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Review

Data-driven decarbonization in the maritime industry: An integrative analytical review

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ABSTRACT: The maritime sector, responsible for around 2.9% of global greenhouse gas (GHG) emissions, is under increasing pressure to decarbonize towards the International Maritime Organization's (IMO) 2050 targets. A number of exisiting reviews have summarized different aspects such as policy frameworks, alternative fuels, and ship technologies, yet few have examined the integrative role of data in advancing maritime decarbonization across these domains. This review establishes a four-pillar framework to capture how data-driven approaches are reshaping maritime decarbonization. It begins by analyzing emerging digital governance policies on the basis of conventional maritime policies. Second, it synthesizes the development of emission datasets, highlighting the indirect databases with direct real-time measurements such as unmanned aerial vehicle (UAV) and portable emission measurement systems (PEMS) monitoring. Third, it reviews methodological advancements in emission modeling, from empirical, economic, and hybrid models to machine learning-based approaches. Finally, it evaluates how these data and modeling advancements support coordinated decarbonization strategies across vessels, fuels, and ports, illustrating the growing role of data-informed decision-making in guiding systemic emission reductions throughout the maritime supply chain. This review links regulatory, data, modeling, and implementation perspectives through a data-centric perspective. By mapping research progress and identifying knowledge gaps across these four pillars, the review offers a structured foundation to support the acceleration of maritime decarbonization efforts.

KEYWORDS: maritime decarbonization policy; data-driven approach; marine data sources; emission modeling; decarbonization strategy; alternative fuel

1 Introduction

The maritime industry, facilitating around 90% of global trade, is among the most energy-efficient transport modes. However, it remains a significant and growing emitter, contributing 1,076 million tonnes of carbon dioxide (CO_2) in 2018 which is about 2.9% of global greenhouse gas (GHG) emissions (IMO, 2020). Recognizing the sector's environmental impact, in 2023, the International Maritime Organization (IMO) set an ambitious target for the shipping industry to achieve net-zero emissions by 2050 (IMO, 2023a). This has spurred a broad wave of decarbonization efforts across the shipping sector, spanning policy development, technological innovation, and operational optimization. Several existing reviews have provided valuable insights into specific topics in shipping decarbonization, such as low-carbon fuel technologies (Ampah et al., 2021; Govindan et al., 2024), ship design and propulsion systems (Kondratenko et al., 2025; McKenney, 2024), activity-based emission modeling (Ortiz-Cea et al., 2025; Xing et al., 2020), port decarbonization strategies (Xiao et al., 2024) and post-combustion carbon capture technologies (Ibigbami et al., 2024). Border syntheses reviews, such as Di Vaio et al. (2023), Fadiga et al. (2024), and Tadros et al. (2023), provide state-of-the-art technologies at the systematic level integrating ship, fuel, port, and supply chains. However, these reviews give limited attention to the role of data in supporting regulatory enforcement, operational decision-making, and technological innovation for decarbonization.

Recent advancements indicate that data-driven approaches are becoming integral to maritime decarbonization. Data-driven maritime decarbonization refers to the use of structured, high-frequency data sources to support environmental governance, emissions modeling, operational optimization, and fuel transitions (Yan et al., 2021). Automatic Identification System (AIS) data (Chen and Yang, 2024; Du et al., 2022a; Yang et al., 2019), satellite-based monitoring (Li et al., 2022; Zucchetta et al., 2025), and sensor-integrated systems (Du et al., 2022b; Karachalios et al., 2024) detail assessments of vessel behavior, fuel utilization, and emissions in real-time modes (Chen et al., 2024b; Liu et al., 2025; Yang et al., 2024c). These capabilities support applications such as remote vessel tracking (Cui et al., 2024), emissions monitoring (Chen et al., 2024a; Qi et al., 2024), port operations and scheduling (Iphar et al., 2024; Liu et al., 2025), and clean fuel system analysis (Šilas et al., 2023; Ziyadi and Al-Qadi, 2019). Despite this growing body of work, there remains no systematic review that examines

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how data is applied across the regulatory, technical, and operational domains of maritime decarbonization. Moreover, the acceleration of digital regulation, the expansion of emissions monitoring capabilities, and the rise of machine learning (ML) models now require an updated understanding of how data drives systemic change.

To address these limitations, this review adopts a data-driven perspective on maritime decarbonization, offering an updated and holistic overview of current research. It structurally contributes to maritime decarbonization in four pillars, which are summarized as follows:

1) **Policy foundations for data-driven decarbonization**. This review traces the evolution of maritime policies from conventional emission control measures through international (e.g., IMO) and regional (e.g., European Union (EU), China, and Singapore) aspects towards digitally enabled governance. It highlights how data-enabled compliance and monitoring tools reshape decarbonization enforcement.

2) **Advancement and integration of emissions data**. This review synthesizes diverse emission data sources, bridging indirect vessel estimation data and real-time measurements, and underscores the importance of unified, high-resolution datasets for tracking maritime emissions.

3) **Methodological innovation in emission modeling**. This review compares empirical, economic, and hybrid models while emphasizing the transformative role of machine learning (ML) and data-driven techniques in improving the accuracy and adaptability of maritime emission estimation.

4) **Strategic pathways for systematic decarbonization**. It consolidates studies on vessel efficiency, operational measures, alternative fuels, and port coordination, offering a holistic view of how integrated strategies drive emissions reduction across the maritime supply chain.

Fig. 1 illustrates the interconnections among the four pillars of the decarbonization framework, which together form a coherent and interdependent system. Data sources, including indirect and direct emission data, provide the empirical foundation for reliable maritime emission analysis. These inputs enable emission modeling, where empirical and machine learning methods transform raw data into systematic estimates and forecasts of maritime emissions. The insights from modeling directly inform decarbonization strategies by identifying high-impact measures, evaluating fuel alternatives, and assessing the effectiveness of vessel- and port-level initiatives. The design and prioritization of these strategies are in turn shaped by decarbonization policies, which set regulatory standards and methodological requirements, and also influence data collection practices. Collectively, these four pillars form an integrated framework for guiding maritime decarbonization.

The remaining sections of this review are structured as follows: Section 2 outlines the methodologies for reviewing existing research. Section 3 provides an overview of key maritime decarbonization regulations, especially the emerging digital policies. Section 4 examines essential marine data sources. The maritime emission models, including both traditional empirical approaches and ML techniques, are explored in Section 5. Section 6 examines the data-informed strategies for vessel optimization, fuel transitions, and port-level interventions. Section 7 discusses future directions for advancing data infrastructure and modeling capabilities. Finally, Section 8 summarizes the key findings and contributions of this review.

2 Methodology

We conducted a structured literature review to assess the evolving research landscape of maritime decarbonization. The review

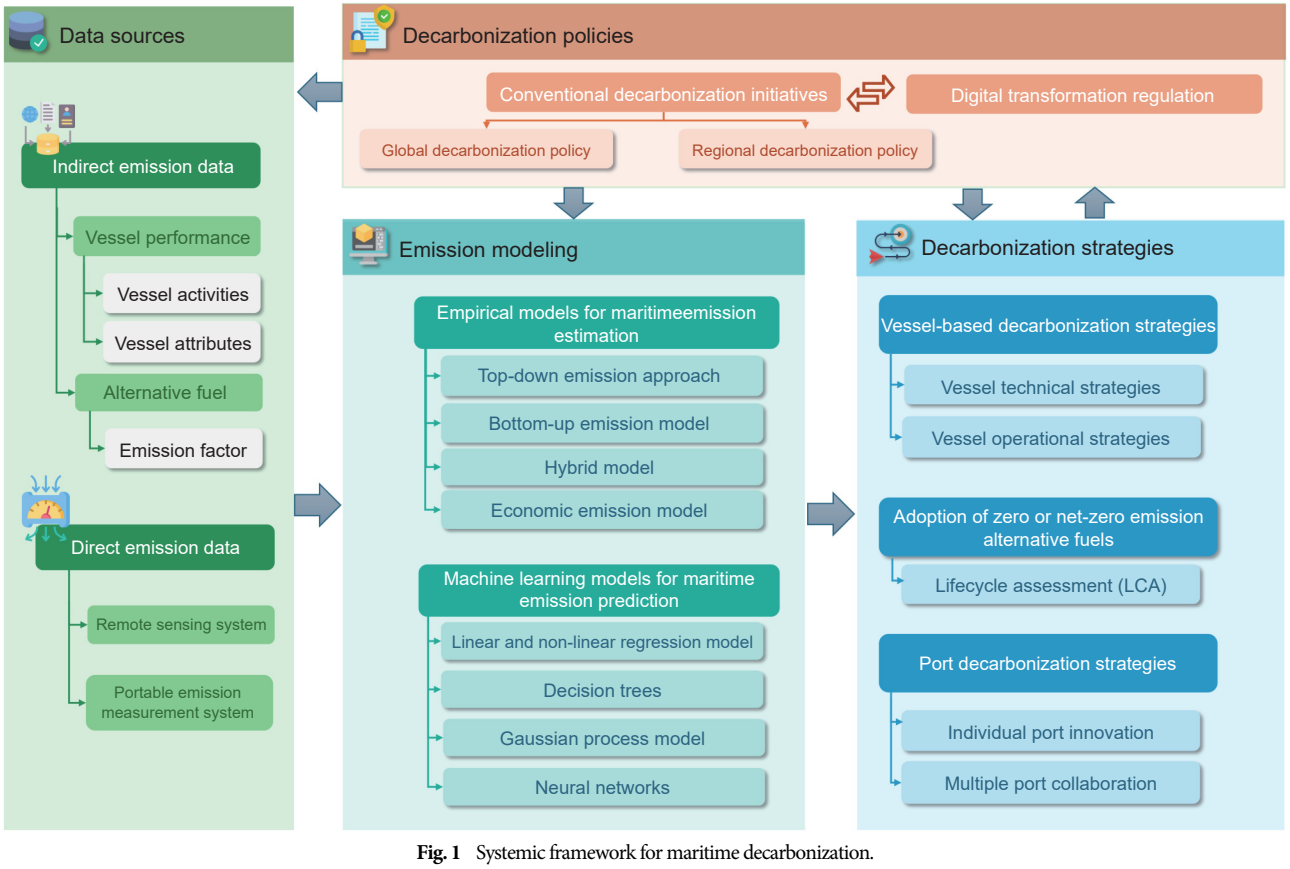

Fig. 1 Systemic framework for maritime decarbonization.

draws on publications indexed in Scopus, Google Scholar, and Web of Science, covering the period from 2010 to 2024. The review begins in 2010 because this period coincides with major international regulatory milestones that reshaped maritime emission research. In 2010, the North American Emission Control Area (ECA) was adopted under MARPOL Annex VI (entered into force in 2012) (United States Environmental Protection Agency, 2010), followed by the US Caribbean ECA, which became effective in 2014 (United States Environmental Protection Agency, 2011). The Energy Efficiency Design Index (EEDI) was adopted by the IMO in 2011 and entered into force in 2013 (IMO, 2013), becoming the first mandatory global regulation on ship energy efficiency. These measures provided a regulatory foundation that stimulated systematic academic studies on maritime emissions and decarbonization.

We used targeted keywords related to four thematic categories: (1) regulatory frameworks (e.g., "IMO GHG strategy"), (2) emission modeling (e.g., "shipping emission models"), (3) alternative fuels (e.g., "ammonia marine fuel", "methanol shipping"), and (4) digital and port-related decarbonization (e.g., "marine data analytics", "port emission reduction"). Our inclusion criteria focus on peer-reviewed journal articles, technical reports, and regulatory documents directly related to maritime decarbonization. Studies were excluded if they: (1) addressed non-maritime sectors, (2) focused solely on non-carbon pollutants (e.g., sulfur), or (3) presented theoretical methods without maritime application. After screening, we retained around 200 publications across four research domains: regulatory development, marine data sources, emission estimation methods, and decarbonization strategies.

Fig. 2 summarizes the publication distribution by year, with maritime decarbonization strategies highlighted in the upper-left corner. Publication trends indicate an over 300% increase in data-driven decarbonization studies since 2018. Interdisciplinary contributions from environmental science, transportation engineering, and computational modeling are integrated to address the technical, operational, and policy dimensions of maritime sustainability.

The analysis of references indicates distinct trends in maritime decarbonization research. Studies on regulatory frameworks have increased notably since the IMO's 2018 GHG reduction strategy. Research on marine data sources has grown steadily, particularly after 2016, driven by the widespread adoption of AIS data. Similarly, publications on maritime emission models have risen significantly, especially after 2020, reflecting the increasing application of ML techniques. Lastly, studies on maritime decarbonization strategies have expanded rapidly since 2021, driven by the growing emphasis on alternative fuels and port emission reduction measures. These trends highlight the evolving focus of maritime decarbonization efforts, highlighting the integration of data-driven approaches and regulatory advancements.

3 Maritime decarbonization policies

To guide maritime decarbonization, a layered framework of global and regional policies has been established. These policies set emission targets, promote alternative fuels, and introduce digital reporting and monitoring requirements. Fig. 3 provides a timeline-based overview of these key regulations at both global and regional levels, reflecting the evolution of policy instruments across jurisdictions. Global frameworks led by the IMO provide foundational principles and standardized targets, such as EEDI, Ship Energy Efficiency Management Plan (SEEMP), and Carbon Intensity Indicator (CII) (IMO, 2023b; Iris and Lam, 2019). As their detailed mechanisms have already been comprehensively reviewed in previous studies, such as Joung et al. (2020), they are not further discussed here. Regional authorities such as the EU, Singapore, China, and USA adopt tailored instruments to reflect local environmental priorities and economic structures (Chang et al., 2018; European Commission, 2024; Cullinane and Bergqvist, 2014; Sun et al., 2020). For example, the EU employed the alternative fuels infrastructure directive (AFID) to promote the deployment of supporting infrastructure such as shore power and alternative fuel bunkering at ports in 2014 (European Commission, 2014). Building on this foundation, the renewable energy directive II (RED II) established renewable energy targets across transport modes, including maritime (European Union, 2018).

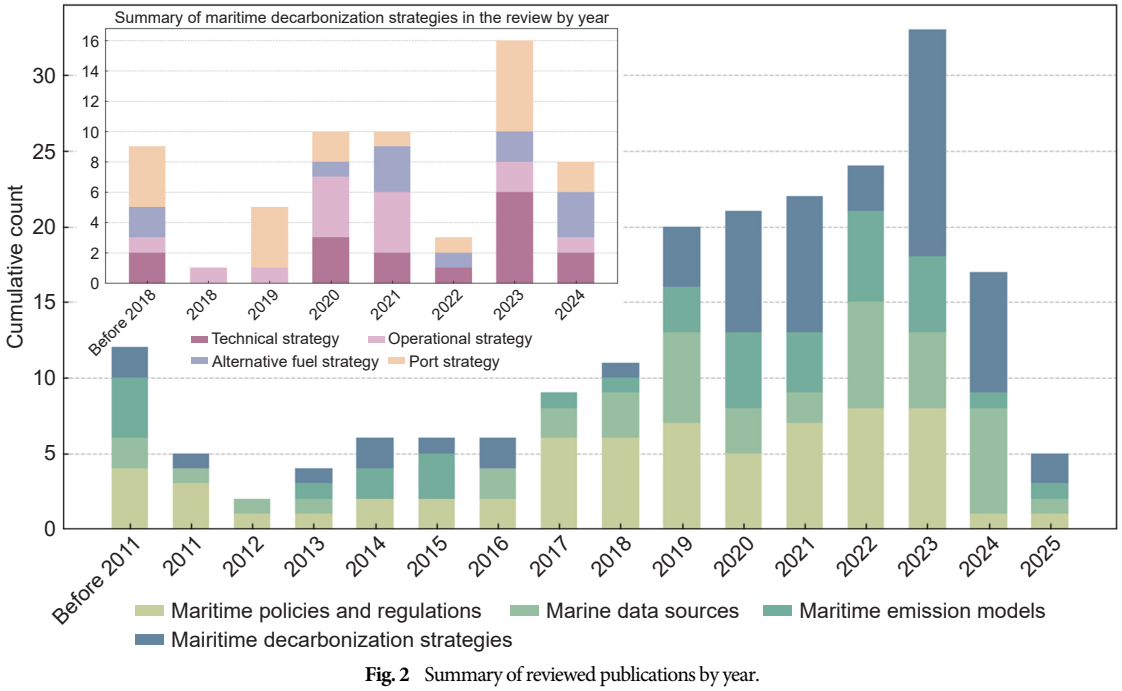

Fig. 2 Summary of reviewed publications by year.

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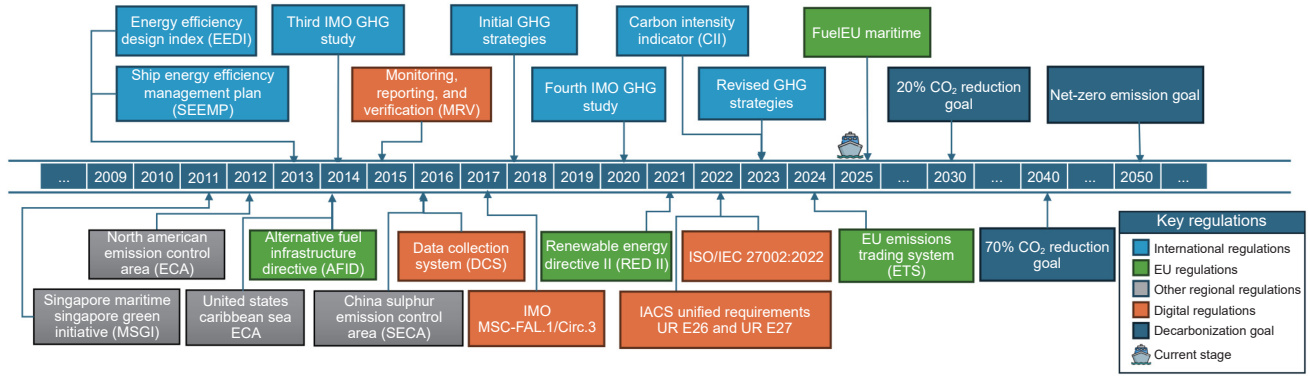

Fig. 3 Overview of regulatory frameworks for maritime decarbonization.

The EU has advanced market-based mechanisms such as the EU emissions trading system (EU ETS)[1] and the FuelEU Maritime Regulation ((EU) 2023/1805)[2]. Singapore's Maritime Singapore Green Initiative (MSGI), China's ECAs, the North American and US Caribbean Sea ECAs exemplify how port states operationalize sustainability goals within their jurisdictions (Cullinane and Bergqvist, 2014; Singapore Maritime and Port Authority, 2025; Sun et al., 2020). The dual-level framework structured by international policies and regional regulations enables alignment on global emission goals while allowing flexibility in addressing local environmental priorities, regulatory capacities, and infrastructure conditions.

In addition to the conventional initiatives for maritime decarbonization, an increasingly important dimension of maritime policy is the integration of digital systems for emissions management. These digital regulations can be categorized into data reporting frameworks and cybersecurity standards. To be specific, digital data reporting initiatives began with the EU monitoring, reporting and verification (MRV) regulation (European Commission, 2021) and the IMO data collection system (DCS) (IMO, 2019). Both systems require ships above 5000 gross tonnage to report fuel consumption and CO_2 emissions. These datasets are now widely used for maritime emissions analysis, benchmarking, and policy evaluation. Their alignment has also facilitated the integration of shipping into carbon pricing systems such as the EU ETS.

With the deployment of digital tools such as internet of things (IoT) sensors, real-time monitoring, and blockchain, safeguarding data integrity has become essential. The IMO's guidelines on maritime cyber risk management (MSC-FAL.1/Circ.3), titled Guidelines on Maritime Cyber Risk Management, advocate a risk-based approach to protecting cybersecurity within maritime safety management systems (IMO, 2021). In addition, the international association of classification societies' cybersecurity requirements (UR E26/E27) mandate proactive risk management for shipboard systems (International Association of Classification Societies, 2024). The ISO/IEC 27001:2022 standard[3], jointly issued by the international organization for standardization (ISO) and the international electrotechnical commission (IEC), is a cross-sectoral standard for information security management. It is increasingly applied to port community systems (PCSs) and terminal operating systems to strengthen cybersecurity across maritime IT infrastructure. By establishing a structured framework for managing information security, it complements regulatory requirements set by the IMO and the international association of classification societies (IACS), enhancing data integrity, cyber resilience, and compliance in digital maritime governance. Regional directives, including the EU's network and information security directive 2 (NIS2) (European Union, 2024) and Singapore's shipping circular No.15 (Maritime and Port Authority of Singapore, 2020), require cyber incident reporting and resilient system design.

Despite progress in digital regulations, the maritime sector continues to face structural challenges in data standardization, system interoperability, and cross-platform integration. Variations in data formats, inconsistent reporting protocols, and limited compatibility across national and industry platforms hinder the seamless aggregation and utilization of emissions data. These limitations reduce the effectiveness of digital tools in supporting real-time emissions monitoring, comparative benchmarking, and automated regulatory compliance. In addition, uneven levels of digital infrastructure across port states constrain participation in global emissions management frameworks, leading to geographic disparities in data quality and coverage. Addressing these gaps requires coordinated international standards, investment in interoperable systems, and policy support for capacity building in digitally lagging regions. Addressing these gaps will enable a more inclusive, coordinated, and effective implementation of digital policies across the global maritime sector.

4 Emission data sources

Effective regulation of vessel emissions relies on integrating diverse data sources and monitoring tools. In this section, we categorize marine emission data sources into two groups, indirectly collected emission data derived from published databases and directly collected emission data measured from *in-situ* facilities, such as UAV and PEMS, capturing real-time emissions.

4.1 Indirect emission data sources

Unlike land-based transportation, where onboard sensors are widely used for direct data acquisition, the maritime sector faces challenges due to high installation costs and operational constraints (Xing et al., 2020). As a result, indirectly measured emission evaluation methods, primarily based on vessel fuel consumption and emission factors, are more prevalent in maritime studies. These methods rely on two key components:

[1]https://climate.ec.europa.eu/eu-action/transport-decarbonisation/reducing-emissions-shipping-sector_en

[2]https://transport.ec.europa.eu/transport-modes/maritime/decarbonising-maritime-transport-fueleu-maritime_en

[3]https://www.iso.org/obp/ui/#iso:std:iso-iec:27001:ed-3:v1:en

vessel performance data, including vessel attributes and operational data, and emission factor databases, providing standardized coefficients for estimating emissions based on fuel type and combustion characteristics.

4.1.1 Data sources on vessel performance

This section outlines key marine data sources related to vessel performance, as summarized in Table 1. The discussion includes commonly referenced databases such as the AIS database[4], Lloyd's Register (LR) database[5], Information Handling Services (IHS) Fairplay database[6], as well as noon reports, meteorological and oceanographic data, and the Port Management Information System (PMIS). All of these sources contribute distinct types of vessel performance data, ranging from technical specifications and operational records to environmental conditions, which are detailed in Table 1.

4.1.2 Data sources on emission factors

Emission factors are essential for estimating pollutant emissions from fuel consumption, forming the basis for environmental assessments and regulatory compliance. These factors vary by vessel type, engine load, fuel characteristics, and operational profile (Schrooten et al., 2009). Recent studies have improved the accuracy of load-dependent factors through meta-analyses, accounting for differences in engine and fuel types (Grigoriadis et al., 2021; Goldsworthy and Goldsworthy, 2015). However, the absence of standardization remains a key challenge, particularly when emission estimates rely on generalized or modeled data (Grigoriadis et al., 2021). Table 2 summarizes emission factor datasets published by major regulatory and research organizations. These databases provide reference emission factor values for CO_2, NO_x, SO_x, PM, and other pollutants, supporting consistent and transparent assessments across studies.

Table 1 Data sources on vessel performance

Database	Introduction	Data type	Key usage	Ref.
AIS database	Real-time vessel positioning and movement data collected via transponders on ships	**Vessel attributes:** IMO number, ship name, call sign, vessel type, size, gross tonnage, deadweight tonnage **Operational data:** Speed over ground, course over ground, heading, navigation status, latitude and longitude, timestamp, destination port, estimated time of arrival	Trajectory prediction, anomaly detection, emissions estimation, traffic management, and real-time operational analysis	Ay et al. (2022); Li et al. (2023a); Yang et al. (2019)
LR database	Static technical and regulatory data about vessels	**Vessel attributes:** Ship dimensions, hull type, engine specifications, fuel capacity. **Certification data:** Class notations, safety certifications, environmental compliance records (e.g., EEDI) **Technical data:** Fuel efficiency metrics, propulsion system details **Operational data:** Vessel historical performance records	Emission modeling, operational efficiency analysis, accident risk mitigation	Alamoush et al. (2020); Huang et al. (2020); Li et al. (2023a)
IHS fairplay database	Comprehensive database on the global merchant fleet, including vessel characteristics and incidents	**Vessel attributes:** Ship name, IMO number, call sign, vessel type, size, gross tonnage, deadweight tonnage **Technical data:** Propulsion and engine details **Operational data:** Historical and real-time voyage data, port call information, routing, operational patterns	Vessel design modeling, accident analysis, emission estimation, regulatory compliance studies	Hassel et al. (2011); IHS (2016); Vladimir et al. (2018)
Noon report	Daily vessel operational reports	**Operational data:** Daily fuel use, engine load, revolutions per minute, power output, speed, distance traveled, weather conditions encountered	Monitoring vessel performance, voyage management	Moreno-Gutiérrez et al. (2019); Smith et al. (2013); Yan et al. (2021)
Meteorological & Oceanographic database	Critical environmental parameters during sailing, such as wind, waves, currents, seawater temperature	**Weather conditions:** Wind speed/direction, air temperature, barometric pressure **Marine conditions:** Sea state, wave height/direction, sea surface temperature, currents **Climate data:** Seasonal trends, historical weather patterns	Enhancing fuel efficiency models, emission accounting, voyage planning	Psaraftis (2019); Ren et al. (2022); Yang et al. (2024a)
PMIS database	Digital platform managed by port authorities for port operations, integrating vessel scheduling, cargo handling, and port resources	**Port call data:** Arrival/departure time, berth allocation, anchorage details **Cargo operations:** Types of cargo handled, loading/unloading time, port equipment utilization **Vessel services:** Bunkering operations, maintenance records, pilotage details **Traffic statistics:** Cargo throughput, operational efficiency metrics, port congestion data	Reducing vessel idling, optimizing port operations, minimizing emissions through efficient resource allocation	Mlimbila and Mbamba (2018); Son et al. (2022)

[4]Information about the AIS database can be found at https://www.aishub.net/

[5]https://www.lr.org/en/about-us/who-we-are/lr-ships-in-class/

[6]https://www.spglobal.com/marketintelligence/en/mi/products/maritime-trade.html

Table 2 Emission factor databases

Database	Source	Version	Coverage	Application	Ref.
IMO emission factors database (IMO, 2019)	MARPOL annex VI	Ongoing updates	Standardized emission factors for CO_2, NO_x, SO_x, and other pollutants based on fuel types	Used for international compliance and CO_2 emission reporting	Grigoriadis et al. (2021)
ICCT marine emissions database[1] (ICCT, 2007)	ICCT research reports	Last updated in 2019	Real-world emission factors for GHG and pollutant estimation	Used for improving accuracy in maritime emission modeling	Comer (2019)
IPCC guidelines for national greenhouse gas[2] (IPCC, 2019)	IPCC guidelines	Last updated in 2019	Emission factors for different fuels used in international and domestic shipping, covering GHGs such as CO_2, CH_4, and N_2O	Used for national GHG inventories and climate impact assessments	Chen et al. (2019a)
EMEP/EEA air pollutant guidebook[3] (EEA, 2022)	EMEP/EEA guidelines	Last updated in 2023	NO_x, SO_x, CO_2, and particulate matter emissions for maritime transport in European areas	Used for emission modeling in European maritime assessments	Grigoriadis et al. (2021); Trozzi (2010)
EPA emission factors[4] (EPA, 2024)	EPA tier standards	Updated annually	Emission factors of NO_x, SO_x, CO_2, PM[5], CO, and VOC[6]. Specialized factors for GHG and air toxics in certain sectors	Used for global regulatory compliance and GHG inventories	Grigoriadis et al. (2021)
National and regional databases	Local regulatory frameworks	Updated periodically	Localized emission factors tailored to regional fuel standards and vessel activities.	Used for compliance with national regulations (e.g., China's MEE database[7])	Xu et al. (2024)

Note: [1] ICCT: International council on clean transportation; [2] IPCC: International panel on climate change; [3] EMEP/EEA: European monitoring and evaluation programme: European environment agency; [4] EPA: Environmental protection agency; [5] PM: Particulate matter; [6] VOC: Volatile organic compounds; [7] MEE: Ministry of ecology and environment.

4.2 Direct emission data sources

To address the limitations of emission factor variability and standardization, increasing attention has been given to direct emission measurements. Onboard systems now enable real-time collection of particulate and gaseous emissions under actual operating conditions (Huang et al., 2018), providing more accurate data across varying engine loads and fuel types. This subsection examines key methods for direct emission data collection and their contributions to improving the reliability of maritime emission assessments. Advancements in monitoring technologies, such as remote sensing and onboard measurement systems, enable real-time emission data collection from ships and port activities. These *in-situ* measurement approaches provide highly accurate data, essential for validating indirect emission estimates and calibrating remote sensing systems.

4.2.1 UAV-based remote sensing systems

The rapid advancement of UAV technology has transformed maritime emissions monitoring (Klimkowska et al., 2016). UAVs equipped with non-dispersive infrared (NDIR) and electrochemical (EC) sensors for ship exhaust plumes measurement have been shown to accurately quantify ship emissions (Šaparnis et al., 2024). UAVs are effective for monitoring hard-to-access ship exhaust areas, typically operating 5–30 m from the stack for 5–20 min to minimize dilution while ensuring safety (Rosewig et al., 2023). However, their deployment is constrained by short flight duration, limited payload, weather sensitivity, high operational costs, and region-specific aviation regulations (Šaparnis et al., 2024). Future developments aim to extend flight time, improve autonomy, and enable more efficient large-scale monitoring. Table 3 presents an overview of key UAV-based emission measurement studies.

4.2.2 Portable emission measurement systems (PEMSs)

Unlike remote sensing methods like UAV-based measurements, PEMS provides a more direct and accurate approach through installation onboard. Integrated with exhaust systems, PEMS continuously collects real-time emission data during voyages (Li et al., 2024). These systems typically include NDIR sensors for CO and CO_2, chemiluminescent detectors for NO_x, and flame ionization detectors for total hydrocarbon (Fan et al., 2024; Zhang et al., 2024b). Recent studies have used PEMS to assess emissions across various ship types under real-world conditions. For instance, Fan et al. (2024) measure emissions using PEMS from a container ship and a bunker ship on the Yangtze River, aiming to develop a localized emission factor database. Zhang et al. (2024b) conducted real-world emission measurements on a large marine cargo ship using PEMS, revealing that NO_x emissions peaked at 29.53 g/kWh and particulate emissions varied significantly with engine speed and operating conditions. Peng et al. (2016) test the emissions of seven vessels—including tugboats, Ro-Ros, and passenger ships—and found elevated pollutant levels during cruising. Zhang et al. (2022) measure real-world emissions on a real-world inland ship using a PEMS, revealing that gaseous (CO, SO_2, NO_x) and particulate emissions (PM and PN) peak during departure and idling, while NO_x and SO_2 were highest during cruising.

PEMS is a versatile tool for measuring diverse pollutants across ship types and operating conditions. However, high costs, complex installation, and operational variability limit large-scale deployment and standardization (Peng et al., 2016; Yang et al., 2022). System malfunctions may also disrupt data continuity (Zhang et al., 2022). Despite these challenges, PEMS remains essential for capturing real-world emissions, refining emission factors, and supporting regulatory compliance.

4.3 Summary

Looking ahead, overcoming the limitations of current approaches requires practical technical improvements and coordinated regulatory efforts. For indirect methods, emission factor databases should be standardized under IMO or regional frameworks, with regular updates based on real-world measurements from different vessel types and operating conditions. Integrating AIS-based operational data with port and vessel statistics into a unified database can improve coverage, consistency, and accuracy of indirect emission estimates. For direct measurements, more challenges still remain including reducing equipment costs through modular PEMS designs, extending sensor durability for unexpected marine environments, and developing standardized installation and calibration protocols to enable wider deployment. Furthermore, unified guidelines are needed on sensor placement on exhaust stacks, calibration procedures under different engine

Table 3 Summary of UAV applications on maritime emission monitoring

Ref.	Data collection year	Ports/areas	GHGs & pollutants	UAV model	Sensor type	Conclusion
Zhou et al. (2019)	2019	Waigaoqiao Port, Yangtze River, China	SO_2, CO_2	DJI Matrice 600 Pro	Sniffing method using UAV-mounted NDIR and EC sensors	Demonstrated consistent measurement accuracy and effective regulatory enforcement
Villa et al. (2019)	2016	Great Barrier Reef, Australia	PN, CO_2	DJI S800 EVO	UAV-mounted sensors of miniature diffusion size classifier and NDIR	Identified emission hotspots and contributed to pollution mitigation strategies near sensitive areas
Hu et al. (2022)	2022	Pearl River Delta, China	SO_2, CO_2	DJI Phantom 4 Pro V2.0	Sniffing method using UAV-mounted NDIR and EC sensors	Verified compliance with sulfur regulations in high-traffic maritime zones
Deng et al. (2022)	2021	Port of Shanghai, China	SO_2, CO_2	DJI Phantom 4 Pro V2.0	Mini-sniffing sensors (unspecified model)	Enabled targeted monitoring in ECAs, improving environmental management practices
Haugen et al. (2023)	2022	Port of Rafina, Greece	PN[1], BC[2], LDSA[3]	DJI Matrice 600 Pro	Near-field dispersion modeling with UAV-mounted particulate sensors	Provided 3D plume dispersion maps for port-level air quality management
Yang et al. (2024b)	2024	Port of Hong Kong, China	NO_x, SO_2, CO_2	DJI Matrice 210 V2	Microsensor sniffing systems with EC sensors	Established microsensor sniffing protocols, creating a standardized UAV-based emission monitoring framework for ECAs

Note: [1] PN: Particle number; [2] BC: Black carbon; [3] LDSA: Lung deposited surface area.

loads, and data reporting formats. UAV-based monitoring can be scaled up by relaxing regulatory constraints on flight ranges and improving battery life through hybrid power systems. In addition, establishing common data-sharing platforms and guidelines will ensure that both indirect and direct sources complement each other, supporting reliable and scalable maritime emission assessments.

5 Maritime emission models

Due to the limited availability of direct emission measurements, emission modeling remains essential for estimating maritime emissions. These models complement empirical observations by providing scalable and context-specific assessments. This section summarizes key modeling approaches used for different purposes, focusing on empirical methods for emission estimation and ML techniques for emission prediction.

5.1 Empirical models for maritime emission estimation

Empirical models help analyze the relationships between vessel activities, fuel use, and emissions. As maritime decarbonization efforts intensify, empirical models have evolved to address increasing complexity. We categorize them into four distinct types: top-down, bottom-up, hybrid (combining top-down and bottom-up approaches), and economically integrated models which incorporate financial parameters into emissions estimation for investment decisions. Table 4 summarizes key models in the field, highlighting their features and applications. The following subsections explore these categories in detail.

5.1.1 Top-down emission estimation approach

Top-down maritime emission models estimate global GHG emissions using aggregated fuel sales data and emission factors, providing macro-level assessments that support international climate policies (IMO, 2020). Foundational studies by Corbett and Fischbeck (1997), Corbett et al. (1999), and Endresen et al. (2007) demonstrate the application of top-down emission modeling by utilizing international marine fuel consumption statistics from the U.S. Energy Information Administration. Top-down models have been widely adopted in IMO's Third and Fourth GHG Studies, generating global shipping emissions inventories such as the Global Shipping Emissions Inventory, which serve as benchmarks for decarbonization and inform international regulatory frameworks (Smith et al., 2015; IMO, 2020).

Table 4 Empirical models for maritime emission estimation

Model	GHGs and pollutants[2]	Analysis scope[3]	Fuel type	Region studied	Developer	Model type	Ref.
EEA	NO_x, SO_x, CO_2, PM	TTW	Conventional marine fuels[1]	EU	European environment agency	Top-down method	EEA (2023)
EPA	NO_x, SO_x, CO_2, PM	TTW	Conventional marine fuels[1]	USA	US environmental protection agency	Top-down method	United States Environmental Protection Agency (2023)
STEEM	NO_x, SO_x, CO_2, PM	TTW	Conventional marine fuels[1]	EU	Chalmers University of Technology	Bottom-up model	Wang et al. (2007)
STEAM	NO_x, SO_x, CO_2, CO, PM	TTW	Conventional marine fuels[1]	Global	Finnish meteorological institute	Bottom-up model	Jalkanen et al. (2009); Saliba et al. (2021)
SEA-Hybrid	CO_2	TTW	Electric, hybrid fuels	Specific areas	Various maritime research groups	Hybrid model	Topic et al. (2021)
GloTraM	GHGs, NO_x, SO_x	WTW	Various marine fuels	Global	UCL Energy Institute	Economic model	Carlo et al. (2020)

Note: [1] Conventional marine fuels refer to heavy fuel oil, marine gas oil, or diesel; [2] NMVOC: Non-Methane volatile organic compounds; [3] WTT: Well-to-Tank phase; TTW: Tank-to-Wake phase; WTW: Well-to-Wake phase.

Beyond global assessments, top-down methods are also widely used at the national and regional emission reporting. For example, the U.S. EPA applies this approach to estimating national shipping emissions using fuel sales data and emission factors (United States Environmental Protection Agency, 2023). Similarly, the EEA employs top-down methodologies in its European Monitoring and Evaluation Programme (EMEP)/EEA Air Pollutant Emission Inventory Guidebook, offering macro-scale regulatory insights (EEA, 2023). Norway imposes a carbon tax on shipping fuel for domestic and offshore operations, levied at the point of fuel purchase rather than measuring actual emissions per voyage, based on the assumption that emissions are proportional to fuel sales (Norwegian Environment Agency, 2024).

Despite their broad use, top-down models lack granularity, as they rely on aggregated data and overlook local variations in vessel operations and fuel types, limiting their effectiveness for localized assessments (Corbett and Koehler, 2003; Kramel et al., 2021).

5.1.2 Bottom-up emission estimation models

Bottom-up maritime emission models, introduced by Corbett and Koehler (2003), provide high-resolution emission estimates by incorporating vessel-specific operational data, such as AIS tracking, engine power ratings, load factors, and fuel consumption parameters. Compared to top-down models, bottom-up models offer greater accuracy, making them particularly valuable for port-level assessments and real-time monitoring (Coello et al., 2015). The Fourth IMO GHG Study (IMO, 2020) further enhanced bottom-up approaches by integrating AIS-based port call identification, enabling precise allocation of emissions between international and domestic shipping. Three typical bottom-up models are categorized: Shipping traffic emission model (STEEM) (Wang et al., 2007), ship traffic emission assessment model (STEAM) (Jalkanen et al., 2009), and shipping emission and energy model (SENEM) (Moreno-Gutiérrez and Durán-Grados, 2021).

STEEM, developed by Wang et al. (2007), uses AIS and traffic data to estimate emissions from ship voyages but lacks detailed fuel-specific emission factors, limiting accuracy. STEAM, developed by the Finnish Meteorological Institute, has undergone continuous refinement. Early versions used aggregated activity data and static emission factors (Jalkanen et al., 2009). Later updates incorporate AIS, vessel-specific attributes, and operational modes (e.g., cruising, maneuvering, hotelling) to enhance precision (Jalkanen et al., 2012, 2014). Subsequent updates in STEAM models introduce vessel-specific operational parameters, such as engine load dynamics and fuel sulfur content (Johansson et al., 2017; Moreno-Gutiérrez et al., 2015). Recent versions model CO_2 and BC, enabling high-resolution spatial and temporal emission inventories, including analyses of pandemic-related changes in shipping emissions (Saliba et al., 2021; Shu et al., 2023). He et al. (2025) apply the model to estimate annual emissions for the Port of Shanghai from January to December 2019 at both the individual ship and fleet levels, integrating waterway and vessel characteristics. SENEM advances bottom-up modeling by including real-time data on propulsion performance, environmental conditions, and hull condition (Durán-Grados et al., 2022). Moreno-Gutiérrez and Durán-Grados (2021) test the SENEM model on four Ro-Pax ships operating in the Strait of Gibraltar. By incorporating additional dynamic variables, SENEM produces emission estimates that differ by up to 40%, highlighting the importance of real-time operational data in improving emission accuracy. While bottom-up models enable high-resolution, vessel-specific analysis, they require intensive data collection and are costly to implement at scale. Their regional focus also poses challenges for global application (Chen and Yang, 2024; Merien-Paul et al., 2018).

5.1.3 Hybrid emission estimation models

To balance macro-level trends with micro-level accuracy, hybrid models integrate top-down and bottom-up approaches, improving the reliability of emissions estimations. According to Miola and Ciuffo (2011), they are categorized into two types: bottom-up-first, which estimate emissions at the vessel level and allocate them geographically using top-down data (e.g., MariTEAM) (Kim et al., 2023), and top-down-first, which refine aggregated estimates using ship-level inputs (e.g., SEA-Hybrid) (Topic et al., 2021).

MariTEAM integrates ship-specific technical and operational data with regional and global inventories to estimate well-to-wake (WTW) emissions Kramel et al. (2021). It first applies a bottom-up approach, incorporating ship-specific technical attributes, operational profiles, and location-based activity tracking. Then it integrates top-down macro-scale fuel consumption data and global/regional emission inventories, ensuring comprehensive coverage and alignment with broader emissions trends. For 2017, it calculated 943 Mt CO_2, 11% lower than the IMO Fourth GHG Study's estimate (Kramel et al., 2021).

The SEA-Hybrid model, introduced by Topic et al. (2021), begins with a top-down approach that utilizes aggregated fleet activity data and generalized emission factors, followed by a bottom-up refinement incorporating vessel-specific operational data. This model has been proved effectively in ECAs, where localized regulations require precise emissions estimation. Applied to container traffic in the Port of Trieste, it supports regulatory compliance and informs emissions mitigation strategies (Topic et al., 2021).

5.1.4 Economic emission estimation models

Understanding the economic mechanisms and investment requirements of maritime decarbonization is crucial for informed decision-making. The global transport model (GloTraM), developed by the Energy Institute at University College London (UCL), integrates emission modeling with economic analysis (Smith et al., 2013). The model projects long-term GHG emissions for the global shipping industry, incorporating macroeconomic factors such as fuel price fluctuations, carbon taxes, regulatory policies, and shipping activity trends to assess the economic impacts on decarbonization efforts.

Applications of GloTraM highlight its value in analyzing the economic feasibility of alternative marine fuels. Carlo et al. (2020) estimate that the cost of ammonia fuel infrastructure accounts for approximately 85%–90% of total decarbonization expenses, with cumulative capital investments with cumulative capital investments projected up to $1.9 trillion by 2050. GloTraM enables a comprehensive analysis of economic and regulatory factors influencing future shipping emissions. Rehmatulla and Smith (2015) apply GloTraM to identify barriers to decarbonization, comparing modeled implementation rates with real-world adoption and evaluating investment trends in both retrofit and new-build shipping sectors. GloTraM can be used to inform IMO policy development, shaping emission control measures and market-based mechanisms at global, regional, and national levels (UCL Transport Institute, 2014).

5.1.5 Summary

Empirical models play a crucial role in maritime emission

estimation, utilizing historical data and established relationships across macro, micro, hybrid, and economic perspectives. At the macro level, top-down models (e.g., EPA and EEA models) rely on aggregate data like fuel sales for broad emission assessments. Micro-level models such as STEEM, STEAM, and SENEM incorporate detailed AIS data to accurately estimate emissions at the port and regional levels, though they are computationally intensive. Hybrid models (e.g., SEA-Hybrid and MariTEAM) integrate broad data sets with detailed operational metrics, improving emissions accuracy in geospatial inventories and enabling the evaluation of hybrid and alternative propulsion systems. These models also include WTW analysis, which are crucial for assessing the impacts of low-carbon fuels. Economic models, such as GloTraM, forecast long-term shipping emissions by analyzing economic trends, fuel costs, carbon taxes, and policy shifts, supporting policy decisions on decarbonization strategies and fuel transitions.

5.2 ML models for maritime emissions prediction

While the empirical models are essential for constructing emission inventories and supporting regulatory frameworks, their reliance on historical data limits their ability to predict future changes in vessel operations, technological advancements, and regulatory shifts. ML techniques offer a data-driven alternative, leveraging historical and real-time data to build predictive models capable of capturing non-linear relationships between emissions and operational variables, under dynamic operational and regulatory conditions.

The section reviews studies that apply ML methods to predict shipping emissions, focusing on the algorithms employed and features used. This growing field leverages data-driven techniques to model the relationship between key variables—such as vessel characteristics, operational conditions, and weather conditions—with emissions as the target variable. Note that here we do not review studies that use ML models to predict vessel fuel consumption, which can then be converted to emissions using conversion factors. This is because studies on fuel consumption prediction have been extensively reviewed in the existing literature. Hence, we refer interested readers to Fan et al. (2022), Gkerekos et al. (2019), Nguyen et al. (2025), and Zuo et al. (2024) for a comprehensive overview of ML approaches for vessel fuel consumption prediction. Our focus here remains on models that directly predict vessel emissions, bypassing intermediate fuel consumption estimations.

Emissions prediction using ML methods is typically a supervised learning task, where the algorithms learn the relation between the input variables and the labeled response variable to produce a function that maps the input variables to the response variable, which in this case, is the vessel emissions. There exists a wide variety of supervised learning algorithms that have been successfully employed to perform vessel emissions prediction, each with its strengths and weaknesses. In the exposition that follows, we shall review a few classes of common algorithms seen in the vessel emission prediction literature. We refer the readers to Table 5 for a summary of ML methods used in the literature for predicting vessel emissions.

5.2.1 *Regression models*

Regression models are widely applied as baseline approaches in maritime emissions prediction, particularly when using structured datasets such as noon reports, MRV data, or vessel technical characteristics. They are effective for bottom-up estimates of CO_2 emissions where relationships between variables are relatively linear. They are commonly used in the emission prediction literature as a baseline model, especially for low-dimensional features.

The simplest method is multiple linear regression (MLR), which assumes a linear relationship between multiple input variables and a response variable (Ay et al., 2022; Cammin et al., 2023; Paternina-Arboleda et al., 2023). Some studies use regularized regression methods like least absolute shrinkage and selection operator (LASSO) (Lepore et al., 2017; Reis et al., 2020; Sun et al., 2022b), elastic net (EN) (Lepore et al., 2017; Reis et al., 2020) and ridge regression (RR) (Lepore et al., 2017; Reis et al., 2020), which includes a penalty on the magnitudes of coefficients to prevent overfitting, especially on small datasets. These models are relatively simple and clearly demonstrate the relationship between independent and dependent variables. However, they cannot capture complex relationships, are sensitive to outliers, and may not generalize well to real-world data.

5.2.2 *Decision trees*

Decision trees are a versatile non-parametric supervised ML algorithm used for both classification and regression. They split data into subsets based on feature values aiming to reduce prediction error, and finally create a tree-like structure where each node represents a decision. Decision trees are used in Ay et al. (2022) to predict shipping emissions.

An extension to single decision trees, an ensemble method, which combines multiple decision trees to make better and more robust predictions. One popular ensemble method is random forest (RF) (Breiman, 2001), which reduces overfitting and improves stability by averaging predictions from multiple trees (Lee et al., 2024; Lepore et al., 2017; Reis et al., 2020). Various other ensemble methods like bagging and boosting techniques (Lepore et al., 2017; Reis et al., 2020), light gradient-boosting machine (LightGBM) (Lee et al., 2024), and extreme gradient boosting (XGBoost) (Feng et al., 2024) are also used.

The main advantage of decision trees is their interpretability and simplicity, but they tend to overfit, especially with complex datasets, leading to poor generalization on unseen data. Despite better performance, ensemble methods can be computationally expensive and difficult to interpret.

5.2.3 *Gaussian process models*

Gaussian process (GP) models are non-parametric algorithms that provide both predictions and uncertainty estimates, making them valuable when quantifying variability in maritime emissions. They have been applied in top-down assessments and inventory calibration, where uncertainty analysis is as important as point prediction. For example, Ay et al. (2022) used a GP model to estimate vessel emissions in the Istanbul Strait, demonstrating its ability to capture complex relationships between traffic patterns and emission outputs. However, GP models are computationally demanding and scale poorly with very large datasets, which limits their use for real-time, vessel-level predictions (Pedersen and Larsen, 2013).

5.2.4 *Neural networks*

Neural networks have been increasingly applied to high-dimensional and time-dependent maritime datasets such as AIS trajectories, meteorological records, and multi-sensor monitoring data (Cammin et al., 2023; Chen et al., 2024b; Feng et al., 2024; Sun et al., 2022b; Šilas et al., 2023). Deep architectures such as long short-term memory (LSTM) networks are particularly effective for capturing sequential dependencies in vessel movements, enabling

Table 5 Summary of ML models for maritime emissions prediction

Ref.	GHGs & pollutant	Vessel type	Data source	Model input	Algorithm (s)[1]
Chen et al. (2024b)	NO_x, CO	Harbour craft	Measured emissions (2 months)	Meteorological conditions, Vessel characteristics	Neural networks (ANNs)
Feng et al. (2024)	CO_2	Various types	Emissions estimated using STEAM (2 years)	Shipping activity data	Ensemble methods (XGBoost), Neural networks (ANNs, SLSTM, CNN, SCLCC, Transformer)
Lee et al. (2024)	CO_2	Unknown vessel type	Fuel consumption converted to emissions (10 months)	Meteorological conditions, Vessel operational data	Ensemble methods (LightGBM, RF), Neural networks (LSTM)
Cammin et al. (2023)	CO_2, NO_x, SO_x, PM	Various types	Measured emissions at a North American port (3 months)	Vessel characteristics	Regression models (MLR, SVR), ANNs
Paternina-Arboleda et al. (2023)	SO_2	Various types	Measured emissions at Port of Barranquilla (1 year)	Vessel characteristics, Vessel operational data	Regression models (MLR, MNLR), AutoML TPOT Regressor
Ay et al. (2022)	NO_x, SO_2, CO_2, HC, PM	Various types	Emissions estimated using ENTEC and EPA (8 years)	Vessel characteristics, Shipping activity data	Regression models (LR, SVR), Gaussian process model, Decision trees and ensemble methods
Reis et al. (2020)	CO_2	Ro-Pax	Measured emissions from one vessel (15 months)	Meteorological conditions, Vessel operational data	Regression models (RR, LASSO, EN), Latent variable methods (FSR, PCR, PLS), Ensemble methods (Bagging, Boosting, RF)
Lepore et al. (2017)	CO_2	Ro-Pax	Fuel consumption of one vessel converted to emissions (1 year)	Meteorological conditions, Vessel operational data	Regression models (MLR, SVR, RR, LASSO, EN), Latent variable and variable selection methods (FSR, PCR, PLS), Ensemble methods (Bagging, boosting, RF)

Note:[1]ANN: Artificial neural network; XGBoost: Extreme gradient boosting; SLSTM: Stacked long short-term memory; CNN: Convolutional neural network; SCLCC: See Feng et al. (2024) for details; LightGBM: Light gradient-boosting machine; LSTM: Long short-term memory; MLR: Multiple linear regression; SVR: Support vector regression; MNLR: Multiple non-linear regression; TPOT: Tree-based pipeline optimization tool; FSR: Forward stepwise regression; LR: Linear regression; RR: Ridge regression; LASSO: Least absolute shrinkage and selection operator; EN: Elastic net; PCR: Principal component regression; PLS: Partial least square; RF; Random forest.

near real-time bottom-up emissions forecasting (Hong et al., 2021; Lee et al., 2024). Convolutional neural networks (CNNs) and Transformers have also been used to integrate spatial–temporal features from AIS and weather grids, supporting large-scale top-down inventory estimations (Feng et al., 2024). These models can capture highly non-linear relationships and often outperform traditional statistical approaches when handling complex, high-dimensional data. However, their widespread deployment is constrained by substantial computational and data requirements, as well as limited interpretability, which hampers transparency and acceptance in regulatory and operational contexts.

5.2.5 Summary

ML techniques have emerged as powerful tools for maritime emissions prediction, addressing the limitations of traditional statistical models by capturing complex and non-linear relationships in diverse datasets. They adapt to evolving operational and regulatory conditions, enabling more accurate and dynamic emission assessments. The reviewed studies highlight a broad range of applications. Regression models (e.g., MLR, LASSO, RR) serve as baseline approaches for structured and smaller datasets such as noon reports and MRV records. Decision tree models are simple and interpretable, while ensemble methods such as RF, XGBoost, and LightGBM improve robustness and predictive accuracy when integrating mixed data sources such as AIS, vessel particulars, and meteorological information. GP models provide probabilistic predictions and uncertainty estimates, making them valuable for top-down inventory assessments. While neural networks, particularly LSTM, CNN, and Transformers, excel with large-scale time-series data like AIS trajectories and sensor measurements, they support near real-time bottom-up predictions.

Overall, the suitability of each ML model depends not only on algorithmic features but also on the scale and quality of data and the specific prediction objective. Linking model choice with data availability and intended application is therefore crucial for advancing reliable and policy-relevant shipping emission assessments.

6 Maritime decarbonization strategies

A growing body of research has proposed strategies for maritime decarbonization. Grounded in data analytics and modeling, these strategies can be categorized into three key levels: vessel, fuel, and port. At the vessel level, shipowners pursue decarbonization through both design improvements, such as hull form optimization and hull cleaning, and dynamic operational measures applied during both ocean-going voyages and port activities. At the fuel level, data analytics play a pivotal role in assessing the life cycle emissions of alternative marine fuels. At the port level, decarbonization is approached from a system coordination perspective. Ports act as critical nodes for energy supply, logistics, and data exchange. Real-time port collaboration, such as digital berthing optimization, and cold ironing, enables synchronized emission reductions across the maritime supply chain. These multilevel strategies and their associated datasets are illustrated in Fig. 4, which provides a visual framework of how vessel-, fuel-, and port-based measures are integrated through data-driven approaches.

6.1 Vessel-based decarbonization strategies

Emission reduction at the vessel-based level is primarily achieved through improving energy efficiency. This can be broadly categorized into two areas: (1) technical strategies, which focus on hull design and surface condition refinement to minimize hydrodynamic resistance, and (2) operational strategies, which

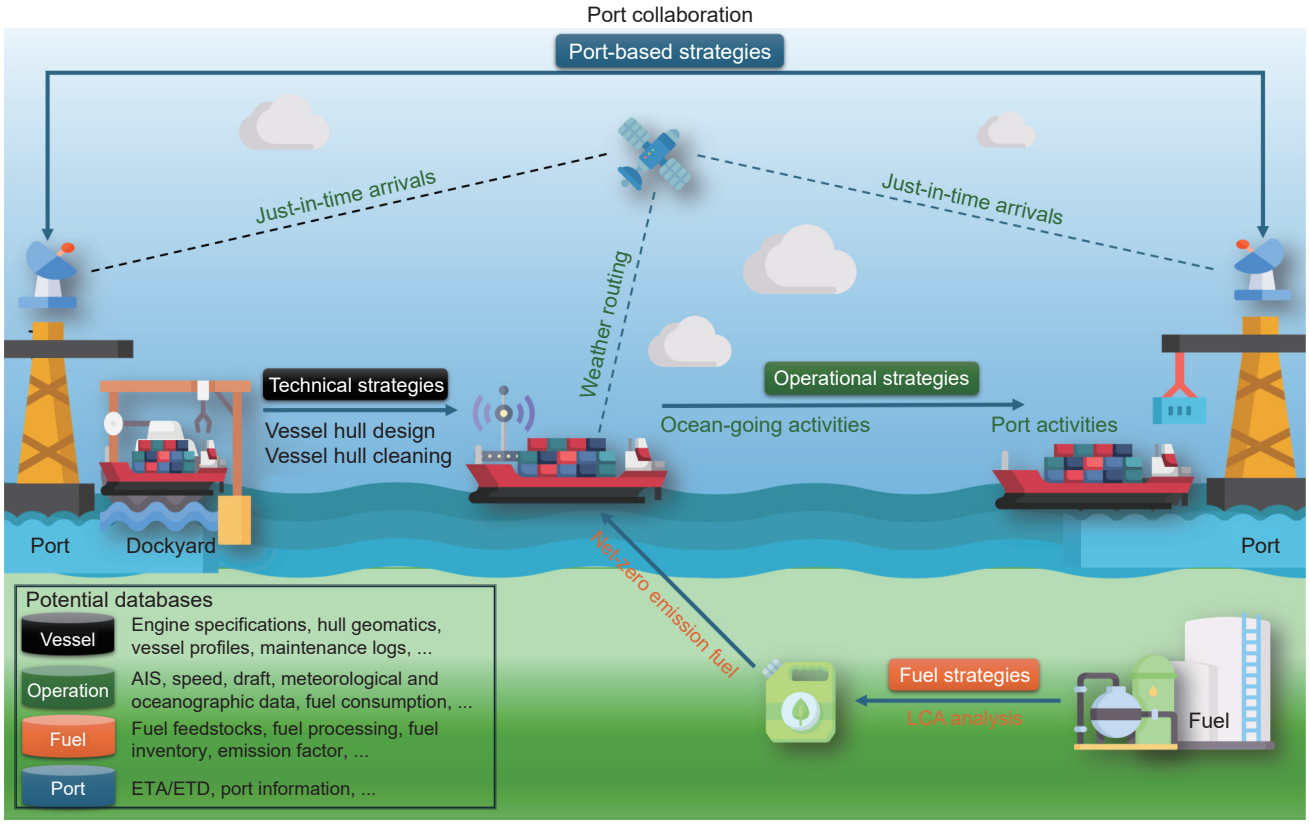

Fig. 4 Integrated maritime decarbonization strategies by vessel, fuel, and port perspectives.

aim to optimize ship performance during ocean-going voyages and port activities. While engineering research focuses more on hull form optimization (Bagazinski and Ahmed, 2023; Hou, 2017; Lindstad and Bø, 2018) and biofouling control (Adland et al., 2018; Le et al., 2021; Oliveira et al., 2022), ship management studies focus on speed reduction, weather routing, and just-in-time (JIT) arrivals for operations (Gkerekos and Lazakis, 2020; Sun et al., 2022a; Sotiralis et al., 2024). Both dimensions increasingly rely on data-driven approaches to enhancing emission reductions across vessel life cycles. The databases and models or methods used in the studies related to the vessel-based decarbonization strategies are displayed in Table 6.

6.1.1 *Vessel technical strategies for decarbonization*

Hull performance is a key determinant of vessel fuel consumption and GHG emissions, making it a critical consideration for technical decarbonization. Advances in data acquisition such as hull geometry databases, AIS records, and Computational Fluid Dynamics (CFD) simulations have enabled the integration of ML models into hull design optimization and resistance prediction. Models such as Recurrent Neural Networks (RNNs), Deep Neural Networks (DNNs), and Deep Belief Networks (DBNs) have been applied to predict hydrodynamic resistance, identify optimal hull forms, and reduce simulation time (Bagazinski and Ahmed, 2023; Vladimir et al., 2018; Hou, 2017). By learning complex nonlinear relationships between hull features and drag characteristics, ML models offer faster and more scalable alternatives to traditional CFD-based evaluations, facilitating iterative design and retrofitting for improved energy efficiency.

Data-driven methods now support both hull design optimization for new-built ships and in-service fouling control, providing scalable pathways to reduce resistance and fuel consumption. For instance, ML models are increasingly adopted to optimize hull form and predict hydrodynamic performance (Tadros et al., 2023). These models efficiently handle high-dimensional design spaces, accelerating the evaluation of design alternatives and identifying configurations that minimize drag (Lindstad and Bø, 2018).

Maintaining a ship hull with minimal surface roughness, by reducing coating roughness and inhibiting marine fouling, leads to significant fuel consumption and air emission savings (Schultz, 2007). For in-service vessels, biofouling management is another major application area. ML-based prediction and control frameworks, such as reinforcement learning, are increasingly used to determine optimal hull cleaning schedules (Le et al., 2021). These tools help maintain hull efficiency while minimizing maintenance costs and emissions associated with fouling-induced resistance.

6.1.2 *Vessel operational strategies for decarbonization*

Operational performance plays a critical role in vessel-based decarbonization. Early research in this area primarily focused on optimizing factors such as sailing speed and engine load, both of which directly affect fuel consumption and emissions (Ng, 2019). Comprehensive reviews of these operational strategies have been conducted by Dulebenets et al. (2021) and Yu et al. (2021), drawing on data sources such as AIS records, noon reports, and engine specification databases. These conventional approaches are not detailed here. Building on this foundation, we summarize recent developments in data-driven vessel operational strategies, particularly those incorporating meteorological and oceanographic data or port information. These strategies are discussed across two key operational phases: ocean-going voyages and port stays, each offering distinct opportunities for emission reduction.

For ocean-going voyages, we focus on weather routing, which utilizes real-time and forecasted meteorological and oceanographic data such as wind speed, wave height, and current

Table 6 Review of vessel decarbonization strategies

Strategy type	Ref.	Data source	Method (s)	Key finding
Hull design	Bagazinski and Ahmed (2023)	Hull geometries Drag coefficients Froude number	Surrogate modeling (ResNet) Genetic algorithm Michell Integral	60% drag reduction can be achieved via surrogate modeling and optimization
	Lindstad and Bø (2018)	Hull geometries Engine specs Wave data Fuel use	ShipX simulation Techno-economic analysis	Slender hulls reduce installed power by 15%
	Hou (2017)	Hull geometries Speed Fuel use CFD outputs	IPSO optimization BPNN	Optimized hulls achieve 9.4% EEOI reduction
Hull cleaning	Oliveira et al. (2022)	Hull geometries Fouling data Vessel activity Fuel use	Simulation software LCC analysis	Hull cleaning and coatings save up to 13% fuel
	Swain (2010)	Hull roughness Coating types Drag tests	Standard testing Empirical data	Surface treatment yields up to 13% fuel savings
	Adland et al. (2018)	Vessel specs AIS data Weather data	LSTM Bi-LSTM Transformer MLP CNN GRU	Bi-LSTM most accurate for ship energy efficiency prediction
	Le et al. (2021)	Hull roughness Coating performance Fuel use	Reinforcement learning	60% drag reduction achieved through optimized biofouling control
Weather routing	Gkerekos and Lazakis (2020)	Noon reports Weather forecasts	Deep ANN Dijkstra with heuristics	DNN supports multi-route fuel-efficient voyage planning
	Sun et al. (2022a)	Noon reports Resistance curves Wind/wave data	ANN Surrogate modeling	Data-driven routing enables fuel-efficient navigation
	Mason et al. (2023)	AIS data Wind/current data	Dynamic programming	Route optimization improves energy efficiency
	Ren et al. (2022)	AIS Wind/wave/current data MRV fuel use	Ridge regression ANN K-means Z-score normalization	Ridge regression outperforms other ML methods
JIT arrival	Arjona Aroca et al. (2020)	AIS Speed ETA Port call data	Clustering Scenario simulation JSON-based fuel modeling	Up to 23% GHG savings, 25 days saved on long-haul routes
	De Andres Gonzalez et al. (2021)	Port call logs ETA/ETD Terminal systems	Scenario simulation	Annual GHG reduction of 6,000 tons with improved port call control
	Alessandrini et al. (2018)	AIS MMSI LRIT data	Path-finding Gaussian fitting K-medians	Higher accuracy in ETA via data-driven algorithm
	Sotiralis et al. (2024)	AIS Sea-Web specifications Operational data	Emission modeling Scenario simulation	Port-to-port JIT achieves 9.3% CO_2 reduction

Note: ETA: Estimated time of arrival; ETD: Estimated time of departure; CFD: Computational fluid dynamics; IPSO: Improved particle swarm optimization; LCC: Life cycle cost; MLP: Multilayer perceptron; GRU: Gated recurrent unit; Bi-LSTM: Bidirectional long short-term memory; LRIT: Long-range identification and tracking.

direction to optimize voyage planning (Zis et al., 2020). A range of data-driven modeling techniques has been applied to weather routing, leveraging environmental and navigational data to optimize voyage planning. For example, methods such as ANNs, heuristic-based routing algorithms, and surrogate modeling have been used to predict weather impacts and identify fuel-efficient routes (Gkerekos and Lazakis, 2020; Ren et al., 2022; Sun et al., 2022a). These approaches have proven effective in handling high-dimensional data, capturing nonlinear relationships, and improving route selection under dynamic ocean conditions, thereby contributing to substantial reductions in fuel consumption and GHG emissions. In addition, recent regulatory discussions have introduced the concept of compliance pooling in fleet-level routing and scheduling. Compliance pooling allows companies to pool the performances of different ships, using the over-performance of one ship to compensate the under-performance of other ships, provided that the total environmental performance is positive (CLdN, 2025). Although the academic

literature on this topic remains limited due to its novelty, compliance pooling is expected to become an important mechanism under decarbonization regulations, such as the FuelEU Maritime Regulation. It requires real-time tracking, coordinated fleet deployment, and data-driven routing optimization to strategically allocate low-emission vessels to intensive routes, thereby enhancing both cost efficiency and decarbonization outcomes.

For port stays, we examine JIT arrival coordination, which refers to the practice of adjusting a vessel's arrival time to match berth availability, thereby avoiding unnecessary anchorage. JIT is considered a direct and effective strategy to reduce emissions during port stays, as it minimizes idling time and lowers auxiliary engine usage (Arjona Aroca et al., 2020; Suvadarshini and Dandapat, 2023) This approach relies on real-time AIS data, berth availability information, and ETA prediction models to synchronize vessel arrivals with terminal readiness (De Andres Gonzalez et al., 2021). Advanced optimization techniques, such as clustering analysis and data-driven path-finding algorithms (Alessandrini et al., 2018; Arjona Aroca et al., 2020), are increasingly applied to enhance scheduling efficiency, reduce port congestion, and support overall emission reduction goals. We specifically summarize the research on operational vessel decarbonization strategies detailed in Table 6.

6.2 Adoption of zero or net-zero emission alternative fuels

Under the IMO's intensified decarbonization agenda, alternative fuels are positioned as a primary driver of emission reductions, offering the greatest potential to cut GHG emissions (Mahmud et al., 2025). A growing number of studies have explored the feasibility of various low- and zero-carbon fuels such as hydrogen, ammonia, and methanol in maritime applications (Di Micco et al., 2024; Svanberg et al., 2018; Van Hoecke et al., 2021; Wang et al., 2025b). More recently, research has increasingly focused on evaluating the emission reduction potential of these fuels in specific operational contexts and regions, underscoring the need for more accurate and location-sensitive assessment frameworks (Chen et al., 2019b; Xu et al., 2025).

Recognizing that the decarbonization impact of fuels extends beyond their use onboard, the IMO emphasizes a life cycle perspective. The 2024 IMO LCA Guidelines (MEPC.1/Circ.905) advocate for a life cycle assessment approach, covering both Well-to-Tank (WTT) and Tank-to-Wake (TTW) stages (IMO, 2023c). Life Cycle Assessment (LCA) is a standardized methodological framework for quantifying the environmental impacts of a product or process across its entire life cycle from raw material extraction and fuel production (WTT) to onboard combustion and propulsion (TTW) (Roux et al., 2024). This approach enables a consistent and holistic assessment of emissions from different fuel pathways. To be specific, WTT emissions are largely influenced by feedstock types, production technologies, and electricity sources. A common classification by "fuel colors" (e.g., green, blue, grey, and brown) reflects the carbon intensity of production by different feedstocks for hydrogen (Panić et al., 2022). Green fuels produced by renewable sources typically offer the lowest WTT emissions (Wang and Wright, 2021). In the TTW phase, emissions are primarily determined by fuel combustion characteristics, which are modeled using standardized emission factors, lower heating values (LHV), and vessel-specific propulsion system configurations (Xu et al., 2023; Wang et al., 2025a). This calculation often leverages the emission modeling methods discussed in Section 5, integrating fuel type, consumption rates, and powertrain efficiency. We compile the LCA of alternative marine fuels of hydrogen, ammonia, and methanol by color for maritime applications in Fig. 5.

Accurate life cycle emission assessments depend heavily on reliable data across different stages. Key parameters for WTT analysis include energy input requirements (e.g., electricity consumption), feedstock conversion efficiencies, and fuel synthesis efficiencies that have significant influence on total upstream emissions (Igos et al., 2019). On the TTW side, accurate modeling of propulsion system performance, such as dual-fuel engines, batteries, and fuel cells, is critical for estimating onboard emissions (Jang et al., 2024). To address the complexity and variability of these parameters, recent LCA research has increasingly adopted data-driven methods to treat the uncertainties (Ziyadi and Al-Qadi, 2019). Song et al. (2022) employ process-level data covering production, storage, loading, transport, and unloading stages to evaluate the life cycle energy efficiency of maritime fuel supply chains for hydrogen, ammonia, methanol, and liquefied natural gas (LNG), revealing that renewable methanol and ammonia outperform LNG in overall efficiency, while hydrogen exhibits the lowest efficiency due to high boil-off losses. ML techniques have been applied to estimate emissions based on large, heterogeneous datasets, enabling improved generalization across diverse production routes (Ghoroghi et al., 2022). In the TTW phase, ML-based LCA models improve emission prediction under variable operational profiles, accounting for route-specific and weather-dependent fuel use (Jang et al., 2024). These innovations enhance the precision, scalability, and adaptability of LCA in real-world applications, supporting more informed decision-making for alternative fuel adoption.

6.3 Port decarbonization strategies

As maritime decarbonization extends beyond vessels and fuels, ports are emerging as data-driven hubs for environmental and operational optimization. Port authorities now play a central role in deploying digital technologies that improve data transparency, enhance energy management efficiency, and enable continuous monitoring of emissions (Song, 2024). Technologies such as energy management systems (EMS) and digital twins are central to these efforts, enabling ports to translate operational data into actionable strategies. As ports become increasingly interconnected, data-sharing and interoperability are key to supporting regional initiatives such as green and digital shipping corridors and JIT operations. This paper reviews data-driven decarbonization strategies at the single-port level in Section 6.3.1 and collaborative approaches across multiple ports in Section 6.3.2.

6.3.1 Individual port innovative decarbonization strategies

Recent research highlights the growing importance of data-driven technologies in supporting single-port decarbonization, particularly through EMS and digital twin platforms (Wan et al., 2025; Xiao et al., 2024). These tools enable ports to monitor real-time energy use, track emissions, and optimize infrastructure and logistics operations.

EMS serve as centralized platforms that integrate data from terminal equipment, grid connections, and renewable energy sources to optimize electricity consumption and reduce carbon intensity. Herazo et al. (2024) identify energy efficiency, smart grids, and AI-based control as emerging research priorities in maritime EMS. Key technical enablers include real-time data acquisition via IoT networks, predictive algorithms for load balancing, and integration with electrified port equipment. At the application level, Buonomano et al. (2024) explore EMS deployment within energy communities at the Port of Vigo, while Mahmud et al. (2024) use fuzzy Analytic Hierarchy Process

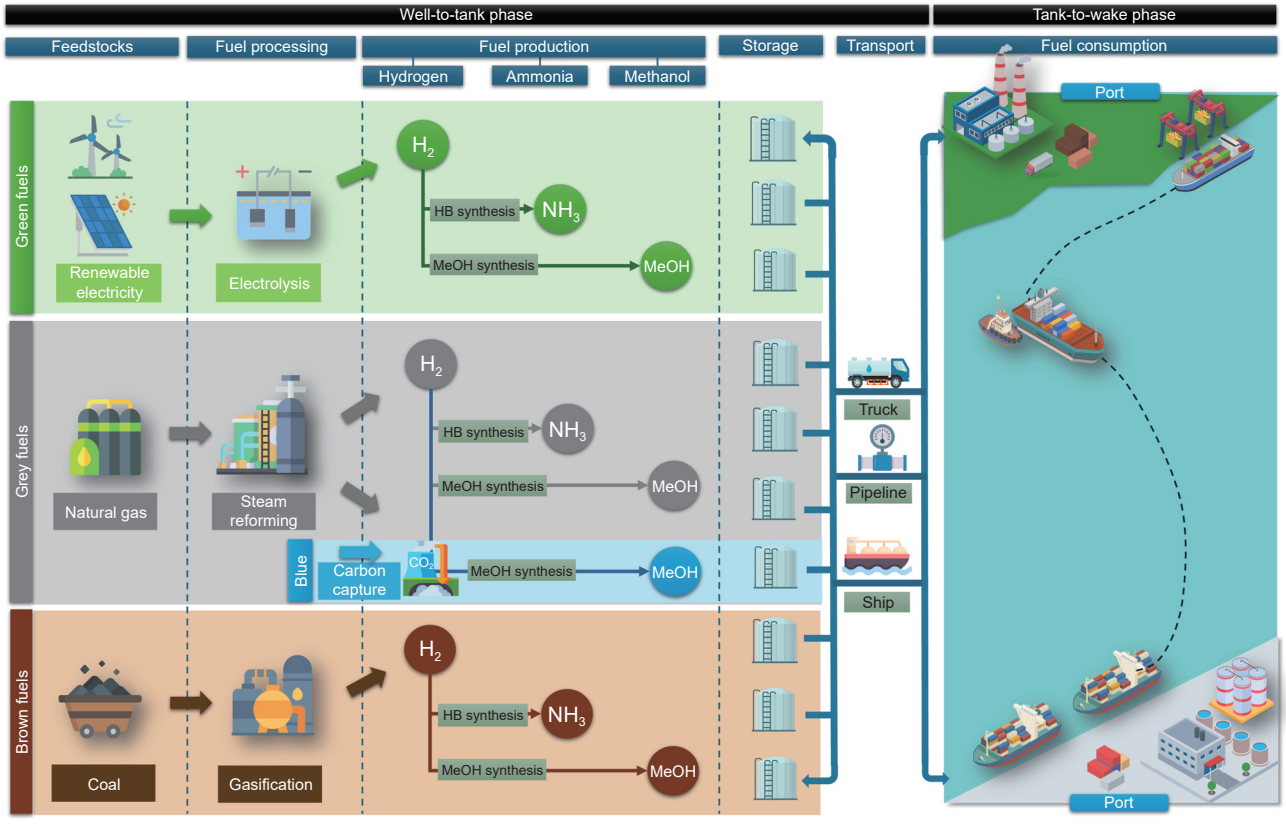

Fig. 5 LCA of alternative marine fuels by colors for maritime applications.

(AHP) to show that digital energy monitoring and infrastructure upgrades are key to effective decarbonization across Asian ports. Vaca-Cabrero et al. (2025) further confirm that institutional support and digitalization underpin sustainability performance in Spanish ports. Collectively, these studies show that EMS-based optimization of energy flows forms a foundational pillar in low-carbon port transitions.

Digital twins, by contrast, model the behavior of port systems under real-time conditions using data from IoT sensors, power systems, and vessel operations (Ding et al., 2023). While traditionally focused on asset management and predictive maintenance (Madusanka et al., 2023; Zhou et al., 2024), recent studies have begun to explore their role in emissions reduction. Karakostas and Katsoulakos (2024) review digital twin applications in green ports and advocate for standardized data acquisition and privacy-preserving ML techniques, such as federated learning, to enable scalable emissions modeling. Wan et al. (2025) underscore the role of AI-enhanced digital twins in monitoring carbon emissions and optimizing port operations for decarbonization outcomes. A leading example of digital twins in port decarbonization is the EU DT4GS (Digital Twin for Green Shipping) project (DT4GS, 2022), which integrates vessel fuel usage, port energy demand, and bunkering data into a federated digital twin infrastructure. The system supports scenario-based simulations and real-time decision-making for carbon mitigation, with targeted emissions reductions of 20% by 2026 and 55% by 2030. These developments highlight the increasing potential of digital twins as systemic, data-enabled tools for emissions management and sustainable port operation.

6.3.2 Multiple port collaborative decarbonization strategies

In addition to technological improvements within individual ports, inter-port collaboration through data-sharing frameworks has become essential for scaling decarbonization efforts (Wan et al., 2025). Integrated digital platforms facilitate real-time information exchange, enabling better coordination, resource optimization, and emissions reduction (Chen et al., 2025; Heikkilä et al., 2022). Information exchange enables synchronized vessel scheduling to reduce congestion and coordinated planning of alternative fuel logistics (Heikkilä et al., 2022). By leveraging these mechanisms, inter-port data sharing becomes a practical tool for advancing collaborative decarbonization strategies, ensuring that efficiency gains at the vessel level are matched by systemic improvements across port networks.

Several data-sharing platforms have been developed to improve port efficiency and environmental sustainability. For instance, PCS facilitates seamless information exchange among stakeholders, improving vessel coordination, cargo handling, and regulatory compliance while reducing congestion and unnecessary fuel consumption (Moros-Daza et al., 2020). Sea traffic management (STM) systems further facilitate dynamic traffic management by exchanging real-time navigational and port data, allowing for speed profiles optimization and fuel-efficient routing for arriving vessels (Homayouni et al., 2024). Emerging technologies are enhancing the transparency and security of these data-sharing networks. Blockchain, a decentralized and tamper-resistant ledger technology, enables secure, transparent, and traceable data exchange among multiple stakeholders without requiring centralized control (Guan et al., 2024; Wei et al., 2024). This technology can be used to safeguard emissions records, vessel schedules, and bunker data, ensuring traceability and trust among participating ports (Durán et al., 2021).

Several collaborative port initiatives have successfully implemented data-sharing frameworks and digital technologies, enabling real-time integration of information across vessel arrival schedules, berth allocation, cargo handling, and other operational processes. Table 7 provides an overview of ongoing port data-sharing projects worldwide.

Table 7 Data sharing projects in port collaboration

Port cluster	Project name	Implementation year	Data sharing content	Technology	Goal	Ref.
Ports of Singapore, Los Angeles and Long Beach	Green Ports Collaborative	2023	Real-time arrival information, berth allocation, and vessel emissions data	PCS, Blockchain	Establish green port corridors; support zero-emission vessels	Xiao et al. (2022)
Guangdong–Hong Kong–Macao Greater Bay Area	Smart Port Initiative	2021	Real-time port logistics data exchange, customs integration, and cross-border digital trade facilitation	PCS, Digital Twins, Blockchain	Enhance port efficiency, strengthen trade connections, and establish a smart port system to support the Greater Bay Area development	Global Maritime Hub (2021); Li et al. (2023b)
Port of Zeebrugge and Antwerp	Hydrogen Import Coalition	2020	Hydrogen storage, transport, and distribution data; berth allocation	Digital Twins, Blockchain	Develop hydrogen energy infrastructure; optimize berth allocation and fuel logistics	Aronietis et al. (2023); Port of Antwerp-Bruges (2020)
Nordic Ports Collaboration	STM Initiative	2017	Vessel trajectories and real-time arrival information	STM platform, Digital Twins	Reduce vessel waiting time and port congestion	Homayouni et al. (2024); Sea Traffic Management (2023)

Despite the growing adoption of digital technologies for port collaboration, several challenges persist. A major barrier is the lack of data standardization and interoperability between ports, as ports use varying data formats and protocols, leading to inefficiencies in cross-border collaboration. Additionally, the stakeholders' reluctance remains a challenge, as some shipping companies and port operators hesitate to share operational data due to concerns over competitive disadvantages and data ownership. These limitations highlight the need for coordinated regulatory frameworks and technological solutions to ensure secure, transparent, and standardized data-sharing practices across the maritime industry.

7 Future directions for data-driven maritime decarbonization

Building on the findings of this review, we identify key areas for advancing data-driven maritime decarbonization. These future directions focus on strengthening data infrastructure, advancing analytical capabilities, and enabling more intelligent and adaptive decarbonization pathways. Two critical priorities are (i) developing integrated, multidisciplinary datasets to support evidence-based decision-making and cross-sector collaboration, and (ii) enhancing modeling techniques to leverage emerging data sources and address the complexity of maritime systems. Together, these directions will help overcome current limitations in data interoperability and predictive insight, enabling more coordinated and responsive decarbonization strategies across vessels, fuels, and ports.

7.1 Multidisciplinary datasets development

Reliable data is essential for accurately assessing maritime emissions, designing effective interventions, and supporting policy formulation. To enable evidence-based decarbonization, the development of transparent, standardized, and interoperable data systems is critical. A key priority is the creation of unified, open-access databases that consolidate directly measured emissions data such as *in-situ* readings from ship engines, port equipment, and onboard fuel use. Integrating additional datasets related to shipbuilding materials, propulsion performance, and combustion properties further supports more accurate LCA and emissions hotspot identification.

Despite this recognized need, current efforts remain fragmented. Emissions data are often collected under incompatible protocols, with limited access and low interoperability between systems. Commercial sensitivities, inconsistent reporting standards, and a lack of trust among stakeholders frequently hinder data exchange. Some initial trials to deal with data trust issues are conducted, and a famous one is TradeLens, which was proposed in 2018 by Maersk and IBM to apply blockchain in container shipping (Najati, 2025). Despite its technical viability, the platform was terminated in 2022 due to limited user adoption, data ownership concerns, and weak incentives for participation across the supply chain. This illustrates the institutional and governance barriers that continue to obstruct shared data infrastructure.

Overcoming these barriers requires more than technical solutions, which demands robust institutional frameworks and stakeholder alignment. Establishing trusted data governance models, such as third-party stewardship, can help resolve concerns about data ownership, access rights, and confidentiality. To encourage participation in shared data ecosystems, regulatory bodies can offer concrete incentives such as access to public decarbonization funding, priority berthing for compliant vessels, or simplified environmental reporting procedures.

7.2 Advanced modeling capabilities

As sensor-equipped vessels, ports, and fuel systems generate increasingly granular and continuous data streams, advanced modeling techniques are needed to extract actionable insights for decarbonization. Time-series deep learning models such as LSTM and temporal convolutional networks have already been applied to predict vessel fuel consumption, emission profiles, and engine load patterns under dynamic operational conditions. These models excel in learning temporal dependencies and have supported short-term forecasting and route-level optimization (Zhang et al., 2024a). However, their effectiveness is often constrained by challenges in multi-source data fusion, especially where differences in data granularity, sampling frequency, and semantic labels complicate model alignment.

Looking ahead, Large language models (LLMs) present a promising but underexplored direction. By processing unstructured and semi-structured data such as maintenance records, regulatory guidelines, logbooks, and vessel specifications, LLMs can serve as semantic integrators across ships, fuels, and

port systems. Potential applications include real-time emissions compliance support, automated reporting, context-aware maintenance advice, and scenario-based planning under regulatory or climatic uncertainty. Moreover, combining LLMs with numerical simulators or control algorithms may enable hybrid decision-support systems that are both data- and knowledge-driven. To realize these potentials, future research must address domain adaptation, explainability, and the computational integration of LLMs with existing maritime digital infrastructure.

8 Conclusions

This review examines recent progress in data-driven approaches to maritime decarbonization, highlighting their role in reshaping regulatory enforcement, emissions monitoring, predictive modeling, and mitigation strategies. By structuring the discussion around four key pillars, policy, data, modeling, and implementation, it clarifies how digital tools and integrated datasets are advancing the shipping sector's response to the IMO's decarbonization targets. It outlines how digital regulatory tools such as the MRV system, IMO DCS, and cyber risk protocols are strengthening compliance by enabling standardized, real-time reporting and supervision. The review also addresses a critical gap in maritime research by highlighting the increasing use of direct emission measurements (e.g., UAV systems and PEMS) to supplement conventional database-driven estimates, thereby improving the accuracy of emissions quantification. For the modeling aspect, it synthesizes recent progress in hybrid, economic, and ML-based emission models, demonstrating their enhanced capability to capture vessel emissions under diverse and variable operating profiles. As for decarbonization measures, this review examines maritime decarbonization strategies across three core domains—vessels, fuels, and ports, highlighting the operational and systemic interventions being pursued to reduce maritime emissions. It emphasizes the integration of heterogeneous data sources and the application of ML methods, which support real-time optimization, predictive decision-making, and lifecycle emissions analysis across different stages of maritime activity.

Overall, this review contributes a data-centered analytical framework that connects regulatory reform, emissions data integration, and predictive modeling to actionable decarbonization pathways, providing a systems-level perspective that has been largely absent in existing maritime literature.

Accelerating maritime decarbonization requires a synergistic approach that aligns policy ambition, data transparency, computational advancements, and collaborative governance. By embedding data-driven methodologies into policy, operations, and research, the industry can navigate the complexities of decarbonization while maintaining economic and operational resilience. This review establishes a coherent roadmap for transforming maritime decarbonization efforts, ensuring that data-driven innovations not only enhance immediate operational efficiencies but also lay the foundation for a sustainable and low-emission future in global shipping.

Author contributions

Jing Wang: Writing – original draft, Methodology, Visualization, Formal analysis, Conceptualization. **Kelvin Lee**: Writing – original draft, Methodology, Conceptualization. **Xiuju Fu**: Writing – review & editing, Supervision, Methodology, Conceptualization. **Ran Yan**: Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

Adland, R., Cariou, P., Jia, H., Wolff, F.-C., 2018. The energy efficiency effects of periodic ship hull cleaning. *J Clean Prod*, **178**, 1–13.

Alamoush, A. S., Ballini, F., Ölçer, A. I., 2020. Ports' technical and operational measures to reduce greenhouse gas emission and improve energy efficiency: A review. *Mar Pollut Bull*, **160**, 111508.

Alessandrini, A., Mazzarella, F., Vespe, M., 2018. Estimated time of arrival using historical vessel tracking data. *IEEE Trans Intell Transp Syst*, **20**, 7–15.

Ampah, J. D., Yusuf, A. A., Afrane, S., Jin, C., Liu, H., 2021. Reviewing two decades of cleaner alternative marine fuels: Towards IMO's decarbonization of the maritime transport sector. *J Clean Prod*, **320**, 128871.

Arjona Aroca, J., Giménez Maldonado, J. A., Ferrús Clari, G., Alonso i García, N., Calabria, L., Lara, J., 2020. Enabling a green just-in-time navigation through stakeholder collaboration. *Eur Transp Res Rev*, **12**, 1–11.

Aronietis, R., Hassel, E. v., Vanelslander, T., 2023. Maritime data collection framework for container port benchmarking. *J Mar Sci Eng*, **11**, 1557.

Ay, C., Seyhan, A., Beşikçi, E. B., 2022. Quantifying ship-borne emissions in Istanbul Strait with bottom-up and machine-learning approaches. *Ocean Eng*, **258**, 111864.

Bagazinski, N. J., Ahmed, F., 2023. Ship-d: Ship hull dataset for design optimization using machine learning. In: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. V03AT03A028.

Breiman, L., 2001. Random forests. *Mach Learn*, **45**, 5–32.

Buonomano, A., Giuzio, G. F., Maka, R., Palombo, A., Russo, G., 2024. Empowering sea ports with renewable energy under the enabling framework of the energy communities. *Energy Convers Manag*, **314**, 118693.

Cammin, P., Yu, J., Voß, S., 2023. Tiered prediction models for port vessel emissions inventories. *Flex Serv Manuf J*, **35**, 142–169.

Carlo, R., Marc, B. J., de la Fuente Santiago, S., Smith, T., Søgaard, K., 2020. Aggregate investment for the decarbonisation of the shipping industry. https://globalmaritimehub.com/wp-content/uploads/2020/02/Aggregate-investment-for-the-decarbonisation-of-the-shipping-industry.pdf

Chang, Y.-T., Park, H. K., Lee, S., Kim, E., 2018. Have emission control areas (ECAs) harmed port efficiency in Europe?. *Transp Res Part D Transp Environ*, **58**, 39–53.

Chen, J., Fei, Y., Wan, Z., 2019a. The relationship between the development of global maritime fleets and GHG emission from shipping. *J Environ Manage*, **242**, 31–39.

Chen, J., Zheng, T., Garg, A., Xu, L., Li, S., Fei, Y., 2019b. Alternative maritime power application as a green port strategy: Barriers in China. *J Clean Prod*, **213**, 825–837.

Chen, L., Dong, T., Li, X., Xu, X., 2025. Logistics engineering management in the platform supply chain: An overview from logistics service strategy selection perspective. *Engineering*, **12**, 236–249.

Chen, X., Lv, S., Shang, W.-l., Wu, H., Xian, J., Song, C., 2024a. Ship energy consumption analysis and carbon emission exploitation via spatial-temporal maritime data. *Appl Energy*, **360**, 122886.

Chen, X., Yang, J., 2024. Analysis of the uncertainty of the AIS-based bottom-up approach for estimating ship emissions. *Mar Pollut Bull*, **199**, 115968.

Chen, Z. S., Lam, J. S. L., Xiao, Z., 2024b. Prediction of harbour vessel emissions based on machine learning approach. *Transp Res Part D Transp Environ*, **131**, 104214.

CLdN, 2025. Pooling for FuelEU maritime compliance. https://www.cldn.com/pooling-fueleu-maritime-compliance

Coello, J., Williams, I., Hudson, D. A., Kemp, S., 2015. An AIS-based

approach to calculate atmospheric emissions from the UK fishing fleet. *Atmos Environ*, **114**, 1–7.

Comer, B., 2019. Including estimates of black carbon emissions in the Fourth IMO GHG Study. https://wwwcdn.imo.org/localresources/en/OurWork/Environment/Documents/CSC-Bryan%20Comer.pdf

Corbett, J. J., Fischbeck, P., 1997. Emissions from ships. *Science*, **278**, 823–824.

Corbett, J. J., Fischbeck, P. S., Pandis, S. N., 1999. Global nitrogen and sulfur inventories for oceangoing ships. *J Geophys Res Atmos*, **104**, 3457–3470.

Corbett, J. J., Koehler, H. W., 2003. Updated emissions from ocean shipping. *J Geophys Res Atmos*, **108**, 4650–4666.

Cui, B., Wang, C., Wu, Y., Zhu, C., Lin, J., Yang, T., 2024. Intelligent monitoring of marine vessel dynamics based on data mining. *Ocean Eng*, **313**, 119387.

Cullinane, K., Bergqvist, R., 2014. Emission control areas and their impact on maritime transport. *Transp Res Part D Transp Environ*, **28**, 1–5.

De Andres Gonzalez, O., Koivisto, H., Mustonen, J. M., Keinänen-Toivola, M. M., 2021. Digitalization in just-in-time approach as a sustainable solution for maritime logistics in the Baltic Sea region. *Sustainability*, **13**, 1173.

Deng, M., Peng, S., Xie, X., Jiang, Z., Hu, J., Qi, Z., et al., 2022. SO2 compliance monitoring and emission characteristics analysis of navigating ships: A case study of Shanghai waters in emission control areas, China. *Atmos Pollut Res*, **13**, 101560.

Di Micco, S., Cigolotti, V., Mastropasqua, L., Brouwer, J., Minutillo, M., 2024. Ammonia-powered ships: Concept design and feasibility assessment of powertrain systems for a sustainable approach in maritime industry. *Energy Convers Manag: X*, **22**, 100539.

Di Vaio, A., Zaffar, A., Balsalobre-Lorente, D., Garofalo, A., 2023. Decarbonization technology responsibility to gender equality in the shipping industry: A systematic literature review and new avenues ahead. *J Shipp Trade*, **8**, 1–20.

Ding, Y., Zhang, Z., Chen, K., Ding, H., Voss, S., Heilig, L., et al., 2023. Real-time monitoring and optimal resource allocation for automated container terminals: A digital twin application at the Yangshan Port. *J Adv Transp*, **2023**, 6909801.

DT4GS, 2022. The digital twin for green shipping (DT4GS) research project. https://www.dt4gs.eu/the-project/#impact

Du, Y., Chen, Y., Li, X., Schönborn, A., Sun, Z., 2022a. Data fusion and machine learning for ship fuel efficiency modeling: Part II–voyage report data, AIS data and meteorological data. *Commun Transp Res*, **2**, 100073.

Du, Y., Chen, Y., Li, X., Schönborn, A., Sun, Z., 2022b. Data fusion and machine learning for ship fuel efficiency modeling: Part III–sensor data and meteorological data. *Commun Transp Res*, **2**, 100072.

Dulebenets, M. A., Pasha, J., Abioye, O. F., Kavoosi, M., 2021. Vessel scheduling in liner shipping: A critical literature review and future research needs. *Flex Serv Manuf J*, **33**, 43–106.

Durán, C. A., Fernández-Campusano, C., Carrasco, R., Vargas, M., Navarrete, A., 2021. Boosting the decision-making in smart ports by using blockchain. *IEEE Access*, **9**, 128055–128068.

Durán-Grados, V., Rodríguez-Moreno, R., Calderay-Cayetano, F., Amado-Sánchez, Y., Pájaro-Velázquez, E., Nunes, R. A., et al., 2022. The influence of emissions from maritime transport on air quality in the Strait of Gibraltar (Spain). *Sustainability*, **14**, 12507.

EEA, 2022. European Environment Agency (EEA) – OPERT 5 Manual. https://unfccc.int/sites/default/files/resource/Manuel%20Copert%205.pdf

EEA, 2023. EMEP/EEA air pollutant emission inventory guidebook 2023. https://www.eea.europa.eu/en/analysis/publications/emep-eea-guidebook-2023

Endresen, Ø., Sørgård, E., Behrens, H. L., Brett, P. O., Isaksen, I. S., 2007. A historical reconstruction of ships' fuel consumption and emissions. *J Geophys Res Atmos*, **112**: D12301.

EPA, 2024. United States Environmental Protection Agency (EPA) GHG emission factors hub (2024). https://www.epa.gov/system/files/documents/2024-02/ghg-emission-factors-hub-2024.pdf

European Commission, 2014. Alternative Fuels Infrastructure. https://transport.ec.europa.eu/transport-themes/clean-transport/alternative-fuels-sustainable-mobility-europe/alternative-fuels-infrastructure_en

European Commission, 2021. EU Monitoring, Reporting, and Verification Regulation. https://https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/monitoring-reporting-and-verification_en

European Commission, 2024. Reducing emissions from the shipping sector. https://climate.ec.europa.eu/eu-action/transport/reducing-emissions-shipping-sector_en

European Union, 2018. Directive (EU) 2018/2001 of the European parliament and of the council on the promotion of the use of energy from renewable sources (RED II). https://eur-lex.europa.eu/legal-content/ZH/TXT/?uri=CELEX%3A32018L2001

European Union, 2024. EU Directive on Network and Information Systems (NIS2). https://www.nis-2-directive.com/

Fadiga, A., Ferreira, L. M. D., Bigotte, J. F., 2024. Decarbonising maritime ports: A systematic review of the literature and insights for new research opportunities. *J Clean Prod*, **452**, 142209.

Fan, A., Xiong, Y., Yan, J., Yang, L., Shu, Y., Chen, J., 2024. Microscopic characteristics and influencing factors of ship emissions based on onboard measurements. *Transp Res Part D Transp Environ*, **133**, 104300.

Fan, A., Yang, J., Yang, L., Wu, D., Vladimir, N., 2022. A review of ship fuel consumption models. *Ocean Eng*, **264**, 112405.

Feng, Y., Wang, X., Luan, J., Wang, H., Li, H., Li, H., et al., 2024. A novel method for ship carbon emissions prediction under the influence of emergency events. *Transp Res Part C Emerg Technol*, **165**, 104749.

Ghoroghi, A., Rezgui, Y., Petri, I., Beach, T., 2022. Advances in application of machine learning to life cycle assessment: A literature review. *Int J Life Cycle Assess*, **27**, 433–456.

Gkerekos, C., Lazakis, I., 2020. A novel, data-driven heuristic framework for vessel weather routing. *Ocean Eng*, **197**, 106887.

Gkerekos, C., Lazakis, I., Theotokatos, G., 2019. Machine learning models for predicting ship main engine fuel oil consumption: A comparative study. *Ocean Eng*, **188**, 106282.

Global Maritime Hub, 2021. China's smart port initiative. https://globalmaritimehub.com/report-presentation/chinas-smart-port-initiative

Goldsworthy, L., Goldsworthy, B., 2015. Modelling of ship engine exhaust emissions in ports and extensive coastal waters based on terrestrial AIS data–an Australian case study. *Environ Model Softw*, **63**, 45–60.

Govindan, K., Dua, R., Anwar, A. M., Bansal, P., 2024. Enabling net-zero shipping: An expert review-based agenda for emerging techno-economic and policy research. *Transp Res Part E Logist Transp Rev*, **192**, 103753.

Grigoriadis, A., Mamarikas, S., Ioannidis, I., Majamäki, E., Jalkanen, J.-P., Ntziachristos, L., 2021. Development of exhaust emission factors for vessels: A review and meta-analysis of available data. *Atmos Environ: X*, **12**, 100142.

Guan, P., Wood, L. C., Wang, J. X., Duong, L. N., 2024. Blockchain adoption in the port industry: a systematic literature review. *Cogent Bus Manag*, **11**, 2431650.

Hassel, M., Asbjørnslett, B. E., Hole, L. P., 2011. Underreporting of maritime accidents to vessel accident databases. *Accid Anal Prev*, **43**, 2053–2063.

Haugen, M. J., Gkantonas, S., El Helou, I., Pathania, R., Mastorakos, E., Boies, A. M., 2023. Particle measurements from in-use maritime traffic using an unmanned aerial vehicle in Rafina, Greece. *Transp Res Procedia*, **72**, 2094–2100.

He, S., Wu, X., Wang, J., Lu, Y., 2025. Shipping emission inventory preparation with AIS data: A stratified random sampling method. *Transp Res Part D Transp Environ*, **138**, 104520.

Heikkilä, M., Saarni, J., Saurama, A., 2022. Innovation in smart ports: Future directions of digitalization in container ports. *J Mar Sci Eng*, **10**, 1925.

Herazo, J. C. M., Castillo, A. P. P., Eras, J. J. C., Fierro, T. E. S., Araújo, J. F. C., Gatica, G., 2024. Bibliometric analysis of energy management and efficiency in the maritime industry and port terminals: Trends. *Procedia Comput Sci*, **231**, 514–519.

Homayouni, S. M., Pinho de Sousa, J., Moreira Marques, C., 2024. Unlocking the potential of digital twins to achieve sustainability in seaports: the state of practice and future outlook. *WMU J Marit Aff*, **24**, 59–80.

Hong, H., Jeon, H., Youn, C., Kim, H., 2021. Incorporation of shipping activity data in recurrent neural networks and long short-term memory models to improve air quality predictions around Busan port. *Atmosphere*, **12**, 1172.

Hou, Y. H., 2017. Hull form uncertainty optimization design for minimum EEOI with influence of different speed perturbation types. *Ocean Eng*, **140**, 66–72.

Hu, J., Deng, M., Peng, S., Qi, Z., 2022. UAV inspection of compliance of fuel sulfur content of sailing ships in the Pearl River Delta, China. *Atmosphere*, **13**, 1894.

Huang, C., Hu, Q., Wang, H., Qiao, L., Wang, H., Zhou, M., et al., 2018. Emission factors of particulate and gaseous compounds from a large cargo vessel operated under real-world conditions. *Environ Pollut*, **242**, 667–674.

Huang, L., Wen, Y., Zhang, Y., Zhou, C., Zhang, F., Yang, T., 2020. Dynamic calculation of ship exhaust emissions based on real-time AIS data. *Transp Res Part D Transp Environ*, **80**, 102277.

Ibigbami, O. A., Onilearo, O. D., Akinyeye, R. O., 2024. Post-combustion capture and other carbon capture and seques-tration (CCS) technologies: a review. *Environ Qual Manag*, **34**, e22180.

ICCT, 2007. Air pollution and greenhouse gas emissions from ocean-going ships: impacts, mitigation options and opportunities for managing growth. *Marit Stud*, **2007**, 3–10.

Igos, E., Benetto, E., Meyer, R., Baustert, P., Othoniel, B., 2019. How to treat uncertainties in life cycle assessment studies? *Int J Life Cycle Assess*, **24**, 794–807.

IHS, 2016. IHS Markit Maritime Portal. https://mirs.maritime.ihs.com/Account2/Index

IMO, 2013. Energy Efficiency Design Index (EEDI). https://www.imo.org/fr/MediaCentre/HotTopics/Pages/EEDI.aspx

IMO, 2019. International Maritime Organization (IMO) Data Collection System. https://www.imo.org/en/ourwork/environment/pages/data-collection-system.aspx

IMO, 2020. Fourth IMO Greenhouse Gas Study 2020. https://www.imo.org/en/ourwork/Environment/Pages/Fourth-IMO-Greenhouse-Gas-Study-2020.aspx

IMO, 2021. Guidelines on Maritime Cyber Risk Management. MSC-FAL.1-Circ.3-Rev.2, https://wwwcdn.imo.org/localresources/en/OurWork/Security/Documents/MSC-FAL.1-Circ.3-Rev.2%20-%20Guidelines%20On%20Maritime%20Cyber%20Risk%20Management%20(Secretariat)%20(1).pdf

IMO, 2023a. 2023 IMO Strategy on Reduction of GHG Emissions from Ships. https://www.imo.org/en/OurWork/Environment/Pages/2023-IMO-Strategy-on-Reduction-of-GHG-Emissions-from-Ships.aspx

IMO, 2023b. Carbon Intensity Indicator. https://www.imo.org/en/MediaCentre/HotTopics/Pages/EEXI-CII-FAQ.aspx

IMO, 2023c. Resolution MEPC.376(80): Guidelines for the Reduction of GHG Emissions from Ships. https://wwwcdn.imo.org/localresources/en/KnowledgeCentre/IndexofIMOResolutions/MEPCDocuments/MEPC.376(80).pdf

International Association of Classification Societies, 2024. IACS adopts new requirements on cyber safety. https://iacs.org.uk/news/iacs-adopts-new-requirements-on-cyber-safety/

IPCC, 2019. 2019 refinement to the 2006 IPCC guidelines for national greenhouse gas inventories. Tech. rep., Intergov-ernmental Panel on Climate Change (IPCC), https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/

Iphar, C., Le Berre, I., Foulquier, É., Napoli, A., 2024. Port call extraction from vessel location data for characterising harbour traffic. *Ocean Eng*, **293**, 116771.

Iris, Ç., Lam, J. S. L., 2019. A review of energy efficiency in ports: Operational strategies, technologies and energy management systems. *Renew Sustain Energy Rev*, **112**, 170–182.

Jalkanen, J.-P., Brink, A., Kalli, J., Pettersson, H., Kukkonen, J., Stipa, T., 2009. A modelling system for the exhaust emissions of marine traffic and its application in the Baltic Sea area. *Atmos Chem Phys*, **9**, 9209–9223.

Jalkanen, J.-P., Johansson, L., Kukkonen, J., 2014. A comprehensive inventory of the ship traffic exhaust emissions in the Baltic Sea from 2006 to 2009. *Ambio*, **43**, 311–324.

Jalkanen, J.-P., Johansson, L., Kukkonen, J., Brink, A., Kalli, J., Stipa, T., 2012. Extension of an assessment model of ship traffic exhaust emissions for particulate matter and carbon monoxide. *Atmos Chem Phys*, **12**, 2641–2659.

Jang, J., Lim, S., Choe, S.-B., Kim, J.-S., Lim, H.-K., Oh, J., et al., 2024. Enhanced predictive modeling vs. *LCA simulation: A comparative study on CO_2 emissions from ship operations*. *Ocean Eng*, **310**, 118506.

Johansson, L., Jalkanen, J.-P., Kukkonen, J., 2017. Global assessment of shipping emissions in 2015 on a high spatial and temporal resolution. *Atmos Environ*, **167**, 403–415.

Joung, T.-H., Kang, S.-G., Lee, J.-K., Ahn, J., 2020. The IMO initial strategy for reducing greenhouse gas (GHG) emissions, and its follow-up actions towards 2050. *J Int Marit Saf Environ Aff Shipp*, **4**, 1–7.

Karachalios, T., Moschos, P., Orphanoudakis, T., 2024. Maritime emission monitoring: Development and testing of a UAV-based real-time wind sensing mission planner module. *Sensors*, **24**, 950.

Karakostas, B., Katsoulakos, T., 2024. State-of-the-art Digital Twin Applications for Shipping Sector Decarbonization. Advances in Logistics, Operations, and Management Science. IGI Global, Hershey, PA.

Kim, Y.-R., Steen, S., Kramel, D., Muri, H., Strømman, A. H., 2023. Modelling of ship resistance and power consumption for the global fleet: The MariTEAM model. *Ocean Eng*, **281**, 114758.

Klimkowska, A., Lee, I., Choi, K., 2016. Possibilities of UAS for maritime monitoring. *Int Arch Photogramm Remote Sens Spatial Inf Sci*, **41**, 885–891.

Kondratenko, A. A., Zhang, M., Tavakoli, S., Altarriba, E., Hirdaris, S., 2025. Existing technologies and scientific advancements to decarbonize shipping by retrofitting. *Renew Sustain Energy Rev*, **212**, 115430.

Kramel, D., Muri, H., Kim, Y., Lonka, R., Nielsen, J. B., Ringvold, A. L., et al., 2021. Global shipping emissions from a well-to-wake perspective: the MariTEAM model. *Environ Sci Technol*, **55**, 15040–15050.

Le, A. V., Kyaw, P. T., Veerajagadheswar, P., Muthugala, M. V. J., Elara, M. R., Kumar, M., et al., 2021. Reinforcement learning-based optimal complete water-blasting for autonomous ship hull corrosion cleaning system. *Ocean Eng*, **220**, 108477.

Lee, J., Eom, J., Park, J., Jo, J., Kim, S., 2024. The development of a machine learning-based carbon emission prediction method for a multi-fuel-propelled smart ship by using onboard measurement data. *Sustainability*, **16**, 2381.

Lepore, A., Dos Reis, M. S., Palumbo, B., Rendall, R., Capezza, C., 2017. A comparison of advanced regression techniques for predicting ship CO_2 emissions. *Qual Reliab Eng Int*, **33**, 1281–1292.

Li, H., Jiao, H., Yang, Z., 2023a. AIS data-driven ship trajectory prediction modelling and analysis based on machine learning and deep learning methods. *Transp Res Part E Logist Transp Rev*, **175**, 103152.

Li, K. X., Li, M., Zhu, Y., Yuen, K. F., Tong, H., Zhou, H., 2023b. Smart port: A bibliometric review and future research directions. *Transp Res Part E Logist Transp Rev*, **174**, 103098.

Li, S., Tong, Z., Haroon, M., 2024. Estimation of transport CO_2 emissions using machine learning algorithm. *Transp Res Part D Transp Environ*, **133**, 104276.

Li, X., Du, Y., Chen, Y., Nguyen, S., Zhang, W., Schönborn, A., Sun, Z., 2022. Data fusion and machine learning for ship fuel efficiency modeling: Part I–voyage report data and meteorological data. *Commun Transp Res*, **2**, 100074.

Lindstad, E., Bø, T. I., 2018. Potential power setups, fuels and hull designs capable of satisfying future EEDI requirements. *Transp Res Part D Transp Environ*, **63**, 276–290.

Liu, W., Xu, B., Li, J., 2025. Data-driven carbon emission dynamics under ship in-port congestion. *J Mar Sci Eng*, **13**, 812.

Madusanka, N. S., Fan, Y., Yang, S., Xiang, X., 2023. Digital twin in the maritime domain: A review and emerging trends. *J Mar Sci Eng*, **11**, 1021.

Mahmud, K. K., Chowdhury, M. M. H., Shaheen, M. M. A., 2024. Green port management practices for sustainable port operations: A multi method study of Asian ports. *Marit Policy Manag*, **51**, 1902–1937.

Mahmud, K. K., Sheikh, W., Chowdhury, M. M. H., 2025. Decision framework for sustainability assessment of alternative fuels to achieve shipping decarbonization. *Ocean Coast Manag*, **265**, 107637.

Maritime and Port Authority of Singapore, 2020. No. 15 of 2020-Maritime Cyber Risk Management. https://www.mpa.gov.sg/media-centre/details/no-15-of-2020—maritime-cyber-risk-management

Mason, J., Larkin, A., Gallego-Schmid, A., 2023. Mitigating stochastic uncertainty from weather routing for ships with wind propulsion. *Ocean Eng*, **281**, 114674.

McKenney, T. A., 2024. The impact of maritime decarbonization on ship design: State-of-the-art report. In: Proceedings of the 15th International Marine Design Conference, 71.

Merien-Paul, R. H., Enshaei, H., Jayasinghe, S. G., 2018. In-situ data vs. bottom-up approaches in estimations of marine fuel consumptions and emissions. *Transp Res Part D Transp Environ*, **62**, 619–632.

Miola, A., Ciuffo, B., 2011. Estimating air emissions from ships: Meta-analysis of modelling approaches and available data sources. *Atmos Environ*, **45**, 2242–2251.

Mlimbila, J., Mbamba, U. O., 2018. The role of information systems usage in enhancing port logistics performance: Evidence from the Dar Es Salaam port, Tanzania. *J Shipp Trade*, **3**, 10.

Moreno-Gutiérrez, J., Calderay, F., Saborido, N., Boile, M., Valero, R. R., Durán-Grados, V., 2015. Methodologies for estimating shipping emissions and energy consumption: A comparative analysis of current methods. *Energy*, **86**, 603–616.

Moreno-Gutiérrez, J., Durán-Grados, V., 2021. Calculating ships' real emissions of pollutants and greenhouse gases: Towards zero uncertainties. *Sci Total Environ*, **750**, 141471.

Moreno-Gutiérrez, J., Pájaro-Velázquez, E., Amado-Sánchez, Y., Rodríguez-Moreno, R., Calderay-Cayetano, F., Durán-Grados, V., 2019. Comparative analysis between different methods for calculating on-board ship's emissions and energy consumption based on operational data. *Sci Total Environ*, **650**, 575–584.

Moros-Daza, A., Amaya-Mier, R., Paternina-Arboleda, C., 2020. Port community systems: A structured literature review. *Transp Res Part A Policy Pract*, **133**, 27–46.

Najati, I., 2025. Exploring the failure factors of blockchain adopting projects: A case study of Tradelens through the lens of commons theory. *Front Blockchain*, **8**, 1503595.

Ng, M., 2019. Vessel speed optimisation in container shipping: A new look. *J Oper Res Soc*, **70**, 541–547.

Nguyen, S., Gadel, M., Wang, K., Li, J., Zhang, X., Siang-Ching, K., et al., 2025. Maritime decarbonization through machine learning: A critical systematic review of fuel and power prediction models. *Clean Logist Supply Chain*, **14**, 100210.

Norwegian Environment Agency, 2024. Guide to Maritime Transport in MRV and the EU ETS. https://www.environmentagency.no/areas-of-activity/eu-emissions-trading-system/guide-to-maritime-transport-in-mrv-and-the-eu-ets/

Oliveira, D. R., Lagerström, M., Granhag, L., Werner, S., Larsson, A. I., Ytreberg, E., 2022. A novel tool for cost and emission reduction related to ship underwater hull maintenance. *J Clean Prod*, **356**, 131882.

Ortiz-Cea, V., Dote-Pardo, J., Geldres-Weiss, V. V., Peña-Acuña, V., 2025. The role of activity-based costing in reducing environmental impact: A systematic literature review. *Sustainability*, **17**, 1275.

Panić, I., Cuculić, A., Ćelić, J., 2022. Color-coded hydrogen: Production and storage in maritime sector. *J Mar Sci Eng*, **10**, 1995.

Paternina-Arboleda, C. D., Agudelo-Castañeda, D., Voß, S., Das, S., 2023. Towards cleaner ports: Predictive modeling of sulfur dioxide shipping emissions in maritime facilities using machine learning. *Sustainability*, **15**, 12171.

Pedersen, B. P., Larsen, J., 2013. Gaussian process regression for vessel performance monitoring. In: 12th International conference on computer and IT applications in the maritime industries (COMPIT 13). Cortona, Italy.

Peng, Z., Ge, Y., Tan, J., Fu, M., Wang, X., Chen, M., et al., 2016. Emissions from several in-use ships tested by portable emission measurement system. *Ocean Eng*, **116**, 260–267.

Port of Antwerp-Bruges, 2020. Hydrogen import coalition maps out roadmap for hydrogen import in Belgium. https://www.portofantwerpbruges.com/en/news/hydrogen-import-coalition-maps-out-roadmap-hydrogen-import-belgium

Psaraftis, H. N., 2019. Decarbonization of maritime transport: To be or not to be? *Marit Econ Logist*, **21**, 353–371.

Qi, Y., Yang, J., Qin, K. S., 2024. Spatial-temporal analysis of carbon emissions from ships in ports based on AIS data. *Ocean Eng*, **308**, 118394.

Rehmatulla, N., Smith, T., 2015. Barriers to energy efficient and low carbon shipping. *Ocean Eng*, **110**, 102–112.

Reis, M. S., Rendall, R., Palumbo, B., Lepore, A., Capezza, C., 2020. Predicting ships' CO_2 emissions using feature-oriented methods. *Appl Stoch Models Bus Ind*, **36**, 110–123.

Ren, F., Wang, S., Liu, Y., Han, Y., 2022. Container ship carbon and fuel estimation in voyages utilizing meteorological data with data fusion and machine learning techniques. *Math Probl Eng*, **2022**, 4773395.

Rosewig, E. I., Schade, J., Passig, J., Osterholz, H., Irsig, R., Smok, D., Gawlitta, N., Schnelle-Kreis, J., Hovorka, J., et al., 2023. Remote detection of different marine fuels in exhaust plumes by onboard measurements in the Baltic Sea using single-particle mass spectrometry. *Atmosphere*, **14**, 849.

Roux, M., Lodato, C., Laurent, A., Astrup, T., 2024. A review of life cycle assessment studies of maritime fuels: Critical insights, gaps, and recommendations. *Sustain Prod Consump*, **50**, 69–86.

Saliba, M., Azzopardi, F., Muscat, R., Grima, M., Smyth, A., Jalkanen, J.-P., et al., 2021. Trends in vessel atmospheric emissions in the central Mediterranean over the last 10 years and during the COVID-19 outbreak. *J Mar Sci Eng*, **9**, 762.

Šaparnis, L., Rapalis, P., Daukšys, V., 2024. Ship emission measurements using multirotor unmanned aerial vehicles. *J Mar Sci Eng*, **12**, 1197.

Schrooten, L., De Vlieger, I., Panis, L. I., Chiffi, C., Pastori, E., 2009. Emissions of maritime transport: A European reference system. *Sci Total Environ*, **408**, 318–323.

Schultz, M. P., 2007. Effects of coating roughness and biofouling on ship resistance and powering. *Biofouling*, **23**, 331–341.

Sea Traffic Management, 2023. STM validation project. https://www.seatrafficmanagement.info/projects/stm-validation/

Shu, Y., Hu, A., Zheng, Y., Gan, L., Xiao, G., Zhou, C., Song, L., 2023. Evaluation of ship emission intensity and the inaccuracy of exhaust emission estimation model. *Ocean Eng*, **287**, 115723.

Šilas, G., Rapalis, P., Lebedevas, S., 2023. Particulate matter (PM1, 2.5, 10) concentration prediction in ship exhaust gas plume through an artificial neural network. *J Mar Sci Eng*, **11**, 150.

Singapore Maritime and Port Authority, 2025. Maritime Singapore Green Initiative. https://www.mpa.gov.sg/maritime-singapore/sustainability/maritime-singapore-green-initiative

Smith, T., O'Keefe, E., Haji, S., 2013. Glotram method. UCL Energy Institute, London. https://www.ucl.ac.uk/energy-models/

Smith, T. W., Jalkanen, J., Anderson, B., Corbett, J., Faber, J., Hanayama, S., O'Keeffe, E., Parker, S., Johansson, L., Aldous, L., et al., 2015. Third IMO Greenhouse Gas Study 2014. Tech. rep., International Maritime Organization (IMO), London, UK, https://www.imo.org/en/OurWork/Environment/Pages/GHG-Studies-2014.aspx

Son, J., Kim, D.-H., Yun, S.-W., Kim, H.-J., Kim, S., 2022. The development of regional vessel traffic congestion forecasts using hybrid data from an automatic identification system and a port management information system. *J Mar Sci Eng*, **10**, 1956.

Song, D.-P., 2024. A literature review of seaport decarbonisation: Solution measures and roadmap to net zero. *Sustainability*, **16**, 1620.

Song, Q., Tinoco, R. R., Yang, H., Yang, Q., Jiang, H., Chen, Y., et al., 2022. A comparative study on energy efficiency of the maritime supply chains for liquefied hydrogen, ammonia, methanol and natural gas. *Carbon Capture Sci Technol*, **4**, 100056.

Sotiralis, P., Annetis, M., Ntachan, F., Diamantis, C., Keratsa, L., Ventikos, N. P., 2024. Just in time port call optimisation: Preliminary regulatory compliance evaluation and environmental performance assessment. *J Phys: Conf Ser*, **2867**, 012010.

Sun, W., Tang, S., Liu, X., Zhou, S., Wei, J., 2022a. An improved ship weather routing framework for CII reduction accounting for wind-assisted rotors. *J Mar Sci Eng*, **10**, 1979.

Sun, Y., Lü, L., Cai, Y.-k., Lee, P., 2022b. Prediction of black carbon in marine engines and correlation analysis of model characteristics based on multiple machine learning algorithms. *Environ Sci Pollut Res*, **29**, 78509–78525.

Sun, Y., Yang, L., Zheng, J., 2020. Emission control areas: More or fewer?. *Transp Res Part D Transp Environ*, **84**, 102349.

Suvadarshini, P., Dandapat, P., 2023. Digitalizing the maritime supply chain: The case of Rotterdam's port call operations. *J Inf Technol Teach Cases*, **13**, 170–174.

Svanberg, M., Ellis, J., Lundgren, J., Landälv, I., 2018. Renewable methanol as a fuel for the shipping industry. *Renew Sustain Energy Rev*, **94**, 1217–1228.

Swain, G., 2010. The importance of ship hull coatings and maintenance as drivers for environmental sustainability. *Small*, **40**, 60.

Tadros, M., Ventura, M., Guedes Soares, C., 2023. Review of the decision support methods used in optimizing ship hulls towards improving energy efficiency. *J Mar Sci Eng*, **11**, 835.

Topic, T., Murphy, A. J., Pazouki, K., Norman, R., 2021. Assessment of ship emissions in coastal waters using spatial projections of ship tracks, ship voyage and engine specification data. *Clean Eng Technol*, **2**, 100089.

Trozzi, C., 2010. Emission estimate methodology for maritime navigation. https://gaftp.epa.gov/air/nei/ei_conference/EI20/session10/trozzi.pdf

UCL Transport Institute, 2014. Shipping and climate change: Scope for growth in an evolving context. https://www.ucl.ac.uk/transport/sites/transport/files/shipping-climate-change.pdf

United States Environmental Protection Agency, 2010. Designation of the North American emission control area for marine vessels. https://www.epa.gov/regulations-emissions-vehicles-and-engines/designation-north-american-emission-control-area-marine

United States Environmental Protection Agency, 2011. Designation of the U.S. Caribbean emission control area for marine vessels. https://www.epa.gov/regulations-emissions-vehicles-and-engines/designation-us-caribbean-emission-control-area-marine

United States Environmental Protection Agency, 2023. Greenhouse Gas Emission Factors Hub. https://www.epa.gov/system/files/documents/2023-03/ghg_emission_factors_hub.pdf?utm_source=chatgpt.com

Vaca-Cabrero, J., Domínguez Rastrojo, J., González-Cancelas, N., Camarero-Orive, A., 2025. Enhancing sustainability in port infrastructure through innovation: A case study of the Spanish port system. *Sustainability*, **17**, 2593.

Van Hoecke, L., Laffineur, L., Campe, R., Perreault, P., Verbruggen, S. W., Lenaerts, S., 2021. Challenges in the use of hydrogen for maritime applications. *Energy Environ Sci*, **14**, 815–843.

Villa, T. F., Brown, R. A., Jayaratne, E. R., Gonzalez, L. F., Morawska, L., Ristovski, Z. D., 2019. Characterization of the particle emission from a ship operating at sea using an unmanned aerial vehicle. *Atmos Meas Tech*, **12**, 691–702.

Vladimir, N., Ančić, I., Šestan, A., 2018. Effect of ship size on EEDI requirements for large container ships. *J Mar Sci Eng*, **23**, 42–51.

Wan, Z., Nie, A., Chen, J., Pang, C., Zhou, Y., 2025. Transforming ports for a low-carbon future: Innovations, challenges, and opportunities. *Ocean Coast Manag*, **264**, 107636.

Wang, C., Corbett, J. J., Firestone, J., 2007. Modeling energy use and emissions from North American shipping: Application of the ship traffic, energy, and environment model. *Environ Sci Technol*, **41**, 3226–3232.

Wang, J., Li, X., Yang, D., 2025a. Uncertainties in life cycle assessment of renewable fuels for green shipping corridors. *Transp Res Part D Transp Environ*, **147**, 104916.

Wang, J., Yang, D., Jia, S., 2025b. Unlocking renewable fuels for green shipping corridors: A comprehensive analysis framework. *Transp Res Part E Logist Transp Rev*, **202**, 104280.

Wang, Y., Wright, L. A., 2021. A comparative review of alternative fuels for the maritime sector: Economic, technology, and policy challenges for clean energy implementation. *World*, **2**, 456–481.

Wei, Y., Yang, X., Xiao, X., Ma, Z., Zhu, T., Dou, F., et al., 2024. Understanding the resilience of urban rail transit: Concepts, reviews, and trends. *Engineering*, **41**, 7–18.

Xiao, G., Wang, T., Chen, X., Zhou, L., 2022. Evaluation of ship pollutant emissions in the ports of Los Angeles and Long Beach. *J Mar Sci Eng*, **10**, 1206.

Xiao, G., Wang, Y., Wu, R., Li, J., Cai, Z., 2024. Sustainable maritime transport: A review of intelligent shipping technology and green port construction applications. *J Mar Sci Eng*, **12**, 1728.

Xing, H., Spence, S., Chen, H., 2020. A comprehensive review on countermeasures for CO_2 emissions from ships. *Renew Sustain Energy Rev*, **134**, 110222.

Xu, J., Chen, J., Li, J., Shi, J., Jiang, H., Mei, Q., et al., 2025. Transitioning to clean energy in global shipping: Country-based differences and industrial chain collaboration. *Ocean Coast Manag*, **269**, 107752.

Xu, J., Guan, Y., Oldfield, J., Guan, D., Shan, Y., 2024. China carbon emission accounts 2020-2021. *Appl Energy*, **360**, 122837.

Xu, L., Xu, S., Bai, X.-S., Repo, J. A., Hautala, S., Hyvönen, J., 2023. Performance and emission characteristics of an ammonia/diesel dual-fuel marine engine. *Renew Sustain Energy Rev*, **185**, 113631.

Yan, R., Wang, S., Psaraftis, H. N., 2021. Data analytics for fuel consumption management in maritime transportation: Status and perspectives. *Transp Res Part E Logist Transp Rev*, **155**, 102489.

Yang, D., Wu, L., Wang, S., Jia, H., Li, K. X., 2019. How big data enriches maritime research–a critical review of automatic identification system (AIS) data applications. *Transp Rev*, **39**, 755–773.

Yang, H., Sun, Z., Han, P., Ma, M., 2024a. Data-driven prediction of ship fuel oil consumption based on machine learning models considering meteorological factors. *J Eng Marit Environ*, **238**, 483–502.

Yang, L., Zhang, Q., Zhang, Y., Lv, Z., Wu, L., Mao, H., 2022. Real-world emission characteristics of an ocean-going vessel through long sailing measurement. *Sci Total Environ*, **810**, 152276.

Yang, S., Ghadikolaei, M. A., Gali, N. K., Xu, Z., Chu, M., Qin, X., et al., 2024b. Evaluating methods for marine fuel sulfur content using microsensor sniffing systems on ocean-going vessels. *Sci Total Environ*, **942**, 173765.

Yang, Y., Liu, Y., Li, G., Zhang, Z., Liu, Y., 2024c. Harnessing the power of machine learning for AIS data-driven maritime research: A comprehensive review. *Transp Res Part E Logist Transp Rev*, **183**, 103426.

Yu, H., Fang, Z., Fu, X., Liu, J., Chen, J., 2021. Literature review on emission control-based ship voyage optimization. *Transp Res Part D Transp Environ*, **93**, 102768.

Zhang, S., Zhang, J., Yang, L., Chen, F., Li, S., Gao, Z., 2024a. Physics

guided deep learning-based model for short-term origin–destination demand prediction in urban rail transit systems under pandemic. *Engineering*, **41**, 276–296.

Zhang, Y., Wang, X., Lou, D., Fang, L., 2024b. Investigation of emission characteristics of a marine cargo ship in real-world conditions. *Sci Total Environ*, **948**, 174991.

Zhang, Y., Zhao, K., Lou, D., Fang, L., 2022. Study on the real-world emission characteristics of gaseous and particulate pollutants from an inland ship using a portable emission measurement system. *Mar Pollut Bull*, **184**, 114205.

Zhou, F., Pan, S., Chen, W., Ni, X., An, B., 2019. Monitoring of compliance with fuel sulfur content regulations through unmanned aerial vehicle (UAV) measurements of ship emissions. *Atmos Meas Tech*, **12**, 6113–6124.

Zhou, F., Yu, K., Xie, W., Lyu, J., Zheng, Z., Zhou, S., 2024. Digital twin-enabled smart maritime logistics management in the context of industry 5.0. *IEEE Access*, **12**, 10920–10931.

Zis, T. P., Psaraftis, H. N., Ding, L., 2020. Ship weather routing: A taxonomy and survey. *Ocean Eng*, **213**, 107697.

Ziyadi, M., Al-Qadi, I. L., 2019. Model uncertainty analysis using data analytics for life-cycle assessment (LCA) applications. *Int J Life Cycle Assess*, **24**, 945–959.

Zucchetta, M., Madricardo, F., Ghezzo, M., Petrizzo, A., Picciulin, M., 2025. Satellite-based monitoring of small boat for environmental studies: A systematic review. *J Mar Sci Eng*, **13**, 390.

Zuo, Z., Niu, Y., Li, J., Fu, H., Zhou, M., 2024. Machine learning for advanced emission monitoring and reduction strategies in fossil fuel power plants. *Appl Sci*, **14**, 8442.

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