, use.names = FALSE)),
                    limits = c(-90L, 90L)) +
  scale_color_viridis(direction = -1L,
                      name = "in p. p.",
                      option = "magma") +
  facet_wrap(facets = vars(toupper(ssp))) +
  geom_point(data = dt_tko_apt[year == dt_tko_apt[which.max(year), year] & type == body],
             mapping = aes(x = lon,
                           y = lat,
                           color = .data[[as.character(cols)]]),
             shape = 20L,
             size = 1L) +
  # Add parallel labels
  geom_text(data = world,
             color = "gray",
             hjust = 0L,
             label = "Arctic circle",
             size = 1.5,
             x = -179L,
             y = unique(unlist(x = geo, use.names = FALSE))[5] - 2L) +
  geom_text(data = world,
             color = "gray",
             hjust = 0L,
             label = "Tropic of Cancer",
             size = 1.5,
             x = -179L,
             y = unique(unlist(x = geo, use.names = FALSE))[4] - 2L) +
  geom_text(data = world,
             color = "gray",
             hjust = 0L,
             label = "Tropic of Capricorn",
             size = 1.5,
             x = -179L,
             y = unique(unlist(x = geo, use.names = FALSE))[3] - 2L) +
  geom_text
data = world,
color = "gray",
hjust = 0L,
label = "Antarctic circle",
size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[-2] - 2L
) +
# Add zonal labels
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[1],
size = 2L,
x = -175L,
y = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[1],
    unique(unlist(x = geo, use.names = FALSE))[2]
  )
)
)
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[2],
size = 2L,
x = -175L,
y = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[2],
    unique(unlist(x = geo, use.names = FALSE))[3]
  )
)
)
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[3],
size = 2L,
x = -175L,
y = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[3],
    unique(unlist(x = geo, use.names = FALSE))[4]
  )
)
)
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[2],
size = 2L,
x = -175L,
y = mean(
c(unique(unlist(x = geo, use.names = FALSE))[4],
   unique(unlist(x = geo, use.names = FALSE))[5]
)
)
) + geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[1],
size = 2L,
x = -175L,
y = mean(
c(unique(unlist(x = geo, use.names = FALSE))[5],
   unique(unlist(x = geo, use.names = FALSE))[6]
)
)
) + theme_light() +
theme(axis.title = element_blank(),
  axis.text = element_blank(),
  axis.ticks = element_blank(),
  legend.key.size = unit(.2, plt$units),
  text = element_text(size = plt$text)
)

# Save the plot
ggsave(
  filename = tolower(
paste(
    "9_tko_map_of_",
    body,
    "_",
    cols,
    ".png",
    sep = ""
  ),
  plot = last_plot(),
device = plt$device,
  path = plt$path,
  scale = plt$scale,
  height = plt$height,
  width = plt$width,
  units = plt$units,
  dpi = plt$dpi
)
)

} # End of the fn_plot function

# Combine the aircraft bodies and output variables to be plotted
mix <- expand.grid(
  body = names(bod),
  cols = cols$ dif
)
mapply(
    FUN = fn_plot,
    body = mix$body,
    col = mix$cols
)

# 2.3 Summarize takeoff outcomes by climate zone
#

# 2.3.1 Calculate LOESS values by climate zone
#

# Create a new data table for summarizing by airport
dt_tko_zon <- copy(dt_tko)

dt_tko_zon <- rbind(
    # Zonal summary by group
    dt_tko_zon[, lapply(X = .SD, FUN = sum),
        by = c("year", "ssp", "zone", "type"),
        .SDcols = cols$bas
    ],
    # Global summary by group
    dt_tko_zon[, zone := "Global"][, lapply(X = .SD, FUN = sum),
        by = c("year", "ssp", "zone", "type"),
        .SDcols = cols$bas
    ]
)

dt_tko_zon[, (cols$rel) := lapply(
    X = .SD,
    FUN = function(x) {
        x / tko
    },
    .SDcols = cols$bas
)][, (cols$loe) := lapply(
    X = .SD,
    FUN = function(x) {
        predict(loess(formula = x ~ year, span = .75, model = TRUE))
    },
    by = c("ssp", "zone", "type"),
    .SDcols = cols$rel
]

# Save the data to disk
fwrite(
    x = dt_tko_zon,
    file = paste(dir$res, "dt_tko_loess_values_by_zone.csv", sep = "/")
)

# 2.3.2 Plot the results onto chronological lineplots
#
# Order the zones so the facets display in alphabetical order
dt_tko_zon[, zone := factor(
    zone,
    levels = sort(unique(levels(dt_tko_zon[, zone])))
)}

# Declare independent variables for grouping
grp <- c("ssp", "zone")

# Create a function to plot results
fn_plot <- function(body, cols) {

    # Build the plot
    ggplot(
        data    = dt_tko_zon[type == body],
        mapping = aes(
            x     = year,
            y     = dt_tko_zon[type == body][[as.character(cols)]]
        )
    ) +
    geom_line(linewidth = .2) +
    geom_smooth(formula = y ~ x, method = "loess", linewidth = .5) +

    # Starting value labels
    geom_label(
        data = dt_tko_zon[type == body][, .SD[which.min(year)], by = grp],
        aes(
            x = year,
            y = dt_tko_zon[type == body][, .SD[which.min(year)], by = grp][
                [paste(as.character(cols), "loe", sep = "_")],
            label = sprintf(fmt = "%1.1f%%", dt_tko_zon[type == body][
                [, .SD[which.min(year)], by = grp][
                [paste(as.character(cols), "loe", sep = "_")]] * 100L)
        ),
        alpha = .5,
        fill = "white",
        label.r = unit(0L, "lines"),
        label.size = 0L,
        nudge_x = 4L,
        size = 2L
    ) +

    # Ending value labels
    geom_label(
        data = dt_tko_zon[type == body][, .SD[which.max(year)], by = grp],
        aes(
            x = year,
            y = dt_tko_zon[type == body][, .SD[which.max(year)], by = grp][
                [paste(as.character(cols), "loe", sep = "_")],
            label = sprintf(fmt = "%1.1f%%", dt_tko_zon[type == body][
                [, .SD[which.max(year)], by = grp][
                [paste(as.character(cols), "loe", sep = "_")]] * 100L)
        ),
        alpha = .5,
        fill = "white",
        label.r = unit(0L, "lines"),
        label.size = 0L,
        nudge_x = -4L,
        size = 2L
    ) +

    scale_x_continuous(name = "Year", n.breaks = 3L) +
    scale_y_continuous
name = "Value",
labels = scales::label_percent(accuracy = .1)
) +
facet_grid(
    rows = vars(zone),
    cols = vars(toupper(ssp)),
    scales = "free_y"
) +
theme_light() +
theme(
    axis.title.y = element_blank(),
    text         = element_text(size = plt$text)
)

# Save the plot
ggsave(
    filename = tolower(
        paste("g_tko_lineplot_of_",
            body,
            ",",
            cols,
            ".png",
            sep = ""
        ),
    ),
    plot = last_plot(),
    device = plt$device,
    path = plt$path,
    scale = plt$scale,
    height = plt$height,
    width = plt$width,
    units = plt$units,
    dpi = plt$dpi
)

} # End of the fn_plot function

# Combine the aircraft bodies and output variables to be plotted
mix <- expand.grid(
    body = names(bod),
    cols = cols$rel
)

# Generate the plots
mapply(
    FUN = fn_plot,
    body = mix$body,
    cols = mix$cols
)

# 2.3.3 Summarize the changes in LOESS values by climate zone

# Calculate the absolute difference between each year and the first, by zone
dt_tko_zon[, (cols$dif) := lapply(
    X = .SD,
    FUN = function(x) {
        (x - x[1:1])
    }
)

# Extract the absolute differences for the average...
```r
# Save the final-year changes in LOESS values by zone to disk
fwrite(
  x = dt_tko_zon[year == dt_tko_zon[which.max(year), year]
    , c("year", "ssp", "zone", "type", cols$dif), with = FALSE
    , (cols$dif) := round(.SD * 100L, 1L), .SDcols = cols$dif
    , melt(data = .SD, id.vars = c("year", "zone", "ssp", "type"))
    , zone := factor(zone, levels = sort(unique(levels(dt_tko_zon[, zone]))))
    , variable := factor(variable, cols$dif)
    , order(variable, zone)
    , file = paste(dir$res, "dt_tko_loess_changes_by_zone.csv", sep = "/")
)
```

```sql
# 3. Research questions summary
#
# 3.1 Create, fetch, and cleanse the data. Variables:
# avg_todr = Mean takeoff distance required in m
# avg_thr_red = Mean thrust reduction in percentage points of TOGA
# avg_tom_rem = Mean takeoff mass reduction in kg
#
# Create the summary table (runtime: ~65 minutes)
fn_sql_qry(
  statement = paste(
    "CREATE TABLE IF NOT EXISTS",
    tolower(dat$an_res),
    "(
      year YEAR,
      ssp CHAR(6),
      zone CHAR(11),
      icao CHAR(4),
      lat FLOAT,
      lon FLOAT,
      type CHAR(4),
      avg_todr FLOAT,
      avg_thr_red FLOAT,
      avg_tom_rem FLOAT
    )
  AS SELECT
    year,
    ssp,
    zone,
    icao,
    lat,
    lon,
    type,
    AVG(todr) AS avg_todr,
    AVG(thr_red) AS avg_thr_red,
    AVG(tom_rem) AS avg_tom_rem
  FROM",
    tolower(dat$tko),

```
"WHERE
todr <= toda
GROUP BY
  year,
  ssp,
  icao,
  type
;
sep = " "
)
)

# Fetch the data
dt_res <- fn_sql_qry(
  statement = paste(
    "SELECT *
    FROM",
    tolower(dat$an_res),
    ";",
    sep = " "
  )
)

# Recast column types
set(x = dt_res, j = "year", value = as.integer(dt_res[, year]))
set(x = dt_res, j = "zone", value = as.factor(dt_res[, zone]))
set(x = dt_res, j = "ssp", value = as.factor(dt_res[, ssp]))
set(x = dt_res, j = "icao", value = as.factor(dt_res[, icao]))
set(x = dt_res, j = "type", value = as.factor(dt_res[, type]))

# Recode frigid airports to temperate
dt_res[zone == "Frigid", zone := "Temperate"]

# Combine the aircraft types to narrow/widebody
levels(dt_res$type) <- bod

# Convert thrust reduction below TOGA to thrust as a percentage of TOGA
dt_res[, avg_thr := (100L - avg_thr_red) / 100L][, avg_thr_red := NULL]

# Convert payload removal in kg to passengers based on pax mass assumptions
dt_res[, avg_pax_rem := avg_tom_rem / sim$pax_avg][, avg_tom_rem := NULL]

# Summarize the data by body type
dt_res <- dt_res[, lapply(X = .SD, FUN = mean),
  by = c("year", "ssp", "zone", "icao", "lat", "lon", "type")]

# Save the base values to disk
fwrite(
  x    = dt_res,
  file = paste(dir$res, "dt_res_base_values_by_airport.csv", sep = "/")
)

# Declare output variables
cols     <- list()
cols$bas <- grep("todr|thr|pax", names(dt_res), value = TRUE) # Base values
cols$loe <- paste(cols$bas, "loe", sep = "_") # LOESS values
# 3.2 Summarize results by airport
# Some airports do not have enough successful takeoffs to use the LOESS method
#
# 3.2.1 Calculate changes in base values by airport
#
# Create a new data table for summarizing by airport
dt_res_apt <- copy(dt_res)

# Define change variable
cols$dif <- paste(cols$bas, "dif", sep = "_")

# Calculate the absolute difference between each year and the first, by airport
dt_res_apt[, (cols$dif) := lapply(
  X = .SD,
  FUN = function(x) {
    (x - x[1:1])
  },
  by = c("ssp", "icao", "type"),
  .SDcols = cols$bas
)][, (cols$bas) := NULL]

# Save the final-year changes in base values by airport to disk
fwrite(
  x = dt_res_apt[year == dt_res_apt[which.max(year), year]],
  avg_thr_dif := avg_thr_dif * 100L # Change to percentage
)[, (cols$dif) := round(.SD, 1L), .SDcols = cols$dif][, melt(
  data = .SD,
  id.vars = c("year", "ssp", "zone", "icao", "lat", "lon", "type")
)][, dcast(
  data = .SD,
  formula = year + zone + icao + lat + lon + variable ~ type + ssp)
],
  file = paste(dir$res, "dt_res_base_changes_by_airport.csv", sep = "/")
)

# 3.2.2 Boxplot the changes in base values by airport
#
# Add a global zone to the plot data
dt_plt <- rbind(
  dt_res_apt[year == dt_res_apt[which.max(year), year]],
  dt_res_apt[year == dt_res_apt[which.max(year), year]][, zone := "Global"]
)

# Order the climate zones so they display in alphabetical order
dt_plt[, zone := factor(zone, levels = sort(unique(levels(dt_plt[, zone]))))]

# Save the quantile values by SSP and aircraft type
fwrite(
  x = dt_plt[
    zone == "Global",
    lapply(X = .SD, FUN = quantile, probs = sim$quantiles),
  ],
  file = "dt_res_base_changes_by_airport_quantiles.csv"
)
.SDcols = cols$dif, by = c("ssp", "type")
], avg_thr_dif := avg_thr_dif * 100L
], (cols$dif) := round(.SD, 1L), .SDcols = cols$dif
], quantile := rep(x = sim$quantiles, times = 8L)
],
file = paste(dir$res, "dt_res_base_changes_quantiles.csv", sep = "/")
)

# Create a function to plot results
fn_plot <- function(body, cols) {

    # Build the plot
    ggplot(
    data = dt_plt,
    mapping = aes(x = zone, y = .data[[as.character(cols)]])
    ) +
    stat_boxplot(geom = "errorbar", linewidth = .3) + # Add whisker ends
    geom_boxplot(outlier.size = .2, linewidth = .3) +
    scale_x_discrete(name = NULL) +
    scale_y_continuous(
        name = NULL,
        labels = ifelse(
            cols == "avg_thr_dif",
            scales::label_percent(accuracy = 1L),
            scales::label_comma(accuracy = 1L)
        )
    ) +
    # Zoom into the canvas with different limits for each variable
    coord_cartesian(
        ylim = if (cols == "avg_pax_rem_dif") { c(-10L, 10L) }
        else if (cols == "avg_thr_dif") { c(-.02, .02) }
        else if (cols == "avg_todr_dif") { c(-100L, 100L) }
    ) +
    stat_summary(fun = mean, size = .01) + # Display the mean onto the boxplot
    facet_grid(
        rows = vars(type),
        cols = vars(toupper(ssp))
    ) +
    theme_light() +
    theme(
        axis.text = element_text(size = plt$axis.text),
        axis.title = element_text(size = plt$axis.title),
        strip.text = element_text(size = plt$strip.text)
    )

    # Save the plot
    ggsave(
        filename = paste("9_res_boxplot_of_",
                        cols,
                        ".png",
                        sep = ""),
        plot = last_plot(),
        device = plt$device,
        path = plt$path,
        scale = plt$scale,
        height = plt$height,
        width = plt$width,
        units = plt$units,
        dpi = plt$dpi
    )
# End of the fn_plot function

# Combine the aircraft bodies and output variables to be plotted
mix <- expand.grid(
  body = names(bod),
  cols = cols$dif
)

# Generate the plots
mapply(
  FUN = fn_plot,
  body = mix$body,
  cols = mix$cols
)

# 3.2.3 Plot the changes in base values by airport onto a choropleth map

# Define the world object from the Natural Earth package
world <- rnaturalearth::ne_countries(scale = "small", returnclass = "sf")

# Create a function to plot results
fn_plot <- function(body, cols, labs) {
  print(cols)
  ggplot() +
  geom_sf(data = world, fill = "gray") +
  coord_sf(expand = FALSE) +
  # Define the scales
  scale_x_continuous(breaks = c(-180L, 180L)) +
  scale_y_continuous(
    breaks = unique(unlist(x = geo, use.names = FALSE)),
    limits = c(-90L, 90L)
  ) +
  scale_color_viridis(
    direction = -1L,
    name = labs,
    option = "magma"
  ) +
  # facet_wrap(~toupper(ssp)) +
  facet_wrap(facets = vars(toupper(ssp))) +
  geom_point(
    data = dt_res_apt[year == dt_res_apt[which.max(year), year] & type == body],
    mapping = aes(
      x = lon,
      y = lat,
      color = .data[[as.character(cols)]]
    ),
    shape = 20L,
    size = 1L
  ) +
  # Add parallel labels
  geom_text(
    data = world,
    color = "gray",
    hjust = 0L,
    label = "Arctic circle",
    size = 1.5,
    x = -179L,
  )
y = unique(unlist(x = geo, use.names = FALSE))[5] - 2L
} +
geom_text(
data = world,
color = "gray",
hjust = 0L,
label = "Tropic of Cancer",
size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[4] - 2L
} +
geom_text(
data = world,
color = "gray",
hjust = 0L,
label = "Tropic of Capricorn",
size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[3] - 2L
} +
geom_text(
data = world,
color = "gray",
hjust = 0L,
label = "Antarctic circle",
size = 1.5,
x = -179L,
y = unique(unlist(x = geo, use.names = FALSE))[2] - 2L
) +
# Add zonal labels
geom_text(
angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[1],
size = 2L,
x = -175L,
ys = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[1],
    unique(unlist(x = geo, use.names = FALSE))[2]
  )))
) +
geom_text(
angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[2],
size = 2L,
x = -175L,
ys = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[2],
    unique(unlist(x = geo, use.names = FALSE))[3]
  )))
) +
geom_text(
angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[3],
size = 2L,
x = -175L,
y = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[3],
    unique(unlist(x = geo, use.names = FALSE))[4]
  )
)
)
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[2],
size = 2L,
x = -175L,
y = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[4],
    unique(unlist(x = geo, use.names = FALSE))[5]
  )
)
)
geom_text(
  angle = 90L,
data = world,
color = "gray",
hjust = .5,
label = unique(names(geo))[1],
size = 2L,
x = -175L,
y = mean(
  c(
    unique(unlist(x = geo, use.names = FALSE))[5],
    unique(unlist(x = geo, use.names = FALSE))[6]
  )
)
)
)
theme_light() +
theme(
  axis.title = element_blank(),
  axis.text = element_blank(),
  axis.ticks = element_blank(),
  legend.key.size = unit(.2, plt$units),
  text = element_text(size = plt$text)
)

# Save the plot

ggsave(
  filename = tolower(
    paste(
      "g_res_map_of_",
      body,
      ",",
      cols,
    )
  )
)
# End of the fn_plot function

# Combine the aircraft bodies and output variables to be plotted
mix <- expand.grid(
  body = names(bod),
  cols = cols$dif
)

mapply(
  FUN = fn_plot,
  body = mix$body,
  cols = mix$cols,
  labs = rep(x = c("in m", "in p. p.", "in pax"), each = 2L)
)

# 3.3 Summarize results by climate zone

# 3.3.1 Calculate LOESS values by climate zone

# Create a new data table for summarizing by airport
dt_res_zon <- copy(dt_res)

dt_res_zon[,
  .SDcols = cols$bas
],
# Global summary by group
  zone := "Global"[,
  .SDcols = cols$bas
]
)

dt_res_zon[, (cols$loe) := lapply(
  X = .SD,
  FUN = function(x) {
    predict(loess(formula = x ~ year, span = .75, model = TRUE))
  }
),]
by = c("ssp", "zone", "type"),
.SDcols = cols$bas
]

# Save the data to disk
fwrite(
x    = dt_res_zon,
file = paste(dir$res, "dt_res_loess_values_by_zone.csv", sep = "/")
)

# Order the zones so they display in alphabetical order
dt_res_zon[, zone := factor(zone,
    levels = sort(unique(levels(dt_res_zon[, zone])))
]

# Declare independent variables for grouping
grp <- c("ssp", "zone")

# Create a function to plot results
fn_plot <- function(body, cols) {

    # Build the plot
    ggplot(
data    = dt_res_zon[type == body],
    mapping = aes(
        x     = year,
        y     = dt_res_zon[type == body][[as.character(cols)]]
    )) +
    geom_line(linewidth = .2) +
    geom_smooth(formula = y ~ x, method = "loess", linewidth = .5) +
    # Starting value labels
    geom_label(
data    = dt_res_zon[type == body][, .SD[which.min(year)], by = grp],
aes(
        x     = year,
        y     = dt_res_zon[type == body][, .SD[which.min(year)], by = grp]
            [[paste(as.character(cols), "loe", sep = "]")]],
    label = sprintf(
        fmt = ifelse(
            cols == "avg_thr",
            "%1.1f\%",
            ifelse(cols == "avg_todr", "%1f", "%.1f")
        ),
        dt_res_zon[type == body][, .SD[which.min(year)], by = grp]
            [[paste(as.character(cols), "loe", sep = "]")]] *
            ifelse(cols == "avg_thr", 100L, 1L)
    ),
    alpha   = .5,
    fill    = "white",
    label.r = unit(0L, "lines"),
    label.size = 0L,
    nudge_x = 4L,
    size    = 2L
) +
# Ending value labels

```r
geom_label(
  data = dt_res_zon[type == body][, .SD[which.max(year)], by = grp],
  aes(
    x = year,
    y = dt_res_zon[type == body][, .SD[which.max(year)], by = grp][
      paste(as.character(cols), "loe", sep = ",")],
    label = sprintf(
      fmt = ifelse(
        cols == "avg_thr",
        "%1.1f\%%",
        ifelse(cols == "avg_todr", "%1.0f", "%1f")
      ),
      dt_res_zon[type == body][, .SD[which.max(year)], by = grp][
        paste(as.character(cols), "loe", sep = ",")]
      *
      ifelse(cols == "avg_thr", 100L, 1L)
    ),
    alpha = .5,
    fill = "white",
    label.r = unit(0L, "lines"),
    label.size = 0L,
    nudge_x = -4L,
    size = 2L
  ),
  alpha = .5,
  fill = "white",
  label.r = unit(0L, "lines"),
  label.size = 0L,
  nudge_x = -4L,
  size = 2L
) +
scale_x_continuous(name = "Year", n.breaks = 3L) +
scale_y_continuous(
  name = "Value",
  labels = ifelse(
    cols == "avg_thr",
    scales::label_percent(accuracy = .1),
    ifelse(
      cols == "avg_todr",
      scales::label_comma(accuracy = 1L),
      scales::label_comma(accuracy = .1)
    )
  )
) +
facet_grid(
  rows = vars(zone),
  cols = vars(toupper(ssp)),
  scales = "free_y"
) +
theme_light() +
theme(
  axis.title.y = element_blank(),
  text = element_text(size = plt$text)
)

# Save the plot

ggsave(
  filename = tolower(
    paste(
      "9_res_lineplot_of_",
      body,
      ", ",
      cols,
      ".png",
      sep = ""
    )
  ),
)
plot = last_plot(),
device = plt$device,
path = plt$path,
scale = plt$scale,
height = plt$height,
width = plt$width,
units = plt$units,
dpi = plt$dpi
)
} # End of the fn_plot function

# Combine the aircraft bodies and output variables to be plotted
mix <- expand.grid(
  body = names(bod),
  cols = cols$bas
)

# Generate the plots
mapply(
  FUN = fn_plot,
  body = mix$body,
  cols = mix$cols
)

# 3.3.3 Summarize the changes in LOESS values by climate zone

# Define change variable
cols$dif <- paste(cols$loe, "dif", sep = "_")

# Calculate the absolute difference between each year and the first, by zone
dt_res_zon[, (cols$dif) := lapply(
  X = .SD,
  FUN = function(x) {
    (x - x[1:1])
  },
  by = c("ssp", "zone", "type"),
  .SDcols = cols$loe
)]

# Save the final-year changes in LOESS values by zone to disk
fwrite(
  x = dt_res_zon[year == dt_res_zon[which.max(year), year]
  ][, c("year", "ssp", "zone", "type", cols$dif), with = FALSE
  ][, avg_thr_loe_dif := avg_thr_loe_dif * 100L # Change to percentage
  ][, (cols$dif) := round(.SD, 1L), .SDcols = cols$dif
  ][, melt(data = .SD, id.vars = c("year", "zone", "ssp", "type"))
  ][, dcast(data = .SD, formula = year + zone + variable ~ type + ssp)
  ][, zone := factor(zone, levels = sort(unique(levels(dt_res_zon[, zone]))))
  ][, variable := factor(variable, cols$dif)
  ][order(variable, zone)
  ],
  file = paste(dir$res, "dt_res_loess_changes_by_zone.csv", sep = "/")
)

# 6 Housekeeping
# Stop the script timer
Sys.time() - start_time

# EOF