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Dynamic Identification and Phased Deployment of Direct Air Capture Demand at Chinese Airports: Evidence from 52 Civil Transport Airports

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Abstract: This study develops a dynamic framework to identify Direct Air Capture (DAC) demand and phased deployment priorities across Chinese airports. Using panel data for 52 civil transport airports from 2006 to 2025, we construct a DAC demand index combining aviation carbon pressure, traffic growth, and post-pandemic recovery, and assess deployment readiness with airport grade and regional electricity prices. Results show marked heterogeneity in DAC demand. Major hubs, including Shenzhen Bao'an, Beijing Daxing, Guangzhou Baiyun, and Shanghai Pudong, rank highest, while some medium-sized airports also exhibit strong medium-term demand due to rapid growth and recovery. However, high demand does not guarantee near-term deployability. Beijing Daxing and Zhengzhou Xinzheng show a better demand-readiness match, whereas Shenzhen, Guangzhou, and Shanghai Pudong face stronger short-term constraints. Airport DAC planning should therefore follow a phased, differentiated strategy.

Keywords: Direct Air Capture; Airport Decarbonization; Dac Demand Index; Deployment Readiness; Phased Deploymen.

1. Introduction

Air transport is among the most difficult sectors to decarbonize because of rigid demand, limited near-term substitution options, long fleet turnover, and costly infrastructure retrofits [1–3]. Even with continued progress in sustainable aviation fuels, hydrogen aviation, and electric aviation, residual emissions are likely to persist for a long period. Direct air capture (DAC) therefore represents an important complementary pathway for aviation decarbonization.

Airports are not only transport nodes but also infrastructure platforms where energy systems, ground support equipment, and future synthetic fuel chains may converge [4]. This gives DAC deployment at airports potential strategic value. However, airports differ substantially in traffic scale, growth trajectory, post-pandemic recovery, electricity prices, and infrastructure conditions, which jointly shape both DAC demand and deployment feasibility [5].

Existing DAC studies mainly focus on materials, energy use, and cost, while airport decarbonization studies often emphasize terminal efficiency, operational optimization, or ground electrification [6]. Quantitative frameworks for identifying which airports should be prioritized for DAC, and how phased deployment should be organized under heterogeneous conditions, remain limited. Static rankings based only on passenger throughput risk conflating airport size with deployment priority.

Using data for 52 major Chinese civil transport airports from 2006 to 2025, this study develops a three-dimensional framework based on carbon pressure, growth, and recovery to identify DAC demand, and combines airport grade with electricity price to measure deployment readiness. Rather than estimating the exact engineering capacity required at each airport, the study addresses a planning question: which airports should be prioritized for near-term DAC assessment, which should be reserved for medium-term advancement, and which should remain under observation.

This study contributes in three ways. First, it shifts DAC analysis from macro-level assessment to infrastructure-level deployment identification. Second, it uses long-term throughput data as a practical proxy for airport-level mitigation pressure in the absence of a unified high-resolution emissions inventory. Third, it links dynamic demand identification, airport typology, and phased deployment pathways within one analytical framework.

2. Research Design

2.1 Research Subjects, Data Sources, and Sample Composition

This study examines 52 civil transport airports in China and constructs an airport-level panel covering 2006–2025, with 2025 used as the key cross-sectional year for DAC demand identification, airport typology, and deployment analysis. the dataset contains 1, 040 airport-year observations.

The data include three components. First, airport throughput data—passenger throughput, cargo and mail throughput, and aircraft movements—are used to construct the aviation-activity carbon pressure index, growth metric, recovery metric, and DAC demand index. Second, airport attribute data, including airport grade and regional electricity prices, are used to assess deployment readiness. Third, city-level socioeconomic variables, including GDP, population, electricity price, and population density, are used in the OLS analysis. Because macroeconomic statistics are typically released with a lag, the 2025 airport analysis is matched with city-level data for 2024.

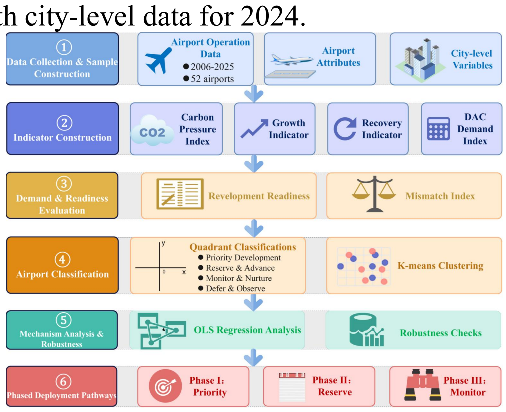

Figure 1. Flowchart

This study does not directly estimate airport carbon emissions. Instead, it uses aviation activity intensity as a proxy for mitigation pressure under current data constraints. This treatment enables consistent comparison across airports and provides an operational basis for identifying relative DAC demand and phased deployment priorities.

2.2 Variable construction

Airport DAC demand is measured using three dimensions: carbon pressure, growth, and recovery. the Carbon Pressure Index is constructed from passenger throughput, cargo and mail throughput, and aircraft movements after log transformation, min-max normalization, and entropy weighting:

$$CPI_{it} = w_1 ZPax_{it} + w_2 ZCargo_{it} + w_3 ZMove_{it} \quad (1)$$

The Composite Aviation Activity Index and growth metric are defined as:

$$AAI_{it} = \frac{1}{3}(ZPax_{it} + ZCargo_{it} + ZMove_{it}) \quad (2)$$

$$Growth_{it} = \frac{AAI_{it} - AAI_{i,t-1}}{|AAI_{i,t-1}|} \quad (3)$$

Recovery is measured relative to 2019:

$$Recovery_{it} = \begin{cases} 1, t < 2020 \\ \dfrac{AAI_{it}}{AAI_{i,2019}}, t \geq 2020 \end{cases} \quad (4)$$

The DAC Demand Index is then defined as:

$$DACDemand_{it} = 0.5CPI_{it} + 0.3Growth_{it} + 0.2Recovery_{it} \quad (5)$$

Deployment readiness is measured using electricity price and airport grade, and mismatch is defined as:

$$Readiness_i = 0.6(1 - PowerPrice_i) + 0.4Grade_i \quad (6)$$

$$Mismatch_i = DACDemand_i - Readiness_i \quad (7)$$

The demand index reflects relative deployment priority rather than actual DAC capacity requirements.

2.3 Airport Typology

For the 2025 sample, airports are classified using two methods: a four-quadrant framework based on carbon pressure and growth, and K-means clustering with four clusters using normalized pressure, growth, recovery, and DAC demand as inputs.

2.4 Econometric Model and Robustness

OLS models are estimated with electricity price, GDP, population density, and airport grade as explanatory variables:

$$Y_i = \alpha + \beta_1 PowerPrice_i + \beta_2 GDP_i + \beta_3 Density_i + \beta_4 Grade_i + \varepsilon_i \quad (8)$$

Robustness is tested by replacing entropy weights with equal weights, min-max normalization with z-score normalization, and adjusting the number of clusters. the results remain stable across specifications.

3. Empirical Results

3.1 Long-Term Evolution of Aviation Activity and Carbon Pressure at Chinese Airports

Based on throughput data for 52 civil transport airports in China from 2006 to 2025, aviation activity shows a clear long-term upward trend (Figure 2). Passenger throughput increased from about 280 million in 2006 to 1.3 billion in 2025, cargo and mail throughput rose from roughly 7 million tonnes to more than 20 million tonnes, and aircraft movements increased from around 3 million to over 9 million. the pandemic caused a temporary decline in 2020, but activity recovered during 2021–2025 and exceeded the pre-pandemic level, while the carbon pressure index fell to a short-term low in 2022 and then rebounded rapidly (Figure 3).

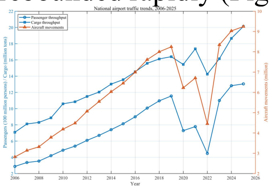

Figure 2.

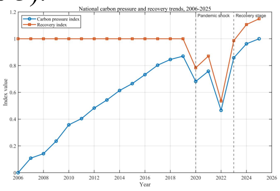

Figure 3.

Entropy-weighting results show that cargo and mail throughput has the highest weight (0.3821), followed by aircraft movements (0.31819) and passenger throughput (0.29971). This indicates that airport carbon pressure is jointly shaped by passenger, cargo, and flight activity rather than by passenger scale alone.

3.2 DAC Demand Identification Results and Airport Typology

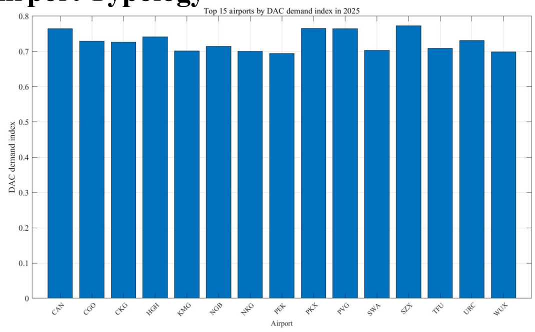

Figure 4.

Based on carbon pressure, growth, and recovery, the 2025 DAC Demand Index is calculated for all 52 airports, with the top 15 shown in Figure 4 and the full results reported in Appendix A. the index ranges from 0.45 to 0.78, indicating clear differentiation across airports.

Shenzhen Bao'an ranks first (0.772), followed by Beijing Daxing (0.766), Guangzhou Baiyun (0.765), and Shanghai Pudong (0.764), confirming that major hub airports remain the core of current DAC demand. Several medium-sized airports also show notable demand, including Ningbo Lishe (0.714), Jieyang Chaoshan (0.703), and Wuxi Shuofang (0.698). In these cases, demand is driven less by absolute activity scale than by strong growth and recovery.

3.3 Four-Quadrant Identification Results for DAC Demand

Figure 5 presents the four-quadrant classification based on carbon pressure and growth, using the sample median as the threshold. Airports are grouped into four categories: high pressure–high growth (priority deployment), high pressure–low growth (reserve advancement), low pressure–high growth (observation and cultivation), and low pressure–low growth (deferred deployment).

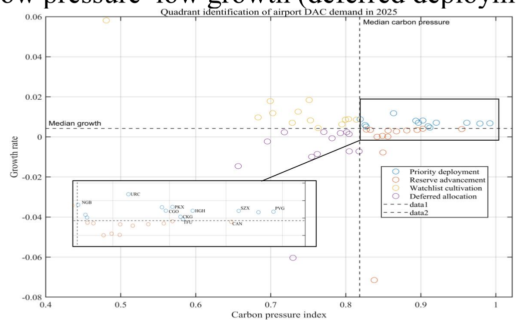

Figure 5.

Shenzhen Bao'an, Beijing Daxing, Guangzhou Baiyun, Shanghai Pudong, Hangzhou Xiaoshan, and Zhengzhou Xinzheng fall into the priority deployment category because they combine high pressure with strong growth. Beijing Capital and Kunming Changshui are classified as reserve advancement because growth is weaker. Ningbo Lishe and Jieyang Chaoshan belong to the observation-and-cultivation group, reflecting stronger growth and recovery despite lower absolute pressure.

3.4 Demand–Readiness Mismatch Analysis

To move beyond demand identification alone, this study further introduces deployment readiness and examines demand–readiness mismatch (Figure 6). Readiness is jointly determined by airport grade and electricity price.

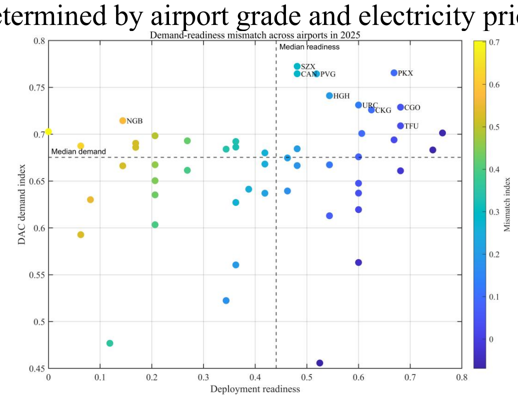

Figure 6.

Among high-demand airports, Beijing Daxing, Zhengzhou Xinzheng, Chengdu Tianfu, Chongqing Jiangbei, Urumqi Diwopu, and Hangzhou Xiaoshan show relatively high readiness and low mismatch, making them more suitable for early pilot deployment. Zhengzhou Xinzheng and Chengdu Tianfu are particularly notable because they combine relatively high demand with strong alignment between demand and deployment conditions.

By contrast, Shenzhen Bao'an, Guangzhou Baiyun, and Shanghai Pudong exhibit higher mismatch because their readiness remains comparatively low. This indicates that stronger mitigation pressure does not necessarily translate into better near-term deployability. Airports such as Ningbo Lishe, Jieyang Chaoshan, and Wuxi Shuofang also show relatively high demand but lag in readiness, and should therefore be included in a forward-looking monitoring framework.

3.5 Analysis of Correlates and Robustness Checks

The OLS results show that airport grade is significantly and positively associated with DAC demand, whereas electricity price, GDP, and population density are not statistically significant in the DAC demand model. the carbon pressure model has stronger explanatory power, and both airport grade and GDP are significantly positive. In the growth model, airport grade remains significantly positive, whereas GDP is significantly negative. the recovery model is not statistically significant overall, suggesting that post-pandemic rebound is more likely shaped by airport-specific factors.

The mismatch model should be interpreted with caution because mismatch is partly constructed from readiness, which already includes airport grade and electricity price. the robustness checks further support the stability of the main findings: the correlation coefficient of the DAC Demand Index reaches 0.9999 between the baseline and equal-weight specifications and 0.9952 between the baseline and z-score specifications.

4. Discussion

This study demonstrates that DAC demand at Chinese airports cannot be inferred from traffic scale alone. Instead, it is jointly shaped by aviation-activity pressure, growth dynamics, and post-pandemic recovery. This extends existing research on aviation decarbonization and DAC by showing that airport-level deployment priority should be identified dynamically rather than through static traffic ranking [4, 8]. the relatively high contribution of cargo and mail throughput further indicates that airport mitigation pressure depends not only on passenger traffic but also on freight intensity and flight operations [8].

The results also reveal that DAC demand and near-term deployability are not equivalent. Some airports exhibit strong demand yet remain constrained by electricity prices and baseline infrastructure, while others show a better alignment between demand and readiness. This aligns with prior studies indicating that DAC suitability depends on both mitigation need and local energy/engineering conditions [4, 7]. Airport DAC planning should therefore adopt a phased strategy rather than simple scale-based rollout [2, 4, 7].

Medium-sized airports should not be overlooked. Although currently smaller than major hubs, their rapid growth and strong recovery may elevate them into higher-demand categories in the medium term. Thus, DAC planning must include not only immediate priority sites but also a forward-looking monitoring list for airports with rising demand potential [8, 9].

Several limitations should be noted. First, this study uses aviation activity as a proxy for mitigation pressure rather than direct airport-level emissions. Second, deployment readiness is assessed only via airport grade and electricity price, omitting land availability, energy access, and broader engineering feasibility. Future research could integrate higher-resolution emissions data and more comprehensive infrastructure indicators [4, 9].

5. Conclusions and Policy Implications

Using panel data for 52 Chinese civil transport airports from 2006 to 2025, this study develops a DAC demand index based on carbon pressure, growth, and recovery, and combines it with airport grade and electricity price to evaluate deployment readiness. the results show pronounced heterogeneity in airport DAC demand. Mature hub airports remain the current core of high demand, but some medium-sized airports also display clear medium-term DAC potential because of rapid growth and strong recovery.

The analysis further shows that high DAC demand does not necessarily coincide with high short-term readiness. Airports such as Beijing Daxing and Zhengzhou Xinzheng show a relatively good match between demand and deployment conditions and are therefore suitable for early demonstration. By contrast, airports such as Shenzhen Bao'an, Guangzhou Baiyun, and Shanghai Pudong face stronger demand–readiness mismatches because of electricity-cost and infrastructure constraints.

Three policy implications follow. First, airports with both high demand and high readiness should be prioritized for demonstration deployment to accumulate operational and engineering experience. Second, airports with high demand but lower readiness should adopt a staged pathway centered on pilot validation, policy support, and infrastructure reservation. Third, airports in the Observation and Cultivation group should be placed under dynamic monitoring, with advance planning for land, power supply, and interface infrastructure to reduce the risk of delayed response as demand rises.

In short, DAC deployment across Chinese airports should follow a phased and differentiated strategy that jointly considers dynamic demand, practical readiness, and evolving infrastructure constraints.

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