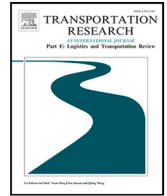




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Uncertainty-aware ship trajectory prediction via Spatio-Temporal Graph Transformer

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ABSTRACT

Accurate trajectory prediction is essential for enabling the autonomous navigation of unmanned ships. Recent advancements in Deep Learning (DL) based trajectory prediction using AIS data have positioned this area as a key focus in maritime transportation research. However, existing studies often fail to address trajectory uncertainty adequately. The ability to model uncertainty is crucial, as it not only quantifies the confidence in prediction results but also enhances a model's adaptability to complex and dynamic maritime environments. Addressing this gap requires innovative approaches to trajectory prediction that effectively account for uncertainty. This paper proposes a new trajectory prediction model, the Spatio-Temporal Graph Transformer with Probability (STGTP), which seamlessly integrates spatio-temporal features with probabilistic trajectory modelling. The proposed STGTP model introduces several innovations, including a temporal attention module to capture dynamic temporal variations in ship movements and a Transformer-based Graph Convolution (TGConv) to model spatial interactions, enhancing predictive accuracy. It employs a Gaussian heatmap representation for probabilistic trajectory modelling and a Vision Transformer to extract features that quantify prediction uncertainty effectively. These components enable STGTP to provide robust and reliable prediction while explicitly modelling uncertainty, improving the safety and adaptability of autonomous navigation systems. The model's performance was systematically evaluated across three distinct maritime regions using established metrics: Average Displacement Error (ADE), Final Displacement Error (FDE), and Fréchet Distance (FD). A comparison with ten baseline models demonstrates that the proposed STGTP model consistently outperforms all existing approaches across all evaluation metrics. These results underscore the model's overall superiority and effectiveness in maritime transportation. By integrating probabilistic and spatio-temporal modelling, STGTP significantly enhances the accuracy of ship trajectory forecasting, marking a key advancement toward achieving robust, real-time autonomous navigation in maritime environments.

1. Introduction

As global maritime activities surge, the importance of ensuring maritime safety has grown significantly. According to the United Nations Conference on Trade and Development (UNCTAD) (Trade and Development, 2024), global maritime trade expanded by

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2.4% in 2023, reaching a total of 12.3 billion tonnes, with container ship port calls surpassing 250,000 in the latter half of the year. This surge, driven by increasing trade volumes and extended shipping routes, has caused significant congestion, particularly in Asia, which handles 63% of global container trade. These trends have placed enormous pressure on logistics systems and over-stressed supply chains.

To address these challenges, Maritime Autonomous Surface Ships (MASS) equipped with autonomous navigation technology have emerged as a promising solution. MASS can mitigate risks associated with human error through the implementation of precise path planning, significantly improving safety and efficiency in complex maritime environments. A cornerstone of autonomous navigation is reliable Ship Trajectory Prediction (STP), which enables accurate forecasting of a ship's future positions in dynamic scenarios (Jiao et al., 2025). This capability supports path planning, collision avoidance, and safe navigation, making it a critical component of MASS technology (Zhang et al., 2024b).

Advances in data acquisition technologies and Artificial Intelligence (AI) have further elevated the importance of STP for MASS. Deep Learning (DL), a core AI technology, has emerged as the dominant approach (Bi et al., 2024), facilitating the realization of intelligent transport management in the maritime sector (Li et al., 2025). By utilising historical navigation data alongside current environmental information, DL models identify optimal navigation routes (Kim et al., 2024), enhancing navigational efficiency, reducing fuel consumption, and lowering operational costs. These advancements accelerate the commercialisation and widespread adoption of MASS technologies in the maritime industry.

Despite its importance, STP faces challenges, particularly regarding data quality and trajectory uncertainty (Yang et al., 2021; Li et al., 2023a). Automatic Identification System (AIS) data, a key source for trajectory prediction, often suffers from limited spatial and temporal coverage and inconsistent quality under varying conditions (Xi et al., 2023). These limitations undermine the global applicability of AIS-based models.

Research methodologies for STP can be primarily categorised into two technical branches: those founded upon classical Machine Learning (ML) frameworks and those implemented through DL architectures. While traditional ML models, like Support Vector Regression (SVR), are effective for short-term trajectory predictions, they struggle with complex trajectory variations in dynamic scenarios. In contrast, DL methods, such as Long Short-Term Memory (LSTM) Networks (Hochreiter, 1997) and Gated Recurrent Units (GRU) (Chung et al., 2014), have proven effective for time-series forecasting. However, these models face limitations, including difficulties with data sparsity, long-sequence predictions, and addressing trajectory uncertainty. Transformer models (Vaswani, 2017; Nguyen and Fablet, 2024) can capture long-term temporal relationships, making them suitable for long-range predictions in complex maritime scenarios. However, their inability to effectively model trajectory uncertainty limits their robustness. Spatio-temporal models (Alahi et al., 2016; Liang et al., 2022), which integrate temporal dynamics with spatial information, have shown promise in representing ship behaviours. Yet, most fail to capture trajectory uncertainty, a critical factor for their generalisation and adaptability in dynamic maritime environments.

Modelling trajectory uncertainty is vital for robust STP. It quantifies prediction confidence, enhances adaptability to dynamic environments, supports risk assessment, and informs decision-making. However, most existing models neglect this aspect, limiting their reliability in high-precision applications. Addressing this gap requires innovative methods that integrate uncertainty modelling.

To effectively assess STP performance, commonly used metrics include Average Displacement Error (ADE) and Final Displacement Error (FDE). ADE quantifies the average deviation between the predicted and actual trajectories across the entire path, while FDE measures the distance between the predicted and actual endpoint. These metrics provide straightforward and practical methods for assessing model accuracy. However, in complex maritime environments influenced by diverse factors, relying solely on ADE and FDE may not fully capture a model's overall performance. To address this limitation, recent research has emphasised the adoption of multidimensional evaluation metrics. These advanced metrics offer a broader multidimensional assessment under various environmental conditions and across different stages of navigation (Li et al., 2024b).

Despite notable advancements in datasets, prediction methods, and evaluation metrics, several critical challenges in STP remain:

- (1) Inconsistent data quality: Raw ship trajectory datasets often exhibit inconsistent formats and contain significant errors, limiting their utility for researchers.
- (2) Limited handling of uncertainty: Current prediction models lack robust mechanisms to incorporate trajectory uncertainty, reducing their adaptability and reliability in dynamic maritime environments.

To tackle these challenges, this paper develops the Spatio-Temporal Graph Transformer with Probability (STGTP). The STGTP model introduces an effective integration of spatiotemporal features and probabilistic trajectory modelling. It incorporates three innovative components:

- (1) Temporal transformer: Captures dynamic temporal variations in ship movements, enhancing the precision of temporal modelling.
- (2) Spatial transformer: Models complex spatial interactions among ships, improving the understanding of navigational patterns in congested maritime environments.
- (3) Vision transformer: Extracts probabilistic features from Gaussian heatmaps of trajectories, allowing the model to quantify and incorporate trajectory uncertainties effectively.

A core innovation of the STGTP model lies in its ability to seamlessly integrate temporal features, spatial features, and probabilistic features, thereby effectively addressing the critical need for uncertainty modelling in trajectory prediction. Compared with traditional models such as Bi-directional GRU (BiGRU) and Bi-directional LSTM (BiLSTM), the proposed model incorporates spatial

modelling and probabilistic modelling modules, enabling more accurate capture of trajectory changes caused by interactions between vessels and trajectory deviations resulting from uncertainties. In comparison with existing methods like Spatio-Temporal Graph Convolutional Network (STGCNN) and Spatio-Temporal Graph Transformer (STAR), the STGTP model demonstrates significant advantages in capturing trajectory uncertainties, a capability that is particularly crucial in short-term prediction scenarios where higher demands are placed on the adaptability and robustness of the model. Through this integrated design, the STGTP model can efficiently capture temporal dynamics, spatial dependencies, and trajectory uncertainties, exhibiting outstanding performance especially in short-term prediction scenarios. The main contributions of this paper are as follows.

- (1) A holistic prediction framework: Develop the STGTP model, a holistic framework integrating temporal, spatial, and probabilistic components to address the complexities of STP in dynamic maritime environments.
- (2) Innovative spatiotemporal and probabilistic integration: Combine spatiotemporal feature extraction with probabilistic modelling using Temporal and Spatial Transformers, along with a Vision Transformer for uncertainty quantification, significantly enhancing predictive accuracy and adaptability.
- (3) Validation with real-world datasets: Conduct extensive experiments using AIS datasets from three diverse maritime regions and systematically compare the STGTP model with ten state-of-the-art (SOTA) methods, demonstrating superior accuracy and robustness.
- (4) Advancing autonomous navigation technologies: Establish a solid foundation for the integration of trajectory prediction and uncertainty modelling into MASS systems. This will be instrumental in improving the safety and efficiency of maritime navigation.

More specifically, the paper is structured as follows: Section 2 analyses of current STP methods from ML and DL systems. Section 3 defines the research question and prediction function. Section 4 details the design and implementation of the proposed STGTP model, outlining the theoretical basis of the temporal, spatial, probability modelling and decoding parts. Section 5 introduces the experimental datasets, evaluation indicators, result analysis and visualisation results of ablation experiments and control experiments. Section 6 discusses the paper's method and points out its applications and potential beneficiaries. Finally, Section 7 summarises the study and discusses future research that will focus on incorporating navigation-specific constraints and dynamic environmental factors.

2. Literature review

2.1. A systematic review

A systematic literature search was conducted in the Web of Science (WoS) Core Collection database (Mongeon and Paul-Hus, 2016) to investigate advancements and emerging trends in STP in April 2025. The research utilised the keywords 'ship trajectory prediction' and 'vessel trajectory prediction', combined with the 'OR' operator, yielding a total of 1111 relevant SCI-indexed papers. Subsequently, 150 highly relevant journal articles were selected for in-depth analysis. Metadata, including authors, titles, journals, keywords, and abstracts, was systematically extracted from these articles.

To analyse keyword trends and relationships, the CiteSpace software (Chen, 2006) was employed to examine the co-occurrence of keywords across the selected articles. This analysis produced a thematic keyword clustering map (Fig. 15) and a keyword timeline visualisation (Fig. 16), providing a systematic overview of the research focus and its evolution.

The research can be broadly categorised into eight key directions, as illustrated in Fig. 15. These directions are further grouped into three primary categories based on their focus areas.

- (1) Automatic Identification System and data processing: This category focuses on research related to #2 AIS data, which is widely used for analysing ship behaviour and predicting trajectories. Studies, including those by Harati-Mokhtari et al. (2007), Emmens et al. (2021) and Tichavska et al. (2015), highlight the critical role of AIS data in maritime research. It supports applications like #3 collision avoidance and situational awareness (Xiao et al., 2015; Svanberg et al., 2019). Due to its extensive coverage and real-time availability, AIS data continues to serve as a critical resource for STP and a wide range of maritime applications.
- (2) STP Methods: Research directions such as #0 Predictive models, #1 Maritime Route Network, #4 Ship Trajectory Prediction, #5 Vessel Trajectory Prediction and #1 Prediction Methods primarily focus on improving methods for mining ship trajectory data (Liu et al., 2025; Li et al., 2019). With technological progress, DL methods have developed rapidly. In particular, GRU and LSTM networks have attracted strong interest (Suo et al., 2020).
- (3) Application Value of Trajectory Prediction: Research directions #3 Collision Avoidance and #6 Vessel State Estimation fully highlight the critical role of trajectory prediction in ocean transportation and intelligent shipping (Tang et al., 2024; Murray and Perera, 2019). Vessel State Estimation (#6) aims to estimate the real-time state parameters of ships (e.g., position, speed, and heading) using trajectory and sensor data Perera et al. (2012). Trajectory prediction also plays a vital role in building smart shipping systems, supporting autonomous navigation, remote monitoring, and traffic management through big data, cloud computing, and Internet of Things (IoT) technologies.

As shown in Fig. 15, the eight research categories are closely connected, reflecting the interdisciplinary nature of this field. Predictive Models (#0)—especially DL models—often rely on AIS data (#2) as input (Yang et al., 2024; Zhang et al., 2021; Li et al.,

2023b). Overall, research in STP showcases a growing integration of AIS data modelling, DL, and decision-support tools, driving innovation in maritime navigation, safety, and traffic management. These trends point to the increasing use of SOTA technologies to tackle the complex challenges in the maritime domain.

As illustrated in Fig. 16, the evolution of STP research can be divided into three key phases:

- (1) Early research (2012–2017): This phase laid the foundation for STP, focusing mainly on the use of AIS (#2). Early studies, such as Yang et al. (2019) and Tu et al. (2017), highlighted the crucial role of AIS in advancing maritime operations. Deng et al. (2014) used AIS data for ship tracking, demonstrating its potential. Although methods were basic and technically simple, this period set the stage for later advancements in intelligent maritime technologies.
- (2) ML era (2018–2020): This period brought rapid progress in modelling techniques, with #0 Predictive Models becoming a central topic. ML was widely adopted to improve prediction accuracy (Bi et al., 2024). Related fields, such as #3 collision avoidance, have also seen advancements. For instance, Singh and Heymann (2020) used ML to detect anomalies in ship behaviour. This era marked a shift toward more reliable and precise maritime traffic management systems.
- (3) DL era (2021–2025): Research shifted toward more advanced models, particularly DL approaches like LSTM and BiLSTM, which enabled better prediction of complex and dynamic trajectories. For instance, Liu and Ma (2022) combined LSTM with attention mechanisms for improved accuracy, while Liu et al. (2024b) explored spatio-temporal features. Li et al. (2023a) evaluated 12 models across three maritime environments, highlighting the adaptability of DL under complex conditions.

In summary, STP has evolved from basic AIS-based studies to a sophisticated, application-driven field. Modern research emphasises advanced data processing, real-time decision-making, and network optimisation, moving from theory to real-world use. These advancements are enhancing maritime safety and efficiency and supporting the future of smart navigation and traffic management.

2.2. Research progress of STP

To provide a clear view of how STP methods have evolved, Fig. 1 outlines the development of five main categories of techniques: (1) Traditional ML methods; (2) LSTM-based methods (including BiLSTM); (3) GRU-based methods (including BiGRU); (4) Attention mechanism-based methods; (5) Spatio-temporal graph-based methods. Fig. 1 highlights a clear shift from basic models to more advanced DL and hybrid approaches.

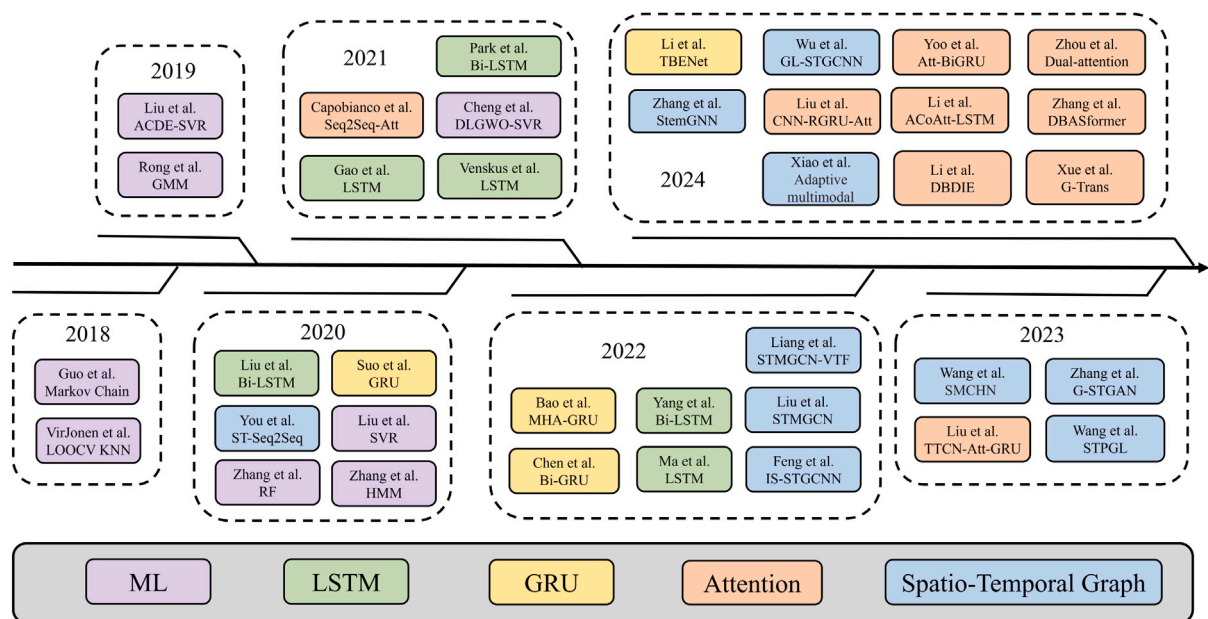


Fig. 1. Evolution of trajectory prediction approaches: From ML to spatio-temporal deep models.

Early STP methods relied on traditional ML, using statistical models and manual feature engineering. As the field progressed, DL models like LSTM and GRU became popular due to their strength in handling time-series data.

The introduction of attention mechanisms marked a major improvement by enabling models to focus on key trajectory points and capture global patterns, thereby improving prediction accuracy. More recently, spatio-temporal graph-based approaches have emerged, integrating spatial and temporal information to better model complex vessel movements and interactions in dynamic maritime environments.

This evolution reflects increasing model sophistication to meet modern maritime needs, where high accuracy and real-time performance are essential. The transition from simple algorithms to advanced DL and graph-based models has been driven by the need for smarter, more reliable predictions.

The next section builds on the trends shown in Fig. 1 by comparing how traditional and DL methods perform in real-world maritime scenarios. It highlights key features of each approach and how they have developed to address practical challenges. These advancements underscore the growing role of trajectory prediction in ensuring safe and efficient maritime operations.

2.2.1. Research progress of STP based on ML

Early studies on STP initially relied on traditional ML algorithms, including Support Vector Machines (SVM), Gaussian Process Models, Markov Models, K-Nearest Neighbours (KNN), and Random Forests (RF). Each algorithm demonstrated distinct strengths suited to specific prediction scenarios, with a summary of the information presented in Table 1.

SVM was widely used for pattern recognition and regression. To improve its performance, researchers applied advanced optimisation techniques. Researchers applied advanced optimisation algorithms to fine-tune SVM parameters for improved performance. For instance, Liu et al. (2019) proposed an Adaptive Chaotic Differential Evolution (ACDE) algorithm, and Chen et al. (2021) introduced a Dimension Learning Grey Wolf Optimisation (DLGWO) algorithm to enhance SVM-based trajectory prediction. However, both approaches encountered limitations related to small sample sizes and complex parameter tuning. Liu et al. (2020b) proposed an online multi-output SVR model that worked well with limited data, but its performance still depended heavily on data quality, a common issue in traditional methods.

Gaussian Processes were also used for regression and probability estimation. For instance, Rong et al. (2019) used Cholesky decomposition to predict the probability density of ship positions off the Portuguese coast. While effective in managing uncertainty, this method relied on strong assumptions, limiting its use in complex scenarios.

Markov Models are designed to handle sequential data through hidden states. Zhang et al. (2019) combined the Hidden Markov Model (HMM) with wavelet analysis to reduce errors and noise effects using the MIT trajectory dataset. Similarly, Guo et al. (2018) used a higher-order multivariate Markov chain to predict trajectories based on position, speed, and heading—achieving up to four-hour forecasts but with high computational demands.

KNN predicted future positions by comparing them with historical data. Virjonen et al. (2018) optimised KNN using Leave-One-Out Cross-Validation (LOOCV) with data from the Gulf of Finland. Although accurate for fixed routes, KNN struggled to generalise in more dynamic environments.

RF, which combines multiple decision trees, was used for destination prediction. Zhang et al. (2020) extracted features like position, speed, and ship type to improve RF performance, showing strong results in pattern learning.

While these traditional methods provided a solid foundation by helping with noise reduction, feature selection, and sequence modelling, they also had limitations. Challenges included reliance on small datasets, complex parameter tuning, and limited adaptability to changing environments. These issues have since driven the shift toward more flexible and powerful DL approaches.

Table 1
Summary of STP based on ML.

Method		Refs	Dataset
SVM	ACDE	Liu et al. (2019)	Tianjin Port Area, March 2015
	Online Multi-output	Liu et al. (2020b)	Tianjin Port Area, March 2015
	DLGWO	Chen et al. (2021)	Gulei Port, September–October 2018
KNN	Nested LOOCV	Virjonen et al. (2018)	Finnish Bay, December 2017–January 2018
Gaussian Process	Cholesky Decomposition	Rong et al. (2019)	Cape Roca, October–December 2015
HMM	Wavelet Analysis	Zhang et al. (2019)	MIT Trajectory Dataset
Markov Chain	High-order Markov Chain	Guo et al. (2018)	Wenzhou Marine Data, January 2016–December 2017
RF	Feature Selection	Zhang et al. (2020)	Southeast China Coastal Area, 2011–2017

2.2.2. Research progress of STP based on DL

DL has become the dominant approach in STP, with popular models including LSTM, GRU, attention mechanisms, and spatio-temporal fusion networks. Each method brings unique strengths for addressing different maritime challenges.

LSTM, a type of Recurrent Neural Network (RNN), is effective for handling long time-series data by overcoming vanishing gradient issues. The effectiveness of LSTM for STP has been demonstrated in several studies, including those by Ma et al. (2022), Venskus et al. (2021), and Gao et al. (2021). Furthermore, studies such as Yang et al. (2022), Liu et al. (2020a), and Park et al. (2021) explored BiLSTM models, reporting significant improvements in prediction accuracy.

GRU is a simpler alternative to LSTM and performs well in time-series forecasting. Bao et al. (2022) demonstrated GRU's capacity in long-term ship trajectory forecasting, though its anomaly-handling ability remains limited. Suo et al. (2020) addressed data redundancy and noise by incorporating DBSCAN and Symmetrised Segment-Path Distance (SSPD) techniques before applying GRU. Chen et al. (2022) utilised BiGRU for trajectory prediction, while Li et al. (2024c) introduced a triple bidirectional enhanced network integrating BiGRU and BiLSTM for improved performance.

Attention mechanisms help models focus on key features in the data, improving prediction accuracy. These mechanisms are often combined with DL models like LSTM and GRU (Xue et al., 2024; Yoo et al., 2024; Li et al., 2024a; Zhao et al., 2024; Li et al., 2024b). In addition, attention mechanisms have been integrated with CNN, combining the advantages of both to improve performance (Lin et al., 2023; Liu et al., 2024a; Zhang et al., 2024c; Capobianco et al., 2021).

Table 2
Summary of DL methods.

Reference	Methods				Input features				
	Spatio-Temporal Graph	Attention	GRU	LSTM	Longitude	Latitude	Speed	Course	Other
Ma et al. (2022)				✓	✓	✓			
Venskus et al. (2021)				✓	✓	✓	✓	✓	
Gao et al. (2021)				✓	✓	✓			
Yang et al. (2022)				✓(Bi)	✓	✓			
Liu et al. (2020a)				✓(Bi)	✓	✓			
Park et al. (2021)				✓(Bi)	✓	✓			
Li et al. (2024c)			✓(Bi)	✓(Bi)	✓	✓			
Chen et al. (2022)			✓(Bi)	✓	✓	✓			
Bao et al. (2022)		✓	✓		✓	✓			
Suo et al. (2020)			✓		✓	✓			
Lin et al. (2023)		✓	✓		✓	✓			
Li et al. (2024a)		✓		✓	✓	✓	✓	✓	
Zhao et al. (2024)		✓		✓	✓	✓			
Liu et al. (2024a)		✓	✓		✓	✓			
Li et al. (2024b)		✓	✓	✓	✓	✓			
Xue et al. (2024)		✓	✓		✓	✓			
Yoo et al. (2024)		✓	✓		✓	✓			
Capobianco et al. (2021)		✓			✓	✓			
Xiao et al. (2024)	✓		✓		✓	✓	✓	✓	✓
Wang et al. (2023a)	✓	✓		✓	✓	✓			
Feng et al. (2022)	✓				✓	✓			
Wu et al. (2024)	✓				✓	✓			
You et al. (2020)	✓				✓	✓	✓	✓	
Zhang et al. (2023)	✓	✓			✓	✓			
Wang et al. (2023b)	✓	✓			✓	✓			
Liang et al. (2022)	✓				✓	✓			
Liu et al. (2024b)	✓	✓			✓	✓			
Zhang et al. (2024a)	✓	✓			✓	✓			

Spatio-temporal fusion techniques have proven effective in capturing the intricate relationships between spatial and temporal features in ship trajectory data (Xiao et al., 2024; Wang et al., 2023a). STGCNN has been extensively explored, with Feng et al. (2022) and Wu et al. (2024) integrating these models with ship dynamics modelling to produce more realistic trajectory predictions. Short-term STP was addressed by You et al. (2020) using a Sequence to Sequence (Seq2Seq) structure that incorporated spatio-temporal data. Advanced models, including the sparse multi-graph convolutional hybrid network by Wang et al. (2023b) and the STGCNN developed by Zhang et al. (2023) and Liang et al. (2022), demonstrate the growing potential in this domain. Noteworthy contributions also include attention-based spatio-temporal probabilistic trajectory prediction by Liu et al. (2024b) and the integration of spatio-temporal attention mechanisms with Spectral Temporal Graph Neural Network (StemGNN) for multivariate data extraction, as proposed by Zhang et al. (2024a).

Table 2 provides a systematic summary of the applications of DL methods in STP, comparing their methods and input features. Fig. 2 presents statistical insights into the usage and performance of these methods, emphasising the transition from traditional approaches to sophisticated, real-time, and probabilistic models. These advancements underline the potential of DL in addressing the complex challenges of maritime trajectory prediction and pave the way for further innovations in this field.

Between 2020 and 2024, the use of latitude and longitude as core features in STP has grown significantly, highlighting their importance in spatial analysis. However, the combined use of latitude, longitude, and speed has varied over time, and studies that include heading remain limited—likely due to challenges in data availability. Although multi-feature models are less common, they can offer valuable insights in specific scenarios.

During the same period, LSTM and GRU models have consistently performed well, especially for capturing long-term patterns. Attention mechanisms have also gained traction, improving prediction accuracy and adaptability in dynamic maritime settings. More recently, spatio-temporal graph models have become increasingly popular, particularly in 2023 and 2024, for their ability to model complex vessel interactions.

Despite these advances, most spatio-temporal models still rely on deterministic predictions, limiting their ability to handle uncertainty. Probabilistic models address uncertainty but often treat spatial and temporal data separately, which can reduce prediction consistency. This limits their effectiveness in real-time maritime environments.

Looking ahead, future research should focus on integrating spatio-temporal and probabilistic approaches, improving model design, and enhancing reliability. These efforts are essential for developing accurate and robust STP models to support safer and smarter maritime navigation.

3. Preliminary

This section provides a problem definition for STP, followed by a detailed overview of the specific methodology adopted in this study. The research problem is mathematically formulated to highlight the characteristics and challenges of the task. This

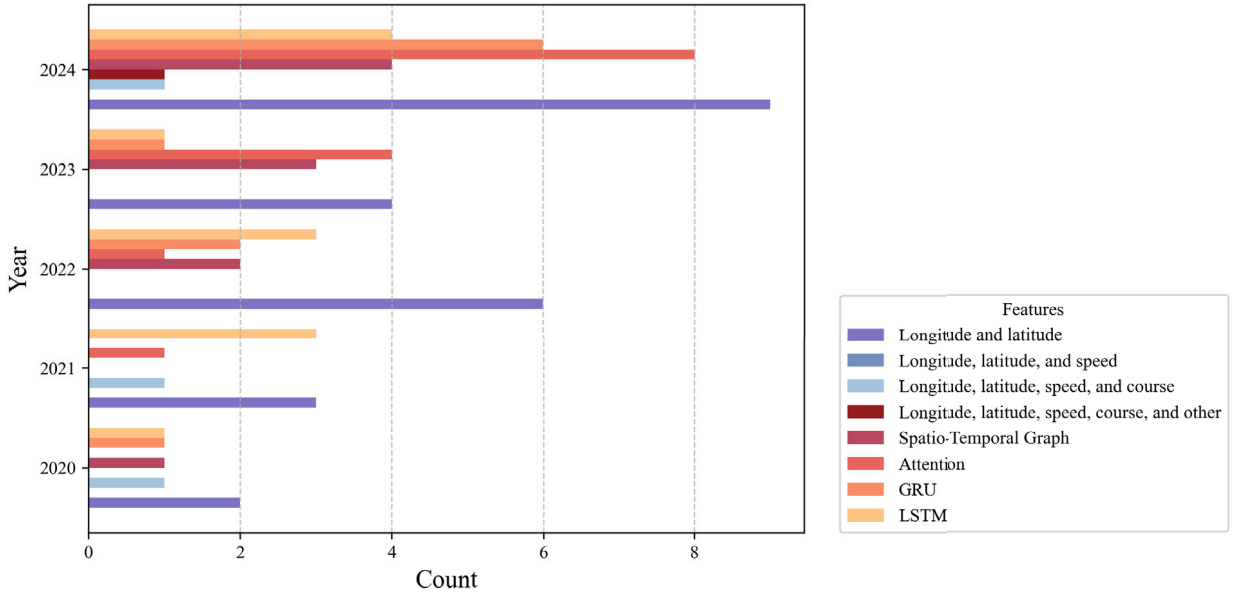


Fig. 2. Statistics on DL applications.

structured approach facilitates an in-depth understanding of the complexities involved in STP and establishes a coherent framework for addressing them.

3.1. Problem definition

A ship's trajectory refers to the path it follows on water, represented as a time-ordered sequence of latitude and longitude coordinates over time.

A STP problem can be formally defined as follows:

$$P_{pre}^n = \{(\text{lon}_1^n, \text{lat}_1^n), (\text{lon}_2^n, \text{lat}_2^n), \dots, (\text{lon}_{t_{pre}}^n, \text{lat}_{t_{pre}}^n)\}, \quad (1)$$

where P_{pre}^n represents the historical trajectory data of ship n . t_{pre} denotes the last observed time step in the historical data.

The goal is to predict the trajectory over the subsequent $pred$ time steps:

$$P_{pred}^n = \{(\text{lon}_{t_{pre}+1}^n, \text{lat}_{t_{pre}+1}^n), (\text{lon}_{t_{pre}+2}^n, \text{lat}_{t_{pre}+2}^n), \dots, (\text{lon}_{t_{pre}+pred}^n, \text{lat}_{t_{pre}+pred}^n)\}, \quad (2)$$

where P_{pred}^n denotes the predicted trajectory data of ship n . $t \in [t_{pre} + 1, t_{pre} + pred]$ represents the time steps within the prediction horizon. The prediction interval is set to 10 seconds.

Specifically, given a sequence of 8 historical trajectory points, the task is to forecast a sequence of 12 future trajectory points. Using 8 historical trajectory points to predict 12 future points balances short-term accuracy with long-term prediction capability (Mangalam et al., 2021; Shi et al., 2021). This ratio ensures the model captures essential motion patterns while avoiding outdated information. It also optimises computational efficiency, providing enough context for reliable prediction without excessive complexity. The choice is often based on empirical validation, ensuring a good trade-off between accuracy and practicality for applications like route planning and decision-making.

3.2. Prediction function

As defined in Fig. 3, a prediction function $f : P_{pre}^n \rightarrow P_{pred}^n$ is used to generate future predicted trajectories P_{pred}^n based on the input historical trajectories P_{pre}^n .

The input consists of the longitude and latitude coordinates recorded over the past 8 time steps:

$$P_{pre}^n = \{(\text{lon}_{t-7}^n, \text{lat}_{t-7}^n), \dots, (\text{lon}_t^n, \text{lat}_t^n)\}. \quad (3)$$

The output provides the longitude and latitude for the subsequent 12 time steps:

$$P_{pred}^n = \{(\text{lon}_{t+1}^n, \text{lat}_{t+1}^n), \dots, (\text{lon}_{t+12}^n, \text{lat}_{t+12}^n)\}. \quad (4)$$

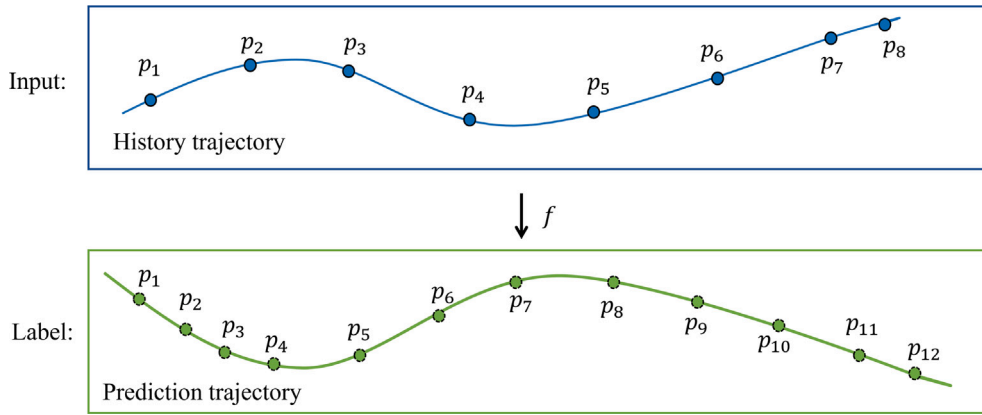


Fig. 3. Visualisation of prediction function.

4. Methodology

4.1. The overall research framework

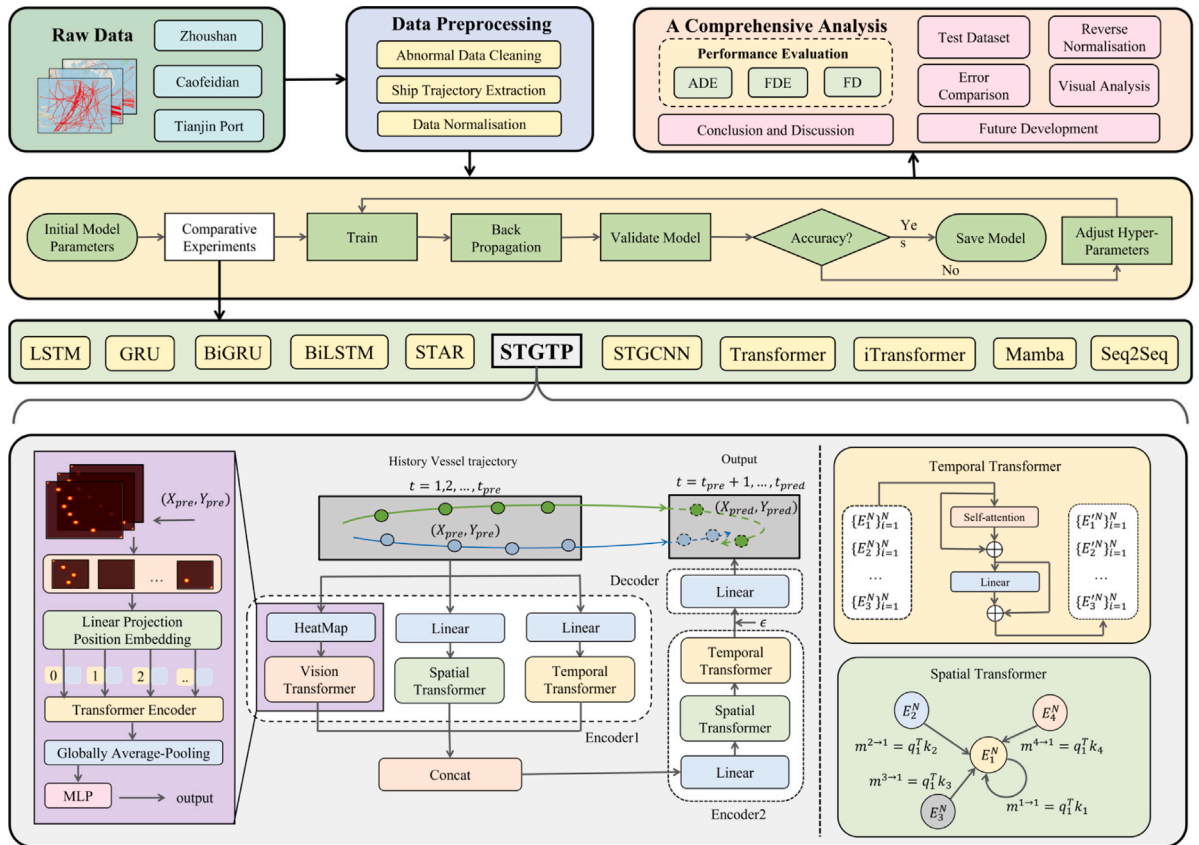


Fig. 4. The overall framework of this paper.

The overall framework of this study, illustrated in Fig. 4, combines data preprocessing, model training, and performance evaluation to develop an advanced trajectory prediction model, STGTP. The framework begins with a systematic data preprocessing phase. Raw data collected from various ports, including Zhoushan, Caofeidian, and Tianjin Port, is processed through three main

steps: abnormal data cleaning, ship trajectory extraction, and data normalisation. These steps ensure the data is reliable, structured, and consistent, forming a solid foundation for the subsequent modelling process.

The next phase involves comparative experiments and model training, where the processed data is used to train multiple trajectory prediction models, such as LSTM, GRU, BiGRU, BiLSTM, STAR, STGTP, STGCNN, Transformer, iTransformer, Mamba, and Seq2Seq. The training workflow includes initialising model parameters, running comparative experiments, and iteratively refining the models through backpropagation, validation, and hyperparameter adjustments. This iterative process ensures that the models achieve optimal performance, with the final trained models saved for evaluation once sufficient accuracy is reached.

To evaluate predictive performance, the study employs three key metrics: ADE, FDE, and Fréchet Distance (FD). These metrics are used to compare the models' effectiveness, with results visualised through error comparisons, reverse normalisation, and visual analysis. This systematic evaluation provides detailed insights into model performance and informs the conclusions drawn to guide future research and development.

To effectively capture the spatio-temporal dynamics of ship trajectories, this study introduces the STGTP model. STGTP is a multi-step prediction framework based on the Transformer architecture that integrates temporal, spatial, and probabilistic trajectory information. It employs a Temporal Transformer to model sequential dependencies, a Spatial Transformer enhanced with graph convolution mechanisms to capture interactions between vessels, and a Vision Transformer to process probabilistic trajectory features derived from Gaussian heatmaps. This innovative combination enables the model to learn intricate temporal patterns, complex spatial dependencies, and uncertainties in ship trajectories, resulting in highly accurate predictions.

The STGTP model is designed to overcome the limitations of traditional trajectory prediction models, which often focus solely on future positions without accounting for movement uncertainties or risk factors. By incorporating risk-aware predictions, the STGTP model enhances its applicability in high-risk scenarios, such as autonomous vessel operations. It provides robust decision support for proactive navigation adjustments and real-time collision risk assessments, ensuring safer and more efficient maritime transport. By capturing the intricate spatio-temporal dynamics and uncertainties associated with ship movements, the STGTP model represents a significant advancement in trajectory prediction, making it a critical tool for autonomous navigation systems in complex maritime environments.

4.2. Temporal modelling

The computation of the 'Temporal Transformer' is illustrated in Fig. 5. For each ship i , its trajectory from time t_{pre} is represented as $p_i^1, p_i^2, \dots, p_i^{t_{pre}}$. The position of the ship is encoded into a feature vector E_i^t , and temporal dependencies are captured using the self-attention mechanism. For each embedded feature vector E_i^t in the time series, the Q_i^t , K_i^t and V_i^t are derived. The attention scores are subsequently calculated using the following formula:

$$Attn(Q_i^t, K_i^t, V_i^t) = softmax\left(\frac{Q_i^t K_i^{tT}}{\sqrt{D}}\right) V_i^t, \quad (5)$$

where D represents the dimension of the Q_i^t , and the *softmax* function is used to normalise the attention scores. The Multi-head Self-Attention (MSA) mechanism is calculated as follows:

$$MSA(Q, K, V) = Concat(h_1, \dots, h_n), \quad (6)$$

where $h_i = Attn(Q, K, V)$ represents the attention output for the i th head, and n denotes the number of attention heads in the MSA mechanism.

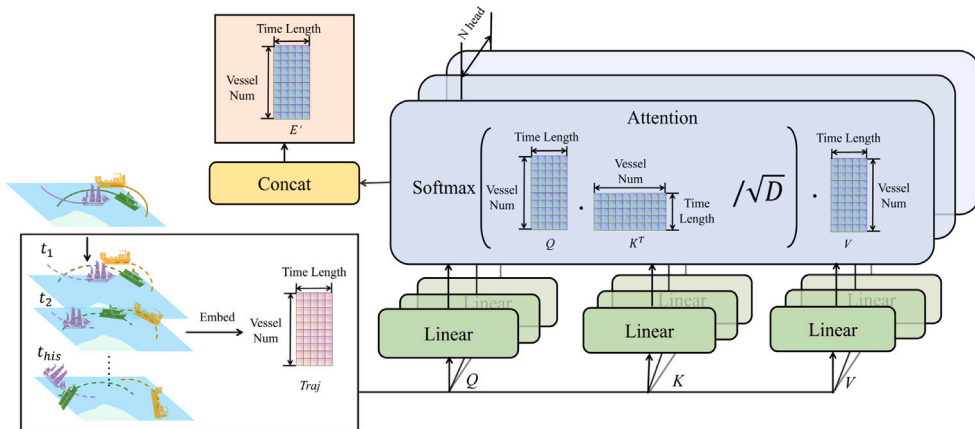


Fig. 5. Illustration of the Temporal Transformer computation.

4.3. Spatial modelling

The observed trajectories of N ships at each time step t (where $t \in [0, t_{pre}]$) are considered, with the trajectory of ship i at time t represented as $p_i^t = (lon_i^t, lat_i^t)$. Here, lon_i^t and lat_i^t denote the two-dimensional (2D) coordinates of ship i at time t .

A spatial graph $G_t = (V_t, E_t)$ is constructed, where V_t denotes the set of nodes corresponding to ships as time t , and E_t captures the spatial interactions between them. The positions of all ships at time t , denoted as $p_i^t = (lon_i^t, lat_i^t)$, are first obtained. Spatial interactions are then modelled by calculating the pairwise distance between ships within the same time period, as defined in Eq. (7).

$$dis(i, j) = |lon_i - lon_j| + |lat_i - lat_j| \quad (7)$$

During navigation, ships primarily interact within a limited spatial range. To accurately capture these localised spatial relationships, this paper proposes an adaptive distance module that dynamically computes spatial dependencies between ships and encodes them into the adjacency matrix A of the spatial graph G_t . This module effectively reduces the influence of distant ships, enabling the model to concentrate on interactions among nearby vessels during the spatial attention process. The pairwise distance $dis(i, j)$ between ships serves as the input to the adaptive distance module, which is then used to calculate the elements of A . The operation of this module is defined in Eq. (8):

$$\begin{cases} p_{i,j} &= ReLU(dis(i, j) - \theta) \\ A_{i,j} &= -p_{i,j} e^{\beta p_{i,j}} \end{cases}, \quad (8)$$

where θ and β are learnable parameters. The parameter θ defines a distance threshold, indicating that spatial interactions are considered only when the distance between two ships is less than this threshold. The parameter β controls the sharpness of the exponential decay, ensuring that edge weights for ships beyond the threshold decrease rapidly—effectively approaching zero and minimising their influence.

The negative value of $A_{i,j}$ attenuates the influence of long-distance edges. For edges with a distance greater than a , their weights tend to be negative infinity. During the calculation of spatial attention, after computing $Q_{i,j} K_{i,j}^T$, $A_{i,j}$ is added, and then *softmax* is applied. This ensures that the attention scores between ships that are far apart are zero, thereby retaining only the interactions between nearby ships.

In the ‘Spatial Transformer’, a Transformer-based Graph Convolution (TGConv) is utilised to model spatial interactions among ships. At each time step t , message passing occurs based on the interaction graph G_t . The ship trajectories at time t , represented as $p_1^t, p_2^t, \dots, p_i^t$, are transformed into feature embeddings E_i^t . These embeddings capture temporal dependencies through the self-attention mechanism. For each embedding E_i^t in the time series, Q_i , K_i , and V_i are generated. Then, the attention scores are calculated using the following formula:

$$Attn(Q_i, K_i, V_i) = \frac{softmax(Q_i K_i^T + A) V_i}{\sqrt{D}}, \quad (9)$$

The computation process of the spatial Transformer is illustrated in Fig. 6.

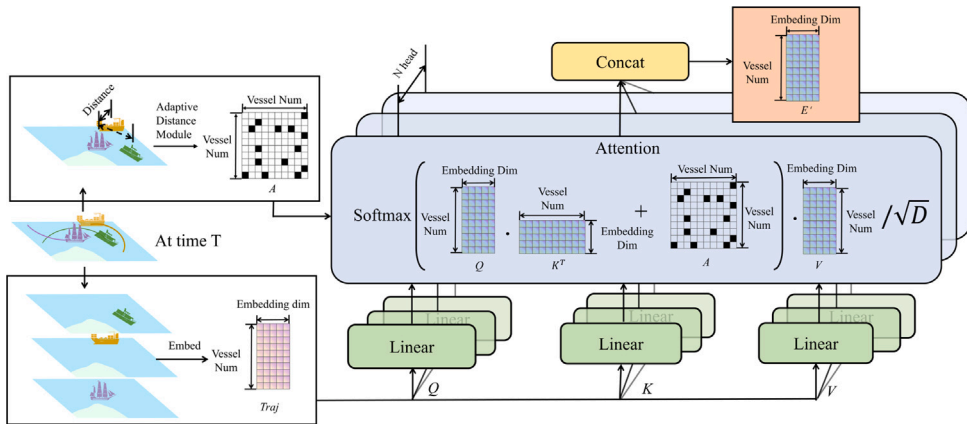


Fig. 6. Spatial transformer module: Computational workflow illustration.

4.4. Probabilistic modelling

Ship trajectories often exhibit characteristics similar to Gaussian distributions (Gao et al., 2021). The random errors observed in these trajectories arise from the accumulation of numerous small, independent disturbances, such as water currents and wind-induced waves. According to the Central Limit Theorem, the aggregation of such independent disturbances results in a distribution that closely approximates a Gaussian form. This makes the Gaussian model particularly well-suited for capturing the statistical

properties of trajectory noise. In this paper, a 2D Gaussian distribution is employed to model the position of a ship at a given time. The coordinates (lon, lat) represent a point in the two-dimensional spatial plane, where μ_{lon} and μ_{lat} are the mean values along the lon - and lat -axes, corresponding to the ship's expected central location. The standard deviations σ_{lon} and σ_{lat} define the spread of the distribution in each direction, effectively capturing the positional uncertainty (Mangalam et al., 2021).

The probability of a ship appearing at position (lon, lat) , given the parameters $\mu_{lon}, \mu_{lat}, \sigma_{lon}, \sigma_{lat}$, is expressed as $P(lon, lat | \mu_{lon}, \mu_{lat}, \sigma_{lon}, \sigma_{lat})$. At any time t , this distribution provides a probabilistic representation of the ship's location, where the highest probability is centred at (μ_{lon}, μ_{lat}) and gradually decreases as the distance from this central point increases. Consequently, the trajectory probability is formulated as:

$$P(lon, lat | \mu_{lon}, \mu_{lat}, \sigma_{lon}, \sigma_{lat}) = \frac{1}{2\pi\sigma_{lon}\sigma_{lat}} \exp\left(-\left(\frac{(lon - \mu_{lon})^2}{2\sigma_{lon}^2} + \frac{(lat - \mu_{lat})^2}{2\sigma_{lat}^2}\right)\right), \quad (10)$$

At each observed time step t_{pre} , a unique Gaussian distribution is employed to model the ship's position at that specific moment. As a result, the entire trajectory of the ship over the observed period can be represented as a sequence of these Gaussian distributions. By aggregating the probability densities across all time steps, a cumulative probability distribution is formed, capturing the likelihood of the ship's presence at various locations over time. This cumulative probability distribution for the full trajectory is mathematically expressed as:

$$P_{total}(lon, lat) = \sum_{t=1}^T P_t(lon, lat | \mu_{lon}^t, \mu_{lat}^t, \sigma_{lon}^t, \sigma_{lat}^t), \quad (11)$$

where T represents the number of prediction time steps, $(\mu_{lon}^t, \mu_{lat}^t)$ represents the central position of the ship at the t th time step, specifically indicating the mean position of the ship at time t .

The cumulative probability distribution formula quantifies the probability density of the ship along its entire trajectory. At each time step t , the ship's position is characterised by a 2D Gaussian distribution, centred at $(\mu_{lon}^t, \mu_{lat}^t)$, which represents the most likely location of the ship at that moment. This distribution captures the probability of the ship being located near $(\mu_{lon}^t, \mu_{lat}^t)$ at that specific time step. By combining this positional information with Eq. (11), the resulting probabilistic trajectory map X is generated, offering a representation of the ship's movement pattern over time.

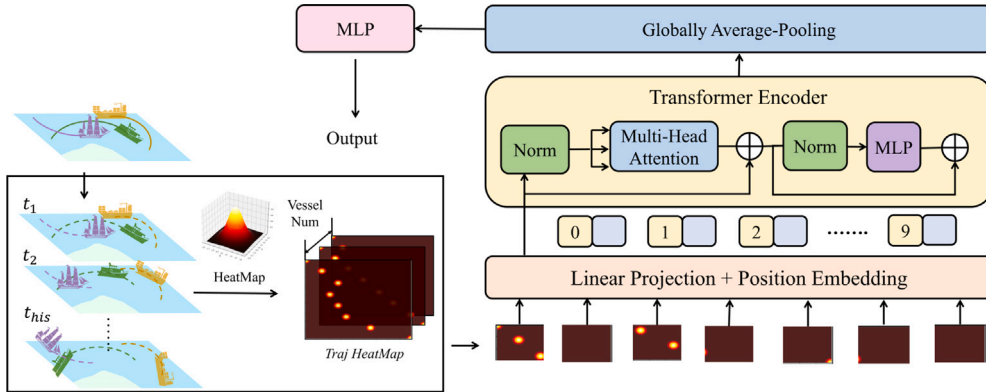


Fig. 7. Schematic of the Probability Transformer computation.

As illustrated in Fig. 7, the probability trajectory is calculated using a Transformer model. The Vision Transformer processes the image $X \in \mathbb{R}^{B \times H \times W \times C}$ by segmenting it into a sequence of image patches.

$$X_p = \text{Reshape}(\text{Flatten}(\text{Conv}(X))), \quad X_p \in \mathbb{R}^{B \times N \times (P^2 \cdot C)}, \quad (12)$$

The sequence of image patches is embedded with positional encodings E_{pos} using Eq. (13), resulting in the initial representation Z_i^0 .

$$Z_i^0 = X_p + E_{pos}, \quad Z_i^0 \in \mathbb{R}^{B \times N \times (P^2 \cdot C)}, \quad (13)$$

The Transformer layers utilise a MSA to process sequential data effectively. By applying Eq. (14), the input sequence, enriched with positional encodings Z_i^L , is iteratively transformed through L layers of the Transformer architecture, ultimately generating the refined output representation Z_i^L .

$$Z_i^l = \text{MSA}(\text{Norm}(Z_i^{l-1})) + Z_i^{l-1}, \quad Z_i^l \in \mathbb{R}^{B \times N \times (P^2 \cdot C)}, \quad l = 1, \dots, L, \quad (14)$$

where MSA denotes the MSA and Norm represents layer normalisation. Using Eqs. (15) and (16), the sequence Z_i^L undergoes global average pooling to generate Z_p . This is subsequently passed through a MLP to produce the embedding E_i^l .

$$Z_p = \sum_{i=0}^N \text{Norm}(Z_i^l), \quad Z_p \in \mathbb{R}^{B \times (P^2 \cdot C)}, \quad (15)$$

$$Z = \text{MLP}(Z_p), \quad Z \in \mathbb{R}^B, \quad (16)$$

4.5. Prediction step

The STGTP model utilises a two-layer encoder to sequentially process temporal and spatial information. In the first encoder, a ‘Temporal Transformer’ extracts temporal dependencies, while a ‘Spatial Transformer’ captures interactions between ships. Additionally, trajectory probabilities are represented using a 2D Gaussian distribution-based probability trajectory heatmap, as elaborated below.

$$\begin{cases} T_i^t = \text{TransformerEncoder}(E_i^t), \\ S_i^t = \text{TGConv}(E_i^t), \\ P_i^t = \text{VisionTransformer}(P_i^t(lon, lat)). \end{cases} \quad (17)$$

The features T_i^t , S_i^t , and P_i^t are concatenated and passed through a Linear layer for feature fusion, as calculated below:

$$E_i^{t'} = \text{Linear}(\text{Concat}(T_i^t, S_i^t, P_i^t)), \quad (18)$$

The second encoder first applies the ‘Spatial Transformer’ for encoding, followed by the ‘Temporal Transformer’ for further encoding, as shown below:

$$E_i^{t''} = \text{Linear}(\text{TransformerEncoder}(\text{TGConv}(E_i^{t'}))), \quad (19)$$

STGTP encodes the features to obtain $E_i^{t''}$ using the feature fusion encoder, then decodes the result by adding Gaussian noise ε , along with additional Gaussian noise σ :

$$P_i^t = \text{Linear}(E_i^{t''} + \varepsilon), \quad (20)$$

where P_i^t corresponds to $t \in [0, t_{pre}]$, and $E_i^{t''}$ corresponds to $t'' \in [t_{pre} + 1, t_{pred}]$. The algorithm performs multi-step prediction.

The STGTP model is trained using the Mean Squared Error (MSE) loss function. The MSE is formulated as follows:

$$MSE(\hat{lon}_t, \hat{lat}_t, lon_t, lat_t) = \frac{1}{T} \sum_{t=1}^T ((\hat{lon}_t - lon_t)^2 + (\hat{lat}_t - lat_t)^2), \quad (21)$$

where T represents the total prediction duration, $\hat{lat}_t$ and $\hat{lon}_t$ are the model predictions for the longitude and latitude at time t , and lat_t and lon_t are the true values at time t . By minimising MSE, the model’s predictions are as close to the true values as possible.

The pseudocode for the proposed STGTP model is as follows:

Algorithm 1 STGTP

Input: A training set $Traj = (lon_i, lat_i), i = 1, 2, \dots, n$ and learning rate η

Output: A Well-trained STGTP model

```

1: Embedding Layer: Emb = Linear(2, 32)
2: Spatial Encoder: Senc = TGConv(emsized, nhead, nlayers)
3: Temporal Encoder: Tenc = TransformerEncoder(emsized, nhead, nlayers)
4: Probability Encoder: Penc = Vision Transformer (emsized, nhead, nlayers)
5: Output Layer: Decoder = Linear(64, 2)
6: Feature Fusion: Fusion = Linear(64, 32)
7: Time Prediction Output: Pred = Linear( $t_{pre}, t_{pred}$ )
8: for all epoch = 1:N do
9:   for all ( $lon_i, lat_i$ ) in Traj do
10:    emb = Emb( $lon_i, lat_i$ )
11:    Temb1 = Tenc(emb) // Temporal Embedding
12:    Semb1 = Senc(emb, mask) // Spatial Embedding
13:    Pemb1 = Penc(emb) // Probability Embedding
14:    Featfusion = Fusion(Concat((Temb1, Semb1, Pemb1), dim=2)) // Feature fusion
15:    Semb2 = Senc(Featfusion, mask) // Spatial Embedding
16:    Temb2 = Concat((Temb1, Semb2), dim=2)
17:    Temb3 = Tenc(Temb2) // Temporal Embedding
18:    Wnoise = Concat((Temb3, noise), dim=2) // Add noise
19:    Output = Pred(Decoder(Wnoise.permute(1, 2, 0)).permute(2, 0, 1)) // Decode the result
20:    Loss = MSE(output, label); // Calculate MSE lost
21:    Loss.backward() // Back propagation of loss
22:    optimiser.step() // Update parameters with optimiser
23:   end for
24: end for

```

5. Experimental results and analysis

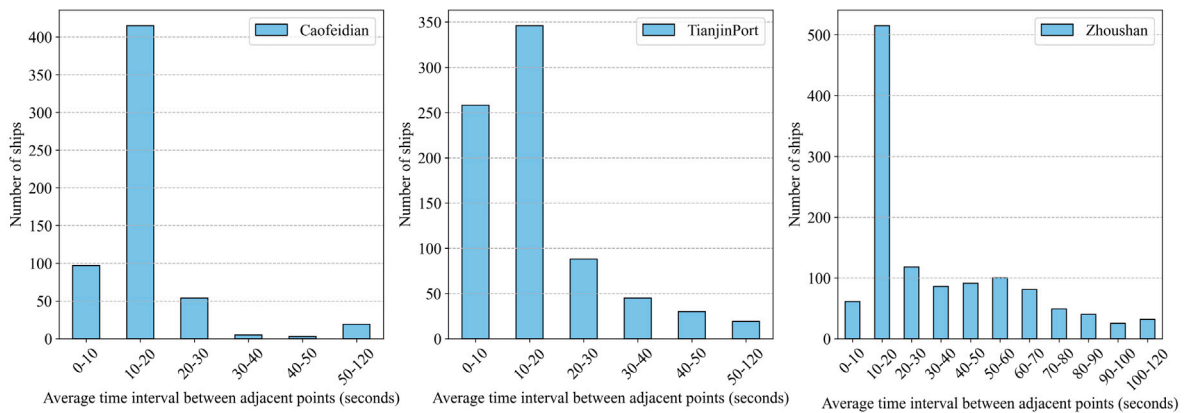
5.1. Experimental datasets and dataset preprocessing

To assess and validate the predictive performance of the STGTP model, AIS trajectory datasets from three distinct maritime regions (i.e., Caofeidian, Zhoushan, and Tianjin Port) are utilised. These regions, located along different coastal areas of China, present unique geographical and economic characteristics, providing a diverse range of scenarios for evaluating the model's effectiveness. The selection includes Caofeidian, a natural deep-water port; Zhoushan, a major maritime transportation hub; and Tianjin Port, one of China's largest ports. Each dataset was collected over different timeframes to capture regional variations in vessel movements and operational complexities. A description of the area represented by each AIS dataset is as follows:

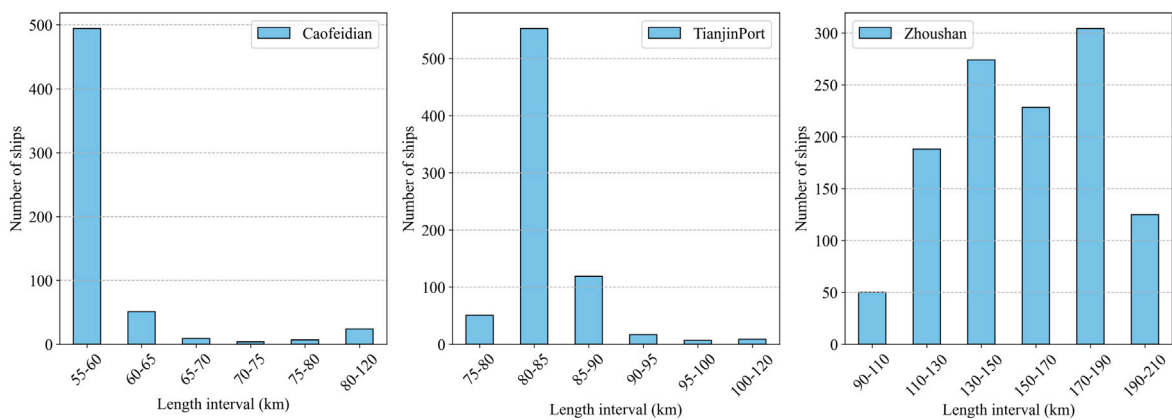
Caofeidian stands out for its naturally deep waters, which make it well-suited for large-scale port operations and capable of handling the world's largest vessels. Its close proximity to major cities like Beijing and Tianjin enhances its strategic value as a logistics hub within the Beijing-Tianjin-Hebei economic zone. The AIS data used for this area were collected in June 2018, covering latitudes from $38^{\circ} 72'N$ to $39^{\circ} 10'N$ and longitudes from $118^{\circ} 25'E$ to $118^{\circ} 92'E$.

Zhoushan, situated along China's eastern coast, plays a crucial role in maritime transport due to its advantageous location and deep-water port capacity. It hosts one of the world's largest oil transshipment hubs, accommodating high volumes of vessel traffic thanks to its unrestricted access for inbound and outbound ships. The AIS data for Zhoushan were collected in April 2018, spanning $29^{\circ} 56'N$ to $31^{\circ} 10'N$ in latitude and $121^{\circ} 51'E$ to $123^{\circ} 61'E$ in longitude.

Tianjin Port, one of China's busiest, serves as a vital gateway for international trade in northern China and the broader Bohai Economic Rim. It handles a wide variety of cargo types, including bulk goods and containers. AIS data for Tianjin were gathered in January 2018, covering latitudes from $38^{\circ} 75'N$ to $39^{\circ} 05'N$ and longitudes from $117^{\circ} 72'E$ to $118^{\circ} 67'E$.



(a) Statistical analysis of time intervals between consecutive AIS points.



(b) Distribution of trajectory lengths.

Fig. 8. Statistics of the three datasets.

As illustrated in Fig. 8, the top row presents histograms of the time intervals between adjacent AIS points for ship trajectories in the Caofeidian, Tianjin Port, and Zhoushan waters. These distributions show that most AIS data points are recorded at intervals of 0–20 s, indicating relatively high-frequency tracking in general. However, a notable proportion of samples exhibit irregular or longer time intervals, highlighting the necessity of the interpolation step included in the data preprocessing pipeline.

Fig. 8(b) shows the distribution of trajectory lengths, measured by the number of AIS points per trajectory, across the three port areas. In the Caofeidian and Tianjin Port datasets, the majority of trajectories are relatively short, with a steep decline in frequency after 60 data points. In contrast, the Zhoushan dataset presents a wider and more evenly distributed range of trajectory lengths, suggesting greater diversity in vessel movement patterns.

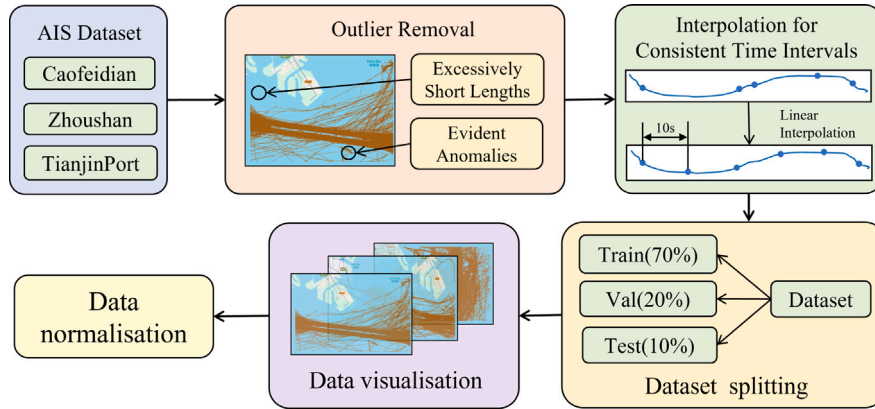


Fig. 9. Overview of AIS data preprocessing steps.

In this study, the model predicts a ship's future positions over the next 12 time steps based on data from the preceding 8 consecutive time steps. Given the inherent irregularities and potential anomalies in raw AIS data—such as inconsistent time intervals and outlier trajectories—a dedicated preprocessing pipeline is employed to enhance data reliability and improve model performance. This pipeline, illustrated in Fig. 9, includes the following steps:

(1) Outlier removal. To enhance data quality and minimise errors, abnormal trajectory points are identified and filtered out. Specifically, trajectory segments with excessively short lengths or evident anomalies are removed to eliminate noise and ensure that the model is trained on reliable trajectory data.

(2) Interpolation for consistent time intervals. As AIS data is often recorded at inconsistent time intervals, linear interpolation is applied separately to longitude and latitude values. This process standardises the time intervals between data points, ensuring that the model operates on a uniform temporal scale, which is crucial for improving the accuracy of time-series predictions.

(3) Dataset splitting for model training and evaluation. To facilitate rigorous training and evaluation, the dataset comprising ship trajectories from three distinct maritime regions is divided into training, validation, and test sets using a 7:2:1 ratio based on the number of ships (Table 3). This structured division ensures that the dataset is appropriately allocated for model development and evaluation. It provides sufficient data for training the model, a dedicated validation set for hyperparameter tuning and performance monitoring, and a test set to assess the model's generalisation ability across diverse maritime environments.

(4) Trajectory data visualisation. Fig. 10 presents visualisation results of the trajectory data across the three maritime regions. These visualisation results provide insights into regional trajectory characteristics, highlighting potential factors—such as geographical complexity and traffic density—that may influence model performance. This step aids in understanding how the spatial distribution of ship movements affects trajectory prediction accuracy.

(5) Data normalisation. To ensure feature consistency and prevent dominant features from skewing the model, min-max normalisation is applied to both the training and test sets. This method scales all features to the range [0, 1], ensuring uniform feature magnitudes. Specifically, for longitude (lon) and latitude (lat), the min-max normalisation formula is used to standardise their values, facilitating more stable and efficient model training.

$$lon' = \frac{lon - lon_{\min}}{lon_{\max} - lon_{\min}}, lat' = \frac{lat - lat_{\min}}{lat_{\max} - lat_{\min}}. \quad (22)$$

where lon and lat are the original values, and lon' and lat' are the normalised values within the range [0, 1].

By implementing these preprocessing steps, the dataset is refined to optimise model learning and ensure robust and generalisable trajectory predictions across diverse maritime environments.

Table 3

The associated datasets in three water areas.

Water areas	Longitude Range	Latitude Range	Time	Number of ship trajectories	Number of time-stamped points
Caofeidian	118°25'E - 118°92'E	38°72'N - 39°10'N	2018-06-01~10	594	500719
Zhoushan	121°51'E - 123°61'E	29°56'N - 31°10'N	2018-04-23,24	1277	2067920
Tianjin Port	117°72'E - 118°67'E	38°75'N - 39°05'N	2018-01	786	1156947

5.2. Description of comparison method

Table 4 provides a summary of the ten comparison methods utilised in this paper. The ten models compared in this study are grouped into three main categories: Time-Series Models (GRU, LSTM, BiLSTM, BiGRU, and Seq2Seq), Transformer-Based Models (Transformer, iTransformer, and Mamba), and Spatio-Temporal Feature Models (STGCNN and STAR). Each category offers distinct

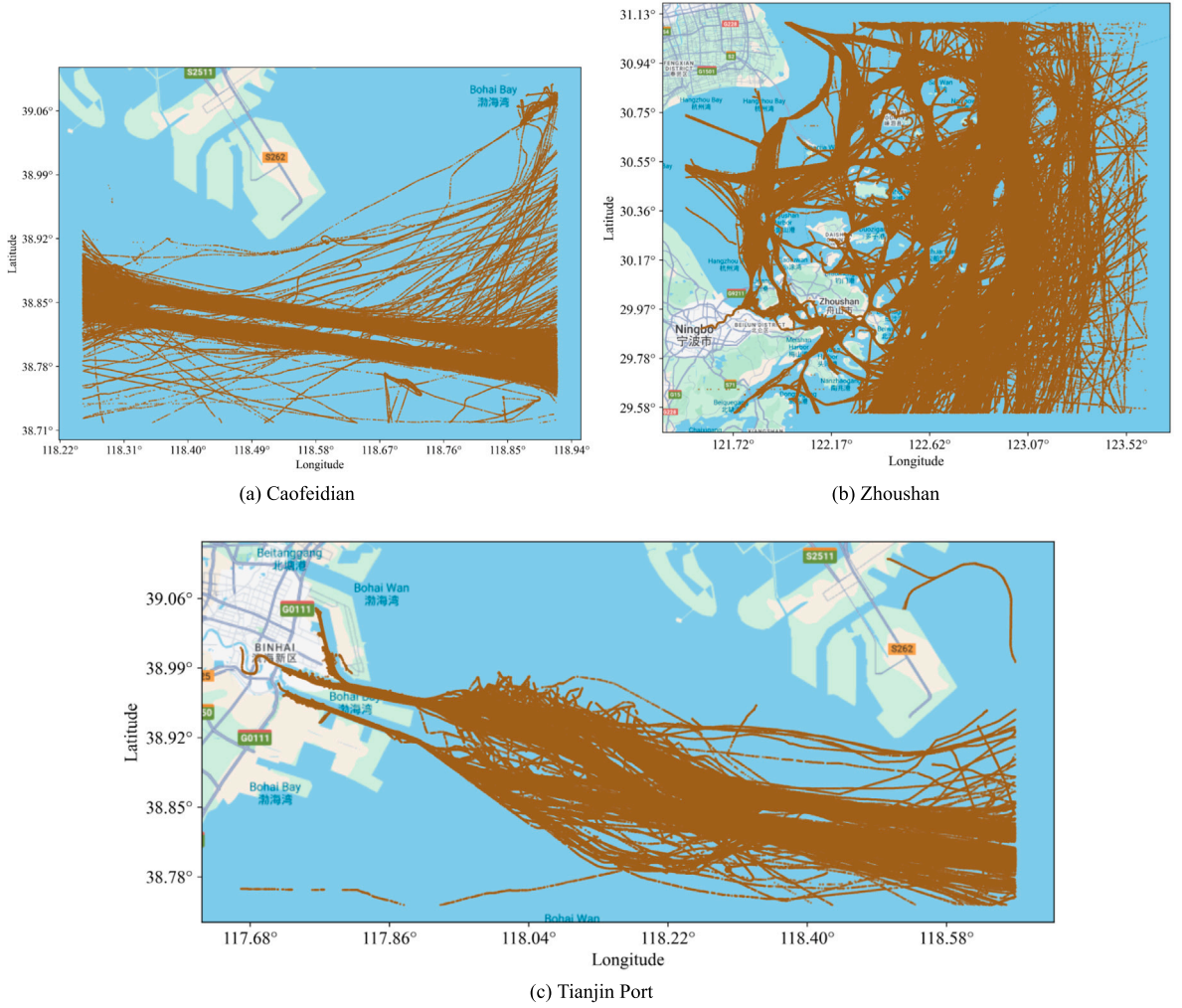


Fig. 10. Visualisation of the three datasets.

advantages depending on the specific demands of STP, striking different trade-offs between prediction accuracy, computational efficiency, and the capacity to capture spatial-temporal dependencies.

5.3. Evaluation indexes

The prediction accuracy of the eleven models is assessed using three key metrics: FD, ADE, and FDE (Jiao et al., 2025). Specifically, lon_t and lat_t indicates the actual value of the t th data point, $\hat{lon}_t$ and $\hat{lat}_t$ denote the predicted value, and T is the total number of data points.

Unlike traditional distance metrics that consider only individual points, FD captures the overall shape of the trajectory, providing a more detailed evaluation of prediction accuracy. This metric effectively highlights the trajectory segments where the predicted path diverges most from the real one.

FD metric is used to measure the spatial similarity between predicted and actual trajectories by focusing on their alignment at corresponding points. It quantifies the maximum deviation between the two trajectories, making it particularly sensitive to significant errors. Unlike traditional distance metrics that consider only individual points, FD captures the overall shape of the trajectory, providing a more detailed evaluation of prediction accuracy. This metric effectively highlights the trajectory segments where the predicted path diverges most from the real one. The mathematical formulation of FD is provided in Eq. (23).

$$FD = \min_{\pi \in \Pi_T} \max_{t=1}^T \sqrt{(\hat{lat}_t - lat_t)^2 + (\hat{lon}_t - lon_t)^2} \quad (23)$$

Table 4
Comparative analysis of baseline models.

Model	Type	Key Feature	Strength	Limitation
GRU	RNN variant	Simplifies RNN architecture, reducing parameters and mitigating the vanishing gradient problem.	Computationally efficient and well-suited for short sequence modelling tasks.	Less effective than LSTM for modelling long sequences.
LSTM	RNN variant	RNN with memory cells and gating mechanisms.	Effective for long sequences.	May be outperformed by GRU on short sequences.
BiLSTM	LSTM variant	Integrates bidirectional context by sequentially processing input data in both forward and backward directions.	Provides high accuracy in context-rich tasks.	Higher computational cost and longer training time than unidirectional LSTM.
BiGRU	GRU variant	Combines GRU's efficiency with bidirectional processing, using fewer parameters than BiLSTM.	Balances computational efficiency and bidirectional modelling capabilities.	Less effective than BiLSTM in capturing deep contextual dependencies.
Seq2Seq	Encoder decoder architecture	Uses an encoder to compress input sequences and a decoder to generate outputs, often with teacher forcing.	Effective for sequence-to-sequence tasks, with partial parallelisability.	Limited performance on long-term dependencies.
iTransformer	Transformer variant	Enhances interpretability of attention weight distribution while retaining Transformer performance.	Improves interpretability in sequential data modelling.	No significant reduction in computational complexity or efficiency gains over standard Transformers.
Mamba	Linear time sequence model	Optimises computation via state space models, enabling linear time scaling.	Extremely fast inference for large datasets.	Less effective at generalisation and complex pattern recognition compared to Transformers.
Transformer	Attention Based	Uses self-attention to model long-range dependencies and positional encoding for sequence order.	Achieves outstanding performance in modelling long-range dependencies, leveraging parallelised training for computational efficiency.	Computationally intensive for long input sequences due to self-attention mechanisms.
STGCNN	Graph-Based CNN	Models spatial relationships via graphs and captures temporal dependencies with convolution.	Performs well in tasks involving social or spatial interactions.	Less adaptable to non-graph-based spatial data.
STAR	Graph-Based Transformer	Explicitly models spatial and temporal dependencies simultaneously.	Offers more comprehensive predictions for spatio-temporal modelling.	Higher computational complexity.

ADE metric calculates the average distance between the predicted and ground-truth trajectories, providing an overall assessment of trajectory similarity. This metric offers insights into the global accuracy of the model's predictions, making it a key indicator of model stability. A lower ADE value indicates that the predicted trajectory closely follows the real movement pattern. The formula is shown in Eq. (24):

$$ADE = \frac{1}{T} \sum_{t=1}^T \sqrt{(\hat{lat}_t - lat_t)^2 + (\hat{lon}_t - lon_t)^2}, \quad (24)$$

FDE metric focuses on the error between the predicted and ground-truth final positions of a ship's trajectory. It specifically quantifies the endpoint error, making it particularly relevant for applications requiring precise final location predictions, such as docking or collision avoidance. The formula is shown in Eq. (25):

$$FDE = \sqrt{(\hat{lat}_T - lat_T)^2 + (\hat{lon}_T - lon_T)^2}, \quad (25)$$

Together, FD captures the maximum deviation along the trajectory, highlighting areas with significant discrepancies. ADE assesses the overall trajectory consistency, ensuring that the predicted path aligns with the actual movement. FDE focuses on endpoint accuracy, which is essential for precise navigation tasks. By combining these three metrics, the evaluation framework enables a thorough analysis of prediction performance, facilitating further model refinement and optimisation.

5.4. Experimental setting

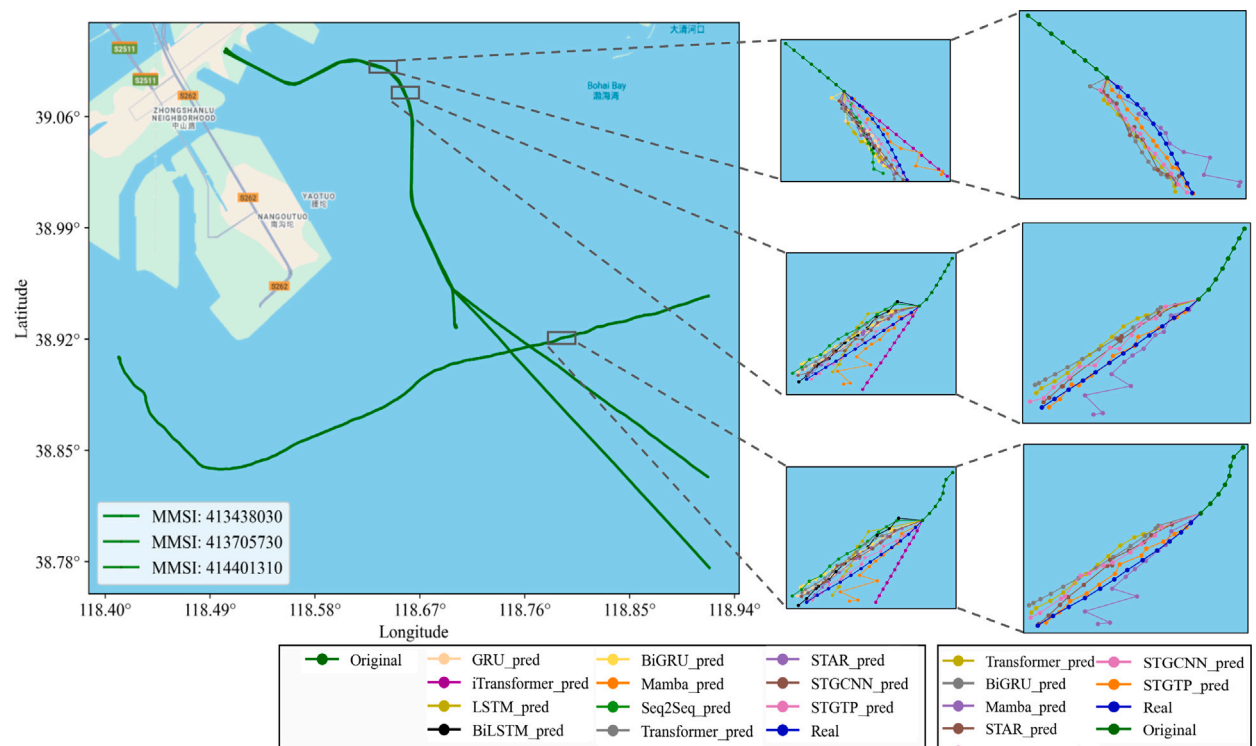
All eleven models are implemented using the PyTorch framework. During training, the Adam optimiser is used to update the model parameters.

Table 5 shows the hyperparameters used to train the STGTP model. All experiments were conducted on a system with a 2.40 GHz, 12-core Intel(R) Xeon(R) Silver 4214R CPU, an RTX 3080 Ti (12 GB), running Ubuntu 20.04 (64-bit). The models were trained in a Python 3.8 environment using PyTorch 2.0.0 and CUDA 11.8.

Table 5

Hyperparameter setting.

Learning Rate	Epoch	Dropout	Hidden size	Temporal transformer hidden layer	Spatial transformer hidden layer	Vision transformer hidden layer
1e-5	100	0.1	32	2	2	2

**Fig. 11.** Visualisation of experimental results in the Caofeidian area.

5.5. Visualisation of prediction results

Figs. 11, 12 and 13 present trajectory visualisation results for three representative maritime regions: Caofeidian, Tianjin Port, and Zhoushan. In each region, three representative ship trajectories were selected to evaluate the performance of ten SOTA prediction models, including Transformer, BiGRU, Mamba, STAR, STGCNN, and the proposed STGTP model. To further highlight key performance differences, a comparative analysis was conducted between the top six models.

In Fig. 11, ship trajectories in the Caofeidian area exhibit significant complexity, characterised by frequent path changes and turning points. The STGTP model demonstrates a clear advantage, as its predicted trajectories closely align with the real trajectories, particularly at sharp turns and intricate curves. In contrast, models such as Transformer, BiGRU, and Mamba show substantial deviations at turning points, while STAR, STGCNN, and STGTP exhibit improved precision. These results underscore the importance of robust spatial modelling in achieving more accurate trajectory predictions.

Fig. 12 presents Zhoushan trajectories, which include both straight paths and complex multi-turn routes. Compared to advanced models such as STAR, BiGRU, Mamba, GRU, and STGCNN, the STGTP model achieves superior alignment with actual ship movements in both local details and overall trends. Visual analysis reveals that alternative models struggle with prediction delays and deviations, especially during abrupt trajectory changes or sharp turns. However, STGTP effectively adapts to these dynamic variations, demonstrating the benefits of probabilistic modelling in handling unpredictable movement patterns.

In Fig. 13, the Tianjin Port water area is analysed, where representative trajectories include curved paths of ships approaching berths at reduced speeds and straight routes of departing ships at higher speeds. The visual results indicate that in complex trajectory scenarios, the STGTP model significantly outperforms methods such as Transformer, BiGRU, Mamba, GRU, and STGCNN, producing predictions that more closely match actual trajectories. By integrating spatial and probabilistic modelling, the STGTP model enhances prediction accuracy and robustness, particularly in dynamic and congested maritime environments.

Through systematic trajectory prediction analyses across Caofeidian, Tianjin Port, and Zhoushan, the STGTP model consistently demonstrates superior performance in diverse maritime environments. Compared to SOTA models such as Transformer, BiGRU, Mamba, and STAR, STGTP exhibits greater robustness and accuracy, effectively capturing both global trajectory dynamics and

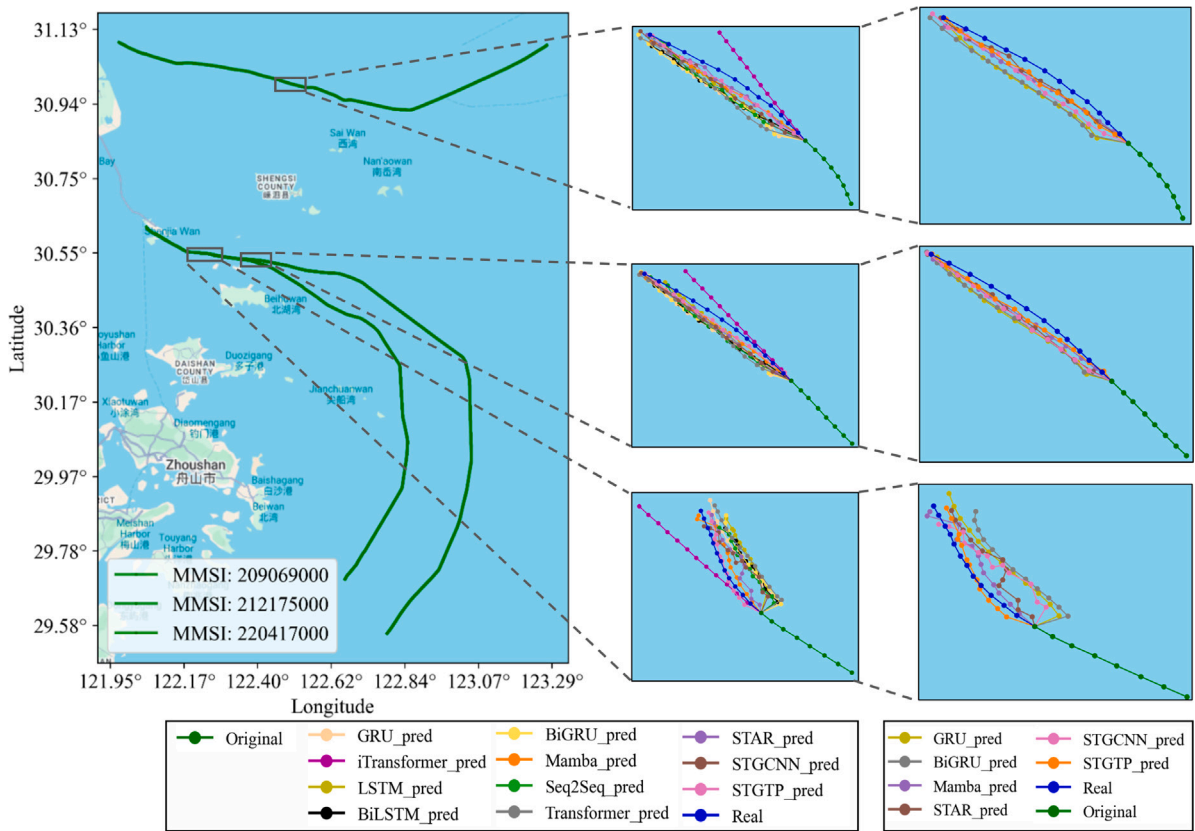


Fig. 12. Visualisation of experimental results in the Zhoushan area.

subtle local variations. These findings highlight the model's practical applicability in STP and its potential for real-world maritime navigation, autonomous vessel planning, and traffic management systems.

5.6. Comparative analysis

As presented in Table 6 and Fig. 14, a comparative evaluation was conducted to assess the performance of multiple trajectory prediction models across three maritime datasets: Caofeidian, Zhoushan, and Tianjin Port, using three key metrics: ADE, FDE, and FD.

The STGTP model achieves the best performance across all three metrics on the Caofeidian dataset, with ADE = 0.0737, FDE = 0.0725, and FD = 0.1289, significantly outperforming competing models such as STGCNN and Transformer. The Caofeidian waters are characterised by strong water flow variations and complex marine environmental factors, which demand high precision in trajectory predictions. The STGTP model, by integrating probabilistic modelling, effectively captures spatio-temporal dependencies, allowing it to adapt to dynamic environmental conditions and optimise path prediction. In contrast, models that lack temporal or spatial feature integration (e.g., LSTM, BiLSTM, and Transformer) exhibit weaker performance, struggling to account for the complexity of the maritime environment and leading to higher trajectory deviations.

The Zhoushan water area, a major shipping hub, experiences dense vessel traffic, substantial tidal variations, and high cargo throughput, making it one of the most dynamic maritime environments. On this dataset, STGTP demonstrates superior predictive accuracy, achieving the lowest values for ADE (0.0312), FDE (0.0234), and FD (0.0621). Given the rapidly changing traffic patterns, probabilistic modelling plays a key role in accurately predicting vessel movements by incorporating uncertainty into the predictions. Compared to other models, STGTP exhibits enhanced robustness and adaptability, particularly in high-density maritime traffic scenarios where conventional models struggle to maintain predictive stability.

In the Tianjin Port dataset, the STGTP model outperforms the other 10 methods, achieving the best performance in ADE (0.0366) and FD (0.0250), as well as FD (0.0699). Tianjin Port, as a complex artificial port environment, presents challenges such as intricate port infrastructure, dynamic waterway layouts, and frequent vessel manoeuvring. The integration of probabilistic modelling in STGTP proves particularly valuable in adapting to uncertainties caused by rapidly changing shipping lanes, vessel arrivals and departures, and human-induced disruptions, ensuring stable and precise trajectory predictions.

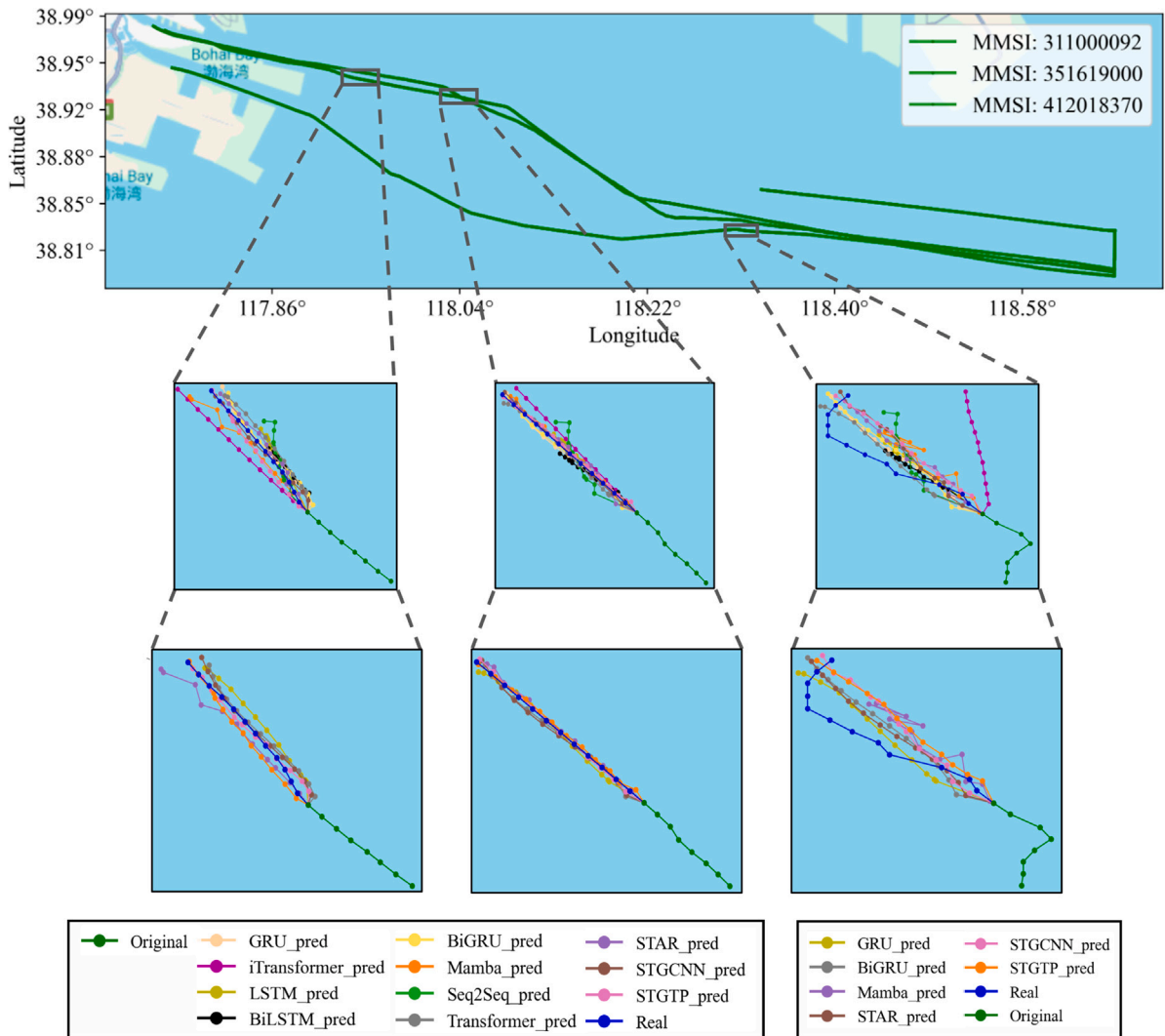


Fig. 13. Visualisation of experimental results in the Tianjin Port area.

To evaluate the efficiency of STGTP in comparison with ten other models, Table 6 presents the number of parameters and Floating-Point Operations Per Second (FLOPS) for each method. STGTP exhibits a relatively low parameter count (0.079 Million) and moderate computational complexity (0.12 Giga Operations Per Second (GOPS) FLOPS), while still maintaining a strong balance between performance and efficiency. Notably, it requires fewer resources than traditional models such as BiGRU, BiLSTM, GRU, and LSTM.

Regarding prediction accuracy, STGTP consistently achieves the best results across all three maritime datasets (Caofeidian, Zhoushan, and Tianjin Port). It records the lowest values in all three key evaluation metrics: ADE, FDE, and FD. These results highlight STGTP's effectiveness in capturing complex trajectory dependencies through the integration of spatial, temporal, and probabilistic modelling components.

By effectively adapting to the distinct characteristics of different water areas, STGTP proves to be highly robust and reliable. In natural deep-water zones (Caofeidian), it accounts for environmental variations, in high-traffic shipping hubs (Zhoushan), it adapts to dynamic congestion patterns, and in artificial port environments (Tianjin Port), it accommodates structural uncertainties. These results indicate that STGTP delivers high-precision predictions while also demonstrating commendable efficiency, making it a powerful tool for real-world maritime applications.

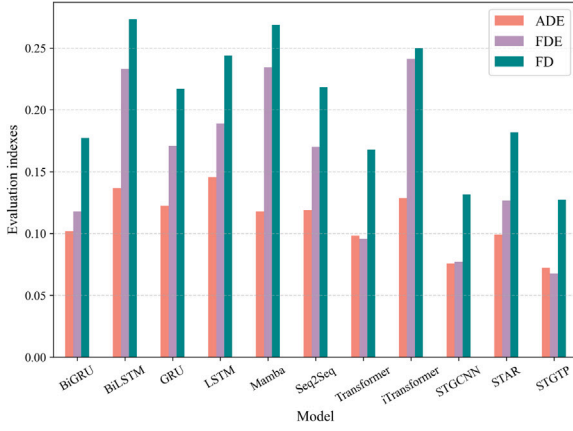
5.7. Ablation experiments

This section compares STGTP with its three variants across all datasets to verify the effectiveness of the STGTP model.

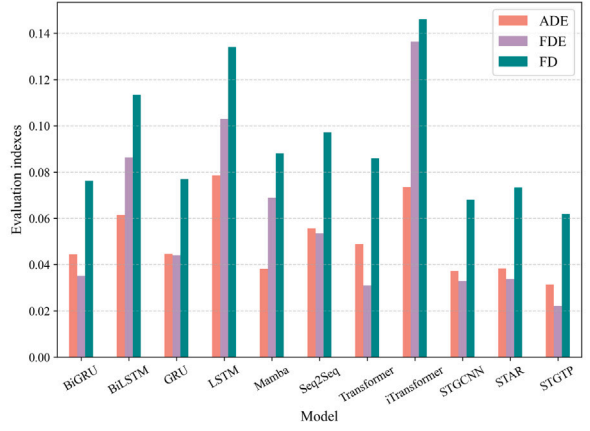
Table 6

Evaluation results of eleven predictive models.

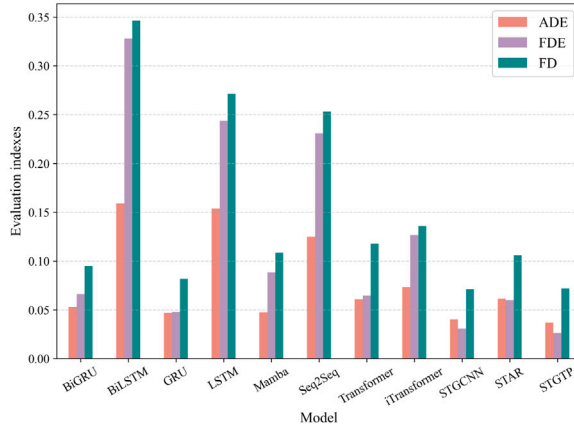
Model	Param	FLOPS	Caofeidian			Zhoushan			Tianjin Port		
			ADE	FDE	FD	ADE	FDE	FD	ADE	FDE	FD
BiGRU	0.104M	0.055G	0.1019	0.1177	0.1772	0.0445	0.0351	0.0762	0.0529	0.0660	0.0948
BiLSTM	0.139M	0.073G	0.1367	0.2331	0.2732	0.0615	0.0864	0.1134	0.1589	0.3280	0.3463
GRU	0.040M	0.021G	0.1223	0.1708	0.2171	0.0446	0.0441	0.0769	0.0470	0.0478	0.0818
LSTM	0.204M	0.106G	0.1456	0.1888	0.2440	0.0785	0.1030	0.1341	0.1539	0.2438	0.2712
Mamba	0.056M	0.115G	0.1177	0.2344	0.2687	0.0382	0.0690	0.0882	0.0473	0.0884	0.1085
Seq2Seq	0.213G	0.409M	0.1189	0.1698	0.2181	0.0557	0.0535	0.0972	0.1250	0.2307	0.2530
Transformer	0.054G	0.017M	0.0983	0.0957	0.1679	0.0489	0.0309	0.086G	0.0607	0.0645	0.1178
iTransformer	0.071G	0.137M	0.1287	0.2411	0.2499	0.0735	0.1364	0.1461	0.0734	0.1268	0.1359
STGCNN	0.001G	0.002M	0.0758	0.0771	0.1316	0.0373	0.0329	0.0681	0.0403	0.0306	0.0712
STAR	0.010G	0.005M	0.0991	0.1267	0.1818	0.0383	0.0337	0.0734	0.0615	0.0600	0.1058
STGTP	0.079G	0.012M	0.0737	0.0725	0.1289	0.0312	0.0234	0.0621	0.0366	0.0250	0.0699



(a) Caofeidian



(b) Zhoushan



(c) Tianjin Port

Fig. 14. Comparative analysis of eleven prediction models.

- STGTP-w/o-SP: Utilises only temporal modelling, without incorporating spatial or probabilistic modelling.
- STGTP-w/o-P: Integrates temporal and spatial modelling, but omits probabilistic modelling.
- STGTP-w/o-S: Combines temporal and probabilistic modelling, without leveraging spatial modelling.
- STGTP-w/-Noise: Adds noise to the data or during the training process of the fully integrated STGTP model.
- STGTP-w/-MDN: Incorporates Mixture Density Networks (MDN) to model the output of STGTP as probability distributions over trajectory points.

- STGTP: Fully integrates temporal, spatial, and probabilistic modelling, serving as the complete model.

A comparative evaluation was conducted using ADE, FDE, and FD metrics, with the results summarised in Table 7. The following key insights were derived:

The STGTP model consistently outperforms all ablation variants, confirming the effectiveness of integrating temporal, spatial, and probabilistic modelling. The combination of these three components enables a multidimensional representation of ship trajectories, leading to enhanced prediction accuracy.

The STGTP-w/o-S model is better than STGTP-w/o-SP in the ADE index of Tianjin Port, and the STGTP-w/o-P model is better than STGTP-w/o-SP in the ADE index of Caofeidian and ZhouShan. This shows that combining temporal modelling with spatial or probabilistic modelling can significantly improve the model's ability to capture global dependencies and improve the accuracy of trajectory predictions.

Interestingly, STGTP-w/o-SP achieves better FDE performance than STGTP-w/o-S and STGTP-w/o-P in all datasets. This suggests that relying solely on spatial or probabilistic modelling may introduce certain biases or lead to overfitting, affecting the accuracy of the final predicted position.

The influence of spatial and probabilistic modelling varies across different maritime regions, reflecting the distinct navigational complexities in each area. In Zhoushan, the STGTP-w/o-P model outperforms STGTP-w/o-S, suggesting that spatial modelling plays a more significant role in improving trajectory prediction accuracy in these regions. Conversely, in Tianjin Port, STGTP-w/o-S achieves better results than STGTP-w/o-P, indicating that probabilistic modelling is more crucial for accurate predictions in this specific maritime environment.

These findings demonstrate that each modelling component contributes uniquely to overall prediction performance, and their effectiveness depends on regional maritime conditions. The fully integrated STGTP model provides the most systematic and accurate trajectory predictions, making it the preferred choice for complex maritime navigation scenarios.

This study further enhances the proposed framework by integrating a Mixture Density Network (MDN) to generate probabilistic predictions of trajectory points. Experimental results reveal that the inclusion of MDN leads to scenario-dependent performance. In certain cases, it improves prediction accuracy—for instance, achieving an FD score of 0.1165 in the Caofeidian scenario, outperforming all other model variants. However, in other scenarios such as Tianjin Port and Zhoushan, the MDN-integrated model shows notable performance degradation, with significantly worse ADE, FDE, and FD metrics compared to the full STGTP model.

To assess the model's generalisation ability under noisy conditions, Gaussian noise ($\mu = 0, \sigma = 0.001$) was added to the original dataset to simulate GPS drift and AIS device errors. Results show that the STGTP model is highly robust to such noise, with ADE increasing by only 1% in Caofeidian and Tianjin Port, and 4% in Zhoushan. These findings confirm the model's reliability and applicability in real-world maritime environments, where sensor noise and data imperfections are common.

Table 7
Ablation experiments.

Evaluation indexes	Model	Caofeidian	Tianjin Port	Zhoushan
ADE	STGTP-w/o-SP	0.1114	0.0551	0.0409
	STGTP-w/o-S	0.1075	0.0531	0.0431
	STGTP-w/o-P	0.0991	0.0637	0.0405
	STGTP-w/-MDN	0.1096	0.0667	0.0587
	STGTP-w/-Noise	0.0748	0.0370	0.0325
	STGTP	0.0737	0.0366	0.0312
FDE	STGTP-w/o-SP	0.0997	0.0497	0.0311
	STGTP-w/o-S	0.1277	0.0518	0.0444
	STGTP-w/o-P	0.1296	0.0638	0.0757
	STGTP-w/-MDN	0.1223	0.0888	0.0678
	STGTP-w/-Noise	0.0755	0.0265	0.0325
	STGTP	0.0725	0.0250	0.0234
FD	STGTP-w/o-SP	0.1899	0.0906	0.0749
	STGTP-w/o-S	0.1800	0.0919	0.0787
	STGTP-w/o-P	0.1826	0.1089	0.0734
	STGTP-w/-MDN	0.1165	0.1881	0.1005
	STGTP-w/-Noise	0.1299	0.0699	0.0730
	STGTP	0.1289	0.0621	0.0699

6. Discussion and implications

6.1. Discussion

The STGTP model represents a significant advancement by integrating temporal, spatial, and probabilistic modelling into a unified framework. This holistic approach is designed to address the complexities and uncertainties of real-world maritime environments more effectively than models that focus on a single aspect.

(1) Temporal modelling. STGTP employs a Temporal Transformer to model temporal dependencies in ship movement data. This component enables the model to dynamically capture changes in ship behaviour over time, particularly in response to external factors such as environmental conditions or operational shifts. Compared to widely used temporal models like GRU, Transformer,

Table 8

Key input features used in different transportation domains.

Feature type	Maritime scenario	Aviation scenario	Autonomous driving
Time features	Ship's latitude and longitude	Aircraft's latitude, longitude, and altitude	Vehicle's latitude and longitude
Spatial features	Ship proximity	Predefined aircraft proximity along the route	Feasible or legally permitted lane changes
Uncertainty features	2D Gaussian distribution of ship positions on the horizontal plane	3D Gaussian distribution of aircraft positions in space	2D Gaussian distribution of vehicle positions

iTransformer, and Mamba, STGTP demonstrates improved prediction accuracy, particularly for short-term forecasting. However, the increased complexity of the Transformer-based temporal architecture leads to higher computational demands, especially when compared to lightweight alternatives such as GRU.

(2) Spatial modelling. To account for interactions between ships, particularly in congested or high-traffic regions, STGTP incorporates TGConv. This allows the model to effectively learn spatial dependencies and relational dynamics between vessels. The inclusion of a spatial attention mechanism further enhances the model's ability to recognise and respond to patterns such as directional movement, proximity-based influence, and collision avoidance. Compared to spatial models like STGCNN, which also use graph convolution for spatial awareness, STGTP offers improved accuracy in predicting ship trajectories in multi-agent scenarios. However, this comes at the cost of greater computational complexity and increased training time due to the combined use of attention mechanisms and graph-based operations.

(3) Uncertainty modelling. STGTP addresses the limitations of deterministic prediction by incorporating Gaussian heatmaps and a Vision Transformer for probabilistic trajectory estimation. This component enables the model to represent predicted ship positions as probability distributions, which is especially valuable for risk assessment and decision-making in uncertain or dynamic maritime environments. In contrast to traditional models that output a single fixed trajectory, this probabilistic approach allows the system to evaluate confidence levels and potential deviations, making it more suitable for applications in autonomous shipping and real-time maritime navigation. However, the additional uncertainty modelling module increases the model's overall complexity and training requirements.

(4) Systematic experiments. To validate the performance of STGTP, this study conducted a systematic comparison between STGTP and ten baseline models across three core evaluation metrics: ADE, FDE, and FD. The experimental results demonstrate that STGTP significantly outperforms the comparative models on all assessed metrics. Furthermore, ablation experiments were carried out to systematically verify the effectiveness of individual modules and their combinations. Additionally, Gaussian noise was introduced to simulate a noisy AIS environment and evaluate the model's robustness. While this ablation study provides valuable insights, it does not fully capture real-world challenges such as sudden data loss, irregular reporting intervals, and prolonged signal outages—common issues in AIS data. Ensuring AIS data accuracy remains critical for reliable STP and effective collision avoidance.

(5) Contributions and limitations of the STGTP model The key innovation of STGTP lies in its integration of temporal, spatial, and uncertainty modelling. While many existing approaches address one or two of these areas, few combine all three to this extent. The Temporal Transformer captures dynamic ship behaviours over time, TGConv models spatial interactions among ships, and the Gaussian-based uncertainty modelling enhances robustness and risk awareness in unpredictable environments. This multi-dimensional integration enables STGTP to deliver accurate, adaptable, and risk-aware trajectory predictions, which are essential for next-generation autonomous maritime systems.

Nevertheless, certain limitations remain. The model's predictive performance may diminish in scenarios involving highly irregular vessel behaviour (e.g., emergency avoidance or unexpected manoeuvres), in data-sparse regions (e.g., low-traffic maritime zones), or during extended AIS signal outages. Future work could focus on improving the model's robustness under these extreme conditions to further enhance its reliability and real-world applicability.

(6) Applicability beyond the maritime domain. The STGTP model is designed with strong generalisation capacity, effectively capturing spatial and temporal dependencies while modelling predictive uncertainty. Although this study focuses on maritime navigation, the model architecture is inherently domain-agnostic and can be readily adapted to other transportation domains, such as air traffic control and autonomous ground vehicle navigation. With appropriate domain-specific data and tailored input features (as outlined in Table 8), STGTP can be retrained and fine-tuned to deliver robust and reliable trajectory predictions across a wide range of non-maritime applications.

6.2. Implications

Trajectory prediction technology holds transformative potential across the maritime sector, providing valuable insights and operational enhancements for various stakeholders. By integrating spatio-temporal prediction models with uncertainty modelling, this technology not only improves navigational safety but also optimises decision-making in shipping, port operations, regulatory enforcement, and maritime research. A detailed analysis of its implications for different stakeholders is outlined below.

(1) Researchers and maritime technology innovators.

The continuous advancement of spatio-temporal prediction models is driven by emerging datasets, novel methodologies, and refined benchmarking techniques. By incorporating uncertainty modelling, researchers gain a more effective understanding

of predictive accuracy, enabling the development of robust, data-driven frameworks for trajectory forecasting. This fosters technological innovation in maritime AI, including adaptive learning models, real-time anomaly detection systems, and AI-assisted decision-making for autonomous navigation. Additionally, interdisciplinary collaboration between AI researchers, marine scientists, and policymakers can lead to enhanced models that account for environmental factors, human behaviour, and evolving traffic patterns in maritime operations.

(2) Shipping companies and fleet operators.

Uncertainty-aware trajectory prediction significantly enhances voyage planning, risk assessment, and operational efficiency for shipping companies. By quantifying potential deviations in ship trajectories, fleet managers can develop adaptive routing strategies that consider dynamic factors such as weather fluctuations, maritime traffic density, and port congestion levels. This results in fuel savings through optimised route selection, minimising unnecessary detours and deviations. Additionally, improved trajectory prediction reduces collision risks in congested or high-risk navigation zones and enhances punctuality, ensuring timely port arrivals and improving logistics coordination. By leveraging real-time trajectory forecasts, shipping companies can proactively adjust schedules, reduce operational uncertainties, and ultimately enhance profitability and sustainability.

(3) Port authorities and terminal operators.

For port authorities, accurate trajectory prediction facilitates berth allocation, cargo handling, and resource planning, ultimately reducing congestion and optimising turnaround times. Uncertainty modelling enables port operators to forecast ship arrival windows, allowing for better berth scheduling and minimising idle port time. Furthermore, it streamlines cargo loading and unloading operations, ensuring synchronised workflows between incoming vessels, dockworkers, and transportation networks. By integrating predictive analytics into port management systems, authorities can develop data-driven policies that improve operational resilience, enhance port capacity utilisation, and facilitate smarter resource allocation, especially in high-traffic environments.

(4) Regulators, maritime safety agencies, and policymakers.

Regulatory bodies and maritime safety agencies can leverage trajectory uncertainty modelling to implement stricter navigation protocols and proactive risk mitigation strategies. One of the key benefits is the identification of high-risk zones, allowing regulators to enforce speed limits, adjust shipping lanes, or introduce enhanced monitoring measures in hazardous areas. Moreover, trajectory prediction enhances maritime surveillance and anomaly detection, helping prevent illegal activities such as poaching, smuggling, and unauthorised entry into restricted waters. It also improves response times to maritime incidents by predicting potential collision hotspots, enabling early intervention strategies to mitigate accidents. By integrating AI-driven trajectory predictions into regulatory frameworks, policymakers can develop intelligent maritime governance strategies, strengthen compliance with international navigation regulations, and ensure safer and more sustainable maritime operations.

(5) Environmental agencies and sustainability advocates.

Trajectory prediction plays a crucial role in environmental conservation by supporting initiatives aimed at reducing maritime emissions, preventing marine pollution, and protecting ecological zones. By utilising uncertainty-aware predictions, environmental agencies can monitor vessel emissions and fuel consumption, encouraging compliance with green shipping initiatives and International Maritime Organisation (IMO) decarbonisation targets. Additionally, it helps identify areas of high marine traffic impact, allowing for targeted interventions to protect marine ecosystems, including coral reefs and marine life habitats. Optimised ship routing minimises ecological disruption, reducing disturbances in environmentally sensitive areas such as protected marine reserves and biodiversity hotspots. By incorporating trajectory forecasting into environmental policies, sustainability advocates can drive greener maritime practices and support the transition toward eco-friendly shipping operations.

The integration of trajectory prediction and uncertainty modelling presents far-reaching benefits across the maritime industry, enabling safer navigation, optimised logistics, enhanced regulatory compliance, and improved environmental sustainability. By fostering collaboration between technology developers, shipping companies, port authorities, regulators, and environmental agencies, this technology paves the way for next-generation intelligent maritime systems, ultimately contributing to a safer, more efficient, and environmentally responsible global shipping industry.

7. Conclusions

Accurate trajectory prediction is crucial for enhancing the autonomous navigation capabilities of unmanned ships, enabling safe and efficient maritime operations. This paper systematically reviews current research on STP and identifies a significant gap in modelling trajectory uncertainty, which limits the applicability of current methods in complex and dynamic marine environments. To bridge this gap, a novel STGTP method for trajectory prediction is proposed. This method leverages a temporal transformer to capture the time-dependent dynamics of trajectories, a TGConv to model spatial interactions between ships, and integrates Gaussian heatmaps with a Vision Transformer to quantify trajectory uncertainty. This integrated approach ensures multidimensional characterisation and efficient prediction of ship trajectories, particularly in complex maritime conditions.

From a performance perspective, STGTP significantly enhances the representation of temporal dependencies through its attention mechanism, enabling highly accurate short-term trajectory predictions. The TGConv effectively models spatial interactions between ships, greatly improving prediction accuracy, particularly in congested waters. Additionally, by modelling trajectory uncertainty

using Gaussian heatmaps, STGTP not only delivers precise trajectory prediction but also quantifies potential deviations, providing valuable support for risk assessment in dynamic environments.

The proposed STGTP algorithm was rigorously evaluated using three real-world AIS trajectory datasets from regions with distinct maritime regions: Caofeidian, Zhoushan, and Tianjin Port. Comparisons were made against ten classic DL models using ADE, FDE, and FD metrics to assess overall trajectory accuracy, endpoint prediction capabilities, and trajectory similarity. The results show that STGTP consistently outperforms all baseline models in ADE, FDE and FD metrics. This demonstrates its strong capability to capture dynamic changes and adapt to various environmental conditions. These findings highlight STGTP's potential as a reliable and effective solution for advancing autonomous ship navigation. Beyond maritime applications, the proposed approach can be adapted to other domains involving spatiotemporal trajectory prediction, such as autonomous driving or air traffic management.

Looking ahead, future research could focus on incorporating navigation-specific constraints and dynamic environmental factors to further refine trajectory prediction in different maritime domains. For deep sea navigations, coastal operations, and inland waterways, factors such as water depth, channel width, and environmental influences play different roles in ship movement patterns and shall be taken into account differently and respectively. Moreover, in complex encounter scenarios, such as ship crossings, obstacle avoidance, or extreme weather conditions, trajectory prediction can be further enhanced by integrating ship dynamics models and real-time environmental sensing data. By capturing vessel behaviours such as turning, acceleration, and deceleration, future models can improve prediction accuracy, ensuring safety at sea in general and improving autonomous operations in specific.

CRedit authorship contribution statement

Jincheng Gong: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Huanhuan Li:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Hang Jiao:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis. **Zaili Yang:** Writing – review & editing, Validation, Project administration, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zaili Yang reports financial support was provided by Horizon European Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. STP keyword theme clustering

See Fig. 15.

Appendix B. STP keyword timeline analysis

See Fig. 16.

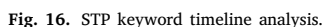
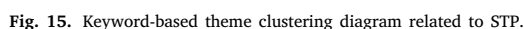
Appendix C. A numerical example of spatial modelling

At time T , there are a total of four ships with their respective latitude and longitude coordinates given as (39.1, 118.5), (39.2, 118.5), (39.5, 119.1), and (39.1, 118.6). According to Eq. (7), the distance matrix D_{dis} is obtained as follows:

$$D_{dis} = \begin{pmatrix} 0 & 0.1 & 1 & 0.1 \\ 0.1 & 0 & 0.9 & 0.2 \\ 1 & 0.9 & 0 & 0.9 \\ 0.1 & 0.2 & 0.9 & 0 \end{pmatrix} \quad (26)$$

The distance threshold θ is set to 0.5, and the steepness parameter β is set to 100. Based on these two parameters, the adjacency matrix A is computed using Eq. (8).

$$A = \begin{pmatrix} 0 & 0 & -\infty & 0 \\ 0 & 0 & -\infty & 0 \\ -\infty & -\infty & 0 & -\infty \\ 0 & 0 & -\infty & 0 \end{pmatrix} \quad (27)$$


$$Q_i K_i^T = \begin{pmatrix} 0 & 0.5 & 0.1 & 0.1 \\ 0.1 & 0 & 0.5 & 0.2 \\ 0.1 & 0 & 0.1 & 0.3 \\ 0 & 0.2 & 0 & 0.1 \end{pmatrix} \quad (28)$$

The intermediate variable x is obtained by summing $Q_i K_i^T$ with the adjacency matrix A :

$$x = Q_i K_i^T + A = \begin{pmatrix} 0 & 0.5 & -\infty & 0.1 \\ 0.1 & 0 & -\infty & 0.2 \\ -\infty & -\infty & 0.1 & -\infty \\ 0 & 0.2 & -\infty & 0.1 \end{pmatrix} \quad (29)$$

Subsequently, the *softmax* function is applied to x , which is defined as follows:

$$\text{softmax}(x) = \frac{e^{x_i}}{\sum_j^N e^{x_j}} \quad (30)$$

The resulting *softmax* values are as follows:

$$\text{softmax}(x) = \text{softmax}(Q_i K_i^T + A) = \begin{pmatrix} 0.27 & 0.44 & 0.00 & 0.29 \\ 0.33 & 0.30 & 0.00 & 0.37 \\ 0.00 & 0.00 & 1.00 & 0.00 \\ 0.30 & 0.37 & 0.00 & 0.33 \end{pmatrix} \quad (31)$$

By comparing Eq. (27) with Eq. (26), it is evident that when the distance between two ships is below the threshold θ , the corresponding value is reset to 0, preserving the original interaction features. Conversely, if the distance exceeds the threshold, the value is replaced by $-\infty$. As derived from Eq. (30), when $x \rightarrow -\infty$, the resulting weight after the *softmax* operation approximately approaches 0. This mechanism effectively masks the interaction features between distant ships. This design facilitates efficient spatial interaction modelling by ensuring that attention is concentrated on ships in close proximity, which are more likely to influence one another.

Data availability

Data will be made available on request.

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