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Con-Accessibility: Logit-based catchment area modeling for strategic airport system planning

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ABSTRACT

National airport system plans serve as the primary programmatic documents employed by policy-makers to outline the roles of different airports and devise strategies for their coordinated and integrated development, encompassing economic, environmental, and social perspectives. This paper proposes a modeling framework to estimate the strength of each airport's influence and contribution to the surrounding territories, providing methodological foundation for assessing airport demand and delineating the scope of airport interactions. We propose a novel origin-based nested logit model of airport demand based on a comprehensive utility function—denoted as *con-accessibility*—integrating advanced metrics of ground accessibility and airport connectivity. To address the lack of extensive pairwise municipality–airport data, we cast the estimation problem as a nonlinear constrained least-squares optimization problem, solved via a differential evolution algorithm. The framework's applicability and insights are demonstrated in a real-world case study of the latest Italian national airport system plan. We highlight the model's capability in addressing three key policy questions: (i) characterizing airport catchments toward investigating the degree of overlap and airport interactions in serving contended areas; (ii) systematically quantifying the overall level of con-accessibility in any region to assess deficits or surpluses and pinpoint areas for strategic interventions; (iii) supporting the assessment and prioritization of various initiatives, including the upgrade of ground access networks, the expansion of airport supply, and the establishment of new airport facilities.

1. Introduction

Commercial aviation plays a pivotal role as a catalyst for development and economic growth. Despite several challenges over the last 20 years, air traffic demand has demonstrated remarkable resilience and the capacity to rebound, demonstrating an enduring ability to grow. Today's global air traffic network features an intricately complex array of capital-intensive resources and interlinked operations. To realize its ultimate potential and deliver intended benefits, effective synchronization in the utilization of these resources and coordinated operations among multiple stakeholders are essential. At its core, aviation relies on an extensive network of airports, which provide the necessary facilities for flight operations and serve as gateways on territories, acting as collectors of air travel demand.

Given the high cost, negative externalities, and long lead times for building or improving airports, effective planning is key in determining what facilities will be needed and devising programs for providing them in a timely manner. Airport planning is a highly

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complex task, spanning several stages and timeframes, involving a multitude of decisions, and demanding careful weighting of the interests of public and private stakeholders—first and foremost, regarding the trade-off between the need for aviation development and societal and environmental concerns.

At individual airports, strategic planning is typically implemented through a structured planning process called airport master planning (AMP). Airport master plans typically contain a variety of analyses aimed at outlining the future airport configuration and the necessary steps to orderly achieve it, along with a financial plan and cost–benefit assessments supporting its viability. Given the medium-/long-term orientation, AMP is subject to substantial degree and multifaceted uncertainty. Accordingly, at most airports, master planning is nowadays an ongoing and continuous process, conducted on a rolling basis and leveraging adaptive and flexible planning practices (Kwakkel et al., 2010; Burghouwt, 2016).

Adding to this complexity, airports do not operate in a vacuum; instead, they extensively interact with each other in various ways. Consequently, the planning of airports should not occur in isolation; rather, an integrated approach at a systemic level is needed to achieve a balanced and coordinated development, ultimately boosting the social effectiveness and efficiency of airport systems (De Neufville, 2020). Orchestrating a harmonious evolution of an airport system is the focus of airport system planning, which is typically overseen by national or sovra-national transport authorities. Airport system planning operates on multiple levels, ranging from the metropolitan to the regional, up to the national level. This study focuses on this latter perspective.

In the United States, airport planning at the national level is the responsibility of Federal Aviation Administration (FAA), which provides guidance for the development of publicly-owned airports and allocation of federal funds for airport investments. In Europe, most of the member states develop their own national airport system plan, which is part of broader national infrastructure plans (European Commission, 2015). In Italy, the technical responsibility falls under the Civil Aviation Authority—Ente Nazionale per L'Aviazione Civile (ENAC). The first Italian national airport system plan was approved in 2015. The latest plan, covering the period 2020–2035, is presently awaiting approval from the Ministry of Infrastructure and Transportation. This study reports on the methodology developed for this current plan.

Despite a lack of harmonization and variations in legal frameworks, national airport plans share a common goal: to systematically assess the existing airport infrastructure, understand current deficiencies, and anticipate future requirements. The ultimate objective is to characterize the roles of different airports and strategize for their optimal development, considering both efficiency and social perspectives. A distinctive aspect of airport system planning is its emphasis on airport interactions. At the network level, this involves recognizing hub-feeding relationships and assessing the overall competitiveness and integration at the supranational level. On the local scale, these considerations encompass both competitive and complementarity dynamics in serving a given contended region. To this end, the careful appraisal of airport catchment, i.e., the geographic area surrounding an airport where it can reasonably expect to draw passenger traffic (ACRP), constitutes an essential ingredient of airport system planning.

Catchment area modeling. Traditional approaches involve a static representation of airport catchments, delineated based on accessibility within a specified threshold criterion—commonly related to access time, but possibly also encompassing costs or generalized travel expenses (Sun et al., 2017, 2020). Overlaps among catchments thus defined offer a simple way to preliminary characterize the strength of airport interactions and competition on a local scale. However, the utilization of static catchments comes with an inherent limitation, as it completely disregards the distinct characteristics of each airport. Considering the airport supply is instead a fundamental component, as it significantly affects (i) the actual stretch of the catchment—possibly beyond theoretical geographical boundaries implied by a static appraisal—and (ii) the extent to which neighboring airports compete or complement each other in serving a given contended region.

Past studies on airport choices have underscored the importance of concurrently considering airport supply and ground accessibility to accurately characterize a specific airport's ability to attract traffic from a given territory. However, prevailing approaches predominantly rely on ad-hoc surveys, focus on a unique destination or a small set provided by all airports, consider detailed itinerary-level features (e.g., price, flight time, and detour), and concentrate on airport system planning at the metropolitan level (e.g., Pels et al., 2003; Hess and Polak, 2005; de Luca, 2012; Lieshout, 2012; Yirgu and Kim, 2024). In turn, these approaches enable the accurate establishment of destination–, or route–, specific catchment areas (Gao et al., 2023). They rely on the inherent assumption that air transport markets are independent, i.e., passengers do not substitute among destinations. However, as evidenced both theoretically and empirically by contributions focusing on footloose passengers, destination choice and substitutability (e.g., Rugg, 1973; Bieger and Wittmer, 2006; ACI Europe/Copenhagen Economics, 2012), this might not always be the case, particularly for leisure passengers who face an expanding array of destination options facilitated by low-cost carriers (LCCs). Moreover, implementing such granular approaches on a national scale with a strategic focus and long-term outlook may not be ideal, as it would necessitate substantial computations and the formulation of strong destination-level network development assumptions, potentially introducing computational complexity and noise to the assessment. In summary, we argue these approaches fall short in terms of generalizability and applicability on a large scale, thus not being ideally suited for supporting national airport system planning. An alternative approach is to model airport catchment areas using a Huff model (Huff, 1963). While acknowledging the complementary role of attractiveness and impedance factors, existing research in this domain (e.g., Huber et al., 2021; Teixeira and Derudder, 2021) tends to rely on a rigid functional form regarding the substitution patterns between the two factors (i.e., direct proportionality to attractiveness and inverse proportionality to impedance). Moreover, they relied on simplistic scores for attractiveness and impedance, which may not suitably address the multifaceted features of air connectivity and ground accessibility.

The proposed approach described in this paper sets out to overcome these challenges by proposing a novel modeling framework at the appropriate level of aggregation to systematically leverage a *dynamic*—dependent on both ground accessibility and connectivity levels—representation of airport catchments to support the crafting of strategic national airport policies.

Paper contributions. More precisely, this paper makes the following contributions:

1. From a modeling standpoint, it proposes a novel framework to assess the territorial spread of airport connectivity, specifically, to quantify the extent of air connectivity provided by airports to the surrounding territories. The proposed framework integrates advanced metrics of ground accessibility and airport connectivity to attain a compound utility function—denoted as "con-accessibility"—that suitably accounts for both factors, accurately reflecting the strength of the relationship between each area and airport. Developing such a measure is the basis for addressing two key issues in the strategic planning of airport systems: (i) from an airport-centric perspective, investigating interactions among neighboring airports to establish airport catchment areas and assess demand potential; (ii) from a regional perspective, quantifying the overall level of air connectivity characterizing any region—given by the sum of the contributions of possibly several neighboring airports—to assess the deficit or surplus of connectivity across regions and inform policies accordingly.
2. From a methodological standpoint, a significant challenge is to estimate the parameters of the con-accessibility utility function, which describe the trade-offs between the two components, and devise a suitable functional form to combine the utilities of various airports. In line with the latest developments in the field and passenger behavior (e.g., Garrow, 2016; Lieshout et al., 2016; Birolini et al., 2020), we postulate a logit-based modeling architecture, specifically, an origin-based nested logit model of airport demand—a state-of-the-art specification that concurrently and consistently captures the generation of demand from each area and its allocation among neighboring airports. Given the lack of sufficient municipality–airport pairwise data—an empirical challenge in practice, especially when conducting nationwide studies—which would straightforwardly allow the estimation of choice models via traditional econometric techniques, we propose an ad-hoc estimation procedure. This procedure minimizes the sum of squared deviations from observed airport demand data, subject to calibration constraints and fundamental demand generation and allocation assumptions inherent in the nested logit formulation. Ultimately, this results in a non-linear optimization problem, which can be solved using global optimization algorithms.
3. From a practical standpoint, we thoroughly validate our framework using a real-world case study of Italy. We demonstrate how it can aid in assessing three key policy questions. Firstly, we calculate the actual size of each airport's catchment area concerning domestic, international, and intercontinental destinations. Additionally, we ascertain the degree of airport concentration at the regional level to underscore dominance and the dependency of each territory on specific airports. Secondly, we compute the level of total con-accessibility of each municipality, map it, and utilize it to identify air accessibility gaps for directing interventions. Thirdly, we delve into a case study of Sicily, showcasing the application of the proposed framework to evaluate the impact of various measures, such as enhancing ground accessibility and/or connectivity of existing or new airport facilities. Ultimately, these results demonstrate the potential of the proposed approach to yield strategic insights into national airport system planning.

The rest of the paper is structured as follows. Section 2 presents the modeling framework, first formulating the con-accessibility model and then detailing the derivations of ground accessibility and airport connectivity metrics. Section 3 introduces the study context, empirical setting, and the estimation of model coefficients. Section 4 delves into the application of the modeling framework and reports the results. Finally, Section 5 summarizes the paper and outlines directions for future research.

2. Modeling framework

2.1. Formalization of the con-accessibility model

Let us consider a set $\mathcal{K}$ of geographic areas partitioning the region under investigation—such as an arbitrary grid or any administrative subdivision (municipalities in our case)—and representing the origin/destination of air trips. We then define the set of airports $\mathcal{A}$, which provide air connectivity to neighboring territories. Central to the con-accessibility framework is the formulation of a metric that proxies the strength of the relationship between each area k and airport a. We consider two main determinants: ground accessibility (GA_{ka})—indicating the ease/convenience to reach an airport from region k—and airport connectivity (AC_a)—quantifying the quality and scope of air services at airport a. Consistent with literature and practice, we define the ground accessibility metric (GA_{ka}) as a composite measure encompassing the availability of diverse transport modes and their attributes, such as travel time and cost, among others. Similarly, AC_a is defined as a composite measure capturing the destination portfolio—comprising both the number and economic importance of the destinations served—and the quantity and quality of air itineraries provided to reach them. A visual representation of GA and AC is provided in Fig. 1, while details on the functional forms of these two metrics are provided in Section 2.2.

Given the two proxies of airport ground accessibility and connectivity, the challenge is to combine them into a unique score that consistently characterizes the utility of airport a for region k. Without loss of generality, we define a "con-accessibility" utility function as the linear combination of the two terms:

$$V_{ka} = \alpha GA_{ka} + \beta AC_a \tag{1}$$

where α and β are empirical coefficients to be estimated, modeling substitution patterns between the two factors and their respective importance in determining the total value of airport a for region k. We then seek to define mapping functions of the form $f(V_{ka}, a \in \mathcal{A}_k)$ for estimating the total con-accessibility of region k provided by its neighboring airports—indicated by $\mathcal{A}_k$ (i.e., the set of airports reachable from k within a maximum distance/time threshold)—and the demand potential of airport a in region k.

To consistently derive these functions, we consider a logit-based formulation—one of the most successful empirical models to represent passenger demand (Ben-Akiva and Lerman, 1985). This allows us to obtain behavioral realism and meaningful substitution

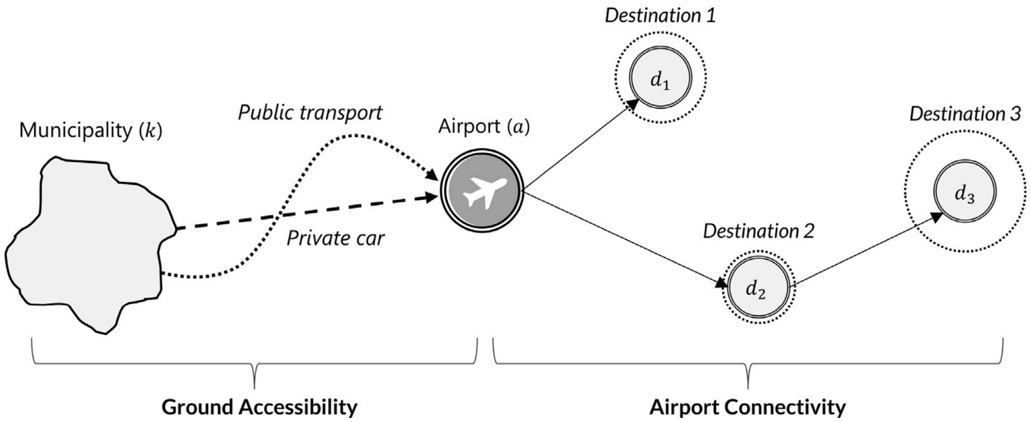


Fig. 1. A depiction of the components of the con-accessibility utility function using a simplified example of a municipality–airport pair featuring two ground access modes and air services to three destinations—two connected directly and one accessible through a one-stop itinerary.

patterns. More specifically, we consider an origin-based nested logit (NL) specification—similar to Birolini et al. (2020) but defined at the territorial scale—that simultaneously captures demand generation (in this case, the total air travel demand generated from a given region) and demand allocation (namely, the redistribution of demand from a given region among neighboring airports), as a function of socio-economic/demographic features and the level/quality of airport supply.

Let T_k indicate the saturated demand of region k, which represents the unconstrained hypothetical maximum number of trips such region could generate. In other words, T_k provides a theoretical upper bound on the maximum travel demand potential of a given region should travel impedance (i.e., the burden of travel) be negligible. Accordingly, T_k does not depend on the availability and quality of air services and should thus be defined as the sole function of socioeconomic/demographic features. We then define the overall utility of air travel as a function of the utilities provided by the set of accessible airports (A_k). In symbols:

$$V_k^{air} = \delta + \rho \underbrace{\log \sum_{a \in \mathcal{A}_k} e^{V_{ka}}}_{\psi_k} \tag{2}$$

where δ is an intercept coefficient and ρ is the nesting coefficient preceding the logsum term (ψ_k) (i.e., the sum of the airports' exp-utilities). In practical terms, the logsum of airport utilities provides a systematic and consistent quantification of the total level of con-accessibility of region k under a logit framework, while ρ describes the extent to which changes in air transport supply affect the utility of air travel and therefore the total air travel demand.

On the same footing of V_k^{air}, we define the utility of the no-fly option, which encompasses both the option of traveling by other modes and no traveling at all. Consistent with common practice, this term can be normalized to 0, and so $e^{V_k^{no-air}} = 1$. The values of V_k^{air} and V_k^{no-air} ascertain the fraction of saturated demand that is "captured" by the air travel alternative, thereby providing an estimation of the total number of air trips originating from region k (Q_k). Similarly, within the inner nest, this value is then allocated among airports (in k's choice set) based on their respective utility values.

Building upon this notation and aligning with the NL function form, the demand originated from k captured by airport a, indicated as q_{ka}, can be synthetically formulated as:

$$q_{ka} = \underbrace{T_k \frac{e^{V_k^{air}}}{1 + e^{V_k^{air}}}}_{Q_k} \underbrace{\frac{e^{V_{ka}}}{\sum_{a' \in \mathcal{A}_k} e^{V_{ka'}}}}_{P_{ka}} \tag{3}$$

where Q_k represents the total demand, while P_{ka} the market share of airport a.

Model estimation. The calibration of the con-accessibility model requires the estimation of four parameters, i.e., α and β in Eq. (1) and δ, ρ in Eq. (2). In symbols:

$$q_{ka}(\alpha, \beta, \delta, \rho) = T_k \frac{e^{V_k^{air}(\alpha,\beta,\delta,\rho)}}{1 + e^{V_k^{air}(\alpha,\beta,\delta,\rho)}} \frac{e^{V_{ka}(\alpha,\beta)}}{\sum_{a' \in \mathcal{A}_k} e^{V_{ka'}(\alpha,\beta)}} \tag{4}$$

If a sufficient amount of municipality–airport pairwise passenger flow data is available (i.e., historical observations of q_{ka}, representing the number of passengers from k using airport a), conventional econometric techniques like maximum likelihood (e.g., Brownstone and Small, 1989; Cadarso et al., 2017) or aggregate log-ratio linearization approaches (e.g., Wei and Hansen, 2006; Birolini et al., 2020) can be employed. This type of data can be obtained from surveys or GPS records generated by mobile phones (e.g., Adler et al., 2022). In practice, collecting such data systematically, especially on a nationwide scale, is often challenging and expensive. Consequently, in many cases, strategic national planning has to rely on sparse information or no information at all regarding q_{ka}.

To address this limitation and extract meaningful parameters under sparse information, we cast the estimation problem as a nonlinear constrained least squares optimization problem, outlined in Eqs. (5)–(8).

$$\min \quad \sum_{a\in\mathcal{A}} \left(\sum_{k\in\mathcal{K}_a} q_{ka}(\alpha,\beta,\delta,\rho) - \bar{Q}_a \right)^2 \tag{5}$$

$$s.t. \quad \sum_{a\in\mathcal{A}_k} q_{ka}(\alpha,\beta,\delta,\rho) = \bar{Q}_k \qquad \forall k \in \Lambda_1 \tag{6}$$

$$q_{ka}(\alpha,\beta,\delta,\rho) = \bar{q}_{ka} \qquad \forall (k,a) \in \Lambda_2 \tag{7}$$

$$\alpha,\beta,\delta,\rho \in \mathbb{R}^+ \tag{8}$$

Eq. (5) formalizes the objective function, which minimizes the sum of squared deviations from observed airport-level historical demand (denoted as $\bar{Q}_a$). The estimated airport demand is endogenous in the model and reconstructed as the sum of q_{ka}—depending on the decisions variables of the model (i.e., the parameters to be estimates) following Eq. (4)—across $\mathcal{K}_a = \{k : a \in \mathcal{A}_k\}$, denoting the set of regions in airport a's catchment area. Constraints (6) and (7) are calibration constraints, ensuring consistency with any available total municipality demand ($\bar{Q}_k$) and pairwise k-a passenger flow data ($\bar{q}_{ka}$), respectively.[1] Set Λ_1 denotes the municipalities for which total demand data is available. Similarly, set Λ_2 is formed by the tuples (k,a) for which demand data is available. Clearly, as the cardinality of $|\Lambda_1|$ and $|\Lambda_2|$—namely, the availability of information—increases, the degrees of freedom of the estimator decrease, resulting in enhanced accuracy and robustness. Ultimately, constraints (8) define the domain of the variables to be positive reals. In practice, each parameter's domain can be restricted to limit the search to a bounded region.

To estimate the model, global optimization algorithms can be used (a review can be found in Pintér, 2009). In this paper, we employ a differential evolution algorithm (DE) (Storn and Price, 1997; Das et al., 2016), which implements an evolutionary approach to iteratively update a pool of candidate solutions toward optimizing potentially nonlinear and non-differentiable functions. The original DE approach works for unconstrained problems over a bounded continuous space. Nonetheless, if calibration constraints are established, a DE approach can still be employed by leveraging constraint-handling techniques. In its simplest form, this entails removing the constraints and integrating them in the objective function, preceded by a parameter penalizing deviations (in a Lagrangian-like fashion). More details on the empirical estimation and validation are reported in Section 3.4.

2.2. Formulation of ground accessibility and airport connectivity metrics

Ground accessibility. Airport ground accessibility refers to the ease and convenience with which individuals can access or leave an airport using various modes of transportation. It involves assessing the quality and availability of travel options, such as private and public transport modes, roads, and rail connections, to and from the airport. Seminal works by Harvey (1986) and Windle and Dresner (1995) pioneered the application of multinomial logit (MNL) formulations to assess passengers' choices in airport access mode. Since then, the use of discrete choice models has been consistently recognized as best practice, with subsequent studies enhancing our understanding and modeling capabilities of access mode choice dynamics. Existing constitutions have shown that alternative-specific factors, including access time, out-of-pocket costs, frequency, and onboard comfort primarily influence the choice of airport access mode. Additionally, individual-specific attributes, such as travel purpose (e.g., business vs. leisure), passenger type (e.g., resident vs. visitor), car ownership, size of the travel party, and the number of pieces of luggage, also play a significant role in this decision-making process (refer to Gosling, 2008, for a review). Subsequent studies delved into the exploration of advanced choice models, such as mixed logit (e.g., Bergantino et al., 2020; Pasha et al., 2020), and latent class (e.g., Zhou et al., 2020) models, which allow attaining greater realism (at the expense of higher complexity) by capturing heterogeneity in passengers' behavior. Moreover, access mode choice models have been deployed to support a vast array of evaluations, spanning the introduction of new transport modes, the impact of airport relocations and extraordinary events, and the formulation and assessment of policies and interventions (Psaraki and Abacoumkin, 2002; Jou et al., 2011; Zaidan and Abulibdeh, 2018; Avogadro et al., 2024).

Building on prior research, we define the municipality–airport accessibility index, GA_{ka}, assuming an MNL specification and considering the log-sum—namely, the natural logarithm of the sum of the exponential utilities across available modes (De Jong et al., 2007)—as a consistent measure of the overall ground accessibility quality for any given region-airport pair. Let $\mathcal{M}$ denote the set of alternative access transport modes, and let u^m_{ka} represent the deterministic component of the utility associated with using mode m from k to a. In symbols, GA_{ka} is defined as:

$$GA_{ka} = \log \sum_{m\in\mathcal{M}} e^{u^m_{ka}} \tag{9}$$

In practice, the appropriate utility specification should be chosen based on the scope of the assessment, as well as the sophistication of the empirical coefficients and the granularity of data available. In our case, given the national-level focus and the lack of comprehensive individual-specific information at the municipality level, we consider a straightforward specification that includes the two key alternative-specific features—access time and out-of-pocket costs—while borrowing coefficients from a recent study (more details in Section 3.2).

[1] Note that the strict equality in Constraints (6)–(7) can be replaced with inequalities, allowing for small deviations (e.g., $\pm\epsilon$), to avoid overfitting with the limited available data and effectively handle the bias–variance trade-off (e.g., Bertsimas and Yan, 2018).

Airport connectivity. The quantification of the quality of air transport services plays a pivotal role in aviation studies and decision-making processes. Early approaches focused on appropriately incorporating both direct and indirect connectivity in hub-and-spoke networks. These methods typically involve identifying the set of viable connections and assessing the attractiveness of each by penalizing stopovers, detours, extended transfer times, and low frequencies. The results are then aggregated to derive comprehensive metrics at various levels of analysis, commonly at the airport or airline level, to investigate the competitiveness of airport or airline networks.

Connectivity models typically strive to offer straightforward methods for conducting network-wide assessments. As such, their emphasis is often on schedule-related features, while overlooking passenger and price information, which are highly market-specific and challenging to collect on a global scale (Burghouwt and Redondi, 2013).

Most early air connectivity studies employed simple criteria, such as binary cutoffs on routing factors and minimum/maximum transfer time thresholds (e.g., Dennis, 1994b,a), or a discrete classification of connection quality (e.g., Bootsma, 1997; Danesi, 2006). Other studies coupled hard cutoffs with continuous measures of connection quality, for example, by weighting transfer time more heavily than in-flight time (e.g., Burghouwt and De Wit, 2005; Burghouwt and Veldhuis, 2006), to enable a refined comparison between hubs and various connections at the same hub. A recent review can be found in Redondi et al. (2020), which also proposed the use of an empirically calibrated MNL formulation, demonstrating superior performance. As a notable weakness, these models exclusively focus on supply quality, overlooking a careful appraisal of network scope and heterogeneity among destinations. To address this limitation, more recent studies (e.g., Allroggen et al., 2015) have expanded connectivity models to incorporate measures of destination quality, proxying the respective economic interaction potential. This is also the case of the IATA connectivity index (IATA, 2020). Such index explicitly incorporates the weights of destination airports while solely relying on direct seat capacity as a proxy for link quality.

In this paper, we introduce a tailored airport-centered connectivity metric for calculating airport connectivity (AC_a). Aligned with the latest advancements, this metric simultaneously takes into account both destination and supply quality, utilizing connection quality weights derived from an MNL specification. Let $\mathcal{D}_a$ be the set of destination airports served from airport a. For each destination, we identify all feasible connections (denoted by $\mathcal{I}_{ad}$, indexed by i), both nonstop and connecting, uniquely identified by the sequence of airports (for example, given airport A and destination airport B, $\mathcal{I}_{AB}$ =[A-B, A-H1-B, A-H2-B, ...], where H1 and H2 act as transfer hubs).[2]

For each connection, we define the respective level of air connectivity, γ_i, given by the product of supply (π_i) and destination quality ($\omega_{d(i)}$) indices. π_i is defined as follows: $\pi_i = \delta_i \log(1 + f_i)$. Here, f_i denotes the frequency of connection i, which is simply given as the total frequency for nonstop connections or the minimum frequency of the respective flight segments for connecting itineraries.

Consistent with prior studies (e.g. Hansen, 1990; Adler, 2005), the logarithm form is utilized to account for diminishing returns concerning the increase in service attractiveness. The term δ_i instead captures the connection quality in terms of transfer and detour times—also referred to as *directness*—relative to a theoretical nonstop flight (i') serving the same airport-pair. It is formulated as follows: $\delta_i = e^{v_i}/e^{v_{i'}}$, where $v(\cdot)$ is a utility function derived from Birolini et al. (2020), considering connecting time, flying time, and service type features. By design, nonstop services are assigned a weight of 1, while connecting ones have a weight lower than 1, indicating poorer service quality as the weight decreases.

Regarding $\omega_{d(i)}$, we follow Allroggen et al. (2015) and utilize the Gross Domestic Product (GDP) as a proxy for destination quality. Specifically, we evaluate the GDP within the static catchment area of the destination airport using high-resolution georeferenced datasets. We utilize a logarithmic functional form and normalize it relative to the maximum value.

Ultimately, we calculate the total airport connectivity by summing across the portfolio of destinations served from each airport:

$$AC_a = \sum_{d \in \mathcal{D}_a} \sum_{i \in \mathcal{I}_{ad}} \gamma_i \tag{10}$$

To enhance the accuracy of the analysis, we practically segment destinations by type, denoted by $\mathcal{R}$ and indexed by r, treating each group separately. This enables a thorough examination of airport connectivity and con-accessibility levels concerning various connectivity targets, while also circumventing potential issues associated with the substitutability (or lack thereof) among destinations of different types. Notably, this stratification approach offers flexibility to capture any correlation patterns that may exist between destinations, such as distinguishing between business and leisure-oriented markets or even considering each destination independently, akin to airport choice models discussed in Section 1. Given the strategic scope and level of aggregation of our study, we contemplate the canonical three-way macro-categorization into domestic, international, and intercontinental destinations as further detailed in Section 3.3.

3. Model development

In this section, we illustrate the application of the proposed framework through a real-world case study of Italy. In Section 3.1, we introduce the Italian national airport system plan, where the con-accessibility framework was developed and implemented. In Sections 3.2 and 3.3 we provide details on the data sources and computation of ground accessibility and airport connectivity metrics, discussing their application to the Italian context. Finally, in Section 3.4, we delve into the calibration of the model's coefficients.

[2] As described above, past studies typically relied on routing factor cutoffs to limit the range of significant connections. In this study, we refine this approach by incorporating explicit itinerary-level passenger data, sourced from the OAG Traffic Analyzer, to focus specifically on connections utilized by passengers in each market. Noticeably, this approach can be further extended to consider unseen destinations—for example, new destinations in the case of network development studies—by developing a classification model predicting the ability of any given connection to attract passengers in the respective market.

3.1. Study context: The Italian national airport system plan

The Italian national airport system plan constitutes the primary programmatic and strategic document developed at the national level to formulate key development directives for the Italian airport system. It is part of the broader National Plan of Transportation and Logistics defined by the Ministry of Infrastructure and Transport. The airport plan, developed periodically by the National Civil Aviation Authority (ENAC), seeks to delineate the contribution and scopes of airports to national mobility. Furthermore, it outlines strategic investments and policies designed to efficiently address the anticipated future demand for passenger and cargo transportation within the Italian airport system.

The latest iteration of the Italian national airport system plan, drafted in 2012 and approved in 2015, shapes the development of the national airport system until 2030. In 2020, the National Civil Aviation Authority initiated the procedure to develop a new national airport system plan, focusing on the period 2020–2035 (ENAC, 2022), taking 2019 as the baseline year. This paper reports on the methodology developed to support the evaluation of airports' roles and the identification of air accessibility gaps and surpluses across Italian municipalities for this new plan.

In the subsequent sections, we consider the Italian airport network—consisting of 45 airports (38 of which reported commercial traffic in 2019)—and the set of Italian municipalities (i.e., Local administrative units according to the NUTS[3]), characterized by its socio-economic features such as population and GDP as reported by the Italian Statistical Office (ISTAT).[4] The list of airports considered, along with their unique IATA code and a set of descriptive statistics regarding passenger volumes, annual movements and potential catchment areas, is reported in Appendix A.

Despite the necessary reference to context-specific details in the following sections, it is important to highlight that the Italian context constitutes an exemplary case study for illustrating the proposed methodology. Fig. 2 provides a visual representation of the five major national airport systems in Europe: the United Kingdom, Spain, Germany, France, and Italy. Table 1 presents descriptive statistics to highlight similarities in key features that justify the adoption of the model, further underscoring the suitability of the proposed case study. First, handling around 193 million passengers in 2019, the Italian airport system constitutes one of the largest in Europe; specifically, it is the fifth largest by total passenger traffic. Second, similar to other major European countries, Italy has a large number of airports of varying sizes and heterogeneous connectivity, highlighting the importance of considering an integrated catchment area model that effectively accounts for the level of airport connectivity to different destinations. Specifically, two airports—Rome Fiumicino (FCO) and Milan Malpensa (MXP)—handled more than 25 million passengers each; four handled between 10 and 25 million passengers; and six handled between 5 and 10 million passengers. Twenty airports handled fewer than five million passengers. Geographically, airports in the north handled 43.5% of the traffic, followed by those in the center (30.2%), the islands (14.2%), and the south (12.1%), reflecting the varying degrees of airport development as well as the differing socioeconomic and industrial conditions across these regions. Third, from a geographical standpoint, different territories exhibit varying levels of population density and accessibility to airports of different sizes. As reported in Table 1, the average (population-weighted) number of Italian airports within 100 km from each municipality in Italy is 2.2. This figure is comparable to France (2.4) and Germany (2.3), higher than Spain (1.8), but significantly lower than the United Kingdom, which has a notably higher value due to the concentration of population in the London metropolitan area. Additionally, airport facilities are relatively well-distributed across Italian territories, with 75% of the population having at least a mid-sized airport (handling over 5 million passengers) within 100 km. Nonetheless, when segmenting by airport size, notable variations emerge: the percentage of the population with access to a large airport (handling over 10 million passengers) drops to 54%, and only 26% have access to mega airports (handling over 25 million passengers). This highlights the need to effectively address and model airport interactions and their roles in serving diverse regions to accurately quantify each region's air accessibility and remoteness. Ultimately, Fig. 2 and Table 1 show that major national airport systems in Europe are characterized by similar challenges in terms of airport heterogeneity, as well as in the uneven distribution of population density and territorial coverage, thereby supporting the generalizability of key insights into the value and potential benefits of the con-accessibility framework.

Another important aspect is the ownership structure of Italian airports, which can influence the degree to which airports compete and/or self-coordinate among themselves. From an ownership standpoint, the Italian airport system is highly fragmented. In 2019, the 38 airports in Italy with commercial traffic were managed by 30 different airport management companies (under concessions from the state) (Paleari et al., 2020). Only six companies managed more than one airport, typically located in the same geographical area. This is the case of airports in Rome, Milan, Venice and Verona, and airports located in the Apulia, Calabria, and Tuscany regions (for more details, refer to Table A.4). Sixteen airports had majority public ownership (with ten entirely publicly owned), while five fully privately owned. The weighted average ownership based on passenger volumes is about 35% public, 42% private, and 23% mixed. Compared to other European contexts, such as Spain where airports are centrally managed by a single government-owned company (Aena), the Italian system is more fragmented. This fragmentation partially fosters competition among airports, while necessitating high-level coordination to ensure alignment with national transport and mobility priorities. This is precisely the goal of the Italian national airport system masterplan, which is not strictly prescriptive regarding the specific development guidelines for each individual airport but rather focuses on ensuring that air connectivity meets territorial needs by balancing organic specialization and market-driven development with interventions where market forces alone fail to deliver the intended benefits.

[3] Nomenclature of Territorial Units for Statistics–Eurostat

[4] As of 1st January 2019, ISTAT divides Italy into more than 7900 municipalities.

Table 1
Characteristics of the major national airport systems in Europe.

	Traffic ('000 pax)[1]				Nr. Apts by traffic[2]				Nr. Apts[3]	% Population[4]		
	Domestic	*Intra-EU*	*Intercont.*	*Tot.*	> 25 *M*	*10-25 M*	*5-10 M*	*<5 M*	≤ *100 km*	> 25 *M*	> 10 *M*	> 5 *M*
United Kingdom	45,993	171,028	83,408	300,429	4	3	6	24	4.23	63%	75%	92%
Spain	85,255	151,844	33,791	270,890	3	4	7	21	1.86	32%	50%	69%
Germany	46,365	124,209	79,373	249,946	3	5	1	15	2.34	38%	64%	71%
France	63,430	76,200	60,812	200,442	2	3	4	32	2.35	22%	40%	52%
Italy	64,723	94,831	33,292	192,846	2	4	6	20	2.18	26%	54%	75%

[1] Annual passenger traffic in 2019 retrieved from Assaeroporti and Eurostat.
[2] Number of airports by annual passenger volume. Airports are categorized into four groups based on annual passenger volume (in millions, M), according to ACI Europe/Copenhagen Economics (2012): Group 1 (mega airports, > 25 M), Group 2 (large airports, 10–25 M), Group 3 (medium airports, 5–10 M), and Group 4 (small airports, < 5 M). Data retrieved from Assaeroporti and national civil aviation authorities. Only airports with more than 100,000 passengers are considered.
[3] Population-weighted average number of national airports within a 100 km radius (as the crow flies). The 100 km threshold is considered a conservative estimate of an airport's typical minimum catchment area (ACI Europe).
[4] Percentage of population with at least a (national) airport of given size within 100 km. Population figures and densities at the Local Administrative Units (LAU) sourced from Eurostat.

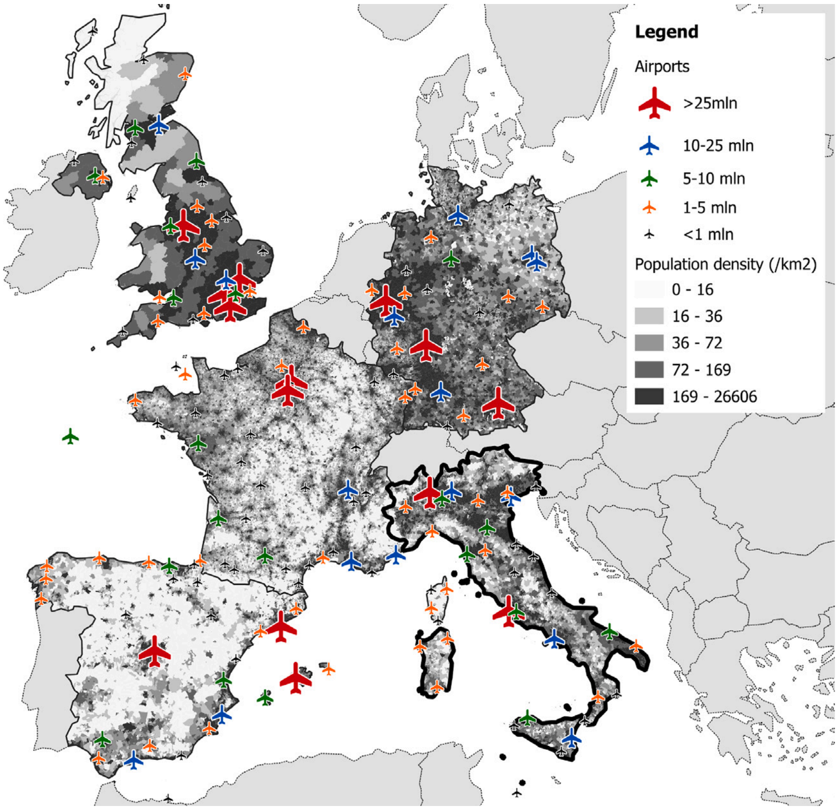


Fig. 2. Major airport systems in Europe. Population density and airports segmented by size. Italy highlighted with a bold contour.

Table 2
Population coverage of Italian airports for different access travel times.

Access time (min)	To the closest airport				To the closest airport within top 30 airports			
	Private car		Public transport		Private car		Public transport	
<30	21,093,505	35.3%	1,839,186	3.1%	17,169,581	28.7%	1,487,648	2.5%
30–60	26,029,527	43.5%	13,994,416	23.4%	24,585,743	41.1%	13,177,743	22.0%
60–90	9,535,344	15.9%	12,313,161	20.6%	11,673,208	19.5%	11,297,513	18.9%
90–120	2,529,013	4.2%	14,258,351	23.8%	4,615,326	7.7%	13,558,007	22.7%
> 120	615,494	1.0%	17,397,769	29.1%	1,759,025	2.9%	20,281,972	33.9%

3.2. Empirical setting: Ground accessibility

As discussed in Section 2.2, in evaluating ground accessibility from individual municipalities to airports, we utilize a composite log-sum measure that considers the availability and level of service of different ground travel options. Specifically, we take into account three modes of ground transportation: private car, public transport, and taxi. From each municipality, we collected data on travel times and costs for different travel alternatives to reach all possible airports within a broad distance cutoff of 300 km.[5] The data were collected from multimodal search engines, specifically Rome2Rio and Google Maps. For public transport, we consider the best option returned by the engine for each origin–destination pair, considering a vast array of transit alternatives, including local and long-distance buses, underground, tram, and rail connections. After collecting and polishing the data, we computed the ground accessibility index (GA_{ka}) for each municipality–airport pair as described in Eq. (9), borrowing coefficients from Birolini et al. (2019).

Figs. 3(a) and 3(b) illustrate the ground access time for each municipality in Italy to the closest airport by private car and public transport, respectively. Table 2 presents the population coverage for various access travel time thresholds to the nearest airport and to the closest airport within the top 30 airports by traffic.[6] On a national scale, the average population-weighted access time to the closest airport by private car is 43 min and 98 min via public transport. These figures increase to 50 min and 104 min, respectively, when only the top 30 airports are taken into account. Approximately 79% of the Italian population can reach the nearest airport within an hour by car. This percentage drops to 26.5% when accounting for access via public transport. Noticeably, slightly lower figures are observed when limiting the analysis to the top 30 airports (69.8% vs. 79% for private car access and 24.5% vs. 26.5% for public transport access within 60 min, respectively). This, coupled with the observed good car accessibility, indicates an overall well-distributed network of airport facilities across the Italian territory. From a spatial perspective, we observe a significant gap between accessibility by private car and public transport. Private car access to the nearest airport within 90 min is feasible for the vast majority of the population, except for those located in remote or mountainous regions (see Fig. 3). A notable contrast appears when assessing public transport access, which falls below 90 min only in very few areas surrounding major cities and urbanized regions, suggesting ample room for potential interventions. A closer examination of the maps also reveals how the distribution of airport facilities across the Italian territory can promote extensive coverage. Accordingly, the Italian national airport system plan does not involve the construction of any new airports but rather focuses on the efficient and effective utilization of existing capacity.

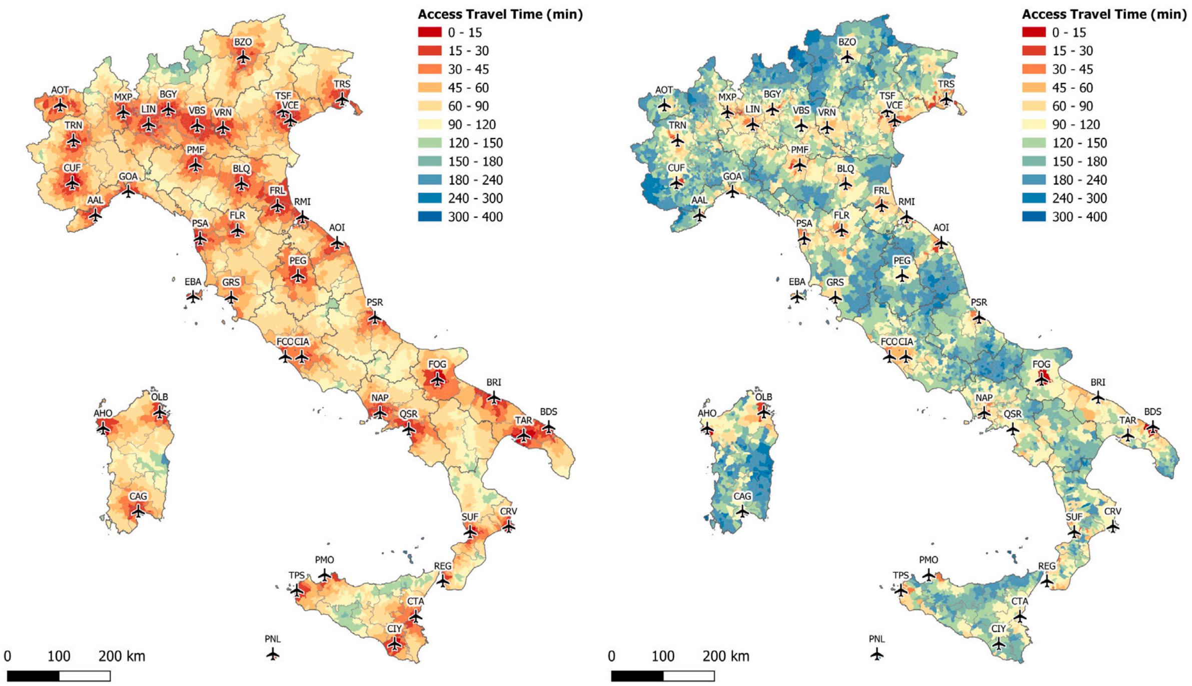
The quality of ground transport infrastructures and availability of (good) access transport options strongly influence the geographical reach of airport catchment areas. When combined with the spatial distribution of the population, this leads to diverse catchment sizes, ranging from tens of thousands of inhabitants (for airports on minor islands) to 7.6 and 17.7 million inhabitants within 60 and 120 min, respectively (refer to Table A.4 for details). Airports in the Milan metropolitan area exhibit the most extensive 1-hour catchment areas by car, hosting approximately 7.6 million people for LIN, 7 million for BGY, and 5.8 million for MXP. These values exceed 14 million when considering a 2-hour threshold. Noteworthy airports with large catchment areas include NAP (4.6 million inhabitants within 1 h by car) and the Rome airports (3.9 million for FCO and 4.3 million for CIA). This emphasizes the considerable heterogeneity between catchments of different airports—a crucial aspect influencing their potential demand and development prospects.

The spatial arrangement of airports, coupled with the quality of ground accessibility, collectively determines the degree to which their catchment areas overlap, thereby exerting a significant impact on airport interactions.

Fig. 4(a) graphically illustrates the airport catchment areas within a 60-min drive for the top 30 airports, while Fig. 4(b) presents statistics on catchment area overlap (60 and 90 min). We define the degree of overlap for an airport a as the percentage of its catchment area that intersects with that of one or more other airports. Within 1 h, the top 30 airports by traffic display an average catchment area overlap of 32.3%. Specifically, 13 airports have an overlap exceeding 20%, with 8 of them having an overlap higher than 50%. This holds mainly for airports serving major metropolitan areas—such as Milan in the North (average overlap 90.6%), Venice in the North-est (80.1%), and Rome in the Center (93.6%)—, forming *de-facto* multiple airport systems with the possibility

[5] Note that our approach explicitly considers the disutility of accessing airports, as the ground accessibility index penalizes access time and costs, both of which structurally increase with distance. Setting a distance cutoff for the definition of each municipality's airport set is thus not strictly necessary. Nonetheless, it is unreasonable to assume a person would travel more than 300 km to access an airport, particularly when there are closer alternatives. Enforcing such a loose threshold thus contributes to enhancing the sparsity and scalability of the model.

[6] We selected the top 30 airports to exclude those with limited services. By setting this threshold, we are considering airports that handled more than 250,000 passengers in 2019 (refer to Table A.4 for details).



(a) Private car (b) Public transport

Fig. 3. Ground access travel time to reach the closest airport by private car and public transport.

to develop significant synergies.[7] More pronounced overlaps become evident when considering the catchment area within 90 min, with an average overlap equal to 64.3%. The majority (16 airports vs. 30) reports an overall catchment area overlap exceeding 70%. Notably, a few of them (8 airports) even exhibits an almost complete overlap—surpassing 95%. Finally, when examining a 120-min travel radius by car, virtually all airports demonstrate a significant overlap in their catchment areas.

The aforementioned analysis has elucidated the granularity and level of details of the ground access data considered in the model, emphasizing the significance of ground accessibility in characterizing the territories served by each airport—a crucial factor in investigating competition dynamics and the overall level of air connectivity spread on a territorial scale. Nonetheless, ground accessibility offers only a partial representation of airport interactions and territorial coverage, as it overlooks considerations of the types of services provided and destinations served by each airport.

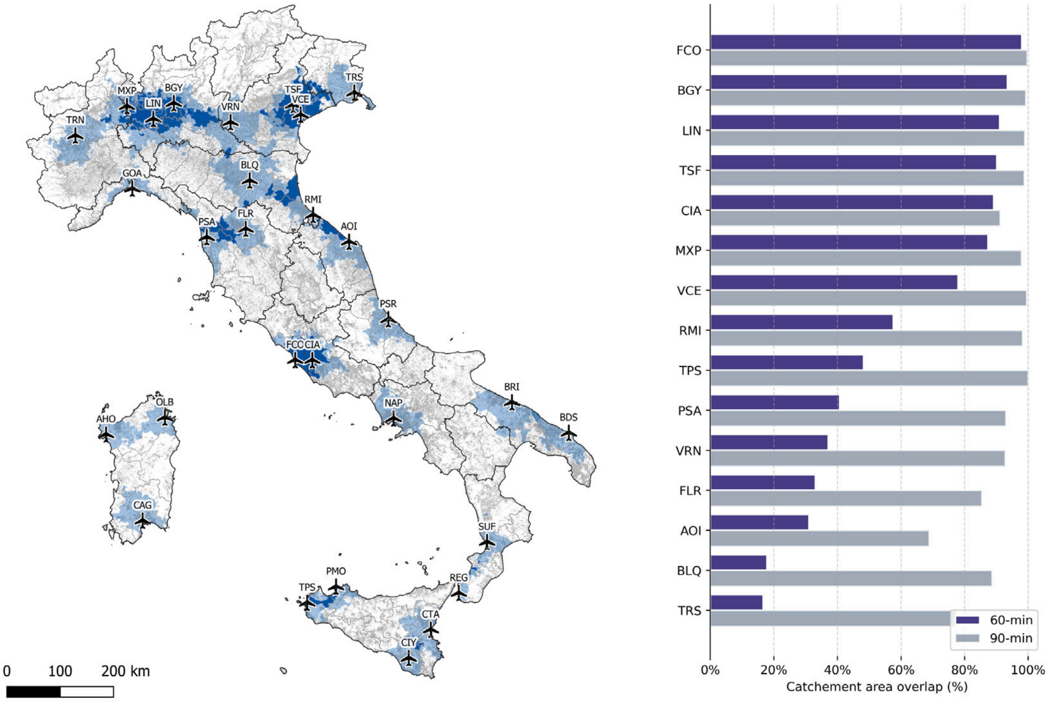
3.3. Empirical setting: Air connectivity

To quantify and characterize airport supply appropriately, we utilize the Total Airport Connectivity Index developed in Section 2.2. This index aggregates, at the airport level, the connectivity contribution derived from individual destinations served by the airport, which is computed as the product of link quality—encompassing the frequency of both nonstop and connecting air services, weighted by the disutility deriving from detours and layovers—and destination quality (defined as a function of the destination's socio-economic features). To compute the link quality, we gathered information on worldwide scheduled flights in 2019 from the OAG Schedule Analyzer and leveraged an itinerary-building procedure, similar to Birolini et al. (2020), to reconstruct all feasible connecting itineraries departing or terminating at one of the airports under consideration. To compute destination quality, we define a circular catchment area with a radius of 100 km around the destination airport, and calculate the Gross Domestic Product (GDP) wherein, based on a high-resolution (30 arcsec) global spatial dataset (Kummu et al., 2018).[8] The connectivity metrics were calculated monthly and subsequently averaged, yielding a consolidated yearly metric.[9] As anticipated in Section 2.2, we stratify our assessment considering three different types of destinations: (i) domestic (within Italy), (ii) international (including Europe, North

[7] Notice that FCO and CIA are managed by the same company, as well as TSF and VCE. In Milan, two airports (LIN and MXP) are managed by the same company, while BGY by another.

[8] We considered estimates as of 2015, i.e., the latest year available in Kummu et al.'s dataset, and projected the values forward to 2019 based on the country-level GDP growth rates from the World Bank.

[9] This follows from the scope of the study and the assessment made within the Italian national airport system plan, which did not require focusing on monthly variations. Note, however, that the proposed framework can be flexibly used to investigate temporal and seasonal dynamics in airport catchment areas (e.g., Teixeira and Derudder, 2021)



(a) Graphical representation (60 min overlap) **(b)** 60 and 90 min overlap by airport

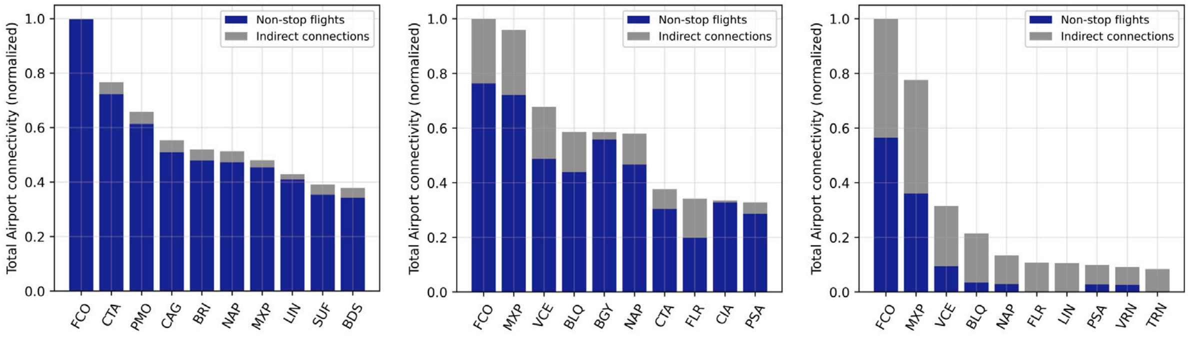
Fig. 4. Catchment area overlap for different access time thresholds. The left-hand chart graphically illustrates the catchment area of each airport within 60 min (light blue shaded areas) and the respective overlap (darker blue). The underlying gray-colored raster depicts the population (at a 1 km^2 resolution), highlighting diverse population density patterns across the peninsula. The right-hand chart reports the total catchment area overlap (weighted by population) for the top 15 airports by overlap in 60 and 90 min. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Africa, and the Levant countries), and (iii) intercontinental destinations. Overall, in 2019, approximately 40.6% of the global GDP could be reached via no-stop flights from Italian airports, while almost 81.6% was accessible through one-stop connecting itineraries.

Fig. 5 represents the Total Airport Connectivity Index for the top 10 Italian airports, categorized by their connectivity to each destination type and highlighting the contribution of nonstop and indirect connectivity. Not surprisingly, domestic connectivity (Fig. 5(a)) is primarily sustained by nonstop flights. The vast majority of domestic flights connect the two major metropolitan areas, Milan and Rome, with the islands (Sicily and Sardinia) and the northern regions to the southern ones, especially in markets where there is a lack of attractive intermodal alternatives. Consequently, airports serving Milan and Rome, as well as those located on the islands and in the South, ranked highest in terms of domestic connectivity. Regarding international connectivity (Fig. 5(b)), connectivity is still primarily sustained by nonstop services, with a strong contribution from low-cost carriers, but it is also complemented by indirect connectivity enabled by feeding routes into major European hubs. Besides merely mirroring traffic volumes or the number of aircraft movements, the Total Airport Connectivity Index also demonstrates the capability to characterize different network structures and connectivity patterns. Take BLQ and BGY—ranked 4th and 5th by the international connectivity index—as an example. On one hand, BGY airport (13.9 million passengers in 2019) relies mainly on point-to-point traffic. On the contrary, BLQ (9.4 million passengers in 2019) features a hybrid network, encompassing a substantial number of point-to-point low-cost connections as well as feeding flights provided by full-service carriers to major European hubs. These connections not only enhance direct connectivity but also broaden the range of destinations available through seamless one-stop connections. A similar case to BGY is CIA, whereas FLR parallels BLQ. Ultimately, nonstop intercontinental connectivity (Fig. 5(c)) is highly concentrated in the two largest airports, FCO and MXP. VCE also provides intercontinental connectivity via nonstop connections. The remaining airports virtually only achieve intercontinental connectivity through connecting itineraries via major hubs. Hence, their intercontinental connectivity indexes tends to be correlated with the strength of feeding connections toward these focal transfer airports. Consistent with the discussion above, low-cost-dominated airports such as BGY do not rank in the top 10 list for intercontinental connectivity.

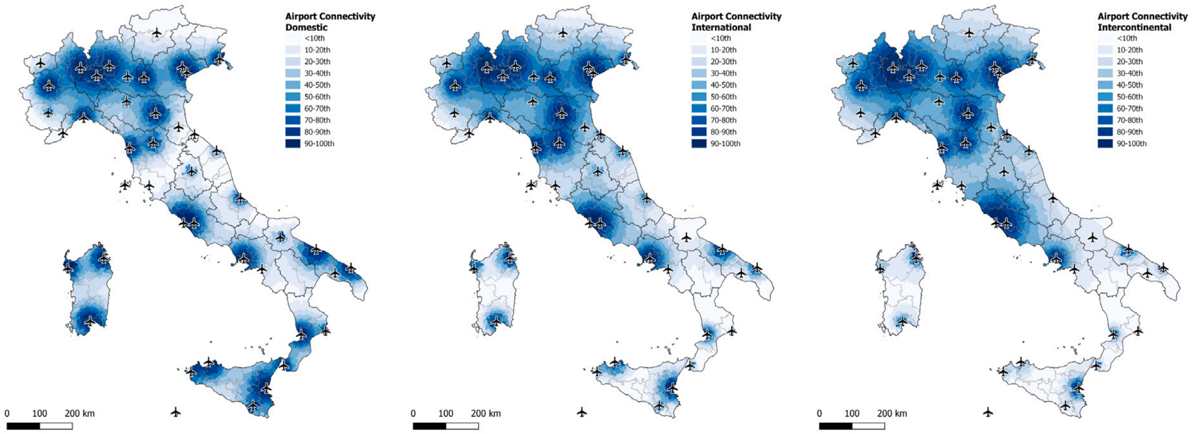
Fig. 6 provides a geospatial visualization of the aforementioned indices. In detail, it depicts the territorial spread of airport connectivity, assuming a decay function inversely proportional to the square distance—similar to a basic Huff model—thus representing a theoretical setting where connectivity spreads uniformly in space. In symbols, the plotted quantity for each municipality k is the following: $\sum_{a\in\mathcal{A}_k} AC_a/dist_{ka}^2$, where $dist_{ka}$ is the geodesic distance between k and a.

While offering initial insights into the geographical distribution of air connectivity at the national level—highlighting significant disparities among regions—, this analysis emphasizes the importance of coupling air connectivity with ground accessibility. Air



(a) Domestic (b) International (c) Intercontinental

Fig. 5. Total airport connectivity index for the Italian airports, segmented by destination type. The blues bar represents the contribution of nonstop flights, while the gray ones the contribution of indirect connections. Values are normalized to the maximum value in each destination class. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Domestic (b) International (c) Intercontinental

Fig. 6. Territorial distribution of airport connectivity.

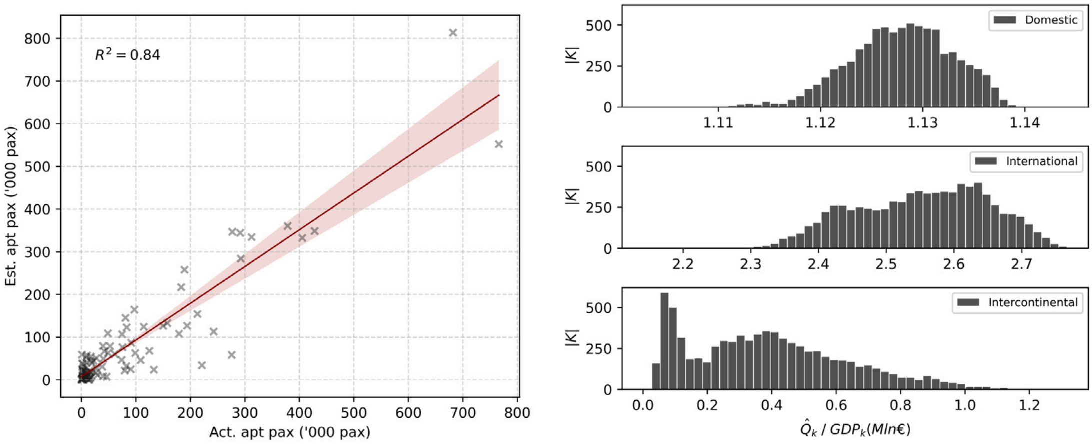
connectivity indeed does not propagate uniformly in space. As highlighted in Section 3.2, the stretch of airport catchment depends on the performance of ground access alternatives, which, in turn, is contingent on the transport infrastructure surrounding any given airport, as well as the level of service provided by the available transport services.

In summary, Section 3.2 has emphasized that solely considering ground accessibility is insufficient for accurately characterizing airport catchments—particularly in regions with alternative airports offering differentiated services. Simultaneously, Section 3.3 has stressed the significance of precisely assessing connectivity, highlighting the necessity for an integrated model that consistently combines both aspects. This integration is the aim of the con-accessibility framework, with its application discussed in detail in Section 4.

3.4. Model estimation

To estimate the parameters of the con-accessibility model, we rely on the tailored optimization-based procedure described in Section 2. Data on airport demand ($\bar{Q}_a$) were retrieved from the OAG Traffic Analyzer for the different destination types in a given representative month (i.e., May 2019). Another key parameter is T_k, i.e., the saturated demand of municipality k. Unfortunately, these values cannot be observed. Nonetheless, prior research has demonstrated that, as long as T_k is (reasonably) assumed to be significantly larger than the realized demand, the setting of T_k does not significantly impact the estimation of the model coefficients, except for the intercept (δ)[10]. Hsiao and Hansen (2011) defined the saturated demand as the product of population and a scaling factor representing the maximum trips per capita—arbitrarily set to 10 per quarter. Following the same logic, we compute parameters T_k as the product of each municipality's Gross Domestic Product (GDP_k)—as a proxy of socio-economic development—and a

[10] For further details, readers are referred to Hsiao and Hansen (2011) and to the sensitivity analysis in Birolini et al. (2020)



(a) Model fit **(b)** Empirical distribution of estimated trips per unit of GDP.

Fig. 7. Model estimation.

proportionality factor (τ)—defined as 3 times the average trips per unit of GDP (i.e., $\sum_{a\in\mathcal{A}} \bar{Q}_a / \sum_{k\in\mathcal{K}} GDP_k$)—and validated the stability of coefficients through sensitivity analysis.

Fig. 7 provides insights into the performance of the estimation model. Fig. 7(a) represents the fit of the model. The overall R^2 is 0.84, denoting a good fit. Notably, this varies from 0.55 for domestic routes to 0.88 for international ones, peaking at 0.93 for intercontinental destinations. The lower performance on domestic routes is not surprising, partly explained by the fact that the model does not account for intermodal competition, which is more intense and significant on these routes. Nevertheless, the returned patterns enabled us to extract meaningful insights, as elaborated in Section 4. The integration of intermodal competition and further enhancements to the model in this direction stand as promising avenues for future research.

Fig. 7(b) illustrates the average trips per unit of GDP across municipalities, calculated as $\hat{Q}_k/GDP_k$, where $\hat{Q}_k$ represents the estimated total demand of region k. This highlights the advantages of employing a nested logit specification. Fig. 7(b) indeed reveals notable heterogeneity across municipalities, especially on intercontinental routes, whose provision is concentrated in a few airports (more details in Section 4). The use of a nested logit model has the advantage of making demand generation elastic to airport supply, recognizing that more developed regions that are closer to good air services tend to be characterized by higher demand. A simpler approach would have been to postulate a basic MNL, comprising solely the inner airport-choice nest and neglecting demand generation. Using such specification would require explicitly formulating assumptions on the realized total municipality demand ($\bar{Q}_k$) instead of $\bar{T}_k$, which are considerably more challenging to make under imperfect information. We tested the use of an MNL instead of and NL assuming equal generation potential for all municipalities, i.e., by setting $\bar{Q}_k$ proportional to their GDP. Results revealed a significant loss in performance, with a loss of fit as high as 30% on intercontinental routes.

4. Results

In this section, we discuss the results and insights derived from the use of the con-accessibility framework. First, we demonstrate the framework's capability to accurately establish each airport's catchment area and area of influence, and show how this information can be used to quantify the level of airport concentration and market power in various regions (Section 4.1). Subsequently, we delve into the systematic mapping and characterization of the overall level of con-accessibility for each municipality (Section 4.2). Finally, we discuss a case study illustrating how the model's decision-support capabilities are utilized in assessing various strategic interventions (Section 4.3).

4.1. Airport catchment areas and airport concentration

As expressed in Eq. (3), the con-accessibility framework enables the derivation of the market share of any airport a in each territory k for a given destination type r (P^r_{ka}). Considering a specific airport a and the set of surrounding municipalities ($\mathcal{K}_a$), each characterized by population φ_k, we quantify the size of airport a's catchment area for destination type r as: $\Pi^r_a = \sum_{k\in\mathcal{K}_a} P^r_{ka}\varphi_k$. Notably, this measure serves as a refined proxy for delineating airport catchments, as it quantifies the actual attraction capability of airport a in region k. Rather than simply considering each airport in isolation and neglecting the strength of its air service portfolio, it explicitly accounts for the presence of other airports and their respective offerings.

To demonstrate the advantages of the proposed approach, we compare it with two benchmark catchment area formulations: (i) the traditional static catchment area approach, obtained simply by setting $P^r_{ka} = 1$ in the expression above; and (ii) an equal connectivity catchment area approach, derived by assuming all airports are characterized by the same (average) connectivity levels.

As an illustrative case study, we consider the airports serving the Milan metropolitan area, namely BGY, LIN, and MXP, which are characterized by extensively overlapping catchment areas and significant differentiation of air services. Fig. 8 presents the three catchment area metrics for the different destination types.

All three airports exhibit large and similar static catchment areas (represented by dashed-dotted lines in gray), owing to their close proximity in a densely populated region. By construction, this metric does not vary across destination types and is solely determined by the airports' locations and the quality of ground accessibility. LIN and BGY's static catchment areas tend to be slightly larger due to their central positions relative to major cities in Lombardy. LIN benefits from its proximity to Milan, while BGY's advantageous location lies between Bergamo and Brescia. Conversely, MXP's catchment area is comparatively smaller, primarily due to its greater distance from the major urban centers.[11]

Turning to the equal connectivity formulation (dashed red lines), the main improvement over a pure static catchment area approach is the explicit consideration of neighboring airports, leading to a downward adjustment of values. Nonetheless, assuming identical connectivity implies that the variations are still influenced solely by location and ground accessibility factors, which are evaluated in this case not only in absolute terms but also comparatively, impacting lower or greater shares in contended areas.

Lastly, comparing our proposed approach (solid dark green lines) with the two benchmarks highlight the role of incorporating airport connectivity—segmented by destination type—to accurately map the role and influence of each airport on the territory. LIN is a city airport with air services concentrated on domestic destinations. BGY's supply is particularly extensive on international routes and predominantly low-cost. MXP is the largest airport in the system, offering robust and diverse connectivity to international destinations, and the only airport providing intercontinental nonstop services (see Fig. 5). Accordingly, on domestic routes, LIN's catchment area slightly exceeds that estimated under an equal connectivity formulation, whereas MXP closely aligns with it, and BGY falls slightly below. Turning to international destinations, MXP boasts the larger catchment area due to its greater connectivity, offset by a significant decrease for LIN, while BGY aligns with the equal connectivity scenario. Fig. 9 visualizes these figures, representing each airport's market share at the municipality level. This highlights both the impact of greater airport connectivity (darker colors around the airport) and its territorial propagation across neighboring areas, in alignment with the underlying road network and constrained by the presence of neighboring airports. Regarding intercontinental destinations, MXP virtually captures its entire static potential catchment area, largely unaffected by competition from BGY and LIN. Only beyond a 1-hour car journey the two curves start to diverge, as the influence of airports in neighboring regions (such as BLQ) gradually increases.

Another direct implementation of airport market shares derived from the con-accessibility model is the study of airport market power and concentration across the surrounding territories. This is illustrated in Fig. 10. For each region (in the rows), it maps the aggregate market share (or level of dominance) of each airport (in the columns). More precisely, the reported shares are computed by averaging the contributions across destination types and then taking the average across municipalities, weighted by their population. The final column presents the Herfindahl–Hirschman Index (HHI), providing a synthetic measure of airport concentration within each region. The study of airport concentration and supply differentiation holds major implications for strategic airport system planning both in shaping market structure policies and from an operational perspective. The presence of diverse options indeed plays a crucial role in mitigating the potential drawbacks of highly concentrated markets and enhancing the resilience of regional aviation systems. Such analysis was conducted within the Italian airport system master plan to systematically evaluate these aspects and delineate the roles of airports within their respective regions (depicted within the black contour), as well as spill-over effects across neighboring areas.

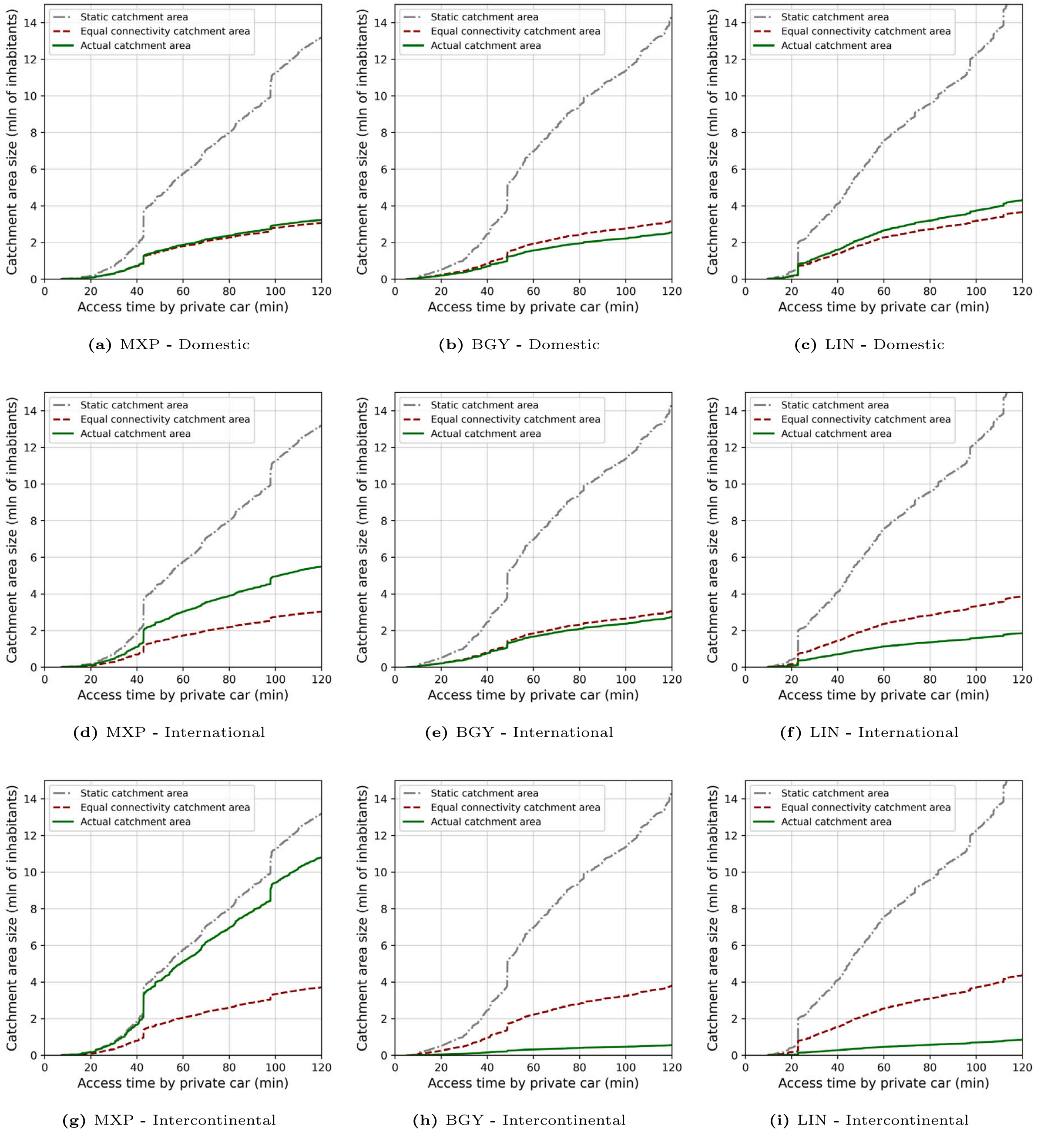
Some regions exhibit a strong dependency on a single airport. This is the case of Lazio (HHI=6393) where Rome-Fiumicino (FCO) contributes to more than 79% of overall con-accessibility of the region. Notably, FCO extends its area of influence to multiple regions in central Italy, with significant spill-over to the Marche (30%), Umbria (53%), Abruzzo (52%), and Molise (44%), due to its strong connectivity—especially on intercontinental routes and comparatively to airports in central Italy. MXP also holds a considerable presence in the entire western–northern part of Italy, although its influence tends to be tempered by other airports with substantial supply. Due to their insular nature, the two major islands (Sicily and Sardinia) exhibit a polarized market structure around their respective regional airports. A more fragmented supply base characterizes regions with multiple airport systems (e.g., Lombardy and Veneto) or regions lacking a significant airport within their boundaries and therefore relying on neighboring regions' airports (e.g., Friuli and Basilicata).

4.2. Territorial con-accessibility

The previous analysis adopted an airport-centric perspective to examine the extent of airport supply concentration and the influence of airports on territories. Our focus now transitions to a territorial-centric viewpoint, aiming to quantify the overall air accessibility of each municipality across different destination segments—an essential consideration for understanding the impact of airport policies on society. As discussed in Section 2, the logsum of airport utilities (ψ_k) provides a consistent estimation of the overall utility of each municipality, depending on the size and scope of neighboring airports and the ease of accessing them. In the following, we compute the total con-accessibility index for each municipality and destination type, normalizing it to the maximum value within each respective destination type. In symbols: $\widetilde{\psi_k^r} = \psi_k^r / \max_{k \in \mathcal{K}} \psi_k^r$.

Fig. 11 illustrates the percentile distribution of total con-accessibility across Italian municipalities by destination type. When considering domestic destinations (Fig. 11(a)), the con-accessibility value is notably high in central-northern regions, as well as

[11] Note that our assessment considers only the Italian population, although MXP could also conveniently serve passengers from nearby Switzerland.

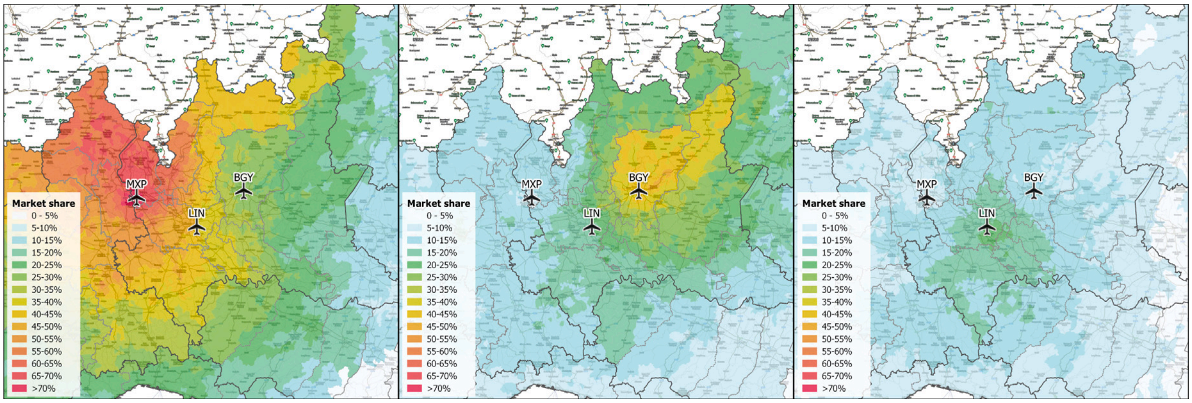


(a) MXP - Domestic **(b)** BGY - Domestic **(c)** LIN - Domestic

(d) MXP - International **(e)** BGY - International **(f)** LIN - International

(g) MXP - Intercontinental **(h)** BGY - Intercontinental **(i)** LIN - Intercontinental

Fig. 8. Comparison between catchment area formulations for airports located in the Milan metropolitan area. Cumulative representation considering varying access time by private car thresholds for the definition of the $\mathcal{K}_a$ sets.



(a) MXP (b) BGY (c) LIN

Fig. 9. Estimated market shares to international destinations for airports located in Milan metropolitan area.

	TRN	GOA	MXP	LIN	BGY	TSF	VRN	VCE	TRS	BLQ	RMI	FLR	PSA	AOI	CIA	FCO	PSR	NAP	BDS	BRI	REG	SUF	CIY	CTA	PMO	TPS	AHO	CAG	OLB	HHI
Aosta Valley	18%	3%	51%	9%	8%																									3,095
Piedmont	20%	5%	43%	10%	7%																									2,440
Liguria	5%	24%	29%	9%	6%					3%		4%	8%																	1,702
Lombardy	3%		46%	16%	15%		4%			3%																				2,672
Trentino-Alto Adige			23%	7%	11%	6%	16%	12%	2%	8%		2%																		1,280
Veneto			8%	4%	6%	13%	12%	31%	5%	10%		3%																		1,546
Friuli Venezia Giulia					3%	13%	5%	34%	31%	5%																				2,384
Emilia-Romagna			10%	5%	4%	3%	7%	8%		28%	8%	7%	3%	3%																1,225
Tuscany		3%					3%	2%		13%	2%	25%	23%			13%														1,574
Marche								2%		8%	11%	3%		21%	3%	30%	7%													1,725
Umbria										3%	3%	5%	2%	5%	5%	53%														3,305
Lazio															10%	79%		5%												6,393
Abruzzo														4%	6%	52%	20%	6%		3%										3,180
Molise															4%	44%	9%	17%		9%										2,536
Campania															3%	38%		47%		4%										3,650
Apulia																11%	2%	6%	25%	32%										2,039
Basilicata																21%		18%	9%	23%		6%								1,562
Calabria																		6%	3%	5%	17%	42%		8%						2,332
Sicily																					5%	3%	11%	40%	27%	10%				2,669
Sardinia																											23%	56%	21%	4,093

Fig. 10. Airport-Region matrix. Population-weighted airport contributions to Italian regions and airport concentration, summarized by the Herfindahl–Hirschman Index (HHI). Regions (in the rows) and airports (in the columns) are sorted from North to South such that higher values are scattered along the diagonal. The set of airports is restricted to the top 30 by traffic volumes, excluding LMP (which exclusively serves the Island of Lampedusa). Black contours enclose airports within each region (e.g., MXP, LIN, BGY are airports in Lombardy). Only contributions higher than 2% are reported. The metric relates to the overall airport influence, computed as the average across destination types.

in Lazio, Campania, Sicily, and Apulia, reflecting the prominence of main domestic routes linking these territories. Other hotspots are in Sardinia, mostly due to public service obligations (PSO) routes. Notably, the territorial spread of connectivity tends to be wider in northern and central regions due to better ground accessibility, while in Sicily, it experiences a stronger decline as one moves away from the airports. The lower domestic air accessibility of central regions can be partly attributed to the predominant role of intermodal options, especially rail, in connecting with both northern and southern destinations. Moving to international destinations (Fig. 11(b)), the map depicts a more homogeneous distribution across continental Italy. Most secondary airports across the peninsula indeed predominantly offer intra-European services, often boosted by low-cost carriers. Particularly, the international connectivity of northern and central Italian airports is significantly high, aligned with the connectivity needs of the most developed regions in this area. Intercontinental total con-accessibility depicts a significantly different pattern, being highly polarized around the two main airports providing nonstop intercontinental services (FCO and MXP). Another hotspot is around Venice (VCE), which

Table 3
As-is con-accessibility and estimated improvements under various scenarios of enhancement of ground accessibility and/or connectivity of existing airport facilities. Population-weighted figures for individual provinces of Sicily.

Province		Con-acc	Access time by car (min)				Scenario**					
Code	Name	AS-IS*	CTA	PMO	CIY	TPS	1	2	3	4	5	6
81	Trapani	0.71	225	70	274	49	2.9%	6.6%	4.4%	0.6%	11.4%	11.9%
82	Palermo	0.89	149	41	201	90	3.4%	4.4%	3.7%	0.7%	3.6%	4.3%
83	Messina	0.55	102	167	174	219	12.2%	6.5%	8.7%	2.6%	1.2%	3.8%
84	Agrigento	0.36	152	148	165	166	20.0%	16.2%	16.8%	10.2%	9.2%	18.8%
85	Caltanissetta	0.54	97	153	95	204	13.1%	6.9%	9.4%	10.0%	1.5%	11.4%
86	Enna	0.58	80	147	121	200	11.7%	5.5%	8.2%	5.9%	1.4%	7.2%
87	Catania	1.00	33	176	97	228	4.5%	1.5%	2.8%	2.7%	0.2%	2.9%
88	Ragusa	0.62	100	226	34	278	10.9%	3.2%	6.6%	16.8%	0.4%	17.1%
89	Siracusa	0.73	55	205	85	258	8.0%	2.2%	4.9%	5.6%	0.3%	5.9%

* AS-IS con-accessibility is computed as the population-weighted average of municipality con-accessibility values across destination types and normalized with respect to the province in Sicily with the highest value (i.e., Catania).
** Scenarios under investigation: (1) 20% reduction in access travel time to CTA; (2) 20% reduction in access travel time to PMO; (3) 10% reduction in access travel time to both CTA and PMO; (4) increase of connectivity of CIY to levels comparable to BDS; (5) increase of connectivity of TPS to levels comparable to BDS; (6) increase of connectivity of both CIY and TPS to levels comparable to BDS.

provides a moderate degree of nonstop intercontinental connectivity, and Bologna (BLQ) due to the significant feeding toward major European intercontinental hubs. Interestingly, the territorial reach of the offering of intercontinental services expands much beyond that of intercontinental and domestic connectivity, determining large red areas (i.e., higher con-accessibility) around the two main fulcrums. This is mainly explained in light of (i) the greater relevance of the air trip along the door-to-door journey—determining, in turn, a lower impact of the ground access component—and (ii) the higher concentration of intercontinental services and the virtual absence of nonstop intercontinental services for the majority of airports (see Fig. 5(c)).

Fig. 11 also supplements the maps with the empirical distribution of the normalized total con-accessibility scores across municipalities. This facilitates a quick overview of the number of municipalities or the extent of the population featuring con-accessibility values within a certain interval. The population-weighted median (gray line) is comparable for domestic and international destinations (0.57 and 0.59, respectively), while it is lower for intercontinental destinations (0.45). Corresponding with the blue areas in the maps, approximately 2.4% of the population (equivalent to 1.4 million inhabitants) experiences relatively low con-accessibility values (below 0.2) concerning domestic destinations. This figure increases to 9.3% (5.6 million) for international destinations, rising further to 17.5% for intercontinental destinations (approximately 10.5 million people in absolute terms).

Ultimately, these maps reveal significantly different patterns compared to those in Figs. 3 and 6, highlighting the effectiveness of the proposed approach in balancing ground accessibility and airport connectivity to accurately characterize the overall level of air accessibility in each region. Additionally, this analysis has illustrated how the proposed approach lays methodological foundations for systematically identifying gaps—deficits or surpluses—and regions with inequitable coverage, thereby aiding in the design and assessment of practical measures.

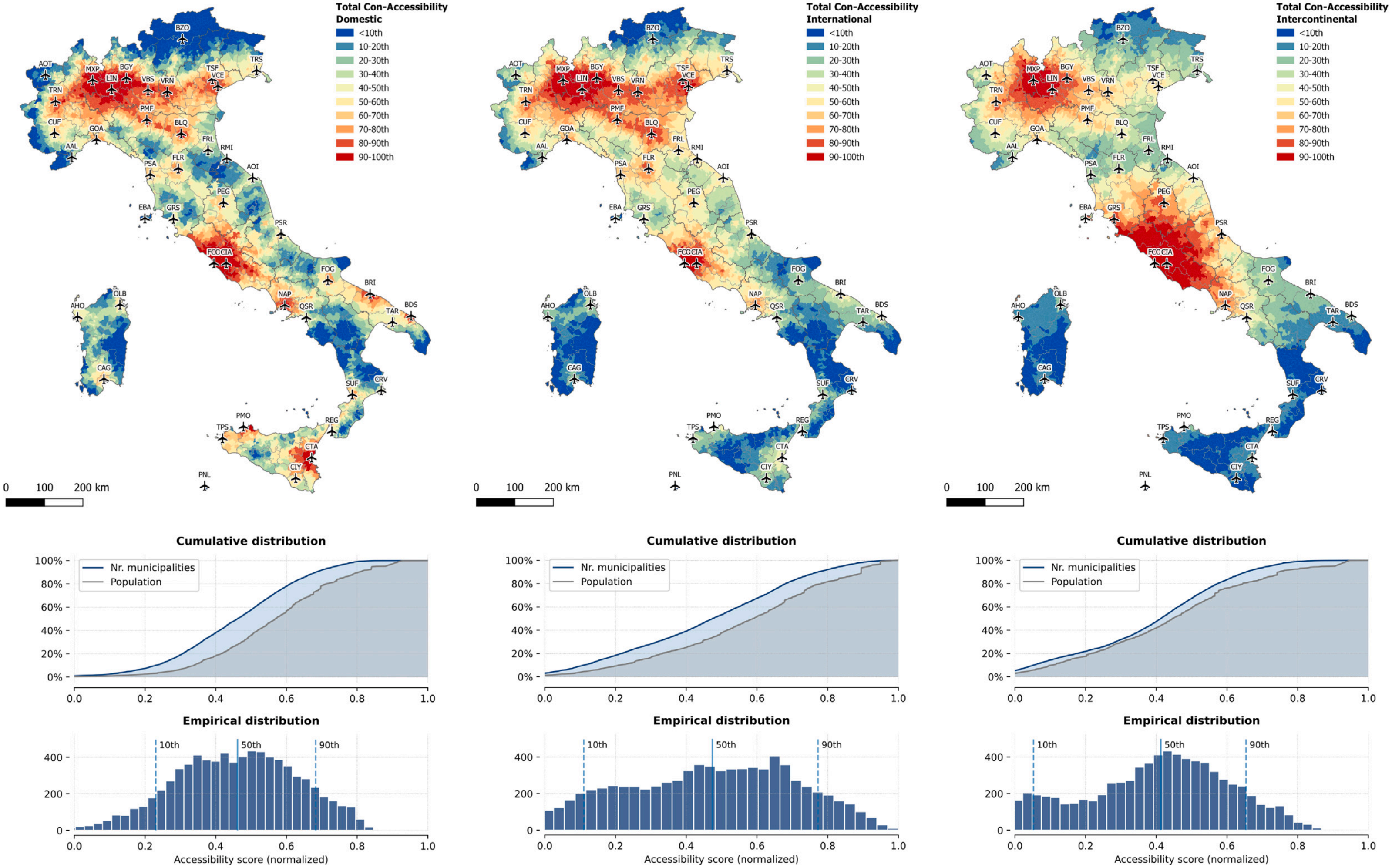
4.3. Evaluation of alternative interventions

In this section, we present a case study of Sicily to showcase the modeling framework's capability to yield prescriptive insights. With a population of approximately 4.69 million inhabitants, Sicily is the 4th most populous region in Italy and the largest Italian region by area. Due to its insular nature, the development of good air transport services from/to Sicily is crucial. This is essential not only for facilitating international and intercontinental travel but also for fostering domestic connectivity with mainland Italy. Currently, air services in Sicily are primarily supported by two major airports, CTA (located in the East) and PMO (situated in the North-West)—ranking as the 6th and 8th busiest airports in Italy by traffic volumes, respectively—, complemented by two secondary airports, CIY and TPS, which offer limited air services.

As discussed in Section 4.2, Sicily has good domestic air con-accessibility, while consistently lying in the bottom percentiles for international and especially intercontinental travel. Furthermore, notable disparities in con-accessibility arise when analyzing the various provinces. Table 3 presents the population-weighted average con-accessibility across different destination types for Sicilian provinces. These values are standardized relative to Catania, which boasts the highest con-accessibility among Sicilian provinces. Overall, it is evident that regions situated distant from the two major airports (CTA and PMO), particularly in central Sicily, exhibit substantially lower con-accessibility. Notable examples are the provinces of Agrigento with a con-accessibility value of 0.36 (i.e., 64% lower than Catania), Caltanissetta with 0.54, as well as Enna and Ragusa with values of 0.58 and 0.62, respectively. Addressing these disparities is a critical planning priority, necessitating the development of initiatives to bridge these gaps and promote more equitable territorial coverage.

Next, we compare two main strategies:

(i) Improving ground access to existing airports, indicative of an enhancement in the quality of ground access infrastructure and services.
(ii) Enhancing airport connectivity at underutilized airports.

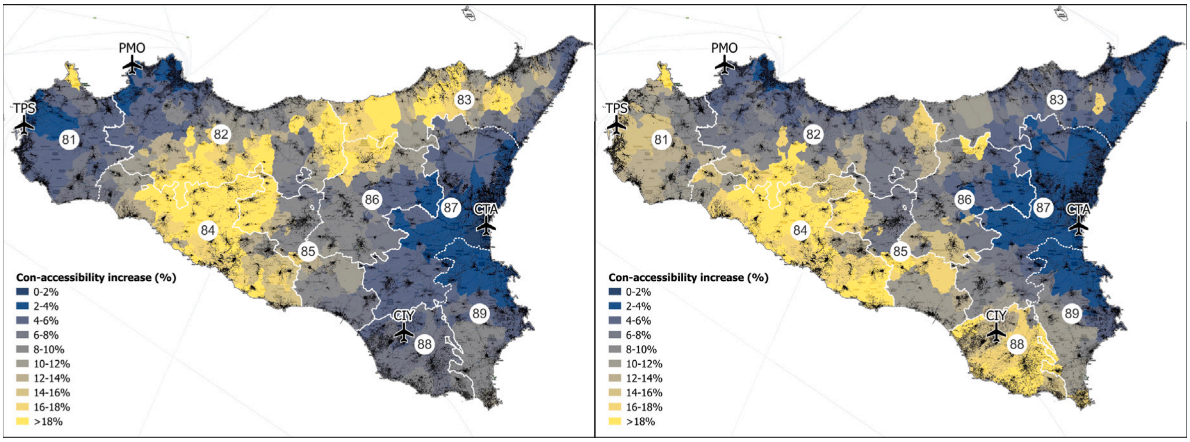


(a) Domestic

(b) International

(c) Intercontinental

Fig. 11. Con-accessibility index.



(a) Scenario 3

(b) Scenario 6

Fig. 12. Variations of con-accessibility in two scenarios simulating a 10% reduction of access time to both CTA and PMO (left-hand graph) and an increase of airport connectivity at CIY and TPS to levels comparable to BDS (right-hand graph). The underlying raster depicts the population (at a 1 km^2 resolution), highlighting diverse population density patterns across Sicily.

Considering the first lever, we investigate three scenarios simulating: (i) a 20% reduction in access travel times to CTA, (ii) a 20% reduction to PMO, (iii) and a 10% reduction to both CTA and PMO simultaneously. These scenarios are labeled from 1 to 3 in Table 3 and a visual representation of the benefits of Scenario 3 is illustrated in Fig. 12(a). Based on the scenario, western or eastern provinces benefit the most (e.g. Ragusa and Siracusa, which are closer to Catania, in scenario 1, while Trapani, which is closer to Palermo, in Scenario 2). Furthermore, it can be noticed that the increase in con-accessibility is more pronounced under scenario 1, primarily attributed to the greater connectivity of CTA compared to PMO.

In all cases, Agrigento is the province reaping the highest benefits, with an increase in con-accessibility ranging between 16.2% and 20%. This can be attributed to Agrigento's notably poor ground accessibility, with average access times by private car to both CTA and PMO exceeding 2 h (such that a saving of 20% results in substantial reductions). While the benefits tend to be more spatially concentrated when focusing on improvements to individual airports (scenarios 1-2), a simultaneous enhancement to both airports in ground accessibility (scenario 3) fosters a more evenly distributed spread of benefits across the region.

Considering the second lever, we simulate an expansion of airport services at CIY and TPS, the two currently underutilized airports located in the southeastern and western parts of Sicily, respectively. To establish a reasonable reference, we consider the Brindisi (BDS) airport, a secondary airport in Apulia characterized by moderate domestic and international connectivity. Specifically, we investigate three scenarios that simulate an increase in airport connectivity to levels comparable to BDS for CIY, TPS, and both airports simultaneously. These scenarios are denoted as 4 through 6 in Table 3. When enhancing airport connectivity at CIY, the neighboring province of Ragusa experiences the highest benefits (+16.8%). This stems from the competitive ground accessibility of CIY compared to CTA for Ragusa inhabitants, with an average access time of 34 min to the former versus 100 min to the latter. However, significant benefits are also observed in the central provinces of Agrigento, Caltanissetta, Enna, and Siracusa. Conversely, the strengthening of air services at TPS primarily benefits Trapani and Agrigento provinces. Noticeably, the spread of benefits from TPS is limited compared to CIY, partly due to the stronger catchment overlap of PMO and TPS (100% within 90 min) compared to CTA and CIY (60% within 90 min), as well as the relatively underdeveloped road infrastructure toward central Sicily. Similar to scenario 3, the benefits are more evenly spread should both airports be set for simultaneous expansion.

Fig. 12 illustrates variations in con-accessibility values across provinces under scenarios 3 and 6, respectively. In the first case, regions located in the central and northeast of Sicily benefit the most, while regions along the southern coast—between CIY and TPS—are the most affected under scenario 6. This underscores how, despite yielding comparable improvements in magnitude, different policies might have different impacts on territories—and how the con-accessibility framework can aid in evaluating them.

Overall, this case study illustrates how the con-accessibility framework can effectively assess the impacts of various initiatives aimed at enhancing the provision and/or the accessibility of air services. When combined with detailed budget information and a thoughtfully crafted set of potential initiatives, these insights can offer policymakers and planners a robust basis for making informed and effective decisions.

5. Conclusion

In this paper, we have developed a modeling framework for catchment area modeling to support national airport system planning and policies. From a modeling standpoint, the proposed approach leverages a state-of-the-art origin-based nested logit formulation of air travel demand. We assume that demand originates at the territorial level and is subsequently redistributed among competing neighboring airports based on a comprehensive *con-accessibility* utility function that integrates airport ground accessibility and connectivity features. Consistent with the considered logit formulation, the inner nest (airport choice) enables the computation of airport market shares across territories, whereas the logsum of airport utility provides an estimate of the overall air accessibility within each municipality. To address the challenge of sparse data availability for calibration—an empirical limitation, especially in nationwide studies—we propose a constrained least squares optimization approach to estimate the key model parameters, solved using a differential evolution algorithm.

From a practical standpoint, we have implemented and assessed the con-accessibility framework in a comprehensive real-world case study involving the latest Italian national airport system plan. Results showcase how the model can address three key policy questions: (i) effectively modeling airport catchment areas dynamically, considering both ground access and flight networks, to assess airport concentration and competition; (ii) systematically quantifying the overall level of connectivity and accessibility in any region to assess deficits or surpluses and pinpoint areas for strategic intervention; (iii) comparatively evaluating the impact of alternative interventions and policies.

In summary, this paper contributes to the literature and practice of airport system planning by advancing existing catchment area modeling techniques with a dynamic and scalable approach that is suitable for strategic airport system plans, and by compellingly illustrating prescriptive capabilities in an exemplary real-world context. Noticeably, the proposed approach aims to provide a useful methodological background to address timely policy questions beyond the specific Italian context and national level. As discussed, other major countries face similar challenges in managing a complex system of airports across areas with varying mobility needs and ground accessibility. Moreover, it could inform the ongoing debate surrounding the expansion and utilization of airport capacity at the supranational level. Effectively estimating airport catchments aligns well with the European Commission's priorities, which focus on making the best use of existing capacity. In particular, the con-accessibility framework can be instrumental in assessing the development of regional airports to address expansion issues and capacity shortages at major airports (European Commission, 2015), and in defining objective criteria for subsidy policies (Mueller, 2021).

Despite these positive results, there are plenty of opportunities for continuing research in the area. First, as it stands, the proposed approach entails a rigorous demand modeling framework. As shown, it can be readily deployed to support decision-making through scenario analysis. A promising avenue for research could be to develop an integrated optimization model to systematically explore the solution space and optimally address location or capacity allocation decisions. The incorporation of uncertainty, which is predominant in strategic applications, also provides an intriguing avenue for future methodological developments. Second, the proposed estimation method could be further generalized and improved. In line with recent contributions (e.g., Li and Wan, 2019; Kinene and Birolini, 2024), this can indeed establish solid methodological foundations for a shift from airport-centered demand estimation to territory-centered demand estimation. Notably, such a shift could lead to enhancements in realism and facilitate applications involving the reallocation of airport supply among under-utilized or new airport facilities. Third, the proposed approach additionally expands the potential to address a vast array of empirical and practical research questions, such as comparing national airport systems, their evolution over time, as well as investigating path dependencies in airport developments and demand evaluations (alongside associated capacity and capital needs) for new airport facilities based on territorial demand capture.

CRediT authorship contribution statement

Sebastian Birolini: Conceptualization, Methodology, Formal analysis, Software, Validation, Writing – original draft, Writing – review & editing. **Nicolò Avogadro:** Formal analysis, Data Curation, Investigation, Writing – original draft, Writing – review & editing.. **Paolo Malighetti:** Conceptualization, Methodology, Supervision, Validation, Writing – review & editing.. **Stefano Paleari:** Conceptualization, Project administration, Supervision, Validation, Writing - review & editing..

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Appendix A. Airports table

See Table A.4.

Appendix B. Model notation

See Table B.5.

Table A.4
Descriptive statistics of passenger volumes, movements, and size of catchment area of Italian airports in 2019.

Airport			Yearly passengers (2019)*			Movements**	Catchment area ('000)	
IATA	Name	Management company	*pax*	%	$\%_{cum}$	(2019)	60-min	120-min
FCO	Rome Fiumicino	Aeroporti di Roma	43,527,905	22.6%	22.6%	306,375	3,923.8	6,066.5
MXP	Milan Malpensa	SEA	28,827,804	14.9%	37.5%	210,319	5,773.5	13,189.7
BGY	Milan-Bergamo	SACBO	13,853,176	7.2%	44.7%	82,171	6,962.8	14,291.6
VCE	Venice	SAVE	11,550,163	6.0%	50.7%	86,413	2,601.2	7,481.2
NAP	Naples	GE.S.A.C.	10,851,062	5.6%	56.3%	75,630	4,546.5	6,823.6
CTA	Catania	SAC	10,218,658	5.3%	61.6%	70,554	1,309.6	2,727.4
BLQ	Bologna	Aeroporto G. Marconi	9,397,308	4.9%	66.5%	68,717	2,757.2	12,034.6
PMO	Palermo	GES.A.P.	7,013,194	3.6%	70.1%	50,013	1,196.2	1,756.0
LIN	Milan Linate	SEA	6,539,120	3.4%	73.5%	70,436	7,550.4	16,035.7
CIA	Rome Ciampino	Aeroporti di Roma	5,852,092	3.0%	76.6%	33,661	4,310.6	6,855.2
BRI	Bari	Aeroporti di Puglia	5,540,914	2.9%	79.4%	37,833	1,608.4	3,492.9
PSA	Pisa	Toscana Aeroporti	5,377,531	2.8%	82.2%	35,817	1,429.9	4,392.0
CAG	Cagliari	Sogaer	4,743,578	2.5%	84.7%	33,162	631.0	974.7
TRN	Turin	SAGAT	3,943,439	2.0%	86.7%	33,975	2,289.0	10,269.8
VRN	Verona	Aeroporto Valerio Catullo	3,629,885	1.9%	88.6%	27,498	2,251.5	15,915.3
TSF	Treviso	AERTRE	3,248,880	1.7%	90.3%	19,164	2,007.4	6,310.0
SUF	Lamezia Terme	S.A.CAL.	2,977,489	1.5%	91.8%	20,209	489.4	1,695.9
OLB	Olbia	GEASAR	2,953,708	1.5%	93.4%	21,644	128.1	584.2
FLR	Florence	Toscana Aeroporti	2,861,701	1.5%	94.8%	29,861	1,878.0	6,729.2
BDS	Brindisi	Aeroporti di Puglia	2,694,806	1.4%	96.2%	17,903	867.5	2,980.7
GOA	Genoa	Aeroporto di Genova	1,530,105	0.8%	97.0%	15,000	981.1	7,023.5
AHO	Alghero	SOGEAAL	1,389,508	0.7%	97.8%	9,650	270.9	523.9
TRS	Trieste	Aeroporto Friuli Venezia Giulia	780,922	0.4%	98.2%	8,290	992.7	3,710.8
PSR	Pescara	S.A.G.A.	700,355	0.4%	98.5%	4,973	798.0	2,709.3
AOI	Ancona	Aerdorica	485,364	0.3%	98.8%	4,582	1,041.7	3,712.5
TPS	Trapani	AIRGEST	410,090	0.2%	99.0%	4,395	381.1	1,555.9
RMI	Rimini	Airminum	392,149	0.2%	99.2%	2,028	1,288.0	4,214.5
REG	Reggio Calabria	S.A.CAL.	364,062	0.2%	99.4%	3,400	360.5	1,407.9
CIY	Comiso	SO.A.CO.	351,829	0.2%	99.6%	1,786	469.7	2,033.8
LMP	Lampedusa	AST AEROSERVIZI	275,972	0.1%	99.7%	4,194	6.4	6.4
PEG	Perugia	SASE	215,852	0.1%	99.8%	1,535	690.0	3,439.8
CRV	Crotone	S.A.CAL.	169,720	0.1%	99.9%	1,022	160.8	604.1
CUF	Cuneo	GEAC	89,787	<0.01%	99.9%	596	775.5	4,452.0
PMF	Parma	So.Ge.AP	73,544	<0.01%	99.9%	492	1,336.1	12,458.3
VBS	Brescia	Aeroporto Valerio Catullo	10,397	<0.01%	99.9%	31	3,904.2	17,723.9
GRS	Grosseto	SEAM	2,160	<0.01%	99.9%	n.a.	244.4	1,780.2
BZO	Bolzano	ABD AIRPORT	1,319	<0.01%	99.9%	n.a.	671.9	3,195.5
TAR	Taranto	Aeroporti di Puglia	603	<0.01%	100.0%	2	1,203.2	3,602.6
AAL	Albenga	n.a.	n.a.	n.a.	n.a.	n.a.	510.7	4,067.3
AOT	Aosta	n.a.	n.a.	n.a.	n.a.	n.a.	313.1	8,713.1
EBA	Elba Island	n.a.	n.a.	n.a.	n.a.	70	31.6	84.5
FOG	Foggia	n.a.	n.a.	n.a.	n.a.	1,830	577.2	3,313.0
FRL	Forli	n.a.	n.a.	n.a.	n.a.	n.a.	1,949.1	8,102.1
PNL	Pantelleria	n.a.	n.a.	n.a.	n.a.	3,741	7.5	7.5
QSR	Salerno	n.a.	n.a.	n.a.	n.a.	n.a.	4,064.2	6,577.9
	Italy		**192,846,151**			**1,398,972**		

* Commercial flight passenger traffic in 2019 retrieved from Assaeroporti.
** Number of scheduled flights in 2019 from OAG Schedule Analyzer.

Table B.5
Notation.

Notation	Description
$\mathcal{K}$	set of municipalities, indexed by k
$\mathcal{A}$	set of airports, indexed by a
$\mathcal{A}_k$	set of airports within municipality k's choice set
$\mathcal{K}_a$	set of municipalities for airport a i.e. $\{k : a \in \mathcal{A}_k\}$
$\mathcal{M}$	set of alternative access transport modes, indexed by m
$\mathcal{D}_a$	set of destination airports served by airport a, indexed by d
$\mathcal{I}_{ad}$	set of air connections from airport a to destination d, indexed by i
$\mathcal{R}$	set of destination types, indexed by r
$dist_{ka}$	geodesic distance between k and a
φ_k	population of municipality k
GDP_k	GDP of municipality k
u^m_{ka}	deterministic utility associated with using mode m from k to a
GA_{ka}	ground accessibility from k to a
π_i	quality of connection i
f_i	frequency of connection i
δ_i	directness of connection i
υ_i	utility of connection i
ω_d	quality of destination d
γ_i	air connectivity of connection i
AC_a	total air connectivity of airport a
$\alpha, \beta, \delta, \rho$	model parameters to be estimated
T_k	saturated demand of municipality k
τ	saturation multiplier per unit of GDP
V_{ka}	con-accessibility utility provided by airport a to municipality k
$V^{air}_k(\alpha, \beta, \delta, \rho)$	total air travel utility provided to municipality k by $a \in \mathcal{A}_k$
V^{no-air}_k	utility of the no-fly option
q_{ka}	total amount of passenger demand from municipality k using airport a
Q_k	total amount of passenger demand from municipality k
P_{ka}	estimated market share of airport a in municipality k
Q_a	passenger volumes at airport a
ψ_k	total con-accessibility of municipality k
$\widetilde{\psi_k}$	con-accessibility of municipality k (normalized)

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