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An Integrated Framework for Estimating Origins and Destinations of Multimodal Multi-Commodity Import and Export Flows Using Multisource Data

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Abstract: Estimating origin-destination (OD) demand is integral to urban, regional, and national freight transportation planning and modeling systems. However, in developing countries, existing studies reveal significant inconsistencies between OD estimates for domestic and import/export commodities derived from interregional input-output (IO) tables and those from regional IO tables. These discrepancies create a significant challenge for properly forecasting the freight demand of regional/interregional multimodal transportation networks. To this end, this study proposes a novel integrated framework for estimating regional and international (import/export) OD freight flows for a set of key commodities that dominate long-distance transportation. The framework leverages multisource data and follows a three-step process. First, a spatial economic model, PECAS activity allocation, is developed to estimate freight OD demand within a specific region. Second, the international (import and export) freight OD is estimated from different zones to foreign countries, including major import and export nodes such as international seaports, using a gravity model with the zone-pair friction obtained from a multimodal transportation model. Third, the OD matrices are converted from monetary value to tonnage and assigned to the multimodal transportation super network using the incremental freight assignment method. The model is calibrated using traffic counts of the highways, railways, and port throughput data. The proposed framework is tested through a case study of the Province of Jiangxi, which is crucial for forecasting freight demand before the planning, design, and operation of the Ganyue Canal. The predictive analytics of the proposed framework demonstrated high validity, where the goodness-of-fit (R^2) between the observed and estimated freight flows on specific links for each of the three transport modes was higher than 0.9. This indirectly confirms the efficacy of the model in predicting freight OD demands. The proposed framework is adaptable to other regions and aids practitioners in providing a comprehensive tool for informed decision-making in freight demand modeling.

Keywords: origin-destination matrices; freight demand modeling; multimodal transportation; commodities; PECAS; input-output table; integrated modeling

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1. Introduction

The accurate freight estimation of origin and destination (OD) is paramount for effective transportation planning and demand modeling at the national, state, and local levels [1,2]. Understanding freight movement within complex multimodal networks helps planners anticipate and manage flows while facilitating the vital growth of economic activities without overburdening existing infrastructure [2–4]. As freight volumes continue to increase, transportation systems face mounting pressure. This calls for more sophisticated methods to track, monitor, and analyze commodity movements, as well as to evaluate their impacts on transportation nodes and networks. Traditional freight demand models, such as direct facility flow factoring, OD factoring, truck models, four-step commodity models, and economic activity models, have been widely used. Commodity-based models, in particular, are valuable for analyzing supply and demand within economic sectors [5–7]. However, these models often face limitations at the regional and international levels, primarily due to data constraints. Consequently, they may not adequately capture the complexity of freight flows across multimodal transportation systems [7,8]. Recent advancements in freight modeling have shifted from traditional regression-based methods to more integrated approaches. These newer methods combine multiple data sources and modeling techniques, offering a detailed understanding of freight flows. Freight OD estimation is closely linked to economic activity and reflects the demand for raw materials, intermediate goods, and finished products across regions [7]. However, freight flow estimation faces challenges related to data availability and methodological approaches, where the appropriate OD matrix estimation model depends largely on the quality of data and the scale of the study area [7–10].

Establishing interregional connections in a Multi-Regional Input-Output (MRIO) analysis is fundamental. In practice, freight OD estimation employs both survey- and non-survey-based methods. While, survey-based methods, particularly for interregional trade flows within a country, are not always available because of the significant workload and financial constraints, making these methods time-consuming, labor-intensive, and expensive [11–13]. Therefore, non-survey methods such as gravity- and behavior-based models were employed [14]. The non-survey approach is more practical and facilitates the operationalization of regional input–output (IO) data estimation [15]. The existing literature on regional and interregional freight OD estimation underscores a variety of methodologies yet reveals persistent gaps that require further exploration. For instance, gravity models have been extensively employed because of their simplicity in estimating interregional trade flows, as evidenced by Ramos and Sargento [16] and Lindall et al. [17]. These models are particularly helpful in situations where data are incomplete, however, they often require additional information to refine parameters, such as distance decay. Moreover, the integration of economic and transportation data via methods such as MRIO analysis have been explored to estimate regional trade flows [18,19]. Nevertheless, challenges arise in reconciling these estimates with provincial data. This issue is particularly pronounced in developing countries, where discrepancies hinder the accurate forecasting of freight demand and efficient planning of multimodal networks [20].

In the case of China, provincial and interregional IO tables released by the National Statistics Bureau often exhibit inconsistencies in trade flow data, such as mismatches between domestic inflows and outflows across provinces [20–22]. Moreover, these IO tables lack sufficient detail regarding the movement of specific commodities across provinces and international borders, providing only aggregate data on domestic flows and limited information on foreign imports and exports [20,23]. Many existing freight models focus on specific planning units or commodity groups, neglect adjacent regions and critical international trade corridors, and fail to account for the interconnected nature of modern logistics networks, where freight flows in one region can have significant downstream effects on industries in neighboring regions or international markets [20,24,25]. Thus, there is an urgent need for a modeling framework that integrates both regional and interregional trade data, accounting for the broader context in which provinces and the country function [26]. A model that links seaports to domestic-foreign OD flows is particularly important for spatial interaction modeling [6,25]. To address these gaps, this study proposes a novel integrated framework for estimating freight flows in intra-regional and international (import and export) contexts, linked through a two-tier multimodal transportation super network.

This approach improves the accuracy of OD flow estimates by incorporating multisource data, including provincial and interregional IO tables, customs data, land use data, transportation networks, truck GPS data, railway waybills, ship visas, and statistical yearbooks. Consequently, it provides a more comprehensive estimation of OD matrices, particularly for the long-distance transportation of key commodities.

The specific contributions of this study are threefold. First, a spatial economic model, the Production, Exchange, and Consumption Allocation System (PECAS) activity allocation is developed to estimate freight OD within a specific region. Second, the international (import and export) freight OD is estimated from different zones to foreign countries, including major import and export nodes such as international seaports, using a gravity model with zone-pair friction obtained from a multimodal transportation model. Third, the OD matrices are converted from monetary value to tonnage and assigned to the multimodal transportation super network using the incremental freight assignment method. The model is calibrated using traffic counts of highways, railways, and port throughput data. Additionally, the calibration of the trip length distribution for extended regions is achieved by integrating data from truck GPS, railway waybills, and ship visas. The proposed framework is tested through a case study of the Province of Jiangxi, which is crucial for forecasting freight demand before the planning, design, and operation of the Ganyue Canal. The proposed framework is adaptable to other regional areas and provides a useful tool that helps practitioners use recent multisource data to make better and more informed decisions.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the methodology used in the study. Section 4 describes the implementation and testing of the proposed integrated model through a case study. Section 5 presents the results and analysis of freight OD flows and multimodal freight assignments. Finally, Section 6 concludes the study with the main findings, recommendations, implications, and avenues for future research.

2. Literature Review

Estimating OD is an inevitable step in passenger and freight demand modeling, impact analysis, and assessment studies, which necessitates the development of OD matrices [27–30]. Although gathering information for OD matrices entails considerable effort and costs in primary data collection, proprietary concerns often limit data sharing by freight companies [7,31]. The literature on freight OD estimation diverges between the structured and unstructured approaches. Structured studies typically employ closed-form distribution models such as the gravity model, which focuses on optimizing the model fit and tailoring it to specific commodities, as seen in the works of Holguín-Veras and Patil [32], and Levine et al. [4], who expanded these models to include truck and rail modes for U.S. container flow estimation. Conversely, unstructured approaches, as discussed by Kalahasthi et al. [33], do not adhere to specific functional forms for trip distribution and often rely on existing data such as partial OD matrices. These methods utilize various techniques including entropy maximization, artificial neural networks, and maximum likelihood. Al-Battaineh and Kaysi [34], and Ma et al. [35], used a genetic algorithm and Bayesian networks, respectively, for truck OD estimation. In addition, Teye and Hensher [36], and Hensher et al. [37], developed new entropy maximization models for freight trip distribution in Australia. Holguín-Veras et al. [38] estimated commodity flow OD matrices based on observed traffic counts. Typically, freight truck demand modeling relies on OD matrices derived from expanded roadside or truck survey data, representing steady-state scalability for future predictions. However, this approach has limitations, notably, the lack of policy responsiveness. The aggregate four-steps model (FSM) is also prevalent for truck trip estimation [39], and conventional travel demand models fail to capture the prevalent trip-chaining behavior in truck trips. In parallel, there has been a growing inclination towards micro-level activity models, which provide detailed insights but are constrained by extensive data requirements [39,40]. This challenge has led to the development of new methodologies that balance data availability with accurate forecasting. For instance, Pan et al. [1] leveraged machine learning and passively collected data to estimate multimodal OD matrices. Similarly, Basso et al. [41] used toll collection data and GPS information to estimate truck OD matrices using a multisource approach and decision tree modeling.

In addition, Holguin-Veras and Thorson [9] utilized a trip length distribution (TLD) for freight demand in Guatemala using survey data to analyze the spatial patterns of freight movements, similar to the use of TLD in passenger transportation, to represent the frequency of trips over varying distances. Their study found that freight generators significantly influenced TLD patterns, and that the shape of the distribution varied depending on the type of movement involved. Notably, Tavasszy and Stada [42], and Al-Battaineh and Kaysi [34], incorporated IO formulations with genetic algorithms for OD matrix estimation, thereby demonstrating the integration of economic and transportation data. By further expanding the horizon, Bachmann et al. [18] introduced a method to estimate regional trade flows using transportation survey data, converting freight OD flows into production–consumption trade flows. This method reconciles trade flow estimates with regional production and consumption, adhering to MRIO accounting principles. Integrated land-use and transportation models have become increasingly valuable for modeling freight demand within a broader spatial and economic context. A prominent example is the PECAS-based Statewide Integrated Model (SWIM) used in Oregon, USA (Versions 2 and 2.5), and the PECAS-based freight model applied in Alberta, Canada [43,44]. PECAS has also been employed in developing statewide transportation and land-use systems for Ohio and Oregon, along with urban land-use models in cities such as Calgary, Edmonton, Caracas, Wuhan, Shanghai, Guangzhou, and Mumbai [45]. The Quick Response Freight Manual of the US department of transportation, used in the Phoenix Metropolitan Area, estimates truck traffic based on employment-related trip-generation rates. However, its default parameters may not be easily transferable between regions, and its focus on vehicle trips rather than commodities may not capture the underlying economic supply and demand dynamics [8].

In the realm of interregional trade flows, gravity models have received significant attention because of their simplicity and effectiveness in estimating such flows even with missing data [46,47]. Ramos and Sargento [16], Sargento et al. [14], Lindall et al. [17], and Nakano and Nishimura [48] exemplify the utility of the gravity model for estimating commodity flows. Moreover, the development of interregional social accounting matrices for comprehensive regional analysis, as undertaken by Jackson et al. [49] using IMPLAN and commodity flow data from the U.S. Bureau of Transportation Statistics, illustrates the integration of detailed economic and transportation data to enhance the understanding of regional dynamics. Park et al. [19] presented a two-step approach to estimate US trade tables between all 50 states plus Washington, D.C., and the rest of the world as the basis for a new MRIO model. Sargento et al. [14] studied three different interregional trade estimation methodologies: a gravity model with an arbitrarily set distance decay parameter, a proportional flow model, and a gravity model with an estimated distance decay parameter. They found that a gravity-based model with an estimated distance decay parameter yielded the most accurate results.

Recent research has made strides to improve multimodal freight OD estimation techniques. Kalahasthi et al. [33] proposed a synthesis model that integrates trip distribution, mode choice, and empty trip estimation for freight. Osorio-Mora, et al. [50] introduced a mixed-integer linear programming model for multimodal, multi-commodity hub location problems by incorporating OD flows as decision variables. Uddin, et al. [51] developed a stochastic freight traffic assignment model that accounts for uncertainties in large-scale intermodal networks caused by disruptions such as natural disasters. Thoen, et al. [52] developed a shipment-based model for tour formation, using an iterative algorithm with incremental allocation of shipments. Yamaguchi et al. [53] presented a global logistics intermodal network simulation model that incorporated land transport submodules using incremental assignment methods. Xia and Ma [54] introduced a multimodal multi-commodity transportation network model for the strategic planning of freight flows, focusing on spatial price equilibrium and network equilibrium. Jain et al. [55] explored perspectives on rail-truck multimodal freight collaboration and online exchange platforms for matching supply and demand in multimodal services. Pompigna and Mauro [56] developed macro-level IO models for freight transport demand analysis, linking the flow of goods transported along a multimodal corridor at the broader economic system.

In summary, existing freight demand studies often focus on a single province or urban areas, specific commodities (such as cereal grains), or multimodal transportation models restricted to individual planning units, frequently overlooking adjacent regions and international trade corridors [7,25]. This represents a critical gap in the literature, as provinces operate within a broader, interconnected logistics network, where the production and flow of goods in one region can be vital to industries in another. Neglecting these external interactions may lead to underestimating freight demand, potentially undermining transportation planning and infrastructure development strategies [6,25]. To address this, this study proposes a novel framework for estimating intra-regional and international commodity flows (imports and exports), linked through a two-tier multimodal transportation super network. This framework aims to estimate regional and interregional OD flows more accurately for the key commodities involved in long-distance transport. By leveraging big data technology, this integrated approach offers a robust tool for generating precise freight OD estimates and improving the understanding of complex flow patterns.

3. Methodology

The development of sophisticated freight demand models remains a challenging task worldwide due to the scarcity of data, theoretical frameworks, and specialized expertise [57]. Freight modeling often resorts to simplistic methods, such as assuming that freight trips follow the same behavioral patterns as passenger trips, which overlooks key differences in the movement patterns and economic drivers of freight transportation [5,6]. Moreover, existing time-series models fail to capture spatial interactions, which are crucial for freight movement across regions [58]. Current approaches, including FSM, often simulate transportation and land-use in isolation, resulting in a static representation that does not reflect the dynamic interplay between transportation systems and broader economic activities [45]. Although logistics and tour-based models have improved accuracy at the local level, they struggle to predict flows at the network level, limiting their applicability in multiscale contexts [8]. In addition, tour-based models rely on survey data, which can be expensive and labor-intensive, thus presenting challenges for their widespread adoption. A review of the literature indicates that no single model can fulfill all the objectives of freight OD demand [5,58]. Each model has its specific strengths and limitations, making the selection of a model crucial, depending on the context, availability, quality of data, and goals of the study [10].

Recent advancements in freight modeling have shifted towards integrated approaches, which offer a more nuanced understanding of freight flows by combining multiple data sources and modeling techniques [45,59]. Therefore, this study proposes an integrated framework to estimate freight flows at multiple scales, including regional and international (imports and exports) levels using multisource data. The primary research steps are as follows:

Step 1: Estimate Intra-regional Commodity-Specific OD

The PECAS activity allocation (PECAS AA) model is used to estimate the OD matrices at the Traffic Analysis Zone (TAZ) level, which corresponds to the counties and districts within a region. The PECAS AA model can be understood as the aggregate result of a joint choice model involving decisions regarding location, production, consumption, and trade destinations for households, businesses, and other institutions. This approach aligns with the principles of micro-simulation for both businesses and households. Additionally, if prices are adjusted over time in response to excess demand (rather than forcing excess demand to zero within each period), the PECAS AA model offers a dynamic representation of the economy consistent with Walrasian economic theory [60]. In this way, PECAS serves as a practical progression toward fully dynamic aggregate models and dynamic micro-simulation models.

Unlike traditional models, the PECAS AA model integrates spatial IO tables with land use and transportation linkages, providing a more accurate spatial representation of freight demand. Drawing from models such as MEPLAN [61], TRANUS [62], DELTA [63], and UrbanSim [64], PECAS enables the integrated and interconnected allocation of activity quantities based on spatial proximity and accessibility. This integration allows for a detailed spatial analysis, providing insights into the location of production, and exchange and consumption activities, which are often oversimplified in traditional models. Thus, PECAS AA offers a sophisticated method for estimating commodity-specific freight flows within a region [65].

Step 2: Estimate international Commodity-Specific OD

To estimate the commodity OD for international imports and exports from provinces to foreign countries, including international seaport entry–exit points, a gravity model with the zone-pair friction obtained from a multimodal transportation model was used. Gravity models are widely used to estimate interregional trade flows by assuming that trade volumes are proportional to production at the origin, consumption at the destination, and the generalized cost of transportation or other forms of impedance between regions. This method is particularly effective for estimating trade flows from provinces to foreign countries, including international seaport entry–exit points [46].

Step 3: Load OD Matrices onto Multimodal Transportation Network

The OD matrices obtained from Steps 1 and 2 are converted from monetary value to tonnage, and assigned to the multimodal transportation supernetwork using the incremental freight assignment method. The model is calibrated using the traffic counts of highways, railways, and port throughput data. In addition, calibration of the trip length distribution for extended regions is achieved by integrating big data sources, including trucks' GPS data, railways waybills, and ship visas. The adoption of big data in transport and logistics sectors can lead to operational improvements and new business values [66].

Data from multiple sources are utilized to estimate both regional and international import/export freight flows. Intra-regional OD estimates are conducted at TAZ levels (district and county), and international import/export estimates are derived from regional zones to international seaport zones. The control totals are used as checks at various points during the process to ensure accuracy and consistency. The PECAS software package (licensed under the Apache License version 2.0.) (https://www.hbaspecto.com/, accessed on 23 September 2024) is used for the activity allocation model, and its results are linked to the Cube Voyage software (Version 6.5.1) (https://www.bentley.com/software/openpaths, accessed on 23 September 2024) for multimodal transportation super network simulation. Additional tools including ESRI's ArcGIS 10.8 for spatial analysis (www.esri.com, accessed on 23 September 2024), Python 3.8 (https://docs.python.org/3.8/, accessed on 23 September 2024), and Microsoft Excel (Microsoft 365) for data processing are used. The overall framework is illustrated in Figure 1, which provides a schematic overview of the proposed integrated approach.

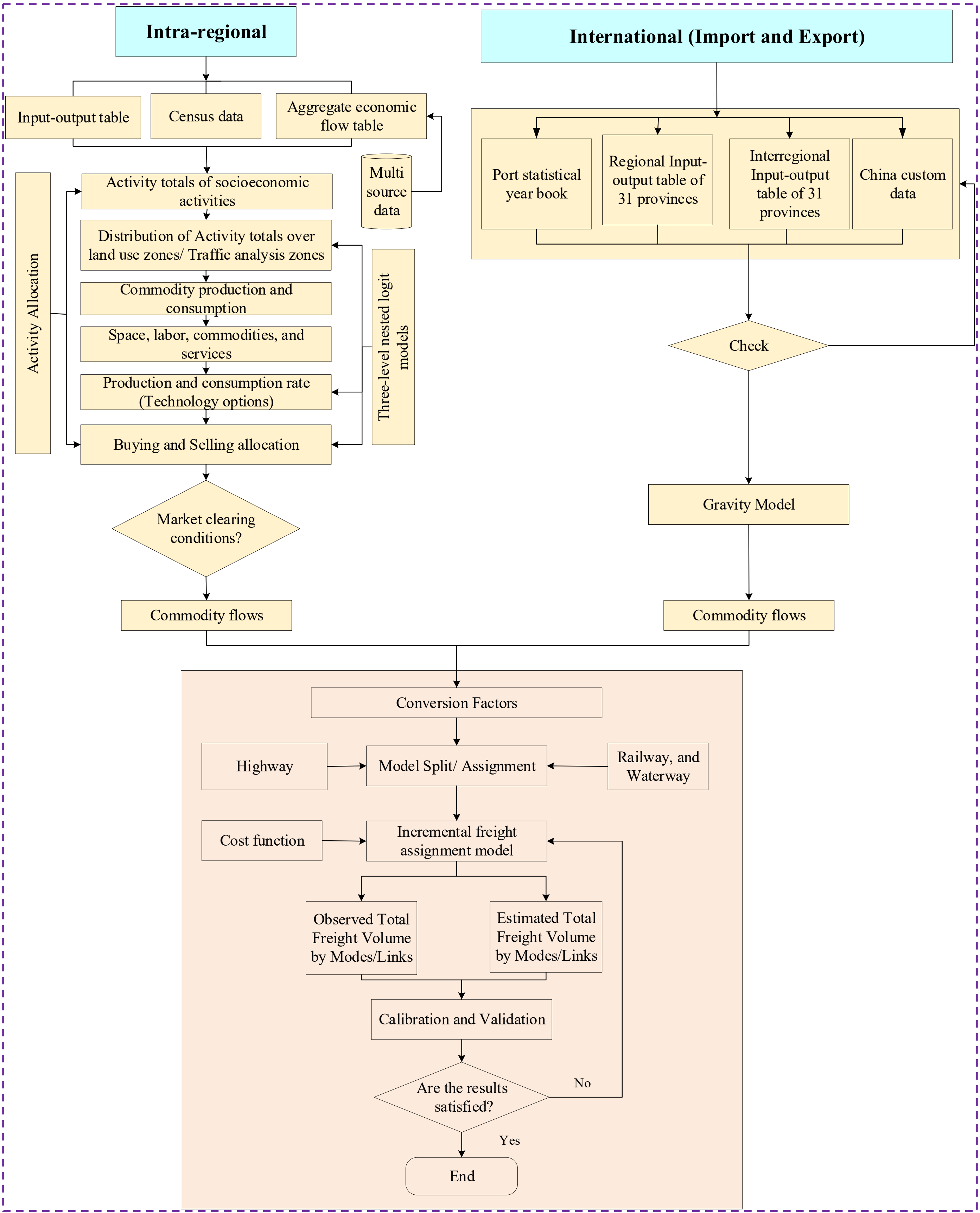

Figure 1. Workflow of the integrated framework for estimation of freight OD flows of regional and international import and export flows.

4. Case Study

This study applies the proposed integrated framework to Jiangxi Province as a case study. Owing to globalization, economic reforms, and the opening-up policy, import and export activities have significantly increased at major ports in Mainland China, particularly in Jiangxi Province. In 2005, Jiangxi's GDP was CNY 394.1 billion, with imports and exports totaling CNY 40.7 billion. By 2019, GDP soared to CNY 2.4758 trillion, and the value of imports and exports reached CNY 508.9 billion [67]. These figures highlight the province's continuous economic growth and expanding international trade during the study period, which can be attributed to Jiangxi's strategic location, resource abundance, and diverse industries [24]. Leveraging its economic and geographical significance, the Chinese government initiated the Ganyue Canal or Jiangxi-Guangdong Canal project, spanning 1300 km (with 800 km in Jiangxi province and 500 km in Guangdong province). The Ganyue canal connects two major rivers: the Ganjiang River in Jiangxi and the Beijiang River in Guangdong, with an estimated investment of over CNY 150 billion (21 billion USD) [11,68]. The Ganyue Canal is expected to boost import and export activities in Guangdong and Fujian, which host international waterway ports and extend benefits to Hubei and Hunan provinces, potentially impacting the entire Yangtze River Basin, Pearl River, and global trade [68]. Thus, accurate OD freight distribution is essential to ensure seamless goods flow across interregional and international borders, which is vital for global economic growth, trade, and regional integration.

4.1. Data Sources and Preprocessing

The PECAS AA model for Jiangxi Province relies on multiple datasets, with the primary input derived from the aggregated economic flow (AEF) table, which is an extension of IO tables. These tables reflect the production and consumption relationships among various activities across different commodities. For commodities, the production and consumption quantities were directly obtained from the IO table. Labor production quantities were estimated using the number of households from the Jiangxi Statistical Yearbook, and the labor compensation data from the IO table. Labor consumption, on the other hand, was allocated to each activity based on labor compensation values from the same IO tables [69]. Space consumption quantities were calculated using employment data and space-use coefficients sourced from related studies [67], and were estimated using remote sensing data.

To ensure the consistency and accuracy of the input data for the PECAS AA model, a rigorous data preprocessing protocol was followed. In Jiangxi Province, two versions of IO tables are available—one with 139 activities and another with 42 activities. We adopted the 42-activity format for its simplicity, while certain sectors were further subdivided based on a more detailed 139-activity table to align with the specific requirements of the PECAS AA model. Sectors corresponding directly to the 42-activity format were used as-is, while others were subdivided based on weights derived from the 139-activity format. This study addressed data anomalies including missing values, outliers, and extreme observations. To mitigate these issues, this study employed exogenous factors and statistical imputation methods [69]. Specifically, GDP growth rates and total output values of production of corresponding activities from the IO table were utilized to align the data with the original trend of activities in Jiangxi province.

Employment data pose formatting challenges, particularly with duplicated county/districts names and administrative codes. These discrepancies were corrected to match the PECAS AA data format and Cube Voyage software requirements. Similarly, the TAZs numbering in the PECAS activity constraints and floorspace files were standardized to align with the TAZ shapefile of the study area, ensuring smooth model execution and avoiding complications.

Transportation network data were obtained from OpenStreetMap (https://planet.openstreetmap.org, accessed on 23 September 2024), however, the extracted network data initially contained discrepancies such as misaligned nodes and links, along with duplicated and dangling links. These issues were addressed through a comprehensive data cleaning process in Cube Voyage and GIS software (ArcGIS 10.8), during which incorrect links were removed, and the actual network structure was reconstructed. Additionally, centroid connectors, which are necessary to link TAZs to the transportation network, were generated using Cube Voyage software as they were not provided by OpenStreetMap.

(1) ***Economic Data:*** Economic data for Jiangxi Province were obtained from multiple sources. These include the Jiangxi Statistical Yearbook (2010–2020) and regional IO tables (2012–2017), available from the Jiangxi Statistical Department (http://tjj.jiangxi.gov.cn/col/col38595/index.html, accessed on 23 September 2024). Additionally, the Interregional IO tables for 2012 were sourced from China's National Statistics Bureau (https://data.stats.gov.cn/, accessed on 23 September 2024), along with demographic data from the 2012 national population census. Employment survey data for 2012 were obtained from China's National Data (https://data.stats.gov.cn/english/index.htm, accessed on 23 September 2024), and the China Labor Statistical Yearbook (2010–2020) (https://www.chinayearbooks.com/tags/china-labour-statistical-yearbook, accessed on 23 September 2024). The regional macroeconomic data incorporate data on population, households, and employment, with regional IO tables compiled for China's 31 provinces based on the 2012 base year (http://www.shujuku.org/, accessed on 23 September 2024).

(2) ***Land Use Data:*** The land use data for Jiangxi Province models incorporating space price data, TAZs, land regulatory data, floor space data, space use coefficients, floor area ratios [67], and remote sensing data were sourced from the Institute of Geographic Sciences and Natural Resources Research of the Chinese Academy of Sciences resources (http://www.igsnrr.cas.cn, accessed on 23 September 2024), and China's environmental data (http://www.resdc.cn/Datalist1.aspx, accessed on 23 September 2024).

(3) ***Multimodal Transportation Data:*** Data for developing multimodal transportation in Jiangxi Province and extended region models were sourced from the China Transportation Statistical Yearbook 2012, the China Customs Statistical Yearbook 2012, and datasets on highways, railways, and waterway networks. These data include highway traffic surveys, railway freight volumes, and port inflow and outflow data. The highway network data covering various road types and tolls were extracted from OpenStreetMap (https://planet.openstreetmap.org, accessed on 23 September 2024). Waterway network data, including navigable waterways, locks, and ports, along with railway network data consisting of railway lines and stations, were sourced from the ArcGIS Online database. This study also integrated cargo reloading times, personnel salaries, freight rates, and monetary values from a multimodal transportation model, including the unit weight values of goods and transport-related socioeconomic activities from the China Customs Statistical Yearbook (http://www.customs.gov.cn/customs/302249/zfxxgk/2799825/302274/tjfwzn/2319672/index.html, accessed on 23 September 2024). Additionally, it encompasses vessel traffic flow, freight data, customs import/export data, port data, truck GPS, railway waybills, ship visas, and navigation-lock data.

4.2. Intra-Regional Commodity OD

In the intra-regional model, the Jiangxi region was selected as a case study and divided into 99 TAZs, corresponding to the province's district and county boundaries (Figure 2). These TAZs were used to estimate the intra-regional freight OD demand using the PECAS AA model [65]. The PECAS AA model identifies optimal activity locations, technologies used, purchasing inputs, and selling outputs under equilibrium conditions. It employed a three-level nested logit model based on the stochastic utility-based framework developed by Hunt and Abraham [65]. The highest layer distributes regional socioeconomic activities across TAZs; the middle layer allocates specific activities to intra-regional zones based on technology patterns; and the lowest layer assigns commodities and services to exchange locations using two logit models where they are bought and sold. The PECAS AA model models exchange zones that serve as markets where commodity supply and demand interact and are influenced by price and transportation impedance.

— *Highest Level:* The highest level allocates the overall activity quantities across specific regional zones (Equations (1) and (2)).

$$W_{a,z} = T_{a\zeta} \cdot \left(\frac{\exp(\lambda_{1,a} \cdot LU_{a,z})}{\sum_{z \in Z} \exp(\lambda_{1,a} \cdot LU_{a,z})} \right) \tag{1}$$

where:

$$\begin{aligned} LU_{a,z} = {} & a_{\text{size},a} \cdot \tfrac{1}{\lambda_{1,a}} \cdot \ln(\text{Size}_{a,z}) + a_{inert,a} \cdot \ln(\text{PrevW}_{a,z} + \text{InertCons}_{a}) \\ & + \text{Const}_{a,z} + \sum_{v \subset V} (a_{a,v} \cdot X_{v,z}) + a_{\text{tech},a} \cdot \text{CUTech}_{a,z} \end{aligned} \tag{2}$$

where the location utility for a unit of activity a in zone $z(LU_{a,z})$ is calculated as a combination of various factors, including the size term ($\alpha_{\text{size},a} \cdot \frac{1}{\lambda_{1,a}} \cdot \ln(\text{Size}_{a,z})$) accounts for the influence of the zone's size, $\lambda_{1,a}$ is the utility function dispersion parameter for allocation of activity a among location zones, and $\text{Size}_{a,z}$ represents relative size of zone z for activity a, the previous quantity term ($\alpha_{\text{inert,a}} \cdot \ln(\text{Prev } W_{a,z} + \text{InertCons}_{a})$), a constant specific to the zone (Const $\text{Con}_{a,z}$), with $\alpha_{\text{inert,a}}$ representing the sensitivity to the previous amount of activity in zone z, and InertCons reducing this effect when the previous quantity is small, other zonal attributes $\sum_{v \subset V} a_{a,v} \cdot X_{v,z}$), with v is the index of the other zonal attributes, V is the set of all other zonal attributes, and $X_{v,z}$ is one of the other zonal attributes, and the composite utility of technology options ($\alpha_{tech,a} \cdot \text{CUTech}_{a,z}$), with $\alpha_{tech,a}$ representing the sensitivity to the technology choices for activity a in zone z. The quantity of activity a in zone $z(W_{a,z})$ is then determined by the total activity $T_{a\zeta}$ allocated to the zones.

— *Middle level:* The middle level distributes activity quantities within each regional zone based on the technology options that determine the production and consumption rates of commodities. Each technology option represents a distinct production and consumption rate for different goods (Equations (3) and (4)).

$$\text{Tech}_{p,a,z} = W_{a,z} \cdot \left(\frac{\exp\left(\lambda_{pa} \cdot \text{UTech}_{p,a,z}\right)}{\sum_{p \in p_a} \exp\left(\lambda_{p,a} \cdot \text{UTech}_{p,a,z}\right)} \right) \tag{3}$$

$$\text{UTech}_{p,a,z} = \frac{1}{\lambda_{p,a}} \cdot \ln\left(\text{OpSize}_{p,a}\right) + \text{UProd}_{p,a,z} + \text{UCons}_{p,a,z} \tag{4}$$

where $\text{Tech}_{p,a,z}$ is the quantity of activity a in zone z applying technology option p; $W_{a,z}$ is the total activity a in zone z; $\lambda_{p,a}$ is the utility function dispersion parameter; $\text{UTech}_{p,a,z}$ is the technology utility of activity a in zone z applying technology option p; $\text{OpSize}_{p,a}$ is the relative size of technology option p for activity a, and $\text{UProd}_{p,a,z}$ and $\text{UCons}_{p,a,z}$ are the utilities from the production and consumption of commodities, respectively.

— *Lowest Level:* The lowest level allocates commodities among exchange locations where they are bought and sold. This involves two logit allocations per commodity in each zone, one for selling and one for buying. The exchange locations are influenced by prices and transportation impedance (Equations (5) and (6)).

$$\text{S}_{\text{c,z,k}} = \text{TP}_{\text{c,z}} \cdot \left(\exp(\lambda_s^c \cdot SU_{c,z,\text{k}}) / \sum\nolimits_{\text{k}} \exp(\lambda_s^c \cdot \text{SU}_{\text{c,z,k}}) \right) \tag{5}$$

$$\text{B}_{\text{c,z,k}} = \text{TC}_{\text{c,z}} \cdot \left(\exp(\lambda_b^c \cdot BU_{c,z,k}) / \sum\nolimits_{\text{k}} \exp(\lambda_s^c \cdot BU_{c,z,k}) \right) \tag{6}$$

where $S_{c,z,k}$ is the quantity of commodity c produced in zone z and allocated for sale at exchange location k, based on total production $TP_{c,z}$ and selling utility $SU_{c,z,k}$, with normalization across all exchange locations. Conversely, $B_{c,z,k}$ represents the quantity of commodity c consumed in zone z and allocated for purchase from exchange location

k, using total consumption $TC_{c,z}$ and the buying utility $BU_{c,z,k}$, also normalized across exchange locations. λ_s^c and λ_b^c are the utility function dispersion parameters for selling and buying commodity c, respectively.

The PECAS AA model uses several key input parameters to adjust and improve the performance of the model. These parameters include dispersion parameters for buying (λ_b^c) and selling (λ_s^c), from the nested logit model, constants of the discrete choice model, and option weights that adjust the sizes of technology options ($\mathrm{OpSize}_{p,a}$) within the nested logit model [60,67]. Adjustments to these parameters are made iteratively to ensure that the model closely aligns with base-year production data as accurately as possible [60]. In the PECAS AA model, exchange zones represent markets where total supply—comprising both selling allocations and imports, which respond to fluctuations in exchange prices—meets total demand, consisting of buying allocations and exports. The algorithm works to find an equilibrium by adjusting the exchange prices within each zone until all markets reach equilibrium (Equations (7) and (8)).

The equilibrium solution is sought through a series of iterations, with this study considering a total of 3000 iterations. During each iteration, allocations are determined based on the current prices, which are subsequently updated according to the resulting supplies and demands. The algorithm calculates the partial derivatives of the total excess demand—defined as the surplus of demand by buyers and exporters over supply from sellers and importers—in each exchange zone with respect to the price in that specific zone. The derivatives with respect to prices in other zones or for other commodities are assumed to be zero, and the price change is then calculated [65].

To enhance the convergence, a step adjustment factor is used. If a price change reduces the total sum of the squared excess demand, the adjustment factor is slightly increased for the next iteration. Conversely, if the price change leads to an increase in excess demand, the adjustment is discarded, the factor is significantly reduced, and a smaller adjustment is applied in its place. This iterative process helps refine the equilibrium and improve the accuracy of the model's predictions [60,65].

$$\mathrm{TE_{c,k}} = \mathrm{TDem_{c,k}} = \mathrm{TSup_{c,k}} \tag{7}$$

— $\mathrm{TE_{c,k}}$ = exchange quantity for commodity c in exchange zone k;
— $\mathrm{TDem_{c,k}}$= aggregate demand for commodity c in exchange zone k for all activities in the model area;
— $\mathrm{TSup_{c,k}}$ = aggregate supply of commodity c in exchange zone k for all activities in the model area.

$$\mathrm{Residual_{c,k}} = \mathrm{TSup_{c,k}} - \mathrm{TDem_{c,k}} \tag{8}$$

$\mathrm{Residual_{c,k}}$ = residual surplus quantity of supply over demand for commodity c in exchange zone k.

In theoretical equilibrium, the residual surplus for all commodities and exchange zones should be zero. In practice, however, to manage computational efficiency and avoid excessively long runtimes, the iterative process is terminated once the residual values meet the specified convergence criteria. These criteria indicate that the residuals are sufficiently close to zero.

Once this iterative process is completed, the PECAS AA model generates commodities output in the form of Open Matrix (OMX) matrices. These matrices are linked with Cube Voyager software. The monetary flows of the OD matrices are then converted into tonnage. This tonnage of OD matrices is subsequently loaded onto the multimodal transport super network, where it is used for mode and route choice analysis [67].

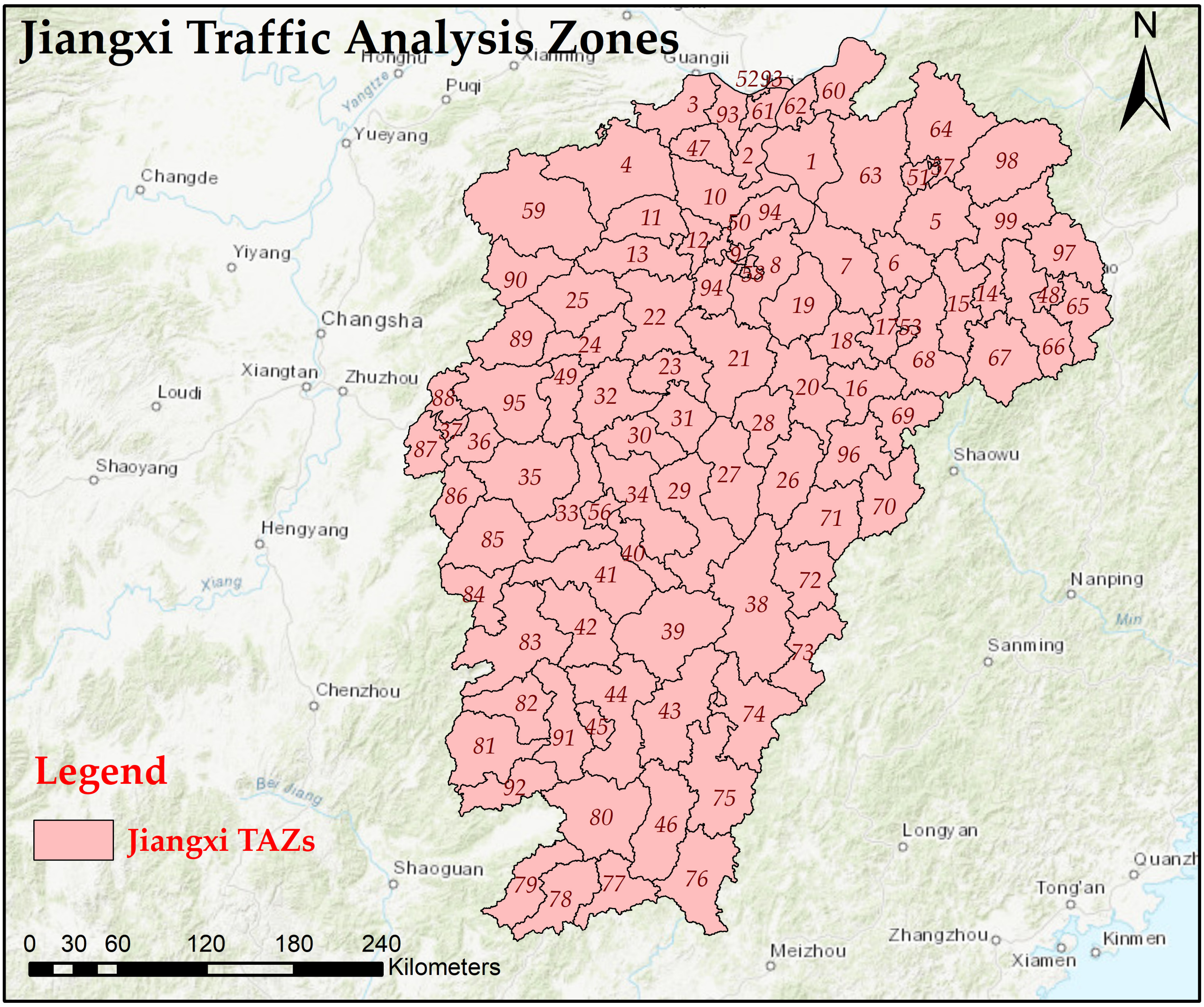

Figure 2. Jiangxi Province traffic analysis zones.

4.3. International (Import and Export) Commodity OD

Freight modeling has traditionally focused on urban areas or single province analyses, particularly in multimodal transportation contexts [70,71]. These studies, however, often neglect the influence of external regions, such as adjacent provinces and international trade corridors, on overall freight demand [25,72]. Therefore, this study expands its scope beyond Jiangxi's intra-provincial freight demand to consider the broader impacts on interregional and international freight transportation, including major import and export nodes such as seaports [73,74]. To estimate international import and export commodity OD matrices, we divided China into three regions [8,23,75].

1. *First Region: Adjacent Provinces (First-Level External TAZs)*

The first region consists of 13 provinces adjacent to Jiangxi, including Hubei, Hunan, Anhui, Zhejiang, Shanghai, Jiangsu, Chongqing, Sichuan, Guangdong, Fujian, Guangxi, Guizhou, and Henan (Table 1 and Figure 3) [68,74]. These provinces were selected due to their direct geographical proximity and their significant trade interactions with Jiangxi. Additionally, their inclusion aligns with the layout of key national railways and waterways, which are essential for medium- and long-distance freight movements. The underlying assumption is that freight follows the most efficient transportation routes, typically via railways and waterways, reflecting the actual interprovincial logistics patterns documented in previous studies [23,76].

2. *Second Region: Outer Combined Provinces*

The second region consists of the remaining provinces of China, which are grouped into seven broader clusters based on historical trade data from China's interregional IO tables and major transportation routes [69,76] (Table 1 and Figure 3). These groups are referred to as outer combined provinces and include Shandong, Hebei (which encompasses Beijing, Tianjin, Hebei, Shanxi, Liaoning, Jilin, and Heilongjiang); Shaanxi (Inner Mongolia, Shaanxi, and Ningxia), and Gansu, Yunnan, Tibet, and Hainan Provinces. The rationale for grouping these provinces is grounded in their historical data and strong economic and transportation linkages to Jiangxi and other provinces. This strategy simplifies the freight OD estimation by reducing the number of individual provinces, ensuring a manageable input while preserving the integrity of major trade corridors.

3. *Third Region: International Import and Export Nodes*

The third region consists of 21 key international seaports, including major export and import nodes along China's southeastern coast, such as Shanghai, Shenzhen, and Ningbo [77,78] (Table 1 and Figure 3). These seaports were selected based on their historical and current importance to international trade, as documented in sources such as the China Transportation Statistical Yearbook and the China Customs Statistical Yearbook [77–79]. These ports are crucial for understanding the interaction between domestic freight movement and international trade, particularly in terms of how goods flow among Jiangxi, other provinces, and global markets.

This categorization aimed to streamline the analysis by focusing on the eight major industries that are crucial to the agricultural and industrial sectors, thereby reducing the number of provinces from 31 to 21. The combination of import and export freight volumes was calculated using Equations (9) and (10), respectively.

$$IMC_{s,k} = \sum_{p \in s} IM_{p,k} \tag{9}$$

$$EXC_{s,k} = \sum_{p \in s} EX_{p,k} \tag{10}$$

where:

— s is one of the first set of combined provinces around a Jiangxi Province;
— k is the type of commodity;
— p is one of the second-set of provinces other than Jiangxi Province;
— $p \in s$ refers to the optimal path from Jiangxi Province to Province P through other provinces;
— IMC is the import freight volume of Jiangxi province after aggregations;
— IM is the volume of imported freight from other provinces to the seven combined provinces in the interregional IO table;
— EXC is the export freight volume of a Jiangxi Province after aggregations;
— EX represents the export freight volume from Jiangxi Province to another province in the interregional IO table.

From the provincial IO tables, we select commodities with inflows and outflows. However, the inflow/outflow and import/export data in the provincial IO table for each province consists of gross values [20]. Therefore, we disaggregated the domestic inflow and outflow using the interregional IO table for the total outputs of agriculture and industry. To achieve consistency with the provincial IO table, the interregional IO table for agriculture and industry was further subdivided into 12 commodities: agriculture (cereal, wood, and other agricultural products) and industry (coal and its products, metallic minerals, non-metallic minerals (salt), oil, gas and its products, cement, chemical fertilizers and pesticides, steel and non-ferrous metals, mineral building materials, and other industrial products). This disaggregation was accomplished by using the ratio of the corresponding activities in each province, as shown in Equations (11) and (12). From the interregional IO table, the ratio of imports and exports for the specified commodity among provinces is calculated as the value of the commodity imported or exported from province i to province j, divided by the total value of the corresponding commodity [8,23].

Through this process, the flow of commodities from a specific province to the first set of adjacent provinces could be determined.

$$IM_{ij}^{q} = \alpha_j \times IM_{ij}^{k} \quad (11)$$

$$EX_{ij}^{k} = \alpha_i \times EX_{ij}^{k} \quad (12)$$

where:

- IM_{ij}^{k} is the import flow of commodity q from province i to j after splitting the interregional gross value of commodity k (q = (1,2,3 for agriculture and 4–12 for industry), (k = agriculture and industry).
- EX_{ij}^{k} is the export flow of commodity q from province i to j after splitting the interregional gross value of commodity k (q = (1,2,3 for agriculture and 4–12 for industry), (k = agriculture and industry).
- α_j, and α_j are the inflow and outflow ratios of the corresponding province from MRIO.
- IM and EX are the total of IO table import and export of different commodity k.

To model freight flows between provinces and international markets, including seaport entry and exit points, we employed a gravity model [46]. Initially, an AEF table was developed using an interregional IO table to quantify commodity values (in 10,000 yuan/year). These values were then converted into freight volumes (tons/year) using conversion factors from previous studies [67]. This study focuses on 21 major southeast coastal ports, identified from the China Transportation Statistical Yearbook, which play a critical role in the trade network (see Table 1 and Figure 3). Given the prominence of railway and maritime routes for international trade, these ports serve as primary hubs for imports and exports [80]. Furthermore, an external zone was established for each port to facilitate the management of its interactions with foreign imports and exports, integrating the connectivity of each port to this zone and the allocation of imports and exports. An integrated transportation supernetwork was developed, incorporating physical networks—highway, railway, and waterway—as well as virtual links and nodes, including connectors, transfer links, and connections between these transportation networks and the TAZ centroids. The supernetwork combines transportation skims, 2012 port throughput data, 2012 IO tables, 2012 AEF table, and conversion factors to compute integrated transportation impedances.

The gravity model estimates OD matrices for trade flows between provinces and international ports, based on the assumption that trade is proportional to production at the origin, consumption at the destination, and the generalized cost of transportation or other forms of impedance between regions [2,18]. Due to differences in routes, costs, and travel times across various transportation modes, generalized costs are applied to adjust the weights accordingly. The generalized cost function incorporates parameters such as transportation distances, times, and costs across three key modes: highway, railway, and waterway [67,69]. These parameters are derived from an integrated multimodal transportation supernetwork developed using the Cube Voyager software, which captures the specific characteristics of each mode and commodity type [69]. The gravity model formulation and generalized cost function are presented in Equations (13) and (14), respectively.

$$q_{ij} = O_i \cdot \frac{D_j \cdot f(c_{ij})}{\sum_{j=1}^{n} D_j \cdot f(c_{ij})} \quad (13)$$

$$f(c_{ij}) = \sum\nolimits_{m=1}^{3} \left(Dis_{ij}^{m} \times KD^{c,m} + Time_{ij}^{m} \times KT^{c,m}\right) \quad (14)$$

where:

- qij is freight flow between province i and port j;

— $f(c_{ij})$ is the generalized transportation cost between the province i and port j, considering the mode-specific distance Dis_{ij}^{m} and time $Time_{ij}^{m}$;
— $KD^{c,m}$ and $KT^{c,m}$ are distance and time cost for commodity c under the mode m;
— Oi and Dj are the freight production and attraction volumes, respectively;
— Dis_{ij}^{m} is the distance between the port i and province j under the mode m;
— n is number of the TAZs.

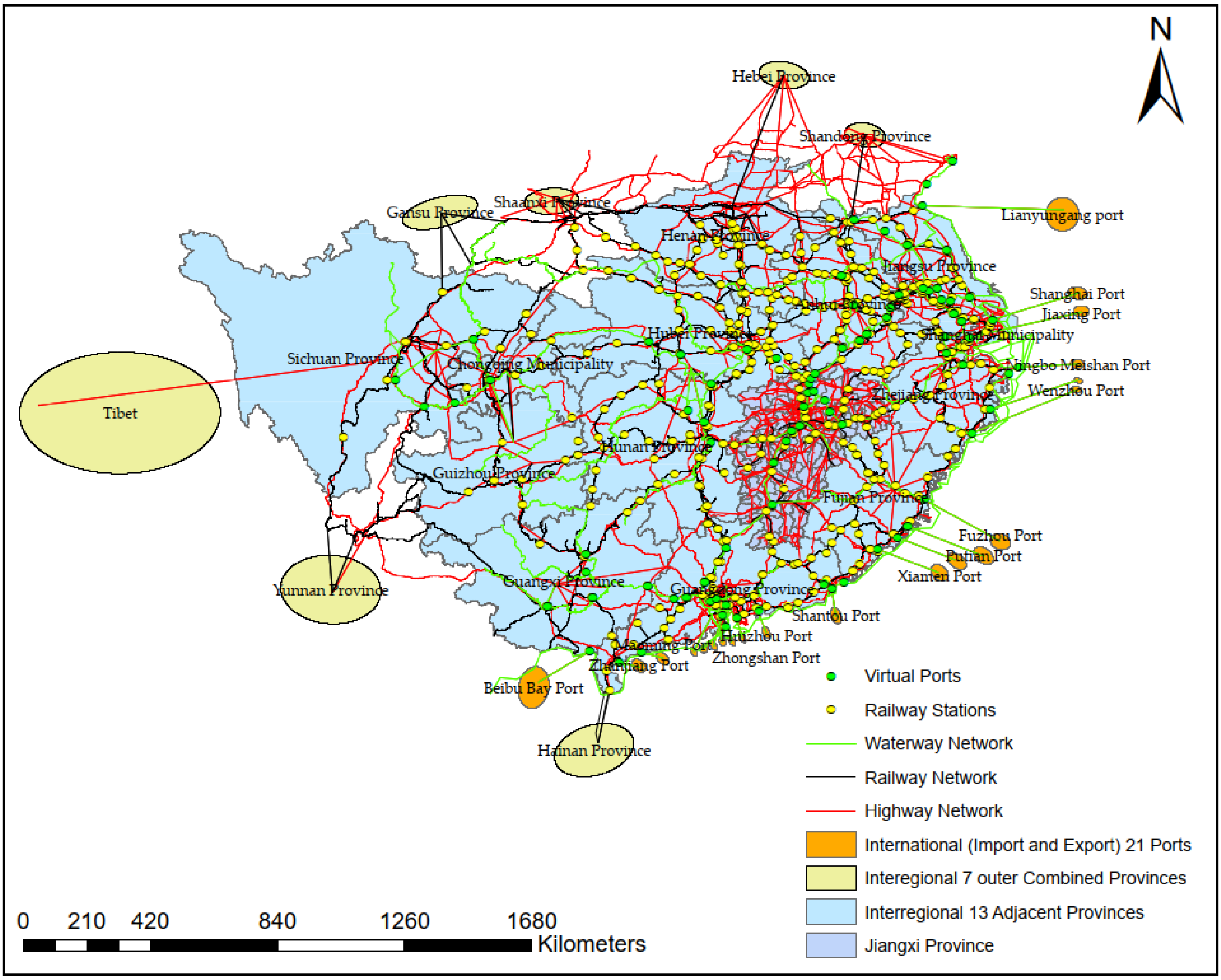

Figure 3. Multimodal transportation network in Jiangxi intra-regional, and international ports.

Table 1. Jiangxi Province and combinations of other provinces and ports.

S. No	Jiangxi Region and Its Adjacent 13 Provinces	Combinations of Provinces	International (Import and Export) Ports
1	Shanghai	Shanghai	Shanghai
2	Jiangsu	Jiangsu	Lianyungang
3	Zhejiang	Zhejiang	Jiaxing, Ningbo–Zhoushan, Taizhou, Wenzhou
4	Anhui	Anhui	

Table 1. *Cont.*

S. No	Jiangxi Region and Its Adjacent 13 Provinces	Combinations of Provinces	International (Import and Export) Ports
5	Fujian	Fujian	Fuzhou, Putian, Quanzhou, Xiamen
6	Henan	Henan	
7	Hubei	Hubei	
8	Hunan	Hunan	
9	Guangdong	Guangdong	Shantou, Huizhou, Shenzhen, Humen, Guangzhou, Zhongshan, Zhuhai, Jiangmen, Maoming, Zhanjiang
10	Guangxi	Guangxi	Beibu Bay Port
11	Chongqing	Chongqing	
12	Sichuan	Sichuan	
13	Guizhou	Guizhou	
14	Hebei	Beijing, Tianjin, Hebei, Shanxi, Liaoning, Jilin, and Heilongjiang	
15	Shaanxi	Inner Mongolia, Shaanxi, and Ningxia	
16	Gansu	Gansu, Qinghai, Ningxia	
17	Shandong	Shandong	
18	Yunnan	Yunnan	
19	Tibet	Tibet	
20	Hainan	Hainan	

4.4. Development of Multimodal Transportation Network

In this study, we developed a multimodal transportation network for Jiangxi Province by integrating highways, railways, and waterways. The planning area was divided into TAZs based on district and county boundaries using GIS spatial operations. The network was built using ESRI's ArcGIS 10.8 (www.esri.com, accessed on 23 September 2024) and Cube Voyager software (https://www.bentley.com/software/openpaths, accessed on 23 September 2024), with shapefiles representing different transportation modes. The network features 20 link function classes across highways, railways, and waterways, reflecting infrastructure types such as motorways, national highways, waterways, and railway lines. The highway network includes expressways, national highways, provincial roads, main roads, and secondary roads. The waterway network comprises navigable waterways, locks, and ports (Jiujiang, Nanchang, Ji'an, and Ganzhou). The railway network includes railway lines and stations. The TAZs are linked to the highway network through centroid connectors, while ports and railway stations are connected to their respective networks (waterways and railways) via virtual intermodal links. These virtual links are crucial in representing the multimodal interactions between freight modes, allowing seamless transitions between highways, railways, and waterways. Furthermore, virtual transfer links are used to simulate multimodal transfers, creating an integrated supernetwork that supports the efficient modeling of multimodal freight flows [81]. Figure 4 shows the structure of the Jiangxi multimodal transportation network.

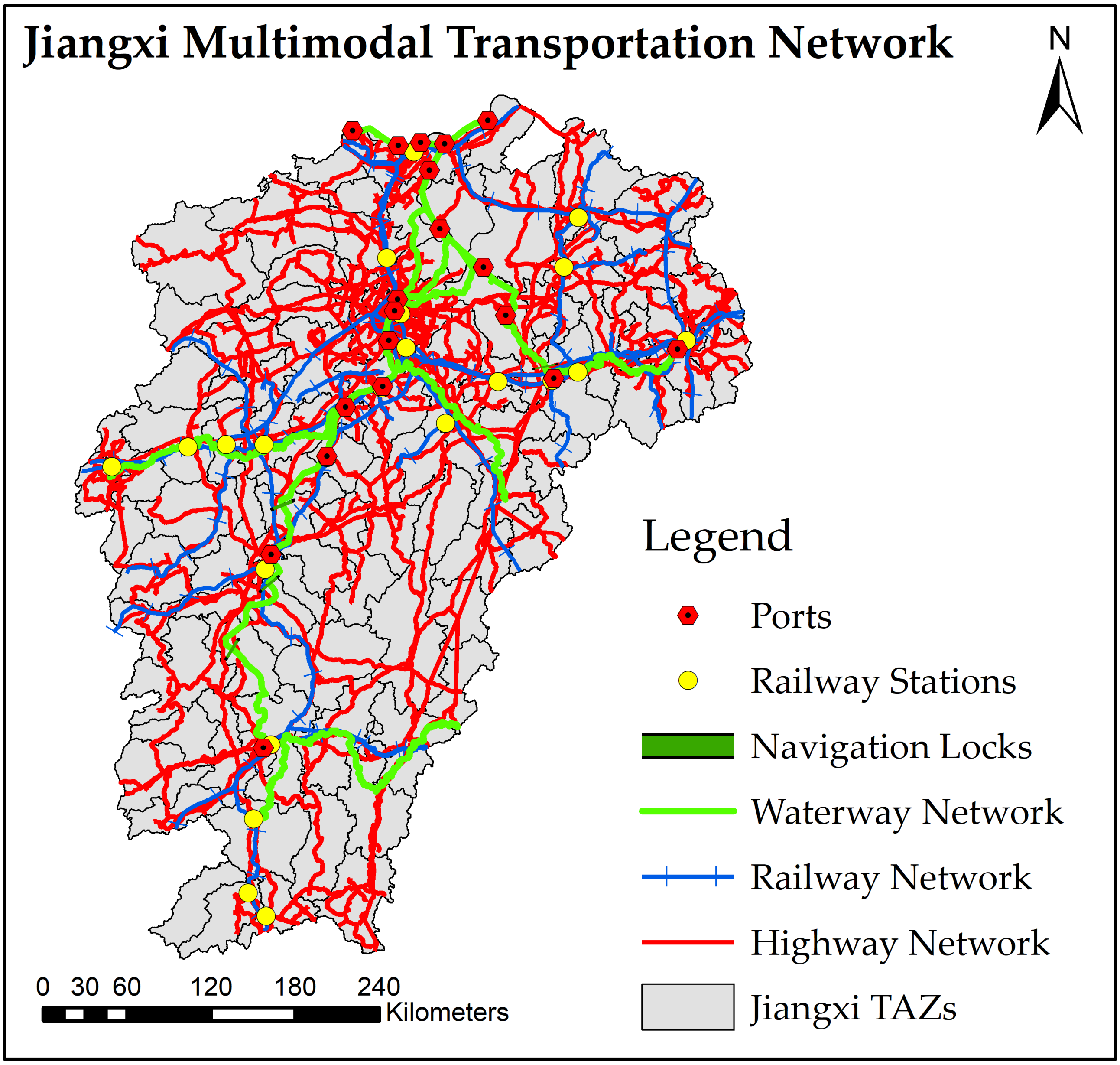

Figure 4. Multimodal transportation network in Jiangxi province.

Development of Multimodal Incremental Freight Assignment Model

This study developed a multimodal incremental freight assignment method for highways, railways, and waterways following the methodology outlined by Yamaguchi et al. [53] (Figure 5). Incremental freight assignment assigns traffic volumes across multiple steps. In each step, a fixed proportion of the total demand is assigned to the network using an all-or-nothing approach. After each step, the link travel times are recalculated based on the updated traffic volumes, ensuring that the congestion effects are captured progressively. This method iteratively allocates freight flows to the optimal paths by minimizing composite costs, which include loading costs, transfer fees, and an alternative specific constant (ASC) term (Equation (15)). A multimodal network incorporates different cost functions for highways, railways, and waterways, each with mode-specific impedance functions. For highways, the Bureau of Public Roads (BPR) function models the relationship between the road travel time and traffic flow [82], as shown in Equation (16). For railways, a modified Davidson function accounts for the capacity constraints and congestion effects on rail travel times (Equation (17)). For waterways, travel times are calculated based on path length, vessel speed, and additional factors influencing waterborne transport (Equation (18)). The ASC term is used to aggregate the link-specific values for each mode, ensuring that all relevant costs are captured. The freight flows are assigned across the super network, respecting capacity constraints, and link travel times are recalculated iteratively until all demands are fully allocated. The final freight assignment considers the interaction between different modes, the costs of mode transfers, and the congestion effects on each network link. To evaluate the performance of the model, we employed standard goodness-of-fit metrics, including the coefficient of determination (R^2) and relative error (RE), as given in Equations (19) and (20), respectively.

$$\begin{aligned} C_{ij}^{(c,r)} = \textstyle\sum_{(a,b)}^{d} \left(t_{ij}^{(c,r)} \times \mathrm{LF}_{ab}^{c}\right) + \textstyle\sum_{(k,l)}^{n} \left(t_{ij}^{(c,r)} \times L_{kl}^{(c,m)} \times \mathrm{F}^{(c,m)}\right) \\ + \textstyle\sum_{(o,p)}^{q} \left(t_{ij}^{(c,r)} \times \mathrm{TF}_{op}^{(c,\mathrm{FT})}\right) \\ + t_{ij}^{(c,r)} \times \mathrm{VPT}^{c} \times \tfrac{\mathrm{ROR}_t}{365\times 24} \\ \times \left[\textstyle\sum_{(a,b)}^{d} \mathrm{LT}_{ab}^{c} + \textstyle\sum_{(k,l)}^{n} T_{kl}^{(c,m)} + \textstyle\sum_{(o,p)}^{q} \mathrm{TT}_{op}^{(c,\mathrm{FT})}\right] + ASC \end{aligned} \tag{15}$$

where;

- $C_{ij}^{(c,r)}$ denotes the cost function of commodity c from zone i to zone j via path r; note : a given OD pair may have multiple valid paths, so $\mathrm{r} \in \mathrm{R}$;
- $\mathrm{LF}_{(ab)}^{(c)}$ is the cost per ton for loading commodity c on $transfer$ $\mathrm{arc}(a,b)$;
- $F^{(c,m)}$ represents the cost per kilometer (RMB/km) for transporting c by mode $\mathrm{m} = \text{highway, waterway, and railway}$;
- $t_{ij}^{(c,r)}$ is the weight of c transported via route r in path (i,j);
- $L_{(k,l)}^{(m)}$ is the distance of the road link (k,l) for mode m;
- $\mathrm{LT}_{(a,b)}^{(c)}$ is the loading time (hours) on $\mathrm{arc}(a,b)$ in path (i,j);
- $T_{(k,l)}^{(c,m)}$ is transportation time (hours) spent in passing through the (k,l) arc. Note: this transportation time should be the link (k,l) obtained by the BPR or similar function used by each mode when the flow assigned to a path is $t_{i,j}^{c,r}$ through the network flow distribution (k,l) transportation time on the link;
- $\mathrm{TF}_{op}^{(c,\mathrm{FT})}$ is intermediate unit commodity transfer fee (RMB/ton) for transporting commodity c from zone i to zone j via route r, where the link (o,p) consisting of nodes o and p belongs to path r, and the road link belongs to the transit link;
- $\mathrm{TT}_{op}^{(c,\mathrm{FT})}$ is the intermediate transfer time (hours);
- VPT^{c} is the value of commodity c;
- ROR_t is the annualized rate of return;
- ASC is the alternative specific constant term.

$$\begin{cases} t_{s,l}^{c,H} = \frac{t_{s,l}^{c,H}(0)}{\alpha_1} \cdot \left[1 + \left(q_{s,l}^{c,H} / C_{s,l}^{H}\right)^{\beta}\right] \\ \beta = \alpha_2 + \alpha_3 \cdot \left(q_{s,l}^{c,H} / C_{s,l}^{H}\right)^{3} \end{cases} \tag{16}$$

where:

- $t_{(s,l)}^{(c,H)}$ is the travel time (hours) for commodity c on highway (H) link (s,l).
- $t_{(s,l)}^{(c,H)}(0)$ is the free-flow travel time (hours) for commodity c on highway link (s,l).
- α_1 is a scaling factor;
- $q_{(s,l)}^{(c,H)}$ is the flow of commodity c on highway link (s,l).
- $C_{(s,l)}^{H}$ is the capacity of highway link (s,l)
- β determines the rate at which the travel time (hours) increases with traffic-flow approach capacity;

— α_2 and α_3 are additional parameters.

$$t_{s,l}^{c,R} = t_{s,l}^{c,R}(0)\cdot\left[1 + \xi\cdot\left(\frac{q_{s,l}^{c,R}}{C_{s,l}^{c,R} - q_{s,l}^{c,R}}\right)\right] \tag{17}$$

where:

— $t_{(s,l)}^{(c,R)}$ is the travel time (hours) for commodity c on railway (R) link (s,l);
— $t_{(s,l)}^{(c,R)}(0)$ is the base (free-flow) travel time (hours) for commodity c on the railway link (s,l);
— ξ is a parameter representing the impedance factor, which influences the rate at which travel time (hours) increases with congestion;
— $q_{(s,l)}^{(c,R)}$ is the flow (or demand) of commodity c on railway link (s,l) during period R;
— $C_{(s,l)}^{(c,R)}$ is the capacity of railway link (s,l) for commodity c.

$$t_{e,g}^{c,W} = \sum_{f_y\in(e,g)} \frac{L_{f_y}^{c,W}}{V_{f_y}^{c,W}} + B_{e,g}\cdot t_0 \tag{18}$$

where:

— $t_{(e,g)}^{(c,W)}$: Travel time (hours) for commodity c on waterway (w) link (e,g);
— $\sum_{f_y\in(e,g)}$: Summation over all paths f_y from node e to node g;
— $L_{(f_y)}^{(c,W)}$: Length of path f_y for commodity c in the waterway;
— $V_{(f_y)}^{(c,W)}$: Flow of commodity c on path f_y in the waterway;
— $B_{(e,g)}$: Bias term representing additional time not accounted for by the path length or flow.
— t_0: Base (free-flow) travel time (hours) on the waterway link.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \grave{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overleftharpoon{y})^2} \tag{19}$$

$$\mathrm{RE} = \left|\frac{\grave{y}_i - y_i}{y_i}\right| \times 100 \tag{20}$$

where;

— $\grave{y}_i$ is the estimated value of the ith observation;
— y_i is the observed value for the i-th observation;
— $\overleftharpoon{y}$ is the mean of the observed values.

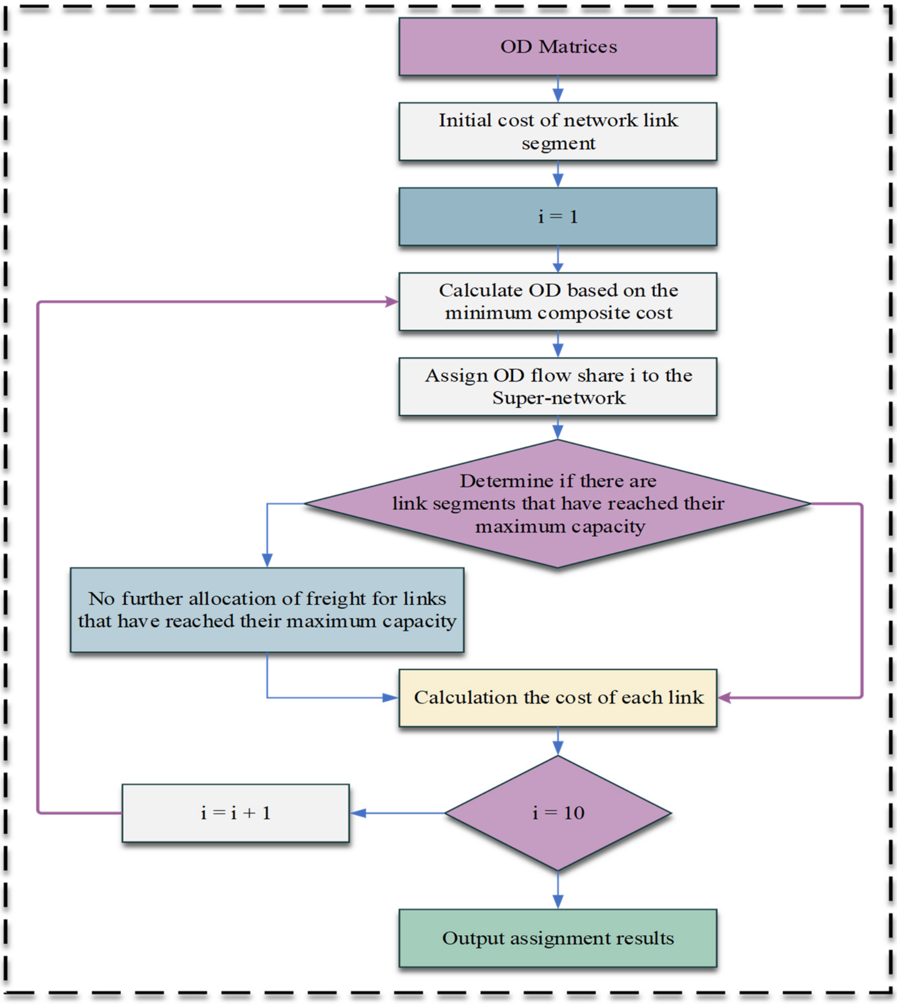

Figure 5. Schematic diagram of the incremental freight assignment method.

5. Results and Discussion

This study proposed an integrated framework for estimating the OD matrices of multimodal, multi-commodity freight flows in regional and international import/export contexts. The integrated framework was implemented and tested in a case study of Jiangxi Province.

5.1. Results of Regional and International Multi-Commodity OD Flows

This section presents an analysis of the OD flows of key commodities in the regional, interregional, and international contexts. Commodities analyzed included cereal, wood, agricultural products, coal and its products, metallic minerals, non-metallic minerals (salt), oil and gas and their products, cement, chemical fertilizers and pesticides, steel and non-ferrous metals, mineral building materials, and other industrial products. The flows were visualized using Python 3.8 and ArcGIS 10.8, providing critical insights into the spatial distribution of these commodities. The findings highlight the interconnectedness of the Jiangxi regional economy, as well as the role of major ports and provinces in facilitating both domestic and international trade.

1. **Cereal**

The OD analysis of cereal commodity domestic inflows/outflows and foreign imports/exports yields significant findings (Figure 6a). Shandong Province is the largest importer, receiving 64,068 tons/day of cereals from Hebei Province. Furthermore, Zhejiang imports 17,593 tons/day and Henan imports 17,138 tons/day, mainly from Hebei. Guangdong imports 8332 tons/day from Guangzhou Port and 7328 tons/day from Beibu Bay Port. Similarly, Jiangsu imports 5512 tons/day from Guangzhou Port and 4812 tons/day from Beibu Bay Port. Conversely, Hebei is the primary exporter, dispatching 17,161 tons/day to Shaanxi Province. Additionally, Guangdong exports 82 tons/day to Beibu Bay Port, while Jiangxi exports 50 tons/day to Beibu Bay Port. The OD results indicate that Ports such as Guangzhou and Beibu Bay play pivotal roles, serving as gateways for cereal imports into Guangdong and Jiangsu. The dominance of Hebei as a central player in the cereal trade aligns with its strategic geographic position and extensive agricultural production capacity. This pattern underscores the region's critical role in balancing the cereal demand across different provinces, while ports in southern China, such as Guangzhou, strengthen international trade linkages [83,84].

2. **Wood**

The OD analysis of wood commodities revealed significant findings regarding domestic inflows/outflows and foreign imports/exports (Figure A1a, Appendix A). Shandong Province is the leading importer, receiving 25,830 tons/day from Hebei Province, followed by Henan with 6909 tons/day and Guangdong with 6326 tons/day from Hebei. Guangdong imports 3976 tons/day from Beibu Bay Port and 3345 tons/day from Xiamen Port. Shanghai imports 2270 tons/day from Shanghai Port. Hebei Province is a major exporter, sending 6819 tons/day to Shaanxi Province. Fujian exports 4169 tons/day to Lianyungang Port, while Guangdong exports 1606 tons/day to the same port. Guangxi exports 431 tons/day to the Lianyungang Port. The prominence of Hebei as a major supplier reflects its extensive forestry resources, while coastal provinces like Guangdong and Fujian capitalize on port facilities to support both domestic and international wood trade. These patterns align with the existing literature that emphasizes the importance of Hebei and Guangdong in facilitating wood distribution, leveraging their strategic locations and port infrastructure [85].

3. **Other Agricultural Products**

The OD analysis of other agricultural commodities revealed significant findings on domestic inflows/outflows and foreign imports/exports (Figure A1b, Appendix A). Shandong Province is the largest importer, receiving 73,276 tons/day from Hebei Province. Shaanxi and Henan Provinces import 19,627 tons/day and 19,601 tons/day, respectively, from Hebei. Zhejiang Province imports 18,012 tons/day from Hebei Province. Shandong imports 16,129 tons/day from Shaanxi Province. Guangdong Province imports 2469 tons/day from Beibu Bay Port and 2840 tons/day from Guangzhou Port. On the export side, Fujian Province exports 740 tons/day to Beibu Bay port, followed by Guangdong at 299 tons/day and Hubei at 180 tons/day. These findings highlight Hebei's importance in domestic agricultural distribution and the strategic role of Guangdong's ports in facilitating international trade. This analysis underscores the interconnectedness of China's agricultural supply chain, with Hebei as a central supplier, and coastal provinces like Guangdong ensuring the flow of both imports and exports [83,86].

4. **Coal and its Products**

The OD analysis of coal and its products, domestic inflows/outflows, and foreign imports/exports revealed significant patterns (Figure 6b). Hebei Province is the leading importer, receiving 267,482 tons/day from Shaanxi Province. Guangdong imports 52,830 tons/day through Beibu Bay Port, 27,616 tons/day through Guangzhou Port, and 22,937 tons/day through Ningbo Zhoushan Port. Shanghai and Fujian are also importers, with Shanghai importing 22,709 tons/day through its port, Fujian importing 19,923 tons/day from Fuzhou Port, and 17,846 tons/day from Humen Port. Guangxi imports 15,137 tons/day through Beibu Bay Port. Shaanxi Province is a major exporter, sending 254,416 tons/day to Jiangsu Province. Hebei exports 205,604 tons/day to Jiangsu and 118,225 tons/day to Shandong. Shaanxi exports 150,922 tons/day to Shandong and 138,224 tons/day to Zhejiang, while Hebei exports 111,182 tons/day to Zhejiang. Fujian exports 946 tons/day to Shanghai and 462 tons/day to Lianyungang, while Jiangsu exports 209 tons/day to Shanghai. These findings align with a previous study that identified thermal power plants, smelters, ceramic businesses, and non-ferrous metal companies as the major coal consumers in Guangdong Province [68]. Guangzhou Port in Guangdong Province, China's main coal import hub in 2021, highlights its logistical advantage of being almost equidistant between Inner Mongolia's largest coal mines and Indonesia [87].

5. **Oil, Gas, and their Products**

The OD analysis of domestic inflows/outflows, foreign imports, and exports of oil, gas, and their products yields interesting findings (Figure A1c, Appendix A). Guangdong Province imports 249,367 tons/day from Ningbo Zhoushan Port, 72,147 tons/day from Huizhou Port, 54,150 tons/day from Zhanjiang Port, and 42,074 tons/day from Maoming Port. Hebei Province exports 147,792 tons/day to Shandong, 72,225 tons/day to Jiangsu, and 54,514 tons/day to Zhejiang. Zhejiang exports 11,010 tons/day to Ningbo Zhoushan Port, while Hebei sends 5,140 tons/day to Gansu. Fujian Province exports 3160 tons/day to Zhuhai port. The findings highlight the interconnectedness of China's energy supply chain, with Guangdong and Hebei acting as crucial nodes for both imports and exports of oil and gas [88,89]. The strategic role of coastal ports like Ningbo Zhoushan is vital for managing the flow of these critical energy resources.

6. **Metallic Minerals**

The OD analysis of domestic inflows/outflows and foreign imports/exports of metallic mineral commodities yields intriguing findings (Figure 6c). Shanghai imports 94,069 tons/day through the Port of Shanghai. Hebei Province imported 87,430 tons/day from Guangdong Province, underscoring the importance of its supply. Zhejiang Province and Shanghai import 65,753 and 57,276 tons/day, respectively, via Ningbo Zhoushan port, followed by Jiangsu Province with 53,461 tons/day. Hebei Province is a major exporter, sending 265,765 tons/day to Shandong Province, and 211,498 tons/day to Jiangsu Province. Guangdong Province exports 116,793 tons/day to Guangxi Province. Anhui and Hubei Provinces export 45,127 and 41,618 tons/day, respectively, to Jiangsu Province. This analysis highlights the strategic roles of Guangdong in both importing and exporting metallic minerals, with key ports such as Shanghai and Ningbo Zhoushan acting as crucial gateways for these commodities. The trade flows indicate a highly integrated supply chain that is essential for sustaining industrial production across multiple provinces. This flow pattern is consistent with a previous study that highlight the shift of metallic mineral transportation from overland routes to waterway routes, optimizing the use of key ports along the Yangtze River and coastal regions [90].

7. **Non-metallic Minerals**

The OD analysis of domestic inflows/outflows of non-metallic minerals and foreign imports/exports revealed significant findings (Figure A1d, Appendix A). Jiangsu Province imports 197,547 tons/day from Hebei Province, indicating a high demand. Hebei Province exports 49,062 tons/day to Shaanxi Province, 27,950 tons/day to Shandong Province, and 25,028 tons/day to Zhejiang Province, underscoring its role as a major supplier. Gansu Province exports 22,751 tons/day to Jiangsu Province, highlighting robust interprovincial trade flows. Fujian Province exports 3159 tons/day, and Guangdong Province exports 2089 tons/day to Beibu Bay Port, contributing to international trade dynamics. This analysis indicate the importance of Hebei as a major exporter and Jiangsu as a critical consumer of non-metallic minerals, while coastal provinces like Fujian and Guangdong maintain essential links to international trade routes [90,91].

8. **Chemical Fertilizers and Pesticides**

The OD analysis of domestic inflows/outflows and foreign imports/exports of chemical fertilizers and pesticides revealed significant results (Figure A1e, Appendix A). Anhui Province imports 3726 tons/day from Jiangsu Province. Jiangsu exports 7388 tons/day to Hebei Province, while Guangdong exports 6520 tons/day to Guangxi Province. Hebei exports 5078 tons/day to Jiangsu and 3156 tons/day to Chongqing. Jiangsu exports 6199 tons/day to Yunnan and 3710 tons/day to Beibu Bay port in Guangdong. This analysis highlights the strategic roles of Jiangsu, Hebei, and Guangdong in facilitating both regional and international flows of chemical fertilizers and pesticides, reflecting a well-integrated supply chain that is crucial for agricultural productivity across China [92,93].

9. **Cement**

The OD analysis of domestic inflows/outflows and foreign imports/exports of cement revealed significant results (Figure 6d). Zhejiang Province imports 56,335 tons/day of these products from Henan Province. On the export side, Henan Province was a significant contributor, exporting 117,522 tons/day of cement to Jiangsu Province and 49,388 tons/day to Yunnan Province. Hebei Province is also a major exporter, sending 115,271 tons/day of cement to Jiangsu Province, 62,923 tons/day to Zhejiang Province, and 44,455 tons/day to Chongqing. Additionally, Guangdong Province exports 937 tons/day, and Jiangsu Province exports 891 tons/day to Beibu Bay Port. This analysis demonstrates the central role of Henan and Hebei as major cement suppliers, with robust trade flows to key industrial provinces like Jiangsu and Zhejiang, while coastal regions like Guangdong and Jiangsu maintain international trade connections [94].

10. **Mineral Building Materials**

The OD analysis of domestic inflows/outflows and foreign imports/exports of mineral building materials revealed these results (Figure A1f, Appendix A). Guangdong province imports 2310 tons/day, and Fujian province imports 1884 tons/day, both from Xiamen port. On the export side, Gansu province is a significant sender, exporting 35,878 tons/day of mineral building materials to Shanghai, 29,297 tons/day to Zhejiang province, 22,025 tons/day to Jiangsu province, 19,535 tons/day to Shaanxi province, and 16,291 tons/day to Chongqing. Additionally, Guangdong Province plays a notable role in exporting 11,703 tons/day of mineral building materials to the port of Xiamen. Fujian Province exports 8155 tons/day to Fuzhou Port and 7913 tons/day to Xiamen Port. This analysis highlights the significant role of inland provinces like Gansu in supplying mineral building materials to major industrial and coastal regions, while Guangdong and Fujian maintain robust links to international markets through their ports [95].

11. **Steel and Non-Ferrous Metals**

The OD analysis of domestic inflows/outflows, as well as foreign imports/exports of steel and non-ferrous metals, revealed intriguing results (Figure 6e). Guangdong province imports 126,271 tons/day from Ningbo Zhoushan Port and 75,551 tons/day from Lianyungang Port. Shanghai imports 82,386 tons/day from its port and 70,574 tons/day from Ningbo Zhoushan port, underlining the importance of these coastal hubs in supplying steel and non-ferrous metals to key industrial regions. Hebei Province exports 114,169 tons/day to Jiangsu Province, and 68,462 tons/day to Zhejiang Province. Guangdong exports 168 tons/day to Zhanjiang port, Jiangsu exports 111 tons/day to the same destination, and Shanghai exports 106 tons/day to its port (Shanghai port). This analysis emphasizes the strategic role of coastal ports like Ningbo Zhoushan and Lianyungang in supporting heavy industrial demand in Guangdong and Shanghai, while Hebei continues to be a key exporter of steel and non-ferrous metals to neighboring provinces.

12. **Other Industrial Products**

The OD analysis of domestic inflows/outflows and foreign imports/exports of other industrial products reveals intriguing results (Figure 6f). Shanghai is a significant destination, importing 216,778 tons/day of other industrial products through the Shanghai port. Guangdong imports 84,315 tons/day from Shenzhen Port and 60,992 tons/day from Ningbo Zhoushan Port. On the export side, Shanghai exports 188,323 tons/day to its port (Shanghai Port). Hebei exports 74,561 tons/day to Jiangsu, 71,483 tons/day to Shanghai, and 72,978 tons/day to Guangdong. Guangdong exports 171,513 tons/day to Guangxi, 120,402 tons/day to Shenzhen Port, and 85,811 tons/day to Ningbo Zhoushan Port. Jiangsu exports 78,372 tons/day to Shanghai, while Guangdong exports 67,718 tons/day to Shanghai. This analysis indicates the central role of Shanghai in both importing and exporting industrial products, along with significant export activities from Guangdong and Hebei. The flow patterns indicate Shanghai's dominance as a trade hub, with notable contributions from Guangdong and Hebei to the broader trade network.

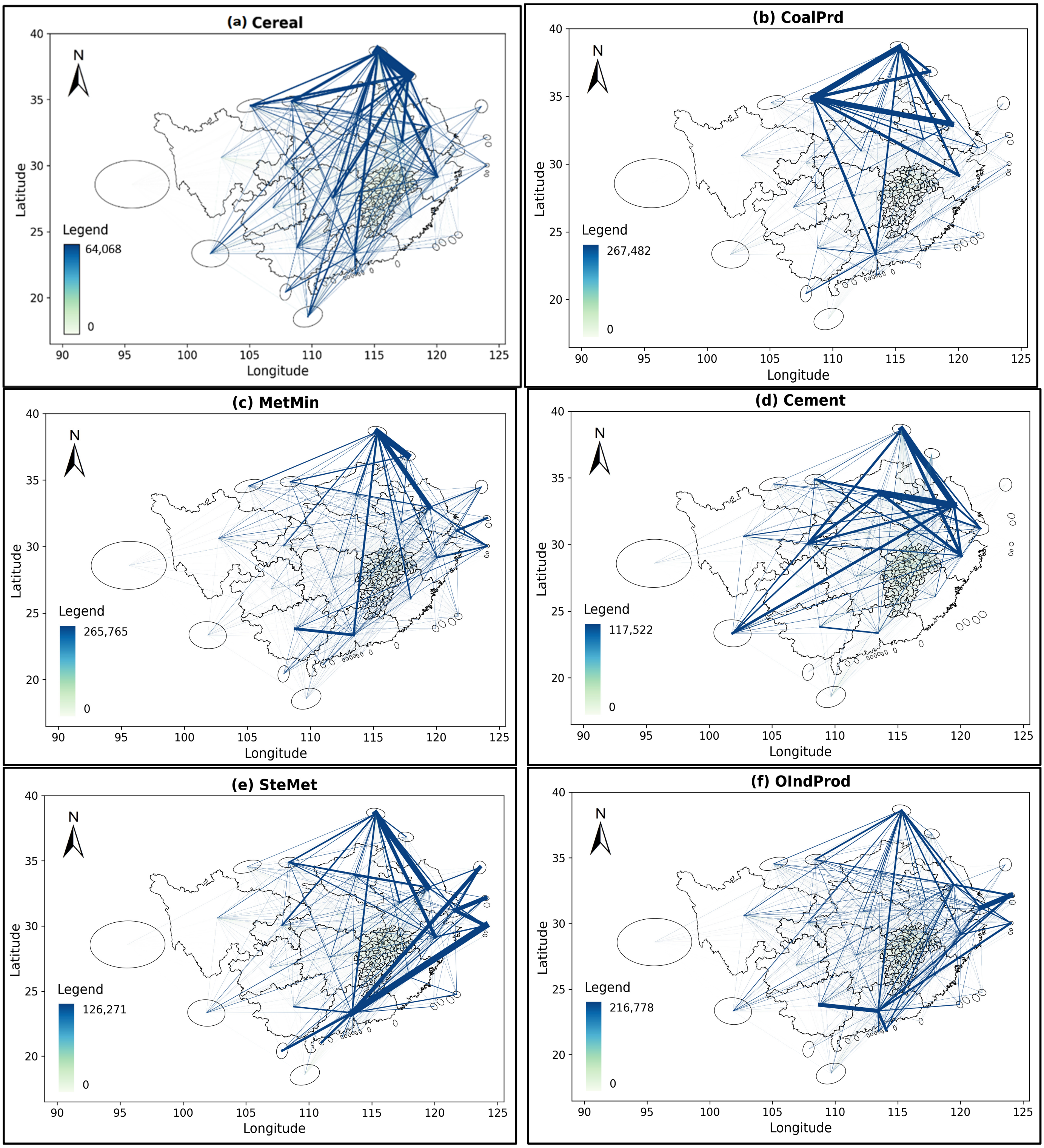

Figure 6. Commodity OD flows of imports and exports among provinces and international ports: (**a**) cereal; (**b**) coal products; (**c**) metallic minerals; (**d**) cement; (**e**) steel and non-ferrous metals; (**f**) other industrial products.

5.2. Results of the Multimodal Incremental Freight Assignment Model

The estimated OD flows are allocated to the multimodal transportation network. This assignment process integrates the mode-split and freight distribution, ensuring an accurate representation of freight flows within the model. Freight assignment involves allocating freight volumes between each OD pair within a multimodal transportation supernetwork consisting of highways, railways, and waterways. This study utilized Cube software and its GIS-supported select link analysis tool to identify the relationship between the assigned traffic on specific network links and the corresponding OD-specific freight flows routed over those links [6]. This allocation provides detailed information on transport routes, transfer processes, and freight volumes of specific links [67]. The incremental assignment method used in this study incrementally assigns freight volumes to the network, which mitigates potential congestion that could arise from simultaneously assigning the entire OD volume at once. This method prevents unrealistic loading conditions and enhances the plausibility of the traffic assignment by progressively distributing flows. Consequently, the model avoids congestion-related inaccuracies and provides a more realistic simulation of freight movement across different network segments.

Model calibration followed approaches from relevant studies [67,69], adjusting for mode-specific shares across the transportation modes. To evaluate the accuracy of the assignment results, we calibrated the model by comparing the estimated mode share data to the observed traffic mode share in the Jiangxi Province. The comparison showed an error of less than 0.3% across different transport modes, demonstrating the model's high accuracy in representing real-world freight flows (Figure 7). This level of precision confirms the robustness of the incremental freight assignment method and its effectiveness in modeling multimodal transport systems.

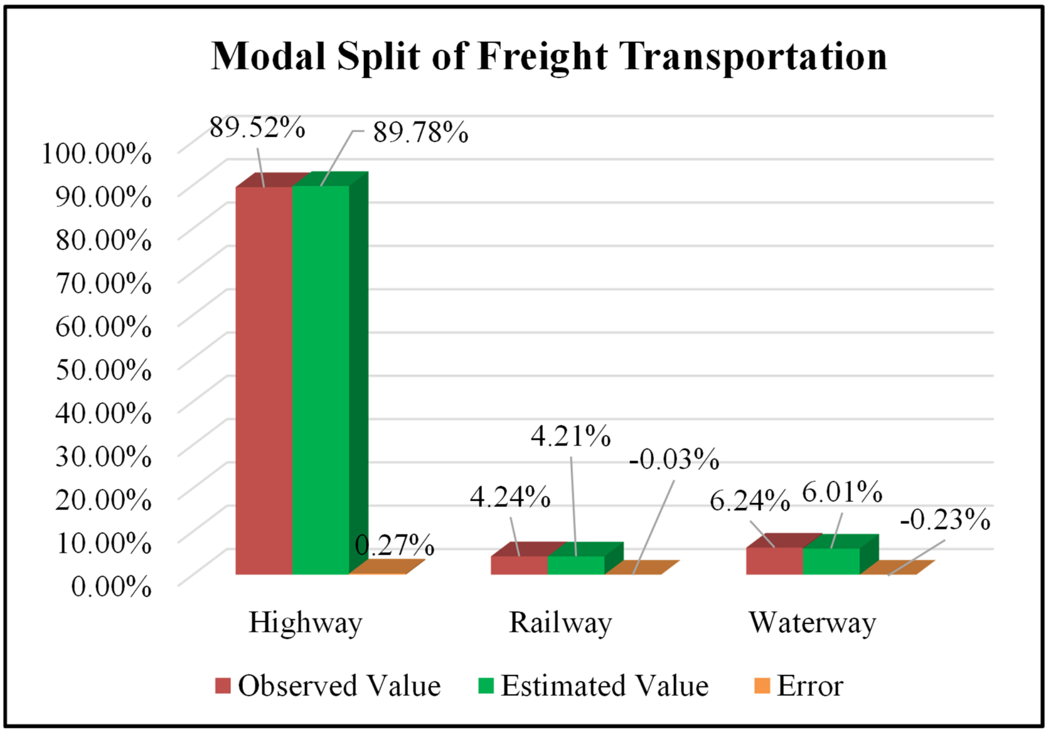

Figure 7. Modal split of freight transportation for Jiangxi province.

The freight assignment results for the intra-regional (99TAZs), interregional (20 TAZs), and international (import and export 21 TAZs) flows are presented using the incremental freight assignment method (Figure 8a,b). The developed incremental multimodal freight assignment model systematically assigns freight traffic across highways, railways, and waterways, using a composite cost function. As described in Equation (15), the composite cost function incorporates four primary attributes: loading costs, transfer costs, modal-specific constant terms, and value per ton. Loading fees, transfer fees, and value per ton are integrated into the model to accurately represent the costs incurred at different stages of transportation.

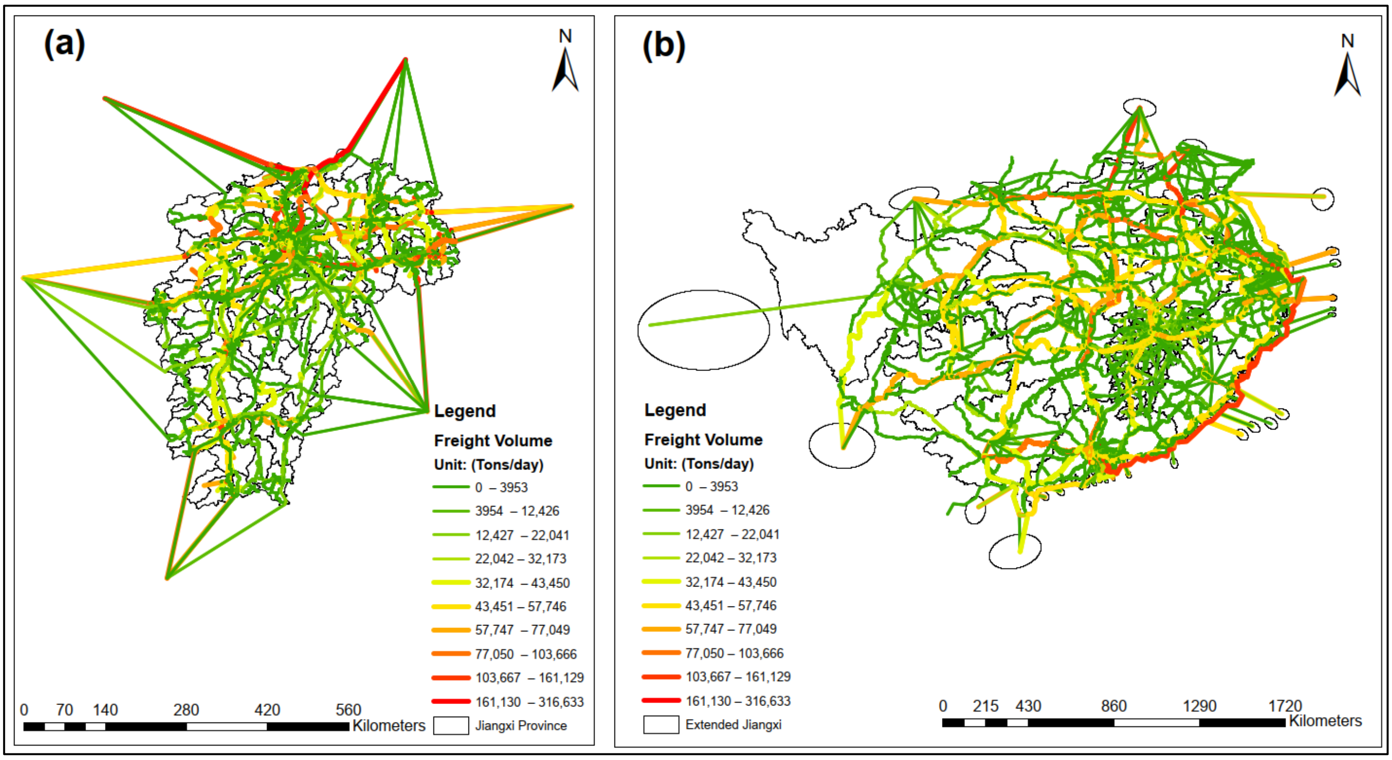

Figure 8. Freight assignment results: (**a**) Jiangxi intra-region; (**b**) international (import and export).

To account for the interaction between vehicular flow and travel time on highways and railways, the model employs an adapted BPR function for roadways (Equation (16)) and the Davidson impedance function for railways (Equation (17)), which considers the volume-to-capacity ratio of each segment. Additionally, a novel BPR function was introduced for waterway navigation (Equation (18)), which estimates travel time by considering the path length and commodity flow, with an additional bias term to account for unique waterborne transport conditions.

From the freight assignment results of the Jiangxi model, it is evident that the Beijing–Kowloon Railway and the Ji-Guangzhou Expressway serve as the primary freight channels for the north–south corridor in Jiangxi Province. Additionally, the Shanghai–Kunming Expressway acts as the main freight channel for the east–west corridor in the province. Furthermore, the freight assignment results from the extended model indicate that the Beijing–Guangzhou railway and sea transport are the primary freight channels in the north–south region. This observation is consistent with the actual traffic situations. Finally, the R^2 of the estimated freight volumes of the specific links by mode was calculated for further validation. To further validate the model, the estimated freight volumes on specific links by transport modes were compared with observed data, such as the Annual Average Daily Traffic (AADT) for highways, railway station data, and port throughput data. It can be seen from Figure 9a–c that the R^2 of estimated freight volumes on specific links for highways, railways, and waterways are 0.953, 0.925, and 0.931, respectively. This indicates that the high R^2 of freight volumes on specific links by mode suggests that the model performs well in predicting freight volumes. These high R^2 values affirm the model's reliability and highlight its potential for real-world freight planning and policy-making. By accurately identifying key freight corridors, such as the Beijing–Kowloon Railway and the Shanghai–Kunming Expressway, the model provides critical insights for infrastructure investment and capacity planning. Enhancing the capacity of these primary channels can significantly improve freight mobility and reduce transportation costs, thereby ensuring a more efficient regional logistics network.

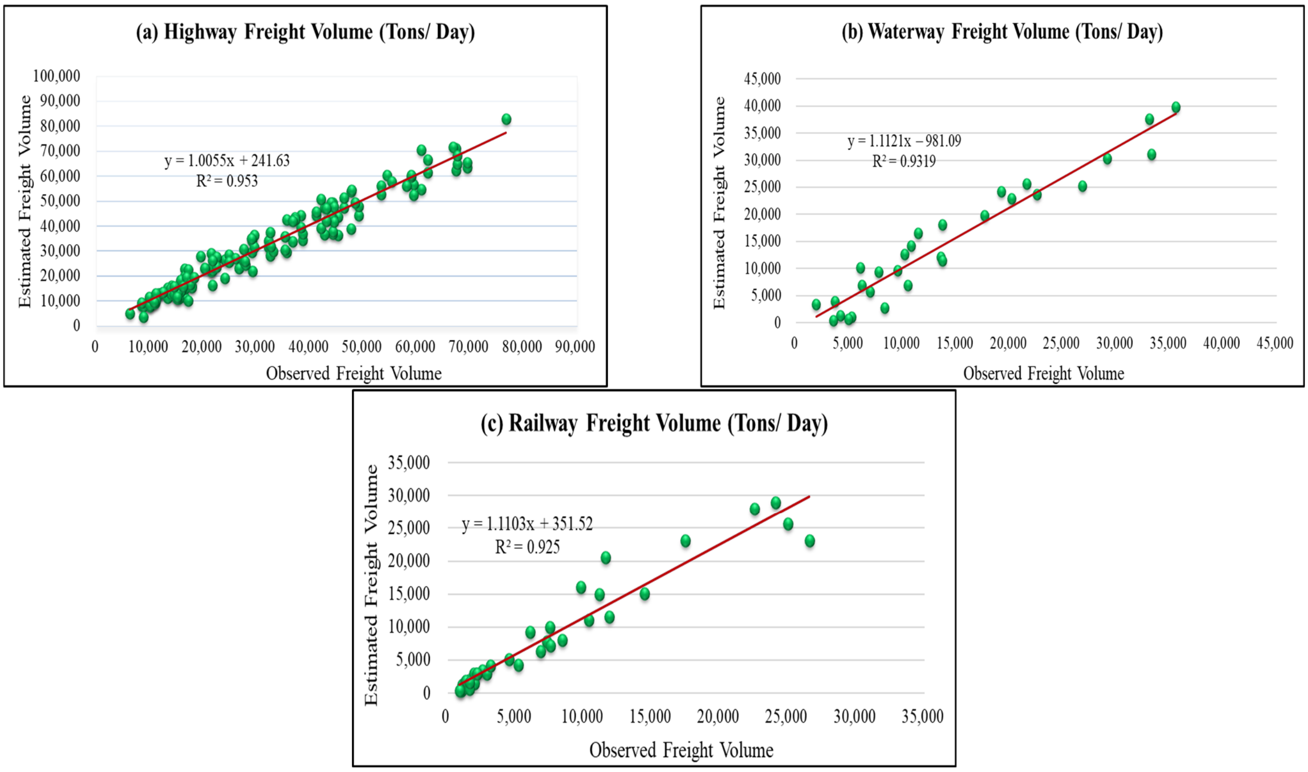

Figure 9. Comparative results of observed and estimated OD flows of freight: (**a**) highway; (**b**) waterway; (**c**) railway.

The use of a super-network approach, in which all transportation modes are integrated into a single network model, offers a significant advancement over traditional multimodal freight assignment models. This method enables a more detailed representation of intermodal operations, such as loading, unloading, and transshipment, through the use of virtual links [82]. By incorporating these logistical processes, the model delivers a more comprehensive assessment of freight flow dynamics, including the cost and time implications of the mode transfers. This approach is particularly useful for understanding complex freight movement patterns across multiple transportation modes, especially in a region like Jiangxi, where a diverse set of transport infrastructure—highways, railways, and waterways—plays a pivotal role [96]. Furthermore, the results emphasize the importance of improving intermodal connectivity, particularly at transfer points between the highway, railway, and waterway modes. These findings are crucial for developing strategies to enhance the resilience of Jiangxi's freight transportation system, particularly considering the growing freight demand driven by economic expansion and international trade. The integration of multiple transportation modes into a single modeling framework provides a holistic understanding of freight flow dynamics, which is essential for addressing the challenges of modern freight transportation.

Trip Length Distribution (TLD) calibration was performed for various transportation modes, including highways, waterways, and railways, as shown in Figure 10a,c. The observed TLD data were sourced from diverse large-scale datasets: truck GPS data for highways, waybill data for railways, and vessel tracking data for waterways [69,97,98]. For the truck GPS data, trip lengths were determined based on the recorded routes. Due to the absence of specific freight volume data, travel frequency was used as a weighting factor to establish the distribution pattern. The overall TLD for all commodity groups illustrates the geographic distribution of economic activities such as production and consumption. Conversely, the TLDs for individual transportation modes reflect freight movement patterns across the extended region (Figure 10a,c). Notably, the shapes and ranges of TLDs vary significantly among transportation modes, thereby highlighting their distinct usage patterns.

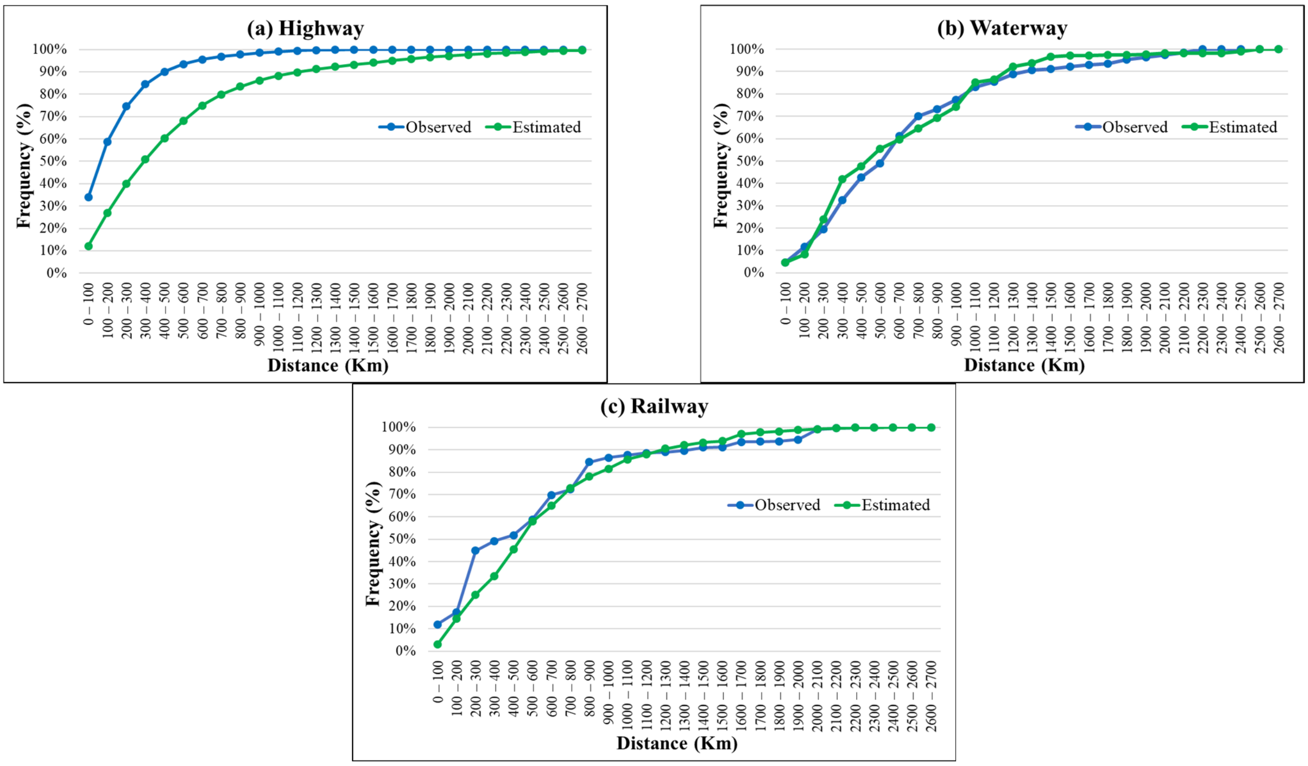

Figure 10. Trip length distributions: (**a**) highway; (**b**) waterway; (**c**) railway.

Highway freight movements are predominantly intra-regional and regional, dominated by short-to-medium-distance trips, and relatively smooth TLDs. This pattern is likely influenced by factors such as cost, time, and convenience, suggesting that highway transportation is well suited for localized and varied movements (Figure 10a). This observation is consistent with findings of previous studies [9,99]. In contrast, the waterway freight movements exhibited a stable TLD pattern across a broad range of distances (Figure 10b). This stability reflects the nature of waterway transportation, where longer trips are typical and trip frequency remains consistent over extended distances. The fixed routes and infrastructure constraints, such as ports and designated waterways, contribute to this systematic pattern, making waterway transport less subject to local variations observed in highway transportation. Railway freight movements are primarily long-distance, particularly for bulk commodities, as evidenced by the mid-range spike in the observed TLD for rail transport (Figure 10c). However, the model may not fully capture the complexity of medium-distance rail movements, potentially due to competition with highways for shorter trips. The relative error between the observed and estimated TLDs was less than 15% for all three transportation modes. TLDs are influenced by specific land uses such as ports and agricultural areas, which create peaks in the data. These distributions reflect the distance ranges at which each transportation mode is most effective, with certain modes exceeding particular distances.

6. Conclusions

This study proposes a novel integrated framework for estimating freight flows in the intra-regional and international (import/export) contexts, linked through a two-tier multimodal transportation super network. This approach improves the accuracy of OD flow estimates by incorporating modeling techniques, and multisource data, including provincial and interregional IO tables, customs data, land use data, transportation networks, truck GPS data, railway waybills, ship visas, port statistical data, and statistical yearbooks. Consequently, it provides a more comprehensive estimation of OD matrices, particularly for long-distance transport of key commodities. The specific contributions of this study are threefold: First, a spatial economic model, PECAS activity allocation, was developed to estimate freight OD demand within a specific region. Second, the international (import and export) freight OD was estimated from different zones to foreign countries, including major import and export nodes, such as international seaports, using a gravity model with zone-pair friction obtained from a multimodal transportation model. Third, the OD matrices were converted from monetary value to tonnage and assigned to a multimodal transportation super network consisting of highways, railways, and waterways using the incremental freight assignment method.

The proposed framework was tested through a case study of Jiangxi Province, which is crucial for forecasting freight demand before the planning, design, and operation of the Ganyue Canal, acclaimed as a "project of the century". The framework was calibrated using traffic counts from highways, railways, and port-throughput data. The calibration results demonstrated high reliability, with an error of less than 0.3% for different transport modes in Jiangxi Province, indicating a high level of accuracy. To further verify the validity of the model, the estimated freight volumes on specific links by mode were compared with the observed data, including the AADT of highway links, railway station data, and port throughput data. The results showed R^2 values of 0.953 for highways, 0.925 for railways, and 0.931 for waterways, demonstrating the model's highly predictive performance for freight volumes on specific links. In addition, the calibration of the trip length distribution for extended regions was performed by integrating data from truck GPS, railway waybills, and ship visas. The relative error between the observed and estimated TLDs was less than 15% for all three transportation modes.

The findings of this study provide valuable insights that can guide and improve transportation infrastructure planning and policy-making in Jiangxi Province and similar regions. Prioritizing investments in multimodal transport networks, particularly by upgrading intermodal facilities and expanding critical freight corridors, is essential to meet growing freight demand. By enhancing key freight routes such as the Beijing–Kowloon Railway and the Shanghai–Kunming Expressway, policymakers can alleviate congestion, improve freight mobility, and reduce overall transportation costs. Additionally, promoting sustainable modal shifts, particularly towards railways and waterways for long-distance freight, can significantly mitigate environmental impacts. This shift is crucial for regions aiming to reduce greenhouse gas emissions and to align with national and international climate goals. To further optimize freight transport, policymakers should leverage the model's predictive capabilities to proactively address infrastructure bottlenecks and enhance data-driven planning. The model can forecast future freight demands, enabling targeted investments that align with regional economic needs. Moreover, aligning transport infrastructure development with strategic economic zones will boost regional trade and industrial growth, thus supporting economic expansion and resilience. All in all, these findings are crucial for policymakers and stakeholders involved in Jiangxi's long-term sustainable and efficient freight transportation infrastructure planning, underscoring the importance of proactive measures to accommodate future growth.

Within the proposed integrated framework, the PECAS AA model is based on a stochastic utility-based approach, enabling its application to any region with available data (IO tables, labor compensation, land use, employment data, transportation skims, and space data). However, a calibration process and adjustments may be necessary for regions with different economic structures or transportation networks. In regions where such data are scarce or less detailed, implementing the PECAS AA model may be challenging. Nevertheless, it is posited that a consistent treatment within a comprehensive framework is of even greater importance when data are not readily available.

The primary inputs for the PECAS AA model are derived from the AEF table. However, a significant challenge lies in systematically organizing and preparing the AEF table, which necessitates organizing and cleaning extensive datasets (economic, space, employment, and transportation). This study faced limitations with official government data, such as IO tables, employment, labor compensation, statistical yearbooks, and activity and commodity categories, which often exhibited inconsistencies and other shortcomings. A crucial takeaway was the importance of consistency checks to maintain data integrity, especially when aligning sectoral and commodity classifications in regional and interregional IO tables that vary across countries and regions. To further improve the generalizability of the model, region-specific parameters calibration is necessary. Specifically, utility dispersion parameters and technology option weights within PECAS AA should be adjusted to capture local economic and transport dynamics. Adjusting activity and commodity classifications, based on the regional economic structure, is also essential for capturing accurate intra-regional dynamics. Transportation network data can be obtained from open-source platforms such as OpenStreetMap, which provides a foundation for network development that can be extracted to the other regions. However, extensive data preprocessing is necessary, including the elimination of dangling links, realignment with the actual network, and proper alignment of network topology. Ensuring congruence between land use zones and TAZs is essential for accurate integrated modeling. In addition, we made simplifying assumptions to reconcile the provincial and interregional IO table data. In cases where such data are explicitly defined in other regions, these steps may be excluded, enabling the direct utilization of the data.

Furthermore, incorporating region-specific zone-pair frictions of multimodal transportation within the gravity model enables it to reflect the unique characteristics of local zones. International (imports and exports) OD flows, which consider a broader geographical scope, derive data from regional and interregional IO tables, port statistics, and customs data. However, challenges arise in developing countries such as China, where the nascent state of freight databases and integrated modeling impedes the study of economic exchanges between provinces. Obstacles such as data and comprehensive customs databases further complicate the process. Nevertheless, this study endeavored to provide a benchmark for import and export freight modeling, both regional and international, and presented results based on reliable multisource data. Ongoing advancements in information technology have facilitated the acquisition of the required data and utilization of state-of-the-art tools, which can enhance the accuracy and applicability of our models.

Overall, the proposed framework provides a more scientifically rigorous approach for the estimation of freight OD matrices in long-distance transport, albeit with significantly greater effort required for data preparation, model specification, calibration, and validation. This study focuses on Jiangxi Province and its international import and export nodes. Future research could extend this analysis to encompass the Yangtze River Economic Belt, a major trade corridor with significant regional, national, and international impacts. Additionally, the proposed framework can be applied to assess the effects of policy changes or infrastructure investments, such as the Ganyue Canal project, on freight demand.

Author Contributions: Conceptualization, M.S. and M.Z.; methodology, M.S., M.Z., Z.R., and J.D.H.; software, M.S. and Z.R.; validation, M.S., Z.R., and M.Z.; formal analysis, M.S.; investigation, M.S. and M.Z.; resources, M.S., Z.R., and M.Z.; data curation, M.S., Z.R., and M.Z.; writing—original draft, M.S. and M.Z.; writing—review and editing, M.S. and M.Z.; visualization, M.S. and Z.R.; supervision, M.Z. and J.D.H.; project administration, M.Z.; funding acquisition, M.Z. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data supporting the findings of this study are openly available, as indicated by the URLs provided in the data section. Additionally, the data and related information may be obtained from the first author upon reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

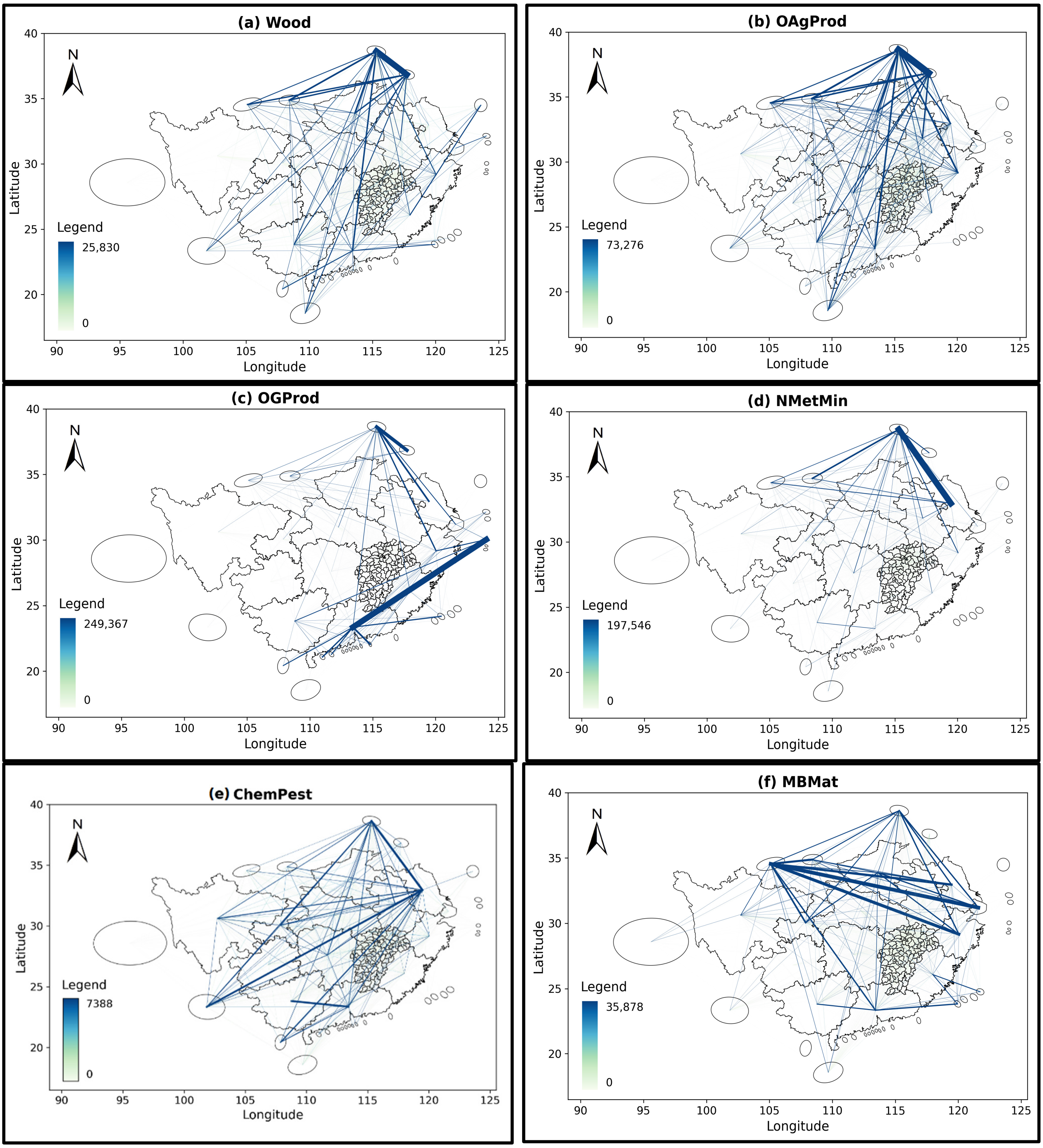

Figure A1. Commodity flows of imports and exports among provinces and international ports: (**a**) wood; (**b**) other agriculture products; (**c**) oil and gas products; (**d**) non-metallic minerals; (**e**) chemical fertilizers and pesticides; (**f**) mineral building materials.

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