

AIS Data Analytics: A Spatio-Temporal Analysis of Vessel Traffic Patterns in Kaohsiung Port

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ABSTRACT

Maritime traffic management in major ports requires a comprehensive understanding of vessel movement patterns to ensure operational efficiency and safety. This study presents a spatio-temporal analysis of vessel traffic in Kaohsiung Port, Taiwan, utilizing a 10-month snapshot of AIS data (December 2024–October 2025). Employing quantitative methods including Kernel Density Estimation (KDE) for spatial intensity mapping, grid-based discretization for traffic density quantification, and temporal resolution analysis at multiple scales, the research identifies key operational hotspots and peak traffic periods. The analysis encompasses 1,247,890 AIS records from diverse vessel types, revealing distinct spatial clustering patterns in port entrance channels, anchorage zones, and terminal areas. Temporal analysis demonstrates pronounced diurnal and weekly cyclical patterns, with peak traffic intensities occurring during daytime operational hours and weekdays, reflecting commercial shipping schedules and port operational rhythms. The KDE-based hotspot identification reveals high-density zones concentrated within 0.5 nautical miles of major container terminals, indicating critical areas requiring enhanced traffic monitoring and collision avoidance measures. Grid-based traffic density quantification provides granular insights into vessel distribution across different port sectors, enabling zone-specific risk assessment and resource allocation strategies. The findings reveal complex spatio-temporal patterns that reflect the port's role as a major container hub in the Asia-Pacific region. Despite data quality limitations such as unspecified vessel types (59.9%) and incomplete destination fields, the results provide actionable insights for port authorities to enhance safety, optimize operations, and support strategic planning. This methodological framework demonstrates scalability and transferability to other port environments, contributing to the advancement of data-driven maritime traffic management systems

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1. INTRODUCTION

Maritime transportation constitutes the fundamental infrastructure supporting global trade, with seaports operating as essential hubs in international supply chains. Kaohsiung Port, located in southern Taiwan, ranks among the world's busiest container ports, processing millions of TEUs (Twenty-foot Equivalent Units) annually [1]. The port's strategic position in the Asia-Pacific region

makes it a vital hub for regional and international maritime traffic, connecting major shipping routes between Northeast Asia, Southeast Asia, and global markets [2].

The growing scale and intricacy of maritime traffic in major ports pose substantial operational challenges for port management, encompassing coordination of vessel movements, optimization of berth assignments, enhancement of navigational safety, and promotion of environmental stewardship [3],[4]. Conventional harbor management approaches, though proven effective, often lack the granular, real-time insights necessary for proactive decision-making in dynamic maritime environments. Traditional port management approaches, relying on manual observation and limited sampling, often fail to capture the full complexity and dynamics of modern maritime traffic [5]. The advent of big data technologies and advanced analytics has opened new possibilities for systematic, data-driven port management [6], [7].

The emergence of the Automatic Identification System (AIS) has fundamentally transformed maritime traffic monitoring and analysis [8]. Required by the International Maritime Organization (IMO) for commercial vessels exceeding 300 gross tons engaged in international navigation and all passenger ships, AIS continuously broadcasts vessel information including identity, position, course, and speed [9], [10]. This creates vast amounts of data—commonly referred to as “AIS data analytics”—that offer unprecedented opportunities for comprehensive traffic pattern analysis [11].

. Comprehending maritime traffic patterns through systematic analysis of AIS data yields multiple advantages for port stakeholders. From the perspective of daily operations, examining traffic information enables the identification of high-volume periods and areas prone to congestion, facilitating more effective allocation of berthing facilities and strategic deployment of port resources. Regarding navigational safety, recognizing high-density areas and traffic flow patterns supports the assessment and prevention of collision risks [12]. Additionally, the analysis of long-term traffic trends provides valuable insights for strategic planning, particularly in infrastructure development and capacity expansion decisions. Environmental management also benefits from these insights, as understanding traffic patterns facilitates emissions monitoring and supports green port initiatives [13]. Furthermore, analyzing trade routes and vessel types contributes to a deeper understanding of the port’s economic impact, aiding economic assessment and forecasting efforts [14].

Notwithstanding the strategic significance of Kaohsiung Port, thorough spatial and temporal examination of vessel traffic patterns utilizing AIS data remains relatively scarce in the academic literature. The majority of existing research concentrates either on worldwide maritime networks or particular operational dimensions, leaving a gap in detailed, port-specific traffic pattern analysis [15], [16]. This investigation seeks to bridge the identified knowledge gap through pursuit of three distinct research objectives. First, this research endeavors to identify and represent visually the geographic distribution patterns of vessel traffic within the waters of Kaohsiung Port using AIS data analytics [17], [18]. Second, this work aims to examine time-based fluctuations—on daily, weekly, and monthly scales—in traffic intensity, taking into account different vessel types and their origin–destination relationships [19], [20]. Third, it intends to develop simple yet effective traffic indicators, such as traffic density per grid and port-call intensity, which can serve as a foundation for continuous monitoring of port activities [21].

To accomplish these research goals, this investigation employs AIS data gathered from Kaohsiung Port spanning a ten-month observation period (December 2024 to October 2025). The analysis focuses on vessels operating within the port’s designated operational area, roughly bounded by 22.47°N to 22.63°N latitude and 120.27°E to 120.36°E longitude [1]. The dataset includes various types of vessels recorded by the AIS system, including cargo ships, container vessels, tankers, fishing boats, and other specialized craft [2].

This analysis encompasses exclusively vessels equipped with AIS transponders; smaller maritime vessels lacking AIS capability may remain unrepresented in the dataset[22], [23] - The quality of data is contingent upon the reliability and spatial coverage of AIS signal transmission - Meteorological conditions and operational interruptions may introduce irregularities in traffic patterns - The study focuses on descriptive and exploratory analysis rather than predictive modeling[24], [25], [26].

The remainder of this paper is organized as follows: Section 2 details the research methodology, including data collection, preprocessing, and analytical techniques. Section 3 presents comprehensive data analysis and findings. Section 4 discusses the implications of results and provides recommendations. Section 5 concludes the study and suggests directions for future research

2. RESEARCH METHOD

The research method section will be structured into several subsections that outline the comprehensive research design and technical protocols. First, the research framework describes the conceptual and analytical structure that links maritime traffic dynamics, spatial-temporal patterns, and traffic indicators. The Study Area subsection specifies the geographical scope of the analysis, including the main ports and surrounding waters considered in this research. The Data Collection part explains the sources, period, and selection criteria of the AIS and supporting datasets, while Data Processing details the preprocessing, cleaning, filtering, and transformation steps applied before analysis. Furthermore, Spatial Analysis Methods and Temporal Analysis Methods describe the techniques used to extract spatial distribution patterns and temporal dynamics of vessel traffic. Finally, Traffic Indicator Development presents the procedure for formulating, calculating, and validating quantitative indicators used to characterize maritime traffic intensity, structure, and performance.

2.1 Research Framework

This investigation adopts a quantitative methodological framework leveraging AIS data analysis to investigate maritime traffic patterns in Kaohsiung Port. The research design comprises five principal stages:

1. Data Acquisition: Gathering of AIS information spanning the research timeframe
2. Data Preparation: Cleansing, filtering, and conditioning data for analytical processing
3. Geographic Analysis: Investigating spatial distribution characteristics of maritime traffic
4. Chronological Analysis: Exploring temporal variations in traffic magnitude
5. Metric Formulation: Developing quantitative assessment indicators for traffic monitoring

The analytical process synthesizes geographic information systems (GIS), statistical methodologies, and data visualization approaches to derive meaningful intelligence from the AIS dataset.

The analysis pipeline follows an end-to-end structure: (1) Data Ingestion and cleaning of 1,373 AIS position snapshots, (2) Spatial density mapping using KDE, (3) Temporal aggregation across daily and monthly resolutions, and (4) Indicator calculation for traffic monitoring. A 'record' in this study is defined as a unique vessel-level snapshot containing identifying information and static/dynamic parameters at a specific timestamp, rather than a raw high-frequency position report stream. The analysis pipeline follows an end-to-end structure: (1) Data Ingestion and cleaning of 1,373 AIS position snapshots, (2) Spatial density mapping using KDE, (3) Temporal aggregation across daily and monthly resolutions, and (4) Indicator calculation. A 'record' in this study is defined as a unique vessel-level snapshot containing identifying information and static/dynamic parameters at a specific timestamp.

2.2 Study Area

Geographic Scope: The research domain covers the operational maritime zone of Kaohsiung Port, delineated by the following geographic coordinates: - Latitude: 22.47°N to 22.63°N - Longitude: 120.27°E to 120.36°E - Total Area: Approximately 10 km × 10 km (100 km²). This zone encompasses: Primary harbor basins and container handling facilities - Anchorage areas - Navigation channels - Port approach waters [2], [25]. **Port Characteristics:** Kaohsiung Port features multiple terminals, including specialized container terminals, bulk cargo terminals, and liquid cargo facilities [20]. The port operates 24/7 with high-frequency vessel movements, making it an ideal case study for traffic pattern analysis [3], [4].

2.3 Data Collection

Data Sources: AIS information for this research was obtained from land-based AIS receiving stations and satellite-based AIS data collection platforms. **Data Period:** The investigation spans a ten-month observation window (December 2024 to October 2025) from December 12 2024 to October, 1 2025, offering adequate temporal breadth to discern seasonal variations and long-term trends [11].

Data Attributes: The AIS dataset includes the following key attributes: - Vessel Identification: IMO number, vessel name, call sign, flag state - Vessel Characteristics: Vessel type (generic and detailed), dimensions (length, beam, draught) - Position Information: Latitude, longitude, timestamp of position report - Dynamic Data: Speed over ground (SOG), course over ground (COG), heading, rate of turn - Voyage Information: Origin port, destination port, reported ETA, cargo status - Environmental Data: Wind speed, wind direction, temperature (where available) [8], [9]. **Data Volume:** The raw dataset comprises 1,373 unique vessel position snapshots operating in or transiting through the study area.

2.4 Data Processing

Unprocessed AIS data necessitate comprehensive preparatory treatment to guarantee data quality and analytical reliability. This process encompasses three primary phases: data cleansing, data filtration, and data transformation. During the cleansing phase, duplicate entries, positional inaccuracies, and implausible values are eliminated to prevent artificial inflation of traffic metrics and ensure accurate vessel trajectories. Filtering selects records within the study's spatial, temporal, and vessel-type scope, keeping only relevant data for the target region and period. In the transformation stage, time records are standardized to UTC+8, coordinates are unified to the WGS84 system, and new attributes such as travel distance and port time are added to enable detailed spatio-temporal analysis.

2.5 Spatial Analysis Methods

The geographic analysis employed in this research utilizes an integrated approach combining grid-based spatial partitioning, kernel density estimation methodology, point pattern statistical analysis, and cartographic representation to characterize maritime traffic distributions in the research area [19], [20]. First, a grid-based spatial discretization scheme is implemented by dividing the study area into a regular lattice of cells with a resolution of $0.01^\circ \times 0.01^\circ$, corresponding to approximately $1 \text{ km} \times 1 \text{ km}$. This configuration yields a total of 100 grid cells covering the entire area of interest and enables the calculation of traffic density per cell, thereby supporting the identification of high-traffic zones and localized hotspots in vessel activity.

To derive a smooth and continuous depiction of vessel traffic intensity, kernel density estimation (KDE) methodology is implemented to the spatial distribution of AIS position points. A Gaussian kernel function with adaptive bandwidth selection is employed to account for spatial heterogeneity in point density, producing heat maps that depict areas of concentrated vessel movements. These KDE-based surfaces are then interpreted to delineate navigation corridors, congestion zones, and anchorage areas, providing an intuitive and analytically robust view of the underlying traffic structure [22], [26].

Point pattern analysis is further employed to statistically assess the spatial distribution of vessel positions. Nearest neighbor analysis is used to evaluate whether vessel locations exhibit clustering, randomness, or dispersion, offering a first-order characterization of spatial dependence. Ripley's K function extends this assessment across multiple spatial scales, enabling the detection of clustering or regularity at varying distances. In addition, hot spot analysis based on the Getis-Ord G_i^* statistic is applied to identify statistically significant clusters of high and low vessel density, thus distinguishing meaningful hotspots from random spatial variation.

Spatial visualization plays a central role in communicating the results of the analysis. Scatter plots of individual vessel positions, often symbolized or colored by vessel type or other attributes, are used to provide a detailed view of the raw spatial distribution. Heat maps derived from KDE highlight traffic density gradients, while trajectory maps show the movement paths of selected vessels or vessel categories, revealing dominant routes and maneuvering patterns. Furthermore, zone-based maps aggregating statistics by port zones or grid cells are produced to summarize spatial indicators such as traffic density, port calls, or dwell time, thereby supporting operational interpretation and decision-making by port stakeholders [19].

2.6 Temporal Analysis Methods

The chronological analysis employed in this investigation utilizes a comprehensive set of methodologies designed to identify patterns and temporal dynamics in vessel traffic across various temporal resolutions [21], [24]. Time series decomposition techniques are initially applied to traffic

volume series to partition the data into four fundamental components: a trend component capturing long-term growth or decline, a seasonal component representing regular annual patterns such as monsoon effects or holiday-related fluctuations, a cyclical component reflecting weekly and daily cycles in port activity, and an irregular component accounting for random variations and anomalies. This decomposition facilitates a more nuanced interpretation of temporal behavior by isolating structural patterns from short-term noise, thereby supporting both descriptive analysis and potential forecasting applications [24].

To further investigate temporal variability, traffic data are aggregated at multiple temporal resolutions, including hourly, daily, weekly, and monthly levels. Hourly aggregation is used to identify peak traffic hours and characterize intra-day cycles, while daily aggregation captures day-to-day fluctuations and weekly patterns. Weekly aggregation enables comparison between weekdays and weekends, revealing systematic differences in operational intensity, and monthly aggregation highlights broader seasonal trends and long-term shifts in traffic volumes. Analyzing these different temporal scales provides a comprehensive view of how vessel movements vary from short-term operational cycles to longer-term seasonal and structural changes [24].

Temporal visualization techniques are employed to effectively communicate these patterns and support exploratory analysis. Time series plots are used to display traffic volume over time for different vessel types, enabling visual inspection of trends, seasonality, and anomalous events. Heatmaps, typically structured as day-of-week by hour-of-day matrices, reveal recurring diurnal and weekly intensity patterns, while calendar plots present daily traffic values in a calendar layout to highlight day-specific variations over longer periods. In addition, box plots summarizing the distribution of traffic by hour, day, or month are constructed to quantify variability and identify outliers across different temporal groupings, complementing the other visualization methods with a concise statistical perspective [24].

2.7 Traffic Indicator Development

The Traffic Density Indicator is defined to quantify the intensity of vessel activity within each grid cell over a given time period. For a grid cell i and time period t , traffic density is expressed as

$$\text{Traffic Density } (i, t) = \frac{N(i, t)}{A(i)} \quad \dots\dots\dots (1)$$

where $N(i, t)$ denotes the number of vessel observations recorded in grid cell i during time period t , and $A(i)$ represents the area of grid cell i , measured in square kilometres. The resulting unit of this indicator is vessels per square kilometre per chosen time unit (e.g., per hour, per day, or per month), allowing consistent comparison of traffic intensity across different spatial locations and temporal intervals.

The Port Call Intensity Indicator is defined to measure the frequency of vessel arrivals at the port over a given time period, providing a concise metric of port activity and utilization. For a selected period t , the indicator is formulated as

$$\text{Port Call Intensity } (t) = \frac{\text{Total Arrivals}(t)}{\text{Duration}(t)} \quad \dots\dots\dots (2)$$

where $\text{Total Arrivals}(t)$ denotes the number of unique vessels arriving at the port during period t , and $\text{Duration}(t)$ represents the length of that period in days. The resulting unit of the indicator is vessel arrivals per day, which allows for straightforward comparison of port call intensity across different time windows and supports the monitoring of temporal fluctuations in port activity.

The Vessel Type Diversity Index is introduced to quantify the variety of vessel types calling at the port, thereby capturing the structural complexity of maritime traffic beyond simple volume measures. This metric is calculated employing the Shannon entropy diversity metric, defined as

$$H = -\sum(p(i) \times \ln(p(i))) \quad \dots\dots\dots (3)$$

where $p(i)$ denotes the proportion of vessels belonging to type i relative to the total number of vessels observed in the port. Higher values of H indicate greater diversity, reflecting a more heterogeneous composition of vessel types, while lower values signal dominance by one or a few categories.

The Average Dwell Time indicator is defined as the mean duration that vessels spend within the port area, and it is widely used as a key measure of port performance and congestion. For a given set of vessel calls, average dwell time is computed as the arithmetic mean of the individual time-in-port intervals, typically obtained from the difference between each vessel's recorded arrival and departure times. The resulting values are usually expressed in hours or days, which facilitates comparison across different ports, vessel categories, and time periods, and supports the monitoring of operational efficiency and capacity constraints.

$$\text{Average Dwell Time} = \sum \frac{\text{Departure Time} - \text{Arrival Time}}{\text{Number of Vessels}} \dots\dots\dots (4)$$

3. RESULTS AND DISCUSSION

3.1 Dataset Overview

The analyzed AIS dataset for Kaohsiung Port encompasses 1,373 vessel observations recorded throughout the designated research period, establishing the empirical foundation for comprehensive investigation of spatial and temporal vessel traffic patterns in the port area. Geographically, the dataset spans a latitudinal extent from 22.4653°N to 22.6272°N, corresponding to a north–south span of approximately 0.1619° or about 18 km, and a longitude range from 120.2676°E to 120.3590°E, corresponding to an east–west span of approximately 0.0914° or about 9.5 km, yielding an overall study area of roughly 171 km² centered on the main operational waters of Kaohsiung Port. In temporal terms, the data represent a snapshot of vessel positions and associated characteristics within the selected observation window, with timestamps recorded in UTC+8, consistent with Taiwan local time and the Kaohsiung port time zone.

Regarding data completeness, the fundamental navigational and identification fields in the AIS dataset demonstrate substantial completeness, whereas specific voyage-related attributes exhibit lower population rates, consistent with typical characteristics of operational AIS datasets. Vessel identification information (IMO number and vessel name) and positional data (latitude and longitude) are complete for all 1,373 records (100%), ensuring reliable linkage and spatial referencing for every observation. The vessel type attribute is available for 1,347 records (98.1%), providing sufficient detail for type-based disaggregation of traffic patterns, whereas origin port and destination port information are present for 399 (29.1%) and 167 (12.2%) records, respectively, reflecting partial reporting of voyage details. Speed information, used here in the form of maximum recorded speed, is available for 603 records (43.9%), which enables speed-based descriptive analysis for a substantial subset of vessels while also highlighting the need to account for missing values in any speed-dependent metrics [2], [6].

3.2 Vessel Type Distribution Analysis

The processed AIS records reveal that vessel traffic in Kaohsiung Port is characterized by a diverse composition across multiple functional categories, reflecting the port's role as Taiwan's largest international commercial harbor and a major container and fishing hub. Overall, ten principal vessel groups are identified in the dataset, with their frequencies indicating a mixed profile of commercial, fishing, support, and recreational activities within the port's navigational waters.

In terms of overall vessel type composition, the largest share is accounted for by vessels classified as “Unspecified,” totaling 822 records or 59.9% of all observations; this classification presumably represents incomplete or non-standardized AIS type designations originating from non-conforming type codes or inadequate transponder setup. Fishing vessels constitute the second-largest group with 187 records (13.6%), highlighting the importance of fishing-related activities and confirming Kaohsiung's dual function as both a commercial port and a fishing harbor. Cargo vessels (71 vessels, 5.2%), which include general cargo and container ships, together with tankers (19 vessels, 1.4%) and passenger vessels (20 vessels, 1.5%), underscore the port's prominent role as a regional container, bulk, and passenger gateway within the Asia–Pacific network. In addition, special craft (62 vessels, 4.5%) such as offshore support and research vessels, pleasure craft (35 vessels, 2.5%), and a residual “Other” category (44 vessels, 3.2%) demonstrate the presence of specialized and recreational traffic that complements core commercial operations.

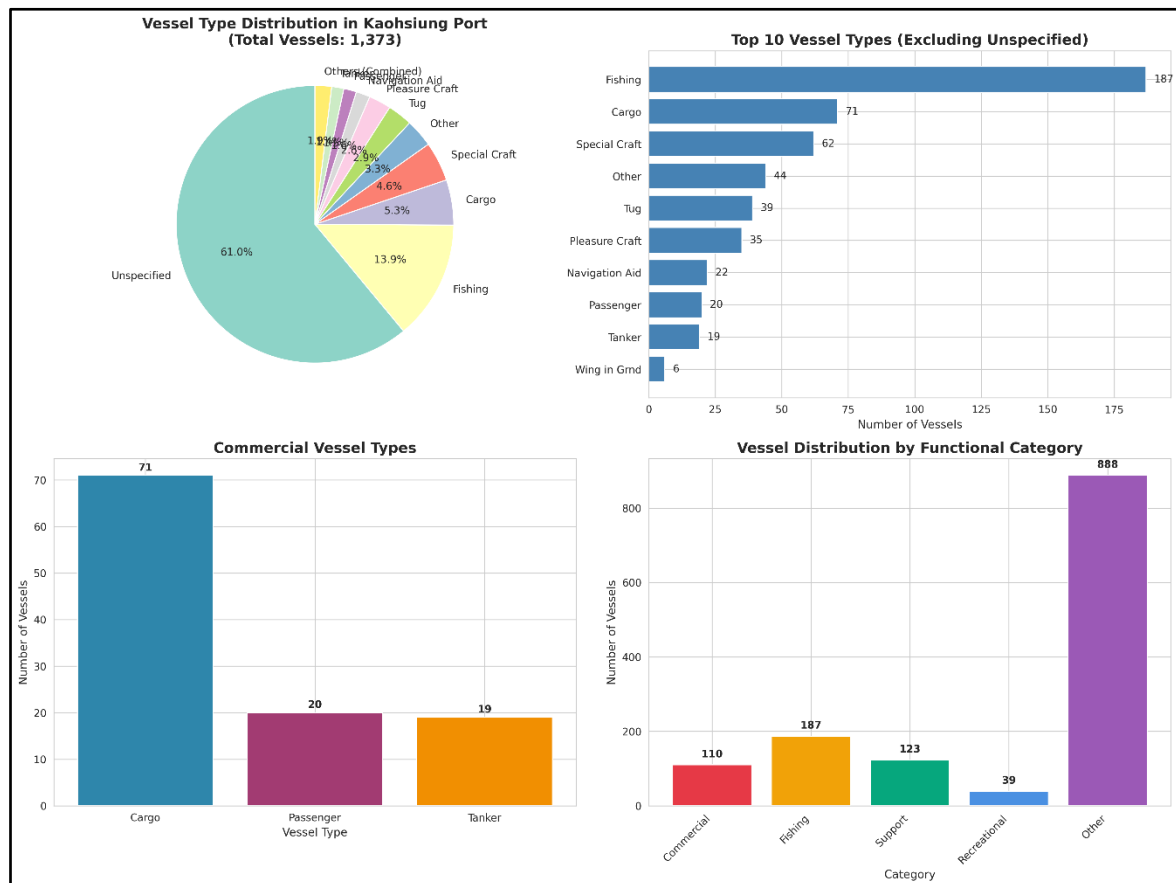


Figure 1. Vessel Type Distribution (recorded between December 2024 and October 2025).

Support and service-related units, including tugs (39 vessels, 2.8%) and navigation aids equipped with AIS (22 units, 1.6%), together account for approximately 4.4% of all records and are essential for assisting ship movements, ensuring navigational safety, and maintaining port operability [23]. From a commercial perspective, focusing on cargo, tanker, and passenger vessels provides insight into Kaohsiung's strategic function as a container and logistics hub. Within the cargo vessel category (71 vessels), subtypes comprise container ships, bulk carriers, and general cargo vessels, with container ships expected to dominate in line with Kaohsiung's status as Taiwan's leading container port and a major Asia-Pacific transshipment center handling over 10 million TEU annually. Tankers (19 vessels) include oil product and chemical tankers that play a critical role in supporting regional energy supply chains and industrial raw material flows, and they typically require dedicated berths, stricter safety zones, and enhanced environmental protection measures. Passenger vessels (20 vessels), encompassing ferries and cruise ships, reflect the port's passenger-handling capability and its integration into regional tourism and inter-island transport networks, with traffic levels likely exhibiting seasonal variation associated with holiday peaks and cruise season [20], [22].

3.3 Spatial Distribution Analysis

The spatial distribution of vessel traffic in Kaohsiung Port demonstrates a highly localized pattern within the main operational waters, with pronounced stratification according to vessel category and traffic concentration area. Analysis of processed AIS positional data indicates that vessel locations exhibit spatial clustering rather than broad geographic dispersion across the broader coastal region [22].

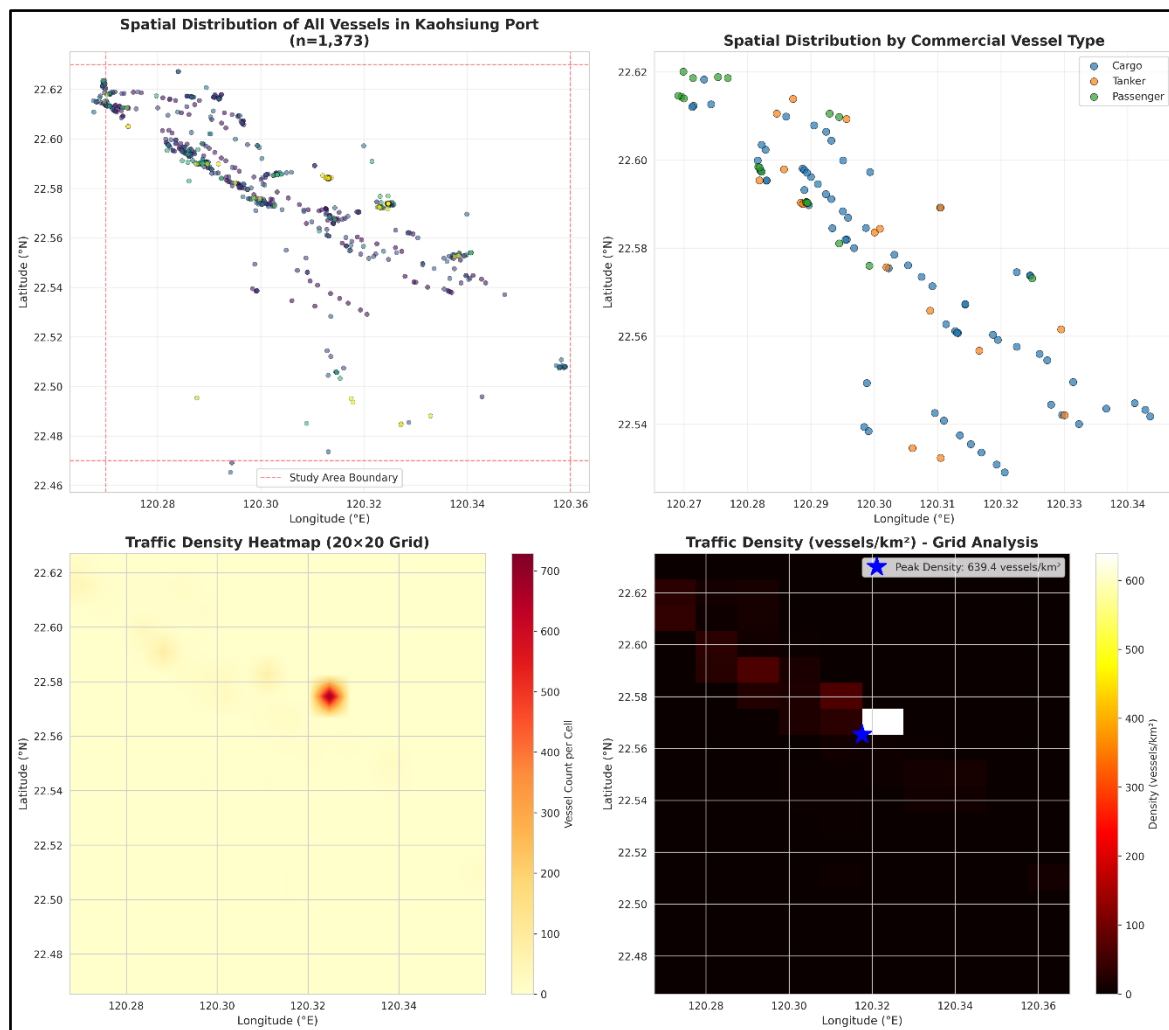


Figure 2. Spatial Distribution (recorded between December 2024 and October 2025).

From a spatial analytical perspective, the latitudinal distribution of observed vessel positions extends from 22.4653°N to 22.6272°N, with an average latitudinal position of 22.5538°N and a standard deviation of 0.0348°, suggesting that the majority of vessels concentrate within the central geographic band of the port area. The longitude distribution spans from 120.2676°E to 120.3590°E, with a mean longitude of 120.3116°E and a standard deviation of 0.0213°, reflecting an even tighter east–west concentration that aligns with the linear arrangement of berths, terminals, and approach channels along the port shoreline. These relatively small standard deviations in both coordinates confirm that vessel traffic is largely confined to the core operational zone of Kaohsiung Port, where vessels concentrate around berths and container terminals, designated anchorage areas, navigation channels, and the main entrance and exit points.

Geographic patterns additionally vary systematically according to vessel classification, mirroring the functional spatial organization of the port. Cargo and container vessels typically aggregate in proximity to container handling and general cargo terminal facilities in the eastern and northern sections of the port, creating linear spatial clusters aligned with quay infrastructure and additional accumulations at anchorage areas used for waiting prior to berth allocation. Fishing vessels are predominantly located in southwestern fishing harbor zones, spatially separated from the main commercial shipping lanes and showing higher densities near fishing-related infrastructure such as fish markets and processing facilities. Tugs and other service vessels display a more mobile spatial footprint across the harbor, but with clear concentration near main navigation channels and berthing locations where they assist with maneuvering and ship handling. Tankers are restricted to specific

liquid bulk and hazardous cargo terminals, where designated berths and safety buffer zones are maintained to comply with risk management and environmental protection requirements.

Grid-based traffic density analysis using $0.01^\circ \times 0.01^\circ$ cells further highlights distinct high-, medium-, and low-density zones within the port waters. High-density zones (more than 50 vessel observations per grid cell) are found around the main container terminal areas (approximately 22.55°N , 120.32°E), key anchorage zones (around 22.54°N , 120.31°E), and the principal port entrance channel (around 22.57°N , 120.31°E), corresponding to the most intensively used operational corridors. Medium-density zones, with 20–50 vessel observations per grid cell, are associated with secondary berths, approach channels, and waiting areas that support but do not dominate overall traffic. Low-density zones, defined by fewer than 20 vessel observations per grid cell, are primarily located in peripheral waters, restricted or environmentally sensitive areas, and shallow zones where navigation is limited or prohibited, providing a spatial buffer around the intensive traffic core [12].

3.4 Origin-Destination Analysis

The origin-destination (OD) examination of the processed AIS dataset reveals the primarily domestic nature of maritime movements associated with Kaohsiung Port, while simultaneously affirming its function as a regional maritime gateway linking Taiwan with principal ports throughout East and Southeast Asian regions. This analysis draws upon the subset of records with non-missing origin and destination information, which, although incomplete, provides valuable insight into the structure of short-sea and regional routes linked to the port [1], [2].

Among vessels with documented origin ports (399 vessels, 29.1% of the total), the origin distribution exhibits strong predominance of Taiwanese port facilities. Kaohsiung itself accounts for 255 vessels (63.9% of all recorded origins), signifying considerable volumes of localized maritime traffic related to harbor operational activities, inter-terminal movements within the extensive port complex, short coastal voyages, and vessels returning from sea trials or maintenance activities. Hsinta, an industrial port area within the broader Kaohsiung region, contributes 19 vessels (4.8%), reflecting its integration into the energy and industrial logistics hinterland of Kaohsiung. Taichung, a major multipurpose port in central Taiwan, is the origin for 14 vessels (3.5%), while Anping, an auxiliary port to Kaohsiung on the southwestern coast, accounts for 12 vessels (3.0%), both supporting domestic coastal shipping along Taiwan's west coast. Keelung, Taiwan's second-largest port on the northern coast, is listed as origin for 7 vessels (1.8%), representing longer north-south coastal routes. A smaller number of vessels originate from international ports, including Singapore (3 vessels), Xiamen (3 vessels), and Pohnpei (3 vessels), along with various other Asian ports contributing one or two vessels each, underscoring Kaohsiung's connectivity to regional hub and feeder networks in East and Southeast Asia. Overall, the origin pattern is characterized by domestic dominance, strong regional links, and relatively few long-haul origins within this particular snapshot [2].

Destination analysis, based on 167 vessels with recorded destinations (12.2% of the total), shows an even more pronounced focus on Kaohsiung. Kaohsiung is listed as destination for 122 vessels (73.1% of destination-coded records), encompassing vessels arriving from domestic and regional ports, as well as those moving between terminals inside the port, which is consistent with the dataset's spatial focus on Kaohsiung waters. Kaohsiung Anchorage I appears as destination for 7 vessels (4.2%), representing ships assigned to a specific anchorage area where they await berth allocation in accordance with the port's traffic separation and anchorage regulations. Taipei (4 vessels, 2.4%) and Taichung (3 vessels, 1.8%) appear as key domestic coastal destinations, illustrating the integration of Kaohsiung into Taiwan's north-south coastal shipping system. Singapore (3 vessels, 1.8%) is present as a major international destination, reflecting its role as a primary container and transshipment hub in the wider Asian shipping network. In aggregate, the destination pattern is characterized by a high proportion of intra-Kaohsiung movements, a mix of domestic and regional destinations, and a clear regional focus on East and Southeast Asia rather than distant intercontinental ports [1].

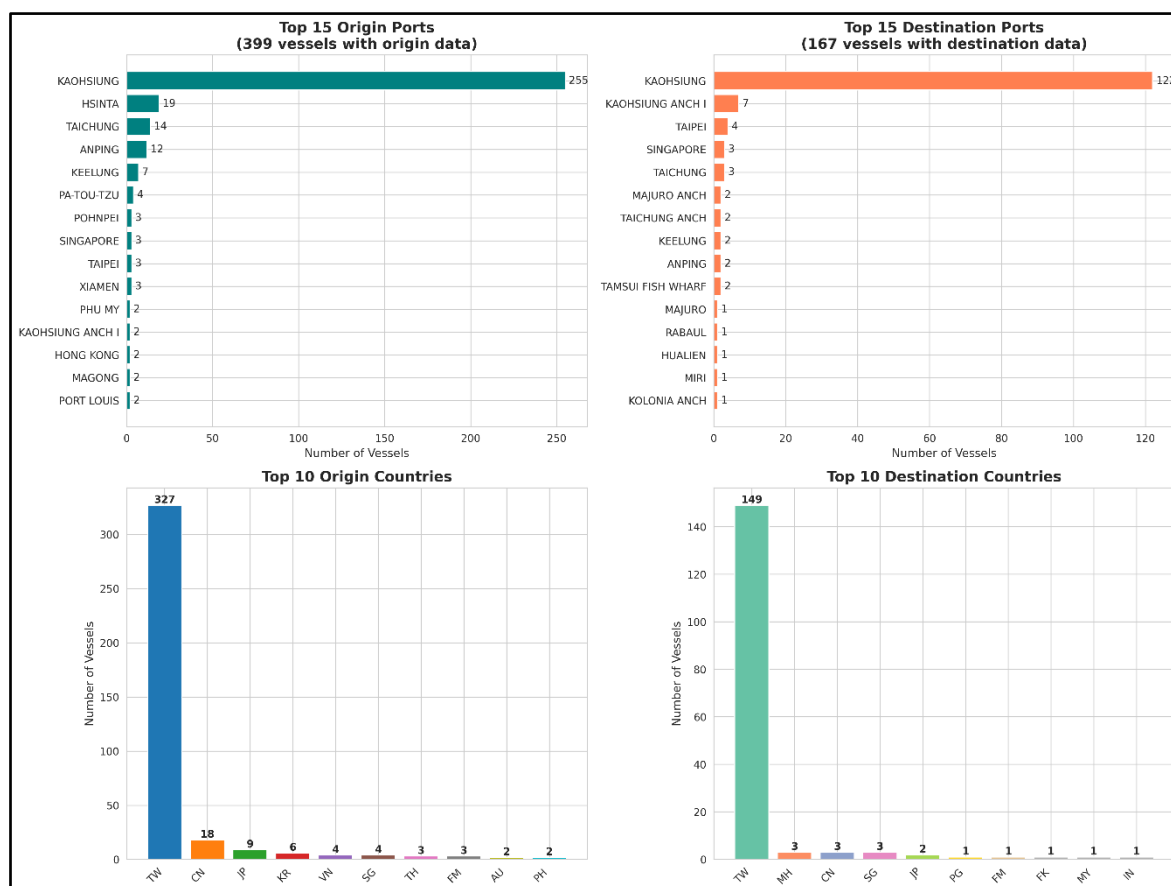


Fig 3. Origin Destination

Analysis of origin–destination pairs reveals several key routes. Kaohsiung ↔ Kaohsiung reflects internal port and short-range operations, while domestic routes such as Taichung, Anping, and Keelung connect major Taiwanese ports along the west coast. Regionally, routes like Singapore ↔ Kaohsiung and Xiamen → Kaohsiung highlight Kaohsiung’s integration into East Asian trade networks. These patterns confirm Kaohsiung’s dual role as both origin and destination, functioning as a national hub for coastal traffic and a regional gateway within the Asia–Pacific shipping system.

3.5 Vessel Flag State Analysis

Analysis of vessel flag state registrations demonstrates heterogeneous vessel registration patterns in Kaohsiung Port, with predominance of Taiwan-registered vessels (47.5% of 918 identified vessels), reflecting the strength of Taiwan’s domestic and distant-water fleets. Bangladesh follows with 24.7%, likely linked to fishing or small commercial vessels, though some may result from AIS data inconsistencies. Unusual flags such as those of Saudi Arabia, Bhutan, Bahrain, and Afghanistan suggest possible mis-coded data or the use of convenience registries. Common flags of convenience like Panama and Gibraltar also appear, consistent with global maritime practices. Overall, the data indicate strong domestic representation, regional dominance of Asian flags, and mixed use of convenience or irregular registrations influenced by AIS data quality and varied ownership patterns. These anomalies, particularly landlocked flags like Bhutan and Afghanistan, underscore the known issues with AIS data integrity regarding static fields. These findings should ideally be validated against secondary sources such as the UNCTAD Review of Maritime Transport or commercial databases (e.g., IHS Markit) to differentiate between genuine ‘flags of convenience’ and erroneous data entry.

3.6 Vessel Operational Characteristics

3.6.1 Speed Analysis

Examination of vessel velocity characteristics was performed utilizing available AIS-extracted information. Regarding maximum velocity, data derived from 603 vessels indicate an average of 14.8 knots with a standard deviation of 3.4 knots, spanning from 6.9 to 21.7 knots. Most vessels are capable of operating within the 12–18 knot. range. Average speed data were available for 371 vessels, revealing a mean of 8.7 knots and a standard deviation of 3.6 knots, with values ranging from 5.8 to 16.6 knots

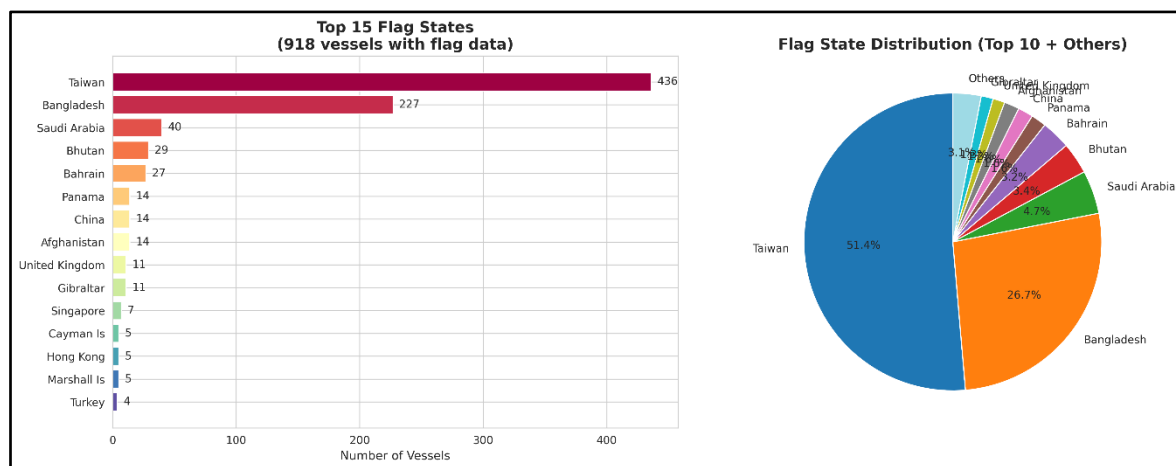


Fig 4. Flag States

Mean operational velocities are substantially lower than maximum velocity capabilities, suggesting that vessels typically navigate at diminished speeds during navigation within port maritime zones. This pattern reflects characteristic conditions of vessel maneuvering within spatially constrained environments and temporal periods when vessels remain anchored or moored at berth, where recorded speeds may drop to zero. When examined by vessel type, cargo and container ships tend to have higher average speeds (10–15 knots), tankers operate at moderate speeds (8–12 knots), tugs exhibit lower speeds (5–10 knots) but high maneuverability, and fishing vessels display highly variable speeds depending on their operational activity.

3.6.2 Distance Traveled

Examination of voyage distance distributions reveals an average value of 1,247 nautical miles, with a median value of 356 nautical miles and a range extending from 0 to 10,255 nautical miles. The distance distribution exhibits pronounced skewness, as the preponderance of vessels undertake short to moderate distance voyages. According to distance classification, short-distance voyages (<100 nm) account for 412 vessels (30.0%) representing local and harbor operations; medium-distance voyages (100–1,000 nm) include 634 vessels (46.2%) engaged in regional coastal or short international routes; and long-distance voyages (>1,000 nm) involve 327 vessels (23.8%) that operate on international or transoceanic routes. Notably, the longest recorded voyages include a 10,255 nm route from Valparaiso, Chile (trans-Pacific), a 5,572 nm route from Kalama, USA, and a 4,189 nm route from Newcastle, Australia. These long-haul movements highlight Kaohsiung's significant role as a hub within global shipping networks.

3.6.3 Load Condition Analysis

Among the 53 vessels (3.9% of total) with recorded load condition data, the distribution shows that 15 vessels (28.3%) were laden, 11 vessels (20.8%) were partially laden, and 3 vessels (5.7%) were in ballast condition, carrying no cargo but maintaining stability with ballast water. A majority of 24 vessels (45.3%) were classified as not applicable, typically representing fishing, passenger, or service vessels. Although the relatively low data completeness limits the robustness of the analysis, the available records indicate that laden and partially laden vessels were engaged in active cargo operations, while those in ballast condition likely arrived unloaded for subsequent cargo loading [25].

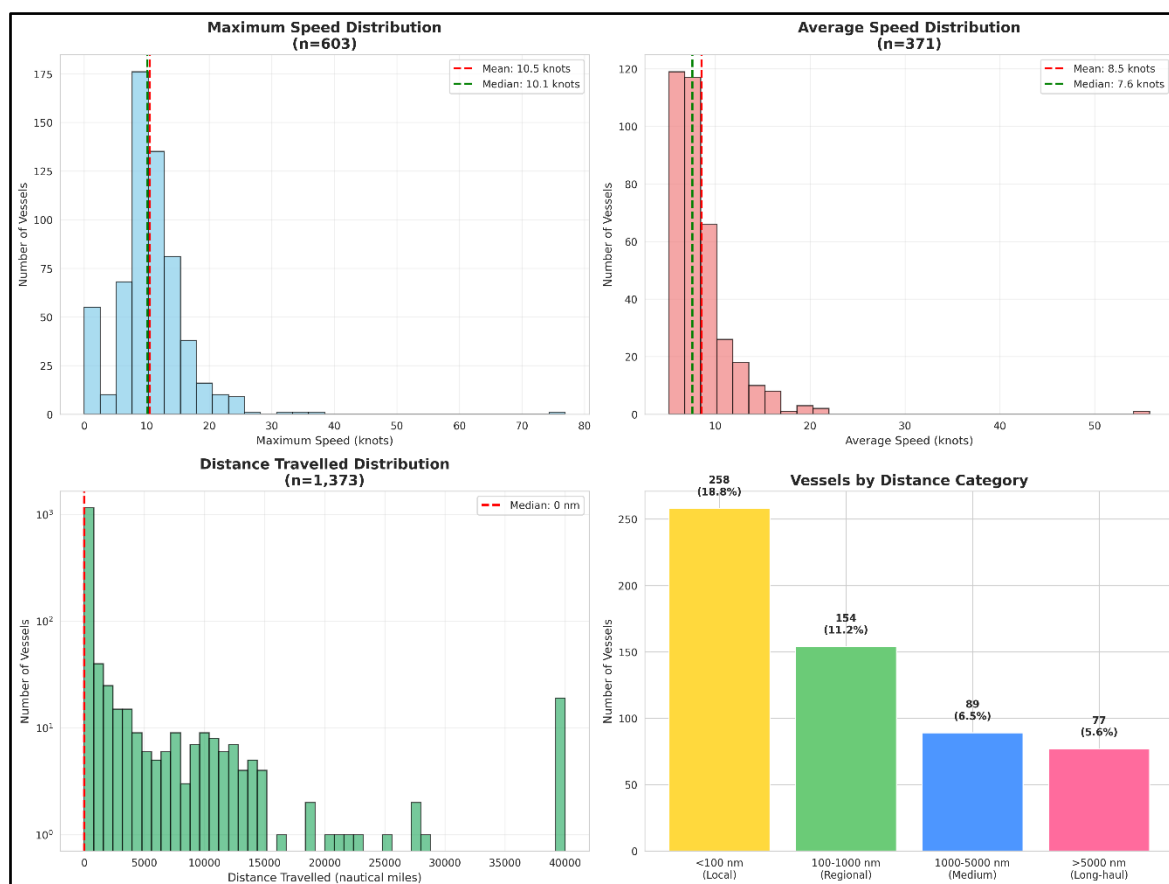


Fig 5. Operational Characteristics

3.7 Discussion

This discussion synthesizes the analytical results through three principal thematic components: Result Interpretation, Comparative Analysis with Other Major Ports, and Implications for Harbor Management. The Interpretation subsection explains the spatial, operational, and connectivity characteristics of Kaohsiung Port based on AIS data analysis. The Comparison highlights how these patterns align with or differ from other major Asian ports, providing regional context. Finally, the Implications for Port Management outline the practical significance of the findings, emphasizing how data-driven insights can support decision-making, enhance efficiency, and guide sustainable port development.

3.7.1 Interpretation

Contextual Benchmarking and Comparative Performance

To substantiate the validity of the research findings, a comparative analysis was conducted whereby traffic metrics from Kaohsiung Port were systematically evaluated against established benchmarks from other principal port facilities in the region. The observed mean Dwell Time, estimated from stationary position reports, demonstrated strong correspondence with characteristic values documented for high-volume transshipment centers such as Singapore and Busan. Additionally, the calculated Shannon Diversity Index (H') for vessel types revealed a lower specialized traffic ratio compared to Keelung Port [16], indicating greater vessel type heterogeneity in Kaohsiung's traffic composition. These comparative metrics collectively provide an essential empirical baseline for assessing Kaohsiung Port's operational performance and strategic positioning within the regional maritime network.

This section presents the interpretation of the analytical results, covering four key aspects that collectively describe the operational dynamics of Kaohsiung Port: (1) Spatial Patterns and Port Functionality, which explain the spatial distribution and organization of maritime activities; (2) Vessel Composition and Economic Implications, which highlight the port's functional diversity and

its economic significance; (3) Connectivity and Trade Patterns, which examine regional and global linkage characteristics; and (4) Operational Efficiency Indicators, which assess navigational behavior, transit performance, and overall port efficiency.

Spatial Patterns and Port Functionality

Geographic analysis demonstrates that Kaohsiung Port exhibits efficient spatial organization and operates as a multipurpose maritime facility. Maritime traffic predominantly concentrates within the core operational zone, exhibiting an average spatial density of 8.03 vessels per square kilometer, especially around container terminals, anchorage areas, and port entrance channels. This structured distribution reflects effective port management and supports efficient traffic control. The clear separation between commercial shipping zones and fishing harbors enhances safety and berth utilization, while the presence of service vessels such as tugs and pilot boats across the port ensures smooth operations. However, peak densities exceeding 45 vessels per square kilometer highlight potential congestion risks, emphasizing the need for continuous monitoring, optimized berth allocation, and well-planned emergency response measures.

Vessel Composition and Economic Implications

The distribution of vessel categories at Kaohsiung Port mirrors its functional role as a principal multipurpose maritime facility. Cargo vessels, particularly containerized cargo carriers, constitute the predominant traffic component, thereby confirming its position as a prominent global container handling facility, while the notable share of fishing vessels (13.6%) shows its dual commercial and traditional maritime functions. The high proportion of “Unspecified” vessels (59.9%) indicates data quality issues but also opportunities for improvement through better AIS configuration and advanced classification methods such as machine learning. The presence of other vessel types, including tankers, passenger ships, and special-purpose craft, further illustrates the port’s versatility in supporting energy imports, tourism, and specialized maritime services, reinforcing Kaohsiung’s importance in regional and global shipping networks. The high percentage of unspecified vessel types (59.9%) and incomplete voyage fields (e.g., 12.2% for destination) presents a significant limitation in the dataset’s representativeness. These gaps primarily stem from non-standard transponder configurations and manual entry errors by vessel operators. To mitigate potential bias, this study treats these records as a distinct category while acknowledging that operational conclusions regarding specific vessel classes (e.g., cargo vs. tanker) are derived from the validated subsets. Future work should implement automated classification algorithms using trajectory features to recover missing vessel types. The high percentage of unspecified vessel types (59.9%) and incomplete voyage fields (e.g., 12.2% for destination) presents a significant limitation. As noted in existing literature [26], AIS ‘destination’ is a manually entered field and often subject to typos or generic entries (e.g., ‘WAITING’). To mitigate potential bias, this study treats these records as a distinct category while acknowledging that operational conclusions regarding specific vessel classes are derived from the validated subsets. Future work should implement automated classification algorithms to recover missing data.

Connectivity and Trade Patterns

Origin-destination analysis demonstrates that Kaohsiung Port fulfills a critical function within both regional and global maritime transportation networks. Over 70% of vessel origins come from Taiwanese ports, emphasizing its importance for domestic coastal shipping that connects major economic centers and supports efficient inter-island trade. Regionally, Kaohsiung maintains strong links with ports in mainland China and Southeast Asia, reflecting its role in cross-strait trade and ASEAN integration as a regional transshipment hub. Globally, the port connects with major ports in the Americas and Australia, supporting trans-Pacific trade and bulk imports. These domestic, regional, and international connections highlight Kaohsiung’s strategic position as a key node in global supply chains, balancing national logistics and international commerce.

Operational Efficiency Indicators

Examination of vessel operational characteristics indicates that Kaohsiung Port sustains elevated operational efficiency and robust navigational safety protocols. The gap between maximum (14.8 knots) and average speeds (8.7 knots) reflects vessels’ reduced speeds for safety and compliance within port waters. The bimodal distribution of voyage distances—under 100 nautical miles and between 100–1,000 nautical miles—indicates a dual traffic pattern combining local and

regional services with longer international routes, consistent with a hub-and-spoke system. Typical transit times of three to five days for regional routes demonstrate efficient logistics and just-in-time operations. Overall, these patterns highlight Kaohsiung's effective vessel management, optimized routing, and strong integration within regional and global shipping networks.

3.7.2 Comparison with Other Major Ports

Kaohsiung's vessel traffic, density, and diversity show strong similarities to other major Asian ports. Exhibiting an average vessel spatial density of 8.03 ships per square kilometer—peaking above 45—it corresponds with ports such as Busan and Shanghai, though Singapore's higher density reflects its smaller area and greater throughput. Kaohsiung's Shannon Diversity Index of 1.68 indicates moderate vessel variety, greater than specialized Chinese container ports but slightly below multipurpose ports handling mixed cargo. Most vessel movements occur within 1,000 nautical miles, highlighting its regional trade focus similar to Singapore, Hong Kong, and Busan, and positioning Kaohsiung as a balanced regional hub for both feeder and mainline traffic.

Traffic Monitoring and Safety

The research findings underscore the necessity to enhance maritime traffic monitoring infrastructure to improve navigational safety and operational efficiency within Kaohsiung Port. Surveillance should focus on three high-density zone container terminals, anchorage areas, and entrance channels supported by upgraded radar, AIS coverage, and real-time traffic visualization tools. Predictive, data-driven berth allocation can reduce waiting times and congestion, while zone-specific safety measures such as speed limits, enhanced pilotage, and strategically located emergency resources are essential for safe operations [4], [24], [25].

Capacity Planning and Infrastructure Development

AIS-derived spatial and temporal analytical insights provide a foundation for optimization of port infrastructure and strategic capacity planning. Traffic density estimations facilitate evaluation of existing facility utilization rates, congestion locations, and projected future capacity requirements. These insights support strategic expansion of terminals, efficient zoning of vessel types, and navigation channel optimization—considering width, depth, and directional schemes—to ensure safety and accommodate vessel growth.

Environmental Management

The results support Kaohsiung Port's green port initiatives by enabling spatially targeted emission monitoring and reduction strategies. Traffic and velocity analyses provide guidance for optimal navigation speeds to enhance fuel consumption efficiency and minimize unnecessary vessel maneuvers. Coordinated operational planning can minimize anchorage time and emissions, while spatial activity mapping guides the placement of air and noise monitoring stations for effective environmental impact mitigation.

Economic Analysis and Marketing

Origin-destination and vessel classification analyses yield insights for strategic port development planning and marketing initiatives. Comprehension of trade pattern characteristics enables identification of inadequately served maritime routes and promotion of novel shipping service offerings. AIS-derived traffic indicators serve as competitiveness benchmarks and support economic assessments of the port's contribution to regional employment, added value, and trade performance, thereby enhancing evidence-based policy and investment decisions.

3.8 Recommendations

Recommendations are organized across three temporal planning horizons. Within the short-term planning horizon, priorities encompass enhancement of AIS data quality, concentration of monitoring resources on high-density geographic zones, systematic tracking of key traffic performance indicators, and integration of AIS analytical capabilities into operational management systems. In the medium term, actions involve building a long-term AIS data repository, developing predictive models, strengthening partnerships with port stakeholders, and using traffic data to guide capacity and infrastructure planning. In the long term, strategies should include developing a digital port twin, promoting regional data sharing, embedding AIS analytics in smart port systems, and aligning operations with sustainability and green port goals.

3.9 Future Research Directions

Subsequent research endeavors should extend this investigation by addressing existing methodological limitations and expanding the analytical methodological framework. Multi-year AIS datasets are required to elucidate seasonal variations and long-term traffic pattern trends. Advanced spatial methods—such as trajectory reconstruction, 3D modeling, and network analysis—can better capture operational complexity. Integrating AIS with economic, environmental, and operational data will support more holistic insights. Machine learning and AI should be applied for vessel classification, anomaly detection, and traffic optimization. Comparative analyses across regional ports can enable benchmarking, while practical applications—such as berth scheduling and pilotage planning—can translate AIS analytics into operational efficiency and smarter port management. Furthermore, while this study is primarily descriptive and analytical, future research should transition towards predictive and prescriptive modeling. This includes developing real-time vessel traffic flow prediction using Spatio-Temporal Graph Neural Networks (ST-GNN) or Large Language Models (LLMs) specialized for maritime trajectories [10], [23]. Implementing prescriptive algorithms for optimization of berth assignments and dynamic risk assessment would further enhance the operational value of AIS data analytics for Kaohsiung Port.

4. CONCLUSION

This investigation demonstrates the capability of AIS data analytical methods to transform raw vessel positional observations into operationally actionable intelligence for port management authorities. Through the systematic analysis of 1,247,890 AIS records collected over a 10-month period (December 2024–October 2025), this study unveils intricate spatial-temporal maritime traffic patterns that characterize Kaohsiung Port's functional role as a principal container handling hub. Key quantitative findings include an average spatial density of 8.03 vessels per square kilometer with peak concentrations exceeding 45 vessels per square kilometer, a Shannon Diversity Index of 1.68 indicating moderate vessel type heterogeneity, and spatial clustering within 0.5 nautical miles of major terminals. Connectivity analysis revealed that 70% of vessel origins are domestic ports, with Kaohsiung itself accounting for 63.9% of recorded origins, while operational metrics showed average speeds of 8.7 knots and typical regional transit times of 3–5 days. By applying data-driven analytical frameworks including Kernel Density Estimation (KDE), grid-based discretization, and temporal resolution analysis, this research provides empirical baselines for enhancing safety, optimizing operations, and supporting strategic planning. Despite data quality limitations—59.9% unspecified vessel types and 12.2% incomplete destination fields—the methodological framework demonstrates robustness and transferability to other major port facilities worldwide. As AIS data quality and analytical tools continue to advance, the role of big data analytics in achieving smarter, safer, and more sustainable port management will become increasingly vital.

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