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ESTIMATING AIR TRAVEL DEMAND IN NORTH SUMATRA USING GRAVITY MODEL APPROACH WITH ECONOMIC AND ROUTE ANALYSIS

Ahnis Zulkarnain(1), Hisar Monongam Pasaribu(2), Javensius Sembiring (3)
[1,2,3] Institut Teknologi Bandung
e-mail: [1]23622024@mahasiswa.itb.ac.id, [2]hmpasaribu@itb.ac.id, [3]javen.sembiring@itb.ac.id
coresponding: [3]javen.sembiring@itb.ac.id

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Abstract: This study estimates regional air travel demand in North Sumatra Province using variations of the gravity model. The objectives are to identify key factors influencing air travel demand, estimate demand through different model formulations, and assess airport infrastructure adequacy for regional connectivity. Three models were developed, progressively incorporating economic indicators such as GDP per capita, population, and distance, alongside socio-economic variables like leisure attractions, hotel accommodations, universities, and health facilities. The methodology involved log-linear transformations and regression analysis to estimate parameters. Results revealed significant variability in air travel demand, driven by proximity and economic activity, with the population coefficient shifting from 0.707 in Model 1 to -0.178 in Model 3, as socio-economic variables like leisure attractions (0.811) and GDP per capita (0.813) became more influential. Findings also exposed disparities in airport coverage, highlighting the need for strategic infrastructure improvements, particularly for high-demand pairs like Medan - Mandailing Natal.
Keywords: air travel demand, gravity model

Introduction

The aviation industry is a critical component of regional development, particularly in archipelagic nations like Indonesia, where air travel facilitates connectivity across vast geographical boundaries. North Sumatra, as one of Indonesia’s prominent provinces, exemplifies the need for effective air transportation to support economic and social growth. However, challenges such as uneven airport coverage, limited route networks, and underutilized aviation infrastructure hinder the province’s ability to fully harness the benefits of air travel. Addressing these issues requires a detailed understanding of regional air travel demand and connectivity gaps.

Despite its strategic location and the presence of Kualanamu International Airport as a primary gateway, North Sumatra's aviation sector faces persistent challenges, including gaps in airport coverage and limited integration of socioeconomic factors in demand modeling. While traditional gravity models have effectively estimated travel demand based on GDP, population, and distance, they often fall short in developing regions like North Sumatra where factors such as education, healthcare, and tourism infrastructure significantly influence mobility. The traditional approach also lacks the spatial validation necessary to ensure the alignment of infrastructure development with real-world accessibility.

This research addresses these gaps by employing an enhanced gravity model that integrates both economic and socioeconomic variables including leisure attractions, hotel accommodations, education and healthcare infrastructure to estimate air travel demand across North Sumatra’s regencies. By applying isochrone analysis in QGIS to validate airport catchment areas, this study bridges the gap between statistical demand estimation and spatial accessibility.

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The research is conducted in North Sumatra Province using secondary data sourced from the Ministry of Transportation, 2023 economic conditions datasets from BPS Indonesia, four consecutive years (2020–2023) of OAG Flight Database, and regional government agencies. Data collection included economic indicators, demographic profiles, tourism-related infrastructure, and geospatial data. The analysis uses log-linear regression on paired inter-regional data, followed by spatial validation and scoring for route suitability.

Unlike traditional gravity models that rely solely on core variables such as GDP, population, and distance, this study introduces a multilayered modeling approach that integrates additional socioeconomic indicators including leisure attractions, hotel accommodations, education facilities, and healthcare infrastructure to capture more nuanced drivers of air travel demand. Moreover, this research advances the conventional use of gravity models by spatially validating demand estimates using airport catchment areas through isochrone analysis in QGIS. A key distinction of this model lies in the inversion of the typical gravity model logic: rather than assuming that shorter distances automatically generate stronger travel demand, this study tests a formulation in which longer ground distances between regions can increase estimated air demand. This reflects real-world preferences in regions like North Sumatra, where poor ground connectivity or travel time constraints may make air travel more attractive over longer distances.

This combination of economic modeling and geospatial validation provides more actionable insights, not only for estimating unserved or underserved routes but also for identifying mismatches between demand and airport accessibility. The model also contributes practical value by offering a structured scoring system for route feasibility that incorporates infrastructure adequacy and population, supporting better informed decisions for route planning and infrastructure investment. Importantly, the methodology is transferable and can be adapted to other regions with similar data availability, offering a replicable framework for regional air demand estimation in developing countries or archipelagic settings.

The academic contribution of this research lies in enhancing the gravity model with socioeconomic and spatial data, offering a more context sensitive approach to travel demand estimation. For the airline industry, the model offers a systematic tool for identifying high potential routes and improving network planning, especially in emerging markets. For policymakers and airport managers, the findings provide a strategic basis for optimizing infrastructure investments, addressing accessibility gaps, and supporting regional development initiatives.

This study seeks to answer the following research question: How can an enhanced gravity model that incorporates socioeconomic and spatial variables be used to estimate regional air travel demand and validate feasible routes for improving air connectivity in North Sumatra?

Method

The datasets used in this study span several years due to limitations in data availability. GDP per capita and population data were obtained for the year 2023 from BPS Indonesia. Socio-economic indicators such as leisure attractions, hotel accommodations, university facilities, and healthcare infrastructure were collected from 2017, 2019, 2021, and 2022 based on the most recent data published by regional government sources. Air travel data, including route frequency and available seat kilometers (ASKs), were sourced from the OAG Flight Database for the years 2020 through 2023, allowing for a multi-year perspective on existing flight services in North Sumatra.

This research employed a comprehensive approach to estimate regional air travel demand in North Sumatra Province. Key materials included economic and demographic data, such as Gross Domestic Product (GDP) per capita, population, and distance, alongside socio-economic indicators, including leisure attractions, healthcare facilities, and educational institutions. These datasets were sourced from reliable agencies, including the Central Bureau of Statistics (BPS) and the Official Airline Guide (OAG). Geospatial data, including the coordinates of regency capitals, were used to calculate distances through Dijkstra’s Algorithm, a well-established technique for determining the shortest path between locations (Teresco, (2010); Lanning et al., (2014). Visualization and spatial analyses were conducted using Quantum Geographic Information System (QGIS), which was also used for isochrone analysis to define airport catchment areas (Śleszyński et al., 2023).

The study developed three gravity models to progressively refine the estimation of air travel demand. Model 1 served as a foundational model, incorporating GDP per capita, population, and distance as core variables, following frameworks established by Grosche et al., (2007). Model 2 introduced modifications to how distance was treated, shifting its role from a denominator to a multiplier to better capture the impact of proximity on air travel behavior (Das et al., 2022). Lastly, Model 3 enhanced the model further by integrating additional socio-economic variables, including leisure attractions, hotel accommodations, university facilities, and healthcare infrastructure, which have been shown to significantly influence travel demand (Cattaneo et al., 2023). All models were linearized using logarithmic transformations to facilitate regression analysis (Samunderu, 2023a).

For classification of airport coverage for each regency in North Sumatra was based on the percentage of the regency's area within a 180-minute driving time to the nearest airport, under normal traffic conditions. The coverage levels were categorized into five tiers: "Fully Covered" for regencies with 100% coverage, "Mostly Covered" for 75%-99% coverage, "Partially Covered" for 25%-74% coverage, "Minimally Covered" for 1%-24% coverage, and "Not Covered" for areas entirely outside the 180-minute range. This classification, detailed in Table IV.3, helps identify disparities in airport accessibility and guides the assessment of route suitability and air travel demand across the region.

Several assumptions were made to ensure consistency in model development and regression interpretation. First, the socio-economic and infrastructural conditions were assumed to remain stable during the analysis period, meaning that variations within the years of data collection were considered negligible for estimation purposes. Second, it was assumed that airline behavior aligns with estimated demand, meaning that higher predicted demand could translate into potential airline interest or route feasibility. Lastly, during the log-linear regression analysis, the coefficients (β) were interpreted as elasticities, indicating the percentage change in estimated air travel demand for a 1% change in the corresponding explanatory variable. The use of logarithmic transformation and the addition of a constant ($1 + X$) also assumed that all variable values are non-negative, allowing the model to handle zero values while maintaining mathematical validity and estimation robustness.

Finally, the airports class in North Sumatra is based on their runway infrastructure characteristics, specifically the length and width, which determine their capacity to accommodate different aircraft sizes and passenger volumes. Airports are categorized into three classes: Class A, with runways exceeding 2500 meters in length and 45 meters in width, capable of handling the largest aircraft and the highest passenger volumes; Class B, with runways between 1800 to 2500 meters in length and 30 to 45 meters in width, supporting a significant number of passengers and aircraft types; and Class C, with smaller runways that do not meet the criteria of Class A or B, designed for smaller aircraft and lower air traffic volumes. This classification provides a structured assessment of each airport's operational capabilities and its role within the regional transportation network.

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Gravity Model Variables

The gravity model for estimating air travel demand in North Sumatra incorporates several key variables that influence connectivity between regions. These variables include origin-destination pairs, GDP per capita (GDP), population (Pop), and socio-economic drivers such as leisure attractions (*Lei*), hotel accommodations (*Hot*), university facilities (*Uni*), and health services (*Hea*). Factors like GDP per capita and population provide insights into economic and market size dynamics, influencing air travel demand. High-GDP regions like Medan and Batu Bara tend to exhibit stronger economic activity and higher air travel potential, while lower-GDP areas face constraints that limit demand. Population, as a measure of market size, also plays a critical role, with larger populations generally correlating to higher travel demand. Despite pandemic-induced disruptions, a recovery in air travel aligned with population growth trends was evident by 2023.

Model Development

Equation (1) describes the travel demand between cities i and j, where Tij represents the passenger volume between these cities, excluding instances where i equals j. The variables GDPij and Popij represent the economic size and population, respectively, calculated as the multiplication of GDP per capita and population for regencies i and j. While dij indicates the ground distance between them, and G serves as a constant. The parameter a reflects the impact of attraction factors, whereas the parameter β1, β2, and β3 represent the influence of GDP per capita, population, and distance on travel demand, respectively.

$$T_{ij} = G \cdot \frac{GDP_{ij}^{\beta 1} \cdot Pop_{ij}^{\beta 2}}{Dist_{ij}^{\beta 3}} \quad (1)$$

Going from Model 1, Model 2 was formulated to refine the relationship between distance and air travel demand. In Model 1, distance was positioned as an inverse factor, implying that greater distances would reduce air demand. However, considering the unique characteristics of North Sumatra's air travel needs, it is hypothesized that greater distance may, in some cases, increase air demand due to the attractiveness of air travel for longer distances. Consequently, in Model 2, the distance variable was moved to the numerator, which allowed us to investigate the direct impact of proximity on air travel volume.

$$T_{ij} = G \cdot GDP_{ij}^{\beta 1} \cdot Pop_{ij}^{\beta 2} \cdot Dist_{ij}^{\beta 3} \quad (2)$$

As shown in Eq. (2), Model 2 modifies the initial gravity model by reconfiguring the placement of the distance variable. This adjustment aims to determine whether this new specification could enhance the model’s explanatory power in estimating travel demand between regencies. After analyzing Model 2, it became evident that additional factors might influence air travel demand beyond the economic and population variables included so far. Therefore, Model 3 expands on the previous formulation by incorporating new attraction-related variables to better capture the nuances of air travel behavior in North Sumatra. As shown in Eq. (3), Model 3 integrates leisure attractions (Lei), hotel accommodations (Hot), university facilities (Uni), and health facilities (Hea) as additional variables influencing air travel demand:

$$T_{ij} = G \cdot GDP_{ij}^{\beta 1} \cdot Pop_{ij}^{\beta 2} \cdot Dist_{ij}^{\beta 3} \cdot \left(1 + Lei_{ij}^{\beta 4}\right) \cdot \left(1 + Hot_{ij}^{\beta 5}\right) \cdot (1 + Uni_{ij}^{\beta 6}) \cdot (1 + Hea_{ij}^{\beta 7}) \quad (3)$$

Model 3 aims to explore whether tourism, educational institutions, hotel infrastructure, and healthcare facilities play a meaningful role in driving air travel demand between regions. By adding these variables, the model can provide a more comprehensive understanding of the different aspects that attract passengers to choose air travel as their mode of transport.

To facilitate estimation in a linear form, the equation is transformed by applying a logarithm to both sides, resulting in the following log-linear representation:

$$\begin{aligned} ln(T_{ij}) = ln(G) + \beta_1 \cdot ln(1 + GDP_{ij}) + \beta_2 \cdot ln(1 + Pop_{ij}) + \\ \beta_3 \cdot ln(1 + Dist_{ij}) + \beta_4 \cdot ln(1 + Lei_{ij}) + \\ \beta_5 \cdot ln(1 + Hot_{ij}) + \beta_6 \cdot ln(1 + Uni_{ij}) + \\ \beta_7 \cdot ln(1 + Hea_{ij}) \end{aligned} \tag{4}$$

Several assumptions were made to ensure consistency in model development and regression interpretation. First, the socio-economic and infrastructural conditions were assumed to remain stable during the analysis period, meaning that variations within the years of data collection were considered negligible for estimation purposes. Second, it was assumed that airline behavior aligns with estimated demand, meaning that higher predicted demand could translate into potential airline interest or route feasibility. Lastly, during the log-linear regression analysis, the coefficients (β) were interpreted as elasticities, indicating the percentage change in estimated air travel demand for a 1% change in the corresponding explanatory variable. The use of logarithmic transformation and the addition of a constant (1 + X) also assumed that all variable values are non-negative, allowing the model to handle zero values while maintaining mathematical validity and estimation robustness.

The development of these three models provides a comprehensive framework for estimating air travel demand across regencies in North Sumatra. Each model incrementally incorporates more variables that capture both economic and social dimensions, allowing for a nuanced understanding of the factors influencing travel behavior. This approach ensures that the demand estimation is robust, accounting for not only economic factors like GDP and population but also socio-cultural aspects such as the availability of leisure attractions, hotels, universities, and healthcare facilities. The transformed log-linear models facilitate easy estimation and interpretation of the relationships, highlighting which variables most significantly drive air travel demand.

Discussion

The estimation results of air travel demand in the North Sumatra region are presented in Table 1. The first column displays the outcomes derived from Model 1. The results in the second column reflect the modified gravitational model, where certain adjustments were made to better fit the regional characteristics. Finally, the third column contains the estimation results obtained by incorporating additional socio-economic variables into the model.

Table 1. Estimation Result

	Model 1		Model 2		Model 3	
	Coeff.	Std Error	Coeff.	Std Error	Coeff.	Std Error
Intercept	2.326742	0.001411	2.36713	0.001519	2.371999	0.002671
$Dist_{ij}$	-0.75218	0.004105	0.801289	0.004418	0.708471	0.004111
GDP_{ij}	0.766236	0.007786	0.764879	0.008381	0.813482	0.00695
Pop_{ij}	0.70768	0.002442	0.702253	0.002629	-0.17819	0.049404
Lei_{ij}					0.811235	0.007977
Hot_{ij}					0.801939	0.010078

Uni_{ij}			0.768256	0.016235
Hea_{ij}			1.458074	0.032184
R^2	0.992299	0.990853	0.992478	
Adj. R^2	0.992277	0.990827	0.992428	

In Model 1, which follows the initial specification of the gravity model based on distance, GDP, and population as mentioned in Eq. (1), the coefficients are consistent with expectations. The coefficient for Distij is negative (-0.75218), indicating an inverse relationship between distance and air travel demand. As distance increases, the travel demand decreases, which is in line with the typical behavior in gravity models. Both GDPij and Popij have positive coefficients (0.766236 and 0.70768 respectively), implying that higher GDP and larger populations in connected regions increase air travel demand. The R^2 value for Model 1 is 0.992299, indicating that approximately 99.23% of the variation in air travel demand is explained by the model, which suggests a good fit.

Model 2 includes modifications to the gravity model by altering the placement of the distance variable as seen in Eq. (2), making it a direct influencing factor rather than an inverse one. In Model 2, the coefficient for Distij is positive (0.801289), reflecting that closer distances increase air travel demand, as expected. The coefficients for GDPij and Popij are similar to those in Model 1, with positive impacts on travel demand. The R^2 value for Model 2 is 0.990853, which is slightly lower compared to Model 1, but still represents a very high explanatory power.

By using Eq. (5) Model 3 expands upon the previous models by incorporating additional variables to better capture the impact of socio-economic and infrastructure factors, including Leisure Attractions (Leiij), Hotel Accommodations (Hotij), University Facilities (Uniij), and Health Facilities (Heaij). The coefficients for the added variables, Leiij (0.811235), Hotij (0.801939), Uniij (0.768256), and Heaij (1.458074), all indicate positive relationships with air travel demand, meaning that regions with more leisure attractions, hotels, universities, and health facilities are likely to generate higher air travel demand. Notably, the coefficient for Popij becomes negative (-0.17819), which could suggest complex interactions between population and other variables in the model. The R^2 value for Model 3 is 0.992478, slightly higher than in Models 1 and 2, suggesting that the additional variables provide a more comprehensive view of the determinants of air travel demand.

Final Estimated Air Demand

The final estimation of air travel demand for the North Sumatra region was conducted using three variations of the gravity model: Model 1, Model 2, and Model 3. Each model builds on a different version of the gravity equation to progressively capture the unique factors affecting air travel demand in the region. Model 1 establishing a foundational approach. Model 2, represented modifies this approach by repositioning the distance variable to better reflect the impact of proximity, recognizing that shorter distances typically encourage greater travel demand. Model 3 further enhances the model by incorporating additional socio-economic variables, such as leisure attractions, hotel accommodations, universities, and health facilities, offering a more comprehensive understanding of the various factors that drive air travel demand beyond economic and demographic components.

By applying the three models, we obtained the estimated air demand values (Tij) for different regions in North Sumatra. To provide a deeper understanding, we present the city of Medan, the capital of North Sumatra, as an example. The estimated air demand values from Medan to other regencies are analyzed and visualized in three distinct maps corresponding to the three models.

Figure 1.(a) shows the estimated air demand from Medan to various regencies based on Model 1. In the map, darker blue represents a higher estimated air demand (Tij) value, while lighter blue represents a lower estimated demand. This model, which heavily relies on distance as a factor, indicates that nearby cities have a higher air travel demand with Medan.

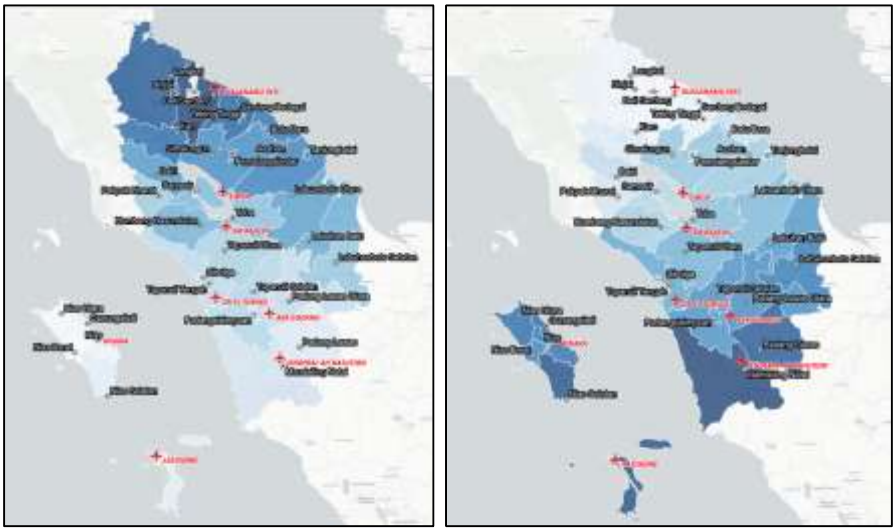

Figure 1. Estimated Air Demand from Medan (a) Model 1; (b) Model 2

The top-ranking cities include Deli Serdang, Binjai, Langkat, Serdang Bedagai, and Karo, all of which are relatively close to Medan. This trend reflects the emphasis that Model 1 places on proximity, where closer distances correspond to higher air travel demand. The lowest-ranking cities, such as Nias Selatan, Gunungsitoli, Nias, Nias Utara, and Nias Barat, are all significantly farther away, resulting in lower estimated air demand

Figure 2. Estimated Air Demand from Medan for Model 3

Figure 1.(b) represents the estimated air demand using Model 2, which modifies the gravity model by adjusting the importance of distance. In this case, Mandailing Natal, Nias Selatan, Padang Lawas, Gunungsitoli, and Nias Utara emerge as the top-ranking cities in terms of air travel demand. These cities are significantly farther from Medan compared to those in Model 1. This suggests that, unlike Model 1, the distance is not a dominant limiting factor for Model 2, indicating the importance of other contributing factors such as the need for enhanced regional connectivity. Interestingly, cities that were top ranked in Model 1 such as Binjai, Deli

Serdang, and Langkat, now fall to the lowest ranks, highlighting the different weight assigned to distance in Model 2.

Figure 2 shown the estimated air demand for Medan to other regencies using Model 3, which includes additional socio-economic variables beyond distance, GDP, and population. In this model, cities like Mandailing Natal, Nias Selatan, Tapanuli Tengah, Padangsidimpuan, and Padang Lawas Utara show the highest air travel demand. This indicates that socio-economic factors, such as tourism, hotel facilities, and education infrastructure, significantly impact air travel demand, even for distant locations. The socio-economic infrastructure in these cities drives the demand for air connectivity. On the other hand, cities like Nias, Serdang Bedagai, Nias Utara, Binjai, and Pakpak Bharat have lower estimated air demand, suggesting a comparatively lower socio-economic influence despite their distance from Medan.

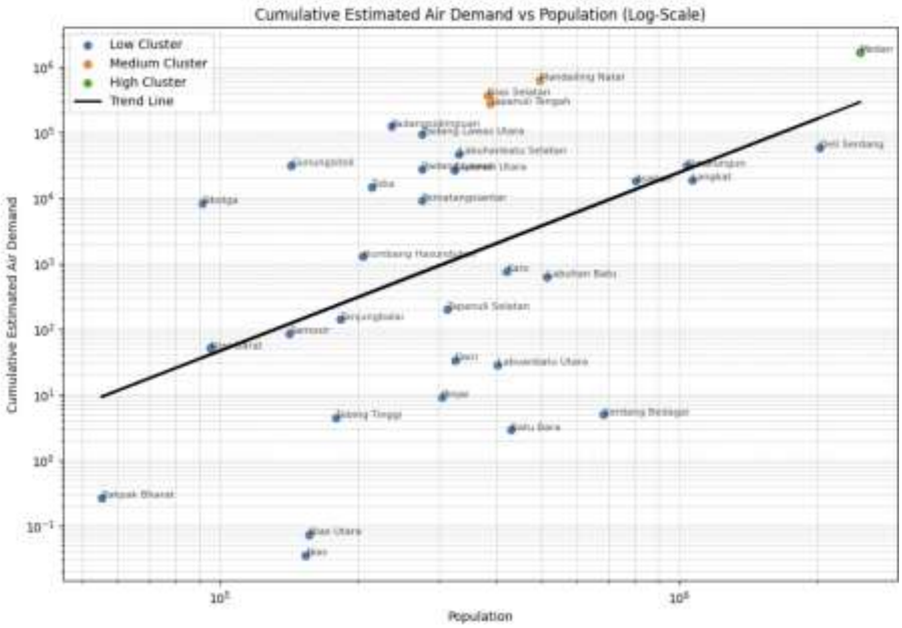

Figure 3. Cumulative Estimated Air Demand vs Population (Log-Scale)

A graph in Figure 3 illustrating the relationship between population size and cumulative interaction values highlights a strong positive correlation. Medan, in the high cluster, stands out with significantly larger population and interaction values, underscoring its role as a major hub. Medium-cluster regencies like Mandailing Natal, Nias Selatan, and Tapanuli Tengah exhibit high interaction values despite lower populations, indicating that socio-economic factors significantly contribute to air travel demand. Low-cluster regions show both lower populations and interaction values, reflecting disparities in air travel demand across the province.

The cumulative air travel interaction values (Tij) for all regencies were aggregated and analyzed to reveal patterns in demand. Using K-Means algorithm, regencies were classified into three clusters: low, medium, and high, based on their total of estimated air travel demand values. The cumulative interaction was calculated by summing air travel activities as both origin (regencyi) and destination (regencyj) using the concatenation function in Model 3. These analyses provide valuable insights into the spatial distribution and drivers of air travel demand, enabling more targeted planning for route development and connectivity improvements across North Sumatra.

Following the analysis of estimated air travel demand, Table 2 is compiled to assess the relationship between these estimates, derived from gravity Model 3, and the real-world situation. This helps contextualize the potential demand within existing regional conditions. The covered area refers to the smallest geographical region that can be serviced by trips originating from the nearest airport. It also considers the availability and classification of airport facilities to determine the capabilities of the nearest airports. Furthermore, population is taken as a combined average between the two interacting regencies. These three aspects, covered area, airport facility class, and population, collectively contribute to determining the Route Suitability Level.

The results of this study confirm that an enhanced gravity model that incorporates socioeconomic and spatial variables can effectively estimate air travel demand and validate feasible routes in North Sumatra. Model 3, which includes variables such as leisure attractions, hotel infrastructure, education, and healthcare access, achieved the highest explanatory power ($R^2 = 0.992478$) and reflected real-world dynamics more accurately than traditional models. These findings demonstrate that air travel demand is not solely dependent on population or distance but is better predicted through a multidimensional approach.

The results align with studies in other regions. Samunderu (2023) showed the effectiveness of gravity models in East African countries such as Kenya, Tanzania, Uganda, and Rwanda for identifying viable direct routes, especially for low-cost carriers. The importance of GDP as a demand driver is reinforced Ozmec-Ban & Škurla Babić (2023) and Venkadavarahan et al. (2024), while the variation in GDP's influence across different regions is shown in South America, where it is more prominent in Uruguay and Chile than in Argentina (Brida et al., 2023) The role of tourism infrastructure in stimulating air connectivity is highlighted by Dimitriou (2018) and the necessity of air travel for accessing healthcare in remote regions is supported by Artemiev et al., (2023) and Guillaume Burghouwt (2017) underscores the role of air connectivity in enabling international education mobility. Spatial accessibility studies by Tome et al., (2019) and Franca et al., (2012) support the use of isochrone-based GIS analysis, as adopted in this study. Methodological innovation through machine learning and big data integration into gravity models has also proven effective in similar contexts, as demonstrated by Erjongmanee & Kongsamutr (2018) and Boelrijk (2019). The development of infrastructure, such as airports and flight routes, is also crucial in facilitating air travel demand. In Southeast Asia, rapid infrastructure and connectivity improvements have supported aviation growth, even as population growth is expected to stabilize or decline by 2050 (Joyce et al., 2021). The presence of alternative transportation options can influence demand patterns. For example, in China, the introduction of high speed rail has significantly impacted aviation markets, demonstrating how substitutes can alter the traditional relationship between distance and travel frequency (Zhang et al., 2018). Similarly, in the Tasman market between New Zealand and Australia, geographic isolation makes air travel the dominant mode, with factors like expanded seat capacity and seasonal effects having greater influence than distance alone (Flatley et al., 2025).

By improving connectivity, airline route planning contributes directly to the economic development of underserved regions. Enhanced air transport links can stimulate local economies by enabling trade, tourism, and investment (Gordijn & Coevering, 2006), (Sindhwani et al., 2024). The implementation of PSO subsidies helps maintain air routes that might otherwise be unprofitable, ensuring that essential air services continue to operate. This is particularly important in regions where air transport is the only feasible mode of transportation (Braathen, 2011), (Pita et al., 2013). However, the negative coefficient of population in Model 3 suggests that in some regions, socio-economic and infrastructure factors play a more decisive role than population size alone.

Table 2. Cumulative Estimated Air Demand vs Population (Log-Scale)

Origin	Destination	Covered Area	Airport Facility	Population	Rank	Route Suitability	Existing Flight
Medan	Mandailing Natal	Minimally Covered	Class C	High	1	Moderate	0
Medan	Nias Selatan	Partially Covered	Class B	Medium	2	Moderate	1
Medan	Tapanuli Tengah	Partially Covered	Class B	Medium	3	Moderate	1
Medan	Padangsidimpuan	Mostly Covered	Class B	Low	4	Moderate	1
Medan	Padang Lawas Utara	Partially Covered	Class B	Low	5	Low	1
…	…	…	…	…	…	…	…
Nias	Nias Selatan	Partially Covered	Class B	Low	524	Low	1
Nias	Pakpak Bharat	Minimally Covered	Class C	Low	525	Low	0
Nias	Sibolga	Mostly Covered	Class B	Low	526	Moderate	0
Tapanuli Tengah	Sibolga	Partially Covered	Class B	Low	527	Low	0
Nias Barat	Gunungsitoli	Mostly Covered	Class B	Low	528	Moderate	0

Conclusion

This study aimed to estimate regional air travel demand in North Sumatra using an enhanced gravity model and validate it through spatial analysis. The findings indicate that GDP, leisure attractions, and hotel accommodations are significant drivers of air travel demand, while population size alone does not consistently predict demand. The spatial validation of airport catchment areas further revealed accessibility gaps in several regencies, notably Pakpak Bharat, Labuhan Batu, and Labuhanbatu Utara, which remain underserved despite showing potential demand.

For local governments, these findings suggest a need to improve airport accessibility in underserved areas through infrastructure investment or multimodal integration. Establishing new airports or enhancing road connections to existing ones could help unlock unmet demand. Airlines, on the other hand, can use the insights from this model to identify and test high-potential routes, such as Medan–Mandailing Natal, which shows strong demand despite currently lacking service.

The study is limited by data availability and the assumption of stable socio-economic conditions across the selected years. Additionally, the model does not currently account for factors such as ticket prices, flight frequency, or government incentive programs, which could further influence air travel behavior. This gravity model could also be applied in other provinces across Indonesia, provided that similar datasets such as GDP, population, distance, and socioeconomic indicators are available and reliable. Its adaptability allows regional planners to estimate air travel demand even in areas with limited direct travel data.

Future research could expand this framework by incorporating dynamic pricing data, analyzing the impact of airline subsidy schemes such as Public Service Obligations (PSOs), and evaluating seasonal travel patterns. Incorporating behavioral data, such as traveler preferences and willingness to pay, could also provide deeper insights into demand drivers and support more accurate route planning.

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