Marine Traffic Risk Assessment Using Spatio-Temporal AIS Data in Makassar Port, Indonesia

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Abstract. Makassar Port plays a crucial role in the Ministry of Transport's hub-and-spoke strategy, significantly impacting the reduction of economic disparities between the eastern and western regions of Indonesia. As a vital port, the safety of the port and the marine environment must be safeguarded at all costs. In this regard, the Ministry of Transport has established a Vessel Traffic Service (VTS) to monitor and supervise the daily activities of inbound and outbound ships at Makassar Port. To enhance operational safety, this article discusses the utilization of historical Automatic Identification System (AIS) data to assess hazardous areas that require the utmost attention from VTS and the harbor master. By analyzing seven days of AIS past data using Geographic Information System (GIS) software, we were able to calculate traffic density based on the number of points per grid cell. The results revealed persistent dark red grid squares, indicating substantial congestion across all days, particularly on Days 1, 3, 5, and 7. The variance in traffic volume on different days suggests that certain periods of the week experience higher traffic levels. These findings highlight that the port entrance is a critical hub for maritime traffic, and if not managed effectively, it could lead to bottlenecks and navigational difficulties.

Keywords: First Keyword, Second Keyword, Third Keyword.

1 Introduction

The development of Makassar Port, particularly the Makassar New Port (MNP), has been a subject of extensive research and strategic planning. Several studies have focused on various aspects of the port's development, including eco port management, capacity utilization, and integration with transportation modes [1,2]. The strategic importance of the Makassar New Port in supporting international trade and transportation connectivity has been highlighted [3]. Additionally, the role of feeder ports, such as Tanjung Ringgit Port, in supporting the main port and the program of sea tollways has been emphasized [4]. Furthermore, the development of the port has been linked to the acceleration of the Eastern Indonesian Region's development [5].

The sustainable development of ports, including environmental sustainability and green port concepts, has been a growing concern in the industry [6,7,8]. The impact of the digital economy on economic growth and development strategies, particularly in

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the post-COVID-19 era, has also been recognized as an important factor [9]. Moreover, the potential cargo demand and the role of ports as international hub ports have been subjects of analysis and strategic planning [10]. The historical significance of Makassar as a strategic port city with established commerce networks has been acknowledged, emphasizing its role in regional and international trade [11,12]. The economic and regional development effects of transport infrastructure, particularly in the context of trade gateway regions, have been studied, highlighting the importance of port infrastructure development [13].

In conclusion, the development of Makassar Port, particularly the Makassar New Port, is a multifaceted and strategically significant endeavor that addresses various dimensions, including eco-port management, sustainability, regional economic impacts, and historical significance. The research and strategic planning undertaken in these areas offers valuable insights for the sustainable and strategic advancement of the port, aligning with broader goals of regional economic development and enhancing international trade connectivity.

2 Literature Review

Utilizing spatiotemporal AIS data for marine traffic risk assessment is a vital area of study that involves analyzing historical AIS data to understand traffic distributions, densities, and trends. This analysis is crucial for assessing risks, preventing accidents, and enhancing maritime safety. Numerous studies have highlighted the significance of using AIS data to evaluate marine traffic patterns, assess collision likelihood, determine congestion levels, and facilitate automated maritime routing [14,15,16]. By leveraging AIS data, it is possible to identify high-risk areas, detect anomalies, and recognize marine traffic patterns. These capabilities are essential for enhancing safety protocols and optimizing traffic management [17,18]. Further evidence shows that integrating AIS data with Geographic Information Systems (GIS) methodologies provides effective spatiotemporal risk assessment capabilities, facilitating a more comprehensive understanding of maritime traffic dynamics [19,20].

Additionally, researchers have stressed the significance of using AIS data for maritime spatial planning, which includes examining fishing zones, shipping lanes, navigation flows, maritime traffic density, and possible uses that conflict or complement one another in marine regions [18]. Beyond collision avoidance, marine surveillance, environmental effect assessment, traffic monitoring, forecasting, and commercial activity appraisal are among the applications of spatiotemporal AIS data processing [21]. Researchers have extracted useful insights from AIS data to predict traffic flow, congestion, and anomalies by using sophisticated techniques like spatiotemporal clustering, non-negative matrix factorization, and attention-based neural networks [22,23,24].

Moreover, research has indicated the value of spatiotemporal AIS data analysis for a range of real-world uses beyond maritime traffic, including crime prediction, traffic forecasting, traffic emissions analysis, and flood risk simulation [25,26,27]. The adaptability of such techniques in solving complex environmental concerns is demonstrated by the integration of spatiotemporal GIS with hydrodynamic models for flood risk assessment [27]. Furthermore, the creation of novel models for traffic forecasting, such as multi-head attention spatiotemporal graph neural networks, emphasizes the ongoing development of techniques to capture complex spatiotemporal interactions in a variety of datasets [28].

In conclusion, the synthesis of spatiotemporal AIS data for maritime traffic risk assessment is a multidisciplinary field utilizing knowledge from environmental science, geography, transportation engineering, and computer science. Researchers can improve maritime safety, optimize traffic management tactics, and support the sustainable development of marine habitats by utilizing the capability of AIS data analytics. Spatiotemporal analysis methods' ongoing development and the incorporation of cutting-edge technology will boost the field's progress toward more precise risk assessment and proactive marine decision-making.

3 Method

The method of spatiotemporal analysis using AIS (Automatic Identification System) data has been a subject of interest in various fields, including maritime studies, computer science, and medicine. AIS data, which provides information about vessel movements, has been leveraged for spatiotemporal analysis to understand vessel behaviors, detect patterns, and support decision-making. In the maritime domain, studies have utilized AIS trajectories to discover vessel spatiotemporal co-occurrence patterns, enabling the differentiation of vessel behaviors in terms of space, time, and other dimensions. Additionally, the application of AIS data in analyzing collision-avoidance patterns using AI-based methods has been explored, demonstrating the potential for effective learning of ship encounter data.

In the context of medical research, AI and machine learning methods have been employed to analyze medical imaging data, such as PET/CT scans and retinal photographs, for the detection and prediction of diseases, including lymph node metastases, glaucoma, and cerebral ischemia. These studies highlight the potential of AI in processing and analyzing spatiotemporal medical data for diagnostic and predictive purposes. Moreover, the application of spatiotemporal analysis methods using AIS data has been extended to other domains, such as environmental research and public health. For instance, spatiotemporal patterns of the 2019-nCoV epidemic were detected using nonparametric statistical tests and spatial autocorrelation indexes implemented in Python and ArcGIS, demonstrating the utility of spatiotemporal analysis in understanding the spread of infectious diseases. In summary, the research method of spatiotemporal analysis using AIS data has been applied across diverse domains, including maritime studies, medicine, and public health. The utilization of AIS trajectories for understanding vessel behaviors, the application of AI in medical imaging analysis, and the detection of spatiotemporal patterns of epidemics exemplify the broad applicability and significance of spatiotemporal AIS analysis in various research fields [29,30,31,32,33,34].

The research flow summarizes in the figure below:

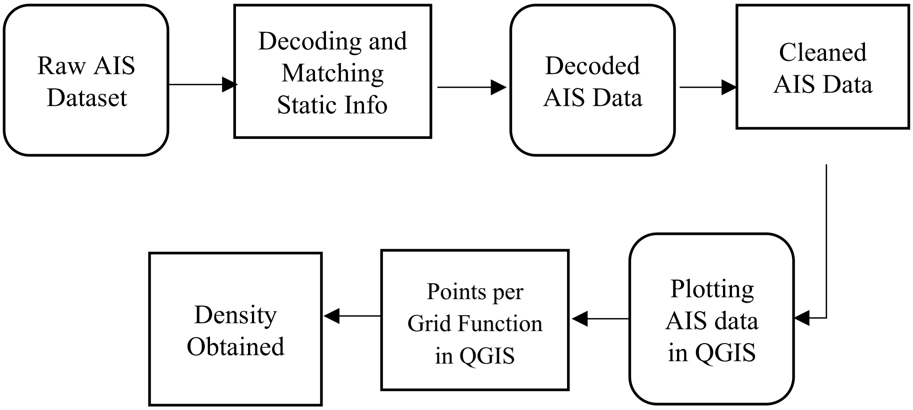

Fig. 1. Research flow.

Marine traffic density is a critical factor in understanding the impact of human activities on marine ecosystems. Several studies have focused on analyzing marine traffic density and its implications. conducted a study in the Eastern Mediterranean Sea of Turkey, where they retrieved two years of monthly marine traffic density data, indicating an average density of 0.37 hours of monthly vessel activity per square kilometer during the study period [35]. This demonstrates the quantification of marine traffic density in a specific region. Additionally, it utilized Automatic Identification System (AIS) big data to extract density-based maritime traffic routes, employing kernel density estimation (KDE) within a Geographic Information System (GIS) framework [36]. This approach provides a method for analyzing and visualizing marine traffic density patterns. In addition, significant sulfur and nitrogen oxide emissions from global marine traffic highlight the environmental implications of high marine traffic density [37].

4 Result & Discussion

Upon analyzing the ship particularly according to the AIS data, we managed to identify a total of 121 ships. On average, 35 ships traverse the designated area daily, with a peak of 40 ships recorded in a single day. The largest vessel measures 230 meters in length and on average, these vessels weigh 7,622 gross tons (GT), with the heaviest ship reaching 47,366 GT, underscoring the range of vessels handled by Makassar Port. The diversity of vessels consists of container ships that account for the largest proportion, comprising 21% of the fleet, followed closely by general cargo ships, which make up 20%. Tankers represent 17% of the traffic, while passenger vessels, including roll-on/roll-off (RORO) ships, constitute 15%. Other vessel types include bulk carriers (10%), LPG carriers (8%), and car carriers (3%), with a small percentage (5%) classified under 'Other.' In terms of vessel size, the AIS data reveals that the fleet is varied, with a significant concentration of ships in the 51-100-meter range (40%), and an equal proportion in the 101-150-meter range. Fewer ships fall into the larger size categories, with 12% measuring between 151-200 meters and just 1% exceeding 200 meters. The age of the vessels is also recorded, showing a wide range, with the oldest ship being 50 years old and the fleet's average age being 22 years. This suggests a mix of both older, possibly less technologically advanced vessels, and newer, more modern ships.

For the density analysis, upon cleaning all the AIS data we then plotted the latitude and longitude of the AIS data according to each vessel in GIS and then converted it to the point per grid function. We divided based on color where the reddish colored was the densest square. The grid is layered based on 1x1 Nautical Mile (NM) with the result of the analysis as follows:

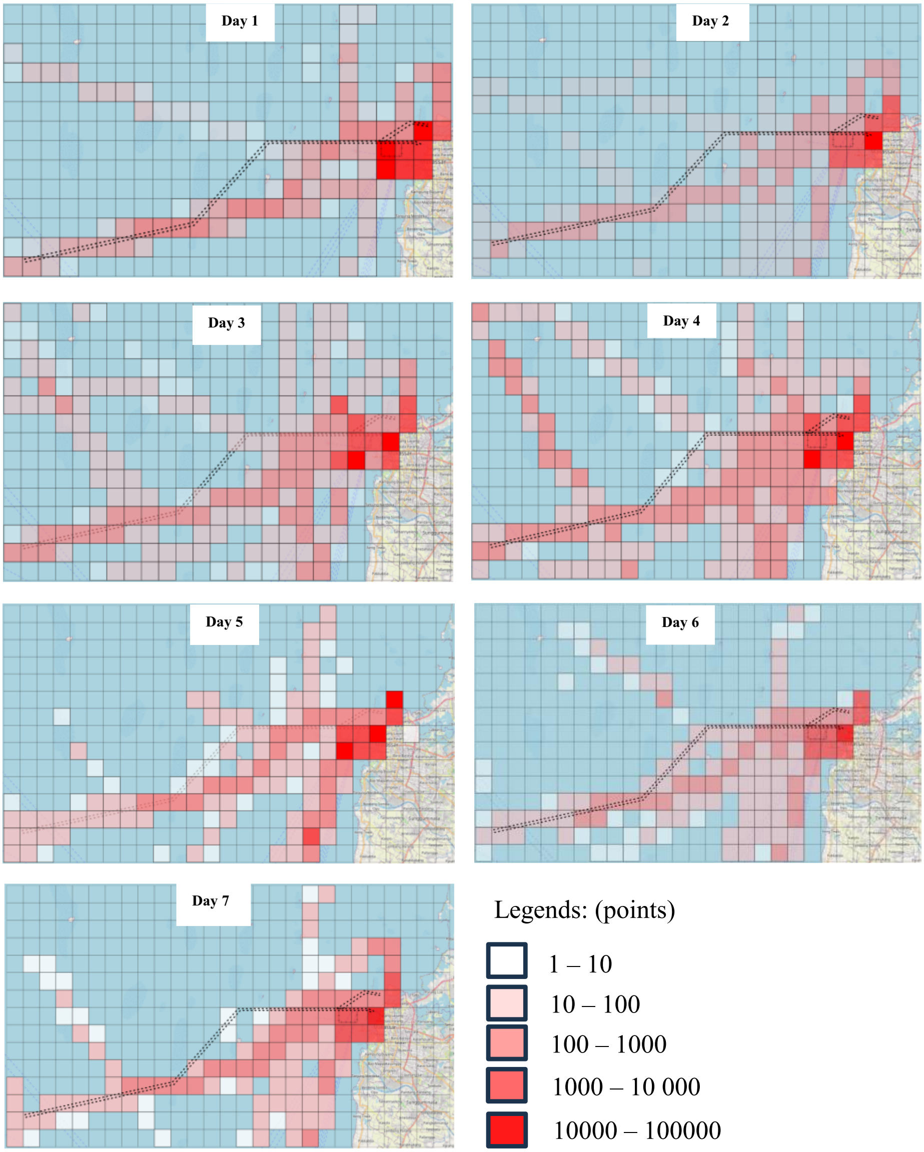

Fig. 2. Visualization of the marine traffic density in GIS using number of points per grid cell function

5 Conclusion

A constant region of high traffic density at the entrance of Makassar Port where various shipping routes meet is shown in Figure 2 over seven days. Persistent dark red grid squares indicate substantial congestion on all days, especially on Days 1, 3, 5, and 7.

The variance in traffic volume on various days indicates that there are periods of the week with higher traffic volume. These findings imply that the port entrance is an important center for maritime traffic and that if it is not handled appropriately, there may be bottlenecks and navigational difficulties. The regular pattern of heavy traffic highlights the necessity of planned traffic control to guarantee effective and safe passage through this region. This might entail introducing new rules, improving navigational aids, or optimizing traffic separation systems to control vessel flow and lower the likelihood of mishaps connected to congestion, or in this case, creating a new anchorage area in nearby Makassar Port.

The density analysis of Makassar Port indicates that certain areas require attention regarding ship traffic, particularly in the adjacent waters. Coastal traffic frequently deviates from the fairway, and many vessels visiting or departing Makassar Port do not comply with the established regulations for navigating the fairway. It is crucial to clarify and communicate the regulations governing the main fairway for entering and exiting Makassar Port to all vessels to ensure adherence, thereby enhancing the safety of both ships and the marine environment. Based on the AIS data analysis, it is essential to monitor the anchorage area and the interactions between vessels traveling in the fairway and local traffic, as they are likely to encounter each other in close quarters.

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