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Global shipping emissions prediction in the era of large language models: a review

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Global maritime transport carries nearly four-fifths of world merchandise trade and is a significant source of greenhouse gas (GHG) emissions. With the GHG reduction strategies from the International Maritime Organization (IMO), the EU's inclusion of shipping in the Emissions Trading System and the introduction of fuel GHG-intensity standards, there is an urgent need for prediction frameworks that are more robust, transparent and adaptable to evolving policy landscapes. Drawing on a structured search of the Web of Science Core Collection for the period 2020–2024, this review synthesises 1,012 peer-reviewed studies on global shipping emissions, decarbonisation measures and AI-enabled modelling. It first compares conventional approaches—fuel-based top-down inventories, AIS-driven bottom-up models and statistical or machine learning techniques—highlighting their respective strengths and limitations in terms of spatial and temporal resolution, data requirements and policy relevance. It then examines the emerging capabilities of large language models (LLMs) in knowledge integration, code generation and tool orchestration, and proposes five LLM-enabled paradigms for shipping emissions prediction, including multi-source information extraction, model orchestration, scenario construction and intelligent compliance auditing. Key technical and governance challenges are discussed, such as data quality and confidentiality, physical consistency, explainability and the environmental footprint of AI. The study argues that coupling LLMs with physics-based and data-driven models can enhance the flexibility and policy relevance of shipping emissions prediction, while a clearly defined research agenda is needed to ensure their responsible and effective use in supporting the decarbonisation of maritime transport.

KEYWORDS

decarbonisation, emission prediction, global shipping emissions, large language models, logistics and transportation, maritime policy

1 Introduction

Global maritime transport is the backbone of international trade, carrying the vast majority of seaborne goods and connecting production and consumption centres across the world (Brooks, 2023; Clarke et al., 2023). At the same time, ocean-going vessels are an important source of GHG emissions and air pollutants, contributing a significant share of anthropogenic CO_2 and short-lived climate forcers (United Nations Conference on Trade and Development (UNCTAD), 2023; Roy and Chakraborty, 2024; United Nations Conference on Trade and Development (UNCTAD), 2024). International assessments indicate that shipping emissions could increase substantially in the absence of effective policy intervention, even under scenarios where other sectors accelerate decarbonisation (Johansson et al., 2017).

In response, the IMO has established a long-term GHG reduction strategy, recently revised in 2023 (IMO (Marine Environment Protection Committee), 2018; IMO, 2023), which aspires to reach net-zero GHG emissions from international shipping around 2050 and sets indicative checkpoints for 2030 and 2040 relative to 2008 levels (Naghash et al., 2024). Regional initiatives, such as the European Union's inclusion of maritime transport in its Emissions Trading System and the FuelEU Maritime regulation, further increase the pressure on shipping companies, cargo owners and financial institutions to manage and reduce emissions (Deng and Mi, 2023; Huang et al., 2025). These ambitions define a phased decarbonisation pathway for the sector. Figure 1 summarises the main milestones of the 2023 IMO GHG strategy, from the 2008 base year to the 2030 and 2040 checkpoints and the net-zero objective around 2050.

Shipping emissions prediction is crucial for several reasons (Traut et al., 2018; Agnolucci et al., 2024). First, regulators need robust projections to design proportionate policy instruments, including carbon pricing and fuel standards. For example, Azizi et al. (2025) analyses carbon pricing strategies and policies for unified global carbon market, while Inal (2024) examines emerging legislative frameworks for hydrogen and fuel cells in the maritime sector. Fu et al. (2023) reviews maritime applications of fuel cells and hydrogen from the perspectives of key technologies, costs and regulatory standards. Second, industry actors rely on emissions forecasts to guide fleet investment and retrofitting decisions (Zeng et al., 2024; Omholt-Jensen et al., 2025). Altarriba et al. (2025) compares alternative fuels and emission reduction technologies for sustainable shipping, constructing a sustainability index that considers life-cycle emissions. Similarly, Torvanger et al. (2023) evaluates the potential for GHG mitigation with environmental requirement in Norwegian short-sea shipping, and Tian et al. (2025) proposes a data-driven optimisation framework that integrates ensemble machine learning with mathematical programming to optimise container ship bunkering decisions under multi-port price uncertainty. Third, climate-related financial disclosure frameworks increasingly require forward-looking assessments of transition risk associated with shipping-related assets and supply chains (Soner, 2025; Wu, 2025). Wu et al. (2025) assesses ports' adaptation investment decisions under shipping alliance scenarios, and (Melkonyan et al. (2024) analyses mitigation and adaptation strategies in the transport sector under extreme weather conditions. Chen Y. et al. (2024) explores whether climate policy uncertainty contributes to extreme spillovers among carbon, energy and shipping markets, highlighting the importance of policy stability for financial risk management.

Traditional approaches to emissions prediction have advanced substantially (Hong et al., 2023; Hellström et al., 2024). Top-down methods offer global coverage and historical continuity. For instance, Lu et al. (2026) develops a BN–GBM-based method, coupled with tailored feature construction, to predict fuel consumption of LNG dual-fuel ships, illustrating how advanced statistical learning can be embedded in operational energy analysis. In parallel, bottom-up methods based on Automatic Identification System (AIS) data offer vessel-level and route-level granularity (Chen J. et al., 2025; Choi et al., 2026). Sun et al. (2025)

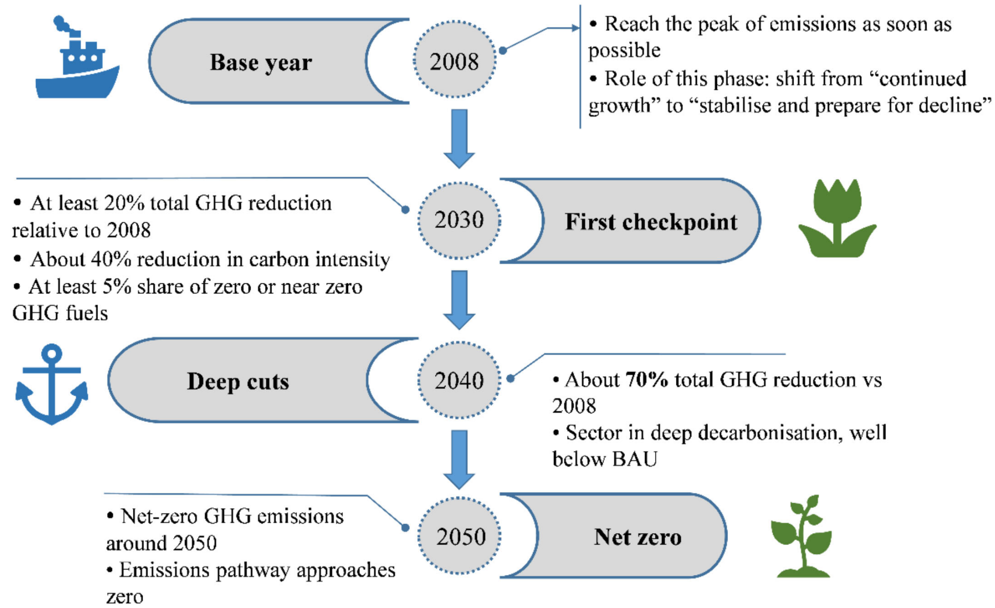

FIGURE 1
Phased milestones in the 2023 IMO GHG strategy for international shipping.

characterises the spatial-temporal patterns of ship carbon emissions using AIS-based activity data. Machine learning and statistical models have further improved predictive accuracy for specific sub-problems, such as fuel consumption under varying operating conditions (Han P. et al., 2024; Qingyao and Lam, 2025). Chen ZS. et al. (2023) develops a machine-learning-based model for harbour vessel fuel consumption that integrates ship-related and meteorological features. Xu et al. (2025a) compares machine learning approaches with econometric models for forecasting global shipping CO_2 emissions, meaning the conditions under which each class of models performs better. Yet these approaches still face significant challenges when confronted with highly heterogeneous data sources, changing policy and technology landscapes, and the need to embed expert knowledge and behavioural responses in a transparent way.

In parallel, LLMs have emerged as powerful AI systems with impressive capabilities in natural language understanding, code generation, tool calling and multi-step reasoning (Chen T. et al., 2025; Zha et al., 2025). Li Y. et al. (2025) demonstrates that the advent of LLMs substantially enhances the ability to interpret complex semantic patterns. Liu X. et al. (2025) uses LLMs to automatically extract complex use-case diagram elements from natural language requirements, addressing limitations of traditional requirement modelling and improving both accuracy and efficiency. Wang (2025) examines LLM-based error detection and correction in English writing within the EDCEW framework, illustrating how LLMs support high-level text quality control. Recent evidence shows that LLMs can be used to interface with energy system models, climate databases, and remote-sensing products, enabling more natural interaction and complex workflow orchestration (Martín-Domingo et al., 2025; Zheng et al., 2025). Wang P. et al. (2025) proposes an intelligent logistics framework that combines a spatiotemporal knowledge graph with AI agents to support berth allocation and related operational decisions. These and related studies highlight the potential of LLMs to act as an orchestration layer – a cognitive interface that connects complex models and human decision-makers.

Compared with previous reviews of global shipping emissions, decarbonisation measures and AI or machine-learning-based emissions modelling, this paper makes three distinctive contributions. First, it jointly maps the landscape of conventional shipping emissions prediction approaches and the emerging capabilities of large language models, providing a unified view of how these strands of work relate to each other. Second, it proposes an explicit conceptual framework in which LLMs augment rather than replace existing numerical models, highlighting their role as a semantic and organisational layer that can connect heterogeneous data sources, modelling tools and stakeholders. Third, it formulates a structured research agenda that links concrete maritime use cases —such as regulatory compliance, fleet planning and scenario analysis—to specific LLM-enabled paradigms and associated technical and governance challenges.

Accordingly, this review is guided by four questions: (i) how have global shipping emissions and the associated regulatory framework evolved, and what demands do they place on prediction tools? (ii) what are the main strengths and limitations of current top-down, AIS-based bottom-up and statistical or machine-learning approaches to shipping emissions prediction? (iii) which capabilities of LLMs are most relevant for addressing the integration, adaptability and human–computer interaction gaps identified in existing practices? and (iv) what concrete LLM-enabled paradigms and research directions can support the responsible use of these models in maritime decarbonisation policy and decision-making?

The remainder of this paper is organised as follows. Section 2 provides background on global shipping emissions and the evolving decarbonisation policy framework. Section 3 describes the literature landscape and reviews conventional approaches to shipping emissions estimation and prediction, including top-down fuel-based inventories, AIS-driven bottom-up models and statistical or machine learning methods. Section 4 introduces core LLM capabilities and summarises existing applications in climate, energy and environmental domains that are relevant to shipping. Section 5 analyses several LLM-enabled paradigms for global shipping emissions prediction, focussing on data integration, model orchestration, scenario construction, multi-modal coupling and compliance support. Section 6 discusses key challenges and outlines a research agenda related to data governance, physical consistency, evaluation frameworks and human–AI collaboration. Section 7 concludes with implications for researchers, practitioners and policymakers in the maritime sector.

2 Global shipping emissions and regulatory context

International shipping contributes a notable share of global anthropogenic GHG emissions (Handl, 2023). IMO greenhouse gas studies and other assessments have documented a gradual rise in absolute emissions over the past decades, with variations driven by trade volumes (Xu et al., 2024b; Wang X. et al., 2025), fleet composition (Gu et al., 2019; Li et al., 2023; Xin et al., 2023), fuel mix (Ha et al., 2023; Rony et al., 2023; Tang et al., 2025) and operational practices (Alamoush et al., 2020; Robalo-Cabrera et al., 2025). While improvements in energy efficiency and slow steaming have moderated emissions growth, total emissions have generally increased in line with expanding seaborne trade (Watson, 2020; Aakko-Saksa et al., 2023; Liu M. et al., 2025).

From a modelling perspective, these trends underline the importance of capturing both macro-level drivers—such as global trade dynamics, commodity flows and supply-chain restructuring—and micro-level drivers, including vessel operations, maintenance practices and adoption of energy-saving technologies (Xu et al., 2024a; Xu et al., 2025b). Emissions prediction models must therefore be able to represent interactions among these drivers over multiple time scales.

The revised IMO GHG strategy is supported by a series of technical and operational measures, and by ongoing discussions on mid-term instruments. These include technical and operational efficiency requirements—such as the Energy Efficiency Design

Index (EEDI), the Energy Efficiency Existing Ship Index (EEXI) and the Carbon Intensity Indicator (CII) (Bayraktar and Yuksel, 2023; Kim et al., 2023; Lee, 2024); consideration of market-based measures, such as a global maritime carbon price or levy (Mundaca et al., 2021; Pereda et al., 2025); and the development of standards and incentives for zero- and near-zero GHG fuels (Ruslan et al., 2025; Sandford et al., 2025).In parallel, regional initiatives add further complexity. The EU, for example, has decided to gradually include maritime emissions in its Emissions Trading System and introduce fuel GHG-intensity requirements under the FuelEU Maritime regulation (International Maritime Organization, 2020; von Malmborg, 2023). Other jurisdictions explore green corridor initiatives, investment subsidies and tax incentives for low-emission vessels.

The combination of global climate targets, sector-specific regulations and regional policies creates a highly dynamic decision environment for shipping stakeholders (Bayramoğlu et al., 2025; Türkistanli et al., 2025). Emissions prediction models must therefore be capable of handling multiple time horizons, from near-term compliance strategies to long-term transition pathways, representing interactions between technology choices, operational strategies, fuel markets and regulations, and communicating complex results to diverse audiences including regulators, industry practitioners, financial analysts and civil society. These requirements motivate the search for modelling paradigms that can integrate diverse data sources and model components within a flexible and transparent architecture.

3 Literature landscape and conventional prediction approaches

To map the existing knowledge base, we conducted a structured search of the Web of Science (WoS) Core Collection. We focussed on studies published between 2020 and 2024 in order to capture the most recent developments in global shipping emissions prediction and AI-enabled modelling, while still covering a sufficiently long period to identify emerging trends. The search was restricted to peer-reviewed journal articles and review papers written in English and used four groups of keywords designed to cover both sectoral and methodological aspects: (i) "shipping emissions" AND "forecast"; (ii) "maritime decarbonisation" AND "policy"; (iii) "ship fuel consumption" AND "machine learning"; and (iv) "large language model" AND "shipping". These queries were applied to all fields in the WoS Core Collection and combined using logical OR to construct a single search string. The retrieved records were exported to a reference manager for de-duplication (based on DOIs and titles), screened on the basis of titles and abstracts to exclude studies not focussed on maritime transport or not providing quantitative insights into emissions or energy use, and cleaned to remove items with incomplete bibliographic information. After removing duplicates and irrelevant records, 1,012 publications were ultimately identified for analysis.

Based on this corpus, we conducted a comparative analysis of the journals in which these studies were published. Figure 2 reports all journals that published at least ten articles in the dataset, together with the corresponding citation counts. The orange bars indicate the number of publications for each journal, while the superimposed line with markers represents the total number of citations. Overall, 19 journals meet the threshold of ten or more publications. Among them, Ocean Engineering and the Journal of Marine Science and Engineering are the most productive outlets, with 51 and 46 papers, respectively. In terms of citations, Ocean Engineering again ranks first with over 1,200 citations, followed by the Journal of Marine Science and Engineering with more than 700 citations. These two journals thus occupy central positions in the dissemination of research on shipping emissions, decarbonisation and related intelligent technologies.

To further characterise the thematic structure of the literature, we constructed a keyword co-occurrence network based on author keywords and Keywords Plus. After harmonising synonyms and removing semantically redundant terms, 28 high-frequency keywords with at least 22 occurrences were retained. The co-occurrence matrix was then analysed using standard bibliometric network techniques and visualised as a clustered network in Figure 3, where link thickness reflects co-occurrence frequency and node size denotes keyword prevalence. The network can be broadly divided into three colour clusters. The red cluster centres on emissions, decarbonisation, alternative fuels and regulations, reflecting work on policy instruments and low- or zero-carbon propulsion technologies. The green cluster groups studies on machine learning and optimisation, representing data-driven approaches to fuel-consumption prediction, speed and energy-efficiency optimisation. The blue cluster covers topics such as information systems, digital twins and human factors, pointing towards more integrative modelling and natural-language-related tasks. Notably, generic keywords such as "machine learning" and "model" occupy central positions, bridging traditional shipping emissions research with emerging deep-learning- and large-model-based frameworks.

Within this literature, conventional approaches to shipping emissions prediction can be grouped into three broad categories. The first category comprises top-down methods, which estimate emissions based on aggregate fuel consumption statistics, usually using data from energy balances or bunker sales (Chen et al., 2019; Krantz et al., 2022; Feng et al., 2024). Emissions are computed by multiplying fuel quantities by appropriate emission factors, adjusted for fuel type, combustion technology and control measures. These methods offer consistent coverage at national, regional or global levels and are closely linked to official energy and emissions statistics, but provide limited spatial and temporal resolution and capture operational and behavioural changes only indirectly. The second category consists of bottom-up models that use ship-level data, often derived from AIS messages, combined with vessel characteristics and engine performance relationships (Weng et al., 2020; Chen and Yang, 2024; Chen X. et al., 2024; He et al., 2025; Yang et al., 2025). These models reconstruct vessel trajectories, classify operating modes, estimate engine loads and fuel consumption, and apply fuel-specific emission factors to calculate emissions. AIS-based models can produce high-resolution emission

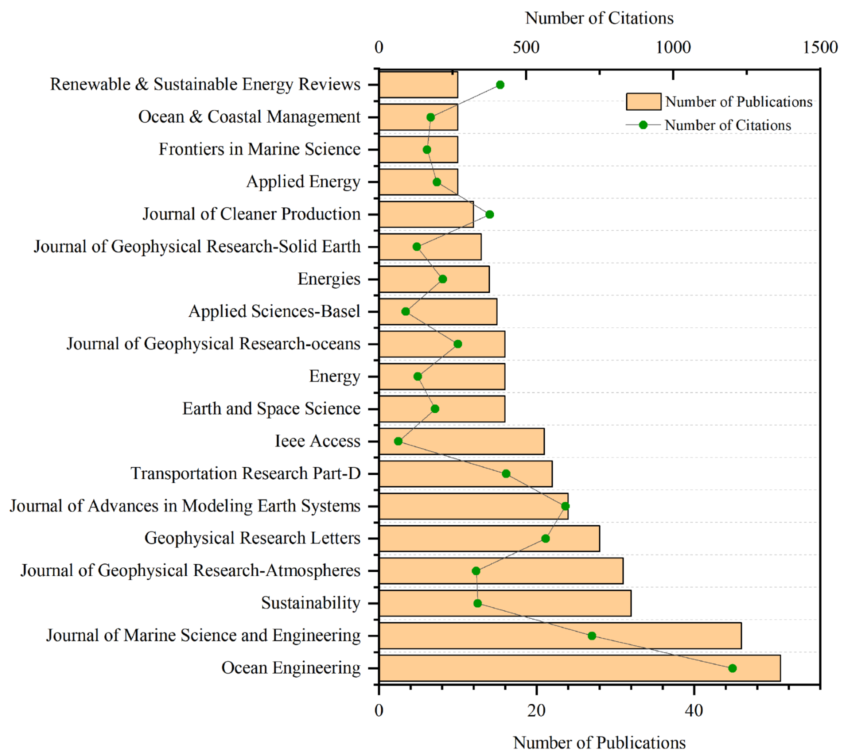

FIGURE 2
Publication sources and citation counts for journals with ≥10 articles in the WoS corpus (2020–2024).

inventories by ship type, route, port and sea area, making them particularly useful for policy evaluation and operational studies. However, they are data-intensive, sensitive to AIS data quality and vessel parameter uncertainties, and computationally demanding, especially for global, long-term projections.

The third category encompasses statistical and machine learning approaches applied to specific sub-problems within shipping emissions prediction (Chen K. et al., 2023; Huang et al., 2024; Dinh-Quoc et al., 2025; Wang W. et al., 2025; Zhang et al., 2025) These include regression and time-series models for fuel consumption and emissions at ship or fleet level; supervised learning algorithms such as random forests, support vector machines and gradient boosting for fuel consumption under different operating conditions; and deep learning models, such as as

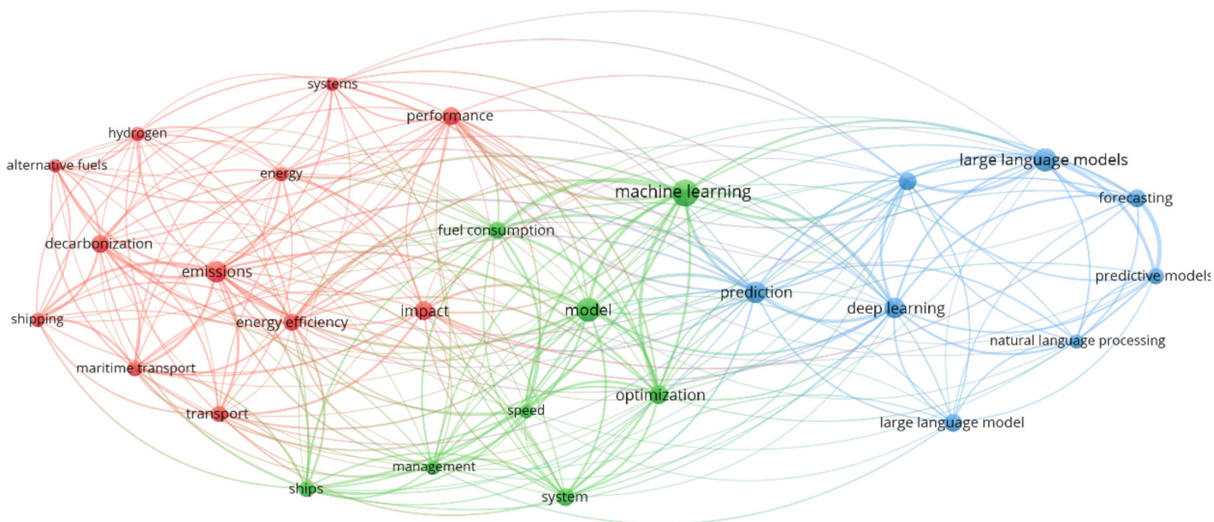

FIGURE 3
Keyword co-occurrence network of the WoS corpus (2020–2024).

recurrent or convolutional neural networks, for trajectory-based fuel use and emissions and for port-level emission forecasting. These models can capture non-linear relationships and interactions among multiple explanatory variables, often delivering improved predictive accuracy for specific tasks. Nonetheless, they frequently rely on manual feature engineering and task-specific model design, have limited ability to ingest and reason over unstructured or semi-structured information, and tend to lack explicit mechanisms for enforcing physical constraints and behavioural realism.

Collectively, traditional approaches form a strong foundation for shipping emissions prediction and have generated substantial insights into emission levels, drivers and mitigation options at different scales. However, they leave important gaps in terms of integration, adaptability and human–computer interaction.

4 Large language models: capabilities and climate/energy applications

Large language models are typically based on Transformer architectures trained on large corpora of text and code (Lei et al., 2024). Through self-supervised learning, they acquire rich representations of language and world knowledge. Subsequent instruction tuning and feedback alignment improve their ability to follow user instructions and perform tasks in interactive settings.

Several capabilities are directly relevant to shipping emissions prediction. First, cross-domain knowledge integration: LLMs can process and relate information from policy documents, technical standards, academic papers and corporate reports, thereby building a shared semantic layer across otherwise fragmented sources (Garry et al., 2024; Han T. et al., 2024; Liu et al., 2024). Second, code generation and tool calling: by generating code in languages such as Python, R or SQL, and interacting with computational tools via application programming interfaces, they can orchestrate complex data processing and modelling workflows (Wysocki and Ochodek, 2025; Surisetty et al., 2021; Hassouna et al., 2025). Third, interactive reasoning and scenario design: In multi-turn dialogues, LLMs can help stakeholders iteratively specify and refine scenarios and model assumptions (Lu et al., 2024; Pei et al., 2024). Fourth, multi-modal extensions: emerging models can integrate text with tables, time series and images, opening the door to richer interactions with AIS data, weather fields and remote-sensing imagery (Chen and Huang, 2025; Wen et al., 2025). These characteristics suggest that LLMs can function as an orchestration layer on top of existing numerical models, coordinating data flows, model execution and user interaction rather than replacing them. In this paper, we use the term “orchestration layer” to denote this mediating role of LLMs within the modelling ecosystem.

Recent studies have begun to explore LLMs in energy and climate contexts. Examples include using LLMs to interface with energy system optimisation models, generating model code from textual problem descriptions and performing sensitivity analyses based on conversational inputs (Li TT. et al., 2025); Applying LLMs to building energy management, where they assist in analysing consumption patterns, suggesting retrofit measures and interpreting technical standards and guidelines (Almeida et al., 2025); Evaluating LLMs as climate information agents, assessing their accuracy, completeness and potential biases when answering climate-related questions (Chen L. et al., 2025);and integrating LLMs with environmental monitoring systems—for instance, using LLM-based interfaces on top of satellite-derived methane emission datasets to provide natural language explanation and query capabilities (Chen Z. et al., 2025). Although these applications are still at an early stage, they illustrate both the promise and the limitations of LLMs and motivate more systematic exploration in the shipping domain.

Shipping-specific applications of LLMs are still at a nascent stage, but a small body of work is beginning to emerge in the maritime and transport domains. Early studies explore, for example, the use of LLMs for ship-handling theory assessment and training, for generating natural-language explanations of collision-avoidance rules and navigation decisions, and for supporting port-logistics planning through conversational interfaces that query schedules, hinterland connections and infrastructure constraints. Although these prototypes remain far from large-scale deployment, they demonstrate how the core capabilities outlined above—code generation and tool calling, multi-modal understanding and interactive reasoning—can be adapted to maritime data and workflows. They also foreshadow the LLM-enabled paradigms proposed in Section 5, in which LLMs are tightly integrated with domain-specific models and data streams rather than acting as standalone conversational agents.

5 LLM-enabled paradigms analysis

Building on the preceding sections, this review identifies five complementary LLM-enabled paradigms through which LLMs can augment, rather than replace, existing tools for global shipping emissions prediction. These paradigms are summarised schematically in Figure 4 and elaborated in the following subsections: (i) multi-source data extraction and integration; (ii) model orchestration and workflow automation; (iii) scenario construction and policy simulation; (iv) multi-modal integration with physical and data-driven models; and (v) real-time monitoring, anomaly detection and compliance auditing.

5.1 Multi-source data extraction and integration

In the first paradigm, LLMs act as flexible interfaces for extracting and harmonising information from heterogeneous, often weakly structured, data sources relevant to shipping emissions. These include international and regional regulations, technical standards, classification society rules, shipowner sustainability reports, charterparty contracts, port environmental programmes and insurance or finance documentation. LLMs can be prompted or fine-tuned to identify entities such as ship types,

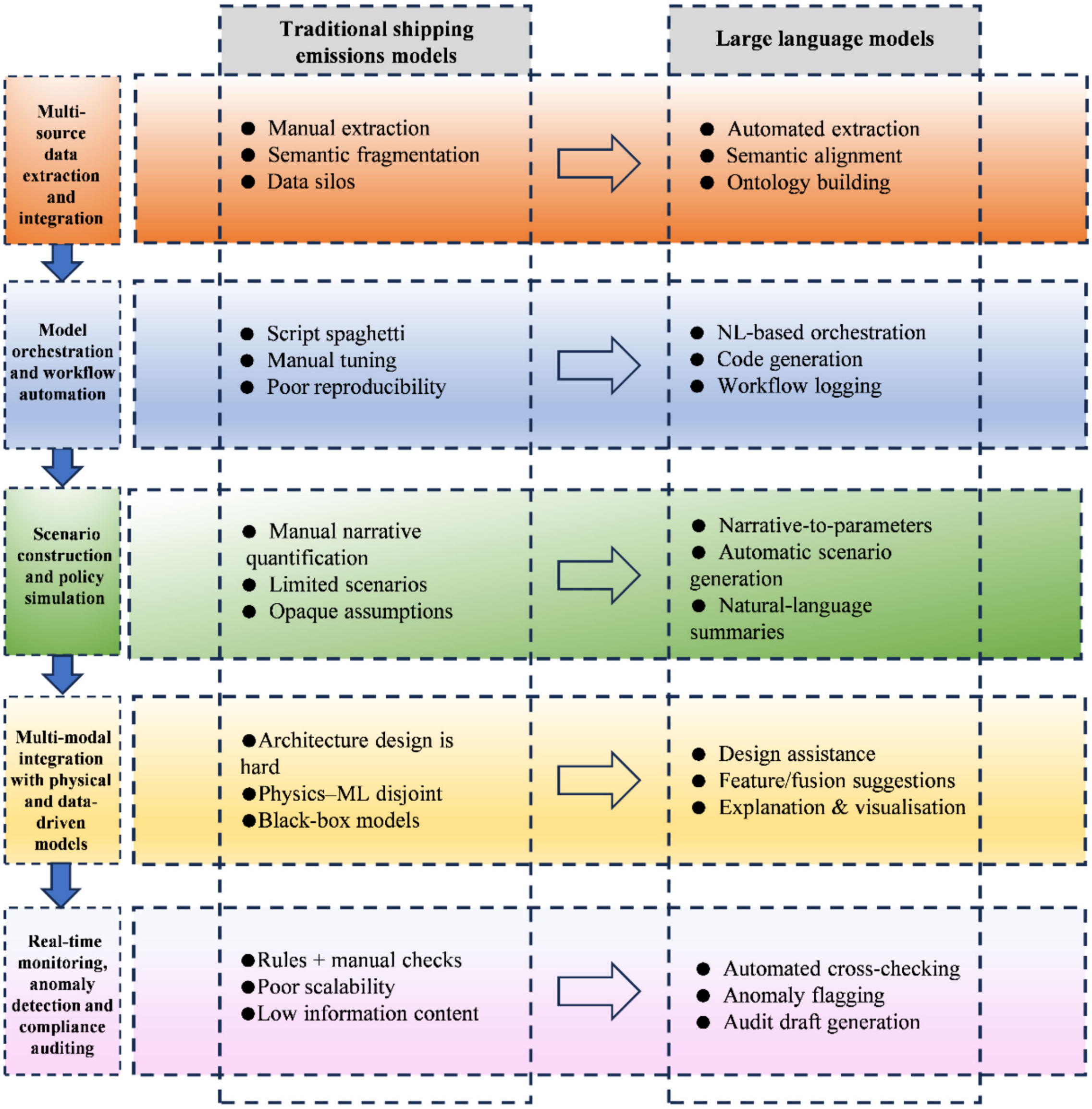

FIGURE 4
Workflow layers where LLMs complement traditional shipping emissions models.

engine technologies, fuel types, operational measures and compliance obligations, and to convert them into structured formats aligned with existing data schemas and model input requirements.

A concrete use case is the automated extraction of key parameters from evolving regulatory texts—such as the revised IMO GHG strategy, EU ETS extension to maritime transport and FuelEU Maritime requirements—and their mapping onto model parameters (e.g., carbon price trajectories, energy intensity benchmarks, allowable fuel mixes). Another example is the alignment of information across AIS-based movement records, vessel registries and company-level disclosures to construct more complete and internally consistent datasets for emission inventories and predictive models. In this paradigm, LLMs address a major bottleneck in current practice: the manual, time-consuming translation of legal, technical and narrative documents into machine-readable model inputs.

5.2 Model orchestration and workflow automation

The second paradigm views LLMs as "orchestrators" that help design, document and execute complex modelling workflows. Given a natural-language query—such as "estimate how the introduction of a regional carbon price and speed limits in the North Atlantic would affect emissions and operating costs of container services over the next decade"—an LLM can decompose the request into sub-tasks, select appropriate models and datasets (e.g., trade scenarios, fleet stock models, AIS-based routing models, cost modules) and generate or adapt code required to run the individual components.

Rather than performing numerical prediction themselves, LLMs interact with existing models through tool-calling or code-generation interfaces. They can automatically wire together data preprocessing, simulation runs and result aggregation, while logging assumptions and parameter choices in human-readable form. This paradigm has the potential to lower the entry barrier for regulators and analysts who are not modelling experts, to reduce errors in complex workflows and to make scenario analysis more transparent and reproducible.

5.3 Scenario construction and policy simulation support

The third paradigm concerns the co-design of scenarios and policy packages. Current scenario work in shipping often combines assumptions about trade growth, technology costs, fuel availability, policy stringency and behavioural responses, many of which are derived from disparate documents such as technology roadmaps, corporate strategies or consultation reports. LLMs can help parse these narratives, identify key drivers and their plausible ranges, and map them onto formal scenario parameters in integrated assessment models or shipping-sector models.

For example, LLMs can be prompted to compare alternative decarbonisation roadmaps, extract assumptions on fuel price differentials, retrofit rates or efficiency improvements, and translate them into structured inputs for fleet turnover or cost-optimisation models. They can also be used interactively: users can iteratively refine narratives ("more conservative fuel price assumptions", "stronger congestion impacts in key chokepoints") and receive updated quantitative scenarios in return. The paradigm does not replace rigorous quantitative modelling; rather, it aims to make the link between textual, stakeholder-facing narratives and formal models more explicit, traceable and responsive.

5.4 Multi-modal integration with physical and data-driven models

In the fourth paradigm, LLMs interface with physical, statistical and machine-learning models that operate on numerical or spatio-temporal data. Examples include bottom-up emissions simulators driven by AIS and weather data, ML models for ship-level fuel consumption, and port-level demand forecasting systems. While these models typically do not use natural language as input, they can benefit from an LLM layer that interprets user questions, selects relevant model components, configures runs and explains results.

Emerging multi-modal extensions further broaden this space. For instance, LLMs linked to trajectory or image analysis models could support the interpretation of remote-sensing products and radar or AIS patterns in congested sea areas, summarising implications for local air quality and GHG emissions in human-readable form. In all such cases, physical and ML models remain responsible for numerical prediction, while LLMs specialise in semantic mediation: generating prompts and configuration files, aligning variable names and units, and providing consistent narrative explanations of model outputs and uncertainties.

5.5 Real-time monitoring, anomaly detection and compliance auditing

The fifth paradigm focuses on near-real-time monitoring and compliance contexts, where LLMs can aid both regulators and companies. As ship operators increasingly report fuel consumption and emissions under corporate disclosure frameworks and regulatory schemes, there is a growing need to cross-check reported figures against independent activity-based estimates derived from AIS and other data sources. LLMs can assist by automatically comparing reported and modelled values, identifying unusual discrepancies, and generating preliminary audit narratives that highlight suspicious voyages, time periods or vessel segments for human review.

Beyond numeric checks, LLMs can synthesise information from inspection reports, satellite observations, port-state-control databases and incident records to flag patterns that may indicate systematic under-reporting or non-compliance. They can also help companies internalise complex rules by providing conversational compliance support—explaining how new measures apply to specific vessel portfolios, routes and contracts—while documenting the reasoning steps taken. In this paradigm, careful attention must be paid to accuracy, traceability and governance, but the potential benefits in terms of targeted enforcement and reduced administrative burden are substantial.

Across all five paradigms, LLMs function as enablers of integration, coordination and explanation. They do not replace detailed emissions models or domain expertise; instead, they seek to make existing tools more accessible, adaptable and responsive to evolving information and stakeholder needs. The next section discusses key technical, institutional and ethical challenges associated with deploying these paradigms in practice and outlines a research agenda for their further development.

6 Challenges and research agenda

Despite their promise, LLM-enabled approaches to shipping emissions prediction face several significant challenges. Data quality, privacy and commercial sensitivity are central concerns. Shipping data often contain sensitive information on routes, contracts and operations. Deploying LLM-based tools therefore requires robust data-governance arrangements, including clear agreements on data access and use, privacy-preserving mechanisms and, where appropriate, local or on-premise deployment to avoid unintended data leakage. AIS and other operational data can be incomplete, noisy or manipulated, and LLM-assisted data cleaning must avoid introducing "hallucinated" corrections or inferences that are not grounded in verifiable evidence. Transparent logging of transformations and a clear distinction between factual and inferred information are critical.

A second challenge concerns physical consistency and model reliability. LLMs are not inherently constrained by physical laws or engineering principles and may generate or endorse scenarios that violate basic constraints such as energy balance, vessel stability or realistic fleet-turnover dynamics. To maintain reliability, quantitative inferences produced or orchestrated by LLMs should be systematically checked by physics-based or data-driven models with explicit constraints. Hybrid architectures should clearly delineate responsibilities, with specialised models handling numerical predictions and LLMs focussing on semantics, orchestration and explanation. Calibration and validation procedures must be documented, and uncertainty communicated explicitly.

Explainability, governance and accountability form a third area of concern. As LLM-assisted tools begin to inform regulatory and investment decisions, questions arise about responsibility for errors, the traceability of assumptions and the ability of human experts to interrogate and override AI-generated recommendations. Addressing these questions requires both technical solutions—such as logging, provenance tracking, version control and interpretability tools—and institutional arrangements and legal frameworks tailored to the maritime sector. Classification societies, regulators and industry associations may need to develop guidelines for the responsible use of LLMs in emissions-related decision-making.

A fourth challenge relates to the computational cost and environmental footprint of AI. Training and operating large models consume substantial energy and can generate non-negligible emissions. For a sector under pressure to decarbonise, it is important that digitalisation initiatives, including LLM-based tools, align with sustainability objectives. This calls for work on model compression and distillation, specialised architectures for domain-specific tasks, deployment on energy-efficient hardware and the use of low-carbon electricity for data-centre operations. Metrics and reporting practices are needed to help stakeholders evaluate the climate benefits of improved decisions against the emissions associated with AI tools themselves.

These challenges give rise to several research directions. One priority is the development of domain-specific knowledge bases and retrieval-augmented systems that integrate regulatory texts, technical standards, peer-reviewed literature and open datasets on shipping emissions and activity. Such resources would allow LLMs to operate on grounded, up-to-date information and facilitate systematic benchmarking. A second direction concerns LLM-augmented hybrid modelling approaches, including standard interfaces between LLMs and existing shipping emissions models, co-simulation strategies in which LLMs dynamically configure model runs based on user queries and intermediate results, and embedding physical constraints and domain rules into prompting strategies and fine-tuning corpora. A third research avenue is the creation of evaluation frameworks and benchmarks for LLM-assisted emissions prediction, covering tasks such as data integration, scenario generation, policy analysis and compliance support and employing multi-dimensional metrics that assess robustness, interpretability, user trust and computational efficiency in addition to predictive accuracy. Further work is also needed on cross-scale and multi-stakeholder modelling and on human–AI collaboration and capacity building within regulatory bodies, port authorities, shipping companies and financial institutions.

7 Conclusions

This paper has reviewed the state of global shipping emissions prediction and examined how large language models can contribute to the next generation of modelling frameworks. Conventional approaches—fuel-based top-down methods, AIS-based bottom-up models and statistical or machine learning techniques—have provided substantial insights into emission levels, drivers and mitigation options, but face persistent challenges in integrating heterogeneous information, representing policy-induced behavioural change and supporting transparent scenario analysis for diverse stakeholders.

LLMs bring complementary capabilities in cross-domain knowledge integration, code generation and tool orchestration, interactive scenario design and multi-modal reasoning. When embedded in carefully designed hybrid systems, they can act as orchestration layers that make existing models more accessible, flexible and responsive to evolving information. Realising this potential will require addressing issues of data governance, physical consistency, explainability, accountability and the environmental footprint of AI, as well as investment in domain-specific knowledge resources, evaluation frameworks and human–AI collaboration. In the maritime context, institutional and regulatory conditions will also be critical: LLM-assisted tools will need to comply with IMO and flag-state requirements, data-protection regulations and emerging standards for trustworthy AI, and their use in safety- and compliance-critical processes will depend on appropriate certification, clear allocation of liability and targeted capacity building for regulators, classification societies and industry practitioners.

At the same time, the review itself has limitations. It is primarily based on WoS-indexed, English-language literature from 2020–2024 and focuses on global and large-scale emissions prediction, leaving out some regional studies and practice-oriented reports. Future work could extend the analysis to additional databases, grey literature and non-English sources, and could develop quantitative benchmarks to evaluate LLM-assisted tools against established modelling workflows. Overall, LLM-assisted global shipping emissions prediction is best understood not as a replacement for existing models, but as an opportunity to reorganise and augment the modelling ecosystem. By leveraging LLMs to better connect data, models and stakeholders, the maritime community can develop more robust and actionable insights to support the decarbonisation of logistics and transportation.

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