A Survey of Ocean Drift Simulation and Trajectory Prediction Techniques

Abstract

This survey paper provides a comprehensive examination of ocean drift simulation and trajectory prediction techniques, emphasizing the integration of high-resolution oceanographic modeling, geospatial analysis, and predictive algorithms. Ocean drift simulation is crucial for understanding ocean dynamics, with significant applications in maritime navigation, environmental management, and climate science. The paper explores the role of advanced simulation techniques, such as deep learning and AI, in enhancing the accuracy and efficiency of predictive models. Key methodologies include the use of the haversine formula for precise distance calculations and the integration of wind-driven dynamics into forecasting models. The survey highlights the challenges and limitations of current models, such as data quality issues and computational demands, while also discussing innovative frameworks that leverage machine learning and real-time data integration. Real-world applications and case studies underscore the transformative impact of these models in addressing environmental and maritime challenges. The paper concludes by outlining emerging technologies and future research directions, including the integration of data-driven models with traditional forecasting systems and the development of standardized frameworks for uncertainty analysis. By advancing these methodologies, researchers can enhance the reliability and applicability of oceanographic models, supporting sustainable development and informed decision-making.

1 Introduction

1.1 Importance of Ocean Drift Simulation

Ocean drift simulation is essential for understanding ocean dynamics, with significant implications for environmental studies and maritime operations. Accurate vessel trajectory predictions are crucial for maritime traffic management and environmental forecasting, ensuring safe and efficient navigation [1]. While traditional machine learning algorithms have been utilized for real-time trajectory prediction, they often face challenges in balancing accuracy and performance, particularly in big data stream analysis [2].

Beyond navigation, ocean drift simulation plays a vital role in environmental applications, such as oil spill mitigation and tracking marine plastic debris. The oil particle method exemplifies the necessity of precise ocean drift simulation in these contexts [3]. Moreover, accurate predictions of buoyant object trajectories are critical for search and rescue operations, underscoring the broader relevance of ocean drift simulation [4].

Understanding ocean dynamics is also imperative for addressing climate change impacts, as illustrated by the significant decline in Antarctic sea ice extent from 2014 to 2016. This decline emphasizes the need for comprehensive oceanographic models to predict and manage the consequences of changes in polar regions [5]. Global ocean circulation models are indispensable in climate science due to the ocean's substantial heat capacity and its buffering role in the climate system [6].

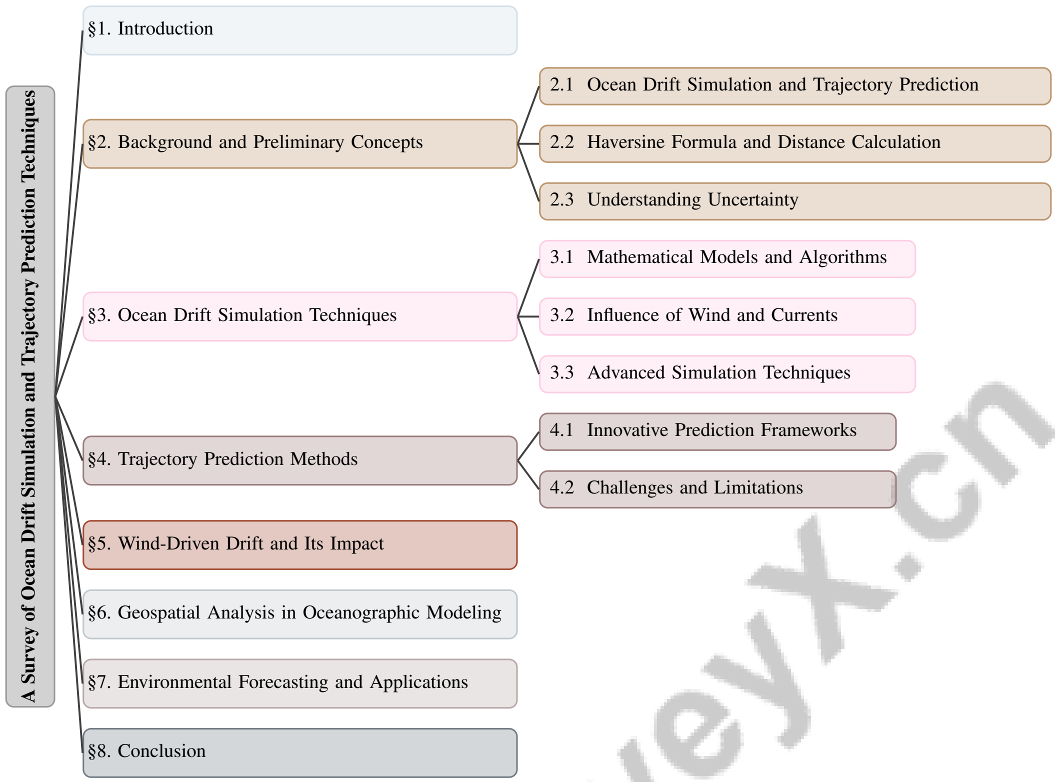

Figure 1: chapter structure

In maritime navigation, ocean drift simulation is crucial for managing the complexities of mixed autonomous and human-operated vessels in dynamic environments [7]. The importance of accurate trajectory prediction extends to naval navigation, where real-time analytics and operational efficiency are essential [8]. These diverse applications highlight the indispensable role of ocean drift simulation in enhancing our understanding of ocean dynamics and improving environmental forecasting and management.

1.2 Scope and Keywords

This survey provides a comprehensive examination of ocean drift simulation and trajectory prediction techniques, focusing on high-resolution oceanographic modeling, geospatial analysis, and predictive algorithms. It addresses challenges and advancements in simulating ocean dynamics, particularly the development of accurate and efficient data-driven models for global ocean forecasting, capable of operating at high resolutions (1/12°) and matching or exceeding the forecasting accuracy of existing numerical global ocean forecasting systems (GOFSs) [9]. The survey also explores the complexities and indeterminacies in maritime vessel maneuvers, emphasizing the need for improved prediction models [10].

A significant focus of the survey is the prediction of vessel trajectories using Automatic Identification System (AIS) data, navigating the challenges of heterogeneous and multimodal motion data [11]. It also examines the methodologies and objectives of the Surface Water Ocean Topography (SWOT) mission, which aims to enhance our understanding of ocean dynamics at fine spatial scales. Furthermore, the survey analyzes state-of-the-art predictive algorithms for future location and trajectory prediction, drawing insights from over 50 works spanning the last two decades.

Key terms addressed throughout the paper include trajectory prediction, contextual information, dynamic factors, surface winds, vector winds, surface stress, air-sea heat fluxes, ocean currents, and precipitation. The survey emphasizes the critical need for enhanced accuracy and speed in forecasting extreme weather events, underscoring the limitations of existing predictive models and the importance of integrating real-time data. This integration is vital for improving forecast reliability, especially as advancements in weather prediction techniques have demonstrated that modern forecasting can significantly mitigate the impact of extreme weather on society, as evidenced by the evolution of hurricane tracking accuracy over recent decades [12, 13, 14, 15]. Additionally, the role of ocean science in fostering sustainable development and informing policy decisions is highlighted.

The survey also examines methods for accurately predicting drift trajectories influenced by surface currents and winds, as well as the associated uncertainties. It encompasses the integration of geospatial analysis techniques within environmental informatics, specifically their application alongside the Internet of Things (IoT) in environmental contexts. This includes a review of six distinct geospatial analysis methods and 26 relevant IoT initiatives utilizing these techniques. The analysis considers various factors, such as IoT device types, deployment status, data transmission standards, and measurement reliability, highlighting the potential of combining IoT with geospatial analysis to enhance our understanding, modeling, and visualization of both natural and artificial ecosystems while addressing pressing environmental challenges [12, 16].

1.3 Structure of the Survey

This survey is structured to provide an in-depth analysis of various ocean drift simulation and trajectory prediction techniques, incorporating critical factors such as wind-driven drift currents, modeling uncertainties, and hydrodynamic forces, as highlighted in recent research on particle tracking and mechanistic forecasting [17, 18, 4, 19, 20]. The paper begins with an **Introduction** that emphasizes the significance of these techniques in understanding ocean dynamics and their applications in environmental and maritime studies. Following the introduction, the survey outlines the **Scope and Keywords**, establishing thematic boundaries and essential terminology pertinent to the study.

The second section, **Background and Preliminary Concepts**, provides foundational insights into the principles and methodologies underlying ocean drift simulation, elucidating critical concepts such as the haversine formula for distance calculation and addressing uncertainties in oceanographic modeling. This section sets the stage for a detailed exploration of simulation techniques.

In **Ocean Drift Simulation Techniques**, the survey investigates various methodologies employed in simulating ocean drift, including mathematical models and algorithms. It emphasizes the significant impact of wind and currents on drift predictions for buoyant objects at the ocean surface, detailing complexities introduced by depth-dependent drift currents, such as Stokes drift and wind-induced shear currents. Advanced simulation techniques, including deep learning and AI, are explored, alongside a fuzzy-based framework for quantifying uncertainties in drift predictions. These innovative approaches are transforming the field by enhancing the accuracy of trajectory models through improved parameterization of wind drag and the incorporation of real-time ocean current data, ultimately leading to more reliable predictions in various marine applications [18, 4].

The section on **Trajectory Prediction Methods** examines innovative frameworks and methods for predicting the trajectory of oceanic objects, focusing on machine learning and data-driven approaches, while discussing challenges and limitations in achieving accurate drift predictions.

The impact of wind-driven drift on ocean currents and trajectory predictions is analyzed in **Wind-Driven Drift and Its Impact**, discussing the modeling of wind patterns and the influence of environmental factors on drift simulations.

Geospatial Analysis in Oceanographic Modeling explores the role of geospatial techniques in enhancing oceanographic models, detailing sophisticated computational methodologies, recent advancements in data integration and analysis, and the pivotal role of satellite and remote sensing technologies, particularly in the context of geospatial analysis and the Internet of Things (IoT). It highlights six distinct geospatial analysis methods and 26 relevant IoT initiatives, examining device types, deployment status, data transmission standards, and measurement reliability. Additionally, it discusses how deep learning techniques, such as Neural Networks, enhance geospatial data analysis, offering improved solutions for tasks like object recognition and image classification, thereby transforming applications in military and civilian sectors, including traffic monitoring and weather reporting [16, 21].

The penultimate section, **Environmental Forecasting and Applications**, examines the application of oceanographic models in environmental forecasting, providing real-world case studies and discussing

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model validation processes. It highlights advancements that have improved predictive accuracy and reliability.

Finally, the **Conclusion** synthesizes the key findings of the survey, reflecting on the current state of ocean drift simulation and trajectory prediction techniques, and identifying promising avenues for future exploration and innovation, particularly in integrating emerging technologies such as the Haversine formula for distance estimation and predictive analytics for moving objects, which could enhance mobile applications and environmental modeling efforts [22, 14, 12, 23, 16].The following sections are organized as shown in Figure 1.

2 Background and Preliminary Concepts

2.1 Ocean Drift Simulation and Trajectory Prediction

Ocean drift simulation and trajectory prediction are fundamental for understanding the movement of entities across the ocean's surface, impacting both natural phenomena and human activities. Accurate modeling of near-surface wind drift currents is crucial, reflecting the complex interactions among wind, waves, and the ocean surface [24]. Advanced models like FESOM enhance our understanding of ocean dynamics, particularly in polar regions [25], while the XiHe model, with its transformer-based approach, advances global ocean forecasting by delivering high-resolution predictions across multiple variables [9].

Trajectory prediction incorporates numerous environmental factors. The drifting behavior of semi-submersible drifters is influenced by tidal, wind, and wave conditions, necessitating robust modeling [19]. Integrating wave dynamics, such as combining Phillips-type Stokes drift profiles with monochromatic profiles for swell, enhances simulation accuracy [26]. In vessel trajectory prediction, frameworks like MSTFormer and Traisformer utilize historical AIS data to improve prediction accuracy by analyzing historical motion data and dynamic vessel movements [27, 28, 1].

Challenges in predicting buoyant objects' transport are addressed by considering wind-driven drift currents' vertical profiles [4]. Wind-driven sea ice drift significantly impacts sea ice extent [5]. IoT technologies and geospatial analysis enhance environmental monitoring, addressing critical issues in environmental informatics [16]. Adaptive navigation systems are essential for mixed autonomous and human-operated vessels, addressing challenges in communication and decision-making [7]. Context-agnostic trajectory prediction, using batch and streaming data, improves accuracy in dynamic maritime environments [8]. Trajectory prediction research categorization into distance-based and density-based clustering approaches highlights the importance of trajectory similarity measurement [11].

These advancements underscore the critical role of ocean drift simulation and trajectory prediction in oceanographic studies, with applications in environmental management, maritime navigation, and climate science, vital for sustainable ocean resource management and supporting societal well-being [29].

2.2 Haversine Formula and Distance Calculation

The haversine formula is essential for calculating the shortest distance between two points on Earth's surface using latitude and longitude, crucial for navigation, mapping, and trajectory predictions. It employs spherical trigonometry to accurately reflect Earth's curvature [30], making it indispensable in oceanographic modeling and maritime navigation [31]. In geospatial analysis and GPS data interpretation, the haversine formula provides a robust framework for spatial relationship analysis and route optimization [32].

In ocean drift simulation, the haversine formula enhances model accuracy by facilitating precise distance calculations between waypoints, vital for predicting vessel trajectories and understanding object movement influenced by ocean currents and wind patterns. This is particularly relevant in addressing the complexities of predicting turning directions at waypoints along maritime routes [28]. Moreover, the formula is critical for evaluating trajectory prediction accuracy and prediction error distribution, reflecting simulation models' effectiveness [20]. This metric enhances oceanographic model reliability, supporting accurate environmental forecasting and management strategies.

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The haversine formula's mathematical principles, coupled with its GIS applications, improve oceanographic modeling and optimize maritime services, such as Marine Cargo Expedition Services (EMKL) in densely populated areas like East Jakarta. By accurately calculating distances between user locations and service providers, it facilitates real-time decision-making and optimizes shipping service selection [31, 33]. Its accurate distance measurements contribute to precise trajectory predictions, enhancing navigation, mapping, and environmental management strategies.

2.3 Understanding Uncertainty

Uncertainty in oceanographic modeling challenges prediction accuracy and reliability in ocean drift simulations and trajectory forecasts. This uncertainty arises from the unpredictability of oceanic and atmospheric conditions and modeling limitations. Inadequate wave dynamics representation leads to inaccuracies in predicting mean horizontal near-surface motion [24], emphasizing the need for comprehensive wave dynamics in models to enhance accuracy.

Uncertainty analysis in environmental science is often insufficient, complicating its integration into decision-making processes. Effective communication of uncertainty to non-expert stakeholders is crucial for informed environmental management [23]. Challenges such as rain contamination, calibration difficulties at high wind speeds, and limited observations near land and ice hinder accurate oceanographic modeling measurements [34]. The vertical structure of drift currents contributes to uncertainty, as existing methods often overlook this aspect, resulting in significant trajectory prediction errors [4].

In trajectory prediction, clustering methods and the effectiveness of similarity measures and clustering algorithms contribute to outcome uncertainty. Data pre-processing techniques' impact on clustering results necessitates careful consideration in model development [11]. Addressing these uncertainties requires advancements in measurement techniques, data processing algorithms, and model development. Improving oceanographic model accuracy and dependability enhances predictive capabilities, facilitating informed ocean management and policy development decisions. This progress is vital for better environmental forecasting and maritime safety, integrating high-resolution data on ocean currents, wind patterns, and iceberg dynamics. Models like XiHe and AI surrogates for coastal circulation optimize forecasting speed and precision, addressing local and global ocean dynamics complexities, supporting effective climate change impact and maritime hazard responses [17, 9, 19, 35, 34].

3 Ocean Drift Simulation Techniques

Category	Feature	Method
Mathematical Models and Algorithms	Kinetic and Wave Dynamics	MDFM[19], CSDP[26], WMM[24], SVR-PM[3]
	Motion and Trajectory Prediction	DT[10], NPC[36], MSTFormer[27]
	Uncertainty Quantification	FDPF[18]
	Advanced Model Architectures	CATP[37]
Influence of Wind and Currents	Dynamic Interaction Modeling	WWT[38], POS[39], EWSM[40], XiHe[9], FBCTA[7]
Advanced Simulation Techniques	Trajectory Modeling	PSMLM[41], TAS[28], TPM-MG[42]
	Hybrid Architectures	GT[15]
	Probabilistic Approaches	VarLSTM[43]
	Sequential Data Processing	EncDec[1]

Table 1: This table provides a comprehensive overview of various methodologies employed in ocean drift simulation, categorized into mathematical models and algorithms, influence of wind and currents, and advanced simulation techniques. Each category highlights specific features and methods, emphasizing the integration of AI, deep learning, and uncertainty quantification to enhance predictive accuracy and reliability. The table serves as a detailed reference for understanding the diverse strategies utilized in simulating ocean dynamics and their applications in maritime contexts.

Exploring the dynamics of ocean drift necessitates examining the simulation techniques that accurately model these processes. This section delves into the foundational mathematical models and algorithms that underpin ocean drift simulations. By employing diverse computational strategies, these models capture the complexities of oceanic movements, providing insights into the interactions among various environmental factors. Table 3 presents a detailed classification of ocean drift simulation techniques, illustrating the integration of mathematical models, the influence of environmental factors, and the application of advanced simulation methods. As illustrated in Figure 2, the hierarchical structure of ocean drift simulation techniques categorizes them into mathematical models and algorithms, the influence of wind and currents, and advanced simulation techniques. Each category further breaks down into specific methodologies, highlighting the integration of AI, deep learning, and uncertainty quantification in enhancing predictive accuracy and reliability. The subsequent subsection will detail the mathematical approaches and algorithms utilized in this field, emphasizing their significance in advancing our understanding of ocean drift phenomena.

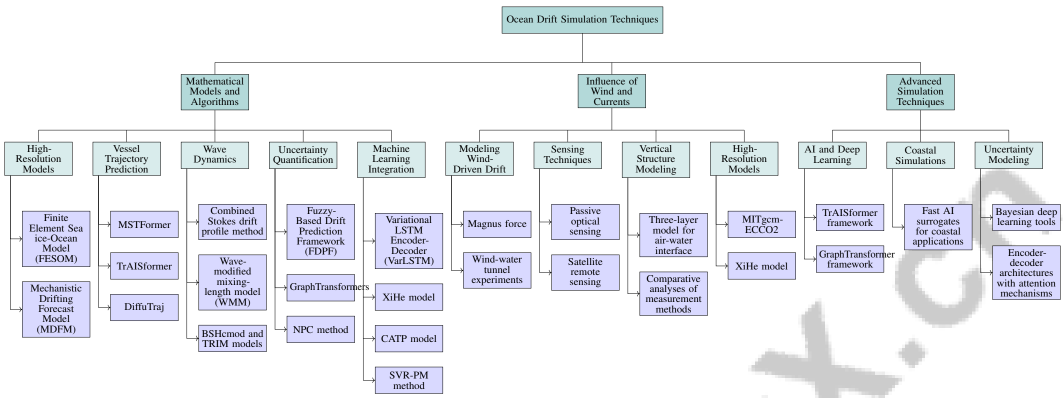

Figure 2: This figure illustrates the hierarchical structure of ocean drift simulation techniques, categorizing them into mathematical models and algorithms, the influence of wind and currents, and advanced simulation techniques. Each category further breaks down into specific methodologies, highlighting the integration of AI, deep learning, and uncertainty quantification in enhancing predictive accuracy and reliability.

3.1 Mathematical Models and Algorithms

Method Name	Model Types	Predictive Techniques	Application Domains
MDFM[19]	Numerical Models	Kinetic Analysis	Environmental Management
MSTFormer[27]	Neural Network Models	Machine Learning Algorithms	Vessel Trajectory Prediction
TAS[28]	Transformer Network	Probabilistic Approach	Maritime Applications
DT[10]	Stochastic Models	Machine Learning	Maritime Navigation
CSDP[26]	Wave Models	Numerical Simulations	Ocean Dynamics
WMM[24]	Mathematical Models	Numerical Simulations	Environmental Management
FDPF[18]	Numerical Models	Fuzzy Numbers	Emergency Responses
GT[15]	Mathematical Models	Numerical Simulations	Environmental Management
NPC[36]	Trajectory Prediction Models	Clustering-based Approach	Vessel Movement Tracking
VarLSTM[43]	Mathematical Models	Bayesian Modeling	Maritime Navigation
XiHe[9]	Numerical Models	Transformer Framework	Marine Activities
CATP[37]	Mathematical Models	Machine Learning	Maritime Navigation
SVR-PM[3]	Mathematical Models	Machine Learning	Environmental Management

Table 2: Overview of ocean drift simulation models categorized by method name, model types, predictive techniques, and application domains. This table highlights the diverse range of models employed in oceanographic predictions, illustrating their respective methodologies and application areas in environmental management, maritime navigation, and vessel trajectory prediction.

Ocean drift simulation employs various mathematical models and algorithms to represent the complex dynamics of oceanic movements. The Finite Element Sea ice-Ocean Model (FESOM) provides high-resolution simulations in polar regions, enhancing the accuracy of interactions between sea ice and ocean currents [25]. The Mechanistic Drifting Forecast Model (MDFM) predicts the trajectories of small semi-submersible drifters by integrating numerical simulations of hydrodynamic forces with kinetic analysis, capturing the interplay of wind, water currents, and waves [19].

In vessel trajectory prediction, advanced models like MSTFormer utilize motion-inspired spatial-temporal transformers to enhance long-term predictions by leveraging dynamic knowledge and historical motion data [27]. The TrAISformer network excels in extracting long-term temporal patterns in AIS vessel trajectories, forecasting positions hours in advance [28]. Additionally, DiffuTraj employs a stochastic approach to improve future trajectory forecasts through a guided motion pattern uncertainty diffusion process [10].

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Incorporating wave dynamics is crucial for accuracy in ocean drift simulations. The combined Stokes drift profile method integrates both swell and wind sea contributions for precise calculations of shear and transport in crossing seas [26]. The wave-modified mixing-length model (WMM) enhances momentum balance simulations of near-surface currents by accounting for wave effects [24]. Models like BSHcmod and TRIM incorporate windage and Stokes drift effects, underscoring the importance of these dynamics in improving simulation accuracy [20].

The Fuzzy-Based Drift Prediction Framework (FDPF) employs fuzzy numbers to quantify and propagate uncertainties in trajectory predictions of drifting objects [18]. GraphTransformers model geospatial sequences by capturing both local and global contexts, enhancing trajectory prediction [15]. The NPC method utilizes a clustering-based approach to reconstruct and predict vessel trajectories [36].

Moreover, the Variational LSTM Encoder-Decoder (VarLSTM) method combines an encoder-decoder architecture with attention mechanisms and Bayesian uncertainty quantification to predict vessel trajectories, illustrating the integration of machine learning techniques to enhance predictive accuracy [43]. The XiHe model, utilizing a hierarchical transformer framework, focuses on ocean dynamics to deliver high-resolution predictions for multiple ocean variables, marking a significant advancement in data-driven ocean forecasting [9].

Innovative approaches like the CATP model combine a manager and multiple worker models, employing a competition symbiosis mechanism to enhance simulation accuracy [37]. The SVR-PM method dynamically computes the wind drift factor using real-time wind speed data, exemplifying a mathematical model for simulating ocean drift [3]. Additionally, a depth-dependent drift current correction factor improves particle tracking simulations [4].

As illustrated in Figure 3, this figure presents a hierarchical classification of ocean drift simulation models, categorizing them into mathematical models, vessel trajectory prediction, and wave dynamics. Each category includes specific models that address various aspects of ocean drift, enhancing simulation accuracy through innovative approaches. Table 2 provides a comprehensive summary of various mathematical models and algorithms utilized in ocean drift simulation, detailing their predictive techniques and application domains. Collectively, these models exemplify the diverse strategies employed in simulating ocean drift. By integrating physical forces such as wind and ocean currents, leveraging advanced machine learning algorithms for real-time trajectory prediction, and applying statistical techniques to quantify uncertainties, researchers enhance the accuracy and reliability of oceanographic predictions. This improved predictive capability supports applications in environmental management, maritime navigation, and efficient vessel movement tracking, ultimately leading to better resource utilization and decision-making in marine contexts [18, 34, 2].

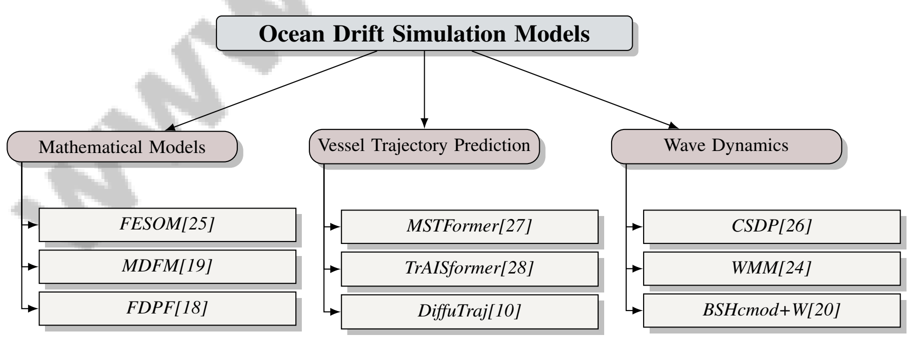


Figure 3: This figure presents a hierarchical classification of ocean drift simulation models, categorizing them into mathematical models, vessel trajectory prediction, and wave dynamics. Each category includes specific models that address various aspects of ocean drift, enhancing simulation accuracy through innovative approaches.

3.2 Influence of Wind and Currents

Integrating wind and currents into ocean drift simulation techniques is vital for accurately predicting the movement of objects across the ocean surface. The dynamic interplay between atmospheric forces and oceanic responses necessitates sophisticated modeling to capture the complexities of wind-driven drift. The Magnus force, influenced by both the angular velocity and centroid velocity of rotating objects, exemplifies the intricate nature of modeling these interactions for trajectory prediction [42].

Experimental methodologies, such as wind-water tunnel experiments, provide precise measurements of how varying wind speeds affect surface flow and wave dynamics, offering insights into the coupling between atmospheric and oceanic processes [38]. These experiments underscore the importance of understanding the physical mechanisms driving surface currents and their implications for drift predictions.

Advanced sensing techniques, including passive optical sensing, utilize the Doppler effect to estimate current velocities by analyzing frequency shifts in waves influenced by underlying currents [39]. This method enhances the accuracy of current velocity measurements, crucial for simulating wind-ocean interactions.

Satellite remote sensing data refines simulation techniques by assessing changes in drag coefficients due to substances like oil on the ocean surface [40]. This innovation improves modeling of surface conditions' influence on wind-driven drift, enhancing trajectory prediction precision.

The introduction of a three-layer model for the air-water interface, focusing on turbulent momentum flux, highlights the significance of vertical structure in generating drift currents [44]. This approach emphasizes the need to account for vertical profiles in wind-driven currents to accurately simulate the transport of buoyant objects [4].

Comparative analyses of wind speed and direction measurement methods reveal the effectiveness of scatterometers in rain-free conditions and the potential of L-band radiometers in high wind scenarios [34]. These tools are integral to capturing variability in wind patterns that drive ocean currents, informing simulation techniques.

High-resolution ocean-sea ice models, such as MITgcm-ECCO2, demonstrate the incorporation of wind patterns into simulations to analyze atmospheric contributions to sea ice variability [5]. This integration is essential for understanding the broader implications of wind-driven dynamics on oceanographic processes.

The XiHe model exemplifies advanced data-driven approaches, utilizing a transformer framework to efficiently process high-dimensional data and learn complex ocean dynamics [9]. Its ability to reduce computational costs while maintaining high accuracy underscores the potential of integrating machine learning techniques with traditional physical models to enhance predictions of wind and current interactions.

Additionally, incorporating real-time environmental data and communication constraints into navigation decisions enhances the adaptability of mixed fleet operations, crucial for effective management in dynamic maritime environments [7].

These methodologies highlight the critical role of wind and currents in shaping ocean drift simulations. By integrating experimental data, cutting-edge sensing technologies, and sophisticated modeling frameworks, researchers significantly enhance the precision of oceanographic predictions. This improvement supports applications in effective environmental management, maritime navigation, and accurate tracking of buoyant objects and icebergs, essential for understanding climate dynamics and mitigating risks associated with shipping and offshore exploration [17, 4, 34].

3.3 Advanced Simulation Techniques

Advanced simulation techniques in ocean drift and trajectory prediction leverage cutting-edge technologies, including deep learning and artificial intelligence (AI), to enhance the precision and efficiency of predictive models. A notable innovation is the TrAISformer framework, which reframes the prediction task as a classification problem, effectively modeling the heterogeneity of Automatic Identification System (AIS) data and the multimodality of vessel trajectories [28]. This approach allows for more accurate predictions by addressing the diverse nature of maritime data.

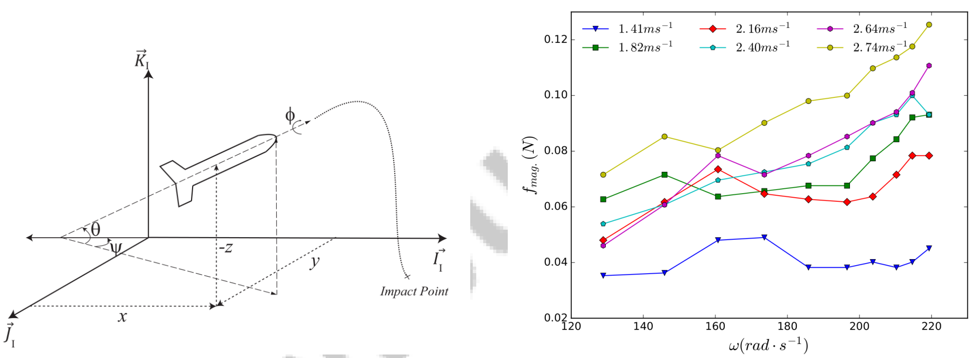
The GraphTransformer framework exemplifies the integration of graph neural networks and transformers to predict hurricane trajectories, capturing both local and global contexts [15]. This methodology illustrates the potential of combining different AI models to enhance forecasting accuracy for complex oceanographic phenomena.

In coastal simulations, combining deep learning architectures with physics-based constraints offers significant advancements, maintaining high accuracy while improving speed over traditional methods, as demonstrated in the development of fast AI surrogates for coastal applications [35]. The incorporation of physical constraints ensures model outputs remain consistent with established oceanographic principles, enhancing reliability.

Bayesian deep learning tools model both aleatoric and epistemic uncertainties, representing a key innovation in trajectory prediction reliability. This approach provides a comprehensive understanding of uncertainties inherent in oceanographic modeling, enhancing the robustness of predictive models [43]. Integrating Bayesian methods with deep learning frameworks offers a powerful tool for addressing complexities in ocean drift simulations.

Furthermore, encoder-decoder architectures with attention mechanisms in deep learning models capture vessel movement dynamics effectively [1]. This architecture extracts relevant features from complex datasets, facilitating accurate trajectory predictions by focusing on critical data aspects.

These advanced simulation techniques underscore the transformative impact of AI and deep learning in oceanographic modeling. By integrating advanced algorithms and harnessing diverse machine learning frameworks, researchers achieve remarkable accuracy and efficiency in predicting ocean drift and trajectory patterns. This integration supports applications such as real-time vessel tracking using AIS data, enhancing oil spill simulation models through improved wind drift factor computation, and assessing uncertainties in drift predictions based on environmental conditions. These innovations facilitate environmental monitoring and maritime navigation while significantly improving resource utilization and operational effectiveness across various maritime sectors [18, 1, 36, 3, 2].



(a) A diagram illustrating the orientation of a missile in a coordinate system[41]

(b) The image shows a graph with multiple lines representing different data points at different angular velocities () and mass fractions (f$_m ag$).[42]

Figure 4: Examples of Advanced Simulation Techniques

As shown in Figure 4, advanced techniques in ocean drift simulation achieve high precision and reliability in predicting the movement of objects across oceanic environments. The examples in Figure 4 illustrate two distinct yet complementary simulation techniques that highlight the complexity of these methodologies. The first image (a) presents a diagram depicting a missile's orientation within a coordinate system, emphasizing the intricate calculations required for trajectory determination. The second image (b) showcases a graph representing various data points at differing angular velocities () and mass fractions (f$_m ag), demonstrating the dynamic interplay of these variables in simulation models. Together, these examples undersc$
42].

4 Trajectory Prediction Methods

The integration of advanced algorithms and data-driven approaches has significantly enhanced trajectory prediction methods, particularly in understanding vessel movements within dynamic maritime environments. Researchers focus on improving predictive model accuracy and reliability by leveraging machine learning techniques and contextual data. This subsection explores innovative

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Feature	Mathematical Models and Algorithms	Influence of Wind and Currents	Advanced Simulation Techniques
Predictive Technique	Numerical Simulations	Experimental Measurements	Deep Learning
Environmental Factors	Wind, Currents, Waves	Wind, Currents	Ais Data
Modeling Framework	Fesom, Mdfm	Three-layer Model	Traisformer, Graphtransformer

Table 3: This table provides a comparative overview of ocean drift simulation techniques, categorizing them into mathematical models and algorithms, the influence of wind and currents, and advanced simulation techniques. Each category includes specific predictive techniques, environmental factors considered, and the modeling frameworks utilized, highlighting the integration of numerical simulations, experimental measurements, and deep learning approaches. The table underscores the diverse methodologies employed in simulating ocean drift, emphasizing the role of AI and deep learning in enhancing predictive accuracy and reliability.

frameworks that exemplify this trend, detailing their methodologies and contributions to trajectory prediction.

4.1 Innovative Prediction Frameworks

Innovative frameworks in ocean drift and trajectory prediction increasingly utilize machine learning and data-driven methodologies to enhance model accuracy and efficiency. The MSTFormer framework exemplifies this trend, integrating vessel motion dynamics with a transformer-based architecture, thus enhancing trajectory prediction capabilities by merging dynamic knowledge with historical motion data [27]. This approach enables precise modeling of vessel trajectories, accounting for complex maritime navigation interactions.

Similarly, the TrAISformer network employs a probabilistic approach to capture the multimodal distribution of vessel trajectories, reframing the prediction task as a classification problem to effectively model the heterogeneity of Automatic Identification System (AIS) data, thereby improving prediction accuracy [28]. This framework underscores the potential of combining machine learning techniques with maritime data to address vessel movement intricacies.

DiffuTraj enhances trajectory predictions by explicitly modeling uncertainty in vessel motion and incorporating contextual information, leading to more accurate forecasts [10]. This method highlights the significance of addressing uncertainty in predictive models, thereby enhancing forecast reliability.

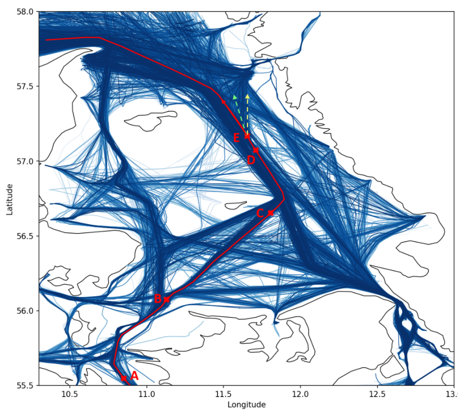
The NPC method advances trajectory prediction by enabling real-time predictions without extensive model training, emphasizing the necessity of adaptability in dynamic maritime environments [36]. In contrast, the XiHe data-driven model significantly improves ocean current predictions, achieving higher accuracy and faster forecasting speeds than traditional numerical models [9], illustrating the role of machine learning in enhancing long-term predictive accuracy.

The constructed AIS database serves as a benchmark for maritime trajectory learning, prediction, and data mining, providing a comprehensive dataset for developing and testing new predictive frameworks [45]. Fuzzy numbers characterize uncertainties in drift predictions, enhancing robustness by incorporating various environmental forces [18]. The Effective Wind Speed Method (EWSM) quantifies wind speed over oil-covered areas, illustrating the importance of environmental conditions in drift simulation accuracy [40].

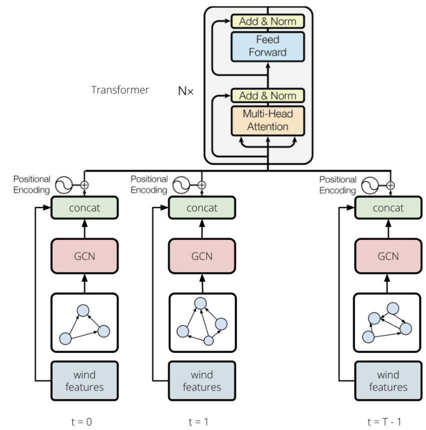
The AI surrogate model offers a significant speedup compared to traditional simulations, making it a viable solution for real-time coastal forecasting and disaster response [35]. Additionally, leveraging the graph structure of trajectory data enhances prediction accuracy over traditional sequential models [15]. The CATP framework improves contextual factor integration in trajectory prediction, enhancing adaptability and accuracy [37]. The SVR-PM method accurately represents wind effects on oil drift by adapting the Wind Drift Factor (WDF) based on actual wind conditions, showcasing another innovative approach in trajectory prediction [3].

The sequence-to-sequence model employing LSTM networks incorporates contextual information, such as destination, significantly enhancing prediction accuracy [1]. Additionally, the context-agnostic trajectory prediction framework combines predictions from batch and streaming models to generate accurate trajectory forecasts across various time intervals [8].

These innovative frameworks demonstrate the transformative impact of machine learning and data-driven techniques on trajectory prediction, particularly in leveraging vast tracking data from GPSenabled devices and positioning technologies. They encompass predictive analytics for diverse moving objects, contextual information integration, and advanced architectures for batch and stream analytics. Collectively, these methodologies improve trajectory prediction accuracy and efficiency across applications, from real-time maritime vessel tracking to context-aware animal movement predictions [37, 2, 14, 8]. By integrating advanced algorithms and historical data, researchers can achieve greater accuracy and reliability in predicting ocean drift and trajectory patterns, supporting a wide range of applications from environmental management to maritime navigation.



(a) Ocean Currents and Pathway[28]



(b) Transformer-based GCN for Wind Power Forecasting[15]

Figure 5: Examples of Innovative Prediction Frameworks

As illustrated in Figure 6, trajectory prediction methods have advanced significantly through innovative frameworks leveraging cutting-edge technologies. This figure illustrates the hierarchical categorization of innovative prediction frameworks in ocean drift and trajectory prediction, highlighting the key methodologies and their significant contributions to enhancing prediction accuracy and efficiency. The first example, "Ocean Currents and Pathway," presents a network map detailing the complex flow of ocean currents across a geographical region, using color-coded lines to indicate flow direction and strength. This visualization aids in understanding intricate pathways, marked by red lines and a green arrow, traversing from a starting point (A) to an endpoint (C). The second example, "Transformer-based GCN for Wind Power Forecasting," demonstrates a sophisticated model integrating a transformer block with graph convolutional network (GCN) layers for predicting wind power, utilizing an attention mechanism and a feed-forward network within the transformer block, while GCN layers process wind features over various time steps. Together, these examples underscore the versatility and potential of innovative prediction frameworks in enhancing forecasting capabilities across diverse environmental and energy domains [28, 15].

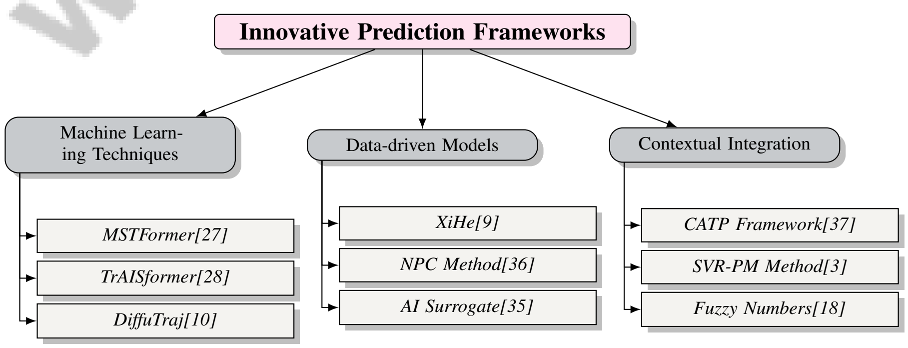


Figure 6: This figure illustrates the hierarchical categorization of innovative prediction frameworks in ocean drift and trajectory prediction, highlighting the key methodologies and their significant contributions to enhancing prediction accuracy and efficiency.

4.2 Challenges and Limitations

Accurate drift prediction in oceanographic modeling faces numerous challenges due to the complexities of ocean dynamics and methodological constraints. A significant challenge arises from the irregular time sampling and poor data quality of AIS messages, complicating vessel movement predictions and hindering trajectory model accuracy [1]. This issue is exacerbated by traditional machine learning methods, which often require extensive historical data for optimal accuracy, posing difficulties in scenarios with limited data availability [2].

Integrating diverse contextual factors into existing models remains a critical limitation, affecting drift prediction precision [37]. This is particularly relevant in dynamic environments where unpredictable human-operated ship behavior and local information quality limitations can significantly impact trajectory prediction accuracy [7]. Moreover, the need for real-time analytics on streaming data challenges traditional methods that require predefined prediction intervals, complicating drift prediction efforts [8].

Reliance on fixed empirical values for parameters such as the Wind Drift Factor (WDF) presents another challenge, as these values may not accurately reflect the dynamic nature of oceanic conditions [3]. The introduction of a depth-dependent drift factor highlights the importance of considering the vertical profile of the wind-driven drift current to improve particle tracking simulations, underscoring the need for models that incorporate vertical dynamics [4].

Despite advancements in modeling techniques, existing approaches still struggle to accurately capture the intricate dynamics of ocean drift, particularly due to their inability to account for depth-dependent variations in wind-driven drift currents and complex interactions between buoyant objects and ocean currents influenced by factors such as iceberg size and wind velocity [4, 17]. Addressing these challenges necessitates developing innovative methodologies that enhance model resolution, improve contextual information integration, and leverage real-time data analytics. Overcoming these limitations will enhance the reliability of oceanographic models and support more accurate environmental forecasting and maritime navigation.

5 Wind-Driven Drift and Its Impact

5.1 Modeling Wind Patterns and Drift Dynamics

Accurate oceanographic simulations, particularly for predicting trajectories of drifting objects, hinge on sophisticated modeling of wind patterns and drift dynamics. The intricate interplay between wind and ocean surface necessitates advanced modeling techniques. Studies indicate wind patterns significantly influence surface flow velocity and wave conditions, underscoring the importance of precise wind representation in drift models [38]. Integrating wave effects into momentum balance models enhances the accuracy of wind-driven drift simulations [24], while considering both swell and wind sea contributions provides a comprehensive depiction of Stokes drift dynamics [26].

To elucidate the hierarchical structure of key concepts related to modeling wind patterns and drift dynamics, Figure 7 categorizes the main research areas into wind pattern modeling, drift dynamics, and advanced simulation techniques. This figure highlights the contributions of various studies in each domain, providing a visual representation that complements the textual discussion.

Simulations incorporating windage and Stokes drift outperform those using only Eulerian currents, emphasizing the need to integrate these factors for reliable trajectory predictions [20]. Furthermore, oil presence on the ocean surface modifies wind stress and drift dynamics, requiring adaptable models for accurate predictions under variable conditions [40]. The SVR-PM method exemplifies model adaptability to real-time wind conditions, enhancing oil spill simulation accuracy by dynamically responding to current patterns, crucial for environmental management [3]. Fuzzy-based approaches further enrich trajectory representation by encapsulating a spectrum of potential forces acting on drifting objects [18].

Advanced frameworks, such as the 4D Swin Transformer, improve coastal circulation predictions by accurately modeling wind patterns and their drift effects [35]. Wind-driven effects on sea ice dynamics highlight the necessity for precise wind pattern modeling in drift simulations, as these significantly influence sea ice extent and movement [5]. However, challenges remain in representing

AI-generated, for reference only.

small-scale processes like diapycnal mixing, which often result in poorly resolved thermohaline circulation simulations, critical for understanding broader ocean dynamics [6].

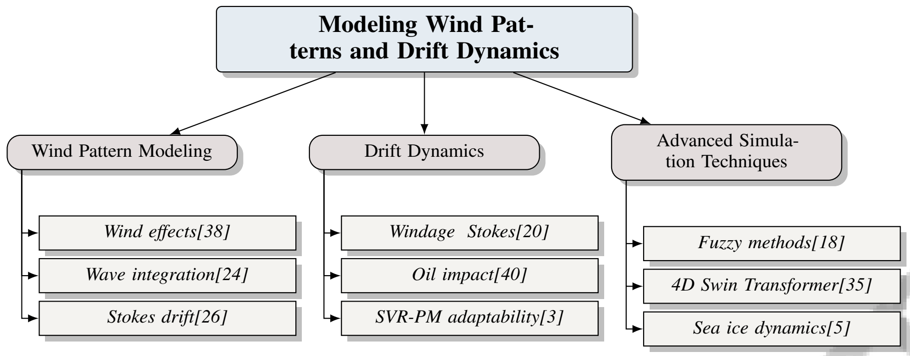


Figure 7: This figure illustrates the hierarchical structure of key concepts related to modeling wind patterns and drift dynamics. It categorizes the main research areas into wind pattern modeling, drift dynamics, and advanced simulation techniques, highlighting the contributions of various studies in each domain.

5.2 Impact of Environmental Factors on Drift Simulations

Drift simulation precision is critically influenced by environmental factors, including wind patterns, surface currents, wave dynamics, and surface substances. Wind variability, highlighted by scatterometer and radiometer measurements, necessitates model adaptability to diverse atmospheric conditions for maintaining prediction accuracy [34]. The efficacy of scatterometers in rain-free conditions and L-band radiometers in high wind scenarios underscores the importance of precise wind data in enhancing drift simulations.

Surface substances like oil alter the drag coefficient, affecting wind-water interaction and drift dynamics [40]. Models must account for surface condition changes to ensure trajectory prediction accuracy. The Effective Wind Speed Method (EWSM) exemplifies an approach that improves drift simulation accuracy by incorporating environmental conditions [40].

Wave dynamics significantly impact drift simulations. Integrating wave effects into momentum balance models, particularly through swell and wind sea contributions, offers a comprehensive representation of Stokes drift dynamics [26], crucial for capturing wave pattern influences on drift trajectories in complex environments.

The vertical structure of drift currents is another critical environmental factor. Models considering the vertical profile of wind-driven currents, including depth-dependent drift factors, enhance particle tracking simulation fidelity [4]. This consideration is vital for improving prediction accuracy in environments where vertical dynamics are significant.

Model adaptability to real-time environmental conditions is essential for precise drift simulations. The SVR-PM method, which dynamically adjusts to current wind patterns, underscores the importance of real-time adaptability in predicting oil drift dynamics [3]. This adaptability facilitates more accurate drift trajectory predictions, crucial for effective environmental management and mitigation efforts.

6 Geospatial Analysis in Oceanographic Modeling

Geospatial analysis is integral to oceanographic modeling, underpinning various computational methodologies and data integration techniques. This section delves into advanced computational techniques that refine geospatial analysis, highlighting their transformative impact on the precision and robustness of oceanographic models. The following subsection will explore these techniques in detail, underscoring their significance in oceanographic research.

6.1 Advanced Computational Techniques for Geospatial Analysis

Advanced computational techniques enhance geospatial analysis in oceanographic modeling, enabling the extraction of complex patterns from high-dimensional data and improving simulation accuracy. Deep learning methods effectively analyze intricate geospatial data, refining the precision of oceanographic models [21]. These methodologies identify critical patterns and trends essential for understanding ocean dynamics and environmental changes.

GPU-accelerated computations, exemplified by the Batched Vecchia Approximation, significantly enhance computational efficiency by estimating the log-likelihood of Gaussian processes using batched linear algebra routines on GPUs [46]. This advancement facilitates the management of large datasets and complex calculations, crucial for high-resolution ocean modeling. Unstructured meshes, as demonstrated in the Finite Element Sea ice-Ocean Model (FESOM), achieve high resolution in challenging environments like the Arctic Ocean [25], improving simulations in polar regions by accurately capturing sea ice and ocean current interactions.

Integrating batch and streaming data analyses enhances trajectory prediction accuracy, vital for maritime navigation and environmental monitoring [8]. The Kiel Fjord experiments illustrate the effectiveness of computational techniques in trajectory adaptation, enabling high-resolution data collection and adaptive modeling [7]. The Ocean Model Intercomparison Project (OMIP) provides a framework for evaluating ocean models, fostering collaboration and improvement in simulations [47]. This initiative underscores the importance of computational techniques in standardizing and enhancing oceanographic model quality.

Integrating geospatial analysis methods within the Internet of Things (IoT) framework into six distinct approaches offers a structured understanding of their application in environmental informatics [16]. This categorization aids in systematically applying geospatial techniques, ensuring robust and adaptable models across various environmental contexts. The combination of AI-driven surrogates and innovative geospatial analysis methods significantly enhances the precision and efficiency of oceanographic modeling, supporting applications from environmental forecasting to maritime safety [12, 35, 16, 17].

6.2 Innovations in Data Integration and Analysis

Innovations in data integration and analysis have significantly advanced oceanographic modeling by enhancing spatial data processing accuracy and efficiency. GPU-accelerated techniques, such as the Vecchia Approximation method, achieve remarkable speedups while maintaining accuracy, enabling the handling of large-scale geospatial datasets [46]. This advancement facilitates more precise oceanographic simulations. Integrating machine learning algorithms with traditional oceanographic models improves data analysis by extracting complex patterns from high-dimensional data, crucial for understanding ocean systems' dynamics [23, 34, 17].

Innovative data fusion techniques enable seamless integration of diverse datasets, including satellite imagery and in-situ measurements, leveraging advanced geospatial analysis and IoT technologies [12, 23, 16, 14]. This comprehensive approach enhances the reliability and robustness of environmental predictions, addressing uncertainties related to climate change and disaster management. Real-time data processing frameworks further advance data integration and analysis, facilitating ongoing data integration into ocean models and significantly enhancing prediction accuracy in rapidly changing marine environments. The XiHe data-driven model exemplifies this by improving forecasting performance and adapting to complex factors such as iceberg drift [9, 17].

6.3 Satellite and Remote Sensing Contributions

Satellite and remote sensing technologies are vital for collecting and analyzing geospatial data, significantly improving the precision and detail of oceanographic models. These technologies provide critical information, including remotely sensed winds and fine-scale ocean surface topography, as demonstrated by the Surface Water and Ocean Topography (SWOT) mission [48, 34]. High-resolution, large-scale observations from satellites are essential for monitoring ocean dynamics and environmental changes, enhancing prediction reliability across applications from climate monitoring to disaster management.

Remote sensing technologies monitor critical parameters such as sea surface temperature, ocean color, and sea level, vital for understanding ocean circulation patterns and ecosystem dynamics. Observations from the SWOT mission provide a nuanced understanding of the ocean surface, enabling researchers to monitor temporal changes and discern significant trends indicative of climate patterns or environmental conditions [48, 39, 17]. Geospatial analysis techniques, demonstrated in experiments utilizing datasets such as soil moisture from the Mississippi Basin and wind speed data from the Middle East, showcase the versatility of remote sensing technologies in oceanographic contexts [46].

Remote sensing technologies also play a critical role in validating and calibrating ocean models. Satellite data provides independent observational evidence for comparison against model outputs, ensuring ocean models accurately reflect real-world conditions. This verification process is essential for identifying discrepancies and improving model accuracy. For instance, remotely sensed winds and wind stresses are utilized in marine forecasting and ocean modeling, while missions like SWOT provide global observations of ocean surface topography, further enhancing oceanographic models' reliability [48, 17, 18, 47, 34]. This validation process is crucial for building confidence in ocean model predictions and refining model parameters to enhance performance.

7 Environmental Forecasting and Applications

7.1 Real-World Applications and Case Studies

Oceanographic models have significantly advanced environmental and maritime management, particularly through the integration of geospatial analysis and IoT technologies. These advancements enable real-time data collection and analysis, enhancing decision-making in resource management and waste systems [12, 23, 16, 49]. In emergency response, models using support vector regression for wind drift factors improve oil spill trajectory predictions, crucial for disaster management [15, 3, 40]. AI integration further enhances forecasting reliability in coastal hazard scenarios, allowing for timely interventions.

Predictive models incorporating high-level intention information for vessel trajectories effectively manage uncertainties in complex maritime environments, as demonstrated by the MS Wavelab case study in Kiel Fjord [7]. The Haversine formula, combined with geospatial tools like the Google Maps Library, enhances distance and routing systems, improving user experience in regional planning and marine logistics [12, 22, 33].

Reliable benchmarks for surface drift currents are essential for accurate measurement, improving maritime navigation and environmental monitoring. High-resolution data on surface velocity and temperature enhance ocean dynamics simulations, crucial for assessing climate change impacts on marine ecosystems. AI and machine learning further optimize model forecasting speed and reliability, vital for disaster response and coastal resource management [34, 17, 33, 35, 2]. Enhancements in wind measurement accuracy and multi-satellite products bolster operational forecasting, with models of sea ice dynamics illustrating their real-world impact [5].

Traditional machine learning methods have proven effective in real-time vessel trajectory predictions, surpassing simpler models and demonstrating scalability across maritime navigation and logistics [8]. Particle tracking simulations using drift factors validate trajectory predictions, offering insights into drifter movements and significantly enhancing predictive capabilities for climate change impacts and coastal hazard forecasting [35, 34, 17].

These applications highlight the transformative role of oceanographic models in tackling environmental and maritime challenges. By integrating AI and real-time data, researchers enhance prediction accuracy and reliability, crucial for developing early warning systems and promoting sustainable development. Innovations in deep learning allow AI surrogates to simulate coastal tidal wave propagation rapidly, supporting timely disaster response and climate change mitigation efforts [35, 34, 17].

7.2 Validation and Real-World Applications

Model validation is crucial for ensuring the accuracy and reliability of oceanographic forecasts. This involves evaluating model performance with skill metrics that assess trajectory accuracy, as seen in fuzzy-based drift prediction models [18]. Table 4 presents a selection of benchmarks that are instrumental in the validation of oceanographic models, highlighting the diversity in size, domain,

Benchmark	Size	Domain	Task Format	Metric
AISDB[45]	403,599	Maritime Trajectory Prediction	Trajectory Prediction	Accuracy, Error Distribution
Udw/u*[50]	42	Oceanography	Drift Current Measurement	Udw/u*

Table 4: Table showcasing representative benchmarks used in oceanographic model validation, detailing their size, domain, task format, and evaluation metrics. These benchmarks provide a foundational basis for assessing the performance and applicability of models in maritime trajectory prediction and oceanography.

task format, and metrics used for evaluation. Despite advancements, challenges persist, particularly in computational demands and data quality in geospatial analysis. Deep learning integration shows promise but requires extensive computational resources and faces difficulties in cross-data learning [21]. This underscores the need for robust computational frameworks to manage large datasets and adapt to diverse conditions.

The GPU-accelerated Vecchia Approximation method addresses computational challenges in geospatial analysis, though real-world application may be limited by memory constraints with large conditioning sets [46]. Validated models are vital for decision-making in environmental management, maritime navigation, and disaster response, supporting timely interventions and strategic planning [23, 2, 17]. By refining validation processes and addressing computational challenges, researchers can enhance oceanographic models' applicability and impact.

7.3 Advancements in Predictive Accuracy and Reliability

Recent advancements in predictive modeling have significantly improved oceanographic forecasts. The integration of machine learning frameworks like the TrAISformer network reframes trajectory prediction tasks, enhancing vessel trajectory accuracy by incorporating environmental factors [28]. Advanced deep learning techniques extract intricate patterns from high-dimensional datasets, essential for understanding complex ocean dynamics, such as vessel trajectories and iceberg drift influenced by environmental factors [17, 36, 3, 2, 6].

Model compression techniques enhance operational feasibility by reducing computational demands, facilitating deployment in real-time applications [28]. Selecting appropriate models based on application contexts is crucial for accuracy and reliability, highlighting the need for further research to develop adaptable models for diverse scenarios [14].

8 Conclusion

8.1 Impact of Wind-Driven and Stokes Drift on Forecasting

Incorporating wind-driven and Stokes drift dynamics is vital for enhancing the precision and reliability of oceanographic forecasts. The mechanistic drifting forecast model effectively captures interactions among tidal, wind, and wave forces, demonstrating its capability in predicting small semi-submersible drifters' trajectories. This highlights the necessity of integrating detailed wind-driven dynamics to refine drift prediction accuracy. Benchmark analyses reveal that windage and Stokes drift significantly enhance surface drifter simulation accuracy, underscoring the need for advanced modeling approaches that incorporate these dynamics. In oil spill forecasting, wind dynamics play a critical role, significantly impacting trajectory prediction accuracy. The XiHe model exemplifies this by achieving superior ocean current prediction accuracy through comprehensive wind-driven dynamics, outperforming existing numerical global ocean forecasting systems over extended lead times. Advanced distance calculation methods, such as the Haversine formula, further enhance trajectory prediction precision by improving spatial measurement accuracy, which is crucial for effective forecasting systems. The inclusion of wind-driven and Stokes drift dynamics in forecasting models markedly improves oceanographic predictions, supporting applications ranging from environmental management to maritime navigation.

8.2 Emerging Technologies and Future Directions

Advancements in ocean drift simulation are poised to benefit from emerging technologies and novel research directions. Integrating data-driven models with numerical Global Ocean Forecasting Systems (GOFSs) holds promise for enhancing forecasting capabilities by bridging the gap between traditional numerical models and modern data-driven techniques. Developing standardized frameworks for uncertainty analysis is crucial for improving environmental predictions' reliability, ensuring robust and transparent models for informed decision-making. Incorporating real-time data and exploring additional factors influencing consumer decisions and logistics are vital for enhancing oceanographic models' applicability. Refining measurement techniques and validating models against field data are essential for improving models like the wave-modified mixing-length model, ensuring accurate representation of diverse ocean dynamics. Future research should investigate the impact of different buoy types on drift modeling and incorporate the wind drift angle into parameterization models. Automating fine-tuning processes and exploring pre-trained models offer promising directions for improving trajectory prediction frameworks. Exploring mixture density models and addressing the multimodal nature of vessel trajectories are crucial for enhancing prediction robustness. Future research should also focus on refining algorithms for better adaptability and exploring practical implementations of field-based computation methods in maritime navigation. Developing comprehensive benchmarks, expanding datasets, and exploring new algorithms to address maritime traffic management's diverse needs are critical. Improving model accuracy and understanding long-term trends in Antarctic sea ice are vital for emerging research directions in ocean drift simulation. Finally, refining model parameterizations for unresolved processes and exploring new modeling frameworks that better capture ocean dynamics will expand the applicability of oceanographic models, supporting a wide range of applications from environmental monitoring to maritime navigation.

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