Discussion Paper

India's Maritime Trade and Its Implications for Future Energy Demand

Evidence from Shipping Energy Efficiency and Non-Oil Cargo at Major Ports

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Key Points

- India's non-oil cargo increased from 88 million metric tonnes (mmt) in 1990 to nearly 593 mmt in 2023. It is projected to reach about 1.09 billion metric tonnes by 2050, an 84% increase from 2023 levels.

- Energy demand from India-related seaborne trade was around 57 million barrels of oil equivalent (mboe) in 2023. By 2050, it is projected to reach 92 mboe under the Business-as-Usual (BAU) scenario, 68 mboe under the Efficiency scenario, and 55 mboe under the Sustainable scenario.

- By 2050, shipping emissions are estimated at 47 million metric tonnes of carbon dioxide ($MtCO_2$) under BAU, 35 $MtCO_2$ under the Efficiency scenario, and 28 $MtCO_2$ under the Sustainable scenario.

- Energy use from grab cranes (GCs) and wheel loaders (WLs) handling non-oil cargo increased from about 149 thousand barrels of oil equivalent (tboe) in 2018 to 184 tboe in 2023. By 2050, it is projected to reach 339 tboe under BAU but could fall to 169 tboe with automation, 265 tboe with electrification, and 132 tboe under a combined strategy.

- By 2050, emissions from port equipment are projected at 200 kilotonnes of carbon dioxide ($ktCO_2$) under BAU, 100 $ktCO_2$ with automation, 48 $ktCO_2$ with electrification, and 24 $ktCO_2$ under a combined decarbonization strategy.

Abstract

India's expanding seaborne trade will increasingly shape regional energy markets, port energy demand, and progress toward the International Maritime Organization's (IMO) decarbonization targets. This study examines how India can align maritime trade and infrastructure growth with long-term climate objectives. It addresses a gap in the literature by integrating non-oil cargo growth, shipping, and port energy demand and emissions across alternative transition pathways. Oil and petroleum-related cargo is excluded because it uses specialized infrastructure distinct from the cargo-handling equipment (CHE) examined and lacks comparable port-level equipment data. Using a system-level vector error correction framework, the study integrates macroeconomic drivers, cargo throughput, energy intensity, and crane operations to estimate energy demand and emissions through 2050. Energy demand from India-related seaborne trade rises from 57 million barrels of oil equivalent (mboe) in 2023 to 92 mboe under the Business-as-Usual (BAU) scenario, compared with 68 mboe under the Energy Efficiency (EE) scenario and 55 mboe under the Sustainable Development (SD) scenario. At ports, combined automation and electrification reduce crane energy demand from 339 thousand barrels of oil equivalent (tboe) under BAU to 132 tboe by 2050. Overall, coordinated port-shipping decarbonization could reduce India's maritime CO_2 footprint by nearly 40% by 2050, while combined automation and electrification could cut port crane energy demand by around 61% relative to BAU.

Keywords: India; maritime trade; non-oil cargo; port decarbonization; shipping emissions; energy demand forecasting; port electrification; cargo-handling equipment; vector error correction model; IMO decarbonization; maritime energy transition; seaborne trade.

Introduction

01

Maritime trade is central to the functioning of the global economy, but it also creates a growing energy and emissions challenge. Shipping enables the movement of raw materials, manufactured goods, food, and energy commodities across long distances, while ports provide the infrastructure required to handle, store, and distribute these flows.

As global trade expands, energy demand from vessel operations, cargo handling, and associated port services will continue to rise unless improvements in operational efficiency, electrification, renewable power use, and low-carbon fuels are accelerated. This challenge has become more pressing in the context of the IMO's decarbonization agenda, which calls for a progressive reduction in greenhouse gas emissions from international shipping while maintaining the reliability and affordability of global trade.

India provides an important case for examining this transition. Maritime transport carries nearly 95% of India's merchandise trade by volume and around 70% by value, making ports and shipping critical to the country's industrial development, trade competitiveness, and energy security (MoPSW 2026a). India's expanding trade links, manufacturing ambitions, growing import requirements, and role in regional supply chains are likely to increase demand for maritime transport and port services over the coming decades.

This growth has implications not only for fuel consumption by ships serving Indian trade, but also for electricity and fuel use within ports, particularly in cargo-handling operations. The energy implications of maritime growth are therefore closely linked to India's broader objectives in logistics modernization, infrastructure development, renewable energy deployment, and emissions reduction.

The transition is especially relevant for non-oil cargo, which includes commodities such as coal, iron ore, fertilizers, food grains, containerized cargo, and other general cargo categories. These cargo flows support industrial activity, agricultural production, construction, and consumer markets, but they also generate energy demand across two connected segments of the maritime supply chain: the movement of non-oil cargo by sea and its handling at ports.

Reducing this energy demand will require a combination of measures. At the shipping level, these include improvements in vessel efficiency, operational optimization, fleet renewal, route planning, and the gradual adoption of lower-carbon fuels. At the port level, relevant measures include the electrification of cargo-handling equipment (CHE), automation, improved equipment utilization, renewable electricity procurement, and more effective energy-management systems. The scale, timing, and interaction of these measures will determine whether growth in non-oil cargo translates into substantially higher energy use and emissions or can be partially decoupled from them.

Existing research provides valuable insights into shipping decarbonization, port electrification, and energy efficiency. However, much of this literature focuses either on global shipping pathways, individual vessels, specific ports, or single technology interventions. There remains limited analysis that connects long-term growth in non-oil cargo with both shipping-related energy demand and port energy use in a major emerging economy. This gap is particularly important in India, where cargo volumes are expected to grow alongside continuing investments in port capacity, logistics infrastructure, industrial development, and clean-energy technologies.

Moreover, the energy implications of non-oil cargo growth cannot be fully understood by examining shipping or ports in isolation. Shipping-related fuel demand reflects the scale and distance of cargo flows, while port energy use depends on throughput, equipment characteristics, operational practices, and the pace of technological modernization. This study addresses this gap by developing an integrated, scenario-based assessment of how India's non-oil cargo could shape future energy demand and carbon dioxide emissions through 2050.

Specifically, this study assesses the long-term energy and emissions implications of India's maritime growth, focusing on non-oil cargo flows and major port operations through two complementary models:

- The Shipping-Level Energy (SLE) model, which estimates energy demand and emissions associated with India-related non-oil maritime trade.
- The Port-Level Energy (PLE) model, which evaluates energy use and emissions from CHE at major ports.

Together, they provide a structured basis for examining how trade growth, operational efficiency, infrastructure modernization, and decarbonization pathways shape India's maritime energy future, while identifying practical strategies to reduce emissions and sustain trade competitiveness and port performance. The results are intended to support policy discussions on port modernization, maritime decarbonization, electricity planning, equipment replacement, and the prioritization of investments in clean maritime infrastructure.

The remainder of the paper is organized as follows. Section 2 provides background on India's maritime trade structure, major-port development, and relevant policy context. Section 3 describes the data, modeling framework, assumptions, and scenarios used in the cargo forecast, SLE model, and PLE model. Section 4 presents the projected results for non-oil cargo, energy demand, and emissions. Section 5 discusses the limitations of the study. Section 6 concludes.

Box 1. Key terms.

Term	Definition
SLE	Shipping-Level Energy: The model estimating energy demand and emissions from India-related seaborne trade.
PLE	Port-Level Energy: The model estimating energy demand and emissions from cargo-handling equipment at ports.
CHE	Cargo-handling equipment: Grab cranes (GCs) and wheel loaders (WLs) used to handle non-oil cargo at ports.
VECM	Vector error correction model: The econometric framework used to forecast cargo volume and its macroeconomic drivers.

Background: India's Maritime Trade Structure, Major-Port Development, and Policy Context

02

India's maritime sector plays a strategically important role in the country's trade and economic development, carrying nearly 95% of merchandise trade by volume and about 70% by value (MoPSW 2026a). This trade is supported by an extensive port network comprising 12 major ports and more than 200 notified non-major ports.

Together, these ports handle a diversified cargo mix that includes petroleum products, coal, iron ore, fertilizers, agricultural bulk cargo, breakbulk commodities, and containerized cargo. Major ports occupy a distinct position within India's maritime system. They are administered by the central government under the Major Port Authorities Act, 2021, and generally have stronger infrastructure, deeper hinterland connectivity, and a greater role in international trade, containerized cargo movement, strategic freight flows, and national logistics integration (Ministry of Law and Justice 2021; NITI Aayog 2025; and BRIEF 2025).

In FY 2023-24, petroleum, oil, and lubricants (POL) accounted for around 28% of total cargo handled at India's major ports, while non-oil cargo collectively accounted for approximately 72%. Within non-oil cargo, container cargo represented the largest share at 24.2%, followed by other cargo, including breakbulk, miscellaneous cargo, and other non-bulk categories, at 20.1%, and coal at 18.1%. Iron ore accounted for 7.5%, while fertilizers and fertilizer raw materials represented 2.1% of total cargo handled (MoPSW 2026b).

The development of major ports has varied across regions and cargo segments, shaped by cargo specialization, hinterland connectivity, industrial geography, and the degree of containerization. East Coast ports account for roughly two-thirds of major-port throughput, while West Coast ports account for the remaining share. Ports with diversified cargo portfolios and stronger container operations generally exhibit more stable throughput growth, whereas ports that depend heavily on one or a few commodities are more exposed to commodity-market cycles and trade volatility (CRISIL Market Intelligence & Analytics 2023).

Institutional and operational reforms have supported the expansion and modernization of India's major ports. The Major Port Authorities Act, 2021, increased the administrative, operational, and planning autonomy of major-port boards, while the Draft Indian Ports Bill, 2022, seeks to further update port governance in line with contemporary environmental, safety, and regulatory requirements (Ministry of Law and Justice 2021; MoPSW 2022). Earlier reform efforts, including the Major Port Trusts Act, 1963, the National Maritime Development Programme, and the Sagarmala Programme, focused on strengthening port governance, infrastructure modernization, port-led development, and hinterland connectivity (Government of India 1963; MoS 2016).

These reforms have been complemented by investments in mechanization, digitalization, multimodal connectivity, inland waterways, port-based industrial zones, and improved road and rail links. As a result, several ports have recorded improvements in berth productivity, vessel turnaround times, logistics integration, and cargo-handling capacity. India's 38th overall ranking and 47th ranking for infrastructure in the World Bank's 2023 Logistics Performance Index reflect this progress while also indicating remaining infrastructure gaps relative to global peers (World Bank 2023).

From an energy perspective, the expansion of port activity has important implications for both shipping and port operations. Higher cargo throughput increases demand for shipping services, CHE, terminal operations, storage systems, lighting, cold chains, buildings, and at-berth vessel services. As cargo volumes rise, energy demand and emissions from maritime activity are expected to increase unless efficiency improvements and decarbonization measures are accelerated. This makes port modernization not only a logistics and competitiveness issue but also an energy transition challenge.

India's maritime policy context increasingly reflects this transition. While earlier policy frameworks emphasized capacity expansion, connectivity, and operational efficiency, recent policies have linked port competitiveness with renewable energy, CHE electrification, cleaner fuels, and emissions reduction. The Maritime India Vision 2030 and the Draft Green Port Policy promote the use of renewable energy, the electrification of CHE, alternative-fuel readiness, and improvements in local air quality.

The Harit Sagar Guidelines provide a more operational decarbonization framework, including targets for at least 60% renewable electricity use at major ports by 2030, around 90% by 2047, and a 30% reduction in carbon dioxide emissions per tonne of cargo by 2030 (MoPSW 2023b). Additional measures further support this policy direction. The Green Tug Transition Programme establishes a phased pathway for green-tug deployment through 2040, while shore-to-ship power standards are intended to reduce vessel emissions at berth (MoPSW 2024; DGS 2025).

The Maritime Amrit Kaal Vision 2047 and the National Green Hydrogen Mission also support the development of low-carbon fuel infrastructure, including the potential emergence of port-based hydrogen facilities (MoPSW 2023a; MNRE 2023). Key interventions include the electrification of CHE, shore power, energy-efficient buildings, renewable electricity, energy storage, advanced energy management systems, and cleaner marine fuels such as liquefied natural gas and green hydrogen (Spiegelenberg 2025).

However, implementation remains uneven across ports, particularly in renewable-electricity uptake, equipment electrification, shore-power readiness, and alternative-fuel infrastructure. This unevenness highlights the need to assess India's maritime energy future through both trade-growth and port-operation lenses. Understanding how non-oil cargo growth interacts with major-port modernization and evolving policy priorities is therefore essential for identifying practical pathways to reduce energy demand and emissions while sustaining trade competitiveness and port performance.

Methodological Framework, Data, Assumptions, Scenarios, and Results

03

This section presents the methodological framework, data sources, assumptions, scenarios, and model specifications used to estimate future maritime energy demand and emissions associated with India's non-oil cargo and port cargo-handling equipment (CHE).

The analysis adopts a hybrid framework that combines an econometric non-oil cargo-forecasting shipping model with a bottom-up, activity-based CHE energy and emissions model. This structure is necessary because cargo demand is shaped by macroeconomic and trade drivers, whereas maritime energy demand depends on physical transport and operational characteristics, including commodity type, route distance, load factor, energy intensity, and CHE.

The methodology is structured into three sequential stages. First, a vector error correction model (VECM) is employed to generate a conditional baseline projection of aggregate dry bulk cargo throughput at India's major ports through 2050. Second, the projected cargo volumes are translated into cargo-handling activity by estimating the operational requirements of relevant CHE. Third, the associated energy demand and emissions are quantified separately for two distinct components of the maritime system: seaborne transport and port-based cargo-handling operations.

The SLE model estimates energy demand and emissions associated with moving non-oil cargo between India and its trading partners, while the PLE model estimates energy demand and emissions from bulk CHE at ports. This hybrid approach allows the study to combine the strengths of macroeconomic trade forecasting and bottom-up maritime energy modeling.

The VECM provides a transparent and reproducible baseline for future non-oil cargo growth, while the bottom-up component ensures that energy demand is not estimated solely on the basis of non-oil cargo shipping volume. Instead, the model links projected cargo to the physical characteristics of maritime transport and port operations. This is important because coal, iron ore, fertilizers, food grains, and other non-oil commodities require different handling systems.

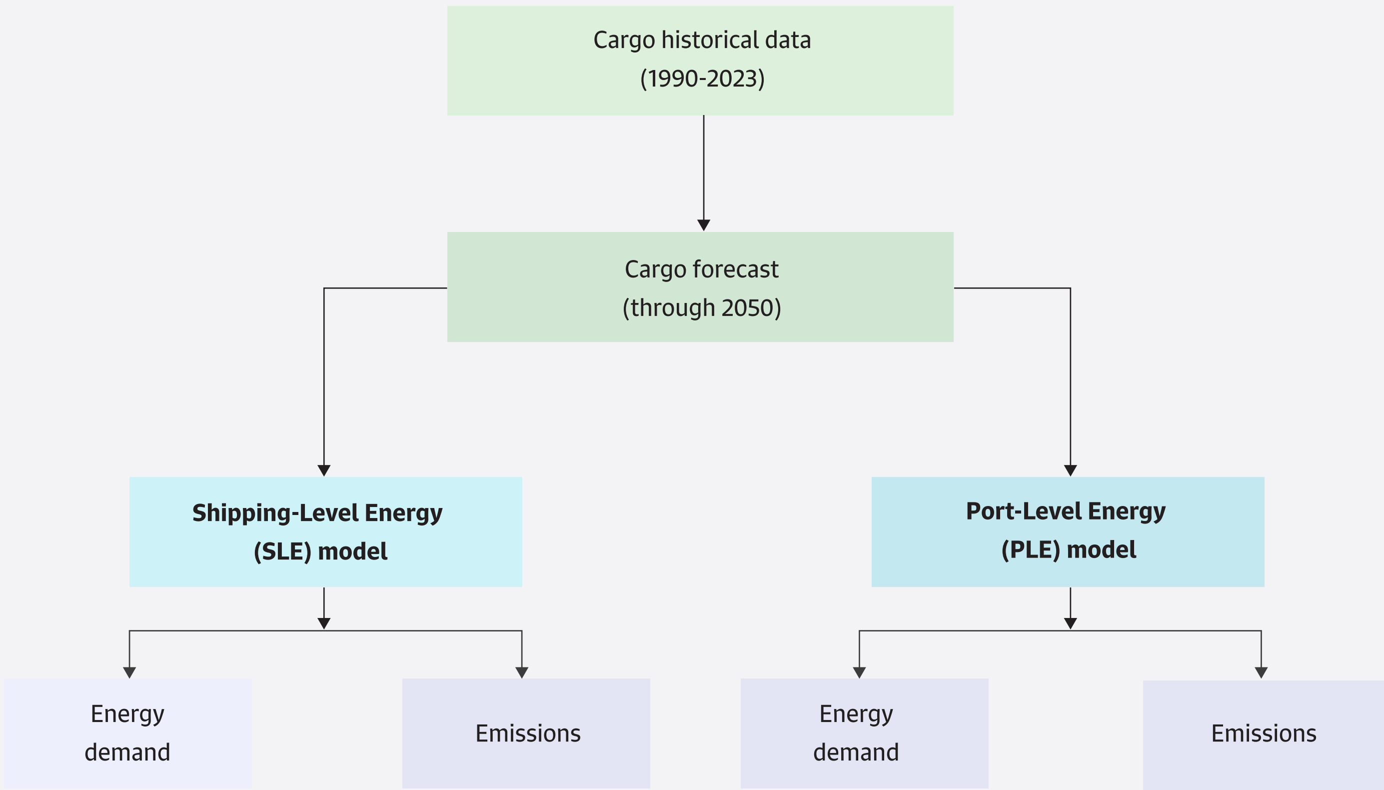
3.1 Methodological Framework

This study adopts a two-stage analytical framework to estimate the energy demand and emissions implications of India's non-oil maritime cargo trade and major port operations. The first stage develops a long-term forecast of non-oil cargo volumes using historical cargo data for 1990-2023. The second stage uses the projected cargo volumes to estimate energy demand and emissions from two segments of the maritime system: shipping activity and port cargo-handling operations. Figure 1 summarizes this analytical framework.

To forecast non-oil cargo volumes, the study applies a VECM within an inferential quantitative framework using secondary data. The VECM approach is suitable because it captures both short-run dynamics and long-run equilibrium relationships among the variables, following its application in the maritime trade literature (Michail 2020; Kim 2017; Tsioumas et al. 2017).

The model relates non-oil cargo handled at major ports to India's GDP per capita and the GDP of India's major trading partners. GDP per capita reflects India's domestic income and its impact on non-oil cargo demand, since higher per capita

Figure 1. Methodological steps for analysis.



Source: Authors.

income drives changes in consumption, industrial activity, and commodity demand. Conversely, the GDP of India's major trading partners indicates external economic activity and demand. Together, these variables represent complementary domestic and external demand channels that affect India's seaborne cargo volumes.

Accordingly, GDP is used as a proxy for economic activity, while cargo handled is used as a proxy for maritime trade, covering both import and export flows. Non-oil cargo data are drawn from the *Basic Port Statistics of India*, published by the Ministry of Ports, Shipping and Waterways, while GDP data are sourced from Oxford Economics (Oxford Economics 2025; MoPSW 2026a).

The study does not distinguish between international and domestic shipping. Instead, it focuses on total non-oil cargo handled at major ports, regardless of origin or destination. Non-oil cargo includes coal, iron ore, fertilizers, and other non-bulk categories.

The resulting non-oil cargo forecast provides the common activity basis for the two energy and emissions models. The SLE model estimates energy demand and emissions associated with India-related non-oil maritime trade, while the PLE model estimates energy use and emissions from bulk CHE at major ports.

In the PLE model, energy use and emissions are estimated for grab cranes (GCs) and wheel loaders (WLs). This study focuses on these two types of equipment because they are the primary diesel-powered CHE used in conventional bulk cargo terminals. Grab cranes handle ship-to-shore loading and unloading, whereas wheel loaders manage stockpiles and truck loading. Together, they account for most diesel-powered bulk cargo-handling activities.

The U.S. Environmental Protection Agency (EPA 2022) identifies cranes and loaders as core categories of CHE in port emissions inventories. It recommends prioritizing equipment types that are most frequently used or contribute most to emissions when detailed data for all equipment are unavailable. These two equipment types provide a representative and significant basis for estimating emissions from bulk cargo-handling operations while maintaining methodological transparency and data reliability.

Unlike conveyors, stackers, and reclaimers, which are often electrically powered in modern bulk terminals, grab cranes and wheel loaders are mainly diesel-powered. They therefore represent the primary focus for evaluating fuel consumption, electrification potential, and operational greenhouse gas emissions.

Together, the SLE and PLE models provide a structured perspective on the energy and emissions footprint of India's maritime sector, covering both shipping and port-level activities. This framework enables a scenario-based assessment of future sustainability pathways and supports the identification of practical strategies to reduce emissions while sustaining trade competitiveness and port performance.

3.2 Scenarios and Assumptions

This section outlines the scenarios and assumptions applied in both the SLE and PLE models.

3.2.1 Shipping-Level Energy (SLE) Model

The IMO has implemented energy-efficiency mandates, such as the Energy Efficiency Design Index (EEDI), to enhance energy efficiency across various ship types and reduce CO_2 emissions. These measures are projected to achieve at least a 30% reduction in CO_2 emissions by 2050 (IMO 2025).

In this paper, we employ energy intensity reduction as a strategy to improve efficiency. Achieving a cumulative 30% improvement between 2023 and 2050 necessitates an annual improvement rate of approximately 1%-1.5%. Accordingly, we assume a 1.5% annual improvement in energy intensity under the Energy Efficiency (EE) scenario and a 2% annual improvement under the Sustainable Development (SD) scenario, with the latter reflecting additional efficiency gains from the adoption of alternative fuels. The following discussion presents additional evidence supporting these assumptions.

Annual energy intensity improvement rates were derived from published literature to represent conservative, moderate, and ambitious decarbonization pathways. In the BAU scenario, energy intensity is projected to decline by 0.5% per year, which serves as a conservative lower bound for autonomous efficiency improvement and aligns with low-efficiency transport scenarios lacking additional mitigation measures (Tibesigwa et al. 2024; Lightfoot and Green 2001). The BAU scenario therefore assumes gradual energy efficiency improvements of 0.5% annually, attributable to routine fleet renewal, incremental technological advancements, and standard operational optimization, without the introduction of new decarbonization policies.

The EE scenario assumes a 1.5% annual reduction, consistent with modeling studies of efficiency improvements for new ships and within the 1%-2% annual carbon intensity improvement range reported in the *Fourth IMO GHG Study* (van Heerden et al. 2025; IMO 2020). An annual improvement of approximately 1.5% is thus considered to reflect the combined effects of mandatory IMO energy efficiency regulations (EEDI, EEXI, and CII) and operational measures such as voyage optimization, slow steaming, and engine enhancements.

The SD scenario adopts a 2% annual reduction, representing an ambitious pathway aligned with the increasingly stringent IMO operational carbon intensity framework and maritime decarbonization studies that project approximately 2% annual fleet efficiency improvements under strengthened policy measures (Fragkos 2022; IMO 2021). The SD scenario therefore assumes a 2% annual improvement in energy intensity, reflecting the accelerated adoption of energy-efficient technologies, low-carbon fuels, digitalization, electrification, and operational optimization. This value represents an ambitious yet plausible transition pathway consistent with international decarbonization scenarios.

Thus, we developed three scenarios for the SLE model, as summarized in Table 1.

Table 1. Scenarios and assumptions for the SLE model.

Scenarios	Assumptions	Development source
Business-as-Usual (BAU)	• Development growth is assumed to rely primarily on fossil fuels. • No substantial mitigation policies are incorporated. • A 0.5% annual improvement in routine energy efficiency is assumed through 2050.	Tibesigwa et al. 2024; Lightfoot and Green 2001
Energy Efficiency (EE)	• The scenario assumes compliance with IMO energy efficiency mandates such as EEDI. • An improvement of approximately 1.5% in energy intensity is assumed annually.	IEA 2021; IMO 2025; van Heerden et al. 2025
Sustainable Development (SD)	• The scenario represents a comprehensive pathway for deep decarbonization that combines energy efficiency measures with the adoption of alternative fuels • An improvement of approximately 2% in energy intensity is assumed annually.	Fragkos 2022; IMO 2021

India has not yet established a national target for the annual reduction of energy intensity in seaborne freight transport that diverges from the IMO framework. Therefore, this study uses energy intensity improvement assumptions consistent with internationally recognized maritime decarbonization literature and the IMO's mandatory energy efficiency measures, including the Energy Efficiency Existing Ship Index (EEXI), Carbon Intensity Indicator (CII), and Ship Energy Efficiency Management Plan (SEEMP), all adopted by India through the Directorate General of Shipping.

In addition to the International Energy Agency's (IEA) global average energy intensity assumptions, the proposed scenarios are contextualized using India's maritime decarbonization ambitions under the National Green Shipping Policy, which aims for a 30% reduction in carbon intensity by 2030 and a 70% reduction by 2047 (MoPSW 2023b). The selected annual energy intensity improvement rates represent conservative, moderate, and ambitious pathways aligned with both international regulatory requirements and India's long-term maritime decarbonization objectives.

Based on this discussion, we formulated energy intensity values through 2050 for the scenarios described earlier.

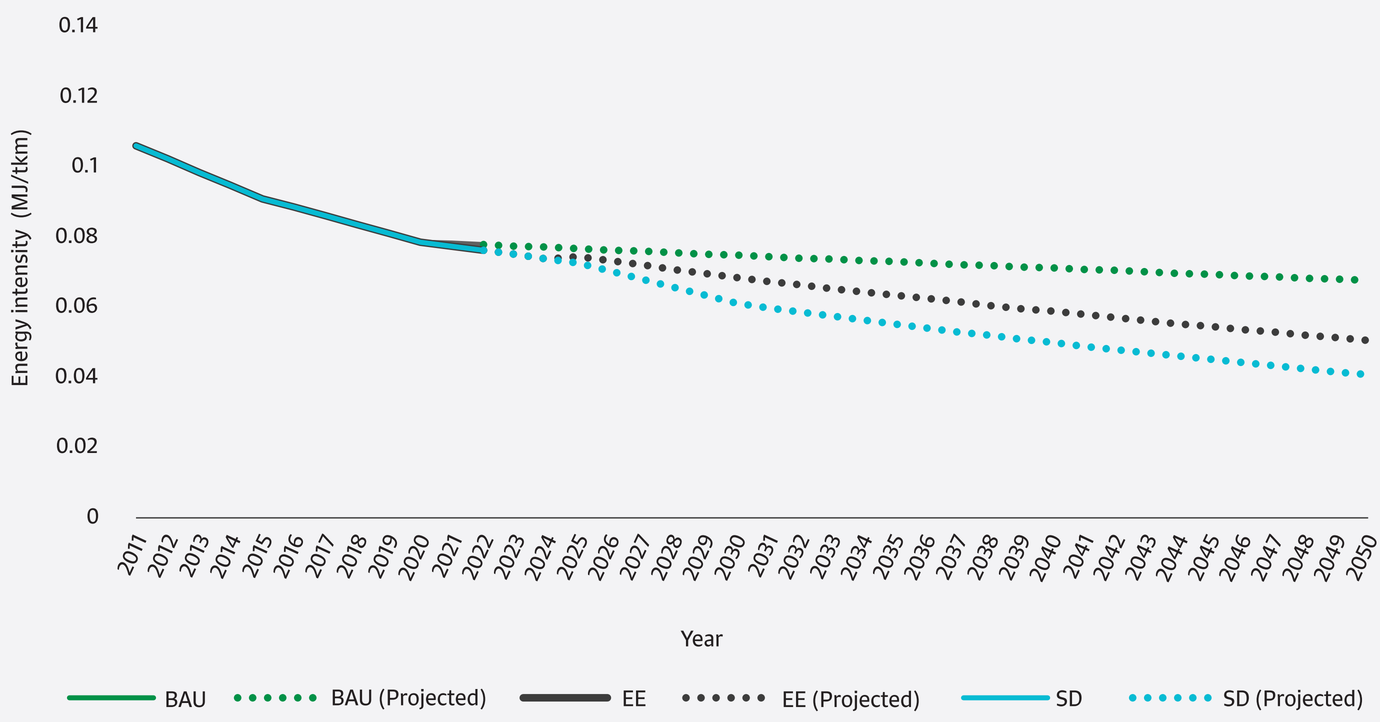
The projected decline in energy intensity beyond 2030, as illustrated in Figure 2, is based on an extrapolation of historical trends and serves as an exploratory scenario assumption rather than a definitive forecast of future technological progress. In practice, energy efficiency improvements may slow as technologies mature and opportunities for low-cost efficiency gains decrease. Therefore, the projected energy intensity pathways should be regarded as indicative scenarios that illustrate the potential impact of ongoing technological advancements on future maritime energy demand rather than as deterministic forecasts.

Under the SD scenario, energy intensity decreases from approximately 0.076 MJ/tkm in 2022 to 0.040 MJ/tkm in 2050. This represents an average compound annual improvement rate of approximately 2.2%, consistent with historical efficiency rates in the transport and maritime literature, such as the 2.6% traditional ocean cargo improvement rate identified by Benson et al. (2018).

Since India-specific data are unavailable, the plausibility of this trajectory was assessed by cross-referencing the projections with historical empirical benchmarks and international targets. According to the IEA (2021), energy intensity is projected to improve by 13% and 22% between 2020 and 2030 under its EE and SD scenarios, respectively. Applying a conservative 2% compound annual rate over the 28-year period from 2023 to 2050 results in a 42% cumulative improvement.[1] This closely aligns with the projected 47% reduction from the 2022 baseline, indicating that the extrapolated trend is supported by both historical evidence and established energy transition pathways.

1 Cumulative improvement = 1 – (1 – *r*)^*n*, where r represents the compound annual improvement rate, and *n* is the projection horizon in years.

Figure 2. Energy intensity from 2011 to 2050 for international shipping.



Source: IEA (2021) and Anwar et al. (2024).

Energy demand for India-related seaborne trade is estimated using two principal inputs: average shipping energy intensity and a representative sailing distance. The model adopts the global mean energy intensity reported in Figure 2 and applies a weighted mean export distance of 4,100 nautical miles to approximate typical India-partner routes.

The model assumes a constant average sailing distance of 4,100 nautical miles to represent India's aggregate seaborne freight system rather than individual trade routes. This study specifically examines the impacts of cargo demand growth and energy efficiency improvements on maritime energy demand and emissions while intentionally excluding the effects of geopolitical disruptions and structural changes in global trade geography.

In practice, average sailing distances may increase due to rerouting around geopolitical hotspots such as the Red Sea or the Black Sea, or may change as a result of nearshoring, regional trade agreements, supply chain restructuring, and shifts in trading partners (UNCTAD 2024). Projecting such changes over a long-term horizon (2023-2050) would require additional assumptions about future geopolitical conditions, trade patterns, and route selection, thereby introducing substantial uncertainty beyond the scope of this analysis. Consequently, the average sailing distance is treated as an exogenous parameter and held constant to isolate the effects of cargo growth, technological progress, and decarbonization measures.

3.2.2 Port-Level Energy (PLE) Model

Table 2 presents the scenarios and assumptions used in the PLE model to assess future energy demand and emissions from bulk CHE. Four scenarios are developed to capture varying levels of technological transition.

The BAU scenario assumes no automation or electrification, with operations continuing under current practices. The Automation scenario envisions complete automation, with 100% automation of grab cranes (GCs) and wheel loaders (WLs) achieved by 2050, thereby eliminating manual operations. The 100% automation scenario serves as an exploratory technology pathway rather than current commercial practice and is aligned with state-of-the-art heavy machinery and maritime literature.

Table 2. Scenarios and assumptions for the PLE model.

Scenarios	Assumptions
BAU	No automation or electrification measures are adopted; operations continue under current practices.
Automation	Full automation is implemented, with 100% automation of grab cranes (GCs) and wheel loaders (WLs) by 2050.
Electrification	Progressive electrification is implemented, with 50% of equipment electrified by 2030, increasing to 90% by 2050 (MoPSW 2023b).
Combined	Both measures are integrated, with full automation and progressive electrification.

Existing research demonstrates that automated crane control, optimized autonomous wheel loader performance, and intelligent bulk terminal frameworks can significantly improve operational efficiency and reduce energy demand. Consequently, fully autonomous cargo handling is recognized as a viable long-term objective as remaining technical barriers are resolved (Ngo et al. 2024; Dadhich 2018).

Furthermore, leading facilities such as Rotterdam World Gateway and APM Terminals Maasvlakte II demonstrate that near-complete process automation is technically feasible. Rather than reflecting immediate commercial deployment, this scenario outlines a clear multidecadal technological trajectory to evaluate the theoretical upper-bound potential for energy and emissions reductions achievable through complete equipment automation.

The Electrification scenario models a progressive shift toward electrification, with 50% of CHE electrified by 2030 and 90% by 2050. Finally, the Combined scenario integrates both measures, applying full automation alongside progressive electrification. These scenarios provide a structured framework for analyzing how alternative technological pathways can reduce port-level energy consumption and emissions, thereby supporting long-term sustainability goals in India's maritime sector.

For the Automation scenario, the analysis employs the following assumption. In line with ABB guidance, automating 33% of CHE reduces handling time by 17%, whereas full automation reduces it by 50% (ITF 2021). Fuel use per tonne is set at 0.012 liters for GCs and 0.04 liters for WLs, with corresponding electricity requirements of 0.10 kWh and 0.30 kWh per tonne, respectively (Uzun et al. 2024; Ligteringen 2022; Caterpillar 2022; EIA 2026).

Life-cycle CO_2 emissions from fuel are calculated using an emission factor of 3.532 kg CO_2 per liter of diesel and 0.72 kg CO_2 per kWh of electricity produced (Geerlings and Duin 2011; ecoinvent 2024; Central Electricity Authority 2023).

3.3 Data

This analysis draws on non-oil cargo volume data for Indian ports from 1990 to 2023, obtained from the MoPSW Basic Port Statistics of India 2024-25 (MoPSW 2026a), for both the SLE and PLE models. To capture the economic drivers of trade, we incorporated India's GDP per capita and the GDPs of its top seven trading partners, sourced from Oxford Economics (Oxford Economics 2025). These countries collectively account for more than 75% of India's total trade, making them critical to understanding trade-linked energy demand and emissions.

By combining port activity with macroeconomic indicators, the analysis establishes a robust basis for modeling future shipping and port-related energy requirements through 2050. In this context, the relationship between GDP and seaborne trade is empirically robust in the long run, supporting its use in forecasting trade flows. Empirical studies demonstrate a strong correlation and cointegration between the two variables, confirming GDP as a key driver of maritime demand, although variations exist across cargo types and regions (Michail 2020; Anwar et al. 2024).

3.4 Econometrics Model Specifications

The specification for the model follows the general form:

$$C_t = f(P_t, T_t, D_t) \quad (1)$$

where *C* represents the volume of non-oil cargo handled, *P* represents the GDP per capita of India, and *T* represents the GDP of India’s top seven[2] trading partners, t represents time, *D* represents a dummy variable that captures systemic shocks in exports.

The series were transformed into their natural logarithmic form in order to directly estimate elasticities, as expressed by:

$$ln(cargo) = \alpha_0 + \alpha_1 \ln(gdpp) + \alpha_2 \ln(gdpt) + \alpha_3(dumm) + \mu \quad (2)$$

where *ln* denotes the natural logarithm; GDP is used as a proxy for economic growth; cargo represents shipping trade; and μ is the error term. The variable *gdpp* denotes India’s GDP per capita; *gdpt* denotes the combined GDP of India’s top seven trading partners; and dummy denotes a *dummy* variable capturing systemic shocks.

Following the identification of one or more cointegrating equations, the VECM is constructed in its general representation as:

$$\Delta C_t = \alpha_0 + \lambda_{ECT_{t-1}} + \alpha_1 \Delta C_{t-1} + \alpha_2 \Delta P_{t-1} + \alpha_3 \Delta T_{t-1} + \alpha_4 \Delta D_{t-1} + \mu_t \quad (3)$$

where Δ denotes the first difference operator; λ represents the speed of adjustment parameter associated with the error correction term (ECT); and ECT captures deviations from the long run equilibrium. The coefficients α^1, α^2, α^3, and α^4 capture the system's short-run dynamics, while *C*, *P*, and *T* denote the study variables; μ^t represents the residual term; and α^0 is the intercept.

Accordingly, the VECM specified for this study accounts for both short-run adjustments and long-run equilibrium relationships among the cointegrating equations, and is expressed as:

$$\Delta \ln (cargo)_t = \delta_1 + \alpha_1 \Delta\, ln(cargo)_{t-1} + \alpha_2 \Delta \ln(gdpp)_{t-1} + \alpha_3 \Delta \ln(gdpt)_{t-1} + \lambda_1 ect_{t-1} + \mu_{t1} \quad (4)$$

$$\Delta \ln (gdpp)_t = \delta_2 + \alpha_1 \Delta\, ln(cargo)_{t-1} + \alpha_2 \Delta \ln(gdpp)_{t-1} + \alpha_3 \Delta \ln(gdpt)_{t-1} + \lambda_2 ect_{t-1} + \mu_{t2} \quad (5)$$

$$\Delta \ln (gdpt)_t = \delta_3 + \alpha_1 \Delta\, ln(cargo)_{t-1} + \alpha_2 \Delta \ln(gdpp)_{t-1} + \alpha_3 \Delta \ln(gdpt)_{t-1} + \lambda_3 ect_{t-1} + \mu_{t3} \quad (6)$$

These equations are used to forecast the volume of non-oil cargo traded and handled. Based on the forecast, we estimate the energy demand and emissions associated with projected non-oil cargo traded and handled by equipment as functions of cargo throughput. Using projected volumes of India’s seaborne trade through 2050, we then calculate the future fuel consumption of CHE required to handle this trade, along with the corresponding emissions from that energy use. Detailed VECM results and tests are provided in the Appendix.

The 2050 projection generated by the VECM should be interpreted as a conditional baseline forecast, contingent on the continued validity of the historical long-run relationship between GDP and cargo tonnage throughout the projection period. It also provides a parsimonious and reproducible benchmark for evaluating the potential impact of GDP-driven growth in trade on future maritime energy demand.

2 China, Russia, UAE, U.S., Saudi Arabia, the Netherlands, and Singapore.

Results

04

This section presents the results of the integrated modeling framework. It begins with the cargo forecast, followed by an analysis of energy demand and emissions for both the SLE and PLE models. The findings provide a comprehensive view of how projected cargo volumes influence energy consumption and environmental impacts across the different modeling scenarios.

4.1 Current and Future Non-oil Cargo Volume

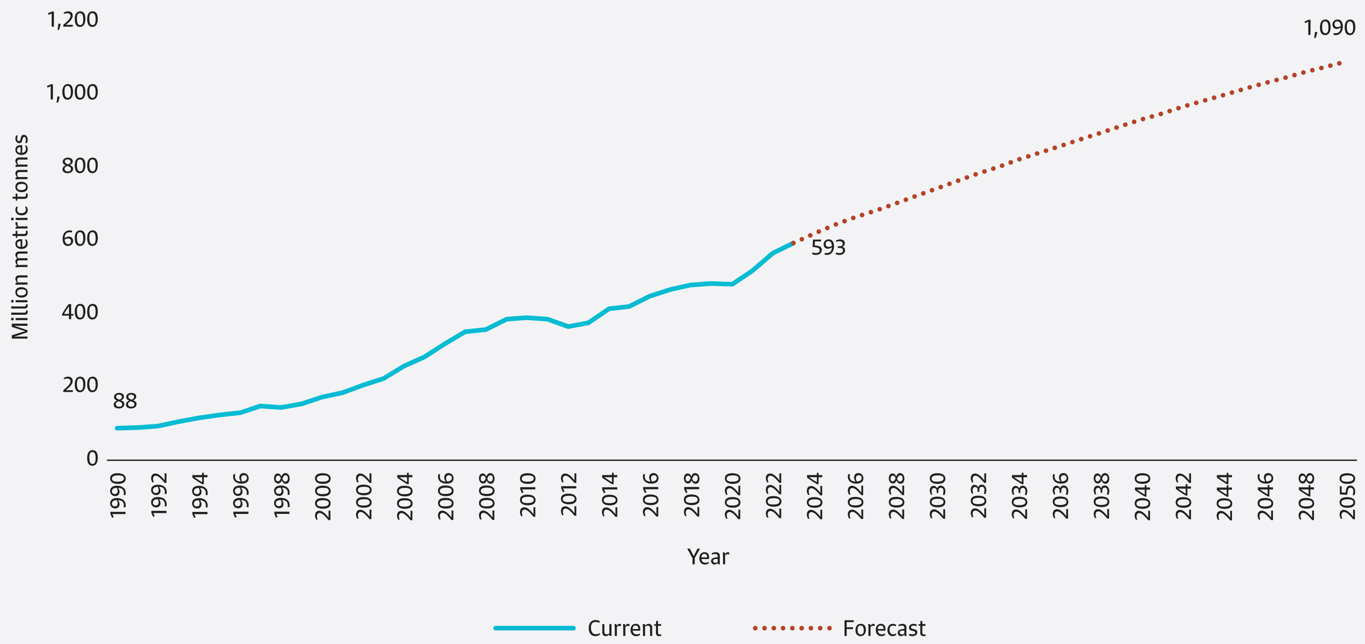
Over the past three decades, India's major ports have undergone a significant transformation, with non-oil cargo increasing from 88 mmt in 1990 to approximately 593 mmt in 2023, a 6.7-fold expansion that translates to an average compound annual growth rate of nearly 6.0%. The path has been uneven, with strong gains through the mid-2000s, a soft patch from 2011 to 2013, a renewed climb through 2019, a brief dip from 2020 to 2021, and a rapid rebound to the 2023 peak. On average, the historical period added about 15 mmt per year.

Looking ahead, modeled throughput is expected to reach approximately 1.09 billion metric tonnes by 2050 (see Figure 3). This implies an 84% increase over 2023, an average annual addition of approximately 18 mmt, and a slower compound annual growth rate of around 2.3% compared with the historical period. The 2050 projection is derived from the VECM long-run equilibrium forecast using the macroeconomic variables and cargo relationships described above.

The deceleration is consistent with a maturing system in which growth comes from incremental capacity, efficiency improvements, and deeper trade integration rather than rapid scale-up. For policy and planning, a higher absolute cargo base combined with moderate growth carries two clear implications. First, substantial annual additions will continue to put pressure on berth capacity, yard space, and hinterland connectivity. Second, if efficiency does not improve, higher cargo volumes will result in greater energy consumption and emissions.

Addressing these efficiency gaps is therefore essential to keeping emissions in check. Meeting national port decarbonization goals will require sustained gains in cargo-handling efficiency, wider adoption of shore power, electrification of equipment such as grab cranes and wheel loaders, and a progressively cleaner electricity mix over the forecast horizon.

Figure 3. Cargo handled at major ports (non-oil commodities), FY 1990-2050.



Source: Authors' analysis.

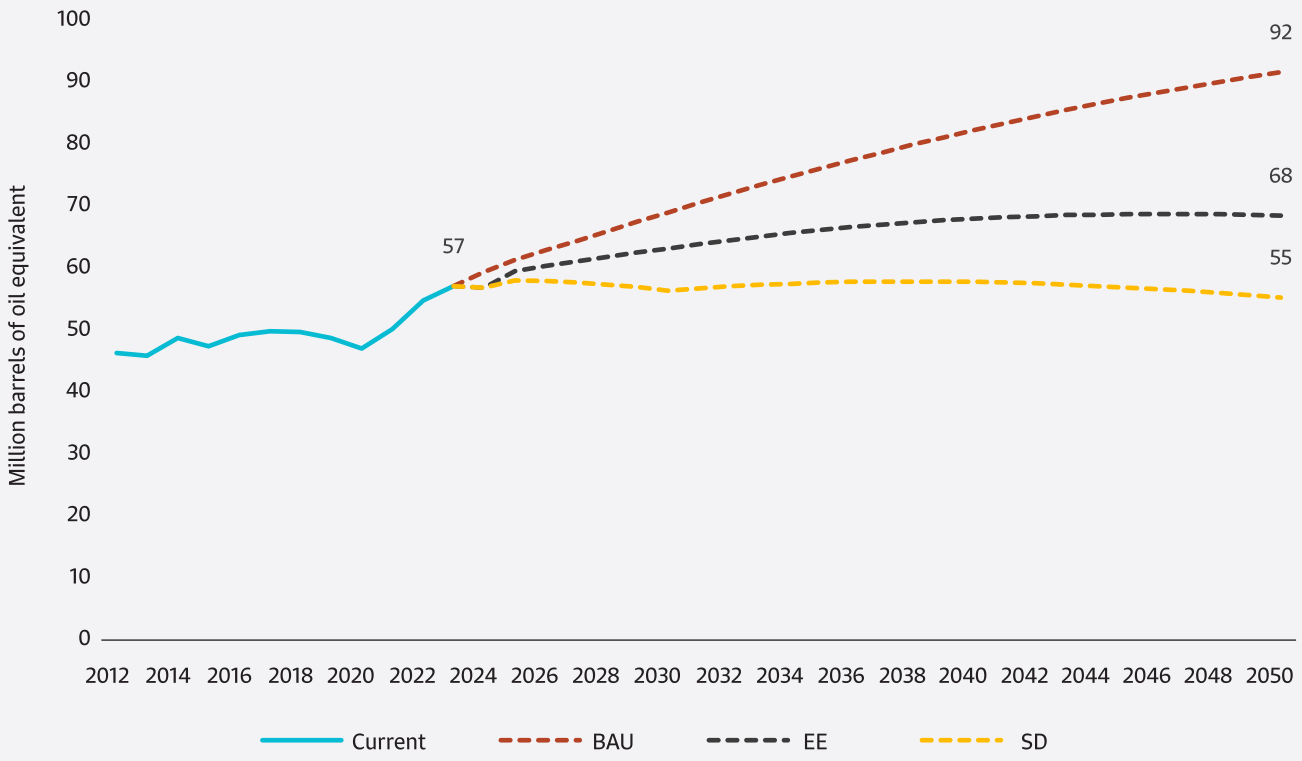
4.2 Shipping-Level Energy Model

This section presents the energy demand (tank-to-wake) for cargo transport between India and its trading partners in both directions (inbound and outbound). It also estimates the associated emissions, providing insights into the environmental impacts of trade-related non-oil cargo movements and highlighting patterns in energy consumption.

4.2.1 Energy Demand

This section examines energy consumption and emissions associated with trade-related activities, including the import and export of non-oil cargo.

Figure 4. Energy demand related to India's maritime trade (non-oil cargo shipping, both import and export), 2012-2050.



Source: Authors' analysis.

India-related seaborne trade has been expanding, and energy demand reflects this pattern. It hovered around 45-50 mboe during 2012-2021, dipped in 2020, and then rebounded to roughly 57 mboe in 2023.

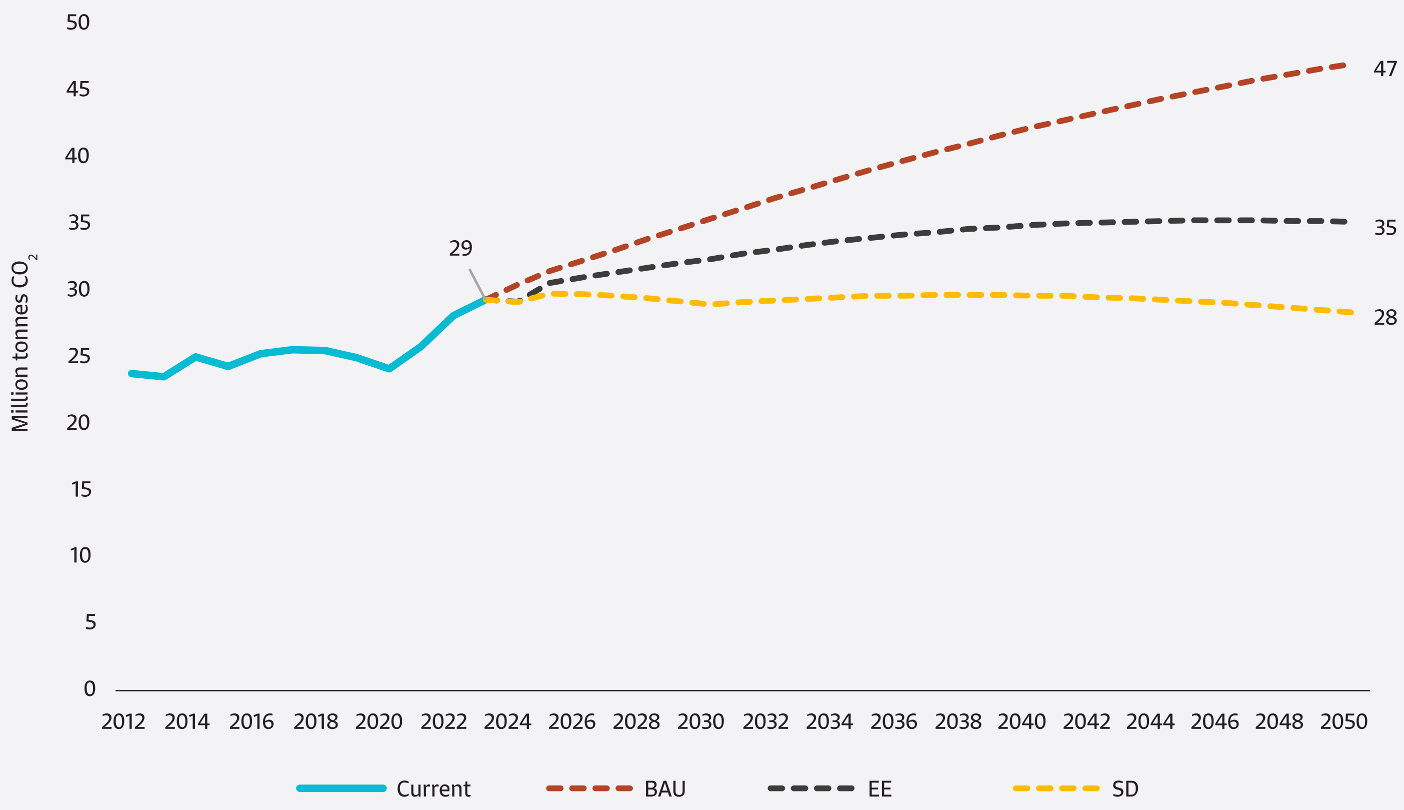
From this baseline, the outlook varies across scenarios. The BAU scenario would steadily increase demand to approximately 92 mboe by 2050, representing an increase of roughly 35 mboe, or 61%, over 2023 levels and implying an average annual growth rate of nearly 1.8%. The EE scenario moderates this rise, reaching approximately 68 mboe by 2050, about 11 mboe, or 19%, above 2023 levels. This corresponds to approximately 0.6% per year and reflects systematic technical and operational savings, excluding fuel switching.

The SD scenario keeps demand near current levels through the 2030s and then lowers it slightly to around 55 mboe by 2050, representing a reduction of about 3%-4% relative to 2023, or roughly 0.1% per year (Figure 4). In short, unchecked trade growth drives materially higher energy use, targeted efficiency largely decouples demand from trade, and a stronger package that includes deeper operational measures and speed management achieves absolute reductions by midcentury.

4.2.2 Estimated Emissions

Subsequently, as illustrated in Figure 5, India-related shipping emissions from non-oil seaborne cargo are projected under three scenarios through 2050.

Figure 5. Emissions reduction related to maritime trade (cargo shipping, both import and export), 2012-2050.



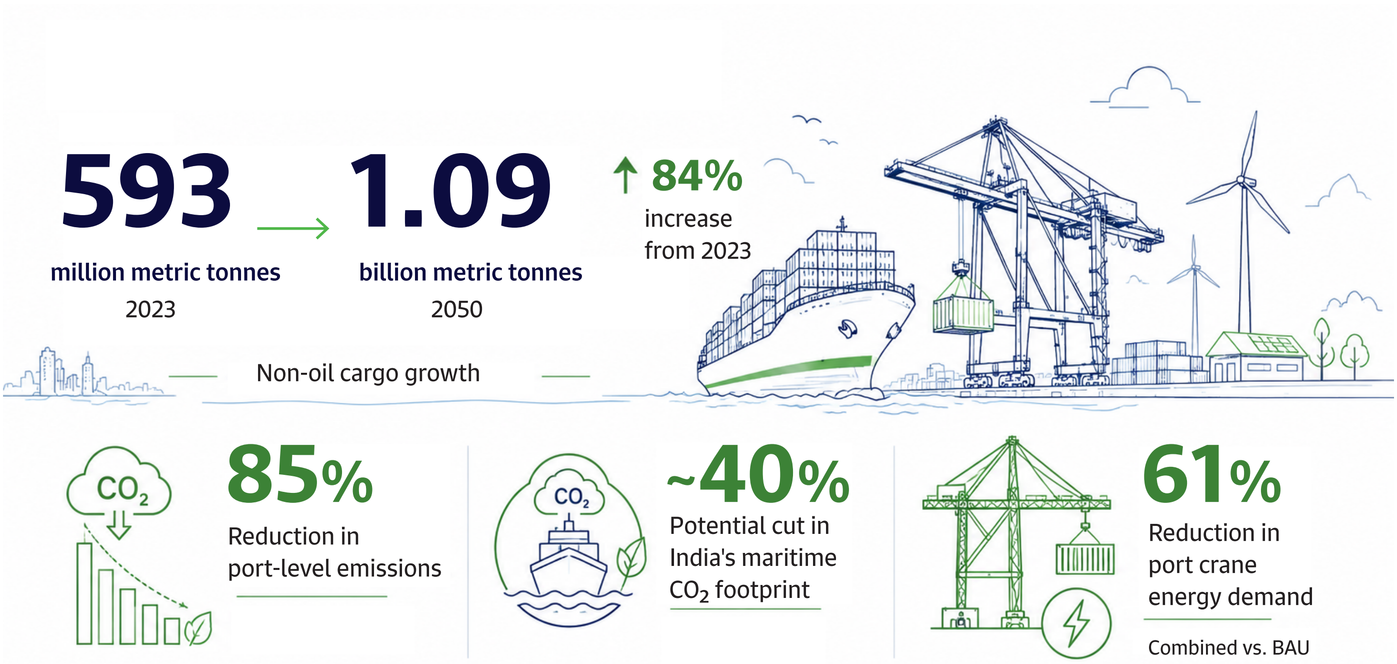
Source: Authors' analysis.

Historical emissions remained broadly stable from 2012 to 2021, dipping briefly in 2020, likely due to COVID-19, and then recovering to the high 20s by 2023.

Under the BAU scenario, emissions rise steadily to approximately 47 million tonnes of CO_2 ($MtCO_2$) by 2050, representing an increase of roughly 60% over 2023 levels, reflecting growth in tonne-kilometers and unchanged operating practices. The EE scenario moderates this growth, with emissions reaching about 35 $MtCO_2$ by 2050, approximately 25% below BAU but still around 20% above 2023 levels. This indicates that efficiency improvements alone slow rather than reverse the upward trend.

The SD scenario delivers a flat-to-declining emissions profile, ending near 28 $MtCO_2$ in 2050, about 40% below BAU and slightly below 2023 levels. This suggests that stronger operational measures combined with technological improvements can offset trade-driven increases.

Taken together, the results show that efficiency improvements decouple CO_2-eq emissions from activity, while a comprehensive package of measures is required to achieve absolute reductions by midcentury. However, decarbonization trajectories will depend on the pace of technology diffusion across vessel classes, the adoption of slow steaming and other operational practices, the availability of cleaner fuels and bunkering infrastructure, and logistics choices that influence routing distances and load factors (Trosvik and Brynolf 2024; van Leeuwen and Monios 2022; Bouman et al. 2017; Brynolf et al. 2014).



4.3 Port-Level Energy Model

This section examines the energy demand of non-oil CHE at Indian ports based on non-oil cargo volume. It also quantifies the resulting emissions, providing insights into the environmental impacts of CHE operations and revealing trends and patterns in energy consumption.

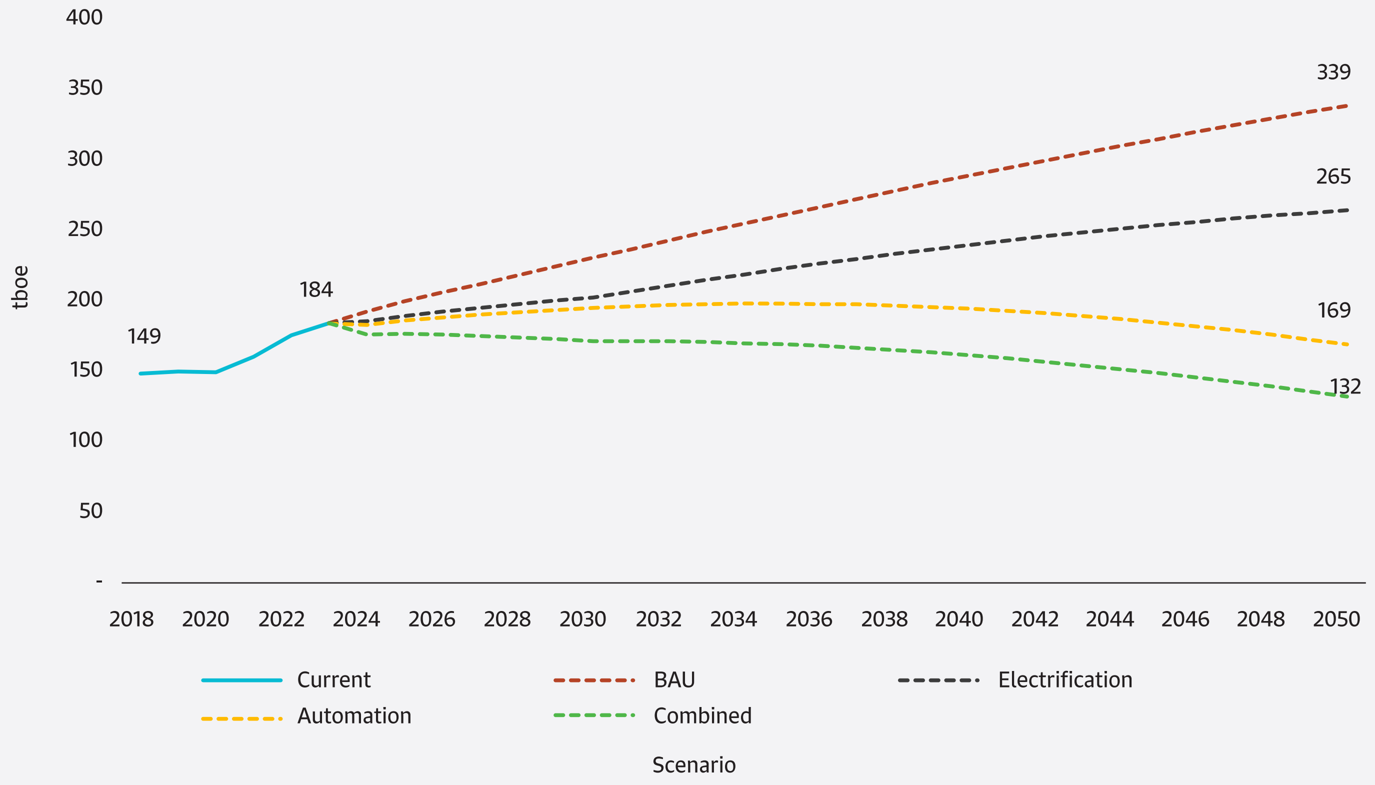
4.3.1 Energy Demand

Fuel use by grab cranes and wheel loaders increased from about 149 tboe in 2018 to roughly 184 tboe in 2023, in line with rising cargo volumes. Under the BAU scenario, demand would grow to approximately 339 tboe by 2050, representing an increase of 80%-85% over 2023 levels.

The mitigation scenarios substantially alter this trajectory. Automation stabilizes consumption at approximately 169 tboe by 2050, about 50% below BAU, while electrification reduces demand to approximately 265 tboe, roughly 21% below BAU. A combined automation and electrification scenario delivers the largest reduction, lowering demand to about 132 tboe by 2050, nearly 61% below BAU and 28% below 2023 levels (see Figure 6).

Automation is the primary driver of absolute energy savings, while electrification improves efficiency and moderates growth. Achieving the combined outcome depends on timely equipment replacement, widespread adoption of electric drives, reliable shore power and charging infrastructure, and continued reductions in grid emissions intensity.

Figure 6. Fuel consumption from cargo handled at major ports (bulk cargo).



Source: Authors' analysis.

4.3.2 Estimated Emissions

CO_2 emissions from grab cranes and wheel loaders at India's major ports increased with throughput, rising from about 88 kilotonnes (kt) in 2018 to nearly 109 kt in 2023. Figure 7 shows that under the BAU scenario, emissions rise steadily from about 109 $ktCO_2$ in 2023 to 200 $ktCO_2$ by 2050, reflecting growth in cargo throughput without technological changes.

Electrification substantially reduces emissions to 48 $ktCO_2$ by 2050, while automation alone reduces emissions to 100 $ktCO_2$ by improving operational efficiency without eliminating fossil fuel use. The Combined scenario achieves the greatest mitigation, lowering emissions to 24 $ktCO_2$ by 2050.

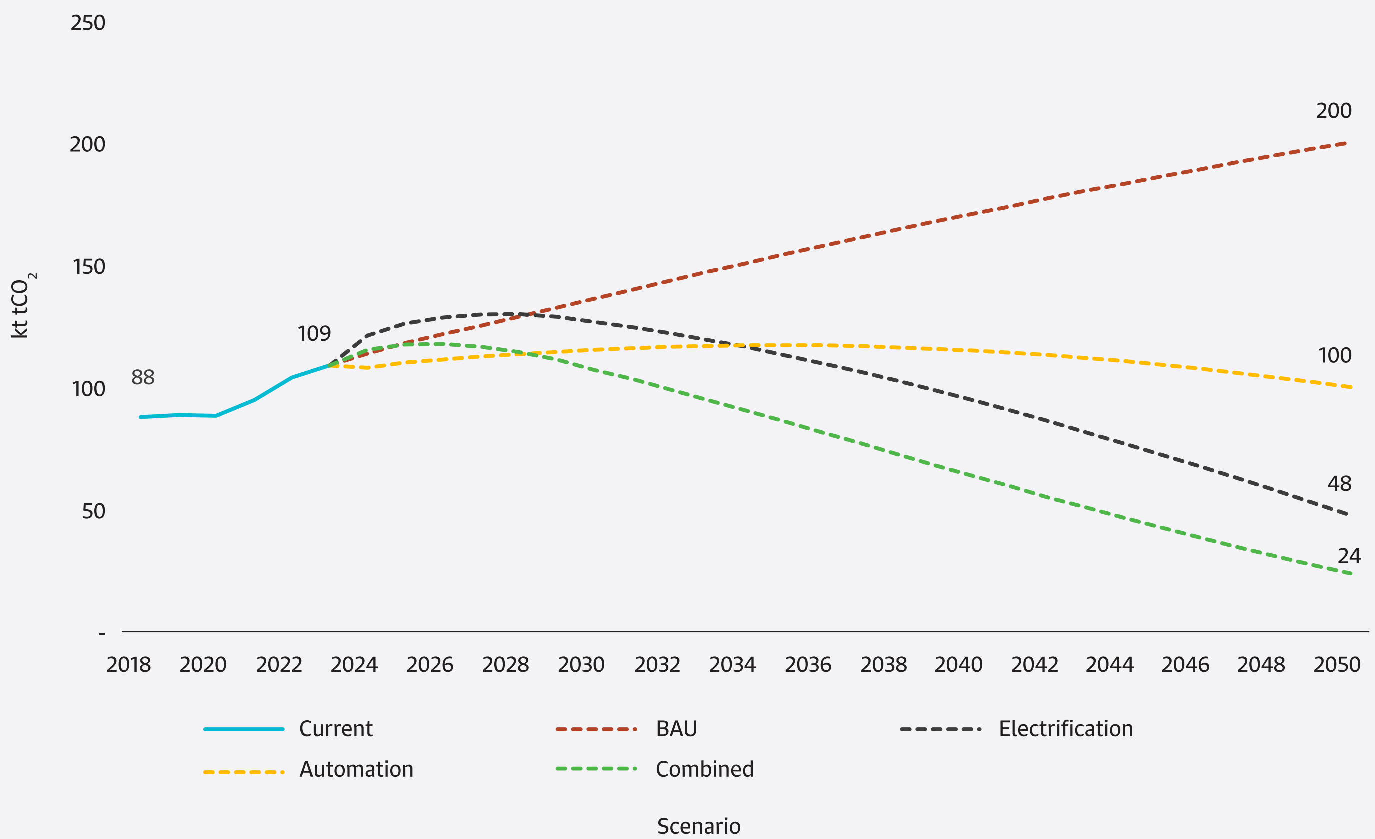
The overlap among scenarios during 2023-2028 reflects gradual technology implementation and limited short-term benefits before adoption reaches a critical scale. As technology penetration accelerates, the scenarios diverge, highlighting the cumulative long-term benefits of electrification and automation.

> "The Combined scenario achieves the greatest mitigation, lowering emissions to 24 $ktCO_2$ by 2050.

Around 2028, the Electrification and BAU trajectories intersect, signaling delayed mitigation benefits, likely due to high upfront infrastructure requirements or a carbon-intensive power grid that gradually shifts toward renewables. By 2034, the Electrification trajectory crosses the Automation trajectory, showing that while automation provides immediate but limited efficiency gains, with emissions reaching 100 ktCO_2 by 2050, electrification delivers greater long-term decarbonization, with emissions reaching 48 ktCO_2.

The results from the two models show a clear pattern: As trade and port activity grow, energy use and emissions also increase under the BAU scenario. Targeted measures, such as electrifying port equipment and improving ship efficiency, can significantly reduce energy use and emissions. When combined, these measures could deliver the greatest reductions by 2050, allowing maritime activity to grow without a corresponding increase in energy use and emissions.

Figure 7. Emissions reduction potential in cargo handled at major ports (non-oil commodities).



Source: Authors' analysis.

Limitations

05

The findings presented should be regarded as indicative baseline estimates rather than precise operational measurements or long-term forecasts because of several data limitations and simplified structural assumptions.

The analytical framework is limited by the granularity of available maritime and port-level data. Specifically, detailed information on individual port oil throughput, domestic fleet movements, inter-port cargo flows, ship arrival and departure logs, and comprehensive CHE profiles was not available.

Given these data gaps and incomplete 2024 port datasets at the time of analysis, a bounded, throughput-based approach was adopted to isolate the relationship between trade growth and energy demand. The scope of port operations is limited to grab cranes and wheel loaders handling non-oil cargo, which accounted for approximately 72% of India's total trade in 2023. Comparable data for the remaining 28% of oil-handling infrastructure were insufficient.

To operationalize the exploratory framework, several parameters were established using proxy data and historical trends, including liters per tonne handled, emission factors, global export distances, and post-2030 energy intensity pathways from the IEA.

The shipping-level and port-level energy models operate independently and nonsequentially, representing distinct segments of the maritime supply chain. As a result, this study does not provide a comprehensive structural model that incorporates behavioral responses, technological transitions, modal shifts, or broader system-level feedback mechanisms.

Future research should refine these indicative pathways by integrating higher-quality, consistent datasets, expanding CHE coverage, and incorporating dynamic structural feedback as more granular data become available.

06 Conclusion

This study establishes a robust baseline for the potential evolution of India's maritime energy system under scenarios of increasing trade activity and alternative decarbonization pathways. The primary insight from the SLE and PLE models is that continued growth in cargo throughput does not necessarily require proportional increases in energy demand and emissions.

The results indicate that targeted efficiency improvements, electrification, and operational enhancements can partially or substantially decouple maritime emissions from trade expansion. Notably, the most actionable findings for policymakers are the significant mitigation effects of port electrification and the Combined scenario, which integrates automation and electrification and reduces port-level emissions by more than 85% relative to BAU projections by 2050.

> "Continued growth in cargo throughput does not necessarily require proportional increases in energy demand and emissions.

At the shipping level, the SD scenario maintains emissions near current levels despite substantial increases in cargo volumes, underscoring the importance of integrating operational measures, cleaner fuels, and vessel efficiency strategies. The model indicates that, under BAU conditions, increasing trade volumes, expanding port activity, and continued reliance on fossil fuel technologies will drive both shipping and port emissions upward through 2050. In contrast, the alternative scenarios demonstrate that India has significant decarbonization potential if infrastructure modernization and energy transition policies are accelerated.

Electrification is identified as the primary driver of long-term emissions reductions because it directly reduces reliance on diesel-powered CHE. Automation provides additional emissions savings through enhanced operational efficiency. However, the effectiveness of electrification depends heavily on the decarbonization of India's electricity grid. Without cleaner grid electricity, a portion of the emissions burden is transferred upstream rather than eliminated. Therefore, maritime decarbonization should be integrated into a broader national energy transition strategy that includes expanding renewable electricity, developing green hydrogen, and planning for low-carbon industrial development.

Future research should extend the analytical framework in several directions. First, subsequent models should incorporate well-to-wake emissions rather than only tank-to-wake accounting to more accurately capture the life-cycle impacts of alternative fuels. Second, dynamic electricity grid decarbonization scenarios should be integrated into the PLE model to enhance the realism of electrification outcomes. These analytical extensions would yield more policy-relevant insights into India's transition toward a low-carbon maritime economy.

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Appendix

The vector error correction model (VECM) is employed to analyze the short- and long-term relationships between India's shipping trade and economic growth. This modeling approach accommodates series with different orders of integration, providing flexibility in the analysis.

Unit Root Tests

The study employs the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to examine the stationarity of the data. The results, presented in Table A1, indicate that none of the variables are stationary at their levels; however, all become stationary after first differencing (I(1)). Since the variables are integrated of the same order, they are suitable for cointegration analysis to explore both short- and long-term relationships.

Table A1. Unit root test at level.

Variables	At level				At first difference				Integration order
	ADF		PP		ADF		PP		
	Test statistics	*p* value	Test statistics	*p* value	Test statistics	*p* value	Test statistics	*p* value	
ln(cargo)	1.991	0.2904	1.712	0.4250	2.807	0.0573	4.312	0.0004	I(1)
ln(gdpp)	0.229	0.9350	0.378	0.9807	5.019	0.0000	4.715	0.0001	I(1)
ln(gdpt)	0.703	0.8460	0.472	0.8973	5.188	0.0000	5.382	0.0000	I(1)

Lag Length Selection

Before conducting the cointegration test, it is necessary to determine the appropriate lag length for both the cointegration analysis and model estimation. Table A2 indicates that the optimal lag length for the unrestricted VAR model is two, as suggested by the major information criteria. Specifically, the study relies on the Akaike information criterion (AIC), which recommends two lags for constructing the VECM. Similarly, both the likelihood ratio (LR) test and the final prediction error (FPE) criterion suggest two lags.

All lag selection criteria are statistically significant at $p = 0.000$. Consequently, a lag length of two is adopted for the Johansen cointegration test and the VECM, confirming it as the optimal choice.

Table A2. Lag order selection criteria results.

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	35.3827				0.000023	2.15885	2.11402	2.01873
1	174.558	278.35	9	0.000	4.00E 09	10.8372	10.6579*	10.2767*
2	185.549	21.983*	9	0.009	3.5e 09*	10.97*	10.6562	9.98911
3	190.67	10.241	9	0.331	4.80E 09	10.7113	10.2631	9.31011
4	195.656	9.9736	9	0.353	7.00E 09	10.4438	9.86103	8.6222

Cointegration Test

After establishing that all variables are stationary at I(1), the next step is to examine the presence of cointegration among them. A cointegrating relationship exists between cargo volume and economic growth, indicating that these variables share a common trend and are in long-run equilibrium.

The study employs the Johansen cointegration test to identify the number of cointegrating equations within the model. As shown in Table A3, the results reveal at least one cointegrating equation, highlighting the long-term relationship between shipping trade and economic growth in India. This finding suggests that shipping trade exerts both short- and long-term effects on economic growth. Specifically, the trace statistic of 13.1744 is below the 5% critical value of 15.41 at rank 1, confirming the existence of at least one cointegrating equation in the model.

Table A3. Johansen co-integration test.

Maximum rank	Parms	LL	Eigenvalue	Trace		Max	
				Statistics	5% critical value	Statistics	5% critical value
0	12	174.21242		32.2315	29.68	19.0570	20.97
1	17	183.74094	0.44873	13.1744*	15.41	10.6843	14.07
2	20	189.08307	0.28386	2.4902	3.76	2.4902	3.76
3	21	190.32815	0.07487				

*At least one cointegrating equation in the model.

VECM Modeling Results

The results in Table A3 confirm the presence of at least one cointegrating equation in the system, indicating that the series are suitable for applying the VEC model to analyze both short- and long-run causality between shipping trade and economic growth in India.

Table A4 further demonstrates significant correlations among the variables, with R-squared values of 0.8175 for ln(cargo), 0.6167 for ln(gdpp), and 0.7985 for ln(gdpt). These findings suggest a strong positive relationship between shipping trade and economic growth in India.

Table A4. VECM results.

Equation	Parms	RMSE	R sq	chi2	P>chi2
D_ln(cargo)	7	0.0368	0.8175	107.5095	0
D_ln(gdpp)	7	0.069868	0.6167	38.62217	0
D_ln(gdpt)	7	0.035327	0.7985	95.13023	0
D_dum	7	0.17101	0.2689	8.826849	0.2653

The intervention dummy is statistically insignificant. Nevertheless, this variable was incorporated to account for extraordinary export shocks during 2021-2023, specifically the COVID-19 pandemic recovery and subsequent geopolitical disturbances such as the Russia-Ukraine war, rather than to test a behavioral relationship. Its inclusion enhances the overall specification of the VECM, as demonstrated by satisfactory diagnostic tests and stable model performance.

The lack of statistical significance suggests that the long-run effects of these shocks are primarily captured by the model's macroeconomic variables and dynamic adjustment process, while the dummy variable accounts for temporary structural disturbances. Enders (2015) similarly notes that intervention dummies may be included to capture extraordinary events and improve model specification, even when they are not individually significant.

Using this VECM model, we forecast India's seaborne cargo volume through 2050.

Diagnostic Tests

Several diagnostic tests were conducted to assess the reliability and validity of the model results, including checks for serial correlation using the Lagrange multiplier (LM) test, normality using the Jarque-Bera test, and model stability through the eigenvalue stability condition.

Lagrange Multiplier for Autocorrelation Test

The Lagrange multiplier (LM) test was applied to determine whether the residuals of the specified model exhibit autocorrelation. The hypotheses for the test are as follows:

a) Null hypothesis (H_0): No first-order autocorrelation exists.
b) Alternative hypothesis (H_1): First-order autocorrelation exists.

Table A5. Lagrange multiplier test.

lag	chi2	df	Prob> chi2
1	14.6408	16	0.55109
2	14.4125	16	0.56801
	H0: no autocorrelation at lag order		

As shown in Table A5, the results indicate that the null hypothesis cannot be rejected at the 5% significance level, suggesting no evidence of autocorrelation in the residuals. Consequently, this finding supports the correct specification of the model.

Normality Test

The multivariate Jarque-Bera test was employed to assess the normality of the residuals by comparing their skewness and kurtosis coefficients with those of a normal distribution. The null hypothesis assumes that the error terms have skewness and kurtosis consistent with a normal distribution. As shown in Table A6, the results indicate that the null hypothesis of multivariate normality cannot be rejected, suggesting that the residuals are normally distributed.

Table A6. Jarque-Bera test: Normality test.

Equation	chi2	df	Prob > chi2
D_ln_mt	1.483	2	0.4764
D_ln_gdpcap	0.478	2	0.78731
D_ln_gdp_top7	2.879	2	0.23699
D_dum	30.743	2	0.00000
ALL	35.584	8	0.00002

Model Stability Test

The stability of the VECM is assessed to ensure the stationarity of the cointegrating relationships and the correct specification of the cointegration rank. The study applies the eigenvalue stability test to the VECM.

According to the decision criteria, the model is considered stable if the number of unit moduli equals the number of endogenous variables, which corresponds to the number of cointegrating vectors, meaning that all eigenvalues lie within the unit circle.

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About the Project

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